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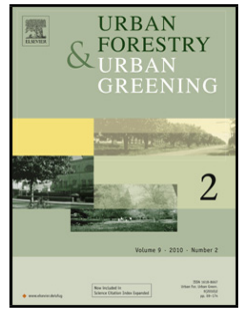

Using a geographical detector to identify the key factors that influence urban forest spatial differences within China

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ABSTRACT

Increasing urbanization is a global phenomomen that has led to numerous urban problems, including air pollution and traffic noise. Urban forests are important, therefore, because they are able to effectively alleviate such unsustainable problems. Systematic analyses of spatial differences in urban forest coverage (UFC) and the factors that influence this cover type, however, need to be further explored within Chinese cities, especially on the basis of spatial data. The intensity gradient (IG) method was applied in this study to identify urban areas across China using Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS) data. Urban forests were then extracted from the global land cover dataset GlobeLand30 to enhance comparability of this land cover type between cities. The factors influencing spatial differences in UFC in 286 major Chinese cities were then detected using a geographical detector method, an approach which differs from the more traditional use of multiple regression as it better illustrates the explanatory power of variables and their interactions. The results of this study reveal that average UFC across China was 19.7% in 2010 and that clear differences were present between south China (27.6%) and north China (11.1%). The factors underlying UFC differences between Chinese cities are complicated; data show that biogeoclimatic factors have exerted the greatest impact while the effects of socioeconomic factors have generally been weak. The impact of variables interacting with one another has also tended to be stronger than the influence of single factors. The results presented here also imply that there were no significant spatial differences in average UFC between cities with the title Chinese 'National Forest City' (NFC) and others.

***Keywords*:** Urban Forest Coverage, Major Chinese cities, Influencing factors, Geographical detector method

Abbreviations: UFC: urban forest coverage; NFC: National Forest City; IG: intensity gradient; DMSP/OLS: Defense Meteorological Satellite Program/Operational Linescan System

1. Introduction

Urbanization is increasing globally (United Nations, 2018). Indeed, the global urban population rose rapidly from 751 million people to 4.2 billion people between 1950 and 2018; estimates suggest that by 2050, 6.7 billion people will live in urban areas (United Nations, 2018), accounting for 68% of the global population. Rapid urban population growth has also led to numerous unsustainable problems, including reduced biodiversity, deteriorating air quality, and reductions in the amount of green spaces (Bonneau et al., 2018; Guetté et al., 2017; Lin and Zhu, 2018; Shahbaz et al., 2017; Xu et al., 2018; Yang et al., 2018).

Urban forests (Carter, 1994; Endreny, 2018; FAO, 2016), including residential trees and forests in parks, are known to be able to effectively alleviate these urban problems (Carreiro and Zipperer, 2008; Endreny, 2018; FAO, 2016; Konijnendijk van den Bosch et al., 2004; Kraxner et al., 2016; Patarkalashvili, 2017; Sundara et al., 2017). For example, they mitigate air pollution by absorbing gaseous compounds (Nowak et al., 2018; Yang et al., 2005), reduce the greenhouse effect via carbon sequestration (McPherson, 2007; Zhang et al., 2015), reduce noise (Samara and Tsitsoni, 2011), provide the shade for residents, and reduce air temperatures via transpiration (Greene and Millward, 2017). They also provide shelters for animals within cities and therefore alleviate biodiversity losses in urban ecosystems (Alvey, 2006), have been shown to be important for both the mental health and social cohesion of urban residents (Annerstedt et al., 2012; Nesbitt et al., 2017), and have economic benefits (Endreny, 2018). These positive effects cannot be replicated by other kinds of vegetation within urban areas. One study on the effects of tree shade and grass on local temperatures within a UK urban area showed that while the grass exerted a minimal effect on local temperatures, tree shade was able to reduce this variable by between 5°C and 7°C, while also enabling effective global and local cooling (Armson et al., 2012). Urban forests impart significant benefits to city dwellers; for this reason, the theme of 'Forests and Sustainable Cities' was chosen to mark the 2018 International Day of Forests (FAO, 2016).

As urban forest coverage (UFC) varies markedly between different cities, it is important to develop an understanding of both its spatial distribution and the factors that influence this variable if we are to more effectively sustain and increase UFC (Chen and Wang, 2013). A range of different methods have been used in research to date to map urban forests, including remote sensing (Canetti et al., 2018; Myeong et al., 2001; Walton et al., 2008) and the application of modern technologies such as unmanned aerial vehicles (Kulhavy et al., 2016). Most studies based on spatial data to date, however, have been assessed within a single city (Canetti et al., 2018) and it has proved challenging to define urban areas on a global scale because of their varied definitions (Zhou Yixing and Yulong, 1995). China, for example, usually defines the scope of urban areas according to administrative units in statistical materials (Zhou Yixing and Yulong, 1995).

Numerous studies have nevertheless attempted to find the factors that influence UFC. The germination and growth of trees are determined by biogeoclimatic conditions (Chen and Wang, 2013; Nowak et al., 1996). For example, Nowak et al. (1996) showed that UFC in the United States is mainly influenced by the biogeoclimatic environment and is the highest in cities developed in naturally forested areas, followed by grassland counterparts and then desert agglomerations. As important components of the urban landscape (FAO, 2016), urban forests are also influenced by a range of socioeconomic factors; increasing population levels compact urban landscapes and tend to mean that forested areas are replaced by buildings, roads, and other artificial areas (Tyrväinen, 2001). In one earlier study, Fuller and Gaston (2009) were able to demonstrate a decline in green space coverage across European cities as population density increased. However, as green space coverage declines in urban areas, increasing income and consumption levels can raise the demand for urban forests (Endreny, 2018; Gerrish and Watkins, 2018; Zhu and Zhang, 2008). For example, Zhu and Zhang (2008) demonstrated that a 1% increase in income within the United States led to a concomitant 1.76% increase in demand for urban forests. Besides income, race (Watkins and Gerrish, 2018) and education (Krafft and Fryd, 2016; Nesbitt et al., 2019) can also influence the distribution of urban forests. Those white Americans and residents with higher levels of education were more likely to have more access to urban forests in US cities (Krafft and Fryd, 2016; Watkins and Gerrish, 2018). Other complicated factors were also considered in some studies, such as historical legacy (Boone et al., 2010; Roman et al., 2018) and the lifestyle characteristics of neighborhood residents (Roy Chowdhury et al., 2016).

China is experiencing the fastest urbanization rate anywhere in the world (Muldavin, 2015; United Nations, 2018). The national urban population is projected to reach one billion people by 2030 (Muldavin, 2015). Thus, in response to the increasing ecological problems caused by this rapid urbanization process, the Chinese government launched the 'National Forest City' (NFC) programme in 2004, and granted the first NFC title to Guiyang, a city in southern China. (Bureau, 2007; FAO, 2016). According to the programme, the UFC of cities with the NFC title should be higher than 30% in northern China and 40% in southern China, to restore and improve the natural ecosystems between urban and rural areas, and provide a close-to-nature path for dwellers (FAO, 2016). Since 2013, nearly 20 cities per year were newly awarded the NFC title. As of 2017, 137 cities have been granted an NFC title. Earlier research on urban forests within China mainly emphasized ecological structure and function (Jim and Chen, 2009; Yan and Yang, 2017; Zhang et al., 2015), including encapsulated species diversity (Yan and Yang, 2017), carbon storage and sequestration functions (Liu and Li, 2012; Zhang et al., 2015), and the reduction of air pollution (Yang et al., 2005). The distribution of urban forests and its influential factors need to be further systematically analyzed in China with a large geographical scope. The objectives of this research were to:

- Extract urban forest area data with enhanced comparability between cities;
- Analyze the UFC spatial distribution within Chinese major cities, and;
- Systemically analyze the impact of biogeoclimatic and socioeconomic factors on UFC within China using a geographical detector method. Meanwhile, as a dummy variable to represent the influence of policy, the NFC programme was also assessed.

2. Methods

2.1. Data

2.1.1. Study area

In this study, 286 major cities were selected to examine the urban forest spatial differences within China, including four direct-controlled municipalities and 282 prefecture-level entities in the mainland.

2.1.2. Urban areas and urban forests

Data for urban areas and urban forests were extracted from a DMSP/OLS nighttime lighting image and GlobelLand30 dataset for 2010. DMSP/OLS nighttime lighting data was downloaded from the National Geophysical Data Center (NGDC) website of the National Oceanic and Atmospheric Administration (NOAA), as obtained by the Defense Meteorological Satellite

Program (DMSP) F18. This image excludes the effects of sunlight and moonlight on the data as well as that of clouds, has a 1 km spatial resolution, and covers almost all areas on Earth where human activity is seen (Xiang and Tan, 2017). On this image, each pixel is denoted by a digital number (DN value) between zero and 63 which refers to average light intensity.

GlobeLand30 is a land cover dataset at 30 m spatial resolution derived from Landsat TM/ETM+ and Chinese HJ-1 satellite images with a pixel-object-knowledge (POK)-based operational mapping approach (Chen et al., 2017a). It can be downloaded from the National Geomatics Center of China (NGCC). Numerous scholars have verified that the overall classification accuracy of this data is greater than 80% (Chen et al., 2017a); forests are defined as land with more than 30% tree canopy cover (Chen et al., 2017b) with the accuracy of 89% in 2010.

2.1.3. Proxy variable sources

Precipitation and temperature data were obtained from the China Meteorological Data Service Center (CMDC) at a 0.5° × 0.5° spatial resolution. Elevation data were extracted from Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) data at a 90 m spatial resolution as, provided by the National Aeronautics and Space Administration Jet Propulsion Laboratory (NASA-JPL), while socioeconomic datasets were obtained from the China City Statistical Yearbook in 2011 (NBSC, 2011) and included urban population density, total city populations, urbanization level, urban per capita GDP, and secondary industry share.

2.2. Methods

2.2.1. Urban forest extraction

Figure 1 presented that the extraction of urban forests mainly covered two steps: 1) Extract urban areas; 2) Extract urban forests by the mask of urban area polygon from forest cover data.

Fig.1

Urban areas were extracted using the IG method (Tan, 2017). IG is defined as the maximum rate of change in nighttime light from the cell to its neighbors across the corresponding spatial distance, and was expressed using the angle of slope (θ). The IG method mainly comprises two steps: 1) Use of DMSP/OLS nighttime light data to extract an area with an angle of slope (θ) greater than 89.85° to define urban boundaries, and; 2) Extracting central portions of lit area with DN values greater than 30, in order to avoid the loss of some areas which have complicated spatial distribution and unclosed boundaries, especially large coastal cities, when converted into polygon features using the software ArcGIS (Tan, 2017). The urban areas identified using this approach are shown in Fig. 2. It is noteworthy, however, that the approach used here is based on the assumption that there is a border around urban areas at which nighttime light intensity (NTLI) value changes sharply because of vast differences in this variable between a city and its surrounding areas.

Fig.2

Urban forests were then extracted using the "extract by mask" tool in the software ArcGIS.

2.2.2. Potential driving factors and proxies

Values for UFC (%) discussed in this article refer to the percentage of urban forest areas versus the total urban areas. As discussed, the aim of this study was to develop an explanatory framework for UFC differences between Chinese cities based on previous studies (Chen and Wang, 2013; Fuller and Gaston, 2009; Gerrish and Watkins, 2018; Iverson and Cook, 2000; Nowak et al., 1996; Zhu and Zhang, 2008). The framework developed here encompassed biogeoclimatic factors as well as socioeconomic ones which describe the characteristics of each city alongside political factors.

Biogeoclimatic factors

As forest growth bears a close relationship with biogeoclimatic factors (Nowak et al., 1996), precipitation (Pre), temperature (Tem), and elevation (Ele) were all used as proxy variables to represent biogeoclimatic conditions (Fig. 3). In order to be useful within a geographical detector model, proxy variables need to be stratified. Thus, precipitation, temperature, and elevation were stratified according to the climate division reference for China (Zheng et al., 2010) (Fig.4).

Socioeconomic factors

As constituent parts of urban systems, urban forests are affected by both urban areas and human populations within these regions, as shown in the cases of European cities (Fuller and Gaston, 2009), tropical Southeast Asian cities (Richards et al., 2017), Chinese cities (Dou and Kuang, 2020; Song et al., 2019), and New York City (Grove et al., 2014). The city size can be measured by urban population (UN-DESA, 2018); the urbanization level is the percentage of urban population in the total population of a city; and the urban population density, which is a measurement of population per unit area, can reveal the pressure on land that may result in changes in land use structure (Li et al., 2015). Therefore, city size variables (Size) as well as those for urbanization levels (Urban_L) and population density (Upop_D) were all utilized to reflect the characteristics of cities.

Economic factors were also considered as independent variables in this analysis, as more revenue is allocated to urban forests in more prosperous cities (Warren et al., 2011), and higher income levels lead to increased demand for urban forests and green spaces in some cases (Zhu and Zhang, 2008). GDP per capita (GDP_per) was therefore selected as an appropriate proxy variable to reflect the level of economic development. It is also the case that the share of secondary industry comprising manufacturing and construction industry in overall GDP can exert an influence on urban forests because industrial zones take up a large proportion of urban areas (Canetti et al., 2018). Moreover, policies play an important role in both urban planning and spatial patterns (Conway and Urbani, 2007). Thus, considering data accessibility and comparability across cities, we designed a dummy variable, 'NFC', and denoted cities as either NFC, or not.

These above proxy variables were used to explain the UFC differences between the cities assessed in the study (Fig. 3). Similarly, according to the demand of a geographical detector model, city size was stratified according to the new national standard classification for this variable (QI et al., 2016). Urbanization level, urban population density, GDP per capita, and the secondary industry share were all stratified on the basis of Natural Breaks in the software ArcGIS; Natural Breaks were used to minimize the average deviation of each class from its mean while maximizing its deviation from those of other groups (Jenks, 1967), thus avoiding any human-made interference (Liu and Yang, 2012). The discretized variables used in this study are shown in Fig. 4.

Fig.3

Fig.4

2.2.3. Geographical detector

The geographical detector was used in this analysis to detect the factors influencing differences in UFC based on the assumption that if an independent variable has an important influence on its dependent counterpart then similarities in their spatial distribution should also be evident (Wang and Hu, 2012; Wang et al., 2016a). This similarity is expressed using the value of *q* within the range [0, 1]; thus, when *q*-statistic value approaches 1, the explanatory power of the proxy variables to UFC is stronger. Similarly, this power is weaker when *q* is closer to 0, as follows:

$$q = 1 - \frac{\sum_h^L N_h \sigma_h^2}{N\sigma^2} \quad .$$

In this expression, China is composed of *N* units and is stratified into $h = 1, 2 \ldots L$ strata. In addition, N_h denotes the number of units in stratum *h*, while σ^2 and σ_h^2 denote UFC variance in population and stratum *h*, respectively.

The geographical detector can also be used to determine the interaction intensity between different proxy variables (X_a and X_b) (Wang et al., 2010) which can then be classified into five types (Table 1). The *q* value of the interaction (q ($X_a \cap X_b$)) is then obtained via a new polygon distribution formed by merging the layers of the two variables X_a and X_b; this is then compared with q (X_a), q (X_b), and (q ($X_a \cap X_b$) to detect interaction intensity (Table 1).

Table 1.

The geographical detector has been used in a range of studies to detect influential factors (Wang et al., 2018; Zhang and Zhao, 2018; Zhou et al., 2018). This approach was used here to detect the impact and interactions of the nine proxy variables on UFC differences across cities. This method was chosen because, in the first place, stratified independent variables enhance the representation of a sample unit and so afford a greater level of statistical accuracy compared to other models at the same sample size (Wang et al., 2010). Secondly, the use of a *q*-statistic value enables a higher level of explanatory power but does not require the presence of a linear relationship between independent and dependent variables (Wang et al., 2010). Third, the geographical detector is able to determine the true interaction between two variables and is not limited to pre-established econometric multiplicative interactions (Wang et al., 2010). Lastly, the use of a geographical detector does not require consideration of the collinearity of multiple independent variables (Wang et al., 2010).

3. Results

3.1. UFC spatial differences

Fig.5

Data show that average 2010 UFC in China was 19.7%. Examination of Fig. 5 also reveals that UFC in northern China was 11.1%, much lower than the national average, while the average value for southern China was 27.6%. UFC values in about one-third of cities nationally were lower than 5%, revealing very low urban forest area in many Chinese cities.

3.2. Factors influencing UFC

3.2.1. Proxy variable q-statistics

Fig.6

The data presented here in Fig. 6 reveal that elevation, urbanization level, and NFC have all exerted no significant impact on UFC values ($p > 0.1$). At the same time, however, the proxy variables precipitation and temperature were significant at the 0.01 level, while the variables of urban population density, GDP per capita, and share of secondary industry all exerted significant impacts on UFC at the 0.05 level, and city size was statistically significant at the 0.1 level. Data show that precipitation had the greatest impact on UFC, followed by temperature, while socioeconomic variables (i.e., share of secondary industry, city size, urban population density, and GDP per capita) remained relatively weak.

3.2.2. Interactive q-statistics for proxy variables

Table 2.

The interactive *q*-statistic values derived here were greater than the values of all single variables (Table 2); the interactions between precipitation-temperature, NFC-precipitation, elevation-precipitation, and urban population density-NFC all exhibited binary enhancement over the time period of this analysis, while others exhibited nonlinear enhancement. Calculations show that when precipitation and elevation variables interacted, explanatory power reached a maximum value of 0.50. The effects of biogeoclimatic variables on UFC differences within China remained much stronger than those of socioeconomic factors. Data also show that socioeconomic factors can enhance the explanatory power of the biogeoclimatic factors on UFC; for example, perspective values for precipitation and city size were 0.38 and 0.04 but their interactive *q*-statistic reached as high as 0.49.

4. Discussion

4.1. Impacts of biogeoclimatic factors on the urban forest spatial differences

The *q*-statistic values calculated here using the geographic detector method reveal that the major variables influencing UFC within China have been precipitation and temperature, for 286 major cities, including municipalities and prefectural-level entities in the mainland. This result is similar to previously-reporting findings (Nowak et al., 1996). This earlier work noted that the amount of available natural precipitation can influence the tree cover across the United States (Nowak et al., 1996). Temperature can also impact tree growth as values that are either too high or too low influence the balance of tree metabolism (Xie et al., 2015). Data also show that elevation has exerted no significant influence on urban forests; if this variable is entered into the model, however, it acts to greatly enhance the explanatory power of other variables. It can be seen that the interaction *q* value of precipitation and elevation had the greatest influence on UFC, at least in this study.

4.2. Impacts of socioeconomic factors on the urban forest spatial differences

City size and urban population density both significantly influence UFC, consistent with earlier work (Fuller and Gaston, 2009; Nesbitt et al., 2019; Richards et al., 2017; Wu et al., 2019). These authors noted that green space coverage has declined with increasing human population density. This has also been the case in China; UFC is quite low in cities with high population densities because as urban populations increase in size, more space is needed, which results in urban forest shrinkage.

The data presented in this paper also shows that UFC values are low in cities that have high GDP per capita. This result conflicts with research by Chen and Wang (2013) who argued for a positive impact of economic development on UFC. The data Chen and Wang (2013) used was statistical panel data between 2002 and 2009, while cross-section data in 2010 extracted in remote sensing data was used in our study, where the time series was not considered. It is possible that the time series data may interfere with the results of spatial distribution of UFC. The result presented here also differs from previous findings for cities within developed countries, where high-income neighborhoods are more likely to have high UFC in many previous studies about environmental justice (Krafft and Fryd, 2016; Nesbitt et al., 2019; Schwarz et al., 2015). Compared with cities in developed countries, Chinese cities are in a stage of rapid development (Kuang et al., 2014). Cities with high GDP per capita will have strong economic strength for urban construction, and thus the available land in the urban forest is compressed (Yin et al., 2011). Original forests within urban areas are often destroyed and converted to other land use types such as roads, residential, commercial, and industrial zones.

Results also reveal that secondary industrial share is negatively related to UFC as these zones often encompass large proportions of urban areas. In the quantification of urban land area conducted by Canetti et al. (2018) within Araucaria, industrial zones cover approximately 30% of the total urban areas. This means that urban forests and secondary industry must compete with each other for urban land.

The results of this study also suggest that the NFC programme has exerted no significant effects on the spatial differences of UFC. Indeed, 2010 average UFC of the NFCs was 16.3%, lower than the average UFC in other non-NFC cities (19.9%). Furthermore, according to the qualifications of the programme that the UFC of NFCs should be higher than 30% in northern China and 40% in southern China (Bureau, 2007), this result also shows that the average UFC of NFCs was much lower than the required standards. Throughout the process of urban development, interactions between residents and nature will increasingly depend on urban forest networks, and the demands for well-designed and well-managed urban forests will increase (FAO, 2016). The NFC programme was proposed under this background. It is noteworthy that more professional assessment is needed for the NFC title awarding. Urban forests need to be further emphasized in future urban planning for the sustainable development.

4.3. Limitations

The urban forest used for this analysis was defined as the land use type with more than 30% tree canopy cover within an urban area. This definition is different from some definitions which can encompass all forms of urban vegetation (Chen and Wang, 2013). Indeed, grassland exerts a limited effect upon ecological environments (Armson et al., 2012). However, this definition and the dataset also has some limitations. This definition of urban forests would exclude some sparsely-treed neighborhoods, for example, as many residential neighborhoods have canopy covers below 30% (Chen et al., 2019), especially in dense cities. The spatial resolution of land cover dataset is 30 m, and thus that some newly planted forests and street trees cannot be identified, which underestimated the values of UFC. In addition, tree height, tree crown depth and plant species cannot be captured in remote sensing images; thus the quality of the urban forests were not included in this research. Another limitation relates to statistical data used in this study, which inevitably has some errors and uncertainties in data collection. Even so, analyses based on all Chinese major cities are useful for understanding spatial differences of UFC and provide a theoretical basis for urban forest development. In the future, we can use higher-resolution images, such as Sentinel-2 and QuickBird images, to extract more accurate urban forest cover dataset. In addition, Light Detection and Ranging (LiDAR) data (Wang et al., 2016b) can also be integrated to obtain the height and quality information of urban forests.

5. Conclusion

This analysis extracted urban areas across China by applying the IG method in order to examine the spatial distribution of UFC values. The geographical detector method was then applied to systemically analyze the impact of biogeoclimatic and socioeconomic factors on UFC in 286 Chinese major cities. The results of this analysis lead to a number of conclusions.

(1) The average UFC of major cities within China was 19.7% in 2010 but nearly one-third of these data points were less than 5%. The distribution of UFC values also exhibits marked differences between the northern and southern parts of China; average values for cities in northern China were 11.1%, while average values were 27.6% in the southern part of the country.

(2) Urban forests in Chinese major cities have been influenced by both biogeoclimatic (i.e., precipitation and temperature) and socioeconomic factors (i.e., secondary industrial share, city size, urban population density, and GDP per capita). Overall, data show that

biogeoclimatic factors have exerted a stronger influence on the spatial differences of UFC, while the impacts of socioeconomic factors have been weaker.

(3) The use of geographical detector model also reveals that the explanatory power of interactions are all higher than those of a single factor, and that interactions between precipitation and elevation have exerted the greatest impact on UFC values.

(4) Data show that the Chinese NFC programme has had no significant impact on spatial differences of UFC. Indeed, it is notable that average UFC of the NFCs remain lower than those of other cities; and average UFC of cities with the NFC title were also much lower than standards which the NFC programme required. Thus, urban forests need to be emphasized within future urban planning and the government should take a leading role in ensuring the supply of investment and lands.

Conflict of Interest

The authors declared that they have no conflicts of interest to this work.

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Figure legends

Fig. 1. The technical route used in this study to extract urban forest data.

Fig. 2. Urban areas in China (2010) extracted using the IG method.

Fig. 3. Determinants, proxy variables, and their descriptions.

Fig. 4. The spatial distribution of discretized variables in 2010: **a.** precipitation; **b.** temperature; **c.** elevation; **d.** city size; **e.** urbanization; **f.** urban population density; **g.** GDP per capita; **h.** share of secondary industry, and; **i.** NFC.

Fig. **5**. 2010 UFC values for major cities within China. The Qin Mountains–Huai River Line is an important geographical boundary nationally as it divides China into southern and northern parts.

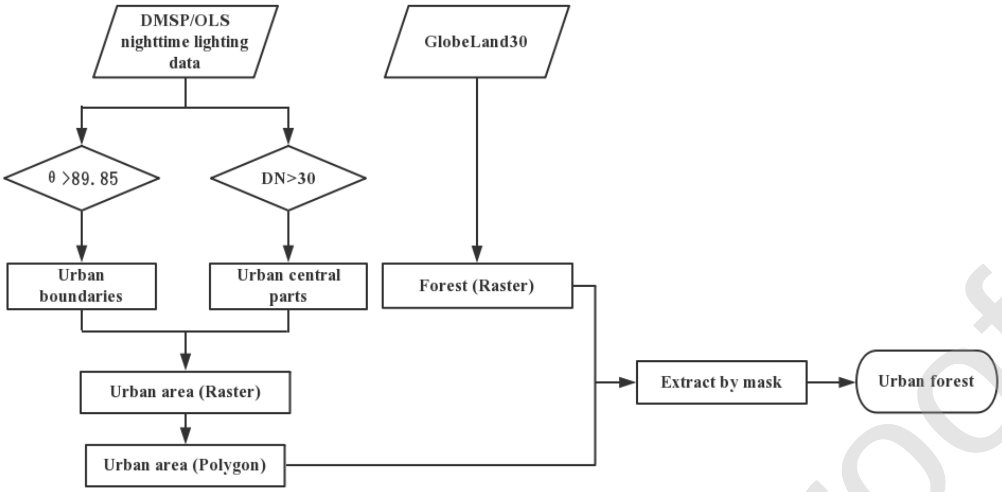
Fig. **6**. UFC *q*-statistics for China. Abbreviations: * p-value < 0.1; ** p-value < 0.05; ***p-value < 0.01).

Table legends

Table 1. Defined interaction relationships (Wang and Hu, 2012).

Table 2. Interactive proxy variable *q*-statistics for urban forests.

Figures



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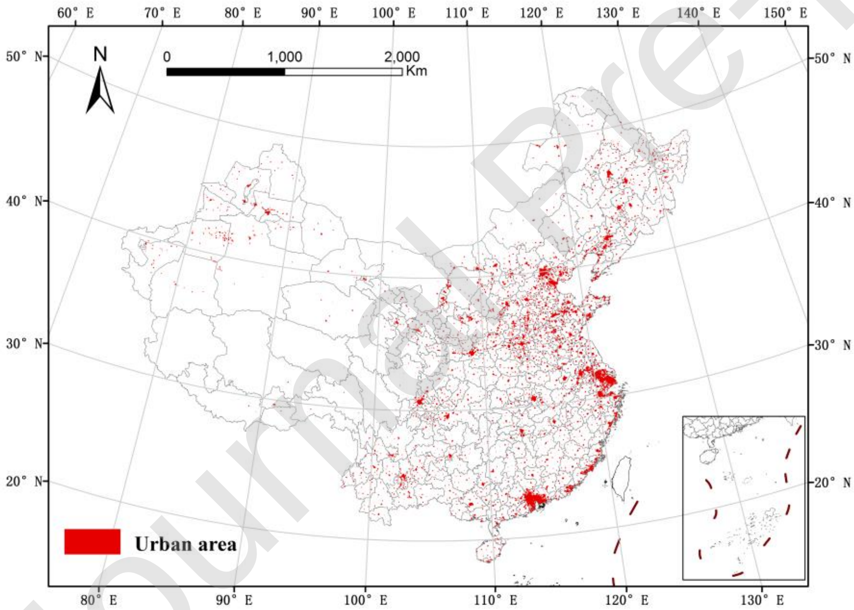

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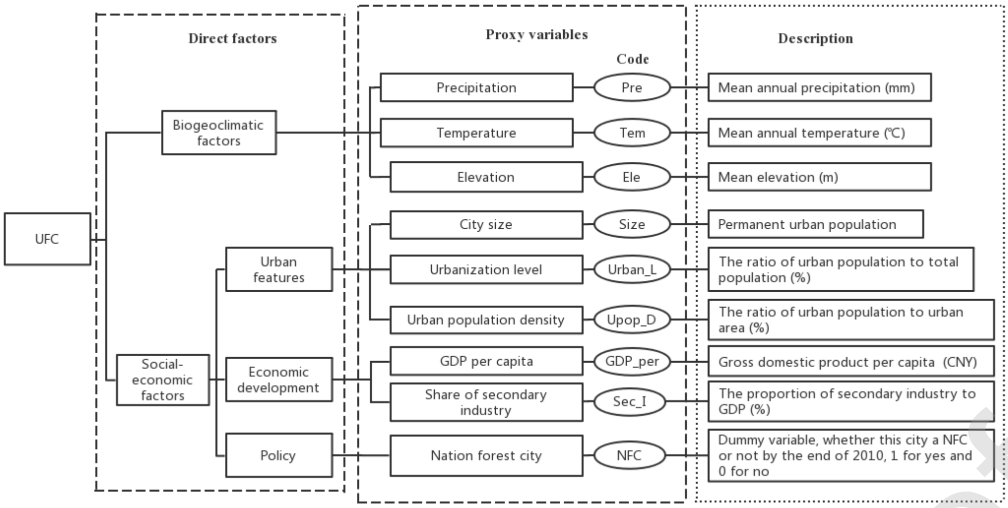

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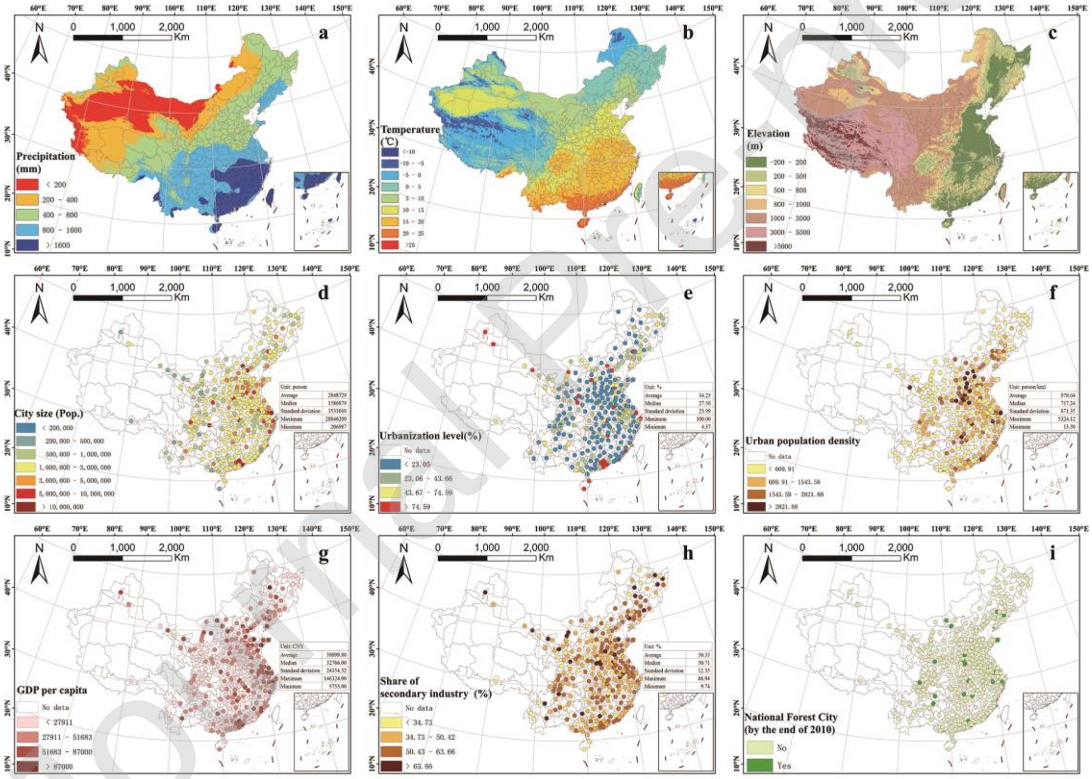

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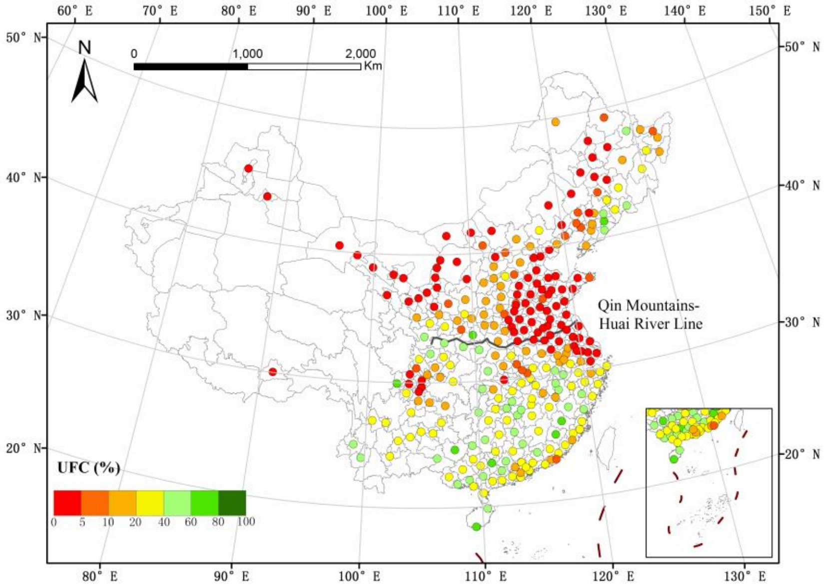

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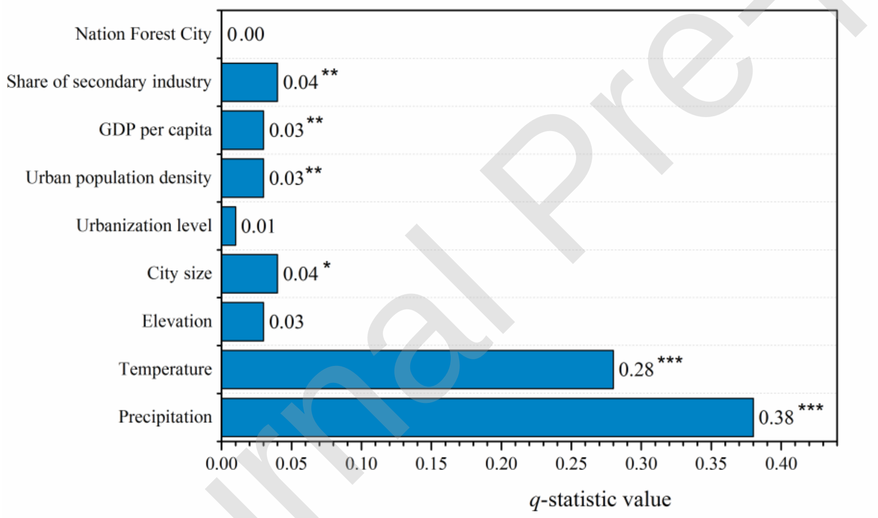

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Tables

Table 1. Defined interaction relationships (Wang and Hu, 2012).

Description	Interaction
$q\ (X_a \cap X_b) < \mathrm{Min}\ (q\ (X_a),\ q\ (X_b))$	Weakened, nonlinear
$\mathrm{Min}\ (q\ (X_a),\ q\ (X_b)) < q\ (X_a \cap X_b) < \mathrm{Max}\ (q\ (X_a),\ q\ (X_b))$	Weakened, unique
$q\ (X_a \cap X_b) > \mathrm{Max}\ (q\ (X_a),\ q\ (X_b))$	Enhanced, bilinear
$q\ (X_a \cap X_b) = q\ (X_a) + q\ (X_b)$	Independent
$q\ (X_a \cap X_b) > q\ (X_a) + q\ (X_b)$	Enhanced, nonlinear

Table 2. Interactive proxy variable *q*-statistics for urban forests.

	Precipitation	Temperature	Elevation	City size	Urbanization level	Urban population density	GDP per capita	Share of secondary industry	Nation Forest City
Precipitation	0.38								
Temperature	0.46 (EB)	0.28							
Elevation	0.50 (EN)	0.41 (EN)	0.03						
City size	0.49 (EN)	0.37 (EN)	0.16 (EN)	0.04					
Urbanization level	0.41 (EN)	0.33 (EN)	0.09 (EN)	0.07 (EN)	0.01				
Urban population density	0.48 (EN)	0.34 (EN)	0.11 (EN)	0.09 (EN)	0.06 (EN)	0.03			
GDP per capita	0.43 (EN)	0.33 (EN)	0.12 (EN)	0.13 (EN)	0.08 (EN)	0.08 (EN)	0.03		
Share of secondary industry	0.44 (EN)	0.36 (EN)	0.11 (EN)	0.12 (EN)	0.09 (EN)	0.10 (EN)	0.08 (EN)	0.04	
National Forest City	0.39 (EB)	0.29 (EN)	0.04 (EB)	0.05 (EN)	0.02 (EN)	0.04 (EB)	0.05 (EN)	0.04 (EN)	0.00

Abbreviations: (EN) denotes the nonlinear enhancement of two variables, and; (EB) denotes the binary enhancing of two variables (see Table 1) (Wang and Hu, 2012).