Multi-scale targeting of land degradation in northern Uzbekistan using satellite remote sensing

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With patience, it is possible to dig a well with a teaspoon.

Ukrainian proverb

To see a friend no road is too long.

Ukrainian proverb

ABSRACT

Advancing land degradation (LD) in the irrigated agro-ecosystems of Uzbekistan hinders sustainable development of this predominantly agricultural country. Until now, only sparse and out-of-date information on current land conditions of the irrigated cropland has been available. An improved understanding of this phenomenon as well as operational tools for LD monitoring is therefore a pre-requisite for multi-scale targeting of land rehabilitation practices and sustainable land management.

This research aimed to enhance spatial knowledge on the cropland degradation in the irrigated agro-ecosystems in northern Uzbekistan to support policy interventions on land rehabilitation measures. At the regional level, the study combines linear trend analysis, spatial relational analysis, and logistic regression modeling to expose the LD trend and to analyze the causes. Time series of 250-m Moderate Resolution Imaging Spectroradiometer (MODIS) normalized difference vegetation index (NDVI), summed over the growing seasons of 2000-2010, were used to determine areas with an apparent negative vegetation trend; this was interpreted as an indicator of LD. The assessment revealed a significant decline in cropland productivity across 23% (94,835 ha) of the arable area. The results of the logistic modeling indicate that the spatial pattern of the observed trend is mainly associated with the level of the groundwater table, land-use intensity, low soil quality, slope, and salinity of the groundwater.

To quantify the extent of the cropland degradation at the local level, this research combines object-based change detection and spectral mixture analysis for vegetation cover decline mapping based on multitemporal Landsat TM images from 1998 and 2009. Spatial distribution of fields with decreased vegetation cover is mainly associated with abandoned cropland and land with inherently low-fertility soils located on the outreaches of the irrigation system and bordering natural sandy deserts. The comparison of the Landsat-based map with the LD trend map yielded an overall agreement of 93%. The proposed methodological approach is a useful supplement to the commonly applied trend analysis for detecting LD in cases when plot-specific data are needed but satellite time series of high spatial resolution are not available.

To contribute to land rehabilitation options, a GIS-based multi-criteria decision-making approach is elaborated for assessing suitability of degraded irrigated cropland for establishing *Elaeagnus angustifolia* L. plantations while considering the specific environmental setting of the irrigated agro-ecosystems. The approach utilizes expert knowledge, fuzzy logic, and weighted linear combination to produce a suitability map for the degraded irrigated land. The results reveal that degraded cropland has higher than average suitability potential for afforestation with *E. angustifolia*. The assessment allows improved understanding of the spatial variability of suitability of degraded irrigated cropland for *E. angustifolia* and, subsequently, for better-informed spatial planning decisions on land restoration.

The results of this research can serve as decision-making support for agricultural planners and policy makers, and can also be used for operational monitoring of cropland degradation in irrigated lowlands in northern Uzbekistan. The elaborated approach can also serve as a basis for LD assessments in similar irrigated agro-ecosystems in Central Asia and elsewhere.

ZUSAMMENFASSUNG

Die zunehmende Landdegradation (LD) in den bewässerten Agrarökosystemen in Usbekistan behindert die nachhaltige Entwicklung dieses vorwiegend landwirtschaftlich geprägten Landes. Bis heute sind nur wenige und veraltete Informationen über die aktuellen Bodenbedingungen der bewässerten Anbauflächen verfügbar. Ein besseres Verständnis dieses Phänomens sowie operationelle Werkzeuge für LD-Monitoring sind daher Voraussetzung für ein nachhaltiges Landmanagement sowie für Landrehabilitationsmaßnahmen.

Ziel dieser Studie war es, das räumliche Verständnis der Degradierung von Anbaugebieten in den bewässerten Agrarökosystemsn des nördlichen Usbekistans zu verbessern, um staatliche Interventionen in Bezug auf Landrehabilitationsmaßnahmen zu unterstützen Auf der regionalen Ebene kombiniert die Studie lineare Trendanalyse, räumliche relationale Analyse sowie logistischer Regressionsmodellierung, um den LD-Trend darzustellen und Gründe zu analysieren. Zeitreihen von 250-m Moderate Resolution Imaging Spectroradiometer (MODIS) normalized difference vegetation index (NDVI) Bildern wurden für den Zeitraum der Anbauperioden zwischen 2000-2010 untersucht, um Bereiche mit einem offensichtlich negativen Vegetationstrend zu ermitteln. Dieser negative Trend kann als Indikator für LD interpretiert werden. Die Untersuchung ergab eine signifikante Abnahme der Bodenproduktivität auf 23% (94,835 ha) der Anbaufläche. Zudem deuten die Ergebnisse der logistischen Modellierung darauf hin, dass das räumliche Muster des beobachteten Trends überwiegend mit der Höhe des Grundwasserspiegels, der Landnutzungsintensität, der geringen Bodenqualität, der Hangneigung sowie der Grundwasserversalzung zusammenhängt.

Um das Ausmaß der Degradation der Anbauflächen auf der lokalen Ebene zu quantifizieren, kombiniert diese Studie objektbasierte Erkennung von Veränderungen und spektrale Mischungsanalyse für die Abnahme der Vegetationsbedeckung auf der Grundlage von multitemporalen Landsat-TM-Bildern im Zeitraum von 1998 bis 2009. Die räumliche Verteilung der Felder mit abnehmender Vegetationsbedeckung hängt überwiegend mit verlassenen Anbauflächen sowie mit nährstoffarmen Böden in den Randbereichen des Bewässerungssystems und an den Grenzen zu natürlichen Sandwüsten zusammen. Ein Vergleich mit der Karte des LD-Trends ergab insgesamt eine Übereinstimmung von 93%. Der vorgeschlagene Ansatz ist eine nützliche Ergänzung zu der häufig angewendeten Trendanalyse für die Ermittlung von LD in Regionen, für die keine Satellitenbildzeitreihen mit hoher Auflösung verfügbar sind.

Als Beitrag zu Landrehabilitationsmöglichkeiten, wird ein GIS-basierter Multi-Kriterien-Ansatz zur Einschätzung der Eignung von degradierten bewässerten Anbauflächen für Elaeagnus angustifolia L. Plantagen beschrieben, der gleichzeitig die spezifischen Umweltbedingungen der bewässerten Agrarökosysteme berücksichtigt. Dieser Ansatz beinhaltet Expertenwissen, Fuzzy-Logik und gewichtete lineare Kombination, um eine Eignungskarte für die bewässerten degradierten Anbauflächen herzustellen. Die Ergebnisse zeigen, dass diese Flächen ein überdurchschnittliches Eignungspotenzial für die Aufforstung mit *E. angustifolia* aufweisen. Diese Studie trägt zu einem verbesserten Verständnis der räumlichen Variabilität der Eignung von solchen Flächen für *E. angustifolia* bei.

Die Ergebnisse dieser Studie können als Entscheidungshilfe für landwirtschaftliche Planer und politische Entscheidungsträger sowie für verbesserte Landrehabilitationsmaßnahmen und operationelles Monitoring der Degradation von Anbauflächen im nördlichen Usbekistan eingesetzt werden. Zudem kann der beschriebene Ansatz als Grundlage für LD-Untersuchungen in ähnlichen bewässerten Agrarökosystemen in Zentralasien und anderswo dienen.

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LIST OF ACRONYMS

ADB	Asian Development Bank
AUC	Area under (ROC) curve
asl	Above sea level
ACIAR	Australian Centre for International Agricultural Research
AVHR	Advanced Very High Resolution Radiometer
BS	Bright soil
CA	Central Asia
CACIM	Central Asian Countries Initiative for Land Management
CGIAR	Consultative Group on International Agricultural Research
CVA	Change vector analysis
DS	Dark soil
FAO	Food and Agriculture Organization of the United Nations
GDP	Gross domestic product
GIMMS	Global Inventory Modeling and Mapping Studies
GIS	Geographic information system
GV	Green vegetation
GWT	Groundwater table
GWS	Groundwater salinity
GLASOD	Global assessment of human-induced soil degradation
Landsat TM	Landsat Thematic Mapper
LD	Land degradation
LULC	Land use and land cover
MCE	Multi-criteria evaluation
MNF	Minimum noise fraction
MERIS	Medium Resolution Imaging Spectrometer
MODIS	Moderate Resolution Imaging Spectroradiometer
MCDM	Multi-criteria decision making
NDVI	Normalized difference vegetation index
IFPRI	International Food Policy Research Institute
OWA	Ordered Weighted Averaging
P	Precipitation
PPI	Pixel Purity Index
PCP	Percentage of correct predictions
OBIA	Object-based image analysis
OBCD	Object-based change detection
RMSE	Root mean square error
ROC	Receiver Operating Characteristic
RS	Remote sensing
SANIRI	Central Asian Scientific Research Institute on Irrigation
SKKP	Southern part of Autonomous Republic of Karakalpakstan
SMA	Spectral mixture analysis
Stdev	Standard deviation
T	Air temperature
VI	Vegetation index

VIF	Variance inflation factors
WLC	Weighted linear combination
WT	Water
WUA	Water use association
UN	United Nations
UNDP	United Nations Development Programme
UNCCD	United Nations Convention to Combat Desertification
UTM	Universal Transverse Mercator coordinate system
UZSTAT	State Committee of the Republic of Uzbekistan on statis

1 INTRODUCTION

1.1 Cropland degradation in the irrigated lowlands of the Amu Darya River

1.1.1 Problem of land degradation

According to the Millennium Ecosystem Assessment report of the United Nations (UN), land degradation (LD) is one of today's greatest environmental challenges (Adeel et al. 2005). The concerns of the world community about this issue resulted in the proclamation of the United Nations Convention to Combat Desertification (UNCCD) in 1996 (http://www.unccd.int/) that aims at a reduction of LD and desertification in all affected countries.

The UNCCD defines LD as the "reduction or loss in arid, semi-arid and dry sub-humid areas, of the biological or economic productivity and complexity of rainfed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from land uses or from a process or combination of processes, including processes arising from human activities and habitation patterns" (§ 5, UNCCD 1994). Degradation of land can be caused by various factors, including climatic variations and human activities. The human-induced LD occurs mainly due to overexploitation of land resources for cropping and livestock farming, including irrigation practices, overgrazing of rangelands, and fuelwood exploitation (Adeel et al. 2005).

The increasing rates of human-induced LD in arid and semi-arid environments have already affected ca. 2.6 billion people worldwide (Sivakumar and Stefanski 2007a). The livelihood of millions of farmers around the world is threatened by cropland degradation. It is estimated that, globally, LD in drylands causes a loss of land productivity estimated around USD 13–28 billion a year (Scherr and Yadav 1996). In addition, LD not only causes economical losses but also adversely affects the environment. It is, therefore, important to monitor LD and to determine its causes so that it can be reversed.

To date, several spatial assessments have been conducted to map LD globally, for example, the Global Assessment of Human-induced Soil Degradation (GLASOD) (Oldeman et al. 1990) and the Land Degradation Assessment in Drylands (LADA) (Figure 1.1) (Bai et al. 2008). Yet, due to the differences in definition of LD and field data scarcity, the existing global assessments differ in the selection of measurable attributes of LD, in their spatial coverage, and in the quality of the datasets (Safriel 2007). Moreover, the coarse spatial resolution of global LD maps is not appropriate for region-based analysis, while national maps are not always in place for all countries. The availability of spatial data on LD is, however, a precondition for implementation of land rehabilitation measures as well as for sustainable use of land resources (Winslow et al. 2011).

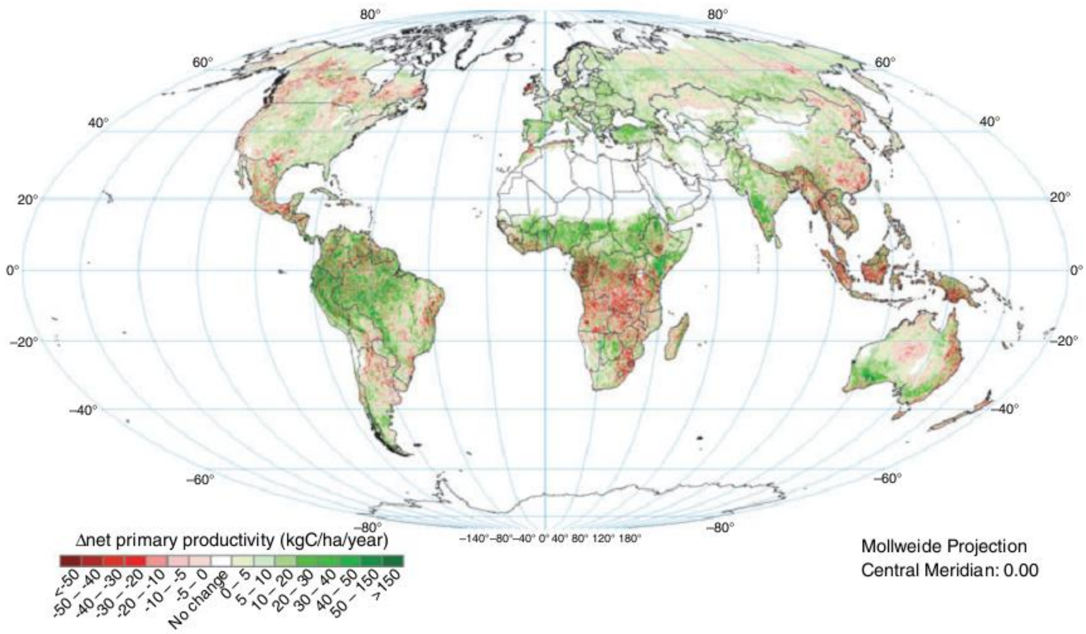

Figure 1.1: Global change in net primary productivity (Bai et al. 2008)

1.1.2 Land degradation in Central Asia

Agricultural activities influence significantly the state of the land worldwide (Sivakumar and Stefanski 2007a). Specifically, agriculture-induced LD is strongly evident in drylands due to their natural fragility, which makes them susceptible to degradation (Gao and Liu 2010).

Irrigated agriculture contributes about 30% of the world food production, while in some arid and semi-arid regions, such as former-Soviet Central Asia (CA) (Figure 1.2), it is the backbone of the economy (Ji 2008). About 70% of the irrigated areas worldwide are located in Asia (East, South, Southeast and Central Asia). The heavily irrigated cropland in Asia is found in CA. During the 70 years of the Soviet Union, the agricultural sector in the five CA countries Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan and Uzbekistan was modernized through extensive land-use transformations aiming to increase overall agricultural production and the arable area (Glantz 1999). This vision was motivated by the view that not the amount of the irrigable land was limiting for the development of the agricultural sector in CA but rather the amount of irrigation water that needed to be diverted to unexploited areas (Field 1954). Since 1961, the irrigated areas have tripled to about 7.9 Mha in 1999, mainly along the rivers Amu Darya and Syr Darya (Saiko and Zonn 2000). This made CA one of the largest irrigated zones in the world and raised the value of the land. The massive expansion of irrigated agriculture resulted in significant increases in food and cotton production. Today, irrigated agriculture in CA is still the centerpiece for the livelihoods of about 63% of the rural population of in total 41.8 million (Ji 2008).

Figure 1.2: Overview of Central Asia and its irrigated areas (modified from Bucknall et al. 2003)

While the large-scale irrigation systems supplied the production factor water for generating crop yields, the supply of irrigation water was irrespective of ecological consequences especially in the downstream regions of the river systems. The desiccation of the Aral Sea is the most prominent example of this neglect (Martius et al. 2012), but valuable natural ecosystems, such as the Tugai forests and wetlands in the reaches of the Amu Darya River, have also nearly disappeared (Krutov and Glantz 1999). Furthermore, agricultural land-use practices in the CA countries, introduced during Soviet Union times and maintained after independence in 1991, have resulted in an overexploitation and, consequently, degradation of cropland. This has caused yields to decline by as much as 30% (Létolle and Mainguet 1993). Today, 47.5% of the irrigated land in CA is affected by soil salinity, ranging from 11.5% in Kyrgyzstan to 95.9% in Turkmenistan (Saigal 2003). Since available soil degradation maps are static and seldom updated, the concerns have risen about the accuracy of the mapped LD.

Overall, the entire region faces enormous challenges in preventing, mitigating and reversing the processes of LD. The annual costs for CA countries due to LD are estimated to USD 31 million (Ji 2008). Moreover, in combination with the expected water scarcity, due to the impact of climate change, which for CA is predicted to be far above world average (Lioubimtseva et al. 2005; Lioubimtseva and Henebry 2009; Qi et al. 2012), and the growing population (Glantz 1999), the necessity of sustainable use of land resources is immense. The international concern about LD in CA led to the launch of the Subregional Action Programme for the Central Asian Countries on Combating Desertification (UNCCD 2003).

1.1.3 Land degradation in Uzbekistan

Uzbekistan is probably the most vulnerable of the CA countries regarding water resources and irrigated agriculture, as it has the largest irrigated area (4.3 million ha), the largest rural population (more than 14 million) and the highest population density (49.6 pers/km^2) (CACILM 2006). Being an arid country and the same time a large consumer of water resources, Uzbekistan is significantly affected when water shortages occur, especially in drought years. Degradation of land is widespread throughout Uzbekistan (Figure 1.3). The most affected areas are, however, concentrated in the lowlands of the Amu Darya River and in the districts of Bukhara, Navoi, and Kashkadarya. Reportedly, about 885,000 ha are marginal, and up to 53% of irrigated land are exposed to varying degrees of soil salinity, leading to low or no profits from annual crops (Djanibekov et al. 2012b). Over 50% of the croplands suffer from wind and water erosion, and continued losses of the fertile topsoil layer are observed every year (Nkonya et al. 2011).

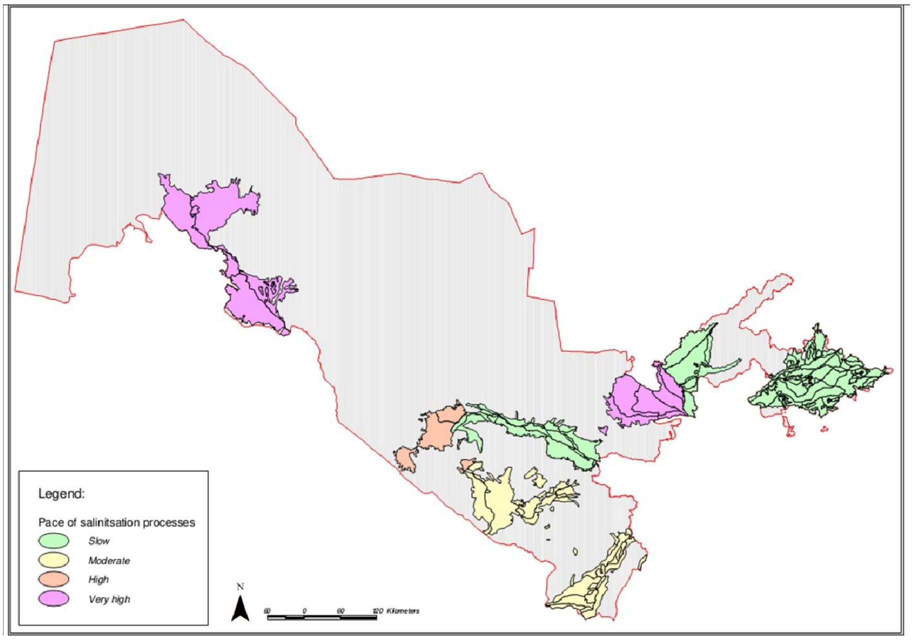

Figure 1.3: Current pace of soil salinization in irrigated areas of Uzbekistan (FAO 2003)

While agriculture accounts for about 22% of the gross domestic product (GDP) and employs 33% of the labor, the annual costs associated with LD in Uzbekistan amount to as much as USD 1 billion a year (Sutton et al. 2007).The decreasing land productivity and decreasing crop yields have been a crucial factor, causing a decline in rural living standards (CACILM 2006).

The economic costs due to LD are imposed at three levels: (i) at the field level, in terms of decline in land productivity, (ii) at the national level, in terms of decrease in the agricultural GDP and export earnings due to the loss of productive capacity of the arable land, and (iii) at the global level, in terms of pollution of transboundary water resources, loss of biodiversity, and negative impact on carbon sequestration and climate change (ADB 2006). A governmental policy that constrains production growth and reduces incentives to invest in land improvement challenges further management of land resources in the country (World Bank 2002; Ji 2008). Urgent actions are, therefore, required in Uzbekistan to mitigate the causes and negative impacts of LD through sustainable land management practices as a contribution to improving economic wellbeing and people’s livelihoods (ADB 2006; CACILM 2006; Nkonya et al. 2011). Despite the numerous alarming signals, land managers in CA in general and in Uzbekistan in particular have insufficient spatial information on LD to implement rehabilitation and mitigation measures and to follow sustainable land-use practices (Dregne 2002; Ji 2008).

1.1.4 Remote sensing of land degradation

Degradation of drylands manifests itself in reduced productive potential (Reynolds et al. 2007) indicated by a gradual loss of vegetation cover over time. In irrigated agro-ecosystems in Uzbekistan, the declined productive potential is triggered by soil salinization that adversely affects crop growth (Akramkhanov et al. 2012). It can also be a consequence of reduced irrigation and of other agricultural inputs or overall disruption in cropping activities. Reduced frequency of irrigation and occurrence of fallow land may serve as indirect indicators of cropland degradation because farmers, particularly in drought years, tend to reduce cultivation primarily in areas least responsive to agricultural inputs (Dubovyk et al. 2013a). Regardless of whether caused by decreasing soil quality or decreasing cultivation, the vegetation cover loss over time signifies a decline in economic productivity of irrigated cropland and can be considered as degradation of its productive function (UNCCD 1994).

Elaboration of recommendations on sustainable land management, which would reduce vulnerability to water scarcity and decrease dependency on irrigation while guaranteeing a sustainable livelihood for the rural population, requires accurate information on the long-term changes in the state of the land. Assessment of these changes needs to be based on objective, repeatable, and spatially explicit approaches (Winslow et al. 2011). In this context, remote sensing (RS) is of significant value.

The data archives from the earth observation sensors, being operational for several decades, allow retrospective analyses of the state and development of (agro)-ecosystems on different spatial scales. Satellite imagery conforms to the principles of objectivity, repetitiveness, and consistency, which are preconditions in the framework of monitoring (Prince et al. 2009). Therefore, it provides important information for integrated approaches combining RS data with specific tools and modeling techniques (Röder et al. 2008). Among different methods for studying and monitoring LD, RS provides a cost-effective evaluation over extensive areas, whereas *in-situ* process studies are resource demanding and thus usually conducted at a small scale (e.g., Vlek et al. 2008; Bai and Dent 2009; Prince et al. 2009; Gao and Liu 2010). In addition, RS-based assessment is currently the only means for LD monitoring at a regional scale, specifically in the less developed countries such as Uzbekistan, where funds for environmental programs are often limited (Sivakumar and Stefanski 2007b).

Earth observation provides a variety of techniques to study land surface dynamics and assess LD quantitatively (van Lynden and Mantel 2001; Kessler and Stroosnijder 2006; Lu et al. 2007; Wessels et al. 2008; Jones et al. 2011). However, until recently, most of the RS applications for LD dealt with direct observation of visible features such as different forms of soil erosion (Almeida-Filho and Shimabukuro 2002; Li et al. 2009), while less attention was paid to monitoring gradual changes in land cover (Hostert et al. 2003). Furthermore, most of the studies focused on natural and semi-natural environments (Heumann et al. 2007; Röder et al. 2008), even though degradation of cropland cannot be overlooked in the light of increasing demand for agricultural production. With the advance of RS sensors, the variety of images has increased, laying a promising basis for assessment of (irrigated) cropland degradation on the medium and high spatial scales.

1.1.5 Spatial assessment of land degradation in Central Asia and Uzbekistan

Despite the recognized severity of LD in CA, there are only few published studies that aimed at spatial assessment of this problem in the region (Ji 2008). Kharin et al. (1999 cited in Ji, 2008) created a LD map of 4 by 4 arc-minutes based on expert opinions and existing soil maps. It shows that LD is generally present throughout CA, and that it is differentiated by land-use type and degradation cause. Based on this data, desertification in this region is mainly characterized by vegetation cover degradation on rangelands and meadows. Given the fact that this map is partly based on expert opinions, objective and updated assessment is necessary.

More attention was paid to the analyses of land use and land cover (LULC) in the region. For example, Chen et al. (2013) assessed changes in LULC and ecosystem services in CA during 1990–2009. Klein et al. (2012) presented a classification approach for regional land-cover mapping of CA. Spatial analyses on the aeolian geomorphic processes of the CA ergs were conducted by Maman et al. (2011). Kariyeva and van Leeuwen (2011) studied environmental drivers of vegetation phenology in CA based on the normalized difference vegetation index (NDVI) calculated from the AQUA/TERRA-Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI and NOAA-Advanced Very High Resolution Radiometer (AVHRR) NDVI time series (1981-2008). Spatial cropping patterns were observed in the Khorezm region in Uzbekistan (Conrad et al. 2011). Inter-annual changes in vegetation activities and their relationship to temperature and precipitation in CA from 1982 to 2003 were analyzed by Propastin et al. (2008). De Beurs and Henebry (2004) assessed LULC changes in Kazakhstan using NDVI satellite time series (1985–1988 and 1995–1999) from AVHRR. O'hara (1997) conducted a statistical analysis of the data on the extent of irrigated land, variations in groundwater table (GWT), soil salinity, waterlogging and quality of irrigation water in Turkmenistan for the period 1984 to 1994. Yet cropland degradation per se and the relevant aspects for assessing, for instance, relations between the degradation and their possible triggers have been neglected (Dregne 2002; Dubovyk et al. 2013a).

1.2 Spatial targeting of land rehabilitation in the irrigated agro-ecosystems in northern Uzbekistan

1.2.1 Afforestation as an option for rehabilitation of degraded irrigated cropland

In Uzbekistan, about one-third of all irrigated land has a shallow and saline GWT, while the share of shallow GWT within irrigated cropland reaches 80% in study region (Ji 2008; Ibrakhimov et al. 2011). To reduce soil salinity in the root zone, local farmers practice leaching that requires a substantial share (~40%) of the water directed for irrigation (World Bank 2002). Considering the increasing water scarcity predicted due to the impact of climate change (Lioubimtseva and Henebry 2009) and population growth, the sustainable use of land resources is becoming of uttermost importance.

Among different methods available for rehabilitation of degraded lands (e.g., Houérou 1976; Cano et al. 2009; Kapur et al. 2011), afforestation of degraded cropland is considered a viable land-use option to address the problem of LD and irrigation water scarcity and secure income of local population in study region in northern Uzbekistan (Martius et al. 2003; Khamzina et al. 2006b).

Planting trees on such land improves soil fertility through enhancing nitrogen and carbon contents, simultaneously reducing elevated GWT via transpiration, and contributes to the global effort of climate change mitigation by sequestering carbon in biomass and soil (Khamzina et al. 2012). Trees can also benefit rural livelihoods by providing valuable timber and non-timber products (e.g., fuelwood, fodder, and fruits) (Lamers et al. 2008; Djanibekov et al. 2012b). The irrigation demand of the trees was observed to be lower compared to the traditional crops (cotton, rice, and winter wheat) due to tree reliance on the groundwater. By drawing on groundwater resources, establishment of the forest plantation on degraded cropland could release irrigation water for the use on productive cropland (Khamzina et al. 2008).

1.2.2 Spatial decision support for afforestation of degraded irrigated cropland

Land suitability for establishing tree plantations on degraded cropland differs spatially due to the variability of factors that determine suitability of land for tree growth (Hansen et al. 2007). For the land manager, such information is needed to enhance effective allocation of land resources by providing options for selection of appropriate locations for tree plantations and for creating a basis for efficient environmental policy interventions (van der Horst 2006).

There is little published research on afforestation in arid CA. For irrigated agro-ecosystems in northern Uzbekistan, previous studies investigated tree species' suitability, early growth, and water use of tree plantations as well as their restoration functions on the degraded irrigated cropland (Lamers et al. 2006; Khamzina 2006a; Khamzina et al. 2008; Khamzina et al. 2009; Djumaeva et al. 2010; Djumaeva et al. 2012). Yet little was done to spatially assess land suitability for afforestation on degraded land in irrigated agro-ecosystems of CA, though a few studies were conducted on land evaluation for afforestation worldwide (e.g., Dent and Murtland 1990; Bydekerke et al. 1998; Hansen et al. 2007; Zomer et al. 2008; Eslami et al. 2010).

Afforestation decisions should consider the location-specific conditions that determine suitability of the area for establishment of tree plantations. The benefits of afforestation are also location-specific, e.g., biomass production and carbon sequestration, which depend on the site quality, its spatial organization within its surroundings, and the stakeholders involved (Hansen et al. 2007). The complexity of land suitability assessment for tree planting is also caused by the multi-functional nature of afforestation including numerous trade-offs and compromises between conflicting interests of the involved parties (Kangas and Kangas 2005).

In forestry and agroforestry, decision-support tools have been applied extensively (e.g., Crookston and Dixon 2005; Ellis et al. 2005; Gilliams et al. 2005; Lexer et al. 2005; Rauscher et al. 2005; Jarnevich and Reynolds 2011; Schwenk et al. 2012). The reviewed models are, however, often location-specific, and thus cannot be directly applied to other geographical areas. As suggested by Bansouleh (2009), the development of the site-specific land suitability assessment that considers local conditions, data availability, and socio-economic settings is a solution for this problem. In this light, land suitability model for afforestation in irrigated agro-ecosystems in northern Uzbekistan has to be developed to facilitate agroforestry decisions and to contribute to land rehabilitation efforts in the region.

The proposed study is part of an interdisciplinary research project "Opportunities for climate change mitigation via afforestation of degraded lands in Central Asia" (http://www.zef.de/1631.html) aiming to assess the role of plantation forestry for ecological restoration and for improvement of rural livelihoods in Uzbekistan. This project encompasses agroforestry and spatial, socio-economic, and policy aspects to identify the environmental, economic, institutional, and informational conditions under which afforestation projects can be realized in the context of Uzbekistan. The current doctoral study represents the spatial component of the project, focusing on monitoring of cropland degradation and assessing the biophysical potential for afforestation to support decisions on land rehabilitation as well as sustainable use of land resources.

1.3 Research objectives

In the downstream of the Amu Darya River in Uzbekistan, degradation of irrigated cropland is a serious problem that has its implications for the economic, social, and environmental sustainability of the country (Vlek et al. 2012). Moreover, the absence of accurate up-to-date spatial information on the extent of LD as well as on its triggers forestalls implementation of land rehabilitation measures, which threatens sustainability of irrigated agriculture and people's livelihoods. The demarcation of the irrigated cropland area affected by LD, and identification of the LD factors would make it possible to target areas for mitigation efforts and to prioritize those in need of immediate policy attention.

Afforestation of the degraded cropland is claimed to be a feasible option to combat LD and at the same time guarantee income sources for the rural population in the downstream of the Amu Darya River in northern Uzbekistan (Djanibekov et al. 2012b; Khamzina et al. 2012). Its implementation should be based on the spatial assessment of suitability of degraded land for afforestation with the selected tree species.

The overall aim of this research was to enhance spatial knowledge on the cropland degradation in the irrigated agro-ecosystems in northern Uzbekistan to support policy interventions on land rehabilitation measures and sustainable land management. The following specific objectives were defined for the study area:

1. To analyze extent and factors of irrigated cropland degradation at the regional scale,
2. To derive parcel-specific information on irrigated cropland degradation,
3. To assess land suitability for afforesting degraded irrigated cropland with the selected tree species.

1.4 Thesis outline

The thesis is structured in six interrelated chapters. Following an introduction (chapter 1) to the research problem, the study area is described in chapter 2. The chapters 3-5 consist of the brief introduction to the topic of the analyses, methods used, the analyses per se, discussion of the results, and drawn conclusions. Chapter 3 deals with RS-based assessment of irrigated cropland degradation at the regional level using time series of 250-m MODIS NDVI images. The resulting spatial LD patterns are explained using logistic regression modeling and by relating the observed patterns to a number of biophysical and socio-economic factors, such as soil quality, GWT, groundwater salinity (GWS), population density, irrigation infrastructure, etc. To facilitate site-specific decisions on land rehabilitation measures, chapter 4 presents the findings of the object-based analysis of vegetation cover decline using 30-m Landsat imagery. The results of the land suitability assessment for afforestation of the degraded irrigated cropland with the selected tree species are described and discussed in chapter 5. Chapter 6 concludes the thesis by summarizing the main findings of the research and providing an outlook on the further implications of this work.

2 GEOGRAPHY OF NORTHERN UZBEKISTAN

2.1 Geographic location, population, and administrative structure

The study area consists of the Khorezm Province and the southern part of the Autonomous Republic of Karakalpakstan (SKKP) located in the north-western part of Uzbekistan in the lower reaches of the Amu Darya River. It spreads between latitude 40°62′ and 42°71′ N and longitude 60°02′ and 62°44′ E, which is about 225 km south of the former shore of the Aral Sea (Figure 2.1). The region borders on the natural sandy deserts Karakum and Kyzylkum in the south and east. It covers an area of about 662,042 ha[1] of which 410,000 ha (270,000 ha in Khorezm and 140,000 ha in the SKKP) are irrigated cropland (Dubovyk et al. 2013b).

Due to its location in the downstream of the Amu Darya River, Khorezm and the SKKP are among the final receivers of the water. In the last years, the water supply has significantly decreased and has become unreliable because of the increasing upstream water use and frequent droughts, which resulted in major crop failures in 2000, 2001, 2008 and 2011 (CACILM 2006). Moreover, the amount of water is predicted to reduce further given the impacts of climate change and increasing demand from the continuously growing population (Perelet 2007; Lioubimtseva and Henebry 2009).

The region's population of 2 million people is increasing at an annual rate of about 2% (UZSTAT 2010b). Khorezm has a population of 1.5 million, while 0.5 million people live in the SKKP. About 70% of the population is engaged in crop production and in animal husbandry and horticulture. Agriculture accounts for 35% of the Uzbek GDP (UZSTAT 2010b). The socio-economic and public health situation in the region has been negatively affected by the proximity to the environmental disaster area of the Aral Sea Basin. The study area is divided into administrative units, called districts. Khorezm consists of ten districts with the capital in Urgench. The SKKP is a part of Autonomus Republic of Karakalpakstan, and it consists of three districts with the capital in Nukus.

[1] The study region excludes the area of the former Pytnak district of Khorezm and covers irrigated areas in Khorezm and the SKKP.

Figure 2.1: Location of the study area Khorezm and southern part of Autonomous Republic of Karakalpakstan in Uzbekistan and in Central Asia

2.2 Climate

The study region belongs to the Central Asian semi-desert zone with an extreme continental climate (Glazirin et al. 1999). The annual precipitation, averaging 100 mm (Tischbein et al. 2012), falls mostly outside the crop-growing season (April-October) and is greatly exceeded by annual evaporation (Figure 2.2) (Conrad et al. 2007). Thus, crop production depends entirely on irrigation. The mean annual temperature is about +13°C, while the absolute daily minimum and maximum temperatures may reach up to -28°C and +45°C, respectively (Djalalov et al., 2005). The frost-free period lasts about 205 days (Khamzina 2006a).

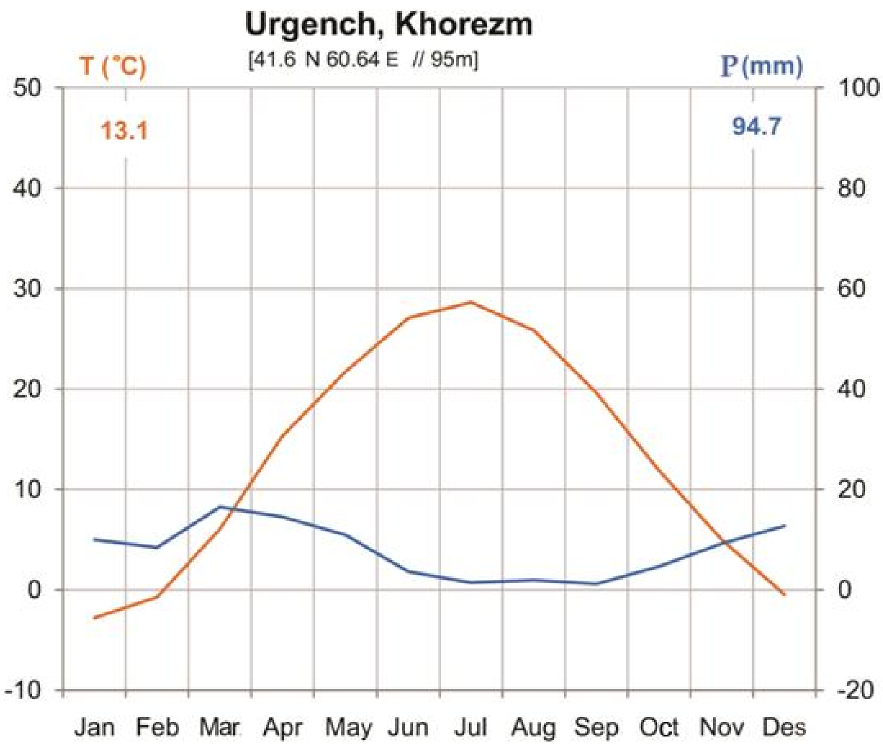

Figure 2.2: Monthly mean air temperature and monthly precipitation in Urgench during 1980-2006 according to Walter-Lieth (modified from Conrad et al. 2012)

2.3 Relief, geomorphology, soils, and hydrogeology

The region is located on the alluvial plain of the Amu Darya River with the floodplain strip, varying from 0.3-0.5 km to 3-5 km in width. In the study area, the current state of the soils is a result of the meandering Amu Darya River that deposited sediments along the banks and in depressions. Alluvial deposits along the meanders mostly consist of sand, while the depressions are mainly filled with clay and loam (Fayzullaev 1980).

When irrigation was introduced in the 1950s, sediments were deposited on the cropland forming spatially distinct features in the topsoils. Long-term irrigation formed a layer of uniform topsoil, i.e., an agro-irrigation horizon, which consists of a multi-layered alluvium. Today, the soil texture is dominated by silty loam, sandy loam and loam (Akramkhanov et al. 2012).

According to the FAO classification, the following soil types dominate in Khorezm: arenosols, cambisols, and fluvisols (FAO 2003). In the SKKP, most of the soils in the irrigated area are fluvisols, often flanked by dune areas of regosols, and with salt pans of solonetz (Mott-MacDonald 2011).The main characteristic of the soils is low humus content in a range of 0.1-0.5%, and low organic matter averaging about 0.75% in Khorezm (Akramkhanov et al. 2012) and not more than 1% in the SKKP (Mott-MacDonald 2011) in the topsoil layers and decreasing in the deeper layers. Cation exchange capacity varies between 5 and 10 meq/100g. Total nitrogen and phosphorus contents are also low, ranging between 0.03-0.15% and 0.01-0.18%, respectively, while the available potassium content is classified as low to moderate (Fayzullaev 1980; Mott-MacDonald 2011). Overall, the soils are characterized by rather low fertility. Crop cultivation thus requires fertilizer inputs (Khamzina 2006a).

Virtually all the soils in the region are subjected to degradation mainly due to various degrees of salinity, primarily as a consequence of the salt transport from the shallow saline GWT (Figure 2.3). Soil salinization is dominated by sulphate-chloride and chloride characteristics. A higher level of soil salinity occurred in the downstream parts of the irrigation system, where the GWT is 1-2 m and where drainage is inadequate (Mott-MacDonald 2011). For crop cultivation, seasonal salt leaching is practiced for coping with soil salinization (Ibrakhimov et al. 2007).

Khorezm and the SKKP are predominantly flat with elevations ranging between 85 m and 205 m asl. Slopes do not generally exceed 10% with the exception of the very northern part of the SKKP where slopes can reach up to 27% (Dubovyk et al. 2013b).

Due to the small phreatic gradient, the lateral groundwater flow is slow, averaging about 0.02 m3/d*ha in the SKKP (Mott-MacDonald 2011). This, coupled with the prevailing heavy soil textures and arid climate, restricts groundwater outflow and increases evaporative losses. Besides poor natural drainage conditions (low-lying location, relief flatness), the shallow GWT results from losses from the irrigation system (Ibrakhimov et al. 2007). Fluctuations of the GWT are also driven by irrigation and leaching activities (Ibrakhimov 2004; Mott-MacDonald 2011). The GWT may rise up to 1 m below the soil surface during salt leaching (March-April) and irrigation events (April-September) and drop to about 2 m in October. The result is secondary soil salinization throughout the entire irrigated cropland, which triggers degradation processes (Mott-MacDonald 2011; Akramkhanov and Vlek 2012).

Figure 2.3: Degraded highly saline cropland in the Khorezm (left) and degraded abandoned cropland in the southern Karakalpakstan (right) during the crop growing season of 2010–2011

Regardless of the shallow GWTs in Khorezm and the SKKP, the use of groundwater for irrigation is limited due to the cost of energy for pumping, and to GWS, which mostly makes soils unsuitable for crops. On average, the groundwater was moderately saline during 1990-2000 in Khorezm averaging 1.75±0.99 g/1 (Ibrakhimov et al. 2007). The portion of the cropland with a high GWS of 3-10 g/l was observed on about 10% of the total irrigated area. In the SKKP, the areas with a GWS of 1-3 g/l occurred on 81,360 ha (58% of irrigated area) in July 2009, while areas with GWS of 3-5 g/l were observed on 17,090 ha (0.12% of irrigated area) (Mott-MacDonald 2011). Under such conditions, crop cultivation is possible only with well functioning drainage network (Khamzina 2006a).

2.4 Irrigation and drainage network

The irrigated land in the study region is served by the extensive irrigation and drainage network established in 1950s (Alimov and Kadurov 1979). The irrigation water is supplied from the Amu Darya River via a dense network of 16,000 km and 6,000 km of irrigation canals and 8,000 km and 5,000 km of drainage collectors in Khorezm (Conrad et al. 2007), and in the SKKP (Mott-MacDonald 2011), respectively (Figure 2.4, Figure 2.5). Only 11% (Khorezm) and 0.04% (SKKP) of these canals are lined, while the on-farm systems consist mostly of earth canals, which greatly reduce the amount of water that is ultimately delivered to the crop fields. The irrigation water is supplied by both direct gravity flow and pumped flow via a hierarchically constructed irrigation network, including main, inter-farm, and on-farm canals. Though also used in Khorezm, water pumping is more frequent in the SKKP, where around 96% of irrigated cropland is served by pumps within the on-farm network (Mott-MacDonald 2011).

The drainage system is mainly open horizontal. The water is drained away via a hierarchically arranged network to the lakes and depressions outside the irrigated area. This has been causing flooding of the neighboring fields, leading to elevated GWT and, eventually, soil salinization and waterlogging (Alimov and Kadurov 1979). The observed shallow GWT and increasing soil salinization indicate a sub-optimal performance of the irrigation and drainage system (Ibrakhimov 2004).

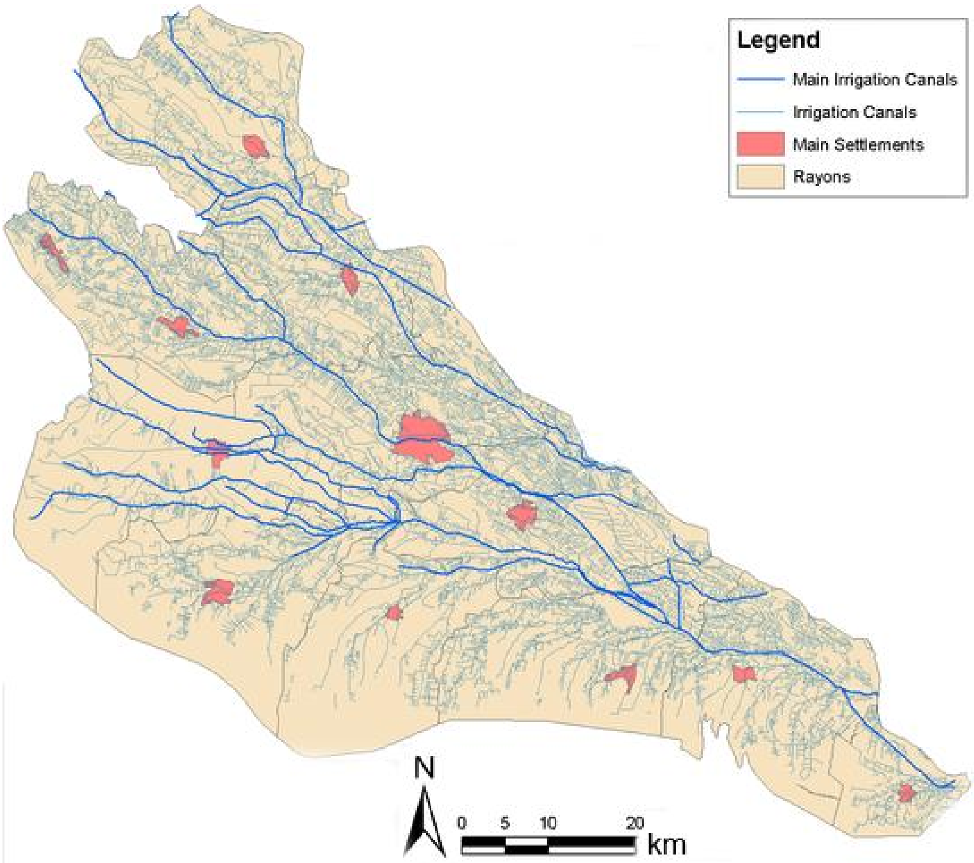

Figure 2.4: Irrigation network in the study region: example of Khorezm[2]

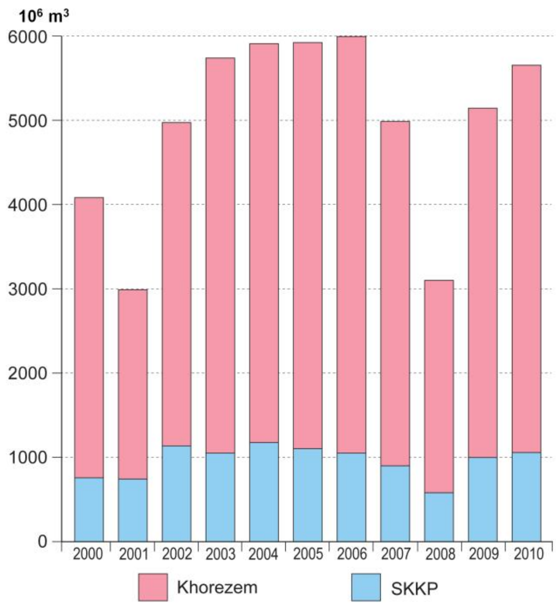

Figure 2.5: Total irrigation water use in Khorezm and southern Karakalpakstan during the vegetation periods 2000-2010

[2] Source: ZEF/UNESCO project database (http://www.khorezm.zef.de/)

2.5 Land use and land cover

The study region is an important center of irrigated agriculture in the country. The main crops are cotton and winter wheat, which occupy 50-70% (cotton) and 20-30% (winter wheat) of the arable land (UZSTAT 2010a; Mott-MacDonald 2011). Cotton has always been produced in Uzbekistan as a means of gaining export earnings, whereas wheat was introduced in the 1990s for national wheat self-sufficiency. Cotton can be rotated with winter wheat, followed by summer crops (Figure 2.6). These crops are cultivated under the state procurement system introduced in the Soviet Union era, when cotton cultivation was regulated by a state order (Djanibekov et al. 2010).

After independence in 1991, the Uzbek government maintained the centrally planned economy in the cotton production sector and added the quotas for winter wheat for national self-reliance. The spatial cropping patterns for these strategic crops are also defined by the government according to the standards established in the Soviet era. The state-order system requires cropping of wheat and cotton over at least 50% of the total irrigated area (Mott-MacDonald 2011). On the area of land that is not assigned to cotton, and following the winter wheat, farmers grow maize, sorghum, watermelons, melons, and vegetables (Conrad et al. 2007). Irrigation water supply to crop fields is determined according to the standard guidelines set up in the 1960s (Rakhimbaev et al. 1992).

The natural vegetation is represented by the Tugai floodplain forest along the banks of the Amu Darya River and vegetation in the transition areas on the margins of irrigated cropland. The major species of the desert areas belong to the genera *Calligonum, Haloxylon, Salsola* and *Tamarix* (Figure 2.7). The main tree species of the Tugai forest are *Populus euphratica* Oliv., *Elaeagnus angustifolia* L., and *Salix songarica* Anderss (Khamzina 2006a). The Tugai forest covered about 39,000 ha in 2005 in Khorezm (Tupitsa 2010) and 65,000 ha in 2000 in the SKKP (Mott-MacDonald 2011), but its area has decreased by as much 90% during the last decades. The forest of the SKKP, which includes shelter belts, occupied an area of 475 ha in 2009.

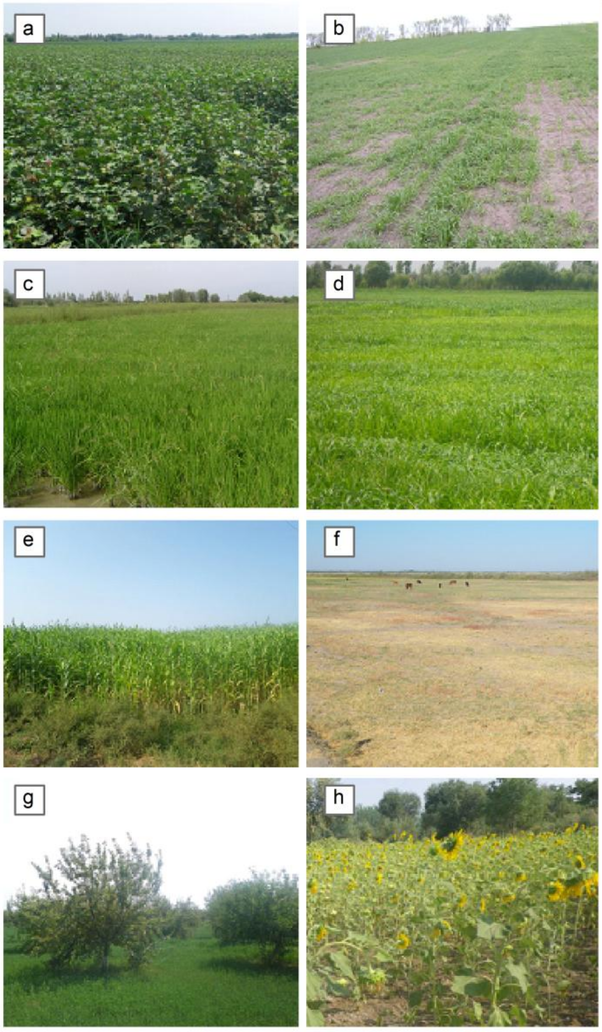

Figure 2.6: Agricultural land use in Khorezm and southern Karakalpakstan: a) cotton, b) winter wheat, c) rice, d) winter wheat – summer crop (on the photo: rotation with maize), e) sorghum, f) fallow uncultivated land, g) permanent crops (on the photo: apple trees), h) other crops (on the photo: sunflowers)

In the study region, tree cultivation was introduced in the 1950s mainly to fulfill ecological functions by protecting agricultural fields from wind erosion and preventing desertification at the margins of the irrigated areas. Such tree plantations mainly include *Morus, Populus, Ulmus, Salix*, and *Elaeagnus* species (Appendix 8.1). The trees are usually planted as strips on field borders (tree windbreaks) and along on-farm canals (Tupitsa 2010).

Figure 2.7: Common species of the Tugai forest: *Populus euphratica* (top) and Tamarix species (bottom)

Since 1991, the reform of the agricultural sector has taken place and has been characterized by state-induced farm restructuring, land transfer from collective to individual use, state ownership of land, and area-based state targets for cotton at fixed prices (Djanibekov et al. 2012a). Being planned according to the developed irrigation network, the boundaries of the field parcels in the cadastral maps have not been changed over last 20 years.

3 SPATIO-TEMPORAL ANALYSES OF CROPLAND DEGRADATION AT REGIONAL SCALE

3.1 Introduction

Dryland degradation manifests in the reduction of the productive potential of the land (Reynolds et al. 2007). It is a gradual process that becomes obvious particularly in the long run, and thus requires frequently recorded land-productivity data spanning over years. As RS-based vegetation indices (VIs) are proven as indicators for biomass productivity, the degraded land can be detected via analyses of their gradual changes (Tucker et al. 1985; Bai et al. 2008). In arid and semi-arid areas, the sum of NDVI over a growing season (∑NDVI) is strongly correlated with the vegetation production (Nicholson et al. 1998), revealing that a decreasing linear trend is a good indicator of the vegetation loss and can serve as an early warning of LD (Budde et al. 2004; Wessels et al. 2004). A statistical trend analysis is often applied to analyze satellite time series to detect spatial patterns and rates of land-cover changes (Lambin and Linderman 2006). Such analysis can separate seasonal and annual variations from long-term phenomena (Sonnenschein et al. 2011), enabling mapping of land productivity changes caused by degradation processes (Eastman et al. 2009). This allows overcoming limitations of the commonly applied bitemporal change detection methods and mapping subtle land-cover changes, caused by land-use practices (Röder et al. 2008).

Trend analysis of RS time series has been used to effectively describe a vegetation trend in natural environments (Sonnenschein et al. 2011) and agricultural ecosystems similar to the presented case (Fuller 1998; Tottrup and Rasmussen 2004). This analysis was routinely used for phenological and LD studies using a coarse-scale imagery (Wessels et al. 2008; Reed et al. 2009). For example, the Global Inventory Modeling and Mapping Studies (GIMMS), Bai and Dent (2009) used the 23 years of NDVI datasets to reveal recent LD and improvement in China. Similarly, mapping of long-term negative changes in savannah crop productivity in Senegal was implemented through trend analysis of time series of the AVHRR NDVI data and related to the LD problem (Tottrup and Rasmussen 2004). Wessels et al. (2004) used the AVHRR NDVI time series (1985-2003) for assessing the human impact on desertification in South Africa.

Only a limited number of studies used satellite time series of medium and high spatial resolution, which are likely to be more appropriate for monitoring of fragmented landscapes of drylands (Sonnenschein et al. 2011). The reason is that the medium-scale data, such as from MODIS, until recently did not cover sufficiently long periods to allow trend analyses (Prince et al. 2009; Fensholt and Proud 2012). The comparatively higher-scale images from the Landsat program, recorded since 1972, are not always in place for all geographical areas, e.g., CA, on the frequent and repeatable basis required for trend analyses. The current availability of the over-decade MODIS imagery gives an opportunity to advance LD monitoring of irrigated drylands.

Despite a considerable amount of literature available on the subject of LD, only a few studies have explicitly linked this phenomenon with its factors (Gao and Liu 2010). Some studies implemented statistical analyses to correlate observed trends with individual drivers. Bai and Dent (2009) analyzed relationships between degraded areas and LULC, population density, aridity index, and poverty in China. Vlek et al. (2008) correlated LD in sub-Saharan Africa with population, terrain, soil, and LULC. The relative importance of factors contributing to the spread of LD in irrigated agricultural regions has been less studied. Information on the relevant LD factors can be gathered by integration of RS techniques and spatial statistical modeling.

In this context, an adopted approach for mapping of irrigated cropland degradation in the study area included spatial analysis of the LD trend based on the MODIS-NDVI time series (2000-2010). To explain the observed trend and its causes, the areas of vegetation decline, used as a proxy of LD, were analyzed by comparing these with supplementary datasets, including environmental and socio-economic parameters. Further, logistic regression modeling was used to assess the relative importance of the possible LD factors. These factors were employed to map areas at risk of LD as a means to draw attention to the degraded cropland in urgent need of rehabilitation.

3.2 Data sources and processing

The data used in the study include (i) raster data: MODIS images (MOD13Q1, https://lpdaac.usgs.gov/) and (ii) vector data: LULC maps (2001-2009) derived from the 250-m MODIS data, infrastructure and environmental data with accuracy mainly equivalent to a map scales 1:25,000, 1:50,000 and 1:100,000, and (iii) ancillary data: datasets of GWT and GWS. All raster and vector data were converted to the same coordinate system (ED 1950 UTM Zone 41N). The vector and ancillary data were collected from the ZEF/UNESCO project database (http://www.khorezm.zef.de/) and South Karakalpakstan Water Resources Management Improvement Project (Mott-MacDonald 2011); the LULC maps were developed by Machwitz et al. (2010). In addition, informal discussions and guided field visits were held with the irrigation engineers and cadastral mangers during field visits in 2010-2012 (Appendix 8.2).

3.3 Methods

The analyses were performed in three stages: (i) LD mapping based on the MODIS-NDVI time series, (ii) relational analysis of the vegetation trends, and (iii) spatial logistic regression modeling. All stages involved data preparation, i.e., pre-processing of the MODIS images and making a set of factor maps as inputs to the model. The spatial modeling stage included logistic regression analysis comprising a multicollinearity check, modeling, and validation. Subsequently, the model results were used to produce a risk map of LD.

3.3.1 Linear trend analysis

Following a trend analysis of remote-sensing time series, long-term changes could be described in vegetation productivity (e.g., Sjostrom et al. 2011; Fensholt and Proud 2012), land surface phenology (e.g., de Beurs and Henebry 2004; Verbesselt et al. 2010b), land cover (Propastin et al. 2008; Lhermitte et al. 2011), and LD (Budde et al. 2004; Wessels et al. 2007; Bai et al. 2008; Röder et al. 2008; Paudel and Andersen 2010). In arid and semi-arid environments, the sum of NDVI over the vegetation growing season (ΣNDVI) was strongly correlated with the vegetation [including crop] productivity (Nicholson et al. 1998; Hilker et al. 2008). For example, Rasmussen (1998) showed a high correlation between sorghum and millet crop yields and ΣNDVI in Senegal. Hence, a decreasing ΣNDVI trend can be used as an indicator of the vegetation loss and serve as an early warning of the LD occurrence (Tottrup and Rasmussen 2004; Wessels et al. 2004).

Among the methods used to analyze time series of satellite images, i.e., principal component analysis (Eastman and Fulk 1993), harmonic regression (Eastman et al. 2009), change vector analysis (Lambin and Ehrlich 1997), and Fourier transformation (Jeganathan et al. 2010), the trend analysis provides a clearly interpretable and consistent measure of change, regardless of study area and time period considered (Rigina and Rasmussen 2003; Verbesselt et al. 2010a; Fensholt and Proud 2012). Moreover, in contrast to the other methods, trend analysis is capable of quantifying gradual degradation processes within one land-use class, thus allowing monitoring subtle land-cover changes, caused by degradation (Röder et al. 2008).

In this study, the time series of NDVI images, acquired from the MODIS MOD13Q1 product (collection 5) for the period 2000-2010, were used. The 250-m MODIS imagery was selected due to its higher spatial and temporal resolution compared to the other easily accessible RS time series spanning over longer time periods. The MOD13Q1 datasets are atmospherically corrected (Vermote et al. 2002) and composed of the best observations during 16-day periods with regard to overall pixel quality (aerosol content, low view angle, and absence of clouds/cloud shadows) and observational coverage (Justice et al. 2002).

The data were pre-processed by (i) identifying and removing low-quality pixels based on the data quality flags specified in MOD13Q1, (ii) filling data gaps with linear interpolation, and (iii) smoothing images with an adaptive Savitsky-Golay filter (Jonsson and Eklundh 2002). During the smoothing procedure, the data quality flags were applied to weigh the data; higher weights were assigned to higher-quality pixels, while lower-quality data had a minor influence on the curve fit (Figure 3.1). The ΣNDVI was calculated for each crop growing season (April-October) of the years 2000 till 2010 from the preprocessed NDVI time series.

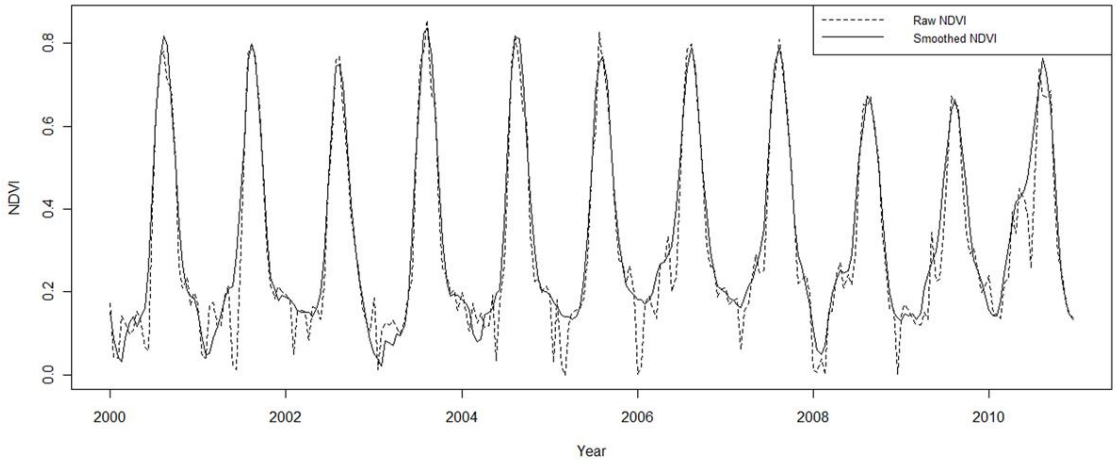

Figure 3.1: Raw and smoothed 16-day, 250-m MODIS-NDVI time series of one pixel

For each pixel on the map, trend coefficients, regression constant (*a*) and coefficient of linear regression (*b*), were calculated using a least-square fit for every pixel according to:

$$\mathrm{f(x)} = \mathrm{b} \times \mathrm{x} + \mathrm{a} \tag{3.1}$$

where $f(x)$ is a ΣNDVI over the crop growing season at year x.

The slope of the trend *b* shows the direction and magnitude of the vegetation changes over the analyzed period of time. As these parameters are calculated pixel-wise, the derived temporal changes can be shown in a spatially differentiated way (Röder et al. 2008).

The statistical significance of the estimated trend was tested with a *T*-test. The class boundaries were defined for 90% and 95% confidence levels. The resulting trend map was regrouped into four classes (Table 3.1). A detailed analysis of neutral and positive slopes of the linear trend was outside the scope of this study, where the main research focus was on LD.

Table 3.1: Definition of classes for mapping the negative vegetation trend in the study area

Class name	**Class boundary**
High negative vegetation trend	*P*-values of the negative slope > 0.025*
Medium negative vegetation trend	*P*-values of the negative slope > 0.05*
Low negative vegetation trend	*P*-values of the negative slope <0.05*
Other	Other slope values

** P-values of both tails of the distribution*

The quality of the calculated trends can be evaluated by assessing the impact of the errors associated with a particular image and its position in the time series (Hostert et al. 2003). The effect is greater at the beginning and end of the time series, while errors in the middle of the series have less influence on the direction of the trend (Röder et al. 2008). To test an impact on the trend by individual scenes, the calculated trend map was compared to the full set of 11 ∑NDVI images and 2 reduced sets of 10 images without the 2000 and 2010 scenes. In addition, direct field observations were conducted for validation of the derived trend map. Altogether, 828 fields bigger than 6.25 ha were randomly sampled in summer 2011 (Figure 2.3). For sampling, two classes were considered: class 'degraded land', representing the first two classes and the class 'other' (Table 3.1).

3.3.2 Relational analysis of land degradation and its factors

The areas that showed a significant negative vegetation trend were spatially related to the ancillary datasets, i.e., population density, land use, soil quality, and terrain, to interpret the decline in vegetation productivity, and specify the direction of any remedial action. In the irrigated study area, vegetation cover fluctuates depending on the stage of crop growth, which is influenced by irrigation water availability, soil quality, and the intensity of land use. Population density and changes in land use were taken as a proxy for the intensity of land use (Vlek et al. 2008; Bai and Dent 2009). Irrigation overrides the usually strong relationship between vegetation productivity and precipitation observed in rain-fed agricultural and natural ecosystems (e.g., Wessels et al. 2007). Reduced irrigation water supplies negatively influence vegetation growth in the study region as experienced in the cropping seasons of 2000-2001 and, to a lesser extent, in 2008 and 2011 (Tischbein et al. 2012). In other years, the annual water supply to the study region through the Tuyamuyun reservoir remained stable between 2000 and 2010, except during the drought years 2001, 2002, and 2008 (Figure 2.5 and Appendix 8.4). In addition, the total size of the irrigated area hardly changed during this period, and the main crops cotton and winter wheat were irrigated according to the standardized guidelines (Rakhimbaev et al. 1992).

Natural soil fertility is an important factor to consider in the analysis of LD. It not only determines land suitability for agriculture, but can also serve as an indicator for vulnerability to LD, since low-quality soils are more prone to degradation. Soil *bonitation* is a measure of a relative quantitative assessment of land suitability for cropping introduced in Soviet times and still used in many post-Soviet countries (Ramazonov and Yusupbekov 2003). It is an aggregate of several parameters, varying from the physical soil characteristics (e.g., texture) to chemical soil properties (e.g., salinity) (Karmanov 1980). Values range from 0 to 100 points, grouped in four fertility rate classes: class VI 'low' (<40 points), class III 'average' (41-60 points), class II 'increased' (61-80 points), and class I 'very high' (81-100 points). To analyze how degraded cropland is distributed within these *bonitation* classes, each of the pixels marked as degraded was differentiated according to the corresponding *bonitation* class.

In a next step, spatial distribution of LD was analyzed with respect to slope. In general, terrain characteristics such as elevation and slope define also land suitability for agriculture. For example, cropland with an elevation of more than 3500 m asl or slopes >25° (ca. 47%) is considered unsuitable for cropping (e.g., Sheng 1990). The terrain of the agricultural study area is flat with elevations ranging between 85 m and 205 m and slopes of below 10%, except in the very north of the SKKP, where slopes could reach up to 27%. On the other hand, the flat, low-laying terrain restricts natural outflow of water, making it susceptible to soil salinization, which is at present wide-spread (Ibrakhimov et al. 2007). Likewise, the supply of irrigation water and its distribution over the fields depends on terrain characteristics (Martius et al. 2012), eventually impacting crop growth.

The following analysis differentiated LD in relation to population density as a proxy for population pressure, as recommended by the Global Assessment of Human-induced Soil Degradation (GLASOD) (Oldeman et al. 1990). The population densities were calculated per water user association (WUA), now called water consumer associations, within every district in Khorezm and the SKKP in 2009-2010, since statistics were only available for this administrative level (UZSTAT 2010b). The population densities were then reclassified into the four classes using a natural breaks algorithm: low density (0-2 pers/ha), medium density (2-17 pers/ha), high density (17-39 pers/ha), and very high density (39-79 pers/ha).

In the study area, two agricultural land-use periods can be distinguished: a spring season (October-June) dominated by winter wheat, and a summer season (April-October) dominated by cotton. The NDVI temporal profiles differ between spring and summer crops and among the summer crops (Conrad et al. 2011). Although the cropping pattern is largely consistent due to the cotton-wheat policy, a choice of the summer crop (after the harvest of winter wheat in June) or fallowing land can alter the NDVI trend. To avoid misinterpretation due to changes in cropping patterns, the negative NDVI trend map was cross-referenced with the land-use data. The LULC maps for the years 2001-2009 (Machwitz et al. 2010) were used for this analysis. In case the agricultural land use of one pixel remained unchanged for six years between 2001 and 2009, these areas were described as 'no change' areas. The same approach was used to derive a map of abandoned cropland, which was defined as a land in fallow for at least six years during the monitoring period. Previous studies in Khorezm showed that land abandonment occurred mostly in areas least suitable for cropping due to low water availability, uneven terrain, infertile soils, shallow GWT, and declining irrigation infrastructure (Dubovyk et al. 2012a).

3.3.3 Spatial logistic regression modeling

Data compilation for logistic regression

The list of factors determining LD in the study area was summarized based on informal discussions with local experts from the ZEF/UNESCO Khorezm project (http://www.khorezm.zef.de/) and a review of literature for the study region (e.g., Akramkhanov et al. 2011; Ibrakhimov et al. 2011). In addition to the factors described in section 3.3.2, the identified factors ranged from groundwater and relief characteristics to land ownership and management. The main factors for which the data were available served as inputs to the logistic regression model (Table 3.2).

The corresponding factor maps were prepared for each factor (independent variables x_i). The nature of the maps was binary (presence of a factor = 1, absence = 0) and continuous; they had the same spatial extent, 250 m × 250 m cell size, map projection, and coordinate system. The binary map for the dependent variable (y) was represented by the significant negative ΣNDVI trend through merging the classes 'high negative vegetation trend' and 'medium negative vegetation trend' into a new class 'degraded land' (section 3.3.1).

Table 3.2: Variables included in the spatial logistic regression model

Variable		**Description**	**Nature of variable**
I *Dependent*	y	Degraded land (1–degraded land, 0–not)	Binary
II *Independent:*			
a) Site-specific characteristics			
Change in land use	x_1	Change in land use (1–no change, 0–change)	Binary
Uncultivated land	x_2	Uncultivated land (1–lack of cultivation; 0–cultivation)	Binary
Soil *bonitation* I*	x_3	Class I "very high" (1–class I, 0–other classes)	Binary
Soil *bonitation* II	x_4	Class II "increased" (1–class II, 0–other classes)	Binary
Soil *bonitation* III	x_5	Class III "average" (1 – class III, 0 – other classes)	Binary
Soil *bonitation* IV	x_6	Class IV "low" (1 – class IV, 0 – other classes)	Binary
Canal density	x_7	Density of irrigation canals (m/m^2)	Continuous
Collector density	x_8	Density of drainage collectors (m/m^2)	Continuous
Water use	x_9	Average delta of water use per district (million m^3)	Continuous
Slope	x_{10}	Slope (%)	Continuous
Groundwater table	x_{11}	Level of groundwater table (m)	Continuous
Groundwater salinity	x_{12}	Groundwater salinity (g/l)	Continuous
b) Proximity characteristics			
Proximity to canals	x_{13}	Proximity to irrigation canals (m)	Continuous
Proximity to collectors	x_{14}	Proximity to drainage collectors (m)	Continuous
Proximity to pumps**	x_{15}	Proximity to water pumps (m)	Continuous
Proximity to roads	x_{16}	Proximity to roads (m)	Continuous
Proximity to settlements	x_{17}	Proximity to settlements (m)	Continuous
Proximity to water bodies	x_{18}	Proximity to lakes and the Amu Darya River (m)	Continuous

** Class soil bonitation I does not occur in the SKKP*
***Available only for Khorezm region*

The site-specific characteristics included land use (change in land use, lack of cultivation), soil suitability for crop production (as determined by soil *bonitation)*, density of irrigation and drainage network, irrigation water use, slope, GWT level and GWS. The information on land-use change and lack of cultivation were derived from the LULC maps for 2001-2009 based on post-classification comparison.

For Khorezm, the maps of GWT levels and GWS were derived via spherical kriging interpolation based on values measured in April, July and October and averaged over the years 1990-2004 for 1,798 observation points, as suggested by Ibrakhimov et al. (2007). These authors showed that GWT and GWS did not significantly fluctuate over the years except for the drought year 2000. Thus, the 1990-2004 data were assumed a reasonable approximation for the time period 2000-2010 covered by the NDVI analysis. As the natural and socio-economic conditions are similar in Khorezm and the SKKP, the same method was used for interpolation of GWT and GWS in the SKKP based on values measured in April, July and October and averaged over the years 2006-2009 for 721 observation points.

Available shapefiles of irrigation and drainage network were used to calculate the density of canals and drains. Factor maps depicting proximities to roads, settlements, irrigation canals, drainage collectors, and water bodies were derived based on the Euclidean distances. The water use, showing differences in water supply, was calculated per district for each pair of years 2000-2010 and averaged over 11 years for the study area.

Logistic regression

Coupled with GIS, logistic regression is an appropriate tool for explanatory analysis of the factors of LULC changes (Menz et al. 2010). In this study, this model was applied to quantify the contribution of the LD factors and to identify areas at risk of LD. Spatial distribution of LD was explained as a function of these factors (Table 3.2). The nature of LD was regarded as binary, where values 1 and 0 were used to denote its presence and absence, respectively. Consequently, the probability of LD occurring was computed with a logistic regression model (Eq. 3.2) (Hosmer and Lemeshow 2000):

$$\mathrm{P(y)}=1/1+\boldsymbol{exp}^{-(\boldsymbol{\beta}_0+\sum_{i=1}^{n}\boldsymbol{\beta}_i x_i)} \qquad (3.2)$$

where $P(y)$ is probability of the dependent variable y being 1 given the independent factors $x_1 \dots x_n$, β_0 is an intercept of the model, β_i (with: $1 <= i <= 18$) are estimated model parameters, which can be interpreted by analyzing odds of the model (Rothman et al. 2008). Considering differences in data availability, separate models were built for Khorezm and the SKKP.

To avoid multicollinearity among model predictors, Variance Inflation Factors (VIF) were calculated, and correlated factors were removed when VIF exceeded the threshold value of 5 (Belsley et al. 1980). The sample size for logistic regression of 8,112 observations for Khorezm and 2,939 observations for the SKKP resulted from the systematic unbalanced random sampling with a 3×3 cell window (750 m × 750 m). Sampling was applied to minimize the impact of spatial dependency between observations, which might cause unreliable estimation of the model parameters (Irwin and Geoghegan 2001). The sample was equally divided into calibration and validation datasets. The former was used to fit the logistic regression following a backward stepwise procedure. The resulting stepwise model was compared to the ordinary model with a Receiver Operating Characteristic test (ROC; Hanley and McNeil 1982), which checks the equality of the area under ROC curve (AUC) of each modality. The best-performing model was selected to generate the LD risk maps for Khorezm and the SKKP.

Model validation

The statistical measures ROC and Percentage of Correct Predictions (PCP) were calculated to evaluate the model performance (Christensen 1997). The AUC ROC value ranges from 0 to 1, where 1 indicates a perfect fit and 0.5 indicates a random fit, (Pontius and Schneider 2001). The PCP is defined as the percentage of correctly predicted pixels to the total number of pixels in the map.

For validation, the final model was applied to the validation dataset, and the probability of LD was computed for every pixel with the fitted logistic regression model (Eq. 3.2). The AUC ROC and PCP were used for comparison of the actual degradation and computed probabilities. In the case of the PCP, the modeled degradation was assigned to the pixels, i.e., if the probability exceeded a commonly accepted threshold value of 0.5, the cell was marked as degraded land (Manel et al. 1999). In addition, the goodness of fit was evaluated with chi-square statistics (Moore and McCabe 1998).

3.4 Results and discussion

3.4.1 Linear trend analysis

The mean seasonal NDVI and significant negative slope of the NDVI trend over the years 2000-2010 are shown in Figure 3.2. For each pixel in the ΣNDVI-based trend map (Figure 3.2b, Figure 3.3), the retained value was the slope of the fitted linear regression between the values of each pixel over time and a perfectly linear time series; thus, the results express the rate of vegetation loss per observation year. The maps reveal the overall correspondence between the low NDVI values (Figure 3.2a) and areas of vegetation decline (Figure 3.2b). The low vegetation cover, found along the southern border of Khorezm and in the north and north-west of the SKKP (Figure 3.2a), reflects the less intensive use of the cropland compared to the rest of the agricultural areas during the monitoring period (Dubovyk et al. 2012b).

Around 40% (331,597 ha) of the study region experienced significant vegetation trends of a different magnitudes during 2000-2010. A pixel-wise trend of vegetation decline, expressed via a negative slope of the linear trend, highlighted the areas of a considerable and alarming loss of vegetation cover, thus signifying LD (Figure 3.2b, Figure 3.3).

Overall, the spatial distribution of the LD trend was highly variable, but several clusters were distinguished mainly on the outskirts of the irrigation system near the borders with the Karakum (Yangiaryk and Khiva districts) and Kyzylkum deserts (north of the Ellikkala district and north and north-east of the Turtkul districts). These areas, located on the edges of the irrigated cropland, were characterized by a relatively low vegetation cover at the beginning of the observation period, and experienced gradual vegetation losses thereafter. A big cluster of degraded land was found in the western part of Khorezm (north of the Kushkhupyr, Yangibazar, and Shavat districts) in the former riverbed of the Amu Darya River.

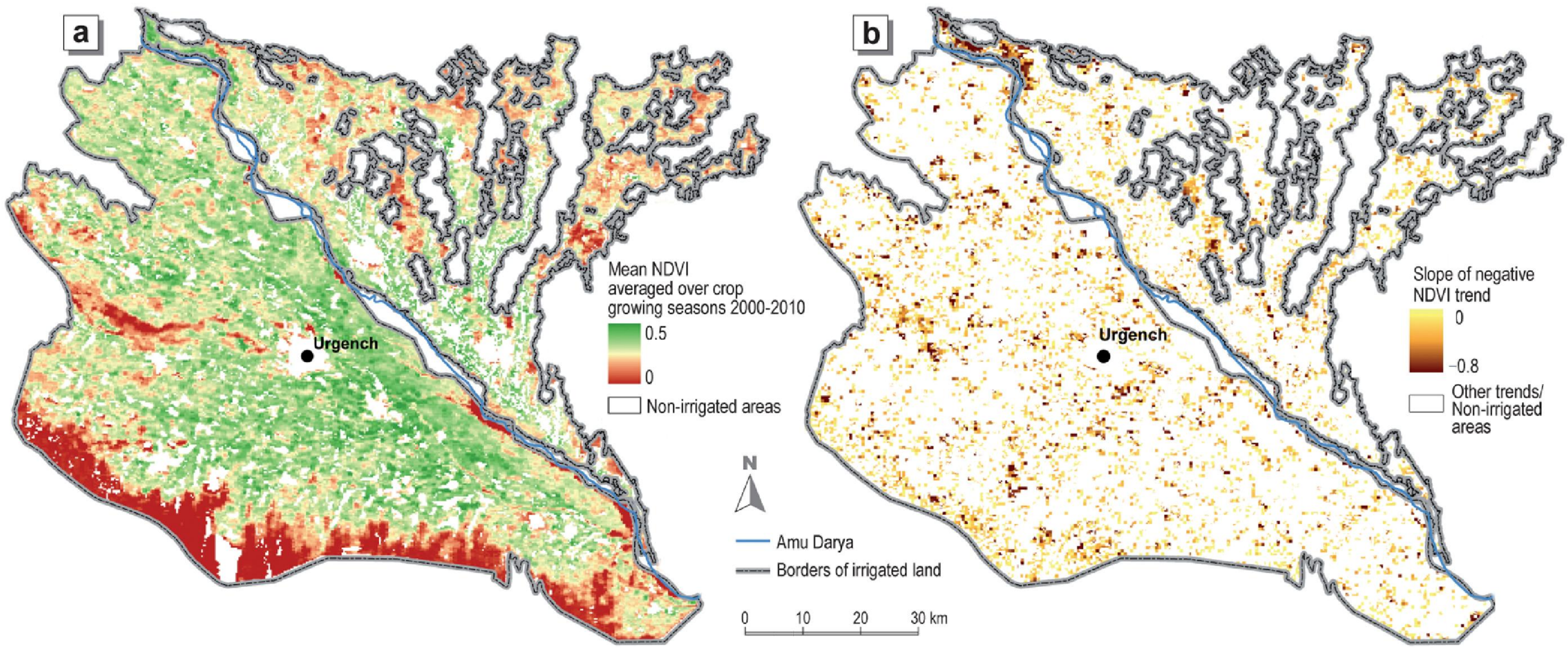

Figure 3.2: Spatial distribution of mean NDVI values, averaged over the crop growing seasons 2000-2010 (a), and negative significant linear trend of NDVI, summed over the crop growing seasons 2000-2010 (b)

Another cluster was formed in the northern and north-eastern part of the SKKP where problems of irrigation water supply were reported (Dubovyk et al. 2012b). Smaller degraded patches were scattered throughout the region and did not show any particular spatial pattern.

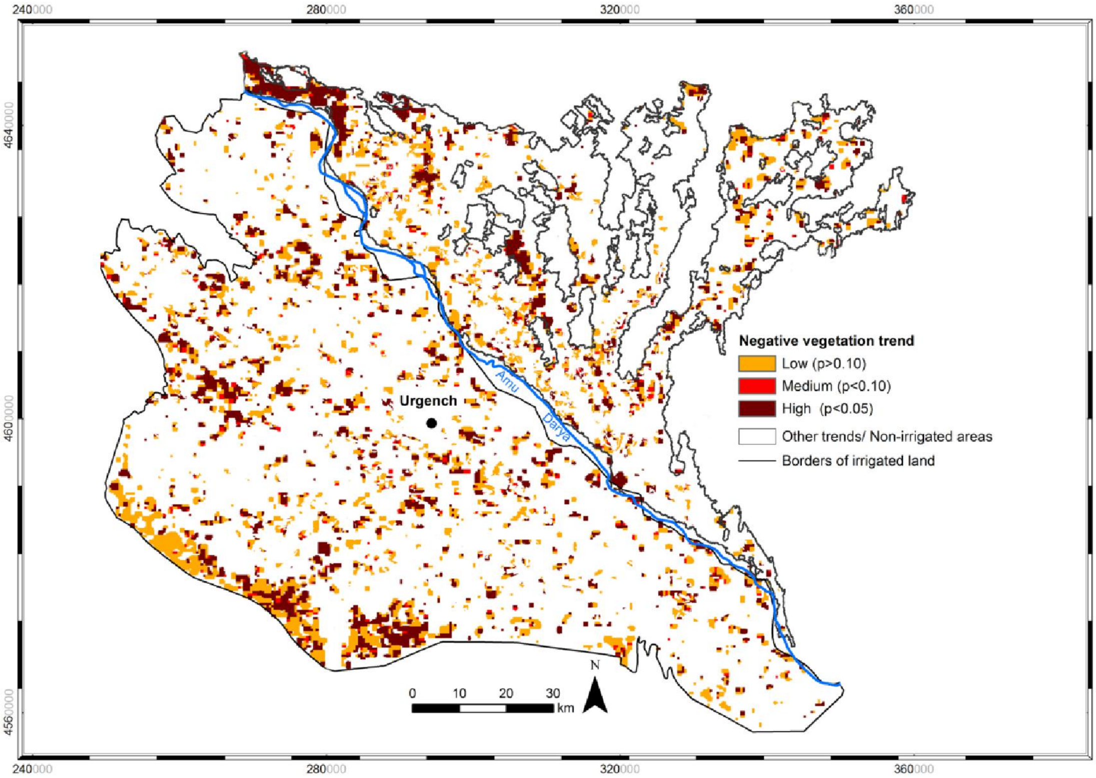

Figure 3.3: Negative vegetation trend in Khorezm and Southern Karakalpakstan, calculated from slope of linear trend of NDVI time series, summed over the growing seasons 2000-2010

An increasing trend in vegetation occurred on 19.6% (80,538 ha) of the arable area, mostly along the banks of the Amu Darya River and near irrigation canals. The vegetation cover on 38% (156,225 ha) of the agricultural area did not change (not shown here). In Khorezm, a very close association (R^2=0.98) of LD hotspots and the soil *bonitation* class IV, which characterizes soils with inherently low fertility, confirmed the low suitability of this land for cropping. As revealed by the calculated trend on desert margins in the southwest, this low-*bonitation* cropland experienced the strongest decline in vegetation cover and was abandoned.

The distribution of negative trends per district area is shown in (Table 3.3). About 21% of the overall area of the study region experienced degradation processes of low, medium and high magnitude during 2000-2010. The areas with the low and high negative trend yielded higher percentages compared to the area with the medium-magnitude trend. In Khorezm and the SKKP, a similar proportion of the area was affected by the high and medium trends, i.e., about 14% and 16%, respectively. In Khorezm, the Khazarasp district had the largest area percentage affected by LD, while the Beruniy district of the SKKP was more affected by LD compared to the other districts.

The cross validation, implemented between two pairs of the trend maps (trend map, based on the full set of images and two reduced sets) yielded overall agreement of 86% and 90%, while omitting images from 2000 and 2010, respectively. This confirms the robustness of the calculated trend. The validation of the trend map, based on the field data, yielded an overall accuracy of 68%, i.e., 72% for Khorezm and 66% for the SKKP. The results of this assessment confirm the validity of the elaborated approach.

The robustness of the calculated LD trend was comparable with that observed in other dryland studies using trend analysis (Hostert et al. 2003; Röder et al. 2008). The result of the comparison of the trend map, based on direct field observations, was similar to or higher than the accuracies reported in related studies. For example, Chen and Rao (2008) yielded an overall accuracy of 65% for the regional LD map derived from the MODIS data in a transition zone between grassland and cropland in northeast China. The resulting degradation trend was also comparable with that observed in other studies in CA, suggesting a reliability of the obtained results. While using the Mann-Kendall trend analysis of the 300-m Medium Resolution Imaging Spectrometer (MERIS) NDVI time series for the years 2003-2011, Dubovyk et al. (2012c) revealed similar spatial patterns of a negative ΣNDVI trend for the same study area (Appendix 8.3). The assessment by Propastin et al. (2008) of vegetation trends in CA, based on 1-km AVHRR time series, showed the presence of the negative linear trend for our study region in the rate from -10% to -20% already in the summer seasons 1982-2003.

Table 3.3: Areal statistics per district of Khorezm and Southern Karakalpakstan for different classes of land degradation in percent

District	**Low**		**Medium**		**High**		**High and Medium**		**District**
	(ha)	**(%)**	**(ha)**	**(%)**	**(ha)**	**(%)**	**(ha)**	**(%)**	**area (ha)**
Bagat	11,981.58	21.91	1,649.20	3.02	5,792.80	10.59	7,442.00	13.61	44,379.92
Gurlen	10,394.84	22.89	1,913.06	4.21	5,126.04	11.29	7,039.10	15.50	42,045.18
Khanka	9,635.70	22.92	1,110.32	2.64	3,529.58	8.39	4,639.90	11.04	45,419.09
Khazarasp	10,102.87	24.59	1,456.93	3.55	6,054.39	14.74	7,511.32	18.28	52,118.61
Khiva	10,040.41	24.07	1,644.60	3.94	5,006.26	12.00	6,650.86	15.94	46,302.80
Kushkhupyr	7,398.91	16.67	979.90	2.21	2,865.47	6.46	3,845.37	8.66	54,694.48
Shavat	10,080.17	21.77	1,429.34	3.09	5,754.96	12.43	7,184.29	15.52	41,719.22
Urgench	8,096.92	22.65	1,726.44	4.83	4,280.70	11.97	6,007.14	16.80	47,930.04
Yangiaryk	9,415.64	18.07	1,147.32	2.20	3,839.87	7.37	4,987.19	9.57	41,079.81
Yangibazar	10,897.64	22.74	1,617.68	3.38	5,278.79	11.01	6,896.48	14.39	35,755.55
TOTAL (Khorezm)	*98,044.69*	*21.72*	*14,674.78*	*3.25*	*47,528.87*	*10.53*	*62,203.65*	*13.78*	*451,444.70*
Beruniy	14,813.13	20.09	2,465.34	3.34	12,394.16	16.81	14,859.50	20.15	73,739.59
Ellikkala	7,695.37	12.73	1,447.50	2.39	5,359.73	8.86	6,807.23	11.26	60,464.01
Turtkul	13,007.61	17.03	1,885.22	2.47	9,079.30	11.88	10,964.52	14.35	76,393.50
TOTAL (Southern Karakalpakstan)	*35,516.11*	*16.86*	*5,798.06*	*2.75*	*26,833.19*	*12.74*	*32,631.25*	*15.49*	*210,597.10*
TOTAL	**133,560.80**	**20.17**	**20,472.84**	**3.09**	**74,362.06**	**11.23**	**94,834.90**	**14.32**	**662,041.80**

In this study, the LD trend was analyzed based on a decrease in the vegetation cover which, in land-use systems, may also occur due to changes in land management (Bai and Dent 2009). In Uzbekistan, the land-use decisions largely remained unchanged during the study period given the area-based, state production targets for cotton and the prevalence of cotton and winter wheat in the cropland area (UZSTAT 2010a; Mott-MacDonald 2011). Furthermore, summing of NDVI over the whole growing season, thus integrating vegetation peaks in the fields with different land uses, reduced the possibility of misinterpretations, particularly for the remaining land fraction with a variable cropping pattern. This approach was previously applied in studies conducted in arid and semi-arid cropland environments (Fuller 1998; Tottrup and Rasmussen 2004).

For this assessment, seasonality in the data was dealt with by integrating NDVI over the crop growing seasons (e.g., de Jong et al. 2011). In irrigated croplands of Uzbekistan, the effects of precipitation on NDVI trends can be neglected due to its minor influence on vegetation dynamics in contrast to the effects of irrigation water management, which cannot be assumed constant (Dubovyk et al. 2013a). Although the standard guidelines are reportedly followed for crop irrigation, the regional water supplies fluctuate from year to year, drastically decreasing during seasonal and long-term droughts (Tischbein et al. 2012). Nevertheless, the existing yield quotas assigned for the dominant crops allow the assumption that, to fulfill these production targets in drought years, the fertile croplands are prioritized in leaching and irrigation decisions rather than the areas of low *bonitation.* Such strategy is likely to aggravate the LD processes occurring in these areas. The absence of reliable and spatially explicit information prevented the quantification of water-related effects on the degradation trend but should be addressed in the follow-up study if the necessary data are available.

The use of time series with a finer spatial resolution than the 250-m MODIS data could disclose an additional level of information, particularly considering the patchy structure of the agricultural landscape in the study area. With respect to the direction of the LD trend and its landscape patterns, results from coarse and fine resolution imagery are expected to correspond, based on the experience of Stellmes et al. (2010) in Mediterranean drylands.

In a recent study, based on the example of the South African semi-arid rangelands Wessels et al. (2012) showed that timing and rate of the degradation influence the detectability of the degradation trend. The authors demonstrated that trend analyses are able to detect only the extreme degradation in ΣNDVI lasting several years. A further study should, therefore, investigate in more detail how and why the changes in trends emerge under these particular environmental and land-use conditions. Nevertheless, RS-based assessment is currently the only means for monitoring vegetation dynamics at a regional scale.

3.4.2 Spatial analysis of land degradation trend

Relational analysis of land degradation and its factors

Spatial patterns of the LD trend were overlaid with the maps of soil *bonitation* (Figure 3.4a,Table 3.4) and slope (Figure 3.4b, Table 3.5). Almost 50% of the degraded areas were found within the low-*bonitation* classes IV and III. These areas, less suitable for agriculture due to soil quality constraints, require the urgent attention of land managers to decide on mitigation measures and cultivation techniques to forestall LD or whether to vacate land from cultivation.

Table 3.4: Area of soil constraints (*bonitation*) classes calculated for the degraded land as revealed by the negative ΣNDVI trend over 2000-2010

***Bonitation* class**	**Total degraded area, ha**	**% of irrigated cropland**	**% of degraded land within *bonitation* class**
Negative trend-*Bonitation* IV	27,762.50	6.77	29.27
Negative trend-*Bonitation* III	17,287.50	4.22	18.23
Negative trend-*Bonitation* II	13,181.20	3.21	13.90
Negative trend-*Bonitation* I	112.50	0.03	0.12
No *bonitation* data	36,491.20	8.90	38.48
Total	*94,834.90*	*23.13*	*100.00*

Around 14% of the cropland degradation was observed in areas with the steepest slopes (2-10%). The local differences in the land relief play an important role in water distribution and management. Water pumping from the main irrigation canals into lower-level channels is commonly practiced in the elevated areas on the south-western border of Khorezm and in the SKKP when electricity costs can be afforded (Dubovyk et al. 2012b). The importance of micro-topographical features for soil salinity distribution on field level was reported by Akramkhanov and Vlek (2012), who used neural networks to study the impact of environmental and management factors on the spatial patterns of soil salinity in Khiva district of Khorezm. In our analysis, the observed small percentages of degradation on the elevated areas are due to the fact that slopes steeper than 6% are found only on about 1% of the study area. The use of higher spatial resolution datasets may disclose more details of degradation distribution with respect to the terrain that were partly masked out by the 250-m cell size. Yet, even the use of the coarse data was confirmed by the field-level analysis limited in space.

Table 3.5: Area of terrain constraint (slope) classes calculated for the degraded land as revealed by the negative ΣNDVI trend over 2000-2010

Slope class	**Total degraded area, ha**	**% of irrigated cropland**	**% of degraded land within slope class**
Negative trend slope 0-2%	81,168.75	19.80	85.59
Negative trend slope 2-4%	12,941.15	3.16	13.65
Negative trend slope 4-6%	556.25	0.14	0.59
Negative trend slope 6-10%	168.75	0.04	0.18
Total	*94,834.90*	*23.13*	*100.00*

The map in Figure 3.4e shows clearly that most of the degraded areas have a low population density and constitute marginal land of limiting carrying capacity (compare Figure 3.4a and Figure 3.4e). Cropping of such marginal land is not profitable for farmers (Djanibekov et al. 2012b), and is likely to aggreveate degradation processes. About 3% and 19% of the degraded land were found in the areas of high and medium population pressure, respectively, mostly in the central parts of the study region (Table 3.6). Considering the high population pressure on this land, restoration of such land should be prioritized to sustain the livelihoods of the people.

Up to 15% of the degradation area was found within the areas of stable agricultural land use (Figure 3.4c, Table 3.7), out of which about 7% was mainly fallow land (Figure 3.4d, Table 3.7). The latter are usually characterized by low-*bonitation* values (compare Figure 3.4a and Figure 3.4d), and are often abandoned from cultivation, particularly in drought years (Dubovyk et al. 2013a). These areas have lost their protective vegetation cover, and should be prioritized for rehabilitation measures that aim at establishing a healthy vegetation cover. This could be achieved by planting salt-tolerant crops, such as sunflowers (Gao and Liu 2010).

The present analyses were also subject to data constraints, particularly on the irrigation water distribution. The analytical framework of the study is, however, valid and can be applied again when additional data are available.

Table 3.6: Area of population density classes calculated for the degraded land as revealed by the negative ΣNDVI trend over 2000-2010

Population density	**Total degraded area, ha**	**% of irrigated cropland**	**% within population density class**
Negative trend-low density (0-2 pers/ha)	635,37.50	15.5	67.00
Negative trend-medium density (2-17 pers/ha)	181,56.25	4.43	19.15
Negative trend-high density (17-39 pers/ha)	241,8.75	0.59	2.55
Negative trend-very high density (39-79 pers/ha)	287,50	0.07	0.30
No data	104,34.9	2.55	11.00
TOTAL	*94,834.9*	*23.13*	*100.00*

Table 3.7: Area of land-use classes calculated for the degraded land as revealed by the negative ΣNDVI trend over 2000-2010

Land-use class	**Total degraded area, ha**	**% of irrigated cropland**	**% within land-use class**
Negative trend-No land-use changes	59,384.90	14.48	62.62
Negative trend-Land-use changes	35,450.00	8.65	37.38
Negative trend-Fallow	28,578.65	6.97	30.14
Negative trend-Not fallow	66,256.25	16.16	69.86

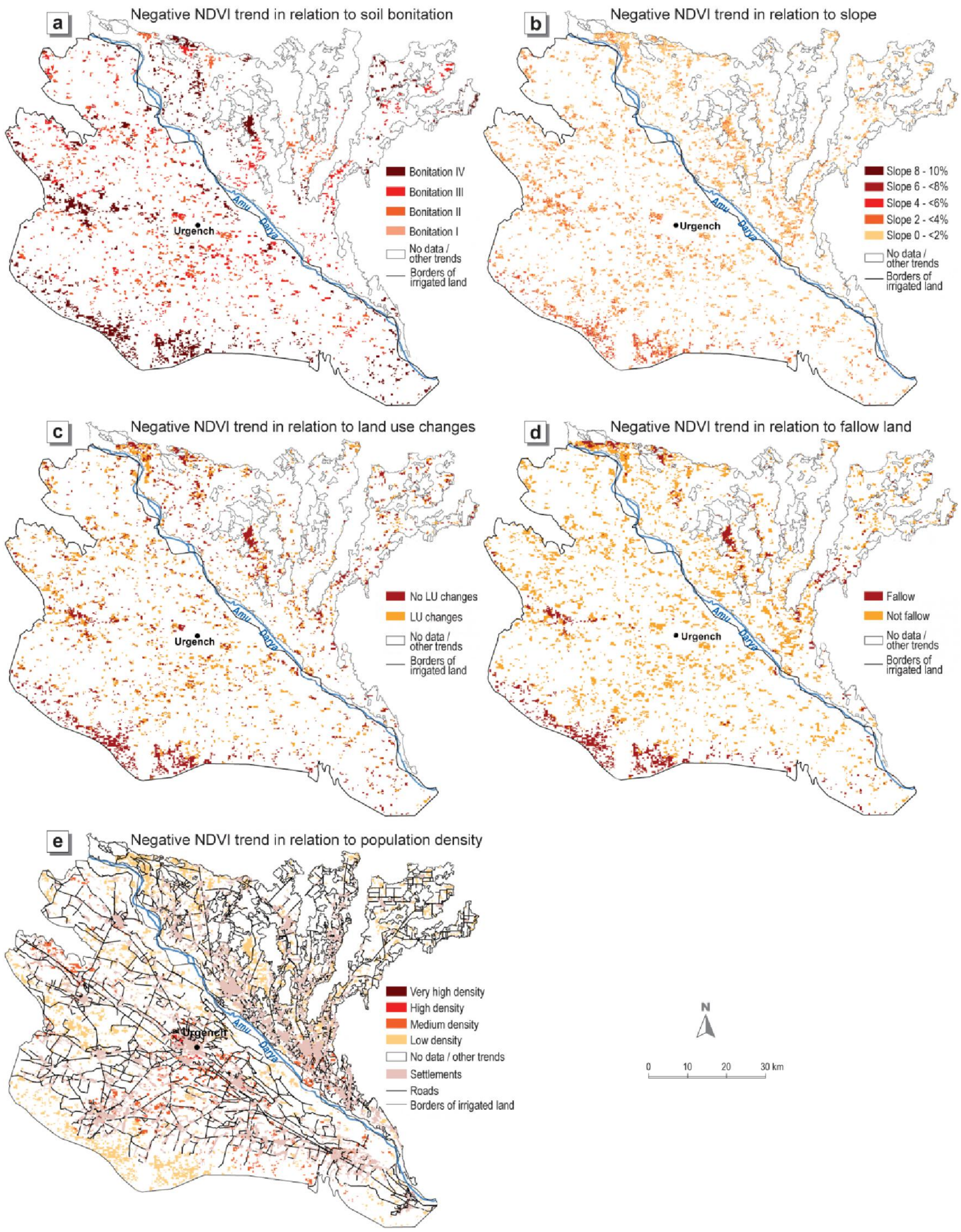

Figure 3.4 Spatial distribution of degraded areas in relation to soil *bonitation* (a), terrain (b), land use (c, d) and population density (e)

Spatial logistic regression modeling

Statement of logistic regression model and interpretation

For the Khorezm model, after the multicollinearity check, the final list of LD factors (Table 3.8) was reduced by one variable, i.e., soil *bonitation* class IV “low” (x_6), with the corresponding VIF value of 6.23. Two models were built: the full model incorporating all variables, and the reduced model resulting from the backward stepwise procedure. The ROC test yielded a significant result with *p*-values < 0.05 (α = 0.05), suggesting a difference in prediction power between these models. Thus, the full model was employed for logistic regression. The final full model was significant with chi-square values of 801.11 and corresponding *p*-values < 0.001 (α = 0.05). The model validation results with an AUC ROC value of 0.70 suggesting a good prediction power which exceeds a random assignment by 20%. The PCP of 69% indicates higher than average agreement between predictions and reality.

The logistic regression ruled out statistically insignificant variables, including all *bonitation* classes (x_3, x_4, and x_5), density of canals and collectors (x_7, x_8), and proximity to collectors, pumps, and water bodies (x_{14}, x_{15} and x_{18}) (Table 3.8).

Table 3.8: Estimated parameters of logistic regression model for Khorezm

Variable		**Coefficient (β_i)**	**Odds, %**	**Standard error**	***z***	***P* > |*z*|**
Change in land use	x_1	0.14	14.76	0.08	2.04	**
Uncultivated land	x_2	0.71	102.72	0.26	5.59	****
Soil *bonitation* I	x_3	0.40	48.59	0.62	0.95	n.s
Soil *bonitation* II	x_4	0.01	1.16	0.08	0.13	n.s
Soil *bonitation* III	x_5	-0.12	11.34	0.07	-1.57	n.s
Soil *bonitation* IV	x_6	Omitted due to multicollinearity				
Canal density	x_7	-0.00	-0.27	0.00	-1.45	n.s
Collector density	x_8	0.00	0.00	0.00	0.41	n.s
Water use	X_9	-0.09	-9.71	0.02	6.86	****
Slope	x_{10}	0.25	28.96	0.15	2.23	**
Groundwater table	x_{11}	1.46	329.73	0.65	9.71	****
Groundwater salinity	x_{12}	0.23	25.96	0.07	4.13	****
Proximity to canals	x_{13}	0.08	8.39	0.02	4.91	****
Proximity to collectors	x_{14}	-0.02	-1.49	0.02	0.62	n.s
Proximity to pumps	x_{15}	0.00	0.28	0.00	0.65	n.s
Proximity to roads	x_{16}	0.04	3.62	0.01	-4.81	****
Proximity to settlements	x_{17}	-0.02	-1.75	0.01	2.06	**
Proximity to water bodies	x_{18}		1.57	0.01	0.63	n.s.
Constant	βi	-3.55	-	0.16	-22.33	****

** =< 0.1; ** =< 0.05; *** =< 0.01; **** =< 0.001; n.s. = not significant*

In accordance with the estimated model parameters, the level of GWT, uncultivated land, slope, and GWS had the strongest impact on the spatial distribution of LD in Khorezm (Table 3.8). Specifically, the degraded areas were associated with the land that was abandoned from cultivation for six or more years, and that were characterized by a deeper GWT level and steeper slopes. The odds of LD were 330%, 103% and 29% higher on land with deeper GWT level, uncultivated land, and areas with steeper slopes, respectively, than on other land. These results correlate with the observed clusters of the negative vegetation trend. There, irrigation water is supplied up to the elevated areas via pumps, which are not in use when maintenance and electricity costs cannot be afforded.

The importance of GWS was reflected by the odds of the factor x_{12}, suggesting that an increase in GWS by 1 g/l increases the chance of LD by 26%. The availability and distribution of water were also observed to influence the spatial patterns of LD. The negative relation with the factor water use (x_9) showed that degraded areas tended to occur in the districts with shorter water supplies. The areas further away from the irrigation canals (factor x_{13}) were more prone to degradation. Degradation dependence on the vicinity to roads (x_{16}) indicates that easily accessible land was better managed. Though the estimated odds of the factor proximity to settlements (x_{17}) showed a negative relation to degradation, the low value indicates a comparatively weak influence on the observed spatial patterns.

In explaining the LD trend with logistic regression, the influence of contiguous areas with the relatively deep GWTs outweighed that in scattered land patches with a shallower GWT. This contrasts with the expected impact of a shallow GWT, which causes soil salinization and thus LD. However, given that the deeper GWT was observed on cropland abandoned from cultivation for at least six years, a deepened GWT can be a consequence of reduced irrigation inputs. The GWT levels observed in these locations remained above the critical threshold of 2 m (Ibrakhimov et al. 2007), thus still posing the risk of soil salinization and, therefore, decline in crop growth. Akramkhanov and Vlek (2012) in Khiva district of Khorezm also identified higher soil salinity when the GWT was deeper, and attributed this phenomenon to great differences in capillary fluxes in various soil textures.

For the SKKP model, multicollinearity of independent variables was not significant and subsequently all variables were employed for modeling. The ROC test between the full model, incorporating all variables, and the reduced model resulting from the backward stepwise procedure, yielded a non-significant result with *p*-values > 0.05 (α = 0.05), suggesting a difference in prediction power between these models. The reduced model was, therefore, employed for logistic regression.

The final model was obtained on the eighth backward step after elimination of the predictor x_1 (p=0.33, α=0.05), x_4 (p=0.57, α=0.05), x_9 (p=0.09, α=0.05), x_{10} (p=0.16, α=0.05), x_{13} (p=0.21, α=0.05), x_{16} (p=0.93, α=0.05), x_{17} (p=0.10, α=0.05), and x_{18} (p=0.87, α=0.05). The model was significant with chi-square values of 108.84 and corresponding *p*-values < 0.001 (α = 0.05). The model validation results with an AUC ROC value of 0.88 suggesting a very good prediction power. The PCP of 91% indicated very good agreement between predictions and reality. A summary of the results of the SKKP model is presented in Table 3.9

Table 3.9: Estimated parameters of logistic regression model for Southern Karakalpakstan

Variable		**Coefficient (β_i)**	**Odds, %**	**Standard error**	***z***	***P* > |*z*|**
Uncultivated land	x_2	1,58	383,72	2,75	2,77	***
Soil *bonitation* III	X_5	1,31	73,03	0,15	-2,44	**
Soil *bonitation* IV	X_6	1,69	81,61	0,09	-3,57	****
Canal density	x_7	-0,97	-164,43	0,62	-4,14	****
Collector density	x_8	-0,44	-54,61	0,20	-3,13	***
Groundwater table	x_{11}	-0,02	-2,04	0,01	-2,37	**
Groundwater salinity	x_{12}	1,75	474,62	3,10	3,24	****
Proximity to collectors	x_{14}	0,00	0,001	0,00	-2,38	**
Constant	βi	0,46	-	0,99	0,74	*

** =< 0.1; ** =< 0.05; *** =< 0.01; **** =< 0.001; n.s. = not significant*

In accordance with the estimated model parameters, GWS, uncultivated land, and irrigation canal density had the strongest impact on the spatial distribution of LD in the SKKP (Table 3.9). Specifically, the degraded areas were associated with the land that was located in the areas with a less developed irrigation network (x_7, x_8, x_{14}) and abandoned from cultivation (*x_2*) for six or more years, and characterized by a higher level of GWS (*x_{12}*) and shallower GWT (*x_{11}*). The odds of LD were 475%, 384% and 164% higher on land characterized by higher GWS, uncultivated land, and areas with a less dense irrigation network, respectively, than on other lands. The LD was associated with the poor-quality soils, as odds were 82% and 73% higher on land with the soil *bonitation* IV (*x_5*) and III (*x_6*), respectively, than on other lands. These results correlate with the mapped clusters of the negative vegetation trend (Figure 3.3), and were confirmed during the informal discussions with the irrigation engineers during the field campaigns. In the northern and north-eastern part of the SKKP, where the main clusters of LD were observed, the irrigation network is less developed compared to the rest of the territory, maintenance problems are also reported (Mott-MacDonald 2011).

The results of the logistic regression models for Khorezm and the SKKP confirm the occurrence of degradation on the land abandoned from crop cultivation, suggesting the need for prioritizing such areas for rehabilitation measures (Table 3.8, Table 3.9). Both models highlighted GWS in explaining the spatial distribution of the LD in Khorezm and the SKKP. The SKKP model revealed the irrigation and drainage network as an important factor influencing degradation in contrast to the Khorezm model, where these factors were not significant. The need for improvement of the irrigation network is a known problem in the SKKP, which is currently dealt with by the planned Water Resources Management Improvement project (Mott-MacDonald 2011).

Generally, very few studies have analyzed the impact of environmental and management factors on LD trends in irrigated croplands. Akramkhanov et al. (2011) focused on the spatial distribution of soil salinity at the farm scale in Khiva district of Khorezm. The study, confined to the year 2002, revealed a low, though a significant, correlation with band 7 of Landsat TM, proximity to drainage collectors, and the groundwater parameters, thus suggesting that management practices, particularly water management, outweighed the impact of environmental factors on the pattern of soil salinity. In a following study, Akramkhanov and Vlek (2012) used an artificial neural network as an alternative to the regression technique, and detected that soil salinity distribution was influenced by the micro-topographical features, which tended to affect surface water retention. The observed correlations with the RS parameters and groundwater depth and salinity (Akramkhanov et al. 2011) are in line with the results of the presented regional assessment. The contrasts can be explained by the different spatial as well as by the different temporal scales of the analyses, given that crop production decline and LD due to salinity only becomes obvious in the long run, as annual leaching practices counterbalance the salinization process.

Mapping areas at risk of land degradation

Spatial patterns of land at risk of LD were derived by applying the estimated coefficients of the model to the factor maps following Eq.3.2. The resulting map was reclassified into ten classes, allocating sequentially 10% of total probability values per class (i.e., 10% of the highest probability values are grouped in class 1) Figure 3.5 and (Figure 3.6)

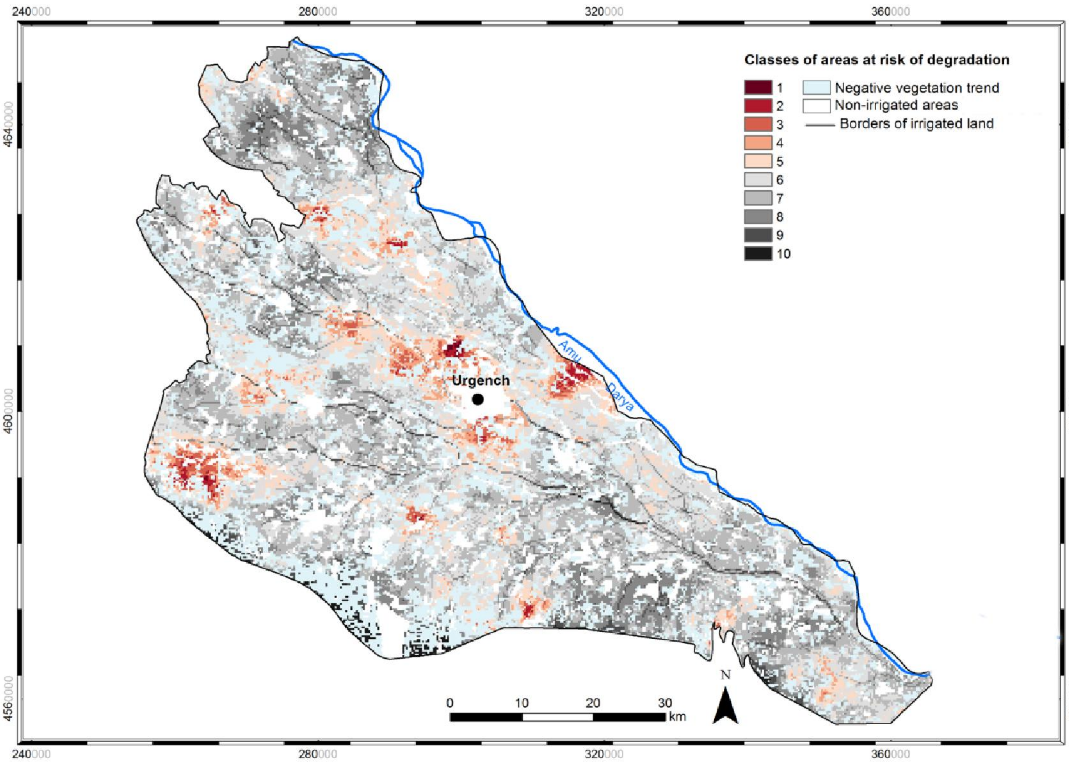

Figure 3.5: Risk map of land degradation in the Khorezm region of Uzbekistan. Class 1 indicates areas with the highest risk of degradation that gradually reduces to class 10. Blue areas represent land with negative vegetation trend, derived from trend analysis of 250-m MODIS-NDVI time series

In Khorezm, several clusters of areas at risk of LD (classes 1 to 5) were predicted: central part of the region near the capital, north of the region (border between the Gurlen and Yangibazar districts), Kushkhupyr district, and the southern parts of Khorezm bordering the Karakum Desert. The rest of the region was classified as having a medium to very low risk of LD (classes 6 to 10) (Figure 3.5).

Generally, compared to Khorezm, more areas of the SKKP were predicted to be further affected by degradation processes (Figure 3.6). Specifically, the LD clusters were predicted for the central part of Ellikkala district and northern parts of Beruniy and Turtkul districts. Less degradation was predicted for the areas along the Amu Darya River and central part of the SKKP.

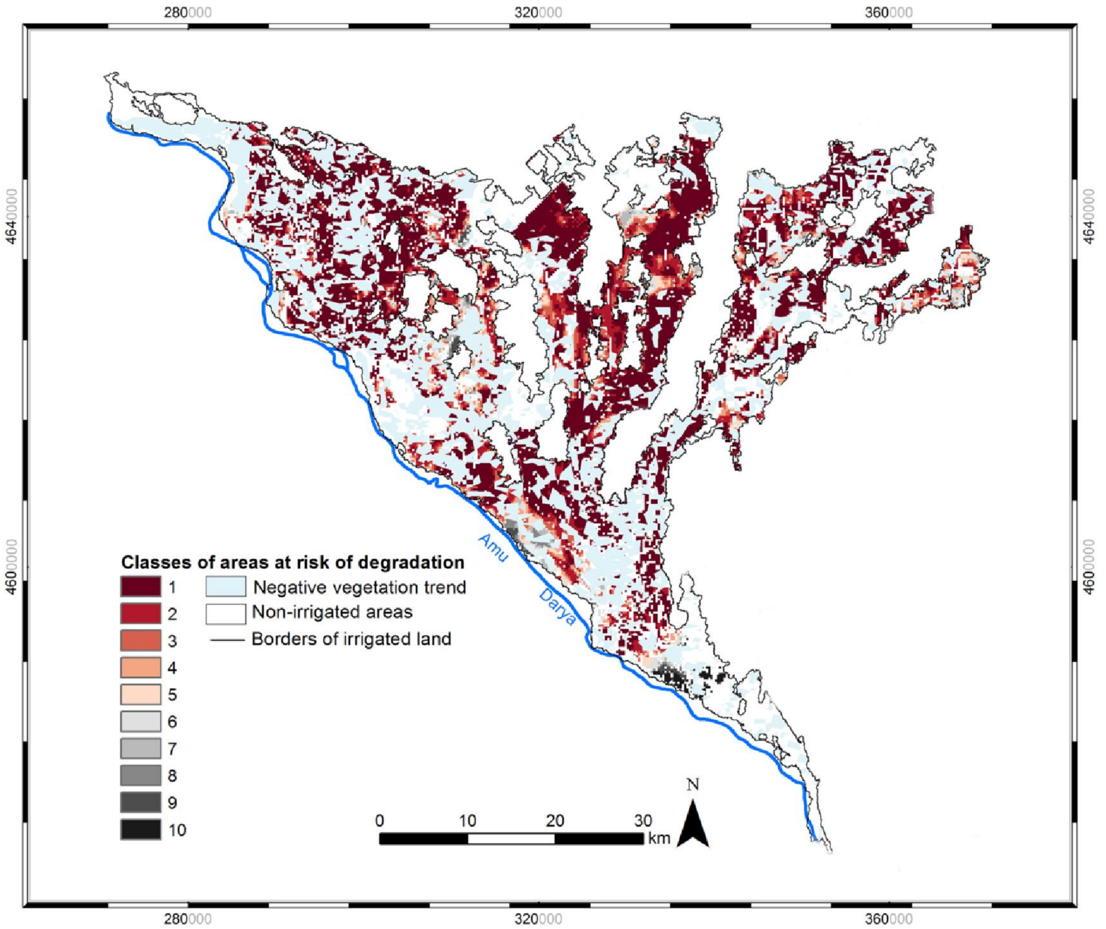

Figure 3.6: Risk map of land degradation in the southern Karakalpakstan, Uzbekistan. Class 1 indicates areas with the highest risk of degradation that gradually reduces to class 10. Blue areas represent land with negative vegetation trend, derived from trend analysis of 250-m MODIS-NDVI time series

The prediction power of the elaborated models, reflected in the PCP and ROC values, is comparable to the previously reported studies for ecological and LULC applications of logistic regression. For example, Manel et al. (1999) reported PCP values in the range of 67-81%, and Pontius and Schneider (2001) reported ROC values of 65-70%. The present results from the models highlight the main advantages of logistic regression, such as spatial explicitness and quantitative analysis of the factors. Moreover, predictions are possible based on the observed relationships as also mentioned by Koomen and Stillwell (2007). The models' prediction results were conditioned to the incorporated variables, which were assumed to represent the most important factors influencing the spatial distribution of LD. Incorporation of more variables was subject to data constraints, a common issue for LULC models (Dubovyk et al. 2011). Aiming to provide a regional overview, the derived risk maps render a visual representation of areas under risk that could be prioritized in more detailed analyses and the attention of decision makers.

3.4.3 Spatial targeting of rehabilitation of degraded cropland

The trend analysis of the MODIS-NDVI time series, spatial relational analysis of the mapped negative vegetation trend, and logistic regression modeling were able to accurately detect the spatial dynamics of cropland degradation. These findings could, therefore, be used to support identification and targeting of appropriate and effective land management measures. If supporting corresponding policy decisions were implemented by the Uzbek authorities, degraded areas identified and located in this study could be targeted for mitigation and rehabilitation measures. As an example, degraded croplands located within areas of high population density could initially be subjected to measures designed to halt ongoing cropland degradation while supporting the future livelihoods of the people. Prompt actions are also necessary to restore croplands that have become unfavorable for agriculture. These include poor-quality land located on elevated areas within zones of lower population density. If such cropland remains under the present management approach, ongoing degradation could become irreversible or the required investments in soil improvement measures may no longer be economically viable (Vlek et al. 2008).

The rate of degradation has substantial impacts upon decisions regarding the suitability of cropland for further agricultural use. Continuing cropping of severely degraded land is not profitable for farmers (Djanibekov et al. 2012b). A possible solution might involve releasing such land from cropping and implementing alternative land uses, preferably uses that include remedial functions. Studies in Khorezm have documented successful rehabilitation of degraded croplands through afforestation efforts using well adapted tree species that increased the productive and economic capacity of the land (Khamzina et al. 2012). In such cases, farmers should be offered additional incentives, such as payments for ecosystem services, to encourage the adoption of rehabilitation practices (Thomas 2008).

The cost of corrective measures may be substantial. However, compelling reasons remain for investing in sustainable land-use measures that should consider compensation for the opportunity costs of farmers' foregone income. Delaying or postponing implementation of such measures will increase the costs of such compensations. If actions are not immediately implemented to reverse the on-going land degradation, farming will require additional financial support or subsidies. Such future support would very likely exceed the present costs of implementing sustainable practices. It has been repeatedly demonstrated that the long-term benefits of soil protection practices such as yield stabilisation, yield improvement, and natural resources protection more than compensate for the costs of implementation. Additionally, convincing evidence is emerging that it is possible to adopt agricultural conservation practices that enhance agro-ecological restoration in this study region (Kienzler et al. 2012).

The regional assessment presented in this study used medium-resolution satellite data to identify hotspot areas for which more detailed understanding of the cropland degradation process is required. Further steps toward such understanding could include on-site validations of results to enable development of site-specific recommendations for land rehabilitation and/or conservation measures. At the scale of individual fields, detailed information on the critical factors leading to degradation (such as soil salinization and soil nutrient loss) as well as land and water management practices should be identified and compiled. This would facilitate the development and introduction of the most appropriate restoration technologies to counter on-going cropland degradation - technologies that are economically viable, socially acceptable and ecologically sound (Akramkhanov et al. 2011; Le et al. 2012)..

3.5 Conclusions

The decreasing greenness of the vegetation signal from the MODIS-NDVI time series for 2000-2010 is adequate to generate spatial information on the distribution of degraded irrigated cropland. The resulting maps could support the prioritization of remediation measures in the Khorezm region and the SKKP in Uzbekistan.

The MODIS data were found suitable for regional-scale monitoring of negative vegetation trends, which can be interpreted in relation to LD. For improving the understanding of underlying factors that have caused the observed LD trend a series of secondary datasets were utilized. A major share of the detected cropland degradation occurred in marginal agricultural areas typified by poor-quality soils and low population density. These degraded areas were often abandoned from regular cropping practices. The degradation of cropland located in the more densely populated areas and showing better-quality soils can be considered for the introduction of more sustainable cropping practices. The marginal areas can be considered for appropriate rehabilitation measures including, for example, vacating the land from annual cropping.

The results of this study demonstrate the use of geospatial tools for LD assessment. They also offer an insight into the processes involved in LD and provide spatial decision support for planning rehabilitation measures. The applied integrated approach combining spatial logistic regression and trend analysis of satellite time series allowed the inclusive evaluation of irrigated cropland degradation at the regional scale. The model made it possible to explain the factors of the observed trend and to map areas at risk of LD that could be targeted in a finer resolution assessment.

4 PARCEL-BASED IDENTIFICATION OF VEGETATION COVER DECLINE IN IRRIGATED AGRO-ECOSYSTEMS IN NORTHERN UZBEKSITAN

4.1 Introduction

The regional assessment based on medium resolution satellite data, identified hotspot areas of cropland degradation (chapter 3). For spatial targeting of cropland rehabilitation programs, parcel-specific information on land condition and LULC characteristics is required (Dubovyk et al. 2013a). This information will allow better informed agricultural management decisions and land restoration planning at scales appropriate for targeted land management.

Remote-sensing-based LD monitoring relies on a wide range of change detection methods. The gradual LD processes within one class are commonly detected by applying either algorithms that measure spectral change between the image acquisition dates (i.e., band algebra, regression analysis) (Lambin and Strahlers 1994; Zhao et al. 2004; Stellmes et al. 2010), or algorithms based on the objects consisting of adjacent pixels with similar spectra (Bontemps et al. 2008; Gao 2008). Another approach employs image classification when multi-temporal LULC maps are compared to identify changes in the mapped LD class (Li et al. 2009; Yiran et al. 2011). Even though these algorithms are relatively easy to implement, their applicability depends on accuracies of prior classifications and availability of training data (Cardille and Foley 2003; Zanotta and Haertel 2012). The classification-based analysis also fails to evaluate gradual degradation processes within one class. Such processes can be captured by trend analyses of multi-year satellite images (Hostert et al. 2003). Trend analyses were routinely employed for LD assessment using coarse-scale imagery (e.g., Wessels et al. 2007). However, for landscape-scale assessment, the high-resolution Landsat imagery recorded since 1972 is not always available on the frequent and repeatable basis required for trend analyses for all geographical areas, including Central Asia. Therefore, no optimal change detection method exists for all cases, and the choice of the technique often depends on data availability and quality, cost and time constraints, and the analyst’s experience (Radke et al. 2005).

Among the spectral-based change detection methods, change vector analysis (CVA) (Malila 1980) has a few advantages, as it can detect gradual land-cover changes, using different spectral bands or their derivatives, and provide information on change direction and change magnitude (He et al. 2011).

Recent studies also demonstrated that object-based change detection (OBCD) could provide improvements over the pixel-based approach by addressing shortcomings of a per-pixel strategy such as noisy outputs and isolated changed pixels (Blaschke 2010; Chen et al. 2012). The OBCD monitors the change of meaningful image objects as a single unit to minimize the within-object reflectance variation and to provide consistent units for analyses (Bontemps et al. 2008). The method is also able to operate with user-defined units such as field parcels of agricultural landscapes (Pena-Barragan et al. 2011).

In degraded cropland areas, where exposed soils and sparse vegetation predominate, the assessment of vegetation decline as a main LD indicator is challenging with the conventionally applied vegetation indices such as NDVI mainly due to their sensitivity to soil background (Baret et al. 1993; Huete et al. 2002). Spectral mixture analysis (SMA) provides an accurate quantitative estimation of land covers at a subpixel level by decomposing all the ground-cover components within a pixel (Adams et al. 1986), and can thus be used as an alternative to vegetation indices (e.g., Elmore et al. 2000). Several studies have shown that spatio-temporal changes in vegetation and soil fractional covers accurately describe the land health in drylands (Collado et al. 2002; Harris and Asner 2003; Jafari and Lewis 2012); however, irrigated agro-ecosystems have not been specifically addressed.

Given the potential of SMA-based change detection for LD monitoring in drylands (e.g., Collado et al. 2002; Dawelbait and Morari 2012), our study comprised adaptation of the SMA-based OBCD for the analysis of land conditions in irrigated drylands of Central Asia. In this context, by combining the Landsat-based SMA and object-based CVA, we aimed to derive parcel-specific information on land-cover changes to provide spatial guidance for land management interventions at local scales.

4.2 Materials

4.2.1 Satellite data and processing

The analyses are based on 30-m Landsat 5 Thematic Mapper (TM) imagery recorded in 1998 and 2009 (Table 4.1 and Figure 4.1). The selection of the years was driven by (i) availability of multitemporal images to cover the key crop-growth stages, and (ii) comparable supplies of irrigation water between the years, as crop growth is reduced with decreased water availability. The images with anniversary acquisition dates were selected to minimize the impact of crop phenology and illumination conditions.

Table 4.1: Acquisition dates of Landsat 5 TM images (path 159, row 31)

1998		2009	
16	June	14	June
18	July	16	July
03	August	01	August
04	September	02	September

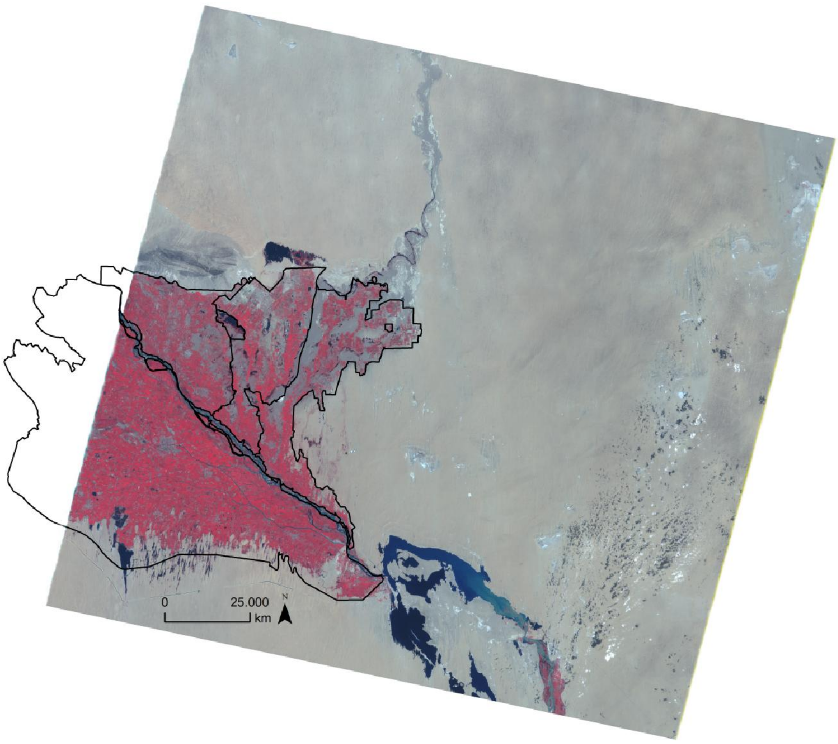

Figure 4.1: Coverage of Landsat 5 TM images (path 159, row 31) over study region illustrated by the 16th of June 1998 false-colour composite (bands 4, 3, 2) image

All images were geometrically adjusted to a 2.5 m SPOT-5 image and projected to the UTM coordinate system (zone 41) based on the differential GPS points

(Conrad et al. 2010). On average, 550 tie points per image, selected via an automated point matching (LeicaGeosystems 2006), were used to co-register the images, resulting in an overall positional error of less than 0.5 pixels. Radiometric calibration and atmospheric correction was performed for the July 2009 image using the ATCOR2 (version 10) software (Richter 2010). Subsequently, all other images were radiometrically normalized to this reference, applying the Iteratively Re-weighted Multivariate Alteration Detection transformation (Canty and Nielsen 2008).

The Quickbird image, acquired on 12 July 2009, with a spatial resolution of 2.4 m and 0.6 m in the multispectral and panchromatic bands, respectively, was acquired to assess the accuracy of the SMA.

4.2.2 Ancillary data

To derive field objects, the current cadastral maps were collected from the regional offices of the Uzbek State Committee on Land Resources, Geodesy, Cartography and State Cadastre and digitized. The field samples collected through stratified random sampling in 2009 showing cultivated crops on 346 fields and 3,155 fallow fields were taken from the German-Uzbek project database (http://www.zef.de/1631.html) and digitized from cadastral maps. These are based on information on spatial distribution of uncultivated fields provided by cadastral managers during field visits in 2010-2012 in SKKP. The samples were used to derive maps of agricultural land use in 2009 and 1998 for interpreting the change detection results. The LD trend map (chapter 3) was used to evaluate the change maps.

4.3 Methods

The methodology for providing the object-specific change information consisted of two stages as illustrated in Figure 4.2. First, fraction images were derived from the preprocessed Landsat data applying the linear spectral unmixing model. Second, the object-based values of vegetation and soil fraction images were used as an input for the CVA to detect per-field changes between 1998 and 2009. The results were subsequently evaluated and interpreted with respect to the current land use.

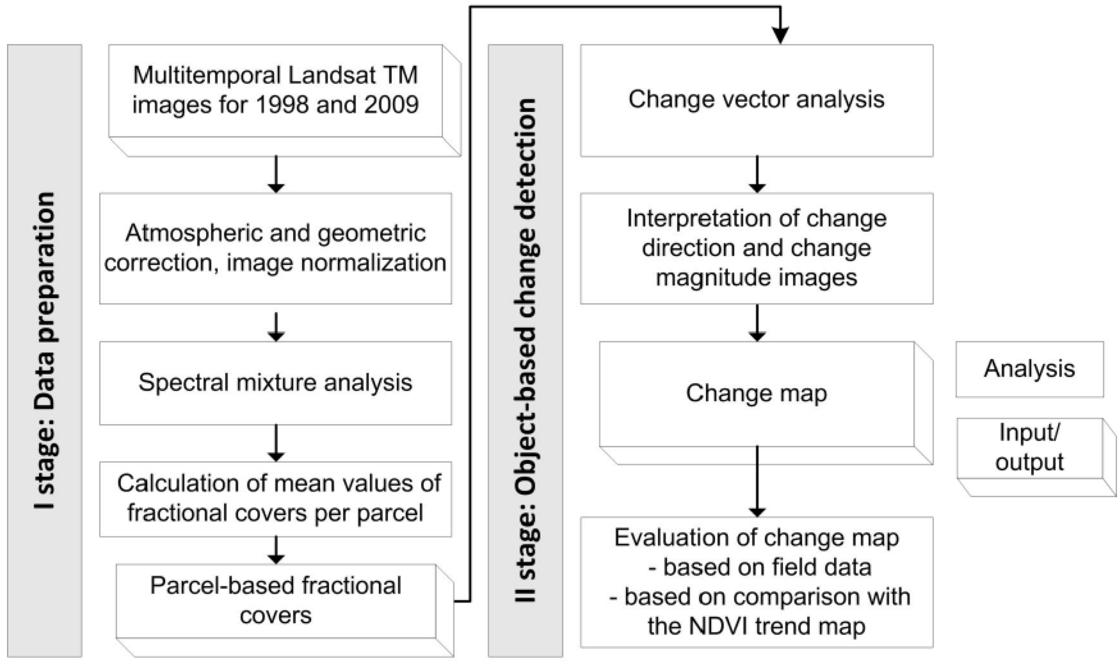

Figure 4.2: Flow chart of parcel-based change detection for vegetation cover monitoring

4.3.1 Spectral mixture analysis

As an input for the SMA, reference spectra or endmembers can be derived from spectral libraries (Asner and Lobell 2000), field spectra (Chikhaoui et al. 2005), the imagery itself (Plaza et al. 2002), or simulated using radiative transfer models (Dennison et al. 2006). In this study, the image-based approach was implemented, so that the derived endmembers represent the spectra measured at the same scale as the satellite data used (Lu et al. 2007). A mask comprising cadastral parcel boundaries was applied to only include cropland areas in the analysis.

To segregate noise in the image data and to determine the inherent dimensionality of the data, the Minimum Noise Fraction (MNF) transform (Green et al. 1988) was applied to the July 2009 image. Subsequently, the first three bands of the MNF images, containing high eigenvalues, were further used to extract endmembers with the Pixel Purity Index (PPI) (Boardman et al. 1995).

In view of the successful application of the linear mixture approach for LD studies (e.g., Sonnenschein et al. 2011), a linear constrained unmixing model was applied to derive a fraction image for four endmembers, i.e., green vegetation (GV), bright soil (BS), dark soil (DS), and water (Zerger et al.), considering the spectral dimensionality of Landsat TM (Small 2004). The GV was associated with photosynthetically active vegetation within the fields. The BS and DS represented bright soils, often associated with sandy soils and salt crust on the fields, and dark soils, respectively. The WT referred mainly to shallow water surfaces within the flooded rice fields. After analysis of the SMA results, the set of endmembers selected from the July 2009 image was applied to the other images. Applying the same model to the full set of Landsat images allows consistent estimations of green vegetation and soil fractions (e.g., Collado et al. 2002; Hostert et al. 2003; Quintano et al. 2012) and for direct comparison of calculated fraction images, which ultimately improves the accuracy of change detection (Elmore et al. 2000).

To assess the fit of the spectral unmixing model, the root mean square error (RMSE) was calculated and the histograms of the derived images were analyzed. Further, the accuracy of the vegetation fraction was assessed by analyzing the scatter plot correlation comparing per-field percentages of the vegetation cover calculated from the pan-sharpened QuickBird image (12 July 2009), and the corresponding Landsat-based vegetation fraction image (16 July 2009) for 92 randomly selected fields. The QuickBird-based vegetation cover estimates were classified using the object-based approach in the commercial software eCognition 8.7 (Trimble Geospatial Imaging, Munich, Germany).

4.3.2 Change detection

Object-based change vector analysis

The parcels from the cadastral maps were used as the input objects for the OBCD. The parcel boundaries were assumed the same in 1998 and 2009. This was confirmed by a visual assessment of the images and discussions with the local cadastral engineers, and explained by the area-based, state-driven cultivation of irrigated crops that relies on the constructed irrigation-drainage network (Van Assche and Djanibekov 2012).

An input for the parcel-based CVA was the fraction images of the DS, BS and GV. The WT was not considered, as the presence of the water on the fields was mainly associated with rice cultivation. For each cadastral parcel, the mean values of DS, GV and BS were calculated for each time step. Further, the mean parcel values were averaged over the growing seasons 1998 and 2009 to minimize the influence of crop phenology and vegetation variability within the parcels.

The CVA allows determining the magnitude of change and change direction between two or more time steps (He et al. 2011). If a pixel's spectral values in two images, acquired on dates T_1 and T_2, are represented by $A_{T1}=(a_1, a_2, \ldots, a_n)$ and $A_{T2}=(a_1, a_2, \ldots, a_n)$, and n is the number of spectral bands, a change vector is defined as:

$$\Delta A = \mathrm{A}_{\mathrm{T}_1} - \mathrm{A}_{\mathrm{T}_2} \qquad (4.1)$$

where ΔA represents change information between T_1 and T_2 for a pixel. The change magnitude $\|\Delta A\|$ can be calculated as:

$$\|\Delta A\| = \sqrt{(\mathrm{a}_{1\mathrm{T}_1} - \mathrm{a}_{1\mathrm{T}_2})^2 + (\mathrm{a}_{2\mathrm{T}_1} - \mathrm{a}_{2\mathrm{T}_2})^2 + \ldots + (\mathrm{a}_{n\mathrm{T}_1} - \mathrm{a}_{\mathrm{n}\mathrm{T}_2})^2} \qquad (4.2)$$

A decision on change is made when the change magnitude exceeds a certain threshold that can be defined quantitatively or qualitatively (Rogerson 2002). The threshold's value of 0.26 was selected for change detection after testing several thresholding algorithms (Otsu 1979; Johnson and Kasischke 1998; Rosin 2001). This threshold value resulted from both the empirical method based on the analysis of $\|\Delta A\|$ distribution (Johnson and Kasischke 1998) and the OTSU-based method and produced a plausible change image (Bruzzone and Prieto 2000).

As three spectral dimensions were involved in the CVA, the type of change was determined using sector coding, where the change category is assigned by a combination of the symbols "+" (for increase) or "-" (for decrease) of each band and by image interpretation (Chen et al. 2003). A decrease in GV and increase in either or both BS and DS indicated a declined vegetation cover per parcel. In contrast, an increase in GV and decrease in either or both BS and DS signified increased vegetation cover per parcel. All other combinations of sector codes showed increased, decreased or stable DS, GV and BS, indicating persisting land-cover conditions between the two time steps.

Evaluation of change map

To assess the CVA performance specifically in relation to LD detection, the change map was compared to the MODIS-based LD trend map. Two maps were clipped to the same spatial extent and the change map was resampled to the MODIS resolution. The LD trend map consists of the class 'LD' indicating the significant negative vegetation trend and the class 'other trends'. In such way, only two classes from the change map were considered, i.e., class 'vegetation cover decrease' and class 'other'. The maps were compared based on the random stratified sample of 21,394 pixels; each subset contained 25% pixels of the sampled class so that both classes had the same chances of being evaluated (Morisette and Khorram 2000). Also, 379 randomly selected fields with decreased vegetation cover were visited in the study region in summer 2012.

In cropland areas, a decreased vegetation cover may be associated with changes in cropping patterns. To investigate whether variations in cropping pattern cause substantial differences in the detected land-cover changes as opposed to disrupted cultivation (fallow), we conducted a simulation based solely on available field samples for which the land-use type (i.e., cropping or fallow) was known in 2009. Subsequently, changes in the cropping patterns were compared in aggregated soil fraction per parcel between two groups of crop rotations: (I) changes caused by common crop rotations, i.e., cotton-winter-wheat/summer crop (such as rice, maize, sorghum), and (II) changes caused by crop rotations among any crop to fallow.

4.3.3 Land-use classification

For interpreting the change detection results, the agricultural land-use map for 2009 and the land-use map showing cropped and fallow parcels in 1998 were used. Random Forest, a non-paramtetric classification algorithm, (Breiman 2001) was applied according to Liaw and Wiener (2002) to derive parcel-specific land-use information for 2009 as suggested by Conrad et al. (2010). The 2009 samples were split in two halves for training and validation. The mean and standard deviation of the Landsat TM bands (except the thermal band 6) and NDVI for every available image (Table 4.1) were used as input features for classification. The mapped classes in 2009 included cotton, winter wheat, rotation of winter wheat with the summer crop (maize and sorghum) rice, fallow land and other crops such as maize, sorghum, watermelons, melons, and sunflower. The input features for classification of the land use in 1998 was a randomly selected subset of fallow parcels identified by experts (section 3.2) complemented by the samples of cropped parcels derived via visual interpretation of multitemporal images from 1998. In this way, the 250 fields cropped in 1998 were randomly selected. The final reference layer consisted of 500 samples (250 cropped and 250 fallow fields).

4.4 Results and discussion

4.4.1 Spectral mixture analysis

The accuracy assessment suggested overall plausibility of the SMA results (Figure 4.3 and Figure 4.4). For all images, the statistical validity of the spectral unmixing was confirmed by the low values of the RMSE. The histograms of the fraction images did not generally exceed the range from 0 to 1, and the residual bands showed no systematic patterns. The comparison of the QuickBird-and Landsat-based vegetation covers yielded an R^2-value of 0.80.

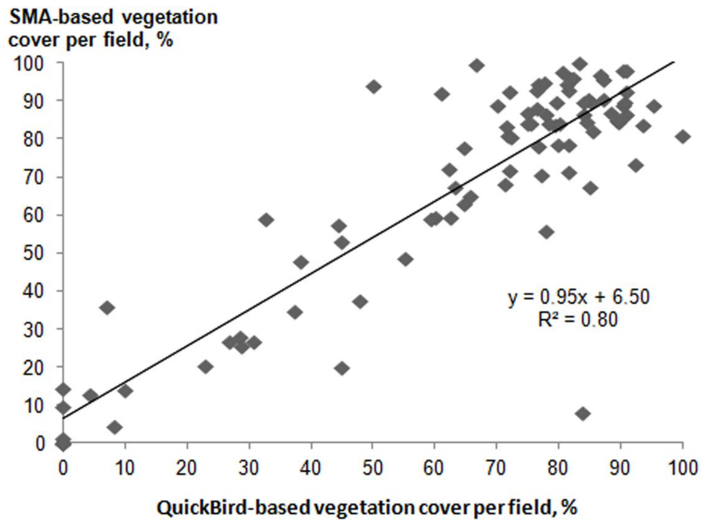

Figure 4.3: Scatter plot correlation between per-field percentages of vegetation cover, calculated from the QuickBird image and the Landsat-based green vegetation fractional cover image

The obtained correlation was good, but the R^2-value was slightly lower than values reported in other dryland studies using field data for validation. For example, LD monitoring with Landsat-based SMA by Dawelbait and Morari (2012) in Sudan and by Röder et al. (2008) in the Mediterranean region reported an R^2-value of 0.91. The observed misestimates in the lower values of the SMA-based vegetation fractions as shown in Figure 4.3 was also reported by Dawelbait and Morari (2012).

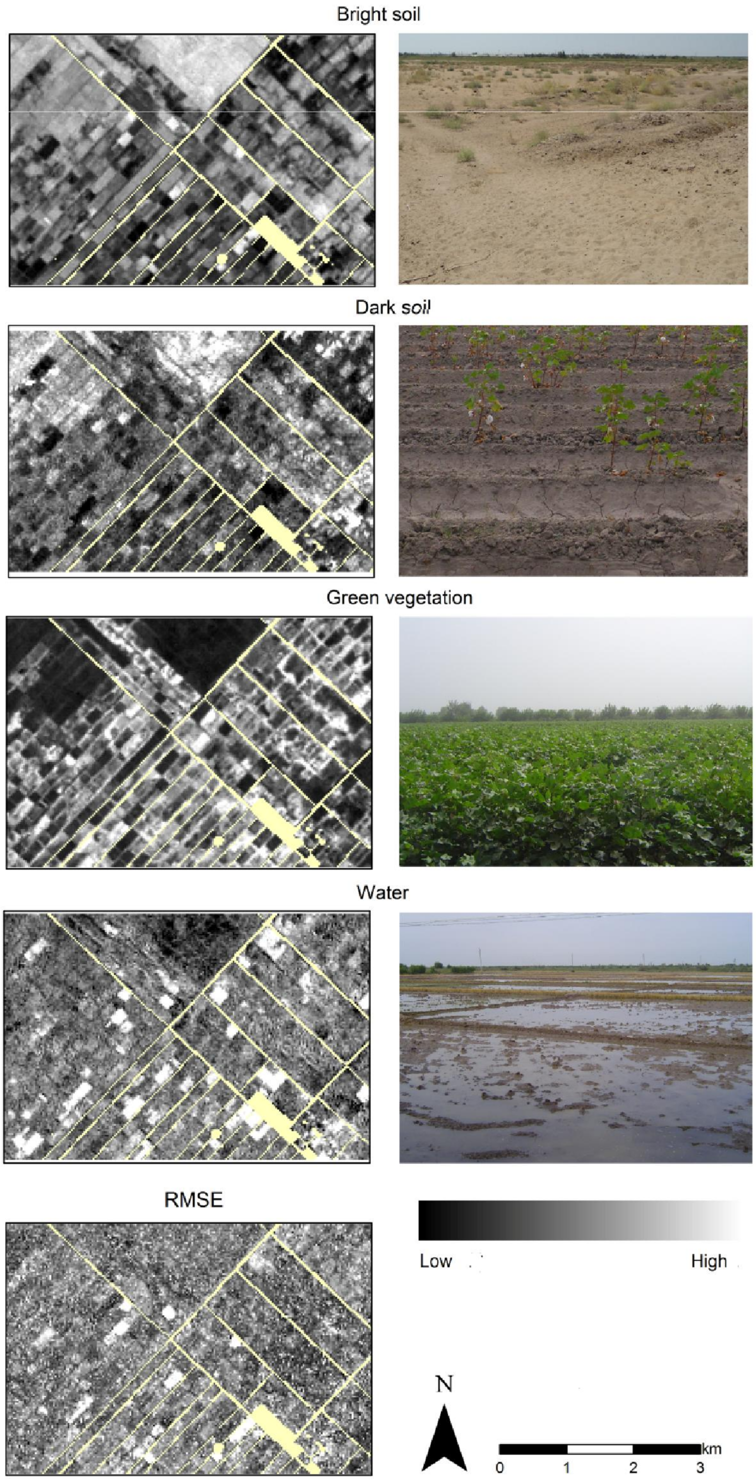

Figure 4.4: Subset of fraction images derived from linear unmixing of the July 2009 Landsat TM image and their corresponding landscape elements. Areas that donot belong to agricultural parcels are shown in yellow

After conducting the field survey, the authors stated that SMA provided consistent estimates of vegetation fractions for the values higher than 0.2. In this study, this could be mainly attributed to the difference in the spatial scales of observations as discussed by Elmore et al. (2000) and Kuemmerle et al. (2006) or to the complex nature of irrigated agro-ecosystems.

4.4.2 Cropping patterns in 2009 and 1998

Spatial patterns of crop classes in the study area formed several clusters in 2009 (Figure 4.5). The cotton and winter wheat fields were scattered throughout the region according to the state order system. The mapped rice cluster close to the Amu Darya River and along the big canals could be due to good access to irrigation water. Crop diversity was highest in the central part of the irrigation system in Khorezm, where winter wheat rotation was mainly found. The distribution of cropping areas in 1998 and 2009 were similar, with the distinguished patterns of fallow areas mainly on the outskirts of the irrigation system on the borders with natural deserts.

The accuracy assessment confirmed the validity of the produced maps (Table 4.2 and Table 4.3). They were also comparable to the results of the existing crop classifications in the Khorezm region, based on MODIS (Conrad et al. 2011) and ASTER data (Conrad et al. 2010). The commission errors for the classes rice and winter wheat-summer rotation and omission errors for class other crops in the agricultural land-use map for 2009 were higher compared to the other mapped crops, probably due to the smaller number of sampled parcels available for these classes.

Table 4.2: Accuracy assessment of the agricultural land-use map for 1998

Land-use map		**Reference (parcels)**		
		Cropped	Fallow	**TOTAL**
	Cropped	122	14	**136**
Result (parcels)	Fallow	3	111	**114**
	TOTAL	**125**	**125**	

Overall accuracy=93%

Omission error	*Commission error*
Cropped=2%	Cropped=10%
Fallow=11%	Fallow=3%

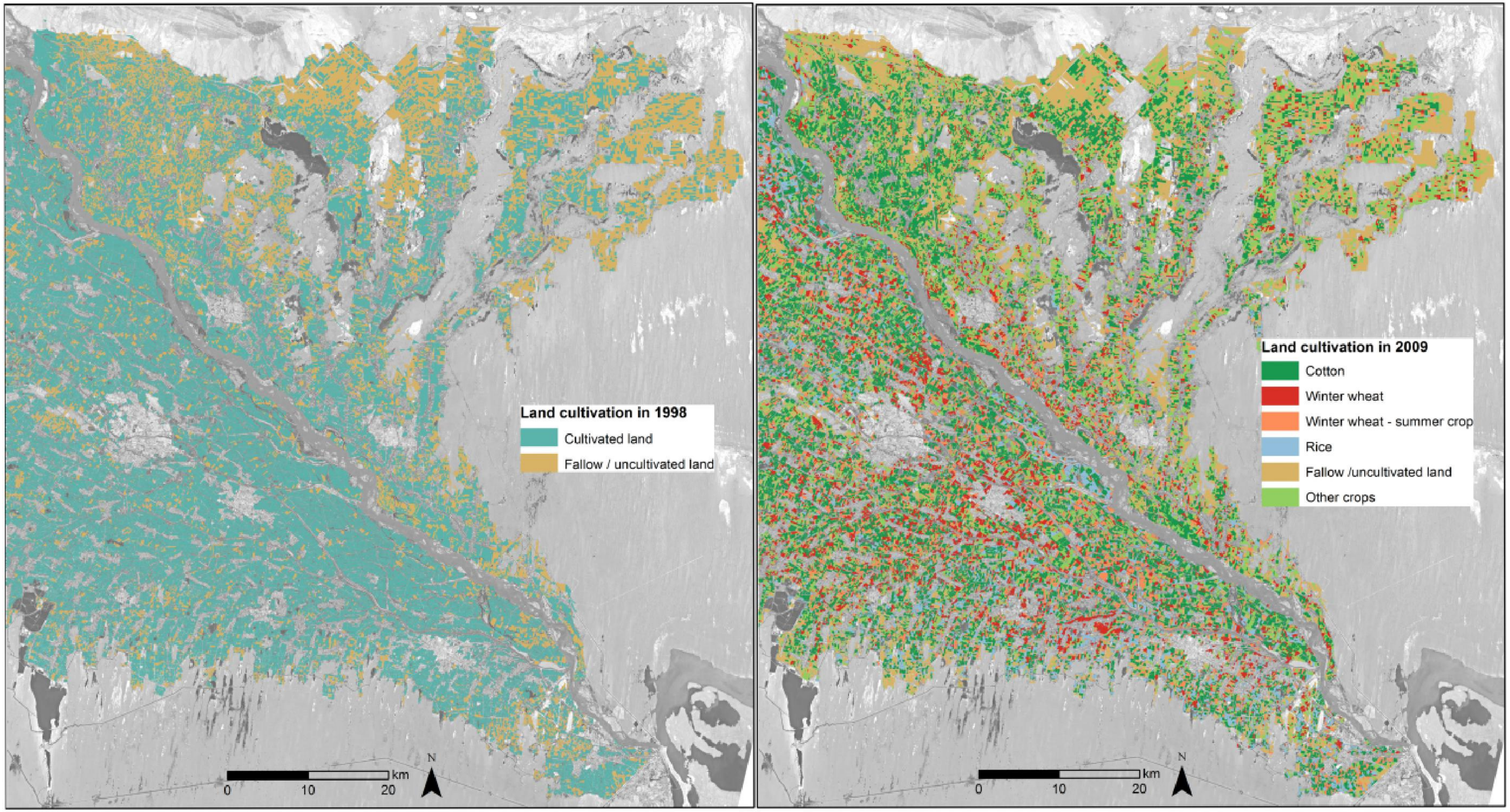

Figure 4.5: Agricultural land-use maps of study region in 1998 (left) and 2009 (right) based on multitemporal 30-m Landsat TM image

Table 4.3: Accuracy assessment of the agricultural land-use map for 2009

Land-use map	**Reference (parcels)**							
Result (parcels)	Cotton	Fallow	Rice	Winter wheat	Winter wheat-summer crop	Other	**TOTAL**	*Commis-sion error*
Cotton	39	2	0	0	0	2	**43**	9
Fallow	1	30	0	0	0	3	**34**	12
Rice	4	0	8	0	1	0	**13**	38
Winter wheat	0	0	0	31	0	3	**34**	9
Winter wheat-summer crop	0	1	0	3	16	3	**23**	30
Other	0	4	1	2	1	18	**26**	31
TOTAL	**44**	**37**	**9**	**36**	**18**	**29**		
Omission error	11	19	11	14	11	38		
Overall accuracy=82%								

4.4.3 Spatial distribution of parcel-based vegetation cover decline

The produced change map highlights areas that experienced vegetation cover decline between 1998 and 2009 (Figure 4.6). In general, distribution of such parcels was spatially variable, but several clusters were distinguished along the borders with the natural deserts of Karakum and Kyzylkum in the south and north of the study region. The parcels with decreased vegetation cover were mainly found in the far reaches of the irrigation system, where poor sandy soils and hampered water supply trigger poor crop development (Dubovyk et al. 2012b).

The 29% (15,343 ha) of the area with decreased vegetation cover was under cotton cultivation in 2009 (Figure 4.7). Cotton cropping has remained the predominant land use in the study area due to the area-based state production (Djanibekov et al. 2010), and was grown on approximately the same cropland area in Khorezm in 1998 (100,000 ha) and 2009 (95,000 ha) (UZSTAT 2010a). Given the standard guidelines for crop irrigation and fertilizer application and an adequate water supply, amounting to 3.5×10^6 m^3 in 1998 and 3.3×10^6 m^3 in Khorezm in 2009 (SIC-ICWC 2012), the decrease in vegetation cover within the cotton fields was likely caused by LD rather than by reduced agricultural inputs.

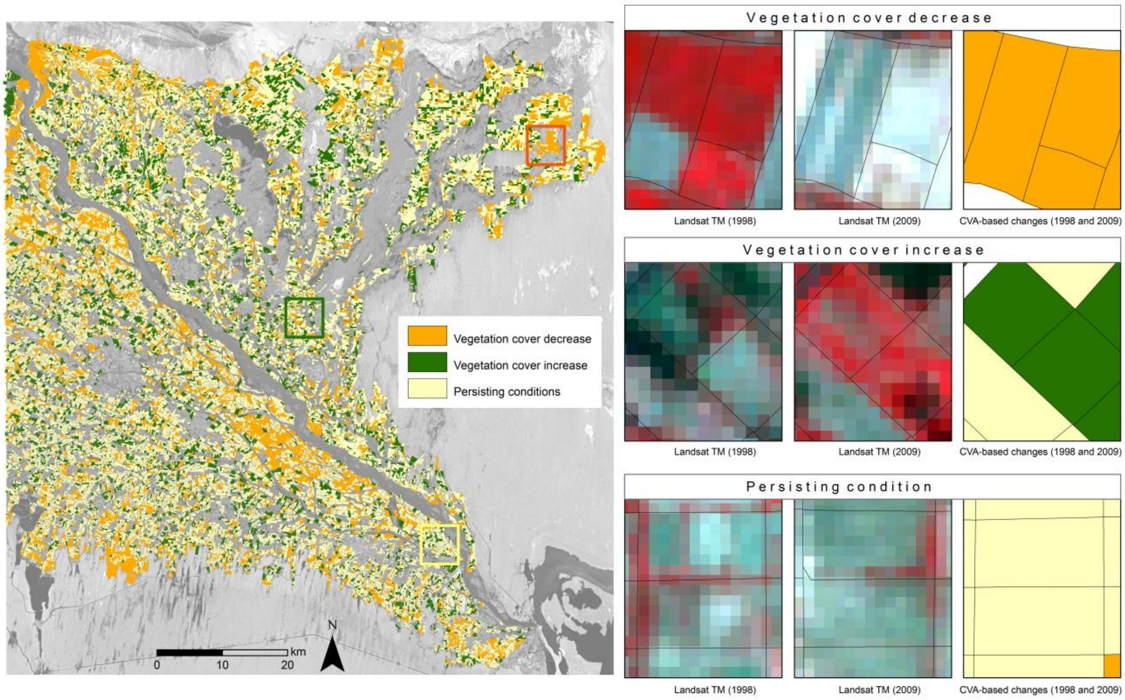

Figure 4.6: Object-based change image based on change vector analysis and fraction images calculated from multitemporal Landsat TM. On the right, the corresponding enlarged subsets of the July 1998 and July 2009 images and the parcel-based change map are shown. The 16 July 2009 Landsat image (band 4) is in the background

The comparison with the land-use maps (Figure 4.7) showed that 17% (29,029 ha) of the analyzed cropland area with decreased vegetation cover was fallow in both 1998 and 2009. As uncultivated lands are commonly used for herding livestock, this change might be associated with grazing of the fallow vegetation (Djanibekov 2006). About 20% (11,064 ha) of the vegetation decline areas was cultivated in 1998 and left fallow in 2009. The field visits to these parcels revealed that 74% were also fallowed in 2012, and thus likely abandoned from cultivation. Abandonment of cropping sites characterized by a low fertility status appeared a common phenomenon in the study area (Dubovyk et al. 2013a). Furthermore, 12% (6,580 ha) of the cropland with decreased vegetation cover was fallow in 1998 and cultivated in 2009. Such land parcels, small in size were sporadically distributed over the study regions and did not form distinct clusters.

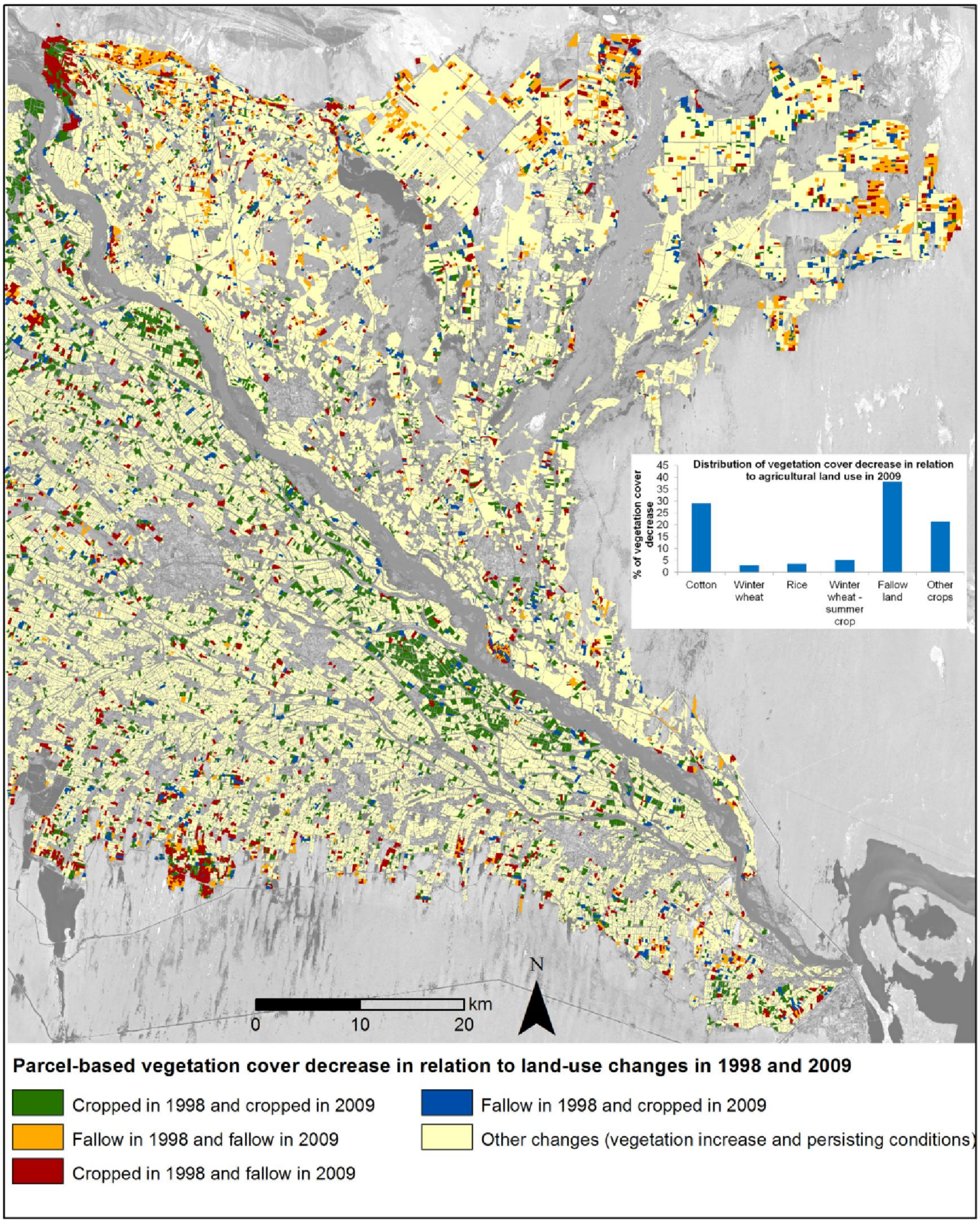

Figure 4.7: Spatial distribution of parcels with decreased vegetation cover in relation to land-use changes between 1998 and 2009

The rest of the parcels with decreased vegetation cover (26,142 ha) were found within the cropping areas, and could be attributed to either LD processes or changes in agricultural management, thus requiring further investigation into the causes of the vegetation decline.

The results of the change detection also reveal increasing vegetation cover on 19% (54,673 ha) and persisting conditions on 63% (185,312 ha) of the cropland. Vegetation cover mostly increased along the river and near the main irrigation channels, likely due to a better accessibility of the cropped fields to water (Dubovyk et al. 2012a). Only 4% of the area with increased vegetation cover was fallow in 1998 and 2009, probably signifying natural succession and low grazing pressure on these parcels.

4.4.4 Evaluation of change map

The change map evaluation using the MODIS-based LD trend map confirmed the validity of the elaborated approach. The map comparison, based on two classes, yielded an overall agreement of 93%. The omission and commission errors, i.e., 2% and 5% respectively, were small for the class ‘other trends’, suggesting an agreement between both maps for this class. The commission error of 23% for the LD class was acceptable, whereas the omission error of 43% for the LD class showed that the CVA underestimated the vegetation cover decline. This confirms the main drawback of applying bi-temporal change detection for LD monitoring in contrast to trend analysis, which monitors gradual LD processes within one class based on continuous information from image time series (Röder et al. 2008). The prerequisite of trend analysis is, however, availability of satellite data spanning several years, which is not fulfilled for Central Asia due to absence of continuous Landsat coverage. However, the CVA, based on the finer resolution satellite data of two years, may thus detect subtle changes not captured by the MODIS-based assessment. The combination of both methods is, therefore, advisable in the complex context of irrigated agro-ecosystems in Central Asia. In detecting desertification in drylands , SMA-based CVA analysis was found robust in providing landscape-scale information on land condition (Dawelbait and Morari 2012).

The simulation results based on the field samples suggest that the proposed method was able to discriminate between changes due to crop rotation and LD. The differences in soil cover per parcel due to all crop combinations in 2009 were minor, mostly from -0.1 to 0.1. In the case of cropland conversion to fallow, the differences were a great deal higher (Figure 4.8). In the overlapping area of the two distributions, only 1% of the crop-fallow differences (values > -0.08) and 5% of the crop-crop differences were located (values < -0.08). Thus the detected CVA-based changes referred to land-cover changes and were not caused by crop rotations but rather by other factors, such as LD.

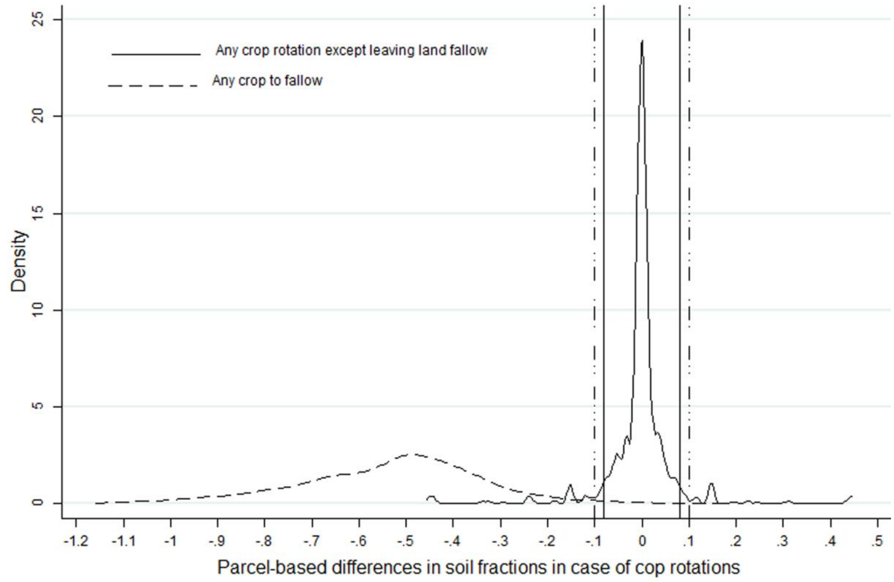

Figure 4.8: Kernel density plot showing differences in aggregated soil cover per parcel due to crop rotations. Vertical lines indicate reference lines for overlapping areas of two distributions

The object-based CVA approach has several limitations. Good data quality impacts the change detection results (He et al. 2011). Additional challenges are the selection of the optimal threshold (e.g., Zhang et al. 2009) and availability of the ancillary data for interpreting the change map for irrigated cropland, where changes are largely driven by agricultural management.

4.4.5 Implications for land-use planning

The lowlands of the Amu Darya River are among the oldest agricultural areas in the world and have been under intensive farming since the 1950s (Saiko and Zonn 2000). The major agricultural constraints in the study area are physical, i.e., shallow soils, arid climate, flat terrain with enclosed saline lakes and depressions, and can lead to LD (Akramkhanov et al. 2012; Dubovyk et al. 2013a). In order to sustain the productive capacity of these valuable agro-ecosystems, land- and water-use practices need to consider the site-specific suitability of the land for agriculture, and that some landscape fractions are better left for provision of other essential ecosystems services.

The parcel-based differentiation of landscape segments in need of reclamation as well as resilient farming areas could support the decision making of agricultural planning institutions, cadastral authorities and individual farmers, as the developed maps identify LD hotspots at the scale relevant to agricultural planning. Our analysis reveals higher prevalence of areas with decreased vegetation cover, often caused by the occurrence of uncultivated land, in the outreaches of the irrigation system and on borders with natural deserts. The farmers would, thus, benefit from having this cropland exempted from cotton cultivation towards more appropriate land-use practice that sustains and enhances their productive capacity.

To enable development of site-specific recommendations for land conservation and rehabilitation measures, further steps could include systematic field surveys and on-site validation of remote-sensing results. For individual parcels, the main drivers, including management practices, leading to vegetation decline and LD should be identified and analyzed. In our case, it was not necessary to apply image segmentation to derive field objects for OBCD as a cadastral map was available. However, for the cases when the cadastral information is missing, segmentation can be used to derive objects that match field parcels (e.g., Pena-Barragan et al. 2011).

4.5 Conclusions

The results of the assessment reveal a vegetation cover decline of significant spatial extent within the cropland area in the irrigated lowlands of the Amu Darya River. The detected decline was most strongly associated with reduced cultivation, and thus occurrence of fallow land in areas presumably less suitable for farming. Such areas at the tail ends of the irrigation canals or on sandy desert soils should be considered for alternative land uses.

This paper demonstrates the use of the OBCD based on multitemporal imagery of high spatial resolution for monitoring land conditions in irrigated agro-ecosystems in Uzbekistan. The analysis involved several consecutive steps, i.e., SMA, parcel-based CVA, and map interpretation. The derived information on vegetation cover decline in the study region and the associated maps can directly support parcel-specific agricultural planning decisions, including land rehabilitation measures in Khorezm and southern Karakalpakstan, Uzbekistan.

The proposed automated technique is based on high-resolution Landsat TM data available free of charge, and thus especially attractive for developing countries with limited funds available for environmental monitoring. The proposed approach can be used as an alternative to routinely used trend analysis of image time series for cases when spatial information is required on scales appropriate for targeted land management interventions and high spatial resolution time series are not available.

5 LAND SUITABILITY ASSESSMENT FOR AFFORESTATION WITH *ELAEAGNUS ANGUSTIFOLIA* L ON DEGRADED IRRIGATED CROPLAND

5.1 Introduction

Agricultural land evaluation aims to estimate land suitability for a specific agricultural land use such as planting of a specific crop. By analyzing various land conditions including topography, water supply, soil, etc, such evaluation can be carried out by matching the requirements of specified crops with the land characteristics (FAO 1976).

The approaches for land evaluation are both quantitative and qualitative. Qualitative methods, which are less detailed and less data-driven, are used for land appraisal using expert knowledge and literature resources (e.g., Joss et al. 2008; Eslami et al. 2010; Jarnevich and Reynolds 2011). The results of these analyses are quite broad and often expressed in qualitative terms. The quantitative approaches use computer models (e.g., tree growth models, crop yield simulation models) to provide detailed outcomes; however, such models are very data demanding (van Lanen et al. 1992; Rossiter 1996). The choice of the method is thus case specific and depends on data availability and the level of detail of the required output (Mandere et al. 2010).

Multi-criteria decision making (MCDM) is a useful approach to serve land evaluation purposes due to its ability to combine qualitative and quantitative criteria to select a suitable alternative. Geographic information systems (GIS) are well suited for manipulating a wide range of data from various sources for a cost-effective and time-efficient analysis (Chen and Paydar 2012). A number of GIS-based multi-criteria evaluation methods have been used for different studies (Store and Kangas 2001; Malczewski 2004; Mashayekhan et al. 2012) and purposes including land-use planning (Shalaby et al. 2006; Kurtener et al. 2008; Bandyopadhyay et al. 2009), water management (Wang et al. 2011), and habitat suitability assessment (Joss et al. 2008; Nekhay et al. 2009; Armin and Abdolrassoul 2010; Jarnevich and Reynolds 2011; Davis et al. 2012).

Generally, a GIS-based MCDM for agricultural land suitability analysis for cultivation of a specific crop involves: (i) specification of the environmental requirements of a target crop, (ii) identification of the quantitative relationship between crop establishment/growth/productivity and each considered environmental criterion, (iii) calculation of a suitability class for each criterion, and (iv) combination of the classes in order to determine the overall suitability. The most important issue is how to parameterize and combine land characteristics to model the target response of the crop to the considered environmental criteria so as to rank each evaluation unit (e.g., cell, polygon) with an overall suitability score (Malczewski 2006a). To address this issue, a specific rule set is usually constructed. It consists of a number of decision rules used to define the range of criteria values for a suitability class and of a weighting system that assigns the degree of importance for each considered criterion according to the attribute values and decision maker's preferences (based on criteria weights) (Corona et al. 2008).

For multi-criteria aggregation of the weighted criteria, the Ordered Weighted Averaging (OWA) is often used (Yager 1988). Malczewski (2006b) incorporated the concept of fuzzy set theory or fuzzy logic (Zadeh 1965) into a spatially explicit OWA-based land suitability analysis in order to generate a broad range of decision scenarios. Land evaluation based on fuzzy logic has been used in land evaluation studies since the 1980s (e.g., Burrough 1989). Whereas classical methods assume that land parcels are crisply delineated in both geographic and attribute space, which results in homogenous polygons with a single suitability class, fuzzy logic generates realistic continuous classifications (Schlüter et al. 2006; Liu et al. 2013). A number of studies showed that combination of fuzzy logic and OWA yield promising results for land suitability analysis (Eastman and Jiang 2000; Jacek 2006; Malczewski 2006b; Armin and Abdolrassoul 2010; Chen and Paydar 2012). Weighted linear combination (WLC) is one of the most frequently used decision rules in GIS, and is also a specific case of an OWA. The WLC allows a fusion of OWA operators and fuzzy variables (e.g., Boroushaki and Malczewski 2008), an approach that was also adapted in this study.

The main aim of this study was to contribute to sustainable land management options as well as to land restoration efforts in the irrigated lowlands of the Amu Darya River. This was achieved by applying a GIS-based MCDM methodology for assessing suitability of degraded irrigated cropland for establishing tree plantations considering the specific environmental setting of irrigated agro-ecosystems in northern Uzbekistan. The selected tree species for assessment is *E. angustifolia (*Appendix 8.1), a local species that was proven to be a promising species for afforestation of the degraded land in the study region (Khamzina et al. 2006b; Khamzina et al. 2008; Djanibekov et al. 2012b; Schachtsiek et al. submitted). Also, the farmers would prefer this tree species for establishment of tree plantations among other tree species that can grow on degraded cropland in the study region such as *Populus euphratica* and *Ulmus pumila* L. (Khamzina et al. 2006b; Schachtsiek et al. submitted), as suggested by the results of the survey conducted in 2012 (Dubovyk, unpublished).

5.2 Multi-criteria evaluation

The analyses were accomplished in the following stages: criteria development, GIS-based land suitability modeling, and results interpretation. The first stage produced a set of fuzzy maps reflecting the relation of each evaluation criterion to suitability for the considered objective. The suitability assessment comprised the weighted-order multi-criteria evaluation (MCE) procedure based on the developed criteria maps and weights assigned by experts. The results were subsequently evaluated and interpreted with respect to the current land use.

5.2.1 Selection of evaluation criteria and generation of criterion maps

Fundamental for land suitability assessments is an understanding of how environmental conditions control tree species growth. Optimal conditions of different species vary depending on their physiological requirements. Thus, a unique set of site-specific environmental conditions determines tree growth of different species (van Straaten et al. 2005).

The suitability criteria for afforestation are usually selected based on literature review (Bydekerke et al. 1998; van Straaten et al. 2005) and expert knowledge (Al-Kloub et al. 1997; Hansen et al. 2007). In this study, the final list of criteria was compiled based on both literature and expert opinions and included environmental requirements of *E. angustifolia* as well as the specific characteristics of Khorezm and the SKKP (e.g., irrigation water availability). The selected criteria for which data were available included parameters describing irrigation water availability, groundwater parameters, and slope (Table 5.1).

Table 5.1: Evaluation criteria and their value ranges used for assessment of land suitability for *E. angustifolia*

Evaluation criteria*	**Khorezm**		**SKKP**	
	min	**max**	**min**	**max**
Average groundwater salinity, g/l	0.05	9.04	2.01	7.21
Average groundwater table level, m	0.45	2.72	1.07	4.59
Canal density, m/m^2	0.00	11.78	0.00	14.76
Proximity to canals, m	0.00	6,000.00	0.00	6,000.00
Collector density, m/m^2	0.00	8.45	0.00	11.15
Proximity to collectors , m	0.00	4,256.30	0.00	9,999.54
Delta water use, milliom m^3	-2,371.53	-214.72	-4,238.00	4,037.00
Slope, %	0.00	10.00	0.00	27.97

**For details on calculation of evaluation criteria see section 3.2, section 33.2 and section 3.3.3.*

To quantify the relation between evaluation criteria and site suitability, literature review was performed, and two experts for afforestation from the research project “Opportunities for climate change mitigation via afforestation of degraded lands in Central Asia” (http://www.zef.de/1631.html) were interviewed. This information was formalized using a fuzzy set approach. For each criterion, a suitability curve was defined that assigned a degree of suitability to every value of the variable. A fuzzy set is characterized by a fuzzy membership grade that ranges from 0 to 1 (or from 0 to 255 for a byte scaling), indicating a continuous increase from non-membership to complete membership.

In this study, the following types of fuzzy membership functions were used: the monotonically decreasing/increasing linear function and monotonically decreasing/increasing sigmoidal function (Appendix 8.5). Mathematical definitions of specified functions are provided by Dubois and Prade (1982) and Eastman and Jiang (2000). To shape a fuzzy curve, the positions of four crossover points should be specified to indicate a point where membership rises above 0 (point a), membership becomes 1 (point b), membership falls below 1 (point c), and membership becomes 0 (point d). When "monotonically increasing" or "monotonically decreasing" curves are chosen, two control points are needed to define the fuzzy set membership function (Eastman 2012).

The corresponding criterion maps were prepared for each evaluation criterion using earlier collected and preprocessed data (section 3.2, section 33.2 and section 3.3.3). The nature of the maps was continuous; they had the same spatial extent, 250 m × 250 m cell size, map projection, and coordinate system.

Irrigation water availability

Irrigation water use

Irrigation water input secures the initial establishment of tree plantations until trees are able to rely on shallow groundwater (Khamzina et al. 2008). To account for this important condition, the regional irrigation water use showing differences in water supplies for each pair of years between 2000 and 2010 was calculated per district and averaged over 11 years. Negative values indicate that the water supply has decreased for some districts over the last decade, whereas positive values indicate an increase. The district with the highest increase was considered as the most suitable for establishment of tree plantations (suitability score 1), while the district with the highest decrease in water supply was considered as the least suitable (suitability score 0) (Table 5.1, Table 5.5).

To rescale the water use criterion, the monotonically decreasing linear function was selected. This function used minimum and maximum values from the water use image as the control points at the end of the linear curve.

Irrigation network

As an access to irrigation water depends on a location's proximity to irrigation infrastructure, the criteria 'proximity to irrigation canals' and 'density of irrigation canals' were incorporated into the analysis. The criterion 'proximity to irrigation canal' was rescaled using the monotonically decreasing linear function. Areas closest to current irrigation canals were considered most suitable (suitability score 1) than areas further from the canal (suitability score 0) (Table 5.1, Table 5.5). The criterion 'density of irrigation canal' was rescaled using a monotonically increasing linear function. Areas with the highest canal density were considered most suitable (suitability score 1) in contrast to the areas with lowest density of the canals (suitability score 0) (Table 5.1, Table 5.5).

In addition, the criteria 'proximity to drains' and 'density of drains' were included in the analysis. Although these factors donot directly influence irrigation water availability, operation of the drainage network is important for controlling the salt balance in the irrigated areas (Ibrakhimov et al. 2011). In the past years in the study region, irrigation water has frequently been insufficient for irrigation and human consumption (Glantz 1999). In water-scarce years, local drainage canals are occasionally used for irrigation in some districts (Ibrakhimov 2004)

The rescaling of these criteria was performed similarly to that of the factors related to irrigation canals. Available shapefiles of irrigation and drainage network were used to calculate the Euclidean distances to canals and drains and their density.

Groundwater table

A crucial environmental parameter is access of the trees to groundwater when this is the only available water resource due to lack of rainfall and low availability of irrigation water (Horton et al. 2001; Khamzina et al. 2012). Within the irrigated cropland of the study area, the depth of the GWT and the associated levels of soil salinity and GWS determine tree growth, as tree establishment with low irrigation input is conditioned to the presence of the shallow GWT (Horton et al. 2001; Schachtsiek et al. submitted). In general, a shallow GWT usually prevails in the region but can be reduced on the sites long-term abandoned from cropping and irrigation (Ibrakhimov et al. 2007; Ibrakhimov et al. 2011; Tischbein et al. 2012).

A shallow GWT significantly contributes to soil salinity when it exceeds a certain threshold level above which it rises by capillarity towards the soil surface (Hillel 2000; Forkutsa et al. 2009). For the study region, this threshold level was defined as 1.5 m (Rakhimbaev et al. 1992). An optimal GWT for *E. angustifolia*, which is a salt-tolerant plant, occurs in a range of 1.5-3 m (Katz and Shafroth 2003; Kang et al. 2004). Although experts noted that the very shallow GWT (>0.5 m) could be suitable during the establishment phase when tree roots are not completely developed, this groundwater depth would restrict root growth in the long-run (Ruger et al. 2005). The sites characterized by a GWT deeper than 3.0 m would require higher irrigation inputs when planting *E. angustifolia.* It was also observed that this species didnot grow well on the sites with a GWT in the range of 3-5 m. A few of them degenerated and died, and many trees died if the GWT>5 m due to lack of soil moisture (Kang et al. 2004). Suitability of the site, therefore, decreases when the GWT exceeds 3 m.

Consequently, a symmetric sigmoidal curve was selected to rescale the GWT layer into a continuous variable. The suitability increases monotonically from 0.5 m to 1.5 m. Then it does not change for GWTs in the range of 1.5-3 m, and decreases monotonically with further increasing GWT level. To capture within-seasonal fluctuations of the GWT, three factors representing the GWT in spring, summer, and autumn, averaged over years (section 3.3.3), were included in the analysis (Table 5.2, Table 5.5). The maps of GWT level and GWS were derived via spherical kriging interpolation, as suggested by Ibrakhimov et al. (2007).

Table 5.2: Ranges of values for GWT and GWS used for assessment of land suitability for *E. angustifolia*

Evaluation criteria	**Khorezm**		**SKKP**	
	min	**max**	**min**	**max**
Groundwater salinity in spring, g/l	0.22	8.57	1.96	9.88
Groundwater salinity in summer, g/l	0.55	7.66	1.97	7.03
Groundwater salinity in autumn, g/l	0.95	7.75	-	-
Groundwater table in spring, m	0.57	2.34	1.00	4.39
Groundwater table in summer, m	0.45	1.81	1.37	3.69
Groundwater table in autumn, m	0.58	3,23	1.17	4.15

Groundwater salinity

Elaeagnus angustifolia is known as a salt-tolerant species (Miyamoto et al. 2004; Khamzina 2006a; Sudnik-Wójcikowska et al. 2009; Shah et al. 2010; Hbirkou et al. 2011). However, the reported tolerable soil and water salt concentrations vary among studies, as they depend on plant growth stage, soil moisture and nutrient conditions as well as on type of salinity, and methods applied for determining the salt tolerance (Katz and Shafroth 2003). Kefu and Harris (1992) mentioned that growth of *E. angustifolia* was not affected by applying 8 g/l solution of sodium chloride (NaCl) every week with only slight damage resulting from a 10 g/l salinity level, severe damage occurring at 14 g/l, and frequent mortality at 16 g/l and higher. In view of the highly dynamic nature of soil salinity under irrigation, presence of shallow GWT, and absence of data on soil salinity, the land suitability parameters only included GWS.

Information on the relationship between establishment and growth of *E. angustifolia* and GWS is still very sparse. In Khorezm, several studies reported that *E. angustifolia* was established on the sites with GWS ranging from 0.6 g/l to 3.2 g/l (Khamzina et al. 2009; Khamzina et al. 2012). Schachtsiek (submitted) observed establishment of *E. angustifolia* on a silt-loamy site in Khorezm with GWS in the range of 0.5-3.8 g/l over the crop growing season, and on a sand-loamy site in the SKKP with GWS in the range of 0.6-3.8 g/l over the crop growing season.

Cramer et al. (1999) observed that tree species with high salt tolerance used more groundwater to restrict uptake of salts from the upper, drier and more saline soil layer. A high groundwater use by salt-tolerant, non-halophytic plants results in higher accumulation of salts in the soil profile, due to their exclusion from the uptake. In the study region, the salinity in the plots of *E. angustifolia* was higher than in the plots with less groundwater consuming species, even though there was no evidence that the tree roots took up the water directly from the groundwater; the roots rather resided in unsaturated soil layers above the GWT (Khamzina et al. 2009; Hbirkou et al. 2011).

Due to the absence of experimental data on GWS tolerance of *E. angustifolia* in the study region, after discussion with the afforestation experts and considering the salt tolerance of *E. angustifolia,* the GWS tolerance levels for this species were assumed according to the FAO classification (Rhoades et al. 1992). The optimal GWS level was assumed up to 7.0 g/l (Table 5.3). Suitability of the site for *E. angustifolia* was assumed to decrease exponentially with a further increase in GWS. Such relationship is best described by a monotonically decreasing sigmoidal curve (Table 5.5).

Similar to the GWT, the analysis on three factors representing GWS in spring, summer, and autumn averaged over years were included in the analysis to capture within-seasonal fluctuations of GWS (Table 5.3, Table 5.5).

Table 5.3: FAO classification of saline waters

Water class	Salt concentration, g/l	Type of water
Non-saline	<0.50	Drinking and irrigation water
Slightly saline	0.50 - 1.50	Irrigation water
Moderately saline	1.50 - 7.00	Primary drainage water and groundwater
Highly saline	7.00 - 15.00	Secondary drainage water and groundwater
Very highly saline	15.00 – 35.00	Very saline groundwater
Brine	>45.00	Seawater

Slope

The terrain characteristics elevation and slope define the suitability of land for agriculture (section 3.3.2). Even small differences in the terrain influence accumulation of topsoil salt in the fields (Akramkhanov et al. 2011) and also the supply of irrigation water and its distribution in the fields (Mott-MacDonald 2011). The suitability of a site in relation to slope can be based on the generally accepted criteria for slope suitability for agriculture (Table 5.4) (Sheng 1990). This classification was, however, not applicable for the analysis due to predominantly flat study area (Table 5.1).

Table 5.4: FAO classification of slopes according to their suitability for agriculture

Suitability class	Range of slope values, %
Suitable	0° ≤ slope ≤ 26.8
Marginally suitable	26.8 < slope ≤ 46.6
Unsuitable	slope > 46.6

In order to incorporate the small but nevertheless important differences in slope, it was assumed that the site suitability for *E. angustifolia* decreases with increasing slope steepness. Thus, the criterion slope was rescaled using the monotonically decreasing linear function (Table 5.5).

5.2.2 Weighted linear combination

An overall land suitability was computed using the convex combination rule, which is a weighted linear combination (WLC) of membership values of each factor A_i:

$$I = \sum_{i=1}^{n} w_i \times \mu_{A_i} \tag{5.1}$$

where w_i are the weights of the memberships values.

Table 5.5: Evaluation characteristics and membership function parameters for land suitability modelling

Evaluation criteria	Type of fuzzy membership function	Inflation points of fuzzy membership function				Rank assigned by experts	Weight
		a	b	c	d		
Irrigation water use in Khorezm	Monotonically increasing linear	2,371.53	-214.72	-	-	5	0.14
Irrigation water use in SKKP		-4,238.00	4,037.00				0.15
Proximity to canals in Khorezm	Monotonically decreasing linear	-	-	0.00	6000.00	4	0.11
Proximity to canals in SKKP				0.00	6000.00		0.12
Canal density in Khorezm	Monotonically increasing linear	0.00	11.78	-	-	4	0.11
Canal density in SKKP		0.00	14.76				0.12
Proximity to collectors in Khorezm	Monotonically decreasing linear	-	-	0.00	4,256.30	2	0.06
Proximity to collectors in SKKP				0.00	9,999.54		
Collector density in Khorezm	Monotonically increasing linear	0.00	8.45	-	-	2	0.06
Collector density in SKKP		0.00	11.15				
Groundwater table in Khorezm*	Symmetric sigmoidal	0.50	1.50	3.00	5.00	3	3*0.08
Groundwater table in SKKP*							3*0.09
Groundwater salinity in Khorezm*	Monotonically decreasing sigmoidal	-	-	7.00	max value of corresponding layer**	3	3*0.08
Groundwater salinity in SKKP*							2*0.09
Slope in Khorezm	Monotonically decreasing linear	0.00	10.00	-	-	1	0.03
Slope in SKKP		0.00	27.97				

** Separate factor maps representing groundwater table and groundwater salinity were prepared for land suitability assessment (Table 5.2). Their ranks and weights were the same. ** For value ranges of groundwater salinity see Table 5.2*

In WLC, criterion weights indicate the relative importance of each criterion to the objective under consideration. In general, the higher the criterion weight, the more influence that factor has on the final suitability map. A criterion with a high weight may compensate for low suitability in other factors that have lower weights (Eastman 2012). Therefore, the choice of weights is very important for determining the overall land suitability (Braimoh et al. 2004). Davidson et al. (1994) suggest that weights should be selected based on knowledge of the relative importance of evaluation criteria to crop growth. In this study, simple ranking was applied to rate criteria from 1 (least important) to 5 (most important). This ranking is based on the knowledge of experts who supervised the establishment of experimental tree plantations on the degraded cropland in the study region (Khamzina et al. 2006b; Schachtsiek et al. submitted). The final parameters of the evaluation criteria used in the land suitability analysis are shown in Table 5.5.

5.2.3 Model evaluation

The analysis was conducted to test the sensitivity of the results to the changes in the assigned weights. Subsequently, the suitability map based on the equal-weight WLC was computed and compared with the suitability map based on the WLC with expert-defined weights. The validation of the results based on commonly conducted comparison with the field data on crop distribution (Braimoh et al. 2004; Chen and Paydar 2012) was not possible, as tree planting is not a conventional land use in the study region, and only few E. *angustifolia* experimental plantations currently exist (Khamzina et al. 2006b; Schachtsiek et al. submitted).

5.3 Results and discussion

5.3.1 Land suitability for *E. angustifolia*

The result of MCE is a continuous layer of land suitability where values 0 and 1 indicate not suitable and most suitable sites, respectively. The assessment revealed that most of the irrigated cropland is characterized by average and higher than average suitability values for *E. angustifolia* (Figure 5.1). The suitability was lower in eastern and central parts of the SKKP, in the central part of Khorezm, and along the desert margins of the irrigated land. The visual comparison of the resulting map and criterion maps (not shown here) revealed that spatial distribution of suitability was largely predefined by irrigation water use. High suitability values were observed in the north-west of the region where irrigation water use has increased over the last decade, whereas the areas with the low suitability values experienced a decrease. The lowest suitability was detected in the eastern part of the SKKP, also likely due to the enhanced GWS reinforced by poorly developed drainage network (Mott-MacDonald 2011).

For further interpretation of the suitability map in relation to the selected criteria, the reduced-criteria suitability maps were calculated by sequentially omitting one criterion per calculation. The obtained maps were compared with the full-criteria suitability map. The results show that omitting the factor irrigation water use had the strongest impact on the suitability results as the correlation between the maps was average (R^2=0.65). Almost no impact was observed when omitting the criteria slope (R^2=0.99), GWS (R^2=0.95) for GWS in spring, and summer and R^2=0.99 for GWS in autumn), and factors related to irrigation network (R^2=0.98 for all criteria) excluding proximity to irrigation canals (R^2=0.90). By omitting criteria related to GWT, the correlation between the maps dropped (R^2=0.85). This confirms the importance of the criteria choice and assigned weights for suitability assessment (Lu et al. 2012).

In this study, the evaluation criteria were selected by experts and based on a literature review. Such selection procedure is rather subjective compared to statistical methods, e.g., multiple discriminant analysis (Joss et al. 2008). As a consequence, the selected criteria, while considered reasonable, might not necessarily be the most optimal to fully reflect the variability of land suitability for *E. angustifolia*. While the study identified cropland potentially suitable for *E. angustifolia* it was not possible to include all the relevant information, e.g., soil characteristics. Whereas the absence in the model of parameters such as soil type and texture could be neglected, as *E. angustifolia* grows under a wide range of soil types and textures from sand to heavy clay (Tu 2003), the absence of spatial data on soil salinity dynamics could have influenced the results of this assessment. Nevertheless, land management practices in the study region such as annual soil leaching, which is also recommended for the establishment phase of *E. angustifolia* plantations (Khamzina et al. 2006b), partly justify exclusion of this factor. There might also be an effect on the results due to the data quality and their resolution, which is a common problem of data-driven GIS-based studies especially in the developing countries (e.g., Ruger et al. 2005).

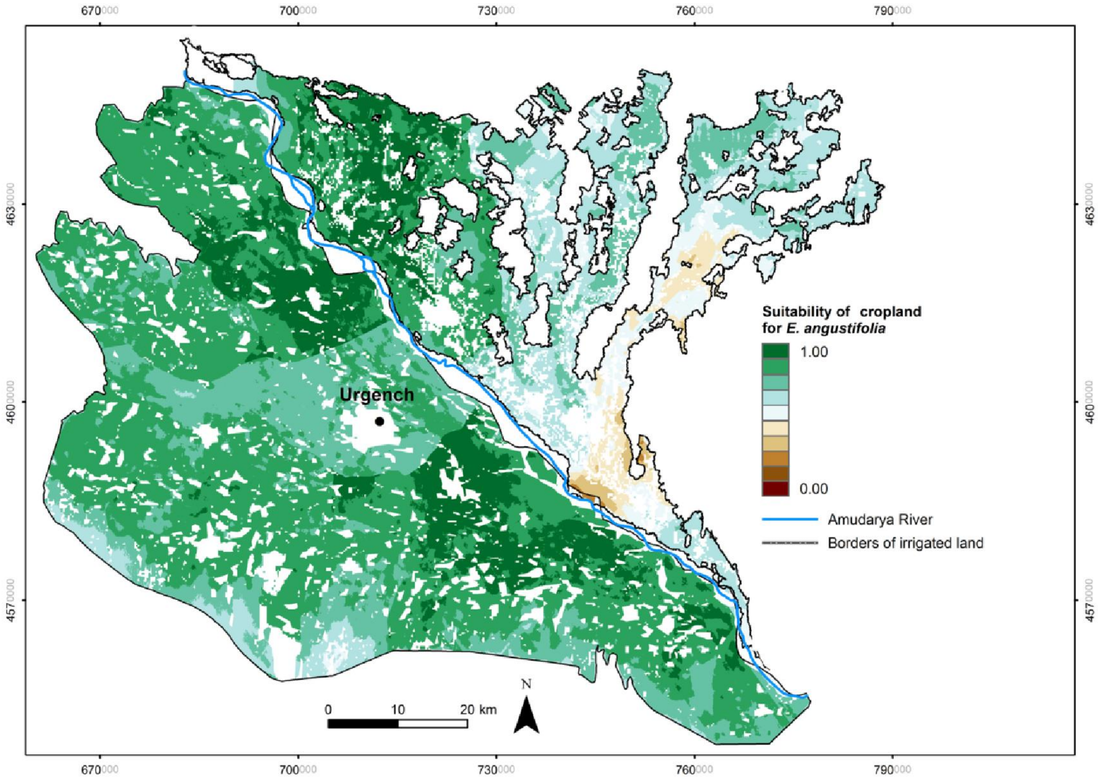

Figure 5.1: Overall suitability of land for *E. angustifolia* in the irrigated agro-ecosystems of northern Uzbekistan

The test of the model's sensitivity to the change in the assigned weights did not reveal substantially different results, as the compared maps (i.e., the suitability map based on the equal-weight WLC and the suitability map based on the WLC with expert-defined weights) were similar (R^2=0.93 for Khorezm and R^2=0.89 for the SKKP). The knowledge-based approach, commonly applied in land evaluation studies (e.g., Nekhay et al. 2009; Tuan et al. 2011; Krueger et al. 2012), was also used here to assign weights and determine fuzzy membership functions. This approach is rather subjective compared to the automated approaches (Lu et al. 2012; Liu et al. 2013). Implementation of the data-driven approach to model suitability is, however, preconditioned to availability of extensive quantitative information on environmental variables (e.g., Bradshaw et al. 2002). Still, the applied approach based on fuzzy logic and WLC allowed formalizing available expert knowledge in the formal algorithm (Ruger et al. 2005) and eventually achieving the objectives of the study. Further work could incorporate an empirical approach towards parameterization of the land suitability model if the necessary data are available, for example, from the established network of permanent *E. angustifolia* plantations in an environment similar to that of the presented case.

5.3.2 Suitability of degraded land for *E. angustifolia*

The overall suitability map (Figure 5.1) was subsequently overlaid with the MODIS-based LD trend (chapter 3) to highlight the suitability of *E. angustifolia* for degraded cropland (Figure 5.2). The parcel-specific Landsat-based map (chapter 4) was not used due to the differences between the spatial scales of this map and the suitability map.

The descriptive statistics of the suitability values of the degraded cropland (only significant NDVI trends were considered) is shown in Table 5.6. Overall, suitability was higher for Khorezm compared to the SKKP, while the highest suitability was observed for the Yangibazar district of Khorezm and the lowest suitability for the Turtkul district of the SKKP. Also, the range of suitability values was wider for the SKKP, suggesting higher spatial variability of the evaluation criteria in this area compared to Khorezm. In general, higher suitability was observed in the districts bordering the Amu Darya River such as Gurlan, Bagat, Khanka, and Khazarasp, most probably due to the better access to irrigation water. This degraded cropland, located inside high population density areas, should be preliminary targeted by land rehabilitation measures including afforestation in order to support the livelihoods of the people (Dubovyk et al. 2013b). In contrast, lower suitability was found in the districts in the tail-ends of the irrigation system such as Khiva, Kushkhupyr and Ellikkala. Even though prompt action is also required to stop ongoing LD in these areas, abandoned degraded cropland at the far reached of irrigation systems, are more prone to water scarcity and deeper GWT due to infrequent irrigation water supply (Dubovyk et al. 2012a; Dubovyk et al. 2013a). In these areas, establishment of tree plantations will require higher irrigation water inputs which, in turn, will increase transactions costs. Afforestation decisions for such cases should also be based on economic assessment of whether afforestation actions under increased irrigation is a viable alternative land use.

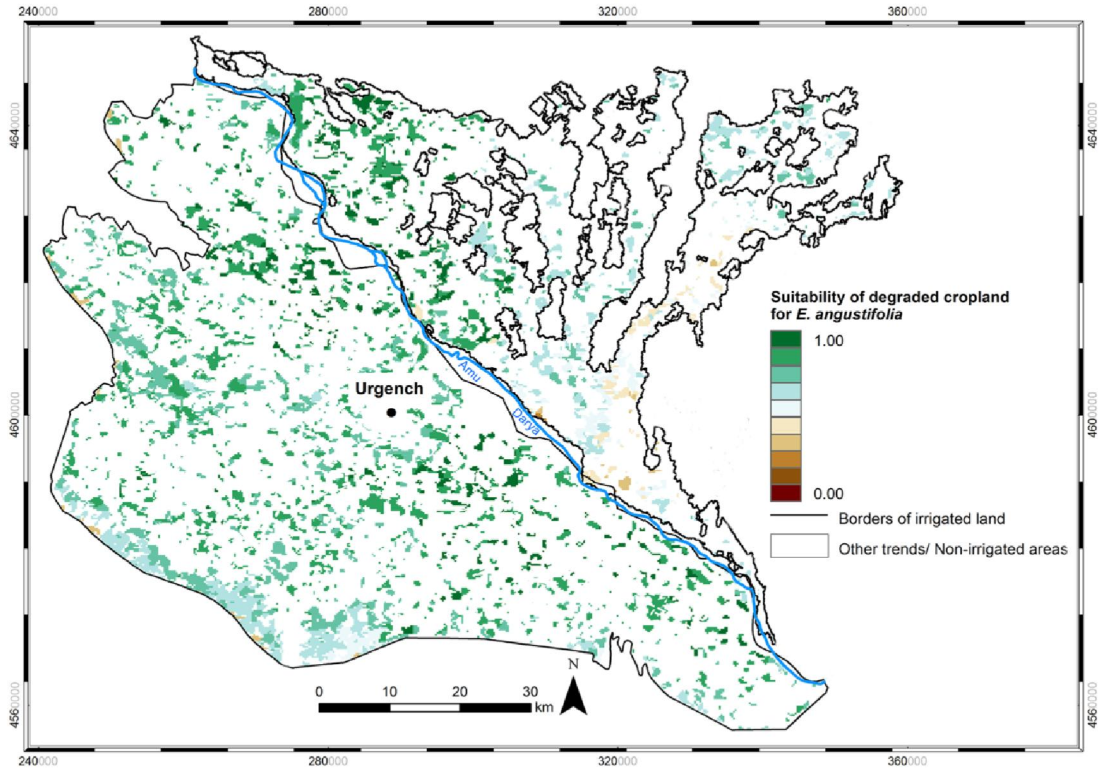

Figure 5.2 Land suitability map for *E. angustifolia* in relation to all classes of negative vegetation trend in Khorezm and Southern Karakalpakstan

Table 5.6: Descriptive statistics of degraded cropland suitability for *E. angustifolia*

Districts' name	**Land suitability for *E. angustifolia***			
	min	**max**	**mean**	**Stdev***
Bagat	0.62	0.88	0.78	0.05
Gurlen	0.66	0.85	0.78	0.03
Khanka	0.65	0.91	0.82	0.03
Khazarasp	0.59	0.87	0.76	0.05
Khiva	0.58	0.84	0.71	0.06
Kushkhupyr	0.56	0.79	0.72	0.04
Shavat	0.67	0.85	0.75	0.02
Urgench	0.63	0.85	0.71	0.02
Yangiaryk	0.50	0.83	0.66	0.07
Yangibazar	0.68	0.88	0.83	0.02
Khorezm	*0.44*	*0.91*	*0.76*	*0.06*
Beruniy	0.33	0.91	0.78	0.07
Ellikkala	0.26	0.83	0.61	0.04
Turtkul	0.18	0.74	0.53	0.10
Southern Karakalpakstan	0.18	0.91	0.65	0.13

**Standard deviation*

The irrigated croplands are not conventional forestry areas, thus there is little published research on tree growth in this environment in general (Khamzina 2006a), and studies on spatial suitability assessments for afforestation of the degraded irrigated cropland are missing. Laube (2005) focused on the spatial distribution of land suitability for different ecosystem services of 11 tree species (including *E. angustifolia*) at the farm and district level (Khiva and Kushkhupyr districts, Khorezm). The study demarcated 31% very suitable and suitable areas for timber production, 23% for biodrainage, and 44% for fruit production at district level. Overall, the spatial patterns of suitability values were similar for fruit and timber production. The revealed dissimilarities can be attributed to the differences in research objectives, methods and datasets used as well as to the spatial scale of the analyses. However, the results of both studies reveal a trend of decreasing suitability values towards the southern borders of the considered districts.

5.3.3 Implications for land-use planning

Agroforestry practices are not a common land use in the irrigated agro-ecosystems in northern Uzbekistan. A number of bio-physical and socio-economic studies were therefore conducted during the last decade in the study region aiming to assess the potential of plantation forestry as an alternative land-use option, which could rehabilitate degraded cropland, provide ecosystems services, and generate opportunities for income generation for the local population (Martius et al. 2003; Lamers et al. 2008; Hbirkou et al. 2011; Djanibekov et al. 2012b; Djumaeva et al. 2012). In total, evidence was obtained on ecosystem rehabilitation and financial benefits, suggesting that afforestation of the degraded cropland is an attractive land use (Khamzina et al. 2012). In this context, the performed land suitability assessment allows improved understanding of the spatial variability of suitability of degraded irrigated cropland for *E. angustifolia* and, subsequently, for better-informed spatial planning decisions on land rehabilitation via afforestation. The generated data also provide a basis for assessment of spatial distribution of the potential costs and benefits, and thus eventually allow efficient environmental policy interventions (van der Horst 2006).

The developed suitability model can be easily modified and has relatively small input data requirements. This enables its further use for suitability analysis for other tree species and ecosystem services from tree plantations, always considering the specific conditions that apply to the species/services concerned. Furthermore, the obtained results could be used as input for other types of analysis (e.g., economic assessment) and coupled with other models (e.g., agent-based models).

The performed assessment was intended only for broad-scale planning purposes due to data constraints and absence of validation datasets. Subsequently, caution is needed when deciding on the most suitable outputs for spatial planning. Nevertheless, the results facilitate a better understanding of the suitability potential of alternative land use of the degraded cropland which, in turn, forms a basis for future land rehabilitation action in this region (Dubovyk et al. 2013b).

5.4 Conclusions

A GIS-based multi-criteria decision-making tools was utilized for a regional-scale suitability assessment for *E. angustifolia* on the degraded cropland in the irrigated agro-ecosystems in northern Uzbekistan. The approach used expert knowledge, fuzzy logic and WLC to produce a suitability map for the irrigated land in the study region. This map was further overlaid with the MODIS-based LD trend map to extract suitability values for degraded cropland. Altogether, the results reveal that degraded cropland has higher than average suitability potential for afforestation with *E. angustifolia*.

The generated information can support planning of spatially explicit policy incentives for agricultural land on a regional level. For more specific recommendations, possible implications of the changing land use to tree plantations, for example on the water balance, socio-economic assessment of future land-use scenarios as well as higher spatial scale datasets for suitability modeling should be considered.

6 CONCLUSIONS AND OUTLOOK

Irrigated agro-ecosystems in Central Asian drylands have experienced observable degradation due to anthropogenic factors mostly related to land management and water-use practices. Despite the profound social and ecological implications of LD, spatially explicit information on land conditions is rare, and particularly lacking for irrigated agro-ecosystems in the region. Concerns are also raised about the accuracy of locally available soil degradation maps, which are often static and irregularly updated. Moreover, the existing assessments based on satellite data mostly focused on LULC changes and were implemented at large scales using low to medium resolution satellite data (e.g., Klein et al. 2012; Gessner et al. in press).

In Uzbekistan, irrigated agriculture remains the basis of the economy, while the share of the land affected by high soil salinity, waterlogging, and declined soil fertility has increased over years. For guiding the measures for land rehabilitation planning, up-to-date information on land conditions on different spatial scales should become available. To derive such information, RS techniques have been commonly applied (Wessels et al. 2007; Prince et al. 2009; Le et al. 2012); however, irrigated agro-ecosystems have not been yet explicitly addressed.

Afforestation has proved to be an effective land restoration measure for saline environments elsewhere and also in northern Uzbekistan (Khamzina et al. 2012). As land suitability for trees differs spatially, planning of afforesting the degraded irrigated cropland has to be based on the results of spatial land evaluation for the region considered.

In order to contribute to sustainable land management options as well as land restoration efforts in the irrigated lowlands of the Amu Darya River, this research provides multi-scale information on land conditions and the drivers of LD as well as spatial evaluation of the suitability for afforesting degraded land with the selected tree species, i.e., *E. angustifolia*. This study also contributes to the development of methods that will support future assessments in similar landscapes.

In the following sections, the major findings of this research are highlighted. These are used to provide an outlook on the implications of this research and to provide recommendations for follow-up studies.

6.1 Reflections on multi-scale targeting of land degradation in irrigated agro-ecosystems in northern Uzbekistan

Degradation of cropland is a typical phenomenon of irrigated agro-ecosystems in CA. In the Central Asian region, a huge expansion of irrigated land occurred during the Soviet era when the massive irrigation infrastructure was constructed. Irrigated agro-ecosystems of CA have thus several common characteristics and similar problems such as elevated soil salinity. Also, it is evident that there are some dissimilarity between the irrigated landscapes, mainly due to the differences in land and water management after the collapse of Soviet Union and the states' independence in the beginning of the 1990s.

The aim of this research was to illustrate the situation of LD in the irrigated lowlands of the Amu Darya River in northern Uzbekistan. The case study was implemented at two different but inter-related spatial scales, i.e., a region-wide analysis of cropland degradation that is typically concerned with the strategic planning process, and the local level in which the subset of the study area was used to describe LD patterns in detail. The findings for both scales are presented below.

6.1.1 Lessons related to the regional scale

The research at the regional level provided insights into several topics related to LD in the irrigated agro-ecosystems, and into the applicability of a diversity of methods that were developed and applied in the course of this study. These are discussed briefly in the following section.

Spatio-temporal analyses of cropland degradation

In general, vegetation cover loss over time, irrespective of whether caused by worsening soil quality or decreased cultivation, denotes a decline in the economic productivity of irrigated cropland and can be considered as degradation of its productive function (UNCCD 1994).

Spatial trends of vegetation cover decline, calculated from the MODIS-NDVI time series for the monitoring period 2000-2010, revealed a gradual negative vegetation trend on 23% (94,835 ha) of the arable area. Spatial distribution of the trend was highly variable and scattered throughout the region, but several clusters were observed on the outskirts of the irrigation system near the borders with the natural deserts Karakum and Kyzylkum. In Khorezm, a big cluster of degraded land was located in the western part in the former river bed of the Amu Darya River, and another big cluster was formed on the northern and north-eastern part of the SKKP. The validation results based on collected field data for the LD trend map (overall accuracy is 68%) and statistical tests affirm the validity of the developed approach.

The results of spatial relational analysis based on a suite of ancillary datasets explain the observed patterns of degraded cropland in the study area. The majority of cropland degradation was observed on marginal cropland. These marginal areas are typically characterized by poor-quality soils and low population density. In addition, these areas are commonly taken out of the regular cropping cycle and are often abandoned. Fewer degraded cropland patches were found within areas of high population density.

The results of logistic regression modeling allowed explanatory analysis of the causative factors of LD and identification of areas at risk of LD. In Khorezm, the factors GWT, GWS, uncultivated land, and slope (odds=330%, odds=26%, 103%, and odds=29%, respectively), had the strongest impact on the spatial distribution of degraded cropland, while for the SKKP these factors were GWS, uncultivated land, and irrigation canal density (odds=475%, odds=384%, and odds=-164%, respectively). For Khorezm, the remaining factors, i.e., change in land use, proximity to irrigation canals, and proximity to roads, were positively related to LD occurrence, whereas factors water use and proximity to settlements were negatively related. Similarly, for the SKKP, the factors soil *bonitation* classes III and IV and proximity to collectors were positively related to spatial distribution of degraded areas, whereas the factors collector density and GWT were negatively related. The predictions of areas at risk of LD show that more areas are likely to be affected in the region if no preventive measures are taken. The computed evaluation and validation statistics indicate that the model results are valid (AUC ROC=0.70 for Khorezm and 0.88 for the SKKP).

From the point of view of land management implications, those degraded croplands that are located in more densely populated areas and include higher quality soils may be appropriate areas for the introduction of more sustainable cropping practices. Marginal croplands, however, should be considered as candidate areas in which to implement appropriate rehabilitation measures. Such measures may include cessation of annual cropping and fallowing or vacating the land.

6.1.2 Lessons related to the local scale

The issues investigated at the local level were mainly related to generation of spatial information on land conditions and LULC characteristics at a scale appropriate for targeted land management interventions.

Plot-based assessment of irrigated cropland degradation

The agricultural land-use map, derived from the analysis of the multi-temporal Landsat TM images, revealed the following cropping patterns in 2009. The cotton and winter wheat fields were scattered throughout the area, while there were several rice clusters close to the Amu Darya River and along the big irrigation canals. Diversity of crops and crop rotations were mainly found in the central part of the irrigated area. The distribution of cropping areas in 1998 and 2009 was comparable to that of fallow land mainly on the desert outreaches of the irrigation system. The accuracy assessment confirmed the validity of the produced maps (overall accuracy=93% for the 1998 map and overall accuracy=82% for the 2009 map).

An adaptation of the SMA-based OBCD for the analysis of land conditions in irrigated agro-ecosystems yielded a change map that highlights parcels that experienced vegetation cover decline between 1998 and 2009. Similar to the MODIS-based map, spatial distribution of the parcels with decreased vegetation cover was variable, but large clusters were found along the borders of irrigated land in the south and north of the study region. The comparison with the land-use maps showed that 17% (29,029 ha) of the analyzed cropland area was fallow in both 1998 and 2009 and experienced decreased vegetation cover probably due to grazing pressure. About 20%

(11,064 ha) of the areas with vegetation decline was cultivated in 1998 and left fallow in 2009. As revealed by field visits, these parcels are likely abandoned from cultivation. The remaining parcels with decreased vegetation cover (26,142 ha) were located within the cropping areas. The areas under cotton cultivation (15,343 ha) that exhibited vegetation cover decrease seem to be more affected by degradation processes than by reduced agricultural inputs.

The evaluation of the change map using the MODIS-based LD trend map confirms the overall similarity between both maps (overall agreement=93%). The evaluation results also show that the Landsat-based change map based on the bitemporal dataset underestimated the vegetation cover decline compared to the MODIS-based trend map based on satellite time series spanning over 11 years (omission error=43% for the LD class).

6.1.3 Spatial decision support for land rehabilitation via afforestation

MCDM approaches based on MCE are closely related to GIS overlay analyses, and the development of spatial MCE applications is thus a useful GIS application for agricultural planning. In this study, a MCE model for assessing suitability of degraded land for *E. angustifolia* was developed incorporating criteria based on biophysical and spatial characteristics of the studied agro-ecosystems. Even with the relatively small dataset, it was possible to discriminate between degraded irrigated areas on the basis of their potential suitability for planting this tree species. This could be considered by local authorities as a possible land rehabilitation measure.

The assessment revealed that most of irrigated cropland is characterized by average and higher than average suitability values for *E. angustifolia*. The higher suitability values were observed in the north-west of the region, which is characterized by adequate water use, whereas the lower values were found in the eastern and in central parts of the SKKP, in the central part of Khorezm, and along the desert margins of the irrigated land.

Suitability of the degraded irrigated cropland for *E. angustifolia* was higher for Khorezm than for the SKKP (mean=0.76 and mean=0.65, respectively). Also, the range of suitability values was wider for the SKKP, suggesting higher spatial variation of the evaluation factors within the region. Higher suitability was observed in the areas bordering the Amu Darya River, whereas lower suitability characterized the outskirts of the irrigation system.

Similar to the general recommendation on the prioritization of the land for land rehabilitation measures, it is advised to first select degraded land located inside high population density areas for establishing *E. angustifolia* plantations in order to not only contribute to land restoration but also to support the people's livelihoods. Establishing tree plantations on the degraded margins of the irrigated area, which are characterized by deeper GWTs, will require higher management inputs, and thus should be subjected to further evaluation to determine the economic feasibility of tree planting on such land.

6.1.4 Methods and techniques for spatial data analyses

The results of this study clearly demonstrate the use of a variety of geospatial tools for multi-scale LD assessment and spatial targeting of land restoration in irrigated agro-ecosystems. The resulting increased knowledge on cropland degradation could provide improved spatial decision support for planning land rehabilitation measures and sustainable land management options.

The basis for the analyses of the LULC changes was the freely available satellite imagery from the MODIS and Landsat TM sensors. Even though the free of charge distribution of this imagery makes its use for land management applications an attractive option for resource-sparse countries, it has not been routinely applied for environmental monitoring and agricultural planning purposes in Uzbekistan. This research has demonstrated how such data can be used in the analysis of cropland degradation in a manner that can generate potentially useful datasets for spatial planning and policy making. In such a setting, where reliable data are in short supply and resources are constrained, methods that create added value from free-of-charge satellite data could be of considerable benefit. An important asset is the generation of broad-scale spatial information, e.g., on LULC changes, which would be otherwise unavailable to the agricultural planning community.

However useful these examples are, they were only made available through considerable investment in image processing and analyses. This weakness was not overwhelming though, and the staff training in the use of the elaborated geospatial tools as well as the development of automated routines for data capture and analyses would do much to enhance the usability of satellite data in the local setting. More importantly, this would facilitate the establishment of a periodic LD monitoring system (Sommer et al. 2011) that would produce useful data on land conditions, thus enabling operational decisions on land management.

The development of the approach to generate spatial information on the scales required for targeted land interventions using multi-temporal Landsat imagery from 1998 and 2009 was a useful means to accommodate the disadvantage of the medium scale (250 m) MODIS images. Although Landsat images were also freely available and their spatial resolution (30 m) allowed generation of the parcel-specific LULC data, the suitability for LD monitoring is constrained due to the absence of the continuous time series in this part of the world; this is needed for trend analysis. Although the use of Landsat imagery has been shown to be beneficial in a technical sense, the generated information should be regarded as supplementary to the results of the MODIS-based trend analysis, and should be placed in the specific context utilizing additional datasets such as agricultural land-use maps as used in this work.

Despite the above reservation concerning the use of Landsat imagery, the performed analyses were able to successfully generate the historical LULC data on a per-parcel basis that could not otherwise have been collected for this region with the available resources. Furthermore, the Landsat archive is currently the only available source of RS images dated back to the 1970s, and thus has to be utilized when a retrospective assessment on high spatial scale is intended.

The maps showing changes in NDVI and also other vegetation indicators over time are operationally produced for LD monitoring (Buenemann et al. 2011). While broadly available and well documented data is in principle creditable, there is a call within the scientific community for caution with the interpretation of such information (Bai et al. 2008; Wessels et al. 2012). Specifically, for irrigated agro-ecosystems only when placed in the context of land-use changes and land-use systems via utilizing secondary datasets and expert knowledge, vegetation-related indicators may provide an indication where problems can arise. Independent of the above-mentioned criticism, it should be noted that the general approach based on vegetation monitoring, as applied in this research, is currently the only available option for operational LD observation over large areas (Vogt et al. 2011).

This research used a set of ancillary datasets and a number of geospatial tools including logistic regression modeling, relational analysis, and MCE to understand cropland degradation in the study region and to guide land management interventions for afforesting degraded land. The results of these analyses are, however, conditioned to the data availability and quality. The utilized ancillary datasets were collected from a variety of sources in different formats over an extended period of time, and were processed by several persons, most of them with basic knowledge and skills in GIS. Also, problems were anticipated related to the general availability of some datasets (e.g., soil salinity, crop yields), and to the availability of data at the required spatial unit and with their temporal correlation. The datasets were available only on a scale appropriate for regional-wide analyses. Further, as LD is a dynamic process, the additional spatially explicit data for some of the variables such as water use, GWT and GWS should ideally be available in a uniform continuous manner and cover the same monitoring period as satellite data. Given the resources available for such work in Uzbekistan, however, pragmatic approaches that rely as much as possible on accessible data might offer the best possibility of application and acceptance by local decision makers.

6.2 Recommendations for future work

In the course of this research, several issues were encountered that were not directly addressed mainly due to resource constraints. In the following section, these issues are highlighted along with other topics where additional research could further enhance the scope for sustainable land management based on spatial data provision in Khorezm and the SKKP. The section concludes with some remarks on the need for integrated assessment of LD and sustainable land management.

6.2.1 General remarks on issues for further investigation

The results of this research contribute to formation of a more complete and spatially explicit picture of the cropland degradation that was previously not available in the study region. The outputs and the elaborated approach to generate such information are useful contributions to the spatial data provision for agricultural planning and management; however, a diversity of issues can be further investigated.

From the technical side, the approaches developed at the regional and local scales showed usefulness and applicability, but also require further validation and refinement, and ideally the inclusion of additional environmental and socio-economic datasets at the higher spatial scale to unable further insights into drivers of land-cover changes as well as for land suitability analysis at the local level. Also, historical mapping of agricultural land-use changes with Landsat images can allow more comprehensive interpretation of the observed patterns of vegetation cover decline in the study area.

From the application side, further refinement of the developed tools should be done in close cooperation with local agricultural planners, land managers, and scientists to capture the local needs and to assure applicability of the results. This research ignored the important issues related to institutional and organizational setting, as well as sociological aspects of the geospatial tools adoption in the study region that must be considered in an operational environment. These issues can be a part of further research that should be conducted with the full cooperation of local actors and the potential user community for the developed tools and generated spatial information. The legal settings which would allow alternative land management of degraded cropland in Uzbekistan have also to be looked at, as currently there is no legal support for alternative use of agricultural land (Djanibekov et al. 2012b).

6.2.2 Specific remarks on issues for further investigation

This section elaborates on some topics which ideally should be addressed in the course of follow-up studies to support the findings of this research and also to assure their further applicability to similar environments in CA and elsewhere.

Integration of remote sensing data and terrestrial/*in situ* measurements

Earth observation can considerably contribute to the LD identification and monitoring of land conditions over time. The obtained RS-based results highlight hotspots of significant change that need subsequent detailed investigation on the ground. A meaningful interpretation of satellite imagery, for example, requires the careful calibration and validation of RS data against ground measurements such as vegetation productivity and soil fertility. It is therefore advisable to conduct ground measurements in the study region for further affirmation of the validity of produced results and for creating linkages with quantitative *in situ* data.

This research relied on different types of satellite imagery as well as on various indicators (i.e., NDVI and SMA). SMA is known for its superiority over simpler vegetation indices in quantifying vegetation cover elsewhere (Sonnenschein et al. 2011). Still, for the specific settings of irrigated agro-ecosystems, the trade-off between these different estimates should be a subject of further investigation. In addition, the nature of the differences in spatial information generated from MODIS and Landsat has to be studied in more detail to allow improved interpretation of the obtained results and their supplementary usage.

Multi-criteria evaluation for spatial decision support

The aim of the performed land suitability assessment was to demonstrate applicability of GIS-based decision support tools with the available data for regional planning of land rehabilitation measures using an example of afforestation with *E. angustifolia*. It illustrates the principles involved and shows that there is scope for further refinement of the operational model. This should be done in close cooperation with local actors. The model can be improved by (1) adding criteria in addition to the sort of data already used in the analysis that were not available for this study, (2) incorporating quantitative methods for weights generation and criteria ranking, (3) considering preferences of different groups of local actors (e.g., farmers, cadastral engineers, and agricultural planners), and (4) adding new modules to accommodate the multi-functional nature of afforestation (Webb and Thiha 2002; Lexer et al. 2005). Furthermore, the spatial MCE approach can be used in a similar fashion to generate information on land suitability for other tree species or different types of land restoration measures as well as alternative land uses of degraded land (e.g., Zerger et al. 2011).

6.2.3 Towards an integrated assessment of land degradation and sustainable land management

Current approaches for LD assessment and sustainable land management increasingly aim to integrate information and data from different sources in order to achieve an accurate representation of this complex problem (Reynolds et al. 2011). Approaches aimed at assessing only selected aspects of these issues such as net primary productivity or farm income often do not provide adequate information for sound policy and decision making (Buenemann et al. 2011). Such approaches, for example, do not provide an understanding of interactions between elements of environmental and human systems and of costs and benefits of alternative land management options or of conflicting interests of different stakeholders.

The follow up study should thus link generated spatial information and a variety of environmental and socio-economic data in a spatially explicit framework for comprehensive assessment of the sustainable land management options of the degraded land in the studied agro-ecosystems. For example, valuation of the economic costs of LD would increase awareness of the spatial extent of the cropland degradation phenomenon and its impacts on agriculture and rural development. While linking generated spatial information to human processes on the ground, i.e. 'socializing the pixel', new insights on land management sustainability and its relation to human well-being could be obtained. The results of such integrated assessment could not only facilitate agricultural planning and land management decisions but also be a useful tool for decision-making on sectoral orientations for development assistance that will target cropland degradation.

6.3 Overall conclusions

This research allows to highlight the following points related to the multi-scale targeting of LD with satellite RS in the irrigated lowlands in northern Uzbekistan:

- The problem of irrigated cropland degradation is very acute in the irrigated agro-ecosystems in Khorezm and the SKKP.
- The obtained spatial knowledge on the irrigated cropland degradation allows an improved understanding of LD patterns and the driving factors at both regional and local levels.
- The generated spatial data can contribute to the policy and decision-making process on land rehabilitation and sustainable agricultural land use.
- The proposed methodological approach based on the RS tools combined with GIS and statistical analyses allows multi-scale targeting of irrigated cropland degradation.
- The developed approach can contribute to spatio-temporal analyses of cropland productivity decline and spatial decision-support on land rehabilitation via afforestation in other Central Asian countries and in similar agro-ecosystems worldwide.
- Vegetation productivity decline and vegetation cover decline are used as proxy for LD. In agricultural areas, additional information should be employed for interpretation of the observed vegetation decline to avoid misinterpretations.
- To enable development of site-specific recommendations for land rehabilitation and/or conservation measures, on-site validations of RS and land suitability results should be carried out.
- In order to obtain accurate and reliable results, the tools applied in this study should be used according to the confirmed procedures.
- Data availability and quality are crucial factors for successful applications of spatio-temporal analyses of LD and for determining land suitability for alternative land uses.
- The generated spatial information should be further integrated with socio-economic and biophysical data in a spatially explicit way for inclusive LD assessment and sustainable land management planning in the studied irrigated agro-ecosystems.

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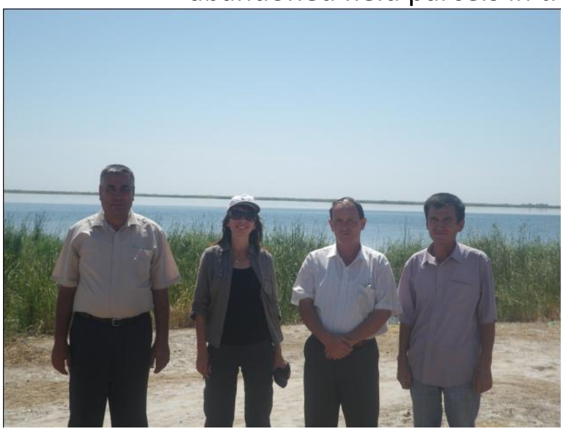
8 APPENDICES

Appendix 8.1: *E. angustifolia* in one of the abandoned sites in Gurlen district of Khorezm region of Uzbekistan in 2011

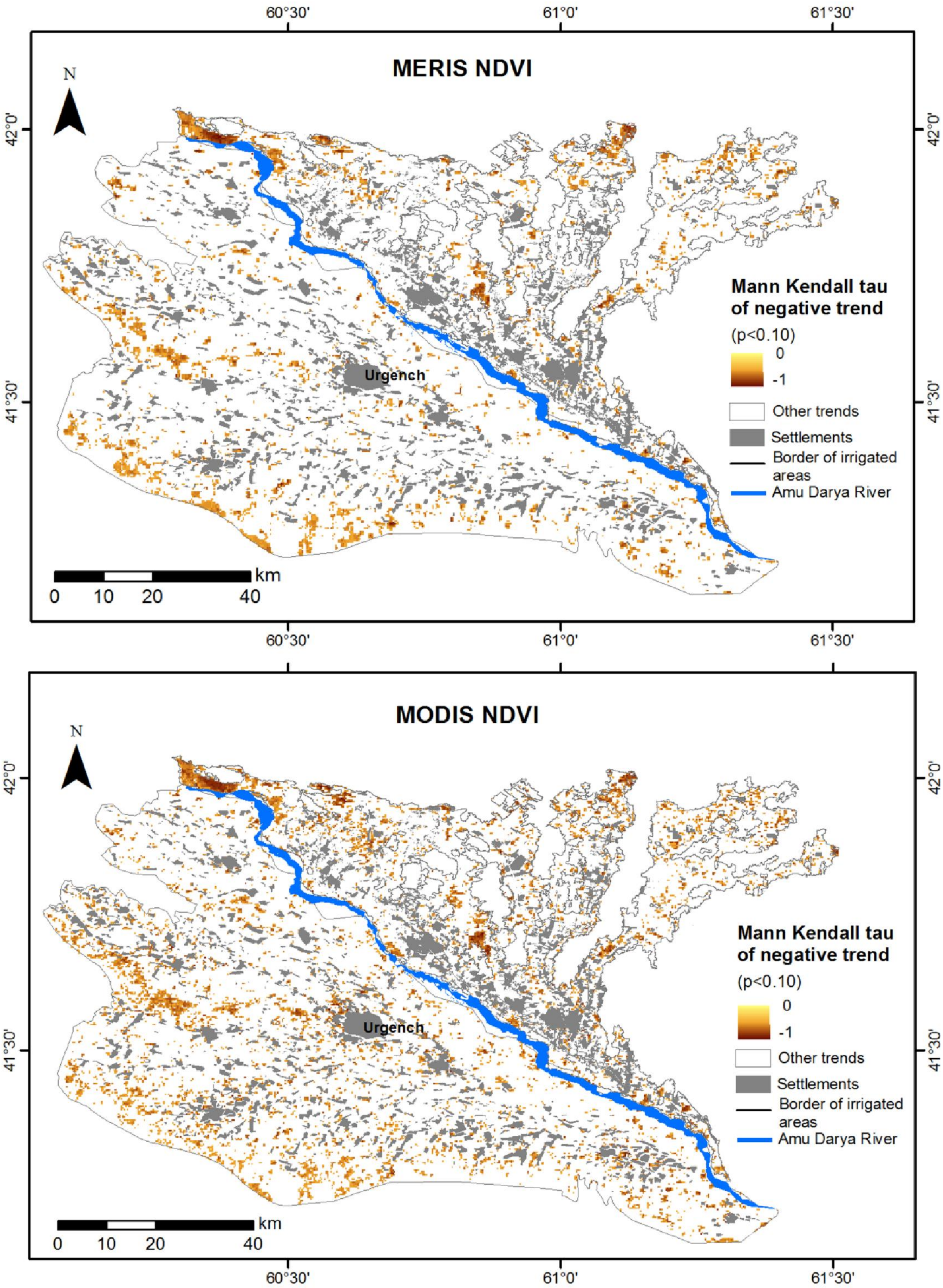
Appendix 8.2: Guided field visits by the irrigation and cadastral engineers to the abandoned field parcels in the southern Karakalpakstan in 2010



On the photo from left to right: Baxtiyor Bobaev (irrigation engineer), Olena Dubovyk (ZEF), Dr. Sattar Hudaybergenov (cadastral engineer), Ilhom Madaminov (driver)

On the photo from left to right: Dr. Sattar Hudaybergenov (cadastral engineer) and Oybek Qalandarov (research assistant)

Appendix 8.3: Negative vegetation trend in Khorezm region and southern Karakalpakstan based on Mann-Kendall trend analysis of 250-m MODIS and 300-m MERIS NDVI time series for 2003-2011 (Dubovyk et al. 2012c)



Appendix 8.4: Linear regression trend analysis of irrigation water use between 1998 and 2008 for Khorezm region of Uzbekistan

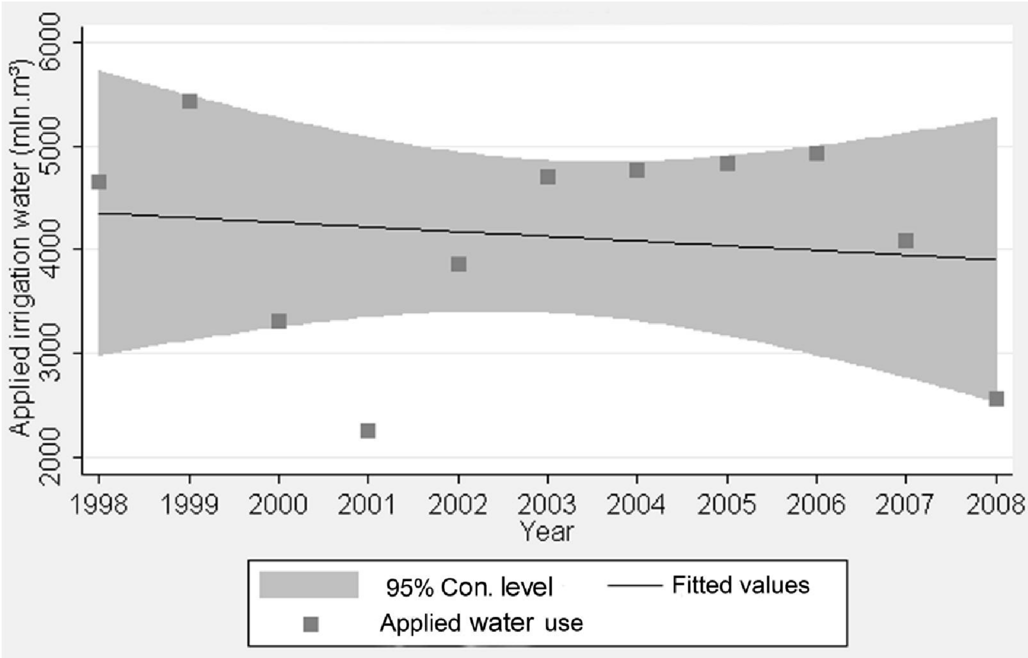
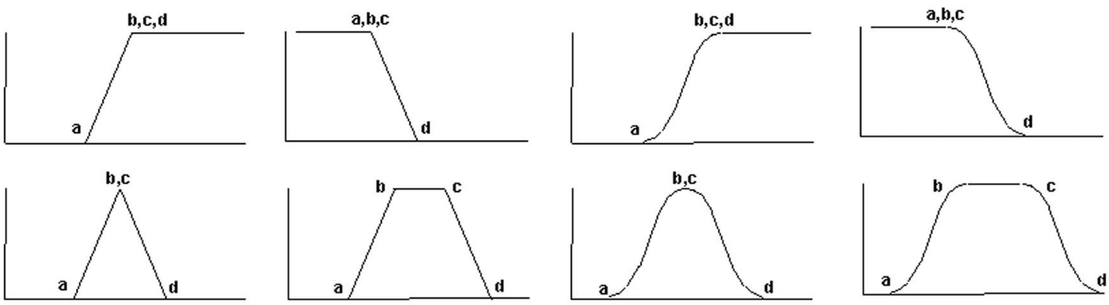


Table 8.1: Results of linear regression trend analysis of irrigation water use between 1998 and 2008 for Khorezm region of Uzbekistan

	Coefficient	**Standard error**	**t**	**P>|t|**	**[95% Conf. Interval]**	
Applied irrigation water use	-6,33	26,43	-0,24	0,81	-58,55	45,90
Constant	13241,82	52945,99	0,25	0,80	-91363,25	117846,90

Appendix 8.5: Types of fuzzy set membership functions for criterion map standardization used in this study (Eastman 2012).



The Linear Membership Function

The Sigmoidal Membership Function

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