Land Use, Soil Degradation and Soil Conservation in the Loess Hills of Central Tajikistan

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Bettina Wolfgramm

von Rubigen BE

Leiter der Arbeit:

Prof. Dr. Hans Hurni,

Dr. Hanspeter Liniger

Centre for Development and Environment (CDE)

Geographisches Institut, Universität Bern, Bern

Summary

Since Tajikistan's independence in 1991, the hill zone of central Tajikistan has undergone considerable land use change. The challenges of poverty and food insecurity triggered by the transformation of the economy and by the civil war were met with widespread cultivation of steep slopes. The hill zone consists of loess deposits, which are susceptible to water erosion. Today land degradation is widespread and severe, and only few areas appear to have developed well adapted field management systems successfully sustaining the land's productivity.

The overall objective of this study was to attain an improved understanding of the link between land cover / land use and soil resources, which will allow the identification of opportunities for sustainable land management in the loess hills of central Tajikistan. A specific focus was placed on the exploration of how GIS and remote sensing in conjunction with soil near-infrared spectroscopy may contribute to planning and assessment of sustainable land management. The key question addressed in this thesis was whether it was possible to determine land cover classes which would characterise the impact of land use on soil resources in such a way as to highlight typical interrelations between erosion, as the dominant soil degradation process, and soil organic carbon (SOC), as an integrative soil quality measure.

A data-driven, scientifically rigorous approach was adopted. A spatially explicit assessment was used, based on a systematic, clustered random sampling design. The sampling design complied with the assumption of randomized sampling and provided a dataset suitable for assessing spatial characteristics. Furthermore, it allowed efficient sampling of the variation of vegetation and soil within the study area. For prediction of soil properties on a large sample set, a soil spectral library based on diffuse infrared reflectance was used.

Input data consisted of Landsat 7 imagery from two different seasons, a digital elevation model and extensive groundtruthing. Additionally, black-and-white Corona images from 1970 were acquired for change detection. Field observations were collected from 600 sampling sites and included indicators on land cover / land use, soil degradation and soil conservation measures. Furthermore, on every sampling site, soil samples were collected and subsequently soil spectral reflectance was measured under standardized conditions in the laboratory. Sheet and rill erosion (affected site or non-affected site) and soil organic carbon were selected as indicators of different degrees of soil degradation and soil conservation. The high silt fraction is characteristic for loessial soils, and in the absence of sufficient clay, SOC is crucial for aggregate stability and soil nutrient cycling in these areas. To predict SOC contents on over 1500 soil samples reflectance readings were calibrated with results of SOC chemical analysis (N=254) using combined regression tree modelling. The resulting model statistics for soil degradation assessments are promising (R^2=0.71, RMSEV=0.32). Geological sub-groups did not influence model performance for the combined regression tree models established.

Classification tree modelling was applied to determine data-driven, statistically based decision trees for mapping of land cover types, soil erosion occurrence and SOC content classes ("low" and "high"). This study showed that in an area in which difficult terrain and small cultivated plots prevailed, a spatial assessment of the three indicators was possible, with overall accuracy for classification of land cover types = 51%, for major land cover types = 72%, for erosion occurrence = 73%, and for SOC content classes = 75%. Decision trees established were not merely empirical constructs, but were interpretable in terms of physical processes. This

increased confidence in the models. More importantly empirically based rules and thresholds were determined, useful for gaining a better understanding of generally relevant controls of land degradation and conservation processes.

Critical indications with regard to land use dynamics were provided by a visual comparison between groundtruth data from 2004/2005 and Corona images from 1970. No expansion of cropland to virgin grazing land during the 1990s was observed. In fact, present-day cropland sites were almost identical with cropland sites in 1970. A historical reconstruction of changes in the agricultural system, direct and indirect drivers of change and human well-being was conducted using the conceptual framework of the Millennium Ecosystem Assessment, and provided qualitative explanations for these land use dynamics. The main conclusion was that annual cropping on the slopes in the loess hills appears to have been an emergency measure, in the 1990s and likely also in Soviet times, in response to food shortage.

The soil occurrence and SOC content class maps elaborated were overlaid and interpreted according to the rules of a hot/bright spot matrix; this matrix was developed for application in loess areas, where land use strongly determines erosion and SOC content. The quarters of this hot/bright spot matrix may be interpreted as different stages of degradation, from well conserved land (bright spots) to hot spots of soil degradation. The analysis showed that large areas were affected by erosion, with 21% of the study area being classified as hot spots and 24% as degrading areas. Areas with well conserved soil resources accounted for 33% of the study area.

Finally, to address the hypothesis of this thesis, the land cover classes derived from classification tree modelling were linked with the hot/bright spot matrix. The results showed that sub-classes of a specific land cover type (e.g. annual cropland) may differ greatly with regard to erosion occurrence and SOC content. The high within-class variability of SOC and erosion, however, did not allow determination of significant differences (in erosion or SOC contents for any of the land cover classes. Nevertheless, there were strong indications for interrelations between high perennial fractional vegetation cover, low erosion occurrence and high SOC content, and accordingly between low perennial fractional vegetation cover, high erosion occurrence and low SOC content. This pattern did not apply to perennial land cover classes on slopes < 14% and mountainous locations, where other degradation processes or inherently low SOC content were expected. Markedly lower SOC content levels were observed for areas with temporary crop cultivation, where cultivation was widespread during the 1990s and has now frequently been abandoned again. On the other hand, there were strong indications for afforestation and fruit orchards established in the 1980s being successful in conserving soil resources, also when transformed into intercropping systems. The sites with well conserved soil resources could be classified into the following land use systems: fruit, cereal and fodder plots, either traditionally cultivated or newly established during the 1980s; large area conservation systems implemented in Soviet times and diversified into agroforestry systems during the 1990s; and more recently, mainly agronomic conservation measures on cropland.

The maps elaborated for erosion occurrence and SOC content classes “low” and “high” provide a baseline that enables future evaluation of the land conservation efforts currently being undertaken in the loess hills of central Tajikistan. Further, the hot/bright spot map is expected to be a valuable basis for planning of sustainable land management. The soil spectral library elaborated, allows SOC content prediction for soil samples from the loess hills in a rapid manner and at low cost.

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Abbreviations

asl	above sea level
CART	Classification and regression tree modelling
DEM	Digital elevation model
DPSIR	Drivers, Pressures, State, Impact and Response indicator framework
ETM	Enhanced thematic mapper (Landsat ETM+)
FA	Faizabad test area
FVC	Fractional vegetation cover
GEF	Global Environment Facility
GIS	Geographic Information System
GPS	Global Positioning System
IQR	Interquartile range (range between the first and third quartiles)
MA	Millennium Ecosystems Assessment
N	Number of samples
NCCR	National Centre of Competence in Research
NDVI	Normalised Difference Vegetation Index
OSAVI	Optimised soil adjusted vegetation index
Pc	Soil sealing and crusting (WOCAT classification)
Pk	Soil compaction (WOCAT classification)
PSR	Pressure-state-response
QB	Quickbird
RS	Remote sensing
rs	Spearman rank correlation coefficient
(R)USLE	(Revised) Universal Soil Loss Equation
SLM	Sustainable land management
SRTM	Shuttle Radar Topography Mission
SWC	Soil and water conservation
UTM	Universal Transverse Mercator coordination system
VNIR	Visible and near infrared
VZ	Varzob test area
WGS	World Geodetic System
WOCAT	World Overview of Conservation Approaches and Technologies
Wt	Soil erosion by water (WOCAT classification)

Land cover types:

Ca	Annual cropland
Cp	Perennial cropland
T	Tree and shrub cover
G	Grazing land
Os	Settlement
Oa	Aquatic area

Statistical parameters and model abbreviations (chapter 3):

CART	Classification and regression tree
CRT	Combined regression tree
CV	Coefficient of variation
MAPE	Mean absolute percentage error
MLR	Multiple linear regression
MSC	Multiplicative scatter correction
PC	Principal component
PCA	Principal component analysis
RMSE	Root mean square error
RMSEC	RMSE of calibration
RMSEV	RMSE of validation
RMSPE	Root mean square percentage error
RPD	Ratio of standard deviation of prediction
SEL	Standard error of laboratory measurement
SEP	Standard error of prediction

Soil properties:

Ca	Calcium
CaCO3	Calcium carbonate
K	Potassium
Mg	Magnesium
OM	Organic matter
P	Phosphorus
SIC	Soil inorganic carbon
SOC	Soil organic carbon
TC	Total carbon
TN	Total nitrogen

1 Introduction

1.1 Background and problem statement

Since Tajikistan became independent in 1991, the hill zone of central Tajikistan has undergone considerable land use change and shows widespread and severe land degradation. Only in a small number of areas do well adapted field management systems appear to have developed, sustaining the land's productivity. Taking into account the overall population growth, the increasing percentage of the rural population, widespread poverty triggered by the civil war during the 1990s and the impact of transition from a planned to a market economy, sustainable land management (SLM) is a key issue for western Tajikistan.

1.1.1 Land resources of central Tajikistan

There are three main land use systems in central Tajikistan, each determined by a specific landform: the valley floors, the hill zone, and the mountainous areas (Figure 1-1). The flat valley floors have been developed for irrigated agriculture. In these areas mainly cotton is cultivated, the major cash crop in Tajikistan during Soviet times and still today (ICG 2003). In the mountainous areas, characterised by steep slopes and shallow soils, grazing lands prevail. Such areas can be found in the East-West running Hissar mountain range, which divides the central part of Tajikistan from northern Tajikistan. At the foot of the Hissar, the hill zones are situated. These foothills consist of loess deposits. Soils which have formed on these loess deposits are defined as brown carbonate soils according to the local Tajik definition system (Kuteminskij & Leonteva 1966). Towards the higher mountain ranges, the loess deposits diminish, and soils dominated by granodiorite mother rock prevail, referred to as brown typical mountainous soils (Leonteva et al. 1968). Soils which have developed on loess deposits are well known to be highly erodible, due to the silty texture resulting in little aggregation. Water erosion is therefore considered the dominant soil degradation process in these areas, especially on steep slopes (Safarov & Novikov 2000). Thus, in Soviet times land use in the hill zone was generally restricted to tree and shrub cropping as well as grazing. In selected areas, however, rainfed cereal cropping took place as well.

The hill zone of central Tajikistan is here referred to as a region, since it is characterised by ecological conditions (the rainfed areas situated mainly on loess deposits) and spreads over various administrative districts (touching, from West to East, the districts of Varzob, Rudaki, Vahdat and Faizabad, and Yavan in the South).

The climate in the hill zone of central Tajikistan is dry subhumid throughout the year according to Thornthwaite (1948), and continental. Total rainfall in the loess hills is 600 to 900 mm per year, with the higher rainfall amounts observed in the Faizabad area and the lower amounts in the Yavan area. Rainfall distribution over the year is similar for all of central Tajikistan and rainfall is concentrated in the period from November to April. Highest rainfall amounts are observed during March, April and May, with highest rainfall intensities expected in May, when storm rainfalls are common. The time from June to October is the dry season.

Figure 1-1 shows a Landsat ETM+ satellite image, recorded in the middle of the dry season, on 22 August 2000. The irrigated areas are easily distinguished as the large green areas. Perennial crops can be identified as small patches in the hill zone. Generally, after the end of June there is very little green vegetation, and the yellow soil that developed on the loess deposits is clearly visible from space.

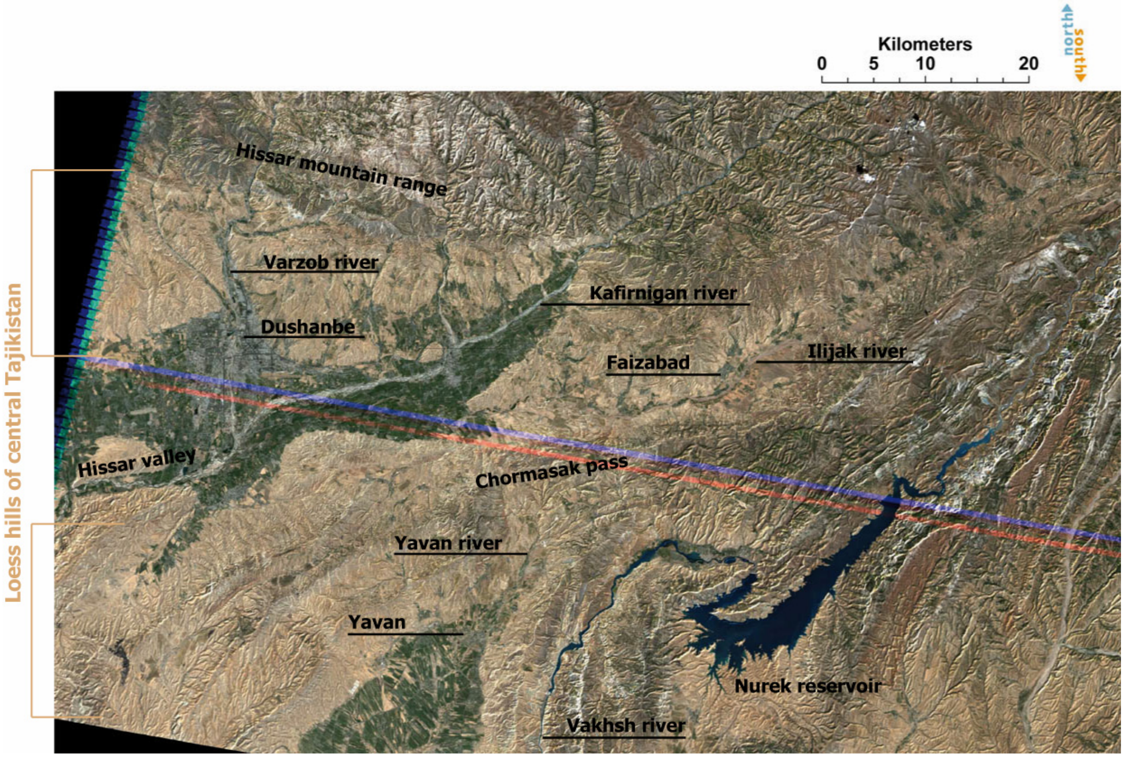

Figure 1-1 Central Tajikistan with the Hissar mountain range, the loess hills and the irrigated lowlands (Landsat ETM+, recorded on 22 August 2000, bands 3, 2, 1, with line dropouts)

1.1.2 Economic transition and civil war triggering rapid land use change

In Tajikistan, political transformations and the resultant economic changes have determined the major land use changes from the 1920s until the late 1990s. A study carried out in the Surkhob valley, in the East of central Tajikistan (Merzliakova & Sorokine 2001), can be considered exemplary in highlighting the changes in the hill zone. These primarily included change from subsidiary and traditional agriculture undertaken by private farmers to the planned economy conducted by collective and state farms from 1927 onwards. This change was further supported by resettlements from the hill zone to the southern cotton-growing areas in the late 1940s. Traditional agriculture consisted of a mixed land use system including cereal cultivation and grazing lands. After the 1940s, land use was dominated by grazing and fruit cultivation.

Upon Tajikistan's independence in 1991, land reform efforts were initiated with the aim to privatize land use rights. Privatized agricultural production was further promoted, to combat the severe food shortages during the civil war that had started in 1993 due to a power struggle between the leaders of the communist era and an opposition consisting of islamists and democrats, and that lasted until 1997. The conflict left 60,000 to 100,000 persons dead and another 600,000 to 1,000,000 internally displaced (ICG 2003). Two presidential decrees were enacted, allocating land of the collective and state farms, formerly used as grazing land, to rural families (Porteous 2003). Rural households now started to cultivate plots on the slopes of the loess hills for wheat production. By 1995, private farmers had several types of access to land, ranging from land lease to fixed-term land use rights and life-long inheritable user rights

(Giovarelli 2004). The land use changes in the Tajik foothills were apparent and widely discussed. There were two main perceptions:

(1) Crop cultivation had been expanded to marginal areas which were not suited for cultivation (e.g. Safarov & Novikov 2000, Babu & Reidhead 2000); and

(2) Especially in these newly cultivated areas, land management was not appropriate and thus led to increased soil degradation (e.g. Sadikov 1999, Safarov & Novikov 2000).

By the year 2000, "most of the rural population was engaged in agriculture – even doctors and teachers, who were often not paid their meagre salaries, received their primary income from subsistence agriculture" (World Bank 2000). Food security, however, was low. This became apparent during the drought in 2000 and 2001, which exacerbated food shortage so that over one million people received emergency food assistance in 2002 (ICG 2003). According to the government programme, the land reform was planned to be completed by 2005. However, it lagged behind in many districts (ADB 2001, Tajik Land Committee 2004) and, moreover, the new land distribution had led to unequal access to land, with socially and politically well established persons (former heads of state farms and local government officials) taking over large areas with fertile land, leaving field plots on steep hills to the others (Duncan 2000, ICG 2003, Nissen 2004). While production on these plots provided subsistence for rural families (Duncan 2000, World Bank 2000), they could hardly make a living from farming. As a coping strategy, many households opted to send their young men to Russia to take seasonal jobs (ADB 2001). In the early 2000s, remittances[1] contributed significantly to household income in many families (WFP 2005). Therefore, cultivation of rainfed plots was partly abandoned, as remittances began to replace agricultural income, while previously cultivated land is now left fallow (Hostettler 2006, Jokisch 2002). This tendency was also supported by local administrations as a strategy to stop land degradation by erosion in the hill zone: "*Until 1992 the slopes were only used as grazing land. In 1992 the President gave the farmers permission to use this land for crop production. Today the aim is to stop the crop production on the slopes. When problems with siltation of irrigation channels became severe, the decision was taken to stop the cultivation on the slopes. 30% of the land under annual crops has already been reverted to grazing land*" (personal communication, 2004, land planning office of Osodin, Yavan district).

1.2 Land use – pressure and potential

All over the world, humans have radically transformed land cover by intensive land use and land use changes (Turner et al. 1990). There has been a sharp increase in agricultural productivity over the last few decades, but in many places this is only possible by (over)exploiting the natural resources (Richards 1990). Inappropriate land use is understood to be a direct cause of degradation of natural resources. Unsustainable use of land resources is widespread and resources are at risk worldwide (Oldeman et al. 1991). Especially erosion processes, causing rapid degradation of resources, are a threat to the soil functional capacities (Toy et al. 2002). Driving forces of land degradation processes range from socio-economic to political and cultural factors, and as such are indirect causes of land degradation (Eswaran et al. 2001). Despite this generally negative trend, *"there are many winners in the struggle*

[1] Remittances are transfers of assets by members of immigrant communities or foreign nationals from the country where they live and work back to relatives or other individuals in their country of origin (Hostettler 2007).

against degradation"; conservation measures have successfully been applied for cropland as well as for grazing land, including high- and low-cost measures (Liniger & Critchley 2007). There are great differences in the abilities of countries to cope with the problems of land degradation (Hurni et al. 1998). Especially for countries in which a large part of the population is dependent on subsistence farming, it is crucial to minimise pressure on resources and to maximise the potential of SLM. In these countries, a sustainable way to use the land will not only provide food security but also job opportunities, thereby increasing self-dependency for rural areas.

1.2.1 Pressure on natural resources – vicious circles

Land use changes and land resource degradation are processes that often reinforce each other: while intensified land use and/or expansion of cultivated areas often leads to depletion of soil resources, the degraded state of resources in turn leads to expansion of cultivated areas. Therefore, the response to degradation of natural resources may be the cause of even more degradation, whether by increasing degradation in a specific place or by expanding the area under pressure. Thus, land resource degradation often constitutes part of a vicious circle. Furthermore, expanding cultivated areas and depleted soil resources are in many places interlinked with a growing and pauperised rural population. As the revenues from farming of small plots often situated in marginal areas do not allow for any investments into conservation measures, the result is often increased degradation and reduced yields. Farmers working such plots find themselves in a poverty trap (MA 2005). Self-accelerating processes may also be observed within the soil. Such a process can be described in a simplified way by the following selectively chosen interactions: When water erosion processes remove the topsoil, it is the part of the soil with the highest amount of soil organic matter, which is lost. Organic matter influences a number of soil characteristics and functions, among them aggregate stability and thus water infiltration characteristics, as well as moisture storage capacity and nutrient balance. In this way, soil erosion leads to soil depletion, which again increases the erodibility of the soil, e.g. by changes in aggregate stability. A "downward spiral of soil degradation" (Ditzler 2002) is set in motion. [2]Thus, the key processes exerting pressure on natural resources are often vicious circles. In order to ensure efficient mitigation of degradation processes, early identification of areas in which natural resources are at risk or already under pressure, is crucial.

1.2.2 Soil resources affected by land use and land use change

The health of soil is the foundation of sustainable land management (Hurni et al. 2006). Healthy soil forms the basis to sustain plant and animal productivity, to maintain or enhance water and air quality, and to support human health and habitation. The capacity of a specific kind of soil to provide these services within a natural or managed ecosystem has been defined as the soil quality concept (Soil Quality Institute, internet source[3]). Soil dynamics, soil formation and therefore soil restoration are slow, indeed much slower than land use dynamics. Soil quality is therefore determined not only by the current land use, but also by the history of land use and the according impact on the soil. Therefore, an assessment of soil quality, and more generally of SLM, requires not only looking at the current land use system, but has to include land use dynamics (history and trends). With rapid land use change taking place, it is assumed that land use change is the dominating factor determining soil functions. Thus, soil

[2] A more extensive discussion on soil degradation processes in provided in section 4.4.1.

[3] http://soils.usda.gov/sqi/

conservation is of central importance, and constitutes a critical factor for sustainable land management.

1.2.3 Locally applied conservation measures

Pressure on natural resources and the resulting state of resources trigger not only intensified and extended unsustainable use of resources, but also (local) responses of adopting and implementing measures to conserve the resources (Hurni et al. 1999). All over the world, there are many examples of successfully implemented conservation measures (Liniger & Critcheley 2007). In order to further spread conservation measures, it is important to learn from these successes. As each situation is unique, conservation measures need to be adapted and optimised to the particularities of the respective environment as well as the socio-economic conditions (Herweg & Ludi 1999). This requires a good understanding of the interlinkages between land use and the natural resources (Liniger et al. 2002a), including underlying driving forces. Thus, examples of locally applied conservation measures are an excellent source of knowledge, in order to enhance understanding about prevalent degradation processes in specific circumstances. They allow an estimation of the potential of an area in its specific environmental conditions, provide insights that make it possible to learn in detail as to how to implement and maintain specific conservation systems, and facilitate an evaluation of sustainable land management (Liniger & Critcheley 2007).

1.3 Assessments contributing to SLM – state of the art

Systematic and spatially explicit assessments of soil resources are needed to support decisions in planning and propagating of sustainable land management (SLM). In this section, a brief introduction is provided of such assessments contributing to SLM, focusing especially on approaches using geographic information systems (GIS) and remote sensing (RS). Assessments with regard to specific topics will be examined in more detail in the main chapters (chapters 2, 3, 4 and 5).

1.3.1 Important aspects when assessing SLM

GIS and RS assessments contributing to SLM are generally focused on biophysical processes. These encompass, on the one hand, land cover / land use and land use change studies (e.g. Verburg & Veldkamp 2005, Lambin & Geist 2006), and on the other hand, land degradation assessments (e.g. Young 1998, LADA 2002, Röder & Hill 2006), including many erosion assessments (cf. chapter 4). A topic that has more recently emerged is digital soil mapping with a focus on mapping of soil types, specific soil properties, or soil functional attributes (e.g. McBratney et al. 2003, Scull et al. 2003, Lagacherie et al. 2007). With soils being a core subject of SLM, digital soil mapping has high potential for contributing to SLM (cf. chapter 4).

In order to provide data useful for implementation of conservation measures, the integrative character of sustainable land management must be taken into account. It is necessary to link the results of land degradation assessments with the underlying socio-economic forces to put them into a wider perspective. Conceptual frameworks are available, which help to characterize processes leading to land degradation or conservation (e.g. Smyth & Dumanski 1993, European Comission 1999, MA 2003).

Assessments as pointed out above, allow to build up knowledge, which is needed for decision support. However, when assessing SLM it should be considered that at the basis of SLM, there is the concept of sustainability, which is a normative concept. Thus, the definition of sustainability in a specific situation has to be negotiated by society (Wiesmann 1998). Furthermore, integration of multi-actor perspectives are central, as decisions on land use are influenced by stakeholders at different levels (Hurni 2000, Herweg & Steiner 2002). Thus, contributions by GIS and RS must be seen in providing a basis for participatory assessing and planning of sustainable land management (Hurni 1997).

1.3.2 Land degradation assessments

The UNCCD defines land degradation as a natural process or a human activity that causes the land no longer to be able properly to sustain its economic functions or its original ecological functions (FAO 1998). The aim of land degradation assessments is to determine both status and trends of land degradation. Trend analysis will include prediction where land degradation is likely to occur and the risk of this happening (Evans 2002). Assessments include judgment, evaluation and/or comparison, and thus require a baseline or a set of reference data (Ponce-Hernandez & Koohafkan 2004). Such comparison may be conducted between two points in time, or between two land use systems (or ecosystems) in comparable situations, both assessed at the same time. As discussed in previous sections, soils are pivotal with regard to land degradation assessments and thus, investigating soil degradation often forms the starting point of such assessments. Land cover and land use as controlling (or causative) factors of soil formation and degradation, are generally included in soil degradation assessments (Oldeman et al. 1991, FAO 1995, Jones et al. 2005).

The main initiatives to provide globally consistent information on land and soil degradation include the Global Assessment of Soil Degradation (GLASOD) and the SOil and TERrain Digital Database (SOTER 1995, Dobos et al. 2005). The latest effort to facilitate effective land degradation assessments is the Land Degradation Assessment in Drylands (LADA) (LADA 2002). While GLASOD is based on expert assessments, and resulted in a world map of the status of human-induced soil degradation at a scale of 1:10,000,000 (Oldeman et al. 1991), SOTER aims at establishing a global soil database at the scale of 1:1,500,000 and will be based on existing (national) soil databases. The LADA programme has compiled a range of methods facilitating land degradation assessments and has defined a 7-step work procedure (Ponce-Hernandez & Koohafkan 2004). Besides these global initiatives, many local and regional land degradation assessments have been conducted, including many assessments of degradation by erosion, since erosion is globally considered to be one of the most important land degradation processes (e.g. Röder & Hill 2006).

There are two main objectives in conducting a land degradation assessment: first, to produce spatially explicit information, and second, to improve the understanding of degradation processes so as to enable trend prediction. While the first facilitates determination of the extent of land degradation, and thus allows actions to be prioritized, the second aims at deriving cause/effect relationships, which make it possible to predict ecosystem responses and to distinguish controlling factors and risk variables in a spatially explicit manner. With regard to work procedures applied, the first steps are similar for both types of assessments, as both seek to elaborate a spatially explicit information base. The most important steps are: selection of input variables, data integration technique and validation (Vrieling 2006). Deriving information on cause and effect requires additional analysis using either empirical or physical approaches.

Remote sensing data and scale

Satellite imagery is a readily available source of spatially explicit data, representing the state of land cover (land cover as seen from space, including e.g. settlements, bare soil and rocks) and has been widely applied in land use change studies (Rogan & Chen 2004) and erosion assessments (Vrieling 2006). It allows not only extrapolation of point observations, but may be mined for additional consistent information on large areas, which is difficult to obtain by field surveys only. There is a tendency for researchers in the field to recognise what they already know, whereas remote sensing furnishes new information that enhances knowledge of the environment, provided researchers are able to extract and gather such information (Gomer & Vogt 2000). Thus, satellite imagery taps new sources for mining data on natural resources.

In order to provide decision support with regard to planning of SLM and for project implementation, assessments at district or provincial levels are required. Despite the technological advances in satellite sensors, availability of high-quality spatial data is often poor at this scale. However, readily available medium-resolution satellite imagery still has the potential to represent spatial patterns of erosion risks (e.g. Landsat ETM+ with a resolution of 30 m) (Vrieling et al. 2006), which is useful for reconnaissance or semi-detail[4] studies. Burrough (1997) stressed that it is identified physical and economic processes influencing SLM that should determine the scale at which data are needed. However, as the choice of images is limited, there is a risk that satellite imagery will determine the scale of a study. Furthermore, it is often a specific challenge to define the appropriate level of an assessment that will be suitable both for the process studies and the available data and e.g. to determine a land cover classification system (Cingolani et al. 2004). Especially with regard to erosion models, it has often been criticized that models are applied even if not appropriate for the specific level of an assessment (Morgan 1995, Cohen 2003, Cohen et al. 2005, Vrieling 2007).

Data integration

Various data integration techniques are used: Univariate and multivariate correlations and regressions have come to represent a dominant factor influencing other factors in the system. More complex models also integrate feedback mechanisms, e.g. integrated assessment models (Mulligan 2006).

A straightforward approach for integration of expert knowledge is provided by rule-based models, and especially decision trees. Such systems provide the opportunity to determine the hierarchical levels at which a specific factor is influential. As Jones et al. (2005) stated, rule-based systems are closely linked to field procedures, where e.g. soil types are distinguished using hierarchical systems. Decision trees are widely used for classification of raster data, especially in land degradation assessments (cf. chapter 4). Further, they have been used for soil mapping (Daroussin & King 1996, Jones et al. 2005) and have been proposed as promising tools to support spatially explicit assessments contributing to SLM (Skidmore et al. 1996).

Lately, rule-based classification – based on machine-learning algorithms – have been applied in land cover / land use studies (cf. chapter 2) as well as for digital soil mapping (cf. chapter 4). Besides providing a non-parametric method for classification and regression, such methods facilitate statistically based determination of the hierarchical structure of controlling factors, and of suitable thresholds. Hence, they are efficient data mining tools (Aksoy et al. 2004).

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[4] Commonly applied levels of assessments as defined by FAO (1976): Reconnaissance (broad inventory), semi-detailed (decision support for project implementation) and detailed (decision support accompanying a project, farm level advice) (FAO 1976).

Assessing cause/effect and risk factors

Cause/effect studies aiming at explaining soil variability pose serious challenges: First of all, variability of soil properties is high, even in the case of similar land management and also within fields (Nael et al. 2004, Jones et al. 2005). Furthermore, as many ecological variables are interlinked, identification and quantification of controls is difficult. Finally, changes in soil properties are often slow and small, making high demands on measurement methods.

To simplify the task, plot experiments are designed to minimize the impact of spatial or temporal heterogeneity in field soils, thereby enhancing the efficiency of statistical analysis (Nielsen & Wendroth 2003). In other fields of science, often case studies are conducted, as they allow collection of more detailed information and for better control of variables. A major drawback of plot experiments and case studies is, however, that rules derived in this way may not be generally applicable. Or, as Heinimann (2006) put it, "any approach based on case studies is a dead end when it comes to generalization". Especially erosion research has long been focused on results from runoff plots. It has also been recognised, though, that to indicate erosion rates and to reveal the relevance of erosion at a regional scale, field studies are necessary (Evans 2002).

Therefore, regional land degradation assessments are today's preferred option. Shepherd and Walsh (2007) have proposed an evidence-based diagnostic surveillance approach to provide scientifically well-founded decision support. According to them, important first steps include the general problem definition and subsequently the formulation of a case definition regarding the level of e.g. soil resource degradation that is acceptable or not acceptable. This then allows classification of areas into degradation affected and non-affected areas. Subsequently, for efficiently distinguishing between affected and non-affected areas, screening tests need to be established. Additionally, in order to facilitate a spatially explicit approach to land degradation risk analysis, designs for efficient randomized sampling are required (Shepherd & Walsh 2002, 2007). Randomly collected samples provide the basis for the determination of prevalence (number of cases per area) and incidence (number of cases per area and time) of e.g. soil degradation affected sites. If environmental and/or socio-economic factors which control the degradation processes, are measured in conjunction, the statistically-based identification of risk factors will be possible. Such generally applicable information is expected to provide reliable information needed for early detection and as a prerequisite for planning prevention and rehabilitation. Shepherd and Walsh (2007) stress the crucial role that infrared spectroscopy[5] plays in such approaches. As a cost-effective, rapid and highly reproducible analytical technique, infrared spectroscopy is well suited to conduct the above-mentioned screening tests (Shepherd & Walsh 2007). Soil reflectance spectroscopy has been successfully applied in a number of studies to predict a range of soil properties (cf. chapter 3) as well as soil fertility indices (Vagen et al. 2006), soil erosion (Cohen et al. 2005), or as an indicator of ecological condition (Cohen et al. 2006). Furthermore, as this method enables rapid assessment of soil at a low cost, and thus allows prediction of important soil quality indicators for a large number of sampling sites, it facilitates extrapolation to larger areas in a spatially explicit manner using satellite imagery (Shepherd & Walsh 2007, cf. chapter 3 of this present study).

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[5] The aim of NIR-SWIR reflectance spectroscopy is to measure and interpret reflected radiation in the visible (0.4-0.7 µm), near infrared (0.7-1.4 µm) and short-wavelength infrared (1.4-3 µm) ranges of electromagnetic radiation.

1.3.3 A focus on soil conservation

The definition of soil conservation is closely related to the definition of land degradation. Soil conservation, in a broad sense, has been described as the "non-exploitive use and wise overall stewardship of natural resources" (Hurni 1996). However, only by focusing on soil conservation instead of soil degradation may opportunities for sustainable land management be identified. Conservation of soils has often been the objective of case studies and seldom been dealt with in assessments at a district, provincial or even national or regional scale. This can be attributed to the fact that conservation measures need to be well adapted to the specific situation. Nevertheless, these case studies are helpful by raising awareness of the fact that in order efficiently to plan sustainable land management, soil conservation must be seen as an opportunity and successes in land and soil conservation must be taken into account (Hurni 1996, Liniger & Critchley 2007). This adds a new perspective to the many assessments largely focused on land degradation.

With a view to obtaining a quality measure regarding the state of soil resources, the soil quality concept has been developed. The soil quality concept was defined as "the capacity of a specific kind of soil to function within natural or managed ecosystem boundaries to sustain plant and animal productivity, maintain or enhance water and air quality and support human health and habitation" (Karlen et al. 1997). However, this concept has been controversially debated among soil scientists (Letey et al. 2003). The opposing viewpoints have been attributed "to the complexity involved in integrating various soil properties into indices of soil quality and differential effects of soil management on different soil properties" (Vagen et al. 2006).

Approaches referring to soil quality need to clearly define the soil function(s) concerned. Erosion affects a range of soil functions. Erosion leads to the loss of organic matter and clay particles, resulting in reduced fertility, biological activity, aggregation and rooting depth (Ditzler 2002). Further, infiltration and water holding capacity of soils may be negatively affected (cf. chapter 4). By referring to soil quality, the effects of soil erosion on the soil resources on a specific field may be more adequately addressed than by referring to a specific characteristic (e.g. soil loss).

Various options to assess soil quality have been proposed, including large sets of soil chemical and physical indicators (Mausbach & Seybold 1998). As such approaches are restricted by the cost for soil analysis involved, Shepherd and Walsh (2002) proposed to develop integrative soil quality indicators based on soil spectral reflectance, and such indices have been successfully developed (Vagen et al. 2006, Cohen et al. 2006). A simpler and more frequently adopted approach is to use soil organic carbon (SOC) as an integrative indicator of soil quality. SOC supports key functions in maintaining the productive capacity of the world's agro-ecosystems (Smith & Parris 2002) and has thus been chosen as the main indicator in various land degradation assessments, especially in drylands (e.g. Palacios-Orueta & Ustin 1998, Hill & Schütt 2000, Sarah 2006). Also at the European level, an SOC map has been established, to provide decision support with regard to soil protection as well as to develop strategies for mitigation of global warming (Jones et al. 2005). Among other things, the European mapping experience, as well as a study conducted on loessial soils, has shown a strong relationship between land use and SOC content (Brejda et al. 2000, Jones et al. 2005).

1.3.4 Conceptual frameworks for assessing sustainability of land use

The need for integration of socio-economic and political perspectives into landscape analysis has long been recognized, but is still hampered by the distinct differences in the approaches of social and bio-physical science, respectively. However, “the contributions of social science might allow remote sensing experts to ‘see’ landscape features in the remotely sensed data not previously apparent” (Rindfuss & Stern 1998). Thus, taking steps towards widening the perspective to include socio-economic and political aspects supports GIS and RS-based approaches. This is especially relevant for studies contributing to SLM, as SLM is a multi-disciplinary activity including agricultural productivity, food security, resource protection, economic viability and social acceptability of land use options (Smyth & Dumanski 1993).

In order to take account of the integrative character of sustainable land management, frameworks are applied to identify core issues and meaningful indicator sets. Especially in Europe, the DPSIR (Drivers-Pressures-State-Impact-Response) concept is widely used (European Commission 1999). For the Millennium Ecosystem Assessment (MA), a conceptual framework was developed which includes the four components of human well-being, indirect and direct drivers, and ecosystem services (MA 2003).

In applications of the DPSIR framework, drivers are generally seen as underlying socio-economic and political factors. According to an example of application in agricultural systems (Smaling & Dixon 2006), land management is defined as the pressure component, e.g. nutrient stocks as the state, and nutrient flows as the impact component. In line with the DPSIR framework, the impact on nutrient flows (e.g. leading to soil degradation) directly triggers responses with regard to nutrient management. When comparing the DPSIR and the MA frameworks, drivers and pressures – or as they are referred to in the MA, indirect and direct drivers – are included in both. Instead of analysing the specific aspects of state and impact as in the DPSIR framework, however, the focus in the MA is on ecosystem services as they contribute to human well-being and poverty reduction. By introducing the human-well being component, the MA conceptual framework clearly differs from the DPSIR framework, which has been criticised as being behaviouristic (Hurni et al. 1999). The situation of humans with regard to their well-being will likely have a crucial influence on their decisions, e.g. vis-à-vis land degradation. Furthermore, there are links between human well-being and indirect drivers influencing strategies with regard to sustainable land management. For sound identification of opportunities for sustainable land management, considering the specific situations of humans will be crucial.

Thus, while the DPSIR framework, characterised by a mechanistic link between components, facilitates impact and risk analysis of indirect and direct drivers in a straightforward manner, the MA framework places its focus on the link between ecosystem services and human well-being, which is likely to constitute a decisive factor in planning for sustainable land management.

1.4 Goal, research approach and content of this thesis

1.4.1 Overall goal and key question

The **overall goal** of this study was to attain an improved understanding of the link between land use and soil resources, which will allow the identification of opportunities for sustainable land management in the loess hills of central Tajikistan. A specific focus was placed on the exploration of how GIS and remote sensing may contribute to sustainable land management. The specific objectives were:

- To provide spatially explicit information on the types, the extent and the dynamics of land cover / land use
- To predict soil organic carbon (SOC), as an integrative indicator of soil quality, from a soil spectral library
- To locate hot spots of soil degradation and bright spots of soil conservation in a spatially explicit manner using readily available datasets
- To reveal the links and dependencies between land cover / land use, land degradation, and soil conservation, in order to identify options for sustainable land management

The methodological aim was formulated as follows:

- To evaluate, adopt, adapt and develop methodologies for the assessment and analysis of land degradation and conservation, and the impact of land use on land resources.

The **key question** addressed in this thesis was whether it was possible to determine land cover classes which would characterise the impact of land use on soil resources in such a way as to highlight typical interrelations between erosion, as the dominant soil degradation process, and soil organic carbon (SOC), as an integrative soil quality measure.

1.4.2 Research approach

A spatially explicit approach to assessing land degradation and conservation was adopted, based on a systematic clustered random sampling design as proposed by Shepherd and Walsh (2002, 2007). The assessment was thematically structured and included the following components: land cover / land use, soil degradation and soil conservation (cf. Figure 1-2).

As described in the previous sections, links between land cover / land use and soil resources often lead to vicious circles. Detailed knowledge with regard to planning of interventions to prevent or stop severe degradation is thus critical. In the loess hills of Tajikistan, the direct driver of land degradation was assumed to be land use, triggering erosion by water, which in turn would adversely affect soil quality. As the rigorous determination of cause and effect is a challenging undertaking (see previous sections), the focus of this study was on exploring interrelations to elaborate valuable knowledge for future studies aiming at obtaining more detailed results.

When selecting data and indicators for this study, the aim was to use readily available data, easy to integrate with other data and applicable in future studies as well. Included in the study area were parts of the loess hills of central Tajikistan, including various districts; the study was thus considered to be at a provincial level. For this level, the Landsat ETM+ image was the only one available complying with the above criteria and was thus chosen, even though the resolution was rather low for accurate detection of small field plots in a highly dissected terrain, and even though the time lag of 2 to 5 years between the recording date of the images and the field survey was rather large (cf. chapter 2).

Rapid field observation, using a classification system widely used to document soil degradation types in connection with soil conservation technologies, was considered to be most easily applicable in an extensive land survey and to provide best possible comparability with case studies. In section 1.3.3, the application of SOC as a soil quality indicator in land degradation assessments has been discussed. With regard to the study presented here, the following two important points were additionally considered when selecting SOC as an indicator:

- SOC links up to soil chemical as well as to soil physical characteristics. But compared to physical soil characteristics, SOC is relatively easily determined in the laboratory. It allows efficient field work, as only soil samples have to be collected and no field experiments (e.g. infiltration measurements) have to be conducted.
- SOC links up to OM in a straightforward manner, which is important as OM has long been used in Tajik soil science, especially in erosion studies, and is also applied in case studies today. Thus SOC was also selected as an indicator that enables comparison with past and present measurements of soil properties.

With a view to making information from land degradation assessments available for planning of sustainable land management, importance was attached to assuring interchangeability with other datasets and thus to choosing suitable classification systems. The classification system provided by WOCAT (World Overview of Conservation Approaches and Technologies) has been established to support documentation of conservation measures worldwide. The WOCAT methodology is based on standard questionnaires for collecting information on conservation approaches and technologies (Liniger et al. 2002a, WOCAT 2003). Furthermore, the WOCAT system is hierarchical and thus also applicable to land degradation assessments at local, national or even regional levels.

Methods were selected which were considered suitable to provide scientifically valid and objective data, allow for data replication, identify key indicators of the causes of land degradation, and work in multi-level systems according to the criteria formulated by LADA (2001): On the one hand, this included soil reflectance spectroscopy for efficient, cheap and reproducible prediction of soil properties based on large numbers of soil samples. On the other hand, classification and regression tree modelling based on machine-learning algorithms was chosen as a powerful data-driven approach for data integration. Classification tree modelling was expected to be useful for achieving a number of goals: Classification tree modelling was expected to be useful for digital soil mapping of erosion occurrence as well as of SOC content classes. By setting the focus not only on soil degradation but also on well conserved soils, it was expected that crucial information for SLM planning would be obtained. As up-to-date data were rare in Tajikistan, a set of maps was to be produced which could also be used as a baseline for future monitoring activities.

For map information to be most useful for planning, it should provide a basis for prioritization of SLM activities. The hot/bright spot concept has been adopted for application within the LADA framework (Ponce-Hernandez & Koohafkan 2004). The combined use of erosion occurrence, representing a degradation process, and SOC content, representing the state of soil resources, was considered promising in order to define hot spots of soil degradation and bright spots of soil conservation.

Apart from the collection and integration of biophysical data, the aim was also to document socio-economic and political factors which influenced land degradation and conservation processes. The conceptual framework of the Millennium Ecosystem Assessment was applied to provide a historic reconstruction of the links between the agro-ecosystem in the loess hills, the human-well being of the rural population and the indirect and direct drivers of changes in land use.

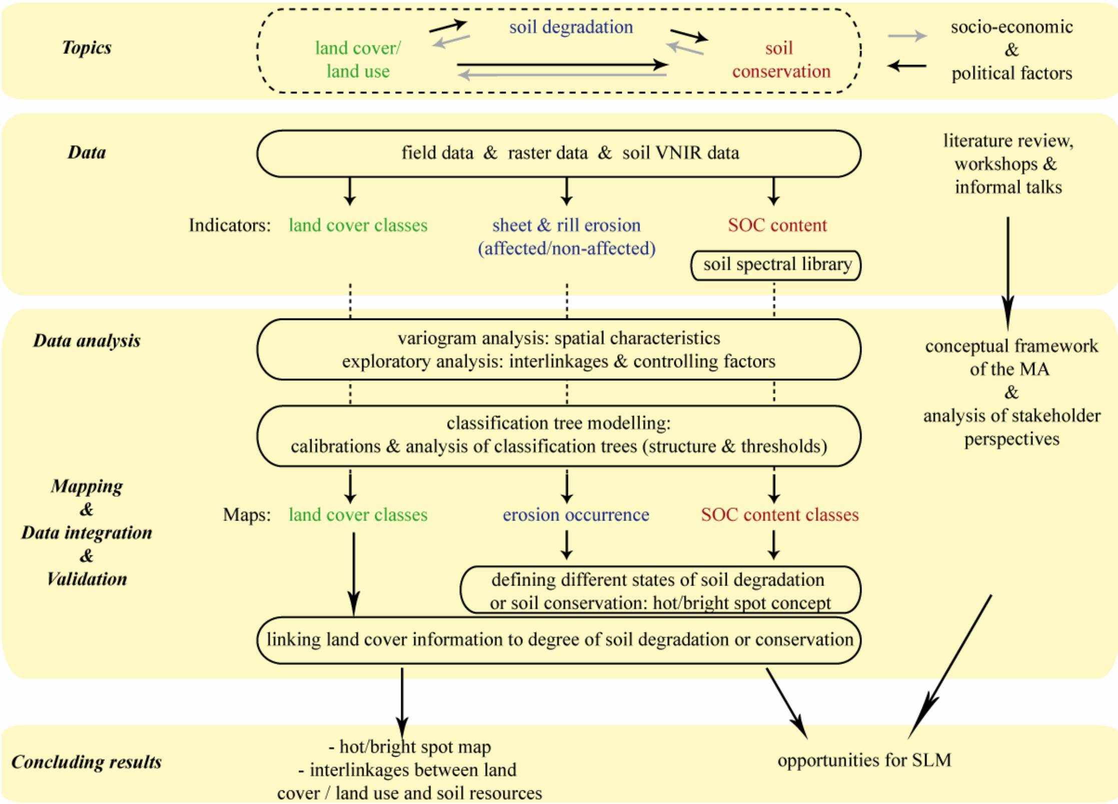

Figure 1-2 Research approach

1.4.3 Study outline

This thesis is organised thematically. The major chapters 2, 3, 4 and 5 are organised as self-contained chapters, each including the sections *Introduction, Materials and Methods, Results and Discussion* and *Conclusions*.

In chapter 2, the topic of land cover and land use is examined. An overview of the types, the extent and the dynamics of land cover and land use is provided on the basis of extensive groundtruth data and readily available raster datasets (satellite imagery and a digital terrain model).

Chapter 3 presents the establishment of a soil spectral library for the determination of soil organic carbon content. Soil organic carbon is an important soil quality indicator, as it influences various soil functions such as soil nutrient exchange, soil structure, and soil moisture capacity. Soil spectral reflectance data from the visible and near infrared (VNIR) range were used for prediction of soil organic carbon content. A soil spectral library was developed for the highly variable soils in the hill zone of central Tajikistan using combined regression tree modelling.

Chapter 4 addresses the detection of different states of soil degradation and conservation in a spatially explicit manner. In a first part, it includes an exploratory analysis of field survey data, which focuses on interrelations between various soil degradation types and soil organic carbon as well as topographic influences on soil erosion and soil organic carbon. Subsequently, the extrapolation of information on soil erosion and soil quality to the whole study area is discussed. Finally a straightforward approach, the hot/bright spot matrix, is presented. By linking soil erosion and soil organic carbon, the following four states are distinguished: hot spots of soil degradation, degrading areas, stable areas and bright spots of soil conservation.

Chapter 5 is arranged in three parts: First, pressures and potential of existing land cover / land use are explored with regard to soil resources. Second, a wider perspective on soil resource management is presented, by a descriptive review of human well being and indirect and direct drivers leading to soil degradation or soil conservation. Third, opportunities for sustainable land management for the loess hills of central Tajikistan are presented.

The final chapter (chapter 6) summarises the major findings of this thesis, and gives general directions and recommendations for future work.

1.4.4 The institutional framework

This research project was conducted under the umbrella of the National Centre of Competence in Research (NCCR) North-South[6], as one of the activities of the Joint Area of Case Studies (JACS) Central Asia. The NCCR North-South research programme is funded by the Swiss National Science Foundation, the Swiss Agency of Development and Cooperation, and the participating institutions. The research for this study was first conducted as part of the Individual Project 2 (IP2). Since the beginning of the second phase of the NCCR North-South in 2005, it formed part of the Work Page 4 (WP4). The main issue to be addressed by the IP2 was unsustainable use of natural resources and how to restore and maintain the various functions attributed to natural resources. In the JACS Central Asia, the main syndrome contexts[7] were identified to be the mountain areas, the intermediate settings located along foothills, and in the lowlands, and the semi-arid areas. Soil degradation was determined as the most important core problem (Keshikbaev et al. 2004).

Within the NCCR North-South project, there was close collaboration between this study and other PhD and MSc studies that were all carried out in the loess hills of central Tajikistan. The NCCR North-South PhD study carried out by Gulniso Nekushoeva focuses on the analysis of case studies in which land conservation has successfully been established. The two studies complemented one another during different phases of the studies, primarily so during the preparatory phase, during data collection, and during field research. Four MSc research projects which were connected to this PhD work, were carried out during 2004-2006. The diploma thesis by Anke Winnig (University of Bonn) analysed socio-economic factors for land

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[6] www.north-south.unibe.ch

[7] Syndromes of global change are problems of non-sustainable development that are closely interrelated and appear in specific combinations in different regions of the world. As the syndromes of global change are specific to concrete situations, circumstances or regions, one can also speak of so-called syndrome contexts (Hurni et al. 2004)

use changes (Winnig 2005). Erik Bühlmann (Centre of Development and Environment, University of Berne) assessed soil erosion and conservation in the Faizabad test area (Bühlmann 2006). David Guntli and Bruno Seiler both carried out their diploma theses at the Remote Sensing Laboratories (RSL) of the University of Zurich. Guntli tested an object-oriented approach to classification of land cover and land use in Western Tajikistan (Guntli 2006) and Seiler elaborated a soil spectral library for quantitative assessment of soil parameters in western Tajikistan (Seiler 2006).

Collaboration with various institutions was crucial for this study. In administrative and organisational matters, there was strong collaboration with the Tajik Soil Science Institute (Tajik Academy of Agricultural Science, Dushanbe, Tajikistan). New methodological approaches for land degradation assessments have recently been developed at the World Agroforestry Centre (ICRAF) in Nairobi, Kenya, which provided a starting point for this study. For documentation of conservation measures, collaboration with the World Overview of Conservation Approaches and Technologies (WOCAT) in Berne, Switzerland was highly beneficial. The spectroradiometer used in this study was provided by the Remote Sensing Laboratories (RSL) of the University of Zurich, Switzerland.

2 Land cover and land use information for SLM

Land use prevailing in the late 1990s and early 2000s in the loess hills of central Tajikistan was cause for great concerns regarding its impact on natural resources. This chapter provides spatially explicit information on the state of land cover/land use, as required for planning of sustainable land management (SLM). Satellite imagery has the potential to provide information on the state of land cover and land use as a controlling factor of land degradation, as well as on the degree of land degradation as reflected by land and vegetation cover. In order to facilitate planning of sustainable land management, the choice of the classification system to be used is of some importance.

The chapter starts with an introduction to the type of land use and land cover information which can be captured by remote sensing, and presents classification tree modelling as a promising method for deriving such information (section 2.1). An introduction to land cover and land use characteristics in the loess hills is provided in section 2.2. Further, the sampling design and the study area boundaries applied for this study, as well as spatial characteristics of the datasets are presented. The materials employed included field observations and raster datasets. Characteristics of these materials, especially with regard to land cover and land use information required for sustainable land management (SLM) studies, are presented in section 2.3. In section 2.4 the different methods used are described: Classification tree modelling provided a powerful method to link field observations on land cover types with raster data. Additionally, regression analysis was applied for inferring fractional vegetation cover from Landsat ETM+ information, from the optimised soil adjusted vegetation index (OSAVI). In section 2.5, the results are presented and discussed. Finally, in section 2.6, conclusions are drawn on the land cover and land use situation in the loess hills of central Tajikistan, and the suitability of classification tree modelling for producing information beneficiary for sustainable land management is reflected.

2.1 Introduction

Land cover / land use data derived from satellite imagery have been extensively used as an information base in land use planning. Both identification of the current state of land use (e.g. extent of land use types, degree of land degradation) and land cover / land use change detection (e.g. deforestation, expansion of cropland) have benefited from the availability of these spatially and temporally high-resolution data sources.

In Tajikistan, different types of land cover and land use maps elaborated using remote sensing approaches are available. In Soviet times, it was black and white photographs, taken either from space or from aircraft, that formed the basis for large area mapping (at a scale of 1:500,000) and for updating the land cadastre (at a scale of 1:5,000 and 1:10,000), respectively. These maps were processed manually, depending on the purpose, by the respective governmental organisations, which required considerable financial and human resources. Digital processing of satellite imagery is more efficient and has been widely applied all over the world.

An assessment of land cover and land use must provide suitable information to support SLM planning in the loess hills of central Tajikistan. Opportunities and challenges with regard to deriving land cover and land use information for sustainable land management from remotely sensed imagery are discussed in section 2.1.1. Classification tree modelling offers a range of advantages for mining remote sensing data, which are discussed in section 2.1.2.

2.1.1 Remotely sensed land cover / land use information for sustainable land management

Data captured from satellites provides information about the biophysical state of the Earth's surface. In agricultural areas, land cover characteristics (vegetation and soil) are recorded on satellite imagery. In contrast to land cover, land use involves activities and inputs people undertake in a certain land cover type to produce, change or maintain it (Turner et al. 1990). This has also been called the "land cover versus land use-dilemma" (Heinimann 2006), with land cover being monitored easily, but providing limited information on processes, and land use granting insight into ongoing processes, but without possibility to inventory it over large areas. However, the connection between land use and data from satellite imagery is twofold, and thus providing opportunities for data mining with regard to land use: On the one hand, land cover is directly influenced by land management decisions, such as choice of crop and cropping pattern; on the other hand, land cover is affected by land use indirectly, since vegetation growth is also determined by soil conditions. This is especially true if agricultural inputs (e.g. fertilizers) are low (as applies to subsistence farming in Tajikistan) and low soil fertility is not "corrected" by increased inputs. In this case, land cover reflects the degree of natural resource degradation or conservation, as it may have resulted from some specific land use, or as it may be determined by some specific ecological condition. Hence, while land management activities as such are not captured on imagery, their impact on the land resources are in more than one way (Figure 2-1).

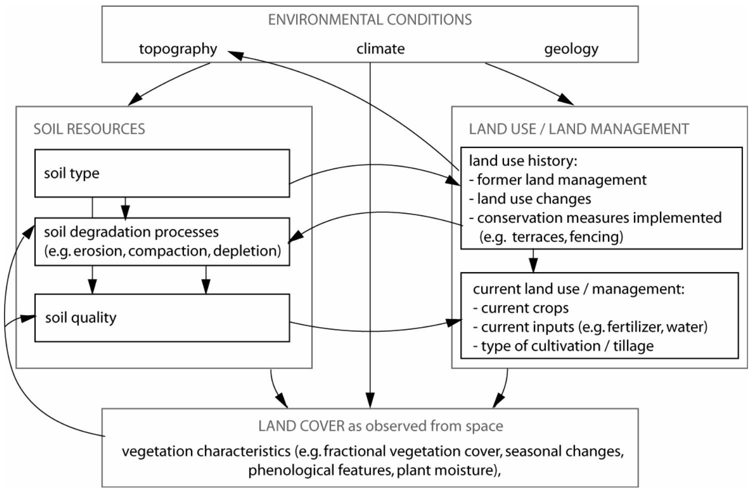


Figure 2-1 Controlling factors of land cover (sketch by author)

Phenological features, captured by satellite imagery at a suitable spectral and spatial resolution, allow distinction between crop types. Thus many remote sensing based studies aim at mapping specific crops. Even though similar management practices can often be assumed for one crop type, already small management adjustments often affect land cover distinctively (e.g. application of fertilizer, contour ploughing). A study carried out in the Faizabad test area (Bühlmann 2006) showed that fractional vegetation cover varied greatly among fields cultivated with the same crops. Therefore, even if suitable satellite imagery is available to distinguish crops, crop type alone is not a suitable indicator for sustainable land management.

The target of sustainable land management is to conserve the natural resources (including vegetation, soil, water and animals). While agricultural land use, especially in marginal areas, may immediately lead to land degradation (e.g. soil erosion), soil and water conservation measures implemented all over the world have successfully maintained the quality and fertility of the land, stopped degradation processes and restored already degraded lands (Liniger & Critchley 2007). Considering the limitations discussed above, for remote sensing-information to be beneficial to sustainable land management, it will ideally provide (1) information on land cover / land use as a controlling factor of land degradation, (2) information with regard to the overall ecological condition reflected by land cover characteristics and (3) spatially explicit land cover data as a basis for planning sustainable land management. As for the first goal, it is important to identify what land cover characteristics control the prevalent degradation type and subsequently to determine these characteristics for specific land cover / land use classes. In order to address the second goal, characterisation of land cover in specific ecological conditions is needed. And to facilitate the third goal of planning sustainable land management, the land cover / land use classification system used is crucial. The chosen system should ideally comply with existing classification systems for conservation planning, such as the hierarchical system provided by the World Overview of Conservation Approaches and Technologies (WOCAT).

In the loess hills of central Tajikistan, soil erosion by water is a major concern with regard to degradation of land resources (cf. chapters 1 and 4). Vegetation cover plays an important role as an erosion-controlling factor. Vegetation cover is characterised by various aspects inherent to land cover and land use, some of which may well be captured by remote sensing (e.g. fractional vegetation cover [FVC], vegetation types and seasonal characteristics [Vrieling 2006]). Also of great importance in this context are land use changes, which often go together with land cover changes. Remotely sensed images are excellent sources for identifying historical land use systems and may serve as a basis for simple visual comparisons of the state of land use or for more elaborate change detections.

2.1.2 Classification trees for RS data mining

Whe faced with heterogeneous terrain, integrating GIS information and human expert knowledge into digital image processing has long been used for improving remote sensing image analysis and has proven crucial to retrieve pivotal information. Expert systems organised as decision trees have successfully been applied for land degradation assessments (Huang & Jensen 1997, Shrestha & Zinck 2001) and for land cover detection in the mountainous terrain of the Pamir, Tajikistan (Hergarten 2004). However, the main restriction to expert systems is the a priori knowledge required, which is not always available. Machine learning techniques are well suited to extracting information from satellite imagery that is not a priori known, since they are inductive, data-driven modelling approaches (Recknagel 2001), leading to statistical land cover models (Aksoy et al. 2004). A precondition is that databases representative for the ecological problem domain are available (Recknagel 2001).

Classification tree algorithms are machine learning algorithms, which can be categorized into classification and regression trees (CART). CART has been used in a number of studies for land cover classification (DeFries & Chan 2000, Baker et al. 2006) and for land use change detection (Parmenter et al. 2003, Rogan et al. 2003). CART has been applied to satellite imagery from a variety of sensors: Ikonos (Aksoy et al. 2004, Lawrence et al. 2004), Landsat ETM+ (DeFries & Chan 2000, Parmenter et al. 2003, Rogan et al. 2003, Lawrence et al. 2004) and AVHRR (DeFries & Chan 2000). In almost all cases, these classifiers have proven superior to conventional classifiers (e.g. maximum likelihood), often accomplishing overall accuracy improvements of 10 to 20% (Rogan et al. 2003).

CART is a promising approach for classification of satellite imagery, because it is a non-parametric approach. Hence, CART does not require normal distribution of the histograms of raster information, in contrast to the widely applied maximum likelihood algorithm. In mountainous or dissected landscapes, variations in reflected energy may be considerable due to variations in illumination, even within a specific land cover type, and may thus lead to non-normal distribution of the reflectance values of calibration samples (Shrestha & Zinck 2001). Non-parametric approaches are also better suited to analyzing noisy data (e.g. haze, shades) (Rogan & Chen 2004). Furthermore, rule-based classification allows ancillary data (e.g. topographic information) to be incorporated, which can increase classification accuracy and precision (Lawrence and Wright 2001). CART does not require independence of variables, which is especially important in the case of raster datasets from different sources of spectral data and topographic data being merged (Aksoy et al. 2004). Another major advantage is that classification trees yield a set of rules which are easy to interpret and suitable for deriving a physical understanding of the land cover system (Steinberg & Colla 1995, DeFries & Chan 2000), and which also allow detection of important interactions (Steinberg & Colla 1995). CART is thus well suited to exploring data in order to enhance understanding of the land cover system, especially in areas for which there is little experience in terms of remote sensing studies.

As Cingolani et al. (2004) pointed out, identification of an adequate hierarchical level for mapping and definition of discrete land cover units discernible by satellite imagery are major problems encountered in mapping natural vegetation on the basis of mid-resolution satellite images (e.g. Landsat ETM+). Regarding the heterogeneous land cover in the hill zone of central Tajikistan, it is expected that this problem also applies to managed areas. Cingolani et al. (2004) showed that statistical analysis of signatures is a promising approach to solving the problem. An important step in tree modelling is the determination of the appropriate complexity of a classification tree as represented by the number of sub-classes distinguished (terminal nodes). Hence, CART represents another statistical approach to identifying an adequate hierarchical level of classification and mapping.

However, CART also has its limitations, especially (1) that it is unable to search for optimal tree structures, and (2) that it is adversely affected by inaccurate training data, and unbalanced datasets (Lawrence et al. 2004). That is to say, classification trees are not necessarily stable vis-à-vis small perturbations in the data (Zhang et al. 1998), which makes tree stability an important concern. Researchers adopting tree modelling approaches to satellite imagery thus prefer refined classification tree analysis, e.g. using not single but combined trees[8], thereby ensuring greater robustness of models and thus of classification (e.g. DeFries and Chan 2000, Lawrence et al. 2004). However, only single trees provide direct insight into the structure of the model and thus the underlying physical structure of the land use system. For exploration of land cover / land use datasets with a view to increasing the overall understanding of the interrelations between environmental condition, vegetation characteristics and land use, the possibility for interpretation of the tree structure is thus crucial. Furthermore, Lawrence et al. (2004) compared a combined tree model to a single tree model and reported that accuracy improvements were not significant for the Landsat image classification in that specific case.

[8] Various methods to combine trees are available, for instance bootstrap aggregation (referred to as bagging) and adaptive resampling and combining (referred to as ARCing) (Steinberg & Colla 1995).

Thus, combined tree models are not always outperforming single tree models, but this is strongly dataset specific.

In statistical approaches, including machine learning algorithms, there is an inherent danger of derivation of spurious correlations. A proper validation is thus crucial. There are two major aspects of validation: 1) validation of the performance of the model and 2) validation of the accuracy of the resulting thematic map (Atkinson & Foody 2002). Evaluation of the classification tree structure is an important step. Relationships between vegetation properties and remotely sensed variables are generally well known (Skidmore et al. 1997) and make such an evaluation possible.

2.2 The Study Area

Section 2.2.1 provides a short introduction to land use in the loess hills of central Tajikistan. Since soil erosion is deemed to be the major soil degradation process in the loess hills, special attention is paid to land cover characteristics considered important as erosion controlling factors. The following sections give details with regard to the sampling design (section 2.2.2) and the analysis of spatial characteristics (section 2.2.3). These descriptions and analyses are not only valid for the land cover and land use assessment, but also for the assessment of soil resources described in chapter 4.

2.2.1 Land cover / land use in the loess hills of central Tajikistan

In Soviet times, there were general rules regulating the use of land according to slope steepness (personal communication by staff of the Soil Science Research Institute in Dushanbe): On areas in the valley floors with moderate slopes (< 10%), irrigated agriculture was developed; if irrigation was not applicable, these lands were used for intensive rainfed cropping. On slopes with 10 to 20% steepness, orchards and vineyards were the recommended land use type. Orchards were also implemented on moderate to steep slopes (20-40%), but only on terraced land. All areas with slopes steeper than 40% were used as grazing lands. These rules shaped the landscape over at least 30 years, and the resulting typical pattern of land use types remains easily visible today.

Grazing land is located in the valley floor and on the slopes at lower altitudes, but is predominant at higher altitudes. Over the whole study area, grazing land covers around 50%. The perennial vegetation cover generally provides good protection against erosion processes. However, grazing land is often common land and its use is not regulated, leading to overstocking and degradation of vegetation cover. Hawthorns (*Crataegus pontica*, Tajik *dulona*) are growing even on rocky slopes (Pistrick & Mal'cev 1998) and can be found growing wild in the whole study area.

Figure 2-2 Dulona trees on grazing land, Karsang area, Faizabad test area (photo by Wolfgramm)

Large cropland areas are located on the valley floors and plateaus and are mainly used by (former) state farms for cereal production. A study conducted in the Faizabad test area showed that irrigated land covered 17% of the total annual cropland, and was cultivated also by state farms mainly for vegetable production (Bühlmann 2007). After the land use changes that took place in the 1990s (cf. chapter 1), land on moderate to steep slopes is now temporarily used for wheat cultivation by subsistence farmers. The main crop on the hill slopes is winter wheat (accounting for 60% of the annual cropland in the Faizabad test area [Bühlmann 2006]). Wheat is the staple food in rural families and is usually cultivated on field plots considered the most fertile of the farm. Furthermore, peasants cultivate chickpeas, which can be found in many traditional dishes, and flax, which is used for oil production, comprising each between 6 and 7% of the total annual cropland in the Faizabad test area (Bühlmann 2006). The wheat fields are prepared (ploughed or harrowed either manually, by animal traction or using machinery) at the beginning of the wet season in November. The wheat seedlings provide minimal vegetation cover during the heavy rains in April and May. Crop rotation (every 2-4 years) is carried out with flax, chickpeas and beans. These crops are sown in late March and thus do not provide any vegetation cover during the spring rains.

As pointed out by Guntli (2006), today land cover and land use are highly heterogeneous in the hill zone, which influences assessments applying remote sensing methods. There are often no clear boundaries in between fields cultivated with different crops and often also between cropland and grazing land. Wide grass strips between fields are also difficult to interpret on satellite imagery. Since inputs to cropland (e.g. fertilizers, herbicides) are very restricted, cropland is often strongly weed infested. Furthermore, fallow land is common. The boundaries between good cropland with healthy grain crops, bad cropland with high weed percentages, and fallow land with nothing but weeds used as fodder for animals (cut-and-carry or extensive grazing) are often blurred and thus hard to identify, especially when using remote sensing methods. Many fields are ploughed manually or with animal traction and are thus not necessarily rectangular. Furthermore, land user rights are not fixed. Thus, in the late 1990s and the early 2000s, agriculture showed some characteristics of shifting cultivation: Whenever the soil was exhausted on one plot, farmers aimed at gaining access to another plot. In such circumstances, it is possibly less the state of a specific plot that is of interest, but rather the overall land cover condition of a certain area since land degradation does not conform to field boundaries.

2.2.2 Sampling design and study area delineation

In the first paragraph, the sampling design used for this study is outlined. The field survey was conducted in the three test areas of Yavan, Faizabad and Varzob. However, in the course of the study, the Southern parts of the loess deposits represented by the Yavan test area had to be excluded from the final study area. In the Yavan test area, vegetation cover as recorded by the Landsat ETM+ imagery in May 2002 did not represent the field data collected in May 2004. Regression analysis conducted to link field and raster data clearly showed this, as confirmed by results presented in section 2.5.1. The delineation of the final study area, including only the Faizabad and Varzob test areas, is described in the second paragraph.

Sampling design

For efficient sampling of the full range of natural resource characteristics over the study area, the ground survey campaign was conducted using a spatially stratified sampling design developed by Markus Walsh and Keith Shepherd (personal communication in February 2004 at ICRAF, Nairobi). With the initial site being chosen at random and the remaining sites specified so that all were located according to some regular pattern, this sampling design characterised a typical “randomized systematic clustered” sampling design (Cressie 1991). The campaign included 3 test areas situated in the districts of Yavan, Faizabad and Varzob, respectively (Figure 2-3). They were selected for being representative for three regions in central Tajikistan, but locate on one single scene of the Landsat satellite imagery[9]. The Yavan test area was representative for the rural areas South of Chormasak mountain pass, was situated at an altitude of 680-1700 m asl and characterised by an average temperature over the summer half year of 24^{o}C. The Faizabad test area was representative for the rural areas North of Chormasak mountain pass and East of Kafirnigan River, with an altitude between 1200 and 2400 m asl and an average temperature over the summer half year of 20 ^{o}C. Finally, the Varzob test area was representative for the loess hills situated close to the capital, Dushanbe, at an altitude of 850-2100 m asl. Average temperature was not available for Varzob test are, but would be expected between the one of Yavan and Faizabad test areas.

Each test area covered 10 by 10 km, which is large enough to capture landscape features and at the same time small enough to be logistically efficient. Every test area included 15 randomly placed clusters; and each cluster included 13 sampling sites, where field observations were collected. Sampling sites are described in detail in section 2.3.1. A total of 600 sampling sites were located as described above, using a Global Positioning System (GPS) and sampled. The sampling sites were lined up at 58 m, 115 m, 230 m and 460 m, that is 2, 4, 8 and 16 times the plot diameter distances, along three radial lines running at 120° angles to one-another. One radial line was aligned in North-South direction. This arrangement is most efficient with regard to geo-statistical analysis, e.g. semivariogram analysis (Wolfgramm & Hett 2004).

Delineation of the study area

In part, the study area boundaries were predetermined by the given digital terrain model (indicated by the straight lines). More importantly, areas featuring distinct ecological conditions that were not of interest for this study were excluded from the study area. The focus of this study was on the rainfed areas in the loess hills. Thus, irrigated areas in the valley floors as well as the mountainous regions of the Hissar range were both masked. The following procedure was applied: The classification system elaborated by David Guntli for his MSc thesis, which clearly distinguished irrigated areas as well as cloud and snow covered areas on the Landsat 7 ETM+ imagery (Guntli 2006), was adopted. Further, the mountainous regions in the Hissar range were delineated along watershed boundaries. Watershed boundaries from the generated DEM were calculated in ArcGIS. The exact watershed to be used as the Northern delineation of the study area was determined by visually selecting the southernmost watershed of the Hissar range running in East-West direction. In the same way the Southern boundary was determined: The watershed running in East-West direction along the Chormasak mountain pass was visually selected and defined as the study area boundary. The final study area used for all further analysis covered an area of 1,105 km^2 (Figure 2-3).

[9] Standard worldwide reference system (WRS) path 153, row 33

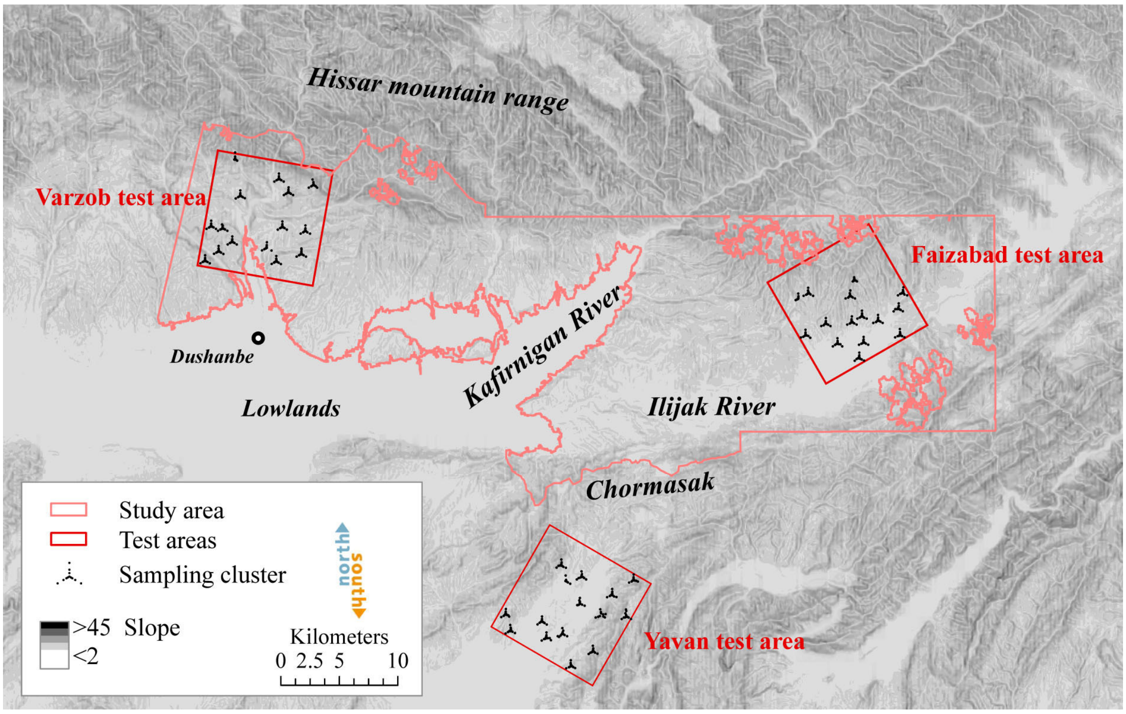


Figure 2-3 Delineation of the study area.

2.2.3 Spatial characteristics: DEM resolution and spatially independent observations

Scale issues are known to be of special importance when working with GIS in mountainous (Cassel-Gintz et al. 2003) or heterogeneous environments. As discussed by Cassel-Gintz et al. (2003), the importance of scale issues is closely linked to the degree of spatial heterogeneity. Lower resolution aggregates more information within one data unit and thus represents a summary measurement. Extremes (e.g. peaks, edges, gullies) are evened out. This smoothing of information decreases variance and increases spatial autocorrelation (Anselin & Getis 1993; Ling 1996). Cassel-Gintz et al. (2003) concluded that analysis of the degree of spatial autocorrelation would provide crucial information on the relevance of the scale-related issues.

In this study, spatial structure was assessed by means of semivariogram analysis. In the following paragraphs, two semivariogram analyses are presented: first for determining the resolution of the digital elevation model, and second for identification of spatially independent observations. The analyses were conducted on the basis of the Faizabad dataset.

Resolution of the digital elevation model (DEM)

Derivatives from digital terrain models (DEM) such as slope, aspect and curvature are important variables in assessments of land resources; slope, for instance, is an important erosion controlling factor. In the case of a digital elevation model being calculated from point or contour information, determining a resolution suitable for best reflection of topographic characteristics is of major significance. Data smoothing, which accompanies working with lower resolution as described above, might affect information pertinent to slope ranges which is possibly of high interest: Slope values derived from a coarse DEM do not accurately reflect reality in that they are lower for steep slopes and higher for gentle slopes - an effect, which has been discussed in several studies (e.g. Wolock & McCabe 2000, Thompson et al. 2001).

In this study, the basis for calculation of a digital elevation model and the DEM products of slope, curvature, and aspect, was provided by Russian topographic maps at a scale 1:50,000, with a contour distance of 10 m for flat areas and 20 m for sloping areas. The DEM calculation was conducted using the topo-to-raster interpolation method implemented in ArcGIS, which is based on the ANUDEM program developed by Hutchinson (1989). One DEM was produced with a horizontal resolution of 10 m, another with a resolution of 30 m matching the Landsat ETM+ resolution. For both DEMs, slope was calculated using the slope definition of Horn (1981) implemented in all ESRI software. The resulting slope raster layers were named *slope10* and *slope30*.

In order to decide on suitable DEM resolution for production of reliable slope information, semivariograms were analyzed. Semivariograms are ideal reconnaissance tools for discovering the approximate spatial scale of a study (Oliver & Webster 1986). The basic idea of semivariogram analysis is to test the variation between two points as the function of the distance between the two point observations. Thus, semivariance (γ) is a model of the average degree of similarity between observations as a function of distance (Rossi et al. 1992). Semivariance is defined by the following equation (Nielsen & Wendroth 2003):

$$\gamma(h) = \frac{1}{2NP(h)} \sum_{i=1}^{NP(h)} [A_i(x_i) - A_i(x_i + h)]^2$$

NP:	Number of sample pairs
h:	Distance between the sample pairs
x:	location
A_i (x_i):	Observation or measurement taken at location x_i
A_i (x_i +h):	Observation or measurement taken at location x at a distance h from location x_i

Semivariance values range between 0, which indicates complete autocorrelation, and ∞, which indicates complete randomness in the data. Generally, for observations at short distance (h) the variation (for example of slope values) is expected to be smaller than for observations at long distance. This effect is called spatial autocorrelation. However, beyond a certain distance between two sampling sites, variation between the two sites will not increase anymore. Observations are then expected to be spatially independent. By plotting the semivariance γ (h) on the y-axis against the lag distance (distance between two observation plots) on the x-axis, these effects can be visually assessed. Clustered (or nested) sampling designs are efficient in providing the bases for calculating such experimental variograms (Oliver et al. 1989, Oliver & Badr 1995, Lark 2005).

The clustered sampling design used in this study for field surveying (section 2.2.2) provided a large number of lag distances to be compared (distances between two sample plots). Semivariance was calculated for sample pairs of one sampling cluster as shown in Figure 2-4d, either along one leg (indicated in blue) of the cluster or in between two legs (indicated in green). Semivariance analysis was conducted in an exemplary way for the Faizabad test area only. The total number of along and in between leg sample pairs was 457 for the Faizabad test area. The results were averaged each for the 3 along-leg and the 3 in-between leg semivariance values to give omni-directional semivariance. Figure 2-4 displays plots of semivariograms calculated for 3 different slope datasets. The 3 datasets included slope measured in the field using an inclinometer (Figure 2-4a), slope values derived from *slope10* for each sampling site (Figure 2-4b) and slope values derived from *slope30* resolution (Figure 2-4c).

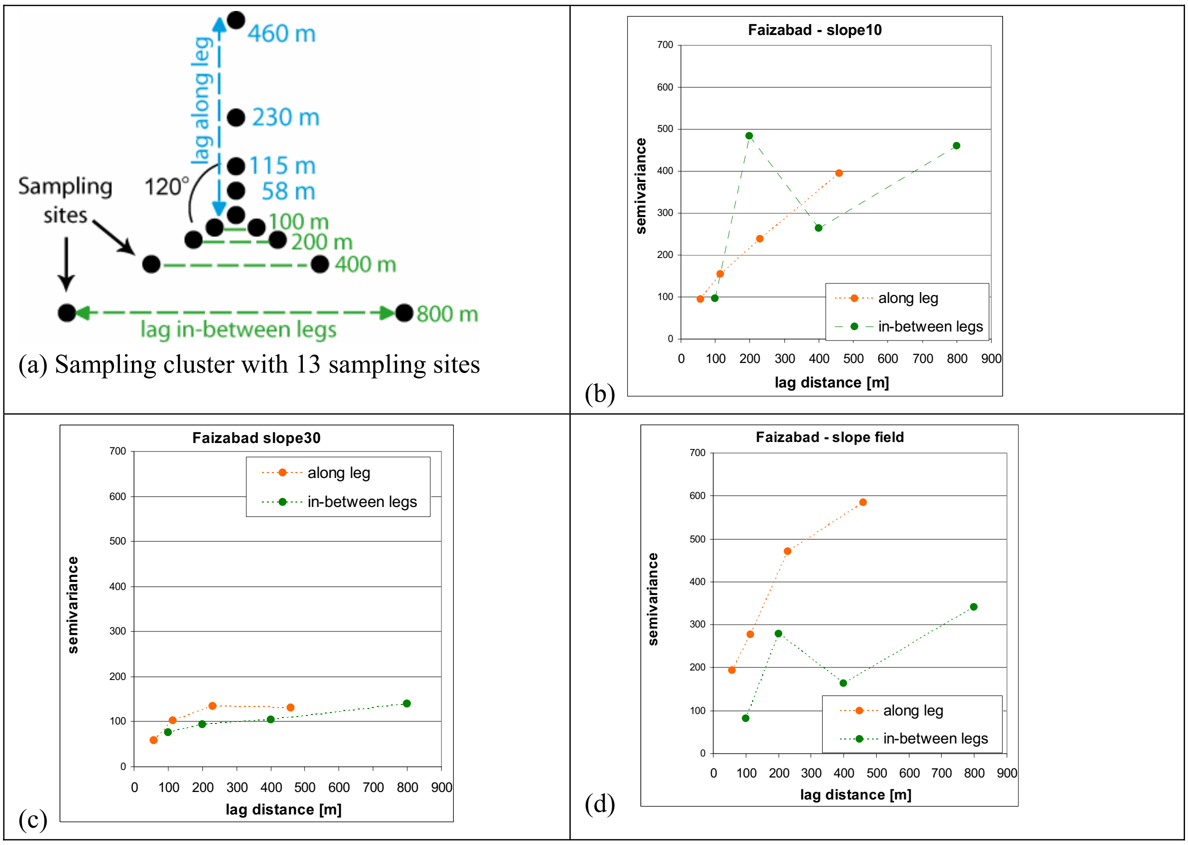


Figure 2-4 Omni-directional semivariograms for slope steepness derived from (a) field data, (b) slope raster data with 10 m resolution and (c) slope raster data with 30 m resolution. Semivariance is plotted against lagged distance along the legs and in between legs as displayed in (d).

The results show that the overall magnitude of semivariance as well as the curve described by the semivariance plot are comparable for the field slope measurements and the *slope10* raster values. In contrast, the results derived from the *slope30* semivariogram analysis indicate generally much lower variance, thus reflecting the smoothing effect due to coarse resolution as described above. The shape of the semivariograms of slope field data and slope10 raster data resembled each other; while the semivariograms of the along-leg components are unbound and continue to increase with growing sample-pair distance, the semivariograms of the in-between leg components show a peak at 200 m sample-pair distance, followed by distinctly lower semivariance at 400 m distance and finally again an increase in semivariance for samples at 800 m distance.

These results indicated that the *slope10* raster quite accurately depicted the spatial structure of the topography in the area. Thus, the DEM with 10 m resolution was selected as the basis for deriving the DEM products of slope, aspect and curvature.

Independent sample set, learning and testing samples

Semivariograms are also very helpful for checking the validity of the random sample assumption (Nielsen & Wendroth 2003). When applying a clustered sampling design as in this study, spatial independence is not expected for all observations and thus the random sample assumption might be violated. The random sample assumption is an important criterion in parametric calibration and a pre-condition for statistical testing. In this study, classification tree modelling was applied, a non-parametric calibration technique requiring independence between learning and testing sample sets (these requirements are discussed in detail in section 2.4.3). Thus, determination of the distance between two samples at which spatial independency of observations can be assumed was important on the one hand for partitioning the samples into independent learning and testing sample sets, and on the other hand for selecting an independent dataset used for statistical tests (cf. chapter 4).

Semivariogram analysis was conducted for soil organic carbon (SOC) content values available for each sampling site (determined as described in chapter 3), for field observations on erosion (a dichotomous dataset separating sampling sites into erosion affected or non-affected areas (cf. chapter 4) and for pixel values extracted for each sampling site from the slope10 raster dataset and from the OSAVI values (section 2.3.2) derived from the May 2002 Landsat 7 ETM+ imagery data. The resulting semivariogram plots are displayed in Figure 2-5.

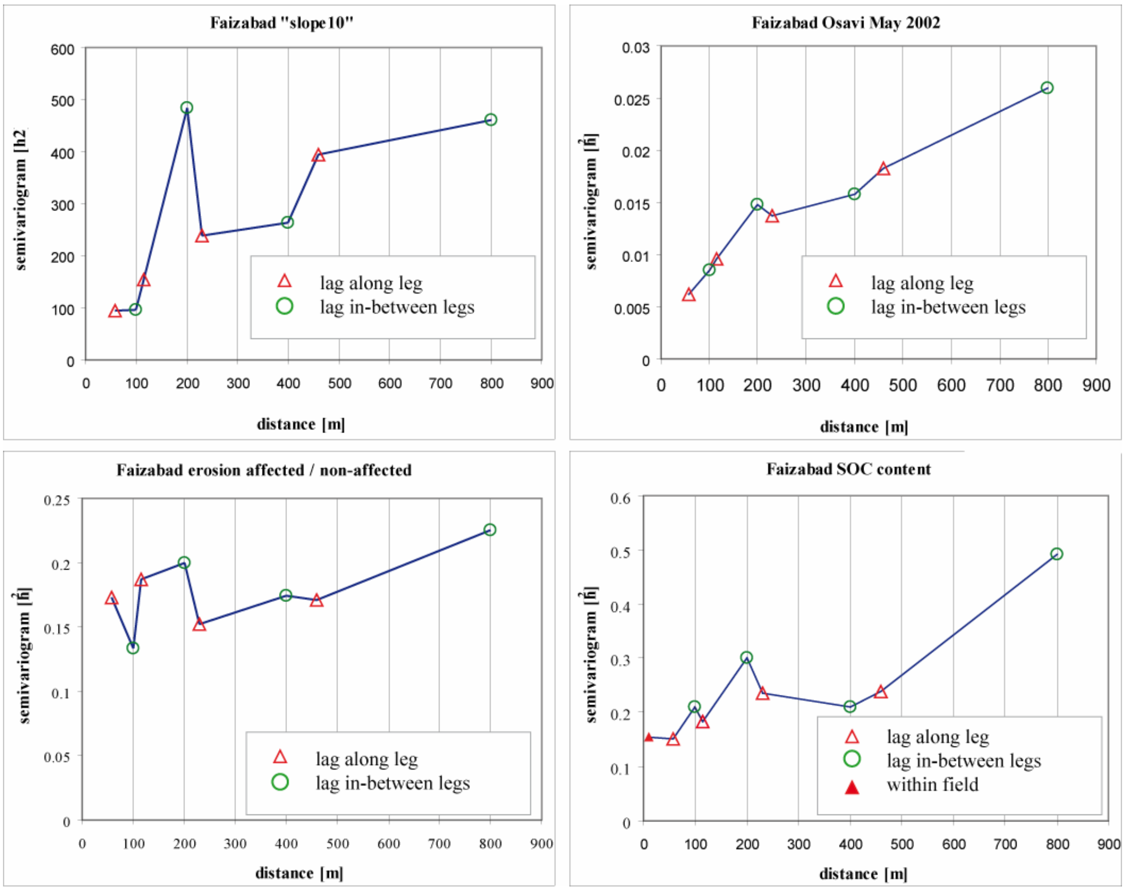


Figure 2-5 Semivariances plotted for the indicators slope (upper left), OSAVI in May 2002 (upper right), erosion (affected / not-affected) (lower left) and SOC content (lower right)

Comparison of the 4 semivariograms indicated that the spatial structure of variance shows high similarities for all the indicators, and especially for SOC, slope10 and OSAVI May 2002 values. Semivariance was lowest but slightly increasing for samples at distances of 58, 100, and 115 m. Sampling sites at 200 m distance showed a peak in semivariance. The semivariance for 230 and 400 m lag distances was constant at the same or an even lower semivariance than for 200 m lag distance. Finally, for samples at distances of 460 and especially 800 m, semivariance increased again. Since erosion values analysed were dichotomous (0 or 1), results of semivariance were less distinct than for the other indicators, which offered continuous values. However, the semivariogram for erosion, too, showed a peak at 200 m sampling distance and constant semivariance for samples at distances of 230 and 400 m, and 460 m, and finally an increase in semivariance for sampling sites at 800 m lag distance. Sites up to a lag distance of 115 m seem to be strongly autocorrelated. As for SOC content, 2 samples collected within a single sampling site at a distance of around 7 m were available. This allowed calculation of the within-site semivariance. Results showed that within-site semivariance was almost the same as in-between site variance for two sampling sites separated by 58 m and normally situated on two different fields (Figure 2-5, Faizabad SOC content). Thus, variability of SOC content was high even over very short distances. The similarity of the semivariograms of the 4 indicators can be tentatively interpreted as the result of interrelations between slope, vegetation cover, erosion processes and SOC content. These interrelations are further discussed in this and throughout the next chapters.

The Faizabad test area is characterized by many North-South running ridges extending from high altitudes and generally steeper slopes in the North to lower altitudes and generally gentler slopes in the South. With ridges of typically 400 to 800 m width, the high variance at 200 m distance might be explained as follows: while one sampling site might be situated on the ridge (nearly level ground), the paired sampling point might be situated on the steep slope of the ridge. For lag distances of 230 to 400 or 460 m, variance was then constantly high. For lag distances of 800 m, possibly the overall spatial structure of the test area dominated: there was a systematic difference (in altitude) for at least one of the 3 outermost sampling sites of the sampling cluster, which seems to have increased the variance between the sampling sites at 800 m lag distance. The high semivariance for sampling sites at 800 m lag distance was thus attributable to the overall topographic characteristics of the Faizabad test area. As discussed above, unchanging semivariance indicates spatial independency of observations. The lag of 230 m was determined as indicating the distance at which samples are spatially dependent to a very small extent only, small enough for this to be considered the "independent sample distance". For the statistical tests (as detailed in chapter 4), only 7 samples per cluster, all separated by 230 m distance, were included in the so-called "independent sample set" (Figure 2-6a).

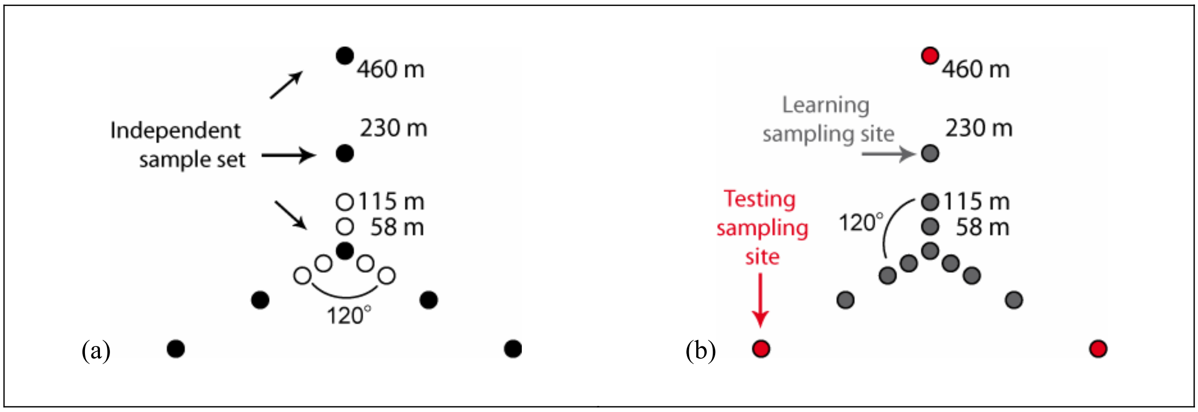


Figure 2-6 (a) Independent sample set and (b) learning and testing sample sites

For classification tree modelling, independent learning and testing sample sets were determined: While the 3 samples situated at the outermost end of the legs of a sampling cluster were determined as testing samples (Figure 2-6b, red), all other samples (10 samples) were included in the learning sample set.

2.3 Materials

The basis for land cover and land use assessment was formed by (i) field observations collected during field surveys on 400 sampling sites, and (ii) raster datasets, including satellite imagery and a digital elevation model. The following sections provide details with regard to the land cover and land use observations recorded in the field (section 2.3.1), and also about the satellite imagery available and its specific characteristics pertaining to land use and land cover modelling (section 2.3.2).

2.3.1 Field survey – visual observation of land cover and land use characteristics

Groundtruth data were collected during the time of highest vegetation activity. The field survey was conducted during May and June 2004 in the Yavan and Faizabad test areas, and in early June 2005 in the Varzob test area. A sample field protocol, as completed for every sampling site, is provided in appendix 2. With a diameter of 30 m, every sampling site covered approximately the area represented by a Landsat TM pixel. However, the specific pixel finally attributed to a sampling site did not necessarily coincide exactly with the sampling site. Hence, it was important that the extent of the area with uniform land cover surrounding the 30x30 m site area was also recorded. The cultivated plots on the hill slopes were often extremely small. On cultivated land, the uniform area around the sampling site was smaller than 30x30 m for 25% of the sampling sites. For 65% of the sampling sites on cultivated land, the field size was between 30x30 m and 100x100 m, and only 10% were recorded as being larger than 100x100 m (1 ha). Sampling sites with a field size (or homogeneous area with regard to grazing land) smaller than 30x30 m were excluded from land cover classification modelling, which helped to improve modelling results considerably.

For this study, satellite imagery showing vegetation during its main stage of activity had been recorded two years prior to the field survey. To check for land use changes within these two years, it was noted for every site whether it was likely that the land use had been changed in the last two years. Land cover and land use characteristics were recorded in the field in accordance with the FAO land cover classification system (LCCS) (Di Gregorio & Jansen 1998). The following indicators were included: The dominant life form (uppermost canopy layer) and the secondary life form, classified either as trees, shrubs, or herbaceous forms, and their particular fractional vegetation cover (FVC) estimated from visual inspection. Crop residue and bare soil percentages were also estimated for each 30x30 m sampling site. Furthermore, plant species, field size and type of water supply (rainfed, irrigated, specific type of irrigation) were noted, as well as any observations with regard to land use history. Undesirable bushes (area coverage in %), non-palatable herbaceous species and animal tracks were recorded as indicators of vegetation degradation.

Characteristics of the land use system were classified according to the WOCAT classification system. This hierarchical system combines three basic sets of information: first, on the prevailing land use; secondly, on the degradation type; and thirdly, on the conservation measures (Liniger et al. 2002). Definitions are provided in the WOCAT technology questionnaire (WOCAT 2003). The land use classes defined by WOCAT were adjusted for classification of Landsat satellite imagery in the study area and are discussed in section 2.4.4.

Degradation types are discussed in chapter 4, and land management and conservation characteristics found in the study area in chapter 5.

2.3.2 Satellite imagery

The data basis for spatial assessment consisted of a digital elevation model (DEM) calculated from Russian topographic maps (scale 1:50,000, contour distance of 20 m and 10 m in flat areas) and Landsat ETM+ imagery from two different seasons. Information about land use in Soviet times was derived from Corona satellite imagery. The digital elevation model was discussed in section 2.2.3. The following paragraphs describe timing of available recent images, rectification of satellite images and enhancement of spectral information. The last paragraph in this section 2.3.2 gives detailed information on the black and white photographs from the Corona satellite mission.

Landsat 7 ETM+ imagery

ETM+ imagery was the only readily available satellite imagery covering the study area. Despite its rather low spatial resolution, it was chosen for mapping land cover in an area dominated by small agricultural fields and a rugged terrain, in order to test its usefulness for preliminary studies.

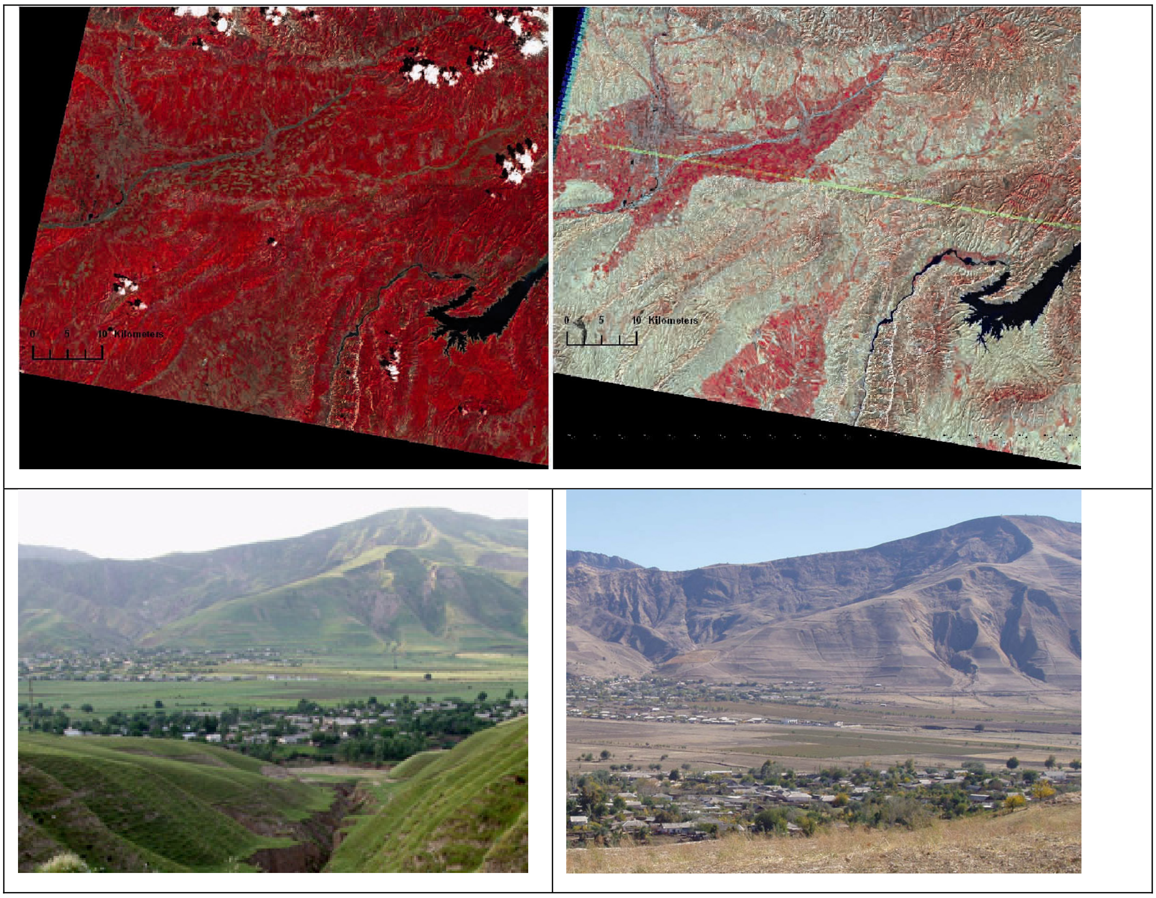


Figure 2-7 Illustration of the difference in green cover between end of May and end of August. Landsat ETM+ (bands 4, 3, 2, red indicating dense vegetation cover) recorded on 24 May 2002 (upper left) and 22 August 2000 (upper right). Photographs showing the same landscape in Yavan district, taken in May 2004 (lower left) and in October 2004 (lower right). (Photos by Wolfgramm)

In semiarid and sub-humid climate, comparison of images from the main cropping season with images from the time after harvest of annual crops readily reveals the boundaries between rainfed and irrigated areas, and also between annual and perennial crops (with irrigated areas and perennial vegetation showing green cover even in the dry season). This is illustrated in Figure 2-7 with false colour images of the two Landsat images (red indicating vegetation cover) and two photographs representing the wet spring and dry summer seasons. The state of maximum vegetation activity was represented on an image recorded on 24 May 2002, and the situation during the dry season (best visibility of bare ground) was represented on an image recorded on 22 August 2000. As the Scan Line Corrector (SLC) of Landsat 7, failed on 31 May 2003, Landsat imagery was no longer available in a suitable form after this date[10]. Thus, more recent imagery could not be obtained for this study.

Geocoding of satellite imagery as well as atmospheric correction were conducted by David Guntli. For measuring ground control points, a handheld Garmin receiver (Garmin GPS eTrex, no differential signal) was available, for which the manufacturer claims an accuracy of around 15 m. Image rectification was performed using GPS ground control points measured in the field and additional control points extracted from the Russian topographic maps. Residuals in x direction were 53 m on average for both images, y-residuals amounted to 11 m for the 2002 image and 20 m for the 2000 image dataset. Residuals larger than 1 pixel (30x30 m) are generally considered rather large; with the methods at hand, however, it was impossible to achieve more accurate image rectification. The atmospheric correction of the geo-referenced images was conducted using ATCOR3 (Richter 2005). For more detailed information see David Guntli's diploma thesis (Guntli 2006).

The World Geodetic System (WGS) is the reference system used by the Global Positioning System (GPS). GPS field measurements were recorded in WGS84, the latest revision of the WGS system dating from 1984. Satellite imagery was first geocoded to the local coordinate system, Transverse Mercator with Krasovsky 1940 spheroid and Pulkovo 1942 datum, which is also the coordinate system of the Russian topographic maps. The Universal Transverse Mercator (UTM) coordinate system is a grid-based method of specifying locations on the surface of the Earth. The WGS84 ellipsoid is used as the underlying model of the Earth. The UTM system is not a single map projection. The system instead employs a series of sixty zones, each of which is based on a specifically defined Transverse Mercator projection (Snyder 1987). Central Tajikistan is located in UTM Zone 42. The UTM42-WGS84 system is widely applied today and is compatible with both the image processing software ERDAS Imagine and the geo-information system (GIS) software ArcGIS by ESRI. In contrast, there were different Pulkovo definitions for the two computer programs. For this reason, all datasets were re-projected to UTM42, WGS84 for processing and analysis.

Indices and tasselled cap transformation

Techniques to enhance spectral information and its interpretability are commonly applied in vegetation studies. This includes vegetation indices, which are based on information from the red spectral range (Landsat ETM+ band 3, 0.63-0.69 µm) and the near-infrared range (Landsat ETM+ band 4, 0.78-0.90 µm). While near-infrared range radiation is largely reflected by leafy vegetation and especially by the chlorophyll in leaves (resulting in high reflectance values from dense vegetation), red range radiation is absorbed by plants in the course of photosynthetic activity (resulting in low reflectance values from dense vegetation). Thus, the

[10] http://edc.usgs.gov/products/satellite/landsat7.html#description

significant differences between red and near-infrared range information provide a reliable indication of the amount of biomass present in a given area. The Normalised Difference Vegetation Index (NDVI) is the most widely used vegetation index to account for the amount of biomass present (ERDAS 2003). It is calculated as follows:

NDVI = (near-infrared – red) / (near-infrared + red)

For applications in areas with low vegetation cover and high visibility of soil, a great deal of research has been undertaken to develop vegetation indices corrected for visible reflectance from bare soil (Rondeaux et al. 1996). Soil adjusted vegetation indices (SAVI) rely on the so-called soil line concept, named after the generally linear relationship between near-infrared and red range reflectance for bare soil (Huete 1988). While these indices are most valuable when matched to specific locations, Rondeaux et al. (1996) devised an Optimised Soil Adjusted Vegetation Index (OSAVI) that is generally suitable for agricultural applications. The OSAVI is very similar to the NDVI and calculated as follows:

OSAVI = 1.16 * (near-infrared – red) / (near-infrared + red + 0.16)

Low vegetation cover was expected in the study area for the dry season. In order to differentiate between perennial land cover types, it is important to distinguish different levels of vegetation cover for the dry season as well. Hence, the OSAVI index was adopted for this study.

Tasselled cap transformation is a more elaborate way of enhancing spectral data. It optimizes data viewing for vegetation studies by transforming information from several bands (e.g. Landsat bands) into more readily interpretable data. Tasselled cap transformation is based on linear combinations of the original sensor bands, which respond primarily to particular physical scene class characteristics and capture 95% or more of the total data variability (Crist et al. 1986). The transformation produces three commonly applied datasets: brightness (a weighted sum of all bands, defined in the direction of the principal variation in soil reflectance), greenness (orthogonal to brightness, a contrast between the near-infrared and visible bands strongly related to the amount of green vegetation in the scene) and wetness (related to canopy and soil moisture) (Lillesand & Kiefer 2000).

For identification of settlements, the reflection from tin roofs was best distinguished by the band indices 3/1 (also called iron oxide index [ERDAS 2003]). All spectral enhancements were calculated in ERDAS Imagine. The full dataset consisted of bands 1, 2, 3, 4, 5 and 7, band indices 3/1 (iron oxide index), OSAVI, tasselled cap layers for brightness, greenness and wetness, each for both ETM+ scenes, as well as slope and curvature as described in section 2.2.3.

Corona satellite imagery

Historical land use information is highly valuable in order to gain a better understanding of the land use changes which may have taken place. Satellite imagery, which has been available ever since the 1950s, is a very reliable source of such information. Photo reconnaissance images from US spy satellites that had been recorded between 1959 and 1972 were made available to the public in 1995. These images had primarily been collected by the CORONA satellite series that was operating at a nominal altitude of 322 kilometres. Corona imagery originating from the KH-4B Mission was available for central Tajikistan, covering the full study area. The images had been recorded on a panchromatic film and with a maximal ground resolution of 1.8 m. Recording date of the images was 30 May 1970, reflecting the season of high vegetation activity, and recorded almost exactly 32 years prior to the Landsat ETM+ imagery dating from 24 May 2002. The Corona film positives were scanned at 21 microns spot size. In a first step, the scans were co-registered in ERDAS Imagine to the Landsat 7 ETM+ scenes and bilinear-resampled into UTM projection (zone 42 North, WGS 84). As the Corona images showed considerable distortion, a second work step was conducted to achieve higher position accuracy. Further reference points for the Corona and Landsat imageries were collected and a *rubber sheeting* (ERDAS Imagine) was performed, which greatly improved position accuracy for most regions of the Corona image compared to the ETM+ scenes.

2.4 Methods

In a first step, for each sampling site, data was extracted from the raster datasets (2.4.1). The core method used to assess land cover and land use data was classification tree modelling. It was applied in order to calibrate raster datasets to field observations (section 2.4.3), which produced a pixel based land cover map for the whole study area. The land cover classification system and the two step classification applied are described in section 2.4.4. The map was validated using three different datasets (section 2.4.5). Furthermore, the modelled classification tree was analysed in order to derive further information relevant to SLM (section 2.4.6). Additionally regression analysis was applied to related FVC observed in the field to the vegetation index OSAVI (section 2.4.2). Finally, to add a temporal dimension to the land management issues, land use changes were estimated for all sampling sites based on field observations and on a visual comparison with satellite imagery from the year 1970 (section 2.4.6).

2.4.1 Extraction of raster data

To establish calibrations between reference datasets collected in the field (land cover types) and raster data (satellite imagery and topographic information; cf. above), information from raster data was extracted for each sampling site and pixel based calibrations were elaborated. In a first step, the centre coordinate of the pixel representing the respective sampling site was calculated in a spreadsheet. Calculation of pixel centre coordinates was necessary because subsequently conducted pixel extraction using the ERDAS "pixel to ASCII" function only extracts pixel values for points that lie clearly in the centre of a specific pixel. For each xy-coordinate recorded by GPS measurement in the field and representing a sampling site, the centre coordinate of the pixel representing the sampling site was calculated using the following equation:

$$x_{centre} = \frac{x_{field-coord} - x_{raster-UL}}{n}$$

x_{centre}:	x-coordinate of the pixel representing the sampling site
$x_{field-coord}$:	x-coordinate of the plot as measured in the field (GPS measurement)
$x_{raster-UL}$:	x-coordinate of the upper left corner of the raster layer
n:	resolution of raster layer (pixel size in metres)

Secondly, a shapefile was created from the spreadsheet, and thirdly, the shapefile created was imported to ERDAS and converted into an aoi-file, which thus contained an "area of interest" point for every sampling site. The ERDAS function "convert pixels to ASCII" allows extraction of pixel values from a raster layer (also stacked layers) for each point defined in the aoi-layer, which was conducted as a fourth and last work step.

2.4.2 Fractional vegetation cover from Landsat ETM+ OSAVI information

Regression analysis was performed between field estimates of FVC and the corresponding OSAVI values derived from the Landsat image. The resulting relationship was used to obtain an FVC map of the complete study area. The field estimates included in the regression analysis were based on samples with a homogeneous area larger than 30x30 m and with unchanged land use ("90% same land use type" as described in section 2.2). The regression was established using the "independent sample set" and validated with the remaining samples. In order to assess possible differences, field–raster relationships for fractional vegetation cover were established for each test area. Finally, an overall relationship was established based on 44 field estimates. The validation dataset also encompassed 44 field estimates.

2.4.3 Classification tree modelling

Information from raster data was extracted for each sampling point (cf. section 2.4.1) and pixel based calibrations were elaborated in order to establish relationships between land cover types as recorded in the field and raster data (satellite imagery and topographic information as described above). So far, relatively few studies have applied classification tree modelling to land cover classification. Important aspects to be considered when employing the method are discussed in the next paragraphs.

The CART methodology

Classification and regression trees (CART) are rule-based machine learning algorithms, which are grown by partitioning the data into relatively homogeneous groups (also called nodes). This is done by subdividing each group into exactly two subgroups, which subsequently again are each divided into two subgroups; a process technically known as binary recursive partitioning (Steinberg & Colla 1995). In this study, classification tree modelling was conducted using the software CART 5.0 (Breiman et al. 1984, Salford Systems). Below, a short introduction to the main steps conducted by tree modelling algorithms is provided and illustrated in Figure 2-8 by means of an extract from the land cover type classification tree elaborated in this study. The full tree is presented in Figure 2-17.

The CART algorithms comprise three important steps: (1) splitting each node, (2) deciding on an optimal tree, and (3) assigning each terminal node to a class outcome (Steinberg & Colla 1995). During the first step, variables included in the modelling are assessed with regard to their capability to split the dataset into more homogeneous subgroups. Following a splitting rule, the best split is selected. Several splitting rules are available. The work done by Zambon et al. (2006) indicated that the gini and the class probability splitting rules are the most appropriate ones for image classification. In this study the gini splitting rule was used. In line with this rule, it is attempted to find the largest homogeneous category within the dataset and to isolate it from the remaining data. In the same manner each subsequent node is subdivided until no further divisions are possible (Zambon et al. 2006). In this way a maximal tree is grown. Figure 2-8 displays one branch of the land cover type classification tree arrived at in this study, which is characterised by high OSAVI values as recorded on the August ETM+ image (ETM+08_OSAVI). All sampling sites attributed to this branch of the tree show OSAVI values higher than the determined threshold of 0.28 and thus go to the right (as indicated by the arrow), while sampling sites with lower OSAVI values go to the left. In a subsequent attempt to split off a homogeneous subgroup of sampling sites, the iron oxide index (ETM+08_B3/1) plays a decisive role. It allows identification of settlement areas (Os), based on the specific absorption behaviour of roofs best captured by the iron oxide index. Samples, for which the respective pixel information shows iron oxide index values below 1.98, go to the left to terminal node N15. In summary, by splitting each node of a tree into two child nodes, a rule-based tree is grown.

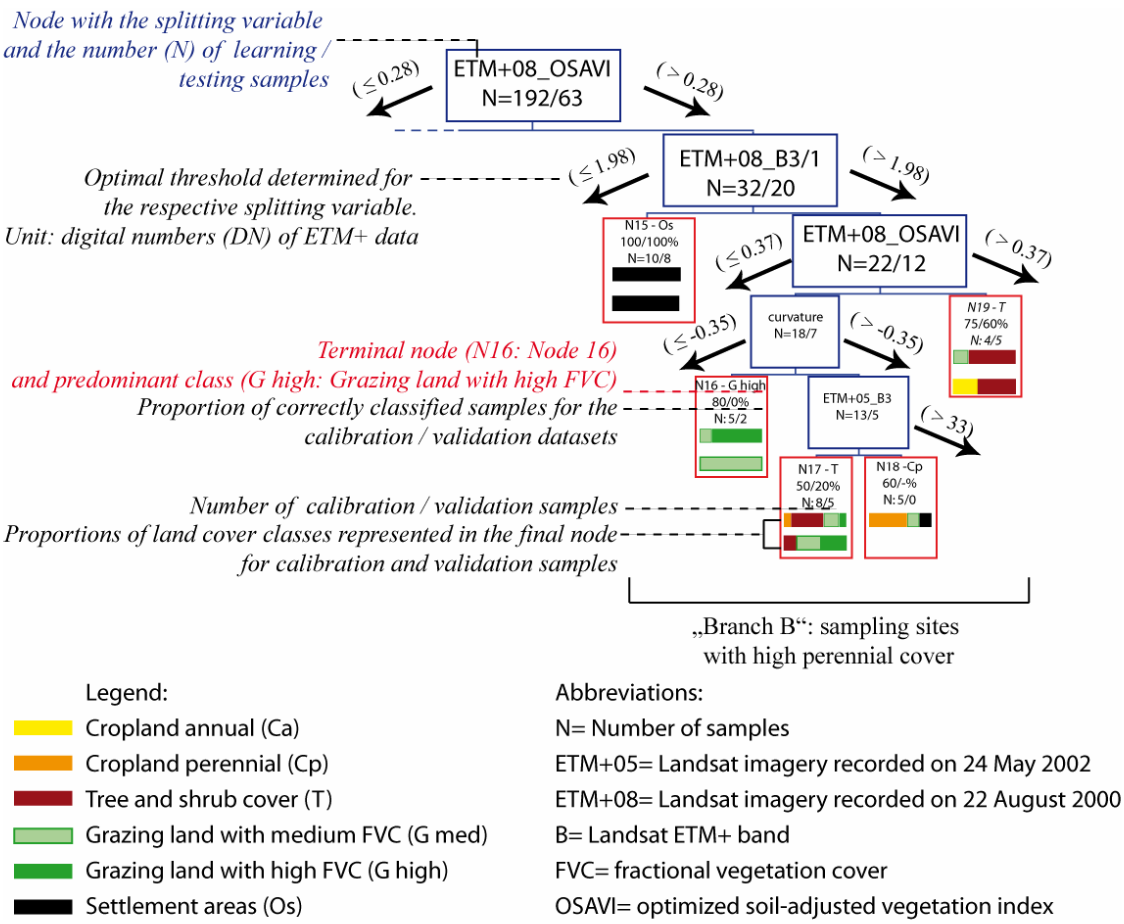


Figure 2-8 Tree branch (extract of the land cover classification tree)

The second step of the CART algorithm is to determine the optimal tree. Non-parametric methods are not based on known data structures (e.g. normal data distribution) and are thus less susceptible to non-randomness or spatial dependency. They require, however, a method for determining how complex a model to select or, more specifically in the case of classification trees, “how complex a tree to select” (Steinberg & Colla 1995). This is achieved by partitioning the data into learning and testing sample sets. While the learning sample set provides the basis for determination of the data structure (the tree structure) and will derive a maximal tree, the testing sample set is used to identify the appropriate level of complexity of the tree and thus selects the optimal tree by estimating error rates not only for the maximal tree but also for smaller trees. When comparing the proportion of the correctly classified samples of different terminal nodes displayed in Figure 2-8, it can be seen that the classification accuracy is higher for terminal nodes split off from higher hierarchical levels of the tree (N15 and N19) than for those split off at lower levels (N16, N17 and N18). The tree grows by splitting off more and more sample subgroups. However, proceeding in this way leaves samples with increasingly exceptional characteristics unclassified. The optimal tree will be determined based on the relative error rate (cost) of a specific tree, taking into account error rates of each terminal node as well as the total number of terminal nodes (representing the complexity of the tree). The error rate is calculated from the test sample set. Independence of observations is not required within both testing and learning sample sets, although it will improve the efficiency of the model building. It is critical, however, that the partitions (learn and test sample sets) be independent of each other (personal communication by Scott Cardell of Salford Systems, 2006). An independent test dataset was determined for this study as described in section 2.2.3. In the case of independent observations and small datasets, it is advisable to determine the optimal tree by cross-validation. This is expected to provide the most stable results. In this study the best classification tree was determined using both the test sample set and 10-fold cross-validation, resulting in highly comparable trees.

Finally, in the third step, the dominant class observed in a terminal node is determined and attributed to one specific class (e.g. node 15 is attributed to “settlement areas”, node 16 to “grazing land with high fractional vegetation cover”, and so on). Decision trees often produce several terminal nodes, representing subtypes of one single land cover type (e.g. in Figure 2-8, the terminal nodes N17 and N19 are both attributed to the land cover type “tree and shrub cover”). These terminal nodes are expected to contain detailed land cover information at a suitable hierarchical level of mapping. The terminal nodes will hereinafter be called *land cover classes*.

The knowledge classifier provided by ERDAS Imagine facilitates rule-based classification of raster datasets. Rules as determined by CART were thus implemented using the knowledge classifier. The land cover map was produced with a resolution of 10 m to ensure compliance with the underlying topographic raster data.

Learning and testing sample sets

A large number of learn and test samples is required for fine-tuning of a classification tree model. Every class to be modelled should be representative of all possible ecological conditions in the study area. The learning and testing sample sets available for this study were rather small, especially for highly diverse land cover types such as “tree and shrub cover”. All in all, 219 learn samples and 83 test samples were available. With regard to the eight land cover types in the a-priori classification system, sampling site distribution was as follows: Aquatic area (17); Settlement area (15); Annual cropland (33); Perennial cropland (30); Tree and shrub cover including rangelands (19); Grazing land FVC < 30% (7), 30-75% (61) and > 75% (37), respectively.

2.4.4 Land cover classification system

A-priori classification refers to attributing field sites to an existing and generalised classification system. In contrast, a-posteriori classification refers to the grouping of field samples collected, based on similarity or dissimilarity of the sampling sites. While a-priori classification systems represent the most effective way to produce standardization of classification results between user communities (Di Gregorio & Jansen 1998), a-posteriori classification provides regionally adjusted systems that characterise land cover / land use more accurately for a specific area. Such a-posteriori classification systems allow full exploitation of data provided by satellite imagery (cf. Gomer & Vogt 2000) and represent information for specific land cover units at an adequate hierarchical level as defined by Cingolani et al. (2004).

For this study a two-step classification approach was chosen which combines a-priori and a-posteriori classification:

(1) General classification of land cover types (a-priori classification): Field survey data were classified according to the WOCAT land cover / land use classification system, which is well suited for future applications for SLM planning.

(2) Detailed classification into land cover classes (a-posteriori classification): Raster data[11] driven classification using classification tree modelling.

The a-priori classification system was presented and discussed in section 2.3.1 and the method employed to derive the a-posteriori system was outlined in the paragraphs above.

A-priori land cover classification

The aim was to derive a land cover classification system that is suitable for RS studies, is fine-tuned to be applied on the available satellite images and complies with the WOCAT classification system in order to facilitate future documentation and mapping using the WOCAT methods. The WOCAT land use classification system takes into account seasonal aspects of vegetation by differentiating between annual and perennial cropping, which is especially important when assessing land cover as an erosion controlling factor. The highly differentiated "mixed land" category poses a major challenge for remotely sensed classification and had to be greatly simplified. For calibration of field observations to raster datasets, each land cover class to be distinguished needs to be adequately represented by the field observations. Representation must be ensured with regard to different ecological conditions and on the basis of a minimal number of sampling sites.

The a-priori classification system applied for this study is displayed in Figure 2-9 and described in the paragraphs below. For calibration of satellite imagery a two-step approach was applied, including a-priori and a-posteriori classification, which is presented in 2.4.3.

Annual cropping (Ca): Annual crops usually harvested within one, at the most within two years are attributed to this class (WOCAT 2003). The most widespread annual crops in the loess hills of central Tajikistan were cereals and especially winter wheat. Flax and chickpeas were also cultivated, but these crops are clearly of minor importance.

Perennial (non-woody) cropping (Cp): This class included on the one hand typical perennial crops such as alfa-alfa, and on the other hand spontaneously growing herbaceous vegetation (e.g. grasses) on fallow land. Even though these areas are expected to be vegetated all year round, intensive grazing by animals as well as drying up of herbaceous vegetation during the dry season may cause almost complete absence of green vegetation. Such fields will then show a seasonal vegetation cycle similar to a field with annual cropping.

Tree and shrub cover (T): Most areas where trees and shrubs composed the dominant land cover type were cropping systems (fruit orchards or vineyards). Except for a few very restricted spots of dense natural tree and shrub vegetation, there was no natural forest (Fn) within the study area. In the Varzob test area, there were some afforested areas (Fp), which most often included some fruit trees, or which were intercropped and used as mixed land (Mf, Ma, Ms). Large parts of the Faizabad test area could also be attributed to rangelands (grazing land with sparse and scattered tree cover) (Ms), but here the tree layer was not the dominant

[11] Landsat ETM+ satellite imagery from two different seasons (described in section 2.3.2) and DEM products of slope and curvature (described in section 2.2.3).

vegetation layer and thus class distinction with remote sensing methods was difficult. These areas were accordingly classified as grazing land (G). All in all, there was only a limited number of sampling sites including woody vegetation as defined by LCCS (1998). Thus, areas with dominant woody vegetation were all subsumed in class T, tree and shrub cover. Further, 10 additional sampling sites representing woody vegetation were visually selected from the satellite image: The so-called "kitchen gardens" situated within the settlement areas are characterised by dense fruit tree cover and thus provided ideal calibration samples.

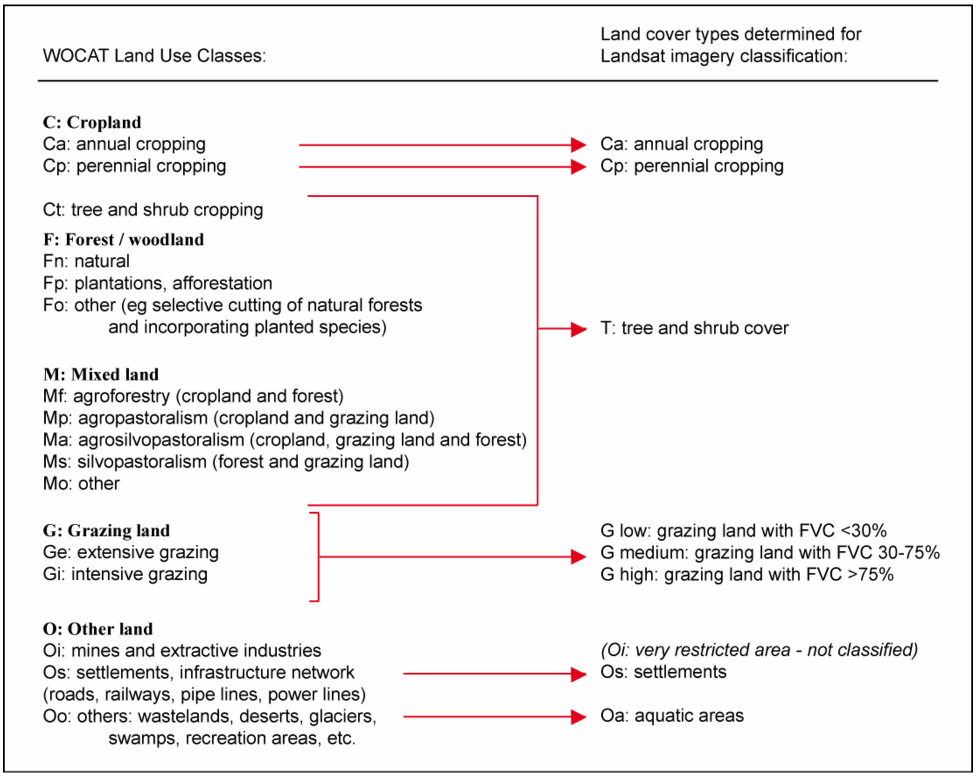


Figure 2-9 A-priori land cover classification system suitable for Landsat ETM+ classification in the study area (sketch by author), FVC = fractional vegetation cover

Grazing land (G): The WOCAT classification system differentiates between extensive (pastures) and intensive (haymaking) grazing land. Differentiation between the two classes using remote sensing techniques was not feasible, however. Since FVC has been used as an indicator for the degradational stage of plant communities (Hill et al. 1998), three grazing land classes reflecting FVC were distinguished in this study: low FVC (< 30%), medium FVC (30-75%), and high FVC (> 75%).

Other land; settlements (Os) and aquatic areas (Oa): Land not under cultivation was classified either as settlements (Os) or as aquatic areas (Oa). The definition for aquatic areas provided in the LCCS system was adhered to, mainly including rivers, streams and lakes. Additional point information was extracted from the satellite image for the land cover types "aquatic" (N=32) and "settlement area" (N=15). These cover types can be easily distinguished visually on the satellite images.

2.4.5 Validation of the land cover map produced

In a first step, the test sample set was used for validation. Thus, these validation samples were not completely independent from the model building process. What was critical with regard to a sound validation was also the number of samples available: The sample quantity required to validate a complex classification tree is considerable, as a sufficient number of samples should be available to validate all of the terminal nodes. In this study only 86 validation samples, unequally distributed among the 23 terminal nodes, were available, whereas at least 5 samples per terminal node would have been required for complete validation. Thus, validation was only possible at the level of the eight land cover types, albeit not completely so: The number of validation samples available for certain land cover types was still insufficient (e.g. only 2 validation samples for "T", tree and shrub cover). In order to validate the land cover map produced (i) in a spatially explicit manner and (ii) for sites situated in between the test areas, the map was compared to other maps and to groundtruth sample sets (see next paragraph). Producer's and user's accuracy as well as the overall accuracy were determined for all validation datasets, as described by Foody (2002). Producer's accuracy refers to a specific class of the validation test set (e.g. tree and shrub cover) and gives the percentage of correctly classified samples of this class. In contrast, user's accuracy refers to a class resulting from modelling and gives the percentage of samples for which model result and field observation coincides. Further, to accommodate for the effects of chance agreement, Cohen's kappa coefficient (Cohen 1960) is generally applied. The kappa coefficient was also calculated for additional validation of classification accuracy in this study.

Additional sample sets available for validation

Two additional land use datasets have been collected in Tajikistan within the framework of the NCCR North-South. The first dataset is a land use map for the Faizabad test area, which was created based on field boundaries digitized from a Quickbird high resolution satellite image. The crops cultivated were visually determined and classified for each field within the test area (Bühlmann 2006). The second dataset comprises a number of groundtruth samples across the study area (Varzob and Faizabad) and was collected with the aim of applying an object-oriented approach to classify the ETM+ May 2002 image (Guntli 2006). Figure 2-10 shows the location of areas from which these additionally available sample sets were collected.

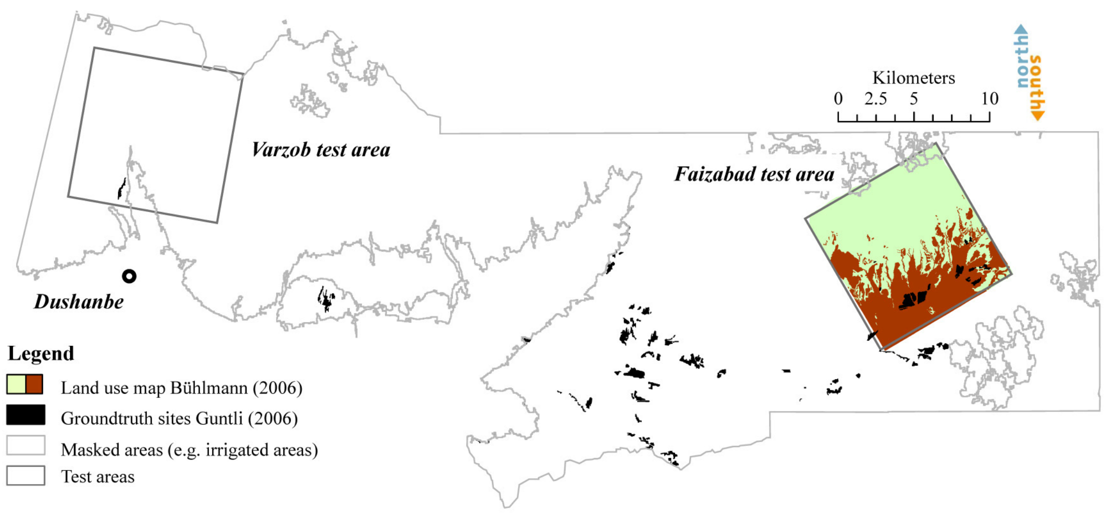


Figure 2-10 Overview of additional validation datasets available

For the first dataset, land use mapping was carried out in June 2005. A Quickbird image recorded on 22 June 2005 and with a spatial resolution of 0.6 m formed the basis for digitization of field boundaries. The resulting map was reclassified according to the classification system used in this study (section2.3.1) and included the following land cover types (number of polygons given in brackets): annual cropland (749), perennial cropland (231), tree and shrub cropping (240), aquatic area (1), settlement area (33); the remaining area was grazing land (554). As Bühlmann's study focused on cropland, no further information on grazing land (e.g. percentage of vegetation cover or tree cover) had been recorded.

For the second dataset, groundtruth data were collected in May and June 2005. Local farmers were interviewed about the crops cultivated in 2002. It proved highly useful to consult collective farms since they keep records (maps with numbered fields [cadastre] and statistical yearbooks referring to these maps). Samples of orchards, vineyards, forest, grassland and villages were visually determined and assigned to print-outs of the satellite imagery during field visits (Guntli 2006). Subsequently all samples collected were made available as a polygon vector layer. A total of 585 samples had been collected, of which only 84, however, were situated within the area pertinent to this present study. These samples were assigned to land cover types as defined for this study, representing the land cover types as follows: annual cropland (26 sites covering 184 ha), perennial cropland (2 sites covering 31 ha), tree and shrub cropping (42 sites covering 428 ha), grazing land (12 sites covering 86 ha), and settlement areas (2 settlements areas covering 18 ha). These groundtruth sites did not represent area coverage of the specific land cover classes and were dominated by trees and shrubs, with half of the groundtruth sites being orchards and vineyards. Unfortunately no information was available with regard to which of these orchards were intercropped with annual crops.

2.4.6 Mining land cover information for SLM

A classification tree was calibrated as described in section 2.4.3. It was expected that the classification tree would provide useful information on the underlying characteristics of land cover in the study area. The determinants of the classification tree are as illustrated in Figure 2-8: Splitting variables and their thresholds defining classification rules, tree branches including sampling with common characteristics, and terminal nodes attributed to a land cover type and representing a specific subtype of this land cover type. For terminal nodes also the correctly classified learning and testing samples were taken into account. The analysis of the classification tree was interpretative and the information derived with a view to supporting SLM planning not formally validated. Comparison with information on soil resources (cf. chapter 5) complemented this characterisation.

First, the rules provided by the classification tree were taken advantage of in that information about land cover as an erosion controlling factor was extracted. The OSAVI index as determined for the May and August images revealed land cover characteristics during the time of high vegetation activity and during the dry season, as well as details on seasonal changes. On the one hand, dense vegetation cover in spring (March to May) was expected to provide protection against the highly erosive rainfalls occurring during this time of the year. On the other hand, perennial vegetation was expected to protect the soil from the forces exerted by the rainfalls during the winter season. Second, the branches of the classification tree were examined in order to learn more about the specific ecological conditions. And third, the different terminal nodes attributed to one specific land cover type were compared with field data (e.g. additional indicators as recorded on the field protocol and photographs), in order to characterise each node and thus to accomplish a more detailed classification than it was provided by the 8 land cover types only.

2.4.7 Field observations of major land management types and subsequent change detection using Corona imagery

During the field survey, visual observations indicating land use change were collected in order to assess such change in the loess hills, and specifically possible expansion of cropland into grazing land.

Two simple questions on land use history posed on every plot proved very helpful for classifying sampling sites into major land management types: "Has the site ever been cultivated?" and "Has the land use been the same over the last 15 years?" Subsequently, three land management types were distinguished, as displayed in Figure 2-11, and were defined either as "never cultivated" for land that had never been under cultivation, "cropland temporarily cultivated" for plots that were not cultivated every year, but were left fallow for at least one, but more often several years until the next cultivation period, and finally "cropland permanently cultivated" for cropland that was usually cultivated every year. While permanently cultivated cropland was expected to have been under cultivation by collective and state farms in Soviet times, the temporarily cultivated cropland was hypothesised to have been newly cultivated during the 1990s (cf. section 2.2.1). In order to distinguish between areas never cultivated and temporarily cultivated cropland which had been abandoned several years ago, various indicators were identified in the field: signs of former ploughing, former field boundaries, and indications by plants (renewed germinating seeds on fallow land indicating the crop of previous years). Further, the following indicators were used to distinguish between temporary and permanent cropland: slop steepness (according to Soviet rules, only land with slopes flatter than 10% were to be ploughed), field size and form (permanently cultivated fields were generally larger than 1 ha and of rectangular shape), and accessibility by tractor (assuming that only fields accessible by tractor would have been permanently cultivated in Soviet times). Based on the current land use type as recorded during the field survey in 2004 and 2005, the cropland management types were further subdivided: Permanently cultivated land was further subdivided into *annual cropland* and *tree and shrub cropping*[12]. For temporarily cultivated land, information on the state applicable in 2004/2005 (cultivated or fallow, respectively) was drawn on.

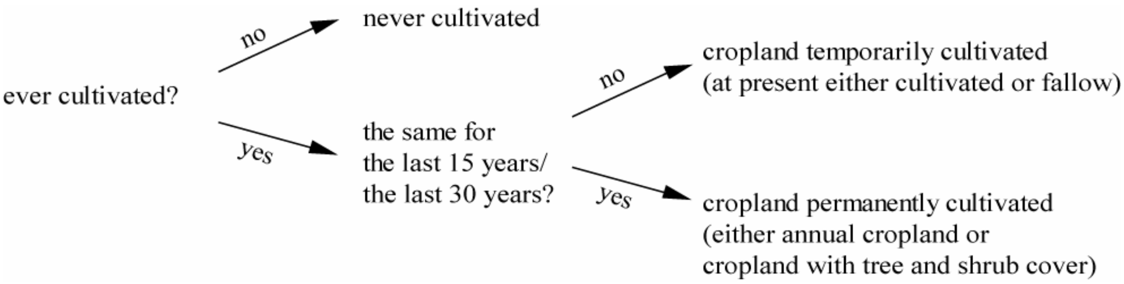


Figure 2-11 Classification into major land management types

In order to identify land use changes, the major land management classes were then visually compared with Corona satellite imagery recorded on 30 May 1970. For the Faizabad and Varzob test areas, 200 sampling sites of the independent sample set[13] were checked on the Corona imagery for changes with regard to the major land management classes. A spatially explicit change detection between land cover / land use as recorded by the Corona imagery and

[12] Here only sampling sites from cropland with tree and shrub cover were included. Rangelands with tree and shrub cover were classified as "never cultivated".
[13] Defined in section 2.2.3

more recent satellite imagery was not possible within the course of this study since the black and white information of the Corona imagery differs considerably from that of the other satellite imagery available, whether in spatial (Landsat 7 ETM+ imagery) or spectral resolution (Quickbird and Landsat satellite imagery). Furthermore co-registration of the Corona imagery to the other raster datasets was very poor in some areas, due to considerable spatial distortion of the Corona imagery. Eventually, each sampling site was classified according to Figure 2-11.

2.5 Results and Discussion

The results of the land cover / land use assessment are presented in four sections: Section 2.5.1 outlines the linear regression that was derived from the OSAVI vegetation index based on the May 2002 ETM+ imagery with the aim of predicting fractional vegetation cover (FVC). The land cover map resulting from classification tree modelling and thorough validation of the map is presented in section 2.5.2, while section 2.5.3 offers a discussion and interpretation of the structure of the classification tree and the information contained therein. Comparison between today's land use and historical land use information resulted in a classification of sampling sites into the major land management classes "never cultivated", "cropland temporarily cultivated" and "cropland permanently cultivated", as described in section 2.5.4.

2.5.1 Prediction of fractional vegetation cover from OSAVI information

Figure 2-12 shows the calibrations between field estimates of FVC and OSAVI values derived from the Landsat ETM+ image recorded on 24 May 2002 for the Yavan, Faizabad and Varzob test areas. It displays the fitted regression line, the 95% confidence interval for the regression line (blue curves next to the regression line) and the 95% prediction interval band (black lines) (Analyse-it 2006).

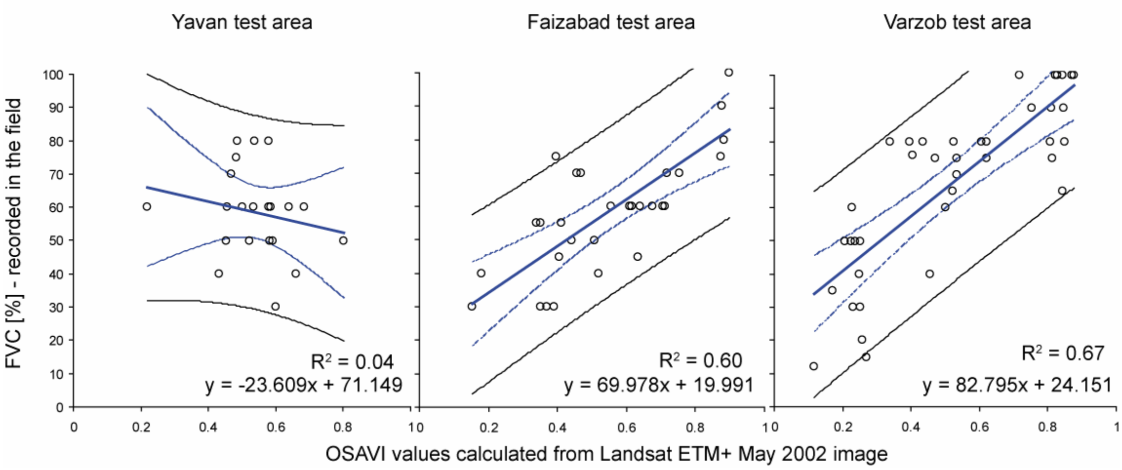
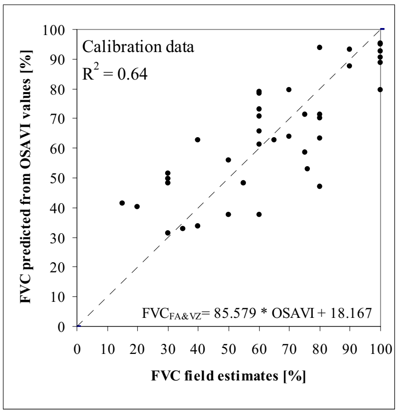


Figure 2-12 Results of linear regressions between field estimates of fractional vegetation cover and OSAVI values from Landsat ETM+ image recorded on 24 May 2002.

For the Faizabad and Varzob test areas, FVC field estimates were successfully regressed to OSAVI values, producing similar regression equations at an acceptable level of determination (coefficients of determination were R^2=0.60 for Faizabad and R^2=0.67 for Varzob). In contrast, the results for the Yavan test area showed no relationship between the field estimates of FVC and the May 2002 Landsat image, indicating that the situation observed in the field in late May 2004 differed a great deal from the situation represented by the satellite image from 24 May 2002. The advanced state of vegetation development in Yavan compared to Faizabad and Varzob was discussed in section 2.2 and is the most likely cause for the discrepancy between field data and satellite imagery in the Yavan test area. Furthermore, the time gap between the recording date of the Landsat image in 2002 and the field survey conducted in 2004 possibly influenced the discrepancy between the two datasets to a greater extent than was the case in the other test areas; possibly land cover changes were more pronounced in Yavan than in Faizabad or Varzob. Finally, wide variance in vegetation development between different years was observed: while in 2004 the wheat plots were harvested before the end of June, in 2005 wheat was still in a maturing stage in the middle of June. In 2005 the vegetation development was delayed by around three weeks compared to the preceding year, due to cold and rainy weather in April 2005 (personal communication by various farmers in the Faizabad and Varzob test areas). However, this discrepancy did not make it impossible to calibrate field data from Faizabad collected in 2004 and from Varzob collected in 2005 to the 2002 image. For the Yavan test area, it can not be ruled out that a difference in vegetation development between 2002 and 2004 influenced the calibration; as the recording date for Yavan was closer to the harvesting date than the dates for the other test areas, differences in the vegetation development may have been crucial. If in 2002 wheat and hay had already been harvested at the time of image recording, this would explain the impossibility of establishing any calibration for fractional vegetation cover for the Yavan test area.

Due to this lack of coherence between field data and satellite image data, the study area for which spatially explicit data presentation was elaborated, had to be restricted to the parts north of the Chormasak mountain pass, as described in section 2.2.2.



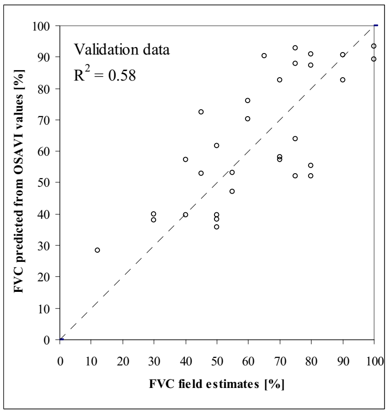


Figure 2-13 Relationship between fractional vegetation cover (FVC) estimated in the field and OSAVI values calculated from the Landsat image (calibration samples N=38, validation samples N=30)

One single linear regression equation was determined for the Faizabad and Varzob test areas. Calibration and validation results are displayed in Figure 2-13. The relationship between FVC and OSAVI for samples from these two test areas yielded the following linear equation:

$FVC_{FA\&VZ} = 85.579 * OSAVI + 18.167$

The coefficient of determination was R^2=0.64 for the calibration set, and 0.58 for the validation set. Linear relationships between vegetation indices (e.g. NDVI) and FVC would be expected to yield a higher coefficient of determination of around 0.80. However, as discussed by Vrieling (2006), some studies found poor linear relationships between NDVI and FVC. In part, these difficulties can be attributed to inadequate methodologies for determination of FVC in the field. Especially for highly heterogeneous vegetation cover with tree and herbaceous plant layers as well as patchy distribution of eroded areas – a situation that applies to the study area for the research presented here – visual estimation of fractional vegetation cover is a major challenge. Moreover, the above discussed causes for discrepancies between field and image data for Yavan test area apply also for the Faizabad and Varzob test areas and have certainly negatively influenced the calibration.

2.5.2 Land cover map and validation

Raster data, satellite imagery from two different seasons and topographic information were calibrated to field observations of land cover types (section 2.4.3) that allowed land cover types to be predicted across the entire study area. The land cover map produced as a result is displayed in Figure 2-14, together with area statistics calculated per land cover type for the entire study area and the Faizabad and Varzob test areas. A brief overview of land cover characteristics is given in the following paragraph. Subsequently, the reliability of the map is discussed on the basis of validation results.

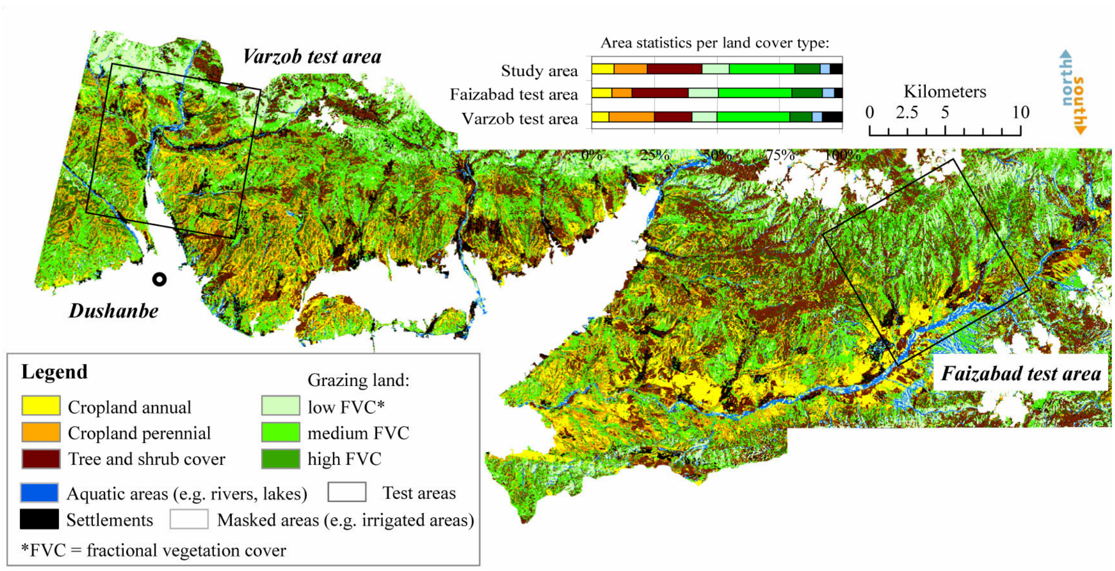


Figure 2-14 Land cover map as predicted by classification tree modelling

The proportions of area coverage for the 8 land cover types are similar in the two test areas and the study area. Both cropland (shades from yellow to brown) and grazing land (shades of green) cover around 45% of the area, with settlements and aquatic areas (rivers, lakes) covering around 10%. Along the Northern boundary of the study area, where the mountainous areas of the Hissar range begin, grazing land and especially grazing land with low fractional vegetation cover dominate. Generally, grazing land with medium fractional vegetation cover is the most widespread land cover type, covering more than 25% of the area. Differences were observed with regard to area covered by cropland: while in Faizabad both “cropland annual” and “cropland perennial” covered an area of 8 km^2 each (8% of the test area of 100 km^2), cropland in Varzob was more extensive, covering 7 km^2 (annual) and 18 km^2 (perennial) (of a total of 100 km^2). In contrast, areas with tree and shrub cover were larger in Faizabad, where rangelands are more frequent than in Varzob. In the Faizabad test area, cropland (yellow and orange) is concentrated in or close to the valley floor, which is also where the villages are situated. In the Varzob test area, there are various tributaries to the Varzob River, along which roads lead to settlements all over the test area and run at higher altitudes towards the Hissar range in the North. Cropland is spread in patches over the whole area. While the Varzob test area is representative of the area to the west of the Kafirnigan River, the Faizabad test area exhibits typical characteristics of the area east of the Kafirnigan River.

Validation

Accuracy of the land cover map was assessed on the basis of different datasets (section 2.4.4). Each of these validation exercises showed limitations; altogether they constituted a good appraisal of the user accuracy of the map, though.

Table 2-1 shows confusion matrixes for the test sampling sites, one matrix for all eight land cover types and one for the 4 major land cover types. Field observations are presented in rows and classification results in columns. Figures in bold show sampling sites for which field observation and predicted classification coincide. Accuracy levels for predicted land cover types were low except for aquatic areas and settlements. However, general land use types such as "cropland[14]", "grazing land", "settlements" and "aquatic areas" were identified at an acceptable level of accuracy in terms of the targets discussed in section 2.4.4. Misclassification occurred more often within the major land use types than between them. For the major land use types, producer's accuracies[15] ranged from 53% for cropland to 100% for aquatic areas, and user's accuracies[15] ranged from 65% for grazing land to 89% for aquatic areas. 72% of the validation samples were correctly classified. High accuracy achieved for the "aquatic area" and "settlement" classes demonstrates that a relatively low number of calibration samples suffice when dealing with easily identifiable classes (17 sampling sites for "aquatic areas" and 15 for "settlements").

Table 2-1 Accuracy assessment regarding land cover classification based on the validation sample set containing samples from the Faizabad and Varzob test areas. Rows represent field observations and columns represent classification data.

Land cover types, overall accuracy: 51%	**Oa**	Ca	Cp	T	G low FVC	G med. FVC	G high FVC	Os	Row total	Producer's accuracy	User's accuracy
	[Number of samples]									[%]	[%]
Aquatic areas (Oa)	**16**	1	1						18	94	89
Cropland annual (Ca)		**5**	1	3		2	2		13	50	38
Cropland perennial (Cp)		3	**3**	1	1	2			10	25	10
Tree and shrub cover (T)			1	**1**					2	8	50
Grazing land with low FVC (G low FVC)					**1**				1	17	100
Grazing land with med. FVC (G med. FVC)			5	2	4	**5**	2		18	42	28
Grazing land with high FVC (G high FVC)		1	1	2		3	**5**		12	56	42
Settlement areas (Os)	1			3				**8**	12	100	67
Column total	17	10	12	12	6	12	9	8	86		

Major land use types, overall accuracy: 72%	Oa	C	G	Os	Row total	Prod. acc.	User's acc.
Aquatic areas (Oa)	**16**	2			18	94%	89%
Cropland (C)		**18**	7		25	53%	72%
Grazing land (G)		11	**20**		31	74%	65%
Settlement (Os)	1	3		**8**	12	100%	67%
Column total	17	34	27	8	86		

Abbreviations are defined as follows: C=cropland, a=annual, p=perennial, G=grazing land, FVC=fractional vegetation cover, Oa=aquatic areas, Os= settlements

[14] As the land cover type "tree and shrub cover" (T) was dominated by sampling sites showing cropland with tree and shrub cover, this class was attributed to the major land use type "cropland" (C).
[15] (as defined in section 2.4.3)

A spatially explicit validation was conducted for the land cover map produced, based on the existing vectorised land use map for the Faizabad test area described in section 2.4.4. The land use types distinguished by Bühlmann (2006) were subsequently reclassified in order to comply with the 8 land cover types of the land cover map.

The bar plot in Figure 2-15 (left) shows 8 bars for the 8 land cover types as predicted by the classification tree model. Proportions of the different land cover types as mapped on the vectorised land use map based on the Quickbird imagery are shown within each bar. The map extract (Figure 2-15, right) shows areas with matching classification on the two maps (green) and with differences in classification (red), with the underlying hillshade layer indicating topographic characteristics. The overall accuracy of the land cover map produced was 58% when compared to the vectorised land use map. A Kappa coefficient of 0.27 was determined. This indicates no more than fair quality (Analyse-it 2006) and thus rather high chance agreement.

Spatially explicit validation based on the vectorised land use map. User's accuracy:

Agreement of classifications for Faizabad test area:

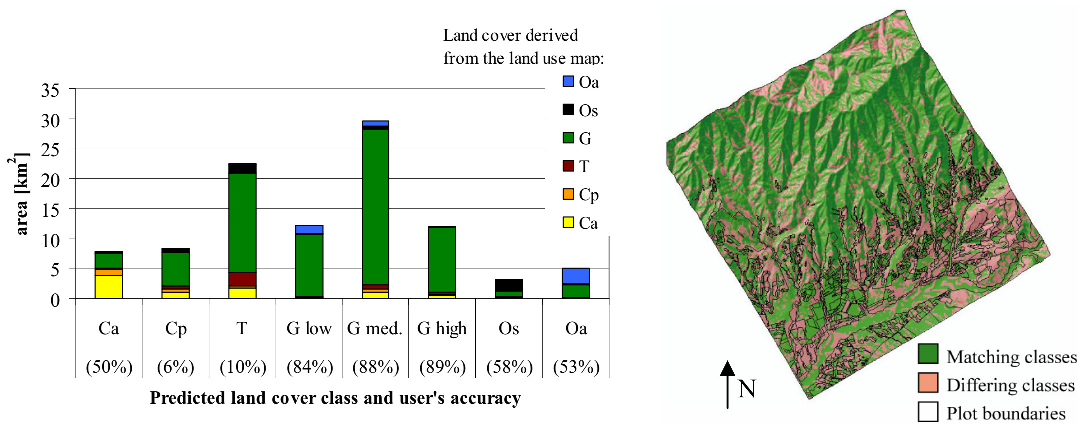


Figure 2-15 User's accuracy of the land cover map produced as compared with a vectorised land use map elaborated on the basis of Quickbird imagery from June 2005 (Bühlmann 2006)

62% of the area predicted to be annual cropland (Ca) had also been mapped as cropland (either annual or perennial). However, 30% of the area predicted to be cropland had been mapped as grazing land, which must be attributed to classification errors of the classification tree model. This rather high incidence of misclassification is not surprising, though, since many wheat fields are highly weed infested, which renders clear distinction difficult (Figure 2-16a). As much as 66% of the area predicted to be perennial cropland (Cp) on the pictures of 2000 and 2002, had been mapped as grazing land during the field survey in 2005. However, this high percentage is due to different classification of areas in the field: while Bühlmann (2006) attributed plots to cropland only if they were under field crops in 2005 and classified all other plots as grazing land, fallow land was regarded as cropland in the classification tree model used in the present study. Fallow plots are generally used as grazing areas for animals, which means that the transition from cropland to grazing land is not distinct. Areas situated close to the valley floor in the Southern half of the Faizabad test area (Figure 2-15) reflected this difference in classification. Further, areas predicted to be tree and shrub cover (T) by the classification tree model had been largely mapped as grazing land (73% of the "tree and shrub cover" area). This can be explained as being due to the rangelands (grazing areas with tree and shrub cover), which were predicted as "tree and shrub cover" by the classification tree model.

Especially with regard to sustainable land management, it is advisable to distinguish such rangeland areas from pure grazing lands. In future, such rangelands should be classified separately from tree and shrub cover.

Figure 2-16a) Weed infested wheat field

Figure 2-16b) Trees and shrubs along creeks (North boundary of the test area, facing South)

Figure 2-16c) Bird's eye view of settlement area

Figure 2-16d) Riverbed of Ilyak River, with large parts dried up for most of the year

Figure 2-16 Land cover types posing challenges for classification (Photos by Wolfgramm)

Trees and bushes on rangelands often grow along creeks (Figure 2-16b); accordingly, these areas were classified differently on the two maps, which is clearly visible on the map extract in Figure 2-15. 6% of the areas predicted to be tree and shrub cover were mapped as settlement areas: Tree and shrub cover is high within settlements due to "kitchen gardens" situated next to the houses (Figure 2-16c). There was also considerable confusion between aquatic areas and grazing land: Since many rivers and creeks are dry during the summer months and even partly vegetated, the distinction is often difficult (Figure 2-16d).

In order to validate the accuracy of the land cover map produced for areas in between the Faizabad and Varzob test areas, user's accuracy was compared to groundtruth samples collected by David Guntli (Guntli 2006). It should be noted that since half of the groundtruth sites belonged to "tree and shrub cover" (T) and included mainly fruit orchards, this validation primarily determined the accuracy of the land cover map produced with regard to areas with orchards. Overall accuracy for the groundtruth areas was 45% and thus distinctly lower than that of the test sample set and of the Faizabad land use map, respectively. ??? The Kappa coefficient of 0.25 was lower, too. However, predicted annual cropland showed similar user's accuracy for this as for the other two validation datasets (58% if annual and perennial cropland were combined). This indicated that the low accuracy was probably mainly linked to the difficulties in clearly distinguishing orchards. For this heterogeneous land cover type (including orchards, vineyards, intercropping on flat areas as well as on steep terraced land), a rather small number of learn and test sampling sites had been available for classification tree modelling. Some of the orchards which were predicted to be cropland, were in fact sites with intercropping and rather sparse tree cover. For 75% of the area predicted to be tree and shrub cover, groundtruth data proved this classification to be correct. 41% of the grazing land was correctly predicted, but for 39% of the area groundtruth data deviated by showing tree and shrub cover, thus indicating that some of the orchards were misclassified as grazing lands. The same was true for settlement areas: 74% of predicted settlement areas were actually orchards. Map verification showed that within orchard areas some pixels had been misclassified as settlements.

To summarize, the land cover map produced showed a moderate level of accuracy for annual cropland, although this accuracy was consistent both with the test areas and outside of the test areas. On the one hand, large areas in the grazing land of Faizabad that had been attributed to tree and shrub cover, were actually natural rangelands with sparse tree and shrub cover and thus attributable to the grazing land classes according to the classification system used in this study. On the other hand, the areas of large fruit orchards situated between the Faizabad test area and the Kafirnigan River (Figure 2-10) were under-predicted.

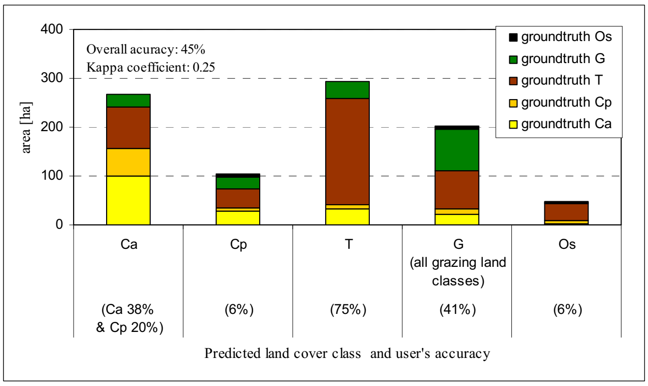


Figure 2-17 User's accuracy of the land cover map produced as compared with groundtruth data collected by Guntli (2006)[16]

Detailed comparison of the map produced with the different validation datasets showed frequent occurrence of single pixels misclassified within otherwise homogeneously classified areas (e.g. pixels misclassified as settlements within orchards). This is typical for pixel-based classifications and may contribute to the low overall accuracy of the map presented here. Post-processing using a majority filter could improve homogeneity of unit areas, but this would entail a loss of information in heterogeneous areas.

2.5.3 Land cover and land use information for SLM

The classification tree for prediction of land cover classes from raster data is presented in Figure 2-18. It was modelled according to the descriptions provided in section 2.4.3. With a view to supporting sustainable land management decisions, the information derived from classification tree modelling was analysed and interpreted in detail. Figure 2-18 shows the indicators used for this analysis: each splitting variable applied and, where easy to interpret, also the fixed threshold. Further, it shows the land cover type assigned for each terminal node, the percentage of correctly classified samples for the learning and testing sample sets and also the number of samples (N). The coloured bars provide visual information about the samples contained within each terminal node, the first bar for the learn sample set and the second bar for the test sample set. The complexity of the tree, as indicated by the number of terminal nodes, was expected to reflect the complexity of the land cover / land use system as represented by the information derived from the mid-resolution Landsat ETM+ satellite imagery. Nevertheless the identification of the optimal tree was probably also influenced by the number and characteristics of the available sample sets (both learn and test samples), as

[16] The dataset of Guntli included no groundtruth for "aquatic areas" (Oa) and is thus not present in Figure 2-17. Further, Guntli's dataset included only few grazing land samples (N=12) and thus, the 3 grazing land classes, grazing land with low, medium and high FVC were all subsumed in one class, grazing land (G).

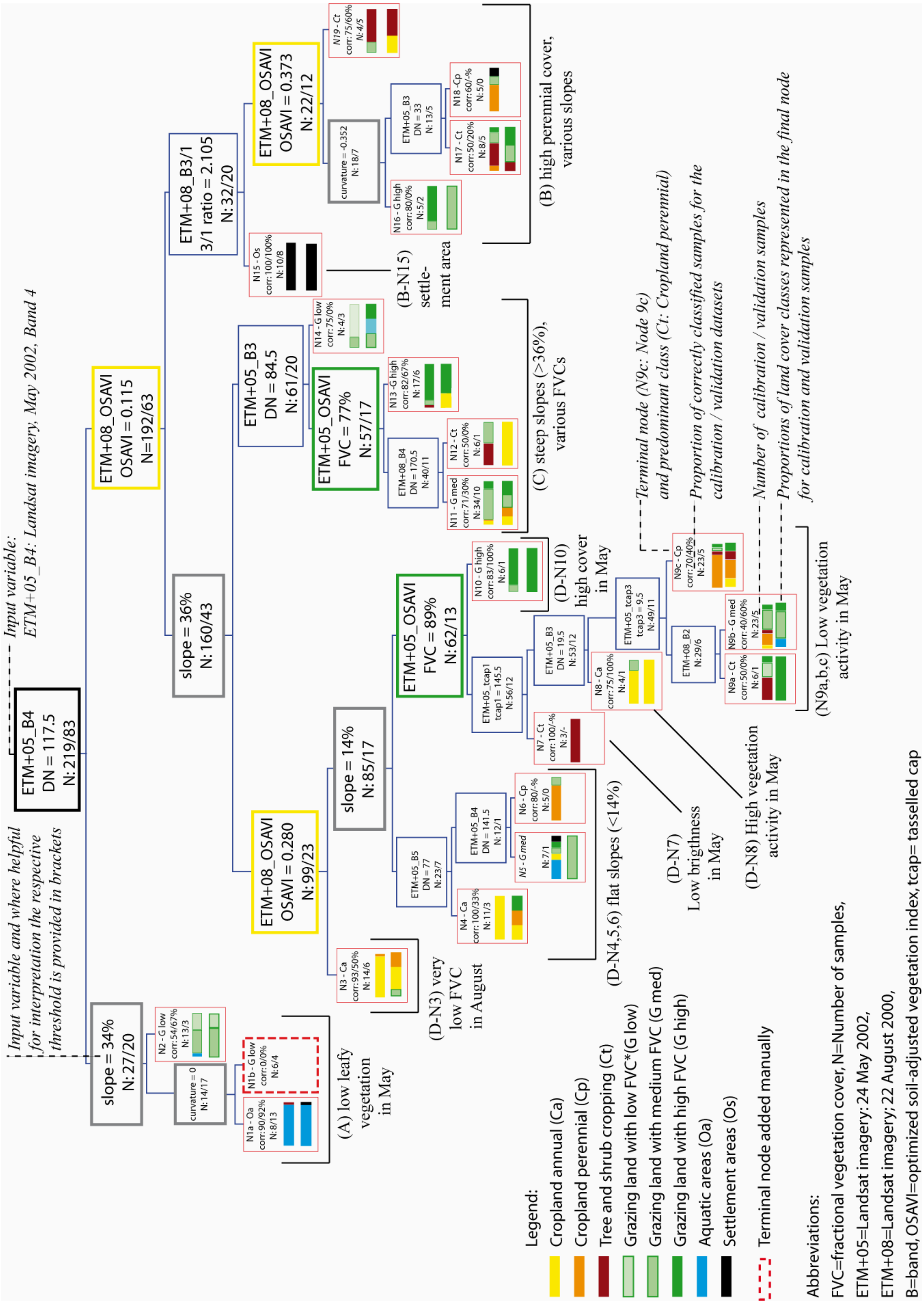


Figure 2-18 Land cover classification tree

these sets were rather small. The structure of the classification tree (selected variables, thresholds and terminal nodes) was an important source of information on land cover and land use characteristics. These characteristics were further elaborated and will be discussed in the next paragraphs.

(1) Land cover classes

The resulting land cover classification tree had 23 terminal nodes. Each of these terminal nodes was assigned to one of the 8 land cover types: annual cropping (Ca), perennial cropping (Cp), tree and shrub cover (T), grazing with low, medium and high cover (G low, G medium and G high), aquatic areas (Oa) and settlements (Os); and each terminal node was representing a subtype of these land cover types referred to as land cover class (Table 2-2).

Table 2-2 Land cover class characteristics contributing to SLM planning (excluding aquatic areas (Oa) and settlement areas (Os))

A-priori defined land cover types	A-posteriori derived land cover classes
Annual cropland (Ca)	Node 3: on various slopes with very low vegetation cover in August Node 4: on flat slopes (<14%) often with high input annual cropping Node 8: on medium slopes (14-36%) with high vegetation activity in May
Perennial cropland (Cp)	Node 6: on flat slopes Node 18: on various slopes with high vegetation cover in August Node 9c: on medium slopes, often fallow land with low to medium FVC
Tree and shrub cover (T)	Node 7: with sparse tree cover including intercropped areas Node 9a: various land use types often with sparse tree cover Node 12: on very steep slopes (foremost on river banks and along old gullies) Node 17: with large strips / patches of grass in between, typical also in vineyards Node 19: with dense tree cover (definitely tree cover > 30%)
Grazing land with low FVC (G low FVC)	Node 1b: on animal paths on ridge Node 2: on very steep slopes with high occurrence of animal tracks Node 14: on very steep slopes sometimes with shallow and/or stony soils
Grazing land with medium FVC (G medium FVC)	Node 5: on the alluvial cone in the Faizabad test area Node 11: on very steep slopes Node 9b: a heterogeneous land cover type, including all other grazing lands with medium vegetation cover
Grazing land with high FVC (G high FVC)	Node 16: close to creeks and rivers Node 13: on very steep slopes often used for haymaking Node 10: often showing high fractions of forbs

The well distinguishable land cover types “aquatic areas” and “settlements” were each represented by a single terminal node, node 1 and node 15, respectively. With regard to sustainable land management planning, this is of high importance as the following example shows: “annual cropland” is a generalized land cover type which may contain areas on which unsustainable management prevails as well as areas with sustainable management. While node 3 included annual cropland on various slopes (low to high degrees of steepness) and with very low vegetation cover in August possibly indicating unsustainable land management concerning erosion control, node 4 included only annual cropland situated on flat slopes (< 14%). Further, node 8 included a small group of sampling sites on hill slopes with high vegetation activity in May, indicating that soil fertility was especially high or that possibly fertilizer had been applied. Thus, the different land cover classes as defined by nodes 3, 4 and 8 provide more specific information with regard to SLM than the eight land cover types. Such characteristics useful for SLM planning have been elaborated for all land cover types and are listed in Table 2-2.

With regard to the reliability of these characterisations, it has to be borne in mind that they have not been thoroughly validated so far. However, the information extracted from the satellite imagery into a readily interpretable classification tree, provided spatially explicit and consistent information on land cover characteristics, which should be taken advantage of. In the context of soil classification, Gomer and Vogt (2000) reported that classification on the basis of remote sensing data was more precise than classification carried out in the field.

(2) Rule-based classification – rules for SLM

ETM+May and *ETM+August OSAVI* information together provided specific information on vegetation cover seasonality: Of the 24 raster variables, 12 were selected for splitting of sampling sites into homogeneous land cover classes, and OSAVI information from the ETM+ image recorded in August 2000 was of key importance in the model. This is not surprising, as it provided crucial information for distinction between annual and perennial land cover types (e.g. annual and perennial (non-woody) cropland, or annual cropland and perennial tree and shrub cover). OSAVI information from the ETM+ May 2002 image appeared twice; on the one hand, sampling sites with very high FVC in May (FVC > 89%) were sub-divided in node 10, and on the other hand, it classified grazing land with high FVC on very steep slopes in node 13 by differentiating between sampling sites with FVC lower than 77% and those with FVC higher than 77%.

Analysis of precipitation data showed that the winter rains were generally of low erosivity, while spring rains were of high erosivity (cf. chapter 4.2). The potential of the seasonal vegetation cover for erosion control was characterised for six vegetation types as determined by the land cover classification tree (Table 2-3).

Table 2-3 Seasonal vegetation characteristics and their potential with regard to erosion control (excluding aquatic areas (Oa) and settlement areas (Os))

Land cover type	Seasonal vegetation characteristics determined by the land cover classification tree	Potential with regard to erosion control
G	Low-medium FVC all year (nodes 11-12, 14)	Little protection against winter and spring rains.
Ca	Very low FVC in August (node 3)	No protection against the erosive impact of winter rains.
C, T, G	Medium FVC all year (nodes 4-9)	Fair protection against winter and spring rains.
G	Seasonal changes in FVC, high in May and low-medium in August (node 13)	High protection against spring rains, fair protection against winter rains.
G	Very high FVC in May (node 10)	Very high protection against spring rains.
Cp, T, G	High to very high FVC in August (nodes 16-18, and node 19 very high FVC)	High protection against winter rains.

Abbreviations: annual cropland (Ca), perennial cropland (Cp), tree and shrub cover (T), all cropland (C), all grazing land (G).

At a lower level of the classification tree hierarchy, *ETM+ May band 3* was an important variable. Band 3 is capable of distinguishing between areas with different percentages of photosynthetic activity, with low reflection indicating high absorption by photosynthesis. In the model developed for this study, *ETM+ May band 3* made it possible to separate grazing land with low fractional vegetation cover from grazing land with medium and high FVC (N14 vs. N11-N13), to separate tree and shrub cover from perennial herbaceous vegetation (N17 vs. N18) and to separate highly active vegetation, such as maturing wheat, from perennial crops and grazing land (N8 vs. N9a, 9b, 9c). Future studies should further investigate how band 3 information may contribute to SLM studies.

Finally, three slope categories were identified by the land cover classification tree model: slopes ≤ 16%, 17 to 36%, and > 36% (or > 34% respectively for node 2). Since slope is an important erosion controlling factor, identification of dominant slope categories which are connected to land cover types will contribute additional information with regard to erosion control. These three slope categories are further discussed in the next paragraph.

(3) Tree branches characterising ecological conditions

Dominant variables defining the classification tree included the OSAVI information of the ETM+ August image, slope, and band 4 of the ETM+ May image. These variables determined four main branches of the classification tree (branches A-D; cf. Figure 2-18), which may be considered also to represent typical ecological conditions in the study area. Each branch is characterised below, with illustrative images of the different branches provided in Figure 2-19.

The first branch, branch A, was defined by low reflectance in *ETM+ May band 4*. *ETM+ May band 4* is known to be especially responsive to the amount of vegetation biomass and emphasizes soil/crop and land/water contrasts. It allowed splitting off aquatic area (rivers and riverbeds that are dry for most of the year) and grazing land with low leafy vegetation cover. Visual assessment of a preliminary land cover map showed that areas on ridges were classified as aquatic areas. In order to eliminate this misclassification, an additional terminal node was manually added which classified areas with convex curvature (curvature > 0) as grazing land with low vegetation cover (node 1b).

The second branch, branch B, was defined by OSAVI information derived from the ETM+ August image and included sampling sites with high vegetation cover in August 2000. Within this tree branch, the iron oxide index (ratio of ETM+ band 3 to band 1) from the August image singled out the settlement area, showing reflection from tin roofs (branch B, node 15). Sampling sites belonging to this branch were not restricted to a specific slope class. In contrast, sampling sites with perennial high vegetation cover especially during the dry season and the winter months, were observed all over the study area.

In contrast to sampling sites in branch B, the main bulk of sites showed medium to low vegetation cover in August. This main bulk of sampling sites was subsequently divided according to slope steepness. Sampling sites situated on very steep slopes (> 36%) were separated and formed branch C, which was clearly dominated by grazing land and rangeland. This branch comprehended all grazing land classes (grazing land with low, medium and high FVC) as well as a rangeland land cover class (node 12). Branch C thus characterised the ecological condition of grazing lands on very steep slopes, most often found at higher altitudes in more mountainous conditions but also on the steep slopes of strongly incised valleys.

The remaining sampling sites constituted the fourth major branch, branch D, which included almost half of the sites (99 learn sampling sites and 23 test sampling sites). This branch was subsequently subdivided into a number of sub-groups. First, sites with very low vegetation cover in August were singled out (node 3, annual cropland). Subsequently, flat areas with slopes < 14% were isolated in a sub-group (nodes 4, 5 and 6). The remaining samples, situated on slopes between 14 and 36%, were subdivided into areas with very high fractional vegetation cover in May (node 10: grazing land with high fractional vegetation cover), areas with relatively low overall reflectance in May (node 7: tree and shrub cover), areas with comparatively high photosynthetic activity in May (node 8: annual cropland), and areas with comparatively low photosynthetic activity in May (Nodes 9a, 9b and 9c: tree and shrub cover, grazing land and perennial cropland).

Branch A: very low leafy vegetation in May, various slopes (FA, May 2004)

Branch B: high perennial cover, various slopes (FA, June 2004)

Branch C: very steep slopes, various FVCs (VZ, June 2005)

Branch D:

D-node 3: very low FVC in August (FA, August 2005)

D-nodes 4, 5, 6: flat (slopes < 14%) (FA, June 2004)

D-node 7: low brightness in May (VZ, June 2005)

D-node 8: high brightness, high vegetation activity in May (VZ, June 2005)

D-node 9: low vegetation activity in May (VZ, June 2005)

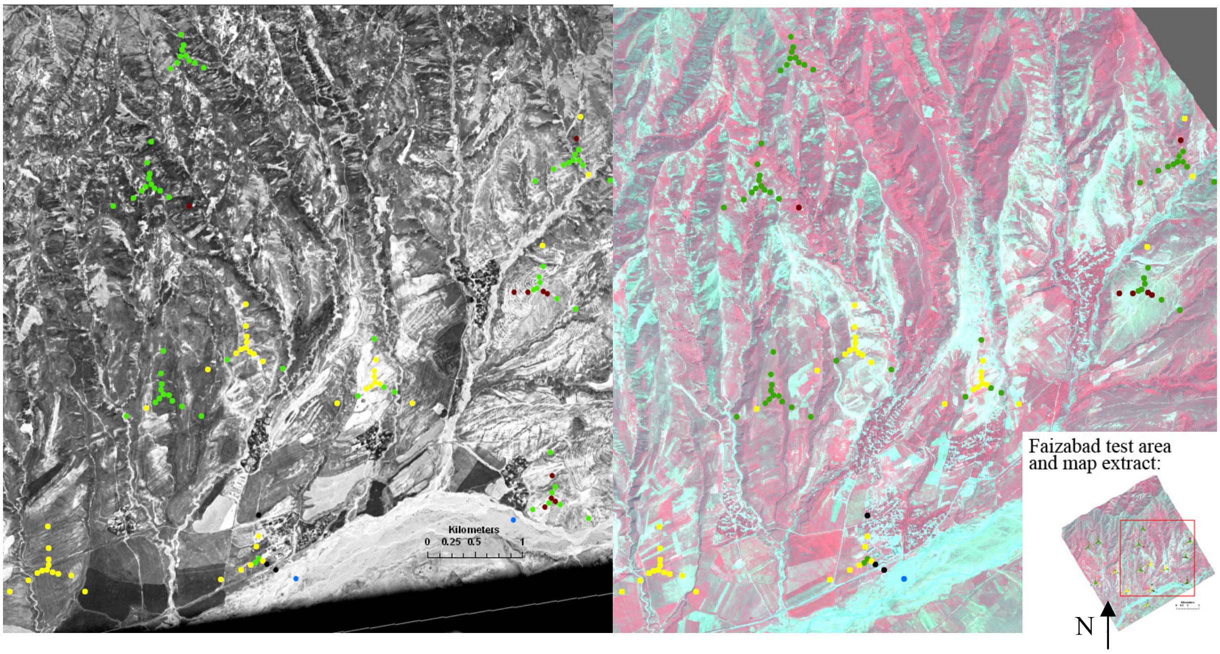
D-node 10: very high vegetation cover in May (VZ, June 2005)

Figure 2-19 Different branches of the land cover classification tree highlighting different characteristics of the land cover system. Place and data of photo recording are provided in brackets, FA=Faizabad test area and VZ=Varzob test area.

The gini splitting rule was chosen for modelling this land cover classification tree (cf. section 2.4.3), as it is designed to separate homogeneous sample groups from a main bulk of samples. Effects of the gini splitting rule can be observed in the terminal nodes of branch D: As described above, homogeneous nodes were split off with the nodes 3, 4, 5, 6, 7, 8 and 10. These nodes, except for node 5, all show a level of at least 75% accuracy in terms of correct classification of sampling sites. All sampling sites which failed to comply with the criteria of these nodes, remained in the nodes 9a, b and c. This large group of remaining samples (49 learn sampling sites and 11 test sampling sites) proved difficult to classify, and the nodes accordingly showed lower classification accuracies: node 9a correctly classified only 43% of learn sampling sites, with node 9b it was 46%, and 64% for node 9c. Thus, even though nodes 9a, b and c comprise a rather large class, a clear assignment to a specific land cover type is not possible for the sites concerned. These areas are characterised by heterogeneous and temporary land use, and by land management changing not only in the course of years but also within any given year (e.g. areas may irregularly be used for grain cropping, for haymaking as well as for extensive grazing of animals). To summarize, branch D represented the medium slopes of the hill zone with highly heterogeneous land cover and land use.

2.5.4 Major land management types

A visual comparison of three datasets made it possible to come to general conclusions with regard to land use changes in the loess hills over the last 30 years. The three datasets included field observations collected during the field surveys in 2004 and 2005, Corona satellite imagery recorded on 30 May 1970, and Quickbird imagery recorded on 22 June 2005 (the Quickbird imagery only covers the Faizabad test area), and the analysis was conducted as described in section 2.4.7.



Legend for land cover types as recorded for sampling sites in Faizabad test area, in early June 2004:

• cropland • tree and shrub cropping • grazing land • aquatic area • settlement

Figure 2-20 Map extracts for Faizabad test area. Left side: Corona satellite image recorded on 30 May 1970; right side: Quickbird satellite image recorded on 22 June 2005 (false colour image of bands 4, 3 and 2, with red colour representing vegetation cover) and sampling sites as indicated by coloured dots: land cover types recorded during field survey in June 2004.

Map extracts for the Faizabad test area (Figure 2-20) show the Corona image with overlaid sampling sites next to the Quickbird image with overlaid sampling sites. The important observations which were made in the Varzob and Faizabad test areas, can be exemplified based on these map extracts. These observations included:

- Cropland in the valley floor is much the same, in some areas large fields have been subdivided into many small plots;
- Cropland in the hill zone is located in almost exactly the same places in 1970 and in 2004/2005;
- As in the years 2004/2005 also in 1970 no conservation measures seem to have been applied on cropland;
- The assessment for the grazing lands situated mainly in the Northern parts of the test areas showed that the patchy vegetation cover observed in 2005 must have been by and large the same in 1970;
- The settlement areas have become much larger, indicating a rapidly increasing population.

Upon close assessment of each sampling site, it was not unequivocally clear for 21 out of the 200 sampling sites checked whether the site had already been used as temporary cropland in 1970 or had not been cultivated until the 1990s. For the large majority of sites, the assessment confirmed that plots used for grain production in the hill zone had already been tilled in 1970. Thus it can be concluded that it is unlikely that there was a significant extension of cropland grazing areas which had never been cultivated before.

Based on the field observations conducted in 2004/2005, sampling sites were assigned to three major land management types: land permanently, temporarily or never cultivated (Table 2-4). Examples for each land management type are displayed in Figure 2-21.

Table 2-4 Overview of major land management types as recorded in the field in 2004/2005. Abbreviations: TA = test area, N = number of observations.

Major land management type	Faizabad TA [N=99]	Varzob TA [N=101]	All [N=200]
Permanently cultivated	12%	10%	11%
thereof cropland	9%	3%*	6%
thereof tree and shrub cropping	3%	7%	5%
Temporarily cultivated	29%	42%	35%
thereof cultivated (in 2004/2005**)	13%	20%	16%
thereof fallow (in 2004/2005)	16%	22%	19%
Never cultivated (grazing land)	53%	44%	48%
No records	6%	4%	6%
Total	100%	100%	100%

** In the Varzob test area, distinguishing between permanently and temporarily cultivated cropland in the field proved difficult. In uncertain cases, it was assumed that the area was temporarily cultivated, thus possibly underestimating the extent of permanently cultivated cropland. ** Field work was conducted in the Faizabad test area in 2004, and in the Varzob test area in 2005.*

Permanent cropland | Permanent tree and shrub cover | Temporarily cultivated cropland, cultivated and fallow plots | Grazing land that has never been cultivated

Figure 2-21 Major land management types

As indicated by the high percentage of temporarily cultivated land that was fallow in 2004/2005, there has been a recent trend to stop cultivation on hill slopes. A number of processes may explain this observation: on many plots, soil fertility had dropped sharply after a few years of cereal cultivation not accompanied by conservation measures, and these plots were thus left fallow; many families receive remittances partly substituting for subsistence farming; and state agencies also aim to stop the cultivation of hill slopes in order to halt soil degradation. A more detailed discussion is provided in chapter 5.

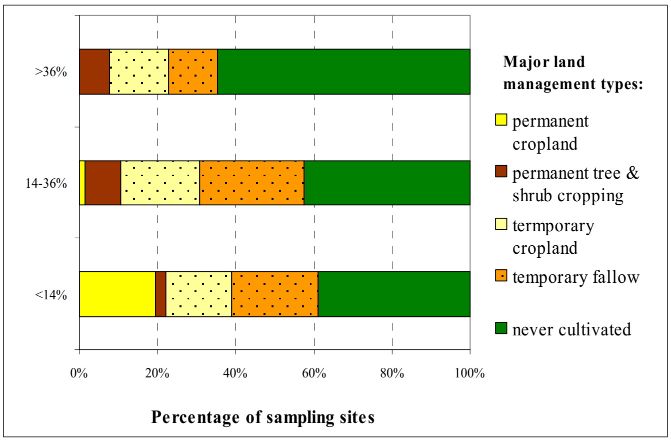


Figure 2-22 Frequency of major land management types per slope class, as determined from field observations

Comparison between the slope classes defined by the classification tree model (cf. section 2.5.3) and the major land management classes showed that the percentage of specific classes of the major land management types observed, differed with regard to the slope class. While on flat slopes (< 14%), 20% of all sampling sites were categorised as permanent cropland and only 2% as tree and shrub cover, on moderate to steep slopes (14-36%) only 1% of all sites were permanent cropland and 9% showed tree and shrub cover. While around 40% of all sites on flat and moderate slopes were classified as grazing land, on very steep slopes the respective figure was over 60%. These observations were not surprising as they generally reflected the rules in force during Soviet times. The percentage of temporarily cultivated sites was found to be similar on flat slopes and on very steep slopes, with temporarily cultivated sites amounting to 20% for both slope classes. On moderate slopes, fallow fields dominated over temporarily cultivated fields, which is an indication as to cultivation of fields situated on slopes being abandoned first. On very steep slopes, the number of temporarily cultivated fields still amounted to 15% and 13% for cultivated and fallow fields, respectively.

2.6 Conclusions

Conclusions with regard to sampling design and spatial resolution will be drawn in the synthesis chapter (chapter 6), as they apply to the whole of this study.

2.6.1 Land cover / land use characteristics in the loess hills of central Tajikistan

The two test areas of Faizabad and Varzob had been well chosen: While Varzob was representative of the area to the West of the Kafirnigan River, Faizabad exhibited typical characteristics of the area East of the Kafirnigan River. Not surprisingly, grazing land dominated at higher altitudes, towards the mountain ranges. In the Faizabad test area, large areas of cropland were situated on the valley floor and there was a relatively clear separation between permanently cultivated cropland[17] on the valley floor, temporarily cultivated cropland[18] at lower altitudes in the hill zone and grazing land at higher altitudes in the hill zone. In the Varzob test area, the pattern was not as distinct. There is no valley floor that could be used for intensive annual cropping. The plateaus with their flat slopes and fertile soils do not cover a large continuous area, but are distributed across the test area. The whole land cover / land use pattern was much more patchy. Only in the very North of the test area towards the Hissar range did grazing land dominate clearly.

The information extracted from the classification tree enabled land cover to be characterised in much more detail than would be possible using the 8 a-priori defined “land cover types”. It can be concluded that the characterisation of land cover according to the a-posteriori determined “land cover classes” revealed a detailed picture of the different types of seasonal vegetation cover, of ecological conditions and of differences within the individual land cover types. This specifically included the following characteristics: Seasonal vegetation characteristics, as derived from the OSAVI values from satellite imagery recorded during two different seasons, were interpreted with regard to their potential as erosion controlling factors. Sub-classes of the land cover types differed significantly with regard to their potential as erosion controlling factors. The results showed that it was the seasonal fractional vegetation cover of grazing land that provided both the lowest and the highest potential protection from erosion. As expected, annual crop cover showed a tendency of low fractional vegetation cover and especially little potential for erosion control against winter rains. Most land cover / land use systems in the study area were determined by different slope steepness (≤ 14%, 17 to 36%, and > 36%). A large group of sampling sites was characterised by areas with slopes > 36%, for which differentiation into grazing land with low, medium and high vegetation cover as well as rangelands was possible. At a lower hierarchical level of the tree model, areas with slopes < 14% were identified either as annual or as perennial cropland, or as grazing land with medium cover. Finally, areas situated on slopes with a very steepness between 14 and 36% showed a high variety of land cover types. Areas with high vegetation cover even in the dry season in August were not included in these slope classes. These sampling sites were located on all manner of slopes, all over the test areas. Moreover, sites classified as annual cropland (node 3) were also located on all slopes flatter than 36%. This cropland type showed exceptionally low vegetation cover in August. This detailed land cover information should make it possible to

[17] Permanently cultivated cropland as defined in section 2.4.7 being cropland that is cultivated every year over many years.

[18] Temporarily cultivated cropland as defined in section 2.4.7 being cropland that was cultivated only in some years, with extended fallow periods in between.

link specific land cover classes to differing degrees of soil degradation and soil conservation, which is the topic of chapter 5.

Cultivation of fields in the hill zone is not a new phenomenon. As analysis of Corona imagery showed, grain cultivation in the loess hills of central Tajikistan was widespread in the 1970s. In the 1990s, with food insecurity driving people to new and/or intensified cultivation of sloping lands, such temporary cropland was used once again. The question of whether cultivation of temporary cropland had fully ceased in the late 1970s and the 1980s would have to be answered by including relevant satellite imagery in the analysis (e.g. KFA-1000 imagery recorded from the Russian space station MIR and available for the 1980s). For detailed analysis of the extent of land use changes from grazing land to cropland and vice versa, higher spatial resolution of recent satellite imagery would be required. However, the conducted visual assessment based on sampling sites demonstrated that referring to the land use processes observed in the 1990s as an extension of cropland to grazing areas, did not appropriately describe the land use changes. The history of land use, of rotations of fallow and cropping periods, is much more complex. In order to understand the specific impact of land management, a more detailed study would have to be conducted.

2.6.2 Assessing land degradation and conservation

A land cover map distinguishing 8 land cover types was produced and validated. The results showed that in an area in which difficult terrain and small cultivated plots prevailed, a spatial assessment of land cover was possible. Major land cover types (cropland, grazing land, settlements and aquatic areas) were detected with sufficient accuracy (overall accuracy of 72%), but detection of the eight land cover types was low (overall accuracy of 51%). Thomlinson et al. (1999) set the target for the overall accuracy at 85%, with an accuracy of at least 70% for every single class. However, as Foody (2002) stated, this target accuracy is rarely attained. As pointed out by Guntli (2006) and had been discussed in section 2.2.1 land cover is highly heterogeneous in the study area. It is well known that heterogeneous land cover is a challenge for remote sensing studies. Such mosaic landscapes are some of the most important ones worldwide, but are also some of the hardest to classify (MA 2005). Furthermore, the time lag between Landsat ETM+ imagery dating from August 2000 and May 2002 and the field survey conducted in 2004/2005 posed an additional error source. Albeit at a rather low level of accuracy, the produced maps nevertheless provided important information for preliminary studies (cf. chapter 5).

A classification tree model established on the basis of groundtruth data from an extensive field survey, Landsat 7 ETM+ imagery and a digital elevation model, provided the means to distinguish and map 8 a-priori defined land cover types and 23 a-posteriori derived, more specific land cover classes. The model established using the classification tree algorithm was not merely an empirical construct, but represented a data structure that allowed conclusions to be drawn on the specific characteristics of land cover classes present in the study area. This increased confidence in the model, but more importantly it permitted exploration of physical characteristics of the land resources (mainly vegetation).

The two-step classification approach employed, including a-priori and a-posteriori classification. The combination of a standardized classification system and data driven regionally adjusted classification was considered highly useful for this study. Even though the more detailed land cover classes were not properly validated, analysis of the classification tree structure showed that the tree structure was not arbitrary at all. When calibrated with a sufficiently large number of sampling sites, single classification trees may reveal highly relevant information. Even though combined classification trees are likely to be more robust and have thus been preferred for land cover / land use mapping in other studies, the potential of single tree classification should not be underestimated. Especially in areas in which land cover types may be highly heterogeneous, the proposed two-step classification approach using classification tree modelling should be considered carefully.

Calibration of vegetation indices to *fractional vegetation cover (FVC)* determined in the field makes information easily comparable with field situations and thus supports data interpretation and land management planning. Thus, it also revealed that the May 2002 Landsat image available was not representative for fractional vegetation cover in the Yavan test area. A number of possible reasons for this were given in section 2.5.1, the most probable reason being that vegetation development in Yavan is ahead of vegetation development in Faizabad and Varzob. Consequently, the areas South of the Chormasak mountain pass, as represented by the Yavan test area, were excluded from further analysis. Timing of satellite imagery for land classification is crucial. In central Tajikistan, regions characterised by exactly the same climate conditions are rather small. This requires different satellite images for land cover classification in the different climatic zones.

Classification of tree and shrub cover (including both tree and shrub cropping as well as rangeland with tree and shrub cover) was greatly supported by the Landsat ETM+ August imagery. However, this land cover type should be further differentiated. The limiting factor in this regard was the sample set. As representative sampling was conducted, only a small number of samples were available for this infrequent land cover type. In order to collect more samples of this land use type, which is of great interest for SLM studies, thematic sampling could be conducted, based on the land cover map elaborated.

2.6.3 Future research needs

The study conducted forms the basis for future studies, especially (i) with regard to the spatial characteristics of the Faizabad test area, (ii) for future land management assessments, (iii) for more detailed land cover mapping, (iv) for enhancing the understanding of the interrelations between ecological conditions and land cover, and (v) for assessing the land use dynamics in the hill zone of central Tajikistan.

Land management is decisive with regard to the impact of land use on natural resources. In a subsequent step, a more detailed assessment of land management needs to be conducted. This should include land management types, which leads to issues of land degradation as well as conservation of natural resources. The land cover map elaborated may serve as a basis for planning and focusing of future activities. The land cover / land use classification used is directly applicable for WOCAT assessments. The map is suitable as a starting point for discussions with a variety of stakeholders: actors involved in land use planning as well as land users.

More detailed and more accurate land cover mapping are expected to be achieved when calibrating the existing field data to raster datasets with higher spatial and spectral resolution, such as Aster[19] satellite imagery. Further collection of groundtruth data should be planned on the basis of the existing map. Additional groundtruth data should better characterise the heterogeneous land cover classes of importance with regard to sustainable land management,

[19] http://asterweb.jpl.nasa.gov/

such as tree and shrub cover, which includes rangelands in this study. Validation data for all land cover classes should be collected.

Further enhancing the understanding of the land cover characteristics and how these are interlinked with both land use and ecological conditions has great potential. There are a wide variety of spectral indices (Ustin et al. 2006) which facilitate calibration of spectral information with physical characteristics. For data mining using classification tree modelling and subsequent interpretation of classification tree structure, such calibrated indices would increase the value of the derived information. Calibration of field data on dry vegetation covering the ground in the dry season by means of spectral information (e.g. OSAVI information) should be conducted next. Indices well known to be significantly contributing to ecological studies, such as the leaf area index (Asner et al. 2003), should be considered as well. Quantification of primary production of vegetation, too, could provide highly interesting information with regard to land degradation, especially vegetation degradation (Bai & Dent 2006). As noted by Bricklemeyer et al. (2007), multiple image dates within a year would be necessary for monitoring and verifying management practices that influence soil carbon sequestration.

Spatially explicit information on land cover / land use dynamics would form the basis for spatially explicit impact assessments aiming at analysing the impact of land use on soil resources. Corona satellite imagery is a readily available source of spatially highly resolved land cover information. Limitations for straightforward application to land cover / land use change studies include its low spectral resolution (black and white imagery) and the considerable image distortion. Efforts should be made to automatically derive land cover / land use information from Corona imagery. The datasets available could then be used in a straightforward manner.

3 A soil spectral library for soil quality assessments

Many developing countries struggle with widespread soil degradation. Information on soil quality is crucial to improve decision making for efficient support of sustainable land management at a regional scale. Thus methods are needed that allow fast and inexpensive prediction of important soil quality indicators such as soil organic carbon (SOC). The potential of diffuse reflectance spectroscopy in the visible and near infrared (VNIR) range for fast prediction of soil properties in a non-destructive and efficient way has been demonstrated in a number of studies (cf. section 3.1). The aim of this study was to apply a soil spectral library approach to predict SOC contents for soils in the hill zones (the loess deposits) of central Tajikistan, based on spectral reflectance information. Prediction of SOC contents for a large number of sampling sites is a precondition for subsequent calibration of SOC content classes to Landsat satellite imagery (see chapter 4).

3.1 Introduction

In the last decade, efforts have increased to develop VNIR spectrometry for soil science. It has been shown that especially for land degradation assessment, and in particular for developing countries, these methods are of major significance (Shepherd & Walsh 2002, Vagen et al. 2006, Shepherd & Walsh 2007).

This introduction provides an overview of the specific requirements and challenges for soil quality determination in land degradation assessments (section 3.1.1). Advances in VNIR spectrometry for soil science and their suitability to meet the requirements defined in section 3.1.1 are discussed in section 3.1.2. Section 3.1.3 addresses challenges and potentials of VNIR spectrometry in practical application, including prediction of additional sample sets, and refers especially to the context of developing countries. A short summary of the MSc thesis by Bruno Seiler conducted on the same sample set is provided in section 3.1.4. In section 3.1.5, the research objective for this study is defined.

3.1.1 Soil quality information for land degradation assessments

Soil information for regional land degradation assessments must be representative for the state of soils in the study area and permit application of statistical methods, for example for risk analysis. Degradation processes are likely to lead to increased variability of soil properties (e.g. Schlesinger et al. 1990, Nael et al. 2004), which may be even more pronounced in regions with young soils and in marginal areas. Specific requirements for such studies thus include a sampling design that facilitates representative sampling, sufficiently high sampling density and efficient sampling of larger areas. Furthermore, quantitative or at least semi-quantitative soil quality data are needed. In order to process such sample sets, methods permitting time and cost efficient prediction of soil quality indicators, also applicable to heterogeneous soil sample sets, are essential. Especially in preliminary assessment, determination of soil properties at medium accuracy is often sufficient, if it permits screening of soil samples with regard to soil quality thresholds.

As discussed in chapter 1, when using term “soil quality”, it must be linked to a specific soil function. In this study, soil quality was seen in relation to soil conservation in agricultural systems, which aims at sustaining the productive capacity of soils and to enhance the environment at the same time (soil and water conservation society). The soil quality concept has been proposed to be applied in studies on sustainable land management (Doran 2002). In order to measure soil quality, on the one hand minimum datasets have been proposed that allow detailed description by including soil chemical and physical indicators (Mausbach & Seybold 1998). On the other hand, integrative indicators are more appropriate for preliminary studies since they efficiently provide insight into general soil quality.

Soil organic matter (OM) is one such integrative measure of soil quality, influencing soil fertility, soil stability as well as hydrological soil properties. OM plays a crucial role with regard to soil erosion: When the surface soil is removed through erosion, organic matter and clay are lost, resulting in reduced fertility, biological activity and aggregation (Ditzler 2002). In highly calcareous silty soils and in the absence of clay, organic matter is particularly important with regard to the structural organization of the soil, which again crucially determines erodibility (Hill & Schütt 2000). Hill and Schütt found that organic matter is positively correlated to growth conditions for cereal crops in dryland agriculture and has a strong connection with qualitative erosion indicators. In the Tajik loess zone, the soils have characteristically high silt fractions and calcium carbonate contents. OM is traditionally used as an indicator of soil health. To determine the state of erosion, Russian and Tajik soil scientists rely on organic matter, calcium carbonate and soil texture (Yakutilov et al. 1963).

Changes in soil organic matter typically take place on a midterm range of 1-5 years (Sparling 2002). Accordingly, OM is not influenced by singular land management changes (e.g. one time application of fertilizer), but will provide information on major land management / land use changes. Soil organic matter has also been given a high level of acceptance as a soil quality indicator by farmers (Doran et al. 1999).

Soil organic carbon (SOC) is a major component of soil organic matter (OM). OM consists of the cells of micro organisms, plant and animal residues at various stages of decomposition, stable "humus" synthesised from residues and nearly inert and highly carbonized compounds. SOC is considered the most reliable analytical measure of OM (Smith & Parris 2002). Soil organic carbon may be used interchangeably if the OM to SOC ratio applicable for the specific soils has been determined, subsequently making it possible to calculate SOC contents from OM values. In this study, the terms SOC and OM will be used interchangeably.

Finally, the relationship between SOC and soil spectral reflectance has long been recognized (Baumgardner et al. 1985). Various studies have reported high predictive accuracy from soil spectral reflectance for SOC content (Shepherd & Walsh 2002, Islam et al. 2003, Udelhoven et al. 2003, Brown et al. 2005, Brown et al. 2006, Vagen et al. 2006). A number of studies have also aimed at calibrating SOC contents to satellite imagery information (Palacious-Orueta & Ustin 1998, Hill & Schütt 2000, Udelhoven et al. 2003), permitting SOC content or SOC content classes to be mapped. Spatially explicit information on soil quality would be highly useful for land degradation assessments.

3.1.2 VNIR spectroscopy and soil science

The potential of diffuse reflectance spectroscopy for fast and simultaneous prediction of several soil properties in a non-destructive way has been demonstrated during the last few years in a number of studies (Ben-Dor et al. 1995, Chang et al. 2001, Shepherd & Walsh 2002, Islam et al. 2003, Udelhoven et al. 2003). Furthermore, VNIR spectroscopy has also been applied for assessing soil condition or quality by directly calibrating soil quality indices or soil functions to soil reflectance spectra (Vagen et al. 2006, Cohen et al. 2005, Shepherd & Walsh

2007). Soil reflectance spectra in the VNIR range are affected by soil moisture, organic matter, particle size, iron oxides, to name but a few of the most influential soil properties (Baumgardner et al. 1985). The VNIR reflectance signal is a cumulative property, derived from the inherent spectral signature of the heterogeneous combination of minerals, water and organic matter. Therefore, the resulting complex spectrum and the non-existence of physical models to link VNIR light and matter itself requires establishment of purely empirical calibrations for every individual sample set (Blanco 2002). With a view to this becoming an alternative to soil chemical analysis, it is crucial to develop robust, generally applicable models (Shepherd & Walsh 2002).

Central factors in establishing calibration models for soil properties from soil reflectance spectra include (i) The accuracy of the chemical reference dataset, (ii) Characteristics of the calibration sample set, (iii) Pre-processing of spectral information, (iv) The model approach, especially with regard to soil heterogeneity, and (v) Validation procedures.

The reference dataset: It is not uncommon for VNIR measurements to be more precise than those obtained using the reference method (Naes et al. 2002). Especially in content ranges where samples are scarce, such outliers may greatly affect modelling. Soil spectral data can be usefully applied in conjunction with chemical analysis, since it has proved very efficient in detecting analytical errors (Coûteaux et al. 2003, Shepherd et al. 2005).

When determining the calibration sample set, various issues need to be considered: The most efficient way of building a soil spectral library is to draw on existing soil sample archives that provide soil properties as determined by traditional chemical analysis (Brown et al. 2006, Hauert 2007). Otherwise, costly chemical analysis required for compiling an extensive reference dataset is a likely limiting factor. Calibration sample size influences prediction performance, which decreases rapidly for sets smaller than 100-200 samples (Shepherd & Walsh 2002). However, it has been demonstrated that it is not only the number of samples which is important, but also the way in which the samples are selected. Additional requirements for reference datasets are broad coverage of soil types present in the region (Shepherd & Walsh 2002), the sample set's suitability for detection of model problems and errors (Naes et al. 2002), and, with regard to validation sets, independency of validation samples, which is crucial for accurate estimation of the model's predictive power (Brown et al. 2005). Selection from spectral data space has proven efficient (Naes et al. 2002, Brown et al. 2005).

Pre-processing of spectral reflectance signals in order to minimize light scatter effects and thus to enhance the signal to noise ratio is commonly being applied. Many methods for scatter correction are available (Naes et al. 2002), the one most often applied being the transformation of soil reflectance curves by calculating their first derivatives (e.g. Chang et al. 2001, Shepherd & Walsh 2002). Vagen et al. (2006) have combined first derivatives with multiplicative scatter correction (MSC) (for a more detailed description of MSC, see for example Naes et al. 2002). Another promising method is the use of continuum removed spectra (Jarmer et al. 2003, Seiler 2006).

A variety of modelling approaches have been applied to calibrate VNIR data to soil properties: The major quantitative multivariate analysis methods used in VNIR spectroscopy are either linear or non-linear approaches (Blanco & Villarroya 2002). Linear approaches commonly applied include multiple linear regression (MLR), principal component regression (PCR) and partial least square regression (PLS). MLR is somewhat problematic due to its insufficiency in addressing the problem of multicollinearity (Naes et al. 2002). It is, however, the most simple and straightforward model approach. Linear methods allow establishment of calibrations on relatively small sample sets. However, in the case of widely varying soil sample sets, the performance of linear and parametric models is likely to be inferior to that of nonparametric models (Brown et al. 2006). Multiple adaptive regression splines (MARS) (Shepherd & Walsh 2002), classification and regression tree (CART) models (Shepherd & Walsh 2002, Cohen et al. 2005, Hett 2005), including combined regression tree (CRT) models (Seiler 2006, Hauert 2007), and boosted regression trees (BRT) (Brown et al. 2006) are nonparametric modelling approaches that have been tested on soil spectra. Advantages include their ability to handle more complex relationships, relative immunity to over-fitting and their ability to utilize a large number of weak classifiers and thereby make maximum use of the entire VNIR spectrum (Brown et al. 2006). Nonparametric models require a large sample size, which may not be easy to provide. A drawback especially for combined regression tree models is that while single tree models offer easy interpretation of variable importance, the output of combined regression tree models allows no specific conclusions to be drawn with regard to the link between spectral information and soil properties.

Heterogeneity of the soil spectral dataset is likely to lead to non-linearity in the spectral data. Different strategies are available for handling non-linearity problems. These include pre-processing of variables (e.g. statistical transformations), deleting problematic wavebands, splitting data into homogeneous subsets and using non-linear/nonparametric calibration methods (Naes et al. 2002). Results have shown that nonparametric model approaches are superior to linear approaches when modelling non-uniform sample sets (Brown et al. 2006). Applying partial least squares (PLS) regression, Udelhoven et al. (2003) concluded that calibrations between soil properties and soil spectral reflectance were only applicable to areas of homogeneous geological background. In contrast, Brown et al. (2006) succeeded in building a first global soil spectral library, including soils from various backgrounds. However, no precise rules have so far been established for determining sufficient spectral similarity to ensure reliable prediction (Brown et al. 2006). Calibrations could be improved by restricting geographical scope (e.g. Sudduth & Hummel 1996); on the other hand, global models may be more robust than local models (Shepherd & Walsh 2002). Moreover, high variability of soils may pose a major challenge for spectral libraries even for restricted geographical regions.

Exploratory analysis of soil spectral patterns provides key information for appropriate selection of a model approach (see discussion above), estimation of the behaviour of a model with regard to heterogeneous sample sets, and estimation of the potential of the model to predict additional sample sets. Many studies have applied principal component analysis (PCA) for characterization of major tendencies in the spectral data space. PCA has proven successful for outlier detection (Shepherd & Walsh 2002, Brown et al. 2005) and for increasing the understanding of spectral variability (Islam et al. 2005). The visible range of the spectrum is also very effective in assigning soils to different soil groups and in distinguishing soils with differing iron-oxide contents (Scheinost & Schwertmann 1999). The CIE colour system has proven useful in soil studies (Leone & Escadafal 2001). Jarmer and Schütt (1998) have shown that colour values calculated from spectra as determined by the CIE system (Wiszecky & Stiles 2001) provide information on the sample's predominating iron mineral composition. Such information is of specific interest for studies involving soil organic matter, since both constituents affect the same spectral regions (Palacios-Orueta & Ustin 1998).

Validation of prediction accuracy may heavily depend on the spatial structure of validation and calibration models (Brown et al. 2005). Brown et al. (2005) have shown that the model's capacity for extrapolation to additional sample sets may be over-predicted if validation sets are used that are not fully independent. It followed accordingly that if 20-35% of the samples from a new test area were included in model calibration, prediction accuracy of the rest of the additional sample set could be substantially increased (Shepherd & Walsh 2002, Brown et al. 2005).

3.1.3 Practical application of soil spectral libraries

In order to put soil spectrometry to practical use, a standardized procedure is needed for the development of calibration between soil properties and VNIR reflectance, including subsequent incorporation of new sample sets. Shepherd and Walsh (2002) have proposed a framework that would facilitate the development of soil reflectance spectral libraries based on a limited number of samples, and subsequent systematic enlargement of the library. Such a framework also facilitates establishment of regional libraries, if not global spectral libraries. A first application has shown that for global spectral libraries, the number of samples required for calibration of global soil spectral variability would be extremely high, but regional approaches seem feasible (Brown et al. 2006).

Many developing countries struggle with widespread land degradation (e.g. Oldeman et al. 1991), but especially for these countries or regions, the high costs involved in large-scale soil sampling and analysis using standard procedures, prevent collection of crucial information on soil resources needed (Vagen et al. 2006). This is also true for Tajikistan. While, in Soviet times, well-functioning soil laboratories and well-educated and trained field teams were available, both financial and human resources have been drastically reduced since the country's independence in 1991, and infrastructure has deteriorated. In this context, soil chemical analysis, which provides reliable reference data for calibration to VNIR data, is of particular importance.

Once relationships between soil properties and spectral reflectance, or soil quality indices and spectral reflectance, have been established, soil spectral libraries could become very useful for countries like Tajikistan. Additional samples could be predicted solely from VNIR information, enabling efficient and cheap prediction of important soil quality indicators. A major challenge remains as to applying existing calibrations to additional sample sets: In advance of prediction, screening of new samples for congruency with the existing soil spectral library is required (Shepherd & Walsh 2002). If samples are identified as outliers, the existing spectral library needs to be extended. Thus additional reference values from soil chemical analysis have to be obtained and calibration models for an extended reference sample set need to be developed. Shepherd and Walsh (2002) proposed a method called soft independent modelling of class analogy (SIMCA) for identification of outliers to existing soil spectral libraries. Seiler (2006) has proposed a method suitable for application with MLR models, which is based on the range of reflectance values present in a soil spectral library for the specific wavebands included in the MLR model.

3.1.4 Previous soil spectrometry study carried out in Tajikistan

Bruno Seiler from the Remote Sensing Laboratory (RSL) of the Department of Geography at the University of Zurich conducted his MSc thesis within the framework of the NCCR North-South research carried out in Tajikistan. In November 2004, measurements of soil spectral reflectance at the Soil Science Research Institute in Dushanbe, Tajikistan were carried out in collaboration with Bruno Seiler. The following paragraph provides a summary of the results of Seiler's diploma thesis entitled "Quantitative Assessment of Soil Parameters in Western Tajikistan Using a Soil Spectral Library Approach" (2006): Since soil degradation is a major problem in the predominately agricultural country of Tajikistan, it is necessary to determine and monitor the state of soils. For this purpose a soil spectral library was established as it enables the determination of soil properties at relatively low costs and with relatively little effort. A total of 1465 soil samples were collected from three 10x10 km test sites in western Tajikistan. The diffuse reflectance of the samples was measured with a FieldSpec PRO FR from Analytical Spectral Devices (ASD) in the spectral range from 380 to 2500 nm in the laboratory. 260 samples were finally selected based on their spectral information and analyzed for total C and N, organic C, pH, $CaCO_3$, extractable P, exchangeable Ca, Mg and K, and their fractions of clay, silt and sand. Three approaches for building calibration models were tested against each other: multiple linear regression with continuum removed data, principal component regression and regression tree with first derivative data. One third of the chemically analyzed samples were used for random hold out validation. Multiple linear regression turned out to be the best performing approach for the dataset used and was therefore applied to calibrate the prediction models. In order to improve prediction accuracy, the given soils were grouped using a classification tree and only the soil group of main interest (loess samples) was used for modelling. Very good prediction accuracy was obtained for total C (R^2 = 0.76, RMSEP = 4.36 g kg^{-1}), total N (R^2 = 0.83, RMSEP = 0.30 g kg-1) and organic C (R^2 = 0.81, RMSEP = 3.30 g kg^{-1}), good accuracy for pH (R^2 = 0.61, RMSEP = 0.157) and $CaCO_3$ (R^2 = 0.72, RMSEP = 4.63%). No models could be developed for extractable P, exchangeable Ca, Mg and K, and the fractions of clay, silt and sand.

3.1.5 Objective

The overall goal of this study was to achieve an adequate prediction of soil organic carbon (SOC), as an integrative indicator of soil quality, from soil spectral reflectance data for regional land degradation assessments by adopting a soil spectral library approach and applying it to the highly variable soils in the hill zone of central Tajikistan.

3.2 Materials and Methods: Building a soil spectral library

3.2.1 Overview of procedure

The soil spectral library for prediction of SOC was established following the procedure described by Shepherd and Walsh (2002), that includes the following steps: (1) Representative sampling of soil variability in the study area, (2) Establishing the soil reflectance spectral dataset using VNIR spectrometry, (3) Selecting a reference dataset to be analyzed with traditional soil chemical methods required as reference values, (4) Determination of soil properties by means of soil chemical analysis, (5) Calibrating soil property data to soil reflectance spectra by applying multivariate calibration models and finally (6) Prediction of new samples using the spectral library. In this study, an additional step was included preceding step 5: Spectral heterogeneity was linked to the geological characteristics of soil samples. Table 3-1 provides an overview of the procedure followed in this study, and can be used as the central thread leading through the subsequent sections.

Table 3-1 Building a soil spectral library for Tajikistan: Overview of procedure

Steps		**Methods**	**Datasets**
Representative sampling of soil variability in the study area (section 3.2.3)	~ Soil variability in the study area (soil types, geology, spatial extent) ~ Representation of variability	~ Review of existing information (local expertise, literature, maps) ~ Sampling design	~ Representative samples for the study area consisting of samples from Yavan test area (N=400), Faizabad test area (N=660) and Varzob test area (N=410)
The soil reflectance spectral dataset (section 3.2.4)	~ Measuring soil reflectance spectra	~ Instrument and measurement set up	~ Test areas YA&FA (November 2004) ~ Test area VZ (October 2005)
	~ Pre-processing soil reflectance spectra ~ Repeatability of predictions from soil reflectance spectra, influenced by pre-processing techniques	~ Pre-processing techniques: continuum removal, first derivatives and multiplicative scatter correction ~ Coefficient of variation and standard error of laboratory measurement applied to analyze results from repeat reflectance spectral measurements	~ Noise corrected and reflectance data transformed ~ Repeat reflectance measurements on samples from two sampling clusters (*FA64* and *YA24*) ~ SOC predictions for samples of holdout sampling clusters *FA64* and *YA24*
The reference dataset (section 3.2.5)	~ Selecting calibration and validation datasets	~ Selecting samples based on PCA and geographical sample location	~ Soil reflectance data from test areas 1&2 (1,007 samples)
	~ Comparison of different laboratories ~ Determining soil chemical attributes	~ Repeatability and reproducibility assessment ~ Soil chemical analysis methods	~ Lab test set (N=10) ~ Reference soil property values from Yavan & Faizabad test areas (N=248)
	~ Outlier detection in the soil chemical reference dataset using preliminary models	~ Preliminary models for detection of possible outliers and comparison of CV for samples with repeat analysis	~ Reference dataset from Yavan & Faizabad test areas ~ Repeat chemical measurements
Spectral heterogeneity explained by geological characteristics (section 3.2.6)	~ Exploring patterns of soil reflectance spectral information ~ Classifying samples into geological sub-groups using CIE colour values	~ PCA for characterization of spectral patterns ~ Classification trees for determination of spectrally homogeneous sub-groups ~ Iron-oxide characteristics determined from CIE colour space	~ Soil reflectance data from Yavan and Faizabad test areas ~ Calibration dataset for geological sub-groups, including additional samples for spectrally under-represented groups (paleosol sample set with 12 samples)
Calibrating SOC to soil reflectance spectra (section 3.2.7)	~ Combined regression tree (CRT) modelling ~ Testing model performance in relation to soil heterogeneity ~ Evaluating model performance	~ Determination of best model settings by comparing RMSEs ~ Prediction accuracy for loess models versus full sample set models ~ CRT models (full holdout of samples from two clusters)	~ Calibration and validation sample sets ~ Loess sample set (N=174) and full reference sample set (N=253) ~ SOC predictions for samples of clusters *FA64* and *YA24*
Predicting SOC from soil reflectance spectra (section 3.2.8)	~ Checking reliability of predictions	~ Compatibility of spectral data space ~ Validation with OM results ~ Congruency of prediction results from CRT and MLR models	Sample sets to be predicted: ~ Samples from test areas YA&FA (N=750) ~ Samples from test area VZ (N=410) ~ Samples from case studies (N=655)

Abbreviations: YA = Yavan, FA = Faizabad, VZ = Varzob

3.2.2 Statistical parameters

A set of statistical parameters was applied and an overview of abbreviations, formulae and sources is provided below. N = total number of samples, y = predicted value, x = reference value (Table 3-2).

Table 3-2 Overview on statistical parameters

• Assessing accuracy of laboratory measurements (based on repeat measurements):	
The coefficient of variation (CV) is the ratio between the standard deviation (SD) and the mean predicted value $\bar{y}$.	$CV = \frac{SD}{\bar{y}}$, where SD is: $SD = \sqrt{\frac{\sum(y-\bar{y})^2}{N-1}}$
Standard error of laboratory measurement (SEL), where the i index and the number n represent different samples and the j index and the number r different measurements on the same sample (Workman & Mark 2006).	$SEL = \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(x_{ij}-\bar{x}_i)^2}{n(r_i-1)}}$
• Assessing accuracy between reference method and predicted value:	
Root mean square error (RMSE), which gives the root mean square error of calibration (RMSEC) and of validation (RMSEV) for calibration and validation sample sets. Instead of the RMSEV, many spectrometry studies apply the standard error of prediction (SEP), which uses "*N-1*" in the denominator.	$RMSE = \sqrt{\frac{\sum(y-x)^2}{N}}$, $SEP = \sqrt{\frac{\sum(y-x)^2}{N-1}}$
The bias defines the systematic error. RMSEV and SEP (if not corrected for bias) encompass the systematic and the random error.	$BIAS = \frac{\sum(y-x)}{N}$
Root mean square percentage error (RMSPE) is the relative equivalent to the RMSE. Due to the squaring, the RMSPE, just like the RMSE, is highly susceptible to errors.	$RMSPE = 100\sqrt{\frac{1}{N}\sum\left[\frac{y-x}{x}\right]^2}$
The mean absolute percentage error (MAPE) is also a relative measure. The MAPE is a simpler measure than the RMSPE and thus easier to interpret.	$MAPE = 100\frac{1}{N}\sum\frac{\lvert x-y\rvert}{x}$
• Unitless model performance parameters:	
The coefficient of determination (R^2) describes the proportion of the total variation accounted for by the model, with the remaining variation being attributed to random error. The R^2 is highly dependent on the spread of the calibration samples.	$R^2 = \left(\frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2\sum(y-\bar{y})^2}}\right)^2$
The ratio of standard deviation of prediction (RPD) is a measure of model quality that takes into account the spread of the reference samples (Chang et al. 2001, Islam et al. 2003, Coûteaux et al. 2003).	$RPD = \frac{SD}{SEP}$, (with SEP as described above) Target classes as defined by Chang et al. (2001): >2 (high accuracy), 1.4-2.0 (calibration to be improved), < 1.4 (no reliable predictions)

3.2.3 Representative sampling of soil variability in the study area

Soil properties in the study area

The focus of this study was on the rainfed areas in the hill zone of Western Tajikistan, located at the foot of the Gissar mountain range. The Gissar range is situated north of Dushanbe and runs from West to East. The range is dominated by granodiorite-granite complexes (Brookfield 2000) and forms the boundary for wind-borne silt carried from the Afghan deserts. Thus, south of the Gissar range loess deposits have accumulated, forming characteristic foothills. The soils which have formed on the loess are brown carbonate soils and, at higher altitudes and in areas with more precipitation, typical brown soils, according to Tajik soil classification (Kuteminskij & Leonteva 1966).

In the study area, brown soils are thus prevailing; these soils are fairly homogeneous. Only at higher altitudes, where the loess cover is diminishing, can a pattern of mountainous, stony soils (leptosols) and brown soils be observed. Here the bedrock consists of granodiorite (oral communication from PM Sosin). On the valley floors, quaternary river sediments prevail. Furthermore, in areas with strong historic erosion processes, paleosols are present at the surface. This is especially true for the easternmost test area, test area 2, which is situated in Faizabad district. While the loess horizons can be described by a yellowish colour and a massive structure, the paleosols are characterized by a brownish or reddish colour and a subangular blocky structure (Ding et al. 2002). Paleosols contain increased amounts of hematite and goethite. Their formation in amorphous or poorly crystallized phases can be attributed to weathering of primary minerals in the parent rock (loess). These processes are facilitated by increased temperatures, alternating moistening and drying, and relatively intense soil aeration, during interglacial periods (Dodonov et al. 2002).

Typical values for soil organic carbon (SOC) are 1-2%. Assessments carried out in the Faizabad area determined soil organic matter contents for various states of eroded soils. OM results were reported and are provided here together with the respective SOC values, as calculated based on the OM/SOC ration determined in this study (cf. section 3.3.1): for soil without erosion, OM content in the topsoil was 3.58% (SOC = 2.4%); for slightly eroded soil, OM was 2.5% (SOC = 1.7%); for moderately eroded soil, OM was 1.48% (SOC = 1.01%); for strongly eroded soil, OM was 1.57% (SOC = 1.10%); and for very strongly eroded soil, OM was 0.78% (SOC = 0.50%) (Yakutilov et al. 1963). $CaCO_3$ contents vary between 2-30%, depending on the mother rock, but also on the state of erosion (Kuteminskij & Leonteva 1966). Kuteminskij & Leonteva (1966) and Yakutilov et al. (1963) analyzed the texture of four representative profiles for soils from Faizabad, taking samples from locations showing different states of degradation by erosion. The soil layers between 0 and 40 cm depth were reported to show uniform results, with the clay fraction of < 0.001 mm amounting to 15-27%, the silt fraction of 0.001-0.05 mm amounting to 63-78%, and the sand fraction of 0.05-1.0 mm amounting to 0.5-5%.

Sampling design and overview of soil sample sets

For full characterization of the area, a randomized sampling design was chosen. Rare soil types (e.g. paleosols) were included on purpose, in order to cover the full variation of soil in the study area. The set included samples from 600 sampling sites, clustered in groups of 13 sites. These clusters were again grouped in 3 test areas of 10 by 10 km each, each including 15 clusters (Figure 3-1 and Figure 3-2). Sampling sites measured approximately 30 by 30 m, corresponding to the pixel size of Landsat 7 scenes. On each sampling site, topsoil (0-20 cm depth) and subsoil (20-50 cm depth) samples were collected from two sampling pits at a distance of around 7 m and stored either as composite samples (for 445 sampling sites) or kept as separate samples (for 117 sampling sites). The separately kept samples were used for assessment of within field variation of soil properties. Samples from the Yavan test area (N=400) were collected in May 2004, from the Faizabad test area (N=660) in June 2004 and from the Varzob test area (N=410) in June 2005.

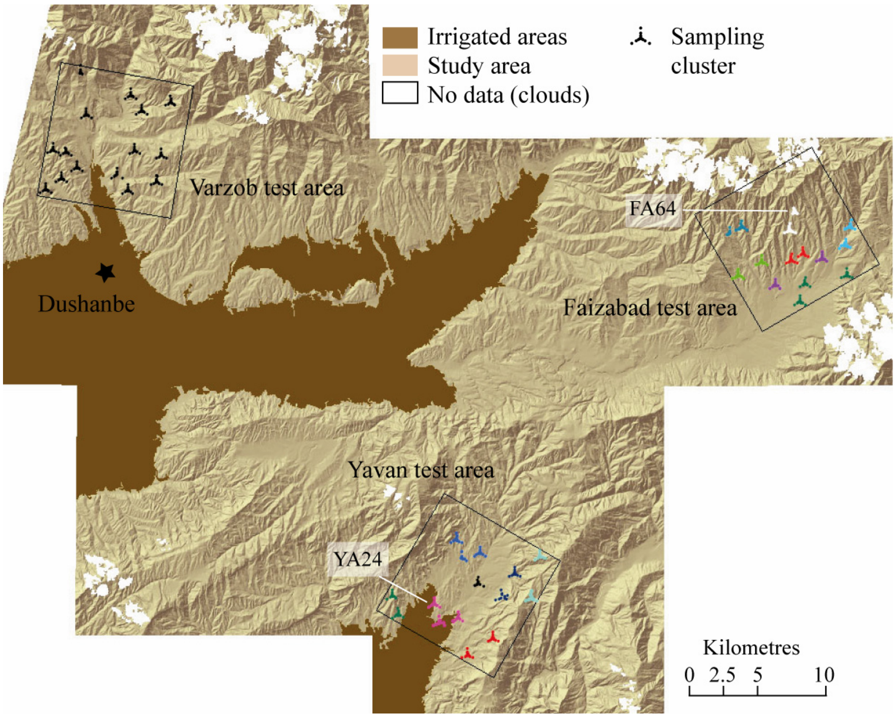


Figure 3-1 *Overview of central Tajikistan with the capital Dushanbe and the test areas of Yavan, Faizabad and Varzob, measuring 10 km by 10 km each. Each of these test areas contains 15 sampling clusters, which in turn contain 13 sampling sites each. Two sampling clusters (FA64 and YA24) were used for holdout validation; their locations are indicated. Colour of clusters indicate the cluster groups used when selecting calibration and validation datasets as described in section 3.2.5.*

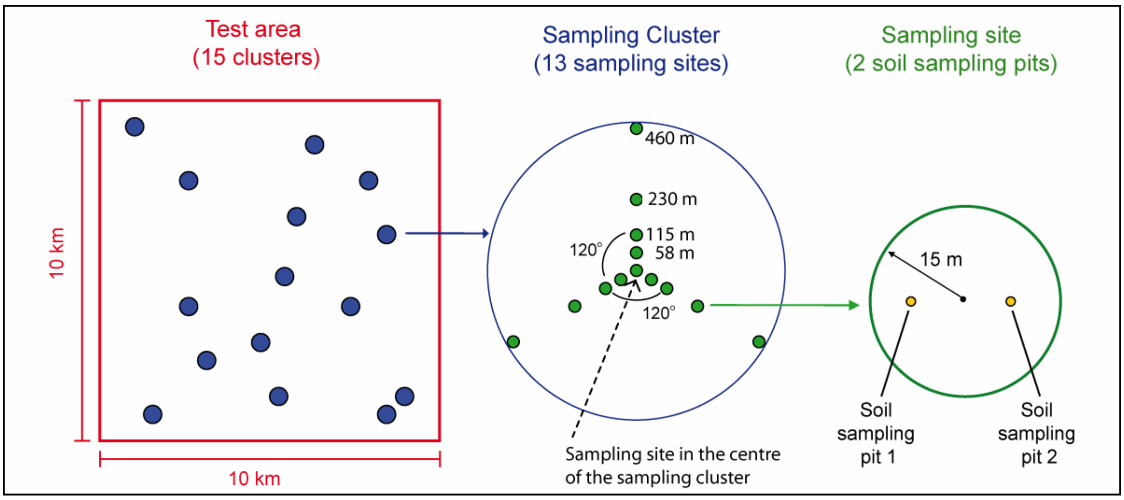


Figure 3-2 *Sampling design consisting of 4 levels: test areas selected based on expert judgment, randomly determined sampling clusters, systematically determined sampling sites, and systematically placed soil sampling pits.*

3.2.4 The soil reflectance spectral dataset

Measuring soil reflectance spectra

The soil spectral library for prediction of SOC was established following the procedure described by Shepherd and Walsh (2002), adjusted by using a muglight for illumination as described by Mutuo et al. (2006). Soil spectral reflectance was measured under standard conditions in the laboratory (Figure 3-3a). Air-dried ground soil samples of 2 mm thickness were filled into borosilicate Duran glass Petri dishes with optimal optical characteristics. The Petri dishes were placed on a muglight equipped with a Tungsten Quartz Halogen light source (Analytical Spectral Devices, Boulder, CO). Spectral reflectance readings were collected through the bottom of the Petri dishes using a FieldSpec PRO FR spectroradiometer (Analytical Spectral Devices, Boulder, CO). Every sample was measured twice, with the sample being turned by 90 degrees for the second measurement. The two measurements were averaged, which minimized light scatter effects from uneven particle size distribution on the Petri dish floor. The instrument works with three spectroradiometers to cover the wavelengths from 350 to 2500 nm at an interval of 1 nm. The fore-optic view was set to 8 degrees. For dark current readings 25 scans were averaged, while for white reference and soil spectral readings 10 scans were averaged by the spectroradiometer. Before each sample reading, white reference readings were taken from a spectralon (Labsphere) that was placed on a trimmed Petri dish bottom.

Spectral measurements on the samples of the Faizabad (FA) and Yavan (YA) test areas (the FAYA sample set) were conducted in October 2004. Samples for chemical analysis, and thus serving to establish the reference dataset, were selected from the FAYA sample set. Spectral measurements of the Varzob (VZ) test area samples were conducted in November 2005.

3a)

3b)

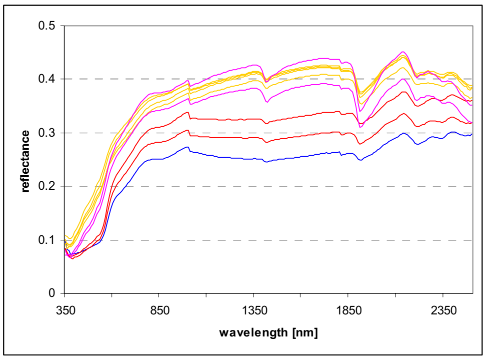


Figure 3-3 a) Measurement set-up with spectroradiometer to the right and muglight with sample on top to the left. b) Typical spectra of samples from different geological sub-groups named according to their bedrock (cf. section 3.2.3): river sediments (blue), granodiorite (red), paleosol (pink), loess (yellow).

Pre-processing soil reflectance spectra

Pre-processing of soil reflectance data to decrease the noise present in the data and thus to increase robustness of reflectance spectral data is common in VNIR spectrometry, and is especially important in the case of measuring set-ups that are difficult to control (e.g. due to power fluctuations, different operators during different measuring sessions). Pre-processing of the data used in this study was conducted by Bruno Seiler and is described in detail in his MSc thesis (Seiler 2006). The main pre-processing steps conducted were as follows: Spectra were compressed by selection of every 10th nm. Spectral bands in the lowest (350-430 nm) and highest (2440-2500 nm) measurement ranges were omitted due to low signal to noise ratio (lower than 90). The final number of wavelengths used as model input was 205. Information for these 205 wavelengths was further processed: The instrument covers the full wavelength range with three spectroradiometers. Steps in the spectral reflectance curves were observed at the spectrometer changeovers. Most likely, this effect resulted from the Petri dishes used as sample holders and their specific index of refraction. According to Analytical Spectral Devices, the manufacturer of the spectroradiometer, such steps are common whenever sample holders are used. The steps were removed in order to achieve a continuous spectrum (cf. Seiler 2006).

The visible range of the spectrum is very effective in assigning soil to different soil groups and in distinguishing soil with differing iron-oxide contents (Scheinost & Schwertmann 1999). The CIE system (Commission Internationale de l'Eclairage 1931) has been developed for transformation of diffuse reflectance information into colour space (Wiszecky & Stiles 2001). For each sample, CIE tristimulus values (named X, Y, Z) and chromaticity coordinates (named x, y, z) were calculated from spectral information in the visible range according to CIE colour matching functions (cf. Seiler 2006).

Repeatability of predictions from soil reflectance spectra

Three different approaches for noise elimination by pre-processing of spectra were tested: (i) Transformation of the data by first derivative processing using a Savitzky–Golay filter with a 20 nm window (Seiler 2006), (ii) Applying multiplicative scatter correction to the first derivatives of spectra and (iii) Continuum removal conducted with ENVI software (Seiler 2006). Seiler (2006) showed graphically that the repeat measurements for two soil spectral reflectance curves were most congruent if spectral information had been pre-processed using continuum removal. Further, his study demonstrated that SOC contents predicted from multiple linear regression models for two repeat spectral measurements were only consistent when using continuum removed spectra as input variables. These findings were tested for the combined regression tree models applied in this study (cf. section 3.2.7). For samples from the FA64 (N=38) and YA24 (N=24) clusters, spectral measurements were recorded twice. For calibration datasets from which samples from the FA64 and YA24 clusters had been excluded, additional calibration models between SOC content and VNIR spectra were established. The double spectral measurements were subsequently used to predict SOC from two independent spectral measurements. The standard error of laboratory measurement (SEL) and the coefficient of variation (CV) were used to assess the precision of the method (for definitions of SEL and CV, see section 3.2.2).

3.2.5 The reference dataset

Accuracy and further applicability of established calibrations are strongly co-determined by the reference dataset. Thus special attention was paid to the compilation of an accurate and representative reference dataset for establishing the soil spectral library. The following aspects were considered:

- Calibration and validation sample sets should be selected by taking into account the size of the sample sets (with a minimum of 200 calibration samples according to Shepherd and Walsh [2002]), representation of the spectral as well as the geographical space, and the independency of the validation dataset.
- The laboratory conducting the soil chemical analysis should preferably be equipped to determine a number of the most important soil quality / soil fertility properties, should

produce results with satisfactory precision (repeatability and reproducibility), and should preferably apply modern methods, to make results comparable to future chemical analysis. However, these soil chemical properties should be comparable with previous measurement data available in Tajikistan.

- Identification of outliers in the reference dataset is crucial. VNIR measurements, expected to be more precise than chemical measurements, provide the basis for efficient outlier identification.

Selecting the calibration and validation datasets

For selection of spectrally representative samples to be included in the calibration dataset, principal component analysis was applied. In a first step, principal components (PCs) for the full dataset were calculated from first derivatives of soil spectra, and samples were plotted in the biplot determined by PCs 1 and 2. Vague spectral clusters reflecting geographical location of samples were observed. Therefore, in a second step, all samples originating from 2 or 3 sampling clusters, situated next to each other and representing similar ecological conditions (same land use systems and land forms) as indicated by colours in Figure 3-1, were selected for re-calculating principal components. For these groups of sampling clusters, samples were selected using the available software function, which automatically subdivides samples into sub-groups, based on the datasets values of the first 4 PCs. Subsequently samples of these subgroups with minimum and maximum values are selected (Unscrambler, CAMO Inc)[20]. On average 6 samples per cluster were selected for chemical analysis, a minimum of 4 and a maximum of 12 samples per cluster. All in all, this resulted in 204 samples, of which 195 were finally used as the calibration sample set. Nine samples originating from identical sample plots were shifted to the validation set to assure independency of calibration samples.

When choosing the validation set, care was taken to assure that validation samples were representative for the whole region. Thus, samples were systematically chosen by selecting from every centre point of a sampling cluster (Figure 3-2), one topsoil and, where available, one subsoil sample (totalling 38 samples). In order to make sure that samples expected to have high amounts of SOC were well represented in the validation set, 5 additional samples were included that were taken mainly from vegetable gardens, the owners of which had declared that they applied manure. Finally, 7 samples originating from the laboratory test set were also included in the validation sample set. A total of 254 samples were selected for soil chemical analysis out of the full sample set (N=1,007) from the Yavan and Faizabad test areas.

Repeatability and reproducibility of chemical results from different laboratories

Prior to the analysis of the reference sample set, a small laboratory test series was performed. The aim was to assess repeatability of results for a specific laboratory and reproducibility of results between the 4 laboratories included in the test series. The lab test sample set consisted of 10 samples, each divided into 8 sub-samples. For the blind test conducted, each laboratory was provided with 2 identical sub-samples per lab test sample, adding up to a test set of 20 randomly numbered samples per laboratory.

[20] The software function may be found in the pull-down menu of Unscrambler by selecting the following menu choices: edit/mark/evenly distributed samples/classes.

The following laboratories were involved in the test series:

- Soil Science Research Institute in Dushanbe, Tajikistan (SSRI)
- “Committee of land resources” in Dushanbe, Tajikistan (GIPROSEM)
- Department of Geography at the University of Berne in Berne, Switzerland (GIUB)
- Laboratory of the World Agroforestry Centre in Nairobi, Kenya (ICRAF)

While the Tajik laboratories determined OM, the GIUB and ICRAF laboratories measured SOC contents (cf. Table 3-3). Organic carbon is a major component of soil organic matter and may be used interchangeably if the OM to SOC ratio applicable for the specific soils has been determined, subsequently making it possible to calculate SOC contents from OM values. In order to calculate the OM to SOC ratio, 60 samples were analyzed for both SOC and OM contents and subsequently the mean OM to SOC ratio was determined (cf. Figure 3-5a). The results of the laboratory test series were assessed for within laboratory consistency (repeatability) and between laboratory comparability (reproducibility), including comparability of the different methods. Simple qualitative (Youlden plot) and quantitative (coefficient of variation) measures were applied in the evaluation.

Determination of soil properties by means of soil chemical analysis

A set of commonly used agronomic indicators of soil fertility was selected for characterization of the reference dataset. These included pH, total soil carbon (TC), soil organic carbon (SOC) and inorganic carbon (IC), total nitrogen (TN), extractable phosphorus (extrP) and exchangeable potassium (exK), cation exchange capacity (CEC) calculated as sum of calcium (Ca), magnesium (Mg) and potassium (K), as well as soil particle size.

In this study, the focus was on the SOC content and was thus the only soil property, which was calibrated to soil reflectance spectra. However, chemical analysis of a wider range of soil properties made it possible to analyze correlation between properties and dependency of residuals from other soil properties. Furthermore, the results provided an overall picture of soil fertility in the study area. Soil organic matter (OM) content is commonly determined using the Walkley-Black method (Soil Survey Staff 1996) but it is becoming increasingly popular to measure SOC content using high temperature induction furnace combustion methods (Sherrod et al. 2002). In Tajik soil laboratories the method of Turin, comparable with the Walkley-Black method, is being applied.

SOC content is often classified into 3 to 5 quality classes. For this study, the classification as defined by WOCAT was employed (WOCAT 2003): low (OM < 1%), medium (OM = 1-3%) and high (OM > 3%). These thresholds translate to content SOC = 0.7% and SOC = 2%, when applying an OM to SOC ratio of 1.47 as determined for the soils in the study area (cf. section 3.3.1).

Table 3-3 Methods for soil chemical analysis conducted by different laboratories

Soil property	Laboratory	Method
Total nitrogen (TN) [%]	ICRAF	Dry combustion using a Roboprep automatic C/N analyzer (Europa Scientific, Crewe, UK)
Total carbon (TC) [%]	ICRAF	Dry combustion (as described above)
Soil organic carbon (SOC) [%]	ICRAF	Dry combustion on decarbonized samples: Samples were pre-treated with diluted HCl to remove calcium carbonates and subsequently analyzed by combustion in a CN analyzer.
	GIUB	Difference calculated between total carbon (TC) determined from dry combustion and soil inorganic carbon determined from the Scheibler apparatus as described by Schlichting and Blume (1966)
Inorganic carbon (IC) [%]	ICRAF	Calculated: TC – SOC
Organic matter (OM) [%]	SSRI	Method of Turin based on oxidation of OM by an excessive amount of $K_2Cr_2O_7$ (Stolbovoi et al. 2002). The method gives results compatible with the widespread method of Walkley-Black (Kogut & Frid 1993).
pH	ICRAF	pH determined in water using a 1:2.5 soil/solution ratio
Extractable phosphorus (extrP) [mg P / kg soil]	ICRAF	Samples were extracted with 0.5 M $NaHCO_3$ + 0.01 M EDTA (pH 8.5, modified Olsen) using a 1:10 soil/solution ratio and analyzed by flame photometer for exchangeable K and colourimetrically (molybdenum blue) for extractable P (ISFEIP 1972; Yurimaguas Experiment Station Staff 1989).
Exchangeable potassium (exK) [me/100 g soil]	ICRAF	
Exchangeable calcium (exCa) [me/100 g soil]	ICRAF	Samples were extracted with 1 M KCl using a 1:10 soil/solution ratio, and analyzed by NaOH titration for exchangeable acidity and by atomic absorption spectrometry for exchangeable Ca and Mg (ISFEIP 1972, Yurimaguas Experiment Station Staff 1989).
Exchangeable magnesium (exMg) [me/100 g soil]	ICRAF	
Clay (%) < 0.002 mm	ICRAF	Particle size distribution was determined using the hydrometer method after pre-treatment with H_2O_2 to remove organic matter (Gee & Bauder 1986) and 10% HCl to remove soluble salts.
Silt (%) 0.002 to 0.05 mm	ICRAF	
Sand (%) > 0.05 mm	ICRAF	

Outlier detection in the soil chemical reference dataset using preliminary models

This paragraph presents an excursus about outlier detection in chemical reference datasets. In this study, as regards SOC content, outliers were not identified as described below. Due to a delay in SOC content analysis, extensive random repeat SOC analysis was performed instead. Several results from chemical SOC content analysis are expected to be outliers, for which so far no repeat analysis was possible. However, the potential of outlier detection using VNIR data shall be presented taking the example of the soil properties total carbon (TC), total nitrogen (TN) and exchangeable calcium (exCa).

Since spectral measurements are usually more precise than soil chemical measurements, soil property predictions from soil reflectance spectra may be used to identify possibly false chemical reference values that need repeat analysis (Naes et al. 2002, Coûteaux et al. 2003, Shepherd et al. 2005). Therefore, prior to the actual calibration, preliminary models were elaborated, linking soil property results from chemical analysis with VNIR spectra. The following procedure was used: Samples were randomly chosen as calibration samples (two-thirds) or validation samples (one-third). For each of these 10 different calibration and validation sets, a calibration model was established. These preliminary calibration models were built by applying multiple linear regression (MLR) as described by Seiler (2006). For each model, residual plots with soil property predictions on the y-axis and measured soil properties on the x-axis served for a visual assessment of x-residuals. Samples with significantly above average residuals were sent back to the laboratory for repeat chemical analysis. This procedure of selecting samples for repeat analysis was termed “informed sample selection”. Further, repeat chemical analysis was also performed for randomly chosen samples. Subsequently, the coefficient of variation (CV) was calculated from the repeat chemical analysis results. The CV from samples selected based on informed selection were compared both with existing laboratory internal CVs and with the CVs determined from random repeat analysis.

3.2.6 Soil spectral heterogeneity and geological characteristics

Exploration of soil spectral variability provides information on patterns present in the soil reflectance data space and makes it possible to assess advantages and disadvantages of both spectrally homogeneous and heterogeneous calibration datasets. The aim of the subsequent steps was thus to identify spectrally homogeneous sample sub-groups and to classify samples which had not yet been classified in the field on the basis of spectral information.

Exploring patterns of soil reflectance spectral information

For analysis of spectral patterns, the reflectance spectral information of the FAYA sample set was plotted in standardized principal component space. Homogeneous sample sets are grouped around the centre of the principal component space. Thus spectrally dissimilar samples can be detected outside of the main bulk. The biplot for the first and second principal components provided indications that the geological origin of samples (loess, paleosol, granodiorite mother rock or river sediments [cf. section 3.2.3]), would allow determination of geological sub-groups with lower spectral variation than that of the full calibration sample set (Figure 3-4).

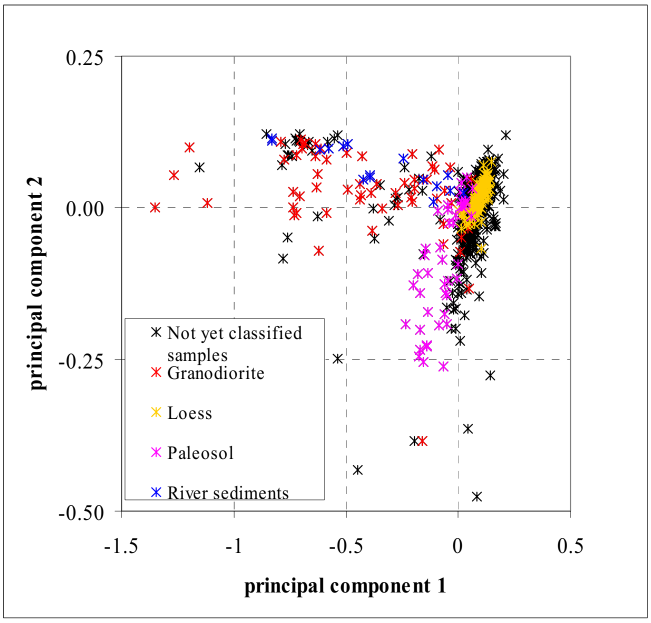


Figure 3-4 Biplot of principal components 1 (x-axis) and 2 (y-axis) calculated from continuum removed spectral data. Samples visually classified as belonging to specific geological sub-groups are displayed as follows: loess (yellow), granodiorite (red), paleosol (pink) or river sediments (blue). Not yet classified samples are displayed with black marks.

Classifying samples into geological sub-groups using CIE colour values

Jarmer and Schütt (1998) have shown that the chromaticity values from the CIE colour space indicate the sample's predominating iron mineral composition. In order to distinguish paleosol and granodiorite bedrock samples from loess samples, differences in soil colour caused by iron –oxides, which are well characterized by CIE colour space, thus seemed especially promising and were consequently applied. Compilation of the calibration sample set necessitated collection of an additional paleosol sample set from areas where undisturbed, clearly identifiable paleosols had been observed in the field. For the soil groups "loess", "river sediments" and "granodiorite", samples from the FAYA set were chosen. Samples were assigned to a specific class based on the Munsell Colour Code as determined in the field, and on their sampling location. Additionally, each calibration sample was visually checked for correct class assignment. Expecting non-linear relationships, nonparametric classification tree modelling with CART software (Breiman et al. 1984) was used to establish a model for classification of geological sub-groups. All CIE colour values (X, Y, Z and x, y, z) as well as the x-z ratio served as input variables. For small sample sets, cross-validation is most effective and was thus applied. For more detailed information on classification tree modelling see chapter 2.

3.2.7 Calibrating SOC to soil reflectance spectra

Combined regression tree modelling

Combined regression tree (CRT) models are based on the method of single regression trees. The method is to grow regression trees by partitioning the data into relatively homogeneous groups, using binary recursive partitioning (Steinberg & Colla 1995). The resulting groups form the tree's terminal nodes. The mean values observed in the terminal nodes of a tree are then used as the predicted values. The variance within a specific node provides a measure for goodness of fit. The structure of single regression trees are readily interpreted and thus are capable of revealing the underlying structures of a variable set (Steinberg & Colla 1995). A disadvantage of single tree models is that the best models often consist of a limited number of terminal nodes, leading to prediction with ordinal characteristics even though input data are continuous (Hett 2005).

Combined regression tree (CRT) modelling is rather better suited to continuous datasets, since it typically accommodates a much higher number of terminal nodes. CRT modelling generates a single predictive engine from many regression trees by resampling with replacement from the original training data. The trees are combined by averaging their outputs. Two methods for resampling are available: bootstrap aggregation (bagging) and adaptive resampling and combining (arcing) (Steinberg et al. 2002). In bagging, each new resample is drawn in an identical way, while in arcing the way a new sample is drawn for the next tree depends on the performance of the prior trees. In arcing, cases that are difficult to classify receive an increasing probability of selection while cases that are classified correctly receive declining weights from resample to resample (Steinberg et al. 2002). Arcing models are therefore more sensitive to outliers in the reference data.

Even though efforts have been made to increase the accuracy of the reference sample set and the robustness of input variables, presence of outliers in the calibration dataset could not be precluded. In view of the relatively small sample set, the focus was thus on bagging. For achieving optimal results, bagging with around 100 trees and/or arcing with an exponent of 4 and around 250 combined trees is suggested (Steinberg et al. 2002). Model settings for bagging with 50, 100 and 150 combined trees were tested and the test models were designated bag50, bag100 and bag150, respectively. Furthermore, bagging with 100 combined trees, including CIE colour values as additional input variables, was also tested (designated bag100-CIE). Only one test was conducted for arcing (exponent set to 4 and number of trees to 250, designated arc250).

Calibration and validation sample sets were determined as described in section 3.2.5. Since cross-validation is used for internal tree improvement, there is a strong incentive to assure independency of samples in the calibration sample set. Since samples had been collected to represent spectral variation, it was expected that sample characteristics would be highly independent even if the samples originated from neighbouring sampling sites at a distance of only 58 m.

Testing model performance in relation to soil heterogeneity

For a spectrally uniform geological sub-group (the loess sample set as defined in section 3.2.6), less complex relationships between soil spectral reflectance information and soil properties were expected. Thus, it was initially assumed that higher spectral uniformity of the loess sample set would lead to higher prediction accuracy. One hundred and sixty-six samples attributed to the loess sample set made up the calibration dataset for a multiple linear regression (MLR) model, which was established for Bruno Seiler's MSc thesis (Seiler 2006). Two-thirds of the loess samples were used to calibrate the MLR model, 1/3 of the randomly chosen samples was used for validation.

For comparison of different model approaches, a combined regression tree (CRT) model, based on the loess sample set only, was also established. Calibration and validation sample sets were the same as for the CRT models described above (section 3.2.5), but non-loess samples had been removed prior to modelling. This resulted in 131 calibration and 44 validation samples, all from the geological sub-group "loess". The model was built using the "bagging" option, and the number of trees to be combined was 100; the model was designated CRT bag100-loess.

For comparison of the MLR and CRT loess models, root mean square errors for the calibration and validation sample sets were analyzed.

Evaluating model performance

Distinguishing between interpolation and extrapolation is important when validating models. The respective model's capacity for extrapolation to additional sample sets may be over-predicted if validation sets are used that are not fully independent (Brown et al. 2005). The final SOC model developed in this study was based on calibration samples from all sampling clusters, and its capacity for predicting new samples was tested using samples from the centres of the sampling clusters (calibration and validation sample set as described in section 3.2.5, and centre of sampling clusters as shown in Figure 3-2). As calibration and validation samples thus originated from the same sampling clusters, the validation procedure was not considered completely independent and was thus referred to as interpolation. Extrapolation to fully independent areas was assessed by completely excluding samples from one sampling cluster in Faizabad (FA64) and one sampling cluster in Yavan (YA24) from the calibration data (full holdout of samples from 2 clusters) (location of these 2 sampling clusters as indicated in Figure 3-1). Validation RMSE was then calculated from the holdout samples only, allowing estimation of maximal RMSE for prediction of samples from new sample locations.

To evaluate the predictive performance of the SOC prediction model, the following statistical criteria were applied (for detailed definitions see section 3.2.2): The coefficient of determination R^2 is a widely used criterion. $R^2 > 0.8$ allows a quantitative prediction while with R^2 between 0.5 and 0.7, the model allows a rough screening (Coûteaux et al. 2003). Another quality indicator often used is the ratio of standard deviation of the reference values to the standard error of prediction (RPD). RPD > 2 is generally considered acceptable for VNIR studies (Chang et al. 2001, Brown et al. 2005) even though Islam et al. (2003) stated that in agricultural studies RPD > 3 would be classified as acceptable. With regard to practical applications, percentage measures are most meaningful. For this purpose, the root mean square percentage error (RMSPE) and the more stable mean absolute percentage error (MAPE) were calculated.

Model performance was evaluated comparing RMSEs for the following 3 sample set characteristics: (i) SOC content classes low, medium and high, (ii) test areas 1 and 2, and (iii) different geological sub-groups. These comparisons allowed conclusions to be drawn on the model's performance regarding samples with specific characteristics.

3.2.8 Predicting SOC from soil reflectance spectra

For the additional sample sets below, SOC was predicted from soil spectral reflectance information:

- Additional samples from within the Faizabad and Yavan test areas, collected within the same Y-sampling clusters as the reference sample set
- Samples from a third test area, the Varzob test area, from which no samples had been included in the reference dataset
- Samples from 7 independent case studies, some situated within the Faizabad test area, others situated within the Varzob test area

Compatibility with the soil spectral library was evaluated by visually checking accordance between the spectral data space (defined by principal components 1 to 4) of samples from the soil spectral library and of samples from the new sample sets. In the absence of additional validation datasets with SOC content values, reliability of SOC predictions was tested by comparing predictions with existing OM values from soil chemical analysis conducted at the SSRI in Tajikistan. However, such chemical reference values were not available for most samples. To determine whether results were likely to be reliable, prediction results from two independently developed models were compared. It was assumed that models would be applicable for prediction of SOC for the particular sample set, if there was correlation of soil properties of loess samples predicted using the CRT model and the MLR model (Seiler 2006).

3.3 Results and discussion

In this section, the resulting soil spectral library for prediction of SOC content is presented. The potential and limitations of SOC prediction from VNIR data in comparison to soil chemical analysis is discussed on the basis of a well-analyzed chemical reference dataset, further influences of soil heterogeneity on prediction accuracy are considered and finally the applicability to further sample sets from the rainfed areas of central Tajikistan is evaluated.

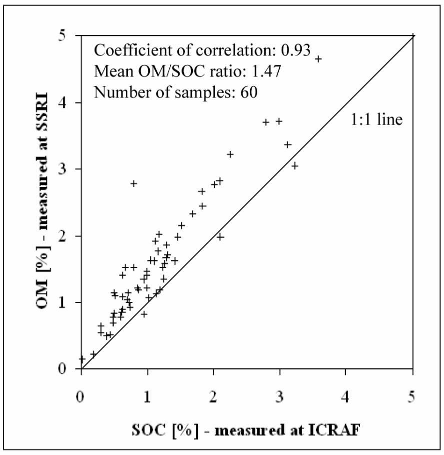
3.3.1 Characteristics of the reference dataset

Results from the lab test set

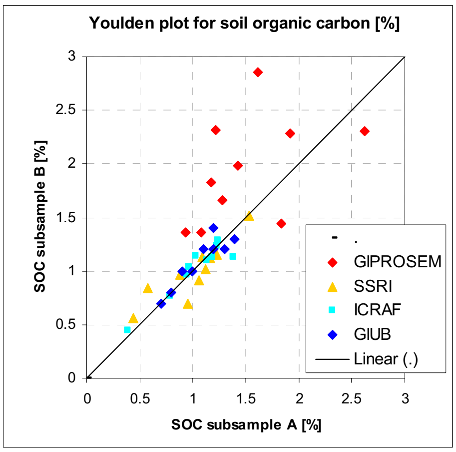
Results of a small test between laboratories in Tajikistan and collaborating laboratories in Switzerland and Kenya gave insight into repeatability and reproducibility of the soil chemical results. While a number of soil properties were analyzed at two or more laboratories, only SOC and OM, respectively, were determined at all four laboratories and are thus presented here.

For comparability of SOC and OM results, first the OM to SOC ratio was determined for the specific soils. Figure 3-5a shows a scatter plot providing soil chemical results for samples' SOC contents (determined at ICRAF) on the x-axis and OM contents (determined at SSRI) on the y-axis. The correlation coefficient between the two results for these 60 samples was 0.93. A mean OM to SOC ratio of 1.47 (and respectively a SOC to OM ration of 0.68) was calculated and subsequently used for transformation of OM to SOC values.

Tendencies towards within laboratory inaccuracies were visually tested by analyzing the so-called Youlden plot (Figure 3-5b). For three laboratories (SSRI, GIUB and ICRAF) the analysis results of sub-samples A and B, both originating from the same soil sample, approached the 1:1 line, which indicated good repeatability of SOC contents. This result was also reflected by the CV determined for results of sub-samples A and B, with 6.8% for SSRI, 2.5% for GIUB and 4.9% for ICRAF. A slight increase in variance for higher SOC values was noted for the ICRAF and the GIUB sample sets, while for the SSRI sample set variance increased for lower SOC contents. By contrast, the GIPROSEM laboratory was biased high and had serious within laboratory variability problems, also reflected by the high CV of 16.7%.



5a)



5b)

Figure 3-5a) Comparison between SOC content and OM content for 60 samples

Figure 3-5b) Youlden plot for SOC results reported by the four laboratories, with sub-samples A and B being double blind test samples

For testing inter-laboratory comparability between SSRI and ICRAF, the coefficient of variation for SOC content was determined for 60 samples which had been analyzed at both laboratories. The resulting CV was 13%. This is double the value expected for CVs determined from within laboratory tests, which is not surprising, though, when considering that at the SSRI laboratory a different method was applied and SOC contents were calculated from OM contents. Comparability of the results from the two laboratories can be considered satisfactory for application in reliability tests.

SOC reference values for establishment of the soil spectral library were determined by the ICRAF laboratory. Since it was not possible to send additional samples to ICRAF in Kenya, additional soil chemical analysis was conducted at the SSRI laboratory. This allowed checking of reliability of SOC contents predicted using the established calibration.

Outliers detected using preliminary models

Comparison of soil properties predicted using preliminary models developed from soil reflectance spectral information with results of soil chemical analysis, proved very efficient for identification of outliers in the chemical reference dataset. The overview in Table 3-4 shows the CV for results of chemical analysis of these repeatedly analyzed samples, and also provides comparative CV values as available from the Soil Survey Laboratory Methods Manual (Soil Survey Staff 1996), the ICRAF laboratory internal repeatability tests, and the results of the lab test series conducted for this study. Further, the CV of random repeat analysis of SOC is presented as well.

The CVs of total carbon (TC), soil organic carbon (SOC), total nitrogen (TN) and exchangeable calcium (exCa) determined by means of repeat analysis from randomly selected samples were in the range of the comparative values available. CVs of TC, SOC and TN were slightly higher, those of exCa lower. In contrast, with samples selected based on information from the preliminary models, the CV for repeat analysis was considerably higher. This is a strong indication that these samples were actual outliers of soil chemical analysis. Outliers are likely to remain undetected when random repeat sampling is carried out. Thus, this procedure allowed informed selection of samples for which repeat analysis was necessary. However, in the lower content ranges, small residuals, difficult to detect visually, may contribute a great deal to the CV. Systematic repeat analysis (of every sample, or every second sample) is inevitable in these content ranges if measurement accuracy is to be improved.

*Table 3-4 Overview of coefficients of variation (CVs) for repeat chemical analysis. Abbreviations are used as follows: total carbon (TC), soil organic carbon (SOC), total nitrogen (TN), exchangeable calcium (exCa). * USDA-NRCS National Soil Survey Center (Soil Survey Staff 1996), ** different method*

	TC	SOC	TN	exCa
Comparative values:	CV [%] (Number of samples)			
Soil Survey Laboratory Methods Manual*	2.5	-	2.7	5.1**
ICRAF laboratory (lab internal reference value)	4 – 5	-	7 – 8	5 – 7
Lab test series (10 sample pairs)	1.3	4.9	3.4	5.7
Reference dataset:				
All repeat analysis	8.5 (35)	-	18.6 (35)	20.8 (31)
Random selection for repeat analysis	5.7 (21)	6.5 (92)	10.4 (12)	2.4 (22)
Informed selection for repeat analysis	11.4 (14)	-	22.8 (23)	36.7 (9)

Extensive random repeat analysis was conducted for the SOC content reference dataset; a total of 92 samples (corresponding to 1/3 of the samples) were chosen for random repeat analysis, and this included the 6 samples with lowest SOC contents. Precision of SOC chemical analysis was good, the CV was 6.5% and the SEL was 0.05. However, comparison of SOC prediction results and OM results indicated that there might be outliers included in the dataset that failed to be detected by random repeat analysis. If 6 such possible outliers are replaced by OM values and the SEL is recalculated, the new SEL value of 0.21 is considerably higher.

Range of soil chemical analysis

An overview of the range of soil properties determined from the reference sample set is presented in Table 3-5. The median SOC content determined was 0.95%, the minimum was 0.03% and the maximum 4.60%. Thus, the library covered a relatively wide range of SOC contents, but the number of samples with high contents (SOC > 2% as defined by the WOCAT classification) was, typical for many libraries, rather low. Compared with typical SOC values (1-2%) reported for brown carbonate soil in the study area (for soil samples from Faizabad district) the median was at the lower end (0.95% SOC). The sample set represented the $CaCO_3$ contents reported in the Faizabad area (2-30%), the median being 15%, the 1st quartile 8.6% and the 3rd quartile 22.6%. Also the soil texture contents of the sample set were in good accordance with reported contents. Sand contents were comparatively high; this can be explained by the fact that the highest values were from samples taken from river sediments. The median pH was high for the samples analysed (corresponding to the high $CaCO_3$ contents) and varied in a very narrow range (lower quartile = 8.0, higher quartile = 8.2). The CN ratio was around 8, which was relatively low compared with the CN ration of 12 which can be normally expected. Phosphorus levels of less than 10 mg/kg are generally considered very low, while 20-30 mg/kg are optimal for most field crops. Thus, the 3rd quartile for extractable phosphorus content of 5 mg/kg observed, indicated very low phosphorus levels in the study area.

Table 3-5 Minimum, maximum and quartiles for each soil property for the samples selected for chemical analysis (N=254), for abbreviation see Table 3-3.
** SIC was calculated (SIC = TC SOC). 3 results were slightly negative, indicating inaccuracy in TC or SOC determination.** CaCO3 was calculated from soil inorganic carbon (SIC) values for comparability reasons. *** Clay < 0.001, Silt 0.001-0.05, Sand > 0.05, according to the Russian classification system*

	SOC	*SIC	** Ca-CO_3	TN	C/N	pH	exCa	exK	ex Mg	extr P	*** Clay	*** Silt	*** Sand
Unit []	[%]	[%]	[%]	[%]	-	-	me/(100g soil)			mg/kg	[%]	[%]	[%]
Min.	0.03	0.00	0.00	0.02	0.0	7.0	00.70	0.08	0.12	0.13	3	12	6
1st quartile	0.61	1.04	8.6	0.08	6.8	8.0	10.49	0.21	0.50	1.40	7	58	14
Median	0.95	1.89	15.7	0.12	8.2	8.1	12.05	0.30	0.70	2.40	17	65	18
3rd quartile	1.39	2.71	22.6	0.15	9.4	8.2	14.00	0.46	1.00	5.03	20	71	24
Max.	4.60	5.16	43.0	0.38	31.4	8.7	67.80	1.26	7.10	212	31	89	82

Calibration between specific soil properties and VNIR data is possibly influenced by other soil properties. Thus, for the dataset presented here, the correlation coefficients between SOC and the other soil properties were determined (Seiler 2006): SOC and TN (R = 0.87) had the highest correlation coefficient, followed by SOC and exchangeable potassium (R = 0.54). Low correlation was determined for SOC and extractable phosphorous (R = 0.19), and no correlation with exchangeable Ca and Mg. Negative correlation with SOC was observed for pH (R = -0.43) and $CaCO_3$ (R = -0.21). The correlation coefficient between SOC and soil texture was low and was about the same for all fractions, with a coefficient between R = -0.19 and R = -0.21. The pH was positively correlated with SIC (and $CaCO_3$) (R = 0.54).

3.3.2 Homogeneous spectral datasets defined by geological sub-groups

In order to characterize the high soil spectral variability of the sample set, soil samples were attributed to geological sub-groups. These sub-groups showed characteristic iron-oxide contents, which again were well captured by CIE colour values, calculated from the VNIR spectra. Thus a classification tree model was developed to attribute every soil sample to a geological sub-group based on its CIE colour values, also applicable to samples not classified during field sampling.

Classification model for attributing samples to geological sub-groups

The most suitable model for classification into geological sub-groups resulted in 6 terminal nodes (Figure 3-6): two nodes for loess, two nodes for granodiorite, one node for paleosol and one node for river sediment samples. For each variable (CIE colour value), a splitting rule (a threshold) was determined by the model. A sample goes to the left if the value of the specific variable is below the threshold, and to the right if the value is above the defined threshold. An overview of the results of the validation dataset by 10-fold cross-validation led to a confusion matrix (Table 3-6).

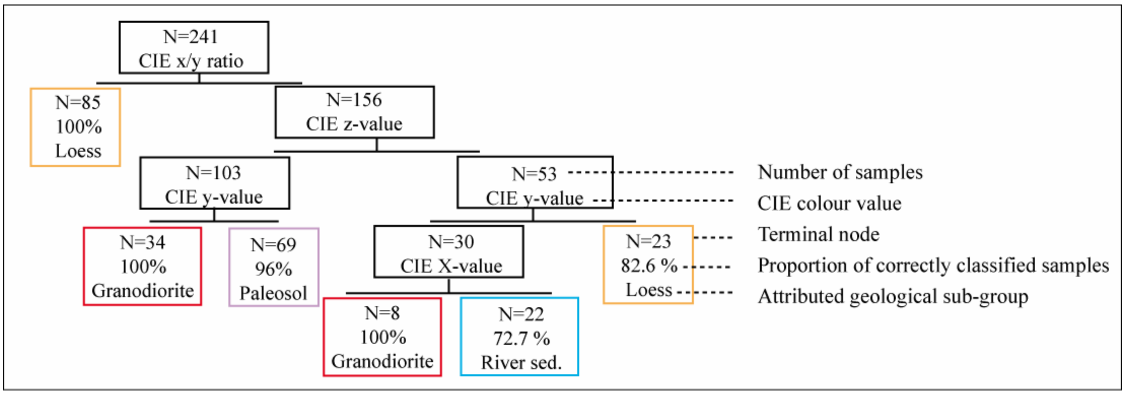


Figure 3-6 Classification tree model for attributing soil samples to geological sub-groups using CIE colour values

Table 3-6 Confusion matrix based on the results of 10-fold cross-validation

Overall accuracy 88%			Predicted geological sub-group			
Actual geological sub-group	Total cases N=241	User's accuracy	Loess N=108	Paleosol N=68	Granodiorite N=44	River sediments N=21
Loess	103	97%	100	3	0	0
Paleosol	63	92%	4	58	1	0
Granodiorite	59	70%	3	7	41	8
River sediments	16	81%	1	0	2	13

Overall accuracy was 88%. User's accuracy for predicted loess samples was very high, with 97% of the samples being correctly classified, while predictability was ranging between 70 and 92% for the other classes. The main aim was to determine a homogeneous set of loess samples, thus misclassified samples among the other geological sub-groups were not considered a severe model drawback. However, around 6% of the paleosol samples were mis-classified for loess, and also 5% of the granodiorite samples.

The geological sub-groups and their iron-oxide characteristics

The characteristics of the four geological sub-groups can be described according to the relationship between colour values x and y of the system defined by the Commission Internationale de l'Eclairage (CIE) and iron-oxide contents as determined by Jarmer and Schütt (1998).

Figure 3-7 shows classification results for the geological sub-groups with regard to CIE colour values x and y. With increasing x values corresponding to rising Fe2O3 contents (Jarmer & Schütt 1998), the loess samples can be identified as the sub-group with the lowest iron-oxide contents. Furthermore, it was also the best delimited group, although it contained the highest number of samples. The paleosol samples were also clearly distinguishable from the other subgroups. For the samples classified as granodiorite mother rock samples and, to a lesser degree, also the ones classified as river sediments, the low CIE y values indicated dominance of hematite over goethite (Jarmer & Schütt 1998). The samples belonging to these two sub-groups cover a wide range of CIE y colour space. Confusion between the sub-groups granodiorite and river sediments, as indicated by the confusion matrix, is also reflected in the biplot for CIE colour values x and y.

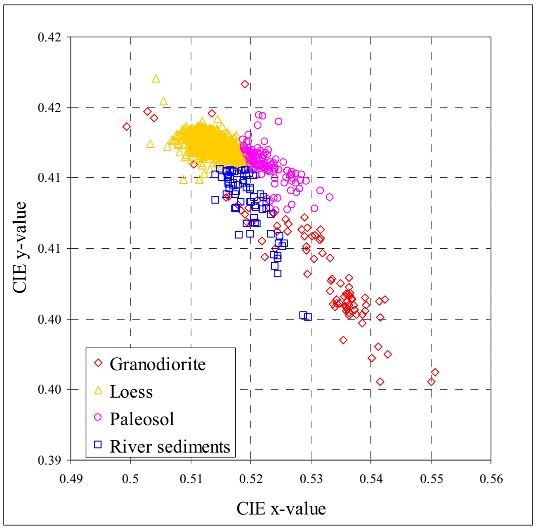


Figure 3-7 CIE colour values x versus y plotted for all samples from the Faizabad and Yavan test areas. According to Jarmer and Schütt (1998), increasing x values are corresponding to rising Fe2O3 contents.

Soil spectral variability

Biplots for principal components (PCs) provided the basis for a visual assessment of spectral variability with regard to the four geological sub-groups (Figure 3-8).

Figure 3-8a shows PC1 and PC2 calculated from continuum removed spectral data of the full dataset while Figure 3-8b shows PCs calculated for loess samples only. Spectral variability was greatly reduced when excluding all non-loess samples. Only some "outlier regions" (circled red) and 3 outlier samples (FA060203 and FA060204 collected from the same sampling pit, and FA640702 originating from a completely different sampling cluster) remained. No common characteristics were identified for these outliers. PCA for the full sample resulted in PC1 accounting for 81% of the variation, PC2 for 10%, PC3 for 6% and PC4 for 1%, adding up to 98% for the first four PCs. PCA for the loess sub-group reflected the higher homogeneity of the sample set with PC1 accounting for 58%, PC2 for 18%, PC3 for 14% and PC4 for 3%, adding up to 93%.

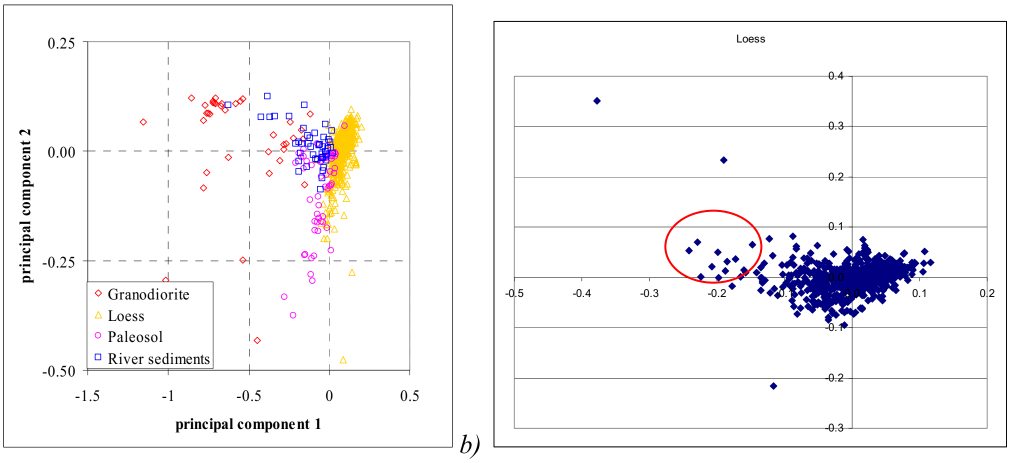


Figure 3-8 Biplots of principal components 1 (x-axis) and 2 (y-axis) calculated from continuum removed spectra. Figure 3-8a) shows principal component space calculated for the full sample set and Figure 3-8b) for the loess samples only.

Correlations between soil properties (including soil fertility and soil texture as described in section 3.3.1) and PCs were unexpectedly weak. This was true for the full sample set and for the loess sample set. The strongest correlation was observed between SOC content and PC3, with a correlation coefficient of R=0.3 for the full sample set and R=0.6 for the loess sample set. Thus further determination of characteristics of the soil spectral data space, as characterized by principal components, was not possible. But the strong influence of the geological sub-groups was considered in the evaluation of the SOC prediction model (cf. section 3.3.3).

Overview map

The map in Figure 3-9 provides an overview on the sampling sites and their classification with regard to geological sub-groups. The map shows that sampling sites classified as loess are dominating, and non-loess sites were mainly located close to rivers, ridges, or at high altitudes, where loess deposits had eroded by natural processes. Sites with paleosol samples were mainly observed in Faizabad test area, where in the East of the test area a number of paleosol sequences can be observed.

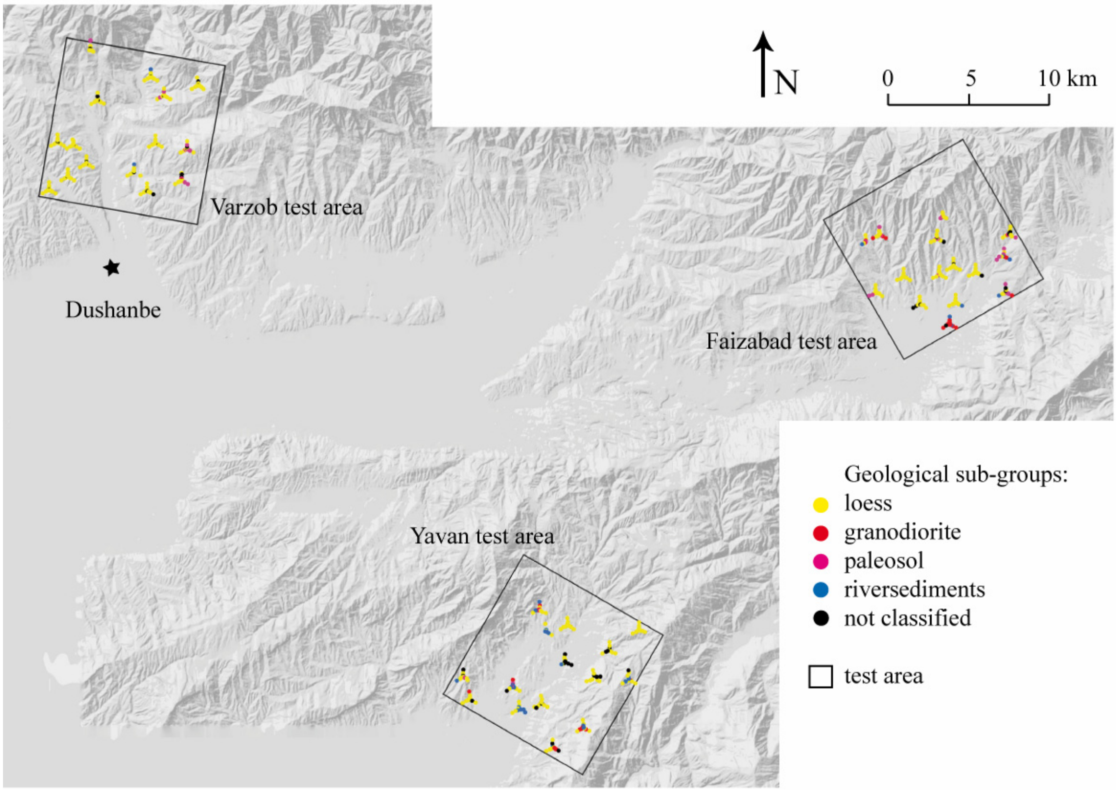


Figure 3-9 Sampling sites with specific geological sub-groups in the three test areas

3.3.3 Combined regression tree (CRT) models for prediction of SOC

The SOC content classes "low" (SOC < 0.7%), "medium" (SOC = 0.7 and < 2%) and "high" (SOC ≥ 2%) as well as soil heterogeneity defined by the geological sub-groups were considered crucial for validating SOC models. Thus model input data, trials involving various CRT model settings and final SOC prediction were assessed with regard to these characteristics. Additional models that were established using a reduced calibration dataset, served to assess the influence of pre-processing techniques on repeatability of SOC prediction and for holdout validation of specific sampling clusters.

Calibration and validation dataset

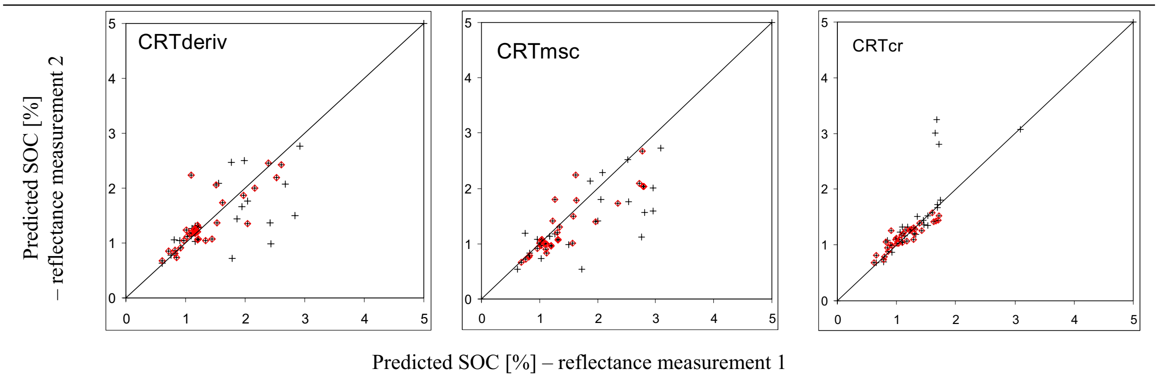
Uneven occurrence of samples with specific characteristics in calibration and validation sample sets may influence model performance and model validation, and was thus analyzed prior to modelling. Percentages of calibration and validation samples with regard to the three SOC content classes were very similar (Table 3-7, column far right). Modelling was restricted by the low representation of samples in the high SOC content range (11% of the calibration set and 12% of the validation set). Representation with regard to the geological sub-groups was generally well balanced. Paleosol samples were underrepresented in the validation set and, more importantly, non-loess samples (including granodiorite, paleosol and river sediment sub-groups) were underrepresented in the calibration set for SOC contents > 2%, with only 2% (4 samples) being non-loess samples in this content range.

Table 3-7 Representation of calibration and validation samples with regard to SOC content classes and geological sub-groups. Percentages of samples with regard to the total number of calibration samples (N=193) are listed to the left of the slash, and percentages with regard to the total number of validation samples (N=61) are listed to the right of the slash.

geological sub-group:	loess	granodiorite	paleosol	river sediments	Total
SOC-low	21 / 17	5 / 7	3 / 0	3 / 7	32 / 30
SOC-medium	39 / 50	3 / 2	9 / 3	6 / 3	57 / 58
SOC-high	9 / 8	2 / 0	0 / 2	0 / 2	11 / 12
Total	69 / 75	10 / 8	12 / 5	9 / 12	100 / 100

Repeatability of SOC prediction

Repeatability of SOC content prediction from VNIR reflectance depended on the transformations applied to the reflectance spectra during pre-processing. Figure 3-10 shows the SOC prediction results based on models developed from spectral reflectance data that were pre-processed in three different ways: (a) first derivatives of spectral reflectance (CRTderiv model), (b) first derivatives followed by multiplicative scatter correction (CRTmsc model), and (c) continuum removed spectral data (CRTcr model). SOC prediction results from one spectral measurement were plotted on the x-axis against prediction results from a second (repeat) spectral measurement on the y-axis (Figure 3-10). The first two transformations produced results that deviated highly from the optimal 1:1 line. Continuum removal produced the most congruent prediction results. Repeatability of prediction seemed not to be influenced by samples' belonging to loess or non-loess samples (encircled red). Discrepancies in repeatability of predictions were most distinct for the content range of SOC > 2%. Continuum removed spectral data produced much more stable results in this content range. However, the CRTcr model, too, produced three outliers, where SOC content was highly over-predicted for the first spectral measurements. These outliers indicate model instability for predictions of high SOC contents, likely to be caused by the small number of calibration samples in this content range (see also section 3.3.4).



a)	CV = 14%, SEL = 0.31	b)	CV = 15%, SEL = 0.35	c)	CV = 9 (6*) %, SEL = 0.24 (0.09*)

Figure 3-10 Comparison of predicted SOC contents (%) from repeat measurements of soil spectral reflectance. Samples encircled red are non-loess samples. The spectral reflectance data were pre-processed by applying (a) 1st derivatives (deriv), (b) 1st derivatives followed by multiplicative scatter correction (msc) and (c) continuum removal (cr), respectively. Coefficient of variation (CV) and standard error of laboratory measure¬ment (SEL) were calculated as statistical measures. (*) For the CRTcr model, these measures were recalculated for SOC contents < 2%.

The statistical measures confirm the above-mentioned superiority of the CRTcr model developed from continuum removed spectral data. Furthermore, they allowed comparison of precision of SOC content predicted from spectra to precision of traditional soil chemical laboratory measurements. While the CV for repeat measurements of the reference chemical analysis was 6.8% (section 3.3.1), it was 9% for SOC values predicted from the CRTcr model, and 6% for SOC contents < 2%, for which the model was generally more reliable (cf. below). Comparison with the SEL determined for SOC repeat chemical measurements showed that the SEL for SOC determination from VNIR data was only slightly higher. The SEL for soil chemical analysis was 0.05, and for prediction using the CRTcr model 0.24, but only 0.09 for SOC < 2%.

These findings showed that for the dataset presented here, SOC results predicted from VNIR information in the content range < 2% were repeatable and precision was comparable to that achieved by the traditional soil chemical method. This, however, necessitated pre-processing of reflectance data using continuum removal, as was also indicated by earlier work on the same data (cf. Seiler 2006).

Model performance for different combined regression trees

CRT models with different parameter settings were tested and are presented in Table 3-8. The root mean square errors of calibration (RMSEC) and validation (RMSEV) of the different models built with the "bagging" algorithm, with 50 combined trees, with 100, and with 150, were all very similar. The RMSEC values ranged between 0.20 and 0.21 and the RMSEV values were all 0.32. To test whether there was higher accuracy of prediction for loess samples, the RMSEV was also calculated for loess validation samples only.

Table 3-8 Comparison of combined regression tree models (CRT) with differing parameter settings. Root mean square errors are presented for calibration (RMSEC) and validation (RMSEV), calculated each for the full sample set, and for loess samples only. Additionally, for these sample sets also samples with SOC content < 2% were separately analysed.

Name	CRT bag50*	**CRT bag100***	CRT bag150*	CRT bag100 & CIE variables	CRT arc4/250
Tree combination method	bagging	bagging	bagging	bagging	arcing
Number of trees	50	100	150	100	250
	All[a)] / < 2%[b)]	all / < 2%	all / < 2%	all / < 2%	all / < 2%
Number of calib. samples	193 / 172	193 / 172	193 / 172	193 / 172	193 / 172
Number of valid. samples	61 / 55	61 / 55	61 / 55	61 / 55	61 / 55
Number of loess valid. samples	44/ -	44/ -	44/ -	44/ -	44/
RMSEC	0.21 / 0.16	0.20 / 0.16	0.20 / 0.15	0.20 / 0.15	0.15 / 0.13
RMSEV	0.32 / 0.25	0.32 / 0.24	0.32 / 0.24	0.32 / 0.24	0.35 / 0.26
Loess RMSEV	0.34 / -	0.34 / -	0.34/ -	0.34 / -	0.37 / -

** bagging algorithm, with 50 combined trees (CRT bag50), with 100 (bag100), and with 150 (bag150)*
a) full sample set or full loess sample set, respectively, b)samples with SOC content < 2% only

Unexpectedly, the RMSEVs for the loess samples were slightly higher, ranging between 0.34 and 0.36. The RMSE for SOC values < 2% were distinctly lower for all models, with RMSEC between 0.15 and 0.16, and RMSEV between 0.24 and 0.25. Including CIE values in the input variable set (CRT bag100&CIE) did not improve the RMSEV. Arcing models are prone to over-fitting, which is reflected by the big difference between the RMSEC (0.15) and the RMSEV (0.35) of the model developed. In the SOC range < 2%, the number of calibration samples is much higher and more appropriate for arcing and the RMSEV drops to 0.26, which is comparable with the RMSEV of the bagging models.

As would be expected, the RMSEV was distinctly higher than the RMSEC in all models, indicating that the calibration set was not completely covering the variance of the soils in the study area and that a larger calibration sample set would be needed to produce more stable models. For this reference dataset, the most efficient model was the CRT bag100 (cf. Figure 3-11). Accordingly, the CRT bag100 model was used for all further comparisons and for prediction of the additional sample sets.

Model performance in relation to soil heterogeneity

The CRT bag100 model, calibrated on the full sample set, was compared with two models calibrated on loess samples only. One of them was a combined regression tree (CRT) model, the other a multiple linear regression (MLR) model developed for Bruno Seiler's MSc thesis (Seiler 2006). Results are presented in Table 3-9. RMSEC and RMSEV differ slightly from results reported by Seiler, since a number of lab test samples were excluded from the validation sample set for the dataset presented here, but had been included in Seiler's study. Exclusion of lab test samples guaranteed independency between calibration and validation sets.

*Table 3-9 Comparison of models developed for samples from all geological sub-groups with models developed for loess samples only. * Including samples from all geological sub-groups*

Name	**CRT bag100**	CRT bag100-loess	loess MLR
Model approach	Combined regression trees	Combined regression trees	Multiple linear regression
Tree combination method	bagging	bagging	-
Number of trees	100	100	-
Number of calib. samples / < 2%	193 / 172	131 / 125	121 / 106
Number of valid. samples / < 2%	61 / 55	123 / 116	133 / 120*
Number of loess valid. samples	44/ -	44 / 42	53 / 46
RMSEC / < 2%	0.20 / 0.16	0.24 / 0.23	0.24 / 0.30
RMSEV / < 2%	0.32 / 0.24	0.38 / 0.33	0.70 / 0.69
Loess RMSEV/ < 2%	0.34 / -	0.33 / 0.24	0.32 / 0.22

Model performance for SOC prediction – validation results

Calibration results for the final SOC content prediction model (CRT bag100 as described above) are provided in Figure 3-11, which shows scatter plots comparing measured against predicted SOC contents for calibration (left) and validation samples (right). Observations made are expected to be close to the optimal 1:1 line, which is also indicated.

Statistical parameters provided quantitative measures for evaluating model performance and allowed comparison with existing studies (for details on the statistical parameters used, see section 3.2.2). The coefficient of determination for the calibration sample set was high (R^2 = 0.94); it was distinctly lower for the validation set (0.71), but still adequate for screening purposes. The big difference between calibration and validation R^2 indicates some model instability. However, the RPD was 2.3 and thus complying with the target of RPD > 2. At 0.07, the contribution of bias to the overall lack of fit of the model is negligible. Comparison of the SEL with the SEP provides some explanation regarding the dependency of prediction accuracy on the reference dataset error. As a rule of thumb, the SEP should be no higher than twice the SEL (Carl Zeiss MicroImaging GmbH 2007). Calculation of the SEL from the available sample set gave a value of 0.05, but it may be considerably higher (0.21) if identified possible outliers are confirmed (section 3.3.1). Since no systematic outlier detection was performed for SOC values of the reference dataset, it had to be assumed that further outliers are present in the reference dataset. The SEP for the validation sample set was 0.32 and 0.24 for SOC contents < 2%, which can thus be considered a good value, difficult to improve unless the reference dataset's accuracy were improved.

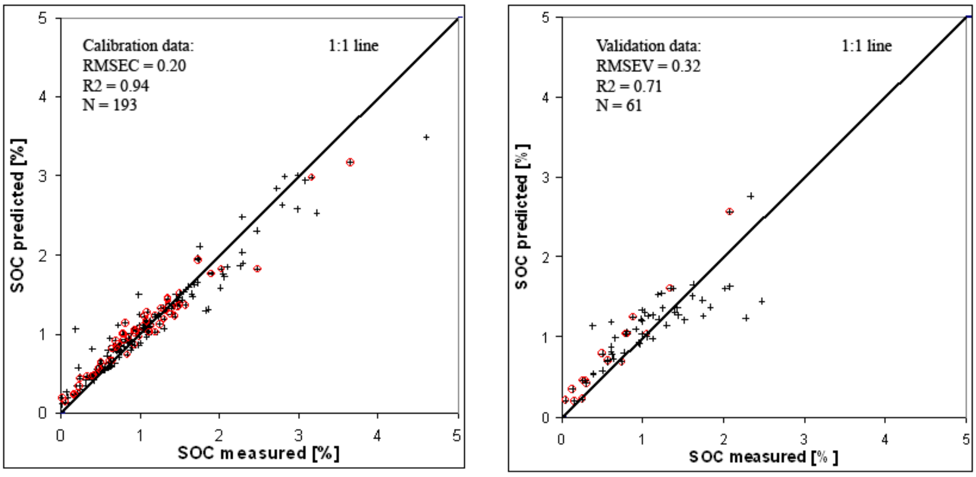


Figure 3-11 Scatter plots of measured against predicted SOC contents for the calibration (left) and validation (right) datasets for the CRT bag100 model based on continuum removed spectral data. Samples belonging to the geological sub-groups of non-loess samples are marked red.

The root mean square error of validation (RMSEV) was 0.32. In comparison to other studies for which SOC models have been reported with RMSEVs between 0.1% (1 mg/kg, Brown et al. 2005) and 0.31% (3.1 mg/kg, Shepherd & Walsh 2002), the RMSEV determined for the dataset presented here was rather higher. Brown et al. (2005) also reported distinctly higher RMSEV (0.35%) for site holdout predicted SOC content, showing that RMSEV may increase markedly if samples to be predicted are slight outliers to the soil spectral library. Therefore, for the highly heterogeneous soils of the study area, the overall RMSEV of 0.32% was considered satisfactory.

With regard to the specific test areas, the RMSEV was 0.38 for test area 1 (Yavan) and 0.24 for test area 2 (Faizabad) (Table 3-10). The RMSEV for the Yavan test area is strongly influenced by large residuals in the high SOC content class. When evaluating performance in practical applications, RMSPE and MAPE are expressive measures. They reveal that the large residuals in the high SOC content range result in percentage deviation of 34% (RMSPEV) and 32% (MAPEV), respectively. Much more influential with regard to percentage deviation are residuals in the low SOC content range, where they result in 113% for RMSPEV and 69% for MAPEV.

Detailed assessment of RMSE allowed determination of characteristics of samples with lower prediction accuracy, valuable when interpreting prediction results of additional sample sets.

Table 3-11 provides an overview of RMSEs for samples attributed to specific geological sub-groups. Even though calibration samples for non-loess sub-groups were relatively few, the RMSEs for these sub-groups were virtually identical with the RMSEs for the loess samples. This is a remarkable result with regard to conjunctive prediction of highly differing soil types. Disparity between RMSEC and RMSEV observed for the full dataset was also reflected in the sample sets of the geological sub-groups. The RMSEs for the SOC content classes low and medium were consistently lower than those for the class with high SOC content (SOC > 2%).

Table 3-10 CRT bag100 model: Overview of root mean square error (RMSE), root mean square percentage error (RMSPE) and medium absolute prediction error (MAPE) of calibration (to left of slash) and validation (to right of slash) with regard to SOC content classes, and test areas. Test area 1 = Yavan and test area 2 = Faizabad.

		RMSE	RMSE	RMSE	RMSPE	MAPE
	Number of samples	All samples 193 / 61	Test area 1 88 / 29	Test area 2 105 / 32	All samples 193 / 61	All samples 193 / 61
SOC-low	61 / 20	0.17 / 0.27	0.13 / 0.30	0.19 / 0.24	115% / 113%	51% / 69%
SOC-medium	111 / 34	0.15 / 0.23	0.15 / 0.24	0.14 / 0.21	13% / 18%	9% / 15%
SOC-high	21 / 7	0.41 / 0.65	0.30 / 0.79	0.44 / 0.38	15% / 34%	13% / 32%
Total	193 / 61	0.20 / 0.32	0.16 / 0.38	0.23 / 0.24	66% / 67%	23% / 35%

No other distinct tendencies, except from the described bias with regard to high SOC contents, were detected. There were neither any indications of a relationship between residuals of the SOC content model and other soil properties (e.g. soil texture), nor a relationship between residuals and principal components.

Table 3-11 Overview of root mean square error of calibration (RMSEC) and of validation (RMSEV) with regard to SOC content classes, and geological sub-groups, with RMSEC to the left of the slash and RMSEV to the right.

		Geological sub-groups				
	All samples	Loess	Non-loess total	Non-loess: Granodiorite	Non-loess: Paleosol	Non-loess: River sed.
N	193 / 61	133 / 46	60 / 15	20 / 5	23 / 3	17 / 7
SOC-low	0.17 / 0.27	0.17 / 0.32	0.15 / 0.18	0.15 / 0.16	0.18 / -	0.13 / 0.20
SOC-medium	0.15 / 0.23	0.15 / 0.23	0.14 / 0.22	0.14 / 0.25	0.14 / 0.26	0.15 / 0.17
SOC-high	0.41 / 0.65	0.42 / 0.73	0.36 / 0.39	0.36 /	- / *	- / *
Total	0.20 / 0.32	0.21 / 0.34	0.17 / 0.23	0.21 / 0.18	0.15 / 0.26	0.14 / 0.25

N = Number of samples, SOC-low (< 0.7%), SOC-medium (0.7-2%) and SOC-high (> 2%).
** Since only 1 validation sample is available for these sub-groups, calculation of RMSEV is not possible*

Clear distinction between interpolation and extrapolation is important for evaluating a model's prediction capacity (cf. section 3.2.7). Validation samples for evaluation of the final SOC content prediction model originated from the same sampling clusters as used for the calibration samples. Thus validation as conducted above (cf. Table 3-10) must be seen as an assessment of interpolation performance. For an estimation of extrapolation performance, prediction of samples from full-holdout sampling clusters (FA64 and YA24) was evaluated (cf. Table 3-12). This allowed model evaluation with regard to SOC content prediction of samples from areas not included in the calibration dataset. For these samples, repeat reflectance measurements were available and thus SOC prediction is presented for two soil reflectance spectra from the same sample.

Table 3-12 Extrapolation performance: RMSEV for sampling clusters FA64 and YA24 (excluded from the calibration sample set), with results of reflectance measurement 1 to the left of the slash and reflectance measurement 2 to the right.

	Interpolation RMSEV	Extrapolation $RMSEV^{measurement\ 1}$ / $RMSEV^{measurement\ 2}$		
	All samples	All samples	Test area 1	Test area 2
N	61	16	7	9
SOC-low	0.27	0.17 / 0.18	*	*
SOC-medium	0.23	0.51/ 0.30		
SOC-high	0.65	0.38 / 0.30		
Total	0.32	0.46 / 0.28	0.18 / 0.22	0.59 / 0.33

** Not enough samples available*

The root mean square error of validation (RMSEV) was low for test area 1 (Yavan), for SOC predicted from both reflectance measurements. For test area 2 (Faizabad), RMSEV was very high for SOC predicted from spectral measurements 1 (RMSEV = 0.59). As shown in Figure 3-11c, some spectral measurements are prone to SOC content over-prediction. This was also reflected in the high RMSEV determined for all samples in reflectance measurement 1 (RMSEV = 0.46). Reflectance measurement 2 showed an overall low RMSEV (0.28), mainly due to the comparably low RMSEV contribution of the high SOC content range. The RMSEV calculated for medium SOC contents only is higher (RMSEV = 0.30) than that determined for interpolation performance (RMSEV = 0.23). The root mean square prediction error (RMSPE) was 27%. On such samples repeat chemical analysis and possibly repeat spectral measurements would have to be conducted, in order to detect possible measurement outliers, which had not been possible within the course of this study. A lower accuracy for extrapolation performance had to be expected. These figures gave a quantitative indication of the decline of performance. The results discussed above clearly indicated that not only reference data needed repeat analysis, but possibly also spectral measurements showed some inconsistency, which had to be traced. All in all, it can be concluded that the model has a high degree of applicability to both test areas and all soil types. Satisfactory prediction accuracy has been achieved foremost in the SOC content range between 0.7 and 2%.

3.3.4 Predicting additional sample sets – an estimation of SOC model performance

All additional sample sets were predicted using the CRT bag100 model. In the absence of SOC validation data, the prediction results are discussed with regard to spectral data space, compared with OM results and SOC predictions of the MLR model.

Soil spectral library coverage

Principal components were calculated for the reference dataset (used to establish the SOC calibration model) together with all additional sample sets, which were to be predicted using the SOC prediction model established. The spectral data space characterized by the first and second principal components (PC1 and PC2), as well as the third and fourth (PC3 and PC4), is displayed in Figure 3-12. For prediction of additional samples, it is crucial that the calibration dataset be represented in all areas of the spectral data space. Visual assessment confirmed that calibration samples (marked blue) were well distributed. Exceptions include samples in the lower left quarter of the biplot PC1 versus PC2 (indicated by the arrow), where samples from the sampling cluster VZ12 in the Varzob test area dominated. These samples were characterized by coarse soil texture. The arrow in the biplot for PC3 and PC4 points at the Faizabad samples from the Chinoro and Karsang case study areas (marked brown), which are badly predicted by the SOC model (see paragraph below). Frequency of calibration samples for this spectral space is not very high, but calibration samples are not completely missing, either.

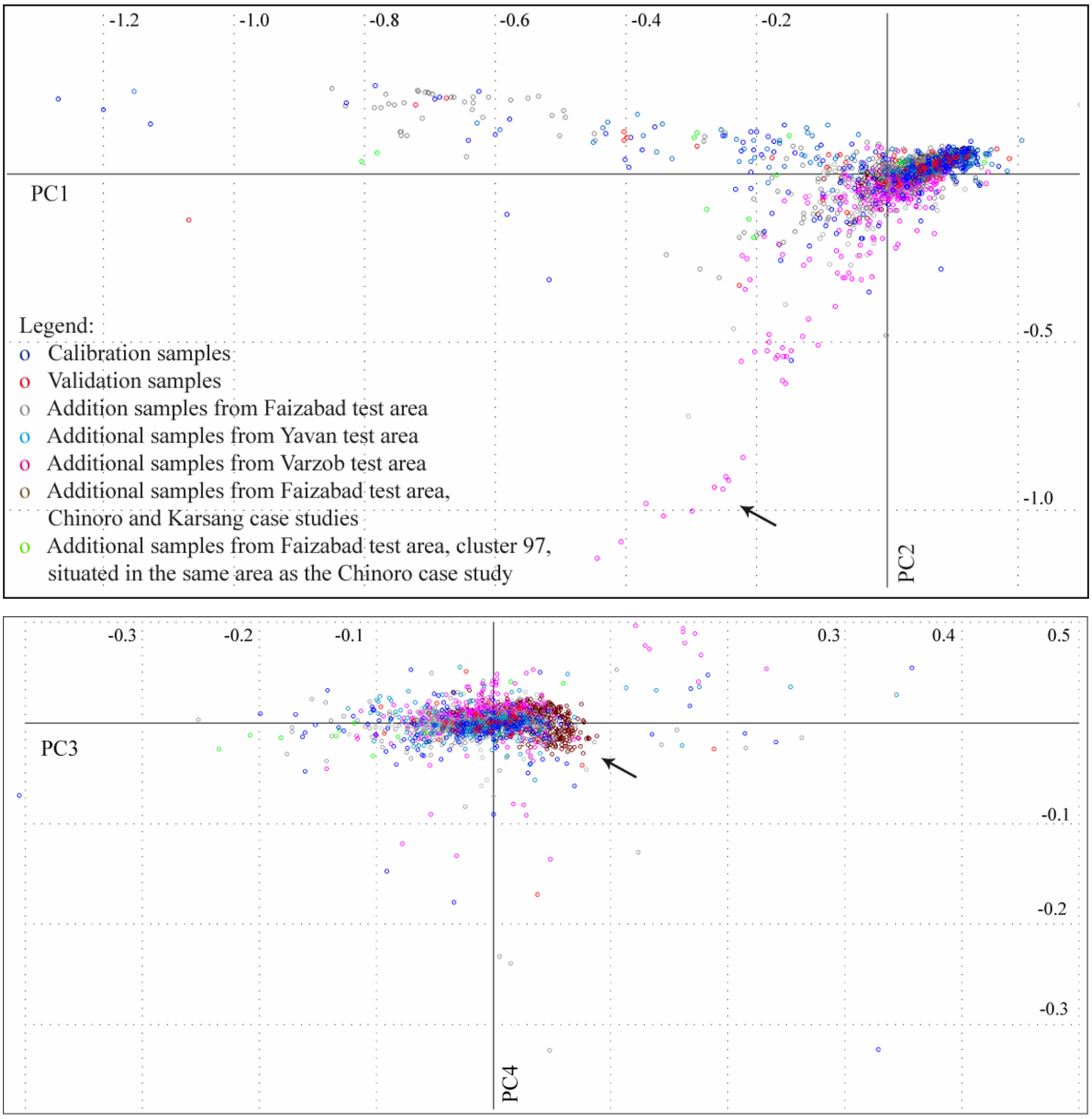


Figure 3-12 Distribution of principal components calculated from continuum removed spectral data for samples of the reference dataset as well as all additional samples to be predicted (number of all samples = 2,328). PC1 accounted for 62%, PC2 for 27%, PC3 for 6% and PC4 for 1% of the variation, adding up to 96% for the first four PCs. Arrows indicate areas badly represented by calibration samples.

Principal component space has been successfully applied in other studies to identify outliers. For example, as one of a number of options, Shepherd and Walsh (2002) proposed a method called soft independent modelling of class analogy (SIMCA) for identification of outliers in existing soil spectral libraries. However, for the dataset presented here it is questionable how well spectral regions not represented by the calibration model established can be identified from PC space; visual assessment of principal component space with regard to SOC prediction outliers was not successful for the validation dataset, and neither did residuals and principal components correlate. Therefore, no further outlier identification based on principal component analysis was conducted.

Estimating reliability of predictions

For a sample set collected for case studies in the Faizabad and Varzob test areas (Nekushoeva forthcoming), organic matter (OM) analysis was conducted at the laboratory of the Soil Science Research Institute (SSRI) in Dushanbe, Tajikistan. OM values determined at SSRI were transformed to SOC contents (cf. section 3.3.1). These SOC contents were plotted against the SOC content predictions as displayed in Figure 3-13a) and b). For all other additional sample sets, no chemical analysis was available for validation of SOC model prediction.

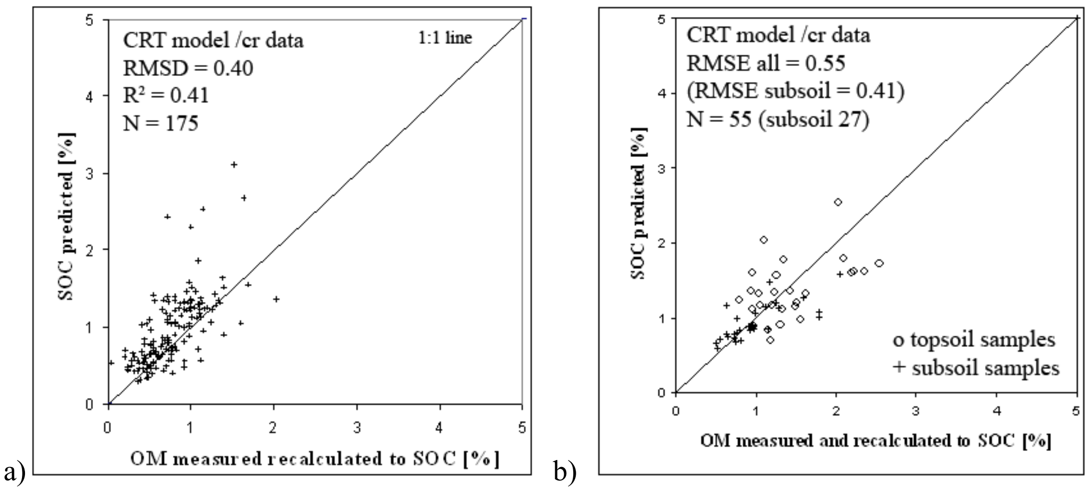
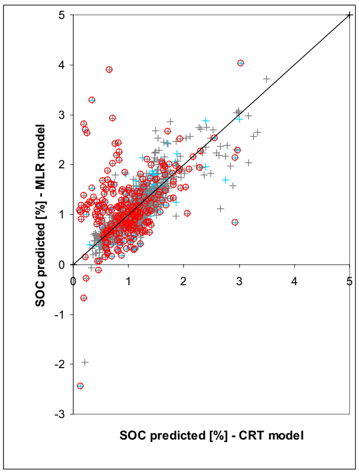


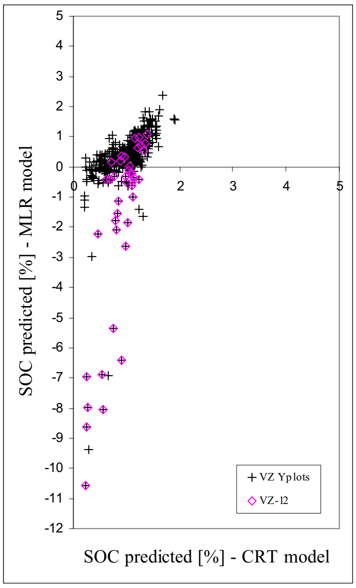
Figure 3-13a) Samples from the case studies in Chinoro and Karsang (Faizabad test area) and

Figure 3-12b) Samples from the case study in Kharangon (Varzob test area): OM values from chemical analysis recalculated to SOC, plotted against SOC predicted values by the CRT model.

Comparison of SOC predictions with OM analysis results was constrained not only by the difference in analysis methods but also by differences in the soil samples examined. While soil spectral measurements were carried out on composite samples for sampling depths 0-20 and 20-50 cm, chemical analysis was conducted for sampling depths 0-10, 10-20, 20-30 and 30-50 cm, with the respective results subsequently averaged to allow comparison. Also, if no formal validation is possible from these results, a very general conclusion with regard to the applicability of SOC prediction can still be drawn. From the sample set from the Faizabad test area, SOC content was highly over-predicted again for 5 samples. These results re-confirmed that the model heavily misclassified and over-predicted certain samples (cf. Figure 3-11c and Table 3-12). These results clearly indicated that the CRT bag100 model needed to be further improved and extended with additional reference values. At 0.40, the overall RMSE was also relatively high in comparison to the RMSEV determined during validation, but no lower RMSE had been expected due to the error sources discussed above. The RMSE for the samples from the Varzob test area was 0.55, but only 0.41 when subsoil samples only were assessed. The plot in Figure 3-13b) indicates, however, that the SOC prediction model is generally suited to application to samples from the Varzob test area, even though no such samples had been included in the calibration dataset. This is a very promising indication for further development of the spectral library.

In the absence of SOC reference values, which is the case for most samples, validity of prediction results was estimated by comparing results from the CRT model to results from the MLR model. Figure 3-14a) shows that there were similar predictions for most additional samples from the Faizabad and Yavan test areas. The same is generally true for samples from the Varzob test area, with the exception of the above-mentioned samples with coarse texture (Figure 3-14b, marked pink). Predictions for samples from the case studies in Faizabad (Figure 3-14c, marked red and orange) do not correlate at all, while predictions for samples from the case studies in Varzob correlate much better (marked green and blue). As expected, congruency of prediction results existed mainly for loess samples and in the content range 0-2%. While CRT models are limited to the content range they have been calibrated for, MLR models are able to extrapolate to somewhat higher and lower SOC content ranges. This implies that predictions from MLR models may also contain negative values, a problem that is not encountered with CRT models. The MLR model, which was calibrated exclusively on loess samples, and was used for comparative purposes in this study, showed high RMSEV for non-loess samples (cf. Table 3-11). The high RMSEV can be explained by the limitations of MLR models (discussed in detail in section 3.4.1). However, the model seemed to predict a large part of the non-loess samples from additional sample sets in congruency with the CRT model.





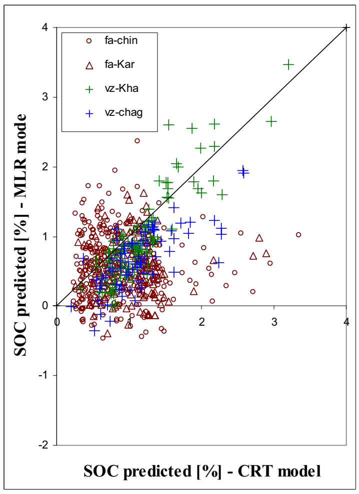


Figure 3-14a)
grey – Faizabad samples
blue – Yavan samples

Figure 3-14b)
black – Varzob samples
pink – Varzob samples, cluster VZ12

Figure 3-14c)
brown – Faizabad samples, case studies Chinoro and Karsang
green – Varzob samples, case study Kharangon
blue – Varzob samples, case study Chagatai

Figure 3-14a, b and c: Comparison of predicted SOC values from CRT and MLR models.
Figure 3-14a) additional samples from the Faizabad and Yavan test areas,
Figure 3-14b) samples from the Varzob test area,
Figure 3-14c) samples from case studies in Faizabad and Varzob.

3.4 Conclusions

In general, it can be concluded that combined regression tree models can be applied successfully to establish a sufficiently accurate soil spectral library to predict soil organic carbon (SOC) contents, even from a small reference dataset (250 samples) and for soil samples from highly differing geological sub-groups. Specific conclusions are given below and relate to the procedural steps as listed in section 3.2.

3.4.1 Conclusions for specific steps

The *sampling design* employed in this study had been developed for land degradation risk analysis. It was ideal for efficient collection of soil samples representative for the study area. The systematic random sampling design facilitated proportional sampling and allowed inferences to be drawn, for instance on the prevalence of specific soil quality states. Rare cases, however, which might be of specific interest (e.g. well-conserved soils with high SOC contents situated in an area where degraded soils with generally low SOC contents dominate), are often not adequately captured by a randomized sampling design. For better coverage of such rare cases, additional sampling would have to be done in order to obtain the minimal sample size required for robust calibration of soil spectra.

Pre-processing of soil reflectance spectra in order to increase the signal to noise ratio proved to be of decisive significance in this study. Continuum removal (removal of the convex hull of the reflectance curve, which allows best representation of spectral features, e.g. reflectance peaks) yielded the most repeatable prediction results, as became clear when comparing results from repeat spectral measurements. It is possible that variations in the reflectance spectral data for the dataset presented here were large compared to those in other studies. This may be due to the measurement set-up applied not having been optimal (especially the white reference readings conducted through a trimmed petri dish bottom may have increased variation). In any case, for informed decision making as to a specific pre-processing technique, it is recommended to test repeatability of predictions from spectral measurements for a number of different pre-processing techniques.

Possible outliers were detected for the chemically determined soil properties total carbon (TC), total nitrogen (TN), and exchangeable calcium (exCa) by assessing results of preliminary calibration models between soil spectral reflectance data and the mention three soil properties[21]. Model outliers were expected to provide an indication of possibly inaccurate results of chemical analysis, and were accordingly sent for repeat chemical analysis. Testing chemical reference datasets for outliers using preliminary calibrations proved very effective in increasing the accuracy of the reference dataset. Thus, combination of soil chemical analysis with visible near infrared (VNIR) spectrometry could help laboratories to improve laboratory standards for soil chemical analysis.

Classification of samples into geological sub-groups was successfully conducted using the CIE colour system defined by the Commission Internationale de L'Eclairage (CIE colour system). Spectral measurements of samples collected from various geological sub-groups resulted in highly non-uniform spectral data. Geological sub-groups well explained the high variation of spectral data as characterised by the first principal components. As shown by Seiler's results,

[21] Due to time constraints, finally no calibration models were established for these three soil properties (cf. section 3.2.5).

multiple linear regression (MLR) models were considerably improved when restricted to samples from the geological sub-group “loess” only (Seiler 2006). Misclassification into geological sub-groups is, however, critical as calibration models might be sensitive to classification errors. Especially linear models, such as the MLR model, may be affected by non-loess samples which are falsely attributed to the loess sample sub-group. While classifying samples based on the full spectra would possibly increase accuracy and increase stability of models, the relationships determined by Jarmer an Schütt (1998) between CIE colour values and iron-oxide contents allowed interpretation of modelling results with regard to iron-oxide contents. As expected, the geological sub-group “loess” was identified as the group with the lowest iron-oxide contents.

A map providing an overview on the spatial distribution of sampling sites and their attribution to geological sub-groups showed that non-loess samples were situated in specific locations; close to rivers, on ridges, or at high altitudes, where loess deposits had eroded by natural processes. The majority of sampling sites was classified as loessial soils.

Advantages and disadvantages of model approaches: The advantage of multiple linear regression (MLR), as the simplest way of performing a multivariate calibration, has mainly been seen in providing a direct link to spectral reflectance characteristics, since the models are based on a few wavelengths only (Seiler 2006). Calibration equations are simple and thus facilitate comparison between different studies. In contrast, more complex algorithms (e.g. combined regression tree algorithms), have until recently been complete black boxes. Due to the complexity of such models, it may not be feasible or useful to reveal details of their structure. However, information on relative wavelength importance is now accessible, for example for boosted regression trees, as implemented in the TreeNet software package (Salford Systems, San Diego, CA) (cf. Brown et al. 2006) so that it has now also become possible to make comparisons between different studies using complex studies.

While linear models, such as MLR, allow some extrapolation to higher and lower soil property values than originally modelled, models based on machine-learning algorithms (such as regression trees) can only predict what they already “know”. Consequently, MLR models tend to require a smaller number of calibration samples. Furthermore, regression tree models are sensitive with regard to defects or errors in the spectral reflectance curve (edges at spectrometer crossovers), more so than models using linear regression techniques[22].

However, MLR models have a number of deficiencies including the handling of non-linear relationships common in soil reflectance spectrometry, problems with heteroscedasticity (non-normally distributed residuals), an the insufficiency in terms of addressing the problem of multicollinearity. Thus, more sophisticated approaches are generally chosen today (Naes et al. 2002). Future modelling efforts for Tajik soils should thus concentrate on powerful approaches such as boosted regression trees.

Influence of soil spectral heterogeneity on prediction of SOC content: For the nonparametric combined regression tree (CRT) models presented, no negative influence of geological sub-groups on model performance was observed. There was even some indication that prediction improved when including samples from all geological sub-groups (while the RMSEV determined for loess samples from the CRT-loess model was 0.33, the RMSEV for the CRT model including all samples was 0.32, thus improved slightly). Although the size of calibration

[22] However, such edges in the spectral reflectance curve, may just be removed from the dataset and thus do generally not pose a problem.

sample sets available for the different sub-groups varied to a large extent, samples from underrepresented sample sets were not predicted any less accurately when the CRT model was applied. Furthermore, CRT models developed for the loess samples only (the sub-group with the lowest spectral variation) did not improve predictive accuracy of the loess samples. As expected, the SOC prediction accuracy for non-loess samples decreased, but the decrease in prediction accuracy was small, much smaller in fact compared to the MLR-loess model, which failed to reliably predict non-loess samples. Possibly, modelling with heterogeneous calibration sample sets reduces the likelihood that spectral calibrations of soil properties reflect interdependencies among soil variables. As indicated by results from MLR loess sample based models for SOC, this might be the case when using models that rely on specific wavebands (Seiler 2006).

For the CRT model, the geological sub-groups were neither helpful in determining library outliers, nor could variable prediction accuracy of the model in general be attributed to specific sub-groups. Moreover, CIE colour values, which were decisive for sub-group modelling, only had a negligible effect on CRT model performance. All in all, this may indicate that there is fundamental spectral reflectance information that allows prediction of SOC for highly variable sample sets.

Establishing a soil spectral library: It might be costly to come up with a sufficiently large reference dataset if no soil archive with previously conducted soil chemical analysis results is available. For nonparametric modelling, 200 calibration samples, as available for this study, are an absolute minimum. A good basis would be provided by 300-400 calibration samples and at least another 100-200 representative validation samples.

Close collaboration with a chemical laboratory during the establishment phase of a soil spectral library is crucial. If possible, the laboratory should be located near to where samples are stored. Otherwise the requirement of flexibility needed to analyze additional, specifically chosen sample sets can hardly be met. When working with a small reference dataset, this is of even greater relevance, since additional analysis for samples identified as library outliers will be even more important.

3.4.2 Future steps

Seiler's MSc thesis (Seiler 2006) and the results presented here form the basis of a soil spectral library for the rainfed areas of central Tajikistan. However, the existing library needs to be systematically developed and expanded. A number of tasks to establish an improved soil spectral library are listed below, in order of importance:

1) Outliers in the SOC reference dataset need to be identified systematically and repeat soil chemical analysis has to be conducted in those cases.

2) There is an urgent need for further reference samples in the high SOC content range. Additional samples to be chemically analyzed could be selected from the existing sample set, from samples for which high SOC content was predicted by the soil spectral library.

3) Throughout, validation of prediction accuracy for additional sample sets is required (e.g. for samples from the case studies and especially for samples from the Varzob test area). Chemical reference data representing all soil characteristics are required. Sample selection may be from principal component space, as conducted in this study for the reference sample set used, or random selection is also possible if the number of samples to be chemically analyzed is large enough.

4) Once additional chemical reference data are available, regression tree models will have to be recalculated. In the course of setting up new calibrations, more powerful tree-based algorithms should be applied (as available, for example, in the TreeNet software by Salford Systems and successfully applied by Brown et al. 2006).

5) Seiler tested the predictability of soil properties from spectral information for a whole range of soil fertility properties. The models were established for the restricted calibration dataset, including loess samples only, and by applying multiple linear regression (MLR). Very good results were obtained for total carbon, total nitrogen and soil organic carbon. Good results were obtained for pH and calcium carbonate. No calibration was possible for extractable phosphate, exchangeable calcium, magnesium, potassium and CEC and for the fractions of clay, silt and sand (Seiler 2006). In a next step, regression tree models for the full reference dataset need to be developed for soil properties for which successful calibration is promising and which are decisive for soil quality studies; this mainly concerns calcium carbonate and total nitrogen. For soil properties for which model development was not successful, the reference datasets need to be critically re-assessed.

6) The soil spectral library established was calibrated based on samples from the Yavan and Faizabad test areas. Should this library be used to predict soil properties of samples from other regions (or even of samples within those two test areas but from highly differing soils, e.g. carbonate soils), there is a danger that the characteristics of the additional samples are not adequately represented by the library, and that predictions are thus not reliable. Therefore, a procedure needs to be developed which allows the screening of samples with regard to their representation by the existing library, thereby identifying outliers to the library. Since the relationship between soil properties and characteristics of the spectral data space as described by principal component space was not fully understood for this dataset, outlier detection on the basis of principal component space, as proposed by other authors, was not considered reliable.

4 Hot spots of soil degradation and bright spots of soil conservation

Soil organic carbon (SOC) is an important soil quality indicator, especially for highly erodible loessial soils, and was thus selected for this study. Chapter 3 presented the establishment of a soil spectral library. This library allowed prediction of SOC content for all samples collected, from soil reflectance spectra measured under standard conditions in the laboratory.

In this chapter, soil erosion and the effect on the state of soil quality (as characterised by SOC content) will be assessed in a spatially explicit manner in order to identify hot spots of soil degradation and bright spots of soil conservation. The localization of hot spots of soil degradation and bright spots of soil conservation forms a very useful basis for efficient planning of soil conservation measures. The first step included the analysis of field observations collected. Subsequently, information on soil erosion occurrence and SOC content classes was extrapolated over the entire study area using raster datasets (satellite imagery and digital terrain model) as input variables in classification tree models. Finally, the spatially explicit information obtained was combined in the hot/bright spot map, allowing the differentiation of various stages of soil degradation from degraded (hot spots) to well-conserved areas (bright spots).

4.1 Introduction

Soil degradation is closely linked to land degradation. The UN Convention to Combat Desertification (UNCCD) defines land degradation as a natural process or a human activity that causes the land no longer being able to sustain properly its economic functions or the original ecological functions (FAO 1998). Several important processes involving vegetation growth, overland flow of water, infiltration, land use and land management take place in the soil (Stocking & Murnaghan 2001). Furthermore, soils provide a sensitive, integrative indicator for which sampling and analysis techniques are well defined (Cohen et al. 2006).

In this introduction, first a brief overview of soil degradation and conservation processes of relevance for the study area is provided (section 4.1.1). Hot spots and bright spots are defined in section 4.1.2. In section 4.1.3, field observations as efficient means for identification of the occurrence of soil degradation processes are introduced. In order to extrapolate from point observations collected in the field to larger areas, digital soil mapping is becoming increasingly important. A brief introduction to this more and more widely applied mapping technique is provided in section 4.1.4. In section 4.1.5, the specific objectives of the subsequent chapters are outlined.

4.1.1 Soil degradation and conservation processes

Sustainable soil management generally ensures a balance of soil formation and degradation, or may even lead to improved soil quality. However, if specific processes are accelerated or decelerated, changes will take place for the worse or the better. These changes are of great concern with regard to soil functional capacities. Forces acting on the soil as well as forces within the soil determine the dynamics of the degradation and conservation processes. Soil degradation processes have been extensively defined, described and studied, and may be grouped into water and wind erosion, and chemical and physical deterioration (Oldeman et al. 1991). The most recent global initiative is the land degradation assessment in drylands

(LADA)[23]. While soil restoration means the reversal of soil degradation (Lal 1997), soil conservation is defined as the maintenance or enhancement of the productive capacity of soil resources (WOCAT 2000). Thus, soil degradation and soil conservation processes are not separate processes, but they differ by their direction as well as the state of soil quality.

Different soil degradation processes are often interlinked, e.g. sealing of soil surface is related to soil erosion by water. Figure 4-1 shows important degradation processes and their interconnection: processes and determinants of these processes within the soil, as well as external factors and their links to soil degradation processes. The five factors determining soil development (Jenny 1941, cited in McBratney et al. 2003) are a. within soil factors, such as parent material and "organisms" transforming the soil (e.g. by humus formation [soil organisms] or by specific land management practices such as ploughing [land users]); b. external factors influencing the soil, such as climate and topography; or act at the interface between the soil body and the external environment, for instance the vegetation layer.

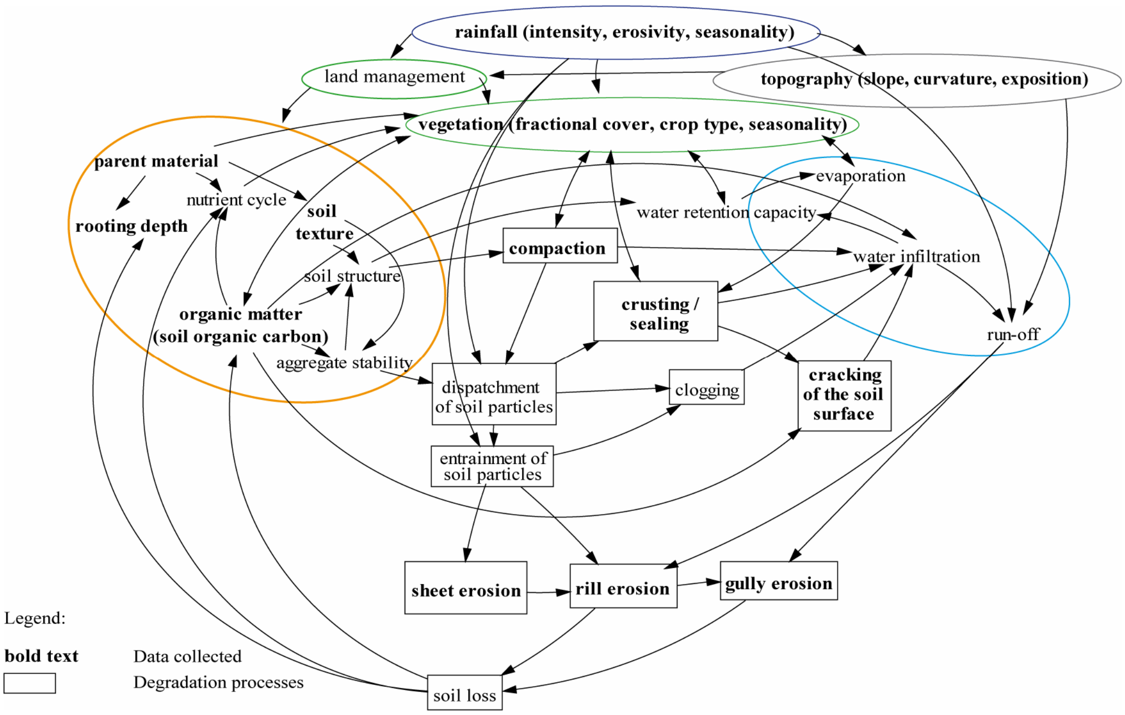


Figure 4-1 Soil degradation and conservation processes (sketch by author)

In the soil, organic matter is crucial since it holds a key position with regard to soil functions (e.g. moisture storage capacity, nutrient cycle; see also chapter 3). Soil organic matter (OM)[24] is also strongly interlinked with various soil degradation processes. On the one hand, OM influences the dynamics of these processes as a crucial force within the soil (e.g. by determining soil aggregate stability, which again is crucial for soil crusting, compaction and sheet erosion), and on the other hand, it is also affected by degradation processes. The impact on OM content be either direct, through loss of topsoil enriched with organic matter as a result of rill erosion, or indirect, through reduced vegetation growth and subsequently reduced amounts of biomass available for decomposition and transformation into soil organic matter.

[23] http://lada.virtualcentre.org/pagedisplay/display.asp

[24] In this study soil organic matter (OM) and soil organic carbon (SOC) are used interchangeably. OM and SOC content show a specific ratio for specific soil types, which was determined for the soil sample set collected for the here presented study (for more details see chapter 3).

OM content may be conserved by adapted land management, especially by erosion control, and enriched through agronomic and vegetative measures involving cover of the soil (e.g. no removal of crop residues or through permanent vegetative cover).

Erosion is crucial not only with regard to the quantity of soil being lost, but also, especially for farmers, with regard to the quality of the soil remaining in the field. The top soil layer, the first to be eroded, in most cases contains the highest amount of organic matter, as well as soil nutrients. The remaining soil is thus of inferior quality and fertility. Generally coarser soil particles are left behind as well. Thus, quantity of soil loss is but one item of information needed when assessing on-site damage in terms of soil degradation. With regard to subsistence farming and food security, it is the production capacity of a specific plot of land which is of primary concern. The focus of this study was thus on the on-site assessment of soil degradation and conservation processes.

4.1.2 Field survey and visual observations

For evaluations of the condition of natural resources, especially for preliminary assessments, visual observations have been successfully employed, also in conjunction with soil quality information derived from near infrared spectrometry (Cohen et al. 2005, 2006). Visual observations offer a number of advantages: As described by Stocking and Murnaghan (2001), field observations are rapidly collected, which is a major advantage over measurements collected from experimental plots, which require many years of data collection. Feasibility of data collection is a crucial issue for large area assessments, especially in developing countries, where resources available are limited. Furthermore, field observations are directly linked to the situation in the field, whereas measurements collected from experimental plots often differ from the situation in the field. Therefore, field indicators are highly relevant.

Furthermore, visual indicators may also be of greater interest for farmers, and may be observed and monitored by farmers themselves. Transparency and user-orientation of such indicators is thus more easily achieved. In many cases, one specific degradation process can be observed using a variety of field indicators, which assures stability of evidence collected. This shows that field observations comply with requirements for indicators applied in rural development projects (Herweg & Steiner 2002). To assure quality of collected datasets, further important aspects include time and place (temporal and spatial resolution) of data collection as well as standardization of observations, thereby making comparisons possible. Internationally applicable soil degradation classification systems have been developed (Oldeman et al. 1991, WOCAT 2003). Various methods for visual assessment of degradation processes, foremost of erosion by water, are available, whether using a semi-quantitative (Herweg 1996, McGarry 2004) or a qualitative approach (Stocking & Murnaghan 2001). Albeit these efforts in making visual observations more reliable, replicable and thus comparable, they will always be prone to subjectivity, especially if basing on a one-time / one-person observations only. Possible approaches to this problem are to link observations with measurements (e.g. visual observations with soil spectral measurements [Cohen et al. 2005]), and/or judging on the site condition using a team of experts (Cohen et al. 2006). Better control is also achieved, with photo monitoring, which allows to virtually “re-visit” a site, especially when files of photographs are linked to geo-referenced sampling sites and may be displayed interactively in a GIS system.

Soil degradation is a continuous process and affects soil quality in a continuous manner. However, for practical reasons it is often helpful to distinguish between “affected” and “non-affected" cases, a common practice in health research, a field in which major efforts are directed towards the development of case definitions and associated screening tests (Shepherd & Walsh 2007). For soil conservation planning, it can be crucial also to differentiate between severely affected areas and moderately or little affected areas: Efforts to prevent, restore or rehabilitate severely degraded areas may be disproportionate, whereas measures available at low cost and simple to implement may be highly effective in stopping or reversing degradation processes in areas showing moderate soil degradation (Liniger & Critchley 2007).

4.1.3 Hot spots and bright spots

Hotspot concepts have been applied in various disciplines from biology to geology and have mostly served for the identification of areas of interest. Heinimann (2006) generalized the use of the term "hotspots" as follows: "… *[it] is principally used for areas in which the status of the object under investigation reaches a certain level (e.g. level of biodiversity) and at the same time exceeds a specific threshold of dynamics or endangerment*". Within the scope of land degradation assessments, the term "hot spots" has been used to refer to areas in which degradation and degradation risk are high (Ponce-Hernandez & Koohafkan 2004). Furthermore, the terms "bright spots" or "green spots" (Ponce-Hernandez & Koohafkan 2004, Liniger & Critchley 2007) is also increasingly being used, referring to areas in which degradation has been prevented, mitigated and even rehabilitated. Efficient planning of soil conservation measures necessitates identifying both hot spots of soil degradation and bright spots of soil conservation: Hot spots make it possible to focus soil conservation efforts, while bright spots provide an idea of the potential of the land resources and may serve as examples for successfully implemented soil conservation measures (Wolfgramm et al. 2007). There is a great deal of potential in widening the focus from hot spots to bright spots. Liniger and Critchley (2007) have taken a strong stand in favour of this, with the following arguments: "*All over the world there are examples of winners in the struggle against land degradation. However, these positive soil and water conservation efforts – spontaneous or project-based – are hidden away and local achievements are not recorded, let alone documented and disseminated in a systematic way. There are lessons 'out there' that deserve recognition, and can help guide others to conserve or rehabilitate their land, raise production, and improve rural livelihoods*".

4.1.4 Digital soil mapping for identification of hot spots and bright spots

Digital soil mapping, which is also known as predictive soil mapping, can be defined as "*the development of a numerical or statistical model of the relationship among environmental variables and soil properties, which is then applied to a geographic data base to create a predictive map*" (Scull et al. 2003). The technological advances achieved during the last few decades, leading to availability of large raster datasets and the means to analyze these datasets using geographic information systems (GIS), have motivated a large number of studies to model soil variation. Raster data used are foremost derivatives from digital elevation models (DEM) and satellite imagery, but also include vector datasets (such as existing soil or geological maps, drawn up using conventional methods).

Challenges in digital soil mapping are diverse. Satellite imagery from spectral sensors provides a lot of information on environmental variables and is widely available. However, spectral reflectance from soil is subject to interfering effects, in addition to atmospheric effects and general observation condition, which also interfere when the study objective has characteristics that can be more easily distinguished, such as vegetative land cover. The principal factors influencing soil reflectance are soil moisture and physical soil characteristics (Ben-Dor 2002, McBratney et al. 2003). It must also be considered that remote sensing (RS) of the earth using sun radiation is only able to capture information pertaining to the uppermost 50 µm of the soil (Ben-Dor 2002). A major concern is vegetation, as it covers the soil and thus makes it necessary to obtain indirect evidence. However, vegetation itself also reflects the condition of the soil and may therefore be used as proxy information. Other proxies used for deducing soil characteristics include topography or drainage patterns (McBratney et al. 2003).

Particularly in areas with (seasonally) low vegetation cover, the signal received by satellites is dominated by soil spectral properties and can thus be interpreted in terms of varying soil surface conditions, permitting soil degradation assessments (Heboudane 2002). Various studies have aimed at mapping OM or SOC contents based on satellite imagery using various approaches and techniques (Palacios-Orueta & Ustin 1998, Fox & Sabbagh 2002, Hill & Schütt 2002, Udelhoven et al. 2003, Henderson et al. 2005, Jones et al. 2005).

In the field of soil erosion mapping, satellite imagery has been widely applied in the past 30 years, since it provides information with regard to erosion controlling factors (e.g. land cover) and also enables direct erosion detection (e.g. gullies) (Vrieling 2006). In areas in which data availability poses severe limitations to application of physically based models, the empirically based universal soil loss equation (USLE) and its successors have often been applied as part of an RS/GIS approach. However, as with any empirical model, application in new regions may require substantial calibration (Jetten et al. 1999, Cohen et al. 2005). Additionally it should be considered that USLE involves a multiplication of erosion controlling factors, and thus, is highly susceptible to error propagation (Burrough 1986). An advantage of the widely applied USLE is, however, that once parameters have been properly calibrated for the respective environment, it provides the opportunity for comparison with other areas.

In areas in which the application of erosion models is difficult as the requisite parameters for local conditions may not have been determined yet, qualitative degradation and erosion maps offer an efficient alternative (Vrieling 2006). Expert systems in the form of decision trees have been successfully implemented in various land degradation and erosion risk studies all over the world (LeBissonnais et al. 2001, Shrestha et al. 2004, Vrieling et al. 2006, Breu 2006). Decision trees determined using machine learning algorithms have also proven promising: Classification tree models have been successfully applied to link ordinal classes of soil erosion from field observations and Landsat 7 (ETM+) data (Cohen et al. 2005). An advantage of digital soil mapping using classification tree modelling is that it has the capability of integrating different approaches and procedural steps which are often conducted separately, especially so in erosion mapping. Vrieling (2006) differentiated between the following applications: (i) erosion detection or detection of erosion consequences (e.g. areas with sedimentation, sediment plumes in lakes), (ii) assessment of erosion controlling factors and (iii) data integration using erosion models or qualitative methods. Employing a digital soil mapping approach, areas affected by erosion may be directly detected from readily available raster datasets, of which the most suitable predictors (raster variables), appropriate thresholds and the model structure are determined by means of a statistical model that is easy to interpret.

4.1.5 Objectives

The aim of this study was to locate hot spots of soil degradation and bright spots of soil conservation in a spatially explicit manner. This included the following specific objectives:

- To characterize soil erosion based on visual observations, as the dominant soil degradation process in the study area, and to explore its effect on soil organic carbon.
- To extrapolate information on soil erosion and soil organic carbon to the whole study area using raster datasets (satellite imagery and a digital terrain model) as input variables for classification tree modelling.
- To develop an approach for the loess hills of central Tajikistan, for identifying various states of soil degradation and conservation from hot spots to bright spots which can be applied to point and raster data.

4.2 The Study Area: Soil Erosion Research and Erosion Controlling Factors

In the loess hills, erosion is considered the fastest and most widespread soil degradation process (Safarov & Novikov 2002). Section 4.2.1 gives a succinct overview of soil erosion research conducted by Tajik scientists. Further, a summary is provided of the findings of Erik Bühlmann's diploma thesis, which was conducted within the framework of the NCCR North-South programme. In section 4.2.2., the environmental conditions in the study area are discussed, as reflected by erosion controlling factors.

4.2.1 Soil erosion research in Tajikistan

Tajik soil science and research

Soil scientists in Tajikistan have always been aware of their country's situation embedded in a highly vulnerable landscape. Hence, the Soil Science Research Institute (SSRI) of the Tajik Academy of Agricultural Science has carried out research on erosion over a long period of time. The methodologies applied included field inventories, erosion plot experiments, laboratory experiments, mapping on the basis of satellite imagery, and statistical analysis (Jakutilov et al. 1963, Sanginov et al. 2000, Nekushoeva & Ahmadov 2006). Since the end of the 1990s the spreading of unsustainable land management, and the resultant widespread and accelerated degradation of land resources, has been reported by many Tajik researchers (Sadikov 1999, Djumankulov et al. 2000).

NCCR North-South research

A study (Bühlmann 2006) was recently carried out as part of the National Centre of Competence in Research (NCCR) North-South activities in Tajikistan. It focused on assessing soil erosion and conservation for the 10 by 10 km test area in Faizabad. A soil prediction model based on the revised universal soil loss equation (RUSLE) was applied. Erodibility (K-factor) and erosivity (R-factor) were discussed and calculated or estimated, respectively, for the Faizabad test area as follows[25]: K-factor = 0.04 t h MJ^{-1} cm^{-1} and R-factor = 2441 MJ cm ha^{-1} h^{-1}. Modelling results indicated a current average soil loss of 33 t per ha and year from cropland. The determined factors and the average soil loss seemed realistic, when compared to similar situations (e.g. soils, yearly precipitation). However it should be noted, that the K-factor derived from the USLE nomograph may fail in describing local erodibility, as it has been developed for a specific situation and may not be transferable (Cohen 2003). In the study of Bühlmann spatially explicit results for soil loss were compared to land use information. The results of this assessment supported the general perception that the marginal cropland farmed by peasants shows generally higher erosion rates than the relatively flat land cultivated by state farms.

4.2.2 Soil erosion controlling factors in the Tajik loess hills

In the loess hills of Central Tajikistan, characteristics of the different factors controlling soil erosion are indicating susceptibility to erosion. Primary factors influencing soil erosion are: (1) climate, (2) topography, (3) soil, and (4) land cover and land use (Toy et al. 2002). In the following paragraphs these factors are outlined in detail.

[25] Bühlmann (2006) reported an average annual R factor of 244.1 MJ mm ha^{-1} h^{-1}, while the correct unit would be as above 244.1 MJ cm ha^{-1} h^{-1}

Climate

Rainfall distribution is similar in the whole area, and rainfall is concentrated in the period from November to April. Total rainfall for the hill zone is 500-900 mm per year (Table 4-1). Around 50% of the rain falls in the months of March, April and May. In the mountainous areas (starting immediately north of the Varzob test area), mean annual rainfall is considerably higher, amounting to 1256 mm for the years 1988-2002. Locations of the meteorological station are indicated on the map in Figure 4-3.

As daily rainfall measurements were available for 1988-2002, and thus allowed the estimation of erosivity as defined by the revised universal soil loss equation (RUSLE) (Renard et al. 1997), erosivity was calculated here for the sake of comparability to other studies. The calculations carried out are described in detail in Bühlmann's diploma thesis (2006). Further information on the procedure is provided in Annex 4. R-factors were calculated for five meteorological stations in Central Tajikistan (Table 4-2), and estimated rainfall durations were assumed to be the same for all stations. In the absence of more detailed climate data, it was assumed that erosivity was uniform in the whole study area. No climatic data was included in subsequent erosion modelling (cf. section 4.3.4).

Table 4-1 Precipitation data for 5 climatic stations in Central Tajikistan: Annual rainfall, estimated erosivity as defined by the RUSLE (R-factor) in MJ mm ha^{-1} h^{-1} and R-factor in dimensions commonly reported

Meteorological station	Landform of location of meteorological station	Mean annual rainfall for the years 1988–2002 [mm]	Estimated erosivity (R-factor) for the years 1988–2002 [MJ mm ha^{-1} h^{-1}]	R-factor in commonly reported dimensions [MJ cm ha^{-1} h^{-1}]
Kusheri	mountainous	1256	3987	398
Hissar	lowland	529	884	88
Faizabad	hill zone	894	2436	243
Chormasak	hill zone	628	1533	153
Yavan	hill zone	694	1688	168

Source: Tajik Meteorological Service, Ministry of Environment

Figure 4-2 shows the monthly precipitation and the R-factor for the Faizabad meteorological station (graphs for all five stations are provided in Annex 4). Even though highest amounts of rainfall occur in March and April, highest erosivity must be expected in May. By the end of May, rainfall events have become less frequent and take the form of thunderstorms as the seasonal change to summer and the dry season is accompanied by rapidly increasing air temperature (cf. chapter 2). In dry years, however, precipitation decreases already in April, and thus erosivity is strongly reduced by May. Throughout the summer months, some storm rainfalls are possible, which may contribute significantly to mean annual erosivity, but generally during these months erosivity is close to zero. Winter rains start in November and precipitation and R-values increase continuously throughout January, February, March and April, with maximum R-values reached in May.

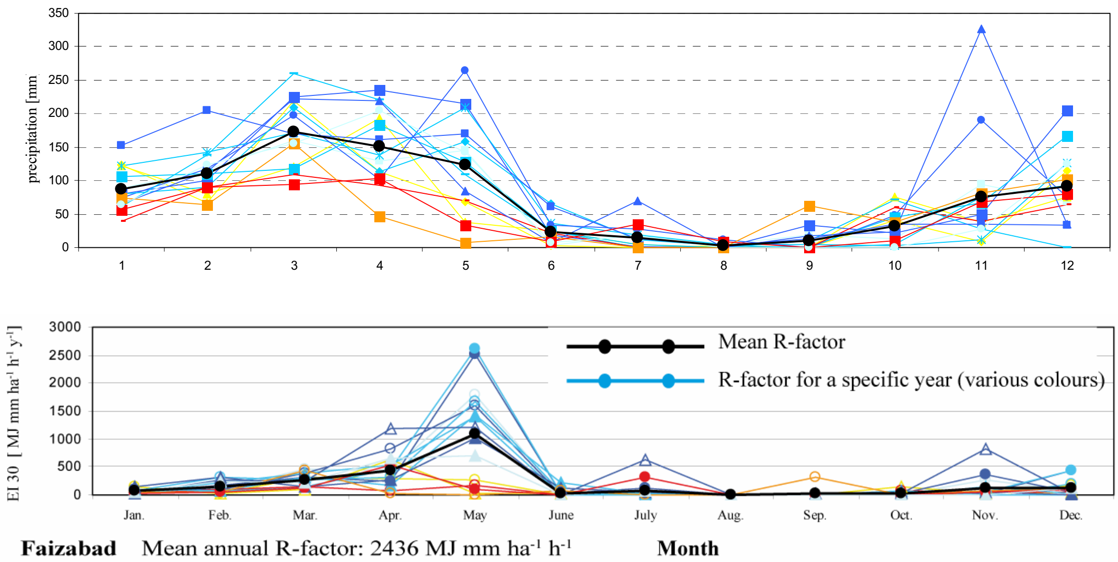


Figure 4-2 Monthly precipitation and monthly R-factor (EI30 value) for the years 1988-2002 (blue colours represent wet years and yellow to red colours increasingly dry years) and mean precipitation and R-factor for the same years (black line).

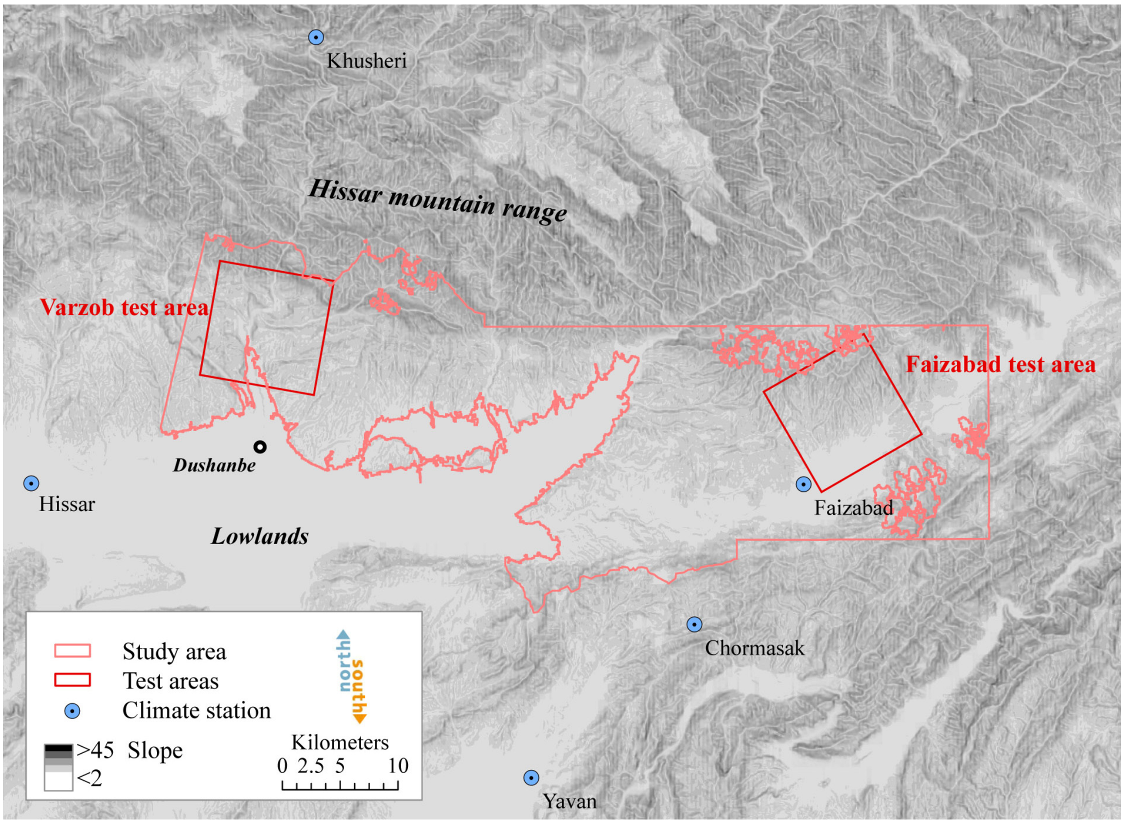


Figure 4-3 Map of Central Tajikistan showing slope steepness [%] derived from SRTM3[26] data, location of the five meteorological stations, study area and test areas

[26] http://www2.jpl.nasa.gov/srtm/

Topography

The area is characterized by dissected terrain, with steep slopes. For thousands of years, loess has been carried from the Afghan and Turkmen deserts to Central Tajikistan by aeolian processes, and was and is deposited in front of the Hissar range (Figure 4-3). Over time, the loess deposits have been severely eroded by natural processes, creating the typical topography seen today (Figure 4-4, left). The mountainous and rocky areas of the Hissar range can easily be identified from slope steepness > 45% (marked red) in these areas. In the hill zone characterized by the loess deposits, slope gradients are on average 15-30%, but they may go up to 45% (yellow and orange).

Soil

The main characteristics of the soils which have developed on the loess deposits will now be briefly discussed with regard to their susceptibility to soil degradation, and especially erodibility. Loessial soils are characterized by "their yellow color, absence of beddings, silty texture, looseness, macroporousness and wetness-induced collapsibility" (Liu 1965 in Zhang 2004). This description also applies to the loess deposits in Tajikistan. Loess soils are yellow (Figure 4-4, left) and landslides are frequently observed (Figure 4-4, right).

Figure 4-4 Left: Overview of the foothills consisting of loess deposits, with the Hissar range in the background (Photo by Bettina Wolfgramm, August 2004)

Right: Landslide opposite from Gulpista village, North exposition, Varzob district (Photo by Bettina Wolfgramm, June 2005)

With regard to erodibility, it is a soil's inner strength to resist erosion that is decisive. Thus, overall particle size distribution and organic matter content have been determined as the main indicators of erodibility, although a soil's erodibility is a function of complex physical and chemical interactions (Wischmeier & Smith 1978). Figure 4-1 shows such interactions. Results of actual measurements of erodibility of loess soils have not been available for the here conducted study. Jakutilov et al. (1963) analysed soil properties of brown carbonate soils that had been variously affected by erosion, and determined silt contents (0.001-0.05 mm fraction, according to the Russian classification system) between 58 and 72%. The medium silt fraction for samples analysed for the Faizabad and Yavan test areas was 65% (see section 3.3.1). Such medium textured soils are most erodible, with soil particles easily detached, and sediment eroded from these soils is easily transported (Toy et al. 2002). In the case of soils with low clay fractions, soil organic matter is a primary driver of aggregate stability (Dalal & Bridge 1996 in Hill & Schütt 2000). The median value for SOC content as determined for the SOC predicted for the here presented sample set (cf. chapter 3) was 1.4% in the Faizabad test area, and 1.1% in the Varzob test area (maximum 3% and 1.9%, respectively, and minimum 0.2% and 0.3%, respectively). For subsequent generation of simple erosion models, erodibility was assumed to be uniform in the study area and was thus not specifically included as model variable.

4.3 Materials and Methods

A field survey was conducted in order to compile a representative dataset reflecting the state of soil resources in the test areas. Details with regard to the visual observations collected are provided in section 4.3.1. In order to explore characteristics of the field dataset, various non-parametric statistical tests were applied (section 4.3.2). This analysis formed the basis for the determination of soil information to be extrapolated to the whole study area using satellite imagery information and digital terrain data. Both potential and restrictions of the available raster datasets for digital soil mapping are discussed in section 4.3.3. In section 4.3.4, specifications on classification tree modelling applied to calibrate raster datasets to field observations are outlined. To determine different states of soil degradation and conservation, a hot/bright spot matrix was developed (section 4.3.5). Maps produced were validated with regard to classification accuracy and significance of class differentiation (section 4.3.6).

4.3.1 Field survey – visual observations on soil degradation

Data for the land degradation and conservation assessment were collected on the same sampling sites as used for the land cover / land use assessment (chapter 2), and where soil samples for determination of soil organic carbon had been collected (chapter 3).

Sampling sites were located using a Global Positioning System (GPS). Data collection for the soil survey included visual assessment of soil characteristics and soil degradation types. On the field protocol (cf. Annex 2), the following soil characteristics were recorded: soil texture, stone cover on the surface, soil colour of the top, and the subsoil layer according to the Munsell colour system. However, Munsell colour attribution was not found to be reliably predictable in the field and was thus not used any further. Soil degradation types were distinguished according to the WOCAT classification system (WOCAT 2003), originally defined by Oldeman et al. (1991). Soil degradation types applicable to the study area included soil erosion by water (loss of topsoil, gullying, and mass movements) and by wind (loss of topsoil), soil chemical deterioration (fertility decline and reduced organic matter content), and physical deterioration (compaction, and sealing / crusting). Ultimately, each plot was documented in several pictures allowing reconstruction of conclusions made on the spot. Brief descriptions of these soil characteristics and degradation types, together with the visual indicators used, are provided below.

Groundtruth data were collected in the three test areas of Yavan (May 2004), Faizabad (early June 2004) and Varzob (early June 2005), according to the sampling design employed as specified in chapter 2. Finally, the study area had to be limited to an area including the Faizabad and Varzob test areas only, as time differences in vegetation development did not allow integration of all three test areas (cf. chapter 2). The timing of the field survey was determined with regard to the following aspects: It is preferable that visible indicators of soil degradation processes (primarily of soil erosion by water as well as of sealing / crusting) be assessed shortly after their development. Otherwise these signs may be obliterated by harvesting activities (on cropland) or trampling of grazing animals (on grazing land and cropland after harvest). Highest rainfall amounts are recorded in March and April (cf. section 4.2.1), while in May rainfall events are generally infrequent and of short duration, which leads to drying of the soil. In May and June, signs of erosions are still fresh and thus well visible. Furthermore, traces of erosion which has taken place during the winter months, were expected still to be visible. As crusts develop when the soil is drying out, May and June is a suitable time for crust assessment in Central Tajikistan, since later on in the dry season, soils will have completely dried out and crusts can not be identified as easily any more. Finally, since rains have become infrequent by the end of May, such timing of the field survey ensures that conditions for site assessments are comparable at all sampling sites.

Erosion by water (W) and by wind (E)

Various types of soil erosion by water can be observed in the study area: loss of topsoil and surface erosion (Wt), gully erosion (Wg), and mass movements (Wm). Since the focus of this study was on the state of soil resources available on field plots, offsite degradation effects were not explicitly included in the survey but were recorded where observed. Observation of visible signs of erosion processes was carried out following the procedure described by Stocking and Murnaghan (2001). The following indicators for rill and inter-rill erosion were included: rills, pedestals, armour layer, plant/tree root exposure, tree mounds and rooting depth, defined as depth to which shovelling was possible (< 50 cm or ≥ 50 cm depth). In some cases, signs of the splash effect caused by raindrops were also observed on the soil surface. Even though different degrees of erosion had been noted in the field (none, low, moderate, and great), it was due to poor separability of erosion degrees that, for further analysis, sample locations were separated into two classes only: sites with visible signs of erosion and sites without any signs of erosion. Classification in this way was considered robust also for vegetated sites.

Wind erosion is considered to be of major importance in loess areas. Especially in the Faizabad test area, strong winds are being observed throughout the spring months. The assessment of wind erosion by visual indicators is difficult so that this type of soil degradation was not addressed in this study, but effects may have been recorded indirectly: Once soil aggregates are destroyed and soil particles detached (cf. Figure 4-1), wind (or water) will remove soil from unprotected areas (e.g. areas without vegetation cover). Thus, signs of splash effects and crusting provide some indication with regard to water and wind erosion risk.

Chemical deterioration (C)

Taking into consideration the overall land management during the last 15 years and the soil characteristics in the area, the focus in this study was on soil fertility decline (Cn). Other types of chemical deterioration were precluded: Loessial soils normally contain sufficiently high amounts of $CaCO_3$ (Kuteminskij & Leonteva 1966), which buffers the soil system with regard to the pH value. Thus, acidification (Ca) should not be a problem in the study area. No cases of soil pollution (Cp) on agricultural land were known in the study area, and Cp was thus not assessed. Salinisation (Cs) is a well known problem in irrigated areas in Tajikistan. Since the study area was restricted to rainfed areas and included only a small number of irrigated plots, Cs was not specifically covered in the survey, either.

The study area is marked by fertility decline (Cn) caused by leaching and soil mining. Loss of nutrients and/or organic matter occurs if agriculture is practiced on poor to moderately fertile soils, without sufficient application of manure or fertilizer (Oldeman et al. 1991). Application of fertilizer and manure was very low during the last 15 years in the study area. Loess soils are generally considered “fertile”. Soil chemical deterioration was not assessed in the field, but conclusions were drawn from the results of analysis of the soil organic content of soil samples.

Physical deterioration (P)

Physical deterioration by soil compaction (Pc) and sealing / crusting (Pk) is widely observed. Compaction includes the deterioration of soil structure by trampling or through the weight and/or frequent use of machinery (WOCAT 2003). Especially trampling leading to soil compaction is of major concern on intensely used pastures, while the use of machinery is limited, since availability of machinery is low in Tajikistan. Sealing and crusting includes clogging of pores with fine soil material and development of a thin impervious layer at the soil surface that obstructs the infiltration of rainwater (WOCAT 2003) (Figure 4-1).

Field observation of Pc and Pk was conducted according to field methods proposed by Liniger (personal communication). A measure for compaction was provided by the penetration depth of a pocket knife within sampling pits at around 10 cm depth (topsoil compaction) as well as at around 40 cm depth (subsoil compaction). In the field, four classes of penetration depth were distinguished: soft (> 5 cm), medium (2.5-5 cm), hard (0-2.5 cm) and very hard (0 cm). The method is only robust, in the case of comparable water content on all sites, as humid soil is much more easily penetrable. During the field surveys in June, precipitation in the area was very low. Few field days were preceded by a rainfall event. In the case that the soil had been distinctly wetted, observations with regard to physical deterioration were skipped. For subsequent analysis, only the cases “not affected by compaction” (soft and medium) and “affected by compaction” (hard and very hard) were distinguished. Separability into four compaction classes was not possible.

Sealing (with wet soils) and crusting (with dry soils) can easily be observed at the edge of a sampling pit, where sealing / crusting is characterised as a hard layer at the soil surface, normally developed to around 2 cm depth. Cracks in the soil surface provide further indication of crusting, as they develop when a crust is further drying and suspension within the crust is getting too high, so that the crust subsequently cracks.

Water logging (Pw) and acidification (Pa) are not normally observed on sloping lands. The highly dissected hill zone is generally not suited for industrial activities. Thus, loss of bio-productive function due to other activities (e.g. construction and mining) (Pu) was not considered in this study.

Soil organic carbon (SOC)

As described in chapter 3.1.1, soil organic carbon (SOC) is considered an integrative measure of soil quality, and was selected for this study as soil quality indicator. SOC is a major component of OM, with the SOC to OM ration being 0.68 for the soils in the study area (cf. section 3.3.1).

Topsoil (0-20 cm depth) and subsoil (20-50 cm depth) samples were collected from each sampling plot as composite or separate samples from two sampling pits, resulting in 1450 soil samples from all three test areas. Soil reflectance spectral measurements were conducted for all soil samples, and soil organic carbon (SOC) contents were predicted from the soil spectral library established as described in chapter 3. It must be mentioned here again that effects of inaccuracy in SOC content predictions originating from errors in the soil spectral library can not be fully precluded. As explained in chapter 3, although the established calibration between

SOC content and soil reflectance spectra proved suitable for exploratory analysis, no validation of samples from the Varzob test area has been carried out.

4.3.2 Exploratory analysis based on field survey data

A variety of techniques derived from exploratory data analysis were applied, including graphical techniques and simple statistical tests, in order to characterise soil degradation processes in the study area and to explore their effect on soil organic carbon content. The aim was to extract information from the observations made on sampling sites during the field survey as to important soil degradation types and inter-linkages between these, to uncover underlying structures and to determine optimal factor settings for further analysis, especially spatial analysis.

An introduction to approaches used in exploratory data analysis and a very helpful and inspiring compilation of simple exploratory data analysis techniques can be found in the e-Handbook of Statistical Methods provided by the US National Institute of Standards and Technology (NIST/SEMATECH 2006). Non-parametric statistics are suitable for exploratory analysis, since they do not make too many assumptions about the population from which the data were sampled as parametric statistics. Furthermore, there are various methods for analysis of categorical datasets. However, non-parametric tests are often less powerful than parametric tests. The Microsoft Excel add-in software “Analyse-it” (Analyse-it 2006) facilitates calculation of different non-parametric tests, many of which have been described by Siegel and Castellan (1988).

Table 4-2 Overview of the questions examined and the methods applied

	Questions	Methods*
(A)	What is the occurrence of the different soil degradation types in the different areas and on different major land use types? What is the median SOC content for specific sampling sites?	Summary statistics
(B)	Is there an association between erosion and topographic factors? Is there an association between soil organic carbon content and topographic factors?	Spearman rank test for correlation (non-parametric)
(C)	What is the pattern of soil erosion occurrence with regard to other soil degradation processes (e.g. compaction), different land use types and test areas in the study area today?	Chi-square tests on 2x2 contingency tables
(D)	What is the effect of the different soil degradation processes on SOC content?	Mann-Whitney test (non-parametric)
(E)	What is a suitable threshold for soil organic carbon content in order to express an effect of soil erosion?	Frequency distribution and cumulative frequency

** For all tests, the statistical significance level was defined as $p \leq 0.05$.*

Table 4-2 provides an overview of the questions examined and the methods applied in the course of this study. As preliminary test showed that the here presented datasets were generally non-normally distributed and showed non-linear relations, respectively, only non-parametric tests were applied. A first step (A) in the analysis was to gain an overview of the occurrence of observations. Shepherd and Walsh (2007) distinguish between prevalence (number of cases per area) and incidence (number of cases per area and time) of observations of soil degradation cases. The dataset presented here provides information about proportions of areas affected or not affected by erosion. However, sampling clusters in Faizabad test area, were not fully randomly distributed; one of the clusters situated at higher altitudes in the North was not accessible within the available time frame and had to be moved further south. Thus, it can be seen as a preliminary assessment of prevalence and the term “occurrence” was used.

Second (B), the Spearman rank test for correlation was conducted to find out more about the relationship between topographic factors and erosion occurrence, and between topographic factors and SOC content, respectively. To make sure that correlation was tested for comparable situations, the Spearman correlation test was conducted separately for cropland and grazing land, and for sites with erosion and sites without erosion.

In a third step (C), chi-square analysis was performed to test for an association between soil erosion and other soil degradation types and soil characteristics (e.g. soil texture). As it was expected that different soil degradation types were interlinked (cf. Figure 4-1), one aim was to explore these linkages for the study area. Chi-square tests are commonly used for this purpose (Siegel & Castellan 1988).

Fourth (D), the effect of various soil degradation types on soil organic carbon (SOC) was assessed by conducting Mann-Whitney U tests, which formally tests for a difference between the medians of 2 independent samples (Conover 1999).

Finally (E), an SOC content threshold was determined. For preliminary assessments, thresholds are very practical. A threshold helps to focus, since it allows the distinction between different general states (of soil resources). In this study, the aim was to distinguish between erosion affected soils and non-affected soils. Therefore, a threshold for soil organic carbon had to be determined which separated the sites in which erosion occurrence had been recorded from the sites without any erosion occurrence. A threshold should be generally applicable, including various land use types as well as different areas. Moreover, it should provide for simple implementation and application, and facilitate comparison of sites with different land use types. Finally, for spatially explicit modelling it is important to determine classes that contain a sufficiently high number of samples in order to facilitate calibration of SOC contents to raster data. In this study, this was only achieved by limiting the SOC content classes to the classes “low” and “high”. The threshold was first determined by visual assessment of frequency histograms of SOC content observed on erosion affected and non-affected sites, and was then tested for best modelling results when predicting the two SOC content classes from raster datasets.

An independent sampling set is required to perform statistical analysis. In this study, a clustered sampling design had been applied for efficient sampling and in order to obtain information on the spatial characteristics in the study area. For this sampling design, spatial autocorrelation among the samples had to be considered and was assessed using semivariogram analysis (chapter 2). Spatial independency of samples for the dataset collected for this study was determined for samples at a distance of 230 m, as a result of which only 7 of the 13 sampling sites of a sampling cluster were selected for statistical analysis. This sample set was termed *independent sample set* and included a total of 202 samples. Three samples collected in riverbeds (aquatic area) and two samples collected in kitchen gardens were excluded from analysis, as their number was too small to be representative. Additionally, observations were missing for some sampling sites, reducing the number of observations to 160-180, depending on the indicator. The statistical tests were carried out on “all” data of the independent sample set, on data disaggregated according to test areas, and on the sub-classes “cropland” and “grazing land”. The “cropland” class included all cropped areas: annual and perennial (fallow) cropland as well as areas with tree and shrub cropping, also including sites with intercropping. As the statistical tests were based on field survey data, sampling sites classified as tree and shrub cropping were not mixed with rangelands with tree and shrub cover and thus attributed to cropland. “Grazing land” included extensive and intensive grazing lands as well as rangelands (with partial tree and bush cover).

4.3.3 Raster data

The input data for spatial assessment basically consisted of the same raster dataset as that used for land cover / land use modelling (cf. chapter 2). It included a digital elevation model (DEM) calculated from Russian topographic maps (scale 1:50 000, contour distance 10 m) and ETM+ imagery from two different seasons. A number of critical issues have to be considered when assessing soil characteristics using remote sensing data. In the following paragraphs, timing of images for predicting soil erosion occurrence and for predicting SOC content classes is discussed.

Information from raster data useful for determining soil erosion includes, on the one hand, information on soil erosion controlling factors, especially vegetation cover, as derived from satellite imagery, and on the other hand, topographic characteristics provided by digital elevation models. Hence, such raster data have formed the basis of many erosion studies in the past 30 years (Vrieling 2006). Thus, information on vegetation cover will contribute to identifying soils that need protection from erosive forces during certain critical times. This concerns the spring months (April and May) and the period before winter rains start and when fields are prepared for sowing winter wheat (November). The Landsat satellite imagery dating from 24 May 2002, used for land cover / land use modelling, was assumed to reflect the general situation of vegetation cover during spring rains. The Landsat image recorded on 22 August 2000 was chosen to represent the state of vegetation cover at the end of the dry season. It was assumed that fields barren in August would be barren in November, too. Further, this image was thought to be most suitable, since rains starting in November make it difficult to obtain cloud-free satellite imagery for this time of the year. And finally, wetness of soil in parts of the study area in November could possibly hamper modelling over the whole study area.

In arid and semi-arid areas, the preconditions are good for establishing a direct relationship between SOC content classes and data from satellite imagery, since the disturbance by vegetation is small at least during part of the year. In the rainfed areas of Tajikistan, large areas show minimal vegetation cover during the dry season from August to October. Cropland lies barren after harvest in June, and stubbles are often removed by grazing animals. On grazing land vegetation cover (at least green vegetation cover) is often low too, after grass is cut on haymaking sites and many extensively used grazing areas have been strongly grazed. Furthermore, the situation is comparable over large areas during the dry season, which is not true for the time of main vegetation activity, due to shifts in vegetation development (cf. chapter 2). Employing imagery from the dry season only would allow the calibration of soil properties to larger regions. However, for areas in which climatic influences can be assumed to be negligible, an important factor for mapping soil characteristics is vegetation varying in response to different soil conditions (Skidmore et al. 1997). Thus, in the present study, information contained in the satellite imagery dating from 24 May 2002 was considered to be of importance also for mapping soil organic carbon content classes.

The full dataset consisted of bands 1, 2, 3, 4, 5 and 7 and the optimised soil adjusted vegetation index (OSAVI) (Rondeaux et al. 1996). In addition to the input data used for land cover / land use classification, for soil characterisation tasselled cap layers (brightness, greenness and wetness) (Crist & Cicione 1984) were calculated for for both ETM+ scenes. Tasselled cap information is considered especially promising for soil mapping (Crist et al. 1986). Finally, the dataset also included slope and curvature, derived from the digital elevation model (cf. chapter 2).

4.3.4 Digital mapping of soil erosion and SOC content using classification tree models

Classes and thresholds which allowed the calibration of point observations to the raster datasets, were determined by exploratory analysis as described in section 4.3.2. For this study, soil erosion classes “occurrence of erosion present” versus “no occurrence of erosion”, and SOC content classes “low” (≤ 1.1% SOC content) and “high” (> 1.1% SOC content) proved most suitable for extrapolation over the whole study area.

Soil samples were collected representatively for a sampling site of 30x30 m (same as the Landsat ETM+ pixel size). As for land cover classification, sites with homogeneous areas smaller than 30 x 30 m were excluded from modelling[27]. Topsoil samples (0-20 cm sampling depth) were used for the calibration to raster datasets. Even though Landsat ETM+ data only contain information with regard to the upper 50 µm (Ben-Dor 2002), it was supposed that the SOC content in the surface (50 µm) and that in the topsoil layer (0-20 cm) would correlate. This assumption is particularly appropriate for regularly ploughed cropland, which often shows little change in SOC contents in the topsoil layer. Thus, the SOC content values determined from the topsoil samples were expected to represent the average SOC content for the topsoil layer within the grid cell.

To establish relationships between reference data collected in the field (SOC content classes or soil erosion occurrence), and raster data (satellite imagery and topographic information as described above), information from raster data was extracted for each sampling point and pixel based calibrations were elaborated. Classification tree modelling was done using the software CART 5.0 (Breiman et al. 1984), with the same calibration and validation sample sets and the same model settings as for the land cover / land use model described in chapter 2.

While classification tree models are able to determine locally optimal criteria (that is, optimal for the next split only), their limitation as to determining an optimal tree topology is well known (Breiman et al. 1984). To avoid effects caused by this limitation, combined tree models have been proposed (Steinberg & Colla 1997) and are now generally being applied (Cohen et al. 2006, Bricklemyer et al. 2007). Combined models were tested for this study, but since classification accuracy improved only slightly compared to the best single tree model, the single tree model was chosen because it also reveals information about the classification structure. Instead preliminary models were tested in order to select the best performing input variables. Test models yielded results of lower accuracy when band 3 (corresponding to red reflection) was included as input variable, especially for low SOC contents. When band 3 was excluded, it was replaced in the classification tree by tasselled cap brightness information, which yielded higher classification accuracy for low SOC content classes. Thus, for the SOC content model, information of band 3 of ETM+ imagery was excluded from modelling. This effect seems to be linked to the red coloured soils originating from granodiorite mother rock (cf. section 3.2.3) and must be further explored in future studies. The vegetation index OSAVI

[27] Cf. section 2.3.1

from the ETM+ May imagery was the only layer which was decisive for establishing the most accurate model and was thus included.

Each classification tree is defined by a certain number of *terminal nodes*, which divides sampling sites into sample sub-classes with specific characteristics, as defined by the raster data variables. These sub-classes often provide a great deal of insight into ecological characteristics present in an area.

4.3.5 Hot/bright spot matrix

A simple approach, the hot/bright spot matrix, was developed to link soil erosion occurrence and the state of soil quality with a view to distinguishing hot spots of soil degradation and bright spots of soil conservation (Wolfgramm et al. 2007). In land degradation assessments, the term “hot spots” refers to areas in which degradation and degradation risk are high; and the term “bright spots” refers to areas in which degradation has been prevented, halted or even reduced (Ponce-Hernandez & Koohafkan 2004, Liniger & Critchley 2007).

Results of the exploratory analysis as presented in section 4.4.1 confirmed that the relationship between erosion and SOC content, and topographic factors (as possible controlling factors of erosion and SOC content) were complex, but also weak. However, when developing the hot/bright spot matrix, it was based on a number of simplifications, which need to be considered when applying the matrix and interpreting its results. The hot/bright spot matrix was developed for application in the loess areas of central Tajikistan and based on the following assumptions:

- Variation in erosion and SOC content was attributed to land management, no soil inherent variation was considered (an assumption which is strongly linked to the next assumption following below);
- Loessial soils were assumed to be homogeneous. Generally, SOC content is known to be linked to soil texture. However, little variation in soil texture was expected for loessial soils: Based on the assessment carried out on soil property results from soil chemical analysis, no correlation between SOC and soil texture had been determined. Further, percentage of silt was generally high and showed little variation (cf. chapter 3);
- Loessial soil were assumed to be dominant in the study area. As the overview on soil types for the sampling sites showed, non-loessial soils were only to be expected close to rivers and towards mountain ridges and were thus considered insignificant (cf. chapter 3);
- Erosion was assumed to be the dominant soil degradation type. The exploratory analysis conducted showed that SOC content on sites with erosion was significantly lower than on sites without erosion. The same was true for sites with sealing / crusting. Further, sites with erosion were highly coinciding with sites with sealing / crusting. It was thus assumed that sealing / crusting was not as such a separate soil degradation type but that it was closely linked to erosion and was impacting on SOC content conjunctively with erosion (cf. section 4.4.1).
- According to the results of the exploratory analysis conducted, influences of topographic factors on erosion occurrence SOC content were assumed to be low (cf. section 4.4.1) and thus minor, when compared to land management.

Thus, in the context of this study, hot spots were characterized as areas affected by soil erosion and with low soil quality. Bright spots, on the other hand, were characterized as areas not affected by soil erosion and with high soil quality. By combining information on soil quality with the occurrence of erosion, it is possible to learn about the state of the soil resources and about soil degradation processes impacting on the specific state of resources. This allowed not only a differentiation to be made between hot spots and bright spots as “extreme” classes, but also a distinction between areas in the process of becoming hot spots and areas in which these processes had been halted or there were other causes for low SOC content (other soil degradation processes or SOC content was inherently low). Basically such a combination may be applied to various soil quality and soil degradation indicators, depending on the focus of a specific study.

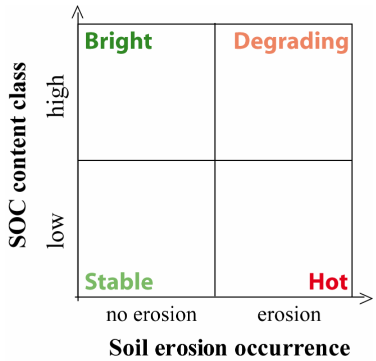


Figure 4-5 Concept of the hot/bright spot matrix

The concept of the hot/bright spot matrix is visualized in Figure 4-5. The four states designated “hot spots”, “degrading areas”, “stable areas”, and “bright spots” may be characterized as follows: (A) Bright spots of well conserved land characterised by a non-degraded state of soil resources (high SOC contents) and limited soil erosion processes, (B) Stable areas of land subject to other degradation processes (e.g. soil nutrients exploitation) since SOC content is low but occurrence of soil erosion is limited, (C) Degrading areas of land that may have been subject to land use changes and is characterised by a non-degraded (i.e. not yet degraded) state of soil resources and widespread soil erosion processes, and (D) Hot spots of degraded land, where SOC contents are already low and which is degrading further since erosion processes are widespread.

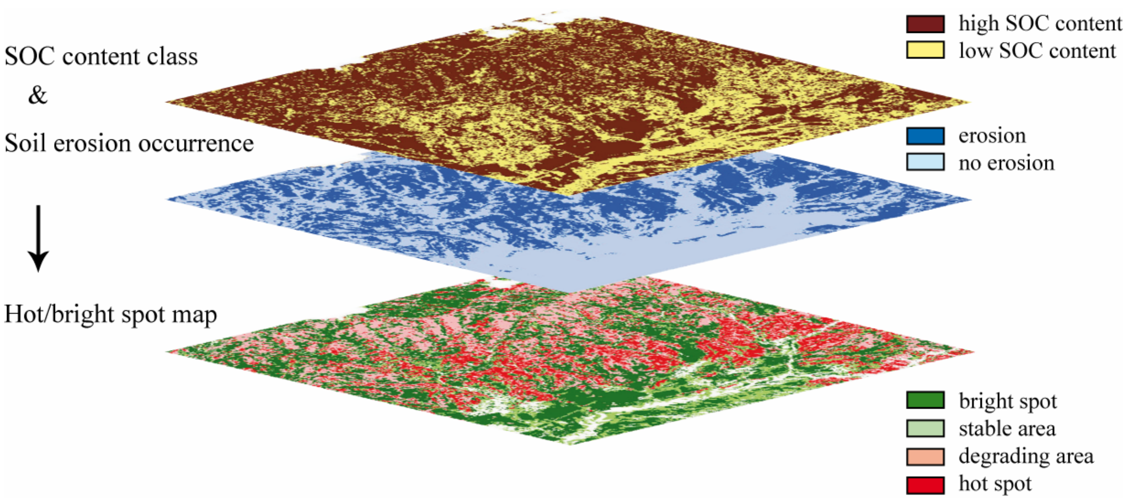


Figure 4-6 Mapping of hot and bright spots

To produce hot/bright spot maps, the soil erosion occurrence map and the SOC content map were simply combined according to the rules defined by the hot/bright spot matrix and were implemented using the "Combine" function in ArcMap (ESRI Inc.).

4.3.6 Validation: Classification accuracy and significance of class differentiation

Two methods were applied to validate the maps produced. First, classification accuracy regarding soil erosion, SOC content classes and the hot/bright spot map was assessed. Second, the significance of differences in SOC content between the hot/bright spot classes was assessed.

Classification accuracy

All models were validated by determining producer's and user's accuracy as well as the percentage of correctly classified samples for the validation sample set, as described by Foody (2002). The kappa coefficient represents the proportion of agreement obtained after removing the proportion of agreement that may be expected to occur by chance (Foody 1992). Weighted kappa coefficients may be calculated for ordinal classifications. The four classes of the hot/bright spot matrix were ordered as follows for calculation: bright, stable, degrading, hot. The weighted kappa coefficient was calculated using the Excel add-in Analyse-it (Analyse-it 2006). According to the Analyse-it user's manual, the kappa coefficient can be roughly interpreted as follows: < 0.20 = poor, < 0.40 = fair, < 0.60 = moderate, < 0.80 = good, 0.8-1.0 = very good agreement.

Significance of differences in hot/bright spot classes

It was expected that the four classes distinguished by the hot/bright spot map would exhibit high within-class variation of SOC contents. On the one hand, variation of SOC contents in the field is expected to be high. 53 sample pairs collected from a single sampling plot and separated by a distance of around 7 m showed that the mean coefficient of variation (CV) within fields is 23% for grazing land and 14% for annual and permanent cropland. The variance, as determined by semivariance analysis, was thus the same for within field variance and for between plot variance at a distance of 58 m, both resulting in a semivariance of 0.15 (chapter 2). On the other hand, errors resulting from the calibration of plot data regarding soil erosion and SOC content to raster data additionally increased within class SOC content variability. Moreover, erosion features may vary highly at short distances or even within a single field plot.

To test whether differences in occurrence of erosion and SOC content between the various states of soil resources described by the hot/bright spot map were of a significant level, ordinal erosion classes and continuous SOC content values of samples attributed to a specific class of the hot/bright spot map were examined. For this purpose, non-parametric Kruskal-Wallis tests (for determination of the overall p-value) and post hoc all-pairwise Conover tests (for identification of precisely which pairs were differing) with Bonferroni correction (correction for chance agreement) were carried out (Siegel & Castellan 1988). The analysis was conducted using Analyse-it (Analyse-it 2006).

4.4 Results and Discussion

The results of this chapter are based on analysis of field survey data (point data) as well as on classification of satellite imagery and topographic factors derived from a digital elevation model (spatially explicit data). Results of the exploratory analysis of field survey data are discussed in section 4.4.1. Soil erosion occurrence and the SOC content maps are presented in section 4.4.2, and finally the hot/bright spot map is discussed in section 4.4.3.

4.4.1 Results of exploratory analysis of field survey data

The exploratory analysis of field survey data provides an overview of the state of soil resources in the study area as it had been recorded in the field (cf. section 2.3.1). This analysis was restricted to the sampling sites (point data), but it allowed the detailed analysis of various indicators which could not be extrapolated to the whole study area. All results presented in this section were derived from the "independent sample set", a subset of the full field dataset as described in section 4.3.2.

(A) Occurrence of soil erosion and other soil degradation types

Figure 4-7 provides an overview of different soil degradation types as they were observed at the sampling sites. The results of the field survey confirm that soil degradation is widespread: of all sampling sites in the Faizabad and Varzob test areas, 41% showed compaction, 58% sealing / crusting, and 64% erosion by water (sheet erosion [59%] and/or rill erosion [28%]). Erosion is thus the most widely occurring soil degradation type. The figures obtained in this study are somewhat lower than results reported by Djumankulov et al. (2000), who stated that over 78% of the areas in the hill zone (the hill zone is referred to as areas in the belt of the middle mountain range) were affected by water erosion. However, there were some differences between the Faizabad and Varzob test areas: while in Faizabad 59% of the sites were erosion affected, in Varzob this percentage was 69% and thus much higher.

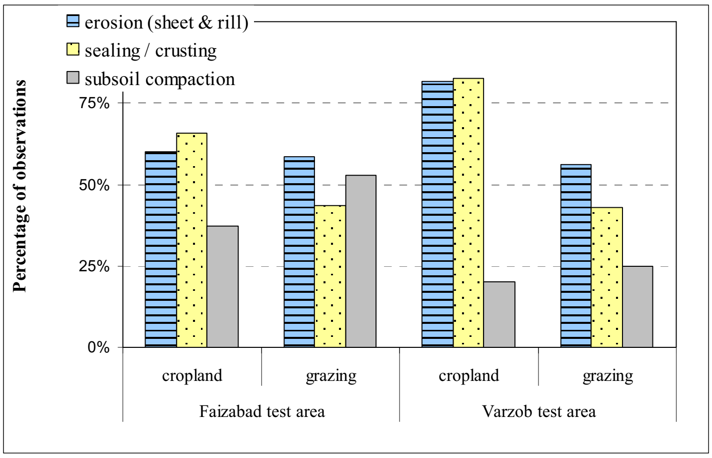


Figure 4-7 Occurrence of different soil degradation types observed in the field

The survey results highlighted a number of differences between the two test areas and also between cropland and grazing land sampling sites: While rill erosion was more frequent on cropland than on grazing land (Faizabad 40 and 17%, respectively, and Varzob 45 and 15%, respectively), signs of sheet erosion were observed at almost the same frequency on cropland and grazing land for sites in the Faizabad test area (53 and 49%, respectively), but not for sites in the Varzob test area, where sheet erosion was much more frequent on cropland (81% on cropland and 54% on grazing land). Generally, soil degradation occurrence on grazing land was similar in the Faizabad and Varzob test areas, but on cropland it was distinctly higher in Varzob than in Faizabad. Compaction and sealing / crusting also displayed a typical pattern: As expected, compaction was more frequent on grazing land than on cropland (Faizabad 25% and Varzob 5% difference) but sealing / crusting was more frequent on cropland than on grazing land (Faizabad 23% and Varzob 40% difference). Compaction is generally due to either animal trampling or a plough pan having developed. Since a lot of the land in the study area is ploughed manually or by animal traction, the former outweighs the latter by far. Sealing / crusting is a result of impact on soil surfaces with little aggregate stability (Lado et al. 2004) and is thus most often observed on ploughed soils.

Although the data point to some distinct differences in occurrence of sheet and rill erosion, "*sheet and/or rill erosion observed*" was considered to be a suitable definition of *erosion occurrence* for this study. Rill erosion (often developing during single storm events) is generally considered to be responsible for the largest amount of soil loss (e.g. Boardmann 2006). On ploughed cropland, rills may quickly develop. However, they are not necessarily an indication of the degree of degradation affecting the whole field. For example, in the case of badly eroded and crusted soils, rills will not necessarily develop. Frequency at which erosion (sheet and/or rill erosion) was observed was similar on cropland and grazing land in Faizabad (60% and 58% of sampling sites) and on grazing land in Varzob (56%), only cropland in Varzob showing distinctly higher frequency (82%). In the WOCAT classification system (WOCAT 2003), the abbreviation "Wt" is used for rill and sheet erosion by water and was used in this study as well.

Table 4-3 Median and interquartile range of, SOC content, and topographic factors for all sampling sites of the independent sampling set

Median (Interquartile range)	all	all		cropland		grazing land	
		crop-land	grazing land	FA	VZ	FA	VZ
Number of samples	188	85	103	35	50	53	50
SOC content [%]	1.18 (0.5)	1.14 (0.4)	1.24 (0.6)	1.14 (0.5)	1.14 (0.3)	1.39 (0.6)	1.13 (0.5)
Slope [%]	33 (23)	27 (22)	37 (23)	16 (17)	32 (16)	34 (26)	40 (19)
Curvature[28] (converx = 1, concave = -1)	0.0 (0.8)	0.1 (0.6)	0.0 (0.9)	0.0 (0.4)	0.2 (0.7)	0.0 (1.0)	-0.1 (1.0)
Sine slope aspect [29] (East = 1, West = -1)	0.0 (1.4)	-0.1 (1.3)	0.1 (1.3)	-0.4 (1.3)	0.0 (1.3)	0.1 (1.25)	0.0 (1.4)
Cosine slope aspect[29] (North = 1, South = -1)	-0.2 (1.4)	-0.2 (1.4)	-0.2 (1.4)	0.0 (1.5)	-0.2 (1.3)	-0.2 (1.3)	-0.12 (1.4)
Altitude [m asl]	1312 (314)	1284 (238)	1383 (412)	1395 (172)	1180 (179)	1541 (259)	1153 (169)

Abbreviations: FA = Faizabad test area, VZ = Varzob test area, asl = above sea level.

[28] *Curvature refers to curving of a raster surface at each cell centre, as calculated by ArcMap (ESRI Inc.). Positive values indicate an upwardly convex surface, negative values upwardly concave surfaces, the value 0 a flat surface.*
[29] *Slope aspect is generally indicated by values between 0 and 360°. For practical reasons, slope aspect values were transformed by applying the sine and cosine functions. The sine function then represents East/West exposition, and the cosine function North/South exposition.*

An overview of median and interquartile range (the range between the third and first quartiles) of soil organic carbon content (SOC) and topographic factors for the Faizabad and Varzob test areas and for the major land use classes is provided in Table 4-3. The overall median SOC content was 1.18%, with an interquartile range (IQR) of 0.5%. At 1.14% SOC, the median for cropland was the same in both test areas, but variability in Faizabad was higher (IQR = 0.60%) than in Varzob (IQR = 0.44%). The data indicate that grazing land in Faizabad had distinctly higher SOC contents than grazing land in Varzob, with a median for Faizabad of 1.39% and for Varzob of 1.13%, and with similar IQRs. For the correlation test presented in Table 4-4 this means that the situation with regard to cropland is similar in both test areas. But when interpreting results pertaining to grazing land, the differences between the two test areas have to be taken into account. Additionally, when interpreting these results, it should be kept in mind that the SOC content had been predicted from the soil spectral library, which had been calibrated for soil samples from the Yavan and Faizabad test areas. There was unfortunately no possibility to systematically validate the SOC content predictions for the Varzob test area (cf. chapter 3). Median and IQR of the topographic factors will be discussed in conjunction with the results of the correlation test presented in the following paragraph.

(B) Association with topographic factors

Since topographic factors (e.g. slope or aspect) are important with regard to soil formation as well as soil erosion control, these variables possibly affect both soil erosion processes and SOC content. The slope affects the overall rate of movement down slope (mainly water, but also sediment movement). While, the profile curvature affects the acceleration and deceleration of flow, the planform curvature influences convergence and divergence of flow, Thus, overall curvature influences erosion and deposition patterns. Finally, slope aspect is crucial with regard to the amount and intensity of solar irradiation and may also be decisive with regard to impacts of wind erosion.

Association between topographic factors and soil erosion (Table 4-4) and between topographic factors and SOC content (Table 4-5) were assessed using Spearman rank correlation, as described in section 4.3.2. Furthermore, association between topographic factors and SOC contents was assessed with regard to the sub-groups “erosion affected areas” and “non-affected areas” (Table 4-6), thus precluding any mixing of effects of topographic factors and of erosion, respectively. The here presented results, can however only capture influences of topography in a preliminary way, as interrelations between factors were not captured with this analysis.

Slope: The median slope percentage is 33%, with an interquartile range of 23% (Table 4-3). Grazing land is generally situated on steeper slopes than cropland (median 37% compared to 27%, respectively). This is especially true for the Faizabad test area, where the median slope for cropland is 16% and that for grazing land 34%. This difference was smaller for Varzob than for Faizabad (32% compared to 40%, respectively). What is conspicuous is the difference in slope steepness of cropland sampling sites in the two test areas, with cropland situated on much steeper slopes in Varzob. Table 4-4 shows Spearman rank correlation coefficients (r_s) determined for slope and erosion. A significant correlation was only determined for grazing land in Faizabad. The correlation coefficient was r_s = 0.29, indicating positive correlation, as expected. With regard to the correlation between SOC content and slope, only for grazing land in the Faizabad test area, a significant positive correlation was determined (r_s = 0.30, Table 4-5). This positive correlation can be explained by grazing land being not affected by erosion (r_s = 0.29, Table 4-6), for which there is a significant association between SOC content and slope. Steep slopes that are not used for extensive grazing, but for haymaking, are often very well conserved (cf. chapter 5), which possibly explains this association. No other indications were found that would point to an association between slope and SOC content.

Table 4-4 Spearman rank correlation coefficient r_s for correlation between erosion and topographic factors, for various sub-groups of major land use classes and for the two test areas.

Spearman correlation coefficient r_s for erosion 0 and 1*	all	all		cropland		grazing land	
		cropland	grazing land	FA	VZ	FA	VZ
Number of samples	173	79	94	35	44	53	41
Slope	0.08	0.16	0.11	0.13	-0.05	<u>0.29</u>	-0.08
curvature28	0.08	0.14	0.02	0.27	0.04	0.01	0.02
sine aspect (East = 1)[29]	-0.01	-0.06	0.06	-0.13	-0.01	<u>0.24</u>	-0.17
cosine aspect (North = 1)[29]	-0.10	-0.05	-0.15	-0.08	0.07	-0.04	<u>-0.27</u>
altitude	0.11	0.09	<u>0.20</u>	<u>0.35</u>	<u>0.27</u>	<u>0.32</u>	-0.04

Table 4-5 Spearman rank correlation coefficient r_s for correlation between SOC and topographic factors, for various sub-groups of major land use classes and for the two test areas.

Spearman correlation coefficient r_s * for SOC content	all	all		cropland		grazing land	
		cropland	grazing land	FA	VZ	FA	VZ
Number of samples	183	83	100	34	49	52	48
slope	0.09	0.02	0.04	0.13	0.13	<u>0.30</u>	-0.11
curvature[28]	<u>-0.14</u>	<u>-0.20</u>	-0.07	<u>-0.48</u>	-0.04	-0.09	-0.01
sine aspect (East = 1)[29]	0.10	0.02	0.12	0.20	-0.16	0.07	0.18
cosine aspect (North = 1)[29]	0.06	0.16	0.00	0.19	0.13	0.00	0.04
altitude	<u>0.24</u>	0.04	<u>0.33</u>	0.07	0.09	<u>0.46</u>	0.08

Table 4-6 Spearman rank correlation coefficient r_s for correlation between SOC and topographic factors, for various sub-groups of major land use classes and for erosion occurrence classes.

Spearman correlation coefficient r_s * for SOC content	cropland (FA & VZ)		grazing land (FA & VZ)	
	erosion	no erosion	erosion	no erosion
Number of samples	56	21	52	39
slope	0.07	-0.15	0.07	<u>0.29</u>
curvature[28]	-0.12	-0.21	0.01	<u>-0.37</u>
sine aspect (East = 1)[29]	-0.03	0.1	<u>0.32</u>	-0.07
cosine aspect (North = 1)[29]	0.14	<u>0.39</u>	0.02	-0.12
altitude	-0.12	<u>0.49</u>	<u>0.54</u>	0.21

** Correlations significant at the level $p < 0.05$ are underlined.*

Curvature: Observations were equally distributed over convex (positive curvature values) and concave areas (negative curvature values) (median = 0.0, Table 4-3). In the Varzob test area, there was a tendency for cropland to be more often situated on convex than on concave curvature (median = 0.2), while grazing land was on concave curvature primarily (median = –0.1). There was no significant correlation between erosion and curvature for any of the sub-groups tested (Table 4-4). However, association between erosion and curvature is positive for all sub-groups, indicating that convex areas might be at a slightly higher risk of erosion, especially cropland areas in the Faizabad test area (r_s = 0.27). In contrast, SOC content is consistently associated with negative curvature values, indicating concave slopes (Table 4-5). Significant and comparatively strong negative correlation between curvature and SOC content (higher SOC on concave slopes) was found for cropland sites in the Varzob test area (r_s = -0.48). This was also reflected in the significant correlation coefficient determined for all cropland sites (r_s = -0.20) and possibly also in the correlation coefficient for all sampling sites (r_s = -0.14). When distinguishing between erosion affected and non-affected sites, a significant correlation was found for grazing land not affected by erosion (r_s = -0.37, Table 4-6).

East/West exposition (sine aspect 1 to -1): East and West expositions were equally distributed among all sampling sites, with a median sine aspect of 0.0 (Table 4-3). For the Faizabad test area, the median of the sine aspect indicated that cropland was more often situated in areas with West exposition (median = -0.4), and grazing land more often on East exposition (median = 0.1). However, the large interquartile ranges show that both cropland and grazing land was found on all expositions. Results of Spearman rank correlation tests showed no significant association between erosion occurrence and East or West exposition. Only, for grazing land in the Faizabad test area, there was a significant correlation between East exposition and erosion (r_s = 0.24, Table 4-4). Also the results with regard to associations between SOC content and East/West exposition, were all not-significant (Table 4-5). As shown in Table 4-6, there was a significant correlation between SOC contents and East exposition for erosion-affected grazing land (r_s = 0.32), indicating that sites affected by erosion maintain higher SOC contents on East exposition than on West exposition.

North/South exposition (cosine aspect 1 to -1): The two test areas are situated on the Southern foothills of the Hissar mountain range (cf. Figure 4-3). Thus South exposition is generally dominating as demonstrated by the negative median for cosine aspect values (Table 4-3). The median cosine aspect for cropland sites in the Faizabad test area, however, was 0.0, indicating that cropland was relatively often situated on the rare slopes with North exposition. There was some indication that erosion was associated with South exposition, with all correlation coefficients showing negative values, except for cropland sites in the Varzob test area, which showed a very slight positive correlation (r_s = 0.07, Table 4-4). The only significant correlation was determined for grazing land sites in the Varzob test area (r_s = -0.27). Again, there was some indication that the association between North-South aspect and SOC content was the opposite of the association between North-South aspect and erosion occurrence: all correlation coefficients concerning North-South aspect and SOC content exhibited positive or zero values (representing North exposition) (Table 4-5). The correlation between North exposition and SOC content was significant for cropland not affected by erosion (r_s = 0.39, Table 4-6).

Altitude: The median altitude for all sampling sites was 1312 m above sea level (asl), with an interquartile range of 314 m (Table 4-3). The Faizabad test area is situated at a higher altitude than the Varzob test area. The median altitude for cropland is 1395 m asl in Faizabad and 1180 m asl in Varzob, and the median altitude for grazing land is 1541 m and 1153 m, respectively.

Significant correlations between altitude and erosion were determined for cropland and grazing land in the Faizabad test area (Table 4-4). The same was true for cropland in the Varzob test area. This observation may be partly attributed to steeper slopes at higher-altitude locations in the test areas, especially with regard to the Faizabad test area (the Spearman rank correlation coefficient for altitude and slope was r_s = 0.72 for Faizabad and r_s = 0.20 for Varzob, both correlations being significant) and partly to higher rainfall intensities applicable to areas closer to mountain ridges. The correlation coefficients for SOC content and altitude were strongly influenced by the grazing land sampling sites in the Faizabad test area (Table 4-5). A significant positive correlation was found between SOC content and altitude (r_s = 0.46), which in turn led to a significant positive correlation for all grazing land (r_s = 0.33) and for all sampling sites (r_s = 0.24). Inverse relationships between SOC content and temperature are worldwide observed. Such a relationship results from much reduced mineralization rates of organic matter in cold temperature. In Europe, a rough rule is to expect an in increase in OM by 2 to 3 times per 10^{o}C temperature reduction (Jones et al. 2005). However, the fact that grazing land affected by erosion displayed an especially high correlation between SOC content and altitude (r_s = 0.54, Table 4-6), might indicate a problem with SOC determination for specific soil types found at high altitudes.

In summary, at the level of all sampling sites, no significant correlation was determined between topographic factors and erosion occurrence. The only correlation significant at the level of all sampling sites, namely that between topographic factors and SOC content, resulted from associations dominated by one specific sampling site sub-group: As for the association between curvature and SOC content, it was the cropland sites in the Faizabad test area which predominated, and as for the association between altitude and SOC content, it was the grazing land sites in the Faizabad test area which predominated. Nevertheless, with regard to the association between concave curvature and SOC content, the observation was consistent for almost all sampling site sub-groups tested, even if most correlations were not significant. Together with the association between convex curvature and erosion, this suggested a typical pattern of curvature as an erosion controlling factor (erosion for convex areas and sedimentation in concave areas), which again influences SOC contents (low SOC contents for erosion affected areas and high SOC contents in areas with sedimentation). However, as most correlations were not significant, it must be assumed that curvature was not the only influencing factor. No consistent association was found between slope, erosion and SOC content, as might be expected especially for cropland areas. There are some weak indications that slopes with greater East and North exposition show less erosion and higher SOC content, which applies both to cropland and to grazing land. Grazing land in Faizabad test area showed a strong correlation with altitude, which can be explained by decreasing mineralization rates in lower temperatures at higher altitude. However, as especially for sites with erosion occurrence this relationship was observed, it might also indicate spurious predictions of SOC content for soils at higher altitudes. As only a small number of samples from higher altitudes had been available for calibrating the soil spectral library. All in all, this might indicate that topographic factors are not predominant in the study area, but that other factors such as vegetation cover and land use have at least the same level of impact.

(C) Association between soil erosion and other soil condition indicators

The dataset was tested for associations between soil erosion and other soil condition indicators (soil degradation types and soil characteristics) using chi-square tests. P-values of the chi-square tests are provided in Table 4-7.

Table 4-7 Chi-square test results for relationship between visible signs of erosion (Wt = 1) and soil characteristics as well as other soil degradation indicators. P-values are underlined for classes showing a significant relationship (p < 0.05).

P-values determined by chi-square tests (confidence interval = 95%)	all	cropland		grazing land	
		FA	VZ	FA	VZ
Sealing / crusting (Wt and Pk)	<u>0.018</u>	0.827	0.478	0.979	0.106
Compaction (Wt and Pc)	0.919	0.617	0.849	0.624	0.700
Rooting depth (Wt and < 50cm)	0.990	0.712	0.985	0.286	<u>0.018</u>
Texture (Wt and coarse texture)	0.265	*	0.614	*	<u>0.015</u>

Abbreviations: FA = Faizabad test area, VZ = Varzob test area, Wt = sheet and rill erosion, Pk = sealing / crusting, Pc = compaction, "< 50 cm" rooting depth in contrast to "> 50 cm" rooting depth, coarse texture (sand fraction) in contrast to medium texture (silt fraction)
**all samples with medium texture*

Test results for the full sample set indicated that an association existed between occurrence of erosion and sealing / crusting. However, sub-sample sets differentiating between the two test areas as well as cropland and grazing land did not show a significant association for any of the sub-groups. No association was found between erosion and compaction for any of the specific groups. There was some indication of an association between shallow rooting depth and erosion on grazing land. While there were very few cropland sampling sites with rooting depth of less than 50 cm, two interpretations are plausible for such sites on grazing land: Either the association concerns marginal mountainous areas with low vegetation cover, which are thus at high risk of erosion, or erosion has affected the area so severely that rooting depth has diminished to less than 50 cm. In Faizabad, the only samples with coarse texture were from riverbeds. As for the Varzob test area, the test result revealed a significant association between erosion and coarse soil texture on grazing land. This might be explained by the fact that it is generally the silt fraction which is eroded, thereby enriching coarse particles in the topsoil of erosion affected areas.

(D) Differences in SOC content on sites with different soil conditions

Possible effects on SOC content were analysed by testing for differences in the medium SOC content of sample sites "affected" and "non-affected" by soil degradation types or characterised by specific soil conditions (rooting depth and soil texture). Even though this list is not conclusive, with other factors and conditions affecting SOC content levels in the study area, it includes some of the most important indicators. P-values of the Mann-Whitney tests are provided in Table 4-8.

P-values for the full sample set indicated significantly higher median SOC contents for the following sample groups: sampling sites without erosion compared to sites with erosion, sites without sealing / crusting compared to sites with sealing / crusting, sites with rooting depth of more than 50 cm compared to sites with rooting depth of less than 50 cm, and sites with medium soil texture compared to sites with coarse soil texture.

Upon examining sample sub-classes separately (both cropland and grazing land for the Faizabad and Varzob test areas), results indicated that these significant differences in median SOC content were not consistently represented by all sub-classes. While SOC content of sampling sites from grazing land in Varzob exhibited the same effects as the full sample set, cropland in Varzob showed no differences in median SOC content except for sites with coarse particle size.The association between erosion and sealing / crusting that was revealed by the results of the chi-square tests also appeared to be reflected in the SOC content distribution: Grazing land in Varzob and cropland in Faizabad both recorded significantly higher median SOC contents in areas without erosion, and higher SOC contents in areas without crusting. Cropland in Varzob did not display any significant differences except for medium and coarse soil texture.No difference in median SOC content was found for sites affected and not affected, respectively, by compaction. This result applied to the full dataset as well as to all the sub-classes analysed.

Table 4-8 Mann-Whitney test results (for one-sided tests) comparing the median of SOC content between two sub-groups of sampling sites. The alternative hypothesis is indicated for each test group. Test results at the level of $p < 0.05$ are underlined.

P-values determined by the Mann-Whitney test	all	cropland		grazing land	
Alternative hypothesis:		FA	VZ	FA	VZ
Erosion: no Wt > Wt	<u>0.0030</u>	<u>0.0397</u>	0.7914	0.6094	<u><0.0001</u>
Sealing / crusting: no Pk > Pk	<u>0.0197</u>	0.0973	0.7851	0.6472	<u>0.0237</u>
Compaction: no Pc > Pc	0.8563	0.9384	0.4725	0.6636	0.1409
rooting depth: more than 50 cm > 0-50 cm	<u>0.0191</u>	0.1361	0.3306	0.5411	<u>0.0031</u>
Texture: medium > coarse	<u><0.0001</u>	*	<u>0.0143</u>	*	<u>0.0101</u>

** all samples with medium texture*

(E) SOC content threshold

An SOC content threshold was determined according to the requirements described in section 4.3.2, based on SOC content histograms for erosion affected and non-affected areas. SOC content histograms of sampling sites disaggregated for the test areas and for the major land use classes (cropland and grazing land) were visually assessed. Two such histograms are featured in Figure 4-8. The plots show frequency of SOC content observations separated according to erosion affection (light red bars) or non-affection (green bars), as well as the SOC content threshold that was finally determined at 1.1% (grey vertical line). While grazing land in Varzob showed almost perfect separation into low and high SOC content classes for erosion affected and non-affected areas, the picture for all sampling sites was more complex. This, however, was not surprising since it had not been expected that erosion was the dominating controlling factor for SOC content for all sampling sites. With less than 50% of the sampling sites not affected by erosion showing low SOC contents and more than 50% of the affected sites also showing low SOC contents, the threshold determined at 1.1% SOC content was considered to be most appropriate for the detection of areas with low SOC contents, probably due to erosion. Furthermore, an assessment focusing on the brown carbonate soils in the Faizabad test area, carried out in order to compare SOC contents of soils not affected by soil erosion and of soils in various states of erosion, confirmed that the threshold of 1.1% SOC corresponds to the threshold determined between lightly and moderately eroded soils

(Jakutilov et al. 1963). 85 samples from the independent dataset were classified as having low SOC content and 115 as having high SOC content. Of the areas not affected by erosion, 77% had higher SOC content than 1.1%, this result being exactly the same for cropland and for grazing land.

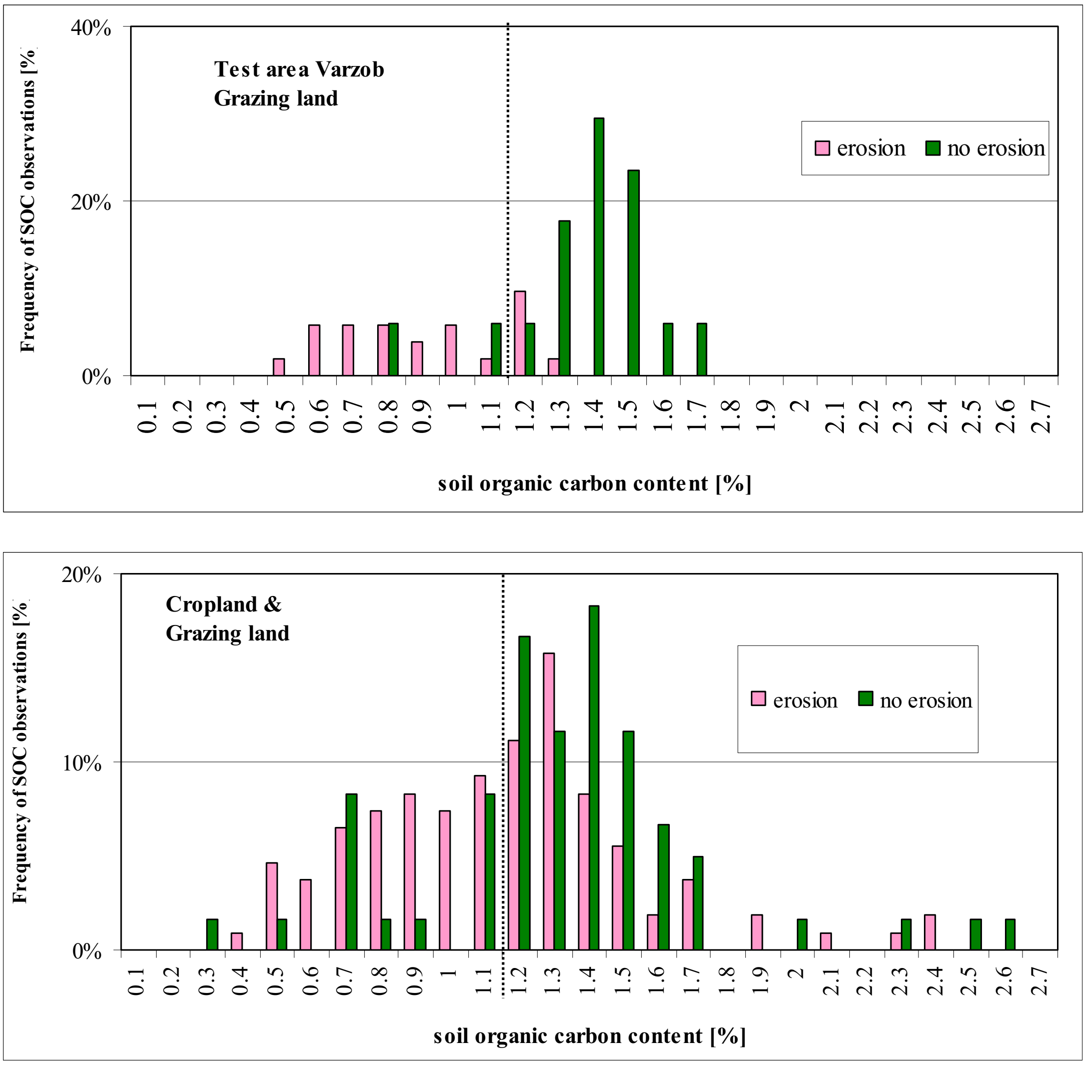


Figure 4-8 Frequency distribution (bars) and cumulative frequency (lines) of SOC content for sampling sites with/without erosion.

4.4.2 Soil erosion occurrence map and SOC content map

Classification tree modelling resulted in two simple classification trees, as displayed in Figure 4-9, making it possible to extrapolate the point information available to the whole study area. For each variable, a splitting rule (threshold) was determined using the model: A sample goes to the left if the value of the specific variable is below the threshold, and to the right if the value is above. Validation of the soil erosion map demonstrated that 73% of all samples had been correctly classified (producer's accuracy and user's accuracy being 80% and 76% for "erosion", and 61% and 67% for "no erosion"). The validation dataset of the SOC content class map confirmed that 75% of all samples had been correctly classified (producer's accuracy and user's accuracy being 62% and 72% for low SOC content, and 83% and 76% for high SOC content).

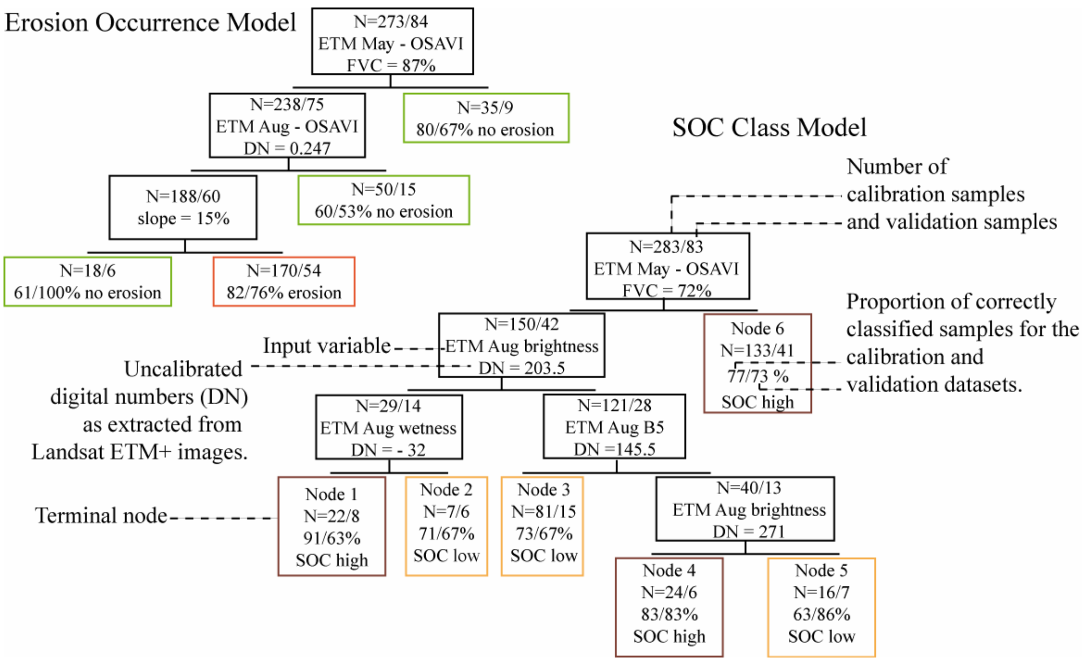


Figure 4-9 Classification tree models for mapping erosion occurrence (left) and SOC content classes low SOC (≤ 1.1%) and high SOC (> 1.1%) (right). The abbreviations for input variables used are: ETM May (Landsat 7 scene from May 2002 imagery), ETM Aug (Landsat 7 scene from August 2000 imagery), B5 (band 5), optimised soil adjusted vegetation index (OSAVI), brightness (tasselled cap band 1), wetness (tasselled cap band 3), and slope (slope raster information). For the ETM May OSAVI layer, the threshold expressed as fractional vegetation cover (FVC) – as determined in section 2.5.1 – is provided, other thresholds are indicated as digital numbers (DN).

Erosion occurrence map

From the 22 raster layers used as input variables, information derived from the OSAVI of May 2002 and the August 2000 image, and the slope raster layer were most effective in distinguishing between the two states of erosion (Figure 4-9, left). The highest level of accuracy was achieved by the decision tree model with four final nodes. Three of the nodes classified samples of soil showing no signs of erosion and one node classified samples of erosion affected soil. First, areas without any erosion and with a high OSAVI vegetation index in May were identified (node 4). According to the regression determined between field data of fractional vegetation cover and OSAVI values (see chapter 2), sites classified in node 4 showed a fractional vegetation cover higher than 87%. Subsequently, areas without any erosion and with a high OSAVI vegetation index in August were isolated (node 3). For OSAVI values derived from the August imagery no field observations for fractional vegetation cover had been collected. Thus, no calibration of OSAVI values to actual cover was possible. Therefore, for comparison of OSAVI August information with other models (e.g. the land cover classification) the digital numbers (DN) from the Landsat image were directly used. Comparing the August OSAVI threshold determined for distinguishing between erosion affected and not affected sites (DN ≤ 0.25, Figure 4-9), with the land cover classification tree model showed that only perennial land cover classes qualified as non-affected by erosion with regard to this criterion. All annual cropland sites showed a lower OSAVI value (DN ≤ 0.12). Finally, areas without any erosion and with slope steepness of less than 15% were attributed to node 1. Especially for cropland, this slope threshold seemed rather high. As cropland and grazing land sites had been jointly modelled, it seemed likely that this threshold was better suited for grazing land than for cropland. The remaining sampling sites were mainly sites affected by erosion (node 2). This demonstrated that it is mainly factors controlling erosion that determine the soil erosion occurrence model, i.e. slope and vegetation cover. Such information is highly valuable for planning of erosion controlling measures.

In Figure 4-10, spatial information on soil erosion occurrence is provided for the whole study area. Areas affected by erosion (node 2) are marked blue; they covered 46% of the whole study area. 45% of the study area was classified as showing no occurrence of erosion: 10% with slopes < 15%, 26% with high vegetation cover in August, and 9% with high vegetation cover in May. 9% of the study area had been classified as settlements and aquatic areas and was excluded from these calculations.

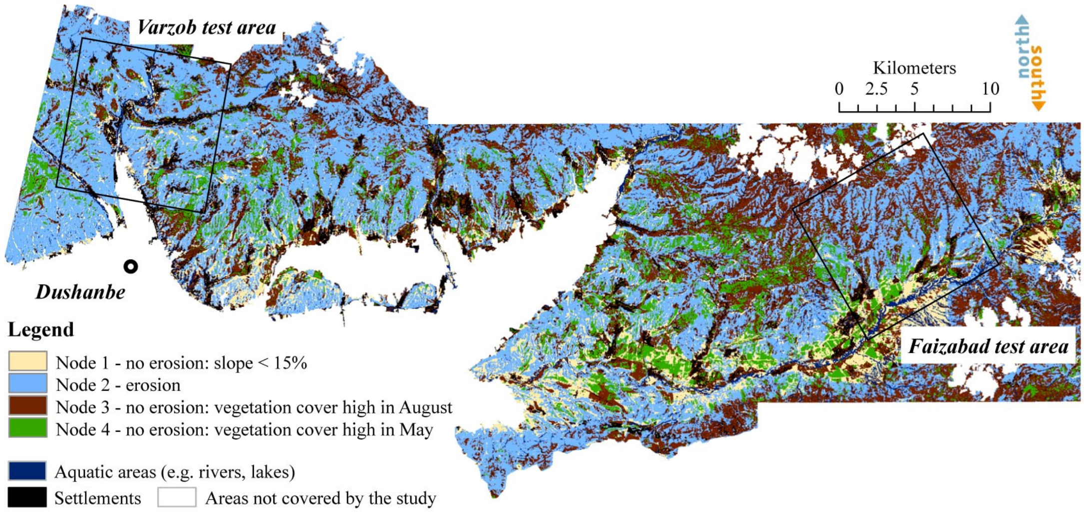


Figure 4-10 Erosion occurrence map. Erosion classes as differentiated by the classification tree model are also displayed.

The following results were obtained for the two test areas: 46% of Faizabad and 68% of Varzob were classified as showing occurrence of erosion; 42% and 18%, respectively, were classified as "without occurrence of erosion". The rest of the test areas (12% in Faizabad and 13% in Varzob) concerned aquatic areas and settlements and had thus not been included in the statistics. One reason for the difference in the level of erosion between the two test areas is the difference in their landforms: while around 20% of Faizabad is characterised by a wide and flat valley floor with slopes of 5-10%, almost the whole of Varzob is situated on slopes of > 10% (see also Figure 4-3).

SOC content class map

The SOC content class model was characterised by 6 final nodes (Figure 4-9, right). Not surprisingly, it was the ETM+ August 2000 image, representing the dry season when sparse vegetation cover and high fractions of barren soil prevail, which dominated the SOC content class model. However, in order to obtain a sufficiently accurate SOC content class model, inclusion of the OSAVI information derived from the ETM+ May 2002 image was required. As in the soil erosion occurrence model, high OSAVI values on the ETM+ May image (FVC > 75%) matched well with conserved soil resources, which were first separated from the rest of the sampling sites. Subsequently, tasselled cap brightness (DN = 203.5, and DN = 271) and/or wetness (DN = -32) as well as band 5 information derived from the ETM+ August 2000 image (DN = 145.5) were of major relevance.

The threshold determined from OSAVI May values indicated that high SOC content can be expected for sites with fractional vegetation cover > 75% (terminal node 6). Classification accuracy for this specific terminal node was 73% for the validation samples and prediction may be considered sufficiently reliable. Almost half of the sampling sites were attributed to this specific terminal node. Therefore, this threshold must be valued as important with regard to SOC content management using vegetative conservation measures.

Overall reflectance of the soil, as indicated by tasselled cap brightness information[30], was crucial in two ways: first to identify non-loess sampling sites, often with reddish granodiorite mother rock, which showed lowest overall reflectance (nodes 1 and 2), and second to identify areas with very low SOC content and characterised by whitish soil colour, such as animal paths on ridges (node 5). Nodes 1 and 2 showed a significantly larger proportion of samples from non-loess sampling sites than the other nodes. For these areas, tasselled cap wetness was decisive with regard to classification into low and high SOC content classes. Low tasselled cap wetness values, indicating higher soil moisture (Crist et al. 1986), characterised areas with SOC content higher than 1.1% (node 1) and thus separated them from those with lower SOC content. This can be explained by the fact that areas with higher SOC content also have better water retention capacity (cf. Figure 4-1).

Nodes 3, 4 and 5 classified sampling sites with high soil reflectance (high tasselled cap brightness values on the August image), and node 5 with very high soil reflectance. Bright soil colour generally indicates low soil organic matter content. However, samples attributed to node 4 were samples with high SOC content. Nodes 4 and 5 were distinguished from node 3 by the information of band 5 on the Landsat August image. The spectral response of band 5 is in the middle infrared (1.55-1.75 nm) portion of the electromagnetic spectrum. This portion of the spectrum is sensitive to variations in water content in both leafy vegetation and soils. Sites attributed to node 3 showed lower values in band 5 than those attributed to nodes 4 and 5, indicating higher absorption and thus higher water contents, which again is generally linked to higher soil organic matter content. Thus, it proved difficult to interpret the physical information represented by the classification model leading to the separation of node 4. The assessment of the SOC content map showed that areas attributed to node 4 were generally located on westward oriented slopes. Further research would be necessary. In the whole study area, however, only 7% of the area was classified as node 4.

The above discussion highlights that digital soil mapping for an area including heterogeneous soil types does not provide straightforward information. However, for successful mapping of SOC content, it was crucial to include information from all soil types in the calibration. Preliminary mapping attempts conducted on the basis of a highly uniform sample set only (the loess samples as defined in chapter 3) had not been successful (Wolfgramm et al. 2007a), which must at least partly be attributed to the insufficient representation of soil heterogeneity.

Figure 4-11 shows the area distribution of the SOC classes attributed to the different SOC nodes. The high SOC content class covered 58% of the study area. High SOC content areas as defined by node 6 covered 40% of the study area. 11% of the study area was attributed to node 1, and only 7% to node 4. Areas with low SOC content were mainly determined by node 3 (22% of the area), then by node 5 (6% of the area) and by node 2 (5% of the area), adding up to 33% of the study area showing low SOC content. The 9% classified as settlements and aquatic areas were not included in this analysis. Nodes 1 and 2 were mainly situated along the

[30] Lillesand & Kiefer 2000

Hissar range running along the Northern boundary of the study area. In this area, the loess cover diminishes quickly and soils prevail which developed on granodiorite mother rock.

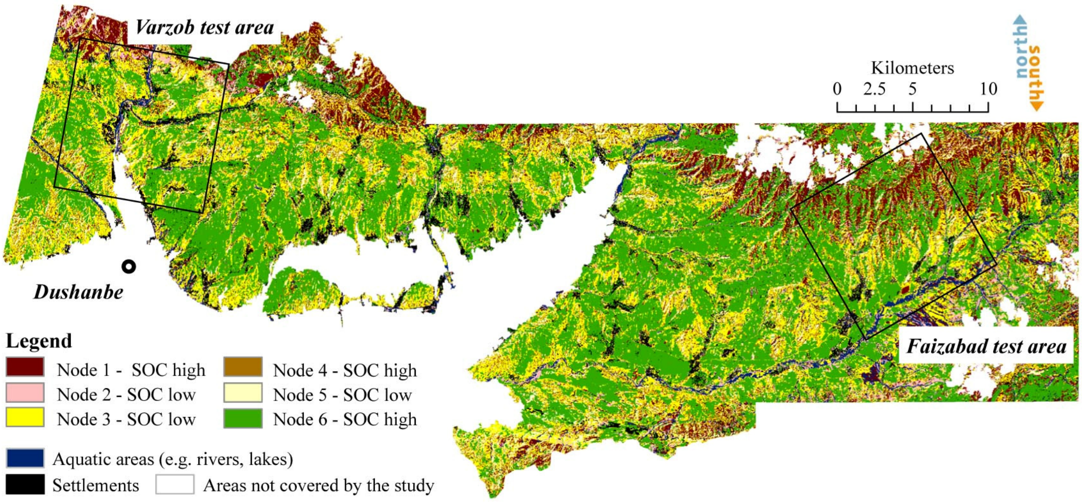


Figure 4-11 SOC content class map. SOC content classes as differentiated by the classification tree model are also displayed.

Analogous to the larger proportion of area classified as showing signs of erosion in the Varzob test area, there is a difference in area classified as having "high" SOC content (67% in Faizabad, and only 55% in Varzob). Some of the areas in Varzob showing low SOC content are situated along the higher mountain ranges in the North, where stony soils prevail. However, in the Varzob and Faizabad test areas, large low SOC content areas are at medium altitude and close to villages, so that it can be assumed that the original fertile brown soils have been depleted.

Links between soil erosion classes and soil organic carbon content

In order to obtain a better picture of the effect of erosion on SOC content, both median SOC content and interquartile range (the range between the third and first quartiles) were calculated for each class (node) of the erosion model (Table 4-9).

Table 4-9 SOC content for the topsoil layer (0-20 cm depth) for sampling sites attributed to different erosion classes (N=183, sites in aquatic areas and settlements [N=5] were excluded)

Erosion class determined by the classification tree	Number of samples	Median SOC content	Inter-quartile range
Erosion present (node 2)	107	1.13	0.47
No erosion – slope < 15% (node 1)	18	1.05	0.64
No erosion – vegetation cover high in August (node 3)	35	1.34	0.58
No erosion – vegetation cover high in May (FVC > 87%) (node 4)	24	1.31	0.25

"No erosion" classes defined by high fractional vegetation cover (FVC) in August or in May both showed high median SOC content (median = 1.34% and 1.31% SOC, respectively). The "no erosion" class characterised by moderate slopes showed a surprisingly low median SOC content (median = 1.05%). Even sampling sites classified as showing signs of erosion had a higher median SOC content (median = 1.13%).

Sites attributed to node 4 (high FVC in May) showed little variation, with an interquartile range of only 0.25%. A possible interpretation for the clear characterisation of samples attributed to node 4 was that healthy and dense vegetation cover at these sites in May actually reflects the high soil quality. The interquartile range of the other classes was between 0.47% and 0.64%. High variation in SOC contents of sampling sites attributed to the "erosion" class was not surprising, since the class comprises sites with varying degrees of soil erosion, from mere sheet erosion to severe rill and gully erosion. High variation in SOC contents of sampling sites classified in node 3 can be explained by the high variation in areas with perennial vegetation cover; some orchards or vineyards (planted during Soviet times) were located on steep slopes, where terraces had to be constructed. Such areas had possibly been severely degraded before implementation of the conservation measures. In various areas, subsoil with low organic matter content had been moved to the top during construction of terraces (personal communication by farmers). The lower soil quality in these areas may still be noticed today (Figure 4-12, right). In contrast, grazing land that had never been cultivated, and with medium to high fractional vegetation cover, generally showed much higher SOC contents (Figure 4-12, left).

Furthermore, while the OSAVI vegetation index based on the August image permits identification of perennial vegetation, it does not allow any conclusions to be drawn about the vegetation cover present in November when the winter rains start. The leaves present in August will have fallen by November and the herbaceous layer then becomes decisive. For sites with moderate slopes and little erosion risk (node 1), the low SOC content must be attributed to other soil degradation processes than erosion, most likely chemical deterioration due to intensive cropping at low fertiliser input levels during the last 15 years.

All in all, it can be concluded that the erosion model provides useful information about erosion controlling factors and their specific interlinkage with SOC content.

Figure 4-12 Two areas with perennial vegetation cover, both attributed to node 3 of the erosion classification tree ("no–erosion"), but showing highly differing SOC content. Right (sampling site FA2306): SOC = 2.33%; left (sampling site FA8004): SOC = 0.50%

4.4.3 Hot/bright spot map

Figure 4-13 presents the hot/bright spot map as it was determined by combining the erosion occurrence map and the SOC content class map. In separate subsections, both accuracy of the map and the spatial patterns of hot and bright spots are discussed. An assessment of causal factors for hot and bright spots is given in the context of the implications for sustainable land management in chapter 5.

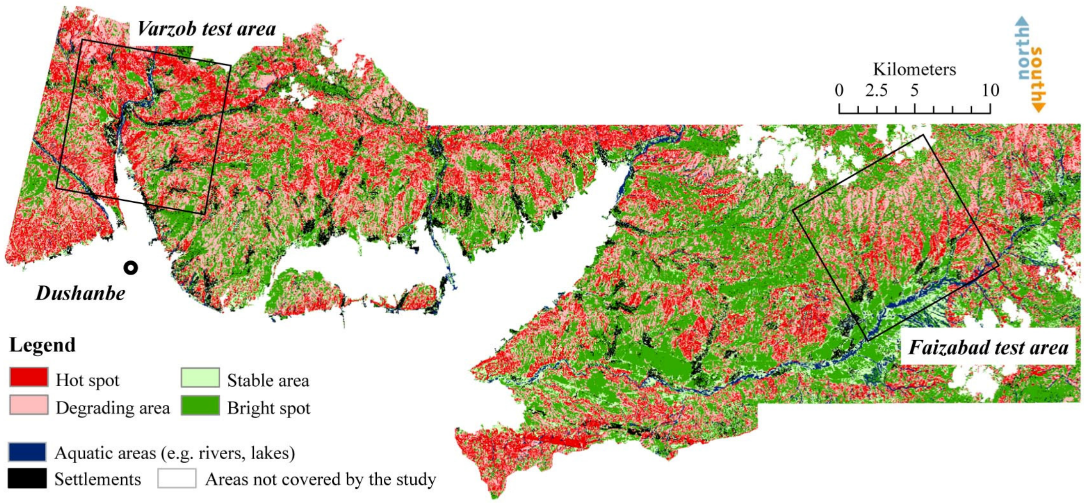


Figure 4-13 Hot/bright spot map

Validation

Validation was conducted applying accuracy measures as discussed in section 4.3.6. Results are presented in Table 4-10.

*Table 4-10 Accuracy assessment of hot/bright spot classification based on the validation set containing samples from Faizabad and Varzob test areas. *Land cover types "aquatic areas" and "settlements" were excluded (4 samples)*

	Degradation classes - classification data:						
Degradation classes - field data:	bright	stable	degrading	hot	Row total	Producer's accuracy	User's accuracy
bright	**13**	1	4	2	20	65%	57%
stable	2	**1**		3	6	17%	13%
degrading	6	2	**14**	3	25	56%	54%
hot	2	4	8	**10**	24	42%	56%
Column total	23	8	26	18	75		

Overall accuracy: 51%, weighted kappa coefficient: 0.36

It is no surprise that overall classification accuracy is rather low, with 54% of the validation samples being correctly classified. The weighted kappa coefficient was 0.36, which can only be considered a fair agreement. As this hot/bright spot map is the product of various analyses and predictions, and of a combination of models, errors inherent in every single step have propagated to this final product. However, overall accuracy of the calibration dataset was 57%, with a moderate kappa coefficient of 0.45, showing that the actual calibration of the model was quite efficient. Furthermore, only 10% of the areas which were bright spots according to the field classification were misclassified as hot spots and only 8% of the hot spots were misclassified as bright spots.

Kruskal-Wallis tests, which determine significant differences in medians of sample groups, were performed on the field data; this confirmed significant differences between the different states of degradation, but it also revealed classes which do not allow any differentiation to be made (Table 4-11). The SOC content of samples from different classes of the hot/bright spot matrix were significantly different, with $p \leq 0.05$ for all comparisons. P-values for soil erosion occurrence were $p \leq 0.0001$ for comparison of classes "bright" and "degrading", p=0.0015 for comparison of classes "bright" and "hot", p=0.4962 for comparison of classes "stable" and "degrading", and p=0.8929 for comparison of classes "hot" and "stable".

Table 4-11 Test results for differences in medians of SOC contents and erosion classification between hot, degrading, stable and bright spots and/or areas.

SOC content values		Erosion class (0 or 1)	
Contrast	p-value*	Contrast	p-value
bright versus stable	0.0092	bright versus degrading	0.0001
bright versus hot	< 0.0001	bright versus hot	0.0015
degrading versus stable	0.0345	stable versus degrading	0.4962
degrading versus hot	< 0.0001	stable versus hot	0.8929

** P-values were determined by Kruskal-Wallis and subsequent Conover tests, corrected for chance agreement by Bonferroni correction.*

It can be concluded from these results that the simple approach presented here accomplishes a clear differentiation between hot and bright spots. More detailed class distinction requires more reliable information on soil erosion. Since topographic information is available at a more appropriate resolution than satellite imagery (pixel resolution 10 and 30 m, respectively), improved results are likely to be achieved by further enhancing the modelling of topographic factors.

Spatial patterns of hot and bright spots

According to the area statistics calculated from the hot/bright spot map presented here, distribution of hot, degrading, stable and bright spots and/or areas was not uniform across the study area (Table 4-12).

Table 4-12 Area percentages of hot, stable, degrading and bright spots and/or areas for the whole study area, as well as for the Faizabad and Varzob test areas.

Degradation class	Study area [1105 km^2]	Faizabad test area [10 km^2]	Varzob test area [10 km^2]
Hot spot	21%	16%	30%
Degrading area	24%	25%	29%
Stable area	13%	13%	9%
Bright spot	33%	35%	18%
Excluded area (Os and Oa)	9%	10%	14%
Total	100%	100%	100%

Varzob was more strongly affected than Faizabad in terms of both severely degraded areas (hot spots) as well as degrading areas. In comparison to the whole study area, Varzob is in worse condition and Faizabad in better condition. Areas classified as hot or degrading, and areas classified as stable or bright each cover around 45% of the study area, while the remaining 9% concerned areas excluded from analysis. Furthermore, distinct patterns with regard to the distribution of hot and bright spots can be distinguished on the hot/bright spot map (Figure 4-13).

Varzob test area: Hot spots and degrading areas were widespread over the whole Varzob test area. The strip of land classified as hot spot along the Northern boundary of the test area is, however, due to natural conditions, which are characterised by mountainous terrain and stony soils. On the other hand, easily distinguishable larger patches of bright spots, representing the afforestations, can also be identified in various parts of the test area, showing that this conservation measure has been successful on different slopes and in different expositions.

Faizabad test area: In the Faizabad test area, the well conserved areas along the river in the valley floor are well recognisable. On this flat land, former state farms (today in some cases privately managed) cultivate large grain fields. Villages are situated at the foot of the hill slopes. Many of the hill slopes in the vicinity of the villages are hot spots which can be linked to the intensive cultivation during the 1990s. These findings are in accordance with the results obtained in a study conducted in the Faizabad test area (Bühlmann 2006). Areas in the hills which are classified as bright spots point to conservation measures having been implemented (afforestations and fruit orchards). Two large areas classified as bright spots were identified as the Soil Science Institute research station and the Horticultural Institute. Large areas in Faizabad, situated at higher altitudes and mainly used as grazing land, were classified as degrading areas. As considerable soil erosion was observed and/or predicted to occur in these same areas, it was somewhat surprising to note that the soils in these areas still had SOC contents above 1.1%. However, on grazing land that has never been cultivated, erosion risk is greatly reduced (cf. section 4.4.2); furthermore, sheep dung probably provides considerable inputs of organic C, which would explain the comparatively high SOC contents of these areas. A steep mountain ridge that runs along the Northern boundary of the Faizabad test area, distinctly separates areas to the South that are generally classified as degrading areas, and areas to the North that are generally classified as conserved areas. More detailed assessments would be required for clearer identification of the respective influence of topographic factors and grazing land management.

The results indicate high pressure on soil resources in the Varzob test area, which is certainly partly due to its proximity to the capital, Dushanbe. While the Varzob test area is well developed with regard to public transportation, and thus transportability of agricultural products to markets in Dushanbe is guaranteed, the opposite is true for the Faizabad test area. Transportation between Faizabad town and Dushanbe is infrequent and insufficient, while public transportation between Faizabad town and the villages in the Faizabad test area is non-existent. The conclusion suggests itself that market accessibility is a crucial factor with regard to soil resource conservation.

4.5 Conclusions

4.5.1 Thematic conclusions

Characteristics of soil erosion and SOC content

Results from the exploratory data analysis performed on the basis of the sampling sites highlighted some influence by topographic factors on soil organic carbon (SOC) content and, to a lesser degree, also on erosion. However, as results were inconsistent, it has to be concluded that no reliable controls for erosion occurrence and SOC content were identified based on the here performed analysis. In order to better control the highly interlinked factors, accuracy of the analysed data sets will have to be improved and methods allowing multivariate analysis (e.g. analysis using classification trees) will need to be applied in future studies. A more objective dataset with regard to soil erosion occurrence could be achieved by calibrating field observations of erosion occurrence to soil spectral information (cf. Cohen et al. 2005). There is also potential in improving SOC predictions (cf. chapter 3). Finally, also geo-referencing of raster datasets would have to be improved. Nevertheless, the exploratory analysis conducted here yielded some indications: It was primarily the association between curvature and SOC content, with a significant negative correlation (high SOC contents being associated with concave curvature), which stood out. However, associations between soil condition and topographic factors were generally very weak. Further analysis indicated that soil erosion was often observed on the same sampling sites as those that showed soil crusting. Sites affected by both erosion and crusting generally had significantly lower SOC content than non-affected sites. Good evidence for such effects was produced by the datasets representing cropland in the Faizabad test area and grazing land in the Varzob test area.

For this study, the threshold for differentiating between sites with SOC content affected by erosion (and crusting) and sites with non-affected SOC content was set as 1.1% SOC. This threshold allowed calibration of raster datasets to SOC content classes "low" and "high", determined for specific sampling sites. As successful calibration was also contingent on sufficient attribution of samples to both "low" and "high" SOC content classes, the threshold of 1.1% was selected not least on account of its suitability in this regard. Although the threshold was in line with earlier studies conducted on brown soils in the loess hills (Jakutilov et al. 1963), which showed topsoil SOC contents of > 1.1% for slightly eroded soils and of < 1.1% for moderately and more strongly eroded soils, it has to be noted that this threshold should not be regarded as some kind of "law of nature". Further research is required to confirm robustness of this threshold, or to identify the need to adjust it, especially also by taking into consideration different soil types.

The assessment of the classification trees established for mapping provided further opportunities to explore the characteristics of the soil indicators. As for the land cover / land use classification, information from the classification tree model can be interpreted and often provides simple rules useful for SLM planning. The soil erosion occurrence model yielded thresholds for vegetation cover in May and for slope steepness below which erosion was unlikely: If fractional vegetation cover in May was > 84% or if slope steepness was < 15%, the risk of erosion occurring was significantly reduced, with 67% and 100%, respectively, of the validation samples showing no erosion. The SOC model also yielded readily applicable thresholds: Almost 50% of the sampling sites were classified as showing high SOC content based on the OSAVI May information. If FVC in May was higher than 72%, then it was likely that SOC content was high (72% correctly classified validation samples). For those with FVC lower than 72%, mainly soil brightness, but also soil wetness, was crucial. So far the thresholds determined for soil brightness and wetness tasselled cap information derived from the Landsat image have not been calibrated to field data (e.g. the Munsell Colour Code), which would make them readily applicable for evaluations directly in the field. So far, only the digital numbers of these raster datasets were applied in the models. However, straightforward approaches to calibrate the raster information with field data may be tested, for example by using colour charts, such as the Munsell Colour Code.

A baseline for erosion occurrence and SOC content classes high and low

The field survey conducted confirmed widespread soil degradation. The soil map elaborated classified 46% of the study area as affected by erosion and 33% as having low SOC content (< 1.1% SOC). Overall 21% of the area were classified as hot spots of soil degradation, with significantly higher percentages of hot spot areas in Varzob (35% of the test area) than in Faizabad (18% of test area). This result indicated higher pressure on soil resources in the test area situated in the vicinity of the city of Dushanbe. In Faizabad test area, grazing lands situated at higher altitudes classified as erosion affected, showed high SOC contents. This can be explained, by increased SOC contents at higher altitudes, where lower temperature restricts mineralization of SOC contents.

The maps elaborated for erosion occurrence and SOC content classes “low” and “high” provide a baseline that enables future evaluation of the land conservation efforts currently being undertaken in the loess hills of central Tajikistan.

4.5.2 Methodological conclusions

Extrapolation of visual observations of soil erosion occurrence and SOC content

This study showed that in an area in which difficult terrain and small cultivated plots prevail, a spatial assessment of soil erosion occurrence and SOC content based on a multi-date composite of Landsat ETM+ imagery and topographic information is possible. The here achieved accuracy, 73% for the erosion occurrence and 75% for the SOC content map, is perfectly acceptable for a semi-detailed study, compared to targets of 85% overall accuracy for highly accurate maps. What was decisive for successful calibration of SOC content information to raster datasets was representation of the different geological sub-groups (as defined in chapter 3). A first attempt to calibrate SOC content values to raster datasets based on loess samples only, had not been successful (Wolfgramm et al. 2007a).

Furthermore, it was crucial not only to use satellite imagery representing the dry season with little vegetation cover (August), but to include imagery covering the season of main vegetative activity (May). It turned out that vegetation cover reflected the state of soil quality in a highly accurate way. This effect was helpful for digital soil mapping. However, the need to include information regarding vegetation limited the models established to areas with similar seasonal vegetation development. In the case of the study presented here, it was not possible to extrapolate to the third test area (Yavan) located further South, where vegetation development was more advanced by around 3 weeks. Additional, satellite images from the winter season, when tree and shrub cover would be mostly free of foliage, is expected to provide data on soils and should thus be obtained for future mapping tasks.

Identification of hot spots of soil degradation and bright spots of soil conservation

The hot/bright spot matrix developed for this study constitutes a simple approach that allows the soil erosion information to be linked with soil quality indicators in a flexible manner, since it may be used at various spatial resolutions and either for raster derived data (as in this study) or for field data. Furthermore, the level of information detail (4 classes including hot spot, degrading, stable and bright spot areas) was considered well suited for applications.

However there are also limitations in the explanatory power of the hot/bright spot classification, which need to be addressed before wider application of the hot/bright spot map is possible:

- Not only **land management** lead to "hot spots of soil degradation". As the example of the Varzob test area showed, stony soils in mountainous regions with presumably inherently low SOC content may also be classified as hot spots. Thus, in areas, where also non-loessial soils are present the classification using the hot/bright spot matrix will likely lead to spurious results.

- A spatially explicit **soil type classification** is needed, in order to incorporate effects, which must be attributed to a specific soil type. The classification tree derived in this study for SOC content class mapping already includes useful information with regard to areas characterised by non-loessial soils. Terminal nodes 1 (high SOC content) and 2 (low SOC content) (cf. Figure 4-9), were identified as containing increased numbers of sampling sites with samples from the geological sub-group "granodiorite". These results indicated, that there is much potential for mapping soil types based on Landsat ETM+ imagery.

- The assumption with regard to **loess soils being generally homogeneous** (if not affected by degradation) requires more detailed analysis / validation. More detailed analysis is needed with regard to sites with inherently low SOC. Especially, the relationship between soil texture and SOC needs to be analysed in more detail. Calibrations between measured fractions of soil particle size (available for the reference soil sample set [cf. chapter 3]) and soil spectral reflectance data, which would allow prediction of particle size fractions for the full sample set, could facilitate such an assessment.

4.5.3 Future research

As this was a first attempt for determining the state of soil resources in the study area, there is a great deal of potential to improve the approach and methods to be used in future assessments, based on the experience gained in the course of this study. The following improvements should be considered:

The **field dataset** presented here (200 samples) was relatively small for an assessment aiming at exploring possible impacts of erosion on soil organic carbon content. Furthermore, establishment of more reliable classification tree models for calibration of raster data to field data would also require a larger sample set.

When collecting additional samples, crucial gaps in the existing dataset should be closed. One such gap concerned grazing land situated at higher altitudes in the Faizabad test area. A field survey should be carried out specifically to sample these rather inaccessible areas. Furthermore, it is necessary to sample locations situated within the study area, but outside of the test areas. The existing hot/bright spot map could serve as a basis for selection of additional sampling sites. The distance between sampling sites needs to be at least 230 m in order to comply with spatial independency assumptions (cf. section 2.3.4).

As argued by Shepherd and Walsh (2007), reliable “case definitions” for areas affected or non-affected by soil degradation are crucial in order to produce valuable information for decision-makers. The definition for hot spots, degrading areas, stable areas and bright spots used in this study was based on only two indicators (erosion occurrence and SOC content classes “low” and “high”). The exploratory analysis carried out showed that it is not only erosion which affects the soil resources. Thus, this case definition needs to be elaborated in more detail and be based also on functional variables, such as important soil fertility properties (e.g. phosphorous and total nitrogen, which seem to be low in the area [cf. chapter 3]) and e.g. infiltration capacity. A procedure should be developed to integrate different soil degradation indicators in a systematic way. Collaboration with various scientists, land managers and farmers could help to define hot spots of soil degradation and bright spots of soil conservation, relevant for all actors involved.

The **raster dataset** used was of low spatial resolution (30 m pixel resolution) for an area with small fields situated on steep slopes (cf. chapter 2). Furthermore, the satellite imagery used predated the field survey by several years. With regard to soil mapping, especially the time gap between the field survey and the image representing the dry season (4 or 5 years, respectively) was rather large. Thus, satellite imagery should be used that is in better compliance with the requirements for such a study. As already mentioned in chapter 2, especially ASTER imagery, much more easily available since May 2006[31], should be considered. Topographic information was available at a more appropriate resolution than satellite imagery (20 m pixel resolution, respectively 10 m for flat areas). Furthermore, ASTER images also provide a distinctly increased spectral resolution, which is expected to contribute to improvements in classification accuracy. Thus, the same dataset could be applied also in future studies. Improved results are likely to be achieved by enhanced modelling of topographic factors, e.g. by deriving hydrological characteristics such as flow length and flow accumulation from a digital elevation model.

Furthermore, the potential for mapping SOC content using satellite imagery with high spectral resolution (e.g. Hyperion imagery covering the spectral range between 0.4 and 2.5 µm in 220 bands) is considerable. In chapter 3, the soil spectral library for predicting SOC content from soil spectral reflectance data measured in the laboratory was presented. Since Hyperion imagery covers the same spectral range as the spectral measurements conducted in the laboratory, application of the elaborated regression to satellite imagery data should be tested. However, as such images are very data intensive, and are thus not suited for application over large areas.

[31] Since 24 May 2006 processing of Aster Level 1A data to Level 1B is provided on demand (http://asterweb.jpl.nasa.gov.asp)

5 Opportunities for sustainable land management

In chapter 2, it was described how detailed land cover classes had been first distinguished and subsequently characterised, among others with regard to seasonality of vegetation cover and their potential as erosion controlling factors. Chapter 3 detailed the elaboration of a soil spectral library in order to predict soil organic carbon (SOC) content from visible near infrared measurements for all 400 sampling sites of the study area. The SOC information as well as visual field observations of soil erosion occurrence had been calibrated to raster datasets. The combination of these 2 map products finally allowed the determination of 4 degrees of soil degradation and conservation: bright spot, stable, degrading and hot spot areas. In this chapter interlinkages between the various datasets will be analysed and land cover / land use and soil resources will be assessed from a wider perspective including underlying socioeconomic and political factors.

5.1 Introduction

5.1.1 Supporting sustainable land management

Sustainable land management is a concept that includes the various dimensions of an agricultural system, and as such has been defined as a “system of technologies and/or planning that aims to integrate ecological with socio-economic and political principles in the management of land for agricultural and other purposes to achieve intra- and intergenerational equity” (Hurni 1996). Unsustainable use of land resources has globally led to widespread land degradation (Oldeman et al. 1990) and has negatively impacted on ecosystems as a whole (MA 2005).

In SLM assessments, identification of cause and effects is an important step for further decision taking (Smyth & Dumanski 1993). Identification of cause/effect relationships is needed for primary prevention, early detection and rehabilitation of areas affected by land degradation (Shepherd & Walsh 2007). As described in chapters 1, 2 and 4, land degradation is a vicious circle, with land cover / land use, soil erosion and soil quality being interlinked and creating feedback loops. However, in the case of rapid land use change, land use can be considered the dominant factor for changes in soil quality (cf. chapter 1). While soil quality is a good indicator of the state of land resources (cf. chapter 4), it is still a major challenge to distinguish between land management effects on soil quality and the natural inherent variation of soil quality. Shepherd and Walsh (2007) propose an evidence-based approach for rigorous quantification of impacts on soil, for instance. It is crucial to have large sample numbers, which allow the determination of prevalence of sites affected by land degradation, for which also environmental and socio-economic correlates are measured. Such sample sets then make it possible to identify risk factors and to target conservation measures accordingly.

It is important to understand not only the direct effects of land use and land management, but also the indirect causes of unsustainable land management (e.g. socio-economic and political causes). Understanding these is crucial in order to reverse land degradation by generating win-win scenarios which allow the protection of natural resources and entail improvements of rural household livelihoods. Furthermore, decisions on land use are influenced by stakeholders at different levels and thus integration of multi-actor perspectives is central to assessments of SLM (Hurni 2000, Herweg & Steiner 2002). Hurni differentiates between 4 stakeholder levels:

the household, community, national and international levels. A study recently conducted in the Tajik Pamir confirmed that the stakeholder level criterion is most suitable as a selection criterion for analysing SLM (Breu 2006).

At the field level, the focus is on soil and water conservation (SWC). SWC has been defined as "activities at the local level which maintain or enhance the productive capacity of the land in areas affected by or prone to degradation" (WOCAT 2003, Liniger & Critchley 2007). Today, land and ecosystem services are no longer restricted to their productive capacity but are considered in a more holistic way and include provisioning, regulating, cultural and supporting services (MA 2003, cf. section 5.3.2). While a SWC technology consists of one or more agronomic, vegetative, structural and/or management measures, a SWC approach defines the ways and means used to promote and implement a conservation technology and to support it in achieving more sustainable soil and water use (WOCAT 2003). Thus, land management causes impacts on land resources, through the measures applied (or not applied) in the field. However, as discussed in chapter 2, remotely sensed information from satellite imagery provides mainly land cover data (vegetation type, fractional vegetation cover, information on vegetation seasonality and characteristics reflecting the state of natural resources). Nevertheless, identifying land use systems present in a specific area provides valuable information with regard to land management and may thus enhance understanding of agricultural inputs to a specific system, workforce available, etc.

5.1.2 Frameworks for assessing agricultural systems

A concept of SLM was first introduced by Smyth and Dumanski (1993), stressing that sustainability is a multi-disciplinary activity founded on the following subjects: agricultural productivity, food security, resource protection, economic viability and social acceptability of land use options.

The pressure-state-response (PSR) framework (OECD 1993) and the DPSIR framework (European Commission 1999), that succeeded it, are both content-based frameworks. The DPSIR framework comprises drivers, pressures, state, impact and response. These quantities have been developed to analyze environmental processes and have been successfully applied to studies focusing on sustainable land management and soil quality issues (e.g. Smaling & Dixon 2006). A weakness of the different versions of the PSR framework consists in their focus on "enforced" changes only, characterized by pressures subsequently leading to responses. Hurni et al. (1999) pointed out that *"this is a behavioural explanation of human adaptation to change"*, as changes may also be triggered by potentials, which then lead to innovations in land management.

In 2001, the Millennium Ecosystem Assessment (MA) was initiated with the objective of assessing the consequences of ecosystem change on human well-being, and of enhancing the conservation and sustainable use of ecosystems and their contribution to human well-being (MA 2005). In order to facilitate this assessment, a conceptual framework was elaborated, including human well-being, indirect and direct drivers of change, and ecosystems. People are seen as integral parts of ecosystems, with dynamic interaction between them and other parts of ecosystems. As human well-being changes, it drives changes in ecosystems, both directly and indirectly, thereby causing changes in human well-being (MA 2003). The advantages of the conceptual framework elaborated for the MA are that it regards pressures and potentials as inherent to the system, it explicitly recognizes the role of decision-makers who affect ecosystems at different levels and finally, it takes into consideration dynamic interactions as well as different scales.

5.1.3 Aim and content of chapter 5

The aim of this present chapter is to reveal the links and dependencies between land cover / land use, land degradation, and soil conservation, in order to identify options for sustainable land management. The results should serve as a basis for future planning of sustainable land management (SLM). An overview on the work procedure is provided in Figure 5-1. Chapter 5 is arranged in three parts: First, the interrelations between land cover / land use and soil resources are analysed in order to establish the effects of different land cover types on the degree of soil degradation and conservation. Results and discussion are presented in section 5.4. Second, a wider perspective to land management is presented, by discussing interlinkages between agricultural systems, human well-being and indirect and direct drivers of land use change (section 5.5). Third, priority areas for implementation of SLM and local opportunities for SLM are identified (section 5.6).

In this chapter, the information sets elaborated and presented in chapters 2 and 4 are linked; accordingly, frequent reference is made to previous chapters.

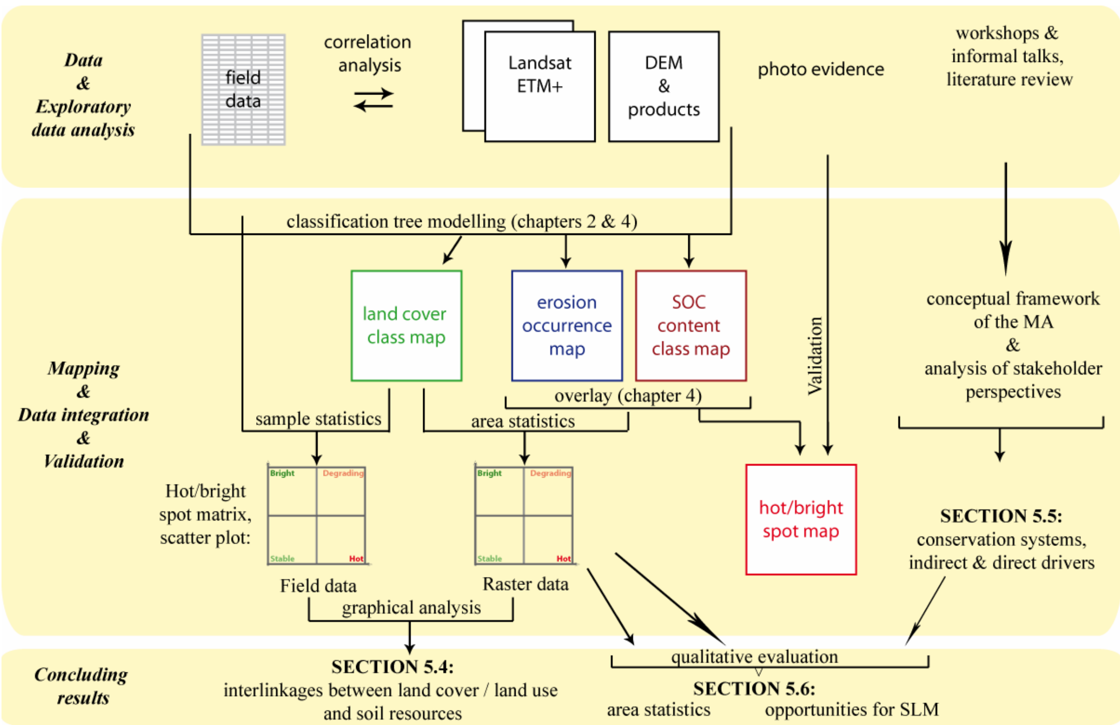


Figure 5-1 Flow chart showing work procedures applied in chapter 5

5.2 Study area

Underlying socio-economic driving forces for land use change

Anke Winnig conducted her MSc study within the framework of the NCCR North-South studies in Western Tajikistan (Winnig 2005). She assessed socio-economic factors for land use change in the hill zone of Western Tajikistan. Her findings indicated that land use change was the result of political and economic transformations in Tajikistan. Winnig's analysis concerning the socio-economic factors revealed one major proximate cause of land use change in the loess hills, namely agricultural activities. Socio-economic factors were identified to be a dominant underlying cause of changes over the last 15 years. The land use change process was highly dynamic due to exceptional trigger events (civil war, economic collapse) since the independence of Tajikistan in 1991. Land use and land management were mainly characterised as being in response to given situations (e.g. food scarcity) and enforced action (by pressure from outside). Thus, Winnig (2005) concluded that there was no actual land management over the last decade.

Land reform

Even before independence, work had begun on a new land code for the Republic of Tajikistan. Since 1990, a series of laws and decrees have been issued (Table 5-1). The restructuring of the collective and state farms was the main goal of the new regulations. Using a Tajik term, self-managed farms resulting from this restructuring are called "dekhan farms" (WFP 2005). The main laws pertaining to the establishment of dekhan farms were passed in 1992, 1993 and 1996 (Table 5-1). For many rural households, the allocation of fields for private use was of at least equal importance (1995 and 1997, Table 5-1), as it provided the basis for subsistence farming.

Table 5-1 Overview of major steps of Tajik land reform and farm reorganization (list compiled by Anke Winnig based on Duncan [2000], Herbers [2004] and Giovarelli [2004]).

1990	Land Code of the Republic of Tajikistan
1990	Law "On Leasing in the Republic of Tajikistan"
1992	Law "On Land Reform"
1992	Law "On Dekhan Farms"
1993	Presidential Decree "Regulations on Organization of Dekhan Farming in the Republic of Tajikistan"
1995	Presidential Decree "On Assignment of 50,000 hectares of Land for Personal Husbandry of Citizens"
1995	Presidential Decree "On the Structural Reorganization of *Kolkhozes* and *Sovkhozes* and Other Agricultural Enterprises"
1995	Law "On Lease"
1996	Presidential Decree "On the Reorganization of the Agricultural Enterprises and Organizations"
1997	Presidential Decree "On Allocation of 25,000 hectares of Land for Personal Subsidiary Farming of Citizens"
1997	Amendment of the Land Code
1998	Presidential Decree "On Ensuring the Right to Land Use"
2003	Presidential Decree "On Mechanism of Settlement of Debts of the Reorganized and Reorganizing Agricultural Enterprises and Organizations"

5.3 Assessing SLM – materials and methods

For purposeful planning of sustainable land management (SLM), information is required regarding the effect of land cover / land use on soil resources. Section 5.3.1 provides descriptions of exploratory data analysis approaches used for deriving a general picture of interrelations between land cover types and soil degradation or conservation. In order to integrate socio-economic and political dimensions together with information on land resources, the conceptual framework of the Millennium Ecosystem Assessment (MA) was applied as described above. Furthermore, perspectives of stakeholders at different levels were reviewed. These assessments are outlined in section 5.3.2. Finally, section 5.3.3 describes how area statistics useful for planning were calculated and opportunities for SLM identified.

5.3.1 Exploring links between land cover / land use and soil reosurces

In order to establish links and dependencies between land use, land degradation and soil conservation, a number of exploratory data analysis approaches were applied. More details on exploratory data analysis have been provided in section 4.3.2. Analysis approaches conducted included (i) correlation analysis between fractional vegetation cover (FVC) derived from satellite imagery and soil indicators, (ii) analysis of scatter plots displaying the hot/bright spot matrix and land cover classes, and finally (iii) an evaluation of the usefulness of the hot/bright spot map for deriving information for SLM planning based on visual evidence from photos.

Exploratory analysis for links between fractional vegetation cover derived from satellite imagery and erosion occurrence or SOC content

In chapter 4, the results of the explorative analysis of the relationship between topographic factors and erosion occurrence, and topographic factors and SOC, respectively, were presented. In that chapter, the relationship between OSAVI values and soil resource information was explored. The Spearman rank correlation between FVC as presented by the OSAVI[32] vegetation index derived from Landsat satellite imagery from August 2000 and May 2002, and soil indicators (erosion occurrence[33] and SOC content[34]) was analysed. The 200 sampling sites of the independent sample set[35] were used for this analysis. For all tests, the statistical significance level was defined as $p < 0.05$.

Linking the hot/bright spot matrix with land cover classes

As observed in chapter 2, the land cover types defined a priori were heterogeneous with regard to their potential as erosion controlling factors or the ecological conditions of the sampling sites. It was expected that sub-classes of these land cover types, i.e. the land cover classes as derived (a posteriori) from the classification tree model (nodes 1 to 23), would characterise the impact of land use on soil resources in such a way as to highlight a typical interrelation between erosion, as the dominant soil degradation process, and soil organic carbon (SOC), as an integrative soil quality measure. While these land cover classes have been characterised in chapter 2, here in chapter 5, the characteristics of land cover classes are related to the degrees of soil degradation and soil conservation as distinguished by the hot/bright spot matrix developed in chapter 4.

[32] OSAVI: Optimised Soil Adjusted Vegetation Index (cf. section 2.3.2)
[33] Field observations recorded during the field survey as described in chapter 4.
[34] SOC content values were predicted from the soil spectral library as described in chapter 3.
[35] The independent sample set is described in section 2.2.3.

In an initial step, the land cover classes were linked to the field data: for each land cover class, percentages of samples with occurrence of soil erosion (x-axis) and percentages of samples with high SOC content (y-axis) were plotted against each other in a scatter plot. The analysis was based on the 200 sampling sites from the Faizabad and Varzob test areas belonging to the independent sample set[35]. In a second step, the same characterisation was conducted using data extracted from the raster data products presented in chapters 2 and 4. The data were extracted for evenly distributed points at a distance of 230 m, in order to comply with the spatial independency assumption (cf. section 2.2.3). The percentage of pixels per land cover class classified as "erosion observed" and as "SOC content high" (SOC > 1.1%), were counted. For each land cover class, these percentages were then plotted against one another. If a specific land cover class shows occurrence of soil erosion for less than 50% of the samples (or of the area), only limited erosion is expected for this land cover class, whereas land cover classes with occurrence of soil erosion in more than 50% of the samples (or of the area) are considered to be subject to widespread erosion processes. The same approach was applied with regard to SOC content classes.

An important threshold was slope steepness of 14% (cf. section 5.3.3). As the only cropland class, "annual cropland" as determined by node 3 had not been characterised with regard to this slope criterion. For the hot/bright spot matrix elaborated in this study, the land cover class of node 3 was thus split into two classes and named N3 (< 14%) and N3 (14-36%), respectively.

Excursus on the statistical significance of the differences in SOC content and erosion occurrence for different land cover classes: Variation of SOC contents was expected to be high. Sample pairs separated by a distance of around 7 m collected from 53 sampling sites showed that the mean coefficient of variation (CV) within fields is 23% for grazing land and 14% for annual and permanent cropland (cf. sections 2.2.3 and 4.3.6). Land cover classes belonging to different quarters of the hot/bright spot matrix were expected to show significant differences. Differences between the land cover classes were analysed based on field data (percentages of samples with soil erosion occurrence and with high SOC content). Tests applied included non-parametric Kruskal-Wallis tests (for determination of the overall p-value) and post hoc all-pairwise Conover tests (for identification of precisely which pairs showed differences) with Bonferroni correction (correction for chance agreement) (Siegel & Castellan 1988), as described in chapter 4. However, none of the classes showed significant differences at the level of $p \leq 0.05$.

In Wolfgramm et al. (2007), results of the above Kruskal-Wallis tests have also been presented. However, these tests did not include correction for chance agreement and thus have been revised in the work presented here. The results reported in the earlier publication were interpreted rather too optimistically as confirming the significance of differences between land cover classes.

For proper statistical testing, a larger sample set would be required. Regarding the "annual cropland" land cover classes described by nodes 3, 4 and 8, the number of samples from the independent sample set available for this study only amounted to 13, 10 and 6, respectively. The analysis conducted here is thus purely descriptive, but may serve as a valuable first appraisal of interrelations between land cover classes and soil resources.

Validation based on visual evidence

The hot/bright spot map was compared to additional visual evidence collected during field surveys. While the map products presented in earlier chapters showed rather low accuracy (land cover map = 51%, erosion occurrence map = 73%, SOC content class map = 75%, and hot/bright spot map = 51% overall accuracy), the assessment of the hot/bright spot matrix at the level of land cover classes had demonstrated that specific land cover classes were inaccurately predicted (e.g. annual cropland on flat slopes, tree and shrub cover with low FVC). Thus, the hot/bright spot maps were visually evaluated with regard to their potential usefulness, especially for future activities in planning of sustainable land management. An illustrative example for the Faizabad and Varzob test areas is presented in section 5.4.3.

5.3.2 Integrating socio-economic and political aspects, together with land use information

Below, interlinkages between indirect and direct drivers, human well-being and agricultural systems are elaborated on in a descriptive manner for three different time periods and are illustrated graphically (Figure 5-8) based on the conceptual framework of the Millennium Ecosystem Assessment (MA 2003). Furthermore, dominating perceptions among stakeholders at the local, national and international levels are reflected on as they constitute a central part of SLM assessments (Hurni 2000).

The conceptual framework of the Millennium Ecosystem Assessment

The MA conceptual framework was developed to assess interactions between ecosystem services, human well-being, and indirect and direct drivers of change (MA 2003). The interactions among these four components were investigated by explicitly considering various spatial and temporal scales, as shown in Figure 5-2.

An overview of the MA conceptual framework is provided in Figure 5-2. The conceptual framework has been described in detail in the documentation provided by the MA (MA 2003). Below, a brief introduction is given with a focus on the study at hand.

The aim of the Millennium Ecosystem Assessment was to provide an overall picture of agricultural systems and their changes over various periods; accordingly, not every single point was elaborated on. In this study, the focus is on **agricultural systems** (or agro-ecosystems) as a specific type of ecosystems According to the MA framework, four different services are attributed to ecosystems: provisioning, regulating, cultural and supporting services. With the focus on agricultural systems, foremost, aspects with regard to regulating services of the land use systems have been in the focus of the previous chapters, and especially in the previous section, section 5.4. In the here presented assessment, the focus has been extended to include the following ecosystem functions: provisioning with food, fodder and fuel wood, regulation of soil degradation processes (especially erosion), and supporting of primary production and soil formation.

The MA conceptual framework applies five factors to characterise **human well-being**: basic material for a good life, health, good social relations, security and freedom of choice and action. For the present study, all these factors were assessed in a highly generalized manner with a focus on food, fodder and fuel wood, which may be provided by the agricultural systems in the study area. Thus, basic material for a good life was considered to include crops cultivated in the area (as described in chapter 2), as well as food for animals and wood used as fuel wood. Health was examined in connection with food insecurity leading to malnutrition, and security also with regard to food security. Freedom of choice was referred both to accessibility to land and to land use rights.

Indirect drivers of land use change are also called "underlying driving forces" and describe, according to Geist and Lambin (2004), fundamental social and biophysical processes, such as human population dynamics or agricultural policies, that underpin the "proximate causes" or "direct drivers". Indirect drivers operate at the local level or reflect influences at the national or global levels and can be categorised into demographic, economic, socio-political, science and technology, and cultural and religious drivers. During the last decade, remittances have played a major role for rural incomes in Tajikistan (WFP 2005). Remittances are considered indirect drivers of land use change and may lead to veritable remittance landscapes. Remittance landscapes are defined as *an emerging type of landscape driven by the investment of remittances* and apply to landscapes in which remittances drive investments, leading to land use change, or in which remittances are used to cover certain expenses, thereby freeing other sources of income that are invested in such a way as to induce land use changes (Hostettler 2007).

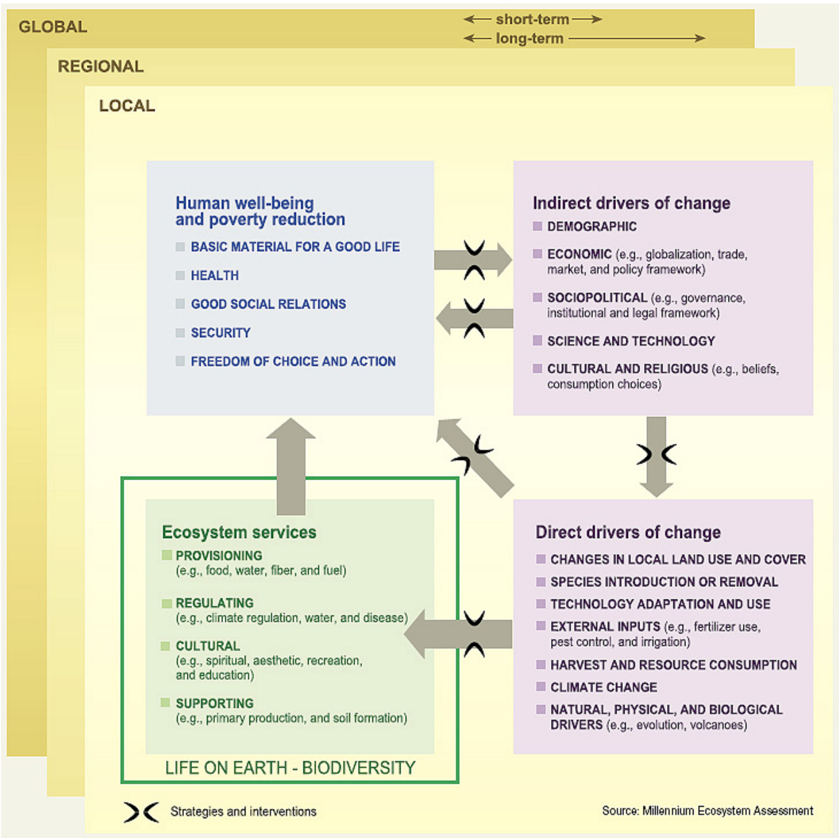


Figure 5-2 Millennium Ecosystem Assessment conceptual framework (MA 2003)

Direct drivers of land use change are human activities or immediate actions at the local level, such as cropland expansion, that originate from intended land use and directly affect land cover. The main direct drivers relevant for this study were technological adaptation of machinery and infrastructure, land use change, external agricultural inputs (e.g. fertilizer), labour and harvest.

Materials

The relevant information was collected from various sources, including published literature, Winnig's diploma thesis carried out as part of this research project (Winnig 2005), WOCAT case studies documented for publication (Liniger & Critchley 2007) or compiled by Bühlmann (2006). Further information was collected during workshops and training courses in which the author participated, such as a workshop organised by the Central Asian Mountain Partnership (CAMP) – Tajikistan in Karsang (9-11 June 2005), at which farmers and land managers came together to discuss opportunities for SLM. Furthermore, 3 regional training courses that were organised by the NCCR North-South and took place in Kyrgyzstan (March 2003), Tajikistan (May 2004) and Kyrgyzstan and Kazakhstan (May 2005), facilitated extended discussions among Central Asian and Swiss researchers; during field visits, there were many additional discussions between Central Asian and Swiss researchers and groups of local farmers. Finally, a lot of information was gathered during informal talks with farmers in the field or after fieldwork, and last but not least during many discussions with experts from the Soil Science Research Institute in Dushanbe.

Time periods

Drivers of land use change may be associated with a clearly defined period of time. However, even after the influence of certain drivers may have decreased or stopped altogether, the land use systems which have emerged as a result of their previous influence are often still present. Thus pathways of land use change are made up of initial conditions, causes and feedback loops. The environmental and land use history of each region defines the initial conditions for each subsequent round of land use and ecosystem change (Lambin et al. 2003).

Three time periods were distinguished that differed distinctly with regard to indirect and direct drivers: the Soviet period (1960s-1991), the period of violent political and economic transformation (1991-1997), and the post-war period (1997-2006). Until independence of the Republic of Tajikistan in 1991, the agricultural system had been determined by the planned economy of the Soviet Union, in which Tajikistan was integrated. Datasets available (Corona satellite imagery dating from 1970, Russian topographic maps dating from 1979 and literary sources) served for reconstruction of a general picture of driving forces and pathways to land degradation or conservation back to the 1960s. The period between 1991 and 1997 was dominated by abrupt political and economic transformation, of which there were two major causes: first the independence of the Republic of Tajikistan, which was declared in 1991, and second a civil war lasting from 1993-1997. After 1997 the political and subsequently the economic situation stabilized. This process of stabilization and reformation continues until today.

Pressure and potential – Major land management types

In the here presented study, land management was defined as the "pressure and potential" component, and the potentials of land management were explicitly considered. Pathways to degradation and conservation were analyzed with regard to major land management types as defined in sections 2.4.5 and 2.5.4. These land management types also facilitated, to a certain degree, the analysis of the impact of land use dynamics in the absence of detailed land use change information.

The major land management types were defined as follows:

- Never cultivated (grazing land)
- Permanently cultivated (more than 30 years)
    - annual cropland
    - tree and shrub cropping
- Temporarily cultivated
    - cultivated (in 2004 / 2005)
    - fallow (in 2004 / 2005)

Perceptions on unsustainable land management

Decisions taken at various stakeholder levels influence land use changes (Hurni 2000, MA 2003). When assessing SLM, it is thus important to consider limitations as they are perceived at different stakeholder levels. With regard to organisational levels, decision-makers have been described by the MA (2003) as follows:

- individuals and small groups at the local level (such as a field or forest stand) who directly alter some part of the ecosystem;
- public and private decision-makers at the municipal, provincial and national levels;
- public and private decision-makers at the international level, such as through international conventions and multilateral agreements.

Reflection on the materials used for this analysis as presented above, revealed that similar statements were made when the conversation was focused on the topic of unsustainable land management. It was thus chosen to present, for each of the three stakeholder levels, the one perception which was considered to be dominant. Being aware of the cliché inherent in linking one stakeholder level with one perception only, this procedure was still regarded as suitable in order to pinpoint conflicting views and major obstacles when searching for approaches to SLM.

5.3.3 Planning

Area statistics

Efficient planning of sustainable soil conservation measures includes prioritising of actions. Area statistics provide a useful basis for negotiating priorities among stakeholders and for subsequent decision-making. Thus, the aim was to derive area statistics for bright spot, stable, degrading and hot spot areas coinciding with different land cover types (the land cover types "settlement areas" [Os] and "aquatic areas" [Oa] were excluded from the analysis). Generally, conservation measures have to respond to specific land use systems, as they are not applicable everywhere (Smyth & Dumanski 1993, Hurni 2000). The land cover types distinguished for this analysis were cropland (annual and perennial) (C), areas with tree and shrub cover (T), and grazing land (G). No further differentiation between annual and perennial cropland was made since the validation of the land cover map had shown that misclassification between the two classes was high (cf. section 2.5.2). Further, the analysis was conducted with regard to specific slope steepness as these proved to be an important factor with regard to spatial distribution of land cover classes: The classification tree model had determined the slope classes of < 14%, 14-36% and > 36% for distinguishing specific land cover classes (section 2.5.3). The major land management types (never, permanently and temporarily cultivated) also showed characteristic distributions with regard to these slope classes (section 2.5.4). Furthermore, as described in section 2.2.1, in Soviet times slope classes had been important with regard to land management planning. And even though no significant correlation between slope and erosion or between slope and SOC content had been determined (section 4.4.1), the erosion occurrence model established for mapping erosion had determined slope steepness of 14% as a threshold. For sites with a slope steepness below this threshold, erosion occurrence was considerably lower. Area statistics were calculated in ArcMap (ESRI Inc.) from the elaborated maps.

Identifying local opportunities for sustainable land management

In order to identify opportunities for SLM, the subsequent section presents an account of land management opportunities as defined using the MA conceptual framework (cf. previous section). These opportunities are discussed against the specific background of the land cover / land use and soil resource information presented in section 5.4

5.4 Effects of land cover / land use on soil resources

5.4.1 Fractional vegetation cover and soil indicators

In chapter 4, Spearman rank correlations were calculated to explore the relationship between the soil indicators *soil erosion occurrence* and *soil organic carbon (SOC) content* on the one hand, and topographic factors on the other. Moreover, there was an assessment of the general relationship between soil indicators and fractional vegetation cover (FVC) as reflected by the OSAVI values calculated from the Landsat images from May 2002 and August 2000.

Table 5-2 Spearman rank correlation coefficient r between erosion occurrence observed in the field and OSAVI value calculated from the May and August images, for various sub-groups of major land use classes and for the two test areas. Abbreviations: FA=Faizabad, VZ=Varzob.

Spearman rank correlation coefficient r_s for erosion 0 and 1*	Faizabad & Varzob test areas	FA & VZ crop-land	FA & VZ grazing land	cropland** FA	cropland** VZ	grazing land*** FA	grazing land*** VZ
Number of samples	183	83	100	34	49	52	48
OSAVI May	-0.29	-0.16	-0.38	-0.33	-0.13	-0.24	-0.54
OSAVI August	-0.20	-0.11	-0.15	0.05	-0.38	-0.09	-0.23

Spearman rank correlation coefficient r_s for SOC content*	Faizabad & Varzob test areas	FA & VZ crop-land	FA & VZ grazing land	cropland FA	cropland VZ	grazing land FA	grazing land VZ
Number of samples	173	79	94	35	44	53	41
OSAVI May	0.31	0.21	0.39	0.21	0.21	0.36	0.59
OSAVI August	0.22	-0.10	0.37	0.00	-0.15	0.34	0.36

** Correlations significant at the level $p < 0.05$ are underlined.*

*** Including all sampling sites classified during field survey as annual and perennial cropland or as tree and shrub cropping*

**** Including sampling sites from all grazing land classes (with FVC low, medium or high)*

Regarding soil erosion, it was mainly the FVC derived from the May image which showed low but significant correlations. The relationship between low FVC in May and high erosion was strongest for grazing land in the Varzob test area, followed by cropland in the Faizabad test area. In contrast, FVC derived from the August image showed a significant correlation only for cropland in Varzob and for all sampling sites together. As more detailed analysis showed, this result was strongly influenced by sampling sites with tree and shrub cover; the Spearman rank correlation coefficient between erosion and OSAVI August values was r_s = -0.54, for sampling sites from the Varzob and Faizabad test areas together (N=13). These sampling sites also showed a comparatively high correlation between OSAVI May values and erosion occurrence (r_s = -0.45).

Thus, especially on sites with tree and shrub cover it appears to be crucial that a vegetation cover can be maintained. It can be assumed that especially a dense ground cover (e.g. the herbaceous or, in case of intercropping, the crop layer) plays an important role. Overall, the highest Spearman rank correlation coefficients were found for SOC content and FVC on grazing land. Among these, the coefficient between SOC content and FVC in May derived for grazing land in the Varzob test area was the highest (r_s = 0.59). On grazing land, FVC in August was also correlated with high SOC content. These results were consistent for both Faizabad and Varzob test areas. The results for sampling sites on cropland were less unambiguous; most correlation coefficients were positive, but correlations were all below 0.25. The correlation test between FVC in May and SOC content for cropland sampling sites from both test areas together proved significant. Thus, also for cropland sites there was some indication that high FVC in May was linked to high SOC content.

The results in Table 5-2 show that the correlations were generally weak. Nevertheless, these correlations between soil indicators and FVC were stronger and more consistent than the correlations between soil indicators and topographic factors presented in Tables 4-4 and 4-5. This preliminary assessment allows the conclusion to be drawn that, especially on sites which had not been cultivated, FVC was linked with erosion processes and soil quality: as would be expected, FVC was negatively correlated with erosion occurrence and positively with SOC content.

5.4.2 Hot/bright spot matrix – different degrees of soil degradation and soil conservation for specific land cover classes

Land cover classes were related to the different degrees of soil degradation and soil conservation using the hot/bright spot matrix (Figure 5-3). The graphical display in a scatter plot facilitates a qualitative analysis, allowing the formulation of hypotheses on the effect of land cover / land use on soil resources which will have to be followed up in future studies. In Figure 5-3, the scatter plot to the left displays the land cover classes characterized by the degree of soil degradation as determined based on field data, while the scatter plot to the right is based on information derived from the elaborated raster maps (extent of analysis being the test areas of Faizabad and Varzob). Comparison of the two plots showed that by and large the field dataset and the raster maps reflected the same interrelations between land cover classes and the degrees of soil degradation and soil conservation. Due to the way in which the hot/bright spot matrix was calculated, land cover classes situated towards the corners of the matrix were determined by more homogeneous soil erosion or SOC content characteristics (e.g. in the upper left corner, almost all sampling sites of a specific land cover class would show high SOC content and no occurrence of erosion), while those situated towards the centre of the matrix showed heterogeneous characteristics.

In the scatter plot based on field data, the land cover classes were assembled more in to the centre than was the case in the plot based on the raster data products. This indicated that the land cover classes may not be as homogeneous with regard to soil resources as the modelled raster data suggested. This was not surprising, though, as the models present reality in a simplistic manner. Since the distribution of land cover types over the 4 quarters of the matrix characterising hot spot, degrading, stable and bright spot areas was by large the same for the two hot/bright spot scatter plots. Thus, an analysis of the overall trends of interrelations between land cover classes and soil resources was still possible.

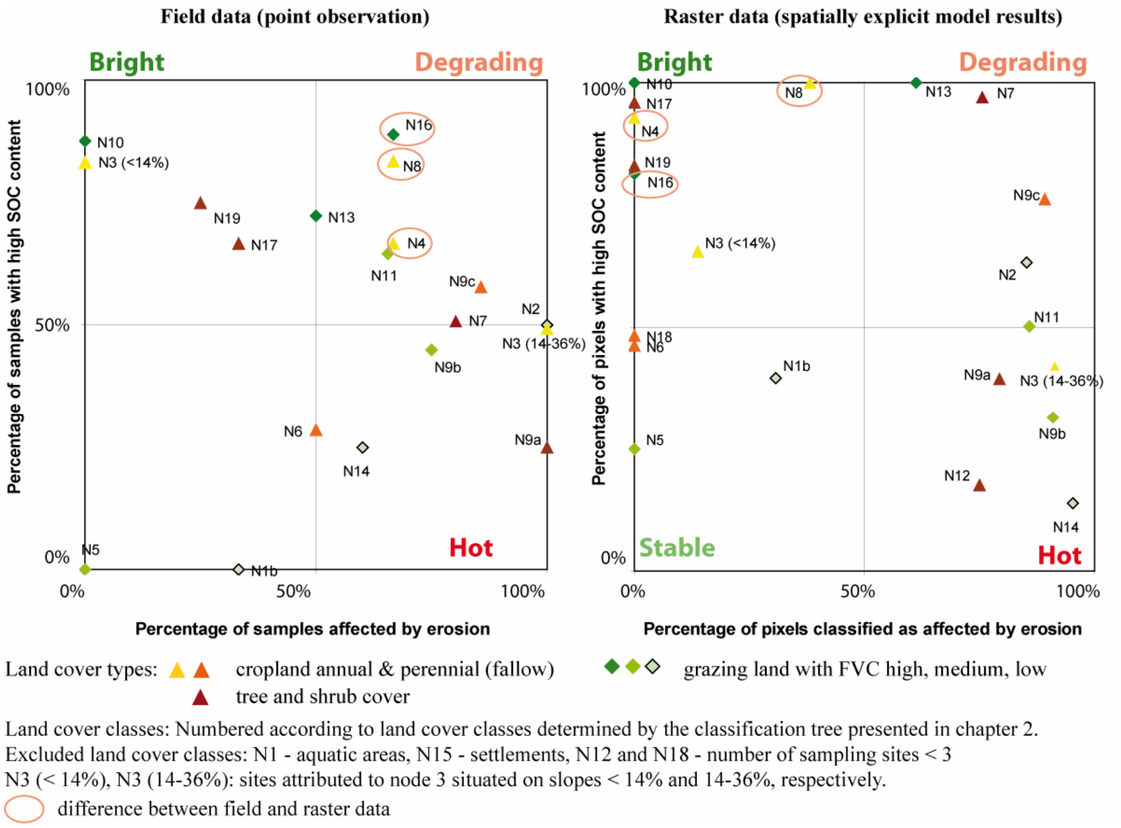


Figure 5-3 Hot/bright spot matrix for land cover classes based on field data (left) and raster data (right) [36]

Comparison of the two scatter plots also provided a validation of the erosion occurrence and SOC content class model for different land cover classes: Depending on whether the assessment was based on field or on raster data, 3 land cover classes were attributed to different quarters of the hot/bright spot matrix (circled light red); this concerned nodes 4, 8 and 16. For all of them, occurrence of erosion was underestimated. Node 4 determined annual cropland on slopes flatter than 14%. As pointed out in chapter 4, the threshold for slopes indicating sites not affected by erosion seemed to be too high for cropland sites, which was further confirmed by this observation. Node 8 determines annual cropland, too. Thus, there are indications that the erosion occurrence model does not give adequate consideration to the increased risk of erosion on annual cropland (e.g. due to loss of soil structure from ploughing). Node 16 classifies grazing land with high FVC. As this class included sites on river banks and along old gullies (cf. section 2.5.3), the vegetation cover may be highly heterogeneous, which

[36] A hot/bright spot matrix for land cover classes had previously been published by Wolfgramm et al. (2007). The differences between the matrix presented here and the previously published matrix are due to the different datasets which were used for calculation. Both of the matrixes presented here were calculated on the basis of spatially independent sampling sites (sampling sites were considered spatially independent at a distance of 230 m; cf. section 2.2.3); comparison between field and raster data appeared to produce more reliable results than using the full dataset as it was done in the earlier work.

would explain the occurrence of erosion on these sites with generally high vegetation cover. Other classes which stood out as inaccurately predicted were node 7 and node 17, both classes with tree and shrub cover, and primarily sites featuring intercropping and vineyards (cf. section 2.5.3). SOC content was over-predicted by the model for these land cover classes. High variability of SOC content on sites with intercropping and, furthermore, subsoil of low quality which has been moved to the surface during construction of terraces (cf. section 4.4.2) are among the possible explanations for this difference between model and field results.

In the field data scatter plot (Figure 5-3, left), a linear trend can be depicted: with increasing erosion occurrence, land cover classes show decreasing SOC contents, thus indicating that there is a link between erosion occurrence and SOC content applicable to most land cover classes. The exceptions may also be interpreted: Nodes 5 and 6 referred to classes on slopes < 14% and both included sites with perennial cover. It can therefore be concluded that there were other soil degradation processes involved than erosion. N1b and N14 referred to grazing land classes with low FVC. These sites were located in or near the mountainous areas of the Hissar range, with shallow and stony soils likely to have naturally lower SOC contents.

The characterisation of land cover classes conducted in chapter 2 showed that within one land cover type (e.g. annual cropland) sites may be rather heterogeneous. The land cover classes, as sub-classes of the land cover types, were expected to define more homogeneous groups of sampling sites. This expectation was confirmed when linking land cover information with soil resource information in the hot/bright spot matrix; e.g. the 4 different annual cropland classes differed to a great extent with regard to erosion occurrence and SOC content. However, as described in section 5.3.1, variance of soil erosion occurrence and SOC content was high even within the land cover classes, and thus, determination of significant differences between classes was not possible when applying stringent statistical tests. Sites in land cover classes determined by nodes 4, 5 and 6 were all on flat slopes (< 14%) (cf. chapter 2). As described in section 5.3.1, to comply with this slope threshold of 14%, annual cropland sites attributed to node 3 were further subdivided into 2 classes: sites on flat slopes were named “N3 (< 14%)”, and those on moderate to steep slopes “N3 (14-36%)”. For the land cover classes comprising sites on flat slopes, SOC content increased in the following order: grazing land, perennial cropland (e.g. fallow areas) and annual cropland. This indicated that on flat areas only sites with very low soil quality were used as grazing land. It further indicated that cropland was only left fallow if soil resources were degraded. Surprisingly, annual cropland sites with very low OSAVI values in August (indicating low FVC), as attributed to “N3 (< 14%)”, showed higher SOC content and less erosion occurrence than sites with higher OSAVI values, as attributed to node 4. In contrast, sites attributed to “N3 (14-36%)”, on moderate to steep slopes, showed high erosion occurrence and the highest percentage of sampling sites / pixels attributed to low SOC content of all annual cropland classes.

The perennial cropland classes mainly included the fallow cropland sites. Node 9c was the most widespread land cover class determining perennial cropland, especially in the Varzob test area. There it covered 15.6% of the agricultural area (cf. section 2.5.3). Even though these sites showed perennial cover, occurrence of erosion was very high. A comparison of the thresholds for OSAVI values in August regarding erosion occurrence and the land cover model shows that FVC of sites attributed to node 9c is too low to classify these sites as non-affected by erosion. This reflects the situation observed during field surveys: a lot of fallow land is further degrading. If, after annual cropping and upon abandonment of the plot, no measures are taken to ensure vegetation cover to develop, development of vegetation cover on these plots with rather low SOC content will be limited, allowing erosion processes to continue (cf. Figure Figure 5-4).

Figure 5-4 Land use on steep slopes. Left: severe erosion on fallow cropland; middle: well conserved haymaking area; and right terraced vineyard intercropped and used for haymaking

Data presented in the hot/bright spot matrix indicated that tree and shrub cover classes that differed with regard to their respective FVC also differed with regard to occurrence of soil erosion: While tree and shrub cover classes characterised by high FVC (nodes 17 and 19) showed a low percentage of sampling sites with occurrence of erosion, the land cover classes characterised by only medium cover (nodes 7 and 9a) showed high occurrence of erosion. Furthermore, as expected, generally low cover and high erosion occurrence coincided with higher percentages of sampling sites / pixels with low SOC content for the respective land cover class.

The correlation analysis presented in section 5.4.1 showed that on grazing land there was, on the one hand, a negative correlation between fractional vegetation cover in May and erosion occurrence and, on the other hand, a positive correlation between vegetation cover and SOC content. This was also reflected in the analysis based on the hot/bright spot matrix. It was striking that grazing land with low FVC, as defined by node 14, showed low SOC content for most sampling sites but occurrence of erosion only for a little more than 50% of sampling sites. According to the characterisation of the sampling sites attributed to node 14 (cf. chapter 2), these sites were located on very steep slopes in mountainous areas, sometimes on stony and shallow soils. Thus, it is likely that the low SOC content must primarily be attributed to the specific environmental conditions of these areas rather than to especially intensive degradation processes. Grazing land sites on slopes > 36% were attributed to nodes 11-14, or also to node 2 in the case of sites with low FVC situated on slopes > 34%. These sites all showed high occurrence of erosion, both from field and raster data. However, the higher the FVC of the respective land cover class, the higher was the percentage of sampling sites / pixels with high SOC content. As there was only a differentiation between sites affected and non-affected by erosion, severe erosion occurring on grazing land with low FVC was accounted for in the same way as moderate or light erosion occurring on sites with high FVC. It is expected that the distinction of different levels of erosion would reveal differences in erosion occurrence for these sites as well. An example of a steep slope with high FVC used for haymaking is displayed in Figure 5-4.

5.4.3 The hot/bright spot map compared to evidence from visual observations

A direct comparison with photographs taken during the field survey indicated that the hot/bright spot map provides useful preliminary information for further planning of SLM. Overall, based on this comparison it can be concluded that the hot/bright spot map shows some inaccuracies (cf. validation in section 4.4.3), but that it generally offers a satisfactory level of accuracy for further SLM planning. An illustrative example each from the Faizabad and Varzob test areas is subsequently provided.

Karsang village and surroundings, Faizabad test area

The area around Karsang village was selected for detailed visual assessment (Figure 5-6) as it included easily distinguishable areas with hot and bright spots. Comparison between a photo, the extracts of the hot/bright spot map, the land cover map, and a Quickbird satellite image revealed the potential of providing detailed information for many locations, but also showed its limitations.

The locations of small wheat plots on sloping land (covering around 150 by 50 m), as indicated by circle number 1 in Figure 5-6, were precisely identified. In the Faizabad test area, annual cropland located on slopes was generally classified as hot spots, as illustrated by the fields located within this map extract (Figure 5-6, circles number 1, 2 and 3). The cropland in the valley floor was generally classified either as bright spot or as stable area (Figure 5-6, circle number 4). As can be identified on the Quickbird image (Figure 5-6,), in 2005, some of the fields were cultivated with perennial crops (alfa-alfa). On the land cover map (Figure 5-6, d) these fields were not homogeneously classified. The raster information was partly attributed to annual cropland, perennial cropland and grazing land with medium FVC. Areas with dense tree and shrub cover were correctly classified, such as the field stations of the Soil Science Research Institute and the Horticulture Institute (Figure 5-6, circles number 5 and 6), which were classified as bright spots. The grazing land indicated by circle number 7 showed a very patchy pattern on both map extracts. As the comparison with the photo and the Quickbird image showed, the grazing land was indeed characterised by patches of trees. Tracks running along the ridges (Figure 5-6, circle number 8) and used by flocks of sheep when moving to the summer pastures at higher altitudes or by cow herds on their daily way from the settlements to the pastures at middle altitudes, are clearly identifiable as areas with low FVC (Figure 5-6, d) and hot spots (Figure 5-6, b). A close-up photograph of such a track is provided in chapter 2 (Figure 2-18).

Figure 5-5 Young orchard with sparse tree cover and intercropping, Novobod, Faizabad test area, from the hills behind Novobod village looking South (Photo by Wolfgramm, 23 June 2004)

While the examples described above concerned clearly identifiable areas, the difficulties in extracting land cover information for SLM from mid-resolution satellite imagery (e.g. Landsat images) are illustrated using the example of a young orchard with sparse tree cover and intercropping next to Novobod village (Figure 5-5 and Figure 5-6, circle number 9). On the land cover map, the area shows patches of annual cropland, perennial (non-woody) cropland, grazing land and only small patches of tree and shrub cover. The hot/bright spot map is more homogeneous, and shows the area classified as bright spots and partly degrading land (Figure 5-6, b).

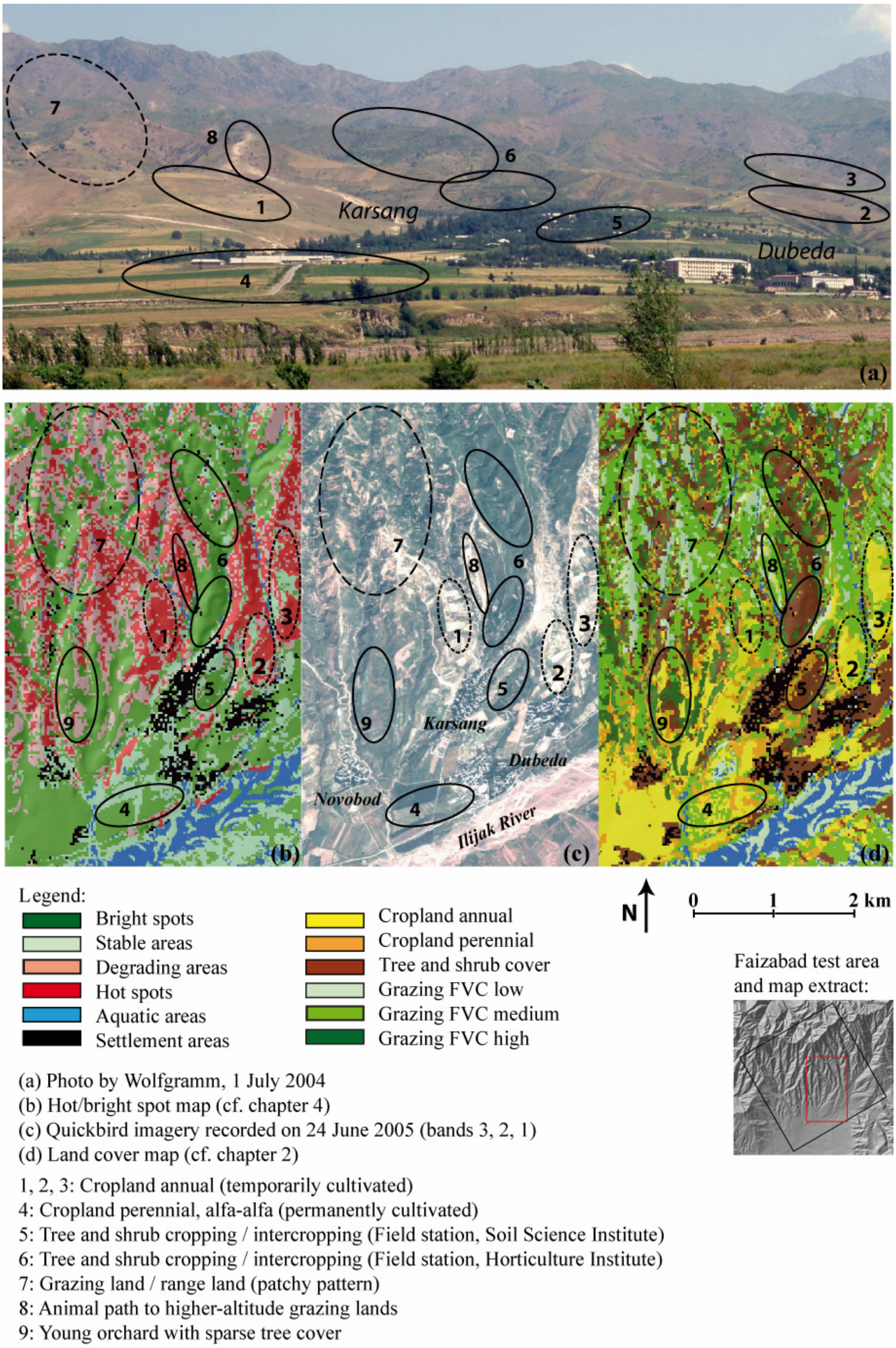
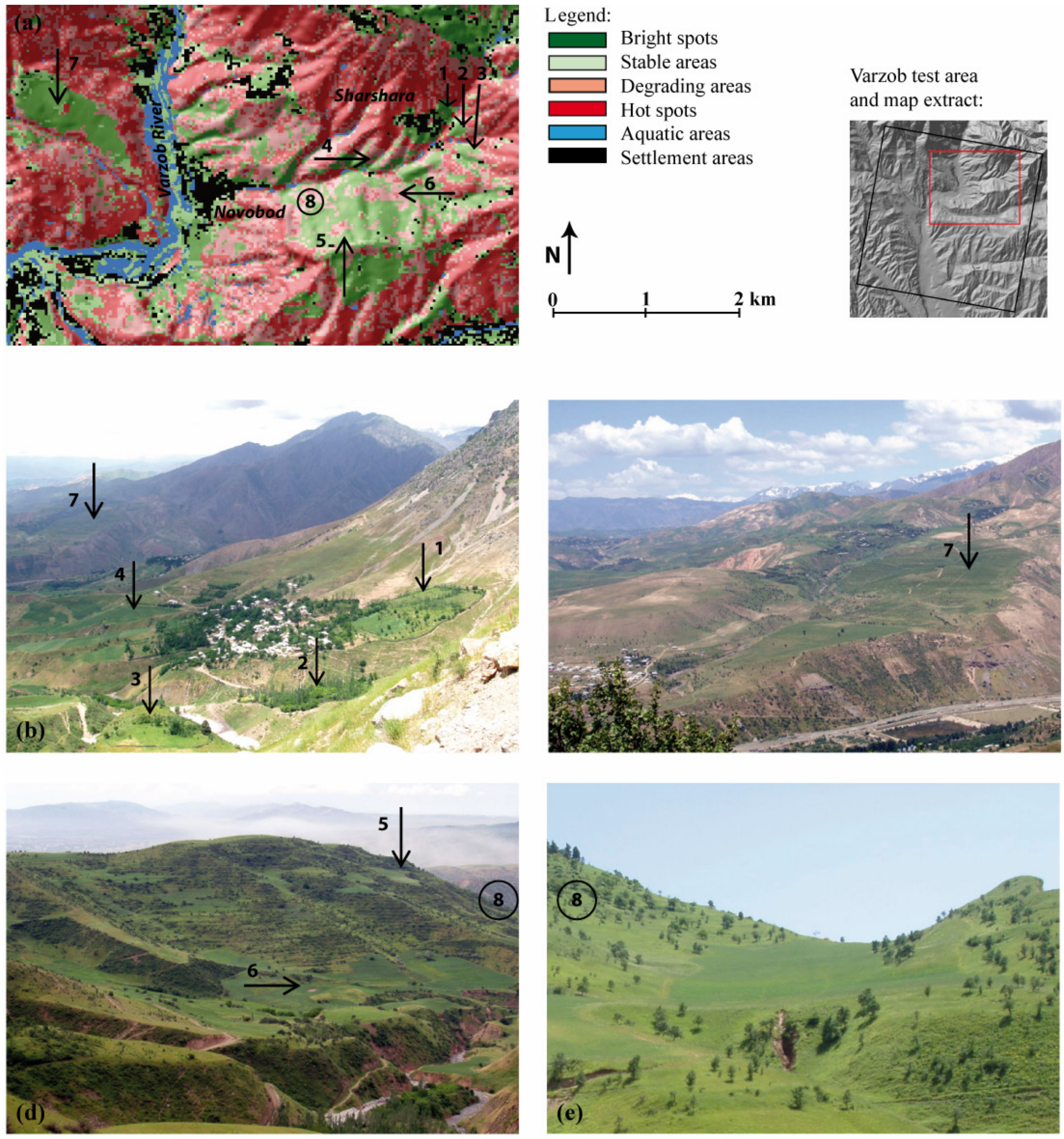


Figure 5-6 Example of Karsang village and surroundings, Faizabad test area

Sharshara village and surroundings, Varzob test area

In the Varzob test area, bright spots are rare, but generally stand out as clearly defined areas. Accuracy of the predicted bright spots for the Varzob test area in comparison to field observations and photo documents is illustrated using the example of the surroundings of Sharshara village (Figure 5-7) and discussed below.



(a) Hot/bright spot map (cf. chapter 4)
(b) Looking from the East towards Sharshara village
(c) Vineyard East of Varzob river and Alakjin village in the background
(d) Afforestation opposite of Sharshara with Dorisharshara River in the foreground
(e) Cropland with new gully below, on the Northeast slope opposite Sharshara village

Figure 5-7 Example of Sharshara village and surroundings, Varzob test area (Photos by Wolfgramm, 13 June 2005)

Photo (b) in Figure 5-7 shows Sharshara village situated at the Northern boundary of the Varzob test area. The mountainous slopes of the Hissar range are only covered with shallow loess deposits. The grazing land surrounding the village was heavily overgrazed and was classified as hot spot or degrading area. In strong contrast to the degraded area were the traditional fruit and fodder plots. These fenced plots were clearly distinguished on the hot/bright spot map as bright spots (arrows number 1, 2 and 3). On the plot pointed out by arrow number 1, maturing wheat can be identified by its bluish-green colour in the lower left corner of the plot. Unlike other wheat fields, which were generally classified as degrading or hot spot areas (arrow number 4), the area within the fruit and fodder plot used for wheat production did not appear to be affected by erosion. The dense grass cover above the wheat plot is likely to reduce run-on to the plot, and the wheat plot itself is narrow, so that run-off is unlikely to accumulate. Such conservation measures appear to be effective in conserving the soil resources on wheat plots. Further, a vineyard, situated on the Western side of Varzob River, was also classified as a bright spot (Figure 5-7, c, arrow number 7). The slope with North exposition facing Sharshara village (Figure 5-7, d) represented another example of a bright spot: slopes which had been terraced and afforested during Soviet times. However, the afforested area had been partly cleared, the terraces evened out, and wheat plots established, most likely during the civil war in the 1990s. Such areas were classified on the hot/bright spot map as degrading areas (Figure 5-7, a, arrows number 5 and 6). Photo (e) in Figure 5-7 shows a gully which had developed where the runoff from a wheat field accumulated. This gully is a clear indication of uncontrolled runoff in the loess hills causing land degradation, which may also lead to severe off-site damage. This comparison showed that also in the Varzob test area, the hot/bright spot map reveals differences in the state of land resources at a remarkable level of detail.

5.5 Integral aspects of sustainable land management

5.5.1 Indirect and direct drivers, the agricultural system and human well-being during different periods of time

Three specific time periods can be distinguished for the rainfed areas of central Tajikistan, each characterized by its own indirect and direct drivers of land use change, ultimately leading to changes in the state of natural resources providing the basis of the agricultural system. An illustration of the main issues is provided in Figure 5-8.

The period 1960s – 1991

In the Soviet Union, driving forces of land use change were mainly determined by the centrally managed planned economy (Figure 5-8). New directives were adopted in a top-down approach and implemented by the collective and state farms. In the 1940s to 1960s, not only in the Soviet Union, but also in the Western hemisphere and in many developing countries, great efforts were undertaken to increase outputs from the agricultural sector. Land evaluation focused on the identification of cropping systems which promised maximum outputs in a specific agroclimatic zone. The Soviet term used for this maxim was “rational use of land”. On the irrigated areas which had been developed in the Southern parts of the country (Khatlon Oblast[37]), production of monocultural technical crops, in particular cotton and tobacco, was dominant. These crops were produced for export to other Soviet republics.

[37] Oblast is the Russian term for “province”.

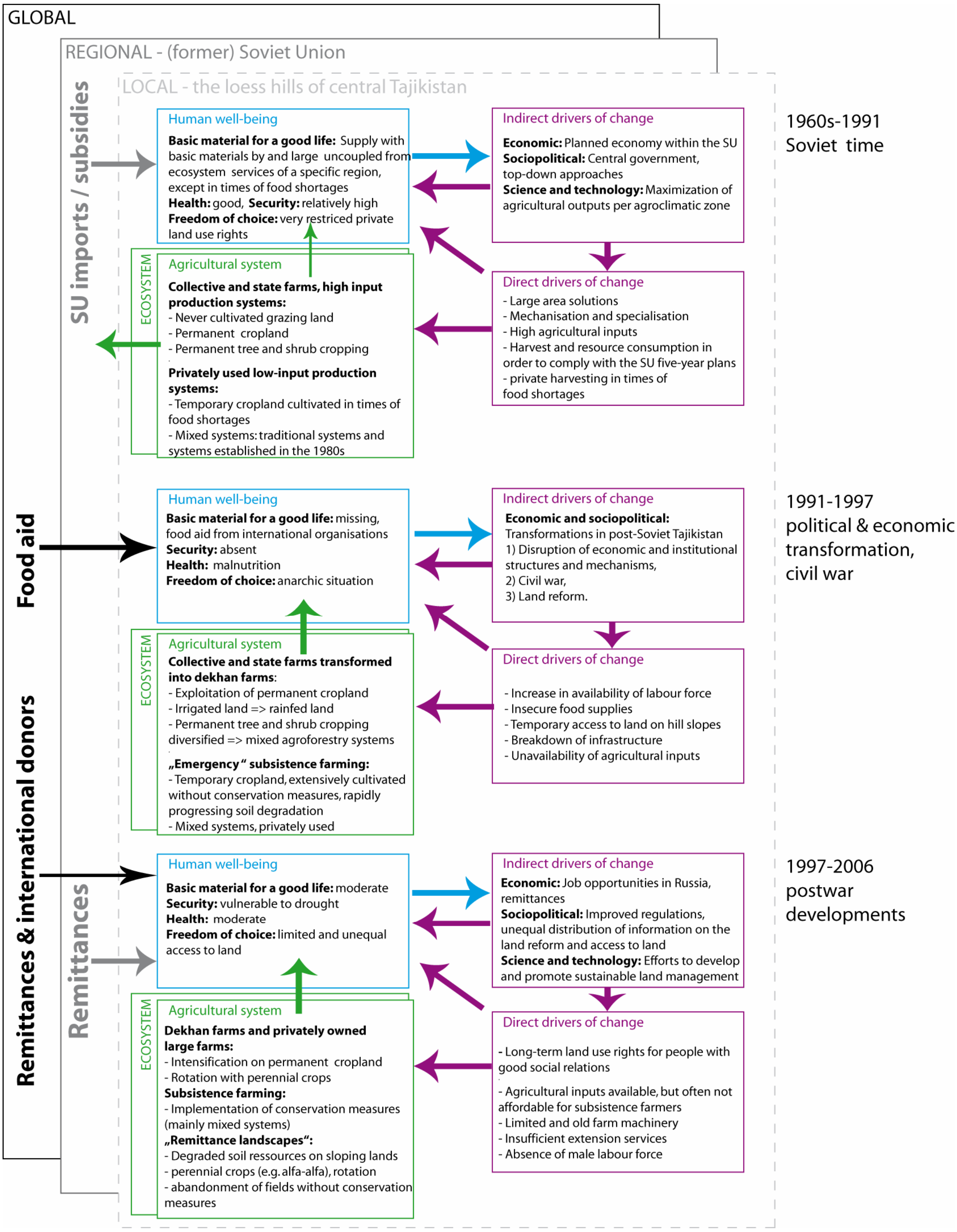


Figure 5-8 Interactions between indirect and direct drivers, the agricultural system and human well-being for the time periods 1960s-1991, 1991-1997, and 1997-2006 (MA 2003).

In the hill zone, traditional agriculture had consisted of a well balanced system of wheat plots, fruit production and grazing areas. Following the "rational use of land" maxim, cereal production was concentrated on large fields in the more fertile valley floors of the hill zone and land use on the hill slopes was restricted to grazing (Badenkov et al. 1994, Merzliakova & Sorokine 2001). While grazing lands at moderate distance from settlements were used by the local collective and state farms, grazing lands at higher altitudes were used for seasonal grazing by herds of collective and state farms from Khatlon Oblast.

In the Soviet economy, human well-being in a specific Soviet republic was by and large uncoupled from the local ecosystem services. This was reflected by the high grain imports to Tajikistan, that secured food supplies: As a consequence of the development of cotton and tobacco monocultures, cereal production was low in Tajikistan and cereals were imported to a large part from other Soviet republics. In 1987/88, 84% of the Tajik cereal demand was covered by imports from other Soviet republics (World Bank 1992 cited in Herbers 2006). Further, Tajikistan was the Soviet republic that profited most from subsidies, for example through cotton export, which was heavily subsidied in the 1960s and 1970s (Patnaik 1995). In general, Tajikistan was highly dependent on budgetary support from Moscow (ADB 2001).

However, planned economy and production was not always able to cover the food needs. Exploitation of natural resources was common in the Soviet Union. The impacts on ecosystem services, which have been interpreted as a result of depleted soil resources, included an incisive crop failure in parts of the Soviet Union in 1963 (Herbers 2006, p. 112). An important pillar of food and income security of the rural population in the Soviet Union was provided by plots in the vicinity of villages, which were used for private purposes (*priusadebny uchastok* – Russian for ‘plot close to the homestead’) (Paitnak 1995, Merzliakova & Sorokine 2001). Production on these plots was supported, merely tolerated in spite of official rules, or outright restricted by the government, depending on the overall state of food supplies (Giese 1983). Even though the relevant fields were located on the highly erodible loess deposits and on slopes, it must be assumed that cultivation was conducted without conservation measures. This is also documented by the Corona imagery available from 30 May 1970, which shows no indications of vegetative or structural measures, such as bunds or terraces (chapter 2). For some fields, even up-down plough direction was visible on the Corona images.

In the Soviet Union, a great deal of attention was paid to monitoring the state of land resources and ecosystem services (e.g. yield, soil loss). Monitoring activities included inventories and research on land resources, and resulted in a large volume of well-documented and published datasets, maps as well as descriptive information (Stolbovoi & McCallum 2002). These materials served as a basis for decision making, and especially for the elaboration of the five-year plans for agricultural production, which was conducted at the national or even regional levels.

In response to land degradation, efforts to improve the high-input production systems were redoubled. Under the leadership of Leonid Brezhnev (1964-1982), the agricultural sector in the Soviet Union was rapidly industrialized, which included an increase in the application of agrochemicals (Herbers 2006). On grazing land, for example, grass seeds and fertilizers were applied over large areas from the air (personal communication). Efforts to reduce erosion risks on the hill slopes included prohibition of tillage in such areas. A study focusing on the Surkhob valley (150 km Northeast of the Faizabad test area) concluded that between 1949 and 1991, cropland was reduced by 34%. However, large abandoned areas subsequently constituting poor pastures were still severely affected by erosion (Merzliakova & Sorokine 2001). Additional strategies to maximize outputs from agricultural production in rainfed areas focused on the establishment of standardized conservation systems. The hill slopes were terraced over large areas (cf. section 5.6.1) using machinery. In Faizabad district, fruit orchards (mainly apple but also almond and grapes) were established. In Varzob district, terraced areas were afforested preferentially. These measures capitalized on the potential of natural resources in the area and improved the state of natural resources. In many areas with tree and shrub cropping, this effect can still be observed today.

An initiative of the Tajik government dating back to the 1980s aimed at supporting the establishment of private gardens in areas that were not used by the collective and state farms. Discouraged by the degraded state of the land that was made available, however, not many families profited from this opportunity. Nevertheless, in Varzob and Faizabad districts, examples have been documented of private initiatives converting degraded grazing areas into well conserved fruit, fodder and also vegetable plots (Bühlmann 2005, Ergashev et al. 2007).

Thus, the agricultural systems in the hill zone of central Tajikistan mainly consisted of three land use systems operated by the collective and state farms: permanent annual cropland (on the valley floors and plateaus), grazing land (on the hill slopes) and, since the 1970s, tree and shrub cropping systems often established on previously terraced land on slopes. There was private land use on pre-existing or newly established fruit and fodder plots, and in times of food shortage, on temporarily cultivated cropland on hill slopes.

The period 1990-1997

The Republic of Tajikistan became independent in 1991. The economic and socio-political transformations triggered by independence caused abrupt changes with regard to the drivers of land use change. On the one hand, the collapse of the Soviet planned economy led to the cessation of industrial plants in Tajikistan, which released many workers with no other employment opportunities than in the agricultural sector. The employment share of agriculture increased from 45% in 1990 to 65% in 2000 (ADB 2004). Furthermore, economic relations to other former Soviet republics were cut, and subsequently grain imports decreased rapidly. On the other hand, a struggle for power within Tajikistan resulted in civil war (1993-1997). Altogether, this left many households in extremely difficult situations, including high food insecurity (ADB 2001). The government hoped to overcome these problems by providing private land use rights to farmers. First land reform efforts date back to 1989. After independence, increased efforts led to the 'Law on Land Reform', which was passed in 1992. During civil war, poverty and food scarcity were counteracted by means of two presidential decrees (1993 and 1995) temporarily allocating land of the collective and state farms to rural families (Porteous 2003).

Thus the period from 1991 to 1997 was characterised by high pressure on soil resources. The expansion of cropland to hill slopes primarily included areas which had been temporarily used as cropland during Soviet times as well, the *priusadebny uchastok.* This expansion of cropland was inevitably at the expense of grazing land, thus increasing stocking rates and also pressure on the grazing land systems (Gomart 2003). Cereal production on the slopes was seen as an emergency measure, as it had been during Soviet times. Furthermore, agricultural machinery, spare parts, fuel, seeds, seedlings, fertilizer and herbicides were either not available or not affordable for rural families. Thus, soil resources were generally heavily exploited and implementation of conservation measures was neglected. However, the changes in actors and land use rights also created new potentials with regard to changes towards more sustainable land management. Already in the early 1990s, the land reform resulted in first transformations of state farms into dekhan farms. These dekhan farms, even though still organised much as in Soviet times, were now taking independent decisions on land management. Orchards, vineyards and afforestations established during Soviet times were transformed into agroforestry and mixed systems, allowing cereal, fruit and also hay production while at the same time conserving natural resources (Sanginov & Wolfgramm 2007).

Overall, the state of natural resources was negatively affected. A rapid decrease in fertility was reported (Sadikov 1999), especially for the rainfed hill zone. The impact on ecosystem services was severe. Yields were low, and also provisioning of food was low. Human well-being deteriorated rapidly, foremost due to food insecurity. Thus Tajikistan became dependent on international food aid, for example through the World Food Program (WFP), ending only in June 2007 (WFP 2007).

The period 1997-2006

The land reform process was an important driving force of land use change in the post-war period. On the one hand, land legislation was complemented. Between 1997 and 2004 a great number of resolutions and decrees regulating land reform, farm reorganization, enterprises, transactions and land management were adopted (Giovarelli 2004). By 1995, there were several types of access to land for private farmers, ranging from land lease to fixed term land use rights and life-long inheritable user rights (Giovarelli 2004). This permitted the establishment of a category of individual actors in the agricultural sector aiming at investing into agriculture. On the other hand, there was an evident lack of distribution of information among rural actors about the procedures of obtaining access to land (Nissen 2004), as well as a lack of transparency regarding the reorganisation of state farms (Duncan 2000, Giovarelli 2004). Overall, implementation of the land reform was slow, as an audit by the Tajik Land Committee confirmed, and this is also true for the two districts in which this present study was conducted (Faizabad and Varzob) (Land Committee 2004). An explanation of the inadequacies of the land reform process was given by the chairman of the State Land Committee (D. Gulmahmadov, Chairman of the State Land Committee, cited in Nissan 2004): The government had hoped that a privatised agricultural sector could efficiently cover a large part of the country's basic food needs, and therefore had rapidly launched the land reform. This insufficiency in planning gave rise to a situation in which it was mainly well educated and socially influential individuals that profited from the new legislation (Gomart 2003). These persons took control of large tracts of land. Sometimes they subsequently rented out land to other farmers (Nissen 2004).

The availability of (seasonal) job opportunities in Russia also played an important role. Among young rural men, migration was (and is) very common: It was estimated that in 2004 about one million Tajik people were working abroad, mostly in Russia (FAO 2005). Thus remittances constituted a considerable part of many rural households. However, many migrants worked illegally on construction sites and in retail markets. On 1 January 2007, new laws came into force in Russia that stipulated heavy punishment for firms employing workers without work permits[38]. Thus job opportunities in Russia became highly uncertain and in the future (beyond 2006) it remains to be seen whether migration will be an option for as many people as it has been to date.

In line with changing indirect drivers, the direct drivers and the agricultural systems also changed. Newly created large private farms (individual dekhan farms) in the rainfed areas were located mostly on the valley floors with little risk of erosion. Financial resources of the owners of such farms allowed resumption of intensive agricultural production, involving fertilizers and pesticides and intended for sale. In contrast to this, even today subsistence farmers often lack long-term land use certificates, and their access to machinery and other agricultural inputs is limited due to the insufficiency both of their financial resources and of their social relations. Widespread migration led to reduced workforce availability, and at the

[38] E.g. World Peace Herald on-line, published on 23 January 2007 by Michael Mainville: Russia cracks down on illegal immigration (http://wpherald.com/articles/3139/1/Russia-cracks-down-on-illegal-immigration/Moscow-limits-foreign-labor-to-fight-illegals.html).

same time to additional household income from remittances (Li 2007, [UNIFEM]). Both resulted in abandonment of formerly cultivated land on hill slopes. Depending on the soil quality of abandoned plots and whether additional efforts were undertaken to re-establish perennial vegetation (grasses or even fodder crops such as alfa-alfa or lucernes), soil erosion was subsequently reduced or even halted, with the potential for regeneration of soil resources, or else soil erosion continued or even increased (cf. section 5.4.2). Whether the term "remittance landscapes" as described by Hostettler (2007) indeed applies to the resulting landscape in the hill zone of central Tajikistan can not be definitively answered with the present study. It is likely that more than 50% of remittance-receiving land users abandoned cereal cultivation on hill slopes. The results presented in section 2.5.4 support this assumption, as more than 50% of the temporarily cultivated plots were abandoned in the years 2004 and 2005. This process constitutes a remittance driven change from cropland to grazing land. Additionally, during the field survey examples of crop rotation (wheat – fodder production – wheat) were encountered. For a number of temporarily cultivated cropland plots on hill slopes, implementation of low-cost soil conservation measures has been documented (Bühlmann 2006). As shown in a case study of a village in Kyrgyzstan, remittances were primarily used to satisfy daily needs such as food and clothes, but also covered medical expenses, if necessary (Bichsel et al. 2005). In general, a similar pattern of spending remittances is assumed to apply to Tajikistan, and thus little investment into agriculture was assumed. Further research would be required to obtain a more detailed picture with regard to the utilization of remittances and possible investments into sustainable land management.

5.5.2 Perceptions of different stakeholders

Stakeholders at all levels were concerned by the widespread degradation in the hill zone of central Tajikistan. The land use changes as well as the changes in agricultural actors in the Tajik foothills were apparent and widely discussed. In the following paragraphs, the dominant perceptions at each stakeholder level are being discussed in the light of the agricultural systems, human well-being and the indirect and direct drivers as discussed in the previous section. The limitations of this simplified way of discussion have been pointed out in section 5.3.2 and should be borne in mind. The areas of most concern are areas on the slopes which show most degradation (cf. section 5.6.1). Thus in this list, the dekhan farmers as stakeholders are missing, as they are mostly cultivating land easier to conserve, on the valley floor, or where conservation systems have been implemented in Soviet times.

When talking to ***farmers and people active at the community level***, the general notion was that one of the main reasons for unsustainable land management was lack of resources. Resources included financial means for spare parts, fuel, seeds and fertilizer/herbicides, but also access to land which would be more appropriate for cereal cultivation than the fields on the hill slopes: *"On the plots in the hills around Karsang you can not get any yield if you are not applying fertilizer"* (Members of the Karsang Workshop 2005). The statement likely resulted from a variety of factors. First, there was the faith in technological solutions. In Soviet times, many members of households who since the 1990s have been engaged in subsistence farming, had formerly been employed on collective and state farms. As such, they took part in the modernisation of agriculture involving mechanisation and development towards agricultural high-input systems. As Liechti (forthcoming) showed for pasture management in Kyrgyzstan, the maxims of Soviet agriculture are also reflected in today's perceptions. If this is also true for the farmers in Tajikistan, it would explain why farmers now see the main problem of declining yields and land degradation as a consequence of the financial and technical limitations of their land use systems. Further, the fields in the hill zone were perceived to be of low fertility, and obviously greater efforts are required to successfully cultivate these plots than on the valley floors. For many households, however, it was only possible to gain access to fields in the hill zone. Thus, farmers felt that the difficult ecological condition of their fields was an additional burden which required additional resources, which they lacked: *"Most villagers were unsure whether they would cultivate the land they had received, since it would take considerable water, fertilizer, and labour to prepare it"* (Gomart 2003). Finally, rural households have been dependent on land use decisions taken at higher levels during Soviet times and until today. In Soviet times, land management was organized mainly in a top-down approach. Not only decisions but also the means to achieve land use changes were provided by governmental bodies or the collective and state farms. In recent years, many rural households relied on food aid. Thus, the farmers' arguments must also be seen in the context of their expectation that they would be provided with the necessary means from outside.

In contrast, the perception of ***local authorities and local researchers*** was that unsustainable land management on the temporarily used land in the hill zone was due to inadequate agricultural knowledge of the "new farmers", the households engaged in privately cultivating land since the 1990s: *"Another constraint is that Tajik farmers have lost much of their agricultural skills and know-how, partly because Russians were in charge of farm production during the Soviet era, and partly because of inactivity during the five-year civil war. Farmers no longer know the range of crops they can grow, how to irrigate the fields and when to seed and harvest, Mr. Gulmahmadov says" [Davlatsho Gulmahmadov, Chairman of the State Land Committee]* (Nissen 2004). As in Soviet times, land evaluation, land management planning and actual field work were each conducted by governmental institutions and specialised staff of these institutions or the collective and state farms, the general notion being that the non-specialised farmers did not have the required knowledge. However, in contrast to this perception there is the fact that in periods of food shortage, private cultivation always greatly contributed to food security. Farmers themselves mentioned that private cultivation of land had not been something completely new to them, but that they had always cultivated small private plots (Winnig 2005). The results from a study conducted in the Pamir (Tajikistan) showed that there were no significant differences regarding knowledge of land management opportunities among the different stakeholder levels. From an external perspective, the level of knowledge of SLM was satisfactory and unlikely to constitute an obstacle to the implementation of SLM (Breu 2006). It is likely that this also applies to the situation in central Tajikistan. The study conducted in the Pamir provided evidence of the fact that communication between the stakeholder levels, particularly among the Tajik stakeholder levels, does not work properly, even today (Breu 2006). Thus, ways should be found to transfer knowledge efficiently among different stakeholders.

International organisations see private land use rights for rural households as an important step on the way to poverty alleviation, and also as a precondition for sustainable land management: *"The benefits of secure tenure include: increased productivity and investment, facilitation of the transfer of land from less efficient to more efficient uses, reducing the occurrence of land disputes, increasing the availability of credit, reducing environmental degradation to land, and creating political and social stability"* (Giovarelli 2004). International organisations have been following the land reform in Tajikistan closely, as the large number of reports published by international organisations between 2000 and 2006 shows: Rural Development Institute (Duncan 2000), United Nations Development Fund for Women (Sabates-Wheeler 2002), Action Against Hunger (Porteous 2003), United States Agency for International Development (Giovarelli 2004), United Nations Development Fund for Women (UNIFEM 2005), and Agha Khan/Mountain Societies Development Support Program (Robinson et al. 2006). The land reform process has not been completed yet, and will thus remain an issue of major relevance for the rural population in the coming years. However, while secure private land use rights have the potential to contribute to the general conditions required for furthering implementation of sustainable land management, private land use alone will not guarantee SLM. Furthermore, examples of privately established conservation systems show that secure land use rights were not a precondition for such efforts (Ergashev et al. 2007).

In summary, the main issues at stake are (i) resources influencing direct land use, (ii) knowledge of SLM and (iii) aspects of access to land and land use rights. It appears that the maxims of Soviet land use and land use planning are strongly reflected in the arguments used by the local stakeholders. While for the (subsistence) farmers it is resources and technological aspects that are foregrounded, for authorities it is the scientific achievements in land use planning, which are attributed to Soviet times when planning was conducted in a top-down approach. Even the international stakeholders might be influenced by their reflections on land use in Soviet times, in that they focus on present-day degraded lands and ignore the achievements of the planned economy with regard to the implementation of conservation systems, thus implying that private land use rights are a precondition for improving land management in the area today.

5.6 Towards sustainable land management

5.6.1 Area statistics as a basis for setting priorities

Figure 5-9 presents area statistics for the 4 different degrees of soil degradation and conservation, for the Varzob test area to the left and for the Faizabad test area to the right. Spatial units were distinguished with regard to slope classes and land use types (cf. section 5.3.1). As pointed out before, the situation with regard to the distribution of slope classes was different for the Varzob and Faizabad test areas: slopes flatter than 14% cover 881 ha in Varzob, but twice as much, namely 1789 ha, in Faizabad. The same was true for moderate to steep slopes (14-36%), which cover 4211 ha in Varzob and 2425 ha in Faizabad. The very steep slopes, however, cover a larger area in Faizabad (4766 ha) than in Varzob (3538 ha).

The erosion occurrence model classified slopes < 14% as not affected by erosion, so that in the area statistics this slope class only showed stable and bright spot areas. As discussed in section 5.4.2, this is probably an over-optimistic rule for cropland. But severity of erosion is in any case likely to be less on slopes < 14% than on slopes > 14%, also on cropland. Slopes flatter than 14% showed a similar pattern in both areas with regard to area coverage by land cover types and with regard to classification as stable or bright spot areas, even though in Faizabad coverage is always around twice as large as in Varzob: the largest proportion of area was used as cropland, followed by grazing land and tree and shrub cover. As rangelands are unlikely to occur on flat slopes, the area with tree and shrub cover is assumed to be under tree and shrub cropping. For the “cropland” and “tree and shrub cover” land cover types, bright spot areas were larger than stable areas. As for grazing land, stable areas dominated over bright spot areas. The results show that (i) the largest possible number of flat slopes among the areas with high soil quality are used for annual cropland, which is by and large well conserved, (ii) many well conserved tree and shrub cropping systems are maintained on flat slopes, and (iii) mostly areas with low soil quality are used as grazing lands. Such grazing lands included marginal areas such as on the alluvial cone situated South of the Iljiak River in the Faizabad test area, as well as heavily compacted animal paths running along the ridges.

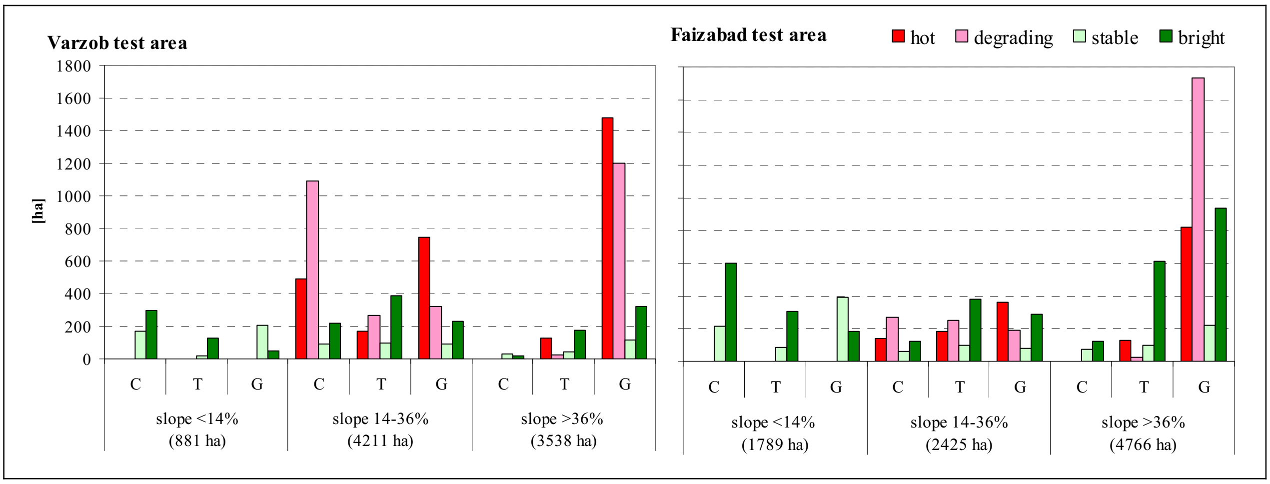


Figure 5-9 Area statistics for bright spot, stable, degrading and hot spot areas. Abbreviations: C=cropland, T=tree and shrub cover, G=grazing land

As for moderate to steep slopes (14-36% slope steepness), the area coverage differs considerably for the Varzob and Faizabad test areas. But with regard to proportions of hot spot, degrading, stable and bright spot areas for each land cover type, the two test areas are still comparable. In Varzob, cropland dominates these moderate to steep slopes. Area statistics confirm that erosion risk is high for such areas: Almost 1100 ha of the Varzob test area were classified as degrading cropland areas and another almost 500 ha as hot spots. The extent of well conserved cropland is considerably smaller, covering only around 200 ha. On grazing land, hot spots account for the largest proportion (around 750 ha). However, as for tree and shrub cover, the areas classified as bright spots dominate, covering almost 400 ha. Also in Faizabad, degrading areas dominate on cropland, bright spots on areas with tree and shrub cover, and hot spots on grazing land. However, the area proportion of moderate to steep slopes used as cropland is much lower in Faizabad than in Varzob.

Grazing land clearly prevails on very steep slopes (> 36%) in both test areas, and erosion is widespread. While in Varzob the largest proportion of areas was classified as hot spots (almost 1500 ha) followed by degrading areas (1200 ha), in Faizabad the largest proportion was classified as degrading (over 1700 ha) followed by hot spots (800 ha). Possibly the higher SOC content can be explained with the high altitude; grazing land in Faizabad is situated at considerably higher altitudes than in Varzob test area (cf. section 4.4.1). Besides these large areas showing degradation, there is also some grazing land classified as bright spots, especially important in the Faizabad test area (over 900 ha). Significant bright spot areas were further identified for tree and shrub cover: in Faizabad this class accounted for 600 ha of land. The very small proportion of cropland that had been identified for the very steep slope class was all perennial cropland with high FVC throughout the year.

The following large areas where degradation is widespread, and for which therefore conservation strategies should be developed are:

- In terms of area, grazing land is most important on very steep slopes. As the hot/bright spot matrix indicates, most areas classified as degrading or hot spots are grazing land with medium or low vegetation cover. Further area statistics showed that grazing lands with medium FVC cover 29% of the study area, but account for 57% of all hot spots and 34% of all degrading areas. Thus, if the area extent of land degradation is to be reduced, grazing land with medium vegetation cover will clearly have to be the main target of land management planning.
- Grazing land on slopes with 14-36% steepness is also subject of widespread and strong degradation, with almost half of the grazing land sites in this category being classified as hot spots.
- Conservation measures are urgently needed for cropland on moderate to steep slopes, especially in the Varzob test area. This also includes perennial cropland, which is abandoned annual cropland in most cases. Analysis of the hot/bright spot matrix indicated that abandoned cropland also urgently requires implementation of erosion controlling measures.

5.6.2 Opportunities for sustainable land management

During the last few decades, land use systems in the loess hills of central Tajikistan have been newly established, abandoned, taken up again and transformed during various time periods. The assessment of agricultural systems (cf. section 5.5.1) showed that successful approaches to conservation over the last few decades had been implemented by state and collective farms, newly established dekhan farms and individuals with or without official land use documents. In the present section, emphasis will be given to land management systems currently existing in the loess hills that conserve resources and provide opportunities for application on the degrading and hot spot areas. High-input cropping systems, such as the annual cropland on the valley floors and some large plateaus in the Varzob test area, that were classified as bright spots will not be discussed.

Traditional fruit and fodder plots

Traditional plots for fruit, fodder and cereal production conserve the natural resources and secure high productivity. Such plots are generally smaller than 1 ha and have been traditionally worked by rural families. In the Faizabad test area, farmers explained that these plots had been privately cultivated by their families "in earlier times", some farmers stated that cultivation had "later" (likely in the 1980s) been given up, but that cultivation had been resumed during civil war in the 1990s (personal communications with farmers during the field survey). In the Varzob test area, the plots seem to have been cultivated continuously. The Corona imagery confirmed that both in Faizabad and in Varzob, these plots had been cultivated in the 1970s.

In the Faizabad test area, these plots were located in locations difficult to access, far from the settlements, on narrow plateaus at higher altitudes (Figure 5-10, left). The plots were generally not fenced in. In contrast, in the Varzob test area, the plots were generally located in close vicinity of the settlements and were fenced in (Figure 5-10, right). The contrast between these well conserved plots and the surrounding degraded slopes, which are common grazing grounds, could not be any more distinct. The fruit and fodder plots were generally classified as bright spots (cf. the example in section 5.4.3), but they were sometimes too small to be identified on the Landsat imagery. Information on land use rights during Soviet times and today, together with detailed land management information, is needed to understand in detail the approach and technology used in these conservation systems.

Figure 5-10 Privately cultivated fruit, wheat and fodder plots in Faizabad (left) and Varzob (right) (Photos by Wolfgramm, June 2004 and 2005)

Soviet conservation systems

In the 1970s and 1980s, the collective and state farms in the hill zone increased the rate of establishment of fruit orchards and vineyards, as it was thought to be the most suitable land use system for this particular agro-ecological climate. Pure-stand orchards were most common. During establishment, the land was levelled in many places (Figure 5-11, right), and on slopes exceeding 20% terraces were constructed mechanically (Sanginov & Wolfgramm 2007). Establishment required considerable resources (e.g. machinery, labour), which were provided by the state farms. In the Faizabad test area, primarily apple orchards were established. Many of these systems were established on previously terraced slopes. Slopes which had been terraced but not necessarily afforested, can be found over large areas and also at higher altitudes, where typically grazing lands are the dominating land use system (Figure 5-11, left). It was not ascertained in this study whether it had originally been planned to afforest these slopes. To find out more about these (planned) systems, their problems and opportunities would be an interesting topic for future studies.

Figure 5-11 Terraced slopes in the Faizabad test area used as grazing lands (left) and vineyards on levelled and terraced slopes in the Yavan test area (right) (Photos by Wolfgramm, end of June 2005)

On the hot/bright spot map, these areas were classified as bright spots or degrading areas, depending on whether erosion had taken place on the riser of the terrace. In the Varzob test area, new forests planted during Soviet times are usually situated on slopes with North exposition. In general, the ecological condition on these slopes is more humid, due to comparatively low solar irradiation. In the Varzob test area, North-facing slopes are often highly unstable as well, with frequent landslides (cf. chapter 4). As grapes require sufficient solar irradiation, the vineyards were established on South-exposed slopes. As discussed in sections 4.4.2 and 4.4.3, the hot/bright spot map indicated that soil resources were well conserved in areas in which such systems had been established. In some places, however, subsoil with low SOC content had been moved to the surface during implementation, resulting in low soil quality for the respective systems.

Private plots initiated in the 1980s

During the 1980s the Soviet government supported the establishment of private gardens. This was mainly possible in areas not used by the collective and state farms (Ergashev et al. 2007). Some examples from both Varzob district (Ergashev et al. 2007) and Faizabad district (Bühlmann 2006) have been reported of farmers taking up the opportunity and establishing their own fruit and fodder plots, even if land use rights had not been certified. As implementation of such systems often overburdened a single family, especially labour-intensive work such as terracing was conducted with the voluntary help of relatives and neighbours, a tradition locally termed *hashar* (Bühlmann 2005, Ergashev et al. 2007a).

Figure 5-12 Privately established fruit and fodder plot in the foreground, with fenced-in haymaking plot above surrounded by areas with severe rill and gully erosion; Chinoro, Faizabad (photo by Wolfgramm, 2005)

Just like the traditional fruit and fodder plots, these newly established plots were often smaller than 1 ha and thus sometimes failed to be identified on the hot/bright spot map. If identifiable, these plots were classified – depending on the specific land use / land management – as bright spots or as degrading areas. In the case of large cultivated spaces, such as the one shown in Figure 5–16, the edge of the plot adjacent to a degrading area (cf. Figure 5-12, to the right) would be classified as “degrading area” as well, indicating that it was possible that some erosion processes took place. In this specific case, however, conservation measures as they can be identified in Figure 5–16 (cut of drain above the plot and permanent grass boundary below the plot) would make it possible to control erosion and sedimentation processes.

Diversified Soviet systems

As mentioned above, in the course of the land reform carried out in the 1990s, private land user rights have been adapted, and the amount of privately used land has subsequently increased. Initiatives to use the limited areas with fertile lands in a productive and sustainable way have been reported since. Especially because former state farms are now independently managed as dekhan farms, existing orchards and vineyards have been transformed into intercropping systems (Sanginov & Wolfgramm 2007, Romer 2005). Thus, such conservation systems are widespread and have been established practically in all orchards belonging to dekhan farms. Whether soil is conserved or degradation imminent, depends to a large extent on the specific situation. As in the example above, some of the areas were (correctly) classified as degrading, being areas with high SOC content but showing erosion, as sheet or minor rill erosion may occur on the ploughed parts. But even if there was erosion occurrence, the possible negative effects were by and large under control, as the displaced soil was deposited at the foot of the terrace and could be distributed again while preparing the field for the next season.

Figure 5-13 Diversified vineyard (left) and afforestation (right) (Photos by Wolfgramm, June 2004 and 2005)

Newly emerging SWC systems

Many farmers have adapted their land management in order to conserve soil resources. Most farmers tried to include crop rotations, whether wheat-flax-wheat or wheat-beans-wheat, as well as rotations with fallow periods during which just naturally germinating vegetation grows on the field (personal communication during the field survey and at the Karsang workshop 2005).

Figure 5-14 Slopes with young and old Dulona trees, intercropped or used as haymaking areas, on North exposition (right) and on East exposition (left) (Photos by B. Wolfgramm, June 2005)

Bühlmann (2006) assessed 4 low-cost conservation measures which had been implemented by farmers on their annual cropland. These case studies, all located in the Faizabad test area, covered (i) poplar trees on field boundaries to stabilize the land after it had been levelled, (ii) maintaining a grass strip between two wheat plots, in order to reduce run-on onto the lower field, (iii) cultivation of perennial fodder plants such as alfa-alfa, and (iv) graded drainage ditches on steep wheat plots to divert excessive rain water. Agronomic and structural measures were not detected on the hot/bright spot map. Often these measures had not been implemented long enough to affect the SOC content by the years 2000 and 2002, when the Landsat images used in this study had been recorded. Thus, these areas were generally classified as degrading areas or even hot spots.

In addition, examples of newly established orchards were observed during the field survey. Furthermore, on many fields naturally germinating Dulona trees had not been removed, but were regarded as a stabilizing element on the field and as future fuel wood. Dulona trees are the most widespread naturally growing tree species in the study area (cf. section 2.2.1). The Dulona tree seems to grow spontaneously very well, especially on North-oriented slopes, and younger trees were frequently observed. Possibly, the frequency of young Dulona trees (1-2 m in height) observed in 2004/2005 was due to re-growth of Dulona trees since the late 1990s. During the civil war (1993-1997) wood logging had been widespread, but was generally stopped when other fuels became available again on the markets. Taking into consideration the high instability of the North-oriented slopes, “low-cost” afforestations with Dulona trees, providing both firewood and fruits, appear to be an opportunity for conservation worthwhile to be further investigated.

5.7 Conclusion

Interrelations between land cover / land use and soil resources

The results of the exploratory correlation analysis conducted confirmed that for grazing land fractional vegetation cover, especially in May, was negatively correlated with erosion and positively with SOC content. The Spearman correlation coefficients indicated low correlations, but were significant at the level of $p < 0.05$ and were also consistent for both test areas. For cropland the results were less homogeneous, which must be attributed to the high variety of land cover types subsumed (annual and perennial cropland, as well as cropland with tree and shrub cover). While not all sub-groups showed significant results, trends were nevertheless consistent (positive correlation between FVC and SOC content, and negative correlation between FVC and erosion). Compared to the results of the correlation analysis between soil indicators and topographic factors presented in section 4.4.1, the correlations between FVC and soil indicators were more marked, thus reinforcing the strong influence of vegetation cover on soil resources.

When linking land cover classes with the degree of soil degradation and soil conservation in the hot/bright spot matrix, the same pattern was reflected at the level of the land cover classes: There were strong indications for interrelations between high perennial FVC, low erosion occurrence and high SOC content, and accordingly between low perennial FVC, high erosion occurrence and low SOC content. This pattern did not apply to slopes < 14% and mountainous locations, where other degradation processes or inherently low SOC content were expected. Thus, land cover classes have a potential in providing information needed to separate areas with inherently low SOC contents from areas where low SOC contents are management induced. Furthermore, the results showed that sub-classes of a specific land cover type (e.g. annual cropland) may differ strongly, highlighting their singularity with regard to erosion occurrence and SOC content. However, the high within class variability of SOC and erosion did not allow determination of significant differences for any of the land cover classes.

Thus, this study provided good indications on certain erosion controlling factors (e.g. fractional vegetation cover as such, specific land cover types, and slope steepness) and interrelations with SOC content, but the full range of controls affecting variability of SOC content and their specific influence has not been determined yet. Based on the results obtained so far, additional controls to be included in future assessments are land use history, land management, as well as further indicators allowing determination of where SOC content is inherently low. These issues are further discussed in chapter 6.

Maps and inventories supporting planning of sustainable land management

The land cover maps, elaborated on the basis of satellite images, showed some drawbacks with regard to the identification of soil conservation systems: While spatial resolution is too coarse to identify e.g. intercropping systems, especially so if tree cover is sparse, the resolution is fine enough to depict a variety of land cover classes on a single field. E.g. depending on the amount of weeds in a specific corner of the field, pixels were classified as annual or perennial cropland or even as grazing land with medium fractional vegetation cover. In contrast, the hot/bright spot map, based on soil information (erosion occurrence and SOC content class maps), was less influenced by the heterogeneity of the given land cover, and gave a more homogeneous overall picture of the land resources. Thus, the level of detailed provided by the hot/bright spot map is likely to be highly useful for future planning of sustainable land management on field plot basis.

Areas with fractional vegetation cover > 75% were classified by the SOC content class model as showing high SOC content. As indicated by the visual comparisons between the hot/bright spot map and various land use systems (section 5.4.3), and also between the hot spot map and conservation systems (section 5.6.2), this threshold seems to be very effective in identifying well conserved soils and non-degraded land in general.

Changes in the agricultural system of the loess hills over the last decades

Over the three time periods referred to – the Soviet period (1960s-1991), the period of political and economic transformation and civil war (1991-1997), and the post war period (1997-2006) – the agricultural system in the loess hills of central Tajikistan changed in accordance with changes in human well-being, and indirect as well as direct drivers. The historical reconstruction of these changes was crucial to establish a better understanding of the observed land cover / land use changes and their interrelations with soil resources. The main conclusion is that annual cropping on the slopes in the loess hills appears to have been an emergency measure, in the 1990s and also in Soviet times. Thus, soil resources of temporary cropland on slopes were exploited without planning or implementing of conservation measures. Degradation was thus inevitable, but appears to have been mainly attributed to cereal cultivation on slopes. Subsequently, in order to stop degradation, cultivation was prohibited in the 1980s, and today there are efforts going in the same direction. However, it has been reported that in Soviet times, as today, erosion processes often continued on abandoned fields and that such areas provided low-productivity grazing lands only (Merzliakova & Sorokine 2001). From 1997 to 2006, a tendency towards "remittance landscapes" was manifest for the slopes in the loess zone: Seasonal migration, mainly of young men, was providing many households with remittances, which again made it unnecessary to continue cultivating the already degraded fields on hill slopes.

Enhanced understanding will be especially helpful in planning of more detailed studies targeted at concretisation and implementation of sustainable land management. Three main points were considered important for future sustainable land use planning:

- Low-input conservation systems are needed that comply with the resources available to subsistence farmers;
- There should be more extensive exchange between stakeholders at different levels, in order to share and broaden knowledge on sustainable land management and to negotiate on and to coordinate actions, in which the maps produced could play an important role;
- Sustainable land management and especially rehabilitation of degraded areas can not only be the responsibility of subsistence farmers, who have no other option (i.e. no access to other land) than to cultivate the easily degrading slopes. Watershed projects, which involve communities as a whole in planning of SLM and implementing of conservation measures, could have a more immediate effect in improving land resources than providing individuals with access to land.

Risks and potential of the loess areas, opportunities for SLM

Based on area statistics, the following large degrading areas were identified, for which therefore conservation strategies should be developed: Grazing land on very steep slopes (> 36%) covers large areas, usually with medium fractional vegetation cover. Also on grazing land on moderate to steep slopes (14-36%) degradation is severe and widespread, with almost half of the grazing land sites being classified as hot spots. However, on moderate to steep slopes, degradation is equally important on cropland in terms of area affected. As discussed above, for cropland on these slopes a trend towards remittance landscapes was identified, with many fields left fallow without conservation measures, which causes ongoing land degradation.

In contrast to the widespread land degradation, it should be noted that the potential for improved management of loess areas is considerable, as also examples from China show: Over the whole Chinese Loess plateau, approximately 73,350 km^2 of erosion prone slopes have been conserved by terraces. In an average rainfall year, crop yields on terraced land are more than three times higher than they used to be on unterraced, sloping land (Yaolin et al. 2007).

For the loess hills of central Tajikistan, local opportunities for sustainable land management have been identified in this study: Successful approaches to conservation were implemented over the last few decades by state and collective farms, newly established dekhan farms, and individuals with or without official land use documents. Markedly lower SOC content levels were observed for areas with temporary crop cultivation, where cultivation was widespread during the 1990s and has now frequently been abandoned again. On the other hand, there were strong indications as to afforestations and fruit orchards established in the 1980s being successful in conserving soil resources, also when transformed into intercropping systems. The sites with well conserved soil resources could be classified into the following agricultural systems: fruit, cereal and fodder plots, either traditionally cultivated or newly established during the 1980s; large area conservation systems implemented in Soviet times and diversified into agroforestry systems during the 1990s; and more recently, mainly agronomic conservation measures on cropland.

6 Synthesis and recommendations

This chapter synthesizes important issues raised in the previous chapters. Specific aspects of the land degradation and conservation assessment conducted in this study are reconsidered and discussed. Recommendations for planning of sustainable land management, for future land degradation assessments and with regard to future research are provided.

6.1 Interrelations between land cover / land use and soil resources

The key question addressed in this thesis was whether it was possible to determine land cover classes which would characterise the impact of land use on soil resources in such a way as to highlight a typical interrelation between erosion, as the dominant soil degradation process, and soil organic carbon (SOC), as an integrative soil quality measure. Different methods were applied which helped to explore and analyse the links between characteristics of land cover on the one hand, and erosion and SOC on the other. They included (i) semivariogram analysis, providing insights into the spatial structure of the variance of these indicators, (ii) Spearman rank correlation tests, (iii) the interpretation of classification tree models, and (iv) a graphical analysis applying the hot/bright spot matrix. All results obtained confirmed that links between land cover and soil resources are strong. The analysis revealed trends and thresholds which are of importance with regard to SLM planning. Here below, the main results contributing to an improved understanding of the aforementioned interrelation are synthesised:

Semivariograms of two field indicators and two indicators derived from raster data were compared including erosion occurrence and SOC content, slope steepness (10 m pixel resolution) and fractional vegetation cover (FVC) as indicated by the optimised soil adjusted vegetation index (OSAVI) derived from the Landsat ETM+ image recorded in May 2002 (30 m pixel resolution). The spatial structure of variance was highly congruent with regard to all indicators. This similarity can be interpreted as an indication of the processes influencing FVC, erosion and SOC content occurring at similar spatial scales, and of these processes also being linked to slope steepness.

Spearman rank correlation tests revealed that the links between soil indicators and vegetation cover were distinctly stronger than those between soil indicators and topographic factors. Correlations were generally stronger between FVC and SOC content than between FVC and erosion, and were stronger for grazing land than for cropland. These observations could be interpreted as a confirmation both of the importance and of the potential of well managed vegetation cover, especially on grazing land.

As discussed in chapter 1, land degradation processes are often vicious circles and it is thus crucial not to exceed a certain degree of degradation beyond which accelerated degradation must be expected. With regard to this issue, the identification of thresholds can be of great value. **Classification tree models** provide statistically based, hierarchically organized rules. Thus, classification trees allow interpretation of physical processes, even more so if meaningful variables are used as model input. Information derived from satellite imagery can be more easily interpreted if linked to ground observations. OSAVI values from the May image were regressed to fractional vegetation cover (FVC) determined by visual observation in the field (chapter 2). The calibrated OSAVI values were especially useful when subsequently interpreting results of classification tree modelling, both for erosion (affected / non-affected) and for SOC content class (low / high): From the 22 input variables used, FVC in May was selected as the one most effective in distinguishing both erosion non-affected sites and sites with high SOC content (SOC > 1.1%). While FVC in May must be higher than 87% for a significant reduction of erosion risk to be expected, an FVC > 72% was sufficient for SOC content to be classified as "high". Assuming that accelerated land degradation is linked to reduced FVC, which in turn leads to increased erosion and subsequently to reduced SOC content, with low SOC content subsequently limiting vegetation growth (due to its negative effects on nutrient exchange capacity) and further accelerating erosion (due to the generally observed increased erodibility of soils with low SOC content), the threshold of 72% FVC could be critical with regard to land management. Hence, it maybe ought to be applied as a general rule to the effect that if end-of-May FVC on a specific site is higher than 72% (or for practical reasons 75%), SOC contents are likely to be maintained at a level that is higher than 1.1%. Further, it could be expected that even for sites showing (some) occurrence of erosion, FVC > 72% in May would indicate that the vicious circle described above had not started yet. In order to support land users more effectively, more such rules applying to different stages of the vegetation cycle would be needed.

The graphical analysis conducted using the **hot/bright spot matrix** provided information at the level of land cover classes and their interrelation with erosion and SOC (chapter 5). Even though it had to be concluded that the land cover classes determined in this study could not sufficiently explain variability in erosion occurrence and SOC content, the specific patterns for erosion and SOC content observed at the level of land cover classes highlighted the potential of such an approach. Land cover classes, which are assumed to reflect present and past land use, may be promising with regard to bridging the gap between land cover (observed from space) and land use (directly impacting on soil resources). However, before such land cover classification could become useful for determining the effect of land use on soil resources, a land cover classification would have to be elaborated which links land cover and land use more closely than in the study presented here. When applying classification tree modelling, more accurately characterised land cover classes could well be derived by including additional land cover information (e.g. satellite data from various dates throughout the year) as well as further variables potentially determining land use (e.g data on accessibility).

6.2 The potential of land resources in the loess hills of central Tajikistan

Since loessial soils are prone to erosion by water, the general notion in Tajikistan was that the loess hills constituted marginal areas not suited for cultivation. In Soviet times, the aim was to restrict land use on slopes steeper than 10% to grazing and tree and shrub cropping (chapter 2). Thus, the cultivation of slopes in the loess hills during the period of food shortage in the 1990s was unilaterally considered a pure emergency measure and regarded as the cause of spreading degradation. Subsequently, it was generally the aim to stop cultivation of slopes and to revert land use to grazing.

Results of this study confirm that today large areas are affected by soil erosion (46% of the study area) and show a low SOC content of < 1.1% (33% of the study area (chapter 4). Classification tree modelling demonstrated that there was little occurrence of erosion on sites with less than 14% slope steepness. It can be concluded from this that in the study area slopes steeper than 14% are generally more likely to be subjected to erosion processes.

In contrast to the assumptions made at the beginning of the study, cultivation on slopes of the loess hills, as undertaken in the 1990s, was neither a new phenomenon nor, as such, an expansion of cropland to grazing lands. A comparison with Corona satellite imagery showed that in 1970, cultivation in the loess hills on slopes steeper than 10% was widespread. Furthermore, the visual assessment showed that the location of fields on the slopes was much the same as during the field survey in 2004/2005 (chapter 2). Literature confirmed that at least until the 1970s, that is even under the Soviet planned economy, cultivation of sloping land was common, foremost for domestic use in times of low wheat yields within the Soviet Union (chapter 5). According to the visual interpretation of the Corona images, also in 1970 no conservation measures had been applied on cropland. It was therefore concluded that, even though cultivation systems traditionally extended over large areas including remote fields on slopes at higher altitudes (Merzliakova & Sorokine 2001), even during Soviet times cultivation on the slopes of the hill zone seems to have been considered primarily an emergency measure. Thus, it was not the aim to make such cultivation more sustainable, but rather to abandon cultivation altogether. Furthermore, even though annual cropping was re-expanded to the hill zone repeatedly, for the last time in the 1990s (chapters 2 and 5), and has significantly contributed to the cereal supply at the household level, the potential of these areas appears to be underestimated, since the dissected terrain precludes large-scale solutions usually aimed at in the mechanisation of agriculture (chapter 5).

Today a trend towards “remittance landscapes” can be observed. Especially on moderate to steep slopes (14-36%), cropland is abandoned and, more importantly, erosion processes are ongoing in many cases so that such areas have been classified as degrading or hot spot areas (chapter 5).

In spite of these trends, there are opportunities for sustainable land management in the loess hills, as demonstrated by a variety of examples, and the potential for production of fruits, fodder and also cereals is considerable (chapter 5). Thus, it can be concluded that crop cultivation on the slopes in the loess hills is not necessarily linked to erosion and decreasing SOC contents. If cultivation on these slopes was not considered an emergency measure only, and if the potential of the loessial soils was fully acknowledged, this could create win-win situations by improving a range of ecosystem services in these areas, including improved soil productivity and reduced off-site damage, e.g. by siltation of water channels.

6.3 Data mining using classification and regression trees

In this study, five models were elaborated based on classification and regression tree modelling (CART). Application of such models, and their specific needs and opportunities will be discussed in the paragraphs below.

There are two main fields of application for such models: (i) accurate prediction and (ii) “data mining”. Modelling, with the primary aim of deriving calibrations for accurate prediction, is highly suitable for the prediction of soil properties from soil spectral information, but also applies to mapping of, e.g., land cover. The model input variables and the tree model itself may then be treated as a black box, which is of no specific interest to the user. This is how the prediction of SOC from soil reflectance spectral data was approached in this study; the physical information of the over 200 spectral bands available for the soil spectral measurements were not analysed. Combined regression tree modelling was applied, which is expected to yield more robust calibrations, but does not allow model interpretation, due to the complexity of such models.

Further CART models were used for mining the data of satellite images. Application of classification trees is helpful in identifying suitable levels for class distinction. A “two-step” classification approach was used including calibration of classes defined a priori, as well as analysing the sub-classes (terminal nodes) determined a posteriori. This allowed land cover classes to be analysed at a level of detail suitable for the dataset available. Furthermore, classification trees allowed straightforward determination of useful thresholds, e.g. for the erosion controlling factors “fractional vegetation cover” (low risk of erosion occurrence for sites with vegetation cover in May > 87%) and “slopes flatter than 15%” (chapter 4). Finally, the classification tree models provided insights into the underlying physical structure of land cover, erosion and SOC classes; e.g. the land cover model revealed predominant slope classes, and the SOC content class model indicated that non-loessial soil types called for specific rules to differentiate between low and high SOC content.

The aim of modelling for data mining differs considerably from that of obtaining calibrations. Here, readily interpretable models are to be derived, for which purpose single classification trees are well suited. Furthermore, input variables also need to be readily interpretable, as in the case of topographic information. Otherwise, variables may first be calibrated to available groundtruth data, as done in this study by regressing the vegetation index OSAVI against visual observations of fractional vegetation cover. Accordingly, there is potential in using more meaningful variables, including commonly applied indices such as the leaf area index, or biomass estimated from satellite images from different seasons, but also raster datasets elaborated using GIS, such as layers representing accessibility or flow patterns.

From the points discussed above, the conclusion can be drawn that generally two models will be required, if both prediction and mining of information are to be achieved for the same dataset.

A great potential can be seen in using classification tree modelling for mining of satellite data: Satellite images provide consistent information in a spatially explicit manner. This data source could be exploited to a far greater extent. Often satellite images are used only as a basis to extrapolate in space, whereas they might provide many more insights which can not be gained otherwise. Thus, the SOC content class model has indicated that brightness (linked to low SOC content and possibly to crusts) and wetness are important factors in classifying SOC. Such insights may encourage researchers to look more closely at the interrelations between SOC and crusts, and between SOC and wetness.

6.4 Recommendations

Recommendations for future planning of sustainable land management

Land use systems have been identified which show a variety of **opportunities for sustainable land management** (chapter 5). Locally applied conservation measures show high potential for wider application by individual farmers or by large farms (dekhan farms). Such examples clearly demonstrate the potential of the loess hills of central Tajikistan and should be promoted among farmers.

A **set of maps** has been elaborated which provides a suitable basis for planning of sustainable land management. Various applications of these maps are conceivable. The hot/bright spot map appears particularly suitable for planning of activities, as it allows prioritizing. As a basis for negotiation on future activities in sustainable land management, the maps are well suited to be used at the community, district and provincial levels. However, the resolution of the maps is too coarse for planning at the field level. In this case, overlaying the maps with watershed boundaries provides a suitable tool for project planning. With regard to monitoring activities, both the erosion occurrence map and the SOC content map provide crucial baseline information.

Recommendations for future land degradation assessments

Integration of soil reflectance spectral data into land degradation assessments: As discussed in chapter 3, there are a number of possibilities to expand the soil spectral library established in this study. These include extension of the library for prediction of additional soil types found in Tajikistan, as well as calibrating additional soil properties to soil spectral information. Furthermore, as soil spectral data provide an integrative measure of the state of soil resources (cf. Shepherd & Walsh 2002, 2007), their potential to be integrated into land degradation assessments as a highly differentiated and reliable information source should be further developed, specifically for the loessial soils of central Tajikistan. Especially calibration of soil spectral data to soil functional attributes (e.g. aggregate stability, nutrient exchange capacity) could make essential contributions to future studies, as this would allow a detailed analysis of the effects of erosion on various soil functions. In order to better capture the potential of the loess areas for cultivation, the focus will be on information regarding soil fertility. Thus, future efforts should aim at calibrating soil spectral reflectance data to a soil fertility index.

This study aimed at providing a basis for future studies to determine, in more detail, the impacts of land use on soil resources. Based on the results of this study, **critical controls of erosion and SOC variability** have been identified as follows:

High variability of soil indicators hampers straightforward impact assessment. Thus, with regard to effective determination of impacts on specific soils, better control of soil heterogeneity should be attained by stratifying the study area according to the soil type of most interest. The focus should be on loess areas which show widespread degradation and at the same time great potential to be used as productive areas if managed in a sustainable way. As the resolution of available or accessible soil maps, respectively, is too coarse to be useful for such purposes, digital soil mapping based on satellite data should be used to ensure effective stratification of areas. As indicated by the SOC content class model established for this study, classification of satellite imagery from the dry season is promising with regard to soil type mapping (chapter 4).

Land use change plays an important role in triggering soil degradation. Especially in the case of slopes being cultivated in response to food shortage, that is to say as an emergency measure perceived as a short-term solution and thus without any consideration of soil conservation issues, highly adverse impacts on soil resources are likely to result (chapter 5). With regard to the temporarily used fields situated on slopes in the loess hills of central Tajikistan, more detailed knowledge of land use history would be required in order to determine the effect of typical patterns of cultivated and fallow periods on soil resources. Of specific interest would be the determination of conservation measures which are effective in reversing degradation processes (e.g. cultivation of perennial fodder crops such as alfa-alfa).

Comparison between the Varzob and Faizabad test areas indicated that **indirect and direct drivers of land use change**, such as population pressure and accessibility, might be critical factors with regard to soil degradation and soil conservation (chapter 4). Integration of raster datasets, which provide a link to socio-economic and political drivers, is considered promising for identification of indirect as well as direct drivers of land use changes leading to degradation or conservation. In this respect, information generally available as vector data (e.g. polygon layers defining administrative units, land cadastre information) should also be considered; e.g. classification and regression tree models can integrate raster and polygon information in a straightforward manner. In this way, databases including datasets at different resolutions and with heterogeneous information may be explored with regard to patterns that would help to explain land degradation and conservation.

Recommendations with regard to future research

Spatial characteristics and issues of up- and down-scaling should be addressed. For detailed planning, it would be necessary to identify links between assessments conducted at the local level (e.g. on a scale of 1:5,000) and the present study's assessment at the provincial level (on a scale of approx. 1:50,000). As mentioned before, classification tree models facilitate integration of datasets at various scales. Linking datasets derived from case studies conducted at the field and local levels across the study area with the spatially explicit information elaborated here, could constitute a promising approach to reveal critical information with regard to the scale at which specific indicators may be applied, and at which specific interrelations between land cover / land use, soil degradation processes and soil quality may be determined.

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Annex

Annex 1: Field protocol

1) List of materials

- GPS
- Compass
- Inclinometer
- WOCAT mapping legend
- Shovel
- Munsell Colour Code
- Plastic bags
- Pens
- Knife

2) Definitions

Slope length – according to USLE: Slope length is defined as the distance from the point of origin of overland flow to the point where either the slope gradient decreases enough that deposition starts or the runoff water enters a well-defined channel that may be part of a drainage network or a constructed channel (Wischmeier & Smith 1978).

Landforms (Modified after ISRIC 1993):
Plateau / plains: extended level land (slopes less than 8%).
Ridges: narrow elongated area rising above the surrounding area, often hilltops or mountain-tops.
Mountain slopes (including major escarpments)**:** extended area with altitude differences of more than 600 m per 2 km and slopes greater than 15 %.
Hill slopes (including valley and minor escarpment slopes): altitude difference of less than 600 m per 2 km and slopes greater than 8%.
Footslopes: zone bordering steeper mountain / hill slopes on one side and valley floors / plains / plateaus on the other side.
Valley floors: elongated strips of level land (less than 8% slope), flanked by sloping or steep land on both sides.

Life form:

Graminoides: all grass-like in appearance, such as sedges, reeds, cattails, bamboos (Kuechler & Zonneveld 1988)
Non-graminoides are non-narrow leafed. For example: Root and tuber crops, pulses and vegetables, some fodder crops (e.g., certain legumes) and fibre crops (e.g., flax) (Di Gregorio & Jansen 1998)
Forbs: broadleaf herbaceous plants in contrast to the narrow leaf graminoides (Kuechler & Zonneveld 1988)
Distinction between trees and shrubs: A condition of Height is applied to separate Trees from Shrubs: woody plants higher than 5 m are classified as Trees. In contrast, woody plants lower than 5 m are classified as Shrubs. This general rule is subject to the following exception: a woody plant with a clear physiognomic aspect of trees can be classified as Trees even if the Height is lower than 5 m but more than 3 m. In this case, a sub-condition of physiognomic aspect is added to the Height condition (Di Gregorio & Jansen 1998).

Plant combinations **(Di Gregorio & Jansen 1998)**:

Simultaneous - More than one crop is cultivated at the same time in a defined area. This is often indicated as mixed cropping. Therefore the different crops can be intermingled or they grow in distinct patterns on the same field.
Overlapping - Planting or sowing one crop into another crop which has reached an advanced growing stage before the harvest of the first crop (Lipton, 1995).
Sequential - The growing of two or more crops in sequence on the same field within one growing season. The succeeding crop is planted after the preceding one is harvested.

Field Protocol		***Plot code:***	
General Information			
Date		Local time	
Collector (Name)		Last rainfall	....................Days ago
GPS Info, record number		Exposition *(test site)*	
Easting (X_Coord)		Northing (Y_Coord)	
Elevation (m asl)		Photo: overview 2m above 1m above	

Land form						
Macro	Land form	Plateau /plains	Ridges	Mountain / Hill slopes	Foot slopes	Valley floors
Test site	Position on slope	Top	upper	middle	lower	bottom
	Slope length	<100 m	> 100 m	> 300 m	Estimation:	
Plot	Slope	Up from centre:		Down from centre:		
	Slope shape Perpendicular to s.	straight	convex	concave	variable	
	With the slope	Straight	convex	concave	variable	

Diagram / Sketch

Size of area observed: <30x30m 0 30x30m – 100x100m 0 > 100x100m 0	**Indicate orientation!** **Mark position where you stand!** **Indicate whether surroundings are similar!**
Rational for choosing location for hole digging:	
Overall situation	Technical drawing

Contact with farmers					
Settlement			Name		
Land Use History					
Site cultivated (ever)?	YES	NO	Probably same LU for more than 15 years?	YES	NO
Comments					

Land Cover (LCCS)						
Dominant life form (upper most canopy layer, unless its land cover is sparse)	Trees (>5m): Height: Broadleaved 0 Needle leaved 0 Evergreen 0 Deciduous 0		Shrubs (<5m): Height: Broadleaved 0 Needle leaved 0 Evergreen 0 Deciduous 0		Herbaceous: Height: graminoids 0 non-graminoids 0	
Cover dominant life form (at the time of fullest development)	Closed (> 75%)	Closed (75-65%)	Open (65-30%)	Open (30-15%)	Sparse (15-4%)	Sparse (<4%)
Plant combination	Single plant layer		Multiple plant layer		Simultaneous 0 Overlapping 0 Sequential 0	
Second life form	Trees (>5m):		Shrubs (<5m)		Herbaceous Graminoids0 non-graminoids 0	
Cover second life form	Closed (> 75%)	Closed (75-65%)	Open (65-30%)	Open (30-15%)	Sparse (15-4%)	Sparse (<4%)
Crop residue /stubble	(> 75%)	(75-65%)	(65-30%)	(30-15%)	(15-4%)	(<4%)
Bare soil	(> 75%)	(75-65%)	(65-30%)	(30-15%)	(15-4%)	(<4%)

Land Use System					
Major land use type	Terrestrial managed	Agricultural production given up	Terrestrial semi-natural / natural	Terrestrial artificial non-vegetated	Aquatic natural, non-natural
Land Use Type if mixed tick all necessary	Pasture	Cropland, rainfed	Vineyard	Forest , natural	Fallow land
	Haymaking	Cropland, irrig.	Orchard	Afforestation	Animal path
Field (or area) size	Large (> 5 ha)	Medium (2-5 ha)	Small (1- 2 ha)	Very small (< 1 ha)	
Water supply	Rainfed	If additionally irrigated, how:			
Plant species	Dominant life form	2nd life form	3rd life form		

Land management and conservation characteristics (WOCAT)					
Land cultivation	Manual labour	Animal traction	mechanised		
Conservation type	Agronomic	Vegetative	Structural	Management	Combinations
Describe SWC **Note WOCAT class!!**					
Vegetation Degradation	Undesirable bushes/trees %	Non-palatable herbaceous species / weeds %	Animal tracks covering %		

Soil sampling				
Sample numbers	**VZ.............01**	**VZ............. 02**	**VZ............. 03**	**VZ............... 04**
Sample depth	0-20 cm	20-50 cm	0-20 cm	20-50 cm

Soil type / characteristics (WOCAT)				
Soil Surface aspect	Fine (clay)	Medium (silt)	Coarse (sand)	Very coarse (gravel)
	Surface covered by rock or stones %	Stonyness (40-80%) % (5-40%) %	Visible CaCO3 deposits on the soil surface	Visible CaCO3 deposits in subsoil
Munsell colour code	Layer 1 dry / wet		Layer 2 dry / wet	
Rooting depth	0-20cm	20-50 cm	> 50 cm	Subsoil compaction

Soil degradation (WOCAT)					
Water erosion, Area covered / severity[1]:	Sheet .... Splash effects 0........... Pedestals 0.......... Armour layer 0........... Exposed roots 0...........	Rill .... Width......................... Frequency........................ Length........................... Depth............................		Gully .... Width......................... Frequency........................ Length........................... Depth............................	Mass mov. Off-site effects
Other physical degradation	Sealing / crusting (Pk)	Cracks None 0 < 1cm 0 > 1 cm 0	Frequency: Low medium high		Deposition of sediments, flooding (Wo)
Topsoil compaction knife (cm)	Soft (> 5cm)	Medium (2.5-5cm)	Hard (0-2.5 cm)		Very hard (O cm)
Additional comments	(e.g.poor crop growth in patches and strips, signs of earthworms, root growth)				

[1] For each type indicate the severity of the state/process: **none / low / moderate / great**

Annex 2: R-factor estimation

The following description of the calculation for the R-factors is based on the diploma thesis of Erik Bühlmann (Bühlmann 2006), who worked in the Faizabad test area. He described the procedure for estimating the R-factor based on daily rainfall data as follows:

"In order to take into account seasonal fluctuations of rainfall erosivity, EI30 values were estimated following an approach of Mannaerts and Gabriel (2000). A daily database from January 1988 until December 2002 was created with rainfall parameter rain10 (amount of rainfall for days with precipitation ≥ 10.0 mm) and an estimated average storm duration as second independent predictor variable. The maximum 30-minute intensity of a rainfall event (I30) was predicted, dividing rain10 by estimated average storm durations. For months January-March and October-November, average storm duration was assumed to be 3 hours; for April and September and average of 2 hours was assumed. In May-August very high rainfall intensities were observed. Since precipitation during these months exclusively falls during air mass thunderstorms, average storm duration of 1 hour is suggested. The estimates of average monthly storm duration are based on field observations and farmer-information and proved to be consistent with figures from areas with similar climatic conditions (e.g. Hevesi et al., 2003; Lebel and Amani, 1999; Marai, 2003). Calculating rainfall intensities, the assumption was made that two third of the total precipitation of a storm event fall during half of its duration.

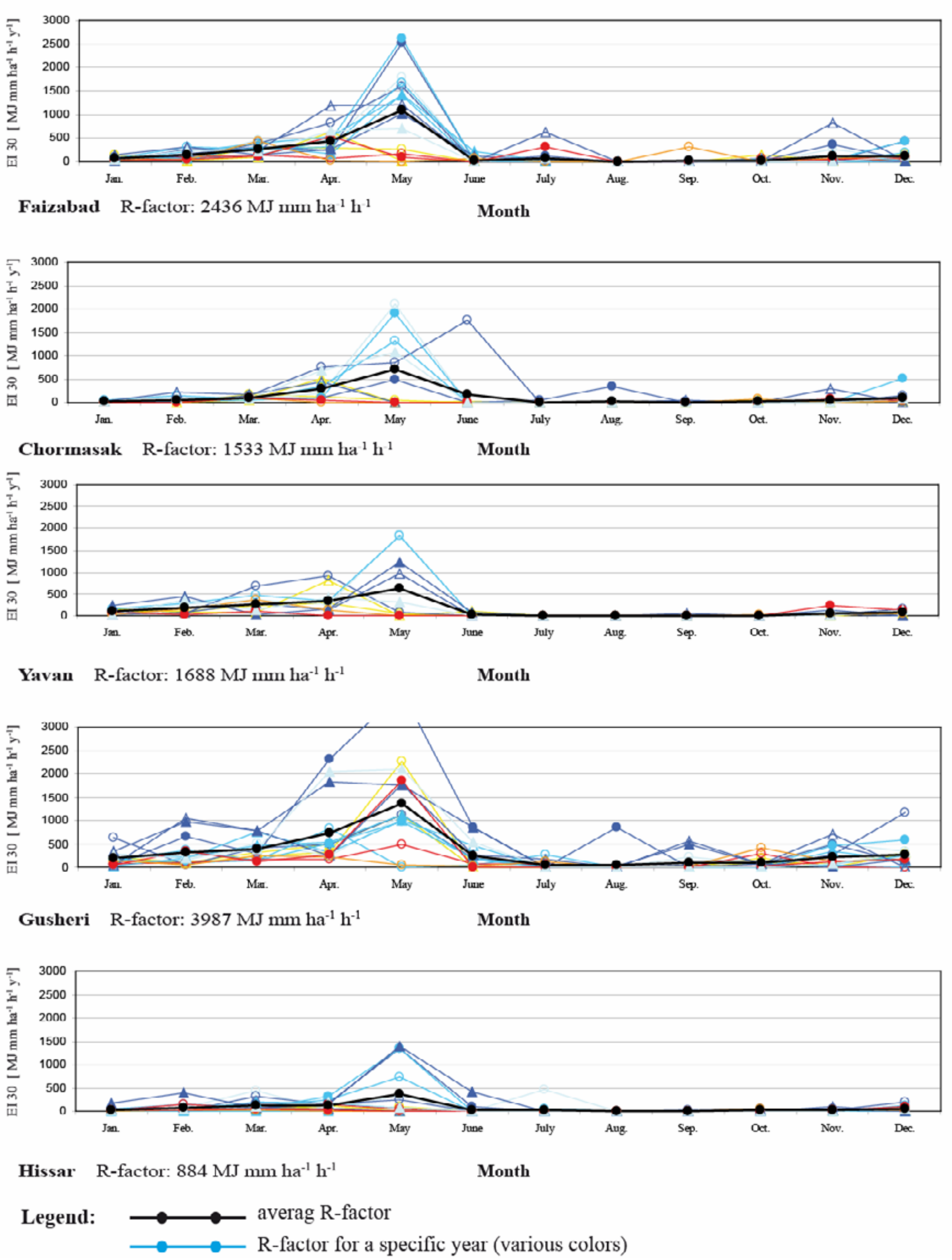
The kinetic energy of a given amount of rain depends on the sizes and terminal velocities of the raindrops which are related to rainfall intensity (Renard et al., 1997). Unit energy was calculated according to an energy-intensity-relationship proposed in the RUSLE. It determines the energy of rain fall (e_m) for a short interval within a rainstorm event in which rainfall intensity is assumed to remain constant

$$e_m = 0.29\ [1-0.72 \exp(-0.05\ i_m)],$$

where e_m has units of MJ ha^{-1} mm^{-1} of rain and i_m is rainfall intensity and has units of mm h^{-1}. Total storm energy E was then calculated by summing up the em values of a rainstorm. The fifteen year average of monthly rainfall erosivity (EI30, month) is the sum of computed EI30 values for all rain periods within that time." The R-factor calculated has the units MJ mm ha^{-1} h^{-1}.

Figure A-1 below shows estimated average R-factors for the years 1988-2002 for 5 climatic stations in Central Tajikistan. These R-factors are estimations, as there was no possibility to validate the results with measured rainfall intensities.

Figure A-2 *Estimated (unvalidated) average R-factors for the years 1988-2002 for 5 climatic stations in Central Tajikistan*



Curriculum Vitae

Bettina Wolfgramm was born on 24 February 1974 in Berne and grew up in Rubigen (BE). From 1989-1994 she attended gymnasium, the Wirtschaftsgymnasium Bern-Neufeld in Berne, which included an AFS school exchange year in Dunedin, New Zealand. In 1994 she received her baccalaureate.

Bettina Wolfgramm holds a M.Sc. in environmental engineering from the Swiss Federal Institute of Technology (ETH) Zurich, Switzerland (2001). During her studies, she completed a practical training at the Environmental Research and Management Centre of the American University of Armenia in Yerevan, Armenia. The duties included an assessment of operational details and potential environmental impacts of Yerevan sanitary landfill, participation in field sampling, and GIS mapping for Ararat Valley agricultural region. For her M.Sc. thesis she carried out a research study at the International Water Management Institute IWMI in Lahore, Pakistan. The study aimed at assessing hydrological properties of degraded and non-degraded cotton fields. Flow patterns in the unsaturated soil were visualised with a dye tracer and analysed for possible effects of preferential flow paths and plough pans. Further training she obtained during a postgraduate course in Geographical Information Systems (GIS) at ETH Zurich, which she completed in 2002.

From 2001 to 2003 she worked as a consulting environmental engineer in the field of soil and groundwater contamination at the Dr. Heinrich Jäckli AG in Zurich, Switzerland. The tasks included historical and technical assessments on sites suspected of being contaminated, planning and budgeting of remediation projects as well as expert monitoring of excavation and waste disposal on construction sites.

She joined the Centre for Development and Environment (CDE) of the University of Bern in 2003 as a PhD researcher within the National Centre of competence in Research (NCCR) North-South program. Her PhD study aimed at assessing the impact of land use on soil resources in the rainfed areas of the loess zone of Central Tajikistan. Her research included studies on sustainable land management, indicators of land degradation and conservation, remote sensing techniques, soil spectral reflectance libraries and spatial assessment of erosion risk. Data collection in Tajikistan was conducted in collaboration with the Soil Science Research Institute of Tajikistan and students of the Tajik Agrarian University. Field research included data inquires at various ministries and institutions, three field surveys, and two laboratory measurement campaigns. Time spent in Tajikistan in 2003, 2004 and 2005 totalled 12 months. The major part of her activities consisted of the PhD research, but she also co-supervised five MSc students.

Erklärung

gemäss Art. 28 Abs. 2 RSL 05

Name/Vorname: Bettina Wolfgramm

Matrikelnummer: 95-910-584

Studiengang: Geographie

Bachelor ☐ Master ☐ Dissertation ☒

Titel der Arbeit: Land Use, Soil Degradation and Soil Conservation in the Loess Hills of Central Tajikistan

....

....

LeiterIn der Arbeit: Prof. Dr. Hans Hurni, Dr. Hanspeter Liniger

....

Ich erkläre hiermit, dass ich diese Arbeit selbständig verfasst und keine anderen als die angegebenen Quellen benutzt habe. Alle Stellen, die wörtlich oder sinngemäss aus Quellen entnommen wurden, habe ich als solche gekennzeichnet. Mir ist bekannt, dass andernfalls der Senat gemäss Artikel 36 Absatz 1 Buchstabe o des Gesetztes vom 5. September 1996 über die Universität zum Entzug des auf Grund dieser Arbeit verliehenen Titels berechtigt ist.

Bern, 22.08.2007

B. Wolfgramm