

Article

Spatiotemporal Patterns, Driving Factors, and Low-Carbon Mitigation of Land-Use Carbon Emissions in the Tarim Basin Oasis Urban Agglomeration (Arid Northwest China)

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Abstract

Against the backdrop of global climate change and carbon neutrality strategies, land use carbon emissions have become a prominent topic amid regional efforts toward low-carbon transformation. However, existing studies on land-use carbon emissions have predominantly focused on humid and economically developed regions, while the unique carbon metabolism pathways of arid oasis–desert ecosystems, which are characterized by extremely low environmental carrying capacity and high sensitivity to land-use disturbance, remain largely unexplored. This study takes the oasis urban cluster in the Tarim Basin in southern Xinjiang Uygur Autonomous Region as the research object. This region belongs to a typical oasis–desert composite ecosystem, with a simple structure and low environmental carrying capacity (reflected by sparse vegetation cover <20%, annual precipitation <100 mm, extremely limited water resources, and high sensitivity to land disturbance). Its carbon metabolism pathway (i.e., the dynamic balance between carbon sources and sinks induced by land-use change) is fundamentally different from that in humid areas, and thus merits dedicated investigation. This study selects the period from 2000 to 2020 as the research period, which completely covers the acceleration period of urbanization and agricultural expansion in the Tarim Basin oasis urban cluster since the advancement of China’s Western Development Initiative. The data have a temporal resolution of 5 years (samples in 2000, 2005, 2010, 2015, 2020) and a spatial resolution of 30 m for land use and prefecture level for socio-economic indicators. Based on this, to fill the above-mentioned research gap, a research framework integrating the carbon emission coefficient accounting method, landscape pattern index, spatial autocorrelation analysis and geographic detector is adopted. Specifically, this study aims to systematically quantify the spatio-temporal evolution of land use carbon emissions and identify the most robust driving factors in the Tarim Basin oasis urban cluster by integrating multiple models, an approach that has not been previously applied to arid oasis regions. The research results show: (1) Based on the carbon emission coefficient method, total carbon emissions increased from 1.4455 million tons to 22.364 million tons, following a ‘slow-then-fast’ trajectory. In terms of temporal evolution, the study period can be further divided into three sub-stages: 2000–2005 (slow diffusion, with emission center skewed toward the northern energy-intensive zone), 2005–2015 (rapid restructuring, characterized by a ‘unipolar surge’ in Aksu and spread to the central oasis belt), and 2015–2020 (high-intensity stabilization, forming a cross-regional emission belt). Meanwhile, the land use structure has un-

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dergone a significant transformation. Construction land and cultivated land have continued to expand, while ecological land has significantly shrunk, resulting in a complex transformation pattern of oasis–desert ecotone. (2) The overall landscape became increasingly fragmented and diversified, the integrity of ecological space was damaged, and the regional carbon sink function was weakened. (3) The spatial autocorrelation analysis indicates that the spatial distribution of carbon emissions shows a heterogeneous pattern, forming a high-emission concentration area centered around Aksu-Bayingol. However, the global Moran's I index is negative (such as -0.171 in 2020, $p > 0.05$), suggesting that carbon emissions have not formed a significant spatial clustering. (4) Carbon emissions are dominated by human and economic factors, and the interaction of factors is significant. The geographic detector identifies population density (average q value 0.904) and the proportion of construction land (average q value 0.858) as the key determinants of spatial variation in carbon emissions, reflecting the sensitive response of the human-nature system of arid zones to the urbanization process. These findings not only clarify the spatio-temporal features and driving forces of land use carbon emissions in the Tarim Basin oasis urban cluster, but also provide a replicable analytical framework for carbon-emission research in other arid and semi-arid regions worldwide. Based on these findings, we discuss the unique driving mechanisms of carbon emissions in arid regions, conclude that construction land expansion and population density are the dominant factors, and recommend a three-tier zoning governance system (carbon source control zone, carbon sink enhancement zone, coordinated development zone) for low-carbon spatial planning in arid areas.

Keywords: oasis urban agglomeration in the Tarim Basin; carbon emissions; global Moran's I index; spatial heterogeneity; driving factors

1. Introduction

Land is the spatial medium of human socio-economic activities, and its utilization change is a vital driving force for the worldwide cycle of carbon dynamics. In the context of escalating global climate change and the pressing urgency of achieving carbon neutrality goals [1], changes in land utilization, including deforestation, agricultural expansion, and industrial land development, have become the second-greatest contributor to carbon emissions, after the combustion of fossil fuels [2,3]. Besides fossil fuel combustion, land-use activities also release carbon through biomass burning (e.g., forest and grassland fires), soil organic matter decomposition triggered by tillage, deforestation, agricultural practices (such as rice cultivation and fertilizer application), livestock enteric fermentation, and waste decomposition. According to data from the World Bank in 2020 and the "Global Carbon Budget 2022" report, China contributes over 30% of global carbon dioxide emissions, remaining the world's top contributor [4,5]. To this end, China has established the strategic goals of "Attaining carbon neutrality by 2060 and reaching peak carbon emissions by 2030" [6]. Understanding the coupling between land use and carbon emissions has become a central scientific problem for achieving the Sustainable Development Goals (SDGs) of the United Nations and national carbon neutrality strategies [7].

Currently, numerous studies on the emission of carbon from land utilization have been conducted by scholars both domestically and internationally [8]. Research directions primarily include the spillover effects and prediction of land-use carbon emissions [9], temporal and spatial effects [10,11], temporal and spatial patterns [12,13], influencing factors [14,15], carbon balance and carbon compensation [16], and the relationship with ecosystem service value [17]; the research scales include provincial [18,19], municipal [20],

county-level [21,22], urban agglomeration [23–25], economic belt [26], and river basin [27]; the methods mainly include geographical detectors [28,29], LMDI model [30,31], SBM model [32], Gini coefficient [33], etc. Previous studies have clarified the association between land-use structure, land-use intensity, and carbon emissions, and have revealed spatiotemporal patterns and influencing pathways, laying a theoretical foundation for this paper. However, the current academic perspective shows a significant geographical bias: research mostly focuses on the central and eastern regions with good ecology [34–38], while the research on the western ecologically fragile areas, especially the arid regions, is still insufficient. This study aims to address three main research gaps: (1) a geographical gap (the lack of research on arid oasis–desert ecosystems), (2) a methodological gap (the absence of an integrated landscape pattern-spatial autocorrelation-multi-factor interaction framework), and (3) a quantitative gap (the lack of quantitative characterization of driving factors in the Tarim Basin).

Specifically, relevant studies regarding land use carbon emissions in arid regions have the following key gaps: First, few studies have focused on a systematic analysis of the carbon metabolism mechanism of the oasis urban agglomerations in arid regions. The ecosystem structure in arid areas is simple and the environmental carrying capacity is low. The carbon metabolism pathways under the “natural–human” coupling effect in arid areas are fundamentally different from those in humid areas, but existing studies rarely have dedicated discussions on this geographical type. Second, most existing studies adopt a combination of single or two methods and have not yet formed a comprehensive analysis framework of “landscape pattern-spatial autocorrelation-multi-factor interaction” applicable to arid oasis areas. Landscape pattern indices can depict the fragmentation process of ecological land use, analysis of spatial autocorrelation can effectively describe the heterogeneous distribution of carbon emissions, while the geographic detector model enables quantitative assessment of interactive effects among multiple influencing factors. The combination of these three methods—namely landscape pattern indices, spatial autocorrelation analysis, and geographic detector—is uniquely valuable when analyzing the intricate driving elements of carbon emissions in the human-land system in arid regions. This integrated framework (i.e., the unified analytical framework combining landscape pattern indices, spatial autocorrelation analysis, and geographic detector) has not yet been applied in the oasis urban agglomerations of the Tarim Basin. Third, as a key region within the Silk Road Economic Belt and an important national strategic energy base, the accelerated urbanization and cropland expansion across the Tarim Basin have led to spatial heterogeneity and driving elements of carbon emissions, which have not been quantitatively characterized to date. Several previous studies have investigated land-use carbon emissions in other regions using methods similar to ours. For instance, in the Yellow River Delta, Zhang et al. (2022) employed a land-use transfer matrix, carbon footprint model, and geographic detector to analyze spatiotemporal patterns, revealing that construction land expansion was the primary driver of emission increases [1]. In Sichuan Province, Cai et al. (2023) corrected carbon emission estimates with socioeconomic driving factors and confirmed that land-use transitions and human factors (GDP, population) dominate the spatiotemporal pattern [10]. In Shaanxi Province, Zhao et al. (2023) applied a geographic detector to identify socio-economic factors as the dominant drivers and proposed low-carbon strategies [15]. These studies consistently show that built-up expansion and human activities are key drivers across different settings, yet the specific contribution rates vary with local conditions. Importantly, they also discussed corresponding mitigation strategies (e.g., optimizing land use structure, controlling construction land expansion), which directly align with the three-tier zoning system proposed in this study.

The oasis urban agglomeration in the Tarim Basin is positioned in the central area of the arid region in northwest China. Based on the oasis–desert composite ecosystem, it is

undergoing a significant transformation in land use. This area is not only an ideal case study region for exploring the carbon metabolism mechanism of the human-environment system in arid regions, but also a key area with current research gaps. To date, studies have covered the general patterns of land use change and carbon emission trends in Xinjiang at the provincial scale. However, the spatiotemporal evolution, spatial heterogeneity, and driving mechanisms of carbon emissions at the oasis urban agglomeration scale have not been systematically addressed through multi-model integration. These combined factors, including ecological fragility, rapid urbanization, and strategic importance as a national energy base, make this region a compelling and representative case for investigating land-use carbon emissions in arid areas. Remote sensing and GIS technologies provide support to fill these gaps: multi-temporal remote sensing images can accurately monitor long-term land use changes, while landscape pattern measurement, spatial autocorrelation analysis, and geographic detector models offer powerful tools for quantifying spatial heterogeneity and diagnosing its driving forces. Methodologically, this study addresses three gaps: (1) the absence of an integrated analytical framework combining landscape pattern, spatial autocorrelation, and multi-factor interaction in arid oasis research; (2) the lack of quantitative characterization of carbon emission driving factors in the Tarim Basin oasis urban agglomeration; and (3) the limited application of geographic detector models to oasis urban agglomerations in arid regions. To the best of our knowledge, no previous study has integrated landscape pattern indices, spatial autocorrelation analysis, and geographic detector into a unified analytical framework to investigate land-use carbon emissions in the Tarim Basin oasis urban agglomeration.

Based on the identified gaps, we propose the following hypotheses:

H1. *Construction land proportion and population density are the dominant drivers of carbon emission spatial heterogeneity in the Tarim Basin oasis urban agglomeration.*

H2. *Significant synergistic effects exist among driving factors, particularly between construction land expansion and population agglomeration.*

These hypotheses are tested using the single-factor and interaction detection functions of the geographic detector model.

Therefore, this study focuses on the period from 2000 to 2020, which is a crucial period for the oasis urban agglomerations in the Tarim Basin. The reason for choosing this period is that 2000 marked the start of China's Western Development Initiative, which led to rapid urbanization and agricultural expansion in the region, while 2020 marked the year before China announced dual-carbon targets. This twenty-year window comprehensively captures the period when the land use transformation and carbon emissions growth in the research region were the most intense. Based on this, this study constructs a "pattern-process-driver" analysis framework, aiming to: (1) characterize the dynamics of land use and landscape pattern using land use change analysis and landscape pattern indices; (2) quantify the temporal and spatial evolution of carbon emissions following the carbon emission accounting framework; (3) identify the dominant driving factors and their interactions through spatial autocorrelation and geographic detector analyses; (4) propose low-carbon spatial zoning strategies for arid regions based on the empirical findings.

To provide a visual synthesis of the theoretical logic outlined above, Figure 1 presents a comprehensive framework that integrates the research gaps, hypotheses, methodological components, and research objectives into a coherent structure. The arrows indicate the logical flow from theoretical reasoning to empirical investigation.

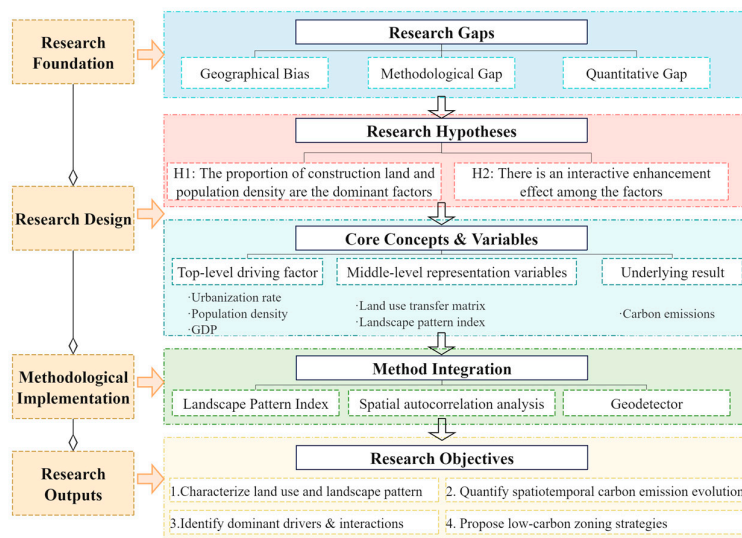


Figure 1. Theoretical framework of the study. Note: The framework illustrates the logical flow from research gaps and hypotheses through methodological integration to the final research objectives and policy implications. Arrows indicate the direction of theoretical reasoning and empirical investigation.

2. Materials and Methods

2.1. Profile of the Research Zone

The Tarim Basin Oasis Agglomeration (TBOA) in Xinjiang Uygur Autonomous Region, China, is located in the southern part of Xinjiang. It is centered around the Tarim Basin, with the Tianshan Mountains to the north and the Kunlun Mountains to the south, extending from the eastern foothills of the Pamir Plateau to the area around Rub'ulobu. An inland river, the Tarim River, has developed along the northern edge of the basin. Its geographical location and administrative boundaries are shown in Figure 2. This agglomeration covers three regions, two autonomous prefectures, and four cities of the military region, with a total area of approximately 1.05 million km². As a vital node along the Silk Road Economic Belt, it also functions as a key national energy base. This area is a typical oasis–desert composite ecosystem in a drought zone, with sparse vegetation, weak carbon sink capacity, and a low environmental carrying capacity. During the last twenty years, urbanization and agricultural expansion have been rapid, as construction land and cropland expand steadily, while natural grasslands and unused areas have gradually shrunk. It is an ideal case study area for exploring the carbon metabolism of the human–land system in a drought zone.

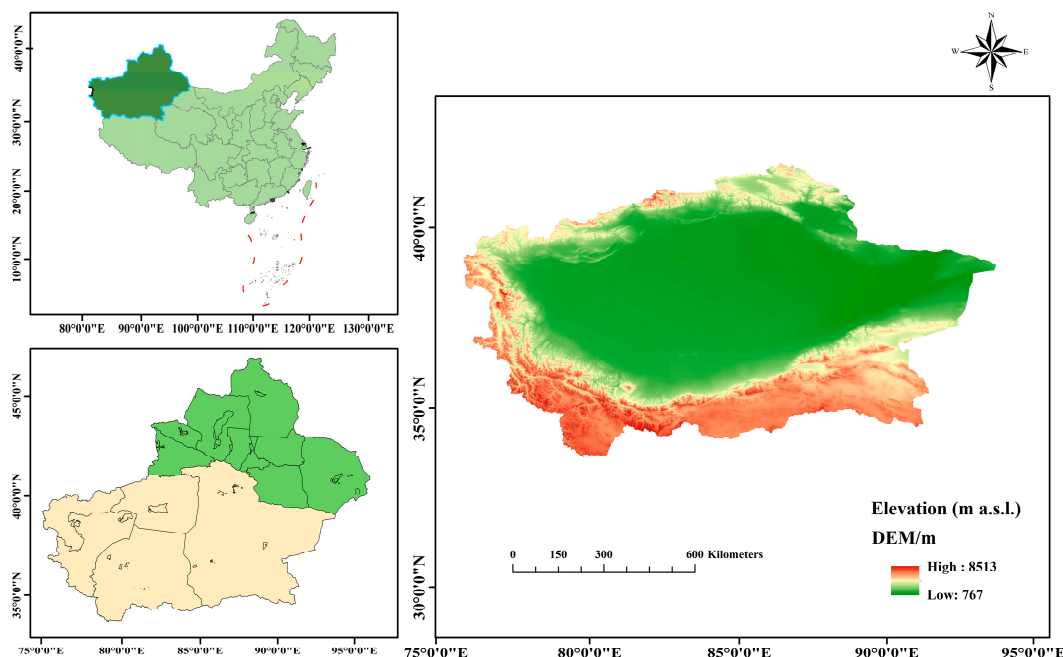


Figure 2. Overview map of the study region. Note: This map was produced based on the standard maps from the Ministry of Natural Resources’ standard map service website. The review number is GS (2024) 0650. The base map has not been modified. The same as below.

2.2. Data Source and Preprocessing

(1) Land use data: The CLCD (China Land Cover Dataset) product released by Huang Xin’s team from Wuhan University (<https://zenodo.org/record/4417810> (accessed on 12 April 2025)) was adopted. Five sets of data from 2000, 2005, 2010, 2015, and 2020 were selected. This dataset was produced based on Landsat remote sensing images, with a spatial resolution of 30 m. The CLCD product was generated by the team led by Huang Xin at Wuhan University using the Google Earth Engine platform, based on Landsat imagery, and applying a random forest classifier (supervised classification). According to the official documentation and related publications, the dataset has an overall accuracy of 84.2% and a Kappa coefficient of 0.82 [39]. According to the “Land Use Status Classification” (GB/T21010-2017) [40], using ArcMap 10.8 software, the original land categories (a total of 9 categories) were reclassified into six categories: cropland, forest land, grassland, water bodies, construction land, and unutilized land. This reclassification follows the standard land-use categories recommended by the IPCC Guidelines for National Greenhouse Gas Inventories [41], which define six broad land-use categories as the basis for estimating and reporting greenhouse gas emissions and removals from land use and land-use conversions. The consolidation of the original nine categories into six classes was based on (1) functional similarity in carbon source/sink characteristics (e.g., forest and bush were merged into forest land due to their similar carbon sequestration functions; waters, ice and snow, and wetlands were merged into water bodies as they all exhibit carbon sink effects with comparable emission coefficients); (2) consistency with previous studies in Xinjiang and other arid regions to ensure cross-study comparability [42–44]; and (3) data availability and classification accuracy of the CLCD product, as finer subdivisions may introduce greater classification uncertainty. It should be noted that this aggregation may to some extent smooth out the local differences within each category (for example, there may be differences in the carbon sequestration capacity of different types of wetlands). However, given that the overall accuracy of the CLCD product is 84.2% and the combined

subcategories account for a relatively small proportion in the study area, this smoothing effect is unlikely to affect the main conclusions. This potential limitation has been acknowledged in Section 4.4 of the main text. The projection coordinate was uniformly set as WGS_1984_UTM_zone_45N. The area was aggregated and statistically calculated after clipping with the TBOA administrative boundary.

(2) Digital Elevation Model (DEM): Derived from the Geospatial Data Cloud Platform (<https://www.gscloud.cn/> (accessed on 12 April 2025)), the SRTM V4.1 product with a spatial resolution of 90 m, is only used for extracting the research area boundary and for terrain illustration.

(3) Supplementary Data: Energy consumption data, covering 8 types of energy sources such as raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas. Social economic data, including population (permanent population, population density), regional GDP (Gross Domestic Product), per capita GDP, proportion of output value of the primary industry, local general public budget revenue and expenditure, and fixed asset investment, etc. All of these mainly come from the “New Xinjiang Statistical Yearbook”, “New Xinjiang Production and Construction Corps Statistical Yearbook”, and the “National Economic and Social Development Statistical Bulletins” of various prefectures and cities (from 2001 to 2021). For the missing data of some prefectures and cities in certain years, the linear interpolation method is used to fill in the blanks.

(4) Analytical software: Spatial data processing and study area mapping use ArcMap 10.8; landscape pattern index calculation uses Fragstats 4.2; spatial autocorrelation analysis uses GeoDa 1.20. The Queen adjacency method is adopted to build the spatial weight matrix (i.e., prefectures sharing boundaries or vertices are regarded as adjacent); GeoDetector uses the 2018 version, selects the quantile method, and sets the number of categories to 3.

The rationale for selecting the data sources and analytical tools is as follows. The CLCD product was chosen because it provides 30 m resolution land cover data at five-year intervals (2000–2020), which aligns precisely with the temporal design of this study. Its overall accuracy of 84.2% and Kappa coefficient of 0.82 ensure reliable classification for the study area. The eight energy types (raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas) were selected because they represent the primary fossil energy consumption categories in the Tarim Basin, covering over 95% of the region’s total energy use, with well-documented conversion coefficients in the China Energy Statistical Yearbook and emission factors in the IPCC guidelines. The analytical software was chosen because it is widely recognized and extensively applied in land-use carbon emission studies: ArcMap 10.8 for GIS processing, Fragstats 4.2 for landscape pattern indices, GeoDa 1.20 for spatial autocorrelation, and GeoDetector 2018 for factor and interaction detection [30,31,45–48].

(5) Applicability of carbon emission coefficients in arid regions: The carbon emission (absorption) coefficients for cropland, forest land, grassland, water bodies, and unutilized land used in this study were not directly adopted from the default values of the IPCC or the results of studies in humid areas. Instead, they were locally modified in light of established academic results in Xinjiang and the arid regions of Northwest China [42–44]. The basis for the adjustment of each coefficient is presented in Table 1. To assess the robustness of our results to coefficient uncertainty, we conducted a sensitivity analysis by varying the cropland and grassland emission (absorption) coefficients by $\pm 20\%$ (see Supplementary Material S1 for details). The results show that after excluding two low-carbon-emission units (Kizilsu Prefecture and Kunyu City) where local ranking swaps occurred under the S1 and S4 scenarios, the Spearman rank correlation coefficient of the remaining prefectures was 1.00, indicating that the spatial ranking of carbon emissions remained perfectly

consistent across all scenarios. This confirms that the core conclusions of this study are robust to coefficient uncertainty.

Table 1. Carbon emission coefficient and its applicability in arid regions.

Land Use Category	Coefficient (t/hm ²)	Applicability for Arid Regions	References
Cropland	0.497	In arid areas, cropland relies on irrigation and the extraction of fossil energy for water supply, resulting in high energy consumption for agriculture and a higher emission coefficient than the national average.	[42]
Forest Land	−0.628	The Tarim Basin is dominated by desert riparian forests (such as poplar forests), with sparse tree cover and slow growth, resulting in limited carbon sequestration capacity.	[42,44]
Grassland	−0.039	The vegetation coverage in arid grasslands is low, and it is significantly limited by water resources. The carbon sink capacity of arid grasslands is much lower than that of grasslands in humid areas.	[43,44]
Water Body	−0.248	Based on the measured water body data from the arid areas surrounding the Tarim Basin, this reflects the actual situation of sediment carbon burial.	[42,44]
Unutilized Land	−0.005	The organic carbon content in desert soil is extremely low, and its carbon sink capacity is negligible.	[43]

Note: The sign of the coefficient indicates the direction of carbon flux. A positive value denotes a net carbon emission source, while a negative value denotes a net carbon sink (absorption).

To quantify the influences of coefficient uncertainty on the research results, a sensitivity analysis was conducted in this study (see Supplementary Material S1). When the coefficients of cropland and grassland were changed by $\pm 20\%$, the local rankings of the two low-carbon emission zones (Kechuan and Kunyu City) in Kuning Prefecture swapped in the S1 and S4 scenarios. However, after excluding these two zones, the rankings of the remaining prefectures and cities were completely consistent with the baseline scenario (Spearman rank correlation coefficient = 1.00). The local swaps did not affect the macroscopic division of high, medium, and low carbon emission zones, and the core conclusion was robust.

2.3. The Basis for Scale Selection

(1) In terms of spatial scale, this study takes prefectures and cities as the basic analytical unit, for three reasons. Firstly, prefectures and cities within the TBOA region exhibit significant gradient differences in natural conditions and social economy, providing sufficient sample diversity for identifying spatial heterogeneity of carbon emissions. Secondly, the land use area is derived from 30 m remote sensing images, while data such as energy and population are based on prefecture and city as the statistical unit. Analyzing with a unified unit can avoid calculation errors caused by mismatch in scale. Thirdly, global Moran's I and geographic detectors require samples to have clear spatial adjacency relationships. The boundaries of prefectures and cities are clear and they are adjacent to each other, meeting the requirements for constructing the spatial weight matrix. In addition, aggregating the grids to the prefecture and city scale retains the area information while effectively suppressing random noise of pixels and enhancing the robustness of the calculation.

(2) In terms of time scale, the observation window is set from 2000 to 2020, and five sections are defined at 2000, 2005, 2010, 2015, and 2020. The reasons are as follows: Firstly, 2000 was the starting year of the Western Development Program, and 2020 was the year before the proposal of the “carbon neutrality” goal. This period fully covers the acceleration period of regional land use transformation and carbon emission growth. Secondly, the 5-year interval can capture the medium-term trend and avoid false signals caused by annual fluctuations. Thirdly, the CLCD product precisely provides the data for the aforementioned equally spaced years, ensuring the temporal comparability; energy and social-economic data are selected for matching years to achieve data alignment from multiple sources and reduce information redundancy.

In conclusion, the multi-scale scheme adopted in this study, which involves “grid extraction-aggregation by prefectures and cities-five-section analysis”, achieves a reasonable balance among data availability, statistical robustness, and spatial heterogeneity characterization. It is suitable for carbon emission research of the human-land system in dryland areas.

2.4. Research Methods

As shown in Figure 3, the methodological framework of this study consists of six interconnected modules: (1) land use data preprocessing and reclassification; (2) land use change analysis (structure and transfer matrix); (3) landscape pattern index calculation (Fragstats 4.2); (4) carbon emission accounting (direct + indirect); (5) spatial autocorrelation analysis (GeoDa 1.20); and (6) geographic detector modeling (GeoDetector 2018) for single-factor and interaction detection. The arrows indicate the logical flow from data preparation to result interpretation and policy recommendations.

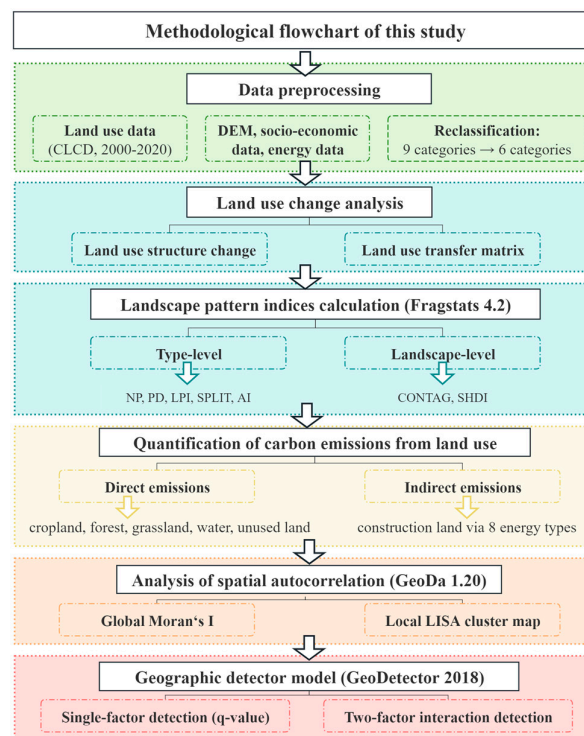


Figure 3. Methodological flowchart of the study.

2.4.1. Land Use Change Analysis

Land use transfer matrix analysis is a standard approach in land use change studies to quantify transitions between land categories over time [1,10].

The land use transfer matrix can quantitatively represent the transformation direction and area change in various land categories in different periods, and directly reflect the evolution characteristics of land use structure. Its expression is:

$$S_{ij} = \begin{bmatrix} S_{11} & S_{12} & \dots & S_{1n} \\ S_{21} & S_{22} & \dots & S_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & \dots & S_{nn} \end{bmatrix} \quad (1)$$

In the formula: S_{ij} represents the area of transformation from land category i to land category j within the study period; n is the number of land use types. The values on the diagonal represent the area where no transformation occurred among land categories, while the other values represent the area of mutual transfer between land categories.

2.4.2. Landscape Pattern Index

Landscape pattern indices were calculated following the methodological framework established by McGarigal and Marks (1995) [49].

With available land use data, the landscape patterns of the oasis urban agglomerations in the Tarim Basin in 2000 and 2020 were analyzed using the landscape pattern index. The index was calculated using Fragstats 4.2, a dedicated software for landscape pattern analysis. All landscape pattern indices (NP, PD, LPI, SPLIT, AI, CONTAG, SHDI) were computed using this software. Seven indicators at the type level and landscape level were selected to reflect the changes in landscape patterns before and after 20 years of land use. The definitions and calculation formulas of each landscape pattern index are presented in Table 2.

Table 2. Meaning and calculation formula of landscape pattern index.

Landscape Pattern Index		Meaning	Calculation Formula
Type Level	Number of Patches (NP)/each	Indicates the number of patches within the same kind of landscape mosaic; a higher value indicates a larger quantity of patches.	$N_p = q_j(q_j \text{ denotes the number of patches of land use type } j \text{ within the landscape mosaic})$
	Patch Density (PD)/(number/km ²)	Indicates the number of patches per area of unit; a higher value indicates better patch segmentation.	$P_D = \frac{q_j}{A} (q_j \text{ is the same as above, } A \text{ represents the total area of the landscape})$
	Largest Patch Index(LPI)/%	Helps identify predominant landscape classifications that indicate the trajectory and magnitude of human endeavors.	$I_{LP} = \frac{\max \sum_{j=1}^m a_{ij}}{A} \times 100\% (a_{ij}: \text{The area of the } j\text{-th patch in the } i\text{-th type of landscape; } m: \text{The total number of patches})$
	Splitting Index (SPLIT)	Directly reflects the extent of fragmentation resulting from the division of landscape space; a superior value indicates greater human impact on the ecosystem.	$I_{SPLIT} = \frac{A^2}{\sum_{j=1}^m a_{ij}^2} (a_{ij}, A, m, j \text{ are defined in the same way as above})$
	Aggregation Index (AI)/%	Indicates the degree of clustering among landscape patches;	$I_A = \left[\frac{g_{ii}}{\max(g_{ii})} \right] \times 100\% (g_{ii}: \text{The number of similar adjacent patches of type } i, \text{ that is, the actual number of})$

	higher values indicate greater clustering of similar patches.	adjacent boundaries between patches of the same type; $\max(g_{ii})$: The maximum possible number of adjacent edges.)
Land-scape Level	Contagion Index (CONTAG)/% Reflecting the extent of aggregation or tendency toward extension across several patch types within a landscape, a higher value indicates better patch connectivity.	$I_{\text{CONTAG}} = \left[1 + \frac{\sum_{i=1}^n \sum_{k=1}^n \left[P_i \left(\frac{g_{ik}}{\sum_{k=1}^n g_{ik}} \right) \right] \left[\ln(P_i) \left(\frac{g_{ik}}{\sum_{k=1}^n g_{ik}} \right) \right] \right]}{2 \ln n} \right] (P_i:$ The proportion of the area occupied by the i-th landscape type; g_{ik}: The number of adjacent edges between land class i and land class k; n: The total number of landscape types)
	Shannon's Diversity Index (SHDI) Reflect the landscape heterogeneity, the higher the value indicates greater land use diversity and increased fragmentation.	$I_{\text{SHD}} = - \sum_{i=1}^n (P_i \cdot \ln P_i)$ (where P_i is the proportion of the total landscape area occupied by land use type i, and n is the total number of land use types.)

Note: The meanings of the same variables in the table are the same; the meanings of all variables in the table are consistent with the definitions provided in the user manual of the Fragstats software.

The above landscape pattern indices were calculated to characterize the spatial configuration and fragmentation of different land use types in the TBOA region. These indices serve as quantitative proxies for landscape structure, which are subsequently linked to carbon emissions in Section 3.2.3. Specifically, we analyze how landscape fragmentation (e.g., increasing NP and PD) and aggregation (e.g., changing AI) relate to the strengthening of carbon sources and the weakening of carbon sinks, thereby establishing a quantitative connection between landscape pattern evolution and carbon emission dynamics.

2.4.3. Quantification of Carbon Emissions from Land Use

Based on the existing research and the classification criteria proposed by related studies, land use-related carbon emissions fall into the category of direct emissions arising from structural changes in land use itself, and indirect emissions generated during land use activities.

Of these, direct emissions are derived from cropland, forest land, grassland, water bodies and unused land. In contrast, construction land hosts human production and residential activities and thus represents indirect emissions.

Accordingly, the formula used to estimate land use carbon emissions is as follows:

$$C = C_x + \sum C_y, \quad (2)$$

where C is the sum of carbon emissions and C_x is the indirect carbon emissions. C_y is the direct carbon emissions, which can be obtained through the IPCC carbon accounting coefficient method. The calculating formula is as follows:

$$C_y = S_y \times f_y, \quad (3)$$

In the formula, S_y denotes the area of the corresponding land category (in hectares), and f_y represents the carbon emission (absorption) coefficient for each category, with the unit being t/hm^2 . The sign of f_y has a clear physical meaning: a positive value indicates net emission (carbon source), while a negative value indicates net absorption (carbon sink). The specific values for each category are listed in Table 1. Because construction land serves multiple human production activities, its indirect carbon emissions cannot be directly calculated using the above formula. By contrast, indirect carbon emissions are estimated from energy consumption linked to construction land.

Based on the accessibility of the existing data, this study chooses eight types of energy: coal, coke, crude oil, gasoline (known as petrol in British English), kerosene, diesel, fuel oil, and natural gas, and includes them in the calculation.

The following is the calculating formula:

$$C_x = \sum C_i = \sum E_i \times j_i \times k_i, \quad (4)$$

where C_x is the indirect emissions of carbon; C_i is emissions of carbon resulting from energy usage of type i ; E_i is the energy consumption of type i ; j_i is the discounted coal coefficient of type i ; and k_i is the emissions of carbon coefficient associated with the consumption of energy of the specified type i . The specific coefficients in the formula are detailed in Table 3.

Table 3. Conversion factors for energy standard coal and carbon emission factors.

Type of Energy	Standard Coal Conversion Coefficient/t·t ⁻¹	Carbon Emission Coefficient/t·t ⁻¹	References
Raw Coal	0.7143	0.7559	methodological framework [42,43]; coefficient sources [41,50]
Coking Coal	0.9714	0.855	
Crude Oil	1.4286	0.59	
Gasoline	1.4714	0.59	
Kerosene	1.4714	0.57	
Diesel Fuel	1.457	0.59	
Fuel Oil	1.4286	0.62	
Natural Gas	12.143	0.4483	

The data sources for energy consumption, land-use area, and carbon emission coefficients are described in Section 2.2 (1), Section 2.2 (3), Section 2.2 (5) and Tables 1 and 3, respectively.

2.4.4. Analysis of Spatial Autocorrelation

Moran's I index was initially established by Moran (1950) [45]. It is a statistical indicator used to measure spatial autocorrelation, which can effectively detect and quantify the autocorrelation in spatial data, helping to better grasp the spatiotemporal evolution patterns of land use-related carbon emissions across the research region. It has been extensively used in research on spatial patterns of carbon emissions from land use [2,46]. Generally, the global Moran's I index is used to explore the spatial layout of land use carbon emissions. Its value range is $[-1, 1]$. A positive correlation is indicated when the index > 0 , a negative correlation when the index < 0 , and an insignificant spatial correlation when the index $= 0$. The calculation formula is presented below:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij} \sum_{i=1}^n (x_i - \bar{x})^2}, \quad (5)$$

where I is the global Moran's I index, n represents the quantity of units of the prefecture and municipalities in the research zone, W_{ij} represents the spatial weighting matrix between neighboring prefecture and municipalities, x_i and x_j are the carbon emissions of neighboring prefecture and municipalities, and $\bar{x}$ denotes the average value of carbon emissions of units of prefecture and municipalities.

The global Moran's I and local LISA cluster maps were computed using GeoDa 1.20, a software package designed for spatial autocorrelation analysis.

Conducting spatial autocorrelation studies requires establishing an appropriate spatial weighting matrix. In the oasis urban agglomerations of the Tarim Basin studied herein, adjacent prefectures and cities share spatial contiguity, and each spatial unit exhibits ir-

regular area and shape. Consequently, the spatial weighting matrix created is an adjacency matrix. Establishment of the spatial weight matrix usually adopts the Queen adjacency method (i.e., units sharing boundaries or vertices are regarded as adjacent). This method has become a standard practice in spatial autocorrelation analysis, and its theoretical basis can be found in classic literature such as Anselin (1995) [47] and others. The formula for calculation is as follows:

$$W_{ij} = \begin{cases} 1 & \text{if spatial units } i \text{ and } j \text{ are adjacent} \\ 0 & \text{if spatial units } i \text{ and } j \text{ are not adjacent} \end{cases} \quad (6)$$

2.4.5. Geographic Detector Model

Geographic detector is a quantitative tool used to analyze the disparities in the distribution of space of geographic things and their influencing factors, which can decompose complex geographic phenomena into multiple influencing factors, and then analyze the independent role and interaction of each factor. This method was proposed by Wang Jinfeng et al. [48] and has been extensively applied in research fields such as land use change, spatio-temporal variation of carbon emissions, and driving mechanisms of carbon storage [1,15,18,29]. All single-factor and interaction detection analyses were performed using GeoDetector 2018 software (<http://www.GeoDetector.cn/> (accessed on 12 April 2025)). It also provides strong support for the study and practice of driving factors of carbon emissions from land use.

This research focuses on utilizing the identification of factors and the detection of interaction functions of the GeoDetector. The factor identification module evaluates the interpretation of the geographical patterns of land utilization and carbon emissions by each influencing determinant predicated on the q-value, with the specific formulas outlined as follows:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} \quad (7)$$

where q is the explanatory strength of impacting usage emissions of carbon, $h = 1, \dots, L$ is the categorization or division of land usage emissions of carbon in determinant X , N_h and N are the number of samples in stratum h and the study region, respectively. σ_h^2 and σ^2 are the variance of Y values in stratum h and the entire region; $q \in [0, 1]$, and the larger the value of q , the more potent the factor's effect regarding the Y value of the dependent variable.

Based on the above principle, this study selected 11 influencing factors from six dimensions: land use structure, economic development, population size, ecological greening, fiscal revenue and expenditure, and investment level (Table 4). Referring to the relevant theoretical framework of land use carbon emission drivers [29,30], the selection logic of each factor is as follows: Land use structure (X_1, X_2) relies on the transmission mechanism of "land use transformation $\rightarrow$ carbon emission", which has been applied in related studies [1,10]. Level of economic development (X_3, X_4) and industrial structure (X_5) are key influencing factors, based on the analytical framework for separating economic growth from carbon emissions [14]. Population size (X_6, X_7) represents the direct driving force of human activities on energy consumption and land use pressure [11]. Greening level (X_8) represents the regional ecological carbon sink capacity. Financial status (X_9, X_{10}) and investment level (X_{11}) reflect the indirect influence of local government macro-control and capital expansion on carbon emissions [15].

All these variables are mature indicators widely used in the research of carbon emissions from land use [2,3,8,12].

Table 4. Factors affecting emissions of carbon from land usage.

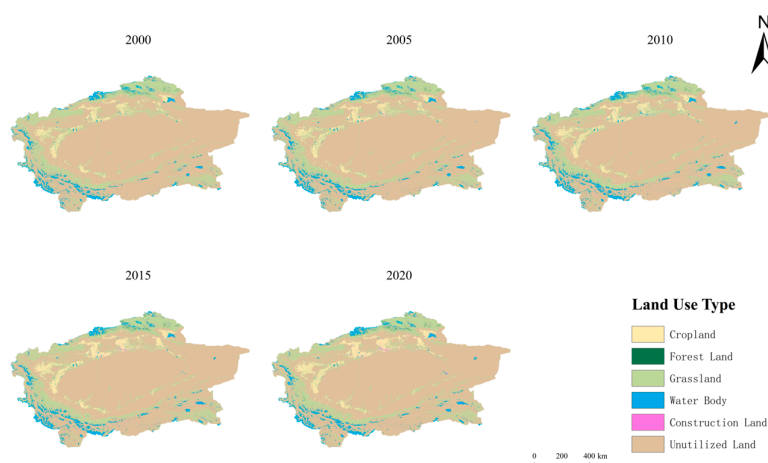
Impact Factor Perspective	Specific Relevant Variables	Unit/Explanation
Land Utilization Structure	X1: Proportion of the construction site area to total area	%
	X2: Cultivated land area as a proportion of total area	%
Degree of Economic Advancement	X3: GDP (10,000 RMB/person)	10,000 yuan per person
	X4: GDP per capita (10,000 RMB/person)	10,000 yuan per person
Level of Industrial Structure	X5: Share of primary sector output	%
Size of Population	X6: Permanent population (10,000 persons)	Ten thousand people
	X7: population density	people/km ²
Greening Level	X8: normalized difference vegetation index(NDVI)	Dimensionless
Financial Position	X9: Local general public budget revenues (10,000 RMB)	Ten thousand yuan
	X10: Local general public budget expenditures (10,000 RMB)	Ten thousand yuan
Regional Investment Level	X11: Investment in fixed assets (10,000 RMB)	Ten thousand yuan

3. Results and Analysis

3.1. Characteristics of Land Use Structure Changes in 20 Years

3.1.1. Spatial Distribution of TBOA Land Use Types

The spatial distribution of land use types in TBOA from 2000 to 2020 is presented in Figure 4. The spatial distribution presents a macroscopic pattern of “unused land as the dominant type, followed by grassland”. Unused land accounts for more than 70% of the region’s total area, while grassland is mainly distributed in the periphery of the basin (about 18%). Cropland and water bodies are scattered in patches within the oasis area (accounting for between 2% and 5%), and forest land and construction land are both less than 0.5%.

**Figure 4.** Spatial distribution of land use types in TBOA from 2000 to 2020.

The land utilization types in the TBOA region underwent significant changes during the study period (as shown in Table 5 and Figure 4). During the period 2000–2020, the net area of unused land decreased by 16,100 km² (−1.534%), while the net area of cropland increased by 13,700 km² (+1.305%). The growth of construction land was the most intense, with an area increase from 36777 km² to 2459.95 km², representing a growth rate of

568.88%. It should be noted that this substantial percentage increase is largely attributable to the very small baseline area in 2000 (367.77 km²); the absolute increase of 2092.18 km² is moderate relative to the total area of the region. The changes in the other land categories were all less than 0.3%.

Table 5. 20-year changes in TBOA land utilization types.

Land Type	2000		2020		2000–2020	
	Area/km ²	Ratio/%	Area/km ²	Ratio/%	Area Change/km ²	Change Ratio/%
Cropland	29,932.62	2.851	43,634.54	4.156	13,701.92	1.305
Forest Land	1216.71	0.116	1618.5	0.154	401.79	0.038
Grassland	192,505.26	18.334	189,908.08	18.087	−2597.18	−0.247
Water Body	33,134.77	3.156	35,641.81	3.395	2507.04	0.239
Construction Site	367.77	0.035	2459.95	0.234	2092.18	0.199
Unutilized Land	792,820.33	75.508	776,714.54	73.974	−16,105.79	−1.534

3.1.2. Distribution of TBOA Land Use Transfers

Regarding the conversion of land utilization types (Figure 5), the TBOA region underwent significant structural adjustments in its land use patterns between 2000 and 2020. The total scale of land type transfers amounted to approximately 8.06×10^4 km², accounting for 7.8% of the aggregate land area of the region. The unutilized land transfer constituted 48.3% of the total transfer volume, mainly flowing to grasslands (2.79×10^4 km²); the grassland transfer accounted for 42.1%, mainly deteriorating into unutilized land (1.94×10^4 km²) or being converted into cropland (1.21×10^4 km²) (Figure 5). The transfer volumes of other land types were all less than 10%.

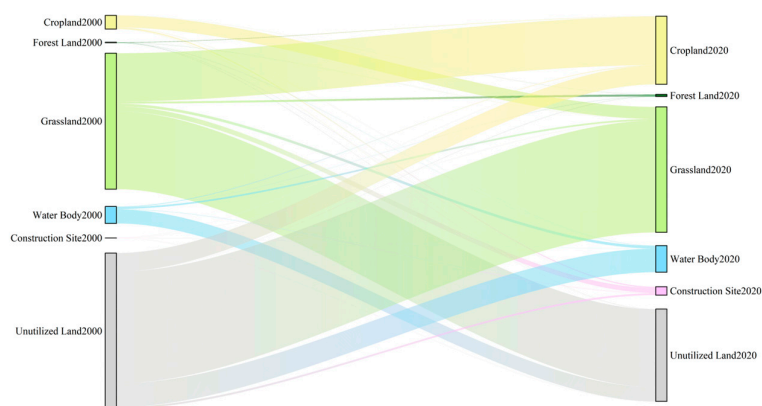


Figure 5. 2000–2020 TBOA land usage change Sankey diagram. Note: Colors represent different land use types, with the width of the flows proportional to the area transferred.

As demonstrated in Figure 6, the conversion of land use across the TBOA region indicates that unutilized land turning into grassland displays prominent spatial agglomeration. This conversion is predominantly concentrated along the eastern and southern margins of the Tarim Basin, with a particular focus on the outer periphery of oases surrounding Bayingolin Mongol Autonomous Prefecture and Hotan City. In contrast, the process of grassland degradation into unutilized land is widespread in Hotan Prefecture, manifesting as multiple discontinuous patches. This phenomenon also occurs in western Aksu Prefecture, but exhibits a more fragmented spatial pattern. The transformation of grassland into cropland is notably concentrated along the eastern and southern borders of the Kashgar region. Additionally, across the western and southern sides of the Hotan area,

such transitions have also formed concentrated distribution zones along the foothill oasis belt at the northern base of the Kunlun Mountains. Transformations among different land categories not only reveal the dynamic changes in regional ecosystem structure, but also reflect the spatial complexity and diversity of driving forces.

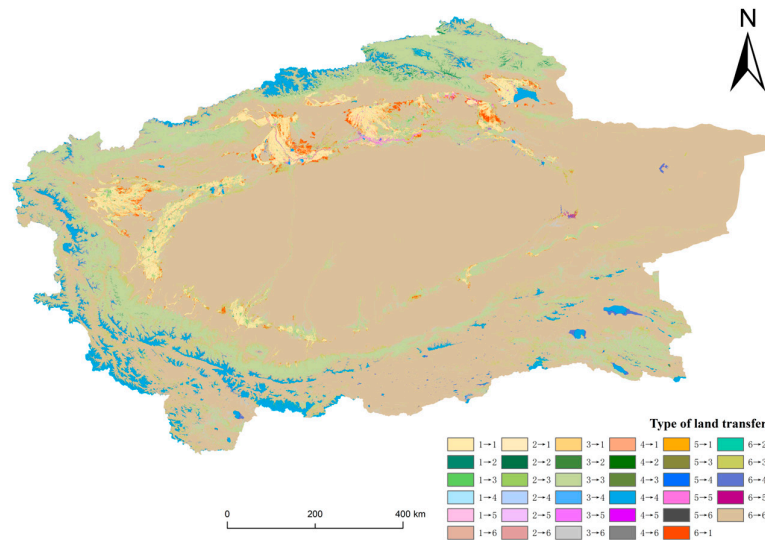


Figure 6. Geographic distribution of land usage conversion types in TBOA from 2000 to 2020.

3.2. Analysis of Land Use Landscape Pattern Indices

3.2.1. Landscape Pattern Index Analysis at the Type Level

Landscape pattern indices at the class level were calculated using the Fragstats model and TBOA land use data over the period 2000–2020 (Table 6). This enabled a comparative analysis of landscape changes across TBOA 20a.

Table 6. TBOA20a-type landscape pattern index at the horizontal level.

Period	Land Type	NP/Each	PD/(Each/km ²)	LPI/%	SPLIT	AI/%
2000	Cropland	51,278	0.0497	0.2538	39,835.8745	85.9596
	Forest Land	17,341	0.0168	0.0050	188,470,644.5800	54.0156
	Grassland	463,871	0.4492	6.5076	208.5421	84.7445
	Water Body	81,887	0.0793	0.2251	47,159.6553	84.4468
	Construction Site	16,806	0.0163	0.0004	14,047,343,488.9612	23.5737
	Unutilized Land	252,756	0.2448	72.2984	1.9131	96.4525
2020	Cropland	52,550	0.0509	0.5466	10,917.4215	87.0216
	Forest Land	22,378	0.0217	0.0038	190,877,909.2025	55.5721
	Grassland	487,214	0.4718	5.9696	228.4193	83.4649
	Water Body	56,675	0.0549	0.2469	38,002.7721	88.3242
	Construction Site	47,771	0.0463	0.0059	64,337,694.3617	45.7856
	Unutilized Land	251,159	0.2432	70.8363	1.9929	96.3731

Based on an analysis of the regional landscape pattern index for TBOA from 2000 to 2020, its spatial heterogeneity exhibits significant dynamic differentiation characteristics. The cropland shows a trend of concentration (with an increase in LPI and a decrease in SPLIT); although grassland serves as the landscape base, the core patches have shrunk and become more fragmented; the number of construction land patches has sharply increased and their concentration degree has risen, reflecting the coexistence of expansion

and intensification in urbanization; forest land continues to be highly fragmented, restricting its ecological functions. Water bodies tend toward structural stability and spatial connectivity, while unutilized land maintains a highly continuous, super-stable state, forming the regional natural baseline. Overall, the evolution of spatial heterogeneity in the TBOA region reflects the spatial reorganization driven by the interaction between anthropogenic activities and natural processes.

3.2.2. Landscape Pattern Index Analysis at the Landscape Level

Throughout the duration of the research, two indices at the TBOA landscape level exhibited distinct trends (Table 7).

Table 7. TBOA20a landscape pattern index at the landscape level.

Period	CONTAG/%	SHDI
2000	71.9836	0.7471
2020	69.9857	0.8063

From 2000 to 2020, the overall spatial configuration of the TBOA region exhibited significant structural reorganization and enhanced heterogeneity. The spread index decreased from 71.98% to 69.99%, indicating a weakening of connectivity and control among dominant patch types within the landscape, with spatial aggregation tending to diminish. Meanwhile, the Shannon diversity index increased from 0.7471 to 0.8063, indicating enhanced richness in landscape composition types and improved uniformity in area distribution, with spatial heterogeneity patterns becoming more complex.

The coupled dynamics of these changes reveal that under the simultaneous influences of swift urbanization and ecological management, the landscape matrix in the TBOA region—originally dominated by one or several land use types—is gradually being replaced by a diverse, mixed pattern. The proliferation of construction land, internal consolidation of cropland, and fragmentation of natural factors including forests and grasslands collectively contribute to an overall trend toward landscape diversity and dispersion. This evolutionary trajectory profoundly embodies the characteristic transformation of regional landscape spatial structures from relative homogeneity to heterogeneous diversity under human intervention.

3.2.3. Relationship Between Landscape Patterns and Carbon Emissions

The landscape pattern in the TBOA region from 2000 to 2020 was closely coupled with carbon emissions. First, the rapid expansion and clustering of construction land dominated the growth of carbon emissions. The increase in patch quantity and density broadened the spatial scope of energy consumption, substantially raising fossil fuel use and direct carbon emissions. Meanwhile, the scale effect of such expansion became a major contributor to the growth of carbon sources. Secondly, the fragmentation of natural ecological land weakened the carbon sink function: the core patches of forests and grasslands shrank and isolated, lowering the vegetation carbon sequestration capacity, and having a continuous negative effect on regional carbon balance. Furthermore, the “internal optimization” of cropland had a dual impact: the concentration of dominant patches could reduce agricultural energy consumption and lower unit carbon emissions, while the abandonment of marginal cultivated land might promote the restoration of natural vegetation, forming potential carbon sinks. In conclusion, the evolution of the landscape pattern towards heterogeneity and fragmentation intensified the regional carbon metabolic pressure through two paths: “strengthening carbon sources” and “weakening carbon sinks”. Optimizing the landscape pattern and enhancing the connectivity and stability of ecological space should become the key path for future low-carbon territorial spatial governance.

It should be noted that the landscape pattern indices reported in this study are descriptive metrics calculated from land-use raster data at two time points (2000 and 2020). The interpretations of landscape pattern changes (e.g., fragmentation, aggregation, diversification) are based on direct comparisons of index values between the two time points. While these indices are standard measures in landscape ecology and have been widely used to characterize landscape structural changes, they do not involve statistical significance testing. Future studies could employ permutation-based tests or time-series landscape analyses to further validate the observed trends.

3.3. Spatiotemporal Development Trends of Land-Use-Related Carbon Emissions

With rapid advances in urbanization, energy consumption in the oasis cities of the Tarim Basin has steadily increased. Land utilization carbon emissions in the Tarim Basin Oasis Area (TBOA) also showed a continuous increasing trend over the period 2000–2020, rising from 1.4455 million tons in 2000 to 22.364 million tons in 2020. The apparent 15.5-fold increase is largely attributable to the very low baseline in 2000 (construction land was only 367.77 km², with minimal energy consumption), combined with rapid urbanization and industrial development during 2000–2020, which led to a sharp rise in fossil energy consumption. The annual growth rate of carbon emission levels in the study area was approximately 14.68%. Significant variations in carbon emission growth rates were observed during the duration of the research (Figure 7), exhibiting an overall pattern of initially slow growth followed by rapid acceleration.

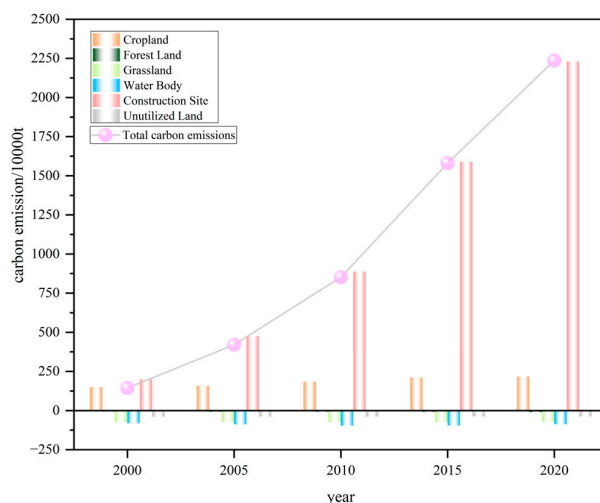


Figure 7. Changes in carbon emissions by land utilization type in TBOA from 2000 to 2020.

The construction land is the dominant carbon source (with the proportion decreasing from 139.9% to 99.8%, but the total amount increasing), while the cropland is the secondary carbon source; grassland and water bodies are the main carbon sinks, and the forest land has limited carbon sink capacity due to the sparse desert riverbank forests (Figure 7). Due to the study area's unique topography, vast tracts of unutilized land also exhibit a pronounced carbon sink effect.

To provide a more intuitive understanding of carbon emissions across prefectures and cities, this article categorizes carbon emissions (and absorption) into four distinct levels: ① Carbon Absorption Zones (annual carbon emissions below 0 t); ② Low Carbon Emission Zones (annual carbon emissions ranging from 0 to 100×10^4 t); ③ Moderate Carbon Emission Zones (annual carbon emissions ranging from 100×10^4 to 500×10^4 t);

④ High Carbon Emission Zone (annual carbon emissions exceeding 500×10^4 t). The spatiotemporal pattern of TBOA's carbon emissions within the research timeframe is shown in Figure 8. The carbon emissions in the TBOA area exhibit a distinct “core-periphery” structural feature and a phased evolution pattern in both spatial and temporal dimensions.

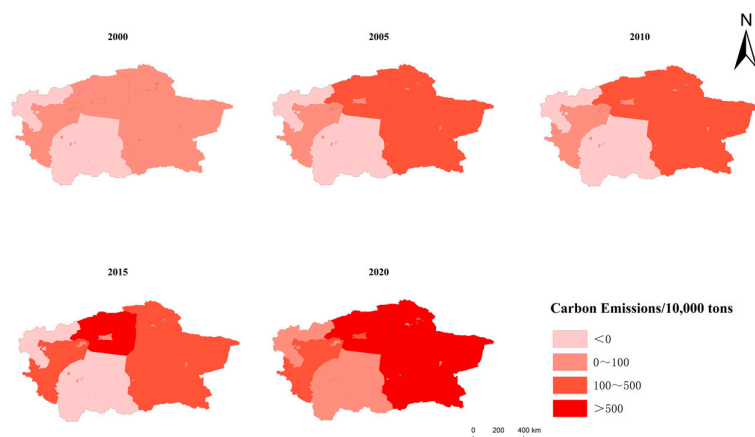


Figure 8. Spatio-temporal patterns of land utilization carbon emissions in the TBOA Region.

In spatial distribution, carbon emission intensity exhibits distinct zonation patterns: the high-emission core zone centered on Aksu-Bayingolin continues to intensify; the medium-emission belt spanning Kashgar-Aral shows axial expansion; while Kunyu City at the northern foothills of the Kunlun Mountains consistently maintains its low-carbon peripheral characteristics. Notably, Kizilsu Kirghiz Autonomous Prefecture consistently exhibits negative carbon emissions, forming a unique ecological carbon sink region.

The heat map in Figure 9 further reveals the phased evolution of carbon emissions. Time series analysis identified three distinct developmental phases: 2000–2005 marked a period of slow diffusion, with the spatial center of carbon emissions skewed toward the northern energy-intensive zone. 2005–2015 marked a rapid restructuring phase, characterized by a “unipolar surge” in carbon emissions in Aksu Prefecture, while emissions spread toward the central oasis urban belt. Post-2015 entered a high-intensity stabilization phase, with significantly enhanced spatial connectivity among high-emission zones, forming a continuous transregional carbon emission belt. This spatio-temporal evolution pattern maintains dynamic coupling with regional urbanization processes, energy base construction, and ecological security frameworks, reflecting the dual response mechanism of carbon emissions from arid region human-land systems to both the geographical environmental substrate and regional development policies. These findings offer valuable insights for optimizing low-carbon development pathways in the central Silk Road Economic Belt.

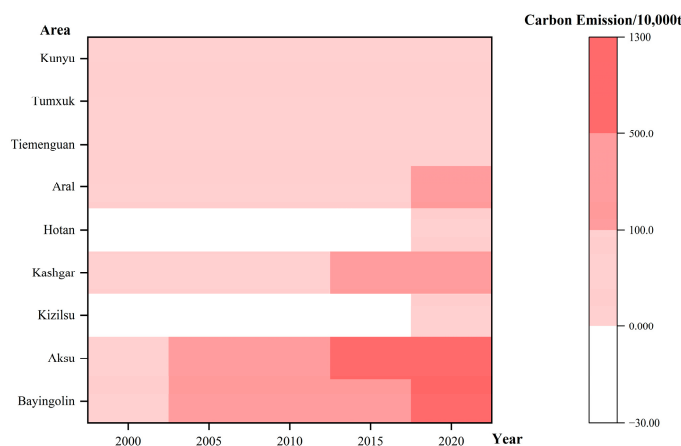


Figure 9. 2000–2020 TBOA carbon emissions spatiotemporal heat map.

3.4. Analysis of Spatial Autocorrelation of Carbon Emissions from Land Utilization

Using GeoDa software, we calculated the global Moran's I index for land-use carbon emissions across all prefecture-level cities in the TBOA region from 2000 to 2020, and tested its significance using the Z test. The results are presented in Table 8.

Table 8. Global Moran's I index for land utilization carbon emissions in TBOA (2000–2020).

Year	2000	2005	2010	2015	2020
Moran's I	−0.177	−0.174	−0.087	−0.176	−0.171
Z	−0.1498	−0.1635	0.2242	−0.2535	−0.1925
P	0.50	0.44	0.36	0.42	0.45
Sd	0.2531	0.2203	0.2459	0.1661	0.1863

The Moran's I values for each year were all negative (ranging from −0.177 to −0.087), but were not statistically significant ($p > 0.05$ for all years). This indicates that the spatial distribution of carbon emissions does not exhibit significant spatial clustering and is essentially random. The high-emission and low-emission units were distributed alternately, with a weak spatial dependence and a clear random pattern. This might be attributed to the imbalance in regional economic development and the complex natural geographical conditions. Future studies could further explore its spatial characteristics by combining local indicators.

The local LISA clustering map in Figure 10 shows that the low-high clustering areas are mainly distributed in administrative units such as Hotan, Aral, and Tegemenkou. Among the 9 prefecture-level units in the study area, local Moran's I was calculated for each unit using GeoDa 1.20 with 999 permutations. Only two units (approximately 22.2% of the total) exhibited statistically significant local spatial association at the $p < 0.05$ level, both classified as low-high clusters (Hotan and Aral). No high-high, low-low, or high-low clusters reached statistical significance. This low proportion of significant local units is consistent with the non-significant global Moran's I results reported in Table 8. During the period from 2000 to 2020, there were always two stable units, while the high-high and low-low clustering types were absent throughout the entire study period, indicating that the region has not yet formed a significant high-emission polarization core or a low-carbon collaborative plate. This low-high clustering pattern is consistent with the global Moran's I results, further indicating that the spatial dependence of carbon emissions is weak. This spatial structure may result from the interactive effects of various factors, including

differences in the economic development stages of various regions, industrial layout characteristics, and diverse land cover types, leading to an unstable spatial correlation structure of carbon emissions.

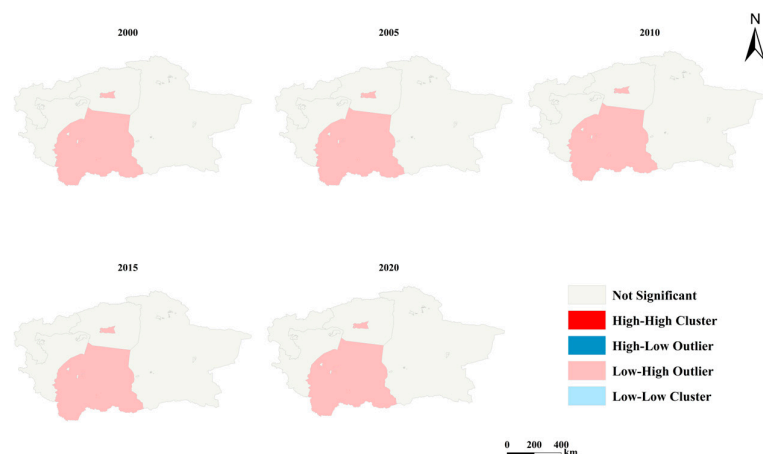


Figure 10. Spatial LISA cluster map of total carbon emissions.

3.5. Analysis of Factors Affecting Carbon Emissions from Land Utilization

3.5.1. Test for Multicollinearity

To avoid the influence of strong correlation among the driving factors on model interpretation, this study diagnosed the continuous variables in 2020 adopting the variance inflation factor (VIF). Results from the analysis show that the VIF values of some variables (X3 per capita GDP, X6 permanent population, X7 population density, X11 fixed asset investment) exceeded 10, indicating a certain degree of multicollinearity, which is relatively common in socio-economic variables. It merits attention that the geographic detector model rests on classification variance analysis and does not rely on linear regression assumptions, and has good tolerance for the problem of multicollinearity [29,30]. To further verify the robustness of the core conclusion, we deleted X3 and X6 from the high VIF variables and re-ran the geographic detector on the original three categories of classification. The results showed that X1 (construction land proportion) and X7 (population density) remained in the top two positions before and after deletion, with the q values being completely consistent (0.83996 and 0.75162), and the Spearman rank correlation coefficient was 1.00, indicating that multicollinearity did not affect the identification of the core driving factors (see Supplementary Material S2).

3.5.2. Single Impact Factor Analysis

Using GeoDetector software, the q -values for various factors influencing carbon emissions from land utilization in the oasis urban clusters of the Tarim Basin were calculated for the years 2000, 2005, 2010, 2015, and 2020. The q -values for each factor are presented in Table 9. The q values of all factors were tested through the built-in random permutation test of GeoDetector (100 times), with $p < 0.05$, indicating that each factor has statistically significant interpretation capacity for the spatial heterogeneity of carbon emissions.

Table 9. Ranking of influential factors affecting land use carbon emissions in TBOA.

Influencing Factors	2000	2005	2010	2015	2020	Average
X7	1 (0.986)	1 (0.893)	1 (0.951)	2 (0.938)	2 (0.752)	1 (0.904)
X1	7 (0.910)	2 (0.869)	3 (0.786)	3 (0.886)	1 (0.840)	2 (0.858)
X4	3 (0.915)	4 (0.758)	2 (0.946)	1 (0.944)	9 (0.148)	3 (0.741)
X9	4 (0.911)	3 (0.758)	4 (0.763)	6 (0.506)	4 (0.557)	4 (0.699)
X3	5 (0.910)	7 (0.758)	6 (0.762)	5 (0.506)	3 (0.558)	5 (0.699)
X11	6 (0.910)	6 (0.758)	5 (0.762)	4 (0.506)	5 (0.557)	6 (0.699)
X10	2 (0.913)	5 (0.758)	9 (0.241)	11 (0.009)	11 (0.038)	7 (0.392)
X5	8 (0.635)	10 (0.116)	7 (0.245)	9 (0.009)	8 (0.158)	8 (0.233)
X2	10 (0.128)	9 (0.122)	10 (0.216)	8 (0.260)	6 (0.199)	9 (0.185)
X8	11 (0.004)	8 (0.209)	11 (0.206)	7 (0.274)	7 (0.181)	10 (0.175)
X6	9 (0.237)	11 (0.112)	8 (0.241)	10 (0.009)	10 (0.038)	11 (0.127)

Note: Values in parentheses represent the q-values of land utilization carbon emissions for each influencing factor in the Tarim Basin oasis urban clusters. Values outside parentheses indicate the ranking of q-values for these factors.

The explanatory strength of each factor on the spatial heterogeneity of land use carbon emissions is measured by the q value. All factors passed the 5% significance test (Table 9). The carbon emission spatial pattern of the oasis urban agglomeration in the Tarim Basin presents a typical human-driven characteristic. Population density (X7) and the proportion of construction land (X1) are the dominant factors (average q values of 0.904 and 0.858), which are much higher than other factors; per capita GDP, fiscal revenue, and fixed asset investment rank behind, reflecting the boosting effect of economic level and investment expansion. The radar chart (Figure 11) visually shows that X7 and X1 form a “double core” dominant pattern, followed by X4, X9, X3, and X11, with the contributions of the remaining factors being relatively small. Overall, the spatial differentiation of carbon emissions in this area is mainly dominated by the degree of concentration of social and economic elements, forming a driving mode with “population–construction–economy” as the core link, profoundly revealing the reshaping effect of anthropogenic activities on the natural carbon cycle in the arid region human-land system, and providing a clear target for regional low-carbon national spatial governance.

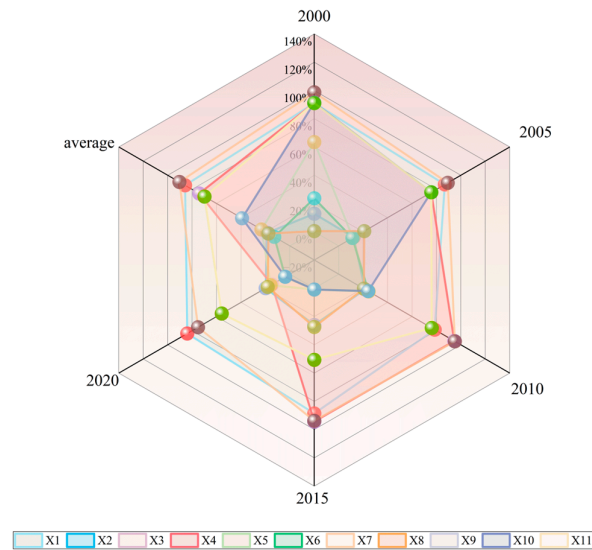


Figure 11. Contribution radar chart of influencing factors.

3.5.3. Analysis of Double Impact Factors

Figure 12 exhibits the interactive q-values of respective factor pairs (the diagonal represents single-factor q-values, and the off-diagonal values denote interaction q-values). All interaction pairs are greater than any single factor, exhibiting a dual-factor enhancement effect. There are differences in the high q-value combinations across different years: In 2000, $X1 \cap X6$, $X2 \cap X3$, and $X2 \cap X11$ were dominant; in 2005, $X1 \cap X6$, $X1 \cap X5$, and $X7 \cap X8$ were dominant; in 2010, $X1 \cap X2$, $X1 \cap X6$, $X1 \cap X10$, and $X4 \cap X9$ were dominant; in 2015, $X1 \cap X10$, $X3 \cap X7$, $X7 \cap X11$, and $X3 \cap X4$ were dominant; in 2020, $X1 \cap X2$, $X1 \cap X6$, $X1 \cap X10$, and $X6 \cap X7$ were dominant. The interaction combinations with higher average influence were $X1 \cap X2$, $X1 \cap X5$, $X1 \cap X6$, and $X7 \cap X8$. Among them, factors such as $X1$, $X4$, $X5$, $X6$, and $X10$ frequently appeared, indicating a significant comprehensive effect of land use structure, economic development level, population size, and financial status.

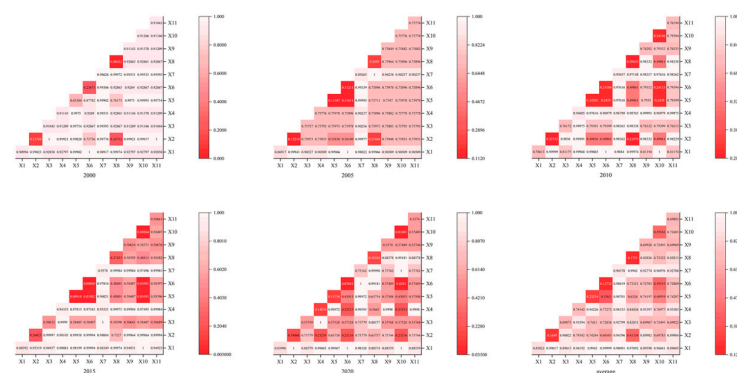


Figure 12. Two-factor analysis of carbon emission impact factors.

When analyzing temporal evolution, the changes in the high-q value combination reflect the influence of policies and regional transformation: the continuous synergy between the ratio of construction land and the permanent resident population highlights the combined pressure of urbanization and population concentration; the repeated interaction of $X1$ and $X2$ reveals the ecological-economic trade-off in land use competition; $X4$,

X5, and X10 confirm the spatial imbalance in development models and fiscal resource allocation, and through nonlinear coupling, exacerbate the scale effect of carbon emissions.

In 2020, all significant interaction pairs exhibited a dual-factor enhancement ($q(A \cap B) > \max(q(A), q(B))$), and no independent or weakening relationships were observed. Typical high-value interaction pairs included $X1 \cap X2$ ($q = 1.000$), $X1 \cap X5$ ($q = 0.9997$), $X1 \cap X7$ ($q = 0.9833$), and $X7 \cap X10$ ($q = 1.000$). Taking $X1 \cap X7$ as an example, its interaction q -value (0.9833) was significantly greater than the individual values of $X1$ (0.8400) and $X7$ (0.7516), showing a typical synergistic amplification effect. This demonstrates that the spatial differentiation of carbon emissions is driven by multi-factor synergy, with the synergy between the expansion of construction land and population concentration being particularly prominent.

The above results indicate that the ratio of construction land and population density are the primary factors causing spatial differentiation of carbon emissions in the oasis urban clusters of the Tarim Basin, and there is a significant synergistic amplification effect between the two.

It should be noted that the q -values approaching 1.0, particularly for certain interaction pairs (e.g., $X1 \cap X2$, $X7 \cap X10$), should be interpreted with caution. Two methodological factors may contribute to the observed high explanatory power: (1) the discretization procedure: the conversion of continuous variables into categorical classes (3 classes using the quantile method) may influence the magnitude of q -values; and (2) the limited sample size: the study area comprises only 9 prefecture-level units, which may inflate the explanatory power. However, several lines of evidence support the robustness of our core findings: (1) the top two dominant drivers ($X1$ and $X7$) remained consistent across multiple sensitivity scenarios with different discretization schemes (Supplementary Material S3.1) and after removal of collinear variables (Supplementary Material S2); (2) the spatial patterns were consistent across different time periods (Supplementary Material S3.2). Thus, while the absolute q -values should be interpreted with caution, the identification of the dominant drivers is robust.

4. Discussion

Based on the research results of Section 3, this section discusses four aspects of the study: the uniqueness of the driving mechanism in arid regions, regional comparisons, theoretical policy implications, and research limitations.

4.1. The Uniqueness of the Carbon Emission Driving Mechanism in Arid Regions

This research found that the dominant elements governing the spatial differentiation of carbon emissions in the oasis urban clusters of the Tarim Basin are the proportion of construction land and population density. This is significantly different from the research conclusions of urban agglomerations in humid areas (such as the Yangtze River Delta and the Pearl River Delta) [35–37]. This difference can be further substantiated by quantitative comparisons with studies in humid-region urban agglomerations. In the Pearl River Delta, Li et al. (2023) found that construction land expansion consistently emerged as a predominant factor driving carbon emission growth throughout the study period [37]. In Hangzhou (Yangtze River Delta), Xia et al. (2023) showed that carbon emissions increased by 4.47 times from 2010 to 2015, dominated by the growth of carbon emissions from industrial land, with significant positive spatial spillover effects [35]. In the Middle Reaches of the Yangtze River urban agglomeration, Liu et al. (2024) applied the geographic detector model and revealed that secondary industry output, tertiary industry output, land electricity consumption, and land urbanization rate were the key driving factors of land-use net carbon emissions, with q -values exceeding 0.6 [51]. By contrast, in our arid-region study area (the Tarim Basin), the dominant drivers were population density (average $q =$

0.904) and construction land proportion (average $q = 0.858$), while industrial structure-related factors showed much lower explanatory power (e.g., X5 primary industry proportion, average $q = 0.233$). This quantitative comparison confirms that economic development and industrial structure play more prominent roles in humid urban agglomerations. In arid areas, due to the fragile ecosystem and low environmental carrying capacity, the population concentration and land expansion during the urbanization process have a more direct and intense impact on carbon metabolism. This difference reveals the response differentiation of the “natural-human” coupled system in different geographical environments: the ecosystem in humid areas has a stronger buffering capacity and can absorb the interference from human activities to a certain extent; while the oasis system in arid areas is more sensitive to land use changes, and any spatial expansion behavior may trigger a rapid carbon metabolism response.

4.2. Comparison with Similar Regions

Compared with the study on the inland river basin of Hexi in the arid region [52], the conclusions of this study are consistent: both regions show that the expansion of cultivated land and construction land is the main cause of increased carbon emissions. However, the difference lies in that the study in the inland river basin of Hexi shows that the carbon emission intensity of industrial cities (Jiayuguan, Jinchang) is the highest, while the administrative units, mainly based on irrigation agriculture, have a relatively lower intensity. Whereas, in the Tarim Basin, due to the special positioning of the energy base, the contribution of fixed asset investment and public budget income is more prominent. This difference reflects the differentiation characteristics within the arid region caused by different regional policy positioning and industrial structure. In addition, compared with the study on land use carbon emissions in Qinghai Province [53], the carbon emission driving mechanism of the Tarim Basin shows stronger “policy sensitivity”. The study on Qinghai Province shows that changes in land use composition are the dominant factor affecting its carbon emissions, while in the Tarim Basin, in addition to the land use structure, the driving effect of fixed asset investment and public budget income is more significant, which is intimately connected with the continuous promotion of national strategies such as the Western Development Strategy and the “Belt and Road Initiative” in the Tarim Basin. At the same time, compared with the study on the Lanzhou-Xinjiang urban agglomeration [54] in the same arid region of Northwest China, the core findings of this study are consistent: both regions identify the expansion of construction land and population density as the main drivers of carbon emissions. However, in the Tarim Basin, the investment factors related to the energy industry (fixed asset investment, public budget income) contribute more, while in the Lanzhou-Xinjiang urban agglomeration, the regulatory effect of industrial structure upgrading is relatively stronger, further confirming the essential differences in the carbon emission driving mechanisms between regions with resource advantages and those without.

The above comparative study from the arid regions of China indicates that the dominant role of urban land expansion and population concentration is universal within the region, but the contribution rates of specific driving factors vary due to regional policy positioning and industrial structure. To further verify the extensibility of our conclusions, we compared our findings with studies from other arid and semi-arid regions worldwide. In the Asir region of Saudi Arabia, Alqadhi et al. (2023) found that urbanization was significantly positively correlated with carbon emissions, consistent with our finding that construction land is the core carbon source [55]. Studies in the Central Asian Aral Sea Basin [56] and the Jiroft plain of Iran [57] similarly confirmed that agricultural and urban expansion led to significant declines in carbon storage. In the savanna of Nigeria [58] and the New Delta region of Egypt [59], and the multifunctional landscape of Central Asia [60],

construction land expansion was also identified as a primary driver of carbon emission increases and carbon stock decreases. These studies collectively demonstrate that, despite regional differences in resource endowment and development stage, the dominant role of construction land expansion and population concentration in driving carbon emission changes is consistent across arid and semi-arid regions worldwide. This cross-regional consistency supports the extensibility and transferability of our analytical framework and zoning control approach, while also reinforcing the need for local calibration of specific policy indicators.

4.3. Theoretical Contributions and Policy Implications

4.3.1. Empirical Theoretical Contributions

From a theoretical perspective, the “landscape pattern-spatial autocorrelation-multi-factor interaction” analytical framework constructed in this study can provide a reusable technical method system for the research on carbon metabolism in the human-land system in arid areas. Based on the measured statistical data of the oasis urban agglomeration in the Tarim Basin, this study confirmed that in the special human-land relationship system of arid areas, the spatial heterogeneity of carbon emissions is not the result of the independent action of a single factor, but is the comprehensive effect formed under the collaborative amplification of the three types of factors in the urbanization process: “land expansion-population concentration-capital investment”. The conclusion of this study expands the application scenarios and applicable boundaries of the land use carbon emission theory in ecologically fragile areas.

Based on the dominant driving factors (population density, proportion of built-up land) identified through empirical statistical tests, these factors have certain potential for universal interpretation in the spatial differentiation patterns of carbon emissions in similar arid oasis regions. The analytical framework of this study is built using publicly available datasets and standardized spatial statistical methods. Researchers can adjust parameters such as time scale, spatial resolution, and the number of discrete classifications of factors according to the data basis of different regions.

4.3.2. Conceptual Expansion and Policy Directional Implications

From a policy perspective, the conclusions drawn through empirical analysis in this study can provide the following practical implications for the low-carbon planning of territorial space in the Tarim Basin and similar arid regions: First, carbon emission control should focus on areas where land expansion and population concentration occur simultaneously, and implement a dual-focused zoning control strategy of “incremental constraints + structural optimization”. Second, priority should be given to maintaining the spatial continuity of ecological land. In the transition zone between oases and deserts in arid areas, ecological corridors are not only key channels for the migration and gene exchange of wild animals, but also the fundamental guarantee for maintaining the integrity of regional carbon sink functions and avoiding the fragmentation of carbon storage space. By delineating and strictly adhering to ecological corridors, it can effectively alleviate the cutting effect of uncontrolled land expansion on the ecosystem, and enhance the stability and landscape connectivity of regional carbon sinks. Third, the low-carbon transformation of energy bases requires financial transfer payments and supporting policies for industries, and the construction of a “carbon source-carbon sink” horizontal ecological compensation mechanism. The detailed policy provisions will be elaborated in the countermeasures and suggestions section of Section 5 of the paper.

The “landscape pattern-spatial autocorrelation-multi-factor interaction” analytical framework established in this study can be applied conceptually to other oasis urban agglomerations facing urbanization and agricultural expansion pressures, such as the Hexi

Corridor in China, the Fergana Basin in Central Asia, the desert fringe oases in Iran, and the Nile Delta in Egypt.

It should be noted that although the core driving laws extracted from empirical data have certain regional applicability, specific policy tools such as the reform of oil and gas resource taxes cannot be directly copied and applied. They need to be adjusted and optimized based on local resource endowments, institutional environment, and development stage. The core value of this study lies in providing a set of replicable spatial analysis methods and zoning control ideas (carbon source strict control zone, carbon sink enhancement zone, coordinated development zone), rather than a set of rigidly quantified control indicators that can be directly copied.

4.4. Research Limitations and Prospects

The potential coarse-graining of spatial scales is the primary limitation of this study. This study uses prefectures and cities as the basic analytical units. Although the systematic lack of energy and socio-economic data at the county level in the arid area restricts this choice, it inevitably smoothens the carbon emission differences within the county to some degree. Especially for the correlation between landscape pattern index and carbon emission driving factors, a more detailed administrative unit (such as county-level or township-level) can reveal more local spatial heterogeneity and scale-dependent effects. Thus, the spatial patterns identified in this study should be interpreted with caution at finer scales. Prospective research may be strengthened in the following regards: using nighttime light data or enterprise-level carbon emission inventories to downscale carbon emission accounting to county or grid units; using geographically weighted regression at multiple scales to test the scale sensitivity of driving factor effects; combining with field research data to supplement the mechanism of the impact of micro-subject behaviors on carbon emissions.

5. Suggestions

In light of an analysis of the spatial differentiation patterns and dynamic mechanisms of carbon emissions in the oasis urban clusters of the Tarim Basin, this research proposes a practical, implementable, and assessable three-tier zoning governance system comprising “target zoning-core strategies-quantitative indicators-guarantee mechanisms”.

The following recommendations are derived from the empirical patterns identified in this study. The zoning boundaries are informed by the spatial emission patterns (Figure 8), the selection of control measures is guided by the factor detection results (Table 9), and the ecological protection strategies are supported by the landscape pattern analysis (Table 6). However, these recommendations are proposed as scenarios for low-carbon spatial planning rather than as directly validated policy prescriptions. They are intended to translate the empirical findings into actionable planning strategies, complementing the conclusions with policy implications. The specific quantitative targets (e.g., the 15 min low-carbon living circle, the 80% carbon intensity threshold, and the 5% annual energy intensity reduction target) are illustrative examples based on current policy frameworks and technical feasibility; they should be calibrated according to local development levels, data availability, and policy goals. Decision-makers and planners are encouraged to adapt these scenarios to their specific contexts rather than applying them as rigid standards.

It should be noted that the following suggestions are specifically formulated for the conditions of the oasis urban clusters in the Tarim Basin. However, the core principles—zoning control, collaborative governance, and ecological compensation—can offer implications for other arid areas.

(1) Strictly Controlled Carbon Source Zone (Core Area of Aksu-Bayingolin Energy Base): Consistent with the high-emission core pattern shown in Figure 7 and the factor

detection results identifying construction land proportion (average $q = 0.858$) and population density (average $q = 0.904$) as the dominant drivers (Table 9), this zone prioritizes both incremental constraints and structural optimization to advance the green and low-carbon transition of the regional energy base.

Implement carbon budget management for new projects: For new high-energy-consuming projects exemplified by coal-fired power plants and chemical plants, adopt an “industry benchmark value” access standard. The project’s full-lifecycle carbon emission intensity must rank within the top 20% nationally among contemporaneous projects in the same industry; otherwise, approval will not be granted.

Set binding targets for energy intensity: Establish an annual energy intensity reduction target of no less than 5% for the district during the 14th Five-Year Plan period, allocate these targets to key industrial parks and enterprises, and incorporate them into local government performance evaluations.

Advance oil and gas resource tax reform: Seek national policy support to pilot injecting 30% of local oil and gas resource tax revenues into the “Southern Xinjiang Green Industry Fund.” These funds will be specifically allocated to support energy-saving technological upgrades for regional enterprises, hydrogen energy industry chain development, and further exploration of carbon capture, utilization, and storage (CCUS) technical systems.

(2) **Key Carbon Sink Enhancement Zones (Kizilsu Kirghiz Autonomous Prefecture, Northern Foothills of the Kunlun Mountains):** Based on the persistent negative carbon emissions (carbon absorption) observed throughout the study period in these areas (Figure 8) and the grassland fragmentation revealed by the landscape pattern analysis (Table 6), this zone focuses on ecological restoration and functional enhancement to transform the value of “lucid waters and lush mountains” into “gold mountains and silver mountains.”

Establish a Grassland Carbon Sink Compensation Mechanism: Funded jointly by provincial finances and the “Southern Xinjiang Green Industry Fund,” this initiative provides livestock herders (‘herders’ refers to people who raise livestock on natural grasslands, which is the traditional livelihood in the arid zones of the Tarim Basin) with “carbon sink equivalent” ecological compensation based on satellite-derived net primary productivity data. For every additional ton of CO₂ equivalent carbon sink capacity, a fixed monetary compensation is granted, directly benefiting herders.

Delineate and Strictly Protect Ecological Corridors: Clearly define key wildlife migration routes and water conservation corridors in national land-use planning. Strictly prohibit encroachment by construction land, and connect existing fragmented patches through measures such as artificial assistance to natural restoration.

(3) **Coordinated Development Zones for Optimized Development (Kashgar-Aral Urban Agglomeration, Hotan Oasis Belt):** Informed by the medium-emission levels and the phased spatial diffusion patterns shown in Figure 9, along with the rapid construction land expansion (568.88% growth, Table 5) that has not yet reached the core zone’s emission levels, this zone focuses on spatial optimization and efficiency enhancement, exploring low-carbon urbanization pathways for population-concentrated areas.

Implement carbon intensity thresholds for construction land: New commercial and residential projects must ensure their carbon emissions per unit of floor area do not exceed 80% of the existing average level in the region (that is, the new project is required to achieve a 20% reduction level of carbon emission intensity when benchmarked against the current average level. This ratio is based on the commonly used target range for green building certifications and local energy-saving standards in China). This mandatory requirement will drive the widespread adoption of green buildings, distributed photovoltaic systems, and low-carbon transportation infrastructure.

Establish a “15-min low-carbon living circle”: In urban new district planning and old city renovation, prioritize the development of mixed-use community centers to ensure residents can meet basic needs such as shopping, schooling, healthcare, and recreation within a 15 min walk.

Develop Agricultural Carbon Sequestration Programs: Promote low-carbon agricultural practices, such as returning crop residues to the soil, conservation tillage, and water-saving irrigation techniques. Provide agricultural subsidies or carbon credit certification incentives to farmers implementing these measures.

To ensure the effective implementation of the aforementioned zoning strategy, a cross-regional coordination mechanism must be established. The interaction detection results (Figure 12) reveal significant synergistic amplification effects between construction land expansion and population agglomeration ($X1 \cap X7$, $q = 0.9833$), indicating that carbon emission drivers operate across administrative boundaries. This finding necessitates the following cross-regional coordination mechanisms:

(1) Fiscal Horizontal Transfer Payments: Establish a “carbon source-carbon sink” horizontal compensation mechanism. It is proposed that 10% of oil and gas tax revenues from core carbon source areas be allocated as ecological compensation funds, specifically supporting the development of carbon sink functional zones.

(2) Collaborative Management Platform: Create a “Tarim Basin Low-Carbon Development Joint Conference” system. Led by provincial-level departments with participation from municipal governments, this platform will jointly assess the carbon impacts of cross-regional projects and coordinate conflict resolution.

6. Conclusions

This research performed a comprehensive analysis into the alterations in carbon emissions resulting from land utilization changes in the oasis urban clusters of the Tarim Basin, Xinjiang, between 2000 and 2020. By analyzing land use structure through land use landscape patterns, calculating emissions using the carbon emission coefficient approach, examining spatial heterogeneity with the global Moran’s I index, and employing geographic detectors, the research examined: (1) Spatiotemporal changes in land use structure, (2) land utilization landscape patterns, (3) spatial patterns of carbon emissions induced by land usage, and (4) drivers of land usage carbon emissions. The findings indicate the subsequent points:

(1) Regarding land usage structure, the oasis urban agglomeration in the Tarim Basin exhibited significant transformation characteristics over the period 2000–2020. Over the two decades, construction land and cropland increased by 2092.18 km² and 13,701.92 km² respectively, forming the dominant trends of rapid construction land expansion and sustained cropland growth. Unutilized land and grassland continued to shrink, becoming the principal land categories transferred out in the regional land structure change. Overall, a complex spatial pattern emerged where ecological land and agricultural land mutually converted within the oasis–desert transition zone.

(2) Landscape pattern evolution manifests as increased overall heterogeneity coexisting with localized aggregation. Declining sprawl and rising diversity jointly indicate a trend toward dispersed and diverse landscape structures. Rapid expansion of construction land and fragmentation of natural land usage have weakened the integrity of ecological spaces and their carbon sink functions, intensifying regional carbon metabolism pressures.

(3) Spatiotemporal patterns of carbon emissions from oasis cities in the Tarim Basin show a continuous upward trend. During the research period, emissions have surged dramatically from gradual growth to rapid escalation, which is closely associated with the swift proliferation of construction land. This suggests a persistent and significant increase

in pressure on carbon sources from regional economic development and human activities. A high-value cluster centered on Aksu-Bayingolin has formed spatially, exhibiting phased diffusion characteristics. Spatial autocorrelation analysis of carbon emissions shows a heterogeneous distribution pattern without significant spatial clustering, which is consistent with uneven regional development and localized variations in carbon emission drivers.

(4) Geographic detector analysis indicates that land utilization carbon emissions are associated with multiple interacting factors, with population density, proportion of construction land, and economic development level identified as the pivotal contributing factors. The interaction between the two factors generally increases explanatory power, suggesting the dominant role of human factors in the spatial differentiation of carbon emissions. This reflects the sensitive response of carbon emissions from human-land systems in arid regions to urbanization and regional development policies.

In conclusion, the patterns of carbon emissions in oasis cities in the Tarim Basin result from the synergistic impacts of natural geographical foundations and anthropogenic activities. Before generalizing these findings to other arid regions, it should be noted that the analytical framework was developed within the specific context of the Tarim Basin oasis urban agglomeration, and the empirical relationships are derived from correlation-based analyses. Therefore, while the methodological framework and zoning concepts are transferable, the specific findings should be applied with caution to regions with different ecological or institutional characteristics. Future efforts should focus on optimizing landscape configurations, enhancing ecological connectivity, and regulating urban development pathways to advocate for low-carbon land utilization and sustainable development in the region.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18146982/s1>, File S1: Sensitivity analysis of land-use carbon emission coefficients (coefficient variations $\pm 20\%$, Spearman rank correlation). File S2: Robustness test after removing collinear variables (multicollinearity, VIF diagnostics). File S3: Robustness checks for geographic detector and spatial autocorrelation (different discretization schemes, time periods, and spatial weight matrices).

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Abbreviations

The following abbreviations are used in this manuscript:

TBOA	The Tarim Basin Oasis Agglomeration
SDGs	Sustainable Development Goals
CLCD	China Land Cover Dataset
DEM	Digital Elevation Model
NDVI	Normalized Difference Vegetation Index
VIF	Variance Inflation Factor
LMDI	Logarithmic Mean Divisia Index

SBM	Slack-Based Measure
Gini	Gini coefficient
LISA	Local Indicators of Spatial Association
IPCC	Intergovernmental Panel on Climate Change

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