



MULTI-TEMPORAL LAND USE/LAND COVER CHANGE ASSESSMENT IN KANNIYAKUMARI DISTRICT, INDIA, USING LANDSAT IMAGERY AND SAGA GIS

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ABSTRACT :

Land-use and land-cover (LULC) patterns in rapidly changing regions require repeated spatial assessment to identify the conversion of agricultural and natural resources into built-up surfaces. This study evaluates multi-temporal LULC change within a selected area of Kanniyakumari District, Tamil Nadu, using Landsat imagery and SAGA GIS. Three harmonized epochs—2015–2016, 2019–2020 and 2023–2024—were investigated using Landsat 8/9 imagery. Green, red and near-infrared bands were processed to generate false-colour composites and the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Normalized Difference Built-up Index (NDBI). A supervised Maximum Likelihood classification was applied to identify major land-cover classes, followed by area estimation and accuracy assessment. The mapped built-up area increased from 111.40 to 142.00 km² between the first and third epochs, corresponding to a 27.47% increase. Over the same period, agricultural area decreased from 79.29 to 68.29 km² (13.87% decrease), while mapped water bodies declined from 68.78 to 42.47 km² (38.25% decrease). The classification assessment reported 55 correctly classified reference points out of 64, giving an overall accuracy of 85.93%. The results demonstrate substantial spatial transformation within the selected area and illustrate the value of freely available Landsat data and open-source GIS for local environmental monitoring and planning.

Keywords: Land use/land cover; Landsat 8; Landsat 9; remote sensing; SAGA GIS; NDVI; NDWI; NDBI; Kanniyakumari.

1. Introduction

Land use and land cover represent the physical and functional characteristics of the Earth's surface and are strongly influenced by interactions among environmental processes, demographic growth and economic activity. Changes in agricultural land, vegetation, surface water and built-up surfaces are important indicators of landscape transformation. Conventional field-based inventories are valuable for local verification but become time-consuming when repeated over large areas. Multi-temporal satellite observations provide a complementary means of detecting and quantifying such changes.

Remote sensing records the electromagnetic energy reflected or emitted by surface materials, allowing different land-cover types to be separated according to their spectral responses. Landsat imagery is particularly useful for long-term LULC investigations because of its consistent spatial coverage and freely accessible archive. Previous studies have demonstrated the application of multi-temporal Landsat data and supervised classification for detecting urban growth, agricultural decline and changes in natural land cover [1–4]. More recent work has also demonstrated the use of SAGA GIS for satellite-image classification and environmental mapping [5].

Kanniyakumari District is a sensitive landscape in southern Tamil Nadu containing agricultural areas, settlements, surface-water resources and remnant natural vegetation. The project report on which this paper is based identified substantial changes in the selected area between 2015–2016 and 2023–2024. The present article reformulates that project as a concise research paper, emphasizing the satellite-data workflow, spectral indices, supervised classification, area changes and accuracy assessment.

2. Study Area

Kanniyakumari District is located at the southern tip of Tamil Nadu. The source study describes a landscape containing agricultural fields, built-up settlements, surface-water bodies, sparse scrub and remnant tree cover within a tropical monsoon setting. The selected area includes urban expansion corridors, village clusters, drainage features and tank or lake systems. Relief is generally low to gently undulating, which supports the discrimination of major land-cover classes in 30-m Landsat imagery.

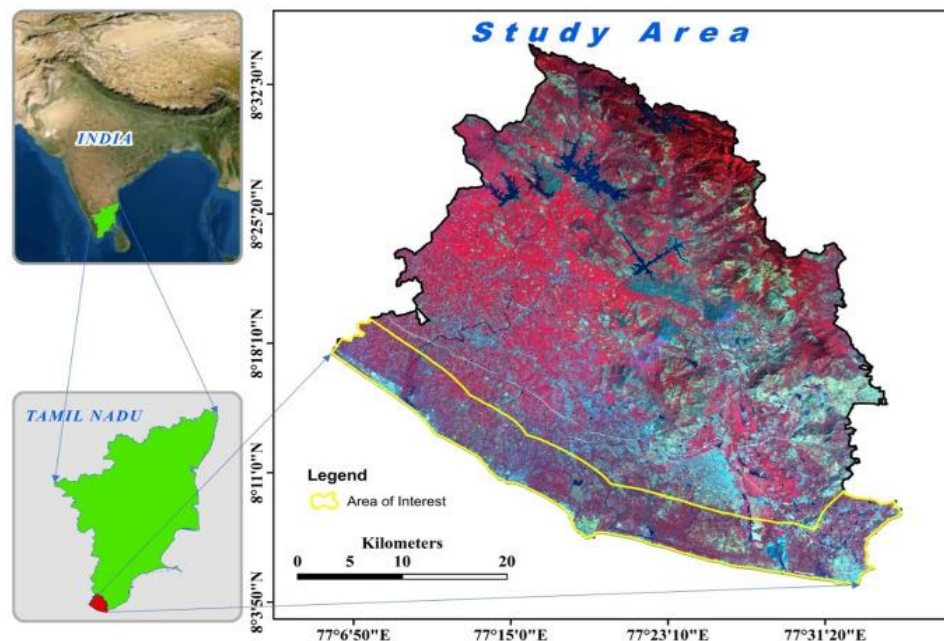


Fig. 1. Study-area map reproduced from the project dataset, showing the selected area within Kanniyakumari District.

The project methodology standardized the spatial data to WGS 84 / UTM Zone 44N (EPSG:32644). The source report describes the broader district as approximately 715 km², while the reported class-area table represents the selected mapped area rather than the entire district. Accordingly, the quantitative results in this paper are interpreted as changes within the selected area and are not presented as complete district-wide area totals.

3. Materials and Methods

3.1 Satellite data and preprocessing

Landsat 8 OLI/TIRS and Landsat 9 OLI-2/TIRS-2 imagery were obtained from the USGS Earth Explorer archive. The operational bands used in the analysis were Band 3 (green, 0.53–0.59 µm), Band 4 (red, 0.64–0.67 µm) and Band 5 (near-infrared, 0.85–0.88 µm). These are 30-m bands in Landsat 8/9. Scenes with less than 10% cloud cover were preferred, and images from comparable seasonal windows were selected to reduce phenological differences. Preprocessing included AOI clipping, band stacking, radiometric conversion, atmospheric normalization, geometric registration and cloud/shadow masking.

3.2 Spectral indices

Three indices were used to characterize vegetation, surface water and built-up surfaces:

$$\text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$$

$$\text{NDWI} = (\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR})$$

$$\text{NDBI} = (\text{SWIR} - \text{NIR}) / (\text{SWIR} + \text{NIR})$$

The project report states that NDVI values in the study ranged approximately from –0.2 to +0.8, with higher values associated with denser and healthier vegetation. NDWI was used to delineate open-water features, while NDBI was used to identify built-up or impervious surfaces.

3.3 LULC classification

A five-class LULC framework was adopted: water, vegetation, agriculture, built-up/impervious surface and barren/open land. Training regions were developed from the index maps, false-colour composites and high-resolution contextual imagery. A supervised Maximum Likelihood classifier was implemented in SAGA GIS. The SAGA GIS documentation confirms that its supervised image-classification tool supports training areas and Maximum Likelihood classification [6].

Following classification, majority filtering and raster-to-vector processing were used where required for map preparation. Class areas were calculated from the classified raster, with areas reported in square kilometres in the principal results table.

3.4 Temporal design and change analysis

Three analysis epochs were used: 2015–2016 (baseline), 2019–2020 (intermediate condition) and 2023–2024 (recent condition). Post-classification comparison was used to interpret changes in mapped classes. An additional early-2025 image was described in the project as a qualitative validation snapshot where cloud-free imagery was available.

3.5 Accuracy assessment

Accuracy was evaluated using 64 reference locations. The project report states that locations identifiable from Google Earth, Google Maps, high-resolution Landsat imagery and the ISRO Bhuvan geoportal were considered during reference-label selection. Of the 64 reference points, 55 were correctly classified. The overall accuracy was therefore calculated as:

$$\text{Overall accuracy} = (\text{number of correctly classified points} / \text{total reference points}) \times 100 = (55/64) \times 100 = 85.93\%$$

4. Results and Discussion

4.1 Spectral-index observations

The NDVI analysis produced values between approximately -0.2 and $+0.8$. High positive values represented dense vegetation, whereas low or negative values were associated with built-up, barren and water-dominated surfaces. The spatial distribution of NDVI was used to support training-region selection and interpretation of vegetation change. NDWI provided an additional means of distinguishing water bodies from surrounding land, exploiting the strong absorption of near-infrared radiation by water. NDBI was used as a complementary indicator of built-up expansion.

4.2 Land-cover change

Epoch	Built-up (km ²)	Agriculture (km ²)	Water bodies (km ²)
2015–2016	111.40	79.29	68.78
2019–2020	135.22	75.01	68.78
2023–2024	142.00	68.29	42.47

Table 1. Reported variation in the principal mapped land-cover classes within the selected area.

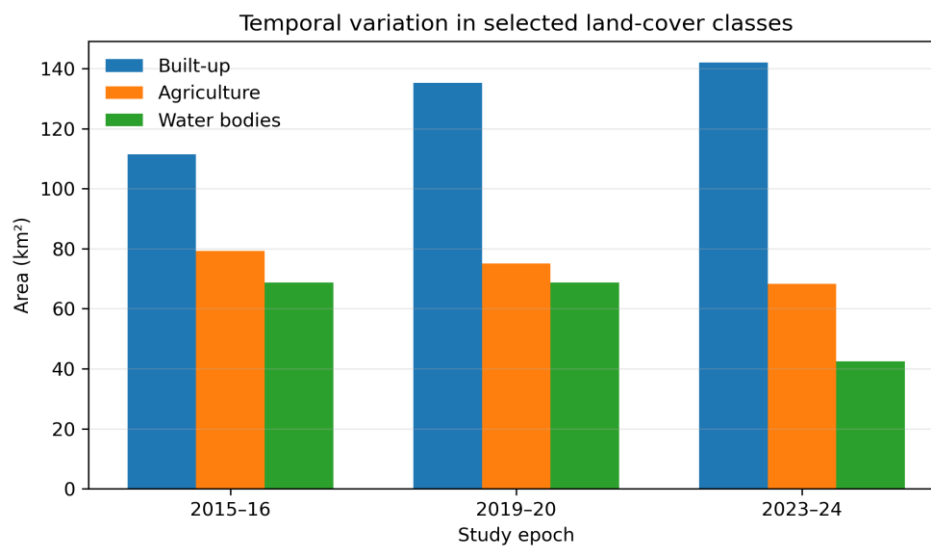


Fig. 2. Temporal variation of built-up area, agricultural area and mapped water bodies derived from the reported class-area data.

The built-up class increased consistently from 111.40 km² in 2015–2016 to 135.22 km² in 2019–2020 and 142.00 km² in 2023–2024. Relative to the first epoch, this represents an increase of 30.60 km², or 27.47%. The increase indicates a progressive expansion of settlement or impervious surfaces in the selected area. Such a pattern is consistent with the general role of remote sensing in identifying urban expansion and land conversion reported in earlier LULC studies [1,3,4].

Agricultural land decreased from 79.29 km² to 75.01 km² and subsequently to 68.29 km². The net reduction between the first and third epochs was 11.00 km² (13.87%). The spatial interpretation in the source project associates this reduction with conversion of agricultural land to residential, commercial and other built-up uses. Because the present analysis is based on spectral classification rather than parcel-level land records, the conversion mechanism should be interpreted as a remotely sensed land-cover transition rather than a legally verified land-use transaction.

Mapped water bodies remained at 68.78 km² in the first two epochs but declined to 42.47 km² in 2023–2024. This corresponds to a net reduction of 26.31 km², or 38.25%, relative to 2015–2016. Changes in surface-water extent can reflect hydrological variability, seasonal conditions, land conversion, water extraction and other environmental factors. The result therefore demonstrates a strong change in the mapped water class, but it should not by itself be interpreted as proof of permanent hydrological loss without seasonal water-level observations and field validation.

4.3 Classified LULC maps

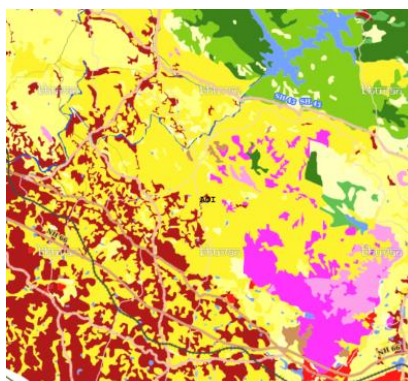


Fig. 3. Classified LULC output for the 2015–2016 epoch.

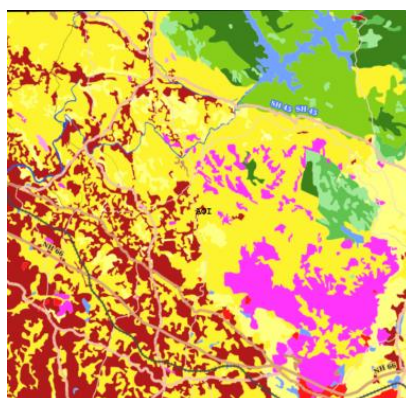


Fig. 4. Classified LULC output for the 2019–2020 epoch.

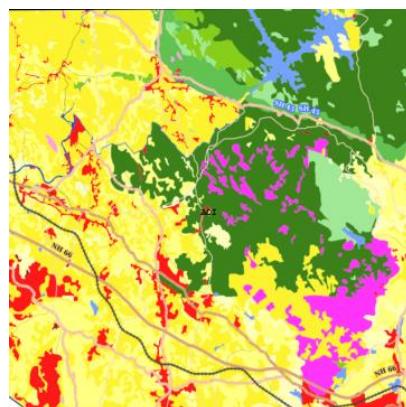


Fig. 5. Classified LULC output for the 2023–2024 epoch.

The classified outputs show the progressive spatial prominence of built-up surfaces and the reduction of areas identified as agriculture and water. Visual comparison is particularly useful for identifying the spatial character of change, while the tabulated areas provide the quantitative summary.

4.4 Classification accuracy

The reported validation dataset contained 64 reference points, of which 55 agreed with the classified result. The resulting overall accuracy of 85.93% indicates that most validation locations were assigned to the correct reference class. The source report uses Google Earth, Google Maps, high-resolution Landsat imagery and Bhuvan as contextual reference sources. Because the project does not provide complete epoch-wise confusion matrices or class-specific producer's and user's accuracies, the present paper reports the overall accuracy only and does not infer class-specific performance.

Reference points	Correctly classified	Overall accuracy
64	55	85.93%

Table 2. Summary of the reported classification validation.

5. Discussion

The observed changes indicate a shift in the composition of the selected landscape toward greater built-up coverage and lower mapped agricultural and water areas. This pattern is broadly comparable with findings from other multi-temporal remote-sensing studies in which urban growth is accompanied by conversion of agricultural or open land [1,3,4]. The value of the present study lies in its local-scale application using freely available satellite data and an open GIS environment, making the workflow accessible for educational institutions and regional environmental monitoring.

However, the interpretation must recognize several limitations. Landsat's 30-m spatial resolution can produce mixed pixels at class boundaries, especially in fragmented agricultural and settlement landscapes. Seasonal differences, cloud/shadow effects and differences in water level can also influence index values. The source methodology attempted to reduce these effects through cloud screening, seasonal harmonization and preprocessing, but field observations and a longer seasonal time series would strengthen future assessments.

6. Conclusions

A multi-temporal remote-sensing framework was developed to assess LULC change within a selected area of Kanniyakumari District using Landsat imagery and SAGA GIS. NDVI, NDWI and NDBI provided complementary information on vegetation, water and built-up surfaces, while supervised Maximum Likelihood classification enabled thematic LULC mapping.

Between 2015–2016 and 2023–2024, the reported built-up area increased from 111.40 to 142.00 km² (+27.47%), agricultural area declined from 79.29 to 68.29 km² (–13.87%), and mapped water bodies declined from 68.78 to 42.47 km² (–38.25%). The reported overall classification accuracy was 85.93% based on 64 reference points. These results demonstrate measurable landscape transformation and support the continued use of satellite-based monitoring for local planning and environmental assessment.

Future work should incorporate additional seasonal images, field-based ground truth, class-wise accuracy measures, transition matrices and higher-resolution imagery. Combining Landsat/Sentinel observations with machine-learning classifiers such as Random Forest or Support Vector Machine could further improve the discrimination of fragmented land-cover classes.

Data availability

The study used Landsat satellite imagery obtained from the USGS Earth Explorer archive, as described in the source project. Processing was carried out using SAGA GIS.

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