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Correlation between the Development of Scenic Tourism and the Evolution of Landscape Climate Patterns

Xianjie Zhou
Associate Professor, Industry College of Infinite Sky Digital Communication and Operation; School of Public Administration, Nanfang College Guangzhou, Guangzhou, 510970, China, E-mail: zhouxianjiexjz@outlook.com

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Abstract: As cities expand rapidly, the protection and inheritance of urban historical landscapes face unprecedented challenges. This study uses the Yeji River Basin in the southwestern karst region from 2015 to 2023 as the research object and employs Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), landscape index analysis, stationarity tests, cointegration regression, and Granger causality tests to comprehensively examine the relationship between scenic tourism development and the evolution of the landscape-climate pattern. Research found that the relative closeness of landscape climate patterns ranged from 0.407 to 0.561, with the best in 2017 and the lowest in 2021. There was a long-term equilibrium relationship and bidirectional Granger causality between tourism development and landscape climate patterns. During the research period, the construction land area of scenic spots increased by 150%, and soil compaction was significantly and positively correlated with tourist density. The results indicate a significant dynamic feedback mechanism between tourism activities and landscape-climate evolution. Therefore, in sustainable development, it is necessary to coordinate ecological protection and tourism development, optimize landscape patterns to enhance climate adaptability, and improve the economic benefits of scenic tourism.

Keywords: Scenic tourism, landscape climate pattern, stationarity test, cointegration regression.

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1. Introduction

With the increasing severity of global climate change, scenic areas with high-quality natural and cultural landscapes as their core attraction are facing unprecedented opportunities and challenges (Cao et al, 2024). Climate change directly affects natural ecological processes by altering key meteorological elements such as temperature, precipitation, and sunshine, leading to the evolution of landscape elements such as vegetation coverage, phenological rhythms, and water resource distribution, reshaping the visual landscape quality, environmental comfort, and tourism suitability of scenic spots (Chen et al 2024; Zhang et al., 2025). At the same time, the booming tourism industry is significantly altering the surface cover and local climate through transportation infrastructure, hotel expansion, tourist activities, and other behaviors, creating a unique microclimate effect of "tourism urbanization". This bidirectional interaction between "climate change landscape" and "tourism affecting climate" constitutes a complex and dynamic feedback system that profoundly affects the sustainable development capacity and ecological security patterns of tourist destinations (Yi et al., 2024). At present, most research has yielded fruitful results in evaluating tourism climate comfort, the macro impacts of climate change on the tourism industry, and the driving forces of landscape pattern evolution. However, most studies view "climate" as a static background condition or one-way coercive factor, and "tourism development" as a simple socio-economic process, lacking in-depth analysis of the nonlinear coupling relationship between "landscape climate tourism". Particularly at the mesoscale level of scenic areas, the intrinsic mechanisms of this chain reaction, how tourism activities function as an active driving force to participate in and modulate the evolution of local climate patterns, and how the resulting climate patterns subsequently feed back into landscape ecological processes, thereby influencing tourism experiences and resource values, remain unclear. Systematic empirical research and quantitative analysis in this area are lacking. In current research on the interaction between scenic tourism and climate landscapes, scholars mainly focus on three areas: first, the evaluation of tourism climate comfort, and second, the macro impact of climate change on the tourism industry. The second is to pay attention to the natural and human driven mechanisms of landscape pattern evolution. The third is to explore the efficiency and spatial structure characteristics of tourism resource development. However, most of these studies view "climate" as a static background or one-way coercive factor, simplify "tourism development" as a socio-economic process, and lack a systematic deconstruction of the nonlinear coupling relationship between “landscape climate tourism”. Therefore, this study aims to systematically reveal the inherent correlation and dynamic feedback loop between the development of scenic tourism and the evolution of landscape-climate patterns through quantitative analysis using multiple methods.

To this end, innovative methods such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) evaluation, stationarity tests, cointegration analysis, and Granger causality tests are used to analyze the correlation between scenic tourism development and landscape-climate patterns. By analyzing the relationship between scenic tourism development and landscape-climate patterns, the research aims to reveal the multi-scale correlation mechanism and the bidirectional impact path between the two. This not only enhances understanding of complex feedback processes in the tourism ecosystem but also provides new research directions for regional landscape planning, sustainable tourism management, and climate adaptation strategies.

2. Materials and Methods

2.1. Basic Theory of Scenic Tourism Development and Landscape Climate Pattern Evolution

The advancement of scenic tourism is based on the concept of sustainable development, emphasizing the coordinated development of ecological protection, economic benefits, and social harmony through systematic planning, scientific management, and rational utilization while protecting the integrity of natural and cultural resources. The development theory of scenic spot tourism integrates multiple disciplines, including resource economics, recreation studies, environmental psychology, and community participation theory. It focuses on the valuation of tourism resources, dynamic responses to market demand, and improvements in the quality of the tourism experience. At the same time, it emphasizes community participation and benefit sharing, aiming to promote the efficient operation, cultural heritage, and environmental friendliness of tourist attractions through multi-level, multi-party cooperation mechanisms, ultimately achieving long-term competitiveness and maximizing comprehensive benefits for regional tourism. The evolution of landscape climate patterns is a multidisciplinary theoretical system that integrates geography, climatology, and systems science, with global climate change as the macro background and landscape ecology theory as the core framework. The evolution of landscape climate patterns suggests that, under the combined action of natural and human driving forces, a dynamic feedback mechanism forms between surface landscape structure and climate elements through multi-scale interactions in energy flow, material cycling, and biological processes. The evolution process includes landscape fragmentation, changes in vegetation cover and adjustments in the hydrological cycle, ultimately leading to the reconstruction and evolution of regional climate characteristics (Cui et al., 2025; Yang et al., 2024).

The landscape climate pattern shapes and maintains specific local climate characteristics by regulating ecological processes such as energy flow and material cycling. This theory is based on the framework of “pattern-process-scale”, emphasizing that the spatial configuration of different landscape elements such as water bodies, vegetation, and buildings determines the distribution of climate elements such as surface temperature, humidity, and wind through four main mechanisms: radiation regulation, energy allocation, wind field changes, and material exchange, forming typical climate phenomena such as cold/heat islands and ventilation corridors (Yang, 2025). There is a strong linkage between tourism development and landscape-climate patterns, as shown in Fig. 1.

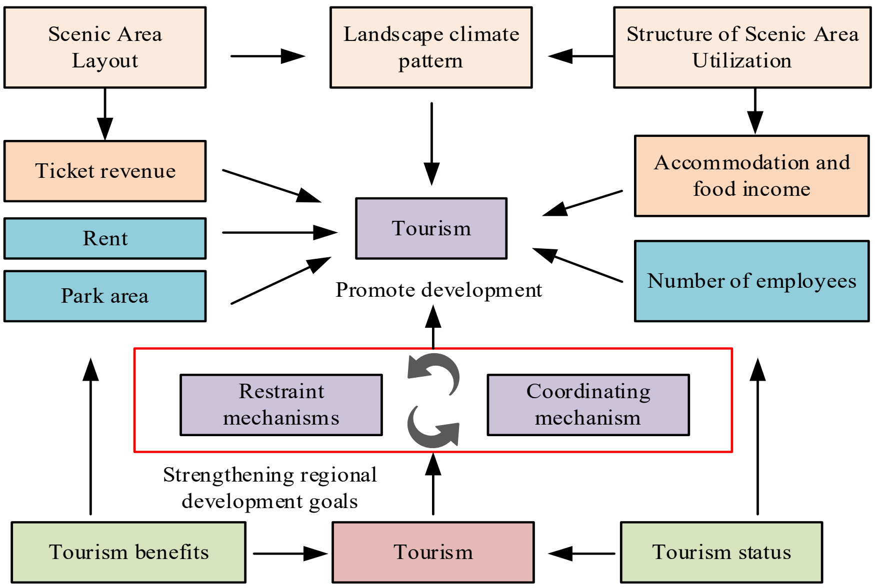

Fig. 1. Mechanism of linkage between tourism development and landscape climate pattern

As shown in Fig. 1, tourism development is based on land spatial layout, landscape patterns, and land-use structures. It is driven by ticket revenue, rent, park area, accommodation income, and employee numbers, and is regulated by constraint and coordination mechanisms. The system continuously optimizes through feedback and adjustment, guidance and regulation processes, ultimately strengthening regional development goals and clarifying regional development positioning, thereby enhancing industrial efficiency and status, and achieving a positive interaction and dynamic balance between tourism development and landscape patterns. The landscape climate pattern can affect a region's basic tourism infrastructure, and a better landscape pattern can drive changes in the region's tourism development pattern. For example, good climate conditions can attract more tourists and promote tourism development. Moreover, a favorable climate change can also affect the region's tourism landscape and enhance its attractiveness.

To quantitatively analyze the correlation between the development of scenic tourism and the evolution of landscape climate patterns, this study proposes the following testable research hypotheses:

H1: The improvement of landscape climate patterns has a significant positive promoting effect on the development of scenic tourism. It is assumed that the expected increase in the landscape climate pattern index will significantly raise the tourism development index.

H2: The increase in annual average temperature will shorten the suitable travel time in the region. Assuming that average annual temperatures are rising, the increase in extremely unsuitable weather will suppress tourism activities, thereby affecting the macro level of tourism development, as reflected in the annual number of tourists.

2.2. Construction of Research Indicators and Evaluation System

The study focuses on karst landforms in the southwestern region and analyzes the development of scenic tourism and changes in landscape-climate patterns in the area. (Cao et al., 2024; Kong et al., 2025). The study evaluates landscape-climate evolution indicators using metrics such as Patch Density (PD), the maximum patch index, and the landscape shape index. PD represents the number of patches of a specific type within a unit area or the total number of patches across the entire landscape; higher values indicate greater landscape fragmentation. There is a close relationship between the evaluation of landscape climate patterns and their evolution, encompassing both basic and extended, static and dynamic aspects. Together, they form a complete, closed loop of understanding the regional landscape-climate system. The landscape climate pattern evaluation method uses TOPSIS for evaluation and analysis. First, a standardized decision matrix is constructed as denoted in Eq. (1) (Yang et al., 2025).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{1}$$

In Eq. (1), x_{ij} represents the raw data of the i th scheme on the j th evaluation metric, r_{ij} denotes the normalized matrix of the i th scheme on the j th evaluation metric, and the weighted decision matrix equation is shown in Eq. (2).

$$v_{ij} = w_j \cdot r_{ij} \quad (2)$$

In Eq. (2), v_{ij} denotes the weighted normalized decision matrix, and w_j indicates the weight of the j th evaluation indicator. The calculation equation for determining the ideal solution and negative ideal solution (NIS) is denoted in Eq. (3) (Ding, Zhang, & Dai, 2024).

$$A^+ = \{v_1^+, v_2^+, \cdots, v_n^+\} = \begin{cases} (\max\limits_i v_{ij} \mid j \in J_1) \\ (\min\limits_i v_{ij} \mid j \in J_2) \end{cases} \tag{3}$$

In Eq. (3), A^+ represents the optimal solution of the ideal optimal solution, J_1 means the set of benefit indicators, and J_2 means the set of cost indicators. v_n^+ represents the positive ideal solution (PIS) of the n th evaluation metric. The equation for calculating the NIS is shown in Eq. (4).

$$A^- = \{v_1^-, v_2^-, \cdots, v_n^-\} = \begin{cases} (\min\limits_i v_{ij} \mid j \in J_1) \\ (\max\limits_i v_{ij} \mid j \in J_2) \end{cases} \tag{4}$$

In Eq. (4), A^- represents the worst solution of the ideal worst solution. v_n^+ represents the NIS of the n th evaluation metric. The distance of the ideal solution is calculated as shown in Eq. (5).

$$\begin{cases} S_i^+ = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_j^+)^2} \\ S_i^- = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_j^-)^2} \end{cases} \tag{5}$$

In Eq. (5), S_i^+ means the Euclidean distance from the i th scheme to the ideal optimal solution, and S_i^- represents the Euclidean distance from the i th scheme to the worst solution. The equation for calculating closeness is denoted in Eq.

(6).

$$C_i = \frac{S_i}{S_i^+ + S_i^-} \tag{6}$$

In Eq. (6), C_i represents the relative closeness of the i th scheme.

The comprehensive indicators for the development of scenic tourism are not based solely on economic scale, but also on the annual number of tourists received, total tourism income, and per capita consumption. In terms of resource attractiveness, indicators also evaluate the uniqueness and brand value of resources, and reflect market recognition through tourist satisfaction, revisit rates, and online reputation. Facility and service guarantees cover hardware and software capabilities such as transportation accessibility, completeness of tourist facilities, level of intelligence, and service quality. The region's development situation is assessed. Due to the fact that both the tourism development index and the landscape climate pattern index are typical time series data and are susceptible to random trends, direct regression may lead to the problem of "spurious regression". Therefore, it first performs a stationarity test to confirm the integration order of the sequence. On this basis, although the two types of sequences themselves may not be stationary, a long-term equilibrium relationship (i.e., cointegration) indicates a stable internal linkage mechanism between tourism activities and landscape climate patterns, rather than accidental correlation. The Granger causality test further reveals the leading lagging relationship between variables, which can effectively identify whether the optimization of climate patterns promotes tourism development or whether tourism development activities feedback to local climate through changes in underlying surfaces, thus statistically verifying the authenticity of the dynamic feedback loop of "climate shaping landscape attracting tourism affecting climate".

3. Results and Analysis

3.1. Analysis of Landscape Historical Climate Change

The weight calculation results for the current landscape climate pattern, based on the above calculation formula, are shown in Table 1.

Table 1. Weight values of landscape climate pattern

Structural Dimension	Specific Indicator	Information Entropy Value	Weight Coefficient
Scale Characteristics	Largest Patch Dominance	0.9809	0.0492
Distribution Features	Patch Distribution Intensity	0.9211	0.2206
Edge Characteristics	Edge Effect Index	0.9339	0.1839
Morphological Traits	Mean Shape Complexity	0.9426	0.1591
Spatial Relationships	Patch Spatial Configuration Index	0.9428	0.1585
Heterogeneity	Landscape Type Heterogeneity Index	0.912	0.2468

The highest value of the landscape heterogeneity index in Table 1 was 0.2468, which had the greatest influence on landscape pattern evaluation. The weight values of patch distribution intensity and edge effect index were 0.2206 and 0.1839, respectively. The average shape complexity and patch spatial configuration index had similar weights of 0.1591 and 0.1585, respectively. The lowest weight of the maximum plaque dominance was only 0.0492. These weight distributions objectively reflected the relative importance of various landscape pattern characteristic indicators. At the same time, the PIS and NIS for the landscape climate pattern were calculated and are shown in Table 2.

Table 2. PIS and NIS of landscape climate patterns

Structural Dimension	PIS	NIS
Scale Characteristics	0.0491989	0.0000036
Distribution Features	0.2206111	0.0000188
Edge Characteristics	0.1839416	0.0000151
Morphological Traits	0.1590863	0.0000126
Spatial Relationships	0.1584878	0.0000125
Heterogeneity	0.2467744	0.0000214

The optimal maximum plaque dominance in Table 2 was 0.0491989, while the NIS value was 0.0000036. The NIS for plaque distribution intensity was 0.0000188, while its PIS was 0.2206111. The optimal measurement value for the edge effect index was 0.1839416, while the PIS was 0.0000151. The morphological complexity index showed a positive ideal value of 0.1590863 and a negative ideal value of 0.0000126. The spatial configuration index reached an optimal value of 0.1584878, compared to a minimum of 0.0000125. Finally, the landscape heterogeneity index reached the highest PIS of 0.2467744 compared to the NIS of 0.0000214. The proximity of the research object is calculated as denoted in Table 3.

Table 3. Comparison of proximity calculation results

Year	Distance to PIS (D-)	Distance to NIS (D+)	Relative Closeness
2015	0.2412	0.2935	0.5491
2016	0.2876	0.2732	0.4873
2017	0.2268	0.2901	0.5612
2018	0.2335	0.2918	0.5556
2019	0.2719	0.3045	0.5283
2020	0.2638	0.2126	0.4462
2021	0.2942	0.2024	0.4076
2022	0.2391	0.2189	0.4781
2023	0.2537	0.2854	0.5295

In Table 3, the highest relative closeness in 2017 reached 0.5612, indicating that the comprehensive evaluation result for that year was the best. At the same time, the relative proximity could reach 0.555 in 2018 and 0.5491 in 2015. In 2021, the lowest relative proximity was only 0.4076. This indicates that the overall performance over the past two years has been relatively poor. Overall, the relative closeness of each year ranges from 0.4076 to 0.5612, indicating a relatively strong dynamic trend in the comprehensive status of the evaluated object during this period. The study analyzed landscape rainfall in the Yeji River Basin from 2015 to 2023 and identified changes in landscape rainfall, as shown in Fig. 2.

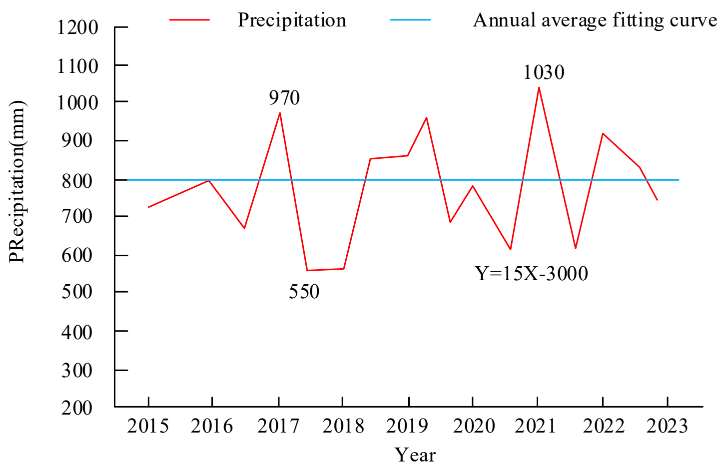

Fig. 2. Changes in annual rainfall in the landscape of the Yeji River Basin from 2015 to 2023

In Fig. 2, over the study period, the highest annual rainfall in the Yeji River Basin reached 1030mm, while the lowest was only 550mm. According to linear fitting of the survey years, the annual average rainfall in this region increased by 15mm per decade, and the overall annual rainfall showed a fluctuating trend. Research across different time periods showed that during 2015-2016 and 2017-2018, precipitation fluctuations were relatively flat and the trend was relatively stable. At the same time, a landscape-wide analysis of temperature changes was conducted, as shown in Fig. 3.

In Fig. 3, the maximum temperature across years showed a relatively flat trend, but the overall trend was upward, with a maximum of 19.4 ℃ in 2022. At the same time, the minimum temperature also showed a gentle trend, with the lowest at 14.9 ℃ in 2016. The average temperature also showed a fluctuating trend. This indicates that the temperature change trend in the region is relatively smooth.

3.2. Analysis of Correlation Between Scenic Tourism Development and Landscape Climate Pattern

Based on landscape climate patterns and tourism development data for the Yeji River Basin from 2015 to 2023, the correlation between tourism development and landscape climate patterns was analyzed, and the comprehensive evaluation indicators and relative closeness of the area were assessed. The study conducted a quantitative analysis of tourism development and the landscape's climate patterns, as shown in Table 4.

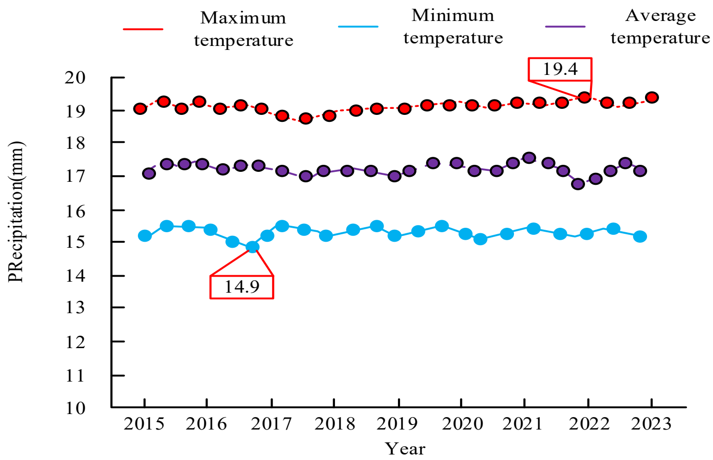

Fig. 3. Temperature changes in different years

Table 4. Results of quantitative analysis of tourism development and climate pattern of landscape

Year	Tourism Development Index	Landscape-Climate Pattern Index
2015	0.495	0.336
2016	0.398	0.284
2017	0.389	0.142
2018	0.564	0.324
2019	0.630	0.413
2020	0.526	0.512
2021	0.365	0.435
2022	0.468	0.446
2023	0.587	0.438

In Table 4, the overall tourism development index fluctuated, reaching 0.495 in 2015 and then declining sharply thereafter. It reached a peak of 0.630 in 2019 and began to show a significant downward trend again from 2020 to 2021. In 2023, it would rebound to 0.587. The landscape climate pattern index also showed fluctuating characteristics, dropping to a minimum of 0.142 in 2017, gradually recovering thereafter, reaching a maximum of 0.512 in 2020, and finally maintaining around 0.44 between 2021 and 2023. The two indices showed a similar trend in some years, such as a synchronous increase from 2018 to 2020 and a synchronous decrease from 2020 to 2021. However, the trends in other years are not entirely consistent, reflecting a correlation between tourism development and landscape climate patterns, but each is influenced by different factors. In 2017, the landscape climate pattern index was relatively low, while the tourism development index did not decrease synchronously. This is because the tourism development index is not only constrained by climate conditions, but also more easily affected by social and economic factors, tourism marketing efforts, regional policy support, and even sudden public events that year. Therefore, a short-term divergence in a given year does not negate the long-term equilibrium relationship confirmed by cointegration tests between the two, but rather indicates that, in short-term fluctuations, socio-economic factors may temporarily become the primary driving force of tourism development. The stationarity verification of the two-factor indicators is shown in Table 5. Among them, (Y) represents the landscape climate pattern, and (X) represents the development of scenic tourism.

In Table 5, the original sequences lnY and lnX failed the stationarity test under all three test settings, and their ADF statistics exceeded the 5% and 10% critical values, indicating that these two variables are non-stationary. After first-order differencing, the ADF test statistics for the D(lnX, 1) and D(lnX, 1) sequences decreased to -3.315 and -3.282, respectively, in the absence of intercept and trend terms, and were below the corresponding critical values, indicating that the differenced sequences exhibit stationary characteristics in this testing form. However, it still appeared non-stationary in other tests that included intercept or trend terms. This result confirms that lnY and lnX are first-order integrated sequences (I(1)) that meet the prerequisites for subsequent cointegration analysis and the establishment of error-correction models. From the table, the two factors follow the I (1) process, indicating a long-term stable correlation. Therefore, to analyze the equilibrium relationship between the two factors, cointegration was tested. The validation findings are denoted in Table 6.

Table 5. Comparison of stability verification results

Variable	Test Type (c,t,k)	ADF Statistic	5% Critical Value	10% Critical Value	Stationary
lnY	(1,0,0)	-2.103	-3.812	-3.401	No
	(0,0,0)	-1.723	-3.145	-2.733	No
	(1,N,0)	-0.428	-3.928	-3.452	No
lnX	(1,0,0)	-2.481	-3.812	-3.401	No
	(0,0,0)	-1.362	-3.145	-2.733	No
	(1,N,0)	-0.785	-3.928	-3.452	No
D(lnX,1)	(1,0,0)	-3.192	-3.845	-3.418	No
	(0,0,0)	-3.315	-3.145	-2.756	Yes
	(1,N,0)	-3.124	-3.928	-3.452	No
D(lnX,1)	(1,0,0)	-3.021	-3.845	-3.418	No
	(0,0,0)	-3.282	-3.145	-2.756	Yes
	(1,N,0)	-2.973	-3.928	-3.452	No

Table 6. Comparison of cointegration validation results

Variable	Coefficient	Std. Error	t-Statistic	p-Value
C	-0.486	0.071	-6.845	0
LnX	0.287	0.075	3.827	0.0018
R2	0.521	/	/	/
Adjusted R2	0.482	/	/	/
D-W Stat	1.763	/	/	/
F-Statistic	15.117	/	/	/

In Table 6, the parameter estimation results indicate that the coefficient for the constant term C was -0.486, which was significant at the 1% level. The coefficient for the explanatory variable LnX was 0.287 and significant at the 1% level, indicating a significant positive impact on the dependent variable. The model's goodness-of-fit R^2 was 0.521, and the adjusted R^2 was 0.482, indicating that the model has some explanatory power. The Durbin-Watson statistic was 1.763, close to 2, indicating no significant first-order autocorrelation in the model residuals. The F-statistic was 15.117 and significant at the 1% level, denoting that the overall model setting is effective. The model can improve the stationarity of the variables by eliminating autocorrelation, and there is a long-term equilibrium relationship between the two. Based on the above table, it was found that there is a mutual influence between tourism development and climate patterns. Therefore, an autoregressive model was constructed to analyze the linkage between the two, as denoted in Table 7.

In Table 7, both equations had high goodness-of-fit R^2 values of 0.796 and 0.752, indicating strong explanatory power for the relationships among the variables. In the LnX equation, the first-order lag term for LnY was significantly positive at the 5% level, with a coefficient of 1.198 and a t-value of 2.463. The previous values of LnY had a significant positive impact on the current LnX. In the LnY equation, the first-order lag term for LnX was also significantly positive, with a coefficient of 0.437 (t=2.781), indicating a dynamic relationship of mutual influence between the two variables. The t-statistics for most variables were significant at the 10% level, and the constant term was significantly negative in the LnY equation. The F-statistic indicated that both models were effectively set as a whole. There is a significant linkage between the advancement of scenic tourism and the evolution of landscape and climate patterns. The correlation analysis between changes in landscape soil conditions and the development of scenic tourism is shown in Table 8.

Table 7. Autoregressive calculation results between two factors

Variable	Equation for LnX		Equation for LnY	
	Coefficient	t-Stat	Coefficient	t-Stat
LnX(-1)	0.518	1.635	0.437	2.781
LnX(-2)	-0.362	-1.482	-0.159	-1.298
LnY(-1)	1.198	2.463	0.683	2.624
LnY(-2)	0.524	0.783	-0.692	-1.967
C	0.592	1.583	-0.537	-2.941
R^2	0.796	/	0.752	/
Adjusted R^2	0.719	/	0.638	/
F-Statistic	9.325	/	6.874	/

Table 8. Correlation of soil condition changes with landscape tourism development

Soil Indicator	Tourism Impact Indicator	Correlation Coefficient	*p*	Strength and Direction of Correlation
Soil Compaction	Tourist Density	0.78	0.003	Strong Positive
Soil Organic Matter	Tourism Facility Coverage	-0.62	0.021	Moderate Negative
Soil Erosion Degree	Annual Tourist Number	0.71	0.005	Strong Positive
Soil pH	Tourism Activity Intensity	0.35	0.112	Weak Positive (Not Significant)
Soil Microbial Diversity	Human Disturbance Index	-0.67	0.018	Moderate Negative
Topsoil Moisture Content	Tourist Activity Frequency	-0.54	0.038	Moderate Negative
Heavy Metal Pollution Index	Tourist Waste Accumulation	0.59	0.026	Moderate Positive

In Table 8, tourist density was strongly positively correlated with soil compaction degree ($r=0.78$, $p=0.003$), and annual tourist volume was also strongly positively correlated with soil erosion degree ($r=0.71$, $p=0.005$), indicating that tourism activities directly degrade soil physical properties. The coverage rate of tourism facilities was moderately negatively correlated with soil organic matter content ($r = -0.62$, $p = 0.021$), and the human disturbance index was also moderately negatively correlated with soil microbial diversity ($r = -0.67$, $p = 0.018$), indicating that tourism development inhibits soil ecological functions. The surface soil moisture content was moderately negatively correlated with the frequency of tourism activities ($r = -0.54$, $p = 0.038$), indicating a negative impact of frequent human activities on soil water-holding capacity. Although the soil pH value showed a weak positive correlation with the intensity of tourism activities ($r=0.35$), it did not reach statistical significance ($p=0.112$), indicating that tourism activities have a limited impact on soil acidity and alkalinity. Tourism development activities in the visible landscape will affect soil conditions and the landscape's climate change. Based on the actual impact changes, Hypothesis 1 proposed in the study is valid, and the improvement in the comprehensive index of landscape climate evolution has a significant positive impact on the comprehensive index of scenic tourism development.

4. Discussion

In 2020-2021, due to the impact of global extreme climate and intensified local human activities, the landscape climate pattern showed significant fluctuations, indicating that the landscape climate pattern system is highly sensitive to external disturbances. This may be due to the impact of changes in rainfall and temperature on vegetation, ecological processes and hydrological cycles, thereby altering the landscape's capacity to regulate microclimate. Based on changes in tourism development indicators, the indicator reached its highest level in 2019, which may be due to increased investment in tourism facilities and publicity efforts driven by policies. The research results showed that the relative closeness of landscape climate patterns fluctuated between 0.4076 and 0.5612, with the highest at 0.5612 in 2017 and the lowest at 0.4076 in 2021. This indicates that the degree of matching between landscape climate conditions and landscape structure in the region decreased from 2015 to 2021. After 2023, the indicator increased to 0.5295, indicating that the landscape system would gradually return to stability. Meanwhile, cointegration tests indicated a significant long-term stable relationship between the tourism development index and the landscape climate pattern index. Granger causality analysis further revealed a bidirectional relationship between the two, with LnY having a significant positive impact on the current LnX, indicating that a favorable climate pattern can promote tourism development, and tourism activities feed back into the climate system through changes in land cover. Between 2015 and 2023, the construction land area increased from 22 km^2 to 55 km^2, with a growth rate of 150%, and the proportion increased from 1.84% to 4.61%. The cultivated land area decreased from 985 km^2 to 955 km^2, a 3.0% decline. Forests and grasslands also showed a fluctuating downward trend. The land transfer matrix indicated that the main transfer direction of cultivated land and forest land was to construction land, indicating that during this period, scenic areas began to develop tourism facilities. According to relevant analysis, tourism density was positively correlated with soil compaction degree ($r=0.78$, $p<0.01$), and annual tourist volume was positively correlated with soil erosion degree ($r=0.71$, $p<0.01$). The coverage rate of tourism facilities was negatively correlated with soil organic matter content ($r = -0.62$, $p < 0.05$) and microbial diversity ($r = -0.67$, $p < 0.05$), indicating that tourism development has a clear negative impact on soil ecological functions.

Short-term data are insufficient to capture the complete cycle and long-term feedback mechanisms of the "tourism climate" system, while insufficient spatial resolution masks heterogeneous interactions at the local level, leading to uncertainty in deriving causal mechanisms from statistical associations. To address this issue, long-term remote sensing data and high-frequency tourism statistical data can be integrated to extend the observation period, and higher-precision multi-source geospatial data, such as land-use and mobile signaling data, can be introduced. At the same time, by combining time-varying parameter models and geographically weighted regression methods, dynamic causal paths and local driving mechanisms are analyzed from both temporal and spatial dimensions to verify and reveal the inherent causal relationships between variables at a finer spatiotemporal scale.

5. Conclusion

To analyze the correlation between the development of scenic tourism and the landscape-climate pattern, this study uses landscape-climate, soil, and tourism development data for the Yeji River Basin from 2015 to 2023. Using comprehensive methods such as TOPSIS evaluation, stationarity tests, cointegration analysis, and Granger causality tests, the correlation mechanism between scenic tourism development and the evolution of the landscape-climate pattern is analyzed. This enables an analysis of the correlation between the development of scenic tourism and the landscape climate pattern. The research findings indicate a strong connection between scenic tourism development and landscape-climate patterns. Although the research has achieved good results, there are still certain limitations, such as the short time span and limited spatial resolution of the data used in the study, which make it difficult to fully capture the long-term dynamics of the climate landscape tourism system. At the same time, key disturbance factors, such as policy regulations and sudden public events, were not fully incorporated into the model construction, and the characterization of nonlinear interaction mechanisms remains insufficient. Therefore, in future research, more different landscape area data will be used to analyze their correlation.

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Institutional Review Board Statement

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Declaration of Artificial Intelligence (AI) Tools

The authors used ChatGPT for formatting and organizational assistance only. There were no AI tools used to generate scientific content, analysis, conclusions, or references. All content was reviewed and validated by the authors.

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Xianjie Zhou obtained his PhD in Agriculture (2014) from NCHU, Taiwan. Presently, he is working as an Associate Professor and the Associate Dean of Teaching in the Industry College of Infinite Sky Digital Communication and Operation and the School of Public Administration of Cultural Industry at Nanfang College, Guangzhou. He has published articles in more than twelve internationally reputed peer-reviewed journals and conference proceedings. His research interests include cultural tourism planning, digital cultural tourism, and sustainable development of tourist attractions.