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Manuscript ID:
IJWGAFES-2026-030302

DOI: 10.5281/zenodo.21822180

DOI Link:
<https://doi.org/10.5281/zenodo.21822180>

Volume: 3

Issue: 3

March

Year: 2026

E-ISSN: 3066-1552

Submitted: 05 Feb.2026

Revised: 15 Feb.2026

Accepted: 06 Mar.2026

Published: 31 Mar. 2026

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How to cite this article:
Kalbhor, B. & Patil, P. T. (2026). Impact of Land Use Land Cover (LULC) Dynamics on Urban Development: A SWOT-Based Assessment of Satara City, Maharashtra. International Journal of World Geology, Geography, Agriculture, Forestry and Environment Sciences, 3(3), 7–21.
<https://doi.org/10.5281/zenodo.21822180>

Impact of Land Use Land Cover (LULC) Dynamics on Urban Development: A SWOT-Based Assessment of Satara City, Maharashtra

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Abstract

This study analyzes the impact of Land Use and Land Cover (LULC) dynamics on urban development in Satara City using an integrated geospatial and SWOT based framework. Multi temporal satellite data from 2001, 2011, and 2021 were processed through object-based image classification techniques within a GIS environment to quantify spatial changes and assess their implications for sustainable planning. The study area expanded from 8.15 km² to 26.54 km², reflecting significant administrative and physical growth. Results indicate a rapid increase in built-up land from 23.55% (7.50 km²) in 2001 to 59.92% in 2011, and 51.56% (13.92 km²) in 2021, demonstrating accelerated urbanization and spatial restructuring. In contrast, agricultural land declined sharply from 29.78% to nearly 10%, while vegetation cover reduced from 17.06% to 11.64%, indicating environmental degradation and land-use imbalance. Water bodies remained critically low, accounting for less than 0.5% throughout the study period. Accuracy assessment confirms the reliability of the classification, with overall accuracy improving from 70% (Kappa = 61.92) in 2001 to 88% (Kappa = 85.10) in 2021. The SWOT analysis reveals that urban growth has enhanced economic development and infrastructure expansion but has also intensified challenges such as infrastructure stress, ecological decline, and unregulated peri-urban expansion. Opportunities exist in the planned use of fallow land and ecological restoration, while threats include urban sprawl and resource vulnerability. The study emphasizes the need for geospatially informed, sustainable urban planning strategies to ensure balanced development and long-term urban resilience.

Keywords: Land Use/Land Cover, Object-Based Classification, SWOT Analysis, Urban Growth, Satara City, Remote Sensing, GIS

Introduction

Urbanization is a dominant global process reshaping spatial, economic, and environmental structures of cities. In developing countries like India, medium-sized cities are experiencing rapid and often unplanned expansion, resulting in significant transformations of Land Use and Land Cover (LULC). Monitoring these changes is essential for sustainable urban planning, infrastructure management, and environmental conservation.

Remote Sensing and Geographic Information Systems (GIS) provide robust tools for analyzing urban LULC dynamics across time and space. Simultaneously, SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis offers a strategic framework for evaluating urban development conditions. However, limited research has integrated geospatial LULC analysis with SWOT-based urban planning assessments.

Satara City, a historically significant urban center in Maharashtra, presents an ideal case for examining the interaction between spatial land transformations and urban development challenges. This study aims to bridge geospatial analysis with strategic urban evaluation by correlating LULC changes with SWOT components.

Objectives

1. To analyze multi-temporal LULC changes in Satara City (2001–2011–2021).
2. To evaluate classification accuracy using standard assessment metrics.
3. To examine the implications of LULC dynamics on urban Strengths, Weaknesses, Opportunities, and Threats.
4. To derive strategic planning insights for sustainable urban development.

Study Area

Satara City is located in southwestern Maharashtra between 17.68°N latitude and 73.98°E longitude. The city serves as the administrative headquarters of Satara District and exhibits a mix of urban, agricultural, and natural landscapes. The original municipal extent covered approximately 8.15 sq. km, later expanded to over 26.54 sq. km. The city's strategic location along National Highway 48 and proximity to ecologically significant zones contribute to its developmental importance.

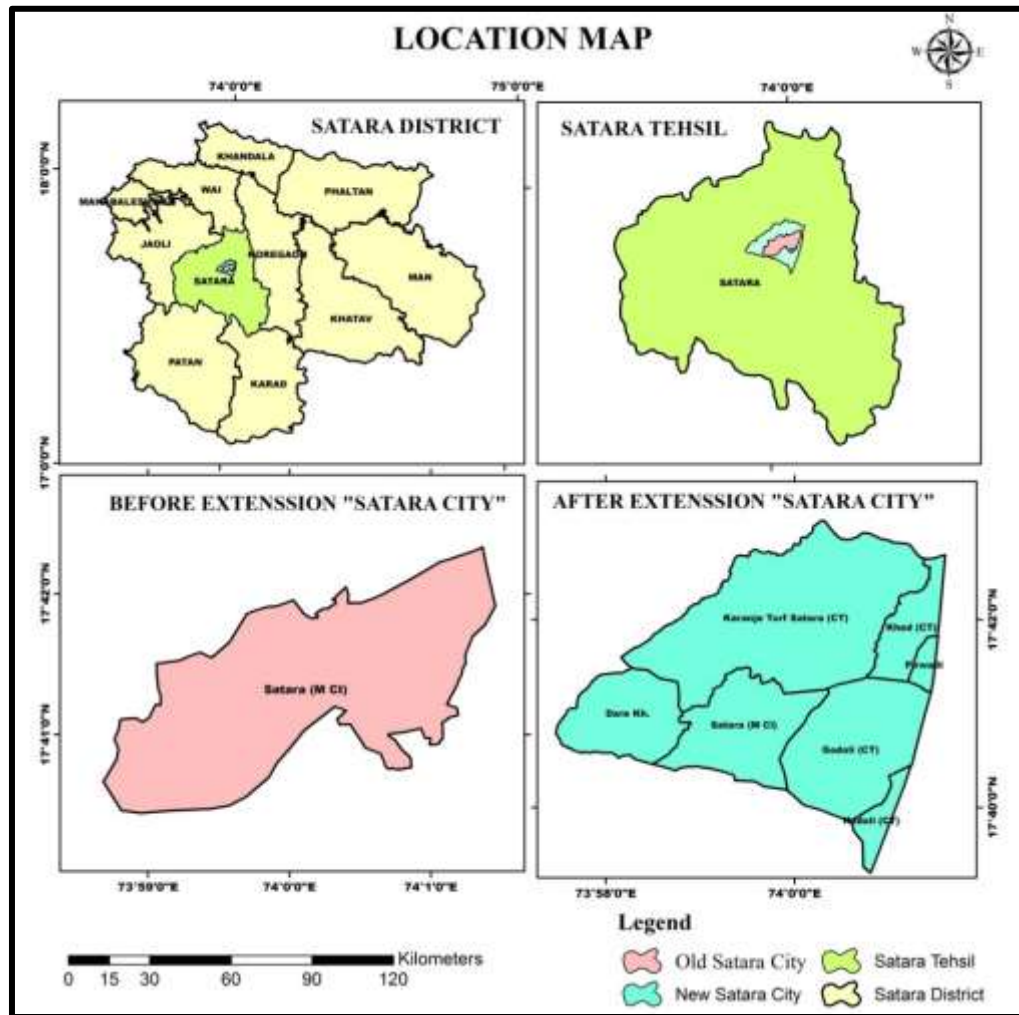


Fig. 1: Location map of Satara City

Database and Methodology

1. Data Sources

The table 1 offers a thorough summary of satellite data used to detect changes in land-use/land-cover (LULC) and urban expansion. It contains information from NRSC that spans 20 years, from 2001 to 2021. After preprocessing the 2001 Resourcesat LISS III and Cartosat PAN images using the resolution merge technique, they were categorized and a LULC map was produced. Sensors like 1C-LISS 3 and RS2-LISS 4 have different resolutions; RS2-LISS 4 has a finer spatial resolution of 5.8 meters, while 1C-LISS 3 has a resolution of 23.5 meters. These developments in satellite technology improve LULC analysis accuracy. Multiple bands, which are necessary for a variety of spectral analyses, are present in the data, and it is aligned with certain path/row coordinates for accurate geographic coverage. The significance of high-resolution satellite imagery and developing remote sensing technology in efficiently tracking urbanization and its effects is highlighted by this dataset.

Table 1: Multi-Date Satellite Data Employed for Urban LULC Mapping of the Satara City

Sr. No.	Date	Satellite Sensor	Satellite Id	Product code	Resoluti-on (mt)	No.of Bands	Path/Row	Source
1	18-Dec-2001	1C-LISS 3	IRS-1C	STUC00OTD	23.5	4	0.95/0.60	NRSC
2	09-Dec-2001	LISS III	Resourcesat	PAN Band	5.8	1	0.95/0.60	NRSC
3	26-DEC-2011	RS2-LISS 4	IRS-R2	STUC00GTD	5.8	3	0.95/0.60	NRSC
4	26-Dec-2021	RS2-LISS 4	IRS-R2	STUC00GTD	5.8	3	0.95/0.60	NRSC

Source: Band Metadata Product Information from NRSC, 2023

2. Object-Based LULC Classification

Instead of examining individual pixels, object-based categorization is a sophisticated method of image analysis that organizes pixels into meaningful objects according to their spectral, spatial, and contextual characteristics. This procedure starts with picture segmentation in eCognition software, which uses methods such as multi-resolution segmentation to split the image into uniform segments. These segments are used to extract features like spectral values, forms, textures, and contextual relationships. Following that, classification is carried out either supervised, where algorithms like Random Forest or SVM are guided by labeled training samples, or rule-based, which depend on predetermined criteria. By correcting for noise or incorrectly categorized items, post-classification refining increases accuracy and produces accurate and trustworthy thematic maps.

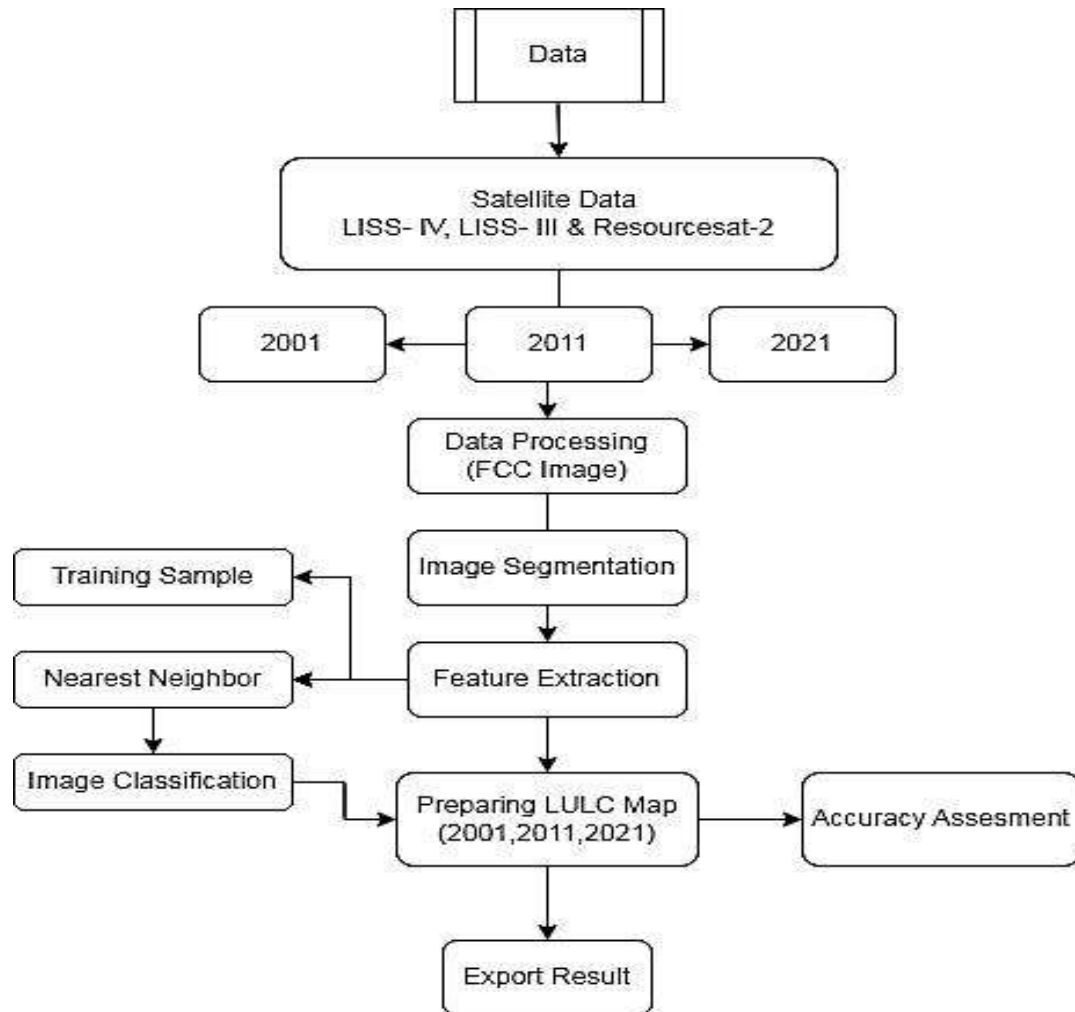


Fig. 2: Flowchart of research methodology

3. LULC Classification Scheme

Land use/land cover analysis and preparation of land use/ land cover maps are the basic need for all urban planning (Sawant, 1978). The terms land use and land cover is often used interchangeably, but each term has its own unique meaning. Land cover refers to the surface cover on the ground like vegetation, urban infrastructure, water, bare soil etc. Identification of land cover establishes the baseline information for activities like thematic mapping and change detection analysis. Land use refers to the purpose the land serves, for example, recreation, wildlife habitat, or agriculture.

When used together with the phrase Land Use / Land Cover (LULC) generally refers to the categorization or classification of human activities and natural elements on the landscape within a specific time frame based on established scientific and statistical methods of analysis of appropriate source materials.

Table 2: Description of land use classes

Sr.No.	Class Name	Sub Class	Class Description
1	Agriculture	Crop Land	Kharif, Rabi, Zaid, Two cropped, More than two cropped
		Plantation	Plantation - Agricultural, Horticultural, Agro Horticultural
2	Barren Land	Scrub land	Dense / Closed and Open category of scrub land, waste land, and infertile land
		Barren rocky	Barren rocky
3	Built-Up	Rural	Rural
		Urban	Residential, Mixed built-up, Public / Semi Public, Communication, Public utilities /facility, Commercial, Transportation, Reclaimed

			land, Vegetated Area, Recreational, Industrial, Industrial / Mine dump, Ash / Cooling pond
4	Fallow land	Fallow Land	the agricultural lands, which are uncropped for a particular time
5	Vegetation	Evergreen / Semi evergreen	Dense / Closed and Open category of Evergreen / Semi evergreen
		Deciduous	Dense / Closed and Open category of Deciduous and Tree Clad Area
		Forest Plantation	Forest Plantation
6	Water body	River and lakes	Perennial & Dry River, lakes, reservoirs and tanks
		Canals	

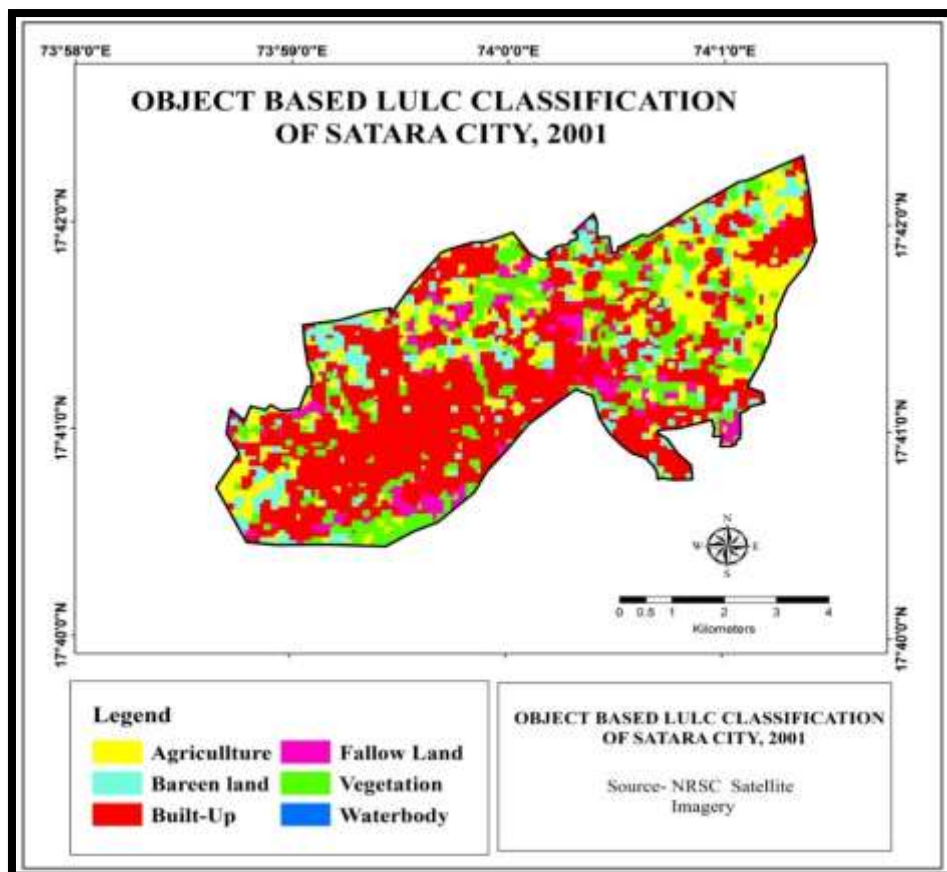
Source: NRSC, Manual of National Land Use/Land Cover Mapping Using Multi-temporal Satellite Data, Department of Space, Hyderabad, 2023

Results

1. LULC Change Analysis

The analysis indicates:

- Substantial increase in Built-Up Area
- Gradual decline in Vegetation Cover
- Reduction in Agricultural Land
- Expansion into peri-urban zones



Source: NRSC Satellite Imagery, 2001

Fig. 2: Land Use Land Cover Classification of the Satara City, 2001

Table 3: Land Use Land Cover Classification the Satara City 2001

Sr.No.	Class Name	Area % (2001)	Area in %
1	Agriculture	7.98	29.78
2	Barren Land	5.86	21.6
3	Built-Up	7.50	23.55
4	Fallow land	2.06	7.758
5	Vegetation	4.53	17.06
6	Water body	0.07	0.26
7	Total	27.00	100.0

Source: Based on LU/LC analysis Data, 2001

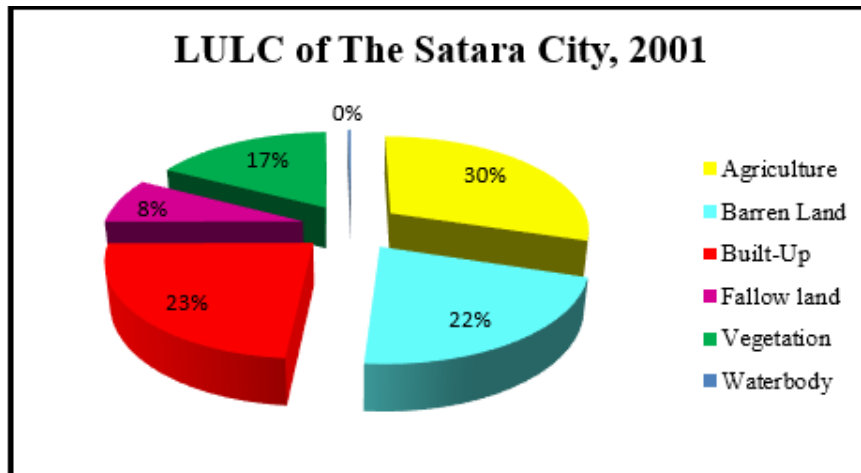


Fig. 3: LULC Area of the Satara City, 2001

Table 4: Land Use Land Cover Classification of the Satara City, 2011

Sr.no.	Class Name	Area Sq.km (2011)	Area in %
1	Agriculture	0.75	8.82
2	Barren Land	0.68	7.99
3	Built-Up	5.10	59.92
4	Fallow land	1.61	18.91
5	Vegetation	0.31	3.77
6	Water body	0.05	0.59
7	Total	8.51	100

Source: Based on LU/LC analysis Data, 2011

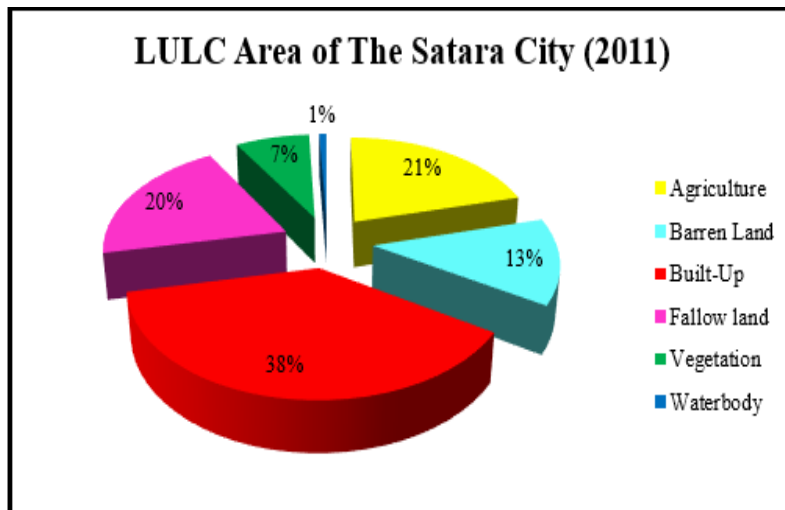
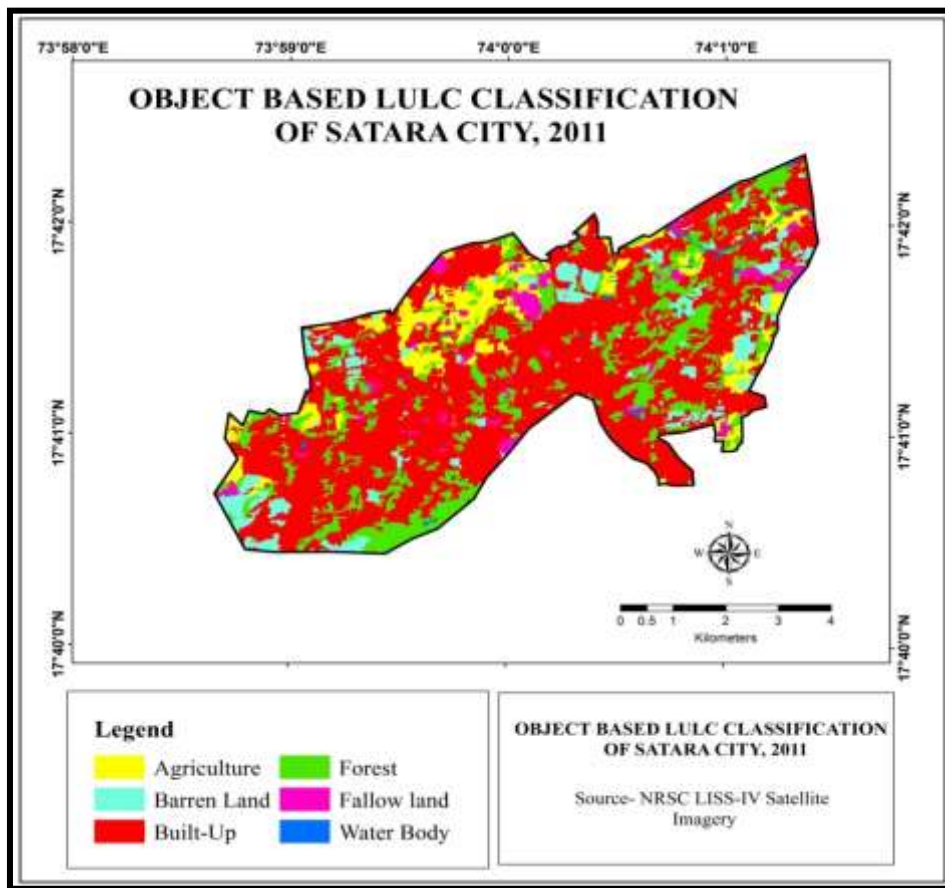
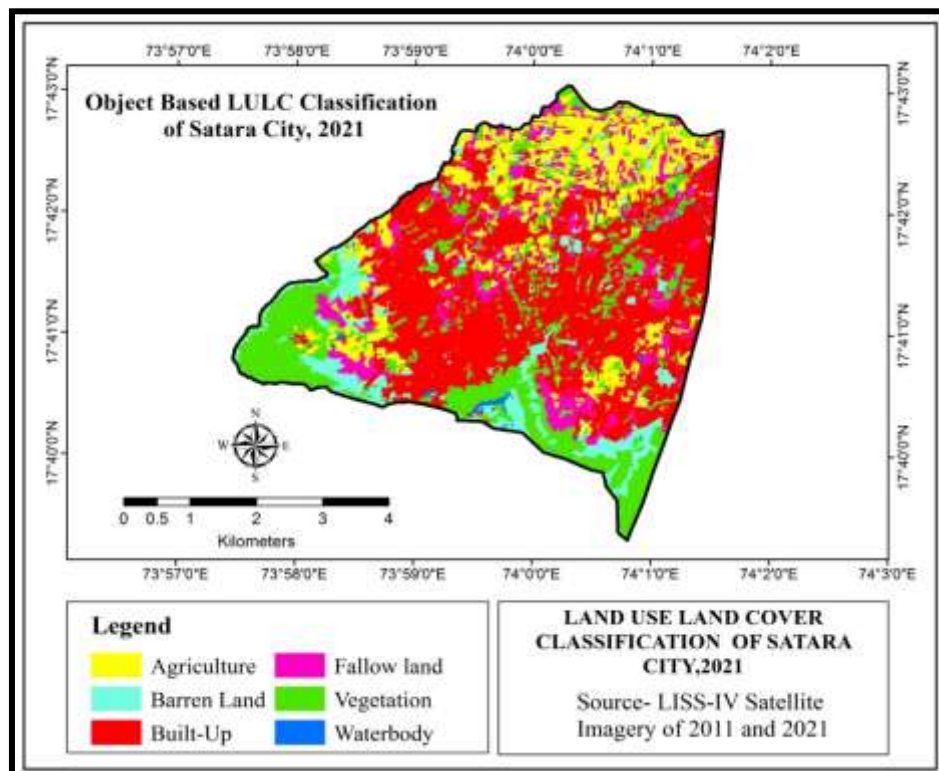


Fig. 4: LULC Area of Satara City, 2011



Source: NRSC Satellite Imagery, 2011

Fig. 5: Land Use Land Cover Classification of the Satara City, 2011



Source: NRSC Satellite Imagery, 2021

Fig.6: Land Use Land Cover Classification of the Satara City, 2021

Table 5: Land Use Land Cover Classification of the Satara, 2021

Sr.no.	Class Name	Area Sq.km (2021)	Area in %
1	Agriculture	4.60	17.02
2	Barren Land	2.29	8.50
3	Built-Up	13.92	51.56
4	Fallow land	2.93	10.85
5	Vegetation	3.14	11.64
6	Water body	0.12	0.43
7	Total	27.00	100

Source: Based on LU/LC analysis Data

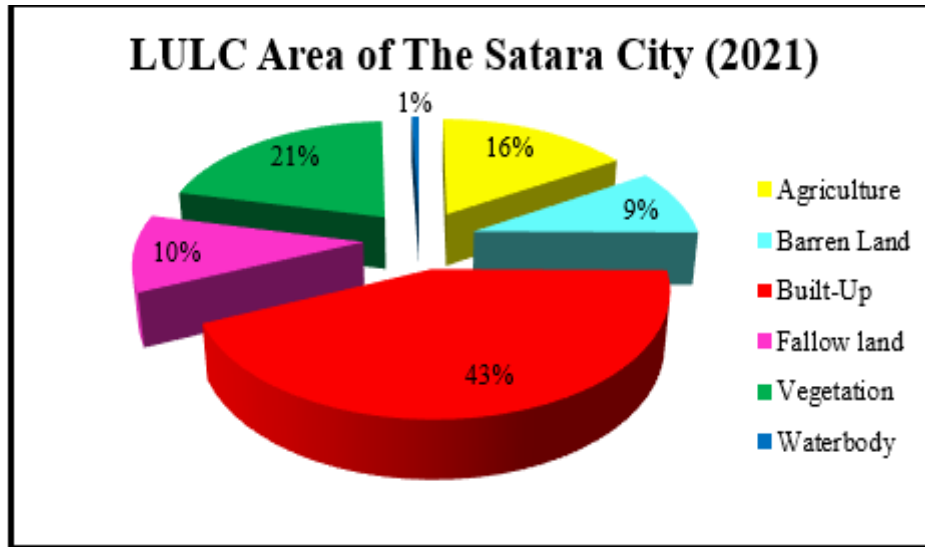


Fig.7: LULC Area of the Satara City, 2021

2. Urban Growth Trends

Built-up expansion demonstrates:

- Horizontal urban spread
- Land conversion pressure
- Intensification of urban footprint

3. Accuracy Assessment

Classification accuracy was evaluated using:

- Error Matrix
- User's Accuracy

$$\text{User Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Classified Pixels in that Category (The Row Total)}} \times 100$$

- Producer's Accuracy

$$\text{Producer Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Referenced Pixels in that Category (The Column Total)}} \times 100$$

- Overall Accuracy

$$\text{Overall Accuracy} = \frac{\text{Total Number of Currently Classified Pixel (Diagonal)}}{\text{Total Number of Reference Pixel}} \times 100$$

- Kappa Coefficient

$$\text{Kappa Coefficient (T)} = \frac{(TS \times TCS) - \sum (\text{Column Total} \times \text{Row Total})}{TS^2 - \sum (\text{Column Total} - \text{Row Total})} \times 100$$

Results indicated strong classification reliability, particularly for Built-Up and Water Body classes.

Accuracy Assessment 2001

Table 6: Accuracy Assessment Table 2001

Class Name	Agriculture	Barren Land	Built-Up	Fallow Land	Vegetation	Water body	Total (User)
Agriculture	4	1	1	2	1	0	9
Barren Land	1	5	1	0	1	0	8
Built-Up	1	0	9	0	2	0	12
Fallow Land	0	0	1	3	1	0	5

Vegetation	1	0	1	0	10	0	12
Water body	0	0	0	0	0	4	4
Total (Producer)	6	6	12	5	17	4	50

Source: Based on accuracy assessment Data

$$\text{Overall Accuracy} = \frac{\text{Total Number of Currently Classified Pixel (Diagonal)}}{\text{Total Number of Reference Pixel}} \times 100$$

$$= \frac{44}{50} \times 100$$

$$= 70\%$$

$$\text{User Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Classified Pixels in that Category(The Row Total)}} \times 100$$

Table 3.7: User Accuracy Results 2001

Agriculture	=	4/9x100	= 44.44%
Barren Land	=	5/8x100	= 62.5%
Built-Up	=	9/12x100	= 75%
Fallow Land	=	3/5x100	= 60%
Vegetation	=	13/13x100	= 83.33%
Water body	=	4/4x100	=100%

$$\text{Producer Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Referenced Pixels in that Category(The Column Total)}} \times 100$$

Table 3.8: Producer Accuracy Results 2001

Agriculture	=	4/6 x 100	= 67.66%
Barren Land	=	5/6 x 100	= 83.33%
Built-Up	=	9/ 12 x 100	= 75%
Fallow Land	=	3 / 5 x 100	= 60%
Vegetation	=	10/17 x100	= 58.82%
Water body	=	4/4x100	= 100%

$$\text{KappaCoefficient}(T) = \frac{(TS \times TCS) - \sum(\text{Column Total} \times \text{Row Total})}{TS^2 - \sum(\text{Column Total} - \text{Row Total})} \times 100$$

$$= \frac{(50 \times 35) - [(7 \times 9) + (6 \times 8) + (13 \times 12) + (5 \times 5) + (15 \times 12) + (4 \times 4)]}{2500 - [(7 \times 9) + (6 \times 8) + (13 \times 12) + (5 \times 5) + (15 \times 12) + (4 \times 4)]} \times 100$$

$$= \frac{1750 - 481}{2500 - 481} \times 100$$

$$= \frac{1269}{2019} \times 100$$

$$= 61.92 \%$$

Here,

TS= Total Sample

TCS= Total Corrected Samples

Table 3.9: Kappa Coefficient Assessment, 2001

Class Name	References Total	Classified Total	Number Totals	Producer Accuracy (%)	User Accuracy (%)
Agriculture	4	9	6	67.66	44.44
Barren Land	5	8	6	83.33	62.5
Built-Up	9	12	12	75	75
Fallow Land	3	5	5	60	60
Vegetation	12	12	17	58.82	83.33
Water body	4	4	4	100	100
Total	50	50	50		
Overall Accuracy = 70%					
Overall, Kappa Accuracy = 61.92 %					

Source: Based on accuracy assessment Data, 2001

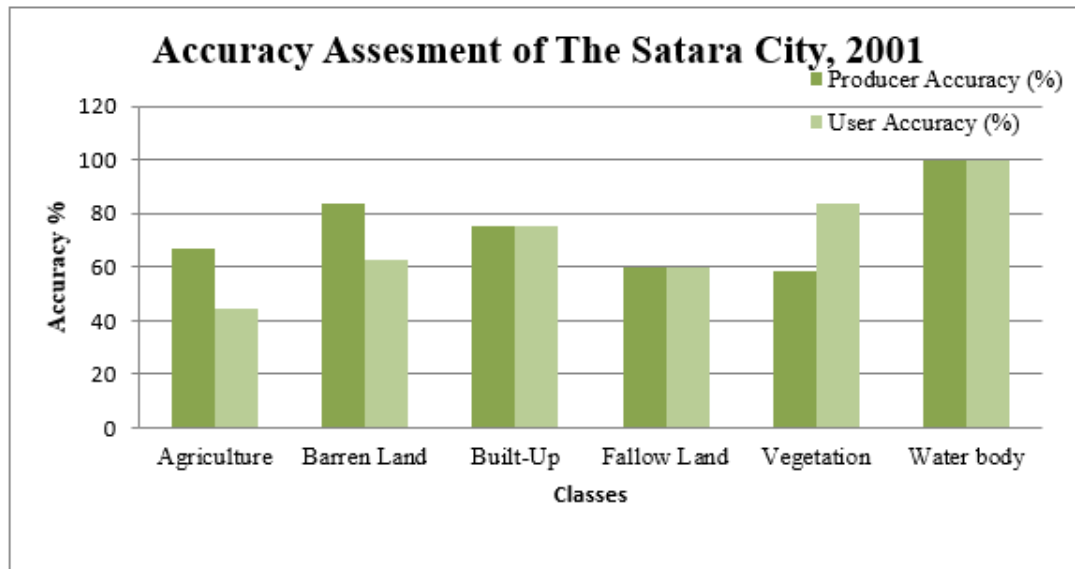


Fig.8: User and Producer Accuracy 2001

Accuracy Assessment 2011

Table 10: Accuracy Assessment Table 2011

	Agriculture	Barren Land	Built-Up	Vegetation	Fallow Land	Water body	Total (User)
Agriculture	8	0	1	1	0	0	10
Barren Land	0	5	0	0	1	0	6
Built-Up	0	0	13	0	0	0	13
Vegetation	1	0	0	6	0	1	8
Fallow Land	1	1	0	0	5	0	7
Water body	0	0	0	0	0	6	6
Total (Producer)	10	6	14	7	6	7	50

Source: Based on accuracy assessment Data

$$\text{Overall Accuracy} = \frac{\text{Total Number of Currently Classified Pixel (Diagonal)}}{\text{Total Number of Reference Pixel}} \times 100$$

$$= \frac{43}{50} \times 100$$

$$= 86\%$$

$$\text{User Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Classified Pixels in that Category (The Row Total)}} \times 100$$

Table 3.11: User Accuracy Result 2011

Agriculture	= 8 / 10 x 100	= 80%
Barren Land	= 5 / 6 x 100	= 83.33%
Built-Up	= 13 / 13 x 100	= 100%
Fallow Land	= 5 / 7 x 100	= 71.43%
Vegetation	= 6 / 8 x 100	= 75 %
Water body	= 6 / 6 x 100	= 100%

$$\text{Producer Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Referenced Pixels in that Category (The Column Total)}} \times 100$$

Table 3.12: Producer Accuracy Result 2011

Agriculture	= 8 / 10 x 100	= 80%
Barren Land	= 5 / 6 x 100	= 83.33 %
Built-Up	= 13 / 14 x 100	= 92.86 %
Fallow Land	= 5 / 6 x 100	= 83.33%
Vegetation	= 6 / 7 x 100	= 85.71 %
Water body	= 6 / 7 x 100	= 85.71 %

$$\text{Kappa Coefficient (T)} = \frac{(TS \times TCS) - \sum (\text{Column Total} \times \text{Row Total})}{TS^2 - \sum (\text{Column Total} - \text{Row Total})} \times 100$$

$$\begin{aligned}
 &= (50 \times 43) - [(10 \times 10) + (6 \times 6) + (14 \times 13) + (7 \times 8) + (6 \times 7) + (7 \times 6)] \times 100 \\
 &\quad 2500 - [(10 \times 10) + (6 \times 6) + (14 \times 13) + (7 \times 8) + (6 \times 7) + (7 \times 6)] \\
 &= 2150 - 458 \times 100 \\
 &\quad 2500 - 458 \\
 &= 1692 \times 100 \\
 &\quad 2042 \\
 &= 82.86 \%
 \end{aligned}$$

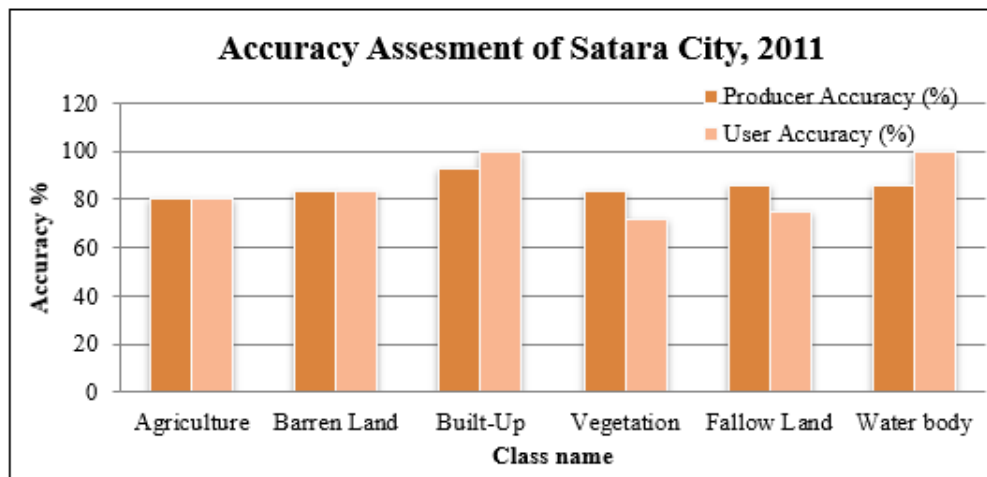
Table 13: Kappa Coefficient Assessment, 2011

Class Name	References Total	Classified Total	Number Totals	Producer Accuracy (%)	User Accuracy (%)
Agriculture	10	10	8	80	80
Barren Land	6	6	5	83.33	83.33
Built-Up	14	13	13	92.86	100
Vegetation	7	8	6	83.33	71.43
Fallow Land	6	7	5	85.71	75
Water body	7	6	6	85.71	100
Total	50	50	50		
Overall Accuracy = 86%					
Overall, Kappa Accuracy = 82.86%					

Source: Based on accuracy assessment Data, 2011

The 2011 Kappa Coefficient Assessment, which assesses the precision of land-use classification, is shown in the table. Along with accurately categorized instances ("Number Totals"), it compares the actual ("References Total") and expected ("Classified Total") land-use counts. Fallow Land and Water body (85.71%) and Built-Up (92.86%) have the highest producer accuracy (the probability of accurately identifying reference data), followed by Barren Land and Vegetation (83.33%) and Agriculture (80%). For Built-Up and Waterbodies, User Accuracy (the likelihood that an identified point is in the reference class) is 100%; however, it is lower for Barren Land (83.33%), Agriculture (80%), Fallow Land (75%), and Vegetation (71.43%).

Fig. 9: User and Producer Accuracy, 2011



With a Kappa accuracy of 82.86%, the overall categorization accuracy is 86%. These numbers show a high degree of agreement between reference and categorized data, however there is considerable accuracy variation by class.

Accuracy Assessment 2021

Table 3.14: Accuracy Assessment Table 2021

Class Name	Agriculture	Barren Land	Built-Up	Fallow Land	Vegetation	Water body	Total (User)
Agriculture	5	0	0	2	1	0	8
Barren Land	0	7	0	0	1	0	8
Built-Up	0	0	11	0	0	0	11
Fallow Land	0	0	1	3	1	0	5
Vegetation	0	0	0	0	13	0	13
Water body	0	0	0	0	0	5	5
Total (Producer)	5	7	12	5	16	5	50

Source: Based on accuracy assessment Data

$$\text{Overall Accuracy} = \frac{\text{Total Number of Currently Classified Pixel (Diagonal)}}{\text{Total Number of Reference Pixel}} \times 100$$

$$= \frac{44}{50} \times 100$$

$$= 88\%$$

$$\text{User Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Classified Pixels in that Category (The Row Total)}} \times 100$$

Table 3.15: User Accuracy Result, 2021

Agriculture	= 5/8x100	= 62.5%
Barren Land	= 7/8x100	= 87.5%
Built-Up	= 11/11x100	=100%
Fallow Land	= 3/5x100	=60%
Vegetation	= 13/13x100	=100%
Water body	= 5/5x100	=100%

$$\text{Producer Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Referenced Pixels in that Category (The Column Total)}} \times 100$$

Table 3.16: User Accuracy Result, 2021

Agriculture	= 5/5 x 100	= 100%
Barren Land	= 7/7 x 100	= 100%
Built-Up	= 11 / 12 x 100	= 92%
Fallow Land	= 3 / 5 x 100	= 60%
Vegetation	= 13/16 x100	= 81%
Water body	= 5/5x100	= 100%

$$\text{Overall Accuracy} = \frac{\text{Total Number of Currently Classified Pixel (Diagonal)}}{\text{Total Number of Reference Pixel}} \times 100$$

$$\text{Kappa Coefficient (T)} = \frac{(TS \times TCS) - \sum(\text{Column Total} \times \text{Row Total})}{TS^2 - \sum(\text{Column Total} - \text{Row Total})} \times 100$$

$$= \frac{(50 \times 44) - [(8 \times 5) + (8 \times 7) + (11 \times 12) + (5 \times 5) + (13 \times 16) + (5 \times 5)]}{2500 - [(8 \times 5) + (8 \times 7) + (11 \times 12) + (5 \times 5) + (13 \times 16) + (5 \times 5)]} \times 100$$

$$= \frac{2200 - 486}{2500 - 486} \times 100$$

$$= \frac{1714}{2014} \times 100$$

$$= 85.10 \%$$

Table 17: Kappa Coefficient Assessment, 2021

Class Name	References Total	Classified Total	Number Totals	Producer Accuracy (%)	User Accuracy (%)
Agriculture	10	10	8	80	80
Barren Land	6	6	5	83.33	83.33
Built-Up	14	13	13	92.86	100
Vegetation	7	8	6	83.33	71.43
Fallow Land	6	7	5	85.71	75
Water body	7	6	6	85.71	100
Total	50	50	50		
Overall Accuracy = 86%					
Overall, Kappa Accuracy = 82.86%					

Source: Based on accuracy assessment Data, 2021

The accuracy evaluation of land categorization data is shown in this table, which also includes performance indicators for every land-use class. The "Number Totals" column reveals cases that were correctly classified, the "Classified Total" column shows the projected counts, and the "References Total" column displays the actual observed counts. For Agriculture, Barren Land, and Water body, the Producer Accuracy (the likelihood of properly identifying a reference class) is 100%; however, it decreases for Built-Up (92%), Fallow Land (60%), and Vegetation (81%). For Barren Land, Built-Up, Vegetation, and Water body, User Accuracy (the likelihood that a defined region truly falls into the reference class) is 100%; however, it is lower for Agriculture (62.5%) and Fallow Land (60%).

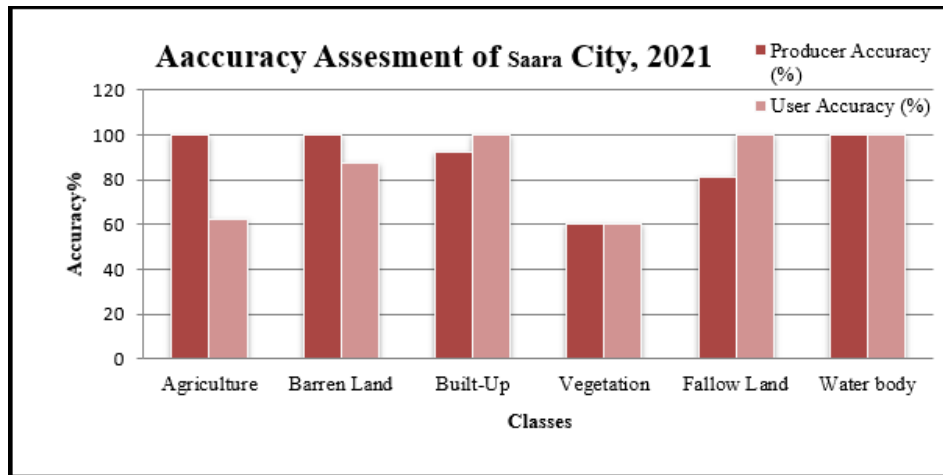


Fig. 10: User and Producer Accuracy2021

Although there is significant variation in class-specific performance, the overall classification accuracy is 88%, with a Kappa accuracy of 85.10%, indicating good agreement between reference and classified data.

LULC Implications for SWOT Analysis

The Land Use/Land Cover (LULC) analysis of Satara City for the years 2001, 2011, and 2021 reveals significant spatial transformations that have directly influenced the city's developmental structure. The integration of LULC dynamics with the SWOT framework provides a comprehensive understanding of how land-use changes shape urban strengths, weaknesses, opportunities, and threats.

Table 4: SWOT Analysis of Satara City Based on LULC Dynamics (2001-2021)

SWOT Component	LULC-Based Evidence	Interpretation
Strengths	Built-up area increased from 23.55% (2001) to 43% (2021)	Indicates rapid urban growth, economic development, and expansion of residential and commercial infrastructure
	Presence of vegetation cover (17.06% in 2001)	Contributes to environmental quality, scenic landscapes, and tourism potential
	Agricultural land (29.78% in 2001)	Supports agro-based livelihoods and urban–rural economic linkages
	Expansion along transport corridors	Enhances connectivity, accessibility, and regional integration
Weaknesses	Decline in vegetation cover (2001–2021)	Leads to ecological imbalance, micro-climatic stress, and reduced urban green spaces
	Agricultural land reduced to 10% (2021)	Reflects loss of productive land and increasing land-use imbalance
	Rapid built-up expansion	Strains infrastructure such as waste management, sewage, and traffic systems
	Fragmented peri-urban growth	Indicates weak land-use regulation and planning control
Opportunities	Fallow land (7.76% in 2001)	Potential for planned urban expansion, housing, and green infrastructure
	Remaining vegetation patches	Scope for ecological restoration and eco-tourism development
	Compact built-up clusters	Opportunity for transit-oriented and sustainable urban design
	Agricultural zones (remaining)	Potential for agro-processing and urban agriculture initiatives
Threats	Built-up expansion from 23.55% → 43%	Risk of urban sprawl and haphazard development
	Continued vegetation decline	Threatens biodiversity, climate regulation, and environmental sustainability
	Agricultural land conversion	Threatens food security and rural livelihoods
	Limited water bodies (0.26% in 2001)	Vulnerable to encroachment, causing water scarcity and flood risk

Source: Based on classification, 2001, 2011 and 2021

Strengths Influenced by LULC

One of the most prominent features observed in the LULC analysis is the steady expansion of built-up land. In 2001, built-up areas accounted for 23.55% of the total geographical area. This proportion increased substantially by 2011 and further expanded to approximately 43% in 2021. The increase in built-up land can be interpreted as a reflection of urban growth and economic development. Expanding residential zones suggest population growth and improved housing availability, while the development of commercial and institutional areas signifies strengthening economic activities. Infrastructure expansion, including transportation networks and public amenities, enhances accessibility and urban functionality.

Furthermore, the presence of vegetation cover (17.06% in 2001) contributes to the environmental strengths of Satara City. Vegetated areas, particularly those associated with hill slopes and heritage surroundings, enhance scenic quality, improve urban microclimate, and support ecological balance. These natural features strengthen the city's tourism potential and environmental identity.

Agricultural land, which constituted 29.78% of the total area in 2001, also represents a developmental strength. These zones support agro-based livelihoods, local food systems, and urban rural economic linkages, contributing to socio-economic stability.

Weaknesses Driven by LULC

Despite contributing to urban growth, LULC changes have also generated notable weaknesses. A gradual decline in vegetation cover is observed over the study period. The reduction of green spaces indicates the conversion of natural landscapes into built-up land, which may lead to ecological imbalance and environmental stress.

The loss of vegetation can result in reduced air quality, increased land surface temperatures, and diminished biodiversity. Such environmental degradation negatively affects urban livability and sustainability.

Similarly, agricultural land experienced a substantial decline, decreasing from 29.78% in 2001 to nearly 10% by 2021. This reduction reflects increasing pressure on peri-urban agricultural zones, driven by urban expansion and land conversion. The transformation of productive agricultural land into urban land uses represents a structural weakness, as it reduces local food production capacity and disrupts rural livelihoods. Additionally, the rapid expansion of built-up areas without proportional infrastructure development contributes to urban inefficiencies. Increased population density and spatial expansion intensify pressure on waste management systems, sewage networks, transportation infrastructure, and public services.

Opportunities Emerging from LULC

The LULC analysis also highlights several developmental opportunities. The presence of fallow land (7.76% in 2001) indicates the availability of underutilized land resources. These areas present potential for planned urban expansion, affordable housing projects, recreational spaces, and green infrastructure development.

Remaining vegetation patches offer opportunities for urban ecological restoration, biodiversity conservation, and eco-tourism development. Preservation and enhancement of these areas can improve environmental sustainability and urban resilience.

Agricultural zones, though reduced, continue to offer opportunities for agro-processing industries, urban agriculture initiatives, and rural-urban economic integration.

Furthermore, compact built-up clusters observed in recent years create opportunities for adopting transit-oriented development and sustainable urban design principles, promoting efficient land utilization and reduced commuting distances.

Threats Associated with LULC Dynamics

The LULC transitions also reveal emerging threats. The sharp increase in built-up land from 23.55% to approximately 43% indicates a risk of urban sprawl. Unregulated horizontal expansion can lead to fragmented land-use patterns, inefficient infrastructure provision, and increased transportation costs. The decline in vegetation cover poses threats related to urban heat island effects, increased flood vulnerability, and ecological degradation. Reduced green cover limits natural climate regulation and stormwater absorption capacity.

Similarly, the conversion of agricultural land threatens food security, rural livelihoods, and land-use sustainability. Continued land transformation may exacerbate socio-economic disparities and environmental stress. Water bodies, which accounted for only 0.26% of the area in 2001, are particularly vulnerable. Even minor encroachments or degradation of these limited resources may result in urban water scarcity, drainage problems, and increased flood risks.

Discussion

The multi-temporal LULC analysis of Satara City reveals substantial spatial transformations between 2001, 2011, and 2021, reflecting the complex interplay between urban expansion, environmental change, and socio-economic development. These changes provide critical insights into the city's growth trajectory and its implications for sustainable urban planning.

One of the most prominent findings is the significant increase in built-up land, which expanded from 23.55% in 2001 to approximately 43% in 2021. This near doubling of built-up area over two decades clearly indicates accelerated urbanization. The spatial expansion pattern suggests both densification within the urban core and horizontal growth into peri-urban areas. Such growth is characteristic of medium-sized cities undergoing demographic expansion and infrastructural modernization.

The expansion of built-up land can be attributed to several interrelated factors. Population growth, increased demand for housing, expansion of transportation networks, and development of commercial and institutional infrastructure have collectively driven land conversion. For example, peripheral agricultural lands have been progressively transformed into

residential layouts, mixed-use developments, and road infrastructure. This reflects increasing pressure on the urban fringe, where land is comparatively more available and economically attractive for development.

However, this growth has not been without consequences. The decline in vegetation cover, which constituted 17.06% in 2001, indicates gradual reduction of green spaces. The conversion of vegetated land into built-up areas suggests a weakening of the city's ecological base. Reduced vegetation can influence urban microclimate, leading to increased land surface temperatures and diminished air quality. Moreover, the loss of natural landscapes affects biodiversity and disrupts ecological services such as carbon sequestration and storm water regulation.

Similarly, the reduction in agricultural land presents a significant concern. Agricultural areas declined from 29.78% in 2001 to nearly 10% in 2021, highlighting intense land conversion pressure. This transformation signifies a shift from agrarian land use toward urban land functions. While such conversion may reflect economic transition and urban growth, it also raises sustainability issues. The loss of productive agricultural land can impact local food systems, rural livelihoods, and urban-rural economic linkages.

The expansion into peri-urban zones further illustrates the dynamic nature of Satara's urban growth. Peri-urban areas often experience fragmented land-use transitions, where agricultural land, fallow land, and natural vegetation coexist with emerging built-up structures. These transitional landscapes typically lack adequate planning regulation, resulting in uncoordinated development patterns. The emergence of scattered settlements and mixed land uses in Satara's periphery reflects this phenomenon.

From a strategic planning perspective, the integration of LULC dynamics with SWOT analysis provides deeper insights. The increase in built-up land enhances urban strengths by indicating economic growth, infrastructural expansion, and improved accessibility. Expanding commercial and residential zones suggest rising urban functions and service-sector development.

Conversely, declining vegetation and agricultural land expose structural weaknesses. Environmental degradation, reduced ecological resilience, and land-use imbalance are notable challenges. For instance, diminishing green cover may contribute to urban heat stress, while agricultural land loss may reduce local resource sustainability.

Opportunities identified through LULC patterns include the utilization of fallow land (7.76% in 2001) for planned development. Remaining vegetation zones offer potential for eco-tourism and ecological restoration. Compact built-up clusters provide scope for sustainable urban design strategies.

Nevertheless, emerging threats such as urban sprawl, infrastructure overload, and ecological vulnerability require careful consideration. The rapid increase in built-up land without proportional infrastructure augmentation may strain waste management systems, sewage networks, and transportation facilities.

Overall, the discussion underscores that LULC transformations in Satara City represent both developmental progress and sustainability challenges. The findings emphasize the need for integrated urban planning approaches that balance growth with environmental conservation.

Conclusion

The present study examined the Land Use/Land Cover dynamics of Satara City over a twenty-year period (2001-2021) using object-based image classification supported by Remote Sensing and GIS techniques. The results reveal significant spatial restructuring driven by rapid urbanization.

The most notable transformation is the expansion of built-up land from 23.55% in 2001 to approximately 43% in 2021. This substantial increase reflects accelerated urban growth, infrastructural development, and demographic expansion. The outward spread of built-up areas into peri-urban zones indicates horizontal urban expansion alongside densification processes.

Simultaneously, vegetation cover experienced a gradual decline from 17.06%, indicating reduction of urban green spaces. The loss of vegetation highlights emerging environmental concerns, including ecological imbalance and potential microclimatic changes.

Agricultural land exhibited the most pronounced decline, decreasing from 29.78% in 2001 to nearly 10% in 2021. This reduction signifies increasing land conversion pressure and reflects the transition of peri-urban landscapes toward urban land uses. While such changes may support urban development, they also pose risks to land-use sustainability, food systems, and rural livelihoods.

The integration of LULC analysis with SWOT evaluation demonstrates that spatial transformations have reinforced certain urban strengths, particularly economic growth and infrastructural expansion. However, these changes have also intensified weaknesses related to environmental degradation, infrastructure stress, and land-use imbalance.

Opportunities emerging from LULC patterns include the strategic utilization of fallow land and conservation of remaining vegetation zones. Conversely, threats such as urban sprawl, ecological degradation, and resource vulnerability require proactive planning interventions.

In conclusion, the study highlights that LULC dynamics are critical determinants of urban development trajectories. Sustainable urban planning in Satara City must prioritize controlled expansion, ecological conservation, infrastructure strengthening, and efficient land management.

Acknowledgement

I express my sincere gratitude to the Chhatrapati Shahu Maharaj Research, Training and Human Development Institute (SARTHI), Pune, for providing financial assistance and funding support for my research paper titled "Impact of Land Use Land Cover (LULC) Dynamics on Urban Development: A SWOT-Based Assessment of Satara City, Maharashtra."

Financial support and sponsorship

Nil.

Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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