Multi-Scenario Simulation of Land Use for Sustainable Development Goals

Min Cao, Lijiao Chang, Shangjing Ma, Zijun Zhao, Kai Wu, Xue Hu, Qiushi Gu, Guonian Lü, and Min Chen

***Abstract*—Considering the UN sustainable development goals (SDGs) released in 2015, this article constructed an SDG-oriented land use simulation (SDG-LUS) model incorporating SDG-oriented system dynamics (SDG-SD) and SDG-oriented cellular automata (SDG-CA), and utilized it to simulate land use changes in the Yangtze river delta region. The SDG-SD model was developed to predict the land use demands from 2021 to 2030 under the constraints of multiple SDG indicators, including economic indicators (SDG2.3.1 and SDG8.1.1), social indicators (SDG3.c.1, SDG4.1.2, SDG5.b.1, SDG9.C.1, SDG 9.1.2, SDG11.2.1, and SDG11.7.1) and environmental indicators (SDG6.3.1 and SDG11.6.2). Four sustainable development scenarios, including reference, economic development, environmental protection and social progress scenarios, were established by utilizing the index and indicator board of the SDG indicators in 2030. Then, the SDG-CA model was applied to spatialize and simulate the land use evolution from 2021 to 2030 under different sustainable development scenarios. The results validate the applicability of the SDG-LUS model, and confirm that scenario simulations of different sustainability levels are conducive to supporting the formulation of sustainable land use plans.**

***Index Terms*—Cellular automata, land use, sustainable development goals (SDGS), system dynamics (SD), Yangtze river delta.**

I. Introduction

HUMANS and nature compose a community of life that requires humans to respect and protect nature, and to develop ways to rationally and sustainably use natural resources [1]. The UN sustainable development goals (SDGs) are a universal call to achieve the overall SDGs of economic development, environmental protection and social progress. The 17 goals with 169 targets were adopted by all of the UN countries in 2015 to achieve these goals [2]. Remote sensing is an irreplaceable means for observing the globe and offers basic technical support for implementing sustainable development strategies [3]. Remote sensing methods have been applied to quantify various SDGs, including: zero hunger (SDG2); clean water and sanitation (SDG6); sustainable cities and communities (SDG11); climate action (SDG13); life below water (SDG14); and life on land (SDG15). A large number of cases are shown in the annual series of reports "Big Earth Data in Support of the SDGs (2019), (2020)" [4], [5]. Remote sensing products play an important role in the urban ecological environment, sustainable land use, residential comfort, social economy, and other aspects of sustainability that can be evaluated [6]. For example, some scholars assessed land degradation in semiarid Tanzania by using multiscale remote sensing datasets to support SDG 15.3 [7]. Furthermore, the SDG11.3.1 index has been defined as a reliable evaluator of the relationship between the land consumption rate and population growth rate by using remote sensing images, land use, population census and other data [8].

Land resources are important natural resources. The impact of human activities on land use has intensified with the continuous development of the economy and society, the gradual increase in population, and the increasing frequency of human activities [9]. The sustainable use of land resources can satisfy not only the current needs of production and life, but also those of our successive generations on the basis of maintaining productivity and ecological stability. Hence, the discussion of land use change is a significant part of the research of global change and sustainable development.

Scholars have performed many studies on the SDGs and land use change [10]–[12]. Some scholars have built SDG index systems and methods for monitoring and evaluating different regions [13]–[16]. Some studies have used multisource big data to establish an indicator system for the quantitative evaluation of sustainable development processes [17]–[20]. Many scholars have constructed land use models to simulate land use evolution [21]–[28]. It is worth mentioning that urbanization system dynamics (SDs) models have been constructed to explore how land use changes during rapid urbanization [29]. In addition, SD models and future land use simulation models were coupled to simulate future land use changes under three environmental policy scenarios [30]. However, few studies have analyzed sustainable land use goals based on the SDGs [31].

This article presents an SDG-oriented land use simulation (SDG-LUS) model for simulating land use changes with different sustainability levels by taking the Yangtze river delta, China,

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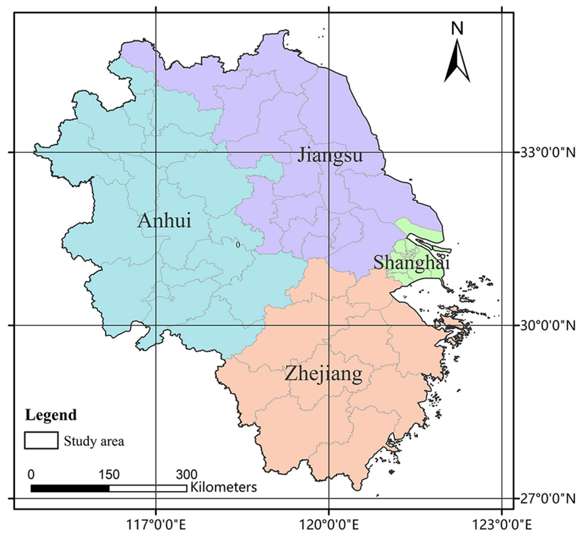

Fig. 1. Study area.

as the research area. The model consists of SDG-oriented system dynamics (SDG-SDs) and SDG-oriented cellular automata (SDG-CA) models. Four sustainable development scenarios were designed on the basis of SDG indicators to provide a reference for sustainable land-use planning, and to help promote sustainable regional land use.

The rest of this article is organized as follows. In Section II, the study area and data acquisition are described. Section III explains the method for constructing the SDG-LUS model, including the model structure, the construction of the SDG-SD model and the multi-scenario land use simulation based on SDG-CA model. Section IV applies the SDG-LUS model in the research region and discusses the land use differences under four scenarios. Finally, Conclusion is drawn and future research contents are considered in Section V.

II. Research Area and Data Acquisition

A. Research Area

This article takes the Yangtze River Delta region as the research area in Fig. 1. The Yangtze river delta region lies downstream of the Yangtze river in China, and consists of 41 cities in Shanghai, Jiangsu, Zhejiang and Anhui Provinces. The region was home to 227 million people in 2019. It had a GDP of 23.72 trillion yuan, and a railway network density of 325 km per 10 000 km^2 by the end of 2019. As one of the regions with the highest level of economic development and innovation ability in China, the research region occupies an important position in the overall situation of national sustainable development and modernization.

B. Data Acquisition

In this article, the utilized data mainly involved land use data, SDG statistical data, and spatially variable data of the driving factors affecting land use change. The land use data included the climate change initiative (CCI) land use data product (downloaded from[1]) updated by the European Space Agency on an annual basis from 2001 to 2015 with a spatial resolution of 300 m, and the global 30-m land cover dataset (GlobeLand30) with a resolution of 30 m (downloaded from[2]), which has three phases of 2000, 2010, and 2020. The data source used to develop 30-m multispectral images, including Landsat TM5, ETM+ and OLI multispectral images and HJ-1 multispectral images from the China Environmental Disaster Mitigation Satellite. The data of the 2020 edition were added with a 16-m resolution GF-1 multispectral image.

This article collected and collated statistical data related to the population, economy, society and environment from 2001 to 2015. Various statistical data were obtained from the economy prediction system (EPS) data platform and the official website of the Chinese National Bureau of Statistics, and the spatial resolution is expressed for each province. In addition, basic geographic information data, such as administrative divisions, road networks, and digital elevation models (DEMs) were collected.

III. Methods

A. SDG-LUS Model Structure

The SDG-LUS model was constructed to simulate and predict land use under multiple scenarios of different sustainability levels. The structure diagram of the SDG-LUS model is shown in Fig. 2. The SDG-LUS model consists of SDG-SD and SDG-CA models. The SDG-SD model was designed to first quantitatively predict the land use demand under four sustainable development scenarios, including a reference one and three others prioritizing economic development, environmental protection, and social progress. The SDG-SD model included four steps: determining the spatiotemporal system boundary; designing the model structure flow diagram; selecting the main variables of the model; and implementing the model accuracy verification.

On this basis, the SDG-CA model was developed to subsequently simulate the spatial process of land use evolution process according to the land use demand obtained by the SDG-SD model. The SDG-CA model comprehensively considers the initial probability of land use transformation obtained by artificial neural network (ANN) training, the empirical transfer weights between different land types calculated by the transfer matrix, the influence of the cell neighborhood, the competition mechanism among various land types, and other constraint conditions.

B. Construction of the SDG-SD Model

An SD model can simulate and predict the behavioral characteristics of an entire system under conditions by splitting the simulation of the whole system into several steps and analyzing the causal relationship and driving mechanisms among the internal variables of the system. In this article, the SDG-SD model was developed to predict the land use demands under different scenarios. Various index variables of the population, economy, society and environment were selected to act in the

[1][Online]. Available: http://maps.elie.ucl.ac.be/CCI/viewer/index.php
[2][Online]. Available: http://www.globallandcover.com/

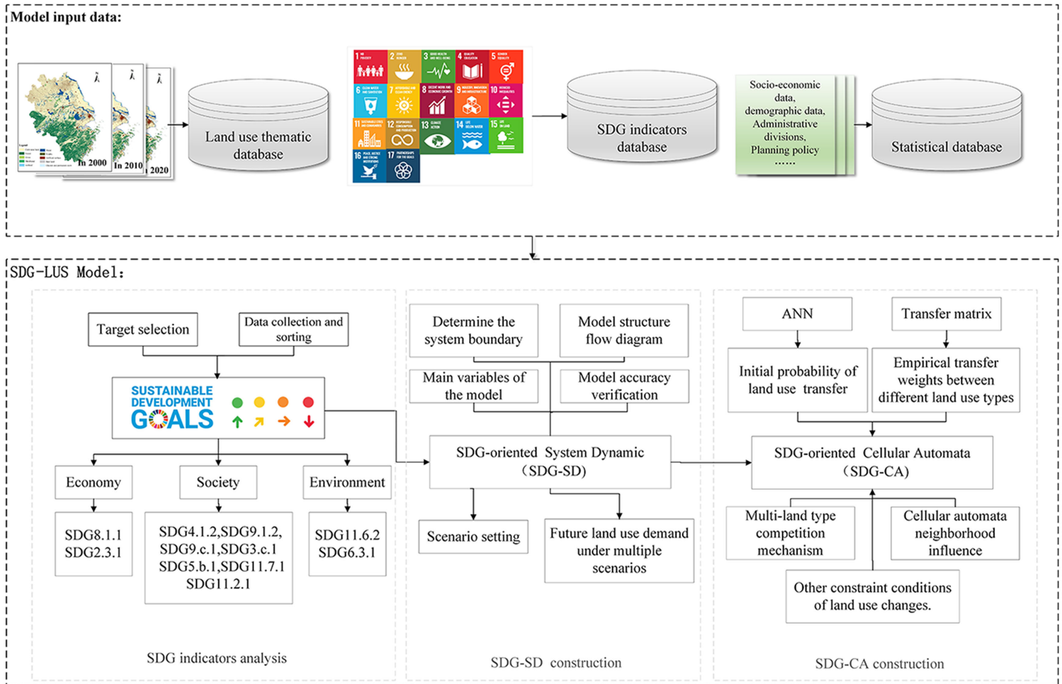

Fig. 2. Structure diagram of the SDG-LUS model.

SDG-SD model. The variables in each subsystem are given in Table I. It is worth mentioning that the variables involved many SDG indicators, such as economic indicators (SDG2.3.1, SDG8.1.1), social indicators (SDG3.c.1, SDG4.1.2, SDG5.b.1, SDG9.C.1, SDG9.1.2, SDG11.2.1, and SDG11.7.1) and environmental indicators (SDG6.3.1 and SDG11.6.2). Generally, the model variables can be divided into five types: state variables; flow rate variables; auxiliary variables; constants; and shadow variables.

In the SDs model, the structural flow diagram explores and shows the internal connections between the index variables in the complex system from a qualitative perspective [29]. The structural flow diagram of the SDG-SD model was designed to describe the causal relationship among the various factors affecting land use changes. Through the determination of model parameters, the parameter values extracted from the data and the equations between variables can be input into the SDG-SD model to quantitatively describe the relationships between model variables. The SDG-SD model was trained and assigned values by using the statistical methods of a comprehensive regression model and correlation analysis. Four subregions, namely Jiangsu, Zhejiang, Anhui, and Shanghai, were taken as the spatial system boundaries of the SDG-SD model by considering the different economic and social development levels and spatial differences in the study area. The structural flow diagram of the SDG-SD model in Jiangsu Province was drawn in Vensim software, as shown in Fig. 3.

The SDG-SD model was developed to predict the future land use demand under four scenarios, including reference, economic development, environmental protection, and social progress scenarios, with different sustainability levels. The different sustainability levels were reflected according to the values of the SDG indicators, such as the GDP growth rate (SDG8.1.1), air quality factor (SDG11.6.2), pollution control factor (SDG6.3.1), infrastructure factors (SDG9.c.1, SDG5.b.1, SDG11.7.1, SDG11.2.1, and SDG9.1.2), medical factors (SDG 3.c.1), and education factor (SDG4.1.2). The index and indicator board of SDG indicators was constructed according to the description of the indicator board in the Sustainable Development Report 2020 [32], and the sustainability of each SDG indicator was divided into green, yellow, orange, and red levels. Radar charts of the sustainable development degrees of the indicators for the four provinces in the Yangtze river delta region in 2015 are shown in Fig. 4. In the figure, different color ranges of green, yellow, orange, and red represent the levels of sustainable development of the indicators. The gray isometric regular pentagon represents different score values between 0 and 100. The blue line represents the score values and the range of the sustainable degree of each indicator in this region. In combination with the current sustainability degree, the scenario settings are given in Table II, green indicates that the sustainable development degree of the indicators of the city is excellent; orange indicates that this indicator of the city is far from achieving the goal of sustainable development; and red indicates that the city has fallen far short of the SDGs. Blue indicates that the index has maintained the current (actual) development trend. The specific values of green, yellow, orange, and red in the scenario setting, namely the future development trend of each indicator, were determined by the slope of linear development from the value of the indicator in the current year to the lowest value of each grade in 2030.

As given in Table II, the reference scenario maintains the current development trend of land use change. The economic development scenario focuses on GDP growth and increased investment in pollution control. Therefore, the GDP growth rate

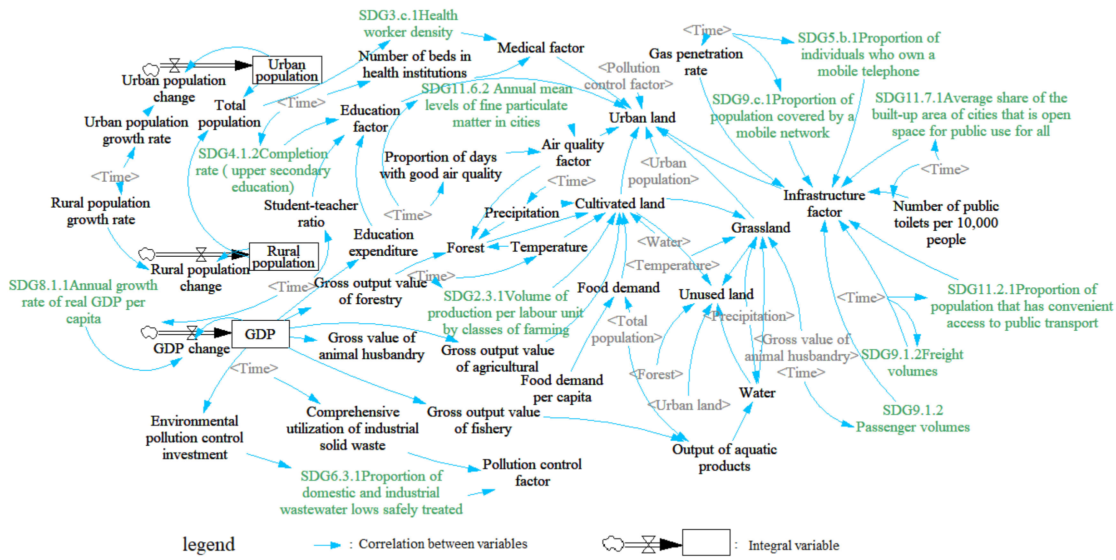

Fig. 3. Structural flow diagram of the SDG-SD model.

TABLE I
SDG-SD MODEL AND ITS CHILD VARIABLES

Primary goal	Secondary goals	Specific indicators
Population	Urban areas	Urban population, Urban population change, Urban population growth rate
	Rural areas	Rural population, Rural population change, Rural population growth rate
Economic	Output values	GDP, SDG8.1.1, GDP change, Gross output value of agricultural, Gross output value of forestry, Gross output value of animal husbandry, Gross output value of fishery
	Output	SDG2.3.1, Food demand, output of aquatic products
Society	Education	SDG4.1.2
	Medical	SDG3.c.1, Number of beds in health institutions
	Infrastructure	SDG5.b.1, SDG9.c.1, SDG11.7.1, Number of public toilets per 10,000 people, SDG11.2.1, SDG9.1.2
Environment	Natural environment	Temperature, Precipitation
	Pollution control	SDG6.3.1
	Air quality	SDG11.6.2, Proportion of days with good air quality

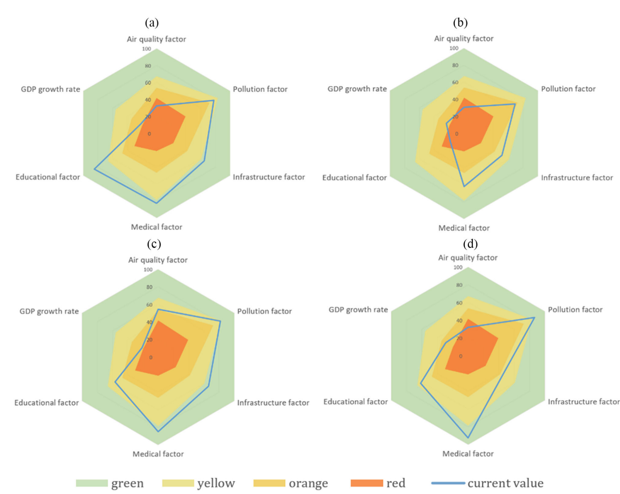

Fig. 4. Sustainability degree of indicators in 2015.

and pollution control factor are expected to reach the green level by 2030. The rapid development of the economic level may have a negative impact on air quality, so the air quality factor is slightly lower than the current grade. The environmental protection scenario maintains air quality and pollution control at green levels by 2030, but may inhibit the rapid development of the economic level, so the GDP growth rate is set to reach the red level. The social progress scenario is mainly related to human activities. Therefore, infrastructure factors, medical factors, and education factors are set to reach the green level in 2030. The social progress scenario cannot only realize sustainable social development but also promote the fairness of education and medical treatment and realize the fair and coordinated development of society. Since the economic foundation determines the superstructure and the improvement of the economic level is

TABLE II
DESCRIPTION OF THE SCENARIO SETTINGS IN EACH REGION

Scenarios	GDP growth rate	Air quality factor	Pollution control factor	Infrastructure factor	Medical factor	Educational factor
Reference scenario	🔵	🔵	🔵	🔵	🔵	🔵
Economic development scenario	🟢	🔴	🟢	🔵	🔵	🔵
Environmental protection scenario	🔴	🟢	🟢	🔵	🔵	🔵
Social progress scenario	🟠	🔵	🔵	🟢	🟢	🟢

where 🟢, 🟠, 🔴, 🔵 stand for the green, orange, red and actual levels, respectively, on the indicator board.

the prerequisite for rapid social development, the GDP growth rate is set to reach the orange level.

C. Multiscenario Land Use Simulation Based on the SDG-CA Model

The CA model has been widely applied to simulate the spatial evolution of land use [33]–[35]. The SDG-CA model was implemented herein by comprehensively considering the initial transfer probability of land use transformation, the empirical transfer weights between different land types, the influences of cell neighborhoods, the competition mechanism among various land types, and other constraint conditions. Spatial variables, including the population, DEM, slope, silt content, clay content, sand content, soil pH, temperature, precipitation, distance to city, distance to railway, and distance to road, were employed to represent the factors driving land use changes, as these variables are commonly used in land use change models [33], [36].

The initial probability of land use transformation was obtained by ANN model training. The empirical transfer weights were determined by calculating the transfer matrix of land use changes. Considering the neighborhood influence, the greater the number of a certain land type in the neighborhood of a cell, the greater the probability that the cell will be transformed into that land type. Land use transformation is a complex development process that reflects the complex interactions between different land types. The land type transition probability can be calculated by the following formula:

$$CP_{i,k}^{t} = P_{i,k}^{t} \cdot \Omega_{i,k}^{t} \cdot \omega \cdot P_{\text{cons}} \cdot r \tag{1}$$

where $CP_{i,k}^{t}$ is the combined probability of cell i transforming into land class k at time t; $P_{i,k}^{t}$ is the initial transition probability of cell i transforming into land class k at time t; $\Omega_{i,k}^{t}$ represents the influence of the neighborhood on the current cell, which is calculated in the iterative process; ω refers to the empirical transfer weights; P_{cons} represents the conditional constraints on the model transformation rules; and r represents a random variable between 0 and 1.

The main idea of the simulation is that a cell is transformed into the land type possessing a higher combination probability.

TABLE III
AVERAGE RELATIVE ERROR OF EACH LAND TYPE FOR THE SDG-SD MODEL (%)

Regions	Cultivated land	Forest	Grassland	Urban land	Water
Jiangsu	0.05	0.31	0.91	1.18	0.34
Zhejiang	0.31	0.34	1.08	2.98	1.31
Anhui	0.06	0.11	0.69	1.91	0.60
Shanghai	0.05	6.92	1.35	0.20	0.64

The demands of different land types obtained by the SDG-SD model were used to control the transformations of land types. The transformation process was continued until the total number of all land types under this scenario reached the land use demands obtained by the SDG-SD model.

IV. MODEL APPLICATION AND DISCUSSION

A. Application and Results

The proposed SDG-LUS model was applied to simulate the land use evolution under four sustainable development scenarios in the Yangtze river delta region. CCI land use data with a spatial resolution of 300 m from 2001 to 2015 were used for SDG-SD model training and to forecast the evolving land use demands from 2016 to 2030. GlobeLand30 land use data with a spatial resolution of 30 m in 2010 and 2020 were utilized for SDG-CA model training, and the SDG-oriented land use evolution was conducted from 2021 to 2030.

The relative error is commonly taken when applying an SD model to verify the model accuracy and obtain more accurate results [37]. The relative error between the estimated value and the real value of each land type from 2001 to 2015 and the average relative error of each land type in the four subregions are calculated accordingly, as given in Table III. The results show that the average relative error was less than 10%, which means that the simulation results could better fit the real land class changes [38].

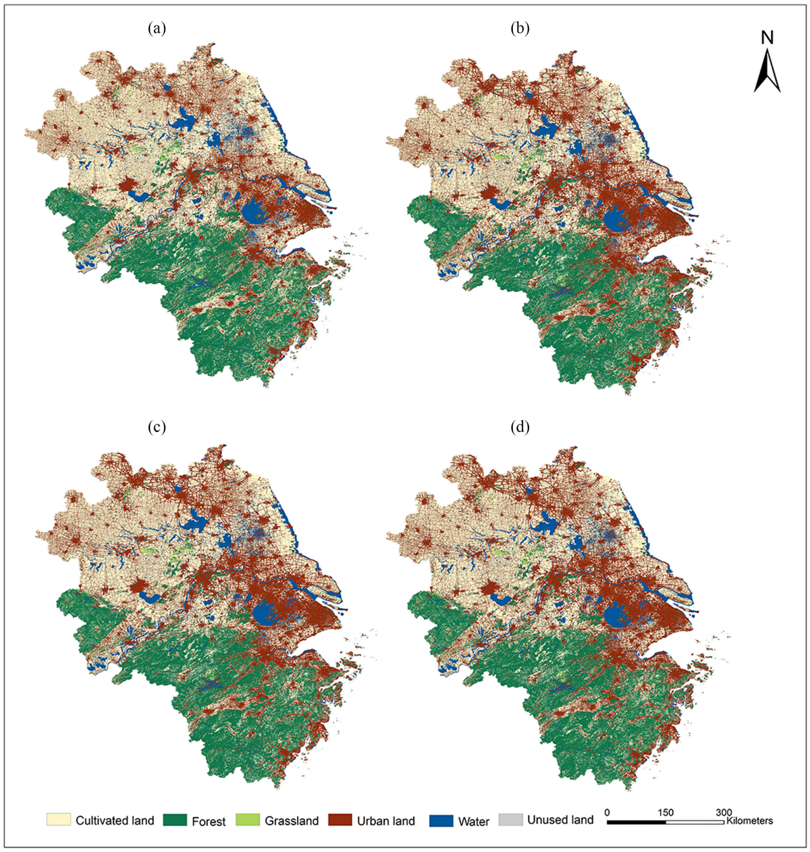

Fig. 5. Predicted land use distributions in 2030 under the four scenarios. (a) Reference scenario. (b) Economic development scenario. (c) Enviromental protection scenario. (d) Social progress scenario.

TABLE IV
ACCURACY OF THE SDG-CA MODEL

Evaluation index	Cultivated land	Forest	Grassland	Urban land	Water	Unused land
Precision(%)	80.61	88.53	72.22	74.80	72.60	78.49
Overall accuracy(%)	81.58					
Kappa	0.712					

GlobeLand30 data in 2010 and 2020 were used to calibrate the SDG-CA model. The predicted results in 2020 were compared with the GlobeLand30 data in 2020 to verify the accuracy of the SDG-CA model predictions. The precision of each land class, overall classification accuracy and kappa coefficient were utilized to quantitatively evaluate the accuracy of the SDG-CA model, as given in Table IV. The overall classification accuracy of the model was 81.58%, and the kappa coefficient was 71.22%. As an index to evaluate the classification accuracy, the kappa coefficient can effectively avoid the deviation caused by the overall classification accuracy. In this article, the kappa coefficient was greater than 0.7, which indicates a high degree of consistency between the two groups of samples [39]. The results showed that the land uses predicted in 2020 by the SDG-CA model were highly consistent with the real pattern in 2020. Therefore, the proposed SDG-CA model can be applied to simulate the land use changes from 2021 to 2030. The predicted land use distributions in 2030 under the four scenarios are shown in Fig. 5.

B. Discussion

Spatially, the northern part of the study area is dominated by cultivated land, while the southern part is dominated by forest. The urban land in the study area has shown obvious star-shaped outward growth over time, especially in the Taihu Lake basin and on both sides of the Yangtze River, which more than replaced the cultivated land area around the city. Based on SDG-SD model, the simulated land use distribution under the four scenarios in 2030 were statistically analyzed, the results of which are plotted as a pie chart is shown in Fig. 6, indicating that the main land types were cultivated land, forest, urban land, and water in the study area.

To further analyze the land use differences among the four scenarios, the land use areas relative to the reference scenario were statistically analyzed. Fig. 7 shows a bar chart of the differences among the land use areas. The areas of cultivated land, forest and grassland under the environmental protection scenario were slightly greater than those under the reference scenario, while the area of urban land was slightly lower than that under the reference scenario. The area of urban land use under

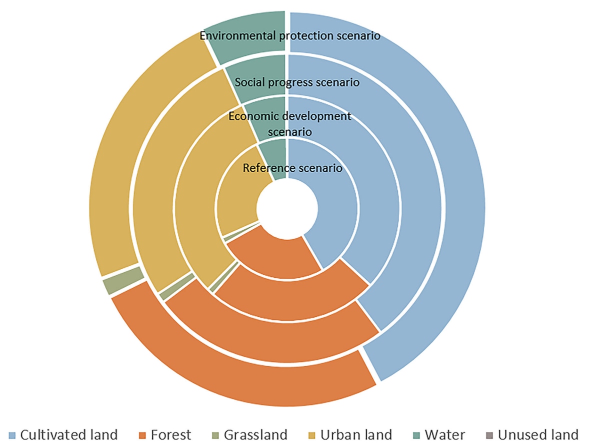

Fig. 6. Pie chart of land use areas.

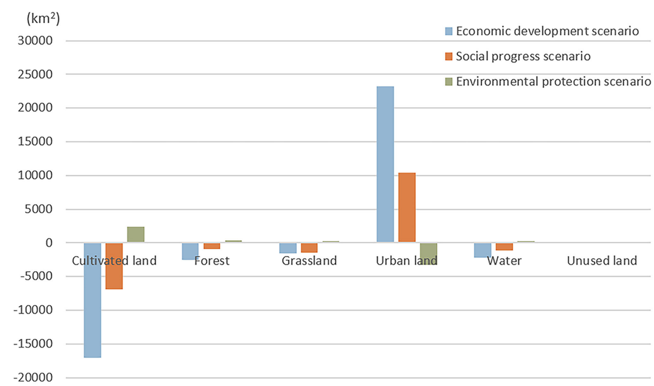

Fig. 7. Bar chart of the differences in land use areas relative to the reference scenario.

the economic development and social progress scenarios was significantly higher than that under the reference scenario, while the areas of cultivated land, forest, and grassland were significantly lower than those under the reference scenario. Moreover, the area of urban land under the economic development scenario was higher than that under the social progress scenario, while the area of the other land types was lower than those under the social progress scenario.

In summary, the reference scenario reflects the changes in land use with the current development trend; this scenario shows that urban land area will increase steadily with urbanization and economic development. The economic development scenario shows the changes in land use during rapid economic development; the urbanization process intensifies with economic and social development, and the degree of urban land expansion is intense, which has a certain negative impact on the development of cultivated land, forest, grassland, and water. The environmental protection scenario represents land use development when the sustainability of each environment-related indicator is relatively high; the urbanization process is sustainable under the coordinated development of the economy, society, and environment, which meets the requirements of the SDGs. The social progress scenario has the same level of economic development as the economic development scenario; however, the social infrastructure is more improved, the levels of medical care and education are better, and pollution control measures are carried out in a timely manner. Furthermore, the areas of cultivated land, forest and grassland under the social progress scenario are slightly greater than those under the economic development scenario. In general, these four scenarios can demonstrate the differences in land patterns considering different SDG indicators.

V. Conclusion

In the context of the UN SDGs, research on the sustainable use of land resources is crucial to achieving sustainable development. This article proposes an SDG-LUS model integrating SD and CA amid interactions among SDG indicators. In the model, four sustainable development scenarios, including reference, economic development, environmental protection, and social progress scenarios, were designed according to the values of various SDG indicators, which reflect different sustainability levels. The presented model was employed to simulate the spatiotemporal land use evolution in the Yangtze river delta, and its accuracy was verified.

There was significant land use transformation under each sustainable development scenario during the next ten years in the study area, and the changes in each scenario were different. Cultivated land, forest, grassland and water areas could be effectively protected under the environmental protection scenario, and the increase in urban land was less than that under the other three scenarios. The environmental protection scenario promoted the development of the ecological environments to a certain extent. Conversely, the increase in urban land under the economic development scenario and social progress scenario was higher than that under the other two scenarios, while the decrease in the areas of other land types was higher. The simulation results under the different scenarios can provide scientific suggestions for the planning and implementation of sustainable land use and provide support for promoting regional sustainable development.

In follow-up research, the internal correlation and interaction mechanism among SDG indicators will be further explored to summarize the regional geographical correlation and dynamic change regularity, which would be conducive to providing a scientific and effective comprehensive decision-making model for sustainable development.

VI. Data Availability Statement

The data that support the findings of this article are available at: https://geomodeling.njnu.edu.cn/dataItem/SDG-LUS.

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