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RESEARCH ARTICLE

URBAN AREA EXTRACTION AND LAND USE LAND COVER MONITORING OF CHARSADDA DISTRICT, PAKISTAN

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ABSTRACT

The research of land use and land cover (LULC) changes aids in the management of environmental sustainability. The study investigates fluctuations in urban development, LULC, and the advancement of an environmentally sound area of Charsadda in Pakistan's Khyber Pakhtunkhwa province. The method of classification algorithm of maximum likelihood for Landsat 7 and 8 obtained from 2007 to 2019 has been evaluated and carried out for a period of 12 years using a geographic information system and remote sensing data. For the extraction of the urban area and calculating changes in the composite of classed images, the raster Boolean approach has been utilized. To reduce negligible noise objects, post-classification filtering methods have been used. According to the classification findings from 2007 to 2013, the built-up area increased by 13.76 percent. Barren land has seen a 10.12% decline and vegetation has had a 3.73 percent gain, while aquatic bodies have seen a 0.08 percent increase. During the six-year period between 2013 and 2019, the built-up area increased by 11.52 percent, although vegetation (2.49 percent) and bare land decreased rapidly (8.90 percent). Water bodies also decreased by 0.12% at this time. The study's findings suggest that the most significant changes have been found in built-up land, which increased by 25.29 percent overall between 2007 and 2019, despite a significant reduction in the vegetation zone and bare land. For the years 2007, 2013, and 2019, the total accuracy of land use and land cover classification has been 0.78 percent, 0.79 percent, and 0.76 percent, respectively. The study's findings reveal a number of important changes in land-use and land-cover patterns in the studied area, which can be used to make recommendations and serve as a foundation for urban planning.

KEYWORDS

LULC Classification, Change Detection, Urban Area Extraction, Remote Sensing and GIS

1. INTRODUCTION

In the last two centuries, the expansion of urbanization and industrialization has resulted in a change in land use and land cover (LULC), leading in the degradation of future sustainable conditions (Abijith and Saravanan 2021). This rapid urbanization is not proceeding in a straight line (Bose and Chowdhury 2020). Pakistan is one of the world's most populous countries, and it has experienced dramatic changes in LULC during the last seven decades, including a decline in forest, a shift in cropland, and an increase in urbanization. Remote sensing and Geographical information systems application in natural and land resources management is widely used globally. A strong tool for storing, analyzing, and displaying geo-referenced data utilized in change detection investigations is Geographic Information Systems (GIS). In many researches, the integration of the two technologies is rarely investigated (Yasir et al., 2021). A combination of remote sensing and geographic information systems (GIS) is widely regarded as a useful and efficient method for detecting landuse and landcover variations over time. Land use and land cover variation as one of the main forces of global environmental changes, and for sustainable development. Current technologies such as remote sensing and Geographical information systems provide a cost effective and accurate alternative to understand the dynamics of landscape. In compared to earlier methodology, RS and GIS techniques offer enormous benefits; these instruments are particularly effective and efficient for monitoring dynamic changes in land use-land cover (Yasir et al., 2020; Ouedraogo 2010). Digital satellite image base recognition of landuse and landcover (LULC) constructed on multi-spectral and multi-temporal remote sensing data have portrayed an abundant capacity to know the landscape changing aspects to observe, recognize the map and to monitor modifications in an arrangement of LULC for a specific period of time. GIS and RS, for example, have made it possible to analyse landscape patterns in a cost-effective and precise manner (Raziq et al., 2016). Land use land cover change is a continual process influenced by both natural and man-made factors. In order to fully comprehend the temporal dynamics and possible changes in land cover, anthropogenic and environmental mechanisms must be properly studied (Chughtai et al., 2021; Silva et al., 2020; L. Singh et al., 2021). The study of land use land cover change necessitates a thorough understanding and assessment of all the elements that cause these environmental changes. In impervious areas, the chances of turning rural land into urban land increase (Rahman et al., 2012). Agricultural land, built-up land, nature reserves, wildlife protection areas, and other types of land are included in

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the phrase land-use. While land-cover is used to show the many types of physical land on the surface of the earth. Water, snow, grassland, woodland, and bare soil are common terrain covers (Zafar and Zaidi 2015). The changes in LULC have important uses in urban area planning and environmental management (Deng et al., 2009, Lambin et al., 2000, Jensen 1996, Regos et al., 2015, Rimal 2011, Asselen and Verburg 2013, Vizzari, 2011). Geographical information systems and remote sensing applications are crucial in LULC calculations of any land capability and appropriateness, particularly for urban sprawling operations, research, and investigation. It is important for LULC recognition, land cover modification, transformation recognition, post-classification approaches, spatial and temporal investigations of urban expansion, and its impact on the environment and climate (Abdel Rahman et al., 2016, Appiah et al., 2015, Nahiduzzaman et al., 2015, Raziq et al., 2016). The rapid increase of urban encroachment and LULC alterations, particularly in the cities of developing countries, has drew the attention of regional and urban planners. One of the important aspects that causes LULC variations and urban area expansion is an increase in population density and growth (Alphan, 2003; Yuan et al., 2005; Al-Dosary and Khan, 2010; Dewan et al., 2012). Urban sprawl also raises the living cost, land values, social and economic stratification (Rahman, 2011). Changes in land use and land covers are one of the driving factors of global climatic changes and environmental sustainability.

Based on the above discussion, the current study analyzes the variations in LULC and sprawl of the urban area in the district Charsadda by using the remotely sensed data of Landsat for the years of 2007, 2013 and 2019. The current study's objective is to classify LULC classes during these time periods, as well as change recognition that occurred in each LULC class, in order to track and calculate the sprawling of urban region changes discoveries and reactions to population growth in the Charsadda district over the last twelve years. The study region is heavily cultivated and expanding rapidly in terms of agriculture. The study's findings may aid decision-makers in enacting better policies and planning in the areas of land use and urban growth, as well as resource management.

2. Materials and Methods

2.1 Study Area

The District Charsadda situated in the province of Khyber Pakhtunkhwa, Pakistan (Figure 1). It positioned between 71° 53' to 71° 28' East longitudes and 34° 03' to 34° 38' North latitudes. The whole research area is approximately 996 km2 (Khan et al., 2013). The Kabul, Jindi, and Swat rivers all flow through Charsadda, and these rivers are the main source of irrigation for the district and its neighboring areas. Because the Swat and Kabul Rivers are primarily snow-fed, the discharge rate increases in the spring owing to snowmelt in the Hindu Kush Range (Fida et al., 2020). The area surrounded by the River Swat and the River Kabul is known as Doaaba and is quite important in the district, whereas the River Kabul separates the Charsadda and Peshawar districts. The Warsak dam, which is located on the south bank of the Kabul River, keeps the river at a trickle for most of the year.

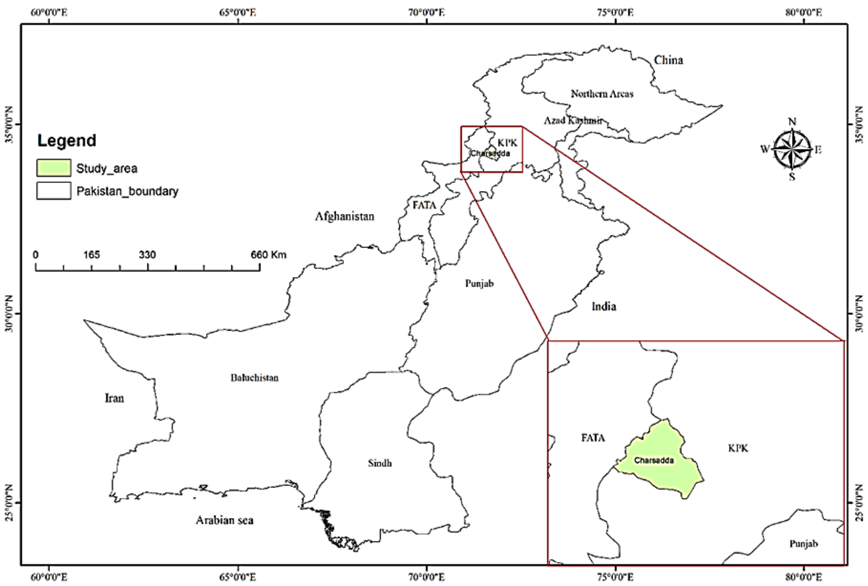

Figure 1: Location map of the research area (Google Earth 2019)

2.2 Dataset and Preprocessing

Three different images that are not even influenced by the atmosphere Landsat 7, 8 data for the research region were taken from the US Geological Survey's (USGS) Earth Explorer Explorer (http://earthexplorer.usgs.gov) website for the specified time periods of 2007, 2013, and 2019 (Table 1). The data for this project was formal preprocessed by the USGS and delivered as level-one terrain-corrected (LIT), Landsat data in WGS84 geodetic datum, Universal transverse Mercator Map projection (UTM, Zone 42N). Due to the nature of LIT data, the radiometric distortion and geometric were previously adjusted prior to the provision of the data (Jensen, 1996, Raziq et al., 2016, Seilheimer et al., 2007).

Table 1: Details of the Landsat datasets utilized in this investigation.

Year/Month	Sensor	Path/ Row	S.R	Cloud	No of Band	Format
21/8/2007	Landsat_7 ETM+	151/36	30	0	7	Geo TIF
21/8/2013	Landsat_8 OLI	151/36	30	0	11	Geo TIF
15/08/2019	Landsat_8 OLI	151/36	30	0	11	Geo TIF

2.3 Research Methods

The maximum likelihood supervised classification method was used to classify Landsat satellite images from 2007 to 2019 into four LULC classes: built-up land area, barren land area, water body, and vegetation. Both Landsat imaging and the MLC produce excellent results. The employment of histogram and scatter plot methods for the separation of the used bands in the LULC classes, on the other hand, is extensively investigated for the signatures of LULC classes. The research area was identified, and signature files for each LULC class were created. To calculate the LULC training samples, a histogram and scatter plot were used (Bhatta, 2010, Chen et al., 2014). After that, supervised MLC was used to categorize the three images, and Boolean approaches were used to extract the urban zone from both satellite images, as well as statistical analysis for LULC classes. Several post-classification approaches were used to completely polish the LULC classed image and remove noise; the filter used in this study is the common filter 3 x 3 neighborhood relationship. Finally, the LULC raster calculator was used to calculate the statistic in terms of hectares and percentages. The program Arc GIS 10.5 from the Environmental Systems Research Institute (ESRI) was utilized for the entire analysis in this paper.

3. Results and Discusion

3.1 Signatures of Training Samples

For the comprehensive study of the satellite images for the years 2007, 2013, and 2019, the spectral signature of LULC as vegetation in green, barren land in sandy, built-up zone in red, and water body in blue color was chosen for the analysis of the signatures of LULC by histogram and scatter plot methods for bands 1-5.The LULC signatures in the scatter plot from the 2007 image improved the findings of bands separable and greatly improved the discovery of spectral features of distinct classes of zones (Figure 2). It denotes that the majority of landuse and landcover classes are split logically. The entire landuse classes, as well as the vegetation class, are finely divided in whole bands, primarily in bands 1-2, 1-3. Though the results in the histogram of the 2007 satellite image depict the best calculation of training samples to parting among the classes, particularly in bands 1 and 2 (Figure 3). The built-up area produces the best results, though the vegetation area has high separation and spectral data in bands 3 and 5. In the image of 2007, the water bodies have the best separation in bands 4 and 5, although the barren zone in band 4 has high spectral values in the histogram results (Figure-3). From sensibly divided to moderate separation, separability in the 2013 image signatures defined the best minimum separation in overall landuse and landcover classifications (Figure-4). The overall landuse classifications are well divided, especially in bands 1 and 5. In the classes of landcover and landuse, however, there is a little parting result in bands 1, 2, and 3, while in bands 1 and 4, there is a far better split-up than in bands 1, 2, and 3.

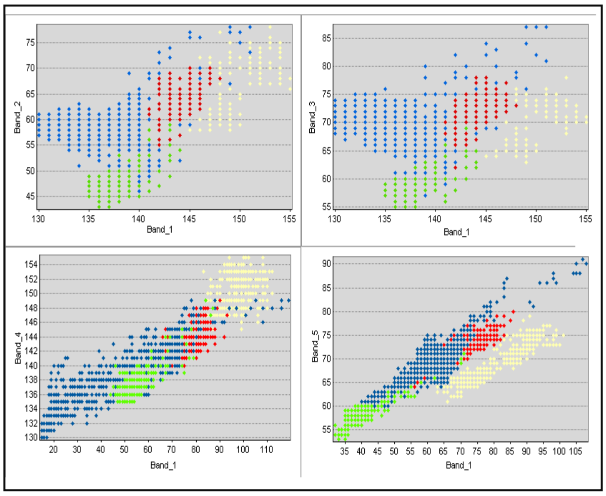

Figure 2: Various Bands From 2007 Image Characterized Using LULC Signatures and Scatter Plot Techniques.

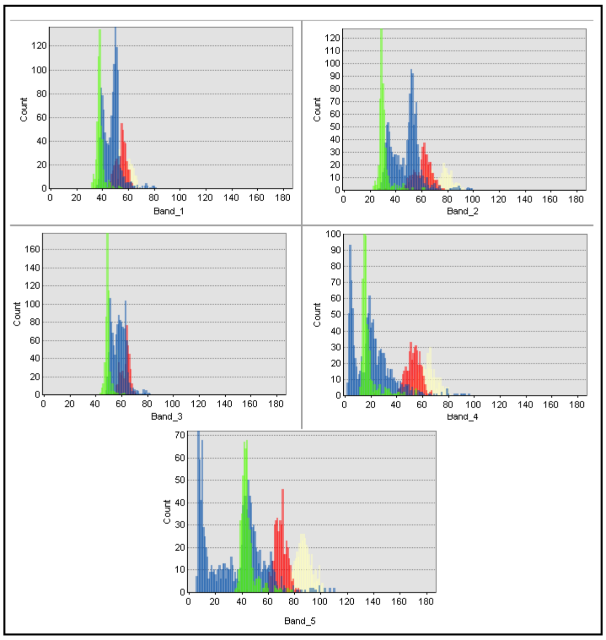

Figure 3: Landuse Landcover Signatures and Histogram Methods Illustrate Various Bands From 2007 Image.

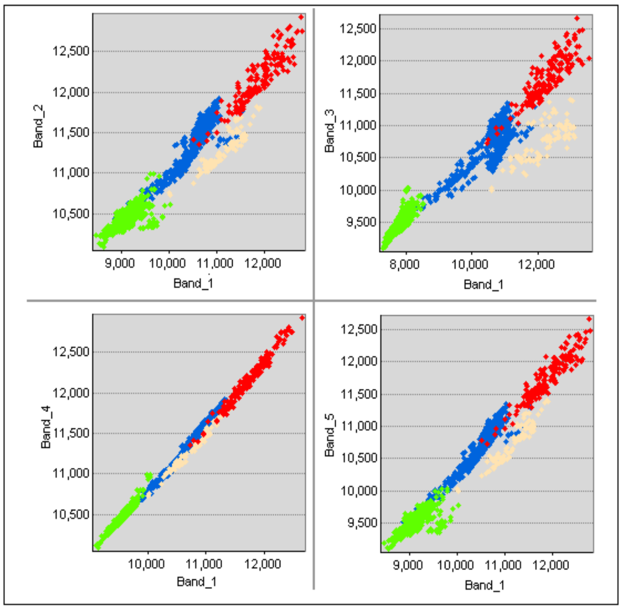

Figure 4: Land Use Land Cover Signatures and Scatter Plot Methods Illustrate Various Bands From 2013 Image.

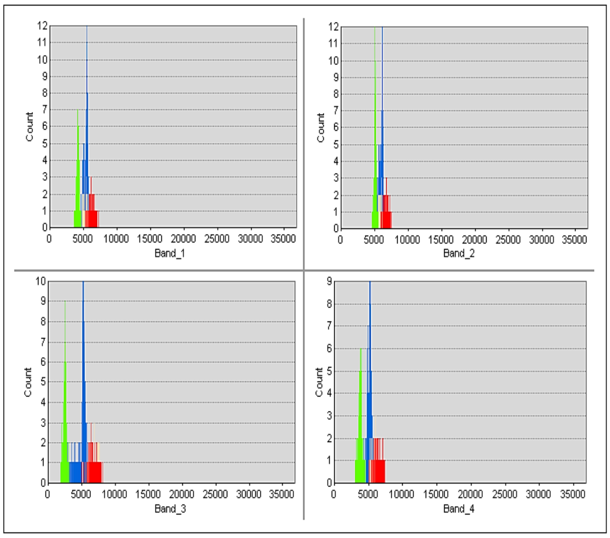

Figure 5: Land Use Land Cover Signatures and Histogram Methods Illustrate Various Bands From 2013 Image.

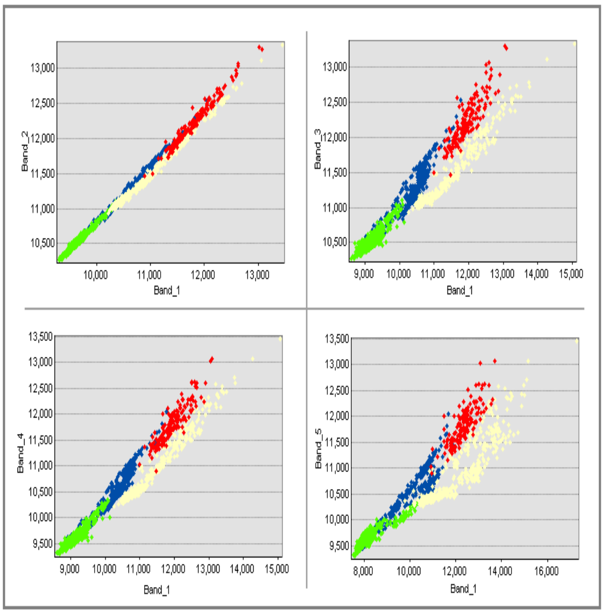

Figure 6: Land Use Land Cover Signatures and Scatter Plot Represent Various Bands From 2019 Image.

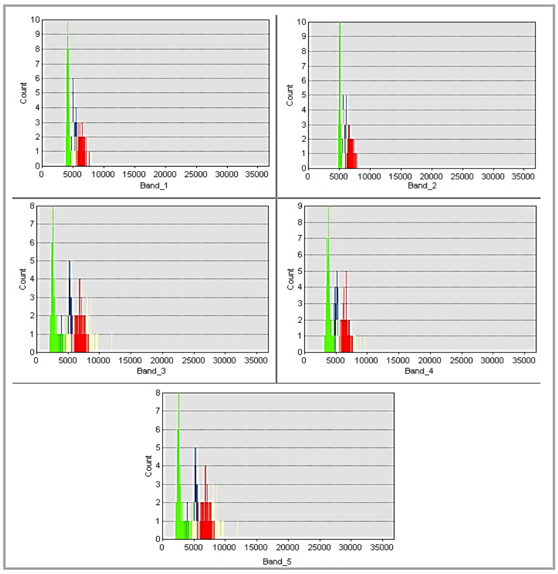

Figure 7: Land Use Land Cover signatures and histogram represent various bands from 2019 image

In comparison to the findings of the 2007 image of the signature of histogram of landcover and landuse classes, the results of the histogram in Figure 5 from the 2013 image signature do not exhibit good results (Figure 5). In 2013, as seen in Figure 5, the histogram signatures show the water bodies to be exceptionally distinct in all five bands. The built-up area is divided fairly, however the barren land and vegetation are not perfectly divided (Squires 2002, Lillesand et al., 2008, Rahman 2016). From sensibly divided to moderate separation, the 2019 image signatures defined the best smallest separation in overall land-use and land-cover classifications (Figure 6). Overall land-use classes are well split, particularly in bands 1 and 5. However, there is little parting in the bands 1, 2 and 1, 3, whereas in the classes of land-cover and land-use, there is a significantly greater split-up in bands 1 and 4. When compared to the results of the 2007 image of the signature of histogram of land-cover and land-use classes, the results of the histogram from the 2019 image signature do not show a satisfying outcome (Figure 7). The vegetative bodies are clearly defined in the five bands of the histogram signatures in the 2019 image (Figure 8). The built-up area is divided fairly, however the barren land and water are not precisely divided (Squires 2002, Lillesand et al., 2008, Rahman 2016).

3.2 Analysis of Landuse and Landcover Images

3.2.1 LULC Analysis for the year 2007

Figure 8 (a, b, c) shows the classification results of LULC obtained using the maximum likelihood classification approach for three different time periods within the study region, whereas Figure 8(d) and 10 shows the classification results of urban area. For the classification of Landsat-7 ETM+ 2007 and Landsat-8 OLI 2013 and 2019 imageries, four classifications are constructed for both satellite images to generate exact results. Table 2 presents the statistical analysis for each land cover class from the 2007 Landsat 7 images. However, the outcome of the maximum likelihood classification technique for the 2007 image is stated (Figure 8a). The built-up in percentages is 4.90 percent, and water bodies are 1.76 percent, vegetation is 57.36 percent, and barren land is 35.98 percent, according to statistical analysis of the 2007 images categorization outcome. In terms of square kilometers, the built-up area is 48.58 km2, the vegetation is 567.42 km2, the barren land is 356.11 km2, and the water body is 18.34 km2. As demonstrated in the findings of the classification of the 2007 image, an extraordinarily significant change is identified among the vegetative zones and built-up land, which are measured in percentages of 57.36 percent and 576.42 Km2 respectively (Table 2).

Table 2: Land use and land cover classes statistical analysis for the years 2007, 2013, and 2019.

Research Area		2007		2013		2019	
District Charsadda	LULC classes	Km2	%	Km2	%	Km2	%
	Water	18.34	1.76	18.34	1.85	17.12	1.73
	Built Up	48.58	4.90	184.84	18.67	298.85	30.19
	Barren Land	356.11	35.98	255.93	25.86	167.84	16.96
	Vegetation	567.42	57.36	530.47	53.62	505.77	51.12
	Total	989.59	100.00	989.59	100.00	989.59	100.00

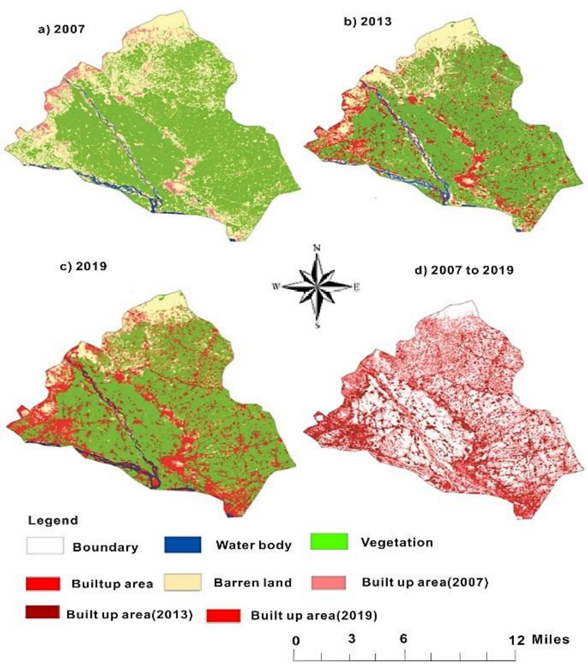

Figure 8: a) Map of LULC for the year of 2007, b) map of LULC for the year of 2013, c) map of LULC for the year of 2019, and d) urban extraction and change map for the years of 2007to 2019.

3.2.2 LULC Analysis for The Year 2013

The 2013 Landsat 8 OLI classified image result shows a rapid rise in the built-up zone (Figure 8b). According to statistical analysis, 1.85 percent of the land is covered by water, 53.62 percent by vegetation, 25.86 percent by barren land, and 18.67 percent by built-up zone. In terms of square kilometers, the built-up zone is 184.84 square kilometers, vegetation is 530.47 square kilometers, barren ground is 255.93 square kilometers, and the water body is 18.34 square kilometers (Table 2). While the statistics of landuse and landcover classes have been measured, it has been found that a rapid growth is occurring in the built-up zone, a significant decline in barren land and vegetation has been disclosed. The differences and changes in vegetation and built-up areas of the research region are 34.95 percent and 345.63 km2, respectively (Table 2).

3.2.3 LULC Analysis for The Year of 2019

The 2019 Landsat 8 OLI categorized image result shows a rapid rise in the built-up zone (Figure 8c). According to statistics, the water body accounts for 1.73 percent, vegetation for 51.12 percent, barren ground for 16.96 percent, and built-up area for 30.19 percent (Table 2). Although a rapid rise has been observed in the built-up zone, several key reductions have been uncovered in the barren land and vegetation. The research area's vegetation and built-up area differ by 20.93 percent and 206.92 km2, respectively (Table 2).

3.2.4 Detection Changes Between 2007 and 2013

The identification of total changes in comparison to the results of the 2007 Landsat 7 ETM+ and 2013 Landsat 8 OLI imageries reveals that statistical analysis is used to obtain the results of changes from previously classed satellite images from 2007 and 2013 (Figure 9). The built-up zone underwent the most changes from 2007 to 2013, accounting for 13.76 percent, vegetation 3.75 percent, barren area 10.12 percent, and water bodies 0.087 percent of the entire LULC (Table 3). Between these two time periods, there is a total change of 26.17 percent and 274.24 Km2 in all classes. To summarize the LULC changes during the preceding six years, satellite images from 2007 and 2013 show that built-up land increased rapidly due to local population density and the transition from surrounding rural to urban areas, which has accelerated urban sprawling and built-up areas. However, the vegetative area and barren zone are being converted into built-up zones, resulting in a rapid growth in urban expansion over the last six years.

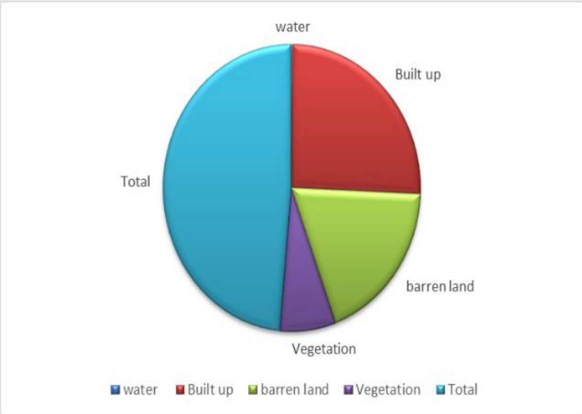

Figure 9: Detection of LULC changes trend from 2007 to 2013

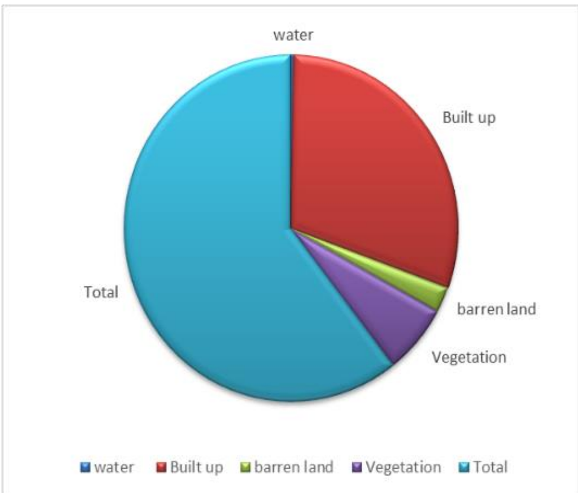

Figure 10: Detection of LULC changes trend from 2013 to 2019

3.2.5 *Detection Changes Between 2013 and 2019*

The identification of total changes when compared to the results of the 2013 Landsat 7 ETM+ and 2019 Landsat 8 OLI imageries demonstrates that statistical analysis is used to obtain the results of changes from previously classed satellite images from 2013 and 2019 (Figure 10). It depicts landcover and landuse zone variations in percentages, where abrupt changes are identified in every LULC. From 2013 to 2019, the built-up zone saw major fluctuations of 11.52 percent, vegetation area of 2.49 percent, barren area of 8.91 percent, and water bodies of 0.12 percent (Table 3). Between these two periods, the overall shifting is 23.04 percent and 228.01 Km2 in all classes (Table 3).

3.2.6 *Accuracy Assessment of Classified Images*

The error matrices are constructed and inspected in this study to illustrate the outcomes of the accuracy assessment. Error matrices are a common means of broadcasting classification errors particular to a specific site (Campbell et al., 2011). It demonstrates the "dependency of the class to which each pixel appropriately fits (columns) on the map unit to which it is assigned by the particular analysis (rows)" (Myint et al., 2011). The error matrix is also used to calculate the user's accuracy (UA) and producer's accuracy (PA) for each classified dataset. For the years 2007, 2013, and 2019, the total accuracy of LULC classification using the maximum likelihood technique is 0.78 percent, 0.79 percent, and 0.76 percent, respectively (Table 4).

Table 3: Detection of LULC Changes Trend from 2007 to 2013 and 2013 to 2019.

		2007-2013		2013-2019	
Research Area	LULC classes	Km2	%	Km2	%
District Charsadda	Water	0.86	0.087	1.21	0.12
	Built-Up	136.26	13.76	114.00	11.52
	Barren Land	100.17	10.12	88.09	8.91
	Vegetation	26.94	3.75	24.70	2.49
	Total	274.24	26.17	228.01	23.04

Table 4: Accuracy Assessment for The Years 2007, 2013, and 2019 Using The Method of Maximum Likelihood Classification.

Research area	**LULC Classes**	**2007 (%)**	**2013 (%)**	**2019 (%)**
District Charsadda	Water	0.80	0.80	0.77
	Built up	0.83	0.78	0.77
	Barren Land	0.72	0.79	0.70
	Vegetation	0.79	0.77	0.80
Overall Accuracy (OA)		0.78	0.79	0.76

3.2.7 *Urban Area Extraction*

Significant variations and assessments can be seen in the urban area in the classed images of 2007 Landsat 7 ETM+ and 2013, 2019 Landsat 8 OLI (Figure 8d, and Figure 11). The results were calculated using the 2007 Landsat image in percentages of 4.90 percent and hectares of 48.58 Km2 of urban zone. Whereas, in the 2013 Landsat 8 classed image, fast enlargement is detected in a percentage of 18.67 percent and a hectare of 184.84 Km2, and in the 2019 classified image, it is discovered in a percentage of 30.19 percent and a hectare of 298.85 Km2. Between 2007 and 2019, the total variations enlarged in the urban zone are 25.29 percent and 250.27 Km2 urban zones, demonstrating the rapid expansion of the urban sector (Table 5). Between 2007 and 2019, the total change modifications are measured in percentages of 25.29 percent and areas of 250.27 km2. The area of barren ground has decreased by 19.02 percent, while vegetation has increased by 6.24 percent, and water bodies have grown by 0.03 percent (Figure 12).

Table 5: Urban area changes trend from 2007, 2013 and 2019.

Years	**Sq. km**	**Percentage (%)**
2007-13	136.26	13.76
2013-19	114.00	11.52
Total Changes	22.26	2.54

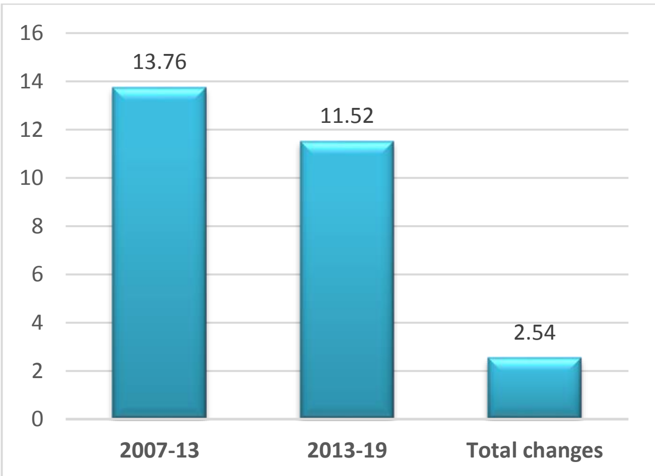

Figure 11: Trend of urban area changes of LULC among 2007, 2013 and 2019

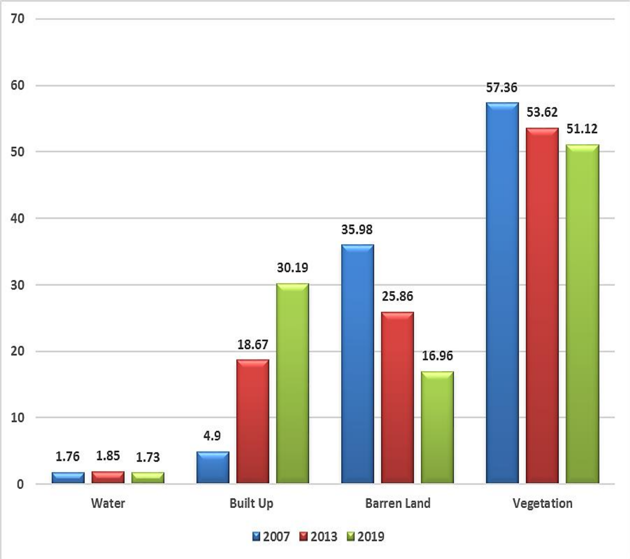

Figure 12: Analysis of Land Use Change of Charsadda District for years 2007, 2013, 2019

3.3 Discussion

The current study seeks to explain the spatiotemporal aspects of urban growth, which is regarded one of the most major anthropogenic alterations of the environmental framework. Experiments have been conducted using Landsat imagery for the years 2007, 2013, and 2019, and the current study identified vegetation, water bodies, built-up zones, and barren areas as four distinct LULC classes in the Charsadda district of Khyber Pakhtunkhwa, Pakistan. However, due to the high population growth and other framework services in the study area, such as health facilities and education, rapid urban expansion is detected. Rural-urban migration, better job opportunities, improved quality of life, natural development, and urban redefinition are all tied to urban expansion (Bank, 2007; Kafy et al., 2021). The transformation of major portions of the vegetation zone and barren land areas into urban zones has been observed in the classification of LULC. The MLC supervised technique has been used to classify Landsat images for LULC and resulted in a high level of precision across all four classes, with the least spectral characteristics. For each Landsat satellite image collected in 2007, 2013, and 2019, a total of 330 spectral signatures have been created. The spectral signatures of all four classes are analyzed using the histogram and scatter plot methods, which are used to separate bands and determine the spectral features of different LULC classes. In this work, a post-classification majority filter approach with a kernel window in the vicinity of 3 x 3 has been used to obtain the desired result. The main two findings in current research work, firstly, the MLC divided Landsat images from 2007, 2013, and 2019 into four separate classes, where vegetation cover and barren areas are often rapidly turned into built-up zones. The second result is the urban region extraction, which is evaluated during a 12-year period between the Landsat images of 2007, 2013, and 2019. In the district Charsadda, the research shows that considerable LULC classes and immediate urban sprawl are prominent. As a result, throughout the construction process, cautious demand is essential. With the passage of time, the city's size has grown, and suburbanization has developed quickly from the city's epicenter, albeit with a sluggish pace on the outskirts. Such rapid growth altered the natural landscape and impacted the district's water drainage system, signaling the possibility of flooding whenever it rains. The research assigns of transportation overcrowdings in the study assigns of urbanization has exacerbated the sewage system of water, and the study assigns of transportation overcrowdings mostly in the middle of district Charsadda.

4. Conclusions and Future Work

Using multi-temporal Landsat data, this research effort has been very valuable in understanding and examining the LULC variations and sprawling of urban areas in Charsadda district, Khyber Pakhtunkhwa, Pakistan. The current research work classified LULC classes of the district Charsadda using the maximum likelihood classification (MLC) algorithm and method employing Landsat data from 2007, 2013, and 2019. In terms of overall time of multi-temporal satellite imageries, the MLC provided satisfactory results. In the years 2007, 2013, and 2019, the MLC studied Landuse Landcover variations during the preceding 12 years and saw a significant increase in the built-up zone as a result of maximum vegetation and barren area transition, which would have been the main driver of urban expansion. The current classification results for the last 12 years show that the built-up area increased by 25.29 percent from 2007 to 2019. Although there has been a rapid decline in barren land of 19.02 percent and vegetation area of 6.24 percent. The size of water bodies has increased by 0.03 percent. A number of notable changes in landcover and landuse trends occurred in the district. The built-up zone experienced the most dramatic changes, growing by 25.29 percent between 2007 and 2019, despite a significant decline in the vegetation area and barren area. The development of population density and infrastructure are two major factors driving rapid urbanization. The urban growth of the city is spread in the city border and well thick in the city center, and the city boundary pronounces the urban expansion shape of the city. As a result, spectral signatures of all four classes are analyzed using histogram and scatter plot methods to separate bands and find the spectral features of various LULC classes' as exceptional outcomes. The findings of this study can be used to create municipal future development plans that city officials, project planners, and other organizations can utilize to make decisions about LULC policies for sustainable development, resource management, and public planning. The current study's findings have important practical and methodological implications, and future research should focus on the entire Charsadda district as well as socio-economic and environmental aspects of urban sprawl. This future research will assist us in better planning urban sprawl and the development of an environmentally sound area in Pakistan's Khyber Pakhtunkhwa region.

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