RESEARCH ARTICLE

Enhancing Low-Carbon Urban Landscape Pattern Analysis through Scene-Registered Gradient Feature Extraction

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Abstract

Conventional gradient feature extraction methods for low-carbon urban landscapes often fail to differentiate spatial structures clearly, resulting in a relatively low aggregation index. To address this limitation, we propose a scene-registered gradient feature extraction framework that integrates three components: (1) ecological landscape indexing for spatial classification, (2) carbon emission estimation for environmental evaluation, and (3) target detection algorithms for optimizing green space layout. Scene registration ensures the precise alignment of multi-temporal spatial data, thereby enhancing the robustness of gradient extraction. Experimental results across four vegetation coverage levels (2,000, 1,500, 1,000, and 500 km²) demonstrated that the proposed method consistently achieves higher aggregation indices than DEM-based and GIS-based approaches. Independent-sample t-tests confirmed the statistical significance of these improvements ($p < 0.01$). These findings suggest that the integration of scene registration and target detection provides a more reliable tool for low-carbon urban landscape analysis, offering practical insights for urban sustainability planning and ecological zoning.

Keywords: *Scene registration, low-carbon city, landscape spatial pattern, gradient characteristics, extraction method, target detection algorithm*

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Introduction

Urban landscapes play a critical role in shaping ecological processes, as different landscape types have distinct effects on resilience, biodiversity, and carbon balance. Rapid urbanization alters the composition, structure, and function of urban ecosystems, often exceeding the adaptive capacity of natural systems (Ejiagha et al., 2020; Li et al., 2023; X. Liu, 2020; Yuan et al., 2020). Such transformations significantly reshape the spatial configuration of peri-urban and core urban areas, with long-term consequences for ecological sustainability.

Existing research on landscape patterns has largely focused on regional-scale analysis and short-term pattern dynamics. However, approaches that incorporate multi-temporal gradient analysis remain limited, and studies addressing long-term transformations are particularly rare. This lack of temporal depth restricts our ability to detect structural transitions in low-carbon urban areas and hampers effective ecological planning. Current gradient extraction methods face a particular issue in that they struggle to capture spatial heterogeneity introduced by urban expansion, leading to insufficient insights for planning low-carbon cities.

As a spatial alignment technique, scene registration offers a potential solution to these shortcomings. Widely applied in medical imaging and remote sensing, it ensures consistency across multi-temporal datasets by correcting alignment errors. When applied to urban spatial analysis, scene registration enhances the reliability of gradient feature extraction by enabling accurate comparisons of land use, vegetation, and built structures over time (Brown et al., 2019; Choo et al., 2019). This makes it highly relevant to the detection of urban ecological transitions and the optimization of spatial patterns in sustainability-oriented planning.

Against this backdrop, the present study developed a novel gradient feature extraction method for low-carbon urban landscapes based on scene registration. By integrating ecological landscape indexing, carbon emission estimation, and target detection algorithms, the method aims to improve spatial aggregation analysis and provide actionable insights for urban sustainability planning. Through empirical testing across different vegetation coverage scenarios, this research both contributes to methodological advancement and offers practical guidance for low-carbon urban development.

Gradient Feature Extraction Method of Low-Carbon Urban Landscape Spatial Patterns Based on Scene Registration

Research on urban landscape patterns has evolved from qualitative spatial morphology analysis to quantitative, multi-source, and multi-phase feature analysis. Particularly in low-carbon urban studies, the spatial configuration and temporal transformation of landscape units are crucial for assessing ecological resilience and sustainable urban forms (Mitrović et al., 2023; Mohy & Rasheed, 2022). In this context, computational methods such as landscape indices, spatial registration, and target recognition have been increasingly integrated. The following review summarizes key research strands relevant to this topic.

Obtaining a Landscape Type Index

The optimization of the ecological spatial patterns of urban landscapes means adjusting unreasonable distributions of landscape elements, the proportion of land use, and the size and shape of landscape elements (Ashiagbor et al., 2019; Quesnel & Ajami, 2019). In order to coordinate the proportion between external landscape elements and internal landscape elements, planners must simultaneously identify the quality, ecological value, aesthetic value, and visual value of the landscape to achieve the goal of maximizing its overall value. An urban landscape is a dissipative structure with structural characteristics. Due to the effects of the external environment and adjustments to its internal structures, its attributes will show varying degrees of variability (Derbel et al., 2020; Dissegna et al., 2019). These attributes include the spatial composition, spatial type, and spatial correlation. Heterogeneity is closely related to anti-interference ability, resilience, stability, and biodiversity. A landscape index is highly concentrated information about landscape quantity, characteristics, and distribution patterns, and it quantitatively reflects the characteristics of pattern composition and spatial configuration. At present, landscape indices are mainly divided into three levels, as shown in Figure 1.

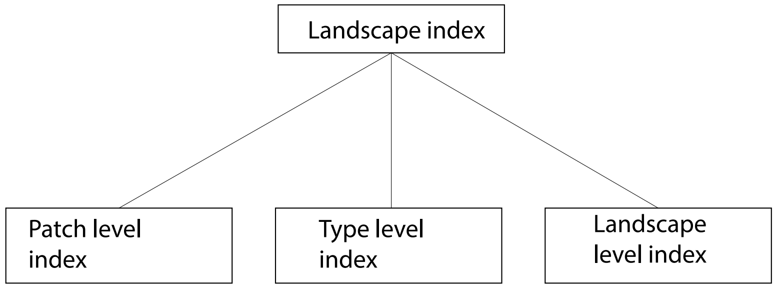

Figure 1: Landscape Index Composition Diagram

According to Figure 1, the three levels of the landscape index are the patch level index, type level index, and landscape level index, respectively. Patch types are mainly composed of a certain number of single patches, and multiple patch types together form a landscape mosaic. At present, landscape pattern analysis mainly relies on landscape pattern index analysis, landscape pattern spatial statistical analysis, and dynamic simulation. With the rise and widespread application of 3S technologies such as the Geographic Information System (GIS) and Remote Sensing (RS), urban landscape pattern analysis is paying more attention to the application of remote sensing image information, and two or more methods are used in a specific analysis of landscape patterns (Ambrus et al., 2020; Kinoshita et al., 2021; H. Liu et al., 2019). The patch shape index can quantitatively reflect the complexity of patches at a certain scale. The smaller the patch index, the more regular the patch shape. The larger the patch index, the more complex the patch shape. The quantification of a patch shape index is unaffected by the patch area. Under the action of human activities, the shape indices of cultivated land and water areas are relatively small due to the planning of natural economic activities. This indicates that these land types are relatively simple in shape, distributed in a large number of contiguous patches, and considerably disturbed by human beings. In contrast, the shape indices of forestland and grassland are both large, maybe because the distribution of the forestland landscape type and grassland landscape type is mainly affected by climate and other natural factors, producing irregular distribution and complex shapes. Conversely, a small value on a sprawl index means that there are many small patches in the landscape, indicating that the landscape is a scattered pattern with multiple elements and that the fragmentation degree of the landscape is high. Meanwhile, the sprawl index is highly correlated with the dominance and diversity indices. Theoretically, the value of a sprawl index tends toward 100, indicating the existence of highly connected dominant patch types in the landscape. The topographic position is a composite topographic factor that comprehensively reflects elevation and slope, and it is used to describe the combined features of landforms at a macro level. Its expression formula is as follows:

$$Q=\left[\left(\frac{P}{\overline{P}+1}\right)\times\left(\frac{E}{\overline{E}+1}\right)\right] \qquad (1)$$

In formula (1), P (unit: m) represents the elevation of a certain point in a city, $\overline{P}$ (unit: m) represents the average elevation of the city, E represents the slope of a certain point in the city, and $\overline{E}$ represents the average slope of a certain point in the city. The terrain distribution index refers to the probability of a certain land use type appearing on different terrain gradients. Quantitative analysis of land use patterns under different landforms can reveal the spatial and temporal patterns of land use and the topographic gradient characteristics of its changes. The specific expression formula is as follows:

$$T = \frac{\left(F_1 / F_0\right)}{\left(\alpha / F\right)} \quad (2)$$

In formula (2), F_1 represents the land use type, F_0 represents the terrain grade, α (unit: km²) represents the terrain distribution area, and F (unit: km²) represents the total area of the research area. The transfer distribution index reflects the probability of land transfer at different topographic positions, for which the specific expression formula is as follows:

$$R = \frac{\beta / D_c}{\varepsilon / D} \quad (3)$$

In formula (3), β (unit: km²) represents the total area of transfer in the study area, D_1 (unit: km²) represents the total area of land, ε represents topographic dominance, and D (unit: km²) represents the area of transfer $c$in the th level of the topographic area. The aggregation index is calculated by the proximity matrix at the level of the patch type. When patches of the same type are dispersed to the maximum extent in the landscape, the aggregation index is 0. When the patch type is densely clustered, the aggregation index also increases: if a patch type in the landscape is aggregated into a single, compact patch, the aggregation index is 100. Landscape fragmentation is an important component of landscape heterogeneity and refers to the fragmentation degree of landscape segmentation. The urban landscape fragmentation index is an important indicator reflecting the impact of human activities on landscape patterns (X. Liu et al., 2023; Shukla & Jain, 2021) type scale, and overall landscape scale, utilizing the method for calculating the LPI, which is based on site type data and land use data for the years 1987 to 2020. At the same time, the degree of landscape fragmentation is closely related to the protection of natural resources, and the living environments of some species must reach a certain size to survive. According to the results after analyzing the landscape fragmentation index, the fragmentation indices of the cultivated land landscape type and the construction land landscape type are lower than those of other land types, which also reflects the impact of human activities on landscape patterns. This may be due, it may be because relevant government departments strictly implement a basic state policy of cultivated land protection and forbid the destruction of cultivated land. Meanwhile, the expansion of construction land is orderly and conforms to the requirements of urban development planning and overall land use planning. In agricultural management, on the other hand, having a certain size and concentration of cultivated land is conducive to the mechanization of agricultural production and scale operation, and the construction land fragmentation index will fall. On the one hand, this may be due to the area of construction land increasing. The increase in construction land results from the conversion of other land types into built-up areas, which in turn reduces the overall degree of fragmentation. On the other hand, human activities may regulate and plan construction land so that the initially scattered construction land becomes concentrated. Based on this, the steps of obtaining the landscape type index are completed.

Identifying Types of Low-Carbon Urban Structures

From the perspective of the formation process of urban physical space, urban planning and construction often create a distinct separation between the human and nature. While harmonious coexistence is the ultimate goal of urban life systems and ecological spatial development “emphasizing their organic interrelationship” this process often overlooks the spatial structure as a complex and collaborative construct. City spread leads to the erosion of the ecological environment, so urban land use and transportation development are not harmonious. As cities expand and grow, the industrial and energy structures, along with other aspects of urban development, have exposed inherent defects in the spatial structure of the urban material environment, resulting in serious negative impacts on the balance between urban systems and nature. The spatial structure of low-carbon cities should be guided by integrated planning frameworks that align their ecological carrying capacity with land use intensity (Mollaei et al., 2019; Shou-yi et al., 2023; Zhang et al., 2023). Models such as TOD (Transit-Oriented Development) and compact city planning emphasize reducing carbon footprints through spatial proximity and multifunctional land use, which provided the theoretical underpinnings of spatial optimization in this study. From the perspective of the reality of low-carbon urban development, in the context of increasingly tight resources and significant climate change and to achieve sustainable growth of the urban economy, the urban space system is bound to move toward an overall coordinated development path (Mollaei et al., 2019; Ronald, 2020). With the optimization of material space in the process of continuous layering and structuring, as shown in Figure 2, the coordinated control framework underscores the importance of aligning ecological capacity with urban development intensity, which directly informed the proposed gradient extraction method.

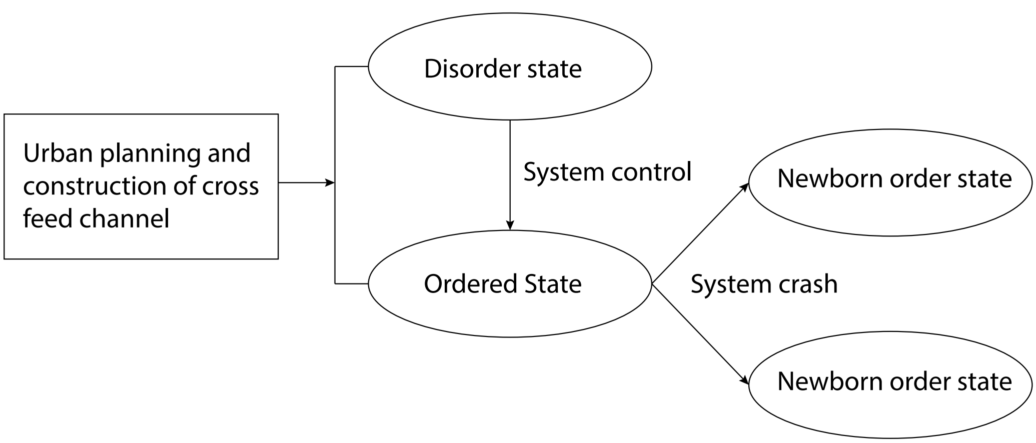

Figure 2: Action Mechanism of Collaborative Control Process of Low-Carbon Cities

As can be seen in Figure 2, the failure of the spatial structure organization of low-carbon cities is the key to the current "morbid" nature of cities. The key to the disordered development of low-carbon cities is the lack of effective scientific theoretical guidance (Keough & Ghitter, 2020; Sununta et al., 2019). The efficient utilization of land space, low-carbon travel characteristics, public transport-guided development mode, and continuous growth of social and economic activities all provide a basic guarantee that a city can enter the stage of the overall spatial coordinated development of low-carbon growth. On this basis, the basic expression formula of carbon emissions was obtained:

$$L = \sum l \times H \frac{\delta}{r} \tag{4}$$

In formula (4), l (unit: tCO_2) represents the carbon emission per unit of energy, H (unit: TJ) represents the consumption of primary energy, δ (unit: TJ) represents the consumption per unit of energy and r represents gross domestic product (GDP). Urban carbon dioxide emissions mainly come from energy consumption in construction, transportation, industrial production, and other fields. To verify the relationship between carbon dioxide emissions and different levels of energy consumption, the coefficient method formula is expressed as follows:

$$C = Z \times U \tag{5}$$

In formula (5), Z (unit: tCO_2/TJ) represents the carbon emission intensity and U (unit: TJ) represents the consumption of different types of energy, which can be uniformly converted into standard coal. Under the synergistic influence of economic and environmental development, the effective coordination of urban spatial functions provides a foundation for integrating land use and transportation. This integration enables key urban nodes to achieve highly mixed land use patterns, along with the coordinated development of public transport and pedestrian networks. This not only provides economic value through increased land and space utilization efficiency but also promotes the development of a low-carbon transportation system and facilitates the synergistic functioning of urban systems. The dynamic mechanism of urban spatial development is shown in Figure 3.

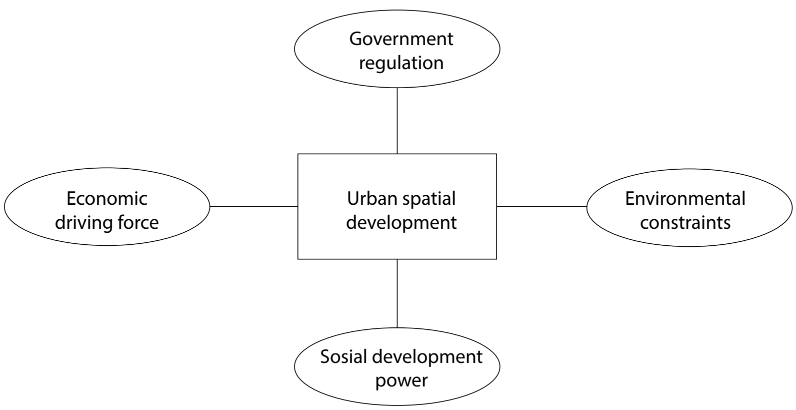

Figure 3: Dynamic Mechanism Structure of Urban Spatial Development

As shown in Figure 3, urban development is primarily driven by three key factors: policy directives, economic advancement, and social dynamics. The urban spatial structure is always accompanied and intertwined with form, function, and system, while the dominant party in urban spatial development decides whether a city is self-organized or organized. The development of cities has always been controlled by human rational thinking, so rationality has become the basic criterion of the modern social development model. The city is the carrier of entities of physical space, carrying multi-dimensional aspects of society, economy, and culture. Based on the complex urban system, urban space development cannot only rely on technical rational thinking to guide practice. The maturity of information and motorization technologies has facilitated the decentralized development of urban space aimed at improving the urban environment. However, the so-called "ideal new city," driven primarily by technological progress but lacking environmental values, may relieve population pressure in central urban areas while at the same time generating greater challenges, particularly in terms of traffic management and spatial control. The history of urban development has proven that the professional technology of planning space under material and technical criteria tends to lead to the expansion and development of urban space under economic dominance. Under the tide of the global economy, the material and technological criteria led by technological rationality provide basic requirements for urban development. However, in the face of urbanization, such criteria tend to be exaggerated and ignore the environment and climate change. Therefore, adhering to the values of ecology, low carbon, and sustainable development, the "steering wheel" must control the "fast train" of rapid urban space development, so that this development will be humanized and sustainable. Based on the above description, the steps of identifying the type of low-carbon urban structure are completed.

Target Detection Algorithm Optimizes the Landscape Spatial Pattern Planning Process

The primary problem with a target detection algorithm is how to find the representation of representative features in the target and then combine these features with mathematical theoretical knowledge for the representation of the target object (Asad et al., 2020). The general idea of target detection is as follows: first, obtain a set containing many redundant features. Then, using the theoretical method of machine learning, by learning and training those features that represent the target object in the feature set, a classifier that can accurately distinguish the target from the object is constructed. Finally, the target object is detected from the complex environment. For example, several windows of different sizes are used to traverse the whole image, and the selected object features are used to screen the windows in combination with the corresponding classifier. If the number of windows is less than 104 and a high response value is guaranteed, the target detection speed will be significantly improved. The algorithm flow is shown in Figure 4. Figure 4 demonstrates the workflow of the target detection algorithm, which identifies spatial opportunities for green infrastructure. By integrating this process into gradient feature extraction, the method strengthens landscape connectivity and planning precision.

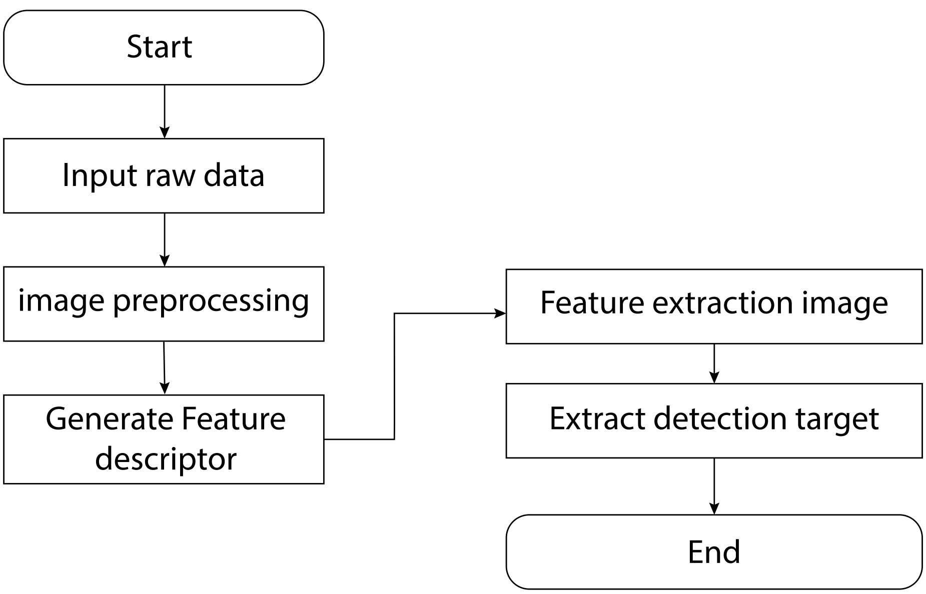

Figure 4: Target Detection Algorithm Flow

As can be seen from Figure 4, in target detection, objectification is considered a key indicator. It aims to measure the possibility that a generated candidate area contains the target. The landscape pattern generally refers to the spatial pattern. Broadly speaking, it includes the types, numbers, spatial distribution, and configuration of landscape units. The spatial distribution of landscape elements includes three basic modes: uniform distribution, random distribution, and aggregation distribution. The high degree of landscape heterogeneity is conducive to the symbiosis of species but not the survival of rare species within the landscape. Landscape heterogeneity can also be understood as the uncertainty of the distribution of landscape elements. The spatial heterogeneity of an urban landscape is one important principle of landscape planning, which is of great significance to the ecological balance and sustainable development of urban landscapes. An urban landscape is highly artificial, with more patches than green patches, resulting in a serious imbalance of patch types. This phenomenon not only affects the ecological load of the urban landscape but also causes environmental problems such as air pollution and water-quality deterioration. Therefore, based on the principle of heterogeneity, green patches should be added to the urban landscape structure. Moreover, the optimal locations and areas of green space should be determined according to a city's existing road conditions to achieve uniform distribution in the urban landscape. In addition, in green space landscape design, visual landscape design effects should not be overemphasized, and local conditions should be improved. Based on ecological principles and aesthetic characteristics, the combination of trees and shrubs is intended to improve the stability and biodiversity of the system, gradually improve landscape heterogeneity, and facilitate the symbiosis of species. This would make full use of the space resources and promote the natural coordination of green space. The premise of urban landscape planning is to fully understand the status quo of the urban landscape and take the needs of urban development as the starting point for considering the long term. This is conducive to not only contemporary people but also the sustainable development of cities. Studies have shown that the best spatial scale for planning and sustainable development management is the landscape. When planning, planners can consider many possible spatial configurations, and the rearrangement of landscape elements always improves or reduces ecological integrity. Based on this, the steps of optimizing the landscape spatial pattern planning process are completed. In this study, the ”target” refers to potential green infrastructure units, such as underutilized open spaces or linear corridors suitable for greening. The algorithm identifies spatial opportunities for ecological enhancement within high-fragmentation zones, enabling planners to prioritize regions for green connectivity interventions.

Gradient Feature Extraction for Scene Registration

Scene registration has been widely employed in medical imaging and remote sensing but remains underutilized in urban spatial analysis. Recent studies (Bellavia et al., 2021; Brown et al., 2019; Choo et al., 2019) when appropriate, the translation have demonstrated its potential in aligning multi-source imagery to track urban structural change. In the context of low-carbon city planning, such alignment enables consistent comparisons of vegetation, land use, and built forms across temporal scales, which are vital for detecting spatial transformation patterns. Firstly, the phase relationship in the Fourier transform domain is directly determined by the amount of translation in the time domain; that is, when two images are translated in the time domain, and then the Fourier transform of the two images is taken, the phase relationship is different. Second, the two images rotate in the time domain, and when the Fourier transform of the two images is taken, they rotate at the same angle. Finally, when the image is scaled in the time domain, it is transformed it into a shifted image in the time domain by moving it to a logarithmic coordinate system, and you can do it in the same way you did before. Based on the above transformations, it is identified that the advantages of Fourier transform in translation, rotation, scaling, and other geometric transformations. The set of all the features that need to be matched is the feature space of the of the image, where one can choose gray features, boundary features, brightness, or straight-line features, or statistical features. The restrictions of feature selection are as follows: the first consideration is whether there are common features among the images to be selected. The second consideration is whether these features are evenly distributed in the image and the number of features is too small. Finally, the features chosen can be conveniently extracted for matching and registration. Based on these requirements, one can consider consider clearly when selecting features in order to effectively improve the image registration algorithm and reduce the impact of noise and other uncertain factors on the algorithm. As a part of matching, the similarity measure has a unique function. It evaluates the similarity between images by selecting a specific measure method and then completes the matching. Micro gradient factors include the slope, slope aspect, and ground curvature, which describe and reflect the topographic information characteristics of specific ground points. In the extraction and analysis of such terrain factors by scene registration technology, the single grid or small window grid processing method is generally adopted. The ground slope can be expressed as follows: the slope of a certain point on the ground is the angle between the tangent plane passing the point and the horizontal ground. This is the maximum ratio of height change, which represents the slope degree of the ground surface at this point. The ground slope is essentially a differential concept, and every point on the ground has slope. It is a concept on a point, rather than a concept on a surface. The slope calculation expression formula is as follows:

$$\eta = \arctan \sqrt{m^2 + n^2} \times \frac{180}{\pi} \qquad (6)$$

In formula (6), m represents the elevation change rate in the longitudinal direction, and represents the elevation change rate in the transverse direction. The angle between the horizontal projection of the normal line of the tangent plane of any point on the ground and the due north direction passing through that point is called the slope direction of that point. Calculated clockwise, the slope direction value ranges from 0° to 360°. On this basis, the mathematical expression formula for slope direction is as follows:

$$U = arctg\left(\frac{m}{n}\right) \qquad (7)$$

In formula (7), m and n have the same meaning as in formula (6). Topographic relief, also known as relief, relief energy, local relief, or relative height, refers to the difference between the maximum and minimum elevation of all the grids in a specified analysis area. This can be expressed by the following formula:

$$K = \lambda_{\max} - \lambda_{\min} \qquad (8)$$

In formula (8), λ represents the ground relief in the study area. In the process of gradient extraction, the same green space index, uniform, and non-uniform distribution have different landscape and ecological effects. Public green space is the main part of urban green space. Its quantity and quality reflect local economic construction and urban development. Therefore, we should pay attention to the distribution of public green space. In addition to building more urban parks, efforts should be made to develop district and tourist parks that reflect local features, thereby enhancing the diversity of public green spaces and meeting the varied needs of residents. From dispersion to connection and from connection to integration, the urban green space system presents a gradual pattern of network connection and suburban integration. This makes the relationship between man and nature increasingly close in the city. The gradient characteristics of the landscape index at the landscape level are more complex than those at the top level. The boundary density and landscape shape index still show the characteristics of the bimodal gradient and are similar to urban construction land and agricultural land. The peak tends to move to both ends of the transect over time. The long-term effects of many urban factors on the urban green space landscape form the existing green space landscape pattern. Quantitative description of the spatial patterns and heterogeneity of urban green patches is the basis of analyzing the structure and function of a landscape. Landscape elements such as parks, green spaces, railways, highways, streets, and architecture combine to form heterogeneous urban landscapes. On the one hand, the heterogeneity of the two-dimensional plane space is the main manifestation of urban landscape heterogeneity, that is the difference is, differences in the nature and functions of parks, green spaces, water, buildings, and streets and vertical spatial heterogeneity. The spatial pattern is the specific manifestation of spatial variations of the ecosystem or system attributes, including spatial heterogeneity, spatial correlation, and spatial regularity. This restricts various ecological processes and is closely related to disturbance, the restoration of system stability, and biodiversity.

The Experimental

Experimental Preparation

Gradient feature extraction was performed using spatial gradient metrics, including the topographic relief, slope, and land-use entropy gradient (Wu et al., 2023). The extraction process was anchored on a scene registration baseline to ensure that multi-year image sets aligned pixel-wise. After alignment, terrain features were extracted from each image using a 3×3 window to calculate local variances in elevation and curvature. These were then cross-referenced with land-use transition layers to derive spatiotemporal gradient trends (Wang & Wang, 2022).

The experimental process used multi-temporal satellite imagery and land-use maps sourced from national geospatial databases. ArcView was used for pre-processing and spatial classification, while FRAGSTAS was used to calculate landscape indices. QT Creator was used as an integrated development environment to build the user interface for visualizing multi-source data overlays and interacting with the gradient feature maps. The procedure involved data collection, spatial alignment via registration, gradient calculation, index analysis, and comparative testing.

Experimental Results

The selection process employed three gradient feature extraction methods for analyzing the spatial pattern of low-carbon urban landscapes, namely the GIS-based method, the DEM-based method, and the experimental contrast method. The test was conducted under the conditions of different vegetation coverage, with three methods of calculating the feature extraction concentration index. It was proven that the more concentrated the landscape distribution, the better the greening effect. The experimental results are shown in Table 1-4.

Table 1: Aggregation Index of Vegetation Coverage Area of 2,000 Km^2

Number of experiments	**Gradient feature extraction method of landscape spatial pattern of low-carbon city based on GIS**	**Gradient feature extraction method of low carbon urban landscape spatial pattern based on DEM**	**The gradient feature extraction method of a landscape spatial pattern of low-carbon city is proposed in this paper**
1	72.614	67.512	78.654
2	69.584	70.005	81.206
3	68.779	72.454	79.416
4	73.150	71.069	78.203

As shown in Table 1, across all four experimental runs, the proposed method consistently achieved the highest aggregation index, with an average of 79.370 compared to 71.032 (DEM-based) and 70.260 (GIS-based). This indicates that the proposed scene-registration-enhanced gradient extraction method captures spatial coherence more effectively in large-scale green spaces. Higher aggregation implies stronger landscape connectivity, reduced ecological fragmentation, and potentially more efficient carbon sink performance in broader ecological networks.

Table 2: Aggregation Index of Vegetation Coverage Area of 1,500Km^2

Number of experiments	Gradient feature extraction method of landscape spatial pattern of low-carbon city based on GIS	Gradient feature extraction method of low carbon urban landscape spatial pattern based on DEM	The gradient feature extraction method of a landscape spatial pattern of low-carbon city is proposed in this paper
1	50.224	52.691	62.131
2	53.677	53.106	59.446
3	52.941	52.865	58.707
4	51.248	54.109	62.598

Table 2 demonstrates similar results over a moderately smaller spatial extent. The proposed method yielded an average aggregation index of 60.721, significantly higher than those obtained using the DEM-based (53.193) and GIS-based (52.023) approaches. This suggests that even as vegetation coverage decreases, the method maintains its advantage in preserving the spatial clustering of green patches. Such consistency indicates robustness across mid-scale urban sub-regions, which is valuable for zoning-based green space planning.

Table 3: Aggregation Index of Vegetation Coverage Area of 1,000Km^2

Number of experiments	Gradient feature extraction method of landscape spatial pattern of low-carbon city based on GIS	Gradient feature extraction method of low carbon urban landscape spatial pattern based on DEM	The gradient feature extraction method of a landscape spatial pattern of low-carbon city is proposed in this paper
1	46.525	47.515	53.215
2	48.363	45.669	56.419
3	48.612	44.358	58.155
4	44.255	43.225	56.902

The trend continued, as shown in Table 3, whereby the average aggregation index for the proposed method was 56.173, outperforming the DEM-based (46.939) and GIS-based (45.192) techniques. This implies that the proposed approach is effective even in fragmented or mixed-use areas. It is especially beneficial for identifying green infrastructure potential in transitional zones where construction and ecological patches interweave, thus aiding in fine-grained landscape optimization.

Table 4: Aggregation Index of Vegetation Coverage Area of 500Km^2

Number of experiments	Gradient feature extraction method of landscape spatial pattern of low-carbon city based on GIS	Gradient feature extraction method of low carbon urban landscape spatial pattern based on DEM	The gradient feature extraction method of a landscape spatial pattern of low-carbon city is proposed in this paper
1	36.941	33.484	42.518
2	35.828	32.659	43.262
3	36.925	34.151	41.594
4	35.779	33.622	43.606

In Table 4, despite the test area being considerably smaller, the proposed method still showed a marked improvement in the aggregation index (mean = 42.745) compared to the DEM-based (36.368) and GIS-based (33.479) results. This highlights the method's capacity to enhance spatial coherence even in high-density urban cores or edge zones with limited green coverage. Such improvements are critical for micro-scale interventions, such as pocket parks or corridor-based ecological restoration in inner cities.

Table 1 shows that the average aggregation index of the low-carbon urban landscape spatial pattern gradient feature extraction method and the other two extraction methods reached 79.370, 71.032, and 70.260, respectively. Table 2 shows that the average aggregation index of the low-carbon urban landscape spatial pattern gradient feature extraction method and the other two extraction methods reached 60.721, 52.023, and 53.193. respectively. Table 3 shows that the average aggregation index of the low-carbon urban landscape spatial pattern gradient feature extraction method and the other two extraction methods reached 56.173, 46.939, and 45.1920, respectively. Table 4 shows that the average aggregation index of the low-carbon urban landscape spatial pattern gradient feature extraction method in this paper and the other two extraction methods reached 42.745, 36.368, and 33.479, respectively. The aggregation index was higher when using the low-carbon urban landscape spatial pattern gradient feature extraction method.

These findings support earlier assertions in the literature that urban green space configuration is sensitive to spatial fragmentation and planning logic (Ashiagbor et al., 2019; X. Liu et al., 2023) not much information exists on the changes in the structure of the peri-urban landscape in Ghana. The aim of this paper is to examine the extent to which urban expansion is driving changes in landscape structure of the peri-urban fringes of Accra. We submit that rapid peri-urbanisation will fragment the existing agricultural and forested landscape with consequent ecological, socio-economic and urban governance implications. Using Landsat satellite images for the years 1985, 1991, 2002 and 2015 the study area was classified into four land cover classes. The study adopted the use of Urban Intensity Index (UII). The observed aggregation increase confirms that the target-detection-assisted layout optimization effectively enhances landscape continuity, consistent with the ecological heterogeneity principles reported in previous studies.

In real-world applications, a higher aggregation index indicates reduced landscape fragmentation and increased ecological integrity, which supports low-carbon goals by facilitating species movement and enhancing carbon sink efficiency. Urban planners can utilize these findings to prioritize compact green space layouts, mitigate urban heat island effects, and guide zoning regulations toward ecological corridors and multifunctional green infrastructure.

To assess whether the observed improvements in the aggregation index were statistically significant, independent-sample t-tests were performed comparing the proposed method with the GIS-based and DEM-based methods across all four spatial extents. The results indicated that the aggregation index obtained via the proposed method was significantly higher than those obtained using the other benchmark methods at the 0.01 level of significance. Specifically, the p-values for all pairwise comparisons (Proposed vs. DEM; Proposed vs. GIS) were less than 0.005 across the four vegetation coverage areas (2,000 km^2, 1,500 km^2, 1,000 km^2, and 500 km^2). These findings confirm that the improvements are not due to random variation; instead, they reflect the substantive effectiveness of integrating scene registration and gradient feature refinement in extracting low-carbon spatial structures.

Conclusion

This study proposed a novel scene-registered gradient feature extraction method to improve the analysis of low-carbon urban landscape spatial patterns. By integrating landscape indexing, carbon emission estimation, and target detection, the method enhanced spatial coherence and achieved significantly higher aggregation indices than the existing approaches. These results confirm the method’s capacity to reduce ecological fragmentation and strengthen connectivity within urban green infrastructures.

Nevertheless, certain limitations remain. First, residual distortions in areas with complex terrain may affect the accuracy of scene registration and subsequent index calculations. Second, while the method is optimized for meso-scale landscapes (500–2,000 km^2), its applicability to finer parcel-level or larger metropolitan scales requires further validation. Therefore, future research should explore cross-scale adaptability, especially in high-density urban cores and small municipal districts.

In terms of practical implications, the method offers actionable insights for urban planning practice. Local councils and city planners may apply the aggregation index outputs to guide zoning regulations, identify ecological corridors, and prioritize regions for green infrastructure interventions. By supporting compact green layouts and ecological connectivity, the method can contribute to mitigating urban heat island effects, enhancing carbon sequestration, and promoting resilient low-carbon urban development.

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