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ASSESSMENT OF LAND COVER CHANGES DUE TO ANTHROPOGENIC CAUSES IN THE MOUNTAINOUS AREA OF ISHKOMAN WATERSHED, GILGIT, PAKISTAN

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Abstract: *Remote Sensing (RS) provides the best ways to monitor temporal changes and to understand land use dynamics. Remote sensing analysis can be further enhanced when community perception regarding major drivers of change is integrated. The present study was an attempt to assess the land use land cover changes in the Ishkoman watershed in the Ghizer district. The study explored Landsat-5 and Landsat-8 images to assess the LULC dynamics from 1998 to 2018, and also used questionnaires for community perception regarding LULC changes in the past two decades. Supervised classification was used to monitor changes between 1998 and 2018 and the maximum likelihood technique was used to categorize the pixels into six classes: vegetation/forest area, bare rocks, water bodies, glaciers/snow area, rivers, water, and agriculture. Regarding the questionnaires, the correlation matrix and regression models were developed between independent variables (population, land type cleared, and extra land required for new family members) and dependent variables (land use dynamics factors and socio-economic variables). The results showed that all six land cover classes have shown temporal changes between 1998-2018 and the most significant change was observed in forests and pastures (which decreased from 18.7% to 5.9 %). Similarly, glaciers, water, rivers, and agriculture have changed from 13.1, 6.5, 9.3, 1.5 to 15.8, 4.0, 11.32, 3.1, respectively between 1998-2018. The largest change was observed in bare rocks which increased from 50.2 % to 60.06%. Moreover, temporal NDVI analysis showed a decrease in vegetation cover (conversion to bare rocks) between 1998-2018. The questionnaire results revealed that the highest correlation was shown between population increase and decrease in crop production (R^2 = -0.348), whereas the lowest correlation was found in population increase and population access to bus stops (R^2 = -0.167). Similarly, the highest correlation was found between access to roads and markets (R^2 = 0.349) and dependent variable (land type cleared), whereas the lowest correlation was*

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observed in access to water resources (R^2 = -0.021). The study concluded that land use land cover has been significantly changed from 1998 to 2018 in the Ishkoman Watershed. The study suggested more in-depth research to examine land use land cover changes at finer scales by using high resolution satellite imagery, and conducting details surveys regarding the underlying anthropogenic causes of land use dynamics.

Key words: *LCLU Changes, Landsat-8, Maximum Likelihood, Questionnaire, Ishkoman valley.*

1. Introduction

Land use/cover dynamics are widespread, accelerating, significant processes driven by human actions, which also produce changes that impact humans [1], [15], [39]. Change detection is a temporal effect whereby the spectral appearances of vegetation or other features on the earth in a specific region vary with time. In the last few decades, forest cover has been deteriorating due to anthropogenic activities, which is a global environmental issue. Four steps have to be taken into consideration while detecting natural resources; detecting the changes that have occurred; classifying the changes occurring in the environment; determining the level of change and its patterns. Major land cover/land use changes during the last decades also include clearing of forest areas and converting them for other land uses such as agriculture, infrastructure, engineering works, and barren lands. Land Use Land Cover (LULC) mapping is very important for land management purposes and ecological research, and provides information about the proper planning and management of natural resources [18, 19], [36]. Remote sensing is the most efficient and effective tool for environmental studies [7]. Globally, remote sensing is widely used to monitor the LULC changes spatiotemporally in order to understand the impact of land use changes on the climate, on human life, and on biological diversity [17]. Remote sensing is one of the best ways to monitor the changes on Earth, and image processing techniques offer good solutions for LULC mapping [20]. Remote sensing techniques are successful tools for detecting forest cover changes, starting with bi-temporal classifications of land use (change/no-change maps generated from two land-use maps created at two different moments in time) to time series analysis [6]. There are many open sources, and commercial remote sensing products are available which are used by different researchers for land use change and deforestation mapping [10], [24].

Medium-resolution satellite images (e.g., Landsat images) allow for mapping urban areas at a large spatial scale, but it is still difficult to extract socioeconomic features of urban areas from these images [17]. Presently, the Landsat constellation has two functional satellites: Landsat 7, Enhanced Thematic Mapper Plus (ETM+), and Landsat 8, Operational Land Imager (OLI) [16]. Landsat-8 provides continued temporal images with global coverage and is available to the public free of cost on the platform of the United States Geological Survey (USGS) [37], therefore Landsat temporal data availability enables us to assess land cover changes both retrospectively and prospectively. In addition to being timely and cost effective, satellite based monitoring is a transparent and reliable means to monitor forest cover conditions [27]. Previously, many researchers used remote sensing in the Himalayas region of Pakistan to identify and analyze the Land Use Land Cover (LULC) pattern [12], [33]. Through the analysis of the spatial and temporal patterns of deforestation and the identification of key variables related to deforestation, efforts are being made to identify the driving forces behind changes to forest cover [26]. Trend analysis, direction, and the spatial pattern of land use change detection have been efficiently analyzed using GIS and remote sensing [35]. Prakasam [25] studied land use and land cover changes in the Ishkoman region of the Ghizer district in the Gilgit-Baltistan province of Pakistan to observe the changes during a span of 20 years, from 1998 to 2018. The present study is also an attempt to assess the landscape changes of the Ishkoman watershed area situated in the Ghizer district of Gilgit-Baltistan, Pakistan. For a detailed comparative analysis, the study conducted a temporal analysis of two decades and used a land use map from 1998 and Landsat satellite imagery from 1998, 2008, and 2018. In addition to remote sensing temporal analysis, community perception was also explored regarding the major drivers of land cover/land use changes. Previous studies showed that local communities recognized firewood collection, charcoal production, agricultural expansion, settlements, and timber as the important proximate drivers of LULC changes [23]. Overdependence and unsustainable extraction of natural resources without alternative economic strategies, such as forests, land, and water, result in serious environmental problems, including biodiversity loss and deforestation [14], [22]. The present study demonstrated community perception through structured questionnaires regarding LULC changes in the study area. Therefore, the main objectives were to assessland cover changes between 1998-2018 in the Ishkoman watershed and to identify community perception regarding land cover changes in the study area.

2. Materials and Methods

2.1. Study Area

The study area of the present research was the Ishkoman valley which is tehsil (sub-administrative unit) of the Ghizer district, Gilgit-Baltistan, Pakistan (Figure 1). The Ishkoman watershed is part of a larger spur of Hindu Kush ranges (called Hindu Raj) which is further subdivided into catchment areas between Pakistan and Afghanistan. Besides, the Ishkoman watershed is linked with other major areas of Hindu Kush such as southern Chitral, Ghizer, and Yasin. Similarly, the Ishkoman catchment is an important sub-basin of the Gilgit river basin which is itself connected to the larger upper Indus river basin. Ishkoman River is one of the main tributaries of the Ghizer River. The Ishkoman valley is mostly covered by snow and splendid glaciers at higher elevations, while lower mountains are mostly barren. Having a splendid natural landscape, the Ishkoman Mountains are also considered a rich reservoir of precious minerals. Moreover, it has been reported that the Ghizer catchment basin has approximately 155 lakes and ponds many of which are found in the Ishkoman

Watershed. There are many lakes and water bodies that have been created as a result of glacier melting. Debris flow and river bank erosion are predominant hazards in the area.

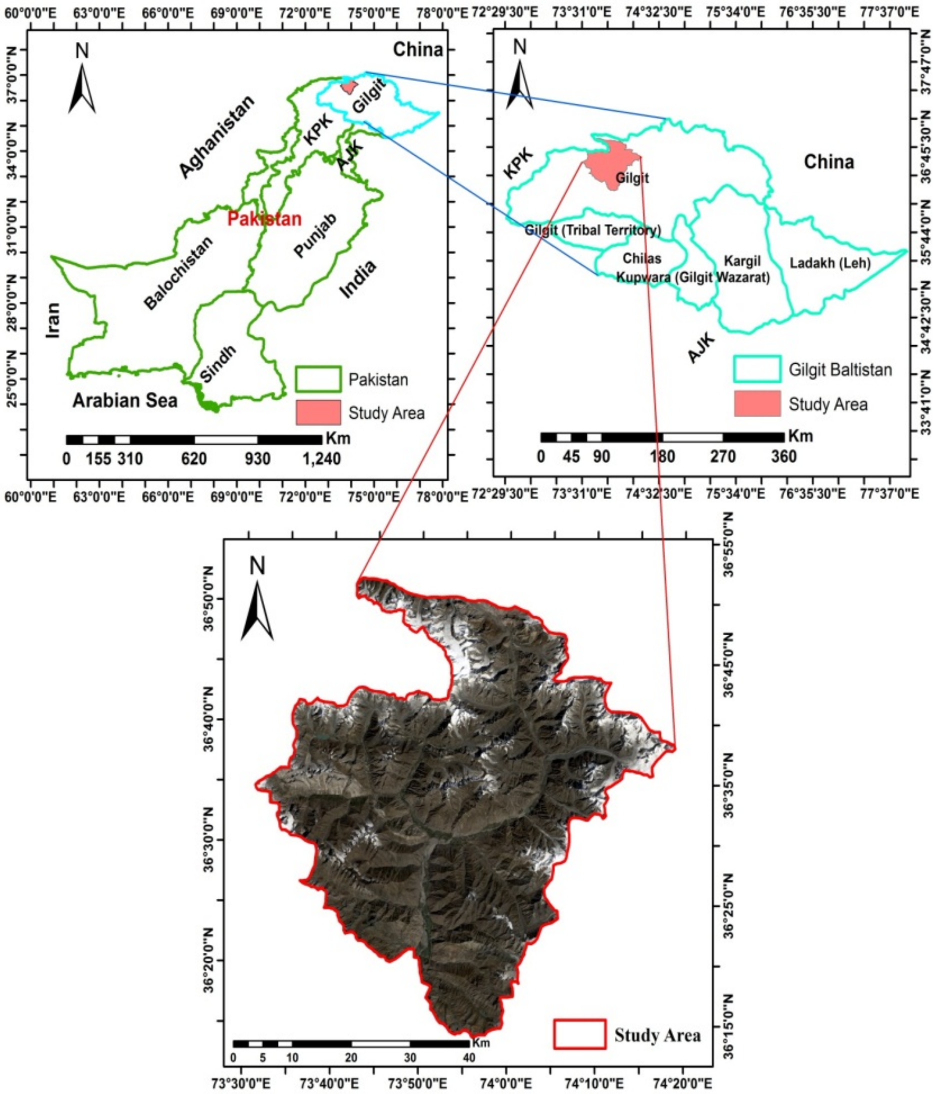

Fig. 1. *Study area*

The Ishkoman valley is gifted with beautiful glaciers and tranquil lakes. The Gilgit River joins the Ishkoman River at Gahkuch. Ishkoman is famous for the good quality production of apricots. The Ishkoman valley has four distinct seasons throughout the year; a beautiful spring starts in March and ends somewhat in May, followed by summer in June until September. Similarly, a pleasant autumn starts in mid-September until November, followed by winter in December until

February every year. Most of the precipitation occurs between December and May and normally touches its peak values sometime in March; rainfall/snowfall may fall anytime depending on the local conditions. During summer, many rivers arise intensely which carry more water many times compared to those in winter. The reason behind river formation is probably not heavy rainfall, but actually they are the result of the melting of glaciers and snow cover. Geographically all the valleys are categorized by very high snow covered mountains, alpine forests, and pastures. Previously, extreme climatic events (such as floods) greatly affected roads, vegetation, livestock, and farmlands in the Ishkoman valley.

2.2. Methods

In order to assess land cover changes between 1998-2018 in the Ishkoman watershed, Landsat temporal images were used to identify various LCLU changes. Dynamics of forest and rangeland, bare soil and rocks outcrops, agricultural land, water bodies, and snow cover were taken into account. Secondly, questionnaires investigated the community perception regarding land cover changes and explored the reasons and agents that caused the land cover changes over the last two decades. Moreover, the impacts of land cover/ land use changes on the community livelihood and on the surrounding environment were also assessed through questionnaires.

2.3. Remote Sensing Part

The present study used Landsat satellite data because it is one of the pioneer satellites, as the platform was created in 1972 with the Landsat-1 satellite. The Landsat satellites are composed of many sensors, i.e. Thematic Mapper (TM), Multi Spectral Scanner, etc. To interpret the land cover, Level 1 terrain corrected (L1T) temporal Landsat data, which is available from the USGS Earth Explorer [40] for 1998 and 2018, were used. For the acquisition of optical satellite data in northern Pakistan, the months of August to October were considered to be the most suitable because of the least amount of cloud and snow cover during this period (Preprocessing).

The prior step before carrying out the analysis was data preparation in which refined satellite imagery was used to carry out detailed analysis. Subsetting an image can be useful to minimized computational time when working with large images. The study area was specified using the area of interest (AOI) option in the subset interface and the subset was ready for further processing. The steps for image processing were: data preparation which includes atmospheric correction, supervised image classification using training data sets, analysis of LULC changes, and classification analysis. Supervised classification of the satellite images of the study area and a field-based survey were carried out to analyze the land cover change (1998 to 2018). ENVI 5.3 and ArcGIS 10.3 were used for the analysis part.

Supervised training was directly controlled by the analyst. In this method, the investigator chooses pixels that make up patterns or land cover characteristics that can identify information of the data and of the classes desired, which is necessary before categorization. By distinguishing patterns, one can put the data into the computer system to classify pixels with related features. If the sorting is correct, the output classes represent the categories within the information that were initially recognized. The images were processed and classified into six LULC classes through geospatial packages, and change detection maps were prepared for each division and time period. Our study images were categorized into six classes; (1) Glaciers, (2) Water, (3) Forest, (4) Agriculture, (5) Rivers, and (6) Barren lands. The output of the training is a set of signatures that determine a training cluster or sample. Each signature represents a class and is applied with a decision rule to allot the pixels within the image file to a class. Once the signatures are determined, the pixels of the image are classified into categories based on the signatures through application of a classification decision rule. The maximum likelihood classification was applied to the entire Landsat-5 and Landsat-8 images step by step in ENVI classification workflow keeping in mind protocols. It is a classification system in which unidentified pixels are allocated to classes through the outline of likelihood around training areas using the maximum-likelihood statistic. The classified images were further smoothed using a majority filter with a 3 × 3 kernel to reduce the number of misclassified pixels. Moreover, the Normalized Difference Vegetation Index (NDVI) was also derived from Landsat images in order to evaluate vegetation change between 1998-2018. The NDVI values range from (-1) to (+1) and the zero value means no flora, while a value close to +1 (0.8 - 0.9) shows the maximum probable density of green leaves.

$$NDVI = (\boldsymbol{\rho}NIR - \boldsymbol{\rho}RED)/(\boldsymbol{\rho}NIR + \boldsymbol{\rho}RED)$$

where: $\boldsymbol{\rho}$*NIR* is the spectral reflectance at near-infrared region and $\boldsymbol{\rho}$RED is the spectral reflectance at red region (band). In the case of the NDVI of Landsat-5 and Landsat-8; spectral reflectance of Band 4 and Band 5 was used for Red and NIR, respectively.

Accuracy assessment was done by KAPPA analysis based on the error matrix analysis. The accuracy of the land cover maps was assessed by comparing with Google Earth polygons based on very high resolution satellite images. Accuracy assessment of 1998, 2008, and 2018 land cover maps was done, random 16504, 17326, and 18244 pixels were selected, respectively and the confusion matrix was created using the regions of interest method in ENVI 5.3.

2.4. Questionnaire Survey Part

The questionnaire was developed to evaluate community views and comments regarding the past two decades, and the indigenous knowledge helped to understand basic agents and causes of land use/land cover changes in the Ishkoman valley. The survey is an appropriate method for the study of public opinion to measure attitudes and orientation among a large population. The questionnaire is a survey tool designed to elicit useful information for analysis. The questionnaire survey method is applicable for several of the research questions in this study because the study focuses on the degree of understanding or agreement about the events occurring in the study area. To check the accuracy of the questionnaire, pretesting was done in 2 villages of population. Mistakes and irrelevant questions were removed from the final questionnaire and then the survey was applied. The aggregate number of respondents to be met was settled as 30 from all the villages. To have the same sampling intensity, the respondents' number was calculated with the help of sampling fractions (Table 1).

Table 1

Total households and the number of respondents to be interviewed in each village

S. No	Name of villages	Population	Household	Sample fraction	No. of respondents
1	Bilhan	1100	125	0.097	11
2	Barswat	374	60		6
3	Mansoorabad	388	34		4
4	Gangabad	300	40		4
5	Borth	350	50		5
	Total	2512	309		30

Further, the sample size was calculated to characterize the reference population based on the Equation:

$$n = \frac{Np(1-p)}{(N-1)\frac{c^2}{z^2} + p(1-p)} \quad (1)$$

where:

N is the size of the population which is equal to 2512;

p – the percentage value set at 0.5;

c – the margin of error set (Confidence Interval was 17.79%);

z – the z score which is equal to 1.96 (Confidence level was 95%).

In order to have a relative number of respondents in each village, the quantity of family units in each village was multiplied with the sampling portion to attain the required number of respondents (Table 1).

2.5. Statistical Analysis

The raw data were analyzed using MS Excel 2010 and SPSS version 21. Emission of errors and cleaning of the calculated data was done. After cleaning the data, the analysis was done using SPSS for all the variables. Simple statistical techniques of percentages, frequencies, and bar graphs were used for the discussion of the data. Multiple linear regression [significance level of $\alpha = 0.05$] was used to analyze and predict the values of the dependent variables which were responsible for LULC changes. The dependent variables were land cover changes, agricultural activities, and deforestation. The independent variables were: (i) occupation, (ii) monthly income, (iii) population, (iv) level of dependency, and (v) access to infrastructure and services.

3. Results and Discussion

3.1. Supervised Classification of Landsat Images from 1998, 2008, and 2018

The classified images from 1998, 2008, and 2018 can be seen in Figure 3a, 3b, and 3c, respectively, which showed the spatial distribution of six land cover classes that include agriculture & communities, bare rocks, forests & pastures, glaciers, rivers and water. The information about the covered areas and the percentages by each class are described in Table 2. The total area of the classification was recorded as 2431.54 km^2. In 1998, the largest land cover area was occupied by Bare Rocks which was 1221.24 km^2 (50.2% of the total area), while the smallest area was covered by agriculture, namely 36.40 km^2 (only 1.5% of the total area). Forests and Pastures covered 454.314 km^2 (18.7%) and were extended over central and southern parts of the study area (Table 2 and Figure 2). Similarly, in 2008, the largest land cover area was covered by Bare Rocks, which was 1280.383 km^2 (52.7% of the total area), while the smallest area was covered by agriculture, namely 22.594 km^2 (only 01% of the total area). The area covered by Forests and Pastures has decreased to 297.867 km^2 (12.3%) and other classes of areas are presented in Table 2 and Figure 2. Likewise, in 2018, the results showed that out of the total classified area (2431.54 km^2), the largest land cover area (1460.38 km^2) was occupied by Bare Rocks which determined 60.06 percent of the total area, whereas the smallest area was covered by agriculture, namely 74.44 km^2 (3.1% of the total area). Forests and Pastures have decreased to 141.05 km^2 (5.8% only), which showed deforestation by local communities (Table 2 and Figure 2).

Table 2

Supervised Classification Classes of the Ishkoman Watershed (1998, 2008, 2018)

Class	Area [km^2] in the year ...		
	1998	2008	2018
Agriculture & Communities	36.4	22.59	74.44
Bare Rocks	1221.24	1280.38	1460.38
Forests & Pastures	454.31	297.87	141.05
Glaciers	318.62	409.10	384.06
Rivers	226.39	276.24	275.21
Water	157.16	145.35	96.4

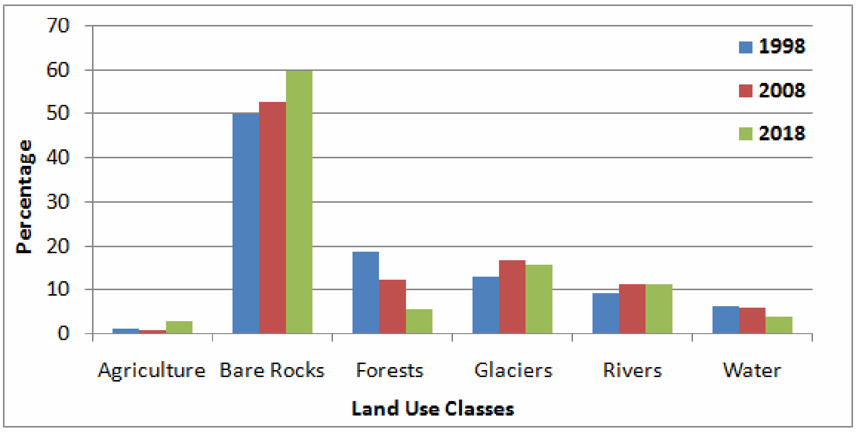

Fig. 2. *Temporal change in area percentage during 1998, 2008, and 2018*

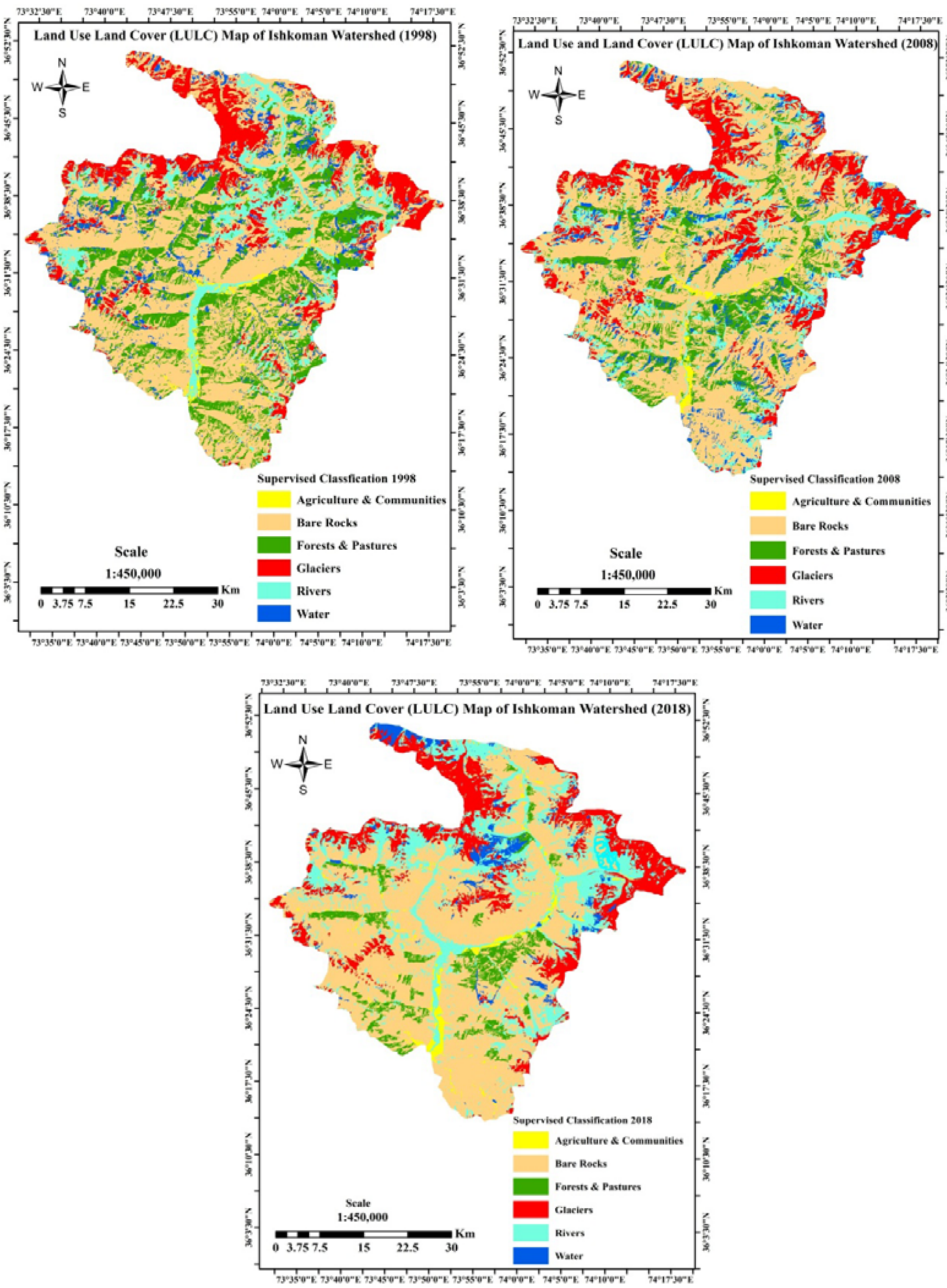

Fig. 3. *Supervised Classification Classes: a) 1998; b) 2008; c) 2018*

The results indicated that the overall classification accuracy of 78.16% was achieved using the kappa coefficient was 0.72, as 12899 out of 16504 pixels have correctly been classified, as shown in Table 3. While examining the user accuracy of all six classes (glaciers, rivers, water, forests, agriculture, and bare rocks), three land use classes were classified very accurately and obtained more than 80% accuracy, which includes agriculture, glaciers, rivers with 88.91%, 84.18%, and 80.56% accuracy, respectively. In the context of the producer accuracy, only two land cover classes (glaciers and agriculture) achieved above 80% accuracy, whereas significant confusion was observed in the rest of the classes. The results showed that the land cover map from 2008 has an overall accuracy of 88.08% with a Kappa coefficient of 0.81, which means that out of 15261 pixels, 17326 were correctly classified, as shown in Table 4. In terms of user accuracy, three out of six land cover classes (glaciers, rivers, and agriculture) obtained more that 90% accuracy. Similarly, the producer accuracy showed that three classes achieved more than 90% accuracy, which include glaciers, bare rocks, and forests, with 90.8%, 91 %, and 91.6% accuracy, respectively.

Results showed that land cover map of 2018 has overall accuracy of 89.72% with the Kappa Coefficient of 0.81 as shown in Table 5. In the context of user's accuracy, four land cover classes (glaciers, forests, bare rocks and rivers) have obtained 88% accuracy. Whereas, in producer's accuracy, glaciers and agriculture have achieved 90% accuracy followed by rivers with 87% accuracy.

Table 3

Accuracy Assessment of Supervised Classification of Landsat-5 Image 1998

Class	Water	Forests	Glaciers	Rivers	Bare Rocks	Agricul-ture	**Total**	User Accuracy [%]
Water	391	0	564	29	0	0	**984**	57.32
Forests	0	292	0	67	93	192	**644**	45.34
Glaciers	41	31	2788	0	452	0	**3312**	84.18
Rivers	113	0	83	4310	844	0	**5350**	80.56
Bare Rocks	0	34	0	511	3129	303	**3977**	78.68
Agriculture	0	79	0	169	0	1989	**2237**	88.91
Total	**545**	**436**	**3435**	**5086**	**4518**	**2484**	**16504**	
Producer Accuracy [%]	71.74	66.97	81.16	84.74	69.26	80.07		

Overall Accuracy = (12899/16504) = 78.16%
Kappa Coefficient = 0.72

3.2. Land Use Land Cover Change Dynamics between 1998 and 2008

The dynamics of the six land cover classes and their proportionate coverage area derived from Landsat-5 images from 1998 to 2008 are shown in Table 6. All six land cover classes have shown temporal changes between 1998-2008 and the most significant change was observed in the forests and pastures class, followed by the Glaciers, whereas the least significant change was observed in water (Figures 4 and 5).

Table 4

Accuracy Assessment of Supervised Classification of Landsat-5 Image 2008

Class	Water	Forests	Glaciers	Rivers	Bare Rocks	Agricul-ture	**Total**	User Accuracy [%]
Water	782	2	184	14	0	0	**982**	79.6
Forests	0	326	0	47	77	206	**656**	49.7
Glaciers	135	0	3801	0	134	0	**4070**	93.4
Rivers	0	0	199	4707	147	0	**5053**	93.2
Bare Rocks	0	14	0	509	3638	253	**4414**	82.4
Agriculture	0	14	0	180	0	1957	**2151**	91.0
Total	**917**	**356**	**4184**	**5457**	**3996**	**2416**	**17326**	
Producer Accuracy [%]	85.3	91.6	90.8	86.3	91.0	81.0		

Overall Accuracy = (15261/17326) = 88.08%

Kappa Coefficient = 0.81

Table 5

Accuracy Assessment of Supervised Classification of Landsat-5 Image 2018

Class	Glaciers	Agriculture	Water	Forests	Bare Rocks	Rivers	**Total**	User Accuracy [%]
Glaciers	4256	0	21	0	74	97	**4448**	95.68
Agriculture	0	2502	0	145	193	369	**3209**	77.97
Water	32	0	429	0	0	312	**773**	55.50
Forests	0	37	0	325	0	0	**362**	89.78
Bare Rocks	76	29	0	13	3587	0	**3705**	96.82
River	286	14	109	11	23	5304	**5747**	92.29
Total	**4650**	**2582**	**559**	**494**	**3877**	**6082**	**18244**	
Producer Accuracy [%]	91.53	96.90	76.74	65.79	92.52	87.21		

Overall Accuracy = (16370/18244) = 89.72%

Kappa Coefficient = 0.859

Table 6

Land Use Land Cover (LULC) Change Statistics between 2008-2018

Class	Area [km^2] in the year …			Area change [km^2] in the period …	
	1998	2008	2018	1998-2008	2008-2018
Agriculture	36.4	22.59	74.44	-13.804	51.846
Bare Rocks	1221.24	1280.38	1460.38	59.140	180.00
Forests	454.31	297.87	141.05	-156.447	-156.820
Glaciers	318.62	409.10	384.06	90.489	-25.048
Rivers	226.39	276.24	275.21	49.845	-1.031
Water	157.16	145.35	96.4	-11.809	-48.946

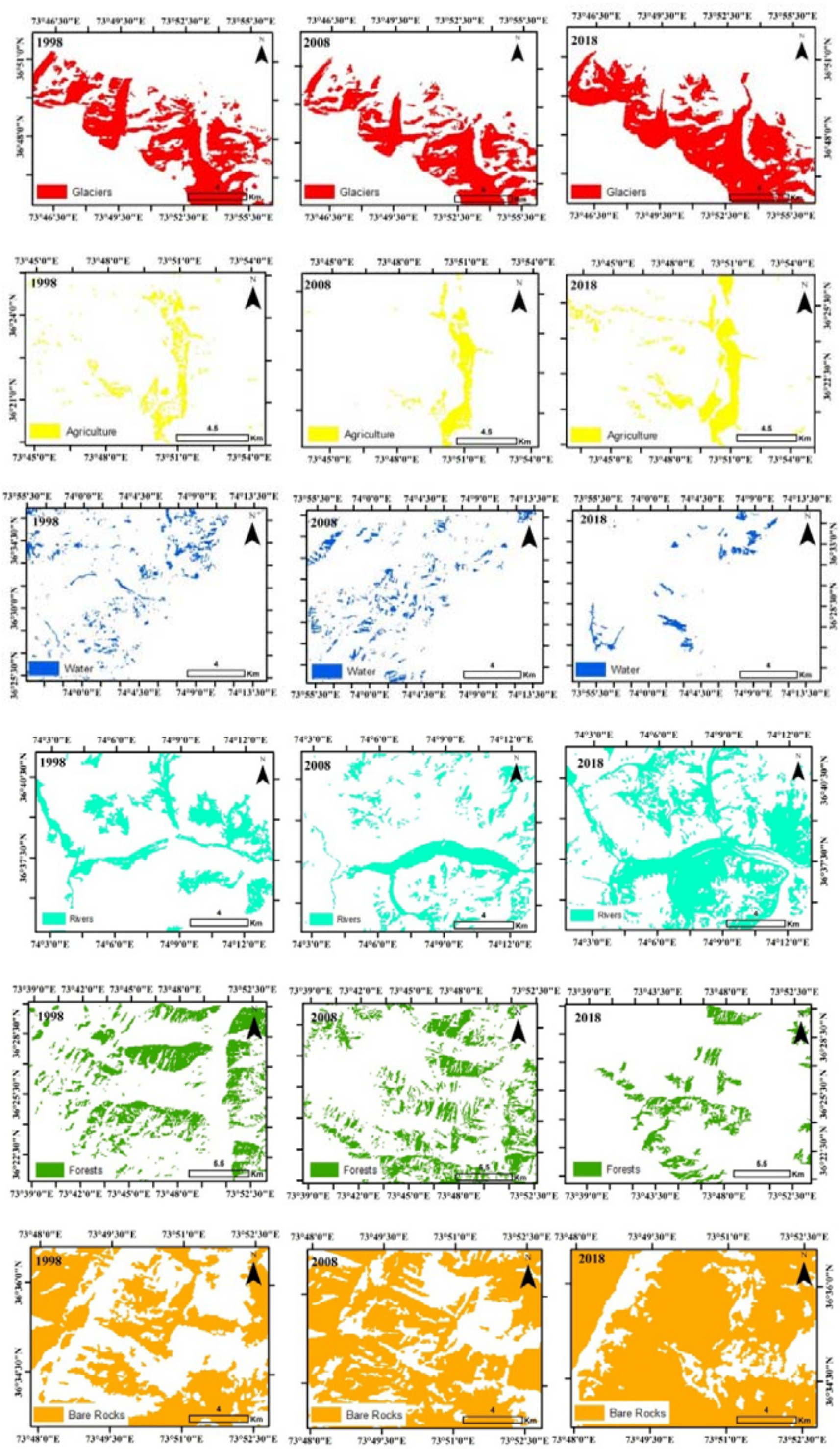

Fig. 5. *Land Use Land Cover (LULC) Changes of Different Classes between 1998-2018*

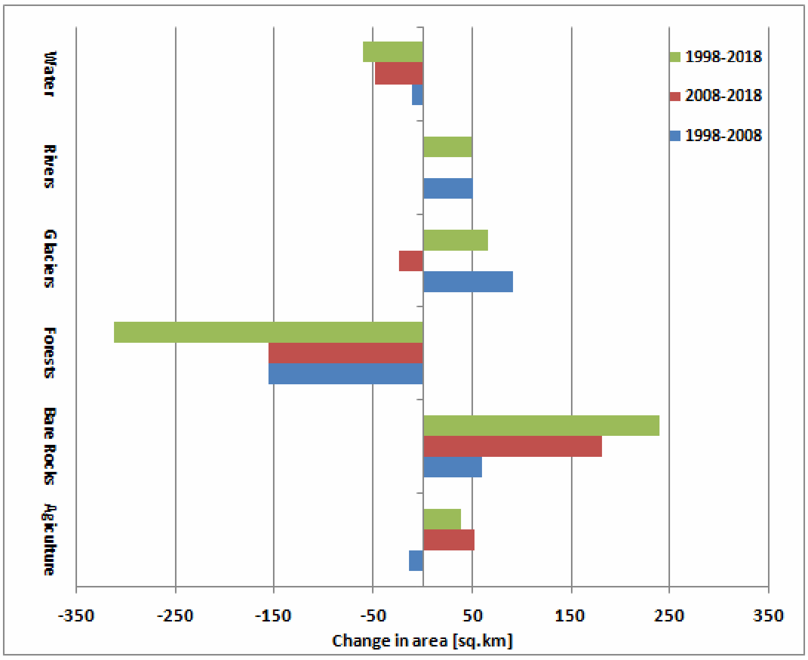

Fig. 4. *Net Land Use Land Cover (LULC) Changes between 1998-2018*

3.3. Spectral Indices Analysis

The Normalized Difference Vegetation Index (NDVI) was calculated for 1998 and 2018, and shown in Figures 6a and 6b. The NDVI in 1998 ranges from (-0.66) to (0.68) where the negative values show areas other than vegetation, such as glaciers, water, rivers, bare rocks, etc., while the positive values show forests, pastures, and agriculture, as shown in Figure 6a. Based on pixel values, the NDVI in 1998 was classified into three land cover classes: (1) Glaciers, Water & Rivers, (2) Bare Rocks, and (3) Forests and Agriculture. The NDVI range for the first class was (-0.66 to -0.005) and similarly, the second class values range from -0.006 to 0.10, while the third class values range from 0.11 to 0.68.

Figure 5a shows that forest area was present mostly in the central and southern parts of the study area, whereas agriculture mostly showed along river sides in the central part. Similarly, Glaciers and water bodies were present at the periphery of the study area, and bare rocks occupied the space between vegetation and glaciers. The NDVI in 2018 showed significant differences in the spatial coverage of these three classes, most importantly, vegetation areas have been reduced and changed into bare rocks.

However, Glacier areas have been less reduced by changing into water bodies (by melting), however they remained intact with the spatial distribution similar to 1998. Vegetation of the central and southern parts of the study area has mostly been cleared and changed into bare rocks. What is more, the overall NDVI values have also decreased compared to 1998, and the range of the NDVI value in 2018 was (-0.28 to 0.54), as shown in Figure 5b.

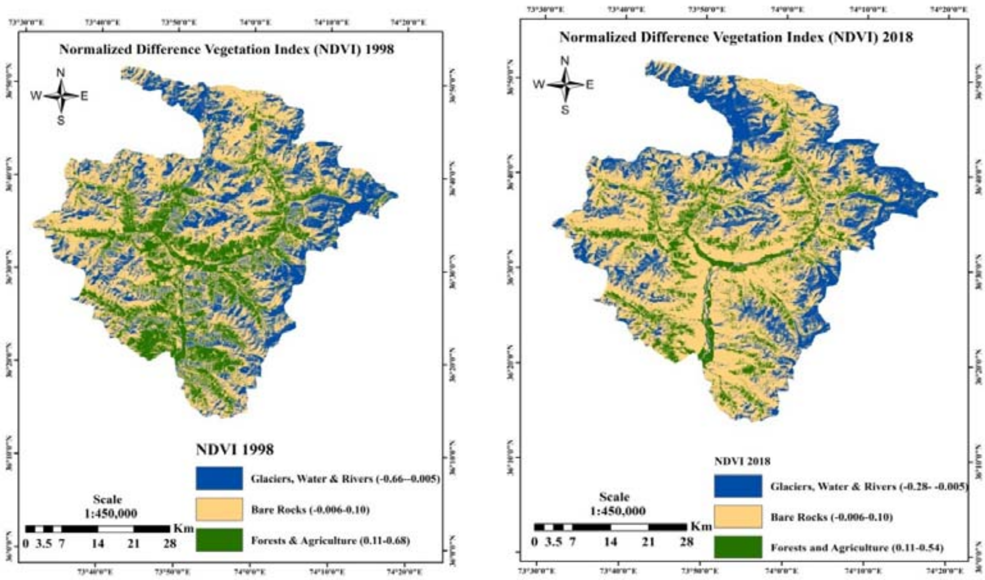

Fig. 6. *LULC Changes based on NDVI: a) 1998 and b) 2018*

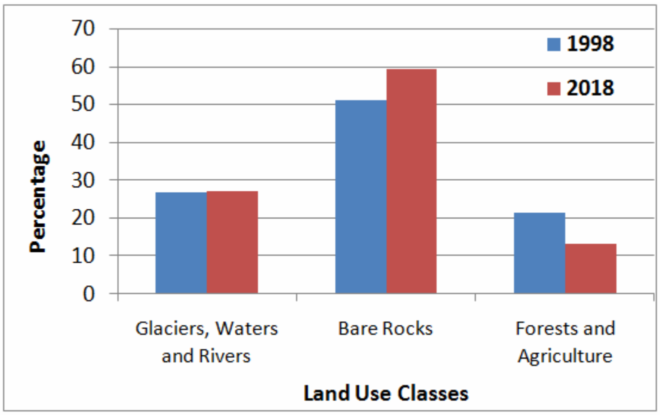

Fig. 7. *LULC Changes based on NDVI 1998 and 2018*

Therefore, the NDVI was a powerful and efficient index for different vegetated and non-vegetated areas, because it also expressed Glaciers and water bodies as negative values [2], [5]. Gong and Liu [9] used the NDVI for monitoring land use land cover change between 1993-2009, and the study showed that the NDVI range has decreased from (-0.37-0.63) to (-0.73-0.52), which showed that the vegetated area has been changed into non-vegetated area. Jeevalakshmi et al. [11] derived the NDVI from multi-spectral data to examine various land cover classes such as water bodies, urban areas, and vegetation types, and explored the differences between various spectral indices by developing its supervised classification maps. Zaitunah et al. [38] assessed land use change and vegetation thickness (NDVI) in the range of 2005 and 2015 and confirmed that the wide-ranging of forest zones had been deteriorated in the middle of one decade.

In the context of the Land Use Land Cover Change analysis, are been presented in Table 8. According to Table 7, in 1998 the NDVI based forest and agricultural area was 21.58 % of the total area in 1998, while the area has been reduced to 13.26% in 2018. Thus, the area change in vegetation cover was (-198.59 km^2) between 1998 and 2018, and most of the area changed into bare rocks. Similarly, an increase in the bare rocks area was also evident from the 1998 and 2018 NDVI, as shown in Table 8. The bare rocks area was 51.16 % of the total area in 1998 and has increased to 59.51% in 2018. The area changes (increase in bare rocks) were caused by deforestation and vegetation reduction from 1998 to 2108. Regarding the glaciers, water and rivers land cover class, minimum changes occurred between 1998-2018, and the percent change with the base year 1998 was 0.60, which increased in 2018.

Table 7

Land Use Land Cover (LULC) Change Statistics between 2008-2018

Class name	Area [km^2] in the year …		Area change [km^2] in the period 1998-2018
	1998	2018	
Glaciers, Water and Rivers	658.16	662.15	3.99
Bare Rocks	1252.5	1447.1	194.6
Forests and Agriculture	520.93	322.34	-198.59

According to Table 7, in 1998 the NDVI based area of Glaciers, water and rivers was 27.06% of the total area while the area has increased to 27.23% in 2018. The results of the present study were also consistent with the published studies in the region, e.g., Qasim et al. [28] studied temporal land cover change analysis for 1968, 1990, and 2007, and revealed annual deforestation rates from 0.80 % to 1.86% in different vegetation zones in the Swat district, whereas Qamer et al. [26] reported an annual gross deforestation of 0.81% in the same region between 2001-2009. Further, Fischer et al. [8] observed an annual forest cover rate of change of 1.32% between 1996-2008 in the Malakand and Hazara regions. The LULC changes shown in Table 7 can also be interpreted from the field questionnaire survey which showed that population has increased during the last 30 years and land area has been cleared for the new family members. Sudhira et al. [30] reported that economic and population growth were the main causes of land use changes over time.

3.4. Multiple Linear Regression between Population Increase and Land Use Change Variables

A correlation matrix was developed between the increase in population and other land use change variables. The results showed that population increase has a positive correlation with land required for new family members, land type clearing and school accessibility, while it showed a negative correlation with the decrease in crop production and bus stop accessibility (Table 8). The highest correlation was shown between population increase and decrease in crop production (R = -0.348), whereas the lowest correlation was found in population increase and population access to bus stops (R = -0.167). Further, all variables given in the correlation matrix were put forward to multiple linear regression and its results are showed in Table 9.

Table 8

Correlation Matrix between Population Increase and Land Use Change Variables

	Population Increase	1	2	3	4	5
Population Increase	1	.184	-.167	.263	.179	-.348
1	.184	1	-.254	.226	.125	.172
2	-.167	-.254	1	-.015	-.182	.249
3	.263	.226	-.015	1	.152	.103
4	.179	.125	-.182	.152	1	-.025
5	-.348	.172	.249	.103	-.025	1

Codes: 1. Schools Accessibility; 2. Bus Stop Accessibility; 3. Land Required for New Family Members; 4. Land Type Cleared for new family members; 5. Decrease in Crop Production.

Dependent variable: Population Increase.

Significant variables (correlation is significant at the 0.05 level): Land Required for New Family Members, Land Type Cleared for new family members, Decrease in crop production.

Table 9

Multiple Linear Regression between Population Increase and Land Use Change Variables

<table>
<tr><th colspan="4">Model Summary</th><th colspan="6">ANOVA</th></tr>
<tr><td>R</td><td>R Square</td><td>Adjusted R Square</td><td>Std. Error of the Estimate</td><td></td><td>Sum of Squares</td><td>df</td><td>Mean Square</td><td>F</td><td>Sig.</td></tr>
<tr><td rowspan="3">.508</td><td rowspan="3">.258</td><td rowspan="3">.104</td><td>.986</td><td>Regression</td><td>8.124</td><td>5</td><td>1.625</td><td>1.671</td><td>.049</td></tr>
<tr><td rowspan="2"></td><td>Residual</td><td>23.342</td><td>24</td><td>.973</td><td></td><td></td></tr>
<tr><td>Total</td><td>31.467</td><td>29</td><td></td><td></td><td></td></tr>
<tr><th colspan="10">Coefficients</th></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td colspan="2">Unstandardized Coefficients</td><td>Standardized Coefficients</td><td>t</td><td>Sig</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td>B</td><td>Std. Error</td><td>Beta</td><td></td><td></td></tr>
<tr><td colspan="4">(Constant)</td><td>1.426</td><td>.900</td><td></td><td>1.584</td><td>.126</td><td>1.426</td></tr>
<tr><td colspan="4">Land Required for New Family Members</td><td>.220</td><td>.163</td><td>.246</td><td>1.348</td><td>.046</td><td>.220</td></tr>
<tr><td colspan="4">Land Type Cleared for new family members</td><td>.098</td><td>.164</td><td>.109</td><td>.600</td><td>.049</td><td>.098</td></tr>
<tr><td colspan="4">Decrease in Crop Production</td><td>-.502</td><td>.234</td><td>-.404</td><td>-2.14</td><td>.042</td><td>-.502</td></tr>
<tr><td colspan="4">Accessibility to Schools</td><td>.402</td><td>.418</td><td>.185</td><td>.963</td><td>.345</td><td>.402</td></tr>
<tr><td colspan="4">Accessibility to Bus Stops</td><td>.007</td><td>.305</td><td>.004</td><td>.021</td><td>.983</td><td>.007</td></tr>
</table>

Dependent Variable: Population Increase.

Predictors in the Model: (Constant), Land Required for New Family Members, Land Type Cleared for new family members, Decrease in crop production, Accessibility to schools, Accessibility to Bus stops.

According to Table 9, the results showed that the overall coefficient of correlation was 0.258 with the standard error estimate of 0.98. Among the variables however, the relationship of three variables (land required for new family members, land type cleared for new family members, decrease in crop production) were significant and were selected in the final model.

The findings of the present study are supported by previous studies [34] which reported that a high percentage of communities dwelling in the mountainous zones are largely dependent on the forest for their continued existence, as these forest products are regularly collected and used for their livelihoods. The results of the present study showed that farming (agriculture) and forest resources played a vital role in the communities' subsistence. Reflections from the interview revealed that they derived benefits from their farms and the forest. They obtained fuelwood, charcoal, poles, and different non-timber produce.

A correlation matrix was developed between the type of land cleared and the corresponding land use change variables. The results showed that the land type cleared has a positive correlation with the land type cleared for new family members, and decrease in forest cover, access to roads, markets, health centers and schools. On the other hand, the distance from home to farm, decrease in crop production, access to water resources and bus stops showed a negative correlation with decrease in crop production and bus stop accessibility (Table 10). The highest correlation was found between access to roads and markets (R^2 = 0.349) and dependent variable (land type cleared), whereas the lowest correlation was observed in access to the water resources (R^2 = -0.021). Decrease in crop production also showed lower correlation (R^2 = -0.025). The results of the present study are also consistent with other similar studies conducted in the region, e.g., Khan et al. [13] reported on the underlying driving forces of land use change (decrease in vegetation) and its socio economic impacts on the local community of the Swat district. Fuelwood collection and use for domestic purposes speed up forest cover change. Ali et al. [3] assessed that 50 percent of the forest in the Basho Valley (Northern Areas) vanished after the construction of link roads. Rao and Marwat [29] reported that direct and indirect causes of land use change in Pakistan comprised land tenure, illicit activities, population growth, and commercial activities. Ali et al. [4] considered that in Mansehra, 90% of the respondents had been using forest wood for cooking. Tariq et al. [32] described that 96% of the respondents had been using fuelwood for cooking purposes, and 84% of the respondents used forests for their wooden needs in the Swat district. Similarly, Tariq and Aziz [31] found that fuelwood, timber, and fodder were the main and key causes of forest cover change in DirKohistan. Moreover, the more the access roads (roads, rivers and railroads) open the forests, the faster the market accelerates the changes in terms of land use [21].

The results of multiple linear regression of land type cleared and the explanatory variables showed that the overall correlation was 0.262 with the standard error estimate of 1.61 (Table 11). The relationship of three variables (decrease in forest cover, access to markets, and decrease in crop production) was significant, whereas the rest of the variables were not statistically significant, as their P-values were greater than the minimum threshold.

Table 10

Correlation Matrix between Land Type Cleared and Land Use Change Variables

	Land Type Cleared	1	2	3	4	5	6	7	8	9
Land Type Cleared	1	.284	.349	.349	.133	.125	-.021	-.18	-.02	-.21
1	.284	1	.675	.67	.274	.047	.555	-.27	-.01	.19
2	.349	.67	1	1.00	.398	.196	.175	-.17	.059	-.141
3	.349	.675	1.00	1	.398	.196	.175	-.17	.059	-.141
4	.133	.274	.398	.39	1	.780**	.114	-.16	.182	-.102
5	.125	.047	.196	.196	.78	1	.255	-.25	.172	-.131
6	-.021	.555	.175	.175	.114	.25	1	-.09	-.029	.134
7	-.182	-.274	-.177	-.177	-.162	-.254	-.093	1	.249	-.095
8	-.025	-.016	.059	.059	.182	.172	-.029	.24	1	.158
9	-.214	.199	-.141	-.141	-.102	-.131	.134	-.09	.158	1

Dependent variable: Land Type Cleared.

Significant variables (correlation is significant at the 0.05 level): Market access, road access, decrease in forest cover, decrease in crop production.

Codes: 1. Decrease in forest cover, 2. Access to roads, 3. Access to markets, 4. Access to health centers, 5. Access to schools, 6. Access to water resources, 7. Access to bus stops, 8. Decrease in crop production, 9. Distance from home to farm.

4. Conclusion

The present study was an attempt to assess the land use land cover changes of the Ishkoman watershed area situated in the Ghizer district, Gilgit-Baltistan. The present study used Landsat-5 and Landsat-8 images to assess the LULC dynamics from 1998 to 2018 through supervised classification and NDVI analysis. Land cover was classified into six classes, namely Glaciers, Water, Forest and Pastures, Agriculture, Rivers, and Barren lands. In addition to Landsat temporal analysis, community perception was also explored regarding the major drivers of land cover/land use changes. A questionnaire was used to assess community perception, comments were evaluated regarding the past two decades, and the indigenous knowledge helped to understand the basic agents and causes of land use/land cover changes in the Ishkoman valley. The results showed that all six land cover classes have shown temporal changes between 1998-2008 and the most significant change was observed in the forests and pastures class, followed by the Glaciers, whereas the least significant change was observed in rivers (and water).

Table 11

Multiple Linear Regression between Population Increase and Land Use Change Variables

Model Summary				**ANOVA**					
R	R Square	Adjusted R Square	Std. Error of the Estimate		Sum of Squares	df	Mean Square	F	Sig.
.512	.262	-.019	1.160	Regression	10.041	8	1.255	.933	.041
				Residual	28.259	21	1.346		
				Total	38.300	29			

Coefficients					
	Unstandardized Coefficients		Standardized Coefficients	t	Sig
	B	Std. Error	Beta		
(Constant)	3.025	1.845		1.640	.039
Decrease in crop production	.012	.287	.009	.043	.966
Access to schools	1.139	.990	.475	1.150	.263
Access to bus stops	-.023	.399	-.013	-.057	.955
Distance from home to farm	-1.667	1.358	-.265	-1.228	.233
Decrease in forest cover	1.464	.959	.646	1.527	.040
Access to markets	.033	.728	.014	.045	.043
Access to health centers	-1.078	1.022	-.403	-1.055	.303
Access to water centers	-.864	.615	-.423	-1.404	.175

Dependent Variable: Population Increase.

Predictors in the Model (Constant): Decrease in crop production, Access to schools, Access to bus stops, Distance from home to farm, Decrease in forest cover, Access to markets, Access to health centers, Access to water resources.

Excluded variable: Access to roads.

The covered areas of Agriculture, Bare Rocks, Forests, Glaciers, Rivers and Water were 36.4, 1221.24, 454.31, 318.62, 226.39, and 157.16 km^2, respectively in 1998, which have changed into 74.44, 1460.38, 141.05, 384.06, 275.21, and 96.4 km^2, respectively in 2018. The accuracy assessment of the classified land cover maps showed an overall classification accuracy of 78.16%, 88.08%, and 89.72% for the years 1998, 2008, and 2018, respectively. Moreover, as far as anthropogenic causes are concerned, LULC showed a significant relationship with population growth, land type cleared, decrease in forest cover, access to markets, and decrease in crop production during the last two decades. The study suggested more in-depth research to examine land use land cover changes at finer scales by using high resolution satellite imagery and conducting details surveys regarding the underlying anthropogenic causes of land use dynamics.

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