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Integrating Machine Learning, Cellular Automata-Artificial Neural Network Model for Projecting Future Land Use Patterns in Urban Landscape of Jaipur, India

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ABSTRACT

Jaipur, India, is experiencing rapid urbanization that is significantly altering its land use and land cover (LULC) patterns, presenting both challenges and opportunities for sustainable development and socio-economic advancement. This study utilizes advanced geospatial and remote sensing technologies to assess these changes and project future scenarios. Specifically, satellite data were processed using Google Earth Engine, land cover was accurately classified using the Random Forest algorithm, and future projections were modeled through QGIS-MOLUSCE using a polynomial-based Cellular Automata–Artificial Neural Network (CA-ANN) approach. Analysis of Landsat imagery for the years 2000 and 2020 reveals a dramatic 188.59% increase in urban built-up areas and a 145.44% rise in vegetation cover, largely due to successful afforestation efforts. Meanwhile, barren land declined by 47.37%, and water bodies exhibited fluctuating trends, reflecting the intricate interplay between urban development and climatic variability. Looking ahead to 2045, model projections estimate that built-up areas will expand to approximately 1303.08 square kilometres, potentially threatening the integrity of vital green spaces and aquatic ecosystems. These findings highlight the urgent need for integrated policy interventions aimed at mitigating environmental risks such as urban heat island effects and biodiversity loss. By providing a detailed account of past and present LULC dynamics, this research delivers actionable, data-driven insights to support sustainable urban planning. Moreover, the integration of urban growth models with climate resilience strategies offers a replicable framework for managing urban expansion in other rapidly developing cities, particularly those situated in semi-arid regions.

Keywords: Google Earth Engine; Machine Learning; Modules of Land Use Change Evaluation; Land Use Land Cover

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1. Introduction

Land Use and Land Cover (LULC) refers to the utilization of land, the resources it encompasses, and the physical or biological cover present on the Earth's surface, including forests, water bodies, vegetation, agricultural fields, and built-up areas [1]. Globally, over 75% of the terrestrial environment has been significantly altered by human activity, and more than one-third of the Earth's land surface is now used for agriculture [2]. In India alone, urban areas increased by over 54% between 2001 and 2021, significantly impacting agricultural land, forests, and wetlands [3]. The city of Jaipur, Rajasthan, exemplifies this transformation, with urban built-up areas expanding rapidly at the expense of natural ecosystems. Between 1990 and 2020, Jaipur's urban land cover expanded by nearly 200%, while green spaces and water bodies declined sharply [4]. Changes in LULC are among the most significant human-induced environmental disruptions, leading to various macroclimatic alterations [5]. Understanding these changes is essential for the sustainable and efficient management of natural resources and the environment [6]. Effective land use planning and resource management necessitate a comprehensive understanding of LULC patterns within a specific area [7]. Moreover, analysing both qualitative and quantitative land-use changes over time is crucial for sustainable urban planning and management [8]. In rapidly developing cities, LULC changes are inevitable, necessitating the identification of emerging trends [9]. Insights into these shifting patterns are vital for developing strategies that balance developmental needs, prevent conflicts, and support sustainable urban planning [10]. Over time, human activities have significantly modified the Earth's surface to enhance food production through various agricultural practices [11].

Currently, more than half of the Earth's surface has undergone transformation, with agricultural land constituting over one-third of the planet [12]. The ongoing conversion of natural landscapes into agricultural land continues to be a pressing issue [13]. Experts and land use administrators are increasingly assessing the effects of these changes on hydrological processes due to their extensive impact [14]. By analysing patterns of land use change, decision-makers and land managers can gain deeper insights into the interactions between human activities and natural systems [15]. Research highlights that rapid population growth is the primary driver behind the global shift in land use [16]. Recognizing shifts in LULC is essential for formulating strategies that balance developmental needs while preventing conflicts and supporting effective city planning and conservation efforts [17]. Changes in LULC are influenced by various factors, including a city's socioeconomic, political, and meteorological conditions [18]. However, in many urban environments, population growth remains the principal driver of these changes [19]. It is crucial to identify changes in LULC, as these can impact the arrangement of various spatial elements across different land surfaces [20]. Accurate image classification techniques are essential for obtaining LULC data from remotely sensed images [21]. In recent decades, machine learning classifiers have emerged as powerful tools for LULC classification, enhancing accuracy and performance [22]. Several models have been developed to predict future LULC dynamics, assisting in the evaluation of land use management policies [23].

Understanding the patterns and drivers of LULC change is essential for sustainable urban planning, resource management, and mitigation of the adverse effects of unplanned development [24]. By analysing historical LULC trends, policymakers and urban planners can identify factors contributing to these changes and develop strategies that balance urban growth with environmental conservation [25]. The integration of advanced technological tools is transforming LULC analysis, enabling more accurate assessments and predictions [26]. Remote sensing technologies and Geographic Information Systems (GIS) are now essential for capturing and analysing spatial data related to land use changes [27]. These technologies facilitate the monitoring of LULC dynamics over time, providing critical insights into the interactions between human activities and natural environments [28]. Furthermore, the application of machine learning algorithms in image classification has significantly enhanced the precision of LULC mapping, enabling researchers to classify land cover with greater accuracy and efficiency [29-31].

As urban areas continue to expand, the need for real-time monitoring and data-driven decision-making becomes increasingly essential, underscoring the role of technology in addressing contemporary urban challenges [32]. The implications of LULC changes extend beyond immediate environmental concerns, affecting socioeconomic dimensions such as public health, equity, and resource distribution [33]. Urbanisation often increases pollution levels, adversely impacting community health and well-being [34]. Additionally, the displacement of communities due to land conversion for urban development raises critical social justice issues, necessitating the examination of how land use policies can be more inclusive and equitable [35]. Understanding the multifaceted impacts of LULC changes is crucial for developing holistic urban policies that promote economic growth while safeguarding the rights and livelihoods of vulnerable populations [36].

Urbanization and its environmental consequences are closely tied to LULC changes, particularly in rapidly growing cities. As observed in previous studies, urban expansion often leads to the irreversible loss of agricultural land and natural habitats, exacerbating issues such as habitat fragmentation and biodiversity decline [37]. This transformation is particularly evident in developing regions, where unplanned urban sprawl outpaces sustainable land management practices [38]. Addressing these challenges requires integrated planning frameworks that reconcile urban growth with ecological preservation [39]. Advancements in geospatial technologies have revolutionized LULC monitoring, enabling precise tracking of land transformations [40]. According to a study in United States, remote sensing and machine learning now allow for high-resolution mapping of urban expansion patterns, providing critical data for policymakers [41]. Similarly, various studies emphasize the role of predictive modeling in forecasting future LULC scenarios, which is essential for proactive land-use planning [42,43]. These tools are indispensable for mitigating the adverse effects of urbanization while promoting sustainable development. Despite growing scholarly attention to LULC dynamics, several critical research gaps persist, particularly in the context of rapidly urbanizing regions. Many existing studies focus predominantly on historical LULC changes, with limited integration of predictive modeling tools that account for socioeconomic and environmental drivers. There is often a lack of spatially explicit, high-resolution analyses that can capture localized impacts of land transformation, especially in peri-urban and fringe areas. Another major gap lies in the insufficient incorporation of machine learning techniques and advanced remote sensing platforms for more accurate classification and forecasting. Opportunities exist to bridge these gaps by leveraging geospatial technologies such as Google Earth Engine and machine learning classifiers like Random Forest, alongside simulation models like MOLUSCE. This integration allows for more comprehensive, forward-looking assessments that can inform policy interventions. Additionally, there is a pressing need for interdisciplinary approaches that connect LULC dynamics to broader concerns such as climate resilience, social equity, and resource governance. Addressing these gaps offers a valuable opportunity to enhance land use planning frameworks, support sustainable urban development, and contribute to evidence-based decision-making in complex urban ecosystems.

What sets this research apart is its focus on the complex challenges posed by rapid urbanization and its far-reaching environmental implications. The study of LULC change is particularly critical in rapidly growing metropolitan areas, where the expansion of built-up spaces, depletion of water bodies, and loss of vegetation are transforming urban landscapes. These shifts contribute to pressing issues such as urban heat islands, water scarcity, reduced biodiversity, and heightened vulnerability to climate change. By employing the MOLUSCE tool to project LULC scenarios for 2045, this research not only analyses historical patterns but also adopts a forward-looking perspective that integrates socioeconomic and environmental variables. This comprehensive approach provides a nuanced understanding of the interactions between urban expansion, conservation efforts, and climate dynamics. The predictive capability of MOLUSCE is instrumental in informed decision-making, enabling policymakers and urban planners to design interventions that support sustainable development, protect critical ecosystems, and enhance urban resilience. Through the use of advanced modelling techniques and a multidisciplinary framework, this study addresses significant knowledge gaps in understanding LULC dynamics. By forecasting potential futures and assessing their implications, it aims to offer actionable insights that guide cities toward more sustainable and liveable futures.

2. Materials and Methodology

2.1. Study Area

Jaipur, the capital of Rajasthan in Northern India, ranks as the tenth-largest city in the country and lies between 26°25′ to 27°51′ N latitude and 74°55′ to 76°10′ E longitude (**Figure 1**). Celebrated for its rich history, vibrant culture, and iconic pink-hued architecture, Jaipur is also known as the "Pink City". This city was founded in 1727 by Maharaja Sawai Jai Singh II as one of India's first planned cities. Characterised by a grid-like layout and architectural marvels such as the Hawa Mahal, City Palace, and Amer Fort, Jaipur is a unique confluence of heritage and urbanisation. Over recent decades, the city has undergone rapid urban expansion driven by economic growth, tourism, and population inflows. Between the 2001 and 2011 Census periods, Jaipur's urban population rose from 2.3 million to 3.07 million, and this trajectory is projected to continue, positioning Jaipur as a key metropolitan hub in North India. The city's accelerated urban growth has placed immense pressure on infrastructure, housing, and essential services. Environmental issues such as worsening air quality, water scarcity, urban heat islands, and the loss of green spaces are becoming increasingly pronounced. The rising surface temperatures have increased reliance on artificial cooling systems, resulting in higher energy consumption and placing strain on the city's power infrastructure, especially during peak summer months. These social and environmental stresses underscore the urgency of integrated, forward-thinking urban planning approaches. In this context, the present study gains particular significance as it aims to project future land use patterns using a combination of machine learning and CA-ANN models.

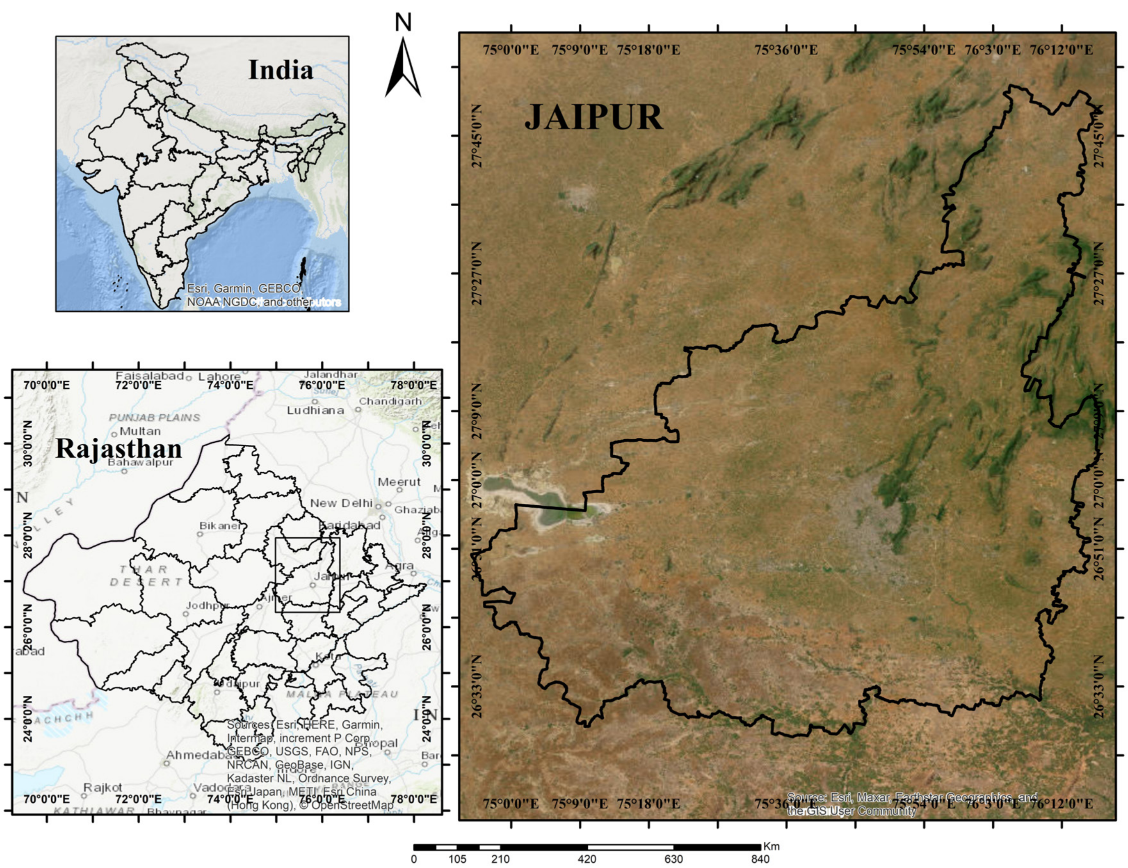

Figure 1. Study Area Map - Jaipur.

2.2. Data Collection and Pre-processing

2.2.1. Satellite Imagery Acquisition

The study utilized Google Earth Engine (GEE), a cloud-based geospatial platform, to analyse Landsat satellite imagery without requiring extensive local computing resources. **Figure 2** illustrates the methodological workflow employed for LULC classification. The researchers began by accessing GEE through a Google account and navigating to the Code Editor interface. The study area was defined by uploading a Jaipur city boundary shapefile created in ArcGIS 10.8, which was then visualized on the GEE map. For historical LULC assessment, Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery from 2000 was acquired and processed (**Table 1**). The dataset was filtered to include only images from January 1 to December 31, 2000, with cloud cover limited to less than 1% to minimize atmospheric interference. The same spatial extent (Jaipur city) and quality criteria were applied when processing Landsat 8 Operational Land Imager (OLI) imagery for 2020. The standardized 30-meter resolution imagery from both sensors enabled consistent spatial analysis across the two decades. All datasets were obtained from the USGS Earth Explorer portal as part of the Landsat Collection 2 inventory, which provides radiometrically calibrated top-of-atmosphere (TOA) reflectance values suitable for time-series analysis.

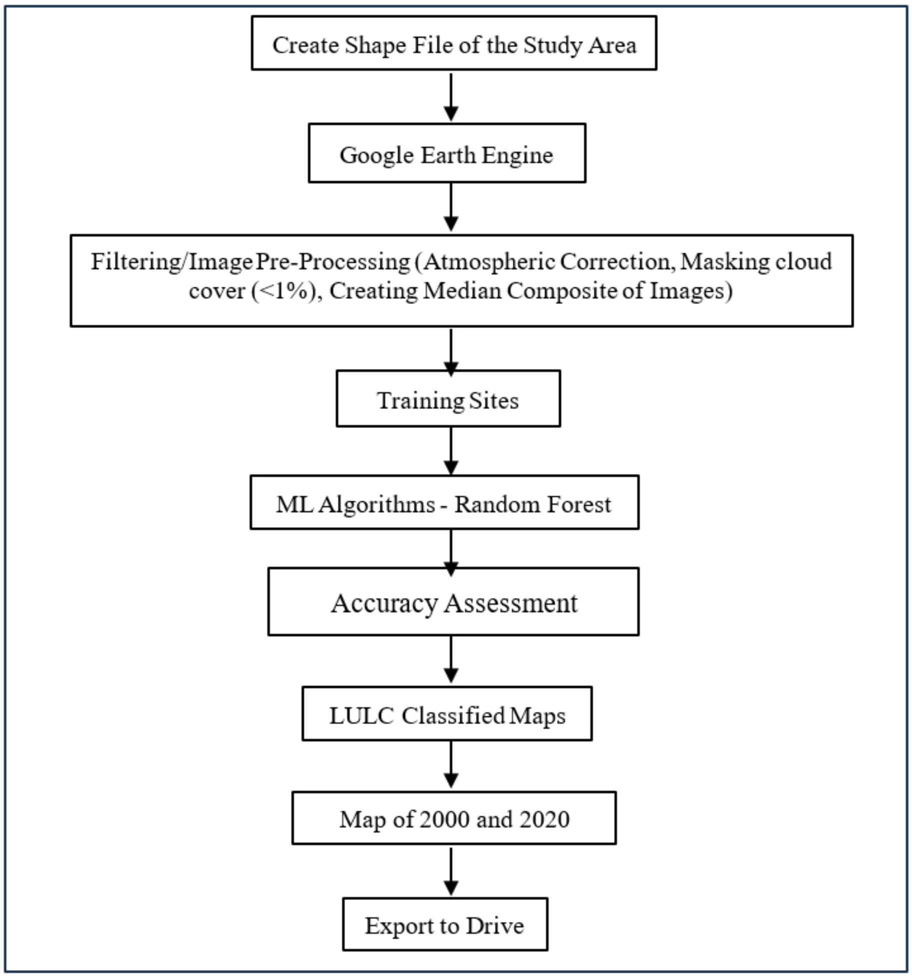

Figure 2. Flowchart showing methodology of LULC mapping.

Table 1. Satellite Data and specifications.

Satellite	Acquisition Period	Resolution(m)	Source	Description
Landsat 7 ETM+	From 01/01/2000 to 31/12/2000	30 x 30	USGS	Landsat 7 Collection 2 Tier 1 and Real-Time data calibrated top-of-atmosphere (TOA) reflectance.
Landsat 8 OLI	From 01/01/2020 to 31/12/2020	30 x 30	USGS	Landsat 8 Collection 2 Tier 1 and Real-Time data calibrated top-of-atmosphere (TOA) reflectance.

2.2.2. Auxiliary Spatial Datasets

Multiple geospatial datasets were used to derive critical parameters for land use modelling, as summarized in **Table 2** below. The Digital Elevation Model (DEM) was acquired from USGS Earth Explorer (accessed April 1, 2025) and served as the foundational dataset, enabling the derivation of five key terrain parameters: slope, aspect, curvature, hill shade, and contours through spatial analysis in ArcGIS. Hydrographic data obtained from HydroSHEDS (accessed April 1, 2025) provided the stream network used to calculate distance from water features. Transportation infrastructure layers, including roads and railways, were sourced from BBBike extracts (accessed April 1, 2025) and processed to generate proximity buffers. These parameters collectively address some fundamental dimensions of land use dynamics, such as topographic constraints (through DEM derivatives), hydrological considerations (via stream distance), and accessibility influences (through road/railway proximity). The integration of these datasets in MOLUSCE modelling ensures comprehensive representation of both biophysical constraints and anthropogenic factors driving land use changes in Jaipur's unique geographic context, where the Aravalli terrain and linear infrastructure corridors create distinct urban growth patterns. **Figure 3** illustrates the spatial variables employed in forecasting land use changes. The April 2025 data acquisition ensures the model works with the most recent pre-processed datasets available at the time of analysis.

Table 2. Spatial Variable Data and specifications.

Data	Source	Acquisition Date	Utility
DEM	earthexplorer.usgs.gov/	01/04/2025	Slope Aspect Curvature Hill shade Contour
Stream	hydrosheds.org/	01/04/2025	Distance from Stream
Road	extract.bbbike.org/	01/04/2025	Distance from Road
Railway	extract.bbbike.org/	01/04/2025	Distance from Railway

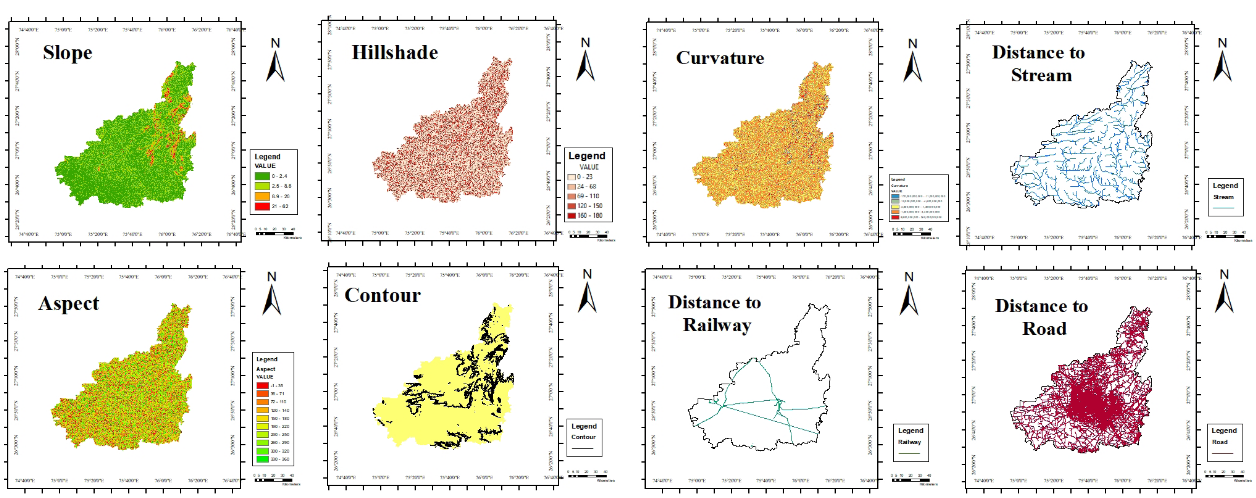

Figure 3. Surface Variable Maps used for future simulation.

2.3. LULC Classification

2.3.1. LULC Classification and Training Data

Supervised classification was conducted using labelled training data to generate accurate LULC maps. Representative land cover classes were first identified through visual interpretation of high-resolution base maps. Training samples were then manually delineated for five main LULC categories: Built-up Land, Water Bodies, Dense Vegetation, Cropland, and Barren Land. The details of the LULC classification scheme are presented in **Table 3**. Each digitized polygon was assigned a corresponding class label, enabling the extraction of spectral signatures from the satellite imagery. For Landsat 7 (2000), spectral information was derived from bands B1 to B5 and B7, while for Landsat 8 (2020), bands B2 to B7 were utilized, as these bands provided optimal separability between land cover types. A Random Forest (RF) classifier comprising 50 decision trees was trained using the sampled data. This ensemble-based classifier was chosen for its robustness in handling noisy datasets and capturing complex, non-linear relationships among input features. Once the classifier was trained, it was applied to the entire satellite imagery to produce classified LULC maps for the years 2000 and 2020. The classified outputs were visualized within the Google Earth Engine environment, with distinct colour schemes assigned to each class, such as red for built-up areas, blue for water bodies, green for dense and sparse vegetation, yellow for cropland, and brown for barren land, thereby enhancing interpretability and thematic clarity. The classified images were visualized in GEE using distinct colour palettes for each land cover class. An accuracy assessment was conducted by splitting the training data into training and validation subsets (70/30 split). The accuracy was evaluated using a confusion matrix, and metrics such as overall accuracy and the kappa coefficient were calculated to ensure reliability.

Table 3. Description of LULC Classification Scheme.

LULC Type	Description
Built-up Land	Residential, Commercial, and Other Infrastructure
Water Body	Rivers, lakes, ponds, and dams
Dense Vegetation	All types of forest cover land
Crop Land	Agricultural Land, Farm Land, Fallow Land
Barren land	All types of barren land

2.3.2. Future Simulation Using MOLUSCE

The subsequent step involved predicting the future LULC scenario for Jaipur in the year 2045. This was achieved using the MOLUSCE plugin in QGIS, which facilitates dynamic modelling of land use transitions through spatial analysis and machine learning. The process began with the preparation of suitable input layers. The classified maps of 2000 and 2020, derived from GEE, were exported as GeoTIFF raster files and imported into QGIS. These raster files were then meticulously pre-processed to ensure uniform spatial resolution, consistent geographic extents, and a common coordinate reference system. Each map was reclassified to ensure that identical land cover classes shared the same numerical codes across the temporal datasets, a crucial step for comparative change detection. In parallel, ancillary spatial datasets such as aspect, slope, curvature, hill shade, contour, distance to roads, and proximity to water bodies were prepared to serve as influencing factors or driver variables that might affect land use change. These layers enhanced the accuracy of the simulation by incorporating environmental and infrastructural variables that typically govern land transformation patterns in urban settings like Jaipur. Once the datasets were in place, the MOLUSCE plugin was launched and the classified LULC rasters for 2000 and 2020 were loaded as the primary input layers. MOLUSCE performed a detailed land cover change detection analysis to compute the transitions between different land categories over the 20-year interval. Based on these transitions, the tool automatically generated a transition probability matrix, which quantified the likelihood of a specific land class changing into another. Subsequently, a suitable simulation algorithm was chosen within the MOLUSCE framework to model future land use transitions. Among the available methods—such as Logistic Regression, Weights of Evidence, and CA-ANN—the CA-ANN model was selected due to their proven ability to capture complex, non-linear relationships in geospatial data. The ANN model was trained using observed land cover transition data between 2000 and 2020, effectively learning how different land categories evolved over time in response to environmental and infrastructural driving factors such as aspect, slope, curvature, hill shade, contour, distance to roads, and proximity to water bodies. Once the ANN was calibrated, it was employed to simulate the projected land use and land cover for the year 2045, advancing the temporal horizon by 25 years from the last observed data. The MOLUSCE tool utilized these trained ANN parameters to generate a predictive LULC map for Jaipur in 2045. This output spatially represented expected land categories based on transition probabilities derived from past changes. A corresponding confidence layer was also generated, indicating the model's certainty levels regarding each class prediction. An accuracy assessment, including the computation of a confusion matrix and the Kappa Index of Agreement (KIA), confirmed the model's reliability. A satisfactory KIA value affirmed that the ANN-based model had a strong capacity to replicate real-world changes and, therefore, was dependable for future projection. The final predicted LULC map for 2045 was then thematically styled and interpreted to identify potential spatial patterns of change. The visualization clearly indicated a pronounced expansion of built-up areas, especially along the northwest and southern edges of Jaipur, consistent with the city's ongoing urban sprawl. **Figure 4** illustrates the methodological workflow employed for future simulation.

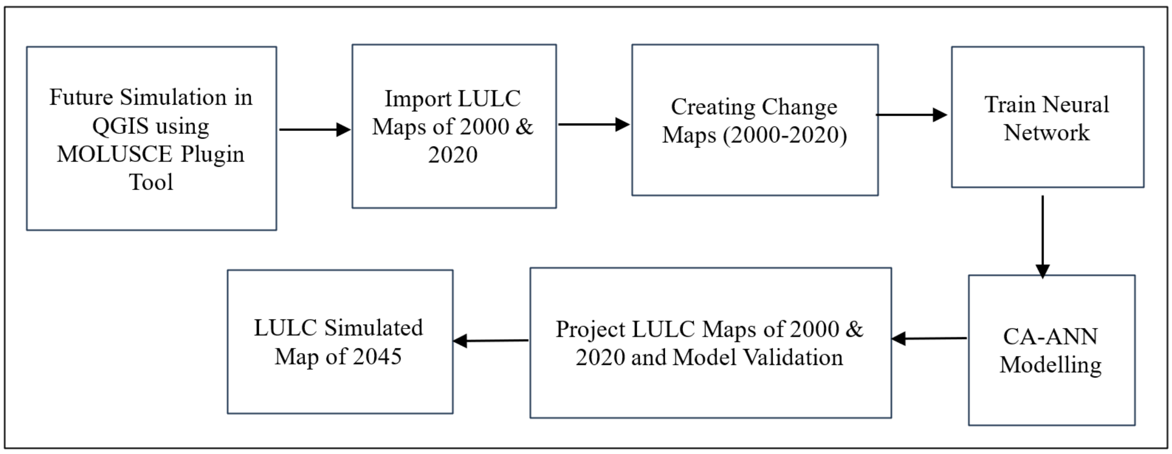

Figure 4. Flowchart showing the methodology of LULC simulation.

3. Results and Discussion

3.1. Land Use and Land Cover Changes in Jaipur from 2000 to 2020

Jaipur's LULC patterns between 2000 and 2020 were classified into five main categories: built-up areas, water bodies, vegetation, cropland, and barren land. During these twenty years, the city witnessed notable shifts in its landscape. As depicted in **Figure 5**, cropland and vegetation were the most dominant land cover types throughout this period, significantly influencing Jaipur's environmental and agricultural profile.

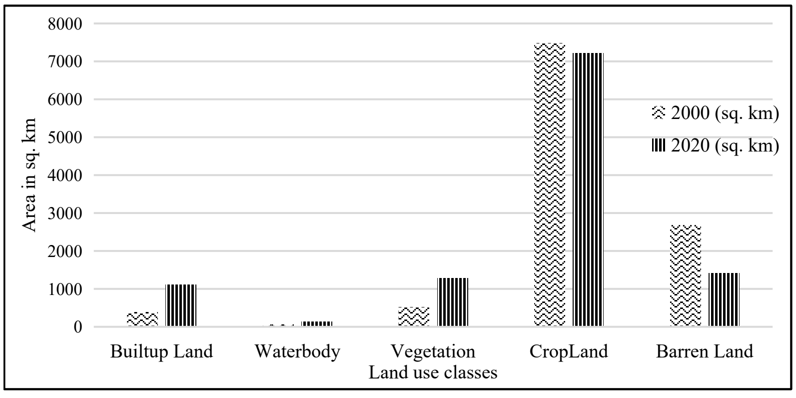

Figure 5. Changes in different land use classes from the year 2000 and 2020 in Jaipur.

Table 4 presents a comparison of LULC in Jaipur between the years 2000 and 2020, Over the past two decades, Jaipur has undergone major transformations in LULC, as depicted in maps shown in **Figures 6** and **7**, reflecting rapid urbanization and shifting environmental dynamics. The data reveals key trends that highlight both progress and challenges in the region's development. One of the most striking changes is the dramatic expansion of built-up areas, which nearly tripled, increasing from 382.15 sq. km in 2000 to 1102.67 sq. km in 2020. This surge points to intense urban growth, likely driven by population increase, economic activity, and infrastructure projects. While this development signals prosperity, it also raises concerns about resource strain, overcrowding, and environmental stress.

Table 4. Total area covers by different LULC classes and the percentage of cover for the years 2000, 2020 in Jaipur.

Classes	2000 (sq. km)	In Percentage	2020 (sq. km)	In Percentage
Built-up Land	382.15	3.43	1102.67	9.91
Waterbody	67.95	0.61	130.55	1.17
Vegetation	520.39	4.68	1277.15	11.48
Cropland	7483.88	67.25	7209.92	64.80
Barren Land	2672.85	24.03	1406.92	12.64

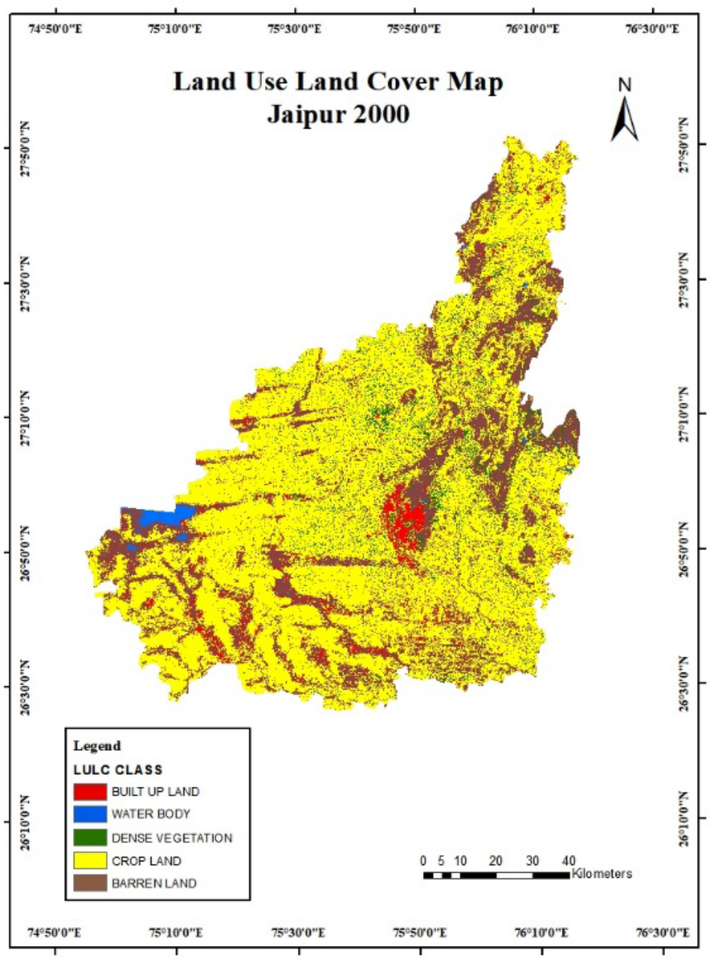

Figure 6. Land Use Land Cover Map of Jaipur for the year 2000.

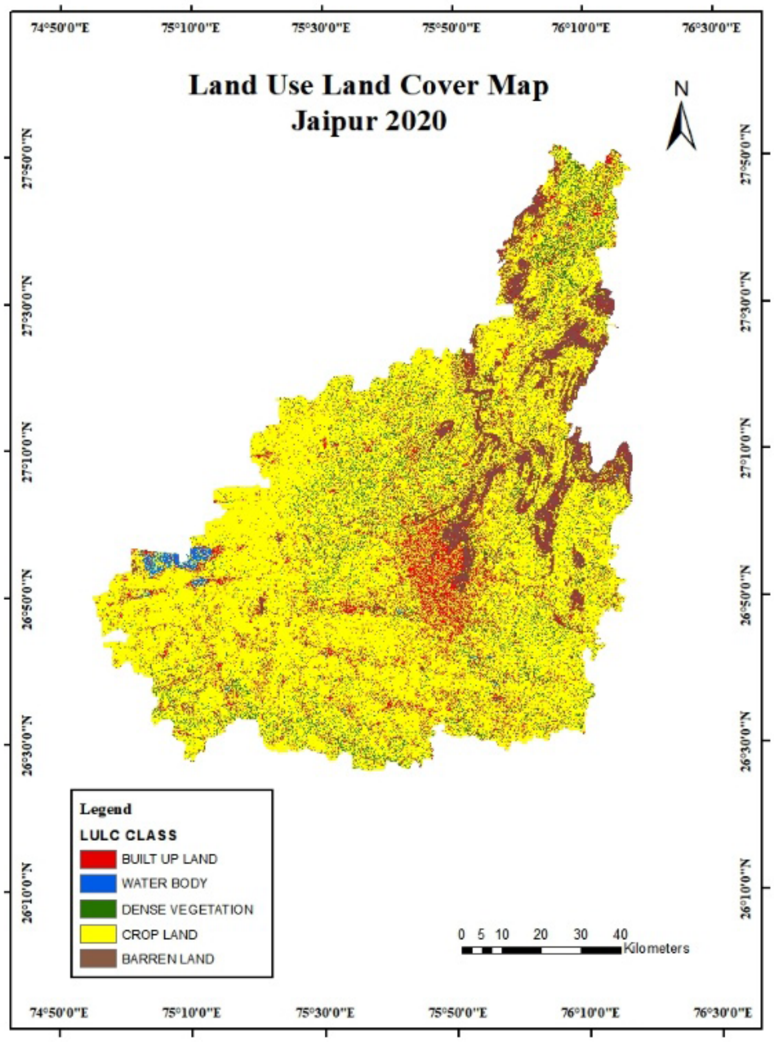

Figure 7. Land Use Land Cover Map of Jaipur for the year 2020.

At the same time, barren land has decreased considerably, dropping from 2672.85 sq. km to 1406.92 sq. km. This suggests that previously unused land is being repurposed, possibly for urban expansion or agriculture. The decline aligns with the rise in built-up areas, showing how urban sprawl is reshaping the region's landscape. Interestingly, water bodies have nearly doubled in size, increasing from 67.95 sq. km to 130.55 sq. km. This could indicate better water management practices or the construction of artificial reservoirs to meet growing demand. Vegetation cover has also seen a significant boost, expanding from 520.39 sq. km to 1277.15 sq. km, a positive sign that green spaces are being prioritized despite urban growth. More trees and plants can help mitigate pollution, support wildlife, and enhance residents' quality of life.

On the other hand, cropland has decreased from 7483.88 sq. km to 7209.92 sq. km, likely due to farmland being converted into housing or commercial zones. This loss of agricultural land could threaten food security if not managed carefully, underscoring the need for sustainable land-use policies. Overall, Jaipur's land use changes reflect a city in transition—embracing urban development while grappling with its consequences. The growth in infrastructure and greenery is promising, but the reduction in farmland and natural landscapes calls for balanced planning to ensure long-term sustainability. As Jaipur continues to expand, finding ways to harmonize urban progress with environmental and agricultural preservation will be crucial.

3.2. Accuracy Assessment of LULC Maps

The accuracy of the LULC classification for the years 2000 and 2020 was evaluated by comparing the classified land use categories with reference satellite imagery and ground truth data. A pixel-by-pixel assessment method was used, where 100 random points were generated on each LULC map. These points were cross-checked using satellite images and spatial data from the study area to ensure they accurately represented the different land use categories. A confusion matrix was then created to identify misclassified pixels and calculate the overall classification performance. As shown in **Table 5**, the results indicate a high level of accuracy for both years. The overall classification accuracy was 91.1 percent for 2000 and increased to 94.4 percent for 2020. The corresponding Kappa coefficients were 86.1 and 87.4, indicating strong agreement between the classified data and the reference imagery. Looking at user accuracy, both Built-Up Land and Water Bodies achieved perfect scores (100 percent) in both years, suggesting these classes were very clearly identifiable. Dense Vegetation and Crop Land had moderate accuracy levels, around 70 percent, while Barren Land showed the lowest user accuracy, declining from 66.2 percent in 2000 to 62.4 percent in 2020, indicating frequent confusion with similar land cover types, such as developed areas.

Table 5. Accuracy Assessment of LULC Maps from the Years 2000 and 2020.

	Classes	2000	2020
User Accuracy (percentage)	Built-Up Land	100.0	100.0
	Water Body	100.0	100.0
	Dense Vegetation	70.1	70.4
	Crop Land	71.0	72.4
	Barren Land	66.2	62.4
Producer Accuracy (percentage)	Built-Up Land	100.0	91.4
	Water Body	100.0	100.0
	Sparse Vegetation	83.4	81.7
	Crop Land	92.1	88.7
	Barren Land	100.0	66.4
Overall Accuracy		91.1	94.4
Kappa		86.1	87.4

Producer accuracy tells a similar story. Built-Up Land and Water Bodies were accurately captured in 2000, but the accuracy for Built-Up Land dropped slightly to 91.4 percent in 2020. Sparse Vegetation remained fairly consistent at around 82–83 percent, while Crop Land saw a small decrease from 92.1 percent to 88.7 percent. Barren Land experienced the largest drop, from 100 percent in 2000 to just 66.4 percent in 2020, again highlighting the challenge of distinguishing it from other classes. Overall, the classification results were most reliable for Water Bodies and Built-Up Land due to their distinct appearance in satellite images. Meanwhile, areas like Barren Land, Forest, and Agriculture were more prone to misclassification, likely due to overlapping spectral characteristics and the presence of mixed pixels in heterogeneous landscapes.

3.3. Transition Dynamics in ANN Modelling

To assess the model's accuracy and validate the predictions, the MOLUSCE plugin utilizes the Kappa validation method along with a comparison between actual and simulated LULC maps. During the ANN training process, the following parameters were applied: 1000 iterations, a neighborhood size of 1 × 1 pixels, a learning rate of 0.1, 10 hidden layers, and a momentum value of 0.05 to forecast the LULC for the year 2045. **Table 6** presents the ANN parameter for LULC simulation in MOLUSCE plugin.

Table 6. ANN parameters for LULC simulation.

Parameter	Value
Neighborhood	1 x 1 pixel
Learning Rate	0.100
Maximum iterations	1000
Hidden layers	10
Momentum	0.050

The classification accuracy assessment for the years 2000 and 2020 reveals a strong and reliable performance of the LULC classification model. The overall accuracy improved from 91.1 percent in 2000 to 94.4 percent in 2020, indicating a high level of concordance between the classified maps and ground truth data. This enhancement reflects improved data quality, refined classification methodologies, or more distinct land cover signatures over time. Similarly, the Kappa coefficient, which accounts for the possibility of agreement occurring by chance, also increased from 86.1 to 87.4, signifying a substantial agreement between the observed and predicted classifications. These metrics confirm the robustness and reliability of the classification results, suggesting that the maps can be confidently used for further spatial analysis and predictive modeling of LULC changes in the Jaipur.

3.4. Land Use and Land Cover Changes in Jaipur of the Predicted year 2045

This study employs a polynomial-based CA-ANN model within the MOLUSCE framework to predict Jaipur's urban growth. Unlike linear models, the CA-ANN captures complex, non-linear patterns of accelerating urbanization by analyzing how multiple factors (roads, slope, population) interact multiplicatively. The ANN processes these complex relationships, while Cellular Automata applies spatial rules to simulate realistic expansion. This approach more accurately reflects Jaipur's actual growth dynamics, where development accelerates near infrastructure and economic centers, thereby producing more accurate 2045 projections than simpler linear methods. CA-ANN model simulates future LULC patterns in Jaipur, projecting changes up to the year 2045 (**Figure 8**). Key surface variables including contour, slope, aspect, curvature, hill shade, distance to streams, distance to roads, and railways were integrated into the model to enhance prediction accuracy (**Figure 3**). **Figure 9** highlights the anticipated shifts across different LULC classes, while **Table 7** provides a detailed breakdown of the area and percentage coverage for each class in 2045.

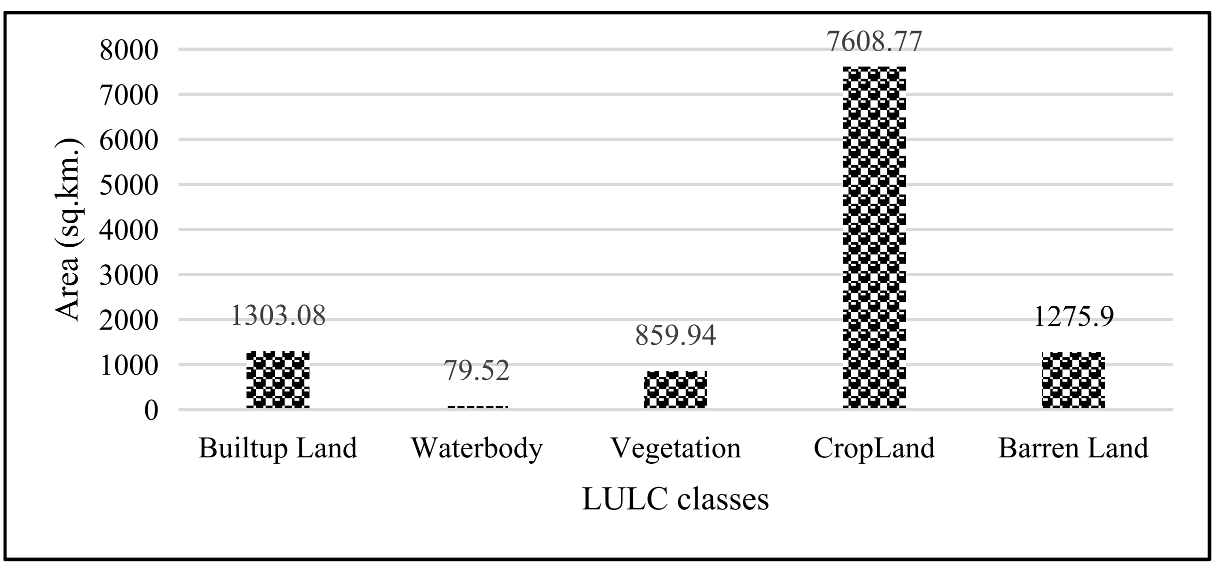

Figure 8. Predicted changes in different LULC classes in the year 2045.

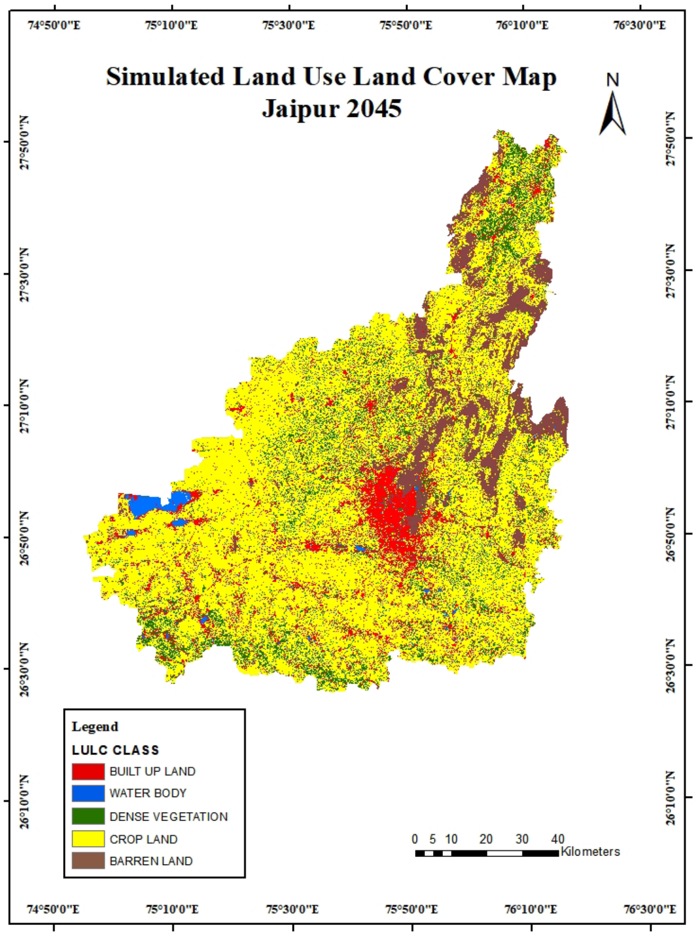

Figure 9. Simulated Land Use Land Cover Map of Jaipur for the year 2045.

Table 7. Area cover of different LULC classes in the year 2000, 2020 and 2045.

Classes	2000 (sq. km)	2020 (sq. km)	2045 (sq. km)
Built-up Land	382.15	1102.67	1303.08
Waterbody	67.95	130.55	79.52
Vegetation	520.39	1277.15	859.94
Cropland	7483.88	7209.92	7608.77
Barren Land	2672.85	1406.92	1275.9

The analysis of Jaipur's LULC patterns from 2000 to 2045 shown in **Table 4**, reveals significant transformations in the urban landscape, with important implications for urban planning and environmental management. The data highlights distinct trends across five major land cover categories, highlighting both positive developments and emerging challenges that demand policy attention.

One of the most prominent trends is the substantial expansion of built-up areas, which nearly tripled from 382.15 km² in 2000 to 1,102.67 km² in 2020, with projections indicating further growth to approximately 1,303 km² by 2045. This rapid urbanization mirrors Jaipur's emergence as a major economic and population centre in Rajasthan. However, the slower rate of expansion between 2020 and 2045 (an increase of only 200 km² compared to 720 km² in the previous two decades) suggests potential constraints on urban growth, possibly due to geographical limitations, policy interventions, or natural barriers to expansion. Vegetation cover presents an interesting pattern, showing remarkable growth from 520.39 km² in 2000 to 1,277.15 km² in 2020, followed by a projected decline to 859.94 km² by 2045. The initial increase likely resulted from urban greening initiatives and afforestation programs, while the anticipated decrease may reflect competing land use pressures from urban expansion and agricultural needs. This projected loss of green cover could have significant implications for urban heat island effects, biodiversity, and overall environmental quality in the region. Water resources demonstrate a concerning trajectory, with water bodies expanding from 67.95 km² in 2000 to 130.55 km² in 2020, but then projected to contract sharply to 79.52 km² by 2045. This pattern suggests that while water conservation efforts may have been successful in recent decades, future climate variability, increased water demand, and potential mismanagement could reverse these gains. The predicted reduction in water bodies raises serious concerns about water security and ecosystem health in the region. Agricultural land use shows a more optimistic trend, with cropland decreasing from 7,483.88 km² in 2000 to 7,209.92 km² in 2020, but then projected to recover to 7,608.77 km² by 2045. This rebound may indicate successful implementation of agricultural protection policies, technological improvements in farming efficiency, or possibly the recognition of food security needs in regional planning. The parallel decline in barren land (from 2,672.85 km² in 2000 to a projected 1,275.9 km² in 2045) suggests ongoing efforts to bring marginal lands into productive use, whether for agriculture or other purposes.

3.5. Land Use Land Cover Trends in Jaipur (2000–2045)

The breakdown of LULC changes in Jaipur between 2000 and 2020, along with projections up to 2045, reveals profound transformations influenced by urban expansion, agricultural transitions, and environmental conditions. These changes reflect broader socioeconomic and ecological dynamics, underscoring the need for strategic and sustainable urban development planning. The built-up area has shown a substantial increase, rising from 382.15 sq. km. in 2000 to 1102.67 sq. km. in 2020. This represents a growth of approximately 188.59 percent, largely driven by rapid population growth, expanding infrastructure, and intensified economic activities. Projections indicate that built-up areas will further expand to 1303.08 sq. km. by 2045. This trend highlights the pressing need to implement sustainable urban planning measures to address challenges such as the urban heat island effect, reduced green space, and growing pressure on urban infrastructure. **Table 8** illustrates the trend of LULC change in Jaipur.

Table 8. Area cover of different LULC classes in the year 2000, 2020 and 2045.

Classes	2000 (sq. km)	2020 (sq. km)	2045 (sq. km)	2000 (percent)	2020 (percent)	2045 (percent)	Change (2000–2020) (sq. km)	Percent Change (2000–2020)	Change (2020–2045) (sq. km)	Percent Change (2020–2045)
Built-up Land	382.15	1102.67	1303.08	3.43	9.91	11.71	720.52	188.59	200.33	18.17
Waterbody	67.95	130.55	79.52	0.61	1.17	0.71	62.6	92.15	-51.03	-39.09
Vegetation	520.39	1277.15	859.94	4.68	11.48	7.73	756.76	145.44	-417.21	-32.68
Cropland	7483.88	7209.92	7608.77	67.25	64.80	68.38	-273.96	-3.66	398.85	5.53
Barren Land	2672.85	1406.92	1275.9	24.03	12.64	11.47	-1265.93	-47.37	-131.02	-9.31

Water bodies experienced growth from 67.95 sq. km. in 2000 to 130.55 sq. km. in 2020. This expansion may be attributed to enhanced water conservation and rehabilitation programs. However, a decline to 79.52 sq. km. is projected by 2045, suggesting that continued urban expansion and inefficient management could undermine these gains. This anticipated reduction underscores the need for comprehensive water resource management to ensure long-term ecological and human water security. Vegetation cover, which includes both dense and sparse vegetation, increased significantly from 520.39 sq. km. in 2000 to 1277.15 sq. km. in 2020. This improvement likely reflects effective afforestation and greening initiatives. However, it is projected to decrease to 859.94 sq. km. by 2045. The decline could have negative implications for biodiversity conservation, carbon storage, and urban climate mitigation. This projection reinforces the importance of preserving and enhancing urban green infrastructure. Cropland experienced a slight decline between 2000 and 2020, but it is projected to increase significantly to 7608.77 sq. km. by 2045. This recovery may indicate a shift toward more sustainable and productive agricultural practices. Reinforcing rural land-use policies and advancing agroecological methods can enhance food security, safeguard rural livelihoods, and limit farmland loss to urban encroachment. Barren land has been consistently declining, from 2672.85 sq. km. in 2000 to an estimated 1275.90 sq. km. in 2045. **Figures 10** and **11** show area in sq. km. and area in percentage for the year 2000, 2020, 2045 respectively. **Figures 12** and **13** depict percentage area changes and area changes in sq. km for the year 2000, 2020, 2045 respectively. This reduction reflects improvements in land utilization through agricultural and urban development. However, the continued decrease also raises concerns regarding land degradation, soil erosion, and the loss of natural open spaces, necessitating targeted efforts in land restoration and soil conservation.

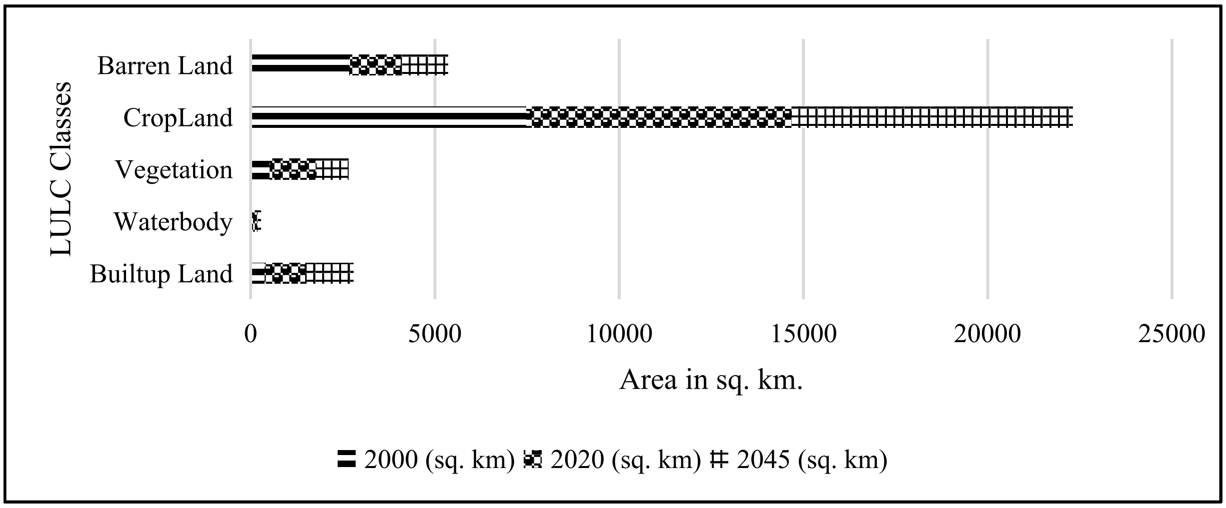

Figure 10. Area in sq.km. for the year 2000, 2020, 2045.

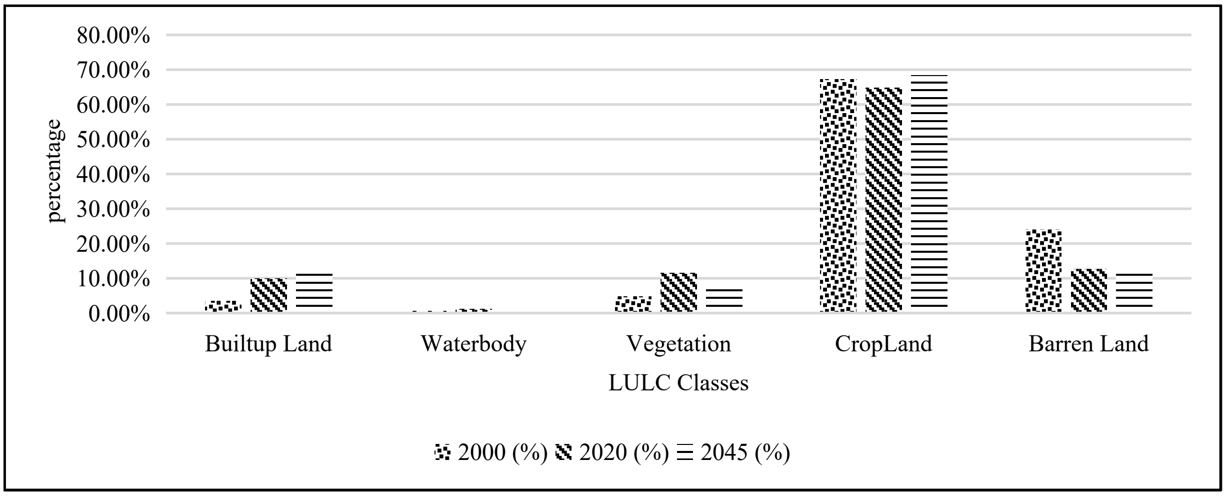

Figure 11. Area in percentage. for the year 2000, 2020, 2045.

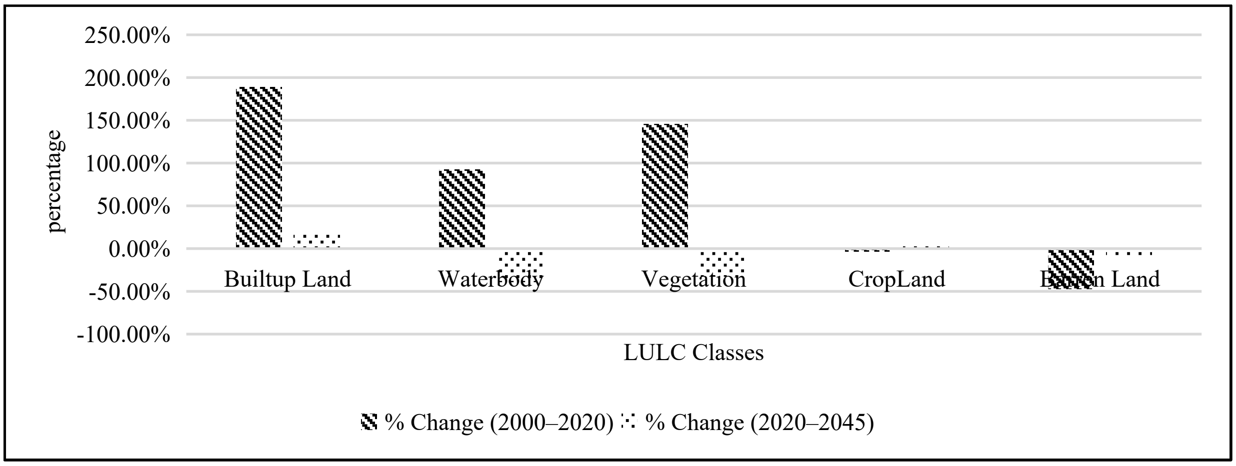

Figure 12. Percentage area changes for the year 2000, 2020, 2045.

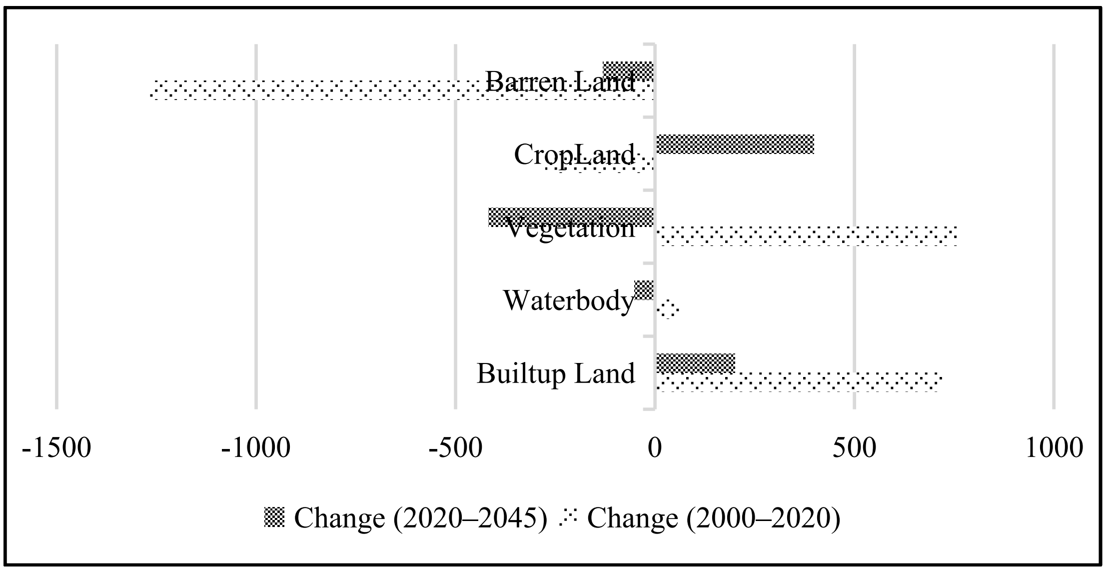

Figure 13. Area Changes in sq.km. for the year 2000, 2020, 2045.

These changing land use patterns demonstrate the complex interdependence between urban development, agricultural sustainability, and environmental stewardship. The application of advanced geospatial technologies such as Google Earth Engine, the MOLUSCE module in QGIS, and machine learning classifiers has enabled a comprehensive analysis and projection of LULC changes. These tools provide critical insights that can inform evidence-based policy interventions and enhance land management practices. To ensure Jaipur's sustainable and resilient future, it is essential to implement integrated land-use strategies that align urban growth with ecological preservation. This includes establishing and maintaining green belts, adopting robust water resource governance, protecting agricultural land, and reinforcing climate-resilient infrastructure. Equally important is fostering community participation in urban planning and promoting inclusive governance that reflects the needs of all stakeholders. Future research should aim to identify the specific drivers of LULC changes in Jaipur and assess the effectiveness of current land management policies. By understanding the interactions between demographic shifts, policy frameworks, economic development, and environmental pressures, researchers and planners can contribute to the creation of forward-looking strategies that support sustainable urban transformation.

4. Conclusion

This study provides a comprehensive and spatially detailed analysis of LULC dynamics in Jaipur from 2000 to 2020, with future projections extending to 2045 using the CA-ANN model integrated with remote sensing and GIS tools. The results reveal significant patterns of urban expansion, shifts in ecological land covers, and the implications of these changes on the region's environmental sustainability. The findings also reflect broader trends observed in other urbanizing contexts, while highlighting distinct features of Jaipur's urban ecological trajectory. In alignment with earlier findings, this study confirms a substantial increase in built-up area rising by 188.59 percent from 3.43 percent in 2000 to 9.91 percent in 2020 and projects continued growth to 11.71 percent by 2045 [44]. While previous research predicts more rapid decadal increases in built-up land (exceeding 100 percent in some cases), the current study presents a relatively moderate yet persistent urban growth trend, suggesting that the expansion in Jaipur is both substantial and sustained but may be following a more gradual trajectory than in some other Indian cities [44]. Unlike the continuous degradation of vegetation and forest cover reported by a study in Linyi, China, the present study observes a significant increase in vegetation cover in Jaipur from 4.68 percent in 2000 to 11.48 percent in 2020 [45]. This positive trend may reflect successful afforestation drives, green infrastructure projects, and efforts to enhance urban livability. However, the projections indicate a reversal, with vegetation expected to decline by 32.68 percent by 2045 due to increasing urban encroachment, revealing the vulnerability of urban green spaces under continued land development pressures. Water bodies in Jaipur also exhibited temporary gains, expanding by 92.15 percent until 2020. This may be attributed to improved water resource management and the restoration of traditional water systems. However, the projected 39.09 percent reduction by 2045 aligns with concerns raised by a study in Manisa, about the long-term threat of urbanization to natural hydrological systems [18]. If unaddressed, this could exacerbate water scarcity and degrade ecosystem services in the region. Cropland dynamics in Jaipur diverge from the trends typically observed in rapidly urbanizing cities, where agriculture is often displaced. While a minor decrease of 3.66 percent occurred between 2000 and 2020, a 5.53 percent recovery is projected by 2045. This suggests a possible rebound in peri-urban agriculture or a reallocation of underutilized land back to cultivation, offering a potential pathway for enhancing food security and rural livelihoods within the urban fringe. Despite its strengths, this study has several limitations. First, the LULC projections are derived from historical land change patterns and assume that past trends will continue, potentially overlooking the effects of future land-use regulations, infrastructure development, or unexpected socio-political shifts. Second, while the CA-ANN model achieved high classification accuracy, it does not explicitly account for key socio-economic drivers such as population density, income levels, migration, or land tenure patterns, which are critical to understanding urban growth dynamics. Additionally, the study primarily uses decadal satellite imagery, which may mask short-term or seasonal fluctuations in land cover, particularly for croplands and water bodies. This research contributes to the growing body of knowledge on urban land transformation by offering a detailed case study of Jaipur's changing LULC profile. It not only reinforces the broader concerns about the environmental impacts of rapid urbanization but also highlights unique local dynamics, such as the initial increase in green cover and the potential for agricultural resurgence [18,44,45]. These findings highlight the urgent need for proactive, spatially-informed urban planning and policy interventions that prioritize ecological balance, water resource management, and the preservation of productive land amidst ongoing urban expansion.

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Institutional Review Board Statement

Not applicable. This study involved the analysis of publicly available satellite and environmental data and did not require ethical approval.

Informed Consent Statement

Not applicable, as no human participants were involved in this study.

Data Availability Statement

The data used in this study are publicly available from NASA-MODIS, Landsat 8, Bhuvan Resourcesat-2, and relevant remote sensing repositories. The Satellite data for this study were obtained from open, publicly accessible platforms, including the USGS Earth Explorer (https://earthexplorer.usgs.gov) and NASA's Earthdata portal (https://earthdata.nasa.gov), according to their data use policies.

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Conflict of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

References

[1] Gharaibeh, A., Shaamala, A., Obeidat, R., et al., 2020. Improving land-use change modeling by integrating ANN with Cellular Automata–Markov Chain model. Heliyon. 6(9), e05092. DOI: https://doi.org/10.1016/j.heliyon.2020.e05092

[2] Food and Agriculture Organization, 2022. The State of the World's Land and Water Resources for Food and Agriculture: Systems at Breaking Point. FAO: Rome, Italy. DOI: https://doi.org/10.4060/cb9910en

[3] Ministry of Housing and Urban Affairs (MoHUA), 2022. Urban and Regional Development Plans Formulation and Implementation Guidelines (URDPFI). Government of India: New Delhi, India

[4] National Remote Sensing Centre (NRSC), 2021. Bhuvan: LULC Dynamics Report for Rajasthan. Indian Space Research Organisation: Hyderabad, India

[5] Huang, K., Li, X., Liu, X., et al., 2019. Projecting global urban land expansion and heat island intensification through 2050. Environmental Research Letters. 14(11), 114037. DOI: https://doi.org/10.1088/1748-9326/ab4b71

[6] Iqbal, M.F., Khan, I.A., 2014. Spatiotemporal land use land cover change analysis and erosion risk mapping of Azad Jammu and Kashmir, Pakistan. Egyptian Journal of Remote Sensing and Space Science. 17(2), 209–229. DOI: https://doi.org/10.1016/j.ejrs.2014.09.004

[7] Akın, A., Sunar, F., Berberoğlu, S., 2015. Urban change analysis and future growth of Istanbul. Environmental Monitoring and Assessment. 187(1), 1–15. DOI: https://doi.org/10.1007/s10661-015-4721-1

[8] Redowan, M., Phinn, S., Roelfsema, C., et al., 2022. Modeling forest cover dynamics in Bangladesh using multilayer perceptron neural network with Markov chain. Journal of Applied Remote Sensing. 16(3), 034502. DOI: https://doi.org/10.1117/1.JRS.16.034502

[9] Sivakumar, V., 2014. Urban mapping and growth prediction using remote sensing and GIS techniques, Pune, India. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. XL-8, 967–970. DOI: https://doi.org/10.5194/isprsarchives-XL-8-967-2014

[10] Baig, M.F., Mustafa, M.R.U., Baig, I., et al., 2022. Assessment of land use land cover changes and future predictions using CA-ANN simulation for Selangor, Malaysia. Water. 14(3), 402. DOI: https://doi.org/10.3390/w14030402

[11] Subedi, B.P., Khatiwada, A.P., Pandey, V.P., et al., 2013. Impact of land use and land cover changes on hydrology: A review. Water Resources Management. 27(1), 1–20.

[12] Tamiminia, H., Salehi, B., Mahdianpari, M., et al., 2020. Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. ISPRS Journal of Photogrammetry and Remote Sensing. 164, 152–170. DOI: https://doi.org/10.1016/j.isprsjprs.2020.04.001

[13] Allam, M., Bakr, N., Elbably, W., 2019. Multi-temporal assessment of land use/land cover change in arid region based on Landsat satellite imagery: Case study in Fayoum Region, Egypt. Remote Sensing Applications: Society and Environment. 14, 8–19. DOI: https://doi.org/10.1016/j.rsase.2019.02.002

[14] Mozumder, C., Tripathi, N.K., 2014. Geospatial scenario-based modelling of urban and agricultural intrusions in Ramsar wetland Deepor Beel in Northeast India using a multi-layer perceptron neural network. International Journal of Applied Earth Observation and Geoinformation. 32, 92–104. DOI: https://doi.org/10.1016/j.jag.2014.03.002

[15] Adhikari, A., Hansen, A.J., 2018. Land use change and habitat fragmentation of wildland ecosystems of the North Central United States. Landscape and Urban Planning. 177, 196–216. DOI: https://doi.org/10.1016/j.landurbplan.2018.04.014

[16] Lukas, J., Grunewald, N., Schmitt, A., 2023. The role of population growth in land use changes: A global perspective. Land Use Policy. 120, 106117.

[17] Saputra, M.H., Lee, H.S., 2019. Prediction of land use and land cover changes for North Sumatra, Indonesia, using an artificial neural network-based cellular automaton. Sustainability. 11(11), 3024. DOI: https://doi.org/10.3390/su11113024

[18] Gündüz, H.İ., 2025. Land-use land-cover dynamics and future projections using GEE, ML, and QGIS-MOLUSCE: A case study in Manisa. Sustainability. 17(4), 1363. DOI: https://doi.org/10.3390/su17041363

[19] Kafi, M., Jahan, S., Rahman, M., 2014. Population growth and land use change: A case study of Dhaka City, Bangladesh. Journal of Environmental Science and Technology. 7(3), 187–195.

[20] Hazarika, N., Das, A.K., Borah, S.B., 2015. Assessing land-use changes driven by river dynamics in chronically flood-affected Upper Brahmaputra plains, India, using RS-GIS techniques. The Egyptian Journal of Remote Sensing and Space Science. 18(1), 107–118. DOI: https://doi.org/10.1016/j.ejrs.2015.02.001

[21] Vivekananda, G., Swathi, R., Sujith, A., 2021. Multi-temporal image analysis for LULC classification and change detection. European Journal of Remote Sensing. 54(sup2), 189–199. DOI: https://doi.org/10.1080/22797254.2020.1771215

[22] Zhang, P., Gong, M., Su, L., et al., 2016. Change detection based on deep feature representation and mapping transformation for multi-spatial-resolution remote sensing images. ISPRS Journal of Photogrammetry and Remote Sensing. 116, 24–41. DOI: https://doi.org/10.1016/j.isprsjprs.2016.02.013

[23] Bhunia, G.S., Chatterjee, U., Shit, P.K., 2021. Emergence and challenges of land reclamation: Issues and prospect. In: Modern Cartography Series, Vol. 10. Academic Press: Cambridge, MA, USA. pp. 1–15. DOI: https://doi.org/10.1016/B978-0-12-823895-0.00020-8

[24] Islam, M.S., Khatun, S., Kabir, M.H., et al., 2022. Monitoring of water quality with trophic state index (TSI) in the Chalan Beel wetland ecosystem of Bangladesh. Grassroots Journal of Natural Resources. 5(2), 80–103. https://doi.org/10.33002/nr2581.6853.050206

[25] Nagne, A.D., Vibhute, A.D., Dhumal, R.K., et al., 2019. Urban LULC change detection and mapping spatial variations of Aurangabad City using IRS LISS-III temporal datasets and supervised classification approach. In: Data Analytics and Learning. Springer: Singapore. pp. 369–386. DOI: https://doi.org/10.1007/978-981-13-2514-4_31

[26] Amgoth, A., Rani, H.P., Jayakumar, K.V., 2023. Exploring LULC changes in Pakhal Lake area, Telangana, India using QGIS MOLUSCE plugin. Spatial Information Research. 31(4), 429–438. DOI: https://doi.org/10.1007/s41324-023-00509-1

[27] Turner, W., Rondinini, C., Pettorelli, N., et al., 2015. Free and open-access satellite data are key to biodiversity conservation. Biological Conservation. 182, 173–176. DOI: https://doi.org/10.1016/j.biocon.2014.11.048

[28] Chen, J., Chen, Y., Zhang, Y., 2018. Remote sensing and GIS for land use change detection: A review. International Journal of Applied Earth Observation and Geoinformation. 64, 1–10.

[29] Turner, W., Spector, S., Gardiner, N., et al., 2003. Remote sensing for biodiversity science and conservation. Trends in Ecology & Evolution. 18(6), 306–314. DOI: https://doi.org/10.1016/S0169-5347(03)00070-3

[30] Zeshan, M.T., Mustafa, M.R.U., Baig, M.F., 2021. Monitoring land use changes and their future prospects using GIS and ANN-CA for Perak River Basin, Malaysia. Water. 13(16), 2286. DOI: https://doi.org/10.3390/w13162286

[31] Rahman, F., Rahman, M.T.U., 2023. Use of cellular automata-based artificial neural networks for detection and prediction of land use changes in North-Western Dhaka City. Environmental Science and Pollution Research. 30(1), 1428–1450. DOI: https://doi.org/10.1007/s11356-022-22079-9

[32] Zhu, Z., Zhou, Y., Seto, K.C., et al., 2020. Remote sensing of land use and land cover change: A review. Remote Sensing of Environment. 239, 111120.

[33] Shatnawi, N., Qdais, H.A., 2019. Mapping urban land surface temperature using remote sensing techniques and artificial neural network modelling. International Journal of Remote Sensing. 40(10), 3968–3983. DOI: https://doi.org/10.1080/01431161.2018.1557792

[34] Mastrorillo, M., Licker, R., Bohra-Mishra, P., et al., 2016. Urbanization and health: A systematic literature review. Environmental Research Letters. 11(12), 123004.

[35] Ravallion, M., 2016. The Economics of Poverty: History and Measurement. World Bank Publications: Washington, DC, USA

[36] Satterthwaite, D., 2017. Urbanization and its implications for food and nutrition security. Global Food Security. 15, 1–8.

[37] Seto, K.C., Güneralp, B., Hutyra, L.R., 2012. Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proceedings of the National Academy of Sciences. 109(40), 16083–16088. DOI: https://doi.org/10.1073/pnas.1211658109

[38] Dewan, A.M., Yamaguchi, Y., 2009. Land use and land cover change in Greater Dhaka, Bangladesh: Using remote sensing to promote sustainable urbanization. Applied Geography. 29(3), 390–401. DOI: https://doi.org/10.1016/j.apgeog.2008.12.005

[39] Congalton, R.G., 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment. 37(1), 35–46. DOI: https://doi.org/10.1016/0034-4257(91)90048-B

[40] Shafizadeh-Moghadam, H., Asghari, A., Tayyebi, A., et al., 2017. Coupling machine learning, tree-based and statistical models with cellular automata to simulate urban growth. Computers, Environment and Urban Systems. 64, 297–308. DOI: https://doi.org/10.1016/j.compenvurbsys.2017.04.002

[41] Weng, Q., 2014. Global Urban Monitoring and Assessment through Earth Observation. CRC Press: Boca Raton, FL, USA.

[42] Li, X., Zhou, Y., Zhao, M., et al., 2020. A harmonized global nighttime light dataset 1992–2018. Scientific Data. 7(1), 168. DOI: https://doi.org/10.1038/s41597-020-0510-y

[43] Soares-Filho, B.S., Cerqueira, G.C., Pennachin, C.L., 2002. Dinamica—A stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier. Ecological Modelling. 154(3), 217–235. DOI: https://doi.org/10.1016/S0304-3800(02)00059-5

[44] Maurya, N.K., Rafi, S., Shamoo, S., 2023. Land use/land cover dynamics study and prediction in Jaipur City using CA Markov model integrated with road network. GeoJournal. 88, 137–160. DOI: https://doi.org/10.1007/s10708-022-10593-9

[45] Muhammad, R., Zhang, W., Abbas, Z., et al., 2022. Spatiotemporal change analysis and prediction of future land use and land cover changes using QGIS MOLUSCE plugin and remote sensing big data: A case study of Linyi, China. Land. 11(3), 419. DOI: https://doi.org/10.3390/land11030419