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ORIGINAL ARTICLE

Classification and Evaluation of Land Cover Variations Using Landsat Data

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ABSTRACT

The importance of the quantitative statistics related to earth's natural resources and its land cover maps is undeniable. The data obtained from satellite platforms can offer a detailed overview of the natural processes and physical activities at incredible temporal and spatial resolutions. Mapping satellite images, classifying them and determining the vegetation area is a very important task for management and future planning of natural resources. The change detection practices are very important for discerning the spatial features and their conversion to urban lands. Over the years, the importance of timely and precise information presenting the extent and nature of natural land resources, especially in mountainous areas, has increased. In this paper, we have determined the vegetation cover and derived change maps using remotely sensed image data of the Abbottabad region of Pakistan. For this study, land cover mapping was achieved through interpreting satellite images of the region using ENVI 5.3 and ArcGIS Pro. Landsat images were utilized to estimate changes in land utilization pattern. To identify the changes between the years 1990 and 2016, the images were pre-processed and were categorized into five classes -i.e. forest, water bodies, settlements, agriculture land, and barren land using the maximum likelihood classifier. The post classification change detection performed over classified images shows a positive change in forest class, water bodies and settlements while a negative change in barren land, with most of the barren land been converted into agricultural land. Some of the previously cultivated areas have been converted into forest.

Keywords: Supervised classification, Maximum likelihood classifier (MLC), Post classification change detection, Change matrix

Author`s Contribution
[1,2,3,4]Manuscript writing, Data analysis, interpretation, Conception, synthesis, planning of research, Interpretation and discussion, Data Collection

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INTRODUCTION

In physical world, over the course of time, human activities are changing land cover characteristics. In such a situation, studying the features of land and its characteristics helps in detecting the changes in land cover patterns. In urbanized areas, the LULC (land use land cover) is generally the assemblage of human-induced land usage, which comprises of infrastructure such as roads, railway tracks, settlements, bridges, water-bodies, waste lands, grasslands, etc. [1, 2]. Therefore, the traditional manual mapping of land cover is fairly time consuming. In swiftly progressing environments, over the time, these maps may become obsolete and require revisions. Olorunfemi [3] states that the time series monitoring and investigation for spatiotemporal changes is extremely hard to implement with the long-established method of manual surveying. Many researches have been accomplished on changes in LULC in the past two to three decades, [4].

Studying the chronological data, observing the changes in LULC and mapping them, at regular intervals is now feasible with the advancements and provision of imagery from satellite platforms[5]. After the launch of USGS's first remote sensing satellite, Landsat-1, in 1972, many researchers have carried out numerous studies at different levels on LULC. It is concluded that that proper information regarding the transformations in earth natural resources is critical for revamping the land use analysis and managing the earth resources effectively [6]. Therefore, by utilizing GIS approaches on the multi-temporal images of the study area, the researchers can retrieve, examine and assess the changes that have occurred in the earth resource depletion patterns at a specific time period, referred to as landcover resource change detection (CD) [7, 8].

Change detection has proved to be of an immense assistance for monitoring the spatial changes, especially in the proceeding of urbanization and transformation of different land cover types into urban patterns [9, 10].

Change detection is a very important process as it gives a comprehensive insight into the spatial characteristics of LULC for examining and managing the natural reserves and the process of urbanization [11]. This information has huge significance for researchers, environmentalists and urban planners [12], who design, plan and create land-use models and predict future changes and evaluate the environmental impacts of these changes for the better management of resources.

The key purpose of this study is to figure out ground truth statistics for the land use/ land cover (LULC) of the study area for the past 26 years and to highlight the subsequent changes. However, the detailed aims include (1) to classify and demarcate different land cover types and detect the pattern of changes in land utilization for the study area from 1990 to 2016 (2) to find change statistics (3) to generate change matrix showing relative changes through the comparison of spatial maps.

LITERATURE REVIEW

Remote Sensing (RS), by deploying multiple techniques and data sets, is used to classify land and map the changes [13]. The Landsat images, at the larger scale, specifically are the most used images for the classification of landscapes into representative classes [14]. Around the world, a huge number of supervised classification techniques are extensively being used for the analysis of changes in land use [15]. Supervised [16], unsupervised, fuzzy or hybrid techniques [17] are the most widely used methods of classification.

Supervised classification requires background knowledge about the study area [18]. In this method, signatures per-pixel are recorded in the signature files in the form of digital numbers (DN) [19].

Change detection (CD) plays a very important role in bringing out the variations in images [20]. Numerous change detection (CD) practices that use remotely sensed data have been developed. Image differencing, change vector analysis (CVA), vegetation index differencing, principal component analysis (PCA) [21], are some of the direct methods of change detection. Unsupervised change detection, supervised change detection method such as post classification analysis, hybrid change detection etc. are other most frequently practiced methods of change detection [22].

RESEARCH METHODOLOGY

3.1 Study Area and Data Acquisition

After examining the topography of various regions Abbottabad was selected as the study area. It is a region in Khyber Pakhtunkhwa with highly varying topography. It lies specifically at latitude of 34.92°N and longitude of 73.13°E with a height value of 4120 feet above the sea level. It covers an area of 1,967 sqm (source: PSB)

The images for this study were of Landsat TM and Landsat 8, gathered from USGS's Landsat mission [23] for the years 1990 and 2016. Both the images were Tier-1, Level-1 data from USGS's repository. For spatiotemporal analysis, images of the onset of the summer season were acquired. The details of images are shown in Table 1.

The Landsat images acquired from USGS had other regions besides Abbottabad. To extract the study area, images were clipped using ArcGIS Pro and the shapefile extracted from PSB's level 3 data. Figure 1 shows the shapefile placed on Landsat image for the year 1990 and Figure 2 shows the study area for the year 1990 after clipping.

Table 1: Image details		
Source	Scene Date	Scene Center Time
Landsat 5	1990-04-24	05:02:12.8490750
Landsat 8	2016-05-17	05:41:32.8662720

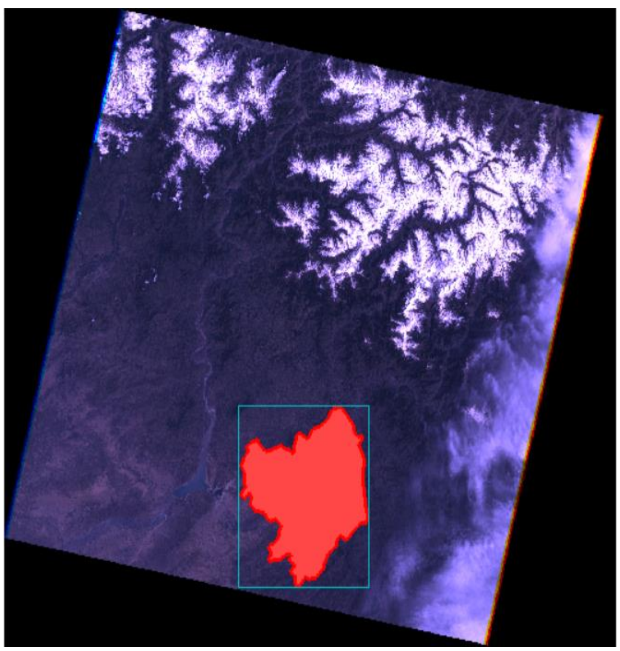

Figure 1. Extracting study area from Landsat image

3.2 Image Pre-processing and Classification

In remote sensing, prior to classification and change detection few preprocessing operations are required [24]. Image pre-processing has multiple stages which are 1- detection of bad lines and their restoration, 2- geometric rectification or co-registration, 3- absolute methods such as atmospheric and radiometric calibration, 4- relative methods like topographic correction for rugged terrain and 5- cloud masking if needed. In this research, as the images for the study area were mostly cloud free so atmospheric correction, radiometric correction and image smoothing were applied to remove any kind of artefacts. Images were co-registered with the ground truth and were found to be geometrically correct. Figure 3 shows the preprocessed image for 1990.

Figure 2. Sub-setting of pilot region

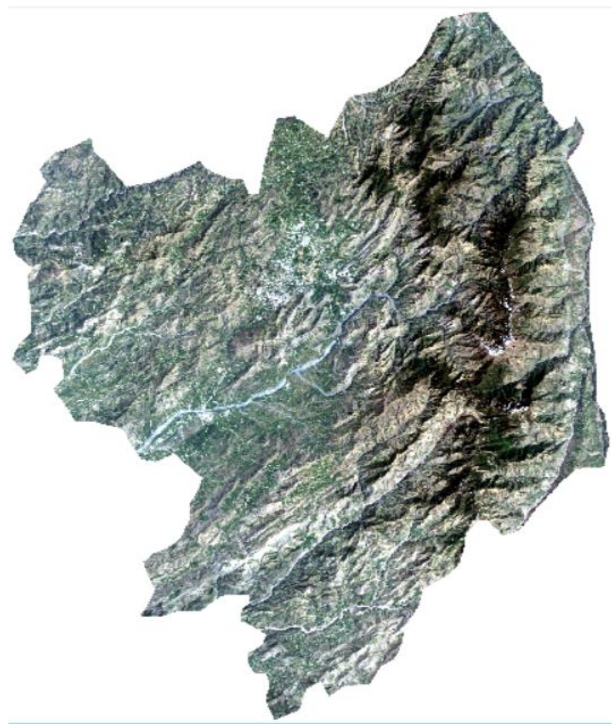

Figure 3. Pre-processed pilot region

After pre-processing, bands 1,2,3,4,5,7 and 2,3,4,5,6,7, corresponding to all the visible and Infra-Red bands for Landsat-5™ and Landsat-8 (OLI), respectively, were combined for classification using pixel-based supervised classification technique. Training the classifier using training samples is a very important step [25]. The classifier was trained by drawing 389 polygons for the year 1990 and 416 for 2016.

To classify the images, based on their spectral characteristics Maximum likelihood classifier (MLC) was used. The classification system explained in [26, 27] was used for data classification and analysis. The images were classified into forest, agricultural (cultivated) land/week vegetation, water bodies, barren land, and settlements.

3.3 Post Processing and Accuracy Assessment

The spectral variability experienced by the classifier results in salt and pepper noise. Statistical filters are usually applied for post classification processing and clearing to improve the accuracy of classification [28]. Median filter was applied to the classified images to reduce classification noise.

During classification, errors can arise from several sources, therefore accuracy assessment and knowing the accuracy associated with each class of the classified images is necessary [29]. Accuracy assessment of the classified information was done to determine its the overall reliability. Calculating error matrix and determining kappa coefficient is the widely implemented methods [30]. By implementing ISO-Cluster algorithm [31], an unsupervised classification was done to manually determine the ground truth and to assess the accuracy and generate error matrices.

3.4 Change Detection

In multitemporal images, one of the key remote sensing technique for land cover analysis is change detection [32]. To detect changes, generate the change matrix and change map post classification method was applied.

The post classification assessment (PCA) method presents the relative changes that can be interpreted easily. Progressive changes in LULC of the pilot region over for the past 26 years were investigated and the change matrices were produced. The overall workflow of the employed mechanism is presented in Figure 4.

RESULTS AND DISCUSSION

The statistics for classification, indicating the percentage cover and total area in km^2 are tabulated in Table 2.

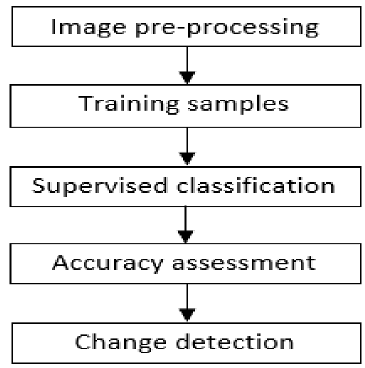

Figure 4: Change detection workflow

Table 2. Class statistics

Land cover types	1990		2016	
	Km^2	%	Km ^{2}	%
Water	59.5	3.02	74.8	3.8
Settlement	53.98	2.74	104.2	9.87
Barren	523.3	26.6	329.5	16.75
Forest	430.1	21.87	563.3	28.64
Cultivated	855.9	43.51	844.4	42.9
Others	44.22	2.25	50.8	2.58

Table 3 shows the overall accuracy and kappa coefficients. For classification accuracy assessment, according to Lea [33], an overall-accuracy of around 90% and kappa-coefficient values of around 0.9 are required. From the results presented in Table 3 it can be clearly observed that these measures have successfully been achieved.

Table 3. Accuracy assessment

	Overall Accuracy	Kappa Coefficient
1990	95.492	0.9232
2016	95.492	0.946

LULC maps in Figure 5 show a shift in vegetation patterns. Some areas in the west, having weak vegetation or were being cultivated in 1990, now have been converted into barren land. Agricultural land in the

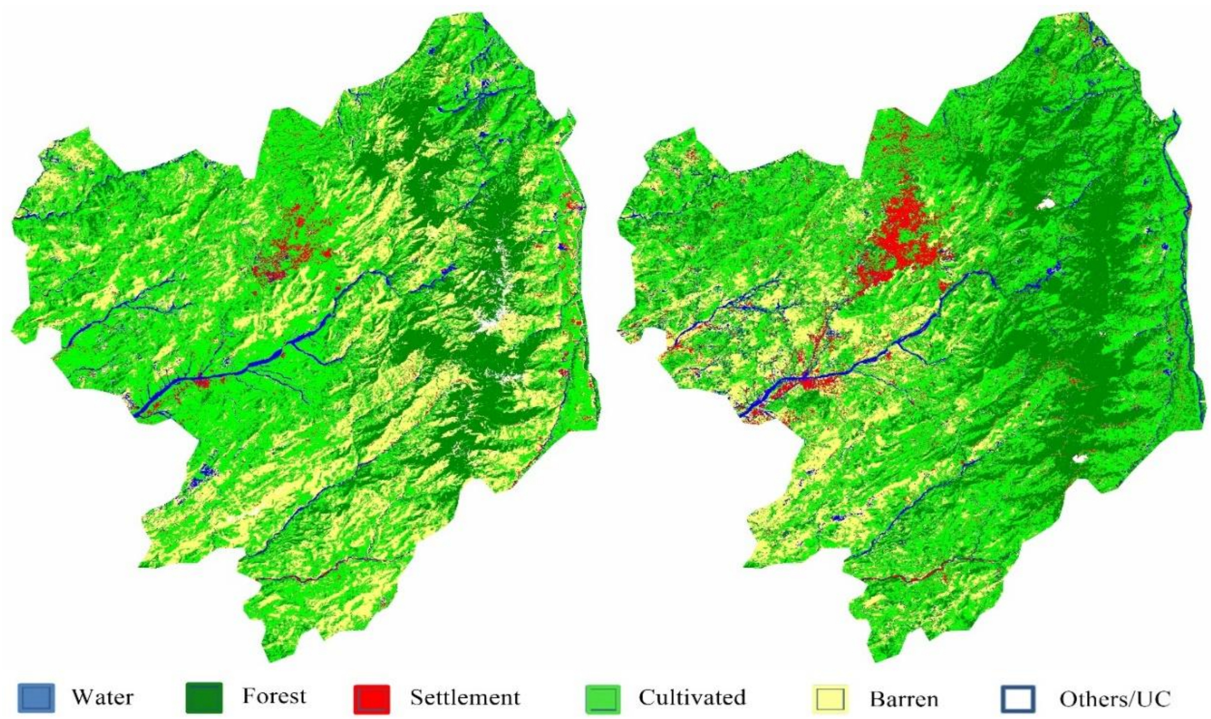

Figure 5. LULC maps for 1990 (right) and 2016 (left)

heart of the district lost its area to settlements while vegetation in the eastern part has been converted into forest.

Areas that were previously used for agricultural purposes have been converted into settlements. As a result of snow melting, due to increase in temperature, a subtle supply of water during the onset of the summer season has been noticed which resulted in the increase in area of water bodies. A shift in vegetation pattern has also been observed. The agricultural land in the west has changed into barren land, due to lack of rain as agriculture in this area mainly depends on rain water. The barren land in the center and some of the forest has changed into agricultural land.

Due to increase in awareness as a result of Green drive and less use of timber for household and industrial purposes forests have flourished. Change detection of the pilot region for the years 1990-2016 was performed using supervised type of classification technique. Furthermore, change detection results in terms of change in area in km2 is presented Table 4. Figure 6 shows the class wise percentage of each category in the pilot landcover for the considered time period of years 1990-2016 based on maximum likelihood classifier (MLC) [34]. The results show a noticeable increase in area of forest and a decline in barren land/rocks. Forest class that covered 21.87% of the total area in 1990 now covers 28.64%, while barren land declined from 26.6% to 16.75%.

Settlements, 2.74% in 1990, have increased by almost 4 times now covering 9.8%. A slight positive change of 0.78% in water bodies and a slight negative change of 0.61% in agricultural area/weak vegetation has been noted.

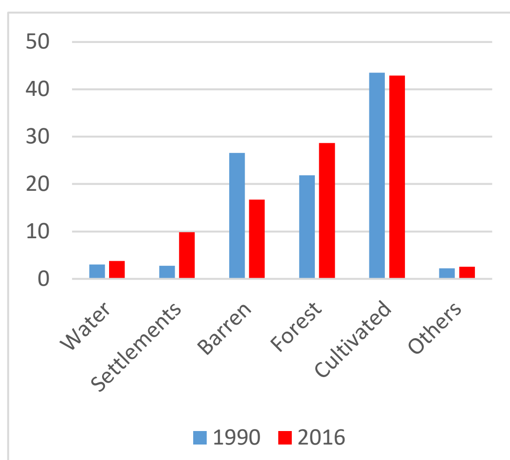

Figure 6. Class wise percentage land cover

Table 4: Relative change in area (km2) of land cover types between 1990 and 2016							
		1990					
		Barren	Cultivated	Settlements	Forest	Water	Total
2016	Barren	156.302	145.277	3.738	14.045	10.174	329.536
	Cultivated	286.875	477.356	17.793	53.884	8.47	844.378
	Settlements	17.92	55.58	25.726	1.416	3.542	104.184
	Forest	39.746	159.175	1.3	355.088	8.036	563.345
	Water	19.167	16.689	5.076	4.769	29.108	74.809
	Total	523.276	855.853	53.975	430.047	59.398	

Table 4 shows the nature of relative changes in the five representative classes. Settlements that now cover 104.2 km2, 53.98 km2 was still developed area in 1990 and gained 17.79 km2 from agricultural land. Increase in area of forest from 430.1 km2 in 1990 to 563.3 km2 in 2016 is mainly from cultivated area. Out of 855.9 km2 cultivated area 477.4 km2 originally belonged to the same class while it gained 159.2 km2 from forest and 145.3 km2 from the barren land.

CONCLUSION

It is concluded that by utilizing remotely sensed imagery and supervised method of classification for the pilot Abbottabad region of KP, Pakistan that the pattern of land use has greatly changed over the past 26 years.

The process of urbanization in the heart of the Abbottabad district endangers vegetation. An unrestricted growth in urban land cover, increase of nearly 300%, may result in many challenges. Therefore, proper management of land utilization pattern is needed to maintain a balanced ecosystem. Proper planning of settlements, considering all the challenges as a result of urban sprawl, must be done on the basis of Environmental Impact Assessment.

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