Quantifying the Spatiotemporal Dynamics of Vegetation Cover in Eastern Pamir Mountains in Tajikistan Using Landsat Images from 2004 to 2014

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Abstract

Context A research gap exist on the characterization of the dynamic changes of vegetation distribution in the eastern Pamirs. To provide a better understanding of the current status of the vegetation resources and improve resource management, it is important to present baseline vegetation cover maps and quantify significant changes of the vegetative cover.

Objectives (1) Define areas of change and non-change of the vegetative cover. (2) Determine specific locations of areas of large changes. (3) Determine temporal vegetation status.
Methods Landsat images acquired from three time periods – 2004, 2006, and 2014 – were used to demonstrate their efficacy for mapping the temporal vegetative cover in an arid environment. We utilized ancillary data to enhance the image classification and a high spatial resolution imagery to assess the accuracy.

Results The overall classification accuracy showed more than 85% for all maps produced. Results indicated that the use of the 30-m medium-coarse resolution images plus a variety of ancillary data could satisfactorily classify the spatiotemporal trends of vegetative cover changes in a high elevation arid environment. We observed a larger area of vegetation cover lost (15,000 ha) than gain (4,000 ha) since 2004. Approximately 35% of the vegetation cover was converted to barren land.

Conclusions Our results supplement existing vegetation research and improve our ability to measure and understand the degradation trend of the vegetative cover over time. This medium-coarse spatial resolution vegetation mapping analysis should serve as a first step in developing a land management plan.

Keywords Pamir Mountains Dynamics, Landsat, Remote Sensing, Vegetation Cover Change

Introduction

The vegetation cover in the eastern Pamir Mountain of Tajikistan is sparse (Breckle and Wucherer 2006; Salas et al. 2016). Given the harsh biophysical conditions (Vanselow 2011) and with low mean annual precipitation of less than 100 mm (Vanselow and Samimi 2014) at elevations above 3000 m, the region is a high mountain desert and where vegetation is adapted to climate extremes and slow-growing (Abdullaev and Akbarzadeh 2010; Kraudzun et al. 2014). The productive rangelands of the eastern Pamirs occur at elevations between 3500 to 4600 m a.s.l., with estimated pastureland area of 7740 km^2 (Breu and Hurni 2003). Hay fields, which are located near rivers, are used as a source of winter livestock fodder.

The three vegetation ecosystems are classified based on vegetation distribution (GBAO 2000): high-mountain meadow- steppe, high-mountain nival desert, and high-mountain nival glacial. Prominent plants with high biomass production are classified in high mountain meadow- steppe. Those in the high mountain nival desert ecosystem are vegetation that thrives in extremely cold and low precipitation environment, while those in the high mountain nival-glacial ecosystem are vegetation cover in the extremely cold, rocky, and oftentimes ice and snow-covered mountains.

Breckle and Wucherer (2006) identified about 700 plant species in the upper vegetation belts of the arid eastern Pamir region and highlighted the dominance of the dwarf shrubs. While approximately 52% of the eastern Pamir is bare open scree, rocks, and glaciers, about 29% of the region has a plant cover of teresken (*Krascheninnikovia ceratoides*). This woody perennial vegetation, which is typical for arid environments (Nechaeva 1985; Schenk 1999), occurs at 4400 m a.s.l. (Kraudzun et al. 2014) to even 4500 m a.s.l (Ikonnikov 1963).

Among shrub species, teresken has been studied extensively in the past decade, providing synopsis of the extent of dwarf shrub distribution and degradation. Vanselow and Samimi (2014) indicated the partial overuse of the teresken and rated it as a vulnerable resource. Previous studies (e.g. Akhmadov et al. 2006; Vanselow et al. 2012a) concluded the same, even describing the heavy strain on the shrub as an “alarming degree of exploitation” (Breu and Hurni 2003). The overexploitation and decrease of teresken cover has been labelled as the “teresken syndrome” (Breckle and Wucherer 2006). However, Kraudzun et al. (2014) argued that the use of the term “teresken syndrome” was an inappropriate description of the resource. One of the four reasons cited was that the clearcutting of teresken was only limited to areas near main roads and other locations accessible to villagers (Breu et al. 2005). Foremost, management for sustainable resource needs to focus on avoiding long-term degradation changes in vegetative structure.

While the dwarf shrub has been acknowledged as an important plant for slope protection, it has also been the source of fuel for heating and cooking and a winter food source for wild ungulates. Heavy removal of teresken in the Pamirs for firewood use has been documented by Breu and Hurni (2003), Droux and Hoeck (2004), Akhmadov et al. (2006), and Kraudzun (2012), with a decrease in vegetation cover being observed (Breckle and Wucherer 2006; Michel and Muratov 2010). Although studies of teresken date back to the 1960’s (Ikonnikov 1963) and 1970’s (Jusufbekov and Kasach 1972), they only described the shrub’s biophysical characteristics. Most of the knowledge about current state of teresken (Vanselow and Samimi 2014; Kraudzun et al. 2014; Zandlera et al. 2015) did not take into account the temporal cover changes of the shrub, although all of them made use of remote sensing data. There was less attention paid to the quantification of the so-called “teresken syndrome.” Maps capturing the temporal disturbance and regrowth of the vegetative cover in the eastern Pamirs are nonexistent. Zandlera et al. (2015) acknowledged this research gap for dwarf shrub biomass studies, citing only two unpublished theses exist that used remote sensing image data, but which had limited information regarding vegetation cover.

Satellite imagery is an essential resource for capturing disturbance processes and for the estimation of land cover change (Kennedy et al. 2007). For mapping in regional scales, the 30-m resolution of the Landsat is suitable (Giri and Muhlhausen 2008), but could be challenging due to the scarce vegetation cover in the region. Zandler et al. (2015) modelled shrub biomass in eastern Pamirs and determined that Landsat performing equally well as the high-resolution RapidEye sensor (5-meter pixel size). The vegetation cover in the eastern Pamirs ranges between 5% and 40% (Kraudzun et al. 2014) and generally covers patches big enough to be detected by the resolution of the Landsat; using high-resolution sensors may not offer a better performance (Zandler et al. 2015). Very high resolution satellite data such as QuickBird, Geoeye, and IKONOS are impractical to apply to the total study area due to its high cost and requires more time to implement data analysis than medium spatial resolution image data (Lu and Weng 2005). Currently, there is no complete existing coverage of high resolution images of the region.

Despite the numerous scientific studies, a research gap remains about the characterization on the dynamic changes of vegetation cover in the eastern Pamirs, resulting in an insufficient evaluation of the vegetative cover. The use of multitemporal data has not yet been fully investigated in arid environments of the Pamirs. We hypothesize that a multitemporal image analysis would yield a more precise classification of vegetation than that of a single date. This paper investigates the potential of time-series Landsat data to generate vegetation maps in an arid community that will enable us to analyze spatiotemporal vegetation dynamics. We present baseline vegetation cover maps and determine whether there have been significant changes of the vegetative cover from 2004 to 2014. Information on the extent and the vegetation status could help enhance the current knowledge of vegetation communities on the Pamirs, provide critical information needed for understanding ecosystem dynamics, and improve resource management by defining vegetation cover during the last decade.

Study Area

Tajikistan, situated in southern central Asia and with a human population of 7 million, is bordered by China in the east, Afghanistan in the south, Uzbekistan in the northwest and Kyrgyzstan in the north. More than 90% of the country is mountainous with several mountains exceeding 7,000 m in the eastern portion of the country and form the Pamir massif.

The study area is located in the southeastern Pamir Mountain of Tajikistan (Fig. 1) in the Gorno-Badakhshan Autonomous Region, between the latitudes 37°N to 38°N and longitudes 74°E to 75°E and covers an area of approximately 223,000 ha. The rocky mountainous terrain has an altitude of 3500 m to 5500 m a.s.l. The study area roughly corresponds to the area of a wild ungulate hunting concession and in which 45 hunting permits are issued yearly at a cost of $40,000 permit. Wild ungulates include argali (*Ovis ammon*), Asiatic ibex (*Capra sibirica*), wolf (*Canis lupus*), red fox (*Vulpes vulpes*), snow leopard (*Panthera uncia*), Eurasian lynx (*Lynx lynx*), brown bear (*Ursus arctos isabellinus*), and red marmot (*Marmota caudate*) (Valdez et al. 2015; Salas et al. 2017; Salas et al. 2018).

Average annual precipitation is about 100 mm with sub-zero average temperatures from October to March (Salas et al. 2020). With such extreme climate conditions, herding of yaks, sheep, and goats has been the primary agricultural option (Vanselow et al. 2012b) with domestic the most numerous. Domestic animals are transported to lower pastures during the fall, winter, and early spring (October-May) to avoid the harsh winter weather. The summer pastures are dominated by *Artemisia* and *Festuca* species, with productivity of 0.3 to 0.4 $t.ha^{-1}$ and 0.8 to 1.2 $t.ha^{-1}$, respectively (Breckle and Wucherer 2006). Grazing competition between wild ungulates and livestock can be found on pastureland near human settlements (Breu et al. 2005; PALM 2011). One of the pressing concerns lately is the reduction of the teresken cover, which is a crucial winter food source for the wild ungulates (Breckle and Wucherer 2006). The deterioration of desert ecosystems directly affects the populations of herbivorous mammals as they depend on teresken communities as a habitat (PALM 2011).

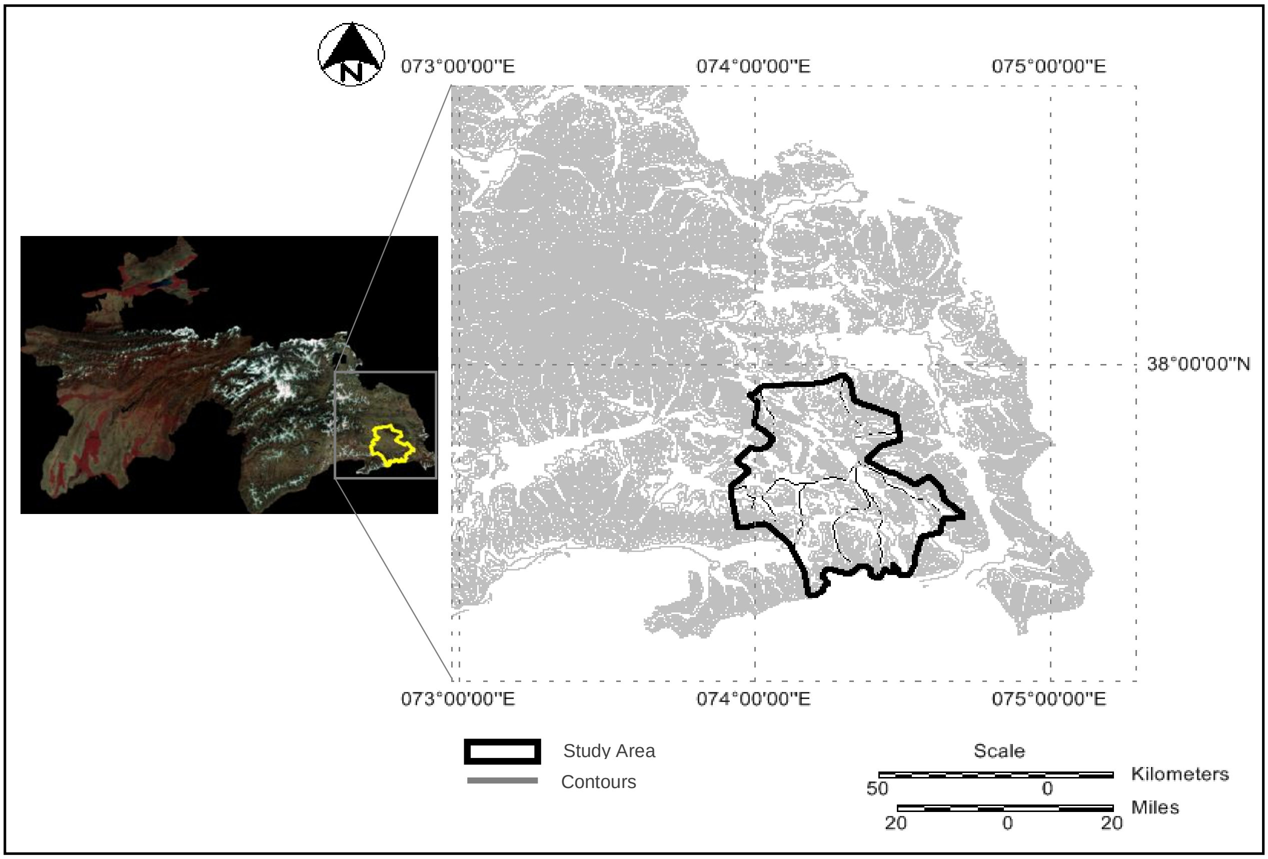

Fig. 1: The study area is located in the southeastern region of the country and consists of a single Landsat scene (July 11 2004, p150/r34). The whole of Tajikistan (left mosaicked image) is presented with false color composite (bands 4,3,2).

Data and Methods

Freely-available 30-meter spatial resolution Landsat images were employed to monitor the temporal changes of the vegetative cover. We used the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) satellite images from July 2004 and July 2006 and the Landsat 8 OLI image from July 2014. The level-1-terrain corrected product (L1T) Landsat time-series data were obtained from the U.S. Geological Survey Earth Resources Observation and Science (USGS EROS) resource archive (http://eros.usgs.gov/), as listed in Table 1. We acquired data of the same summer month for the years 2004, 2006, and 2014, using images with minimal cloud cover. The month of July is within the period identified to be the vegetation peak for shrubs (Walter and Breckle 1986); the time of year when the development stage of the vegetation produces the highest spectral signals.

Table 1: Satellite data from 2004 to 2014 covering the study area in the eastern Pamirs in Tajikistan.

Satellite	Date Acquired	Path/Row	Scene Cloud Cover
Landsat 7 ETM+	July 11, 2004	150/34	3 %
Landsat 7 ETM+	July 17, 2006	150/34	1 %
Landsat 8 OLI	July 15, 2014	150/34	4 %

Image Preprocessing

Preprocessing of the images is necessary to enhance the quality of the data and to remove inherent noise that can have negative impacts on the classification and the scene-to-scene comparisons over time, such as change detection (Chavez 1988; Mather 1997). Using ERDAS Imagine v.2013 (ERDAS Imagine 2013), we normalized the images by converting the measured digital number (DN) values to top of atmosphere (TOA) reflectance units using the method employed by Homer et al. (2004). This conversion from DN to TOA reflectance has been applied in many studies (e.g. Teillet 1986; Yang and Lo 2000; Darren et al. 2006) to remove variations between time series images caused by sensor differences, Earth-sun distance, and solar zenith angle (Chander and Markham 2003). It is also deemed the most important step in producing vegetation ratio indices products, such as the Normalized Difference Vegetation Index (NDVI) (Guyot and Gu 1994).

Screening of cloud patches, cloud shadows, and mountaintop snow was performed to ensure that the images were devoid of obstructions that may result in false classification. In the case of the clouds, we did visual and/or spectral examinations of the three images to assess for cloud presence and shadow contaminations, delineated them and then masked out from the analysis. Most of the contaminations were located north of the study area where vegetation is scarce. Thus, clouds and shadows did not affect our ability to classify the vegetative cover. A combined cloud mask was applied to all images to completely exclude the contaminated areas in our analysis.

As for the snow mask, we created the Normalized Difference Snow Index (NDSI) (Hall et al. 1995) image to distinguish snow from other surrounding features. A threshold was applied to the NDSI to filter the non-snow features that may have been misclassified as snow by examining reflectance at other wavelengths. Further, for each image, we did extensive manual deleting of isolated snow artifacts especially in transition areas between snow and non-snow features located in steep slopes. A combined snow mask was then applied to all three images.

Variable Integration

Studies have highlighted that adding digital elevation model (DEM), Normalized Difference Vegetation Index (NDVI), Principal Component Analysis (PCA) (Eiumnoh and Shrestha 2000; Dorren et al. 2003; Lu and Weng 2005), and Modified Soil-adjusted Vegetation Index (MSAVI) (Vanselow and Samimi 2014) help improve image classification results in terms of feature discrimination and accuracy of featured classes. Incorporating a topographic variable like the DEM did not only depict the distribution of terrain components that influence spectral response (Strahler et al.1978), but also it increased the classification accuracy of digital data (Janssen et al. 1990; Palacio-Prieto and Luna-GonzBlez 1996; Kirui et al. 2013). In this study, the processed DEM was sourced from NASA’s Shuttle Radar Topography Mission (SRTM) 90-m digital elevation dataset that is available for download through the USGS website (http://srtm.usgs.gov/index.php). A rescaling of the DEM was performed to the spatial resolution of the spectral variables (30 m). NDVI (Rouse et al. 1974; Tucker 1979) exploits the strong differences in the red and NIR reflectances, where contrast between vegetation and soil is maximal (Salas and Henebry 2014). Sensitive to pixel-level changes in greenness, NDVI is calculated as the difference between the spectral reflectance measurements of the NIR and red bands divided by the sum of the same measurements. It is the most commonly used vegetation index to map spatial and temporal variation in vegetation (Tucker 1979). PCA explores image data in multiple dimensions (Dawelbait and Morari 2012), and reduces the dimensions according to the number of principal components that cover a sufficient amount of variation in it. It can produce an output result that better preserves the spectral integrity of the input dataset (Lu and Weng 2005). For this purpose, we ran PCA on the three images and components were generated. The first component (PC1) that accounts for most of the important information (Abdi and Williams 2010) was the only variable used in our analysis. With desert soils characterizing much of the Eastern Pamirs, we also integrated MSAVI (Qi et al. 1994) into the classification for vegetation sensitivity and soil noise reduction. The index automatically adjusts to the energy proportion detected by the sensor, while retaining the dynamic range of the NDVI (Chehbouni et al. 1994). We derived MSAVI for all images. Finally, we introduced the band 4 and band 5 NIR data space to separate vegetation surfaces from soil and rock (Pickup et al. 2003) – the same spectral bands employed by Richardson and Wiegand (1977).

Image Classification

Before starting the supervised classification, we first performed the unsupervised ISODATA algorithm (Erdas 2013) to retrieve spectral classes. Test images from different Landsat scenes were classified using different numbers of clusters to determine the number needed to discriminate classes. Too large a number will produce significant mix-up in the classification resulting into a number of possibilities for rule generation. We ran the unsupervised classification using 30 clusters, and a better discrimination of the major classes ensued. The Iterative Self-Organizing Data (ISODATA) results were used as benchmark for the supervised maximum likelihood classification using training areas to obtain thematic classes (Serra et al. 2003). Supervised method is easy to apply and accessible in image processing and statistical software packages (Langley et al. 2001). Additionally, the method has shown outstanding results for the classification of land cover classes and demonstrated its accuracy in change detection analysis (Rozenstein and Karnieli 2011; Shalaby and Ryutaro 2007), and produced accurate classifications than object-based method (Flanders et al. 2003). Apart from utilizing the unsupervised classification results for the training samples, we relied on Google Earth engine, expert analysis and knowledge of the area, and the spectral signatures of the features. Several ground control points (GCP) that were obtained during the summer of 2014 fieldwork using a hand-held GPS were helpful in making assignment decisions. Furthermore, three-band false color composite images were referred to in order to distinguish differences in features.

The characteristics of the Pamirs – an area mostly barren with rocky terrain, permanent snow and debris, and limited biomass production (Breu and Hurni 2003; Salas et al. 2015) – made the identification and separation of the spectral reflectance properties of surface features easier. The shape of the spectral signatures in Figure 2 show the distinctive spectral patterns of the four classes – vegetation-1, vegetation-2, water, and barren land – in our analysis. The choice of these classes was grounded on three things: the objective of the research that is to map vegetation cover, the expected degree of accuracy in the image classification, and the easy identification of the classes on the Landsat images.

We opted to use two vegetation classes based solely on the spectral separability in the Landsat data. The spectral reflectance response of vegetation-1 class in the visible red channel (0.66 µm) is significantly lower than the NIR (0.83 µm). We found similarities of the spectral characteristics of vegetation-1 to those of the western region of the country where vegetation cover is abundant. Vegetation-2 class has higher reflectance in the visible region and exhibits much flatter pattern than the vegetation 1 class. Both vegetation classes display the general characteristics of high NIR but low visible reflectances due to absorption by chlorophyll for photosynthesis. Barren land is considerably less variable. The difference in reflectance values in red and NIR is insignificant for bare ground. Water is the easiest to detect as it only reflects in the visible light range. We used these characteristics of the surface to help distinguish one training sample from another in the supervised classification. Finally, we filtered the classified products to clean up some of the “salt and pepper” noise apparent in the images. Small image objects were aggregated with a minimum mapping unit (MMU) of 0.8 hectares or 9 contiguous Landsat pixels. MMU minimizes geometric and positional errors or reference data interpretation errors when comparing image classification results (Knight and Lunetta 2003).

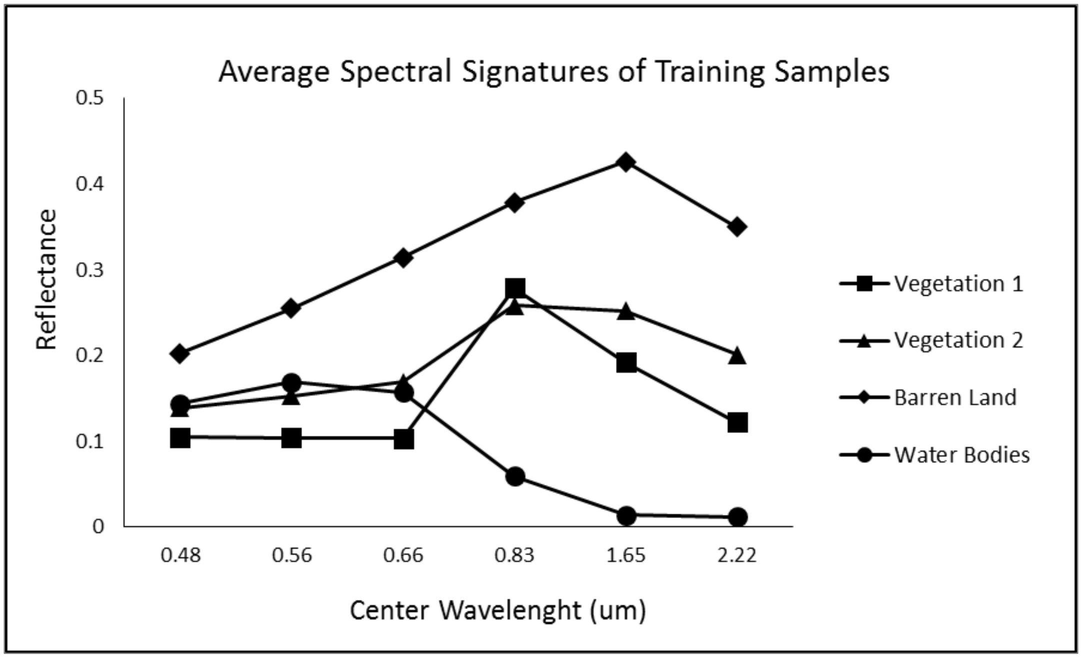

Fig. 2: Graphs of spectral signatures of vegetation, barren land, and water averaged from the training samples used in the classification.

Maps Accuracy Assessment

Map classification accuracies were assessed using overall accuracy (OA), producer’s accuracy (PA), user’s accuracy (UA), and kappa coefficient. PA quantifies the error of omission, while UA quantifies error of commission. Kappa is the measure of agreement or accuracy of the classification (Congalton and Mead 1983). It has been found to be more robust than OA as it takes into account the agreement occurring by chance (Jensen 2005). Janssen and van der Wel (1994) and Foody (2002) described each of the accuracy metrics in detail. Confusion matrices were constructed to assess the result of each image classification (e.g., Fuller et al. 2003; Yuan et al. 2005), providing an indication of the classification agreement between two maps (the classified vs. referenced maps) that is not attributable to chance.

A total of 150 test samples were randomly selected from the high resolution images of QuickBird (60-cm resolution) and WorldView-2 (50-cm resolution), which covered the dates from 2003 to 2013, and were used to compute the overall accuracy of the classified images. For the Kappa statistics values, we referred to Monserud and Leemans (1992) who suggested that values lower than 0.4 represent poor or very poor agreement, 0.4 to 0.55 means fair agreement, from 0.55 to 0.7 means good agreement, from 0.7 to 0.85 means very good agreement, and higher than 0.85 means excellent agreement between images.

Change Detection

We applied a post-classification-comparison change detection using ENVI IDL v5.2 (ENVI Guide 2009) procedure to establish the vegetative cover changes in three periodic intervals: 2004 to 2006, 2006 to 2014, and 2004 to 2014. Post-classification is the most straightforward and most common method for change detection of land cover (Petit and Lambin 2002; Kamusoko and Aniya 2009) that can be used to identify pixels that are not classified the same at different times (Jensen 2005; AlFugara et al. 2009). We analyzed the net vegetation gain and loss of the changed areas detected.

Results

The areal estimates of the four classes for the three time periods are shown in Table 2. Features smaller than the mapping unit of 0.8 hectares were not considered and generalized. Vegetation-1 class decreased by a large amount (62.6%) from 2004 to 2006 and further decreased by 68.9% from 2006 to 2014. Overall, a decrease of 88.4% in areal proportion of vegetation-1 was observed for the past decade, 2004 to 2014. Class vegetation-2 had only a 4% decrease from 2004 to 2006 and even increased from 2006 to 2014 by 14%.

Table 2: Estimates of area (ha) for the four land cover classes considered in the study in the eastern Pamirs, Tajikistan.

Class	**Area (ha)**		
	2004	**2006**	**2014**
Vegetation-1	18,358.7	6,872.2	2,137.5
Vegetation-2	26,719.5	25,605.4	29,310.8
Water Bodies	529.2	687.0	387.5
Barren Land	177,622.2	190,065.0	191,393.8
Total	223,229.6	223,229.6	223,229.6

The change in water bodies is evident from 2006 to 2014 – it shrunk by about 44%. Figure 3 shows the disappearance of a large body of water in 2014 (Fig. 3c) located in the northwestern part of the study area. A check in Google Earth's August 2013 image confirmed the disappearance of the lake. Barren land has been increasing in area since 2004. A 7.8% increase was observed in the last 10 years. All in all, the vegetation-1 class has shown the most change in terms of area among the four classes considered.

The change matrix in Table 3 shows the percent change of the vegetative cover from 2004 to 2006, from 2006 to 2014, and from 2004 to 2014. Unchanged pixels are located along the major diagonal of the matrix. The net loss of vegetation-1 is much higher than the turnover. For example, areas covered in vegetation-1 in 2004 has changed to vegetation 2 (47.7%) and barren land (18.5%) in 2006 – a total of 66.2% loss. The matrix also shows that only 1.4% of the other classes were converted to vegetation-1 from 2004 to 2006. The same pattern of change was observed for the other time periods. In 2006 to 2014, most of the losses of the vegetation-1 were attributed to vegetation-2 conversion (69.7%) and barely 3% was converted to barren land. Reviewing at the decade of change for vegetation-1, only 11% has been retained, the rest changed to vegetation-2 (74.4%) and barren land (14.6%). No turnover, or the conversion of the other classes to vegetation-1, has been observed.

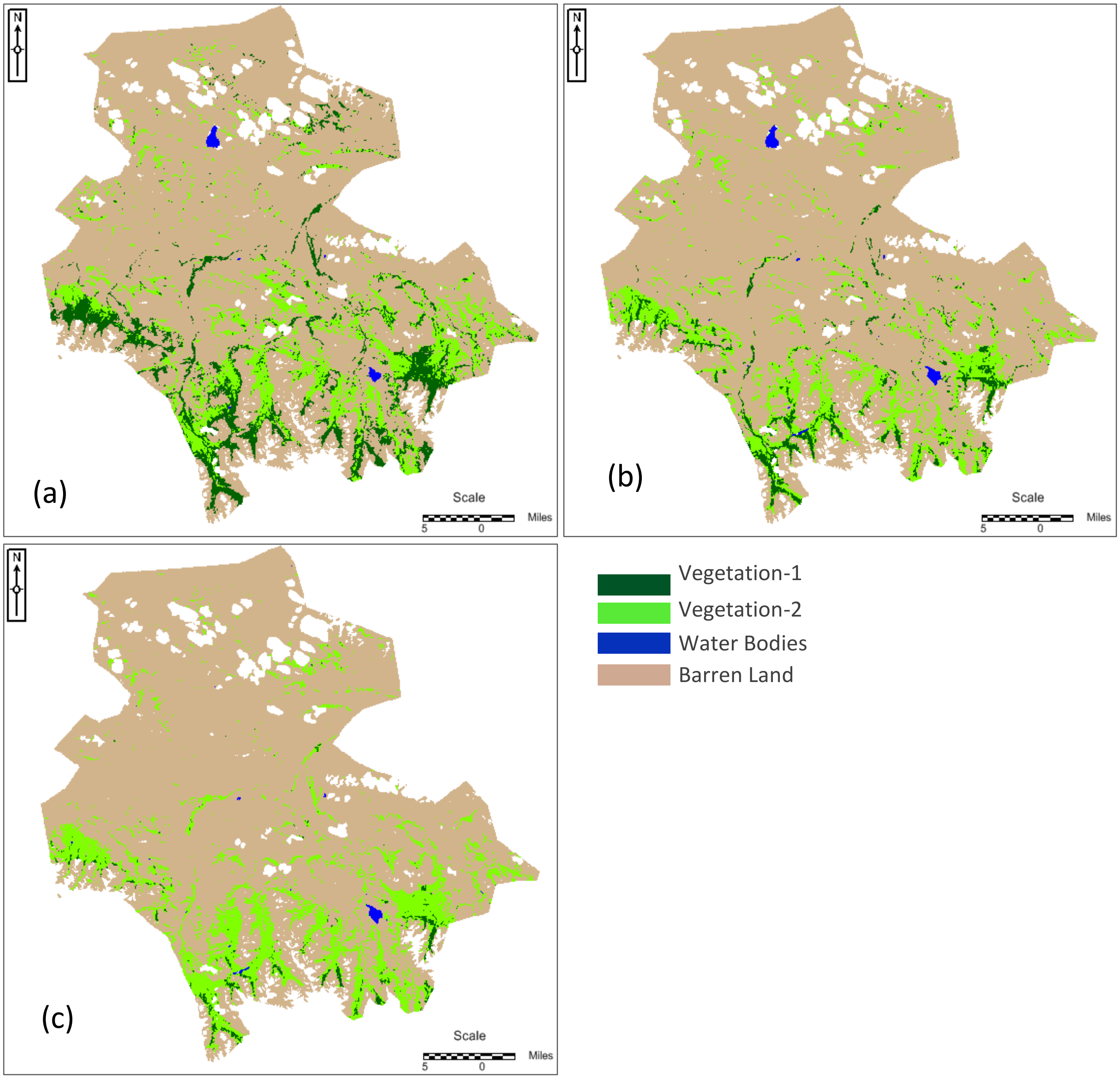

Fig. 3: Classification maps of Landsat TM+ for (a) July 2004, (b) July 2006, and Landsat 8 OLI for (c) July 2014, showing the four classes analyzed in the eastern Pamirs, Tajikistan.

In all classes, increases in vegetation-2 areas came mainly from dramatic turnovers of vegetation-1 in the 10-year period. From 2004 to 2006, approximately 48% of vegetation-1 was converted to vegetation-2, in addition to a small percentage of barren land (2.8%). In the same period, more than half of the vegetation-2 area was changed to barren land (54.6%), and only 44.4% was retained. These huge numbers of turnovers from vegetation-1 to vegetation-2 were also observed from the 2006 to 2014, and from 2004 to 2014 periods. In our assessment, in the last ten years, 50% of the vegetation-2 region was converted to barren land. Looking at all three classifications, 11—34% of vegetation-1, 45—75% of vegetation-2, 43—98% of water bodies, 97—98% of barren land did not change.

Table 3: Land cover changes (%) from 2004 to 2006, from 2006 to 2014, and from 2004 to 2014 in the study area in the eastern Pamirs, Tajikistan.

2004-2006	**2004**			
2006	Vegetation-1	Vegetation-2	Water Bodies	Barren Land
Vegetation-1	33.8	1.0	0.2	0.2
Vegetation-2	47.7	44.4	0.1	2.8
Water Bodies	0.0	0.0	98.0	0.2
Barren Land	18.5	54.6	1.7	96.8

2006-2014	**2006**			
2014	Vegetation-1	Vegetation-2	Water Bodies	Barren Land
Vegetation-1	27.6	0.8	0.0	0.0
Vegetation-2	69.7	74.7	0.5	3.9
Water Bodies	0.0	0.0	52.1	0.0
Barren Land	2.7	24.5	47.4	96.1

2004-2014	**2004**			
2014	Vegetation-1	Vegetation-2	Water Bodies	Barren Land
Vegetation-1	11.0	0.0	0.0	0.1
Vegetation-2	74.4	51.0	0.2	2.2
Water Bodies	0.0	0.0	42.8	0.0
Barren Land	14.6	49.0	57.0	97.7

High concentration of vegetation-1 was found on high mountain altitudes, as well as along rivers and streams (Figures 3a and 3b). Major changes of vegetation-1 were also observed in the same locations as shown in the change detection map in Figure 4, where vegetation-1 changed to vegetation-2 and barren land. The 15% loss of vegetation-1 to barren land from 2004 to 2014 was clearly evident on the southern regions of the study area.

For the sake of analysis, we combined the two vegetation classes into a single class for years 2004 and 2014. (Figure 5). In the last decade, approximately 35% of the vegetation class was converted to barren land, and the rest of the areas (65%) was retained. Decreasing vegetation cover is also shown in Figure 6. Close to 15,000 ha of total vegetative cover were lost between 2004 and 2014. The major decrease occurred in the early years from 2004 to 2006. Over the period of ten years, the overall increase of vegetation area was a little over 4,000 ha. It seems that most of the gains are located in the southern region, specifically on the base of the mountains and in relatively lower elevations (Figure 7a). Subsequently, vegetative cover has shown a general trend in actual loss in relatively flatter regions, occurring in elevations between 4200 m and 4400 m a.s.l. (Figure 7b).

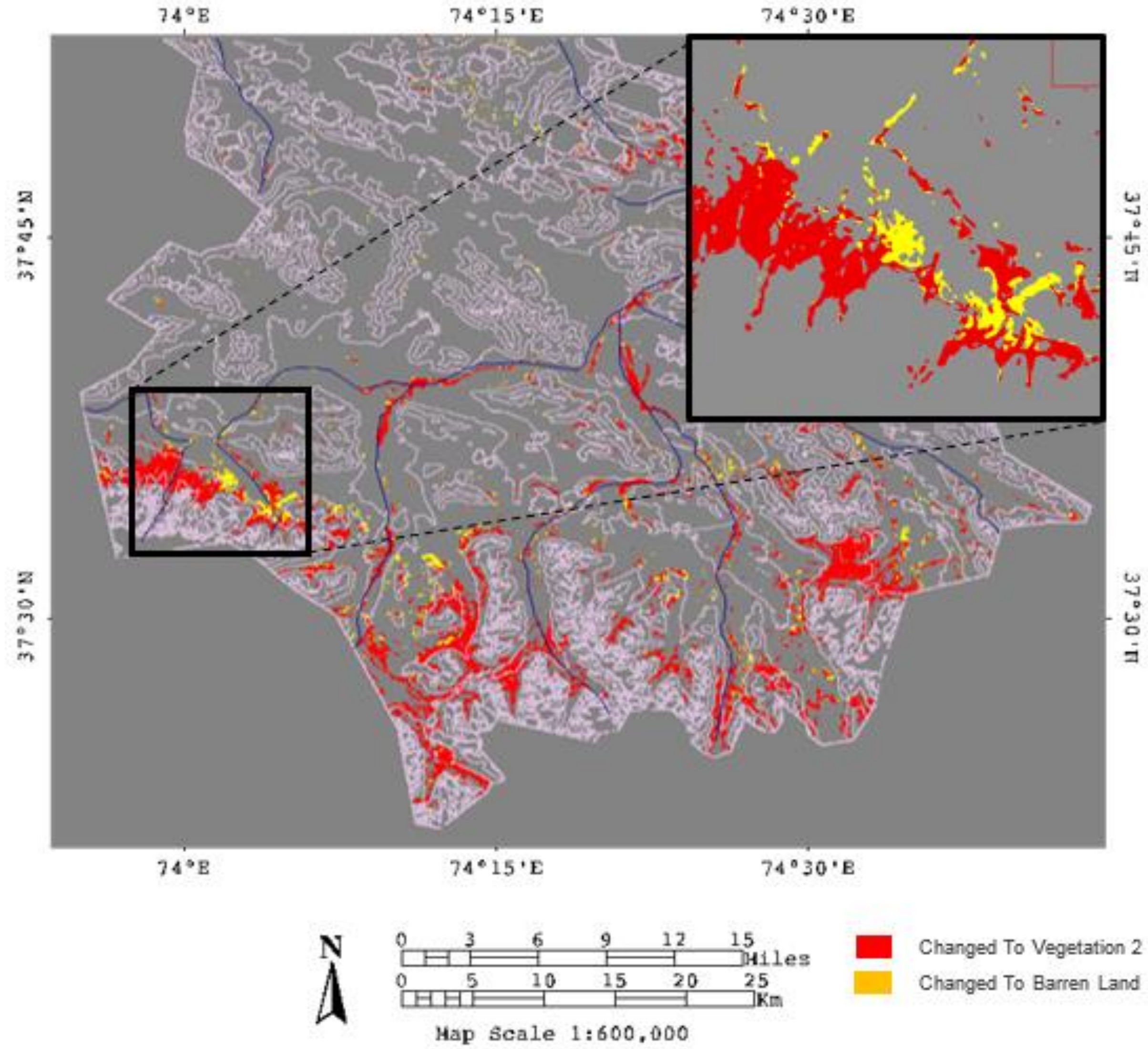

Fig. 4: Change map for the period 2004 to 2014 showing the conversion of the vegetation-1 to vegetation-2 and to barren land in the study area in the eastern Pamirs.

Classification results for the years 2004, 2006, and 2014 show an overall accuracy of 86.2%, 85.4%, and 90.4%, respectively (Table 4). Vegetation-2 and barren land classes had lower user accuracies for all time periods, 78.9% and 81.1%, respectively for 2004; 77.5% and 78.1%, respectively for 2006; 89.6% and 81.3%, respectively for 2014. The class vegetation-1 and water bodies achieved adequate results with 92.7% and 100%, respectively for 2004; 97.7% and 100%, respectively for 2006; 94.9% and 100%, respectively for 2014. The overall kappa statistics for the three years (0.81, 0.80, and 0.87) indicate good agreements between the references and the classified maps (Monserud and Leemans, 1992). Our mapping strategy produced maps that have more than 80% of the pixels classified correctly than would be expected by random assignment.

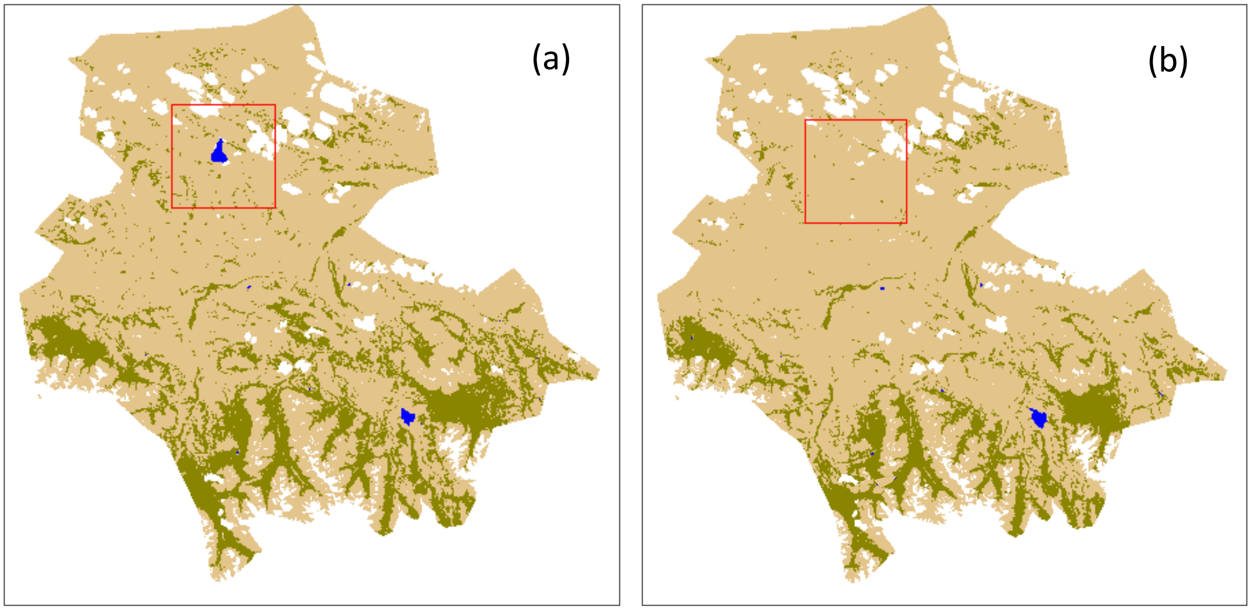

Fig. 5: Classification maps for (a) July 2004 and (b) July 2014, showing a combined class for vegetation-1 and vegetation-2 in the study area. Inset shows the disappearance of a body of water.

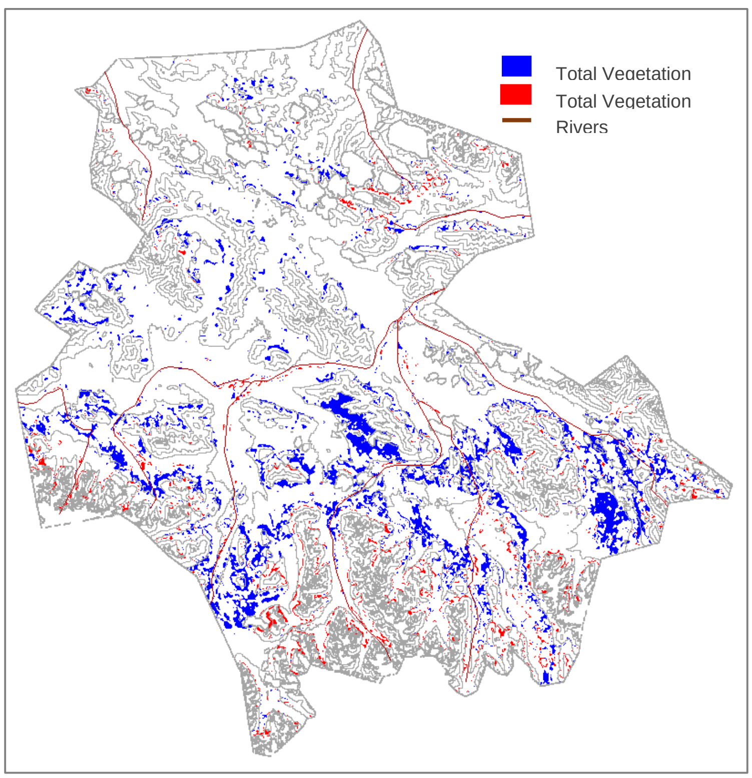

Fig. 6: Total vegetation cover change for the eastern Pamir study area for the period July 2004 to July 2014 overlaid with the elevation data and major rivers. Total area lost is approximately 15,000 ha, while total area gained is approximately 4,000 ha.

Table 4: Results of the confusion matrices of the vegetation classification maps for the periods 2004, 2006, and 2014.

Class	**Producer Accuracy (%)**	**User Accuracy (%)**	**Overall Accuracy (%)**	**Kappa Statistics (Khat)**	**Overall Kappa Statistics**
2004					
Vegetation-1	82.6	92.7		0.89	
Vegetation-2	83.3	78.9		0.71	
Water Bodies	93.3	100.0	86.2	1.00	0.81
Barren Land	90.9	81.1		0.75	
2006					
Vegetation-1	82.4	97.7		0.96	
Vegetation-2	91.2	77.5		0.70	
Water Bodies	86.7	100.0	85.4	1.00	0.80
Barren Land	83.3	78.1		0.72	
2014					
Vegetation-1	92.5	94.9		0.92	
Vegetation-2	86.7	89.6		0.86	
Water Bodies	93.8	100.0	90.4	1.00	0.87
Barren Land	89.7	81.3		0.75	

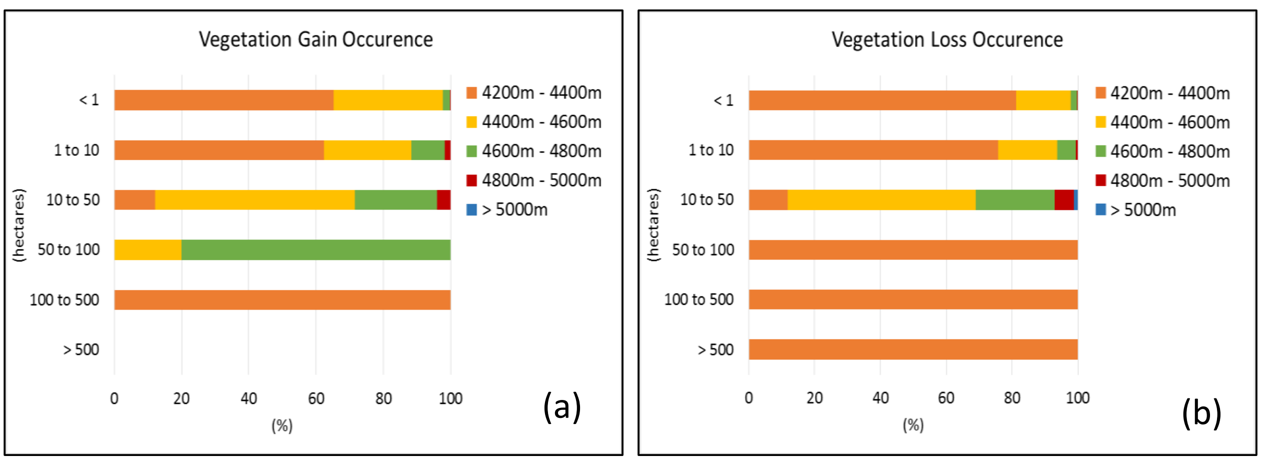

Fig. 7: The distribution of the locations of vegetation gain (a) and loss (b) in terms of the elevation data for the eastern Pamir study area. Note that large areas of vegetation loss is found in relatively much lower elevations.

Discussion

The mapping of vegetation in the eastern Pamirs is basic for managing natural resources in the arid region. Although we employed a coarse mapping scheme by not taking into account vegetation species, the four classes selected made delineation of groups more substantial (Mallinis et al. 2011). Adding a time context to the mapping offers an understanding of the regeneration or degeneration of the vegetative cover and addressing issues related to the alarming degree of exploitation (Breu and Hurni 2003) of the shrubs, which is abundant in the region.

The change from 2004 to 2014 represents a ten year change and the longest time series study that has been conducted in the eastern Pamirs. A negative trend is apparent: there is a larger area of vegetation cover lost (15,000 ha) than gained (4,000 ha) since 2004. This decrease of vegetation could be directly related to overgrazing and heavy harvesting of shrubs (Kraudzun et al. 2014, Zandlera et al. 2015). The period between 2004 and 2006 represents the most change between any year combinations of classified images.

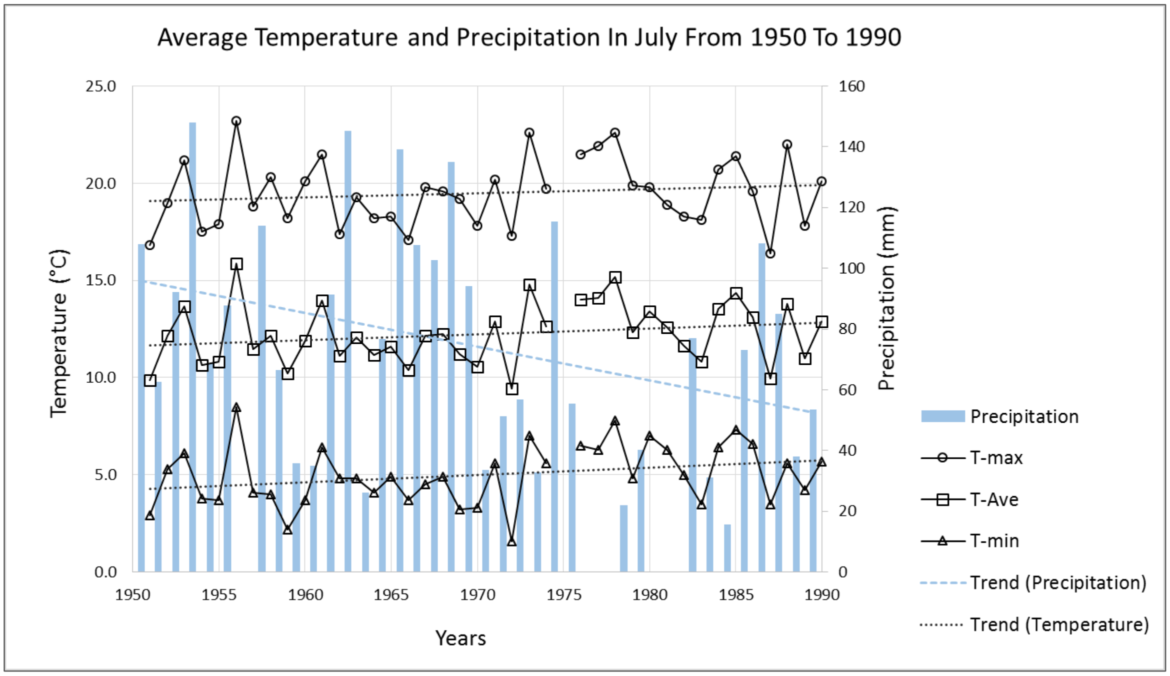

Fig. 8: Average July temperature and precipitation from 1950 to 1990 (earlier datasets are missing) taken from the Murgab weather station. Trend lines are added to show the decreasing amount of precipitation and increasing temperature for the 40 years of archived climatic dataset.

For vegetation-1, the major change was the conversion from one vegetation class to another (48%), rather than from vegetation class to non-vegetation class (19%). The large conversion from vegetation-2 to barren land (55%) occurred in close proximity to a water body and areas of much lower elevations. This observation is apparent in Figure 5 where large patches of the total vegetation have disappeared from the central region and it continued towards the south-eastern region where a water body exists. Although the cause of the land cover conversion is not explained in this study, a time frame has been identified in which vegetation management practices, history of disturbance, and other climate-related influences in the eastern Pamir Mountains need to be studied further.

Accuracy of Classification

The high accuracy obtained in the classification may be due to the increased control in selecting signatures for the classification. The overall classification results of the Landsat images showed more than 85% for all three maps, satisfying the minimum 85% accuracy as stipulated by the Anderson classification scheme (Anderson et al. 1976). An examination of the error matrix showed that the greatest amount of confusion, thus, poor discrimination, occurred between vegetation-2 and barren land classes. In 2004 for example, the poor discrimination between vegetation-2 (user's accuracy 78.9% and K*hat* 0.71) and the barren land (user's accuracy 81.1%

and K*hat* 0.75) may be attributed to the limitations of the way in which the reference samples were collected. We observed some test samples falling in patches of barren land surrounded by vegetation-2 class, which may eventually lead to barren land misclassified as vegetation-2 class. Vegetation-1 and water bodies were well discriminated. However, we observed some confusion between vegetation-1 and vegetation-2, especially with small patches of vegetation-1 along river streams. Also, there was an overlap in the spatial transition from one vegetation class to another and, therefore, the chance of confusion is inevitable.

Landsat for Arid Environments

In this paper, the image classification approach was found effective in producing vegetative cover maps for the eastern Pamirs for the years 2004, 2006, and 2014. Although we acknowledge the challenge in using Landsat images for mapping vegetation in our study area, mapping using medium to coarse resolution images in semi-arid environments has been successful in other studies (e.g., Storms et al. 1998; Langley et al. 2001). One drawback is the subpixel mixing of surficial materials at the scale of a Landsat image pixel. Due to sparse vegetation, a pixel of Landsat in the eastern Pamirs may represent multiple classes. This mixed-pixel problem can lead to mismatch in the accuracy assessment, therefore introducing classification errors. For example, vegetation-1 class maybe bordered by vegetation-2 class and would therefore give a reflectance response for a heterogeneous pixel. Also, training samples for supervised classification may not be pure, causing the confusion between vegetation-1 and vegetation-2. Use of higher resolution could help to alleviate this difficulty by allowing the definition of "pure" training regions, resulting in a more accurate sampling.

It is important to look at the results of this study within the context of a MMU used. Objects smaller than the minimum mapping unit of 0.8 hectares are not considered in the mapping approach. These objects represent a vegetation structure descriptive of an arid environment. In this sense, our results only presented an all-inclusive picture of the vegetative cover.

Addition of Variables

No single factor dominates the effectiveness of vegetation mapping, but rather a combination of several variables. The addition of variables to enhance the image classification has shown to be an effective approach and that spectral information alone is not sufficient for classifying Landsat images in an arid environment. First, the spectral response of vegetation in semiarid to arid environments tends to be affected by soil reflectance, therefore the MSAVI was chosen as being the most appropriate index to take into account the soil effects. Shaded soil features were better discriminated against vegetation, especially those on the slopes (Huete et al. 1992). Second, the inclusion of the DEM as one of the bands of the image helped improve the classification results with higher accuracy (Eiumnoh and Shrestha 2000). We found that without DEM a number of dark soil pixels along steep slopes were misclassified as water pixels. DEM eliminated the problem in the unsupervised classification process by discriminating both classes. In general, the integration of ancillary data as features for classification confirmed previous applications of satisfactorily discriminating land cover classes, with relatively better results than just the Landsat spectral information alone.

Limitations

Owing to limitations on resources, we only searched and included studies in the English language. Due to the location of the Pamirs, the possibility of peer-reviewed literature regarding the temporal vegetation cover mapping written in Chinese, Persian, Arabic, or Russian may exist, of which we may not have any knowledge. Concerning the drivers behind the disappearance of a large body of water, climate-related factors such as minimal precipitation and the trend of increasing temperature over the years are most possible reasons.

Although access to global climatic data are available online, the data from the closest weather station to the study area, which is the Murgab, are missing certain dates. From the limited temperature and precipitation data, we were still able to show patterns and found indirect relationship between temperature and precipitation from 1950 to 1990 (Figure 8). The decreasing amount of rainfall and increasing temperature could be the underlying basis for the loss of a body of water and perhaps to some extent, the areal decline of the vegetation cover. The record gap of climatic data from the late 1990s to 2013 made it hard to verify the impacts of climate to the cover changes that we have seen in the classification results. We could only hypothesize that the preceding patterns continued to the present time and could be the controlling factor for the areal variation of the body of water in the study area.

Conclusion

During the past decades, important advances in the use of satellite images and computer processing have been applied to the study of vegetation patterns in the eastern Pamirs. However, there has not been a study conducted on the vegetation cover distribution and temporal changes. The use of the 30-m resolution Landsat images plus a variety of ancillary data satisfactorily classified the spatiotemporal dynamics of vegetation cover. Although the decision to use a medium-coarse resolution image over a high-resolution one invites questions of its accuracy in mapping sparse vegetation in the region, our results at least supplement existing vegetation research and improve our ability to measure and understand the degradation trend of the vegetative cover over time. This medium-coarse-level vegetation mapping analysis should serve as a first step in developing a land management plan.

The methodology employed in this study was designed to assess the spatial and temporal changes of vegetation at the landscape scale. Our methods and results would make it possible to (1) observe a portion of the Eastern Pamirs in larger extent, (2) define areas of change and non-change of the vegetative cover, (3) determine specific locations of areas of large changes, and (4) determine temporal vegetation status. Overall, our results provide a better understanding of the current status and condition of the vegetation resources in the study area.

One major downside of the research is constrained by limited resources for fieldwork to collect sufficient information that are helpful in mapping the vegetative cover in the region. In-situ data would have been a boost in picking training samples and cross-referencing classified maps. Another obstacle for accurate mapping in a mountainous arid environment with often less-accessible, less-studied slopes are the unavailability of high-resolution aerial photos, previous land cover maps, and other ancillary data that may benefit in enhancing classification results. Also, with sufficient field data, we could employ other classification methods such as the Classification and regression trees (CART) process similar to Lowry et al. (2005).

The degradation process that we observed in the study area in the eastern Pamir Mountains includes: (1) mainly, the decrease of the vegetative cover especially on and near mountain slopes, and (2) partly, the disappearance of a lake in the northern region that may be vital to wildlife existence as water source. If recent studies are linked to the loss of vegetative cover (Kraudzun 2012; Vanselow and Samimi 2014; Kraudzun et al. 2014; Zandlera et al. 2015), human-induced and natural stressors, i.e., over harvesting of the teresken shrub and excessive livestock grazing, could play an important factor in the changing composition and pattern. The main goal of this research was not to identify causation of degradation, however, it is clear that vegetation types that exist on high mountain meadow- steppe, high mountain nival desert, and high mountain nival-glacial ecosystems are declining in area coverage. According to our results, vegetation-2 and barren land are the most important conversions in the area. These areas of change need to be studied further in an attempt to explain the trends shown in this study, for instance, the complex interactions of factors including vegetation, soil, climate, topography, wildlife, and land use and disturbance (Salas et al. 2018; Salas et al. 2017)

For the next step, we hope to make use of the vegetative map to document the grazing practices and degradation of the woody shrub teresken in the region; the lands have been the main feeding source for cattle, goats, and sheep (Breckle and Wucherer 2006). Future work also includes determining reasons for the vegetation change response during the time periods identified in this study, so landcover management plans could be improved. Although this study showed that Landsat data can sufficiently produce baseline maps of degradation in vegetation cover over long periods of time, we also hope to improve the classification by introducing hyperspectral imagery to extract and map vegetation species in arid environments. In this era of spaceborne sensors such as the EO-1 Hyperion (Pearlman et al. 2003) and NASA's Hyperspectral InfraRed Imager (HyspIRI) (Mariotto et al. 2013) that may be launched in the future, vegetation studies can be conducted with optimal use of the spectrum and using wavelengths not sampled by any broadband system (Roberts et al. 2012). Unlike broadband sensors such as the Landsat that have few bands, both spaceborne sensors have many spectral channels that span from the visible to NIR—regions considered as essential for vegetation studies.

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