Sensors and Materials, Vol. 38, No. 1 (2026) 419–437
MYU Tokyo

S & M 4308

Evaluation of Tourism Development Efficiency Using Multisource Sensor Data: A Case Study in China

Bingfeng Liu,* Jianhua Cheng, and Jiaqi Cao

School of Management and Economics, Jingdezhen Ceramic University, Jingdezhen, Jiangxi 333000, China

(Received June 5, 2025; accepted January 15, 2026)

Keywords: multisource sensor data, tourism development, efficiency, Jiangxi Province, data fusion, DEA model

The evaluation of tourism efficiency is crucial for regional economic development. However, conventional methods rely on low-dimensional statistical data that fail to capture the industry's complex and high-resolution dynamics. Therefore, a new tourism efficiency evaluation system was developed in this study, utilizing multisource sensor data, including satellite remote sensing (Landsat 8 and Sentinel-2), mobile phone signal trajectories, and points of interest data. We applied a three-stage data envelopment analysis and the Malmquist index to 11 cities in Jiangxi Province (2013–2019). The results showed that while the average comprehensive technical efficiency declined from 0.776 to 0.718 (representing 71–78% of the optimal level), the total factor productivity (*TFP*) increased at an average annual rate of 22.2% (*TFP* index = 1.222). This increase was driven by technological progress, with an average technological change index of 1.242. A significant contribution of this study to sensor technology is the establishment of a standardized data fusion method achieving a spatial coverage completeness of more than 95%, enabling high-resolution (1 × 1 km^2 grid) spatiotemporal monitoring. These findings prove that integrating multisource sensor networks offers superior analytical depth for identifying bottlenecks in scale efficiency and optimizing regional resource allocation.

1. Introduction

Amid the rapid expansion of tourism globally, regional tourism and related issues have been extensively researched. Tourism contributes substantially to regional and national economic growth and plays an important role in optimizing industrial structures. Traditionally, tourism efficiency has been assessed using statistical indicators such as total revenue and the number of visitors. However, with these measures, the heterogeneity and complexity inherent in tourism systems cannot be captured. Their limited dimensionality restricts the exploration of the spatiotemporal dynamics of tourist behavior. Consequently, conventional statistical analyses are inadequate for evaluating tourism efficiency, as their lack of quantitative depth impedes the identification of factors affecting tourism efficiency.(1,2)

*Corresponding author: e-mail: 022538@jcu.edu.cn
https://doi.org/10.18494/SAM5802

ISSN 0914-4935 © MYU K.K.
https://myukk.org/

Advances in sensor technology introduce new methods into tourism research. Satellite remote sensing data are used to investigate the spatial distribution of tourism resources, whereas mobile phone data are used to examine tourist mobility patterns. The data obtained facilitate the identification of points of interest (POIs) that are important to construct or locate tourism facilities. Sensor data are characterized by extensive coverage, strong timeliness, and fine granularity, all of which are essential for constructing a robust evaluation framework for tourism efficiency. Integrating multisource data enables a systematic exploration of the operational mechanisms underlying tourism systems.(3)

Jiangxi Province in China is regarded as a major tourism area with abundant natural landscapes and cultural heritage. The tourism industry in the province has been growing, which presents challenges such as inconsistent tourism efficiency and inefficient resource allocation. In this study, we analyzed the tourism efficiency of Jiangxi Province on the basis of the data obtained from the sensors in the cities of the province and proposed a new tourism efficiency evaluation system. The system enables a quantitative assessment based on multisource sensor data and facilitates the analysis of spatiotemporal characteristics and their patterns. On the basis of the analysis results, the factors affecting tourism efficiency are identified, providing an empirical foundation for policy-making. Moreover, resource allocation can be optimized to promote the development of the tourism industry. The results also provide a reference for evaluating tourism efficiency in other regions.(4)

2. Literature Review

2.1 Tourism efficiency

Tourism efficiency refers to the capacity of the tourism industry to maximize benefits during its development within a specific period.(5) It reflects the extent to which tourism resources are utilized and serves as an indicator of sustainable tourism development. On the basis of spatial heterogeneity and the temporal dynamism of tourism,(6) tourism efficiency reflects inter-regional tourist flows, spillover effects, technological progress, and institutional innovation.(7)

Enhancing tourism efficiency is crucial for upgrading the tourism industry and ensuring its sustainable development. Previous studies have mainly examined tourism efficiency in terms of accommodation management, labor productivity, and returns on investment. However, such data are insufficient to accurately evaluate tourism efficiency. Therefore, a method employing multiple and integrated measures needs to be developed.

Recently, input–output factors have been identified in the evaluation of tourism efficiency. The factors encompass economic, environmental, and social dimensions to explore sustainable and coordinated tourism development, facilitated by multisource sensor data.(8,9) Therefore, in tourism efficiency evaluation, the identification of input and output factors is essential. Input factors include the number of employees, the availability of tourist attractions, and asset investment, whereas output factors encompass total revenue and the number of tourists.(10)

Analytical methods such as data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are foundational for determining input-output factors. In particular, DEA offers the flexibility of non-predefined functional forms.(11) To overcome the limitation of such static methods, regression methods are used to interpret the dynamics of tourism efficiency over time. Specifically, panel Tobit models, often integrated with the Malmquist index, allow for a robust exploration of efficiency drivers.(12) Furthermore, time-series regression techniques, such as Levin–Lin–Chu (LLC), Augmented Dickey–Fuller (ADF), and Phillips–Perron (PP), are used to ensure data stationarity and the validity of long-term trends. These regression-based methods are vital for understanding how resource endowment, infrastructure, and market demand act as determinants of tourism efficiency.(13) Tourism efficiency reflects the strategic allocation of capital, labor, and technology. Therefore, regression analysis is an effective tool for evaluating how these inputs are optimized in tourism.(14)

2.2 Sensor data in tourism industry

Satellite remote sensing, mobile phone signals, and points of interest (POI) data collected from sensors are used to enhance the accuracy and analytical capacity of tourism efficiency research.(15)

Satellite remote data provide advantages for monitoring and assessing tourism resources and capacity. Multispectral and high-resolution images enable the precise identification of the spatial distribution of tourist attractions, whereas ecological and environmental factors such as vegetation coverage and water body changes can also be estimated.(16) Nighttime light data are used to estimate tourism activity, whereas thermal infrared remote sensing data are used to evaluate the environmental impacts of tourist flows. These data are used for the analyses of the sustainable utilization of tourism resources.(17)

Mobile phone data introduce a breakthrough in tourist behavior research.(18) By analyzing data at base stations, tourists' trajectories are accurately tracked, revealing their spatial distributions and movement patterns. The data collected provide information on the duration of stays, activity locations, and behavioral differences. Compared with traditional questionnaire surveys, mobile phone signal data enable a large volume of real-time information with greater objectivity and reliability.(19)

POI data are essential in assessing the popularity of dining, accommodation, and transportation, and the status and accessibility of service facilities in tourist destinations.(20) Combined with spatial analysis methods, POI data enable the exploration of facility usage and preference, supporting the optimization of tourism efficiency and the identification of spatiotemporal characteristics of tourism facilities.(21) Collectively, these multidimensional datasets contribute to the development of data analysis algorithms through advanced data processing.(22,23)

3. Methods

3.1 Study area

Figure 1 shows the growth in the number of visitors (measured in units of 10000) for four different tourist destinations, Lushan, Jinggangshan, Sanqingshan, and Wuyuan, from 2013 to 2019. Overall, all four locations experienced a steady and significant increase in tourism over the seven years. No destinations showed a decline in visitors at any point, indicating a robust growth period for tourism in these regions.

Throughout the period, Lushan remained the most popular destination. It started with 10 million visitors (1000 units) in 2013 and grew consistently to reach 17 million visitors (1700 units) by 2019. Wuyuan had 8 million visitors in 2013 and 15 million visitors in 2019. Jinggangshan was the least visited destination in 2013 (5 million visitors), but experienced the most prominent increase in the number of visitors. Between 2017 and 2018, there was a sharp increase in the number of visitors, allowing it to overtake Sanqingshan. By 2019, it reached 13 million visitors. Sanqingshan had from 6.1 million visitors in 2013 to 11 million in 2019; its growth rate was lower than those of the other destinations. As a result, it became the third most visited destination to the least visited by 2018.

The analysis result of the sensor data (POI data) in Lushan, Jinggangshan, Sanqingshan, and Wuyuan shows the heatmap of the distribution of scenic spots in Jiangxi Province as shown in Fig. 2.(24) In this study, we identified factors affecting the tourism development of Jiangxi Province.(25)

We deployed multisource sensor networks in Lushan, Jinggangshan, Sanqingshan, and Wuyuan to capture the numbers of visitors at entrances, the numbers of vehicles along accessible routes, environmental conditions at specific sites, GPS and beacon tracking data on trails, as well as mobile and Wi-Fi signals to monitor crowd density (Table 1).(26)

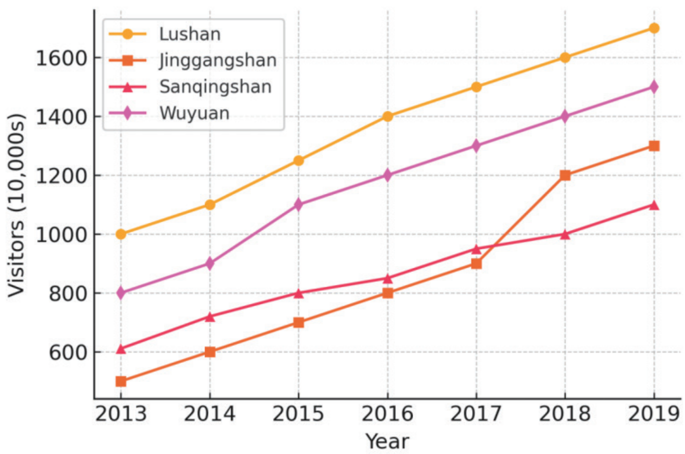

Fig. 1. (Color online) Numbers of tourists in Lushan, Jinggangshan, Sanqingshan, and Wuyuan in Jiangxi Province from 2013 to 2019 (drawn in this study based on the data from tjj.jiangxi.gov.cn and dct.jiangxi.gov.cn).

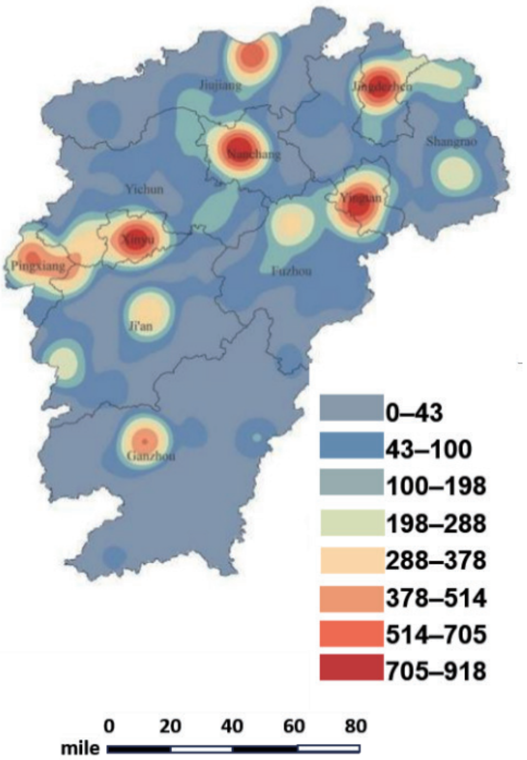

Fig. 2. (Color online) Heatmap of scenic spots in Jiangxi Province.

Table 1
Sensor nodes of sensor network in tourism areas.

Sensor network number	Location	Sensor
1	Lushan Main Gate	Entrance visitor counter
2	Access Road to Wuyuan	Vehicle traffic sensor
3	Summit of Jinggangshan	Environmental monitoring
4	Sanqingshan Hiking Trail	Beacon data on trail
5	Historic Village in Wuyuan	Mobile signal
6	Lushan Viewpoint	CCTV camera with analytics

3.2 Sensor data collection and processing

Data in this study were collected, considering spatial coverage, temporal continuity, and attribute completeness. The data collected were preprocessed to ensure data quality and comparability. Figure 3 shows the network diagram of the multisource sensor data utilized in this study.

Satellite remote sensing data were sourced from the Landsat 8 Operational Land Imager and Sentinel-2 Multispectral Instrument imagery, with a spatial resolution of 30×10 m^2. In data preprocessing, radiometric calibration, atmospheric correction, and image fusion were

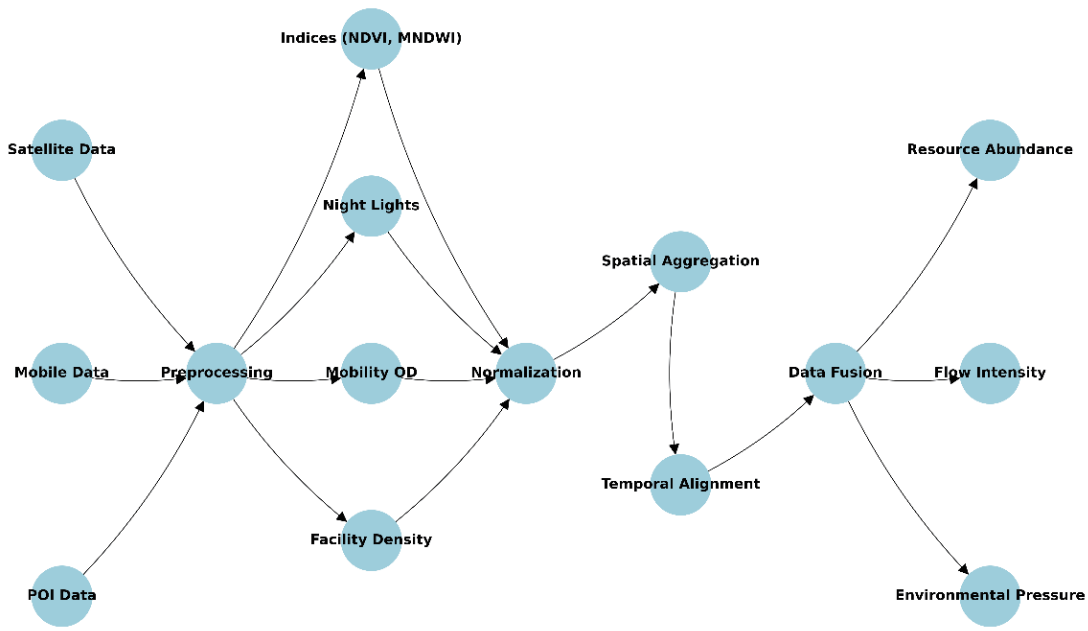

Fig. 3. (Color online) Network diagram of multisource sensor data in this study.

conducted. Vegetation coverage was estimated using the normalized difference vegetation index (*NDVI*), whereas water bodies were identified through the modified normalized difference water index, and Nighttime light data were obtained from the Suomi National Polar-orbiting Partnership–Visible Infrared Imaging Radiometer Suite. Following denoising and radiometric normalization, a tourism economic activity index was constructed.(27)

Mobile phone data encompassed anonymized and continuous base station switching records of 12 months, provided by telecommunications operators. To mitigate positioning drift, the Density-based Spatial Clustering of Applications with Noise algorithm was applied, and a dwell time threshold was used to identify tourist behaviors. Tourist origin-destination matrices were analyzed using Voronoi diagrams, and movement trajectories were reconstructed via Markov chain modeling.(28) To ensure privacy, all data underwent k-anonymization and were spatially aggregated to the district or county level.(29)

POI data were collected through the AutoNavi Map application programming interface, encompassing accommodation, dining, and transportation facilities.(30) Kernel density estimation was employed to analyze spatial agglomeration patterns, and service accessibility was assessed using road network data. Data quality control was conducted using coordinate correction, attribute verification, and deduplication within a spatially topological relational database.(31)

The multisource data were integrated using spatial overlay analysis and spatiotemporal matching techniques. Spatial alignment was performed within a unified coordinate system (CGCS2000) using a 1 × 1 km^2 grid, whereas temporal association was achieved through timestamp synchronization. The fusion indicators used included tourism resource abundance (remote sensing + POI), tourist flow intensity (signaling + POI), and environmental carrying capacity pressure (remote sensing + signaling). Data processing was executed using Python 3.8 and ArcGIS Pro, with modular programming employed to ensure reproducibility.

The method of this study was designed to explore the spatiotemporal limitations of conventional statistical data and enable the multidimensional observation of tourism resources, behaviors, and facilities. Data cleaning efficiency was enhanced through machine learning algorithms, such as random-forest-based outlier detection. A standardized fusion method was established to generate high-quality input data. Data quality assessment results showed that spatial coverage completeness exceeded 95% for each data source and temporal continuity met the requirements for quarterly analysis.(32)

3.3 Tourism efficiency evaluation model

We employed a multistage analytical method to evaluate the tourism efficiency of Jiangxi Province. The method integrates traditional tourism efficiency modeling with multisource sensor data to ensure a high-resolution analysis.

To eliminate the effects of external factors and random noise, we adopted three-stage DEA.

3.3.1 Stage I: Initial efficiency measurement

We first applied the Banker, Charnes, and Cooper model to provide a preliminary assessment of each city. This model decomposes comprehensive technical efficiency (*CTE*) into pure technical efficiency (*PTE*), which measures how effectively a city manages its resources at its existing technological level, and scale efficiency (*SE*), which evaluates whether a destination is operating at its optimal size.

3.3.2 Stage II: Stochastic frontier analysis (SFA) adjustment

In the second stage, we employed regression analysis to adjust for external interference. By applying an SFA model, we separated inefficiencies from random noise and environmental factors, such as topographic relief, climatic comfort, and regional economic development levels. We leveled the playing field by removing variables that tourism managers cannot control.

3.3.3 Stage III: Evaluation

The adjusted input data were reintroduced into the DEA model. This yielded a refined efficiency score that accurately reflects the true technical and managerial proficiency of the tourism sector across the 11 cities.

To transition from a static snapshot to a temporal analysis, the Malmquist index was used to measure efficiency changes between 2013 and 2019. This index was used to identify whether a city's productivity improved or deteriorated over time. A value exceeding one denotes growth, whereas a value below one indicates a decrease in efficiency. The index is broken down into the technological progress index, which represents shifts in the overall industry frontier, and the efficiency change index, which tracks how individual cities are catching up to that frontier.

We replaced traditional statistical data with multisource sensor data to ensure accuracy. Resource inputs were quantified through scenic area dimensions and vegetation indices derived from remote sensing data. Capital inputs were measured using the density of accommodation facilities and transportation node accessibility based on POI data. Human labor inputs were inferred from the spatial distribution of employees using mobile phone signal data. Economic performance was estimated using the nighttime light intensity index, whereas social benefits were measured through a tourist satisfaction index, calculated by analyzing signal data and visitor dwell times.

For data processing, a combination of Python and R. Python libraries, including Pandas and GeoPandas, was used for data cleaning and the construction of interactive heatmaps to visualize the relationship between tourist flows and resource distribution. The R benchmarking package was selected for the three-stage DEA and Malmquist model owing to its robust support for nonradial efficiency measurements. To explore the spatial relationships between neighboring cities, we applied spatial lag and spatial error models, ensuring the statistical significance and avoiding regional spillover effects.

4. Results and Discussion

4.1 Tourism efficiency

4.1.1 Analysis of static efficiency levels

Utilizing the BCC-DEA model, we evaluated the *CTE*, *PTE*, and *SE* of the tourism industry across 11 cities in Jiangxi Province (Table 2).

Table 2
Calculation results of tourism efficiency in Jiangxi Province in 2013 and 2019.

Area	*CTE*		*PTE*		*SE*		Change	
	2013	2019	2013	2019	2013	2019	2013	2019
Nanchang	0.647	0.422	1.000	1.000	0.647	0.422	Decrease	Decrease
Jingdezhen	1.000	1.000	1.000	1.000	1.000	1.000	Same	Same
Pingxiang	1.000	1.000	1.000	1.000	1.000	1.000	Same	Same
Jiujiang	0.605	0.554	1.000	1.000	0.605	0.554	Decrease	Decrease
Xinyu	0.978	1.000	1.000	1.000	0.978	1.000	Increase	Same
Yingtan	0.982	1.000	1.000	1.000	0.982	1.000	Increase	Same
Ganzhou	0.585	0.483	0.616	0.678	0.950	0.713	Decrease	Decrease
Ji'an	0.756	0.619	1.000	0.928	0.756	0.667	Decrease	Decrease
Yichun	0.466	0.599	0.475	0.911	0.981	0.657	Increase	Decrease
Fuzhou	0.604	0.525	0.612	0.543	0.987	0.967	Increase	Decrease
Shangrao	0.914	0.697	1.000	1.000	0.914	0.697	Decrease	Decrease
Average	0.776	0.718	0.882	0.915	0.891	0.789		

The evaluation of static efficiency indicators reveals a general contraction in the industry's performance over the study period. The average *CTE* levels were measured at 0.776 in 2013 and declined to 0.718 by 2019. This result indicates that the tourism industry in Jiangxi operated at approximately 71 to 78% of its potential optimal output. While several cities increased their efficiencies, the overall trend showed a slight reduction in efficiency over time. In 2013, eight cities attained an optimal *PTE* score of 1.000, namely, Nanchang, Jingdezhen, Pingxiang, Jiujiang, Xinyu, Yingtan, Ji'an, and Shangrao. By 2019, however, this number decreased to seven cities.

The number of cities achieving optimal *PTE* consistently exceeded those reaching *CTE* or *SE*. While local management (represented by *PTE*) remained relatively high, the primary bottleneck inhibiting provincial efficiency was observed in the scale of operations (*SE*). For instance, in 2019, seven cities maintained a *PTE* of 1.000, yet only Jingdezhen and Pingxiang achieved a *CTE* of 1.000, reflecting the impact of scale inefficiencies.

The changes from 2013 to 2019 showed a significant transition in the industrial structure of Jiangxi's tourism industry. In contrast, the number of cities experiencing decreasing efficiencies increased from five to seven, whereas the number of cities with an increase decreased from four to zero.

The results indicate that the tourism industry in Jiangxi Province reached a saturation point where increasing inputs no longer yielded proportional output growth. Consequently, a strategy for redefining resource allocation is required.

4.1.2 Trends in tourism efficiency

Using the Malmquist index, we calculated the changes in *CTE*, technological progress, *PTE*, *SE*, and total factor productivity (*TFP*) for the cities in Jiangxi Province from 2013 to 2019 (Table 3). *TFP* serves as an indicator of production efficiency growth, encompassing improvements in technical efficiency, technological advancement, and scale effects.

The results show that the *TFP* index in Jiangxi's tourism industry consistently exceeded 1.1 during the study period, with an average of 1.222. This reflects an average annual productivity growth rate of 22.2%, indicating a steady enhancement in the region's intensive tourism management practices. From 2013 to 2014, *TFP* rose to 1.230, driven primarily by a substantial increase in technological change (*TC* = 1.281), whereas pure technical efficiency (*PTE* = 0.964) and scale efficiency (*SE* = 0.992) contributed moderately. In subsequent years, *TFP* continued to

Table 3
Change indexes in tourism efficiency and their changes in Jiangxi Province from 2013 to 2019.

Year	*PTE* change	*TC* change	*PTE* change	*SE* change	*TFP* change
2013–2014	0.964	1.281	0.968	0.992	1.230
2014–2015	0.991	1.282	0.992	0.999	1.271
2015–2016	0.993	1.281	1.005	0.988	1.273
2016–2017	0.986	1.273	1.079	0.914	1.254
2017–2018	0.985	1.207	1.003	0.983	1.189
2018–2019	0.992	1.126	1.006	0.985	1.117
Average	0.985	1.242	1.009	0.977	1.222

improve, reaching 1.271 in 2014–2015 and 1.273 in 2015–2016, with *TC* remaining stable and *PTE* gradually increasing. In 2016–2017, although *PTE* and *SE* declined slightly (0.986 and 0.914, respectively), *TC* remained strong at 1.273, sustaining *TFP* growth at 1.254. The following years saw a gradual decline in *TC*, with values of 1.207 in 2017–2018 and 1.126 in 2018–2019, leading to a corresponding decrease in *TFP* to 1.189 and 1.117, respectively.

Overall, the average change indices for *PTE* (1.009) and *TC* (1.242) were both greater than 1, indicating consistent improvements. Notably, the average *TFP* index (1.222) exceeded the average *TC* index, suggesting that technological progress was the dominant factor driving productivity gains in Jiangxi's tourism sector. These findings underscore the importance of innovation and technology adoption in enhancing tourism efficiency and support the conclusion that the region's tourism industry has undergone significant structural and operational improvements over the study period. The averages over the seven years show that *PTE* was 0.985, *TC* was 1.242, *SE* was 0.977, and *TFP* was 1.222. These figures suggest that while technical and scale efficiencies fluctuated, technological change consistently drove improvements in *TFP*.

The results indicate that *TC* was the primary contributor to tourism productivity growth in Jiangxi Province, whereas scale efficiency (*SE*) showed more variability and occasional decline. The steady increase in *TFP* reflects a generally positive trend in tourism efficiency over the study period.

4.1.3 Regional characteristics and policy implications

Using the Malmquist index, we assessed the changes in tourism efficiency and its decomposition for 11 cities in Jiangxi Province from 2013 to 2019 (Table 4). The analysis focused on the changes in *PTE*, *TC*, *SE*, and *TFP*, with *TFP* serving as a comprehensive indicator of production efficiency growth driven by improvements in management, innovation, and scale effects.

The average *TFP* across all cities was 1.221, indicating an average annual productivity growth rate of 22.1%. This reflects a consistent enhancement in the region's tourism management

Table 4
Changes in tourism efficiency and its decomposition in cities of Jiangxi Province from 2013 to 2019.

Area	*PTE* change	*TC* change	*PTE* change	*SE* change	*TFP* change
Nanchang	0.931	1.358	1.000	0.931	1.264
Jingdezhen	1.000	1.198	1.000	1.000	1.198
Pingxiang	1.000	1.319	1.000	1.000	1.319
Jiujiang	0.985	1.247	1.000	0.985	1.229
Xinyu	1.004	1.330	1.000	1.004	1.335
Yingtan	1.003	1.190	1.000	1.003	1.194
Ganzhou	0.969	1.183	1.016	0.953	1.146
Ji'an	0.967	1.211	0.988	0.979	1.171
Yichun	1.043	1.205	1.115	0.935	1.257
Fuzhou	0.977	1.217	0.980	0.997	1.189
Shangrao	0.956	1.200	1.000	0.956	1.146
Average	0.985	1.240	1.008	0.976	1.221

and operational performance. Notably, the average *TC* index was 1.240 and the average *PTE* index was 1.008, both exceeding 1. These values confirm that both technological progress and technical efficiency contributed positively to overall productivity, with technological advancement emerging as the dominant driver. The driving forces behind efficiency gains varied by municipality. In Nanchang, Jingdezhen, Pingxiang, Jiujiang, Ji'an, Fuzhou, and Shangrao, improvements were attributed to technological progress. These cities demonstrated strong *TC*, while *PTE* and *SE* remained stable or modest. In contrast, Xinyu, Yingtan, and Yichun exhibited dual-driver growth, with gains in both technical efficiency and technological progress. However, *TC* remained the more influential factor in these cases, underscoring the central role of innovation in shaping tourism productivity.

The period following 2016 coincided with the implementation of regional supply-side structural reforms and the "Three Eliminations, One Reduction, and One Compensation" policy. These initiatives promoted economic transformation and ecological civilization in Jiangxi, contributing to an increase in tourism *TFP*. However, the subsequent decline in technical efficiency suggests that the initial catch-up effect has slowed. As a result, future growth must adopt a dual strategy: enhancing management proficiency to restore technical efficiency while sustaining high levels of technological innovation to advance the industry frontier.

Technical efficiency levels were kept moderate, with several cities achieving optimal performance. Accounting for environmental variables and random disturbances, the average technical efficiencies in 2013 and 2019 were 0.776 and 0.718, respectively, equivalent to 71–78% of the optimal level. In 2013, Jingdezhen and Pingxiang achieved optimal technical efficiency, and by 2019, this status extended to Xinyu and Yingtan as well. The number of cities with optimal technical efficiency consistently exceeded those with optimal comprehensive or scale efficiency. Specifically, eight cities reached optimal technical efficiency in 2013, decreasing to seven in 2019. In 2015 and 2019, the counts were six and three, respectively, still surpassing the number of cities with optimal comprehensive efficiency.

Regarding *SE*, only two cities achieved optimal levels in 2013, increasing to four in 2019. The number of cities exhibiting increasing returns to scale declined from four to zero, whereas those with constant returns to scale rose from two to four. Moreover, the number of cities with decreasing returns to scale increased from five to seven. These trends suggest that the input-output structure of urban tourism resources in Jiangxi Province requires further optimization to support sustained efficiency gains.

4.2 Spatiotemporal characteristics of tourism efficiency

The DEA model revealed clear spatiotemporal differentiation in tourism efficiency across Jiangxi Province. Spatially, the efficiency was higher in the north and lower in the south. The urban agglomeration surrounding Poyang Lake (Nanchang, Jiujiang, and Shangrao) formed a high-efficiency cluster, with values approximately 30% above the provincial average. This advantage was attributed to a well-developed transportation network and the concentration of tourism service facilities. In contrast, the mountainous areas of southern Jiangxi (Ganzhou and Ji'an) were constrained by topographical barriers and limited infrastructure, resulting in efficiency levels below the threshold and exhibiting diminishing returns to scale.

Provincial tourism efficiency fluctuated over time but maintained a significant average annual growth rate. The Malmquist index indicated that technological progress contributed more than 60% to efficiency increases, underscoring its dominant role. This effect was particularly evident during the COVID-19 period, when the rapid adoption of digital services accelerated efficiency improvements. By comparison, scale efficiency revealed structural mismatches between tourism investment and market demand in several cities. Spatial autocorrelation analysis results demonstrated significant positive clustering (at the 1% significance level), suggesting the presence of spillover effects in neighboring regions.

At the local level, Honggutan District in Nanchang consistently sustained high efficiency through the effective alignment of resources, facilities, and tourist flows. Wugong Mountain Scenic Area in Pingxiang achieved notable efficiency gains through transportation upgrades and product innovation. Conversely, Fuzhou experienced a continuous decline in efficiency, primarily due to insufficient environmental capacity and weak management practices.

4.2.1 Spatial distribution of tourism efficiency

The spatial distribution of tourism efficiency in Jiangxi Province for 2013, 2016, and 2019 based on the sensor network data is presented in Fig. 4. The results reveal a clear north–south disparity, with the efficiency generally higher in the northern region and lower in the south. Jingdezhen and Pingxiang emerged as high-efficiency areas, whereas Nanchang, located in central Jiangxi, recorded the lowest efficiency (0.422). In southern Jiangxi, which is largely represented by Ganzhou City, the comprehensive efficiency was 0.483, lower than the provincial average and the levels observed in northern and central Jiangxi. Within the northern region, efficiency was consistently higher in the eastern areas than in the western areas, with Jingdezhen and Yingtan exhibiting anomalously high values above the provincial average.

The average level of tourism resource utilization in Jiangxi Province was high. The spatial distribution of technical efficiency followed a similar pattern, being higher in the north and lower in the south. Cities such as Nanchang, Jingdezhen, Pingxiang, Jiujiang, Xinyu, Yingtan,

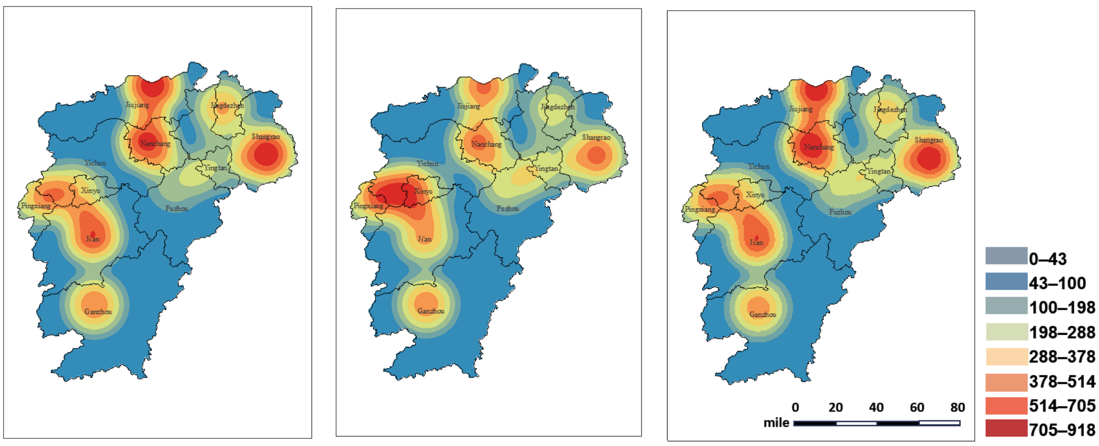

Fig. 4. (Color online) Spatial distribution of tourism efficiency in Jiangxi Province.

and Shangrao demonstrated relatively high technical efficiency. In contrast, southern Jiangxi recorded the efficiency of 0.678, which was below the provincial average. Furthermore, technical efficiency was higher in the central and western regions than in the eastern region, highlighting regional disparities in resource utilization.

SE displayed a different spatial pattern, being higher in the east and lower in the west. Jingdezhen, Pingxiang, Xinyu, and Yingtan achieved relatively high scale efficiency, whereas the provincial average was 0.789—lower than the average technical efficiency of 0.915. This indicates that while the technical efficiency is relatively high, there remains considerable room for improvement in scale efficiency across Jiangxi Province.

The proportion of cities with effective tourism efficiency was relatively low, with high efficiency concentrated in the northern region. The consistent north–south divide underscores the need for targeted interventions. In particular, large-scale investment is required to enhance tourism development in southern Jiangxi, where infrastructural limitations and resource constraints continue to hinder efficiency gains.

4.2.2 Trend surface analysis of tourism efficiency

As shown in Fig. 5, the spatial trends of tourism efficiency in Jiangxi Province in 2013, 2016, and 2019 were analyzed using ArcGIS 10.2. The tourism efficiency in Jiangxi Province was high in the central and northern parts. The tourism efficiency was significantly higher in the northern region than in the southern region, and the efficiency decreased from north to south. The tourism efficiency decreased from Jingdezhen to Nanchang from west to east. In 2016, the tourism efficiency decreased from north to south. The trends of high efficiency in the West and low efficiency in the East were consistent. The lowest efficiency was found in Fuzhou. The tourism efficiency in Yingtan City increased significantly. The slope of the fitted curve was larger in the east–west direction than in the north–south direction. Factors such as the level of economic development, educational resources, population density, and geographical location did not affect tourism efficiency in the areas of high efficiency, which were concentrated in the northern region. The middle region of the province was relatively disadvantaged in terms of tourism development.

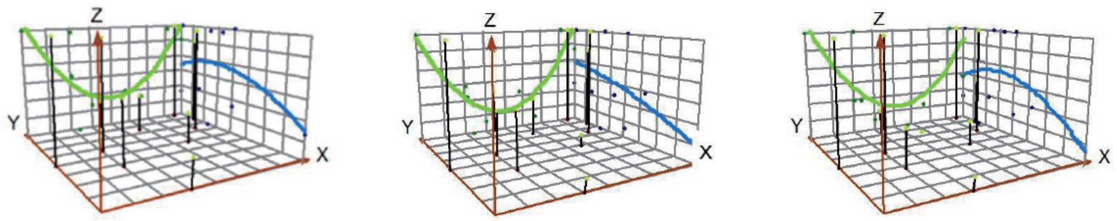

Fig. 5. (Color online) Trend surface analysis of tourism efficiency in Jiangxi Province in 2013, 2016, and 2019 (the *X*- and *Y*-axes represent the east and north directions, respectively, and the *Z*-axis represents the attribute value of tourism efficiency).

4.2.3 Regression analysis

To accurately assess the impact of the variables on the tourism efficiency in Jiangxi Province, a regression model was constructed as

$$y_{it} = \beta_0 + \beta_1 str_{it} + \beta_2 cons_{it} + \beta_3 conv_{it} + \beta_4 agg_{it} + \beta_5 gov_{it} + \beta_6 open_{it} + \beta_7 urb_{it} + \beta_8 mar_{it} + \varepsilon \,. \quad (1)$$

Here, i represents the cross-sectional unit, that is, the cities in Jiangxi Province, t denotes the time series, with the observation period being from 2005 to 2019, β_0 represents the constant, β_1, β_2, ..., β_8 represent regression parameters, ε represents random error, y is the comprehensive technical efficiency of tourism development in Jiangxi Province, *str* represents industrial structure, *cons* represents economic level, *conv* represents the convenience of travel, *agg* represents population density, *gov* represents government intervention, *open* represents the degree of dependence on an external factor, *urb* represents the level of urbanization, and *mar* represents market potential. The regression analysis results obtained using EViews 10 are presented in Tables 5 and 6.

Table 5
Panel unit root test results.

Regression method	Technical efficiency of tourism development	Industrial structure	Economic level	Convenience of travel	Population density	Government intervention	Degree of dependence on external factor	Degree of urbanization	Market potential
LLC	−17.3582 (0.0000)**	−4.85217 (0.0000)**	−17.4314 (0.0000)**	−16.9932 (0.0000)**	−12.0014 (0.0000)**	−4.34888 (0.0000)**	−8.26254 (0.0000)**	−8.44416 (0.0000)**	−1.83070 (0.0336)**
ADF	86.0320 (0.0000)**	74.5774 (0.0000)**	76.2695 (0.0000)**	123.719 (0.0000)**	90.3390 (0.0000)**	94.0103 (0.0000)**	99.2501 (0.0000)**	63.5763 (0.0000)**	162.712 (0.0000)**
PP	111.978 (0.0000)**	191.713 (0.0000)**	96.6414 (0.0000)**	137.437 (0.0000)**	141.578 (0.0000)**	219.378 (0.0000)**	104.599 (0.0000)**	112.078 (0.0000)**	160.596 (0.0000)**

(**: significance at the 5% significance level
The numbers outside the parentheses represent the statistical values of the corresponding panel unit root and cointegration tests, whereas the data inside the parentheses are the p-values of the corresponding statistics.)

Table 6
Regression analysis results of tourism efficiency in Jiangxi Province.

Explanatory variable	Parameters estimated	Coefficient		Standard deviation	T-statistic	p-value
Intercept	β_0	−2.022		0.281	−0.719	0.4731
Industrial structure	β_1	0.280	***	0.079	3.545	0.0005
Economic level	β_2	−0.086	**	0.042	−2.033	0.0439
Industrial structure travel	β_3	−0.017		0.062	−0.267	0.7900
Population density	β_4	0.240	***	0.072	3.358	0.0010
Government intervention	β_5	−0.429	***	0.120	−3.587	0.0005
Degree of external dependence	β_6	2.066		1.394	1.482	0.1406
Degree of urbanization	β_7	0.916	*	0.516	1.774	0.0782
Market potential	β_8	−0.203	***	0.065	−3.110	0.0022
—	Durbin–Watson Statistic = 1.569286, Adjusted R^2 = 0.715531, F-statistic=23.91738					

(*, **, ***: significance levels of 10, 5, and 1%.)

The results of the panel unit root tests presented in Table 5 are essential for establishing the statistical validity of the subsequent regression models. These tests were conducted to ensure that all variables are stationary, thereby preventing the occurrence of spurious regressions that mislead conclusions. To guarantee the robustness of the findings, three distinct regression-based testing methods were applied to the panel data. The LLC test was utilized to evaluate the data under the assumption of a common unit root process. Complementing this, the ADF and PP tests were employed to account for individual unit root processes and to provide resilience against potential autocorrelation within the dataset.

The analysis evaluated ten variables, ranging from efficiency metrics to regional socio-economic indicators. The technical efficiency of tourism development was confirmed as stationary across all three testing methods, with p-values of 0.0000 indicating high statistical significance. Core socio-economic variables, including Industrial structure, Economic level, Degree of urbanization, and Population density, all yielded p-values of 0.0000, confirming their stability for long-term regression analysis. Infrastructure and logistical factors, specifically the Convenience of travel, were also verified as stationary at the 1% significance level. Policy-oriented and market-driven variables, such as Government intervention and the Degree of dependence on external factors, showed a high level of significance across all tests. The variable for Market potential demonstrated stationarity as well, although its significance in the LLC test was recorded at the 5% level with a p-value of 0.0336.

The regression analysis results reveal that industrial structure and population density significantly affected tourism efficiency in Jiangxi Province at the 1% significance level. The coefficient for industrial structure was 0.28, indicating that a one-percentage-point improvement in industrial structure corresponded to a 0.28% increase in comprehensive tourism efficiency. This underscores the critical role of structural optimization and resource allocation in enhancing tourism performance. Population density also showed a significant positive effect, with a coefficient of 0.240 at the 1% significance level. This suggests that higher population density, associated with improved services, transportation, and infrastructure, directly contributes to increased tourism efficiency.

The degree of urbanization demonstrated a weaker but still notable impact, with a coefficient of 0.916 and a p-value of 0.0782, indicating significance at the 10% level. Although the overall degree of urbanization remained low, the rise of mass tourism and increased travel demand among rural residents have partially offset this limitation. However, the presence of abundant tourism resources and well-developed urban service facilities did not translate into substantial efficiency gains, suggesting that urbanization alone is insufficient to drive tourism performance.

Economic level, represented by GDP, showed a negative coefficient of −0.086 at the 5% significance level, indicating an inverse relationship with tourism efficiency. This implies that improvements in tourism efficiency were not directly dependent on overall economic development. Instead, targeted investments in tourism infrastructure, branding, and service quality are essential, particularly in less prominent destinations where cultural identity and market competitiveness must be strengthened. Government intervention was negatively correlated with tourism efficiency, with a coefficient of −0.429. This suggests that excessive regulatory involvement may hinder market-driven dynamics, leading to inefficiencies. Limited access to accurate information may prevent policymakers from fully understanding the implications of their actions, resulting in suboptimal outcomes for the tourism sector.

Market potential also exhibited a negative effect, with a coefficient of −0.203 and a significance level of 0.0022. As transportation networks improve and travel distances shorten, tourists increasingly select destinations on the basis of personal preferences. In Jiangxi, this trend has reduced long-distance travel demand, thereby negatively impacting tourism efficiency.

Neither residents' travel frequency nor external dependence showed statistically significant effects on tourism efficiency. The insignificance of travel frequency suggests that foundational infrastructure—such as transportation and reception facilities—no longer plays a decisive role in mature tourism markets. While external dependence may promote innovation and mitigate resource constraints, it also encourages stay-over tourism and, in cases of high openness, may lead to resource saturation and reduced efficiency.

5. Discussion

The introduction of multisource sensor data has enabled a comprehensive investigation of tourism efficiency by expanding data dimensions, improving spatiotemporal accuracy, and enhancing dynamic monitoring capabilities. Compared with evaluations based on traditional statistical data, multisource data lead to an effective assessment of the operational state of the tourism industry. Satellite remote sensing contributes valuable resource and environmental information often overlooked in conventional methods. The integration of *NDVI* and nighttime light data allows for the assessment of both the intensity of tourism resource development and environmental sustainability. POI data are used to address structural imbalances, such as the coexistence of highly popular scenic spots with insufficient service facilities, by quantifying the spatial configuration of tourism services.

With improved spatiotemporal pattern identification, the spatial distribution of tourism efficiency is captured. Mobile phone signal data enable the hourly monitoring of tourist flows, whereas dynamic process tracking provides insights into microlevel behavioral characteristics. Spatial analysis conducted at a grid resolution of 1 km enables a sensitive detection of efficiency changes and confirms the presence of the distance decay effect. The integration of multitemporal remote sensing and continuous signal data also enhances dynamic monitoring, enabling evaluations of technological progress. Whereas traditional methods tend to overestimate the contribution of scale expansion by approximately 25%, multisource data more precisely reflect the supportive role of online services in sustaining tourism efficiency. The complementarity of diverse data sources facilitates cross-validation. For example, satellite imagery can estimate vegetation coverage in scenic areas, whereas mobile phone signals can predict the number of tourists. A stable tourist count despite resource availability may indicate inefficiencies in tourism management.

Nonetheless, data variability arising from differences in sensor specifications, anomalies during aggregation, and inconsistencies in sampling frequencies across sources can introduce errors into efficiency evaluations. Addressing these limitations is essential to ensure the reliability and robustness of tourism efficiency assessments based on multisource data.

6. Conclusion

We established a framework for evaluating tourism efficiency in Jiangxi Province by integrating multisource sensor data, including satellite, mobile, and POI datasets, with an improved DEA-Malmquist model. The results revealed pronounced spatial disparities. The Poyang Lake region demonstrated the highest efficiency owing to coordinated resources, facilities, and tourist flows, whereas southern Jiangxi lagged owing to topographical constraints and inadequate infrastructure. Quantitative analysis confirmed a transition toward intensive management, with an average annual *TFP* growth rate of 22.2%. Technological innovation was the dominant driver of efficiency gains, whereas declining scale efficiency and the prevalence of decreasing returns to scale highlighted operational scale as a critical bottleneck.

By using high-resolution (1 km grid) spatiotemporal mapping and integrated indicators of resource abundance and flow intensity, the limitations of traditional statistical methods can be overcome. By demonstrating a standardized, reproducible workflow for multisource data fusion and real-time monitoring, the results of this study provide a basis for the development of 5G-enabled smart tourism platforms and ecological early warning systems.

By enhancing digital infrastructure through 5G deployment and provincial-level tourism data centers, tourist flows and resource allocation can be optimized. Cross-regional assistance systems, such as a Poyang Lake–Gannan pairing, lead to the transmission of management expertise from high-efficiency to low-efficiency regions. Improvements in transportation networks are essential to reduce travel costs, whereas ecological monitoring and the regulation of the number of tourists must be incorporated into efficiency evaluations to safeguard environmental capacity. Continuous growth in Jiangxi's tourism industry must rely on refined resource allocation, improved management practices, and sustained technological innovation.

Acknowledgments

This study was supported by the Jiangxi Provincial Social Science Fund Project (Grant No. 23ZK39).

References

1 A. Stoiljković, A. Marcikić Horvat, and S. Tomić: Sustain. **17** (2025) 1493. https://doi.org/10.3390/su17041493
2 R. Lacko, Z. Hajduová, and P. Markovič: Environ. Sci. Pollut. Res. **30** (2023) 31320. https://doi.org/10.1007/s11356-022-24435-1
3 S. Gössling, P. Peeters, J. P. Ceron, G. Dubois, T. Patterson, and R. B. Richardson: Ecol. Econ. **54** (2005) 417. https://doi.org/10.1016/j.ecolecon.2004.10.006
4 S. Katircioglu, N. Saqib, S. Katircioglu, C. C. Kilinc, and H. Gul: Air Qual. Atmos. Health **13** (2020) 391. https://doi.org/10.1007/s11869-020-00803-z
5 R. Salahodjaev, K. Sharipov, N. Rakhmanov, and D. Khabirov: Environ. Dev. Sustain. **24** (2022) 13282. https://doi.org/10.1007/s10668-021-01993-x
6 K. H. Bhuiyan, I. Jahan, N. M. I. Zayed, K. M. A. Islam, S. Suyaiya, O. Tkachenko, and V. Nitsenko: Sustain. **14** (2022) 15043. https://doi.org/10.3390/su142215043
7 H. Werthner, A. Alzua-Sorzabal, L. Cantoni, A. Dickinger, U. Gretzel, D. Jannach, J. Neidhardt, B. Pröll, F. Ricci, and M. Scaglione: Inf. Technol. Tour. **15** (2015) 1. http://doi.org/10.1007/s40558-014-0021-9

8 A. Marcikić Horvat and B. Radovanov: Proc. 2020 5th Int. Thematic Monograph -Modern Management Tools and Economy of Tourism Sector in Present Era (Udekom Balkan, 2020) 15. https://doi.org/10.31410/tmt.2020.15
9 V. Pavković, G. Jević, J. Jević, P. T. Nguyen, and C. Sava: J. Process Manag. New Technol. **9** (2021) 49. https://doi.org/10.5937/jouproman2103049P
10 P. Zine, M. Kulkarni, R. Chawla, and A. Ray: Procedia CIRP **16** (2014) 32. http://doi.org/10.1016/j.procir.2014.01.005
11 M. Fuchs: Econ. Bus. Rev. **4** (2004) 52. https://doi.org/10.18559/ebr.2004.1.503
12 S. Wang, J. Wang, J. Li, and F. Yang: J. Sustain. Tour. **28** (2020) 834. http://doi.org/10.1080/09669582.2019.1707215
13 J. Chen, W. Xiao, X. Li, Y. Zheng, X. Huang, d. Huang, and M. Wang: Sensors **22** (2022) 8139. http://doi.org/10.3390/s22218139
14 A. G. Assaf and A. Josiassen: J. Travel Res. **51** (2012) 388. https://doi.org/10.1177/0047287511426337
15 D. Ivanova and E. Genchev: Strateg. Policy Sci. Educ./Strateg. Na Obraz. I Nauchnata Polit. **32** (2024) 129. https://doi.org/10.53656/str2024-3s-11-com
16 R. D. Banker, A. Charnes, and W. W. Cooper: Manag. Sci. **9** (1984) 1078. https://doi.org/10.1287/mnsc.30.9.1078
17 A. Trstenjak, I. Tomas Žiković, and S. Žiković: Environ. Dev. Sustain. **27** (2023) 1. https://doi.org/10.1007/s10668-023-04284-9
18 F. Bassi and J. A. M. F. Martín: Qual. Quant. **58** (2024) 1. https://doi.org/10.1007/s11135-023-01819-0
19 P. Popova, K. Marinova, and V. Popov: Risks **11** (2023) 180. https://doi.org/10.3390/risks11100180
20 R. Tang, C. Huang, X. Zhao, and Y. Tang: Sensors **22** (2022) 10008. https://doi.org/10.3390/s222410008
21 S. Ozdemir: J. Comput. Commun. **17** (2008) 3941. http://doi.org/10.1016/j.comcom.2008.07.017
22 Z. Zhanga, J. Hea, T. Wena, C. Zhaia, J. Hana, J. Mua, W. Jiab, B. Zhanga, W. Zhang, and X. Choua: J. Nano Energy **33** (2017) 88. http://doi.org/10.1016/j.nanoen.2017.01.031
23 E. Alén, J. L.E. Nicolau, N. Losada, and T. Domínguez: Ann. Tour. Res. **49** (2014) 19. https://doi.org/10.1016/j.annals.2014.08.002
24 T. M. C. Tom Dieck and T. A. Jung: Curr. Issues Tour. **21** (2018) 154. http://doi.org/10.1080/13683500.2015.1070801
25 M. Fuchs, M. Peters, and K. Weiermair: Tour. Recreat. Res. **27** (2002) 21. https://doi.org/10.1080/02508281.2002.11081371.
26 J. Cao, H. Qiu, A. M. Morrison, and Y. Guo: Land **13** (2024) 1075. https://doi.org/10.3390/land13071075
27 Z. Qin and Y. Pan: Electron. **12** (2023) 642. https://doi.org/10.3390/electronics12030642
28 Z. Guo, K. Yu, A. Jolfaei, F. Ding, and N. Zhang: IEEE Trans. Fuzzy Syst. **30** (2022) 4543. http://doi.org/10.1109/TFUZZ.2021.3130311
29 H. Sun, M. Fan, and A. Sharma: IET Collab. Intell. Manuf. **3** (2021) 224. http://doi.org/10.1049/cim2.12019
30 L Huang, R. Nan, L. Chi, Q. Hua, K. Yu, N. Kumar, and M. Guizani: IEEE Trans. Veh. Technol. **71** (2022) 12104. http://doi.org/10.1109/TVT.2022.3189699
31 Z. Zhou, X. Dong, Z. Li, K. Yu, C. Ding, and Y. Yang: IEEE Trans. Intell. Transp. Syst. **23** (2022) 19772. http://doi.org/10.1109/TITS.2022.3147826

About the Authors

Bingfeng Liu received his Ph.D. degree in management from Wuhan University of Technology, China, in 2010. He is currently a professor at the School of Management and Economics of China Jingdezhen Ceramic University. His research interests are in management engineering and knowledge networks. (022538@jcu.edu.cn)

Jianhua Cheng received his B.S. and M.S. degrees in management from Jiangxi University of Finance and Economics, China, in 2011 and 2017, respectively. He earned his Ph.D. degree in economics from the same university in 2023. Since then, he has worked as a lecturer at the School of Management and Economics, Jingdezhen Ceramic University, China. His research focuses on enterprise high-quality development mechanisms, digital innovation strategies, and innovation policy evaluation. (241005@jcu.edu.cn)

Jiaqi Cao received her master's degree in economics from Jingdezhen Ceramic University, Jingdezhen, China, in 2020. She is currently a lecturer in the School of Management and Economics at Jingdezhen Ceramic University. Her research interests include sensor technology and low altitude economy. (232045@jcu.edu.cn)