

Evaluating Carbon Storage Responses to Land Use Change under Multi-Scenario Simulations: A GMOP–PLUS–InVEST Coupled Framework for Border Cities

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1 **Evaluating Carbon Storage Responses to Land Use Change under Multi-Scenario**
2 **Simulations: A GMOP–PLUS–InVEST Coupled Framework for Border Cities**

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Abstract

Terrestrial ecosystems are critical to the global carbon cycle, yet land use/land cover change (LULC) driven by urbanization and policy interventions significantly disrupts carbon storage dynamics. This study develops an integrated multiple-model framework to analyze the evolution of carbon storage in Dandong, China, a rapidly urbanizing border city facing ecological–economic conflicts. The results revealed a "decline-then-increase" trend (2000–2020), with net carbon gains ($+52.56 \times 10^5$ t) driven by forest expansion ($+102.41 \times 10^5$ t) offsetting cropland loss (−8.74%). Multiple scenario projections for 2030 highlight trade-offs: the ecological protection scenario (EPS) maximizes sequestration (+6.23%) but requires extensive cultivated land conversion, whereas the economic development scenario (EDS) yields minimal gains (+0.93%) due to construction land expansion. The comprehensive development scenario (CDS) balances growth (+28.01% construction land) and sustainability (+5.59% carbon storage). Geodetector analysis revealed the NDVI ($Q = 0.515$) and topography (slope $Q = 0.475$) as the dominant drivers, with their interaction (slope–NDVI, $Q = 0.615$) underscoring synergies between reforestation and terrain optimization. The study advocates zonal LULC policies by prioritizing afforestation in northern mountains and restricting industrial expansion along southern coasts. These findings provide a replicable model for achieving ecological–economic synergy in border regions, aligning with China's "dual carbon" goals and global clean production strategies.

Keywords

Carbon storage prediction; Multi-scenario simulation; GMOP-PLUS model; InVEST model; Geodetector; Border cities

Introduction

Terrestrial ecosystems are central carbon reservoirs in the global carbon cycle, and their dynamic carbon storage directly impacts the atmospheric carbon balance and the stability of the climate system^{1,2}. In the context of intensifying global climate change, land use/land cover (LULC) change has become one of the primary anthropogenic drivers of disturbances to the stability of terrestrial carbon reservoirs³⁻⁶. According to data from the IPCC's Sixth Assessment Report⁷, the global surface temperature increased by 1.09°C between 2011 and 2020 due to rising carbon dioxide emissions, with LULC changes accounting for approximately 23% of anthropogenic carbon emissions, second only to fossil fuel combustion. Studies have shown that the conversion of different LULC types, such as cultivated land, forest and construction land, results in significant differences in carbon effects^{8,9}. Forest expansion generally enhances carbon sequestration functions, whereas the loss of cultivated land (especially when converted to construction land) leads to notable carbon losses¹⁰. This "forest gain, cultivated land loss" bidirectional impact mechanism is particularly pronounced in regions where rapid urbanization and ecological conservation policies are implemented concurrently^{11,12}. Therefore, conducting multiple-scenario predictions of LULC changes and simulating the spatiotemporal evolution of their carbon storage is of significant scientific importance for supporting the realization of China's "dual carbon" strategic goals.

In recent years, research on the coupling mechanism between LULC and carbon emissions has developed into three core directions: assessment of the carbon emission effects of LULC¹³, analysis of the driving mechanisms¹⁴, and spatial differentiation characteristics¹⁵. In terms of simulation methods, models such as CA-Markov (cellular automata Markov)¹⁶, CLUE-S (the conversion of land use and its effects modeling framework)¹⁷, GeoSOS-FLUS (geographical simulation and optimization system-future land use simulation)¹⁸, and PLUS (patch-generating land use simulation)¹⁹ have achieved large-scale LULC change scenario reconstruction through spatially explicit simulation techniques. Among them, the PLUS model innovatively

employs the land expansion analysis strategy (LEAS), which significantly improves the simulation accuracy of patch-level changes in multiple LULC types^{19, 20}. However, existing models largely rely on endogenous conversion rules for LULC structure prediction, and quantitative representations of exogenous constraints such as regional development policies and ecological conservation systems are lacking. To better quantify carbon storage dynamics, we also coupled the InVEST (Integrated Valuation of Ecosystem Services and Trade-offs) model with the PLUS model, which calculates carbon stocks by integrating four carbon pools (aboveground, belowground, soil, and dead organic matter). The carbon density parameters were spatially calibrated via localized climatic and ecological data to increase accuracy^{21, 22}.

As a typical region of rapid urbanization, China experienced a 12.7% decrease in carbon storage in cultivated land due to the expansion of construction land between 1990 and 2020, whereas forest carbon sequestration, driven by ecological engineering, increased by 23.6% over the same period (based on national land survey data). This "carbon loss, carbon gain" symbiotic phenomenon highlights the leverage effect of optimizing the spatial configuration of land to achieve carbon neutrality goals. Therefore, analyzing the impact mechanism of LULC changes on carbon storage requires a comprehensive consideration of multidimensional factors, including natural geographic elements, socioeconomic drivers, and policy regulations. This study introduces the gray multiobjective optimization (GMOP) model, which offers the following advantages: (1) it addresses the uncertainty of objective functions and constraints through gray system theory²³, and (2) it uses Pareto optimal solutions to reconcile conflicts between multiple objectives, thus more accurately depicting the dynamic evolution characteristics of the human–environment system^{24–26}.

This study selects Dandong, a key city at the northern end of China's coastline, as a typical case study area. As important nodes in the Northeast Asia Economic Corridor and border ecological security barriers, cities face multiple challenges in terms of land resource optimization, carbon sequestration enhancement, and

98 sustainable economic development. On the basis of multiple-period LULC data from
99 2000 to 2020, a GMOP–PLUS–InVEST–Geodetector model chain is coupled to
100 construct a full-chain analytical framework of "quantity structure optimization →
101 spatial pattern simulation → carbon storage response → driving mechanism analysis."
102 By setting natural development scenarios (NDSs), ecological protection scenarios
103 (EPSs), economic development scenarios (EDSs), and comprehensive development
104 scenarios (CDSs), this study predicts the spatial distribution pattern of carbon storage
105 in 2030 and reveals its multidimensional driving mechanisms, aiming to provide
106 decision-making support for sustainable land resource management in border regions.

Results

Spatiotemporal evolution characteristics of LULC

Analysis of the contributions of the driving factors of LULC

The main driving factors and their contribution differences across LULC types are shown in Fig. 4. The normalized difference vegetation index (NDVI) had the highest contribution to forests (16.39%), indicating that vegetation coverage is the core determinant of forest distribution. The GDP had a significant influence on cultivated land (15.64%), reflecting the strong driving role of economic activity on cultivated land. Grassland distribution was more dependent on natural factors such as annual precipitation (8.25%) and elevation (6.24%). Notably, soil type contributed minimally to all LULC types (<5%), whereas anthropogenic factors (e.g., distance to urban centers and transportation infrastructure) affecting construction land were not directly displayed in the figure, potentially being embedded within other categories. Overall, natural factors (climate, topography) dominated ecological lands (forests, grasslands), whereas socioeconomic factors (GDP, population density) had more pronounced effects on productive lands (cultivated land).

Characteristics of LULC changes in temporal and spatial dimensions from 2000 to 2020

Temporal analysis revealed a significant evolution in Dandong's LULC pattern from 2000–2020, demonstrating a characteristic "three increases and three decreases" trend (see Table 7). Specifically, forest, water, and construction land showed continuous expansion, whereas cultivated land, grassland, and unused land exhibited declining trends. The most notable reduction occurred in cultivated land, with a cumulative decrease of 340.33 km² (annual decline rate: 0.87%), which was primarily converted to forest and construction land (Fig. 5). Notably, forest expansion displayed distinct phase characteristics: the 2010–2020 increase (123.34 km²) was 13.42 times greater than the 2000–2010 increase (9.19 km²). Construction land expansion showed a decelerating trend, growing by 121.06 km² from 2000–2010 but only 75.94 km² from

2010–2020. Structurally, forest and cultivated land maintained their dominance throughout the period, consistently accounting for more than 90% of the total regional area, indicating relative stability in overall LULC composition despite significant local conversions.

From the perspective of spatial pattern evolution (Fig. 6), Dandong's LULC changes from 2000–2020 exhibited distinct spatial differences. Policy-driven factors played a significant role: in northern mountainous areas, the "Grain for Green" program and ecological protection policies directly promoted prominent cultivated land-to-forest conversion. Urbanization processes dominated the concentrated transformation of cultivated land to construction land around built-up areas. In southern coastal zones, both natural geographical conditions and ecological protection jointly influence the transition of some cultivated land into water bodies and wetlands. Comparatively, conversions among other LULC types displayed relatively scattered spatial distribution patterns.

LULC changes simulated by multiple-scenario GMOP-PLUS in 2030

This study employed the GMOP-PLUS model to simulate and predict LULC changes under four development scenarios for 2030. The results demonstrate that different development objectives exert significant impacts on regional LULC patterns (Table 7 and Fig. 7). Under the NDS, LULC changes followed historical trends observed from 2010 to 2020. The simulation revealed a net reduction of 163.11 km² in cultivated land, an increase of 108.49 km² in forest, and an expansion of 64.29 km² in construction land. Notably, cultivated land was primarily converted into forest (60.07%) and construction land (39.66%), whereas changes in other land categories were relatively minor. In the EPS, the simulation indicated a substantial restructuring of LULC patterns. Approximately 1042.21 km² of cultivated land was projected to undergo conversion, with 96.21% transitioning to forest, 2.52% to water, and 1.27% to grassland. This shift resulted in a significant increase in forests, enhancing critical ecological functions. The EDS data exhibited typical urbanization characteristics. A total of 438.19 km² of cultivated land was converted, with 200.84 km² transformed

into forest and 189.64 km² transformed into construction areas. Notably, the proportion of cultivated land converted to construction land rose sharply to 47.27%, reflecting strong urban expansion demands under this scenario. The CDS demonstrated a balanced approach, achieving both economic growth (194.66 km² increase in built-up areas) and ecological conservation (940.83 km² increase in forest). These results suggest that CDSs can effectively reconcile economic development with ecological protection. The spatial distribution patterns revealed that cultivated land-to-forest conversions predominantly occurred in the northern and western mountainous regions of the study area, whereas construction land expansion was concentrated in Dandong city's urban core and surrounding suburban towns (see Fig. 8 for the predicted LULC for the 4 scenarios, whereas Fig. 9 illustrates the changes in LULC).

Spatiotemporal evolution characteristics of carbon storage

Characteristics of carbon stock changes in temporal and spatial dimensions from 2000 to 2020

Dandong city's terrestrial ecosystem carbon stocks exhibited distinct phase characteristics from 2000 to 2020 (see Table 8 and Fig. 10). The total carbon stock in the study area declined from 2000–2010 but rebounded in 2010–2020, increasing from $8,732.09 \times 10^5$ t in 2000 to $8,784.65 \times 10^5$ t in 2020, a net gain of 52.56×10^5 t, equivalent to an average annual growth rate of approximately 5.26×10^5 t. This trajectory aligns with a dual-phase pattern of "fluctuating decline followed by steady growth." Forest ecosystems, as the region's dominant carbon sink, contributed most significantly to these changes. Over the 2000–2020 period, forest carbon stocks increased by 102.41×10^5 t, accounting for the majority of the regional increase. This underscores their pivotal role in maintaining the stability of their carbon sequestration capacity.

The spatial distribution of carbon stock changes in Dandong city reveals distinct regional heterogeneity. Specifically, carbon stock losses were predominantly concentrated in the southeastern districts of Zhen'an, Yuanbao, and Zhenxing,

whereas gains were mainly observed in Fengcheng city in the western region (Fig. 11). Notably, the southern coastal area of Dandong exhibited a unique temporal pattern: carbon stocks increased between 2000 and 2010 but declined from 2010 to 2020.

Characteristics of carbon stock changes under different scenarios in 2030

The simulation results under the GMMOP–PLUS–InVEST model reveal significant disparities in carbon stocks across different development scenarios in Dandong city by 2030 (Table 8 and Fig. 12). The key findings are as follows:

Natural development scenario

The total regional carbon stock reached 883.86×10^5 t (0.61% greater than the 2020 baseline of 878.47×10^5 t). Forest carbon stocks increase by 1.07% (from 783.31×10^5 t to 791.70×10^5 t), whereas declines in cultivated land, grassland, water, and construction land collectively offset these gains, with a net reduction of 3.90×10^5 t.

Ecological protection scenario

This scenario demonstrates optimal performance, with carbon stocks rising to 894.73×10^5 t (a 6.23% increase). Afforestation and ecological restoration projects drive a 10% growth in forest, grassland, and water carbon stocks (from 786.93×10^5 t to 865.62×10^5 t). However, cultivated land carbon stocks decrease sharply by 29.34% (from 81.65×10^5 t to 57.69×10^5 t). Spatial analysis identified newly emerging carbon sink hotspots in northern mountainous areas, which exhibited dispersed distribution patterns; see (b) EPS in Fig. 12.

Economic development scenario

The carbon stock increased by 8.20×10^5 t, representing a 28.03×10^5 t improvement over the NDS but remaining significantly lower than the EPS. Urban expansion emerged as the primary limiting factor for carbon stock growth, creating distinct carbon loss hotspots along the corridor between the Donggang economic development zone and Dandong New District.

Comprehensive development scenario

The total carbon stocks reach 927.54×10^5 t (a 5.59% increase), closely aligning with EPS (6.23%). Forest carbon stocks increase by 9.28% (from 783.31×10^5 t to 856.02×10^5 t), whereas construction land carbon stocks increase by 28.01% (from 9.87×10^5 t to 12.64×10^5 t). Cultivated land, however, becomes the primary carbon loss source due to area reduction, declining 32.77% (from 81.65×10^5 t to 54.89×10^5 t). Spatial pattern analysis (Fig. 13) confirms that CDS effectively reconciles ecological and economic objectives by integrating carbon gain/loss hotspots from EPS and EDS.

Analysis of the spatial driving forces of carbon storage

Results of the factor detection modules

This study selected eight significant drivers of LULC types (Table 6) to analyze their driving effects on carbon storage. The Geodetector results revealed that during 2000 and 2010, the top three influential factors remained consistent: slope ($Q = 0.475$ in 2000; $Q = 0.413$ in 2010), elevation ($Q = 0.392$ in 2000; $Q = 0.339$ in 2010), and temperature ($Q = 0.326$ in 2000; $Q = 0.275$ in 2010); see (a) and (b) in Fig. 14. However, in 2020, the dominant factor shifted to the NDVI index ($Q = 0.515$), which emerged as the most explanatory indicator among all factors, whereas previously influential factors—slope, elevation, and mean annual temperature—decreased to the second, third, and fourth positions, respectively. A comprehensive analysis of the 2000–2020 findings demonstrated that natural factors (M1–5) consistently dominated the spatial heterogeneity of carbon storage in Dandong city, whereas anthropogenic factors (M6–8) had relatively weaker influences.

Results of the interaction detection modules

The interaction detector, which builds upon single-factor analysis, further quantifies the pairwise interactive effects among influencing factors. The results demonstrate that the interaction intensity (q value) of all the factor combinations significantly exceeds their independent effects, indicating that the carbon stock changes in

Dandong city are driven by multifactor synergies (Fig. 14.). Specifically, in 2000, slope-related interactions exhibited the most pronounced explanatory power. The slope–elevation combination showed the strongest interaction ($q = 0.548$), whereas the slope–urban distance combination contributed minimally ($q = 0.053$). By 2010, the driving pattern shifted: the slope–NDVI combination emerged as the dominant factor ($q = 0.486$), followed by slope–elevation ($q = 0.480$), reflecting tripartite regulation by slope, the NDVI, and elevation during this period. By 2020, the driving effect of the slope–NDVI combination continued to intensify, reaching its peak q value (0.615) within the study period. Notably, all combinations involving slope or the NDVI achieved explanatory power exceeding 0.5, further validating their pivotal roles in carbon stock dynamics.

Discussion

This study reveals the dynamic changes in carbon storage in Dandong city from 2000 to 2020. During the study period, regional carbon storage exhibited a net increase of 52.56×10^5 t, indicating a distinct "decline followed by an increasing" trend (Table 8). This change pattern is significantly consistent in terms of both time and space with the implementation effects of ecological engineering in Northeast China, including projects such as the Grain for Green program and natural forest protection programs^{27–29}. A detailed analysis revealed that between 2000 and 2010, carbon storage decreased by 0.11% (from 8732.09×10^5 t to 8722.69×10^5 t), which was attributed primarily to the rapid decrease in cultivated land area (annual decrease rate of 0.44%) and the uncontrolled expansion of construction land (annual growth rate of 2.43%). In contrast, between 2010 and 2020, carbon storage increased by 0.71% (from 8722.69×10^5 t to 8784.65×10^5 t), with this growth being highly correlated with the continued expansion of forest area (an increase of 95.31 km²). However, notably, the drastic conversion of cultivated land to construction land from 2000–2020 (with an average annual conversion area of 18.28 km²) resulted in an 8.74% reduction in the carbon storage of cultivated land, clearly indicating that the rapid urbanization process significantly inhibited the carbon sequestration function of agriculture.

The spatial analysis results reveal that the intensity of land conversion in carbon loss hotspot areas, such as the Donggang Economic Belt, is significantly greater than that in northern mountainous regions, a spatial differentiation closely related to the regional "South Industry, North Agriculture" development policy. Notably, although the expansion rate of construction land slowed after 2010 (annual growth rate of 1.23%, approximately 50% lower than 2.43% from 2000–2010), the intensity of carbon loss did not decrease correspondingly (Fig. 11). Further research indicates that this phenomenon is related to the shift in urban expansion models from extensive residential development to high-carbon-density construction land development (such as the Dandong Port Industrial Zone). Construction land is often accompanied by rapid mineralization of soil organic matter and complete loss of vegetation cover, with

the carbon loss per unit area being up to 2.3 times greater than that of residential land³⁰.

Previous studies³¹ have shown that converting cultivated land to construction land directly results in carbon sources (average carbon loss rate of 12.3–18.7%), whereas the Grain for Green program enhances carbon sequestration by increasing vegetation carbon density (Yuan et al.³² reported an increase of 4.6 kg/m²), which is highly consistent with the results of this study. This "forest gain–cultivated land loss" game pattern reveals the dual impact mechanism of LULC change on carbon storage in border cities: on the one hand, the implementation of ecological projects, through forest restoration, effectively strengthens regional carbon sequestration capacity; on the other hand, the unique economic development pressures in border regions exacerbate the nonagricultural transition of cultivated land. A comparative analysis with the Yellow River middle and lower reaches²⁶ and the North China Plain³³ revealed that although the rate of cultivated land conversion from agriculture is 3.8% lower in border cities, the proportion of forest restoration area is 22.6% greater, reflecting regional differences in the intensity of ecological engineering implementation. Compared with economic core areas such as Xiamen city²⁴ and the Xiong'an New Area²⁵, Dandong, as an ecological barrier area, exhibits stronger policy sensitivity: its forest carbon sequestration gain is significantly greater than that of nonborder cities at the same latitude, but the rate of carbon loss from cultivated land also exceeds the national average. This contradictory feature provides a unique case for land spatial governance in border regions.

A quantitative analysis based on the Geodetector model indicates that the spatial differentiation of carbon storage in Dandong city is driven by the nonlinear and synergistic interactions between natural and socioeconomic factors. This driving pattern exhibits distinct temporal evolution characteristics.

From 2000 to 2010, topographic factors (slope and elevation) governed the spatial distribution of carbon storage, closely aligning with geomorphological differentiation across the transitional zone between the Liaodong Mountains and the

plains. Specifically, the northern mid- to low-mountain areas (slope > 15°), characterized by high forest coverage (with forest areas reaching 10,136.37 km² in 2020; Table 7), presented aboveground biomass carbon densities of up to 41.68 kg/m² (Table 5), forming contiguous high-carbon sink zones. In contrast, the southeastern coastal plains (elevation < 50 m), affected by the conversion of cultivated land to construction land (182.81 km² converted between 2000 and 2020, with a rate of 5.45%), emerged as core carbon loss zones. This finding is consistent with the conclusion of the IPCC on the terrain gradient regulation of carbon sink spatial patterns⁷; however, this study further reveals that urban development has exacerbated the spatial polarization effect of topographic constraints.

By 2020, the NDVI had surpassed topography to become the most influential driving factor ($Q = 0.515$; Fig. 14e), with its increased explanatory power directly linked to the effects of reforestation initiatives (with a net forest area increase of 123.34 km² between 2010 and 2020; Table 7). High-NDVI regions (> 0.6), which are located primarily in northern forest areas, have significantly increased their forest carbon storage through afforestation efforts (Table 8), reaffirming the role of ecological restoration projects in reshaping carbon sink patterns. This shift marks a departure from the traditional topography-dominant paradigm and spatially resonates with the "policy-driven vegetation recovery" mechanism of carbon sink enhancement observed by Li et al. ³⁴ in the karst region of Southwest China.

The driving effects of socioeconomic factors display significant spatial heterogeneity and threshold characteristics. The explanatory power of GDP for cropland loss (contribution of 10.52%, second only to slope at 11.22%; Fig. 4.) is particularly prominent in hotspot areas such as the Donggang Economic Development Zone. In these areas, high GDP values (> 250 million RMB/km²) spatially overlap with cultivated land to construction land conversion hotspots by 72.3%, which is consistent with the negative feedback loop of “economic agglomeration–land development.” However, the explanatory power of socioeconomic factors for carbon loss remains relatively weak (Fig. 14), potentially due to the staged nature of

Dandong's urbanization process. As of 2020, Dandong's urbanization rate was 63.4%, which was lower than the Liaoning provincial average (72.8%), and the newly added construction land was allocated mainly to industrial parks rather than residential areas, resulting in a decoupling between the population distribution and the spatial pattern of carbon loss.

Notably, interaction effects among factors reveal the nonlinear characteristics of natural–anthropogenic synergies (Fig. 14.). The interaction effect between slope and the NDVI yields an explanatory power of $Q = 0.615$, suggesting that vegetation restoration efforts (e.g., reforestation) in areas with slopes $> 10^\circ$ can increase the carbon sink efficiency by 38.7%. This finding provides a quantitative foundation for optimizing ecological project layouts. It is recommended that degraded cropland and forestland in northern Fengcheng city with slopes of $15\text{--}25^\circ$ and an NDVI < 0.4 be prioritized for inclusion in ecological restoration zones. By applying "topography–vegetation" coupled restoration technical standards, dual benefits in terms of carbon storage enhancement and soil erosion control can be achieved.

This study uses the GMOP–PLUS model to simulate the changes in carbon storage under four development scenarios for the year 2030, revealing the differentiated impacts of various policy orientations on terrestrial carbon sinks. The EPS demonstrates the strongest carbon sink gain (+6.23%), primarily due to the large-scale conversion of cultivated land to forest (1042.21 km²), with the increase in carbon storage concentrated in the northern high-slope mountainous areas, aligning well with the synergistic effects of the NDVI ($Q = 0.515$) and topographic factors ($Q = 0.475$). In contrast, the EDS shows a sharp decrease in cultivated land carbon storage (-11.57%) due to the expansion of construction land (+194.66 km²), with a modest carbon sink increase of only 0.93%. Additionally, the carbon loss intensity from industrial land development (e.g., Dandong Port Area) is 2.3 times greater than that of residential land, highlighting the ecological cost of rapid urbanization. The CDS achieves a relatively balanced outcome, with carbon storage (9275.36×10^5 t) approaching the EPS level while allowing for moderate growth in construction land

(+28.01%). However, the spatial differentiation characteristics (northern carbon sink gain vs. southern carbon loss) suggest that optimizing LULC through "zoning and control" is necessary. This result validates the feasibility of "ecological–economic" coordinated development in border cities, although differentiated management policies (e.g., strict restrictions on cultivated land conversion in southern China and enhanced ecological compensation in northern China) are needed.

This study has several limitations. First, the model parameters (e.g., carbon density, Table 5) are based on literature calibration and lack local field data, which may lead to an underestimation of carbon loss from construction land. Second, the driving factors (Table 6) do not include policy variables (e.g., ecological red lines), which weakens the explanatory power of human interventions. Finally, the spatial resolution (30 m) may overlook small-scale carbon sink units (e.g., farmland ditch vegetation), and the discretization of socioeconomic data (GDP, population) via the RGD method may smooth local variations, affecting the accuracy of the driving mechanism analysis.

Future research could integrate multisource carbon density data (e.g., soil surveys, LiDAR) to enhance parameter localization, incorporate dynamic conversion costs (e.g., policy rewards and penalty coefficients) to optimize the PLUS model simulations, and extend the prediction period to 2060 to assess long-term climate–LULC interactions.

Conclusions

This study constructs a multimodel coupling framework that integrates GMOP, PLUS, InVEST, and Geodetector to systematically analyze the mechanisms by which LULC change influences carbon storage in Dandong city and to predict the evolution of carbon storage under various development scenarios. The findings indicate that, under the implementation of ecological projects such as the Grain for Green Program, carbon storage in Dandong exhibited a “decline-then-increase” trend from 2000 to 2020, with a net increase of 52.56×10^5 t. Multiple-scenario simulations reveal that the

EPS achieves the greatest carbon sink gain (+6.23%), albeit at the cost of a 29.34% reduction in cropland area. The EDS, due to construction land expansion, shows limited carbon sink potential (only +0.93%). In contrast, the CDS strikes a better balance between ecological conservation and economic development, enabling a 5.59% increase in carbon storage while allowing for moderate construction land expansion.

In terms of spatial patterns, the northern mountainous areas, which benefit from ecological restoration, have become core carbon sink zones, whereas the southern coastal regions, which are impacted by the expansion of industrial land, have emerged as significant carbon loss hotspots. This spatial differentiation closely corresponds to Dandong's regional development strategy of "industrial south and agricultural north." Geodetector analysis further identifies the NDVI and topographic factors (slope and elevation) as the dominant drivers of carbon storage spatial heterogeneity, with the interaction effect of the "slope-NDVI" combination being the strongest ($Q = 0.615$), providing critical insight for optimizing the layout of ecological restoration projects.

On the basis of these findings, the following policy recommendations are proposed: First, differentiated spatial management strategies should be implemented by prioritizing vegetation restoration in northern areas with slopes greater than 10° and strictly limiting the conversion of cropland to high-carbon industrial land in southern coastal regions. Second, interregional carbon compensation mechanisms, such as ecological transfer payments, should be established to balance development interests across regions. Third, carbon sink targets should be incorporated into the national land spatial planning system to ensure ecological security while adequate space for economic development should be preserved.

Future research should focus on three key directions: (1) integrating higher-resolution, locally measured carbon density data to improve the accuracy of model parameters; (2) incorporating dynamic policy variables into the modeling framework to increase the timeliness of scenario-based policy simulations; and (3) extending simulations to 2060 to align with carbon neutrality goals and provide more robust

431 scientific support for low-carbon regional development strategie

Materials and methods

Study area

Dandong (123°22′–125°42′E, 39°43′–41°09′N) is located in the southeastern part of the Liaodong Peninsula in northeastern China (Fig. 1). It is bordered to the east by the Yalu River, which separates it from North Korea, and to the south by the Yellow Sea. As an important node in the Northeast Asia Economic Corridor and a border ecological security barrier, Dandong plays a vital role in the region. The city covers a total area of 14,670.25 km², with the terrain primarily composed of hills (60.3%), followed by plains (28.5%). The highest peak, Baiyun Mountain, rises to an elevation of 1176 meters. The region experiences a temperate monsoon climate, with an average annual temperature of 8.5°C and precipitation ranging from 900 to 1,200 mm, which is conducive to forest growth. The forest coverage rate is as high as 63.2%, and it is composed mainly of mixed coniferous and broadleaf forests, providing a crucial foundation for regional carbon sequestration.

The Yalu River stretches 306 km along the border, with an annual runoff volume of 2.54×10^{10} m³. Its estuarine wetland (814 km²) is recognized as an internationally important wetland, and together with coastal tidal flats, it forms a key carbon sink area. As a rapidly urbanizing coastal border city, Dandong faces a significant contradiction between LULC and carbon storage. In 2020, the urbanization rate reached 63.4%, while arable land still accounted for 24.21% (3551.61 km²) of the total area, with conflicts between urban expansion and ecological protection becoming increasingly prominent.

Data sources

The dataset includes LULC data and driving factors. The LULC data are derived from the Chinese land cover dataset (CLCD) developed by Wuhan University³⁵, which covers three periods (2000, 2010, and 2020). These data were reclassified into 6 categories—cultivated land, forest, grassland, water, construction land, and unused land—to align with the research objectives.

This study selects 14 driving factors, including 7 natural factors (such as elevation, slope, and precipitation), 2 socioeconomic factors (population density and GDP), and 5 locational factors (such as distance to roads and rivers). All spatial datasets were standardized to the CGCS2000_3_Degree_GK_Zone_41 coordinate system and resampled to a 30-meter resolution in ArcGIS 10.8. Table 1 and Fig. 2 systematically present the parameter specifications and data sources of the driving factors.

Research methodology

We developed an integrated modeling framework (GMOP-PLUS-InVEST-Geodetector) to sequentially optimize the LULC structure, simulate spatial patterns, quantify carbon storage, and analyze driving mechanisms (Fig. 3), enabling the policy-sensitive assessment of carbon dynamics in Dandong. First, the GMOP model was integrated with the PLUS model, which incorporates regional constraints such as ecological protection and urbanization thresholds, to optimize the LULC structure and spatially allocate future land demand for 2030. On the basis of the *National Spatial Planning of Dandong City (2021-2035)* and the *Land Space Ecological Restoration Planning of Dandong City (2021-2035)*, four policy-driven scenarios were designed: the NDS, EPS, EDS and CDS. Second, the InVEST carbon module was employed to quantify carbon storage under different scenarios, with local carbon density parameters adjusted via Dandong's temperature and precipitation data. Finally, the Geodetector model was used to analyze the dominant driving factors of spatial heterogeneity in carbon storage in Dandong city from 2000 to 2020.

GMOP model: Dynamic optimization of LULC structure under multiple objectives and constraints

The GMOP model is an integrated framework that combines the gray forecasting module with the multiobjective programming module. The primary objective of this model is to address the issue of static parameters in traditional approaches, which fail to reflect long-term dynamic changes²⁶. By dynamically forecasting LULC value

coefficients and performing multiobjective optimization, the GMOP model seeks to resolve "ecological–economic" multiobjective conflicts through Pareto optimal solutions, thereby achieving rational allocation of the regional LULC structure³⁴.

Gray forecasting module

This module utilizes the first-order single-variable gray model from gray system theory. The input consists of the ecological–economic value coefficients for Dandong city from 2000 to 2020 and forecasts the unit area ecological and economic value coefficients for different LULC types in the study area up to 2030, as detailed in Table 2. The ecological value coefficient for Dandong city (2000–2020) is calculated on the basis of the "Unit Area Ecological Service Value Equivalence of China's Terrestrial Ecosystems," followed by necessary adjustments. The economic value coefficients for cultivated land, forestland, grassland, water bodies, wetlands, and built-up land are derived from the annual output per unit area of agriculture, forestry, animal husbandry, fisheries, and secondary and tertiary industries in the Statistical Yearbooks of Liaoning Province and Dandong city, covering the period from 2000 to 2020.

Multiobjective optimization and scenario setup

This module integrates policy regulation constraints (as shown in Table 3) to determine the optimal LULC structure under different development scenarios. NDS, which is unaffected by policy intervention, is directly derived from Markov forecasting. The EPS, EDS, and CDS represent LULC optimization scenarios under specific policy constraints.

The EPS aims to maximize ecological value through ecological protection via Equation (1).

$$F_1(X) = \text{Max} \sum_{k=1}^6 a_k x_k \quad (1)$$

The EDS aims to maximize economic value by maximizing economic benefits via Equation (2).

$$F_2(X) = \text{Max} \sum_{k=1}^6 b_k x_k \quad (2)$$

The CDS targets the coordination between ecological protection and economic development to maximize integrated benefits via Equation (3).

$$F_3(X) = \text{Max}\{F_1(X), F_2(X)\} \quad (3)$$

where a_k and b_k represent the ecological value coefficients (10^4 CNY/km²) of each LULC type and S_k denotes the area (km²) of LULC type k .

PLUS model: LULC spatial reconstruction via random forest and patch-level simulation

The PLUS model is a spatial simulation framework that integrates LEAS and cellular automata based on multiple random seeds (CARS). The core objective of this model is to achieve high-precision simulations of future LULC spatial patterns by analyzing the driving mechanisms of LULC change and landscape pattern evolution¹⁹. In this study, (1) the model combines the optimization results from the GMOP to convert the optimized LULC quantities into spatial configuration schemes, thereby providing fundamental spatial data input for subsequent ecosystem service assessments; (2) the PLUS model is applicable to patch-level simulations, which is suitable for the fragmented landscape characteristics of the border city of Dandong.

Prediction of LULC quantity

The core objective of this module is to forecast the total demand for 6 types of LULC in Dandong city under the NDS for 2030. This is achieved by utilizing the LULC status data from Dandong city for 2010 and 2020 and applying the Markov chain algorithm integrated within the PLUS model.

Land expansion analysis strategy

The core goal of this module is to identify and quantify the spatial expansion trends of various LULC types. On the basis of LULC change data for Dandong city from 2010 to 2020, the expansion areas of 6 LULC types were extracted. The random forest

classification algorithm is used to systematically evaluate the intensity of various driving factors and calculate the development probability values for each LULC type. This model effectively reveals the nonlinear relationships between LULC changes and potential driving factors, providing a more accurate explanatory framework for the evolution of LULC spatial patterns.

Cellular automata based on multiple random seeds

The core function of this module is to achieve a refined spatial configuration of total LULC demand and simulate LULC patterns at the patch level. Specifically, this module integrates the following key input parameters: total demand for each LULC type in 2030 predicted by the Markov chain and GMOP, spatial development probabilities for 6 LULC types output by the LEAS module, neighborhood weight factors, and the LULC transition cost matrix (as shown in Table 4). On the basis of the Monte Carlo simulation method, a multifactor overlay analysis is performed for each grid unit to calculate the comprehensive development potential value for each LULC type. The LULC types are then allocated to the respective grid units in descending order of potential value until the total land demand predicted by the Markov chain model is met.

Model accuracy verification

On the basis of LULC status data from 2000 and 2010, a simulation of LULC change for 2020 was constructed, and the simulated results were spatially validated against actual LULC data for 2020. The results revealed that the model's kappa coefficient was 0.901, and the overall accuracy was 0.954. According to the kappa coefficient evaluation criteria proposed by Landis and Koch³⁶, the model's predictions closely match the actual situation (Kappa coefficient > 0.81), indicating that the model has good predictive accuracy and reliability.

InVEST model: Localization parameter calibration for carbon stock quantification

The carbon storage and sequestration module of the InVEST model calculates the carbon stock by summing four carbon pools: aboveground carbon (C_{above}), belowground carbon (C_{below}), soil carbon (C_{soil}), and dead organic matter carbon (C_{dead}), via Equations (4) and (5).

$$C_i = C_{above} + C_{below} + C_{soil} + C_{dead} \quad (4)$$

$$C_{total} = \sum_{i=1}^n C_i \cdot S_i \quad (5)$$

where C_{total} is the total carbon storage (t); S_i is the area of LULC type i (hm^2); and n is the number of LULC types.

On the basis of the relationship model between carbon density, precipitation, and temperature, carbon density data from previous studies³⁷ were referenced and adjusted to better align with the carbon density parameters of Dandong city. The calculation for carbon density correction was performed via Equations (6)–(12).

$$C_{bp} = 6.798 \times e^{0.0054 \times MAP} \quad (6)$$

$$C_{BT} = 28 \times MAT + 398 \quad (7)$$

$$C_{SP} = 3.3968 \times MAP + 3996.1 \quad (8)$$

$$K_{BP} = \frac{C_{BP}^1}{C_{BP}^2} \quad (9)$$

$$K_{BT} = \frac{C_{BT}^1}{C_{BT}^2} \quad (10)$$

$$K_B = K_{BP} \times K_{BT} \quad (11)$$

$$K_{SP} = \frac{C_{SP}^1}{C_{SP}^2} \quad (12)$$

where MAP represents the mean annual precipitation; MAT represents the mean annual average temperature; C_{BP} and C_{SP} represent the biomass carbon density and

soil carbon density corrected on the basis of precipitation, respectively; C_{BT} represents the biomass carbon density corrected on the basis of the mean annual average temperature; K_{BP} and K_{BT} represent the correction coefficients for the mean annual precipitation factor and mean annual average temperature factor of aboveground biomass carbon density, respectively; K_B represents the correction coefficient for aboveground biomass carbon density; and K_{SP} represents the correction coefficient for soil carbon density. On the basis of the climate bulletin and statistical yearbook of Liaoning Province from 2000 to 2020, as well as the statistical yearbook of Dandong city, the mean annual precipitation (643.77 mm, 933.45 mm) and mean annual average temperature (9.19°C, 9.40°C) were input into the formula, ultimately yielding the corrected carbon density data (for the revised carbon density results, see Table 5).

Geodetector model: Multidimensional drivers of spatial differentiation in carbon storage

The Geodetector model is a spatial statistical method used to quantify the relationships between geographical phenomena and their driving factors. This model is widely applied in factor analysis within both natural geography and socioeconomic fields^{38–40}. In this study, the factor detection and interaction detection modules of the Geodetector model are employed primarily to systematically assess the mechanisms by which different influencing factors drive spatial differentiation in regional carbon storage. Specifically, single-factor detection is used to evaluate the independent explanatory power of a single factor on the spatial distribution of carbon storage, whereas interaction detection is used to analyze the combined effects of two factors on the spatial differentiation of carbon storage.

Eight potential driving factors of carbon storage are selected (see Table 6), and these factors are discretized. Each factor is divided into five levels via the natural breaks method. A regular sampling grid of 1×1 km is constructed to extract the carbon storage values and their corresponding influencing factor values at each sampling point. Finally, the Geodetector model is utilized to conduct an in-depth analysis of the dominant driving factors of spatial differentiation in carbon storage and their

interaction characteristics. The explanatory index (Q) for the carbon storage driving factors in the study area is calculated via Equation (13) as follows:

$$Q=1-\frac{1}{n\sigma^2}\sum_{h=1}^L N_h\sigma_h^2 \quad (13)$$

where h is the number of index grades; n and σ^2 are the sample number and variance of the whole region, respectively; and $N_h\sigma_h^2$ is the number and variance of samples in a specific layer. The Geodetector method provides a robust quantitative framework for analyzing the formation mechanisms underlying the spatial distribution patterns of regional carbon storage. All spatial data processing and analyses were conducted using ArcGIS 10.8.

Data availability

Data will be made available on request.

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Author contributions

J.Z. conceived and designed the study, developed the methodology, provided resources, supervised the research, administered the project, acquired funding, wrote the original draft, and reviewed and edited the manuscript. L.L. conducted the investigation, curated and validated the data, performed the software-based analyses, prepared the visualizations, and contributed to writing the original draft. G.-Y.Z., C.-X.L., Z.-R.H., and N.Z. contributed to the investigation, curated and validated the data. Y.-P.Y. contributed to the investigation and provided resources. J.L. contributed to the investigation and validation. Y.-H.J. provided resources. All authors reviewed and approved the final manuscript.

Competing interests

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.

769 **Table 1 Driving factors and data sources of LULC change.**

Types	Data name	Spatial Resolution	Data Source
Natural factors	Soil types	1 km	Harmonized World Soil Database v2.0 (https://www.fao.org/)
	Annual average temperature	1 km	Chinese Academy of Sciences Resource and Environmental Science Data Platform (https://www.resdc.cn/)
	Annual precipitation	1 km	(https://www.resdc.cn/)
	Altitude	30 m	Geospatial Data Cloud (https://www.gscloud.cn/)
	Slope	30 m	
	Slope direction	30 m	
	NDVI	250 m	National Qinghai Tibet Plateau Science Data Center (https://data.tpdac.ac.cn/)
Socioeconomic factors	Population density	1 km	Chinese Academy of Sciences Resource and Environmental Science Data Platform (https://www.resdc.cn/)
	GDP	1 km	(https://www.resdc.cn/)
Locational factors	Distance to the rivers	30 m	1:1 million national basic geographic database (https://www.webmap.cn/) The Euclidean distance tool is used to process the results in ArcGIS 10.8.
	Distance to railways	30 m	
	Distance to the highways	30 m	
	Distance to national and provincial roads	30 m	
	Distance to the town centers	30 m	

771 **Table 2 Ecological and economic value coefficients (10⁴ CNY/km²) of the six LULC types**
 772 **in Dandong city, 2030.**

LULC types	Cultivated land	Forest	Grassland	Water	Construction land	Unused land
Ecological value coefficients	145.99	728.01	445.85	3282.55	0.00	7.39
Economic value coefficients	529.30	14.20	87384.80	8609.50	18286.40	0.00

773

774 **Table 3 Different LULC type constraints (km²).**

Constraint factors	Constraint formulas	Formula interpretation
Land area	$\sum x_i = 14670.25$	The total LULC area under each scenario equals the total area of the study region.
Ecological value	$\sum a_i x_i \gg \sum a_i y_i$	The ecological value of the region under each optimization scenario exceeds that under the NDS.
Economic value	$\sum b_i x_i \gg \sum b_i y_i$	The economic value of the region under each optimization scenario exceeds that under the NDS.
ultivated land red line	$2387.67 < x_1 < 3906.77$	Pursuant to the <i>Land Space Ecological Restoration Planning of Dandong City (2021-2035)</i> , the cultivated land area shall not be less than 2387.67 km ² , with a maximum expansion limit set at 110% of the 2020 baseline level (3551.61 km ²).
Forest area	$9913.33 < x_2 < 11150.01$	Pursuant to the <i>Land Space Ecological Restoration Planning of Dandong City (2021-2035)</i> , the forest area shall not be less than 9,913.33 km ² , with a maximum expansion limit set at 110% of the 2020 baseline level (10,136.37 km ²).
Grassland area	$22.98 < x_3 < 25.28$	Under all optimization scenarios, the grassland area shall not be less than the 2020 baseline level (22.98 km ²), with its maximum expansion strictly limited to 110% of this baseline.
Water Area	$262.93 < x_4 < 289.22$	Under all optimization scenarios, the water area shall not be less than the 2020 baseline level (262.93 km ²), with its maximum expansion strictly limited to 110% of this baseline.
Construction land area	$625.48 < x_5 < 889.64$	The construction land area shall not exceed the regulated value (889.64 km ²) specified in the <i>National Spatial Planning of Dandong City (2021-2035)</i> , with a minimum threshold set at 90% of the 2020 baseline level (694.98 km ²).
Unused land area	$1.24 < x_6 < 1.37$	The unused land area shall be kept below the 2020 baseline level (1.37 km ²), with a minimum retention threshold set at 90% of this baseline.
Ecological space	$x_2 + x_3 + x_4 > 10422.28$	Under all optimization scenarios, the combined area of forest, grassland, and water shall not be less than the 2020 baseline level.
Vegetation coverage	$0.46 * x_1 + x_2 + 0.49 * x_3 > 11781.37$	Under all optimization scenarios, the vegetation coverage shall not be lower than the 2020 baseline level.

775 Note: x_k and y_k ($k = 1, 2, 3, 4, 5$ and 6) represent the areas of cultivated land, forest, grassland, water, construction land, and unused land under each land optimization scenario and NDS,
776 respectively.

777

778 **Table 4 LULC conversion cost matrix under different scenarios.**

Type	NDS						EPS						EDS						CDS					
	A	B	C	D	E	F	A	B	C	D	E	F	A	B	C	D	E	F	A	B	C	D	E	F
A	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	0	1	1	1	1	1	0
B	1	1	1	1	1	1	0	1	0	0	0	0	1	1	1	1	1	0	0	1	0	0	1	0
C	1	1	1	1	1	1	0	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	0
D	1	1	1	1	1	1	0	0	0	1	0	0	1	1	1	1	1	0	0	1	1	1	1	0
E	1	1	1	1	1	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0
F	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

779 *Note: 1 indicates convertible land types; 0 indicates nonconvertible types. Land type codes: A (cultivated land), B (forest), C (grassland), D (water), E (construction land), F (unused land).*

780 **Table 5 Carbon intensity of different LULC types in Dandong. (kg/m²)**

LULC types	C _{above}	C _{below}	C _{soil}	C _{dead}
Cultivated land	10.21	4.39	8.39	0.00
Forest	41.68	22.30	12.25	1.04
Grassland	6.94	6.85	6.59	0.12
Water	3.36	3.33	4.91	0.37
Construction land	5.09	3.99	4.85	0.28
Unused land	4.42	5.68	2.49	0.00

781

782 **Table 6 Driving factors of carbon storage differentiation analyzed via Geodetector.**

Category	Driving factors
Natural Factors	Altitude (M1), Slope (M2), Annual precipitation (M3), Annual average temperature (M4), NDVI (M5)
Socio-Economic Factors	Population density (M6), GDP (M7), Distance to urban centers (M8)

783

784 **Table 7 Area changes in 6 LULC types in Dandong city under different scenarios from 2000 to 2030 (km²).**

LULC types	2000	2010	2020	2030			
				NDS	EPS	EDS	CDS
Cultivated land	3891.93	3722.35	3551.61	3388.50	2509.42	3140.53	2387.87
Forest	10003.84	10013.04	10136.37	10244.86	11150.01	10324.34	11077.20
Grassland	33.04	40.13	22.98	19.00	25.28	25.28	25.08
Water	236.60	272.70	262.93	257.83	289.22	289.22	289.22
Construction land	497.98	619.04	694.98	759.27	695.08	889.64	889.64
Unused land	6.85	2.99	1.37	0.79	1.24	1.24	1.24
total	14670.25	14670.25	14670.25	14670.25	14670.25	14670.25	14670.25

785

786 **Table 8 Temporal variations in terrestrial carbon storage across development scenarios in Dandong city (2000-2030) (unit: $\times 10^5$ metric tons).**

LULC types	2000	2010	2020	2030			
				NDS	EPS	EDS	CDS
Cultivated land	894.71	855.73	816.47	778.98	576.88	721.97	548.90
Forest	7730.70	7737.81	7833.12	7916.95	8616.43	7978.37	8560.16
Grassland	6.77	8.22	4.71	3.90	5.18	5.18	5.18
Water	28.32	32.64	31.47	30.86	34.62	34.62	34.62
Construction land	70.72	87.92	98.70	107.83	98.72	126.35	126.35
Unused land	0.86	0.38	0.17	0.10	0.16	0.16	0.16
total	8732.09	8722.69	8784.65	8838.62	9331.99	8866.65	9275.36

787

Figure legends

Fig. 1. Hierarchical location analysis: (a) Location of Liaoning Province in China. (b) Location of Dandong in Liaoning Province. (c) Elevation information for the study area.

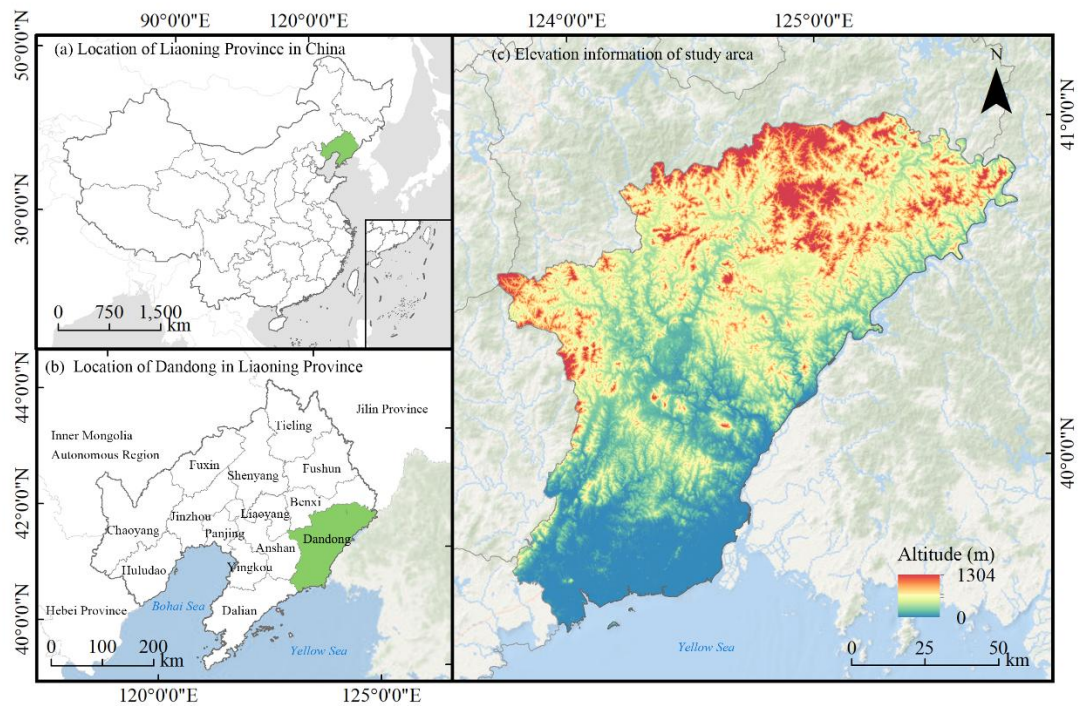
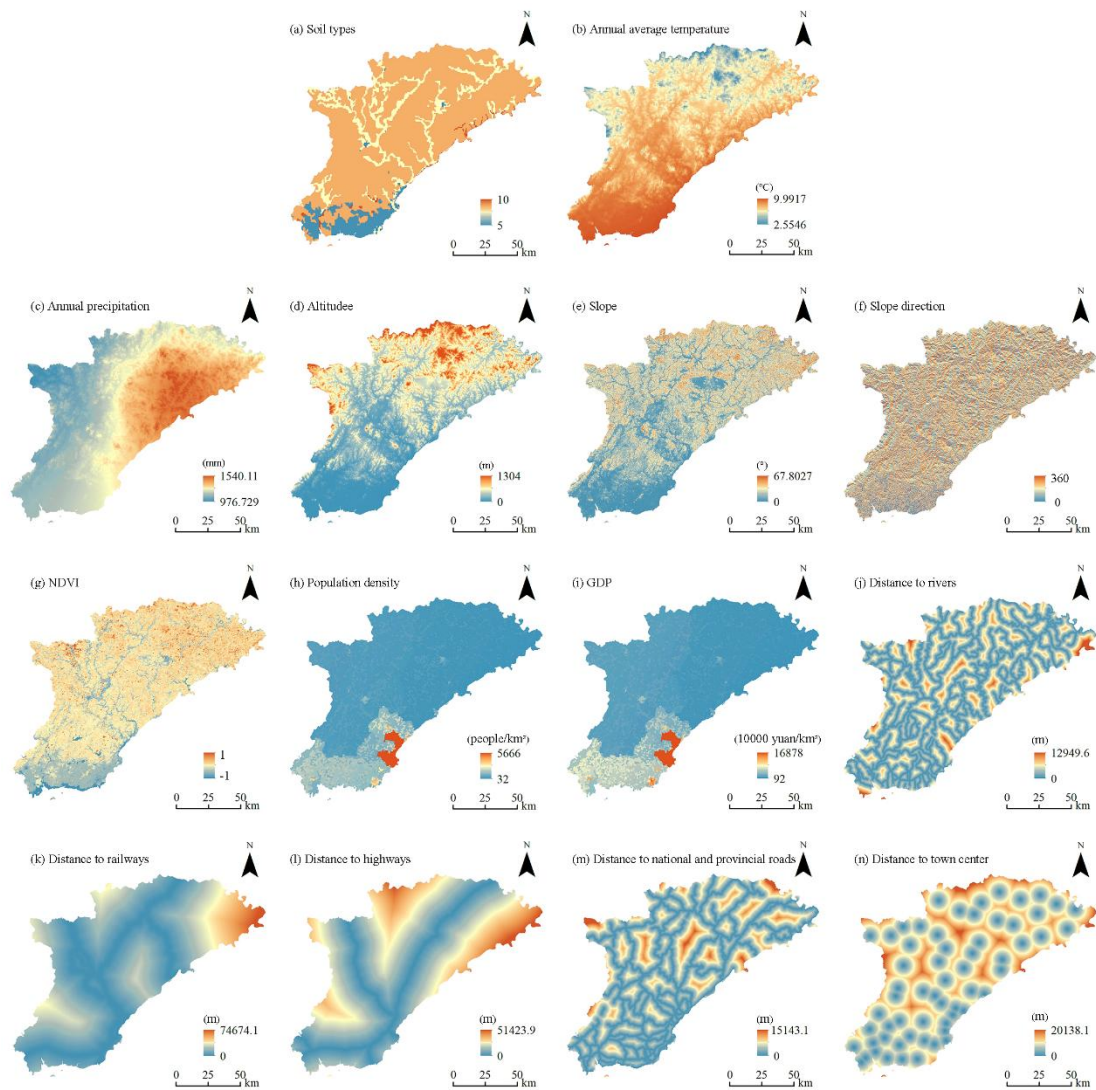


Fig. 2. Spatial distributions of the key driving factors influencing LULC change dynamics.



799 **Fig. 3. Research framework.**

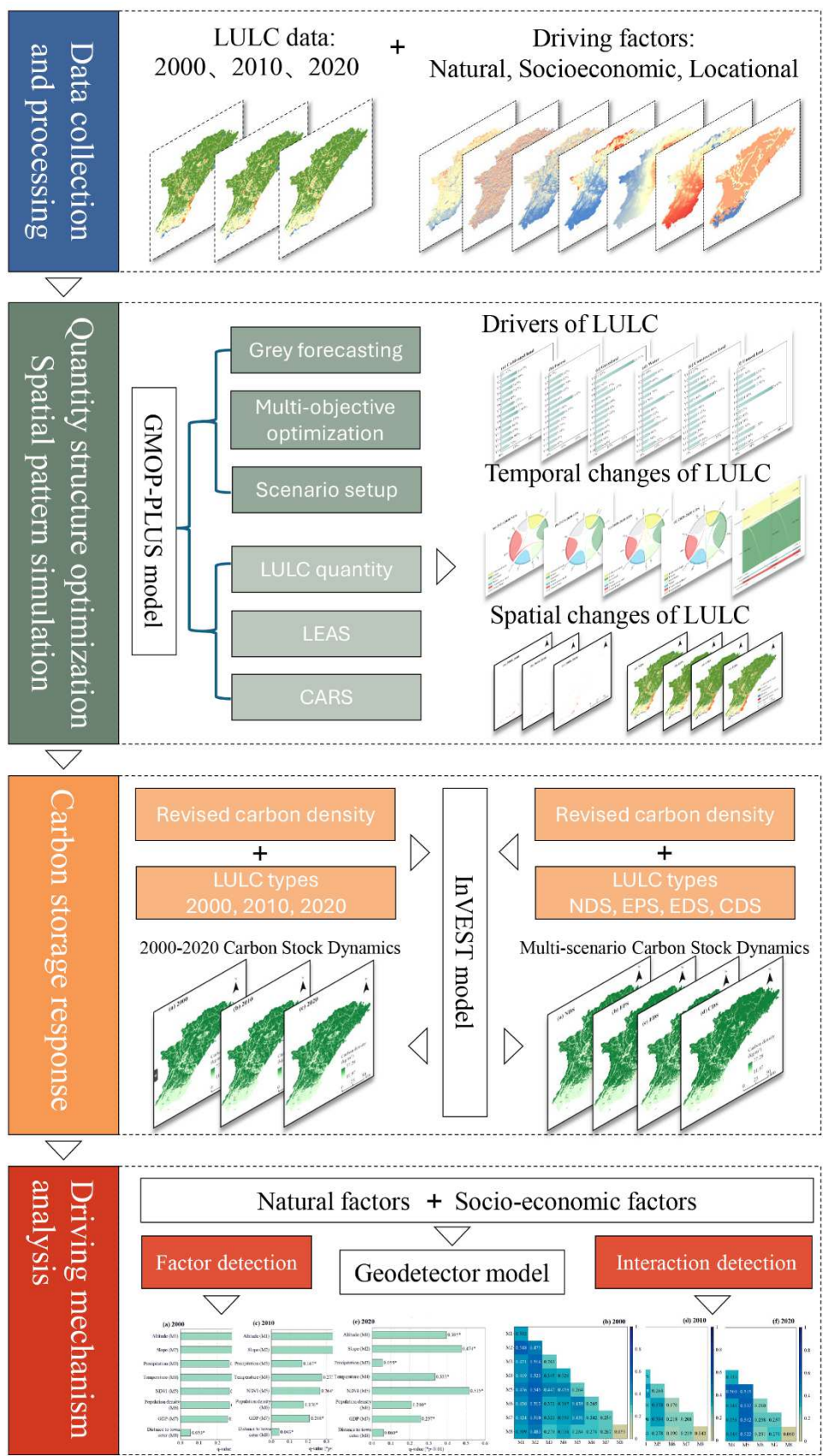


Fig. 4. Quantified contributions (%) of key driving factors to LULC transitions: (a) cultivated land, (b) forest, (c) grassland, (d) water, (e) construction land, and (f) unused land. Y1-13 represent the soil type, annual average temperature, annual precipitation, altitude, slope, slope direction, NDVI, population density, GDP, distance to rivers, distance to railways, distance to highways, distance to national and provincial roads, and distance to town centers, respectively.

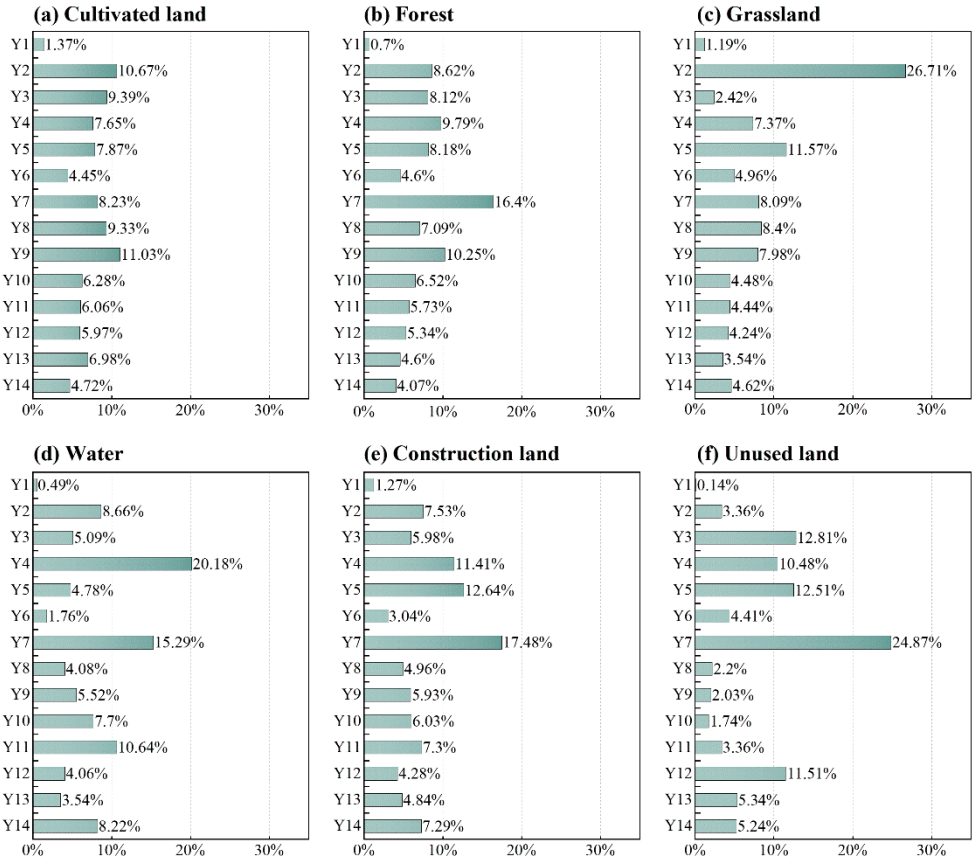
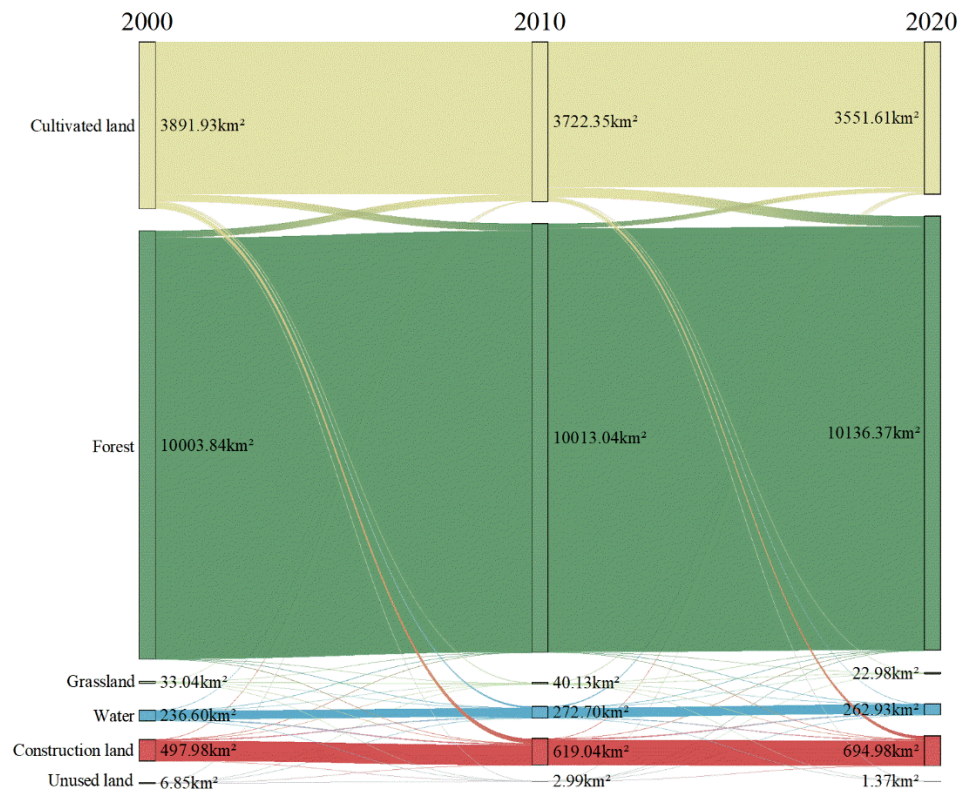
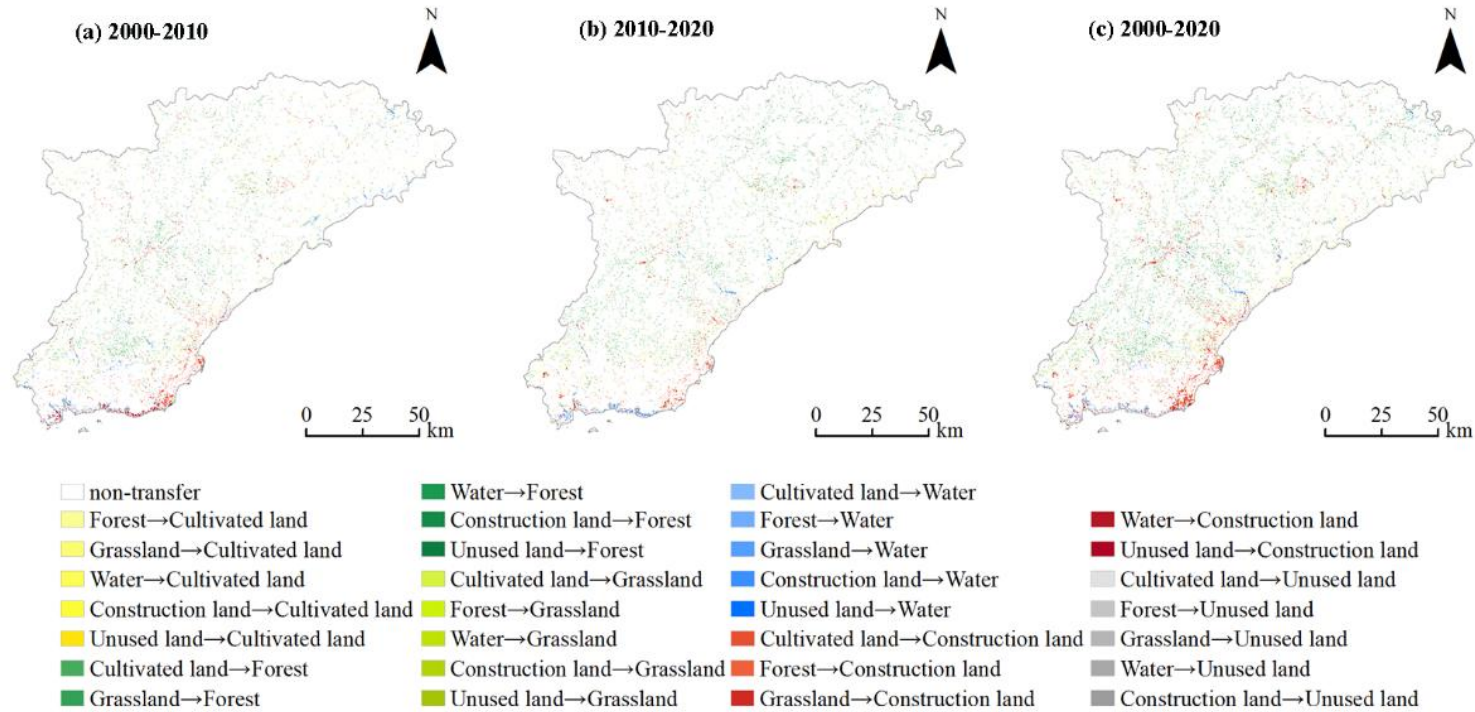


Fig. 5. Temporal dynamics of LULC changes in Dandong city from 2000 to 2020 (km²).



814 **Fig. 6. Spatiotemporal patterns of LULC change in Dandong city: (a) 2000–2010, (b) 2010–2020, (c) 2000–2020.**

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Fig. 7. LULC transition probability matrices under (a) NDS, (b) EPS, (c) EDS, and (d) CDS from 2000 to 2030.

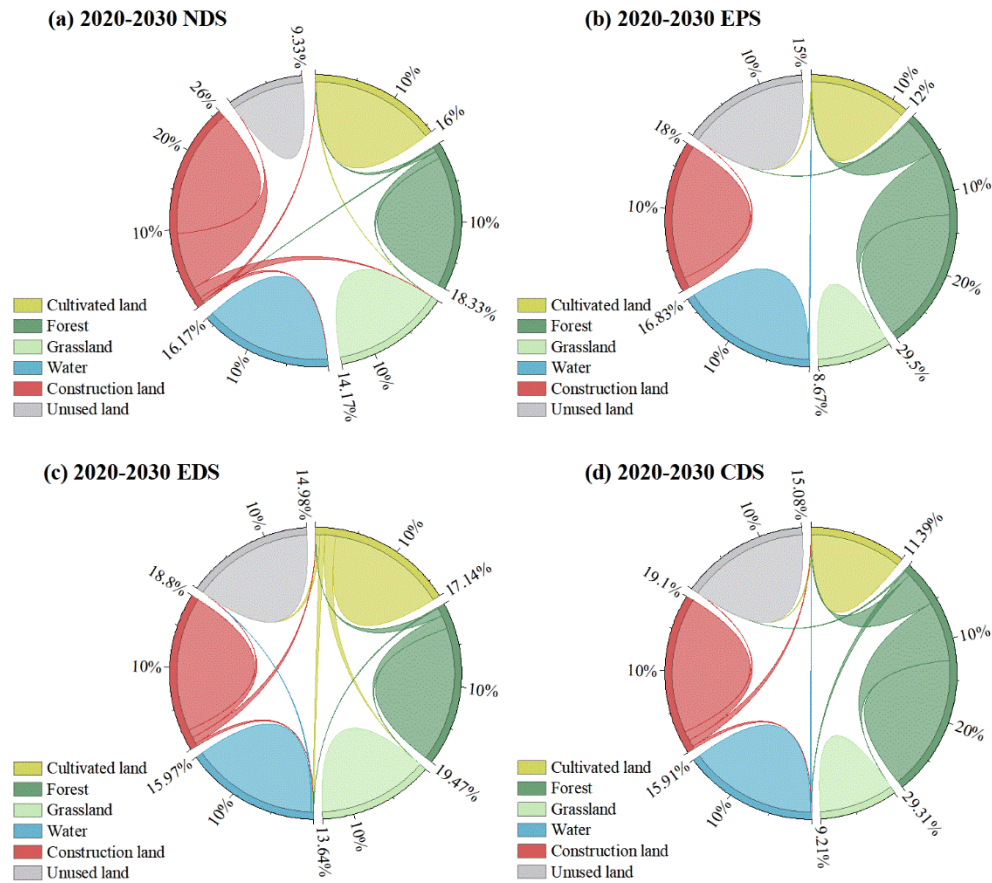


Fig. 8. Projected LULC spatial distributions under (a) NDS, (b) EPS, (c) EDS, and (d) CDS in 2030.

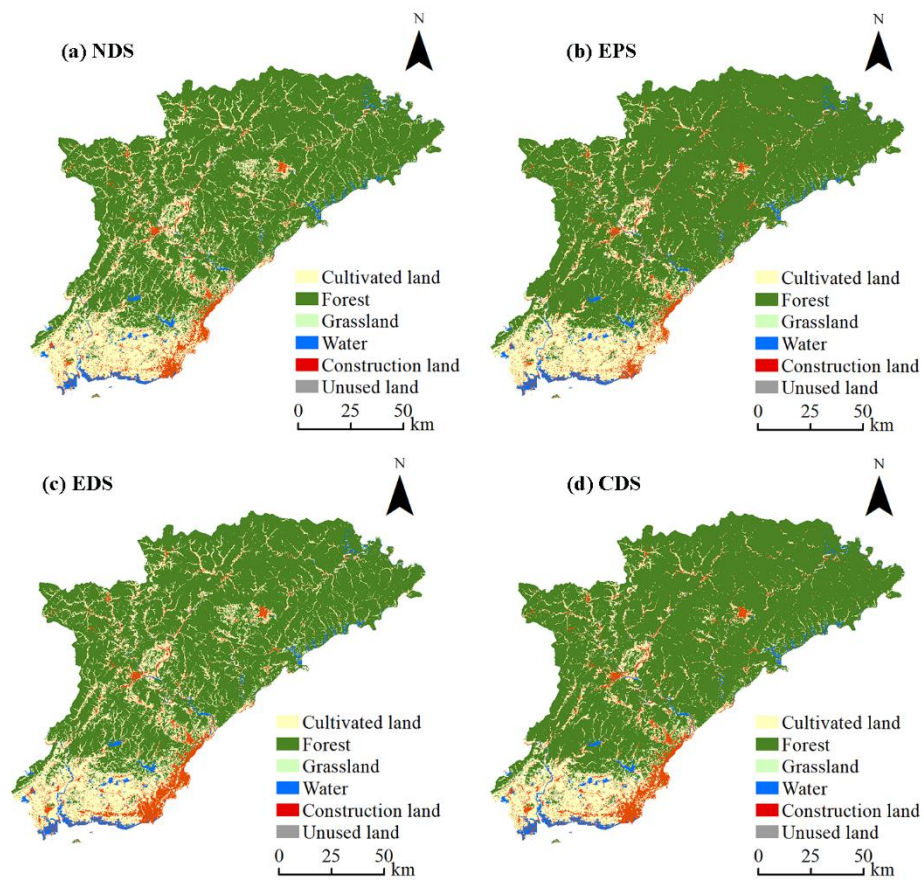
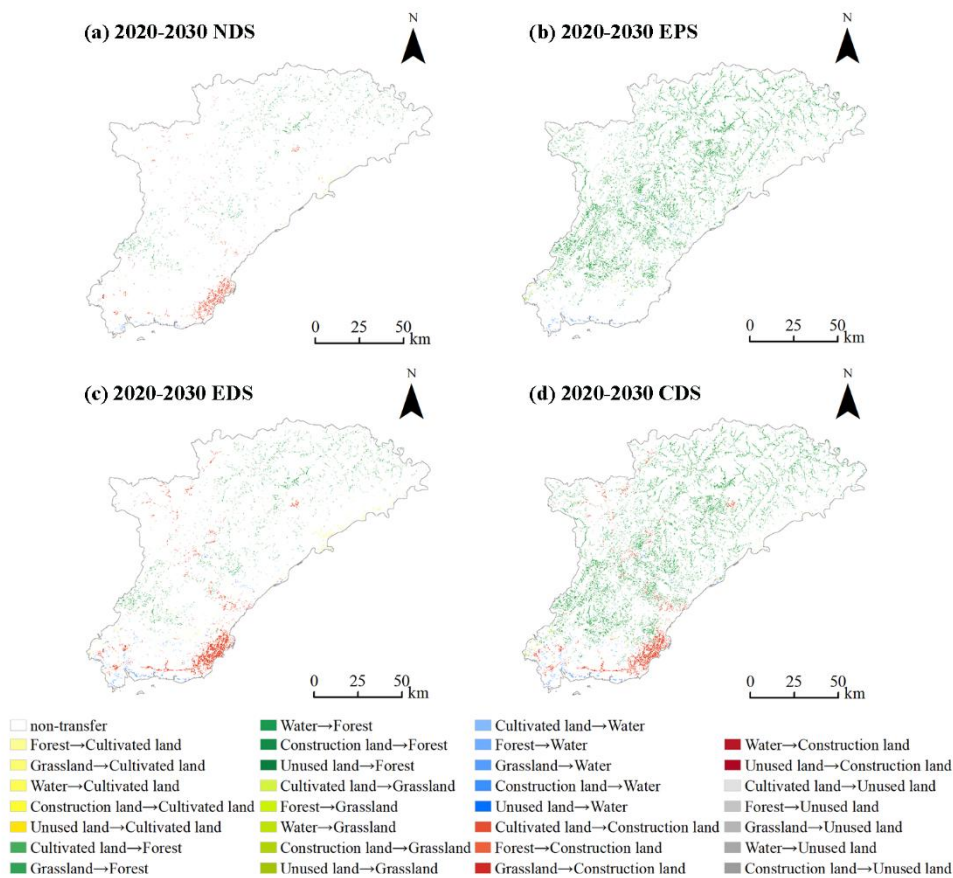
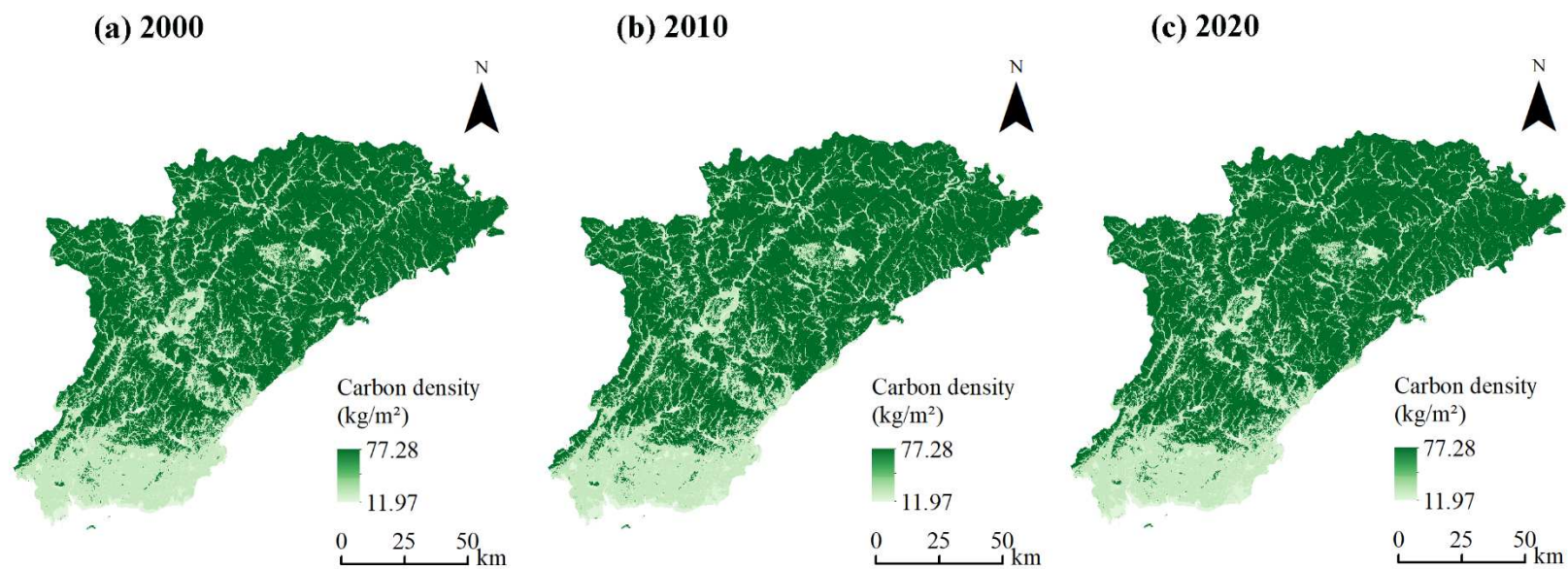


Fig. 9. Spatial distributions of LULC changes under (a) NDS, (b) EPS, (c) EDS, and (d) CDS from 2020 to 2030.



834 **Fig. 10. Spatial distributions of carbon storage in Dandong city during (a) 2000, (b) 2010, and (c) 2020.**

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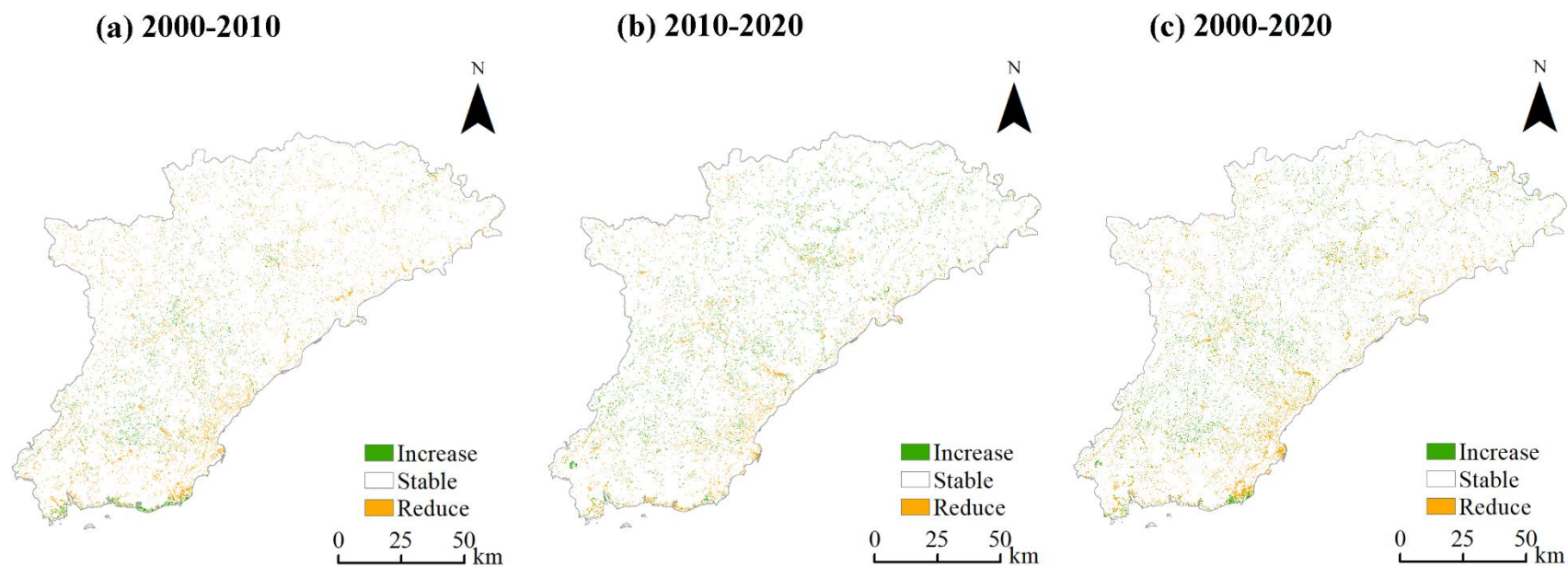


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838 **Fig. 11. Spatiotemporal variations in carbon storage in Dandong city during (a) 2000–2010, (b) 2010–2020, and (c) 2000–2020.**

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Fig. 12. Spatial distribution of carbon storage in Dandong city under (a) NDS, (b) EPS, (c) EDS, and (d) CDS.

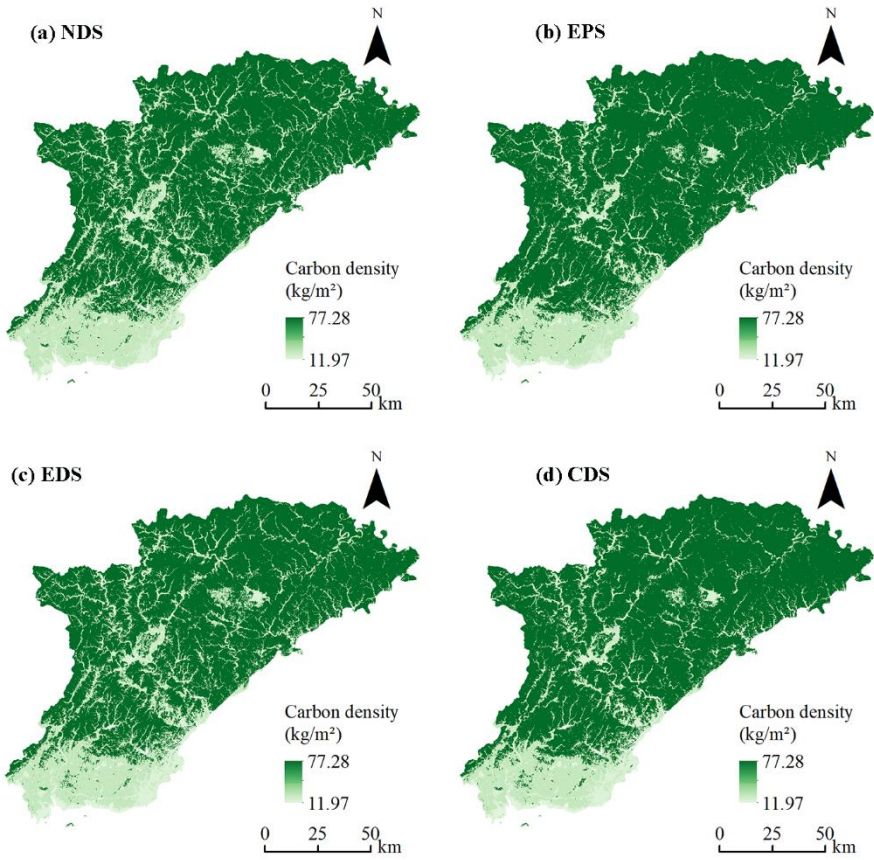


Fig. 13. Spatial variation characteristics of carbon storage in Dandong city under (a) NDS, (b) EPS, (c) EDS, and (d) CDS in 2030

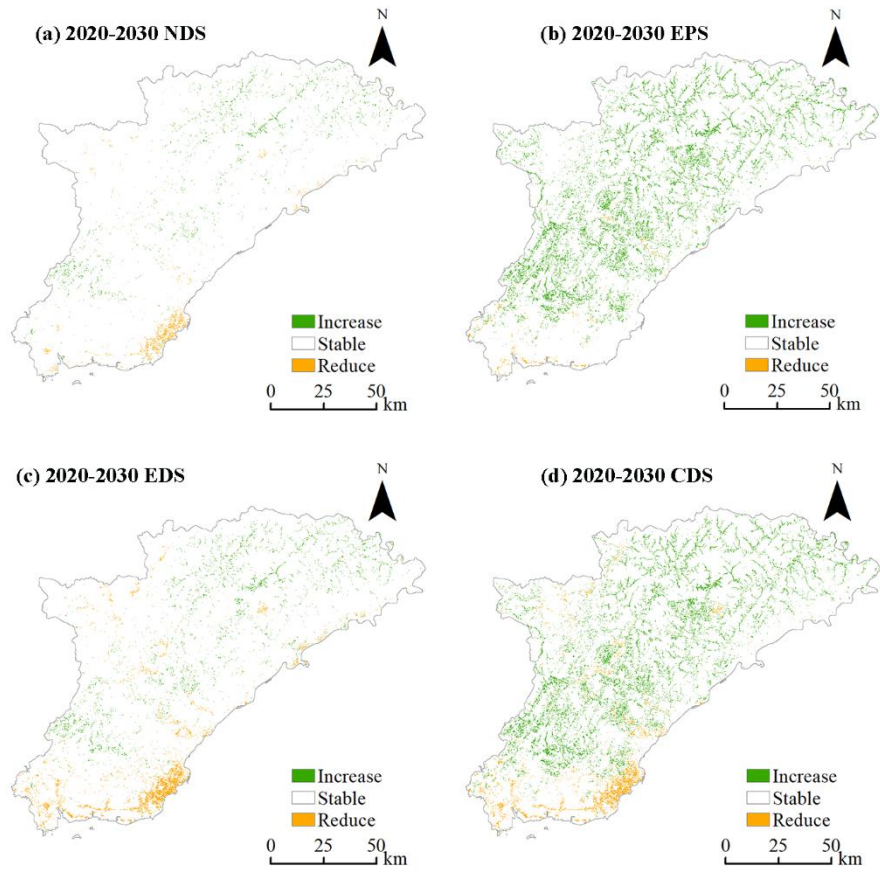


Fig. 14. Driving forces for carbon storage variations: Geodetector-based factor and interaction analyses from 2000 to 2020.

