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Change Detection and Future Land Use Projections in Zhejiang Province, China: A Case Study

Mahdieh Shirmohammadi[1,2,3,4], Jie Shen[1,2,3,4], Saied Pirasteh[*5], Yang Li[1,2,3,4]
[1] Jiangsu Centre for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing 210023, China
[2] Key Laboratory of Virtual Geographic Environment (Nanjing Normal University), Ministry of Education, Nanjing, Jiangsu 210023, China
[3] School of Geography, Nanjing Normal University, Nanjing, Jiangsu 210023, China
[4] State laboratory of climate system prediction and risk management. Email: mshirmohammadi.khu@gmail.com, 31243005@njnu.edu.cn, shenjie@njnu.edu.cn, li.yang@njnu.edu.cn

[5]Institute of Artificial Intelligence, Shaoxing University, Shaoxing, 508 West Huancheng Road, Yuecheng District, Zhejiang Province, Postal Code 312000, China. Email: sapirasteh1@usx.edu.cn

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Abstract

Zhejiang Province is experiencing rapid land use/land cover (LULC) transitions driven by urban expansion, infrastructure development, and increasing environmental pressures. Understanding historical dynamics and future trajectories of these changes is essential for informed regional planning and ecological management. This study analyzes land use changes from 2000 to 2020 and forecasts future patterns for 2025 to 2040 by integrating multi-temporal land use data with key spatial drivers, including elevation, slope, aspect, Normalized Difference Vegetation Index (NDVI), and proximity to roads and built-up areas. Change detection results reveal substantial declines in croplands and green spaces alongside rapid urban expansion, particularly around Hangzhou and Shaoxing and along major transportation corridors, reflecting an early phase of accelerated urbanization from a relatively small baseline. Future land-use dynamics were simulated using a hybrid Convolutional Neural Network - Long Short Term Memory (CNN-LSTM)-Cellular Automata (CA)-Markov framework that captures complex spatiotemporal dependencies and neighbourhood interactions under physical and anthropogenic constraints. Model projections indicate a more moderate growth regime from 2025 to 2040, with urban land increasing by 1.7%, croplands decreasing by 2.2%, and modest gains in water bodies (1.9%) and forest cover (1.1%), suggesting landscape saturation and policy-influenced land management. Validation using the observed 2025 land use map demonstrates strong predictive performance, achieving an overall accuracy of 86% and a Kappa coefficient of 79%. The results provide spatially explicit insights to support balanced development and enhanced ecological resilience.

1. Introduction

Understanding and forecasting land use/land cover (LULC) dynamics is central to environmental research and spatial planning, as they critically influence ecosystem stability, hydrological processes, and sustainable development. In rapidly developing regions, land use change reshapes landscape connectivity, urban resilience, and environmental risk. Zhejiang Province in eastern China has experienced accelerated land transformation driven by urban expansion, infrastructure development, and socioeconomic growth (Tian et al., 2019; Wu et al., 2022; Koko et al., 2023).

Traditionally, LULC forecasting has been dominated by transition-based models, particularly Cellular Automata (CA)-Markov frameworks, which are effective for simulating broad spatiotemporal trends and neighborhood-driven land transitions (Rahnama, 2021). Despite their widespread adoption, these models assume stationary transition probabilities and simplified neighborhood structures, limiting their capacity to represent non-linear interactions among environmental, socioeconomic, and policy-driven drivers (Shirmohammadi et al., 2025). Such assumptions are increasingly inadequate for heterogeneous, rapidly evolving landscapes, where land use transitions are often abrupt, multi-directional, and influenced by dynamic regulatory and climatic conditions.

To overcome these limitations, several advanced modeling frameworks have been developed, including CLUMondo (Yang et al., 2022), multilayer perceptron-Markov, LandTrendr (Parracciani et al., 2024), and the Patch-generating Land Use Simulation (PLUS) model (Mutale et al., 2024). While these approaches have improved long-term change detection and spatial realism, they continue to rely heavily on predefined transition rules, fixed neighborhood configurations, or linear extrapolation of historical trends. As a result, their ability to capture fine-scale spatial heterogeneity and non-stationary transition behavior remains limited, particularly in regions experiencing strong policy interventions or rapid urban transformation. Traditional platforms such as TerrSet and CA-Markov further exemplify these constraints by oversimplifying spatial interactions and lacking adaptability to multi-decadal and policy-driven land dynamics (Madhusudhan et al., 2024). For instance, Aliyu et al. (2020) projected a 38% increase in built-up areas in Akure, Nigeria, using CA-Markov analysis; while informative, such projections are constrained by static transition matrices and fixed neighborhood assumptions.

Recent years have seen growing interest in integrating deep learning into LULC forecasting to represent complex spatial and temporal dependencies better. Hybrid frameworks such as Cellular Automata - Convolutional Neural Network - Long Short Term Memory (CA-CNN-LSTM) models have shown improved predictive performance by learning hierarchical spatial features and temporal patterns (Patel et al., 2022; Aryan et al., 2025). Nevertheless, many of these approaches continue to assume spatially stationary transition behavior or rely on fixed neighborhood rules embedded in CA components (Yang et al., 2025). For example, the Deep Spatiotemporal–Cellular Automata (DST)-CA model proposed by Yang et al. (2025) integrates a 3D Convolutional Neural Network (CNN) for short-term feature extraction with an Long Short-Term Memory (LSTM) for long-term temporal learning. Despite its enhanced accuracy, the fixed neighborhood structure within the CA module limits its ability to capture fine-scale spatial variability and dynamic transition processes in complex landscapes.

Moreover, hybrid models that combine CA with machine learning or artificial neural networks (ANNs) have improved spatial realism by incorporating neighborhood effects (Kamaraj et al., 2022; Mishra et al., 2025b). However, these approaches often struggle to represent non-linear temporal dependencies and rarely integrate multi-temporal environmental sequences alongside static and dynamic drivers. For instance, Madhusudhan et al. (2024) successfully forecasted LULC patterns for 2030 with low deviation using CA-Markov analysis but relied on static transition assumptions and excluded climate and socioeconomic variables, limiting its ability to capture emerging land-use pressures.

The emergence of advanced deep learning architectures, such as CNN-LSTM and ConvLSTM, offers new opportunities for modeling non-linear, multi-scale spatial patterns and long-term temporal dependencies (Boulila et al., 2021; Das et al., 2025). Although recent hybrid systems, including CNN-LSTM-PLUS frameworks, have demonstrated high spatial accuracy in regional case studies (Li et al., 2025), many remain constrained by short historical time series, single-region analyses, and limited integration of multi-sensor and multi-decadal datasets.

These limitations highlight the need for high-resolution, multi-period, and multi-parameter land- use forecasting frameworks to support scenario-based planning and sustainable land management better. To address these gaps, this study introduces a hybrid CNN-ConvLSTM–Markov CA framework implemented in Python for long-term land use forecasting. The proposed approach integrates (i) patch-based CNN encoders to capture fine-scale spatial heterogeneity, (ii) ConvLSTM modules to learn multi-decadal spatiotemporal dependencies, and (iii) a Markov CA module to constrain land transitions using empirically derived probabilities. By incorporating both static drivers (elevation, slope, aspect, distance to roads) and dynamic drivers (NDVI, built-up areas), the framework captures realistic, policy-influenced, and non-linear land use dynamics. Accordingly, the objectives of this study are to (a) develop an advanced deep spatiotemporal modeling framework that overcomes the limitations of stationary and fixed-rule approaches, and (b) generate scenario-based land use forecasts for 2025-2040 to support sustainable planning and flood risk management in heterogeneous landscapes.

2. Materials and Methods

2.1. Study Area

The study area is located in northern Zhejiang Province, eastern China, encompassing the cities of Hangzhou and Shaoxing, as well as parts of the Qiantang Jiang River. To capture key urban dynamic interactions, a rectangular spatial subset was extracted, bounded by latitudes 29°37′28.87″N to 30°51′10.28″N and longitudes 119°43′56.28″E to 120°54′25.37″E. This subset represents a highly heterogeneous landscape characterized by extensive croplands, rapidly expanding urban areas, dense river networks, and patches of mountainous forest, making it a representative sample of dominant land use patterns in northern Zhejiang Province. The coexistence of urban development and agricultural land makes the area particularly suitable for investigating land use dynamics and their environmental implications. The Qiantang Jiang River has historically served as a primary axis of urban development, and sustained urban expansion along its corridor in recent decades has intensified the conversion of croplands and peri-urban green spaces into built-up areas, making it a key hotspot of land use transformation within the region (Figure 1).

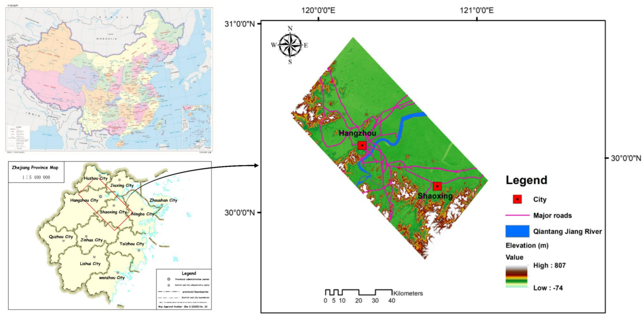

Figure 1. Study area

2.2. Data Collection and Preparation

Historical land use maps for Zhejiang Province from 2000 to 2020 were used as the primary datasets for model training, with 4 classes: cropland, forest, water, and urban, and a real land use map 2025 for validation (Yang et al., 2021). To enhance the performance of the hybrid land use forecasting framework, a set of environmental and anthropogenic driving factors was incorporated, following established practices in recent LULC modeling studies (Floreano et al., 2021; Kamaraj et al., 2022; Yang et al., 2022; Aldileemi et al., 2023; Mutale et al., 2024). Elevation data were obtained from the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM, 30 m) and processed in Google Earth Engine (GEE). Based on the DEM, slope and aspect layers were derived in ArcGIS to represent terrain-related constraints. Distance-to-road layers were also generated in ArcGIS to characterize accessibility and the influence of transportation infrastructure as a static driver of land use change. Dynamic variables were produced for each target year to capture temporal processes. These included the Normalized Difference Vegetation Index (NDVI), calculated in GEE using Landsat 7, Landsat 8, and Sentinel-2 imagery to represent vegetation dynamics, and distance to built-up areas, derived using Euclidean distance analysis in ArcGIS to reflect urban expansion. All maps and ancillary environmental layers were resampled and harmonized to a uniform 30 m spatial resolution to ensure consistency across model inputs and minimize scale-related uncertainty. Integrating these static and dynamic variables with historical landuse data improved the model’s ability to capture spatial heterogeneity and the temporal drivers of land use transitions across the study area (Figure 2).

2.3. Proposed Advanced Framework for Land Use Forecasting

This study proposes an advanced, multi-stage land use forecasting framework designed to capture the complex, non-linear, and spatially heterogeneous dynamics of land use. To address the limitations of traditional CA-Markov and fixed-neighbourhood deep learning approaches, the framework uses a hybrid CNN-ConvLSTM-Markov CA architecture. Training deep spatiotemporal models on full-resolution, multi-decadal raster datasets presents substantial computational challenges, particularly when incorporating multiple static and dynamic drivers. To overcome Graphics Processing Unit (GPU) memory constraints while preserving fine-scale spatial detail, a patch-based sampling strategy was employed. Unlike earlier studies that used patches solely for computational efficiency, this approach systematically partitions the full raster stack into information-rich samples that enhance spatial diversity and model generalization.

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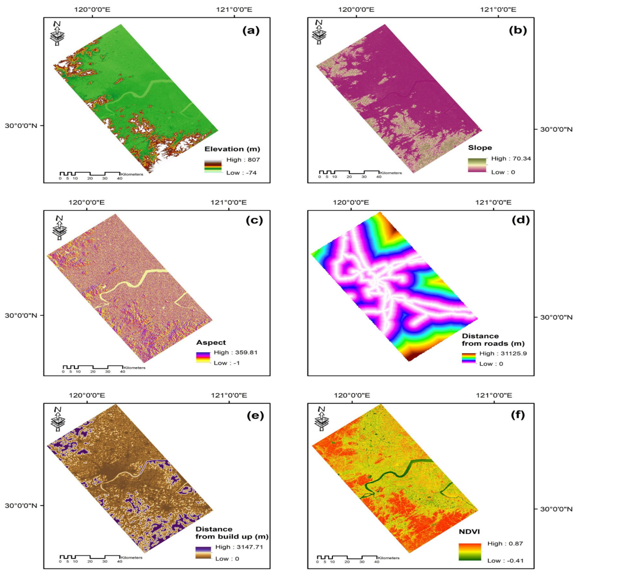

Figure 2. Ancillary Environmental Parameters (a) Elevation, (b) Slope, (c) Aspect, (d) Distance from roads, (e) Distance from build-up, (f) NDVI.

The complete 20-layer raster stack was tiled using a sliding-window approach with a patch size of 256 × 256 pixels and a stride of 128 pixels. From the generated patches, 2,000 spatially distributed samples were randomly selected for training. This strategy improved computational efficiency and allowed the model to better learn heterogeneous landscape patterns across the study area. Formally, the dynamic input tensor is defined as $D \in R^{T\times H\times W\times C}$, where T is the number of temporal layers, H and W are the spatial dimensions, and C denotes the dynamic features. Corresponding land use maps are represented as $L \in R^{T\times H\times W}$. After tiling, each patch produces spatiotemporal samples $X_p \in R^{T\times P\times P\times C}$ and $Y_p \in R^{T\times P\times P}$. Padding was applied where necessary to ensure full spatial coverage. To model temporal land use evolution, spatiotemporal sequences were constructed from the extracted patches. A temporal window of S = 3 years was selected, allowing the model to learn both short-term dynamics and longer-term dependencies. Each training sample consists of three consecutive multi-feature patches used to predict the land use state of the following year:

$$\widehat{X}^{(i)} = [X_p(t), X_p(t+1), X_p(t+2)],\ \widehat{Y}^{(i)} = Y_p(t+3) \quad (1)$$

The CNN extracts spatial features at each time step, while the ConvLSTM learns temporal dependencies across the sequence, improving the model’s ability to forecast abrupt or non-linear land use transitions.

The CNN–ConvLSTM architecture combines TimeDistributed CNN layers for spatial feature extraction with ConvLSTM layers for temporal modeling. At each time step t, the dynamic input patch X_t is processed by the CNN:

$$F_t = CNN(X_t) \quad (2)$$

The resulting feature maps $\{F_1, F_2, F_3\}$ are passed to the ConvLSTM:

$$H = ConvLSTM\ (F_1, F_2, F_3) \quad (3)$$

Transposed convolution layers restore the original spatial resolution, and pixel-wise class probabilities are computed using a softmax function. The model is trained using categorical cross-entropy loss, ensuring accurate multi-class land use prediction. A Markov transition matrix was derived from historical land use maps to quantify class-to-class transition probabilities between consecutive time steps:

$$M_{ij} = P\ (L_{t+1} = j \setminus L_t = i) \quad (4)$$

These probabilities were estimated across all pixels and time steps, normalized so that each row sums to one. The Markov matrix captures long-term transition tendencies and provides prior knowledge that complements deep learning predictions. The CNN–ConvLSTM suitability map S_{DL} was fused with the Markov transition probabilities using a linear mixture: $S_{hybrid} = \alpha M + (1 - \alpha)\ S_{DL}$. An optimal weight of α = 0.6 was selected based on experimental performance, balancing historical transition behavior 60% and data-driven suitability 40%. Final land use classes were assigned by selecting the class with the highest hybrid suitability, followed by a 3 × 3 majority filter to reduce salt-and-pepper noise while preserving spatial structure. To ensure realistic urban expansion, historical urban growth rates were incorporated. Target urban extents were calculated for each future time step, and if predicted urban areas fell below these targets, high-suitability cropland pixels were selectively converted to urban. This adjustment ensured consistency with observed growth trends while maintaining spatial plausibility. Overall, the proposed hybrid framework integrates deep spatiotemporal learning, historical transition modeling, and rule-based adjustments to produce spatially coherent and realistic future land use simulations suitable for land management and planning applications (Figure 3).

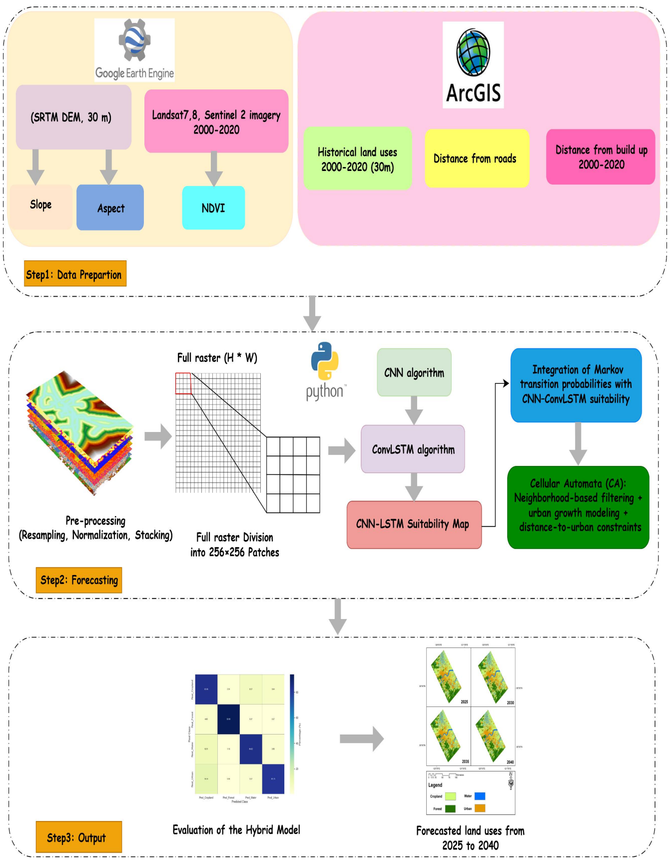

Figure 3. Workflow methodology

2.4. Accuracy assessment of the hybrid CNN-ConvLSTM-Markov Cellular Automata (hybrid CA) model

The performance of the 2025 land use forecast was evaluated by comparing the predicted land use map with the reference 2025 map (Yang et al., 2021). Both rasters were first aligned to a common spatial grid using nearest-neighbor resampling to ensure pixel-wise correspondence, and pixels with NoData values in either map were excluded from the analysis. Overall agreement between the predicted and reference maps was quantified using OA, while Cohen's Kappa coefficient (κ) was computed to account for agreement occurring by chance. A confusion matrix (C) was generated to evaluate class-specific performance. From this matrix, both producer's accuracy (PA, recall) and user's accuracy (UA, precision) were calculated for each land use class i as follows (Yomo et al., 2023):

$$\text{Producer's Accuracy (PA)}_i = \frac{C_{ii}}{\sum_j C_{ij}} \times 100$$
$$\text{User's Accuracy (UA)}_i = \frac{C_{ii}}{\sum_j C_{ji}} \times 100 \quad (5)$$

where C_{ij} represents the number of pixels of class i in the reference map that were classified as class j in the forecast. This systematic accuracy assessment provides quantitative metrics of model performance, providing robust validation of the hybrid CNN-ConvLSTM-Markov CA (hybrid) framework for accurately simulating future land use dynamics.

3. Results and Discussion

3.1. Spatiotemporal land use patterns 2000-2020

The historical land uses for 2000, 2005, 2010, 2015, and 2020, with 4 classes (cropland, forest, water, urban) (Figure 4), provide a clear, spatially coherent representation of landscape patterns across the study area. These maps reveal both persistent land characteristics and significant transitions occurring over the last two decades. Spatially, cropland remained dominant across the region, while dense forest cover continued to occupy the south, north and western highlands. The main water body was clearly detected along the Qiantang Jiang River. Urban areas expanded around city centers, particularly Hangzhou and Shaoxing, confirming the trajectory of continuous demographic and infrastructural growth.

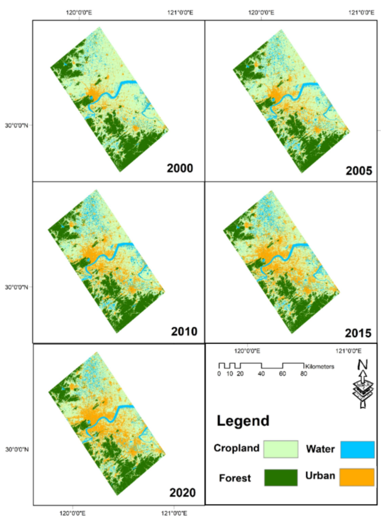

Figure 4. Classified land use maps for 2000-2020

Quantitatively, the percentage changes from 2000 to 2020 indicate pronounced land use transitions: cropland and forest areas experienced substantial declines of 23% and 12.3%, respectively, reflecting increasing pressure from human activities and land conversion processes. In contrast, water bodies expanded by 11.4%, likely associated with hydrological alterations, reservoir development, and flood-related landscape changes. Most notably, urban areas exhibited a 100% increase, underscoring the rapid pace of urbanization across the study region over the past two decades. This dramatic expansion highlights the dominant role of urban growth as a driving force of land use change, often occurring at the expense of agricultural and natural land covers, and signals intensifying anthropogenic influence on regional landscape structure and environmental sustainability (Figure 5).

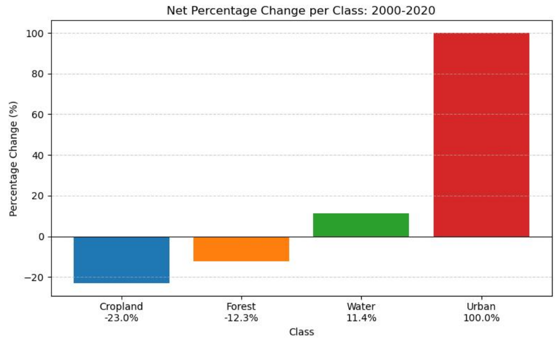

Figure 5. Percentage change of land use classes from 2000 to 2020

Figure 6 illustrates the directional pattern of urban expansion between 2000 and 2020 using a polar (rose) diagram. The results reveal a highly anisotropic urban growth pattern, with pronounced expansion toward the northeast (NE), west (W) and southwest (SW) directions, indicating these corridors as the dominant pathways of urban development over the study period. Moderate growth is also observed toward the west (W) and east (E) sectors, while comparatively limited expansion occurs toward the east (E), southeast (SE), and north (N). This directional asymmetry suggests that urban growth has been strongly guided by underlying geographic, infrastructural, and socioeconomic drivers, including major transportation axes, river corridors, and favorable terrain. The concentration of urban expansion along specific directions reflects constrained spatial development rather than uniform outward growth, highlighting the role of planned infrastructure and natural barriers in shaping long-term urbanization patterns.

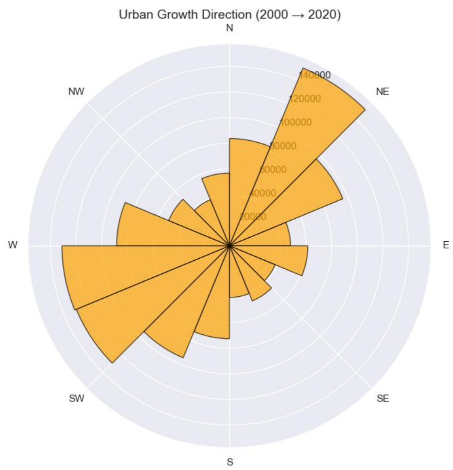

Figure 6. Urban growth direction from 2000 to 2020 derived from land use maps.

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3.2. Future land use dynamics 2025-2040

The projected land use changes for the period 2025–2040 reveal distinct but more moderate transformation trends compared with the historical period (Figure 7). Cropland is expected to decline by 2.2%, indicating continued but decelerating conversion of agricultural land, largely associated with urban expansion and land reallocation. In contrast, forest cover is projected to increase by 1.1%, suggesting relative stability and the potential influence of ecological restoration and land protection policies. Water bodies are forecast to expand by 1.9%, reflecting hydrological adjustments, surface water dynamics, and the possible impacts of climate variability and water management practices. Urban areas are projected to increase by 1.7%, confirming the persistence of urban growth and infrastructure development, albeit at a markedly slower pace than observed during 2000-2020 (Figure 8). Overall, these results indicate a transition from rapid land transformation to a more regulated and policy-constrained development trajectory, characterized by moderated urban expansion and increased emphasis on ecological and water-related land uses. Figure 9 presents the projected directional pattern of urban expansion for the period 2025–2040 based on the forecasting results. Similar to the historical period, urban growth remains highly directional rather than isotropic, with the most pronounced expansion projected toward the northeast (NE) and southwest (SW) sectors. However, compared to 2000–2020, the overall magnitude of expansion is substantially reduced, indicating a deceleration of urban growth under future scenarios. Moderate expansion is expected toward the east (E) and south (S), while limited growth is projected in the southeast (SE) and northwest (NW) directions. The persistence of NE–SW-oriented growth suggests the continued influence of existing urban cores, transportation corridors, and river-aligned development, while the reduced intensity reflects increasing spatial constraints, regulatory policies, and the saturation of available land. This shift highlights a transition from rapid outward expansion to more controlled, corridor-focused urban development in the study area.

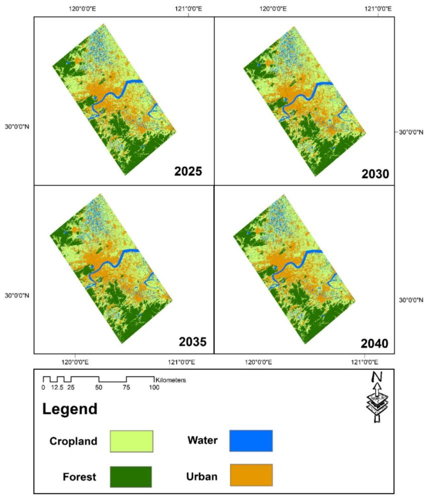

Figure 7. Predicted land use maps for 2025-2040 generated using the Hybrid CNN-ConvLSTM-Markov Cellular Automata (Hybrid CA) model in Python.

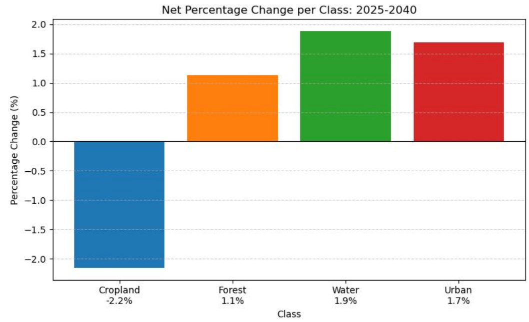

Figure 8. Percentage changes of land use classes from 2025 to 2040 in the forecasted land use maps.

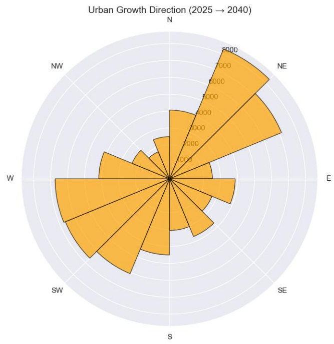

Figure 9. Urban growth direction from 2025 to 2040 derived from forecasted land use maps.

3.3. Evaluation of the hybrid model

The Hybrid CNN-ConvLSTM-Markov CA (Hybrid CA) model was trained using a patch-based approach, dividing the entire study area into smaller patches. This technique allows the model to learn from a larger number of samples, improving its ability to capture local spatial features and enhancing overall predictive accuracy. Using this patch-based approach, the model achieved an OA of 98% and a training and validation loss of 0.12, demonstrating strong predictive performance. This performance indicates that the model can effectively capture both spatial and temporal patterns of land use change, providing reliable inputs for subsequent integration with Markov transitions and suitability-based adjustments.

To evaluate forecasting performance, the 2025 predicted land use map was compared with the observed land use. The forecasted map achieved an overall accuracy of 86% and a Kappa coefficient of 79%, indicating a high level of agreement between the predicted and observed land use patterns. These results suggest that the model can reliably simulate near-future land use dynamics and can be applied to similar environmental regions worldwide. Moreover, class-specific evaluation further demonstrates the model’s effectiveness at capturing the spatial distribution of individual land use classes. Forest class achieved the highest accuracy, with producer’s accuracy (recall) values of 0.94 and user’s accuracy (precision) values of 0.95. Urban areas also performed well, with recall and precision of 0.82 and 0.90, respectively, reflecting the model’s ability to predict concentrated anthropogenic land use. water, and cropland exhibited moderate performance, with user and producer accuracy ranging from 0.84 to 0.85, indicating some misclassification between ecologically similar or spatially fragmented classes (Figure 10).

Thus, the evaluation confirms that the Hybrid CNN-ConvLSTM-Markov CA framework is robust, combining temporal sequence learning, spatial feature extraction, and historical trend integration to generate accurate, spatially coherent land use predictions. These validated projections provide a strong foundation for analyzing future landscape changes and their potential implications for flood susceptibility and land management.

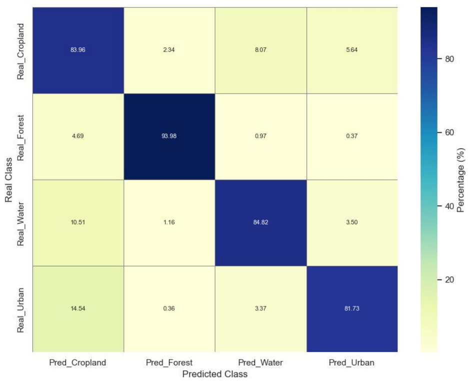

Figure 10. Class-wise confusion matrix of the hybrid model

3.4. Discussion

This study provides an integrated assessment of historical and future land use dynamics in Zhejiang Province using a hybrid CNN-ConvLSTM-Markov CA framework. The results reveal a clear transition from rapid, extensive land transformation during 2000-2020 to a more stabilized and regulated development pattern projected for 2025–2040. Similar transitions from rapid expansion to controlled growth phases have been reported in corridor- and policy-constrained urban systems across China and other rapidly developing regions (Wu et al., 2022; Koko et al., 2023; Mutale & Qiang, 2024).

Historical analysis indicates intense urban expansion accompanied by substantial losses of cropland and forest, reflecting accelerated economic growth, infrastructure development, and population pressure in northern Zhejiang. The observed 100% increase in urban land, despite a small initial base, highlights the dominant role of urbanization as the primary driver of landscape change, consistent with previous findings for canal- and corridor-oriented urban systems (Tian et al., 2019). Concurrent declines in cropland (-23%) and forest (-12.3%) underscore increasing pressure on agricultural and natural landscapes, a pattern widely documented in CA-Markov and deep learning-based LULC studies (Floreano & de Moraes, 2021; Rahnama, 2021). The expansion of water bodies (+11.4%) likely reflects hydrological modifications, canal management interventions, and improved surface water detection using multi-temporal satellite data, as also noted in recent GEE-based studies (Yang et al., 2022).

Directional analysis shows that historical urban growth was highly anisotropic, with dominant expansion toward the northeast, west, and southwest, emphasizing the influence of transportation corridors, waterways, and terrain suitability rather than uniform radial growth. Such corridor-driven expansion patterns are characteristic of linear heritage and infrastructure landscapes, including canal systems and major river basins (Wu et al., 2022). In contrast, projections for 2025-2040 suggest a marked slowdown in land conversion, with modest urban growth (+1.7%), reduced cropland loss (-2.2%), and slight increases in forest (+1.1%) and water bodies (+1.9%). This shift indicates a transition toward more regulated development, likely influenced by land-use planning policies, ecological restoration programs, and increasing land constraints. Directional projections for 2025–2040 further support this interpretation. Although urban growth remains concentrated along northeast–southwest corridors, the overall magnitude of expansion is significantly reduced compared to 2000-2020. This persistence of directional growth indicates the continued influence of existing urban cores and infrastructure networks, while the reduced intensity reflects landscape saturation, stricter zoning policies, and limited availability of suitable land for expansion. The hybrid model demonstrates strong predictive capability, achieving an overall accuracy of 86% and a Kappa coefficient of 79%. Comparable accuracy levels have been reported in recent LSTM, CNN-LSTM-, and hybrid CA-based LULC forecasting studies, particularly for spatially coherent classes such as urban and forest (Patel et al., 2022; Aryan et al., 2025). Lower performance for cropland and water highlights persistent challenges related to spectral confusion, seasonal variability, and inconsistencies in historical land cover products, especially in irrigated and seasonally inundated agricultural areas (Parracciani et al., 2024).

Overall, the findings highlight the effectiveness of combining deep spatiotemporal learning with transition-based constraints for realistic land use forecasting. The projected trends have important implications for sustainable land management, flood regulation and providing valuable spatial insights to support balanced urban development and ecological conservation.

4. Conclusion

In this study, an integrated CNN-ConvLSTM-Markov CA framework was developed to investigate historical trends and forecast future land use dynamics in Zhejiang Province. The proposed approach effectively captures complex spatial patterns, nonlinear temporal dependencies, and realistic transition constraints, enabling reliable simulation of long-term land use trajectories.

Results indicate rapid urban expansion and substantial cropland and forest loss during 2000-2020, driven by economic growth and corridor-oriented development. Directional analyses reveal highly anisotropic urban expansion aligned with transportation networks and water-based development pathways. In contrast, projections for 2025-2040 suggest a clear slowdown in land conversion, with more moderate urban growth and slight recovery of forest and water areas, reflecting increasingly regulated development and ecological protection efforts.

Model validation demonstrates strong predictive performance, with high overall accuracy and agreement between observed and simulated patterns. While urban and forest classes were modeled reliably, remaining uncertainties for cropland and water highlight the need for improved historical datasets and dynamic indicators in future studies.

Overall, the findings underscore the value of hybrid deep learning–CA models for supporting sustainable spatial planning, flood risk management. The proposed framework is transferable and can be applied to other regions.

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Reference

Aldileemi, H., Zhran, M., El-Mewafi, M., 2023. Geospatial monitoring and prediction of land use/land cover (LULC) dynamics based on the CA-Markov simulation model in Ajdabiya, Libya. *Int. J. Geoinfo. 19*(12). https://doi.org/10.52939/ijg.v19i12.2973.

Aliyu, Y. A., Youngu, T. T., Abubakar, A. Z., Bala, A., Jesulowo, C. I., 2020. Monitoring and forecasting spatio-temporal LULC for Akure rainforest habitat in Nigeria. *Rep. Geodesy Geoinfo*. 110, 29–38. https://doi.org/10.2478/rgg-2020-0009.

Aryan, A., Chowdary, V. S., RV, P., Aluvala, S., 2025. Precision land use and land cover mapping with a high-accuracy time series LSTM model. In *2025 IEEE Int. Students' Conf. Elect., Electron, Comput Sci. (SCEECS)* (pp. 1–6). IEEE. https://doi.org/10.1109/SCEECS64059.2025.10940380

Boulila, W., Ghandorh, H., Khan, M. A., Ahmed, F., Ahmad, J., 2021. A novel CNN-LSTM-based approach to predict urban expansion. *Ecol. Info. 64,* 101325. https://doi.org/10.1016/j.ecoinf.2021.101325

Das, B., Prasad, J., 2025: Cellular Automata (CA) and AI-based Recurrent Neural Networks (RNNs) Approaches in Land Use Land Cover (LULC) Change Dynamics Using Multi-spectral and Multi-decadal Landsat Data in Haldia, India. *Remote Sens. Earth Syst. Sci.* 8, pp.1223–1243. https://doi.org/10.1007/s41976-025-00246-z

Floreano, I. X., de Moraes, L. A. F., 2021: Land use/land cover (LULC) analysis (2009–2019) with Google Earth Engine and 2030 prediction using Markov-CA in the Rondônia State, Brazil. *Environ. Monitor Assess.* 193, p.239. https://doi.org/10.1007/s10661-021-09016-y

Kamaraj, M., Rangarajan, S., 2022: Predicting the future land use and land cover changes for Bhavani basin, Tamil Nadu, India, using QGIS MOLUSCE plugin. *Environ. Sci. Pollu. Res.* 29, pp.86337–86348. https://doi.org/10.1007/s11356-021-17904-6.

Koko, A. F., Han, Z., Wu, Y., Zhang, S., Ding, N., Luo, J., 2023. Spatiotemporal analysis and prediction of urban land use/land cover changes using a cellular automata and novel patch-generating land use simulation model: A study of Zhejiang Province, China. Land, 12(8), 1525. https://doi.org/10.3390/land12081525

Li, S., Zhang, C., Chen, C., Yang, C., Zhao, L., Bai, X., 2025. Optimization simulation and comprehensive evaluation coupled with CNN-LSTM and PLUS for multi-scenario land use in cultivated land reserve resource area. *Remote Sens.* 17, p.1619. https://doi.org/10.3390/rs17091619

Madhusudhan, M. S., Shivapur, A. V., Surendra, H. J., 2024. Forecasting land use and land cover changes in the Malaprabha Right Bank Canal Command Area through cellular automata and Markov chain modeling. *Ecol. Eng. Environ. Tech. 25*(6), 54–65. https://doi.org/10.12912/27197050/186598

Mishra, K., Tiwari, H. L., Poonia, V., 2025b. An integrated approach of machine learning methods coupled with cellular automation for monitoring and forecasting of land use and land cover. *J. Arid Environ. 226,* 105293. https://doi.org/10.1016/j.jaridenv.2024.105293

Mutale, B., Qiang, F., 2024: Modeling future land use and land cover under different scenarios using patch-generating land use simulation model: A case study of Ndola district. *Front. Environ. Sci. 12,* 1362666. https://doi.org/10.3389/fenvs.2024.1362666

Parracciani, C., Gigante, D., Mutanga, O., Bonafoni, S., Vizzari, M., 2024. Land cover changes in grassland landscapes: Combining enhanced Landsat data composition, LandTrendr, and machine learning classification in Google Earth Engine with MLP-ANN scenario forecasting. *GISci. Remote Sens. 61*(1), 2302221. https://doi.org/10.1080/15481603.2024.2302221

Patel, R., Patel, S., Ganatra, N., 2022. Multi-level feature extraction for automated land cover classification using deep CNN with long short-term memory network. In *Proc. Sixth Int. Conf. Trends in Electron. Info. (ICOEI 2022)* (pp. 1123–1128). IEEE. https://doi.org/10.1109/ICOEI53556.2022.9777148

Rahnama, M. R., 2021. Forecasting land-use changes in Mashhad Metropolitan area using Cellular Automata and Markov chain model for 2016–2030. *Sustain. Cities Soc. 64,* 102548. https://doi.org/10.1016/j.scs.2020.102548.

Shirmohammadi, M., Pirasteh, S., Mafi-Gholami, D., Isazadeh, V., 2025. Spatiotemporal assessment and projection of social vulnerability of cities in Iran. *Sustain Cities and Soc.* 131:106757. https://doi.org/10.1016/j.scs.2025.106757

Tian, P., Li, J., 2019. Research on land use changes and ecological risk assessment in Yongjiang River Basin in Zhejiang Province, China. *Sustain. 11*(10), 2817. https://doi.org/10.3390/su11102817

Wu, Y., Han, Z., Koko, A. F., Zhang, S., Ding, N., Luo, J., 2022. Analyzing the spatio-temporal dynamics of urban land use expansion and its influencing factors in Zhejiang Province, China. *Int. J. Environ. Res. Public Health*. 19(24), 16580. https://doi.org/10.3390/ijerph192416580

Yang, J., Huang, X., 2021: The 30 m annual land cover datasets and its dynamics in China from 1990 to 2020 (Version 1.0.0) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.5210928

Yang, K., Hu, T., Hou, H., Li, Y., Chen, Y., Wang, L., Wang, P., 2022. Future urban waterlogging simulation based on LULC forecast model: A case study in Haining City, China. *Sustain. Cities Soc. 87,* 104167. https://doi.org/10.1016/j.scs.2022.104167

Yang, W., Zhang, Y., Hou, K., Wang, X., 2025. A hybrid cellular automaton model integrated with 3DCNN and LSTM for simulating land use/cover change. *International Journal of Digital Earth, 18(1).* https://doi.org/10.1080/17538947.2024.2447337.

Yomo, M., Silliman, S., Yalo, E. N., Larbi, I., Dadja-Toyou Gnazou, M., Mourad, K. A., 2023. Forecasting land use and land cover dynamics using combined remote sensing, machine learning algorithm and local perception in the Ago`enyiv´e Plateau, Togo. *Remote Sens. Appl.: Soc. Environ. 30,* 100928. https://doi.org/10.1016/j.rsase.2023.100928.