Review Article

A Review on Future Land Use/ Land Cover (LULC) Prediction Techniques: Global Methodological Shifts and Publication Trends

ABSTRACT

Future Land Use/Land Cover (LULC) prediction is essential for sustainable urban planning, environmental management, and climate resilience. This review aims to systematically examine global methodological shifts, model performance, software ecosystems, and publication trends in future LULC prediction research from 2015 to 2025. Specifically, it seeks to identify the methodologies used for LULC modeling, evaluate their strengths and weaknesses, determine the predominantly used classifiers, assess available software and data portals, and analyze the temporal, geographic, and publisher-wise distribution of related studies.

The review synthesizes traditional approaches such as Cellular Automata–Markov (CA–MC), Logistic Regression, and Agent-Based Models alongside machine learning techniques including Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN), as well as deep learning architectures such as CNN and LSTM. A comparative assessment highlights trade-offs in accuracy, interpretability, computational demand, and spatial–temporal modeling capability. Bibliometric analysis indicates a rapid increase in publications after 2020, reflecting the growing integration of hybrid and data-driven frameworks supported by cloud-based geospatial platforms and open satellite datasets.

The study provides consolidated understandings into evolving research directions and supports informed model selection for future LULC change prediction.

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Keywords: LULC Change prediction, Maximum Likelihood Classification, Markov Chain, Urbanization, Global Trends.

1. INTRODUCTION

Urbanization is reshaping the world, more than 80% of people now live in urban areas, with Asia leading the rise of megacities (FP News Desk, 2025). As of 2025, the world's population is about 8.2 billion, and 81% live in urban areas. This is a dramatic increase from just 20% in 1950 (Department of Economic and Social Affairs, 2025). Global land-use/cover change modeling has not advanced as rapidly in recent years.

1.1 SOCIOECONOMIC DRIVERS OF LULC CHANGE

Land use and land cover (LULC) transformations are fundamentally shaped by demographic and economic forces. Under conditions of increasing population density, there are significant changes in land-use patterns, as evidenced by a large number of studies on landscape dynamics (Sintayehu et al., 2017). Socioeconomic development processes, including population increase, GDP growth, and rural-urban migration, are the main driving forces behind these changes, with urbanization being a major catalyst for the migration of populations to district capitals in search of better educational, job, and business opportunities (Abbas et al., 2021; Singh et al., 2015). The development of tourism activities, employment diversification, and irrigated agriculture have increased household incomes and encouraged more sedentary behavior, thus contributing to changes in land systems (Halmy et al., 2015).

Urban expansion often continues even when population growth rates slow down, indicating that economic transformation and infrastructure development are becoming more important than demographic factors in land transformation (Singh et al., 2015).

1.2 URBAN EXPANSION AND AGRICULTURAL TRANSFORMATION

Urbanization occurs primarily at the expense of agricultural and desert lands (Somvanshi et al., 2020); (Abdelkarim, 2025). The loss of agricultural land is increasingly driven by the expansion of infrastructure, industrial development, and real estate (Somvanshi et al., 2020), as rapid urbanization continues to reshape long-established land use patterns (Uddin et al., 2023). At the same time, efforts to meet growing food demands have led to the expansion of cropland into deserts and forests, often supported by the development of irrigation systems ((Abdelkarim, 2025); Gupta et al., 2020; (W. Wang et al., 2016). While the cultivation of high-value commercial crops such as oil palm has brought economic benefits, it has also contributed to deforestation and heightened ecological vulnerability (Mahamud et al., 2019). Likewise, the growth of shrimp farming has offered new livelihood opportunities, yet it has also resulted in saltwater intrusion, land degradation, and the displacement of local communities (Rahman et al., 2017).

1.3 SPATIAL DETERMINANTS OF URBAN AND FOREST CHANGE

Urban expansion tends to follow natural and built corridors, spreading along rivers, major roads, and railway lines (Han et al., 2015); (Kumar et al., 2016). The physical landscape plays a key role in shaping this growth—flat, low-lying areas are generally easier and more cost-effective to develop (Muhammad et al., 2022), while steeper slopes tend to discourage construction. However, once lowland areas become saturated, development may begin to push into mountainous zones, raising concerns about ecological vulnerability (Han et al., 2015). In many regions, urban growth has become a major driver of forest loss, particularly in areas bordering agricultural land or existing settlements, with deforestation most pronounced in accessible low-elevation zones (W. Wang et al., 2016).

In northeastern India, for instance, forest degradation is linked to a combination of factors: encroachment, shifting (jhum) cultivation (Anand & Oinam, 2020), bamboo extraction, illegal logging, mining, and the spread of agriculture (REDDY et al., 2017).

These pressures are intensified by the needs of local communities and the growth of human settlements (Osman Maysoon A. A. AND Abdel-Rahman, 2023). The expansion of oil palm plantations has also contributed significantly to forest clearance in some areas (Mahamud et al., 2019). More broadly, the long-term health and extent of forests are being shaped by the intertwined forces of economic development and rising global temperatures (Zhang et al., 2023).

1.4 ENVIRONMENTAL AND ECOLOGICAL CONSEQUENCES

The environmental consequences of these transformations are far-reaching. Deforestation often triggers a cascade of environmental consequences, including soil degradation, increased landslide risk, and biodiversity loss (Jalayer et al., 2022). Forests play a critical role in stabilizing

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slopes, whereas the loss of grasslands can heighten susceptibility to landslides (Shu et al., 2019). As natural habitats continue to shrink, human–wildlife conflicts become more frequent, placing additional pressure on already vulnerable species (Gupta & Sharma, 2020); (Halmy et al., 2015). Hydrological systems are also increasingly strained—water bodies are diminishing due to siltation and encroachment (Mishra et al., 2018), while coastal areas face cropland loss from saline flooding and water quality degradation from aquaculture, contributing to growing water scarcity and more frequent urban flooding ((Rahman et al., 2017); (S. W. Wang et al., 2021).

1.5 URBAN CLIMATE EFFECTS AND FUTURE RISKS

Urbanization further alters local climate systems. The built-up areas also function as heat reservoirs, increasing the land surface temperature and increasing the Urban Heat Island (UHI) effect (Ahmad et al., 2025). The increase in land surface temperature is directly related to land use and land cover (LULC) change and is related to groundwater depletion and the density of built-up areas, suggesting cumulative effects on thermal and hydrological systems. The continued expansion of impervious surfaces is also expected to worsen UHI strength, water scarcity, and greenhouse gas emissions (J. Wang & Maduako, 2018). Future projections also indicate increased risks. Climate change can cause more focused precipitation events, flash floods, and soil erosion (Vijayaraghavalu et al., 2025). In some areas, post-seismic reconstruction has also encouraged urban expansion towards geological fracture zones, thus furthering vulnerability to hazards (Nath et al., 2020). The increase in the area covered by sandy regions and river channels may also indicate ongoing river migration processes (Kumar et al., 2016). In view of these cumulative factors, immediate remedial actions are necessary in land and water resource management to maintain ecological harmony (Leta et al., 2021). In addition, rainwater harvesting and wetland restoration are increasingly necessary to address water scarcity (Tahir et al., 2025).

The present review is conducted to answer the following research questions:

1. What methodologies have researchers used to model LULC and predict LULC changes?
2. What are the strength and weakness of various LULC models?
3. Which model/ classifier is predominantly used in LULC Classification and LULC change prediction?
4. What software packages and data portals are available for performing LULC modeling and analysis?
5. How did research on future LULC change prediction using different approaches evolved over time (2015–2025)?
6. How are LULC change prediction studies geographically distributed across regions?
7. How is LULC change prediction research distributed across major publishers?

2. METHODOLOGY

For this review, explorations were conducted across a group of scholarly repositories frequently used in scientific investigation. Databases such as Google Scholar, Scopus, Web of Science and IEEE Xplore were utilized to perform the search. The following keywords: "future LULC change OR LULC change prediction" along with advanced phrase searching keywords: "Traditional OR Hybrid OR Integrated OR Machine OR Deep OR learning" were used to identify a

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set of related research work. The search was conducted for the publications dating from year 2015 to 2025 and a total of 838 studies were identified. After removing duplicate entries, unrelated work was screened out by reviewing titles and abstracts. Final screening is done by reviewing full text articles against pre-defined inclusion criteria. Lastly, 50 studies were identified that fulfilled every criteria were selected and kept for the further data analysis.

Figure 1 illustrates the workflow adopted by researchers in Satellite Image Classification for change detection and future LULC change prediction.

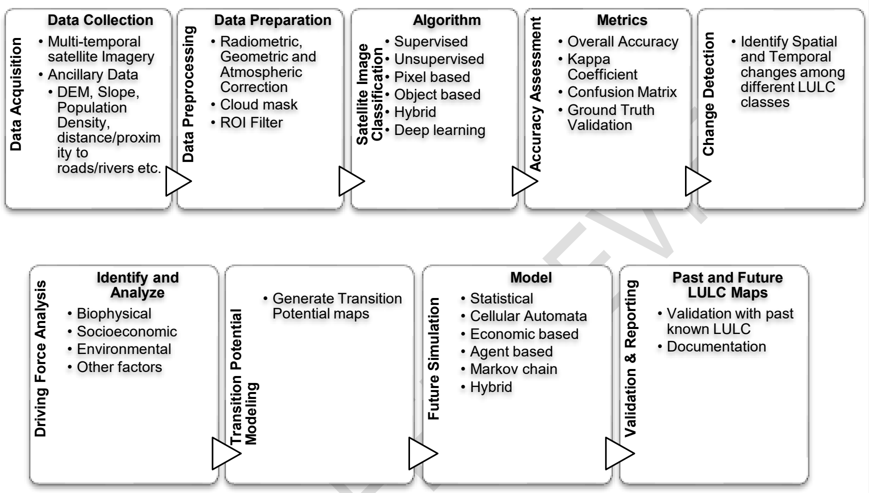

Fig. 1. General workflow in Satellite Image Classification for Change detection & future LULC prediction.

3. RESULTS & DISCUSSION

The choice of a Land Use/Land Cover (LULC) model is primarily determined by the precise objectives of the study, as no single model is capable of satisfying all possible requirements. In practice, model selection is also influenced by factors such as data availability, the underlying modeling framework, and the temporal or spatial scale at which the analysis is conducted (Gaur & Singh, 2023).

Table 1 shows the usage popularity of various classifiers used in the LULC change classification from 2015-2025.

A significant portion, nearly half of the studies, continue to rely on traditional techniques, with supervised and unsupervised methods—particularly Maximum Likelihood Classification—remaining prevalent. In contrast, approximately one-quarter of the studies have adopted machine learning–based classifiers, notably Random Forest (RF) and Support Vector Machine (SVM). Among these, RF is frequently favoured for initial classification tasks due to its robustness to noise and its effectiveness in handling high-dimensional datasets (Niroomand & Pahlavani, 2024). This growing adoption of machine learning reflects a broader disciplinary shift toward flexible, data-driven approaches that often achieve higher accuracy than conventional methods.

This trend toward methodological innovation is further evidenced by the emergence of hybrid strategies, employed in nearly 10% of the studies. These approaches, which might combine algorithms like Decision Forest with image segmentation, are designed to leverage the strengths of multiple classifiers and enhance overall reliability (Jalayer et al., 2022). Alongside these advanced techniques, around 14% of the studies employed alternative methods, including index-based approaches such as NDVI, visual or manual interpretation, and the use of pre-existing LULC datasets. Notably, research has shown that NDVI-based classification can achieve accuracy levels comparable to more complex models like KNN, SVM, and RF (Akbar et al., 2019). This finding underscores that while the field is advancing toward sophisticated machine learning applications, simpler, well-established techniques remain highly effective and contextually valuable (Akbar et al., 2019).

Table 1: Usage Statistics for LULC classification models (2015-2025)

Model (Example)	**Percentage (approx.)**	**Findings and Observations**
Traditional Classifiers (Supervised, Unsupervised, MLC, MDC etc.)	49%	MLC is the predominant method.
Machine Learning Classifiers (RF, SVM, etc.)	24%	RF and SVM are the major ML classifiers.
Hybrid Classifiers (Combinations like RF + DTC, SVM + MLE, Segmentation-based, etc.)	10%	Hybrid classification is emerging.
Others (LULC ready datasets , NDVI/index-based, Visual/manual)	14%	Use of ready-made LULC datasets.

Table 2 shows the usage popularity of different models used in the future LULC change prediction from 2015-2025.

Prediction accuracy tends to improve when the time interval between input datasets is shorter, as this allows models to capture changes more precisely (Lu et al., 2019). A majority of the studies—about 64%—relied on statistical approaches, particularly Markov Chain (MC) models, which form the backbone of many LULC prediction frameworks.

Cellular Automata (CA) and their variants were the second most widely used methods, largely due to their strength in simulating spatial patterns and neighborhood interactions. Artificial Neural Networks (ANN) and Multi-Layer Perceptron (MLP) models were applied in nearly half of the studies, reflecting their growing importance in capturing complex, nonlinear relationships. In particular, ANN has shown strong performance in forecasting short-term urban expansion (Somvanshi et al., 2020).

Around 16% of the studies employed hybrid models that combine multiple techniques, such as CA–MC, MLP–MC, and CA–ANN. These integrated approaches aim to leverage the complementary strengths of different methods—balancing the temporal prediction capability of MC, the spatial realism of CA, and the adaptive learning capacity of ANN/MLP—to produce more reliable and robust LULC forecasts.

CA–Markov model is found well suited for urban landscapes with mixed classes (Mondal et al., 2016) but it performed poorly for waste land & water bodies in long-term simulation (Singh et al., 2015). Its limitation is that it does not incorporate socioeconomic or policy drivers (Lu et al., 2019). The MLP–MC hybrid model is found reliable for modeling complex urban systems (J. Wang & Maduako, 2018). The MLP–MC model proved highly effective (Gupta & Sharma, 2020) and achieved extremely high accuracy with metrics such as Kno, Klocation, & Kstandard (W. Wang et al., 2016). The MLP–Markov model performed best with outstanding AUC (Gaur et al., 2020) and outperformed other models (Mishra et al., 2018). Ensemble Deep learning (CNN+DNN) outperformed traditional ML methods (Habeeb & Mustafa, 2025). Deep learning models (used in 4% of studies) such as CNNs, DNNs, and TCNs are still rare but expected to grow swiftly.

Table 2. Usage Statistics of LULC Prediction models (2015-2025)

Model (Example)	Percentage (%)	Findings and Observations
Statistical Models (Markov Chains (MC), Logistic regression (LR), etc.)	64%	MC is the backbone of LULC prediction.
Cellular Models (Cellular-Automata (CA), PLUS, CLUE-S, SLEUTH, etc.)	56%	CA is the second most dominant approach. Strong in spatial modeling.
Neural Networks (ANN, MLP NN)	46%	ANN/ MLP NN are used in Nearly half of all studies. Show a major rise.
Hybrid Models (CA-MC, ST- MC, MLP-MC, CA-ANN, MLP+ CA + MC, etc.)	16%	Clearly emerging and increasing trend.
Deep Learning Models (CNN, DNN, TCN)	4%	New and expected to grow fast.

Most LULC modeling frameworks overlook the fact that explanatory variables can change over time. Instead, they typically assume these variables remain constant during model validation and future prediction. This reliance on stationary inputs often leads to uncertain or less reliable modeling results (Gaur & Singh, 2023).

(Chisanga et al., 2024) shows how freely available tools and datasets can be harnessed to deliver essential insights into land use and land cover across broad regions. Table 3 summarizes different modeling software and data portals used in recent studies. ArcGIS (ArcMap/Pro), ENVI / ENVI Classic, ERDAS Imagine were identified as the mainstream GIS & remote sensing tools. USGS EarthExplorer / GLOVIS, GCAM, RESDC (CAS), Global GIS Layers (SEDAC, DIVA-GIS, GADM, and OSM) and WorldClim were common as global & reference data portals. Google Earth Engine (GEE) and Google Earth / Pro were used in many studies as a visualization & validation tool. TerrSet / IDRISI, QGIS with MOLUSCE Plugin were most common used modeling & simulation platforms.

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Table 3. Commonly used Modeling Software and Data Portals.

Software / Portal	Observed Usability
ArcGIS (ArcMap / ArcGIS Pro)	Preprocessing (mosaicking, clipping, projection) DEM processing

	Euclidean distance Supervised classification Accuracy assessment Spatial analysis Cartography
ENVI / ENVI Classic	Radiometric calibration Atmospheric correction (FLAASH) Mosaicking Pan-sharpening Supervised classification Segmentation-based workflows Accuracy assessment
ERDAS Imagine	Supervised classification (Maximum Likelihood) Preprocessing Band stacking Map preparation
GCAM	Global land demand modelling SSP–RCP projections Downscaling socio-economic drivers
Global GIS Layers (SEDAC, DIVA-GIS, GADM, OSM)	Rivers and Road networks Admin boundaries Population layers for modelling drivers
Google Earth / Google Earth Pro	Reference data collection Training sample digitization Visual interpretation Classification validation and Ground-truth verification
Google Earth Engine (GEE)	Retrieval of Landsat & MODIS datasets Cloud masking Atmospheric/topographic correction Mosaicking/Compositing Preprocessing RF/DT classification Multi-temporal LULC mapping Accuracy assessment
PLUS Model (LEAS + CARS)	Patch-based CA simulation; Suitability mapping via RF; SSP–RCP future scenario modelling
QGIS + MOLUSCE Plugin	Transition potential modelling (ANN-MLP) CA–ANN simulation LULC change detection Distance rasters Correlation and Validation (kappa metrics)
RESDC (CAS)	Downloading LULC datasets, Population, GDP, hydrology datasets
TerrSet / IDRISI	CA–Markov modelling LCM transition potential mapping MCE; AHP weighting Suitability mapping Future LULC prediction Validation using multiple kappa variants

USGS EarthExplorer / GLOVIS	Downloading Landsat (TM, ETM+, OLI, Landsat-9), MODIS, and SRTM DEM datasets
WorldClim (SRTM DEM)	Elevation, slope, aspect generation Topographic driver extraction

3.1 TREND ANALYSIS & ASSESSMENT

Figure 2 shows a strong upward trend in studies on LULC change prediction using traditional, hybrid and machine learning approaches (2015–2025), especially after 2020. However, a slight decline after 2023 is also observed. Figure 3 shows a steady rise in research on the impact of urbanization on LULC changes from 2015 to 2023, peaking in 2023 and shows decline after 2024.

Fig. 2. Publication Trends in LULC Change Prediction Using Traditional, Hybrid and Machine Learning Approaches (2015–2025)

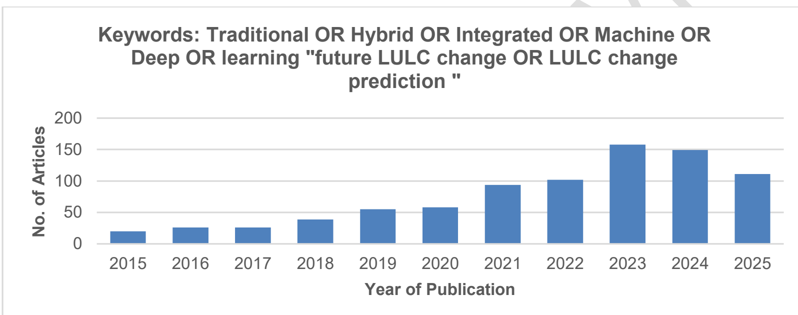


Fig. 3. Publication Trends in Research on the Impact of Urbanization on LULC changes (2015–2025)

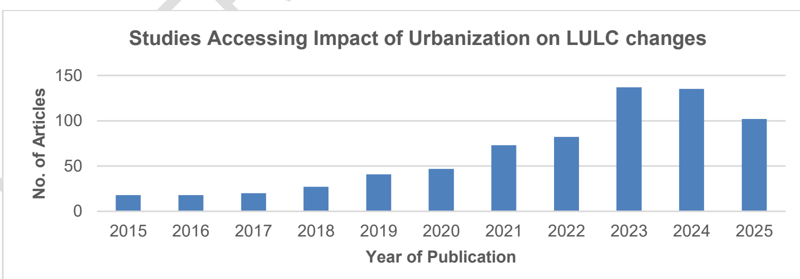


Figure 4 illustrates that MDPI with 26% shares of studies is growing fast due to open-access model and rapid review cycles. It offers journals with broad thematic coverage that attracts interdisciplinary submissions. Sustainability leads in frequency which often hosts LULC and modeling special issues. Elsevier & Springer with 22% shares each maintain strong reputations for rigorous peer review and broad journal portfolios. Taylor & Francis with

Specialized niche in remote sensing, share smaller (8%) but holds strong legacy in geospatial publishing.

Fig. 4. Distribution of selected studies on LULC change prediction by Publisher

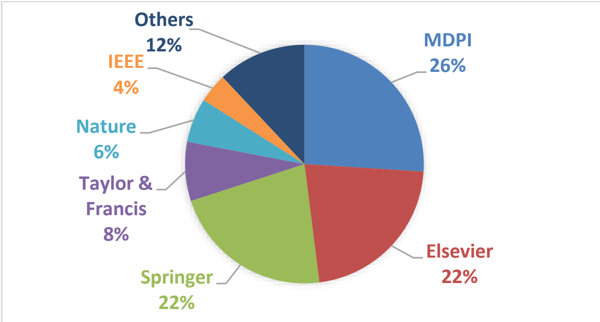
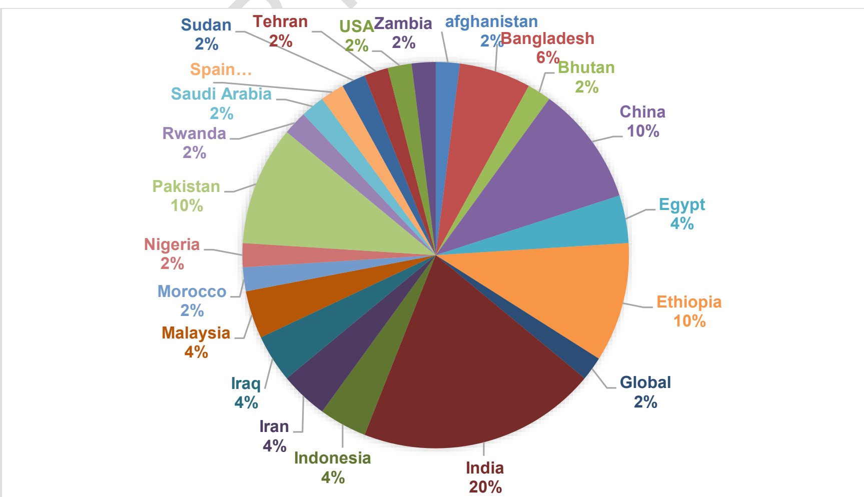


Figure 5 clarifies the geographical distribution showing a strong concentration of LULC change prediction studies in India (20%), followed by China, Ethiopia, and Pakistan (10% each), highlighting a research focus on rapidly transforming developing regions. Most study areas lie in Asia and Africa, reflecting higher policy urgency around land degradation, food security and urban growth in these regions. Europe and North America contribute minimally, pointing to either mature land-management systems or less emphasis on predictive LULC modeling in those regions. Only a small fraction (~2%) of studies adopt a global perspective, suggesting that cross-regional generalization of models remains underexplored.

Fig. 5. Distribution of selected studies on LULC change prediction by Study area



4. CONCLUSION

This review systematically examined global research on future Land Use/Land Cover (LULC) prediction between 2015 and 2025, focusing on methodological evolution, model performance, software ecosystems, and publication trends. The findings reveal that traditional statistical approaches, particularly Markov Chain (MC), remain the backbone of LULC prediction, while Cellular Automata (CA) continues to dominate spatial simulation. However, there is a clear methodological transition toward machine learning and hybrid frameworks, especially CA–MC and MLP–MC models, which balance temporal transition probability with spatial realism and learning capability. Random Forest and Support Vector Machines are the most frequently adopted machine learning classifiers for LULC classification, reflecting a shift toward data-driven techniques.

Although deep learning approaches such as CNN and DNN are currently limited in use, they demonstrate strong potential for improved predictive accuracy. The study also highlights the widespread use of GIS platforms (ArcGIS, ENVI, TerrSet) and cloud-based tools such as Google Earth Engine for scalable modeling. Publication trends show rapid growth after 2020, with strong research concentration in developing regions such as India, China, and parts of Africa. Overall, hybrid and AI-driven approaches represent the future direction of LULC change prediction, though challenges related to dynamic drivers and uncertainty remain.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

Abbas, Z., Yang, G., Zhong, Y., & Zhao, Y. (2021). Spatiotemporal Change Analysis and Future Scenario of LULC Using the CA-ANN Approach: A Case Study of the Greater Bay Area, China. *Land*, *10*(6). https://doi.org/10.3390/land10060584

Abdelkarim, A. (2025). Monitoring and forecasting of land use/land cover (LULC) in Al-Hassa Oasis, Saudi Arabia based on the integration of the Cellular Automata (CA) and the Cellular Automata-Markov Model (CA-Markov). *Geology, Ecology, and Landscapes*, *9*(1), 13–44. https://doi.org/10.1080/24749508.2022.2163741

Ahmad, S., Farooq, R., Waseem, M., & Kohnová, S. (2025). How do land use changes affect temperature and groundwater in urban areas? An integrated remote sensing, and machine learning approach. *Advances in Space Research*, *76*(8), 3963–3987. https://doi.org/https://doi.org/10.1016/j.asr.2025.08.021

Akbar, T. A., Hassan, Q. K., Ishaq, S., Batool, M., Butt, H. J., & Jabbar, H. (2019). Investigative Spatial Distribution and Modelling of Existing and Future Urban Land Changes and Its Impact on Urbanization and Economy. *Remote Sensing*, *11*(2). https://doi.org/10.3390/rs11020105

Anand, V., & Oinam, B. (2020). Future land use land cover prediction with special emphasis on urbanization and wetlands. *Remote Sensing Letters*, *11*, 225–234.

https://doi.org/10.1080/2150704X.2019.1704304
Chisanga, C. B., Phiri, D., & Mubanga, K. H. (2024). Multi-decade land cover/land use dynamics and future predictions for Zambia: 2000–2030. *Discover Environment*, *2*(1), 38. https://doi.org/10.1007/s44274-024-00066-w
Department of Economic and Social Affairs. (2025, November 18). *Latest urbanization data reveal world's most populous cities*. UN DESA. https://www.un.org/en/desa/latest-urbanization-data-reveal-world%E2%80%99s-most-populous-cities
FP News Desk. (2025, November 25). *World is now over 80% urban: UN report redefines global population distribution*. https://www.firstpost.com/world/world-is-now-over-80-percent-urban-un-report-redefines-global-population-distribution-13953823.html
Gaur, S., Mittal, A., Bandyopadhyay, A., Holman, I., & Singh, R. (2020). Spatio-temporal analysis of land use and land cover change: a systematic model inter-comparison driven by integrated modelling techniques. *International Journal of Remote Sensing*, *41*(23), 9229–9255. https://doi.org/10.1080/01431161.2020.1815890
Gaur, S., & Singh, R. (2023). A Comprehensive Review on Land Use/Land Cover (LULC) Change Modeling for Urban Development: Current Status and Future Prospects. *Sustainability*, *15*(2). https://doi.org/10.3390/su15020903
Gupta, R., & Sharma, L. K. (2020). Efficacy of Spatial Land Change Modeler as a forecasting indicator for anthropogenic change dynamics over five decades: A case study of Shoolpaneshwar Wildlife Sanctuary, Gujarat, India. *Ecological Indicators*, *112*, 106171. https://doi.org/https://doi.org/10.1016/j.ecolind.2020.106171
Habeeb, H. N., & Mustafa, Y. T. (2025). Deep learning-based prediction of forest cover change in Duhok, Iraq: Past and future. *Forestist*, *75*(1), 1.
Halmy, M. W. A., Gessler, P. E., Hicke, J. A., & Salem, B. B. (2015). Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. *Applied Geography*, *63*, 101–112. https://doi.org/https://doi.org/10.1016/j.apgeog.2015.06.015
Han, H., Yang, C., & Song, J. (2015). Scenario Simulation and the Prediction of Land Use and Land Cover Change in Beijing, China. *Sustainability*, *7*(4), 4260–4279. https://doi.org/10.3390/su7044260
Jalayer, S., Sharifi, A., Abbasi-Moghadam, D., Tariq, A., & Qin, S. (2022). Modeling and Predicting Land Use Land Cover Spatiotemporal Changes: A Case Study in Chalus Watershed, Iran. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *15*, 5496–5513. https://doi.org/10.1109/JSTARS.2022.3189528
Kumar, K. S., Kumari, K. P., & Bhaskar, P. U. (2016). Application of Markov chain & cellular automata based model for prediction of Urban transitions. *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)*, 4007–4012. https://doi.org/10.1109/ICEEOT.2016.7755466
Leta, M. K., Demissie, T. A., & Tränckner, J. (2021). Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Upper Blue Nile Basin, Ethiopia. *Sustainability*, *13*(7). https://doi.org/10.3390/su13073740
Lu, Y., Wu, P., Ma, X., & Li, X. (2019). Detection and prediction of land use/land cover change using spatiotemporal data fusion and the Cellular Automata–Markov model.

Environmental Monitoring and Assessment, *191*(2), 68. https://doi.org/10.1007/s10661-019-7200-2

Mahamud, M. A., Samat, N., Tan, M. L., Chan, N. W., & Tew, Y. L. (2019). PREDICTION OF FUTURE LAND USE LAND COVER CHANGES OF KELANTAN, MALAYSIA. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-4/W16*, 379–384. https://doi.org/10.5194/isprs-archives-XLII-4-W16-379-2019

Mishra, V. N., Rai, P. K., Prasad, R., Punia, M., & Nistor, M.-M. (2018). Prediction of spatio-temporal land use/land cover dynamics in rapidly developing Varanasi district of Uttar Pradesh, India, using geospatial approach: a comparison of hybrid models. *Applied Geomatics*, *10*(3), 257–276. https://doi.org/10.1007/s12518-018-0223-5

Mondal, Md. S., Sharma, N., Garg, P. K., & Kappas, M. (2016). Statistical independence test and validation of CA Markov land use land cover (LULC) prediction results. *The Egyptian Journal of Remote Sensing and Space Science*, *19*(2), 259–272. https://doi.org/https://doi.org/10.1016/j.ejrs.2016.08.001

Muhammad, R., Zhang, W., Abbas, Z., Guo, F., & Gwiazdzinski, L. (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). https://doi.org/10.3390/land11030419

Nath, B., Wang, Z., Ge, Y., Islam, K., P. Singh, R., & Niu, Z. (2020). Land Use and Land Cover Change Modeling and Future Potential Landscape Risk Assessment Using Markov-CA Model and Analytical Hierarchy Process. *ISPRS International Journal of Geo-Information*, *9*(2). https://doi.org/10.3390/ijgi9020134

Niroomand, M., & Pahlavani, P. (2024). Predictive Analytics for Urban Sprawl Using Machine Learning in Land Cover Mapping. *Earth Observation and Geomatics Engineering*, *8*(2). https://doi.org/10.22059/eoge.2025.393376.1173

Osman Maysoon A. A. AND Abdel-Rahman, E. M. A. N. D. O. J. O. A. N. D. O. L. A. A. N. D. E. M. M. A. N. D. A. M. A. N. D. T. H. E. Z. (2023). Mapping, intensities and future prediction of land use/land cover dynamics using google earth engine and CA- artificial neural network model. *PLOS ONE*, *18*(7), 1–28. https://doi.org/10.1371/journal.pone.0288694

Rahman, M. T. U., Tabassum, F., Rasheduzzaman, Md., Saba, H., Sarkar, L., Ferdous, J., Uddin, S. Z., & Zahedul Islam, A. Z. M. (2017). Temporal dynamics of land use/land cover change and its prediction using CA-ANN model for southwestern coastal Bangladesh. *Environmental Monitoring and Assessment*, *189*(11), 565. https://doi.org/10.1007/s10661-017-6272-0

REDDY, C. S., SINGH, S., DADHWAL, V. K., JHA, C. S., RAO, N. R., & DIWAKAR, P. G. (2017). Predictive modelling of the spatial pattern of past and future forest cover changes in India. *Journal of Earth System Science*, *126*(1), 8. https://doi.org/10.1007/s12040-016-0786-7

Shu, H., Hürlimann, M., Molowny-Horas, R., González, M., Pinyol, J., Abancó, C., & Ma, J. (2019). Relation between land cover and landslide susceptibility in Val d'Aran, Pyrenees (Spain): Historical aspects, present situation and forward prediction. *Science of The Total Environment*, *693*, 133557. https://doi.org/https://doi.org/10.1016/j.scitotenv.2019.07.363

Singh, S. K., Mustak, Sk., Srivastava, P. K., Szabó, S., & Islam, T. (2015). Predicting Spatial and Decadal LULC Changes Through Cellular Automata Markov Chain Models Using Earth Observation Datasets and Geo-information. *Environmental Processes*, *2*(1), 61–78. https://doi.org/10.1007/s40710-015-0062-x

Sintayehu, E. G., Dikinya, O., Sebego, R., Segosebe, E., & Abraha, A. (2017). Cellular automata and Markov Chain (CA_Markov) model-based predictions of future land use and land cover scenarios (2015–2033) in Raya, northern Ethiopia. *Modeling Earth Systems and Environment*, *3*. https://doi.org/10.1007/s40808-017-0397-6

Somvanshi, S. S., Bhalla, O., Kunwar, P., Singh, M., & Singh, P. (2020). Monitoring spatial LULC changes and its growth prediction based on statistical models and earth observation datasets of Gautam Budh Nagar, Uttar Pradesh, India. *Environment, Development and Sustainability*, *22*(2), 1073–1091. https://doi.org/10.1007/s10668-018-0234-8

Tahir, Z., Haseeb, M., Mahmood, S. A., Batool, S., Abdullah-Al-Wadud, M., Ullah, S., & Tariq, A. (2025). Predicting land use and land cover changes for sustainable land management using CA-Markov modelling and GIS techniques. *Scientific Reports*, *15*(1), 3271. https://doi.org/10.1038/s41598-025-87796-w

Uddin, M. S., Mahalder, B., & Mahalder, D. (2023). Assessment of Land Use Land Cover Changes and Future Predictions Using CA-ANN Simulation for Gazipur City Corporation, Bangladesh. *Sustainability*, *15*(16). https://doi.org/10.3390/su151612329

Vijayaraghavalu, S. S., Arumugam, K., & Dange, S. (2025). Spatio-temporal dynamics of urbanization and environmental sustainability: A predictive modelling approach to forecasting land use transitions in Vellore, India. *Results in Engineering*, *27*, 106572. https://doi.org/https://doi.org/10.1016/j.rineng.2025.106572

Wang, J., & Maduako, I. N. (2018). Spatio-temporal urban growth dynamics of Lagos Metropolitan Region of Nigeria based on Hybrid methods for LULC modeling and prediction. *European Journal of Remote Sensing*, *51*(1), 251–265. https://doi.org/10.1080/22797254.2017.1419831

Wang, S. W., Munkhnasan, L., & Lee, W.-K. (2021). Land use and land cover change detection and prediction in Bhutan's high altitude city of Thimphu, using cellular automata and Markov chain. *Environmental Challenges*, *2*, 100017. https://doi.org/https://doi.org/10.1016/j.envc.2020.100017

Wang, W., Zhang, C., Allen, J. M., Li, W., Boyer, M. A., Segerson, K., & Silander, J. A. (2016). Analysis and Prediction of Land Use Changes Related to Invasive Species and Major Driving Forces in the State of Connecticut. *Land*, *5*(3). https://doi.org/10.3390/land5030025

Zhang, T., Cheng, C., & Wu, X. (2023). Mapping the spatial heterogeneity of global land use and land cover from 2020 to 2100 at a 1 km resolution. *Scientific Data*, *10*(1), 748. https://doi.org/10.1038/s41597-023-02637-7