



International Journal of Research in Agronomy

E-ISSN: 2618-0618
P-ISSN: 2618-060X
© Agronomy
NAAS Rating (2025): 5.20
www.agronomyjournals.com
2025; SP-8(10): 221-226
Received: 26-08-2025
Accepted: 29-09-2025

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Geospatial Land Use/Land Cover (LULC) classification of the Upper Wainganga Basin, Madhya Pradesh

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DOI: <https://www.doi.org/10.33545/2618060X.2025.v8.i10Sc.4124>

Abstract

This study investigates the Land Use/Land Cover (LULC) dynamics of the Upper Wainganga sub-basin (8425.72 km²) in Madhya Pradesh, India, using multi-temporal satellite imagery of 2024. Data from Sentinel-2B satellites were processed in ERDAS Imagine 2014 and QGIS 3.38.0. An unsupervised classification based on the maximum likelihood algorithm identified five major land cover categories: forest (45.93%), agriculture/other vegetation (32.01%), fallow/open/barren (15.81%), built-up (4.87%), and water bodies (1.36%). Accuracy assessment using 500 reference points yielded an overall accuracy of 71.6% and a Kappa coefficient of 0.61, indicating substantial agreement. Forest, water bodies, and built-up areas showed high classification reliability, while confusion between agricultural and fallow lands occurred due to spectral overlap. The results demonstrate the effectiveness of remote sensing and GIS techniques in mapping of LULC, providing valuable insights for sustainable land-use planning and resource management in the basin.

Keywords: RS and GIS, land use land cover classification, accuracy assessment

1. Introduction

Land use applications encompass baseline mapping as well as continuous monitoring. While land use is usually derived from land cover, the two concepts are closely connected and frequently used interchangeably (Chaudhary *et al.*, 2018) ^[5]. The primary goal of image classification is to automatically assign each pixel in an image to specific land cover classes or categories. Typically, multispectral data are utilized for this process, where the spectral characteristics of each pixel serve as the numerical foundation for classification (Jensen, 1996) ^[14]. LULC classification is the process of assigning specific land cover categories to individual pixels and organising them into distinct classes. Examples of such categories include water bodies, urban areas, forests, agricultural lands, grasslands, built-up regions, mountains, and highlands (Anderson, 1976) ^[1]. The primary objective of image classification is to automatically categorise all pixels in an image into specific land cover classes or themes. In essence, different surface features exhibit unique combinations of spectral reflectance characteristics based on their inherent properties (Hamad, 2020) ^[11]. LULC maps serve a crucial role in the planning, management, and monitoring of programs across local, regional, and national scales (Hamad, 2020) ^[11]. Land use refers to the human utilisation of land for various purposes such as agriculture, forestry, settlement, and industry, whereas land cover denotes the natural or artificial physical material at the surface of the earth, including vegetation, water bodies, bare soil, and built-up areas (Anderson *et al.*, 1976) ^[1].

The Upper Wainganga Basin, a significant sub-basin of the Godavari River system, is characterised by its diverse physiographic, geological, and climatic conditions. The basin serves as an important source of water for agriculture, domestic use, and industry, while also supporting rich biodiversity and forest ecosystems. Remote sensing (RS) and geographic information systems (GIS) have emerged as powerful tools for analysing spatial and temporal patterns of land use and land cover. The advent of satellite-based earth observation systems provides synoptic, repetitive, and multi-spectral data that can be used to detect changes in land surface conditions with high accuracy (Jensen, 2007) ^[15]. Through the integration of RS and GIS, it becomes possible to analyse and visualise spatial phenomena, identify trends, and model

relationships among various biophysical parameters. Moreover, RS and GIS techniques are cost-effective and time-efficient compared to conventional ground-based surveys (Lu *et al.*, 2011) [22]. The advent of high spatial resolution satellite imagery and more advanced image processing and GIS technologies has resulted in a switch to more routine and consistent monitoring and modeling of land use/land cover patterns. Geographic Information Systems (GIS) provide powerful tools for analyzing land use issues, as well as for land use planning and modeling, as noted by several researchers. Studies by Zsuzsanna *et al.* (2005) [33], Mensah *et al.* (2018), and Harshada *et al.* (2012) [12] examined land use and land cover changes using both unsupervised and supervised classification methods. Remote sensing has been widely used in updating land use/cover mapping has become one of the most important applications of remote sensing (Lo and Choi, 2004).

2. Materials and Methods

2.1 Study Area

The study was conducted in the Upper Wainganga sub-basin. The Wainganga River is a major tributary of the Godavari River, flowing through the states of Madhya Pradesh and Maharashtra. The total Wainganga basin area is 49949.48 km², while the latitude extension is 19°30'N to 22°30' N' and the longitude extension is 79°00'E to 80°30' E'. The total length of the Wainganga River is 638.91 km, of which 270.2 km lies in Madhya Pradesh. This study focuses on the Upper Wainganga Basin, covering an area of 8,425.72 km². The sub-basin is located across the districts of Balaghat, Seoni, Chhindwara, and Mandla in Madhya Pradesh. Geographically, the study area extends between latitudes 21°40'N to 22°45'N and longitudes 79°00'E to 80°30'E. The average annual rainfall in Seoni, Balaghat, and Chhindwara ranges between 1400 mm to 1600 mm. Maximum of the rainfall is received during the South-West monsoon from June to October. In the winter, the minimum temperature is 7 °C and the maximum temperature is 13 °C. In summer, the maximum temperature ranges from 39 °C to 47°.

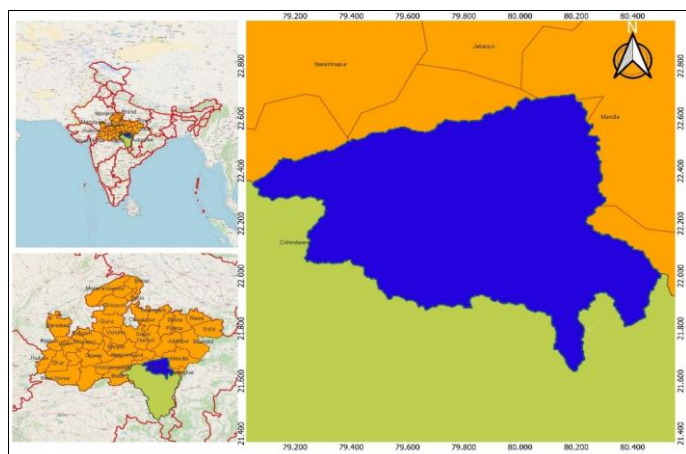


Fig 1: Index map of the study area

2.2 Database preparation

Spatial data used in the study included satellite imagery obtained from the NRSC Bhuvan portal (<https://bhoonidhi.nrsc.gov.in>). The study utilised satellite imagery obtained from the Sentinel-2B mission for the period of November-December 2024. The data, featuring a spatial resolution of 10 meters, was sourced from the Bhoonidhi portal of the National Remote Sensing Centre (NRSC). ERDAS Imagine was employed for spatial data processing and the generation of thematic maps, enabling

efficient handling and analysis of geospatial datasets. QGIS 3.38.0, an open-source GIS platform, was also used for spatial data analysis and thematic mapping to complement ArcGIS outputs. Additionally, Microsoft Excel was utilised for data pre-processing, performing statistical analyses, and Accuracy assessment, ensuring accurate evaluation and interpretation of the results.

The 2024 LULC classification of the Upper Wainganga River Basin was analysed using Remote Sensing (RS), GIS, and multi-temporal Sentinel-2B satellite images downloaded from NRSC. Images were mosaicked in ERDAS Imagine 2014 and QGIS 3.38.0, and the study area was subset for further analysis. Unsupervised classification with different band combinations and the maximum likelihood method was applied, resulting in five land cover classes. Field surveys were conducted to validate the classification accuracy.

2.3 Remote-sensing classification process

Remote-sensing classification is a complex process and requires consideration of many factors. The major steps of image classification may include the determination of a suitable classification system, the selection of training samples, image pre-processing, and feature extraction, the selection of suitable classification approaches, post-classification processing, and accuracy assessment. The user's need, scale of the study area, economic condition, and analyst's skills are important factors influencing the selection of remotely sensed data, the design of the classification procedure, and the quality of the classification results (D. Lu and Q. Weng, 2007) [22]. The classifiers use algorithms to analyse unknown pixels (referred to as false positives) in grayscale images and group them into various land use classes based on standard clustering methods that consider the proximity of similar image values.

1. Choose the number of classes (land use)
2. Group pixels based on spectral similarity (e.g., water, forest, urban, barren land)
3. Assign descriptive names to each cluster
4. Evaluate the classification outcomes

Unsupervised classification groups spectral image pixels based on similarity, relying on spectral distance, particularly the Local Projection Neighbourhood (LPN), with minimal user input. Users may specify the number of classes, which are later assigned physical meanings, though land cover information is not predefined (Liu, 2008) [21]. Clustering algorithms, such as Hierarchical, Centroid-Based, Fuzzy, and Supervised Clustering, organise pixels into spectral classes. Reliable LULC classifications are often provided by institutions like the Survey of India and the Remote Sensing and Geological Survey agencies.

2.4 Accuracy Assessment

Accuracy assessment is essential for evaluating and quantifying a LULC map by comparing classified data with reference data. An error matrix, along with user's and producer's accuracy, is commonly used to measure classification performance (Congalton *et al.*, 1991) [6]. PA measures the probability that a reference pixel is correctly classified, while UA indicates the likelihood that a pixel classified as a certain category actually represents that category in reality (Congalton, 1991; Foody, 2002) [6, 10]. The Kappa coefficient (K) quantifies agreement beyond chance and was computed to assess the reliability of the classified map.

3. Results and Discussion

3.1 Land Use/Land Cover Distribution (2024)

Based on reflectance recoded by the sensor and converted into digital values, which are classified by unsupervised classification of satellite image. In the study False Colour Composite (FCC) of a satellite image was prepared for classification. Mosaic and a subset of satellite images (FCC Image) as per the boundary of basin. Figure 2 depicts the FCC of the study area, and figure 3 refers to the LULC map for 2024. The land use/land cover (LULC) distribution of the Upper Wainganga basin for the year 2024 is presented in Table 2. In the Upper Wainganga basin, five land use and land cover types were chosen: Water body, Forest, Agriculture/Other Vegetation, Fallow/Open/Barren, and Built-up area.

3.2 Land Use/Land Cover Status

Figure 3 illustrates the spatial distribution pattern of land use and land cover across the Upper Wainganga Basin for the year

2024. The analysis indicates that, in 2024, approximately 1.36% (114.78 km²) of the basin area was occupied by water bodies, 45.93% (3870.37 km²) was covered by forest land, 32.01% (2697.18 km²) was utilized for agriculture or other vegetation types, 15.81% (1332.37 km²) comprised fallow, open, or barren lands, and 4.87% (411.04 km²) was identified as built-up or urban area.

Table 2: Land Use/Land Cover Distribution of Upper Wainganga basin during the period

LULC Class	2024	
	Area, Km ²	Area, %
Water body	114.78	1.36
Forest	3870.37	45.93
Agriculture/Other Vegetation	2697.18	32.01
Fallow/Open/Barren	1332.37	15.81
Built-up	411.04	4.87
Total Area	8425.72	100.00

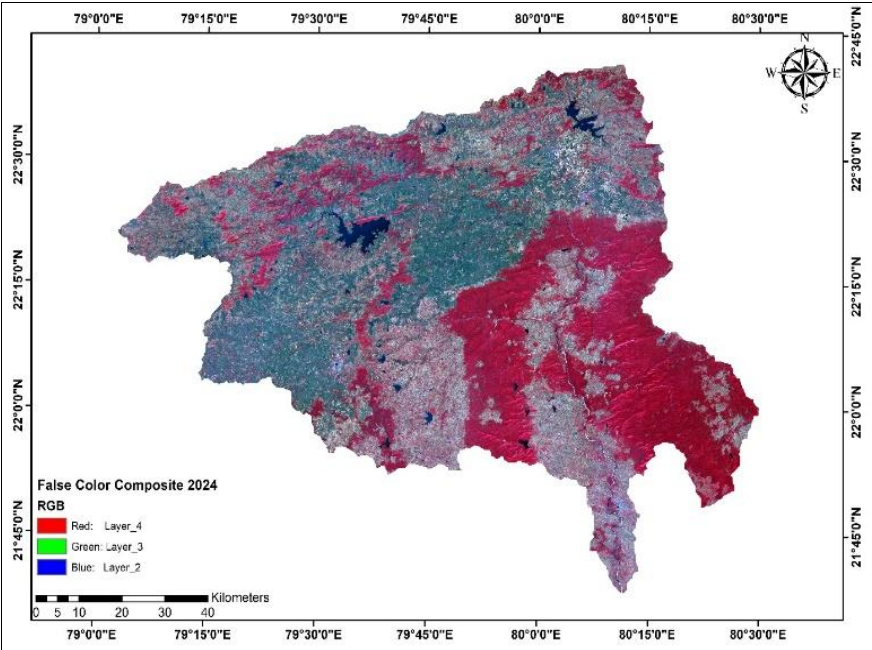


Fig 2: False Colour Composite (FCC) 2024 of the study area

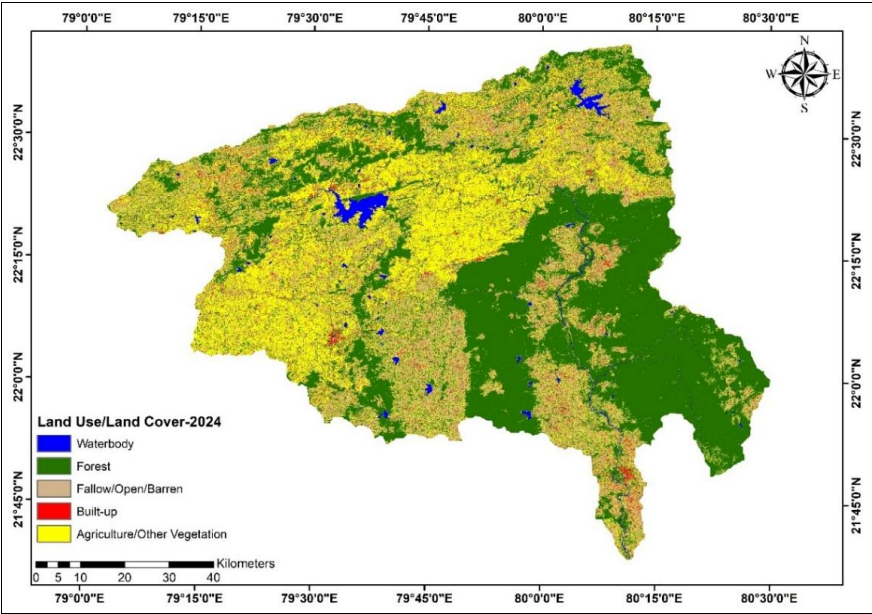


Fig 3: Land use/ Land cover Classification 2024

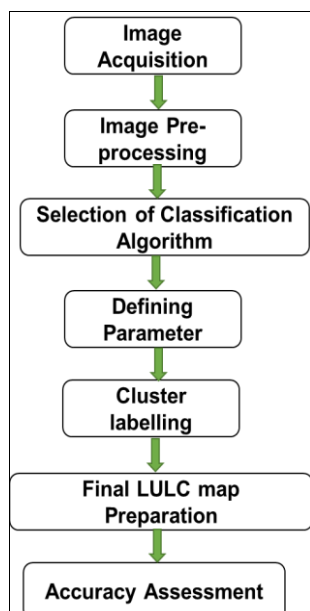


Fig 4: LULC Map Preparation

3.3 Accuracy Assessment of LULC Classification

In this study, the accuracy of the 2024 classified map was evaluated using 500 reference points distributed across the major land cover classes. The results were summarised through a confusion matrix/Error matrix (Table 3), which illustrates the agreement and disagreement between the reference data (rows) and the classified data (columns).

Table 3: Confusion matrix /Error Matrix (2024)

Classified Data	Water body	Forest	Agriculture / Other Vegetation	Fallow/Open/Barren	Built-up	Totals
Water body	16	0	0	4	0	20
Forest	0	167	19	21	2	209
Agriculture/Other Vegetation	4	8	95	33	12	152
Fallow/Open/Barren	0	4	2	54	25	85
Built-up	0	0	2	6	26	34
Column Total	20	179	118	118	65	500

The confusion matrix indicates that forest was the best classified category, with 167 correctly classified samples out of 179 reference points. The water body also showed relatively high accuracy, with 16 correct classifications out of 20 samples. However, notable misclassifications occurred between agriculture/other vegetation and fallow/open/barren, and between forest and agriculture, which can be attributed to the spectral similarity of these classes. Built-up areas, although limited in extent, recorded 26 correct samples out of 34.

Producer's Accuracy (PA) and User's Accuracy (UA) were computed for each class to assess classification performance (Table 4). Forest showed the highest PA (93.30%), followed by agriculture/other vegetation (80.51%), while fallow/open/barren and built-up had lower accuracies. Water body and forest had the most reliable UA, whereas agriculture showed lower reliability due to confusion with barren and forest areas. The overall accuracy was 71.60%, considered acceptable for medium-resolution LULC mapping.

Table 4: Producer's and User's Accuracy (2024)

Class Name	Reference Totals	Classified Totals	Correct Number	Producer's Accuracy (%)	User's Accuracy (%)
Water body	20	20	16	80%	80%
Forest	179	209	167	93.30%	79.90%
Agriculture/Other Vegetation	118	152	95	80.51%	62.50%
Fallow/Open/Barren	118	85	54	45.76%	63.53%
Built-up	65	34	26	40%	76.47%
Total	500	500	358		
Overall Accuracy	71.60%				

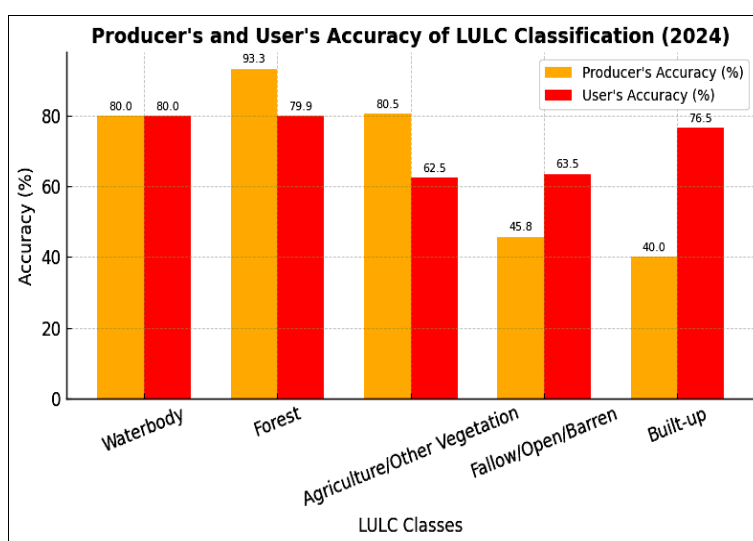


Fig 5: Producer's and User's Accuracy of LULC Classification (2024)

The classification accuracy was evaluated using the Kappa coefficient, which showed a substantial agreement (0.6099) for 2024 (Landis & Koch, 1977) ^[20]. Water body (0.792), built-up (0.732), and forest (0.682) had the highest accuracy, while agriculture/other vegetation (0.499) and fallow/open/barren

(0.516) were lower (Table 5). Overall, the 2024 classification was robust, though distinguishing agriculture from fallow areas remained challenging due to spectral similarity in medium-resolution imagery.

Table 5: Kappa Statistics of LULC Classification (2024)

Class Name	Kappa
Water body	0.792
Forest	0.682
Agriculture/Other Vegetation	0.499
Fallow/Open/Barren	0.516
Built-up	0.732
Overall Kappa Statistic	0.6099

4. Conclusion

Accurate information on land classification is crucial for effective environmental protection and future planning. The data obtained in this study serve as a valuable resource for informed decision-making and sustainable development of the Upper Wainganga Basin, ensuring both growth and environmental preservation. The study reveals that the major land use in the study area is forest (45.93%). The second major category of land in the study area is agriculture/other vegetation (32.01%). The third major category of land in the study area is fallow/open/barren (15.81%). The classification accuracy assessment revealed satisfactory performance, with overall accuracies of around 71.6% (2024) and Kappa statistics of 0.6099, suggesting a strong agreement between classified and reference data. Remote Sensing (RS) and Geographic Information Systems (GIS) are essential for planning and sustainable development of the Wainganga River Basin. They enable accurate analysis of land use and land cover through up-to-date satellite data, supporting environmental monitoring and informed decision-making for effective basin management.

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