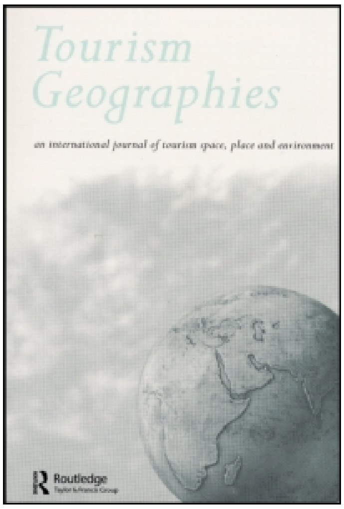

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The Spatial Relationship of Tourist Distribution in Chinese Cities

Yan Zhang[a]; Jian-Hua Xu[bc]; Pei-Jun Zhuang[bd]
[a] College of Historical Culture and Tourism, Guangxi Normal University, Guilin, China [b] College of Resource and Environment Science, East China Normal University, Shanghai, China [c] The Research Center for East-West Cooperation, Shanghai, China [d] Maritime College, Ningbo University, Ningbo, China

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The Spatial Relationship of Tourist Distribution in Chinese Cities

YAN ZHANG[*], JIAN-HUA XU[**‡] & PEI-JUN ZHUANG[**†]
[*]College of Historical Culture and Tourism, Guangxi Normal University, Guilin, China
[**]College of Resource and Environment Science, East China Normal University, Shanghai, China
[†]Maritime College, Ningbo University, Ningbo, China
[‡]The Research Center for East-West Cooperation, Shanghai, China

ABSTRACT *This study investigates the spatial dependence and mechanisms of international and domestic tourist distributions in 299 cities in mainland China through a set of Geographical Information Systems (GIS)-based spatial statistical tools. The results show that during the period of investigation (1999–2007), there was a significant degree of neighbouring effect (i.e. positive spatial correlation) in both international and domestic tourist distributions. We have also highlighted that tourism development in a given city is dependent on the developments in neighbouring cities. Specifically, the tourist distribution shows a polarized (core – periphery) spatial pattern, which is strongly connected to the economic development level and tourism resources of the cities. Furthermore, the findings reveal tourist distribution clusters that underscore the importance of geographical focus. Overall, the results imply that policy makers are encouraged to pay attention to patterns of tourist distribution.*

KEY WORDS: Spatial autocorrelation, exploratory spatial data analysis (ESDA), tourist distribution, China, GIS

Introduction

Tourist activity is an indicator of tourism performance. Along this line, many empirical studies have focused on the categories of and differences among tourists. In most instances, tourists are categorized according to trip characteristics (e.g. tourist motivations, number of visits to the city and length of stay in the city). Further, theoretical analyses in previous studies were based primarily on time-series data, using standard parametric and non-parametric statistical tools (e.g. Van den Berg *et al*. 1995; Page 1996; Mazanec 1997; Judd & Fainstein 1999; Ashworth & Tunbridge 2000; Law 2002; Page & Hall 2003). Meanwhile, only a few made use of spatial data and spatial parametric tools. Cooper (1981) investigated the spatial behaviour

Correspondence Address: Yan Zhang, College of Historical Culture and Tourism, Guangxi Normal University, No. 15 Yucai Road, Guilin, 541004 China. Fax: +86 773 2812961; Tel.: +86 773 5815676; Email: jasminyan@126.com

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of tourists in the Channel Islands of Jersey and identified differences in the spatial patterns of tourism based on two variables: stage in life cycle and socio-economic status. Chadefaud (1981) investigated the time – space patterns of pilgrimages and tourist activities in Lourdes and presented detailed maps showing the activity spaces of organized groups and individual tourists. He found that the activities of organized groups are more concentrated, while those of individuals are more dispersed. Based on Plog's (1987) tourist typology, Debbage (1991) examined the spatial behaviour of tourists in a resort in Bahamas and found that the differences in spatial behaviour of tourists result from personality differences. Montanari and Muscarà (1995) outlined nine typical time – space profiles of tourists travelling to Venice. They found mixed primary purposes behind visits, as well as other trip characteristics, such as length of stay and previous visits to the city. Using the historic city of Leuven in Belgium in a pilot study, Jansen-Verbeke and Lievois (1999) highlighted the theoretical and practical potentials of analysing the spatial patterns of urban tourism.

Spatial data relate via distances and spatial arrangements. They are characterized by spatial dependence and spatial heterogeneity (Anselin 1988). According to Tobler's (1979) First Law of Geography, 'everything is related to everything else, but near things are more related than distant things'. Spatial dependence is usually described by spatial autocorrelation using statistics such as Moran's *I* (Moran 1950). Spatial heterogeneity relates with spatial or regional differentiation, which follows the intrinsic uniqueness of each location (Anselin 1988). Cliff and Ord (1981) defined spatial autocorrelation as the phenomenon of systematic variability in a variable. Accordingly, spatial autocorrelation exists when there is a significant similarity or dissimilarity between the values of variables in all pairs of locations. The importance of making assumptions about the homogeneity or heterogeneity of spatial data was emphasized by Cressie (1993). Spatial heterogeneity can occur in the form of different distributions, means, variances and covariances between subsets. These kinds of data show non-stationarity (Anselin 1988). Typical heterogeneous spatial data contain drifts, that is, the occurrence of trends with either high or low values in one direction (Getis and Ord 1996). Spatial data that are distributed in a pattern and that are placed randomly in different locations exhibit stationarity.

Although spatial autocorrelation was defined decades ago, its application has been limited by statistical constraints and software availability. Current studies with spatial autocorrelation for spatial dependence in global and in local scales focus on spatial econometrics (Anselin 1988; Anselin & Rey 1997; Pace *et al.* 1998; Ping *et al.* 2004; Premo 2004; Dall'erba 2005; Sridharan *et al.* 2007; Cracolici *et al.* 2009; Pouliou & Elliott 2009).

In this study, we used exploratory spatial data analysis (ESDA) based on Geographical Information Systems (GIS) techniques to explore the geographical distribution of tourists in 299 cities in China from 1999 to 2007. The aim is to investigate whether a spatial relationship exists among tourist distribution disparities in these cities. As far as we know, there is currently no report on the application of these statistics to the understanding of the spatial dependence of tourist distribution in cities. Therefore, with this work, tourism planners can hopefully develop suitable tour packages, arrange appropriate schedules and activities, and design regional tourism co-operative policies.

Data were obtained from China InfoBank (http://www.bjinfobank.com). This is an official database linked to the *China Statistical Yearbook*. The variable was derived using the international and domestic tourist numbers of 299 cities in China from 1999 to 2007, and the international tourist numbers include foreign, Hongkongese, Macaoese and Taiwanese travellers. The paper is structured as follows: the next section presents the exploratory spatial data analysis; the subsequent section discusses the empirical findings; and the final section presents the conclusions.

Exploratory Spatial Data Analysis (ESDA)

ESDA is a set of techniques used to describe and visualize spatial distributions, to identify atypical locations or spatial outliers, to discover patterns of spatial associations, clusters or hot spots and to suggest spatial regimes or other forms of spatial heterogeneity (Anselin 1988; 1999; Haining 1990). In this study, a three-step analysis was followed: first, the spatial distribution of international and domestic tourist arrivals in the cities was mapped; secondly, the analysis focused on two aspects of spatial clustering, namely, the overall 'global' spatial clustering and the 'local' patterns of international and domestic tourist distribution.

The global measure of Moran's I is as follows:

$$I = \sum_i \sum_j w_{ij}(x_i - \mu)(x_j - \mu) \Big/ \sum_i (x_i - \mu)^2 \tag{1}$$

where w_{ij} is the row-standardized contiguity matrix, x_i is the risk-scale measure at city i, x_j is the risk-scale measure at city j, and μ is the average level of risk.

The local measure of Moran's I is as follows:

$$I = \frac{(x_i - \mu)}{\sum (x_i - \mu)^2} \sum_j w_{ij}(x_j - \mu) \tag{2}$$

The Moran's I statistic was used as a measure of the overall clustering and was assessed by testing a null hypothesis (i.e. the spatial pattern is random). Rejection of the null hypothesis implies a non-random spatial pattern, which is also termed spatial autocorrelation. In particular, spatial autocorrelation measures the nature and strength of interdependence between data. There is positive spatial autocorrelation when similar values tend to occupy adjacent locations, whereas there is negative autocorrelation when high values tend to be located next to low values. On the other hand, if the spatial arrangement is completely random, then the absence of spatial autocorrelation is implied. Moran's I ranges approximately from $+1$ (for positive spatial autocorrelation) to -1 (negative autocorrelation) and its expected value in the absence of autocorrelation is approximately zero. According to Anselin (1995), neighbour relationships are typically expressed in a row-standardized spatial weights matrix (W), where w_{ij} corresponds to the spatial weights assigned to pairs of units (i and j) (i.e. tourist cities). In the present analysis, neighbours were defined using rooks case adjacency, which considers that all tourist cities with common borders are neighbours.

Moran's I is a global test that does not indicate where the clusters are located or what type of spatial autocorrelation is occurring (i.e. whether positive or negative) (Anselin 1995). The local indicator of spatial autocorrelation (LISA) is therefore applied to indicate local spatial associations (Anselin 1995). LISA measures whether the standardized rate of tourist distribution for each city is closer to the rates of its neighbours or to the national average. To test for significance, a Monte Carlo permutation approach was used. This permutation approach assumes that the data are equally likely to be observed in any location. The observed values were randomly shuffled over all locations and LISA was re-calculated for each permutation. The significance of LISA was then determined by generating a reference distribution using 999 random permutations. Finally, the LISA significance map, incorporating information about the significance of the local spatial patterns, was created. In particular, the map resulted in a spatial typology consisting of five categories of tourism cities: (i) 'high – high' indicates city clusters with high tourist arrivals (positive spatial autocorrelation); (ii) 'low – high' indicates cities with low tourist arrivals that are adjacent to cities with high tourist arrivals (negative spatial autocorrelation); (iii) 'low – low' indicates city clusters with low tourist arrivals (positive spatial autocorrelation); (iv) 'high – low' indicates cities with high tourist arrivals that are adjacent to cities with low tourist arrivals (negative spatial autocorrelation); and (v) 'not significant' indicates cities with no spatial autocorrelation. Analyses were conducted using GeoDA (Anselin 2003) and ArcGIS (ESRI 2006).

Results

Mapping the Distributions

Figure 1 is a choropleth map showing the distribution of international and domestic tourist arrivals in 2007 relative to the national average. A clear core – periphery pattern appears on the map, with the core (darker colour) composed of the cities with the highest numbers of tourist arrivals. The map shows that, in 2007, peripheral cities had the lowest numbers of tourist arrivals. On international tourist arrivals in 2007, the map presents five different categories. The first includes the vast majority of cities in the western area, with tourist arrivals lower than the national average. The other four categories include tourist arrival numbers (1) below the average but lower

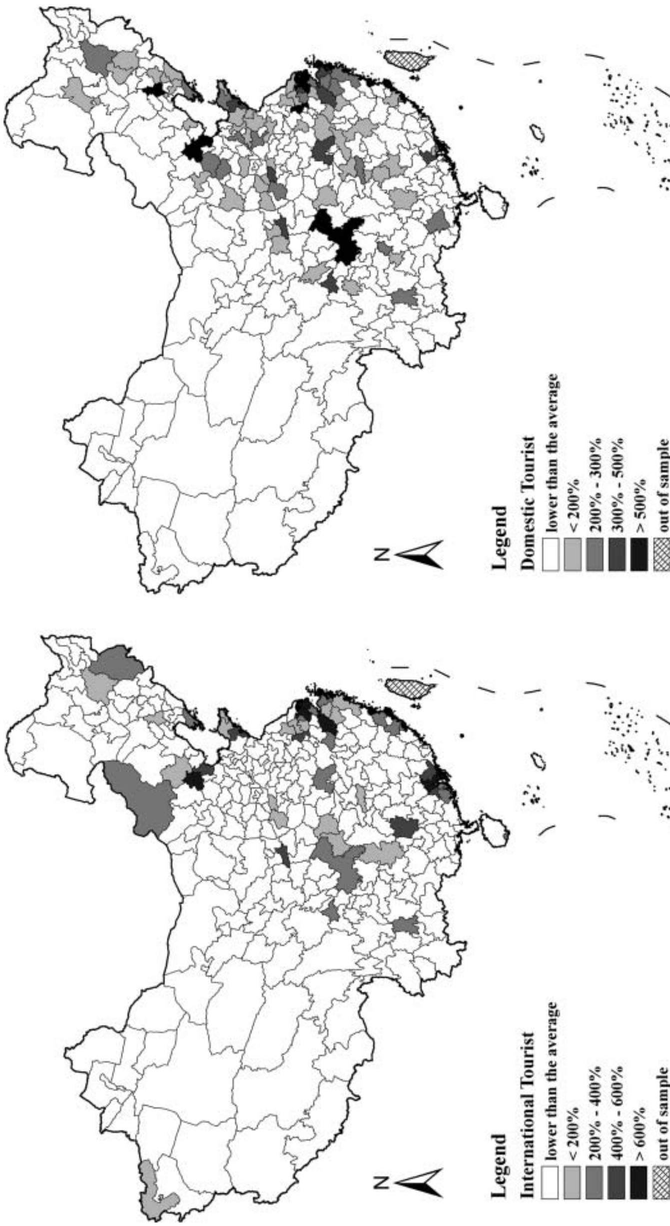

Figure 1. Choropleth map of international and domestic tourist distributions relative to the 2007 national average.

than 200 percent, (2) higher than the average at 200–400 percent, (3) higher than the average at 400–600 percent and (4) much greater than the average at >600 percent. The core – periphery pattern is still observed in the distribution of domestic tourists, showing almost the same distribution pattern in the five different categories.

In 2007, the five core cities in China that enjoyed the highest number of international tourist arrivals were Shenzhen, Shanghai, Guangzhou, Beijing and Zhuhai (Figure 2). Based on the total inbound arrivals, these cities accounted for 40 percent of the total arrivals. In domestic tourism, the five core cities were Beijing, Shanghai, Chongqing, Tianjin and Shenyang. They collectively accounted for 27 percent of the total domestic tourist arrivals. These cities are located in economically developed areas of mainland China. The uneven growth in tourism and its potential to exacerbate regional inequalities in China have been noted by a number of researchers, including Zhang (2001) and Wen and Tisdell (1997).

Moran's I

Table 1 shows the value of Moran's I for international and domestic tourist distributions. Moran's I statistics were positive and significant (p-value $= 0.001$) in both distributions. Hence, high (low) value cities have a propensity to be clustered close to other high (low) value cities. During the period of study (1999–2007), we found a general trend of increasing spatial autocorrelation in both distributions. Two possible explanations may account for this. First, with time, differences in the tourist arrivals in cities belonging to the same cluster are decreasing. Second, the trend might have resulted from the emergence of newly formed clusters. However, Moran's I is similar (but not equal) to a correlation coefficient; hence, we could say that the distributions showed different intensities of spatial association. The intensity was higher in domestic tourist distribution than in international tourist distribution. The high intensity of the global association index (Moran's I) indicates a tendency toward the geographical clustering of similar cities with high (or low) tourist arrivals. Conversely, the low positive value of Moran's I with regard to international tourist distribution could indicate a non-geographical clustering of similar cities; that is, the low value of Moran's I indicates the lack of similarity among cities with respect to international tourist distribution.

Table 1. Moran's I value for the spatial autocorrelation of international and domestic tourist distributions (p-value in parentheses)

	1999	2000	2001	2002	2003	2004	2005	2006	2007
International tourists	0.1409 (0.001)	0.1166 (0.001)	0.1443 (0.001)	0.1475 (0.001)	0.1688 (0.001)	0.1653 (0.001)	0.1835 (0.001)	0.2007 (0.001)	0.2193 (0.001)
Domestic tourists	0.2447 (0.001)	0.2487 (0.001)	0.2592 (0.001)	0.2737 (0.001)	0.1578 (0.001)	0.2687 (0.001)	0.2736 (0.001)	0.3020 (0.001)	0.3258 (0.001)

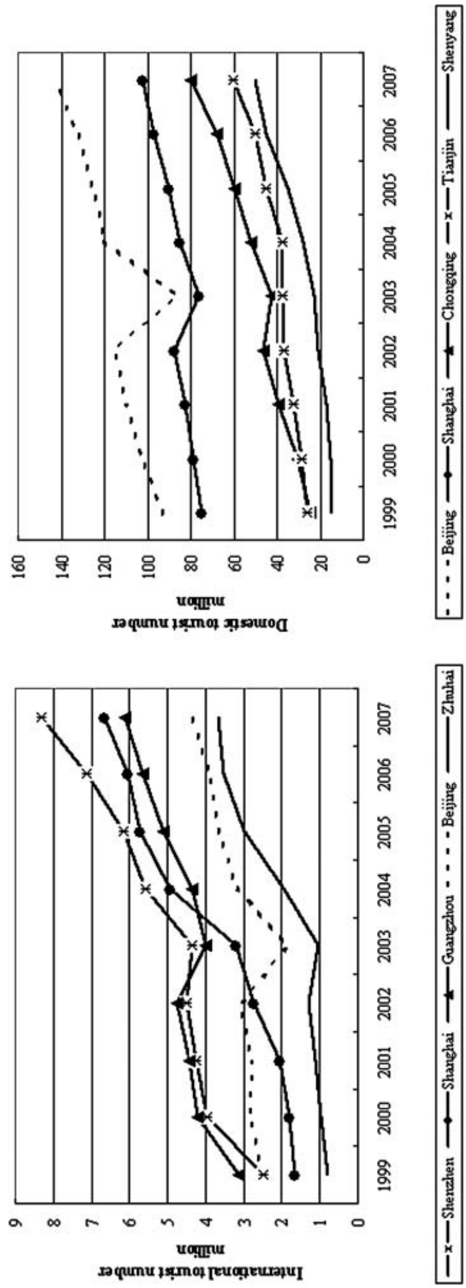

Figure 2. The five core tourism cities in China 1999–2007.

Local Indicator of Spatial Association (LISA)

Moran's I statistic is a global statistic that does not allow an investigation of the structure of each variable's spatial autocorrelation. In addition, it does not enable us to answer certain questions, such as the following: which cities contribute more to the global spatial autocorrelation? Are there local spatial clusters of high or low values? Do variables have the same or similar spatial heterogeneity? Therefore, in order to have a more extensive investigation on the spatial distribution of international and domestic variables, LISA was used.

Table 2 shows that tourism cities are located in a particular Moran scatterplot quadrant. The table reveals significant and greater spatial associations in both international and domestic tourist distributions (HH or LL). The association in most cities is noted to be not significant. Only 19 percent of the international tourist variable and 22 percent of the domestic tourist variable are significant at the 5 percent Bonferroni pseudo-significance level, which can be explained by the fact that regional inequities and uneven growth in tourism have increased the most during this period.

With respect to the international tourist distribution in 2007 (see Table 2), a positive spatial association characterized most tourism cities: 76 percent of the cities had positive associations or similar values (29% in quadrant HH and 47% in quadrant LL). In domestic tourist distribution, the percentage of cities with positive associations was 64 percent (23% in quadrant HH and 41% in quadrant LL). These results imply that although low-value clusters dominate the proportion, the extension of HH cities strengthened the global spatial autocorrelation. This was due to newly formed clusters. This further shows that the vicinity of HH cities caught up with the traditional core cities.

Table 2. Significant LISA at 5 percent pseudo-significance for international and domestic tourist distributions

	1999	2000	2001	2002	2003	2004	2005	2006	2007
Spatial typology for international tourist arrivals									
Not significant	249	249	249	248	249	245	244	244	241
High – high	16	16	16	16	16	17	17	17	17
Low – low	24	24	24	25	24	25	26	26	27
Low – high	5	5	5	5	5	5	5	5	5
High – low	5	5	5	5	5	7	7	7	9
Spatial typology for domestic tourist arrivals									
Not significant	249	248	248	244	243	241	238	237	233
High – high	11	11	11	12	12	13	13	14	15
Low – low	24	24	24	25	25	25	26	26	27
Low – high	4	4	5	5	4	5	6	6	7
High – low	11	12	12	13	15	15	16	16	17

Figures 3 and 4 show the LISA statistics on the Moran significance maps at 5 percent pseudo-significance level. In Figure 3, we observe a slight change from 1999 to 2007 in international tourist distributions. The significant HH-type correlation applies to 17 cities: eight in the Pearl River Delta region (Guangzhou, Zhuhai, Dongguan, Zhongshan, Huizhou, Foshan, Shenzhen and Xiamen), six in the Yangtze Delta region (Shanghai, Hangzhou, Suzhou, Wuxi, Jiaxing and Nanjing), while the other three are Beijing, Tianjin and Qingdao. The spatial association of the LL type includes 27 cities, which are spread from the central to the western region. Nine cities show significant negative spatial autocorrelation, displaying higher dynamism than their neighbours (HL). These are Wuhan, Xi'an, Nanchang, Chengdu, Chongqing, Guilin, Kunming, Sanya and Lhasa. Five cities (Zhoushan, Baoshan, Qingyuan, Shaoguan and Chaozhou) belonging to the LH type failed to develop, despite the dynamism of their neighbouring regions.

With regard to domestic tourist distribution, Figure 4 presents a spatial structure very similar to that of the international tourist distribution. Fifteen cities, the same as those for the international tourist distribution, are characterized as HH type when considering domestic tourist distribution. LL clusters include 27 cities. They are mostly located in the western region of China. There are 17 cities characterized by a high value of tourist arrivals, although they are surrounded by cities with low values (HL). Of the 17 cities, eight are the same as those in the international tourist variable, except Sanya. The other nine cities are Changsha, Nanning, Guiyang, Zhengzhou, Luoyang, Dalian, Harbin, Huzhou and Shenyang. In contrast, seven cities belong to the LH quadrant with a low value of tourist arrivals surrounded by cities with a higher value of tourist arrivals. They are Zhoushan, Xuanzhou and Liaoyang, among others.

All these results lead to the conclusion that there are similarities in the spatial structure of international and domestic tourist distributions. The first corresponds to the HH scheme and includes mainly the south-east 'gateway' regions. The second corresponds to the LL scheme and includes mainly the western regions. Both regimes have a positive spatial association. The third and fourth regimes, respectively, correspond to the LH and HL schemes. Both exhibit atypical negative spatial associations and they primarily include the central and southern regions. Due to the pace of reform and the fact that growth has been uneven across regions in China, the south-east coastal regions grew more rapidly than the mountainous areas in the hinterlands. Therefore, the south-east coastal area benefits from a more favourable economic environment for tourism development as compared to the western region. This result is important for tourism implementation of regional and cohesion policies, as the south-east coastal area will probably benefit more from spillover effects coming from the richer south-east coastal regions. In contrast to the south-east coastal regions, the western regions will most likely have less benefit or will not benefit at all from these spillovers.

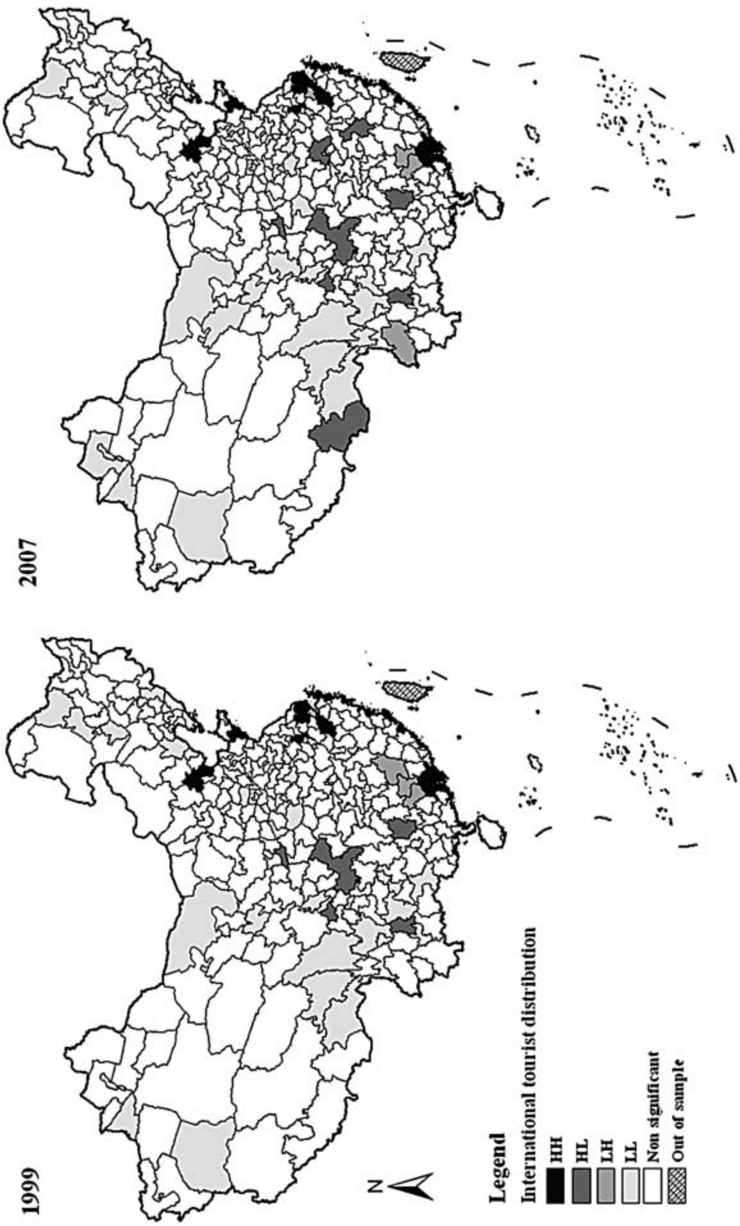

Figure 3. Moran significance maps for international tourist distribution, 1999 and 2007 (5% pseudo-significance level).

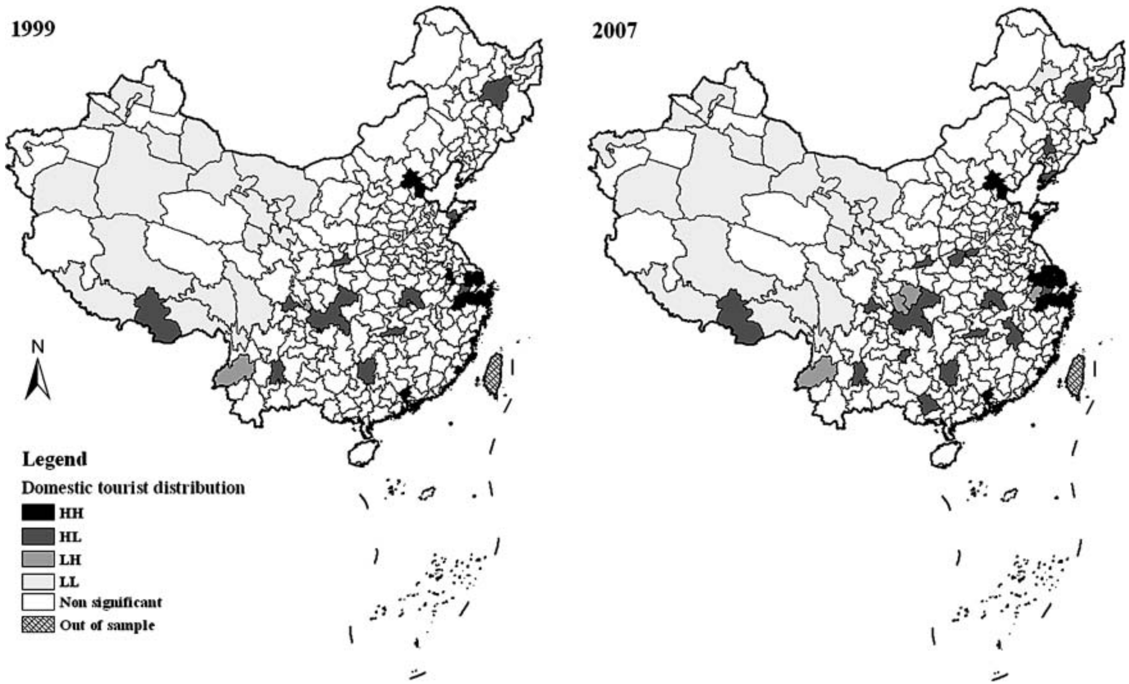

Figure 4. Moran significance maps for domestic tourist distribution, 1999 and 2007 (5% pseudo-significance level).

Hot spots

The most important function of LISA statistics is the detection of significant local spatial clusters (also called 'hot spots'). It is also significant for the diagnosis of local instability, significant outliers and spatial regimes. From the empirical result, we learn that the hot spots of tourist distribution are clustered mainly in Beijing, Tianjin, Shanghai, Hangzhou, Suzhou, Guangzhou, Chongqing, Kunming, Guilin and so on (Figure 5). These are the cities with high levels of economic development or rich tourism resources. Different tourism resources and policies in regional transition and development create diverse tourism market conditions that result in uneven development rates. The high economic inequality can be attributed mainly to the growing inland-coastal tourism disparity in China. Hence, regional economic development level and tourism resources have often been the driving forces behind spatial clusters in tourism (Zhang *et al.* 2005). Therefore, the geographical distribution of tourists' spatial cluster is non-uniform, indicating three tiers according to concentration density, with a declining density found from east to west.

To lessen the unequal distribution of international and domestic tourists in China, an innovative way of developing the natural advantages and factor endowment of the cities must be found. As shown in Figure 5, the hot spots are all HH and HL clusters located in the eastern coastal and central regions. Similar to a core – periphery spatial structure, we consider that regional agglomeration effects may involve core cities, and their interactions with peripheral cities facilitate and promote tourism products, hence achieving sustainable growth in regional tourism. Therefore, a possible way to effectively narrow the gap between core tourism cities and the others is the 'Hot spots (clusters) focus' approach. By linking these hot-spot tourism cities (core) to their peripheral cities, tourism co-operative alliances can be constructed. The formation of an effective link between the core and its peripheral cities would further enhance regional competitiveness and facilitate the better use of existing tourism resources.

In Figure 5, we also found an east – west division, wherein LL and LH clusters agglomerated in the western region. The natural advantages and tourism attractions in this region cannot be matched elsewhere in China. Among others, the area has the oasis city of Urumqi in Xinjiang, the migratory birds on Qinghai Lake, the only known remaining giant panda habitat, the Jiuzhaigou – Huanglong world heritage in Sichuan, 'mysterious Tibet' and the historic Silk Road. Due to the low level of economic development, infrastructure construction and lack of promotional activities, access to and from the coast, as well as high travelling expenses are highlighted as reasons impeding tourism development (Jackson 2006). These unfavourable factors must be overcome. In this regard, several strategies have been adopted. For instance, Lhasa in Tibet and Kunming in Yunnan promote themselves as the 'sparkling cities' and have jointly developed a tourist route connecting them. Another means of contending with the challenges is by devising a creative promotion of a more substantial product. The 'West Development' initiatives have also been established, which intend to foster

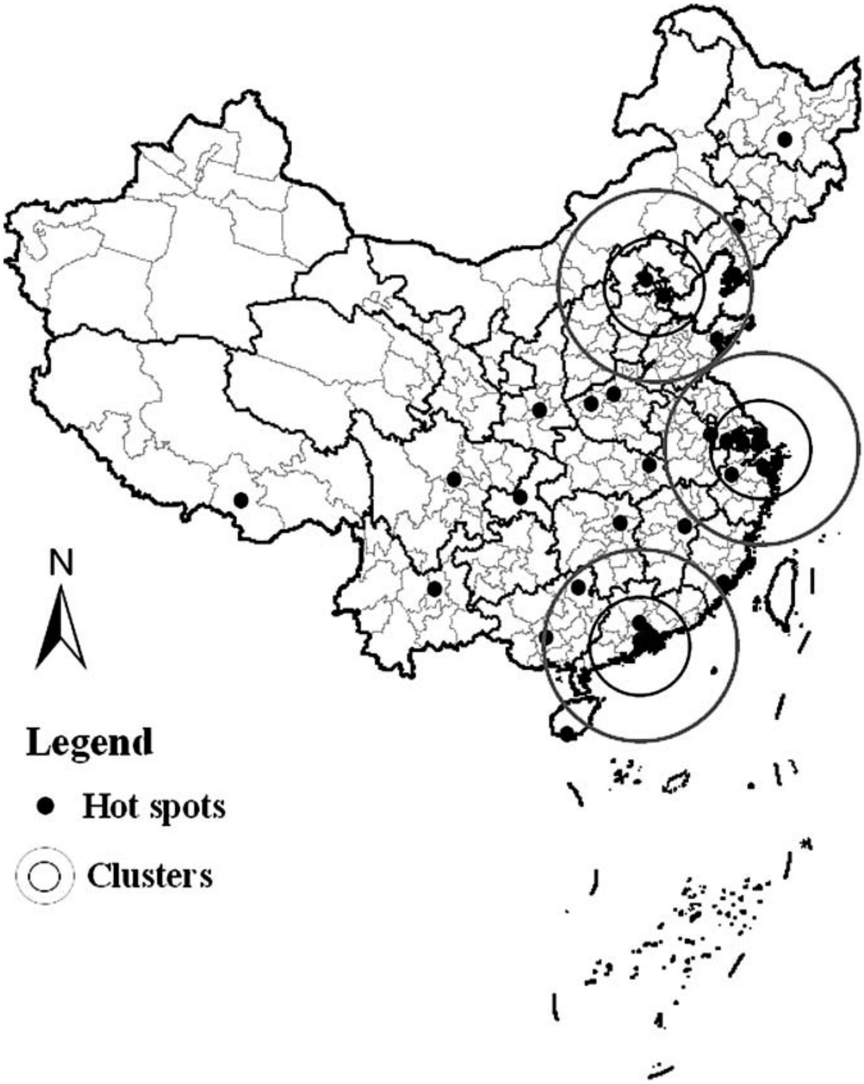

Figure 5. The hot spots and clusters of tourist distribution in mainland China. The hot spots of tourist distribution from north to south are Haerbin, Shenyang, Dalian, Beijing, Tianjing, Qingdao, Zhengzhou, Luoyang, Sian, Shanghai, Suzhou, Wuxi, Hangzhou, Nanjing, Changzhou, Ningbo, Wuhan, Chengdu, Chongqing, Changsha, Nanchang, Xiamen, Guangzhou, Dongguan, Shenzhen, Zhongshan, Guilin, Nanning, Kunming and Lhasa.

regional development via tourism in early stages. All these steps are expected to promote more opportunities in the tourism sector.

Conclusion

This study used recent developments in GIS-based ESDA to analyse the distribution disparities of tourist arrivals in China. It highlighted the importance of spatial effects in tourist activity studies. We demonstrated that ESDA and GIS reveal spatial characteristics and present changing spatial patterns and dynamics in tourist distributions. The spatial distribution disparities of tourist arrivals from 1999 to 2007 were studied using two different variables – international tourist arrivals and domestic tourist arrivals in 299 cities of mainland China.

The analysis indicated a significant positive global spatial autocorrelation, which was dominated by low value clusters with expanding high value clusters. We highlighted that the tourism development level of a given city is dependent on the development of its neighbours, and high (low) value cities tend to be clustered close to other high (low) value cities. Further analysis using Moran's scatterplot revealed the presence of a positive local spatial autocorrelation for each of the previous variables. When LISA was performed, the results confirm the significant presence and persistence over time of local spatial autocorrelations in the form of two distinct spatial clusters of high and low values of tourist distribution. This form of spatial heterogeneity reflected a core – periphery pattern because tourism development non-equilibrium was persistent among the cities. The polarization of tourist distribution is believed to reflect the clustering of activities, and the formation of an effective link between the core and its periphery cities would further enhance regional competitiveness and facilitate the better use of existing tourism resources.

In conclusion, the polarized spatial pattern of tourist distribution implies that the effect of tourism on one city spreads over to neighbouring cities. Policy makers, therefore, have to focus more on the behaviour of a city's tourist distribution because this will benefit neighbouring cities. This finding complements current literature on China's urban tourist development and has important implications for regional tourism co-operation.

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Notes on Contributors

Yan Zhang is a lecturer in the Historical Culture and Tourism College at Guangxi Normal University, and was a PhD student in the College of Resource and Environment Science, East China Normal University. Her research interests include the spatial economics of tourism, ecotourism and geocomputation.

Jian-hua Xu is a Professor in the Resource and Environment Science College at East China Normal University. His research interests include geocomputation, GIS & remote sensing applications, and ecological economics.

Pei-jun Zhuang is an Associate Professor in the Maritime College at Ningbo University, and is a PhD student in the College of Resource and Environment Science, East China Normal University. Her research interests include the economics of tourism, logistics and regional management.