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Towards Intercity Mobility System – Insights into the Spatial Interaction Gravity Model and Determination Approach

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ABSTRACT

The current development of urban agglomeration greatly promotes the intercity connection and elevates the significance of intercity mobility system. However, intercity mobility often exhibits extreme spatiotemporal imbalances due to the diverse urban characteristics. This poses a huge challenge for traffic management and reveals the necessity on understanding the urban attractiveness for intercity mobility, which is represented as spatial interaction gravity in this study. While recent works have explored relevant aspects, they failed to provide insights into temporal variations in spatial interaction gravity or capture the determining factors from multiple perspectives. To fill this gap, this study proposed a two-phase framework to measure the urban spatial interaction gravity and developed determination approaches utilising the large-scale location-based services (LBS) dataset. Specifically, the inverse gravity model was adopted for the measure within multiple urban agglomerations and city sets during weekdays, weekends and holidays. Then, we developed the fitting equations of spatial interaction gravity by incorporating the correlated features associated with social, economic, network accessibility and land use. The findings present spatial interaction gravity across different periods and substantiate the distinct determination effects of features, with a high fitting accuracy. They provide promising supports for the intercity mobility prediction and pre-emptive traffic management.

KEYWORDS

intercity mobility; spatial interaction gravity model; inverse gravity model; determination approach.

1. INTRODUCTION

The current development of urban agglomerations prominently promotes the intercity connection and elevates the significance of intercity mobility system. It underscores the growing necessity for attention on comprehending intercity mobility patterns, aiming to benefit traffic management in the domain of intercity transportation. In contrast to urban transportation, intercity mobility commonly exhibits characteristics of extended travel distance and prolonged travel duration. According to the spatial interaction theory in the field of intercity mobility, the interaction strength is negatively correlated with the distance between cities, demonstrating the weak spatial interaction between distant city pairs [1]. Spatial interaction reflects the interdependence between different cities, which can be well characterised by multiple attributes of urban development, geographical location and economic activity [2]. As a result, a comprehensive investigation into urban characteristics helps to capture distinctive characteristics of spatial interaction and offers valuable insights into the mechanisms that drive urban attractions for intercity mobility [3].

The scale of spatial interaction between one city and other cities represents the magnitude of urban attractiveness within the intercity mobility system, which has been widely represented as spatial interaction gravity in the literature [4]. A greater spatial interaction gravity indicates a stronger attraction strength for intercity mobility. Scholars have utilised a range of approaches to investigate the spatial interaction gravity, specifically the four-step model [5] and attraction index model [6, 7] stand out as well-known. Zhu et al. [5] used the four-step model to describe urban attractiveness with the network topological characteristics of cities, encompassing strength, breadth, density and collaboration. In terms of the attractiveness index model, Shen et al. [6] investigated the total attractiveness index ranking of Chinese cities from the perspective of accessibility, while Zhang et al. [7] calculated the culture attractiveness index of different cities considering cultural attributes. Moreover, the inverse gravity model was used as a common method to calculate various types of spatial interaction gravity in the field regarding high-speed rail passenger flow [8], air passenger flow [9], tourism flow [10] and social media check-in [11]. For instance, Zhang et al. [10] used travel record data to calculate the attractiveness of 170 theme parks in the U.S. He et al. [11] used social media data to estimate the spatial interaction gravity of 348 cities in China. The findings from these works generally demonstrate the outstanding applicability of inverse gravity model in understanding the spatial interaction gravity.

In recent years, several studies have been conducted to measure the spatial interaction gravity across different regions and analyse their spatial distribution [9, 12–13]. For instance, Xiao et al. [9] calculated the city gravity based on air passenger data between major cities in China and analysed the developmental patterns of air transportation in different cities over the years. Similar research was conducted by Ma et al. [12] for the seven urban agglomerations in the Yellow River basin, China. In addition, some novel factors and models were taken into account. Yan et al. [13] employed a coupled coordination model when measuring urban interaction gravity. It is worth noting that recent works have predominantly focused on specific urban agglomerations during the regular periods. However, holidays are far from receiving their deserved attentions in the field of spatial interaction gravity, despite the significant variations in intercity mobility observed during holidays.

Alongside the prevailing research on spatial interaction gravity, extensive attention has been given to its influencing factors and determination approaches [14–16]. Jin et al. [14] investigated the impact of socio-economic factors such as the number of employees, production proportion and urbanisation level on the city quality and used partial correlation analysis to select the influential variables for the city quality determination. Khadaroo et al. [15] applied a gravity framework to identify the importance of transportation infrastructure in determining the tourism attractiveness of a destination. Besides, Fofanova and Sychev [16] analysed the diverse factors of the urban attractiveness using both qualitative and quantitative methods and concluded that the availability of education and housing, as well as the environmental conditions, could considerably influence the choice of the area. The above listed research demonstrates the correlation between spatial interaction gravity and multiple urban attributes.

Drawing from the literature review, existing works have conducted extensive research on spatial interaction gravity, yet they fall short in considering the variations across distinct spatiotemporal scales and a more comprehensive range of determination factors. Firstly, previous works mostly conducted research on specific periods and analysed each of them separately. However, there is no related findings on the temporal variation in urban spatial interaction gravity. Secondly, the identified influencing factors of spatial interaction gravity were concentrated on the macroeconomic and demographic attributes, such as GDP and population. Unfortunately, these attributes are incompetent in capturing the intercity travel purposes, resulting in the limited insights into the underlying mechanism behind spatial interaction gravity. Building upon the aforementioned points, existing works have not studied spatial interaction gravity from a dynamic perspective, and the current findings on influencing factors fail to provide reasonable explanations for this dynamism. To address the aforementioned research gaps, *Table 1* provides a summary of the determination factors and spatiotemporal research scales related to spatial interaction gravity, with contrast to our research concerns, demonstrating the research motivations of this study.

Table 1 – The attribute, spatial and temporal scope of researches

Reference	Determination factors	Spatial scale	Temporal scale
Xiao et al. [9]	Population, tertiary-sector percentage, tourism revenue	Main cities in China	Various years (not distinguishing holidays and weekends, ND)
Jin et al. [14]	GDP, population, production proportion, urbanisation level	Provincial capitals in China	Single year (ND)
He et al. [17]	Economy, society, environment	Single urban agglomeration in China	Various years (ND)
Marrocu et al. [18]	Income, density, accessibility	Provinces in Italy	Single year (ND)
Gao et al. [19]	Economy, population	Prefecture-level cities in China	Various years (ND)
Liu et al. [20]	Population	Prefecture-level cities in China	Various days (ND)
Surya et al. [21]	Economy, society, environment	Single metropolis in Indonesia	Various years (ND)
Xia et al. [22]	Population	Main cities in Australia	Single year (ND)
This study	POI density, land use, economy, society, network accessibility	Multiple study areas in China (covering provincial capitals, first/second- tier cities and urban agglomerations)	Multiple periods (distinguishing weekdays, weekends, traditional holidays and modern holidays)

In this study, we aim to provide novel insights into the spatiotemporal variations in spatial interaction gravity and identify the significant determination factors from multiple perspectives. The main contributions of this study are summarised as follows:

- we proposed a two-phase framework to measure spatial interaction gravity across multiple spatial scales and identify the determination factors from multiple perspectives, involving social, economic, network accessibility and land use;
- we studied the temporal variations in urban spatial interaction gravity by distinguishing distinct periods, including weekdays, weekends and holidays, and analysed the distribution characteristic of spatial interaction gravity in both large-scale and small-scale urban agglomeration;
- we quantified the correlation between spatial interaction gravity and determination factors, then developed the high-accuracy fitting models for spatial interaction gravity in each period.

This study extends the research on spatial interaction gravity to a perspective incorporating differences across multiple spatiotemporal scales and refining its determination factors. It holds promising applications towards the quantitative measurement of intercity connections of a city to other cities, thus providing valuable guidance for the pre-emptive management within intercity mobility systems.

The remainder of this study is organised as follows. Section 2 introduces the multi-source datasets. Section 3 presents the methodology, including the inverse gravity model and the stepwise regression within the proposed two-phase framework. Section 4 measures the spatial interaction gravity; Section 5 presents the determination factors and develops the fitting models. Section 6 concludes this study and provides the future research direction.

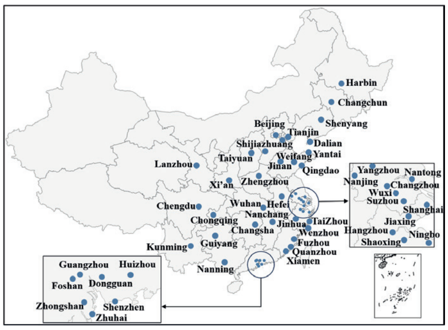
2. DATA SOURCE

2.1 Study area

The research area of this paper is divided into two aspects. One aspect focuses on the long-distance intercity travel, including two city sets: provincial capital cities (*Figure 1a*) and first- and second-tier cities (*Figure 1b*). The second aspect focuses on the short-distance intercity travel, represented by three urban agglomerations: the Yangtze River Delta Urban Agglomeration (*Figure 1c*), the Yangtze River Midstream Urban Agglomeration (*Figure 1d*) and the Beijing-Tianjin-Hebei Urban Agglomeration (*Figure 1e*) in China.

The selection of study areas considers their vast urban scale and strong intercity connections. Provincial capitals and first- and second-tier cities have concentrated populations and active economies. The first- and second-tier cities in China have a total population of 495.12 million, representing 35 percent of the country's

a) Provincial capital cities



b) First- and second-tier cities

c) Yangtze River Delta Urban Agglomeration

d)Yangtze River Midstream Urban Agglomeration

e) Beijing-Tianjin-Hebei Urban Agglomeration

Figure 1 – Cities and urban agglomerations distribution of study area

total population. These cities also have a total GDP of 596 billion yuan, accounting for 49 percent of the country's total GDP. In addition, the three urban agglomerations contain most developed cities in China and account for a large area. For example, the Yangtze River Midstream Urban Agglomeration contains 31 cities with a land area of about 326,100 square kilometres. They all have gathered a large population and formed the coordinated intercity traffic networks.

2.2 Data and processing

LBS data

Recently, due to the widespread use of mobile phones, the real-time location information of travellers can be obtained from location-based services (LBS) provided by the mobile APPs. The LBS data is provided from the published migration data platform (https://qianxi.baidu.com/), which traced travellers based on their location and recorded the intercity mobility for the data analysis. The platform currently has more than 1 billion users in most countries around the world, serves more than 650,000 active APPs and websites, and responds to more than 120 billion global location service requests per day. Once travellers submit a location request, current location will be stored with a unique label. By integrating this information, the platform can provide real-time data on the intercity traffic flow between cities in China, offering a convenient means to understand inter-city traffic demand and identify traffic hotspots.

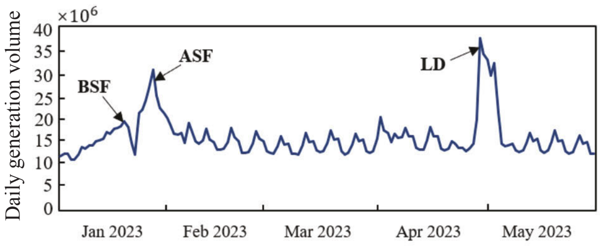
The intercity mobility dataset from 1 January 2023 to 31 May 2023 was downloaded in this paper. This dataset includes a total of 498,222 intercity flow records and contains the following information in each record: date, departure city, arrival city, intercity flow (i.e. OD flow), generation volume of departure city and attraction volume of arrival city.

In order to present the temporal variation in intercity mobility, the daily traffic volume of the whole country was obtained, as shown in *Figure 2a*. It demonstrates the significant difference during various periods, such as weekdays, weekends and holidays (which contain the traditional holidays and modern holidays). On weekdays and weekends, the traffic volume is the lowest at midweek and the highest at weekends, showing a fluctuating trend. On modern holidays (Labour Day), the traffic volume increases sharply and emerges a peak which is significantly larger than the traffic volume on weekdays and weekends. In addition, there is a peak in traffic volume before and after the traditional holidays (Spring Festival), respectively. Considering the above stated differences, the following study focuses on the multiple periods, including weekdays, weekends, the period before the Spring Festival, the period after the Spring Festival and Labour Day (which is on 1 May in China). Among them, we have chosen 6 March to 26 March as the time range of weekdays and weekends, 15 January to 21 January as the time range before the Spring Festival, 24 January to 30 January as the time range after the Spring Festival, and 29 April to 3 May as the time range of a modern holiday. The temporal and spatial scope in this study is summarised in *Table 2*.

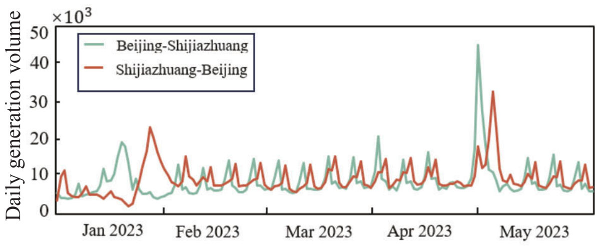
There are also differences in spatial interaction gravity between short-distance and long-distance urban agglomerations. *Figure 2b–2c* exhibits their respective temporal variations by taking two specific origin-destination (OD) pairs as examples. For short-distance city pairs, the travel volume is generally low during midweek and high on weekends, exhibiting regular fluctuations. The overall traffic volume between cities is

Table 2 – The temporal and spatial scope in this study

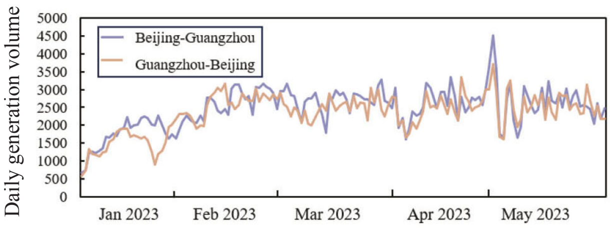
Type	Name	Range	Coverage
Spatial scales	PCC	Provincial capital cities	30 cities
	FSTC	First- and second-tier cities	49 cities
	YRDC	Yangtze River Delta Urban Agglomeration	27 cities
	YRMC	Yangtze River Midstream Urban Agglomeration	31 cities
	BTHC	Beijing-Tianjin-Hebei Urban Agglomeration	13 cities
Temporal scales	BSF	Period before the Spring Festival from 15 January to 21 January	7 days
	ASF	Period after the Spring Festival from 24 January to 30 January	7 days
	WDAY	Weekdays in the time range from 6 March to 26 March	15 days
	WEND	Weekends in the time range from 6 March to 26 March	6 days
	LD	Labour Day period from 29 April to 3 May	5 days



a) Daily traffic volume of the whole country



b) Daily traffic volume of a short-distance specific city pair (Beijing-Shijiazhuang)



c) Daily traffic volume of a long-distance specific city pair (Beijing-Guangzhou)

Figure 2 – The daily traffic volume of different area

smaller, with travel volume fluctuating irregularly during weekdays and weekends. Considering the different distribution of traffic volume, ensuing analysis will focus on the short-distance and long-distance urban agglomerations, respectively.

City attribute data

To comprehensively analyse the factors contributing to temporal variations in urban spatial interaction gravity during different periods, we have selected urban attribute data consisting of land use, social, economic and network accessibility data for subsequent analysis.

The highway distances were obtained through the application programming interface (API) of an online map with the latitude and longitude of departure and arrival cities. In this study, we utilised the points of interests (POI), downloaded from the API of Gaode Map, to characterise the urban land use, as suggested by the recent work [23–25]. Specifically, POIs are divided into eight categories: eating, business, shopping, finance, accommodation, education, tour and entertainment. We calculated the POI density and the percentage of each type of POI in this study. Data on GDP, population, area, primary industry proportion, secondary industry proportion, tertiary industry proportion, airport runways number, rail lines number and expressways number for each city were obtained from the National Bureau of Statistics to present the features related to social, economic and network accessibility. The airport runways number mainly counts the number of runways of civil transport airports. Finally, the name and description of each feature are summarised as shown in *Table 3*.

Table 3 – The name and description of each feature

Type	Index	Name	Unit	Description
Land use	1	POID	km^2	POI density
	2	EAP	/	Proportion of eating category
	3	BUP	/	Proportion of business category
	4	SHP	/	Proportion of shopping category
	5	FIP	/	Proportion of finance category
	6	ACP	/	Proportion of accommodation category
	7	EDP	/	Proportion of education category
	8	TRP	/	Proportion of tour category
	9	ENP	/	Proportion of entertainment category
Social feature	10	POPU	10,000 people	Population
	11	AREA	km^2	Area
Economic feature	12	GDP	100 million yuan	Gross domestic product
	13	PRIP	/	The proportion of the primary industry
	14	SECP	/	The proportion of the secondary industry
	15	TERP	/	The proportion of the tertiary industry
Network accessibility	16	ARN	/	The number of airport runways
	17	RLN	/	Number of rail lines
	18	EWN	/	The number of expressways

3. METHODOLOGY

Figure 3 illustrates a two-phase framework for the spatial interaction gravity in the intercity mobility system. Phase 1 measures the spatial interaction gravity across different spatiotemporal scales using the inverse-gravity-based standard algebra model (SAM) [8]. This model quantitatively measures urban spatial interaction gravity with the nodal attraction solved from the inverse gravity model, which have been proven to have an excellent applicability by relevant research, such as [4] and [14]. Since the SAM takes advantages in accurate computation of spatial interaction gravity for large scale network systems [8], this study adopts it as the computing core of Phase 1. Phase 2 understands the relationship between spatial interaction gravity and multiple urban attributes involving land use, social, economic and network accessibility. On this basis,

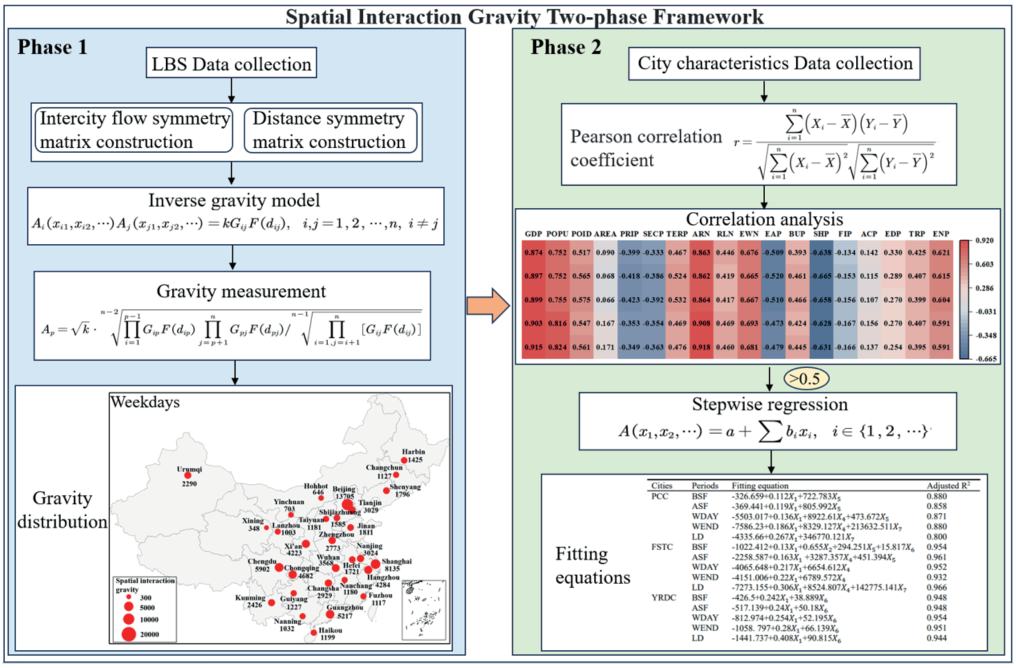


Figure 3 – The two-phase framework for the urban spatial interaction gravity

the determination approach of spatial interaction gravity is developed with the stepwise regression, since it can identify the significant explanatory variables and screen out variables that have multicollinearity issues with other variables [26]. The detailed methodology is presented as follows:

Phase 1: Measuring the spatial interaction gravity

The expression for the gravity model is:

$$G_{ij}=\frac{mA_1(x_{i1},x_{i2},\cdots)A_j(x_{j1},x_{j2},\cdots)}{F(d_{ij})} \tag{1}$$

where G_{ij} is the intercity traffic flow from city i to city j; m is a constant; A_i and A_j are the spatial interaction gravity of city i and j, respectively; x_{i1}, x_{i2}, x_{j1}, x_{j2}, are the social, economic, network accessibility and land use features of city i and city j; $F(d_{ij})$ is the distance constraint function. Let the constant coefficient be k=1/m, the inverse form of the gravity model is obtained by varying *Equation 1*:

$$A_i(x_{i1},x_{i2},\cdots)A_j(x_{j1},x_{j2},\cdots)=kG_{ij}F(d_{i,j}),\ i,j=1,2,\cdots,n,\ \ i\neq j \tag{2}$$

where n is the number of cities. When there are n cities, $n(n$-1)/2 equations like *Equation 2* can be obtained. In these equations, A_i appears (n-1) times. The specific steps for solving the spatial interaction gravity of a city will be described below. Multiply all the equations together and extract a square root:

$$A_1A_2A_3\cdots A_n=\sqrt[n-1]{\prod_{i=1,j=i+1}^{n}[kG_{ij}F(d_{ij})]},\ i\neq j \tag{3}$$

Multiplying the equations containing A_1, A_2, A_3,⋯, A_n,

$$A_1^{n-2}(A_1A_2A_3\cdots A_n)=k^{n-1}\prod_{j=2}^{n}G_{1j}F(d_{1j})$$

$$\vdots$$

$$A_p^{n-2}(A_1A_2A_3\cdots A_n)=k^{n-1}\prod_{i=1}^{p-1}G_{ip}F(d_{ip})\prod_{j=p+1}^{n}G_{pj}F(d_{pj}),\ \ 1<p<n \tag{4}$$

$$\vdots$$

$$A_n^{n-2}(A_1A_2A_3\cdots A_n)=k^{n-1}\prod_{i=1}^{n-1}G_{in}F(d_{in})$$

The spatial interaction gravity for each city is obtained by dividing each term in *Equation 4* by *Equation 2* and then rooting:

$$
\begin{aligned}
&A_1 = \sqrt{k} \cdot \sqrt[n-2]{\prod_{j=2}^{n} G_{1j} F(d_{ij}) / \sqrt[n-1]{\prod_{i=1,j=i+1}^{n} [G_{ij} F(d_{ij})]}} \\
&\vdots \\
&A_p = \sqrt{k} \cdot \sqrt[n-2]{\prod_{i=1}^{p-1} G_{ip} F(d_{ip}) \prod_{j=p+1}^{n} G_{pj} F(d_{pj}) / \sqrt[n-1]{\prod_{i=1,j=i+1}^{n} [G_{ij} F(d_{ij})]}},\ 1 < p < n \\
&\vdots \\
&A_n = \sqrt{k} \cdot \sqrt[n-2]{\prod_{i=1}^{n-1} G_{in} F(d_{in}) / \sqrt[n-1]{\prod_{i=1,j=i+1}^{n} [G_{ij} F(d_{ij})]}}
\end{aligned}
\tag{5}
$$

In this study, the average intercity flow of a certain period was selected as the measure of spatial interaction between cities. The calculation of the inverse gravity model requires a symmetry matrix as it is generally recognised that the intercity traffic exchange maintains equilibrium. This equilibrium has been validated by the average G_{ij} and G_{ji} with close values in our dataset, thereby we use their summation to construct a symmetry matrix of intercity flow.

In this study, a distance constraint function in the exponential form was utilised in the gravity model and inverse gravity model, suggested by its widespread use in previous works [27, 28] to describe the distance decay effect. The distance decay exponent is set to 0.6 and constant coefficient k is set to 100 according to the practice of the gravity model in China [9]. The specific form of inverse gravity model is:

$$A_i(x_{i1}, x_{i2}, \cdots) A_j(x_{j1}, x_{j2}, \cdots) = 100 \cdot G_{ij} \cdot d_{ij}^{0.6},\ \ i,j = 1,2,\cdots,n,\ \ i \neq j \tag{6}$$

Phase 2: Development of influencing factors and determination approaches

The correlation analysis between the influencing factors and the spatial interaction gravity was firstly performed by the Pearson correlation coefficient. The Pearson correlation coefficients for variables X and Y are calculated as follows:

$$r = \frac{\sum_{i=1}^{n} (X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \overline{X})^2} \sqrt{\sum_{i=1}^{n} (Y_i - \overline{Y})^2}} \tag{7}$$

where X_i, Y_i are observations and $\overline{X}$, $\overline{Y}$ are their respective means. Variables with correlations greater than 0.5 were selected for the next regression modelling.

Stepwise regression is chosen for the determination approach as it stands as a widely employed technique for variable screening in multiple regression analysis and possess excellent interpretability. To be more specific, the eligible variables are determined with the significance testing before inputting the model. Moreover, variables that entered the model are tested again to exclude those that are not qualified, considering the possibility of non-significance or covariance of variable combinations. This approach ensures that the explanatory variables finally retained in the model are both significant and not severely multicollinear.

Finally, by incorporating the urban attributes in social, economic, land use and network accessibility, multiple linear fitting equations for the spatial interaction gravity can be constructed using stepwise regression, as follows:

$$A(x_1, x_2, \cdots) = a + \sum b_i x_i,\ \ i \in \{1,2,\cdots\} \tag{8}$$

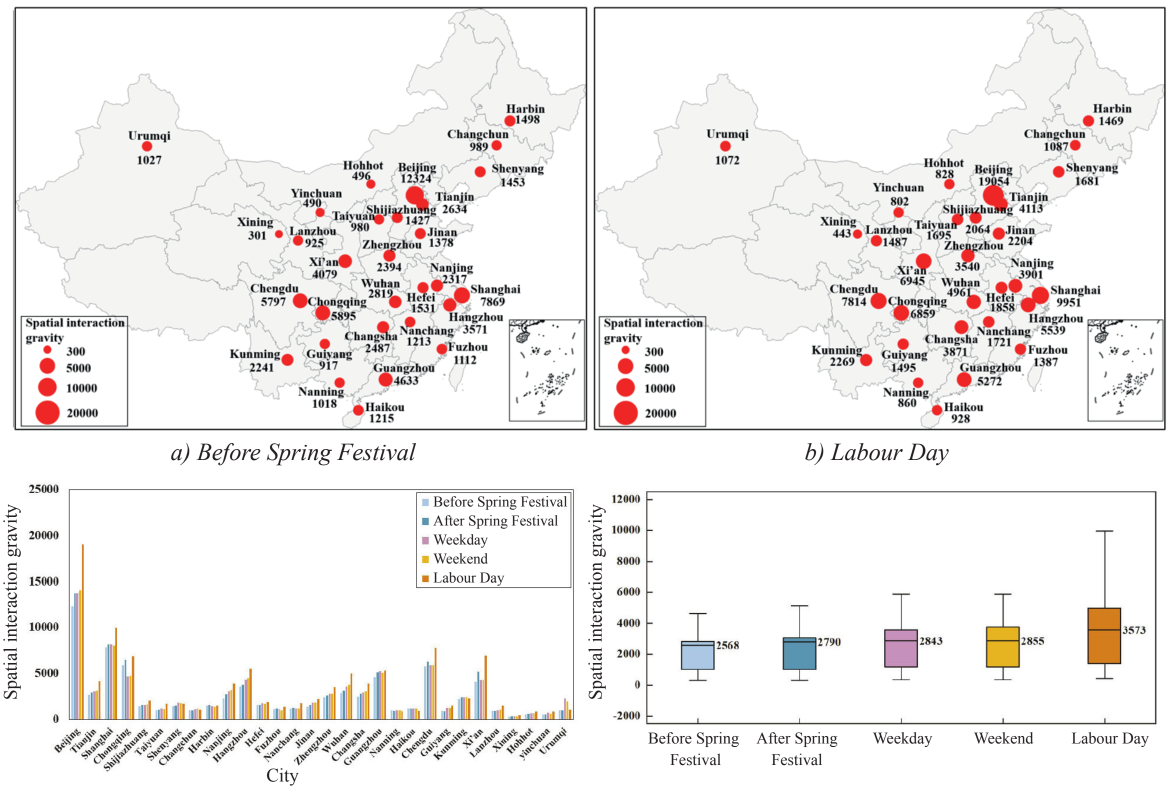
where, a is a constant. b_i is the coefficient of variable. x_i is the selected variable.

4. MEASURING THE SPATIAL INTERACTION GRAVITY

We programmed the inverse gravity model with Python 3.10 on PyCharm Community Edition 2023.1.3 to measure the spatial interaction gravity in different spatiotemporal scales with intercity flow and distances. For each urban agglomeration or city set, gravitational maps are depicted for periods characterised by the minimum and maximum average interaction gravity, serving as examples to illustrate spatial distribution of interaction gravity. Moreover, the overall distribution of spatial interaction gravity across all periods is also showcased in ensuing sections.

4.1 Spatial interaction gravity for long-distance urban agglomerations

The spatial interaction gravity among provincial cities during each period is shown in *Figure 4*. Regarding spatial distribution, the spatial interaction gravity of megacities such as Beijing, Shanghai, Guangzhou and Chengdu is the highest, exceeding 5,000. The spatial interaction gravity of central cities such as Chongqing, Wuhan and Changsha is the second highest, ranging between 2,000 and 5,000. In contrast, the spatial interaction gravity of western cities such as Xining, Lanzhou and Yinchuan is the lowest, below 1,500. The overall distribution exhibits a "spindle" structure, with eastern cities demonstrating a relatively high attractiveness and western cities demonstrating a relatively low one.



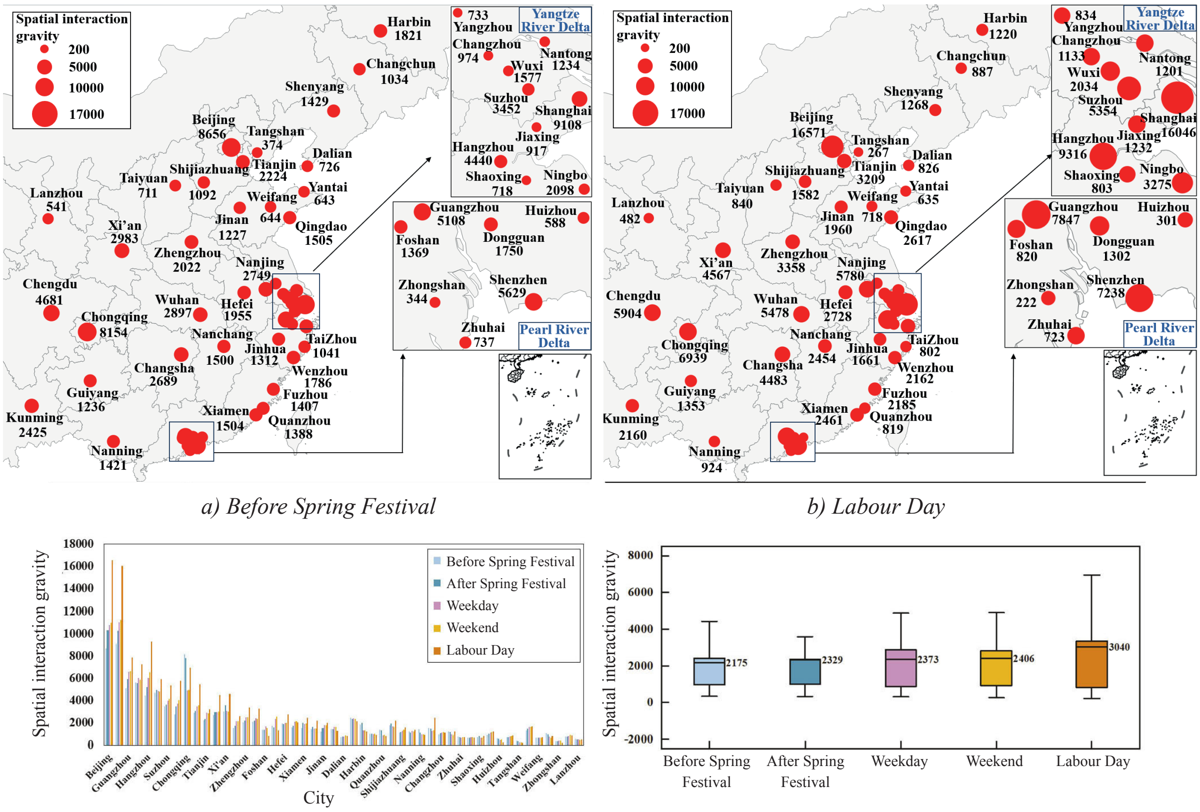
a) Before Spring Festival *b) Labour Day*

c) Distribution of interaction gravity *d) Average interaction gravity*

Figure 4 – Spatial interaction gravity for periods in the provincial capital cities

The spatial interaction gravity among first- and second- tier cities during each period is shown in *Figure 5*. The spatial distribution is broadly similar to that of the provincial capitals, with a general trend of decreasing from south-east to north-west. The difference is that the attractive cities are located in the coastal regions, with the Yangtze River Delta and the Pearl River Delta forming two strongly attractive city clusters.

Comparing the average spatial interaction gravity among long-distance cities over different periods, we find that, in descending order, the highest values are found on Labour Day, followed by weekends, weekdays and post-Spring Festival, with the lowest values before the Spring Festival. It reveals that despite a significant increase in the total intercity flow nationwide during the Spring Festival, interactions among developed cities decrease compared to weekdays and weekends. Comparing between weekends and weekdays, the higher intercity interaction gravity on weekends demonstrates a greater intention for long-distance trips. The spatial interaction gravity after the Spring Festival is higher than that before the Spring Festival and that is contributed by the attractiveness of large cities for people returning to work places. Regarding the variations



a) Before Spring Festival

b) Labour Day

c) Distribution of interaction gravity

d) Average interaction gravity

Figure 5 – Spatial interaction gravity for periods in the first- and second-tier cities

in intercity interaction gravity during modern holidays, there is a concentrated trend towards large cities. Central cities like Beijing, Shanghai, Chengdu, Xi'an and Wuhan have seen a large increase in spatial interaction gravity compared to regular periods, with increments of over 1,000. In contrast, small cities such as Nanning, Urumqi, Shenyang, Foshan and Huizhou have the reduced spatial interaction gravity.

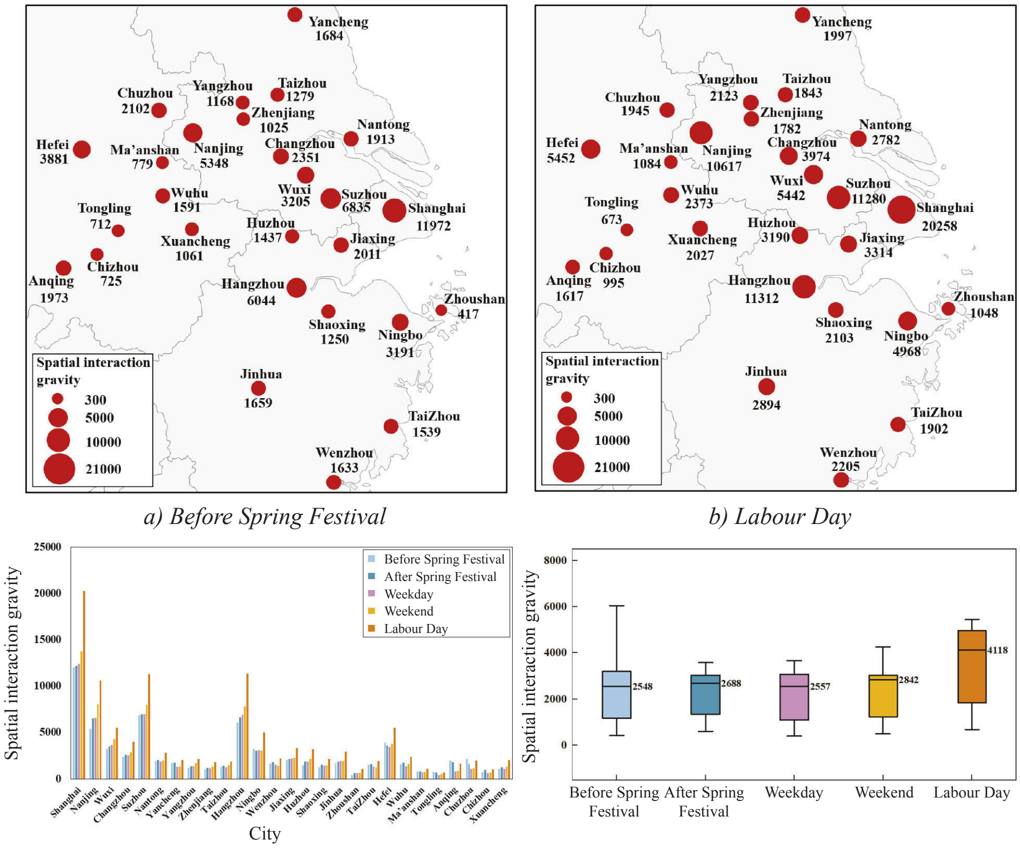
4.2 Spatial interaction gravity for short-distance urban agglomerations

The spatial interaction gravity within the Yangtze River Delta Urban Agglomeration in each period is shown in *Figure 6*. The results demonstrate the concentrated gravity of Shanghai, with values exceeding 10,000 in all periods. Less attractive cities are primarily located along the Yangtze River and the southeast coast. The spatial interaction gravity decreases from the eastern seaboard to the western hinterland.

The spatial interaction gravity within the Yangtze River Midstream Urban Agglomeration in each period is shown in *Figure 7*. Similarly, central cities like Wuhan and Changsha have a larger spatial interaction gravity. The gravity of cities around central cities commonly stays in a low level, which reveals the development patterns of satellite cities within urban agglomerations.

The results of spatial interaction gravity within Beijing-Tianjin-Hebei Urban Agglomeration in each period are shown in *Figure 8*. The distribution of cities is relatively dispersed in this urban agglomeration, with concentrated gravity in provincial capital cities such as Beijing, Tianjin and Shijiazhuang. In addition, the cities located between provincial capital cities have higher gravity compared to surrounding cities.

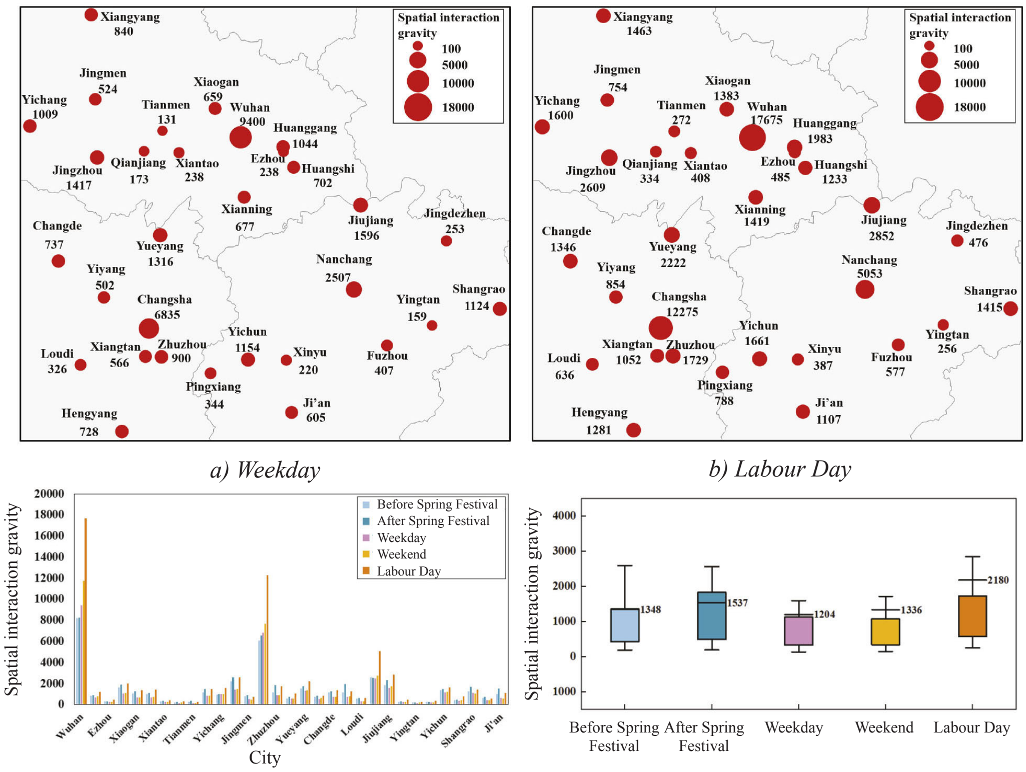
Comparing the average spatial interaction gravity for short-distance urban agglomerations in different periods, common findings reveal the highest spatial interaction gravity on modern holidays, followed by weekends, post-Spring Festival, pre-Spring Festival and weekdays. Compared to the results for long-distance urban agglomerations, the gravity during the Spring Festival is larger than that on weekdays. This indicates that there is strengthened intercity mobility among short-distance urban agglomerations.



a) Before Spring Festival *b) Labour Day*

c) Distribution of interaction gravity *d) Average interaction gravity*

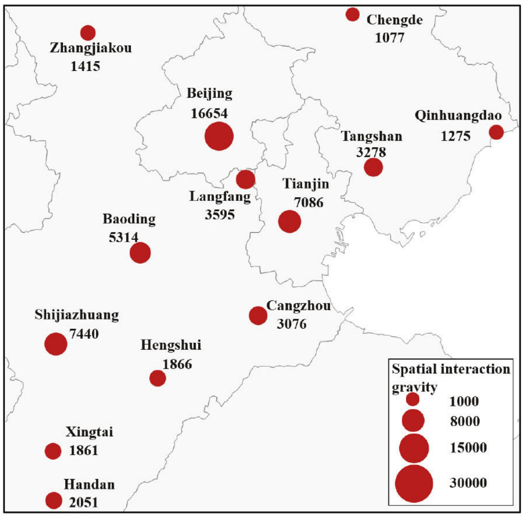
Figure 6 – Spatial interaction gravity for periods in the Yangtze River Delta Urban Agglomeration



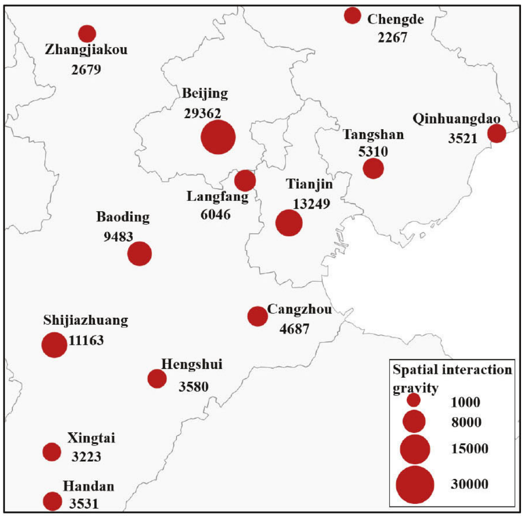
a) Weekday *b) Labour Day*

c) Distribution of interaction gravity *d) Average interaction gravity*

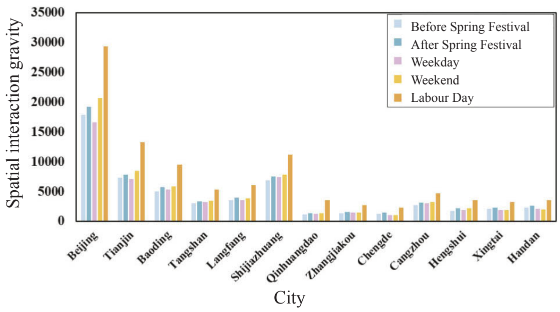
Figure 7 – Spatial interaction gravity for periods in the Yangtze River Midstream Urban Agglomeration



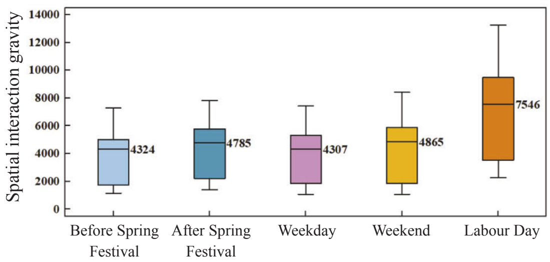
a) Weekday



b) Labour Day



c) Distribution of interaction gravity



d) Average interaction gravity

Figure 8 – Spatial interaction gravity for periods in the Beijing-Tianjin-Hebei Urban Agglomeration

Regarding the variations in spatial interaction gravity during modern holidays, there is also a concentrated trend towards large cities during modern holidays. For instance, the spatial interaction gravity of Shanghai in the Yangtze River Delta Urban Agglomeration on Labour Day is 20,258, much larger than that on weekends, 13,695. Tianjin in the Beijing-Tianjin-Hebei Urban Agglomeration has a spatial interaction gravity of 13,249 on Labour Day, with an increase of 57.41% compared to the weekend. In addition, small cities exhibit a larger spatial interaction gravity during the Spring Festival compared to weekdays and weekends. For instance, Huanggang, Yueyang and Yichun, located in the Yangtze River Midstream Urban Agglomeration, exhibit higher gravity during the Spring Festival compared to weekdays and weekends. Moreover, Anqing in the Yangtze River Delta Urban Agglomeration has even higher gravity during the Spring Festival than that during Labour Day.

5. INFLUENCING FACTORS AND DETERMINATION APPROACH

5.1 Correlation coefficient analysis

The correlation coefficient is utilised to present the influencing degree of each factor on the spatial interaction gravity. For datasets in different spatiotemporal scales, Pearson correlation coefficients between the spatial interaction gravity and urban attributes were calculated utilising the IBM SPSS Statistic 26 software, as shown in *Figure 9*.

Both in long-distance and short-distance urban agglomerations, spatial interaction gravity shows a significant correlation with both GDP and population, with GDP demonstrating the strongest association. Specifically, the airport runways number, tertiary industry proportion, expressways number and the proportions of shopping and entertainment have a large influence on spatial interaction gravity within the long-distance urban agglomerations. In addition, there exists a moderate correlation between POI density and spatial in-

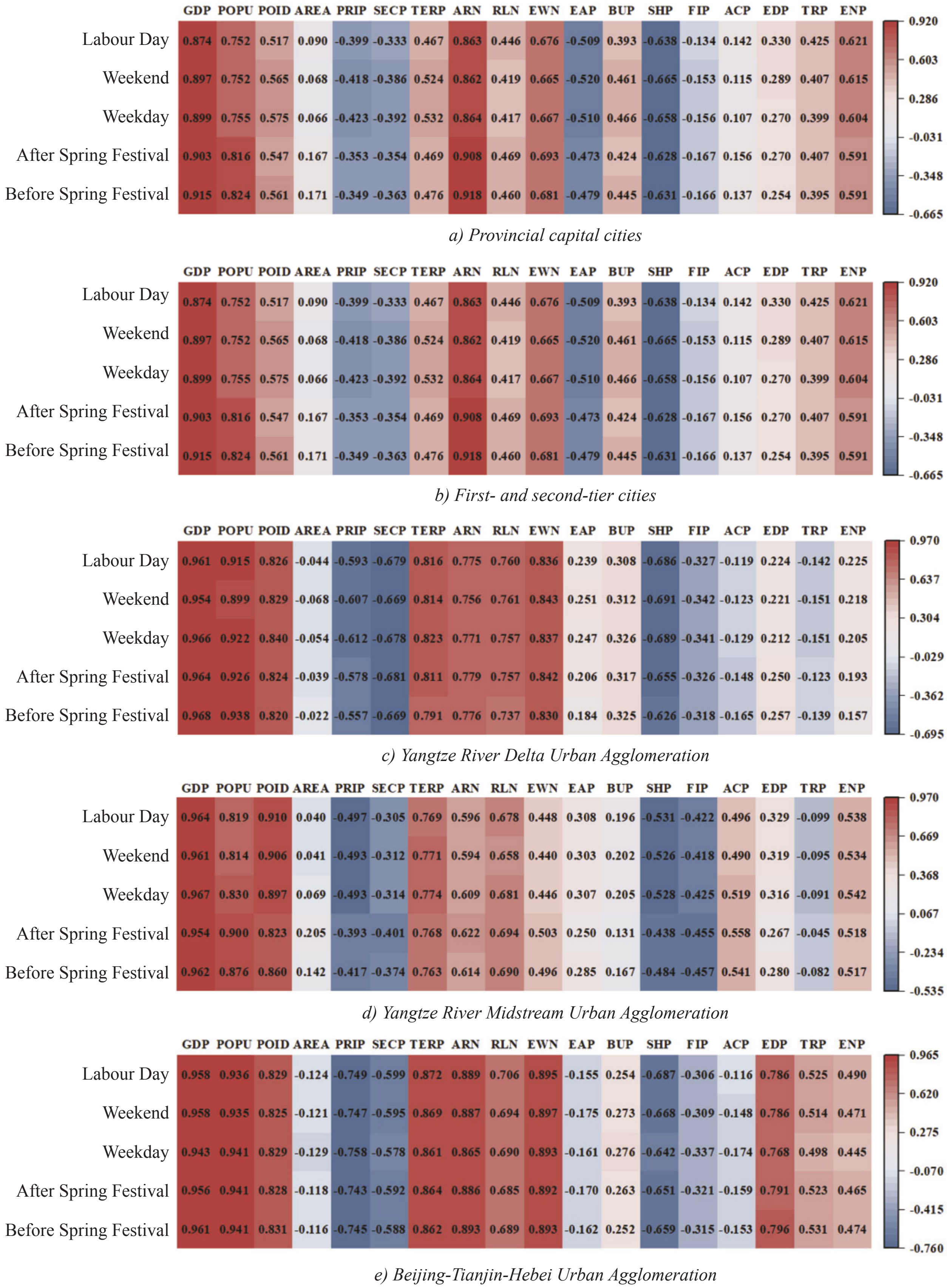


Figure 9 – The Pearson correlation coefficients of each influencing factor on urban spatial interaction gravity in different periods

teraction gravity among provincial capital cities. However, among first- and second-tier cities, the influence of the secondary industry proportion and the number of rail lines is found to be less significant.

The spatial interaction gravity of short-distance cities is strongly influenced by POI density, tertiary industry proportion, airport runways number, rail lines number and shopping. The correlation of the expressways number with spatial interaction gravity in the Yangtze River Delta and the Beijing-Tianjin-Hebei Urban Agglomerations is significant. Moreover, the correlation of accommodation and entertainment is general in the Yangtze River Midstream Urban Agglomeration, while education is strongly correlated with spatial interaction gravity in the Beijing-Tianjin-Hebei Urban Agglomeration.

When comparing the correlation of influencing factors across different periods, the following patterns can be captured. Population and airport runway numbers are strongly correlated with spatial interaction gravity during the Spring Festival than other periods. The tertiary industry proportion has a significant impact on weekdays, weekends and modern holidays. Within long-distance urban agglomerations, the proportion of entertainment has the highest correlation during modern holidays while that of shopping is strongly correlated with spatial interaction gravity on weekends. The correlation between POI density and spatial interaction gravity is generally higher on weekdays, weekends and modern holidays compared to the Spring Festival, within short-distance urban agglomerations. Rail line numbers have the greatest impact on the attractiveness of the Yangtze River Delta Urban Agglomeration during modern holidays. Finally, educational relevance is strong during the Spring Festival in the Beijing-Tianjin-Hebei Urban Agglomeration, which is attributed to the intercity mobility of students returning home for the Spring Festival and then returning to school after the Spring Festival.

Through correlation analysis, significant features whose correlation coefficient is larger than 0.5 were selected for the determination approaches of spatial interaction gravity.

5.2 Regression result and analysis

Multiple linear fitting models were developed with the stepwise regression utilising the IBM SPSS Statistics 26 software. We took into consideration both the fitting goodness and the multicollinearity among variables when developing the fitting models. Variance inflation factor (VIF) was used to characterise the linear relationship between each independent variable and other independent variables. Concerning the VIF threshold, researchers have extensively suggested a value of 10 [29, 30], which corresponds to the tolerance suggestion of 0.1. Drawn from the findings by [31–33], the VIF less than 10 (i.e. the tolerance greater than 0.1) for each independent variable indicates that there is no multicollinearity issue between variables. Hence, this study follows the VIF threshold of 10 to determine the multicollinearity between independent variables considering that the rationality can be guaranteed by the common practice in the literature. Among variables with multicollinearity, the ones that exhibit a stronger correlation with spatial interaction gravity were chosen for selection. The final variable set includes GDP, population, POI density, tertiary industry proportion, airport runways number, rail lines number and the proportion of entertainment, denoted as X_1, X_2, X_3, X_4, X_5, X_6, X_7, respectively. Then, we developed the determination approach with the regression model and evaluated the model performance with adjusted R-square. The fitting results are summarised in *Table 4*.

By comparing the variables and variable coefficients across the fitting models, we know that: GDP, the most highly correlated factor, is widely used for all periods in all city sets. In addition, the fitting models for each spatial scale are respectively analysed below, along with the visual comparison between real values and predicted values shown in *Figure 10*.

Among the provincial capital cities, the airport runways number is selected for the fitting models of the Spring Festival, with a larger coefficient than that in the models of weekdays. The proportion of tertiary industry is contained in the models for weekdays and weekends, which reveals that the development level of provincial capital cities is primarily reflected in the tertiary industry. Furthermore, the proportion of entertainment is included in the models for modern holidays. It demonstrates that our models are capable of capturing the concentrated travel purpose in tourism and entertainment on modern holidays.

Table 4 – The fitting equations of the spatial interaction gravity

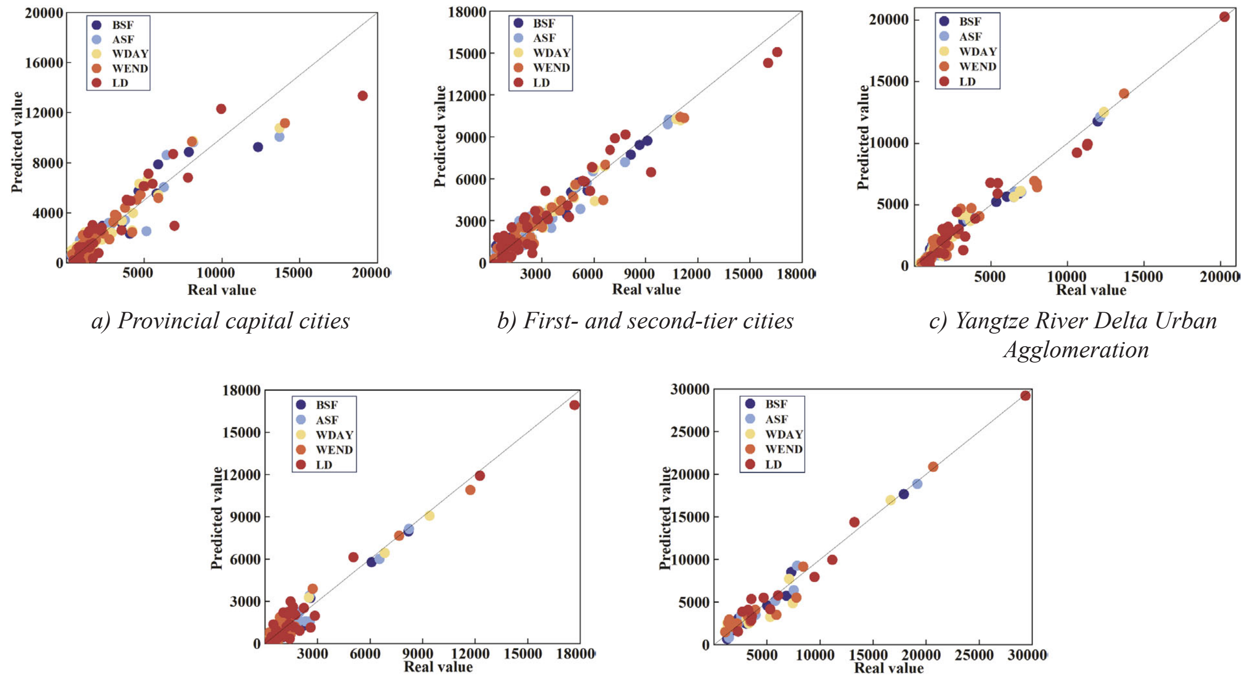
Cities	Periods	Fitting equation	Adjusted R^2
PCC	BSF	$-326.659+0.112X_1+722.783\ X_5$	0.880
	ASF	$-369.441+0.119X_1+805.992X_5$	0.858
	WDAY	$-5503.017+0.136X_1+8922.61X_4+473.672X_5$	0.871
	WEND	$-7586.23+0.186X_1+8329.127X_4+213632.511X_7$	0.880
	LD	$-4335.66+0.267X_1+346770.121X_7$	0.800
FSTC	BSF	$-1022.412+0.13X_1+0.655X_2+294.251X_5+15.817X_6$	0.954
	ASF	$-2258.587+0.163X_1\ +3287.357X_4+451.394X_5$	0.961
	WDAY	$-4065.648+0.217X_1+6654.612X_4$	0.952
	WEND	$-4151.006+0.22X_1+6789.572X_4$	0.932
	LD	$-7273.155+0.306X_1+8524.807X_4+142775.141X_7$	0.966
YRDC	BSF	$-426.5+0.242X_1+38.889X_6$	0.948
	ASF	$-517.139+0.24X_1+50.18X_6$	0.948
	WDAY	$-812.974+0.254X_1+52.195X_6$	0.954
	WEND	$-1058.\ 797+0.28X_1+66.139X_6$	0.951
	LD	$-1441.737+0.408X_1+90.815X_6$	0.944
YRMC	BSF	$-738.73+0.177X_1+2.186X_2+57.417X_3$	0.973
	ASF	$-659.092+0.167X_1+2.813X_2+47.159X_3$	0.970
	WDAY	$-701.046+0.393X_1+56.084X_3$	0.911
	WEND	$-1003.05+0.445X_1+80.048X_3$	0.943
	LD	$-1430.04+0.681X_1+125.301X_3$	0.972
BTHC	BSF	$-5508.312+0.184X_1+3.241X_2+10335.656X_4$	0.944
	ASF	$-6037.005+0.18X_1+3.618X_2+11585.881X_4$	0.945
	WDAY	$-4464.38+0.28X_1+12109.989X_4$	0.946
	WEND	$-5835.515+0.361X_1+14509.422X_4$	0.936
	LD	$-9456.989+0.287X_1+5.051X_2+19122.532X_4$	0.920

Among first- and second-tier cities, intercity mobility concentrates on long-distance travels during the Spring Festival, and the fitting models include the airport runways number and rail lines number. In addition, the tertiary industry proportion appears in the fitting models for weekdays, weekends and modern holidays, and the impact is greater during modern holidays. It demonstrates that first- and second-tier cities have well-developed economies and large service sectors. Furthermore, the proportion of entertainment that appears in the models for modern holiday highlights that first- and second-tier cities are good leisure destinations.

The rail lines number is incorporated in all fitting models for the Yangtze River Delta Urban Agglomeration, which is attributed to the dense rail network and high accessibility. The effect of rail line number is greater during the modern holiday when the number of traveling tourists increases. Moreover, the impact of rail line number is greater during the regular period than Spring Festival. It manifests that the convenience of the rail is more significant when people engage in business travel and visiting friends and relatives on weekdays and weekends.

In the Yangtze River Midstream Urban Agglomeration, POI densities are incorporated in the fitting models for all periods, illuminating that cities with higher POI densities tend to be more attractive and there are significant development gaps between cities. The effect of POI densities is greater during the modern holiday, which indicates that the level of development in a city's culture, tourism, commerce and other aspects has a significant impact on its attraction to passenger flow.

The proportion of tertiary industry is included in the fitting models of the Beijing-Tianjin-Hebei Urban Agglomeration for all periods, proving the tertiary industries are prosperous. It has a noticeable influence on



a) Provincial capital cities

b) First- and second-tier cities

c) Yangtze River Delta Urban Agglomeration

d) Yangtze River Midstream Urban Agglomeration

e) Beijing-Tianjin-Hebei Urban Agglomeration

Figure 10 – The real and predicted spatial interaction gravity values of different urban agglomerations

the spatial interaction gravity on weekdays, weekends and holidays. In addition, spatial interaction gravity is determined by population on the Spring Festival and Labour Day. The influence of population is amplified during modern holidays when there is an influx of tourist arrivals.

6. CONCLUSION

This study focused on the spatial interaction gravity across multiple spatiotemporal scales. It yields new insights into the influencing factors and determination approaches by incorporating the temporal variations and spatial diversity. Specifically, a two-phase framework was proposed to measure and analyse the spatial interaction gravity utilising the large-scale LBS dataset. The main contributions and findings are summarised as follows.

Phase 1 measures the spatial interaction gravity across different urban agglomerations on weekdays, weekends, the Spring Festival and Labour Day with the inverse-gravity-based standard algebra model. The general findings are concluded:

- the average spatial interaction gravity on modern holidays is the highest. Within the long-distance urban agglomeration, the average gravity on weekdays and weekends is greater than that on the Spring Festival. However, in the short-distance urban agglomeration, the average gravity after the Spring Festival is greater than that on weekdays.
- during modern holidays, the spatial interaction gravity exhibits a concentrated trend to large cities, while the gravity of small cities is decreased.
- during the tradition festival like the Spring Festival, the spatial interaction gravity is increased for small and medium-sized cities in short-distance urban agglomeration, with a higher value than that on weekdays and weekends.

Phase 2 captures the significant factors influencing the spatial interaction gravity by incorporating the urban attributions in social, economic, land use and network accessibility, and develops the determination approach with the stepwise regression. The high adjusted R-square indicates the superiority of the developed models. The general findings are concluded:

- GDP exhibits the strongest correlation with the spatial interaction gravity. Within the long-distance urban agglomeration, spatial interaction gravity is largely affected by the airport runways number, tertiary industry proportion, expressways number and the proportion of shopping and entertainment. In contrast, the key influencing factors are POI density, tertiary industry proportion, airport runways number, rail lines number and the proportion of shopping for short-distance urban agglomerations.
- in terms of spatiotemporal differences, population and airport runways number largely determines the spatial interaction gravity on the Spring Festival, whereas the tertiary industry proportion has a notable effect on weekdays and weekends and modern holidays. The proportion of entertainment has the greatest correlation with spatial interaction gravity on modern holidays within long-distance urban agglomerations. In contrast, this role is replaced with the POI density within short-distance urban agglomerations.

This study contributes to providing a practice towards the intercity mobility system by measuring the spatial interaction gravity and analysing their spatiotemporal variations with the real-world LBS dataset. However, due to the limited collection capability of urban attributes, we chose a relatively small alternative attribute set to construct the fitting model of spatial interaction gravity. More urban attributes are expected for the proposed framework to further refine the fitting model and improve the model accuracy. Moreover, in the future work, we aim to incorporate the measured spatial interaction gravity and its key determination factors into the prediction model driven by machine learning algorithms to accurately predict the intercity origin-destination (OD) flow. Also, our findings on spatiotemporal difference of spatial interaction gravity presents a future research direction in modelling the variations in traffic demand across special periods, such as holidays.

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王沁宇，于维杰，王炜，华雪东

面向城际交通系统：空间交互引力模型及确定方法

摘要

当前城市群的发展极大地促进了城际联系，提升了城际交通系统的重要性。然而，由于城市属性的多样性，城际交通往往表现出极度的时空不平衡特征。这给交通管理带来了巨大挑战，同时也揭示了理解城市吸引力（即空间交互引力）对城际交通的必要性。虽然近期研究对相关方面进行了探索，但未能深入了解空间交互引力的时间变化，也未能从多个角度捕捉决定性因素。为填补这一空白，本研究提出了一个测量城市空间交互引力的两阶段框架，并利用大规模的定位服务（LBS）数据集进行了实例分析。具体来说，逆重力模型被用来测量工作日、周末和节假日期间多个城市群和城市集内的空间交互引力。然后，本文结合社会、经济、网络可达性和土地利用等相关特征，建立了空间交互引力的拟合方程。研究结果展示了不同时期的空间交互引力，证实了特征的显著决定效应，具有很高的拟合精度。以上研究及结果为城际交通预测和先发交通管理提供了有力的支持。

关键词

城际交通，空间交互引力模型，逆重力模型，确定方法。