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RESEARCH ARTICLE

Impacts of landscape-level processes on the supply/demand of cultural ecosystem services in urban parks

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Abstract Urban parks provide crucial cultural ecosystem services (CESs) that enhance the well-being of residents. Landscape composition and configuration determine the supply of CESs, which in turn affects the matching of the supply and demand of the CESs. However, there is limited research on how landscape-level processes influence this supply and demand. Therefore, this study focuses on Chongqing's central urban area using a social value model that combines questionnaire surveys and environmental variables to assess the CESs supply, whereas social media data quantify the demand for CESs. Landscape indices are used to evaluate landscape-level processes. Pearson correlation and linear fitting analyses explore the relationships between landscape indices and CESs benefits, whereas multiscale geographically weighted regression (MGWR) further reveals the spatially differentiated impacts of landscape configuration on the relationship between the CESs supply and demand. The results indicate that 1) the supply and demand of CESs are concentrated in the western part of the city, with educational value having the lowest value index of 7, whereas entertainment and aesthetic values have higher demands (42.37% and 31.55%, respectively); 2) the western area has more diverse patch types and a lower proportion of the largest patch type, whereas the eastern area has more concentrated dominant landscapes; 3) landscape diversity and complexity positively correlate with CESs supply and demand, with Shannon's diversity index (SHDI) exhibiting the greatest impact on aesthetic value demand (correlation coefficient = 0.64). In contrast, landscape aggregation and dominance are negatively correlated, with the aggregation index (AI) most strongly affecting educational value supply (correlation coefficient = −0.81). These findings offer insights into enhancing the benefits of CESs, addressing service gaps, and optimizing future urban park layouts.

Keywords cultural ecosystem services, urban parks, supply and demand assessment, impact mechanism analysis, central urban area of Chongqing

1 Introduction

The concept of ecosystem services has become crucial for decision-making in urban planning and management, deepening the understanding of the benefits that natural ecosystems provide to humanity (Wood et al., 2018). Cultural ecosystem services (CESs) refer to the non-material benefits derived from the natural attributes and processes of ecosystems, including spiritual experiences, aesthetic appreciation, and cultural identity (Villamagna et al., 2014). CESs are crucial for sustaining and enhancing human well-being, particularly as cities rapidly urbanize (Xia et al., 2024). Unlike other ecosystem services, CESs are subjective and intangible, making them difficult to evaluate and often leading to their being overlooked (Martin-Lopez et al., 2009; Tilliger et al., 2015). However, they significantly enhance residents' happiness, aesthetic enjoyment, and social interactions (Baltazar et al., 2022; Chen et al., 2024). Rapid urbanization, population growth, and an increasing pursuit of healthy lifestyles have driven the demand for intangible CESs. As significant providers of CESs, urban parks offer various recreational, aesthetic, and spiritual values (Gai et al., 2022), enhancing the physical and

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mental health of users and their overall quality of life (Dong and Qin, 2017; Bing et al., 2021).

The supply of CESs refers to the various products within an ecosystem that provide cultural benefits to beneficiaries (Caputo and Butler, 2017). The demand for CESs refers to the actual use of these products by people (Burkhard et al., 2012). With urban expansion and rapid economic development, CESs in urban ecosystems are not randomly distributed but rather highly localized, resulting in supply–demand mismatches (Gugulica and Burghardt, 2023). Thus, it is essential that the supply and demand of CESs in urban parks be effectively assessed (Dang and Li, 2023; Wei et al., 2024). The supply and demand of CESs also vary with changes in landscape composition and configuration (Assis et al., 2023). Current studies face challenges in exploring the "landscape-function-structure" dimensions, especially with respect to defining the contributions of various landscape elements to CESs (Zhang et al., 2022). Evaluating the supply and demand of CESs in urban parks, as well as understanding landscape-level influences on CESs, has significant theoretical and practical value for planning rational urban park development and enhancing residents' well-being.

Several models are commonly used to assess the supply of CESs, including SolVES, InVEST, ROS, and MIMES. The Social Values for Ecosystem Services (SolVES) model, developed jointly by the United States Geological Survey and Colorado State University, is a GIS application that estimates the social value of ecosystem services and visually displays the distribution of the value of CESs across different areas. Accordingly, it is important to assess social values in various ecological environments. Guan et al. (2023) used the SolVES model to assess and transfer the social values of three urban wetland parks, identifying the importance of water bodies and bridges in enhancing social value and providing recommendations for wetland park planning. Duan and Xu (2022) combined the SolVES model with survey methods to assess CESs in rural communities in Nanjing, China and proposed rural spatial optimization strategies based on social value assessments to promote sustainable rural development. Additionally, the SolVES model has proven effective in large-scale applications, providing scientific support for ecological planning and management decisions (Dang and Li, 2023). Methods for assessing the demand CESs mainly include big data technology applications, consumer willingness-to-pay surveys, and public perception studies, while traditional assessments rely primarily on survey data, which can be affected by data collection limitations and the restricted scope of survey coverage (Larson et al., 2016; Ko and Son, 2018). With advancements in information technology, big data analysis is increasingly being used for the demand evaluation of CESs. Liyan et al. (2023) utilized mobile signal data to map demand by tracking visit volumes to urban parks, whereas Van Zanten et al. (2016) used geotagged social media photos to quantify and identify scenic values at regional, continental, and even global scales. Although many studies rely on keyword frequency or thematic analysis for initial assessments, these methods often miss vocabulary that is deeply connected to the more in-depth premise of the topic, thus resulting in a lack of exploration of nuanced semantic relationships between words.

Different urban parks differ greatly in terms of landscape type and structural composition, and as a consequence, the effects of internal and external landscape structures on public satisfaction have largely been overlooked (Li et al., 2023). Metzger et al. (2021) reported that landscape structure influences the supply and demand areas of CESs, as well as the flows connecting them, through multiple landscape-level processes, such as fragmentation, edge effects, and connectivity. Assis et al. (2023) further highlighted the impact of landscape composition and configuration on the flow of CESs, particularly emphasizing the role of supply, demand, and neutral areas in the landscape, along with individual service characteristics. Bi et al. (2024) investigated how landscape patterns in urban parks affect residents' perceptions of various CESs. To increase the value of CESs for residents and support the sustainable development of urban parks, further research on the relationship between residents' perceptions and urban park landscape structures is essential (Daniels et al., 2018).

Integrating survey data with environmental variables enhances the explanatory and predictive power of the SolVES model (Riper et al., 2012), allowing effective evaluation of the supply of CESs. Online text data can reveal variations in perceptions of different types of CESs, perception frequencies, and associations between perception categories within urban parks (Jiang et al., 2022), while topic modeling can identify and quantify research themes within large data sets, assisting in decision-making (Sun and Yin, 2017). Furthermore, topic modeling enables direct modeling of word–pair co-occurrence data, enhancing accuracy in identifying latent themes and capturing implicit semantic structures within text data. The heterogeneous landscape of urban parks provides different types of CESs, influencing both supply and demand (Guo et al., 2023). Connecting CESs with landscape structures allows for a better understanding of their interactions, leading to optimized design and improved future landscape planning (Enrica et al., 2023).

CESs play a crucial role in maintaining and enhancing human well-being amid rapid urbanization (Kosanic and Petzold, 2020). As urbanization accelerates, the development and construction of urban parks to provide CESs and improve resident well-being becomes increasingly important. Therefore, effectively evaluating the supply and demand of CESs in urban parks is essential (Dang and Li, 2023; Wei et al., 2024). However, two key scientific questions remain. 1) How can social media data, big data technology, and mechanistic models be integrated to quantitatively assess the supply and demand of CESs in urban parks? 2) How can the impact of landscape-level processes on supply and demand CESs be evaluated to reveal the mechanisms by which these processes influence the supply and demand of CESs?

This study establishes an assessment framework for evaluating the CESs supply and demand in urban parks on the basis of the SolVES model driven by social survey data and environmental variables, as well as natural language processing models. By integrating environmental variables and resident perception attributes, this framework analyzes the spatial distribution characteristics of the supply and demand of CESs. Using traditional survey data combined with environmental variables, the SolVES model is applied to fit and obtain a distribution map of the CESs supply value index. Prioritizing human perceptions, big data and social media are used to conduct a multidimensional analysis of CESs (Li et al., 2022), including evaluations of visitor satisfaction and sentiment (You et al., 2022). Public opinions are gathered from social media platforms, and a biterm topic model (BTM) is used for theme identification to reveal the public demand for different types of CESs. Social media data reflect diverse public views, both positive and negative, and these reviews are typically retained on platforms for extended periods as they provide detailed insights valuable for management decision-making. Landscape indices are calculated on the basis of long-term land use data via a moving window method to reveal landscape-level processes. Finally, on the basis of the CESs supply and demand evaluation results of CESs and calculated landscape indices, correlation analysis and linear fitting reveal the effects of landscape-level processes on the supply and demand of CESs, whereas MGWR further reveals the spatially heterogeneous impacts of landscape configuration on the relationship between the supply and demand of the services. This empirical study, which is based on Chongqing's central urban area, provides a scientific foundation for the sustainable and efficient development of urban park ecosystems.

2 Materials and methods

2.1 Study area

Chongqing (28°10′–32°13′ N, 105°11′–110°11′ E) is located in the upper reaches of the Yangtze River and is a typical mountainous city in western China, covering a total administrative area of approximately 82400 km^2, with a permanent population of 32.13 million as of 2022. Chongqing, with 689 urban parks, ranks second among Chinese cities. The central urban area of Chongqing covers 4779 km^2, including nine districts: Yuzhong, Dadukou, Jiangbei, Shapingba, Jiulongpo, Nan'an, Beibei, Yubei, and Banan. This study conducted field surveys, size comparisons, and online data analyses of the parks located in Chongqing's central urban area. Smaller parks and those with lower visitor volumes were excluded, whereas parks with rich social media commentary and greater resident popularity were retained for this study, resulting in 60 major parks providing information regarding the CESs (Fig. 1).

2.2 Methodology

The research approach and framework adopted in this study are presented in Fig. 2. The first step involves data acquisition, which includes field survey data, social media data collected through web scraping, and other basic geographic information. The gathered data are then cleaned and preprocessed to construct a comprehensive database. The second step involves quantifying the supply of CESs. Using field survey data and environmental variable data, the SolVES model is applied within the QGIS platform to fit and produce a value index distribution map, with the AUC value used to evaluate the model's performance. The third step includes quantifying the demand for CESs. On the basis of the BTM topic model, social media data are analyzed to determine the optimal number of topics, quantify the urban parks' demand for CESs and reveal the spatial differences in the distribution of the demands for CESs. The fourth step is the construction of the indicator system for landscape-level processes, which is based on Fragstats for the calculation of the four landscape indices. The results of the multiyear average landscape indices are quantified using the moving window method, revealing the landscape-level processes. The fifth step involves revealing the mechanisms by which landscape-level processes influence the supply and demand of CESs, and the benefits of the supply and demand of CESs. The landscape indices of individual parks are then calculated on the basis of zonal statistics, Pearson correlation coefficients are used for correlation analysis, and linear fitting is employed to reveal trends in their impact. In addition, MGWR further explores the spatially heterogeneous effects of landscape configuration on the supply and demand of CESs, thus providing deeper insights into their relationships.

2.2.1 Quantifying the supply of CESs

The SolVES model, developed jointly by Colorado State University and the US Geological Survey in 2011, is primarily based on the QGIS platform and incorporates the perspectives and preferences of various stakeholders in the trade-offs of CESs. SolVES uses embedded

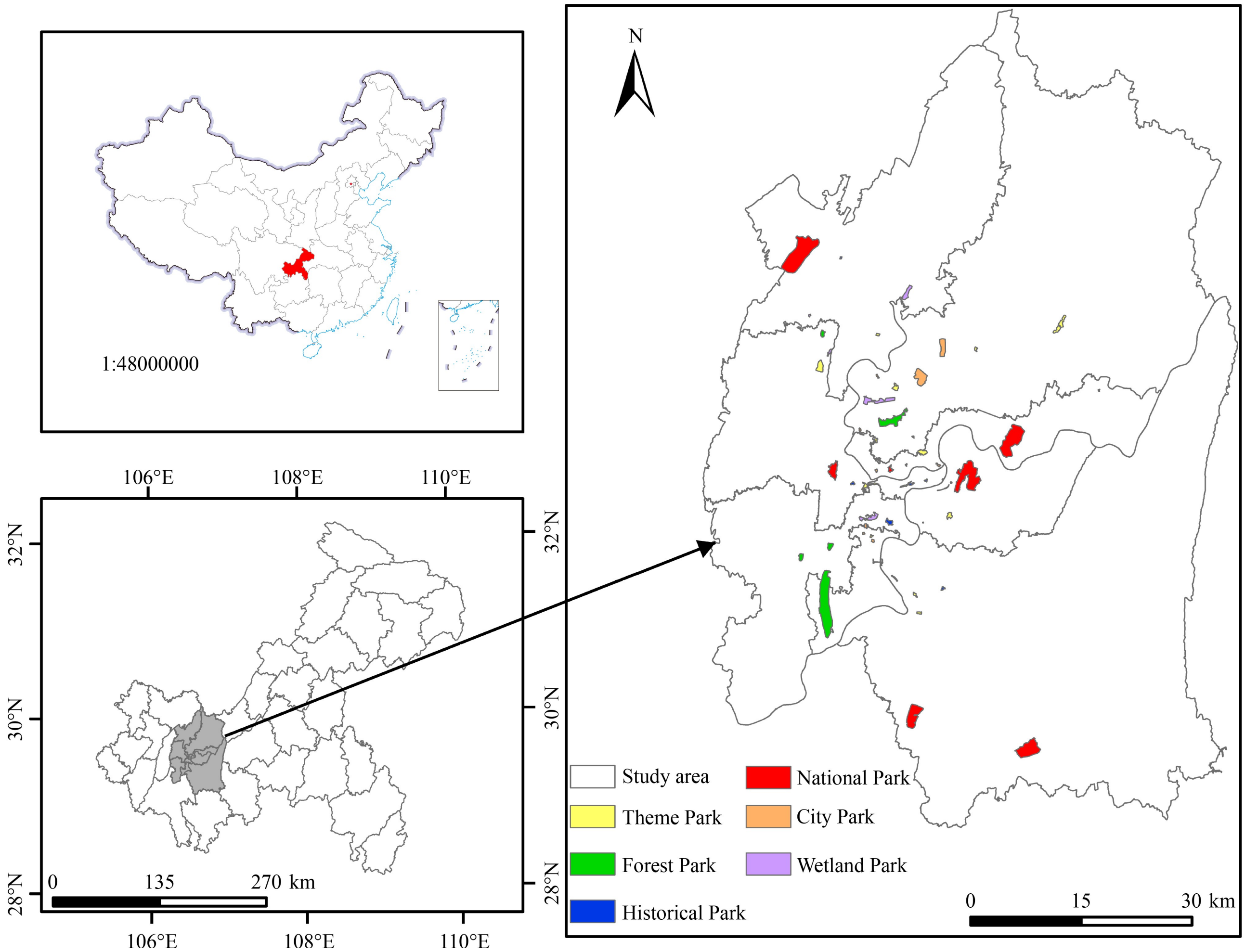

Fig. 1 Location of the case study parks under analysis in Chongqing's central urban area.

MaxEnt (maximum entropy) modeling software to generate comprehensive social value maps and assess the correlation between social values and environmental variables (Zhou et al., 2020). The model consists of three submodules, namely, the social value model, the value mapping model, and the value transformation mapping model, of which the first two submodules of the model are the main ones involved in this study.

From September 2023 to May 2024, 350 research data points were obtained through field research in different parks, 316 of which were valid questionnaires, with an effective rate of 90.29% (see Supplementary Materials, Appendix A provides the details of the questionnaire design). DEM data and remote sensing images were obtained from the Geospatial Data Cloud. The slope was generated via the surface analysis tool of ArcGIS 10.2, and the distances to water (DTW), distance to road (DTR), distance to light rail station (DTLRS), and distance to built-up area (DTBA) were generated via the distance analysis tool. Survey data on assigned value points were spatialized and integrated with environmental variable data into the SolVES model to generate a supply value index distribution map of CESs.

Using MaxEnt modeling within the SolVES model, this study quantified the contribution weights of various environmental variables to the supply of CESs (Table 1). The analysis revealed that the DTLRS plays a dominant role across all types of CESs (with weights ranging from 56.7% to 60.4%), especially for educational value (60.4%) and aesthetic value (59%), which show the highest sensitivity. The DTR contributes the most to spiritual value (15.4%), whereas the DTBA has a significant effect on entertainment value (14.6%). Although slope and land use/land cover (LULC) have relatively lower weights, they still exert certain influences across different types of CESs. These variations in weights reveal that transportation accessibility and proximity to water bodies are the core drivers of the supply of CESs in urban parks.

2.2.2 Quantifying the demand for CESs

The BTM directly captures word co-occurrence patterns across the entire corpus to discover latent topics, enabling

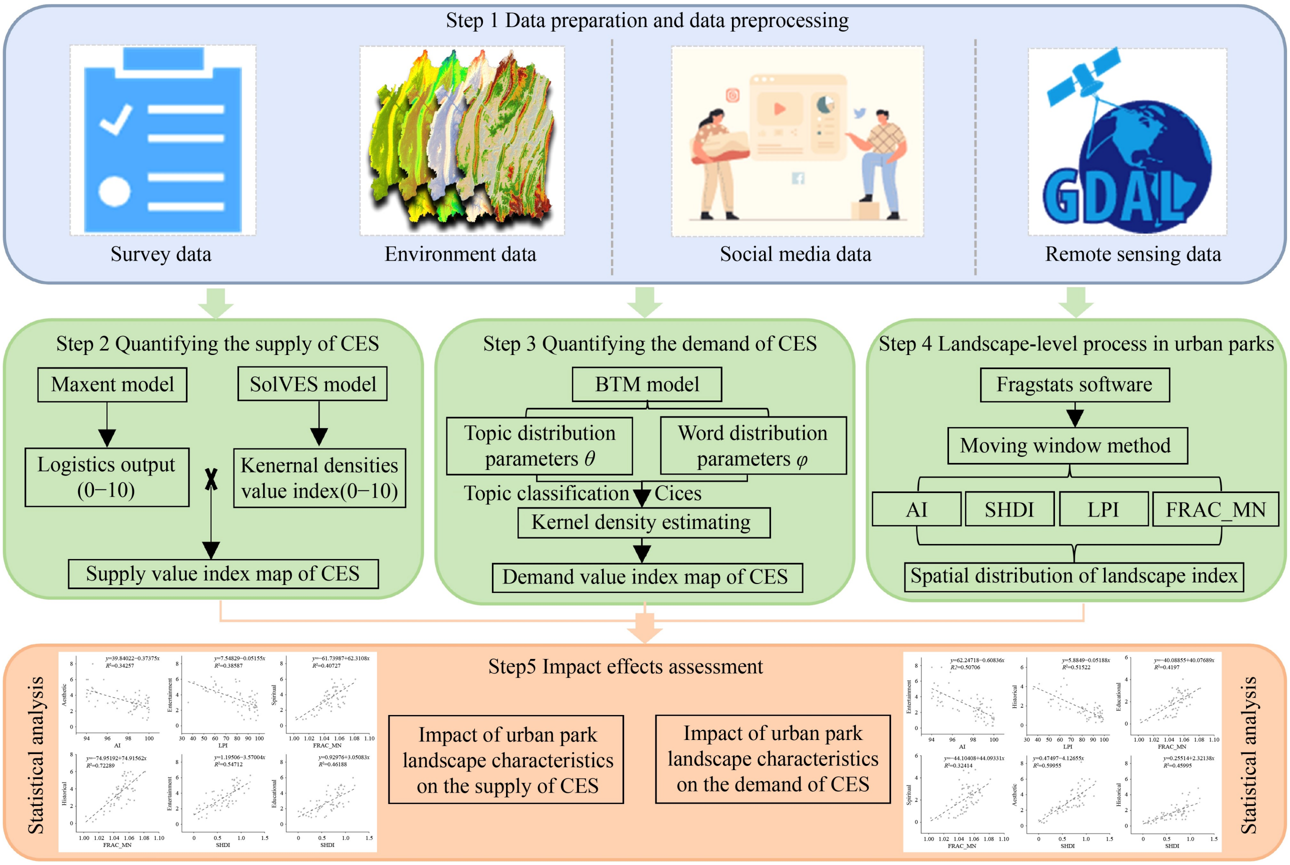

Fig. 2 Research framework.

Table 1 Contribution of environmental variables to CESs supply (%)

CESs	DTLRS	DTR	DTW	DTBA	Slope	LULC
Aesthetic service	59	14.4	11.1	6.3	5.8	3.4
Historical service	59.3	12.9	9.8	8.4	5.6	4
Entertainment service	56.7	11.4	11.1	14.6	4.2	2
Spiritual service	55.9	15.4	12.2	8.2	4.5	3.8
Educational service	60.4	13.5	10.3	5	6.8	4

effective topic inference, particularly for short-text scenarios (Cheng et al., 2014). In this study, the BTM was employed to extract implicit themes from user-generated content on urban park experiences, thereby enabling a deeper assessment of the public demand for CESs provided by urban parks. The social media data set was collected from the Dianping website and was comprised of 109629 user comments related to 60 urban parks, from January 21, 2013 to December 30, 2023.

To ensure the reliability and validity of the data, this study adopted a stratified cleaning strategy to systematically process the original review data set. The procedure consisted of four sequential stages. The first stage, automated preprocessing, was conducted using the NLTK library in Python and included duplicate detection on the basis of regular expressions, removal of non-Chinese characters, and exclusion of commercial advertisements to preliminarily improve data quality. In the second stage, comments irrelevant to CESs in urban parks were filtered out through a combination of keyword screening and manual review, thereby enhancing thematic relevance at the semantic level. The third stage consisted of a sentiment analysis performed using the SnowNLP library to identify negative emotional expressions while retaining feedback related to specific dimensions of CESs, such as aesthetics and educational value, which aided in identifying service shortcomings. Similarly, by associating sentiment polarity with user behavior patterns, potentially fake or misleading comments were identified and excluded, thereby increasing the authenticity and analytical robustness of the data set. Finally, all comments were standardized by removing emojis, special characters, and stop words and were segmented via the Jieba tool in Python, thus providing a solid semantic foundation for the subsequent modeling of visitor demand across various types of CESs. The cleaned and segmented texts were then used as input for the BTM model to extract latent topics, as illustrated in Fig. 3.

In the figure, α and β are Dirichlet prior parameters; θ represents topic distribution probabilities in the corpus; φ is the probability distribution of topic words within specific topics, where the topic words are word pairs (W_i, W_j); Z denotes the topic label for each word pair; and K is the topic count. $|B|$ represents the total number of word pairs in the corpus.

Topic coherence is a crucial indicator of the semantic consistency of generated topics, as it evaluates the semantic associations among high-frequency words within the same topic (Blair et al., 2020), while perplexity measures the model's fit to test data and reflects the uncertainty in predicting the topic distribution. A lower value implies better topic structure capture (Egger and Yu, 2022). The formula is as follows:

$$PPL = \exp^{(-\sum_{i=1}^{N} \lg p(w_i))/N}, \quad (1)$$

where PPL denotes topic perplexity, N is the number of documents in the test set, and $p(w_i)$ is the probability assigned by the model to the i-th document.

The optimal topic number K for the BTM model was determined via a dual-criterion validation method on the basis of perplexity and topic coherence. To determine the number of topics with higher-quality model results, the topic number K ranges from 20 to 50 with an interval of 2. The data set was randomly divided into 80% training and 20% validation sets for a 5-fold cross-validation (Kornblith et al., 2025). As presented in Fig. 4, when the topic number K reached 38, the model exhibited a clear extremum, that is, the perplexity index reached a local minimum, whereas the topic coherence index reached a local maximum, which is consistent with the inflection point selection principle in topic modeling (Zhang et al., 2023). To mitigate the influence of random initialization, ten independent runs were conducted under the parameter setting of K = 38. The results confirmed that the coefficient of variation of the evaluation metrics satisfied the robustness threshold (Ballester and Penner, 2022). This parameter selection process strictly follows the latest methodological standards in short-text topic modeling, thereby ensuring a dynamic balance between model complexity and semantic interpretability, while also achieving both theoretical rigor and practical applicability (Li and Yin, 2025).

The BTM parameters are set as follows: K = 38, α = 50/K, β = 0.01, and the number of iterations is Niter = 1000. The BTM model can obtain two types of probability distributions, one of which is the distribution probability of the topic in the document θ, and the other is the distribution probability of the occurrence of the vocabulary under a particular topic φ. A larger θ indicates that the probability of the topic's occurrence in the corpus is higher, and a larger φ indicates that the vocabulary occurs more frequently under a particular topic.

On the basis of the Common International Classification of Ecosystem Services (CICES) and the concept of CESs from the Millennium Ecosystem Assessment (MA), the team used the Delphi method of expert evaluation and invited five researchers to form an expert team (including three professors and two doctoral students) to extract keywords from different topics associated with the value classifications of the CESs. Five types of CESs value indicators were ultimately selected and categorized by value layers (Table 2).

2.2.3 Establishing a landscape-level process index system

Landscape patterns can reflect the spatial configuration characteristics of various patches, types, and landscapes

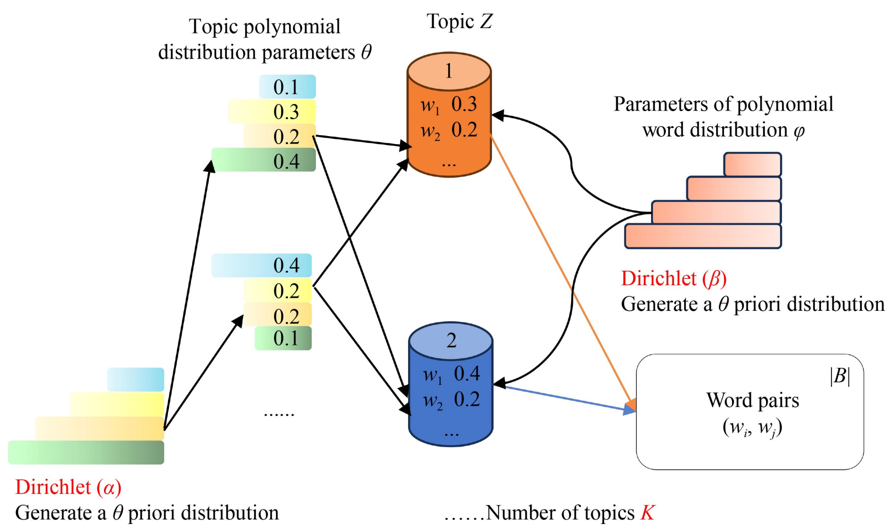

Fig. 3 Schematic diagram of BTM generation model.

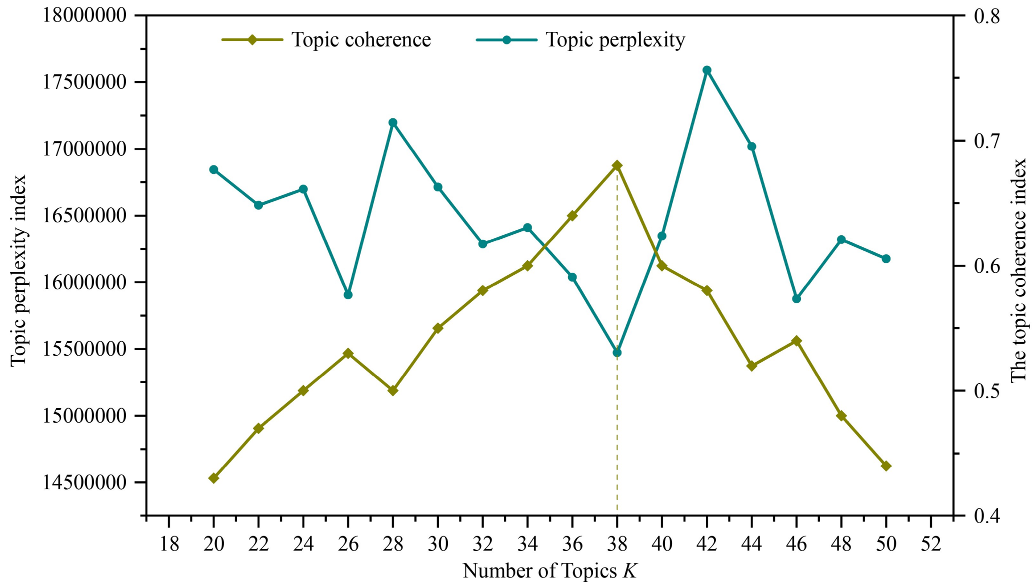

Fig. 4 Topic coherence and perplexity under different numbers of topics.

Table 2 Thematic division of the value of CESs in urban parks

CESs	Description	Keywords example	Keywords example	Representative parks
Aesthetic service	Scenery description	Beautiful, Nice view, flowers	3, 5, 6, 9, 15, 16, 19, 20, 21, 28, 32, 34, 37	Grandma's Garden, Erchang Cultural and Creative Park
Entertainment service	Entertainment, play	Playful, tourists, sports event	1, 2, 4, 8, 10, 11, 13, 23, 24, 26, 33, 38	Pleasant Valley, Green Planet Animal Theme Park
Spiritual service	spiritual fulfillment	Feeling, comfortable, relaxed	7, 12, 17, 18, 27, 29, 31	Nanshan National Forest Park, Fotuguan Park
Historical service	Historical monuments and sites	Historic relics, war of resistance, culture	25, 36	Liziba Anti-Japanese War Heritage Park, Chongqing Kai Bu Ruins Park
Educational service	Learning about nature	Learn, explorations, knowledge-related	14, 22, 30, 35	Geleshan National Forest Park, Lijia Smart Park

within a given area (Lyu et al., 2022). Changes in the landscape patterns of urban parks often lead to shifts in residents' perceptions of these parks (Bi et al., 2024) and also impact the supply of CESs. Landscape pattern indices are essential theoretical tools for quantifying landscape pattern changes.

This study selected four landscape pattern indices, including the AI, average fractal dimension (Frac_MN), largest patch index (LPI), and SHDI, which represent landscape processes that influence the supply and demand of CESs in urban parks. The selection of these indices is based on their strong theoretical relevance to human perception and the assessment of cultural values. Specifically, AI reflects the degree of spatial clustering among similar land cover patches because, in highly homogenized landscapes, excessive aggregation is often linked to aesthetic monotony and diminished recreational appeal (Guo et al., 2023). Frac_MN characterizes the geometric complexity of patch boundaries, with greater shape complexity enhancing visual stimulation and cognitive engagement, thereby supporting the provision of aesthetic and educational services (Lin et al., 2024). The SHDI captures the richness and evenness of landscape types and is widely used as a proxy for perceptual diversity and multifunctionality (Li et al., 2024a). The LPI, which represents the dominance of the largest patch, indicates landscape heterogeneity. In the context of this study, the LPI measures the proportion of the most dominant land use type within a park rather than the overall size of the park, thereby highlighting internal landscape simplification. Higher LPI often suggest a lack of spatial and functional diversity, which may limit the range of cultural services provided (Deng et al., 2024). These indices reflect the degree of landscape aggregation, shape complexity, patch dominance, and compositional diversity, respectively.

The calculation formulas for each index are as follows:

$$\mathrm{AI} = g_{ii} / (\max \rightarrow g_{ii}) \times 100, \tag{2}$$

$$\mathrm{Frac\_MN} = \sum_{i=1}^{m} \sum_{j=1}^{n} \left[2 \ln(0.25 C_{ij}) / \ln a_{ij} \right] / N, \tag{3}$$

$$\mathrm{LPI} = a_{\max} / A \times 100, \tag{4}$$

$$\mathrm{Shannon} = -\sum_{g=1}^{m} P_g \ln P_g, \tag{5}$$

where AI represents the landscape aggregation index and g_{ii} denotes the number of similar adjacent patches for the landscape type. Frac_MN represents the average fractal dimension, a_{ij} is the area of the jth patch in the i-th landscape type (km^2), and C_{ij} represents the perimeter of this patch (km). LPI represents the largest patch index, $a_{\max}$ represents the area of the largest patch within the landscape (km^2), and A represents the total landscape area (km^2). Shannon represents Shannon's diversity index, and P_g denotes the probability of occurrence of the g-th patch type within the landscape.

By comparison, although connectivity and fragmentation metrics play important roles in biodiversity conservation and ecological corridor assessments, they focus primarily on ecological processes such as species movement and network connectivity. Therefore, they are better suited for regulating and supporting services and may not effectively capture urban residents' subjective perceptions of aesthetic or spiritual experiences (Unnithan Kumar and Cushman, 2022; Beele et al., 2024; Deng et al., 2024). Moreover, the four selected indices form a complementary and nonredundant framework that spans four dimensions, namely, spatial configuration (AI), shape complexity (Frac_MN), patch dominance (LPI), and compositional diversity (SHDI). This framework offers a comprehensive representation of how landscape processes influence the spatial distribution and intensity of the values of CESs values, thereby ensuring methodological robustness and enhancing the interpretability and policy relevance of the findings (Cao et al., 2024).

To support spatial analysis, this study employed the moving window method, which quantifies spatial heterogeneity by systematically sliding a fixed-size window across the data set and calculating the metrics within each window (Aguilera-Benavente et al., 2023). This approach enables the calculation of landscape indices, the quantification of spatial configurations, and the identification of potential scale effects (Gustafson, 1998). Here, Fragstats software was used to implement the moving window analysis and calculate the multiyear averages of the four landscape indices for evaluating landscape-level processes.

2.2.4 Evaluating influence mechanisms

Zonal statistics allow for the statistical analysis of landscape grids to calculate values for different landscape indices, thereby enabling evaluation (Che et al., 2023). Pearson correlation analysis and scatter plots are employed to explore the relationships between landscape patterns and various perceptions of CESs in urban parks (Wang et al., 2019). MGWR further quantifies the mechanisms of spatial heterogeneity (Fotheringham et al., 2017), thereby revealing the spatially differentiated impacts of landscape patterns on the supply–demand relationships of CESs. In this study, the CESs supply and demand values and landscape indices for each park are calculated, followed by Pearson correlation analysis and linear fitting to identify trends. The correlation coefficients and coefficients of determination reflect the strength and fit of the relationships, revealing the influence of landscape-level processes on the supply and demand of CESs. The MGWR framework, through localized regression coefficients and adaptive bandwidth optimization, further clarifies the spatially differentiated effects of landscape configurations on the supply–demand relationships of CESs.

3 Results

3.1 Supply and demand results of CESs

The evaluation results for the supply of CESs are displayed in Fig. 5. As indicated, the index with the highest value for aesthetic, historical, and spiritual values of urban parks is 9, whereas the indices with the highest value for entertainment and educational values are 8 and 7, respectively. However, esthetic and historical values are the most widely distributed, with areas for high historical value are concentrated in Yuzhong District, which is known for its rich Ba-Yu and wartime culture and features significant historical sites such as Liziba Anti-Japanese War Heritage Park, Fotuguan Park, and People's Park. Aesthetic values extend outward from Yuzhong District and include popular destinations such as Erchang Cultural and Creative Park, Nanshan National Forest Park, and Grandma's Garden. Popular spots for entertainment services are located primarily in Jiangbei District, with parks such as Hongen Temple Forest Park, Tieshanping Forest Park, and Green Planet Animal Theme Park, all of which offer abundant cultural and recreational resources. High-value areas for spiritual services are concentrated in Nan'an and Yuzhong Districts, where the natural scenery and peaceful environments of green spaces provide spiritual support for residents. Notably, educational value supply is relatively low and is scattered across various locations, with high-value areas located in and around Yuzhong District.

The demand evaluation results for CESs are presented in Fig. 6, with entertainment value accounting for 42.37%, aesthetic value accounting for 31.55%, historical value accounting for 2.22%, educational value accounting for 7.40%, and spiritual value accounting for 16.46%. The high proportions of entertainment and aesthetic values indicate that these types of services are more perceptible and broadly demanded. Spatially, high-demand areas for aesthetic and entertainment value are concentrated in Yuzhong District, the western side of Jiangbei District, the south-western part of Yubei District,

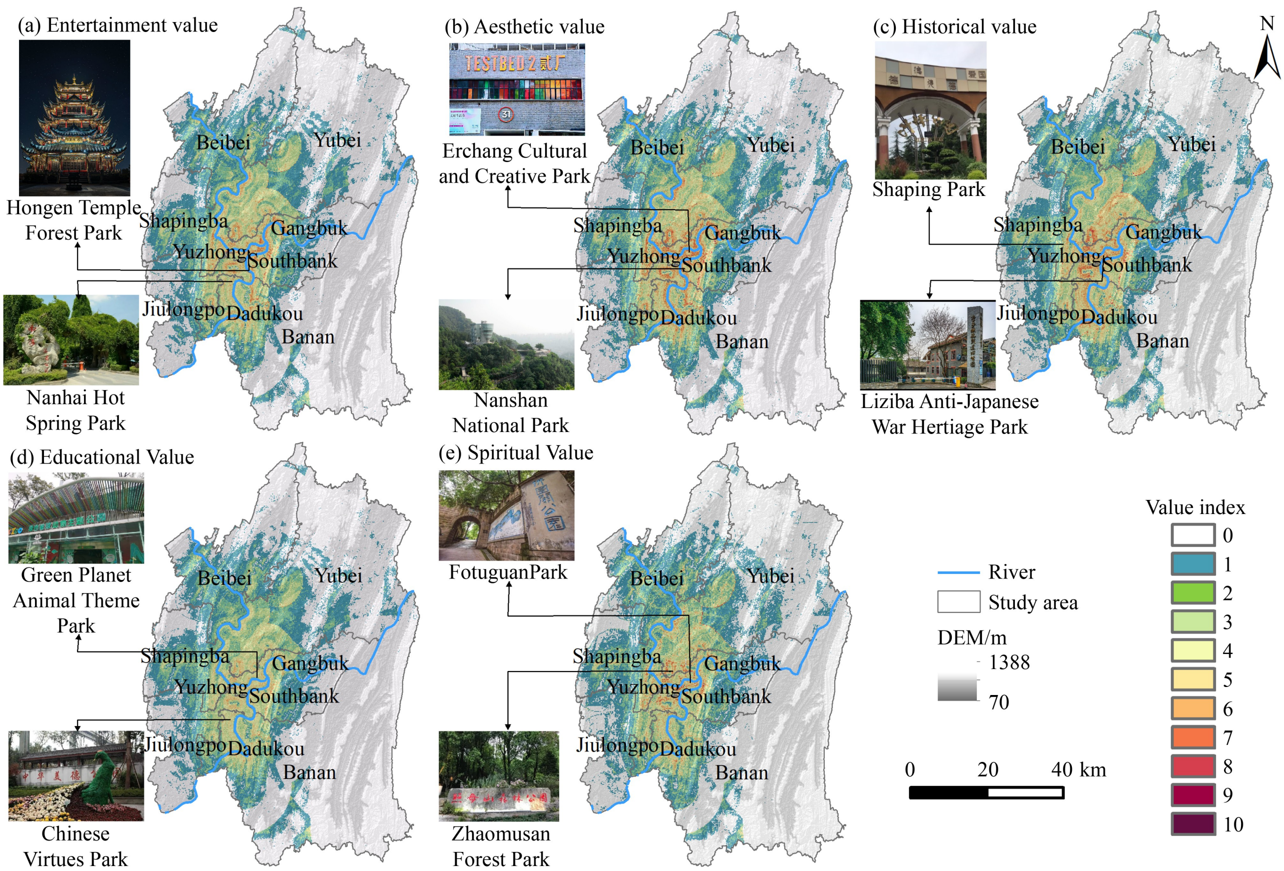

Fig. 5 Assessment results of CES supply.

and the western side of Nan'an District, with demand for entertainment being relatively greater, while high-demand areas for educational and spiritual values are concentrated in Yuzhong District and spread outward, with demand for spiritual value being relatively greater and more widely distributed. Historical value perception is comparatively low across the study area, indicating a lower demand.

3.2 Spatial distribution of landscape-level processes

The spatial distributions of the multiyear average values of the four landscape indices from 2010 to 2020 in Chongqing's central urban area are presented in Fig. 7. The multiyear average for the AI ranges from 89.71 to 100, with an average of 97.38, indicating greater aggregation in central areas and relatively lower values at the edges, suggesting a greater degree of landscape fragmentation in peripheral areas. The multiyear Frac_MN is lowest in northern Yubei and eastern Beibei, with a spatial range of 1 to 1.1 and an average of 1.06, indicating relatively simple patch shapes in these areas, whereas patches in other parts of the central urban area are more complex. The multiyear average LPI and SHDI have spatial ranges of 32.96 to 100 and 0 to 1.33, with averages of 72.51 and 0.54, respectively. The LPI is greater in the east and lower in the west, whereas the SHDI exhibits the opposite pattern, indicating greater patch diversity and a lower proportion of the largest patch type in the west, with a concentration of dominant landscapes in the east.

3.3 Influence effect of landscape-level processes on CESs values

The correlations between the different values of CESs and landscape indices are presented in Fig. 8. The results indicate a positive correlation between the supply and demand values of CESs, with the strongest significant positive correlation between historical and spiritual value supply (p = 0.81***) and with aesthetic and entertainment demand values also revealing a significant positive correlation (p = 0.75***). The LPI shows a weak negative correlation with both the supply and demand values of CESs, but it is significantly associated with the entertainment supply (p = −0.74***) and historical demand (p = −0.72***), while values of some CESs are not significantly correlated, suggesting that further data validation may be needed for these relationships. AI is negatively correlated with both the supply and demand values of CESs, with the strongest correlations found for educational supply (p = −0.81***) and entertainment demand (p = −0.62***). However, SHDI is positively correlated with both the supply and demand values of CESs, with the strongest associations found for

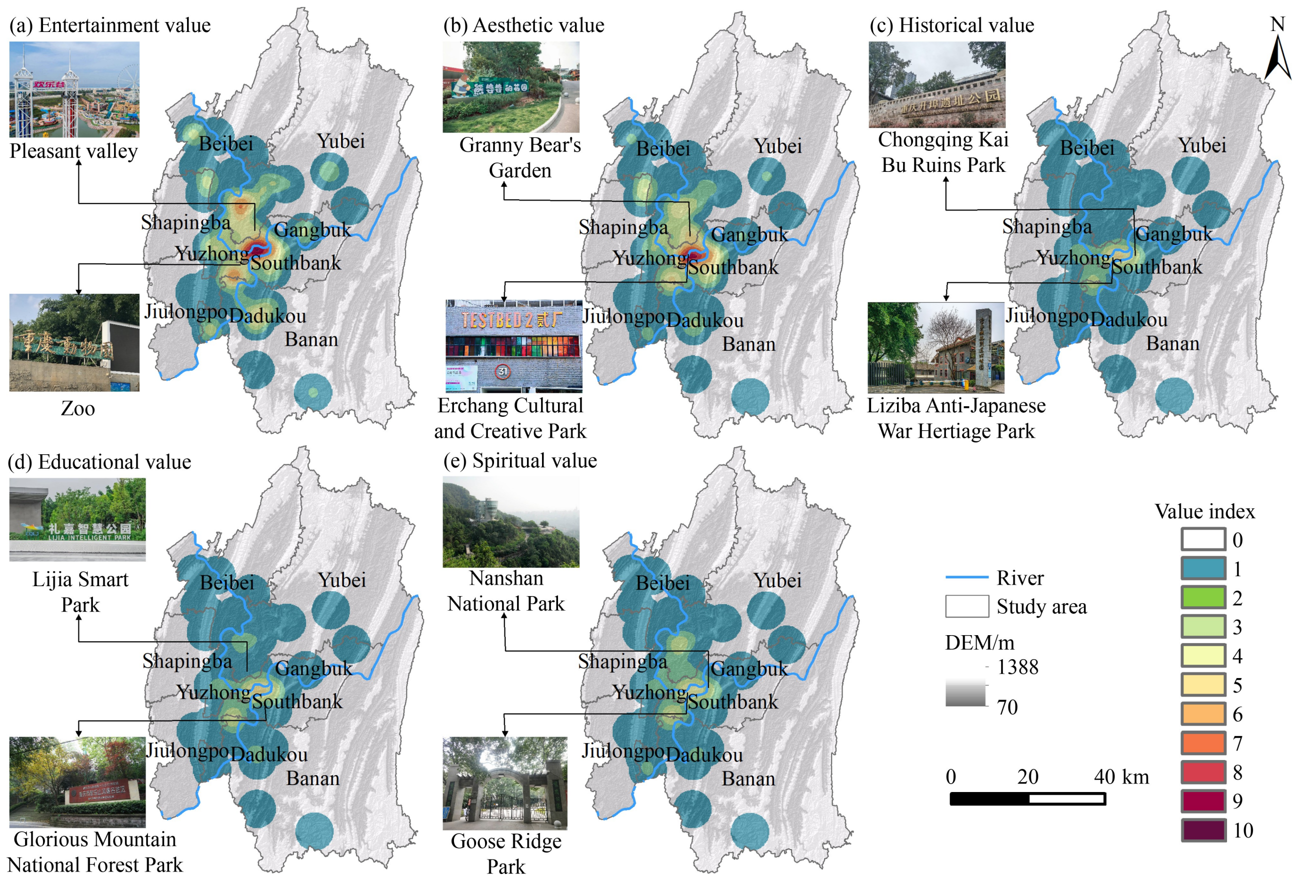

Fig. 6 Assessment results of CES demand.

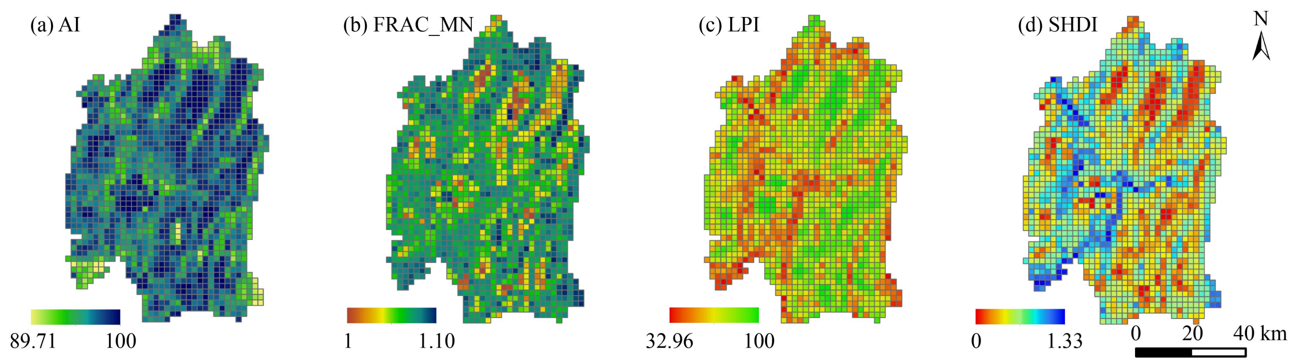

Fig. 7 Spatial distribution of multi-year average of landscape pattern index.

educational supply (p = 0.71***) and aesthetic demand (p = 0.64***), indicating that increased landscape diversity positively impacts the supply and demand values of CESs. Frac_MN is significantly positively correlated with the supply side of CESs and weakly positively correlated with the demand side, with the strongest correlations observed for historical supply (p = 0.72***) and educational demand (p = 0.65***), thus suggesting a degree of influence on the supply and demand of CESs.

The linear fit relationships between the CESs supply and demand values in urban parks and the landscape indices are shown in Fig. 9. Figure 9(a) indicates that the AI and aesthetic value supply are negatively correlated, as increased aggregation can lead to a uniform landscape composition, reducing, to some extent, the supply of CESs. LPI have a significant negative correlation with the entertainment supply, indicating that a reduction in LPI may increase the entertainment value supply, whereas Frac_MN is significantly positively correlated with spiritual and historical value supply, suggesting that increased patch complexity promotes these CESs values. SHDI is also positively correlated with educational and entertainment supply values, indicating that greater landscape diversity increases the educational and entertainment values provided by urban parks. Figure 9(b) indicates that aggregation is significantly negatively

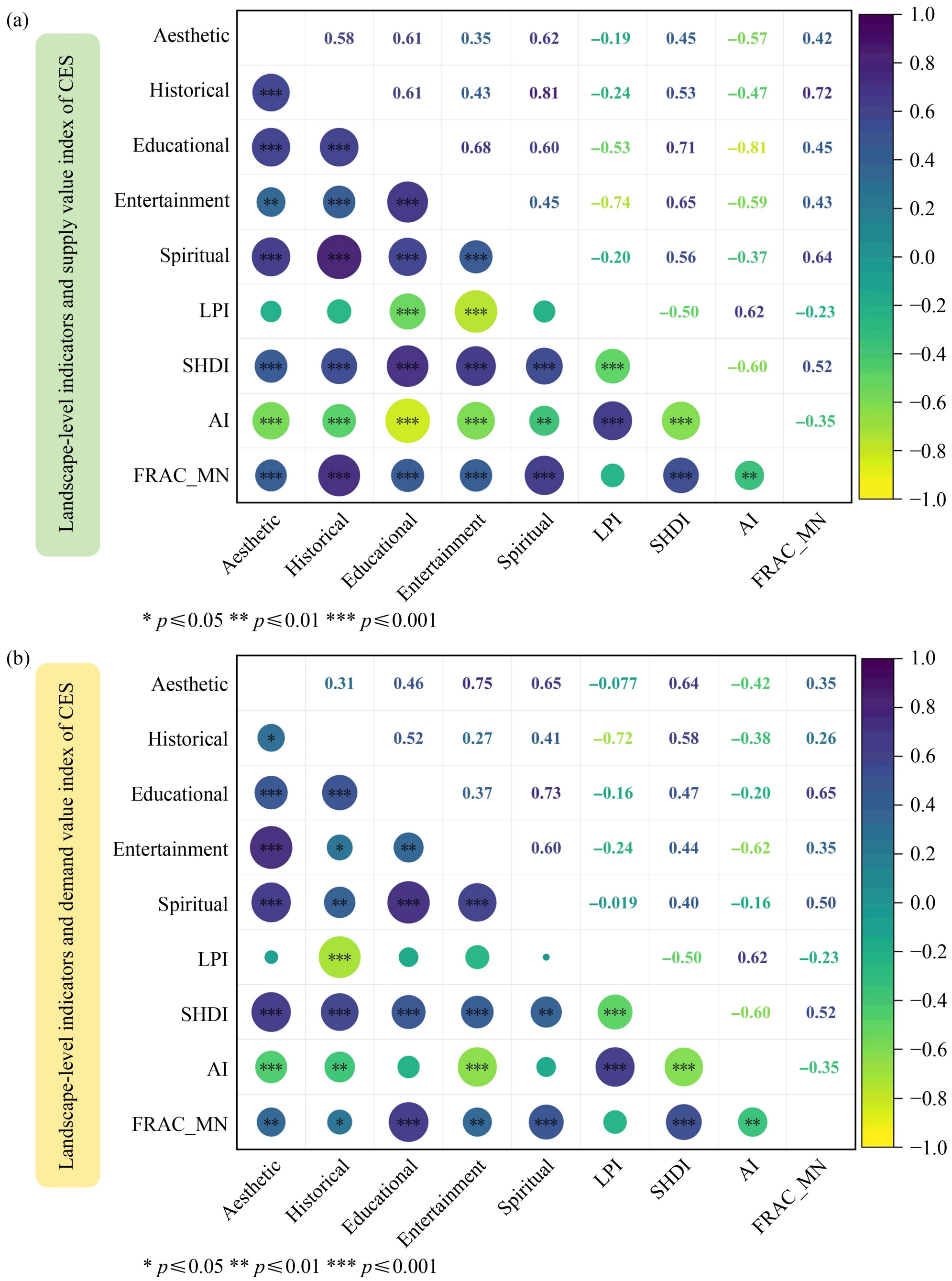

Fig. 8 Correlation analysis between landscape indices and CES value index.

correlated with entertainment demand, meaning that reduced aggregation may increase demand for entertainment value, and that the LPI is negatively correlated with historical demand, as an increase in the largest patch proportion reduces historical demand. Frac_MN, however, is positively correlated with demand for educational and spiritual values, indicating that increased complexity in patch shapes effectively increases the demand for these specific CESs. SHDI has a significant positive correlation with the demand for aesthetic and historical values, as increased landscape diversity increases the demand for aesthetic and historical benefits in urban parks.

In addition, the results of the MGWR model further reveal the spatially explicit relationships and scale-dependent effects between landscape indices and the benefits of CESs (Table 3), with the model's overall performance and key parameters presented in Supplementary Materials (see Table A1). On the supply side, Frac_MN at the regional scale has a significant positive effect on historical supply (α = 0.634***) and spiritual supply (α = 0.469***), highlighting the role of complex patch shapes in supporting narrative and symbolic spatial experiences. At the global scale, SHDI

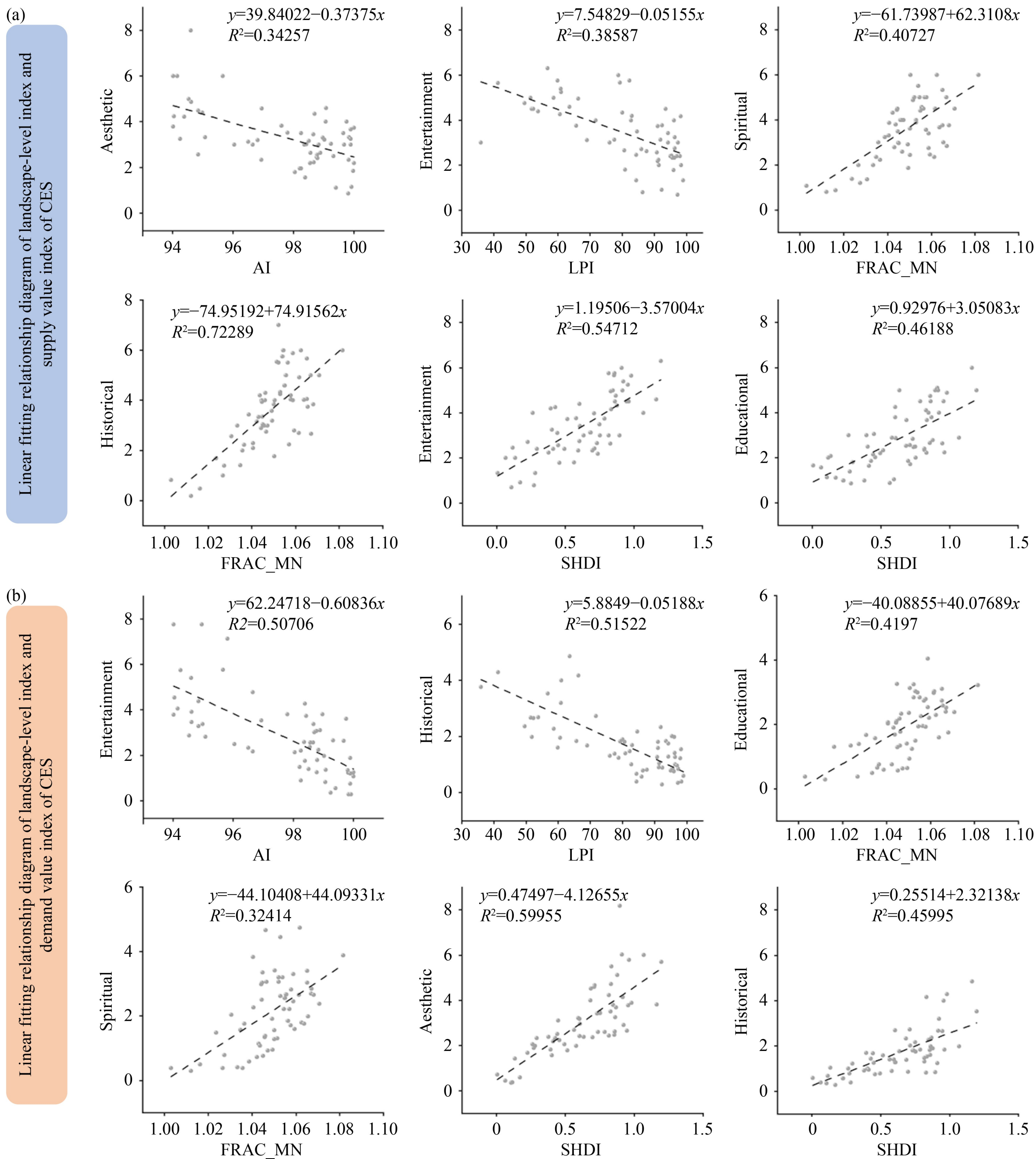

Fig. 9 Linear fitting analysis between landscape indices and CES value index.

positively drives the supply of entertainment (α = 0.471***), spiritual (α = 0.373***), and educational (α = 0.311***) benefits, emphasizing the importance of landscape heterogeneity in increasing the supply of CESs. On the demand side, AI significantly suppresses the demand for entertainment (α = −0.667***) and educational services (α = −0.142*) globally, suggesting that highly aggregated landscape patterns may limit users' accessibility to community services and perceived diversity. At the local scale, LPI has a negative effect on aesthetic demand (α = −0.759***), indicating that the dominance of single patches may reduce visual variation and lower user engagement. In contrast, Frac_MN and SHDI have positive impacts on the cross-scale demand for educational, spiritual, aesthetic, and historical values, suggesting that greater complexity and diversity in landscape configuration can enhance both the supply and demand of CESs.

Table 3 Comparative impacts of landscape metrics on the supply and demand of CESs

Landscape indices	CESs	Supply (Coeff/Bandwidth)	Demand (Coeff/Bandwidth)
	Entertainment service	0.103 (59)	0.360*** (59)
	Historical service	0.634*** (53)	−0.047 (59)
Frac_MN	Spiritual service	0.469*** (53)	0.516*** (59)
	Aesthetic service	0.210* (59)	−0.006 (59)
	Educational service	0.065 (56)	0.034 (59)
	Entertainment service	−0.063 (57)	−0.667*** (59)
	Historical service	−0.171** (59)	−0.135* (57)
AI	Spiritual service	0.041 (57)	0.085 (59)
	Aesthetic service	−0.454*** (54)	−0.132* (59)
	Educational service	−0.376*** (46)	−0.142* (59)
	Entertainment service	−0.372*** (56)	−0.122* (59)
	Historical service	−0.038 (59)	−0.354*** (59)
LPI	Spiritual service	−0.018* (59)	−0.188 (53)
	Aesthetic service	−0.120 (58)	−0.759*** (49)
	Educational service	−0.230** (43)	−0.039 (59)
	Entertainment service	0.471*** (59)	0.516*** (59)
	Historical service	0.095 (59)	0.882*** (59)
SHDI	Spiritual service	0.373*** (59)	0.331* (57)
	Aesthetic service	0.168 (57)	0.641*** (56)
	Educational service	0.311*** (59)	0.433** (56)

Notes: a) Coefficients represent standardized estimates with bandwidths in parentheses. ***, $p < 0.01$; **, $p < 0.05$; *, $p < 0.1$. b) Bandwidth interpretation: Local (⩽ 50), Regional (51−58), Global (59−60).

4 Discussion

4.1 Relationships between the supply and demand of CESs and landscape-level processes

Research has shown that the plant landscapes of urban parks can influence their aesthetic quality (Aboufazeli et al., 2022), with diverse plant community structures supporting enhanced landscape aesthetics (Li et al., 2024a). However, few studies have evaluated the effects of landscape-level processes on both the supply and demand of CESs or examined the influence of landscape-level processes on residents' perceptions of multiple CESs (Bi et al., 2024). This study reveals that landscape-level processes in urban parks have a certain impact on the benefits of both the supply and demand of CESs, with varying effects of the benefits of the different CESs.

Using Pearson correlation analysis, multiple linear regression, and MGWR, this study identifies a significant positive relationship between landscape diversity and the demand for CESs. For example, greater spatial heterogeneity enhances visual appeal and better meets residents' aesthetic and emotional needs (Li and Liu, 2024). Previous findings have found that composite, multielement landscapes prolong visual engagement and yield higher aesthetic ratings than do homogeneous landscapes. Furthermore, rich plant community structures significantly increase the aesthetic supply potential of landscapes (Li et al., 2024a), and diversified landscape element combinations similarly enhance the perceived naturalness and intimacy of the environment, triggering emotional resonance and stimulating the demand for CESs (Zhou et al., 2023). These effects are driven by visual diversity-induced cognitive and emotional responses (Cheng et al., 2024), as well as improved service efficiency from optimized vegetation patterns and spatial accessibility (Li et al., 2024b). Eye-tracking and behavioral studies further indicate that residents exhibit stronger aesthetic preferences and higher usage frequency for diverse landscapes, with usage purposes being highly coupled with landscape characteristics (Liu et al., 2021; Wang et al., 2021). Specifically, in complex landscapes, dynamic shifts in visual focus are positively correlated with aesthetic pleasure (Cheng et al., 2021). These findings further suggest that enhancing landscape diversity effectively optimizes the supply–demand match of CESs, thereby improving residents' sense of gain.

The analysis also identifies a significant negative correlation between landscape spatial aggregation and the supply of educational services. Highly aggregated landscapes characterized by structural homogeneity tend to lack the ecological and cultural diversity required to support educational CESs. In contrast, heterogeneous landscapes provide a broader range of educational opportunities and cultural references (Wu et al., 2024). For example, patchy mountainous terrains support diverse outdoor learning scenarios (Tenerelli et al., 2016), whereas traditional village mosaics convey local knowledge and cultural identity (Kostanjšek and Golobič, 2023). Similarly, greater vegetation richness in forest parks enhances educational activity diversity and depth (Cheng et al., 2024). Thus, landscape aggregation may reduce ecological interface complexity and diminish the capacity for cultural memory transmission. Accordingly, further research should explore threshold effects and design strategies that integrate natural and anthropogenic elements to strengthen the cultural functionality of landscapes.

Additionally, the findings indicate that landscape homogeneity and dominant structure concentration reduce the supply of CESs and weaken the demand of residents. In contrast, increased landscape diversity and moderate fragmentation enhance the perception and provision of multiple CESs (Fig. 10). Previous studies have confirmed that fragmented landscapes with high patch diversity enhance both aesthetic appeal and recreational opportunities (Mao et al., 2023). Social media data further show that fragmented biotic (40.8%) and infrastructural (40.7%) landscapes support multifunctional activity spaces and reinforce perceptions of the CESs (Chen et al., 2024). However, fragmentation has dual effects. For example, excessive fragmentation compromises ecological connectivity, increases patch density, reduces vegetation coverage, and lowers the contribution of core landscape patches (LPI), thereby negatively impacting spiritual and heritage-related CESs (Guo et al., 2023; Sun et al., 2023). Therefore, urban park planning should prioritize maintaining ecological connectivity while promoting spatial heterogeneity. Enhancing landscape diversity, multifunctionality, and accessibility is essential for improving the overall delivery of cultural, educational, and recreational services and for better meeting the residents' multidimensional CESs needs.

4.2 Implications for optimizing urban park design

An increasing number of scholars are studying the impact of landscape-level processes on CESs in urban parks and revealing the mechanisms behind these effects. For example, Deng et al. suggested the need for a more balanced distribution of park types and green corridors to improve the urban park layout, using Nanchang's central area as an example (Deng et al., 2024). The CESs in urban parks have a direct effect on human well-being and sustainable development (Jabbar et al., 2022), while landscape-level processes significantly influence the benefits that CESs of urban parks provide (Plieninger et al., 2015). This study explores the relationships between various CESs benefits and landscape-level processes in parks, providing valuable references for green space planning and landscape design.

Our findings indicate variability in the supply and demand benefits of CESs due to differences in park location and landscape structure. Higher levels of fragmentation and landscape diversity, however, tend to enhance the value of the CESs supply and demand in urban parks, suggesting that managers can leverage these characteristics to develop strategies that promote public well-being. To enhance the delivery of CESs in urban parks, design strategies may be structured around five key dimensions, namely, aesthetic appreciation, historical heritage, entertainment, spiritual experience, and environmental education. Each dimension can be guided by practical and quantifiable indicators. For parks that focus on aesthetics, introducing 30 to 50 native plant species per hectare and setting up 3 to 5 seasonal change observation points every 500 m along walking trails increases landscape diversity and the perception of seasonal variation (Yang et al., 2023). Parks with a historical focus should include ecological buffer zones measuring 10 to 15 m around core heritage areas, as well as equip each hectare with 2 to 3 augmented reality interpretation devices and 5 to 8 digital exhibition panels to strengthen cultural recognition and dissemination. In parks aimed at entertainment, smart fitness facilities should be installed at a density of 8 to 12 units per 10 ha, and approximately 15% to 20% of the area should be dedicated to multifunctional lawns to support a variety of recreational activities. Parks designed for spiritual experiences may allocate 10% to 15% of the total area to quiet meditation spaces, plant 5 to 8 groups of aromatic vegetation per hectare, and ensure that natural soundscapes cover more than 60% of the area to foster a tranquil and restorative atmosphere. For parks focused on environmental education, 4 to 6 species-identification QR codes can be placed along every kilometer of trail, 5% to 8% of the area can be designated for interactive nature zones, and 2 to 3 ecological education activities can be organized each week to promote public environmental awareness and participation. Furthermore, to ensure the alignment of park functions with public expectations, design and renovation processes should incorporate assessments of visitor satisfaction and its determinants (Li et al., 2023). Simultaneously, fostering community participation and educational outreach is essential to promote awareness of the ecological and social value of urban green spaces (Nowak-Olejnik et al., 2024), thereby contributing to the long-term sustainability of the delivery of CESs in urban settings.

4.3 Generalizability of the research framework and findings

Although this study focuses on the central urban area of

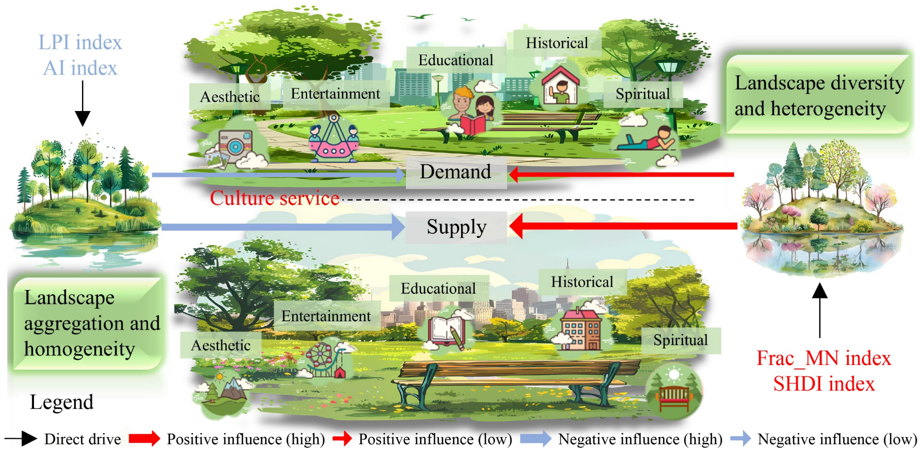

Fig. 10 Relationship diagram between landscape indices and CES value.

Chongqing, its findings are highly applicable to other urban environments in China. The influence patterns of landscape-level processes on CESs, such as the positive role of landscape diversity in promoting aesthetic and educational services and the inhibitory effect of landscape aggregation on service provision, are generally consistent with results from studies conducted in other major cities. For example, Xia et al. (2024) examined the perceptions of suburban residents in Shanghai regarding the supply and demand of CESs and their relationship with subjective well-being. Their research determined that heterogeneous landscapes shape the spatial distribution of CESs and also influence residents' subjective well-being, thus highlighting the importance of landscape structure in urban ecological planning. Similarly, Wang et al. (2022) analyzed outdoor social media images via computer vision techniques to identify three types of CESs in Beijing's urban parks. They further explored how landscape characteristics impact these services and proposed targeted landscape design strategies to improve cultural service provision. The consistency of these findings indicates that the mechanisms identified in Chongqing are not isolated cases but rather part of a broader pattern commonly observed in the spatial distribution of CESs across China's mega-cities.

In addition, the assessment framework developed in this study, which combines the SolVES model based on environmental and perception data with topic modeling of social media content, has demonstrated strong potential for scalability and transferability. Unlike traditional approaches that depend heavily on region-specific surveys, this framework utilizes large volumes of real-time social feedback and ensures spatial accuracy through GIS-based modeling. Its successful application to various landscape types and user perceptions suggests that this integrated, dual-source data approach can serve as a practical toolkit for CESs evaluations in other rapidly urbanizing areas. Future research can also refine the framework by incorporating locally specific variables or demographic characteristics, thereby enhancing its adaptability in diverse urban settings and providing more robust support for evidence-based cultural service assessment and urban park planning.

4.4 Strengths and limitations

Compared with previous studies on CESs in urban parks, this research provides a more comprehensive evaluation of the supply and demand of CESs, including the often overlooked but critical educational value. The study also analyzes the influence mechanisms of landscape-level processes on the supply and demand of CESs in urban parks, thereby contributing scientific guidance and design patterns to support the multifunctional role of urban parks.

However, there are several limitations to this study. First, the supply and demand of CESs in urban parks is evaluated by integrating social media data with survey responses, but it does not account for factors such as age, gender, occupation, or other personal characteristics that might affect the CESs preferences of the resident. Future studies should further explore perceptions across diverse demographic groups to better understand the views and needs of the public with respect to CESs (Li et al., 2024a). Second, this study adopts only four landscape metrics to analyze changes in landscape-level processes, primarily emphasizing linear correlations, fitting relationships, and spatial heterogeneity, while overlooking potential nonlinear patterns and threshold effects. It is suggested that future research delve deeper into the relationships between different landscape indices and the CESs supply and demand values for a more nuanced understanding. Third, while this study uses landscape metrics to characterize green space patterns, it does not incorporate higher-resolution spatial data that could better reflect the complex heterogeneity within urban parks. Recent advances, such as the open-source 2-m resolution urban green space mapping product developed by He et al. (2022), provide a more detailed basis for identifying and analyzing fine-scale landscape structures. Integrating such high-resolution data in future studies could improve the accuracy of CESs evaluations and better support urban green space planning and ecological function assessments. Finally, although many recent studies have focused on assessing the demand for CESs (Zhao et al., 2022) and the relationship between landscape patterns and resident perceptions (Bi et al., 2024), a comprehensive analytical framework is lacking. Future research could develop a CESs supply and demand framework that integrates multiple landscape elements, services, and human well-being indicators, thus enabling causal analysis through surveys and evaluations. With resident well-being as a priority, this approach can facilitate the development of sustainable strategies for rapidly urbanizing regions and providing detailed guidelines for urban park spatial planning and landscape design.

5 Conclusions

Urban parks can enhance the quality of urban environments and enrich cultural heritage, thereby promoting residents' well-being. In urban parks, however, the internal landscape structure is closely connected to the value of the CESs provided. This study revealed that, in Chongqing's central urban area, the highest CESs supply index for aesthetic, historical, and spiritual values is 9, with entertainment and educational values of 8 and 7, respectively. Moreover, it was found that aesthetic and historical values are the most widely distributed. On the demand side, entertainment and aesthetic values have the highest perception rates, at 42.37% and 31.55%, respectively, whereas historical value perception is the lowest, at 2.22%, indicating a higher demand for entertainment and aesthetics in urban parks and a lower demand for historical value. Spatially, the supply and demand for CESs in Chongqing's central urban parks is concentrated in the western area rather than being randomly distributed throughout the city center. This concentration is influenced by the relatively flat terrain, ease of development, and the focus on early urban development in western Chongqing, which resulted in more public green spaces and CESs facilities.

Our research indicates that variations in the location and landscape structure of park spaces lead to differences in the supply and demand values of CESs. Additionally, the AI is negatively correlated with the supply and demand of CESs, especially with respect to educational supply (−0.81) and entertainment demand (−0.62), suggesting that increased aggregation leads to more uniform landscapes, thereby reducing the CESs supply and demand for education and entertainment. The LPI, however, negatively correlates with the entertainment supply and historical demand, with correlations of −0.74 and −0.72, respectively, indicating that a smaller LPI benefits the entertainment supply, whereas a larger LPI diminishes the historical demand. An increased Frac_MN is positively correlated with historical and spiritual supplies, with correlations of 0.72 and 0.64, respectively, indicating that increased landscape complexity enhances the supply of these CESs. SHDI significantly increases the supply and demand for and value of aesthetic, historical, educational, and entertainment development, suggesting that landscape diversity provides residents with varied visual and functional experiences, increasing their enjoyment and demand for CESs.

This study reveals correlations between landscape-level processes and the supply and demand of CESs in urban parks. These findings are valuable for strengthening the service value of each park, addressing service gaps, and informing the rational layout of future urban parks. Accordingly, we recommend a comprehensive evaluation of the CESs value index, integrating various landscape indices, CESs values, and indicators of human well-being. This approach will facilitate a deeper understanding of these relationships and support urban park planning and management, which will ultimately enhance residents' well-being.

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Competing interests The authors declare that they have no competinginterests.

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