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Spatiotemporal Dynamics of Land Use and Land Cover in Bhubaneswar Municipal Corporation: A Decade of Change (2014-2023)

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Abstract

This study analyses the land use and land cover (LULC) changes in the Bhubaneswar Municipal Corporation between 2014 and 2023 using remote sensing and GIS techniques. Multispectral Landsat 8/9 OLI/TIRS satellite images were utilized to assess the changes in major land cover categories, including Built-Up areas, Vegetation, Forest, Barren land, and Water Bodies. A supervised classification method employing the Maximum Likelihood algorithm was applied to classify the satellite imagery and detect LULC changes over time. The analysis revealed a significant expansion of Built-Up areas, increasing by 48.03 sq. km (31.58%) between 2014 and 2023, primarily at the expense of Vegetation and Forest cover, which decreased by 23.02 sq. km (15.13%) and 23.11 sq. km (15.19%), respectively. Other land cover types such as Barren land showed a minor decline, while Water Bodies exhibited a slight increase. The overall classification accuracy for 2014 and 2023 was 89.00% and 87.33%, respectively, with almost perfect agreement in both years based on the Kappa coefficient. The findings underscore the rapid urbanization in Bhubaneswar, with critical implications for sustainable urban development, environmental conservation, and land use planning. This study provides essential data to support future policy-making and urban management initiatives aimed at balancing development with ecological sustainability.

Keywords: Land use and land cover (LULC) change Bhubaneswar Municipal Corporation (BMC), Remote Sensing, GIS, Supervised classification, Maximum Likelihood

Introduction

Land cover refers to the physical properties of the Earth's surface, which are represented by the distribution of flora, water, soil, and other physical elements. Land use refers to how humans and their environments have utilised land (for example, agriculture, towns, and industry) (Chaudhary et al, 2008). The study of land use and land cover dynamics provides valuable insights into the changing patterns and processes that shape our environment. Understanding the dynamics of human-environment interactions is crucial for sustainable development, as it allows us to assess the impacts of human activities on ecosystems, biodiversity, and natural resources. Moreover, the detection and monitoring of land use and land cover changes is essential for effective land management and policy formulation (Ingle, 2012; Vescovi et al., 2002). Over the years, data from Earth sensing satellites have proven crucial in mapping the Earth's features and infrastructures, managing natural resources, and monitoring environmental change (Zubair, 2006).

Various researchers have opted for different methods for identifying these changes in land cover. Unsupervised classification in which the algorithm groups data into clusters based on inherent similarities without prior labelling or training (Rao & Narendra (2006); Boakye et al., (2008). Supervised classification involves using labelled datasets to train an algorithm so that it can accurately predict the class of unseen data (Kim et al., 2008; Remi et al., 2007, Tan et al., 2009). Maximum classification accuracies were acquired by using the Maximum Likelihood Classification (MLC) decision rule.

Bhubaneswar, being a major urban hub, has experienced significant changes to its environment, affecting the local ecosystems, biodiversity, and socio-economic situations. The shift from rural to urban land use, the growth of infrastructure, and modifications in agricultural practices have greatly changed the land cover patterns in the Bhubaneswar Municipal Corporation (BMC). With this aforesaid background, the objective of this paper is to analyse the land use/land cover change in Bhubaneswar Municipality Corporation (BMC) within a span of the past decade from 2014 to 2023 to provide a better understanding regarding the extent and pattern of land use change using supervised classification method.

Study Area

Bhubaneswar is the capital and largest city of the Indian state of Odisha located in the Khordha district. Bhubaneswar, situated on the eastern coast of India in the state of Odisha, enjoys a strategic location with its coordinates at approximately 20.2961° North latitude and 85.8245° East longitude. Its proximity to the Bay of Bengal influences its climate, characterized by a tropical savanna climate. The city experiences distinct wet and dry seasons, with heavy monsoon rains from June to September, followed by drier and cooler months from October to February.

Bhubaneswar's land use and land cover are diverse, reflecting its status as the state capital and an emerging economic hub. It features a mix of urban areas, residential neighbourhoods, commercial districts, and industrial zones. Additionally, Bhubaneswar's landscape incorporates green spaces, parks, and recreational areas, contributing to its reputation as one of India's planned and well-maintained cities. Considered under Class 1 town, Bhubaneswar Municipal Corporation (BMC) and its agglomeration have a population density of 4634 people per km².

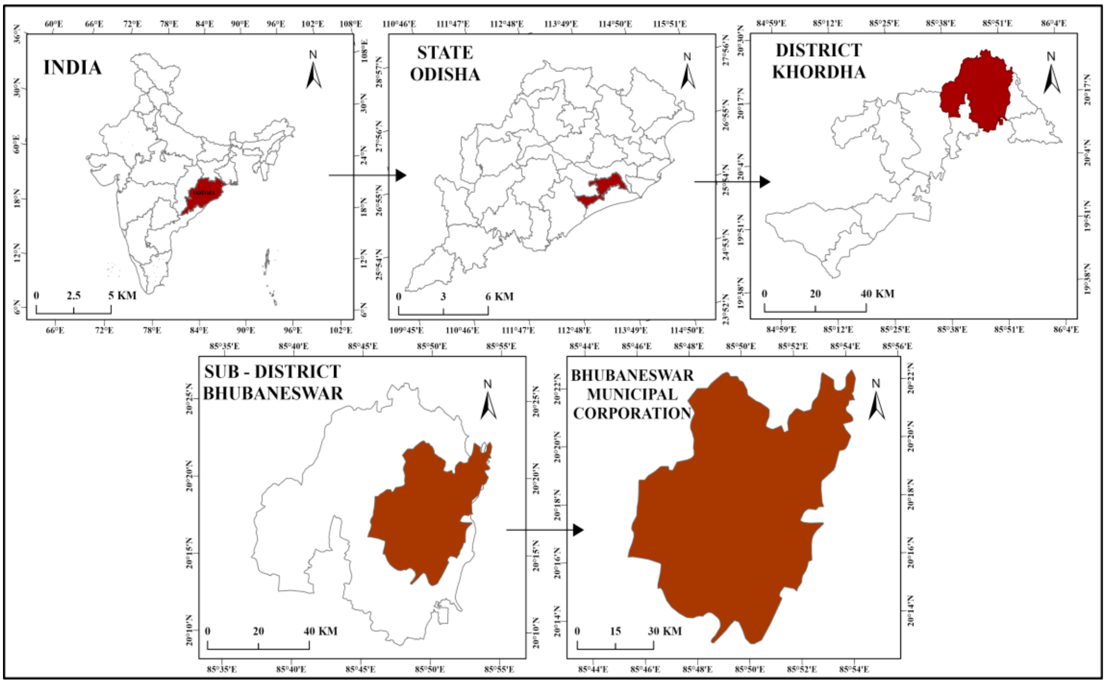

Figure 1: Study Area encompassing BMC region of Bhubaneswar, Odisha, India

Methodology

1 Data Used

This study analyzes land use and land cover changes in the Bhubaneswar Municipal Corporation using Landsat 8 and 9 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) satellite images. The datasets were obtained from the United States Geological Survey (USGS) website, providing access to dependable and high-quality remote sensing data. The exact images utilized in this study were obtained on April 5, 2023 and April 4, 2014. Both photos correspond to the same path and row (140/46), providing a consistent spatial framework for comparison. Importantly, these photos were chosen based on the criteria of being acquired during cloud-free periods, which is critical for the correct interpretation and analysis of land cover data. The cloud-free condition ensures that the satellite data reflects the true surface characteristics without obstruction, thereby enhancing the reliability of the results. Both the images are pre-processed and projected to the Universal Transverse Mercator (UTM) projection system maintaining a 30m resolution.

2 Method Of Land Use/ Land Cover Mapping

After gathering data, a supervised classification method was used with a strong training dataset and ground truth information to classify Landsat satellite images into different categories such as urban areas, vegetation, and water bodies based on land use and land cover (Raju et al., 2018; Reis, 2008). Central to this classification process was the Maximum Likelihood Classification (MLC) method, which operates on the assumption that the spectral values for each land cover class follow a Gaussian distribution (Karan & Samadder, 2016; Nath et al., 2023; Hossain et al., 2023). This approach allows for the calculation of probability of each pixel belonging to each class based on statistical properties derived from the training data. The MLC process involved selecting representative training samples from the imagery, estimating the mean and covariance for each class, and applying the trained model to the entire satellite image. Each pixel was classified into the category with the highest likelihood, thus enhancing the accuracy of the results. By comparing classified images from March 2023 and March 2014, changes in land use and land cover were identified and quantified, providing critical insights for land management and decision-making in BMC.

Results

1 Lulc Classification – 2014

The land use and land cover (LULC) classification for 2014 shows a varied landscape within the study area. The Built-Up category occupies the largest share, making up about 40.87% of the total area, which indicates significant urbanization and development in the region. Following this, Vegetation covers approximately 29.75%, suggesting a healthy amount of green space. Forest areas account for around 23.72%, playing an essential role in maintaining the ecological balance. On the other hand, Barren land is relatively small at about 4.53%, pointing to limited unused land. Water Bodies are the least represented, comprising only 1.10% of the area, but they are crucial for local ecosystems.

2 Lulc Classification – 2023

The land use and land cover (LULC) classification for 2023 reveals a marked shift in the landscape compared to previous years. The Built-Up areas dominate the classification, comprising approximately 72.45% of the total land cover, indicating a substantial increase in urban development and infrastructure in the region. Vegetation is the second-largest category, covering about 14.61%, which reflects the presence of green spaces despite the urban expansion. Forest areas account for around 8.53%, highlighting the continued importance of these ecosystems in the landscape. Barren land represents only 2.76%, suggesting limited unutilized areas within the study region. Water Bodies remain minimal at approximately 1.62%, but they play a critical role in supporting local biodiversity. This updated LULC classification for 2023 underscores the ongoing transformation of the landscape.

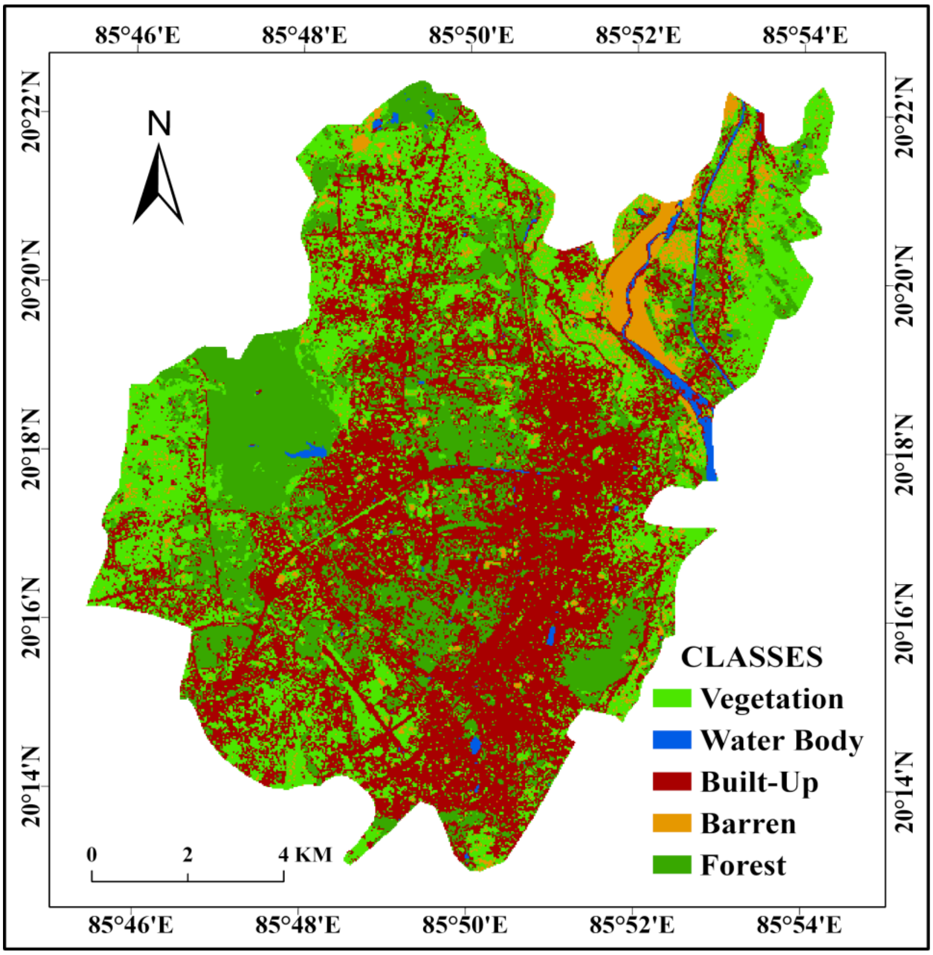

Figure 2: LULC Map - 2014

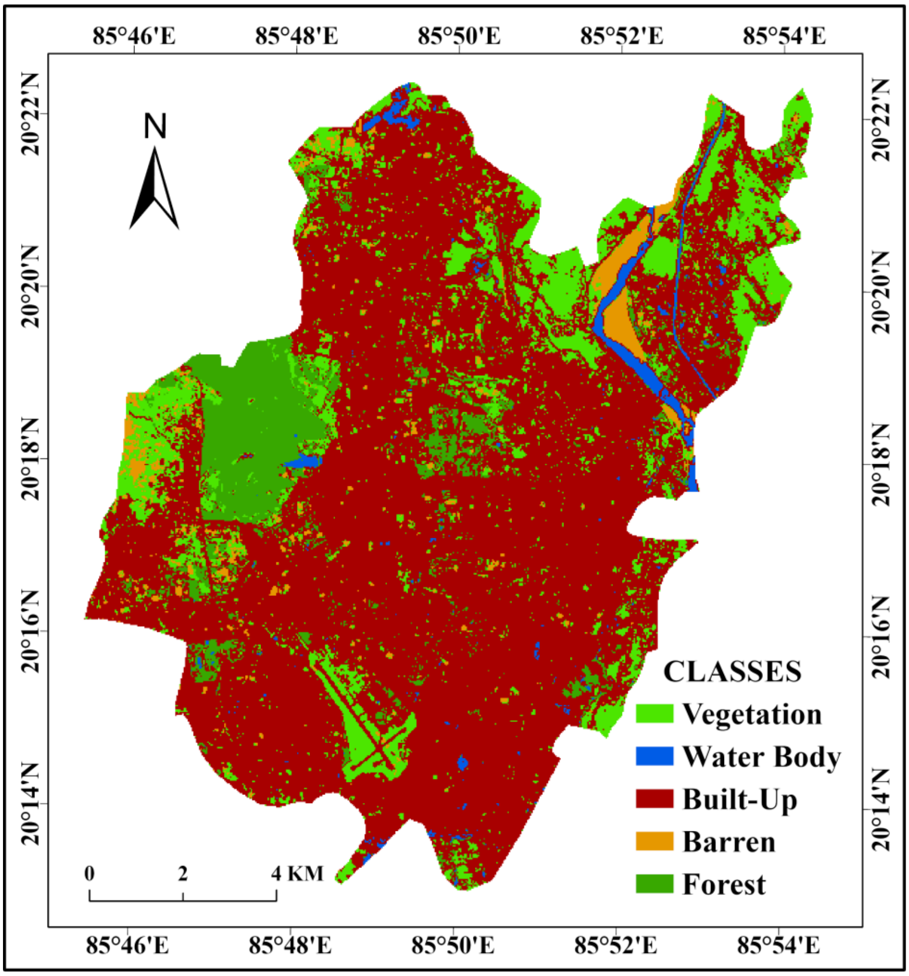

Figure 2: LULC Map - 2023

3 Accuracy Assessment

Accuracy assessment is a crucial step in evaluating the reliability and quality of a Land Use and Land Cover (LULC) classification or change detection analysis. It helps determine how well the classification or change detection results align with the ground truth data or actual conditions on the ground (Rwanga and Ndambuki, 2017).

The accuracy assessment for the 2014 LULC classification reveals a strong performance, with an overall accuracy of 89.00%. The confusion matrix indicates that the classification performed particularly well for the Built-Up and Forest classes, achieving user accuracies of 90.0% and 90.0%, respectively. However, the Barren class exhibited a lower user accuracy of 80.0%, indicating some confusion with other land cover types. The producer accuracy for Vegetation and Water Body classes was also commendable, at 72.0% and 86.4%, respectively. The Cohen's Kappa coefficient (Srivastava et al., 2022) for this classification was calculated at 0.8625, indicating almost perfect agreement between the classified data and the reference data. This high Kappa value reinforces the reliability of the classification results, suggesting that the supervised classification approach effectively captured the land cover dynamics in the region.

Table 1: Confusion Matrix – 2014

<table>
<tr><th colspan="10">CONFUSION MATRIX 2014</th></tr>
<tr><td></td><td></td><td colspan="8">REFERENCE DATA</td></tr>
<tr><td rowspan="9">CLASSIFIED DATA</td><td>Classes</td><td>Vegetation</td><td>Water Body</td><td>Built-Up</td><td>Barren</td><td>Forest</td><td>TOTAL</td><td>Commission</td><td>User Accuracy</td></tr>
<tr><td>Vegetation</td><td>18</td><td>2</td><td>0</td><td>0</td><td>0</td><td>20</td><td>2</td><td>90.0</td></tr>
<tr><td>Water Body</td><td>1</td><td>19</td><td>0</td><td>0</td><td>0</td><td>20</td><td>1</td><td>95.0</td></tr>
<tr><td>Built-Up</td><td>1</td><td>0</td><td>18</td><td>1</td><td>0</td><td>20</td><td>2</td><td>90.0</td></tr>
<tr><td>Barren</td><td>4</td><td>0</td><td>0</td><td>16</td><td>0</td><td>20</td><td>4</td><td>80.0</td></tr>
<tr><td>Forest</td><td>1</td><td>1</td><td>0</td><td>0</td><td>18</td><td>20</td><td>2</td><td>90.0</td></tr>
<tr><td>TOTAL</td><td>25</td><td>22</td><td>18</td><td>17</td><td>18</td><td>100</td><td></td><td></td></tr>
<tr><td>Omission</td><td>7</td><td>3</td><td>0</td><td>1</td><td>0</td><td></td><td rowspan="2">Kappa Coefficient = 0.8625</td><td rowspan="2">Overall Accuracy = 89.00%</td></tr>
<tr><td>Producer Accuracy</td><td>72.0</td><td>86.4</td><td>100.0</td><td>94.1</td><td>100.0</td><td></td></tr>
</table>

In contrast, the accuracy assessment for the 2023 LULC classification yielded an overall accuracy of 87.33%. The confusion matrix shows that the Built-Up class had a high user accuracy of 80.0%, while the Water Body class achieved a perfect producer accuracy of 100%. However, some confusion was noted in the Vegetation and Barren classes, with user accuracies of 83.33% and 93.33%, respectively. The assessment indicates a slight decline in overall accuracy compared to 2014, reflecting the challenges in distinguishing between land cover types in a changing urban environment. The Kappa coefficient for 2023 was calculated at 0.8416, which also indicates almost perfect agreement between the classified data and reference data. This Kappa value suggests that, despite the complexities introduced by urbanization and land cover changes, the classification model remains robust in accurately reflecting the land use dynamics of the study area.

Table 2: Confusion Matrix – 2023

CONFUSION MATRIX 2023									
		REFERENCE DATA							
CLASSIFIED DATA	Classes	Vegetation	Water Body	Built-Up	Barren	Forest	TOTAL	Commission	User Accuracy
	Vegetation	25	0	1	3	1	30	5	83.33
	Water Body	4	25	1	0	0	30	5	83.33
	Built-Up	2	0	24	4	0	30	6	80.00
	Barren	0	0	1	28	1	30	2	93.33
	Forest	0	0	1	0	29	3	1	96.67
	TOTAL	31	25	28	35	31	150		
	Omission	6	0	4	7	2		Kappa Coefficient = 0.8416	Overall Accuracy = 87.33%
	Producer Accuracy	80.65	100	85.71	80	93.55			

4 Lulc Change Analysis (2014 – 2023)

The LULC change analysis between 2014 and 2023 reveals significant shifts in land use patterns within the Bhubaneswar Municipal Corporation region. One of the most striking changes is the increase in Built-Up areas, which expanded from 62.17 sq. km (40.87%) in 2014 to 110.20 sq. km (72.45%) in 2023, reflecting a notable growth of 48.03 sq. km, or 31.58%. This substantial urban expansion is likely driven by population growth, infrastructural development, and industrialization in the area.

Conversely, Vegetation and Forest areas saw substantial declines over this period. Vegetation cover decreased from 45.25 sq. km (29.75%) in 2014 to 22.23 sq. km (14.61%) in 2023, a reduction of 23.02 sq. km (15.13%). Similarly, Forest areas reduced from 36.08 sq. km (23.72%) to 12.97 sq. km (8.53%), representing a loss of 23.11 sq. km (15.19%). These reductions likely reflect deforestation, land clearance for urban development, and other anthropogenic pressures.

Barren land also showed a minor reduction, decreasing from 6.89 sq. km (4.53%) in 2014 to 4.20 sq. km (2.76%) in 2023, a drop of 2.69 sq. km (1.77%). This could suggest the conversion of previously unused land into urban areas or re-vegetation in some parts. On the other hand, Water Bodies increased modestly from 1.67 sq. km (1.10%) to 2.46 sq. km (1.62%), adding 0.79 sq. km (0.52%). This growth could be attributed to enhanced water management practices or the expansion of man-made water bodies.

Table 3: Areal distribution of different Land use/cover

	2014		**2023**		**CHANGE (2014-23)**	
Classes	Area (sq. km)	Percent	Area (sq. km)	Percent	Area (sq. km)	Percent
Built-Up	62.17	40.87	110.20	72.45	48.03	31.58
Vegetation	45.25	29.75	22.23	14.61	-23.02	-15.13
Forest	36.08	23.72	12.97	8.53	-23.11	-15.19
Barren	6.89	4.53	4.20	2.76	-2.69	-1.77
Water Body	1.67	1.10	2.46	1.62	0.79	0.52

The class-to-class transitions indicate notable conversions. A significant portion of the Forest land (19.93 sq. km) was converted into Built-Up areas, followed by the transition of Built-Up from Vegetation (3.07 sq. km). Forest-to-Vegetation conversion also occurred at 2.89 sq. km, reflecting minor reforestation or natural regeneration in some areas. Other transitions include Barren-to-Vegetation (2.74 sq. km) and Barren-to-Built-Up (1.88 sq. km), suggesting dynamic land use patterns. The total unchanged area during this period was 117.32 sq. km, or 77.10%, indicating that more than three-quarters of the region retained its original land cover, despite significant localized changes.

Table 4: LULC Change

Classes	Area	Percent
Forest - Built-Up	19.928554	13.09624
Built-Up - Vegetation	3.0703	2.017678
Forest - Vegetation	2.886349	1.896792
Barren - Vegetation	2.740566	1.80099
Barren - Built-Up	1.882659	1.237208
Vegetation - Barren	1.473128	0.96808
Vegetation - Forest	0.609348	0.400439
Barren - Water Body	0.45309	0.297753
Forest - Barren	0.432728	0.284372
Water Body - Built-Up	0.401827	0.264065
Built-Up - Barren	0.310376	0.203967
Built-Up - Water Body	0.243714	0.160159
Water Body - Barren	0.142938	0.093933
Vegetation - Water Body	0.093492	0.061439
Water Body - Forest	0.050655	0.033288
Barren - Forest	0.026776	0.017596
No Change	117.31563	77.09511

Overall, the analysis shows that Bhubaneswar Municipal Corporation had considerable land use and land cover (LULC) changes between 2014 and 2023, which were predominantly driven by rapid urbanization. Built-up areas have increased significantly, while vegetation and forest cover have decreased, showing that natural land is being converted into urban spaces. The small rise in water bodies and the little decrease in barren land indicate alterations in land use practices. This research underlines the environmental impact of urban expansion and the necessity for sustainable urban design that balances development with ecological protection.

Conclusion

The study highlights major changes in land use and land cover (LULC) in Bhubaneswar Municipal Corporation between 2014 and 2023, indicating a significant increase in built-up areas while vegetation and forest cover decreased. Bhubaneswar's rapid urban growth has led to the transformation of natural surroundings into urban spaces, posing challenges for sustainable development and environmental conservation. The results emphasize the crucial importance of balanced land management strategies that prioritize protecting the environment while still allowing for the city to grow. The thorough evaluation of land use and land cover changes in this research offers valuable insights for decision-makers, city planners, and environmental experts to facilitate sustainable and environmentally conscious development.

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