Effects of land use and vegetation changes on soil erosion of alpine grazing lands

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Fergana Range, Southern Kyrgyzstan

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List of acronyms

ARIMA - Autoregressive Integrated Moving Average
ARMA - Autoregressive Moving Average
ASTER - Advanced Spaceborne Thermal Emission and Reflection Radiometer
CAIAG - Central-Asian Institute for Applied Geosciences
DEM – Digital Elevation Model
DWD – Deutscher Wetterdienst
EOF - Empirical Orthogonal Function
FAO – Food and Agriculture Organization
GDEM – Global Digital Elevation Map
GDP - Gross Domestic Product
GIS – Geographic Information System
GPS – Global Positioning System
ICDC - Integrated Climate Data Center
KRSU – Kyrgyz Russian Slavic University
LOESS - LOcally wEighted regreSsion Smoother
MODIS - Moderate Resolution Imaging Spectroradiometer
MUSLE – Modified Soil Loss Equation
NASA - National Aeronautics and Space Administration
NDVI – Normalized Difference Vegetation Index
PCA - Principal Component Analysis
RUSLE – Revised Universal Soil Loss Equation
SAGA – System for Automated Geoscientific Analysis
SER – Soil Enhancement Ratio
SLR – Soil Loss Ratio
SRTM - Shuttle Radar Topography Mission
STL - Seasonal and Trend decomposition using LOESS
USGS - United States Geological Survey
USLE – Universal Soil Loss Equation

Zusammenfassung

Das Gedeihen der menschlichen Zivilisation hängt stark von den Ökosystemen und den von ihnen erbrachten Dienstleistungen ab. Dazu zählen Bodenbildung und Stoffkreisläufe, Primärproduktion auf Weideland, Niederschlag und Temperaturregime und viele weitere. Viele der bestimmenden Faktoren stehen in ständiger Wechselwirkung und die zunehmende intensive anthropogene Nutzung vieler Ökosysteme verschiebt die Gleichgewichte in empfindlichem Masse. Daher ist es wichtig zu verstehen, wie und in welchem Umfang die Ökosysteme nachhaltig genutzt werden können und was dies konkret für das Nutzungsmanagement natürlicher Ressourcen bedeutet. Daher bestand das Hauptziel der vorliegenden Promotionsarbeit darin, die Wechselwirkungen zwischen Vegetation, Boden und Klima zu modellieren unter Berücksichtigung der Auswirkungen menschlicher Nutzung der natürlichen Ressourcen. Das Hauptziel der Arbeit ist die Untersuchung der Auswirkungen bestehender Weidepraktiken auf das Weideland, die Bodenbeschaffenheit und Vegetationsressourcen, sowie die Abhängigkeit der Weidevegetation von klimatischen Faktoren und damit verbundener Bodenerosion.

Das Forschungsgebiet dieser Dissertation liegt in der Fergana Range im Süden von Kirgisistan. Die Forschung konzentrierte sich auf Berggebiete, die von der lokalen Bevölkerung als Sommerweiden genutzt werden. Das Arbeitsgebiet erstreckt sich über subhumid-semiaride Berghänge mit beweideter subalpin-alpiner Mattenvegetation. Der maximale Niederschlag fällt im Frühling. Die Topographie des Untersuchungsgebietes weist unterschiedliche Hangneigungen und Höhen zwischen 2000 und 3000 M.ü.M. auf.

Die Komplexität des Forschungsgegenstandes bedingt eine umfassende Betrachtungsweise und die Berücksichtigung verschiedenster Aspekte. Während der Feldkampagnen wurden Bodenproben und Vegetationsinformationen zusammen mit Daten zum Beweidungseinfluss gesammelt. Die Bodenproben wurden im Labor des Instituts für physische Geographie der Universität Hamburg analysiert. Die Fernerkundungsdaten stammen von frei verfügbaren Quellen (Landsat, SRTM, ASTER und MODIS). Die Arbeit umfasste die eingehende Analyse aller erhobenen Daten, die Modellierung der Wechselwirkungen zwischen den bestimmenden Umweltfaktoren und die Visualisierung in Form von digitalen Karten, um diese Interaktionen zu veranschaulichen.

Die Risiken der Bodenerosion wurden mit dem RUSLE-Ansatz (Revised Universal Soil Loss Equation) durch die Berechnung der Bodenerodierbarkeit und des Vegetationsschutzfaktors (K-Faktor und C-Faktor) und ihrer Beziehung zu Klimafaktoren bewertet. Für die K-Faktor-Schätzung wurden Bodenproben gesammelt, welche die verschiedenen Geländeeigenschaften repräsentieren. Diese wurden im Labor zur Bestimmung der Korngrößenverteilung und dem Gehalt an organischer Substanz analysiert, welche für die Berechnung des K-Faktors verwendet wurden. Dann wurde eine K-Faktor-Karte mit universellem Kriging erstellt, wobei räumlich explizite Geländefaktoren als Hilfsdaten verwendet wurden. Die Abhängigkeit bestimmender Bodenmerkmale von der Topographie ermöglichte schließlich die Entwicklung eines Schemas für die Modellierung der Bodenerodierbarkeit im Fergana-Gebirge.

Der Vegetationsbedeckungsschutz oder das Bodenverlustverhältnis (C-Faktor) wurde aus Vegetationszustandsdaten berechnet, die im Feld gesammelt wurden. Dann wurde die Karte des C-Faktors mit universellem Kriging für verschiedene Monate entwickelt, die auf monatlichen NDVI (Normalized Difference Vegetation Index) Bildern und jährlichen Phänologiedaten basierte. Klimadaten wie Temperatur und Niederschlag wurden von einer lokalen Wetterstation gesammelt. Der Weidedruck wurde mit Interviews von Hirten im Feld bewertet. Der C-Faktor indiziert zeitliche Korrelationen mit klimatischen Faktoren mit zeitlicher Verzögerung und räumliche Korrelationen mit Beweidungsdruck und Geländeeigenschaften.

Die Modellierung von Vegetations- und Klimazusammenhängen erfolgte in größerem Maßstab - für das gesamte Land. Der NDVI wurde räumlich und zeitlich mit klimatischen Faktoren wie Temperatur und Niederschlag korreliert. Das Korrelationsmuster und die Stärke der NDVI-Vorhersagbarkeit mit dem Klima variierten zwischen verschiedenen Teilen des Landes. Basierend auf dieser Variation wurden fünf Cluster entwickelt, die das Gebiet ähnlicher Vegetations-Klima-Wechselbeziehungen charakterisieren.

Das Resultat zeigt, dass die Artenzusammensetzung der Vegetationsgemeinschaften stark von Beweidungs- und Geländemerkmalen beeinflusst wird. Die Analyse der Bodenstruktur deutet darauf hin, dass eine zu hohe Anzahl von Nutztieren die Bodenaggregatsstruktur durch Trampeln zerstört und die Verwitterung feiner Partikel erleichtert. Die mittlere Erosionsanfälligkeit des Bodens im Untersuchungsgebiet beträgt 0,0374 t ha h ha^{-1} MJ^{-1} mm^{-1} (Standardabweichung 0,0048), was im europäischen

Vergleich mittleren bis feinen Böden entspricht. Weiter zeigt sich, dass die Erodierbarkeit an steilen Hängen und Graten höher und an Tallagen niedriger ausfällt, was auf den Transport feiner Partikel nach unten hinweist. Es wurde festgestellt, dass die Vegetation, die Schutz gegen Bodenerosion bietet, stark von klimatischen Faktoren beeinflusst wird. Die Reaktion auf Niederschlagsänderungen erfolgt mit bis zu drei Monaten Verzögerung, während die Reaktion auf Temperaturänderungen eher unmittelbar erfolgt. Hangneigung und Sonneneinstrahlung waren ebenfalls bestimmende Faktoren für die Vegetationsentwicklung. Im Frühling scheint die Temperatur der bestimmende Faktor für die Vegetation zu sein, wenn höhere Temperaturen das rasche Einsetzen der Begrünung erleichtern, während im Sommer hohe Temperaturen die Vegetationsentwicklung eher unterdrücken. Diese Ergebnisse deuten darauf hin, dass die Beweidung im Frühjahr begrenzt werden sollte, damit die Vegetation an Biomasse gewinnt und sich auch reproduzieren kann.

Das gesamte Gebiet von Kirgisistan schien fünf verschiedene Muster (Cluster) von Vegetation und Klimawechselwirkungen aufzuweisen, wobei die Vegetation unterschiedliche Verzögerungen und Anzeichen von Reaktion auf Temperatur- und Niederschlagsveränderungen aufwies. Die verschiedenen Cluster hatten eine 0-4-monatige Verzögerung der Vegetationsreaktion auf Temperaturänderungen und 1-5 Monate verzögerte Reaktion auf Niederschlagswechsel. In Höhenlagen von 3000-4000 M.ü.M. waren sowohl die Temperatur als auch der Niederschlag förderliche Faktoren für die Vegetationsentwicklung, während in niedrigeren Lagen von 200-1300 M.ü.M. die Temperatur ein begrenzender Faktor im Sommer war. Spärliche und dichte Vegetation schien weniger anfällig für klimatische Schwankungen aufgrund von Abwesenheit der Vegetation (R^2 = 0,1-0,3) oder großer Robustheit aufgrund der akkumulierten Biomasse. Die Gebiete mit durchschnittlicher Vegetationsdichte scheinen stark durch klimatische Faktoren (R^2 = 0,7-0,9) kontrolliert zu werden.

Die durchgeführten Forschungsarbeiten quantifizieren die Wechselwirkungen zwischen Vegetation, Boden und Klimafaktoren, wodurch es möglich wird, die Systemreaktion unter veränderten klimatischen Einwirkungen und intensivierter menschlicher Nutzung zu modellieren. Damit wird ein besseres Verständnis der zukünftigen Prozesse ermöglicht, was als Basis für die notwendigen Entscheidungsprozesse für eine nachhaltige Landnutzung dienen kann.

Abstract

Human civilization depends greatly on ecosystems and the services they provide. These include soil, rangelands, precipitation and temperature regimes and many others. All these factors are in constant interaction and human impact can affect the balance in ecosystems. Thus, it is important to understand how and to what extent the natural resources can be sustainably used without severe consequences. The aim of this research is to assess the interactions between soil, vegetation and climatic factors and quantify them for better prediction in different utilization and climate change scenarios. We attempt to investigate the impact of existing grazing practices on rangelands, its soil and vegetation resources, as well as vegetation dependence of climatic factors and its capacity to prevent soil erosion.

The study area of this Ph.D. thesis included the Fergana range in the south of Kyrgyzstan. The research focused on mountain rangelands, used as summer pastures by local population. The study area represents subhumid-semiarid mountain slopes with grazed subalpine-alpine mat vegetation. The spring season has maximum precipitation. The terrain is rugged with different slope gradients and altitudes between 2000 and 3000 m a.s.l.

It was necessary to cover human, soil, vegetation and climatic factors, so the research included several aspects. Soil samples and vegetation information were collected during field trips, together with human impact data. The soil samples were analyzed in the laboratory of the Department of Physical Geography of University of Hamburg. The remotely sensed data, representing vegetation, soil and climatic factors were collected from open sources, including Landsat, SRTM, ASTER, DWD and MODIS. To understand the interactions, we applied statistical analysis of field data and remotely sensed data, modelling and development of digital maps, illustrating them.

The risks of soil erosion were assessed using RUSLE (Revised Universal Soil Loss Equation) approach by calculating and assessing soil erodibility and vegetation protection factor (K-factor and C-factor) and their relations with climatic factors. For K-factor estimation soil samples were collected, representing different terrain features, they were analyzed in the laboratory for the grain size distribution and organic content, which were used for calculation of K-factor. Then K-factor map was created with universal kriging using spatially explicit terrain factors as auxiliary data. Soil features indicated their relations with terrain, which allowed to develop a scheme for prediction of soil erodibility in Fergana mountains.

Vegetation cover protection or soil loss ratio (C-factor) was calculated from vegetation physical condition data, collected in the field. Then the map of C-factor was developed with universal kriging using NDVI (Normalized Difference Vegetation Index) for different months, based on annual phenology and monthly NDVI images. Climatic data, such as temperature and precipitation were collected from local weather station. Grazing pressure was assessed with interviews of shepherds in the field. C-factor indicated temporal correlation with climatic factors with time lag and spatial correlation with grazing pressure and terrain features.

Modelling of vegetation and climate interrelations were done on a larger scale – for the entire country. NDVI was correlated spatially and temporarily with climatic factors as temperature and precipitation. The correlation pattern and strength of NDVI predictability with climate varied between different parts of the country. Based on this variation five clusters were developed, indicating the areas of different vegetation-climate interrelations.

The species composition of plant communities was found to be greatly affected by grazing and terrain features. Large numbers of livestock appeared to promote soil coarseness by destroying soil structure by trampling and facilitating weathering of fine particles. Mean soil erodibility in the study site was 0.0374 t ha h ha^{-1} MJ^{-1} mm^{-1} (standard deviation 0.0048), which complied with European medium to fine soils. Erodibility was found to be higher on steep slopes and ridges, and lower at mountain bottoms and valleys, which indicates transportation of fine particles down slope. Vegetation, which provides protection against soil erosion, was found to be greatly controlled by climatic factors, indicating 0-3 months lag in reaction to precipitation change and 0 lag in reaction to temperature change. Slope and exposure to solar radiation were also found to be the controlling factors for vegetation. The temperature appeared to be a promoting factor for vegetation in spring, when higher temperatures facilitate rapid onset of greenness, whereas in summer high temperatures oppress vegetation. These findings suggest that grazing in early spring should be limited to let vegetation gain biomass and produce seeds.

The entire area of Kyrgyzstan appeared to have five distinct patterns (clusters) of vegetation and climate interactions, where vegetation had different lags and signs of reaction to temperature and precipitation change. The different clusters had 0-4-months lag of vegetation reaction to temperature change and 1-5-months lag reaction to precipitation change. At high elevations of 3000-4000 m a.s.l. both temperature and precipitation were promoting factors for vegetation development, whereas at lower elevations of 200-1300 m a.s.l. it was a limiting factor in summer. Sparse and dense vegetation appeared to be less susceptible to climatic variations due to vegetation absence (R^2 = 0.1-0.3) or great robustness due to accumulated biomass respectively. The areas with average vegetation density appeared to be greatly controlled by climatic factors (R^2 = 0.7-0.9).

The undertaken research quantifies interactions between vegetation, soil and climatic factors, which allows modeling the system reaction in circumstances of changing climate and human impact. These findings allow for greater understanding of possible outcomes in circumstances of changing climate and human impact, which will facilitate decision-making process.

1. Introduction

Since ancient ages, humankind has been developing maps of the surrounding world, representing features of physical geography, but also natural resources. The development of botanical and soil science and their taxonomy has boosted the thematic mapping of these resources in early 20th century. Technological development of aviation and photography in the middle 20th century led to airborne photography and production of more accurate and sophisticated maps of natural resources (Jelaska 2009). The further development occurred in late 20th century with the advancement of digital technology. Launch of Global Positioning System (GPS), availability of regular spaceborne remotely sensed images of vast areas, accurate Digital Elevation Models (DEM), algorithms of spatial statistical analysis and modelling and great computational power led to a revolution in mapping. Modern mapping technologies represent an infrastructure of spaceborne sensors and positioning systems, ground positioning and smart devices, computing machines and databases together with software and specialists operating and maintaining the system. However, mapping *per se* does not respond to modern demands, being able to predict natural processes in space and time has more value. This is possible

through understanding the underlying patterns of systematic interactions and modelling of natural systems.

Even though the natural resources of the modern world are still not entirely mapped, the level of mapping, growing potential and demand makes the task of understanding interrelations between different natural components and quantifying them for prediction of possible scenarios, i.e. modelling, more and more interesting and important. However, human impact on ecosystem is another rather unpredictable component, which makes the modelling so demanded, and which should be accounted for.

For decades, Kyrgyzstan and Central Asia have been remaining a white spot on the map of international science. First, because most of earlier scientific studies were done in Soviet times, published in Russian, and, as the Soviet Union was a closed country, the publications barely reached the English-speaking world. Second, because modern independent Kyrgyzstan does not have enough resources to conduct large-scale systematic baseline environmental surveys. Sporadic international scholars or institutions coming to the region pursue short-term research interests without much connectivity to the scientific context, and barely contribute to the full knowledge picture. Rarely do they grow into long-term research programs. The baseline information available is based on researches undertaken in 1930th – 1970th, which still can be considered either current or totally outdated, depending on the topic. For example, geological and soil information can be considered accurate, as they do not change so quickly, they just need to be synchronized with international taxonomy. Whereas, vegetation information might need an update.

Kyrgyzstan is a mountain country encompassing Central, Inner and West Tian-Shan as well as the Alai range and part of Pamir. The great terrain variability with different altitudes, slopes and exposures as well as the variable geology causes great diversity in local microclimates, soils and vegetation. The geobotanical diversity is remarkable for such a small territory, which creates unique conditions for scientific research and modelling. Mountains are one of the most fascinating and complex natural ecosystems. The complex terrain and consequently intricate microclimatic patterns generate variable complexes of vegetation and wildlife. For ages, mountains have been attracting attention of travelers and scientists. Humans were settling in mountains, as they provided protection, natural resources and beautiful views. The fruit and nut forests and highland grasslands in the south of Kyrgyzstan are of utmost importance to local population. However, there is no proper system of natural resource use that will ensure their sustainability and availability to future generations. The fruit and nut forests are a biodiversity hotspot, which is rich in species and is a very important site for conservation of wild ancestors of cultivated fruit varieties.

Western Tian-Shan and Fergana valley are one of the most populated areas in the region (NatStatCom 2018). Soil and vegetation are the main resource providing food, one of the primary needs for humankind. Difficult economic situation and lack of livelihoods makes local population rely on natural resources. The predominant model of economic activity is animal husbandry based on seasonal transhumance between summer pastures and settlements, as well as agriculture and collection of wild fruits and nuts. Agriculture and animal husbandry contribute the largest portion to national GDP (NatStatCom 2018). However, unregulated grazing can change the mountain ecosystems in many ways: change of plant communities, soil physical properties, desertification and many others (Schlesinger et al. 1990; Borchardt et al. 2010, 2013) which will result in loss of income and livelihoods for local people.

Fergana range in Kyrgyzstan is the area with the highest precipitation level (Gidromet SSSR et al. 1967; Adyshev et al. 1987; Kuzmichenok 2008). This, together with high grazing pressure (Dörre and Borchardt 2012; Borchardt et al. 2013; Hoppe et al. 2016a) and thin soils (Mikhailov 1949; Mamytov and Ashirakhmanov 1988) create an increasing risk of natural disasters with losses to economy and population (Teshebaeva and Moldobekov 2010; CAIAG 2018; PreventionWeb 2018). The poor economic situation and lack of proper grazing regulation (Crewett 2012; Steimann 2012) lead to the situation where people have to balance between livelihoods and natural disasters. This makes understanding of interactions of soil vegetation and climate an important task in the region.

It is widely accepted that vegetation, soil and climate are in constant interaction and thus, are components of a more complex system. Soil provides substrate for plants' growth, plants protect soil from erosion and contribute to its structure, mineral and organic content. Vegetation phenology is greatly controlled by annual climatic patterns. Air and solar radiation provide energy and material for photosynthesis, and thus, participate in building organics. Precipitation provide water for chemical processes, and snow provides

frost protection in winter (Wieder and Shoop 2018). Despite the importance and demand for soil, vegetation and climate studies, the poor economic situation in the country does not allow for regular assessments of their condition. However, modern developments in GIS, remote sensing and availability of spatial data together with the growth of computational power make this task less expensive. Field work and ground data collection, together with the laboratory work become the most cost and time demanding parts of the research, whereas the auxiliary information and analytical tools do not cost anything nowadays owing to generosity of their kind providers. This allows poor countries to undertake thorough assessment and regular monitoring of natural resources and hazards.

We attempt to combine field work, laboratory analysis and statistical modelling to assess the natural resources and processes. This work is a part of joint German-Kyrgyz research project "The Impact of the Transformation Process on Human-Environment Interactions in Southern Kyrgyzstan", funded by the Volkswagen Foundation, Hannover, Germany. The main aim of this Ph.D. thesis is to demonstrate and quantify the interactions of climate, vegetation, soil and natural resource usage, discuss the modelling approaches and outcomes and identify potential threats to future land use options in different climate change scenarios in Southern Kyrgyzstan.

2. Study area

The study area of this Ph.D. thesis encompasses Fergana range pastures near Arslanbob village in Jalal-Abad region of Kyrgyzstan (Figure 1). The field data collection for assessment of soil, vegetation and grazing pressure was conducted in four pastures: Otuz-Art, Uch-Choku, Jaz-Jarym and Kara-Bulak. The study site comprises an area of 50 km^2 located between 2000 and 3000 m a.s.l. Soil and vegetation research were done in this study site, whereas modelling of vegetation and climate interactions were conducted for the whole country. More details about the study area are provided in the following subchapters.

2.1 Climate

Kyrgyzstan is in the center of Eurasian continent, far away from oceans, so seasonality is very prominent in this region. Considerable roughness of terrain of Kyrgyzstan and different exposures of slopes to sun radiation and winds create a unique diversity of climatic features and determine an apparent vertical climatic gradient. Traditionally four climatic belts are distinguished (Adyshev et al. 1987; Kyrgyzgidromet 1989, 2015; Kuzmichenok 2008).

The Foothill belt (from 500-600 till 900-1200 m a.s.l.) is characterized by hot summers (till 28°C), moderately cool and snowless winters with lack of precipitation. This belt, especially in Fergana valley, has features of subtropical climate. The climate is warm and even hot at the top part of the foothill belt, winters are also warm. The summer temperatures in July reach 20-25°C and in January -4-7°C below zero (Adyshev et al. 1987; Kyrgyzgidromet 1989, 2015).

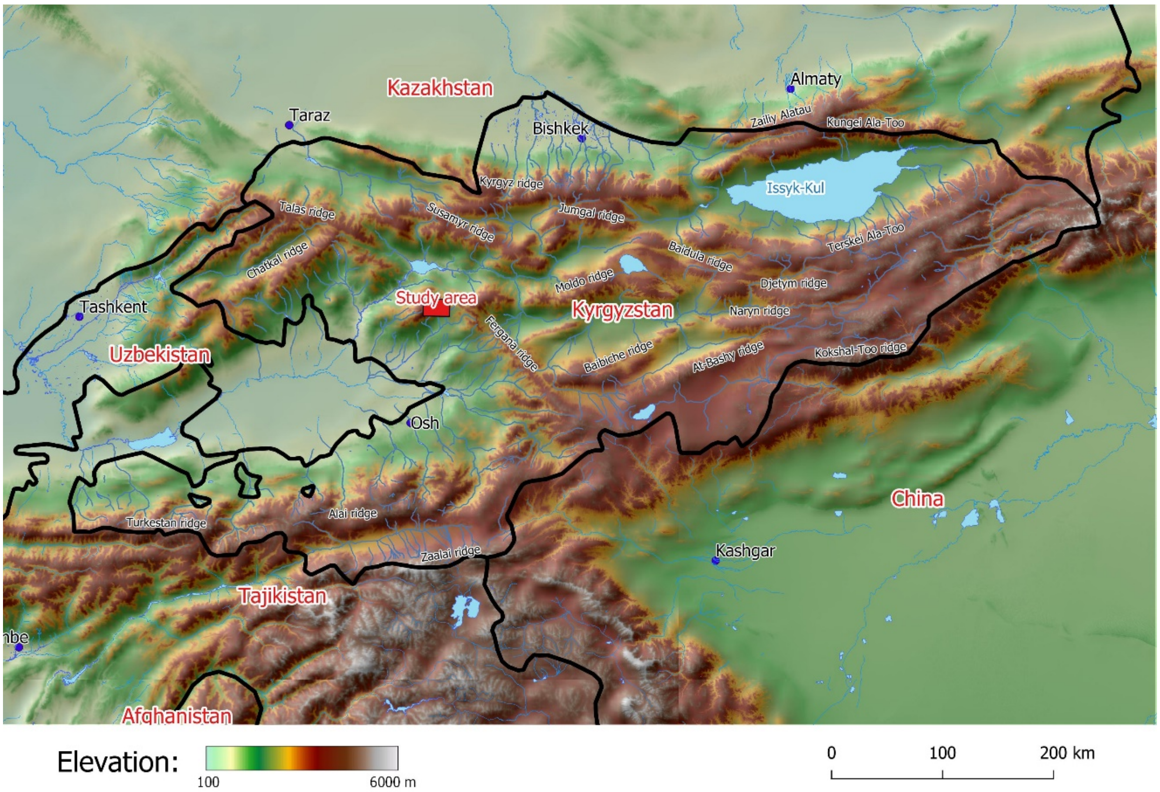

Figure 1. Study area.

The highest temperatures in summer reach 44°C, with elevation they decrease to 27-30°C and the absolute minimums in winter are recorded within the limits of -22-30°C and only in some areas they go down to below -40°C (Toktogul and Chui region) (Adyshev et al. 1987; Kyrgyzgidromet 1989, 2015).

The middle (montane/subalpine) belt (from 900-1200 till 2000-2200 m a.s.l.) has typical moderate climate with warm summers and moderately cold and steadily snowy winters. The temperatures are considerably lower here, summers are warm, 18-19°C in

July and winters are cold – 7-8°C below zero in January, and -3-5°C in December and February (Adyshev et al. 1987; Kyrgyzgidromet 1989, 2015). Frostless period lasts for more than 7 months on 1000-1500 m a.s.l. and at the top part of the belt the period lasts for 6 months.

The alpine belt (from 2000-2200 till 3000-3500 m a.s.l.) has cool summers and cold very snowy winters. The temperature in July reaches only 11-16°C. Winters are long (November-March) with January temperatures of -8-10°C below zero, and -3-7°C in other cold months. Frostless period comprises 3-4 months in the highest part of the belt, and it can be absent above this elevation (Adyshev et al. 1987; Kyrgyzgidromet 1989, 2015).

The nival belt (above 3500 m) is characterized by harsh and very cold climate. This is a belt of glaciers, rocks, and moisture accumulation. July temperatures do not exceed 4-7°C even in the lowest parts of this belt, and January temperatures drop below -19-22°C (Adyshev et al. 1987; Kyrgyzgidromet 1989, 2015).

Despite general altitudinal gradient, it is difficult to speak about simple linear relation of climatic factors and elevation, because they can differ considerably between different climatic zones even on the same elevation (Adyshev et al. 1987; Iliasov et al. 2003). The climatic zoning according to Iliasov et al. (2003) and Kyrgyzgidromet (2015) is provided in Figure 2.

Climatically, Kyrgyzstan is characterized by a great diversity. The warmest area is the foothill belt of Osh region in the south, where mean annual temperature is 11-13°C, whereas in alpine belt the mean temperature goes down to -8°C. Terrain impact is the most prominent in cold seasons, which is related to congestion of cold air in depressions. Complex orographic conditions, which determine great variety of climatic features, make climate mapping a complicated task.

Winds have very different directions and little speeds because of diversity of forms and complexity of terrain. They are determined by the structure of intermontane depressions and direction of gorges, ridges and river valleys. Gradient winds, i.e. the winds determined by pressure field exist only on high elevations, near the land they are mostly determined by directions of the main surface features. Winds with very diverse directions are registered in areas with open terrain, but still they have a prevalent direction corresponding to the main axis of a valley.

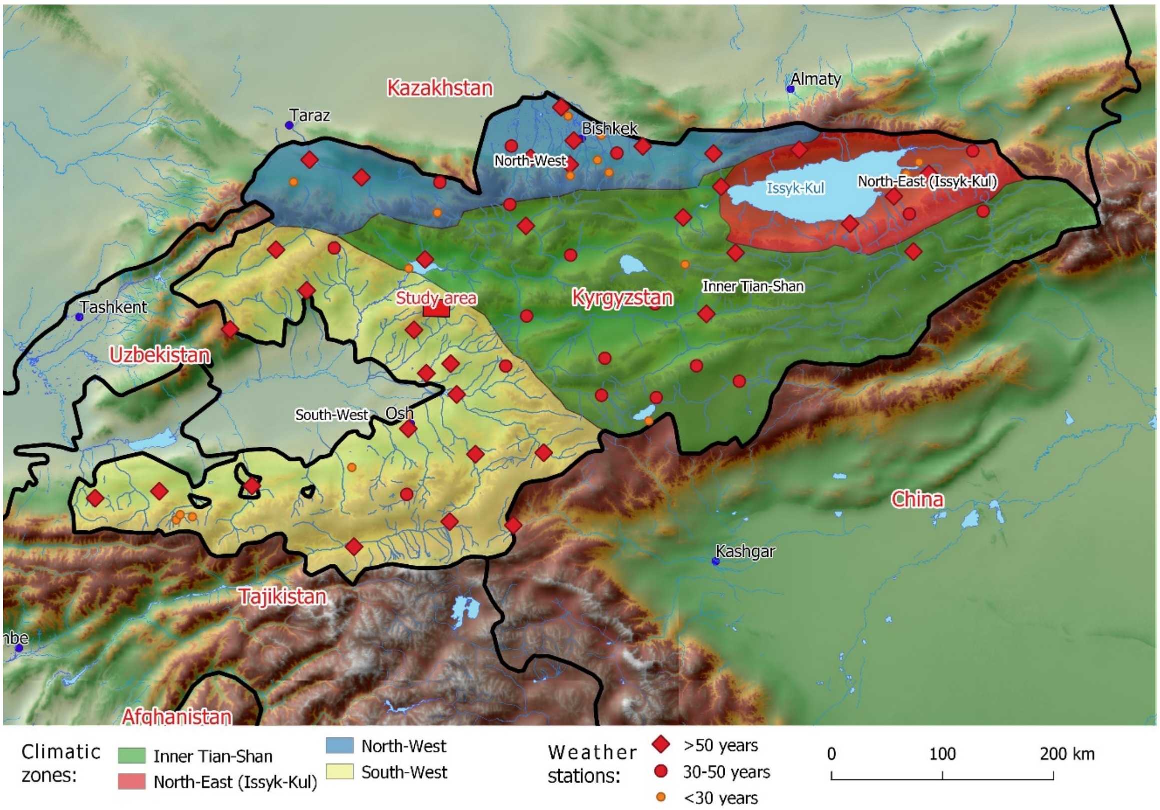

Figure 2. Climatic zones (for details see Table 1).

The warmest months in Kyrgyzstan are July and August. Temperature variations between different areas on same elevations are not very high, despite them being separated by considerable distance and ridges. In general, the southwestern part of the country is warmer in summer than the northern part. The highest temperatures reach 43-44°C. Mean daily temperature in the middle belt in summer does not exceed 20°C, in highlands the temperature is close to 0°C and below 0 at nights. Thus, mean July temperature varies for more than 20°C from -4°C (Tian-Shan weather station, 3600 m a.s.l.) till 27°C (Lenin Jol weather station, 720 m a.s.l.).

In winter, the variation of mean monthly temperature between different areas on the same elevation is considerable, it is conditioned by local air flows, which are determined by terrain and exceeds 15°C (Tamyngen weather station, 3030 m a.s.l. -8.5°C; Arpa weather station, 3000 m a.s.l. -23.3°C in January). The duration of positive air temperature varies from 185 days in lower part of highland belt till 250-300 days in foothill zone (Adyshev et al. 1987; Kyrgyzgidromet 1989, 2015; Iliasov et al. 2003).

Table 1. Characteristics of climatic zones (Iliasov et al. 2003).

Elevation m a.s.l.	**Days in a year with temperatures above**		
	0°	5°	10°
North-West Kyrgyzstan			
800-1000	258	216	176
1000-1600	250	206	162
1600-2800	213	160	101
North-East Kyrgyzstan (Issyk-Kul)			
Western part			
1600-1800	263	207	156
Eastern part			
1600-1800	237	192	144
1800-2000	228	182	129
2000-2600	207	158	79
Inner Tian-Shan			
South-Eastern part			
2800-3000	185	129	34
North-Western part			
1400-1600	223	191	145
1600-2200	213	179	127
2200-2400	206	167	101
2400-2800	192	145	64
South-West Kyrgyzstan			
600-800	302	250	210
800-1000	296	245	204
1000-2400	247	199	151
2400-2800	211	155	94

Air humidity in Kyrgyzstan, as everywhere, has annual and daily cycles, which is the opposite to that of temperature. The lowest air humidity corresponds to summer period (July, August), and the greatest – to winter (December, January). The relative air humidity changes greatly throughout the year (40-80%), as in other regions with temperate climate. It is the least in summer (40-50%) and the greatest in winter (60-80%). Thus, in any month there is a considerable lack of moisture in the air, which reaches 50-60% and more in summer. Vegetation is greatly oppressed in these periods, even in irrigated areas (Adyshev et al. 1987).

Precipitation is distributed very uneven. Some areas get large amounts of moisture (about 1500 mm), the highest in the country, which is comparable to western Caucasus. And in some areas precipitation level is at 150-200 mm annually, which makes the area look like a desert. Large amount of precipitation comes to the middle belt of south-western slopes of Fergana ridge, where it exceeds 1000 mm (Ak-Terek-Gava weather station – 1090 mm, Demidovka – 1084 mm, Chaar-Tash – 1057 mm). Considerable precipitation sums (Teo-Ashu – 1003 mm) are observed in highland and nival belts of the northern slopes of Kyrgyz ridge. The precipitation level is also high on slopes of Chatkal ridge (more than 1000 mm), in Kemin valley and in eastern part of Issyk-Kul valley (900 mm). Considerably less precipitation is observed in Talas and in Chui valleys (from 250 till 500 mm). Air masses, overtaking the mountain ridges to Inner Tian-Shan lose moisture. Therefore, the most of Inner and Central Tian-Shan receive on average 200 – 300 mm of precipitation annually. The least supplied with precipitation is the eastern part of Issyk-Kul valley (Balykchy – 144 mm), some parts of Fergana valley (Batken – 156 mm) and some highland areas of Osh area (Altyn-Mazar – 184 mm). The annual level of precipitation for the entire country is generally sufficient; however, it is not evenly distributed, which leads to artificial irrigation of considerable part of arable land (Adyshev et al. 1987; Kyrgyzgidromet 1989, 2015).

The level of precipitation varies greatly interannually depending on frequency and intensity of different atmospheric processes. With the mean annual precipitation of 400 mm in some years this level can vary from 100 mm till 650 mm. For example, in the eastern part of Issyk-Kul valley the fluctuations of annual precipitation level can reach 250% (from 370 till 930 mm with the mean of 729 mm on San-Tash weather station); in south-western Kyrgyzstan – 530% (from 110 till 580 mm with the mean of 342 mm, Osh weather station). Considerable precipitation variations are observed in the Inner Tian-Shan, which reaches 400% (from 124 till 476 mm with the mean of 281 mm at Naryn weather station); in northern Kyrgyzstan – 260% (from 217 till 579 mm with the mean of 246 mm at Chuiskaya weather station) (Adyshev et al. 1987; Kyrgyzgidromet 1989, 2015).

Vertical precipitation gradient is conditioned by terrain and is particularly prominent in warm season. Precipitation increases with altitude considerably more below 2000 m than above. Vertical gradient for every 100 m of elevation differs greatly among regions; they comprise the values from 83 mm till negative values. Thus, despite of indisputable fact that precipitation level increases with elevation, it is difficult to speak about simple relation, because precipitation level is different at similar elevation among different nature-climatic regions. Thus, in northwestern, northern and northeastern Kyrgyzstan precipitation increases till 3000-3500 m a.s.l. and stays constant (northeastern Kyrgyzstan), or decreases (some areas of northern Kyrgyzstan) above that elevation. In southwestern Kyrgyzstan precipitation increase is recorded till 3500-4000 m a.s.l., and in Inner Tian-Shan this tendency remains even above 4500 m (Adyshev et al. 1987; Kyrgyzgidromet 1989, 2015).

The average duration of rainstorms and snowfalls increases from summer to winter from 2-4 till 10-12 hours. The intensity of precipitation decreases as their duration increases. In the case of intensive rainstorms about 10-15% of annual precipitation can fall in one day. The greatest daily precipitation level was registered on Fergana ridge slopes – 90 mm, in other regions 70-75 mm and less. The intensive precipitation events can trigger mudflows, which can be very strong and destructive (Adyshev et al. 1987).

Snow cover in mountains is determined by the distribution of precipitation, duration of cold season, solar radiation and wind redistribution. The variability of orography determines uneven distribution of snow on different elevations, and different melting terms. Snow cover is thinner in Talas valley than on the same elevation in Chui valley, where it is thinner than in the eastern part of Issyk-Kul valley. The distribution of snow cover is uneven, but in general the thickness of snow increases from west to east, which is about 15-20 cm on average on foothills of north Kyrgyzstan and increases to 20 cm further to the east. Very thick snow cover forms on mid- and highlands of Fergana ridge, where it reaches 150 cm (Adyshev et al. 1987; Kyrgyzgidromet 1989, 2015). This, together with the great terrain and climate diversity provide conditions for great vegetation and habitat diversity.

2.2 Vegetation

Most of Kyrgyzstan is covered with mountains creating complex hydrological, meteorological, rock and soil conditions. This diversity has an impact on vegetation cover, which is also diverse. Vegetation in Kyrgyzstan is prominent for its original coenotic structure, floristic richness, phenology and great number of endemics. The country has deserts, thorn cushion plant formations, steppes, meadows, forests, bushes, marshes, cryophile cushion plant formations and highland tundras. Considerable areas are occupied with sparse vegetation, which can be attributed to plant formations of rocks and talus (Vykhodtsev 1956a, 1966).

The distribution of vegetation in mountains is greatly determined by the vertical climate gradient as well as slope exposure, though plant communities do not match the climatic belts and other plant communities on similar elevations exactly due to other local conditions. Different vegetation is attributed to respective elevational zones, each of which has certain features depending on local geographical conditions, thus plant communities may vary between different parts of the country, however the vertical gradient persists (Vykhodtsev 1956a, 1966). Based on many years of research Vykhodtsev (1956a) outlined the following elevation belts of vegetation considering local variability:

1. The belt of hot foothills (adyrs) of Fergana valley with semidesert and south-steppe climatic conditions, occupying the elevations of 700-1800 m a.s.l.
2. The belt of warm foothills of Chui and Talas valleys, Issyk-Kul basin and Toguz-Toroo gorge with south steppes, dry steppes, steppe and meadow-steppe climatic conditions at the elevations of 700-1800 m a.s.l.
3. The belt of warm high foothills (adyrs) of Alai, Fergana, Turkestan and Chatkal ridges with distinctive steppe climatic conditions at elevations of 1500-2000 m a.s.l.
4. The belt of middle mountains with climatic conditions close to those of steppe, forest-steppe and forest at elevations of 1500-3000 m a.s.l.
5. The belt of cold foothills of mountain valleys and depressions with cold steppe climate at elevations of 1800-2500 m a.s.l.
6. Subalpine belt with distinctive highland complexes of steppe, meadow-steppe and meadow conditions at elevations of 3000-3500 m a.s.l.
7. The belt of alpine mountains with distinctive complexes of steppe, meadow-steppe, meadow and desert conditions approaching arctic natural conditions at elevations of 3200-4000 m a.s.l.
8. The belt of modern glaciation (glacial-nival belt) includes rocky ridges and ranges, talus, moraines, glaciers and snowfields at elevations of 3600-7000 m a.s.l.

Kyrgyzstan encompasses West, Central and Inner Tian-Shan mountains. These areas are different in terms of climatic conditions, orography and consequently – vegetation. The species composition is different among these areas as well, and elevation belts are not directly comparable between different areas. With this regard it is more convenient to split the area of the country into different geobotanical zones and describe them separately. Scientific practice of geobotanical zoning uses a special taxonomy of territorial units, like: zone, province, sub-province, district and region. This taxonomy is satisfactory for planetary and continental scales, as well as for general educative purposes. However, for practical purposes and on finer scales it is reasonable to develop a different approach. It is necessary to consider an area as an independent object, not separating it between different zones and provinces. Based on many years of geobotanical and botanical-geographical researches of the entire area of the country Vykhodtsev (1956a, 1966) developed a geobotanical division of the country into geobotanical regions of the first order, which are divided into several geobotanical regions of the second order, each with distinctive features and in close relation with agricultural potential.

Geobotanically the study area incorporates to **Alai-Fergana-Chatkal region of the first order**, according to Vykhodtsev (1966) or **South-West Tian-Shan** according to Adyshev et al. (1987). The region embraces eastern Alai, southwestern slope of Fergana and Chatkal ridges (Figure 3).

Geobotanical features of the area are (Vykhodtsev 1956a, 1956b, 1966; Korovin 1961; Kamelin 1973; Adyshev et al. 1987; Shishkova et al. 1989; Ionov and Lebedeva 2005; Shukurov et al. 2005):

- Regional presence and distribution of walnut-fruit forests of *Juglans regia*, *Malus sieversii, Prunus sogdiana*, *Fraxinus sogdiana, Acer turkestanica, Crataegus altaica, C. turkestanica, C. songorica, Picea shrenkiana, Abies semenovii, Juniperus turkestanica, J. semiglobosa*.
- Regional presence and distribution of pistachio thickets of *Pistacia vera*, almond thickets of *Amygdalus spinosissima*, and shrubs *of Exochorda tianschanica, Louiseania ulmifolia (Aflatunia ulmifolia), Rosa kokanica* and others; as well as groves of *Abelia corymbosa* and *Ziziphus jujuba*.
- Regional presence and distribution of southern steppes and meadow-steppes with dominance or abundance of *Hordeum bulbosum, Inula macrophylla (Inula grandis), Bothriochloa ischaemum (Andropogon ischaemum),* or *Agropyron trichophorum,* or *Ferula kuhistanica (Ferula jaeschkiana)* and *Ferula spp.*, or *Prangos pabularia, Vinca erecta, Phlomis salicifolia, Perovskia scrophulariifolia, P. angustifolia.*
- Almost entire absence of *Kobresia spp.* wastelands, which are typical for highlands in other parts of the country.

- Wide distribution of speckled sandstone and their typical accompanying vegetation.

More specifically, the study area is on a junction of Fergana and Fergana-Chatkal regions of the second order (Figure 3).

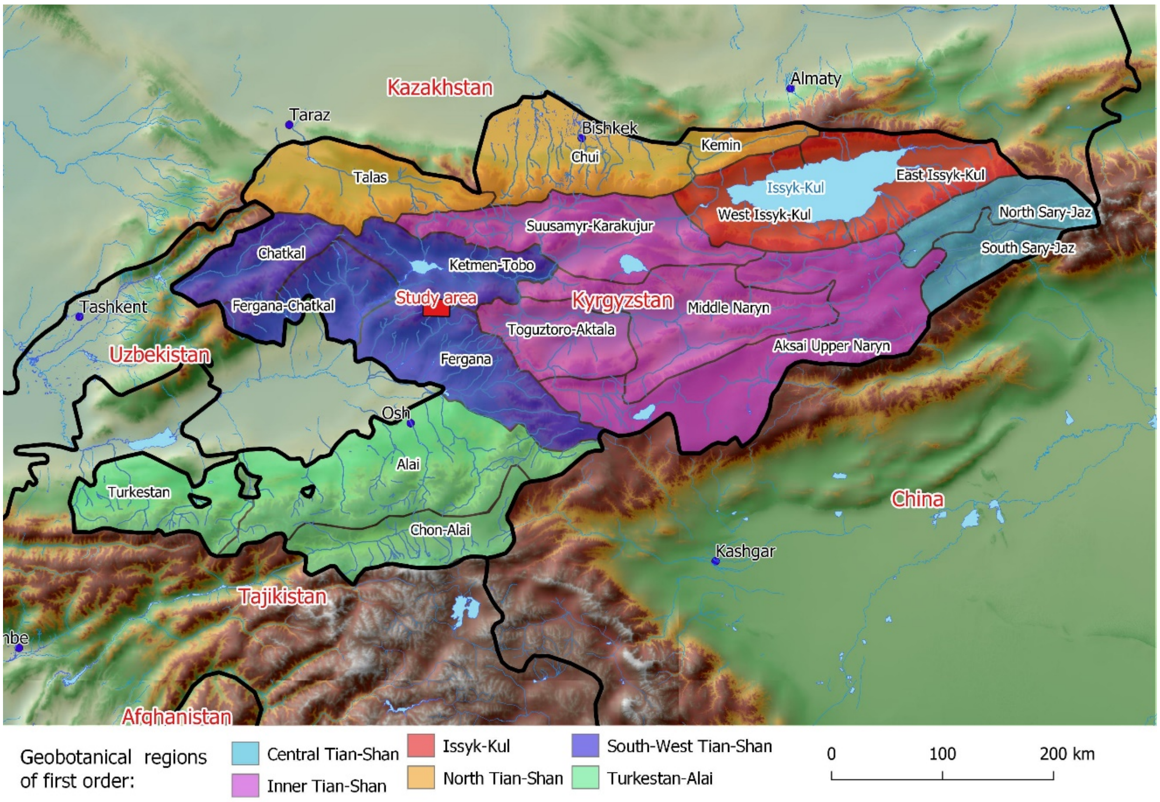

Figure 3. Geobotanical regions of the first and second order, adopted from Vykhodtsev (1966) and Adyshev et al. (1987). The geobotanical regions of the first order are differentiated by colors, and those of the second order – by boundaries and their respective titles.

The Fergana region of the second order includes foothills and mountains of eastern Fergana from Kara-Kulja river till Kara-Unkur-Sai river (Tentek-Sai). It is characterized by rugged terrain but with soft contours and high precipitation humidification. Geobotanically, the region is characterized by wide distribution of walnut-fruit forests *with Juglans regia, Malus sieversii, Crataegus altaica, C. turkestanica, C. songorica, Prunus sogdiana, Fraxinus sogdiana; Hordeum spp. and Inula spp.,* southern steppes with abundance and even dominance of *Hordeum bulbosum* and *Inula macrophylla (Inula grandis)*, shrubs of mainly *Rosa kokanica, Exochorda tianschanica, Louiseania ulmifolia (Aflatunia ulmifolia)* and *Pistacia vera*; as well as typical foothill (adyr) semi-deserts and southern high-grass cereal-forb meadows. This is an area of walnut-fruit forests and rainfed agriculture (Vykhodtsev 1966; Lazkov and Sultanova 2011).

The Fergana-Chatkal region of the second order includes the area of southern slopes of Fergana and Chatkal ranges from Sumsar river on the west till watersheds of Naryn and Kara-Ungur-Sai rivers in the east and is characterized by a great terrain ruggedness, with vast and isolated areas as with more flat terrain (along Ak-Sai and Kara-Suu rivers), so, with very eroded forms like canyons, gorges and defiles (along Sumsar river). In geobotanical sense, the region is characterized by extremely wide distribution of southern *Bothriochloa spp.* steppes with domination of *Bothriochloa ischaemum (Andropogon ischaemum)* and foothill semi-deserts with *Artemisia spp., Salsola spp.* and ephemeral vegetation. Forests of *Juglans regia, Abies semenovii, Picea schrenkiana*; shrubs with *Exochorda tianschanica, Louiseania ulmifolia (Aflatunia ulmifolia),* and *Rosa kokanica*, groves of *Abelia corymbosa* are represented in the northern part of the region. Formations of *Prangos pabularia*, sometimes consisting of only *Prangos spp.* are widely distributed in the belt of forests and shrubs. Vegetation of different types of rock outcrops is also well represented. Meadows, dominated by *Phlomoides spp., Phlomis spp., Geraniaceae* and *Iridaceae (Iris ruthenica)* are distributed above the tree line and shrubs. Southern part of the region basically represents arable lands and pastures, whereas the northern part is mainly forestry area (Vykhodtsev 1966; Ionov and Lebedeva 2005; Lazkov and Sultanova 2011).

These regions of the second order can be further broken down into vegetation types, typical for the study area. The following nomenclature of vegetation types is locally used and accepted (Vykhodtsev 1956a, 1966; Rachkovskaya and Bragina 2012).

Savannoids are the typical vegetation type, providing the remarkable features to the landscapes on Fergana range, as well as on Chatkal and Talas ranges on elevations from 1000 till 2500 m a.s.l., they are also widely represented in mountains of Kazakhstan, Uzbekistan and Turkmenistan (Vykhodtsev 1966; Ionov and Lebedeva 2005; Lazkov and Sultanova 2011). This is the vegetation type including sparse forests with *Acer spp., Crataegus spp., Pistacia vera* and *Juniperus spp.*, shrubs with *Rosa spp., Amygdalus spp., Cerasus spp.* and semi-shrub species with *Artemisia spp.*, communities with ephemeral vegetation with *Poa bulbosa, Carex pachystylis, Agropyron trichophorum, Hordeum bulbosum* (Vykhodtsev 1966; Ionov and Lebedeva 2005; Lazkov and Sultanova 2011).

Midland savannoids (communities of *Bothriochloa ischaemum, Agropyron trichophorum, Hordeum bulbosum, Inula macrophylla, Ferula spp., Prangos spp.*). This is a dominating ecosystem in the region and it is widely represented in all its parts on elevations 1300-3000 m a.s.l. It mostly occupies 2000-2500 m a.s.l. The total area within West Tian-Shan is 19 224 km^2 (Shukurov et al. 2005). Ecosystem engineers of these communities belong to ancient Mediterranean habitat. The grass savannoids relate to shrub communities – “sibljak”. New communities occur because of centuries-old human pressure (cutting of trees and shrubs, grazing) (Kamelin 1973). The vegetation of these formations has developed in conditions of subtropical climate with soft winter, very dry and hot summer with precipitation maximum in winter and spring. The flora of midland savannoids is dominated by large ephemeral *Gramineae* including *Hordeum bulbosum, Agropyron trichophorum, Bothriochloa ischaemum*, as well as *Prangos spp., Ferula spp., Polygonum coriarium (Aconogonon coriarium), Inula macrophylla.* Depending on the dominating species there are *Bothriochloa spp., Agropyron spp.,* and forbs dominating savannoids (Vykhodtsev 1966; Ionov and Lebedeva 2005; Lazkov and Sultanova 2011).

Deciduous shrubs are found in a wide range of elevations – from 1300 till 2800 m a.s.l., mainly on north-exposed slopes and along rivers. In some areas they replaced cut forests and overgrazed pastures. The total area of deciduous shrubs in West Tian-Shan is 1829 km^2. Total area in Kyrgyzstan – 2223 km^2 (Ionov and Lebedeva 2005; Shukurov et al. 2005). The shrubs protect soil from erosion on steep slopes (more than 30°-40°), along rivers and on watersheds. They provide berries, medicinal raw material, firewood and construction material for local population. Deciduous shrubs are a geterogenic type of vegetation. The typical species are: *Exochorda tianschanica*, *Prunus Sogdiana*, *Abelia corymbosa*, *Louiseania ulmifolia (Aflatunia ulmifolia), Berberis integerrima, B. oblonga, B. sphaerocarpa, Tamarix spp., Lonicera spp., Cotoneaster spp., Atraphaxis spp., Hippophae turkestanica (Hippophae rhamnoides), Ribes heterotrichum, R. janczewskii, Spiraea hypericifolia, S. lasiocarpa, S. pilosa, Caragana acantophylla, C. alaica, C. aurantiaca, C. laetevirens, C. turkestanica, Rubus caesius, R. idaeus, R. saxatilis, Amygdalus petunnikowii, A. bucharica, A. communis, A. spinosissima, A. susakensis, Rosa kokanica, R. laxa, R. beggeriana, R. fedtschenkoana, R. platyacantha, Salix iliensis (Salix capra), S. niedzwieckii (S. coerulea), S. linearifolia (S. blakii), S. rosmarinifolia* (Vykhodtsev 1966; Ionov and Lebedeva 2005; Lazkov and Sultanova 2011).

Floristic composition of grasses is poor: *Brachypodium pinnatum, B. sylvaticum, Dactylis glomerata, Poa spp., Agrostis gigantea, A. hissarica, A. stolonifera, A. turkestanica, Prangos fedtschenkoi, P. lipskyi, P. ornata, P. pabularia, Paeonia hybrid (Paeonia* *intermedia), Ligularia alpigena, L. heterophylla, L. karataviensis, L. macrophylla, L. thomsonii, Centaurea adpressa, C. alaica, C. depressa, C. iberica, C. lasiopoda, C. modesti, C. ruthenica, C. squarrosa, Inula Britannica, I. caspica, I. helenium, I. macrophylla, I. salicina, Eremurus aitchisonii, E. alaicus, E. alberti, E. comosus, E. fuscus, E. kaufmannii, E. lactiflorus, E. olgae, E. regelii, E. robustus, E. sogdianus, E. stenophyllus, E. tianschanicus, E. turkestanicus, E. zenaidae* (Vykhodtsev 1966; Ionov and Lebedeva 2005; Lazkov and Sultanova 2011).

Midland meadows with tall grasses are represented in forest-meadow-steppe belt, they grow here because of higher precipitation level than in other parts of Tian-Shan. They are used as summer pastures and hay cutting areas. Flora of the meadows is very diverse and includes about 222 species of vascular plants, which belong to 128 genera and 34 families (Ionov and Lebedeva 2005). The flora is dominated by *Elaeosticta allioides, E. tschimganica, Prangos pabularia, Turgenia latifolia, Eremurus regelii, Centaurea squarrosa, Cousinia microcarpa, Inula macrophylla, Alyssum turkestanicum, Lonicera nummulariifolia, Allochrusa paniculata, Dianthus ugamicus, Convolvulus arvensis, C. pseudocantabrica, Carex turkestanica, Dipsacus dipsacoides, Scabiosa songarica, Astragalus sewertzowii, A. sieversianus, Medicago tianschanica, Hypericum elongatum, H. scabrum, Origanum tyttanthum, Phlomis salicifolia, Ziziphora clinopodioides, Alcea nudiflora, Morina kokanica, Bromus inermis, B. tyttholepis, B. danthoniae, B. oxydon, Agropyron trichophorum, Festuca valesiaca, Hordeum bulbosum, Poa bulbosa, Taeniatherum crinitum, Delphinium semibarbatum, Potentilla orientalis, P. pedata, Spiraea hypericifolia, Galium verum, Veronica campylopoda* (Ionov and Lebedeva 2005; Lazkov and Sultanova 2011).

Subalpine (cryophyte) meadows with mid-tall grasses are usually situated below 2300-3300 m a.s.l. on northern slopes and humid habitats. Their total area is 5307 km^2 (Shukurov et al. 2005). The flora of the meadows is dominated by perennial herbaceous plants, which consist of 197 species, which is 90.4% from the total amount of species (Ionov and Lebedeva 2005). These plant communities are usually represented by *Geranium collinum, Geranium ferganense, Geranium spp., Aconogonon coriarium, A. bucharicum, Polygonum coriarium, Polygonum spp., Trollius altaicus, T. dschungaricus, T. komarovii, T. lilacinus, Allium atrosanguineum, Allium spp., Iris ruthenica, Iris spp., Ligularia alpigena, Ligularia spp., Festuca valesiaca.* Original communities with dominance of *Polygonum coriarium* provide peculiar landscapes and occupy about 80-

85% of surface. Co-dominants are *Bistorta elliptica, Polygonum nitens, Geranium saxatile, Phlomoides oreophila, Anemone protracta, Alchemilla retropilosa, Rhodiola litwinowii.* The vegetation cover percentage varies from 30% till 100% (Vykhodtsev 1966; Ionov and Lebedeva 2005; Lazkov and Sultanova 2011; Rachkovskaya and Bragina 2012). The different vegetation types and diverse climatic, rocks and terrain features condition great variability of soils classes.

2.3 Soils

The principles of soil geographical zoning used in Kyrgyzstan are based on geomorphological and bioclimatic factors, as well as on pattern of altitudinal distribution of soils and its agricultural use. The following geographical taxonomic units are used: soil province, soil sub-province, soil district and soil area. Kyrgyzstan is encompassed by two great Asian mountain systems – Tian-Shan and Pamir-Alai. As a result of a complex geographical position, three major soil-climatic provinces are discriminated: South Kyrgyzstan (mountains of West Tian-Shan), North Kyrgyzstan (mountains of North Tian-Shan), mountain depression (Alai, Central Tian-Shan) (Mikhailov 1949, 1959, Mamytov 1971, 1974; Pomazkov et al. 1972).

Complex geographical conditions, surface ruggedness, geological and climatic conditions, diversity of bedrock, different weathering processes as well as diversity of plants and animals contribute to the development of original and peculiar soils in Kyrgyzstan (Mamytov 1971). The pattern of soil distribution is dominantly linked to topographic elevation, forming altitudinal soil belts or zones. Two forms of this zoning occur in Kyrgyzstan. One of them is slope zoning – from foot to top of a mountain range, and another – that of flat parts on intermountain depressions. The later reveals while moving along a valley bottom from its lower part to the higher, where soil units change within the flat part of the valley. This pattern is specific in different soil-climate conditions. Thus, *Phaeozems* and *Cambisols* (IUSS Working Group WRB 2014) are distributed in intermountain depressions in South Kyrgyzatan, low-carbonate *Phaeozems* and *Kastanozems* in Northern Kyrgyzstan, and *Cambisols*, *Kastanozems* and *Chernozems* in Central Tian-Shan (Mamytov 1971; Mamytov and Ashirakhmanov 1988). According to this taxonomy the study area is situated in the South Kyrgyzstan soil province, in the Fergana and Fergana-Chatkal soil districts (Figure 4).

The South Kyrgyzstan soil province is a continuation of the Turanian soil-climatic province. This province reaches the elevation of 2000 m a.s.l., where *Cambisols* and *Phaeozems* have developed. Several soil districts are clearly discriminated within the province, these are: Turkestan-Alai, Aravan-Kurshab, Kichi-Alai, Fergana, Fergana-Chatkal and Chatkal. This province occupies the biggest part of West Tian-Shan and Pamir-Alai, comprising a mountain edging of Fergana depression, which is surrounded by Talas and Susamyr ranges in the north, by Fergana range in the northwest, and by Turkestan and Alai ranges in the south (Mamytov 1974; Mamytov and Ashirakhmanov 1988).

The Fergana soil district includes most areas of the south slope of the Fergana range. The area is very rich in precipitation, which is why soils are generally well supplied with moisture. Abundance of moisture and heat makes this district rich regarding vegetation cover, including the wild walnut-fruit forests. The main features of the district are the walnut-fruit forests and dry shrub steppes, where *Cambisols* and *Greyic Phaeozems* have developed. *Mollic* and *Umbric Leptosols* occur above this area in subalpine zone (Mamytov 1971, 1974; Mamytov and Ashirakhmanov 1988).

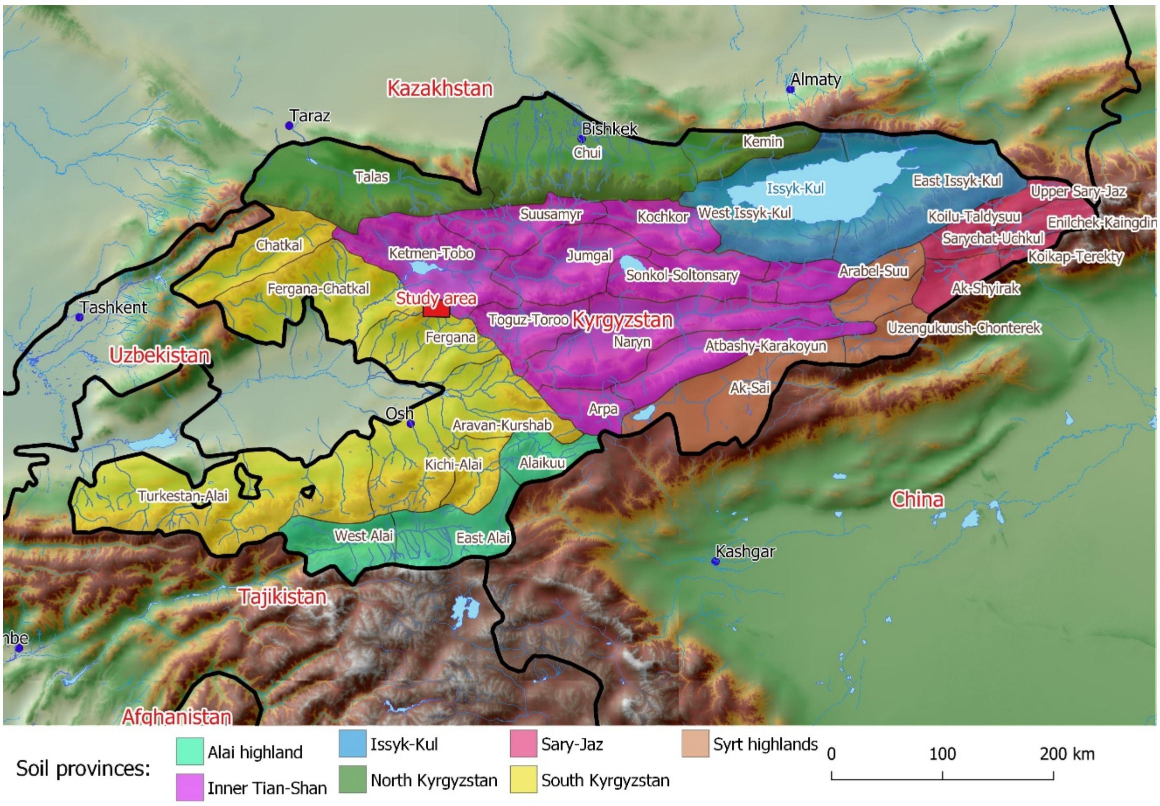

Figure 4. Soil provinces and soil districts, adopted from Mamytov (1974) and Adyshev et al. (1987). The soil provinces are differentiated by colors, and soil districts – by boundaries and their respective titles.

The Fergana-Chatkal soil district embraces southern slopes of Chatkal range and occupies northern mountain frame of Fergana valley from Baubash-Ata mountain. The district is featured with a considerable terrain ruggedness, great erosivity of soil cover, presence of as xerophytic so mesophyte vegetation forms. Walnut-fruit forests also grow in Sary-Chelek area together with spruce and elaeagnus. The area is also featured by *Cambisols* and *Greyic Phaeozems* (Mamytov 1971, 1974; Mamytov and Ashirakhmanov 1988).

The Chatkal soil district includes midland Chatkal valley, which is quite cold. Cold air masses come down to the valley from the adjacent high snowy mountains. Poplar, birch and willow grow along the Chatkal river, which makes the valley look like forest-steppe belt. Two flattened terraces are apparent in the valley. The soils on the lower terrace are represented by *Cambisols* under *Umbelliferae* plants and *Kastanozems* in *Festuca spp.* steppes. The soils on the higher terrace, in subalpine belt, are represented by *Mollic Leptosols*. The soils are peculiar for being leached from carbonates (Mamytov 1971, 1974; Mamytov and Ashirakhmanov 1988).

The bedrock in highland areas and in midlands of South Kyrgyzstan are the weathering products of Paleozoic and Mesozoic deposits, which are represented by sandstone, shale and limestone. Quaternary sediments are the bedrock in intermountain depressions, river valleys and foothills. The layer of quaternary deposits in a form of eluvial, deluvial and proluvial sediments of bedrock also covers slopes in highland areas. However, due to active weathering processes and relocation of bedrock material, which is conditioned by steep slopes and climate, this layer is thin and broken by outcrops of more ancient rocks (Mamytov and Ashirakhmanov 1988).

Carbonate rocks or calcrete are the main bedrock among the quaternary deposits in southern Kyrgyzstan. They occupy the areas of intermountain depressions, foothills and partly midlands. Noncarbonate rocks are of secondary importance and are sparsely distributed only in midlands and high mountains, with high precipitation level. Deep chemical decomposition of rocks with translocation of chlorides, sulfates, and carbonates to deep layers of loose deposits and down the slopes to plains and water bodies takes place in modern times in midlands and high mountains with cool and moist climate. Even deeper weathering down to aluminosilicates, removal of silicic acid and accumulation of sesquioxides happen on southwestern slopes of Fergana range, the most precipitation-rich areas. That is why more clayey soils develop here – *Cambisols* and *Kastanozems* (Mamytov 1974; Mamytov and Ashirakhmanov 1988; IUSS Working Group WRB 2014).

South Kyrgyzstan is the northernmost part of the subtropical belt. That is why the features of subtropical soil formation are weakly expressed. *Greyic Phaeozems* in the area are peculiar for their weakly differentiated profile layers and claying. The peculiarity of South Kyrgyzstan soil is a wide distribution of *Phaeozems* and *Cambisols* (Adyshev et al. 1987; Mamytov and Ashirakhmanov 1988).

A typical feature of *Cambisols* of walnut-fruit forests of South Kyrgyzstan is the high humus content, thick humus horizons (0.5-1 m), little clay content and saturation of the absorbing complex with calcium and good structure, which makes them closer to *Chernozems*. It should be admitted that the entire vertical gradient of West Tian-Shan soils – *Phaeozems*, *Cambisols*, *Mollic* and *Umbric Leptosols* are prominent for a higher humus content in contrast to similar soils of Pamir-Alai and other mountain regions of south Central Asia. *Cambisols*, rich in organic content, occur under fir and spruce forests of West Tian-Shan. Their typical feature is presence of *Umbric* horizon under the forest litter, which is the consequence of development in continental climate, where the lack of heat and moisture limits activity of microorganisms and promotes conservation of new humus. *Mollic Leptosols* and rarely *Umbric Leptosols* develop in alpine and subalpine belts. These *Leptosols* are usually weakly leached and have neutral pH reaction. They have slightly thicker and considerably more differentiated soil profile (Adyshev et al. 1987; Mamytov and Ashirakhmanov 1988). Vegetation, soils and climatic factors provide the main ecosystem services rural population in Kyrgyzstan relies on.

2.4 Human impact

Kyrgyzstan is a developing country with poor economic situation and a rural population largely relying on natural resources. Animal husbandry and agriculture comprise the main livelihoods for the population outside of the capital. Agriculture contributes the most to the country’s GDP (NatStatCom 2018), which makes natural resources the keystone for national economy and food security.

With independence in 1991, subsequent destruction of economic linkages, collective farms and industry, followed by population growth in rural areas livelihood strategies became very limited. Rural people have mainly two sources of income: household-based small-scale farming and labor migration (Farrington 2005; Atamanov and Van den Berg 2012). There is more livelihood diversity in the historically more developed north of the country (Chui valley), where the capital and central government are, that allows people to retreat from traditional farming. In contrast, in the south agriculture and labor migration are more common (Schmidt and Sagynbekova 2008).

There were several studies devoted to pastoral management systems (Steimann 2011, 2012; Kerven et al. 2011; Crewett 2012), but only few of them looked into the environmental consequences and implications for decision makers (Coughenour et al. 2008; Borchardt et al. 2010, 2011, 2013; Dörre and Borchardt 2012; Hoppe et al. 2016a, 2016b, 2017). The several pasture use reforms made the rules complicated and ruined the former management system, consequently making animal husbandry unregulated, as in terms of livestock number, so in terms of their seasonal movement and overall management (Crewett 2012).

The main achievement of different reforms is decentralization of pasture management. This has led to the situation where the pasture leaser, livestock owner and shepherd can be three different persons, and not necessarily the local ones. Disintegration of collective farms, which consistently followed common scientifically-based policies into small private household farms without solid business strategy let to the loss of pasture infrastructure and central management resulting in unregulated grazing practices (Schoch et al. 2010). Current number of livestock has reached the peak values of Soviet times (Farrington 2005; Shigaeva et al. 2016) according to official data (NatStatCom 2018), which, however, is considered inaccurate, because livestock owners tend to report lower numbers to avoid additional taxes and not to reveal exceeding of the grazing limits (Shigaeva et al. 2016). Productivity of livestock remains low due to unprofessionalism of shepherds, who prefer to increase the amount of livestock instead of improvement of their breed and grazing system. The unregulated grazing and complicated pasture distribution system, insufficient law enforcement with destroyed infrastructure led to unsustainable use of natural resources, which resulted in overgrazing of close pastures, underuse of remote pastures and economic losses due to livestock travelling on foot for long distances (Crewett 2012; Dörre and Borchardt 2012; Shigaeva et al. 2016; Isaeva and Shigaeva 2017).

The recent pasture reform of 2009 has delegated pasture management rights to local authorities (pasture committee), which are elected from local people, mainly natural resource use and animal husbandry experts. Pasture committees develop pasture management plans and annual usage plans, decide on pasture carrying capacity, monitor pasture condition, establish grazing quotas, sell pasture usage rights (pasture tickets) and use the revenues to implement the management plans. However, about 30-50% of the pasture committee’s budget covers salaries of its chairman and accountant, which are still low, resulting in high staff turnover (Shigaeva et al. 2016). Furthermore, the budget is not enough to conduct regular assessments of pasture capacity and shepherds usually take more livestock to pastures than they are allowed. Shadow economy is still strong and pasture use is often regulated by informal agreements between shepherds, who do not always have pasture use rights. Because of this, there are no reliable data on the numbers of livestock, their composition and transhumance. Pasture committees do not have enough resources and rights to enforce their decisions. Pasture tickets are perceived by local communities as pasture use tax and pasture committees as a government body, not a local participatory body, which serves for their direct benefits. Participation of different stakeholders in pasture committees is sometimes nominal, some of them do not understand their rights and responsibilities, which leads to misunderstanding of pasture committee’s role and blurs benefits of the reform. So, many communities continue the grazing practices as they have used to, or as convenient for them (Shigaeva et al. 2016; Isaeva and Shigaeva 2017).

Livestock is considered by rural people as a good mean for investment, allowing for money saving and fast capital mobilization. It can also provide fast financial growth, if cheap pastures are used (de la Martinière 2012). Culturally livestock plays a great role in different traditional events (weddings, funerals), it is an indication of well-being and promotes social linkages. However, people in villages try to diversify their income by having livestock, crop fields and collecting fruit and firewood from forest or working as shepherds for other people (Shigaeva et al. 2007; Kerven et al. 2011; de la Martinière 2012), even if they have stable income by being officially employed in local agencies funded from the national budget. Some families have their relatives working abroad and sending remittances back home, which are invested in construction of houses or livestock (Schoch et al. 2010), which again contributes to increasing grazing pressure (Hangartner 2002; Kerven et al. 2011). The richer farmers invest some of their income into further diversification of their livelihoods by opening small village shops, purchasing machinery and providing services for payment or to livestock infrastructure, such as new barns (Hangartner 2002; Steimann 2011; Kerven et al. 2011).

Unregulated animal husbandry is widely spread in the region. It is based on seasonal transhumance, where livestock stays in villages in winter and taken to highland pastures in summer (Kerven et al. 2011). The most popular animals are cattle, sheep and horses, donkeys are also kept, however they are not considered as valuable and most of the time are not taken care of. In early spring local people start taking animals to the low plain pastures near the villages, because of lack of stored forage, which used to be supplied from outside of the republic in Soviet times. In late spring, when grass appears in the forest the animals are taken there, where they eat grass and damage tree seedlings. Starting from early summer people move to the mountain rangelands, which are above the tree line, and stay there till early autumn. In autumn the animals are taken again to the forest and then back to the village for winter. In summer people cut hay in the forest to store it for the winter, but after the animals have eaten the early grass in spring, the meadows do not produce enough hay for the entire winter period, so the vicious circle repeats next year.

Despite of importance of this issue there is no common understanding on the level of rangeland degradation in Kyrgyzstan. The values vary from 11.7% of the territory (Bai et al. 2008) till ~24% (Le et al. 2016) depending on the methods used. There have been several studies on pasture degradation and desertification (Kerven et al. 2012) and degradation costs (Mirzabaev et al. 2016), however the full picture is unclear due to lack of systematic ground observations and unknown spatio-temporal distribution of grazing pressure. The general growth of livestock numbers allows to make a conclusion, that the general pressure on pasture resources is growing, which may lead to rangeland degradation.

Degradation of pastures represents a complex concept, encompassing soil, vegetation, biodiversity and productivity change in comparison to natural condition. Early grazing, unregulated transhumance and large amounts of animals are some of the main impact factors on soil and vegetation in the region. Overgrazing prevents grass on rangelands to achieve significant biomass and produce seeds, which leads to domination of unpalatable species on the pastures and change of plant communities. Livestock trampling leads to destruction of vegetation and soil structure, which results in soil loss. This leads to pasture degradation, expressed in a change of species composition, soil erosion, loss of grassland productivity and animal diseases.

Climate change scenarios for Kyrgyzstan propose considerable changes (Hijioka et al. 2014), which will increase the pressure on natural ecosystems, leading to even more difficult situation. The unsustainable use of vegetation and soil resources leads to their degradation and loss of productivity, which will result in severe economic consequences in future. Different ecosystems have different response to climate change, which can have significant spatial variability across the country. Thus, modelling of interaction within the pastoral ecosystems, identification of risks and potential solutions for decision makers are of utmost importance for the region.

3. Soil erosion modelling

Many methods have been developed for representation of interactions between soil, vegetation and climate (Tiwari et al. 2000; Nearing 2000; Kinnell 2017). One of the most important and widely used equations is the Universal Soil Loss Equation (USLE), which calculates long-term soil loss from the features of soil, terrain, utilization, climate and conservation practices. Both, USLE and RUSLE (as well as many other variations) have been used for a long time in assessment of soil loss worldwide, so this equation is considered as a standard in modern soil science. This equation is based on long-term observation data and can yield mean soil loss values over a long period and is not applicable for estimation of event-driven erosion. However, there are many other alternatives, based on different approaches as empirical, so deterministic, which deserve further development (Karydas et al. 2014).

3.1 USLE and its derivatives

USLE was developed by Wischmeier and Smith (1978), based on soil loss measurements conducted in the USA. The equation was revised by Renard et al. (1996), based on measurements of different soil types from around the world, the revised version of the equation is titled RUSLE (Revised USLE). Both equations are based on multiplication of different factors, affecting soil loss:

$$A = K \times C \times R \times LS \times P \quad \textbf{(1)}$$

where A – annual soil loss, K – soil erodibility factor, C – cover management factor, R – rainfall erosivity factor, LS – terrain factors and P – support practices factor. These factors include the so-called K-factor, which is soil erodibility indicating how much the soil is perceptible to surface runoff and is calculated based on physical parameters, such as grain size, aggregation and organic content. C-factor is the surface management, based on the soil utilization practices, vegetation and residues, protecting soil from erosion. R-factor is the climate factor, based on peak rainfall intensity, which accounts for the precipitation contribution to the soil loss. LS-factor (usually denoted together) are the slope length and steepness factors, which account for the terrain impact on soil loss. And P-factor is the conservation practices factor, indicating soil loss prevention practices and usually is taken equal to 1 on rangelands, as no soil conservation occur.

There were many studies utilizing USLE and its derivatives, primarily RUSLE (Revised USLE) and MUSLE (Modified USLE) to assess soil loss and the areas with high risk of soil erosion worldwide. The relative simplicity of implementation of soil loss research or rather estimation based on USLE made this equation very popular for rapid assessment. However, the equation has its constrains, the main of which is its limited applicability to different conditions it was not based on, which can lead to substantial misjudgment about the scale of soil loss. The estimations still need to be corrected by observations of real soil loss amounts. Despite its relative simplicity, USLE still requires a substantial dataset about terrain, precipitation, vegetation and cover management, and, of course, soil itself. Though, many researches covered the gaps in data availability by using different proxies and regression approaches (Brown and Foster 1987; Renard and Freimund 1994; Zhang et al. 2004; Karaburun 2010; Schönbrodt et al. 2010; Baskan et al. 2010; Lee and Heo 2011; Wang et al. 2016).

Initially, USLE was developed for application on agricultural land, and so the corresponding factors were used. However, estimation of soil erosion was demanded on other types of land use, thus the Revised USLE (RUSLE) has expanded its application to other land uses and soil types. USLE is designed to estimate long-term soil loss, so long-term data should be available. And it is not applicable for short-term soil loss assessments. It is also not applicable for estimation of deposition. The R-factor considers only detachment by rainfall and does not account for snowmelt or other types of surface flow like irrigation, however, this is accounted for in MUSLE. Despite of its many limitations the USLE-based researches became very popular in estimation of soil loss due to its relative simplicity and reasonable data requirements.

The soil erodibility factor or **K-factor**, as denoted in USLE, is estimated based on soil data. It requires substantial set of topsoil samples from the study site, which can be collected during field trips recording soil structural characteristics at the point of sampling. Then the soil samples need to be analyzed in soil laboratory, basically for organic content and grainsize distribution. The K-factor can be calculated by different available equations from soil structure information, organic content and grainsize distribution. Or directly estimated using the nomograph, provided by Wischmeier and Smith (1978). Apart from rather classical ways of K-factor estimation, many other equations were developed for different parts of the world, when some data are not available (Knijff et al. 2000; Fu et al. 2005; Vemu and Pinnamaneni 2011; Shabani et al. 2014; Geng et al. 2015; Guerra et al. 2017; Ostovari et al. 2017; Rabot et al. 2018). These equations are mainly based on regression analysis of different soil and terrain properties as predictors and measured or estimated K-factor values as the predicted variable. The limitations of soil erodibility estimations using classical equations or nomograph sometimes are neglected e.g. Addis and Klik (2015). Even though the K-factor equation was developed based on a limited variety of American soils the nomograph is applied to different parts of the world without proper adjustment or validation. This approach can still be used for relative estimation of soil loss; however, the absolute rates need verification with soil experiments or comparison with other verified data.

The slope length and steepness factors are usually denoted together as **LS-factor**, represent the terrain information. With current availability of digital elevation models for most of the world, estimation of LS-factor becomes a matter of a proper equation selection. There are several equations and even algorithms available which differ algebraically and conceptually. However, the initial equation by (Wischmeier and Smith 1978) was developed based on slopes under 25%, which suggests it should be used with caution on steeper slopes. It also establishes quadratic relation between slope steepness and S-factor, making S-factor growing faster with slope increase. In RUSLE by Renard et al. (1996), this was changed as the authors had demonstrated that S-factor would not grow exponentially with slope increase. So, a different LS-factor equation is used in RUSLE, which should be accounted for when doing calculations.

Rainfall erosivity factor is the factor describing how much the rainfall contributes to soil loss. The initial USLE equation calculates the **R-factor** from total kinetic energy of a rainfall event and a maximum rainfall intensity over a continuous 30-minute period of rainfall. This requires long-term continuous meteorological observations with recordings of precipitation amount and intensity. Such observations are usually done at weather stations equipped with pluviographs, from which precipitation intensity can be derived. Modern automatic weather loggers or rainfall gauges represent a good and affordable tool for collection of such data. They can collect many meteorological parameters and send them in real time if the area is covered with cellular network, otherwise data can be downloaded from the automatic stations manually. However, some regions are not covered with pluviographs, so, many studies dealt with prediction of R-factor from other weather parameters, mainly precipitation level or duration of rainfall (Renard and Freimund 1994; de Santos Loureiro and de Azevedo Coutinho 2001; Zhang et al. 2009). It should also be highlighted that R-factor is naturally prone to seasonal variations together with C-factor.

Surface management factor (**C-factor**) describes the cropping and management of soil, which has a serious impact on soil loss. In USLE, it is defined as a ratio of soil loss at a given surface management system to the soil loss from continuously tilled fallow area. This factor was limiting the application of USLE to only arable land. In RUSLE, application of this factor was expanded to different management systems as rangelands, forests, construction sites, which provided a great variability and applicability of the equation. In RUSLE, C-factor is a multiplication of other subfactors, accounting for canopy cover, surface cover, surface roughness, soil moisture, and prior land use. In case of rangelands, the prior land use subfactor value can be taken for 1 as they normally managed equally (i.e. not plowed etc.). So, for rangeland conditions C-factor is a function of vegetation and their residue properties, and if the land is constantly overgrazed then even residue can be neglected. Vegetation properties can be easily measured in the field and related to remotely-sensed vegetation indices, facilitating estimation of C-factor, which has been done many times in recent studies (Zhang et al. 2008, 2015; Karaburun 2010; Schönbrodt et al. 2010; Schmidt et al. 2018). As with R-factor, C-factor is also prone to seasonal variations, so their reciprocal oscillation should be accounted for when estimating mean annual soil loss. This is covered in RUSLE by seasonal weighting of C-factor with corresponding R-factor.

Support practice factor, or so-called **P-factor,** is a ratio of soil loss from the applied support practice to soil loss from up-and-down hill culture. It is empirically established for different supporting practices and can be calculated based on physical parameters of slope and support practice. It does not consider the protecting features of vegetation or residues, which is accounted for in C-factor. This factor equals to 1 in areas without any support practice, which is the case of rangelands.

Even though the application of USLE requires lots of data and research, its requirements are reasonable and feasible for many parts of the world, which explains its popularity. Though the results require calibration with direct soil loss measurements, the relative risk of soil loss is also important for soil management. However, modern GIS technologies together with remotely sensed data provide a substantial dataset to cover the data gaps and produce soil maps, which are very helpful for decisionmakers.

3.2 GIS and soil loss modelling

With advancement of remote sensing, development of spatial interpolation algorithms and growth of computational power, GIS has become an essential part of soil science. The new technologies and remotely sensed datasets allow for better analysis and accurate results, rapid assessment of soil features, as well as spatial interpolation excluding human factor. USLE factors, as designed, require intensive and long-term measurements on standardized plots, which are laborious, expensive and presume serious long-term commitment. However, there are many researches providing alternatives to the original calculation of the factors, using different statistical techniques to approximate factors of concern. In many cases, prediction of the measured variables with spatially explicit covariates is undertaken to produce maps of ULSE factors and soil loss. This has brought a new dimension to soil modelling allowing for development of maps of soil features and soil loss, as well as modelling of different situations.

Soil erodibility is a function of soil properties, such as soil texture, organic content, permeability and structure. The soil properties, in their turn, are the result of pedogenesis processes, which are controlled by bedrock, terrain, vegetation and other factors (Jenny 1941). Martz (1992) indicated connection of soil erodibility with relative slope position in Canadian prairie landscape, higher erodibility was associated with higher position on slope where soil was leached, lower erodibility was associated with lower slope position. Panagos et al. (2012) used inverse distance weighting for interpolation of soil erodibility factor in Europe, no environmental covariates were used, but the mapping was based on extensive soil sampling. Panagos et al. (2014b) used remotely sensed data in a form of vegetation indices and raw band data or soil enhancement ratios (Boettinger et al. 2008, 2010), terrain features, derived from SRTM DEM and geographic coordinates as predictors for soil erodibility mapping, which increased resolution and accuracy of the result. These surveys indicate that spatial prediction of soil erodibility based on point soil sampling, regression analysis together with spatially explicit predictors comprising remotely sensed data and terrain indices has become a standard approach. However, depending on the used interpolation method, serious considerations should be put into the sampling design, as different methods have different limitations and requirements to distribution of samples. In case of ordinary kriging, samples should be evenly distributed in the area covering the entire space in grid, alternatively random sampling could be used to avoid any bias. Regression kriging will require even coverage of not only geographical space, but rather the feature space, which means that the samples should be distributed so, that they would cover the entire variability of anticipated predictors. In case of mapping of soil features, this would mean sampling of different terrain and geological features as well as evenly sampling the geographical space, ensuring the actual spot is chosen randomly. Different sampling strategies will be further discussed in section “3.4 Soil sampling design and validation”.

Similar approach is used for **mapping of surface management factor (soil loss ratio)**. Vegetation indices, such as NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index) and others are widely used for spatial prediction of **C-factor** (Karaburun 2010; Schönbrodt et al. 2010; Zhang et al. 2015; Panagos et al. 2015; Schmidt et al. 2018). Remotely sensed vegetation indices are good predictors for C-factor on rangelands, as soil loss ratio there is basically a function of vegetation. Similarly to K-factor, soil loss ratio can be measured at certain points, related to spatially explicit predictors using regression analysis and interpolated with a form of regression kriging (Schmidt et al. 2018). The sampling strategy should also be designed according to the interpolation method chosen, which is discussed in section “4.2 Vegetation mapping and sampling design”. On mountain rangelands, vegetation types are also controlled by terrain conditions, such as altitude and slope exposure (Ionov and Lebedeva 2005; Borchardt et al. 2010, 2011), which means that spatially explicit terrain indices can also be used as predictors. Terrain features and remotely sensed vegetation indices combined can provide good prediction power covering variability caused by terrain and species variations. This approach is straight forward for rangelands, as surface management there does not use any mechanical interventions, such as plowing, abruptly changing C-factor value. So, surface management factor changes gradually between seasons, which still requires different assessments for each season. Thus, freely available remotely sensed data, such as Landsat images and SRTM could be used as covariates. In case of arable lands such assessments should occur after every agricultural intervention changing C-factor. Landsat images, taken every 16 days may not be the best choice, however modern development of aviation and availability of drones with various sensors is a good option for collection of remotely sensed data when needed.

Soil support practice factor or **P-factor** is the one rarely used on rangelands, since there are no soil conservation activities undertaken there. It represents an overall effect of all the soil conservation practices, which are difficult to assess deterministically. There are values known for most common conservation practices, however they require adaptation for local conditions and long-term and costly validation experiments. It is also difficult to develop a raster image of P-factor based on regression modelling or any kind of prediction. Soil conservation is a very local activity and a raster should represent discrete areas and values, so, ground-truth data should be available to develop such a raster. However, it is possible to conduct classification of remotely-sensed images of high resolution (Karydas et al. 2009), if ground-truth data is present or soil conservation measures can be identified visually, given P-factor for each class is known. A different approach is to use sophisticated filtering techniques and high resolution elevation models to identify terrain features, preventing soil loss (Panagos et al. 2014a). USLE/RUSLE proposes estimated P-factor values for variety of different practices and conditions (Wischmeier and Smith 1978; Renard et al. 1996; Foster et al. 2002), these values are based on experimental estimations and should be applied with caution in conditions other than they were developed in.

Calculation of LS-factor for USLE is now a matter of finding an appropriate DEM (digital elevation model) and equation. The most popular free DEMs include SRTM and ASTER GDEM and provide, in most cases, satisfactory precision and accuracy and can be used for assessment and modelling of soil loss. Modern GIS software as ArcGIS and many others can be used to calculate LS-factor by using appropriate tools and raster calculator with respective equations. Free GRAS GIS and SAGA GIS provide even more comfortable way of using just one tool to calculate LS-factor straight from DEM with different methods. Soil loss models usually specify which method should be used for LS-factor calculation.

Spatial interpolation of rainfall erosivity factor requires several respective techniques since weather stations spatially represent a point. However, for some areas it is difficult to obtain rainfall intensity data, as pluviographs are not always installed, or installed not long ago so the sufficient dataset has not been collected. Hence, many studies occurred identifying relations between different predictors and **R-factor** based on regression analysis (Renard and Freimund 1994; de Santos Loureiro and de Azevedo Coutinho 2001; Zhang et al. 2009; Lee and Heo 2011). The R-factor values can be interpolated with either ordinary kriging or related to spatially explicit predictors and inferred accordingly. When DEMs and their derivatives are used as auxiliary data for downscaling of climatic parameters, the result will have variability connected with that of the terrain, which may cause collinearity problems if used together with other terrain factors. Climate parameters were often predicted with terrain indices or other climate covariates (Böhner and Antonić 2009; Gerlitz et al. 2014, 2015; Gultepe 2015; Gerlitz 2015; Böhner and Bechtel 2018). These regressions are very much connected to the area they are developed for, as rainfall energy, intensity and their relation to precipitation level varies greatly across the world. R-factor, just like C-factor is prone to seasonal variations, so this fact should be considered for accurate annual assessments of these factors and soil loss. Separate C-factor and R-factor raster images should be developed for every month, or better for every 15 days. The C-factor annual value is a mean of C-factor seasonal images, weighted with corresponding R-factor as outlined in (Renard et al. 1996). And the R-factor annual image is a sum of all seasonal images (Renard and Freimund 1994; Renard et al. 1996).

After development of raster images of all the factors, the resulting soil loss rate is a result of multiplication of all the raster images as suggested by USLE/RUSLE equation (Wischmeier and Smith 1978; Renard et al. 1996).

3.3 Digital soil mapping

Almost every country has undertaken soil mapping efforts, although it is a laborious, expensive and time-consuming task. Despite a long history of nature resource mapping, the conventional paper maps are not considered of good quality and resolution anymore (McBratney et al. 2003). Digital soil maps have become a standard with the development of new calculating power, algorithms, modelling approaches and big sets of spatial data, including digital elevation models, remotely and proximally sensed data. Digital technologies have made soil mapping much easier than ever before and provided a new field for research and experiments. Now the relatively expensive field work and laboratory analysis become the hardest part of high resolution mapping of soil classes and properties. Legacy soil data can cover this gap to some extent, however, they are limited to certain institutions, collected with different protocols and can be incompatible for creation of the world soil map.

Digital soil mapping is largely based on relation of measured soil features at certain sampling points to spatially explicit covariates, which represent terrain features, remotely sensed indices or other factors. This paradigm is rooted in principles of soil forming discovered and further developed, *inter alia*, by Dokuchaev (1883), Jenny (1941) and McBratney et al. (2003). This approach postulates that soil is a product of different pedogenic factors at the place of origin, which include: parent material, terrain, climate impact, organism activity and time, and that similar soils should develop under similar conditions and different soils should develop under different conditions. Soil forming factors are the main covariates of soil types and features, thus, certain soil types can be related to certain combinations of the covariates. Most of the covariates like climatic factors, parent material and terrain have their direct spatially explicit implementations, or proxies, developed from digital elevation models or remotely sensed data. These covariates make it possible to extrapolate soil features measured at certain points over an area of interest by relating the point data to their spatially explicit forming factors.

Mapping of soil features in mountains is very different from that in flat areas. Soil properties in mountains can change either gradually, e.g. along a slope, or abruptly, e.g. going over a ridge. Parent material can change as well as exposure, insolation, exposure to wind and rain, vegetation and many other factors, impacting soil development. Therefore, soil mapping, especially in mountains, relies on the use of auxiliary data and environmental covariates. Also, creation of digital maps with discrete soil classes and continuous soil properties differ in modelling approaches, however, the approximation datasets used are mainly the same. Continuous soil parameters are usually mapped with universal kriging or regression approaches, and discrete soil classes are usually mapped with classification approaches. However, more sophisticated models including machine learning are being applied nowadays and provide better results (Heung et al. 2016).

The most widely used predictors are terrain factors, including elevation, slope gradient, slope position and curvature. These factors can be easily derived from digital elevation models with the means of modern GIS software, e.g. SAGA GIS (Conrad et al. 2015) “Terrain analysis” modules. As terrain represents one of the main covariates, terrain factors usually contribute the most to the model accuracy. Climatic factors, commonly collected at weather stations and spatially extrapolated, are also often used as predictors for digital soil mapping. However, these factors have little spatial variation, which can be helpful for prediction on flat terrains and lead to loss of actual variability predicting soil features in mountains. But, climatic factors, downscaled with terrain indices as auxiliary data should be used with caution, as they will represent mostly terrain variability, which can cause collinearity and overfitting problems if used with other terrain factors for soil prediction. Modern remotely sensed products also provide valuable information as spatially explicit covariates of soil factors. Such products as soil surface moisture, land surface temperature and evapotranspiration can be used as auxiliary data representing soil spatial variability.

The ratios of different spectral bands of remotely sensed images also represent a widely used set of auxiliary data. Soil enhancement ratios (SER) (Boettinger et al. 2008, 2010) were proposed as covariates of soil properties, representing information about parent rock. This can be a good asset for digital soil mapping, especially on overgrazed mountain pastures as SER are efficient in areas with sparse vegetation, as more of soil information will be captured with remote sensing and they will still contain terrain variability.

The classical approach to spatial interpolation of soil properties is **simple or ordinary kriging**; however, this method presumes the persistence of the property’s spatial variance. This is a good approach for soil mapping on flat terrains, where spatial variance is most likely to stay constant. However, variance of soil properties is not always uniform on rugged terrain. Therefore, simple or ordinary kriging are not suitable for prediction of soil properties in mountains, because they can vary gradually or abruptly, depending on terrain. Thus, regression or universal kriging with spatially explicit predictors based on terrain properties or remotely sensed data are preferable.

One of the most widely used approaches in creation of digital soil maps is prediction of continuous soil properties from terrain features, remotely sensed indices and other known soil properties with the means of **regression analysis** and **kriging**. The results can be spatially explicit if spatially explicit predictors are used. Most often the desired soil feature is measured at certain sampling points, which can be chosen as randomly, so arbitrary. Then the spatially explicit predictors for the soil feature should be found, which can be different terrain indices, as elevation, slope or slope position, as they can have an impact on soil formation, and/or indices calculated from remotely sensed multispectral images, which reflect the spatial variability of soil properties. Regression kriging approach is better to apply in mountain areas, as this approach reveals the relations between the dependent variable and predictors, which should capture the spatial variance of the dependent variable, and add the extrapolated residuals to the regression model, which ensures more local variability. However, in contrast to ordinary kriging, regression kriging may not work on flat terrains, where terrain features may not significantly correlate with soil properties due to their little variation.

Geographically weighted regression (Fotheringham et al. 2002) can be even more accurate in mountain areas. This method fits a series of local regressions, which is especially appropriate when regression coefficients vary in space. More sophisticated approaches as tree models, fuzzy statistics, MAXENT and neural networks (Schmidhuber 2015) become more and more popular as computational power grows and software tools become available. These algorithms can be used as for mapping of continuous soil properties, so for prediction of discrete soil classes.

3.4 Soil sampling design and validation

Soil variability is mapped in different ways discussed above and by many other researchers (Heuvelink and Webster 2001; McBratney et al. 2003; Scull et al. 2003; Hengl et al. 2004; Bishop and Minasny 2006). The sampling design itself is a very important part of soil study projects, as this allows or prevents from doing certain statistical inferences, which are the results of most soil researches. There are several approaches to sampling. Depending on the task the sampling points can be distributed in geographical space according to a certain strategy. They can also be distributed in feature space, aiming to cover the variance of the mapped features or their covariates, or be spread in both spaces (Minasny and McBratney 2006; Brus and Heuvelink 2007; Vašát et al. 2010; Clifford et al. 2014; Ließ 2015; Brus 2015; Chang et al. 2016).

Soil sampling, in the framework of this Ph.D. project, means collection of top soil samples, which represent 300 cm^3 of soil, collected from the top 20 cm of soil and analyzed according to “Procedures of soil analysis” (Reeuwijk 2006). A good sampling design should ensure covering the full range of a variable variation, i.e. be representative for the data population (Domenech et al. 2017). In spatial studies, a systematic and monotonous coverage of geographical space was considered to be a practical approach. This approach can be representative if the measured feature’s variation stays constant in geographical space and does not have any spatial trends, which can be the case on flat terrains, where ordinary or simple kriging is applied for spatial interpolation. However, in the case of rugged terrain, where the measured variables can change gradually or abruptly in geographical space this method will not produce correct results. For this purpose, regression modelling using spatially explicit predictors and feature space sampling will produce better results. However, regression kriging or geographically weighted regression will be even better. Regression kriging utilizes regression analysis between dependent variables represented by survey points and spatially explicit predictors, and then interpolates the residuals with the means of ordinary kriging, adding them to the regression model, thus, a combination of geographic and feature space sampling will be the most adequate.

Development of a robust sampling strategy in house prior to the field trip, especially when the covariates and the study area itself are barely known, is not a trivial task. However, this is better than going to the field without any sampling strategy. A researcher should be flexible and have several sampling strategies, as some of them may appear totally inapplicable due to different constrains, related to terrain, infrastructure or legislation.

The most popular approach in recent years was **Latin hypercube** (Minasny and McBratney 2016) which is good for sampling when spatial covariates are known. This approach minimizes the number of samples while maximizing the feature space coverage, taking one sample within each feature space band for multiple predictors. Since the sampling itself should occur in the field, the practical side of Latin hypercube sampling can be more complicated. In real world sampling within different feature distribution bands would mean splitting the study site in patches, representing combinations of different feature bands and choosing a random sampling point within each patch, all done with GIS tools. Another approach is to use not a random point within each patch, but rather its centroid to increase the sample's representativeness and adherence to the patch. Whereas in the field, the indoors chosen points may be inaccessible due to constrains discussed above. So, it is better to generate several points within one band patch or try to come as close as possible to the chosen point. Another option is to take the map with patches to the field and sample within each patch where possible.

The more classical approach is **stratified random sampling**, which is a broader case of Latin hypercube. Here the feature space is divided into strata (clusters), which should be randomly sampled with a certain number of samples per cluster, so that all clusters (or data strata) are equally represented, keeping the randomness for unbiasedness. For this, spatial clusters should be developed based on known or anticipated spatial predictors. The clusters will also represent patches within study site, and randomly placed sampling points should be generated within each patch. The practical limitations of this approach are same as those for Latin hypercube sampling.

Conventional sampling based on expert knowledge is another eligible sampling approach. It basically aims at sampling of representative places or landscape features, identified by an expert in the field. The decision on which spatial interpolation techniques should be used will be based on the results of statistical analysis of collected samples and patterns identified, or expert knowledge again, as each case will be very special. There were many other sampling schemes developed for application in specific cases (Zhang et al. 2016a; Domenech et al. 2017; Yang et al. 2017; Stumpf et al. 2017).

Validation of results of spatial interpolation of soil features is also an important part of digital soil mapping and should be considered at the stage of sampling design. As some complicated models do not allow for direct unbiased assessment of goodness of fit, additional samples should be collected in the field to serve as validation dataset. If Latin hypercube or stratified random sampling approaches are used, then validation points will automatically fall within one of the patches (strata), so in some patches more than 1 sample should be collected. The exact size of the model training dataset as well as validation dataset depends on the study design and aims and should be decided based on expert opinion and statistical implications. Considering this, the number of samples collected should be greater than the minimum needed for representation of features.

Cross-validation is one of the popular methods for estimation of goodness of fit of modelling results. ***K*-fold cross-validation** is one of the options for cross-validation. It basically generates *K* number of datasets of training and validation subsets, each time randomly splitting the entire database in two subsets. Then each time the model is trained based on the training subset and tested against the validation subset. The training and validation happens *K* times as we have *K* number of splits. After that the goodness of fit statistics are averaged for all the *K* simulations. This will require some programming skills and many computations, as the model will be trained and validated *K* times. However, the modern statistical libraries in R or Python allow for automation of this routine and modern computational power does allow for repetitive calculations of many modelling schemes even on desktop computers.

Leave-p-out cross-validation provides for more unbiasedness as it does several random permutations of training dataset and a validation dataset of a chosen size *p*. Each time the training and validation observations are randomly chosen, the model trained on the training dataset and validated against the validation dataset several times. After all the simulations the goodness of fit statistics are averaged.

The sampling design and validation of the results are integral parts of digital soil mapping and should be considered carefully before the research start. Careful planning and thoughtful sampling strategy will allow to achieve a greater accuracy and representation with the given resources. Inconsiderate sampling design can ruin the entire research effort and make statistical analysis and inferences impossible.

4. Modelling of climate and vegetation interactions

Response of vegetation and live systems to climatic factors and human impact is an important issue, especially when climate stability becomes more and more uncertain and human demand for natural resources grow. A large database of spatially explicit information was collected for a relatively short history of remote sensing by different Earth observation programs. These data include digital elevation models, vegetation indices, land surface and air temperature, precipitation, evapotranspiration and many others. The data were collected over some period and represent a 3D dataset where features change as on surface, so over time. The data dimensionality represents the main constrain for analysis and modelling of spatio-temporal systems, such as climate and vegetation.

Vegetation is widely accepted and proved to provide mechanical support to soils on slopes and prevent erosion (Schmidt et al. 2001; Wieder and Shoop 2018). However, humanity has been using soil and vegetation resources during its entire history, and any overuse leads to degradation (Dotterweich 2013). Many studies emerged discriminating human impact on vegetation from that of natural origin. The common discrimination method used is regression analysis based on climatic factors as predictors and NDVI as a response variable (Propastin et al. 2008a; Xin et al. 2008; Omuto et al. 2010; Zhang et al. 2016b; Liu et al. 2018), where residual trends will represent the human impact. However, this approach is limited by implying that all the natural factors, influencing vegetation are covered by climatic factors only, so all the other impacts, be it random variation or e.g. soil impact are attributed to human. But for rapid assessment this method has proven its applicability. The different datasets discussed earlier are prone to seasonality and interannual trends, and have causal interrelationships, which can be immediate or delayed in time. The effects of climate on vegetation can also be displaced, e.g. downstream effects (Apel et al. 2018), or can vary depending on slope exposition. All these effects add complexity to statistical analysis and modelling.

Many surveys in the region dealt with identification of NDVI trends on pixel basis using linear regression, where the value of each pixel would be regressed with time as an independent variable, and the slope of the regression line would represent the trend (Lioubimtseva et al. 2005; Piao et al. 2011; Yin et al. 2016; Dubovyk et al. 2016). The more sophisticated trend analysis methods include the autoregressive moving average (ARMA) (Liu et al. 2015), the more advanced autoregressive integrated moving average (ARIMA) (Qiu et al. 2016), approximation by a sum of trigonometric functions using Fourier harmonics (de Jong et al. 2011), application of empirical orthogonal functions (EOF), which is basically a principal component analysis (PCA) for raster images (Gurgel and Ferreira 2003; Chen et al. 2011; Yin et al. 2016), or using STL (Cleveland et al. 1990), which stands for “Seasonal and trend decomposition with LOESS (LOcally wEighted regreSsion Smoother)” (Maynard and Levi 2017). All these methods have their advantages and disadvantages. The linear regression is the simplest method, it requires data stationarity and cannot handle seasonality or trend change properly, it produces a general trend for the entire period, leaving the explorer making an arbitrary choice for the breaks between the periods. ARMA and ARIMA are more advanced methods with simple concepts, however they can identify changes in trend in the research period and ARIMA can handle nonstationary data. Fourier harmonics will divide the surveyed signal into a sum of simple trigonometric functions, which already accounts for seasonality and trend, and can identify the different components in the signal, which should be interpreted by the researcher. STL is a more sophisticated approach, designed to decompose the signal into seasonal, trend and noise components with great control, accounting for changing seasonality and trend. EOF decomposes the signal into orthogonal functions (like Fourier analysis), yielding several functions, which capture both temporal and spatial patterns, requiring intensive interpretation from the researcher.

The methods described above can be used for analysis of series of spatial data with seasonality and for identification of their trend and seasonal components, which is applicable as to vegetation indices, so to climatic factors. The seasonal component of vegetation indices like NDVI reflects phenology, which can be assessed in terms of response to climatic factors' seasonal component. The trend components of the vegetation indices and climatic factors demonstrate interannual changes which can also be assessed in terms of relation and long-term changes. The interrelations of vegetation and climate seasonal and trend components show how vegetation will respond to changes of annual means or seasonal distribution of climatic factors.

The prediction of climate change and understanding how vegetation will respond to that change is one of the main uncertainties and concerns of modern climate and vegetation science. Many models were developed to predict changing climatic features and vegetation response to that. Also, many conventional statistics tools were used to model relations between climatic factors and NDVI (representing vegetation) (Propastin et al. 2007, 2008b; Klein et al. 2012; Gessner et al. 2013; Lu et al. 2014; Formica et al. 2017). Some of these researches considered time-lag for NDVI response to climatic variables, but some of them did not. Obviously, vegetation needs time to respond to climate fluctuations, especially on seasonal scale (Klein et al. 2012; Gessner et al. 2013), so any regression or correlation analysis should consider the delayed effect of climatic factors on vegetation. The response lag and strength also have considerable spatial inhomogeneity, especially in mountains. So spatial variation should also be considered in the analysis. All these peculiarities lead to a simple conclusion – the spatio-temporal analysis of vegetation and climate interactions should use the methods that would avoid spatial and temporal generalization of data available, i.e. analyze the data in all its spatio-temporal complexity, would account for discretization between seasonal and trend components of the signal and consider time lags in vegetation response.

This means that the least squares in identification of trends is not applicable as it violates the assumption of signal stability. ARMA and ARIMA models are applicable only for analysis of interannual trends, as they do not account for seasonality in signal. The researches should not use any spatial or seasonal means for the analysis, as it leads to generalization and data loss. It could be advised that the seasonal and trend decomposition methods are applied on per pixel basis and vegetation and climatic indices compared and tested for relation on a per pixel basis as well, considering temporal lags. In case of multi-seasonal time series Fourier decomposition or Multiple STL could be used.

4.1 Review of climate and vegetation studies

The climate change scenarios for Central Asia predict severe changes (Hijioka et al. 2014), which is why many researches were conducted in the region to investigate the vegetation response to climate change (Lioubimtseva et al. 2005; Lioubimtseva and Cole 2006; Propastin et al. 2008b; Lioubimtseva and Henebry 2009; Klein et al. 2012; Gessner et al. 2013; Zhou et al. 2015; Yin et al. 2016). The researches mostly modelled vegetation behavior approximated by NDVI time series in response to climatic factors, also represented by spatially explicit data, and applied regression analysis to identify polynomial trend of different areas, loosing information about seasonal variations. Others average spatial data of each raster to a numeric string representation, thus creating a one-variable time series suitable for conventional time series decomposition techniques but loosing spatial data. Spatial averaging is good for smoothing local outliers and identification of vegetation trends of the entire area, whereas temporal averaging captures spatial variations avoiding temporal anomalies. So, for a comprehensive study of vegetation dynamics from the remotely sensed data both should be avoided, and temporal and spatial data should be assessed simultaneously in all their spatio-temporal dimensionality.

Normalized Difference Vegetation Index (NDVI) representing a difference of near infrared and red reflection divided by their sum and indicating the density of vital vegetation has become the most popular remotely sensed index for spatial vegetation researches. Global Inventory Modelling and Mapping Studies (GIMMS) and Moderate

Resolution Imaging Spectroradiometer (MODIS) programs provide global databases of NDVI images for almost entire Earth surface with good temporal and spatial resolution for considerable period and free of charge. These data together with different spectral bands provided by Landsat mission represent a combination of vegetation covariates, which are widely used for different vegetation mapping studies as in the region, so globally (Propastin et al. 2007, 2008b, 2008a; Mulder et al. 2011; Klein et al. 2012; Lu et al. 2014; Qiu et al. 2014; Schmidt et al. 2018). However, in mountain areas the different mountain slopes are lit differently depending on their aspect and time of the day, so different slopes may have generally different reflection power, which can result in reflectance difference, attributed solely to the terrain factor. So, the images should be topographically corrected, if it was not done by the image providing service. Topographic correction can easily be done with SAGA GIS (Conrad et al. 2015).

Gessner et al. (2013) conducted one of the most comprehensive climate-vegetation studies for the region. The authors analyzed Central Asian region for spatio-temporal correlation between NDVI and precipitation monthly anomalies. They used AVHRR NDVI time series and GPCC precipitation spatial data. They were looking for correlation between NDVI and precipitation monthly anomalies and precipitation cumulated anomalies, where the respective rasters were shifted in time against NDVI anomalies rasters for 0-3 months. This is a very straight forward approach saving spatial and temporal variations and allowing for easy interpretation of results. The study indicated time-lagged correlations between NDVI and precipitation anomalies, for most of the lowland Kyrgyzstan the lag was 1 month, rarely – 2 months with very few spots of lag 3, which can be neglected. With regards to correlation of NDVI with cumulated precipitation, for most of the lowland Kyrgyzstan the highest correlation rates were found with precipitation anomalies, cumulated over a period of 3 and more months, rarely 2 months. For most of the mountainous areas correlations were insignificant, presumably due to low capacity of NDVI to capture changes in sparse and low vegetation, which is typical for these areas. Authors discovered different correlation rates in different ecosystems and management types.

Klein et al. (2012) conducted land cover classification of Central Asia according to that of FAO-UNEP using MODIS time series and C5.0 algorithm; they compared land cover and land use classes between the years 2001 and 2009. This method of comparing just between two points in time has a negative side – the vegetation phenology, as it is captured by remote sensing, might be a subject of a temporal nonsystematic variation under influence of abiotic factors as precipitation, temperature or human impact. And thus, lead to misjudgment and misclassification of land classes. As it was the case in identification of temporal transition of desert area in Turkmenistan to semi-desert class. Authors have also identified a significant change in Aral Sea and Shardara Water Reservoir levels and transition from rain-fed agriculture to grassland class in northern Kazakhstan.

Nezlin et al., (2005) used Empirical orthogonal functions (like principal component analysis) to decompose raster data time series of NDVI and precipitation in the area around Aral Sea. The data were decomposed to modes for evaluation of spatial and temporal variability. The set of spatial information was four modes represented by four rasters of NDVI and precipitation. And the set of temporal information was four one-variable time series for NDVI and precipitation, which were checked for lagged correlations. The results show that the pattern of precipitation changes and NDVI development throughout the year is like the pattern in our study area and this study discovered a similar time lagged correlation between the first mode of NDVI and first mode of precipitation on the annual scale. The authors discovered different lagged correlations between precipitation and NDVI time series of EOF modes. The most meaningful was the correlation between the fist EOF mode of NDVI and precipitation, it was a positive four-month lagged correlation.

Propastin et al. (2008b) conducted a study on correlation between NDVI and precipitation and temperature for the countries of Central Asia. They considered general spatial averaging for the entire area, averaging for different plant communities and per pixel calculations. They also used several averaged periods for time series data: the entire growing season, spring, summer, and autumn. The authors conducted regression analysis of NDVI images with time as a predictor to identify polynomial trends. A general NDVI increasing trend was discovered for the entire study area. The trend correlated significantly with summer precipitation, whereas summer temperature limited vegetation development. Positive correlation was found between spring temperature and spring NDVI. Forests demonstrated less correlation with temperature and precipitation due to developed root system which can reach ground water and conserve it for a long period. Significant upward trend of spring and summer NDVI was discovered. Significant positive correlation was identified between summer NDVI and summer precipitation, it defined a weaker generally positive correlation. Strong positive correlation was identified between spring NDVI and temperature, whereas for summer the correlation was weaker but negative. In spring, higher temperatures make the growing season start earlier and assist rapid development of green vegetation, whereas in summer higher temperatures are a limiting factor for vegetation development. The authors discovered that positive trends of NDVI are mostly explained by climate factors, whereas the negative ones are not and most likely attributed to human impact.

In another research, Propastin et al. (2008a) studied precipitation impact on NDVI, its trends and segregated NDVI variations caused by climate factors. The authors conducted a regression analysis on a pixel level of NDVI time series for 1981-2000 and precipitation with the later as predictor and used the residuals as indicators of human-induced changes. Furthermore, they took the areas with high significant correlations of NDVI and precipitation and overlapped them with the areas of high NDVI variation explanation by precipitation; the overlapping pixels indicated the areas with trends, caused by precipitation. The authors successfully identified areas with human-induced degradation, the findings were verified by field trips and high-resolution satellite images.

Yin et al. (2016) conducted a study on correlation of NDVI, precipitation and temperature in Central Asia. The authors used temporally averaged remotely sensed time series of the variables with time-lagged correlation analysis and EOF analysis. The study encompasses a period of 1982-2012. NDVI trend showed significant growth from 1982 till 1994 and decrease afterwards. Both, monthly temperature and precipitation were found to affect monthly NDVI. In mountain areas the vegetation was found to be controlled mainly by temperature, whereas on flat areas the vegetation was mainly controlled by precipitation. Temperature and precipitation had different correlation signs with NDVI in different areas. NDVI response lag to temperature was 1 month whereas there was no response lag to precipitation.

Zhou et al. (2015) conducted another research on identification of NDVI interactions with climatic factors before and after collapse of Soviet Union. The authors also used as spatial, so seasonal and annual temporal averaging of NDVI, temperature and precipitation raster time series to identify trends and seasonal variations. Further, the authors conducted linear regression analysis to identify trends from annual values, represented by the slope of least absolute deviation regression line, and lagged correlation analysis to assess the response delay. The research found generally negative precipitation trend and positive temperature trend in most of Central Asia. NDVI trends were increasing in 1982-1991 and decreasing during 1992-2011. The areas with negative trend were mainly in the north of Kazakhstan and Aral See basin. NDVI indicated a positive correlation with precipitation in vegetation period and a negative one in cold season with time lag of 0-3 months. Temperature was a promoting factor for greenness in 1982-1991, and a limiting factor in 1992-2011.

The conducted researches and ours indicate common patterns for vegetation and climate interactions in Central Asia. Precipitation and temperature can be limiting, as well as promoting factors. In cold seasons or on high elevations where temperature is a valuable resource, it has positive impact on vegetation, acting as a promoting factor. Whereas, in flat drylands and in hot summers, it acts as vegetation suppressor. Precipitation is an even more valuable resource in this largely arid region. It is considered as the main controller of vegetation development. The highlands of Central Asia play a role of water towers for the region, accumulating snow in winter and providing water in summer. The researches considering temporal lags, identify in general 1-3 months delay in NDVI reaction to climate variations. However, the studies described above do not consider water from streams in modelling. This is one of the main limitations, which should be considered in future researches. Despite of major methodological shortcomings such as spatial and temporal averaging and ignoring of temporal correlation lags, the researches described above are consistent in their findings and provide a decent overview and analysis of vegetation and climate interactions in the region.

4.2 Vegetation mapping and sampling design

Mapping of vegetation and corresponding sampling design has its similarities and differences to that of soils. The main similarity comes from the fact that in mountains vegetation, just like soils, is very dependent on terrain and slope exposure. This means that all the different terrain features should be covered with samples. However, vegetation, unlike soils, is prone to seasonal variations due to its natural phenology. The choice of mapping and field methods depends on the planned result. If the anticipated map should contain discrete vegetation classes, then classification schemes should be applied. If the resulting map should contain continuous values, like vegetation density or crown density, then the interpolation techniques should be employed.

Vegetation research and the term "sampling" in the context of vegetation mapping can mean different things. Within the framework of this study vegetation sampling means plot surveys of plant communities, physical condition of plants together with cover density according to relevé plots method (Braun-Blanquet 1964). Mapping of different vegetation classes from remotely sensed data should be based on phenological patterns, as they will be main features different between different plant communities. For this, time series of at least monthly remotely sensed images should be utilized, or preferably of even finer temporal resolution. The regular remotely sensed images capture phenological patterns of vegetation, so they can be applied for discrimination of different vegetation classes and they will have different phenological phases. To increase the difference between different temporal phenological patterns seasonal and trend decomposition should be applied on a pixel basis and the images with seasonal component should be used for the training of classification algorithm.

Vegetation in mountains is expected to vary in geographical space with terrain, soil, parent rock and many other factors of physical nature. So, different terrain indices are good covariates to serve as auxiliary data for spatial interpolation of vegetation features. These covariates include elevation, slope steepness, northness (cosine of aspect), eastness (sine of aspect), and different terrain-based wetness indices. The remotely sensed time series, capturing phenology together with terrain factors represent the main features controlling plant communities (apart from human impact), and provide data for discrimination of different vegetation classes. They can be used for production of very accurate vegetation maps (Klein et al. 2012). However, the interpolation or classification algorithms represent another important part of vegetation mapping routine.

As in digital soil mapping, the algorithms are different depending on the task. The interpolation algorithms include simple kriging as well as regression kriging and many others. Simple kriging, just like with soil mapping, in conditions of availability of auxiliary data, is not advised to be applied in mountains. Regression kriging provides much better results, given the covariates are chosen properly. The covariates should predict the variability of the mapped feature with the greatest similarity possible, however they should not cross-corelate, which will lead to model overfitting and prediction of data noise. Application of stepwise multiple regression analysis is a standard approach for selection of the best combination of predictors, which can be applied, however, after collection of field data.

The classification approaches, used for mapping of discrete vegetation classes vary from cluster analysis to neural networks. The simple *k*-means cluster analysis or unsupervised classification can split the research site into *k* number of patches, representing similar areas. The borders of classes can vary greatly depending on the classified rasters selected, and this method (as any other cluster analysis) is good for identification of structure in data if no other knowledge is available. The result does not necessarily represent the real classes and the researcher will have to interpret the results, which are not always meaningful. However, in the case of vegetation mapping the vegetation classes are usually known before the mapping. In most cases supervised classification will be used, where the researcher trains the classification algorithm with the known classes and statistics describing them, which will be used to classify the rest of the study area.

The mapping of continuous values representing different vegetation features, like surface cover percentage, density of tree stand, or probability of certain species occurrence need different modelling methods. Here kriging with auxiliary data (e.g. regression kriging) is the most common approach. Different combinations of remotely sensed vegetation indices or terrain features are used as predictors, depending on the task. Every time the best combination of predictors, describing the modelled feature should be used. If probability of certain species' occurrence is mapped, then terrain features, capturing the main ecological niche of the species is expected to be the main predictors. And in case of vegetation cover density, the remotely sensed vegetation indices like NDVI or EVI (Enhanced Vegetation Index) should be the main covariates.

Sampling design is another important part of vegetation mapping research. It should be well thought through depending on the mapping task, covariates and methods used for development of the map. As said above, vegetation in mountain is very prone to high heterogeneity and shifts from gradual to abrupt changes in geographical space. This requires mapping with auxiliary data, and thus a proper sampling design should be applied. An ideal sampling should cover geographical and feature space, which is a practical approach for regression kriging and other predictor-based models. Stratified random sampling should be applied and the study area should be divided into strata based on variability of predictors if they are known prior to sampling. If not, then the researcher should make an arbitrary choice of predictors to the best of knowledge, which are most likely to control vegetation patterns in study area. The predictor images can be split into different strata with *k*-mean cluster analysis and random points chosen within each cluster, which can be done in most GIS applications. However, in the field it can be difficult to reach the randomly chosen points, in this case the samples should be taken as close as possible to the planned point.

A mapping study is an integrative activity and all the different stages should be carefully planned before field surveys, to minimize expenses for field trips and laboratory analysis, meet the methods assumptions and produce plausible results.

5. Overview of original publications

The main aim of this thesis is to model the interactions of vegetation, climate and soil considering human impact and soil loss. With this regard a combination of approaches was used, which included assessment of vegetation change due to grazing pressure, assessment of soil features and their relation to overgrazing, as well as assessment of soil protection features of vegetation and its dependence on climatic factors. On a broader scale, identification of vegetation and climate interactions were assessed with identification of different patterns of such interactions for the entire country area. The details of the research are provided in the following peer-reviewed publications.

5.1 Article I

The species composition of vegetation was assessed on plots together with possible vegetation change driving factors including terrain and grazing pressure and analyzed using detrended correspondence analysis (DCA).

BORCHARDT, P.; SCHICKHOFF, U.; SCHEITWEILER, S. and **KULIKOV, M.** (2011): Mountain pastures and grasslands in the SW Tien Shan, Kyrgyzstan - Floristic patterns, environmental gradients, phytogeography, and grazing impact. In: Journal of Mountain Science 8, 363–373 https://doi.org/10.1007/s11629-011-2121-8.

Abstract: Vast grasslands are found in the walnut- fruit forest region of southern Kyrgyzstan, Middle Asia. Located above the worldwide unique walnut-fruit forests and used for grazing, they play a pivotal role in the mixed mountain agriculture of local farmers. Accordingly, these pastures are subject to an increasing utilization pressure reflecting the changing political and social conditions in the transformation process from a Soviet republic to an independent state. A first detailed analysis of mountain pasture vegetation in the Fergana Range answers the following questions: What are the main plant community types among Kyrgyzstan's mountain pastures? What are the main

environmental gradients that shape their species composition? Which phytogeographical distribution types are predominant? How does grazing affect community composition and species richness in these grasslands? Species composition was classified by cluster analysis; underlying environmental gradients were explored using DCA. A dataset of 395 relevés was used for classification, and a subset of 79 relevés was used in a DCA to analyze the correlation between vegetation, environment, and grazing impact. The investigated pastures were classified into four distinctive plant communities. The site factors altitude, heat load, inclination and grazing impact were found to be the major determinants of the vegetation pattern. A significant overlap between floristic composition and structural and spatial properties was shown. The majority of the species pool consisted of Middle Asian endemics and Eurosiberian species. However, disturbance-tolerant species played a significant role with respect to species composition and coverage of the herbaceous layer in vast areas of southern Kyrgyzstan's mountain pastures. In general, an intense grazing impact is clearly reflected by both species composition and structural variables of plant communities. The highly diverse and unique ecosystem is modified by an increasing utilization pressure. In order to maintain vital processes and functioning of this valuable ecosystem - in both economic and ecological terms, it is indispensable to adopt appropriate pasture management strategies.

BORCHARDT, P.: Study design, field data collection, data analysis, writing and editing.
SCHICKHOFF, U.: Contribution to study design, field data collection and editing.
SCHEITWEILER, S.: Assistance in field data collection, discussion of study and editing.
KULIKOV, M.: Assistance in field data collection and editing.

5.2 Article II

The elements of RUSLE factors were used to model soil erodibility and vegetation cover protection, based on vegetation information and soil samples collected in the field. They were assessed together with estimation of human impact from grazing, which was evaluated based on cattle densities and interviews of shepherds in the field.

KULIKOV, M.; SCHICKHOFF, U. and BORCHARDT, P. (2016): Spatial and seasonal dynamics of soil loss ratio in mountain rangelands of south-western Kyrgyzstan. In: Journal of Mountain Science 13, 1–14 https://doi.org/10.1007/s11629-1.

Abstract: Vegetation cover is the main factor of soil loss prevention. The C-factor of the RUSLE (Revised Universal Soil Loss Equation) was predicted with NDVI, ground data and exponential regression equation for mountain rangelands of Kyrgyzstan. Time series

of C-factor, precipitation and temperature were decomposed into seasonal and trend components with STL (seasonal decomposition by loess) to assess their interrelations. C-factor, precipitation and temperature trend components indicated significant lagged correlation, whereas seasonal components indicated more complex relations with climate factors which can be promoting as well as limiting factors for vegetation development, depending on the season. Rainy springs and hot summers may increase soil loss dramatically, whereas warm and dry springs with rainy summers can decrease it. Steep slopes indicated higher soil loss ratio, whereas flat areas were better protected by vegetation.

KULIKOV, M.: Study design, field data collection, laboratory analysis, statistical analysis, modelling, writing and editing.

SCHICKHOFF, U.: Contribution to study design, discussion and interpretation of the results and editing.

BORCHARDT, P.: Assistance in field data collection and editing.

5.3 Article III

Soil erodibility on rangelands and its influencing factors were assessed using K-factor of RUSLE. The spatial variation and its dependence on pasture utilization were analyzed and related to grazing pressure.

KULIKOV, M.; SCHICKHOFF, U.; GRÖNGRÖFT, A. and BORCHARDT, P. (2017): Modelling Soil Erodibility in Mountain Rangelands of South-Western Kyrgyzstan. In: Pedosphere https://doi.org/10.1016/S1002-0160(17)60402-8.

Abstract: The main objective of this study was to map soil erodibility in the mountainous rangelands of Kyrgyzstan. The results of this effort are expected to contribute to the development of soil erodibility modelling approaches for mountain areas. In this case study we map soil erodibility at two sites, both representing grazing rangelands in the mountains of Kyrgyzstan and having potentially different levels of grazing pressure. We collected a total of 232 soil samples evenly distributed in geographical and feature space. Then we analyzed the samples in a laboratory for grain size distribution and calculated soil erodibility values from these data using the Revised Universal Soil Loss Equation (RUSLE) K-factor formula. After that we derived different terrain indices and ratios of frequency bands from ASTER DEM and Landsat images to use as auxiliary data because they are among the main soil forming factors and widely used for prediction of various soil properties. Soil erodibility meaningfully correlated with channel network base level (geographically extrapolated altitude of water channels), remotely sensed indices of short-wave infrared spectral bands, exposition and slope. We applied multiple regression analysis to predict soil erodibility from spatially explicit terrain and remotely sensed indices. The final soil erodibility model was developed using the spatially explicit predictors and the regression equation and then improved by adding the residuals. The spatial resolution of the model was 30 meters and the estimated mean adjusted coefficient of determination was $R^2 = 0.47$. The two sites indicated different estimated and predicted means of soil erodibility values (0.035 and 0.039) with 0.95 significance level, which is attributed mainly to the considerable difference in elevation.

KULIKOV, M.: Study design, field data collection, laboratory analysis, statistical analysis, modelling, writing and editing.
SCHICKHOFF, U.: Contribution to study design, discussion and interpretation of the results and editing.
GRÖNGRÖFT, A.: Contribution to study design, discussion and interpretation of the results and editing.
BORCHARDT, P.: Assistance in field data collection and editing.

5.4 Article IV

The vegetation variation and its relations with climatic factors were assessed based on spatio-temporal analysis of remotely sensed time series, representing NDVI and climatic factors, such as land surface temperature and precipitation.

KULIKOV, M. and SCHICKHOFF, U. (2017): Vegetation and climate interaction patterns in Kyrgyzstan: spatial discretization based on time series analysis. In: Erdkunde 71, 143–165 https://doi.org/10.3112/erdkunde.2017.02.04.

Abstract: Spatio-temporal variations of climate-vegetation interactions in Central Asia have been given a lot of attention recently. However, some serious methodological drawbacks of previous studies prevented thorough assessment of such interactions. In order to avoid the limitations and improve the analysis we used spatially explicit time series of NDVI (normalized difference vegetation index), temperature and precipitation which were decomposed to seasonal and trend components on per-pixel basis using STL (seasonal decomposition of time series by loess). Trend and seasonal components of NDVI, precipitation and temperature were assessed pixelwise for temporal correlations with different lags to understand the patterns of their interaction in Kyrgyzstan and adjoining regions. Based on these results a coefficient of determination was calculated to understand the extent to which NDVI is conditioned by precipitation and temperature variations. The images with the lags of time series correlation minima and maxima for

each pixel and coefficients of NDVI determination by temperature and precipitation were subjected to cluster analysis to identify interaction patterns over the study area. The approach used in this research differs from previous regional studies by implementation of seasonal decomposition and analyzing the full data without spatial or seasonal averaging within predetermined limits prior to the analysis. NDVI response to temperature and precipitation was assumed to be spatially variable in its sign, strength and lag, thus a separate model was developed for each pixel. The results were assessed with cluster analysis to identify spatial patterns of temporal interactions, decrease dimensionality and facilitate their comprehensiveness. The research resulted in 5 spatial clusters with different patterns of NDVI interaction with temperature and precipitation on intra- and interannual scales. The highest correlation scores between NDVI and temperature at the seasonal scale were found at 0-4 months lag and between NDVI and precipitation at 1-5 months lag. At high elevations of 3000-4000 m above sea level, both precipitation and temperature occurred to be facilitating factors for vegetation development, whereas temperature was rather a limiting factor at lower elevations of 200-1300 m a.s.l. We developed maps of the NDVI coefficient of determination by both temperature and precipitation. Only deserts and glaciers had low coefficients of determination (adjusted R^2) on the seasonal scale (0.1-0.3), whereas areas with vegetation were greatly conditioned by temperature and precipitation (0.7-0.95). On the trend scale, dense vegetation and bare areas had low coefficient of determination (0.1-0.3), whereas areas with average vegetation cover were greatly controlled by the climatic factors (0.7-0.9).

KULIKOV, M.: Study design, data collection, statistical analysis, modelling, writing and editing.

SCHICKHOFF, U.: Contribution to study design, discussion and interpretation of the results and editing.

6. Results

A total of 174 species of vascular plants were observed in the study site. The species were identified to form four major plant communities, which explained 12.5% of feature variation. The first community was the richest in species number, occurred on the steepest slopes and was characterized by several alpine species, which included *Aconogonon coriarium*, *Prangos pabularia* and *Ligularia thomsonii* as the most frequent. The second community occurred at high elevations – above 2800 m a.s.l. and typically had *Aulacospermum simplex, Heracleum dissectum, Aster alpinus, Phlomoides oreophila* and *Phlomoides speciosa*. The third community was the highly degraded one with sparse vegetation and included *Medicago lupulina* and *Arenaria serpyllifolia*, together with *Carex turkestanica, Eremurus fuscus* and *Ziziphora clinopodioides*. And the fourth community occurred on flat areas with high grazing and trampling impact and was characterized by *Plantago major, Polygonum aviculare, Taraxacum officinale, Urtica dioica, Malva neglecta* and *Capsella bursapastoris.*

Grazing was indicated to have great impact on floristic gradients on the rangelands of Fergana ridge (grazing impact, $r = -0.6$). The grazing impact on the first community was lower than on the other three, this can be attributed to the steepness of slopes, generally occupied by this community. In the third and the fourth plant community ruderal species occupied relatively high proportion of cover (29% and 59% respectively). Whereas in the first and second plant communities the percentage of ruderal vegetation was relatively low.

Vegetation features for soil protection (C-factor) was identified to follow the following equation (Residual standard error: 0.08677 on 172 degrees of freedom):

$$SLR = exp(-0.7842 - 2.9298 \times NDVI) \quad \textbf{(2)}$$

where *SLR* – soil loss ratio (C-factor) and *NDVI* – Normalized Difference Vegetation Index. This equation indicates nonlinear nature of NDVI-SLR relation. The nonlinear equation also helps do deal with extreme values of NDVI or SLR, as its graph tails never cross the axes. This equation corresponded very closely to similar equation, developed by de Jong et al. (1998) for Europe, which, however, cannot properly handle the extreme values due to its linearity. The slopes steeper than 35° are generally the least protected against soil erosion, mainly because these are the areas of landslides and sparse vegetation. C-factor and slope steepness correlated significantly with a coefficient of +0.38. After modeling, the pasture closer to human settlement indicated a higher soil loss ratio (Uch-Choku, C-factor = 0.27) then the remote one (Otuz-Art, C-factor = 0.20), suggesting a higher grazing pressure on the close pastures then on the remote ones and a greater soil loss consequently.

Temporarily, C-factor is the highest in spring, indicating the lowest soil protection by vegetation due to little vegetation cover after the winter. At the same time spring and early summer are the months with the highest precipitation level, which makes this season contributing the most to the annual soil loss. The lowest C-factor values are observed in May-June when the vegetation is fully developed and not yet oppressed by summer heat or grazed by animals. In summer the C-factor increases gradually due to grazing and solar radiation. Generally, C-factor had immediate positive correlation with temperature (+0.6) and a negative one with 6 months lag with precipitation (-0.6), which follows the common pattern of vegetation development in the study site, where precipitation is generally a promoting factor for vegetation and temperature is an oppressing factor.

The analysis of soil samples has also demonstrated a greater soil erodibility (K-factor) on steeper slopes and higher elevations, and lower erodibility at valley bottoms and flat areas. About 21% of collected soil samples had fine texture, 31% - medium-fine and 48% - medium texture, according to European Soil Bureau Working Group (2015) The mean soil erodibility was 0.0374 t ha h ha^{-1} MJ^{-1} mm^{-1} (standard deviation 0.0048), which, like C-factor, was also comparable with the values of European fine, medium-fine and medium soils reported by Knijff et al. (2000). The K-factor had significant correlation with Channel Network Base Level (Conrad et al. 2015) (+0.55), eastness (sine of aspect in radians) (+0.19), slope degree (+0.21) and Soil Enhancement Ratio (Boettinger et al. 2008) (-0.54). The regression analysis of K-factor and abovementioned covariates gave the following equation (adj. R^2 = 0.3611):

$$K\text{-}factor = 2.684E\text{-}02 + 9.658E\text{-}06 \times CNBL - 2.46E\text{-}02 \times SER + 8.8E\text{-}04 \times \sin(A) \quad \textbf{(3)}$$

where *CNBL* – Channel Network Base Level (Conrad et al. 2015), *SER* – Soil Enhancement Ratio (Boettinger et al. 2008), *A* – aspect in radians (*sin(A)* - eastness). After modeling, the pasture closer to human settlement indicated a higher soil erodibility

(Uch-Choku, K-factor = 0.039 t ha h ha^{-1} MJ^{-1} mm^{-1}) then the remote pasture (Otuz-Art, K-factor = 0.035 t ha h ha^{-1} MJ^{-1} mm^{-1}), again, suggesting a higher grazing pressure on the close pastures then on the remote ones. The model accuracy assessment indicated R^2 = 0.47.

The assessment of vegetation and climate interactions for the whole country revealed that vegetation (approximated by NDVI) in general has a positive correlation with precipitation and a negative one with temperature on flat areas. The cluster analysis of the interaction patterns resulted in five spatial clusters, representing five distinctive patterns of such interactions (Figure 5).

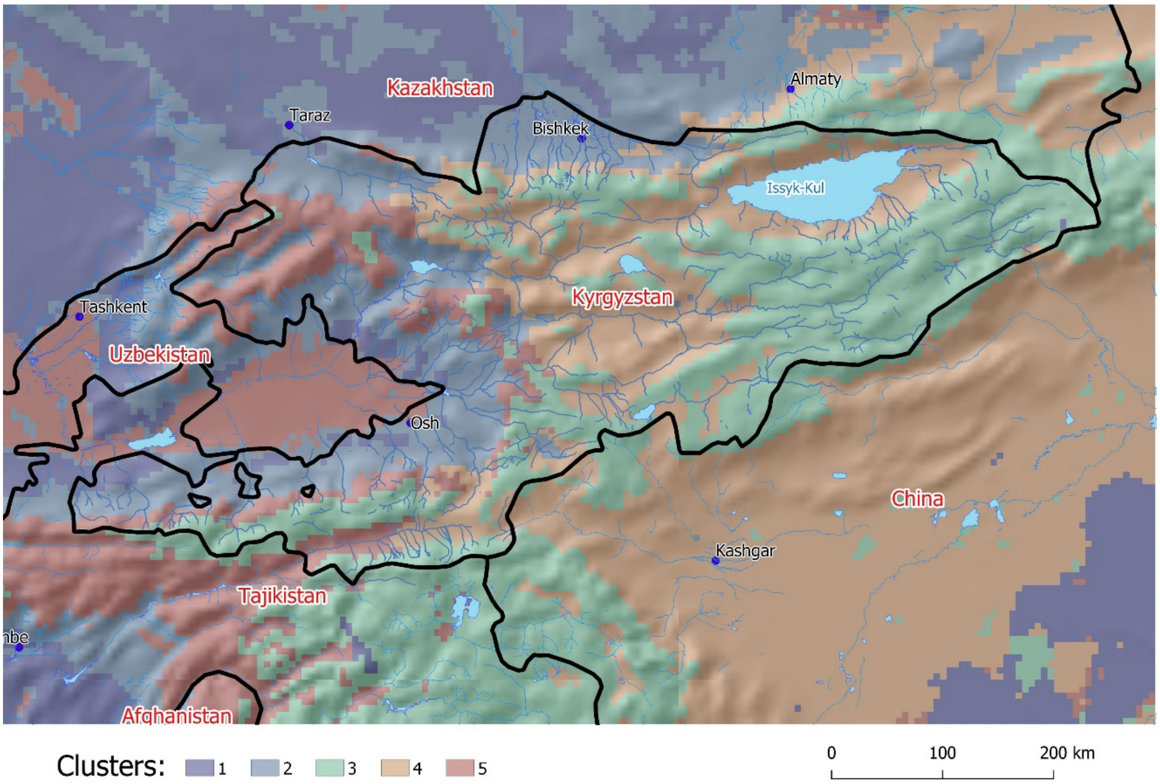

Figure 5. Spatial clusters of vegetation-climate interactions.

The first cluster represents deserts or desert-steppes with strong positive vegetation-precipitation correlation with 1-month lag and strong negative vegetation-temperature correlation with 4 months lag. Precipitation here is clearly a promoting factor for vegetation, but temperature is a promoting factor in spring at the beginning of vegetation period and is a limiting factor in summer when high temperatures and low precipitation oppress vegetation. This is the hottest area among other clusters. About 62% (mean of seasonal and trend variations) of vegetation variation was explained by temperature and precipitation.

The second cluster is mainly foothills of Fergana, Chatkal and Kyrgyz Ala-Too ridges. This area is mainly used for agriculture and pastoralism and is well watered with rivers and irrigation channels. NDVI has positive correlation with precipitation with the lag of 4 months and immediate positive correlation with temperature, but high temperatures do slightly oppress vegetation in late summer. However, interannually vegetation generally develops better in moist years and worse in hot years. This area receives the most precipitation and is the most vegetated among other clusters, including most of the forests in the area. About 74.5% (mean of seasonal and trend variations) of vegetation variation was explained by the climatic factors.

The third cluster is mainly highland tundra in Pamir, Alai and Central Tian-Shan, which are used as winter pastures. Here NDVI has immediate positive correlation with temperature and precipitation – with 1-2 months lag. However, interannually vegetation develops better in warm years and worst in years with lots of precipitation. This is because on this elevation the limiting factor for vegetation is rather low temperature, whereas moistening is largely available due to low evapotranspiration. This is the coldest and the least vegetated area among other clusters. About 73% (mean of seasonal and trend variations) of vegetation variation is explained by temperature and precipitation.

The fourth cluster is mainly intermontane depressions of Inner Tian-Shan and flat plains in Xinjiang region of China. NDVI has positive correlation with temperature and precipitation with 0-1-month lag. Interannually, vegetation tends to develop better next year after a cool year with high precipitation level. About 73.5% (mean of seasonal and trend variations) of vegetation variation is explained by the climatic factors. It is the area with the least precipitation level among other clusters, because they occur in the precipitation shadows of Fergana and Kokshal-Too ranges, at the same time the temperatures here are high with poor vegetation development.

The fifth cluster covers Fergana valley and slopes of Fergana, Chatkal and Alai ridges. This is the area of intensively irrigated agriculture. Seasonally, vegetation (approximated by NDVI) indicates positive correlation with temperature with no lag and positive correlation with precipitation with 5 months lag. This is explained by the system of artificial irrigation, which collects and holds spring precipitation to redistribute the water to crop fields in summer. Otherwise, the vegetation would develop in late spring and be heavily oppressed by summer heat. This is supported by the interannual correlations – vegetation develops better in the years with sufficient precipitation and worse in dry and hot years. About 70.5% (mean of seasonal and trend variations) of NDVI variations are explained by the climatic factors. This area receives slightly below the maximum precipitation (the second cluster) and has about the average level of temperature and vegetation, which explains its agricultural suitability.

The research undertaken quantifies the relations between soil, vegetation and climatic factors, allowing for modelling of potential outcomes in case of changes of the components. The results indicate that grazing has an impact on species richness of plant communities in rangelands. Intensive grazing and trampling leads to vegetation cover decrease and increases soil loss, especially on slopes. A sustainable grazing system considering plant communities and their phenology, annual precipitation cycle and terrain could decrease the grazing impact, while still providing the appropriate level of forage. Terrain is among main factors, influencing plant communities and soil patterns. Mountain areas indicate great heterogeneity with regards to soil, vegetation and climatic factors, which are mainly controlled by terrain features. Climatic factors greatly influence vegetation development. In lowlands, temperature is a promoting factor in spring and a limiting factor in summer for vegetation development, precipitation is a rare and valuable resource. Whereas, in highlands heat is a valuable resource and is always a promoting factor for vegetation, water is always available due to lower evapotranspiration. However, a clever irrigation system can level the water scarcity and extract profit from fertile soils, high temperatures and longer vegetation periods in lowlands.

7. Conclusions and outlook

Mountain ecosystems represent a complex of interacting agents including terrain, soils, vegetation, wildlife, climate, human activities and many others. A good research with practical implications should consider all of them, however it is almost unrealistic to do such a thorough assessment. The project “The Impact of the Transformation Process on Human-Environment Interactions in Southern Kyrgyzstan”, funded by the Volkswagen Foundation, Hannover, Germany, which this Ph.D. work is a part of, is a good example of such systematic approach.

The main aim of this Ph.D. thesis is to quantify the interactions between soil, vegetation and climate, considering the human impact on natural resources. For this field data on soil and vegetation were collected during three field seasons. Local shepherds were interviewed about amount of livestock, pasturing strategies and livelihoods. The soil samples collected in the field were analyzed in soil laboratory for pH, grain size distribution and organic content. The raw data were analyzed with statistical instruments and used in modelling together with spatial remotely sensed auxiliary data.

Soil modelling demonstrated grazing impact on soil erodibility and mapped the risks of soil loss with their relation to topography and grazing pressure. It also revealed soil patterns and suggested possible management solution for decreasing soil loss on mountain rangelands. Modelling and statistical inference allow to decrease research costs, however, this is not enough for thorough assessment and understanding of actual soil loss, as every modelling needs validation by ground experiments. The ground experiments should include long-term regular runoff plots and rainfall registration in all the different soil provinces of Kyrgyzstan, and since there are many of them due to mountainous soil variability, the costs are anticipated to be great. Unfortunately, soil studies are very scarce in modern Kyrgyzstan due to economic situation. There is only one known experiment on runoff plots, which took place in Issyk-Kul region in 1950th and lasted for just several years.

In Soviet times a thorough soil mapping was done for the entire country, it also included soil loss assessment, but the soil classes do not correspond to modern FAO World Reference Base and need translation. However, the soil erosion risk assessments were mostly based on terrain and vegetation features. Kyrgyzgiprozem Institute holds an extensive database on soil and vegetation resources of Kyrgyzstan and conducts regular field trips to update the data, however these field trips are not sufficient, and the data are restricted to governmental use and are not open to wider scientific community.

Development of RUSLE model for the entire country is an important task. And it will not require much investment, the costliest would be the construction of runoff plots for model validation. R-factor could be calculated from the meteorological data collected by Kyrgyzgidromet (Hydro-Meteorological service of Kyrgyzstan). The entire country is covered with a network of metheorological stations conducting regular observations since early 20th century and this agency has large database on weather parameters including rainfall intensity. These data could be used for development of R-factor map of the country, however the data are not digitized, as the old pluviographs record rainfall intensity on paper. Furthermore, Kyrgyzgidromet also does not provide the data openly, but sells them at a restricting price.

K-factor and C-factor can be derived from the data collected by Kyrgyzgiprozem Institute, several field trips and laboratory analysis will be needed to update the existing data on soils and vegetation and some work will be needed to harmonize the collected data to RUSLE standards and measuring units, which is a matter of recalculation. Thorough geobotanical mapping was done also during Soviet times. However, the heavily grazed areas may need updating as plant communities might have changed there. The collected soil and vegetation information can be extrapolated to create K-factor and C-factor maps with the techniques of soil and vegetation mapping outlined above.

Likewise, the LS-factor can easily be calculated for the entire country using SRTM or ASTER GDEM elevation models, openly available for the entire country. P-factor can be generally ignored and accepted being equal to 1 as no soil conservation practices are applied throughout the country on a systematic basis.

Considering the above said, the development of soil loss model for Kyrgyzstan based on RUSLE does not look like a difficult project. However, the disaggregation of state agencies, lack of expertise and motivation, together with mismanagement of valuable data makes this task hardly achievable.

Climate change adaptation is another issue which should be seriously considered in natural resource management. Few studies concentrate on Kyrgyzstan, but rather on broader scale. Economic impact of climate change is also poorly assessed. The assessment should consider impact on separate species as well as ecosystems, modelling of the consequences and possible coping strategies.

The main stressing source for pasture ecosystems is human impact. Many studies were conducted to investigate the social dimension. They covered labor migration, livelihoods strategies, transhumance and grazing pressure together with different economical strategies and reasons influencing natural resource use. However, this did not result in any policies from the government apart from another pasture reform, which is not being successful. Several international development agencies pursue their agendas with different projects, but they do not follow common line, which leads to even more obscurity in regulations.

It is obvious, that there should be programs and policies incentivizing local population to diverse livelihoods to more environmentally-friendly activities like bee-keeping etc., or applying better practices, like pasture infrastructure, transporting or keeping animals in corals at high elevation pastures and using less animals of more productive breeds. Instead of small household farms there should be bigger agricultural enterprises to increase production efficiency and economic capacity. The processing facilities of agricultural products should also be developed to increase the added value to the final product. The vegetation resources and pasture carrying capacity should be assessed and transhumance must be strictly managed accordingly. This will increase the total income of local communities, make resource use more sustainable and create funds for research and nature conservation. However, such programs will require serious investments and proper management.

Given current economic situation in the country, the work outlined above can be only carried out with funding support of international development and research agencies. Despite of the availability of spatial data, the new technologies and the advanced modelling approaches, there is still a lot of work for scientific community on exploration of mountains of Central Asia. With this, there is a hope that the region will no longer be a white spot on the international scientific map.

List of publications

Original publication in the framework of this Ph.D. thesis:

BORCHARDT, P.; SCHICKHOFF, U.; SCHEITWEILER, S. and **KULIKOV, M.** (2011): Mountain pastures and grasslands in the SW Tien Shan, Kyrgyzstan - Floristic patterns, environmental gradients, phytogeography, and grazing impact. In: Journal of Mountain Science 8, 363–373 https://doi.org/10.1007/s11629-011-2121-8.

KULIKOV, M.; SCHICKHOFF, U. and BORCHARDT, P. (2016): Spatial and seasonal dynamics of soil loss ratio in mountain rangelands of south-western Kyrgyzstan. In: Journal of Mountain Science 13, 1–14 https://doi.org/10.1007/s11629-1.

KULIKOV, M.; SCHICKHOFF, U.; GRÖNGRÖFT, A. and BORCHARDT, P. (2017): Modelling Soil Erodibility in Mountain Rangelands of South-Western Kyrgyzstan. In: Pedosphere https://doi.org/10.1016/S1002-0160(17)60402-8.

KULIKOV, M. and SCHICKHOFF, U. (2017): Vegetation and climate interaction patterns in Kyrgyzstan: spatial discretization based on time series analysis. In: Erdkunde 71, 143–165 https://doi.org/10.3112/erdkunde.2017.02.04.

Additional publicaitons:

MALLON, D. and **KULIKOV, M.** (2015): Transboundary Snow Leopard Conservation in Central Asia: Report of the FFI/CMS Workshop, 1-2 December 2014.

Oral presentations

KULIKOV, M. (2011a): Presentation of the Ph.D. project and preliminary results. Arbeitskreis Biogeographie, Hamburg, Germany.

KULIKOV, M. (2011b): Application of the USLE to rangeland condition of Kyrgyzstan. Pastoralism in Central Asia, Bishkek, Kyrgyzstan.

KULIKOV, M. (2012): RUSLE Model of Soil Erosion on Alpine Grazing Lands of South Kyrgyzstan. Arbeitskreis Hochgebirge, Munich, Germany.

KULIKOV, M. (2014a): Soil loss modelling on mountain pastures (poster). Russian Geographic Society, summer school, Kaluga region, Russia.

KULIKOV, M. (2014b): Forest conservation in Kyrgyzstan. Society for Conservation Biology, Asia Section, Melaka, Malaysia.

KULIKOV, M. (2015): Assessment of NDVI reaction to precipitation and temperature in temporal and spatial domains on a country scale. Ingernational Geographic Union annual meeting in Moscow, Russia.

KULIKOV, M. (2016): Conservation of the fruit and nut forests in Kyrgyzstan. Society for Conservation Biology, Asia Section, Singapore.

KULIKOV, M. (2018): Vegetation and climate interaction patterns in Kyrgyzstan: spatial discretization based on time series analysis. Society for Conservation Biology, Asia Section, Bishkek, Kyrgyzstan.

References

ADDIS, H. K. and KLIK, A. (2015): Predicting the spatial distribution of soil erodibility factor using USLE nomograph in an agricultural watershed, Ethiopia. In: International Soil and Water Conservation Research 3, 282–290 https://doi.org/10.1016/j.iswcr.2015.11.002.

ADYSHEV; M.M.; KASHIRIN; F.T.; UMURZAKOV; S.U.; ALMAEV; T.M.; VORONINA; A.F.; GRIGORENKO; P.G.; DZHAMGERCHINOV; B.D.; ZABIROV; R.D.; ZINKOVA; Z.Y.; IZMAILOV; A.E.; ISABAEVA; V.A.; KRAVCHENKO; A.V.; MAMYTOV; A.M.; MAKHRINA; L.I.; MOLDOKULOV; A.M.; MURZAEV; E.M.; OTORBAEV; K.O.; POPOVA; L.I.; YAR-MUKHAMEDOV; G.K.; YASHINA; V.V. and CHERNOVA; L.I. (1987): Atlas Kirgizskoi SSR (vol. I) (in Russian). Moscow.

APEL, H.; ABDYKERIMOVA, Z.; AGALHANOVA, M.; BAIMAGANBETOV, A.; GAVRILENKO, N.; GERLITZ, L.; KALASHNIKOVA, O.; UNGER-SHAYESTEH, K.; VOROGUSHYN, S. and GAFUROV, A. (2018): Statistical forecast of seasonal discharge in Central Asia using observational records: development of a generic linear modelling tool for operational water resource management. In: Hydrology and Earth System Sciences 22, 2225–2254 https://doi.org/10.5194/hess-22-2225-2018.

ATAMANOV, A. and VAN DEN BERG, M. (2012): Heterogeneous Effects of International Migration and Remittances on Crop Income: Evidence from the Kyrgyz Republic. In: World Development 40, 620–630 https://doi.org/10.1016/J.WORLDDEV.2011.07.008.

BAI, Z. G.; DENT, D. L.; OLSSON, L. and SCHAEPMAN, M. E. (2008): Proxy global assessment of land degradation. In: Soil Use and Management 24, 223–234 https://doi.org/10.1111/j.1475-2743.2008.00169.x.

BASKAN, O.; CEBEL, H.; AKGUL, S. and ERPUL, G. (2010): Conditional simulation of USLE/RUSLE soil erodibility factor by geostatistics in a Mediterranean Catchment, Turkey. In: Environmental Earth Sciences 60, 1179–1187 https://doi.org/10.1007/s12665-009-0259-2.

BISHOP, T.F.A. and MINASNY, B. (2006): Digital Soil-Terrain Modeling: The Predictive Potential and Uncertainty. In: GRUNWALD, S. (ed.): Environmental soil-landscape modeling: geographic information technologies and pedometrics. 185–213.

BOETTINGER, J.L.; HOWELL, D.W.; MOORE, A.C.; HARTEMINK, A. S. and KIENAST-BROWN, S. (2010): Digital Soil Mapping. In: BOETTINGER, J. L., HOWELL, D. W., MOORE, A. C., HARTEMINK, A. E. and KIENAST-BROWN, S. (eds.): Progress in Soil Science. Dordrecht, Heidelberg, London, New York, 462, https://doi.org/10.1007/978-90-481-8863-5.

BOETTINGER, J.L.; RAMSEY, R.D.; BODILY, J.M.; COLE, N.J.; KIENAST-BROWN, S.; NIELD, S.J.; SAUNDERS, A.M. and STUM, A.K. (2008): Landsat Spectral Data for Digital Soil Mapping. In: HARTEMINK, A. E., MCBRATNEY, A. B. and MENDONCA-SANTOS, M. DE L. (eds.): Digital Soil Mapping with Limited Data. 193–203.

BÖHNER, J. and ANTONIĆ, O. (2009): Chapter 8 Land-Surface Parameters Specific to Topo-Climatology. In: Developments in Soil Science 33, 195–226 https://doi.org/10.1016/S0166-2481(08)00008-1.

BÖHNER, J. and BECHTEL, B. (2018): GIS in Climatology and Meteorology. Comprehensive Geographic Information Systems. 196–235, https://doi.org/10.1016/B978-0-12-409548-9.09633-0.

BORCHARDT, P.; OLDELAND, J.; PONSENS, J. and SCHICKHOFF, U. (2013): Plant functional traits match grazing gradient and vegetation patterns on mountain pastures in SW Kyrgyzstan. In: Phytocoenologia 43, 171–181 https://doi.org/10.1127/0340-269X/2013/0043-0542.

BORCHARDT, P.; SCHICKHOFF, U.; SCHEITWEILER, S. and KULIKOV, M. (2011): Mountain pastures and grasslands in the SW Tien Shan, Kyrgyzstan - Floristic patterns, environmental gradients, phytogeography, and grazing impact. In: Journal of Mountain Science 8, 363–373 https://doi.org/10.1007/s11629-011-2121-8.

BORCHARDT, P.; SCHMIDT, M. and SCHICKHOFF, U. (2010): Vegetation patterns in Kyrgyzstan’s walnut-fruit forests under the impact of changing forest use in post-soviet transformation. In: Erde 141, 255–275.

BRAUN-BLANQUET; J. (1964): Pflanzensoziologie. Third edition., Wien (in German), https://doi.org/10.1007/978-3-7091-8110-2.

BROWN, L. C. and FOSTER, G. R. (1987): Storm Erosivity Using Idealized Intensity Distributions. In: Transactions of the ASAE 30, 0379–0386 https://doi.org/10.13031/2013.31957.

BRUS, D. J. (2015): Balanced sampling: A versatile sampling approach for statistical soil surveys. In: Geoderma 253–254, 111–121 https://doi.org/10.1016/j.geoderma.2015.04.009.

BRUS, D. J. and HEUVELINK, G. B. M. (2007): Optimization of sample patterns for universal kriging of environmental variables. In: Geoderma 138, 86–95 https://doi.org/10.1016/j.geoderma.2006.10.016.

CAIAG (2018): Kyrgyzstan Disater Risk Data Platform. http://geonode.mes.kg/.

CHANG, X.; BAO, X.; WANG, S.; ZHU, X.; LUO, C.; ZHANG, Z. and WILKES, A. (2016): Exploring effective sampling design for monitoring soil organic carbon in degraded Tibetan grasslands. In: Journal of Environmental Management 173, 121–126 https://doi.org/10.1016/j.jenvman.2016.03.010.

CHEN, F.; HUANG, W.; JIN, L.; CHEN, J. and WANG, J. (2011): Spatiotemporal precipitation variations in the arid Central Asia in the context of global warming. In: Science China Earth Sciences 54, 1812–1821 https://doi.org/10.1007/s11430-011-4333-8.

CLEVELAND, R. B.; CLEVELAND, W. S.; MCRAE, J. E. and TERPENNING, I. (1990): STL: A seasonal-trend decomposition procedure based on loess. In: Journal of Official Statistics 6, 3–73 https://doi.org/citeulike-article-id:1435502.

CLIFFORD, D.; PAYNE, J. E.; PRINGLE, M. J.; SEARLE, R. and BUTLER, N. (2014): Pragmatic soil survey design using flexible Latin hypercube sampling. In: Computers & Geosciences 67, 62–68 https://doi.org/10.1016/j.cageo.2014.03.005.

CONRAD, O.; BECHTEL, B.; BOCK, M.; DIETRICH, H.; FISCHER, E.; GERLITZ, L.;

WEHBERG, J.; WICHMANN, V. and BÖHNER, J. (2015): System for Automated Geoscientific Analyses (SAGA) v. 2.1.4. In: Geoscientific Model Development 8, 1991–2007 https://doi.org/10.5194/gmd-8-1991-2015.

COUGHENOUR, M.; BEHNKE, R.; LOMAS, J. and PRICE, K. (2008): Forage Distributions, Range Condition, and the Importance of Pastoral Movement in Central Asia - A Remote Sensing Study. The Socio-Economic Causes and Consequences of Desertification in Central Asia. Dordrecht, 45–80, https://doi.org/10.1007/978-1-4020-8544-4_4.

CREWETT, W. (2012): Improving the Sustainability of Pasture Use in Kyrgyzstan. In: Mountain Research and Development 32, 267–274 https://doi.org/10.1659/MRD-JOURNAL-D-11-00128.1.

DOKUCHAEV; V.V. (1883): Russian chernozem (in Russian).

DOMENECH, M. B.; CASTRO-FRANCO, M.; COSTA, J. L. and AMIOTTI, N. M. (2017): Sampling scheme optimization to map soil depth to petrocalcic horizon at field scale. In: Geoderma 290, 75–82 https://doi.org/10.1016/j.geoderma.2016.12.012.

DÖRRE, A. and BORCHARDT, P. (2012): Changing Systems, Changing Effects—Pasture Utilization in the Post-Soviet Transition. In: Mountain Research and Development 32, 313–323 https://doi.org/10.1659/MRD-JOURNAL-D-11-00132.1.

DOTTERWEICH, M. (2013): The history of human-induced soil erosion: Geomorphic legacies, early descriptions and research, and the development of soil conservation-A global synopsis. In: Geomorphology 201, 1–34 https://doi.org/10.1016/j.geomorph.2013.07.021.

DUBOVYK, O.; LANDMANN, T.; DIETZ, A. and MENZ, G. (2016): Quantifying the Impacts of Environmental Factors on Vegetation Dynamics over Climatic and Management Gradients of Central Asia. In: Remote Sensing 8, 600 https://doi.org/10.3390/rs8070600.

EUROPEAN SOIL BUREAU WORKING GROUP (2015): HYdraulic PRoperties of European Soils" (HYPRES). Texture classes. http://www.macaulay.ac.uk/hypres/hypressoil.html.

FARRINGTON, J. D. (2005): De-Development in Eastern Kyrgyzstan and Persistence of Semi-nomadic Livestock Herding. In: Nomadic Peoples 9, 171–197 https://doi.org/10.3167/082279405781826191.

FORMICA, A. F.; BURNSIDE, R. J. and DOLMAN, P. M. (2017): Rainfall validates MODIS-derived NDVI as an index of spatio-temporal variation in green biomass across non-montane semi-arid and arid Central Asia. In: Journal of Arid Environments 142, 11–21 https://doi.org/10.1016/j.jaridenv.2017.02.005.

FOSTER; G.R.; YODER; D.C.; WEESIES; G.A.; MCCOOL; D.K.; MCGREGOR; K.C. and BINGNER; R.L. (2002): User's Guide-Revised Universal Soil Loss Equation Version 2 (RUSLE 2). Washington, DC, USA.

FOTHERINGHAM; A.S.; BRUNSDON; C. and CHARLTON; M. (2002): Geographically weighted regression : the analysis of spatially varying relationships.

FU, B. J.; ZHAO, W. W.; CHEN, L. D.; ZHANG, Q. J.; LÜ, Y. H.; GULINCK, H. and POESEN, J. (2005): Assessment of soil erosion at large watershed scale using RUSLE and GIS: a case study in the Loess Plateau of China. In: Land Degradation & Development 16, 73–85 https://doi.org/10.1002/ldr.646.

GENG, R.; ZHANG, G.; LI, Z.-W. and WANG, H. (2015): Spatial variation in soil resistance to flowing water erosion along a regional transect in the Loess Plateau. In: Earth Surface Processes and Landforms 40, 2049–2058 https://doi.org/10.1002/esp.3779.

GERLITZ, L. (2015): Using fuzzified regression trees for statistical downscaling and regionalization of near surface temperatures in complex terrain. In: Theoretical and Applied Climatology 122, 337–352 https://doi.org/10.1007/s00704-014-1285-x.

GERLITZ, L.; CONRAD, O. and BÖHNER, J. (2015): Large-scale atmospheric forcing and topographic modification of precipitation rates over High Asia – a neural-network-based approach. In: Earth System Dynamics 6, 61–81 https://doi.org/10.5194/esd-6-61-2015.

GERLITZ, L.; CONRAD, O.; THOMAS, A. and BÖHNER, J. (2014): Warming patterns over the Tibetan Plateau and adjacent lowlands derived from elevation- and bias-corrected ERA-Interim data. In: Climate Research 58, 235–246 https://doi.org/10.3354/cr01193.

GESSNER, U.; NAEIMI, V.; KLEIN, I.; KUENZER, C.; KLEIN, D. and DECH, S. (2013): The relationship between precipitation anomalies and satellite-derived vegetation activity in Central Asia. In: Global and Planetary Change 110, 74–87 https://doi.org/10.1016/j.gloplacha.2012.09.007.

GIDROMET SSSR; G.U.G.S. PRI S.M.; GIDROMET KSSR; U.G.S. and OBSERVATORIYA; F.G. (1967): Reference book on USSR climate. Kirgizskaya SSR. (in Russian). Leningrad.

GUERRA, A. J. T.; FULLEN, M. A.; JORGE, M. DO C. O.; BEZERRA, J. F. R. and SHOKR, M. S. (2017): Slope Processes, Mass Movement and Soil Erosion: A Review. In: Pedosphere 27, 27–41 https://doi.org/10.1016/S1002-0160(17)60294-7.

GULTEPE, I. (2015): Mountain Weather: Observation and Modeling. In: Advances in Geophysics 56, 229–312 https://doi.org/10.1016/BS.AGPH.2015.01.001.

GURGEL, H. C. and FERREIRA, N. J. (2003): Annual and interannual variability of NDVI in Brazil and its connections with climate. In: International Journal of Remote Sensing 24, 3595–3609 https://doi.org/10.1080/0143116021000053788.

HANGARTNER; J. (2002): Dependent on snow and flour: Organization of herding life and socio-economic strategies of Kyrgyz mobile pastoralists in Murghab, Eastern Pamir, Tajikistan. (Lizentiat), Universität Bern, Bern.

HENGL, T.; HEUVELINK, G. B. M. and STEIN, A. (2004): A generic framework for spatial prediction of soil variables based on regression-kriging. In: Geoderma 120, 75–93 https://doi.org/10.1016/j.geoderma.2003.08.018.

HEUNG, B.; HO, H. C.; ZHANG, J.; KNUDBY, A.; BULMER, C. E. and SCHMIDT, M. G. (2016): An overview and comparison of machine-learning techniques for classification purposes in digital soil mapping. In: Geoderma 265, 62–77 https://doi.org/10.1016/J.GEODERMA.2015.11.014.

HEUVELINK, G. B. M. and WEBSTER, R. (2001): Modelling soil variation: past, present, and future. In: Developments and Trends in Soil Science 100, 269–301 https://doi.org/http://dx.doi.org/10.1016/S0016-7061(01)00025-8.

HIJIOKA, Y.; LIN, E.; PEREIRA, J.J.; CORLETT, R.T.; CUI, X.; INSAROV, G.E.; LASCO, R.D.; LINDGREN, E. and SURJAN, A. (2014): Asia. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. 1327–1370.

HOPPE, F.; SCHICKHOFF, U. and OLDELAND, J. (2017): Plant species diversity of pastures in the Naryn Oblast (Kyrgyzstan). In: DIE ERDE.

HOPPE, F.; ZHUSUI KYZY, T.; USUPBAEV, A. and SCHICKHOFF, U. (2016a): Rangeland degradation assessment in Kyrgyzstan: vegetation and soils as indicators of grazing pressure in Naryn Oblast. In: Journal of Mountain Science 13, 1567–1583 https://doi.org/10.1007/s11629-016-3915-5.

HOPPE, F.; ZHUSUI KYZY, T.; USUPBAEV, A. and SCHICKHOFF, U. (2016b): Contrasting grazing impact on seasonal pastures reflected by plant functional traits: Search for patterns in Kyrgyz rangelands. In: GEOÖKO 37, .

ILIASOV, S. A.; TITOVA, L. I. and YAKIMOV, V. M. (2003): Basic (climate) scenarios for vulnerability assesment (in Russian). In: Vestnik KRSU.

IONOV; R.N. and LEBEDEVA; L.N.; SHUKUROV; E.D. (ed.) (2005): Vegetation cover of West Tian-Shan (review of modern satus of flora and vegetation) (in Russian). Bishkek.

ISAEVA, A. and SHIGAEVA, J. (2017): Soviet Legacy in the Operation of Pasture Governance Institutions in Present-Day Kyrgyzstan. In: Revue de géographie alpine https://doi.org/10.4000/rga.3631.

IUSS WORKING GROUP WRB (2014): World reference base for soil resources 2014. International soil classification system for naming soils and creating legends for soil maps. World Soil Resources Reports No. 106. https://doi.org/10.1017/S0014479706394902.

JELASKA, S. D. (2009): Chapter 21 Vegetation Mapping Applications. In: Developments in Soil Science 33, 481–496 https://doi.org/10.1016/S0166-2481(08)00021-4.

JENNY, H. (1941): Factors of Soil Formation. In: Soil Science 52, 415 https://doi.org/10.1097/00010694-194111000-00009.

DE JONG, R.; DE BRUIN, S.; DE WIT, A.; SCHAEPMAN, M. E. and DENT, D. L. (2011): Analysis of monotonic greening and browning trends from global NDVI time-series. In: Remote Sensing of Environment 115, 692–702 https://doi.org/10.1016/j.rse.2010.10.011.

DE JONG, S. M.; BROUWER, L. C. and RIEZEBOS, H. T. (1998): Erosion hazard assessment in the La Peyne catchment, France.

KAMELIN; R.I. (1973): Floristic-genetic analysis of natural flora of Central Asian mountains (in Russian). Nauka. Leningrad.

KARABURUN, A. (2010): Estimation of C factor for soil erosion modeling using NDVI in Buyukcekmece watershed. In: Ozean Journal of Applied Sciences 3, 77–85.

KARYDAS, C. G.; PANAGOS, P. and GITAS, I. Z. (2014): A classification of water erosion models according to their geospatial characteristics. In: International Journal of Digital Earth 7, 229–250 https://doi.org/10.1080/17538947.2012.671380.

KARYDAS, C. G.; SEKULOSKA, T. and SILLEOS, G. N. (2009): Quantification and site-specification of the support practice factor when mapping soil erosion risk associated with olive plantations in the Mediterranean island of Crete. In: Environmental Monitoring and Assessment 149, 19–28 https://doi.org/10.1007/s10661-008-0179-8.

KERVEN; C.; STEIMANN; B.; ASHLEY; L.; DEAR; C. and RAHIM; I. (2011): Pastoralism and Farming in Central Asia's Mountains: A Research Review. https://doi.org/10.5167/uzh-52730.

KERVEN, C.; STEIMANN, B.; DEAR, C. and ASHLEY, L. (2012): Researching the Future of Pastoralism in Central Asia's Mountains: Examining Development Orthodoxies. In: Mountain Research and Development 32, 368–377 https://doi.org/10.1659/MRD-JOURNAL-D-12-00035.1.

KINNELL, P. I. A. (2017): A comparison of the abilities of the USLE-M, RUSLE2 and WEPP to model event erosion from bare fallow areas. In: Science of The Total Environment 596–597, 32–42 https://doi.org/10.1016/j.scitotenv.2017.04.046.

KLEIN, I.; GESSNER, U. and KUENZER, C. (2012): Regional land cover mapping and change detection in Central Asia using MODIS time-series. In: Applied Geography 35, 219–234 https://doi.org/Doi 10.1016/J.Apgeog.2012.06.016.

KNIJFF, J. VAN DER; JONES, R. R. J. A.; MONTANARELLA, L. and VAN DER KNIJFF, J. M. (2000): Soil erosion risk assessment in Europe.

KOROVIN; E.P. (1961): Vegetation of Middle (Central) Asia and South Kazakhstan (in Russian). Tashkent.

KUZMICHENOK; V.A.; PODREZOV; O.A. (ed.) (2008): Digital models of Kyrgyzstan's moisture characteristics (in Russian).

KYRGYZGIDROMET (1989): Scientific and applied reference book on the climate of the USSR - Kirgizskaya SSR. Issue 32., Leningrad (in Russian).

KYRGYZGIDROMET (2015): Current climate status and change in the Kyrgyz Republic. Bishkek.

DE LA MARTINIÈRE, R. (2012): Rural Livelihood Trajectories Around a "Bull Market" in Kyrgyzstan. In: Mountain Research and Development 32, 337–344 https://doi.org/10.1659/MRD-JOURNAL-D-11-00098.1.

LAZKOV; G.A. and SULTANOVA; B.A.; SENNIKOV; A.N. (ed.) (2011): Checklist of vascular plants of Kyrgyzstan. Bishkek.

LE, Q.B.; NKONYA, E. and MIRZABAEV, A. (2016): Biomass Productivity-Based Mapping of Global Land Degradation Hotspots. Economics of Land Degradation and Improvement – A Global Assessment for Sustainable Development. Cham, 55–84, https://doi.org/10.1007/978-3-319-19168-3_4.

LEE, J.-H. and HEO, J.-H. (2011): Evaluation of estimation methods for rainfall erosivity based on annual precipitation in Korea. In: Journal of Hydrology 409, 30–48 https://doi.org/10.1016/J.JHYDROL.2011.07.031.

LIEß, M. (2015): Sampling for regression-based digital soil mapping: Closing the gap between statistical desires and operational applicability. In: Spatial Statistics 13, 106–122 https://doi.org/10.1016/j.spasta.2015.06.002.

LIOUBIMTSEVA, E. and COLE, R. (2006): Uncertainties of Climate Change in Arid Environments of Central Asia. In: Reviews in Fisheries Science 14, 29–49 https://doi.org/10.1080/10641260500340603.

LIOUBIMTSEVA, E.; COLE, R.; ADAMS, J. M. and KAPUSTIN, G. (2005): Impacts of climate and land-cover changes in arid lands of Central Asia. In: Journal of Arid Environments 62, 285–308 https://doi.org/10.1016/j.jaridenv.2004.11.005.

LIOUBIMTSEVA, E. and HENEBRY, G. M. (2009): Climate and environmental change in arid Central Asia: Impacts, vulnerability, and adaptations. In: Journal of Arid Environments 73, 963–977 https://doi.org/10.1016/j.jaridenv.2009.04.022.

LIU, R.; XIAO, L.; LIU, Z. and DAI, J. (2018): Quantifying the relative impacts of climate and human activities on vegetation changes at the regional scale. In: Ecological Indicators 93, 91–99 https://doi.org/10.1016/J.ECOLIND.2018.04.047.

LIU, Y.; WU, J.; LIU, Y.; HU, B. X.; HAO, Y.; HUO, X.; FAN, Y.; YEH, T. J. and WANG, Z.-L. (2015): Analyzing effects of climate change on streamflow in a glacier mountain catchment using an ARMA model. In: Quaternary International 358, 137–145 https://doi.org/10.1016/J.QUAINT.2014.10.001.

LU, L.; GUO, H.; KUENZER, C.; KLEIN, I.; ZHANG, L. and LI, X. (2014): Analyzing phenological changes with remote sensing data in Central Asia. In: IOP Conference Series: Earth and Environmental Science 17, 12005 https://doi.org/10.1088/1755-1315/17/1/012005.

MAMYTOV; A.M. (1971): Soil Resources and the Issues of Soil Cadastre of Kirgiz SSR (in Russian). Frunze.

MAMYTOV; A.M. (1974): Soils of Kyrgyz SSR (in Russian). Frunze.

MAMYTOV; A.M. and ASHIRAKHMANOV; S.A.; MURZAIKINA MOISEENKO, T.V.; T.K. (ed.) (1988): Soils (in Russian). Natural Resources of Kyrgyz SSR. Tashkent.

MARTZ, L. W. (1992): The variation of soil erodibility with slope position in a cultivated canadian prairie landscape. In: Earth Surface Processes and Landforms 17, 543–556 https://doi.org/10.1002/esp.3290170602.

MAYNARD, J. J. and LEVI, M. R. (2017): Hyper-temporal remote sensing for digital soil mapping: Characterizing soil-vegetation response to climatic variability. In: Geoderma 285, 94–109 https://doi.org/10.1016/J.GEODERMA.2016.09.024.

McBratney, A. .; Mendonça Santos, M. . and Minasny, B. (2003): On digital soil mapping. In: Geoderma 117, 3–52 https://doi.org/10.1016/S0016-7061(03)00223-4.

Mikhailov; D.Y. (1949): Soils of Kirgizia and their erosion (in Russian).

Mikhailov; D.Y. (1959): Soil erosion in Kyrgyz SSR (in Russian). Frunze.

Minasny, B. and McBratney, A. B. (2006): A conditioned Latin hypercube method for sampling in the presence of ancillary information. In: Computers and Geosciences 32, 1378–1388 https://doi.org/10.1016/j.cageo.2005.12.009.

Minasny, B. and McBratney, A. B. (2016): Digital soil mapping: A brief history and some lessons. In: Geoderma 264, 301–311 https://doi.org/10.1016/J.GEODERMA.2015.07.017.

Mirzabaev, A.; Ahmed, M.; Werner, J.; Pender, J. and Louhaichi, M. (2016): Rangelands of Central Asia: challenges and opportunities. In: Journal of Arid Land 8, 93–108 https://doi.org/10.1007/s40333-015-0057-5.

Mulder, V. L.; de Bruin, S.; Schaepman, M. E. and Mayr, T. R. (2011): The use of remote sensing in soil and terrain mapping — A review. In: Geoderma 162, 1–19 https://doi.org/10.1016/J.GEODERMA.2010.12.018.

NatStatCom; Sultanov; A.; Orosbaev; A.; Tekeeva; L.; Turdubaeva; C.; Biryukova; V. and Isenkulova; E. (eds.) (2018): Kyrgyzstan, Brief Statistical Handbook. Bishkek.

Nearing, M. A. (2000): Evaluating soil erosion models using measured plot data: accounting for variability in the data. In: Earth Surface Processes and Landforms 25, 1035–1043 https://doi.org/10.1002/1096-9837(200008)25:9<1035::AID-ESP121>3.0.CO;2-B.

Omuto, C. T.; Vargas, R. R.; Alim, M. S. and Paron, P. (2010): Mixed-effects modelling of time series NDVI-rainfall relationship for detecting human-induced loss of vegetation cover in drylands. In: Journal of Arid Environments 74, 1552–1563 https://doi.org/10.1016/j.jaridenv.2010.04.001.

Ostovari, Y.; Ghorbani-Dashtaki, S.; Bahrami, H.-A.; Naderi, M. and Dematte, J. A. M. (2017): Soil loss prediction by an integrated system using RUSLE, GIS and remote sensing in semi-arid region. In: Geoderma Regional https://doi.org/10.1016/j.geodrs.2017.06.003.

Panagos, P.; Borrelli, P.; Poesen, J.; Ballabio, C.; Lugato, E.; Meusburger, K.; Montanarella, L. and Alewell, C. (2015): The new assessment of soil loss by water erosion in Europe. In: Environmental Science & Policy 54, 438–447 https://doi.org/10.1016/J.ENVSCI.2015.08.012.

Panagos, P.; Christos, K.; Cristiano, B. and Ioannis, G. (2014a): Seasonal monitoring of soil erosion at regional scale: An application of the G2 model in Crete focusing on agricultural land uses. In: International Journal of Applied Earth Observation and Geoinformation 27, 147–155 https://doi.org/10.1016/J.JAG.2013.09.012.

Panagos, P.; Meusburger, K.; Alewell, C. and Montanarella, L. (2012): Soil erodibility estimation using LUCAS point survey data of Europe. In: Environmental

Modelling and Software 30, 143–145 https://doi.org/10.1016/j.envsoft.2011.11.002.

PANAGOS, P.; MEUSBURGER, K.; BALLABIO, C.; BORRELLI, P. and ALEWELL, C. (2014b): Soil erodibility in Europe: A high-resolution dataset based on LUCAS. In: Science of The Total Environment 479–480, 189–200 https://doi.org/10.1016/j.scitotenv.2014.02.010.

PIAO, S.; WANG, X.; CIAIS, P.; ZHU, B.; WANG, T. and LIU, J. (2011): Changes in satellite-derived vegetation growth trend in temperate and boreal Eurasia from 1982 to 2006. In: Global Change Biology 17, 3228–3239 https://doi.org/10.1111/j.1365-2486.2011.02419.x.

POMAZKOV; K.D.; ELYUTIN; D.N.; KNAUF; V.I.; KOROLEV; V.G.; ADYSHEV; M.M.; POYARKOV; B.V. and FEDORCHUK; V.P.; SIDORENKO; A.V..; GORBUNOV; G.I..; MALINOVSKIY; F.M..; PEIVE; A.V..; ASSOVSKIY; A.N..; BELOUSOV; V.V..; BELYAEVSKIY; N.A..; BOGDANOV; A.A..; BORUKAEV; R.A..; BOROVIKOV; L.I..; GARKOVEC; V.G..; DZOCENIDZE; G.S..; ESENOV; S.E..; ZUBAREV; B.M..; KOPTEV-DVORNIKOV; V.S..; KOSOV; B.M..; KUZNECOV; Y.A..; MAGAKYAN; I.G..; MALYSHEV; I.I..; MARKOVSKIY; A.P..; MASHRYKOV; K.K..; MENNER; V.V..; MIRLIN; G.A..; MIRCHINK; M.F..; MURATOV; M.V..; NALIVKIN; D.V..; ORVIKU; K.K..; POPOV; V.S..; ROGOVSKAYA; N.V..; ROJKOV; I.S..; SEMENENKO; N.P..; SEMENOVICH; V.V..; SMIRNOV; V.I..; TROFIMUK; A.A..; SHATALOV; E.T..; SHEGLOV; A.D..; YANSHIN; A.L.. and YALMOLYUK; V.A. (eds.) (1972): Kirgiz SSR, Geological Description (in Russian). Geology of the USSR. Moscow.

PREVENTIONWEB (2018): Kyrgyzstan, Disaster & Risk Profile. https://www.preventionweb.net/countries/kgz/data/.

PROPASTIN, P. A.; KAPPAS, M.; ERASMI, S. and MURATOVA, N. R. (2007): Remote sensing based study on intra-annual dynamics of vegetation and climate in drylands of Kazakhastan. In: Basic and Applied Dryland Research 1, 138–154 https://doi.org/10.1127/badr/1/2007/138.

PROPASTIN, P. A.; KAPPAS, M. and MURATOVA, N. R. (2008a): A remote sensing based monitoring system for discrimination between climate and human-induced vegetation change in Central Asia. In: Management of Environmental Quality: An International Journal 19, 579–596 https://doi.org/http://dx.doi.org/10.1108/14777830810894256.

PROPASTIN, P. A.; KAPPAS, M. and MURATOVA, N. R. (2008b): Inter-annual changes in vegetation activities and their relationship to temperature and precipitation in Central Asia from 1982 to 2003. In: Journal of Environmental Informatics 12, 75–87 https://doi.org/10.3808/jei.200800126.

QIU, B.; LI, W.; ZHONG, M.; TANG, Z. and CHEN, C. (2014): Spatiotemporal analysis of vegetation variability and its relationship with climate change in China. In: Geo-spatial Information Science 17, 170–180 https://doi.org/10.1080/10095020.2014.959095.

QIU, B.; WANG, Z.; TANG, Z.; LIU, Z.; LU, D.; CHEN, C. and CHEN, N. (2016): A multi-scale spatiotemporal modeling approach to explore vegetation dynamics patterns under global climate change. In: GIScience & Remote Sensing 53, 596–613 https://doi.org/10.1080/15481603.2016.1184741.

RABOT, E.; WIESMEIER, M.; SCHLÜTER, S. and VOGEL, H.-J. (2018): Soil structure as an indicator of soil functions: A review. In: Geoderma 314, 122–137 https://doi.org/10.1016/J.GEODERMA.2017.11.009.

RACHKOVSKAYA, E.I. and BRAGINA, T.M. (2012): Steppes of Kazakhstan: Diversity and Present State. 103–148, https://doi.org/10.1007/978-94-007-3886-7_3.

REEUWIJK; V.L. (2006): Procedures for soil analysis, 7th edition. Technical Paper 9. Sixth edition.

RENARD; K.; FOSTER; G.; WEESIES; G.; MCCOOL; D. and YODER; D. (1996): Predicting soil erosion by water: a guide to conservation planning with the Revised Universal Soil Loss Equation. Agriculture Handbook No. 703. Washington, D.C.

RENARD, K. G. and FREIMUND, J. R. (1994): Using monthly precipitation data to estimate the R-factor in the revised USLE. In: Journal of Hydrology 157, 287–306 https://doi.org/10.1016/0022-1694(94)90110-4.

DE SANTOS LOUREIRO, N. and DE AZEVEDO COUTINHO, M. (2001): A new procedure to estimate the RUSLE EI30 index, based on monthly rainfall data and applied to the Algarve region, Portugal. In: Journal of Hydrology 250, 12–18 https://doi.org/10.1016/S0022-1694(01)00387-0.

SCHLESINGER, W. H.; REYNOLDS, J. F.; CUNNINGHAM, G. L.; HUENNEKE, L. F.; JARRELL, W. M.; VIRGINIA, R. A. and WHITFORD, W. G. (1990): Biological feedbacks in global desertification. In: Science (New York, N.Y.) 247, 1043–8 https://doi.org/10.1126/science.247.4946.1043.

SCHMIDHUBER, J. (2015): Deep learning in neural networks: An overview. In: Neural Networks 61, 85–117 https://doi.org/10.1016/J.NEUNET.2014.09.003.

SCHMIDT, K. M.; ROERING, J. J.; STOCK, J. D.; DIETRICH, W. E.; MONTGOMERY, D. R. and SCHAUB, T. (2001): The variability of root cohesion as an influence on shallow landslide susceptibility in the Oregon Coast Range. In: Canadian Geotechnical Journal 38, 995–1024 https://doi.org/10.1139/t01-031.

SCHMIDT, M. and SAGYNBEKOVA, L. (2008): Migration past and present: changing patterns in Kyrgyzstan. In: Central Asian Survey 27, 111–127 https://doi.org/10.1080/02634930802355030.

SCHMIDT, S.; ALEWELL, C. and MEUSBURGER, K. (2018): Mapping spatio-temporal dynamics of the cover and management factor (C-factor) for grasslands in Switzerland. In: Remote Sensing of Environment 211, 89–104 https://doi.org/10.1016/j.rse.2018.04.008.

SCHOCH, N.; STEIMANN, B. and THIEME, S. (2010): Migration and animal husbandry: Competing or complementary livelihood strategies. Evidence from Kyrgyzstan. In: Natural Resources Forum 34, 211–221 https://doi.org/10.1111/j.1477-8947.2010.01306.x.

SCHÖNBRODT, S.; SAUMER, P.; BEHRENS, T.; SEEBER, C. and SCHOLTEN, T. (2010): Assessing the USLE crop and management factor C for soil erosion modeling in a large mountainous watershed in Central China. In: Journal of Earth Science 21, 835–

845 https://doi.org/10.1007/s12583-010-0135-8.

SCULL, P.; FRANKLIN, J.; CHADWICK, O. A. and MCARTHUR, D. (2003): Predictive soil mapping: a review. In: Progress in Physical Geography 27, 171–197 https://doi.org/10.1191/0309133303pp366ra.

SHABANI, F.; KUMAR, L. and ESMAEILI, A. (2014): Improvement to the prediction of the USLE K factor. In: Geomorphology 204, 229–234 https://doi.org/10.1016/J.GEOMORPH.2013.08.008.

SHIGAEVA, J.; HAGERMAN, S.; ZERRIFFI, H.; HERGARTEN, C.; ISAEVA, A.; MAMADALIEVA, Z. and FOGGIN, M. (2016): Decentralizing Governance of Agropastoral Systems in Kyrgyzstan: An Assessment of Recent Pasture Reforms. In: Mountain Research and Development 36, 91–101 https://doi.org/10.1659/MRD-JOURNAL-D-15-00023.1.

SHIGAEVA, J.; KOLLMAIR, M.; NIEDERER, P. and MASELLI, D. (2007): Livelihoods in transition: changing land use strategies and ecological implications in a post-Soviet setting (Kyrgyzstan). In: Central Asian Survey 26, 389–406 https://doi.org/10.1080/02634930701702696.

SHISHKOVA, V. A.; POPOVA, L. I.; MAKAROVA, L. E.; MALYKHINA, G. G. and CHEREMNYKH, M. A. (1989): Vegetion of Kirgiz SSR (in Russian).

SHUKUROV; E.D.; MITROPOLSKIY; O. V.; TALSKIH; V.N.; JOLDUBAEVA; L.Y. and V.V.; S. (2005): Atlas of biological diversity of West Tian-Shan in Russian. Bishkek.

STEIMANN; B. (2011): Making a living in uncertainty : agro-pastoral livelihoods and institutional transformations in post-socialist rural Kyrgyzstan.

STEIMANN, B. (2012): Conflicting Strategies for Contested Resources: Pastoralists' Responses to Uncertainty in Post-socialist Rural Kyrgyzstan. 145–160, https://doi.org/10.1007/978-94-007-3846-1_8.

STUMPF, F.; SCHMIDT, K.; GOEBES, P.; BEHRENS, T.; SCHÖNBRODT-STITT, S.; WADOUX, A.; XIANG, W. and SCHOLTEN, T. (2017): Uncertainty-guided sampling to improve digital soil maps. In: CATENA 153, 30–38 https://doi.org/10.1016/j.catena.2017.01.033.

TESHEBAEVA, K. and MOLDOBEKOV, B. (2010): Monitoring and prediction of natural disasters in Kyrgyzstan. Bishkek.

TIWARI, A. K.; TIWARI, A. K.; RISSE, L. M. and NEARING, M. A. (2000): Evaluation of WEPP and its comparison with USLE and RUSLE. In: Transactions of the ASAE v. 43, 1129-1135–2000 v.43 no.5.

VAŠÁT, R.; HEUVELINK, G. B. M. and BORŮVKA, L. (2010): Sampling design optimization for multivariate soil mapping. In: Geoderma 155, 147–153 https://doi.org/10.1016/j.geoderma.2009.07.005.

VEMU, S. and PINNAMANENI, U. (2011): Estimation of spatial patterns of soil erosion using remote sensing and GIS: a case study of Indravati catchment. In: Natural Hazards 59, 1299–1315 https://doi.org/10.1007/s11069-011-9832-6.

VYKHODTSEV; I.V. (1956a): Vertical zonation of vegetation in Kirgizia (in Russian).

Moscow.

VYKHODTSEV; I.V. (1956b): Vegetation of Pastures and Hayfields of Kirgiz SSR (in Russian). Frunze.

VYKHODTSEV; I.V. (1966): Geobotanical research in Kirgizia (in Russian). Frunze.

WANG, B.; ZHENG, F. and GUAN, Y. (2016): Improved USLE-K factor prediction: A case study on water erosion areas in China. In: International Soil and Water Conservation Research https://doi.org/10.1016/j.iswcr.2016.08.003.

WIEDER, W. L. and SHOOP, S. A. (2018): State of the knowledge of vegetation impact on soil strength and trafficability. In: Journal of Terramechanics 78, 1–14 https://doi.org/10.1016/J.JTERRA.2018.03.006.

WISCHMEIER; W.H. and SMITH; D.D. (1978): Predicting rainfall erosion losses. Agriculture handbook no. 537. Washington, D.C., https://doi.org/10.1029/TR039i002p00285.

XIN, Z.; XU, J. and ZHENG, W. (2008): Spatiotemporal variations of vegetation cover on the Chinese Loess Plateau (1981—2006): Impacts of climate changes and human activities. In: Science in China Series D: Earth Sciences 51, 67–78 https://doi.org/10.1007/s11430-007-0137-2.

YANG, L.; ZHU, A.-X.; ZHAO, Y.; LI, D.; ZHANG, G.; ZHANG, S. and BAND, L. E. (2017): Regional Soil Mapping Using Multi-Grade Representative Sampling and a Fuzzy Membership-Based Mapping Approach. In: Pedosphere 27, 344–357 https://doi.org/10.1016/S1002-0160(17)60322-9.

YIN, G.; HU, Z.; CHEN, X. and TIYIP, T. (2016): Vegetation dynamics and its response to climate change in Central Asia. In: Journal of Arid Land 8, 375–388 https://doi.org/10.1007/s40333-016-0043-6.

ZHANG, K.; LI, S.; PENG, W. and YU, B. (2004): Erodibility of agricultural soils on the Loess Plateau of China. In: Soil and Tillage Research 76, 157–165 https://doi.org/10.1016/j.still.2003.09.007.

ZHANG, Q.; WANG, L. and WU, F. (2008): GIS-Based Assessment of Soil Erosion at Nihe Gou Catchment. In: Agricultural Sciences in China 7, 746–753 https://doi.org/10.1016/S1671-2927(08)60110-8.

ZHANG, S.-J.; ZHU, A.-X.; LIU, J.; YANG, L.; QIN, C.-Z. and AN, Y.-M. (2016a): An heuristic uncertainty directed field sampling design for digital soil mapping. In: Geoderma 267, 123–136 https://doi.org/10.1016/j.geoderma.2015.12.009.

ZHANG, W.; ZHANG, X. and GAO, Z. (2009): Factor value determination and applicability evaluation of universal soil loss equation in granite gneiss region. In: Water Science and Engineering 2, 87–97 https://doi.org/10.3882/J.ISSN.1674-2370.2009.02.010.

ZHANG, W.; ZHOU, J.; FENG, G.; WEINDORF, D. C.; HU, G. and SHENG, J. (2015): Characteristics of water erosion and conservation practice in arid regions of Central Asia: Xinjiang, China as an example. In: International Soil and Water Conservation Research 3, 97–111 https://doi.org/10.1016/J.ISWCR.2015.06.002.

ZHANG, Y.; ZHANG, C.; WANG, Z.; CHEN, Y.; GANG, C.; AN, R. and LI, J. (2016b): Vegetation dynamics and its driving forces from climate change and human activities in the Three-River Source Region, China from 1982 to 2012. In: Science of The Total Environment 563, 210–220 https://doi.org/10.1016/j.scitotenv.2016.03.223.

ZHOU, Y.; ZHANG, L.; FENSHOLT, R.; WANG, K.; VITKOVSKAYA, I. and TIAN, F. (2015): Climate Contributions to Vegetation Variations in Central Asian Drylands: Pre- and Post-USSR Collapse. In: Remote Sensing 7, 2449–2470 https://doi.org/10.3390/rs70302449.

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Article I

BORCHARDT, P.; SCHICKHOFF, U.; SCHEITWEILER, S. and **KULIKOV, M.** (2011): Mountain pastures and grasslands in the SW Tien Shan, Kyrgyzstan - Floristic patterns, environmental gradients, phytogeography, and grazing impact. In: Journal of Mountain Science 8, 363–373 https://doi.org/10.1007/s11629-011-2121-8.

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Mountain Pastures and Grasslands in the SW Tien Shan, Kyrgyzstan – Floristic Patterns, Environmental Gradients, Phytogeography, and Grazing Impact

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Abstract: Vast grasslands are found in the walnut-fruit forest region of southern Kyrgyzstan, Middle Asia. Located above the worldwide unique walnut-fruit forests and used for grazing, they play a pivotal role in the mixed mountain agriculture of local farmers. Accordingly, these pastures are subject to an increasing utilization pressure reflecting the changing political and social conditions in the transformation process from a Soviet republic to an independent state. A first detailed analysis of mountain pasture vegetation in the Ferghana Range answers the following questions: What are the main plant community types among Kyrgyzstan's mountain pastures? What are the main environmental gradients that shape their species composition? Which phytogeographical distribution types are predominant? How does grazing affect community composition and species richness in these grasslands? Species composition was classified by cluster analysis; underlying environmental gradients were explored using DCA. A dataset of 395 relevés was used for classification, and a subset of 79 relevés was used in a DCA to analyze the correlation between vegetation, environment, and grazing impact. The investigated pastures were classified into four distinctive plant communities. The site factors altitude, heat load, inclination and grazing impact were found to be the major determinants of the vegetation pattern. A significant overlap between floristic composition and structural and spatial properties was shown. The majority of the species pool consisted of Middle Asian endemics and Eurosiberian species. However, disturbance-tolerant species played a significant role with respect to species composition and coverage of the herbaceous layer in vast areas of southern Kyrgyzstan's mountain pastures. In general, an intense grazing impact is clearly reflected by both species composition and structural variables of plant communities. The highly diverse and unique ecosystem is modified by an increasing utilization pressure. In order to maintain vital processes and functioning of this valuable ecosystem - in both economical and ecological terms -, it is indispensable to adopt appropriate pasture management strategies.

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Keywords: Central Asia; Classification; Endemics; Gradient Analysis; Grazing impact; Middle Asia; Pasture Management; Ruderals; Transformation Process; Walnut-fruit forest.

Nomenclature: We follow Czerepanov (1995) for all vascular plants except for *Amoria*, which was considered here as *Trifolium*. In accordance with Cowan (2007), we use the term 'Middle Asia' for the region of the former Soviet Central Asian Republics Kazakhstan, Turkmenistan, Uzbekistan, Tajikistan and Kyrgyzstan.

Abbreviations: DCA = Detrended Correspondence Analysis, IV = Indicator Value, ISA = Indicator Species Analysis, NPMR = Non-parametric Multiplicative Regression, CV = Coefficient of Variation, SD = Standard Deviation.

Introduction

The collapse of the Soviet Union and the independence of the Middle Asian republics in 1991 were followed by far-reaching transformation processes that fundamentally reshaped political, socio-economic and ecological conditions in Kyrgyzstan. During the last century, the relationship between humans and the environment has substantially changed for the second time (Schmidt 2001; Schmidt 2005). Kyrgyzstan is well known for the ridges and isolated valleys of the Tien Shan Mountains. Before the 1930s, nomadism was predominant in the region and characterized the type of land use (Ludi 2003). In summer, nomads used to graze their herds on mountain pastures. In winter, low temperatures and snow forced them to descend to lower altitudes. The sedentary lifestyle was imposed upon the Kyrgyz people during Soviet times, when the economic system was defined by strict plans, which were practically implemented by state farms (*sovkhozes* and *kolkhozes*). After 1991, state farms have been dismantled; land and livestock were privatized. For the majority of the population, returning to subsistence economy was the only opportunity to sustain their livelihood (Schmidt 2007), and specialized employees suddenly became farmers. Today, large collective farms and herds no longer exist in Kyrgyzstan, but animal husbandry is again an important source of income at household level. After 70 years of Soviet rule, these new independent farmers are often lacking comprehensive agricultural knowledge. Used to a sedentary lifestyle, they now strongly depend on natural resources and social services available close to their villages. Therefore, farmers today tend to over-utilize pastures close to settlements, whereas less accessible pastures are frequently abandoned (Ludi 2003).

In recent years, several studies focused on the interdependent use of forests and grazing lands within the changing local land use system (e.g. Schmidt 2005; Schmidt 2008). Other studies dealt with aspects of plant communities and vegetation ecology of the walnut-fruit forests (e.g. Epple 2001; Gottschling et al. 2005; Borchardt et al. 2010). By contrast, there is no information on plant communities of mountain pastures and their relationships with the environment so far. In general, research on mountain grassland vegetation is still in its infancy in the Tien Shan, even though phytosociology has a long tradition in the former Soviet Union (e.g. Shennikov 1964; Mirkin & Shelyagsosonko 1984; Mirkin 1987; Korotkov et al. 1991).

Presenting a first detailed analysis of mountain pasture vegetation in the Ferghana Range, SW Tien Shan, this paper is based on a compilation of data that were collected over four years (2005–2009). The baseline study aims at (1) analyzing the floristic-sociological differentiation of (sub-) alpine pastures and providing a classification of the plant communities; (2) examining interrelations between vegetation differentiation, underlying environmental gradients, grazing impact, and α-diversity (species richness); and (3) analyzing composition of phytogeographical patterns of plant communities and interpreting chorological spectra of species assemblages.

1 Study Area

The study was conducted in *rayon* Bazar Korgon, Arslanbob region, north of Jalalabad in the Ferghana Range of southern Kyrgyzstan (41° N, 73° E) (Figure 1), where mountain pastures extend over a vast area of approx. 25,000 ha. They form an extensive altitudinal vegetation zone above the walnut-fruit forests ranging from an altitude of 1,800 to 3,200 m.

New palynological results show that the walnut-fruit forests originated only 1,000-2,000 years BP in their present appearance, and that they had very likely been established as a consequence of human land use (Beer et al. 2008, own unpublished data). The potential natural vegetation of the examined mountain pastures is maple-apple-walnut forests at lower altitudes, followed by open juniper forests above 1,900 m (see Grisa et al. 2008).

According to the engineer-geological map (Osh K-43-B, 1:500,000, 1976–1979) and to Franz (1973), bedrock of the surveyed area is dominated by limestone, whereas sandstone and other siliceous rocks cover a small surface area only. Corresponding to the Kyrgyz soil classification system, which follows classification schemes of the

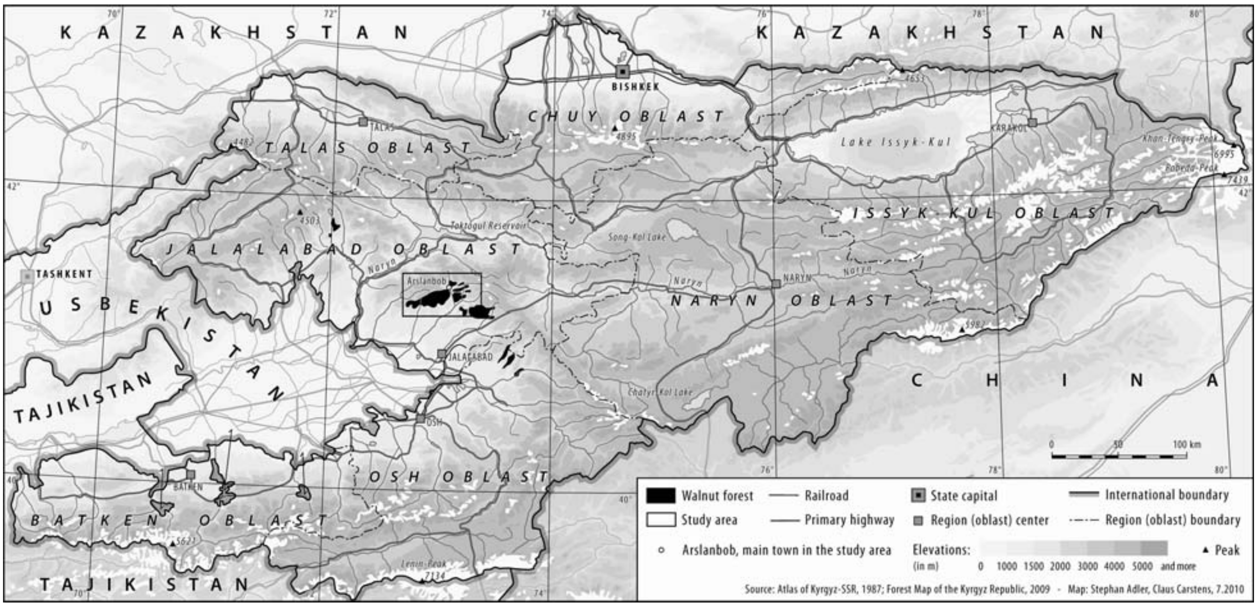

Figure 1 Location of the study area in the Ferghana Range, southern Kyrgyzstan.

Soviet Union (cf. Gottschling et al. 2005), the soils of the study area (soil map: Osh, 1976–1979, K-43-B 1:500,000) are mainly composed of meadow soils and alpine meadow soils (similar to Cambisols and Leptosols) while meadow steppe soils (roughly corresponding to Kastanozems) cover a small area only.

At the climate station of Ak Terek (1,748 m, N 41° 17`20,0; E 072° 49`41,8, Figure 2), mean annual precipitation amounts to 1,090 mm with a maximum in spring (approx. 160 mm month^{-1}) and a dry period in summer (approx. 40 mm month^{-1}). The mean annual temperature is 9°C, with relatively mild winters (average 1°C) and warm summers (average 20°C).

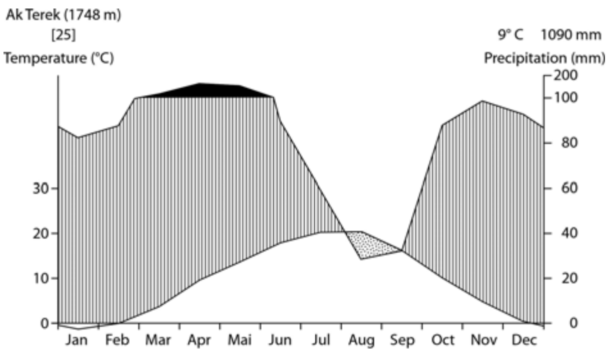

Figure 2 Climate diagram of Ak Terek (1,748 m) based on meteorological data recorded from 1983 to 2007.

Around Arslanbob, pastures in the treeline ecotone are still governed by state owned forest enterprises (*leskhozes*) of the main villages. During Soviet times, the *leskhozes* of these villages kept much smaller numbers of livestock (such as sheep, cows, or horses) than people do today (Borchardt et al. 2010). The increase in livestock numbers and the corresponding higher utilization pressure on mountain pastures must be attributed to the severe economic hardship that people are facing after independence leading to a general shift to subsistence agriculture. The situation is aggravated by the influx of peasants and their herds from settlements outside the forest area, which were allocated to other summer pastures during Soviet times. Furthermore, the number of goats has steadily increased over recent years (Borchardt et al. 2010). Goats pose a major threat to the sensitive ecosystem due to their characteristic feeding habits (Goetsch et al. 2010). However, as goats are officially banned from the investigated pastures (State Forest Agency of the Kyrgyz Republic 1996), it is difficult to obtain reliable information on their amount.

2 Methods

2.1 Data collection

We collected data from a total of 419 relevés, which are located in a relatively homogeneous area in the Arslanbob region. Vegetation sampling followed the Braun-Blanquet approach (Braun-Blanquet 1964). We used a standard relevé size of 5 m x 5 m, which exceeds the minimal area as determined according to Mueller-Dombois & Ellenberg (1974). Relevé analyses included the listing of all vascular plant species as well as the assessment of species cover according to the traditional Braun-Blanquet cover-abundance scale (7 classes). A voucher specimen of each species was collected for final identification in the herbarium of the Kyrgyz Academy of Sciences, Bishkek. The samples were taken randomly along an altitudinal gradient (1,800–3,200 m). In each relevé, stand structure was assessed by estimating percentage cover of herbs and - if present - shrubs and trees. Bryophytes and lichens played a minor role in the recorded samples and were not considered for the analyses.

Field sampling was complemented by a detailed characterization of habitat conditions including an assessment of human impact. We estimated grazing intensity by direct observation of different parameters and by qualitative information from local shepherds. It was categorized as low (1), moderate (2), or high (3) "grazing impact". Soil samples (3 samples of 100 cm^3 per site) were taken from the uppermost mineral soil horizon (10–20 cm depth). Laboratory soil analyses comprised grain size distribution, soil pH (in CaCl), electroconductivity, water and carbon content. Fresh field samples were oven-dried until weight constancy was reached. Soil analyses were carried out at the Soil Laboratory of the Institute of Geography, University of Hamburg.

2.2 Data preparation

Code replacement was done in order to transform the ordinal species abundance estimates to their metric average values prior to data analysis (r: 0.01%, +: 0.5%, 1: 2.5%, 2: 15%, 3: 37.5%, 4: 62.5%, 5: 87.5%). To reduce the impact of large cover values, species relevé data were √-transformed (McCune & Grace 2002). We calculated dissimilarity between relevés using the relative Sørensen Index (Faith et al. 1987). Relevés very dissimilar to others (standard deviation SD > 2 from the mean calculated distance of all relevés) were detected by outlier analysis in PC-ORD (version 5.19., MjM Software Design, Gleneden Beach, OR, US). Since outliers can distort clustering and ordination, such relevés were excluded from the later analyses. Continuous variables with a coefficient of variation (CV%= 100*SD/Mean) > 400% were omitted; and cover values (herb, shrub, tree, total cover) were equalized by $(2/\pi)$*arcsine $\sqrt{(x)}$ transformation, as recommended by Sokal & Rohlf (1987). All recorded species occurring in less than eight relevés were excluded to avoid scarce overvaluation.

Improved estimates of heat load (McCune 2007) - based on aspect, slope and latitude - were obtained by Non-parametric Multiplicative Regression (NPMR) using the program HyperNiche (version 1.12., MjM Software Design, Gleneden Beach, OR, US).

2.3 Classification

Relevés were classified according to their species composition using hierarchical β-flexible cluster algorithm (Lance & Williams 1967) in PC-ORD, with $\beta = -0.25$. Subsequently, relevés were ordered according to these classification results in JUICE (version 7.0.37, Tichý 2002). In order to detect and describe values of different species for indication of environmental conditions and to describe their fidelity for the classified communities, we used Indicator Species Analysis (ISA, Dufrene & Legendre 1997) in PC-ORD. Based on ISA, characteristic species for the classified communities were assessed. A threshold level of 25% ($P < 0.01$) was set as indicator value. ISA was also used to revise the chosen stopping point in cluster analysis (Dufrene & Legendre 1997). Additionally, species were defined as diagnostic by their φ coefficient (> 0.35 / 35%) (Tichý & Chytrý 2006), and as typical through their constancy (≥ 40%).

The classified communities were named by one alphabetic character and by two diagnostic or typical species that could be easily identified in the field.

2.4 Indirect gradient analysis

Detrended Correspondence Analysis (DCA, Hill & Gauch 1980) was conducted on a subset of √-transformed vegetation data. Axes were rescaled to consistent units of β-diversity expressed in Standard Deviations (SD) using 26 segments, as recommended in PC-ORD. This rescaling allows a quantitative interpretation of distances in the ordination space with respect to β-diversity (Lepš & Šmilauer 2003). Moreover, species turnover was estimated and compositional responses to the explanatory variables were quantified by DCA. Pearson's Correlations between DCA ordination axes and measured environmental parameters as well as estimates of grazing impact were calculated. The objective of the DCA was to reveal relationships among floristic composition, α-diversity, continuous environmental variables (altitude, inclination, heat load, bulk density, water content, carbon content, electro-conductivity, soil pH (in CaCl), and grain size distribution), structural variables (vegetation cover, herb cover, shrub cover, and tree cover), and grazing impact. The significance of each fitted gradient (vector) was tested by a Monte Carlo test (999 permutations).

We decided to use DCA in our study since ordination results were supposed to be unimodal related to environmental predictors (gradient length: 3.614 SD; see Lepš & Šmilauer 2003). Moreover, DCA was successfully applied in several studies with similar objectives, and DCA is one of the most accessible and widely applied indirect ordination methods in vegetation science (Lepš & Šmilauer 2003).

2.5 Phytogeographical analysis

Phytogeographical characteristics of the classified communities were assessed using species distribution data obtained from standard literature (Czerepanov 1995; Komarov 1934-1969; Meusel et al. 1965-1992). We assigned the most dominant (mean coverage > 2%) and the most frequent (> 40%) vascular species to one of the following six distribution types: (1) Widespread and/or Ruderal; (2) Eurosiberian; (3) Middle-Asian, (4) Middle-Asian-Caucasian, (5) Pontic-Siberian, (6) Irano-Turanian.

3 Results

3.1 Species composition and classification

A total of 395 relevés and 195 species were included in the classification after identifying 24 relevés as outliers.

On average, one relevé contained 22 ±6 (SD) vascular plant species (min.: 11, max.: 49). Examples for species occurring in ≥ 50% of all relevés were (in decreasing order of constancy) *Trifolium repens*, *Poa pratensis*, *Taraxacum officinale*, *Dactylis glomerata* and *Eremurus fuscus*.

Cluster analysis resulted in four communities, explaining about 12.5% of the variation (Figure 3). The main branching demerged the dataset into two major communities. It coincided with the presence of *Ligularia thomsonii*, *Lamium album*, *Bistorta elliptica* and *Phlomoides*-complex (*Phlomoides oreophila* and *Phlomoides speciosa*) in the first branch (communities A and B), and their absence or rare occurrence in the second branch (communities C and D) (Figure 3, Table 1).

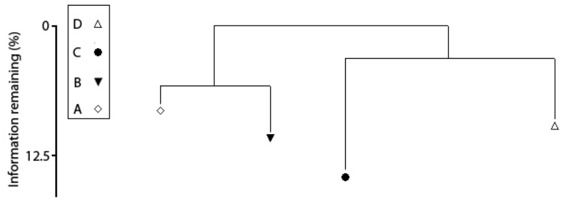

Figure 3 Dendrogram showing clustering results: A *Aconogonon-Prangos-*; B *Phlomoides-Geranium*; C *Eremurus-Arenaria-*; D *Plantago-Polygonum-*community.

Each classified community could be distinguished by significant diagnostic species. In community A, various non-graminoid perennial species and many tall perennial herbs like *Aconogonon coriarium*, *Prangos pabularia* and *Ligularia thomsonii* occurred frequently. Community A displayed the highest species richness values. Several (sub-) alpine species (such as *Aulacospermum simplex*, *Heracleum dissectum*, *Aster alpinus*, *Phlomoides oreophila* and *Phlomoides speciosa*) were diagnostic for Community B. In community C, main diagnostic and typical species included *Medicago lupulina* and *Arenaria serpyllifolia*, together with *Carex turkestanica*, *Eremurus fuscus* and *Ziziphora clinopodioides*. Small ruderal and/or widespread graminoid- and forb-species, such as *Plantago major*, *Polygonum aviculare* and *Taraxacum officinale* s.l., characterized community D with *Urtica dioica*, *Malva neglecta* and *Capsella bursa-pastoris* being frequent companions. This community reached the lowest species richness values.

Synoptic table
with percentage frequency and modified fidelity index (φ-coefficient)

Community	A		B		C		D	
No. of relevé	103		62		95		135	
Average richness / relevé (SD)	25 (?)		20 (?)		23 (?)		19 (?)	
Aconogonon coriarium	**62**	56.9	16	-	-	-	8	-
Prangos pabularia	**41**	48.5	-	-	9	-	1	-
Galium aparine	**47**	39.2	5	-	19	-	8	-
Tanacetum pseudoachillea	**43**	29.6	23	-	4	-	17	-
Stachyopsis oblongata	**41**	24	23	-	9	-	20	-
Pyrethrum parthenifolium	**63**	27.6	2	-	**60**	24	34	-
Asyneuma argutum	26	35.8	6	-	-	-	2	-
Vicia tenuifolia	29	35.2	-	-	11	-	2	-
Carex polyphylla	35	39.1	-	-	6	-	9	-
Dactylis glomerata	**92**	41.4	**58**	-	13	-	**64**	-
Ligularia thomsonii	**81**	40	**74**	32.6	12	-	18	-
Campanula glomerata	**55**	28.4	**44**	-	13	-	18	-
Lamium album	**67**	29.1	**71**	33.7	3	-	27	-
Phlomoides-complex	5	-	**66**	58.6	22	-	-	-
Geranium collinum	25	-	**53**	33.5	2	-	29	-
Rumex paulsenianus	35	-	**47**	-	5	-	39	-
Myosotis spp.	7	-	37	45.7	2	-	1	-
Bistorta elliptica	13	-	34	36.4	1	-	4	-
Heracleum dissectum	2	-	27	40.2	-	-	4	-
Aulacospermum simplex	-	-	23	41.3	-	-	1	-
Gentiana olgae	-	-	19	36.8	-	-	1	-
Aster alpinus	2	-	19	36.1	-	-	-	-
Allium hymenorhizum	-	-	16	35.5	-	-	-	-
Allium atrosanguineum	-	-	16	35.5	-	-	-	-
Allium platyspathum	-	-	16	35.5	-	-	-	-
Arenaria serpyllifolia	9	-	15	-	**82**	58.1	32	-
Medicago lupulina	11	-	-	-	**79**	59.3	36	-
Carex turkestanica	9	-	5	-	**57**	50.5	14	-
Ziziphora clinopodioides	14	-	5	-	**51**	48.5	4	-
Poterium polygamum	6	-	2	-	**48**	55	3	-
Plantago lanceolata	6	-	2	-	**64**	42.9	**49**	23.6
Hypericum perforatum	**43**	-	5	-	**75**	51.9	8	-
Rosa kokanica	35	16.8	2	-	**52**	39.7	3	-
Origanum thytthantum	**54**	-	10	-	**78**	38.7	36	-
Achillea millefolium	14	-	13	-	**68**	37.7	**53**	18.8
Eremurus fuscus	**63**	-	24	-	**89**	43.3	31	-
Euphorbia jaxartica	13	-	11	-	**40**	36.9	1	-
Polygonum polycnemoides	-	-	-	-	20	35.4	3	-
Viola isopetala	**60**	22.4	11	-	**66**	29.6	27	-
Ferula kuhistanica	37	-	2	-	**45**	22.8	27	-
Capsella bursa-pastoris	4	-	16	-	**44**	-	**59**	34.8
Cerastium holosteoides	12	-	21	-	**45**	-	**50**	22
Trifolium repens	**65**	-	26	-	**81**	-	**92**	31.6
Poa pratensis	**57**	-	**50**	-	**81**	18.8	**74**	-
Plantago major	25	-	8	-	21	-	**81**	57.9
Polygonum aviculare	17	-	18	-	**52**	-	**82**	46.7
Malva neglecta	17	-	-	-	**41**	-	**73**	50
Taraxacum officinale s.l.	35	-	**60**	-	**55**	-	**81**	27.8
Barbarea vulgaris	**41**	-	**44**	-	**42**	-	**64**	18.7

Table 1 Synoptic table with percentage constancy and modified fidelity index (φ coefficient, superscript). Values indicating typical species and diagnostic species are highlighted with grey shading. Both typical and diagnostic species are printed in bold.

3.2 Analysis of underlying gradients

The variable "tree layer%" was excluded from DCA as this parameter displayed a high coefficient of variation (CV% > 400). The first two DCA axes explained 0.25% and 0.23% of the total inertia (Figure 4) (R^2, coefficient of determination). All three DCA axes together explained 0.54% of the variation in the data-subset.

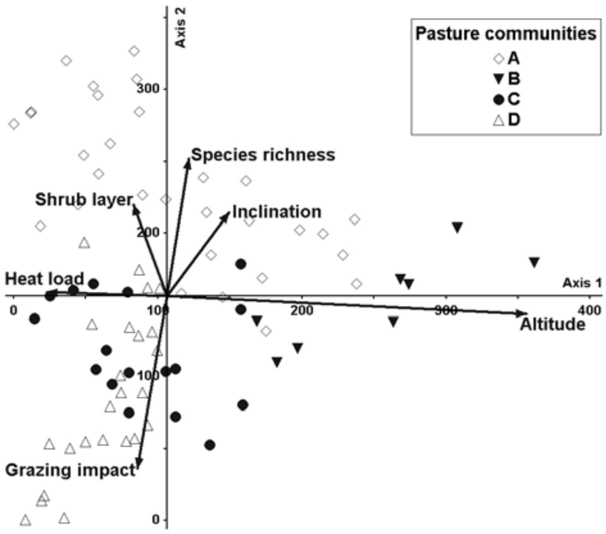

Figure 4 DCA (79 relevés, 171 species, 17 parameters, cutoff r^2 value = 0.150): Position of classified relevés in DCA-space. Overlaid vectors symbolize the dominance of the underlying gradients by their length.

The DCA joint plot showed that axis 1 separated pasture communities along an altitudinal gradient (r = 0.8, Figure 4). Correlations among different parameters and axis 2 revealed that the major floristic gradients were strongly correlated to the prevailing intensity of grazing (grazing impact, r = -0.6). Among the different structural parameters, species richness and the cover of the shrub layer were correlated contrarily in comparison with the factor 'grazing impact'. In order to clarify the role of soil texture (clay %, r = 0.56), further investigations are necessary. The DCA joint plot shows all four communities with their underlying gradients (such as spatial distribution, vegetation structure, and α-diversity): Community A occurred on the steepest slopes. The "alpine" community B occurred at higher altitudes above 2,800 m. Community C represented highly degraded and less densely covered slopes with high heat load. Community D was mostly found on even sites, which were under high impact of trampling and grazing.

The communities A, C and D occured at lower and medium altitudes, whereas community B was distributed at higher altitudes (see Figure 4, axis 1). On axis 2, the communities A, C and D were distributed along an underlying gradient of grazing impact and soil texture. We did not consider the influence of soil water content (%) because of high heterogeneity in daily weather conditions during the soil sampling period. Community A showed an intermediate grazing impact combined with the highest species richness and the highest shrub cover of all communities. By contrast, communities C and D showed a lower α-diversity. All three axes exhibited high differences in species composition with almost one total species-turnover indicated by a gradient length of approx. 3.5 SD (Hill & Gauch 1980) showing that the main DCA axes reflected a high ß-diversity (Table 2). The fitted gradients (vectors) of the DCA were significant at p = 0.05 level (type I error, Monte Carlo test).

3.3 Phytogeographical composition

A total of 174 vascular plants, identified at species level, were subjected to a phytogeographical analysis (Figure 5). The Middle Asian range type was the dominant distribution type within the species pool (Figure 5a). On the other hand, the distribution type 'Widespread and/or Ruderal' showed the highest average cover of all phytogeographical range types (Figure 5b). Regarding the number of species associated with each distribution type, the proportion of types differed little among communities (Figure 5a). However, considerable differences among communities were visible when regarding the average cover of the respective distribution types (Figure 5b). In communities C and D, 'Widespread and/or Ruderal' species occupied a relatively high proportion of the vegetation cover (29% resp. 59%). In both communities A and B, Middle Asian species covered approx. 20%, whereas the 'Widespread and/or Ruderal' species cover was relatively low. Middle Asian endemics played a major role in communities A and B (cf. Figure 5).

Table 2 DCA: Total inertia, eigenvalue, gradient lengths and Pearson's correlations between the environmental variables and DCA ordination axes 1, 2 and 3.

	DCA	relevés: 79	taxa: 171
Total inertia	6.5998		
Axis	1	2	3
Gradient length (SD)	3.61	3.27	3.6
Eigenvalue	0.47	0.39	0.27
Pearson's	r	r	r
Cover	0.02	0.2	0.1
Shrub layer	-0.2	0.4	-0.1
Herb layer	0.1	0.1	0.1
Species richness	0.2	0.5	0.03
Inclination	0.3	0.4	-0.3
Altitude	0.8	-0.2	-0.1
Heat load	-0.5	0.1	0.2
Grazing impact	-0.2	-0.6	-0.1
Soil pH	0.2	0.1	-0.5
Electroconductivity	0.1	0.0	-0.3
Bulk density	0.1	0.1	-0.1
Skeleton	0.3	-0.2	-0.2
Soil water	-0.1	0.6	0.1
Carbon	0.1	-0.1	-0.5
Sand	0.2	0.02	0.02
Silt	-0.1	-0.2	-0.2
Clay	-0.2	0.6	0.2

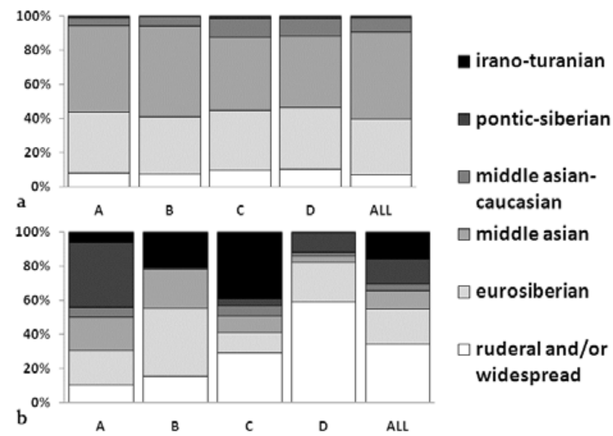

Figure 5 Spectra of distribution types for classified communities and in the total dataset. (a) Proportion of species number per distribution type. (b) Proportion of average cover per distribution type.

3.4 Grazing impact

As community B represents the vegetation type of high altitudes, whereas all three communities A, C and D were found at medium elevations, only the latter were considered to analyze the impact of grazing and environmental factors. Community D was subject to the highest grazing impact, followed by community C. In community A, disturbance through grazing was relatively low (cf. Figure 4, cf. Table 2) and although it showed marks of grazing, the vegetation formation appeared less degraded than those of communities C and D.

4 Discussion

4.1 Actual situation of the Kyrgyz montane pastures

In the SW Tien Shan, not only the rare walnut-fruit forests can be considered to be unique. The grasslands above the treeline are also exceptional with respect to their richness in endemics and to the disjunctive presence of Eurosiberian species (Wagner 2009).

Presently, the grasslands of the Ferghana Range are subject to heavy grazing impact and almost entirely utilized as grazing land since livestock is of increasing importance in sustaining the livelihood of local people. The rising land use pressure is reflected by a gradual expansion of pastures into the adjacent walnut-fruit forest (Borchardt et al. 2010). Small groups of trees remaining on grazing grounds are witnesses of a previously much larger forest area (pers. observations). On dry slopes, occupied by community C, soil erosion and degradation marks on shrubs are obvious consequences of unsustainable grazing and trampling that point to the vulnerability of these habitats. The last UNDP (2007) report on natural resources in Kyrgyzstan assessed the condition of Kyrgyz pastures as poor, and the pressure on pastures close to settlements was identified as main problem of agricultural land use in Kyrgyzstan causing degradation and desertification.

Reinforced degradation must be attributed to the continuous increase in livestock numbers accompanying the process of privatization (cf. Schmidt, M. 2005, Schmidt, K. 2007). In particular, the rising numbers of goats, which strongly harm the shrub and tree layer, and prevent natural regeneration (Fernandez-Lugo et al. 2009, Goetsch et al. 2010), is an object of great concern.

4.2 Regional comparisons

Published information on the classification and ecology of Tien Shan alpine pastures is very scanty. The mountain pastures, in particular those at higher altitudes, have been largely neglected by modern international vegetation ecological research.

Only one comparable study of mountain meadows in the Tien Shan is available, which is based on vegetation sampling in the NW Tien Shan (Wagner 2009).

In general, low floristic-sociological accordance was detected when comparing our results to those of Wagner (2009). Because Wagner´s study was conducted at lower altitudes, no comparison was possible for the alpine community B described in our study. Further, major differences between our study and Wagner's (2009) findings reflect contrasting land use pressure. Wagner took her samples in a preserved area in the NW Tien Shan (Aksu-Jabagly Nature Reserve), whereas we collected data in an area located close to settlements and subject to massive human impact. Accordingly, densities of the herb layer (Borchardt et al.: 58% vs. Wagner: 87%, on average) as well as α-diversity (Borchardt et al.: 22 species vs. Wagner: 26 species, on average) were higher on the preserved meadows. Several 'Widespread and/or Ruderal' species occurring in or even dominating the examined pastures do not occur or play a minor role in Wagner's samples. The clear separation of communities according to the ratio of the distribution types 'Middle Asian' and 'Widespread and/or Ruderal' as it was detected in our study was not present in Wagner´s communities (2009). Consequently, community D occurring at intensely utilized sites in our study area was not found in the area investigated by Wagner. The relatively undisturbed and remote spots of community A showed the highest conformity with the floristic composition of Wagner's communities.

Aconogonon coriarium was the characteristic and eponymous species for community A in the present study and also for one community in Wagner's classification. A strong presence of Eurosiberian species in the vegetation (around 30% in all communities, Figure 5), as shown in both Wagner´s and our phytosociological analyses, is in accordance with previous observations of Rubtsov (1955) and Vykhodtsev (1956).

So far, no studies have been conducted on the relationship between post-Soviet transformation processes and ecological alterations of alpine grazing lands. However, some basic references for ecological analyses of alpine pastures can be found, although most of these sources refer to the extensive steppes and grazing lands of N Kyrgyzstan (Issyk-Kul, Naryn, Chuy, and Talas Oblasts) and rarely deal explicitly with high pastures. Several Russian authors (such as Korovin (1961/62), Ryazantsev (1965), Stanyukovich (1973), Stepanov (1975), Vykhodtsev (1976), Mamytov (1987), Atlas Kirgizskoy SSR (1987), Golovkova (1990) and Mamytov (1996)) provide essential information on climate, soils and vegetation. Further, Russian scientists include assessments of productivity, biomass and grazing value of several pasture types (such as Vykhodtsev et al. (1970), Popova et al. (1972, 1975), Zlotin (1978), Lebedeva (1984), and Golovkova & Chubarova (1987)).

4.3 Global comparison

4.3.1 Impact of grazing

The trend of changing species composition under the impact of grazing is a global phenomenon (Díaz et al. 2007). Various studies investigating the influence of grazing on species richness and on plant community composition showed that disturbance has profound effects on the vegetation (Asner et al. 2004, Steinfeld et al. 2006, Vallentine 2001). However, only very few recent publications describe – in rather superficial country-wide overviews – the influence of grazing on mountain pasture vegetation (e.g. Wilson 1997; Shikhotov et al. 2002).

In the present study, Eurosiberian and Middle Asian species were found to decrease under the influence increasing of grazing pressure. Several rare and endemic plant species (see Davletkeldiev, A.A. 2007, Umralina, A.R. & Lazkov, G.A. 2008, Eastwood, A. et al. 2009) occur in the study area. Many of the rare Middle Asian endemic species are considered to be highly endangered as result of rising human impact.

These observations comply with results from other mountain areas. For example in the Carpathian Mountains, increased grazing pressure on alpine grasslands had detrimental effects on relic and endemic species (Baur et al. 2007), but - due to the presence of competitive ruderals - lead to increased diversity at an intermediate level (Pierce et al. 2007). In this respect it has to be taken into consideration that the high species richness of disturbed areas in our study resulted from the occurrence of 'Widespread and/or Ruderal' species. This observation supports the hypothesis that diversity increases with increasing disturbance provided that disturbance occurs at intermediate scales of frequency and intensity ("intermediate disturbance hypothesis", Connell 1978).

4.3.2 Upper treeline

Depression of the upper treeline is a common phenomenon associated with land use changes in transformation and transition countries (Schickhoff 2005; 2009). In the observed pastures, a close connection to the adjacent walnut-fruit forest is reflected by the occurrence of forbs that dominate the herb layer of the forest understorey (such as *Asyneuma argutum* or *Carex polyphylla*). The presence of trees (e.g. *Acer turkestanicum*) and the relative high coverage of shrubs clearly indicate that the upper treeline has been depressed under the impact of increasing livestock numbers and intense exploitation of forest products in recent years (Schmidt, M. 2005; Grisa et al. 2008; Borchardt et al. 2010). However, further investigations are needed to better describe the relation between both human and environmental impact and the position of the upper treeline.

5 Conclusions & Implications for the Future

The presented results point to a strong grazing impact on the pastures of southern Kyrgyzstan's Ferghana Range regarding vegetation distribution, species composition, and species richness. Human impact favors widespread and/or ruderal species and causes degradation of pastures (Asner et al. 2004) including a reduced availability of ecosystem services (e.g. primary production, and prevention of soil erosion).

In order to ensure the viability and the integrity of these ecosystems in future, an effective implementation of a sustainable pasture management and a rigorous enforcement of existing regulations are urgently needed. Respective strategies include the implementation of rotation systems, a general limitation of livestock numbers and grazing periods, and a ban on goat grazing - at least on potential shrub and forest land. Alternative sources of income (such as tourism or beekeeping) should be promoted in order to reduce the dependency of local people from livestock. According to Schmidt and Sagynbekova (2008), a great majority of households rely on agricultural and forestry activities to sustain their livelihoods. Rents for grazing land are already not only used to support the village administration, but also include a social payment that returns to the local budget and is used for maintenance of high passes that lead to more distant summer pastures. However, a more transparent use could markedly increase the efficiency of such rents. Regarding their efficient utilization, a more transparent and uncorrupt financial system is indispensable. Furthermore, inventory and monitoring should be implemented as grazing land management tools in order to facilitate decision making in future.

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References

Asner GP, Elmore AJ, Olander LP, et al, (2004) Grazing systems, ecosystem responses, and global change. Annual Review of Environment and Resources 29: 261-299.

Atlas Kirgizskoy SSR 1987. Atlas of the Kyrgyz SSR. Moscow. (In Russian)

Baur B, Cremene C, Groza G, et al (2007) Intensified grazing affects endemic plant and gastropod diversity in alpine grasslands of the Southern Carpathian mountains (Romania). Biologia 62: 438-445.

Beer R. Kaiser F,. Schmidt K, et al (2008) Vegetation history of the walnut forests in Kyrgyzstan (Central Asia): Natural or anthropogenic origin? – Quaternary Science Reviews 27: 621-632

Borchardt P, Schmidt M, Schickhoff U (2010) Vegetation patterns in Kyrgyzstan's walnut-fruit forests under the impact of changing forest use in post-soviet transformation. Die Erde: 141: 255-275

Braun-Blanquet J (1964) Pflanzensoziologie. - 3rd ed. - Springer, Vienna.

Connell JH (1978) Diversity in tropical rain forests and coral reefs. Science 199: 1302-1310.

Cowan PJ (2007) Geographic usage of the terms Middle Asia and Central Asia. Journal of Arid Environments 69: 359-363.

Czerepanov SK (1995) Vascular plants of Russia and adjacent states. Cambridge University Press, Cambridge.

Davletkeldiev AA (ed.) 2007. Red data book of Kyrgyz Republic. - 2nd ed. - Bishkek.

Díaz S, Lavorel S, McIntyre S, et al (2007) Plant trait responses to grazing - a global synthesis. Global Change Biology 13: 313-341.

Dufrene M, Legendre P (1997) Species assemblages and indicator species: The need for a flexible asymmetrical approach. Ecological Monographs 67: 345-366.

Eastwood A, Lazkov G, Newton A (2009) The Red List of Trees of Central Asia. Fauna & Flora International. Cambridge.

Epple C (2001) A vegetation study in the walnut and fruit-tree forests of southern Kyrgyzstan. Phytocoenologia 31: 571-604.

Faith DP, Minchin PR, Belbin L (1987) Compositional dissimilarity as a robust measure of ecological distance. Vegetatio 86: 57-68.

Fernandez-Lugo S, de Nascimento L, Mellado M, et al (2009) Vegetation change and chemical soil composition after 4 years of goat grazing exclusion in a Canary Islands pasture. Agriculture Ecosystems & Environment 132: 276-282.

Franz HJ (1973) Physische Geographie der Sowjetunion. VEB Heermann Haack, Leipzig. (In German)

Golovkova AG , Chubarova AV (1987) Fodder Plants of Kyrgyzstan. Frunze. (In Russian)

Golovkova AG (1990) Vegetation of Kyrgyzstan. Efficient Use and Conservation. Frunze. (In Russian)

Goetsch AL, Gipson TA, Askar AR, Puchala R (2010) Invited review: Feeding behavior of goats. Journal of Animal Science 88: 361-373.

Gottschling H, Amatov I, Lazkov G (2005) Zur Ökologie und Flora der Walnuß-Wildobst-Wälder in Süd-Kirgisistan. Archiv

für Naturschutz und Landschaftsforschung 44: 85-100. (In German)
Grisa E, Venglovsky B, Sarymsakov Z, Carraro G (2008) Typology of Forests of Kyrgyz Republic. Bishkek. (In Russian)
Hill MO, Gauch HG (1980) Detrended correspondence analysis: an improved ordination technique. Vegetatio 42: 47-58.
Komarov VL(ed.) 1934-1969. Flora SSSR, T. pp. 1-30. Izd. AN SSSR. Moskva-Leningrad, RU. (In Russian)
Korotkov KO, Morozova OV, Belonovskaja EA (1991) The USSR Vegetation Syntaxa Prodromus. G.E. Vilchek, Moscow. (In Russian)
Korovin EP (1961/62). The Vegetation of Middle Asia and South-Kazakhstan. 2 Vols., Tashkent. (In Russian)
Lance GN, Williams WT (1967) A general theory of classificatory sorting strategies. 1. Hierarchical systems. Computational Journal 9: 373-380.
Lebedeva LP (1984) Dynamics and Productivity of Subalpine Meadows at the North Slope of the Kyrgyz Range. Frunze. (In Russian)
Lepš J, Šmilauer P (2003). Multivariate analysis of ecological data using CANOCO. Cambridge University Press, Cambridge.
Ludi E (2003) Sustainable pasture management in Kyrgyzstan and Tajikistan: Development needs and recommendations. Mountain Research and Development 23: 119-123.
Mamytov AM (1987) Soils of the Mountains of Middle Asia and South-Kazakhstan. Frunze. (In Russian)
Mamytov AM (1996) Soil Resources and Soil Classification of the Kyrgyz Republic. Bishkek. (In Russian)
McCune B, Grace JB (2002) Analysis of ecological communities. MjM Software Design, Gleneden Beach, OR.
McCune B (2007) Improved estimates of incident radiation and heat load using non-parametric regression against topographic variables. Journal of Vegetation Science 18: 751-754.
Meusel H, Jäger E, Weinert E (1965-1992) Vergleichende Chorologie der zentraleuropäischen Flora. Urban & Fischer, Munich. (in German)
Mirkin BM, Shelyagsosonko YR (1984) Classification of meadow vegetation in the USSR - brief survey of history, current status and perspectives. Vegetatio 56: 167-176.
Mirkin BM. 1987. Paradigm change and vegetation classification in soviet phytocoenology. Vegetatio 68: 131-138.
Mueller-Dombois D, Ellenberg H (1974) Aims and Methods of Vegetation Ecology. John Wiley & Sons, New York.
Pierce S, Luzzaro A, Caccianiga M, et al (2007) Disturbance is the principal-scale filter determining niche differentiation, coexistence and biodiversity in an alpine community. Journal of Ecology 95: 698-706.
Popova LI, Ionov RN, Lebedeva LP, et al (1972) Yield Handbook of Pastures and Hay Meadows of the Kyrgyz SSR. Vol. 2, Frunze. (In Russian)
Popova LI, Ionov RN, Lebedeva LP, et al (1975). Yield Handbook of Pastures and Hay Meadows of the Kyrgyz SSR. Vol. 3, Frunze. (In Russian)
Rubtsov NI (1955) Meadows of the northern Tien Shan. Trudy Instituta Botaniki Akademii Nauk Kazakhskoy SSR 1: 5-35. (In Russian)
Ryazantsev ZA (1965) The Climate of the Kyrgyz SSR. Frunze. (In Russian)
Schickhoff U (2005) The upper timberline in the Himalayas, Hindu Kush and Karakorum: a review of geographical and ecological aspects. In: Broll, G. & B. Keplin (eds.) Mountain Ecosystems. Studies in Treeline Ecology, Springer Verlag, Berlin. pp 275-354.
Schickhoff U (2009) Human impact on high altitude forests in northern Pakistan: degradation processes and root causes. In: Singh, R.B. (ed.) Biogeography and Biodiversity, Rawat Publications, New Delhi. pp 76-90.
Schmidt K (2007) Livelihoods and forest management in transition - knowledge and strategies of local people in the walnut-fruit forests in Kyrgyzstan. University of Reading, Reading.
Schmidt M (2005) Utilisation and management changes in South Kyrgyzstan's mountain forests. Journal of Mountain Science 2: 91-104.
Schmidt M (2008) Political ecology in high mountains: the web of actors, interests and institutions in Kyrgyzstan's mountains. Colloquium Geographicum 31: 139-154.
Schmidt M, Sagynbekova L (2008) Migration past and present: changing patterns in Kyrgyzstan. Central Asian Survey 27: 111-127.
Schmidt P (2001) The scientific world and the farmer's reality: Agricultural research and extension in Kyrgyzstan. Mountain Research and Development 21: 109-112.
Shennikov, A.P. 1964. Introduction to Geobotany. Leningr. Gos. Univ. Leningrad. (In Russian)
Shikhotov UM, Joldoshev KG, Filippovskaya LV, Denisov VV (2002) Pastures and grasslands. In: Aidaraliev, A.A. (ed.): Mountains of Kyrgyzstan, Bishkek. pp 242-251.
Sokal RR, Rohlf FJ (1987) Introduction to biostatistics. W.H. Freeman and Company, New York, NY.
Stanyukovich KV (1973) The Vegetation of the Mountains of the USSR. A Botanical and Geographical Account. Dushanbe. (In Russian)
State Forest Agency of the Kyrgyz Republic (1996) Correction on pay-scales to calculate penalties for damage on forestry". In: Order, 13.02.1996 Nr. 8, registered at Ministry of Justice of the Kyrgyz Republic on 22.02.1996 Index 294, Bishkek. (In Russian)
Steinfeld H, Gerber P, Wassenaar T, et al (2006) Livestock's long shadow - environmental issues and options. FAO - Rome.
Stepanov IN (1975) Ecological and Geographical Analysis of the Soil Cover of Middle Asia. Moscow. (In Russian)
Tichý L (2002) JUICE, software for vegetation classification. Journal of Vegetation Science 13: 451-453.
Tichý L, Chytrý M (2006) Statistical determination of diagnostic species for site groups of unequal size. Journal of Vegetation Science 17: 809-818.
Umralina AR, Lazkov GA (2008) Endemic and rare plant species of Kyrgyzstan (Atlas). Bishkek.
UNDP (2007) Kyrgyzstan: Environment and natural resources for sustainable development. United Nations Development Programme in the Kyrgyz Republic & State Agency on Environment Protection and Forestry under the Government of the Kyrgyz Republic, Bishkek.
Vallentine JF (2001) Grazing Management. San Diego.
Vykhodtsev IV (1956) Vegetation of the pastures and hay meadows of the Kyrgyz SSR. AN Kirg, SSR, Frunze. (In Russian)
Vykhodtsev IV (1976) The Vegetation of the Tien Shan and Alai Mountain Systems. Frunze. (In Russian)
Vykhodtsev IV, Nikitina EV, Popova LI, et al (1970). Yield Handbook of Pastures and Hay Meadows of the Kyrgyz SSR. Vol. 1, Frunze. (In Russian)
Wagner V (2009) Eurosiberian meadows at their southern edge: patterns and phytogeography in the NW Tien Shan. Journal of Vegetation Science 20: 199-208.
Wilson R (1997). Livestock, pastures and the environment in the Kyrgyz Republic, Central Asia. Mountain Research and Development 17: 57-68.
Zlotin RI (1978) Structure and productivity of high altitude ecosystems in the Tien Shan, USSR. Arctic and Alpine Research 10: 425-427.

Article II

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Spatial and seasonal dynamics of soil loss ratio in mountain rangelands of south-western Kyrgyzstan

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Abstract: Vegetation cover is the main factor of soil loss prevention. The C-factor of the RUSLE (Revised Universal Soil Loss Equation) was predicted with NDVI, ground data and exponential regression equation for mountain rangelands of Kyrgyzstan. Time series of C-factor, precipitation and temperature were decomposed into seasonal and trend components with STL (seasonal decomposition by loess) to assess their interrelations. C-factor, precipitation and temperature trend components indicated significant lagged correlation, whereas seasonal components indicated more complex relations with climate factors which can be promoting as well as limiting factors for vegetation development, depending on the season. Rainy springs and hot summers may increase soil loss dramatically, whereas warm and dry springs with rainy summers can decrease it. Steep slopes indicated higher soil loss ratio, whereas flat areas were better protected by vegetation.

Keywords: Soil loss ratio; C-factor; RUSLE; NDVI; Time series; Remote sensing

Introduction

Vegetation cover is an important factor of soil loss control, especially on mountain rangelands (Blanco and Lal 2008). In Kyrgyzstan, mountain rangelands are not suitable for growing crops because of topographic, edaphic or climatic constraints, so they are used as summer pastures. The pastures are crucial for the rural economy as they occupy nearly as much area as the arable lands (FAO 2011). In recent years, the number of livestock has been increasing and this tendency is ongoing (FAO 2011) so that pasture use sustainability came into question. In the 1980th during the soviet times, the number of livestock was even higher, however, agricultural land was owned by the state, and grazing was controlled centrally through collective farms, which followed common grazing regulations. Nowadays pastures are divided into land shares under different authorities, which are owned or rented by small-scale farmers (Dörre and Borchardt 2012). There is practically no effective pasture use policy or grazing control, and rangeland management is totally up to herders' decision (Crewett 2012). In a situation of poor economy and little choice of income opportunities such a freedom has resulted in unsustainable pasture use and consequently in overgrazing and soil erosion (Figure 1). Uncontrolled soil erosion, especially on fine soils, can lead to considerable soil loss, water pollution and severe economic consequences (Dotterweich

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Figure 1 Soil erosion due to trampling and overgrazing.

2013).

The first known soil observations in South Kyrgyzstan were conducted in the Fergana Range at the end of the 19th century and published by Middendorff (1882). This report included results of chemical analyses of soils and waters. Regular soil studies started in the beginning of the 20th century. Though there were already much legacy data and reports available, one of the first papers outlining soil erosion on Alai and Chatkal ranges in South Kyrgyzstan was written by Zemlyanitzkiy (1937). In 1940, Mikhailov conducted route surveys of soil erosion in South Kyrgyzstan which resulted in a series of books on soil types, types of erosion and erosion prevention measures (Mikhailov 1959), he outlined the importance of vegetation and surface management for soil loss control. One of the main soil publications was written by Mamytov (1974) who outlined and integrated previous surveys and provided thorough information on soil types and features, zonation, pedogenesis, economic value and erosion. One of the first structured vegetation descriptions of pastures of Kyrgyzstan was conducted by Vykhodcev (1956). The author provides descriptions of main geobotanical regions and vertical zones (with detailed maps), with the main emphasis on agricultural use and pasture resources. Korovin (1961) provides a thorough description of the major vegetation communities for the whole region, which remains until now one of the standard works in Russian language. Nowadays, due to the difficult economic situation in Kyrgyzstan, intensive soil surveys are not conducted. Kyrgyzgiprozem Institute is working on keeping the existing database as up-to-date as it is possible. Thus a cost-effective instrument of soil monitoring is needed.

Dotterweich (2013) gives a comprehensive review of soil erosion history worldwide with a main focus on China in the Asian region. Zhou et al. (2010) investigated topsoil deterioration due to livestock trampling and grazing for similar soil conditions of China's Loess Plateau. Effects of land use type on soil properties was clearly demonstrated by Li et al. (2015) where the same soil types indicated different soil detachment capacity by overland flow depending on cover management. However, human activity with effective soil loss control and sustainable cover management can considerably increase soil retention (Fu et al. 2011) in spite of rugged terrain, which is one of the main factors contributing to soil loss (Sun et al. 2014). Dense grass cover and mixed forests have been proven to be among the best protectors of top soil from surface runoff (Sun et al. 2014; Wang et al. 2014).

The RUSLE (Revised Universal Soil Loss Equation) (Renard et al. 1996) and its components have been extensively used for soil erosion modelling. The cover management factor, or so called C-factor, of RUSLE is a soil loss ratio indicating a level of soil cover management impact on soil loss.

In RUSLE, the implementation framework of original USLE (Wischmeier and Smith 1978) was expanded so that it could be applied to rangeland conditions. As the C-factor calculation procedure (Renard et al. 1996) suggests, vegetation and its residues are of utmost importance for soil conservation. On rangeland pastures, where no tillage occurs and residues are not left due to overgrazing, live vegetation is virtually the only factor to be considered for C-factor estimation.

Satellite imagery and their time series are a complex data source that has been used for surveys of land surface behavior in space and time. They have also been commonly used as predictors of vegetation features and soil loss rate (de Jong 1994). In recent years, many surveys have been implemented on NDVI time series with either spatial or temporal averaging (Bradley et al. 2007; Nezlin et al. 2005; Rigina and Rasmussen 2003), dealing with combination of spatial and temporal analysis methods in different ways to tackle data limitations and identify dynamics patterns and interrelations.

The studies on C-factor and soil loss estimations using RUSLE implementations in GIS rarely consider vegetation phenology throughout the year. This is a big gap, because soil loss ratio depends on both vegetation cover and rainfall erosivity which vary seasonally and are interconnected. This twofold seasonality of C-factor and R-factor of RUSLE should be considered as it is suggested by formula [5-24] of RUSLE (Renard et al. 1996). Though many studies considered the relation of climate and NDVI (Gessner et al. 2013; Iwasaki 2006a; Iwasaki 2006b; Iwasaki 2009; Lioubimtseva et al. 2005; Omuto et al. 2010; Yu et al. 2003), phenological and interannual variations of surface cover (Atkinson et al. 2012; Bradley et al. 2007; de Beurs and Henebry 2010; de Jong et al. 2011; Kariyeva and van Leeuwen 2012; Verbesselt et al. 2010a; Verbesselt et al. 2010b), and prediction of C-factor with NDVI (de Jong 1994; Karaburun 2010; Suriyaprasit and Shrestha 2008; van der Knijff et al. 2000; Zhou et al. 2008), only a few of them took seasonal variations and trends of the C-factor itself and its interrelation with climate factors into consideration, which are one of the main components determining soil loss.

This study predicts the C-factor with NDVI using field data, and analyses spatially averaged C-factor time series, decomposed with STL (Cleveland et al. 1990) into trend and seasonal components, and their interactions with precipitation and temperature. It further analyses temporally averaged C-factor raster images for spatial patterns and response to utilization using remotely sensed and ground-truth data in combination with GIS and statistical methods. In the framework of this integrated approach we intend to test the hypothesis that topographic, climatic and land use settings cause major C-factor spatial and seasonal variations in Kyrgyzstan's mountain rangelands, which have discernible effects on soil loss ratio dynamics. The auxiliary data and software used in this study are available at no cost, thus the approach can be replicated cost-effectively, which is a valuable asset in conditions of a transition economy.

1 Study Area

The research was conducted on mountain rangelands in Arslanbob region, north of Jalalabad in the South Kyrgyz Fergana Range (41°30'N, 73°E), where these grazing lands cover extensive areas above montane and subalpine walnut-fruit forests between 1800 and 3500 m a.s.l. (Figure 2). The meadow-steppe grasslands are degraded to mountain rangelands under long-lasting grazing impact. Researchers have provided a deeper insight into vegetation patterns and grazing impact on plant communities in the study area (Borchardt et al. 2013; Borchardt et al. 2011). Soils are basically represented by Cambisols and Umbrisols, with Leptosols on steep dry slopes, classified according to the "World reference base for soil

Figure 2 Location of the study area in the Ferghana Range, southern Kyrgyzstan.

resources" (FAO 2006).

In total, four pastures were surveyed: Uch-Choku, Kara-Bulak, Jaz-Jarym and Otuz-Art. The first three are situated close to each other and actually represent different slopes of one ridge (Figure 3). These pastures are very close to a big local settlement (Arslanbob), are easily accessible and used by local population. The altitude variation is 2000-2800 m a.s.l. For practical reasons and sampling representativeness, these pastures were united into one study area, processed together and named Uch-Choku, so effectively we have only two study areas: Uch-Choku and Otuz-Art.

Another pasture, Otuz-Art (Figure 4) is situated further away from the others and is used by residents of a local village – Kyzyl-Unkur, and a

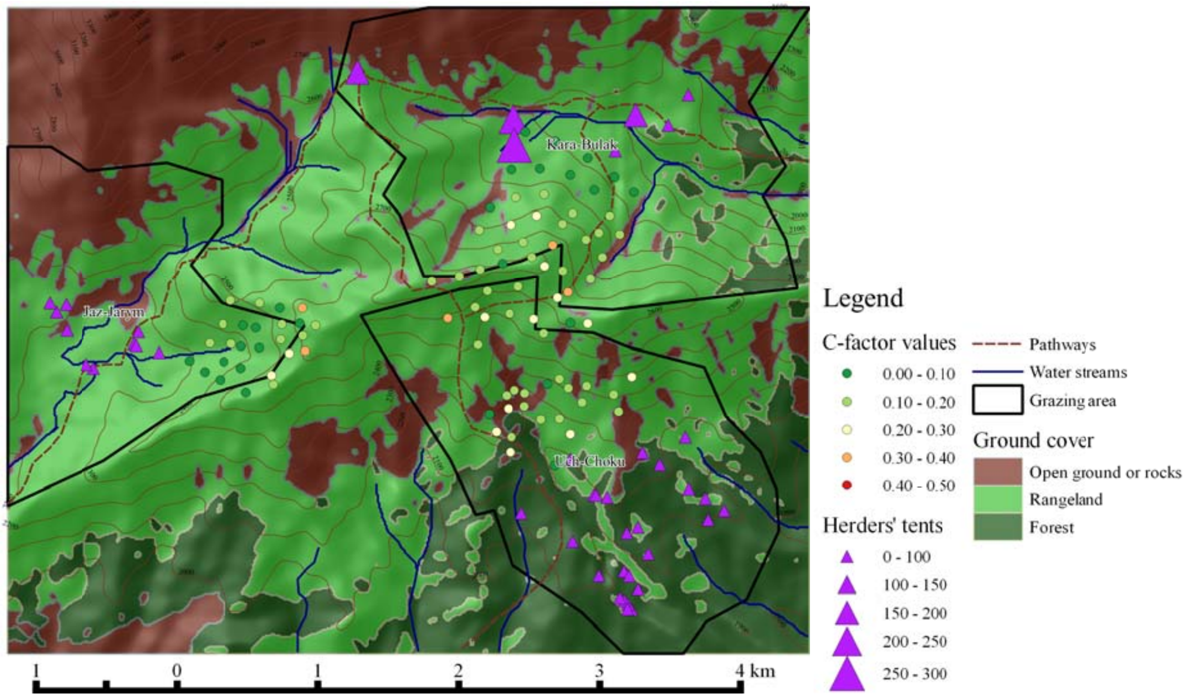

Figure 3 Uch-Choku study area (the dots are survey plots, their colour refer to the C-factor value, triangles are herders' tents with their size referring to the cattle amount belonging to that herder).

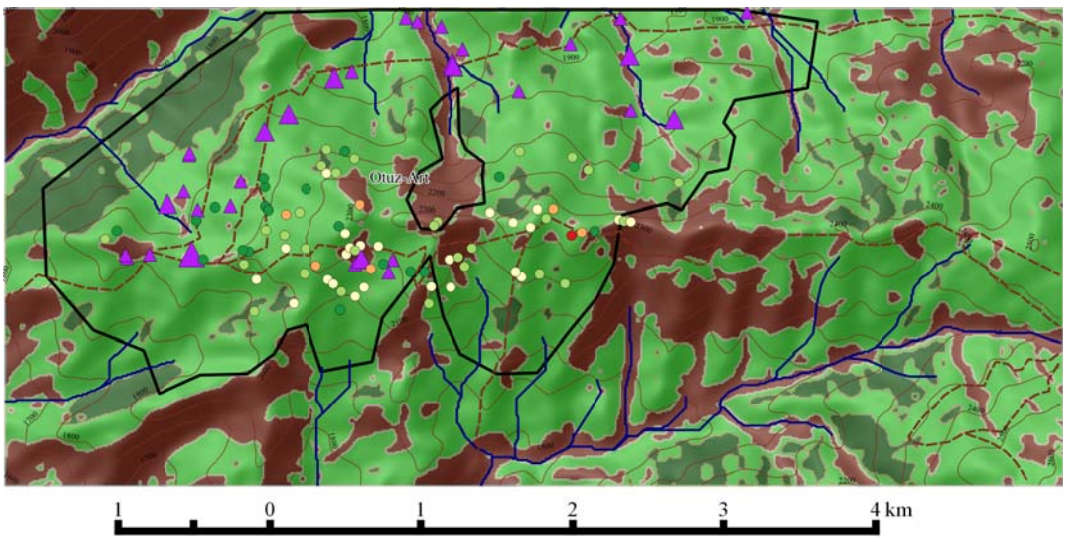

Figure 4 Otuz-Art study area (the dots are survey plots, their colour refers to the C-factor value, triangles are herders' tents with their size referring to the cattle amount belonging to that herder). The legend is the same as Figure 3.

regional center – Bazar-Korgon. It is a rather remote pasture with more difficult access and altitudes of 2000-2400 m a.s.l.. This study area is considered separately from the above-mentioned three pastures (Uch-Choku).

The areas surrounded by black line in Figures 3 and 4 are the study areas; they roughly represent the area used for grazing by respective herders. Herd composition is dominated by cows and sheep with mean density in cattle units of: Uch-Choku – 120, Kara-Bulak – 175, Jaz-Jarym – 40 and Otuz-Art – 280 per square kilometer. In Figures 3 and 4 herders tents are marked with triangles, and their size is related to the size of the owner's herd. The values for Uch-Choku, Kara-Bulak and Jaz-Jarym are considered to be underestimated, because of settlement proximity some livestock is temporarily brought by herders to these pastures directly from the village without staying on pasture in tents, whereas only the livestock of herders residing on the pasture site could be estimated during field interviews.

2 Materials and Methods

2.1 Field data collection

Field trips were undertaken in July – September of 2010 and 2011. Each time new samples were taken, i.e. the sampling was not repeating. The research areas were approached with a network of point surveys covering altitudes between 2000 and 2800 m, eight different bearings and various slope gradients where possible (Figures 3 and 4). At each point, vegetation cover fraction was assessed visually on a 5×5 m plot, and the average vegetation height was measured with a ruler, and surface roughness was assessed using the random roughness charts (Figure C-1 – C-9 in Renard et al. (1996). In Otuz-Art 80 plots were surveyed, in Uch-Choku – 94. Slope steepness, position on the slope, aspect, altitude and GPS coordinates of each survey point were also recorded. Precipitation and temperature data were collected from a local climate station (Ak-Terek Gava). The climate diagram of the station is indicated in Figure 5. Only rainstorms were considered in this study, precipitation data were available for the years 2000 – 2011 and temperature data for the years 2000 - 2009. Herders were interviewed for the amount of livestock and grazing strategies.

2.2 Remotely sensed data and DEM

LANDSAT-5, LANDSAT-7 and LANDSAT-8 (here and afterwards just LANDSAT) images, paths 151 and 152, raw 31 of the years 2000 – 2013, months April – November (as rainstorms occur only in these months) were used as remotely sensed data. The LANDSAT images were topographically corrected with SAGA GIS topographic correction module "Minnaert Correction with Slope" (Law and Nichol 2004) to eliminate illumination difference on different slopes. In most cases, the satellite images with more than 60% of the area covered with clouds were omitted from the research. The areas covered with snow were masked and evaluated as such (i.e. conventionally assigned C-factor value of 0.01). Clouds and snow were masked using supervised classification with learning in "Supervised classification" module (Mahalanobis distance method) of SAGA GIS. The processing of the remotely-sensed images is discussed in more details in 3.3.3.

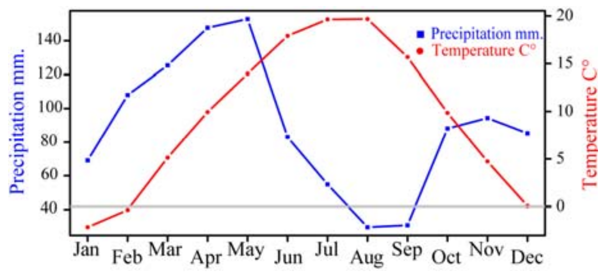

Figure 5 Climate diagram of Ak-Terek station (monthly mean precipitation and temperature for the years 2000 – 2011).

ASTER GDEMs were used for elevation data. Remotely sensed data and the ASTER GDEMs were resampled to 10 m × 10 m pixel size with b-spline interpolation method in SAGA GIS to bring all the raster images to the same resolution and size. The resolution was increased to refine the spatial continuity as sampling was done on a finer scale than the initial resolution of the data and pixel central values could be unrepresentative for sampling points situated closer to a pixel edge. All the subsequent manipulations were done with this grid system. The coordinate system used throughout the study was WGS84 UTM 43N. Statistical analyses were made in R 3.1.2 / Rcmdr 2.1-4, the GIS and satellite images processing were conducted in SAGA GIS 2.1.3.

2.3 Cover management factor

2.3.1 C-factor calculation

C-factor (also denoted as soil loss ratio) is a dimensionless factor that indicates the impact of soil surface management on erosion. The factor values were calculated for each survey point, using the field data. For the calculation a shortened version of the original RUSLE formula [5-3] (Renard et al. 1996) was used:

$$SLR = CC \times SC \times SR \quad (1)$$

where: *SLR* – soil loss ratio for the given conditions (C-factor), *CC* – canopy-cover subfactor, calculated with formula [5-11] (Renard et al. 1996), *SC* – surface-cover subfactor, calculated with formula [5-12] (Renard et al. 1996), *SR* – surface-roughness subfactor, calculated with formula [5-23] (Renard et al. 1996).

As the study area is a rangeland, the C-factor is a function of soil surface roughness and vegetation properties. Tillage effect, prior land use and soil moisture subfactors are not considered as the area has always been used as a pasture and no tillage or irrigation has ever taken place. No significant residues were observed in the field as it is steadily overgrazed. The empirical coefficient used in surface cover subfactor calculation was 0.025 as suggested for the fields with interrill erosion as a dominant one (Renard et al. 1996). Surface roughness and random roughness are considered to be equal and were estimated in the field. On Figures 3 and 4, colour of points denote respective C-factor values.

2.3.2 Regression estimation

Normalized Difference Vegetation Index (NDVI) has been proven to be a good predictor for C-factor and other vegetation characteristics (de Jong 1994; van der Knijff et al. 1999). NDVI is calculated according to the following formula:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (2)$$

where: *NDVI* – normalized difference vegetation index, *NIR* – spectral reflectance measurement in near-infrared region, *RED* – spectral reflectance measurement in visible red region.

In case of LANDSAT 5 and 7 images the near-infrared and red regions are bands 4 and 3 respectively, for LANDSAT 8 these are the bands 5 and 4.

Correlation analysis and analysis of residuals indicated a significant nonlinear relation between NDVI and C-factor. A nonlinear least squares approximation of exponential function was undertaken with “nls” package of R using a default Gauss-Newton algorithm, which resulted in a regression equation, which was used for calculation of C-factor raster data out of NDVI rasters.

2.3.3 C-factor maps creation

NDVI rasters were calculated from all available satellite images of April – November of 2000 – 2013. The areas covered with clouds or cloud shadows were masked and cut out. In cases of several images being acquired in one month (mostly), the images were merged together to produce mean NDVI raster for the respective month. The gaps in images were closed with B-spline interpolation in “Close gaps with stepwise resampling” of SAGA GIS. Table 1 illustrates the percentage of area in gaps, which was closed with b-spline interpolation. If no appropriate images were available for a month, then NDVI images were produced by averaging the images of the next and the previous year of the considered month. These were October 2001, June 2003, May 2005, April 2008 and October 2008. Then the regression equation was applied to NDVI rasters to produce C-factor layers. The resulting images were merged monthwise to produce 13-year mean C-factor maps for each month. Areas, which were covered with snow on most images, were assigned C-factor value of 0.01 as no surface runoff or raindrop splashes were assumed under the snow.

Annual C-factor maps were developed as *EI*-weighted mean of monthly C-factor rasters, as suggested by formula [5-24] (Renard et al. 1996):

$$C = (SLR_1 \times EI_1 + SRL_2 \times EI_2 + \ldots + SLR_n \times EI_n) / EI_t \quad (3)$$

where: *C* – average annual C-factor, *EI* – total rainfall energy times intensity, SLR_i – SLR value for the time period *I*, EI_i – percentage of the annual *EI*, occurring in that time period, *n* – number of

Table 1 The percentage of no data cells missing in averaged images, these gaps were covered with b-spline

Otuz-Art				Uch-Choku			
Name	Data cells	Nodata cells	Percent	Name	Data cells	Nodata cells	Percent
2000 JUL	209411	9447	4.317	2000 MAY	259503	183	0.0705
2001 JUL	209021	9837	4.495	2000 JUL	226521	33165	12.771
2002 JUN	214265	4593	2.099	2001 JUL	217230	42456	16.349
2002 JUL	218759	99	0.045	2002 JUN	167682	92004	35.429
2002 AUG	209468	9390	4.29	2002 JUL	256878	2808	1.081
2003 MAY	213371	5487	2.507	2002 AUG	185481	74205	28.575
2003 JUL	208455	10403	4.753	2003 MAY	195396	64290	24.757
2004 AUG	210335	8523	3.894	2003 JUL	73683	186003	71.626
2005 JUN	217316	1542	0.705	2004 JUL	251190	8496	3.272
2005 AUG	157556	61302	28.01	2004 AUG	198858	60828	23.424
2005 OCT	198200	20658	9.439	2005 JUN	198777	60909	23.455
2006 JUN	187622	31236	14.272	2005 AUG	228993	30693	11.819
2006 AUG	218831	27	0.012	2005 OCT	177594	82092	31.612
2006 OCT	67141	151717	69.322	2006 MAY	241965	17721	6.824
2007 JUL	218636	222	0.101	2006 JUN	173337	86349	33.251
2009 JUL	218723	135	0.062	2006 OCT	111477	148209	57.072
2010 MAY	218822	36	0.017	2007 JUN	254799	4887	1.881
2010 JUN	213548	5310	2.426	2007 JUL	251868	7818	3.011
2011 JUN	209201	9657	4.413	2008 JUN	255084	4602	1.772
2012 JUN	216563	2295	1.049	2009 MAY	243477	16209	6.242
				2009 JUN	249582	10104	3.891
				2009 JUL	255960	3726	1.435
				2010 MAY	247539	12147	4.678
				2010 JUN	153615	106071	40.846
				2010 JUL	228735	30951	11.919
				2011 JUN	219801	39885	15.359
				2012 JUN	181725	77961	30.021
				2012 JUL	253899	5787	2.229
				2012 AUG	255561	4125	1.589

periods used in the summation, EI_t – sum of the EI percentages for the entire time period.

The EI values for each month were calculated from rainfall intensity measurements, available from local climate station (Ak-Terek Gava) according to the original RUSLE formula [B-2] (Renard et al. 1996).

2.4 Time series analysis

Time series of spatially averaged C-factor (2000 – 2013), precipitation (2000 – 2011) and temperature (2000 – 2009) indicated strong seasonal autocorrelation. These time series were decomposed with Seasonal-Trend Decomposition Procedure Based on Loess (Cleveland et al. 1990) with robust fitting as it is implemented in STL package of R. This approach decomposes a time series into trend, seasonal and random components, the sum of which is the original time series. STL utilizes a series of moving average and local polynomial regression smoothings (Cleveland et al. 1992) with weighting, being flexible in adjustments, robust to outliers and allowing for broad variability in curve fitting.

3 Results

3.1 C-factor regression analysis

NDVI and C-factor regression analysis for both research areas yielded the following, Table 2 indicates summary statistics of the equation:

$$SLR = \exp(-0.7842 - 2.9298 \times NDVI) \qquad (4)$$

where SLR – soil loss ratio (C-factor), $NDVI$ – normalized difference vegetation index value.

The nonlinear regression equation curve is indicated in Figure 6 together with observation points and additional regression curves from other studies. The equation (4) is the red bold line on the graph; equations of other researchers are dashed or

Table 2 Regression equation (4) summary statistics

Variables	Intercept	NDVI
Estimate	-0.7842	2.9298
Std. Error	0.1513	0.5065
t value	-5.183	-5.784
Pr(>|t|)	6.07e-07	3.36e-08

Note: Residual standard error: 0.08677 on 172 degrees of freedom.

dotted lines. The line of the equation by (de Jong et al. 1998) goes right through the point cloud and can be used to describe the relation, but the main drawback is that it is unable to handle the NDVI values over 0.535 properly. The equation above was used for the prediction of C-factor values on areas not sampled and for creation of continuous C-factor raster images from NDVI. The approximation curves from different studies in Figure 6 differ a lot from each other, which may be due to different study approaches. The graphs indicate that other existing equations could not be applied to our situation and a new equation suitable for the study area was needed.

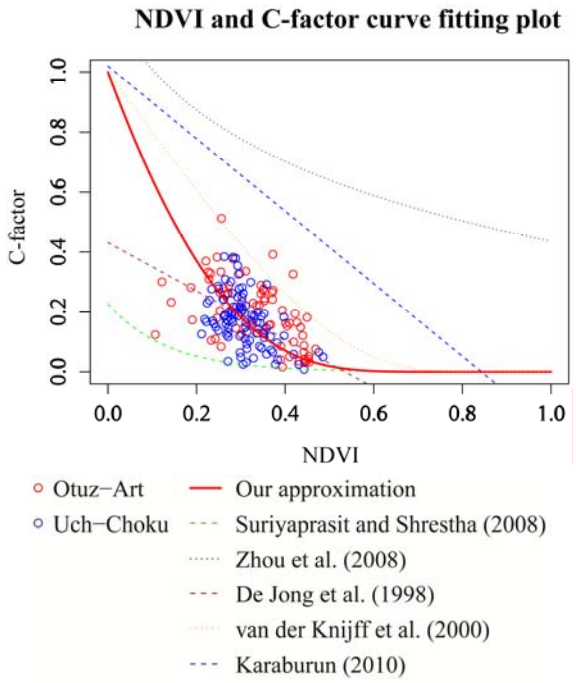

Figure 6 NDVI and C-factor curve fitting.

EI-weighted annual C-factor maps are represented in Figures 7 and 8. These maps show areas with greatest soil loss ratio in brown. The darkest areas are in most cases slopes steeper than 35°. In case of Otuz-Art (Figure 8) these are the areas of landslides with bare soil and extremely sparse vegetation. In case of Uch-Choku (Figure 7) these areas represent sparsely vegetated rocks or talus cones in the North, or areas with little vegetation cover mostly due to overgrazing and trampling in the center of the image. C-factor and slope steepness indicated significant correlation of +0.38. Obviously, vegetation cover on steeper slopes is less dense and more exposed to trampling and cattle track erosion.

Mean C-factor raster values of each month, *EI*-weighted annual average and their standard deviations are represented in Table 3. The mean soil loss ratio is lower in Otuz-Art than in Uch-Choku despite the fact that livestock pressure is lower in Uch-Choku. This can be attributed to the fact that Uch-Choku pasture is situated closer to the village with livestock being taken there on a daily basis, so it was not included in the estimation as only herders residing on pastures during summer season were interviewed. This means that real livestock pressure in Uch-Choku was underestimated. Otuz-Art is situated further away from the village and daily trips to the pasture are very unlikely indicating that all the livestock in Otuz-Art was counted. Also Uch-Choku is generally higher and its slopes are steeper than Otuz-Art. Steeper slopes can increase vegetation degradation from trampling and generally less vegetation is expected on higher altitudes.

3.2 C-factor correlation with temperature and precipitation

In April right after the snowmelt, C-factor shows highest values indicating the weakest cover protection, as vegetation cover is still very sparse in this month. A clear abrupt decrease of soil loss ratio in the beginning of the growing season (Figure 9f, 9l) is visible from April to May, which is caused by rapid vegetation development (onset of greenness). In April – May precipitation levels are quite high, whereas C-factor values decrease abruptly in May and reach their minima in June, i.e. two months after the precipitation maximum. This makes April and May the months with potentially highest soil loss, when the soil is freshly open after snow and still not protected well by vegetation, and subjected to peak precipitation rates. From June, soil loss ratio increases gradually

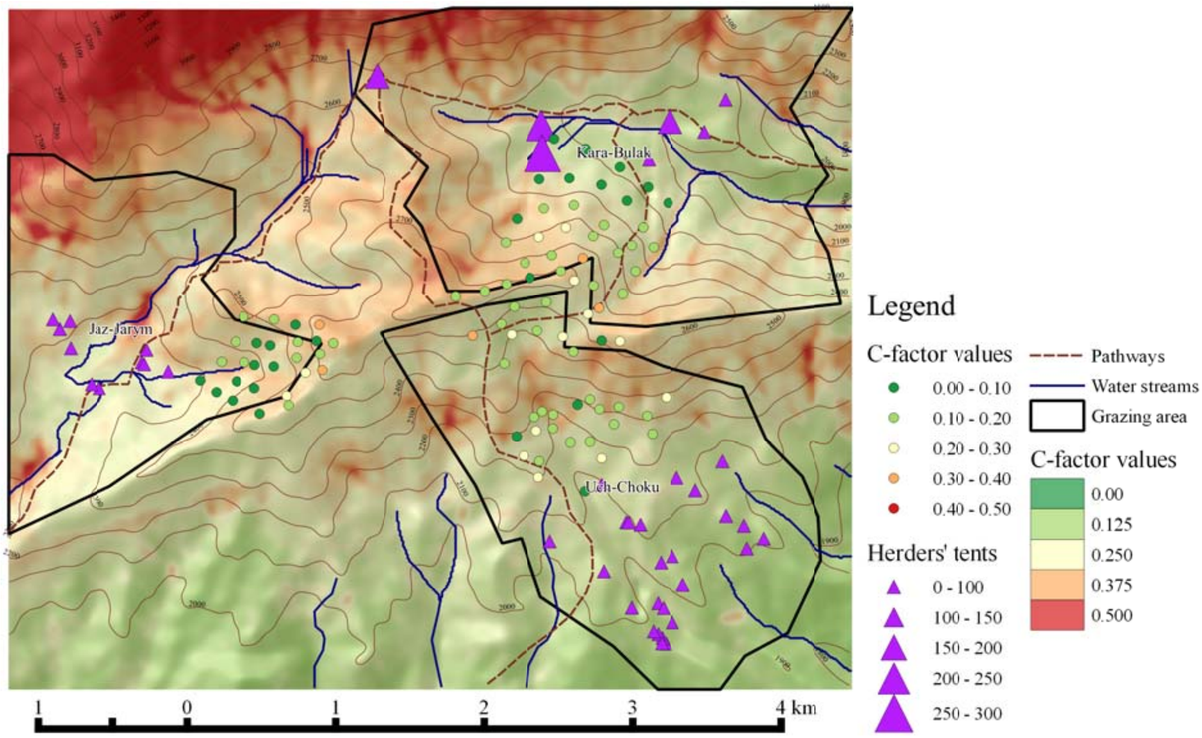

Figure 7 Annual C-factor map of Uch-Choku.

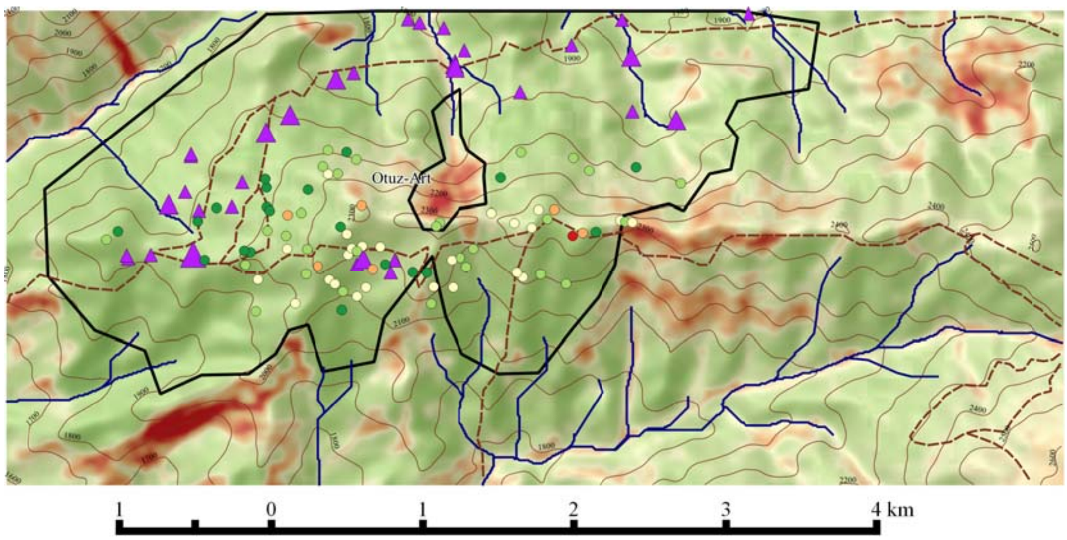

Figure 8 Annual C-factor map of Otuz-Art. The legend is the same as Figure 7.

Table 3 Monthly C-factor values and EI-weighted annual mean

	April	May	Jun	July	August	September	October	November	Year
Mean OA*	0.53	0.18	0.13	0.20	0.25	0.32	0.36	0.32	0.20
Std.dev OA*	0.24	0.09	0.06	0.07	0.07	0.07	0.07	0.20	0.07
Mean UC**	0.46	0.30	0.20	0.26	0.26	0.31	0.35	0.22	0.27
Std.dev UC**	0.28	0.15	0.08	0.08	0.08	0.08	0.07	0.20	0.10

Notes: * - Otuz-Art research area; ** - Uch-Choku research area.

after the abrupt decrease in May when grazing season begins. The increase is assumed to be caused by grazing, decrease of green vegetation due to active sun radiation and precipitation change, as well as natural vegetation decline. In August and September, C-factor values are high and rising, but because precipitation level is at its lowest point soil loss by runoff does not occur in great volumes. In November it decreases slightly because snow is already covering part of the research area providing conventionally high soil protection rate.

Correlation rates of trend and season components of C-factor, temperature and precipitation are indicated on Figure 9. Time series components for all the study areas indicated significant positive cross-correlation between C-factor and temperature trends (Figure 9a, 9g) almost without any lag difference. It also indicates a negative cross-correlation between C-factor and precipitation (Figure 9b, 9h) on trend level with 0.5-1 year lag difference. The trend components themselves are indicated on Figure 9c and 9i. This is mainly attributed to vegetation reaction on temperature increase, in warmer years vegetation development is more intensive primarily due to rapid development in spring. The lagged negative correlation with precipitation is mainly attributed to spring precipitation, which constrains vegetation development.

Cross-correlation analysis of seasonal components indicates an inverse picture – a significant negative correlation between C-factor and temperature (Figure 9d, 9j) and a slight positive correlation between C-factor and

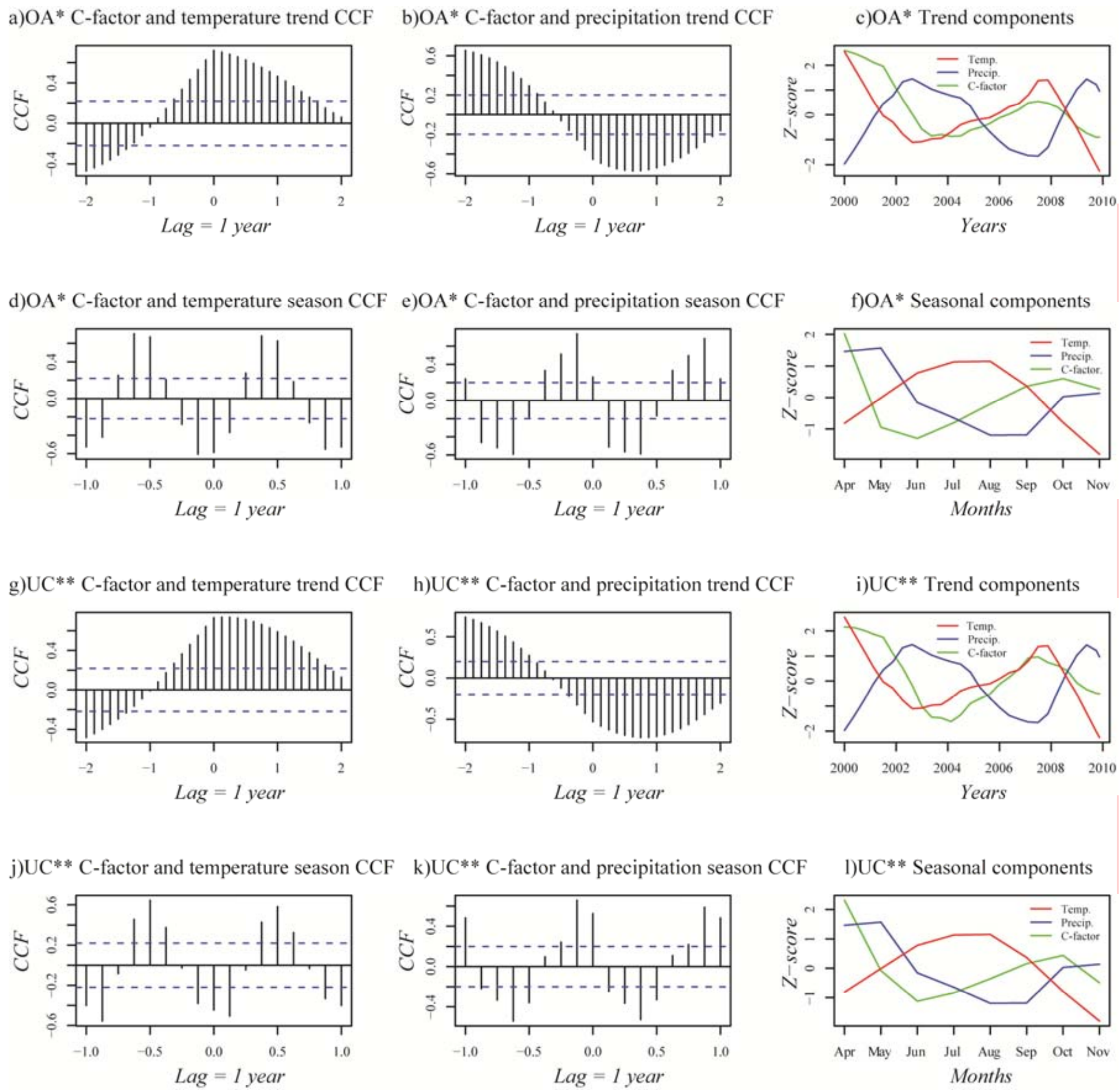

Figure 9 C-factor and precipitation time series decomposition and cross-correlations. (*- Otuz-Art research area; **- Uch-Choku research area).

precipitation (Figure 9e, 9k). Standard scores of seasonal components throughout a year are indicated on Figure 9f and 9l. On the seasonal level, the relations between the three components become more complex and here not only the climate factors, but also phenology and seasonality play a greater role in the system. Temperature makes a positive impact on vegetation in spring, whereas in summer it is a limiting factor for vegetation development, which defined the negative correlation at the seasonal scale. On the contrary, precipitation slows vegetation development in the beginning of the growing season due to limited sunlight, while in hot summers it provides moisture to sustain vegetation. Thus, at a seasonal scale the system has more complex interrelations.

We analyzed NDVI time series with BFAST package in R (Verbesselt et al. 2010b), but no abrupt changes were identified. This indicates that no significant harsh changes of general vegetation cover due to pasture management or natural disasters, for example, have taken place in the years 2000–2013.

4 Discussion

Different regression approaches and different assumptions of soil loss rate and NDVI relations were used, from linear (de Jong 1994; de Jong et al. 1998; Karaburun 2010) to exponential (Suriyaprasit and Shrestha 2008; van der Knijff et al. 1999; van der Knijff et al. 2000) or logarithmic (Zhou et al. 2008) producing very site-specific regression equations. The modelling was done on different scales with different data available from field estimates of C-factor with spatial reference, related to respective values of remotely sensed vegetation indices (de Jong 1994; de Jong et al. 1998; Suriyaprasit and Shrestha 2008) at a local scale, to discriminations between different vegetation types and assigning specific values at a country scale (van der Knijff et al. 1999; van der Knijff et al. 2000).

After examining q-q plots, linear regression did not seem to represent the NDVI and C-factor relation correctly; furthermore, the resulting equation does not cover the entire possible value range. After several trials an exponential equation outperformed as it provided the most plausible curve and lowest residual standard error. As it is indicated in Figure 6, the approximation curve represents the point cloud better than any other equation and covers the entire value range, though the equation of De Jong et al. (1998) came very close. This example demonstrates the difference of C-factor and NDVI relation depending on local conditions and in most cases it will require a specific regression analysis and equation. However this approach would not be applicable for the case of agricultural lands, where assignment of C-factor values based on the crop type and annual rotation can show better results (Bühlmann et al. 2010; Lee 2004).

The average annual soil loss factor is lower in Otuz-Art than in Uch-Choku, which indicates a better soil protection. Even though the estimated cattle density is higher in Otuz-Art, the C-factor is much lower there, which is attributed to more flat terrain, lower position and remoteness. In Uch-Choku, the grazing pressure seems to be considerably higher than estimated, due to proximity to the village, it also has more fragile vegetation cover on slopes due to their greater steepness and altitude compared to Otuz-Art. It indicates that different grazing plans and surface management must be applied to these pastures.

C-factor time series indicate a clear correlation with climate factors on seasonal and trend levels, which is attributed mainly to growing season vegetation dynamics. The general slightly negative trend of the soil loss ratio seen on Figure 9c and 9i should be interpreted with care, as the time span is somewhat short for representativeness and general spatial averaging does not allow for discretization of areas with different response patterns. However, at a bigger regional scale positive NDVI trends, corresponding to negative C-factor trends, were also reported by other researchers (de Jong et al. 2011; Propastin et al. 2008a; Propastin et al. 2008b).

Covariation of precipitation, temperature and C-factor seasonal components is expected to have a cause-and-effect relationship and is also explained by phenological reasons. This indicates that a great portion of C-factor fluctuations is caused by climate parameters. At the same time it is difficult to say which portion of the decline is conditioned by grazing, as data from not grazed areas are not available for comparative analysis. Similar vegetation and precipitation behavior was observed in Central Asia and Mongolia (Iwasaki 2006b; Kariyeva and van Leeuwen 2012; Nezlin et al. 2005; Propastin et al. 2008a; Yu et al. 2003). Using time-lagged or accumulation approaches for correlation or regression analysis provides better and more plausible results, as in most cases vegetation does not react to the change of climatic factors immediately (Gessner et al. 2013; Propastin et al. 2008a). However, in spring, temperature tends to assist rapid onset of greenness, whereas in summer it is a limiting factor, preventing further vegetation densification (Propastin et al. 2008a). Similar correlations were reported by other authors in the region and across the world (Bradley et al. 2007; Bradley and Mustard 2005; Gessner et al. 2013; Nezlin et al. 2005; Omuto et al. 2010; Paudel and Andersen 2010; Propastin et al. 2008a).

Many studies of vegetation time series use the sequences of NDVI raster and apply geostatistical analysis to identify polynomial trends of different areas (Propastin et al. 2008a; Propastin et al. 2008b), thus receiving spatial information and loosing information about seasonal variations. In this case discretization between different vegetation communities or using mixed-effect modelling for identification of relationship between NDVI and climate factors can give better results than general spatial averaging (Omuto et al. 2010; Propastin et al. 2008a). In this study we applied spatial averaging of remotely sensed data which allows for avoiding local outliers and capturing the general vegetation dynamics in its relation to precipitation and temperature.

Many statistical frameworks have been developed to extract phenological and interannual data from remotely sensed vegetation indices (de Beurs and Henebry 2010). Empirical orthogonal functions and principal component analysis are some of the frequently used approaches (Nezlin et al. 2005). The drawback of these approaches is that EOF modes as well as PCA components are very difficult to comprehend and interpret, especially in natural sciences, as they would represent abstract multicomponent variables of the data with the main idea of representing the data structure in fewer dimensions and with highest contrast between observations. Even though these methods are well suited for decreasing dimensionality, they do not provide means of seasonal and trend decomposition of remotely sensed data time series on their own.

Gessner et al. (2013) analyzed the spatio-temporal correlation between NDVI and precipitation monthly anomalies in the Central Asian region with temporal shifts up to three months. The study indicated time-lagged correlations between NDVI and precipitation anomalies, with the lag being one month, rarely two months, for most of the lowland Kyrgyzstan and for the present study area as well. This result is confirmed by our study. For most of the mountainous areas correlations were insignificant, presumably due to low capacity of AVHRR NDVI coarse resolution to capture changes in sparse and low vegetation, which is typical for these areas.

Another common way to fit phenology is to use Fourier harmonics, the results are then represented as sinusoid functions of different frequency and phase. The drawback of this method is that these harmonics do not necessarily represent objectively meaningful oscillations. De Beurs and Henebry (2010) provide a thorough analysis of different frameworks.

The approach we used in this study, application of conventional linear time-series decomposition tools to spatially averaged soil loss ratio values predicted by NDVI, is quite straightforward and produces seasonal and trend components, which are easy to interpret and give a clear view of vegetation annual phenology and interannual change. The method was used at a small local scale and applied to one vegetation community, thus general spatial averaging of data was adopted to eliminate local outliers. In case of applying the method at a broader regional scale, spatial differentiation between different vegetation communities will be necessary.

5 Conclusions

C-factor and NDVI indicated not linear relation. NDVI time series has proven to be a reliable spatial and temporal predictor of vegetation features, which can be attributed to the C-factor. C-factor on a trend level is significantly related to precipitation and temperature trends with a temporal lag. At the same time their seasonal components are parts of a more complex system where vegetation phenology is also a considerable compound. Climate factors can promote or decrease vegetation development depending on its phonological phase. As expected, steep slopes have higher ratios of soil loss both due to terrain and less vegetation cover compared to flatter areas.

Remotely sensed data combined with field data and freely available analytical instruments, as well as computational capacity of modern computers can become a valuable asset for cost effective soil loss monitoring.

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References

Atkinson PM, Jeganathan C, Dash J, Atzberger C (2012) Intercomparison of four models for smoothing satellite sensor time-series data to estimate vegetation phenology. Remote Sensing of Environment 123: 400-417. DOI: 10.1016/j.rse.2012.04.001

Blanco H, Lal R (2008) Principles of Soil Conservation and Management: Springer Science+Business Media B.V. p 626.

Borchardt P, Oldeland J, Ponsens J, et al. (2013) Plant functional traits match grazing gradient and vegetation patterns on mountain pastures in SW Kyrgyzstan. Phytocoenologia 43: 171-181. DOI: 10.1127/0340-269X/2013/0043-0542

Borchardt P, Schickhoff U, Scheitweiler S, et al. (2011) Mountain pastures and grasslands in the SW Tien Shan, Kyrgyzstan: floristic patterns, environmental gradients, phytogeography, and grazing impact. Journal of Mountain Science 8: 363-373. DOI: 10.1007/s11629-011-2121-8

Bradley BA, Jacob RW, Hermance JF, et al. (2007) A curve fitting procedure to derive inter-annual phenologies from time series of noisy satellite NDVI data. Remote Sensing of Environment 106: 137-145. DOI: 10.1016/j.rse.2006.08.002

Bradley BA, Mustard JF (2005) Identifying land cover variability distinct from land cover change: Cheatgrass in the Great Basin. Remote Sensing of Environment 94: 204-213. DOI: 10.1016/j.rse.2004.08.016

Bühlmann E, Wolfgramm B, Maselli D, et al. (2010) Geographic information system–based decision support for soil conservation planning in Tajikistan. Journal of Soil and Water Conservation 65: 151-159. DOI: 10.2489/jswc.65.3.151

Cleveland RB, Cleveland WS, McRae JE, et al. (1990) STL: A Seasonal-Trend Decomposition Procedure Based on Loess. Journal of Official Statistics 6: 3-73.

Cleveland WS, Grosse E, Shyu WM (1992) Local regression models. In: Chambers JM, Hastie TJ (eds.), Statistical Models in S. Chapman & Hall. pp 309-376.

Crewett W (2012) Improving the Sustainability of Pasture Use in Kyrgyzstan: The Impact of Pasture Governance Reforms on Livestock Migration. Mountain Research and Development 32: 267–274. DOI: 10.1659/MRD-JOURNAL-D-11-00128.1

de Beurs K, Henebry G (2010) Spatio-Temporal Statistical Methods for Modelling Land Surface Phenology. In: Hudson IL, Keatley MR (eds.), Phenological Research. Springer Netherlands. pp 177-208.

de Jong R, de Bruin S, de Wit A, et al. (2011) Analysis of monotonic greening and browning trends from global NDVI time-series. Remote Sensing of Environment 115: 692-702. DOI: 10.1016/j.rse.2010.10.011

de Jong SM (1994) Derivation of vegetative variables from a landsat tm image for modeling soil erosion. Earth Surface Processes and Landforms 19: 165-178. DOI: 10.1002/esp.3290190207

de Jong SM, Brouwer LC, Riezebos HT (1998) Erosion hazard assessment in the La Peyne catchment, France. Working Paper EU DeMon-II Project, i.o.v. EU. Utrecht University. The Netherlands (1998). p 27.

Dörre A, Borchardt P (2012) Changing systems, changing effects—Pasture utilization in the post-soviet transition: case studies from southwestern Kyrgyzstan. Mountain Research and Development 32: 313-323. DOI: 10.1659/MRD-JOURNAL-D-11-00132.1

Dotterweich M (2013) The history of human-induced soil erosion: Geomorphic legacies, early descriptions and research, and the development of soil conservation—A global synopsis. Geomorphology 201: 1-34. DOI: 10.1016/j.geomorph.2013.07.021

FAO (2006) World reference base for soil resources 2006 A framework for international classification, correlation and communication. Rome: Food and agriculture organization of the United Nations. p 145.

FAO (2011) FAOSTAT. Available online at: http://faostat3.fao.org/home/index.html> accessed on 17 May 2013.

Fu B, Liu Y, Lü Y, et al. (2011) Assessing the soil erosion control service of ecosystems change in the Loess Plateau of China. Ecological Complexity 8: 284-293. DOI: 10.1016/j.ecocom.2011.07.003

Gessner U, Naeimi V, Klein I, et al. (2013) The relationship between precipitation anomalies and satellite-derived vegetation activity in Central Asia. In: Global and Planetary

Change 110: 74-87. DOI: 10.1016/j.gloplacha.2012.09.007
Iwasaki H (2006a) Impact of interannual variability of meteorological parameters on vegetation activity over Mongolia. Journal of the Meteorological Society of Japan. Ser. II, 84: 745-762. DOI: 10.2151/jmsj.84.745
Iwasaki H (2006b) Study on Influence of Rainfall Distribution on NDVI Anomaly over the Arid Regions in Mongolia Using an Operational Weather Radar. SOLA 2: 168-171. DOI: 10.2151/sola.2006-043
Iwasaki H (2009) NDVI prediction over Mongolian grassland using GSMaP precipitation data and JRA-25/JCDAS temperature data. Journal of Arid Environments 73: 557-562. DOI: 10.1016/j.jaridenv.2008.12.007
Karaburun A (2010) Estimation of C factor for soil erosion modeling using NDVI in Buyukcekmece watershed. Ozean Journal of Applied Sciences 3: 77-85.
Kariyeva J, van Leeuwen WJD (2012) Phenological dynamics of irrigated and natural drylands in Central Asia before and after the USSR collapse. Agriculture, Ecosystems & Environment 162: 77-89. DOI: 10.1016/j.agee.2012.08.006
Korovin EP (1961) Vegetation of Middle (Central) Asia and South Kazakhstan. Tashkent, Akademy of Sciense of Uzbek SSR. p 452. (in Russian)
Law KH, Nichol J (2004) Topographic correction for differential illumination effects on Ikonos satellite imagery. Paper presented at the XXth International Society for Photogrammetry and Remote Sensing Congress: Geo-imagery bridging continents, Istanbul, Turkey.
Lee S (2004) Soil erosion assessment and its verification using the Universal Soil Loss Equation and Geographic Information System: a case study at Boun, Korea. Environmental Geology 45: 457-465. DOI: 10.1007/s00254-003-0897-8
Li ZW, Zhang GH, Geng R, et al. (2015) Land use impacts on soil detachment capacity by overland flow in the Loess Plateau, China. Catena 124: 9-17. DOI: 10.1016/j.catena.2014.08.019
Lioubimtseva E, Cole R, Adams JM, et al. (2005) Impacts of climate and land-cover changes in arid lands of Central Asia. Journal of Arid Environments 62: 285-308. DOI: 10.1016/j.jaridenv.2004.11.005
Mamytov AM (1974) Soils of Kyrgyz SSR. Frunze, Ilim. p 418. (in Russian)
Middendorff AF (1882) Insights in Fergana Valley. Saint Petersburg, Imperial Academy of Sciences. p 303. (in Russian)
Mikhailov DY (1959) Soil erosion in Kyrgyz SSR. Frunze, Kirgizgosizdat. p 190. (in Russian)
Nezlin NP, Kostianoy AG, Li BL (2005) Inter-annual variability and interaction of remote-sensed vegetation index and atmospheric precipitation in the Aral Sea region. Journal of Arid Environments 62: 677-700. DOI: 10.1016/j.jaridenv.2005.01.015
Omuto CT, Vargas RR, Alim MS, et al. (2010) Mixed-effects modelling of time series NDVI-rainfall relationship for detecting human-induced loss of vegetation cover in drylands. Journal of Arid Environments 74: 1552-1563. DOI: 10.1016/j.jaridenv.2010.04.001
Paudel KP, Andersen P (2010) Assessing rangeland degradation using multi temporal satellite images and grazing pressure surface model in Upper Mustang, Trans Himalaya, Nepal. Remote Sensing of Environment 114: 1845-1855. DOI: 10.1016/j.rse.2010.03.011
Propastin PA, Kappas M, Muratova NR (2008a) Inter-annual changes in vegetation activities and their relationship to temperature and precipitation in Central Asia from 1982 to 2003. Journal of Environmental Informatics 12: 75-87. DOI: 10.3808/jei.200800126
Propastin PA, Kappas M, Muratova NR (2008b) A remote sensing based monitoring system for discrimination between climate and human-induced vegetation change in Central Asia. Management of Environmental Quality: An International Journal 19: 579-596. DOI: 10.1108/14777830810894256
Renard KG, Foster GR, Weesies GA, et al. (1996) Predicting soil erosion by water: a guide to conservation planning with the revised universal soil loss equation (RUSLE) Washington, DC, USA. p 404.
Rigina O, Rasmussen MS (2003) Using trend line and principal component analysis to study vegetation changes in Senegal 1986 – 1999 from AVHRR NDVI 8 km data. Geografisk Tidsskrift-Danish Journal of Geography 103: 31-42. DOI: 10.1080/00167223.2003.10649477
Sun W, Shao Q, Liu J, et al. (2014) Assessing the effects of land use and topography on soil erosion on the Loess Plateau in China. Catena 121: 151-163. DOI: 10.1016/j.catena.2014.05.009
Suriyaprasit M, Shrestha DP (2008) Deriving land use and canopy cover factor from remote sending and field data in inaccessible mountainous terrain for use in soil erosion modeling. Paper presented at the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Beijing, China.
van der Knijff JM, Jones RJA, Montanarella L (1999) Soil Erosion Risk Assessment in Italy. Joint Research Centre (European Commission), Space Applications Institute, European Soil Bureau (European Commission). p 58.
van der Knijff JM, Jones RJA, Montanarella L (eds.) (2000) Soil Erosion Risk Assessment in Europe. Joint Research Centre (European Commission), Space Applications Institute, European Soil Bureau (European Commission). p 38.
Verbesselt J, Hyndman R, Newnham G, et al. (2010) Detecting trend and seasonal changes in satellite image time series. Remote Sensing of Environment 114: 106-115. DOI: 10.1016/j.rse.2009.08.014
Verbesselt J, Hyndman R, Zeileis A, et al. (2010) Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. Remote Sensing of Environment 114: 2970-2980. DOI: 10.1016/j.rse.2010.08.003
Vykhodcev IV (1956) Vegetation of Pastures and Hayfields of Kirgiz SSR. Frunze, Academy of Science of Kirgiz SSR. p 336. (in Russian)
Wang B, Zhang GH, Shi YY, et al. (2014) Soil detachment by overland flow under different vegetation restoration models in the Loess Plateau of China. Catena 116: 51-59. DOI: 10.1016/j.catena.2013.12.010
Wischmeier WH, Smith DD (1978) Predicting Rainfall Erosion Losses. Washington, DC, USA. p 69.
Yu F, Price KP, Ellis J, et al. (2003) Response of seasonal vegetation development to climatic variations in eastern central Asia. Remote Sensing of Environment 87: 42-54. DOI: 10.1016/S0034-4257(03)00144-5
Zemlyanitzkiy LT (1937) About soil erosion in mountain areas of South Kirgizia and Uzbekistan In: Soil erosion (collection of articles). Moscow: Academy of Sciences of USSR. pp 59-67. (In Russian)
Zhou P, Luukkanen O, Tokola T, et al. (2008) Effect of vegetation cover on soil erosion in a mountainous watershed. Catena 75: 319-325. DOI: 10.1016/j.catena.2008.07.010
Zhou ZC, Gan ZT, Shangguan ZP, et al. (2010) Effects of grazing on soil physical properties and soil erodibility in semiarid grassland of the Northern Loess Plateau (China) Catena 82: 87-91. DOI: 10.1016/j.catena.2010.05.005

Article III

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Modelling Soil Erodibility in Mountain Rangelands of South-Western Kyrgyzstan

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ABSTRACT

The main objective of this study was to map soil erodibility in the mountainous rangelands of Kyrgyzstan. The results of this effort are expected to contribute to the development of soil erodibility modelling approaches for mountain areas. In this case study we map soil erodibility at two sites, both representing grazing rangelands in the mountains of Kyrgyzstan and having potentially different levels of grazing pressure.

We collected a total of 232 soil samples evenly distributed in geographical and feature space. Then we analyzed the samples in a laboratory for grain size distribution and calculated soil erodibility values from these data using the Revised Universal Soil Loss Equation (RUSLE) K-factor formula. After that we derived different terrain indices and ratios of frequency bands from ASTER DEM and LANDSAT images to use as auxiliary data because they are among the main soil forming factors and widely used for prediction of various soil properties. Soil erodibility meaningfully correlated with channel network base level (geographically extrapolated altitude of water channels), remotely sensed indices of short-wave infrared spectral bands, exposition and slope. We applied multiple regression analysis to predict soil erodibility from spatially explicit terrain and remotely sensed indices. The final soil erodibility model was developed using the spatially explicit predictors and the regression equation and then improved by adding the residuals.

The spatial resolution of the model was 30 meters and the estimated mean adjusted coefficient of determination was $R^2 = 0.47$. The two sites indicated different estimated and predicted means of soil erodibility values (0.035 and 0.039) with 0.95 significance level, which is attributed mainly to the considerable difference in elevation.

Key Words: Kyrgyzstan; predictive soil mapping; RUSLE; spatial models; validation

INTRODUCTION

Soil loss through erosion has been widely recognized as one of the main problems of modern human-environmental interactions (Pimentel *et al.*, 1995; den Biggelaar *et al.*, 2003; Biggelaar *et al.*, 2004; Blanco and Lal, 2008) with its roots going deep into history (Dotterweich, 2013). Soil erosion is a common problem and has an impact on many aspects of human life and environment. It leads to pollution and sedimentation of water streams and bodies (Walling *et al.*, 2002; Rickson, 2014), can cause and be driven by severe vegetation loss (Ludwig *et al.*, 2005; Zhou *et al.*, 2010, 2016; Hou *et al.*, 2016; Wang *et al.*, 2016b), as well as soil productivity loss. Global food security challenges created new tasks for soil science, which provides more and more problem solving as remote sensing and geospatial techniques further develop (Hartemink and McBratney, 2008).

The Universal Soil Loss Equation (USLE) was developed by Wischmeier and Smith (1978) and provides a convenient tool for soil loss estimation for agricultural lands. The Revised Universal Soil Loss Equation (RUSLE)

(Renard *et al.*, 1996) was developed using a larger dataset and is applicable for soil loss estimation in a broader range of conditions including grasslands. RUSLE calculates soil erosion multiplying six main factors: (R) - rainfall and runoff erosivity, (L) - slope length, (S) - slope steepness, (C) - cover management practices, (P) - supporting conservation practices and (K) - soil erodibility. Thus, soil properties are among the main factors controlling soil loss. The K-factor of RUSLE (Renard *et al.*, 1996) has been widely used for estimation of soils' susceptibility to splash detachment and transport by surface flow (Romkins *et al.*, 1986; Knijff *et al.*, 1999a, 1999b; Wang *et al.*, 2013).

Soil erodibility is the factor indicating the susceptibility of the soil to raindrop splash and surface water flow impact. It is an essential parameter for prediction of soil erosion. The most accurate method of soil erodibility estimation is long-term direct measurements of soil loss on runoff plots with controlled conditions. Alternatively it can be measured in the laboratory under simulated rainfall conditions. Both methods require significant time and resource investment which is not feasible where resources are limited. Wischmeier and Smith (1978) provided a soil erodibility nomograph (and its approximation formula) for convenient estimation of the K-factor based on texture, organic content, structure and permeability of the soil. Zhang *et al.* (2016) found the approximation formula to be inappropriate for soil erodibility estimation in China. Singh and Khera (2009) found the nomograph to produce considerably lower soil erodibility values in India. Wang *et al.*, (2016a) indicated the RUSLE equation, based on the grain size data to be a good approximation of K-factor values for soils in China in contrast to the other equations. The nomograph was a result of erosion studies conducted in the United States. The RUSLE equation [3-5] (Renard *et al.*, 1996) considers the K-factor to be the function of solely soil texture. Likewise, Römkens *et al.* (1986) suggest texture to be the main factor of soil erodibility. The K-factor approximation formula [3-5] in RUSLE is a result of regression analysis based on long-term runoff plot observations of 225 different soil types from all over the world (Romkins *et al.*, 1986; Renard *et al.*, 1996), and thus preferable for conditions where direct soil erosion measurements are not available. Zhang *et al.* (2008) found the two formulas overestimating but being appropriate for K-factor estimation in east China. Wang *et al.* (2013) provide a deep analysis of different soil erodibility concepts and their history indicating a common need for validation and calibration methods as well as consideration of its spatial and seasonal variations.

Zhang *et al.* (2004) demonstrated K-factor to be a good measure for evaluation of soil erodibility in the Loess Plateau region of China. They indicated that erodibility of loess soils is mainly conditioned by the size of particles, rather than organic matter content, which is usually low. Panagos *et al.* (2012) developed a soil erodibility map for members of the European Union using a grid of soil samples across Europe and inverse distance weighting interpolation of their values. The authors suggest using the dataset as input for interpolation of the values on a finer local scale with auxiliary data. Extrapolation method is a different approach in contrast to mapping with spatially explicit auxiliary data as used by Tesfa *et al.* (2010) who mapped soil profile depth with terrain indices and generalized additive model.

Modelling spatial continuity and variations of soil properties in general is not a trivial task and different local conditions including soil type, data availability, terrain, climate, etc. influence the choice of method. Terrain features such as slope degree, slope curvature, altitude, etc. and ratios of satellite images' frequency bands have been extensively used as predictors for production of continuous maps of numerous soil properties (De Jong, 1994; McBratney *et al.*, 2003; Bishop and Minasny, 2006; Madeira Netto *et al.*, 2006a, 2006b, Boettinger *et al.*, 2008a, 2008b, 2010; Florinsky, 2012). Processes of soil formation and development depend greatly on the terrain and terrain-driven conditions (Simonson, 1995; Florinsky, 2012), and are often directly or indirectly represented by surface reflectance (Boettinger *et al.*, 2008a, 2010).

Slope and exposition are among mountain-specific terrain factors influencing soil formation (Martz, 1992). Slopes facing different directions get different amounts of solar radiation, wind and precipitation, and snow melts on northern slopes much later than on the southern ones. McBratney *et al.* (2003) and Lagacherie (2008) provide a thorough analysis of different prediction methods of soil properties with auxiliary data including remote sensing and terrain models. Satellite images provide a database of ground reflectance carrying integrated information about the land surface. They represent continuous sets of surface data from large areas collected on a regular basis. Digital elevation models are available for most of the world providing valuable data for modelling soil properties. All these sources provide a solid foundation for development of different modelling approaches.

Ordinary kriging and extensive geographical space sampling to predict soil erodibility in mountain areas of Ethiopia with "one out" cross-validation (Addis and Klik, 2015). However, regression kriging has been demonstrated to be a top performer amongst different soil prediction modeling tools and often outperforms ordinary kriging in mountainous areas and has greater flexibility (Bishop and McBratney, 2001; Zhu and Lin, 2010; Li and Heap, 2014). One of the main reasons for choosing the regression kriging approach over the others is flexibility of different relation models in its regression component. Hengl *et al.* (2004) noted a combination of kriging and regression to be more accurate than co-kriging, plain kriging or regression alone. Sanchez-Moreno *et al.* (2014) also reported kriging with external drift to produce more accurate results for soil loss simulation.

McBratney *et al.* (2003) proposed a new "scorpan" model, a revision of the "corpt" model by Jenny (1941). The new "scorpan" approach views predicted soil properties and classes as a function of prior knowledge of soils, which includes data from legacy maps, proximal sensing or expert knowledge, climate factors, organisms' activities, topography, parent material, time factor, and spatial position. The general approach applied in this study follows this model, as it covers soil development process from many important aspects.

Water erosion is the dominant source of soil erosion in Kyrgyzstan (Thomasson, 1992). Soil loss rates are expected to be high in the south of the country because of the mountain terrain, fine soil texture, high precipitation level, and vegetation loss due to overgrazing. Unfortunately, there is lack of soil erodibility maps for the region. Soil type maps (Mamytov and Ashirakhmanov, 1988) are available for the entire area of the country, however several studies have indicated poor performance of soil erodibility predictions based on soil types (Veihe, 2002; Pérez-Rodríguez *et al.*, 2007; Bonilla and Johnson, 2012). At the same time "scorpan"-based models predicting soil properties from spatially explicit auxiliary data have become a widely used approach (McBratney *et al.*, 2003; Shaw *et al.*, 2004; Boettinger *et al.*, 2010; Florinsky, 2012; Mcbratney *et al.*, 2012) performing well for soil erodibility prediction.

Kyrgyzstan, a developing country with a natural resource based economy, requires a low-cost tool for soil erosion risk assessment derived from existing auxiliary data so that effective management actions can be taken at relatively low economic cost to managers (Mcbratney *et al.*, 2012). There is lack of a common cost-effective soil erodibility mapping approach, which would include the sampling strategy, mapping with field and auxiliary data, and subsequent model quality validation. We attempt to develop an approach for soil erodibility modelling of complex landscapes. More specifically, we identify the appropriate soil sampling strategy. Then we create a continuous K-factor map based on sampling of soil in geographic and feature space, regression analysis with remotely sensed data and terrain indices used as predictors. Then we assess the goodness of fit with permutation approach. For this purpose we will identify the optimal sampling strategy, set of predictors and predicting techniques and cross-validate the model. The approach was developed and tested on pastures in the Fergana Range, in conditions of various human impacts. It can be further used for spatial modelling of soil erodibility in complicated mountainous terrain with limited baseline data.

STUDY AREA AND METHODS

Study area

The study area is situated in Fergana Range in the south of Kyrgyzstan (Fig. 1). Pastures make up 40% of the study area and has some of the highest official average livestock densities in the country – 1.6--2.2 sheep per hectare (Atadjanov *et al.*, 2012). Most of the livestock is concentrated around villages on easily accessible pastures (Borchardt *et al.*, 2010, 2011; Crewett, 2012) leading to uneven distribution of grazing pressure. Around 60% of the population living in rural areas depend directly on natural resources (Atadjanov *et al.*, 2012), with agriculture and animal husbandry being the main components of the rural economy.

This part of the Fergana valley receives the largest amount of precipitation in Kyrgyzstan – as much as 1000 mm annually (Kuzmichenok, 2008; Atadjanov *et al.*, 2012), with most of it falling in spring, resulting in this season contributing the most to the bulk soil loss. Soils are represented by Cambisols, Gypsisols, and Lithosols on rocky slopes (IUSS Working Group WRB, 2006) with medium to fine soil texture. The vegetation is primarily that associated with mountain grasslands with ephemeral species dominated by *Trifolium repens*, *Poa pratensis*, *Taraxacum officinale*, *Dactylis glomerata* and *Eremurus fuscus* (Borchardt *et al.*, 2011). The region is heavily grazed in summer. Overgrazing and trampling are the main degradation factors resulting in heavily grazed grasses and cattle tracks. Aforementioned features were the main reasons to choose the area for the model development and test.

Field data collection occurred at two study sites representing mountainous rangelands known to have been intensively grazed for decades and possibly longer. One site (Uch-Choku) is situated close to the villages of Arslanbob and Kyzyl-Unkur and thus likely more intensively used than the other (Otuz-Art), which is a rather remote pasture (Fig. 2). The area used for simulation in Uch-Choku is about 22 km^2, and it has a more rugged terrain and greater variations in altitude (2000--2800 m a.s.l.) than Otuz-Art (2000--2400 m a.s.l.), which has an area of about 26 km^2.

Modelling

The modelling consisted of several steps (Fig. 3). The first step included collection of soil samples in the field and analysis of the mechanical composition in the laboratory. Then the K-factor was calculated from the laboratory data for each sampling point. These steps are detailed in "*Field data collection*" and "*Soil erodibility*" sections. We will call these K-factor values the "estimated".

Then we used the regression kriging approach to create the spatially explicit model. For that we identified spatially explicit predictors (terrain and remotely sensed) for linear regression analysis, using the K-factor as an independent variable. These steps are detailed in "*Remotely sensed data and DEM*" and "*Predictors used in regression analysis*" sections. Then we calculated a K-factor raster using predictors and the regression equation, derived earlier. The residuals from the regression equation were extrapolated over the entire study area with ordinary kriging, which is described in "*Kriging of residuals"* section. Then we summed up the K-factor raster and the residuals raster to produce the final K-factor map. These spatially explicit K-factor values will be called the "predicted".

The model was assessed for accuracy with 1000-fold cross-validation approach. The pool of K-factor samples was randomly split into the training and testing sets, training the model with the training set and then checking it against the test set (Fig. 3). This routine was repeated 1000 times and a coefficient of determination was calculated each time. This procedure is described in "*Model validation*" section.

Field data collection

To assess soil erodibility, soil samples were collected over a 4 year period during July - August in 2008, 2010 and 2011. The study sites were covered with a network of point surveys (Fig. 2; red dots) designed to cover the altitudes from 2000 m up to the top with 100 m intervals on 8 expositions (N, NE, E, SE, S, SW, S, NW) and different slope gradients (steep 30°--45°, middle 15°--30°, gentle 0°--15°) where possible. The aim of the sampling design was to cover the study areas with a grid of sampling points ensuring representation of the whole range of values of terrain variables, which were anticipated to correlate with soil erodibility.

At each point a soil sample of 300 cm^3 was taken from the top 20 cm soil layer with a 100 cm^3 hammer-driven sampling cylinder. The coordinates of each soil sample were recorded with GPS. In total 232 soil samples were collected: 142 in Uch-Choku and 90 in Otuz-Art. Vegetation and stone cover percentage was visually assessed at each sampling point on a 5×5 m plot. To estimate grazing pressure cattle tracks were counted on 15 m vertical transects and divided into 4 classes according to their width where the 1st class was the most narrow and the 4th class was the widest track. Cattle track counts were repeated at both sites. A cattle track rate was calculated for each survey point using the following equation:

$$CTR = CL1 + 2 \times CL2 + 3 \times CL3 + 4 \times CL4 \quad (1)$$

where:

CTR – cattle track rate;
CL1 – number of class 1 tracks;
CL2 – number of class 2 tracks;
CL3 – number of class 3 tracks;
CL4 – number of class 4 tracks.

Soil erodibility

Soil samples were stored and transported to the laboratory of Institute of Geography, Hamburg University, in plastic bags, dried in ovens at the temperature of 40°C and analyzed for grain size distribution following "Procedures for soil analysis" (Reeuwijk, 2006).

Soil erodibility or K-factor in RUSLE (Renard *et al.*, 1996) is an indicator of how susceptible the soil is to the erosive action of precipitation – drop splash and surface runoff, and is dependent on the physical characteristics of soils (Romkins *et al.*, 1986). We used the equation recommended by Renard *et al.* (1996) for the conditions with limited data. The equation was derived by Römkens *et al.* (1986) and based on a world-wide dataset of directly measured K-factor values.

The K-factor was calculated for each surveyed point using grain size data from the laboratory analysis as an input to the following equations, which are the equations [3-5] and [3-6] in RUSLE (Renard *et al.*, 1996), originally derived by Römkens *et al.* (1986):

$$K = 0.0034 + 0.0405 \exp\left[-0.5\left(\frac{\log(Dg) + 1.659}{0.7101}\right)^2\right] \quad (2)$$

where:

$$Dg(mm) = \exp\left(0.01 \sum f_i \ln m_i\right) \quad (3)$$

where:

K – K-factor;
f_i – percent of the primary soil particle size fraction;

m_i – arithmetic mean of the size limits (mm) of the particle fraction;
Dg – geometric mean of soil particles diameter.

Remotely sensed data and DEM

Satellite derived data was obtained via LANDSAT (7) from 2011 (paths 151 and 152, row 31). These images were cloud and snow free and lacked significant shadowing. The spatially explicit elevation model we used was ASTER GDEM. The coordinate system used throughout the research was the projected coordinate system WGS UTM 43N. All the raster images were brought to the same spatial extent and resolution of 30 m with b-spline interpolation for consistency and compliance of auxiliary data. Statistical computations and graph figures were made in R 3.1.2 x64, all the GIS manipulations and satellite images processing were done in SAGA GIS 2.1.4 x64. The map figures were produced with QGIS 2.12.3 x64.

Predictors used in regression analysis

We assume the population of K-factor values from soil samples to be normally distributed. Terrain derivatives and LANDSAT bands ratios were indicated to be good predictors of soil features (McBratney *et al.*, 2003; Scull *et al.*, 2003; Boettinger *et al.*, 2008a, 2010; Florinsky, 2012). Field observations also indicated variations of soil texture depending on exposition and slope. Short-wave infrared spectral bands of LANDSAT images can be used as covariates for soil parent material and soil properties (Boettinger *et al.*, 2008a). Soil Enhancement Ratios (SER) of LANDSAT bands were identified to be good predictors of soil features, which can be used for modelling, especially in areas with low vegetation cover (Boettinger *et al.*, 2008a, 2010), which is the case in our study area.

LANDSAT image of May 2011 without snow, clouds and shadows was used to produce the soil enhancement ratio images (Boettinger *et al.*, 2008a, 2010) with raster calculator in SAGA GIS. The gaps in LANDSAT images were closed with SAGA GIS "Close gaps with stepwise resampling" module (Conrad, 2012). We calculated different combinations of LANDSAT bands as described by Boettinger *et al.* (2008). The ratio of LANDSAT bands $(5\text{-}7)(5+7)^{-1}$ indicated the highest correlation with K-factor, so it was chosen as a predictor and is referred to as SER further on.

$$SER = \frac{(b5 - b7)}{(b5 + b7)} \qquad (4)$$

Where:
SER – Soil Enhancement Ratio;
b5 – LANDSAT7 band5;
b7 – LANDSAT7 band7.

Channel Network Base Level (CNBL) was derived from ASTER GDEM using SAGA GIS "Basic terrain analysis" module. This raster represents an interpolation of altitude of water streams on the surrounding area. Streams play an important role in soil formation processes and CNBL provides information about distance to streams, relative slope position and altitude, which are also considered important predictors of soil properties (McBratney *et al.*, 2003; Boettinger *et al.*, 2008b).

The slope steepness raster was derived from ASTER GDEM with SAGA GIS "Basic terrain analysis" module (Zevenbergen and Thorne, 1987). Slope is a basic terrain feature and has a high degree of influence on soil development (McBratney *et al.*, 2003; Florinsky, 2012) and erodibility. Water runoff on steeper slopes is greater and soils tend to be coarser due to loss of fine particles, in contrast to soils on gently sloping or even terrain.

The slope bearing (azimuth) raster was derived from ASTER GDEM with SAGA GIS "Basic terrain analysis" module (Zevenbergen and Thorne, 1987). Since bearing is a radial value it was transformed into "eastness" and "northness" rasters using sine and cosine functions respectively. All these variables were tested for appropriateness as K-factor predictors in regression analysis.

The soil samples from the two study sites were comparable with regards to aspect and slope degree, because these had been controlled during collection, and different in SER and CNBL (Fig. 4). The predictors chosen for regression analysis were: SER, CNBL, sine of slope aspect in radians (eastness), and slope inclination in degrees, because they indicated high correlations with K-factor (Fig. 5).

With the intention to avoid collinearity in predictors we conducted a backward/forward stepwise model selection with Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which are generally used to compare efficiency of models.

Kriging of residuals

The residuals of the regression equation were interpolated over the study sites with ordinary kriging (global) module in SAGA GIS. The following function was used to describe the variogram:

$$f(x) = \begin{cases} 10.4044\text{E-}06 + 11.8675\text{E-}09 \times x - 60.3399\text{E-}13 \times x^2, x \leq 1000 \\ 1.63\text{E-}05, x > 1000 \end{cases} \quad (5)$$

where:

f(x) – variance;
x – distance in meters.

The choice of the variogram function was driven by expert opinion and by the fact that it produced lesser residuals in the final model. We did not find any directional trends or anisotropy. As the equation (5) suggests the variance stayed constant after 1000 m distance.

Model validation

As the complexity of the model did not allow for direct unbiased estimation of goodness of fit, cross-validation was employed. The set of 232 measurements was randomly split without replacement in 160 samples training set and 72 samples test set. In total 1000 random permutations were used with separate regression equation estimation for each combination (Fig. 3). The training set based regression equations were used to predict the values for the test sets and residuals were extrapolated with the same routine as described in "*Kriging of residuals"*. The K-factor values predicted using the training set of samples were compared against the test set and a coefficient of determination was calculated for each of the 1000 random permutations (1000-fold cross-validation). Then we calculated a mean of all the 1000 coefficient of determination values, which indicates how good the model is in predicting the K-factor.

RESULTS

Properties of soil samples

The laboratory analysis of soil samples demonstrated that soil had greater erodibility properties on the steepest slopes at higher elevation (Fig. 5). The mean soil erodibility (K-factor) calculated from grain size distribution data of the collected soil samples for both areas was 0.0374 t ha h ha^{-1} MJ^{-1} mm^{-1} (standard deviation 0.0048) (Fig. 6) which complies with the values reported by van der Knijff *et al.* (2000) for European medium, medium-fine and fine soils (Fig. 7a). Fig. 7b represents the texture distribution of the collected soil samples by texture classes used in the soil erodibility nomograph (Wischmeier and Smith, 1978) with textural limits of clay – 0--0.002 mm, silt + very fine sand – 0.002--0.1 mm, and sand – 0.1--2 mm. The results of the grain size distribution analysis with HYPRES textural limits were as follows: in Uch-Choku: 9 soil samples had fine texture, 89 – medium and 44 – medium-fine; in Otuz-Art: 39 samples had fine texture, 23 – medium, 28 – medium-fine (European Soil Bureau Working Group, 2015). Uch-Choku appeared to be more degraded than Otuz-Art as vegetation was sparser, had greater stone cover and higher cattle tracks density (Table I).

Regression of estimated soil erodibility with auxiliary data

Soil erodibility values (K-factor) correlated significantly (Fig. 5) with slope exposition eastness raster, Channel Network Base Level (CNBL), slope degree and SER for May 2011, which represents hydroxyls of clays (Boettinger *et al.*, 2010). SER and CNBL also indicated significant correlation with each other (Fig. 5). This is presumably due to strong altitudinal variation of soil features which was captured by remote sensing in SER and inherited by CNBL from the DEM.

AIC excluded slope and BIC excluded both slope and eastness from the optimal list of predictors. These are the variables with the lowest correlation rates; however they are important spatial predictors of soil features. In this regard it was decided to omit only slope from the list of predictors. Many combinations of predictors were tested and the combination of CNBL, SER and slope exposition eastness provided the highest adjusted R^2 values (R^2 = 0.3611).

Based on AIC suggestion we used CNBL, SER and aspect sine. The resulted regression equation was as follows:

$$K = 2.684\text{E-}02 + 9.658\text{E-}06 \times CNBL - 2.46\text{E-}02 \times SER + 8.8\text{E-}04 \times sin(A) \quad (6)$$

where:

K – Soil Erodibility (K-factor);
CNBL – Channel Network Base Level;
SER – Soil Enhancement Ratio;
A – Slope Aspect (radians).

Analysis of residuals indicated the linear regression to be sufficient in prediction of K-factor, details of the regression equation are provided in Table II.

Mapping

Soil erodibility map was calculated with equation (6). The K-factor residuals were interpolated over the research areas with ordinary kriging using the variogram (5). Then the regression raster and residuals raster were summed up, which created a K-factor raster with globally consistent values and specific local variations, which were represented by the residuals (Fig. 3).

The resulting soil erodibility maps for Otuz-Art and Uch-Choku study sites indicate higher K-factor on slopes and mountain tops, whereas valley bottoms and flat areas indicate lower K-factor (Figs. 8 and 9). The mean of the resulting K-factor map of Otuz-Art was 0.0351 with standard deviation = 0.0025. The mean of the resulting K-factor map of Uch-Choku was 0.039 with standard deviation = 0.0037. In general Otuz-Art indicates lower soil erodibility (Fig. 6). At both sites the erodibility is higher on steeper slopes, ridges and higher parts; and is lower on flat areas and valley bottoms (Figs. 8 and 9).

Predicted K-factor fell within expected limits for this soil type (Figs. 6 and 7). A considerably higher upper limit of Uch-Choku predicted values is explained by relatively high K-factor values on rocky slopes in the top-left corner (Fig. 9) which were not sampled in the field and were not present in Otuz-Art. Medians of the predicted K-factor values have got shifted towards the common mean because the common regression equation was used for both study areas (Fig. 6). Overall, the overlapping quartiles indicate consistency of the value ranges across the datasets.

The model validation procedure resulted in mean adjusted coefficient of determination of all the permutation sets being $R^2 = 0.4701$, which indicates an improved goodness of fit compared to adjusted $R^2 = 0.3611$ of the regression equation (6) (Table II).

DISCUSSION

Sampling strategy

The sampling strategy applied in this study appeared to be sufficient but not the best possible, because predictors were not known prior to sampling. Covering different slopes, altitudes and expositions turned out satisfactory as those were expected to be the main soil erodibility covariates (Fig. 5). Terrain features were anticipated to be the main predictors of soil erodibility (McBratney *et al.*, 2003; Boettinger *et al.*, 2010), thus it was decided to employ a terrain based sampling strategy with regular distribution in geographical space, which would automatically ensure sampling the feature space and even an geographical coverage of the study area.

The aim of the sampling strategy was to cover the study area with a grid of samples ensuring representation of the whole range of the measured values in the population. Covering different terrain features seems a good practical approach as it follows main soil development factors, and is a good combination of sampling geographical and feature space. However, terrain features do not necessarily reflect distribution patterns of parent material and different soil textural classes. In this regard it can be generally recommended for soil mapping in mountain areas to classify the research area into a number of *k*-mean classes (Brus *et al.*, 2006; Heuvelink *et al.*, 2006; Brus and Heuvelink, 2007) with SER (Boettinger *et al.*, 2010) and terrain features when predictors are not known. Taking samples within each class would ensure even spatial distribution, which is crucial for the areas with rugged terrain.

Even though exhaustive auxiliary data were available prior to conducting field surveys, it was not known which would be used as predictors in the regression analysis due to an absence of soil erodibility correlation studies for the area. A combination of geographical and feature spaces were sampled to avoid spatial clustering and increase spatial flexibility as suggested by Brus and Heuvelink (2007). In the case of Latin hypercube sampling strategies (Minasny and McBratney, 2006; Mulder *et al.*, 2012; Clifford *et al.*, 2014) some sampling spots may occur inaccessible or unrepresentative due to rugged terrain. Similar challenges were reported by Kidd *et al.* (2015) and Thomas *et al.* (2012). Viloria *et al.* (2016) used neural networks and fuzzy clustering of geomorphological and remotely sensed data to discriminate between different soil classes.

Modelling approach

RUSLE authors (Renard *et al.*, 1996) suggest equation (2) for estimation of K-factor for soils with limited data and other textural limits than the ones, on which the soil erodibility nomograph (Wischmeier and Smith, 1978) was based. This is mainly because it is based on multiple studies of soil erodibility of different soil types from different parts of the world. This formula takes textural limits of soil as an input ignoring the organic matter content, which can potentially limit the estimation accuracy, however Zhang *et al.*, (2016) and Wang *et al.*, (2016b) report the opposite.

As is discussed by Römkens *et al.* (1986), soil erodibility is a complex factor accounting for intrinsic and constant characteristics of soils, as well as for dynamics, both seasonal and external. The K-factor equation (2) applied in this study uses only soil texture for prediction of soil erodibility. Even though the equation is based on a considerable dataset of runoff plot measurements and simulations, and textural properties are the main factor controlling soil erodibility, ignoring other soil characteristics and seasonal variations implies uncertainty in prediction accuracy. However, Römkens *et al.* (1986) indicate that in the case of long-term observations and broad dataset the dynamic factor will be averaged out and soil erodibility can be reduced to a function of its texture. Zhang *et al.*, (2016) and Wang *et al.*, (2016b) demonstrated the grain size based equation to produce better results for soils in China.

Remotely sensed and terrain data have been a well-used combination of data sources for soil mapping. This is a logical and straightforward approach. Since Dokuchaev's ideas (Florinsky, 2012), formulated by Jenny (1995) and revised by McBratney *et al.* (2003), pedologists have been using terrain, parent material, vegetation, climate etc. as covariates for prediction of soil features. Recent developments in remote sensing and data processing technologies, and availability of vast geographical datasets have resulted in a sharp increase of the number of soil mapping studies. Predictive soil mapping can be divided in two main categories depending on the goal: prediction of continuous soil characteristics or prediction of discrete soil classes. These two categories employ different processing techniques and statistical approaches, but both use spatial predictors, which are in most cases terrain derivatives, indices of remotely sensed data or legacy maps.

Since the available maps of soil classes were assessed as poor predictors of soil erodibility (Veihe, 2002; Pérez-Rodríguez *et al.*, 2007), remotely sensed data and terrain indices were used as auxiliary data. The mapping approach of using regression analysis with subsequent kriging of residuals mimics regression kriging. It was decided to separate the steps to take full control of the regression analysis and residual kriging to produce plausible results and make the approach reproducible in other similar conditions (e.g. Hengl *et al.* 2004).

In general, SER calculated from May LANDSAT images indicated higher correlation rates because vegetation cover is still not well developed in this month and remotely sensed data contain a greater portion of soil information than in other months. The topographical information was provided by ASTER GDEM as it showed a greater compliance with field data than SRTM or manually digitized isolines of topographic maps. This contradicts the findings of de Vente *et al.* (2009) who showed SRTM DEM to be more accurate in south-east of Spain. The chosen predicting variables cover soil formation factors from many important aspects of the "scorpan" model (McBratney *et al.*, 2003). Any plain kriging approach without continuous auxiliary data would fail on a rugged terrain as soil characteristics can change gradually or abruptly depending on different terrain features, which cannot be predicted otherwise.

Model validation

Many studies use two static sets of samples, one for training of the model and another one for unbiased validation (Bishop *et al.*, 2015; Odgers *et al.*, 2015). This is a potentially inefficient use of the validation sample set, which could contribute to a higher accuracy and representativeness of the final model. Furthermore, there is still the chance of bias in one static division into training and test sets. In this study we used 1000 random splits without replacement into training and test subsets of samples. Each time the model was based on the training subset only and validated against the test subset, whereas the final model was based on the entire set of samples (Fig. 3). This approach provides unbiased and conservatively assessed model accuracy.

Model outcome

Estimated K-factor values from the different study areas have different distribution of values (Fig. 6). The sampling strategy applied in both study areas was the same, so it makes the two sets of samples directly comparable with each other. Since the natural conditions of the study sitesare very close, we assumed the estimated K-factor sample sets to come from the same data population. The difference in means of estimated K-factor between the two study areas is basically conditioned by the difference in altitude of sites and soil texture, which is reflected by different CNBL and SER (Fig. 4).

The derived regression equation (6) can be used to a limited extent for creation of K-factor maps in other areas. The resulting values must be used with caution, as they will indicate only a basic tendency of K-factor values spatial distribution, typical for the area in general, without consideration of local variations, as residuals will not be available. The absolute values of predictors and especially CNBL can vary greatly going beyond the scope of the values, on which the regression equation was based. In this case the results are expected to be misleading.

The Uch-Choku study area contains higher elevations than Otuz-Art, which is why CNBL is different. SER is also different between the study areas. CNBL and SER indicate significant negative correlation with each other (Fig. 5), and since the SER used here represents hydroxyls of clays (Boettinger, 2010), we can conclude that hydroxyls of clays are being washed down the slope, which is also supported by distribution of soil texture classes (Fig. 7a). Uch-Choku study area is higher and has coarser soils than Otuz-Art. This is indicated by fine particles of soils accumulating at lower altitudes.

The median of predicted values of K-factor are shifted closer to the common average than the median of estimated values (Fig. 6), which is also due to usage of common regression equation. The overall distribution span of the boxes is very close to each other and overlaps. The outlying maximum of Uch-Choku predicted values is due to high values in the north-western corner of the study area (Fig. 9). This part is mostly steep bare rocks without any soil. Comparison of the distribution of predicting variables between the two study sitesis indicated in Fig. 4. Slope degree and aspect sine distributions and means are very similar, which verifies consistency of sampling strategies. However, CNBL and SER indicate obvious difference between the sites, which complies with different measured mean K-factor values between the study areas.

The predicted K-factor values for the two areas also have significantly different means. This is also partly due to considerably different predictors as well as extrapolated residuals, since common regression equation was used for both study sites. The approach of developing a common regression equation for both study areas ensures regional consistency of the results and broader representativeness of the equation. The addition of extrapolated residuals ensures local variability of predicted values.

Several authors (Wischmeier and Smith, 1978; Romkins *et al.*, 1986; Renard *et al.*, 1996) stress the fact that the factors used in USLE/RUSLE and results of the equations should be considered as a long-term average. So, the resulting maps (Figs. 8 and 9) and their means (Fig. 6) should be considered as long-term average as well. Nevertheless, direct measurements of soil erodibility on runoff plots are needed for validation of the results and applicability of the equation (6), which is time and resource intensive. Furthermore, wider applicability of the regression equation can be restricted by different climate conditions, having an impact on soil erodibility, as discovered by Sanchis *et al.* (2008).

Human pressure

Soil erodibility in Uch-Choku is noticeably higher than in Otuz-Art. This is also supported by vegetation and stone cover, as well as cattle track rates (Table I). Percentage of vegetation cover is lower in Uch-Choku, whereas percentage of stone cover is higher. This means that Uch-Choku pasture has less grass cover, coarser soil and is relatively skeletal, which is an indicator of a higher soil loss than in Otuz-Art. Uch-Choku also has a higher cattle tracks rate (Table I), which can be caused by higher grazing pressure and/or greater susceptibility of soils and vegetation to cattle trampling. We assume that both are the case, as Uch-Choku is closer to the village and has coarser soils than Otuz-Art. This means that grazing pressure in Uch-Choku needs to be lower than in Otuz-Art to decrease the soil loss. Generalizing this idea we can say that pastures located at higher altitudes should have lower grazing pressure than those at lower elevations. Yan *et al.* (2015) discovered vegetation decreasing the runoff on loess hillslopes; however the vegetation management practices did not have a considerable effect. At the same time it is difficult to judge if the absolute values of grazing pressure are too high or too low in both areas with regard to land degradation, as the values of soil loss and the tolerance level are unknown.

CONCLUSIONS

We attempted to identify important factors correlated with soil erodibility, and develop an approach for its prediction using a cost-effective combination of field sampling and free remotely sensed data. Soil erodibility demonstrated a strong relationship between remotely sensed data and terrain indices, which can be used as auxiliary data in mapping. The two study sites showed considerably different soil erodibility, which is attributed to the difference in elevation. The higher study site had higher soil erodibility values.

The mapping approach used in this study uses robust and cost-effective methods for soil erodibility mapping in mountain regions. It was achieved by integrating different field, laboratory, and modelling techniques. When resources are limited, it might be relevant to consider a combination of ground-truth data with open remotely sensed data and GIS modelling using open software to get a good balance between cost and accuracy for mountain conditions.

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REFERENCES

Addis H K, Klik A. 2015. Predicting the spatial distribution of soil erodibility factor using USLE nomograph in an agricultural watershed, Ethiopia. *International Soil and Water Conservation Research*. **3**: 282--290.

Atadjanov S S, Tulegabylov N M, Bekkulova D E, Baidakova N S, Grebnev V V. 2012. National Report on Condition of Environment of Kyrgyz Republic for 2006 - 2011 (in Russian). Atadjanov S S. Bishkek.

den Biggelaar C, Lal R, Wiebe K, Breneman V. 2003. The Global Impact Of Soil Erosion On Productivity: I: Absolute and Relative Erosion-induced Yield Losses. *In* Advances In Agronomy. Academic Press. pp. 1--48.

Biggelaar C, Lal R, Wiebe K, Breneman V. 2004. The Global Impact of Soil Erosion on Productivity. *In* Advances In Agronomy. Academic Press. pp. 1--4.

Bishop T F A, Horta A, Karunaratne S B. 2015. Validation of digital soil maps at different spatial supports. *Geoderma*. **241--242**: 238--249.

Bishop T F A, McBratney A B. 2001. A comparison of prediction methods for the creation of field-extent soil property maps. *Geoderma*. **103**: 149--160.

Bishop T F A, Minasny B. 2006. Digital Soil-Terrain Modeling: The Predictive Potential and Uncertainty. *In* Grunwald S. (ed.) Environmental Soil-landscape Modeling: Geographic Information Technologies And Pedometrics. CRC Press, Taylor & Francis Group. pp. 185--213.

Blanco H, Lal R. 2008. Principles of Soil Conservation and Management. Springer Science+Business Media B.V.

Boettinger J L, Howell D W, Moore A C, Hartemink a. S, Kienast-Brown S. 2010. Digital Soil Mapping. *In* Boettinger J L, Howell D W, Moore A C, Hartemink A E, and Kienast-Brown S. (ed.) Progress In Soil Science. Springer, Dordrecht, Heidelberg, London, New York. pp. 462.

Boettinger J L, Ramsey R D, Bodily J M, Cole N J, Kienast-Brown S, Nield S J, Saunders A M, Stum A K. 2008a. Landsat Spectral Data for Digital Soil Mapping. *In* Hartemink A E, McBratney A B, and Mendonca-Santos M de L. (ed.) Digital Soil Mapping With Limited Data. Springer. pp. 193--203.

Boettinger J L, Ramsey R D, Bodily J M, Cole N J, Kienast-Brown S, Nield S J, Saunders A M, Stum A K. 2008b. Landsat Spectral Data for Digital Soil Mapping. *In* Hartemink A E, McBratney A B, and Mendonca-Santos M de L. (ed.) Digital Soil Mapping With Limited Data. Springer. pp. 193--203.

Bonilla C A, Johnson O I. 2012. Soil erodibility mapping and its correlation with soil properties in Central Chile. *Geoderma*. **189--190**: 116--123.

Borchardt P, Schickhoff U, Scheitweiler S, Kulikov M. 2011. Mountain pastures and grasslands in the SW Tien Shan, Kyrgyzstan - Floristic patterns, environmental gradients, phytogeography, and grazing impact. *Journal of Mountain Science*. **8**: 363--373.

Borchardt P, Schmidt M, Schickhoff U. 2010. Vegetation patterns in Kyrgyzstan’s walnut-fruit forests under the impact of changing forest use in post-soviet transformation. *Erde*. **141**: 255--275.

Brus D J, de Gruijter J J, van Groenigen J W. 2006. Chapter 14 Designing Spatial Coverage Samples Using the k-means Clustering Algorithm. *In* P. Lagacherie A B M and Voltz M. (ed.) Developments In Soil Science.

Elsevier. pp. 183--192.

Brus D J, Heuvelink G B M. 2007. Optimization of sample patterns for universal kriging of environmental variables. *Geoderma*. **138**: 86--95.

Clifford D, Payne J E, Pringle M J, Searle R, Butler N. 2014. Pragmatic soil survey design using flexible Latin hypercube sampling. *Computers & Geosciences*. **67**: 62--68.

Conrad O. 2012. Close gaps with stepwise resampling (SAGA GIS 2.1.0 module).

Crewett W. 2012. Improving the Sustainability of Pasture Use in Kyrgyzstan. *Mountain Research and Development*. **32**: 267--274.

Dotterweich M. 2013. The history of human-induced soil erosion: Geomorphic legacies, early descriptions and research, and the development of soil conservation-A global synopsis. *Geomorphology*. **201**: 1--34.

European Soil Bureau Working Group. 2015. HYdraulic PRoperties of European Soils" (HYPRES). Texture classes. 2015.

Florinsky I V. 2012. Predictive Soil Mapping. Elsevier, USA.

Hartemink A E, McBratney A. 2008. A soil science renaissance. *Geoderma*. **148**: 123--129.

Hengl T, Heuvelink G B M, Stein A. 2004. A generic framework for spatial prediction of soil variables based on regression-kriging. *Geoderma*. **120**: 75--93.

Heuvelink G B M, Brus D J, De Gruijter J J. 2006. Optimization of sample configuration for digital mapping of soil properties with universal kriging. *In* P. Lagacherie A B M and Voltz M. (ed.) Developments In Soil Science. Elsevier. pp. 137--151.

Hou J, Wang H, Fu B, Zhu L, Wang Y, Li Z. 2016. Effects of plant diversity on soil erosion for different vegetation patterns. *CATENA*. **147**: 632--637.

IUSS Working Group WRB. 2006. World reference base for soil resources 2006. *World Soil Resources Reports No. 103*. **43**: 145.

De Jong S M. 1994. Derivation of vegetative variables from a landsat tm image for modelling soil erosion. *Earth Surface Processes and Landforms*. **19**: 165--178.

Kidd D, Malone B, Mcbratney A, Minasny B, Webb M. 2015. Geoderma Regional Operational sampling challenges to digital soil mapping in. *Geodrs*. **4**: 1--10.

Knijff J Van der, Jones R, Montanarella L. 1999. Soil erosion risk assessment in Italy. *Luxembourg: Office for Official Publications of the European Communities*. **EUR 19022**: 58.

Knijff J Van der, Jones R R J A, Montanarella L, Van der Knijff J M. 2000. Soil erosion risk assessment in Europe. *Luxembourg: Office for Official Publications of the European Communities*. **EUR 19022**: 32 pp.

Kuzmichenok V A. 2008. Digital models of Kyrgyzstan's moisture characteristics (in Russian). Podrezov O A. .

Li J, Heap A D. 2014. Spatial interpolation methods applied in the environmental sciences: A review. *Environmental Modelling & Software*. **53**: 173--189.

Ludwig J A, Wilcox B P, Breshears D D, Tongway D J, Imeson A C. 2005. Vegetation Patches and Runoff-Erosion as Interacting Ecohydrological Processes in Semiarid Landscapes. *Ecology*. **86**: 288--297.

Madeira Netto J S, Robbez-Masson J M, Martins E. 2006a. Chapter 17 Visible-NIR Hyperspectral Imagery for Discriminating Soil Types in the La Peyne Watershed (France). *In* Lagacherie P, McBratney A B, and Voltz M. (ed.) Developments In Soil Science. Elsevier, Amsterdam, Boston, Heidelberg, London, New York, Oxford, Paris, San Diego, San Francisco, Singapore, Sydney, Tokyo. pp. 219--233.

Madeira Netto J S, Robbez-Masson J M, Martins E. 2006b. Chapter 17 Visible-NIR Hyperspectral Imagery for Discriminating Soil Types in the La Peyne Watershed (France). *In* Lagacherie P, McBratney A B, and Voltz M. (ed.) Developments In Soil Science. Elsevier, Amsterdam, Boston, Heidelberg, London, New York, Oxford, Paris, San Diego, San Francisco, Singapore, Sydney, Tokyo. pp. 269--278.

Mamytov A M, Ashirakhmanov S A. 1988. Soils (in Russian). Murzaikina Moiseenko, T.V. T K. Tashkentskaya Kartograficheskaya Fabrika, Tashkent.

Martz L W. 1992. The variation of soil erodibility with slope position in a cultivated canadian prairie landscape. *Earth Surface Processes and Landforms*. **17**: 543--556.

McBratney A ., Mendonça Santos M ., Minasny B. 2003. On digital soil mapping. *Geoderma*. **117**: 3--52.

Mcbratney a B, Minasny B, Wheeler I, Malone B P. 2012. Frameworks for digital soil assessment. *In* Minasny B, Malone B P, and McBratney A B. (ed.) Digital Soil Assessments And Beyond. CRC Press, Taylor & Francis Group. pp. 9--14.

Minasny B, McBratney A B. 2006. A conditioned Latin hypercube method for sampling in the presence of ancillary information. *Computers and Geosciences*. **32**: 1378--1388.

Mulder V L, de Bruin S, Schaepman M E. 2012. Representing major soil variability at regional scale by constrained Latin Hypercube Sampling of remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*. **21**: 301--310.

Odgers N P, McBratney A B, Minasny B. 2015. Digital soil mapping and uncertainty estimation using soil class probability rasters. *Geoderma*. **137--238**: 190--198.

Panagos P, Meusburger K, Alewell C, Montanarella L. 2012. Soil erodibility estimation using LUCAS point survey data of Europe. *Environmental Modelling and Software*. **30**: 143--145.

Pérez-Rodríguez R, Marques M J, Bienes R. 2007. Spatial variability of the soil erodibility parameters and their relation with the soil map at subgroup level. *Science of the Total Environment*. **378 (2007)**: 156--160.

Pimentel D, Harvey C, Resosudarmo P, Sinclair K, Kurz D, McNair M, Crist S, Shpritz L, Fitton L, Saffouri R. 1995. Costos economicos y ambientales de la erosión del suelo y beneficios de la conservación. *Science*. 1117--1123.

Reeuwijk V L. 2006. Procedures for soil analysis, 7th edition. 6th ed.International Soil Reference and Information Centre, Food and Agriculture Organization of the United Nations.

Renard K, Foster G, Weesies G, McCool D, Yoder D. 1996. Predicting soil erosion by water: a guide to conservation planning with the Revised Universal Soil Loss Equation. USDA, Washington, D.C.

Rickson R J. 2014. Can control of soil erosion mitigate water pollution by sediments? *Science of The Total Environment*. **468**: 1187--1197.

Romkins M J M, Prasad S N, Poesen J W A. 1986. Soil erodibility and Properties. 492--504.

Salvador Sanchis M P, Torri D, Borselli L, Poesen J. 2008. Climate effects on soil erodibility. *Earth Surface Processes and Landforms*. **33**: 1082--1097.

Sanchez-Moreno J F, Jetten V, Mannaerts C M, de Pina Tavares J. 2014. Selecting best mapping strategies for storm runoff modeling in a mountainous semi-arid area. *Earth Surface Processes and Landforms*. **39**: 1030--1048.

Scull P, Franklin J, Chadwick O a., McArthur D. 2003. Predictive soil mapping: a review. *Progress in Physical Geography*. **27**: 171--197.

Shaw R L, Booth A, Sutton A J, Miller T, Smith J A, Young B, Jones D R, Dixon-Woods M. 2004. Finding qualitative research: an evaluation of search strategies. *In* Boehner J, McCloy K R, and Strobl J. (ed.) BMC Medical Research Methodology. pp. 5.

Simonson R W. 1995. Factors of soil formation. A system of quantitative pedology. *In* Geoderma. McGraw-Hill, New York. pp. 334--335.

Singh M J, Khera K L. 2009. Nomographic estimation and evaluation of soil erodibility under simulated and natural rainfall conditions. *Land Degradation & Development*. **20**: 471--480.

Tesfa T K, Tarboton D G, Chandler D G, McNamara J P. 2010. A Generalized Additive Soil Depth Model for a

Mountainous Semi-Arid Watershed Based Upon Topographic and Land Cover Attributes. *In* Boettinger J, Howell D, Moore A, Hartemink A, and Kienast-Brown S. (ed.) Digital Soil Mapping. Springer Netherlands. pp. 29--41.

Thomas M, Odgers N P, Ringrose-Voase A, Grealish G, Glover M, Gowling T. 2012. Soil survey design for management-scale digital soil mapping in a mountainous southern Philippine catchment. 233--238.

Thomasson a. J. 1992. World map of the status of human-induced soil degradation. *Geoderma*. **52**: 367--368.

Veihe A. 2002. The spatial variability of erodibility and its relation to soil types: A study from northern Ghana. *Geoderma*. **106**: 101--120.

de Vente J, Poesen J, Govers G, Boix-Fayos C. 2009. The implications of data selection for regional erosion and sediment yield modelling. *Earth Surface Processes and Landforms*. **34**: 1994--2007.

Viloria J A, Viloria-Botello A, Pineda M C, Valera A. 2016. Digital modelling of landscape and soil in a mountainous region: A neuro-fuzzy approach. *Geomorphology*. **253**: 199--207.

Walling D ., Russell M ., Hodgkinson R ., Zhang Y. 2002. Establishing sediment budgets for two small lowland agricultural catchments in the UK. *CATENA*. **47**: 323--353.

Wang B, Zheng F, Guan Y. 2016a. Improved USLE-K factor prediction: A case study on water erosion areas in China. *International Soil and Water Conservation Research*.

Wang B, Zheng F, Römkens M J M, Darboux F. 2013. Soil erodibility for water erosion: A perspective and Chinese experiences. *Geomorphology*. **187**: 1--10.

Wang Z-J, Jiao J-Y, Rayburg S, Wang Q-L, Su Y. 2016b. Soil erosion resistance of “Grain for Green” vegetation types under extreme rainfall conditions on the Loess Plateau, China. *CATENA*. **141**: 109--116.

Wischmeier W H, Smith D D. 1978. Predicting rainfall erosion losses. USDA, Washington, D.C.

Yan Q, Lei T, Yuan C, Lei Q, Yang X, Zhang M, Su G, An L. 2015. Effects of watershed management practices on the relationships among rainfall, runoff, and sediment delivery in the hilly-gully region of the Loess Plateau in China. *Geomorphology*. **228**: 735--745.

Zevenbergen L W, Thorne C R. 1987. Quantitative analysis of land surface topography. *Earth Surface Processes and Landforms*. **12**: 47--56.

Zhang K L, Shu A P, Xu X L, Yang Q K, Yu B. 2008. Soil erodibility and its estimation for agricultural soils in China. *Journal of Arid Environments*. **72**: 1002--1011.

Zhang K, Li S, Peng W, Yu B. 2004. Erodibility of agricultural soils on the Loess Plateau of China. *Soil and Tillage Research*. **76**: 157--165.

Zhang K, Lian L, Zhang Z. 2016. Reliability of soil erodibility estimation in areas outside the US: a comparison of erodibility for main agricultural soils in the US and China. *Environmental Earth Sciences*. **75**: 252.

Zhou J, Fu B, Gao G, Lü Y, Liu Y, Lü N, Wang S. 2016. Effects of precipitation and restoration vegetation on soil erosion in a semi-arid environment in the Loess Plateau, China. *CATENA*. **137**: 1--11.

Zhou Z C, Gan Z T, Shangguan Z P, Dong Z B. 2010. Effects of grazing on soil physical properties and soil erodibility in semiarid grassland of the Northern Loess Plateau (China). *Catena*. **82**: 87--91.

Zhu Q, Lin H S. 2010. Comparing ordinary kriging and regression kriging for soil properties in contrasting landscapes. *Pedosphere*. **20**: 594--606.

Table I. Vegetation and stone cover percentage and cattle tracks rate.

	Otuz-Art	Uch-Choku
Vegetation cover (mean)	72 %	63.9 %
Stone cover (mean)	7.4 %	11.5 %
Cattle tracks rate (mean)	8.5	11.8

Table II. Descriptive statistics of regression equation (5).

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2.684E-02	5.727E-03	4.686	4.79E-06
CNBL	9.658E-06	1.983E-06	4.870	2.09E-06
SER	-2.460E-02	5.960E-03	-4.127	5.16E-05
sin (aspect)	8.800E-04	3.838E-04	2.293	0.0228

Residual standard error: 0.003856 on 228 degrees of freedom
Multiple R-squared: 0.3694, Adjusted R-squared: 0.3611
F-statistic: 44.52 on 3 and 228 DF, p-value: < 2.2e-16

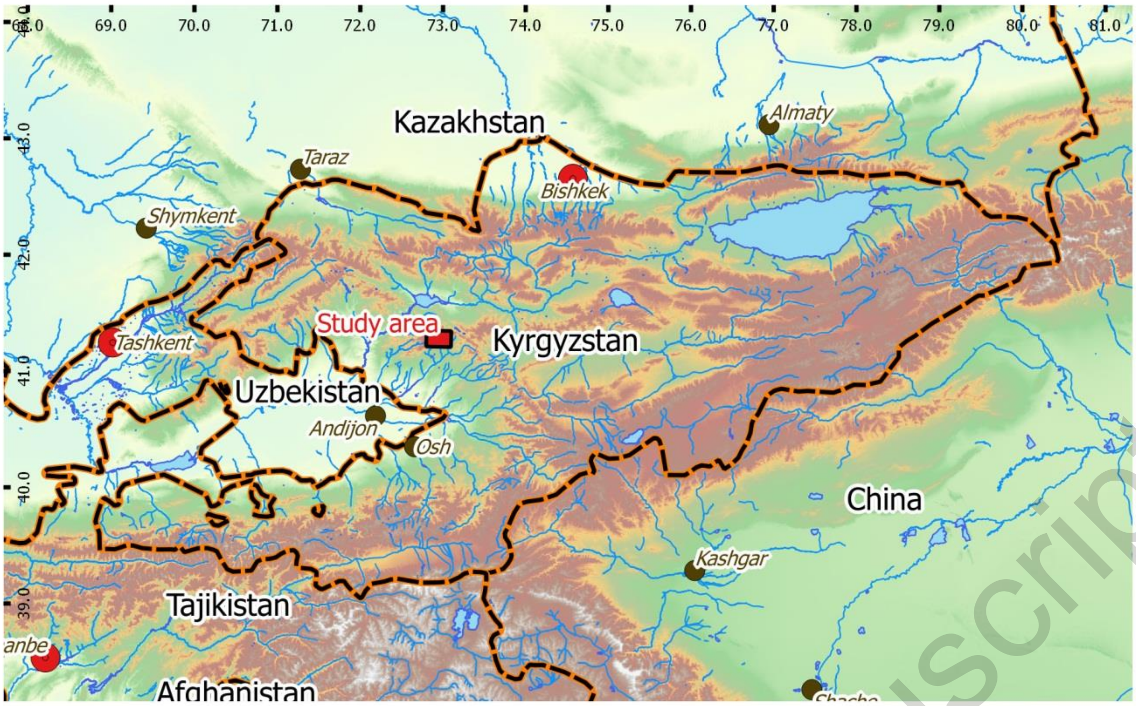

Figure 1. Study area

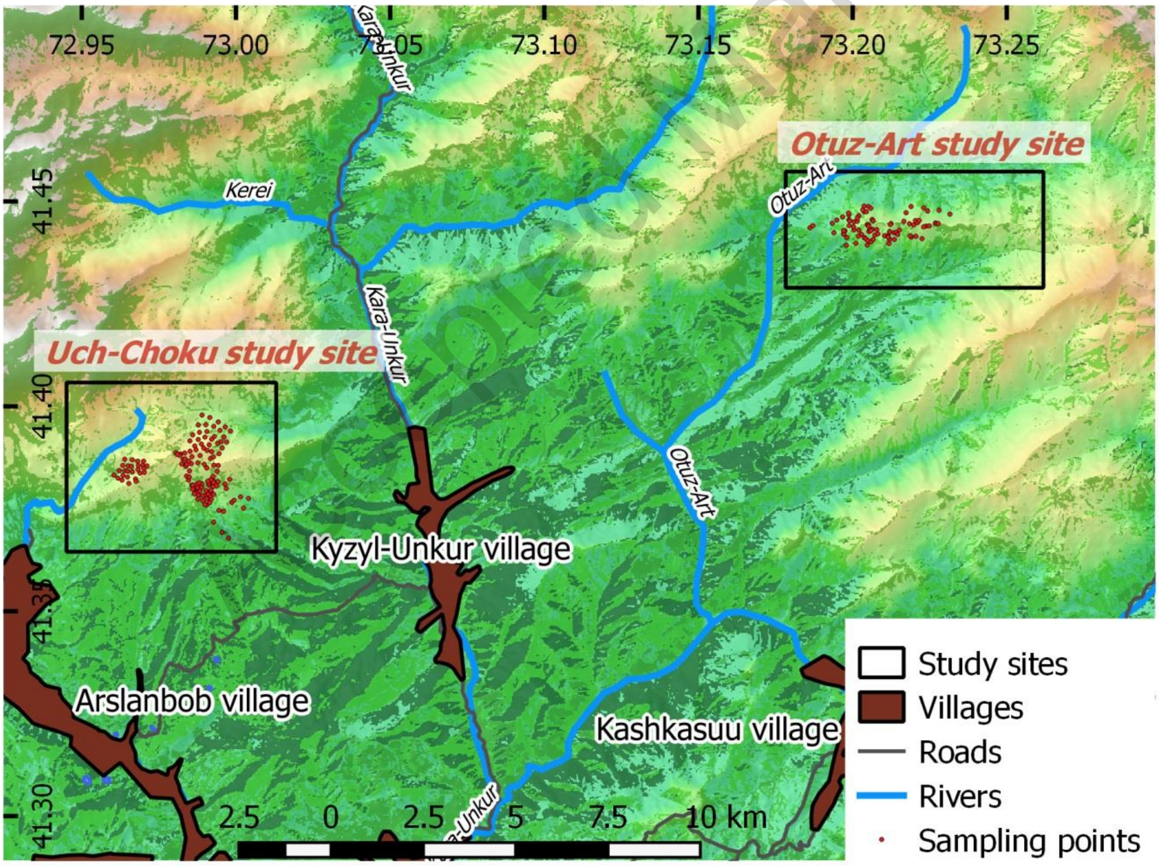

Figure 2. Study sites: Otuz-Art and Uch-Choku. Red dots indicate sampling points.

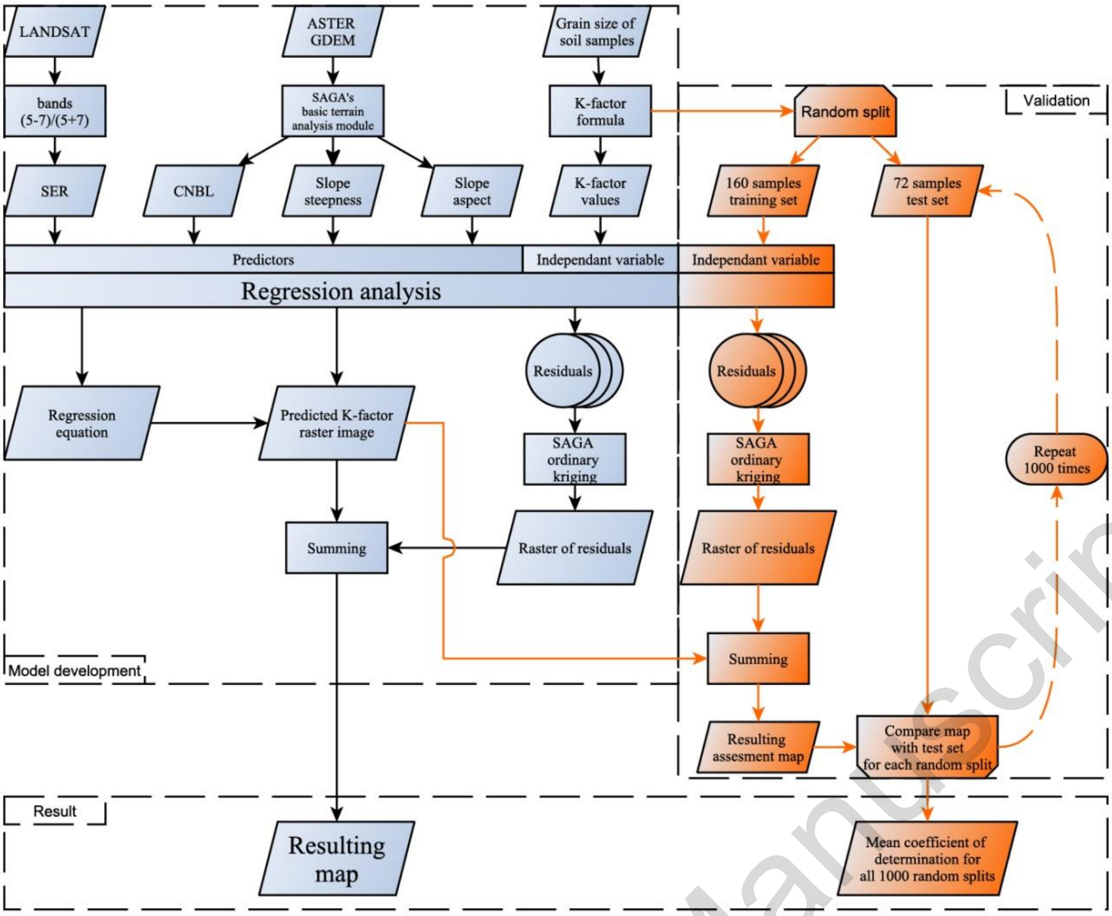

Figure 3. Development and validation of the model.

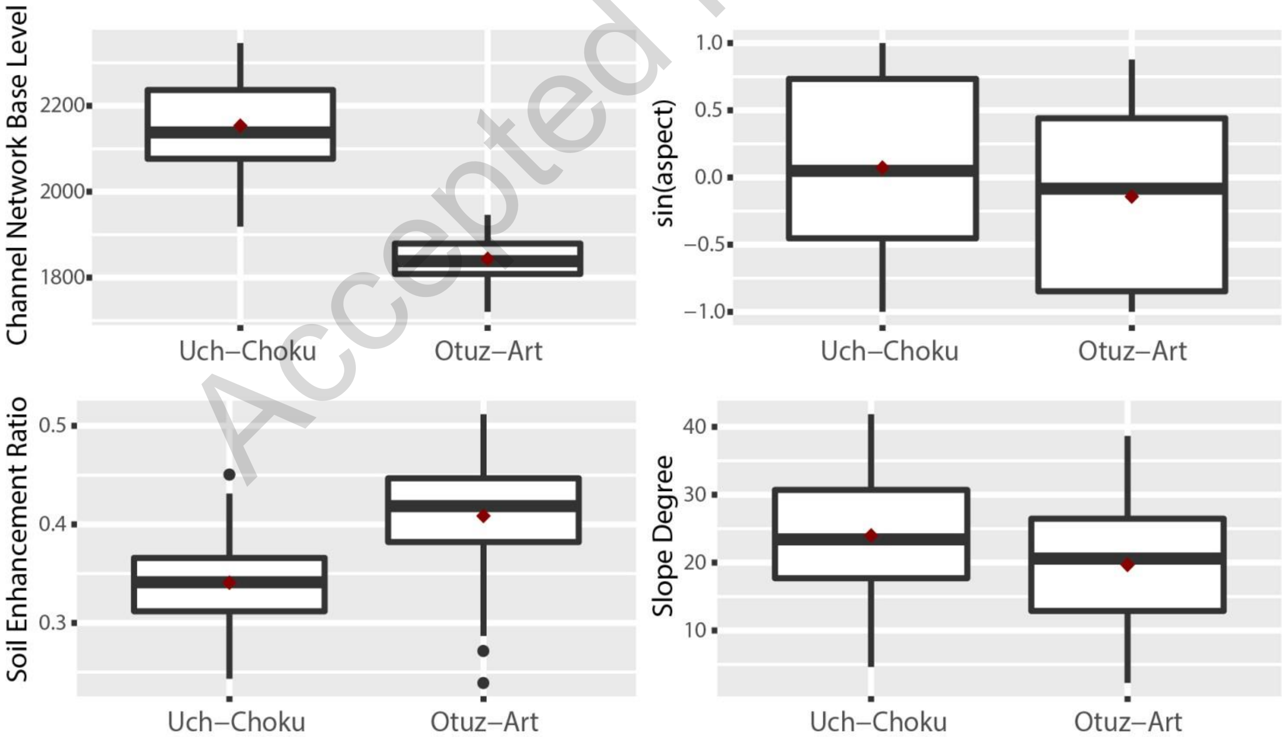

Figure 4. Distribution of predicting variables, red dots represent mean values.

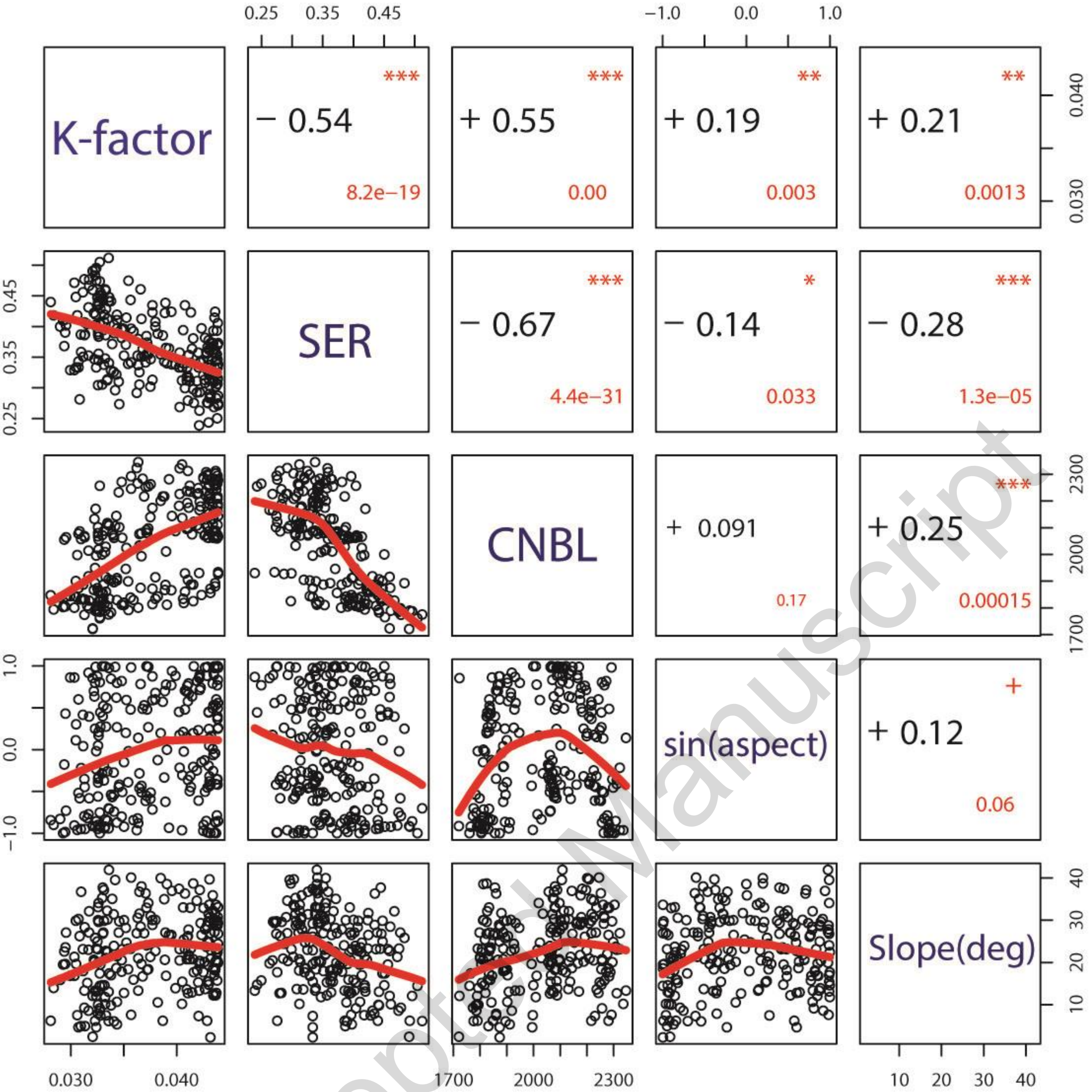

Figure 5. K-factor and predictors' Pearson correlation matrix

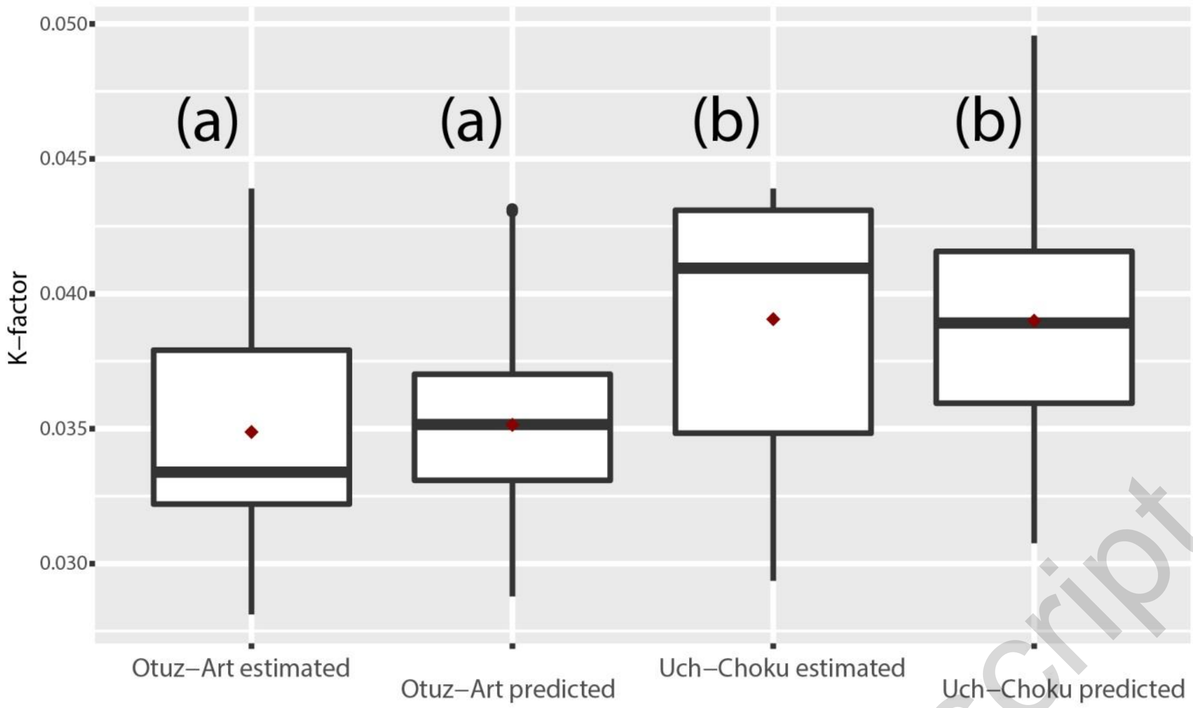

Figure 6. Distribution of estimated and predicted K-factor values, red dots represent mean values.

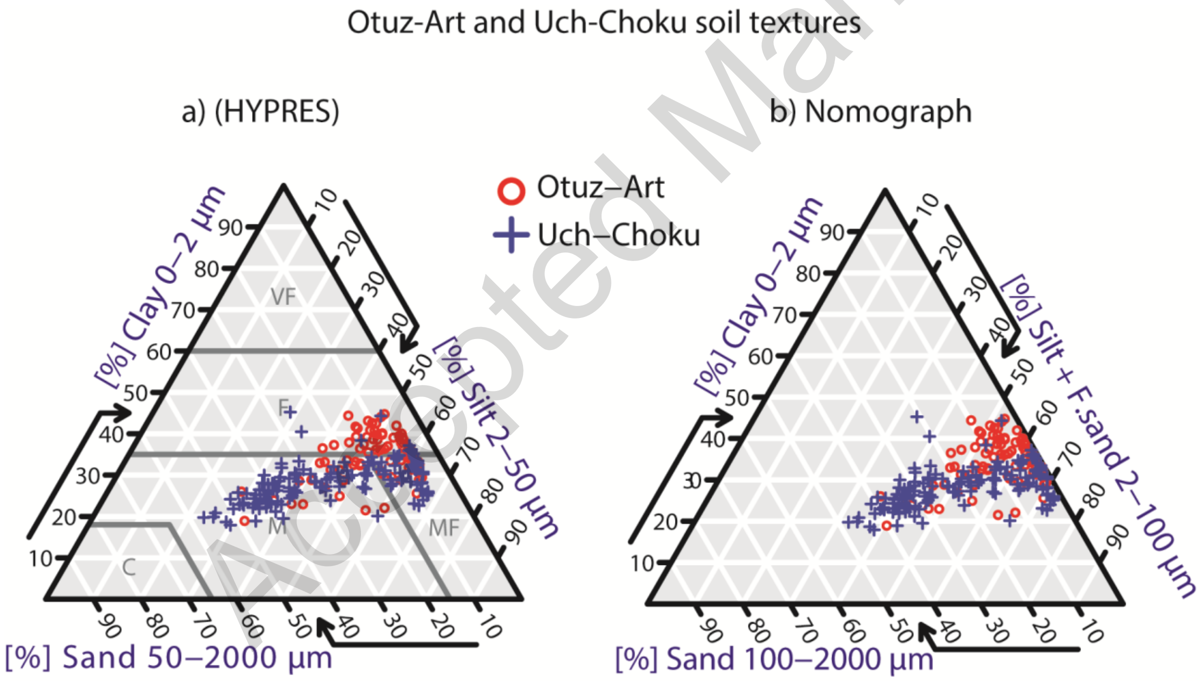

Figure 7. Texture classes of soil samples, according to HYPRES and nomograph division (Wischmeier and Smith, 1978).

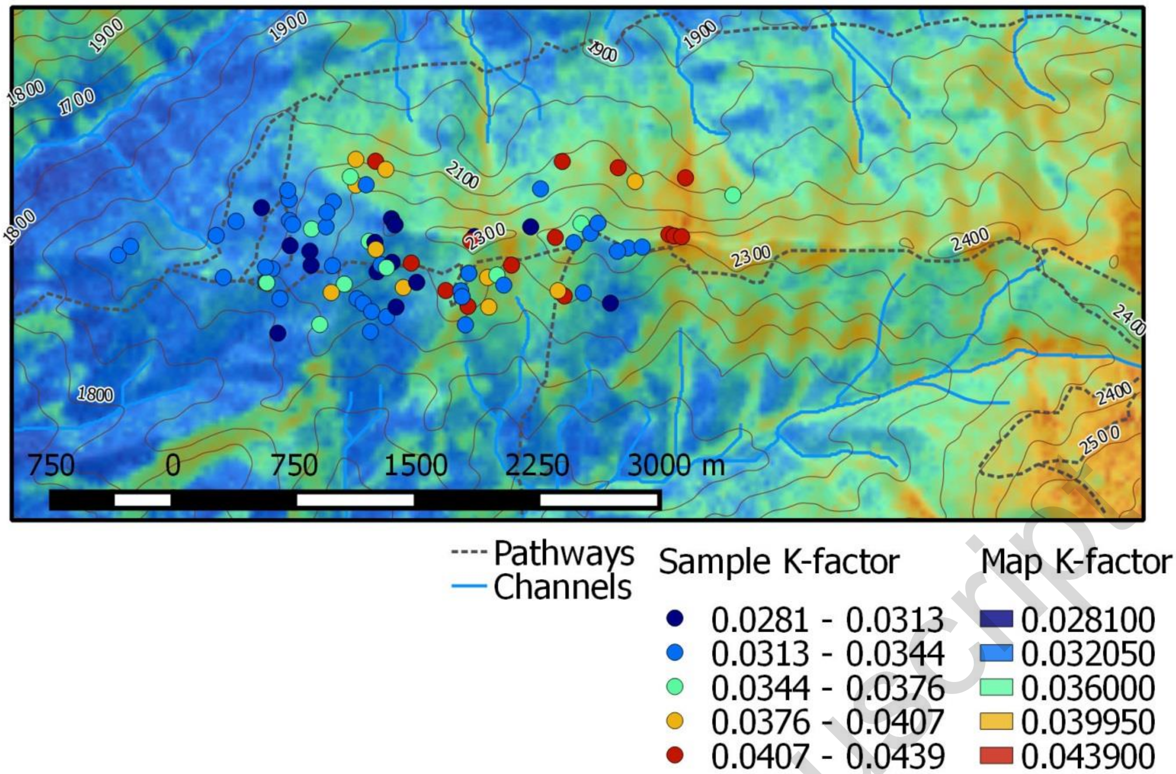

Figure 8. K-factor map for Otuz-Art study area with sampling points.

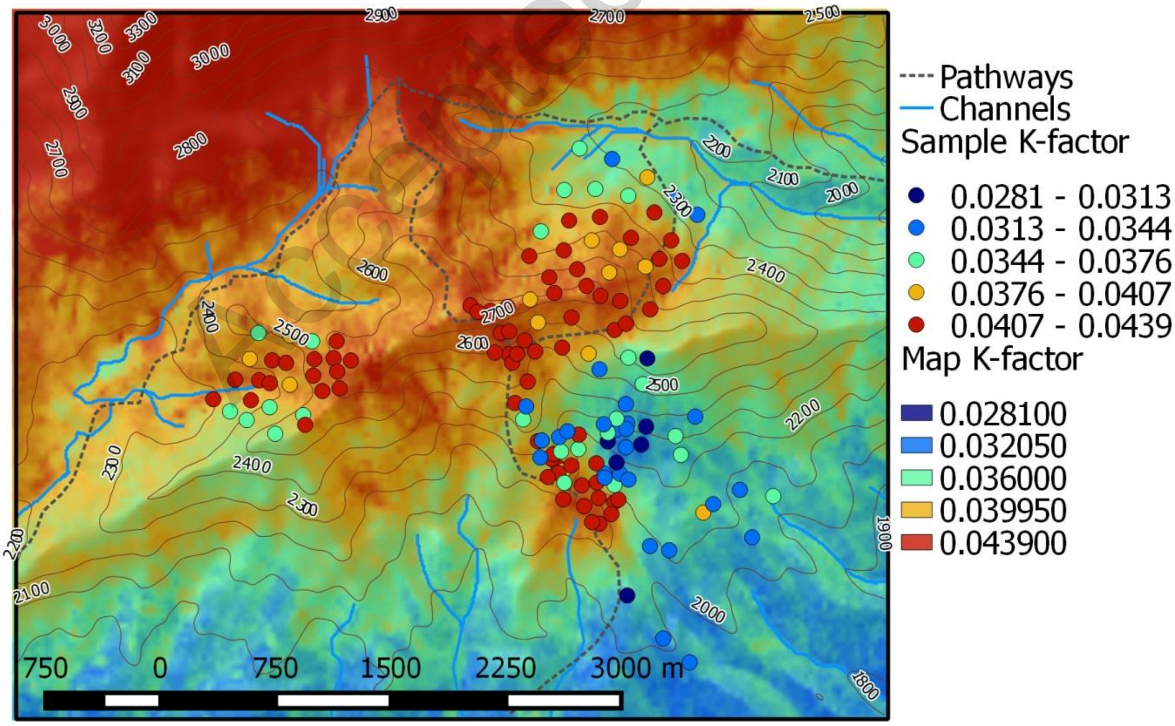

Figure 9. K-factor map for Uch-Choku study area with sampling points

Article IV

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VEGETATION AND CLIMATE INTERACTION PATTERNS IN KYRGYZSTAN: SPATIAL DISCRETIZATION BASED ON TIME SERIES ANALYSIS

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With 12 figures and 2 tables
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Summary: Spatio-temporal variations of climate-vegetation interactions in Central Asia have been given a lot of attention recently. However some serious methodological drawbacks of previous studies prevented thorough assessment of such interactions. In order to avoid the limitations and improve the analysis we used spatially explicit time series of NDVI (normalized difference vegetation index), temperature and precipitation which were decomposed to seasonal and trend components on per-pixel basis using STL (seasonal decomposition of time series by loess). Trend and seasonal components of NDVI, precipitation and temperature were assessed pixelwise for temporal correlations with different lags to understand the patterns of their interaction in Kyrgyzstan and adjoining regions. Based on these results a coefficient of determination was calculated to understand the extent to which NDVI is conditioned by precipitation and temperature variations. The images with the lags of time series correlation minima and maxima for each pixel and coefficients of NDVI determination by temperature and precipitation were subjected to cluster analysis to identify interaction patterns over the study area. The approach used in this research differs from previous regional studies by implementation of seasonal decomposition and analyzing the full data without spatial or seasonal averaging within predetermined limits prior to the analysis. NDVI response to temperature and precipitation was assumed to be spatially variable in its sign, strength and lag, thus a separate model was developed for each pixel. The results were assessed with cluster analysis to identify spatial patterns of temporal interactions, decrease dimensionality and facilitate their comprehensiveness. The research resulted in 5 spatial clusters with different patterns of NDVI interaction with temperature and precipitation on intra- and interannual scales. The highest correlation scores between NDVI and temperature at the seasonal scale were found at 0-4 months lag and between NDVI and precipitation at 1-5 months lag. At high elevations of 3000-4000 m above sea level, both precipitation and temperature occurred to be facilitating factors for vegetation development, whereas temperature was rather a limiting factor at lower elevations of 200-1300 m a.s.l. We developed maps of the NDVI coefficient of determination by both temperature and precipitation. Only deserts and glaciers had low coefficients of determination (adjusted R2) on the seasonal scale (0.1-0.3), whereas areas with vegetation were greatly conditioned by temperature and precipitation (0.7-0.95). On the trend scale, dense vegetation and bare areas had low coefficient of determination (0.1-0.3), whereas areas with average vegetation cover were greatly controlled by the climatic factors (0.7-0.9).

Zusammenfassung: Raumzeitliche Veränderungen von Klima-Vegetation-Interaktionen in Zentralasien stehen seit geraumer Zeit im Fokus wissenschaftlichen Interesses. Gewisse Unzulänglichkeiten methodischer Herangehensweisen früherer Studien verhinderten bislang eine gründliche Abschätzung solcher Interaktionen. Um methodische Limitierungen zu vermeiden und entsprechende Analysen zu optimieren, liegen dieser Studie räumlich explizite Zeitreihen von NDVI (normalisierter differenzierter Vegetationsindex), Temperatur und Niederschlag zugrunde, die mittels STL (saisonale Auflösung von Zeitreihen mit Loess) in saisonale und Trend-Komponenten auf Pixelbasis aufgelöst wurden. Die entsprechenden Komponenten von NDVI, Temperatur und Niederschlag wurden pixelweise im Hinblick auf zeitliche Korrelationen unter Berücksichtigung unterschiedlicher Latenzzeiten analysiert, um die Interaktionsmuster von Klima und Vegetation in Kirgistan und angrenzenden Regionen nachvollziehen zu können. Auf der Grundlage der Ergebnisse wurde ein Bestimmtheitsmaß ermittelt, das zur Abschätzung der Abhängigkeit des NDVI von Niederschlag und Temperatur verwendet wurde. Die graphischen Darstellungen mit den Latenzzeiten der Korrelationsmaxima und -minima der Zeitreihen für jedes Pixel und die Bestimmtheitsmaße zur NDVI-Beeinflussung durch Temperatur und Niederschlag wurden Clusteranalysen unterzogen, um die Interaktionsmuster im gesamten Arbeitsgebiet zu identifizieren. Der methodische Ansatz dieser Studie weicht von früheren Regionalstudien insofern ab, als dass die Zeitreihenanalyse mit saisonaler Auflösung umgesetzt und der gesamte Datensatz ohne vorhergehende räumliche oder saisonale Mittelwertbildung analysiert wurde. Die NDVI-Reaktion auf Temperatur und Niederschlag wurde im Hinblick auf Signal, Stärke und Verzögerungszeit als räumlich variabel angenommen, und somit ein separates Modell für jedes Pixel entwickelt. Die Ergebnisse wurden mit Clusteranalysen untersucht, um räumliche Muster und zeitliche Interaktionen zu erkennen, die Dimensionalität zu reduzieren, und deren Vollständigkeit zu optimieren. Als Ergebnis lassen sich 5 räumliche Cluster differenzieren mit unterschiedlichen Mustern der NDVI-Interaktion mit Temperatur und Niederschlag auf intra- und interannueller Ebene. Die höchsten Korrelationen zwischen NDVI und Temperatur auf saisonaler Ebene wurden bei einer Verzögerungszeit von 0-4 Monaten und zwischen NDVI und Niederschlag bei 1-5 Monaten ermittelt. In Höhenlagen zwischen 3000 und 4000 m NN erwiesen sich sowohl Niederschlag als auch Temperatur als die Vegetationsentwicklung begünstigende Faktoren, während

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in Höhen zwischen 200 und 1300 m NN die Temperatur eher limitierend wirkt. Die entwickelten Kartendarstellungen zeigen die NDVI-Beeinflussung sowohl durch Temperatur als auch durch Niederschlag. Lediglich Wüsten- und Gletscher-Bereiche weisen geringe Bestimmtheitsmaße (korrigiertes R2) auf saisonaler Ebene auf (0,1-0,3), während vegetationsbedeckte Flächen einen sehr deutlichen Zusammenhang mit Temperatur und Niederschlag zeigen (0,7-0,95). Auf der Trendebene sind Bestimmtheitsmaße bei dichter Vegetation und vegetationslosen Flächen gering (0,1-0,3), Flächen mit gewöhnlicher Vegetationsbedeckung zeigen dagegen eine starke Abhängigkeit von den klimatischen Faktoren (0,7-0,9).

Keywords: climatic change, GIS, Kyrgyzstan, remote sensing, vegetation geography, biogeography

1 Introduction

Climate change has become an important issue in recent decades. It has been drawing lots of attention from researchers and many studies have been conducted on climate change scenarios. Among many regions Central Asia was reported to undergo severe climatic changes (Hijioka et al. 2014). Kyrgyzstan is a mountainous country with prominent altitudinal variation in ecosystems. High geodiversity, i.e. a small-scale variety of abiotic habitat conditions, in particular the climatic ones, induce a conspicuous small-scale variety of vegetation types. According to climate scenarios, Kyrgyzstan will face severe annual and seasonal variations of temperature and precipitation (Lioubimtseva and Cole 2006; Hijioka et al. 2014; Huang et al. 2014). Climate change models for Kyrgyzstan indicate future temperature and precipitation increase above the global mean (Christensen et al. 2007; GoKR 2009; Hijioka et al. 2014). Unsustainable use of natural resources aggravated by the effects of climate change may lead to the loss of valuable ecosystems (Kerven et al. 2011; Crewett 2012; Dörre and Borchardt 2012; Borchardt et al. 2013). Thus, considerable impacts of temperature and precipitation changes on vegetation in both spatial and temporal domains are to be expected, the study of which is crucial for land use economy and climate change adaptation planning.

Many numerical studies have been published aiming at assessing the impact of climatic variables on vegetation in Central Asia. Remotely sensed data and their time series have been intensively used for vegetation cover change analysis as well as forecasting based on different regression models (De Jong 1994; Martinez and Gilabert 2009; Verbesselt et al. 2010; de Jong et al. 2011; Eckert et al. 2015). Recently, a few studies have been conducted in the region looking for vegetation change in spatio-temporal domain and its relation to climatic factors (Nezlin et al. 2005; Propastin et al. 2007, 2008a, 2008b; Kariyeva and Van Leeuwen 2011; Kariyeva et al. 2012; Klein et al. 2012; Gessner et al. 2013; Zhou et al. 2015; Yin et al. 2016; Dubovyk et al. 2016). Covering many important patterns of climate and vegetation interactions, especially in mountain areas with diverse terrain and elevation, these studies have their strengths in several aspects, but some disadvantages in others, namely: considering either temperature or precipitation as the main impact factor, spatial averaging of spatially explicit data time-series within predetermined limits, temporal averaging of temporarily explicit data within predetermined limits, not considering temporal lags between climate impact and vegetation response, or considering them at coarse scale, not considering the seasonal and trend components separately, and using analysis that produce abstract components, which are difficult to interpret.

Methods like PCA (principal component analysis) or EOF (empirical orthogonal functions) do not allow for seasonal and trend decomposition, modelling and forecasting. These methods are good in decreasing data dimensionality; however, the results are difficult to interpret as they represent abstract variables which do not necessarily have real equivalents. Quite often temporal or spatial averaging of the data, which are temporarily and spatially explicit, is used within predetermined spans even before the analysis (Kariyeva and Van Leeuwen 2011; Kariyeva et al. 2012; Dubovyk et al. 2016), which leads to loss of data and simplifies the patterns within those limits. Decrease of spatial data resolution by systematic averaging can lead to signal quality improvement, however averaging within vast geographic areas means certainly the loss of valuable data. The very identification of the limits is biased by human aspects (state borders, seasons) which may have no reflection in nature. Another main assumption, which is not always correct, is that climate and vegetation have similar relations within one generalization unit, or that correlation between vegetation and climatic factors have the same sign throughout the study area. For example, Ichii et al. (2002) looked for correlation between NDVI and climate variables globally. They identified positive and negative correlations between the same variables in different areas.

Considering delayed vegetation response to climatic factors was given a lot of attention (Kariyeva and Van Leeuwen 2011; Kariyeva et al. 2012; Gessner et al. 2013; Dubovyk et al. 2016). But doing it on a coarse temporal scale, as in case of seasonal averaging, may lead to failure to identify strong relationships and exact temporal lags (Kariyeva and Van Leeuwen 2011; Kariyeva et al. 2012; Dubovyk et al. 2016), whereas not considering the temporal lags between climate impact and vegetation response may lead to failure to identify any relationship (Zhang et al. 2016a). Several studies use least squares regression for identification of linear trends in NDVI and climatic factors (Zhou et al. 2016; Yin et al. 2016), some of them consider lagged relationships (Nezlin et al. 2005; Propastin et al. 2007; Gessner et al. 2013; Zhang et al. 2016b). Others employ linear regression with time or climatic factors as predictors and spatially averaged NDVI as a response variable (Propastin et al. 2008b; Eckert et al. 2015). Least squares linear regression is not designed for approximation of trends in natural time series, as they are not stationary and have strong seasonal and trend components, and outliers can have considerable impact. Furthermore, it simplifies the interannual and seasonal interactions of climate and vegetation, does not account for trend cyclic behavior, and leads to failure identifying temporal correlations between them. Sometimes the approaches are not flexible in predictors across pixels, and regression models are stuck using a fixed lag of a predictor for the entire area (Kariyeva and Van Leeuwen 2011; Kariyeva and van Leeuwen 2012; Dubovyk et al. 2016). Rarely have authors used the plethora of time series analysis methods for seasonal decomposition and cross-correlation.

The fact that both temperature and precipitation can have a combined impact on vegetation each with its own time lag, which can vary depending on many factors is often left unconsidered. Using the seasonal and trend decomposition of vegetation and climate raster time series on a per-pixel basis and lagged correlation analysis can improve understanding of interactions between the variables. Many studies consider interactions of NDVI either with temperature or precipitation (Propastin et al. 2008a; de Beurs et al. 2009; Gessner et al. 2013). Whereas Cao et al. (2013) used both precipitation and temperature to identify their impact on NDVI and found them to be the main driving factors, but they did not consider correlation with lags. Potter and Brooks (1998) used NDVI and different climate indices as predictors to demonstrate that about 70-80 % of NDVI variations globally could be explained by climate variables only. Propastin et al. (2008b) found that 75 % of NDVI upward trend during growing season in Central Asia is explained by a combination of temperature and precipitation. Qiu et al. (2014) used wavelet transformation for seasonal decomposition, and also discovered NDVI to be conditioned by both temperature and precipitation on seasonal and interannual scales.

The spatio-temporal dimensionality of the imagery time series remains one of the main constraints for a thorough analysis of the existing remotely sensed vegetation and climate data. Many different sophisticated approaches were developed to deal with this issue (Mennis et al. 2005; Mennis 2010; Petitjean et al. 2012; Small 2012; Lai et al. 2016; Qiu et al. 2016; Militino et al. 2017), however, it is obvious that there is no common framework for spatio-temporal studies dealing with climate and vegetation interaction. Quite often spatial or temporal discretization of a study dataset into geographical subareas or seasons is used. This approach addresses data dimensionality and nonstationarity and provides plausible results (Zhao et al. 2011; Mohammat et al. 2013; Zhang et al. 2013; Du et al. 2015; Song et al. 2016). However, averaging of spatially and temporally explicit data within predetermined areas leads to information loss and bias. Spatially explicit analyses are also often limited to temporal averaging or linear regression for identification of trend magnitude and sign. However, vegetation and climate data are nonstationary having seasonal and trend components, which makes the linear least squares method not applicable for its approximation. Considering different seasons separately (Propastin et al. 2008b; Yin et al. 2016) partly solves the issue of non-stationarity, but excludes the intra-annual assessment. Spatial and temporal averaging is often used in one study simultaneously, representing spatio-temporal interactions separately from different perspectives.

The approaches described above solve the issue at the cost of decreasing the resolution in either spatial or temporal domains, which leads to the loss of data and results. The method we use in this study is different from others used in the spatio-temporal domain due to its flexibility, broad applicability and the comprehensiveness of its results. Seasonal decomposition for each pixel and cross correlation with climatic factors does not produce any abstract objects like principal components or orthogonal functions, which are difficult to interpret. At the same time it provides flexibility in using different lags for different predictors on the pixel level and on seasonal and trend scales separately. Considering the drawbacks of previous research it is necessary to conduct a study, which consequently deals with the detailed shortcomings and provides a reproducible example for better climate change adaptation planning.

We hypothesize that estimating vegetation and climatic seasonal components at each pixel will automatically discriminate vegetation types on the finest scale available, and reveal their intra-annual patterns for the entire country. We further assume that trend components will indicate vegetation trends for the whole study area and spatially explicit climatic factors can be used to explain the interannual variations. We also assume that temperature and precipitation can have either positive or negative impact on vegetation in different regions and at different temporal scales. With cluster analysis of trend and seasonal components we seek to identify different patterns of vegetation and climate interactions and different vegetation formations. The combination of methods we use deals with spatio-temporal dimensionality of data in a straightforward and intuitive way, identifying seasonal and interannual patterns of vegetation, precipitation and temperature in a spatial manner.

2 Study area

2.1 Geographical extent

The study area covered the territory of the Kyrgyz Republic including close parts of China, Kazakhstan, Tajikistan and Uzbekistan, limited by a rectangle between 38°N - 44°N and 68°E - 81°E (Fig. 1). The study encompasses different ecological zones and topographies including deserts, steppes, forestry areas, highland tundras, hills, mountains, rocks, and valleys, as well as different management systems including agricultural lands, forestry, pasture rangelands and nature reserves. The elevations vary from 200 m to 6000 m above sea level, providing a great variation in vegetation and climate conditions.

2.2 Climate

The distribution of annual precipitation is very uneven and varies from 144 mm in some parts of Issyk-Kul region to 1090 mm in the Fergana valley (Adyshev et al. 1987). The midlands and southwestern slopes of the Fergana range receive the highest amount of precipitation in the country – around 1000 mm per year. Highlands on the northern slope of Kyrgyz ridge, Chatkal ridge and Kemin valley as well as the eastern part of Issyk-Kul region also receive a considerable amount of precipitation – about 1000 mm per year. Talas and Chui valleys, as well as the Osh lowland regions receive considerably less precipitation – 300-700 mm annually. Precipitation decreases to about 200-300 mm annually in the Inner Tian-Shan as air masses lose their humidity crossing the ridges. The driest areas are eastern Issyk-Kul, Batken and the Osh highland region, which receive only 150-200 mm annually (Adyshev et al. 1987). In general, annual precipitation amount in Kyrgyzstan is sufficient for crop cultivation and pastoralism, however, most of the precipitation falls in late winter and spring. Summers are very dry, which necessitates the artificial irrigation of agricultural lands. The amount of precipitation in the same region varies greatly interannually. The variations can reach 250 % in eastern Issyk-Kul region, 530 % in SW Kyrgyzstan, 400 % in Inner Tian-Shan and 260 % in the northern part of the country (Adyshev et al. 1987). Precipitation has an altitudinal gradient, its amount increases up to 3500-4000 m above sea level, higher up the increase decelerates.

The hottest months are July and August. In summer, the temperatures across identical elevations are equal across the country, whereas in winter the difference is conditioned by terrain and can reach 15°C. In general, the south-western part of the country is warmer in summer than the northern part; the temperature may reach more than 40°C in valleys. A strong vertical temperature gradient is exemplified by the average monthly temperature in July which differs by more than 20°C from 4°C at 3600 m up to 27°C at 720 m above sea level (Adyshev et al. 1987). In winter, the lowest temperatures are recorded in mountain valleys and depressions.

2.3 Vegetation

Vegetation types are distributed along distinct altitudinal zones, conditioned by vertical gradients of climatic variables. Latitudinal zonation is less obvious, but also evident as exemplified by the difference between zonal (lowland) vegetation mosaics of North and South Kyrgyzstan. In some cases a longitudinal zoning can be observed, which is connected with local features of small-scale air circulation, e.g. seasonal valley winds, which is the case for the Issyk-Kul valley. The inland position of Kyrgyzstan and its proximity to the deserts of Central Asia defines the general aridity of land-

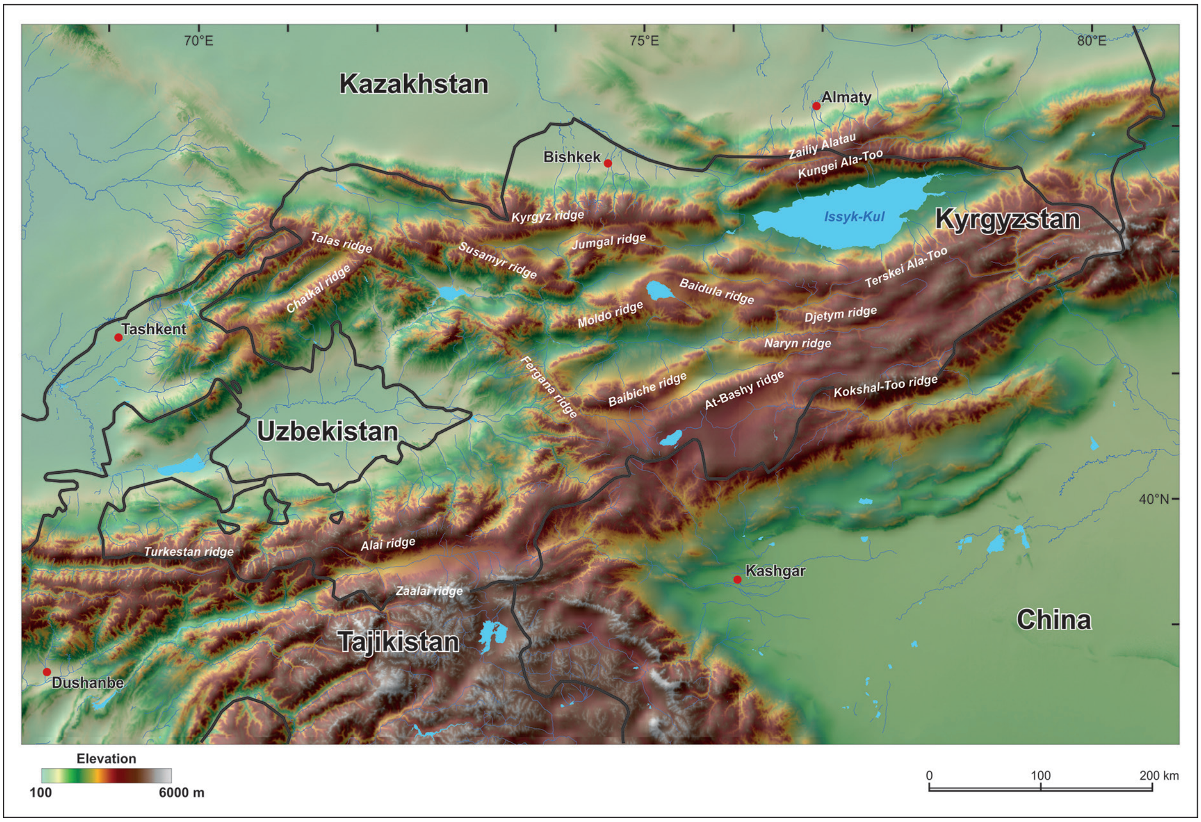

Fig. 1: Study area

scapes and their harsh, exposure-induced contrasts. Arid steppe or desert landscapes occupy about 35 % of the country, while humid landscapes cover only 27 % (Adyshev et al. 1987). Due to arid and semi-arid climatic conditions over vast areas, forest and meadow landscapes are often restricted to favorable north-facing slopes.

Midland meadow and steppe landscapes with tall grass on dark soils are prevalent at elevations of 1000-2200 m above sea level. The grassland vegetation interchanges with trees: *Sorbus tianschanica, Juniperus spp., Picea schrenkiana, Acer spp.,* and *Betula spp.* The trees are the remains of forests, the original ecosystem, which was cleared and replaced by grassland vegetation types. Steppes, dominated by *Festuca spp., Stipa spp.,* and *Avena spp.* occupy south-facing slopes interchanged with outcrops of rocks. In the south of the country, *Prangos spp.* are major constituents of these steppe communities (Borchardt et al. 2011).

Forests cover only 5.7 % of the country; they are distributed at elevations between 1500-3100 m above sea level. Spruce forests of *Picea schrenkiana* occur in the north and east of the country. Juniper forests occupy almost half of the entire forest area and grow in the south and south-west of the country. The forests are very sparse and dominated by *Juniperus spp., Berberis oblonga, Rosa fedtschenkoana, Lonicera microphylla, Cotoneaster melanocarpus,* and *Spiraea hypericifolia.* The forests on the slopes of Fergana and Chatkal ridges are dominated by *Juglans regia* with other fruit tree species such as *Malus siversii* and *Malus niedzwetzkyana, Pyrus korshinskyi, Pyrus regelii, Prunus sogdiana, Ribes janczewskii, Prunus mahaleb,* and *Acer turkestanicum.* Riverine forests are developed along river valleys. They are composed of *Populus laurifolia, Betula spp., Salix spp., Myricaria elegans, Clematis orientalis* and *Hippophae rhamnoides* (Adyshev et al. 1987).

Low grass alpine meadows predominate the alpine zone from 3000 m upwards; these are areas of low temperature and a short growing season. The alpine meadows are dominated by *Kobresia spp., Phlomis spp., Geranium spp., Poa alpina, Allium semenovii, Alchemilla retopilosa, Ligularia alpigena, Carex spp., Leontopodium spp.,* and *Taraxacum spp.* The meadows interchange with rocky ridges, talus, and snow fields. They mostly occupy valleys and slope bottoms, i.e. the areas where fine particles are deposited and soils have developed.

The upper alpine zone is highland cold desert or tundra, which is distributed at elevations of 3600-3900 m above sea level. Strong insolation results in high evapotranspiration, leaving the soil dry. Highland tundras are very much like zonal tundras, 201 species typical of zonal tundras grow here, including many lichens, mosses, grasses, and sedges. The vegetation is dominated by xerophyte cushion plants, dwarf semishrubs (e.g., *Dryadanthe spp.*), and *Calamagrostis tianschanica* growing in patches. The vegetation cover is very sparse near mountain tops and is dominated by *Smelowskia calycina*, *Richteria spp.,* and *Cerastium lithospermifolium* (Adyshev et al. 1987).

Landscapes of intermontane depressions have arid features. Half-closed depressions such as Chui, Fergana, and Talas valleys have desert-steppe landscapes in their lowest parts giving way to steppes with increasing elevation. These lowland depressions are almost entirely used for irrigated agriculture. The midland depressions of the Inner Tian-Shan have desert-steppe and steppe landscapes. The highland depressions at elevations of 3000-3600 m above sea level are characterized by dry climate, low temperatures and sparse vegetation, which are dominated by *Artemisia spp., Festuca spp.*, and *Ptilagrostis spp.* (Adyshev et al. 1987).

3 Materials

3.1 Data

We used remotely sensed monthly MODIS NDVI, day LST (land surface temperature) and GPCC PRC (precipitation) raster time series of years 2000-2013. MODIS Terra (v5 of MOD13C2 product) monthly NDVI data were used as a general proxy of vegetation conditions, as their relation is well established (Li et al. 2010), and MODIS Terra (v5 of MOD11C3 product) monthly LST (land surface temperature) data for temperature approximation. The quality assessment of the MODIS products did not indicate any serious inaccuracy and missed values. GPCC full data reanalysis version 7.0 (Schneider et al. 2015) monthly precipitation rates with initial spatial resolution of 0.5° were used for approximation of precipitation level.

MODIS land surface temperature and vegetation index data are originally distributed by the Land Processes Distributed Arctive Archive Center (LP DAAC), located at the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (lpdaac.usgs.gov), distributed in netCDF format by the Integrated Climate Data Center (ICDC, http://icdc.zmaw.de) University of Hamburg, Germany. MODIS NDVI is produced regularly every 16 days based on daily recordings, NDVI is derived from atmospherically-corrected reflectance in red and near-infrared spectral bands. MODIS LST is distributed in 0.05° grids, produced by the day/night algorithm from pairs of day and night MODIS observations in seven TIR bands (thermal infrared).

The monthly precipitation data we used were those of GPCC (Global Precipitation Climatology Centre) Full Data Reanalysis Version 7.0 with spatial resolution of 0.5° (Schneider et al. 2015). The data represent a centennial reanalysis of monthly global land-surface precipitation based on the measurements of 75 000 stations world-wide. They contain the monthly totals on a regular grid with a spatial resolution of 0.5°. The temporal coverage of the dataset ranges from January 1901 till December 2013.

We used SRTM (Shuttle Radar Topography Mission) for the digital elevation model. The data were acquired by radar on board of Endeavour shuttle in February 2000, which was a joint project of the National Aeronautics and Space Administration (NASA) and the National Geospatial-Intelligence Agency (NGA). The data resolution is approximately 1 arc-second, which is about 30 m and is provided in 1x1 degree tiles.

The study area was limited by a rectangle between 38°N - 44°N and 68°E - 81°E (Fig. 1). The precipitation, NDVI, LST and SRTM images were all resampled to the same resolution, extent and coordinate system with b-spline resampling. We have chosen the resolution of the MODIS dataset to avoid data loss. As a result, we have got raster images with 184 x 115 pixels, with a pixel size of 5700 m. in WGS84 UTM43N projected coordinate system.

3.2 Tools

Free open source software packages were used for the data analysis. The GIS manipulations and analysis were done in SAGA GIS 2.3.1 (Conrad et al. 2015), time series decomposition and analysis were done in R 3.3.1 (R CORE TEAM 2016), data management and routine automatization were done with Python 3.5 (PYTHON SOFTWARE FOUNDATION 2016). The maps for the publication were prepared with QGIS 2.18.3 (QGIS DEVELOPMENT TEAM 2017).

4 Methods

4.1 General approach

In order to analyze each pixel separately we disassembled the time series of NDVI, PRC and LST images into a number of time series for each pixel. So we had 184 x 115 = 21160 (by the number of pixels) sequences of numeric values (time series vectors) for each of the three variables (Fig. 2 – Input). Each time series vector had 168 values (14 years of monthly observations). Then we decomposed each pixel's time series vector of each variable (NDVI, PRC and LST) into trend and seasonal components, omitting the remainder component. This is described in "4.2 Time series decomposition" section. Thus for each pixel of each variable we got trend and seasonal temporal components (Fig. 2 – Step 1). The trend components were used for the interannual assessment, and the seasonal components were used for the intra-annual assessment.

Then we conducted correlation analysis of trend and seasonal components respectively between NDVI and LST, and between NDVI and PRC at different lags (Fig.2 – Step 2). We identified the lags of maximum, minimum, maximum of absolute value and minimum of absolute value (Max, Min, AbsMax, AbsMin) correlation coefficients for each pixel (Fig. 2 – Step 4). This is detailed in the "4.3 Correlation analysis" section.

To understand how much of NDVI variation is explained by PRC and LST we conducted least squares regression analysis. We used NDVI trend and seasonal components as dependent variables and PRC and LST trend and seasonal components respectively as predictors. The predictors were shifted against NDVI time series for the lags of their AbsMax correlation to account for the delayed reaction (Fig. 2 – Step 3). Thus, for each pixel we have got the coefficient of determination (adjusted R^2) (Miles 2014) by climatic factors. This is described in more details in the "4.4 Coefficient of determination" section.

Then the trend and seasonal Max, Min, AbsMax, AbsMin images together with R^2 image and digital elevation model (DEM) were exposed to k-mean cluster analysis (Fig. 2 – Step 5). Thus we have got 5 spatial clusters with similar NDVI and climate temporal patterns considering elevation. Then we spatially averaged the trend and seasonal components of all the pixels within each cluster for each variable to see the general behavior of NDVI, precipitation and temperature in each cluster. These steps are described in the "4.5 Cluster analysis" section.

4.2 Time series decomposition

We approached the raster time series of NDVI, LST and PRC as a number of cross-correlated time series vectors (for each pixel) considering each vector independently from the others. We split the raster time series of NDVI, LST and PRC into a number of series of consecutive numeric values (vectors) –

Tab. 1: STL settings used for time series decomposition

Parameter	Value	Description
s.window	„periodic“	The loess window for seasonal extraction.
s.degree	1	Degree of locally-fitted polynomial in seasonal extraction.
t.window	36	The span (in lags) of the loess window for trend extraction.
t.degree	1	Degree of locally-fitted polynomial in trend extraction.
l.window	NULL	The span (in lags) of the loess window of the low-pass filter used for each subseries. Defaults to the smallest odd integer greater than or equal to the frequency of time series (i.e. 13).
l.degree	1	Degree of locally-fitted polynomial for the subseries low-pass filter.
robust	TRUE	Logical indicating if robust fitting be used in the loess procedure.
inner	2	Integer; the number of 'inner' (backfitting) iterations.
outer	1	Integer; the number of 'outer' robustness iterations.
na.action	na.omit	Action on missing values.

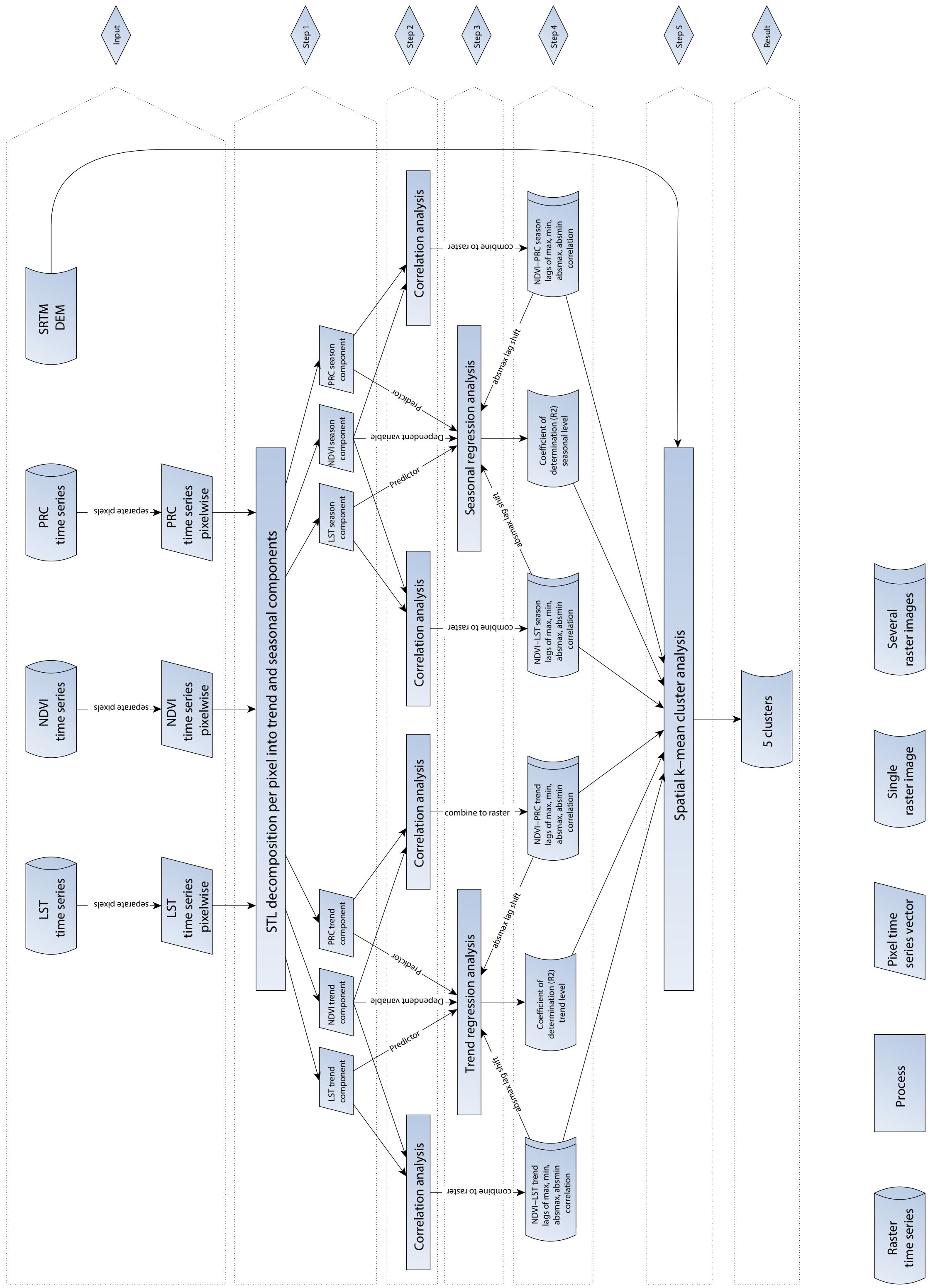

Fig. 2: Workflow chart

one for each pixel, thus we got 21160 vectors (by the number of pixels) of monthly values of NDVI, LST and PRC for the period of 14 years (2000-2013) (Fig. 2 – Input).

Then each time series vector was decomposed to seasonal (intra-annual), trend (interannual) and remainder (error) components (also vectors) using *stl* function (Cleveland et al. 1990) (Tab. 1) of *stats* package of R (R CORE TEAM 2016) (Fig. 2 – Step 1). STL decomposes time series into trend, seasonal and remainder components, which are the summands of the initial time series. The method is easy to implement, provides flexibility in choosing the amount of trend and seasonal variations, handles missing data and is robust against the outliers (Cleveland et al. 1990). STL is based on a sequence of smoothing operations mainly based on locally-weighted regression or *loess* (Cleveland and Devlin 1988; Cleveland et al. 1988).

This resulted in production of trend, seasonal and remainder components (vectors) for each pixel of each variable (Fig. 2 – Step 1). The remainder vectors were omitted from further analysis, thus we have got 21160 (by the number of pixels) trend and seasonal vectors for NDVI, LST and PRC.

4.3 Correlation analysis

We conducted cross-correlation analysis of the trend component vectors of NDVI with those of PRC and LST with different lags. The seasonal component vectors of NDVI were also correlated with respective vectors of PRC and LST (Fig. 2 – Step 2). In case of seasonal components correlation analysis, we looked at lags of up to 6 months, in case of the trend components we used up to 24 months lags. As a result we have got vectors of trend and seasonal components' correlation coefficients at different lags between NDVI and PRC and between NDVI and LST for each pixel. This way we could see how strongly NDVI correlates with PRC and LST on trend and seasonal scales with different lags in each pixel.

Then we identified at which lags NDVI had the Max, Min, AbsMax and AbsMin correlations with PRC and LST on trend and seasonal scales. These values we assembled into raster images of lags of Max, Min, AbsMax and AbsMin correlations of trend and seasonal components (Fig. 2 – Step 4). This provides information of speed and sign of NDVI reaction to precipitation and temperature on seasonal (intra-annual) and trend (interannual) scales.

4.4 Coefficient of determination

To estimate the coefficient of NDVI determination by the climatic factors on the interannual scale we conducted a regression analysis with NDVI trend components being the dependent variable and PRC and LST trend components as predictors. For the intra-annual scale we did the same with the seasonal components of the variables. The predictors were taken at the lags of their AbsMax correlation with NDVI (Fig. 2 – Step 3). The regression analysis was conducted on the pixel basis, i.e. each pixel's NDVI was predicted with its PRC and LST values taken at their respective AbsMax correlation lag. The following equation was used for the regression analysis in Fig. 2 – Step 3:

$$NDVI_t = a * PRC_{t-i} + b * LST_{t-j} + c \quad (1)$$

Where:

$NDVI_t$ – normalized difference vegetation index at lag $t = 0$ (current observation), PRC_{t-i} – precipitation i lags earlier, LST_{t-j} – land surface temperature j lags earlier, a, b, c – first, second and third polynomial coefficients of the regression equation, i – lag of AbsMax correlation of $NDVI$ and PRC, j – lag of AbsMax correlation of $NDVI$ and LST.

Based on the regression analysis we calculated the coefficient of determination, which was the adjusted R^2 (Miles 2014). This was done both for trend and seasonal components of each pixel separately (i.e. each pixel had individual lag shifts for each predictor), thus we could see to which extent the NDVI variations were conditioned by precipitation and temperature variations, considering the predictor- and pixel-specific reaction time, which was the lag of AbsMax correlation with predictors (Fig. 2 – Step 4).

4.5 Cluster analysis

The images of lags of Max, Min, AbsMax and AbsMin correlation coefficients, together with the images of R^2 on both trend and seasonal scales and digital elevation model (DEM) were exposed to k-mean (Rubin 1967) grid cluster analysis (Fig. 2 – Step 5). As a result we have got 5 spatial clusters with different temporal patterns of NDVI, LST and PRC. We have spatially averaged all the pixels within each cluster to see the temporal pattern of vegetation and climate interaction in each of them.

5 Results

The correlation analysis resulted in 32 images, which represent Max, Min, AbsMax and AbsMin correlation coefficients of NDVI correlation with PRC and LST, together with their lags and on trend and seasonal scales (Fig. 2 – Step 4). The representation and discussion of all the images would be too overwhelming, so we present the AbsMax images and their respective lags (Fig. 3). These images (Fig. 3) indicate the different signs of NDVI correlation with PRC and LST and different lags, at which they occur. In general NDVI on low flat areas indicate positive correlation with PRC and negative with LST, whereas highlands indicate the opposite (Fig. 3). Since the maximum of absolute value function was looking for correlation coefficients with lags of up to 6 months on the seasonal scale and 24 months on the trend scale, the weaker correlations with other signs could be covered with the stronger correlations with

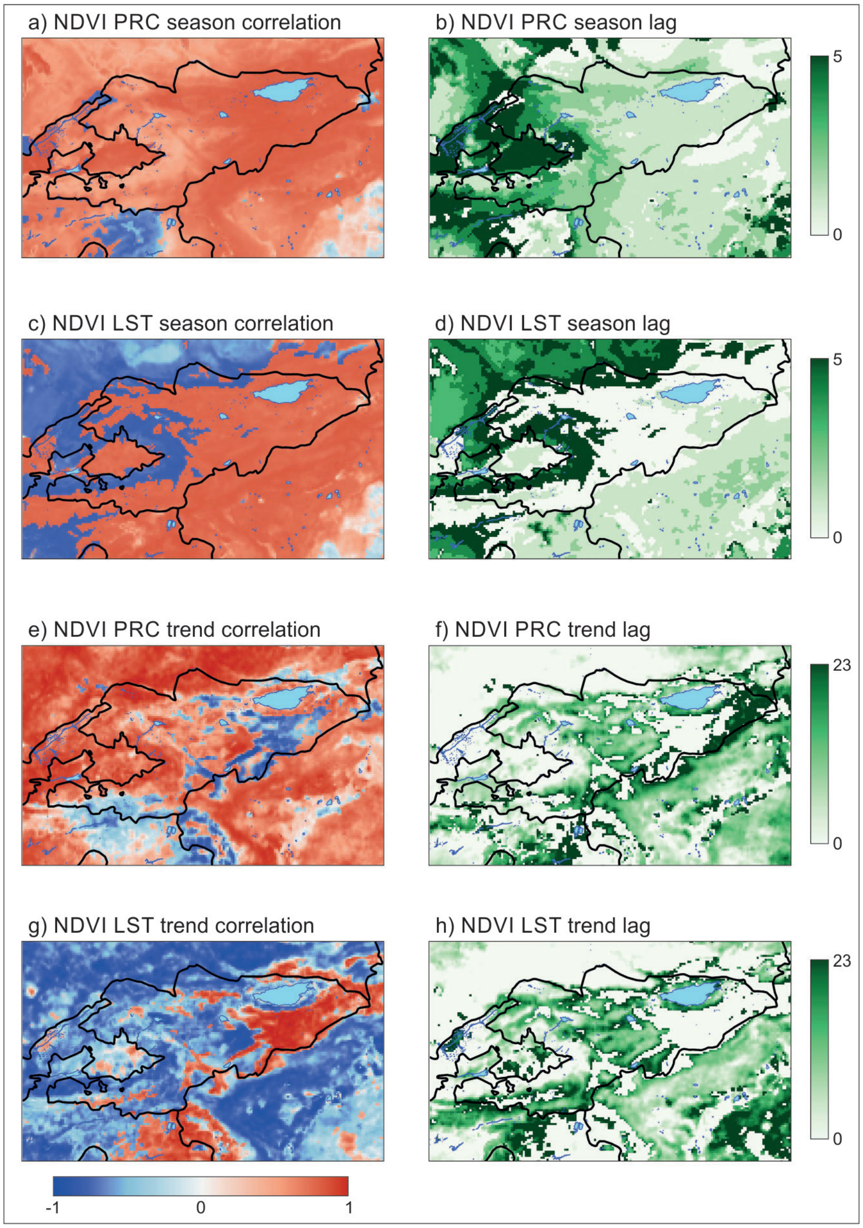

Fig. 3: The maps of AbsMax correlation coefficients (left column) and their respective lags in months (right column)

the opposite sign. These interactions were captured with other extrema functions and the cluster analysis (Fig. 2 – Step 5) is to decrease the dimensionality of results and present them more comprehensively.

The resulting 5 clusters followed the pattern of horizontal temperature and precipitation flow as well as altitudinal gradients (Fig. 4). They indicate the spatial pattern of inter- and intra-annual variations of vegetation and climatic factors. None of the clusters repeat any other with regards to annual mean of precipitation, temperature and NDVI (Fig. 5).

The cluster 1 is basically the flat lands in Kazakhstan and China representing dry deserts or desert-steppes (Fig. 4). In absolute values the mean monthly precipitation level in this cluster is about 25 mm, mean monthly NDVI is 0.23 and mean monthly LST is 24°C (Fig. 5). The seasonal component of NDVI indicates a strong positive correlation with precipitation (Tab. 2) and the seasonal flow of NDVI closely complies with the seasonal flow of PRC with a month lag (Fig. 6c), meaning a delayed reaction of NDVI to precipitation (Fig. 6a). NDVI also indicates a week positive immediate correlation with LST and a negative correlation with 4 months lag (Fig. 6b). This indicates that temperature is a promoting as well as a limiting factor for vegetation development. The summer, which is the seasonal maximum of temperature, coincides with seasonal minimum of NDVI and precipitation, which results in an arid landscape. Vegetation booms in spring and is depressed by high temperatures and low precipitation levels in summer. This cluster has the highest monthly temperature among the other clusters (Fig. 5). On the trend scale, positive correlation with precipitation and negative correlation with temperature is obvious (Fig. 6d, e). The trend component curves of NDVI and precipitation almost entirely match with each other, opposed by the temperature curve (Fig. 6f). About 61 % of NDVI seasonal variation and about 64 % of its interannual variation are explained by PRC and LST (Tab. 2).

The cluster 2 is mainly low mountains in Toktogul, Fergana and Chui valleys, which are foothills of Fergana, Chatkal and Kyrgyz Ala-Too ranges (Fig. 4). The area has dense networks of rivers and irrigation channels, it is mainly used as crop fields or lowland pastures. On the seasonal scale, NDVI indicates positive correlations with precipitation with a lag of 4 months (Fig. 7a) and immediate positive correlation with temperature (Fig. 7b). NDVI curve follows the temperature curve and is also conditioned by the precipitation

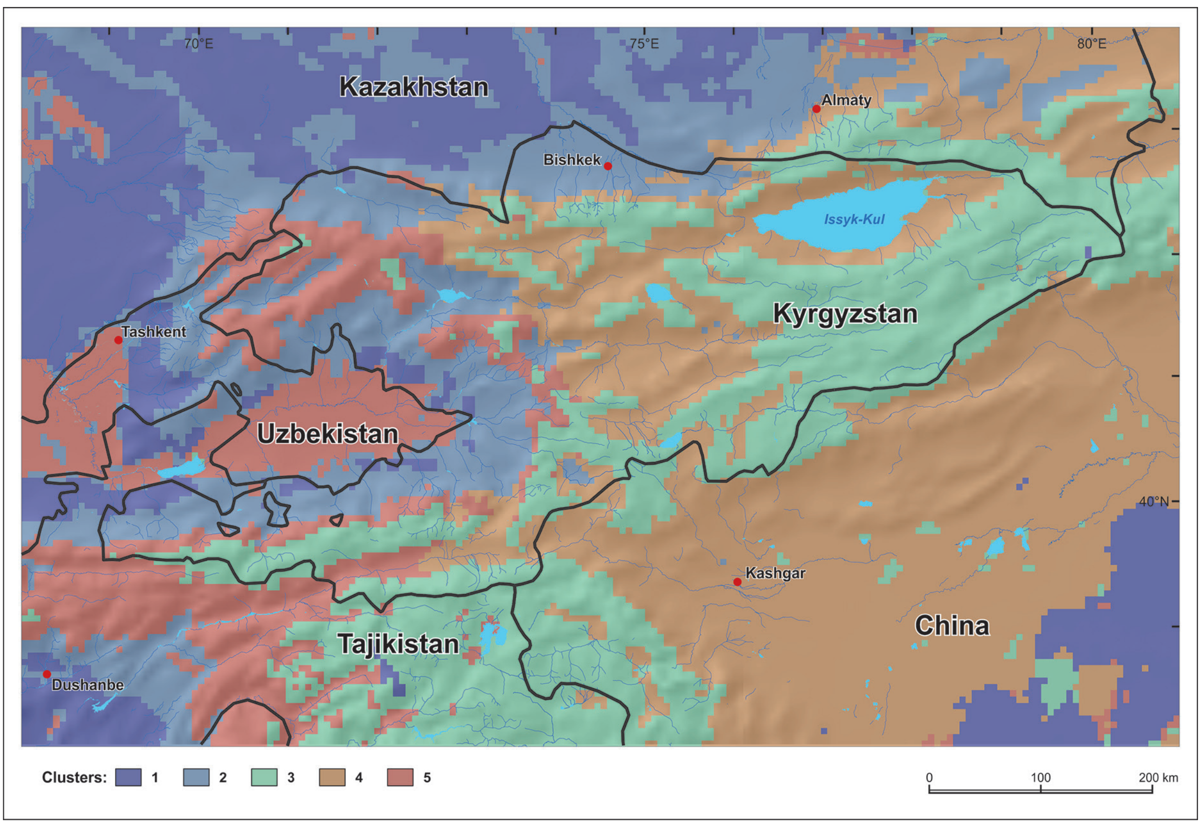

Fig. 4: Spatial clusters of vegetation-climate interactions

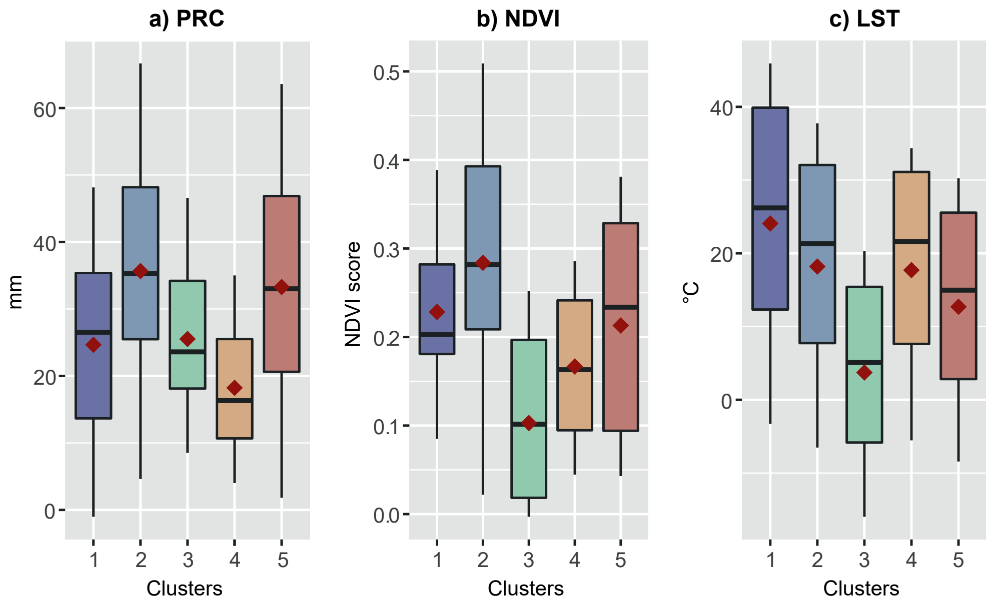

Fig. 5: Cluster spatially averaged values (boxplots) red dots represent mean values

curve (Fig. 7c). NDVI does not drop immediately with the precipitation in summer; however, high temperatures do depress vegetation. On the trend scale, NDVI indicates a strong positive correlation with precipitation and strong negative correlation with temperature (Tab. 2). NDVI trend curve follows very closely the precipitation curve and is opposed by the temperature curve (Fig. 7f). This cluster has the highest monthly mean precipitation level (36 mm per month) and highest mean NDVI (0.28) with a monthly mean temperature of about 18°C (Fig. 5). About 81 % of the seasonal variation and 68 % of the trend variation of NDVI are explained by the climatic factors (Tab. 2).

The cluster 3 represents the areas of highland tundra which are used as winter pastures (Fig. 4). These areas comprise highland plains or tops of ridges with very sparse and low vegetation. Here, NDVI on the seasonal scale shows strong positive no lag correlation with temperature, and strong positive correlation with precipitation with 1-2 months lag (Fig. 8a, b). The NDVI curve basically follows the temperature curve (Fig. 8c), the peak of precipitation curve in May supports NDVI development, which peaks later in July. On the trend scale, NDVI shows a strong negative correlation with precipitation and positive correlation with temperature (Tab. 2), which is different to the other clusters. NDVI trend curve follows closely the temperature curve (Fig. 8f) and precipitation curve lags after NDVI, which is illustrated by the cross correlation function (Fig. 8d). In absolute terms, this cluster has the lowest temperature and NDVI. The mean monthly temperature is about 4°C, NDVI averages at 0.1 and precipitation at 26 mm per month (Fig. 5). About 88 % of the seasonal and about 58 % of the trend NDVI variations are determined by the climatic factors (Tab. 2).

Tab. 2: Cluster characteristics – AbsMax correlation coefficients (CC) and their lags (Lag), mean adjusted R2 of seasonal and trend components for each cluster

Cluster	NDVI, PRC s		NDVI, LST s		NDVI, PRC t		NDVI, LST t		R^2	
	CC	Lag	CC	Lag	CC	Lag	CC	Lag	s	t
Cluster 1	0.61	1	-0.82	4	0.94	0	-0.76	0	0.61	0.64
Cluster 2	0.59	4	0.85	0	0.94	0	-0.79	0	0.81	0.68
Cluster 3	0.92	1	0.93	0	-0.62	0	0.75	0	0.88	0.58
Cluster 4	0.96	1	0.94	0	0.67	10	-0.70	13	0.87	0.60
Cluster 5	0.85	5	0.98	0	0.72	6	-0.55	9	0.89	0.52

s – seasonal, t – trend

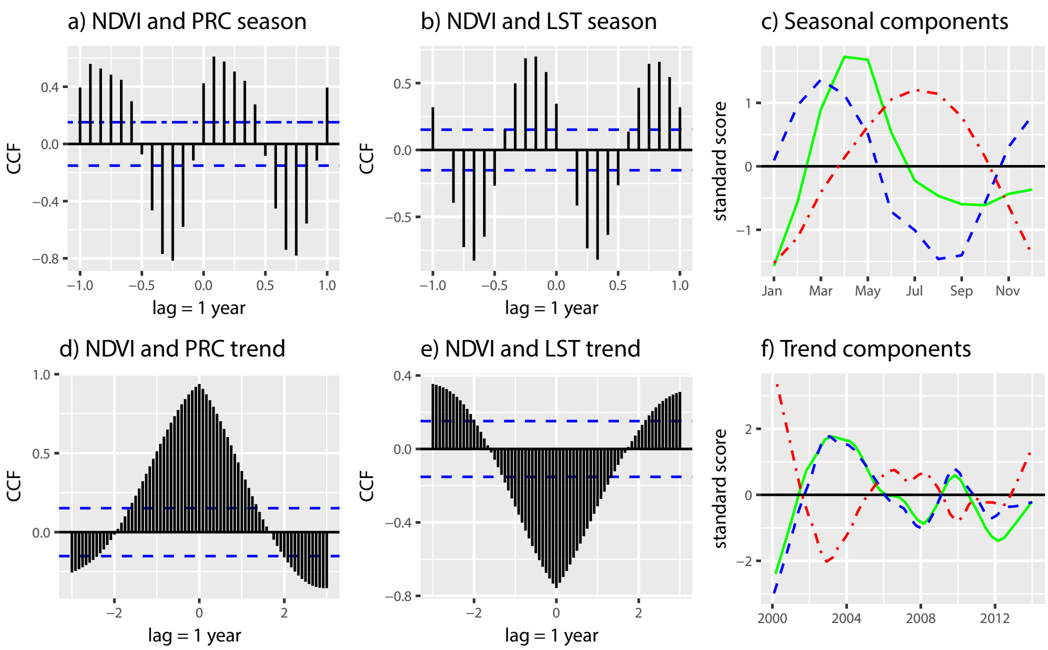

Fig. 6: Cluster 1 seasonal and trend components lagged cross-correlation (for time=*t* and lag=*f* the correlation coefficient is calculated between $NDVI_{t+f}$ and PRC_t or LST_t), and their standard scores: solid green – NDVI, dot-dashed red – LST, dashed blue – PRC

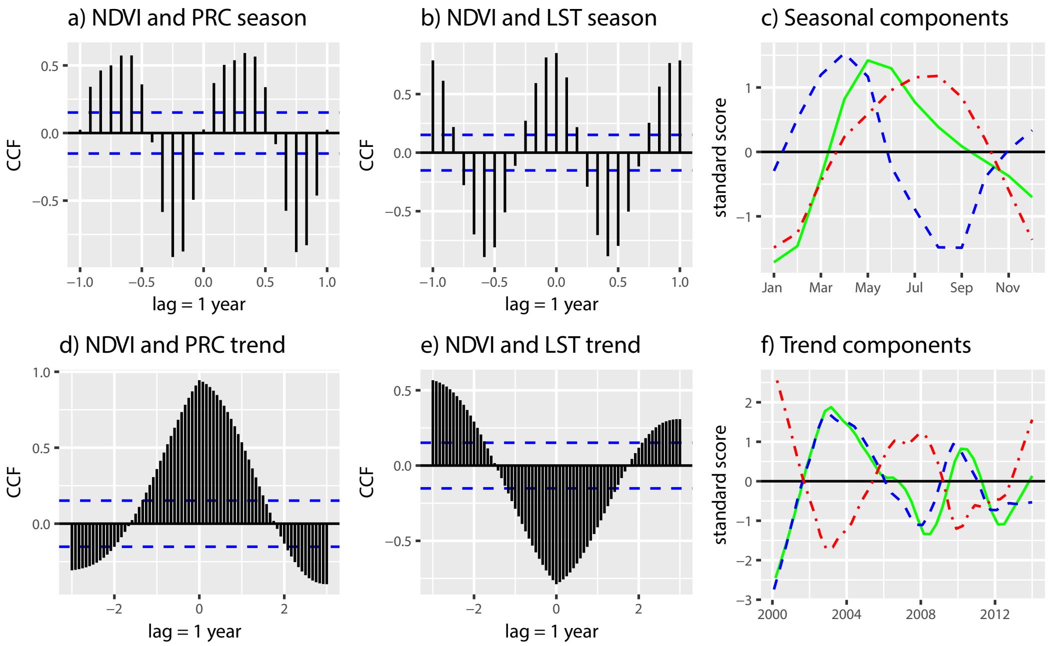

Fig. 7: Cluster 2 seasonal and trend components lagged cross-correlation (for time=*t* and lag=*f* the correlation coefficient is calculated between $NDVI_{t+f}$ and PRC_t or LST_t), and their standard scores: solid green – NDVI, dot-dashed red – LST, dashed blue – PRC

The cluster 4 is mainly dry plains or intermontane depressions (Fig. 4). These areas have the least precipitation amount among the clusters (Fig. 5), because they occur in the precipitation shadows of Fergana and Kokshal-Too ranges. Here NDVI, PRC and LST seasonal curves almost coincide with each other (Fig. 9c) and have strong positive correlation with 0 to 1 lag difference (Fig. 8a, b). On the inter-

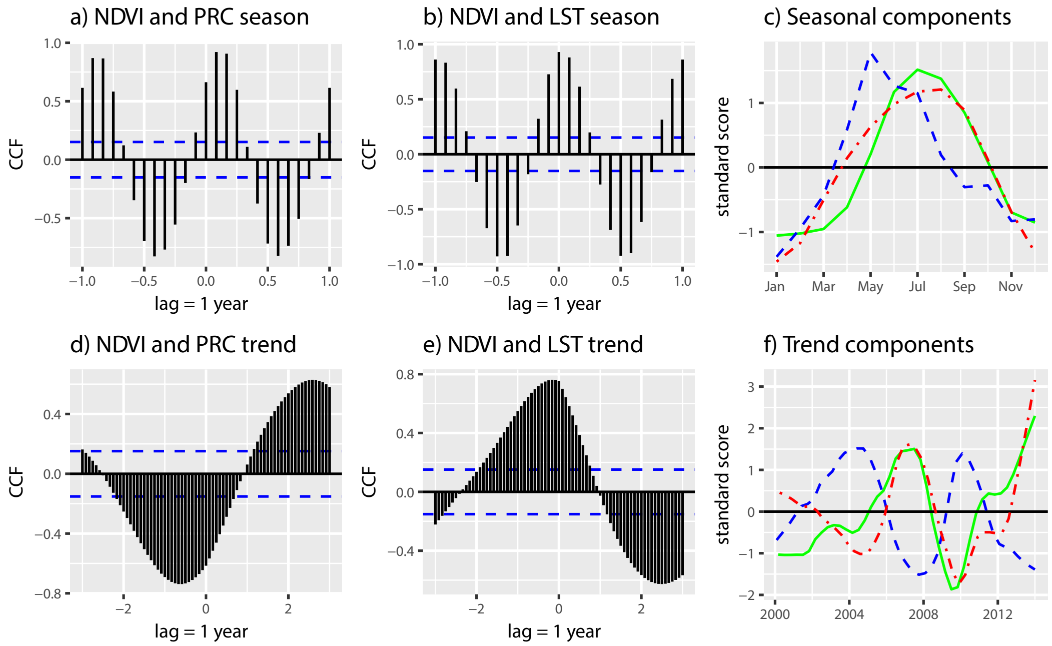

Fig. 8: Cluster 3 seasonal and trend components lagged cross-correlation (for time=*t* and lag=*f* the correlation coefficient is calculated between NDVI$_{t+f}$ and PRC$_t$ or LST$_t$), and their standard scores: solid green – NDVI, dot-dashed red – LST, dashed blue – PRC

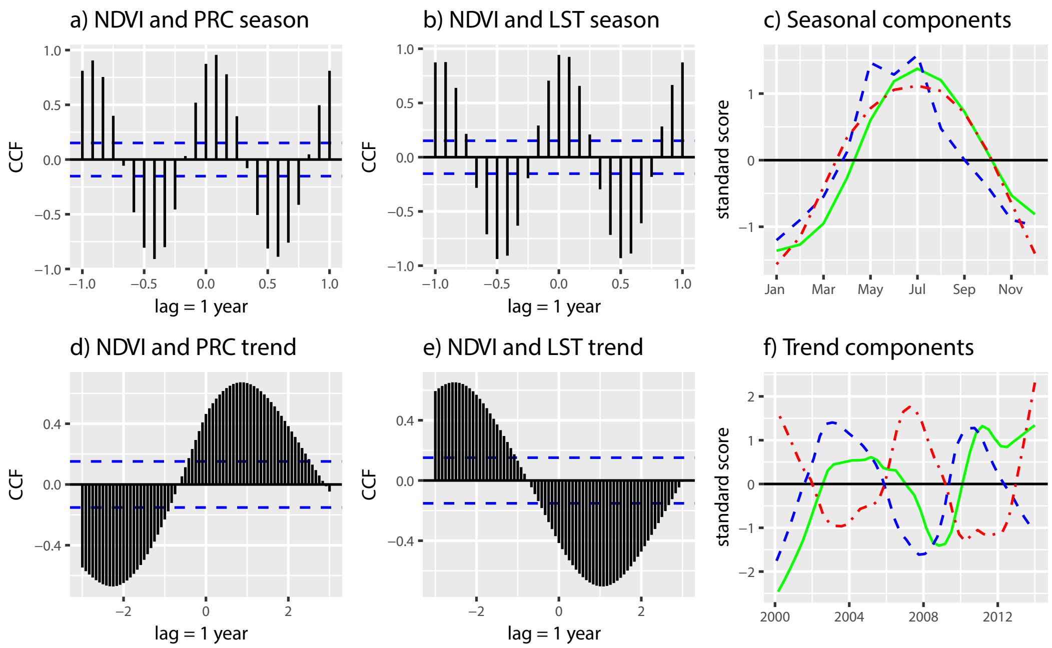

Fig. 9: Cluster 4 seasonal and trend components lagged cross-correlation (for time=*t* and lag=*f* the correlation coefficient is calculated between NDVI$_{t+f}$ and PRC$_t$ or LST$_t$), and their standard scores: solid green – NDVI, dot-dashed red – LST, dashed blue – PRC

annual scale, NDVI indicates a strong positive correlation with PRC and a strong negative correlation with LST with about one year lag (Fig. 9d, e). This is also caused by the rain shadow effect of the ridges, surrounding the cluster areas. Mean monthly precipitation level is about 18 mm, temperature is 18°C and NDVI score is 0.17 (Fig. 5). This cluster has the greatest lag of the trend components correlation with

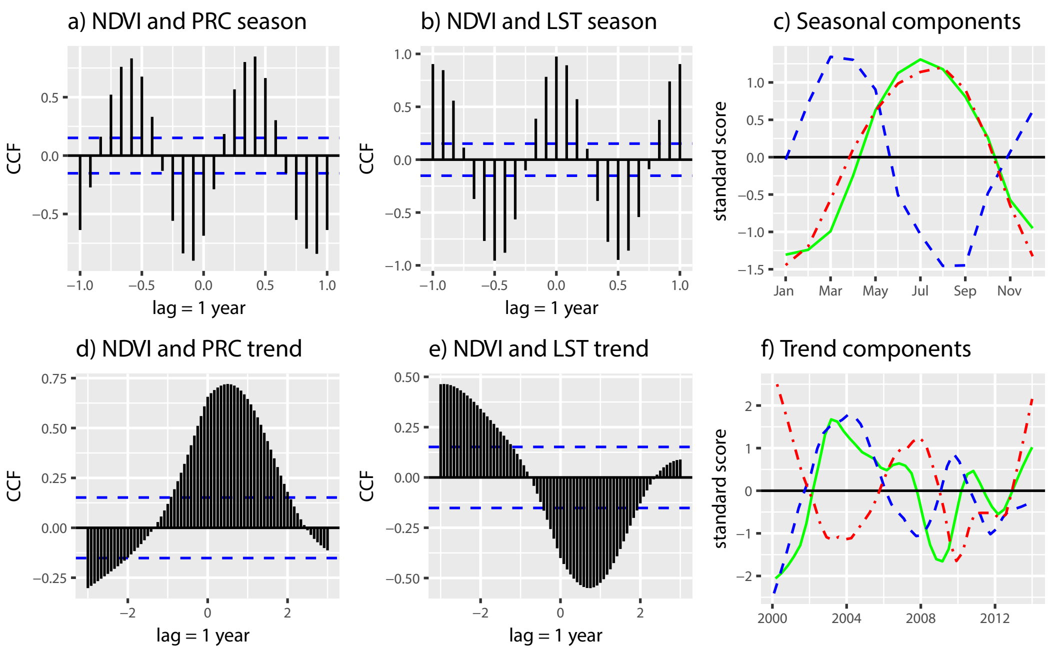

Fig. 10: Cluster 5 seasonal and trend components lagged cross-correlation (for time=*t* and lag=*f* the correlation coefficient is calculated between $NDVI_{t+f}$ and PRC_t or LST_t), and their standard scores: solid green – NDVI, dot-dashed red – LST, dashed blue – PRC

about 87 % and 60 % of NDVI seasonal and trend variations, respectively, being determined by the climatic factors (Tab. 2).

The cluster 5 occupies Fergana valley and some slopes of Fergana, Chatkal and Alai ranges (Fig. 4). These are the areas with one of the highest precipitation levels (Fig. 5). This is a very active agricultural region with developed irrigation network. On the seasonal scale, the NDVI curve follows the temperature curve very closely, indicating a strong positive correlation without a lag (Fig. 10b), whereas precipitation indicates positive correlation with a lag of 5 months (Fig. 10a). On Fig. 10a we can see an artificial negative correlation between NDVI and PRC at lag 0 and a real positive at 6 months lag; this is caused by the system of artificial irrigation, which stocks rain water in spring and provides it in summer. This makes the NDVI peak to shift to summer (Fig. 10c), when vegetation is provided with solar heat and irrigation water, collected from spring rains. The interannual NDVI and precipitation indicate a strong positive correlation and their curves follow each other, whereas temperature has negative correlation with NDVI (Fig. 10d, e). The monthly mean precipitation level here is about 33 mm, mean NDVI is 0.21 and the mean monthly temperature is 13°C (Fig. 5). About 89 % of NDVI seasonal and 52 % of the interannual variations are determined by the climatic factors (Tab. 2).

The coefficient of determination (adjusted R^2) derived from the regression analysis of the seasonal components indicates vast areas to be strongly conditioned by precipitation and temperature. The mean coefficient of determination of all the pixels is 0.82 and standard deviation equals to 0.17. Only the areas in the north-west and south-east, which are Muyun-Kum and Taklamakan deserts in Kazakhstan and China respectively, and Khan-Tengri glaciers, indicate low coefficients of determination (Fig. 11). The Fergana valley with developed agriculture and irrigation system is also less controlled by the climatic factors.

The trend component of NDVI indicates less determination by precipitation and temperature. The mean is 0.60 and standard deviation equals to 0.20. The areas with the least R^2 are the tops of Fergana, Chatkal and Alai ridges, Khan-Tengri, Suusamyr valley as well as At-Bashy, Kemin and Son-Kul valleys (Fig. 12). The plains in Kazakhstan and China, highlands in Inner Tian-Shan and parts of Fergana valley in Tajikistan show high coefficients of determination. These areas are expected to be affected the most in case of temperature and precipitation trend change.

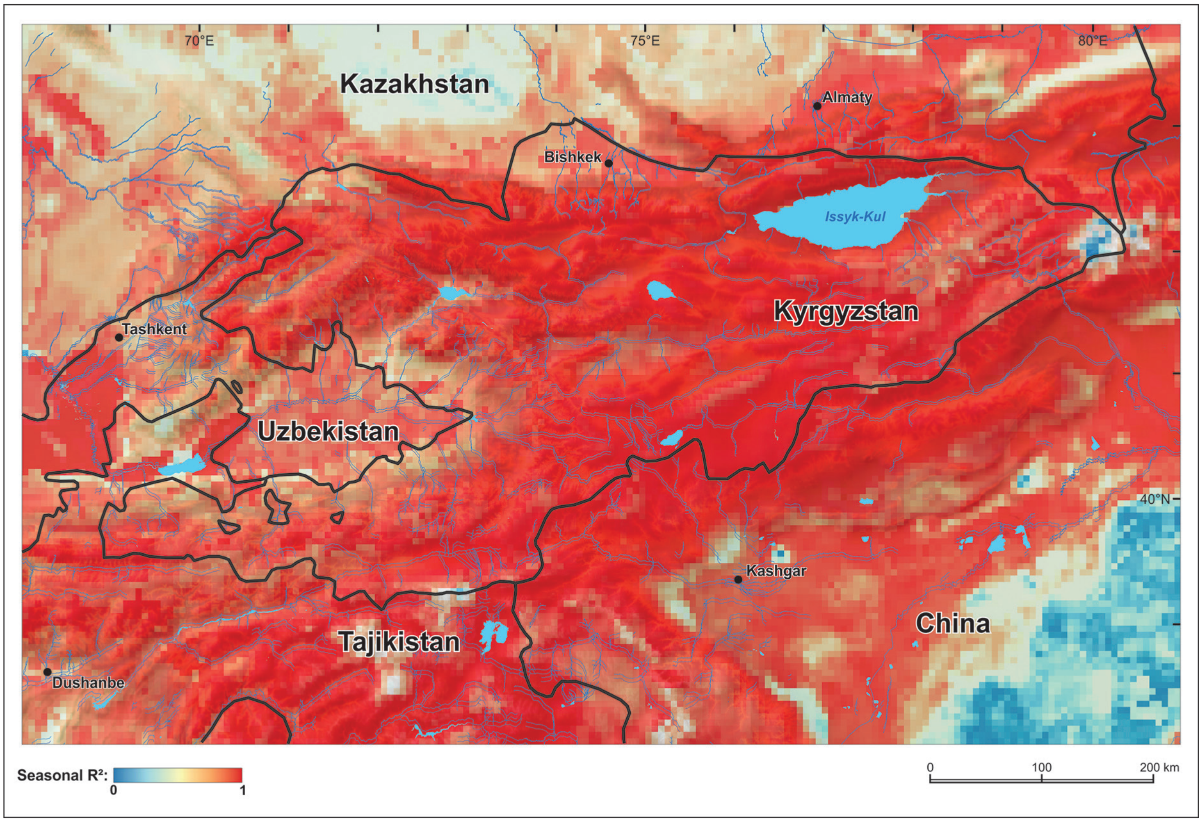

Fig. 11: Coefficient of determination (adjusted R^2) of NDVI seasonal component (indicates to which extent NDVI seasonal variation is determined by precipitation and temperature seasonal variations)

6 Discussion

The 5 clusters identified in this study indicate 5 zones with different patterns of vegetation and climate interaction. The zones have different seasonal flow of NDVI, temperature and precipitation as well as different trends of the variables. On the seasonal scale, all the clusters have positive NDVI correlations with precipitation and temperature, except for cluster 1, which has negative correlation with temperature (Tab. 2). On the trend scale, NDVI in all the clusters has positive correlation with precipitation and a negative with temperature, except for cluster 3, where it is opposite.

In general, both PRC and LST are the promoting factors for vegetation development on the seasonal scale (Tab. 2). Only in clusters 1 and 2 vegetation is boosted by temperature in spring and depressed by it in summer (Figs. 6c, 7c). These clusters are deserts and plains in Kazakhstan and China, and piedmonts of Fergana and Chatkal ridges. Similar results were reported by Propastin et al. (2008a) and Yin et al. (2016), who identified positive correlation between NDVI and temperature in spring and negative correlation in summer for different vegetation types in Central Asia. Both temperature and precipitation can be promoting as well as limiting factors of plant growth if they deviate considerably from their optimal values and timing, which varies with elevation, terrain and other natural conditions.

Temperature seasonal distribution stays constant across the clusters, because generally summers are warm and winters are cold. However, the seasonal distribution of precipitation and its absolute values varies drastically; which conditions vegetation temporal behavior and makes the clusters different. The seasonal maxima of NDVI, temperature and precipitation move in geographical space as the seasons change. Precipitation maximum flows from north-west to south-east over the year cycle. The temperature maximum moves from low valleys to the ridge tops from spring to winter. NDVI maximum basically follows behind the precipitation maximum, suggesting that vegetation development in the region is conditioned more by precipitation than by temperature.

On the trend scale, precipitation appears to be the promoting factor, whereas temperature is always the limiting factor for vegetation develop-

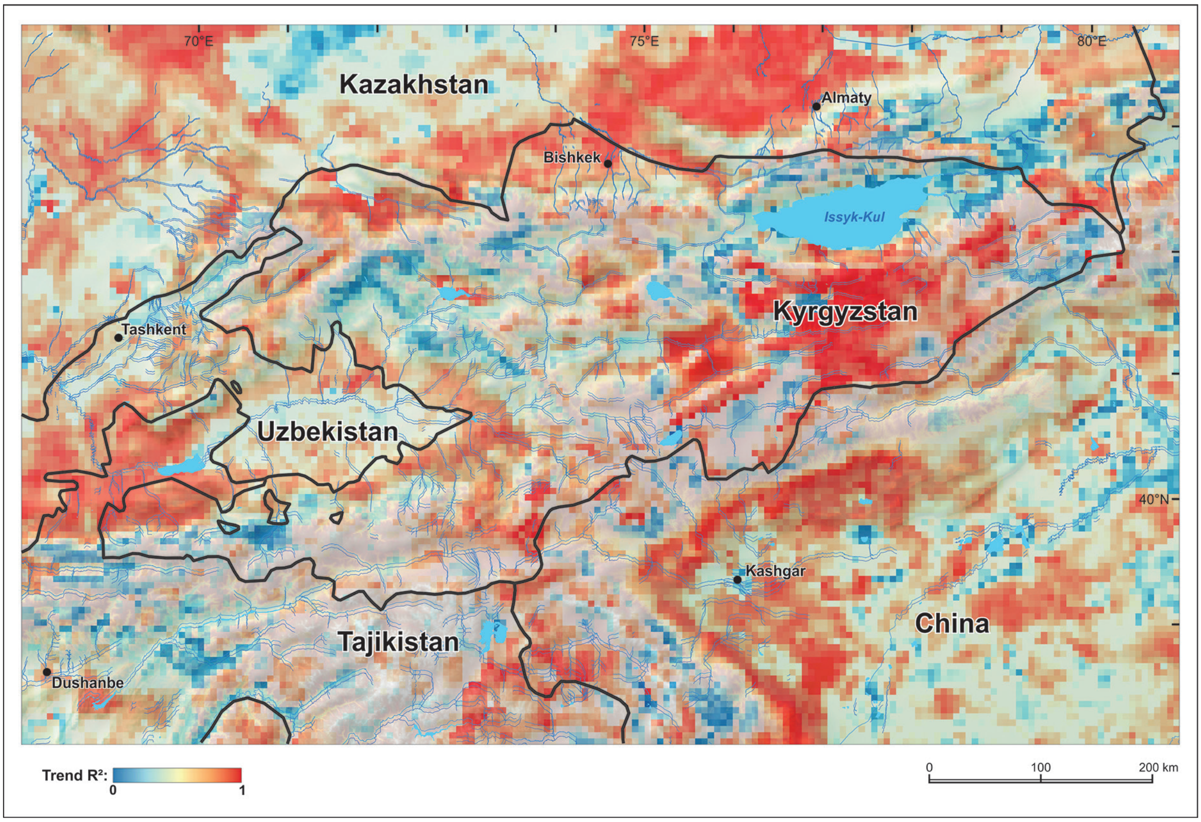

Fig. 12: Coefficient of determination (adjusted R^2) of NDVI trend component (indicates to which extent NDVI trend variation is determined by precipitation and temperature trend variations)

ment (Tab. 2). Thus, an increase in precipitation will promote vegetation, and increasing temperatures will limit it. This indicates the general aridity of the region, similar findings are reported by Yin et al. (2016). Cluster 3 is the only exception indicating the opposite. This cluster occupies the areas of highland plains and ridge tops. These areas usually have low temperatures and significant water deposits, so precipitation in the form of snow retards the vegetation development, but higher temperatures promote its growth. This cluster has the lowest mean annual NDVI and temperature and about the average precipitation (Fig. 5), so not the lack of moisture and high temperature, but lots of snow and low temperature are the main limiting factors for vegetation development on the trend scale. The cluster 3 is the only case where NDVI variations precede those of precipitation and temperature on the trend scale (Figs. 8d, e). This suggests that vegetation has an impact on local microclimate. We can suppose that developing vegetation cover decreases evapotranspiration and albedo in the area, which in turn limits precipitation and increases temperature.

Clusters 2 and 5 show close mean monthly values (Fig. 5); they are close geographically as well (Fig. 4). However, seasonal distribution of NDVI and correlation of trend components are different (Figs. 7, 10). Similar seasonal distribution of precipitation and temperature for cluster 5 was reported by Lioubimtseva et al. (2005) and by Gessner et al. (2013). At the same time the clusters with similar seasonal flow indicate different absolute values, like clusters 3 and 4. This clearly shows a great regional variability of the climate-vegetation system and importance of their discrimination. It is also important to consider not only the absolute values or seasonal flows of NDVI, LST and PRC, but both these factors together with the reaction lag.

The major climate analysis of Kyrgyzstan was conducted by Adyshev et al. (1987). This climate classification was developed from annual sums of temperature and precipitation as well as their seasonal distribution and elevation, based on meteorological observations since 1881 (GIDROMET SSSR et al. 1967) and is broadly applied in the country. Our clusters 1, 2 and 5 correspond to “valley and foothill” climatic belt according to the classification by

Adyshev et al. (1987). Cluster 4 corresponds to the "midland" climatic belt, and cluster 3 corresponds to "highland" and "nival" climatic belts of the same classification (Adyshev et al. 1987). Thus our study discriminated 3 additional classes within the "valley and foothill" class and combined the "highland" and "nival" classes into one. The classification by Adyshev et al. (1987) was based on climatic and terrain variables, whereas our study uses the vegetation component, which makes it more useful with regards to management of natural resources and climate change adaptation.

Lioubimtseva and Henebry (2009) and Hijioka et al. (2014) predicted aridity increase in Central Asia in the coming decades. The summers will be hotter and dryer, and winters will have more precipitation. These will shift the temperature and precipitation seasonal curve and change the trend, which will have corresponding impacts on vegetation. The fact that almost the entire research area has high coefficient of determination scores on the seasonal scale (Fig. 11) indicates that seasonally the vegetation is greatly dependent on climatic factors. Only the arid lands and permanent glaciers indicate little to no NDVI seasonal variation determination by the climatic factors (Fig. 11). These are the areas without much vegetation, which would not normally respond to temperature and moisture variations. In general, on the seasonal scale pastures and forests indicate the highest coefficient of determination, the agricultural areas show the medium, and the areas without vegetation have the lowest coefficient of determination. Propastin et al. (2007) also indicate decrease of correlation between NDVI and climatic factors in different ecosystems as the proportion of grass species shrinks.

On the trend scale, the pattern of determination is more complex and reflects both the areas without vegetation and with dense and stable vegetation cover (Fig. 12). The areas with average vegetation cover indicate the highest coefficient of determination, whereas the areas with either no vegetation or dense vegetation cover indicate very low coefficient of determination. This is because bare areas have nothing to react to climatic factors, and dense vegetation is robust against interannual climate fluctuations. These areas are expected to be more resistant against climate change, whereas the areas with average vegetation cover will be mostly affected by climate change. For example vegetation on some elevated areas like Fergana, Alai and Kyrgyz ridges as well as Pamir mountains are not conditioned by the climatic factors (Fig. 12), which is in agreement with Hu et al. (2014), who found negative correlation between temperature increase and elevation. Chui, Talas, Ili and Fergana valleys are the regions with intensive agriculture; however the trend coefficient of determination in Fergana valley is considerably lower (Fig. 12), suggesting it has more efficient irrigation system. The areas with high coefficient of determination, like eastern part of Inner Tian-Shan, Chui and Talas valleys, Karatau ridge and Ili depression as well as Turkestan ridge foothills, Syr-Daria river valley, and Kyzyl-Suu region in China are expected to suffer most under the conditions of changing climate.

The vegetation response to precipitation change comprises 1-5 months lag, whereas that of temperature is 0 for most of clusters (Tab. 2). Many global-scale studies indicate an average lag of 1-2 month of vegetation reaction to precipitation (Potter and Brooks 1998; Schultz and Halpert 2007). Gurgel and Ferreira (2003) conducted lagged correlation analysis of 3 NDVI time series principal components and precipitation principal components for the entire area of Brazil. They identified that different vegetation types had 0-3 months response time to precipitation. Gessner et al. (2013) found 1-3 months lag between precipitation change and vegetation reaction in Central Asia. Propastin et al. (2007) identified a lag of 0-60 days between precipitation and NDVI and no lag between temperature and NDVI with temperature contributing the most to NDVI variations in central Kazakhstan. All these findings are in agreement with the results of our research (Tab. 2).

Several studies (Propastin et al. 2008a; Zhao et al. 2011; Kariyeva and Van Leeuwen 2011; Mohammat et al. 2013; Zhang et al. 2013; Du et al. 2015; Eckert et al. 2015; Yin et al. 2016) used spatial and temporal averaging of NDVI and climatic factors to identify their inter-annual relations and least squares to find the temporal trend. The spatial averaging was conducted within different vegetation classes and temporal averaging was conducted within spring, summer, autumn and these three seasons together. However these approaches do not consider seasonality, some of them – delayed reactions and do not distinguish between seasonal and trend components. They assume a positive correlation between NDVI and precipitation, which prevents complex assessments of time series data (e.g. Fig. 3). Spatial averaging prevents from identification of fine scale patterns and introduces bias by dividing the study area into predetermined sectors. Instead, Gessner et al. (2013) used lagged correlation analysis between NDVI and precipitation time series on a pixel basis, considering accumulation periods, which allowed for identification of complex interactions.

Our research was based on decomposition of time series of raster data into trend and seasonal components on per-pixel basis and analysis of the components separately. This approach allows for separation of inter-annual and intra-annual behavior of the variables and solves the data stationarity issue. At the same time the pixel-level discretization of the time-series helps to reduce the impact of spatial variability of other unconsidered factors like soil, elevation, exposure etc. Identification of pixel-specific NDVI reaction to temperature and precipitation (Fig. 3) and then grouping them into k-mean clusters with similar behavior (Fig. 4) reduces the bias and helps to identify the natural patterns.

The uncertainties of the methods used in this study include the phenological autocorrelation of NDVI, which can be falsely attributed to precipitation or temperature variations. Temperature and precipitation as predictors can have significant correlation, which can affect the model accuracy. And the fact that predictors have positive effect within a certain value window and otherwise outside of that is not considered in the model. However these issues are addressed by taking the predictors at the lags of their AbsMax correlation with NDVI, not with each other. Snow and rain are also mixed in the precipitation variable which also can potentially lead to errors as snow cover can artificially decrease NDVI score. Also, snow precipitation makes moisture available to vegetation at the time of melting, not at the time of falling, which is not considered in the seasonal analysis, but luckily in our case winter is rarely the season of maximum precipitation. Snow accumulation provides more water in summer with meltwater providing higher discharge in streams, which can induce a delayed effect in the areas downstream. Rivers and accumulated moisture are also not considered here. Different soil types can have an effect. However, using the standard scores of the variables and per-pixel approach can decrease this limitation.

7 Conclusion

We applied time series decomposition with *loess* to raster time series of vegetation, precipitation and temperature on pixel basis, followed by correlation analyses of the seasonal and trend components of the variables in each pixel. We did not assume any patterns prior to the analysis, neither with regard to spatial variations, nor with regard to temporal response to avoid any bias. Thus the data were analyzed at the finest scale possible and the results were subjected to k-means cluster analysis to identify the areas of climate-vegetation interaction similarity.

The results indicate that vegetation can be both positively or negatively affected by the climatic factors, which can result in a complicated pattern of climate-vegetation interactions. Thus vegetation response sign and lag should not be assumed by the methods used. Spatial variability of climate-vegetation interaction can be great so any kind of spatial averaging prior to the analysis should be avoided and all the pixels should be treated independently from each other unless a more sophisticated method, accounting for such interactions is applied. The seasonal averaging of temporarily explicit data should also be avoided, as it can prevent the identification of temporal patterns. Instead, seasonal decomposition of signal and correlation analysis with lags should be applied to assess seasonal and interannual interactions.

The resulting climate-vegetation patterns indicate great variability over the relatively small study area. This is presumably conditioned by complex terrain and mixed influence of neighboring arid areas and humid air masses, coming from the west. The vegetation communities in the region indicate vulnerability to temperature and precipitation trend change as they are conditioned by these factors. In the case of seasonality change of climatic factors most of the study area will be greatly affected, however, further modelling is needed to understand these interactions. The methodical approach, used in this study, can easily be transferred to other regions for assessment of climate change impacts on vegetation.

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References

Adyshev; M.M.; Kashirin; F.T.; Umurzakov; S.U.; Almaev; T.M.; Voronina; A.F.; Grigorenko; P.G.; Dzhamgerchinov; B.D.; Zabirov; R.D.; Zinkova; Z.Y.; Izmailov; A.E.; Isabaeva; V.A.; Kravchenko; A.V.; Mamytov; A.M.; Makhrina; L.I.; Moldokulov; A.M.; Murzaev; E.M.; Otorbaev; K.O.; Popova; L.I.; Yar-Mukhamedov; G.K.; Yashina; V.V. and Chernova; L.I. (1987): Atlas Kirgizskoi SSR (vol. I) (in Russian). Moscow.

Borchardt, P.; Oldeland, J.; Ponsens, J. and Schickhoff, U. (2013): Plant functional traits match grazing gradient and vegetation patterns on mountain pastures in SW Kyrgyzstan. In: Phytocoenologia 43, 171–181. https://doi.org/10.1127/0340-269X/2013/0043-0542

Borchardt, P.; Schickhoff, U.; Scheitweiler, S. and Kulikov, M. (2011): Mountain pastures and grasslands in the SW Tien Shan, Kyrgyzstan - Floristic patterns, environmental gradients, phytogeography, and grazing impact. In: Journal of Mountain Science 8, 363–373. https://doi.org/10.1007/s11629-011-2121-8

Cao, L.; Xu, J.; Chen, Y.; Li, W.; Yang, Y.; Hong, Y. and Li, Z. (2013): Understanding the dynamic coupling between vegetation cover and climatic factors in a semiarid region-a case study of Inner Mongolia, China. In: Ecohydrology 6, 917–926. https://doi.org/10.1002/eco.1245

Christensen, J.H.; Hewitson, B.; Busuioc, A.; Chen, A.; X. Gao, I.H.; Jones, R.; Kolli, R.K.; Kwon, W.-T.; Laprise, R.; Rueda, V.M.; Mearns, L.; Menéndez, C.G.; Räisänen, J.; Rinke, A.; Sarr, A. and Whetton, P. (2007): Regional Climate Projections. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M. and Mille, H. L. (eds.): Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, United Kingdom and New York, NY, USA.

Cleveland, R. B.; Cleveland, W. S.; McRae, J. E. and Terpenning, I. (1990): STL: a seasonal-trend decomposition procedure based on loess. In: Journal of Official Statistics 6, 3–73.

Cleveland, W. S. and Devlin, S. J. (1988): Locally weighted regression: an approach to regression analysis by local fitting. In: Journal of the American Statistical Association 83, 596–610.

Cleveland, W. S.; Devlin, S. J. and Grosse, E. (1988): Regression by local fitting: methods, properties, and computational algorithms. In: Journal of econometrics 37, 87–114.

Conrad, O.; Bechtel, B.; Bock, M.; Dietrich, H.; Fischer, E.; Gerlitz, L.; Wehberg, J.; Wichmann, V. and Böhner, J. (2015): System for automated geoscientific analyses (SAGA) v. 2.1.4. In: Geoscientific Model Development 8, 1991–2007. https://doi.org/10.5194/gmd-8-1991-2015

Crewett, W. (2012): Improving the sustainability of pasture use in Kyrgyzstan. In: Mountain Research and Development 32, 267–274. https://doi.org/10.1659/MRD-JOURNAL-D-11-00128.1

de Beurs, K. M.; Wright, C. K. and Henebry, G. M. (2009): Dual scale trend analysis for evaluating climatic and anthropogenic effects on the vegetated land surface in Russia and Kazakhstan. In: Environmental Research Letters 4, 45012. https://doi.org/10.1088/1748-9326/4/4/045012

de Jong, R.; de Bruin, S.; de Wit, A.; Schaepman, M. E. and Dent, D. L. (2011): Analysis of monotonic greening and browning trends from global NDVI time-series. In: Remote Sensing of Environment 115, 692–702. https://doi.org/10.1016/j.rse.2010.10.011

de Jong, S. M. (1994): Derivation of vegetative variables from a Landsat TM image for modelling soil erosion. In: Earth Surface Processes and Landforms 19, 165–178. https://doi.org/10.1002/esp.3290190207

Dörre, A. and Borchardt, P. (2012): Changing systems, changing effects—pasture utilization in the post-Soviet transition. In: Mountain Research and Development 32, 313–323. https://doi.org/10.1659/MRD-JOURNAL-D-11-00132.1

Du, J.; Shu, J.; Yin, J.; Yuan, X.; Jiaerheng, A.; Xiong, S.; He, P. and Liu, W. (2015): Analysis on spatio-temporal trends and drivers in vegetation growth during recent decades in Xinjiang, China. In: International Journal of Applied Earth Observation and Geoinformation 38, 216–228. https://doi.org/10.1016/j.jag.2015.01.006

Dubovyk, O.; Landmann, T.; Dietz, A. and Menz, G. (2016): Quantifying the impacts of environmental factors on vegetation dynamics over climatic and management gradients of Central Asia. In: Remote Sensing 8, 600. https://doi.org/10.3390/rs8070600

Eckert, S.; Hüsler, F.; Liniger, H. and Hodel, E. (2015): Trend analysis of MODIS NDVI time series for detecting land degradation and regeneration in Mongolia. In: Journal of Arid Environments 113, 16–28. https://doi.org/10.1016/j.jaridenv.2014.09.001

Gessner, U.; Naeimi, V.; Klein, I.; Kuenzer, C.; Klein, D. and Dech, S. (2013): The relationship between precipitation anomalies and satellite-derived vegetation activity in Central Asia. In: Global and Planetary Change 110, 74–87. https://doi.org/10.1016/j.gloplacha.2012.09.007

Gidromet SSSR; G.U.G.S. pri S.M.; Gidromet KSSR; U.G.S. and Observatoriya; F.G. (1967): Spravochnik po Klimatu SSSR. Kirgizskaya SSR. (in Russian). Leningrad.

GoKR; Davletkeldiev, A. and Takenov, Z. (eds.) (2009): The Kyrgyz Republic's second national communication to the United Nations Framework Convention. Bishkek.

Gurgel, H. C. and Ferreira, N. J. (2003): Annual and interannual variability of NDVI in Brazil and its connections with climate. In: International Journal of Remote Sensing 24, 3595–3609. https://doi.org/10.1080/0143116021000053788

Hijioka, Y.; Lin, E.; Pereira, J.J.; Corlett, R.T.; Cui, X.; Insarov, G.E.; Lasco, R.D.; Lindgren, E. and Surjan, A. (2014): Asia. Climate Change 2014: impacts, adaptation, and vulnerability. Part B: Regional aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. 1327–1370.

Hu, Z.; Zhang, C.; Hu, Q.; Tian, H.; Hu, Z.; Zhang, C.; Hu, Q. and Tian, H. (2014): Temperature changes in Central Asia from 1979 to 2011 based on multiple datasets. In: Journal of Climate 27, 1143–1167. https://doi.org/10.1175/JCLI-D-13-00064.1

Huang, A.; Zhou, Y.; Zhang, Y.; Huang, D.; Zhao, Y.; Wu, H.; Huang, A.; Zhou, Y.; Zhang, Y.; Huang, D.; Zhao, Y. and Wu, H. (2014): Changes of the annual precipitation over Central Asia in the twenty-first century projected by multimodels of CMIP5. In: Journal of Climate 27, 6627–6646. https://doi.org/10.1175/JCLI-D-14-00070.1

Ichii, K.; Kawabata, a. and Yamaguchi, Y. (2002): Global correlation analysis for NDVI and climatic variables and NDVI trends: 1982-1990. In: International Journal of Remote Sensing 23, 3873–3878. https://doi.org/10.1080/01431160110119416

Kariyeva, J. and Van Leeuwen, W. (2011): Environmental drivers of NDVI-based vegetation phenology in Central Asia. In: Remote Sensing 3, 203–246. https://doi.org/10.3390/rs3020203

Kariyeva, J. and van Leeuwen, W. J. D. (2012): Phenological dynamics of irrigated and natural drylands in Central Asia before and after the USSR collapse. In: Agriculture, Ecosystems and Environment 162, 77–89. https://doi.org/10.1016/j.agee.2012.08.006

Kariyeva, J.; Leeuwen, W. J. D. van and Woodhouse, C. A. (2012): Impacts of climate gradients on the vegetation phenology of major land use types in Central Asia (1981-2008). In: Frontiers of Earth Science 6, 206–225. https://doi.org/10.1007/S11707-012-0315-1

Kerven; C.; Steimann; B.; Ashley; L.; Dear; C. and ur Rahim; I. (2011): Pastoralism and farming in Central Asia's mountains: a research review. MSRC Background Paper No. 1. Bishkek

Klein, I.; Gessner, U. and Kuenzer, C. (2012): Regional land cover mapping and change detection in Central Asia using MODIS time-series. In: Applied Geography 35, 219–234. https://doi.org/10.1016/j.apgeog.2012.06.016

Lai, C.; Chen, X.; Wang, Z.; Wu, X.; Zhao, S.; Wu, X. and Bai, W. (2016): Spatio-temporal variation in rainfall erosivity during 1960–2012 in the Pearl River Basin, China. In: CATENA 137, 382–391. https://doi.org/10.1016/j.catena.2015.10.008

Li, Z.; Li, X.; Wei, D.; Xu, X. and Wang, H. (2010): An assessment of correlation on MODIS-NDVI and EVI with natural vegetation coverage in Northern Hebei Province, China. In: Procedia Environmental Sciences 2, 964–969. https://doi.org/10.1016/j.proenv.2010.10.108

Lioubimtseva, E. and Cole, R. (2006): Uncertainties of climate change in arid environments of Central Asia. In: Reviews in Fisheries Science 14, 29–49. https://doi.org/10.1080/10641260500340603

Lioubimtseva, E. and Henebry, G. M. (2009): Climate and environmental change in arid Central Asia: impacts, vulnerability, and adaptations. In: Journal of Arid Environments 73, 963–977. https://doi.org/10.1016/j.jaridenv.2009.04.022

Lioubimtseva, E.; Cole, R.; Adams, J. M. and Kapustin, G. (2005): Impacts of climate and land-cover changes in arid lands of Central Asia. In: Journal of Arid Environments 62, 285–308. https://doi.org/10.1016/j.jaridenv.2004.11.005

Martinez, B. and Gilabert, M. A. (2009): Vegetation dynamics from NDVI time series analysis using the wavelet transform. In: Remote Sensing of Environment 113, 1823–1842. https://doi.org/10.1016/j.rse.2009.04.016

Mennis, J. (2010): Multidimensional map algebra: design and implementation of a spatio-temporal GIS processing language. In: Transactions in GIS 14, 1–21. https://doi.org/10.1111/j.1467-9671.2009.01179.x

Mennis, J.; Viger, R. and Tomlin, C. D. (2005): Cubic map algebra functions for spatio-temporal analysis. In: Cartography and Geographic Information Science 32, 17–32. https://doi.org/10.1559/1523040053270765

Miles, J. (2014): R squared, adjusted R squared. In: Wiley StatsRef: Statistics Reference Online. https://doi.org/10.1002/9781118445112.stat06627

Militino, A.; Ugarte, M. and Pérez-Goya, U. (2017): Stochastic spatio-temporal models for analysing NDVI Distribution of GIMMS NDVI3g images. In: Remote Sensing 9, 76. https://doi.org/10.3390/rs9010076

Mohammat, A.; Wang, X.; Xu, X.; Peng, L.; Yang, Y.; Zhang, X.; Myneni, R. B. and Piao, S. (2013): Drought and spring cooling induced recent decrease in vegetation growth in inner Asia. In: Agricultural and Forest Meteorology 178–179, 21–30. https://doi.org/10.1016/j.agrformet.2012.09.014

Nezlin, N. P.; Kostianoy, A. G. and Li, B. L. (2005): Inter-annual variability and interaction of remote-sensed vegetation index and atmospheric precipitation in the Aral Sea region. In: Journal of Arid Environments 62, 677–700. https://doi.org/10.1016/j.jaridenv.2005.01.015

Petitjean, F.; Kurtz, C.; Passat, N. and Gançarski, P. (2012): Spatio-temporal reasoning for the classification of satellite image time series. In: Pattern Recognition Letters 33, 1805–1815. https://doi.org/10.1016/j.patrec.2012.06.009

Potter, C. S. and Brooks, V. (1998): Global analysis of empirical relations between annual climate and seasonality of NDVI. In: International Journal of Remote Sensing 19, 2921–2948. https://doi.org/10.1080/014311698214352

Propastin, P. A.; Kappas, M. and Muratova, N. R. (2008a): A remote sensing based monitoring system for discrimination between climate and human-induced vegetation change in Central Asia. In: Management of Environmental Quality: An International Journal 19, 579–596. https://doi.org/http://dx.doi.org/10.1108/14777830810894256

Propastin, P. A.; Kappas, M. and Muratova, N. R. (2008b): Inter-annual changes in vegetation activities and their relationship to temperature and precipitation in Central Asia from 1982 to 2003. In: Journal of Environmental Informatics 12, 75–87. https://doi.org/10.3808/jei.200800126

Propastin, P. A.; Kappas, M.; Erasmi, S. and Muratova, N. R. (2007): Remote sensing based study on intra-annual dynamics of vegetation and climate in drylands of Kazakhastan. In: Basic and Applied Dryland Research 1, 138–154. https://doi.org/10.1127/badr/1/2007/138

Python Software Foundation (2016): Python language reference, version 3.5.

QGIS Development Team (2017): QGIS geographic information system. Open Source Geospatial Foundation Project. http://www.qgis.org

Qiu, B.; Li, W.; Zhong, M.; Tang, Z. and Chen, C. (2014): Spatiotemporal analysis of vegetation variability and its relationship with climate change in China. In: Geo-spatial Information Science 17, 170–180. https://doi.org/10.1080/10095020.2014.959095

Qiu, B.; Wang, Z.; Tang, Z.; Liu, Z.; Lu, D.; Chen, C. and Chen, N. (2016): A multi-scale spatiotemporal modeling approach to explore vegetation dynamics patterns under global climate change. In: GIScience & Remote Sensing 53, 596–613. https://doi.org/10.1080/15481603.2016.1184741

R Core Team (2016): R: a language and environment for statistical computing. https://www.r-project.org/

Rubin, J. (1967): Optimal classification into groups: an approach for solving the taxonomy problem. In: Journal of Theoretical Biology 15, 103–144. https://doi.org/10.1016/0022-5193(67)90046-X

Schneider, U.; Becker, A.; Finger, P.; Meyer-Christoffer, A.; Rudolf, B. and Ziese, M. (2015): GPCC full data reanalysis version 7.0 at 0.5°: monthly land-surface precipitation from rain-gauges built on GTS-based and historic data. ftp://ftp.dwd.de/pub/data/gpcc/html/fulldata_v7_doi_download.html,. https://doi.org/10.5676/DWD_GPCC/FD_M_V7_050

Schultz, P. A. and Halpert, M. S. (2007): Global analysis of the relationships among a vegetation index, precipitation and land surface temperature. In: International Journal of Remote Sensing. https://doi.org/10.1080/01431169508954590

Small, C. (2012): Spatiotemporal dimensionality and time-space characterization of multitemporal imagery. In: Remote Sensing of Environment 124, 793–809. https://doi.org/10.1016/j.rse.2012.05.031

Song, X.-D.; Brus, D. J.; Liu, F.; Li, D.-C.; Zhao, Y.-G.; Yang, J.-L. and Zhang, G.-L. (2016): Mapping soil organic carbon content by geographically weighted regression: a case study in the Heihe River Basin, China. In: Geoderma 261, 11–22. https://doi.org/10.1016/j.geoderma.2015.06.024

Verbesselt, J.; Hyndman, R.; Zeileis, A. and Culvenor, D. (2010): Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. In: Remote Sensing of Environment 114, 2970–2980. https://doi.org/10.1016/j.rse.2010.08.003

Yin, G.; Hu, Z.; Chen, X. and Tiyip, T. (2016): Vegetation dynamics and its response to climate change in Central Asia. In: Journal of Arid Land 8, 375–388. https://doi.org/10.1007/s40333-016-0043-6

Zhang, C.; Lu, D.; Chen, X.; Zhang, Y.; Maisupova, B. and Tao, Y. (2016a): The spatiotemporal patterns of vegetation coverage and biomass of the temperate deserts in Central Asia and their relationships with climate controls. In: Remote Sensing of Environment 175, 271–281. https://doi.org/10.1016/j.rse.2016.01.002

Zhang, Y.; Gao, J.; Liu, L.; Wang, Z.; Ding, M. and Yang, X. (2013): NDVI-based vegetation changes and their responses to climate change from 1982 to 2011: a case study in the Koshi River Basin in the middle Himalayas. In: Global and Planetary Change 108, 139–148. https://doi.org/10.1016/j.gloplacha.2013.06.012

Zhang, Y.; Zhang, C.; Wang, Z.; Chen, Y.; Gang, C.; An, R. and Li, J. (2016b): Vegetation dynamics and its driving forces from climate change and human activities in the Three-River Source Region, China from 1982 to 2012. In: Science of the Total Environment 563, 210–220. https://doi.org/10.1016/j.scitotenv.2016.03.223

Zhao, X.; Tan, K.; Zhao, S. and Fang, J. (2011): Changing climate affects vegetation growth in the arid region of the northwestern China. In: Journal of Arid Environments 75, 946–952. https://doi.org/10.1016/j.jaridenv.2011.05.007

Zhou, J.; Cai, W.; Qin, Y.; Lai, L.; Guan, T.; Zhang, X.; Jiang, L.; Du, H.; Yang, D.; Cong, Z. and Zheng, Y. (2016):

Alpine vegetation phenology dynamic over 16years and its covariation with climate in a semi-arid region of China. In: Science of the Total Environment 572, 119–128. https://doi.org/10.1016/j.scitotenv.2016.07.206

Zhou, Y.; Zhang, L.; Fensholt, R.; Wang, K.; Vitkovskaya, I. and Tian, F. (2015): Climate contributions to vegetation variations in Central Asian drylands: pre- and post-USSR collapse. In: Remote Sensing 7, 2449–2470. https://doi.org/10.3390/rs70302449

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