

Article

A Combined intPLUS and Emission-Linkage Framework for Provincial Carbon-Balance Projection

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Abstract

Regional carbon balance emerges from the complex interplay between land-use dynamics, spatial economic activities, and ecological processes as a socio-ecological system cannot be captured by any single analytical lens. This study develops an integrated assessment workflow that links three components: (i) coefficient-based carbon emission and sequestration accounting by land-use type; (ii) intra-provincial spatial-interaction analysis operationalized through two complementary tools—the Ecological Support Coefficient (ESC) and Economic Contribution Coefficient (ECC), which characterize the local economy–ecology relationship within each city, and a gravity-based emission-linkage model that uses GDP, population, emissions, and inter-city distance to characterize the network structure of inter-city emission attraction; and (iii) the intPLUS model, which combines random-forest-derived transition probabilities with patch-generation rules to simulate multi-scenario land-use trajectories. The framework is applied to Jiangsu Province, China, across 13 prefecture-level cities, using 1995–2020 historical data and three 2030 scenarios. Model performance is validated against observed 2020 land use, with an overall Kappa coefficient of 0.82. The results reveal a stable “high-south–low-north” gradient in emissions, a contrasting “high-ECC/low-ESC” versus “low-ECC/high-ESC” combining pattern across southern and northern Jiangsu, and a hierarchical core–periphery emission-linkage network anchored on the southern metropolitan cluster. Scenario projections for 2030 show clear divergence in provincial carbon budgets, with emissions of $12,326.59 \times 10^4$ t, $11,745.26 \times 10^4$ t, and $13,243.42 \times 10^4$ t under natural development, ecological protection, and economic development, respectively, and corresponding sequestration of -87.10×10^4 t, -100.29×10^4 t, and -85.61×10^4 t. Rather than treating carbon accounting and land-use simulation in isolation, this workflow bridges the analytical gap between physical land-use transitions and socioeconomic spatial emission spillovers, translating structural interactions into actionable spatial planning strategies. Relying on widely available data, the framework demonstrates strong methodological transferability for comparable subnational systems, provided that local parameters and sink coefficients are properly recalibrated.

Keywords: carbon balance; eco-economic system; emission-linkage network; complex network; intPLUS model; multi-scenario simulation; land-use change; Jiangsu Province; dual-carbon goals



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1. Introduction

Land use and land cover change (LUCC) serves as the spatial substrate of the regional carbon balance [1]. The conversion of cropland, forest, grassland, and water bodies into built-up land alters both the stock of carbon held in vegetation and soils and the flux of carbon released through energy consumption [2–4]. At the provincial scale in China, these conversions have proceeded rapidly over the past three decades and have become a major component of the regional carbon budget [5,6]. Under the dual-carbon agenda of peaking emissions before 2030 and reaching neutrality before 2060, provinces serve as the primary administrative unit for implementing decarbonization policy [7,8]. Understanding and managing this dynamic requires moving beyond single-variable accounting toward an integrated assessment workflow. Rather than treating carbon accounting, spatial interaction, and land-use simulation as separate analytical tasks, this workflow integrates them to evaluate how land-use change shapes the provincial carbon balance as a whole. Quantifying how alternative development pathways may reshape this balance is therefore highly relevant for translating national targets into regional spatial policies [9].

Current research on regional carbon balances generally encompasses four methodological streams. First, land-use carbon source–sink accounting provides the quantitative baseline of the regional carbon budget. The coefficient-based methods used for this estimation have been standardized through IPCC guidance and are routinely applied at the city and provincial scales [10–12]. Second, ecoeconomic coupling indicators—specifically the Ecological Support Coefficient (ESC) and Economic Contribution Coefficient (ECC)—characterize how economic activity and ecological capacity relate within each city [13,14]. Together, ESC and ECC reveal a pattern that gross emission and sequestration totals miss: some cities sustain high economic output but have limited ecological capacity, while others have stronger ecological capacity but lower economic output [15]. Third, spatial-interaction analysis reveals how emissions are organized across cities—whether they cluster in a single core, distribute across multiple poles, or follow industrial corridors—and traces the inter-city linkages along which emission pressure propagates. It is crucial to clarify that these ‘emission linkages’ conceptually denote the economic spillovers and the spatial transfer of embodied carbon driven by inter-city socioeconomic interactions (e.g., trade, investment, and industrial relocation), rather than the physical atmospheric diffusion of CO₂. Gravity-based models are the standard tool for this purpose: they combine socioeconomic mass terms with geographic distance to infer the network structure of regional emissions from city-level statistical inputs [16,17]. Moreover, carbon emissions can exert certain impacts on the health of community residents, socioeconomic conditions, and human activities [18–20]. In order to explore the characteristics and change mechanisms of urban carbon emissions, as well as the influencing mechanisms associated with urban spatial land-use change, artificial intelligence, large language models, and related technologies have already played a considerable role [21–23]. In the process of urban development, industrial growth and various types of environmental emissions have also exerted significant influence on urban carbon emissions and the driving variables have been discovered [24–26]. Finally, multi-scenario land-use simulation models project spatial trajectories under alternative policy assumptions [8,27]. Land-use simulation models have developed through several generations: CA-Markov captures aggregate transition probabilities; FLUS [28] improved suitability estimation through neural-network-based driver weighting, and PLUS [29] added a patch-generation mechanism that better reproduces the contiguity of real land parcels. Building on these, the intPLUS model advances simulation by incorporating random-forest-derived transition probabilities and consistency-based interaction networks, explicitly quantifying driving and inhibiting effects among competing land-use types [30].

Despite the analytical value of these four streams, implementations that run all components on shared spatial units at the intra-provincial scale remain uncommon. When all components are run on shared spatial units, their outputs can be read against one another in ways that separate applications cannot: accounting magnitudes can be interpreted in light of the ESC/ECC configuration that produces them, the ESC/ECC pattern can be located within the inter-city gravity-network structure, and scenario projections can be traced through both the accounting and the ecoeconomic dimensions to identify where projected change concentrates. By integrating spatial emission linkages with land-use changes, a framework is constructed to reveal the scale-dependent relationships between explicit and implicit land-use transitions and carbon emissions [31]. Furthermore, drawing upon the characteristics of core–periphery spatial diffusion and factor mismatches, this integration provides a robust quantitative basis for formulating carbon neutrality strategies and economic policies, including cross-regional industrial compensation and precise land allocation [32–34]. Table 1 summarizes the closest prior studies, illustrating that most existing frameworks combine a subset of tools without formally integrating spatial interaction networks. To bridge this gap, Jiangsu Province serves as an informative setting. Characterized by high economic density, strong south–north differentiation [35], dense urban corridors, coastal wetlands [36], and advanced statistical capacity, Jiangsu represents a critical spatial mismatch between industrial agglomeration and ecological constraints.

Table 1. Methodological comparison of recent regional land-use and carbon-balance studies.

Study	Scale & Study Area	Land-Use Simulation	Carbon Accounting	Spatial Interaction & Coupling
Zhang et al. (2025) [37]	Shandong	None	Super-SBM	Gravity model & SNA
Shi et al. (2024) [38]	Coastal cities	FLUS	InVEST	None
Hua et al. (2025) [9]	Mining area	PLUS	InVEST	Geodetector & Moran's I
This Study	Jiangsu	intPLUS	Emission & Sequestration	Gravity-based network & ESC/ECC

This study develops an integrated computational framework that combines coefficient-based carbon accounting, ESC/ECC ecoeconomic indicators, a gravity-based emission-linkage model, and intPLUS-based multi-scenario land-use simulation within a common data stack (utilizing the China Land Cover Dataset, CLCD). The specific objectives are: (1) to integrate the three components into a single workflow operating on shared spatial units; (2) to benchmark the simulation component against observed 2020 land use through a hindcast; (3) to characterize the spatiotemporal evolution of Jiangsu's carbon balance and emission linkages from 1995 to 2020; and (4) to project the 2030 carbon balance under natural-development (ND), ecological-protection (EP), and economic-development (ED) scenarios to quantify divergence across pathways. It is important to distinguish method transferability from result generalizability: while the modular architecture of this workflow is technically portable to other subnational systems, parameter values, scenario assumptions, and network interpretations must be recalibrated for each unique province.

2. Materials and Methods

2.1. Study Area

Jiangsu Province is located on China's eastern coast in the core area of the Yangtze River Delta and is a key component of the Yangtze River Economic Belt (Figure 1). It covers approximately 107,200 km² and is administratively divided into 13 prefecture-level cities, which serve as the spatial units of the present analysis. The terrain is predominantly low-lying plains, with higher elevations in the southwest around Nanjing and Zhenjiang and in the north around Xuzhou, reaching approximately 571 m (Figure 1). The province also features extensive coastal wetlands along the Yellow Sea and dense river and lake networks supporting diverse ecosystem types [36]. The climate is subtropical to warm-temperate, with mean annual precipitation between roughly 800 mm in the north and 1200 mm in the south.

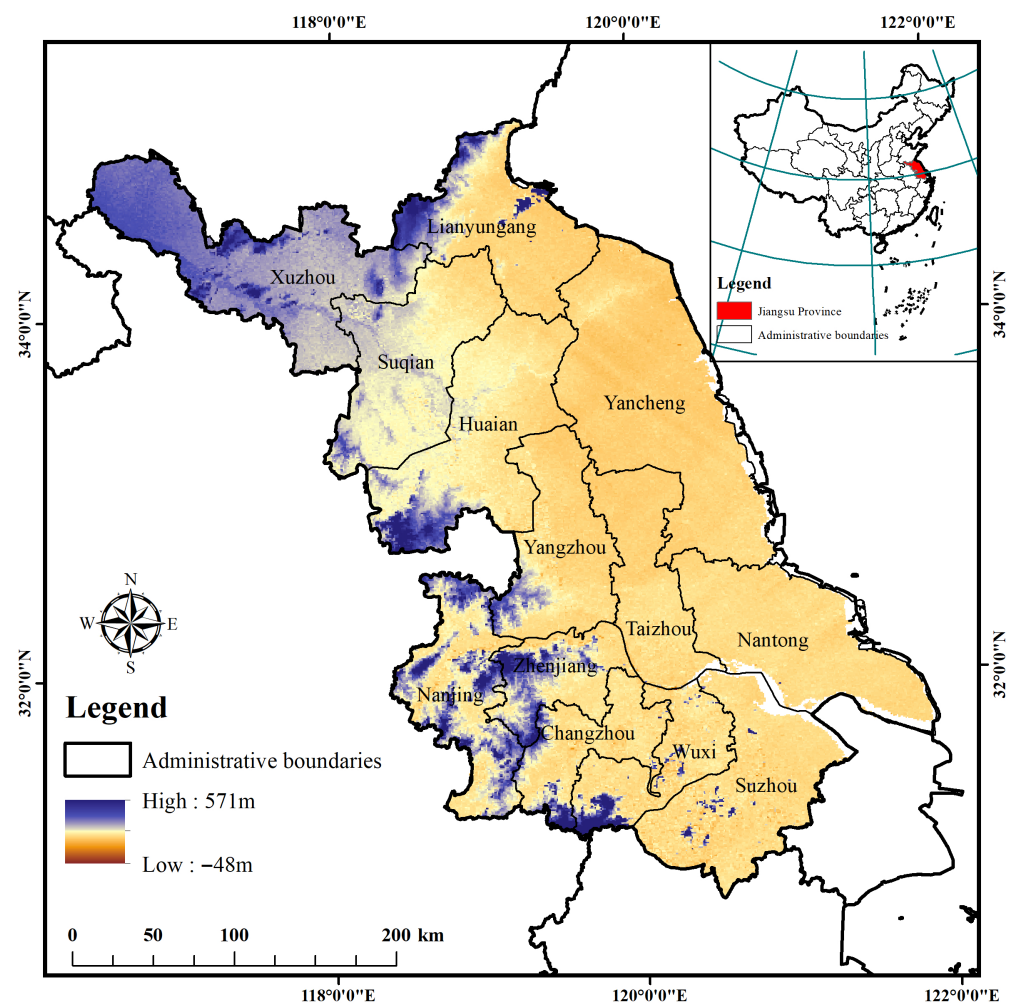


Figure 1. Geographic context of the study area, Jiangsu Province.

Jiangsu exhibits a pronounced south–north gradient in economic structure and land-use composition [35]. The southern subregion—including Nanjing, Suzhou, Wuxi, Changzhou, and Zhenjiang—is highly industrialized and urbanized, with construction land occupying a large share of the territory and per-capita GDP among the highest in China. The central and northern subregions are characterized by larger cropland shares, lower industrial intensity, and more substantial forest and wetland cover. This intra-provincial heterogeneity in economic and ecological conditions, together with active dual-carbon policy implementation across all 13 cities, provides the structural context within which the present framework is applied.

2.2. Datasets

This study employs the 13 prefecture-level cities of Jiangsu Province as the primary spatial units and analyzes historical data at six periods (1995, 2000, 2005, 2010, 2015, and 2020). Land-use data were obtained from the China Land Cover Dataset and reclassified into six categories (<http://geodata.nnu.edu.cn>, accessed on 15 April 2026). Statistical indicators include energy consumption, resource consumption, population, and GDP, with data mainly sourced from the *China Energy Statistical Yearbook*, the *Jiangsu Statistical Yearbook*, and other authoritative publications. Natural geographic factors fundamentally shape land-use patterns, development intensity, and trajectories, thereby constraining the spatial potential for built-up area expansion. Locational factors significantly influence the economic costs of land-use and land-cover change (LUCC) and constitute key external forces attracting the outward expansion of urban construction land. Meanwhile, the immediate driver of construction-land expansion is the intrinsic demand associated with socioeconomic development, which itself is molded by a range of socioeconomic factors.

To enable future scenario simulations, ten explanatory variables were selected across three dimensions—natural, locational, and socioeconomic (<https://www.openstreetmap.org/>, accessed on 1 May 2026; <https://www.resdc.cn/>, accessed on 1 May 2026). Notably, distance-to-road variables were disaggregated into distances to primary, secondary, and tertiary roads. Latent variables focus on core driving forces that may exert profound impacts on future land-use patterns. Drawing on policy documents such as the *Jiangsu Spatial Master Plan (2021–2035)*, policy orientation was incorporated into the latent-variable system to more comprehensively capture and analyze potential trends and drivers of future land-use change. Table 2 details the categorization, sources, spatial resolution, and time coverage of all datasets, addressing the requirements for reproducible modeling.

Table 2. Data description and specifications.

Category	Data	Data Source	Data Type	Spatial Resolution	Time Coverage	Preprocessing/Vintage
Land-use dataset	CLCD	Wuhan University (http://geodata.nnu.edu.cn)	Raster	30 m	1995–2020	Reclassified into 6 classes; projected to WGS_1984_UTM_Zone_50N.
Natural factors	DEM, Slope	Resource and Environmental Science Data Platform, China (https://www.resdc.cn/)	Raster	30 m	2020	Slope derived from DEM using Spatial Analyst.
	Precipitation, Temperature, NDVI	RESDC	Raster	1 km	1995–2020	Annual means; resampled via bilinear interpolation.
Locational factors	Distance to government, railroad, roads, river	https://www.openstreetmap.org/ ; RESDC	Raster	Vector original	2020	Euclidean distance calculated from vector networks.
Raster Socioeconomic factors	Population density, Gridded GDP	RESDC	Raster	1 km	1995–2020	Used exclusively as driving factors for intPLUS allocation.
Restricted area data	Nature reserves, Main streams, Ecological Redlines	RESDC; Jiangsu Spatial Master Plan	Vector	N/A	2020	Binarized as absolute restriction layers (1 = restricted, 0 = allowed).
City-level Statistical data	Energy/resource consumption, Population, GDP, Disposable income	China Energy Statistical Yearbook; Jiangsu Statistical Yearbook	Panel	Prefecture-city level	1995–2020	Used for carbon accounting and Gravity Model. GDP deflated to 2015 constant prices.

Note: CLCD—China Land Cover Dataset; DEM—Digital Elevation Model; NDVI—Normalized Difference Vegetation Index; RESDC—Resource and Environmental Science Data Platform.

2.3. Data Processing and Reproducible Workflow

To ensure strict spatial and temporal alignment across the integrated framework, a standardized data-processing workflow was implemented prior to analysis:

1. **Coordinate Reference System and Resampling:** All spatial raster and vector data were uniformly projected to the WGS_1984_UTM_Zone_50N coordinate reference system to minimize area distortion. Rasters with varying original resolutions (e.g., 1 km meteorological and raster socioeconomic data) were resampled to a consistent 30 m $\times$ 30 m resolution to match the CLCD land-use baseline. The nearest-neighbor assignment was used for categorical data (e.g., land use, restricted areas), while bilinear interpolation was applied to continuous variables (e.g., DEM, climate, distance drivers, raster GDP/Population).
2. **Land-Use Reclassification Crosswalk:** The original CLCD thematic classes were explicitly aggregated into six target land-use types based on ecological functions and carbon-accounting needs: CLCD Cropland $\rightarrow$ Cropland; CLCD Forest $\rightarrow$ Forest; CLCD Shrub and Grassland $\rightarrow$ Grassland; CLCD Water and Snow/Ice $\rightarrow$ Water area; CLCD Impervious $\rightarrow$ Built-up land; CLCD Barren $\rightarrow$ Unused land.
3. **Statistical Data Alignment and Variable Distinction:** A critical distinction was maintained between raster and statistical socioeconomic data. The 1 km raster Population and GDP datasets were used solely as localized explanatory variables (driving forces) for the intPLUS model to capture spatial suitability. Conversely, the city-level statistical population and GDP (sourced from yearbooks) were utilized as macroeconomic mass variables in the gravity-based emission-linkage model. To eliminate inflationary artifacts, statistical GDP was deflated to 2015 constant prices using provincial GDP deflators. For energy accounting, 10 primary categories were extracted from the yearbooks strictly aligned with the exact raster years (1995, 2000, 2005, etc.): raw coal, briquettes, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas, and electricity.
4. **Missing Values and Spatial Aggregation:** Isolated missing values in rasters were filled using a 3 $\times$ 3 focal mean nearest-neighbor algorithm. To convert continuous pixel-level outputs (such as simulated land-use areas and gridded parameters) into prefecture-level city summaries for the ESC/ECC and gravity models, the Zonal Statistics as Table function was employed. To guarantee temporal consistency despite historical administrative adjustments, the 2020 Jiangsu prefecture-level city boundary vector file was applied uniformly as the fixed aggregation baseline for all years (1995–2030).

2.4. Method

This study develops a carbon-balance analysis framework (Figure 2) with three core modules: carbon emission and sequestration accounting, intra-provincial spatial-interaction analysis, and multi-scenario land-use simulation. First, emissions and sequestration are estimated by land-use type—cropland, forestland, grassland, water bodies, and unused land—using coefficient-based methods, while construction-land emissions are derived indirectly from energy consumption and emission factors. Second, spatial-interaction analysis is operationalized through two complementary tools, the Ecological Support Coefficient (ESC) and Economic Contribution Coefficient (ECC), which quantify the local economy–ecology relationship within each city, and a gravity-based emission-linkage model that uses GDP, population, emissions, and inter-city distance to characterize the network structure of inter-city emission attraction. Third, the intPLUS model simulates 2030 land-use and carbon-balance trajectories under three scenarios—natural development, economic development, and ecological protection—to compare carbon budgets across alternative development pathways. Within this integrated assessment workflow, regional socioeconomic

factors (e.g., population, GDP, energy demand) and scenario-specific policy constraints serve as exogenous inputs. The outputs of the multi-scenario land-use simulation module feed directly into the carbon accounting module to generate spatially explicit emission and sequestration totals. These accounting totals, in turn, feed into the spatial-interaction module to calculate the ESC/ECC indicators and construct the gravity-based emission network. The resulting land-use configurations, carbon budgets, and emission network topologies are evaluated as endogenous variables. Consistent with its design as a unidirectional pipeline, the framework does not currently model dynamic feedback; the outputs of the spatial-interaction module do not feed back to alter land-use transition probabilities or energy demand inputs.

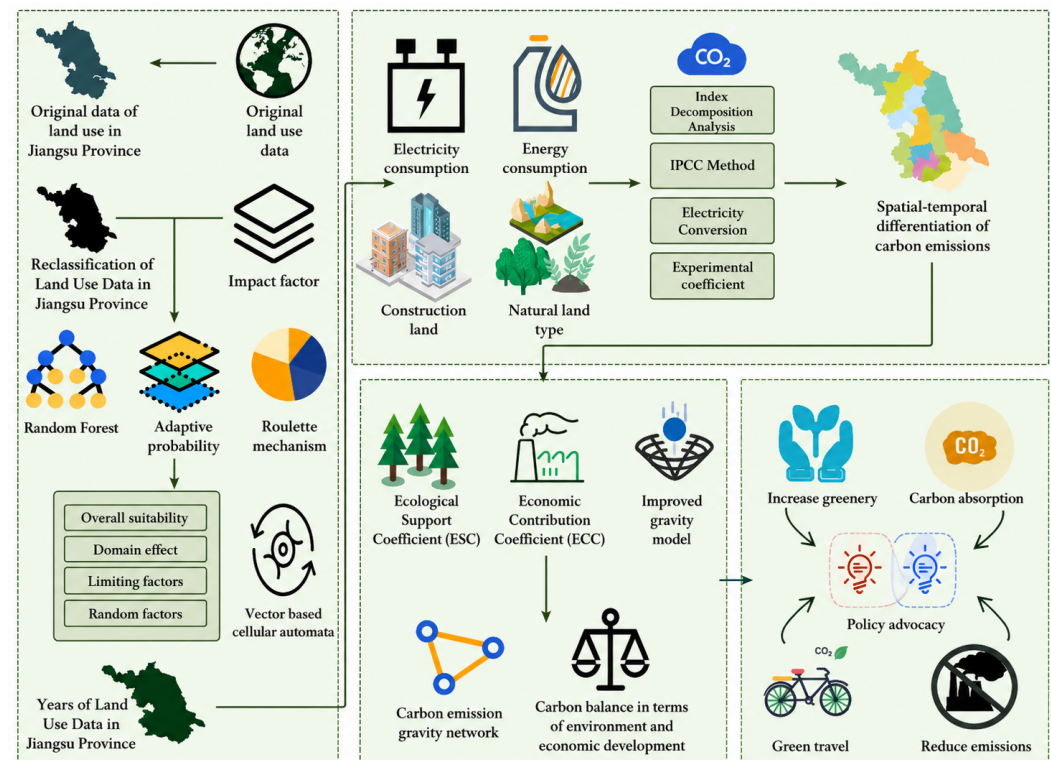


Figure 2. Research framework.

2.4.1. Carbon Emission and Sequestration Balance

Carbon emissions and sequestration are estimated by land-use type. For natural land categories—cropland, forestland, grassland, water bodies, and unused land—total carbon flux is calculated as the product of the area of each land type and its corresponding emission or sequestration coefficient [10]. For construction land, emissions are dominated by human energy use rather than land cover itself and are therefore estimated indirectly from energy-consumption data and emission factors.

For direct measurement, carbon emissions from cropland, forestland, grassland, water bodies, and unused land can be estimated using coefficient calculation methods, represented by the following formula:

$$CE_i = S_i \times \theta_i, \quad (1)$$

where CE_i represents the direct carbon emission, S_i denotes the area of the i th land use, and θ_i indicates the carbon emission coefficient for the i th land-use type.

For indirect measurement, the primary source of carbon emissions from construction land is the emissions resulting from energy consumption. By referring to prior research, the consumption of ten types of energy, such as coal, coke, and electricity, combined with

energy conversion coefficients and CO₂ emission coefficients, can be utilized to calculate the energy consumption in urban production and daily life, as well as the carbon emissions from construction land. The relevant calculation formula is as follows:

$$CE_i = \sum e_i \times \beta_i \times \varepsilon_i, \quad (2)$$

where e_i represents the quantity of the i th type of energy used, β_i denotes the coefficient that converts the i th type of energy into standard coal, and ε_i stands for the carbon emission coefficient of the i th type of energy.

To ensure transparency and reproducibility, the specific carbon sequestration coefficients for natural land-use categories are detailed in Table 3. A strict sign convention is applied herein, whereby positive values denote carbon emissions (sources) and negative values indicate carbon sequestration (sinks). To account for the specific regional characteristics of Jiangsu Province, these coefficients were calibrated using localized ecological data to reflect the net annual carbon sequestration flux per unit area.

Table 3. Carbon sequestration coefficients for natural land-use types.

Land-Use Type	Coefficient Value	Unit	Sign Convention	Represents	Source
Cropland	−0.0095	t C/(ha·yr)	Negative (−)	Annual Sequestration	Localized calibration
Forest	−0.9985	t C/(ha·yr)	Negative (−)	Annual Sequestration	Localized calibration
Grassland	−1.1184	t C/(ha·yr)	Negative (−)	Annual Sequestration	Localized calibration
Water Area	−0.3124	t C/(ha·yr)	Negative (−)	Annual Sequestration	Localized calibration
Unused Land	0	t C/(ha·yr)	Neutral (0)	Annual Sequestration	Localized calibration

For the indirect measurement of built-up land emissions, the conversion factors for standard coal equivalents (SCE) and the carbon emission factors for major energy sources are presented in Table 4. These parameters are strictly derived from the guidelines of the Intergovernmental Panel on Climate Change (IPCC) and the National Development and Reform Commission of China (NDRC).

Table 4. Standard coal conversion and carbon emission factors for major energy types.

Energy Type	Conversion Factor to SCE (β_i)	Unit	Carbon Emission Factor (ε_i)	Source
Raw Coal	0.7143	kg SCE/kg	0.7559 kg C/kg SCE	IPCC (2006)/NDRC
Coke	0.9714	kg SCE/kg	0.8550 kg C/kg SCE	IPCC (2006)/NDRC
Crude Oil	1.4286	kg SCE/kg	0.5857 kg C/kg SCE	IPCC (2006)/NDRC
Gasoline	1.4714	kg SCE/kg	0.5538 kg C/kg SCE	IPCC (2006)/NDRC
Kerosene	1.4714	kg SCE/kg	0.5714 kg C/kg SCE	IPCC (2006)/NDRC
Diesel	1.4571	kg SCE/kg	0.5921 kg C/kg SCE	IPCC (2006)/NDRC
Fuel Oil	1.4286	kg SCE/kg	0.6185 kg C/kg SCE	IPCC (2006)/NDRC
Natural Gas	1.3300	kg SCE/m ³	0.4483 kg C/kg SCE	IPCC (2006)/NDRC

Furthermore, it is essential to clarify the conceptual boundary of our carbon accounting. In this study, the ‘land-use carbon balance’ serves as an integrated proxy rather than a

strict measure of direct land fluxes alone. The emissions assigned to ‘built-up land’ are derived from territorial energy consumption, encompassing industrial, transportation, and residential activities occurring within that spatial footprint, rather than solely emissions triggered by the physical conversion of land. Therefore, our estimates represent territorial energy emissions localized to built-up land areas, combined with the direct biophysical sequestration fluxes of natural lands. This hybrid accounting approach is necessary to bridge socioeconomic metabolic activities with spatial land-use planning.

2.4.2. Ecoeconomic Carbon Balance Simulation

The Ecological Support Coefficient (ESC) evaluates a region’s relative ecological buffering capacity within the broader provincial context. Rather than an absolute ratio of local sinks to local emissions, ESC is measured as the ratio of a city’s share of the provincial carbon sink to its share of provincial carbon emissions. When the ESC value exceeds 1, it indicates that the city contributes a larger share to the provincial carbon sink than it does to provincial carbon emissions, reflecting a relative ecological advantage. Conversely, an ESC value below 1 suggests that the city’s emission share outpaces its sink contribution share. Thus, ESC reflects the relative position and ability of a region to support carbon sink development within the provincial system [13,39]. The formula for ESC is as follows:

$$ESC = \frac{\left(\frac{CS_i}{CS}\right)}{\left(\frac{CE_i}{CE}\right)} \quad (3)$$

where CS_i denotes the carbon absorption of city i , CS represents the total carbon absorption in Jiangsu Province, CE_i is the carbon emissions of city i , and CE is the total carbon emissions in Jiangsu Province.

Similarly, the Economic Contribution Coefficient (ECC) evaluates the relative economic efficiency of carbon emissions. Instead of simple GDP per unit of emissions, ECC is measured as the ratio of a city’s share of the provincial Gross Domestic Product (GDP) to its share of provincial carbon emissions. This relative index allows for evaluating the variability of economic efficiency in carbon emission management across different regions [14]. When ECC exceeds 1, it indicates that the city contributes a larger share to the provincial economy than its share of provincial emissions, signifying high relative carbon-economic efficiency. Its calculation formula is as follows:

$$ECC = \frac{\left(\frac{G_i}{G}\right)}{\left(\frac{CE_i}{CE}\right)} \quad (4)$$

where G_i represents the GDP of city i , G is the total GDP of Jiangsu Province, CE_i denotes the carbon emission of city i , and CE represents the total carbon emissions in Jiangsu Province.

To rigorously characterize the spatial correlation network of carbon emissions among cities, this study employs a modified gravity model. The traditional gravity model, widely used in regional economics, often relies on geographic distance and singular mass variables. Drawing upon the theoretical framework established by Chen et al. (2018) [16] and subsequently refined for carbon network analysis in the recent spatial econometric literature, a multidimensional mass term was constructed. Theoretically, the ‘emission linkage’ (R_{ij}) evaluated by this model is defined as the socioeconomic spatial spillover of carbon emissions. In practical terms, it quantifies the intensity of economic dependencies and embodied carbon transfers between jurisdictions dictated by industrial linkages and factor

mobility, explicitly excluding physical atmospheric dispersion. The improved model is formulated as follows:

$$R_{ij} = k_{ij} \times \frac{\sqrt[3]{G_i \times P_i \times C_i} \times \sqrt[3]{G_j \times P_j \times C_j}}{\left(\frac{d_{ij}}{g_{ij}}\right)^2}, \quad k_{ij} = \frac{C_i}{C_i + C_j} \quad (5)$$

where R_{ij} represents the directed spatial emission attraction from city i to city j , and d_{ij} is the Euclidean geographic distance between the two cities. G , P , and C denote the Gross Domestic Product, year-end population, and carbon emissions of the respective cities. The geometric mean form ($\sqrt[3]{G \times P \times C}$) is adopted as the mass term to assign equal elasticities to economic scale, demographic size, and emission volume, preventing any single extreme metric from skewing the network structure.

Crucially, to reflect the reality that economic and technological disparities mitigate the friction of geographic distance, g_{ij} is introduced as the absolute difference in per capita disposable income ($g_{ij} = |e_i - e_j|$). The absolute value prevents negative attraction values. To avoid the mathematical instability (division by zero) highlighted in previous network studies when two cities possess identical income levels, g_{ij} is bounded by a minimal floor value ($\epsilon = 1$) if $|e_i - e_j| < 1$.

The regulating factor k_{ij} introduces asymmetry into the network, explicitly defining R_{ij} as a directed graph. Theoretically, the directionality signifies the unequal hierarchical influence within the emission network: a city with a larger emission volume ($C_i > C_j$) exerts a stronger gravitational pull on the bilateral linkage, reflecting its dominant role as an industrial core or energy-consumption hub that drives embodied carbon transfers from peripheral neighbors.

To transform the continuous spatial attraction matrix $R = [R_{ij}]$ into a discrete network structure, inter-city emission linkages were conceptualized as a weighted directed graph. Rather than applying a single binary cutoff, the threshold criteria for establishing hierarchical linkages were determined via the Natural Breaks (Jenks) optimization method. This approach discretizes the continuous R_{ij} values into five operational tiers (0–0.2, 0.2–0.5, 0.5–1.5, 1.5–3, and >3), thereby minimizing intra-class variance and explicitly isolating dominant spatial linkages. Furthermore, to quantitatively delineate ‘core’ and ‘periphery’ nodes within the network framework without discarding edge weights, Nodal Spatial Strength (S_i) is employed in place of unweighted degree centrality. This metric is mathematically formulated as the sum of all gravity linkages associated with city i :

$$S_i = \sum_{j=1, j \neq i}^N R_{ij} + \sum_{j=1, j \neq i}^N R_{ji} \quad (6)$$

where $N = 13$. Nodes with the highest S_i values mathematically constitute the network core, dictating the regional emission configuration.

2.4.3. Multi-Scenario Simulation of Jiangsu Province Based on the intPLUS Model

The intPLUS model is a second-generation land-use simulation model based on patch generation (PLUS) that aims to reveal the fundamental mechanisms of land-system evolution by exploring the competition between various land-use types. By introducing interaction networks, the model quantifies the driving and suppressing effects between different land-use types, thereby improving the accuracy of land-use change predictions. The intPLUS model employs a random forest algorithm to analyze the driving mechanisms of land-use changes and constructs an interaction network of land-use types using consistency information, while also incorporating the mutual suppressive effects between

different types to more accurately reflect the competitive relationships among land uses. Compared to traditional models like CA-Markov and FLUS, the intPLUS model has notable advantages in simulating land-use changes, particularly with its innovative introduction of a patch-based generation mechanism. This mechanism moves beyond reliance on pixel-level transitions and better replicates the spatial aggregation and continuity of land use by simulating the growth process of patches. Additionally, the intPLUS model integrates various driving factors, such as natural, socioeconomic, and situational factors, while using machine learning methods to select and optimize their importance, thus enhancing the scientific basis for factor selection and the interpretability of results [30,40,41].

In terms of scenario simulation, the intPLUS model supports multiple scenario settings and the incorporation of policy constraints, allowing for differentiated simulations of future land-use patterns while considering practical planning requirements, such as farmland protection, ecological red lines, and urban boundaries. In comparison to other models, intPLUS excels in predictive accuracy, spatial pattern realism, and flexibility in scenario simulations, particularly in areas impacted by complex human activities, such as regions experiencing rapid urbanization. Therefore, the intPLUS model provides a more robust and efficient technical support for conducting coupled analyses of land use and carbon balance.

To rigorously project future land-use patterns, the macroscopic land-use demand for 2030 was initially calculated using a Markov chain model based on the historical transition probability matrix spanning 2010 to 2020. Subsequently, to reflect divergent policy trajectories, three distinct scenarios were formulated. The specific adjustment factors for transition probabilities were systematically calibrated based on provincial planning documents and historical transition elasticities, ensuring empirical validity. The detailed parameters, policy constraints, and adjustment rules are comprehensively outlined in Table 5.

1. **Natural-Development (ND) Scenario:** As the baseline, this scenario assumes an absence of major policy interventions. It strictly extrapolates the historical land-use evolution trends (2010–2020) driven by natural and socioeconomic inertia. The Markov-derived baseline transition probabilities are applied directly without subjective modifications, establishing a quantitative benchmark for evaluating alternative pathways.
2. **Ecological-Protection (EP) Scenario:** This scenario operationalizes the strict ecological redlines and afforestation mandates stipulated in the Jiangsu Spatial Master Plan (2021–2035) and the 14th Five-Year Plan for Forestry and Grassland. To meet the explicit policy target of achieving a 26% forest coverage rate by 2030, historical transition probabilities were calibrated: the probability of cropland converting to forestland and grassland was amplified by 60% to simulate intensive ecological restoration. Concurrently, to simulate stringent urban growth boundaries, the probability of natural lands (cropland, forest, grassland) converting to built-up land was penalized by 20%. Furthermore, water bodies were designated as absolute restricted areas, with the conversion probability to built-up land constrained to zero.
3. **Economic-Development (ED) Scenario:** This scenario projects a trajectory of accelerated industrialization and infrastructure expansion. The transition probability adjustments were empirically grounded in the peak historical elasticities of urban expansion observed during Jiangsu's rapid growth phase (2000–2010). Consequently, the probabilities of forestland, grassland, and water bodies converting to built-up land were increased by 15%, 10%, and 10%, respectively. To simulate the structural lock-in effect of urbanization, the likelihood of built-up land reverting to other ecological typologies was drastically reduced by 60%.

Table 5. Comprehensive scenario parameters, adjustment rules, and policy constraints for 2030 simulations.

Scenario	Transition Probability Adjustments (vs. Baseline)	Policy Constraints & Restricted Areas	Demand Model
ND	Baseline: Unmodified historical probabilities (2010–2020).	No absolute spatial restrictions.	Markov Chain
EP	- Cropland → Forest/Grassland: +60% - Cropland/Forest/Grassland → Built-up: −20% - Water → Built-up: 0 (Prohibited)	- 14th Five-Year Plan (26% forest target) - Ecological redlines and water bodies strictly protected.	Markov Chain
ED	- Forest → Built-up: +15% - Grassland/Water → Built-up: +10% - Built-up → Other types: −60%	- Calibrated via 2000–2010 peak expansion elasticities. - No ecological restrictions.	Markov Chain

Note: The baseline transition matrix derived from the Markov chain serves as the quantitative foundation. The percentage adjustments listed above are applied as multipliers to these baseline probabilities within the intPLUS model to generate the final scenario-specific transition matrices. The binary allowed/disallowed transitions (0 or 1) are implicitly enforced through the restricted area spatial layers.

3. Results

3.1. Spatiotemporal Patterns of LUCC

Land-use distribution and transitions in Jiangsu Province underwent marked changes between 1995 and 2020, as illustrated in Figure 3. Overall, the period is characterized by a persistent decline in cropland, substantial expansion of built-up land, modest increases in forest and grassland, and generally stable water bodies with fluctuations. From the temporal perspective, cropland remained the dominant land type, yet its spatial extent was progressively encroached upon by urban built-up land. The most pronounced urban expansion occurred along the Yangtze River corridor, in southern Jiangsu, and around coastal urban agglomerations, forming a typical clustered development pattern “along the river, along the coast, and along transport axes.” Meanwhile, in parts of northern Jiangsu, adjustments in agricultural practices led to scattered edge conversions of cropland into forest and grassland, indicating signs of ecological restoration. Water bodies were concentrated mainly in the Taihu Basin and along the main stem and tributaries of the Yangtze River; while the overall configuration remained largely unchanged, alternating expansion–contraction cycles occurred locally, such as in northern Jiangsu wetlands and central Jiangsu lakes.

Sankey-based transition analysis (Figure 4) indicates that the increase in built-up land was driven primarily by the conversion of cropland, followed by contributions from water and grassland, reflecting the crowding effect of rapid urbanization on land resources. Although forest and grassland registered net gains, the overall magnitude was limited, and existing ecological restoration efforts were insufficient to offset the pressure induced by the expansion of built-up land. Overall, LUCC in Jiangsu reflects the spatial demands of rapid economic growth while exposing substantial challenges for cropland protection and ecological space security. Going forward, strict enforcement of the cropland protection redline and the ecological conservation redline, coupled with more intensive and efficient use of built-up land, and enhanced protection and restoration of water bodies and forest–grass systems, will be essential to harmonize economic development with environmental stewardship and to support high-quality development and the implementation of the dual-carbon agenda.

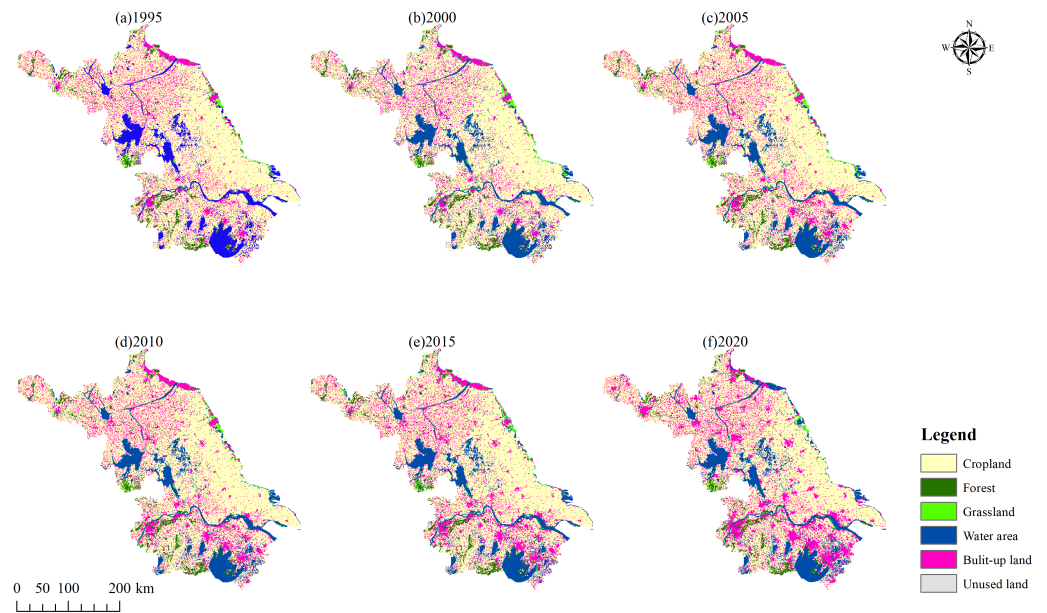


Figure 3. Spatial distribution of land use in Jiangsu Province from 1995 to 2020.

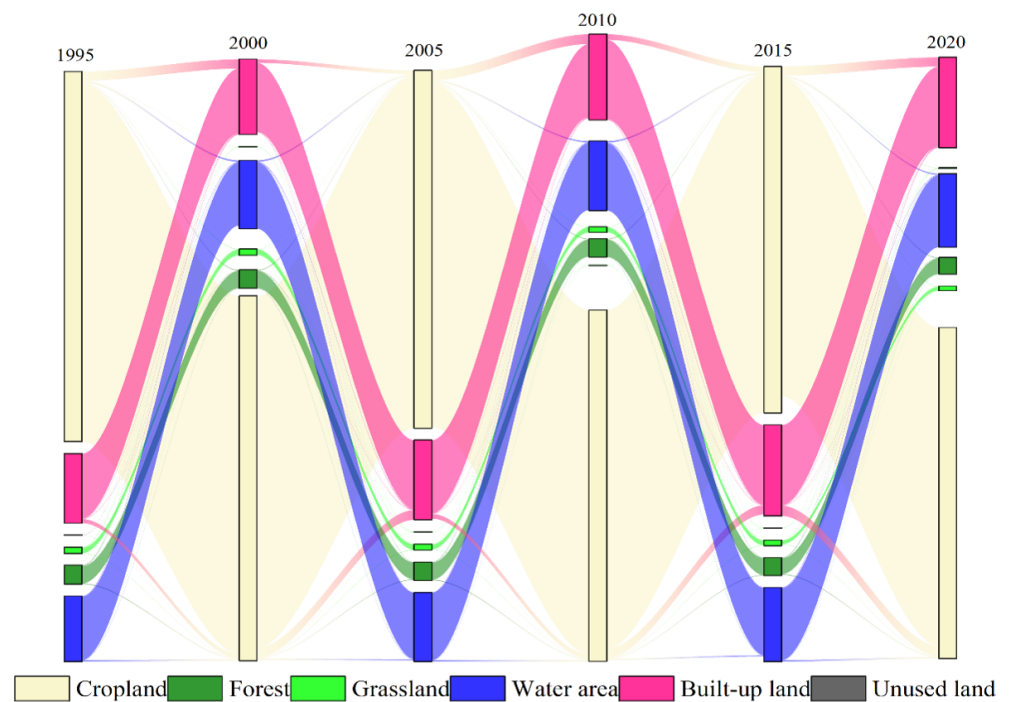


Figure 4. Sankey transition diagram of absolute land-use area changes (km²) in Jiangsu Province across consecutive periods from 1995 to 2020.

3.2. Spatiotemporal Carbon-Balance Dynamics

3.2.1. Carbon Emissions and Sequestration

Based on statistical analyses of Jiangsu's total carbon emissions from 1995 to 2020 (Figure 5) and the city-level spatial distribution (Figure 6), the spatiotemporal evolution of net carbon emissions displays a clear pattern of “year-on-year increase with intensification from north to south.” During 1995–2000, provincial emissions were generally low: most jurisdictions recorded net emissions below 900×10^4 t, with only parts of southern Jiangsu reaching relatively high levels. By 2005, emissions in southern Jiangsu and cities along the

Yangtze River had risen markedly, and the spatial pattern began to exhibit a “high-south, low-north” gradient.

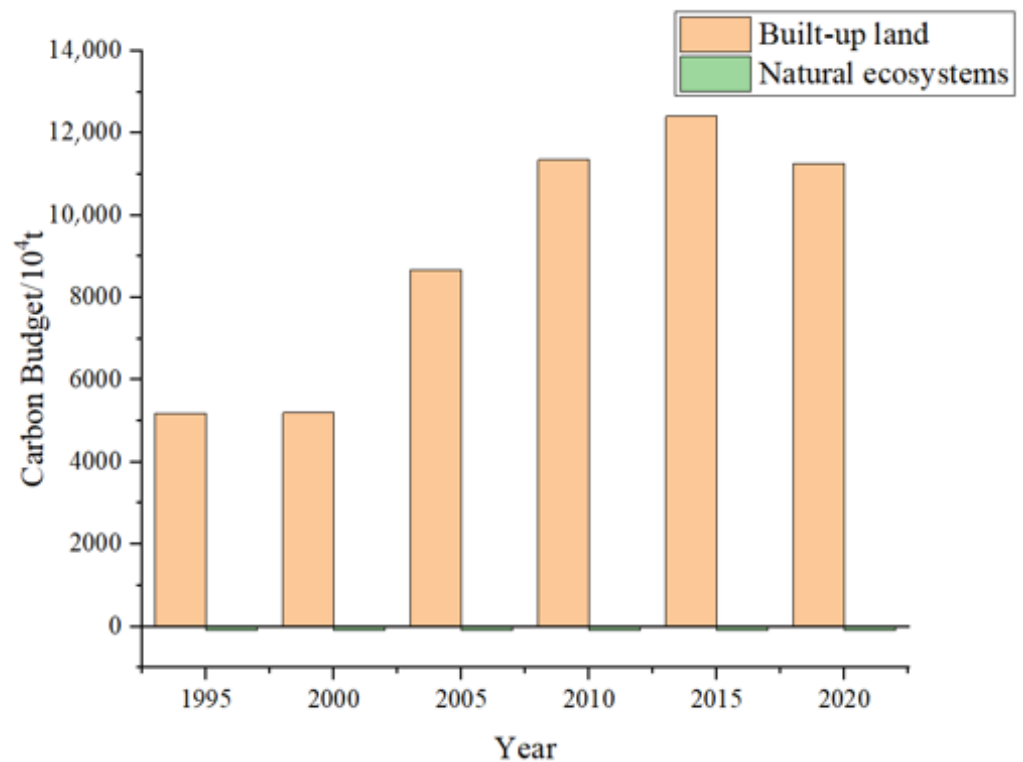


Figure 5. Carbon-balance dynamics in Jiangsu Province.

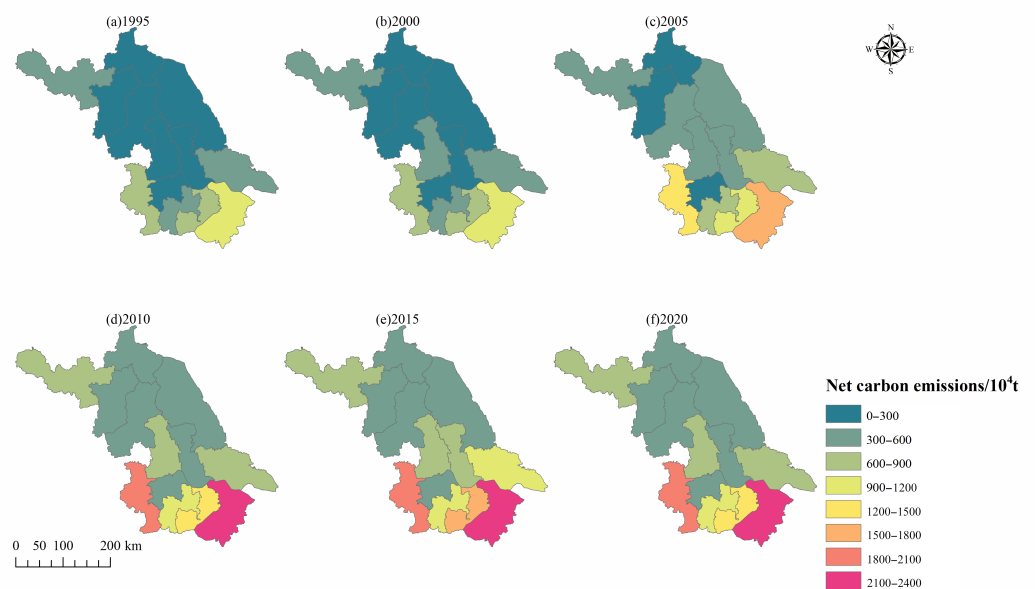


Figure 6. Spatiotemporal patterns of carbon emissions in Jiangsu Province.

After 2010, emissions in southern Jiangsu—particularly Suzhou, Wuxi, and Changzhou—surged rapidly, with some cities exceeding 1800×10^4 t, forming the province’s high-value core. Meanwhile, emissions in central Jiangsu (Yangzhou, Nantong, Taizhou) continued to rise, producing a belt-like expansion contiguous with the south. In contrast, northern Jiangsu (Suqian, Huai’an, Lianyungang) maintained relatively low emission levels; only Yancheng and Xuzhou showed notable increases after 2015, indicating a widening north–south disparity. By 2020, the spatial configuration formed a “high in

the south–moderate in the center–low in the north” pattern. This evolution indicates that emission growth is primarily driven by industrial agglomeration and energy consumption intensity, exhibiting clear spatial differentiation over the past two decades.

This evolution is closely aligned with regional differences in economic development, industrial structure, and urbanization, suggesting that emission growth is primarily driven by industrial agglomeration and the intensity of energy consumption [42,43]. Overall, Jiangsu’s carbon emissions have exhibited pronounced spatial polarization over the past two decades. The southern jurisdictions are characterized by high carbon pressure and high economic output, whereas the northern regions possess stronger ecological carrying capacity but lower economic contributions.

3.2.2. Ecoeconomic Carbon-Balance Analysis

Visualization of the spatial distributions of the ECC (Figure 7) and ESC (Figure 8) indicates that Jiangsu’s ecological carrying capacity (ESC) remained generally low from 1995 to 2020, with high-value pockets occurring in parts of southern and central Jiangsu. This pattern suggests that these areas possessed a certain buffering capacity for carbon emissions on the basis of relatively favorable ecological conditions. During 2005–2010, ESC declined markedly in several locales, especially within the industrially intensive zones of southern Jiangsu, implying that rapid industrialization and urban expansion temporarily pushed emissions beyond the regulatory and self-recovery capacity of local ecosystems. By 2020, ESC had improved in parts of northern Jiangsu, whereas the core metropolitan cluster in the south (Nanjing, Suzhou, Wuxi, Changzhou, etc.) remained in a low-carrying state, yielding a distinct “low in the south–high in the north” gradient.

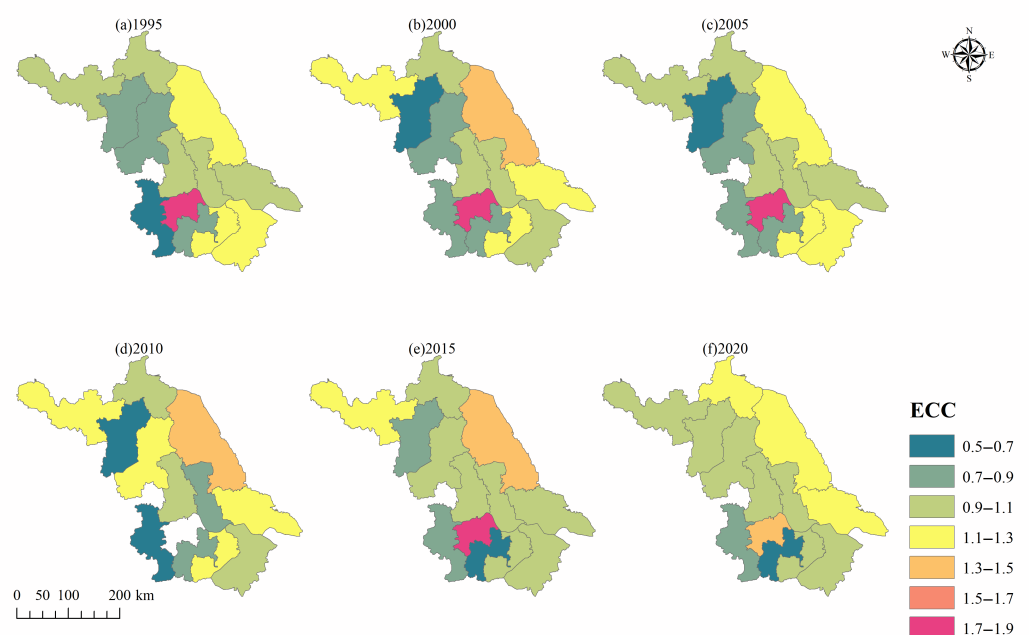


Figure 7. The distribution of ECC in Jiangsu Province.

Temporally, the economic carbon contribution (ECC) stayed at a broadly moderate level province-wide, yet exhibited pronounced spatial heterogeneity. Southern Jiangsu maintained persistently high ECC—most notably in Nanjing, Suzhou, and Wuxi—manifesting a “high-carbon contribution” economic profile in which output is strongly underpinned by carbon-intensive inputs. In contrast, several cities in northern Jiangsu recorded relatively low ECC, indicating limited marginal contribution of emissions to economic output and revealing constraints in development level and a resource-dependent

industrial structure. Overall, ECC displays a “high in the south–low in the north” pattern that closely mirrors the province’s economic development gradient.

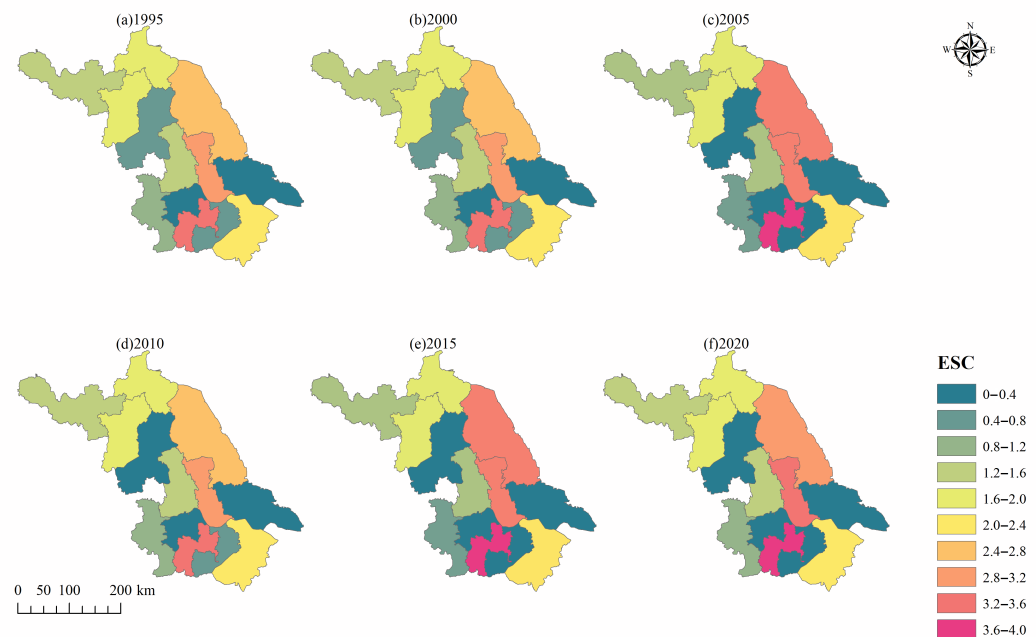


Figure 8. The distribution of ESC in Jiangsu Province.

Juxtaposing ESC and ECC reveals a characteristic coupling pattern: “high contribution–low carrying capacity” in the south and “low contribution–high carrying capacity” in the north. While the southern urban agglomeration delivers robust economic output, its emissions pressure exceeds local ecological capacity, intensifying environmental constraints. Conversely, northern Jiangsu contributes less economically but possesses stronger ecological carrying capacity, implying carbon sink potential and leeway for low-carbon transitions. This configuration underscores a marked imbalance in Jiangsu’s economy–environment system.

3.3. Carbon-Balance Connectivity Analysis

Figure 9 depicts Jiangsu’s carbon-emission gravity network in 2020. Based on the classification criteria defined in Section 2.4.2, the continuous R_{ij} values are mapped into a five-tier discrete hierarchy. At the city scale, the intra-provincial system exhibits a distinctly networked and hierarchical configuration. Southern Jiangsu (Nanjing, Suzhou, Wuxi, Changzhou, etc.), as the most economically advanced and industrially agglomerated subregion, anchors the network’s core, with darker and thicker edges signaling markedly stronger inter-city interactions in energy use and carbon emissions than elsewhere. Central Jiangsu (Nantong, Yangzhou, Taizhou, Zhenjiang) functions as an intermediary belt between the south and the north: its gravity ties with southern cities are relatively strong, whereas its connections to northern cities are weaker, reflecting a tight coupling between the province’s economic gradient and the spatial connectivity of emissions, as well as the downstream transmission of influence from the core to the periphery. In contrast, cities in northern Jiangsu (Xuzhou, Lianyungang, Huai’an, Yancheng, Suqian) generally exhibit weaker gravity strengths with fewer and thinner links, indicative of more dispersed energy consumption and industrial layouts and a lower degree of integration with the core. This does not imply marginality across the board: Xuzhou, as the northern subregional center, still exerts notable radiation and spillover effects on neighboring jurisdictions, serving as a pivotal node within the subnetwork. Taken together, the emission gravity

network presents a “strong south, weak north, and transitional center” spatial structure that aligns closely with disparities in economic development, industrial composition, and energy-use patterns, revealing a tendency for emissions to cluster along economic axes and industrial belts. This network mirrors Jiangsu’s “south-to-north industrial transfer.” Modeled hub-to-periphery linkages physically manifest as co-constructed projects like the Suzhou–Suqian and Wuxi–Xuzhou Industrial Parks. These manufacturing relocations form tangible corridors for inter-city embodied carbon transfers, proving the gravity model’s practical value in capturing real macroeconomic correlations. Policy-wise, the findings call for consolidating southern Jiangsu’s leadership in low-carbon technologies, green finance, and institutional innovation to amplify positive spillovers; strengthening central Jiangsu’s hub-and-transmission role by improving cross-city coordination and factor mobility to align decarbonization pathways and clean-energy substitution; and intensifying support for industrial upgrading and energy-efficiency improvements in northern Jiangsu, leveraging its relatively low network embeddedness to foster green growth. These steps would help harmonize the spatial configuration of emissions and enhance the overall efficiency of the provincial network.

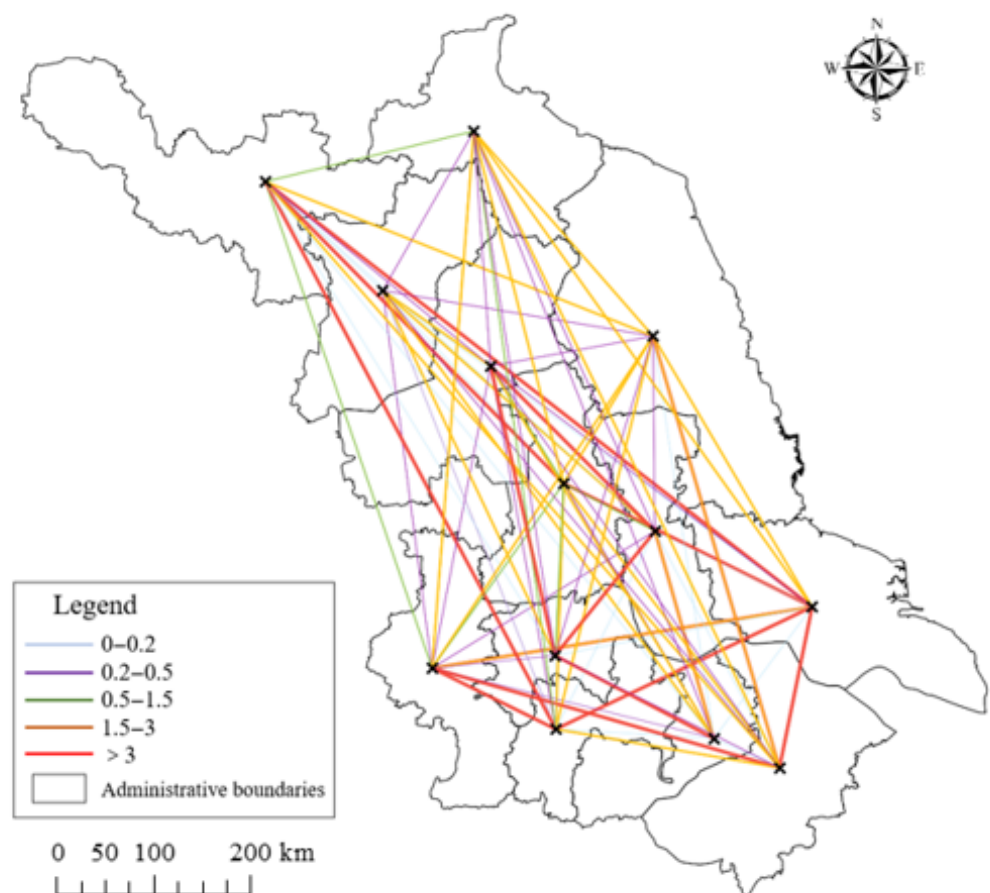


Figure 9. Carbon emission gravity network in Jiangsu Province.

Quantitative network indicators derived from the 2020 gravity matrix provide further validation of this spatial hierarchy. The overall network density reached 0.342, reflecting a highly interconnected emission system across the province. At the nodal level, spatial polarization is evident: southern cities anchor the network core, with Suzhou recording the highest Nodal Spatial Strength ($S_i = 18.45$). Top-tier nodes in this subregion account for approximately 40% of the total weighted connections, mathematically confirming their roles as primary transmission hubs of embodied carbon transfers.

Conversely, central cities function as an intermediary belt, maintaining moderate yet crucial linkages that bridge the north and south. Northern cities generally exhibit substantially lower centrality scores (e.g., Suqian, $S_i = 1.89$), positioning them at the network periphery. However, spatial heterogeneity persists even within the northern subnetwork, where Xuzhou emerges as a localized hub ($S_i = 5.62$) exerting radiation effects on its immediate neighbors. These cross-sectional quantitative metrics substantiate the “strong south, weak north, and transitional center” structural claim, demonstrating that the core–periphery emission architecture is a robust, data-driven feature of Jiangsu’s socioeconomic landscape.

3.4. Future Simulation

To rigorously validate the applicability and robustness of the intPLUS model for provincial-scale land-use forecasting, a historical hindcast (training on 2000–2010 data to predict 2020) was conducted. Recognizing that a single Kappa statistic may conceal simulation errors in minority classes (e.g., forestland and grassland) due to the overwhelming dominance of cropland in Jiangsu, we employed a comprehensive multi-metric evaluation framework.

As detailed in Table 6, the intPLUS model achieved an Overall Accuracy (OA) of 0.895 and a Kappa coefficient of 0.823. To further decompose the simulation errors, we calculated the Quantity Disagreement (QD) and Allocation Disagreement (AD). The intPLUS model recorded a low QD of 0.041 and an AD of 0.064, indicating that the primary source of error was minor spatial misallocation rather than massive quantity misestimation. Furthermore, the Figure of Merit (FoM), a stringent metric explicitly measuring the accuracy of simulated changes, reached 0.214, which is highly competitive for macroscopic regional simulations.

Table 6. Performance comparison between standard PLUS and intPLUS models for the 2020 hindcast.

Model	OA	Kappa	QD	AD	FoM
Standard PLUS	0.871	0.795	0.045	0.084	0.186
intPLUS	0.895	0.823	0.041	0.064	0.214

To justify the methodological choice, we benchmarked intPLUS against the standard PLUS model under identical parameter settings. The intPLUS model outperformed the standard PLUS across all critical metrics (e.g., FoM increased by 2.8%, and AD decreased by 1.5%). This performance gain is primarily attributed to the intPLUS model’s consistency-based interaction networks, which effectively capture the mutual inhibiting effects among competing land uses, particularly improving the simulation accuracy of urban expansion edges. Consequently, these comprehensive validation statistics firmly establish that the intPLUS model is reliable for executing policy-relevant scenario projections in Jiangsu.

Scenario simulations for 2030 (Figure 10) reveal marked spatial heterogeneity and policy orientation in Jiangsu’s land-use dynamics. Under the natural-development (ND) scenario, built-up land expands along its historical trajectory, concentrating in southern Jiangsu and the Yangtze River urban belt. This intensifies pressure on cropland and further compresses ecological space, thus approaching the limits of regional ecological security. The ecological-protection (EP) scenario substantially increases the extent and connectivity of ecological space, particularly around the Taihu Basin and along the Yangtze corridor, where forest and water areas expand and the ecological patch network becomes more coherent. These changes highlight the positive effects of stringent ecological redlines and systemic restoration policies on ecosystem services and carbon sequestration. In contrast, the economic-development (ED) scenario features rapid outward expansion of built-up

land and large-scale growth at metropolitan fringes. Cropland and portions of ecological land are markedly encroached upon, increasing development intensity and impervious surface coverage and exerting greater stress on ecosystem structure and function. Relative to these scenarios, the observed 2020 pattern lies between ND and ED, reflecting a policy mix that promotes built-up expansion while imposing some ecological constraints, yet it still exhibits pronounced cropland loss and ecological fragmentation.

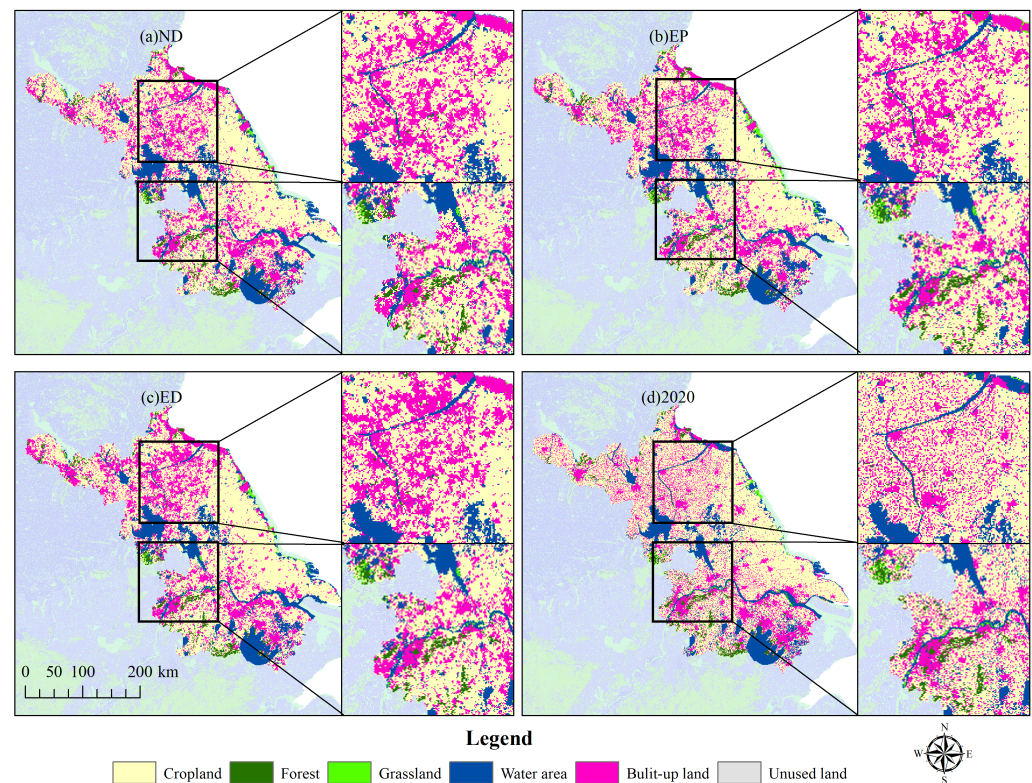


Figure 10. Future simulation of land use in Jiangsu Province under different development scenarios in 2030.

A holistic comparison underscores that Jiangsu’s most favorable land-use pathway hinges on the institutional balancing of economic growth, food security, and ecological protection. Continued emphasis on growth may yield short-term gains through agglomeration and factor-efficiency improvements but risks accelerating ecosystem degradation and carbon emissions, amplifying medium- to long-term environmental and climate risks. Strengthening ecological constraints, by contrast, enhances carbon sinks and climate resilience through increased blue–green space, improved landscape connectivity, and more coherent ecological networks, thereby providing ecological capacity for high-quality development. Consistent with the “14th Five-Year Plan” and dual-carbon goals, forward-looking optimization should strictly safeguard the cropland redline and food-security baseline while coordinating the intensity and spatial layout of urban–rural built-up land. Priority should be given to improving the efficiency of existing built-up land, redeveloping brownfields, and implementing basin- and process-based ecological restoration. In parallel, expanding clean energy and green infrastructure capacity within the spatial system can help build a coordinated configuration of production–living–ecological spaces and dynamically optimize trade-offs among economic benefits, ecological quality, and carbon sequestration for sustainable land-use outcomes.

Table 7 reports land-use structures and carbon accounting under three scenarios—natural development, ecological protection, and economic development; future pathways

exert markedly different and policy-discernible impacts on spatial configurations and the provincial carbon budget. Under the natural-development scenario, built-up land continues its inertial expansion to 23,367 km², increasing fossil energy consumption and impervious surface coverage, with carbon emissions rising to $12,326.59 \times 10^4$ t. Meanwhile, ecosystem carbon uptake remains modest at -87.10×10^4 t, producing a pronounced systemic carbon deficit. This pattern indicates that, absent strong constraints, inefficient built-up stock is not effectively revitalized, while additional built-up intensity persistently encroaches on ecological space and cropland, deviating the carbon balance from the dual-carbon trajectory. In contrast, the ecological protection scenario consolidates the ecological land base and improves landscape connectivity—expanding forests to 3431 km² and grasslands to 1250 km²—with built-up land correspondingly contracting to 22,265 km². Emissions are thereby contained at $11,745.26 \times 10^4$ t, and carbon uptake increases to -100.29×10^4 t, demonstrating that ecological prioritization and systemic restoration can simultaneously curb emission increments and enhance carbon sinks, narrowing the carbon gap and strengthening climate resilience. By comparison, the economic-development scenario reinforces agglomeration-led, extensive expansion: built-up land climbs to 25,105 km², cropland declines to 59,045 km², emissions escalate to $13,243.42 \times 10^4$ t, and carbon uptake drops to the lowest of the three at -85.61×10^4 t. This outcome shows that a singular focus on speed and scale significantly magnifies the carbon–environmental costs of land use by shrinking ecological land and fragmenting blue–green networks, thereby constraining the ceiling of local carbon sinks and ecosystem services. Taken together, the ecological-protection path delivers the most favorable carbon-balance performance by coupling emission suppression with sink enhancement under development constraints and ecological security, whereas the natural and economic scenarios exhibit, respectively, “inertial deficit widening” and “high-pressure deficit exacerbation.” Therefore, to meet 2030 targets, policy optimization should strictly safeguard cropland and ecological redlines, replace disorderly outward expansion with quality- and efficiency-oriented development, advance brownfield redevelopment and ecological network connectivity, and deploy nature-based solutions to co-optimize land-use structure and carbon budgets for durable sustainability.

Table 7. Projections of carbon balance and land-use structure in Jiangsu Province for 2030 under alternative scenarios.

Scenario	Cropland	Forest	Grassland	Water Area	Built-Up Land	Unused Land	Carbon Emission (10 ⁴ t)	Carbon Sequestration (10 ⁴ t)	Net Carbon Balance (10 ⁴ t)
ND	60,086	2867	609	14,786	23,367	151	12,326.59	−87.34	12,239.25
Percentage	58.99%	2.81%	0.60%	14.52%	22.94%	0.15%			
EP	60,086	3431	1250	14,834	22,265	0	11,745.26	−100.29	11,644.97
Percentage	58.99%	3.37%	1.23%	14.56%	21.86%	0.00%			
ED	59,045	2838	643	14,235	25,105	0	13,243.42	−85.61	13,157.81
Percentage	57.96%	2.79%	0.63%	13.97%	24.65%	0.00%			

Land-use areas are in km². ND—Natural development; EP—ecological protection; ED—economic development. Net carbon balance is calculated as the sum of emissions and sequestration; lower positive values denote a more favorable carbon budget.

It is important to acknowledge that the conclusion favoring the ecological protection scenario relies on fixed area-based sink coefficients, which typically abstract away biophysical variations such as forest age, biomass density, and local climate conditions. To address this uncertainty without overstating precision, a sensitivity analysis was conducted by fluctuating the baseline sequestration coefficients by $\pm 20\%$. Even under a pessimistic low-sink scenario (-20%), the EP pathway yields a net carbon balance (emissions plus

sequestration) of $11,665.03 \times 10^4$ t, which remains substantially lower than the baseline net emissions of the ND ($12,239.49 \times 10^4$ t) and ED ($13,157.81 \times 10^4$ t) scenarios. Conversely, under an optimistic high-sink scenario (+20%), the EP net balance improves further to $11,624.91 \times 10^4$ t. This demonstrates that while the absolute magnitude of the carbon sink naturally scales with coefficient variations, the EP scenario consistently maintains the lowest net carbon deficit across all sensitivity thresholds. Consequently, the relative advantage of the ecological-protection pathway is structurally reliable and not merely an artifact of static coefficient selection.

As shown in Figure 11, Jiangsu's carbon-emission patterns display pronounced regional heterogeneity and scenario-driven temporal dynamics. In the 2020 baseline, southern Jiangsu records markedly higher emission intensities than the central and northern subregions; Nanjing, Suzhou, and Wuxi cluster within the high-value band of $1800\text{--}2400 \times 10^4$ t, underscoring the strong pull of industrial agglomeration and rapid urbanization on emissions. Most of northern Jiangsu falls within the lower range of $0\text{--}600 \times 10^4$ t, indicating more modest industrialization and urban development and a smaller marginal contribution to the provincial total. Under the natural-development (ND) scenario, built-up land continues its inertial expansion, with high-emission patches spilling outward and consolidating across the southern belt and Yangtze-adjacent cities, thereby amplifying the province's "high-south, low-north" gradient and entrenching cumulative pressure in the absence of strong constraints.

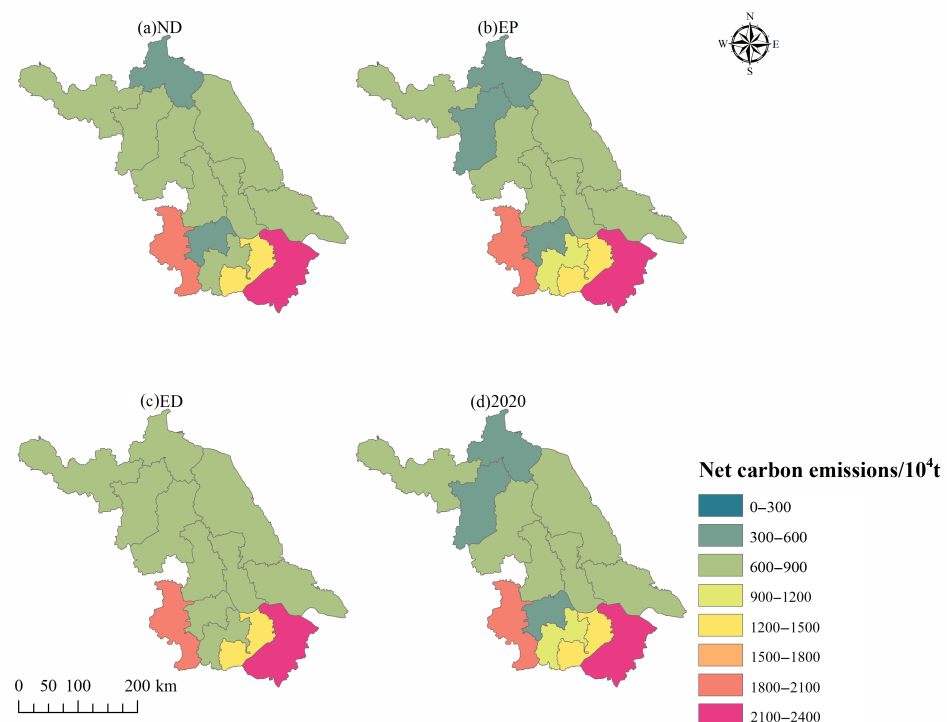


Figure 11. Carbon emission distribution in 2030 under different scenarios.

In the ecological-protection (EP) scenario, increases in forest and water areas and improved ecological connectivity effectively dampen growth in several hotspots, narrowing the spatial footprint of high-value zones and constraining intensity boundaries; while the south remains the emission core, the overall pattern exhibits signs of slope-reduction and spillover-taming. By contrast, the economic-development (ED) scenario intensifies factor-driven outward expansion and rapid sprawl of built-up land, pushing emission intensities in the southern core higher and stabilizing hotspots above 2100×10^4 t, thereby exacerbating regional imbalance [44–46]. Taken together, all scenarios preserve the underlying "high-

south, low-north” structure but diverge in scale and redistribution: ND accentuates inertial accumulation, and EP achieves phased mitigation and hotspot contraction, whereas ED magnifies system-wide pressure. Sustained ecological protection and land-use optimization, coupled with energy-efficiency gains and decarbonization, can ease peak pressures in the southern metropolis belt, unlock the carbon-sink potential of the north, and steer the provincial carbon balance from a single-core concentration toward a more polycentric, coordinated configuration.

4. Discussion

4.1. Carbon Balance in Jiangsu Province

The spatial mismatch between economic carbon contribution (ECC) and ecological sink carrying capacity (ESC) across Jiangsu is driven primarily by regional disparities in industrial agglomeration and land-use priorities. In the southern metropolitan belt, rapid urbanization and energy-intensive manufacturing raise emissions faster than local ecosystems can buffer them, producing a persistent “high-ECC, low-ESC” configuration. Northern jurisdictions exhibit the opposite pattern, retaining latent sink potential while generating lower carbon-economic output (“low-ECC, high-ESC”). Notably, the emission totals derived from our multi-source statistical accounting exceed those reported by conventional remote-sensing inversions [47–49]. This divergence reflects a methodological tradeoff rather than an inconsistency: satellite retrievals offer broad and continuous spatial coverage, whereas city-scale statistical accounting resolves the fine-grained industrial structure and sector-specific energy use that macroscopic proxies tend to obscure.

The progressive weakening of ecological carrying capacity under sustained economic expansion reinforces this economy–environment mismatch [50,51], and correcting it requires measures that extend beyond the unilateral augmentation of carbon sinks [52]. Because the framework links each policy implication to an explicit spatial model output, three priorities follow directly from the results. First, the rapid erosion of sink benefits projected under unconstrained built-up land expansion establishes the need for tighter intensity control of built-up land and for brownfield redevelopment [53–55]. Second, the spatial heterogeneity of the ESC/ECC mismatch points to differentiated mitigation pathways: ecological quotas can be directed toward low-emission, high-capacity jurisdictions to maximize sink potential, while stricter land-use constraints are warranted in high-emission industrial cores. Third, the centrality structure of the emission-linkage network, which identifies the southern Jiangsu cluster as the principal transmission hub, provides the empirical basis for interjurisdictional coordination policies [56]. It should be emphasized, however, that the present framework simulates only land-use change and accounting-based carbon balances. Broader interventions—such as green-finance development [57], clean-energy substitution, industrial upgrading [58], building retrofits, transport electrification [59], and engineered carbon storage [60]—are not represented in the model [61–63]. These options are therefore presented as contextual recommendations rather than model-derived findings, intended to complement the spatially explicit source-control and sink-enhancement strategies and to help reconcile high-quality economic development with long-term ecological protection [64].

4.2. Future Carbon-Balance Prediction Based on Different Scenarios

The 2030 scenario simulations reveal how Jiangsu’s emission–sink balance diverges across development pathways, offering a basis for strategy and policy design. Under the natural-development (ND) scenario, the inertial expansion of built-up land and the gradual loss of cropland keep emissions elevated while limiting sink gains, worsening the overall balance and confirming that, in the absence of stringent constraints, urban expansion

remains the dominant driver of emission growth [65,66]. The ecological-protection (EP) scenario expands forest and water areas and strengthens ecological connectivity, thereby enhancing carbon uptake and moderating the spillover effects of built-up land, with the most pronounced sink gains in northern Jiangsu and along the Yangtze [67–69]. The economic-development (ED) scenario, by contrast, intensifies spatial demand for built-up land and industry; the resulting rise in development intensity across southern Jiangsu and the Yangtze urban belt accelerates emission growth and widens the carbon deficit.

Spatially, the projected 2030 balance follows a “high-emission south–transitional center–high-sink-potential north” gradient that aligns with the province’s economic tiers and land-use structure, lending the simulations both plausibility and explanatory value. Discrepancies from other studies in emission magnitude and spatial configuration largely reflect differences in scale and method [70–72]: metropolitan-scale simulations tend to lose accuracy as internal heterogeneity increases [73], whereas the province-scale, multi-source, intPLUS-coupled approach adopted here more faithfully traces the structural linkages between land-use change and emission–sink dynamics. Taken together, the results indicate that Jiangsu’s future carbon balance is strongly contingent on development orientation: an extensive-growth pathway intensifies emission pressure, whereas a pathway prioritizing ecological protection and carbon-stock enhancement materially improves the balance while generating co-benefits for ecosystem services and habitat integrity [74,75].

Mitigating the projected carbon deficit calls for spatial planning mechanisms mapped precisely onto specific scenario outcomes and network characteristics. Strict ecological-redline protection and green-infrastructure expansion, for instance, follow directly from the carbon-sink improvements observed under the EP scenario [76], while the case for interjurisdictional coordination derives from the hierarchical emission-linkage network, in which the high-ECC, low-ESC southern core operates as the central hub. The spatial reallocation of land-use quotas—constraining new construction-land approvals at saturated southern nodes and directing ecological-restoration quotas northward—is supported directly by the simulation results; the associated economic instruments, such as financial subsidies and green-technology transfers, remain outside the model. These cross-regional compensation mechanisms are therefore offered as contextual recommendations intended to facilitate, in practice, the spatial reallocations that the model does support.

4.3. Limitations and Future Work

Several methodological uncertainties and structural limitations warrant future refinement. First, regarding source–sink accounting, the reliance on generalized, literature-derived coefficients [27] obscures the spatiotemporal heterogeneity of carbon dynamics driven by stand type, species composition, and management practices [77,78]. Replacing these with locally calibrated plot data would mitigate systematic bias, just as integrating dispersed end-use data would improve built-up land emission estimates. Furthermore, the current scenario model implicitly holds the energy structure and carbon intensity constant at historical coefficient levels. Consequently, construction-land emissions are primarily treated as a function of land expansion (a scale effect), without explicitly separating the mitigating impacts of energy-system decarbonization, industrial restructuring, or electricity mix improvements (intensity effects) [79–81]. Future research should decompose built-up-land emissions into distinct scale and intensity terms to better connect spatial planning with the underlying economic drivers of emissions, rather than treating construction land as a black-box carbon source. Additionally, while the ESC and ECC ratios effectively illuminate macro-level economy–ecology coupling, they oversimplify the multidimensional carbon balance [82–84]. Extending these into composite indices would enrich the assessment, albeit requiring rigorous sensitivity analyses to address weighting subjectivity.

Second, the modeling framework faces constraints at both the component and system levels. At the component level, the gravity model captures static mass–distance attractions but omits flow-resolved embodied carbon, such as that embedded in trade networks, pointing to the value of complementary multi-regional input–output (MRIO) integration [85,86]; likewise, the land-use simulation, though reliably validated ($Kappa = 0.82$), is constrained by the resolution of available digital policy datasets, so that incorporating high-resolution urban boundaries and sectoral decarbonization roadmaps would further improve predictive accuracy [87–89]. This latter data bottleneck may itself be eased by ongoing advances in large language models, graphical models, and other deep learning methods—for example, by automatically parsing and structuring land-use constraints such as ecological redlines, zoning provisions, and sectoral decarbonization targets from unstructured planning and policy documents into the machine-readable inputs that scenario design requires [90–92]. At the system level, the framework operates as a unidirectional pipeline: spatial emission linkages do not feed back to update land-use transition probabilities in intPLUS, and endogenizing this feedback loop is vital for capturing genuine socio-ecological dynamics.

Third, a spatial resolution mismatch restricts direct decision-making applicability: macro-level prefecture simulations cannot directly dictate micro-parcel or county-level development permits. To robustly address forecasting uncertainties, future research should employ Monte Carlo or Latin-hypercube sampling to establish formal confidence bounds for 2030 projections [93], and leverage ensemble machine learning within intPLUS to generate probabilistic, rather than deterministic, scenarios.

Despite these limitations, the core contribution of this study is a broadly adaptable framework that integrates land-use simulation, ecoeconomic assessment, and spatial emission-network tracing. Land-use decarbonization is integral to the 2030 Agenda for Sustainable Development. It underpins progress on climate action (SDG 13) and connects closely to sustainable cities and communities (SDG 11) and the protection of terrestrial ecosystems (SDG 15) [94,95]. This linkage matters most across the Global South, where rapid urbanization often outpaces monitoring capacity [96,97]. In such settings, transferable and data-light assessment tools are especially valuable for aligning development with emission-reduction targets. Because it draws on open-access global datasets (e.g., GlobalLand30, ESA CCI, EDGAR), the framework transfers readily to other regions. It is well suited to rapidly urbanizing corridors in the Global South, to agricultural frontiers balancing development with conservation, and to established industrial belts undergoing low-carbon transitions.

5. Conclusions

This study developed a coupled computational framework for provincial carbon-balance projection that integrates three components—coefficient-based carbon accounting, intra-provincial spatial-interaction analysis (operationalized through ESC/ECC ecoeconomic indicators and a gravity-based emission-linkage model), and intPLUS-based multi-scenario land-use simulation—within a common data stack. The framework was applied to Jiangsu Province, China, for the period 1995–2020 and used to project 2030 outcomes under natural-development, ecological-protection, and economic-development scenarios. The main conclusions are as follows:

1. The framework operates coherently at the intra-provincial scale. The intPLUS simulation component reproduced observed 2020 land use with an overall Kappa coefficient of 0.82 in a 2000–2010 → 2020 hindcast, supporting its use for forward projection in Jiangsu. The three components produced internally consistent outputs across the 13 prefecture-level cities and a shared input stack (CLCD land cover, ten driver layers, and provincial statistical yearbooks), demonstrating the feasibility of operat-

ing accounting, spatial-interaction analysis, and scenario simulation within a single workflow at this scale.

2. Jiangsu's carbon balance from 1995 to 2020 displays a stable “high-south, low-north” emission gradient, anchored by Nanjing, Suzhou, Wuxi, and Changzhou in the southern core. The joint application of ESC and ECC reveals an asymmetry that gross emission–sequestration totals obscure: ecological carrying capacity weakened in the south while strengthening in parts of the north, producing a contrasting “high-ECC, low-ESC” versus “low-ECC, high-ESC” coupling pattern across the province.
3. The 2020 emission-linkage network exhibits a “strong south, weak north, transitional center” structure. Southern cities form an interconnected core, central Jiangsu serves as an intermediary belt, and northern cities are less embedded—with Xuzhou functioning as a subregional hub. The network structure follows the provincial economic gradient closely, indicating that inter-city emission linkages reflect industrial agglomeration and energy-use organization rather than geographic proximity alone. Embedding the ESC/ECC pattern within this network shows that southern high-ECC, low-ESC cities anchor not only the emission magnitudes but also the structural connectivity of provincial emissions.
4. Scenario projections for 2030 show variations across pathways. Provincial emissions reach $12,326.59 \times 10^4$ t under natural development, $11,745.26 \times 10^4$ t under ecological protection, and $13,243.42 \times 10^4$ t under economic development, with corresponding sequestration of -87.10×10^4 t, -100.29×10^4 t, and -85.61×10^4 t. The ecological-protection pathway limits emission growth and enhances sink capacity, while the economic-development pathway increases the deficit on both sides. The underlying “high-south, low-north” pattern persists across scenarios, but the magnitude and spatial redistribution of emission intensity and sink capacity are sensitive to policy orientation.

The framework is modular and technically portable, operating on widely available data. However, method transferability does not guarantee result generalizability. Because Jiangsu possesses exceptional characteristics—including high economic density, pronounced south–north differentiation, and dense urban corridors—these findings may not directly apply to resource-dependent or sparsely populated provinces. Therefore, parameter values, scenario assumptions, sink coefficients, and network interpretations must be recalibrated for each unique province prior to application.

Ultimately, this integrated workflow provides spatial planners with a quantifiable method to evaluate how land-use interventions shape regional carbon budgets. While it highlights the spatial imperatives of ecological redlines and urban boundary containment, it cannot infer the impacts of unmodelled energy or financial policies. Future evidence is needed to dynamically couple spatial models with multi-regional input–output (MRIO) and energy-transition models to achieve a fully integrated socio-ecological decision support system.

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