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Current and prospective development trends of farmland resource conservation in coastal cities: a case study of Jiangsu, China

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The rapid economic development of coastal cities has significantly constrained the availability of farmland resource. Therefore, understanding land-use change dynamics over the past two decades in these regions is essential for promoting the sustainable management of farmland. In this study, based on historical land-use data from the coastal cities of Jiangsu Province, we analyzed the spatiotemporal patterns of land-use change from 2000 to 2020 using remote sensing image interpretation with ArcGIS, construction of land-use change transition matrices, and calculation of land-use dynamic indices. Furthermore, we integrated the PLUS model with a Markov chain approach to simulate potential land-use patterns in 2035 under three future scenarios: natural development, ecological protection, and farmland protection. The results showed that paddy occupied the largest proportion of land use in the study area, ranging from 43.1 to 39.5%, followed by upland, which accounted for 37.7 to 36.5%. Both paddy and upland exhibited continuous declines during the study period, with total reductions of 1,086.67 km² and 381.35 km², respectively. The loss of farmland was primarily driven by conversion into built-up land, which expanded by 1,003.61 km². Transition matrix analysis further revealed that between 2005 and 2010, built-up land experienced a net increase of 1,154.93 km², of which 55.4 and 34.0% were converted from paddy and upland, respectively. Additionally, statistical analysis identified GDP, population density, annual precipitation, and annual average temperature as the main driving factors influencing land-use change. Simulation results indicated that under both the natural development and ecological protection scenarios, upland would experience slight increases of 32.8 km² and 10.5 km², respectively, by 2035. However, paddy would decrease significantly by 466.9 km² and 476.8 km² under these two scenarios. In contrast, under the farmland protection scenario, both paddy and upland would increase by 22.6 km² and 63.1 km², respectively, by 2035. In conclusion, under the current trajectory of land-use change, the consistent enforcement of farmland protection policies, together with targeted measures for paddy conservation, is crucial for achieving the sustainable utilization of farmland resource in the coastal cities of Jiangsu Province.

KEYWORDS

sustainable agricultural development, farmland resource, land use change, multiscenario forecasting, coastal cities

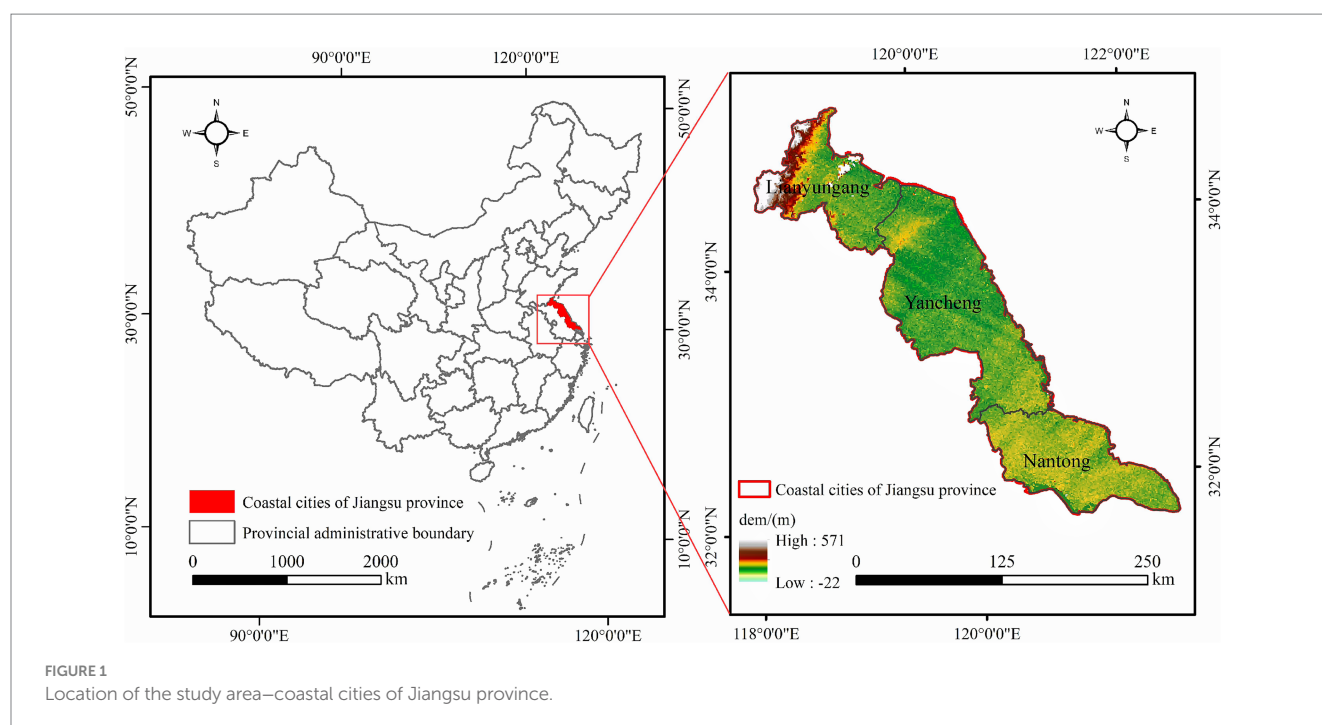
1 Introduction

Land serves as a fundamental resource for human survival and societal development, and the rational utilization of land resources is essential for promoting sustainable regional growth (Xia and Zhai, 2023). Coastal regions are characterized by high population density, rapid urbanization, and strong economic growth. While urban expansion stimulates economic development, it also triggers significant land-use changes, leading to increasing pressure on land resource availability (Xu et al., 2022; Zhou et al., 2022). Jiangsu Province, located in China's economically developed eastern coastal region, covers a total land area of $1.72 \times 10^4 \text{ km}^2$, accounting for 1.12% of the country's total territory. The continuous advancement of economic development and urbanization has intensified resource competition and exacerbated the human-land conflict (Hansen et al., 2014). Notably, Jiangsu possesses a farmland area of $4.58 \times 10^4 \text{ km}^2$, yet its per capita farmland is only 0.86 Chinese acres—considerably lower than the national average (Hagenlocher et al., 2012). Farmland plays a critical role in ensuring food security and supporting sustainable agricultural development (You et al., 2017). As one of China's key grain-producing regions, Jiangsu has prioritized the protection of farmland and the maintenance of stable grain reserves, aligning with its strategic goal of high-quality development. Therefore, achieving sustainable use and scientifically informed management of farmland resource has become a matter of urgent importance in Jiangsu Province.

Since the 1980s, Jiangsu province in China has consistently emphasized farmland utilization within the framework of its farmland protection policy (Qian et al., 2020). Despite the province's firm adherence to the farmland red line during a period of rapid economic growth, urban expansion has continued to be a dominant trend. Between 1990 and 2010, the built-up land area in Jiangsu nearly doubled, with approximately 90% of this increase originating from farmland conversion (Yao, 2013). This transformation in coastal land-use patterns has significantly reduced farmland area, thereby imposing substantial constraints on the sustainable development of the region's economy, society, and ecosystems. To support more effective planning and management of coastal land resources, previous studies have focused on coastal reclamation and the development of coastal zones in Jiangsu. For instance, Xu et al. (2022) used Landsat series images to monitor the spatiotemporal dynamics of coastal reclamation in Jiangsu Province from 1984 to 2019. They highlighted the need to improve the utilization efficiency of reclaimed land and to balance both the benefits and environmental impacts of coastal reclamation in order to promote the sustainable development of tidal flat resources in the province. Li F, et al. (2020) using statistical and remote sensing data, analyzed the extent of coastal reclamation, the introduction of relevant policies, and their impact on sea use practices between 2002 and 2018, aiming to inform improvements in China's marine resource management policies. It is evident that most existing research on coastal land use has primarily concentrated on changes along the coastline, with limited attention given to inland coastal areas, particularly regarding farmland utilization and the underlying drivers of land-use change. Currently, the permanent farmland areas in the three major coastal cities of Jiangsu - Nantong, Yancheng, and Lianyungang - are 5.802 million Chinese acres,

10.813 million Chinese acres, and 4.724 million Chinese acres, respectively, accounting for 45.3, 42.4, and 41.1% of each city's designated farmland red line. Understanding the dynamic process of land-use change is essential for comprehending regional land transformations and promoting the scientific and sustainable management of land resources (Jiang et al., 2021; Xu et al., 2012). Therefore, investigating the spatiotemporal dynamics of farmland resource in these coastal regions is of crucial importance for ensuring the long-term sustainability of agriculture in Jiangsu Province.

Analyzing the spatiotemporal characteristics of land-use change involves examining the transformation patterns and dynamic trends of land-use types across different time periods and spatial scales within a given region (Shen et al., 2006). Temporal and spatial variations in regional land use reflect the historical development stages and distinctive features of the study area, enabling the identification of emerging challenges and providing a solid foundation for the formulation of science-based land-use policies and management strategies (Yan et al., 2007). Moreover, investigating the driving factors behind land-use change is essential for understanding the mechanisms of land-use dynamics and their ecological implications. Predicting future land-use patterns is a critical component of regional land management. Multi-scenario simulation serves as a powerful tool that enables planners to forecast land-use changes under various development pathways, assess associated driving forces, and evaluate potential ecological risks of land expansion. This approach provides valuable insights for formulating more sustainable and evidence-based land management plans. Therefore, multi-scenario simulation has become an increasingly promising and practical method in regional planning and policy design (Chen and Yao, 2023). In this context, our research utilizes satellite remote sensing data and land-use datasets from the coastal cities of Nantong, Yancheng, and Lianyungang in Jiangsu Province. Through the unit area value method and spatial interpolation techniques, we investigate the spatiotemporal evolution of land-use types in these coastal cities and analyze transitions among different land-use categories. Additionally, a random forest algorithm was applied to assess the spatial probability of land-use type development and its key driving factors (Liang et al., 2021). Based on remote sensing data that capture land-use evolution at the patch scale, this study integrates the PLUS model with the Markov chain model to simulate land-use change from both temporal and spatial perspectives (Li et al., 2021). The PLUS model retains the advantages of adaptive inertial competition and roulette competition mechanisms, which enhance its ability to identify the causes of various land-use transitions and accurately simulate patch-based growth patterns (Liang et al., 2021). The primary objective of this research is to model the spatial distribution of land-use types in Jiangsu's coastal cities in 2035 under three distinct scenarios: natural development, ecological protection, and farmland protection. By analyzing the characteristics and patterns of these changes, the study reveals the spatiotemporal dynamics of land-use types, particularly those related to farmland resource evolution, in Jiangsu's coastal cities. These findings will provide valuable insights into the historical trends and future trajectories of farmland use changes in the region, ultimately contributing to the theoretical foundation necessary for sustainable farmland management in coastal zones.



2 Materials and methods

2.1 Description of study area

Jiangsu Province is located in the Yangtze River Delta region along the eastern coast of mainland China, covering a geographical range of approximately 30°45′ to 35°08′ north latitude and 116°21′ to 121°56′ east longitude. The province includes three major coastal cities: Nantong, Yancheng, and Lianyungang (Figure 1). The study area is characterized by flat topography and abundant land and tidal flat resources. The region lies within the East Asian monsoon climate zone, exhibiting a transitional climate between subtropical and warm temperate zones. It features mild temperatures, distinct seasonal variations, concentrated rainfall, sufficient solar radiation, and a relatively long growing season. The average annual temperature ranges from 13.6 to 16.1°C, with annual precipitation varying between 704 and 1,250 mm. Annual total solar radiation energy reaches 110–126 kcal/cm², and the frost-free period decreases from approximately 250 days in the south to around 200 days in the northern parts of the region.

2.2 Data sources

All land use data employed in this study were obtained from the National Earth System Science Data Center.¹ A 1:100,000 scale land use dataset covering five time periods between 2000 and 2020 was acquired. The dataset consisted of 100 × 100 m grid-based land use maps for the years 2000, 2005, 2010, 2015, and 2020, which accurately

captured the land use characteristics, utilization patterns, and spatial distribution across Jiangsu Province.

The dataset categorized land use into six primary classes: cropland, forestland, grassland, water area, built-up land, and unused land. Given the focus of this study on the spatiotemporal dynamics of farmland, the cropland category was further subdivided in accordance with the Classification of Land Use Status standards. This refinement allowed for a more detailed and nuanced analysis of farmland transitions within the study area (Table 1).

The raster database of driving factors was obtained from multiple authoritative sources, including the Resource and Environmental Science and Data Center, the National Earth System Science Data Center, and the National Catalog Service for Geographic Information (see Table 2 for details). These driving factors encompassed a range of natural and anthropogenic variables that influence land use change. To ensure compatibility with the Patch-generating Land Use Simulation (PLUS) model, all datasets were standardized to a spatial resolution of 100 meters and converted into grid format using ArcGIS software.

2.3 Research method

2.3.1 Establish a land use database for the study area

Land use remote sensing image data were processed and analyzed using ArcGIS 10.8 to extract land use information specific to the study area and to establish a comprehensive spatial database. The following methodological steps were carried out:

- (1) A scanned 1:100,000 scale topographic map of the study area was imported into the GIS environment and underwent projection correction to ensure spatial accuracy.

¹ <http://www.geodata.cn>

TABLE 1 Land use classification system in three coastal cities of Jiangsu.

Primary classification	Secondary classification	Representative meaning
Farmland	Upland	Farmland with or without water sources and irrigation facilities.
	Paddy	It refers to farmland with water source and irrigation facilities and is used to grow rice.
Built-up land	—	Urban and rural residential areas and other industrial, transportation areas.
Water area	—	Refers to natural land and land for water conservancy facilities.
Grassland	—	Various types of grasslands mainly composed of growing herbaceous plants.
Woodland	—	Refers to forestry land that grows trees, shrubs, bamboo, and coastal mangrove forests.
Unutilized Land	—	Refers to unused land, including difficult to use land.

TABLE 2 Data source of drive factors.

Type of driving factors	Driving factors	Data resolution/time	Data source
Natural factors	Elevation	90 m/2007	Resource and Environment Science and Data Center (https://www.resdc.cn)
	Slope	90 m/2007	
	Annual average temperature	1 km/2020	National Earth System Science Data Center (http://www.geodata.cn/)
	Annual precipitation	1 km/2020	
	Soil type	1 km/2003	Resource and Environment Science and Data Center (https://www.resdc.cn)
Socioeconomic factors	GDP	1 km/2019	Resource and Environment Science and Data Center (https://www.resdc.cn)
	Population density	1 km/2019	
	Night-time light	500 m/2020	Night-time light data were derived from Chen et al. (2021); Harvard Dataverse, https://doi.org/10.7910/DVN/YGIVCD .
Accessibility factors	Distance to town	1: 1,000,000 vector data (2020)	National Catalog Service For Geographic Information (https://www.webmap.cn/) data, these data are calculated by using the European distance tool in ArcGIS.
	Distance to road		
	Distance to railway		
	Distance to river		

- (2) At least nine representative ground control points (GCPs) with distinct and recognizable features were selected from the Thematic Mapper (TM) satellite imagery and matched to their corresponding locations on the topographic map to ensure geometric consistency.
- (3) Within the GIS environment, a dynamic TM image library representing land use changes over time was constructed for the study area.
- (4) The extracted land use data were stored in the coverage file format in ArcGIS, facilitating the creation of a structured and spatially enabled database.

Land use maps for the years 2000, 2005, 2010, 2015, and 2020 are presented in Figure 2, illustrating the spatial distribution and temporal evolution of land use types across the study area.

2.3.2 Land use change transfer matrix

Using the land use data collected at five-year intervals from 2000 to 2020, a land use change transfer matrix was constructed to quantify transitions among different land use types over time. Based on the principles of map algebra, the land use change map between two consecutive periods k and $k + 1$ can be derived by comparing the land use status A_{ij}^k at period k with that at period $k + 1$, denoted as A_{ij}^{k+1} . By applying Equation 1, the land use change map C_{ij} was generated using map algebra operations. This map visually illustrates

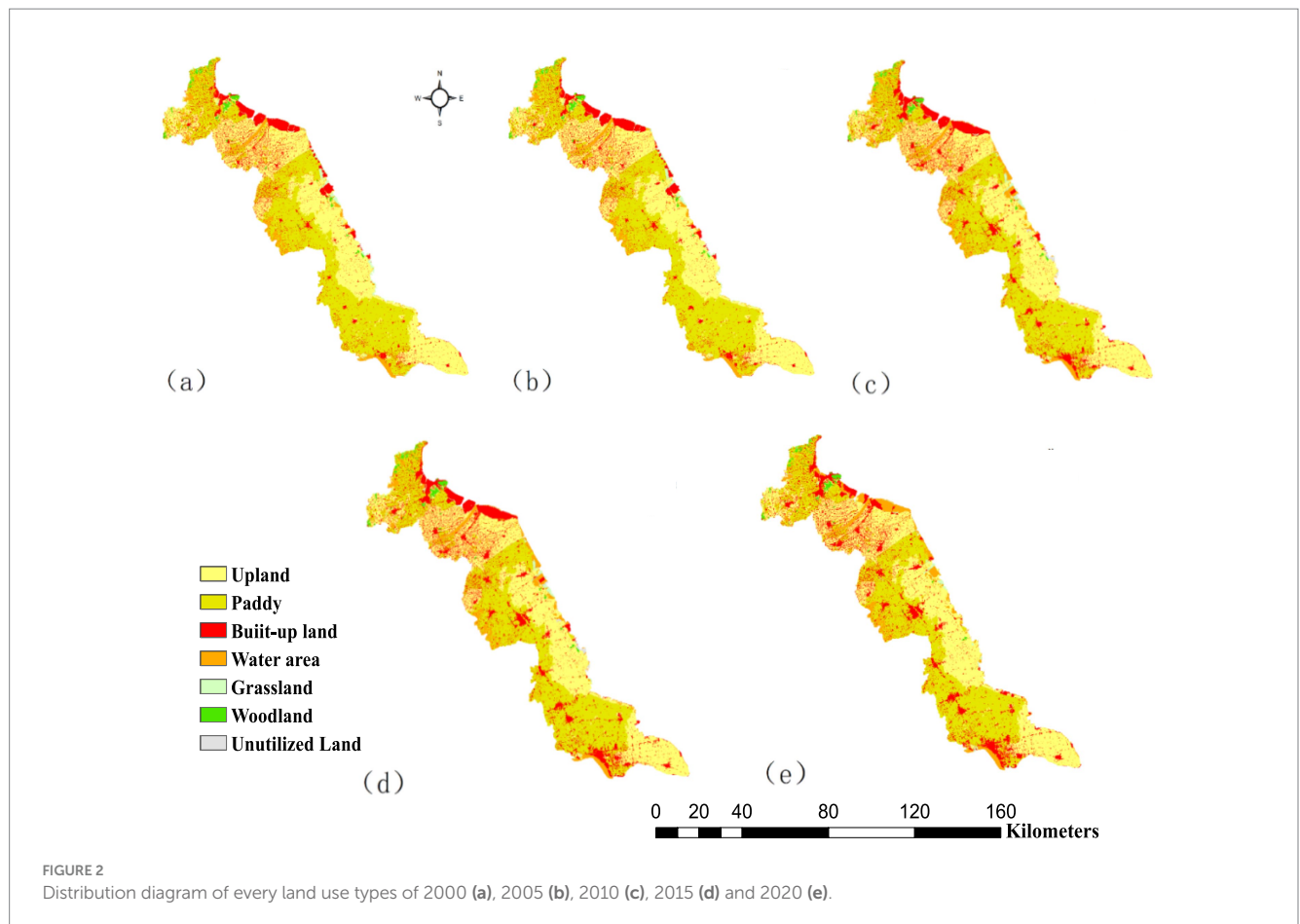
the spatial patterns and types of land use conversions during the specified time interval. In addition to the spatial representation, a quantitative transfer matrix was also produced, capturing the mutual transitions among various land use categories. This approach enables the analysis of both the magnitude and direction of land use changes across multiple periods, thereby facilitating a comprehensive understanding of the temporal evolution and transformation processes of land use in the study area (Qu et al., 2018). The formulation of the land use transfer matrix is presented below.

$$C_{ij} = A_{ij}^k \times 10 + A_{ij}^{k+1} \quad (1)$$

ArcMap software was employed to calculate the land use transfer matrix between any two consecutive periods through a spatial overlay analysis approach. By aligning land use maps from different time slices, the overlay method enabled the identification and quantification of transitions between land use types over time.

2.3.3 Analysis of changes in land use structures

The change in land use structure refers to the characteristics of the total amount and rate of each land use type evolving over time. This evolution is primarily manifested by the magnitude and velocity of land use transitions (Wang et al., 2019). The magnitude of land use change indicates the absolute extent of land use transformation over



the study period, with specific calculation methods detailed in Equations 2, 3.

The Dynamic Degree of Land Use (DDLU) is a widely utilized metric for analyzing changes in land use patterns. DDLU quantifies the amplitude of land use changes during the study period, providing insights into the rate and scale of these transformations (Zhai et al., 2021). The mathematical model for DDLU is presented in Equation 4.

$$K_1 = U_b - U_a \quad (2)$$

$$K_2 = \frac{U_b - U_a}{T} \quad (3)$$

$$DDL U = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \quad (4)$$

where K_1 is the total change in a particular land use type during the study period; K_2 is the annual magnitude of change in a particular land use type during the study period; K_3 is the dynamics degree of change of a particular land use type over the study period; U_a is the quantity of a particular land use type at the beginning of the study period; U_b is the quantity of a particular land use type at the end of the study period; and T is the study period length.

2.3.4 Scenario analysis

Based on land use data, this study integrates the Patch-generating Land Use Simulation (PLUS) model with the Markov chain model to

project the land use patterns of coastal cities in Jiangsu Province in 2035 under three distinct scenarios: natural development, ecological conservation, and farmland protection.

- (1) The Land Expansion Analysis Strategy (LEAS) module was utilized to identify the areas of expansion for various land use types by overlaying land use data from 2010 and 2020. To assess the spatial development probability of each land use type and its driving factors, a random forest algorithm was applied (Liang et al., 2021). The driving factors are detailed in Table 2. For the random forest model configuration, a sampling rate of 0.8 was used, with 50 regression trees and an mTry parameter set to 12. These settings were chosen to optimize the model's predictive accuracy while balancing computational efficiency.
- (2) The Cellular Automaton based on Multiple Random Seeds (CARS) was utilized to simulate land use changes within the study area (Li et al., 2021). This approach utilizes multiple random seeds to enhance the stochasticity and realism of the simulation process. Neighborhood weights for different land use types were calculated following the methodology proposed by Baosheng Wang et al. (2019) Equation 5. These weights are critical for determining the influence of adjacent cells on the state transitions of any given cell, thereby affecting the overall pattern and dynamics of land use change. By integrating these neighborhood weights into the CARS model, the simulation more accurately reflects the complex interactions and

transitions between various land use categories within the study region.

$$W_i = \frac{TA_i - TA_{\min}}{TA_{\max} - TA_{\min}} \quad (5)$$

where W_i represent the neighborhood weights of land use type i , TA_i represent the area of i type of land use expansion, $TA_{\min}$ represent the minimum expansion area of various types of land use, $TA_{\max}$ represent the max expansion area of various types of land use.

- (3) The Kappa coefficient, which ranges from 0 to 1, was used to assess the agreement between simulated and observed land use maps. A Kappa value exceeding 0.7 is generally considered to indicate statistically acceptable model performance (Gao et al., 2022). In this study, the Kappa coefficient reached 0.8935, and the overall classification accuracy was calculated as 0.9274, demonstrating a high level of simulation accuracy and model reliability.
- (4) A Markov chain model was applied to conduct future land use simulations, generating a transition probability matrix for the period 2010–2020. This matrix was subsequently used to project land use demands for the year 2035 under the simulated scenarios (Li et al., 2021).

3 Results

3.1 Land use characteristics

From 2000 to 2020, paddy occupied the largest share of land use, ranging from 43.1 to 39.5%, followed by upland, which accounted for 37.7 to 36.5%. Built-up land constituted 12.1 to 16.3% of the total area, while water area, woodland, grassland, and unutilized land each represented less than 10%. Due to its minimal contribution, unutilized land was excluded from further analysis. Notably, among the remaining categories, water area had the largest proportional coverage (Table 3). Furthermore, during the study period (2000–2020), upland and paddy experienced absolute decreases of 381.35 km² and 1,086.67 km², respectively (Figure 3a).

When the period from 2000 to 2020 was divided into four distinct intervals, the area of paddy showed a continuous decline, with the most significant reduction occurring between 2005 and 2010, amounting to 694.84 km² (Figure 3b). Upland also decreased during 2005–2010 and 2010–2015 by 383.4 km² and 109.6 km², respectively, followed by a partial recovery of 110.96 km² during 2015–2020 (Figure 3b).

In contrast to the decreasing trend in farmland, the areas of water area and built-up land expanded throughout the study period. Specifically, water area increased by 682.67 km² and built-up land by 1,003.61 km² (Figure 3a). The expansion of water area occurred primarily during 2005–2010 and 2015–2020, with increases of 315.6 km² and 347.16 km², respectively. Meanwhile, built-up land exhibited substantial growth in each interval, with increases of 859.96 km², 292.69 km², and 120.6 km², respectively. Notably, both water area and built-up land showed higher rates of change during 2005–2010 compared to other periods, indicating a

significant land conversion dynamic between these two categories during that time.

Regarding woodland and grassland, their areas experienced net decreases of 57.95 km² and 180.90 km², respectively, over the entire study period (Figure 3b).

3.2 Changes in land use composition

Between 2000 and 2005, both paddy and water area experienced net decreases, amounting to 106.64 km² and 61.06 km², respectively. During this period, paddy was predominantly converted into built-up land. Notably, built-up land expanded by a net area of 154.25 km², with 56.5% derived from paddy and 33.9% from upland (Figure 4a).

Since 2005, upland and paddy have experienced net decreases, while built-up land has seen a net increase of 1,154.93 km². The expansion of built-up land was primarily driven by the conversion of paddy (55.4%) and upland (34.0%; Figure 4b). Between 2010 and 2015, both upland and paddy continued to undergo net losses, amounting to 111.55 km² and 194.93 km², respectively, with most of these areas being transformed into built-up land. In terms of contributions to the newly added water area, upland, paddy, and built-up land accounted for 34.7, 25.4, and 29.5%, respectively. Furthermore, the expansion of built-up land during this period was predominantly sourced from paddy (62.3%) and upland (30.9%; Figure 4c).

From 2015 to 2020, paddy and built-up land experienced net decreases of 470.61 km² and 996.47 km², respectively. Paddy was primarily converted into built-up land, water area, and upland, with built-up land accounting for the largest share (79.3%). Meanwhile, built-up land was mainly transformed into water area (49.0%), upland (27.2%), and paddy (22.3%). During this period, both upland and water area showed net increases. The expansion of upland was predominantly driven by conversions from water area (125.92 km², 26.2%) and built-up land (271.14 km², 56.5%). The water area experienced a net increase of 609.51 km², of which 80.0% originated from the conversion of built-up land (Figure 4d). Woodland exhibited a net loss of 86.48 km², with 53.60% of this loss attributed to conversion into upland. Grassland also experienced a net decrease of 258.67 km², with 38.11% of the total outflow corresponding to conversions into water area (98.58 km²).

3.3 Driving factors for land use change

The LEAS module of the PLUS model was employed in this study to evaluate the contributions of multiple driving factors. The selected driving factors were categorized into three groups: natural factors, socioeconomic factors, and accessibility factors, as illustrated in Figure 5. Based on the analysis of 12 explanatory variables, the transition suitability for each land use type was derived. These suitability maps played a dominant role in determining the competitive capacity of each transition unit during the simulation process. The contribution analysis of each driving factor across different land use types revealed that GDP had the greatest influence on the transition of upland farmland, followed by annual precipitation, population density, and annual average temperature, with contribution rates of 15.78, 13.14, 11.91, and 11.24%, respectively (Figure 6). For paddy fields, annual precipitation was identified as the most influential

Land use types	Year									
	2000		2005		2010		2015		2020	
	Area(km ²)	Proportion(%)	Area(km ²)	Proportion(%)	Area(km ²)	Proportion(%)	Area(km ²)	Proportion(%)	Area(km ²)	Proportion(%)
Paddy	13231.2	43.1%	13178.3	42.9%	12483.4	40.6%	12291.6	40.0%	12144.6	39.5%
Upland	11589.6	37.7%	11590.3	37.7%	11206.9	36.5%	11097.3	36.1%	11208.3	36.5%
Woodland	351.3	1.1%	352.7	1.1%	323.4	1.1%	320.5	1.0%	293.3	1.0%
Grassland	422.7	1.4%	374.0	1.2%	254.0	0.8%	237.3	0.8%	241.8	0.8%
Water area	1398.9	4.6%	1378.5	4.5%	1694.1	5.5%	1734.4	5.6%	2081.6	6.8%
Built-up land	3724.4	12.1%	3845.0	12.5%	4704.9	15.3%	4997.6	16.3%	4728.0	15.4%
Unutilized Land	0.9	0.0%	0.3	0.0%	75.1	0.2%	63.1	0.2%	20.0	0.1%

3.4 Spatial pattern of land use in 2035 under three scenarios

The model achieved an overall accuracy of 0.9274 and a Kappa coefficient of 0.8935, indicating strong agreement between the simulated and observed land use maps. These metrics demonstrate that the PLUS model is highly reliable and capable of accurately reproducing historical land use changes. Therefore, it can be confidently applied to predict future land use patterns in Jiangsu's coastal cities for the year 2035.

Based on historical land use change patterns and their associated driving factors, this study simulates potential land use configurations in 2035 under different policy scenarios. Land use change is influenced by a variety of socioeconomic and environmental factors, including local economic development strategies, ecological conservation policies, farmland protection measures, and broader land use planning frameworks (Liu et al., 2017). Accordingly, three distinct future scenarios were developed: natural development, ecological protection, and farmland protection (Figure 8). Under the natural development scenario, paddy and water area exhibited the most pronounced changes. The area of water area was projected to increase by 405.9 km², while paddy decreased by 466.9 km². In addition, upland, woodland, and built-up land expanded by 32.8 km², 9.7 km², and 23.5 km², respectively (Table 4). Among all land use types, grassland was the only one showing a decline, decreasing by 10.5 km². In the ecological protection scenario, similar trends were observed for paddy and water area, with water area increasing by 415.1 km² and paddy declining by 476.8 km². Under this scenario, upland, woodland, grassland, and built-up land increased by 10.5 km², 13.9 km², 19.4 km², and 18.3 km², respectively (Table 4). These results indicate that the ecological protection scenario promotes a greater allocation of land to ecologically beneficial uses compared to the natural development scenario. Under

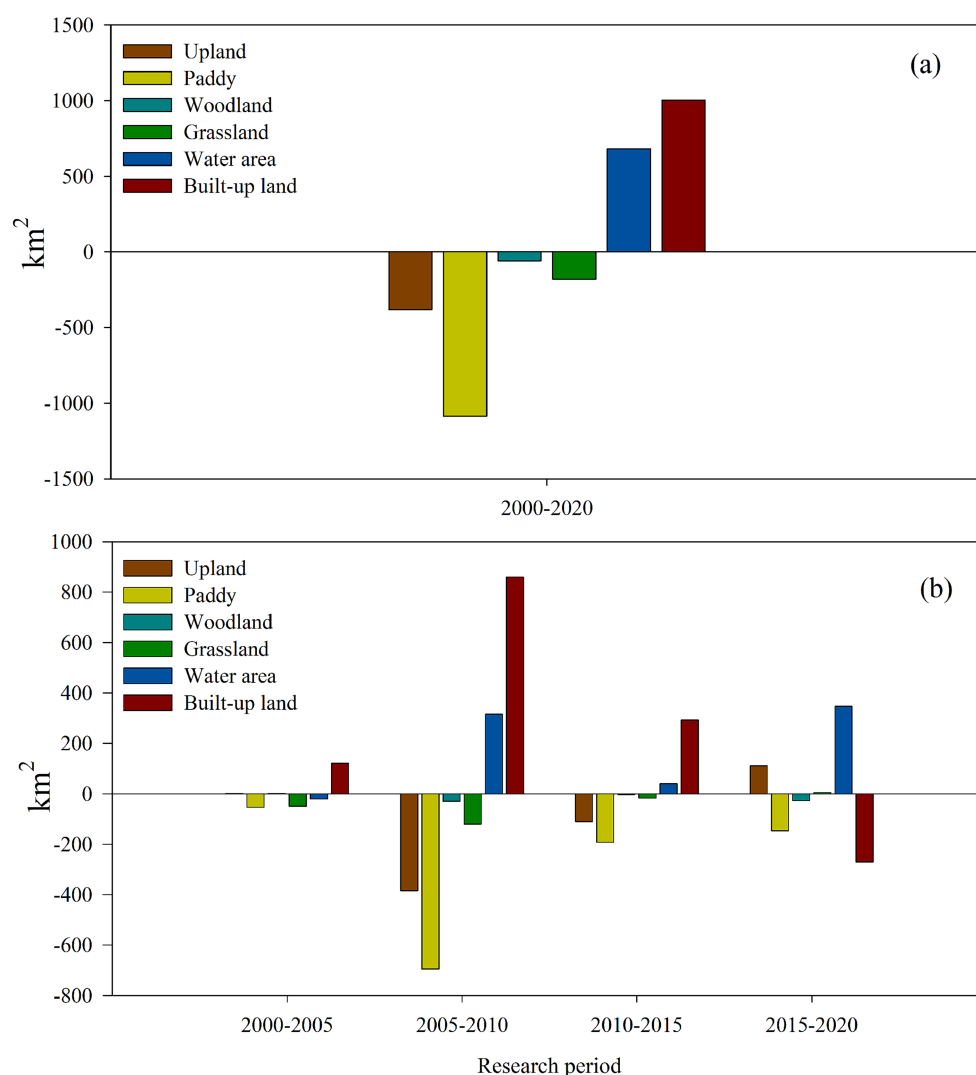


FIGURE 3
Total change amplitude of land use in Jiangsu coast from 2000 to 2020 (a) and the change every 5 years (b).

the farmland protection scenario, the trend reversed significantly. Paddy increased by 22.6 km^2 , whereas water area decreased by 71.7 km^2 , a pattern that contrasts sharply with the projections under the other two scenarios. Upland farmland and built-up land also expanded by 63.1 km^2 and 18.3 km^2 , respectively. However, woodland and grassland experienced reductions of 14.9 km^2 and 22.1 km^2 , respectively (Table 4), suggesting a trade-off between farmland expansion and natural vegetation cover. These findings highlight the significant influence of policy orientation on future land use dynamics and emphasize the importance of scenario-based modeling in supporting sustainable land management and planning decisions.

4 Discussion

The land use change analysis revealed that farmland remained the dominant land use type in the study area from 2000 to 2020. However, both the total area and proportion of farmland in Jiangsu's coastal cities exhibited a gradual decline over this period. Specifically, the

farmland area decreased from 24,820.9 km^2 (80.8% of the total study area) to 23,352.8 km^2 (76.0%). Farmland in this study is categorized into two secondary types: paddy and upland. Over the same period, paddy decreased by 1,086.67 km^2 , while upland declined by 381.35 km^2 . The reduction in both paddy and upland was primarily attributed to their conversion to built-up land, with 1,315.13 km^2 and 846.64 km^2 , respectively, being transformed for urban development. Consequently, built-up land expanded significantly, increasing from 3,724.8 km^2 to 4,997.6 km^2 , with its proportion rising from 12.1 to 15.4%. This trend aligns with previous studies indicating that farmland has historically been the largest land use type in Jiangsu's coastal cities, but has faced substantial loss due to rapid urbanization, particularly in China's more developed eastern regions (Huang et al., 2019). Given the region's accelerated economic growth and high population density (Xu et al., 2022), the pressure on farmland resource has intensified. Farmland serves as a critical resource for ensuring food security; thus, its reduction can significantly impact food production capacity and, consequently, the balance of regional socio-economic development (Kong, 2014). Striking a sustainable balance between urban expansion



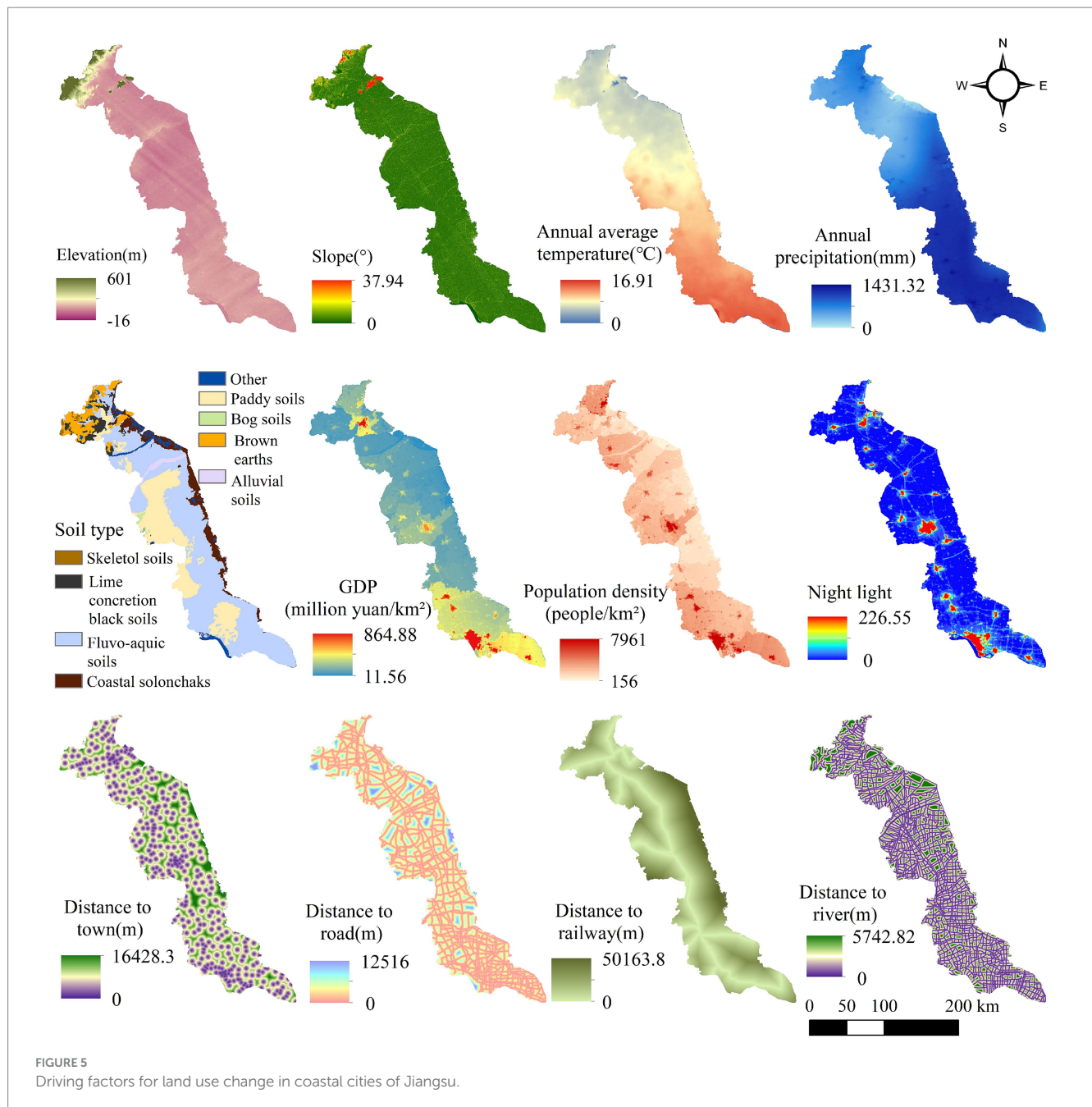
FIGURE 4

Chord diagram of land use transfer matrix in coastal cities of Jiangsu for 2000–2005 (a), 2005–2010 (b), 2011–2015 (c), and 2015–2020 (d).

and farmland protection remains a key challenge for policy-makers in coastal urban areas. Therefore, understanding the mechanisms through which urbanization affects farmland dynamics is essential. To better understand these dynamics, the land use transfer matrix provides valuable insights into the direction and magnitude of transitions among different land use types (You et al., 2023). By analyzing the transfer matrices across multiple time intervals, we further explored the temporal characteristics of land use changes and clarified the transformational relationships between farmland and built-up land (Riao et al., 2020; Wen et al., 2023).

The period from 2000 to 2020 was divided into four distinct intervals to examine the dynamic variation characteristics of paddy, upland, and built-up land. The analysis revealed a significant outflow of paddy and upland between 2005 and 2010, with reductions of 694.84 km² and 383.4 km², respectively. During this time, a strong mutual transformation relationship was observed among these three land use types. Specifically, the area converted from paddy and upland to built-up land was 4.40 and 2.56 times greater, respectively, than the reverse conversion from built-up land back to agricultural uses. This pattern likely resulted from accelerated urban expansion and the implementation of farmland occupation and compensation mechanisms (Chen et al., 2016). Notably, during 2005–2010, the centroid of farmland occupation initially shifted southward before making a sharp northward movement. Meanwhile, the centroid of farmland supplementation migrated from northern to southern Jiangsu. These shifts indicate substantial regional disparities in the balance rate between farmland occupation and supplementation. Moreover, built-up land accounted for the majority of farmland

conversion, with rural residential areas contributing approximately 50.83% of this transformation (Chen et al., 2016). The rapid expansion of built-up land closely corresponded with the swift socio-economic development in Jiangsu Province. By 2015, the area of built-up land had increased by 5,060.3 km² compared to 2004, representing a 30.66% increase relative to the 2004 baseline (Department of Land and Resources of Jiangsu Province, 2017). In contrast, the period from 2015 to 2020 exhibited a reversal trend: upland expanded by 110.96 km², while built-up land decreased by 264.29 km². Although the magnitude of change was relatively small, the underlying causes warrant further investigation. A plausible explanation is the strengthening of farmland protection policies during this period. In particular, the implementation of the Farmland Requisition-Compensation Balance Policy helped mitigate the loss of arable land due to non-agricultural development during China's rapid urbanization (Qie et al., 2023). Despite sustained economic growth, Jiangsu has maintained a firm commitment to farmland protection (Yao, 2013). To reinforce this policy framework, the Jiangsu Provincial Government issued the Interim Provisions for the Accountability of Party and Government Leading Cadres of Jiangsu Province for Violating Land Management Regulations in April 2010. Furthermore, in July 2016, agreements on primary responsibility for farmland protection were signed between the provincial government and local authorities as part of the "13th Five-Year Plan." These agreements mandated that farmland occupation be preceded by prior supplementation ("first supplement, then occupation") and required strict oversight of the balance between land occupation and compensation during land use approval processes (Chen et al., 2016).



As a result of these regulatory interventions, upland experienced net gains, while built-up land declined between 2015 and 2020.

Land use policy represents one of the key anthropogenic factors influencing land use change. In reality, land use dynamics are shaped by a combination of natural conditions and human activities (Wang et al., 2021). Understanding the underlying driving mechanisms and capturing the spatial evolution of land use changes at the patch level is essential for accurately simulating future land use patterns. Such insights can provide critical support for formulating more scientifically grounded land management and planning strategies. In this study, based on 12 driving factors and land use expansion data, we employed the random forest algorithm to analyze both the spatial suitability probability of different land use types and the contribution rates of each driving factor to land expansion. This approach allows for a comparative assessment of the influence intensity of various factors on land use

transitions. The results indicate that each driving factor exerts varying degrees of influence on the expansion of different land use types. A comprehensive analysis reveals that GDP, population density, annual precipitation, and annual average temperature are the dominant drivers of land use change. Specifically, paddy expansion was most strongly influenced by annual precipitation, followed by annual average temperature, GDP, and population density. For upland, GDP, population density, annual average temperature, and annual precipitation also emerged as major contributing factors. Meanwhile, the expansion of built-up land was predominantly driven by night-time light intensity, population density, GDP, and annual average temperature. These findings suggest that the decline in farmland area is influenced by both natural and anthropogenic factors, whereas built-up land expansion is primarily driven by socio-economic development. Wu et al. (2022) similarly emphasized the significant role of socio-economic factors in

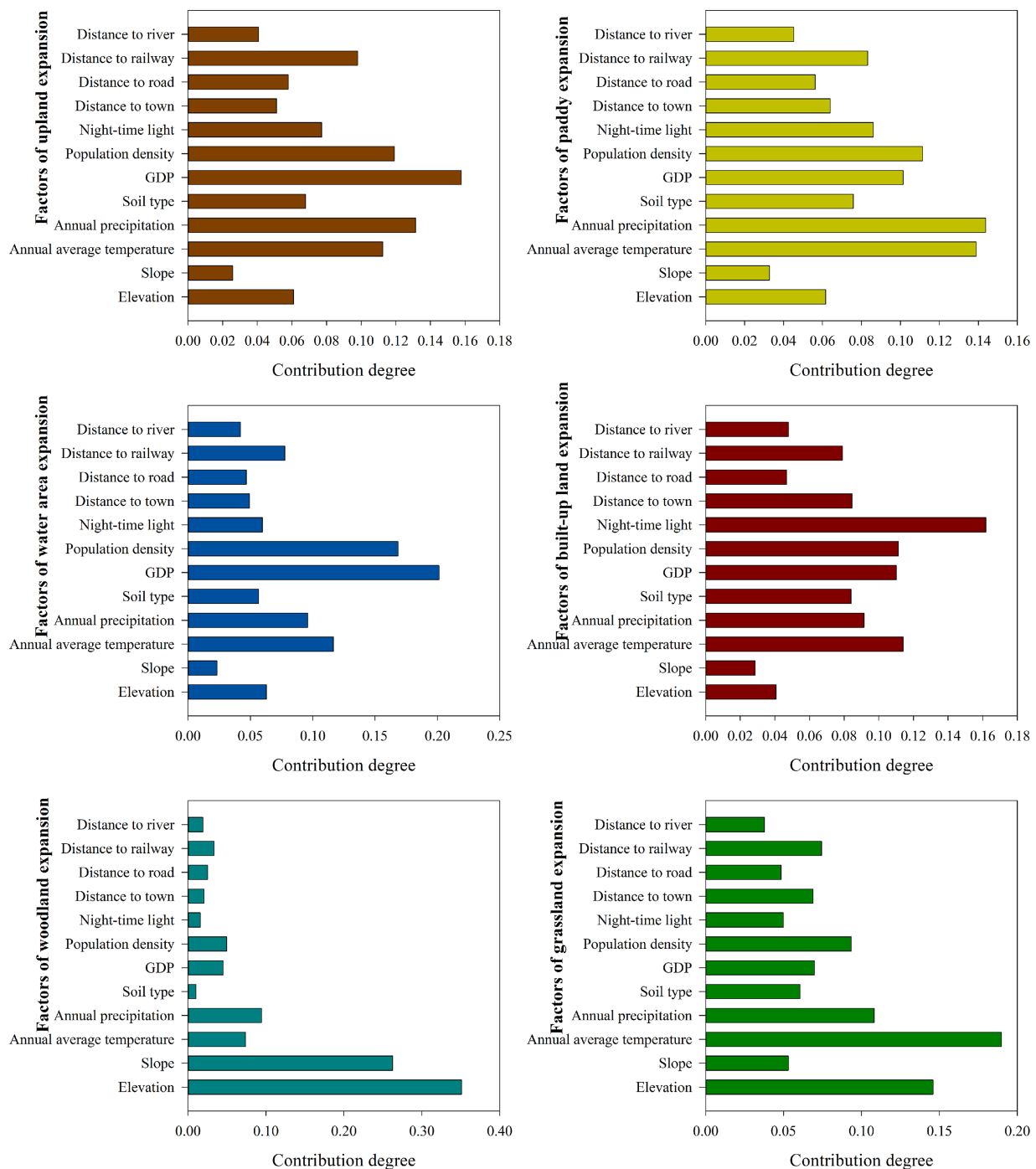


FIGURE 6
Contributions of driving factors for land use change.

shaping built-up land dynamics, further supporting the conclusion that human activities may be the decisive force behind urban expansion in Jiangsu's coastal region. Jiangsu's coastal cities are characterized by rapid economic growth and high population density. As a result, increasing demand for residential housing, public infrastructure, and recreational spaces has led to continuous expansion of built-up land, often at the expense of farmland resource. The excessive concentration of human activity heightens the risk of disharmony between people and nature (Li Y, et al., 2020), potentially triggering land use conflicts. Moreover,

unchecked expansion or reduction of specific land use types can increase the likelihood of such conflicts (Güneralp et al., 2020). Therefore, it is crucial for policymakers in Jiangsu's coastal regions to remain vigilant about the ongoing loss of farmland due to rapid urbanization. Ensuring food security while accommodating urban development requires a balanced and sustainable land use strategy that integrates ecological, economic, and social considerations.

Against the backdrop of ongoing built-up land expansion and declining farmland resource, this study aims to predict future land use

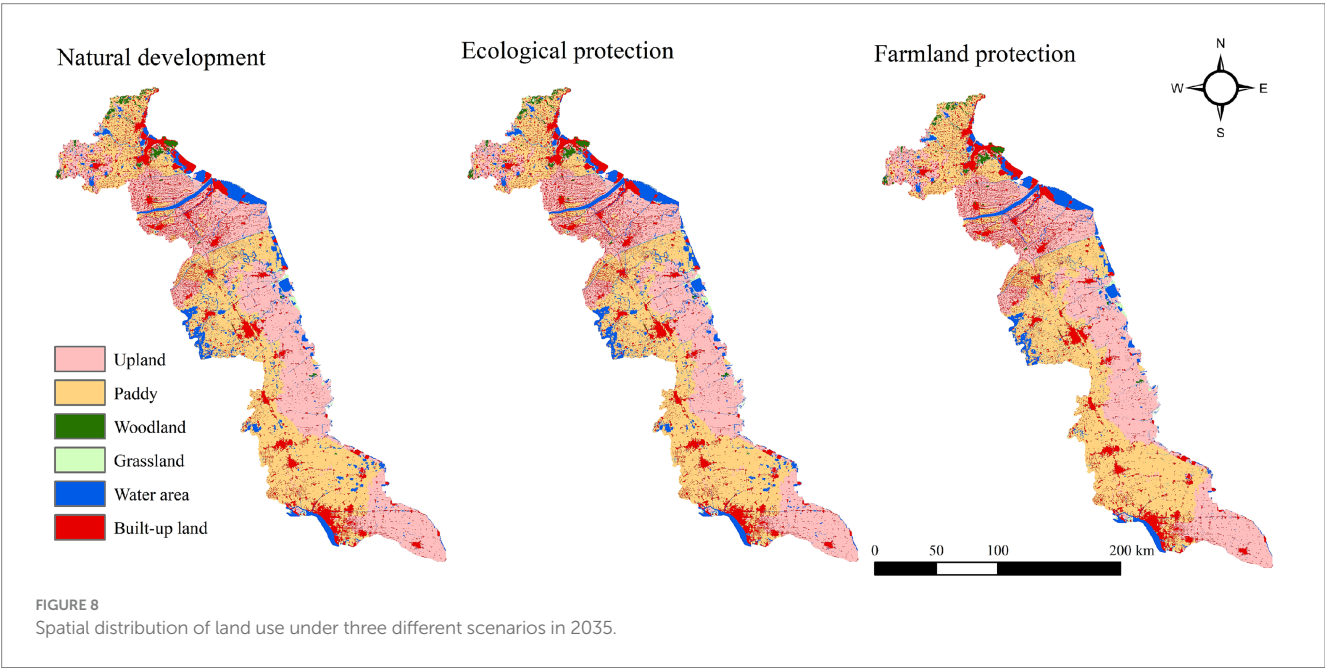
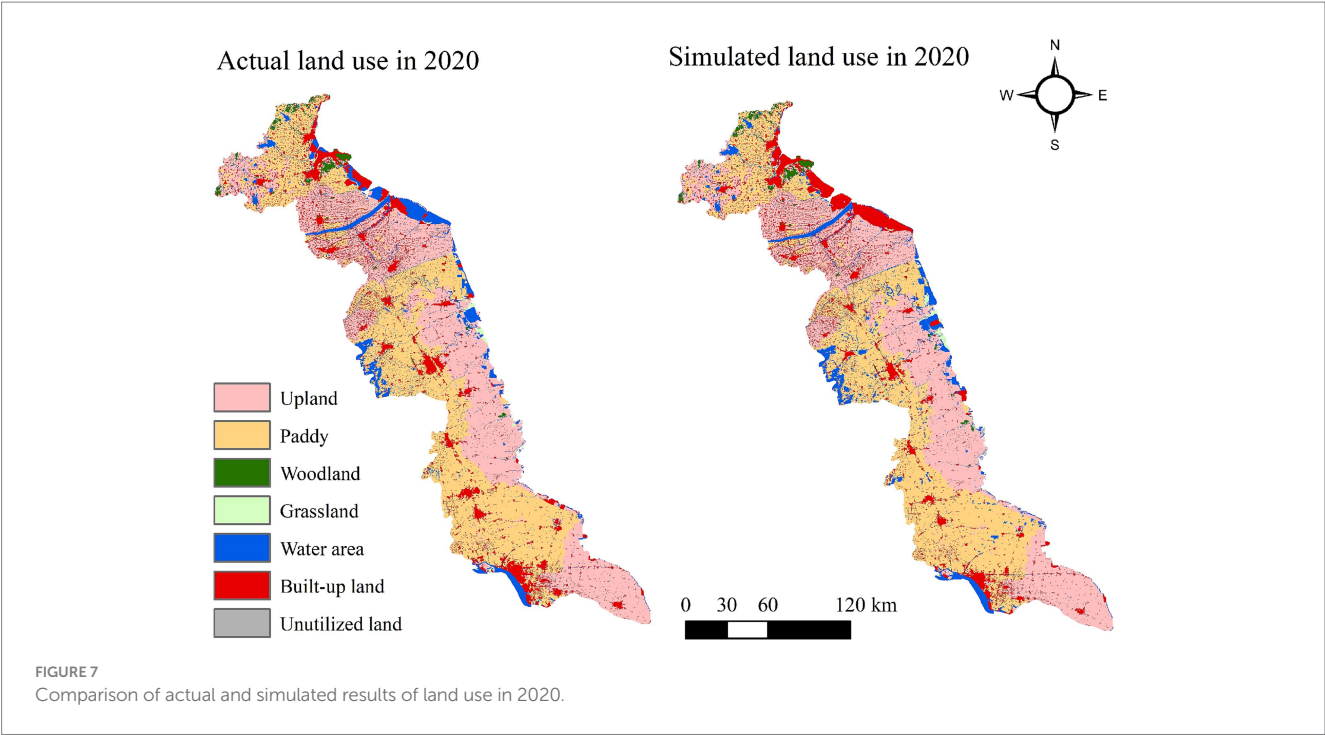


TABLE 4 Changes in land use area of Jiangsu coastal cities in 2035 under different scenarios (km²).

Type of land use	In 2020	In 2035					
		Natural development	Changes	Ecological protection	Changes	Farmland protection	Changes
Upland	11204.9	11237.6	32.8	11215.3	10.5	11267.9	63.1
Paddy	12155.5	11688.6	−466.9	11678.7	−476.8	12178.1	22.6
Woodland	293.6	303.3	9.7	307.5	13.9	278.8	−14.9
Grassland	231.7	221.2	−10.5	251.1	19.4	209.6	−22.1
Water area	2061.3	2467.2	405.9	2476.4	415.1	1989.6	−71.7
Built-up land	4731.5	4754.9	23.5	4749.8	18.3	4749.8	18.3

patterns in Jiangsu's coastal cities. With ecological sustainability and food security as primary objectives, we sought to identify an optimized land use structure that could help alleviate the growing human-land conflict in the region. To achieve this, we simulated future land use spatial patterns under three distinct scenarios: natural development, ecological protection, and farmland protection. The differences in simulated land use patterns for 2035 across these scenarios are illustrated in Figure 6. The simulation results indicate that built-up land growth and urban expansion remained relatively consistent across all three scenarios, with no significant acceleration observed. This finding contrasts with the commonly held assumption that, under a natural development trajectory, built-up land would continue to expand rapidly (Huang et al., 2019). Furthermore, under both the natural development and ecological protection scenarios, water area expanded significantly, while paddy fields decreased compared to the actual land use pattern in 2020. In particular, the emergence of numerous new water patches in 2035 was a notable feature of land use change under these two scenarios. Grassland expansion was only evident under the ecological protection scenario. These simulation outcomes suggest that policy interventions—such as those promoting ecological or farmland protection—can effectively moderate the pace of urban sprawl in Jiangsu's coastal cities. However, current policies appear insufficient in safeguarding farmland, especially paddy. Although upland showed slight increases under two of the scenarios by 2035, the area of paddy declined sharply, primarily being replaced by water area. This highlights the urgent need to develop targeted policies specifically aimed at protecting paddy under the current land use transition trends. In contrast, under the farmland protection scenario, paddy ceased transitioning into other land use types, indicating the effectiveness of this policy framework in preserving arable land. However, this scenario also resulted in losses of water area, grassland, and woodland, suggesting that greater attention must be paid to maintaining the balance between farmland preservation and the conservation of ecological land use types. Food security constitutes a critical component of national security, while ecosystem services are equally vital for long-term sustainable development (Lei et al., 2020). Therefore, achieving a harmonious balance between farmland and ecological land use is essential for ensuring both food supply stability and ecological resilience in Jiangsu's coastal cities. To this end, further research is needed to explore integrated land use policies that can identify and implement optimal land use structures, ones that simultaneously protect farmland and maintain the ecological functions necessary for sustainable urban development in coastal regions.

5 Conclusion

Based on historical land use data from the coastal cities of Jiangsu Province, this study characterizes the spatiotemporal dynamics of farmland resource and simulates future spatial patterns of farmland under three scenarios: natural development, ecological protection, and farmland protection, for the year 2035. The results reveal a continuous decline in farmland area over the past two decades, primarily due to conversions into built-up land. This loss of coastal farmland intensifies the pressure on already limited agricultural resource. However, analysis of the magnitude of land use change between 2015 and 2020, together with the simulated land use patterns for 2035, suggests that the consistent implementation of farmland

protection policies, particularly when integrated with targeted measures for paddy field conservation, could effectively constrain urban expansion while ensuring the preservation of arable land. Therefore, it is crucial to develop integrated land use policies that not only safeguard farmland but also regulate the spatial distribution and intensity of built-up land development. Such strategies can help prevent unplanned urban sprawl and reduce land use conflicts arising from competing demands between urbanization and agricultural production. Simultaneously, greater emphasis should be placed on maintaining a balance between farmland and ecologically significant land use types in Jiangsu's coastal cities. Overall, this research offers valuable insights into the spatiotemporal patterns of land use change and establishes a solid foundation for formulating effective farmland protection strategies in coastal regions.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YtL: Conceptualization, Funding acquisition, Methodology, Resources, Writing – original draft, Writing – review & editing. SZ: Methodology, Software, Writing – original draft. YjL: Formal analysis, Software, Writing – original draft. YX: Writing – original draft. NW: Writing – original draft. YF: Writing – original draft.

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Conflict of interest

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