

Article

Carbon Emission Patterns and Carbon Balance Zoning of Land Use in Xiamen City Based on Urban Functional Zoning

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Abstract

Driven by the “dual-carbon” strategy, the development of zero- and low-carbon parks has become a crucial approach to resolving the conflict between urban expansion and ecological limits. Using urban functional zoning and land use data, this study estimates carbon emissions in Xiamen and examines their spatial distribution at the functional zone level, along with an assessment of carbon balance zoning. The results indicate that (1) Carbon sources far exceed sinks, with spatial concentrations in southern and northern areas, respectively. Commercial, transportation, and industrial zones are major emission sources. (2) A significant negative spatial correlation in carbon emissions exists among functional zones, manifesting as an alternating pattern of high- and low-carbon zones. (3) 72% of the zones have an ecological support coefficient below one, indicating severe carbon imbalance. (4) Xiamen can be categorized into four carbon balance functional zones, with carbon-source regulation zones accounting for 70%, core carbon-source zones accounting for 5%, and carbon-sink stressed zones accounting for 25%. No core carbon sink zones are identified. Based on these findings, targeted strategies are proposed: ecological restoration in northern Xiamen, carbon emission regulation in central areas, and source reduction in the south. These measures provide a scientific foundation for supporting Xiamen’s low-carbon transition and sustainable development.

Keywords: functional zoning; spatial carbon emissions; low-carbon city; spatial correlation; carbon balance zoning



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1. Introduction

As global climate change intensifies, its impacts, such as global warming and more frequent extreme weather events, are becoming increasingly severe, posing significant challenges to human society and the natural environment. In this context, low-carbon development has emerged as a central objective for governments and cities worldwide [1], representing a critical pathway toward mitigating the climate crisis and achieving sustainable development. China currently ranks among the world’s largest carbon emitters, accounting for over 27% of global emissions [2,3], and therefore holds significant responsibility in international climate governance. In response, China has committed to “peak

carbon emissions by 2030 and achieve carbon neutrality by 2060" [4]—a strategy known as the “dual-carbon” goals, which has substantially strengthened global efforts against greenhouse gas emissions. As essential components of urban green transformation, low-carbon communities focus not only on emission reduction but also emphasize carbon sequestration, resource recycling, and environmental protection, playing a pivotal role in advancing urban sustainability [5]. Consequently, promoting the development of low-carbon cities and communities has become a pivotal strategy for China in fulfilling its “dual-carbon” targets [6]. Research on low-carbon communities in Chinese cities is thus imperative for facilitating global sustainable development.

Research on carbon emissions both domestically and internationally has extended into multiple fields. The main focuses include (1) the study of carbon source and sink accounting systems [7,8], particularly innovative measurement methods for key emission sources like energy activities, industrial production, and land use; (2) research on regional carbon cycling mechanisms [9,10], which involves analyzing carbon flux changes in combined natural and human systems; and (3) research on carbon compensation mechanisms, primarily exploring the design of interregional carbon trading mechanisms [11,12]. The deepening of these research areas has not only expanded the dimensions of carbon emission studies but also laid the foundation for the development of more refined accounting methods. Consequently, the need for precise, multi-scale carbon emission accounting is becoming increasingly prominent. Currently, urban carbon emission calculation methods mainly include top-down approaches, such as allocating administrative unit statistical emissions to fine grids based on nighttime light data [13,14], bottom-up methods that integrate carbon emission data from point sources like transportation and construction departments [15], and hybrid methods that combine the advantages of both top-down and bottom-up approaches [16]. While national and provincial carbon accounting systems based on IPCC guidelines provide an authoritative framework for macro-scale carbon budgets, their application to micro-spatial units within cities faces two fundamental challenges: the resolution of the underlying statistical data is too coarse to capture neighborhood-scale variations, and localized emission data for industrial sources are often unavailable.

To systematically define emission sources, the Greenhouse Gas Protocol (GHG Protocol) classifies carbon emissions into three categories: direct emissions, indirect emissions from electricity, and other indirect emissions [17,18]. In micro-scale studies, land use-based carbon accounting methods prove more advantageous owing to their high spatial explicitness and data accessibility. These methods effectively circumvent micro-data limitations by establishing empirical relationships between land use types and carbon source/sink intensities, thereby offering critical support for low-carbon land use planning [19]. For indirect carbon emissions from construction land, this study focuses on energy consumption as the primary quantifiable source and adopts GDP_{23} (where “GDP” stands for Gross Domestic Product, and “23” denotes the secondary and tertiary industries; consistently used hereinafter with the same meaning) as a proxy variable for estimation. While this approach does not encompass all emission sources specified in the IPCC guidelines, it successfully captures spatially heterogeneous patterns of carbon emissions driven by economic activities, thus providing a reliable basis for urban low-carbon planning and the formulation of differentiated emission reduction strategies.

Most existing studies focus on macro- or mesoscale analyses—such as global, national, city-wide, or county-level scales—revealing spatial patterns of carbon emissions across different levels [20–25]. However, there remains a notable lack of research at finer spatial resolutions, particularly at the community or block level. This limitation in micro-scale research hinders the accurate characterization of intra-urban heterogeneity in carbon emissions, which in turn impedes the development of targeted emission reduction strategies.

As key venues for socio-economic activities, urban blocks are closely linked to energy consumption and economic growth, making them ideal units for detailed assessment and regulation [26]. Classifying and integrating blocks according to urban functional zones can help optimize the spatial structure of cities and improve operational efficiency, while also serving as an important strategy for achieving effective urban emission reductions [27,28]. Since macro-scale accounting results struggle to reveal the spatial heterogeneity of carbon emissions within cities, there remains a lack of scientific basis for developing differentiated and precise emission reduction strategies at the block level.

To address this research gap, this study employs Xiamen City—a representative coastal urban center in southeastern China—as its case study area. Located on China’s southeastern coast, Xiamen serves as a major economic and cultural center. In recent years, the city has actively pursued green growth and low-carbon transformation, establishing itself as a model low-carbon city to inspire regional and national efforts [29,30]. In response to environmental challenges and the need for enhanced carbon emission management, Xiamen has implemented a range of low-carbon policies and prioritized the development of low-carbon communities [31]. This study develops a block-scale carbon budget assessment and carbon balance zoning framework by integrating urban functional zoning theory with land use-based carbon accounting and spatial analysis. The novelty of this work lies in two key aspects. First, in terms of research scale, it moves beyond the constraints of traditional administrative units by adopting a functional zoning perspective, which enables micro-scale analysis and reveals fine-grained heterogeneity in carbon emissions. Second, methodologically, it not only combines accounting with spatial analysis but also directly correlates carbon emission patterns with functional partitions, thereby offering a scientific basis for developing spatially explicit and differentiated low-carbon planning strategies.

The remainder of this paper is structured as follows. Section 2 details the study area, data sources, and methodology. Section 3 presents the foundational results, including the spatialized *GDP*, carbon emission accounting, and functional zone delineation. Based on these, Section 4 examines the spatial patterns and correlation characteristics of carbon sources and sinks. Section 5 then performs carbon balance zoning and proposes tailored low-carbon development recommendations. Finally, Section 7 discusses the study’s academic implications and application prospects, and Section 6 provides the concluding remarks.

2. Materials and Research Methods

2.1. Study Area

As a key central city on China’s southeastern coast, Xiamen serves as a major economic, transportation, and cultural center within Fujian Province and stands as one of China’s earliest special economic zones (Figure 1). The city administers six districts: Siming, Huli, Jimei, Haicang, Tong’an, and Xiang’an. The central urban area, comprising Siming and Huli, is located on Xiamen Island, while the remaining districts constitute the off-island areas. In recent years, Xiamen has experienced rapid economic growth, with its regional *GDP* surging from 50.187 billion yuan in 2000 to 781.141 billion yuan in 2023 [32]. Accompanying this economic expansion, the permanent population increased from approximately 2.05 million in 2000 to 5.308 million by the end of 2023, accompanied by an urbanization rate of 90.1%, ranking among the highest in the nation.

According to the “Assessment Report on the Progress of National Low-Carbon City Pilots”, between 2015 and 2022, approximately 38% of the 81 low-carbon pilot cities in China achieved stable or declining carbon emissions. However, as one of these pilot cities, Xiamen has not yet reached its peak in carbon dioxide emissions and continues to exhibit a slowly fluctuating upward trend [33]. Therefore, there is an urgent need to establish an

efficient, coordinated, and sustainable regional carbon balance governance mechanism for Xiamen.

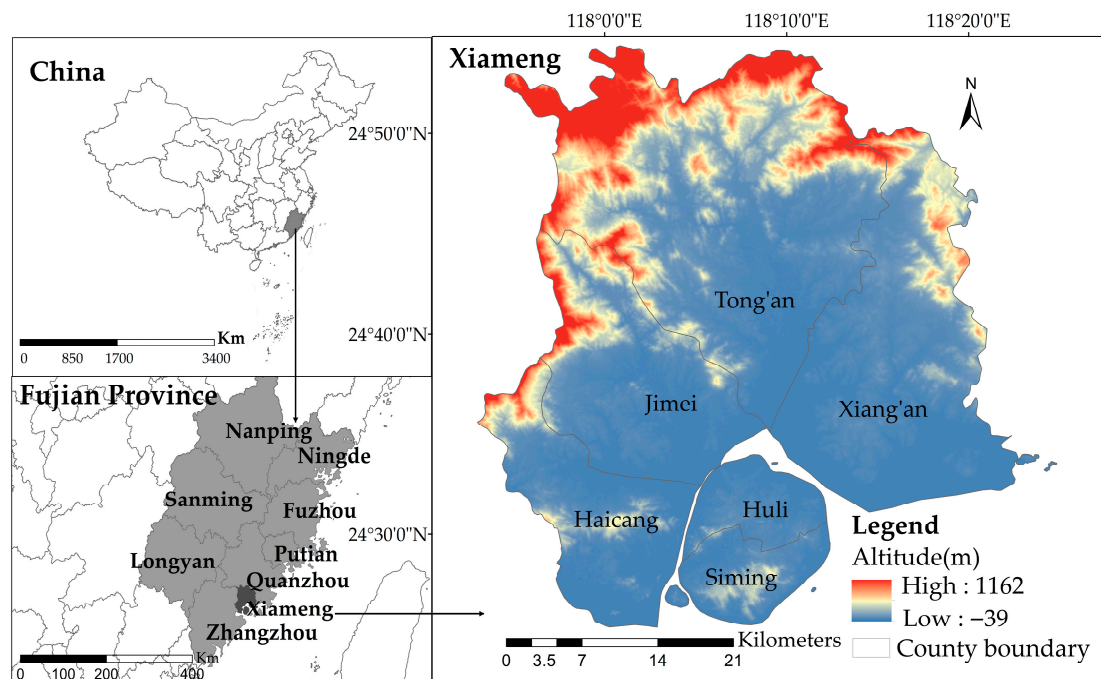


Figure 1. Map of the study area.

2.2. Data Source

This study utilizes NPP-VIIRS nighttime light data and *GDP* statistics for the year 2022 to analyze the spatial and temporal distribution of the secondary and tertiary industries' *GDP* in Xiamen and calculate carbon emissions across its different functional zones. Auxiliary data include administrative division vector data, Point of Interest (POI) data, and OpenStreetMap (OSM) data.

- (1) Administrative boundary data: The national-scale administrative division vector data of China, which serves as the geographic base map, along with the specific municipal and district boundaries of Xiamen City, were both obtained from the China Administrative Division Database (2024 Edition), publicly available from the National Platform for Common Geospatial Information Services (Tianditu) at <https://cloudcenter.tianditu.gov.cn/administrativeDivision> (accessed on 4 October 2024).
- (2) All economic, demographic, and energy consumption per unit of *GDP*, and *GDP* data are derived from the Statistical Yearbook of Xiamen Special Economic Zone [32].
- (3) The NPP/VIIRS nighttime light data, with a spatial resolution of 500 m, can be freely downloaded from the website of the National Oceanic and Atmospheric Administration of the United States [34].
- (4) The land use type data, with a spatial resolution of 30 m, is obtained from the team of Professor Huang Xin at Wuhan University (Figure 2). It is derived from satellite imagery through calculated input features and trained classification samples. These data are openly and freely available at <https://essd.copernicus.org/articles/13/3907/2021/essd-13-3907-2021-discussion.html> (accessed on 10 October 2024) [35].
- (5) The Xiamen POI data, known for their timeliness and high spatial accuracy [36], can be freely obtained from the AutoNavi (Amap) platform (<https://lbs.amap.com/>, accessed on 10 October 2024, accessed on 8 October 2024).

- (6) The Xiamen road network data, which includes roads of different grades, is available for free download from the open-source website OpenStreetMap (OSM) (<https://openmaptiles.org/languages/zh/>, accessed on 8 October 2024).
- (7) Remote sensing imagery data of Xiamen can be acquired through the Google Earth Engine (GEE) platform. Summer and winter remote sensing images of Xiamen were selected, filtered for cloud cover, and processed for cloud removal. Median compositing was then applied to generate quarterly representative images with a spatial resolution of $10\text{ m} \times 10\text{ m}$ (Figure 3).

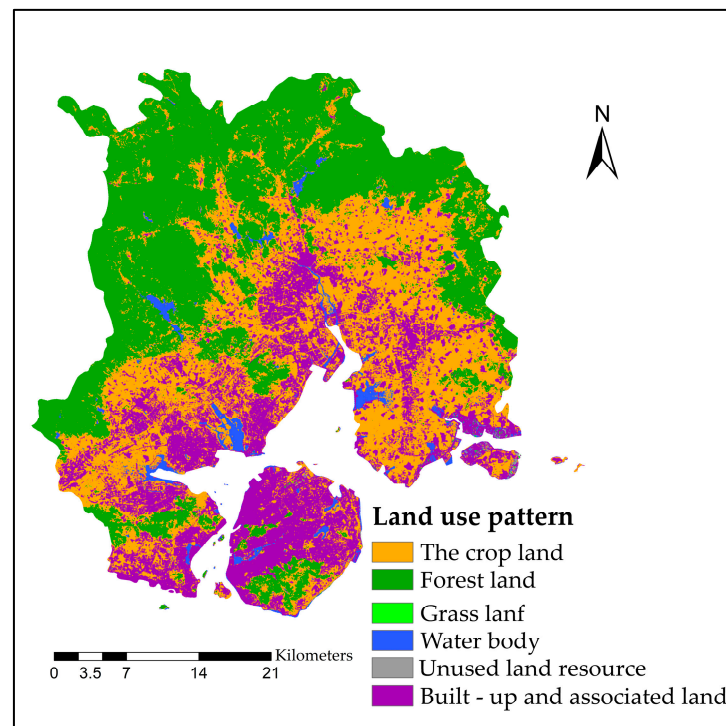


Figure 2. Land use in Xiamen City.

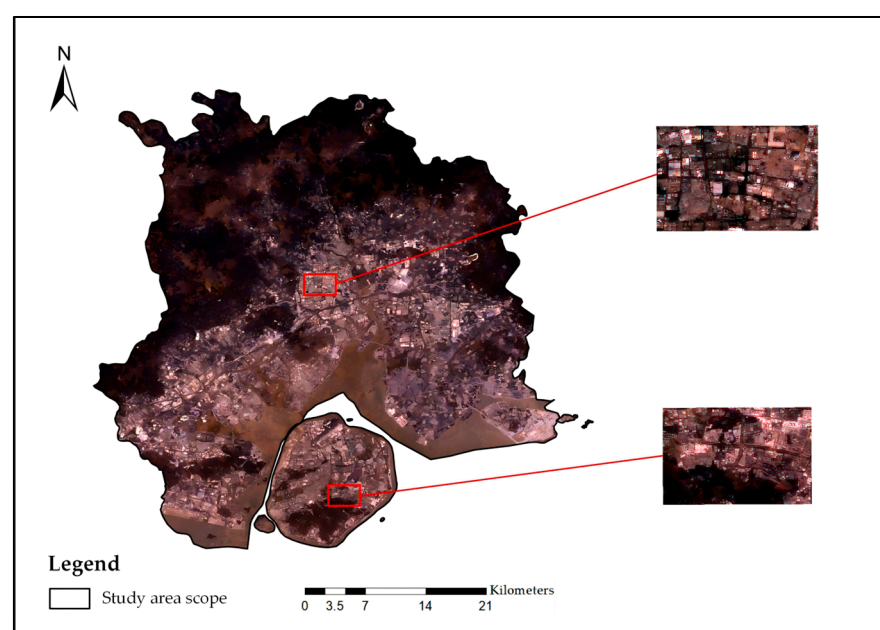


Figure 3. Xiamen City remote sensing using the Gaofen-2 Satellite Imagery Map.

2.3. Methodology

2.3.1. Calculation Method of Land Use Carbon Emissions

The capacity for carbon emissions (sources) and carbon absorption (sinks) varies considerably among different land use functional types. The net carbon emissions of a specific land use category are determined by the balance between its carbon sources and carbon sinks [37]. To systematically delineate the accounting boundaries, this study draws on the conceptual framework of the Greenhouse Gas Protocol (GHG Protocol), with emissions categorized into direct carbon emissions and indirect carbon emissions [17]. Utilizing 30 m resolution land use data, we estimate net carbon emissions by integrating both direct carbon emission accounting and indirect carbon emission accounting methodologies.

(1) Direct Carbon Emission Estimation [38]

The direct carbon emission estimation method is applicable to carbon accounting from cultivated land, forest land, grassland, water bodies, and unused land. The total direct carbon emissions of a region are calculated as the sum of the area of each land use type multiplied by its corresponding carbon emission coefficient. The formula is expressed as follows:

$$C_e = \sum e_n = \sum_{n=1}^5 A_n \times \partial_n \quad (1)$$

where C_e represents the total direct carbon emissions of the region; e_n denotes the direct carbon emissions generated by the n -th land use type (cultivated land, forest land, grassland, water areas, and unused land) in the region; A_n signifies the total area of the n -th land use type within the region; and ∂_n is the carbon emission coefficient of the n -th land use type.

Considering the characteristics of China's socio-economic development, the carbon emission coefficients for different land use types were determined with reference to the relevant literature studies, as shown in Table 1.

Table 1. Carbon Emission Coefficients of Various Land Types in Xiamen City.

Land Type	Carbon Emission Factor (tC/hm ²)	Reference Source
Cultivated land	0.461	Zhou Siyu [39]
Forest land	−0.613	Li Ying [40], Xiao Hongyan [41] et al.
Grassland	−0.021	Shi Hongxin [42], Yin Jingping [43] et al.
Water areas	−0.252	Fang Jingyun [44], Huang Lin [45] et al.
Unused land	−0.005	Lai Li [46], Zhang He [47] et al.

Note: Positive values indicate the carbon emission coefficients for carbon source land types, while negative values represent those for carbon sink land types.

(2) Indirect Carbon Emission Estimation [48]

The indirect carbon emission estimation method is employed for accounting carbon emissions from construction land. This approach indirectly reflects carbon emissions by calculating the consumption of energy sources such as petroleum, coal, and natural gas [49]. According to relevant statistical yearbooks [32], energy consumption data are typically compiled at the provincial level, making it difficult to obtain data that meets the requirements of this study. Therefore, this paper adopts the methodology established by relevant scholars [50]. Given that the gross domestic product from secondary and tertiary industries (hereafter denoted as GDP_{23}) is predominantly generated on construction land, it serves as a comprehensive indicator of energy consumption levels associated with this land type and is suitable for estimating corresponding carbon emissions. The formula is expressed as follows:

$$C_j = GDP_{23} \times K \times L \quad (2)$$

where C_j denotes the carbon emissions generated from construction land; GDP_{23} represents the gross domestic product of the secondary and tertiary industries; K indicates the energy consumption per unit GDP ; and L represents the standard coal emission coefficient. According to the recommended value from the Energy Research Institute of the National Development and Reform Commission (<https://std.samr.gov.cn>, accessed on 8 October 2024), $L = 0.67$ tonnes of carbon per tonne of standard coal equivalent (tC/tec).

2.3.2. Spatialization Method for GDP_{23}

According to data from the Xiamen Statistical Yearbook [32], the minimum reporting scale for GDP_{23} (gross domestic product of secondary and tertiary industries) data in Xiamen is at the district level, which is insufficient to support fine-scale spatial analysis. To accurately simulate the spatial distribution of carbon emissions in Xiamen, this study integrates NPP/VIIRS nighttime light data with a spatial resolution of 500 m and GDP_{23} statistical data. A correlation model between the light index and carbon emissions was constructed, and the function model with the optimal goodness-of-fit was selected for spatial simulation [51].

(1) Selection and Calculation of Nighttime Light Indices

NPP/VIIRS nighttime light data are capable of detecting urban lighting emissions, including small-scale and low-intensity light sources, and have been widely applied in studies related to GDP spatialization and urbanization processes [52].

The spatialization of GDP_{23} requires selecting appropriate light indices and combining them with district/county-level GDP_{23} statistical data to simulate gridded-scale datasets [35]. Based on the existing literature [53,54], this study selects five nighttime light indices for correlation analysis with regional GDP_{23} statistics: Mean Light Intensity (DN_{mean}), Relative Mean Light Intensity (I), Light Area Ratio (S), Composite Night Light Index ($CNLI$), and Total Night Light Index (TNL). The computational formulas for these indices are as follows:

$$DN_{mean} = \frac{1}{N} \sum_{i=1}^{DN_{max}} (DN_i \times n_i) \quad (3)$$

$$I = \frac{1}{N \times DN_{max}} \sum_{i=1}^{DN_{max}} (DN_i \times n_i) \quad (4)$$

$$S = \frac{S_q}{S_{all}} = \frac{N}{n} \quad (5)$$

$$CNLI = I \times S \quad (6)$$

$$TNL = \sum_{i=0}^{DN_{max}} (DN_i \times n_i) \quad (7)$$

where DN_i represents the digital number (DN) value of the i -th gradient within the study area; n_i denotes the number of pixels with DN value i ; N indicates the total number of pixels in the study area; S_q refers to the area where DN values exceed zero; and S_{all} represents the total area of the study region.

(2) Error Correction

Direct use of digital number (DN) values from nighttime light imagery as independent variables may introduce substantial errors in the estimation of GDP_{23} [55]. To mitigate this issue, statistical GDP_{23} values at the district/county level were employed to calibrate the simulated gridded GDP_{23} data, thereby reducing cumulative estimation errors. Specifically, the residual between the simulated and statistical GDP_{23} values for each district/county

was uniformly distributed across all grid cells within the corresponding administrative unit to adjust the value of each pixel. The correction is performed using the following formula:

$$GDP_m = GDP_i \times \frac{GDP_T}{GDP_{SUM}} \quad (8)$$

where GDP_m represents the corrected GDP_{23} value at the grid level; GDP_i denotes the simulated GDP_{23} value for each grid; GDP_T refers to the statistical GDP_{23} value at the district/county level; and GDP_{SUM} indicates the simulated GDP_{23} value for each district/county.

2.3.3. Methodology for Functional Zoning

(1) Functional Zone Classification

The original Points of Interest (POIs) data underwent preprocessing to remove invalid and duplicate entries, followed by coordinate system unification to produce a clean and consistent dataset. In accordance with the classification system established in relevant studies [56], and considering the primary function, scale, and attributes of each POI, the data were reclassified into six core functional categories: transportation, commercial and services, public administration and public services, residential, industrial, as well as green spaces and squares. The classification results are illustrated in Table 2.

Table 2. Functional zone classification map of Xiamen City.

Functional Group	Specific Function	Description
Traffic Function	Transportation Facilities Service	Railway stations, airports, bus terminals.
Business Function Service	Shopping Service	Retail stores, shopping malls, supermarkets.
	Accommodation Service	Hotels, lodges, guesthouses.
	Sports and Leisure Service	Gyms, stadiums, cinemas, entertainment venues.
	Financial and Insurance Services	Banks, insurance companies, financial institutions.
	Catering Service	Restaurants, cafes, food and beverage outlets.
Public Management and Public Service Function	Service for Life	Facilities supporting daily needs (e.g., maintenance, repairs).
	Medical Insurance Service	Hospitals, clinics, pharmacies.
	Public Facility Service	Water, power, and sanitation utilities.
	Science, Education, and Cultural Service	Schools, museums, libraries, research institutes.
Residence Function	Commercial Residence	Buildings combining residential and commercial functions.
Industrial Function	Incorporated Business	Corporate offices, business parks, headquarters.
Green Space and Square Function	Tourist Attraction	Sites of natural, cultural, or historical significance for visitors.

(2) Delineation Method for Urban Functional Zones

Sentinel-2A remote sensing imagery was used to assist in identifying functional zones, while OpenStreetMap (OSM) road network data were employed to delineate basic spatial units within Xiamen. The frequency density of Points of Interest (POIs) within each unit was calculated and further weighted by public recognition levels associated with different POI categories (Table 3) to improve classification accuracy [57].

Table 3. Public awareness of different types of POIs.

Type	Public Awareness	Type	Public Awareness	Type	Public Awareness
Business-residential Property	0.0100	Shopping Services	0.8146	Accommodation Services	0.5562
Food and Beverage Services	0.5562	Financial Services	0.3057	Corporations	0.3057
Lifestyle Services	0.3057	Sports and Leisure	0.5010	Healthcare	0.5069
Government Agencies	0.3550	Science, Education, and Culture	0.6706	Transportation Facilities	1.0000

Based on the preprocessed POI data and the derived spatial units, the following identification rules were applied: Within each basic spatial unit, the count of each reclassified POI category was summarized. If a single functional category accounted for more than 50% of the total, the unit was classified as a single-type functional zone. Units where no category exceeded 50% were designated as mixed functional zones. To enhance classification reliability and reduce bias from pure frequency counts, weight values (ranging from 1 to 100) were assigned to each POI type based on criteria such as building footprint area, land cover extent, and public recognition ranking [58]. POIs associated with larger structures and higher public recognition received greater weights, reflecting their differential capacity to represent functional intensity. After applying these weighted discrimination rules, a spatial distribution map of functional zones was generated for Xiamen, effectively visualizing the patterns of both single-type and mixed functional areas.

$$F_i = W_i \times \frac{d_i}{\sum_{j=1}^6 (W_j \times d_j) \times 100\%} \quad (9)$$

where F_i represents the frequency density of the i -th POI category within the unit; W_i denotes the weight value of the i -th POI category; and d_i indicates the kernel density sum of the i -th POI category within the unit.

2.3.4. Spatial Autocorrelation

Spatial autocorrelation analysis is used to examine the presence of dependency or heterogeneity in the spatial distribution of geographic phenomena [59]. To thoroughly investigate the uneven spatial distribution of carbon emissions and its implications for regional carbon balance, this study employs both Global Moran's I and Local Moran's I indices to assess the spatial association patterns of carbon emission intensity among functional units in Xiamen. This analysis serves to support the identification of spatial clustering and divergence patterns in critical carbon balance zones.

(1) Global Spatial Autocorrelation Analysis

Global spatial autocorrelation reflects the overall characteristics of spatial association degree and can be used to measure the overall spatial correlation of carbon emission data across the study area. This study utilizes the Global Moran's I for calculation [59]; the formula is as follows:

$$I = \frac{n}{\sum_{i,j} w_{ij}} \times \frac{\sum_{i,j} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (10)$$

where n represents the number of spatial units; x_i and x_j denote the carbon emission values of spatial units i and j , respectively; $\bar{x}$ indicates the average value of carbon emissions; and w_{ij} represents the element in the spatial weight matrix, indicating the spatial relationship weight between units i and j . The value of I ranges between $[-1, 1]$. If $I > 0$, it indicates

positive spatial autocorrelation, meaning that high-value carbon emission areas tend to cluster with other high-value areas, while low-value areas tend to cluster with other low-value areas, suggesting clustered distribution characteristics of carbon emissions in space. If $I < 0$, it indicates negative spatial autocorrelation, where high-value areas are adjacent to low-value areas, showing a dispersed spatial distribution of carbon emissions. If $I = 0$, it indicates random spatial distribution, meaning no significant spatial correlation exists among carbon emission values of spatial units.

(2) Local Spatial Autocorrelation Analysis

Local spatial autocorrelation analysis examines the degree of association between adjacent spatial units [59] and can be employed to identify specific clusters or outliers in the distribution of carbon emissions. In this study, Local Moran's I is used to evaluate such local spatial patterns. The formula is given as follows:

$$I_i = \frac{(x_i - \bar{x})}{S^2} \sum_{j=1}^n w_{ij}(x_j - \bar{x}) \quad (11)$$

where I_i represents the Local Moran's Index of spatial unit I ; x_i and x_j have the same meaning as above; $\bar{x}$ denotes the mean value; S^2 represents the sample variance; and w_{ij} indicates the spatial weight.

2.3.5. Ecological Support Coefficient of Carbon Emissions (ESC)

The Ecological Support Coefficient of Carbon Emissions (ESC) is a key indicator for evaluating the carbon balance status of a region. It measures the carbon absorption capacity of a specific functional zone in relation to its carbon emission pressure, as well as its contribution within the broader urban carbon balance framework. This coefficient directly reflects the carbon sink capacity of the area. The calculation formula is as follows [1]:

$$ESC = \frac{C_{xi}}{C_x} \div \frac{C_i}{C} \quad (12)$$

where C_{xi} and C_x represent the carbon absorption amounts of the functional zone and the entire city, respectively; C_i and C denote the carbon emission amounts of the functional zone and the entire city, respectively. An $ESC > 1$ indicates that the proportion of carbon sinks in the area exceeds that of carbon sources, demonstrating strong carbon sink capacity. Conversely, an $ESC < 1$ suggests that the proportion of carbon sinks is lower than that of carbon sources, indicating relatively weak carbon sink capacity.

3. Foundational Results and Preliminary Analysis

This chapter presents the applied results of the computational methodology, which serve as the foundational basis for the in-depth analysis and discussion in the subsequent sections (Sections 4 and 5).

3.1. GDP_{23} Spatialization Modeling

3.1.1. Selection of GDP_{23} Spatialization Modeling Approaches

To ensure the reliability and robustness of spatialization modeling results, this study adopted a complementary modeling strategy integrating both temporal and spatial series approaches. Temporal series modeling focuses on historical evolution patterns within individual regions, whereas spatial series modeling examines spatial correlation characteristics across broader geographical areas at the same temporal cross-section. Through comprehensive evaluation of both methodologies, this study aimed to identify the optimal modeling approach for subsequent GDP_{23} spatialization.

(1) Temporal Series Modeling

GDP_{23} data from various districts and counties in Xiamen over the past decade, along with corresponding nighttime light data, were selected for correlation analysis. Using annual GDP_{23} as the dependent variable and nighttime light indices (DN_{mean} , I, S, CNLI, TNL) as independent variables, regression simulations were conducted, employing linear, quadratic, composite, logarithmic, cubic, S-curve, exponential, inverse, and power functions, as shown in Figure 4. The R^2 values of optimal fitting models varied significantly among different districts. Xiang'an District achieved the highest goodness-of-fit ($R^2 = 0.946$), while Haicang (0.864), Huli (0.829), Jimei (0.807), and Tong'an (0.841) districts all demonstrated R^2 values exceeding 0.80. However, Siming District's optimal model yielded a relatively low R^2 of only 0.544, indicating substantially weaker temporal correlation between light indices and GDP_{23} in this area.

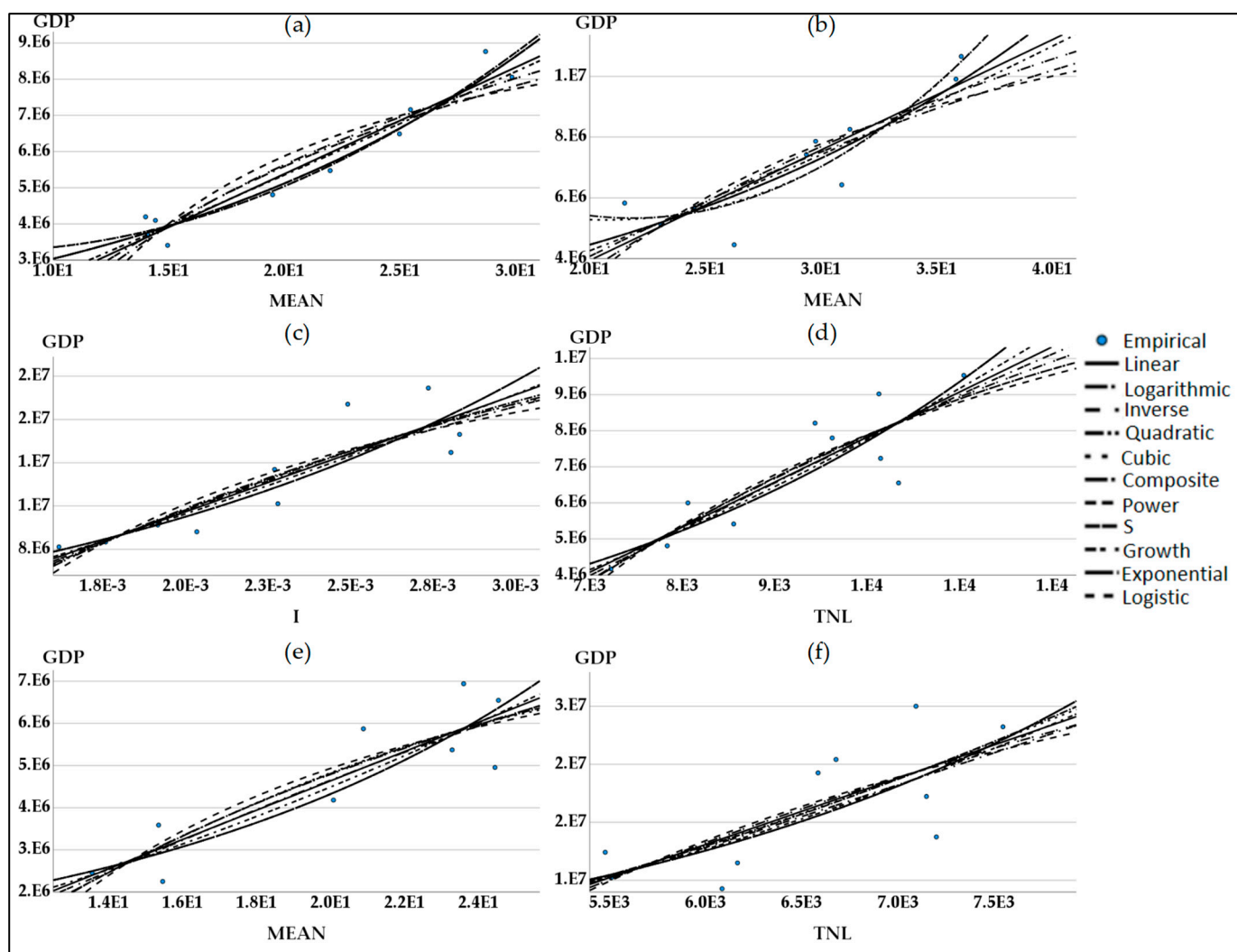


Figure 4. Fitted regression curves for each district: (a) Xiang'an District, (b) Haicang District, (c) Huli District, (d) Jimei District, (e) Tong'an District, and (f) Siming District.

(2) Spatial Series Modeling

Given that Xiamen comprises only six district-level administrative units, the analysis scope was expanded to include all districts and counties across Fujian Province to enhance statistical reliability and model generalizability. Under the same baseline year, correlation analysis was performed between various light indices (DN_{mean} , I, S, CNLI, TNL) and

GDP_{23} values across all districts and counties of Fujian Province. Using GDP_{23} as the dependent variable and the five nighttime light indices as independent variables, respectively, regression analysis was conducted using linear, quadratic, composite, logarithmic, cubic, S-curve, exponential, inverse, and power functions, with results presented in Table 3.

As shown in Table 4, all regression models demonstrated statistical significance in describing the relationship between the five light indices and GDP_{23} , confirming stable correlations between light indices and economic output. However, the goodness-of-fit (R^2) of optimal models varied considerably among different indices: the power function provided the best fit for DN_{mean} ($R^2 = 0.467$), the inverse function was optimal for I ($R^2 = 0.242$), and both S and CNLI achieved best fits with inverse functions ($R^2 = 0.209$). Notably, the power function model for TNL exhibited the strongest explanatory power ($R^2 = 0.801$), significantly outperforming other TNL models and optimal models of other light indices.

Table 4. Fitting results for various light indices and GDP_{23} .

Equation	DN_{mean}		I		TNL	
	R^2	Significance	R^2	Significance	R^2	Significance
Linear	0.373	<0.001	0.086	0.007	0.691	<0.001
Logarithmic	0.383	<0.001	0.199	<0.001	0.561	<0.001
Inverse function	0.307	<0.001	0.242	<0.001	0.287	<0.001
Quadratic function	0.389	<0.001	0.117	0.007	0.692	<0.001
Cube function	0.392	<0.001	0.139	0.008	0.706	<0.001
Composite function	0.411	<0.001	0.253	<0.001	0.602	<0.001
Power function	0.467	<0.001	0.330	<0.001	0.801	<0.001
S function	0.410	<0.001	0.205	<0.001	0.613	<0.001
Growth function	0.411	<0.001	0.253	<0.001	0.602	<0.001
Logistic	0.411	<0.001	0.253	<0.001	0.602	<0.001
Equation	S		CNLI			
Linear	0.120	0.138	0.120	0.334		
Inverse function	0.209	0.004	0.209	<0.001		
Quadratic function	0.026	0.160	0.026	0.034		
Cube function	0.029	0.164	0.029	0.506		
Composite function	0.035	0.303	0.035	0.090		
S function	0.188	0.006	0.188	<0.001		
Growth function	0.035	0.303	0.035	0.090		
Logistic	0.035	0.303	0.035	0.090		

Comprehensive comparison of both modeling strategies reveals that while temporal series modeling can reflect regional evolutionary trends, it is constrained by the limited number of district-level units in Xiamen and suboptimal fitting performance in certain counties. Conversely, spatial series modeling, leveraging a larger sample size of 77 district/county units across Fujian Province, substantially enhanced statistical reliability and achieved superior goodness-of-fit ($R^2 = 0.801$). Consequently, the spatial series modeling approach demonstrated better applicability and robustness in this study. We ultimately selected TNL and GDP_{23} as independent and dependent variables, respectively, to establish a provincial-scale spatial series model for GDP_{23} spatialization. The fitting results are presented in Figure 5, with the optimal model formula as follows:

$$GDP_{23} = 2.907209825590326 \times TNL^{0.6593752912568176} \quad (13)$$

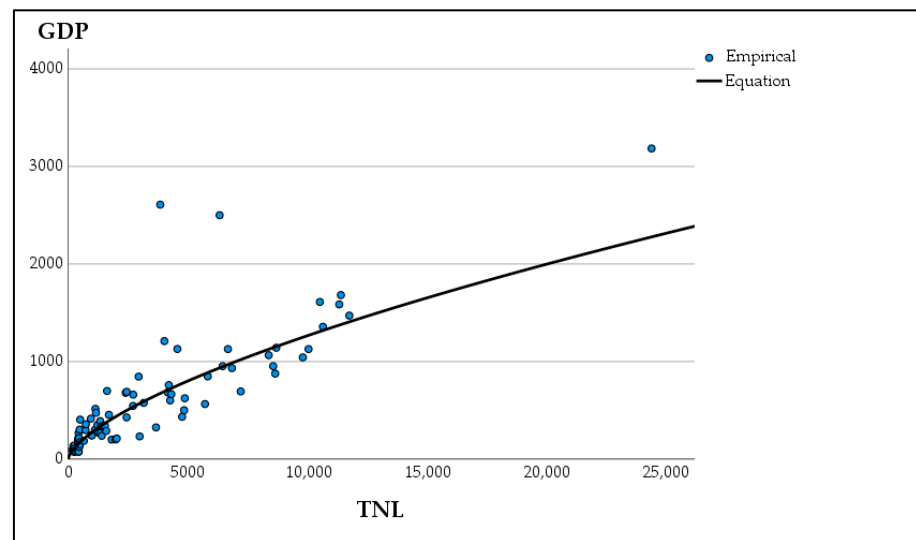


Figure 5. Best-fit regression curve for GDP_{23} .

3.1.2. GDP_{23} Spatialization Results

The grid-scale TNL of Xiamen was first calculated based on NPP-VIIRS data. Subsequently, Formula (13) was applied to compute the grid-scale GDP_{23} with a spatial resolution of 500 m. Pixel-level correction of the fitted values was then performed using Formula (8). The results are shown in Figure 6.

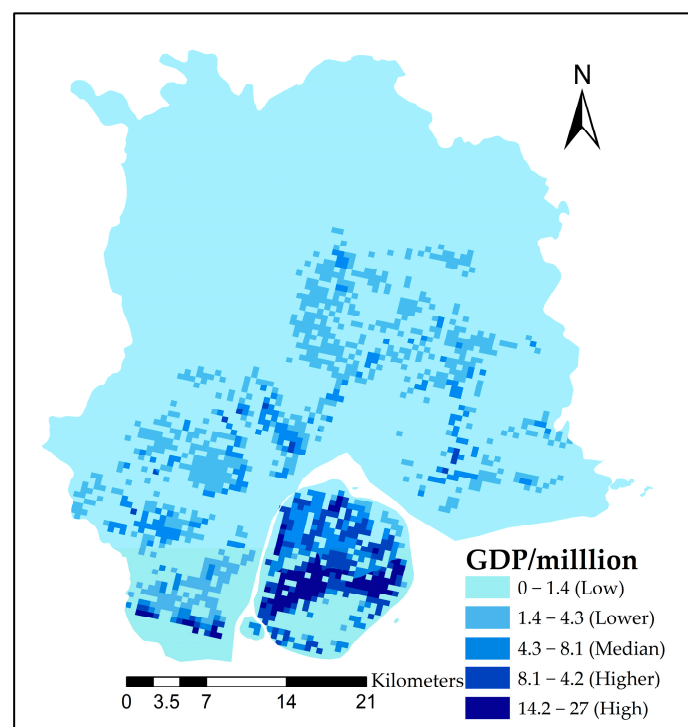


Figure 6. Xiamen GDP_{23} density distribution map.

The spatial distribution pattern demonstrates the following characteristics: Highest-value units are concentrated in the core urban area, forming a distinct high-value economic zone that reflects the strong agglomeration effect of secondary and tertiary industries in the core region. Relatively high-value areas mostly distribute in belt-like or cluster patterns around the high-value core, constituting secondary economic centers and revealing a gradient diffusion pattern of economic development. Medium-value areas are primarily

located in regions such as Tong'an and southern Xiang'an. Lower-value and lowest-value areas are predominantly concentrated in the northern mountainous region of Xiamen and its surrounding undeveloped areas.

3.2. Carbon Emissions Results

The accounting results derived from Formulas (1) and (2) (Figure 7) indicate that carbon emissions in Xiamen display a distinct spatial distribution: “high-intensity concentration within the main island, with a pattern of northern-low and southern-low outside the island.” This pattern is strongly influenced by land use structure and socioeconomic activities.

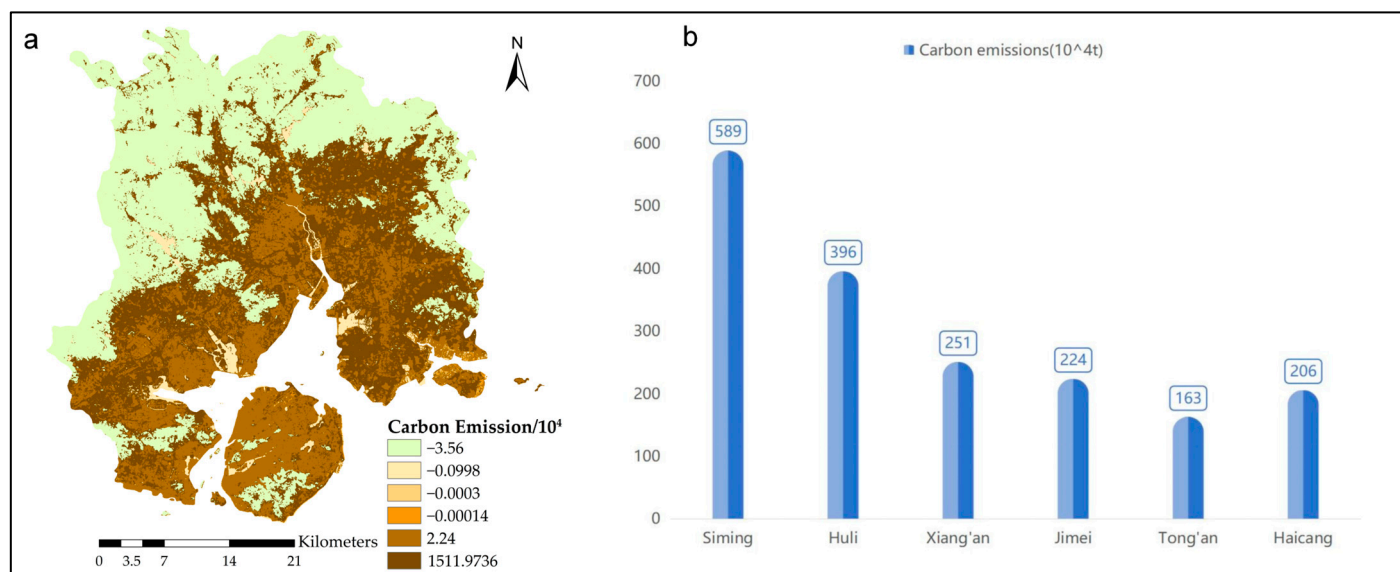


Figure 7. Xiamen carbon emissions results: (a) represents carbon emissions from different land use types; (b) represents carbon emissions from each administrative district in Xiamen.

In terms of land use, construction land acts as the dominant carbon source, accounting for 99.5% of net carbon emissions across the study area. In contrast, ecological lands such as forest and water bodies function as carbon sinks. However, due to their limited coverage and fragmented distribution, their sequestration capacity offsets only 0.24% of total emissions, highlighting the significant carbon balance pressure faced by Xiamen as a highly urbanized region.

Further analysis at the administrative district scale reveals that Siming and Huli districts—the economic, commercial, and transportation hubs of Xiamen—are characterized by concentrated construction land and intensive development. Together, these two districts contribute to 63.2% of the city's total carbon emissions, reflecting the excessive concentration of core urban functions on the main island and the resulting high density of energy consumption and emissions.

Tong'an and northern Jimei districts, which contain extensive combinations of blue and green carbon sinks such as forests and water bodies, form key ecological barriers and core carbon sequestration zones in Xiamen, resulting in relatively low overall emission levels. The total carbon emissions of Xiang'an and Haicang districts are comparable to those of Jimei District. Notably, Xiang'an District features a mix of cropland and water bodies, along with dense forest cover in its northern part. However, ongoing land reclamation projects and the operation of Xiang'an Airport are expected to drive a continuous increase in carbon emissions due to construction land expansion. Haicang District, on the other

hand, maintains steady industrial carbon emissions owing to its layout of port-industrial and petrochemical sectors.

3.3. Functional Zone Classification Results

The functional zoning results of Xiamen are shown in Figure 8, comprising 55.79% single-function zones, 33.20% mixed-function zones, and 11.01% null-value zones. The single-function zones include six categories: Industrial District (I), Common Service Area (CS), Traffic Functional Area (TF), Residential Functional Area (RF), Green Space Functional Area (GS), and Commercial Function Area (CF). Among these, CF dominates absolutely, with an area of 522.50 km² accounting for 83.07% of the total single-function zones. Both GS and RF account for less than 1%, at 0.95% and 0.83%, respectively.

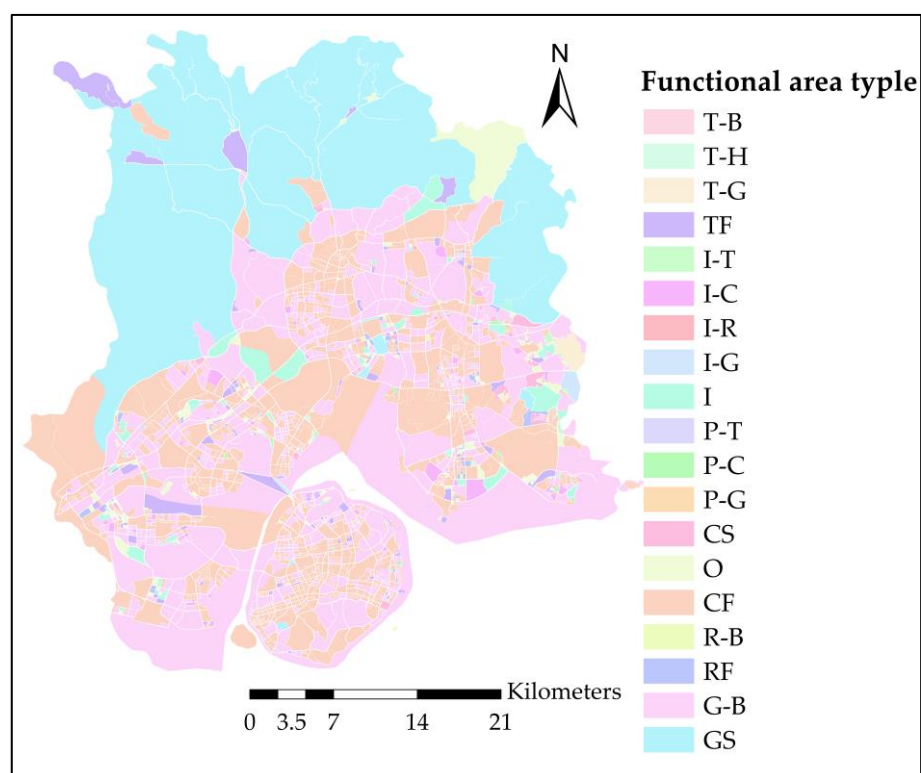


Figure 8. Distribution map of functional zones in Xiamen City.

The mixed-function zones consist of 13 combination types, including Industry-Transportation (I-T), Industry-Residential (I-R), Industry-Green Space (I-G), Industry-Commerce (I-C), Public-Transportation (P-T), Public-Green Space (P-G), Public-Commercial (P-C), Transportation-Housing (T-H), Transportation-Green Space (T-G), Transportation-Business (T-B), Residential-Business (R-B), and Greenfield-Business (G-B). The core type, Greenfield-Business (G-B), covers an area of 518.00 km², representing 95.00% of this category, and exhibits a relatively dispersed spatial distribution.

Additionally, units without POI information were classified as null-value zones, labeled as Other Functional Areas (Os), with an area of 15.59 km². These areas are primarily distributed in non-urban spaces such as lakes, forested areas, and croplands.

4. Spatial Pattern Characteristics of Carbon Sources and Sinks in Xiamen City

4.1. Overall Carbon Emission Patterns Based on Administrative and Functional Zoning

Analysis of 19 functional zones in Xiamen reveals a clear “carbon-source-dominated” spatial heterogeneity, characterized by total carbon sources substantially exceeding sinks and emissions highly concentrated within Xiamen Island (Figure 9).

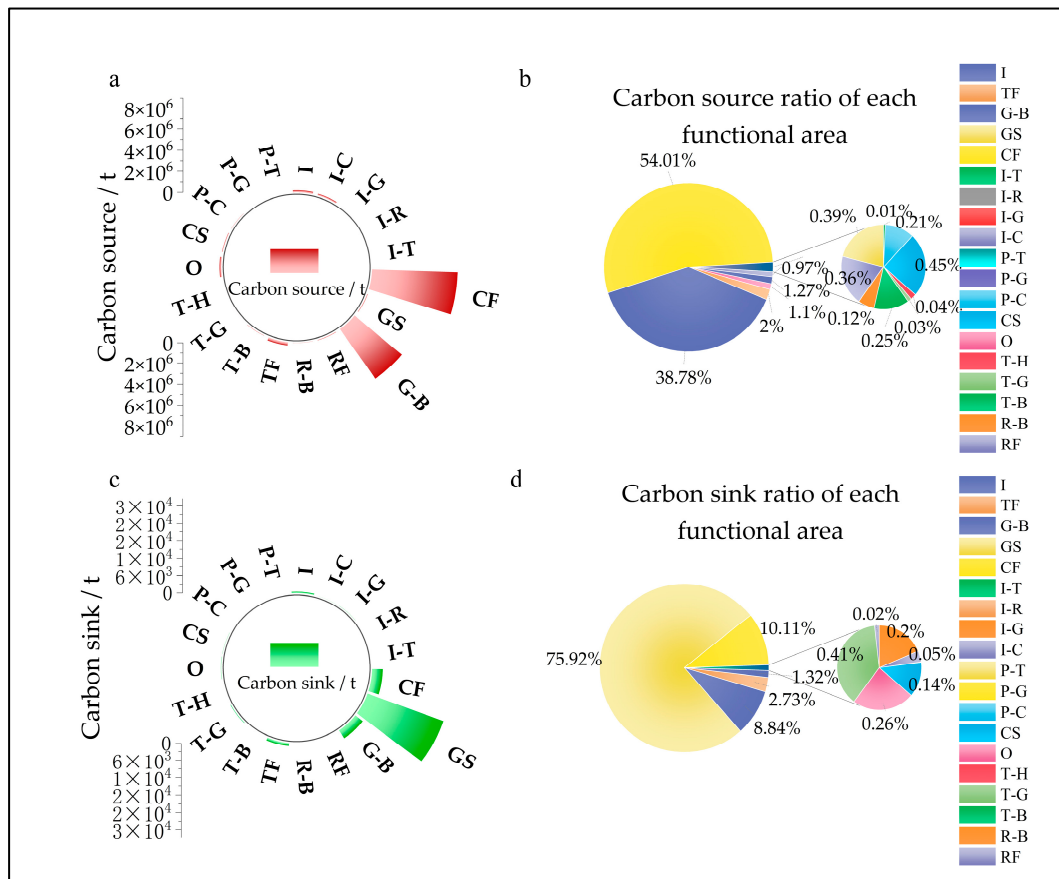


Figure 9. Total carbon sources and sinks by functional zone: (a–d) represent the total carbon emissions, carbon emission proportion, carbon absorption, and carbon sink proportion for each functional zone, respectively.

The spatial distribution of carbon sources strongly aligns with urban economic function layout. Commercial functional zones and green-commercial mixed zones account for 92% of the city’s total carbon emissions. Siming and Huli districts emerge as the core carbon sources, a pattern rooted in Xiamen’s “monocentric” urban structure that leads to high concentration of administrative, commercial, and transportation hubs.

Notably, the commercial functional zone in Siming District and the commercial-transportation mixed zone in Huli District demonstrate the highest energy consumption density, where building energy use and transportation emissions create significant synergistic effects. In contrast, carbon sink functions are primarily undertaken by off-island areas. Green space functional zones serve as the most crucial carbon absorption carriers, contributing 75.92% of the city’s total carbon sequestration, while Tong’an District and northern Jimei District form key buffer zones maintaining the city’s ecological security.

Carbon emission characteristics in off-island areas show distinct variations. Haicang District’s high carbon emissions directly correlate with its role as a port-industrial base,

while Xiang'an District faces substantial carbon emission growth potential due to major projects including the new airport and sports/convention facilities.

Xiamen's carbon emission pattern clearly demonstrates that human economic activity intensity serves as the primary driving factor. Commercial agglomerations form carbon sources through high-intensity energy consumption and transportation flows, while green spaces play an irreplaceable role in carbon sequestration through natural ecological regulation.

4.2. Spatial Correlation Pattern of Carbon Emissions in Xiamen City

The results of the global spatial autocorrelation analysis of carbon emissions across functional zones in Xiamen are presented in Figure 10. The Moran's I index of -0.5057 , passing the Z-test ($p < 0.05$), indicates a significant negative spatial autocorrelation of carbon emissions within the study area. Overall, high carbon emission functional zones and low-carbon emission units in Xiamen exhibit an alternating spatial distribution pattern, forming a heterogeneous "high-low" spatial configuration.

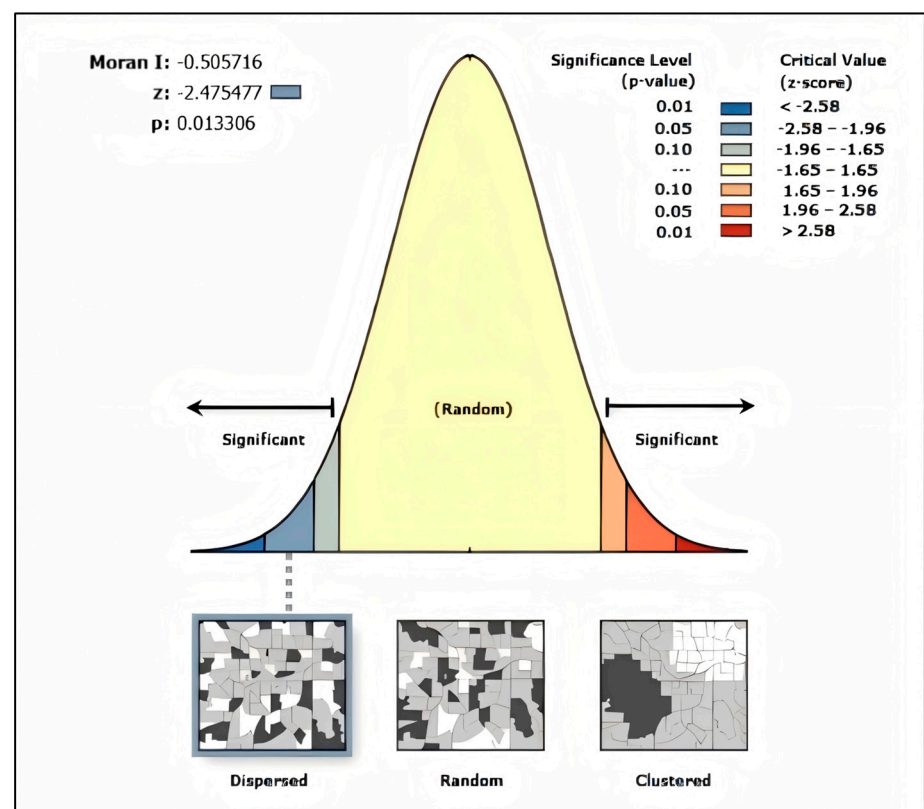


Figure 10. Results of global spatial autocorrelation analysis.

Further spatial autocorrelation analysis using Moran's I reveals significant heterogeneity in carbon emissions across Xiamen's functional zones (Figure 11). The spatial clustering pattern is dominated by high-high (HH) and low-high (LH) clusters, comprising five HH and six LH aggregation zones.

HH clusters are mainly distributed in coastal areas, particularly within Haicang and Xiang'an districts. These zones largely consist of commercial and green-commercial mixed functional types, indicating that large-scale transport infrastructure and industrial clusters are key drivers of local carbon emission hotspots.

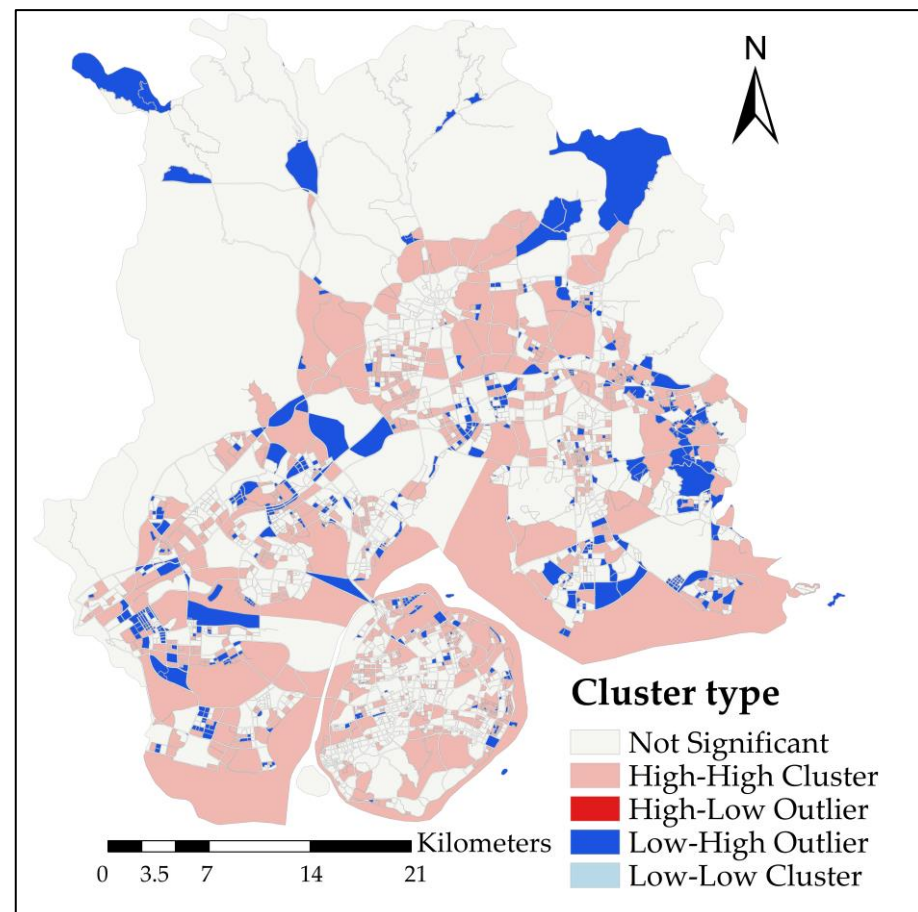


Figure 11. Results of local spatial autocorrelation analysis.

In contrast, LH clusters—representing low-value zones surrounded by high-value neighbors—are scattered across Xiang'an, Jimei, and Haicang districts. These typically correspond to green spaces, protective buffers, or undeveloped plots embedded within transport, industrial, or transport-commercial mixed zones. They form localized low-carbon units within a broader high-emission context, serving as carbon “islands” that demonstrate how reasonable internal spatial planning can create lower-carbon environments even under macro-scale high-emission conditions.

4.3. Carbon Ecological Support Coefficient Pattern of Xiamen's Functional Zones

Based on Formula (12), the carbon ecological support coefficient was calculated for various functional zones in Xiamen. The results reveal a distinct spatial pattern characterized by higher values in the north and lower values in the south, as illustrated in Figure 12. According to the classification criteria in Table 5, functional zones such as Industry-Transportation, Industry-Residential, Public-Transportation, and Public-Green Space all exhibited ESC values below one, indicating that carbon source intensity significantly exceeds carbon sink capacity, resulting in a negative carbon assimilation effect. In contrast, five functional zones—Industrial, Transportation, Transportation-Green Space, Industry-Green Space, and Green Space—showed ESC values greater than one, highlighting their substantial carbon sink contributions and positive carbon assimilation effects.

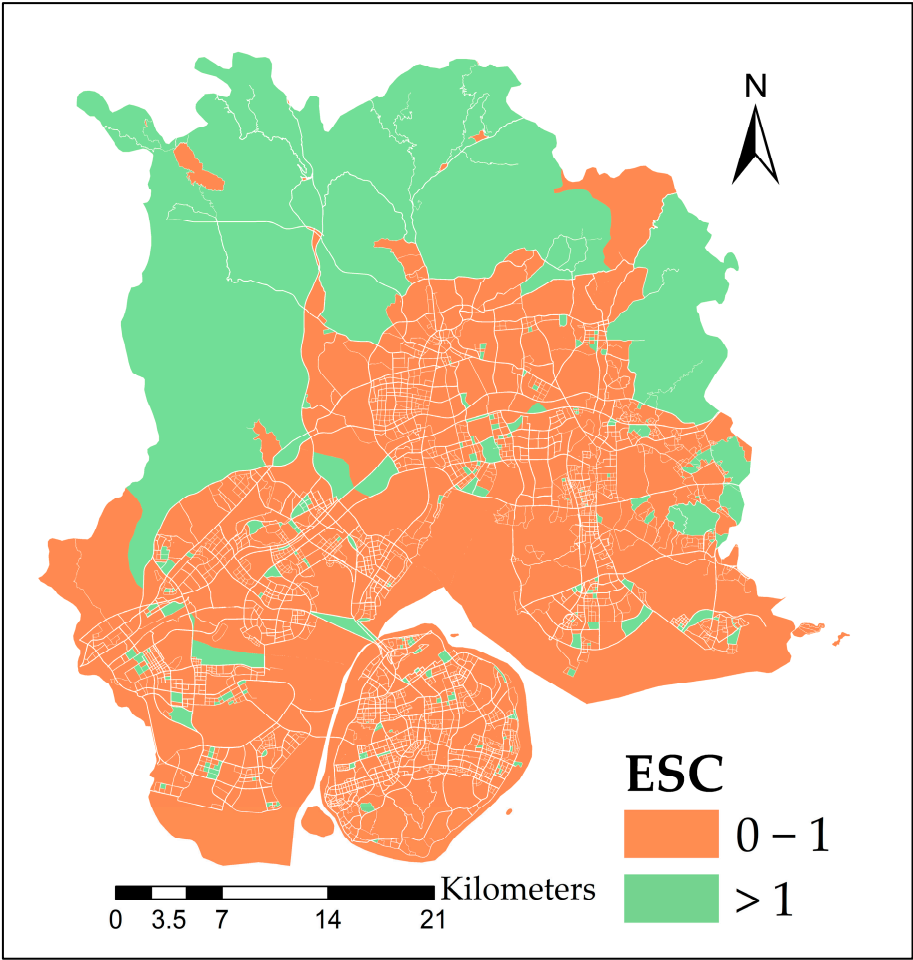


Figure 12. Spatial distribution of carbon ecological support coefficient in Xiamen’s functional zones.

Table 5. Classification of carbon ecological carrying capacity.

ESC	Functional Zone Categories
0–1	I-T, I-R, P-T, P-G, R-B, T-B, T-H, P-C, G-B, RF, CF, O, CS
>1	I, TF, T-G, I-G, GS

Spatially, the central urban districts of Siming and Huli, along with the southern part of Jimei District, which together contain 87% of the built-up area, are dominated by low ESC values. These areas coincide with zones of high development intensity, such as Industry-Transportation and Residential-Commercial functional zones. Tong’an District exhibits extensive high ESC values, particularly in its northwestern mountainous forest areas, where Green Space and Industry-Green Space mixed zones account for 57.10% of the city’s total forest cover. In Xiang’an District, the southeastern region forms a high ESC zone comprising Industrial and Transportation-Green Space areas, while the central Residential-Commercial zone shows low ESC values. This spatial distribution underscores a significant negative correlation between urban development intensity and ecological carrying capacity across the region.

5. Carbon Balance Zoning and Low-Carbon Development Suggestions for Xiamen City

5.1. Demarcation of Carbon Balance Zones

5.1.1. Basis for Carbon Balance Zone Demarcation

Carbon balance zoning aims to classify functional areas based on the spatial patterns and interrelationships of carbon sources and sinks within a region to support differentiated low-carbon management strategies. The core criteria for this demarcation are the carbon ecological support coefficient (ESC) threshold and the spatial clustering types of carbon emissions. First, based on the ESC, functional zones in Xiamen with $ESC \geq 1$ are classified as carbon-sink-dominated zones, while those with $ESC < 1$ are classified as carbon-source-dominated zones. Second, the results of local spatial autocorrelation analysis are used to further define significant clustering types: high–high clustering (HH type), low–low clustering (LL type), low–high clustering (LH type), and high–low clustering (HL type), with non-significant areas categorized separately.

Integrating these two demarcation criteria, four types of functional zones are identified (Table 6): (1) within carbon-sink-dominated zones, LL-type units are designated as core carbon sink zones, while other types (LH/HL/non-significant) are classified as carbon sink pressure zones; (2) within carbon-source-dominated zones, HH-type units are designated as core carbon source zones, while other types (LH/LL/HL/non-significant) are classified as carbon source regulation zones.

Table 6. Primary indicators for carbon balance zones.

Carbon Balance Zone	Classification Criteria	Functional Attributes
Core Carbon Sink Zone	$ESC \geq 1$ and LL-type clustering	Regional core carbon sink nodes require strict protection of ecological spaces, prohibition of high carbon emission industries, and enhancement of carbon sink stability.
Carbon Sink Pressure Zone	$ESC \geq 1$ and LH-type/HL-type/non-significant clustering	Carbon sink capacity compressed by peripheral high emissions or spatial isolation necessitates the establishment of ecological barriers and restrictions on new carbon emissions.
Core Carbon Source Area	$ESC < 1$ and HH-type clustering	High-intensity carbon emission agglomeration areas must implement mandatory emission reduction measures and promote deep low-carbon transformation of industrial structures.
Carbon Source Regulation Zone	$ESC < 1$ and LH-type/LL-type/HL-type/non-significant clustering	Dispersed carbon sources or transitional areas should gradually reduce carbon emission intensity through energy efficiency improvements and energy substitution.

Note: The LL/HL clustering in this region did not pass the significance test, but the partitioning criteria preserve theoretical integrity.

5.1.2. Results of Carbon Balance Zone Demarcation

The carbon balance functional zoning results for Xiamen are presented in Figure 13, revealing a distinct spatial structure characterized by “sources in the south, sinks in the north, and regulation in the central areas.” The proportions and coverage of each functional zone type are summarized in Figure 14.

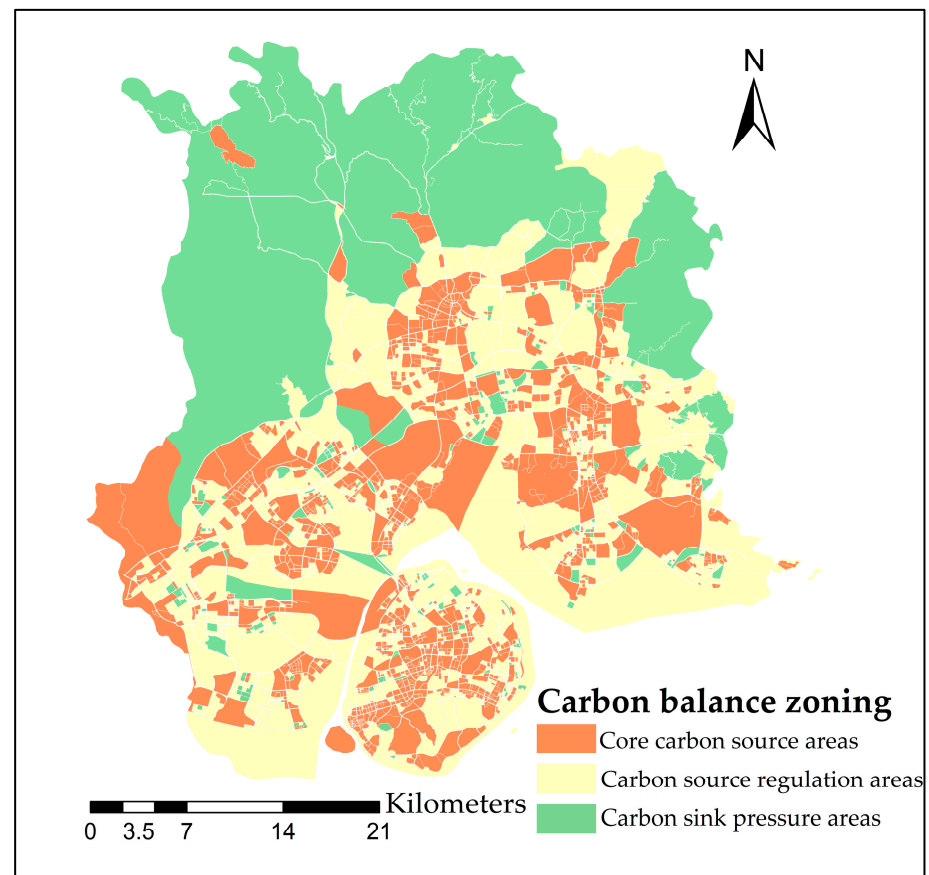


Figure 13. Xiamen City carbon balance zoning map.

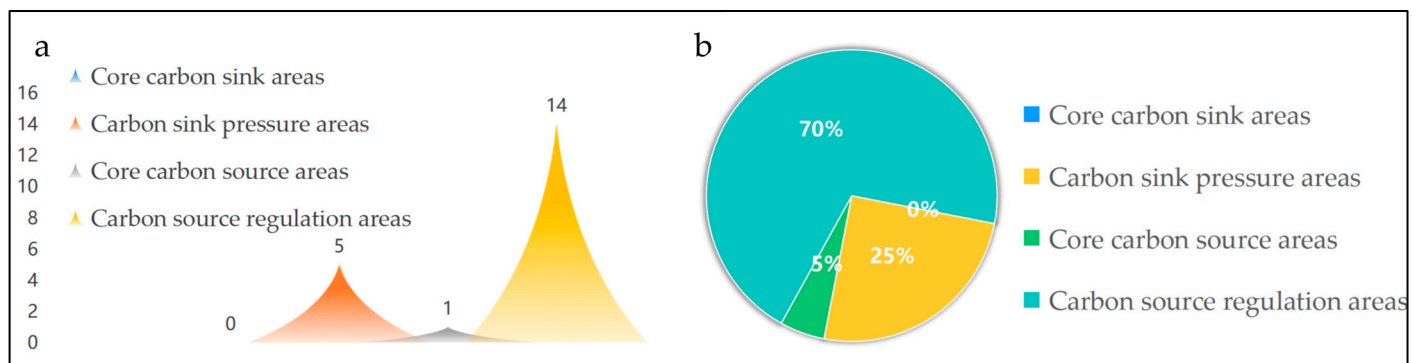


Figure 14. Number and proportion of functional zones in Xiamen City: (a) number of carbon balance subdivision types and (b) proportion of carbon balance subdivision types.

The results indicate that Xiamen currently lacks core carbon sink zones, suggesting an urgent need to enhance its carbon absorption capacity. Core carbon source zones are concentrated within Xiamen Island, accounting for 5% of all functional zones. These areas are dominated by commercial land uses, where carbon emission intensity per unit area exceeds the urban average by eightfold. The primary contributors to emissions include energy consumption in commercial buildings, traffic congestion, and high population density. Carbon sink pressure zones comprise mixed-function units such as industry-green space and transportation-green space, forming a fragmented ring around the core emission areas and accounting for 10% of functional zones. Carbon source regulation zones constitute the remaining 85% of functional zones, representing the dominant spatial category across

the region. This spatial configuration reflects a typical urban carbon emission pattern in which intensity decreases radially from the central urban core toward the periphery.

5.2. Characteristics of Carbon Balance Zones and Low-Carbon Development Recommendations

Xiamen's carbon balance zoning pattern stems from the interaction between urban spatial strategy and land use characteristics. At the macro level, the city's monocentric development model has positioned Siming and Huli districts on the main island as the "core carbon source zones," while the cross-island development strategy has shaped Xiang'an and Haicang into "carbon source regulation zones." At the micro level, the dense distribution of construction land with industrial and transportation functions has raised emission levels in Haicang and Xiang'an, whereas the ecological foundation of Tong'an and northern Xiang'an underpins their role as "core carbon sink zones." Building on this formative mechanism, the study puts forward the following spatially targeted recommendations:

(1) Core Carbon Sink Zones

This study did not identify significant LL-type spatial clusters that would allow delineation of core carbon sink zones. This outcome may be attributed to two main factors. First, the regional ecological foundation remains fragile, with key carbon sink carriers—such as forested areas and wetlands—exhibiting highly fragmented spatial distributions. This fragmentation inhibits the formation of contiguous ecological patches with scale effects, resulting in insufficient statistical significance in local spatial autocorrelation analysis. Second, high-resolution carbon emission data indicate the presence of localized high-emission sources within traditionally ecological units, thereby reducing their net carbon sink performance.

To address these challenges, this study recommends designating key carbon sink functional areas—including the Wuyuan Bay Wetland, the Huliao Mountain–Xian Yue Mountain forest corridor on the main island, and Tianzhushan Forest Park in the northwestern off-island area—as "Core Carbon Sink Cultivation Zones" within Xiamen's ecological control lines, subject to strict regulatory oversight. This approach represents a functionally refined enhancement to the city's existing ecological protection red lines. In terms of public engagement, efforts such as public lectures on ecosystem services, thematic exhibitions on carbon sink functions, and volunteer-led conservation activities should be organized. These initiatives are intended to raise awareness of the ecological value of carbon sink zones and foster public involvement in the protection of ecological spaces, thereby reducing anthropogenic disturbances to critical carbon sink carriers.

(2) Carbon Sink Pressure Zones

Accounting for 10% of the total functional zone area, these zones primarily consist of mixed units such as industry-green space, transportation-green space, and monofunctional green space zones. They are mainly distributed in the northern Tong'an District and within industry-green space composite units in Xiang'an District. Although these areas possess a baseline capacity for carbon sequestration, their efficiency is compromised by pollutant dispersion from adjacent high-emission sources, such as industrial and transportation activities, which pose ongoing risks of ecological degradation.

To alleviate these effects, we propose the establishment of integrated ecological buffer zones along the peripheries of the Tong'an Industrial Zone, Southern Xiang'an New Town, and Haicang's port-industrial areas. These zones should be designed to combine pollution absorption, noise reduction, and ecological conservation functions. In particular, forest belts with noise-abatement and carbon-sequestration capacities should be strategically deployed around noise-affected areas near Xiang'an's new airport. Furthermore, existing green spaces and wetlands in these regions could serve as "low-carbon education bases", enabling nearby

residents and corporate employees to participate in practical conservation activities. Such initiatives would improve public awareness of the link between emission reduction and carbon sink protection, while fostering a cooperative approach to ecological preservation.

(3) Carbon Source Regulation Zones

These zones comprise 85% of the total functional area and are dominated by 15 mixed-use functional types, including industry-residential and public-commercial units. Spatially adjacent to ecological systems, these areas face potential stress risks. Characterized by residential, public service, and commercial functions, they are not classified as high energy-consuming sectors, with carbon emission intensity at approximately one-eighth of core carbon source zones.

Nevertheless, substantial potential for emission reduction persists in these zones, particularly given their role as major population agglomerations in Xiamen. We recommend integrating the ongoing renovation of old residential neighborhoods and the development of complete communities into a coordinated “Low-Carbon Community” initiative. Specific measures could include enhancing carbon sequestration through rooftop and vertical greening, as well as establishing digital monitoring platforms to track community-level energy consumption and carbon emissions.

(4) Core Carbon Source Zones

These zones are predominantly commercial functional areas, comprising less than 5% of all zones in number yet covering 60% of the urbanized area and contributing over 60% of total carbon emissions. They are highly concentrated in economically developed regions such as Siming and Huli districts, where carbon emission intensity exceeds the city’s average by more than eight times. Primary drivers include high energy consumption in commercial buildings and severe traffic congestion. Subsequent optimization strategies should focus on curbing further expansion of construction land and guiding industrial restructuring toward intelligent, green, and low-carbon development.

To further advance emission reduction in key urban areas, we recommend the introduction of carbon quota mechanisms in zones such as the Zhongshan-Lujiang CBD and the Cross-Strait Financial Center. Additionally, “zero-carbon tourism demonstration zones” should be established in scenic regions including Gulangyu Island. To broaden public involvement, visible energy-saving measures in commercial complexes should be coupled with incentivized public transport programs, fostering collaborative emission reduction efforts between enterprises and residents.

6. Discussion

6.1. Spatial Heterogeneity of Carbon Sources and Sinks

The pattern of higher carbon source concentrations in the south and lower in the north, with the opposite trend for carbon sinks, reflects the close relationship between functional zone types and human activity intensity in Xiamen. The southern region, as the core of urban economic activities, is dominated by industrial and commercial functional zones with substantial energy consumption, leading to high carbon emission intensity. In contrast, the northern area is primarily characterized by green space functional zones rich in carbon sink resources such as forests and green spaces, resulting in strong carbon absorption capacity.

Similar spatial distribution patterns have been observed in studies of other cities, such as Shanghai, where carbon emissions are concentrated in the central urban areas, while carbon sink functions are more prominent in the suburbs [60]. This distribution pattern not only highlights the differences in urban functional zones but also empha-

sizes the need to consider spatial heterogeneity in urban planning and carbon reduction strategy formulation.

6.2. Impact of Urban Functional Zoning on Carbon Balance

Research indicates that commercial, industrial, and transportation functional zones form the core spatial units of carbon emissions, displaying marked spatial aggregation features consistent with observations from Shanghai [61]. Further studies in Beijing have revealed that intensive socio-economic activities—such as those in the wholesale and retail sectors—can lead to per-unit-area carbon emissions in commercial zones, exceeding those in residential zones by more than threefold, with high-emission areas predominantly clustered in urban centers and transportation hubs [28].

To optimize carbon balance, differentiated strategies are essential: for carbon emission control, industrial relocation should be integrated with clean production technologies to prevent pollution displacement, transportation hubs should prioritize the adoption of clean energy and electrification, and commercial zones ought to focus on energy structure optimization and enhanced building energy efficiency. In terms of carbon sink enhancement, this study identifies that mixed functional zones—such as green-public, industry-green, and transportation-green—exhibit lower carbon emission intensity, suggesting that mixed-use layouts can synergistically improve carbon sink efficiency. Consequently, tailored governance measures are warranted: core carbon source zones should emphasize industrial emission reduction, carbon source regulation zones should promote the use of green building materials, and carbon sink pressure zones require strengthened ecological protection, collectively forming a systematic regulatory framework.

6.3. Methodological Considerations for Urban Carbon Emission Calculation

With the progressive implementation of carbon peak, carbon neutrality, and low-carbon city pilot policies, carbon emission accounting has become a foundational component of urban low-carbon planning and management. The selection of appropriate methodologies is critical for accurately characterizing emission patterns. This study employed a land use-based coefficient method to estimate carbon emissions in Xiamen, which integrates land use categories with corresponding carbon emission coefficients to achieve a preliminary spatial quantification of urban carbon emissions. This approach offers several advantages, including straightforward data acquisition, computational transparency, and results conducive to spatial visualization, rendering it suitable for small to medium urban scales. A similar framework was applied by Zhang et al. (2014) in their study of carbon metabolism in Beijing [62].

However, this method has certain limitations. First, estimation accuracy is highly dependent on the carbon emission coefficients adopted. If these coefficients do not adequately reflect local energy structures, industrial features, and behavioral patterns in Xiamen, calculated results may be biased. As highlighted by Cai et al. (2021), most studies in China have yet to incorporate high-resolution urban morphological data, which constrains the accuracy of emission accounting [63]. Second, research in Shanghai by Wu et al. (2018) demonstrated that carbon emission estimates based on building functions and land use types may obscure variations at the block or building scale due to factors such as building density and energy efficiency disparities [64]. This indicates an inherent limitation of the land use coefficient method in capturing micro-scale emission differentiations within the same land use category. Future studies should therefore explore the integration of multi-source data and machine learning techniques to enhance spatial resolution and model accuracy, ultimately contributing to a more robust carbon emission estimation framework.

7. Conclusions

7.1. Principal Findings

This study establishes an integrated micro-scale carbon balance assessment framework from the perspective of urban functional zoning, combining land use-based carbon emission accounting with spatial analysis, using Xiamen as an empirical case. The main conclusions are as follows:

- (1) **Spatial Pattern:** Carbon emissions in Xiamen show pronounced spatial heterogeneity, with higher concentrations in the south and lower in the north, while carbon sinks exhibit the opposite tendency. Total carbon emissions reached 15.3 million tonnes, far exceeding the carbon absorption of 36,900 tonnes, reflecting a severe carbon imbalance.
- (2) **Role of Functional Zoning:** Urban functional zoning significantly influences the carbon balance. Commercial, industrial, and transportation zones serve as core carbon source spaces, while green space functional zones contribute 73% of total carbon sequestration. Mixed functional zones show relatively lower emission intensity, suggesting the carbon-reducing potential of mixed land use.
- (3) **Methodological Approach:** Using GDP_{23} as a proxy for energy consumption and combining it with nighttime light data, this study effectively spatialized carbon emissions at the micro-scale. This approach offers a practical solution to the scarcity of fine-grained energy statistics.
- (4) **Spatial Correlation and Zoning:** Spatial autocorrelation analysis reveals a significant negative spatial autocorrelation in carbon emissions, presenting a heterogeneous and fragmented pattern rather than clustered distributions. Carbon balance zoning indicates that carbon source regulation zones dominate (70% of the area), with fragmented governance posing challenges to systematic emission reduction.

In summary, this study provides a replicable framework and empirical support for micro-scale urban carbon governance. The results emphasize the importance of integrating carbon balance considerations into urban planning, particularly through functional-zone-specific strategies and mixed land use, to facilitate progress toward carbon neutrality goals.

7.2. Limitations and Future Research Directions

While this study establishes a carbon balance assessment framework for urban functional zones, several limitations stemming from methodological constraints and data availability should be acknowledged. These limitations also point to clear directions for future research:

- (1) **Incomplete carbon accounting framework:** The current system, based primarily on energy consumption, does not fully align with the internationally recognized IPCC inventory, as it omits non-energy emission sources such as industrial processes and waste treatment. While this simplification supports the core objective of spatial simulation, it may result in an underestimation of emissions in specific industrial clusters, affecting the comprehensiveness of the total emission assessment. Future studies should develop a more integrated accounting framework that incorporates energy activities, industrial processes, and waste management to establish a more complete urban carbon emission inventory.
- (2) **Uncertainty from base geographic data precision:** The reliance on crowdsourced data (e.g., OpenStreetMap) to delineate analytical units introduces heterogeneity in geometric accuracy and attribute completeness, particularly in newly developed or remote areas, which may affect the precision of functional zone boundaries. Moreover, residual errors from coordinate system registration of multi-source data are non-negligible in micro-scale analysis. Subsequent research could strengthen the data

foundation by incorporating higher-precision base geographic data (e.g., official survey data) or employing cross-validation with multi-source datasets to enhance the accuracy of micro-scale carbon accounting.

- (3) Insufficient localization of key model parameters: Although the emission coefficients used in this study were drawn from the existing literature with consideration of regional applicability, they do not fully capture subtle influences from local factors such as Xiamen's energy structure, industrial technology efficiency, and natural conditions on carbon flux rates. Therefore, developing a more region-specific emission factor library through field monitoring, material balance calculations, or cross validation with local energy statistics represents an essential direction for improving the accuracy of model simulations in future research.

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