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Research article

Machine learning-based LULC change detection and environmental implications in Bankura, West Bengal, India

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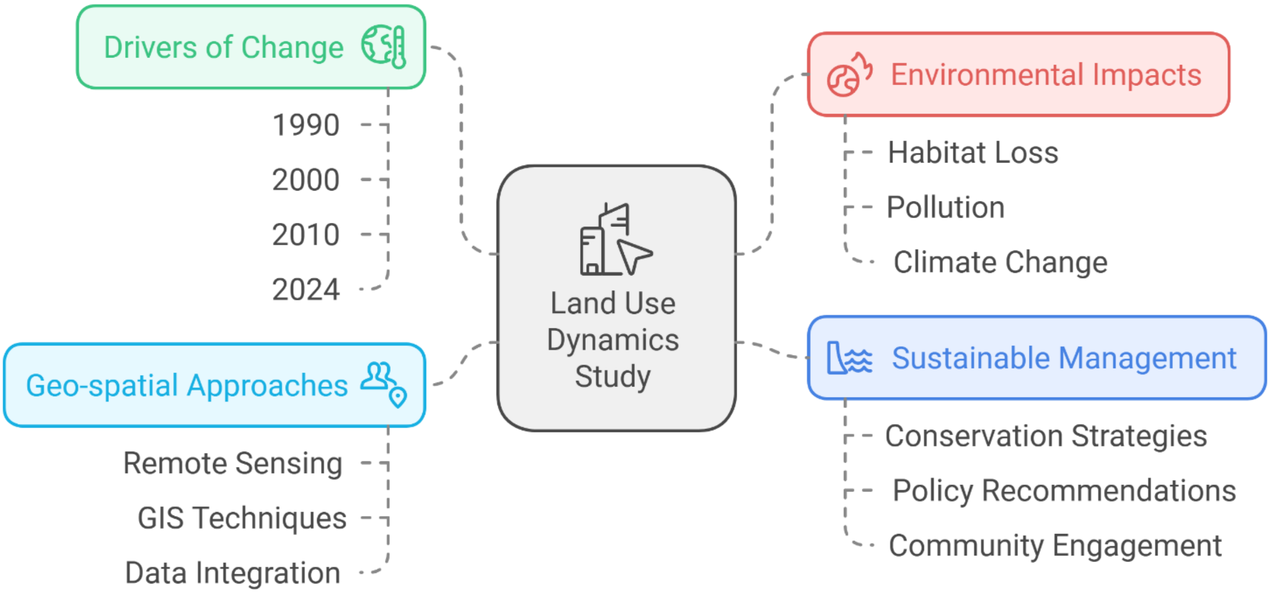
Abstract: In this study, we focused on the rapid land use and land cover (LULC) changes in Bankura in 1990, 2000, 2010, and 2024, employing an integrated remote sensing, geospatial, and statistical approach to track land use changes. The supervised classification technique and change detection analysis were applied with the Supper Vector Machine (SVM), Maximum Likelihood (ML), and Random Forest (RF) methods to identify land use classes in various categories like Dense Forest, Open Forest, water body, agricultural land, settlement, barren land, and sand. The Kappa Coefficient was used for the accuracy assessment, which revealed that the overall accuracy of 1990 was 93.33%, 2000 was 93.23%, 2010 was 93.43%, and 2024 was 90%. The analysis revealed a significant increase in built-up land from agricultural and forested areas, with a higher percentage of agricultural land converted to built-up areas observed between 1990 and 2024. During this interval, the built-up land area increased by approximately 13.6%, primarily due to the conversion of agricultural land and forest cover. Agricultural land decreased by 11.45%, while dense forest cover declined by 7.75%, indicating a significant anthropogenic influence on landscape transformation. Our findings underscore the importance of sustainable land use planning, conservation efforts, and policy interventions in mitigating environmental degradation, leveraging the effectiveness of space-based inputs and geospatial techniques. The research emphasizes the need for continuous monitoring and further investigation into socio-economic drivers and environmental consequences to ensure resilient urban management and sustainable development. This reveals the importance of reforestation, preserving water bodies, and developing ecologically sensitive infrastructure. Moreover, the study highlights the importance of sustainable land use planning in mitigating adverse environmental impacts and preserving ecological balance.

Keywords: LULC; GIS; ML; supervised classification; sustainable management



Graphical abstract

1. Introduction

Land use changes are vital to understanding the human-induced impacts on the environment and natural ecosystems [1]. These changes are influenced by urbanization, agricultural intensification, deforestation, and other factors [2]. In the local context of Bankura, West Bengal, India, the significance of land use changes is underscored by the region's heavy dependence on agriculture and its susceptibility to environmental degradation [3]. The difficulties in monitoring these changes involve the need for high-resolution spatial and temporal data and the integration of different datasets to capture the dynamics of land use [4] accurately. Land degradation, deforestation, and urbanization pose significant threats to biodiversity, climate regulation, and sustainable development [5]. Rapid urbanization, agricultural expansion, and infrastructure development in India have led to changes in land use, affecting local ecosystems and communities [6].

The terms land use and land cover (LULC) are often used interchangeably, but each has a unique meaning [7]. Land cover is a fundamental parameter that examines the content of the surface of the Earth and affects the condition and functioning of the ecosystem [8]. Moreover, land cover is a biophysical state that can be used to estimate the interaction of biodiversity with the environment [9]. The LULC analysis is vital in environmental science and natural resource management [10–12]. Land use and land cover are dynamic, providing a comprehensive understanding of the interaction and relationship between anthropogenic activities and the environment [13–15]. Land use/cover change has become a central component in current strategies for managing natural resources and monitoring environmental changes. The land use/cover pattern of a region gives information about the natural and socio-economic factors, human livelihood, and development [16].

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times [17]. Change detection in land use/cover can be performed on a temporal scale, such as decades, to assess landscape changes caused by anthropogenic activities on the land [18,19]. LULC changes are vital drivers of global environmental change, and space-based inputs, due to their repeatable nature, facilitate change detection analysis [20–22].

In this study, we focus on an integrated approach using remote sensing and geospatial technologies to monitor and analyze land-use changes [23]. Remote sensing, through satellite imagery and aerial photography, offers a comprehensive and cost-effective means of acquiring large-scale environmental data [24]. Geospatial analysis enables the detailed examination of spatial patterns, trends, and relationships within the data [25]. The advantages of this approach include the ability to conduct longitudinal studies, detect subtle changes over time, and identify areas at risk of degradation [26,28]. The applications of this study are extensive, encompassing urban planning, agricultural management, and environmental conservation [27]. Remote sensing (RS) and geospatial technologies provide powerful tools for tracking land-use changes [29,30]. By leveraging these technologies, policymakers, researchers, and stakeholders can make informed decisions, optimize resource allocation, and promote sustainable land use practices [31,32].

Recent research has advanced analyses of land use change by coupling spatial simulation with ecosystem service valuation. in a study, researchers deployed the Markov–FLUS model in Ezhou, China, to project land-cover transitions and estimate ecosystem service value (ESV) across several scenarios, documenting pronounced anthropogenic influences on transformation pathways and the attendant ESV redistributions [33]. Within the Yellow River Basin, the interlinked production, living, and ecological functions were examined, revealing spatial disparities shaped by socio-economic drivers and regulatory frameworks [34]. In the Ji-shaped village, the clustering along the river's bend was analyzed, linking rural land-use choices to topographic and demographic conditions [35]. Furthermore, random forests and support vector machines were applied in Nanjing to quantify the thermal implications of urban expansion, thereby framing the thermal dynamics of land-use/land-cover change within a machine learning context [36]. Collectively, these contributions highlight the rising utility of scenario-driven modelling, integrative human–environment frameworks, and AI-enhanced analytical techniques, thereby providing a methodological benchmark for the subsequent focus on land use dynamics in Bankura.

The need for this study is driven by the urgent requirement to understand and manage land use changes in Bankura, which is essential for promoting sustainable development and environmental conservation [37]. Our objectives are to map current land use patterns, identify the primary drivers of land use change, and assess the impacts of these changes on local ecosystems and communities [38]. The anticipated impact of this study is substantial, offering a robust framework for informed decision-making. Moreover, we aim to contribute to the formulation of sustainable land use policies, enhance the region's resilience to environmental challenges, and support the well-being of local communities by ensuring the sustainable use of natural resources [39].

2. Materials and methods

2.1. Study area

Bankura district is the third-largest district in West Bengal, India, with an area of 6,959 km². The study area is geographically situated within the latitudinal range of 22°38′ to 23°38′ N and the longitudinal range of 86°36′ to 87°46′ E and it is bordered by the districts of Purba Bardhaman, Paschim Bardhaman, Purulia, Jhargram, and Paschim Medinipur, as illustrated in Figure 1. The Damodar River traverses the northern region of the Bankura district, dividing it from the Bardhaman district. The river emanates from the Northeast. Toward the southwest, the courses run in near-parallel alignment with one another. According to the 2011 census, the Bankura district has a total population of 3.6 million.It has a tropical monsoon climate, with a total average annual rainfall of 1,400 mm. The winter days are warm, with nighttime temperatures remaining mild, though they may occasionally dip to around 8°C. In contrast, the summer months experience extreme heat, with average daytime temperatures reaching 38.8°C. The region's eastern and northeastern areas are geographically characterized by flat alluvial plains, while the western terrain gradually ascends.

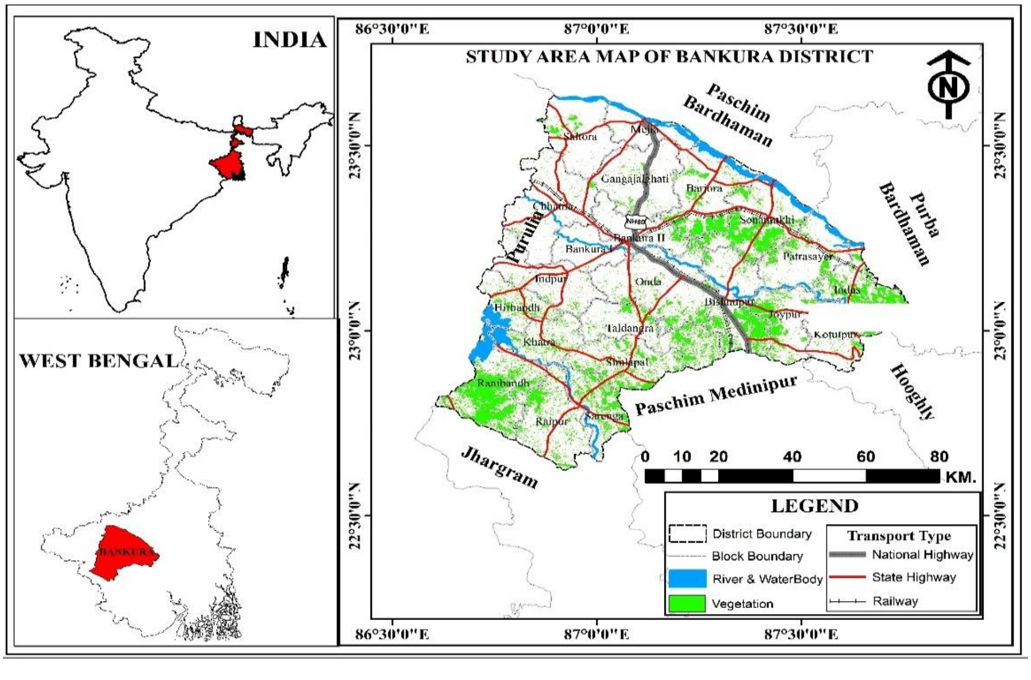


Figure 1. Study area.

2.1.1. Data and methodology

We used a comprehensive approach to analyze the LULC changes for 1990, 2000, 2010, and 2024. The high-resolution Landsat series images from USGS Earth Explorer were utilized (Table 1). For a more accurate analysis, we first corrected all errors in the satellite imagery using image pre-processing methods, which involved preprocessing, atmospheric correction, band composition, and image classification. In image classification, suitable training sets were assigned, followed by different models, including Support Vector Machine (SVM), Maximum Likelihood (ML), and Random Forest (RF). Then, the classified images were validated using the ANOVA single-factor statistical process; specifically, the accuracy assessment and Kappa coefficient method. Finally, the geographical areas of each land use class were extracted, and a map was prepared using ArcMap 10.8, Quantum GIS, and Google Earth Pro tools (Table 2). The detailed process step-by-step is discussed below.

Table 1. Information on the obtained satellite imagery.

Sl. No	Satellite	Sensor id	Path/row	Acquisition Date	Spatial Resolution
1	Landsat 5	TM	139 / 044	20-10-1990	30
2	Landsat 7	ETM+	139 / 044	08-11-2000	30
3	Landsat 7	ETM+	139 / 044	04-11-2010	30
4	Landsat 8	OLI	139 / 044	07-10-2024	30

Table 2. List of software used and function.

Software	Function
ArcMap 10.8	Study area map, LULC Map, Area calculation
Quantum GIS 3.14	Scanline remove of Landsat7 ETM+ Satellite image.
Google Earth PRO	Accuracy assessment, Ground truth

2.2. Pre-Processing

Image-based Preprocessing is a critical method for making a LULC map of a satellite image [40]. When we download satellite images, they contain flaws and deficiencies [41]. Preprocessing refers to the process of addressing deficiencies and eliminating errors in satellite data [42,43].

2.3. Atmospheric Correction

Solar radiation undergoes absorption or scattering by the atmosphere as it travels toward the Earth's surface, and similarly, the radiation reflected or emitted by the surface is also affected by absorption or scattering before reaching the sensor [44]. The surface is exposed to direct solar radiation and scattered radiation, also known as skylight, originating from the atmosphere [45]. A sensor captures the directly reflected or emitted radiation from a target and the scattered radiation from the target and the atmosphere, referred to as path radiance [46]. Since scattering is wavelength-dependent, the extent of path radiance varies across bands [47]. Atmospheric correction methods are employed to compensate for these effects [48]. The formula is:

{(Reflectance multi-band value of each specific band*DN value) Reflectance add band/ Sin sun elevation}

This was done using ArcMap 10.8. All bands of the satellite image were added to the Arc map, and then a raster calculation was performed using the above formula for each band.

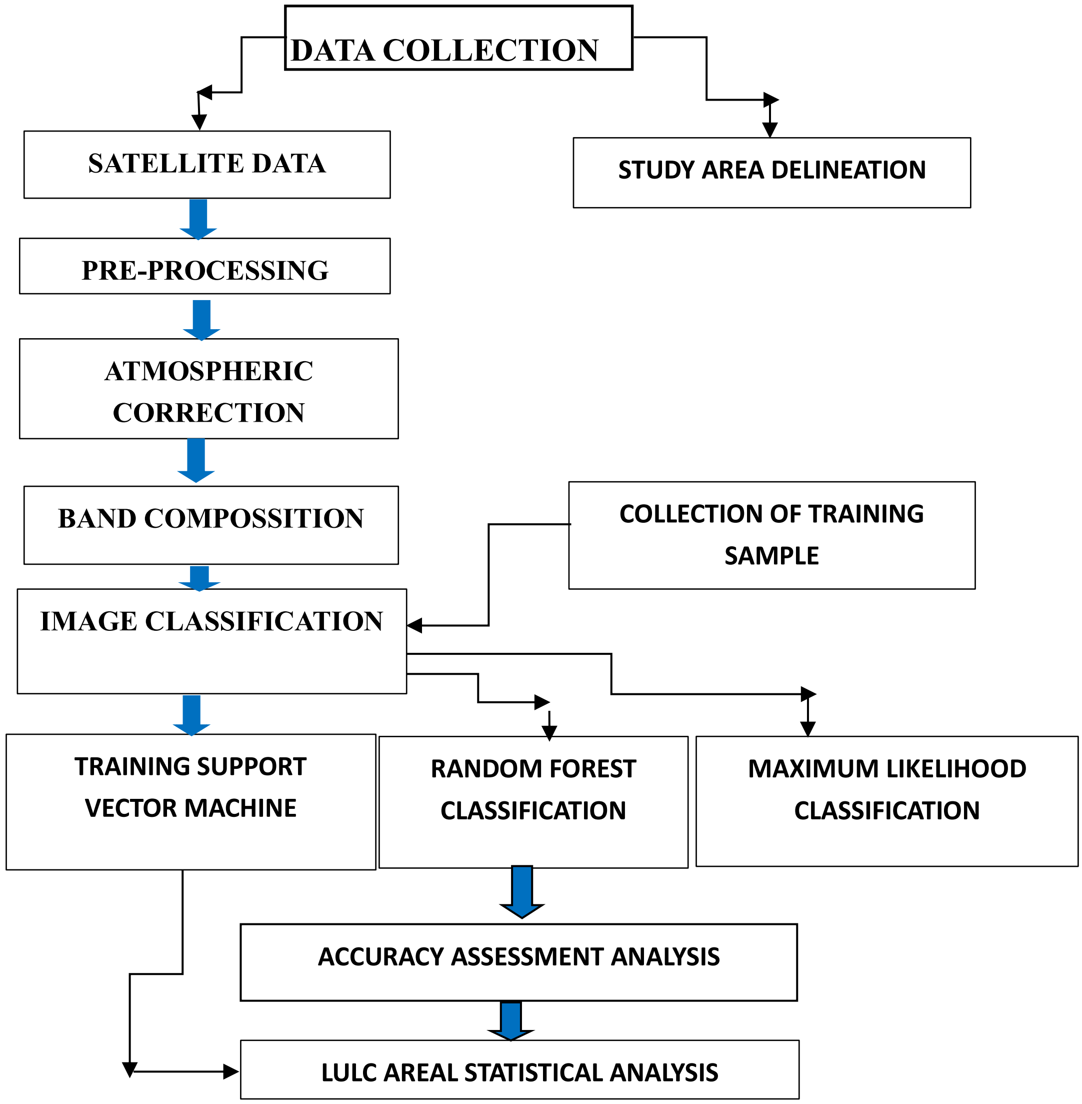


Figure 2. Flowchart of the methodology.

2.4. Image classification

The supervised classification was used with three classifiers: SVM, RF, and ML. The LULC feature is divided into seven classes based on specific digital numbers [49]. The identified categories are Dense Forest, Open Forest, Aquatic Zone, Agricultural Land, Settlement, Barren Land, and Sand [50,51]. A unique color was designated for each category to distinguish them [52]. The raster data was converted to vector data as a polygon in a shapefile (.shp), and the area was calculated in square kilometers [53].

2.5. SVM

SVM is a robust algorithm for performing classification and regression applications. It finds the optimal hyperplane to distinguish categories by maximizing margins and handles non-linear relationships using kernel functions. The SVM is widely used in mining applications in image classification, change detection, and feature extraction.

2.6. ML Classification

This is a supervised classification algorithm that identifies and groups land cover classes based on spectral signatures, where each class has a Gaussian distribution. It also determines the likelihood of each pixel being associated with a particular class.

2.7. RF

RF is a hybrid learning approach integrating multiple decision trees to enhance classification accuracy. It handles high-dimensional data, reduces overfitting, and provides feature importance rankings. It excels in land cover classification, change detection, and predictive modeling. Moreover, it analyzes the multi-temporal satellite data and reveals complex relationships between coal mining activities and landscape dynamics.

2.8. Accuracy Assessment

The LULC maps of 1990, 2000, 2010, and 2024 were verified using Google Earth satellite images and ground truth collection, and the data regrouping process was carried out simultaneously [54]. The map's accuracy was determined by referencing ground control points, which are represented by point shapefiles for each LULC classification map [55]. Then, the point shapefile was converted to a Keyhole Markup Language (.kml) file format using conversion tools (To KML). Thereafter, the KML file was imported to Google Earth PRO [56,57]. Four maps of 1990, 2000, 2010, and 2024 were corrected using Google Earth Pro. Ground control point: A total of 30 were gathered as benchmark data by the POINT shapefile to evaluate the precision for both years [58]. The Kappa coefficient was used to assess the agreement between image classification data and reference points for accuracy assessment, evaluating comprehensive accuracy through statistical analysis [59]. The overall accuracies of the classified images were 93.33%, 93.33%, 87%, and 90% for the years 1990, 2000, 2010, and 2024, respectively [60].

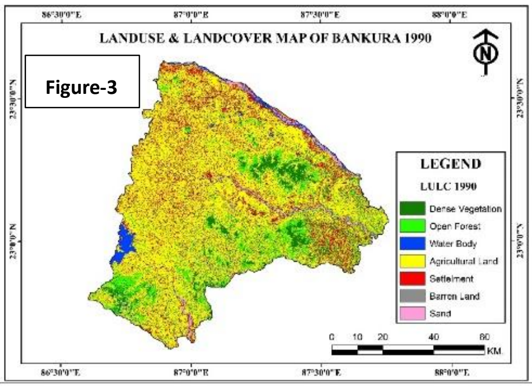
Table 3. Algorithms for Accuracy Assessment.

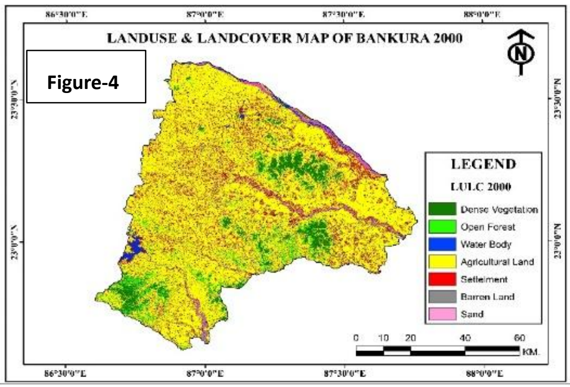
Overall Accuracy	$\frac{N\text{umber of Correctly Classified Pixels (Diagonal)}}{\text{Total Number of Reference Pixel}} \times 100$
User Accuracy	$\frac{\text{Number of Correctly Classified Pixels in each Categor}y}{N\text{otal Number of Classified Pixels in that category (The Row Total)}} \times 100$
Producer Accuracy	$\frac{\text{Number of Correctly Classified Pixels in each Categor}y}{\text{Total Number of Reference Pixels in that category (The Column Total)}} \times 100$
Kappa Coefficient	$\frac{(\text{TS} \times \text{TCS}) - \Sigma(\text{Column} \times \text{Row Total})}{\text{TS}^2 - \Sigma(\text{Column Total} \times \text{Row Total})} \times 100$ *[Where, TS = Total Sample TCS = Total correctly Classified sample]*

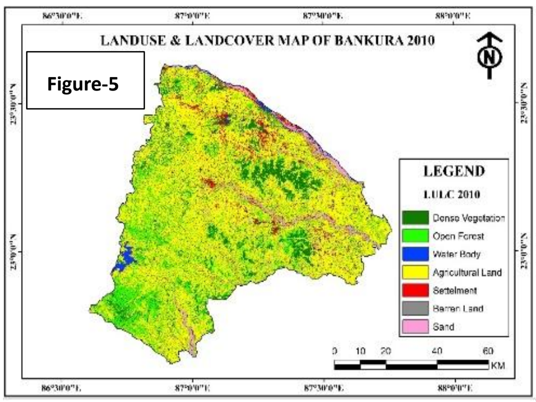
3. Results

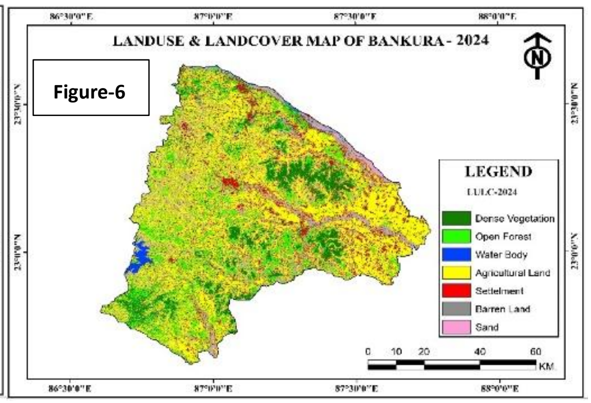
We evaluated the accuracy of three machine learning algorithms: ML, RF, and SVM. These algorithms, integrated into ArcGIS Pro, are widely used for the supervised classification of satellite images. The comparison of these three classifiers revealed that the selected study area spans 6,959 km², encompassing seven major LULC categories: Crops and fallow land, dense forest, open forest, barren land, water bodies, built-up areas, and sandy soil.

The results, illustrated in Table 4 and Figs. 3, 4, 5, and 6, were generated using the SVM algorithm. In 1990, agricultural land was the most dominant land use class, covering approximately 4,446.2 km², followed by built-up areas (800.3 km²), dense forest (680.3 km²), open forest (437.3 km²), water bodies (309 km²), barren land (190.8 km²), and sandy soil (95.1 km²). Analysis of the data from 1990 to 2024 revealed significant changes in LULC. Agricultural land decreased by 179.6 km², dense forest by 62 km², and water bodies by 10.9 km². Conversely, the open forest area increased by 62.3 km² due to the conversion of dense forest into open forest, while barren land expanded by 36 km², and sandy soil increased by 3.1 km². These changes indicated that the study area has experienced increased degraded land and deforestation over time (Table 4 and Figures. 3, 4, 5, and 6).









Figures 3–6 depict LULC maps generated using SVM classifiers for the years 1990, 2000, 2010, and 2024, respectively.

3.1. LULC Analysis (1990–2024)

The LULC analysis was carried out using three classifiers, ML, RF, and SVM, and is presented in Tables 4 and 5, Supplementary Tables 1, 2, and 3, and Figures. 3, 4, 5, and 6.

Table 4. Spatio-temporal distributions of Bankuda district during the years 1999, 2000, 2010, and 2024 using ML, RF, and SVM classifiers.

ML					RF				SVM			
	1990	2000	2010	2024	1990	2000	2010	2024	1990	2000	2010	2024
AG	4441.1	4320.1	4290.1	4286.6	4451.1	4420.1	4410.1	4408.1	4446.2	4336.2	4300.1	4266.6
DF	676.3	654.2	638.1	636.1	686.2	664.2	661.2	660.2	680.3	660.2	640.1	618.3
OF	434.5	456.2	470.2	472.2	445.3	466.2	468.1	474.1	437.3	460.5	481.2	502.6
BL	208.1	221.2	224.4	228.7	212.2	226.3	228.2	230.2	190.8	198.7	201.4	226.8
WB	303	302.2	301.5	301.2	330.2	328.3	326.1	301.2	309	304.3	302.5	298.1
BU	803	910.1	938.4	938.1	766	781.9	788.3	797.2	800.3	903.1	936.4	948.4
SS	93	95	96.3	96.1	68	72	77	88	95.1	96	97.3	98.2

Note: Agriculture crop and fallow land (AG), Dense Forest (DF), Open Forest (OF), Barren land (BL), Water body (WB), Built-up area (BU), and Sandy soil (SS), Maximum Likelihood (ML), Random Forest (RF), and Support vector machine (SVM).

Table 5. Accuracy assessment of Bankuda district during the years 1990 to 2024.

1990, 2000, 2010, 2024												
	ML	RF	SVM	PA %			OA %			Kappa Coefficient		
Class	UA	UA	UA	ML	RF	SVM	ML	RF	SVM	ML	RF	SVM
AG	97.5	91.5	93.4									
DF	93.6	91.2	94.5									
OF	93.6	91.2	94.5									
BL	96.2	91.3	94.2	91	92	94	92	94	96	93	94	96
WB	94.3	97.1	96.2									
BU	89.1	93.1	91.2									
SS	96.2	91.3	94.2									

Note: Agriculture crop and fallow land (AG), Dense Forest (DF), Open Forest (OF), Barren land (BL), Water body (WB), Built-up area (BU) and Sandy soil (SS), Producers accuracy (PA), Users accuracy (UA), Maximum Likelihood (ML), Random Forest (RF), and Support vector machine (SVM).

The evaluation of a user's accuracy for specific land use classes varied significantly across the three machine learning algorithms. Agricultural land was detected with the highest accuracy using the ML algorithm, achieving 97.5%, followed by the SVM and RF algorithms. Built-up areas were identified most accurately using the RF algorithm, which outperformed SVM and ML. Similarly, barren land showed the highest accuracy with the ML algorithm, while water bodies were best detected using the RF algorithm. These variations highlighted the strengths of each algorithm for particular land use categories. When comparing producers' accuracy, the SVM algorithm demonstrated the highest performance at 94%, followed by RF at 92% and ML at 91%. SVM also delivered the best results for overall accuracy, achieving 96%, while RF and ML achieved 94% and 92%, respectively. These findings indicated that SVM outperformed RF and ML in terms of both the producer's and overall accuracy (Table 5).

The overall results suggested that the SVM algorithm was the most effective for classifying LULC across all analyzed years: 1990, 2000, 2010, and 2024. SVM consistently demonstrated superior accuracy, making it the preferred algorithm for complex classifications in the study area. This highlights its reliability and adaptability for satellite image classification, particularly when compared to RF and ML.

Supplementary Tables 1–4 summarize the average spatial distribution and classification variability of various LULC classes for the years 1990, 2000, 2010, and 2024. Throughout this period, cultivated land was the predominant category, with mean spatial extent declining from approximately 4,446.1 km^2 in 1990 to 4,320.43 km^2 in 2024. In contrast, the mean extent of sandy soil was minimal, increasing from 85.3 km^2 in 1990 to 94.1 km^2 in 2024. The coefficient of variation (CV) metric revealed low classification variability for agricultural and forested land (CV ranging from 0.1% in 1990 to 3.5% in 2024) and comparatively elevated variability for urban and sandy categories (CV values of 5.7% in 2024 and 17.7% in 1990, respectively), indicating that classifier uncertainty was greater in these latter classes.

The standard deviation (SD) for each year was consistently highest for built-up areas, indicating significant variability in the distribution of built-up spaces across the study area. In contrast, the minimum standard deviation was observed in land use classes such as agriculture, forest, and barren land, suggesting that these classes exhibited more consistent or uniform distribution patterns over time. Similarly, the CV, which measured the relative variability in land use classes, was highest for sandy soil, indicating considerable variation in its spatial distribution across the study years. For other land use classes, such as agriculture, forest, and barren land, the CV varied but remained relatively lower, reflecting more stable patterns in their coverage over the decades. These findings highlighted the dynamic nature of built-up areas and sandy soil, with built-up areas showing rapid expansion and sandy soil showing considerable fluctuation, while agricultural land and forests experienced more steady coverage over the years.

Table 6. Summary of the ANOVA test.

SUMMARY				
Groups	Count	Sum	Average	Variance
LULC Class	21	84	4	4.2
Machine learning classifiers	21	42	2	0.7
Accuracy of classifiers	21	1965.4	93.59048	5.168905

Table 7. Results of the ANOVA test.

ANOVA						
Source of Variation	SS	df	MS	F	*P*-value	F crit
Between Groups	114934.9	2	57467.44	17122.25	1.92E-83	3.150411
Within Groups	201.3781	60	3.356302			
Total	115136.3	62				

The statistical analysis of LULC data collectively highlighted significant insights. Table 6 provides descriptive statistics for three groups: LULC Class, Machine Learning Classifiers, and Classifier Accuracy, showing differences in their averages (4, 2, and 93.59, respectively) and variances. Table 7 presents an ANOVA test, confirming that the differences between these groups were statistically significant. The F-statistic (17122.25) was much greater than the critical value (3.15), and the P-value (1.92×10−831.92 \times 10^{-83}1.92×10−83) was extremely small, indicating a highly significant result. This suggested that at least one group's mean differed substantially from the others, emphasizing the variability among the groups analyzed.

4. Discussion

4.1. Summary

We conduct our study in the Bankura district of West Bengal. For classification analysis, we employed the SVM method to identify different types of land use classes, including dense forest, open forest, water body, agricultural land, settlement, barren land, and sand. We calculate the accuracy assessment and the kappa coefficient to check the accuracy of the LULC map. We find that the overall accuracy of 1990 is 93.33%, 2000 is 93.33%, 2010 is 93.33%, and 2024 is 90%. We also observe that the kappa coefficient in 1990 is 92.084%, in 2000 is 92.187%, in 2010 is 92.207%, and in 2024 is 87.9194%. Moreover, we find the overall changes in the amount of dense forest, open forest, water bodies, agricultural land, settlements, barren land, and sand to be -185.83 km^2, 740.17 km^2, -213.66 km^2, -1,258.1 km^2, -61.91 km^2, 1,036.86 km^2, and 57.53 km^2, respectively.

4.2. Interpretation

We employ a multidisciplinary approach to investigate land use dynamics in Bankura between 1990 and 2024 [61]. Significant changes are identified using Landsat imagery and GIS spatial analysis, including a decline in forest cover and an increase in agricultural land, which is attributed to population growth, economic development, and infrastructure expansion [62]. The integrated approach demonstrates high accuracy in tracking land use changes, providing valuable insights for sustainable resource management and environmental conservation [63]. The findings have significant policy implications, underscoring the need to strike a balance between economic development, environmental protection, and social welfare [64]. Overall, this study contributes to understanding land use dynamics in rapidly changing regions, informing strategies for mitigating environmental impacts, and promoting sustainable development in Bankura and similar areas [65].

4.3. Local environmental and social factors

Local environmental and social factors play a crucial role in shaping land use changes [66]. Environmental factors, including soil quality, topography, and climate, influence land use patterns. Social factors, including population growth, economic development, and cultural practices, significantly impact land use changes [67]. The growing population has led to an increased demand for housing and infrastructure, resulting in urban expansion. Economic development, driven by agriculture and mining, has also contributed to land use changes, with agricultural land being converted to industrial purposes [68].

Alongside broader trends, several local factors have significantly influenced the trajectories of LULC in Bankura. Major Rural Infrastructure Development Fund (RIDF) initiatives have improved the road network, thereby facilitating the outward spread of settlements in the peri-urban fringe. Concurrently, state-level agricultural subsidy programs, targeting fertilizer and irrigation pump distribution, encouraged intensified cropping, particularly in the early 2000s. The Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) modified land use indirectly by augmenting the rural labor supply, enabling higher land cultivation intensity. Furthermore, hydrological interventions by the Damodar Valley Corporation have influenced the configuration of water bodies and the surrounding land. Local urban planning initiatives led by the Bankura Municipality and village Panchayats have additionally promoted residential plot development and small-scale industry, converting agricultural zones into built-up land. These drivers varied in their influence across the study period: For instance, agricultural subsidy programs and intensified cropping peaked in the early 2000s, while infrastructure-led urban expansion and municipal land-use planning gained momentum after 2010, collectively driving the observed shifts in forest, agricultural, and built-up land categories.

Furthermore, local policies and governance structures influence land use changes. Additionally, community-led conservation efforts have protected forest areas, demonstrating the importance of local involvement in land use management [69]. Understanding these local environmental and social factors is crucial for effective land-use planning and management [70]. This study highlights the need for integrated approaches considering ecological and social dimensions of land use changes [71].

4.4. Comparison with other studies

Our findings are consistent with previous research on land use changes in India, highlighting the significance of agricultural expansion and urbanization [72]. Our analysis reveals more pronounced land use changes in Bankura, West Bengal, than observed in other regions [73]. Internationally, studies have reported similar patterns of land use change. A global assessment revealed that agricultural expansion and urbanization were the major drivers of land use changes [74]. Another study emphasized the importance of considering local environmental and social factors in land-use change analysis [75].

Our investigation deepens the prevailing body of literature by combining three supervised machine learning classifiers, SVM, RF, and LR, while benchmarking their classification resilience over a four-decade period (1990–2024), a longitudinal effort seldom attempted in eastern India. Earlier inquiries have typically converged upon a singular classifier or restricted their analytical scope to discrete, non-continuous temporal snapshots. Our adoption of ANOVA as a statistical validation scheme further elevates the methodological rigor of LULC surveillance by providing a quantitative, comparative framework for assessing classifier dependability and model sensitivity to spatio-temporal variation.

On the data side, we leverage a multi-source validation architecture that integrates in-situ ground truth observations with independent readings from Google Earth Pro. This dual-validation framework fortifies classification accuracy assertions well beyond the levels of verification typically encountered in prior regional examinations. Additionally, by juxtaposing geospatial trajectories with the timing of local policy recalibrations and specific socio-economic initiatives, we delineate a temporal and causal narrative illustrating how land-use patterns have been orchestrated by institutional choices in Bankura.

These advancements hold particular relevance for semi-urban and peri-urban areas throughout eastern India and the broader South Asian landscape, where developmental imperatives and environmental degradation remain inextricably linked. The analytical framework and empirical findings presented herein may thus serve as a transferable template for elucidating land-use trajectories and guiding the design of sustainable land-use planning in ecologically and economically analogous settings.

4.5. Implications

Our findings of this study have significant implications for environmental sustainability, ecosystem services, and human well-being in Bankura, West Bengal, India [76]. The environmental ramifications of land use alteration in Bankura extend beyond mere alterations in land cover; they manifest as quantifiable deficits in biodiversity and the value of ecosystem services. Between 1990 and 2024, the total area of dense and open forest diminished by 185.83 km², yielding a proportional contraction of approximately 13% of the region's forested extent. Research by Surajit Majumder S M et al. [77] has documented marked declines in freshwater biodiversity within forest-fringe aquatic assemblages, with a particular focus on reductions in planktonic diversity, which correlate with land use intensification, increased sedimentation, and elevated nutrient loads. Employing the global ecosystem service valuation framework formulated by Costanza R et al. [78], the forest area contraction in Bankura is estimated to result in an ecosystem service value deficit exceeding USD 5 million, based on an annual valuation of USD 3,000 per hectare of forest. The concomitant transformation of formerly productive agricultural land into barren and shifting sand-dominated zones, which has increased in total area by more than 1,000 km², further indicates a contraction in provisioning services, particularly diminished agricultural yields and impaired water retention. These figures support the qualitative observations and underscore the urgent need for forest conservation and sustainable land-use strategies to maintain ecological balance.

The rapid agricultural expansion and urbanization observed in this study pose a threat to biodiversity conservation and ecosystem services [79]. Furthermore, the increase in wasteland indicates degraded land quality, affecting agricultural productivity and food security [80]. Moreover, this highlights the need for sustainable land use planning and management practices [81].

Additionally, community-led conservation efforts can effectively protect forest areas and promote sustainable land use practices [82]. Our results also affect climate change mitigation and adaptation strategies [83]. The conversion of forest land to agricultural and urban uses contributes to greenhouse gas emissions, underscoring the need for sustainable land use practices to mitigate climate change [84]. Moreover, our findings can inform adaptation strategies that enhance resilience to climate-related hazards, such as floods and droughts [85].

4.6. Limitations

The reliance on Landsat imagery, which has a 30m spatial resolution, limits the accuracy of land use classification, particularly for small-scale changes [86]. Future studies can entail high-resolution satellite imagery, such as Sentinel-2 or Worldview, to improve classification accuracy [87]. Moreover, the focus on Bankura District limits its generalizability to other regions [88]. Land use dynamics can vary significantly across geographic contexts, underscoring the need for region-specific studies [89]. For the analysis, we primarily focus on environmental and spatial factors, neglecting socioeconomic drivers of land use change. Integrating socioeconomic data, such as census data or surveys, can provide a more comprehensive understanding of land use dynamics [90]. Future studies can develop more detailed classification schemes tailored to region-specific land use patterns [91].

4.7. Recommendations

Our results of this research underscore the simultaneous need for on-the-ground policy action and the development of enhanced methodological tools to secure land use sustainability in Bankura and comparable landscapes. A decline in agricultural area necessitates restructuring that integrates ecological and climate-responsive methodologies; the promotion of agroforestry systems, organic cultivation, and diversified cropping rotations should be prioritized. Configuring designated agricultural precincts that incubate value-chain-oriented rural enterprises can sustain output levels while guarding against further land-use conversion. In parallel, the attenuation of urban encroachment and haphazard settlement requires the enforcement of more stringent zoning prescriptions, the institutionalization of peri-urban green corridors, and the promotion of land-fusion initiatives.

Alongside these efforts, systematic reforestation and community-led afforestation initiatives are crucial for restoring degraded forests and reviving essential ecosystem functions.

Future research can benefit from a multidisciplinary framework that integrates remote sensing, geospatial analysis, and socioeconomic information, thereby illuminating the complex human–environmental processes underlying land-use and land-cover change [92]. The incorporation of high-resolution satellite data markedly improves the precision of land classification, and supplementing these observations with machine learning techniques accelerates analysis while broadening its applicability [93,94]. Formulating anticipatory models that simulate LULC trajectories will enable decision-makers to devise preemptive, evidence-based strategies. A multi-layered data ecosystem, comprising satellite imagery, demographic censuses, and ground-based surveys, furnishes a holistic basis for assessing land dynamics [95]. Crucially, continuous engagement with local communities, legislative bodies, and land practitioners will ensure that empirical findings inform practical governance and sustainable management interventions [96].

5. Conclusions

In this study, we demonstrated the effectiveness of an integrated remote sensing and geospatial approach for tracking land use changes in Bankura, West Bengal, India [97]. Our findings revealed significant changes in land use patterns between 1990 and 2024, with agricultural expansion and urbanization emerging as major drivers of change [98]. Integrating Landsat and GIS data enabled the accurate mapping and analysis of land-use changes, providing valuable insights for policymakers and stakeholders [99]. Moreover, our findings underscore the importance of considering local environmental and socioeconomic dimensions in land-use decision-making [100]. This research contributes to the body of knowledge on land use changes in India, highlighting the need for region-specific studies [101]. By applying multiple machine learning classifiers, the methodology adopted here offers a replicable framework for studying land dynamics in comparable regions [102]. The findings will provide valuable insights for stakeholders, policymakers, and researchers, contributing to the achievement of the United Nations' Sustainable Development Goals (SDGs) in Bankura and similar regions. To promote transparency and reproducibility, the datasets and analytical codes used in this study will be made available to interested researchers upon reasonable request.

Use of AI tools declaration

The authors declare they have not used artificial intelligence (AI) tools in creating this article.

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Conflict of Interest

All authors declare that there is no conflict of interest in the manuscript.

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