Spatiotemporal Distribution Pattern and Driving Factors of Tourism Information Flow in Chinese Provinces along the Belt and Road: Postprint

Authors: Yang Li, Fu Yuhui, Wang Jiaojiao

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Abstract

Using spatial field strength, Quadratic Assignment Procedure (QAP), geographic detectors and other methods, this study analyzes the spatial distribution patterns and driving factors of tourism information flow in Chinese provinces along the Belt and Road Initiative. The results show that: (1) The development of total field strength of tourism information flow in Chinese provinces along the Belt and Road Initiative from 2012 to 2022 can be divided into three stages: rapid growth, decelerated growth, and rapid decline. (2) From 2012 to 2022, the agglomeration field strength of tourism information flow in Chinese provinces along the Belt and Road Initiative exhibited a spatial distribution pattern of high agglomeration in the northeast and southeast regions, and relatively low agglomeration in the northwest and southwest regions; the diffusion field strength showed a pattern centered on Yunnan and Tibet, radiating outward from these two regions, forming a spatial distribution pattern that gradually decreases from southwest to northeast; the total field strength displayed a multi-core, multi-level distribution pattern, with Xinjiang, Yunnan, Heilongjiang, and Guangdong playing leading roles in total field strength of tourism information flow in the northwest, southwest, northeast, and southeast regions, respectively. (3) From 2012 to 2019, tourism information flow in Chinese provinces along the Belt and Road Initiative was influenced by three aspects: "push-pull-resistance" factors, with total telecommunications business volume, number of internet broadband users, number of tourism employees, number of accommodation enterprises, number of corporate legal entities, total government investment in tourism, tourism resource endowment, and spatial distance being important factors affecting tourism information flow.

Full Text

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YANG Li[1],[2], FU Yuhui[1],[2], WANG Jiaojiao[1],[2]
[1]School of Tourism, Xinjiang University, Urumqi, Xinjiang, China
[2]Key Laboratory of Sustainable Development of Xinjiang' s Historical and Cultural Tourism, Xinjiang University, Urumqi, Xinjiang, China

Abstract: This study employs spatial field strength, quadratic assignment procedure (QAP) correlation analysis, and Geodetector methods to examine the spatial distribution patterns and driving factors of tourism information flow among Chinese provinces along the Belt and Road. The results reveal three distinct phases in the development of total field strength from 2012 to 2022: high-speed growth, decelerated growth, and rapid decline. The agglomeration field strength exhibits a clear spatial differentiation pattern, with high concentrations in the northeast and southeast regions and lower concentrations in the northwest and southwest. The diffusion field strength demonstrates a radiation pattern centered on Yunnan and Tibet, forming a gradient descending from southwest to northeast. The total field strength displays a multicore, multilevel distribution, with Xinjiang, Yunnan, Heilongjiang, and Guangdong serving as leading provinces in the northwest, southwest, northeast, and southeast regions, respectively. Tourism information flow is significantly influenced by push-pull-resistance dynamics, with key factors including the number of corporate entities, total government investment in tourism, tourism resource endowment, and spatial distance.

Keywords: tourism information flow; provinces along the Belt and Road; driving factors; China

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Introduction

In 2013, President Xi Jinping proposed the major initiatives of jointly building the "Silk Road Economic Belt" and the "21st Century Maritime Silk Road," which have gained widespread support from the international community. At the 2017 Belt and Road Forum for International Cooperation, President Xi emphasized that "state-to-state relations lie in people-to-people bonds, and people-to-people bonds lie in heart-to-heart connections." As a crucial vehicle for fostering such connections, tourism has become a vital link for exchanges and cooperation among Chinese provinces. The rapid development of the internet since the 21st century has propelled online tourism promotion, exerting a strong guiding influence on tourists who increasingly rely on internet searches for destination information to make travel decisions. Tourism information flow refers to the outflow or inflow of tourism information between destinations and

source markets, reflecting destination popularity and tourists' destination selection preferences, thereby exerting a clear guiding effect on actual tourist flows.

Existing research on tourism flows is extensive, yet studies on tourism information flow remain insufficient. In tourism information flow networks, regions serve dual roles as both destinations and source markets. When acting as a source market, tourist flows move outward, prompting continuous information searches about destinations among residents—a process termed spatial agglomeration of tourism information flow. When serving as destinations, tourist flows move inward, with destinations producing information that demonstrates their diffusion capacity to source markets. Smooth regional tourism activities and steady tourism economic development occur when information diffusion and tourist agglomeration are temporally and spatially coordinated.

Previous studies have primarily obtained tourism information flow data through Baidu Index and online tourism platforms, focusing on network structural characteristics at national, provincial, and municipal scales using geographical and social network analysis methods, as well as examining impacts on regional tourism economic linkages. While these studies have identified an east-to-west declining intensity pattern characterized by "one pole, three cores, and multiple driving points" at the provincial level, dynamic comparative analyses of flow directions and volumes across provinces under regional collaborative development remain limited. Research on driving factors of tourism information flow urgently needs supplementation.

This study addresses these gaps by examining Chinese provinces along the Belt and Road, collecting Baidu Index search data to construct a tourism information flow matrix. Using field strength models, we investigate the radiation effects of tourism information flow field strength and analyze driving factors through push-pull theory, QAP correlation analysis, and Geodetector methods. The framework aims to provide insights for accelerating tourism economic recovery and promoting coordinated development of tourism information flow.

[Figure 1: see original paper]

1.1 Study Area

Based on the "Vision and Actions on Jointly Building the Silk Road Economic Belt and 21st Century Maritime Silk Road," this study focuses on 18 provincial-level administrative regions designated as key provinces along the Belt and Road: Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, Hainan, Chongqing, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. These provinces possess abundant world-class and national-level tourism resources, ranging from ancient Eastern cultures to pristine natural wonders in the northwest, attracting considerable attention from academia and the tourism industry. As a pioneering industry in Belt and Road construction, analyzing the spatial patterns of tourism information flow

helps understand each province' s market position and formulate recommendations for regional integrated tourism development.

1.2 Data Acquisition and Processing

Baidu Index serves as a core indicator for measuring large-scale online search behavior and tourism information spatial mobility, reflecting information search volumes for specific keywords across time and regions. This study uses search terms combining "province name + tourism" and "provincial capital name + tourism guide" as inter-provincial search keywords. Given that the 2015 merger and reorganization of China Travel Service significantly impacted tourism information flow, we employed exponential curve forecasting to estimate 2015 data, ensuring maximum accuracy.

Keyword search data were aggregated to construct matrices. Since tourism information flow direction is opposite to tourist flow direction, the information flow matrix was transposed to create an 18$×$18 directed matrix. Considering that China' s internet industry launched its first thematic search engine in 2000 and broadband networks accelerated deployment thereafter, we collected annual average daily inter-provincial tourism information search volumes for 2012–2022 as baseline data. Driving factor indicators were primarily sourced from the *China Statistical Yearbook*, *China Tourism Statistical Yearbook*, and *China Cultural Heritage and Tourism Statistical Yearbook*.

1.3 Methods

1.3.1 Field Strength Model Tourism information flow field strength quantifies the intensity of information forces acting on a region, comprising diffusion field strength (radiating power) and agglomeration field strength (attracting power). The total field strength is calculated as:

$$E = \sum_{j=1}^{n} Q_{ji} \times D_{ij} + \sum_{i=1}^{n} Q_{ij} \times D_{ij}$$

where E represents total tourism information flow intensity; Q_{ji} denotes information flow from node i to node j (specifically, Baidu search index of node j for node i); Q_{ij} denotes information flow from node j to node i (specifically, Baidu search index of node i for node j); and D_{ij} represents spatial distance between nodes i and j, calculated using ArcGIS 10.2 point distance tool.

1.3.2 QAP Correlation Analysis QAP correlation analysis is a non-parametric test method for comparing similarity among elements in one or multiple matrices. Compared with traditional econometric methods, it yields robust and valid correlation coefficients between matrices. This study employs QAP to examine correlations between tourism information flow and various driving factors.

1.3.3 Geodetector Geodetector analyzes driving factors of spatial differentiation in geographical elements, testing both univariate spatial stratified heterogeneity and potential causal relationships between variables. This study uses Geodetector to measure the explanatory power of driving factors on tourism information flow. The detection power is calculated as:

$$q = 1 - \frac{1}{n\sigma^2} \sum_{i=1}^{m} n_i \sigma_i^2$$

where q is the detection power value of factor D; n is the total number of regional samples; σ^2 is the variance of tourism information flow; m is the number of subregions; n_i is the sample size of subregion i; and σ_i^2 is the variance of tourism information flow in subregion i. The q value ranges from [0,1], with higher values indicating stronger influence.

2.1 Spatiotemporal Characteristics of Tourism Information Flow Field Strength

2.1.1 Temporal Characteristics Analysis using the field strength model reveals distinct temporal patterns in tourism information flow field strength from 2012 to 2022 [Figure 2: see original paper]. Overall, total field strength development can be divided into three phases: high-speed growth (2012–2015), decelerated growth (2016–2019), and rapid decline (2020–2022). The agglomeration field strength of Guangdong, Zhejiang, and Shanghai consistently ranked among the top three, with Guangdong maintaining first place from 2012 to 2015. After 2016, Zhejiang surpassed Guangdong and remained the top-ranked province, while Liaoning ranked third. Strong economic foundations and transportation accessibility are crucial factors influencing travel demand.

From 2012 to 2019, Yunnan, Tibet, and Chongqing demonstrated strong tourism information diffusion capacity [Figure 3: see original paper]. Yunnan and Tibet ranked first and second respectively, followed by Hainan. In 2020, Chongqing surpassed Hainan, and provincial rankings stabilized with Yunnan, Tibet, and Chongqing occupying the top three positions. In 2022, significant changes occurred, with the ranking shifting to Tibet, Chongqing, and Yunnan. Yunnan' s tourism industry holds an important position in its economy, boasting abundant and highly recognized tourism resources, thus possessing premier information diffusion capacity. Chongqing' s substantial increase in tourism investment in 2019 and successful bid for the World Federation of Travel Cities Congress significantly enhanced its tourism visibility. Hainan' s average annual tourism revenue growth rate (18.31%) lagged behind the national level (19.98%) during 2012–2019, indicating relatively slower development and constraints from tourism talent and creativity.

The opening of the Lhasa-Nyingchi railway in 2021 and the Nagqu-Lhasa section of the Beijing-Tibet Expressway in 2022 provided a significant boost to Tibet'

s tourism industry. The total field strength of tourism information flow in provinces along the Belt and Road showed a slight decline in 2019 and dropped sharply in 2020 due to COVID-19 impacts.

2.1.2 Spatial Characteristics Using ArcGIS 10.2, average annual tourism information flow agglomeration, diffusion, and total field strengths were classified into five levels, ranging from level five (lowest) to level one (highest) [Figure 4: see original paper].

Agglomeration Field Strength: A pronounced east-west spatial differentiation pattern emerges, with high agglomeration field strength concentrated in the northeast and southeast regions centered on Guangdong, Liaoning, and Zhejiang, while low agglomeration appears in the northwest and southwest regions including Tibet, Qinghai, and Ningxia. The northeast and southeast regions, with superior economic development, transportation location, and internet development, generate strong travel demand and serve as primary agglomeration areas. Low agglomeration areas like Ningxia, Qinghai, and Tibet exhibit contiguous development characteristics, constrained by economic and transportation conditions. Following the COVID-19 outbreak, Yunnan, Chongqing, Heilongjiang, and Shanghai each increased their agglomeration field strength by one level.

Diffusion Field Strength: Centered on Yunnan and Tibet, diffusion field strength radiates outward, forming a gradient descending from southwest to northeast. Yunnan and Tibet serve as primary diffusion centers, with Xinjiang, Chongqing, Shanghai, and Hainan as secondary centers. Shaanxi, Guangxi, Qinghai, Gansu, Heilongjiang, and Zhejiang constitute important supporting nodes, while Jilin and Liaoning remain peripheral. The sacralization of Tibet, tourists' ritual attitudes, spatial distance, and cultural distance collectively position Tibet as a "dream destination" for travelers, securing its significant place in inter-provincial tourism. Post-COVID-19, Xinjiang, Chongqing, and Shaanxi improved their diffusion field strength levels, while Heilongjiang and Shanghai declined.

Total Field Strength: A multicore, multilevel pattern emerges, with Xinjiang, Yunnan, Heilongjiang, and Guangdong leading the northwest, southwest, northeast, and southeast regions respectively. Shanghai, Xinjiang, Zhejiang, Chongqing, Heilongjiang, Tibet, and Liaoning constitute secondary field strength areas. Shanghai excels in both agglomeration and diffusion capacity, representing a typical composite tourism information flow city. Shaanxi and Fujian serve as backbone provinces, while Qinghai and Ningxia exhibit weak agglomeration and radiation capacity, occupying subordinate positions. Post-pandemic, Guangxi and Jilin increased their total field strength levels, while Liaoning and Shanghai decreased.

2.2 Flow Direction Characteristics

Tourism information flow directions show certain similarities across three periods (Table 1). During 2012–2015, primary potential source markets for northwest and southwest regions were southeastern provinces and Shaanxi, while northeast and southeast regions' main source markets remained within their own regions. From 2016–2019, northwest and southwest regions continued to rely on southeastern provinces, with minimal changes in northeast and southeast regions. The COVID-19 outbreak weakened tourism information flow between Shaanxi and other northwestern provinces.

2.3 Driving Factor Analysis

2.3.1 Indicator Selection Push-pull theory, originally developed to study population migration, was first applied to explain tourism motivations and subsequently adapted into push-pull-resistance models for tourism flow research. This study constructs a tourism information flow driving factor indicator system based on this framework.

Push factors primarily include economic development level, population factors, transportation accessibility, and informatization level, measured by: regional GDP, year-end permanent population, regular higher education enrollment, private car ownership, total telecommunications services, and internet broadband users.

Pull factors encompass tourism attractiveness, service level, market activity, and government support, measured by: tourism resource endowment, tourism employment, number of travel agencies, accommodation enterprises, corporate entities, foreign investment, park green space, medical institution beds, and total government tourism investment.

Resistance between source and destination significantly constrains information flow, thus spatial distance is included as a key indicator.

2.3.2 Analysis Results Given severe COVID-19 impacts and limited data availability in 2020–2022, this study analyzes driving factors using 2012–2019 average tourism information flow. First, relative differences in driving factors between provinces were calculated to construct directed difference matrices. QAP correlation analysis then calculated correlation coefficients and significance levels between these difference matrices and the tourism information flow matrix.

Results show that, except for resistance factors, all driving factors exhibit significant positive correlations with tourism information flow. Geodetector analysis reveals significant q-values for all factors, with informatization level as the dominant factor—consistent with the nature of tourism information flow. Tourism service level, government support, economic development level, market activity, tourism attractiveness, and spatial distance serve as secondary dominant factors. Government support influences tourism development investment, pro-

moting flows of people, goods, capital, and information, thereby providing policy guarantees and macroeconomic regulation. Economic development level is essential for leveraging regional advantages and enhancing competitiveness, representing a critical condition for generating tourism demand and information search behavior among source market populations. Market activity indicates regional economic vitality, affecting tourism investment and information technology infrastructure. Tourism resources form the core foundation of destination development, while service level is decisive for achieving high-quality tourism development. Although tourism information flow is primarily online, it can potentially convert to actual travel, making distance a significant barrier. Additionally, tourism information flow development depends on regional population factors, public service levels, and transportation accessibility.

Conclusions and Recommendations

3.1 Conclusions

Using Baidu Index and spatial field strength analysis, this study examined the spatial distribution patterns of tourism information flow among Chinese provinces along the Belt and Road from 2012 to 2022. Based on push-pull theory, QAP correlation analysis, and Geodetector methods, we investigated driving factors, yielding the following conclusions:

1. **Temporal Evolution:** The total field strength of tourism information flow in Belt and Road provinces experienced three phases: high-speed growth (2012–2015), decelerated growth (2016–2019), and rapid decline (2020–2022).
2. **Spatial Patterns:** Agglomeration field strength showed higher concentrations in northeast and southeast regions and lower concentrations in northwest and southwest regions. Diffusion field strength centered on Yunnan and Tibet, radiating outward with a gradient descending from southwest to northeast. Total field strength exhibited a multicore, multilevel pattern, with Xinjiang, Yunnan, Heilongjiang, and Guangdong as leading provinces in their respective regions.
3. **Driving Mechanisms:** Tourism information flow was influenced by push-pull-resistance dynamics from 2012 to 2019. Telecommunications services, internet broadband users, tourism employment, accommodation enterprises, corporate entities, government tourism investment, tourism resource endowment, and spatial distance significantly explained spatial differentiation in tourism information flow.

3.2 Recommendations

For Low Agglomeration-Low Diffusion Regions (Qinghai, Gansu, Ningxia): These regions should "leverage momentum, intelligence, and strength." They should capitalize on Belt and Road cooperation advantages,

fully utilize Gansu' s comprehensive economic and cultural strengths and Ningxia/Qinghai' s ethnic cultural advantages, adopt mature management concepts from established scenic areas, and actively pursue multilateral cooperation with excellent enterprises. Additionally, they should attract tourism talent to optimize regional human resource structures.

For High Agglomeration-Low Diffusion Regions (Heilongjiang, Jilin, Liaoning): Northeast China should fully leverage its ice and snow resources to build the "China Ice and Snow Tourism Destination" brand image. It should strengthen resort and wellness tourism around core resources like Wudalianchi, Changbai Mountain Tianchi, and Qianshan, and accelerate industrial tourism development centered on Harbin, Changchun, and Shenyang.

For Regional Cooperation: Economic development levels and tourism prioritization vary significantly across Belt and Road provinces, severely constraining inter-provincial cooperation. Provinces should strengthen transportation network construction, particularly in northwest China, enhance service levels and reception capacity, and deepen cooperation with outstanding tourism enterprises. Priority cooperation areas should be selected, with northwestern provinces actively establishing linkages with northeastern and southeastern provinces to promote Belt and Road tourism integration.

Analyzing tourism information flow agglomeration and diffusion provides comprehensive insights into travel demand and destination attractiveness. Compared with previous research, this study further examines spatiotemporal changes in tourism information flow before and after COVID-19 and investigates pre-pandemic influencing factors. The pandemic has altered existing tourism flow patterns, and analyzing these changes provides reference points for exploring recovery pathways across regions.

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Note: Figure translations are in progress. See original paper for figures.