Land Use/Land Cover Change Detection During the Last Two Decades in District Ziarat of Pakistan using GIS and RS

Mr. Muhammad Hassan*, Dr. Said Qasim**, Dr. Romana Ambreen***

*MPhil Scholar, Department of Geography and Regional Planning, University of Balochistan, Quetta, Pakistan
**Professor, Department of Geography and Regional Planning, University of Balochistan, Quetta, Pakistan. E-mail saidqasim2@gmailcom
***Associate Professor, Department of Geography and Regional Planning, University of Balochistan, Quetta, Pakistan. E-mail ambgeog@gmailcom

Corresponding Author:
Romana Ambreen

Abstract

For effective natural resource planning and management, land use/land cover change is necessary. The current study is an effort to identify changes in LULC in district Ziarat through Temporal and spatial extents. This research was carried out using Geographic Information Systems (GIS) and Remote Sensing (RS). The official USGS website was used to collect three LANDSAT satellite images. These are LANDSAT-7 and LANDSAT-8 satellites. The data were collected for the years 2002, 2012, and 2022. ArcMap 10.8 was used to examine satellite images, and maximum likelihood supervised image classification was utilized to find the LULC. Results showed that the barren land increased by 3.2%, vegetation decreased by -4.2%, the built-up area increased by 1.4% and water bodies decreased by -04%. The increase in barren land and built-up regions in the research area was attributed to the loss of vegetation. This study highlighted changes that have occurred in the district of Ziarat during the past 20 years, it is crucial for future planning in the study area. Responsible authorities must have jurisdiction over deforestation and tree cutting for the construction of homes and burning. To prevent the water bodies in the research area from shrinking, the competent authorities must build minor storage dams and set up contemporary water supply systems.

Keywords: Satellite Imagery,Land Use Land Cove Change Detection,Image Classification, GIS and Remote Sensing, District Ziarat Pakistan.

1. Introduction

Man's actions on the earth's surface have significantly influenced the natural ecosystem, with just a few landscapes globally surviving in their natural state (Tiwari et al., 2011). Nowadays only a few sites on the earth remain in their original state, unaffected by human activities(Sanaullah et al., 2016). However, changes in land cover are caused by a range of shifting land-use patterns, which are influenced by several socio-economic variables and have an impact on biodiversity, heat budget, water balance, trace gas emissions, and other climate and biosphere processes (Peter et al., 2015). The Earth has experienced tremendous changes in the 21st century as a result of both natural and artificial processes (Foley et al., 2005). Human actions have changed the function and structure of ecosystems, putting people, places, economic processes, and the climate system at risk (Kasperson et al., 2001). As a result, there was a discernable pattern in land use and cover changes. Storms, wildfires, pests, earthquakes, droughts, and other natural catastrophes have all influenced the structure of natural land coverings (Adebayo et al., 2019).

LULC changes are a key driver of worldwide transformation (Vitousek, 1992). According to B.L. Gadiga, and Y Peter (2015) understandinghow LULC affects and interacts with the global earth system requires knowledge of what changes take place? where they take place? and when they take place?(Peter et al., 2015). Satellite data has shown to be particularly useful for tracking changes in LULC patterns over time, so if the geographical datasets generated are of varying scales/resolutions, GIS technologies may be utilized to measure such changes (Li et al., 2014). LULC change is a significant subject in the study of environmental change at the global scale, and over the past 20 years, researchers have created, tested, and evaluated a variety of techniques for detecting changes in satellite images (Chen et al., 2003).

Remote Sensing, GIS, and other tools for rapid and accurate spatial data collection for the spatial distribution of LULC changes across large areas are all useful (Carlson et al., 1999). A flexible framework for gathering, storing, displaying, and understanding digital data is necessary for change detection(Ulbricht et al., 1998). Satellite imagery has been widely used in forest and agricultural areas (Campbell et al., 2011). The most essential reasons for using satellite imageries are their extensive archive and high spectral resolution (Reis, 2008). In comparison to earlier techniques, satellite remote sensing has the potential to be an important instrument for tracking land-use change with high temporal precision and at a lower cost(Bastawesy, 2015). Because of its synoptic view, repeated coverage, and real-time data collecting, remote sensing data is especially helpful(Boori et al., 2014). After being geo-registered and enhanced, the obtained imagery is processed in GIS software programs using a variety of techniques, including supervised and unsupervised categorization (Macleod et al., 1998). As a standard technique, the digital process of maximum likelihood is primarily employed for change detection in a range of geographical setups(Sanaullah et al., 2016). Supervised classificationremains as one the most popular classification techniques (Friedl et al., 2002). Land use change in this research was tracked using GIS as a tool in both the spatial and temporal spheres. For managing satellite imagery, a highly advanced GIS software program named ArcMap 10.5 was used. The main objective of the study is to determine the spatiotemporal changes in LULC of Ziarat district during the period from 2002 to 2022 by using GIS and RS tools. To the author's knowledge, no research has been done on how land usage and cover have changed in the Ziarat district. This study is the first that attempt to detect changes in land use and cover in the study area. It was completed using openly accessible satellite imagery. Based on the current study, using both multi-temporal and multi-spectral images can be quite helpful for this type of research. The study demonstrated that one of the best classification methods for this kind of research is maximum likelihood supervised classification.

2. Study Area

DistrictZiarat covers 3301 square kilometers and has two tehsilsZiarat and Sinjavi(Figure 1). It is located between 67°11'18" and 68°36' East longitudes and 30°09'46" and 30°35'56" North latitudes (Fareed et al., 2021). The area of the district is mountainous and hilly and is interspersed with long, narrow, and vast valleys that support agriculture. Summers in the Ziarat district are typically pleasant, while winters are severely cold. Snowfalloccursfrom November to March.

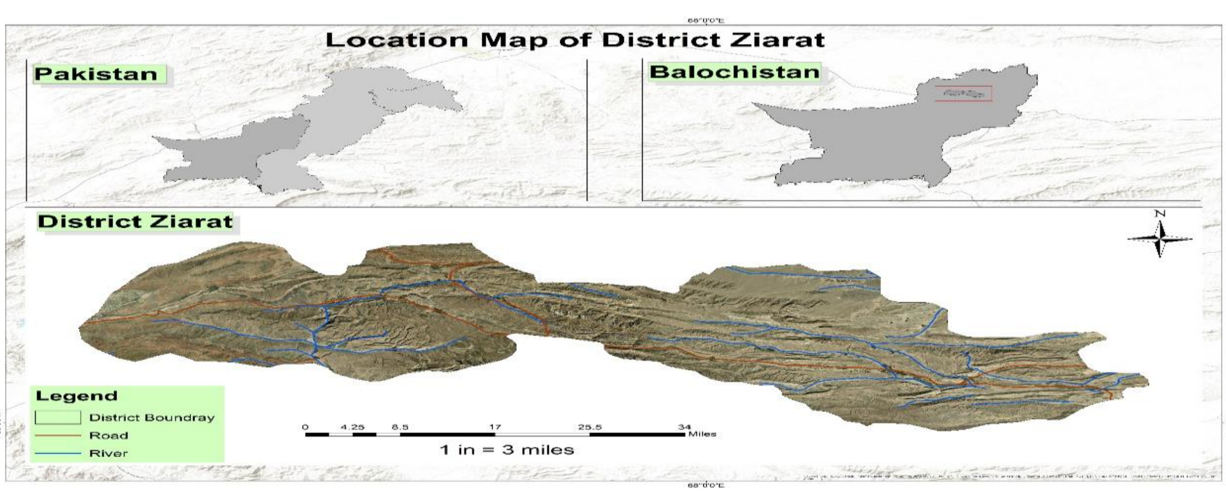

Figure 1. Location map of district Ziarat

The rainfall occurs during July and August. Ziarat is home to one of the largest naturally occurring and rare types of forest, known as a dry temperate Juniper woodland. The Juniper Forest of Ziarat is the second largest Juniper Forest in the world, it is the sole forest in Balochistan, and there are 2500–3500-year-old to 3500-year-old juniper trees here, making it one of the world's oldest juniper trees.

3.Data and Methodology

3.1. Data Sources and Acquisition

Data from various LANDSAT sensors wereutilized to detect LULC changes. Three Satellite images were obtained from two Landsat satellites via the USGS official website. The first satellite, Landsat 7, carries the Enhanced Thematic Mapper (ETM+) sensor,2002 and 2012 imagery was obtained from this sensor. The second is Landsat-8, which is equipped with the Operational Land Imager (OLI) sensor,Images for 2022 were obtained from this sensor. The data collected from these sensors had a significant spectral resolution and a relatively longer temporal range of about 20 years (2002–2022). The results of the GIS werevalidated through ground truthing.

3.2. Data Analysis

Image classification uses the spectral data that is included in the images as digital numeric values to determine the various LULC classifications that are present in the images.Using the maximum likelihood supervised classification script, the supervised classification process was carried out for this research. The selection of training samples was done with great care during this supervised classification process and pan-sharpened imagery was used to identify each LULC class. It is crucial to mention that the classification procedure was supported by the author's observation and understanding of the topic. The error matrix method was used to examine the post-classification accuracy. The accuracy evaluation supported the classification method's correctness. To detecta change in the research area, four classes of land use and land cover were identified. The details of the classes are given in Table.1

Class		Description
1	**Barren Land**	soil, stony places, and uncultivated agricultural plains without vegetation
2	**Vegetation**	All types of green grass, plants, and trees
3	**Built-up Area**	All Kinds of Settlements like cities, Towns, villages, etc.
4	**Water Bodies**	River, lake, and dam

Table 1. Land use land cover classes.

4. Results

To accomplish LULC change detection, the maximum likelihood supervised classification was utilised to categories each of the three images to for the years 2002, 2012, and 2022. Below is a detailed discussion of the classification's findings.

Results of 2002 Classified Image

According to the classified image results (Figure 2), the barren land leads the total area and covers 78.1 % (630795.14 acres) which is followed by vegetation which covers 17.5% (141343.34 acres), and the built-up covers 3.2% (25845.63 acres) of the total area. The water bodies cover the lowest of the total area,covering 1.2% (9692.11 acres) of the area. Additionally, an accuracy assessment for the classified image was also done. The image's results show that in classes the user's accuracy is good. The overall classification accuracy is 89%, which is alsoimpressive.

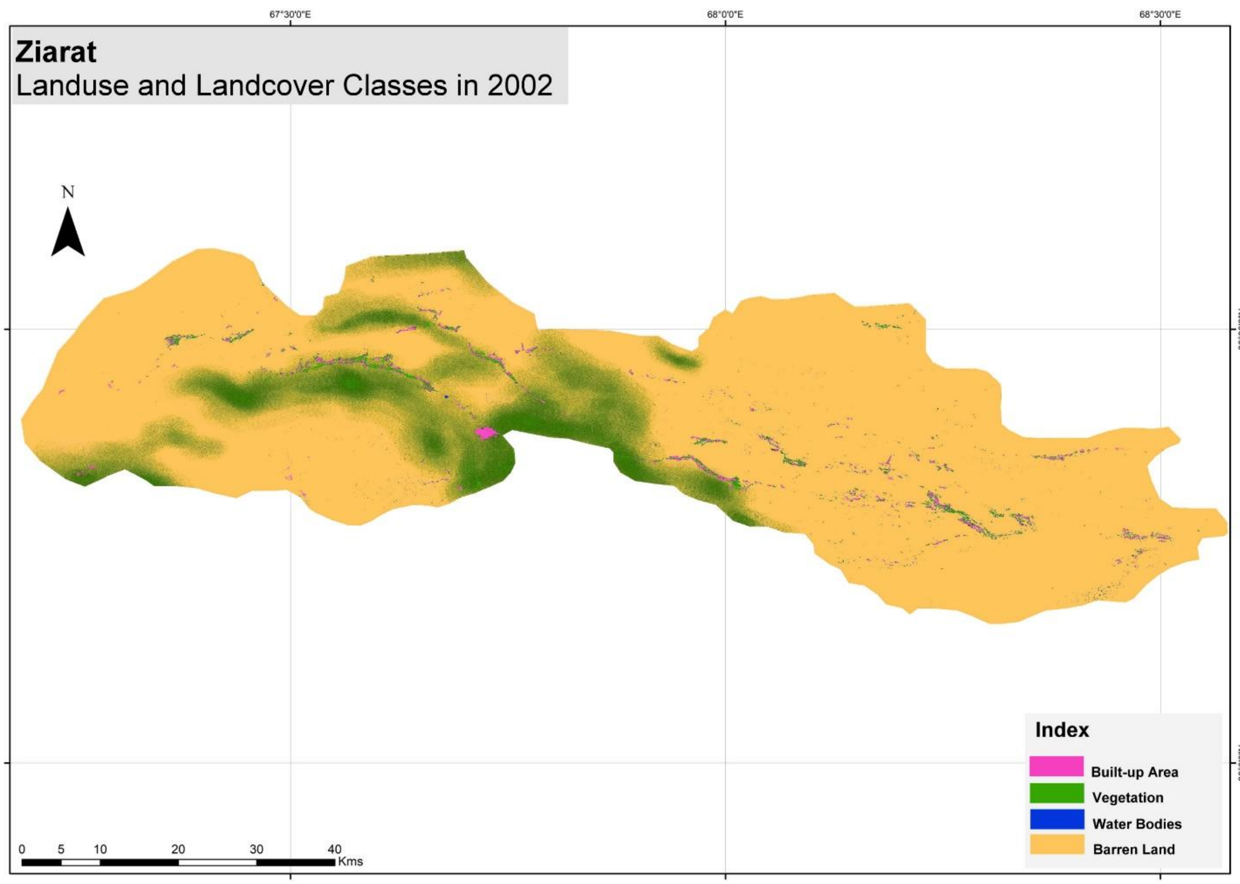

Figure 2: Classification of land use and cover for the year 2002

Results of 2012 Classified Image

The results of classification indicate that the water bodies cover the smallest portion of the study area which is 0.9% (7269.08 acres) only. A significant chunk of the overall area, 79.1%, is made up of barren land (638871.90 acres). Vegetation covers 16.2% (130843.55 acres) of the area and the Built-up area covers about 3.8% (30691.69 acres) of the total area. The overall 2012 image classification accuracy is 93%, which is quite good.

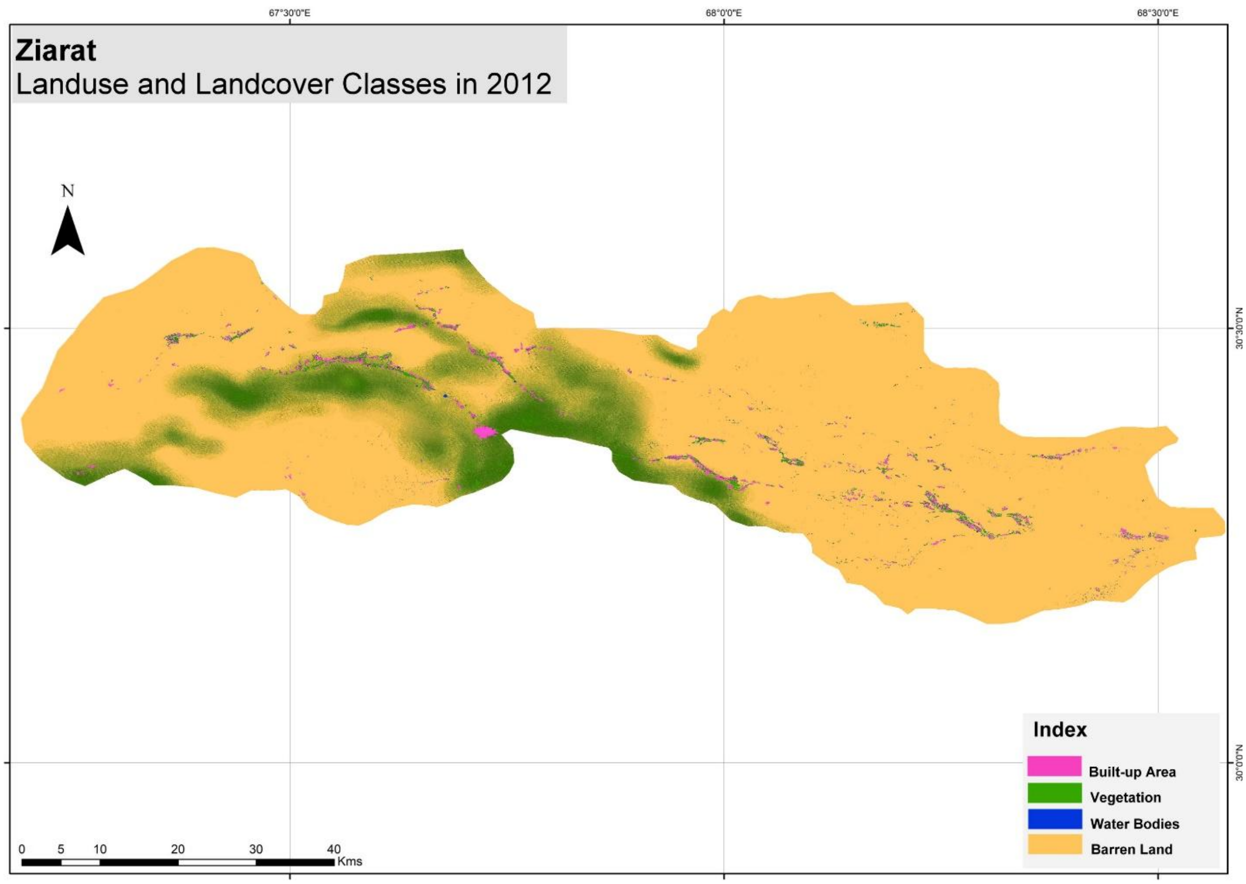

Figure 3: Classification of land use and cover for the year 2012

Results of 2022 Classified Image

According to the classification results (Figure 4), 81.3% (656640.78 acres) area is still covered by barren land. Vegetation covers 13.3% (107420.93 acres) of the total area and the built-up area covers 4.6% (37153.10 acres) of the total land area. Water bodies account for 0.8%(6461.40 acres). of the total area, which is the smallest percentage.The classification's total accuracy result is 91%, which is considered good.

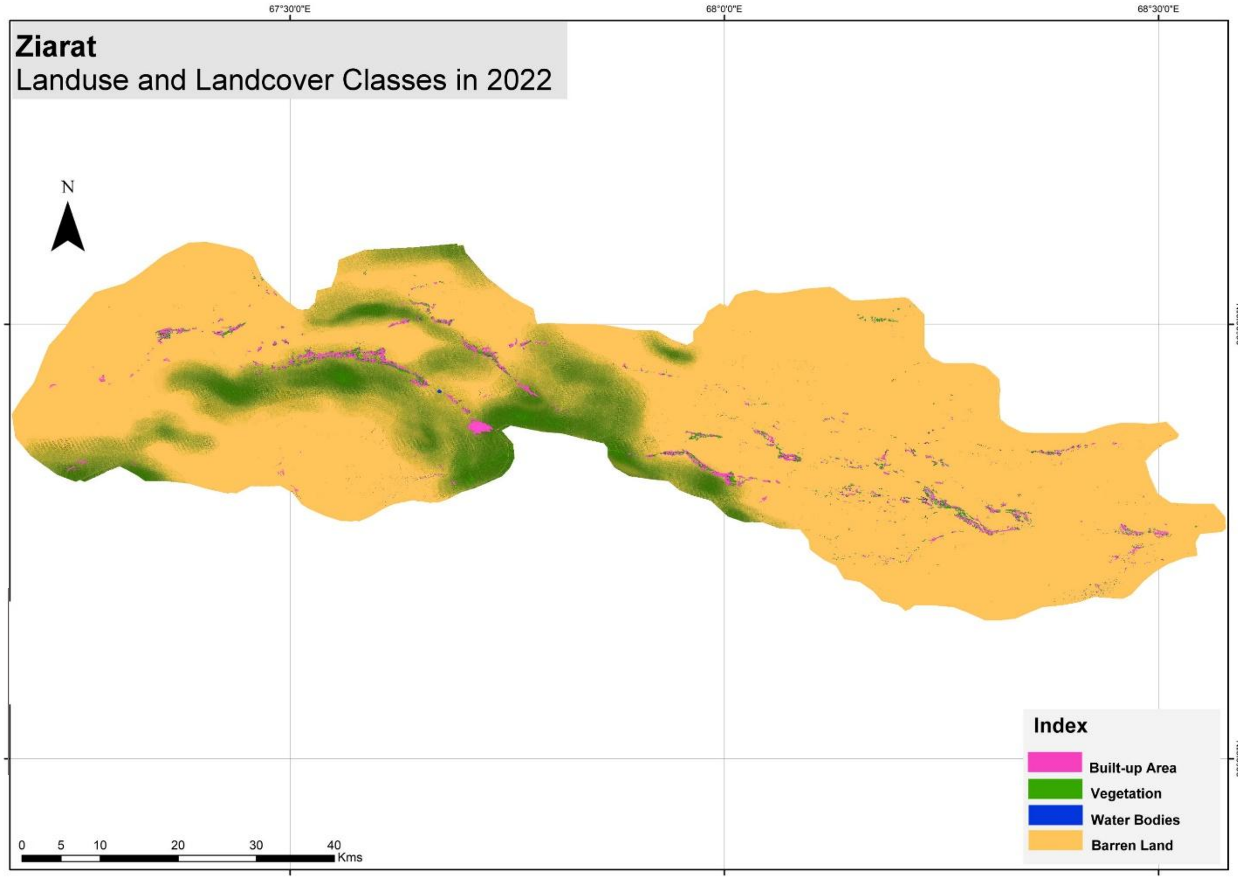

Figure 4: Classification of land use and cover for the year 2022

4.1. Land Use and Land Cover Change

After a thorough review of satellite pictures taken over a relatively long period of time (about 20 years), it was observed that 78.1% of the study area was made up entirely of barren land. in 2002 this was an increase to 79.1% in the year 2012 and its further increased to 81.3% in the year 2022. Thus, over the study period there was an overall 3.2% increase in bare land.In the year 2002, vegetation covered about 17.5% of the total land which was reduced to 16.2% in the year 2012 and to 13.3% in the year 2022.During the study period, there was an overall decline in vegetation is-4.2%. In 2002, the built-up area was 3.2% of the total area, climbed to 3.8% in the year

2012, and increased again to 4.6% in the year 2022. As a result, a 1.4% increase in the overall land use class was noted. Water bodies covered 1.2% of the total area in 2002 which slightly decreased in the year 2012 to 0.9%. By 2022, the percentage of water bodies in the overall area had further reduced to 0.8%. Consequently, a total drop of -0.4% was observed over the study period. The classification of LULC, as well as the percentage of change for each year, are given in detail in table 2.

Land Use Land Cover Class	2002		2012		2022		Change (%)	Trend
	(%)	Acers	(%)	Acers	(%)	Acers		
Barren Land	78.1	630795.14	79.1	638871.90	81.3	656640.78	3.2	Positive
Vegetation	17.5	141343.34	16.2	130843.55	13.3	107420.93	-4.2	Negative
Built-up area	3.2	25845.63962	3.8	30691.69	4.6	37153.10	1.4	Positive
Water Bodies	1.2	9692.11	0.9	7269.08	0.8	6461.40	-0.4	Negative

Table 2. Area covered annually by each class and the percentage of change.

Discussion

Despite numerous factors, including the availability of images for a particular time and recent and updated topographic maps, and the availability of high-resolution images, that made hurdle to detect a change in the research area. The goals stated for the study were successfully met by the current study in a highly effective way.

It was observed that the portion of the bare surface increased to 3.2% from 2002 to 2022. From 2002 to 2022, the area that is covered by vegetation steadily decreases by -4.2%. This indicates the shortage of water and deforestation in the study area. The built-up area is increased by about 1.2% in the last two decades (2002-2022). This can be linked to the rise in the number of settlements in the research area. Water bodies decreased in the district over the period of 20 years. A decrease of -0.4% was found in water bodies in the study area. This could be because of the drought period in recent times. Based on classification results, it is possible to predict that built-up areas and barren land will continue to take the place of vegetation.

For every upcoming research, numerous potential options needs are considered. The following suggestions are given in this regard. Differential GPS can be utilized to gather the reference data needed for accurate evaluation. When evaluating the post-classification accuracy, reference points gathered using differential GPS can produce more precise results.We used readily accessible, medium-resolution imagery to complete the current study. The imagery has a medium spectral resolution and a medium spatial resolution. This raises the risk of misclassification. Consequently, exceptional spectral and spatial resolution satellite imagery that is commercially available can be used to produce more accurate conclusions.The process of classifying and identifying classes can be helped by the use of fresh and current topographic maps. Colored aerial photos can undoubtedly aid in the process of classifying and identifying classes. If such images are accessible, they ought to be used. To notice changes in LULC, several classification techniques may be used. Despite significant findings, the study's limitations should be taken into consideration while analyzing the study's findings. Due to the lack of open sources, this study did not use high-resolution satellite imagery. If the same study is performed on high-resolution imageries, the results can be more favorable.

Accuracy assessment

The error matrix was used to calculate the user's accuracy, producer's accuracy,and kappa coefficient for each classified dataset. Fifty (50) points were taken for each class randomly for all three datasets. The overall accuracy of LULC classification was for the years 2002, 89% (Table 3), 2012, 93% (Table 4), and 2002 91% (Table 5). The overall accuracy level for LULC classification was greater than the established threshold of Anderson (1976) which is 0.85, or 85%.

	Ground truth data						
		Barren Land	**Vegetation**	**Build-up area**	**Water Bodies**	**Total classification**	**Producers accuracy**
Classified data	**Barren Land**	**46**	2	4	1	53	86.79%
	Vegetation	2	**45**	1	3	51	88.24%
	Built-up area	1	3	**43**	2	49	87.76%
	Water Bodies	1	0	2	**44**	47	93.62%
	Total samples	50	50	50	50	200	
	Users Accuracy	92%	90%	86%	88%	**Overall accuracy**	89%

Table 3. LULC classification accuracy assessment for the year 2002

		Ground truth data					
Classified data		**Barren Land**	**Vegetation**	**Build-up area**	**Water**	**Total classification**	**Producers accuracy**
	Barren Land	**49**	1	3	2	55	89.09%
	Vegetation	0	**46**	2	1	49	93.88%
	Built-up area	1	2	**44**	0	47	93.62%
	Water Bodies	0	1	1	**47**	49	95.92%
	Total samples	50	50	50	50	200	
	Users Accuracy	98%	92%	88%	94%	**Overall accuracy**	93%

Table 4. LULC classification accuracy assessment for the year 2012

Table 5. LULC classification accuracy assessment for the year 2022

		Ground truth data					
Classified data		**Barren Land**	**Vegetation**	**Build-up area**	**Water**	**Total classification**	**Producers' accuracy**
	Barren Land	**45**	0	1	2	48	93.75%
	Vegetation	2	**47**	1	1	51	92.16%
	Built-up area	2	2	**46**	2	52	88.46%
	Water Bodies	1	1	2	**45**	49	91.84%
	Total samples	50	50	50	50	200	
	Users Accuracy	90%	94%	92%	90%	**Overall accuracy**	91%

4. Conclusion

This study used geographic information system and RS to examine the LULCC that took place in Ziarat District between 2002 and 2022. Three temporal imageries were used in this research to look for changes in LULC. The images were taken from the United States Geological Survey (USGS) website, The LANDSAT satellite series strongly supports the idea that satellite images can be utilized to detect changes in temporal and spatial extents in almost any region of the world. According to the findings, between 2002 and 2022, the barren land increased by 3.2%, Vegetation decreased -by 4.2% whereas built-up area increased by 1.4% and water bodies decreased by -0.4. The increase in the barren land built-up area was the attributed to decrease in the study area. Consequently, based on this study's findings, it can be concluded that GIS and RS are now among the most efficient methods for identifying and quantifying changes in a given area's land use and land cover.

Declarations

No Conflict of Interest

Data can be provided on request

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