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Predicting Future Peri-Urban Growth in Rahata (Ahilyanagar) Using MOLUSCE and GIS

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Abstract

Rapid urbanization in many Indian regions is rapidly transforming peri-urban areas, where agricultural and rural lands are increasingly being converted into built-up urban spaces. Understanding and predicting these urban growth patterns has become important for effective planning, infrastructure management, and sustainable regional development. This study focuses on analyzing and simulating urban expansion in Rahata Taluka, located in Ahilyanagar District, by integrating geospatial techniques with the MOLUSCE (Modules for Land Use Change Evaluation) tool in QGIS.

The study uses multi-temporal Land Use/Land Cover (LULC) datasets for the years 2017, 2020, and 2023, prepared using Sentinel satellite imagery. These datasets were analyzed to understand historical land use changes and the overall trend of urban expansion in the region. Several important factors influencing urban growth were considered in the modelling process, including slope, proximity to roads, existing urban areas, and exclusion zones such as water bodies and restricted areas. Slope was used to represent physical limitations to development, while road proximity helped capture the impact of transportation networks on urban growth patterns.

All spatial datasets were processed and standardized within a GIS environment to ensure consistency and suitability for modelling. The MOLUSCE tool was then used to analyze land use transitions and simulate future urban growth based on transition probabilities between different land classes. The model was calibrated using the 2017 and 2020 LULC datasets and later validated with the 2023 LULC map to evaluate prediction accuracy.

Based on the calibrated model, future land use scenarios for the years 2026 and 2029 were generated. The findings reveal that urban expansion is likely to continue mainly along major transportation corridors and around existing urban settlements. The study also identifies potential future growth zones and highlights the changing spatial pattern and intensity of urban development in Rahata Taluka.

Overall, this research demonstrates how the integration of remote sensing, GIS, and MOLUSCE modelling can effectively support urban growth prediction and land use planning. The study can assist planners, researchers, and policymakers in making informed decisions for sustainable urban and regional development

Keywords: *Peri-urban areas; MOLUSCE tool; Land Use/Land Cover (LULC); Urban growth; Transition probabilities; Urban expansion..*

INTRODUCTION

Urbanization is one of the most significant drivers of land use and land cover (LULC) change across the globe, particularly in developing countries like India (Jain, 2024; Demessie et al., 2025). Over the past few decades, rapid population growth, economic development, and infrastructural expansion have accelerated the transformation of rural landscapes into urban and peri-urban areas (Nath and Deka, 2025). This process is especially prominent in smaller towns and taluka-level regions, where unplanned growth often leads to inefficient land use patterns, environmental degradation, and pressure on natural resources (Zarin and Esraz-Ul-Zannat, 2023). The transition zone between rural and urban areas, commonly referred to as the peri-urban interface, has emerged as a critical area of study due to its dynamic nature and vulnerability to uncontrolled development.

Peri-urban areas represent a complex mix of land uses, including agricultural land, residential developments, industrial zones, and transportation networks. These areas are character

ized by rapid and often fragmented growth, driven by factors such as proximity to urban centers, accessibility to roads, and availability of land (N-yanbini et al., 2025). In many cases, peri-urban growth occurs in an unregulated manner, leading to challenges such as loss of agricultural land, inadequate infrastructure, and environmental stress. Therefore, identifying and predicting future peri-urban growth centers is essential for guiding sustainable urban planning and ensuring balanced regional development. In recent years, the integration of Remote Sensing (RS) and Geographic Information Systems (GIS) has provided powerful tools for analyzing and monitoring land use changes (Ritu et al., 2023). Multi-temporal satellite imagery enables the detection of changes in land cover over time, allowing researchers to understand past trends and project future scenarios. Various modeling approaches have been developed to simulate urban growth, ranging from cellular automata and agent-based models to machine learning techniques (Kafy et al., 2021; Shovon, 2026). Among these, the MOLUSCE (Modules for Land Use Change Evaluation) tool integrated within QGIS has gained popularity due to its capability to analyze land use transitions and simulate future scenarios based on spatial drivers and transition probabilities (Kumari and Roy, 2025; Kamaraj and Rangarajan, 2021).

The MOLUSCE model utilizes historical LULC data along with various driving factors to predict future land use patterns. It incorporates algorithms such as Artificial Neural Networks, Logistic Regression, and Cellular Automata to simulate the spatial dynamics of land use change (Gündüz, 2025; Ali et al., 2025). The model considers both biophysical and socio-economic factors that influence urban growth, such as slope, proximity to roads, and existing urban areas. Additionally, exclusion layers can be incorporated to restrict development in environmentally sensitive or legally protected zones, making the model suitable for realistic planning scenarios. This study focuses on Rahata Taluka, located in Ahilyanagar District, a region that has been experiencing noticeable changes in land use patterns due to increasing urbanization and infrastructural development. The taluka is influenced by nearby urban centers, transportation corridors, and economic activities, which contribute to the expansion of built-up areas into surrounding rural landscapes. As a result, agricultural lands and open spaces are gradually being converted into residential and commercial uses, leading to the emergence of peri-urban zones. Understanding the spatial patterns and drivers of this transformation is crucial for effective planning and management. In this context, the present study aims to analyze historical land use changes and predict future urban expansion patterns using geospatial techniques. Multi-temporal LULC maps for the years 2017, 2020, and 2023 have been used to assess past trends and generate transition probabilities. Key driving factors such as slope, road proximity, and existing urban areas have been incorporated into the model to understand their influence on urban growth. An exclusion layer representing water bodies and restricted areas has also been included to ensure realistic simulation outcomes. The MOLUSCE tool is employed to simulate future land use scenarios for the years 2026 and 2029. By calibrating the model using historical data and validating it against recent observations, the study ensures the reliability of the simulation results. The predicted maps provide insights into the likely directions and intensities of urban expansion, highlighting areas that may emerge as future peri-urban growth centers.

This study supports informed and data-driven planning for sustainable urban development. By identifying potential growth zones and understanding the factors driving urban expansion, planners and policymakers can develop strategies to manage growth in a sustainable manner. This includes protecting environmentally sensitive areas, optimizing infrastructure development, and promoting balanced land use patterns. Furthermore, the methodology adopted in this study can be replicated in other regions facing similar challenges, making it a valuable contribution to the field of urban and regional planning.

In conclusion, the integration of remote sensing, GIS, and land use change modeling provides a comprehensive framework for analyzing and predicting urban growth. The application of the MOLUSCE model in Rahata Taluka offers a detailed understanding of peri-urban dynamics and helps in identifying future growth centers. Such studies are essential for ensuring sustainable urban development and minimizing the negative impacts of unplanned expansion in rapidly growing regions.

Study Area

The present study is carried out in Rahata Taluka, located in Ahilyanagar District in the state of Maharashtra, India. The taluka covers an approximate geographical area of 759.19 km² and has a total population of 320,485 as per Census 2011.

The region is characterized by predominantly flat to gently undulating terrain, which is suitable for both agriculture and urban development. The climate is semi-arid, with rainfall mainly occurring during the monsoon season. Agriculture is the dominant land use, with crops such as sugarcane playing a major role in the local economy. However, increasing population pressure and infrastructural development have led to noticeable changes in land use patterns in recent years. Rahata Taluka is well connected by road networks, which significantly influence the spatial distribution of development. The proximity to important urban and religious centers such as Shirdi has accelerated urban growth and increased pressure on surrounding agricultural land. The study area is high-

ly suitable for this research as it represents a rapidly developing peri-urban region, where continuous conversion of agricultural land into built-up areas is taking place. The presence of key driving factors such as road accessibility, existing urban centers, and favorable terrain conditions makes it an ideal area for analyzing LULC changes and predicting future urban growth using GIS and the MOLUSCE model.

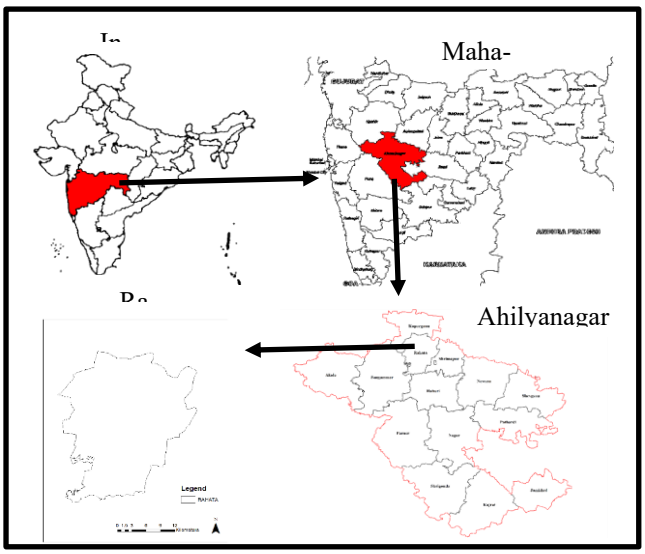


Fig. 1: Study Area - Rahata

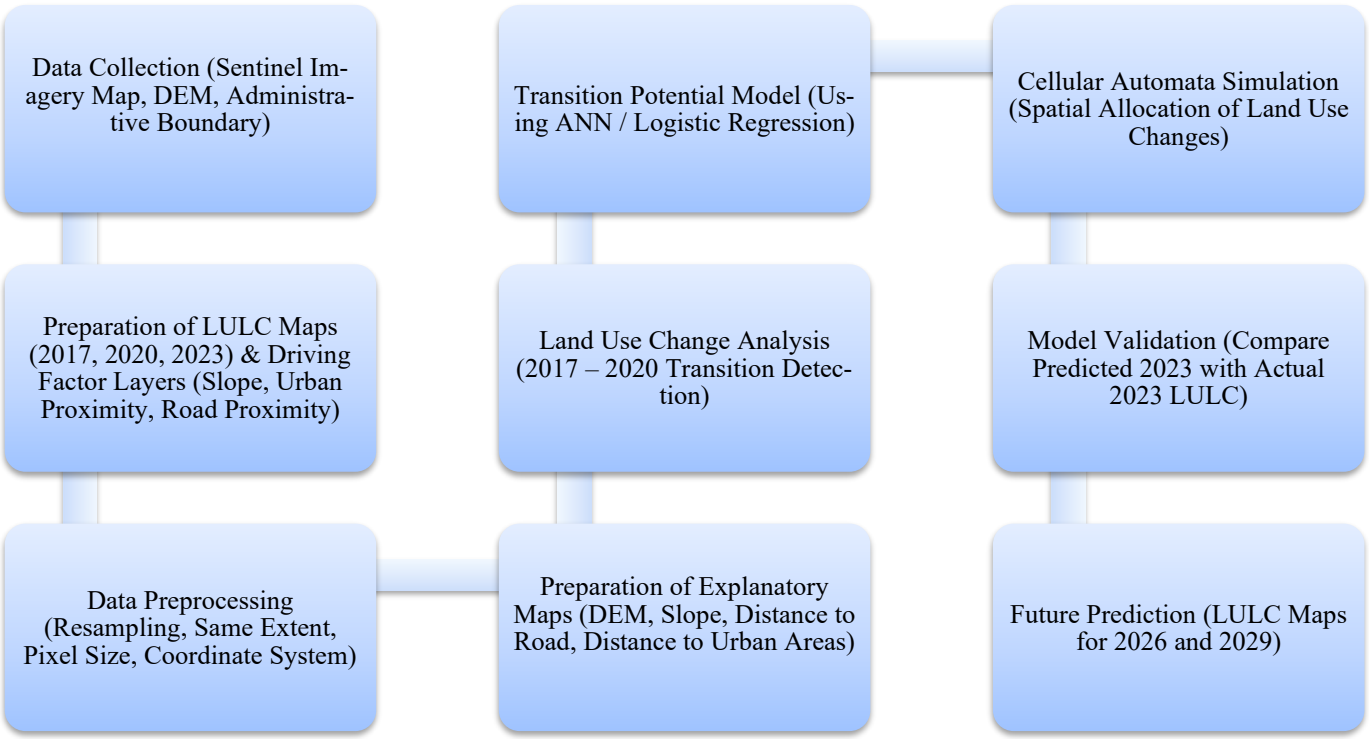
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METHODOLOGY

The methodology is designed to systematically combine Remote Sensing (RS), Geographic Information System (GIS), and land use change modeling techniques using the MOLUSCE (Modules for Land Use Change Evaluation) tool available in QGIS. The overall approach involves multiple stages, including data acquisition, preprocessing, preparation of spatial driving factors, model calibration and validation, simulation of future scenarios, and identification of peri-urban growth centers (Kumari and Roy, 2025; Jain, 2024).

DATA COLLECTION

The foundation of the study is based on multi-temporal spatial datasets representing land use and environmental conditions of the study area. Land Use/Land Cover (LULC) maps for the years 2017, 2020, and 2023 were prepared using sentinel imagery. These datasets capture the temporal dynamics of land transformation (Kamaraj and Rangarajan, 2021) and provide essential input for modeling land use change. In addition to LULC data, several ancillary datasets were collected to represent factors influencing urban growth. The datasets included road network information, Digital Elevation Model (DEM) data, and details of water bodies. Road network data played an important role in understanding accessibility and connectivity, while DEM data was used to derive terrain characteristics such as slope. Water bodies and environmentally sensitive areas were considered while creating exclusion layers to restrict development in unsuitable locations (Gündüz, 2025; Shovon, 2026). All datasets were sys-



tematically organized within a geospatial database and converted into raster format to ensure compatibility with the MOLUSCE modelling framework, as the tool primarily works with raster-based spatial inputs (Demessie et al., 2025).2. Data Preprocessing and Standardization

In this study, all raster layers were projected into a common coordinate reference system to maintain spatial uniformity. The spatial resolution (cell size) of all datasets was standardized to ensure that each raster layer represents the same ground area per pixel. Further, raster alignment was carried out so that all layers have identical spatial extent, number of rows and columns, and pixel grid alignment. This is particularly important for pixel-based modeling techniques such as Cellular Automata (Nandi et al., 2026; Ali et al., 2025), where each cell must correspond spatially across all input layers. The LULC maps were reclassified into a consistent set of land use categories to ensure uniformity across different years. This reclassification simplifies the modeling process and improves the reliability of transition analysis (Ritu et al., 2023; Indhanu et al., 2025).

PREPARATION OF DRIVING FACTOR LAYERS

Urban growth is influenced by a combination of physical, environmental, and infrastructural factors. In order to accurately simulate land use changes, several driving factor layers were prepared and incorporated into the model. The slope layer was derived from the Digital Elevation Model (DEM) using terrain analysis tools in GIS. Slope is an important factor in urban development because flat areas are generally more suitable for construction, while steep slopes often limit or restrict development activities. The road proximity layer was generated by calculating the Euclidean distance from the road network. This layer represents accessibility, which is a key determinant of urban expansion. Areas closer to roads tend to experience higher development pressure due to ease of transportation and connectivity. Urban layers for the years 2017, 2020, and 2023 were extracted from the LULC maps and converted into binary format, where urban areas were assigned a value of 1 and non-urban areas were assigned a value of 0 and then calculated distance to urban area. These layers help in capturing the influence of existing urban areas on future growth, as urban expansion often occurs in proximity to already developed regions. An exclusion layer was also created to restrict development in areas unsuitable for urbanization, such as water bodies. This ensures that the model produces realistic outputs by preventing transitions in restricted zones (N-yanbini et al., 2025).

Data	Year	Description	Source	Data format
LULC map	2017, 2020, 2023	Sentinel Imagery map	Sentinel LULC	.tiff
Road map	2017	The main road map of Rahata	Open street map	.shp
Dem	2020	SRTM (Shuttle Radar Topography Mission) with 30 m spatial resolution	USGS earth explorer	Tiff

LAND USE CHANGE MODELING USING MOLUSCE

Once the data is prepared, all explanatory maps are converted into a uniform raster format with the same coordinate system (UTM Zone 43N) and spatial resolution of 10 m. the model starts analyzing the changes that occurred between 2017 and 2020. Internally, MOLUSCE

compares each pixel of the 2017 map with the same pixel in the 2020 map. If a pixel changes from one class to another (for example, agriculture to built-up), the model records this as a transition. This process is repeated for all pixels in the study area. As a result, the model builds a transition database, which contains information about how frequently each land use class changes into another. This is known as the transition probability matrix. It tells the model, for example, how likely it is for agricultural land to become urban land. After identifying the transitions, the model then studies how the driving factors influence these changes. For each pixel where change has occurred, the model looks at the corresponding values of slope, distance to roads, and urban proximity. For example, it may observe that most urban expansion occurs in areas with low slope and near existing urban regions or roads. Using this information, a machine learning algorithm (such as an Artificial Neural Network or Logistic Regression) is trained. The algorithm internally analyzes how different driving factors influence patterns of land use change. It assigns weights to each factor, indicating how strongly each factor influences land transformation. (Shovon, 2026; Demessie et al., 2025).

During this training process, the model repeatedly adjusts its internal parameters to minimize error between predicted and actual changes. This is done through multiple iterations, where the algorithm improves its understanding step by step. By the end of this stage, the model is able to generate a transition potential map. This map shows, for each pixel, the probability of changing from one land use class to another based on its characteristics (such as slope and proximity to roads). Once the transition potential is calculated, the simulation stage begins using a cellular automata (CA) approach. In this step, the model not only considers the probability of change but also the influence of neighboring pixels. In reality, land use change does not happen randomly; it is influenced by surrounding areas. For example, urban areas tend to expand near existing urban regions. To simulate this, the

model uses a neighborhood window where each pixel is influenced by the classes of its surrounding pixels.

In the background, for each simulation iteration, the model evaluates every pixel and calculates its likelihood of changing into another class. This likelihood is based on three main components: the transition probability derived from past changes, the influence of driving factors (from the trained model), and the neighborhood effect (from surrounding pixels). These components are combined mathematically to decide whether a pixel will change or remain the same. The exclusion layer (water bodies) plays an important role during this stage. Internally, the model assigns a restriction value to these areas, meaning their probability of change is set to zero. As a result, pixels classified as water bodies remain unchanged throughout the simulation, ensuring realistic results. The simulation is carried out iteratively. Since the input data represents a 3-year change (2017 to 2020), the model assumes that one iteration corresponds to one year. Therefore, to simulate the LULC for 2023, the model runs three iterations starting from the 2020 map. In each iteration, the model updates the land use map by applying the transition rules. After the first iteration, an intermediate map (2021) is generated internally, followed by 2022, and finally the predicted map for 2023.

At the end of the simulation, the final output is a predicted LULC map for the year 2023. This map represents the most probable spatial distribution of land use based on past trends, driving factors, and neighborhood influence. The entire process combines statistical analysis, machine learning, and spatial modeling to realistically simulate how land use evolves over time.

MODEL CALIBRATION AND VALIDATION

The model is calibrated to improve the accuracy of the simulation so that it reflects the real land use changes occurring in the study area more effectively. In this study, calibration was carried out using LULC datasets of 2017 and 2020, along with the prepared driving factor layers. The model parameters were adjusted to best replicate the observed transitions between these years. Validation of the model is a critical step to assess its predictive accuracy. The calibrated model was used to simulate the LULC map for the year 2023, which was then compared with the actual 2023 LULC map. Accuracy assessment was performed using statistical measures such as Overall Accuracy (% of Correctness), Kappa (Overall), Kappa (Histogram) - Quantity Accuracy, Kappa (Location) - Spatial Accuracy (Ritu et al., 2023; Indhanu et al., 2025).

SIMULATION OF FUTURE LAND USE SCENARIOS

After calibration and validation, the model was applied to predict future land use patterns for the years 2026 and 2029. The simulation process utilizes the transition probabilities derived from historical data and applies them spatially using Cellular Automata. The output of this step consists of predicted LULC maps that illustrate the spatial distribution of different land use classes in future years. These maps provide a visual representation of potential urban expansion and land transformation patterns (Tola and Deyassa, 2024; Esha and Rahman, 2021).

IDENTIFICATION OF PERI-URBAN GROWTH CENTERS

The simulated LULC maps were analyzed to identify emerging peri-urban growth centers. This analysis was based on the spatial and temporal patterns of urban expansion observed in the predicted maps. Areas showing significant increase in built-up land, particularly along major road corridors and around existing urban settlements, were identified as potential peri-urban growth zones. The transition of agricultural and open land into urban land was also considered as a key indicator of peri-urbanization. Spatial overlay and comparison techniques were used to highlight zones with high growth intensity.

These zones represent areas that are likely to experience rapid development in the near future and therefore require careful planning and management. (Peco-Costas et al., 2025; Nyanbini et al., 2025). The methodology adopted in this study provides a comprehensive and systematic framework for analyzing and predicting land use changes. By integrating remote sensing data, GIS techniques, and advanced modeling tools like MOLUSCE, the study ensures both spatial accuracy and analytical depth. The approach is flexible and can be applied to other regions with similar characteristics, making it a valuable tool for urban planners, researchers, and policymakers. It enables data-driven decision-making and supports the development of sustainable urban growth strategies. (Jain, 2024; Kumari and Roy, 2025; Kamaraj and Rangarajan, 2021).

RESULTS AND DISCUSSION

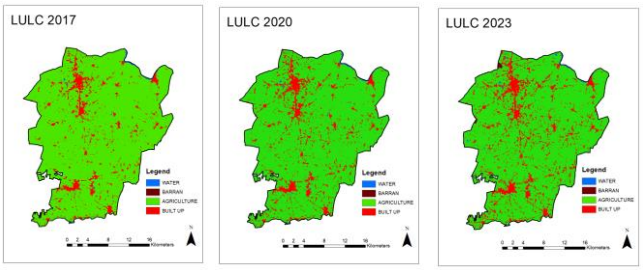
LULC maps

The land use/land cover (LULC) maps for the years 2017, 2020, and 2023 were derived from Sentinel satellite imagery. The maps show four major land use and land cover categories: water bodies, barren land, agriculture, and built-up areas. Agriculture continued to remain the dominant land use during the entire study period. At the same time, the steady increase in built-up areas, shown in red, reflects the ongoing urban growth in the region. Slight changes were also noticed

in barren land and water body areas. The corresponding table presents the percentage changes in each LULC category, highlighting the overall pattern of land use change and urban expansion over time.

Class name	2017 Year (m2)	2020 Year (m2)	Δ (m2)	2017%	2020%	Δ %
Water	4262600	4674500	411900	0.65703	0.72052	0.06349
Barren	140900	159900	19000	0.02171	0.02464	0.00292
Agriculture	593263700	575485900	-17777800	91.44571	88.70544	-2.74027
Built up	51093300	68440200	17346900	7.87552	10.54937	2.67385

Class name	**2020 Year (m2)**	**2023 Year (m2)**	**Δ (m2)**	**2020%**	**2023%**	**Δ %**
Water	4674500	4713400	38900	0.72052	0.72652	0.00599
Barren	159900	1212800	1052900	0.02464	0.18694	0.16229
Agriculture	575485900	559255400	-16230500	88.70544	86.20367	-2.50177
Built up	68440200	83578900	15138700	10.54937	12.88285	2.33348

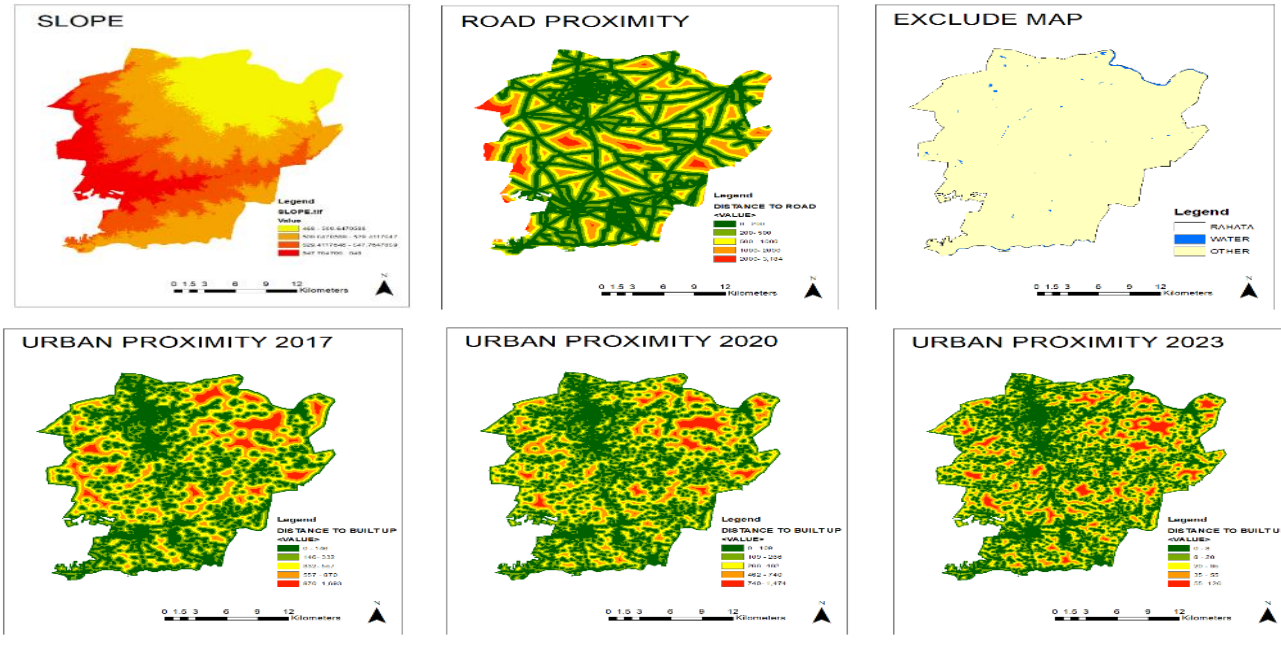


Driving Factor Layers

The spatial driving factors (special variables) used in the MOLUSCE model play a crucial role in controlling the pattern and direction of land use/land cover (LULC) change. In this study, thematic maps such as slope, urban proximity, road proximity, and an exclude map were used to guide the simulation process. The slope map represents the terrain condition of the study area. Areas with low slope

Values (flat regions) are more suitable for development, particularly for built-up expansion and agriculture, whereas high slope areas restrict such activities. Therefore, the model assigns a higher probability of urban growth in flatter regions and limits development in steeper areas. The urban proximity map shows the distance of each pixel from existing urban areas. Locations closer to urban centers have a higher likelihood of becoming built-up due to better accessibility and infrastructure. As distance increases, the probability of urban expansion decreases, resulting in outward growth from existing urban areas.

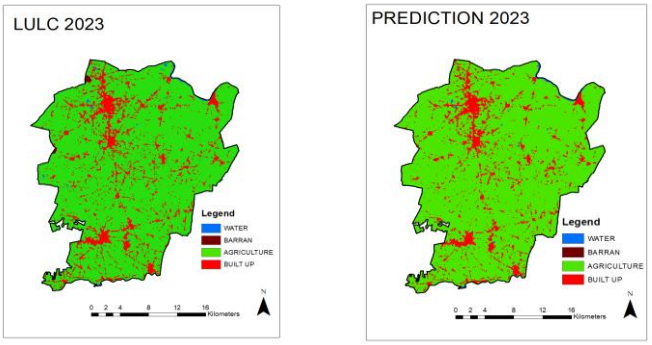
The road proximity map indicates the distance from transportation networks. Areas near roads are more accessible and thus more favorable for development. This factor influences the model to simulate urban growth along road corridors and nearby regions. The exclude map represents restricted areas where land use change is not allowed. In this study, water bodies were used as exclusion zones. These areas are assigned fixed values, preventing them from being converted into other land use classes during the simulation. This ensures that unrealistic changes, such as urban development over water bodies, do not occur in the predicted results. Overall, these driving factors and constraints work together to assign transition probabilities, enabling the model to simu-



late realistic spatial patterns of land use change with improved

Validation

Model validation was carried out by comparing the reference LULC map of 2023 with the simulated LULC map for the same year. The results show a high degree of spatial agreement between the two maps, particularly in the distribution of agricultural and built-up classes. Minor discrepancies are observed in localized areas; however, The overall similarity shows that the model successfully represents both the amount and spatial distribution of land use changes, demonstrating its reliability for future predictions.

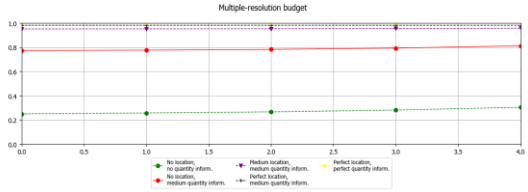


The accuracy of the simulated land use/land cover (LULC) map was evaluated using overall accuracy and Kappa statistics. The overall accuracy of the model was found to be 95.17%, indicating that a large proportion of pixels in the simulated map match the reference map. However, since overall accuracy does not account for agreement occurring by chance, the Kappa coefficient was used to provide a more reliable assessment. The overall Kappa value of 0.787 indicates a strong level of agreement between the simulated and reference map, confirming that the model predictions are significantly better than random assignment. To further assess model performance, Kappa was decomposed into Kappa histogram and Kappa location components. The Kappa histogram value of 0.921 reflects a very high level of agreement in terms of quantity, indicating that the model accurately predicts the overall proportion or area of different land use classes. In contrast, the Kappa location value of 0.854 measures spatial agreement and indicates that the model performs well in predicting the correct locations of land use changes

The multiple-resolution budget graph represents the relationship between spatial resolution (x-axis) and level of agreement (y-axis) between the simulated and reference maps. It helps to understand how model accuracy changes when the map is observed at different scales. In the graph, different colored lines indicate different types of agreement:

The green line (upper line) represents perfect agreement, where both the quantity and location of land use classes are completely accurate. This is the ideal situation, and it forms the highest reference line in the graph. The red line (lower line) represents agreement with no location and no quantity information, meaning the model has very poor performance. This is the lowest baseline, showing almost random prediction. The lines between red and green represent partial agreement, where the model correctly predicts either the quantity or the location, but not both perfectly. The model's performance curve lies closer to the green (upper) line, which indicates that the simulation is highly accurate.

This means the model is able to correctly predict both the amount of land use change (quantity) and the spatial distribution (location). Overall, since the model curve is far from the red line and near the green line, it confirms that the model has strong predictive ability and good spatial accuracy across different resolutions.



PREDICTION MAPS

The predicted LULC maps for 2023, 2026, and 2029 indicate a continuous increase in built-up areas in the study region. The expansion is mainly observed around existing urban areas and along major road networks, reflecting a pattern of outward and corridor-based growth. The tabulated results show that built-up land increases significantly between 2023–2026 and 2026–2029, while agricultural land consistently

decreases due to its conversion into urban uses. Minor fluctuations are observed in water bodies and barren land. Overall, the results highlight a clear trend of urban expansion and reduction of agricultural land, indicating increasing peri-urbanization in the study area.

Class name	2023 Year (m2)	2026 Year (m2)	Δ (m2)	2023%	2026%	Δ %
Water	4498700	4669700	171000	0.69343	0.71978	0.02635
Barren	95900	1174600	1078700	0.01478	0.18105	0.16627
Agriculture	570876500	545914100	-24962400	87.99495	84.14724	-3.84770
Built up	73289400	97002100	23712700	11.29683	14.95191	3.65507

Class name	2026 Year (m2)	2029 Year (m2)	Δ (m2)	2026%	2029%	Δ %
Water	4669700	4589400	-80300	0.71978	0.70741	-0.01237

Class name	2026 Year (m2)	2029 Year (m2)	Δ (m2)	2026%	2029%	Δ %
Barren	1174600	1159800	-14800	0.18105	0.17877	-0.00228
Agriculture	545914100	535079200	-10834900	84.14724	82.47715	-1.67009
Built up	97002100	107932100	10930000	14.95191	16.63666	1.68475

CONCLUSION

This study examined and projected land use/land cover (LULC) changes in Rahata Taluka by applying the MOLUSCE model along with GIS techniques.The model showed high accuracy, with an overall accuracy of 95.17% and a Kappa value of 0.787, indicating strong agreement between the actual and predicted maps. The high values of Kappa histogram (0.921) and Kappa location (0.854) also show that the model is good at predicting both the amount of land change and its location. The prediction results show that built-up areas are continuously increasing. From 2023 to 2026, built-up land is expected to increase by about 23.71 Km² (3.65%), while agricultural land decreases by about 24.96 Km² (−3.84%). From 2026 to 2029, built-up area further increases by 10.93 Km² (1.68%), and agricultural land decreases by 10.83 Km² (−1.67%). This clearly shows that agricultural land is gradually being converted into urban areas. Barren land also increases significantly between 2023 and 2026, which may represent transitional land before development. Water bodies show only small changes. The spatial pattern shows that urban growth is mainly happening near existing urban areas and along roads, forming new peri-urban growth zones.

Overall, the results show that urbanization is the primary factor driving land use changes in the study area. If this trend continues, it may lead to loss of agricultural land and unplanned urban growth. The study proves that the MOLUSCE model is useful for predicting future land use changes and can help in better planning and management of land resources.

Recommendations

The findings of the study recommend adopting well-planned and regulated urban development approaches in the identified peri-urban growth areas to minimize uncontrolled expansion. Protection of agricultural land should be prioritized through appropriate land use policies to ensure long-term sustainability. Infrastructure development should be aligned with predicted growth corridors, particularly along major road networks, to support efficient urban expansion. Additionally, strict zoning regulations and conservation measures should be enforced to protect environmentally sensitive areas such as water bodies. The use of geospatial tools like GIS and models such as MOLUSCE should be encouraged for continuous monitoring and informed decision-making in regional planning.

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