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Scenario forecasting of carbon neutrality by combining the LEAP model and future land-use simulation: An empirical study of Shenzhen, China

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ABSTRACT

Forecasting future carbon emissions and carbon stocks under the influence of land-use changes will offer guidance for achieving urban carbon neutrality. However, a gap exists in the systematic combination of carbon emission forecasting and carbon stock forecasting to simulate the carbon neutrality path. Therefore, we introduced a novel method for scenario forecasting of carbon neutrality, which can integrate dynamic future land-use and NPP data to forecast carbon stocks. CCUS technology was also considered. Shenzhen, a Chinese city with high carbon emissions, was chosen as our case study area. First, the LEAP model was employed for forecasting future carbon emissions. Subsequently, the PLUS method was utilized for forecasting land-use evolution. Then, the carbon stocks were estimated on the basis of land-use forecasting and NPP. Finally, we explored the potential of CCUS for realizing carbon neutrality under integrated carbon emission and land-use scenarios. The results indicate that Shenzhen's future carbon emissions exhibit a tendency of an initial increase, followed by a decline. Due to the increase in ecological land, vegetation carbon stocks may increase slightly in farmland protection and ecological security scenarios. With the support of CCUS technology, the four scenarios are expected to achieve carbon neutrality before 2050. The scenarios presented in this study align more closely with future development trajectories and actual conditions, making them more informative for policy-making. In summary, the proposed framework would facilitate a comprehensive understanding of the pathways to achieving carbon neutrality goals.

1. Introduction

Climate change and greenhouse gas emissions pose severe challenges to humanity and have become pressing global issues (Lai et al., 2016; Lin & Zhu, 2021; Sha et al., 2020). To mitigate the adverse impact of these issues, many regions have endorsed environmental goals, including "carbon peaking" and "carbon neutrality" (Feng et al., 2015; Mahmood et al., 2023a; Mohsin et al., 2021). Carbon neutrality means that the anthropogenic carbon emissions produced in an area during a specific period are offset by natural and anthropogenic processes (e.g., vegetation uptake and carbon sequestration), thereby resulting in net zero carbon emissions. The pathways to carbon neutrality mainly involve reducing anthropogenic carbon emissions, increasing ecosystem carbon stocks, and promoting CCUS technology development (Liang et al., 2024; Wu et al., 2024; Zhang et al., 2021). Due to the high cost and immaturity of CCUS, accurate forecasts of future carbon emissions and carbon stocks, combined with an investigation of CCUS technology's potential, are critical for carbon neutrality (Cai et al., 2020; Hu et al., 2019).

Direct methods for reducing anthropogenic carbon emissions mainly involve energy structure transformation, energy conservation and reduction, that is, increasing the share of renewable energy and fuel utilization efficiency (Du et al., 2024; Launay et al., 2021; Luo et al., 2023). Therefore, future changes in carbon emissions for each economic sector can be forecasted by configuring different energy structures and utilization rates. To this end, previous studies have designed various future development scenarios by using econometric methods (Chai et al., 2022; Wen et al., 2022). LEAP is one of the most successful models in this field (El-Sayed et al., 2023; Li, L. et al., 2023). For example, Emodi et al. (2017) developed future scenarios with this model, proposing strategic policies by adjusting industrial and energy structures. Cai et al. (2023) created both positive and negative future scenarios

Abbreviations: LEAP, long-range energy alternatives planning; PLUS, patch-level land-use simulation; NPP, net primary productivity; CCUS, carbon capture, utilization and storage; InVEST, integrated valuation of ecological services and tradeoff.

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using the LEAP model to forecast Bengbu's future carbon emissions. While carbon emission forecasting methods are relatively well established, carbon stock forecasting still requires further investigation. In addition, few studies have systematically combined future carbon emission forecasting with carbon stock forecasting to explore the timeline and procedures for realizing carbon neutrality.

Increasing carbon stocks is a critical approach to realizing net zero carbon emissions. Carbon stocks refer to the amount of carbon stored by vegetation and soil ecosystems. Vegetated areas (e.g., woodland and grassland) can convert carbon dioxide into carbohydrates through photosynthesis, which are subsequently stored in vegetation and soil. Therefore, carbon stocks are closely linked to land-use changes. Carbon stocks can be estimated through field investigations (Chuai et al., 2022; Quan et al., 2023), remote sensing observations (Bordoloi et al., 2022; Campbell et al., 2022; He et al., 2017), and ecosystem process modeling (Babbar et al., 2021; Feng et al., 2020; Xiang et al., 2022). Ecosystem process models are becoming increasingly prevalent in forecasting future carbon stocks because the first two methods are mainly suitable for monitoring past and present conditions (Tian et al., 2022; Wang et al., 2022). Due to the large computational complexity of some complicated ecosystem process models (e.g., Biome-BGC), previous studies have mainly used the InVEST model, which has a simpler structure (Babbar et al., 2021; Ghafoor et al., 2022; Jiang et al., 2017).

Since land-use conditions exert a dominant influence on carbon stocks, previous studies usually forecasted future carbon stocks by integrating the InVEST and land-use change simulation models. Some widely-used land-use change modeling methods contain the SLEUTH, CLUE-S, FLUS, and PLUS models (Cao et al., 2019; Guan et al., 2016; He et al., 2020; Wang et al., 2020; Wu et al., 2023). Specifically, Ghafoor et al. (2022) revealed the influence of urban land-use dynamics on carbon stocks by using cellular automata and InVEST models. Yang et al. (2020) forecasted the influence of future land-use dynamics on carbon stocks through the combined use of FLUS and InVEST models. However, the InVEST model largely relies on fixed carbon stock density scores. Specifically, the carbon stock density for a particular land-use category always remains spatially constant, which negatively affects the spatialization of carbon stocks. Earlier research has demonstrated that NPP data were strongly associated with ecosystem carbon stocks at the grid scale (Chen et al., 2019; Huang et al., 2020; Li et al., 2022; Zhong et al., 2023). Therefore, a combination of NPP-based carbon stock estimation and land-use change forecasting can address the above deficiencies.

As technology advances, the realization of carbon neutrality should focus not only on reducing carbon emissions and increasing carbon stocks, but also on the deployment of CCUS technology (Iqbal et al., 2019; Mahmood et al., 2023b). CCUS can be used to effectively manage carbon emissions that exceed carbon stock capacity, thereby contributing to carbon neutrality. In fact, this technology must be adapted to the specific conditions of different regions to maximize its effectiveness (Li, L. et al., 2023; Yang et al., 2020). Nevertheless, prior research has concentrated on carbon emissions and carbon stocks, with limited integration of CCUS technology in the pursuit of carbon neutrality.

To sum up, the objectives of this research are twofold: (1) to dynamically adapt carbon stock densities based on NPP information and evaluate the future spatial distribution of carbon stocks at a grid scale and (2) to simultaneously consider carbon emission forecasting, carbon stock forecasting, and CCUS to explore the timeline and procedures needed for achieving carbon neutrality. In this regard, a novel methodology integrating the LEAP and PLUS models to forecast carbon neutrality scenarios was proposed. First, the LEAP model was used for forecasting future carbon emissions under baseline, energy-saving, and green scenarios. Second, the PLUS method was employed to forecast future land-use evolution under several scenarios: natural development, farmland protection, and ecological security. The carbon stocks were estimated by combining the land-use forecasting outcomes and the NPP-based grid-scale carbon stock densities. Finally, we investigated the impact of CCUS technology on carbon neutrality under nine integrated scenarios (Fig. 1). The outcomes could provide policy guidance for the development of low-carbon urban societies.

2. Data and methods

2.1. Case study

Shenzhen is situated on the southern coast of Guangdong Province, China. This city is renowned for being one of the pioneering remarkable economic zones in China that has embraced "reform and opening up" policies. With a wide area of 1997.6 km^2 and a permanent population of 17.66 million in 2022, it is the first city in China to reach a 100 % urbanization rate. Shenzhen experiences a subtropical monsoon climate, with a yearly average temperature of 23.5 Celsius and a multiyear mean precipitation of 1948 mm. The carbon emissions of Shenzhen have been steadily increasing in recent years, reaching 44.57 Mt in 2020.

2.2. Data

The data needed in our analysis included socioeconomic statistics, energy consumption, land-use, and NPP data. The land-use maps (2010, 2015, and 2020) at a resolution of 30 m were acquired from the Chinese Academy of Sciences, which exhibit an overall accuracy of 88.95 % in classification (Lin, Wang, Lin, & Li, 2025). Information on administrative boundaries, residential construction, railways, and roads was acquired from the China Geographical Information Resource Inventory Systems (https://www.webmap.cn). The SRTM-DEM (30 m resolution) was acquired from the Geospatial Data Cloud Service Platform (https://www.gscloud.cn), and the slope and topographic relief were generated through the SRTM-DEM. The NPP data (30 m resolution) were obtained from the Global Resources Data Cloud Platform (http://gis5g.com/data/zbsj/NPP?id=2541). In this product, the MODIS NPP information (MOD17A3HGF Version 6) of NASA has been downscaled through the well-recognized Carnegie-Ames-Stanford (CASA) ecosystem model (Song, S. et al., 2023; Yin et al., 2021). The socioeconomic and energy consumption data from 1980 to 2020 were acquired from Shenzhen Statistical Yearbooks, Chinese Municipal Statistical Yearbooks, and Shenzhen Economic and Social Development Bulletin.

2.3. LEAP model

The LEAP method has been widely employed in the analysis of energy and environmental services, such as energy consumption forecasting and air pollution abatement (Cai et al., 2023; Emodi et al., 2017). This model includes five branches from top to bottom: demand, sector, industry, type, and energy. Using mathematical functions, users can create various scenarios to represent the future development trend of energy intensities for different economic sectors. The LEAP model exhibits various advantages over other comparable models. In particular, it offers more comprehensive and detailed settings for different economic sectors, and it provides a highly structured and flexible system for data input (El-Sayed et al., 2023; Hu et al., 2019; Huang et al., 2023). The future energy consumption can be estimated as follows:

$$E_f = \sum_j AL_j * E_j \tag{1}$$

$$E_{i,j} = E_j * P_i \tag{2}$$

where E_f signifies future energy consumption in sector f; AL_j signifies the activity level of subsector j; E_j signifies the energy use intensity of subsector j; $E_{i,j}$ signifies the energy use intensity of energy source i in subsector j; and P_i signifies the percentage of energy source i in future energy consumption.

We developed the LEAP model in accordance with the carbon emission characteristics in Shenzhen. Then, we used this model to

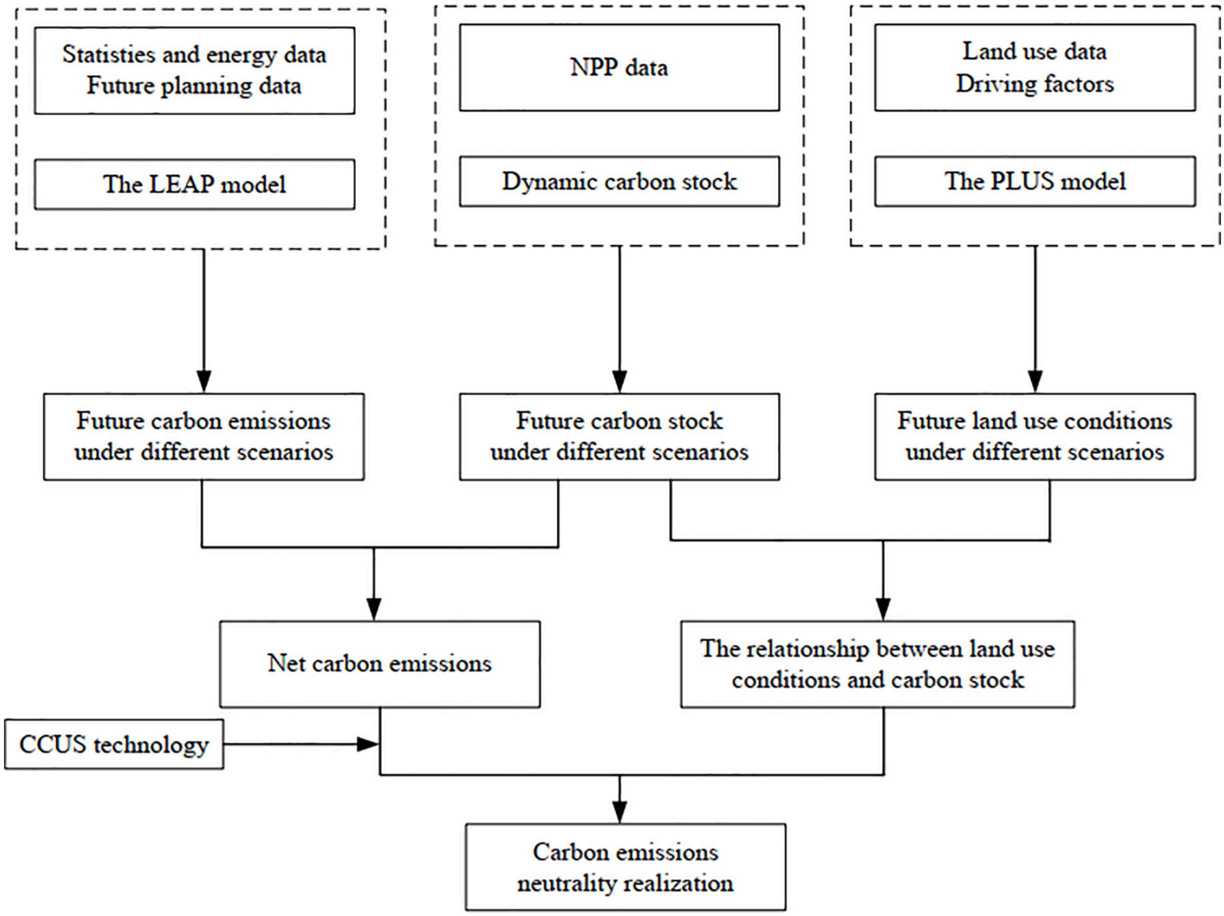

Fig. 1. Research framework for carbon neutrality scenario forecasting.

forecast Shenzhen's future carbon emissions and energy-saving potential, with 2020 as the base year. Energy consumption in Shenzhen was categorized into six sectors based on local conditions: household consumption, agriculture, industry, tertiary sector (excluding transportation), construction, and transportation. The detailed setting for each sector is presented in Table 1.

Table 1
Detailed setting for each sector.

Sector	Subsector	Activity level	Energy intensity	Energy structure	Emission factor
Household consumption	Residence	Permanent population	Energy consumption per unit of residential area	Proportion of nonfossil energy (electricity and heat) Proportion of fossil energy (coal, oil, gas)	CO_2, CO, NO, NO_2, CH_4 (residence, agriculture, forestry, animal husbandry, and fishing)
	Lighting	Number of lighting lamps	Lighting energy consumption per unit	Proportion of nonfossil energy (electricity)	CO_2, CO, NO
Agriculture	–	Value-added in agriculture	Energy consumption per unit of value-added	Proportion of nonfossil energy (electricity and heat)	CO_2, CO, NO, NO_2, CH_4 (residence, agriculture, forestry, animal husbandry, and fishing)
Industry	Direct consumption	Value-added in industry	Energy consumption per unit of value-added	Proportion of nonfossil energy (electricity and heat) Proportion of fossil energy (coal, oil, gas)	CO_2, CO, NO, NO_2, CH_4 (energy and transportation sectors)
	Indirect consumption	Amount of fossil fuels	Fossil fuel energy consumption per unit	Proportion of fossil energy (coal, oil, gas)	
Tertiary sector	–	Value-added in tertiary sector (excluding transportation)	Energy consumption per unit of value-added	Proportion of nonfossil energy (electricity and heat) Proportion of fossil energy (coal, oil, gas)	CO_2, CO, NO, NO_2, CH_4 (manufacturing and construction)
Construction	–	Value-added in construction sector	Energy consumption per unit of value-added	Proportion of nonfossil energy (electricity and heat) Proportion of fossil energy (coal, oil, gas)	CO_2, CO, NO, NO_2, CH_4 (manufacturing and construction)
Transportation	–	Value-added in transportation	Energy consumption per unit of value-added	Proportion of nonfossil energy (electricity) Proportion of fossil energy (oil)	CO_2, CO, NO, NO_2, CH_4 (energy and transportation sectors)

With 2050 as the target year, we created a baseline scenario, an energy-saving scenario, and a green scenario for forecasting future carbon emissions in Shenzhen based on the "Shenzhen Carbon Peaking Implementation Plan". In accordance with the actions outlined in the plan, including the transition to green and low-carbon energy sources, energy conservation, carbon efficiency improvement, and technological empowerment for carbon peaking, we quantified specific targets, taking into account relevant policies in Shenzhen. Table 2 presents the specific descriptions for each scenario (Chai et al., 2022; Li, L. et al., 2023; Song, M. et al., 2023; Wang, S. et al., 2024). The baseline scenario depicts the continuation of current policies and technological development trends without additional adjustments or actions. The energy-saving scenario, which aims to realize the carbon peaking objective by approximately 2030, envisages the implementation of more robust energy policies, including the application of specific energy-saving and emission abatement plans to lower carbon emission intensity. The green scenario refers to the adoption of a maximum level of energy-saving and emission abatement plans, with the objective of accomplishing carbon neutrality by approximately 2050.

2.4. Land-use change modeling

This section introduces the PLUS method, outlines the specific settings for land-use scenarios, and provides an overview of the methodology for calculating carbon stock density at the pixel scale.

2.4.1. PLUS method

The PLUS method integrates random forests and cellular automaton to forecast patch-level land-use changes (Liang et al., 2021). A number of elements, such as socioeconomic and natural environments, are simultaneously considered in this method. This method includes the Land Expansion Analysis Strategy (LEAS) and the Multi-type Random Seed (CARS). Compared with other methods, the PLUS method demonstrates superior modeling accuracy while better capturing the landscape ecological implications of land-use patterns (Guo et al., 2023; He et al., 2023; Tian et al., 2022). We utilized the latest version of the PLUS software (V1.4) to conduct the experiments.

2.4.2. Land-use scenarios

Three land-use simulation scenarios (natural development, farmland protection, and ecological security) were designed according to future land-use planning in Shenzhen and previous relevant literature (Chen et al., 2025; Li et al., 2020; Li, Zhou and Gong, 2023; Liao et al., 2023; Rong et al., 2022). In addition, land-use area requirements were determined based on the latest land-use policies. No external constraints on land-use changes were included in the natural development condition. In the farmland protection condition, farmland area should not fall below the minimum requirement outlined in land-use policies. All land-use categories (excluding urban land) may change to farmland. The ecological protection scenario not only emphasizes economic development but also comprehensively considers land-use structures for ecological, agricultural, and urban land. The probabilities for woodland, farmland, grassland, and water being changed as urban land decreased, and the eco-protection red lines and urban growth boundaries were utilized as constraints.

Table 2
Setting of the carbon emission forecasting scenarios for Shenzhen.

Scenario	Description
Baseline scenario	Historical trend of energy intensity is expected to continue, with an increase in residential energy consumption. However, the upgrades in industrial structure will lead to a slight reduction in energy intensity, along with a gradual increase in the share of eco-friendly energies including wind and solar power.
Energy-saving scenario	Energy-saving policies are implemented to help increase the share of eco-friendly energies and lower energy intensity. Increase technological investment in production so that energy intensity can meet the minimum criterion of national economic development target. The share of nonfossil fuels will reach 75 % after 2060.
Green scenario	Develop wind and solar energy to their maximum potential before the maturity of new techniques, such as hydrogen and nuclear power. The goal is for nonfossil fuels to account for 35 % of the total energy supply. Energy intensity should reach the degree of developed nations after 2030, and the share of nonfossil fuels should continue to grow. After 2060, the share of nonfossil fuels should exceed 80 %.

2.4.3. Parameter setting for the PLUS method

Considering the local conditions, data collinearity and availability (Chen & Feng, 2022; Guan et al., 2023; Huang et al., 2024; Ke et al., 2018; Yao et al., 2023; Yu et al., 2018), elevation, slope, proximity to district centers, proximity to residential areas, proximity to expressways, proximity to subways, proximity to water, annual average NDVI, and population density were adopted as the influencing drivers behind land-use evolution in Shenzhen. In addition, the expansion intensity for each land-use category is reflected by the neighborhood weight ([0,1]), where a value closer to 1 represents a stronger intensity. The neighborhood weight of every land-use category was determined according to manual adjustment and related studies (Liang et al., 2021; Lin et al., 2023; Liu et al., 2017) (Table 3).

The optimal parameters were determined based on relevant studies (Guo et al., 2023; He et al., 2023; Tian et al., 2022) and manual tuning. First, the parameters in the LEAS module were configured as follows: the number of regression trees was set to 60, the sampling rate to 0.7, and the mTry to 8. Second, the parameters in the RMSE module were configured as follows: a patch generation threshold of 0.7, an expansion coefficient of 0.2, and a neighborhood size of 11.

A transformation expense matrix depicts the difficulty of transforming a land-use pixel from the original land-use category to a targeted category. This matrix exclusively comprises scores of either 0 or 1. A score of 0 signifies that this land-use category cannot be transformed to the targeted land-use category, and a score of 1 signifies that the transformations are permitted. We employed the Markov chain provided by the PLUS software to project future land-use demands. In addition, the transformation expense matrices corresponding to the three scenarios (Table S1 of the supplemental materials) were designed in accordance with Shenzhen's land-use policies and scenario specifications.

2.5. Carbon stock density at the pixel scale

The carbon stock density at the pixel scale can be estimated based on NPP data. The fundamental assumption is that the carbon stock will generally increase with NPP (Liu et al., 2023; Schulze et al., 2010; Zhong et al., 2023). Previous studies have usually employed the InVEST method to estimate carbon stocks, which defines the average carbon stock density of every land-use category based on expert knowledge (Babbar et al., 2021; Jiang et al., 2017; Xiang et al., 2022). In reality, however, the carbon stock density for a specific land-use category is also altered by factors such as location and the surrounding environment at the pixel scale. Therefore, the local-scale carbon stock results derived from the InVEST model will be significantly different from the actual results if constant carbon stock densities are applied.

To address this problem, we used NPP data to determine dynamic carbon stock densities at the pixel scale, which will enhance the reliability of carbon stock estimations. The conversion coefficients from

Table 3
Neighborhood weight for each land-use category.

Farmland	Woodland	Grassland	Water	Urban land	Other
0.25	0.1	0.4	0.85	1	0.7

NPP to ecosystem carbon stocks for every land-use category were estimated in light of previous related studies (Table S2). More specifically, these conversion coefficients were adapted to the conditions in China by Quan et al. (2023), building upon the thorough investigation using both top-down and bottom-up approaches (Schulze et al., 2010). Therefore, the estimation of carbon stocks based on these conversion coefficients can be considered highly reliable. In this regard, we can obtain the city-wide coverage of carbon stock densities at the pixel scale for each year. Finally, the land-use change outcomes forecasted through the PLUS method were overlaid with the carbon stock densities, and then the spatial distributions of the pixel-scale carbon stocks under the three land-use change scenarios were obtained.

3. Results

3.1. Carbon emission forecasting from 2020 to 2050

This study estimated Shenzhen's carbon emissions in 2020 to be 45.30 Mt using the LEAP model, which is consistent with the 45.42 Mt estimated by the China Urban Greenhouse Gas Working Group (https://www.cityghg.com), with an error of approximately 0.26 %. This demonstrates the high reliability of the LEAP model calibrated in this study, which can be used to forecast future carbon emissions.

Carbon emissions in the baseline, energy-saving, and green scenarios are expected to reach their peaks at 55.0 Mt, 50.3 Mt and 48.5 Mt, respectively, in 2041, 2032, and 2028 (Fig. 2). The changes in carbon emissions under these three scenarios all exhibit an inverted U-shaped pattern, which continues to rise before the peak and then decline. The yearly growth rate of carbon emissions is significantly greater in the baseline scenario than in the energy-saving and green scenarios. Overall, as the share of coal shrinks, the shares of electricity and natural gas moderately increase, whereas the shares of other nonfossil fuels experience slow growth.

In the energy-saving scenario, advancements in new energy technologies persist, energy intensity decreases, and the share of electricity increases significantly. The carbon emissions in this scenario are forecasted to decrease to the emission level of 2020 (approximately 46.9 Mt) by 2050. In the green scenario, more significant changes occur with respect to the energy structure. The share of nonfossil fuels increases significantly annually, whereas the share of fossil fuels decreases, especially in the case of hard coal, other coals, and natural gas. By 2050, the share of nonfossil fuels will exceed the share of fossil fuels by 20 %, and carbon emissions will drop from 48.1 Mt in 2020 to 42.3 Mt in 2050.

3.2. Historical and future dynamics of land-use and carbon stocks

The objective of this subsection was to investigate the dynamics of land-use and carbon stocks during 2000–2015. Based on data from 2010, the PLUS method was calibrated to forecast land use scenarios from 2020 to 2050. By integrating NPP and land use data, we calculated historical and future carbon stocks at the pixel scale.

3.2.1. Land-use changes

Shenzhen was primarily composed of woodland, urban land, and farmland (Fig. 3 and Table S3). Woodland accounted for the majority (>39 %) during 2000–2010. Nevertheless, the percentage of urban land exceeded that of woodland after 2010. Overall, farmland, woodland, grassland, and water areas all decreased during 2000–2015. Farmland and woodland experienced decreases of 7.46 % and 6.30 %, respectively. By comparison, urban land exhibited the most rapid increase, with a growth rate of 13.81 %. Consequently, a considerable portion of farmland and woodland has been under encroachment.

3.2.2. Land-use evolution forecasting under various scenarios

We further simulated the land-use change during 2010–2015 and compared the outcomes with the actual land-use map. Our comparisons revealed that the kappa indicator was 0.96, the overall accuracy was 97.6 %, and the FoM value was 0.1989. The FoM is a key performance indicator for the accuracy of land use simulation, ranging from 0 to 1. Higher FoM values indicate stronger agreement between model predictions and observed ground conditions (Chen et al., 2017; Yao et al., 2017; Zhai et al., 2020; Zhuang et al., 2022). Therefore, the model demonstrates a high level of performance, implying that the modeling outcomes were reasonable and that the model could be utilized for

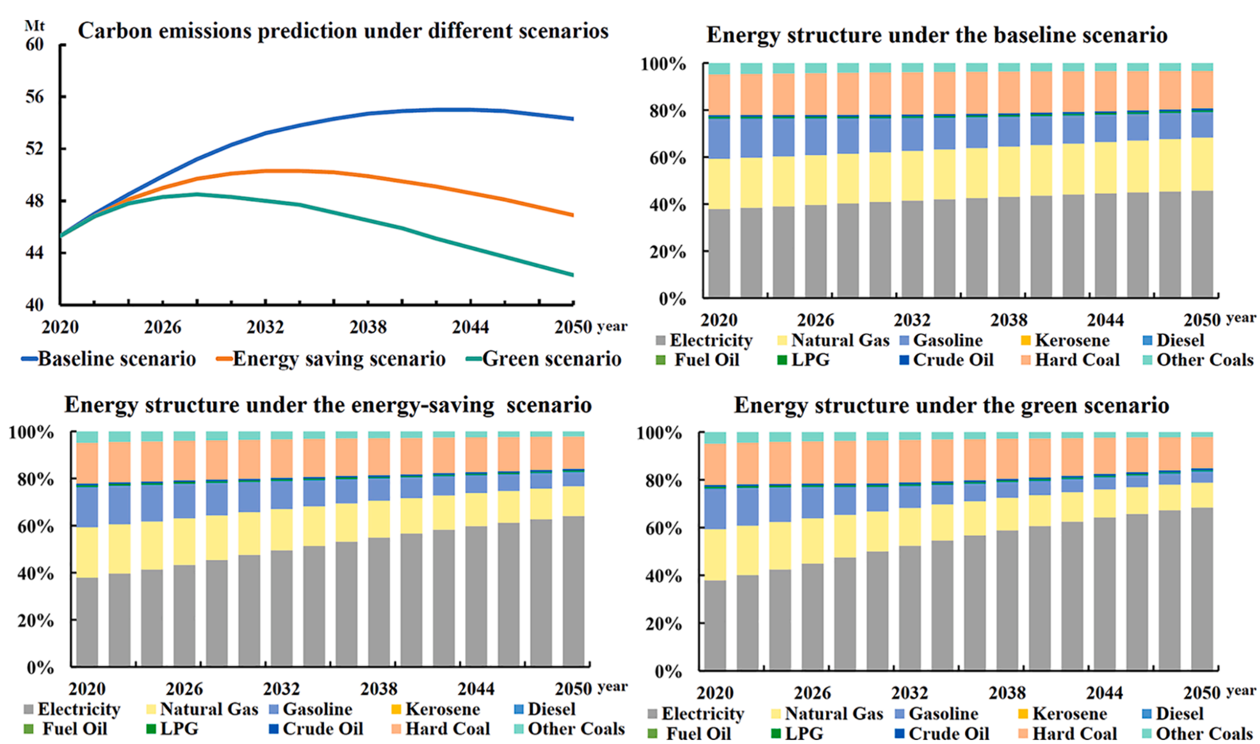

Fig. 2. Forecasting of future carbon emissions and energy structure in Shenzhen.

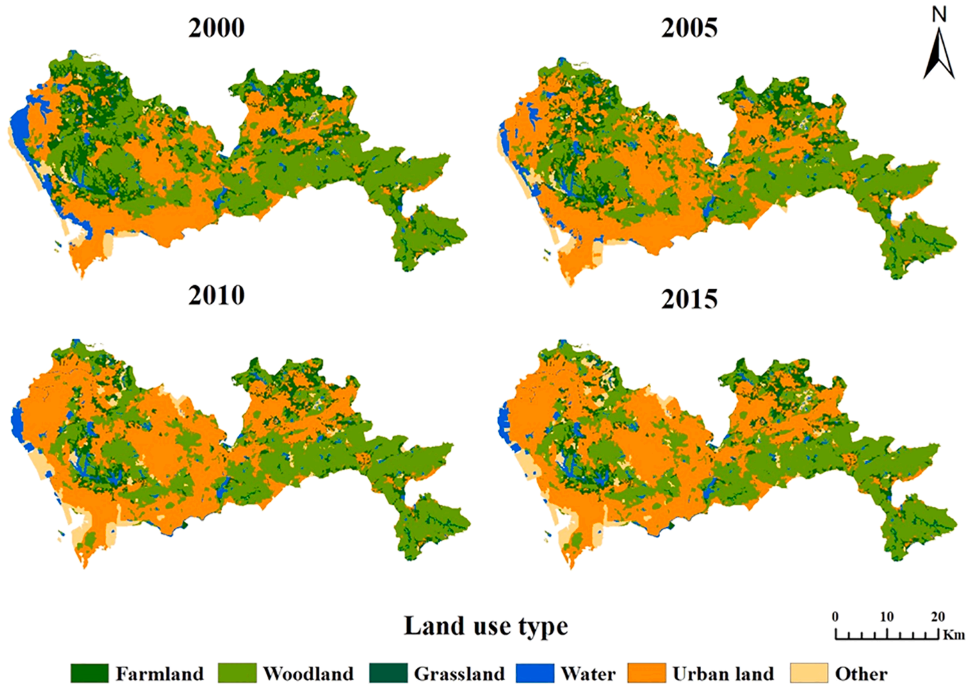

Fig. 3. Land-use maps for Shenzhen during 2000–2015.

forecasting future land-use evolution. Next, we forecasted the land-use in 2025, 2035, and 2050 under the three scenarios (Fig. 4 and Table S4). We found that the proportions of farmland, woodland, and water will decrease, whereas the proportions of urban land will grow and the grassland area will remain relatively stable in the natural development condition. In the farmland protection condition, farmland reduction will occur at a considerably slower rate than in the other two scenarios, while there will be more woodland compared to the previous condition, and the grassland area will steadily decrease. This scenario effectively alleviates farmland loss while providing partial protection for ecological land. Additionally, farmland exhibits the highest reduction rate, followed by grassland, while woodland experiences slower decline compared to the other conditions, the growth rate of urban land will accelerate significantly, and the areas of water will remain relatively stable in the ecological security scenario. Although urban land may still encroach on some ecological land due to socioeconomic development, the regulations for protecting ecological land remain intact.

3.2.3. Changes in carbon stocks

We further estimated Shenzhen's carbon stocks in 2000, 2005, 2010, and 2015 (Table 4). The total carbon stocks decreased by 133.04 $\times$ 10^4 t over these years, showing a sharp downward trend. The greatest drop in carbon stocks occurred between 2000 and 2005, after which the deceleration became slower. Notably, vegetation carbon stocks showed a decreasing trend at first and then increased, with the minimum value in 2005 being 129.79 $\times$ 10^4 t Soil carbon stocks also showed a

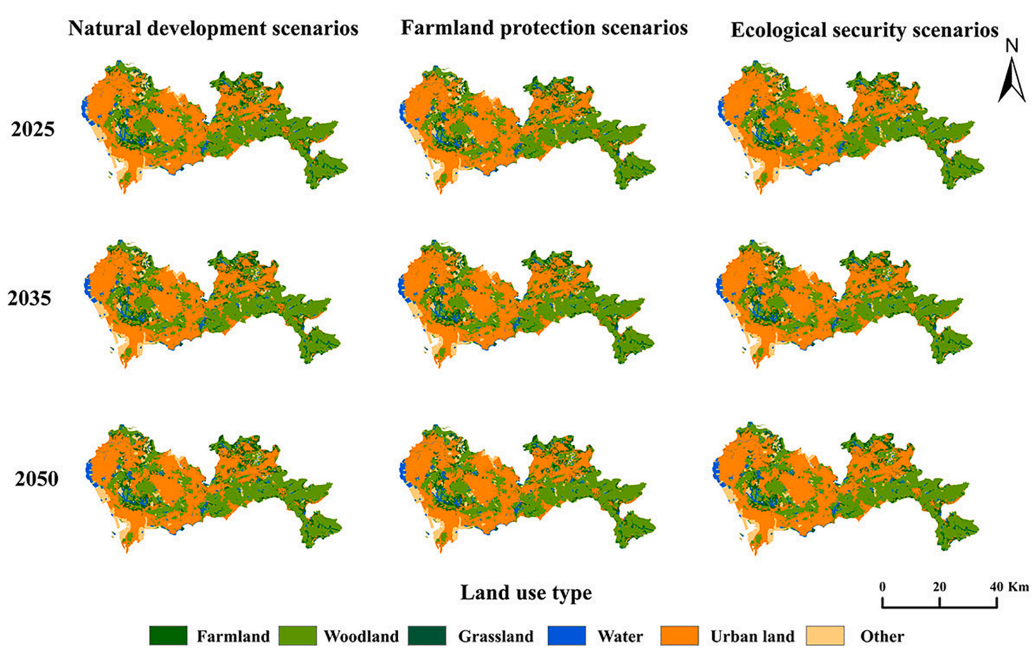

Fig. 4. Land-use forecasting results under different scenarios.

Table 4
Changes in carbon stocks in Shenzhen ($\times 10^4$ t).

	Vegetation carbon stocks	Soil carbon stocks	Overall carbon stocks
2000	147.09	790.94	938.03
2005	129.79	728.19	857.98
2010	142.20	670.88	813.08
2015	145.90	659.08	804.99

decreasing trend over these years.

3.2.4. Carbon stock forecasting in various scenarios

In the natural development scenario, vegetation carbon stocks are projected to initially increase and then decrease, showing a stabilization trend. In addition, soil carbon stocks will decline (with a decline rate of 0.16 %). For the farmland protection scenario, carbon stocks show a downward trend. Specifically, vegetation carbon stocks show an increase during 2015–2030, but will slightly decline from 2030 to 2050. Moreover, soil carbon stocks are projected to decrease by 35.41 $\times 10^4$ t In the ecological security scenario, there will be a downward trend in overall carbon stocks, with a total decrease of approximately 24.79 $\times 10^4$ t Specifically, vegetation carbon stocks will increase by 0.8 $\times 10^4$ t, while soil carbon stocks will decrease by 25.58 $\times 10^4$ t (Table 5).

3.3. Scenario analysis of carbon neutrality in Shenzhen

Nine carbon neutrality scenarios were obtained by integrating the above three land-use scenarios and carbon emission scenarios, namely, natural-baseline, natural-energy-saving, natural-green, farmland-baseline, farmland-energy-saving, farmland-green, ecological-baseline, ecological-energy-saving, and ecological-green. The objective is to analyze the potential for achieving carbon neutrality with or without the support of CCUS technology.

3.3.1. Carbon neutrality forecasting without CCUS

It is evident that a discrepancy exists between the various scenarios and the ultimate objective of carbon neutrality under this pathway (without CCUS). Fig. 5 shows that no situation will accomplish the carbon neutrality goal by relying only on ecosystem carbon stocks. Although the carbon emissions in all scenarios will decrease through decreasing energy intensity and raising the share of eco-friendly energies, there are still considerable gaps between carbon emissions and carbon stocks. Ecosystem carbon stocks will inevitably decrease due to socioeconomic development. Therefore, achieving carbon neutrality depends greatly on reducing carbon emissions. While carbon emissions will decrease through the implementation of reduction measures and technological advancements, CCUS technology is still urgently needed.

3.3.2. Carbon neutrality forecasting with CCUS

CCUS technology is critical for carbon neutrality. Therefore, we set the minimum, moderate, and maximum contribution rates of CCUS technology based on reports from Development Research Center of Chinese National Council, CCUS report from National Bureau of Ecology and Environment, and local conditions (Cai et al., 2023; Chuai et al., 2022; Li, L. et al., 2023) (Table 6 and Fig. 6). Under the maximum contribution rate of CCUS, carbon neutrality could be accomplished by approximately 2050 in the natural-green, farmland-green, and ecological-energy-saving scenarios, while under the ecological-green scenario, carbon neutrality could be accomplished by approximately 2045. Our results reveal a substantial reduction in carbon emissions, and all scenarios have the potential to achieve carbon neutrality by considering CCUS technology.

Table 5
Carbon stock forecasting results under different scenarios ($\times 10^4$ t).

	Scenario	Vegetation carbon stocks	Soil carbon stocks	Overall carbon stocks
2025	S1	145.85	647.58	793.43
	S2	147.28	650.38	797.66
	S3	147.35	650.35	797.70
2035	S1	146.58	634.33	780.90
	S2	147.02	638.41	785.43
	S3	147.09	643.23	790.32
2050	S1	145.60	621.48	767.47
	S2	146.51	623.67	770.18
	S3	146.70	633.50	780.20

Note: S1-S3 represent the natural development, farmland protection, and ecological security scenarios, respectively.

3.4. Discussions

This study makes a notable contribution to energy management by developing a novel framework (integration of the LEAP and PLUS models) for forecasting diverse carbon neutrality scenarios and exploring the effects of land use change on carbon stocks. This approach would facilitate a comprehensive understanding of the pathways and potential to achieve future carbon neutrality goals. The energy structure in the study area will undergo a significant transformation between 2020 and 2050, with a constant growth in the share of electricity consumption and an apparent drop in the share of fossil energy consumption. Such a change in energy structures is anticipated to cause an initial increase in carbon emissions, with a subsequent decline across all projected scenarios. In the baseline, energy-saving, and green scenarios, carbon emissions are expected to reach their respective peaks of 55.0 Mt, 50.3 Mt, and 48.5 Mt in 2041, 2032, and 2028. Likewise, Jiang et al. (2023) utilized the LEAP model to forecast that Shenzhen's carbon emissions will peak between 2025 and 2027. But more importantly, the extensive expansion of urban land in Shenzhen during the past twenty years has led to the continuous degradation of ecosystems such as woodlands, grasslands, and farmlands.

Land use change has been identified as a primary factor influencing carbon stocks. In comparison to previous studies, we proposed a new methodology that integrates dynamic future land-use and NPP data to forecast carbon stocks. This approach yielded a more accurate spatial distribution of carbon stocks than the panel data results obtained through alternative methods. Shenzhen has undergone significant urban expansion in recent decades, resulting in a decline in ecological land use, including farmland, woodland, and grassland. This decline has exerted a substantial adverse effect on carbon stocks. In the natural development scenario, Shenzhen's overall carbon stocks showed an obvious downward trend, with both vegetation and soil carbon stocks decreasing from 2015 to 2050. Vegetation carbon stocks exhibit relative stability. Conversely, in the farmland protection and ecological security scenarios, vegetation carbon stocks show an upward trend, which is mainly caused by the increase in agricultural and ecological land. The decline rate of soil carbon stocks exhibits a significant deceleration, which has consequently led to a corresponding slowing in the decline rate of overall carbon stocks. This result is generally in agreement with the outcomes obtained by Rong et al. (2022), who discovered a close association between land-use evolution and carbon emissions. In addition, Wang, C. et al. (2024) simulated the future carbon emissions and land-use evolution of Shenzhen by coupling an improved RF-CA-Markov with the InVEST model. The research revealed that the transition from high-carbon-stock land-use types (e.g., forestland) to low-carbon-stock categories (e.g., urban land) is the crucial factor driving the decline in regional ecosystem carbon stocks. This finding highlights the pivotal role of land-use transformation in regulating carbon stocks capacity during rapid urbanization processes.

Despite the significant effects of land-use change on carbon stocks, achieving carbon neutrality in urban areas cannot rely solely on increasing carbon stocks. The findings of this study demonstrated that even under scenarios of farmland protection and ecological security, the increase in carbon stocks is impossible to fully compensate for the rise in

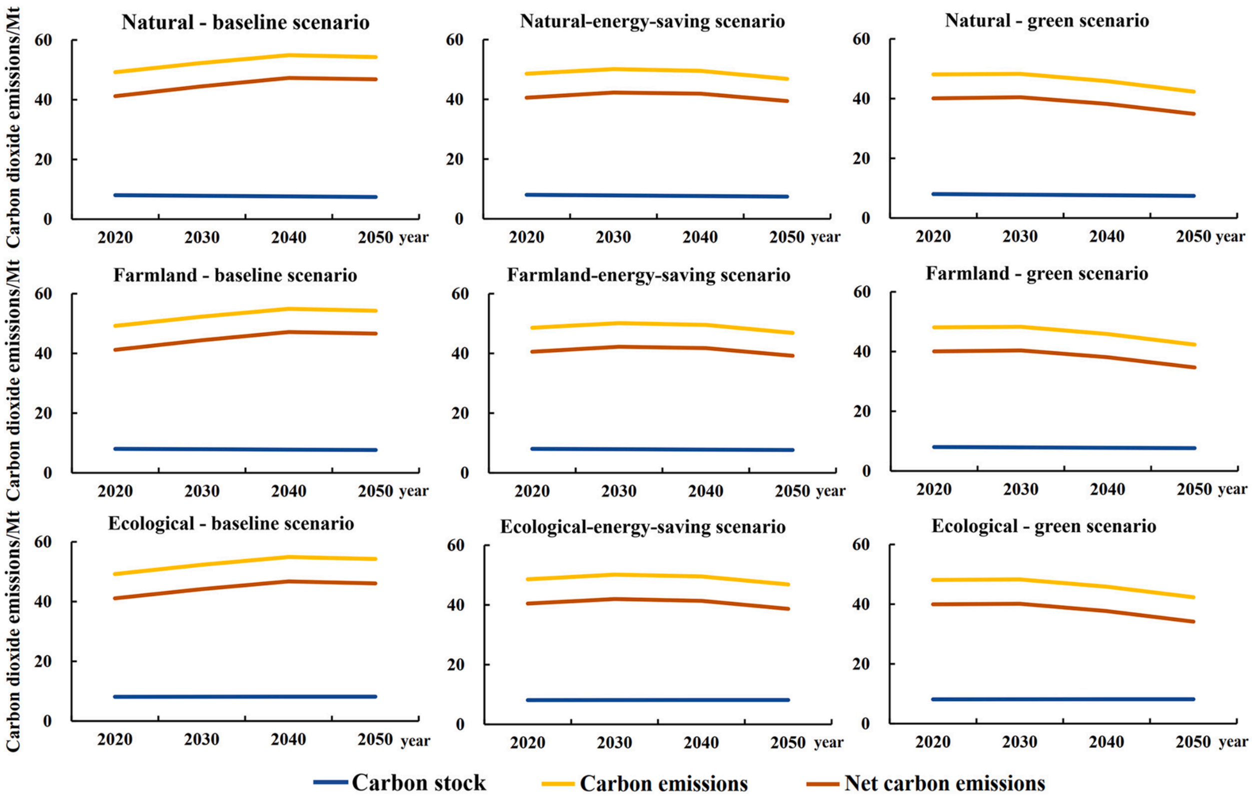

Fig. 5. Carbon neutrality forecasting under nine scenarios (without CCUS).

Table 6
Carbon emission reduction capacity of CCUS.

Contribution rate	2025	2030	2040	2050
Minimum	18 %	30 %	52 %	65 %
Moderate	25 %	42 %	66 %	75 %
Maximum	30 %	60 %	75 %	85 %

carbon emissions. Therefore, this study presented a more informative analysis for carbon neutrality goals by simultaneously considering CCUS technology. After CCUS technology with the maximum contribution rate is considered, carbon neutrality could be accomplished by approximately 2050 in the natural-green, farmland-green, ecological-energy-saving, and ecological-green scenarios. Overall, the ecological-energy-saving scenario provides the optimal pathway for maintaining economic development and optimizing land-use simultaneously. Conversely, the natural-baseline scenario indicates a warning signal for regional development. That is, achieving an equilibrium between urban growth and preservation is an increasingly pressing issue in large cities (Liu et al., 2020; Luo et al., 2023). By simulating the energy consumption and carbon emissions for multiple sectors, earlier research has highlighted the necessity of reducing the energy consumed per unit of gross domestic product, optimizing industrial structure, and increasing the share of clean energies (Simsek et al., 2020; Zhang, G. et al., 2024). Therefore, controlling the shrinkage of ecological land (woodland and grassland) in high-carbon stock areas while also reducing energy intensity and increasing the share of nonfossil fuels are critical keys to accomplishing carbon neutrality goals (Cui et al., 2023; Xu et al., 2023).

From a practical point of view, the scenarios presented in both the LEAP and PLUS models are based on the latest policies enacted in Shenzhen, rather than using general scenarios such as a 100 % renewable energy system, Representative Concentration Pathways, or Shared Socioeconomic Pathways. In other words, the scenarios presented in this study are more closely aligned with future development trajectories and actual conditions, making them more informative for policy making. Furthermore, the PLUS method was developed using historical data during 2010–2015 and the latest situation in 2020, incorporating legislative policy constraints such as environmental protection zones and water, which substantially improves the rationality of the forecasting results.

Our results can also aid in decision-making on low-carbon urban planning and energy structure transformation. In terms of land-use, Shenzhen still has great potential for enhancing transportation and industrial land-use efficiency compared with other major international cities, such as Tokyo and Manhattan (Lu et al., 2024). As the biggest consumer of various oil products in Shenzhen, the transportation sector can significantly reduce fuel consumption by enhancing land use efficiency. In addition, land-use planning should prioritize the protection of ecological land, especially in areas with high carbon stocks. The local government must establish ecological protection redlines to safeguard ecological land. In future land planning, strict measures should be enforced to minimize encroachment on ecological land and ensure its preservation. Regarding energy consumption, authorities need to maximize energy efficiency and lower carbon emission intensity while raising the share of eco-friendly energies, including wind and solar power. In particular, increasing investment in the development of CCUS technology is extremely important for low-carbon development (Jiang et al., 2023; Zhang, J. et al., 2024). Additionally, targeted policies can be actively developed for energy-intensive enterprises to accelerate their energy transition and achieve low-carbon, efficient development (Liu et al., 2024; Wang et al., 2023). More importantly, our comprehensive forecasting results allow for more quantitative and precise decision-making by local governments, such as determining the scale of energy restructuring and allocating detailed investment funds for CCUS technology (Cai et al., 2024; Khajavi & Rastgoo, 2023).

The carbon neutrality scenario forecasting performed in this study still has several limitations. First, the driving factors behind land-use change may not be sufficient due to regional differences. Second, the

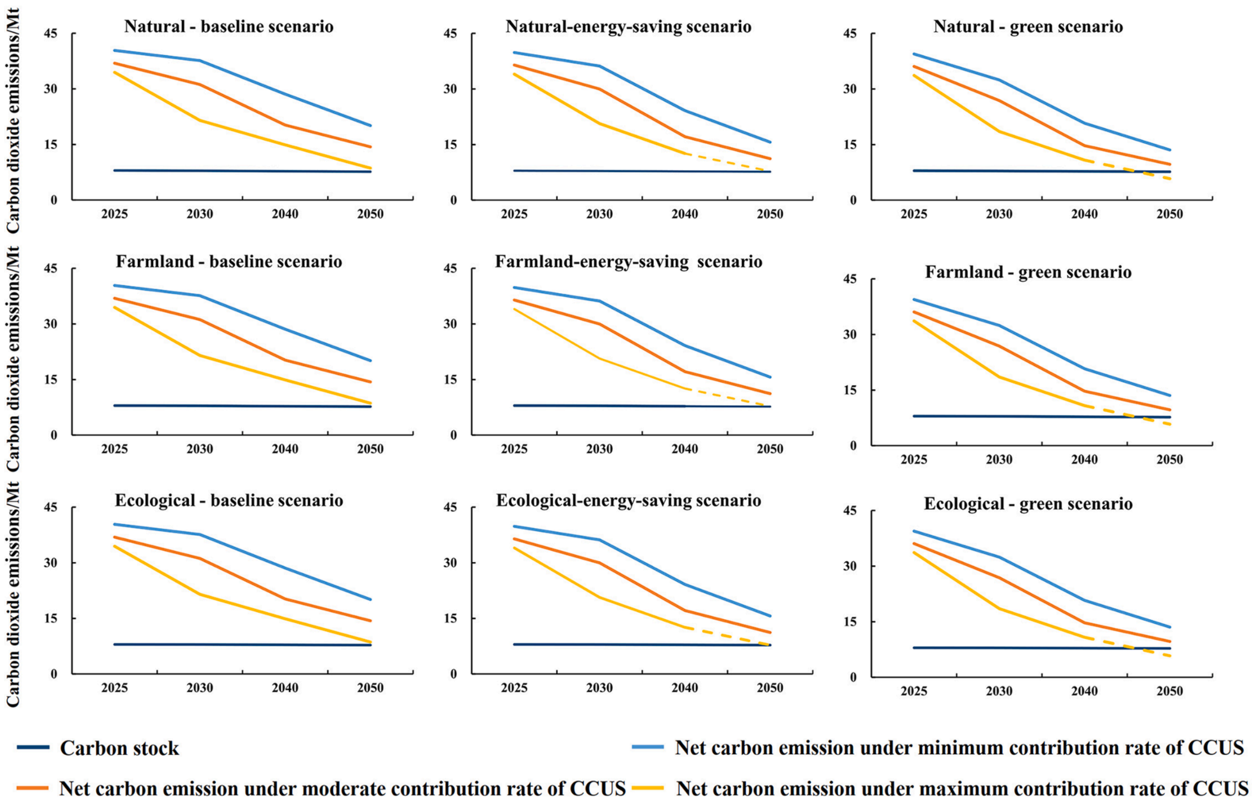

Fig. 6. Carbon neutrality forecasting under nine scenarios (with CCUS).

accuracy of the vegetation carbon stock estimation may be affected by the quality of the NPP data. Third, industrial economic activities (including metallurgical engineering, real property, traffic, iron and steel) were not further subclassified in the LEAP model. Future studies should aim to forecast the detailed carbon emissions for each sector. Furthermore, although environmental factors were considered in the land-use change simulation for each scenario, we did not explicitly incorporate land-use scenarios based on environmental change to fully account for the effects of environmental change on NPP. This limitation may lead to discrepancies between the predicted and actual carbon stocks, as future environmental change may alter the dynamics of NPP and consequently, carbon stock estimations. Future research endeavors should aim to integrate climate change scenarios into land-use modeling to further enhance the accuracy of carbon stock predictions under evolving environmental conditions. Finally, there is absence of substantial integration between the LEAP and PLUS models. At present, the two models face great challenges in terms of data compatibility and model complexity. In future research, we plan to explore ways to deepen the integration of the LEAP and PLUS models through the development of intermediate platforms, data standardization, and enhanced data-sharing mechanisms.

4. Conclusions

Carbon neutrality is a crucial step toward global energy restructuring and sustainable urban development. Forecasting future changes in carbon emissions and carbon stocks is an important task that can help achieve this goal and significantly contribute to low-carbon planning. Although many countries have announced timelines for the carbon neutrality goal, the benchmark for the “carbon peak” has not been specified. While some efforts have been made, there remains a deficiency in the systematic integration of carbon emission forecasting with carbon stock forecasting.

To tackle these issues, we proposed a novel framework for the scenario forecasting of carbon neutrality by coupling the LEAP and PLUS models. The effects of land-use change on carbon stocks and the pathways to carbon neutrality were examined through a combined analysis of carbon emission forecasting, carbon stock forecasting, and CCUS technology. Future carbon stocks were estimated by considering the changes in land-use conditions and NPP. First, the LEAP model was utilized to forecast Shenzhen’s carbon emissions during 2020–2050 in the baseline, energy-saving, and green scenarios. Second, the PLUS method was utilized to forecast land-use in 2050 in the natural development, farmland protection, and ecological security scenarios. Then, the vegetation and soil carbon stocks were estimated based on the NPP data. Finally, we analyzed the potential of using CCUS technology to achieve carbon neutrality under nine integrated scenarios.

By forecasting carbon neutrality pathways under different scenarios, we can explore when carbon emissions will peak and the corresponding peak levels. Identifying pathways could also provide decision support for urban emission reduction policies. In particular, we can examine the route that minimizes the cost of reducing emissions and the necessary policy support to achieve carbon neutrality. Therefore, the proposed methodological framework is expected to offer practical implications and technical assistance for energy structure transformation and sustainable urban design. Although this framework was tested only in Shenzhen, it could be flexibly reused for carbon neutrality forecasting in many other regions.

CRediT authorship contribution statement

Xinyan Zhao: Writing – original draft, Formal analysis. **Zhijie Rao:** Methodology, Investigation, Data curation. **Jinyao Lin:** Writing – review & editing, Supervision, Resources. **Xinchang Zhang:** Validation, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2025.106367.

Data availability

Data will be made available on request.

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