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A Hybrid Approach to Predicting Land Use/Land Cover Change: Integrating Object-Based Detection with Machine Learning

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WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *Existing research confirms that rapid urbanization in cities like Jaipur transforms natural landscapes (green/open spaces) into built-up areas, straining resources and ecosystems.*
- *Hybrid models (e.g., CA-ANN, CA-RF) are widely used to predict LULC changes, leveraging spatial variables (roads, slope) to simulate urban growth patterns.*
- *Prior studies identify proximity to roads, CBDs, and gentle slopes as key drivers of built-up expansion in developing cities.*

WHAT DOES THIS STUDY ADD ON THIS TOPIC?

- *It provides the first high-accuracy, near-future (2031) LULC projections for Jaipur, quantifying how built-up areas will replace green spaces and identifying edge-effect errors in peri-urban zones.*

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ABSTRACT

Urbanization in rapidly growing cities like Jaipur has led to significant land use and land cover (LULC) transformations, impacting natural resources and urban ecosystems. Predicting these changes accurately is critical for sustainable urban planning. This study leverages a hybrid approach combining Cellular Automata (CA) and Support Vector Machine (SVM) to model and predict LULC changes in Jaipur over the periods of 2017, 2024, and projected for 2031. Utilizing Sentinel-2 satellite data, spatial variables such as proximity to roads, central business districts, drainage, and slope were integrated to assess their influence on urban growth patterns. The results reveal that built-up areas have expanded considerably, largely replacing open and green spaces, driven by infrastructure proximity and low-slope zones. The CA-SVM model demonstrated strong predictive accuracy, with key findings suggesting continued urban sprawl that could strain local resources and reduce ecological stability by 2031. These insights highlight the value of data-driven planning strategies that can manage urban growth sustainably. Future research could enhance the model by incorporating additional socio-economic variables and employing high-resolution data for improved accuracy. The hybrid CA-SVM approach offers a robust framework for understanding and predicting LULC dynamics, providing a valuable tool for urban policymakers aiming to balance development with environmental conservation.

Index Terms— LULC prediction, remote sensing, machine learning, hybrid approach

I. INTRODUCTION

Land use and land cover (LULC) transformations are profoundly reshaping urban landscapes, reflecting the pressures of population growth, socio-economic development, and environmental challenges. As cities expand, understanding the dynamics of LULC change becomes increasingly critical for sustainable urban planning and environmental management. Jaipur, a rapidly urbanizing city in Rajasthan, India, exemplifies these dynamics with a marked shift in land cover over recent decades, largely due to rural-to-urban migration and the accompanying rise in infrastructure development [1]. These transformations drive land conversion from agricultural and natural areas to residential, commercial, and industrial zones, contributing to environmental stressors such as habitat fragmentation, resource scarcity, and pollution [2]. Given these complex dynamics, accurately monitoring, analyzing, and predicting LULC change in Jaipur requires advanced, data-driven methodologies that go beyond traditional approaches.

Geographic object detection (GOD) and machine learning (ML) techniques are powerful tools that enhance LULC analysis by providing detailed, accurate assessments of land use patterns. Geographic object detection methods leverage high-resolution satellite imagery to identify and classify land cover types, enabling precise mapping of urban, agricultural, forested, and water areas [3]. This capability is particularly useful in Jaipur, where spatial heterogeneity presents unique challenges for LULC classification. By detecting distinct geographic objects within images, GOD can support more refined LULC models and yield insights into urban expansion and other transformations at a granular level [4]. Such spatial granularity is crucial, as it enables urban planners and environmental policymakers to understand not only the extent of land cover change but also the specific forms it takes, providing a nuanced understanding that informs sustainable development initiatives [5].

Recent advancements in machine learning have expanded the capabilities of GOD by integrating sophisticated algorithms that capture complex spatial-temporal patterns. Support Vector Machines (SVMs) and Cellular Automata (CA) are two such algorithms that have demonstrated success in LULC applications [6]. Support Vector Machines are commonly used for classification tasks, offering high accuracy in mapping complex land cover classes by identifying optimal boundaries between data clusters. Support Vector Machine's ability to manage high-dimensional data and effectively differentiate between diverse land types has proven valuable for analyzing Jaipur's complex LULC, where urban, agricultural, and natural landscapes intersect [7]. Furthermore, CA modeling provides a complementary approach, simulating spatial evolution by applying localized rules to a grid-based cellular structure, thus capturing LULC change over time [8]. This temporal modeling is critical for cities like Jaipur, where rapid land transformation demands predictive models that can guide future land management decisions [9].

The integration of GOD with ML algorithms like SVM and CA facilitates a hybrid modeling approach that enhances LULC accuracy in urban settings. Studies show that these integrated approaches allow for both accurate classification and reliable prediction of future LULC patterns, making them highly suitable for dynamic urban environments such as Jaipur [10]. For example, in [11], the research applied a combined GOD and SVM approach to model urban expansion in Jaipur, achieving high classification accuracy and demonstrating the potential for such models in urban growth forecasting. By learning from existing land cover patterns, these hybrid models offer insights into where and how future developments may unfold, thus helping city planners mitigate negative impacts on natural resources and ecosystem services. Moreover, the use of GOD to extract features before applying SVM classification enables a more detailed characterization of land cover types, addressing the limitations of conventional remote sensing techniques that might struggle to differentiate between, for example, mixed-use urban areas and dense vegetation patches [12].

As Jaipur continues to expand, the need for reliable LULC data becomes even more pressing. Studies have documented those traditional methods of LULC analysis, such as manual interpretation of satellite imagery, often fall short in terms of accuracy and scalability [13]. In contrast, GOD with ML techniques automates much of this process, reducing both time and error while increasing the level of detail captured. For instance, the research in [14] observed that GOD combined with SVM improved classification accuracy by up to 12% compared to manual methods in Jaipur, underscoring the efficiency of these advanced techniques. Furthermore, the predictive power of CA models enables urban planners to simulate various development scenarios and their potential impacts, offering a proactive approach to land management [15].

The application of GOD and ML in LULC monitoring in Jaipur not only enhances understanding of current urbanization trends but also serves as a basis for informed decision-making in areas such as green space preservation, infrastructure planning, and environmental conservation. With the aid of these technologies, urban planners can assess how various factors—such as zoning regulations, population density, and economic policies—affect LULC transitions and identify strategies to promote balanced urban development [16]. For instance, in [17], a study was conducted combining CA and SVM techniques, highlighting that such integrated models can provide city officials with actionable insights into potential areas for sustainable expansion, thus supporting a more resilient urban growth strategy.

While previous studies have employed Cellular Automata (CA) or Support Vector Machine (SVM) independently for urban land use/land cover (LULC) modeling, and Geographic Object Detection (GOD) techniques have been applied for improved classification, there remains a significant research gap in integrating these methods into a unified framework, particularly for semi-arid, rapidly urbanizing cities such as Jaipur. This study addresses this gap by developing a hybrid GOD-CA-SVM model that not only enhances classification accuracy but also strengthens the predictive capacity for future urban expansion. The integrated approach offers a novel methodological contribution, enabling more nuanced spatial and temporal analysis of LULC changes critical for sustainable urban planning in semi-arid environments.

A. Study Area and Dataset Used

Jaipur, the capital city of Rajasthan, India, is an evolving urban hub known for its rich heritage and rapid urbanization. Situated at approximately 26.91° N latitude and 75.79° E longitude, Jaipur spans an area of about 484.6 square kilometers, making it one of the largest cities in northern India. Known as the "Pink City" Jaipur is celebrated for its distinct architectural style and historical landmarks but is now witnessing significant changes in land use and land cover (LULC) due to rising population and infrastructural development. The city is bounded by the Aravalli Range to the north and east, limiting expansion in those directions and intensifying urban sprawl primarily toward the south and west. The schematic sketch of the study area is shown in Fig. 1.

The climate in Jaipur is semi-arid, with seasonal variations influencing vegetation and land cover types across the year. The city's topography comprises plains interspersed with hills, contributing to diverse LULC classifications, including urban areas, agricultural land, vegetation, and scattered water bodies. Jaipur's urban expansion, characterized by an increase in residential, commercial, and industrial zones, is reshaping its landscape. Monitoring these LULC changes is critical for sustainable urban planning, water resource management, and environmental conservation.

To analyze LULC transformations in Jaipur, high-resolution satellite imagery from the Sentinel-2 dataset, provided by the European Space Agency (ESA), is utilized. Sentinel-2, part of the Copernicus Programme, includes two twin satellites—Sentinel-2A and Sentinel-2B—each equipped with a multispectral imager capable of capturing data in 13 spectral bands ranging from visible to shortwave infrared. The spatial resolution varies from 10 meters for visible and near-infrared bands to 20–60 meters for other spectral bands, making Sentinel-2 suitable for detailed urban and environmental analysis. These spectral capabilities enable precise land cover classification and temporal monitoring, essential for accurately identifying and analyzing changes in Jaipur's LULC.

For this study, Sentinel-2 images from the years 2017–2024 were obtained to provide historical and recent LULC data. These images offer a reliable basis for assessing urban growth and vegetation changes over a seven-year period. To simulate future LULC scenarios and project changes, the study will generate a predictive map for

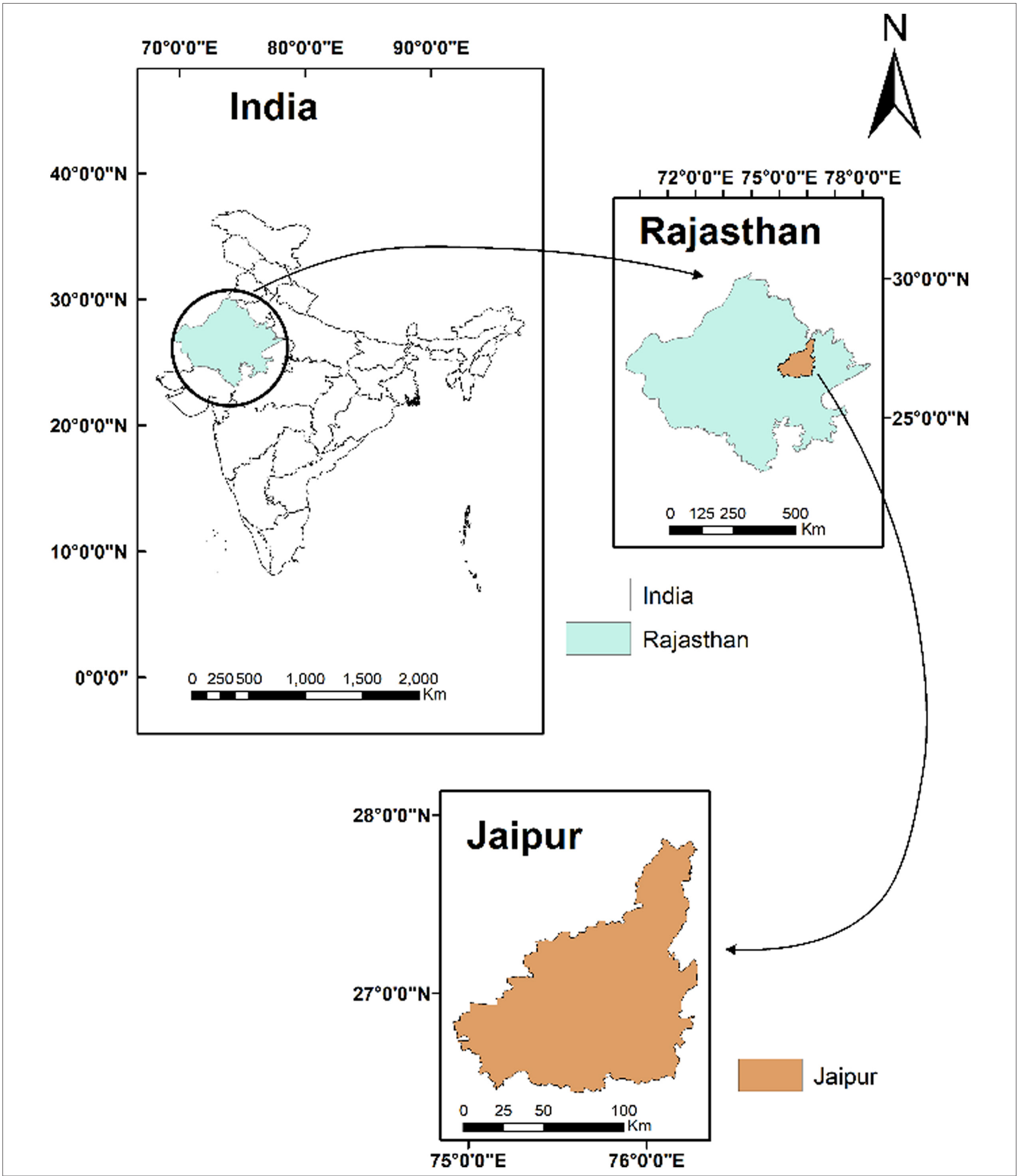

Fig. 1. Study area.

2031 using machine learning models, specifically Cellular Automata (CA) and Support Vector Machine (SVM) algorithms. These models will analyze historical patterns and predict likely changes, offering insights into potential urban expansion and its environmental impacts. By leveraging high-resolution Sentinel-2 data, this study provides a detailed spatial analysis of Jaipur's LULC, identifying the areas most affected by urban sprawl and natural landscape alteration. The anticipated LULC map for 2031 will guide urban planners, environmental managers, and policymakers in crafting strategies for sustainable development, balancing Jaipur's growth with the preservation of natural resources. This combination of past, present, and future LULC data equips stakeholders with the knowledge to make data-driven decisions for Jaipur's evolving landscape.

B. Methodological Framework

The fields of remote sensing and spatio-temporal analysis have experienced a spotlighted range of methodological schemas, and the advancements continue to grow in an exponential manner. However, the fusion of hybrid approaches and the integration of LULC transition with dynamic information only impart proficient wings into the entire framework flow. Fig. 2 portrays the methodological schema of the proposed and executed approach.

Jaipur as already mentioned in the section above, was delineated, and the Sentinel-2 dataset was acquired. The data was pre-processed to ensure no anomalies like clouds, strip errors, and image distortion were present in the processed dataset. The next step acts as the foundation for the entire framework, which involves estimating the remote sensing and geospatial descriptors. These include attributes like built-up dynamics, slope, distance to central business districts, distance to roads, and distance to drainage. These attributes are the fundamental backbone blocks for analyzing it through hybrid machine learning approaches. Additionally, the geographic object detection approach utilized the descriptor estimation necessary to be fed into the computation block. Cellular automata and support vector machine were used in two cascaded-multistep approaches where all the descriptors were utilized, and the output extraction of LULC transition was computed. This computed image was also utilized for validation through the geographic object detection-based descriptor for the year 2031 (predicted LULC).

The CA approach projects/predicts future pixels based on the existing ones, and the SVM approach acts as a trigger input by executing precise supervised classification. In simpler terms, the proposed hybrid approach acts on two major points:

1. Supervised classification of the satellite data for obtaining a precise land use land cover (LULC) layer through SVM.
2. Feeding the classified LULC layer to the CA model for predicting the future LULC.

II. RESULTS AND DISCUSSION

The study's methodology yielded a comprehensive series of results highlighting the progression of land use and land cover (LULC)

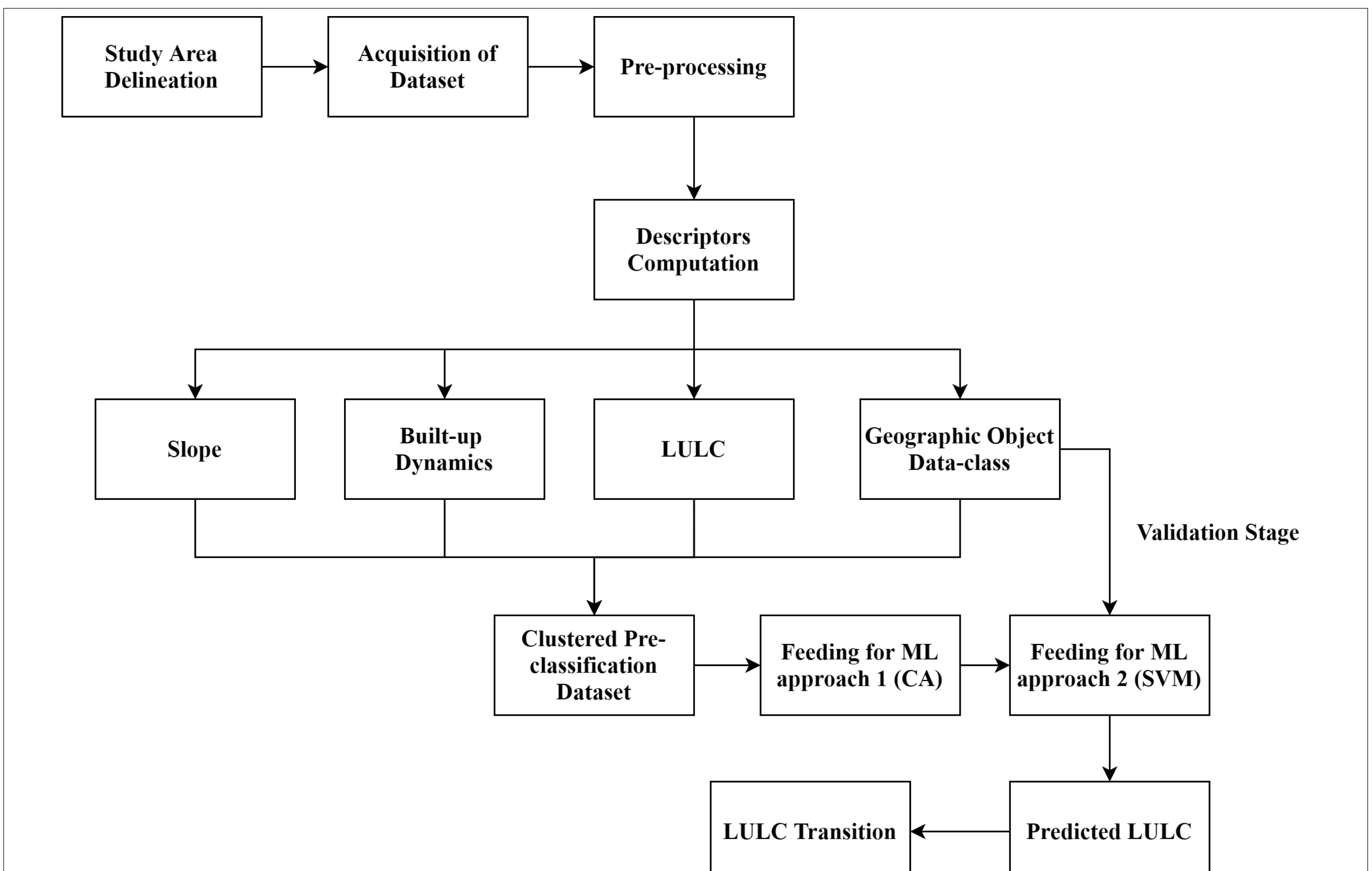

Fig. 2. Methodological framework.

changes within Jaipur city. Fig. 3 shows the LULC maps of the years 2017 and 2024, respectively.

The findings include LULC maps for the years 2017 and 2024, as well as a predicted LULC scenario for 2031, generated through a hybrid geographic object detection and machine learning approach. These maps not only illustrate the spatial distribution of various land cover classes but also allow for a dynamic understanding of the built-up area expansion and natural land loss over time. The accuracy of these predictions has been corroborated through previous studies showing that machine learning models, when combined with geographic object detection, can provide reliable predictive insights into urban growth patterns [18, 19].

The LULC maps reveal substantial changes in built-up areas, vegetation, and open spaces. In 2017, the urban landscape showed relatively balanced distributions of green cover and built-up regions. However, by 2024, an observable shift towards increased built-up areas and decreased vegetative spaces became apparent. This trend aligns with findings from [20], which reported similar patterns in rapidly urbanizing cities, where population growth and infrastructural development often result in the expansion of built-up areas at the expense of natural land. The model predictions for 2031 indicate an intensified urban sprawl, predominantly expanding southwards and westwards, following Jaipur's historical growth patterns and infrastructural layouts. These findings resonate with the predictions of urban expansion in cities of similar size, suggesting that such urban trajectories often lead to heightened pressures on local resources and potential ecological consequences [21].

The study's LULC transition analysis further elucidates the types and frequencies of land cover changes between 2017 and 2024, with a notable trend of open spaces and agricultural lands converting into residential and commercial zones. This observation is in line with past research that shows agricultural areas are often among the most affected as cities expand outwardly [22].

The projected 2031 transition suggests a similar trend, with continuous reductions in green cover. An examination of urban growth drivers, such as proximity to roads, central business districts, and drainage systems, provides additional insights. Fig. 4 portrays the extractions schematically. Areas closer to major roads and central business districts exhibit a higher likelihood of development, aligning with the notion that accessibility factors play a significant role in urban sprawl [23]. This phenomenon has been corroborated in other studies showing that infrastructural accessibility is a major predictor of land cover transformation in cities [24].

The built-up dynamics in Jaipur also underscore the shift in population density patterns, as people increasingly relocate closer to commercial hubs, drawn by employment and infrastructure access as shown in Fig. 5. The expansion of built-up regions near central business districts not only illustrates urban densification but also reflects broader demographic shifts documented in other urban studies [25]. The city's inclination towards a sprawling urban morphology has implications for sustainable land use planning, as sprawling patterns can lead to increased land resource consumption and ecological degradation if left unchecked [26]. These implications underscore the need for policymakers to employ predictive insights from models like these to mitigate unsustainable land use trends. The built-up dynamics are presented in Fig. 6.

Distance-to-road metrics further revealed that regions within a 5-kilometer radius of major roads witnessed more intense land cover changes. This trend reflects the concept of "urban proximity zones," where infrastructure access drives rapid development—a finding consistent with earlier studies that have shown that urban expansion is often most pronounced near well-connected areas [27]. In Jaipur, the data indicates that built-up areas near key transport links have

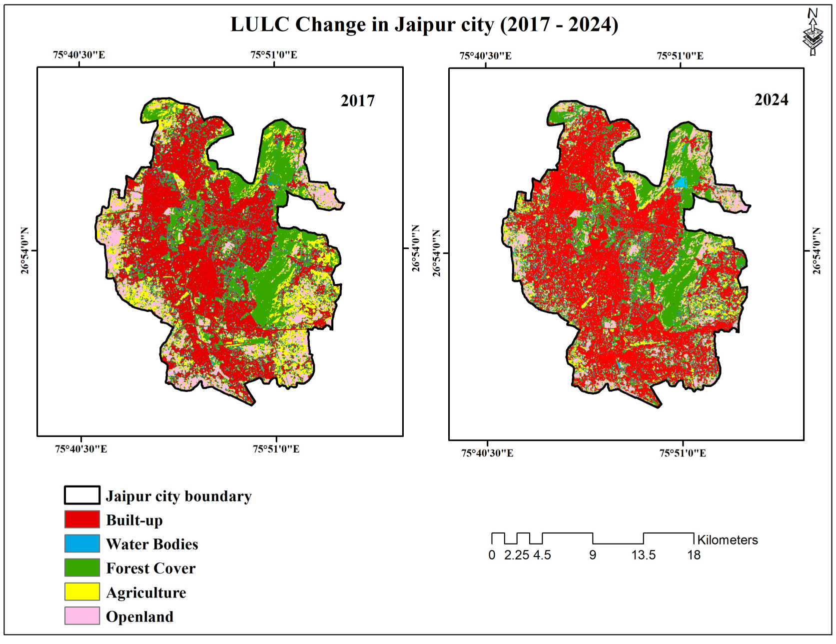

Fig. 3. Land use and land cover of the years 2017 and 2024.

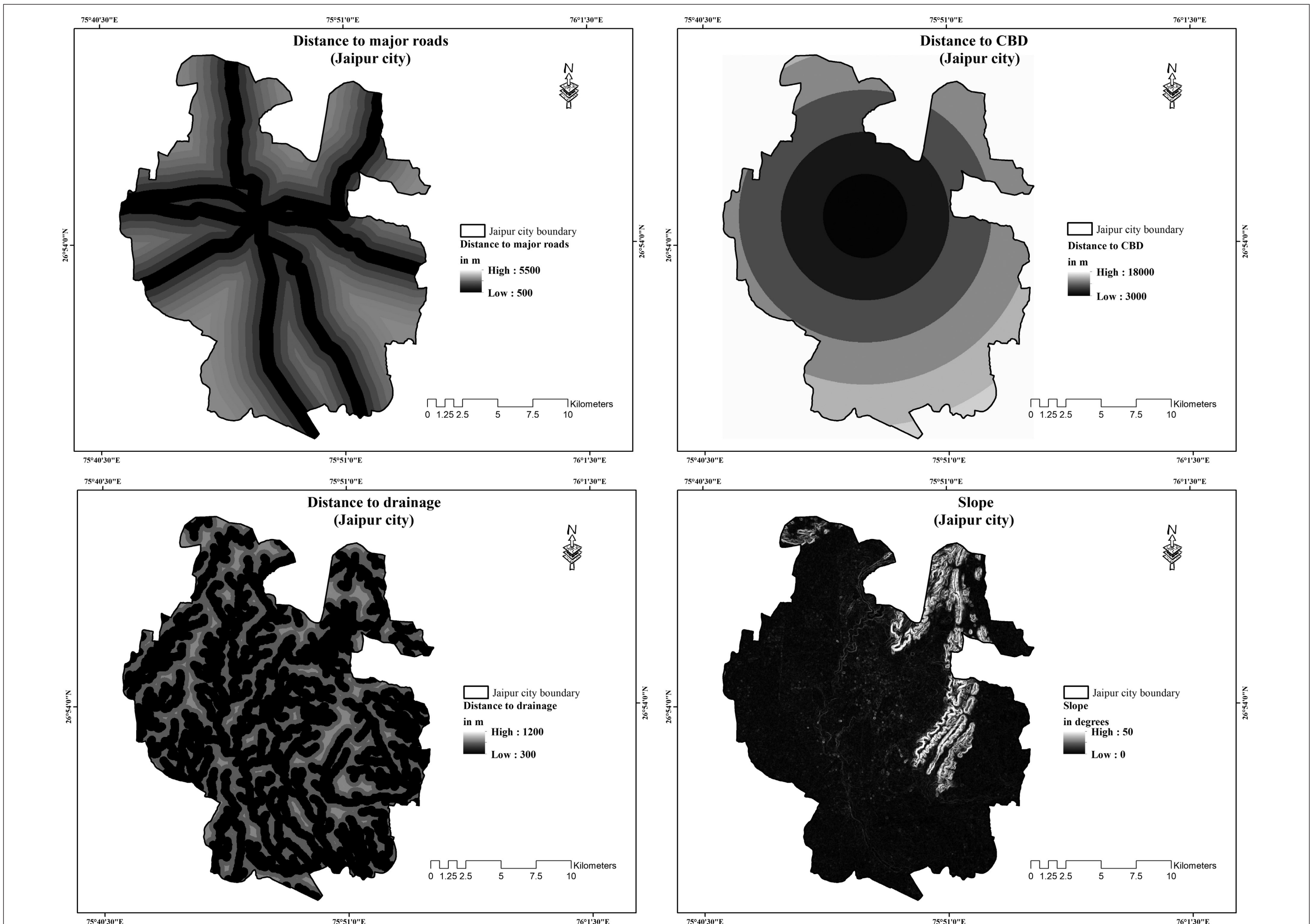

Fig. 4. (a) Distance to roads. (b) Distance to central business districts. (c) Distance to drainage and (d) Slope profile.

grown significantly over the analyzed period, underscoring the need for strategic urban planning that addresses the rapid transformation of these critical zones [28]. Table I shows the transition dynamics in area change over the years.

It is evident from Table I that built up to built up and barren land to built up acts as the most predominant transition changes. Another crucial factor in urban land transformation is the slope, which influences both the pace and direction of urban expansion as shown in Fig. 4 (d). Areas with gentler slopes tend to be more heavily urbanized compared to steeper regions, as flatter terrain facilitates construction and infrastructural development [29]. In Jaipur, slope analysis indicated that low-slope areas closer to the city center experienced greater urban development, which is consistent with similar findings in other topographically diverse cities [30].

Ultimately, the predicted 2031 LULC map emphasizes the extent to which unplanned urban growth can lead to loss of green cover and the encroachment on natural habitats as portrayed in Fig. 7. This projection suggests a substantial increase in built-up areas, with natural land likely diminishing if effective planning and regulation are not enacted. Studies emphasize that urban expansion, if unregulated, can severely affect biodiversity and ecosystem services [8]. Therefore, adopting data-driven land-use policies is vital for promoting sustainable growth. Leveraging findings such as these allow policymakers to make informed decisions regarding land management, urban zoning, and green space conservation, essential for maintaining ecological balance and urban livability in Jaipur.

The hyperparameters and the corresponding metrics are presented in Table II.

Furthermore, CA-SVM offers a granular advantage as compared to the other techniques, especially against CA-RF. For example, CA-RF offers 85% accuracy with an F1 score of 0.9 and a kappa coefficient of 0.79 (as per Table II, CA-SVM yields better performance

TABLE I. TRANSITION CLASS AREA

Transition Class	Area (Sq. Km.)
Built up to built up	68.6943
Barren land to built up	22.6575
Green to built up	20.1645
Water to built up	2.9862

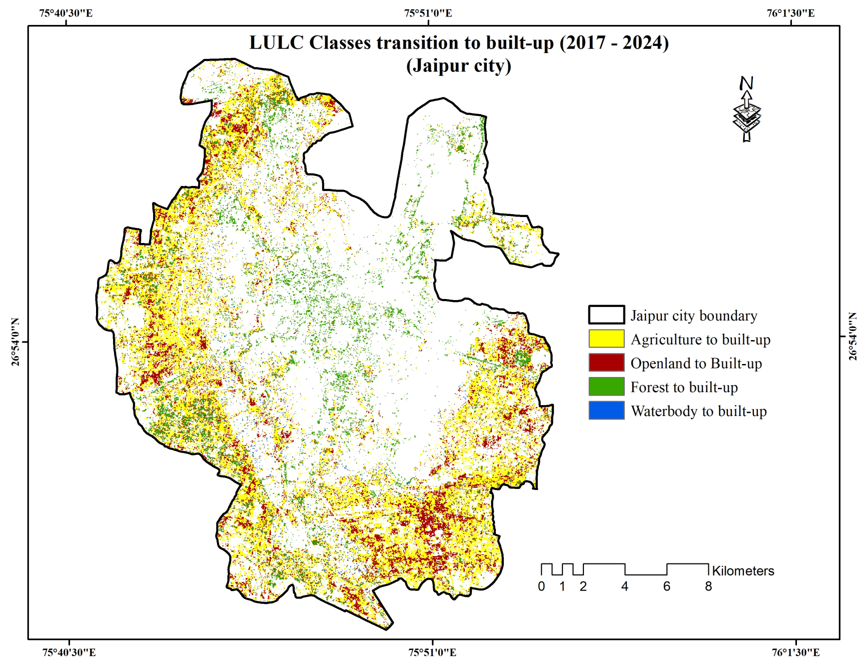

Fig. 5. Land use and land cover transition.

in all aspects). Furthermore, the aggregation index of CA-SVM is 82.7, while CA-RF just yields 74.2. In all aspects, CA-SVM offers better and optimized output attributes compared to CA-RF and other approaches.

The approach for validation raises an alarming challenge. There is no means to assess the potential of future predictions made by any model. For this, in the proposed study, the CA model was applied to 2017 and 2020 data to predict the 2024 LULC layer. The study already had an in-situ 2024 LULC, and one was from the prediction carried out by CA execution. The simulated validation yielded a ±7% offset and hence, provided a strong baseline that the applied CA approach yields good accuracy.

In summary, this study underscores the importance of predictive modeling for understanding urban expansion trends. By examining past, present, and future LULC dynamics in Jaipur, the findings provide valuable insights for urban planners and decision-makers

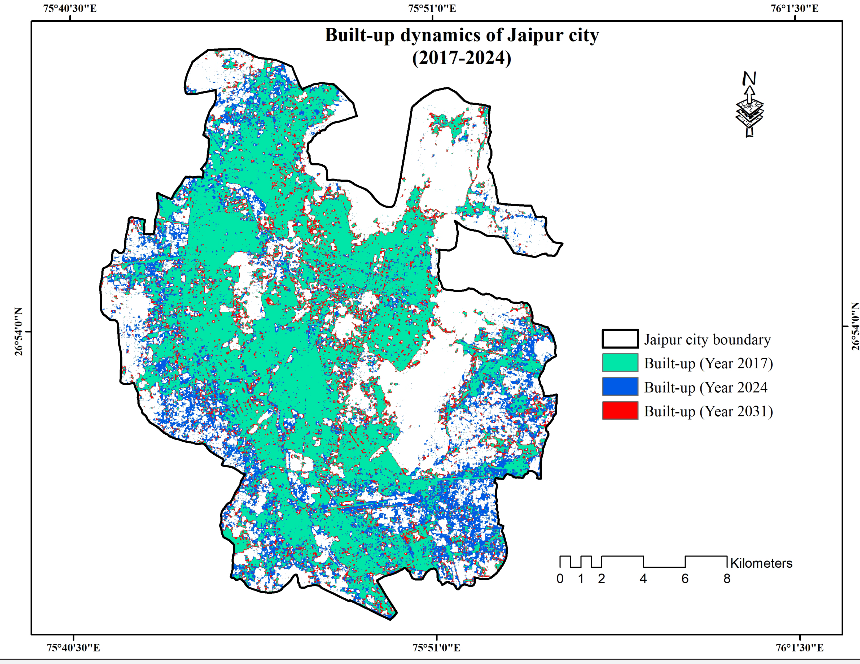

Fig. 6. Built-up dynamics of Jaipur city.

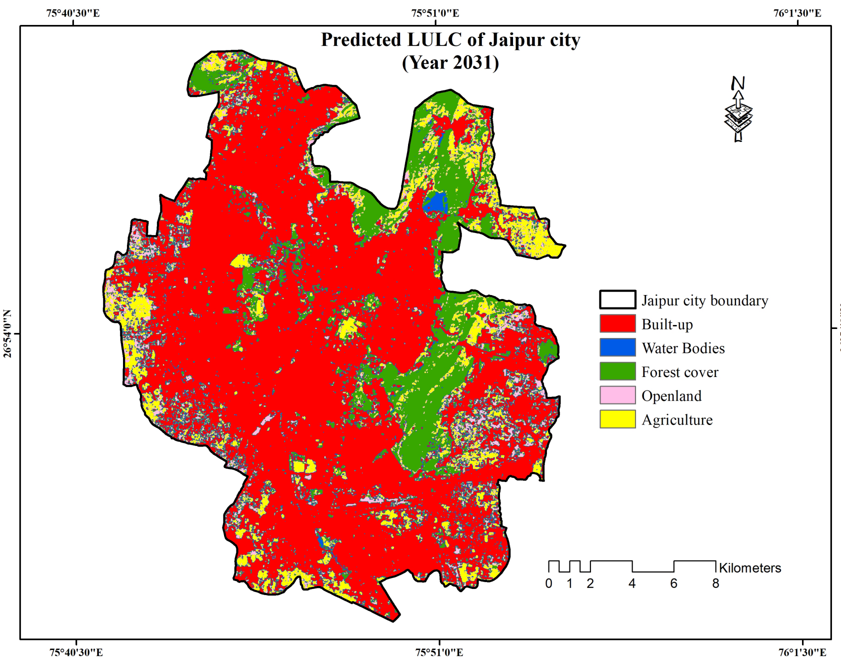

Fig. 7. Predicted land use and land cover of Jaipur for the year 2031.

to navigate growth sustainably, highlighting the need for proactive policies that prioritize balanced land use and environmental resilience. This work contributes to the growing body of knowledge on urban LULC changes, supporting broader efforts to enhance sustainable urban planning practices.

A. Policy Implications

- Sustainable Urban Planning: Implement zoning regulations to balance built-up expansion with green spaces, ensuring environmental sustainability amid rapid urbanization.
- Smart Infrastructure Development: Integrate LULC insights into transportation and housing policies to promote compact, transit-oriented growth and reduce uncontrolled sprawl.
- Environmental Conservation Strategies: Strengthen policies for biodiversity protection by designating conservation zones, afforestation initiatives, and enforcing sustainable land-use practices.
- Data-Driven Decision-Making: Utilize geospatial and machine learning-driven LULC predictions to inform policymakers, enabling proactive urban management and climate resilience planning.

TABLE II. HYPERPARAMETER CHARACTERISTICS

Hyperparameter	Remark
Kappa coefficient	0.842
F1 score	0.901
Overall accuracy	89.3
Patch density	3.4
Aggregation index	82.7
Training-testing split	Standard 60%–30%–10% split for training-testing and validation

III. CONCLUSION AND FUTURE SCOPE

This study effectively demonstrates a predictive approach for LULC transformation in Jaipur city, integrating Cellular Automata (CA) and Support Vector Machine (SVM) techniques. Through a detailed analysis of the city's spatial and temporal land cover changes, the findings highlight a steady increase in urban sprawl, driven by proximity to essential infrastructure and low-slope areas. The projections for 2031 reveal a continuation of these trends, with an expansion in built-up areas at the expense of green and open spaces, mirroring patterns observed in other rapidly urbanizing regions. This shift underscores the necessity for proactive, data-driven urban planning and management to mitigate the adverse impacts of unchecked urban growth on natural resources and ecological balance.

The predictive capabilities of the hybrid CA-SVM model are particularly valuable in providing insights for urban planners and policymakers. By simulating future land cover scenarios, the model can support the formulation of more sustainable urban policies that balance development needs with environmental conservation. The study's approach, leveraging machine learning alongside geospatial techniques, reinforces the potential of advanced modeling tools in creating accurate LULC projections, which can guide decisions on land-use zoning, green space preservation, and resource allocation.

For future research, several avenues to enhance the robustness and applicability of this model. First, incorporating a broader set of socio-economic and environmental variables—such as population density, income levels, and air quality data—could further refine the accuracy of LULC predictions. Additionally, using high-resolution remote sensing data from satellites like Landsat-8 or advanced sensors like LiDAR can improve spatial accuracy, capturing finer-scale urban changes. Integrating deep learning approaches, such as Convolutional Neural Networks (CNNs), into the model might also enable more sophisticated feature extraction, thereby enhancing the model's capacity to discern complex patterns in urban landscapes.

Another promising direction involves extending this predictive model to a regional or national scale, which would allow for a comparative analysis of urbanization trends across different cities and regions. Cross-comparative studies of LULC models across diverse geographic areas can provide valuable insights into the factors driving urban expansion in different contexts and help identify universal vs. region-specific patterns. Finally, linking this predictive model to a real-time spatial decision support system (SDSS) could empower urban management authorities with actionable intelligence. This would enable cities like Jaipur to adaptively respond to emerging pressures of urbanization, ensuring that future development aligns with sustainability goals. In sum, this hybrid CA-SVM approach represents a significant advancement in urban LULC modeling and offers a valuable foundation for future innovations in sustainable urban planning and geospatial analytics.

This study provides valuable insights into Jaipur's LULC transformation, but several areas warrant further exploration. Future research can integrate advanced deep learning techniques with object-based classification to enhance predictive accuracy. Additionally, incorporating socio-economic and climate variables could improve the robustness of urban growth models. While this study employed SVM + CA for urban expansion, exploring hybrid approaches such as deep learning-based Cellular Automata or agent-based modeling could refine spatial predictions.

Further, assessing the Urban Heat Island (UHI) effect in relation to LULC dynamics could offer climate resilience strategies. Biodiversity and ecosystem service assessments linked to land transitions can also guide conservation efforts. Moreover, comparative studies with other rapidly urbanizing cities can provide broader regional insights. Stakeholder engagement and policy-oriented research are essential to translating findings into actionable urban planning strategies. Ultimately, integrating multi-temporal, high-resolution datasets with policy frameworks can foster more sustainable urban development trajectories. Additionally, the utilized CA approach can be extended to its integration/deployment for not only the Landsat satellite image dataset but also to Sentinel-2 optical imagery and hyperspectral images.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

Peer-review: Externally peer-reviewed.

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