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Seasonality of flights in China: spatial heterogeneity and its determinants

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Abstract: Seasonality is an essential issue for service industries but lacks the attention of most transport scholars. To close this gap, this study explored the spatial heterogeneity and determinants of flight seasonality from a supply-side perspective, using the monthly flights of 222 airports in China during 2018 as a sample. The following conclusions were drawn. First, domestic flights in China face seasonality due to the country's vast territory and diverse natural environment. Second, from an airport perspective, seasonality is high in small airports serving remote places and in cities that are tourism destinations. Third, from a route perspective, feeder routes in the air transport network of China face higher seasonality when compared to trunk routes. Finally, airport size and a mix of natural landscape factors shape domestic flight seasonality at the national level. At the local level, most factors (e.g., airport size and temperature) are more evident in the northwest region.

Keywords: Air transport; Seasonality; Flight; Airport; Associating factors

1 Introduction

While the spatial patterns of air transport have widely been investigated, its temporal dimension has remained largely unexplored despite the key implications of seasonality in flows. Yet as flight schedules are commonly characterized by daily temporal imbalances (Barnhart et al., 2003), air services might change across months. There are several reasons for this. First, demand for medium- and long-distance travel varies throughout the year (Xu et al., 2017), resulting in seasonal demand for air travel. Second, the operating seasons of some airports are time inconstant. For example, Burqin Kanasi Airport (KJI) and Xinyuan Nalati Airport (NLT) in Xinjiang, China, close as tourists disappear in winter. Third, some countries use different flight schedules according to the season. For instance, China's air passenger timetable (for regular flights) is divided into the summer and autumn timetable and the winter and spring timetable. However, most studies related to the (spatial) development of air transport are limited to using comprehensive data for one year (Guimera et al., 2005; Wang et al., 2011; Wang et al., 2014), or data for a "typical" period, such as one day, week, or month (Huang & Wang, 2017), which might bias their estimates. Recognizing seasonality can help reduce such bias (e.g., using data from different seasons). Thus, it is essential to explore seasonality.

Seasonality in the airline industry has long been reported by scholars from both air transport and tourism fields. However, most publications have focused on specific case studies, although Dobruszkes et al. (2022) recently proposed a global analysis of passenger air service seasonality at the airport level. Air transport seasonality focusing on the domestic market, route level, or local associating factors is still unknown. As a result, we still lack enough global knowledge about the geography and the determinants of this phenomenon. As a first step toward a more comprehensive understanding of seasonality in air traffic, this paper investigates the temporality of domestic air services in the whole of China. Indeed, China's heterogeneous natural, economic, and institutional landscape provides an excellent case to discuss the spatial heterogeneity and determinants of flight seasonality. On the one hand, China has a vast territory and a complex and diverse natural environment. For example, China is 5,500 kilometers from north to south and 5,200 kilometers from east to west, with Mount Everest 8,849 meters above sea level and Turpan Basin 155 meters below sea level. The same airport has various attractions (comparative advantage) for tourists in different periods (Suau-Sanchez & Voltes-Dorta, 2019); Hainan, located in China's tropical region, becomes the hottest destination for "refuge from the cold" in winter. On the other hand, enormous spatial variations in China's economic and institutional landscape (Zhu et al., 2018) shape heterogeneous sensitivity to season. For instance, airports in tourist cities have significantly reduced flights during the off-season.

Our approach is twofold. In the first step, we computed the well-known Gini index to measure and map flight seasonality from a supply-side perspective. Then we analyzed its determinants through geo-econometric models (i.e., multiscale geographically weighted regression, MGWR). By doing so, we hope to contribute to previous studies in the following aspects. First, considering most existing studies lack discussion on air transport changing across months, we systematically proposed and discussed the seasonality issue for the early time. Second, as stable seat capacity at the airport level might hide seasonality at the route level (Dobruszkes et al., 2022), we tried to map flight seasonality at the route level in this paper. Third, an in-depth understanding of flight seasonality's geographical characteristics allows air transport policy-makers to schedule the air routes rationally from a national perspective. The remaining parts of this paper are as follows. Section 2 provides a brief literature review. Section 3 details data and methods. Section 4 shows the results and Section 5 concludes.

2 Literature Review

Instead of being time-homogeneous, passenger travel flows are often time imbalanced. As Han et al. (2020) reviewed, for an average annual leave of 11 days per year, Chinese people prefer to arrange their travel during seven statutory holidays, including New Year's Day in January, Spring Festival in January or February, Tomb-sweeping Day in April, Labor Day in May, Dragon Boat Festival in May or June, Mid-Autumn Festival in September or October, and National Day in October. Spring Festival travel, known as "spring transport", is a case unique to China when there is a large-scale travel rush around the Spring Festival (Xu et al., 2017). Since the reform and opening, with the relaxation of restrictions on people's movement, more and more people have left their hometowns to work and study. Many migrants return home during the Spring Festival. For tourism, seasonality is a critical topic in academic literature (Cannas, 2012). As Andriotis (2005) reviewed, the primary season for most tourist destinations is summer because of natural phenomena (e.g., climatic conditions determine sporting seasons) and human decision factors (e.g., long school holidays). In winter, ski resorts, typically located in remote mountain areas, become attractive to ski tourists (Suau-Sanchez & Voltes-Dorta, 2019).

From a geographical perspective, research on air transport covers several fields, such as air transport networks, the geography of airports, and the evolution/development of air transport networks/airports (Wandelt & Sun, 2015; Wandelt et al., 2017). On the one hand, air transport has apparent spatial heterogeneity for geopolitical considerations and socioeconomic factors. For example, the worldwide air transportation network is a scale-free small-world network (Guimera et al., 2005), and so is China's air transport network (Wang et al., 2011). From the perspective of airports, connectivity varies among airports: the best-connected airports are concentrated in the United States, Canada, and Germany; in other words, connectivity overall follows a power-law distribution (Arvis & Shepherd, 2016). As Huang & Wang (2017) reviewed, air deregulation and the spatial configuration of airline networks can affect the market share, robustness, and hierarchy of airports, and hub airports are scarce. On the other hand, air transport's spatial patterns are not static. Still, they will evolve, as suggested by pieces of evidence from several countries or regions, such as Northwest Australia (Holsman & Crawford, 1975), Southeast Asia (O'Connor, 1995), the United States (Bonnefoy, 2008), and Central Europe (Kraft & Havlíková, 2016). In China, as the Civil Aviation Administration of China transformed from a regulator and operator to a lesser role of supervision, the evolution of the air transport network of China has followed six stages (Wang et al., 2014). For airports, their ranking fluctuates over time, and their spatial patterns (e.g., the spatial patterns of indirect connections) have heterogeneous evolution trends (Huang & Wang, 2017). Nevertheless, previous geographical research on air transport has not explored the geography of flight seasonality well.

To some extent, studies have illustrated the possible existence of flight seasonality, its spatial heterogeneity, and its determinants. Focusing on seasonality in air transport, Garrigos-Simon et al. (2010) analyzed the seasonality and price behavior of airlines in the Alicante-London market, and showed the relative incidence of variables (e.g., seasonality, the types of firms involved, timetabling) and stressed the relevance of seasonality and competitiveness in the price strategies followed by the different types of companies. Halpern (2011) investigated the seasonal dynamics of passenger demand at airports in Spain using Gini indexes and found that seasonal dynamics are higher at airports that serve holiday areas, related not to airport size but to market (e.g., domestic, international, charter, and scheduled). Similarly, Kraft & Havlíková (2016) analyzed the seasonality of flight offers in ten airports in the Central European region and showed their different spatial and temporal organization. Merkert & Webber (2018) developed a theoretical model of price and seat factor management in airlines, while most cases were opposite to the rational model for more substantial seasonal variation in the average airfare than in the seat factor. Most recently, Dobruszkes et al. (2022) revealed the monthly rhythms of aviation at the airport level from a worldwide perspective, but few studies like this.

Besides these studies, a few scholars have mentioned seasonality in a small part of their research. Chen et al. (2019) found that air traffic was relatively low in winter because the coefficients of seasonal variables were significantly positive, with winter as the reference level, when impacting passenger volume. Suau-Sanchez & Voltes-Dorta (2019) noted the presence of summer seasonality in coastal areas and strong winter seasonality in European regions with a high density of ski resorts. Wu et al. (2020) mentioned that the low-cost carriers network extended to the south in winter and moved to the north in summer; tourism destinations (e.g., Haikou, Sanya and Xiamen) are greatly affected by seasonal variations, while hub cities receive less seasonal impacts. When discussing the relationship between control variables and flight delays, Chen and Lin (2021) found that weather conditions like typhoons could be a significant reason for differences across months.

In conclusion, the above empirical studies have done well in describing seasonality but lack systematic analysis due to case limitations. In this context, this study focused on domestic air services in China, extending the air transportation research perspective to seasonality. While China counts only 222 airports served by domestic air services, this country has become the second-largest domestic air market by various metrics, after the US.[1]

[1] Number of flights, of seats and of seat-kilometers (our own computation based on OAG Schedules 2018).

3 Methods and Materials

Our research methodology framework can be divided into three parts ("existence-spatial patterns-determinants") with the help of domestic monthly flight data in China. First, we provided a global temporal view of flights at the national scale, showing the existence of flight seasonality in China. Traditional statistical methods supported this part. Second, the geography of domestic air traffic seasonality was mapped at the level of both airports and airport-pairs (i.e., routes). Analysis starting from the airport level provides us with basic information about the geography of flight seasonality. Research disaggregating to the route level shows more detailed (or extra) findings. This part was supported by the well-known Gini index, as well as other traditional statistical methods. Third, after descriptive analyses, multiple regression models were set up to investigate the determinants of seasonality. Indeed, we combined the conventional regression method (i.e., OLS) with the geographical regression method (i.e., MGWR) to explore the global effects and the spatially varying effects (i.e., spatial heterogeneity) of variables. The details of the main methods (including the reasons for using them) are described below.

3.1 Measures of flight seasonality

We adopted the Gini index at the airport level to quantitatively measure temporal concentration as a primary index. As data at the airport level is aggregated from data at the route level, we further disaggregate the Gini index (from airport level to route level) to explore extra information. In addition to the Gini index, we combined original monthly data at both airport and route levels (e.g., comparing the peak and off-peak data) to provide a more qualitative discussion.

The method of calculating the Gini index in this paper is shown as Eq. (2):

$$Gini = \left|1 - \sum_{i=1}^{N}(\sigma X_i - \sigma X_{i-1})(\sigma Y_i + \sigma Y_{i-1})\right| \qquad (2)$$

where σX is the cumulative share of months, σY is the cumulative share of the number of domestic flights, and N is the number of months. We used monthly data calculations following the time interval to measure the seasonality suggested by Halpern (2011). A coefficient of 0 represents the perfect equality between months, while a larger coefficient (i.e., tends to be 1) corresponds to more inequality between months. According to Suau-Sanchez & Burghouwt (2011), all concentration and dispersion measures are highly and significantly correlated to each other. Using the Gini index makes comparisons with previous (or future) publications possible, so we adopted the Gini index in our research.

3.2 Global model and variable selection

To explore the determinants of flight seasonality, we set the following model using 222 airports as our observations:

$$Gini = \beta_0 + \beta_1 AIRPORT\ \ SIZE + \beta_2 TOURISM + \beta_3 HSR + \beta_4 TEMPERATURE + \beta_5 PRECIPITATION + \beta_6 PLATEAU + \varepsilon \qquad (1)$$

where *Gini* is the dependent variable—flight seasonality measured by the Gini index at each sample airport in China. We considered a set of independent variables to explore the determinants of flight seasonality. The airport size is expected to positively affect seasonality since "variations in demand between each month are likely to become less acute as traffic grows (De Neufville et al., 2013; Halpern, 2011)", although Halpern (2011) found no significant relationship for Spanish airports. We used the volume of annual passenger movements for airports[2] (*AIRPORT SIZE*) to measure airport size. As we mentioned in the literature review, the tourism industry faces seasonality (Andriotis, 2005). Compared to airports serving heterogeneous metropolitan areas, airports serving holiday areas naturally attract a high proportion of leisure travelers (Halpern, 2011; Wu et al., 2020). Thus, we applied the proportion of domestic tourism revenue and regional GDP (*TOURISM*) to represent the region's dependence on the tourism industry. HSR development brought competition in spatial service hinterlands between HSR and air transport (Wang et al., 2015). Newly launched HSR stations or changed HSR links might induce flight seasonality. In other words, HSR will swing airlines between closing and (re-)opening routes. We used the number of cities linked through HSR networks (*HSR*) to indicate the impact of HSR.

In addition to the economic and institutional landscape, the natural landscape might also result in seasonality. We applied the following three indicators, the absolute value of the difference between the annual average temperature and the so-called universal indoor comfort temperature of 22.5°C (*TEMPERATURE*), annual average precipitation (*PRECIPITATION*), and high elevation airport (i.e., an airport whose elevation is greater than 5,000 feet) defined by the Flight Standard Division, Civil Aviation Administration of China (*PLATEAU*), to measure outdoor human comfortable climate (Stathopoulos et al., 2004). Seasonality can depend on the weather (Merkert & Webber, 2018) because extreme weather can hinder tourism demand and airport operations. For example, cities in Northern China can face severe cold weather in winter, while cities in Southern China can face extremely hot weather in summer. From the coast inland, as precipitation increases, eastern China can face super-rainy days more frequently than western China. The thin air, complicated weather, and complicated terrain of the plateau can challenge aircraft taking off and landing in winter, thus leading to the airport's seasonality. Descriptive statistics are shown in Table 1, and the VIF values of all independent variables are low (namely, less than 1.89); thus, there is no apparent multicollinearity between the independent variables.

[2] Due to data limitations, passengers in 2018 (international + domestic) rather than domestic passengers were used to measure airport size. Source: Airports Council International (ACI, https://aci.aero/).

Table 1 Descriptive statistics

Variable	Unit	Mean	Standard deviation	Min	Max	VIF
Gini	/	0.08	0.09	0.01	0.71	/
AIRPORT SIZE	Number	5,701,693	1.32×10^7	8,349	1.01×10^8	1.41
TOURISM	%	27.61	29.17	0.89	224.73	1.13
HSR	Number	17.88	28.78	0	145	1.55
TEMPERATURE	℃	11.46	6.38	0	27.1	2.89
PRECIPITATION	Millimeters	821.36	512.22	17.1	1951.2	2.72
PLATEAU	Dummy	0.16	0.37	0	1	1.18

3.3 Multiscale geographically weighted regression (MGWR)

Geographically weighted regression (GWR), proposed by Fotheringham et al. (1996), is a commonly used econometric local regression model to account for spatially varying relationships between dependent and independent variables. To deal with the issue of spatial non-stationarity, this paper used the newest version of GWR, the so-called MGWR, to process our regression (Fotheringham et al., 1996; Yu et al., 2020). Considering multiple bandwidths simultaneously, the MGWR model typically has a better estimation effect than the traditional GWR model (e.g., Gu et al., 2022; Lao et al., 2021). The specification of MGWR is given as follows:

$$y_i = \sum_{j=1}^{k} \beta_{bwj}(u_i, v_i)x_{ij} + \varepsilon_i \qquad (3)$$

where observation unit $i \in \{1,2,\ldots,n\}$; y_i denotes the dependent variable; x_{ij} denotes the jth independent variable, $j \in \{1,2,\ldots,k\}$; bwj represents the bandwidth used when estimating the jth parameter; β_{bwj} represents the estimator of the jth parameter at position (u_i, v_i); ε_i represents the error term. Each estimated parameter β_{bwj} in MGWR is obtained based on local regression, different from the requirement of all parameter bandwidths in the GWR model. MGWR can also be expressed in the form of the Generalized Additive Model (GAM):

$$y = \sum_{j=1}^{k} f_i + \varepsilon \qquad (4)$$

where f_j represents the smooth function of the jth independent variable, and the bandwidth can vary with the jth independent variable. The inferential estimation process of MGWR has been proved by Fotheringham et al. (2017) and Yu et al. (2020).

The bi-square kernel is employed to calculate the optimal bandwidth, using the GWR model as the initialization model. The convergence criterion for the MGWR back-fitting algorithm is the residual sum of squares (RSS):

$$SOC_{RSS} = \left|\frac{RSS_{new} - RSS_{old}}{RRS_{new}}\right| \qquad (5)$$

where RSS_{old} represents the residual sum of squares of the previous step; RSS_{new} represents the residual sum of squares of this step.

The MGWR bandwidth selection criterion is based on the modified Akaike Information Criterion (AICc). The bandwidth of the MGWR model is the number of sample points participating in the regression, and this value affects the regression coefficients. This study defines the bandwidth unit as the number of airports, indicating the extent of influence of specific variables.

3.4 Data processing

Chinese mainland's domestic flight supply-side data from January 1, 2018, to December 31, 2018, was obtained from OAG (https://www.oag.com/), including 84,738 records. We dropped the routes that were newly opened, suspended, or out of service in 2018, which might bias our estimation, according to China's *Statistical Bulletin on the Development of Civil Aviation Industry in 2018*. We ended up with 222 airport samples, covering 3,000 routes and 4,164,101 flights in China. Other data for our research came from the following sources. Tourism resource data was from the official website of the Ministry of Culture and Tourism of the People's Republic of China (https://www.mct.gov.cn/), and tourism revenue data came from the national economic and social development statistical bulletin of each local government. High-speed rail (HSR) data was obtained from the Ministry of Railways' train ticket booking (https://www.12306.cn/index/). Climate data was from the Resource and Environment Science and Data Center (https://www.resdc.cn/Default.aspx). Location data (e.g., latitude, longitude, and elevation) was derived from Baidu Maps (https://map.baidu.com/).

4 Results

4.1 Flight seasonality in China

Fig. 1 shows the distribution of domestic flights by month in China between January 1, 2018, and December 31, 2018. The number of flights changed across months, with substantial temporal heterogeneity. Flights were at their lowest during the first half of 2018, as most long holidays (i.e., summer holiday and National Day Golden Week) in China are concentrated in the second half of the year. July and August were the peak months. Flights in the highest month of 2018, August, were 1.15 times (48,661 flights) higher than in the lowest month, February, because students' summer vacation is usually in July and August. Several activities (e.g., parent-child travel, leaving school, returning to school) induced colossal travel demand during this period. Like the European cases, tourist destinations and travel agencies used last-minute holidays (e.g., August in China) to promote cheaper travel (Kraft & Havlíková, 2016). October was another small peak for National Day Golden Week (a 7-day holiday). However, due to the comparatively short holiday period, air travel demand was not as prominent as in July and August.

As China has a vast territory and a complex and diverse natural environment, peak months for Chinese airports can be different (e.g., flights of airports located in the tropics are typically at their highest during the winter months). Due to the large flight base (Wandelt et al., 2019) and different peak months for Chinese airports, the aggregate growth rate (of flights/passenger movements) from the bottom to the peak is fairly low when compared with Spain (Halpern, 2011)[3]. However, flight seasonality in China might significantly vary by airport.

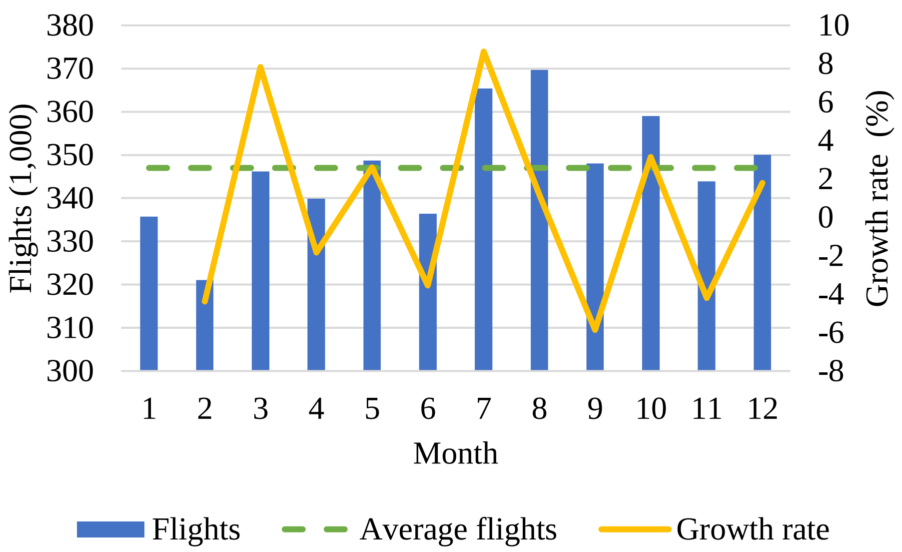


Fig.1. Temporal distribution of domestic flights in China, 2018

[3] Demand (for Spanish airports) in August was 1.8 times higher than in the low month of December in 2008.

4.2 Geography of domestic flight seasonality

4.2.1 Airport perspective

We used the Gini indexes to measure flight seasonality and further explored its spatial distribution. Fig. 2 shows the overall spatial distribution of domestic flight seasonality in China in 2018. Among 222 airports, the Gini index of 0.08 for flights in 2018 is higher than a worldwide indicative minimal threshold for uneven temporal distributions of seats suggested by Dobruszkes et al. (2022) but as reasonably low as in Spain (Halpern, 2011)[4]. However, the Gini index varies by the airport (see Fig. 2). In the work of Dobruszkes et al. (2022), 0.078 is suggested as the threshold to classify no-peak airports and peak airports. Following this threshold, 30.63% of airports in China (accounting for 3.12% of passengers) experience a significant degree of seasonality, similar to the global experience. However, as there is no recognized threshold for judging Gini values to the best of our knowledge, we further made a cross-section comparison of airports. The Gini index of 68 airports has an above-average Gini index. The top ten airports by Gini index (all greater than 0.2) are Burqin Kanasi Airport (KJI, Xinjiang), Kali Huangping Airport (KJH, Guizhou), Qionghai Boao Airport (BAR, Hainan), Ruad Zhongqi Airport (WZQ, Inner Mongolia), Zhangjiakou Ningyuan Airport (ZQZ, Hebei), Aba Hongyuan Airport (AHJ, Sichuan), Daocheng Yading Airport (DCY, Sichuan), Ganzi Kangding Airport (KGT, Sichuan), Manzhouli Xijiao International Airport (NZH, Inner Mongolia), and Hulunbuir Dongshan International Airport (HLD, Inner Mongolia). These airports are almost all small airports[5], as shown in Fig. 2. In addition, there are some links between seasonality and the nature of the area served. Most of the airports facing seasonality are located in areas with extreme terrain (e.g., Junggar Basin, Yunnan-Guizhou Plateau, Qinghai-Tibet Plateau) or extreme climate and service tourist destinations. For example, Burqin, where KJI is, located on the northern edge of the Junggar Basin, has complex and diverse landforms and is hot and dry in summer and severely cold in winter. It was also an important destination listed in the top 100 counties and cities in China for summer leisure in 2020, known as a “fairy tale border town”. In short, seasonality is high in small airports serving remote places and in cities that are tourism destinations.

[4] The Gini index of for Chinese airports using supply-side data in 2018 is 0.08, which is very close to the Gini index of 0.106 for Spanish airports using demand-side data in 2008.

[5] These airport codes are also shown in Fig. 2.

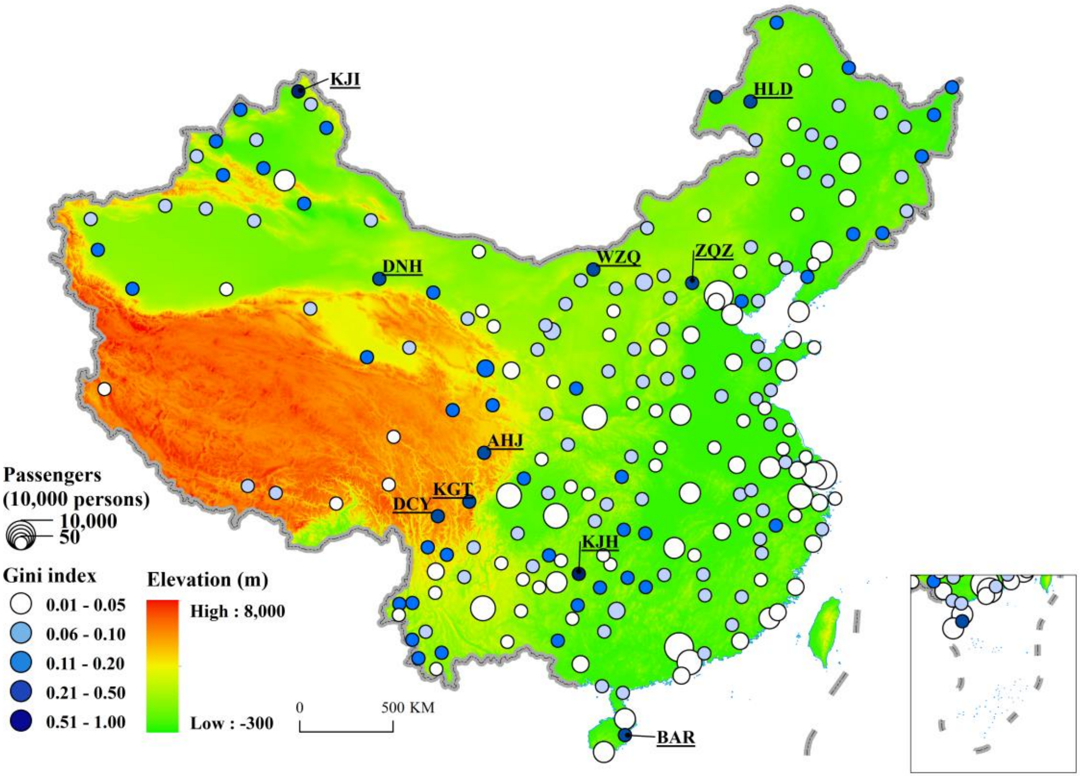


Fig. 2. Spatial distribution of domestic flight seasonality at airports

Note: Borders in the figure (the same hereinafter) refer to the Ministry of Natural Resources of the People's Republic of China (http://www.gov.cn/guoqing/2005-09/13/content_5043917.htm).

To explore the difference between airport flight volume in the lowest month (February) and the highest month (August), also namely absolute seasonality (see Walsh & Lawler, 1981), we calculated the top 10 airports in China based on flight changes (shown in Table 2). Absolute seasonality shows a different picture compared to relative seasonality. That is, airports with high flight change rankings demonstrate low Gini rankings (i.e., below 0.078). It might contribute to the mega airports still serving a high absolute number of leisure travellers, although the large airports handle many business trips (compared to themselves). In this case, we can further explore the spatial patterns (or other features) of domestic flight seasonality in China instead of focusing on airports with low passenger volumes. From a geographical perspective, the rankings (or flights) of airports in northern China rose, and airport rankings (or flights) in southern China declined from winter to summer. For instance, among the Top 10 airports based on flight changes, only Shenzhen Bao'an International Airport (SZX) is in South China. A typical case is Haikou Meilan International Airport (HAK), whose flights dropped from 14,115 in February to 12,834 in August, in the context of 81.08% of airports increase in this period. Besides being a popular tourist destination in the summer, as mentioned above, Haikou has gradually become one of the most popular cities for the elderly to spend the winter. Some older adults even buy real estate in Haikou to live in winter and rent out or leave it vacant in other seasons. To some extent, experience in Haikou is consistent with seasonality in Florida real estate; that is, sales in existing homes tend to spike in warmer months and reach their nadir in colder months.

In another typical case, flights at Urumchi Diwopu International Airport (URC) rose from 12,731 to 16,190, and the reasons might be as follows. First, URC is prone to exceptional winter weather, such as heavy fog and snow. As the visibility is lower than the take-off and landing standards, airport flight volume will be affected. Second, as a regional hub in Xinjiang, most flights to Xinjiang need to transfer from URC. Thus, its flights can be influenced by other seasonal airports in Xinjiang, such as KJI mentioned above. Similar to URC, Dalian Zhoushuizi International Airport (DLC) rose from 9,572 to 11,631. Five important kinds of weather in winter, including solid northerly winds, various snowfalls, low visibility, low clouds, and rain, challenge the flights at DLC. Also, hot tourism in summer could affect flight volume at DLC. According to *Dalian Statistical Yearbook 2019*, the number of inbound overnight tourists in August is 23.78% more than in February, contributing to seasonal differences in domestic flights at DLC.

Table 2 Top 10 airports based on flight changes (Aug vs Feb)

Airport	Code	Flight changes	Ranking of the flight changes	Change ratio	Gini index (2018)	Ranking Gini (2018)
Beijing Capital	PEK	+4,213	1	+11.92%	0.018	213
Xi'an Xianyang	XIY	+4,164	2	+17.72%	0.024	198
Shenzhen Bao'an	SZX	+3,950	3	+18.22%	0.020	210
Xining Caojiapu	XNN	+3,635	4	+120.60%	0.150	23
Shanghai Hongqiao	SHA	+3,555	5	+19.45%	0.022	203
Hohhot Baita	HET	+3,467	6	+49.10%	0.074	77
Urumqi Diwopu	URC	+3,459	7	+27.17%	0.043	152
Dalian Zhoushuizi	DLC	+3,327	8	+34.76%	0.045	143
Nanjing Lukou	NKG	+3,300	9	+23.55%	0.028	187
Shanghai Pudong	PVG	+3,105	10	+15.92%	0.020	207
Haikou Meilan	HAK	-1,281	29	-9.08%	0.044	144

Note: The ranking is based on the number of domestic flights.

4.2.2 Route perspective

Fig. 3 shows the spatial distribution of routes of different Gini levels. Among 3,000 routes, the Gini index for flights in 2018 is 0.26, higher than this indicator from an airport perspective (0.08). Thus, flight seasonality seems higher at the route level. To analyze spatial distributions of routes with different Gini levels, we classified 3000 routes into five groups using the natural breaks method and Jenks' optimization (Jenks, 1967), according to the Gini indexes. "This method calculates the grouping of data values based on data distribution, seeking to reduce variance within groups and maximize variance between groups" (Suau-Sanchez & Burghouwt, 2011, p. 246). Based on the classification results and those at the airport level, we applied the same threshold value at both the airport level (Fig.2) and route level (Fig.3) to map seasonality. In Fig. 3, routes of different Gini levels have different spatial distributions. The spatial distribution of low seasonality routes with a low Gini level (0.01-0.05) forms a national scale "diamond structure" with the Yangtze River Delta, Pearl River Delta, Beijing-Tianjin-Hebei region, and Chengdu-Chongqing region at the core (Fig.3e). In other words, trunk lines in the air transport network of China (ATNC) face low seasonality. Routes become unstructured as their Gini levels increase. High(er) Gini-level routes have a comparative advantage in peripheral areas, and they are usually feeder routes (or lines) in the ATNC. This might be attributed to the fact that low Gini-level routes tend to reflect work patterns (the large proportion of business travelers using the services), compared to high Gini-level routes that tend to service many leisure travelers. In general, seasonality in China is lower for larger airports (e.g., aviation hubs) or routes connected to larger airports (e.g., trunk lines)—the same as airport-level analysis.

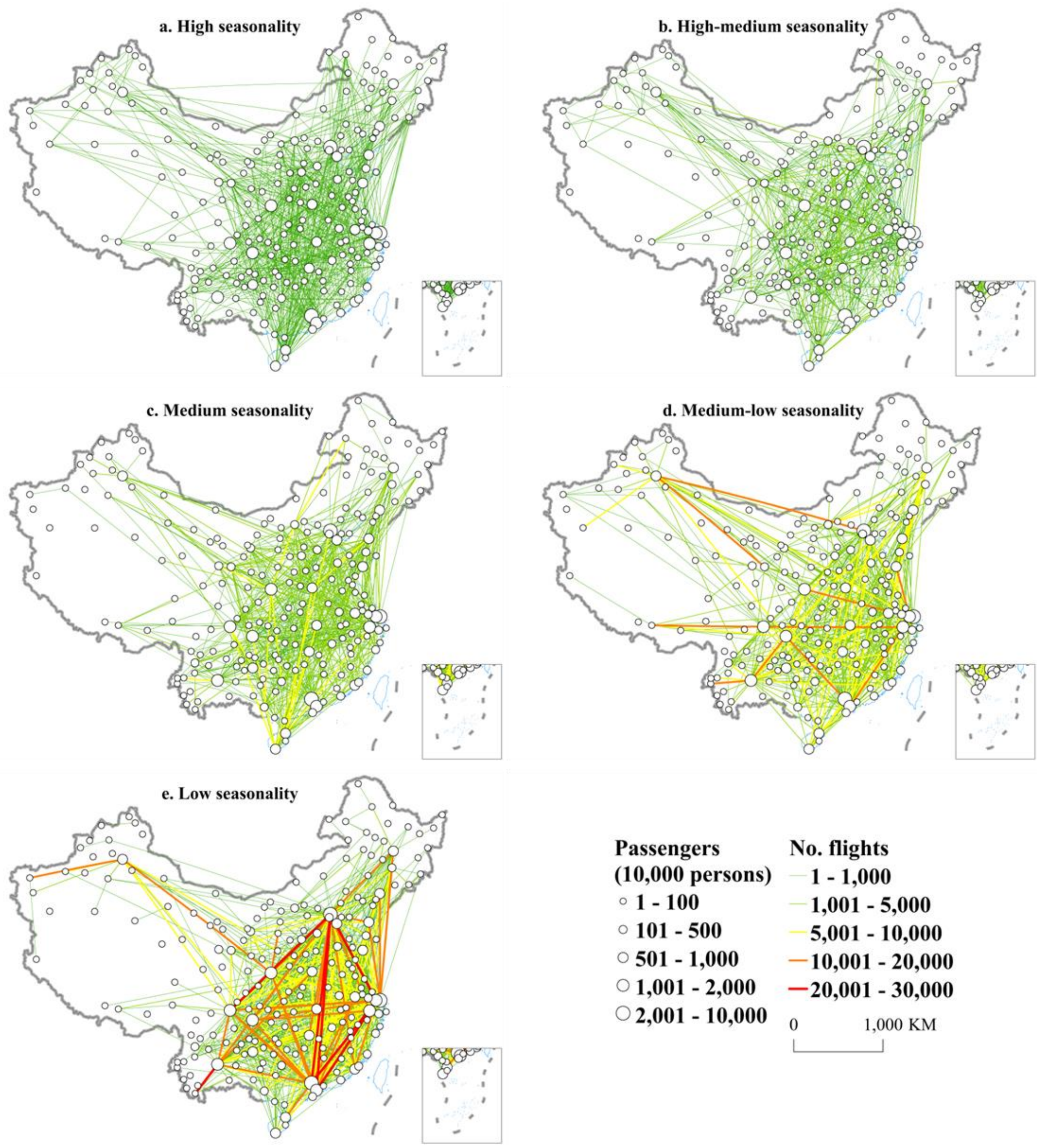
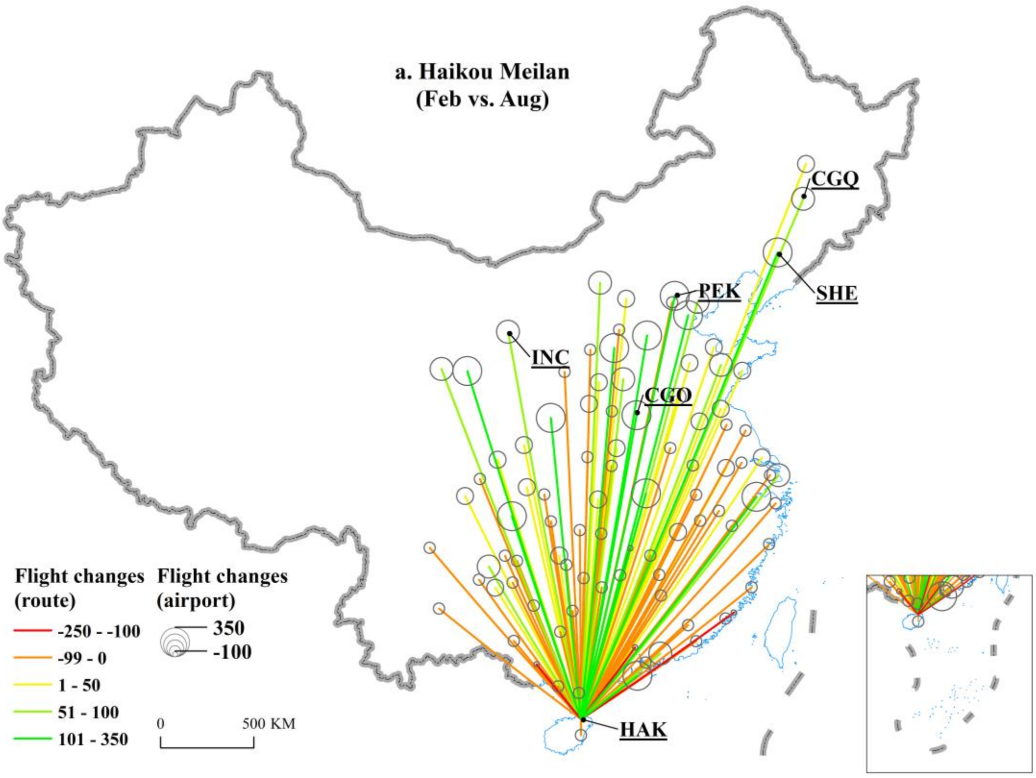


Fig. 3. Domestic routes at different levels of flight seasonality in China

(Note: a. high Gini level: 0.51-1.00; b. high-medium Gini level: 0.21-0.50; c. medium Gini level: 0.11-0.20; d. medium-low Gini level: 0.06-0.10; e. low Gini level: 0.01-0.05)

To further explore some details about absolute seasonality at the route level, we consider seasonal changes in the accessibility of two typical airports with the most changes in ranking from February to August (Table 2), including Haikou Meilan (HAK) and Urumchi Diwopu (URC). The two airports peak at different times; HAK peaks in

February and URC peaks in August. Fig. 4 shows the seasonal changes in accessible airports from typical airports. In general, Fig. 4 offers a stable network of accessible destinations in the major airports, such as Beijing Capital (PEK) and Zhengzhou Xinzheng (CGO), affected by the size and importance of airports and their target customers (Kraft & Havlíková, 2016). However, seasonal changes can be found in some routes. For HAK, its range is more extensive in February than in August, covering more remote airports. Several flights in HAK encountered seasonality, with many flights in February and no flights in August, such as flights to Shenyang Taoxian International Airport (SHE, 111 flights in February), Changchun Longjia International Airport (CGQ), and Yinchuan Hedong International Airport (INC). It seems that seasonality in HAK was affected by northern China, especially northeastern China. For URC, the number of flights to several airports (e.g., Burqin Kanasi Airport, KJI, 217 flights in August; Dunhuang Mogao International Airport, DNH; Yichang Sanxia Airport, YIH) encountered a considerable increase in August from no flights in February. There was a virtual regional hub-and-spoke network around Urumchi in China (Wang et al., 2014). Thus, as a secondary hub, seasonality in URC is also more affected by other seasonal airports nearby than HAK.



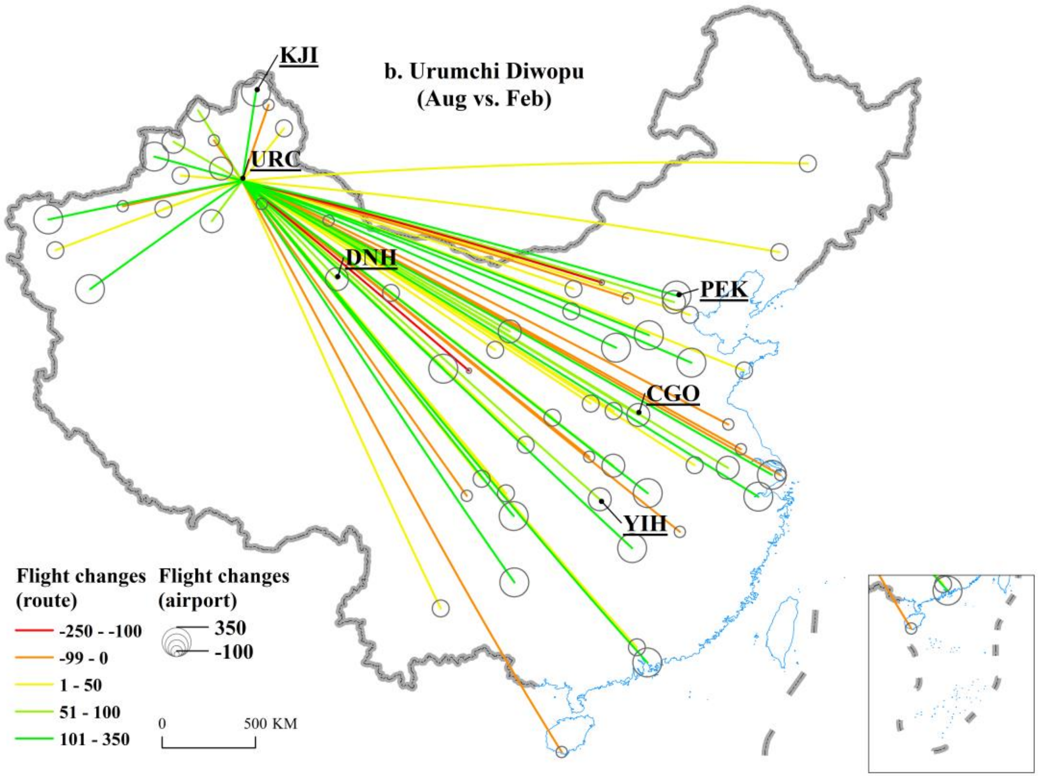


Fig. 4. Seasonal changes in air routes from typical airports (a. Haikou Meilan; b. Urumchi Diwopu)

4.3 Determinants of flight seasonality

4.3.1 Model selection and global results

We first applied the ordinary least squares (OLS) model to explore the determinants of domestic flight seasonality on a global scale. We applied variable standardization and robust standard error coefficient estimations for regression to avoid heteroscedasticity. Also, we constructed GWR and MGWR models to identify spatially varying determinants. Table 3 shows the results of OLS, GWR and MGWR models using 222 sample airports as our observations. From Table 3, we know that the MGWR model can be the most suitable since its indicators, such as R^2, AIC_C and Log-likelihood value, have a better performance than OLS and GWR models. As a result, we select the MGWR model as our primary model.

In general, airport attributes and the natural landscape mainly affected flight seasonality. The regression results indicate that the airport size is one of the strongest estimators of flight seasonality since the coefficients of *AIRPORT SIZE* are negative and significant at 95% confidence in both models (1), (2) and (3). Small airports are more heterogeneous than large airports, some of which orient the peak tourist season (Kraft & Havlíková, 2016). However, it is different from the empirical evidence for the 34 airports in Spain, which had no relationship between seasonality and airport size with a correlation analysis (Halpern, 2011). However, the coefficients of *TOURISM* and *HSR* are insignificant in models (1), (2) and (3).

Table 3 Estimation results of the OLS, GWR and MGWR models

Gini	Model (1): OLS		Model (2): GWR		Model (3): MGWR	
	Coef.	$\lvert t \rvert$	Coef.	$\lvert \bar{t} \rvert$	Coef.	$\lvert \bar{t} \rvert$
AIRPORT SIZE	-0.17***	3.63	-0.002**	2.02	-0.15**	1.96
TOURISM	0.09	1.17	-0.16	1.27	0.16	0.99
HSR	-0.05	0.84	0.09	0.32	-0.03	0.39
TEMPERATURE	0.37***	2.87	-0.02***	3.54	0.59***	2.85
PRECIPITATION	0.19*	1.65	0.50**	2.33	0.33**	2.25
PLATEAU	-0.06	0.83	0.29	0.96	-0.13	1.52
Constant	3.90×10^{-8}	0.01	-0.06	1.19	-0.01	0.35
Number of obs.	222		222		222	
R^2	0.14		0.25		0.34	
AICc	614.34		593.41		586.19	
Log-likelihood	-298.83		-283.83		-269.04	

Note: ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

For the natural landscape, the difference between the annual average temperature and the so-called universal indoor comfort temperature positively affects flight seasonality since the coefficients of *TEMPERATURE* are positive and significant at 99% confidence in both models (1) (2) and (3). Places with comfortable temperature mains facing less super-cold/super-hot days. On the one hand, local tourism resources can be attractive with less seasonality, attracting inflowing air passengers in all seasons. For instance, the average temperature of the Kanas Scenic Area in Xinjiang (Northwest China), where the airport faced the most severe seasonality in China (KJI, location refers to Fig. 2) served, is -0.2℃. The minimum temperature here is -37°C, and the average monthly temperature is below 0°C for six months of the year, with winter lasting seven months. On the other hand, people living in extreme weather can be more willing to spend their time in places with comfortable temperatures. Further, combined with the average temperature distribution in China, airports in the north and south of China faced more seasonality than the airports in the middle. China spans a wide range of latitudes (e.g., cold temperate, middle temperate, warm temperate, subtropical, and tropical temperature zones) from north to south. The amount of solar radiation heat received varies from zone to zone. Thus, airports of middle temperate, warm temperate, and subtropical zones might face less apparent seasonality because of the more temperate and less variable climate (Merkert & Webber, 2018). The coefficients of another indicator, *PRECIPITATION*, are positive and significant at 90% confidence in the model (1) and 95% confidence in models (2) and (3). It shows that precipitation distribution can also affect flight seasonality. For example, coastal areas can experience severe weather phenomena in a specific season, such as typhoons and floods in summer and autumn, and airports serving there are also facing seasonality. A county-level city, Qionghai in Hainan (South China), where another identified airport faced severe seasonality (BAR, location refers to Fig. 2) served, suffered 24 typhoons from 1949 to 2021, accounting for 3.3% of the total in China. Indeed, 24 typhoons include one super typhoon (code "SuperTY" in China), while the Chinese mainland has only suffered five typhoons at the most substantial level (i.e., "SuperTY"). Fig. 5 shows the overview of climate elements in China.

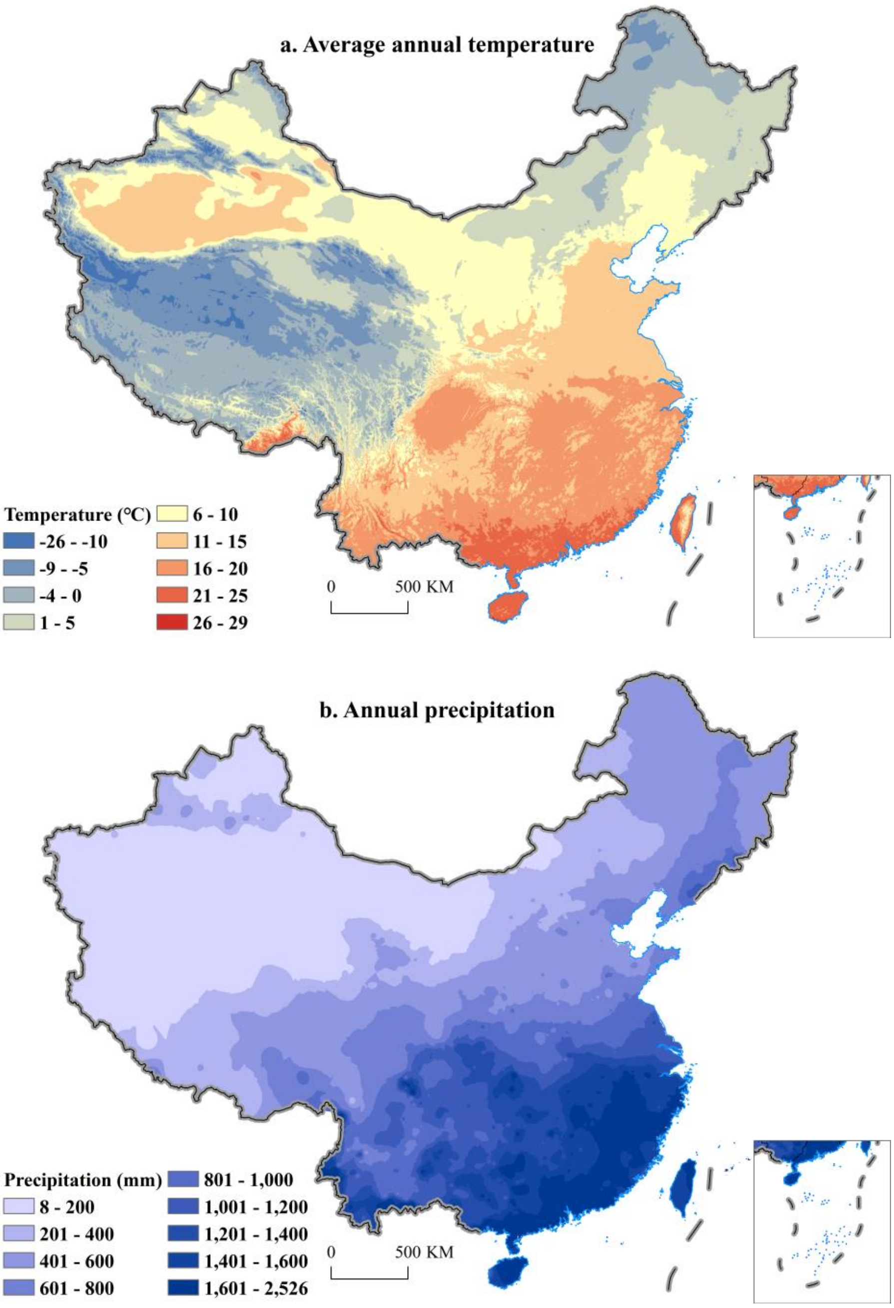


Fig. 5. Spatial patterns of climate elements in China

4.3.2 Spatially varying determinants

We further mapped the MGWR estimation results to explore the spatially heterogeneous characteristics of determinants of flight seasonality. Three significant variables at 95% confidence are considered in the MGWR map, including *AIRPORT SIZE*, *TEMPERATURE* and *PRECIPITATION*. Fig. 6 reveals the spatially heterogeneous characteristics of factors affecting flight seasonality.

In general, parts of the estimates present a spatial pattern of gradient differentiation in the MGWR maps. Compared to the central and western regions, factors (except *PRECIPITATION*) are less significant and more minor in the eastern region because of the pleasant natural, economic, and institutional landscape, which works against seasonality (the mean of Gini indexes in the eastern region is 0.06)[6]. Most of the factors (except *PRECIPITATION*) are most evident in Northwest China. From Fig. 6a, the adverse effects of airport size present a “west-east” pattern that affects the flight seasonality more significantly in the west than in the east. To some extent, small airports in the west are highly reliant on regional hubs. In contrast, small airports in the east can directly link with international hubs (e.g., Shanghai Hongqiao International Airport) and regional hubs, especially in the context of developing multiple-airport systems.

For natural factors, the positive influence of the difference between annual average temperature and comfort temperature is more evident in Xinjiang province (Northwest China) and the Yangtze River Delta, with different mechanisms (Fig. 6b). The former is related to the supply side. It supplies rich seasonal tourism resources (e.g., highland tourism); these places will also encounter heavy snowstorms in winter. The latter might be related to the demand side. People living in the Yangtze River Delta, one of the most developed regions in China, feed their demand for travelling to places with comfortable climates in specific seasons. From Fig. 6c, the positive impact of precipitation exhibits a “south-north” gradient decreasing pattern, partly due to South China having more possibility to experience precipitation-oriented floods and typhoons than North China.

Further, we provided some discussions about two variables (i.e., *TOURISM* and *PLATEAU*) that are significant only in some airports/samples. The positive influence of the tourism economy seems to cluster in Northwest China and Southwest China. Possible reasons are as follows. The spatial distribution of major tourism resources[7] in China is dispersed (Fig. 7), providing opportunities for tourism in place. Compared to the western region with rich highland tourism resources[8], tourism attractions (without highland) in other regions are less seasonal. In other words, those airports in other regions serve year-round holiday areas, which could have a dampening effect on seasonality (Halpern, 2011). The negative impact of the plateau airport is only significant in Western China, partly because of the geography of the plateau (Fig. 2) and the plateau airport is operating for more than economic purposes, such as political purposes. For example, the opening of Zhangye Ganzhou Airport (YZY), a military-civilian plateau airport, has played a positive role in consolidating the national defense construction in Zhangye City.

[6] The Chinese planning agencies initially proposed the three-region level classifications widely adopted for empirical research (Chen & Haynes, 2017).

[7] We applied the total number of 4A and 5A tourist attractions and World Heritage Sites, the highest-ranking attractions in China as specified by the Ministry of culture and tourism of the People’s Republic of China, to represent regional tourism resources (Bo & Ningqiao, 2017).

[8] Highland tourist attractions are normally closed in winter due to heavy snow.

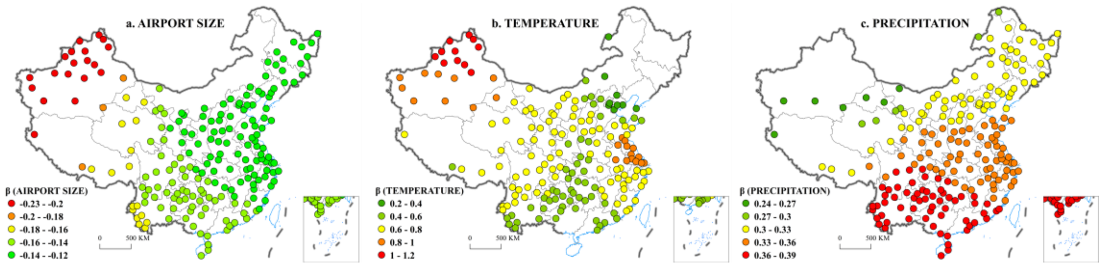


Fig. 6. Spatial differentiation patterns of factors affecting seasonality of flights in China

(Note: Only samples whose P-value is less than 0.1 are included in the map.)

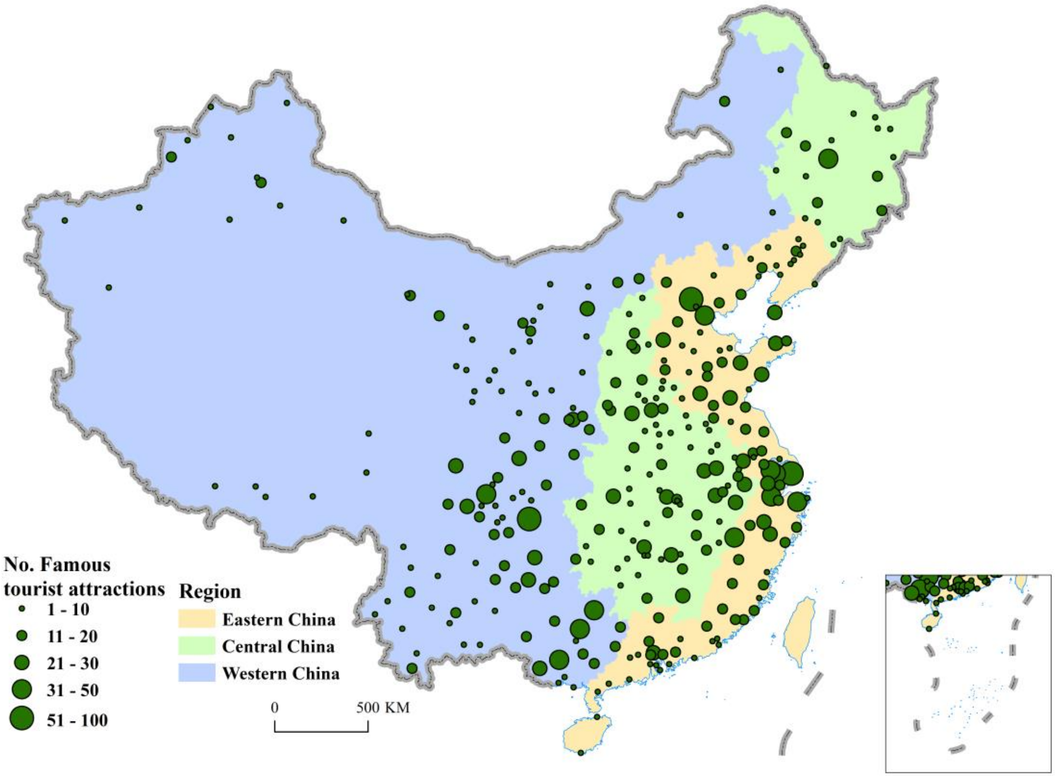


Fig. 7. Spatial distribution of major tourism resources in China

5 Conclusions and discussion

This paper contributes further comprehensive knowledge to the existing literature in terms of transport seasonality. To fill the gap of lacking systematic analysis on flight seasonality, we aim to explore the spatial heterogeneity of flight seasonality and its determinants in China from a supply-side perspective. The empirical evidence shows the following. (1) Domestic flights in China face seasonality, at their lowest in February and peaking in August. (2) From an airport perspective, seasonality is high in small airports serving remote places and in cities that are tourism destinations. The rank of the top 10 airports by flights kept stable in different months in 2018, while those ranked 10 to 20 changed significantly. (3) From a route perspective, trunk routes (or lines) in the air transport network of China face low(er) seasonality, while feeder routes (or lines) face high(er) seasonality. Heterogeneous attributes shape the seasonal accessibility of different airports. (4) At the national level, flight seasonality is shaped by airport size and a mix of natural landscape factors (e.g., average temperature and average rains). Seasonality significantly mattered for smaller airports located in regions facing extreme climates. At the local level, factors explored in this paper were more significant in the northwest area, especially airport size and temperature.

The flight schedule follows IATA seasons, and most of the schedule is well determined before two quarters, but it is more based on a micro-scale temporal perspective and is more market-oriented. From a spatial perspective, our research can still contribute to future air transport research, aviation planning or management (especially in developing countries). In academic terms, scholars who process research on airports or air transport networks are suggested to use the data for a "typical" period (e.g., one day, week, or month) with care. In other words, data for a "typical" period are more suitable for airports or routes with less seasonality, and vice versa. Therefore, air transport researchers can balance the cost of data and its precision according to the monthly rhythms of aviation.

In practical terms, seasonality can result in challenges for air transport management and regional development (Halpern, 2011; Merkert & Webber, 2018). At the national level, our findings provide some reference for aviation planning in developing countries with heterogeneous natural, economic, and institutional landscapes, such as China. Air transport planners are suggested to consider seasonality issues when planning for new airports or routes, which might shape dynamic national air transport systems. If possible, the central government can propose policies promoting collaboration between airports peak in different periods, reducing losses due to seasonality. At the local level, to manage seasonality, air transport managers should focus on airports located in areas with extreme terrain or extreme climate, those in tourist destinations, and those with long-distance routes serving peripheral regions, mainly for western China. Furthermore, the immobility of the natural landscape and regional tourism resources suggests focusing on the airport attributes. For instance, airports can be committed to attracting more heterogeneous passengers and upgrading to airline hubs, which encounter less seasonality (Wu et al., 2020). They can also establish long-term collaborations between air transport managers, local governments, and local industries to deal with flight seasonality (e.g., share the cost, mix with more business travel and attract more off-season leisure travel). For example, many ski resorts in Europe turn to hiking, trail running, and other adventure tourism types during off-peak periods in the summer (Suau-Sanchez & Voltes-Dorta, 2019).

This paper also paves the way for other research, although subject to data availability. Covid-19 can be a crucial factor influencing air transportation and tourism in China, as air services are highly associated with the spread of COVID-19 (Zhang et al., 2020; Li et al., 2022). During the epidemic, the air transport industry worldwide is grappling with shortages of fuel, parts and labor, and China is in the middle of an economic slowdown. This combination of factors makes our findings (based on 2018 data) not so applicable during the pandemic, but our results are still meaningful as the epidemic fades away. As for the dependent variable, it would make sense to consider the number of seats (instead of the number of flights) as well as average fares, which also face high seasonal variations and different situations (Merkert & Webber, 2018). Another issue to consider is charter flights in addition to regular flights. Although charter would likely increase the degree of seasonality, it is very difficult to capture this specific market through usual databases such as OAG Schedules. Consequently, follow-up research is suggested to use other databases covering actual flight data rather than planned flights from a demand perspective. Finally, in addition to domestic flights, seasonality in international services is a topic worth exploring, which can be typical for characteristics of international services (e.g., the international market is less regulated and more market-based). Thus, from the perspective of international routes, seasonality should be further explored.

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