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THE IMPACT MECHANISM OF HUMAN ACTIVITIES OVER CLIMATE SUITABILITY BASED ON SOCIAL NETWORK DATA: EVIDENCE FROM CHINA

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Highlights

- Entertainment and tourism related activities had significant positive impacts on regional climate condition, while that of tourism related activities is negative.
- Human activities showed greater impact on the climate suitability in economically underdeveloped regions and completely opposite impacts in region regions with different topographic conditions.
- The positive impact of entertainment, tourism related activities and the spatial heterogeneity in impact mechanisms could be explained by the special environmental optimization effect of the urban spaces and the urban planning strategies in China, respectively.

Abstract. The impact mechanism of human activities on climate suitability is critical for understanding the human-environment nexus. In this study, social network data from Sina Weibo Platform was collected to quantitatively examined the relationship between the seven major types of human activities and climate suitability. The results indicated that the impacts of entertainment, tourism and daily life related human activities on climate suitability are significant (p-value < 0.05). With one-unit (one check-in record/km^2) increase of entertainment and tourism related human activities, the coverage rate of climate suitable zone and the length of climate suitable period increase by 0.003% and 0.026 months, respectively. In contrast, one-unit of increase of daily life activities made the Theil entropy index of climate inequity and the length of climate suitable period increase 0.00035 units and shorten 0.014 months, respectively. Moreover, the impact mechanism of human activities on climate suitability showed a significant spatial heterogeneity within regions at different economic level or topographical conditions, which could be explained by the discrepancy of environmental policies, urban form and urban ventilation channel design strategies in China. This work exhibited a further step to new possibilities in clarifying the climate effect of human activities using open-sourced social network data.

Keywords: human activities, check-in data, climate suitability, spatial regression models.

Introduction

Rapid urbanization had been recognized as one of the main driving forces of the climate change and ecological environment deterioration in Asia-Pacific regions, represented by China (Gu et al., 2011; Wang et al., 2019). Therefore, clarifying the impact mechanism of urbanization over climate condition is critical for the understanding on relationship between human and environment.

Urban land use cover change, anthropogenic aerosol emission and anthropogenic heat emission are identified as the three main pathways by which the urbanization affect regional climate conditions (Miller & Hutchins, 2017). Specifically, land use cover change and anthropogenic aerosol emissions affect the climate environment by changing the physical properties of the earth's surface (Li et al., 2007) and the thermal radiation absorption capacity of the atmospheric system (Zheng et al., 2012), respectively. However, the majority of research on the impact of anthropogenic heat emission focused on estimating the climate effects of anthropogenic industrial energy consumption,

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vehicle fuel combustion and human metabolism. It has remained a significant challenge to dissect the impact mechanism due to the complexity and unobservability in quantifying human activity patterns (Feng et al., 2014).

With the advent of the big data age, the emergence of large-scale social network data provides the possibility for researchers to accurately track human activities (Yan et al., 2019). Therefore, this study conducted a case study to explore the relationship between the activity patterns of Sina Weibo users and climate conditions in 31 provinces (or regions) of China. Specifically, we hope to utilize Sina Weibo data as a medium to explain the two follow research questions: (1) How different types of human activities affect regional climate? (2) What are the implicit impact mechanisms of human activities on climate?

The rest of this paper are organized as follows. In the methodology section, the primary data, models and algorithms used in this study were introduced. In the results section, the quantitative results on the relationship between human activities and urban climate was presented and discussed. In the conclusions section, we summarized the main findings of this work and pointed out the innovation, defects, future development direction of this study.

1. Literature review

1.1. Anthropogenic heat emission and climate condition

The diversity of spaces carrying human activities, the complex heat exchanges accompany with human activities and the difficulties in obtaining data records of human activities in large-scale regions led to a significant challenge in estimating the climate effect of anthropogenic heat emission (Feng et al., 2014). At present, the relevant research related to the relationship between anthropogenic heat emission and climate condition were mainly focused on estimating the heat emission and temperature variation caused by human activities in particular areas with certain functions. For example, climatologists had estimated the heat emission of human activities in urban centers and residential areas in Tokyo (Ichinose et al., 1999), Europe (Offerle et al., 2005) and Singapore (Quah & Roth, 2012) respectively and pointed that the heat emission of each person in the urban central business district was about 113–400 W/m^2, while that of residential areas was only 13–17 W/m^2, and the additional anthropogenic heat release per 2 W/m^2 could lead to an increase the surface air temperature by 0.15 °C (Block et al., 2004). Similarly, Feng et al. (2014) analyzed the high-resolution remote sensing data and found that the anthropogenic heat release caused a 0.89 °C temperature rise and summer precipitation change in the Yangtze River Delta, China. However, the estimating results of these studies focused on the difference within anthropogenic heat emissions emerged in various urban regions, so there remains poorly understood on the heat emissions from the perspective of the diversity of human activity patterns.

1.2. Assessment methods of climate condition

Climate assessment refers to the analysis of basic meteorological elements and major disastrous weather characteristics in specific regions. Accurate assessment of climate condition is of great significance to understand the social and economic benefits of climate as a natural resource. Climate suitability was one kind of climate condition evaluation index and was designed to conduct quantitative evaluation models of climate condition by summarizing the relationship between basic meteorological elements and human body feelings (Yan et al., 2013). The models related to the evaluation of climate suitability were mainly divided into two categories. On the one hand, the experience-based models had dominated climate suitability evaluation in the early stage. Since the first experience-based model of Effective Temperature Index (ET) was put forward in 1923 (Houghten, 1923), researchers had put forward models for different climate conditions. Among them, the models designed for thermal environment are the Wet Bulb Globe Temperature (WBGT), Discomfort Index (DI) and Temperature Humidity Index (THI) (Minard et al., 1957; Thom, 1959). And the Wind Cold Index (WCI) is mainly for climate evaluation in cold environment (Siple & Passel, 1945). Generally speaking, the experience-based models are statistical models based on the subjective feelings or physiological reactions of human beings. On the other hand, with the development of biometeorology and computer technology, the research of mechanism model based on human body heat balance had attracted extensive attention. According to the voting results of 1396 subjects in the United States and Denmark, Fanger proposed a widely used thermal comfort evaluation index of Predicted Mean Vote (PMV) by regression analysis (Fanger, 1970). The Physiological Equivalent Temperature (PET) model developed from the Munich Energy Balance Model for Individuals (MEBMI) was another widely used climate suitability mechanism model, which comprehensively considered the influence of main meteorological parameters, activities, clothing and individual parameters on comfort (Höppe, 1999). In the 21st century, under the initiative of WMO's climatology Committee, the European science and technology cooperation program 730 established a Universal Thermal Climate Index (UTCI) based on multi node model by integrating the most advanced professional and technical knowledge in fields of physiology, medicine, mathematics, meteorology and computer science (Jendritzky et al., 2012). In summary, climate suitability evaluation model had gone through the era of experience-based model based on statistical results and mechanism model based on human body heat balance. However, the experience-based model had few input parameters, simple structure and easy data acquisition, which still showed a certain application prospect at present and in the future.

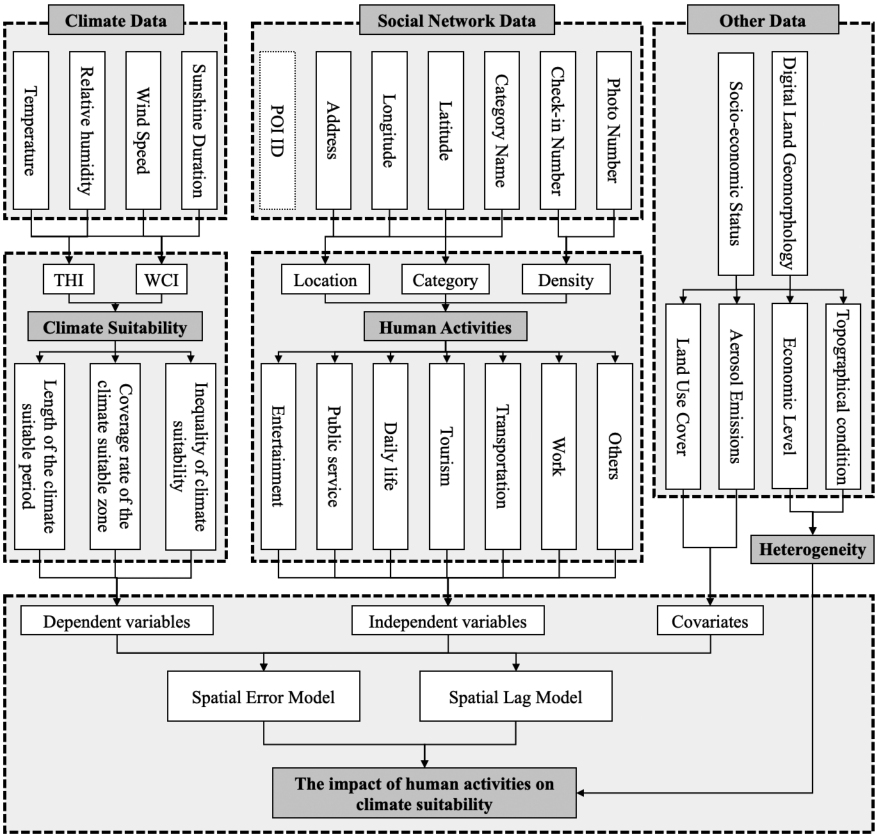


Figure 1. Technical roadmap of the impact mechanism of human activities over climate suitability

2. Methodology

The technical roadmap of this study is shown in Figure 1.

In this study, the impact mechanisms of different human activities on the climatic environment were explored by constructing spatial regression models. Firstly, we collected the climate data from the study area and utilized THI and WCI indices to quantify the climate conditions of 31 provinces or regions in China. Then, we classified Sina Weibo users' check-in data from the study area in 7 subgroups according to the activity type and calculated the intensity of 7 types of human activities in 31 provinces or regions in China. Finally, we took climate conditions and human activity intensity as dependent variables and independent variables respectively and input them into the spatial regression models together with covariates related to China's geography and socio-economic status to explore the relationship between them.

2.1. Climate suitability assessment

2.1.1. Meteorological data

Meteorological data used in this work was mainly collected from the National Meteorological Data Platform of China (http://data.cma.cn/site/index.html). The data included monthly temperature, wind speed, relative humidity and sunshine duration of China recorded by 2170 meteorological stations in 2014. The details of the data are presented in Table 1.

Table 1. Introduction to meteorological data

Type	Description	Unit
Average Monthly Temperature (t)	Monthly average temperature at the location of meteorological station	°C
Average Monthly Wind speed (v)	Monthly average wind speed at the height of 10m at the location of meteorological station	m/s
Average Monthly Relative humidity (h)	Monthly average relative humidity at the location of meteorological station	%
Average Monthly Sunshine duration (s)	Monthly average number of hours of sunshine received at the location of meteorological station	Hour

In addition, as this study was dedicated to exploring the impact of human activities on the climate environment in full extent of China, the study area is divided into 10679 grids (resolution: 0.3×0.3 degree), and the climate state of all grids are estimated by the common Kriging interpolation method, which had been widely used in the field of climate data estimation and simulation (Boer et al., 2001). The interpolation algorithm is implemented by R language using R-Studio.

2.1.2. Evaluation indices of climate suitability

In the process of introducing the western mechanism model to evaluate the climate suitability in China, Chinese researchers are still working on forming a universal mechanism model due to the huge differences in Chinese ethnic characteristics, diet structure and basic metabolic level. On the contrary, the experience-based models introduced into China earlier showed better evaluation performance than mechanism models after being revised according to China's geographical, seasonal and ethnic characteristics and even has been transformed into national standards (Tang et al., 2008; Ma et al., 2009, 2011; Kong, 2020). Therefore, referring to the relevant national standard of "GB/T 27963-2011" issued by the National Meteorological Administration of China, this study selected two climate suitability evaluation indices of WCI and THI to quantitatively evaluate the climate suitability of China. The calculation algorithms were presented in Equations (1) and (2) (Tang et al., 2008):

$$THI = 1.8t + 32 - 0.55(1-h)(1.8t-26); \tag{1}$$

$$WCI = -\left(10\sqrt{v} + 10.45 - v\right)(33-t) + 8.55s, \tag{2}$$

where, t represents the monthly average temperature with the unit of °C; h represents the monthly average relative humidity with the unit of %; v represents the monthly average wind speed with the unit of meters per second; s represents the monthly average sunshine duration in hours per day. In addition, the evaluation criteria for climate suitability are presented in Table 2.

Table 2. Evaluation criteria for climate suitability indices THI and WCI (Tang et al., 2008)

THI	WCI	Bodily sensation	Suitability
<40	<–1200	Extremely cold	Uncomfortable
40~45	–1200 ~ –1000	Cold	Uncomfortable
45~55	–1000 ~ –800	Cold	Uncomfortable
55~60	–800 ~ –600	Cool	Comfortable
60~65	–600 ~ –300	Cool	Comfortable
65~70	–300 ~ –200	Warm	Comfortable
70~75	–200 ~ –50	Warm	Comfortable
75~80	–50~80	Hot	Uncomfortable
>80	>80	Extremely hot	Uncomfortable

Of these, THI mainly takes the influence of temperature and relative humidity on human comfort into account, while WCI is more sensitive to wind speed, temperature and sunshine duration. Therefore, combined with "GB/T 27963-2011" and Tang's work (Tang et al., 2008), the month with average THI quantification result of [55, 75] and WCI quantification result of [–800, –50] is defined as the climate condition of this month reaches suitable level. Similarly, referring to the method in chapter 3.1.1, this study calculated the monthly THI and WCI indices of 10679 grids from January to December in 2014. According to the calculation results, the months when the climate of all grids reached the comfortable level in 2014 were counted, which was defined as the climate suitable period. Furthermore, this study continues to define the area with climate suitable period length greater than or equal to 5 months as the climate suitable zone (Tang et al., 2008). Finally, the calculation method of climate suitable period and climate suitable area for each province in China are presented in Equations (3) and (4):

$$PER = \frac{\sum_{n=1}^{k} l_i^k}{n_i}; \tag{3}$$

$$ZONE = \frac{s_i}{n_i}, \tag{4}$$

where, i represents the province number; k represents the gird number; PER represents the length of climate suitable period in province i; $ZONE$ represents the coverage rate of climate suitable zone in province i; n_i represents the total number of grids in province i; l_i^k represents the number of months in 2014 when the climate of grid k in province i reached comfortable level; s_i represents the number of grids with climate suitable period longer than 5 months in province i.

In addition to the periods and zones with suitable climate, whether the urban residents in the region could enjoy the comfortable climate environment fairly is also the key to evaluate the climate suitability. Therefore, this study also introduces Theil entropy index to measure the distribution of regional climate (Cowell, 2000). The Theil entropy index was originally designed to measure income inequality and social poverty, which was widely used in the field of economics and sociology. In recent years, the Theil index has been used by researchers in the field of environment and climate as the main tool to explore regional environmental equity and justice and has achieved good results (Azimi et al., 2019). The equation of the Theil entropy index used in this study is presented in Equation (5), and the calculation of the index is realized by R language.

$$INEQ = \frac{1}{n}\sum_{n=1}^{n} \ln\left(\frac{\mu}{x_i}\right), \tag{5}$$

where, $INEQ$ represents the Theil entropy index (The calculation result is a rational number between 0 and 1. The closer the calculation result is to 0, the more uniform the feature distribution); n represents the total number of grids in the particular province; μ represents the mean value of the length of climate suitable period of all grids in the particular province; x_i represents the length of climate suitable period at grid i.

2.2. Quantification of human activities

The check-in records data of Sina Weibo, which was seen as the Chinese answer to Twitter, was introduced as a medium to reflect the type and intensity of human activities (Zhen & Wei, 2008). At present, this kind of data has been widely used in the field of urban research to explore urban flow, urban dynamic structure and urban land use identification (Zheng et al., 2019). Specifically, we collected the check-in data generated in 2014[1] in the form of: *POI ID, Address, Longitude, Latitude, Category Name, Check-in Number, Photo Number*. Among them, the *Category Name* parameter records the type of activities the user is engaged in when completing the check-in behavior, and the *Check-in Number* parameter records the frequency of the check-in activities. In addition, the API of Sina Weibo divides all the check-in activities into more than 200 categories by default. Among them, the places and patterns of some parts human activities are similar. Therefore, in order to accurately grasp the relationship between the overall characteristics of human activity patterns and climate suitability, this study, divided over 200 types human activities into 7 categories (Table 3) according to the general patterns of human activities and the Sina Weibo data processing methods proposed in previous works (Yan et al., 2019).

Table 3. Classification of check-in points (Yan et al., 2019)

Activity type	Original POI label
Entertainment	Mall, Restaurant, Gym, Bar, Museum, Gallery, etc.
Public service	Municipal government, Police station, etc.
Daily life	Community, Apartment, Block, etc.
Tourism	Hotels, Temples, Scenic spots, Landmark buildings, etc.
Transportation	Railway station, Bus station, Subway station, Port, etc.
Work	Factory, Company, Office building, etc.
Others	Religious organizations, Construction sites, etc.

Specifically, we calculated the density of the seven main types of check-in records in 31 provinces of China (due to the lack of data, Hong Kong, Macau and Taiwan are not within the scope of the study) to represent the intensity of different types of human activities. The spatial distribution characteristics are shown in the figure below, and the visualization is completed with the help of QGIS (Figure 2).

2.3. Construction of regression models

Since climate elements are spatially continuous variables, this study explores the impact of human activities on climate comfort by constructing a spatial regression model. Specifically, this section will elaborate on how we select suitable variables and regression models.

2.3.1. Variable selection

Specifically, the length of climate suitable period (PER), the coverage rate of climate suitable zone (ZONE) and climate inequality (INEQ) were set as dependent variables and the intensity of seven types of human activities (ENT, PUB, DAI, TOU, TRA, WOR, OTH) were set as independent variables. In addition, in order to ensure that the regression models built in this study can accurately reflect the regression relationship between independent and dependent variables, indicators reflecting urban land use change (PA, GR, CL) and anthropogenic aerosol emission (PM, SO, NO) level[2] are introduced as tool variables. The basic information for all variables selected in the final study is shown in the Table 4.

In addition, considering that China has a vast territory and spans multiple terrain regions, regression models on a global scale might not accurately reflect the relationship between human activities and the climate environment. Therefore, during the process of model building, in order to eliminate the influence of climatic zone and economic level difference on the regression results, we also divided China's provinces into four categories: mountainous region, flatlands region, economically developed region and economically underdeveloped region, and explored the discrepancy of human activities' impact on climate suitability in different part of China. The regional division referred to the GDP level, landform category and land-sea position of each province (i.e., the median value of variable GDP and TOP). The details of relevant data are shown in the Table 4.

2.3.2. Model selection

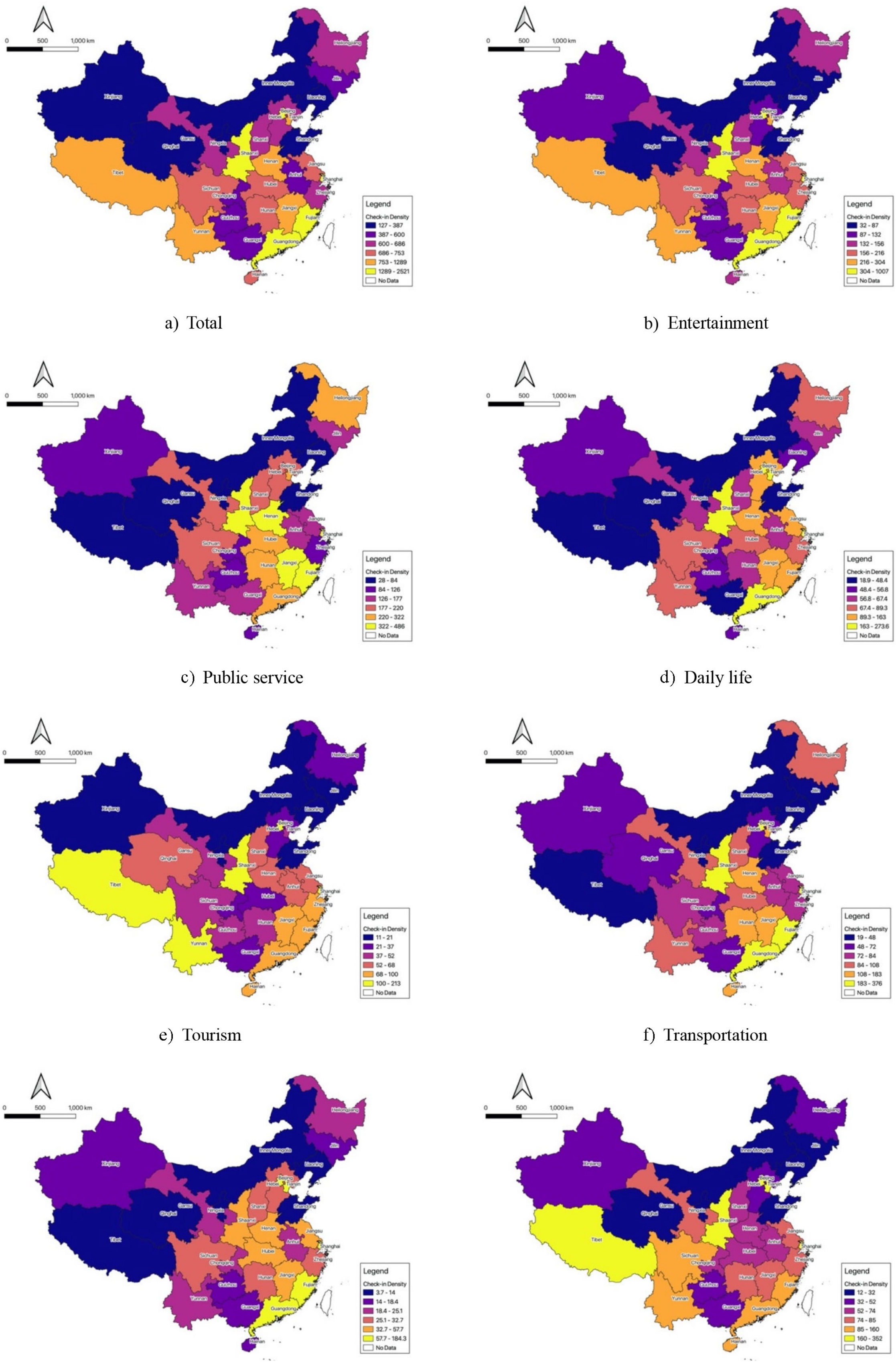
In order to accurately reveal the relationship between various human activities and climate suitability and sort out the impact mechanism quantitatively, we need to work further with appropriate econometric models. When the variables are spatial variables and show significant aggregation or discrete distribution patterns, the estimation results of spatial regression models are significantly better than those of OLS model (Anselin, 2009). Therefore, due to the aggregated distribution characteristics of the main climate variables in this study (see chapter 4.1), the spatial autoregressive model (SAR) and spatial error model (SEM) were selected to analyze the mechanism of human activities on climate suitability. The basic calculation equation of these models is presented in Equations (6) and (7):

$$SAR: y = \rho W_y + X\beta + \epsilon,\ \epsilon \in N\left(0, \delta^2\right); \tag{6}$$

$$SEM: y = X\beta + \lambda W_u + \epsilon,\ \epsilon \in N\left(0, \delta^2\right), \tag{7}$$

[1] There are restrictions on the time interval and time period for Sina Weibo API to obtain public data. After 2015, Sina Weibo gradually closed the free access to data. The data used in this study is the most recently available free data set covering the whole are of China.

[2] SO_x and NO_x produced by motor vehicles, power plants, heating and industry had been demonstrated to be the key influencing factors of urban aerosol particles of PM_{10} and $PM_{2.5}$ (Shi & Xu, 2012). Therefore, the variables of PM, SO and NO were selected in this work to reflect the anthropogenic aerosol emission.



a) Total
b) Entertainment
c) Public service
d) Daily life
e) Tourism
f) Transportation
g) Work
h) Others

Figure 2. Spatial distribution of the check-in density of human activity

Table 4. Descriptive statistics of variables used in regression models

Vari-able	Definition	Data sources	Unit	Type of variable	Mean.	Sd.	Min.	Max.
ENT	The density of entertainment related activities	Sina Weibo	Check-in number/ Square kilometer	Independent variable	211.98	182.86	32.28	1006.75
PUB	The density of public service related activities	Sina Weibo	Check-in number/ Square kilometer	Independent variable	194.18	116.93	27.93	485.59
DAI	The density of daily life related activities	Sina Weibo	Check-in number/ Square kilometer	Independent variable	93.55	63.83	18.94	273.64
TOU	The density of tourism related activities	Sina Weibo	Check-in number/ Square kilometer	Independent variable	63.3	47.66	10.51	213.13
TRA	The density of transportation related activities	Sina Weibo	Check-in number/ Square kilometer	Independent variable	114.73	83.52	18.53	376.36
WOR	The density of work related activities	Sina Weibo	Check-in number/ Square kilometer	Independent variable	37.02	37.12	3.73	184.26
OTH	The density of other activities	Sina Weibo	Check-in number/ Square kilometer	Independent variable	88.98	72.23	12.06	352.37
PER	Length of climate suitable period	Meteorological Data Service Center	Month	Dependent variable	5.47	1.12	2.14	8.74
ZONE	Coverage rate of climate suitable zone	Meteorological Data Service Center	%	Dependent variable	0.5	0.33	0	1
INEQ	Theil entropy index of climate suitability	Meteorological Data Service Center	[0,1]	Dependent variable	0.02	0.03	0	0.12
PM	The total mass of industrial and domestic smoke dust emissions	China National Bureau of Statistics	Tons / million people	Instrumental variables	134.13	111.29	22.39	418.4
SO	The total mass of industrial and domestic SO_x emissions	China National Bureau of Statistics	Tons / million people	Instrumental variable	159.25	121.39	16.58	535.32
NO	The total mass of industrial and domestic NO_x emissions	China National Bureau of Statistics	Tons / million people	Instrumental variables	160.51	106.96	63.39	550.35
PA	Area of green park per person	China National Bureau of Statistics	Hectare per person	Instrumental variable	0.47	1.01	0	5.51
GR	The ratio of green coverage area to regional area in the completed area	China National Bureau of Statistics	%	Instrumental variable	39.11	3.68	29.8	48.4
CL	Area of construction land per person	China National Bureau of Statistics	Square kilometers per 10000 people	Instrumental variable	0.32	0.13	0.11	0.69
TOP	The average level of topography and geomorphology in the whole province	China Landform Datasets (1:1000000)	[0,5]	Classification basis	3.02	0.95	1	4.88
GDP	The final result of production activities of all resident units in a certain period	China National Bureau of Statistics	10000 RMB / person	Classification basis	5.29	2.32	2.61	10.69

where, ρ represents the parameter of spatial lag coefficient; β represents the vector of regression coefficient; W represents the spatial weight matrix; W_y represents spatial lag term of dependent variable; W_u represents spatial lag term of error term; ϵ represents the error term. The error term obeys a normal distribution with mathematical expectation of 0 and variance of δ^2, denoted as $N(0,\delta^2)$. In the two models mentioned above, the spatial lag term of dependent variable is considered in SAR model and the lag term of error term is considered in SEM model.

2.4. Moran's I index

The global and local Moran's I indices were introduced to explore the spatial distribution and heterogeneity of climate suitability. The Moran's I indices are presented in Equations (8) and (9).

$$Global\ Moran's\ I = \frac{N}{W}\frac{\sum_{i=1;j=1}^{N} w_{ij}\left(x_i-\overline{x}\right)\left(x_j-\overline{x}\right)}{\sum_i\left(x_i-\overline{x}\right)^2}; \quad (8)$$

$$Local\ Moran's\ I = \frac{x_i-\overline{x}}{S_i^2}\sum_{i=1;j=1}^{N} w_{ij}\left(x_j-\overline{x}\right),\ S_i^2=\frac{W}{N-1}, \quad (9)$$

where N represents the number of spatial units indexed by i and j; x represents the variable of interest; $\overline{x}$ represents the mean value of x; w_{ij} represents the matrix of spatial weights with zeroes on the diagonal; W represents the sum of w_{ij}. By calculating the value of global Moran's I index and its corresponding z-score and p-value, we can evaluate the distribution pattern (Clustering, discrete or random) and significance of spatial data sets (Moran, 1950). Besides, four types of spatial clusters (HH, HL, LH, LL) were detected by local Moran's I (Anselin, 1995). Specifically, HH cluster denotes the area where high values surrounded by nearby high values; HL cluster denotes the area where high values surrounded by nearby low values; LH cluster denotes the area where low values surrounded by nearby high values; LL cluster denotes the area where low values surrounded by nearby low values. The output of Moran's I were presented in Figure 3.

3. Results

3.1. Assessment results of climate suitability

In the part of empirical research, firstly, the three indicators of length of climate suitability period (PER), coverage rate of suitable zone (ZONE) and Theil index of climate inequity (INEQ) reflecting climate suitability of 31 provinces in China throughout 2014 were calculated and visualized (Figure 3).

3.1.1. Climate suitable period

The average length of the climate suitable period where valid data can be collected is about 5.47 months and showed a relatively significant aggregation distribution pattern (Moran's I: z-value = 1.708; 0.05 < p-value < 0.1). From the perspective of overall spatial distribution characteristics, the distribution of the period with suitable climate in China showed the characteristics that relatively long in the southeast coastal area and relatively short in the northwest inland area (Figure 3a). Specifically, the regions with long period with suitable climate were mainly located in the Yun-Gui Plateau (Yunnan: 8.74, Guizhou: 6.85) and the surrounding central plains areas (Henan: 6.25), while the those with short periods were mainly located in the northwest (Qinghai: 2.14, Tibet: 2.87) and northeast (Heilongjiang: 4.50) of China.

Furthermore, from the results of local Moran's I, it can be seen that the high positive z-values of the four provinces of Xinjiang, Qinghai, Guizhou and Guangxi indicated statistically significant spatial outliers at local scale. Among them, Guizhou and Guangxi were identified as HH clusters, which indicated that these two provinces and their surrounding areas were statistically significant clusters of areas with long period of suitable climate. Qinghai Province, on the contrary, was identified as LL cluster, which indicated for a statistically significant cluster of areas with short climate suitable period. In addition, Xinjiang province was identified as LH cluster. Indicating that Xinjiang was the only outlier which experience long period of suitable climate within its neighbor areas.

3.1.2. Climate suitable zone

The average coverage rate of the climate suitable zone where valid data can be collected is about 49.8% and showed a relatively significant aggregation distribution pattern (Moran's I: z-value = 2.013; 0.05 < p-value < 0.1). From the perspective of overall spatial distribution characteristics, the distribution of the coverage rate of regions with suitable climate in China showed the characteristics of relatively large in the midland areas and relatively small in the northeast, northwest inland and southeast coastal areas. Specifically, the highest coverage rate of climate suitable zone appeared in Shanghai, 100% of the girds in Shanghai are identified as the climate suitable zones. The areas with relatively high coverage rate mainly appear around Yunnan-Guizhou Plateau, Shaanxi Province (97.41%) and Shanxi Province (97.14%). On the contrary, no regions with suitable climate have been found in the four provinces of Heilongjiang, Jiangxi, Hainan and Qinghai (0%).

Furthermore, from the results of local Moran's I, it can be seen that the high positive z-values of the three provinces of Xinjiang, Heilongjiang and Chongqing indicated statistically significant spatial outliers at local scale. Among them, Chongqing was identified as HH cluster, which indicated that Chongqing and its surrounding areas were statistically significant clusters of areas with high coverage rate of climate suitable zone. Xinjiang and Heilongjiang, on the contrary, are recognized as LL clusters, which demonstrated that these two provinces and their surrounding areas were statistically significant clusters of areas with low coverage rate of climate suitable zone.

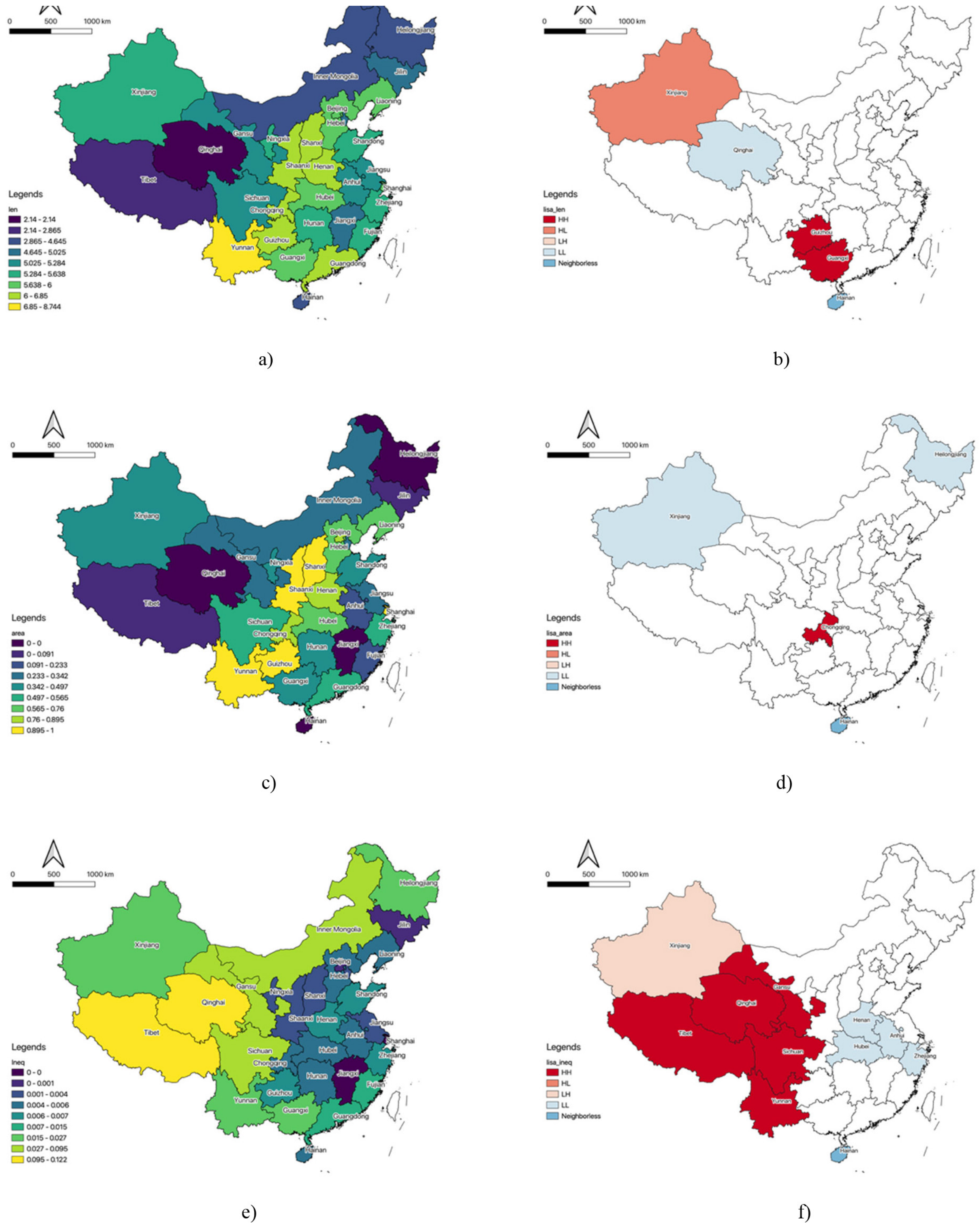


Figure 3. Spatial distribution and association of climate suitability indices: a) spatial distribution of PER; b) local Moran's I of spatial association of PER; c) spatial distribution of ZONE; d) local Moran's I of spatial association of ZONE; e) spatial distribution of INEQ; f) local Moran's I of spatial association of INEQ

3.1.3. Climate inequality

From the calculation results, the Theil entropy index in western China was higher than that in eastern China in 2014 and showed a very significant aggregation distribution pattern (Moran's I: z-value = 4.907; p-value < 0.01). This indicated that compared with the western, the climate conditions in eastern China are more evenly distributed. Specifically, the provinces where the climate condition distributed evenly are Jiangxi and Shanghai. The Theil entropy indices corresponding to these two provinces in 2014 was equal to 0. However, not all of these two provinces were evenly distributed with suitable climatic conditions. The climate suitable period of all grids in Jiangxi province did not reached 5 months, while that of Shanghai exceeded 8 months.

Furthermore, from the results of local Moran's I, it can be seen that the high positive z-values of the provinces in western China and the middle-lower reaches of the Yangtze River basin indicated statistically significant spatial outliers at local scale. Among them, all western regions except Xinjiang were identified as HH clusters, which indicated that these provinces and their surrounding areas were statistically significant clusters of areas where uneven climate distribution (high Theil index). Moreover, Xinjiang was identified as LH clusters, which indicated that Xinjiang was the only outlier which experience even climate condition within its neighbor areas. In addition, the middle and lower reaches of the Yangtze River basin are identified as LL clusters, indicating that urban dwellers in these provinces enjoy relatively homogeneous climatic conditions since conditions in adjacent areas are evenly distributed.

3.2. Impact of human activities on climate suitability

3.2.1. Global scale

Due to the significant aggregated distribution characteristics of the main climate variables (PER, ZONE and INEQ), we constructed 6 spatial regression models with INEQ, PER and ZONE as dependent variables and SAR and SEM as econometric models respectively to analyze the mechanism of human activities on climate suitability. The output of the global regression models was shown in Table 5.

From the goodness-of-fit results (AIC) of global regression models, SAR models (model 1) is more effective in explaining the relationship between climatic inequality and human activities, while SEM models (model 4 and 6) are more suitable for examining the relationship between climate suitable period/zone and human activities. This indicated that climate inequality in China is more correlated to climate conditions during its surrounding areas, while the length of climatic suitable period and the coverage rate of climatic suitable zone might be affected by other hidden variables.

The output of the global regression models showed that: (1) The coefficient of ENT in model 6 was 0.003 (p-value < 0.01), which showed that entertainment related human activities have significant positive impact on the proportion of climatic suitable areas. One unit of increase the density of entertainment activities accompany with the extend of the coverage rate of climate suitable zones by 0.003%. (2) The coefficient of TOU in model 4 was 0.026 (p-value < 0.01), which showed that tourism related human activities had a very significant positive impact on the length of climatic suitable period. Frequent travels could prolong the climate suitable period in related regions, and one-unit intensity of transportation related activity could prolong the climate suitable period by 0.026 months. (3) In contrast, the coefficients of DAI in model 1(0.00035) and 4(–0.01434) demonstrated that with the increase of the density of human activities related to daily life, the level of climate suitability declines (0.01 < p-value < 0.05). With one-unit increase of the density of daily life related human activities, the Theil entropy index of climate inequity and the length of climate suitable period increase 0.00035 units and decrease 0.014 months, respectively. (4) The impact of remaining four types of human activities on climate suitability is not significant according to the p-values of PUB, TRA, WOR and OTH in models from Table 5.

Table 5. Parameter estimation result of global regression models

Variable	INEQ		PER		ZONE	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
CL	–0.11809**	–0.08843**	0.95693	–0.6614	–0.13707	–0.55105
GR	–0.00334**	–0.00212*	0.06047	0.07152*	0.02117	0.02625*
PA	0.02338**	0.02167**	–1.24298**	–1.37431**	–0.13621*	–0.19183**
PM	0.00009*	0.00013**	–0.00416	–0.00687**	0.0001	–0.00084
NO	–0.00007	–0.00009	–0.00332	–0.00218	–0.00289*	–0.00233*
SO	–0.00005	–0.00007	0.00853**	0.00902**	0.00323**	0.00279**
ENT	0.000001	0.000005	–0.0004	0.00346	0.00125	0.00285**
PUB	0.00006	0.000004	–0.00023	0.00335	–0.00093	–0.00008
DAI	0.00035*	0.00052**	–0.00311	–0.01434*	–0.00026	–0.00347
TOU	0.00004	–0.00008	0.02166**	0.02597**	0.00185	0.0032
TRA	–0.00004	–0.00006	–0.00419	–0.00421	0.00059	0.00053
WOR	–0.00039	–0.00051	–0.00702	–0.00333	–0.00343	–0.00414
OTH	–0.00014	–0.00008	0.00389	–0.00329	0.00042	–0.00243
Model Type	SAR	SEM	SAR	SEM	SAR	SEM
AIC Value	–150.811	–150.062	79.273	65.24	17.021	7.044

Note: ** represent that the p-value < 0.01; * represent that the 0.01 < p-value < 0.05.

3.2.2. Heterogeneity of impact mechanism

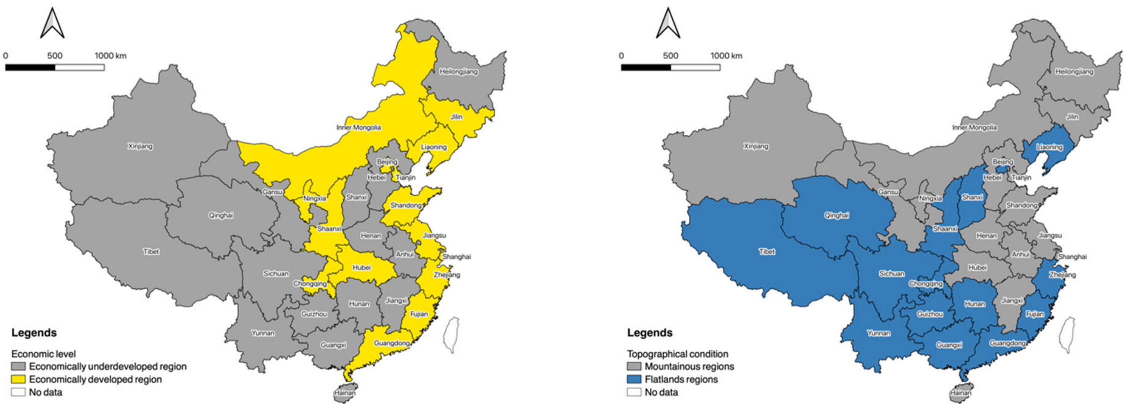
Relevant research results have revealed that economic level and topographical condition can have a significant impact on regional climate and environment (Bulkeley, 2001). Therefore, we divide China's provinces into four categories of mountainous regions, flatlands regions, economically developed regions and economically underdeveloped regions (Figure 4) referring to the GDP level, landform category and land-sea position of each province (see chapter 3.3.1), and the spatial regression models were constructed in four regions respectively to estimate the heterogeneity of the impact mechanism. The output of regression models with better AIC value were selected to represent the impact of human activities on climate suitability in corresponding regions.

(1) Economic level heterogeneity

In order to clarify the diversity of regression relationships in the regions with different economic level, all the girds of China were divided into 2 parts of economically developed and underdeveloped regions based on the GDP level of 2014 (divided by median value). The SAR and SEM were conducted within these two types of regions, and the results were shown in Table 6.

In general, the output of the regression models indicated that the influence and mechanism of human activities that have impact on climate suitability showed a significant heterogeneity in area with different economic levels. Specifically:

Firstly, certain types of human activities didn't show impact on climate suitability in economically developed regions. This was particularly evident in the interactive



a) Economic level b) Topographical conditions

Figure 4. Regional division of provinces in China

Table 6. Parameter estimation result of local regression models in regions with different economic levels

Variable	INEQ		PER		ZONE	
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
CL	–0.01796	0.09284**	–3.34293**	–80.99320**	–2.10614	–27.81950*
GR	0.00135**	–0.00006**	–0.04858**	–1.03611**	–0.02856**	–0.38904**
PA	0.02402**	0.02498**	–0.46438**	–6.25589**	–0.08015	–1.65652*
PM	–0.00003*	0.00041**	–0.00297**	0.04394**	–0.00069	0.01536
NO	0.00007	–0.00048**	–0.00265*	0.11030**	–0.00193	0.03495**
SO	–0.00006	–0.00037**	0.00371**	–0.00994**	0.00172	–0.00227
ENT	0.00003	0.00033**	0.00760**	0.55912**	0.00314	0.18833
PUB	–0.00001	–0.00070**	–0.00086**	0.17200**	–0.00187	0.05396*
DAI	–0.00017*	0.00013**	0.00204	–0.06202**	–0.00403	–0.01966**
TOU	–0.00009	–0.00110**	–0.01244**	–0.27395**	–0.00877	–0.10130
TRA	0.00010	–0.00020**	0.00772**	0.01960	0.00680*	0.00273
WOR	0.00015	0.00383**	–0.03765**	–2.89693**	–0.01111	–0.93224
OTH	–0.00009**	0.00035**	–0.00240**	–0.02900**	0.00153**	–0.00691
Model Type	SEM	SAR	SEM	SEM	SEM	SEM
AIC Value	–164.41	–881.748	–59.9739	–169.728	–31.8565	–215.059

Note: ** represent that the p-value < 0.01; * represent that the 0.01 < p-value < 0.05; Models 7, 9 and 11 are constructed to explore the relationship between climate suitability and human activities in economically developed regions, while models 8, 10 and 12 correspond to economically underdeveloped regions.

relationship between human activities and climate inequity. The p-values of human activities related factors (p-value < 0.01) in model 8 indicated that all seven types of human activities have very significant impacts on climate inequality in economically underdeveloped areas. For comparison, in model 7, only the p-values of DAI and OTH ranged from 0.01 to 0.05, which indicated that climate inequity in economically developed regions is only affected by daily life related and other types of human activities.

Secondly, this study also found that some particular types of human activities have a greater impact on climate suitability of economically underdeveloped regions than developed regions. This was particularly evident in the regression relationships between human activities and the length of the climate suitable period. The coefficients of ENT(0.55912), TOU(–0.27395) and WOR(–2.89693) in model 10 showed that the length of climate suitable period might be prolonged or shortened by 0.56, 0.3 and 2.9 months with the change of one-unit density of entertainment, tourism and work related human activities, respectively. Accordingly, the coefficients of economically developed areas in model 9 are 0.0076, –0.01244 and –0.03765 respectively, which means that the corresponding climate comfort period changes are only 0.008, 0.01 and 0.03 months.

Furthermore, from the output of the regression models, we also found that some types of human activities had completely opposite impact mechanisms on the climate suitability of regions with different economic levels. For example, by comparing the coefficients of PUB in models 9 (–0.00086) and 10 (0.172000), it had been found that human activities related to public services could prolong the climate suitable period of economically underdeveloped regions but shorten that of economically developed areas. Similarly, human activities related to daily life are conducive to promoting climate equity in economically developed regions but aggravate the uneven distribution of climate in economically underdeveloped regions according to the difference of coefficients of DAI in models 7 (–0.00017) and 8 (0.00013).

(2) Topographical condition heterogeneity

In order to eliminate the influence of natural factors such as terrain and climate province on climate conditions and improve the accuracy of the regression models, all the girds of China were divided into 2 parts of mountainous regions and flatland regions followed the landform category and land-sea position. The SAR and SEM were conducted within these two types of regions, and the results were shown in Table 7.

The results showed the heterogeneity in the impact of human activities on climate suitability of areas with different topographical conditions are mainly reflected in the difference of impact factors and the mechanisms. Specifically:

First of all, human activities have a significantly greater impact on the climate environment in mountainous regions. This is mainly reflected in the regression relationships between human activities, climate suitable zone and climate inequity. In model 13 and model 17, six of the seven human activity related variables had p-values less than 0.05, while only two in models 14 and 18. This indicated that most of human activities showed significant

Table 7. Parameter estimation result of local regression models in regions with different topographical conditions

Variable	INEQ		PER		ZONE	
	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
CL	–0.17808**	0.04476**	–2.98240**	–17.27940**	0.52602**	–2.97254*
GR	–0.00377**	–0.00254**	–0.19660**	0.19864**	–0.08882**	0.07493**
PA	0.04132**	0.00216	–1.79426**	–1.52276**	–0.22765**	–0.43454**
PM	0.00071**	0.00020**	–0.02305**	0.01854**	–0.00512**	0.00309*
NO	–0.00121**	–0.00014*	0.03389**	–0.06340**	0.00975**	–0.01223*
SO	0.00025**	0.00004	0.00160	0.04957**	0.00088	0.01142**
ENT	0.00075**	–0.00018	–0.01467**	0.18347**	–0.00006	0.02151
PUB	0.00008	–0.00017**	0.01480**	–0.00155**	0.00119**	0.00380**
DAI	0.00062**	–0.00007	–0.03556**	0.10691**	–0.01122**	0.01066
TOU	–0.00119**	0.00030	0.05414**	–0.15417**	–0.00280*	–0.02021
TRA	–0.00104**	0.00020**	–0.00811	0.03201**	–0.00438**	0.00477*
WOR	–0.00111**	0.00113	0.08917**	–1.00789**	0.03081**	–0.12029
OTH	0.00126**	–0.00014**	–0.01345	–0.02521**	0.00831**	–0.00052
Model Type	SEM	SAR	SEM	SAR	SEM	SAR
AIC Value	–118.123	–178.795	10.191	–592.974	–35.769	–61.6325

Note: ** represent that the p-value < 0.01; * represent that the 0.01 < p-value < 0.05; Models 13, 15 and 17 are constructed to explore the relationship between climate suitability and human activities in mountainous regions, while models 14, 16 and 18 correspond to flatlands regions.

impacts on the coverage rate of the climate suitable zone and the Theil entropy index corresponding to climate inequity of mountainous regions, but only two of them affected the climate condition of flatlands region significantly, in contrast.

In addition, this work also found that human activities had completely opposite impact mechanisms on the climate suitability of regions with different topographical conditions, which is similar to the situation when we discussed the cases of differences in economic levels. When we compare the coefficients of various human activity related variables in models 13, 15, 17 and 14, 16, 18, it could be found that the symbols of the coefficients are in pairs of positive and negative in most cases, which indicated that the impact of human activities on mountainous and flatlands regions is basically opposite. However, this situation only occurred twice when we discuss the heterogeneity of economic level (see Table 6).

Specifically, the coefficients of PUB, TOU and WOR in model 16(–0.00155, –0.15417 and –1.00789) are negative but positive in model 15(0.01480, 05414 and 0.08917). This indicated that with the increase of the density of public services, tourism, and work-related human activities, the length of climate suitable period shortens in flatlands regions and extends in mountainous regions. On the contrary, the coefficients of ENT, DAI in model 16 (0.18347 and 0.10691) and TRA in model 14(0.00020) and model 18(0.00477) are positive, but negative in model 15(–0.01467 and –0.03556), model 13(–0.00104) and model 17(–0.00438). From which, it could be found that high intensity of human activities related to entertainment and daily life showed a positive impact on the climate environment of the flatlands regions and but exacerbate the climate suitability of the mountainous region. In addition, transportation related human activities are special. The increase in the intensity of such activities could expand the coverage rate of the climate suitable zone in the flatlands regions and lead to a depravation in climate equity at the same time.

3.3. Discussions on the regression results

This study quantifies the effects of different types of human activities on climate suitability by constructing spatial regression models. The results suggest a significant link between human activities and climate suitability. However, the human-environment nexus and the impact mechanism of human activities on climate suitability revealed in this work are not completely consistent with the results of previous studies. These findings are understandable because:

3.3.1. Can human beings influence climate suitability in other ways?

Climate elements are continuous spatial variables, and their spatial distribution is significantly associated with adjacent units (Jensen & Jensen, 2012). From the goodness-of-fit of the regression models, it can be seen that the SAR do not perform as well as SEM models. This suggested that some important factors affecting climate suitability had been ignored according to the characteristics of SEM model (Jensen & Jensen, 2012). In fact, since the concept and Sustainable Development Goals (SDG) have been put forward, an important human behavior related factor has been pointed out having significant impact on climate suitability and human-environment nexus, which is the climatic policies and regulations (Schor, 2015). Due to the difference of climate change influence and ability to adapt to climate change, different regions in China have different policy objectives and priorities to adapt to

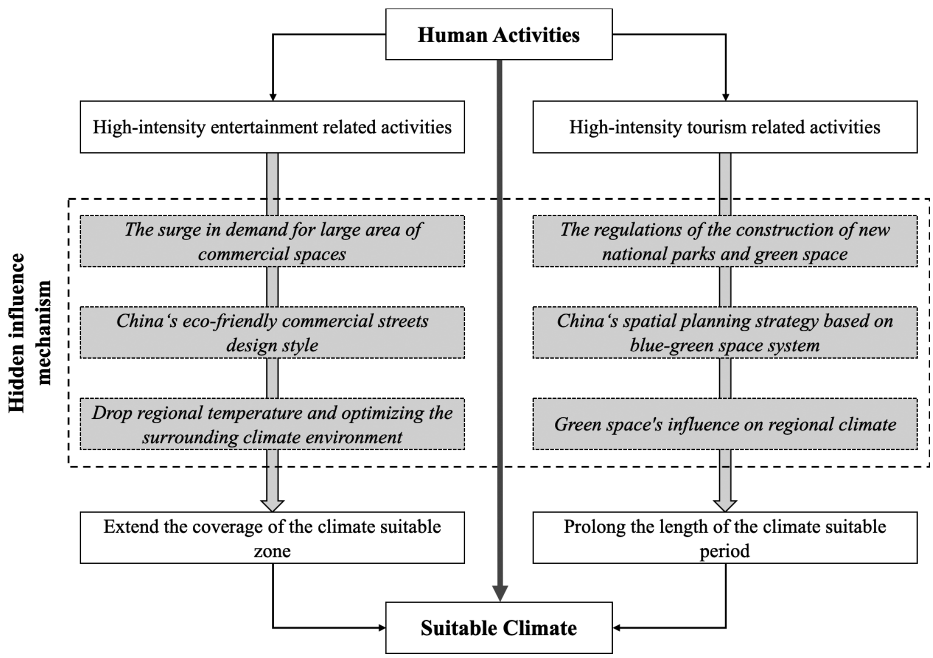


Figure 5. Human activities' optimization mechanism for climate environment

climate change and energy conservation (Wen et al., 2020; Wang & Gong, 2020; Gong et al., 2021), which may be the reason why there are significant differences in the level of governance of regional climate in China (Sun et al., 2015). This conjecture has also been pointed out in studies in the fields of economics, politics and law. Specifically, Peng et al. (2015) concluded that Tianjin, Hebei and other provinces in China take coastal zone as the core of climate governance, while Jiangsu, Anhui and other provinces take public health as the key.

3.3.2. Why does the climate become more suitable with the increase of the intensities of certain types of human activities?

The results showed in Table 5 indicated that the change trend of climate suitability indices (PER, ZONE, INEQ) is the same as of the intensity of entertainment and tourism related human activities. This result is inconsistent with the conclusions of previous studies that high intensity human activities in urban spaces which causes anthropogenic heat emission is a major contributor to the heat island effect that disrupts urban microclimates. In order to further verify our conjecture, we draw our reasoning process as a flow chart (Figure 5) to further illustrate the implicit mechanism by which human activities optimize the regional climate environment.

On the one hand, the China's eco-friendly commercial street design style is likely to be the key to the climate optimization effect of entertainment related human activities. Specifically, Lu (2018) found that special urban street spaces in China reduce heat island intensity through both ecological surface heat absorption cooling and building shadow reduction cooling. Similarly, Li and Wang's (2016) randomly investigated three streets in China and found that the reasonable orientation, aspect ratios, layout of green spaces and water areas of the street design are main characteristics of the eco-friendly design strategies for commercial streets. These findings illustrated that, compared with heat release and temperature rise caused by human activities in commercial districts in developed countries (Block et al., 2004), China's special commercial street design style is likely to produce cooling effect on the contrary. Therefore, the area of eco-friendly commercial blocks which is correlated with the intensity of human activities of shopping and catering is likely to be the reasonable explanation for the relationship between human entertainment activities and the expansion of the climate suitable area reflected in the regression models.

On the other hand, the mechanism of tourism activities prolonging the climate suitable period may be related to the cooling mechanism of urban green spaces (Kong et al., 2013). Qiu (2014) elaborated the mechanism of green space's influence on regional climate and found that green space could significantly reduce the temperature of different types of construction land by 2.384~1.65 °C. At the same time, Chinese government has invested heavily in the construction of new national parks and green spaces to create green tourism destinations for urban residents (Huang et al., 2008) and green spaces are recognized as the main tourism destinations in China. This further indicated that the tourist flows actually reflected the area of regional green space and might be the reason why tourism activities optimized climate suitability.

In summary, there is no doubt that human activities generate metabolic heat. The unexpected results showed in the regression models that entertainment and tourism related human activities could affect and even optimize the climate environment could be explained by the behavior patterns of these two types of human activities and the environmental optimization effect of the spaces that carries these activities.

3.3.3. What makes the spatial heterogeneity in the impact mechanisms of human activities on climate environment?

This work pointed that the types of human activities affecting climate suitability at different economic levels are different.

This might be related to differences in the behavior patterns of residents in regions with different economic levels. Hunecke et al., pointed that travel mode choices and residence choice tendency of residents in high-income regions produced less air pollutants (Hunecke et al., 2001), which could greatly reduce the pressure on the environment effectively. This might be the reason why human activities showed a relatively less significant impact on economically developed regions than underdeveloped.

Moreover, this work also found that human activities had completely opposite impact mechanisms on the climate suitability of mountainous region. This may be related to the special urban form and urban ventilation channel of mountain cities in China. Chongqing, a typical mountainous city in China, was taken as an example to focus on the mechanism of reconstructing urban ventilation channel and optimizing regional climate environment through the rational use of its mountainous terrain in the process of planning and design (Chen, 2012). This work further pointed out that high-rise buildings in mountainous cities have a significant role in promoting the wind speed near the ground (about 1.5 m/s). Therefore, we speculated that the urban planning strategies dominated by the special urban ventilation channel in mountainous cities is the main reason for the topographic heterogeneity.

Conclusions

In this paper, we quantified the relationship between human activities and climate suitability and clarified the implicit impact mechanisms between them with the help of Sina Weibo check-in data and spatial regression models. Based on the above research, the following research results can be obtained.

First, entertainment, tourism and daily life related human activities on climate suitability are significant (p-value < 0.05). With one-unit (one check-in record/km^2) increase of entertainment and tourism related human activities, the coverage rate of climate suitable zone and the length of climate suitable period increase by 0.003% and 0.026 months, respectively. In contrast, one-unit of increase of daily life activities made the Theil entropy index of climate inequity and the length of climate suitable period increase 0.00035 units and shorten 0.014 months, respectively. Second, human activities showed greater impact on the climate suitability of economically underdeveloped regions and completely opposite impact on the climate suitability of region regions at different topographic conditions. Third, the unexpected regression results on the implicit impact mechanisms of entertainment, tourism related human activities and the significant spatial heterogeneity could be explained by the environmental optimization effect of the spaces that carries these two types of activities and the special urban planning strategies in China, respectively.

Based on the above research conclusions, the following suggestions to optimize regional climate condition are proposed. The pedestrian street design in the urban center, especially the size of the street and the allocation of green and water elements unable the cooling effect of pedestrian street. Government should issue relevant urban design regulations to promote the design of environment-friendly pedestrian street. Besides, for mountainous cities, urban ventilation channel structure design is of great importance for the optimization of urban climate and environment. Government needs to focus on the impact of mountain terrain and building patterns on further urban planning strategies.

Due to the data access restrictions of Sina Weibo platform API, we could only obtain the nationwide check-in data of China before 2015. This made it difficult to construct panel data to explore the dynamic relationship between human activities and climate conditions. In the future, we will explore more ways to obtain multi-sourced data, strive to improve the effectiveness of data, and deeply explain the development trend of human-environment nexus through different periods.

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Author contributions

Y. R. and X. T. conceived of the presented idea. Y. R. developed the theory and performed the computations. N. G. and M. D. verified the analytical methods. X. T. supervised the findings of this work. All authors discussed the results and contributed to the final manuscript.

Conflict of interest

The authors certify that there is no conflict of interest with any individual/organization for the present work.

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