MULTI-SCENARIO LAND USE OPTIMIZATION UNDER THE PERSPECTIVE OF LOW-CARBON ECONOMY—A CASE STUDY OF PEARL RIVER DELTA REGION, CHINA

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Abstract. Rising carbon emissions have triggered the threat of climate change to the natural system and human society. Therefore, exploring the carbon emissions and economic benefits of land use changes under different objectives can provide policy support for sustainable regional development. This paper combines a multi-objective optimization model and a land use simulation model to investigate the carbon emissions and economic benefits of land use changes in the Pearl River Delta (PRD) region of China under four different scenarios. The results show that under the Natural Development scenario (NDs) and Economic Development Priority scenario (EDPs), carbon emissions will increase rapidly; under the Low Carbon Development Priority scenario (LCDPs), carbon emissions will decrease but the economic benefits will be correspondingly lower. Compared with the other scenarios, the Integrated Low Carbon Economic scenario (ILCEs) will result in a moderate increase in the economic benefits, slower growth in carbon emissions, and the lowest carbon emissions per 10,000 Chinese Yuan (CNY) of economic benefit. Therefore, the conclusion suggests that the ILCEs is a more suitable scenario for the future sustainable development objectives of the PRD region.
Keywords: *scenario simulation, carbon emission coefficient, multi-objective programming, PLUS model, land use tradeoffs*

Introduction

Climate change triggered by carbon emissions threatens human society and ecosystems (Cinner et al., 2022), the reduction of carbon emissions has become a topic of common concern for all countries. China has put forward a goal of achieving carbon peak by 2030 and carbon neutrality by 2060 (Liu et al., 2022). In this context, how economic growth and carbon emissions can synergize is a priority for achieving sustainable development.

Optimized land use mediates carbon cycling across terrestrial ecosystems and human systems (Wang et al.,2021), achieving emission reduction and economic growth synergistically, which is a cornerstone of sustainable development (Li et al., 2023). Studies such as Han et al. (2019) have simulated optimal land use under three scenarios and obtained the quantitative structure of land use under the low-carbon economic scenarios. He et al. (2021) have simulated optimal land use based on carbon sinks maximization and carbon emissions minimization scenarios. Li et al. (2022a) derived a

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carbon neutral scenario that may be suitable for sustainable development of the region by land use simulating.

Currently, the methods employed to calculate carbon emissions with land use include model simulation (Houghton, 2017), life cycle method (Kulak et al., 2013), sample plot inventory method (Xiao et al., 2014), and the Intergovernmental Panel on Climate Change (IPCC) carbon emission factor method (IPCC, 2006). Among them, the method proposed by IPCC accounts for both direct carbon emissions generated by land use changes and indirect carbon emissions caused by human activities (Tian et al.,2021). At the same time, it is widely used by scholars because its parameters are easy to obtain and simple to calculate (Song et al., 2015; Yi et al., 2022).

As an important tool for regulating regional carbon emissions, land use optimization is important for guiding regional low-carbon sustainable development (Xia et al., 2023). The existing land use optimization is mainly realized through quantitative optimization and spatial simulation Li et al. (2023). Quantitative optimization models are used to obtain the quantitative structure of each class after optimization by limiting the land use area and setting the objective function, including the linear optimization method (Delgado-Matas et al., 2014), Multi-Objective Programming (MOP) (Wang et al., 2018), grey prediction model (Huang et al., 2011) and so on. Among them, the MOP model can be better applied to multi-objective conflicts, especially in joining the optimal allocation of land use under the background of macroeconomic policies (Sadeghi et al., 2009; Wang et al., 2018), therefore, scholars commonly use it in land use multi-objective trade-off planning (Wang et al., 2022a).

The spatial simulation models simulate land use spatial distribution through their quantitative results (Li et al., 2021), including logistic-cellular automata (logistic-CA) model (Xie et al., 2020), the conversion of land use and its effects at a small regional extent (CLUE-S) model Kucsicsa et al. (2019) and patch-generating land use simulation (PLUS) model (Liang et al., 2021). Among them, the PLUS model analyzes the transition rules of land-use change through patches and thereby increasing the reliability of the predictions (Liang et al., 2021).

The Pearl River Delta (PRD) is one of the most economically developed regions in China; it also has high greenhouse gas emissions (Mai et al., 2014). In the context of the current "dual-carbon" goal, reconciling low-carbon development with economic growth is an issue that requires urgent attention. Therefore, based on the land use changes characteristics of the PRD from 2000 to 2020 and aligned with regional low-carbon and economic development goals, this study established four development scenarios: Natural Development scenario (NDs), Low Carbon Development Priority scenario (LCDPs), Economic Development Priority scenario (EDPs), and Integrated Low Carbon Economic scenario (ILCEs). It employed spatial analysis and simulation models, to optimize the. the spatial distribution of land use in 2030 and evaluated carbon emissions and economic benefits under different scenarios. Ultimately, this research seeks to identify synergistic pathways for achieving both carbon mitigation and economic growth in the PRD through comprehensive multi-scenario land-use optimization simulations.

Materials and methods

Study area

The PRD is located in the southeastern part of Guangdong Province and includes nine cities: Guangzhou, Shenzhen, Zhuhai, Foshan, Jiangmen, Zhongshan, Dongguan,

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Huizhou and Zhaoqing (*Fig. 1*). With a high total regional gross domestic product (GDP) and strong economic ties between cities, it is the economic heartland of China. At the same time, the PRD has a high level of urbanization development, dense population and high energy consumption also make it a key area for the implementation of carbon emission reduction policies (Wang et al., 2022b). Therefore, it is particularly urgent to study the low-carbon and economic development of the PRD region.

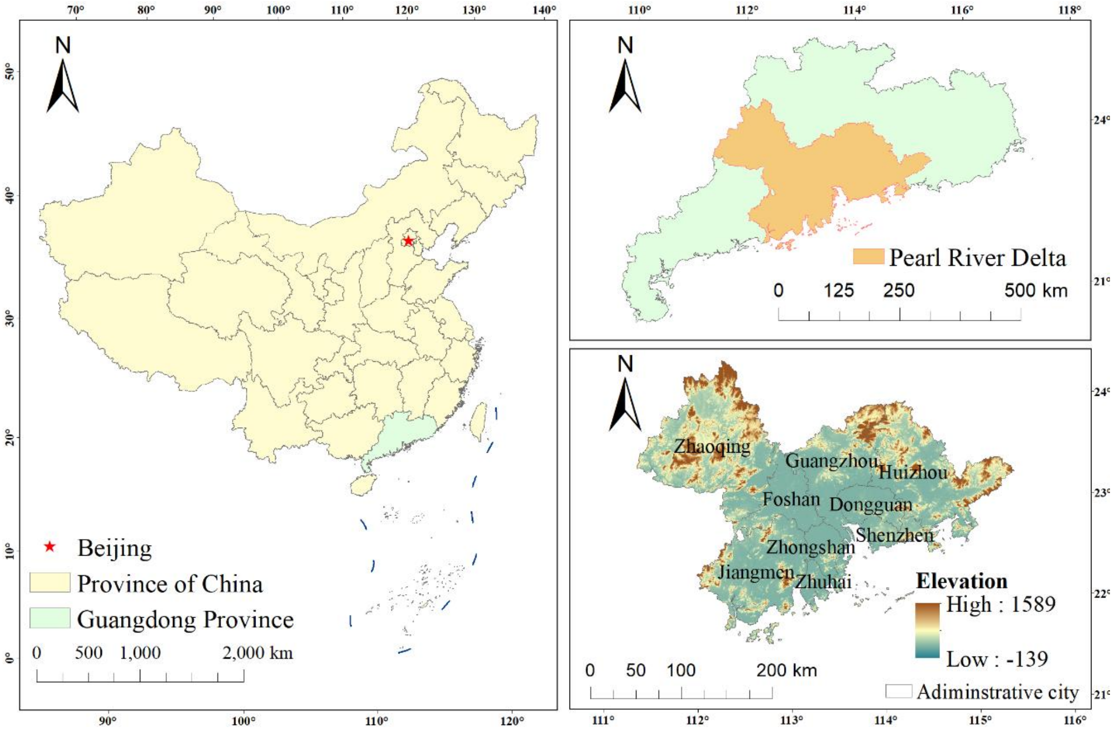

Figure 1. *Location of the study area*

Data

The data for this study primarily comprises land use and vector data such as roads, railways, rivers, settlements and administrative boundaries, along with natural condition and socio-economic condition, and the information on data sources is shown in *Table 1*. Statistical data were obtained from the IPCC Guidelines for National Greenhouse Gas Inventories (2006), the Guangdong Rural Statistical Yearbook, and statistical yearbooks of PRD cities (2000-2020) Taking into account regional realities, we classify land use into six classes: cultivated land, forest land, grassland, water bodies, construction land, and unused land.

Methodology

This study comprises three main components (*Fig. 2*): Firstly, four development scenarios of NDs, LCDPs, EDPs and ILCEs are set, and the optimization of land use quantity for each scenario is achieved by combining different objective functions and constraints through MOP.

Secondly, the spatial distribution of land use in the 2030 scenarios will be obtained by combining the above results with the PLUS model; finally, based on the analysis of

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carbon emissions and economic benefits of different scenarios, we will explore the optimal layout of land use and the development strategy that is suitable for the regional development objectives.

Table 1. *Data sources*

Data	Sub-data	Spatial resolution	Sources
Land dataset	Land use and land cover	30 m	National Earth System Science Data Center (http://www.geodata.cn/)
Vector data	Settlements, rivers, roads, railways	-	National Catalogue Service for Geographic Information (https://www.webmap.cn/)
	Administrative boundaries	-	
Natural condition	Digital Elevation Model (DEM), slope, aspect	30 m	Geospatial Data Cloud (http://www.gscloud.cn/)
	Temperature, precipitation	1 km	Resource and Environment Science Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/)
Socio-economic condition	GDP, population	30 m	Resource and Environment Science Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/)

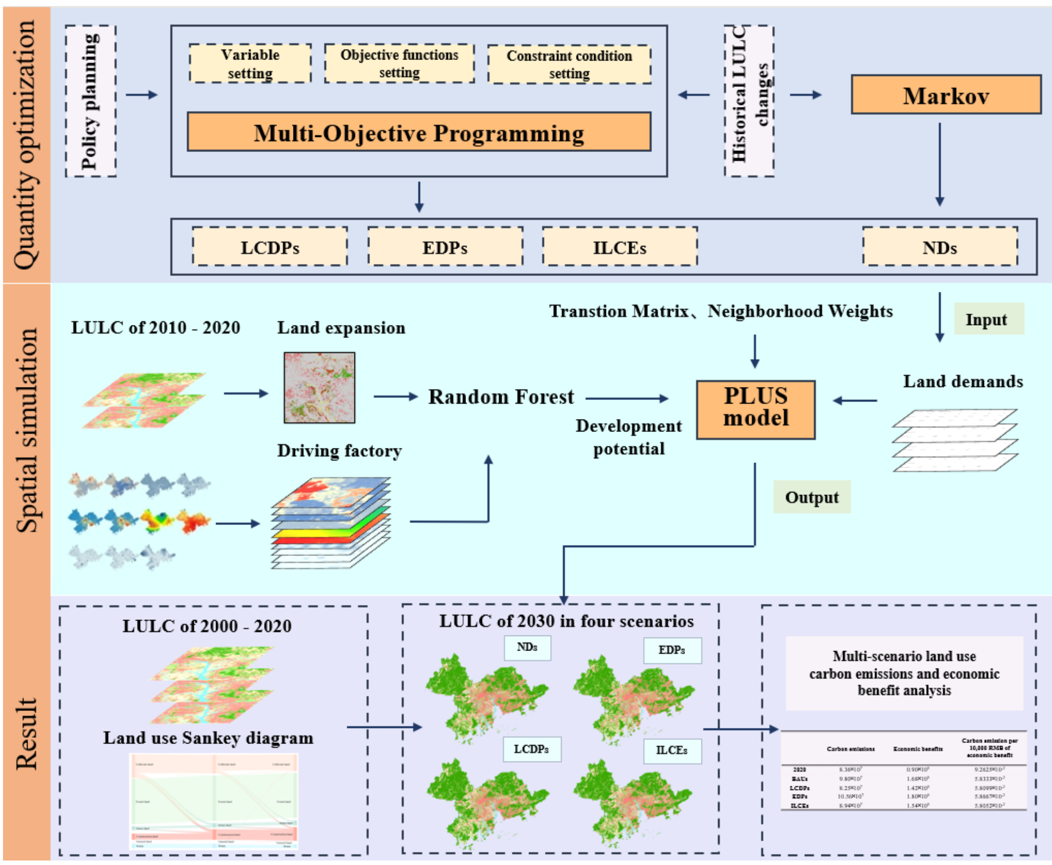

Figure 2. *Research framework*

Determination of carbon emission factor

Carbon emissions for each land use type are calculated as follows: construction land is estimated using the energy consumption method (Jing et al., 2021), cultivated land is estimated using carbon emissions from agricultural production processes (Zhao et al., 2007), and the carbon emission factors for both were calculated by dividing carbon emissions by the corresponding area. The rest of the land use classes are calculated directly using the coefficient method. When the carbon emission coefficient is negative, it is a and vice versa for a carbon sink.

The construction land carbon emissions mainly come from anthropogenic energy consumption, which is calculated as follows:

$$E_c = \sum_{a}^{N} M_a \times f_a \times \theta_a \quad \text{(Eq.1)}$$

where E_c is construction land carbon emission; M_a is the consumption of various fossil energy in production and life; f_a is the conversion coefficient of various fossil energy into standard coal; θ_a is the carbon emission coefficient of various fossil energy; a is the energy class selected in this study, mainly raw coal, gasoline, etc., with a total of ten classes.

The carbon emission coefficients of various classes of energy refer to the "Guidelines for National Greenhouse Gas Carbon Emission Inventories" issued by the Intergovernmental Panel on Climate Change (IPCC, 2006), the standard coal conversion coefficients referred to the China energy statistical yearbook (National Bureau of Statistics, 2020) (*Table 2*). Eventually, the construction land carbon emission coefficient in 2000, 2010 and 2020 were 96.83 t/hm^2, 123.12 t/hm^2 and 95.89 t/hm^2 respectively.

Table 2. *Standard coal energy conversion factor and carbon emission factor of energy*

Energy type	**Energy conversion factor for standard coal (kg standard coal/kg)**	**Carbon emissions factor (kg/kg of standard coal)**	**Energy type**	**Energy conversion factor for standard coal (kg of standard coal/kg)**	**Carbon emissions factor (kg/kg of standard coal)**
Coal	0.7143	0.7559	Fuel oil	1.4286	0.6185
Crude oil	1.4286	0.5857	Liquefied petroleum gas	1.7143	0.5042
Gasoline	1.4714	0.5538	Natural gas	1.3300	0.4483
Kerosene	1.4714	0.5714	Coke	0.9714	0.8550
Diesel	1.4571	0.5921	Electric power	0.1229	0.7935

The unit of the conversion factor for natural gas standard coal is kg/m^3, the unit of the conversion factor for electricity standard coal is kg/kWh, and the rest of the units are kg/kg

The formula of cultivated carbon emissions is:

$$E_t = F + M + R \quad \text{(Eq.2)}$$

where E_t is cultivated carbon emission; F, M, and R are the carbon emissions of agricultural fertilizer production, machinery production and irrigation progress, respectively (Zhao et al., 2007). Their formulas are shown below, where A, B, C and D are conversion factors taken from the reference (West et al., 2002).

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$$F=G_f \times A \quad \text{(Eq.3)}$$

where G_f is the amount of fertilizer used, A = 857.54 kg C Mg^{-1}.

$$M = (A_m \times B)+(W_m \times C) \quad \text{(Eq.4)}$$

where A_m is the area under crop cultivation, and W_m is the total power of agricultural machinery, B = 16.47 kg C hm^{-2}, C = 0.18 kg C kW^{-1}.

$$R=A_s \times D \quad \text{(Eq.5)}$$

where A_s is the irrigated area, D = 266.48 kg C hm^{-2}.

The carbon emissions coefficient of cultivated can be obtained by dividing the carbon emission by the area., which was 0.28 t/hm^2, 0.46 t/hm^2 and 0.43 t/hm^2 for 2000, 2010 and 2020, respectively.

The carbon emission formula for forest, grassland, water bodies and unused land are as follows:

$$E_k=\sum_{i=1}^{4} S_i \times k_i \quad \text{(Eq.6)}$$

where $E_k$is the total direct carbon emissions; S_i is the land area corresponding to each category; k_i is the carbon emission or absorption coefficient corresponding to each land use class.

Since the carbon emission coefficients of forest, grassland, water bodies and unused land change less in the long term (Li et al., 2022b), their carbon emission coefficients are adopted from the existing research results, which are -0.581 t/hm^2, -0.021 t/hm^2, -0.257 t/hm^2 and -0.005 t/hm^2 respectively (Fang et al., 2007).

Determination of economic efficiency factor

The economic benefits of land in this study were measured in conjunction with statistical yearbook data.

$$E_i=\frac{G_i}{S_i} \quad \text{(Eq.7)}$$

where E_i is the economic efficiency coefficient corresponding to each land use class; G_i is the economic output value of each land use class, in which the economic output value of construction land is taken from the sum of the output value of the secondary and tertiary industries, the economic output value of cultivated, forest, grass and water bodies is taken from the total output value of the agriculture, forestry, animal husbandry and fishery, and the economic benefits of unused land are not considered for the time being; S_i is the area of each land use class.

LULC structure optimization using Markov and MOP

In this paper, multi-objective optimization of land use structure under different scenarios is achieved based on MOP algorithm with the help of LINGO18.0 software, which consists of three parts: decision variables, objective functions, and constraints (Cao et al., 2019).

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Scenario setting

(1) Natural Development scenario (NDs): NDs is a scenario model for modeling future land structure based on historical land use change trend and is carried out with a Markov model.

(2) Low Carbon Development Priority scenario (LCDPs): LCDPs is based on the objective of minimization future land use carbon emissions and the optimal solution is obtained by combining the land use carbon emission coefficient through the LINGO software. The specific formula is as follows:

$$F_1(x)=\min \sum_{i=1}^{6} k_i x_i \quad \text{(Eq.8)}$$

where $F_1(x)$ is the carbon emission; I is the different land use classes, with 1-6 denoting cultivated land, forest land, grassland, water bodies, construction land and unused land respectively. k_i is the carbon sequestration/emission coefficient of different land use classes i.

Combined with the grey prediction model and previous studies, the carbon sequestration/emission coefficients in 2030 of the above six classes of land use are obtained as 0.40, -0.581, -0.021, -0.257, 93.93 and -0.005 respectively, *I* is the area of different land use classes.

(3) Economic Development Priority scenario (EDPs): EDPs refers to the optimization of future land use quantity structure based on the maximization of the economic benefits of land use as the objective, and the optimal solution is obtained by combining future land use economic benefit coefficient combined with LINGO software, the specific formula is as follows:

$$F_2(x)=\max \sum_{i=1}^{6} E_i x_i \quad \text{(Eq.9)}$$

where $F_2(x)$ is the economic benefit, E_i is the economic benefit coefficient of different land classes i, and the economic benefit coefficients of different land classes i in the 2030 based on the grey prediction model were 18.46, 0.67, 14.26, 49.61, 1552.35, and 0, respectively.

(4) Integrated Low Carbon Economic scenario (ILCEs): ILCEs refers to the land use scenarios that take into account the synergistic objectives of minimizing carbon emission and maximizing economic efficiency. Firstly, the LCDPs and the EDPs are normalized to obtain $f_1(x)$ and $f_2(x)$ respectively, and then the two objective functions are input into LINGO software for linear weighted summation, with the specific formula as follows:

$$F(x)=\max\left\{-\frac{1}{2} f_1(x) + \frac{1}{2} f_2(x)\right\} \quad \text{(Eq.10)}$$

Constraints

The study assumes that land use change in 2030 will continue the trend of 2010-2020, and it sets limits on the range of quantities of each class of land use based on existing relevant literature and planning texts. The specific descriptions are shown in *Table 3*.

Land use simulation with the PLUS model

The PLUS model extracts the extension of land use classes in the two phases of land use change, calculates the development probability of each land use class using the Random

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Forest algorithm, and then simulates and predicts the future land use change using the CA model based on the seeds of random patches of multiple categories (Liang et al., 2021).

Table 3. *Multi-objective optimization constraints*

Subject to	Description
$x_1+x_2+x_3+x_4+x_5+x_6=5436559.35$	Total land use area remains unchanged
$12078321 \geq x_1 \geq 1041700$	Take the area of cultivated land in 2020 as the upper limit; make reference to the studies of experts and scholars on the PRD region and set the minimum area of cultivated land at 1041700 hm^2 (Du et al., 2015) as the lower limit
$3185279.92 \geq x_2 \geq 2744918.82$	Combined with the literature (Ni et al., 2008) and the Integrated Plan for the Ecological Security System in the PRD Region (2014-2020), the upper and lower limits of the future forest land area were set to be 58.59% and 50.49% of the total area of the study area, respectively
$305334.54 \geq x_3 \geq 304081.38$	Actual grassland area in 2020 is upper limit and projected area is lower limit
$233974.8 \geq x_4 \geq 190301.58\times80\%$	Actual water bodies area in 2020 is upper limit, 80% of projected area is lower limit
$1074317.76\times90\% \geq x_5 \geq 1074317.76\times110\%$	Set 110% of the projected construction land area as the upper limit and 90% as the lower limit
$1696.5\times80\% \geq x_6 \geq 1696.5\times20\%$	Set 80% of the projected unused land area as the upper limit and 20% as the lower limit

Based on the actual situation, 11 drivers in the study area in terms of natural, socio-economic and distance factors were selected (*Fig. 3*). The land use development probability is obtained by extracting the expansion of the land use change from 2010 to 2020.

The weights of cultivated land, forest land, grassland, water bodies, construction land, and unused land were set to 0.3, 0.8, 0.6, 0.3, 0.9, and 0.1, respectively (the parameter range is 0 to 1, with values closer to 1 indicating a stronger capability for landscape class expansion). The construction land is set not to be transferred out, and the unused land is set not to be transferred in. The land use demand is calculated according to the Markov model and MOP model. In order to calibrate the model, we verified the actual land use data for 2020 with the simulation results, and finally obtained an overall accuracy of 0.84, indicating that the simulation results are highly credible.

Results

Land use change from 2000 to 2020

During the period 2000-2020, the most dominant land use classes in the PRD were forest land, accounting for about 54.07% of the total area, and were mainly concentrated in the western and northeastern parts of the PRD. The second class of land use was cultivated land, accounting for about 23.48% of the total area. The third class of land was construction land, accounting for about 12.11% of the total area, and was mainly concentrated in the central part of the PRD. Grassland, water bodies and unused land area accounted for 5.18%, 5.01% and 0.16% respectively (*Fig. 4*).

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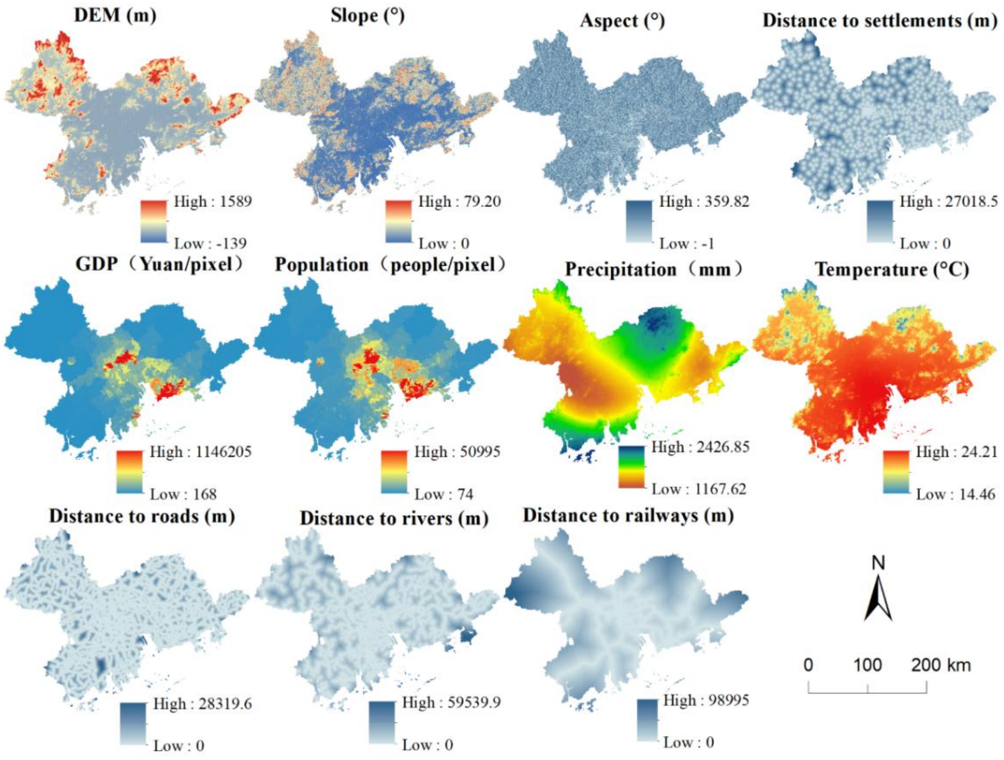

Figure 3. *Driving factors of land use change in the PRD*

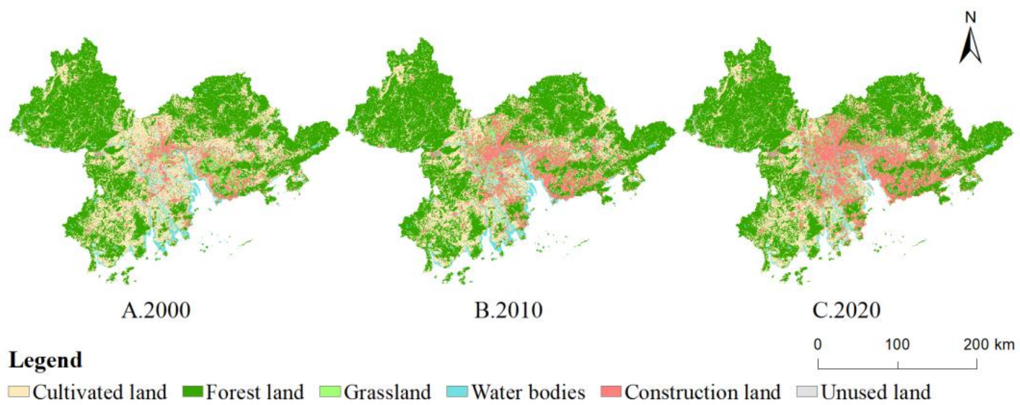

Figure 4. *Land use map of the PRD region, 2000-2020*

From 2000 to 2010, the area of construction, grassland, forest and water bodies increased. Among them, construction land expanded the most, with an area increase of 284,701.14 hm^2, an increase of 70.81%, mainly encroaching on cultivated land, unused land and forest land; followed by grassland, with an area increase of 47,731.23 hm^2, an increase of 19.43%, with the newly added grassland primarily originating from cultivated land. Cultivated land was threatened by construction, grassland and forest, with a total loss of 345,290.76 hm^2 of cultivated land in 10 years, a decrease of 22.37%. The area of unused land decreased, mainly being developed into construction and a small amount of grassland and cultivated land (*Fig. 5*).

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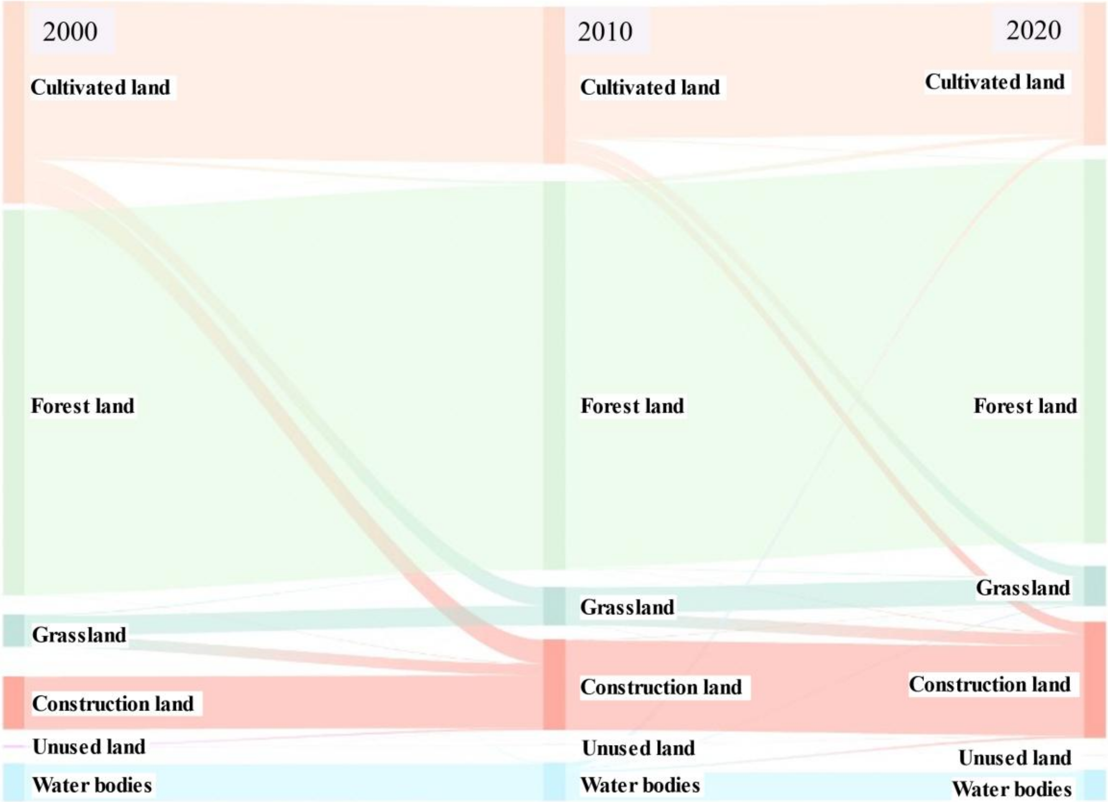

Figure 5. *Sankey map of land-use transfers, 2000-2020*

From 2010 to 2020, the area of construction and grassland continued to increase. Among them, the construction land increased by an area of 199,034.19 hm^2, an increase of 28.98%, mainly occupying cultivated and grassland. The area of water bodies, cultivated forest, and unused land decreased, with the area of cultivated land decreasing the most, by 111,297.69 hm^2, resulting in a decrease of 9.29%. This was followed by water bodies, forest and unused land, with decreases of 58,450.5 hm^2, 39,255.84 hm^2, and 20,025.72 hm^2, respectively, with reduction rates of 19.99%, 1.33% and 44.73%.

Overall, construction and grassland in the PRD region showed a continuous increase trend, while cultivated and unused land continued to decrease in 2000-2020. On the other hand, forest and water bodies showed a changing trend of increase and then decrease.

Optimization and simulation

Multi-scenario land use optimization simulation

The expected area of land use categories under the NDs, LCDPs, EDPs, and ILCEs are shown in *Figure 6a*. Compared with 2020, there is an increase in construction under all scenarios. The NDs has the largest decrease in cultivated; the LCDPs has the minimal expansion in construction but the largest increase in forest; the EDPs has the largest increase in construction but the greatest decreases in forest and water bodies; and the ILCEs has a moderate increase in construction and the smallest decreases in water bodies and grass (*Fig. 6b*).

Combining the land use in the PRD region in 2020 and the spatial distribution of the four scenarios simulated (*Fig. 7*), it can be seen that under the NDs, the construction land in the PRD region exhibits an outward expansion, which is more pronounced in the northeast and southwest directions, with a decrease in the amount of cultivated land and forest land in the region. The LCDPs has limited expansion of the construction land, with the smallest increase. The EDPs has the same direction of expansion as the NDs but the degree of expansion is more significant, mainly occupying forest land and water bodies. The ILCEs has the same direction of expansion in construction land, but the degree of expansion is relatively moderate.

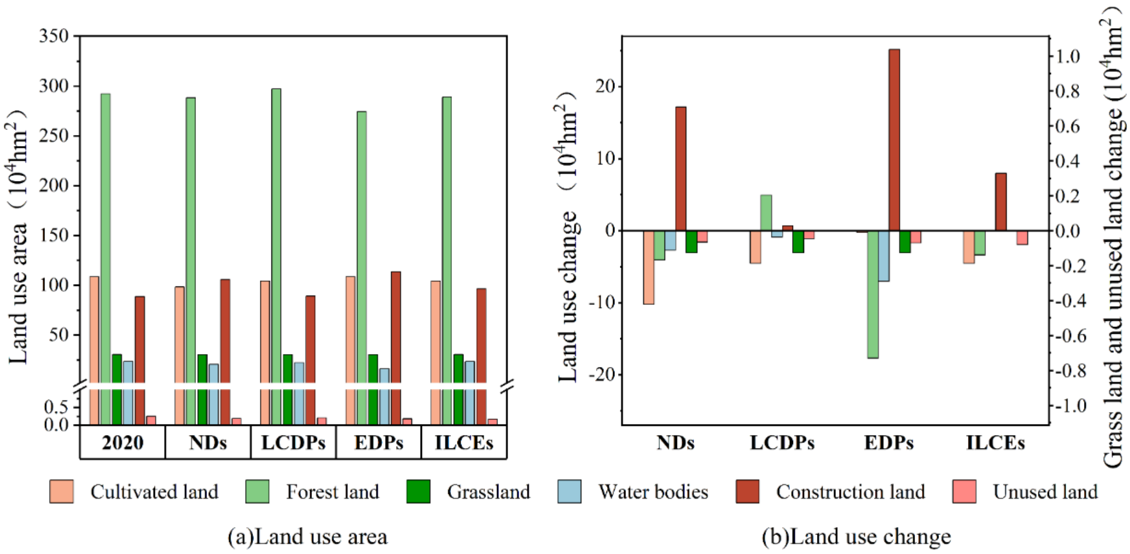

Figure 6. *Land use changes in the PRD, 2020-2030 (NDs, LCDPs, EDPs, and ILCEs represent the expected area of different scenario land use categories in 2030)*

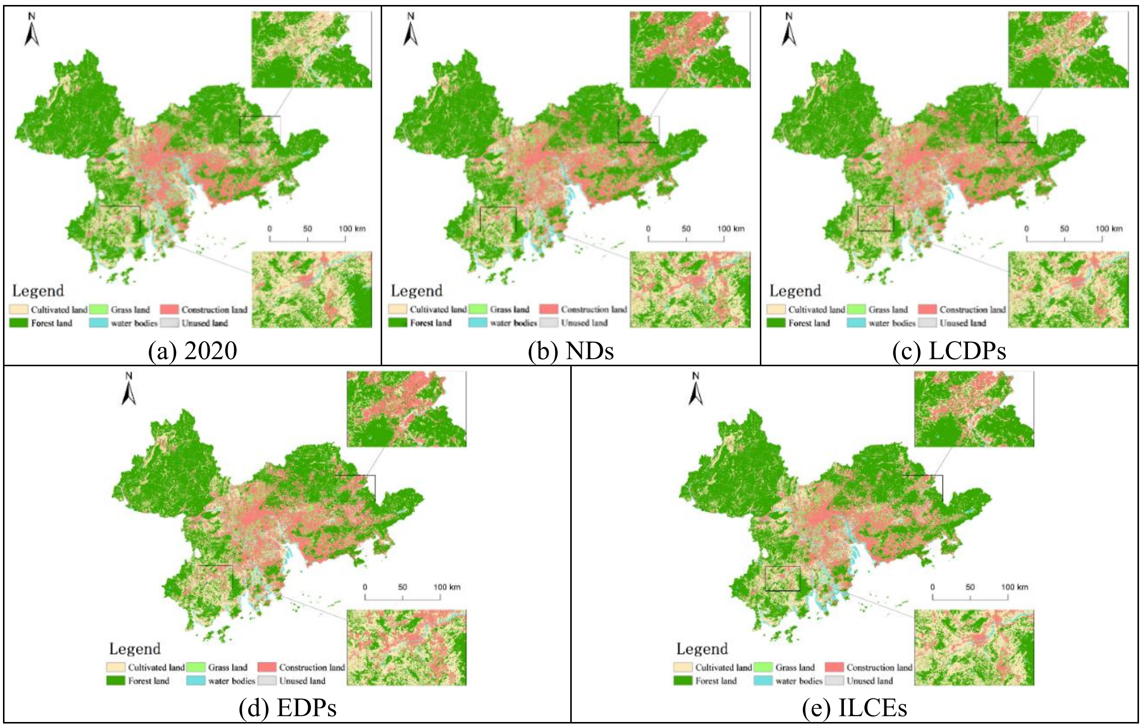

Figure 7. *Land use in the PRD region under different scenarios in 2020-2030*

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Multi-scenario analysis

The carbon emissions, economic benefits and carbon emissions per 10,000 CNY of economic benefits under different scenarios in 2020-2030 are shown in *Table 4*.

Table 4. *Carbon emissions, economic benefits and carbon emissions per 10,000 CNY of economic benefits for different scenarios, 2020-2030*

	Carbon emissions	Economic benefits	Carbon emissions per 10,000 CNY of economic benefit
2020	8.36×10^7	0.90×10^9	9.2625×10^{-2}
NDs	9.80×10^7	1.68×10^9	5.8333×10^{-2}
LCDPs	8.25×10^7	1.42×10^9	5.8099×10^{-2}
EDPs	10.56×10^7	1.80×10^9	5.8667×10^{-2}
ILCEs	8.94×10^7	1.54×10^9	5.8052×10^{-2}

Compared with 2020, the NDs shows a simultaneous increase in economy and carbon, with an increase of 85.95% in economic and 17.16% in carbon emissions. The LCDPs shows an economic increase of 57.48% and a decrease of 1.42% in carbon emissions. The EDPs shows an increase of 99.35% in economic benefits and an increase of 26.29% in carbon emissions, and the ILCEs shows an increase in economic benefits reaching 70.09% and an increase in carbon emissions is 6.84%.

The above results indicate that under the NDs or EDPs, carbon emissions in the PRD region will increase rapidly, which is not conducive to realization of the “dual-carbon” goals. In the LCDPs, carbon emissions decrease, but economic benefits are relatively lower. The ILCEs exhibits a moderate increase in economic benefits, a slower increase in carbon emissions, and a lower level of carbon emissions per 10,000 CNY of economic benefits than the other scenarios. In conclusion, the ILCEs is relatively suitable option for achieving the green development in the PRD.

Discussion

Discussion on multi-objective optimization and carbon emission results

The study shows that the influencing factors constructed on the basis of nature, economy and distance, combined with the PLUS model, are able to simulate the future land use changes better in PRD and with a high degree of reliability. The land use simulation are consistent with the (Li et al., 2022) who simulated future land use changes in the PRD region based on the FLUS model.

This study found that construction land and cultivated land serve as prominent carbon sources, while forest land acts as the primary carbon sink, and this conclusion aligns with the studies of other scholars (Han et al., 2019; Li et al., 2023).

Therefore, by optimizing the layout of construction, cultivated and forest land, is the key to reduce carbon emissions. While pursuing the “dual-carbon” goal, it is important to protect ecological land, especially forest land. At the same time, the boundaries of urban expansion are effectively controlled on the premise of guaranteeing cultivated land and food security (Li et al., 2022).

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Policy recommendations based on optimization and simulation results

We found that under all four scenarios, the construction land in the PRD is expanding externally, which threatens food or ecological security to varying degree, and thus internal growth and low-carbon development of the city are particularly necessary.

It has been shown that an important way to achieve a low-carbon city is to reduce emissions and increase carbon sequestration at simultaneously (Li et al., 2012). Compact cities can reduce part of the carbon emissions from transportation trips (Liu et al., 2019); (Makido et al., 2012), so restraining urban expansion and emphasizing high-density development can effectively slow down urban carbon emissions. Meanwhile, cultivated land contributes to the carbon sources in the PRD region. Therefore, based on guaranteeing the red line for regional cultivated land, the project of returning cultivated land to forest can be carried out in a step-by-step and orderly manner.

Agricultural production methods can also be optimized to achieve the transformation of nature and intensity of agricultural carbon sources to carbon sinks, and the carbon sink potential of cultivated land can be fully tapped (Bao et al., 2022). Meanwhile, measures are strengthened in terms of cultivated protection policies as well as the carbon trading market (Ke et al., 2021). In terms of carbon sequestration enhancement, the carbon sequestration function of cities can be increased through the construction of urban parks and green spaces, protective green spaces and green corridors (Li et al., 2012).

Limitations and prospects

Due to the different statistics of energy consumption statistics in different cities, the uniform calculation of carbon emissions using the coefficient method may bring some bias, but it can still reflect the relative differences in carbon emissions of different land types. Besides, there is a degree of subjectivity in the setting of constraints when performing multi-objective optimization based on the MOP model. Therefore, future research should make wide reference to expert advice and policy planning basis.

Conclusions

We studied the land use changes in the PRD region under different low-carbon and economic objectives, analyzed the carbon emissions and economic benefits, and proposed suitable land use models and corresponding policy recommendations. The study findings are as follows:

Firstly, the study shows that the combination of multi-objective optimization and the PLUS model is better at achieving the optimal spatial layout of land use in the PRD region.

Secondly, the different development scenarios set up in the study can provide different options for regional development. The results show that the ILCEs is more in line with the green development of the PRD region.

Finally, optimizing the spatial layout of construction or cultivated land in carbon source areas and adopting corresponding carbon sequestration or emission reduction strategies can also be a reference for the balanced development of low-carbon economy in other highly urbanized regions.

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