Spatial response of urban land use change and ecosystem service value in the lower reaches of the Yangtze River: A case study of Tongling, China

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Exploring the impact of urban land use change (LUC) on ecosystem services is significant for ensuring urban ecological security and realizing regional economic development. This study used land use data from 1985, 2000, 2014, and 2020 of Tongling city and the CA−Markov model to predict the LUC in 2025 and 2030. The spatio-temporal distribution characteristics of LUC during 1985−2030 were analyzed using the land use dynamics model and Sankey diagram. The vegetation-corrected ecological services value (ESV) equivalent was used to quantify the impact of LUC on ESV. Estimating the profit/loss value and spatial autocorrelation revealed ESV's spatial and temporal dynamics in Tongling city. The results show that: 1) The most obvious LUC in the study area during 1985−2030 is the conversion of cultivated land to built-up land, in which the proportion of cultivated land decreased by 9.6%, and built-up land increased by 12.2%. 2) During 1985−2030, the ESV in Tongling showed an increasing trend at the beginning and then decreased, reaching a maximum value of 274.74 billion yuan in 2000. Regarding individual ecosystem service functions, the hydrological regulation function significantly contributed to ESV changes. The area change in paddy fields and built-up land had the most significant impact on ESV. 3) The total addition of ESV in Tongling during 1985−2030 was 5.98 billion yuan; the total loss was 18.59 billion yuan, and the net loss was 12.6 billion yuan. The proportion of area with ESV gains relative to the whole city is getting smaller, and the proportion of area with ESV losses is growing. The spatial autocorrelation shows the presence of high aggregation in ESV profit and loss areas. Simulating future LUC in Tongling and exploring ESV's response is beneficial to developing new landscape patterns and ecological protection. It also provides a scientific basis for the extensive promotion of sustainable urban development in the future.

KEYWORDS

land use change, ecosystem service value, CA-Markov, characteristics, ESV profit and loss

1 Introduction

Urban land use change (LUC) is a direct manifestation of urbanization. Rapid urban development profoundly affects the changes in the structure and function of different types of urban ecosystems (Dewan and Yamaguchi, 2009; Chatterjee and Majumdar, 2022). Ecosystem services reflect the direct or indirect benefits humans derive from changes in ecosystem structure, processes, and functions (De Groot et al., 2010; Pueffel et al., 2018; Chatterjee et al., 2022). Ecological services value (ESV) is the value generated by natural ecosystems quantified in monetary terms (Vallecillo et al., 2019). Changes in ESV are due to LUC, and substantial LUC has become a major factor in weakening and destroying urban ESV (Rimal et al., 2019; Santos-Martín et al., 2019; Gao et al., 2021a). LUC is also the main driver of changes in the value of ecosystem goods and services (Kindu et al., 2016; Felipe-Lucia et al., 2020). Exploring the impact of urban LUC on ESV has important practical significance for identifying the characteristics of the urban ecological environment changes and optimizing the national landscape planning (Hu et al., 2019; Sun et al., 2020).

Since Costanza et al. pioneered the quantification of global ESV in 1997, ESV research gradually became a hot spot in ecological research and accumulated numerous research results on the impact of urban LUC on ESV (Costanza et al., 1998; Sonter et al., 2017; Himes-Cornell et al., 2018; Syrbe et al., 2018; He et al., 2021; Zhang et al., 2021). Based on this, domestic scholars Xie et al. (2003) developed a Chinese ecosystem service value per unit area scale. Their findings are widely used by scholars in China and abroad. As the research progressed, the direction shifted from global to local and regional scales. Analyzing finer scales and typical regions has prompted more attention to various research questions (Tammi et al., 2017; Sannigrahi et al., 2018). Most studies involve high ESV value areas such as lakes and forests ((Gao et al., 2021b; Schirpke et al., 2021)). The studies mainly focus on the drivers, spatial and temporal changes and influencing factors of ecosystem services (Hu et al., 2022; Devkota et al., 2023). The research methods are mainly based on spatial and statistical analyses (Kubiszewski et al., 2017; Houtven et al., 2019). For example, at a global scale, Nelson et al. (2010) modelled the effects of urban sprawl on ecosystem services. They found that urban sprawl was the main factor contributing to species habitat decline. At the regional scale, Delphin et al. (2016) modelled the effects of urban sprawl on forest ecosystem services in the lower Suwannee River. They found varying degrees of reduction in carbon storage and wood volume. At the local scale, Cao et al. (2021) studied the relationship between regional urbanization characteristics and ecosystem services in China from 2000 to 2015. They found that ESV was positively correlated with economic growth, with significant differences in ESV across ecosystem types.

Aided by remote sensing and GIS technology, many scholars have conducted studies on land use prediction using simulation models. The advantages and disadvantages of these models have also been examined. For example, the FLUS model has unique advantages in simulating complex non-linear problems, but its inherent uncertainty can adversely affect the simulation results (Liang et al., 2018; Liu et al., 2021). The PLUS model can simulate the plot-level changes of multiple land use types and effectively solve the probability of land conversion under the combined effect of natural and human factors. However, it has shortcomings in spatial optimization (Li et al., 2022; Gao et al., 2022). The CLUE-S model systematically simulates the spatial distribution of various land types based on the relationship between land use and driving factors. However, it can only predict land use scenarios for small-scale studies (Chasia et al., 2023; Kiziridis et al., 2023). The CA-Markov model combines the ability of CA models to simulate spatial changes in complex systems. The Markov models are advantageous for long-term prediction since they can effectively simulate urban land use patterns from both temporal and spatial perspectives. They can also accurately predict land use type conversions (Gashaw et al., 2018; Mansour et al., 2020).

Previous studies on the impacts of LUC on ESV have focused mainly on the impact of past land use changes on the current ESV (Clements et al., 2021; Wang and Nuppenau, 2021; Xiang et al., 2022). There is still room for research on potential future trends in ESV. The studies also lack a detailed assessment of the current and future ESV profits and losses. In addition, attention was not given to ESV's spatial differences caused by drastic changes in urban land use. In the context of implementing the Yangtze River conservation strategy and supporting the Yangtze River Economic Belt's green development, Tongling has a typical problem of an unbalanced relationship between urban development and ecological conservation (Peng et al., 2021; Qiao and Huang, 2022). In this study, the CA–Morkov model is used to predict the future land use scenario of Tongling city for 5–10 years. The hot spots of ecological changes and ecological restoration areas were effectively identified by analyzing past and future land use scenario changes and ESV responses. The findings provide a theoretical basis for restoring ecological spots in the city. In addition, identifying ecological spots can also help to understand the ecological evolution mechanism in similar regions and provide scientific reference for the government to develop sustainable land use measures for cities targeted in the national strategic development (Schirpke et al., 2020; Peng et al., 2021).

This study used land use data in 1985, 2000, 2014, and 2020 as the main data source. The CA–Markov model was employed to predict land use patterns in 2025 and 2030 by combining land use information and natural and social driving factors. The spatial and temporal distribution of LUCs from 1985 to 2030 were analyzed using the dynamic LUC model and Sankey diagram. ESV equivalent per unit area was corrected using the normalized difference vegetation index (NDVI). The correction helps to identify ESV's spatial and temporal response to LUC. The profit and loss analysis and spatial autocorrelations were also used to characterize profit and loss changes during 1985–2030. We expect this research to be of practical significance for effective urban planning and the realization of ecological security in Tongling city. The research also provides scientific support for restoring ecological space per the national strategic plan.

2 Study area

Tongling (30°20′–31°09′N, 117°05′–118°10′E) is located in Anhui Province, China (Figure 1). It is located at the intersection of the Yangtze River plains and the mountains of

FIGURE 1
The location of the study area.
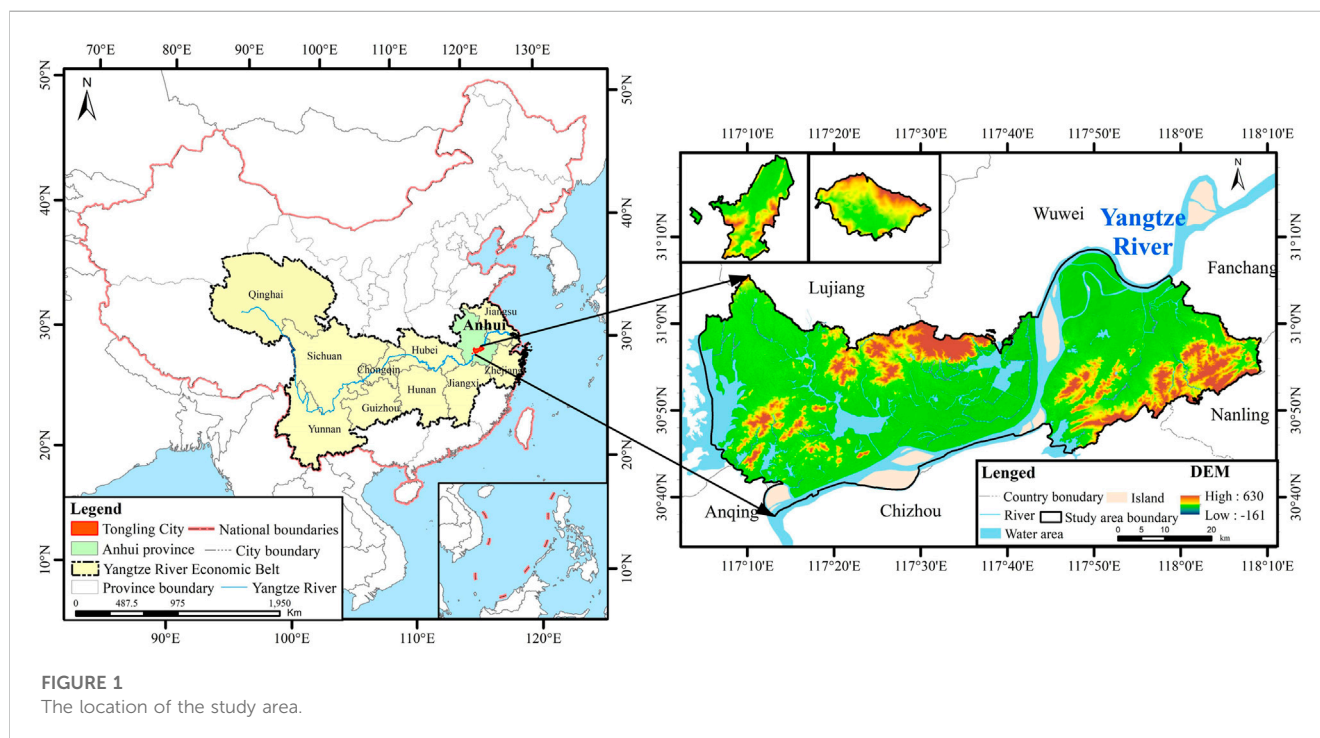
southern Anhui. The main stream of the Yangtze River is 142.6 km long in Tongling. The section is the most curved and branched section in the middle and lower reaches of the Yangtze River. Tongling is situated in a plain landscape in south-central Anhui, and the city's total area is 2993.81 km^2. The altitude ranges between 100 and 350 m. The city's flat plains, basins and hills account for 63.67%, 14.43%, and 21.9% of the total land area. A humid subtropical monsoon climate with an average temperature of 16.2°C characterizes Tongling. It receives total annual sunshine hours of 2000–2050 h and annual precipitation of 1,247–1,558 mm. The rainfall is concentrated from May to September, accounting for approximately 60% of the annual rainfall. By the end of 2020, Tongling had a resident population of 1,312,000 and a gross regional product of 1003.7 million yuan. In addition, the vegetation cover ≥0.78 area accounted for 82% of the whole city in recent year, indicating the extensive green area and high degree of vegetation cover in Tongling.

3 Materials and methods

3.1 Data sources and processing

The data used in this study include digital elevation model (DEM), slope, land use, remote sensing imagery, socioeconomic, road and meteorological data. The details of these datasets are shown in Table 1. The land use data of Tongling in 1985, 2000, 2014, and 2020 are the main data sources. The data were obtained from the Environmental Science Data Center of the Chinese Academy of Sciences with a spatial resolution of 30 m. The classification accuracy of this data is more than 90%. Following the global land use classification systems such as International Geosphere-Biosphere Programme (IGBP), Food

and Agriculture Organization of the United Nations (FAO) and the University of Maryland, the land uses were divided into 6 categories: cultivated land, forest, grassland, water area, built-up land and unused land (Zuo, 2016; Lei et al., 2020). The land covered by human infrastructure and urban construction is defined as built-up land. Considering the local situation of Tongling, the cultivated land and forest classes were further classified into detailed classes. Consequently, the cultivated land is subdivided into dryland and paddy fields, and the forest is subdivided into the broad-leaved forest and shrub wood.

Slope information was obtained from DEM (30 m spatial resolution) using the surface analysis module of ArcGIS10.2 software. The NDVI data were retrieved from the Geospatial Data Cloud, which contains two products, GIMMS and MODIS. This study uses the GIMMS NDVI (8 km spatial resolution) for 1985–2000 and the MODIS NDVI (1 km spatial resolution) for 2001–2020. The remote sensing data from the two sources were downscaled to obtain NDVI data with 30 m spatial resolution. Spatial interpolation of precipitation for 1960–2020 was performed using the spatial interpolation module in ArcGIS10.2 software to obtain the multi-year average surface rainfall in Tongling with 30 m spatial resolution. The food crops' socioeconomic information was obtained from the statistical yearbook of Tongling city. The spatial distribution of the population and gross domestic product (GDP) of Tongling (30 m spatial resolution) was obtained by downscaling the 1 km grid dataset of China's population and GDP. The road data were obtained from the National Center for Basic Geographic Information, and the raster data of highway, expressway and railway with 30 m spatial resolution were generated using ArcGIS10.2 software. The above data were used as drivers for predicting future land use patterns.

TABLE 1 Data types and sources.

Datatype	Main data	Year	Source
Topography	DEM	2002	National Geomatics Center of China http://www.ngcc.cn/ngcc/html/1/index.html
	Slope	—	
Land use	Different land use type	1985, 2000, 2014, and 2020	Resource and Environment Data Cloud Platform of Chinese Academy of Sciences http://www.resdc.cn/
Remote sensing image	NDVI	1985–2020	Geospatial Data Cloud https://www.gscloud.cn/
Climate	Precipitation	1960–2020	National Meteorological Information Center http://www.cma.gov.cn/2011qxfw/2011qsjgx/
Socioeconomic data	Types of food crops	1985, 2000, 2014, and 2020	Bureau of Statistics in Tongling city https://tjj.tl.gov.cn/
	National average price of food crops		
	Grain crop yield per unit area		
	Planting area of grain crops		
	Total acreage of food crops		
	GDP		Resource and Environment Data Cloud Platform of Chinese Academy of Sciences http://www.resdc.cn/
	Population		
Road	Highway	2014 and 2020	The National Center for Basic Geographic Information http:/www.ngcc.cn/
	Expressway		
	Railway		

3.2 Methods

3.2.1 Research ideas

This study simulates the LUC in 2025 and 2030 using the CA–Markov model and five periods of land use data in Tongling. Elevation, slope, precipitation, road, population and GDP data were used as drivers. The dynamic LUC model and Sankey diagram were utilized to characterize each land use type's spatial and temporal changes. Based on the ESV assessment system proposed by previous studies, the equivalence table of each ESV for different land use types in Tongling was constructed. The NDVI was used to correct the ESV equivalents of paddy fields, dryland, broad-leaved forest and shrub wood. Moreover, the equivalence factor method was used to analyze the distribution of ESV of each land use type from 1985 to 2030. In addition, the spatial and temporal dynamics of ESV profit and loss were analyzed using spatial autocorrelation (Figure 2).

3.2.2 Analysis methods
3.2.2.1 CA–Markov model

The CA–Markov model in IDRISI software has been widely used in LUCC simulation studies (Matlhodi et al., 2021; Wang and Wang, 2022). The cellular automata (CA) in land use simulations can generate potential transition maps considering spatial structure and neighborhood states. At the same time, the Markov model can provide a time-varying LUCC transition zone matrix based on time variation. The initial probabilities of the different states of the system and the transfer probabilities between states are used to determine each state's trend at each future moment. The CA–Markov model combines Markov and CA models to compensate for the deficiencies of each model. It can

achieve dual prediction of land use types and their spatial distribution. The simulation process is as follows.

1) Complete merging, cropping, adjusting coordinate system and resolution of land use data using ArcGIS software. Then convert the datasets to IDRISI identifiable data.
2) Set the error parameters and interval years based on the land use data for 2014 and 2020. The land use transfer area and transfer probability matrix were obtained using the Markov model in the study area during 2014–2020.
3) Produce the suitability atlas using the "Decision Wizard" module of IDRISI software. This study selected eight factors that greatly impact LUC to create the suitability atlas. They are DEM, slope, average annual precipitation, roads, highways, railroads, population, and GDP.
4) Import the land use transfer area and transfer probability matrix into CA–Markov model with the suitability atlas to simulate the land use scenarios in 2025 and 2030.

In this paper, the Kappa coefficient is used as the evaluation index for the simulation accuracy assessment of the CA–Markov model. When the Kappa coefficient is greater than 0.75, it indicates high simulation accuracy. When the Kappa coefficient is less than 0.4, the simulation results are less consistent with the actual condition (Aksoy and Kaptan, 2021; Cunha et al., 2021). The expressions are:

$$k = \frac{x_{p,i} - x_{a,i}}{x_{a,i}} \times 100\%$$

Where k is the error precision. $x_{p,i}$ is the predicted area of the type i. $x_{a,i}$ is the actual area of the type i.
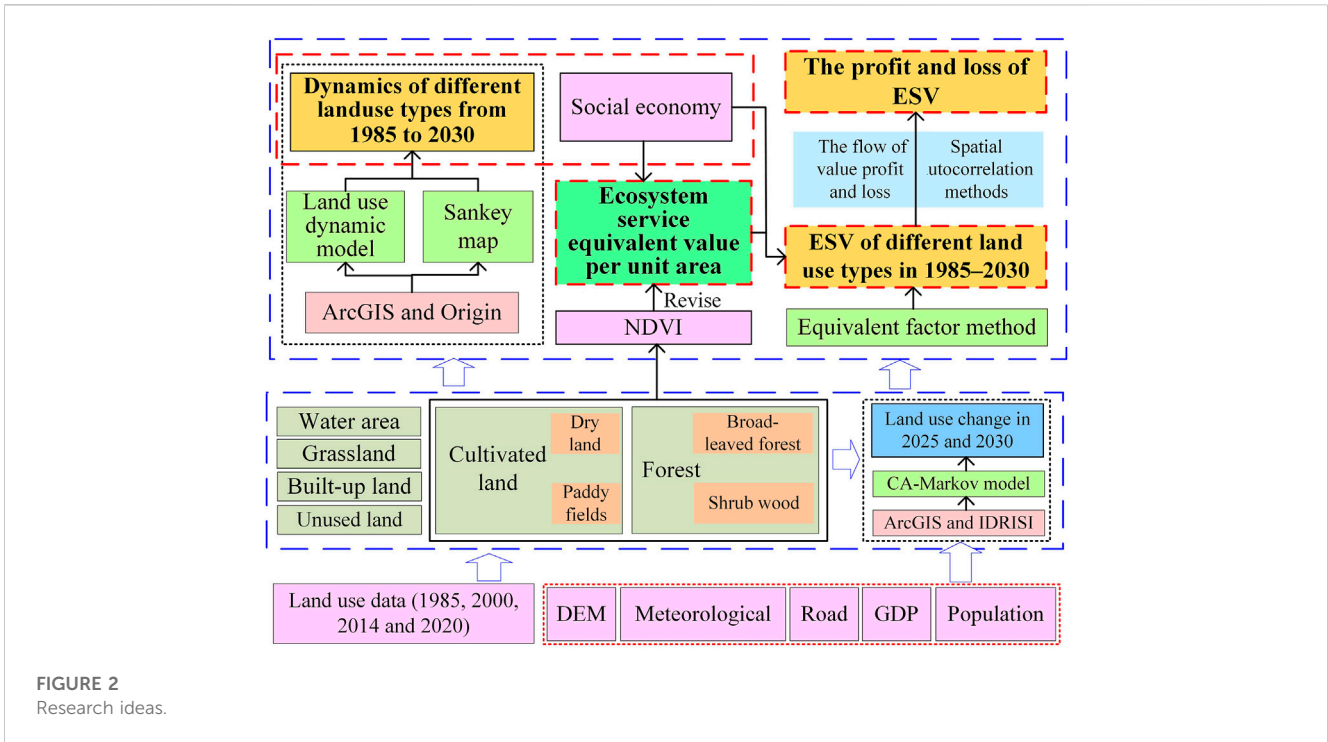
FIGURE 2
Research ideas.

3.2.2.2 Analysis of LUC characteristics

(1) The following land use dynamic models were used to describe the LUC characteristics quantitatively.

$$S_{in} = \frac{\Delta_{in}}{A_{(i,t_1)}} \times \frac{1}{t_2 - t_1} \times 100\% \qquad (1)$$

$$S_{out} = \frac{\Delta_{out}}{A_{(i,t_1)}} \times \frac{1}{t_2 - t_1} \times 100\% \qquad (2)$$

$$V_i = \frac{\Delta_{in} + \Delta_{out}}{A_{(i,t_1)}} \times \frac{1}{t_2 - t_1} \times 100\% \qquad (3)$$

$$V = \frac{\sum\limits_{i=1}^{n} \Delta_{out}}{A_{(i,t_1)}} \times \frac{1}{t_2 - t_1} \times 100\% \qquad (4)$$

Where Δ_{in} refers to the area converted from other land use types to a certain type (km^2). Δ_{out} is the area converted from a certain type of land use to other types (km^2). $A_{(i,t_1)}$ is the area of type t_1 in year i (km^2). S_{in} and S_{out} is the area change rate of a certain type in t_1–t_2 years (%). V_i is the dynamic degree of single land use (%). V is the dynamic degree of comprehensive land use (%)

(2) The Sankey diagram was made by origin software to reveal the conversion characteristics of the various land use types in different years (Zhang et al., 2019). The map depicts a network between start and end states, while the different branching lines inside the network represent the conversion of land use types. The width of the stacked bars proportionally shows the percentage of area occupied by this conversion method. The heights at the nodes represent the area of each land use type.

3.2.2.3 Assessment of ESV

1) The value equivalent of various ecosystem services of land use types in Tongling City was assigned following the "China Terrestrial Ecosystem Service Value Equivalent Table per Unit Area" evaluation system. The system was a revision by Xie following the ESV assessment system proposed by Costanza et al. (1998) (Costanza et al., 1998; Xie et al., 2015) (Table 2). Eqs 5, 6 were used to calculate the ESV of Tongling City.

$$ESV = \sum\limits_{i=1}^{m} A_i \times VC_i \qquad (5)$$

$$VC_i = \sum\limits_{j=1}^{k} EC_j \times E_a \qquad (6)$$

Where *ESV* is ecosystem service value (yuan/a). *i* is the type of land use. *j* is the type of ecosystem service. A_i is the area of land use type (hm^2). VC_i is the ecosystem service value per unit area of land use type i (yuan $hm^{-2}a^{-1}$). EC_j is the value equivalent of ecosystem services for a certain type of land use type item j. E_a is the economic value of 1 unit of ecosystem services (yuan $hm^{-2}a^{-1}$).

The equivalent of ecosystem services for the study area was computed using Eq. 7 below. The economic value of farmland natural grain production in Tongling City in 2014 was calculated, and the economic value of 1 unit of ecosystem services was found to be 3083.8 yuan $hm^{-2}a^{-1}$.

$$E_a = \frac{1}{7} \sum\limits_{g=1}^{n} \frac{w_g p_g q_g}{M} \times MCI \qquad (7)$$

where g is the type of food crops. M is the total planted area of food crops (hm^2). w_g is the national average price of the grain crop g

TABLE 2 Ecosystem service equivalent value per unit area for Tongling.

Ecosystem services		Cultivated land		Grassland	Forestland		Water area	Unused land
Primary classification	Secondary classification	Dry land	Paddy fields		Broad-leaved forest	Shrub wood		
Provisioning services	Food production	0.85	1.36	0.38	0.29	0.19	0.8	0
	Raw material production	0.4	0.09	0.56	0.66	0.43	0.23	0
	Water supply	0.02	−2.63	0.31	0.34	0.22	8.29	0
Regulating services	Gas conditioning	0.67	1.11	1.97	2.17	1.41	0.77	0.02
	climatic conditioning	0.36	0.57	5.21	6.5	4.23	2.29	0
	Purify the environment	0.1	0.17	1.72	1.93	1.28	5.55	0.1
	Hydrological regulation	0.27	2.72	3.82	4.74	3.35	102.24	0.03
Supporting services	Soil conservation	1.03	0.01	2.4	2.65	1.72	0.93	0.02
	Maintain nutrient cycling	0.12	0.19	0.18	0.2	0.13	0.07	0
	Biodiversity	0.13	0.21	7.87	2.41	1.57	2.55	0.02
Cultural services	Aesthetic landscape	0.06	0.09	4.73	1.06	0.69	1.89	0.01

(yuan/ kg). p_g is the unit yield of grain crop g (kg/hm^2). q_g is the planted area of grain crop g (hm^2). MAC is the farmland multiple cropping index, and the value of Tongling City is 1.41.

To study the spatial distribution of ESV, we selected the vegetation coverage index (Eq. 8) as the revision index of grid-scale ESV. We used Eqs 9, 10 to revise grid-level ESV. Due to the scarcity of vegetation in the water bodies, the NDVI value for these land use types is ≤0. This study made further revisions for the cultivated land, forest and grassland.

$$f = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (8)$$

$$f_{vi} = \frac{f_{ir}}{\overline{f_r}} \quad (9)$$

$$Ef_{vi} = E_i \times f_{vi} \quad (10)$$

Where f is the vegetation coverage index. i is the grid cell number. r refers to the type of ecosystem, which refers to five types: dry land, paddy field, grassland, broad-leaved forest and shrubbery. f_{vi} is the vegetation coverage revision coefficient of cell i. f_{ir} is the vegetation coverage of type r ecosystem in cell i. $\overline{f_r}$ is the average vegetation coverage of type r ecosystem in the study area. Ef_{vi} is the value equivalent of ecosystem services revised by vegetation cover for cell i. E_i is the regionally revised ecosystem service value equivalent in cell i.

(2) The degree of impact of LUC on ESV was identified through analysis of ESV profit and loss (Ling et al., 2016). Using ArcGIS's fish net creation tool, Tongling City was divided into 1.25×10^4 grid units of 0.5 km × 0.5 km. The spatial autocorrelation analysis of ESV profit and loss was done using Geoda software.

$$PL_{ij} = \left(VC_j - VC_i\right) \times A_{ij} \quad (11)$$

$$IM_i = \frac{\sum\left(PL_{ij} + PL_{ji}\right)}{2PL} \times 100\% \quad (12)$$

Where PL_{ij} is the ESV profit and loss after the conversion of the category i land use type to the category j land use type. VC_i and VC_j are the ESV coefficients of land use types i and j, respectively. A_{ij} is the area of land use type i converted to land use type j (hm^2). IM_i is the impact of LUC on ecosystem service value (%). PL is the profit and loss of ESV.

4 Results

4.1 Simulation of land use scenario in 2025 and 2030 in Tongling

Before the simulation of land use scenarios in 2025 and 2030 in Tongling, the model's accuracy was tested. The land use data for 2014 and 2020 were imported in IDRISI software, the number of cycles was set to 6 years, and a standard 5 × 5 adjacency filter was applied to obtain the LUCC simulated map for 2020. The Kappa index between the simulated and measured maps in 2020 is calculated to be 0.87. The error in cultivated land and forest area is about 5%. The error in the built-up land area is about 4%, and the error in grassland, water area and unused land is less than 3%. The results prove that the CA–Markov model meets the simulation requirements. Based on the 2020 land use data again, the number of cycles was set to 5 and 10 years. The standard 5 × 5 adjacency filter was also applied to obtain land use scenario maps for 2025 and 2030 (Figure 3).

4.2 Characteristics of LUC in Tongling from 1985 to 2030

The most significant aspect of the LUC in Tongling from 1985 to 2020 is the decrease in cultivated land and the increase in built-up land. The area of built-up land in 2020 is three times larger than in
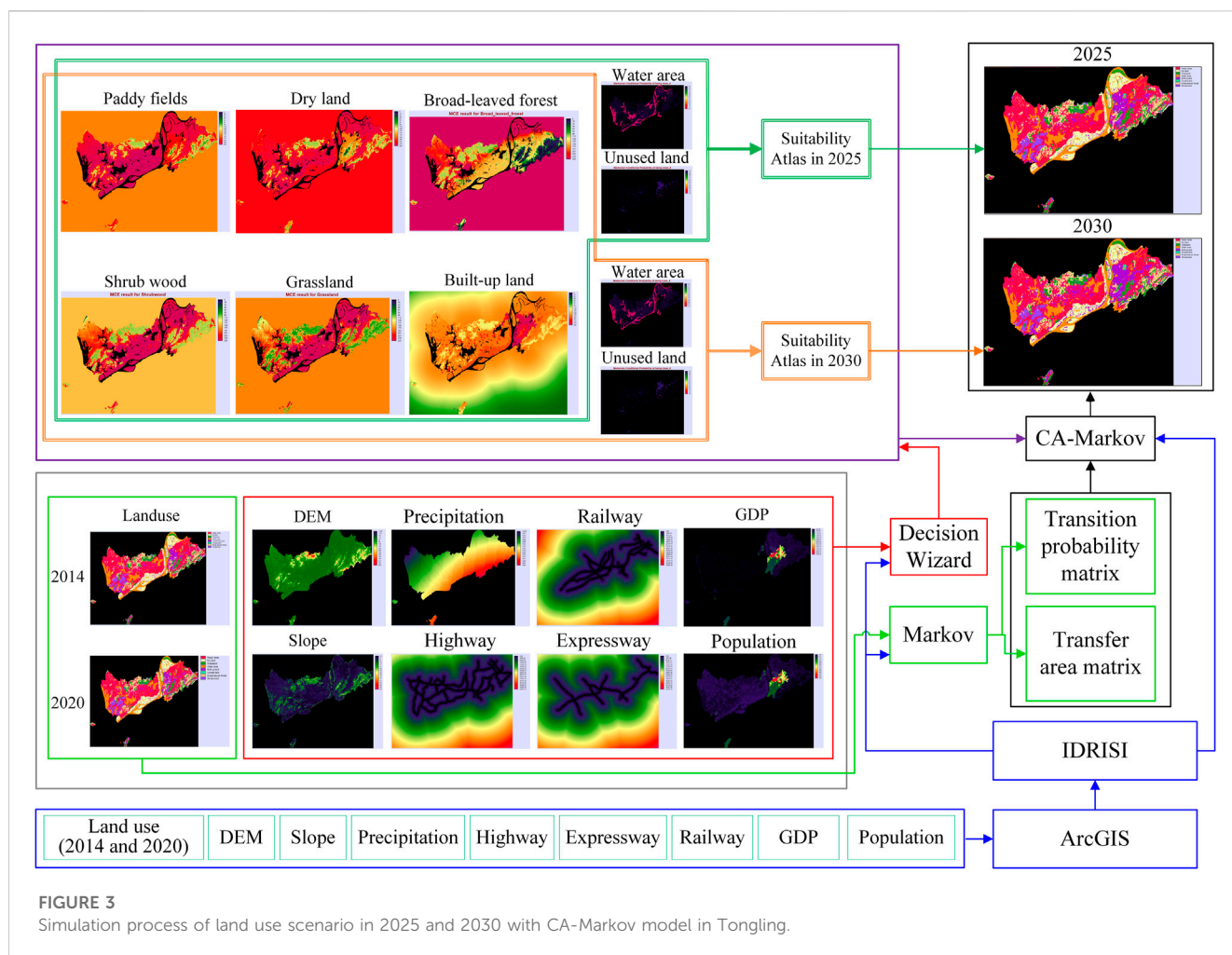
FIGURE 3
Simulation process of land use scenario in 2025 and 2030 with CA-Markov model in Tongling.

1985 (9.25×10^3 hm²) (Figure 4). The increased area is derived from the conversion of 54.35% of cultivated land, 6.52% of forest and 4.8% of grassland. The built-up land continues to increase by 1.84×10^4 hm² in 2020–2030. 72.16% of the area comes from the conversion of cultivated land, and 21.26% and 9.76% of the area comes from forest and grassland, respectively. Generally, the LUC in Tongling from 1985 to 2030 is the conversion between cultivated and built-up land. By 2030, the proportion of cultivated land area in the city will decrease by 9.6%; the proportion of built-up land area will increase by 12.2%; the proportion of forest and grassland area will reduce by 1.4%; and the proportion of both water area and the unused land area will increase by 0.2%.

During 1985–2030, each period's comprehensive land use dynamics fluctuated with an increasing trend. The largest change was observed during 2025–2030 (0.22%), indicating that this period has the most drastic LUC in Tongling (Figure 5). Regarding the individual land use types, all of them maintain an increasing trend except for the built-up and unused land. Built-up land decreased during 1985–2025 and shows an increase during 2025–2030. The change was the largest during 1985–2000 (5.59%) and the smallest during 2020–2025 (0.69%). These two periods are important as the built-up area shows a significant change. The unused land use type increased during 1985–2020 and decreased from 2020 to 2030. The maximum

value (6.32%) was obtained during 2014–2020. The result indicates that unused land undergoes the most drastic change during this period, with a threefold increase in area (258.2 hm²).

4.3 Characteristics of change in ESV in Tongling from 1985 to 2030

4.3.1 Spatial and temporal characteristics in ESV in Tongling from 1985 to 2030

The ESV in Tongling fluctuated from 1985 to 2030, reaching a maximum of 274.74 billion yuan in 2000. The ESV showed an increase of 5.08 billion yuan compared to 1985s (Table 3). The ESV decreased by 27 billion yuan during 2000–2030, with the largest decreases observed in grassland (28.21%), paddy fields (25.22%), and broad-leaved forests (20.96%). The total reduction in ESV from 1985 to 2030 is 15.91 billion yuan. The ESV of cultivated land decreased by 5.27 billion yuan (paddy fields accounted for 80.5%); the ESV of grassland decreased by 4.33 billion yuan; the ESV of forest decreased by 4.96 billion yuan (broad-leaved forest accounted for 65.77%); the ESV of water area decreased by 1.35 billion yuan, and unused land changed very little. In terms of ecosystem service types, from 1985 to 2030, except for the service value of water supply, which
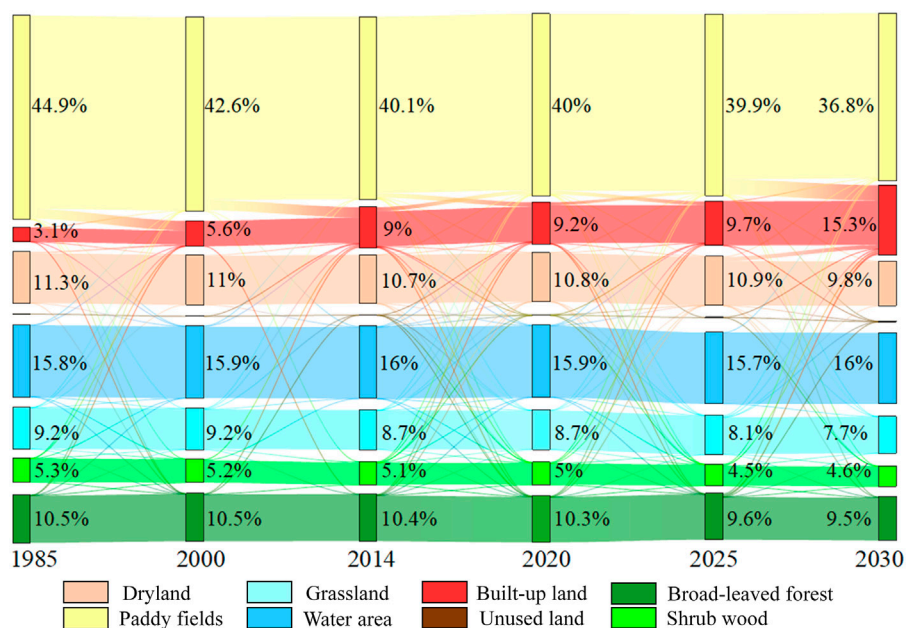
FIGURE 4
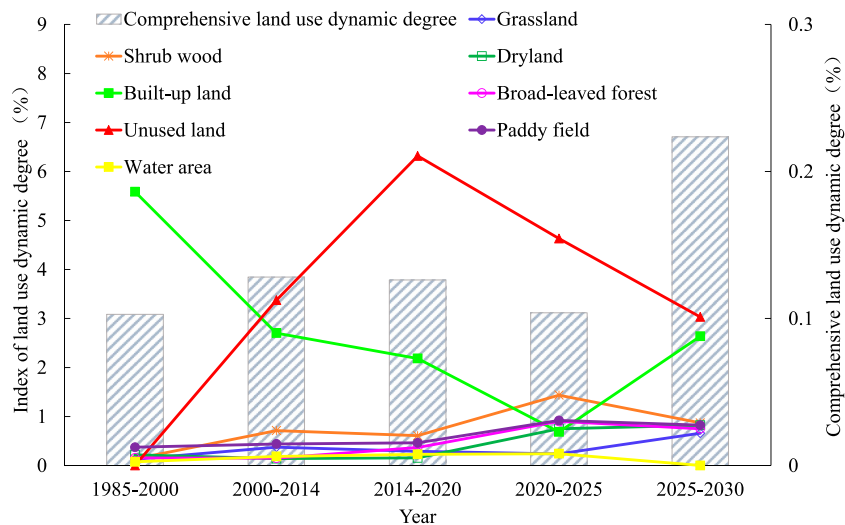The Sankey map of LUC in Tongling from 1985 to 2030.

FIGURE 5
The dynamics degrees of different land use types in Tongling during 1985−2030.

increased (266 billion yuan), the service value of other ecosystem types decreased (Figure 6). The hydrological regulation function of the ecosystem contributed the most to ESV, but the variation trends varied greatly. From 1985 to 2020, the ESV of all ecological services increased, and the ESV of hydrological regulation increased the most (2.21 billion yuan). The ESV reduction of hydrological regulation reached the largest during 2020–2030 (7.96 billion yuan) and 1985–2030 (5.75 billion yuan). From

1985 to 2030, changes in the area of paddy fields and built-up land have the most significant impact on ESV (Figure 7). The average impact degree of the paddy field is 12.14%. The average impact degree of built-up land is −42.35%, indicating that its area's increase (decrease) will lead to a decrease (increase) in ESV. The average impacts of woodland and grassland on ESV are negative (−13.42% and −8.03%); The average impact of dryland on ESV is 1.36%, and the unused land has almost no impact.

TABLE 3 Variations of ecological services value (ESV) of different land use types in Tongling (billion yuan).

Years	Cultivated land		Grassland	Forestland		Water area	Unused land	Total
	Dry land	Paddy fields		Broad-leaved forest	Shrub wood			
1985	4.67	17.51	26.20	23.67	8.04	183.55	0.001	263.63
2000	5.10	20.07	29.49	26.07	8.96	185.04	0.001	274.74
2014	5.04	18.07	27.32	25.00	8.45	185.68	0.001	269.56
2025	3.34	11.43	21.01	20.56	6.84	186.44	0.005	249.62
2030	4.22	12.35	20.85	20.18	6.52	186.12	0	250.24
2000–2030 ΔESV	−0.88	−7.72	−8.64	−5.89	−2.44	1.07	0	−24.5
2014–2030 ΔESV	−0.82	−5.72	−6.54	−6.47	−4.82	−1.93	0	−19.32
1985–2030 ΔESV	−0.45	−5.16	−5.35	−3.49	−1.52	2.57	0	−13.4

FIGURE 6

Variations of different types of ESV of Tongling. Note: Bar charts with the same color represent ecosystem service functions of the same classification level. Blue indicates the provisioning service function, including three secondary classification ecosystem service functions: food production, raw material production and water supply. Yellow indicates supporting service functions, including three secondary classification ecosystem services: soil conservation, maintaining nutrient cycling and biodiversity. Green indicates the regulation service function, including four secondary classification ecosystem services: gas conditioning, climatic conditioning, purifying the environment and hydrological regulation. Pink represents the aesthetic landscape in the cultural service function. The abscissa in the line chart represents the 11 ecosystem service functions. The serial order of the functions is as follows: food production, raw material production, water supply, gas conditioning, climatic conditioning, purifying the environment, hydrological regulation, soil conservation, maintaining nutrient cycling, biodiversity and aesthetic landscape.
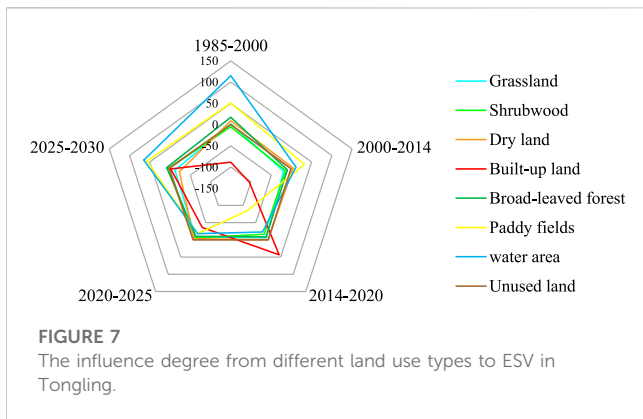
FIGURE 7
The influence degree from different land use types to ESV in Tongling.

4.3.2 Characteristics of ESV profit and loss in Tongling from 1985 to 2030

From 1985 to 2030, the total addition of ESV in Tongling was 5.98 billion yuan. The total loss was 18.59 billion yuan, and a net loss of 12.6 billion yuan (Table 4). The largest contribution to the net loss came from the conversion of cultivated land and forest to built-up land, accounting for 20.03% and 19.04% of the total loss, respectively. The conversion of paddy fields to the water area and shrub forest to the broad-leaved forest are the main sources of value gain, accounting for 30.24% and 42.98% of the total gain in the region. During 1985–2000, the spatial distribution of ESV in Tongling was relatively uniform. With the rapid development of the social economy and the rapid increase in population, the flat right bank of the Yangtze River has been developed into urban centers, significantly increasing the built-up land area. The rapid urbanization forced the low-value areas of ESV to expand from the original sporadic distribution to a large city area. As a result, from 1985 to 2030, the area of ESV gain declined, and the value loss area increased. The loss ultimately led to an increase in the proportion of high-loss ranges. The city's gain area decreased from 0.93% to 0.44%, and the proportion of loss area increased

from 6.82% to 7.33% during 2020–2030 compared to 1985–2020 (Figure 8).

The spatial autocorrelation analysis of ESV profit and loss shows that the global Moran's I > 0, $p < 0.001$ in the three periods and the ESV profit and loss scatter points were mainly distributed in the first and third quadrants (Figure 9). It shows that the ESV profit and loss in Tongling has a high spatial correlation, relatively consistent distribution and high aggregation. For 1985–2020 and 2020–2030, the "high-high" and "low-low" aggregation areas of ESV profit and loss are more widely distributed. From 1985 to 2030, the ESV profit and loss of Tongling showed a "low-low" accumulation, mainly in the central urban areas. The "high-high" aggregation occurred in the water area.

5 Discussion

5.1 Simulation of land use scenario with CA–Markov model

In this study, the driving factors for LUC changes were selected from both natural and social attributes to predict the urban land use pattern of Tongling City in the next 5–10 years based on CA–Markov model. The driving factors in natural attributes include elevation, slope and precipitation. Related studies have shown that elevation and slope are crucial factors affecting the layout of cultivated land. As their values increase, they have a negative effect on cropland layout (Mansour et al., 2020). Precipitation affects woodland changes by influencing soil water content, transpiration, and air humidity (Venkatesh et al., 2022). The driving factors in social attributes include road information, population and GDP. They are important factors in limiting the development pattern and changing trends of urban spatial layout, especially in low and medium-density cities (Fu et al., 2018). Using the CA–Markov model, this study predicts an agricultural and forestry area of 2.03×10^5 hm² and a built-up land area of 4.87×10^4 hm² in Tongling by 2030. The prediction results are consistent

TABLE 4 Loss and profit matrix of ESV in Tongling during 1985–2030 (10^4 yuan).

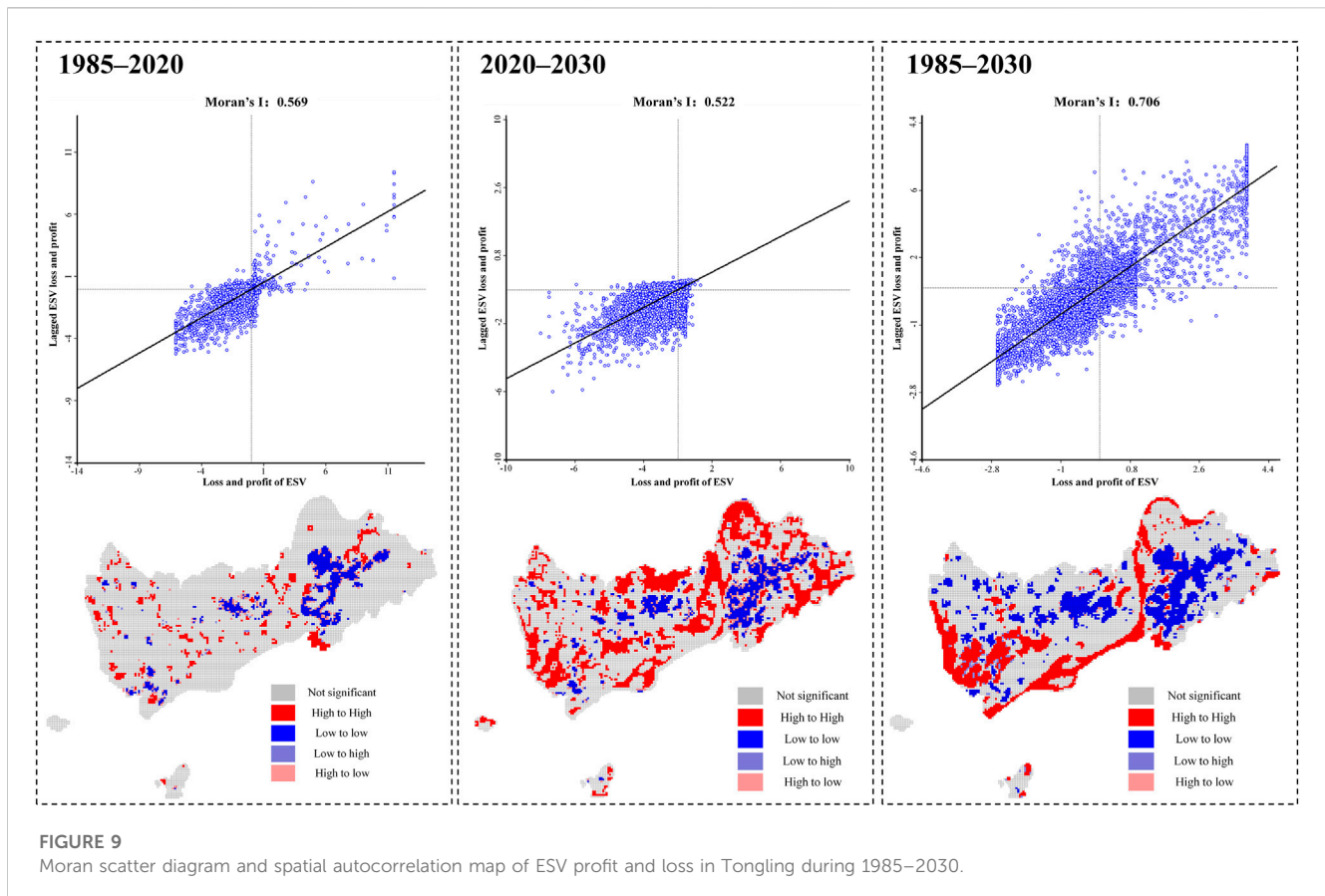| Land use type in 1985	Land use type in 2030								
	Grassland	Shrub wood	Dryland	Built-up land	Broad-leaved forest	Paddy field	Water area	Unused land	Total
Grassland	−12600.95	−1200.36	−190.87	−21699.15	−1351.52	−5398.80	186.68	−0.85	−42255.82
Shrubwood	65.25	0	−7.94	−13912.58	25688.56	−1009.91	284.81	−92.41	11015.78
Dryland	58.26	27.48	−4027.32	−5367.46	81.10	−105.84	4778.15	0	−4555.64
Built-up land	24.27	0.84	29.49	0	12.74	149.31	240.55	0.03	457.24
Broad-leaved forest	282.16	−119.20	−1.13	−21470.88	−12051.02	−5989.11	1219.38	0	−38129.79
Paddy field	2212.49	1334.14	−1.15	−31866.76	4770.25	−10784.83	18072.51	−646.42	−16909.77
Water area	−1349.29	−585.18	−2480.56	−22053.74	−378.95	−8989.50	0	−73.09	−35910.33
Unused land	242.65	3.75	0	−1.30	0	0	0	0	245.10
Total	−11065.17	−538.52	−6679.48	−116371.88	16771.17	−32128.68	24782.09	−812.74	−126043.22
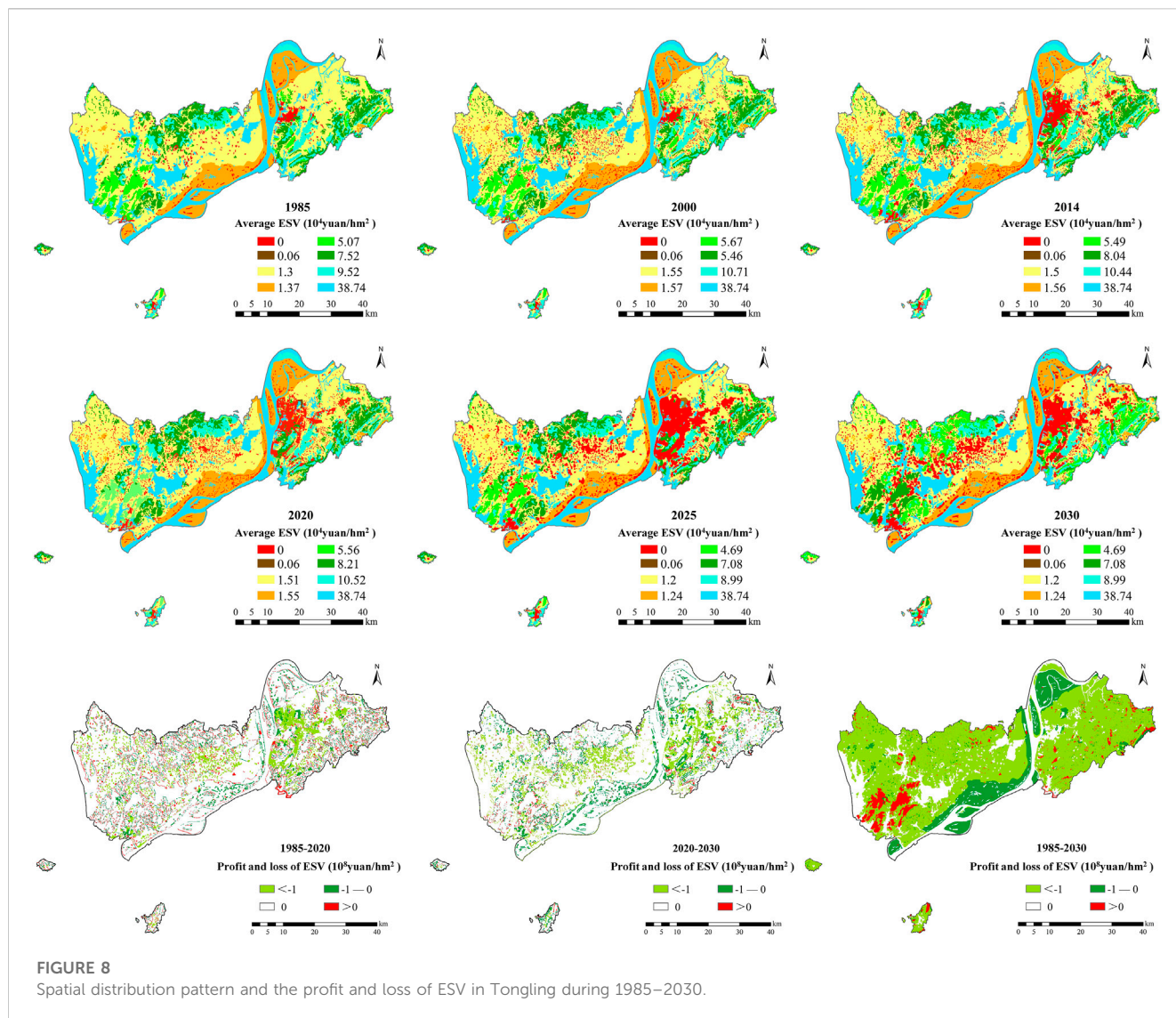
FIGURE 8
Spatial distribution pattern and the profit and loss of ESV in Tongling during 1985–2030.

with the provisions of the Tongling City Urban Master Plan (2016–2030) for agricultural and forestry area ($1.94 \times 10^5 \text{ hm}^2$) and built-up land area ($4.9 \times 10^4 \text{ hm}^2$). The finding shows that the selected drivers and the predicted land use layouts are reasonable.

5.2 Characteristics of LUC

This study found that in the past 35 years, the most significant change in Tongling City is the three-fold increase in the built-up land area, mainly from the transformation of cultivated land, forest land and grassland. Tongling is an important city in the Yangtze River Economic Belt. Since 2000, the efficiency of urban land use in the Yangtze River Economic Belt has increased annually. With rapid industrialization and urbanization, land use has also changed rapidly (Zhang and Sun, 2016). In particular, economic values were overly pursued in past land use development. All these factors have led to the rapidly expanding of the built-up land area. Scholars such as Cao

et al. (2021), Yuan et al. (2018) and Wang et al. (2017) have verified that this problem exists in different scales and different cities. By forecasting the pattern of urban land use in the next 5–10 years, it is found that the area of built-up land will still increase, mainly due to the conversion of cultivated land. Although China's population will decline slightly by 2021, China's urbanization rate has been growing rapidly from 1990 to 2021, rising from 26.44% (1990) to 64.72% (2021) (Cao et al., 2021). A comprehensive analysis of the five levels of commercial resource agglomeration, urban hub, urban population activity, lifestyle diversity, and future plasticity found that Tongling is a city with relatively slow development in China (Zhang and Sun, 2016). Many factories and enterprises were introduced and developed to promote the development of Tongling City into a more prosperous city. In addition, relying on the golden waterway of the Yangtze River, from the perspective of sustainable development, it is proposed to build an urban green and ecological corridor to create a "win-win" pattern of ecology and economy (Zhai et al., 2021). As a result, the types of forest land and water area did not change much.

FIGURE 9
Moran scatter diagram and spatial autocorrelation map of ESV profit and loss in Tongling during 1985–2030.

5.3 Characteristics of ESV

In this paper, the equivalent factor method is adopted. Usually, this method can only reflect the overall situation of the study area, and there is no way to reflect its change characteristics in space. Therefore, the value equivalent per unit area of cultivated land, forest land, and grassland types is corrected cell by cell using the NDVI in each period (Jia et al., 2021; Cao et al., 2021). The value equivalent in 2025 and 2030 is the average value equivalent of the corrected value equivalent of NDVI from 1985 to 2020. This method improves the accuracy of the results to a certain extent. This study found that the ESV of Tongling increased at the beginning and then decreased, reaching the maximum value in 2000 (274.74 billion yuan). Although the biggest change in land use from 1985 to 2000 was the conversion of paddy fields to built-up land, ESV did not decrease. The reason is the influence of ESV on value equivalent correction. The grid-by-grid NDVI values of cultivated land, grassland, and woodland in 2000 were all higher than those in 1985, especially for the forest. Even though the area decreased, the NDVI was higher (Chu et al., 2022). Therefore, reasonably determining the ESV correction coefficient is important in estimating the true response to ESV changes in the study area (Barrera et al., 2016; Fenta et al., 2020). After 2000, a large amount of cultivated land was transferred to built-up land, and the area of forest land also decreased to a certain extent, which greatly reduced the service capacity of the ecosystem.

According to statistics, by 2020, the forest coverage rate and afforestation area in Tongling City decreased by 8.59% and 6.56%, respectively, and the pressure on the ecological environment increased (Wu et al., 2017). These reductions eventually led to a year-on-year decrease in ESV, which is consistent with the continuous decrease in ESV caused by the development of most cities in China during the same period (Rong et al., 2017; Liu et al., 2021). From 1985 to 2030, the total addition of ESV in Tongling was 5.98 billion yuan, and the total loss was 1.859 billion yuan. The ESV profit and loss in Tongling are closely related to urban spatial structure and topography. The loss of ESV in the flat south bank of the Yangtze River has gradually increased with urbanization and cultivated land conversion into built-up land (Li et al., 2022). In the forest land types on the north bank of the Yangtze River, the ESV increased significantly due to the transformation from shrub wood to the broad-leaved forest. This transformation makes the ESV profit and loss show significant positive spatial autocorrelation characteristics on the global scale.

5.4 Strategies to increase ESVs in urban development

Studies have shown that woodlands and watersheds are important aspects of the ESV, illustrating the value of lucid waters and lush mountains for sustainable development (Qiao and Huang, 2022). Tongling is an important city along the

Yangtze River that relies on the Yangtze River's golden waterway to achieve a sustainable economy and ecological environment. In the future, the ecological environment protection of Tongling could focus on forest land and water areas. Under the background of decreasing cultivated land and increasing built-up land, the urban spatial layout needs to be optimized from three aspects.

1) The area of urban green space could be increased, and the interplanting structure of understory land could be optimized. It is recommended to develop urban ecological corridors considering the key water areas along the river.
2) The reduction of cultivated land will reduce the value of food production services. The optimum area of cultivated land could be strictly controlled. Furthermore, advanced technology could be introduced to increase grain yield to ensure food security further.
3) The effective utilization of existing built-up land area could be maximized and planned rationally. The occupation of water bodies and forests could be minimized. The industrial structure could also be adjusted to increase the city's carrying capacity.

In this paper, advanced remote sensing observation combined with the CA–Markov model is used to predict the land use of Tongling city in the next 5–10 years. The method integrates the effects of natural, economic and social factors on LUC, and establishes a model of land use evolution under the combination of different influencing factors and different decision makers. It not only improves the accuracy of the simulation, but also the reasonableness of the land use development scenario prediction. The NDVI was incorporated to revise the ESV coefficients. It is the most widely applied method in China at present. Firstly, the method of accounting for NDVI is mature and the accuracy of remote sensing images used for calculation is high, which increases the accuracy of ESV accounting from the source. Secondly, compared with other vegetation indices, the NDVI can accurately reflect the intra- or inter-annual variation characteristics of vegetation cover on forest, grassland and cultivated land. Furthermore, the research results can provide a theoretical reference for the land use and ecological development of urban areas in the Yangtze River Economic Belt.

However, the limitations of the study that need to be pointed out include four aspects.

1) The main driving mechanisms of urban LUC include five aspects: urbanization, economic development, industrial structure, technological development and land marketization. More drivers need to be considered in forecasting future urban growth from the above five aspects, especially the adjustment of industrial structure and layout.
2) This study has uncertainties in predicting the change of the ESV equivalent in 2025 and 2030. The economic value in 2020 is used for the prediction, which may lead to an under- or overestimation of the ESV. In follow-up research, the future value equivalent of changes in ecosystem services will be carefully evaluated to improve the accuracy of ESV predictions.
3) This study summarizes the types of ecosystem services into four primary categories: provisioning, regulating, supporting and cultural, with a total of 11 secondary categories. But it narrowly defines the types of ecosystem services and lacks thinking about more types of the services, such as: wildlife habitat, healthy functioning soils, number of trees, etc.

4) Future land use pattern is predicted based on the current development trend only. We did not consider other land use scenarios. In follow-up research, we will set up various development scenarios. Further research on the process and mechanism of small-scale LUC could be undertaken to improve understanding of ESV, the trade-offs and the synergistic relationship of various ecosystem services.

6 Conclusion

This study considers actual situations to predict the land use scenario of the study area in the next 5–10 years and correct the ESV equivalent factor. Furthermore, the space-time distribution of LUC, ESV and ESV profit and loss are analyzed. The main conclusions are as follows.

1) During 1985–2030, the most obvious LUC in Tongling was the transformation of cultivated land to built-up land. The proportion of cultivated land decreased by 9.6%, built-up land increased by 12.2%, while other types of land did not change much. Regarding the dynamics of various land use types, the most pronounced changes are observed in built-up and unused lands.
2) During 1985–2030, the ESV of Tongling showed an increasing trend at the beginning and then decreased. It reached a maximum value of 274.74 billion yuan in 2000 and then decreased to 247.73 billion yuan in 2030. The overall ESV showed a downward trend. Regarding the individual ecosystem service functions, the hydrological regulation function greatly contributed to ESV changes.
3) During 1985–2030, the total addition of ESV in Tongling was 5.98 billion yuan; the total loss was 1.859 billion yuan, and the net loss was 1.26 billion yuan. The largest contribution to the net loss comes from converting cultivated land (20.03%) and forest (19.04%) to built-up land. The conversion of paddy fields into water areas and shrub forests to broad-leaved forests are the main sources of value gain, accounting for 30.24% and 42.98% of the total gain, respectively. From 1985 to 2030, the ESV profit showed fewer gain areas and more loss areas. The proportion of high-loss areas increased during this period as well. ESV profit and loss showed a significant spatial correlation on the global scale, showing a high degree of aggregation.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: http://www.ngcc.cn/ngcc/html/1/index.html; https://tjj.tl.gov.cn/; https://zrzyhghj.tl.gov.cn/3227/3262/cxghj; http://www.cma.gov.cn/2011qxfw/2011qsjgx/; http://www.ngcc.cn/ngcc/html/1/index.html; http://www.resdc.cn/.

Author contributions

Conceptualization and methodology, FL; validation, HW; data curation, SL; writing—original draft, FL and HN; writing—review and editing, FL and TQ; supervision, SL; funding acquisition, TQ.

All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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