The Forecast and Low-carbon Performance of Land-use in Rapid Urbanization Area under the Multi-objective Spatial Planning: Evidence from Hangzhou, China

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Abstract:
The introduction of the carbon peak and carbon neutral targets by many countries’ central governments has put low-carbon oriented spatial planning at the forefront of discussions. However, few studies have focused on the balance of carbon emission reduction and economic goals in spatial planning, and the influence of the planning on land-use low-carbon performance remains uncertain. This study addresses this gap by conducting an empirical analysis in the rapidly urbanizing area of Hangzhou, China, taking into consideration low-carbon constraints and economic development demands. Using the STRIPAT model and Linear Programming-Markov, we predicted land use structures under both low-carbon and baseline scenario, and simulated land use patterns by using Ann-CA. The results showed rapid growth in urban and forest land, and a decline in farm and rural land under the low-carbon scenario. Urban land change was concentrated in downtown districts and suburbs, while farm and forest land change was concentrated in exurban areas. The low-carbon performance of land-use was reflected in carbon storage release, carbon emission capability change, and low-carbon capability. The most common conversion of land-use categories under the low-carbon scenario was between farm and forest land, and between rural and urban land, which resulted in
less carbon storage release and carbon emissions compared to the baseline scenario.

Additionally, the compactness and fragmentation of construction land improved under the low-carbon scenario. This study sheds light on the impact of multi-objective spatial planning on urban land expansion, providing empirical evidence for city governments in rapid urbanization areas to improve land-use efficiency.

**Key words:** Land-use change; spatial plan; low-carbon; Linear programming-Markov; Hangzhou.
Introduction

Climate change has become a global issue in last decades. Land-use change (LUC) is one of the most significant causes of global warming, and is also the second largest source of carbon emissions from human activities, next to the fossil fuel burning (Houghton et al. 2012; Yu et al. 2019). With the increase of land utilization intensity, the area with “carbon storage” ability such as woodland and wetland decreased, while the construction land as the major space of carbon emission expanded rapidly, resulting in the continuous increase of the concentration of carbon dioxide (CO$_2$) in the atmosphere (Piao et al. 2018; X. Yang et al. 2022). During the past 150 years, land use change has released about 136 (±50) to 156 Pg of carbon into the atmosphere, accounting for more than 30% of the total human related carbon emissions. The concentration of carbon dioxide in the atmosphere increases from 280 PPM to 360 PPM, and the land use cover change contributed about 24% to the greenhouse effect (Houghton 1999; Klein Goldewijk and Ramankutty 2004). Different types of land use have different impacts on the natural land cover and the intensity of human activities, and thus affect natural and man-made carbon emission. As the areas with the most profound interference of human activities, urban area had huge land use changes and concentrated energy consumption, accounting for 75% of global carbon emission (World Bank 2013). Previous studies have found that excessive consumption of fossil fuels and rapid urban expansion have aggravated greenhouse gas emission, reduced the land carbon fixation capacity, and had a negative impact on the total benefits of urban land (Lu et al. 2022). The governments and scholars around the world have realized that it is possible to curb global warming by properly regulating land use change; however, the regulation of land use change is affected by many social and economic factors (Paudel and Thapa 2004; Long and Qu 2018), which makes the allocation of land resources could not completely meet the expected carbon emission reduction plan, especially in the rapid urbanized regions.
Furthermore, urban construction land is the spatial carrier of urban functions, and the change of its utilization efficiency directly affects the high-quality and sustainable development of urban system (B. Yang et al. 2017). Compared to that in the developed countries, urban land expansion in the developing countries is an inevitable outcome of their rapid socio-economic development. Over the past two decades, the global urban land has expanded by about 280 thousand square kilometers, mainly distributed in Asia and North America (MOST of PRC 2023). China, as one of the most important developing countries, was experiencing this rapid expansion of construction land scale, and also the rapid growth of carbon emissions. The urban land scale has increased from 248 thousand square kilometers in 2000 to 353 thousand square kilometers in 2020 (MNR of PRC 2020), while the carbon dioxide emissions accounted for 30.93% of the total global emission in 2020. Urban land not only provided the shelter for new citizens, but also became a factor of production for industrial development. As the “world factory”, China with its vast industrial land provides the foundation for the development of China’s traditional manufacturing and labor-intensive industries (Choy et al. 2013; Zhuang and Ye 2020). Considering the residential needs of an additional 100 million new citizens in the future, the further expansion of China’s urban land is foreseeable under the following steady and high-level urbanization rate scenario. Thus, how to balance the land use change, which is typical as the advent of social-economic development, and carbon emission reduction has become an important issue in China. In the Paris World Climate Conference 2015, Xi, the president of the People's Republic of China, announced that China will pursue to reach the carbon emission peak in 2030 and the carbon emission per unit of GDP decrease by 60% - 65% in 2030 compared with 2005, trying to balance the carbon emission reduction and economic development. The target was proposed in consideration of China's future development potential and international responsibility for globe warming. However, affected by the structure transformation of the world economy and changes in the international economic environment, such as the impact of the COVID-19, China is facing great pressure both
from the economic development and carbon emission reduction. Its traditional
development mode relying solely on increasing production factors input could no
longer support China's high-quality economic development (Feng and Wang 2019). This
is a big challenge for Chinese government to change the current socio-economic
development mode, which was closely related to the transformation of land use pattern,
and adapt to the comprehensive evolution requirements of land-eco-economic system.
The central and local governments must figure out how to continuously improve the
efficiency and quality of land use under the premise of energy conservation and
emission reduction, so as to regulate the amount, type and spatial layout of production
resources through land input, and finally realize the harmonious relationship between
social-economy and natural ecosystem. Taking Hangzhou as the study area, this paper
integrates the targets of both carbon emission reduction and economic development into
the land use evolution model, and analyzes the low-carbon performance of simulated
land-use layout, so as to estimate the implementation of low-carbon planning and
provide specific planning suggestions for municipal government.

**Literature Review**

**Land use change and carbon emission**

The carbon emissions caused by various land use are significantly different, while
the land use structure and land use distribution pattern determine the spatial variety of
carbon source and carbon storage (Dong et al. 2020; K. Wang et al. 2022). The
adjustment of land use structure and spatial layout will change the intensity of carbon
emission in natural and man-made processes (B. Yang et al. 2020; Lin et al. 2021).
Therefore, the carbon effect of regional land use should be evaluated comprehensively
to satisfy the demand of economic development and construction land use. As for
spatial planning, it is important to apply an appropriate land use structure and spatial
layout which are conducive to the carbon sequestration/emission reduction, and guide the formation of regional low-carbon land use mode through the carbon assessment of land use structure adjustment and land supply mode (G. Wang et al. 2021).

Land urbanization is an important phenomenon affecting carbon emission in the land use change. A case study in SMR proved that rapid land urbanization can promote both carbon emission and land surface temperature (Dewa and Buchori 2023). From 1850 to 1998, the carbon emissions caused by land urbanization accounted for 1/3 of the total emissions of human activities, while from 1950 to 2005, the cumulative carbon emissions from land urbanization in China were 10.6Pg, accounting for 30% of the total anthropogenic carbon emissions in China and 12% of the global carbon emissions of land use change in the same period (IPCC 2012). The combination of land-use category conversion and management had significant effect on vegetation and soil carbon storage (Lai et al. 2016). Besides, the impact of the land urbanization rate on carbon emissions was still uncertain. Some scholars found that the land urbanization contributed to the reduction of total regional carbon emissions, while others suggested that different stages of land urbanization had various relationship with carbon emissions (W. Zhang and Xu 2017; Lv et al. 2022). Because construction land is the main spatial carrier of carbon sources, relevant researches mainly focused on the carbon emission evaluation methods and models, or the impact of urban form on energy consumption. Some studies showed that land use layout affected carbon emissions by affecting urban transportation and residential energy consumption (Jung et al. 2022; Sha et al. 2020; X. Liu et al. 2020). The spatial characteristics of construction land, such as the land landscape index and polycentricity structure, are also strongly correlated with carbon emissions. There are few studies analyzing the relationship between land use layout and residential carbon emissions, which may be partly due to the fact that the rapid growth of transport energy consumption is a more difficult problem for urban planning and policy makers. In addition, the reduction of residential carbon emissions is considered to be more relevant to the energy efficiency and the application of
renewable energy, but not to land use layout. Still, some scholars have found that in the compact land use layout with high population density, due to the high-volume ratio of land use, the per capita exposed area of the building is smaller, thus reducing the indoor and outdoor heat exchange and achieving the effect of reducing carbon emissions (Ewing and Rong 2008; Lee and Lee 2014). Through the systematic design of the future land use structure and layout considering carbon emission and economic goals, the land use system could embody the potential of “carbon storage”, storing atmospheric greenhouse gases in the biological carbon pool and reducing carbon emissions. In order to better achieve this goal, it is urgent to deepen the understanding of the driving factors of land urbanization on urban carbon emissions. Meanwhile, using a scientific simulation model based on the previous analysis, including the combination of multi-objective constraint model and system dynamics model, the optimal allocation of land resources could be effectively realized under the comprehensive consideration of minimizing land use carbon emissions and maximizing economic benefits of land use.

Chinese land use regulation system

Spatial planning is a spatio-temporal strategic deployment and overall arrangement for the rational use of land, including development, utilization, renovation and protection, according to the natural attributes of land resources and the actual needs of social-economic development (Y. Chen et al. 2016; T. Liu et al. 2020). It is an important policy for the governments to carry out macro-control of land and reasonably allocate land resources (Zhou et al. 2017). In China, spatial planning, which was called land use planning before 2018, is also a significant component of land system. After the reform and opening up in the late 1970s, China’s land use planning system was established according to the Land Management Law. It was a top-down and level-by-level land management system, including land quota system and land zoning (Fang and
This land planning system is generally characterized by centralized control, strongly affected by the previous system of long-term planned economies (Tan and Zhou 2015). In addition, urban-rural planning was also another land use planning tool applied by the China’s local governments at that time. Different from the overall planning of land resource which includes construction land and non-construction land in land use planning, urban-rural planning focuses more on the various types of construction lands. Besides, urban-rural planning represents the local social-economic development demands better, and is a typical product of land management in decentralization (Yeh and Wu 1999). Therefore, with the rapid development of social-economic and the acceleration of urbanization, the contradiction between these two kinds of planning has become increasingly prominent. In 2018, the Chinese State Council merged the original land use planning with the urban-rural planning to established the land spatial planning system as a new policy tool for land and natural resources management.

By 2018, land use planning and urban-rural planning have promoted the low-carbon planning exploration and related research respectively. In urban-rural planning, low-carbon city planning was its core practical field of work, involving its development mode, planning framework design, planning strategy and carbon emission reduction technology, etc. (L. Yang and Li 2013; Cheshmehzangi et al. 2018). Through practical cases and experimental analysis, scholars studied the relationship between urban spatial form and carbon emission reduction, and proposed development models such as zero-carbon emission community and positive climate city (Zhu et al. 2022; Urge-Vorsatz et al. 2018). Besides, the evaluation of low-carbon urban planning, the assessment of green space carbon storage function, and the renewal of low-carbon oriented urban gradually received more attention. Meanwhile, scholars engaged in land use planning mainly focused on the impact of natural factors such as water and soil on the carbon emissions from forestry, agriculture or other single land type (Zhao et al. 2018; Bossio et al. 2020). In the mesoscale study, the relationship between regional ecosystem service
value and carbon emissions and the spatial heterogeneity of land use carbon emissions has been extensively discussed (Saha et al. 2022; Deng et al. 2021). Macro-scale researches proposed low-carbon development directions and strategies for various regions on the basis of the spatial differences of land use carbon budget in each country (Friedlingstein et al. 2019; Ciais et al. 2021).

Due to the reform of spatial planning system and the proposal of the “dual-carbon strategy” by Chinese central government, the extant researches focusing on a certain land use type were not enough to support the overall governance of the whole land space. How to achieve the "dual-carbon" goal through the spatial planning system, which is multi-scale, multi-element and multi-agent, has become a hot topic in this field. Some scholars have predicted five important inflection points in the process of achieving carbon neutralization and their impact on spatial planning, and further proposed the planning implementation method from the perspective of supply-side structural reform of space resources (Cui and Zhu 2022; Yan and Yang 2021). Spatial planning would affect the changes in the scale, structure, layout and intensity of land use through four basic regulatory means, including spatial boundary control, land use control and land development index control, forming a binding mechanism for the carbon emissions of land use and a governance framework for the implementation of carbon emission reduction. Some studies have also established a carbon-neutral evaluation system for spatial planning and linked it with the official spatial planning goals and control indicators (Weng et al. 2021; Nieuwenhuijzen 2020). Considering that China's spatial planning is still in its infancy, the target indicators, development strategies and spatial layout related to "dual-carbon" have not been included in the planning guidelines and standards. The current guidelines of city-level spatial planning only emphasize the leading and controlling role of planning in the energy field, lacking of clear carbon emission reduction targets and spatial implementation methods. It also lacks an effective transmission mechanism and implementation supervision means, due to which it is difficult to constitute a comprehensive and effective guidance of carbon
emission reduction and carbon storage increase.

In general, neither theoretical researches nor practical guidelines have much to do with the "dual-carbon" strategy in China’s land spatial planning. The exploration on how to integrate low carbon goals into the five levels of spatial planning system and the whole life cycle of land management system, such as the planning approval, implementation supervision, and effectiveness evaluation, is insufficient. Therefore, it is challenging to prioritize carbon emission reduction in spatial planning, and even more difficult to evaluate the low-carbon effects of land use after the implementation of the spatial planning, which is crucial for verifying the guidance of low-carbon oriented planning.

Methodology and Data

Methodology

This study will transform the relevant low-carbon planning policies and socio-economic development demands into objective functions and constraints firstly. Second, based on the STIRPAT model and carbon emission data, we are going to predict the carbon emissions during 2018 to 2035. The weight of carbon emission targets $\alpha$ will be calculated according to the carbon emission prediction results and economic goals, and therefore build a linear programming model. Next, the model will be integrated into Markov to predict the land use structure that meets the requirements of low-carbon planning. We are going to input the predicted results into Ann-CA, and the land use pattern of low-carbon scenario and baseline scenario will be simulated. Finally, the low carbon performance of the two simulation results in terms of spatial morphology and land-use change are analyzed. The specific research framework is shown as follows:
The STIRPAT model is derived from the IPAT model, which grew out of the discussions taking place in the 1970s about the impact of population on the environment (Commoner 1972; Ehrlich and John P. Holdren 1971). Among IPAT applications, climate change is particularly popular, especially in the energy-related studies (Tang 2022), yet the research areas are diverse.

According to IPAT model, the root causes of environmental degradation are population growth and economic development, while technological development can eliminate these adverse effects. Therefore, environmental impact (I) is the product of three factors: population (P), affluence (A) and technology (T), and the corresponding function is shown as follows:

\[ I = P \cdot A \cdot T \]

In order to eliminate the influence of the assumption that “all factors affect the environment in equal proportion” on the regression, the IPAT model is extended to
random form and the STIRPAT model is built as follows:

\[ I = aP^bA^cT^d e \]

In the function, a, b, c and d are the coefficients of model, population, affluence and technology respectively, and e is the random error to convert the function logarithmically, which is shown as follows:

\[ \ln I = \ln a + b\ln P + c\ln A + d\ln T + \ln e \]

In this study, the environmental impact (I) refers to carbon emissions (CE), the population (P) consists of total population (TP) and Non-agricultural population (NAP), the affluence (A) would take GDP per capita (GPC) together with its second and third power into consideration, and the technology (T) is embodied in industrial output value (IOV). Input \( x_1 = \ln(\text{TP}) \), \( x_2 = \ln(\text{NAP}) \), \( x_3 = \ln(\text{GPC}) \), \( x_4 = (x_3)^2 \), \( x_5 = (x_3)^3 \), \( x_6 = \ln(\text{IOV}) \) to construct the following regression equation, which is the carbon emission prediction model:

\[ \ln CE = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + a_6x_6 + \varepsilon \]  

(1)

### Linear programming-Markov

In the field of land use research, Markov model is widely used to predict land use structure (Das and Sarkar 2019; Kang et al. 2019), which however generally cannot meet the requirements of land policies. This study is going to use the coupling model of linear programming and Markov to predict the land use structure that meets the requirements of low-carbon policy, which consists of the following steps:

(1) The unadjusted Markov matrix P will be obtained based on the land use data, that is t-k and t.

(2) Build the objective function as follows:

\[ f(S) = \sum_{i=1}^{m} z_i s_i^t, z_i = \alpha g_{i1} + (1 - \alpha) g_{i2} \]  

(2)
The function includes both carbon emission targets and economic benefit targets, and the weight of the former is $\alpha$. $g_{i1}$ and $g_{i2}$ stand for the average CO$_2$ equivalent index and the average economic benefit index in different land use categories respectively, and $s^t_i$ is the area of $i$ at the time $t$. In order to facilitate calculation, 30m*30m pixel (pix) is taken as the statistical unit of area in this study, and $s^t_i \in N^*$. The objective function and constraint conditions set on relevant policies are integrated into the following linear programming model:

$$\begin{cases} 
\text{Max} f(S) = \sum_{i=1}^{m} z_i s^t_i \\
\text{s.t} \\
S_t \cdot P^k = S_{t+k} \leq (\geq) B_{t+k} \\
Q S^t_i \leq U 
\end{cases}$$

(3)

$S_{t+k}$ and $B_{t+k}$ are the matrix composed of the area $s^{t+k}_i$ and its control index $b^{t+k}_i$ at the time $t+k$. $P^k = \prod_{k=1}^{K} P$, and U and Q refers to other constraint parameters. Formula (3) is used to calculate the optimal solution $S^*_t$.

The formula is defined as $P^* = P + P_a$, where $P_a$ is the regulatory matrix, and satisfies $P_a = P_c \cdot P_m$, in which $P_c = \begin{bmatrix} C_1 & 0 & \cdots & 0 \\
0 & C_2 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & C_m \end{bmatrix}$, where $C_1 - C_m$ indicates the control parameter, and $P_m = \begin{bmatrix} 1 & -\frac{1}{m-1} & \cdots & -\frac{1}{m-1} \\
\frac{1}{m-1} & 1 & \cdots & -\frac{1}{m-1} \\
\frac{1}{m-1} & \frac{1}{m-1} & \ddots & \vdots \\
\vdots & \vdots & \ddots & 1 \end{bmatrix}$. Therefore,$P_a = \begin{bmatrix} C_1 & -\frac{1}{m-1} C_1 & \cdots & -\frac{1}{m-1} C_1 \\
-\frac{1}{m-1} C_2 & C_2 & \cdots & -\frac{1}{m-1} C_2 \\
\vdots & \vdots & \ddots & \vdots \\
-\frac{1}{m-1} C_m & -\frac{1}{m-1} C_m & \cdots & C_m \end{bmatrix}$, where $m$ stands for the number of land use categories, and $P^*$ is the Markov matrix under the circumstance of low-carbon policy. In addition, we define:

$$W_t = S^*_t - S_t$$
$W_t = S_{t-k} \cdot P_a$

The formulae are transformed into a matrix equation:

$$
\begin{bmatrix}
  s_1^{t-k} & -\frac{1}{m-1}s_2^{t-k} & \cdots & -\frac{1}{m-1}s_m^{t-k} \\
  -\frac{1}{m-1}s_1^{t-k} & s_2^{t-k} & \cdots & -\frac{1}{m-1}s_m^{t-k} \\
  \vdots & \vdots & \ddots & \vdots \\
  -\frac{1}{m-1}s_1^{t-k} & -\frac{1}{m-1}s_2^{t-k} & \cdots & s_m^{t-k}
\end{bmatrix} \ast
\begin{bmatrix}
  C_1 \\
  C_2 \\
  \vdots \\
  C_m
\end{bmatrix} =
\begin{bmatrix}
  W_1^t \\
  W_2^t \\
  \vdots \\
  W_m^t
\end{bmatrix}
$$

Based on equation (4), we are able to obtain the regulatory parameter $C_1$-$C_m$ and then $P_a$ and $P^*$ accordingly. We also define:

$$S_{t+k}^a = S_t \cdot P^*, S_{t+k}^{una} = S_t \cdot P$$

In the formula, $S_{t+k}^a$ is the land use structure under the low carbon constraint, while $S_{t+k}^{una}$ is the land use structure under the baseline scenario.

**Artificial-neural-network-based cellular automata**

In essence, Cellular Automata (CA) is a kind of network dynamics model, which is characterized by discrete time, space and state, and simulates the spatio-temporal evolution process of complex systems according to spatial interaction and temporal causality. The model has been widely used to simulate the spatial pattern of land use, landscape and other factors (Q. Wang and Wang 2022; J. Yang et al. 2019). CA modeling is mainly to learn the historical change process and obtain evolutionary rules through data mining, and its modeling methods include Logistic-regression-based cellular automata (LR-CA), Principal-components-analysis-based cellular automata (PCA-CA), and Artificial-neural-network-based cellular automata (ANN-CA). Compared with the first two methods, the evolution rules obtained through ANN-CA are more accurate and its simulation accuracy is higher. The formula of CA model is as follows:

$$S_{t+1} = f(S_t, N)$$
\( S_t \) and \( S_{t+1} \) are finite and discrete state sets of the cellular at time \( t \) and \( t+1 \). \( N \) is the area of the cellular, \( t \) and \( t+1 \) stand for different moments, and \( f \) the conversion rule of the cellular.

CA simulation accuracy will be tested through Kappa coefficient. When \( 0 < \text{Kappa} < 0.4 \), the consistency between the simulated prediction results and the actual results is not ideal. When \( 0.4 \leq \text{Kappa} < 0.75 \), the degree of consistency is general and the simulation prediction accuracy is medium. When \( \text{Kappa} \geq 0.75 \), it indicates that the simulation prediction result is highly consistent with the actual result, and the simulation effect is satisfied, that is passing the accuracy test.

Study area

Hangzhou is located in the southern Yangtze River Delta, adjacent to Shanghai. It is the capital of Zhejiang Province and is also one of the most developed metropolises in China. In 2020, the regional Gross Domestic Product (GDP) of Hangzhou is 1610.6 billion yuan, ranking sixth in mainland China. Although Hangzhou has undergone a very rapid urbanization process in the past 30 years, it will still maintain a relatively fast pace of urbanization growth in the next 10-20 years. Therefore, in 2022, Hangzhou municipal government unveiled a guiding document to peak carbon emission in 2030 and realize carbon neutrality goals in 2060, in which it proposed a series of planning strategies for the implementation of Hangzhou’s “dual-carbon goals”.

This study selected ten urban districts of Hangzhou city as the study area, which include the newly demarcated urban area—Shangcheng District, Xiacheng District, Gongshu District, Xihu District, Jianggan District, Binjiang District, Yuhang District, Xiaoshan District, Fuyang District and Linan District. Shangcheng District, Xiacheng District, Gongshu District, Xihu District, Jianggan District and Binjiang district have been regarded as urban areas before 2001. Therefore, in this study, we integrate these five districts as the “downtown districts”. Besides, Yuhang District and Xiaoshan
District were classified as urban area since 2001, so we define these two districts as the “suburbs”. In addition, Fuyang District and Linan District were classified as urban area in 2014 and 2017 respectively, so we define these two districts as the “exurbans”.

Data source

The data used in this study include spatial data and non-spatial data. Spatial data consist of land use data, network big data and digital elevation model (DEM) data. The land use data are derived from 30m precision land use raster data of
Chinese Academy of Sciences, including those in 2000, 2010 and 2020. Network big data includes POI data and road data, which are obtained through Baidu Map platform. DEM data is 30m precision DEM which was came from local government of Zhejiang Province.

Non-spatial data cover carbon emission data and socio-economic data. The CO\textsubscript{2} emission estimation data based on the study area from 1997 to 2017 used in this study are originated from the data of 2,735 counties in China(J. Chen et al. 2020), through unifying DMSP/OLS and NPP/VIIRS satellite images by particle swarm optimization and back propagation (PSO-BP) algorithm. Social and economic data, including total population, non-agricultural population, per capita GDP and industrial output value in the study area, are obtained through Hangzhou Statistical Yearbook over the years.

Data processing platforms in this study include ArcGIS10.8, SAS9.4 and FLUS V2.4.

Results

The linear programming of spatial planning from the perspective of the low-carbon constraint and economic development.

Lasso regression model is a kind of compression estimation. It obtains a relatively refined model by constructing a penalty function, which makes it compress some regression coefficients and at the same time set some regression coefficients to zero, so it retains the advantage of subset shrinkage. Moreover, Lasso model itself can also deal with the multicollinearity problem of data(McEligot et al. 2020). Based on the formula (1), the following regression equation is obtained by Lasso regression model, through which $R^2$ is 0.9953, the adjusted $R^2$ is 0.9936, $P\leq 0.0001$, and the goodness of fit is high.
\[ \ln CE = 209.6633 + 1.1831x_2 - 62.1864x_3 + 5.6945x_4 - 0.1757x_5 + 0.9861x_6 + \varepsilon \]

Carbon emissions in study area during 2018-2020 are obtained by substituting the existing population and economic data during 2018-2020 into the regression equation, where \( CE_{2020} = 54.75 \text{Mt} \). Next, the number of non-agricultural populations, per capita GDP and industrial output value in 2021-2035 are estimated through arima method (Barak and Sadegh 2016; Fan et al. 2021), and they are adopted in the regression equation to obtain the carbon emissions in 2021-2035, where \( CE_{2030} = 44.58 \text{Mt} \). As the city government’s carbon peaking and carbon neutrality goals mentioned, by 2030, carbon dioxide emissions per unit of GDP should be decreased by more than 75% compared with 2005, that is:

\[ \frac{CE_{2030}}{GDP_{2030}} \leq 0.25 \times \left( \frac{CE_{2005}}{GDP_{2005}} \right) \]

\[ CE_{2030} \leq 75.88 \text{Mt} \]

Obviously, the estimated \( CE_{2030} \) meets this requirement.

It is found that the amount of carbon emissions presented a continuous growth from 1998 to 2012 and peaked at 59.95 Mt in 2012, and from 2013 to 2021 it showed a fluctuating decline. It is estimated that carbon emissions showed a downward trend from 2022 to 2035, falling by 25.64% in 2035 compared with 2012 (as shown in Fig.3).

![Fig.3 the carbon emission of Hangzhou in 1998-2035](image)
The expected deadline of the carbon peak policy in China is 2030, and the period is 2020-2030, so the weight of carbon emission targets \( \alpha = \frac{CE_{2030}}{CE_{2020}} \), and the calculated \( \alpha = 0.8142 \).

In this study, the land use raster data was reclassified into 6 land use categories, namely farm land, forest land, grassland, water area, urban construction land and rural land, corresponding to \( i = 1, 2, 3, 4, 5, 6 \) respectively. \( g_{i1} \) and \( g_{i2} \) are obtained referring to the statistical yearbook and relevant papers. Then combine the calculated weight \( \alpha \), let \( t = 2020 \), \( k = 10 \), and use formula (2) to get the objective function:

\[
f(S) = 1.1565s_{12020} + 1.6727s_{22020} + 0.0532s_{32020} + 1.1365s_{42020} - 62.8400s_{52020} - 0.0947s_{62020}
\]

Based on the present situation of land use and relevant policies, such as the carbon peaking and carbon neutrality goals, the *Overall Urban Planning of Hangzhou (2001-2020)*, the *Master Plan for Land Use of Hangzhou (2006-2020)*, and the *14th Five-Year Plan for Farm land Protection in Hangzhou*, constraint conditions are set, and equation (3) is used to obtain the linear programming model as follows:

\[
\begin{align*}
\text{Max} f(S) &= 1.1565s_{12020} + 1.6727s_{22020} + 0.0532s_{32020} + 1.1365s_{42020} - 62.8400s_{52020} - 0.0947s_{62020} \\
\text{s.t.} \quad &s_{12020} + s_{22020} + s_{32020} + s_{42020} + s_{52020} + s_{62020} = 9226130 \\
& s_{12030} \geq 2065133 \\
& s_{22020} \geq 5209555 \\
& s_{32020} \geq 131716 \\
& s_{42020} = 370933 \\
& 728669 \leq s_{52020} \leq 815168 \\
& 327176 \leq s_{62020} \leq 411985 \\
\end{align*}
\]

\( S_{2020} = [2305085 \ 5362551 \ 131716 \ 370933 \ 728669 \ 327176] \) is the optimal solution, among which the area of farm land is 2305085pix, the area of woodland is 5362551pix, the area of grassland is 131716pix, the area of water is 370933pix, the area of urban construction land is 728669pix, and the area of rural land is 327176pix.
Change of land-use structure and land-use spatial distribution

First, based on the land use data of the study area in 2010 and 2020, the unadjusted state transition matrix $P$ is obtained as follows:

$$P = \begin{bmatrix}
0.8549 & 0.0188 & 0.0005 & 0.0032 & 0.0861 & 0.0365 \\
0.0091 & 0.9827 & 0.0017 & 0.0003 & 0.0043 & 0.0018 \\
0.0075 & 0.0504 & 0.9210 & 0.0128 & 0.0076 & 0.0007 \\
0.0211 & 0.0036 & 0.0002 & 0.9506 & 0.0215 & 0.0029 \\
0.0129 & 0.0052 & 0.0044 & 0.0018 & 0.9730 & 0.0025 \\
0.0451 & 0.0084 & 0.0004 & 0.0019 & 0.0105 & 0.9336 \\
\end{bmatrix}$$

Second, $S_{2020}$ and formula (4) are used to obtain the regulatory parameters $C_1 - C_m$, and then the regulatory matrix $P_a$ and the adjusted state transition matrix $P^*$ are obtained:

$$P_a = \begin{bmatrix}
0.0085 & -0.0017 & -0.0017 & -0.0017 & -0.0017 & -0.0017 \\
-0.0051 & 0.0256 & -0.0051 & -0.0051 & -0.0051 & -0.0051 \\
-0.0105 & -0.0105 & 0.0527 & -0.0105 & -0.0105 & -0.0105 \\
-0.0036 & -0.0036 & -0.0036 & 0.0181 & -0.0036 & -0.0036 \\
0.0228 & 0.0228 & 0.0228 & 0.0228 & -0.1140 & 0.0228 \\
0.0390 & 0.0390 & 0.0390 & 0.0390 & 0.0390 & -0.1952 \\
\end{bmatrix}$$

$$P^* = \begin{bmatrix}
0.8634 & 0.0171 & -0.0012 & 0.0000 & 0.0844 & 0.0348 \\
0.0040 & 1.0000 & -0.0035 & 0.0000 & -0.0008 & -0.0033 \\
0.0000 & 0.0000 & 0.0000 & 1.0000 & 0.0000 & 0.0000 \\
0.0357 & 0.0280 & 0.0272 & 0.0000 & 0.8590 & 0.0253 \\
0.0841 & 0.0475 & 0.0394 & 0.0000 & 0.0496 & 0.7384 \\
\end{bmatrix}$$

Finally, based on formula (5), $S_{2030}^a$ and $S_{2030}^{una}$ are obtained:

$$S_{2030}^a = \begin{bmatrix}
2065133 & 5339923 & 144576 & 370933 & 915866 & 385603 \\
\end{bmatrix}$$

$$S_{2030}^{una} = \begin{bmatrix}
2041247 & 5179418 & 134945 & 370933 & 1018485 & 481101 \\
\end{bmatrix}$$

Based on ANN-CA model, this study predicts the land use spatial distribution in 2030 under two scenarios: low-carbon scenario and baseline scenario. Low-carbon scenario takes into consideration of carbon emission reduction and economic development, while the baseline scenario only thinks about the economic growth target. Firstly, 15 driving factors (as shown in Table.1) are selected, and the transfer probability maps of different land use categories obtained by ANN analysis are used to generate...
the suitability atlas of land use transition.

Table 1: The statistical description of driving factors

<table>
<thead>
<tr>
<th>Category</th>
<th>Indicators</th>
<th>Variable name</th>
<th>min</th>
<th>max</th>
<th>avg</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Natural factor</strong></td>
<td>Natural factor</td>
<td>Altitude ( y_1 )</td>
<td>0</td>
<td>1</td>
<td>0.1290</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Slope ( y_2 )</td>
<td>0</td>
<td>1</td>
<td>0.1745</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Distance to river ( y_3 )</td>
<td>0</td>
<td>1</td>
<td>0.2473</td>
</tr>
<tr>
<td><strong>Neighborhood factor</strong></td>
<td>Distance to main elements of the city</td>
<td>Distance to urban trunk road ( y_4 )</td>
<td>0</td>
<td>1</td>
<td>0.1731</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Distance to urban main center ( y_5 )</td>
<td>0</td>
<td>1</td>
<td>0.3893</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Distance to urban sub-center ( y_6 )</td>
<td>0</td>
<td>1</td>
<td>0.3336</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Distance to urban scenic area ( y_7 )</td>
<td>0</td>
<td>1</td>
<td>0.3192</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Distance to urban main innovation industrial parks ( y_8 )</td>
<td>0</td>
<td>1</td>
<td>0.3540</td>
</tr>
<tr>
<td></td>
<td>Density of main urban facilities</td>
<td>Density of rail transit station ( y_9 )</td>
<td>0</td>
<td>1</td>
<td>0.2908</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Density of bank ( y_{10} )</td>
<td>0</td>
<td>1</td>
<td>0.2347</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Density of shopping center ( y_{11} )</td>
<td>0</td>
<td>1</td>
<td>0.2284</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Density of general hospitals ( y_{12} )</td>
<td>0</td>
<td>1</td>
<td>0.2363</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Density of government agencies ( y_{13} )</td>
<td>0</td>
<td>1</td>
<td>0.3014</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Density of universities ( y_{14} )</td>
<td>0</td>
<td>1</td>
<td>0.2764</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Density of 550kv substation ( y_{15} )</td>
<td>0</td>
<td>1</td>
<td>0.3044</td>
</tr>
</tbody>
</table>

Second, the land use data of the study area in 2000 and 2010 are input into CA to simulate and predict the land use pattern in 2020, and the comparison is made with the existing land use data in 2020 to verify the simulation accuracy. The calculated Kappa coefficient is \( 0.88 \geq 0.75 \), which passes the accuracy test. Finally, \( S_{2030}^L \) and \( S_{2030}^{una} \) are input into ANN-CA, and the weights of all land use categories are adjusted to simulate land use patterns in the study area under low-carbon scenario and baseline scenario (as shown in Fig.4).
This study mainly focuses on two specific contents, one is the land-use capability of carbon storage or carbon emission, and the other is the low-carbon capability which would influence the energy consumption behaviors, such as private cars’ transportation.

Land-use capability of carbon storage and carbon emission

According to the carbon storage capability of land-use, five land-use categories can be sorted in descending order: forest land, grass land, farm land, urban land and rural land. When the land category with high capability are converted to the low capability category, part of the original carbon storage would be released. Meanwhile, the carbon emissions are concentrated in construction land categories, with urban land being stronger than rural land. The other four land categories generate carbon absorption and the strongest one among them are forest land. When the carbon absorption land category convert to the carbon emission ones or the land category with high carbon absorption capability are converted to the low capability ones, the total
carbon emission capacity will be enhanced. Thus, no matter the land-use carbon storage capability or the carbon emission capability, the key to affecting the comprehensive capacity are the scale of different land-use categories and the conversion amount between different land-use categories.

(1) Change of land-use structure

Under the baseline scenario, the carbon emission capability would grow due to the rising amount of construction lands, while the carbon storage capability would decline compared to that in 2020. However, when considering the low-carbon planning constraint, the growth rate of land-use categories that bears carbon emissions activities is decrease, while the scale of land category that has carbon absorption also increases significantly.

The scale of grassland and urban construction land increase in both scenarios compared to 2020. The growth rates of grassland under low-carbon scenario and baseline scenario are 9.76% and 2.45% respectively, and those of urban construction land are 12.35% and 24.94%. The size of farm land decreases in both scenarios, with growth rates of -9.69% and -10.74% respectively. Both forest land and rural land present significant differences between the two scenarios. Under the low-carbon scenario, forest land increases by 2.5% compared with 2020, but decreases by 0.58% under the baseline scenario. Rural land use increases by 16.78% under the baseline scenario but decreases by 6.4% under the low-carbon scenario (as shown in Table.2).

Table.2 The scale change and growth rate of land use in two scenarios

<table>
<thead>
<tr>
<th>The area change in low-carbon scenario</th>
<th>Farm land</th>
<th>Forest land</th>
<th>Grass land</th>
<th>Water</th>
<th>Urban land</th>
<th>Rural land</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-221639.2</td>
<td>130368.1</td>
<td>12859.94</td>
<td>0</td>
<td>100698.17</td>
<td>-26381.64</td>
</tr>
<tr>
<td>The area change in baseline scenario</td>
<td>-245526</td>
<td>-30137</td>
<td>3229</td>
<td>0</td>
<td>203317</td>
<td>69116</td>
</tr>
<tr>
<td>The area growth rate in low-carbon</td>
<td>-9.69%</td>
<td>2.50%</td>
<td>9.76%</td>
<td>0.00%</td>
<td>12.35%</td>
<td>-6.40%</td>
</tr>
</tbody>
</table>
The area growth rate in the baseline scenario is as follows:

-10.74%  -0.58%  2.45%  0.00%  24.94%  16.78%

The proportions of farm land decrease in both scenarios; specifically, there is a 2.40% and 2.66% decrease under the low-carbon scenario and baseline scenarios respectively. The proportions of grassland and urban construction land area increase under the two scenarios, and the proportion of the former increases by 0.14% and 0.03%, while that of the latter increases by 1.09% and 2.20%. Forest land and rural land area show significant difference under the two scenarios, that is the proportion of the former increases by 2.5% under the low-carbon scenario and slightly decreases by 0.58% under the baseline scenario, while the latter decreases by 0.29% under the low-carbon scenario and increases by 0.75% under the baseline scenario (as shown in Table.3).

Table.3 The structure change of land use in two scenarios

<table>
<thead>
<tr>
<th>The land area</th>
<th>Farm land</th>
<th>Forest land</th>
<th>Grass land</th>
<th>Water</th>
<th>Urban land</th>
<th>Rural land</th>
</tr>
</thead>
<tbody>
<tr>
<td>proportion change in low-carbon scenario</td>
<td>-2.40%</td>
<td>1.41%</td>
<td>0.14%</td>
<td>0.00%</td>
<td>1.09%</td>
<td>-0.29%</td>
</tr>
<tr>
<td>proportion change in baseline scenario</td>
<td>-2.66%</td>
<td>-0.33%</td>
<td>0.03%</td>
<td>0.00%</td>
<td>2.20%</td>
<td>0.75%</td>
</tr>
</tbody>
</table>

Compared with the baseline scenario, the increment of urban construction land under the low-carbon scenario is reduced by 7801pix in the downtown districts, 250,36pix and 37,737pix in the suburbs (i.e. Yuhang and Xiaoshan), and 238,13pix and 10390pix in the exurbs (i.e. Fuyang and Lin’an).

However, under the low-carbon scenario, the increment of farm land in the downtown districts increases by 15365pix compared with the baseline scenario, that of
suburbs like Yuhang and Xiaoshan increase by 49516pix and 63990pix respectively, while as for exurbans, Fuyang and Lin’an decrease by 10967pix and 93140pix. In terms of forest land, under the low-carbon scenario, the land use increment of the downtown district increases by 2993pix compared with the baseline scenario, that in the suburbs of Yuhang and Xiaoshan increase by 15342pix and 4183pix, and that in the exurbans like Fuyang and Lin’an increase by 32362pix and 106757pix respectively (as shown in Table.4).

Table.4 The land use scale change of different urban districts in two scenarios

<table>
<thead>
<tr>
<th></th>
<th>Farm land</th>
<th>Forest land</th>
<th>Grass land</th>
<th>Water</th>
<th>Urban land</th>
<th>Rural land</th>
</tr>
</thead>
<tbody>
<tr>
<td>Downtown district</td>
<td>15365</td>
<td>2993</td>
<td>-1358</td>
<td>0</td>
<td>-7801</td>
<td>-10880</td>
</tr>
<tr>
<td>Yuhang district</td>
<td>49516</td>
<td>15342</td>
<td>-423</td>
<td>0</td>
<td>-25036</td>
<td>-38778</td>
</tr>
<tr>
<td>Xiaoshan district</td>
<td>63990</td>
<td>4183</td>
<td>13</td>
<td>0</td>
<td>-37737</td>
<td>-30945</td>
</tr>
<tr>
<td>Fuyang district</td>
<td>-10967</td>
<td>32362</td>
<td>11288</td>
<td>0</td>
<td>-23813</td>
<td>-11197</td>
</tr>
<tr>
<td>Linan district</td>
<td>-93140</td>
<td>106757</td>
<td>123</td>
<td>0</td>
<td>-10390</td>
<td>-3403</td>
</tr>
</tbody>
</table>

(2) Conversion of land-use categories

Land-use conversion process are completely different under the two scenarios. Under the low-carbon scenario, farmland and rural land are reduced, 52.5% of which are converted into forest land and 40.6% into urban construction land. Under the base scenario, farm land and forest land are decreased, with 73.7% converted to urban construction land and 25.0% to rural land. Compared to the baseline scenario and original land-use in 2020, the release amount of carbon storage during the conversion process is relatively low. Even due to the conversion of low carbon storage capability land categories into forest land, the total capacity of whole land use was further strengthened.
Previous studies found that urban form can reduce carbon emissions by influencing, for example, traffic trips. This paper estimates the low-carbon capability of urban form by introducing two indicators, compactness index (CI) and fragmentation degree (FD), both of which illustrate the level of land intensification. The CI is calculated as follows:

\[
CI = \frac{\sum_{i=1}^{n} L_i / l_i}{N^2}
\]  

(6)

In the formula (7), \(CI\) is the compactness index, \(L_i\) is the patch perimeter, \(l_i\) is the circumference of a circle equal to the patch area, and \(N\) is the number of patches. The FD is calculated as follows:

\[
FD = \frac{N}{A}
\]  

(7)

As shown in formula (8), \(FD\) refers to fragmentation degree, and \(A\) is the area of total land.

Based on the formulae (6) and (7), it is found that under the following three circumstances, namely in 2020, baseline scenario and low-carbon scenario, the compactness of farm land is \(4.7 \times 10^{-4}\), \(3.8 \times 10^{-4}\) and \(4.0 \times 10^{-4}\) separately, of forest land is \(1.40 \times 10^{-3}\), \(1.20 \times 10^{-3}\) and \(1.26 \times 10^{-3}\), and that of urban construction land is \(1.14 \times 10^{-3}\), \(1.24 \times 10^{-3}\) and \(1.26 \times 10^{-3}\) (as shown in Table.5). Compared with the land compactness in 2020, that of farm land and forest land decrease in the baseline scenario and low-carbon scenario, while the compactness of urban construction land increase in both scenarios. In addition, it is shown that the compactness of the three land categories in the low-carbon scenario is higher than that in the baseline scenario.

The fragmentation degree of farm land in 2020, baseline scenario and low-carbon scenario are 0.591, 0.854 and 0.832 separately, and that of forest land are 0.104, 0.194.
and 0.101 respectively. As for the urban construction land, it is 0.839, 0.558 and 0.531 under the above-mentioned three circumstances (as shown in Table.6). Forest fragmentation increases in baseline scenario, but remains unchanged in low-carbon scenario. The fragmentation degree of urban construction land decreases under both scenarios, with that in the low-carbon scenario slightly lower than that in the baseline scenario.

Table.5 The compactness index of farm land, forest land and construction land

<table>
<thead>
<tr>
<th></th>
<th>(CI_{2020})</th>
<th>(CI_{2030}^{una})</th>
<th>(CI_{2030}^{a})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Farm land</td>
<td>4.7 \times 10^{-4}</td>
<td>3.8 \times 10^{-4}</td>
<td>4.0 \times 10^{-4}</td>
</tr>
<tr>
<td>Forest land</td>
<td>1.40 \times 10^{-3}</td>
<td>1.20 \times 10^{-3}</td>
<td>1.26 \times 10^{-3}</td>
</tr>
<tr>
<td>Urban land</td>
<td>1.14 \times 10^{-3}</td>
<td>1.24 \times 10^{-3}</td>
<td>1.26 \times 10^{-3}</td>
</tr>
</tbody>
</table>

*\(CI_{2030}^{una}\) and \(CI_{2030}^{a}\) is the compactness index of the baseline and low-carbon scenario

Table.6 The fragmentation degree of farm land, forest land and construction land

<table>
<thead>
<tr>
<th></th>
<th>(FD_{2020})</th>
<th>(FD_{2030}^{una})</th>
<th>(FD_{2030}^{a})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Farm land</td>
<td>0.591</td>
<td>0.854</td>
<td>0.832</td>
</tr>
<tr>
<td>Forest land</td>
<td>0.104</td>
<td>0.194</td>
<td>0.101</td>
</tr>
<tr>
<td>Urban land</td>
<td>0.839</td>
<td>0.558</td>
<td>0.531</td>
</tr>
</tbody>
</table>

*\(FD_{2030}^{una}\) and \(FD_{2030}^{a}\) is the fragmentation degree of the baseline and low-carbon scenario

Discussion

Compared to the baseline scenario which represents an economic oriented land use planning, the low-carbon spatial planning would promote a land use pattern with more carbon storage capability, less carbon emissions and stronger low-carbon capability. However, due to the different urbanization level and land-use efficiency of downtown districts, exurban districts and suburban districts, the land-use change varies significantly. To better reflect this variation, we introduced an indicator which was
named the land use change concentration index (LCCI) to measure the concentration of land use change. The calculation formula is as follows:

\[
LCCI_{ij} = \frac{\Delta S_{ij}}{\sum_{i=1}^{5} |\Delta S_{ij}|}
\]

\(LCCI_{ij}\) is land use change concentration index, and \(\Delta S_{ij}\) refers to the change value of land category \(j\) in the \(i\) region during 2020-2030, and \(j=1,2,3,4,5\) correspond to downtown districts, Xiaoshan District, Yuhang District, Fuyang District, and Lin’an District respectively. The positive and negative value of \(P_{ij}\) ((+) or (-)) represents the increase or decrease of land use, while the numerical value reflects the degree of concentration of land use change.

Firstly, it is found that under the low-carbon scenario, the LCCU of urban construction land change in the downtown districts, Xiaoshan District and Yuhang district are (+)31.47%, (+)31.35, (+)29.49% respectively, amount to (+)92.31%; besides, that in Fuyang District and Lin’an District are (-)6.41% and (+)1.28% respectively. Meanwhile, the LCCI of rural land in Xiaoshan District and Yuhang district are (-)36.82% and (-)23.88% respectively, larger than other districts. However, the rural land even expands in baseline scenario. Due to lack of planning, the idle use of the original homestead and the new demand for construction lands had caused the continuous expansion of rural construction lands (X. Zhang et al. 2022). Under the low-carbon scenario, the rural land is increasingly occupied by the surrounding urban construction land, demonstrating a shrinking trend. This is because rural land, as a carbon source, has no carbon absorption capacity, and its carbon emission efficiency is lower than that of urban construction land. Thus, according to the carbon emission target and economic benefit target, rural land would be transformed into urban construction land as the latter is embodied with higher carbon emission efficiency. This phenomenon is particularly obvious in the suburbs. In the future, Hangzhou municipal government could revitalize the stock land by land renewal in the suburbs, remold idled residential land and inefficient collective commercial construction land, and improve
the efficiency by means of land use adjustment or function compatibility.

**Table 7** The land use change concentration index of urban districts in two scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Farm land</th>
<th>Forest land</th>
<th>Grass land</th>
<th>Water</th>
<th>Urban land</th>
<th>Rural land</th>
</tr>
</thead>
<tbody>
<tr>
<td>Downtown districts</td>
<td>(-) 14.88%</td>
<td>(+) 1.00%</td>
<td>(-) 8.22%</td>
<td>0.00%</td>
<td>(+) 31.47%</td>
<td>(-) 16.52%</td>
</tr>
<tr>
<td>Yuhang district</td>
<td>(-) 13.05%</td>
<td>(+) 3.15%</td>
<td>(-) 3.15%</td>
<td>0.00%</td>
<td>(+) 31.35%</td>
<td>(-) 36.82%</td>
</tr>
<tr>
<td>Xiaoshan district</td>
<td>(-) 12.31%</td>
<td>(-) 0.32%</td>
<td>(+) 0.16%</td>
<td>0.00%</td>
<td>(+) 29.49%</td>
<td>(-) 23.88%</td>
</tr>
<tr>
<td>Fuyang district</td>
<td>(-) 14.47%</td>
<td>(+) 19.21%</td>
<td>(+) 85.07%</td>
<td>0.00%</td>
<td>(-) 6.41%</td>
<td>(-) 10.63%</td>
</tr>
<tr>
<td>Linan district</td>
<td>(-) 45.30%</td>
<td>(+) 76.32%</td>
<td>(+) 3.40%</td>
<td>0.00%</td>
<td>(+) 1.28%</td>
<td>(-) 12.15%</td>
</tr>
</tbody>
</table>

| Baseline Scenario | Downtown districts | (-) 19.64% | (-) 5.56% | (-) 0.32% | 0.00% | (+) 21.32% | (+) 9.50% |
| Yuhang district  | (-) 31.91% | (-) 37.11%  | (-) 2.95%  | 0.00% | (+) 29.74% | (+) 42.21% |
| Xiaoshan district | (-) 37.14% | (-) 15.30%  | (+) 0.38%  | 0.00% | (+) 34.96% | (+) 35.77% |
| Fuyang district  | (-) 8.54%  | (-) 23.02%  | (+) 83.50% | 0.00% | (+) 8.16%  | (+) 12.19% |
| Linan district   | (-) 2.76%  | (-) 19.01%  | (+) 12.85% | 0.00% | (+) 5.82%  | (+) 0.33% |

Secondly, under the low-carbon scenario, Lin’an District has the highest concentration index of farm land change, which is (-)45.30%, while that in the other four districts are (-)14.88%, (-)13.05%, (-)12.31% and (-)14.47% respectively. Lin’an District also has the highest concentration index of forest land change under the low-carbon scenario, which has achieved (+)76.32%, while another three districts are comparatively lower, which are only (+)1.00%, (+)3.15%, (-)0.32% respectively. Base on the simulation process of land use under the low-carbon scenario, a large number of small plots of farm land in Fuyang and Lin’an were converted into forest land. During the period of rapid urbanization, the rapid expansion of urban construction land led to the disappearance of surrounding forest land. At the same time, in order to protect the total scale of farm land according to its protection plan, the farm land that disappeared in the process of urbanization needs to be replenished by other land use categories, which might further influence forest land in the exurban areas of cities being reclaimed as supplementary farm land. However, most of these reclaimed farm land has a slope
of more than 6 degrees, which is difficult to cultivate; in addition, most of them are
dispersed distributed, which is not suitable for modern agricultural cultivation, resulting
in low-efficiency land use and increasingly prominent contradiction with ecological
protection. Under the dual drive of carbon emission target and economic benefit target,
these small plots of farm land with weak carbon absorbing capacity and low utilization
efficiency will inevitably transform into forest land with the strongest carbon absorbing
capacity per unit area. In the future, it will be an effective way for Hangzhou to attach
importance to the control of farm land and forest land in the exurbans so as to promote
the implementation of low-carbon policies.

Conclusion

This study takes Hangzhou as the research area, and applies linear programming
to incorporate carbon reduction target and economic development target into Markov
model to predict the land use structure under multi-objective spatial planning, which
was used to guide the Ann-CA model simulating the land use pattern. The differences
and similarities between the simulation results in the low-carbon scenario and baseline
scenario in terms of spatial form and regional land use change are analyzed, so as to
evaluate the low-carbon performance of the spatial planning and provide specific
planning suggestions for the local government. It is found that the overall carbon
emission scale of Hangzhou experienced a rapid growth from 1998 to 2012, then
entered the process of gradual decline, and will continue to decline in the next decade.
Therefore, what if fully considering the carbon emission scale and relevant carbon
reduction policies, together with the economic development needs, the scale of quantity
and area proportion of grassland, forest land and urban land all increase, while the farm
land and rural land would decrease. Under the scenario of low-carbon constraint, urban
land change is concentrated in the downtown districts and suburbs, while the change of
farm land and forest land is concentrated in the exurban districts (i.e. Lin’an District). On the other hand, the exurban area shows the largest decrease in farm land and the largest increase in forest land. To evaluate the low-carbon performance of simulated land-use pattern, we estimate the land-use capability of carbon storage or carbon emission and the low-carbon capability. The most common land conversions, which is closely related to the carbon storage release, occur between farm land and forest land, and between rural land and urban land. The release amount of carbon storage during those conversion process is relatively lower than that in baseline scenario, and the total capacity of whole land use was further strengthened. Besides, the compactness of urban land, which could reduce the human energy consumption behavior, are improved under the low-carbon scenario, while the urban land fragmentation degree would decrease. The integration of low-carbon constraint into multi-objective spatial planning can affect the carbon storage and carbon emissions of land use, enhancing the low-carbon effect and promoting the achievement of "Dual-carbon" targets in land management process.

It is the fact that there are still some aspects of this study deserve further exploration. Urban construction land is composed of many land use types and has complex functions and structures. However, this study simply regards urban construction land as a homogeneous region, which cannot truly reflect the development differences within construction land. Therefore, future studies can further subdivide urban construction land into land use categories with different carbon emission intensities, such as residential, industrial and transportation land, and further explore the changes in the structure and pattern of different types of urban construction land under the dual-constraint of low-carbon emission and economic development.

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Weicheng Gu and Mingyu Zhang conducted model construction and data analysis, and wrote the main manuscript text. Weifeng Qi processed the data and provided part of the original data. Mingyu Zhang got the funding to support the research work and designed the research framework. All authors reviewed the manuscript.

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**Reference:**


