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A Study on the Spatio-Temporal Evolution and Determinants of Green Development Efficiency in the Cultural Industry of the Yangtze River Economic Belt

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Abstract: This study builds a super-efficiency SBM framework that takes unintended outputs into consideration. Using the Dagum Gini index, Moran's I statistic, and a principal component regression model, we evaluate the green development efficiency of the cultural sector across 11 provincial-level units within the Yangtze River Economic Belt for the year 2023. The analysis uncovers both the spatial-temporal dynamics and the driving forces behind efficiency. Our key findings are as follows. The overall green development efficiency of the cultural industry in this region remains fairly low, displaying a distinctive pattern: high efficiency in the lower reaches, weak technical capacity in the middle reaches, and limited scale in the upper reaches. Spatial differences mainly come from the gap between the lower and upper reaches, while significant internal variation exists within the upper reaches. Spatial clustering shows a clear "high-high" and "low-low" polarization with pronounced local agglomeration. The scale of the cultural industry acts as a positive driver, whereas energy intensity imposes a notable constraint. Against the background of the 15th Five-Year Plan, this paper puts forward a coordinated approach that spans policy alignment, business model transformation, technological empowerment, and talent development. The aim is to foster sustained improvement in green development efficiency and contribute to high-quality growth of the cultural industry.

Keywords: Yangtze River Economic Belt; Cultural Industry Efficiency; Green Development; Spatio-Temporal Evolution; Influencing Factors

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1. Introduction and Literature Review

1.1 Introduction

The "Opinions of the Central Committee of the Communist Party of China and the State Council on Accelerating the Comprehensive Green Transformation of Economic and Social Development" explicitly stipulate: "Promote the high-quality development of the cultural industry and foster the deep integration of culture and tourism. Actively encourage the accelerated development of new industries, new business models and new commercial formats oriented towards green and low-carbon development." [1] The "Guiding Opinions on Further Strengthening Ecological and Cultural Development" further propose: "Support the development of the 'ecological culture+' industry, explore the deep integration of ecological literary and artistic creation with science and technology, and actively utilise environmentally friendly materials to develop ecological cultural and creative products. " [2] Against this backdrop, the green development of the cultural industry has become an integral part of implementing the "dual carbon" goals and driving the comprehensive green transformation of the economy and society. Its value lies in: guiding the low-carbonisation of the entire chain of cultural production and consumption through green concepts; fostering new growth poles for green consumption; and helping to establish green modes of production and lifestyles. At the same time, the "Outline of the 15th Five-Year Plan for National Economic and Social Development of the People's Republic of China" emphasises, from a regional development perspective, that "we must adhere to the principle of prioritising major conservation efforts over large-scale development, uphold the principle of ecological priority and green development, and continuously advance the high-quality development of the Yangtze River Economic Belt." [3] The Yangtze River Economic Belt is not only a priority area for national ecological conservation but also a region rich in cultural industry resources and characterised by dynamic development; exploring the spatio-temporal evolution of the green efficiency of the cultural industry in this region holds significant exemplary value. Consequently, this study takes the 11 provinces and municipalities of the Yangtze River Economic Belt as its research subjects. By considering a Super-Efficiency SBM model that accounts for unplanned outputs, and utilising the Dagum Gini coefficient, Moran's index and principal component regression models, it systematically evaluates the spatio-temporal evolution and influencing factors of green development efficiency in the cultural industry. This provides empirical support for enhancing regional coordination and promoting the green transformation of the cultural industry, thereby contributing to the realisation of the goal of ecological and sustainable green development in the cultural sector.

1.2 Literature Review

When we look at the theoretical background, scholars have approached this topic from several different angles. Taking an enterprise perspective, Shi Xiaolong et al. (2025) pointed out a clear non-linear relationship between agglomeration and green transformation [4]. Other researchers like Chen Li (2025), Luo Lan (2025), and Huang Xin alongside Hu Angang (2025) shifted the focus slightly to examine the logic of transformation driven by new-quality productive forces [5][6][7]. Adding to this, Chen Yiping (2024) broke down the scientific connotations and structural elements of these new-quality productive forces specifically within the cultural sector [8]. All these studies basically lay a solid conceptual foundation that our own empirical research can build on.

Moving on to research methodology, there are a few standout approaches. Wan Qian (2025) actually used a super-efficiency SBM model to figure out the efficiency of the cultural industry right here in the Yangtze River Economic Belt, successfully tracking down the key influencing factors [9]. For spatial analysis, Li Jian et al. (2025) brought in the Dagum Gini coefficient and spatial differentiation methods. They used these specific tools to map out the spatio-temporal characteristics of green development efficiency for resource-based cities in the region [10]. On the policy side, Chen Lei et al. (2025) designed a quasi-natural experiment to measure the actual causal effects of regional economic policies on green technology innovation performance [11]. Another interesting angle came from Jiang Ziran et al. (2025), who mixed ecological efficiency metrics with strategic evaluation methods [12]. This helped prove how the overall development strategy of the Yangtze River Economic Belt boosts ecological efficiency along the entire corridor. Bringing these various methods into the mix has really made efficiency evaluation and policy identification a lot more precise.

Focusing directly on the Yangtze River Economic Belt, Zhang Xueliang et al. (2025) put together a comprehensive summary covering the outcomes of the implementation of the development strategy. They also suggested some key measures to keep in mind for the upcoming 15th Five-Year Plan period [13]. Technology's role is huge here, Yuan Liang et al. (2025) noticed that higher levels of digitalisation and intelligentisation create a major positive impact on green total factor productivity [14]. Looking at regional influences, Shan Baoyan et al. (2025) used Shandong Province to show how the cultural industry brings about noticeable spatial spillover effects on regional green development [15]. In terms of digital growth, Hu Yanglin (2025) dug into the intrinsic logic and practical pathways that allow new-quality productive forces to empower the digital cultural industry [16]. Other scholars mapped out broader strategies. Li Jinge (2024) relied on the new development philosophy to suggest practical pathways for high-quality development within the cultural industry [17]. Qiu Guiqie (2024) gave us a broad review centered around green cultural development [18], and Zhou Jianxin alongside Zhu Xueping (2025) went ahead and systematically tracked the annual progress in research concerning China's cultural industry as a whole [19].

Even with all this background work, the existing research definitely leaves some gaps. We are still missing a truly systematic measurement of the efficiency of green development in the cultural industry, especially one that includes a holistic evaluation of river basins. Beyond that, past studies haven't done enough to unpack the spatio-temporal evolution of efficiency or pinpoint the specific regional differentiation characteristics. We also really need a deeper dive into the non-linear effects of various influencing factors. To try and fix this, our paper runs a super-efficiency SBM model that specifically accounts for unplanned outputs. We paired this up with the Dagum Gini coefficient, Moran's index, and multiple linear regression models. Doing this lets us carry out a thorough, scientific evaluation of the green development efficiency of the cultural industry across the Yangtze River Economic Belt. By clearly mapping out its spatio-temporal characteristics and influencing factors, we hope to build a really solid foundation that helps achieve those big strategic objectives of high-quality development in the cultural industry.

2. Model Construction, Method Selection and Indicator System Development

2.1 Model Construction

To scientifically evaluate the green development efficiency of the cultural industry in the Yangtze River Economic Belt and identify its influencing factors, this paper constructs two main types of models: firstly, a super-efficiency SBM model that accounts for unwanted outputs for efficiency measurement; and secondly, a principal component regression model for identifying influencing factors.

2.1.1 The Super-Efficiency SBM Model Accounting for Unintended Outputs

The Super-Efficiency SBM model, with SBM standing for Slacks Based Measure of Super Efficiency, provides a way to evaluate efficiency that is neither radial nor angular. Its calculation is built on slack variables. By taking into account undesirable outputs (such as pollutants), this model permits efficiency values greater than 1 for efficient decision-making units and addresses slack issues in inputs and outputs, thereby enabling a more precise evaluation of the green development efficiency of the cultural industry. The core formula is as follows:

$$\rho^{*}=\min\frac{\frac{1}{m}\sum_{i=1}^{m}\left(\frac{\overline{x}}{x_{ik}}\right)}{\frac{1}{r_1+r_2}\times\left(\frac{\sum_{s=1}^{r_1}\overline{y}^{d}}{y_{sk}^{d}}+\frac{\sum_{q=1}^{r_2}\overline{y}^{u}}{y_{qk}^{u}}\right)} \tag{1}$$

Where ρ^{*} is the calculated green development efficiency value; m is the number of input indicators; r_1 and r_2 are the numbers of desired and undesired outputs, respectively; x_{ik} is the i-th input; y_{sk}^{d} and y_{qk}^{u} are the desired and undesired outputs, respectively; $\overline{x}$, $\overline{y}^{d}$, and $\overline{y}^{u}$ are the input-output values adjusted for slack variables.

2.1.2 Principal Component Regression Model

To identify the key factors influencing the efficiency of green development in the cultural industry, a principal component analysis (PCA) is first performed on the three variables with the highest correlation to extract the first principal component (PC1). PC1 is then used as an explanatory variable in a regression analysis with technical efficiency (TE). The core formula for principal component regression is:

$$\mathrm{PC1}=\alpha_1\mathrm{urban}+\alpha_2\mathrm{cult}_{\mathrm{share}}+\alpha_3X_2+\beta_3\mathrm{energy}_{\mathrm{int}} \tag{2}$$

where α is the loading (eigenvector) obtained from the principal component analysis; β is the regression coefficient; urban is the urbanisation rate; cult_share is the share of the cultural industry's value added in GDP; and energy_int is the energy consumption intensity.

2.2 Method Selection

To get a scientific measure of the green development efficiency of the cultural industries in the Yangtze River Economic Belt and how it evolves over time and space, this study brings together several quantitative methods. The Analytic Hierarchy Process and the entropy method are applied to assign weights to composite indicators, including the environmental pollution index and the cultural product consumption satisfaction index, and then to work out the composite scores. In addition, the Dagum Gini coefficient and Moran's I index are used to uncover spatial differences in efficiency and to identify patterns of agglomeration.

2.2.1 Indicator Weighting Methods

Given that the Super-Efficiency SBM model, which accounts for unintended outputs, requires the estimation of indices for "environmental pollution" and "consumer satisfaction with cultural products and services," the Analytic Hierarchy Process (AHP) and the entropy method were employed to determine the weights.

2.2.1.1 Analytic Hierarchy Process

A pairwise comparison matrix $B=(b_{ij})_{p\times p}$ is constructed, where b_{ij} represents the relative importance of indicator i to j(on a scale of 1 to 9). The core formula for calculating the weight vector is as follows:

Calculate the product of the elements in each row of the decision matrix M_I:

$$M_I=\prod_{j=1}^{P} b_{ij}\ (\text{i=1,2,…,p}) \tag{3}$$

Compute the pth root of M_i ω_i':

$$\omega_i'=\sqrt[p]{M_i} \tag{4}$$

Normalise to obtain the weight vector ω_i:

$$\omega_i=\frac{\omega_i'}{\sum_{j=1}^{p}\omega_j'} \tag{5}$$

Calculate the largest eigenvalue $\lambda_{\max}$:

$$\lambda_{max}=\frac{1}{p}\sum_{i=1}^{p}\frac{(BW)}{\omega_i} \tag{6}$$

Consistency check:

$$\text{CI}=\frac{\lambda_{\max}}{\text{p-1}} \tag{7}$$

$$\text{CR}=\frac{\text{CI}}{\text{RI}} \tag{8}$$

2.2.1.2 Entropy Method

The entropy method is an objective weighting method based on information entropy. The calculation steps are as follows:

Normalisation of inverse indicators (environmental pollution indicators):

$$X'_{ij}=\frac{1}{X_{ij}} \tag{9}$$

Calculation of the weight b_{ij} for the jth indicator of the ith sample:

$$b_{ij}=\frac{X_{ij}}{\sum_{i=1}^{n}X_{ij}} \tag{10}$$

Calculate the entropy value e_j:

$$e_j=-K\sum_{i=1}^{n} b_{ij}\, I_n b_{ij} \tag{11}$$

Calculate the coefficient of variation d_j:

$$d_j=1-e_j \tag{12}$$

Calculate the weight ω_j:

$$\omega_j=\frac{d_j}{\sum_{i=1}^{p}d_i} \tag{13}$$

Final composite score:

$$S_i=\sum_{j=1}^{p}\omega_j X'_{ij} \tag{14}$$

2.2.2 Dagum Gini Coefficient

The Dagum Gini coefficient decomposes overall variance into within-group variance, net between-group variance and hypervariability. This method is suitable for multi-regional hierarchical analysis and can accurately identify the primary sources of regional differences. This study applies the Dagum Gini coefficient to measure the disparities in green development efficiency of the cultural industry across the 11 provinces and municipalities in the Yangtze River Economic Belt. The analysis covers both the overall level and subregional comparisons. It also breaks down the contributions made by different groups, which helps identify where the main regional differences come from.

Let the population consist of k regions, with the jth region comprising n_j provinces and cities, and the total number of provinces and cities in the population being $n=\sum_{j=1}^{k} n_j$. Let y_{ji} denote the efficiency value of the ith province or city in the jth region, and $\bar{y}$ denote the population mean.

The overall Gini coefficient G is defined as:

$$G=\frac{\sum_{j}^{k}\sum_{h=1}^{k}\sum_{r=1}^{nj}\left|y_{ij}-y_{hr}\right|}{2n^2\bar{y}} \tag{15}$$

This can be decomposed as:

$$G=G_w+G_{nb}+G_t \tag{16}$$

where G_w represents the within-group variance contribution, reflecting the differences among provinces and cities within each region; G_{nb} represents the net between-group variance contribution, reflecting the differences in average levels between different regions, without considering overlap; and G_t represents the density contribution, reflecting the differences arising from sample overlap between different regions.

2.2.3 Moran's I

Moran's I is a statistical measure used to assess spatial autocorrelation, comprising the global Moran's I and the local Moran's I. This paper employs Moran's I to calculate the global and local spatial autocorrelation indices for the green development efficiency of the cultural industries across the 11 provinces and municipalities in the Yangtze River Economic Belt, and to identify the agglomeration types of each region, thereby revealing their spatial agglomeration patterns. The primary formula for Moran's I is as follows:

Formula for the global Moran's I:

$$I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\left(D_i-\bar{D}\right)\left(D_j-\bar{D}\right)}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\right)\sum_{i=1}^{n}\left(D_j-\bar{D}\right)^2}(i\neq j) \tag{17}$$

where n is the number of provinces and cities; D_i and D_j are the efficiency values of provinces and cities i and j, respectively; $\bar{D}$ is the mean efficiency; and w_{ij} is an element of the spatial weight matrix. This study adopts a binary spatial weight matrix based on the Queen's adjacency rule: if provinces and cities i and j share a common boundary or vertex, then $w_{ij}=1$; otherwise, $w_{ij}=0$.

Formula for the local Moran's I:

$$I_i=\frac{n(D-\bar{D})\sum_{j=1}^{m}w_{ij}\left(D_j-\bar{D}\right)}{\sum_{i=1}^{n}(D-\bar{D})^2}(i\neq j) \tag{18}$$

where m is the number of provinces and cities adjacent to province or city i.

2.3 Construction of the Indicator System

2.3.1 Basis for Indicator Selection

Based on the theory of endogenous economic growth, this paper selects input indicators from four aspects:labour, capital, technology and energy; it takes operating revenue from the cultural industry and consumer satisfaction with cultural products as desired outputs, and a composite index of industrial "three wastes" as undesired outputs. The study covers the 11 provinces and municipalities within the Yangtze River Economic Belt, with data primarily sourced from the 2024 National Statistical Yearbook; missing values have been imputed using interpolation.

2.3.2 Input-Output Indicator System

This paper employs four input indicators, two desired output indicators and one undesired output indicator, and utilises a super-efficiency SBM model that incorporates the undesired output to measure efficiency. The specific composition of the indicators and data sources are shown in Table 1.

Table 1 Efficiency Evaluation Indicators for Green Development in the Cultural Industry

ategory	Indicator Name	Indicator Composition	Unit	Indicator Explanation	Data Source
Input Indicators	Human Resources	Number of employees in the cultural industry	People	Personnel across cultural manufacturing, trade, and services, reflecting human capital investment scale.	*China Statistical Yearbook on Culture and Related Industries*
	Capital Investment	Assets of legal entities in the cultural and related industries	100 million yuan	Capital stock and production scale, the material foundation of cultural industry development	《China Statistical Yearbook on Culture and Related Industries》
	technology Investment	Internal expenditure on R&D	10,000 yuan	R&D investment intensity, reflecting cultural industry's innovation and green transformation potential	Statistical Yearbooks of Provinces and Municipalities
	Energy Input	Energy Consumption	10,000 tonnes	Energy input scale in cultural industry operations, a key constraint for green efficiency assessment	*China Energy Statistical Yearbook*
Output Indicators	Expected Output	Revenue of the cultural industry	10,000 yuan	Operating revenue-weighted index of cultural manufacturing, trade, and services, reflecting economic performance	*China Statistical Yearbook on Culture and Related Industries*
		Consumer Satisfaction with Cultural Products and Services	—	Weighted satisfaction index of cultural consumption, reflecting social benefits	Questionnaire survey
	Unintended Outcomes	Environmental pollution	—	Weighted index of industrial wastewater, air emissions, and solid waste, reflecting environmental externalities	Statistical Yearbooks of Provinces and Municipalities

2.3.3 Variable System for the Principal Component Regression Model

To investigate the factors influencing the efficiency of green development in the cultural industry, this study selects technical efficiency (TE) as the dependent variable, and per capita GDP (rgdp), urbanisation rate (urban), energy intensity (energy_int), the share of cultural industry value added in GDP (cult_share), and the urban-rural cultural consumption gap (cult_gap) as independent variables. As shown in Table 2.

Table 2 List of Variable Definitions

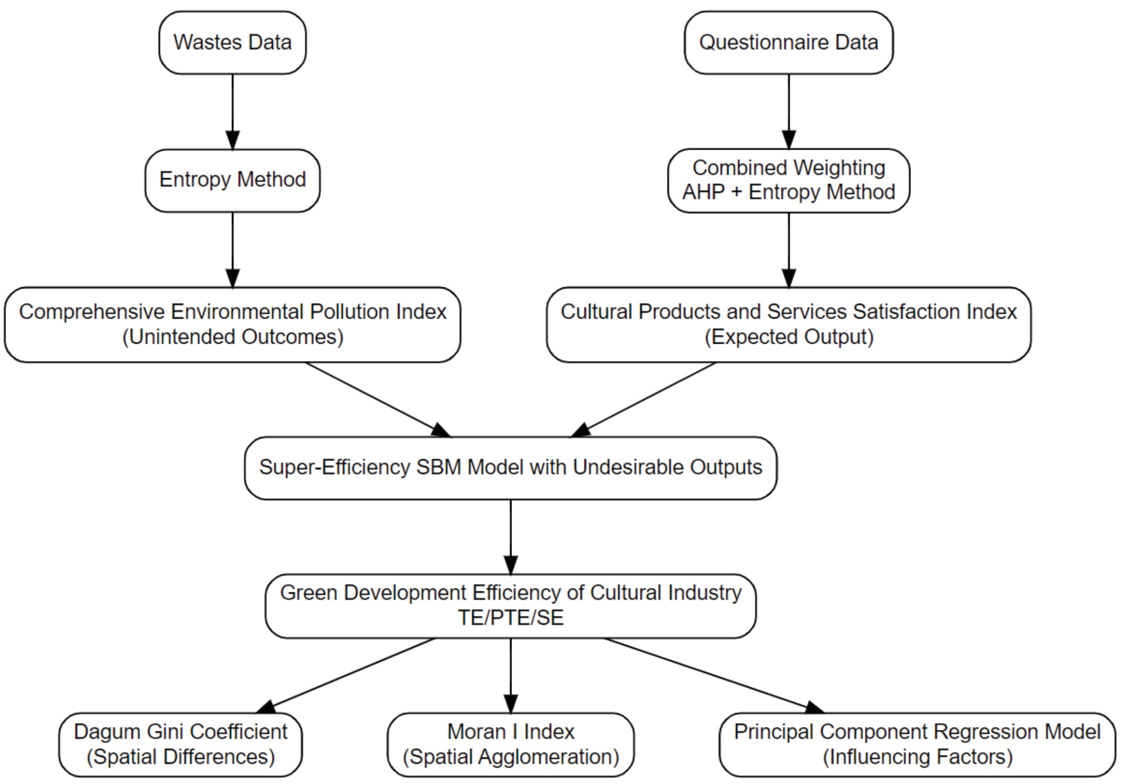
Variable	Variable Name	Unit	Explanation of Indicators
TE	Technical efficiency	-	Measuring the Green Development Efficiency of the Cultural Industry Using a Super-Efficient SBM Model that Accounts for Unwanted Outputs
rgdp	GDP per capita	100 million yuan	Reflecting the impact of economic development levels on green efficiency
urban	Urbanisation rate	%	Reflecting the impact of population concentration and urban development on efficiency
energy_int	Energy intensity	%	Measures energy efficiency and influences the sustainability of green development
cult_share	Share of cultural industry value added in GDP	%	Reflecting the impact of industry scale on green efficiency
cult_gap	Urban-rural cultural consumption gap	%	Reflecting the constraints on efficiency imposed by urban-rural consumption imbalances

It should be noted that, due to multicollinearity among the variables and the small sample size, both rgdp and cult_gap were left out of the final principal component regression model. They were not statistically significant in the univariate tests and also showed a strong correlation with the principal component. As a result, the model only included the first principal component (PC1), which was constructed from urban, cult_share, and energy_int.

3. Empirical Analysis

We went ahead and ran a comprehensive empirical analysis to see exactly how the green development efficiency of the cultural industry is holding up across the 11 provinces and municipalities in the Yangtze River Economic Belt. We started by estimating and breaking down the green development efficiency for each specific province and municipality. To get this right, we relied on the super-efficiency SBM model, making sure it accounts for unplanned outputs. After getting those numbers, we used the Dagum Gini coefficient along with Moran's I to pull back the curtain on spatial variations in efficiency and spot any real agglomeration characteristics. To wrap things up, we plugged the data into a multiple linear regression model to safely identify the key influencing factors driving these changes.

Figure 1 Flowchart of the empirical analysis approach



3.1 Analysis of Green Development Efficiency in the Cultural Industry Using a Super-Efficiency SBM Model Incorporating Unwanted Outputs

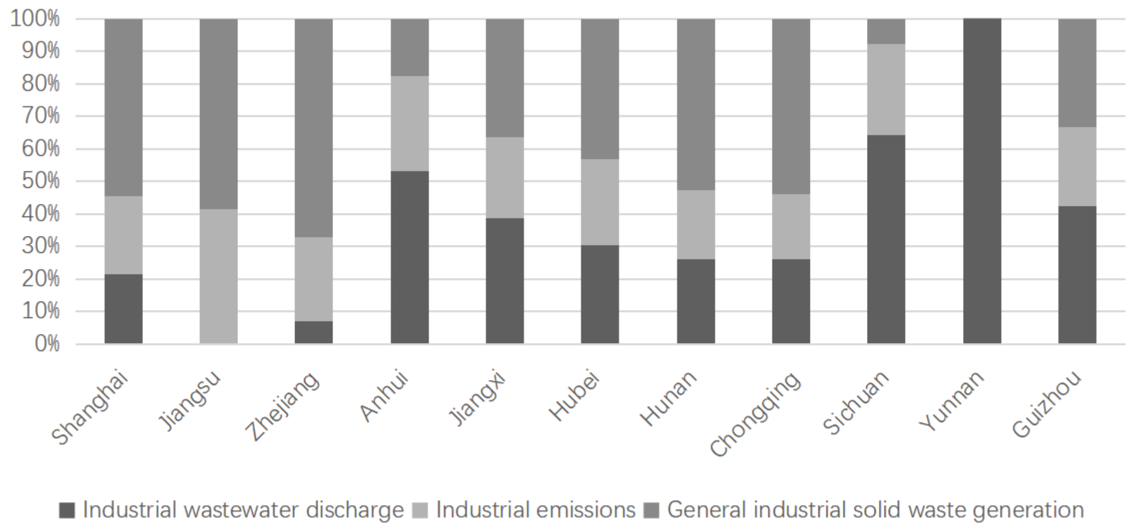
Building upon relevant literature, this paper constructs an evaluation index table for the green development efficiency of the cultural industry (Table 1) and selects the super-efficiency SBM model, which accounts for undesirable outputs, to measure the green development efficiency of the cultural industry across the 11 provinces and municipalities in the Yangtze River Economic Belt. Prior to running the model, it is necessary to calculate the environmental pollution index using the entropy method based on “three wastes” statistical data, and to calculate the cultural product and service consumption satisfaction index using a combination of the Analytic Hierarchy Process (AHP) and the entropy method based on questionnaire data.

This paper employs the super-efficiency SBM model, which accounts for unwanted outputs, to measure the green development efficiency of the cultural industries in the 11 provinces and municipalities of the Yangtze River Economic Belt. An evaluation index table for the green development efficiency of the cultural industries (Table 1) has been constructed. Prior to running the model, it is necessary to calculate the environmental pollution index using the entropy method based on statistical data on the “three wastes”, and to calculate the consumer satisfaction index for cultural products and services using a combination of the Analytic Hierarchy Process (AHP) and the entropy method based on questionnaire data.

3.1.1 Calculation of the Environmental Pollution Index

Based on the statistical data on the “three wastes”, each indicator was subjected to negative standardisation. Subsequently, the following were calculated for each indicator: the proportion of, the weight b_{ij}, the entropy value e_j, and the coefficient of variation d_j, yielding the weights ω_j. Finally, a weighted sum was taken to obtain the comprehensive environmental pollution index $EPI_i = \sum_{j=1}^{n} \omega_j x'_{ij}$ for each region (as shown in Figure 2), serving as a non-desired output indicator.

Figure 2 Stacked bar chart of environmental pollution index percentages



3.1.2 Calculation of Satisfaction with the Consumption of Cultural Products and Services

Consumer satisfaction with cultural products and services, as an expected output indicator in the evaluation of green development efficiency, utilises basic data obtained through questionnaire surveys. The comprehensive satisfaction index is calculated by combining the Analytic Hierarchy Process (AHP) with the entropy method for weighting.

3.1.2.1 Sampling Design

A proportional to size probability sampling (PPS) method was adopted, with the 11 provinces and municipalities of the Yangtze River Economic Belt as the study area. One core city was selected from each province, using the 2023 permanent resident population as the size variable. Under a 95% confidence level and a 5% absolute error margin, the required sample size was calculated to be 502. A total of 500 questionnaires were distributed, with 458 valid responses returned, yielding a response rate of 91.6%.

3.1.2.1 Reliability and Validity Analysis

Table 3 Reliability Test for the Formal Survey and Validity Test

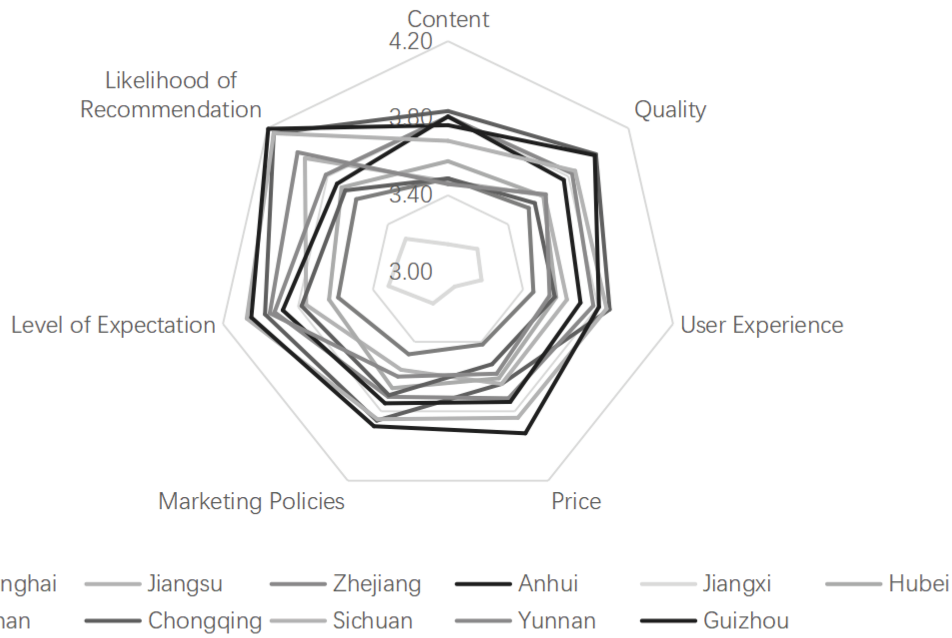
Item	CRONBACH'S ALPHA	Number of Items	Reliability Evaluation	KMO and Bartlett's test		
Q6	0.851	3	High	KMO()value		0.931
Q7	0.797	3	Fair			
Q8	0.701	3	Better	Bartlett's test of sphericity	Approximate chi-squared	1481.276
Q9	0.773	3	Fair			
Q10	0.749	3	Fair		df	136
Q11&Q12	0.703	2	Fair			
Overall scale	0.96	17	Very good		P-value	0

As shown in Table 3, the overall Cronbach's alpha coefficient for the questionnaire is 0.96, the KMO value is 0.931, and the p-value for Bartlett's sphericity test is<0.001; the questionnaire demonstrates good reliability and validity.

3.1.2.1 Calculation of Satisfaction with Cultural Products and Services

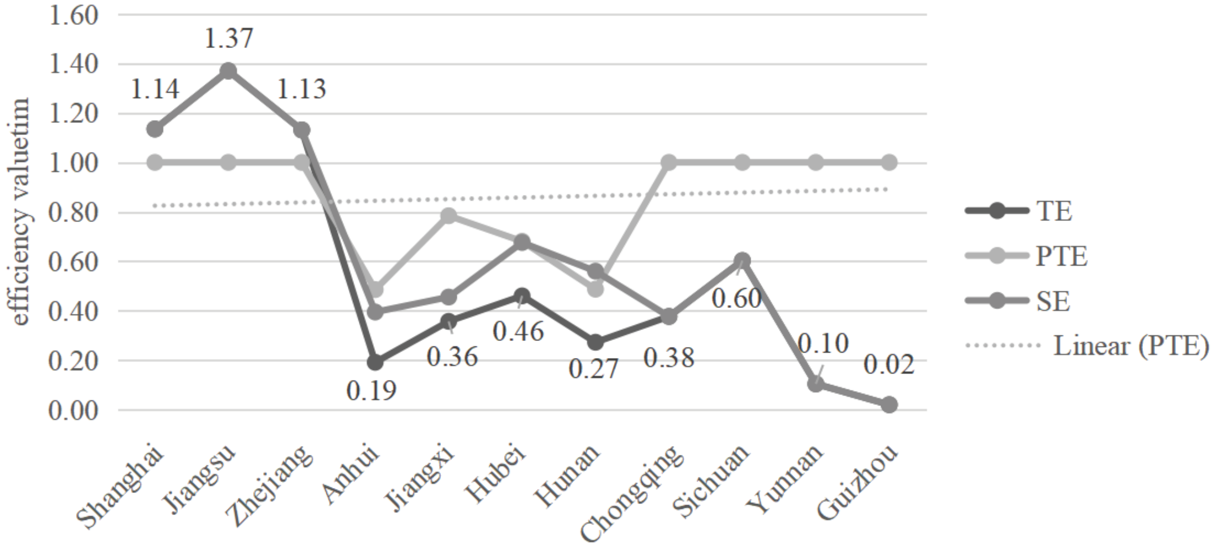
A combination of the Analytic Hierarchy Process (AHP) and the entropy method was employed for weighting. Firstly, the AHP was used to determine subjective weights: a satisfaction hierarchy (objective level, criterion level, and indicator level) was constructed; experts provided scores to create a judgment matrix, which passed the consistency test (CR < 0.1). Secondly, the entropy method was used to calculate objective weights based on data from 458 valid questionnaires. Finally, the mean of the AHP weights and the entropy-based weights was taken as the composite weight for each dimension. The weighted composite satisfaction score for each respondent was calculated, and these were aggregated by province and municipality to derive the average composite satisfaction index (Figure 3), which serves as an expected output variable in the super-efficiency SBM model that accounts for unanticipated outputs.

Figure 3 Radar chart of the cultural products and services consumption satisfaction index



3.1.3 Efficiency Measurement of the Super-Efficient SBM Model Considering Unwanted Outputs()

Figure 4 Line Chart of Efficiency Measurement



According to the calculation results (Figure 4), breaking the numbers down to look at pure technical efficiency (PTE), we saw seven different provinces and municipalities hit a perfect value of 1.0. This group included Shanghai, Jiangsu, Zhejiang, Chongqing, Sichuan, Yunnan, and Guizhou. Things weren't as great in the middle reaches of the Yangtze River, where Anhui (0.486), Jiangxi (0.784), Hubei (0.681), and Hunan (0.488) all struggled and fell below the 0.8 mark. Shifting the focus to scale efficiency (SE), only the three provinces located in the lower Yangtze River region actually managed to exceed 1. Meanwhile, every single region sitting in the middle and upper Yangtze River areas dropped below 0.7. In fact, if you just look at the four provinces making up the upper Yangtze River region—Chongqing, Sichuan, Yunnan, and Guizhou—their average SE was just a really low 0.277.

Looking at the map by region, the Lower Yangtze region leads across the board. They pulled in an average TE of 1.212, a perfect average PTE of 1.0, and an average SE of 1.212. The Middle Yangtze region tells a different story with an average TE of 0.321, an average PTE of 0.610, and an average SE of 0.522, which points to a pattern of dual insufficiency. Up in the Upper Yangtze region, we recorded a mean TE of 0.277 alongside a mean PTE of 1.0 and a mean SE of 0.277. This basically indicates that while they have pure technical efficiency, they are severely lacking in scale. Almost every non-efficient province and municipality ended up showing positive slack in unanticipated output, which usually means environmental pollution. On the flip side, the three provinces in the Lower Yangtze region exhibited negative slack when it came to capital input, suggesting some redundancy.

3.2 Spatial Differences Analysis Based on the Dagum Gini Coefficient

To reveal the sources of spatial disparities in the green development efficiency of the cultural industry within the Yangtze River Economic Belt, this paper employs the Dagum Gini coefficient and its decomposition method for analysis.

The Dagum Gini coefficient and its decomposition method were used to measure spatial variations in the green development efficiency of the cultural industry in the Yangtze River Economic Belt in 2023.

Figure 5 Bar chart of the Dagum Gini coefficient

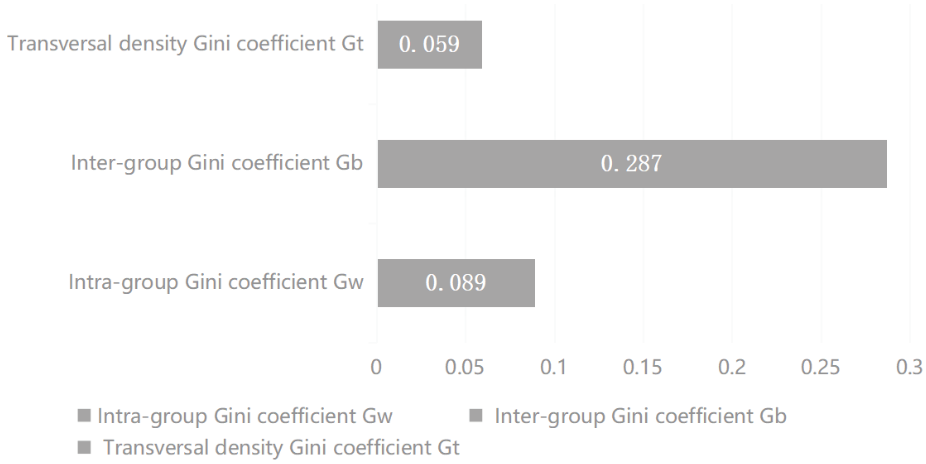
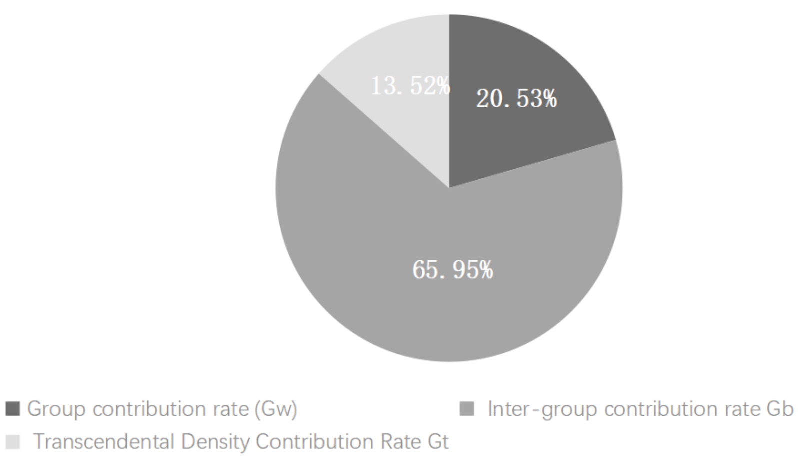
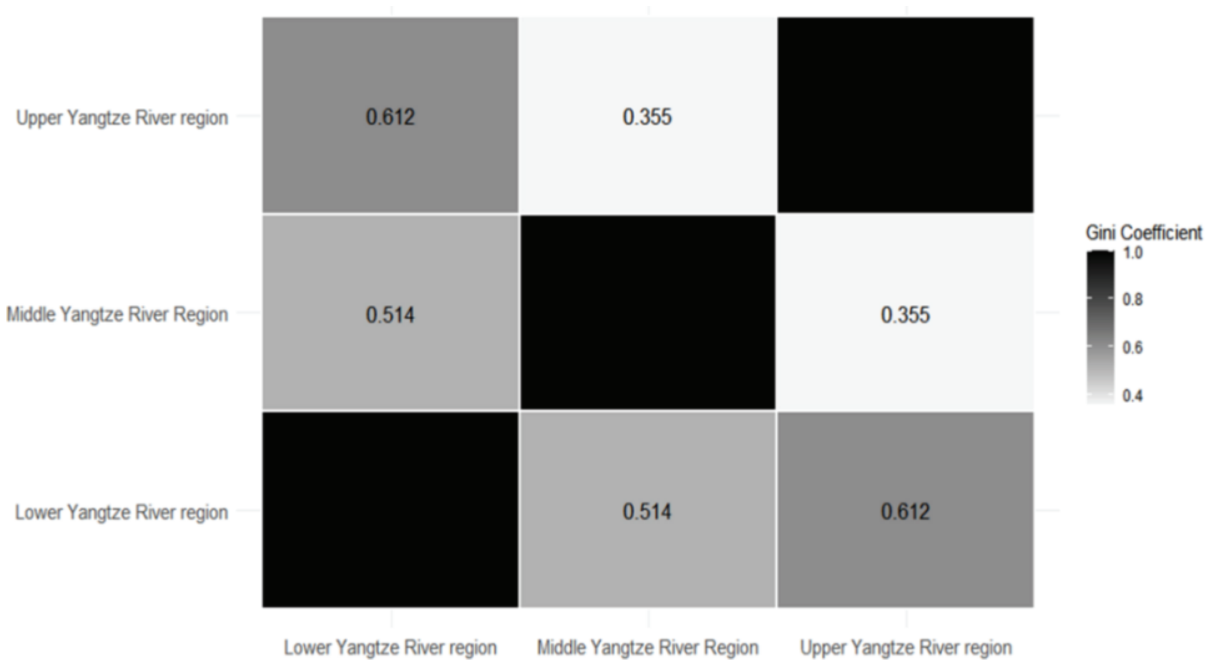


Figure 6 Bar chart of the Dagum Gini coefficient contribution rates



Looking at the actual calculations for the Dagum Gini coefficient shown in Figure 5, the overall Gini coefficient for the green development efficiency of the cultural industry across the Yangtze River Economic Belt sat at 0.436 for the year 2023. This number points straight to a pretty significant spatial imbalance between the different regions. When we break down where this disparity is coming from using the contribution rates in Figure 6, the inter-group contribution rate is clearly the main driver at 65.95%. This completely overshadows both the intra-group contribution rate, which is 20.53%, and the super-variable density contribution sitting at 13.52%. Now, if we zoom in on those intra-group differences, the Gini coefficient hits its peak within the Upper Yangtze region at 0.456. This really highlights some stark disparities in efficiency levels right among its constituent provinces and municipalities—namely Chongqing, Sichuan, Yunnan, and Guizhou. Trailing behind that is the Lower Yangtze region at 0.231, making the Middle Yangtze region the most internally balanced of the bunch with a coefficient of just 0.114. Further analyse the degree of variation within each region and between pairs of regions.

Figure 7 Dagum Gini coefficient variation heatmap



Based on the decomposition of the Dagum Gini coefficient from Figure 7, it is clear that these spatial disparities mostly originate from a stark contrast between the Lower Yangtze region and the Middle and Upper areas. While the Upper Yangtze region struggles with severe internal differentiation, the Middle Yangtze remains relatively homogeneous. As we noted, the internal Gini coefficient for the Upper Yangtze region is incredibly high at 0.456, which easily dwarfs the 0.231 of the Lower Yangtze and the 0.114 of the Middle Yangtze. This huge gap in the Upper region is driven by extremely severe efficiency divergence among its four provinces, especially when comparing Sichuan at 0.6031 with Guizhou way down at 0.0208. The Lower Yangtze region takes second place for internal disparity, largely because Jiangsu's score of 1.3699 is significantly higher than what we see in both Shanghai and Zhejiang. The Middle Yangtze region remains the most balanced internally, keeping its efficiency relatively concentrated across its own four provinces.

Shifting to an inter-regional perspective, the gap between the Lower and Upper Yangtze regions is by far the widest, showing a Gini coefficient of 0.612. This is followed by the gap between the Middle and Lower regions at 0.514, leaving the smallest measured gap between the Middle and Upper regions at just 0.355. Ultimately, this data demonstrates that the Lower Yangtze region leads comprehensively across the board in terms of efficiency. It creates a sharp, distinct divide with the Upper region, while the actual average gap between the Middle and Upper regions stays relatively small.

3.3 Analysis of Regional Aggregation in the Cultural Industry Based on the Moran Index

To reveal the spatial dependence and agglomeration patterns of green development in the cultural industries of the Yangtze River Economic Belt, this paper employs the Moran’s I index to conduct a spatial autocorrelation analysis.

3.3.1 Analysis of the Moran’s I Index

Table 4 Overall Moran's I

Study Item	Moran's I	Expected Value E(I)	Standard Deviation sd(I)	z-value	p-value
TE	0.527	-0.1	0.193	3.178	0.001

Table 5 Local Moran's Index

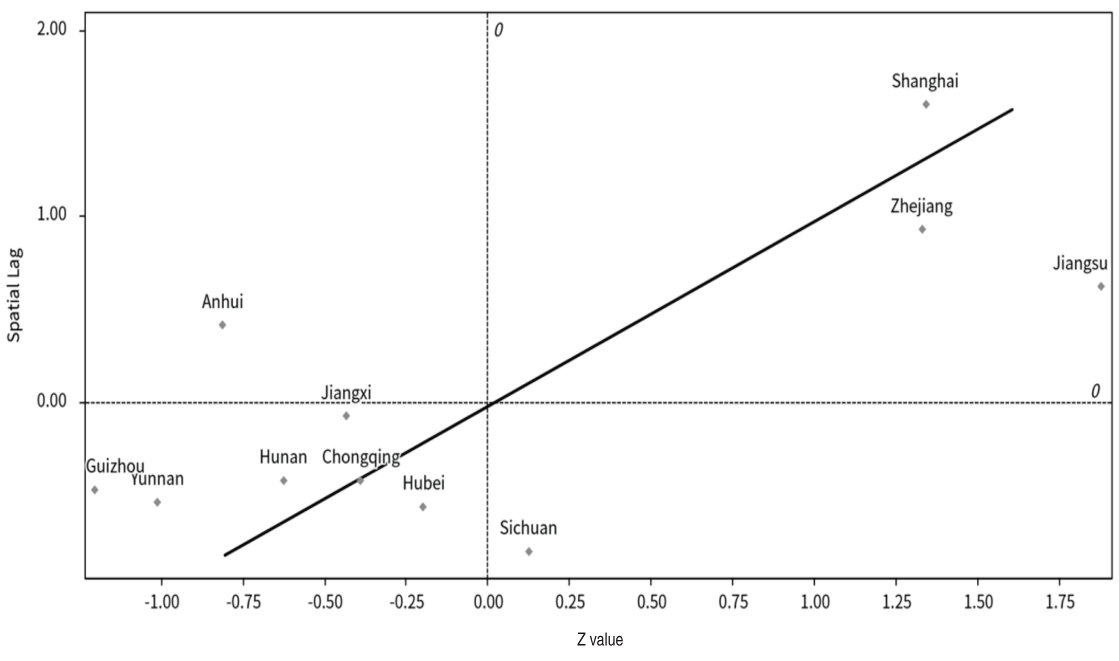
Location	Moran's I	Expected value E(I)	Standard deviation sd(I)	z-value	p-value
Shanghai	1.953	-0.1	0.767	2.866	0.001
Jiangsu Province	1.057	-0.1	0.83	1.66	0.024
Zhejiang Province	1.122	-0.1	0.661	1.929	0.013
Anhui Province	-0.306	-0.1	0.429	-0.533	0.149
Jiangxi Province	0.03	-0.1	0.189	0.221	0.206
Hubei Province	0.102	-0.1	0.087	1.197	0.058
Hunan Province	0.243	-0.1	0.264	1.044	0.074
Chongqing	0.15	-0.1	0.209	0.839	0.1
Sichuan Province	-0.093	-0.1	0.054	-1.705	0.022
Yunnan Province	0.494	-0.1	0.647	0.865	0.097
Guizhou Province	0.519	-0.1	0.472	1.385	0.042

The global Moran's I statistic (Table 4) shows I = 0.527, p=0.001, indicating that there is significant positive spatial autocorrelation in the green development of the cultural industry across the Yangtze River Economic Belt as a whole.

According to the local Moran's I results in Table 5, Shanghai (I = 1.953, p = 0.001), Jiangsu (I = 1.057, p = 0.024), Zhejiang (I = 1.122, p = 0.013), and Guizhou (I = 0.519, p = 0.042) each show a significantly positive spatial autocorrelation. Sichuan (I = −0.093, p = 0.022), on the other hand, has a significantly negative value. The remaining six regions, namely Anhui, Jiangxi, Hubei, Hunan, Chongqing, and Yunnan, are all statistically insignificant (p > 0.05 in each case).

3.3.2 Moran's scatter plot and quadrant distribution analysis

Figure 8 Moran scatter plot



Based on the quadrant distribution of the Moran scatter plot (Figure 8), the overall pattern shows high values in the east and low values in the west, with localised polarisation. Shanghai, Jiangsu and Zhejiang fall into the first quadrant (high-high), indicating a clustering of high values; Guizhou falls into the third quadrant (low-low), and with a significant local Moran's I, forms a clustering of low values; Sichuan falls into the fourth quadrant (high-low), presenting a polarised pattern where high values are surrounded by low values; Provinces such as Anhui, Jiangxi, Hubei, Hunan, Chongqing and Yunnan are mainly distributed near the third quadrant, but their local Moran's I is not significant, and no clear clustering pattern has formed.

3.4 Analysis of Influencing Factors Based on a Principal Component Regression Model

To identify the key influencing factors of the green development efficiency (TE) of the cultural industry in the Yangtze River Economic Belt, this study employs a principal component regression method. First, a multicollinearity diagnosis is conducted on the candidate explanatory variables; then, principal components are extracted to construct a composite index; finally, a regression analysis is performed to examine the relationship between the composite index and efficiency, with robustness tests conducted using univariate regression.

3.4.1 Diagnosis of Multicollinearity

The variance inflation factors (VIFs) for the five explanatory variables are shown in Table 6. The VIFs for both the urbanisation rate and per capita GDP are well over 10, indicating the presence of severe multicollinearity.

Table 6 Variance Inflation Factors (VIF) of Explanatory Variables

Variable	VIF	1/VIF
urban	13.74	0.073
rgdp	12.40	0.081
cult_share	3.80	0.263
energy_int	1.81	0.552
cult_gap	1.78	0.562
Mean VIF	6.70	–

3.4.2 Principal Component Analysis

Multicollinearity exists between the urbanisation rate (urban), the share of value added in cult_share and energy_int. Principal component analysis was performed on these three variables. The KMO statistic was 0.68 and the Bartlett's sphericity test yielded a p-value of <0.01, indicating the presence of common factors among the variables and confirming the suitability of principal component analysis.

Table 7 Eigenvalues and Variance Explained

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.305	1.846	0.768	0.768
Comp2	0.459	0.224	0.153	0.922
Comp3	0.235	.	0.078	1.000

Table 8 Principal component load matrix

Variable	Comp1	Comp2	Comp3
urban	0.587	0.477	-0.654
cult_share	0.601	0.285	0.747
energy_int	-0.543	0.831	0.119

In accordance with the principle that eigenvalues should be greater than 1, the first principal component (PC1) was selected, explaining 76.8% of the variance. The load matrix (Table 8) shows that PC1 is positively correlated with urban and cult_ share, and negatively correlated with energy_int.

3.4.3 Principal Component Regression Results

Ordinary least squares regression was performed with PC1 as the explanatory variable and technical efficiency(TE)as the dependent variable, the results are shown in Table 9.

Table 9 Principal Component Regression Results

te	Coefficient	Standard error	t	P>t	[95%confidence	interval]
pc1	0.251	0.056	4.470	0.002	0.124	0.379
_cons	0.548	0.081	6.730	0.000	0.364	0.732

The regression coefficient of PC1 comes out as 0.251, and it is statistically significant at the 1% level ($t = 4.47$, $p = 0.002$). This means PC1 has a clear positive relationship with technical efficiency: a one-unit rise in PC1 corresponds to a rise of about 0.251 in technical efficiency. The model yields an R^2 of 0.690 and an adjusted R^2 of 0.656, and the F-test gives a p-value of 0.0015, suggesting that the model fits the data quite well overall.

3.4.4 Robustness Tests

To ensure the reliability of the conclusions, univariate regressions were conducted separately for urban, cult_share and energy_int (Table 10). Additionally, the univariate results for per capita GDP and the urban-rural cultural consumption gap are presented for comparison.

Table 10 Results of Univariate Regression

Variable	Coefficient	Std.err.	p	R^2
rgdp	1.308	0.309	0.002	0.666
urban	1.139	0.331	0.007	0.569
energy_int	-0.985	0.431	0.048	0.368
cult_share	1.683	1.023	0.161	0.290
cult_gap	-0.299	0.447	0.521	0.047

The results show that the univariate regression findings are consistent with those of the principal component regression, thereby validating the robustness of the conclusions.

4. Research Conclusions and Policy Recommendations

4.1 Research Conclusions

The overall comprehensive efficiency of green development in the cultural industry along the Yangtze River Economic Belt remains relatively low, exhibiting a pattern of divergence characterised by “high efficiency in the lower reaches, weak technical capabilities in the middle reaches, and limited scale in the upper reaches”. In 2023, the average comprehensive technical efficiency of green development in the cultural industry across the 11 provinces and municipalities of the Yangtze River Economic Belt stood at 0.548, with only Shanghai, Jiangsu and Zhejiang in the lower reaches achieving positive values. In the middle reaches of the Yangtze River, the pure technical efficiency of the four provinces was below 0.8, whilst in the upper reaches, the average scale efficiency of the four provinces was merely 0.277. All non-efficient provinces and cities exhibited positive slack in environmental pollution, and the three provinces in the lower reaches of the Yangtze River showed redundant capital investment.

Spatial disparities stem primarily from the inter-group gap between the Lower Yangtze and Upper Yangtze regions, with the most pronounced differentiation occurring within the Upper Yangtze region itself. The overall Gini coefficient stands at 0.436, with inter-group contributions accounting for 65.95%—the primary source of overall variation. The inter-group Gini coefficient is highest between the Lower Yangtze and Upper Yangtze regions (0.612) and lowest between the Middle Yangtze and Upper Yangtze regions (0.355). The Gini coefficient within the Upper Yangtze region is the highest (0.456), far exceeding that within the Lower Yangtze region (0.231) and the Middle Yangtze region (0.114), with a stark contrast in efficiency between Sichuan (0.603) and Guizhou (0.021).

The pattern of spatial agglomeration is polarized, mainly showing “high–high” and “low–low” clusters with clear local polarization. The global Moran’s I is 0.527 ($p = 0.001$), confirming a strong positive spatial autocorrelation. Shanghai, Jiangsu, and Zhejiang belong to the high-high agglomeration zone. Guizhou falls into the low-low agglomeration zone, with a local Moran’s I of 0.519 ($p = 0.042$). Sichuan, however, presents a high-low polarization (local Moran’s I = −0.093, $p = 0.022$), meaning that a high-value region is surrounded by low-value areas, and no spillover effect is observed.

Urbanisation rates and industrial scale exert a positive driving force,whilst energy intensity imposes a negative constraint. Principal component regression indicates that PC1, derived from urbanisation rates, the share of cultural industry value added (positively correlated) and energy intensity (negatively correlated), has an efficiency coefficient of 0.251 ($p = 0.002$). Univariate tests show that for every 1-unit increase in per capita GDP, efficiency rises by 1.308, whilst for every 1-unit increase in energy intensity, efficiency falls by 0.985.

4.2 Policy Recommendations

4.2.1 Policy Coordination

Strengthen regional coordination and implement targeted measures to address the structural imbalance characterised by “high efficiency in the lower reaches, weak technology in the middle reaches, and limited scale in the upper reaches”, and develop digital cultural industries in a manner tailored to local conditions. We should build upon the high-quality development strategy for the Yangtze River Economic Belt during the 15th Five-Year Plan period, driving the green development of the cultural industry from “localised leadership” towards “overall coordination”. Firstly, we should develop the digital cultural industry in a manner suited to local conditions. Drawing on the differing cultural resource endowments of the middle and lower reaches of the Yangtze River, the lower reaches should focus on developing the metaverse, AI-generated animation, micro-dramas, online literature IPs, and digital films and television series; the middle reaches should focus on developing digital books, audiobooks, and cultural data assets; the lower reaches of the Yangtze River should prioritise the development of animation, gaming, digital music and ecological imaging, thereby reducing physical resource consumption at source. Secondly, a Green Collaborative Development Fund for the Cultural Industry should be established to provide key support for enhancing pure technical efficiency in the middle reaches of the Yangtze River and expanding effective scale in the upper reaches, with priority investment directed towards digital infrastructure such as cloud rendering and copyright blockchain. Thirdly, a “Green Development Efficiency” leader scheme should be implemented, offering green finance and land use incentives to Shanghai, Jiangsu and Zhejiang, whilst requiring them to establish low-carbon standards for the digital cultural sector. Fourthly, implement a special campaign to enhance scale efficiency in the upper reaches of the Yangtze River, addressing the challenge of insufficient scale through the cross-provincial co-construction of digital cultural industrial parks and the sharing of computing power and copyright resources.

4.2.2 Business Model Transformation

Establish a green cultural consumption and production system to overcome the negative constraints of energy intensity and the spatial polarisation pattern. In response to the negative impact—where a one-unit increase in energy intensity leads to a 0.985-unit decrease in efficiency—as well as the polarised clustering patterns of “high-high” and “low-low” regions, as highlighted in, the green transformation of the entire cultural industry chain must be accelerated. Firstly, vigorously develop new digital cultural business models, replacing high-energy-consuming traditional physical formats with animation, online literature, micro-dramas, digital books and audiobooks to reduce energy consumption per unit of added value. Secondly, promote low-carbon cultural venues by implementing energy consumption quota management for theatres, museums and similar facilities, whilst encouraging the use of renewable energy and green building materials. Thirdly, foster eco-digital convergence models—such as virtual performances in the metaverse and cultural and creative products linked to carbon credits—to internalise environmental externalities as economic benefits. Fourthly, establish green cultural consumption demonstration zones in regions experiencing “high–low” polarisation, such as Sichuan, where consumption subsidies and green credits can be used to stimulate demand for green digital cultural products and break the deadlock in spillover effects.

4.2.3 Technology Empowerment

Break through the bottleneck of pure technical efficiency in the middle reaches of the Yangtze River, and drive green technologies from input redundancy towards output conversion. The average pure technical efficiency in the middle reaches of the Yangtze River is below 0.8, and the existence of capital input redundancy in the lower reaches indicates insufficient technological conversion capacity. Firstly, apply artificial intelligence (AI) technology to intelligent editing of micro-dramas and short videos, optimisation of animation rendering, and assisted translation of online literature, thereby reducing computing power consumption and idle labour; deploy metaverse technology to create virtual production, cloud exhibitions and digital cultural tourism spaces, replacing physical set construction with virtual scenes to reduce waste of building materials; introduce blockchain technology to establish a platform for the authentication and trading of cultural data assets, revitalising idle copyright resources, achieving cross-regional resource sharing and avoiding duplicate investment. Secondly, establish a pilot platform for green technologies in the cultural industry, focusing on the research and development of low-energy-consumption stage equipment, biodegradable cultural and creative materials, and intelligent temperature-controlled exhibition systems, to address the issue of technological investment yielding no tangible output. Thirdly, promote the integration of digitalisation and intelligent technologies with green technologies, utilising the Internet of Things (IoT) to monitor energy consumption in cultural enterprises in real time, and employing AI to optimise production scheduling and logistics routes, thereby reducing unintended by-products (such as exhibition waste and high-carbon exhibition set-ups). Fourthly, establish a green technology efficiency assessment mechanism, linking internal R&D expenditure to pollution reduction and energy consumption cuts, thereby preventing technological investments from going to waste.

4.2.4 Talent Support

Cultivate professionals with expertise in both green culture and technology to resolve the inherent contradiction where technology is effective but lacks scalability. In the Upper Yangtze region, pure technical efficiency stands at 1.0, whilst scale efficiency is merely 0.277, reflecting a talent structure skewed towards the technical side and lacking in industrial operational capabilities. Firstly, establish a micro-specialisation in green operations for digital culture, piloted in universities in Sichuan, Chongqing, Yunnan and Guizhou, to cultivate multi-skilled professionals proficient in the mass production of micro-dramas, audiobook recording pipelines, the operation of online literature platforms, carbon accounting and green supply chains. Secondly, implement the Green Culture Leadership Programme, dispatching operational talent familiar with digital cultural business models from high-efficiency regions in the lower reaches of the Yangtze River to take up temporary posts in the upper reaches, thereby facilitating the integration of technical expertise with local scale expansion. Thirdly, “green efficiency performance” will be incorporated into the cultural industry talent evaluation system. Those demonstrating significant achievements in energy conservation, consumption reduction and the development of green digital products will be given priority in professional title promotions and project funding, thereby stimulating talent vitality.

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No

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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