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Temporal and Spatial Dynamics of Land Use and Land Cover in Shirur Kasar Tehsil, Maharashtra Using Geospatial Technology

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ABSTRACT

Geographical information systems and Remote Sensing has become efficient tool for land use and land cover classification. This study was conducted in Shirur Kasar Tehsil, in the Beed district of Maharashtra, India. Multispectral images of the Landsat 8 satellite were downloaded from USGS, and a resolution of 30 m was used for this study. The processing of images was done in Arc GIS, which provides various tools and functions for image classification. The maximum likelihood supervised classification technique was used for land use land cover classification. Land use and land cover (LULC) classification was conducted for the years 2014, 2019, and 2024, spanning a decade. During the period from 2014 to 2019, agricultural land and vegetation declined by 9% and 12%, respectively, while barren land, settlement, and water bodies increased by 1%, 31%, and 81%, respectively. From 2019 to 2024, barren land and water bodies decreased by 13% and 58%, respectively, whereas agricultural land, settlement, and vegetation increased by 9%, 5%, and 19%, respectively. Significant changes were observed over the entire study period (2014–2024), particularly in settlement areas, which exhibited a continuous increase. Conversely, barren land demonstrated a notable decrease. These findings highlight the dynamic shifts in LULC classes over the decade. The study reveals substantial land use change in the study area, which was in settlement. It was increased by 38% due to increased population, migration from rural to urban areas, and demand for settlements. Accuracy assessment was done using the Kappa Coefficient method; according to the Kappa Coefficient, overall accuracy for the years 2014, 2019, and 2024 was found to be 90%, 90%, and 95%, respectively, with Kappa Coefficients 0.9, 0.9, and 0.95. Based on these results, the accuracy and kappa coefficient values have good criteria and can be used for further analysis.

KEYWORDS

Multispectral Images, Landsat, Arc GIS 8, Accuracy Assessment, Kappa Coefficient

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Land cover refers to the natural features on the Earth's surface, such as water bodies, plains, vegetation, deserts, mountains, and valleys. In contrast, land use describes how humans utilize the land for building infrastructure, agriculture, and other developments (Dissanayake *et al*., 2017). Over time, land cover tends to decrease while land use increases, driven by factors such as population growth, industrialization, and urbanization (Mengistu *et al*., 2012). This shift has led to adverse effects, including the greenhouse effect and global warming, as buildings and industrial activities replace natural landscapes (Shinde *et al*., 2022). To manage land resources effectively, countries worldwide regularly assess land cover and land use within their borders. Satellite image processing tools play a crucial role in understanding these changes by tracking land use and land cover transformations and identifying remote objects, water bodies, and soil types (Rwanga and Ndambuki, 2017).

Land Use Land Cover (LULC) maps are valuable in visualizing vegetation, water bodies, and other natural features (Comber, 2008). Various regional and global land cover products have been developed using different methods and classification systems. Satellite imagery, a primary data source for LULC studies, provides images with varying spatial and temporal resolutions, enabling the detection of specific land types. The vast amount of data generated requires efficient processing techniques for global analysis (Deshpande and S. Gurav, 2023). Remote Sensing (RS) is a key technology for LULC studies, offering detailed and accurate data about the Earth's surface (Kumar and Ghosh, 2012). This technology employs satellite imagery and aerial photography to observe and measure land characteristics without direct contact. RS provides crucial information on different land cover types, including forests, water bodies, urban areas, and agricultural lands, while tracking temporal changes (Zaidi *et al*., 2017). By utilizing sensors that capture data in various spectral bands, remote sensing allows for precise identification and classification of land features.

A Geographic Information System (GIS) is a powerful tool for capturing, storing, managing, analyzing, and displaying spatial or geographic data. GIS handles information tied to specific locations, which can be expressed as coordinates, addresses, or other geographic identifiers. GIS enables comparing and analyzing different data types, integrating, storing, editing, analyzing, sharing, and visualizing geographic information (Nagarajan and Poongothai, 2011). GIS applications allow users to create interactive queries, analyze spatial data, edit maps, and present findings. Geographic Information Science underpins these applications, studying the concepts, tools, and systems involved. Change detection involves identifying differences in the state of objects or phenomena by observing them at different times (Shyamala & Hemavathy, 2018). This process helps in understanding how human activities and natural phenomena interact and evolve over time, facilitating better resource management (Shekar & Mathew, 2023). Combining satellite data with GIS enhances change detection capabilities. Digital change detection techniques use multi-temporal and multispectral remote sensing data to monitor landscape changes.

The core idea is that land cover changes are reflected in variations in radiance values, detectable through remote sensing (Rwanga and Ndambuki, 2017). Over the past decade, various techniques have been developed for this purpose, including post-classification comparison, image differencing, image rationing, change vector analysis, and others, with the post-classification method being the most commonly employed (Kundu *et al*., 2020). Land cover changes resulting from land use do not necessarily indicate land degradation. However, shifts in land use patterns can impact biodiversity, water resources, and other processes that influence the climate and biosphere. To preserve existing natural resources and understand the causes and effects of soil and water resource over-exploitation, it is essential to map and monitor land use and land cover changes (More *et al*., 2023). Thus, this research analyzed the impact of urbanization and rapid industrialization on land use and land cover in the Shirur Kasar tehsil area of Beed district using Remote Sensing (RS) data and Geographic Information System (GIS) techniques.

Materials and Methods

Location of Study Area

The study area, Shirur Kasar tehsil, is located in the Beed district of Maharashtra, part of the Marathwada region. Situated on the southern bank of the Sindafana River, a tributary of the Godavari River, Shirur Kasar tehsil lies in the central part of the Beed district. It plays a significant role in the district's agricultural output. The region is located on the Deccan Plateau, an area well-suited for farming and covers approximately 1,317.22 square kilometers. Geographically, the study area extends between 18°7' N to 19°1' N latitude and 75°7' E to 76°1' E longitude, with an average elevation of about 570 meters (1,870 feet) above mean sea level. This elevation provides moderate climatic conditions conducive to cultivating a variety of crops. According to the 2011 Census of India, Shirur Kasar tehsil had a population of approximately 293,081, with a nearly balanced male-to-female ratio, though there is a slight male majority. The literacy rate in Shirur Kasar is below the state average, with male literacy at around 75% and female literacy at approximately 60%.

The sex ratio in the tehsil is about 930 females per 1,000 males, and the child sex ratio is roughly 880 girls per 1,000 boys. Children under the age of six comprise about 12% of the total population. The region is predominantly agricultural, with agriculture serving as the primary occupation. Major crops in Shirur Kasar include cotton, sugarcane, cereals, and pulses. Over the years, farming practices in the tehsil have evolved, combining traditional methods with modern technologies, significantly contributing to the local economy and supporting the population's livelihood. The fig 1 shows the location map of the study area.

Data Collection

Landsat-8 images were downloaded from the USGS Earth Explorer website (https://earthexplorer.usgs.gov/).

The images corresponding to the period between April 1 and May 31 for the years 2014, 2019, and 2024 were selected from this platform. These Landsat-8 images, with a spatial resolution of 30 meters and containing 11 multispectral bands, were chosen due to their relevance to the intended study period and their suitability for image classification tasks. The multispectral bands of the Landsat-8 images were utilized for change detection analysis over a 10-year period from 2014 to 2024. Image processing was conducted using ArcGIS software. A detailed summary of the images collected and processed for Land Use Land Cover (LULC) change detection is provided in the table 1. The fig 2 shows the flow chart showing the procedure for downloading multispectral image.

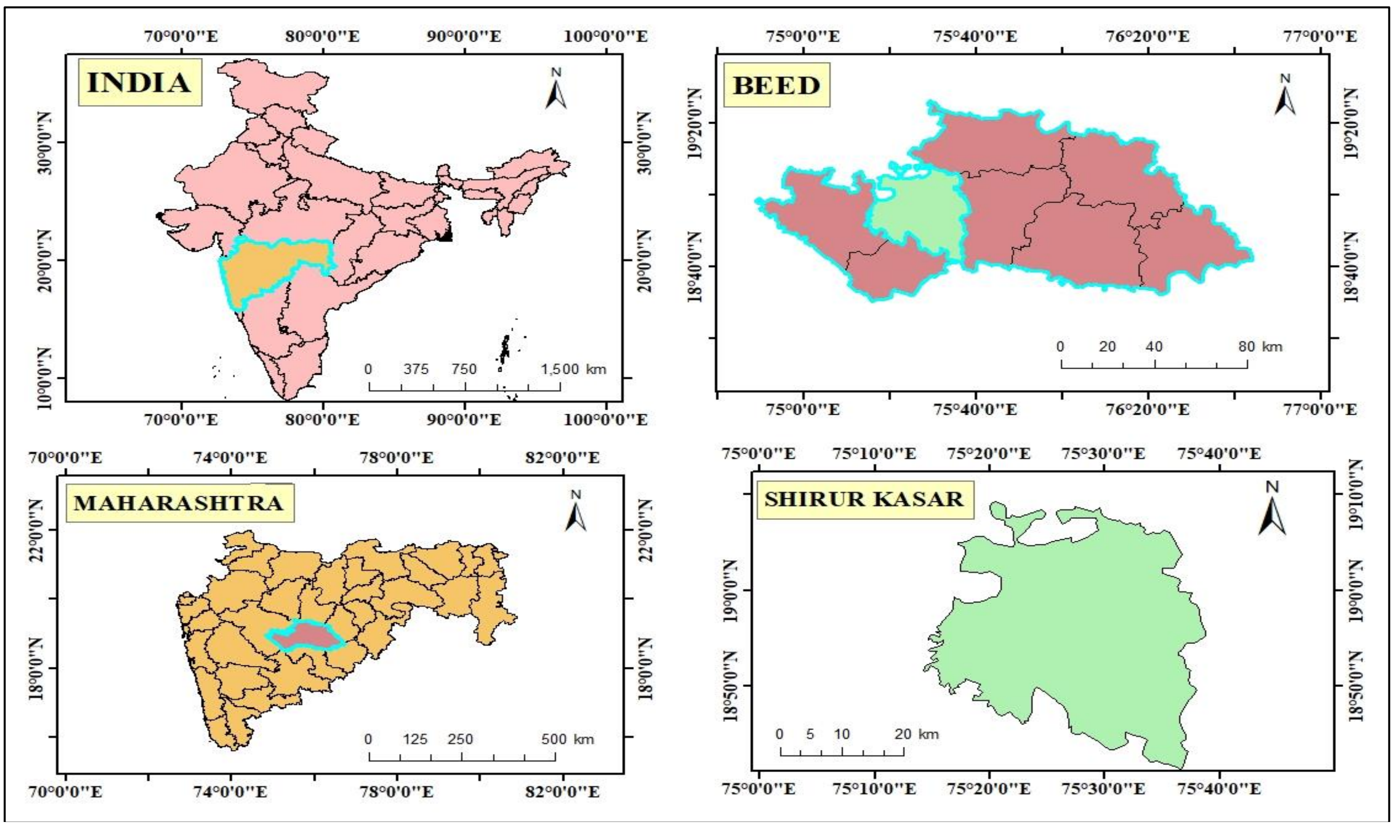

Fig 1. Location map of study area

Table 1. Details of satellite image

S. N.	Path	Date of Acquisition
1.	Landsat 8 OLI/TIRS C2 L1	01/01/2014 to 31/01/2014
2.	Landsat 8 OLI/TIRS C2 L1	01/01/2019 to 31/01/2019
3.	Landsat 8 OLI/TIRS C2 L1	01/01/2024 to 31/01/2024

Methodology

Database Preparation

Landsat-8 data were used to generate land use maps for 2014, 2019, and 2024. Image processing and interpretation for preparing Land Use Land Cover (LULC) maps were conducted using ArcGIS software.

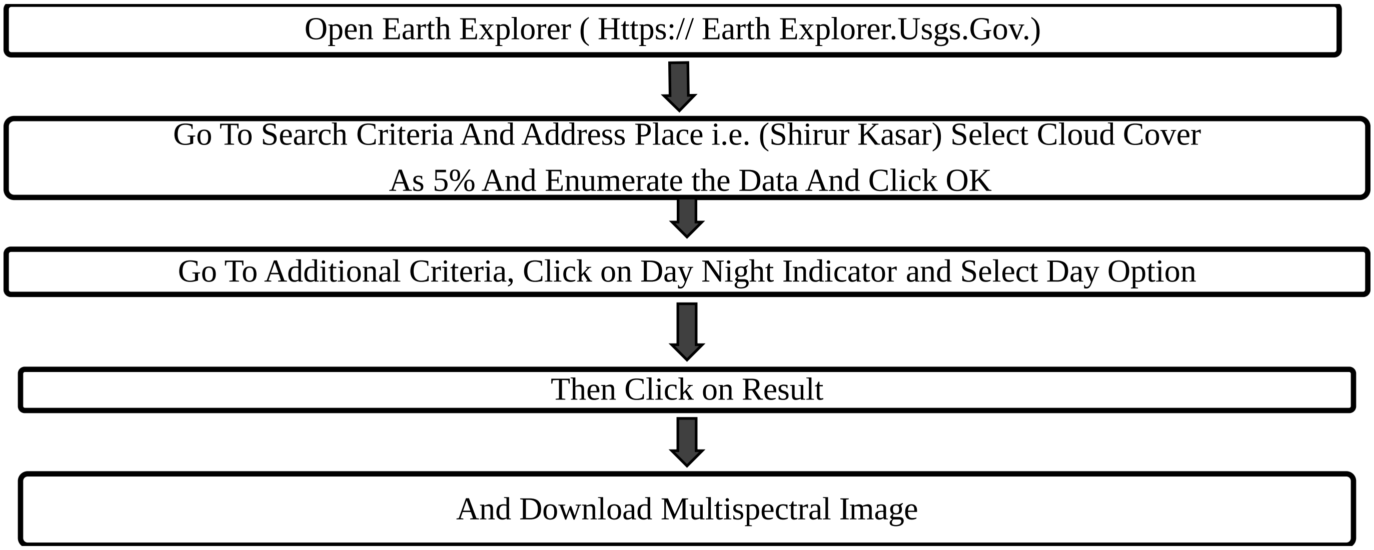

Fig 2. Flow chart showing the procedure for downloading multispectral Image

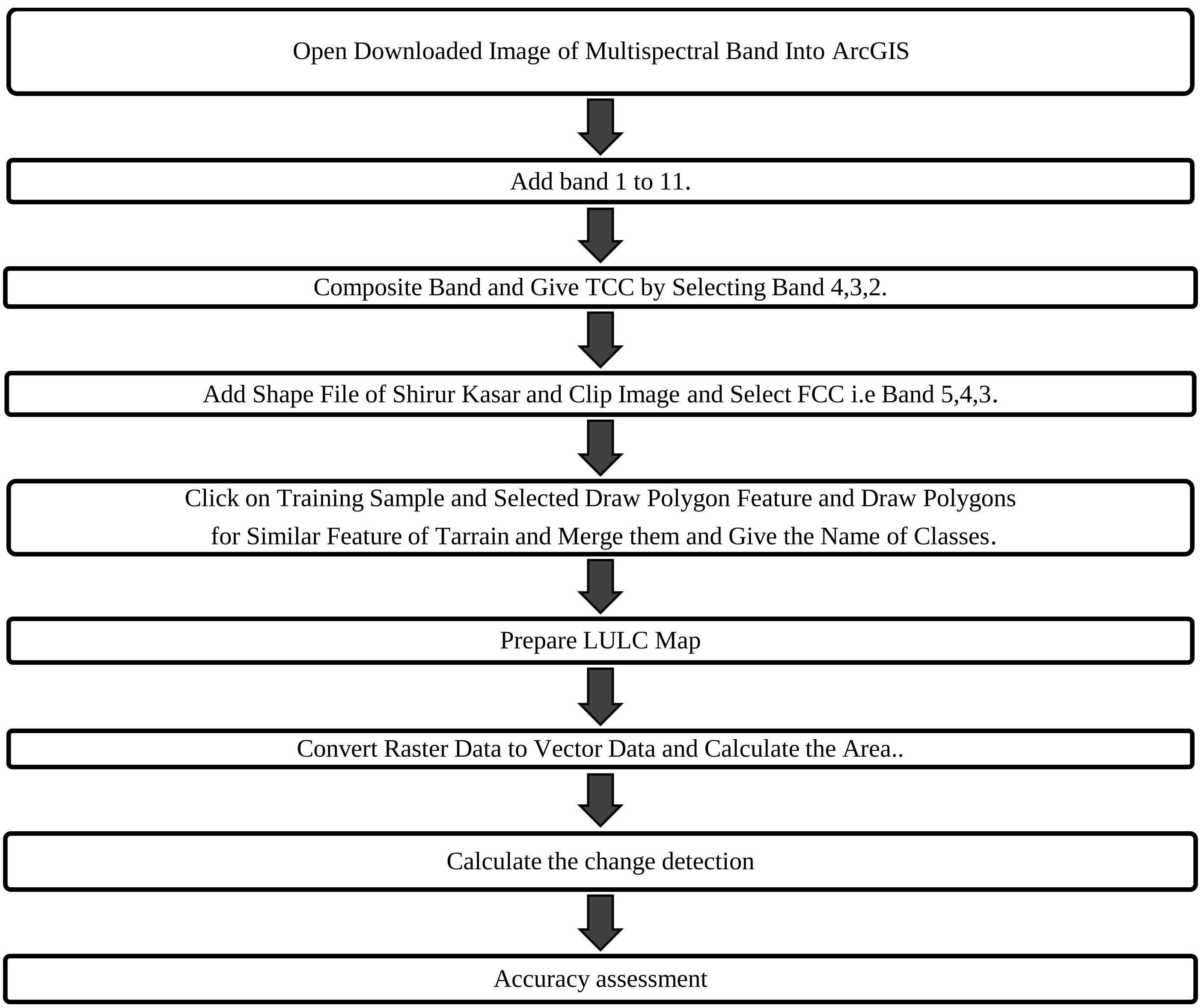

Fig 3. Flow chart showing the procedure preparation of land use land cover map

The downloaded data were imported into ArcGIS, and the area of interest (AOI), corresponding to the study area of Shirur Kasar, was extracted from the complete images for each of the years 2014, 2019, and 2024. ArcGIS, a satellite image processing software, created false color composites (FCC), facilitating the accurate visualization and classification of land use and land cover features.

Image Enhancement

Image enhancement refers to the process of modifying images to improve their effectiveness for image analysis. Various methods are available for enhancing images, each aiding in identifying different categories of information. Standard techniques include filtering, histogram modification, and band composition (Nayak and Mandal, 2019). In this study, the band composition method was employed. Each band composition algorithm emphasizes different types of information within the images. For this research, a false-color composite method was applied, combining near-infrared (band 5), red (band 4), and green (band 3) bands (Kundu *et al*., 2020). In this composite, vegetation appears in red tones, urban areas appear in blue to gray, and water bodies are shown in blue. Delineating urban areas posed a challenge with any composite method due to mixing urban pixels. However, despite this challenge, the false color composite method proved to be the most suitable choice for the study area.

Image Classification

Supervised classification is a remote sensing technique employed to categorize various land use and land cover types in satellite imagery (Dong *et al*., 2016). This method is user driven, wherein the user defines "training samples" or "signature sets" for each land cover class, such as water, urban areas, vegetation, etc. The classification algorithm uses signature sets as reference data to identify similar regions within the image. During the classification process, each pixel in the image is compared against the predefined signatures. A pixel closely matches a signature and is classified into the corresponding land use or cover category. Pixels that do not match any signature remain unclassified and are assigned to a separate category.

This technique is particularly effective for monitoring temporal changes in land use and cover, making it an invaluable tool for natural resource management (Manika and Y. V., 2023). Classifying land cover makes it possible to analyze the distribution of various land types, assess environmental changes, and provide critical insights for informed land management and conservation decisions.

Supervised Classification (Maximum Likelihood Supervised Classification)

This study utilizes the Maximum Likelihood supervised classification method as the primary approach for mapping and analyzing land use and land cover (LULC) changes (Zhu and Woodcock, 2014). This method was selected due to its statistical capability to assign each pixel in a remote sensing image to a specific class based on the likelihood that the pixel's spectral values correspond to that class. Remote sensing data for multiple years (2014, 2019 and 2024) were acquired to capture temporal land use and cover changes. These data included satellite imagery with various spectral bands appropriate for classification. Before classification, image enhancement techniques were applied to improve the quality and interpretability of the remote sensing data. The Maximum Likelihood classification algorithm was then applied in a supervised manner, where training samples representing different land cover types were selected to train the classifier. These training samples were typically identified using ground truth data or expert knowledge. The supervised classification process generated LULC maps for each study year (2014, 2019 and 2024), which illustrate the spatial distribution of various land cover types across the study area.

Land Use and Cover Change Detection

Land use and land cover (LULC) maps were generated for the study area for the years 2014, 2019, and 2024, using satellite imagery captured during April and May of each year. These maps illustrate the spatial distribution of various land types, including water bodies, vegetation, agricultural land, barren areas, and settlements. Satellite images from different years were compared to analyze temporal changes in land cover.

This comparison allows for identifying and assessing changes in land use and land cover over time. A cross-tabulation method was employed to quantify these changes to compare data from the 2014 and 2024 images. This approach facilitated the identification of shifts in land cover categories and allowed for measuring gains and losses in each land use class. The matrix summarizes the extent of land change, detailing the specific gains and losses in each LULC category between 2014 and 2024. This analysis is crucial for understanding the transformation of the landscape over time, which is vital for informed decision making regarding future land management and planning. The results of the classification and change detection analyses were interpreted to highlight trends and patterns in LULC changes. The fig 3 shows that flow chart for preparation of land use land cover map.

Accuracy Assessment

The Kappa coefficient is a widely used statistical metric in remote sensing for evaluating the accuracy of land use and land cover (LULC) classifications (Zhan *et al*., 2002). It measures the agreement between classified data and reference (ground truth) data while accounting for the agreement that might occur by chance.

This makes the Kappa coefficient a robust tool for assessing the reliability of classification results. Within the framework of LULC classification, *the producer's accuracy* represents the accuracy of individual classes from the perspective of the map producer (Dong *et al*., 2016). It quantifies how well reference (ground truth) samples for a specific class are correctly identified in the classification map. Essentially, the producer's accuracy indicates the omission error for that class. High producer accuracy implies that most reference points for the class are correctly classified, reflecting minimal omission errors.

The table 2 shows the rating criteria of Kappa statistics. Researchers can enhance the reliability and validity of remote sensing-based classifications by using the Kappa coefficient and other metrics such as overall accuracy, producer's, and user's accuracy (Arveti et al., 2016). The inclusion of these metrics provides a comprehensive evaluation of classification performance. The importance and interpretation of these statistical measures have been extensively discussed in remote sensing literature, further establishing their role in improving the accuracy and consistency of LULC studies.

$$\textbf{Users Accuracy} = \frac{\textbf{Number of correctly classified pixels in each category}}{\textbf{Total number of classified pixel in that category (The row total)}} \times \mathbf{100}$$

$$\textbf{Producer Accuracy} = \frac{\textbf{Number of correctly classified pixels in each category}}{\textbf{Total number of reference pixel in that category (The column total)}} \times \mathbf{100}$$

$$\textbf{Overall Accuracy} = \frac{\textbf{Total number of correctly classified pixels (diagonal)}}{\textbf{Total number of reference pixels}} \times \mathbf{100}$$

$$\textbf{Kappa Coefficient (T)} = \frac{(\mathbf{TS} \times \mathbf{TCS}) - \boldsymbol{\Sigma}\,(\textbf{Column Total} \times \textbf{Row Total})}{\mathbf{TS}^{\mathbf{2}} - \sum (\textbf{Column Total} \times \textbf{Row Total})}$$

Table 2. Rating criteria of Kappa statistics

S. N.	Kappa Statistics	Strength of Agreement
1.	< 0	Poor
2.	0.00 – 0.20	Slight
3.	0.21 – 0.40	Fair
4.	0.41 – 0.60	Moderate
5.	0.61 – 0.80	Substantial
6.	0.81 – 1.00	Almost perfect

Results and Discussion

The land use and land cover (LULC) map of Shirur Kasar was developed using LANDSAT imagery and applying a supervised image classification approach. Accurate measurement of LULC changes using satellite imagery involves three key steps: (1) image preprocessing, (2) selection of an appropriate change detection method, and (3) accuracy assessment.

The LULC maps were classified into five distinct categories: water bodies, vegetation, agricultural land, barren land, and settlements.

False Color Composition (FCC)

In this study, a false-color composite method was employed, which integrates near-infrared (Band 5), red (Band 4), and green (Band 3) spectral bands (Assefa *et al*., 2020; Bisht and Kothyari, 2001). This technique renders vegetation in red tones, urban areas in shades of blue to gray, and water bodies in distinct blue hues. The false-color composite approach proved particularly effective in differentiating between orchards and other forms of agricultural land, which was a primary objective of this research. However, delineation of urban areas posed challenges due to spectral mixing within urban pixels. Despite these limitations, the method demonstrated a higher degree of utility compared to alternative compositing techniques for the study area. The table 3 shows class delineated on the basis of supervised classification.

Table 3. Classes delineated on the basis of supervised classification

Class	Details	Color
Water Body	Pond, Lake, Canal, Dams, River, etc.	Blue
Vegetation	Land that is mainly covered by vegetation	Light Green
Agricultural Land	Crop Fields	Dark Green
Barren Land	Land without scrub, sandy area, dry grasses, rocky areas, etc.	Orange
Settlement	Settlement including residential; concrete manmade structure	Gray

Land Use Land Cover for 2014

The Land Use Land Cover (LULC) map of Shirur Kasar was generated using LANDSAT imagery and a supervised image classification approach. The distribution of land area across each LULC category for the year 2014 is presented in fig 6. Additionally, the area statistics for the LULC classification of the study region are detailed in table 4.

The fig 3, 4 and 5 shows the false color composition for 2014, 2019 and 2024 respectively.

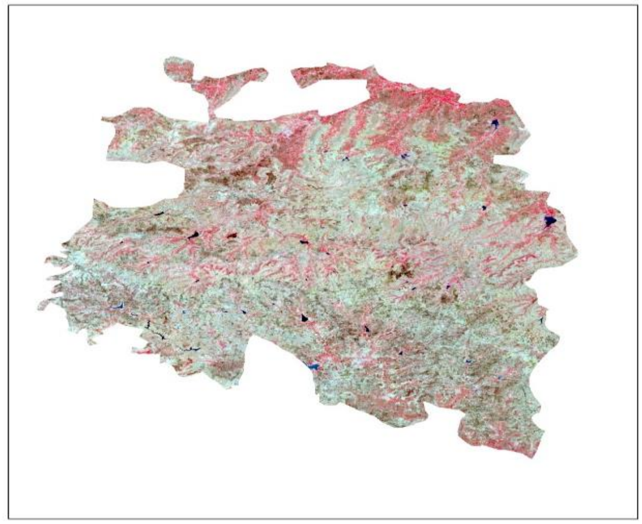

Fig 3. FCC Image of Landsat 8 sensor for year 2019

Fig 4. FCC Image of Landsat 8 sensor for year 2019

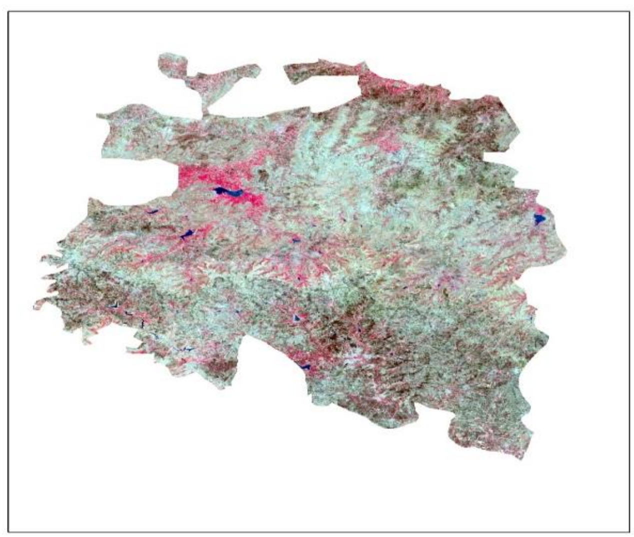

Fig 5. FCC Image of Landsat 8 sensor for year 2024

Table 4. The area distribution of LULC for year 2014

S. N.	LULC Class	Area (km^2)	% Area
1.	Agricultural Land	578.22	43.89
2.	Barren Land	495.81	37.60
3.	Settlement	160.66	12.10
4.	Vegetation	75.29	5.71
5.	Water Body	7.15	0.7
Total		**1317.22**	**100**

Table 4 reveals that in 2014, most of the study area was classified as agricultural land, covering 578.22 km² (43.89%), followed by barren land at 495.81 km² (37.60%). Settlements accounted for 160.66 km² (12.10%), vegetation covered 75.29 km² (5.71%), and water bodies represented the smallest category at 7.15 km² (0.7%). Agriculture emerged as the dominant land use type, occupying 43.89% of the total study area, while barren land was the second most prevalent category. Water bodies constituted the least classified land use type, accounting for only 0.7% of the area.

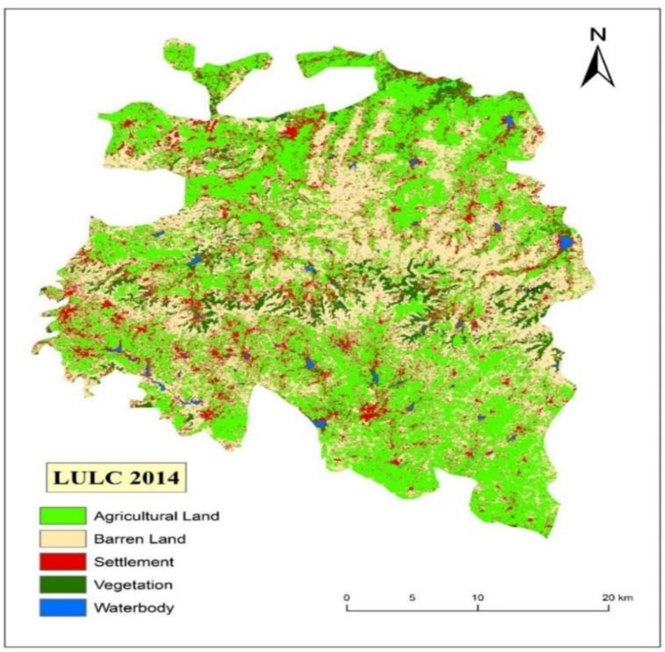

Fig 6. LULC Map of 2014

Land Use Land Cover for 2019

The Land Use Land Cover (LULC) map of Shirur Kasar was generated using LANDSAT imagery and a supervised image classification approach. The distribution of land area across each LULC category for the year 2019 is presented in fig 7. Additionally, the area statistics for the LULC classification of the study region are detailed in table 5.

Table 5. The area distribution of LULC for year 2019

S. N.	LULC Class	Area (km^2)	% Area
1.	Agricultural Land	561.12	42.60
2.	Barren Land	423.21	32.13
3.	Settlement	251.54	19.12
4.	Vegetation	73.76	5.60
5.	Water Body	7.29	0.55
Total		**1317.22**	**1317.22**

Table 5 indicates that in 2019, the largest portion of the study area was classified as agricultural land, covering 561.12 km² (42.60%), followed by barren land, which accounted for 423.21 km² (32.13%). Settlements covered 251.54 km² (19.12%), while vegetation constituted 73.76 km² (5.60%). Water bodies represented the smallest category, covering only 7.29 km² (0.55%). Agricultural land remained the dominant land use type, occupying 42.60% of the total study area, with barren land being the second most prevalent category. Water bodies accounted for the least classified land use type, comprising only 0.55% of the total area.

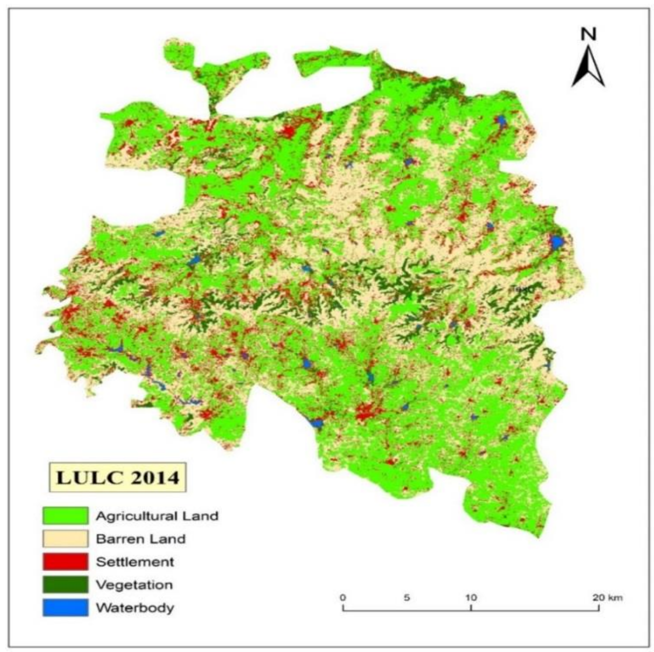

Fig 7. LULC Map of 2019

The Land Use Land Cover (LULC) map of Shirur Kasar was generated using LANDSAT imagery and a supervised image classification approach. The distribution of land area across each LULC category for the year 2024 is presented in fig 8. Additionally, the area statistics for the LULC classification of the study region are detailed in table 6.

Table 6 reveals that in 2024, the majority of the study area was classified as Agricultural land, encompassing 575.36 km² (43.5%), followed by barren land, which covered 436.06 km² (33.11%). Settlements accounted for 222.03 km² (16.86%), while vegetation constituted 78.09 km² (5.93%). Water bodies represented the smallest land use category, covering only 5.55 km² (0.6%). Agricultural land remained the dominant land use type, occupying 43.5% of the total study area, with barren land being the second most extensive category. Water bodies were the least classified land use type, comprising only 0.6% of the total area.

Table 6. The area distribution of LULC for year 2024

S. N.	LULC Class	Area (Km^2)	% Area
1.	Agricultural Land	575.36	43.5
2.	Barren Land	436.06	33.11
3.	Settlement	222.03	16.86
4.	Vegetation	78.09	5.93
5.	Water Body	5.55	0.6
Total		1317.22	1317.22

Land Use and Cover Change Detection

Land use and land cover (LULC) mapping for Shirur Kasar was conducted using LANDSAT 8 images for the years 2014, 2019 and 2024. The observed changes in LULC for these years are illustrated in fig 4 and 7. The percentage changes in LULC for 2014, 2019 and 2024 are presented in table 7. A positive change indicates an increase in the area under a specific land use or land cover category, whereas a negative change signifies a reduction in the area of that category.

Table 7. Changes in area under different LULC

S. N.	Land Use Class	% Change in Area		
		2014-2019	2019-2024	2014 - 2024
1.	Agricultural Land	-3	2	-1
2.	Barren Land	-15	3	-12
3.	Settlement	58	-12	39
4.	Vegetation	-2	6	4
5.	Water Body	-21	9	-14

Table 7 indicates notable changes in land use and land cover (LULC) categories over the study period. The area under agricultural land decreased by 3% from 2014 to 2019 but increased by 2% from 2019 to 2024.

Barren land experienced a significant decrease of 15% from 2014 to 2019, followed by an increase of 3% from 2019 to 2024. The area under settlements showed a substantial increase of 58% from 2014 to 2019 but decreased by 12% from 2019 to 2024. Vegetation cover decreased by 2% between 2014 and 2019, while it increased by 6% from 2019 to 2024. Water bodies witnessed a reduction of 21% from 2014 to 2019, followed by an increase of 9% from 2019 to 2024. A closer examination of settlement patterns reveals substantial urbanization in the region between 2014 and 2019. This urbanization led to a marked reduction in agricultural land (3%) and water bodies (21%) during the same period. These changes highlight the impact of urban expansion on natural and agricultural resources in the study area.

Accuracy Assessment

An accuracy assessment was conducted to evaluate the reliability of the results of the land use and land cover (LULC) classifications. The primary objective of this assessment was to quantitatively determine how effectively pixels were classified into the correct land cover categories. The pixel selection for accuracy assessment was prioritized for areas clearly identifiable on high resolution Landsat images, Google Earth Pro, and through field observations. For the study, a total of 150 points were created on the classified images of the study area. The accuracy assessment reference column was populated based on the best possible interpretation of each reference point.

The Kappa coefficient was employed to analyze the accuracy of LULC classification, leveraging field data for the years 2014, 2019, and 2024 alongside the classification results of Landsat-8 satellite images for the same years. A total of 50 random points were utilized to validate and accurately evaluate the classification results for each year. These random points were strategically selected to represent various land cover classes and to construct a numerical description of the spectral properties of each class. The random points were based on field data and analyzed to generate statistical insights on land use categories. This approach ensured a robust and reliable classification accuracy assessment, validating the study's findings critically.

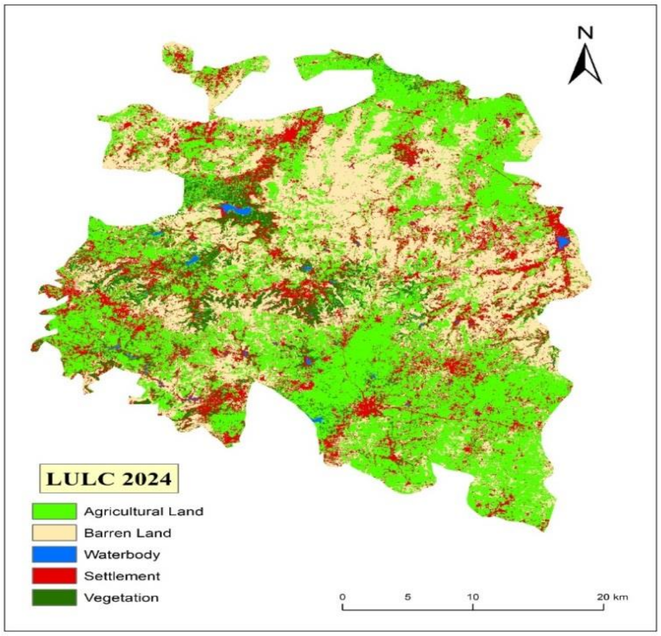

Fig 8. LULC Map of 2024

Based on the overall accuracy and Kappa coefficient results, the land use and land cover (LULC) classifications demonstrated high reliability and consistency across all study years. The overall accuracy for 2014 was 92%, with a Kappa coefficient of 0.90. Similarly, in 2019, the overall accuracy was 92%, with a Kappa coefficient of 0.90. For 2024, the overall accuracy increased to 96%, with a corresponding Kappa coefficient of 0.95. These results indicate a strong correlation between the classified outputs and the reference data, confirming the robustness and reliability of the LULC classification process conducted in this study.

The high accuracy and Kappa coefficients validate the effectiveness of the methodology used for mapping and analyzing land use changes in the study area.

Conclusion

The analysis revealed that 2014 agricultural land constituted 43.89% of the study area, which slightly decreased to 43.5% in 2024. Similarly, the area under barren land decreased from 37.60% in 2014 to 33.11% in 2024. In contrast, the area under settlement increased from 12.10% in 2014 to 16.86% in 2024. Vegetation covered 5.71% of the study area in 2014, which increased marginally to 5.93% in 2024. The area under water bodies decreased from 0.7% in 2014 to 0.6% in 2024.

The results indicate that settlement and vegetation increased over the study period among the five LULC categories, while barren land, water bodies, and agricultural land exhibited a decline. The most significant change occurred in settlements, which increased by 39%, driven by population growth, rural-to-urban migration, and rising demand for residential areas. Vegetation, the second major change category, increased by 4% due to increased awareness and local community participation in conservation initiatives, such as tree planting drives and sustainable land use practices. Agricultural land exhibited minor fluctuations, with a decrease of 1%, while barren land showed a significant reduction of 12%.

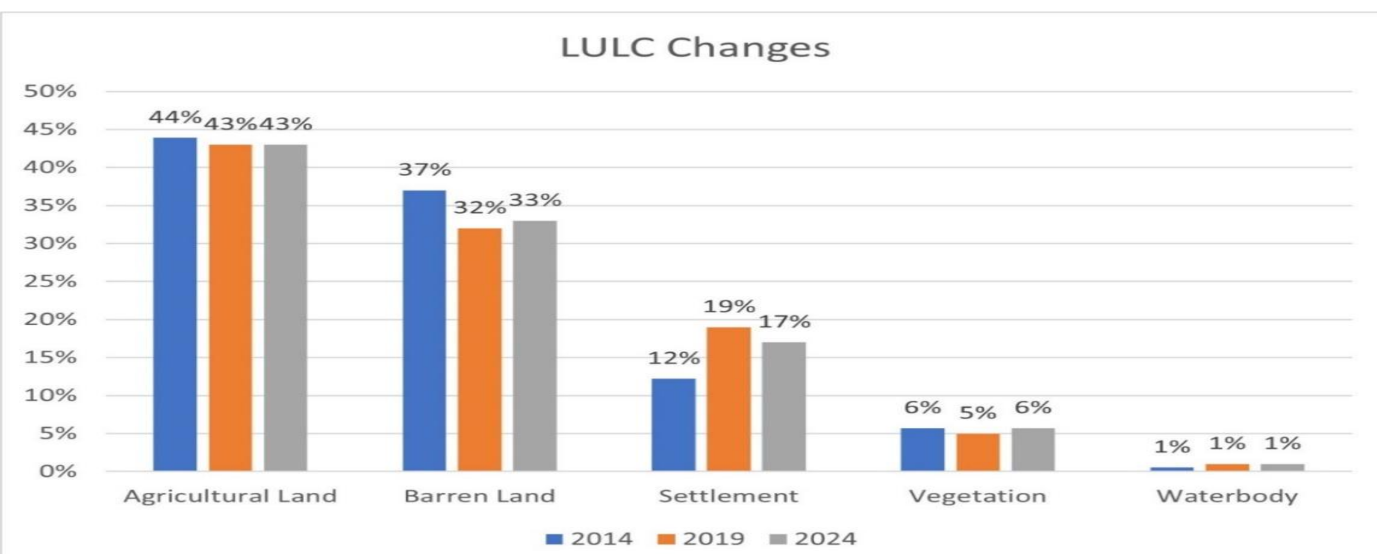

Fig 9. Comparative Study of different LULC Classes

Overall, the results highlight a trend toward increasing urbanization, with more land converted into settlements. The findings underscore the effectiveness of satellite digital image processing and GIS technology for LULC mapping and analysis. The accuracy assessment, conducted using the Kappa coefficient, demonstrated the high reliability of the classification results. The overall accuracy for 2014, 2019, and 2024 was 90%, 90%, and 95%, respectively, with corresponding Kappa coefficients of 0.9, 0.9, and 0.95. These values indicate a high level of classification accuracy, making the results suitable for further analysis and decision-making. In conclusion, this study emphasizes the utility of remote sensing and GIS in monitoring LULC dynamics and provides critical insights for sustainable land management and urban planning.

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