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Exploring Spatiotemporal Dynamics of Urban Fires: A Case of Nanjing, China

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Abstract: Urban fire occurs within the built environment, usually involving casualties and economic losses, and affects individuals and socioeconomic activities in the surrounding neighborhoods. A good understanding of the spatiotemporal dynamics of fire incidents can offer insights into potential determinants of various fire events, therefore enabling better fire risk estimation which can assist with future allocation of prevention resources and strategic planning of mitigation programs. Using a twelve-year (2002–2013) dataset containing the urban fire events in Nanjing, China, this research explores the spatiotemporal dynamics of urban fires using a range of exploratory spatial data analysis (ESDA) approaches. Of particular interest here are the fire incidents involving residential properties and local facilities due to their relatively higher occurrence frequencies. The results indicate that the overall amount of urban fires has greatly increased in the last decade and the spatiotemporal distribution of fire events varies among different incident types. The identified spatiotemporal patterns of urban fires in Nanjing can be linked to the urban development strategies and how they have been reflected in reality in recent years.

Keywords: urban fire; spatiotemporal analysis; ESDA; GIS

1. Introduction

Fire, either caused by humans or nature, can pose a hazard to people, properties and the environment, possibly resulting in psychological damage, physical injuries, death and significant economic losses. For example, there were a total of about 212,500 fires during 2013–2014 in the UK, involving 322 deaths and more than 9700 non-fatal casualties [1]. According to the National Fire Protection Association of the US, there were 3240 deaths, 15,925 injuries and $11.5 billion economic costs of property damage caused by about 1.24 million fires in 2013 [2]. Urban fire is both a physical and a social process [3], in the sense that it occurs within the built environment and affects individuals and socioeconomic activities in the surrounding neighborhood or communities, usually involving both individual casualties and economic losses. For instance, in 2015, the massive explosion in Tianjin, China, left more than 170 dead, 700 people injured, thousands homeless, 7 communities (involving more than 10,000 households) destroyed and $1.044 billion direct economic losses, alongside high levels of environment pollution caused by dangerous chemicals [4]. Given the continuing global trend of urbanization, urban fire safety has been a worldwide concern and presents great challenges to the success of sustainable urban development [5]. Fire and rescue services are therefore critical to the protection of lives and properties. In order to improve the efficiency and effectiveness of fire safety management, it is essential to understand well the spatiotemporal dynamics of fire incidents, which can offer insights into potential determinants of fire events, enabling better fire risk estimation that can assist with future allocation of prevention resources and strategic planning of mitigation programs.

As fires occur in geographic space, geographical information system (GIS)-based spatial analysis is well suited for the needs of fire and rescue services, which has been widely applied in urban fire analysis due to the increasing availability of high-resolution spatiotemporal data in recent years. For example, spatial distribution of fire events can be visualized by desktop mapping in a straightforward manner [6]. Also, spatial/temporal/spatiotemporal patterns of fire events can be explored by a range of spatial analytical techniques. For instance, continuous surfaces generated by kernel density estimation (KDE) can reflect the spatial variations in fire risks [7]. The comap developed by Brunsdon [8] has been used to explore the spatiotemporal patterns of fire events [9–11]. Further, of more interest is often the relationship between the occurrence of urban fires and the associated driving factors. For example, it was found that socioeconomic variables such as population density, building conditions and household level generally have more influence on urban fires compared to the physical environment [3,6,7,12]. Corcoran et al. [12] examined the impact of calendar events (e.g., public and school holidays and major sports events) and found that fire incidents would significantly increase during school holidays. Guldåker and Hallin [13] found that living conditions and socioeconomic stress can greatly affect the spatiotemporal patterns of intentional fires. So far, most of the existing work on urban fires, however, has focused on the cases in developed countries, such as the UK [7,9,11,12], Canada [10], Australia [11] and Sweden [13]. Few studies have been carried out in developing countries and regions.

The aim of this paper is to explore the spatiotemporal dynamics of urban fires in Nanjing, China, over the twelve years during 2002–2013. The average number of fires per ten thousand people in China has increased from 36.1 in 1980s to 62.2 in 1990s and 148.7 since 2000 [14]. Particularly, recent years have witnessed a number of large-scale urban fires, such as the high-rise fire in Shanghai in 2010 that caused 58 deaths and 71 injuries [15] and the Tianjin explosions mentioned above, which has presented significant stress on communities, governance, operations and policy. The rapid increase in urban fires has been considered closely related to the massive urban construction and urban population growth during the unprecedented urbanization in the last few decades [14]. The built-up areas of Chinese metropolises have expanded by almost 60% since 2000, and currently more than 50% of the population are living in cities [16]. Chinese cities are challenged by new and increased fire risks especially at locations such as high-rise buildings, underground transport, shanty towns and large warehouses. To this end, this research attempts, using Nanjing as a case study city, to understand the characteristics of urban fires during its urban development and expansion over the last decade.

The remainder of the paper is structured as follows: The next section introduces the research methods, including the study area, the data and the spatial analysis approaches. Then, the spatiotemporal patterns of fire incidents in Nanjing, China, are presented. The paper concludes with discussion of major findings and their association with the urban development strategies and reality in recent years, as well as the implications for future urban fire safety management and planning.

2. Methods

2.1. Data and Study Area

The study area is located in the south of Yangtze River within Nanjing, China, covering seven districts of the city: Xuanwu, Qinhuai, Jianye, Gulou, Yuhuatai, Qixia (about 40% of entire area) and Jiangning (about 15% of entire area) that are bounded by the expressway ring road in the city, which is considered the main urban area of the city (the first four also known as the city core) and includes fifty-three Jiedao—the smallest statistical geography in Chinese Census. Figure 1 shows the study area, alongside the location of Nanjing in China and the location of the study area in Nanjing. The total area is about 598.1 km^2 (about 9.1% of total area of Nanjing), occupied by a population (permanent residents hereafter, unless stated otherwise) of 5.06 million (2010) (about 54.4% of total population of Nanjing) [17]. Nanjing is the capital of Jiangsu Province with an approximate 2500-year history.

Located in the Yangtze River Delta region and about 300 km northwest of Shanghai, Nanjing nowadays is an important center of education, commerce, transportation and tourism in East China.

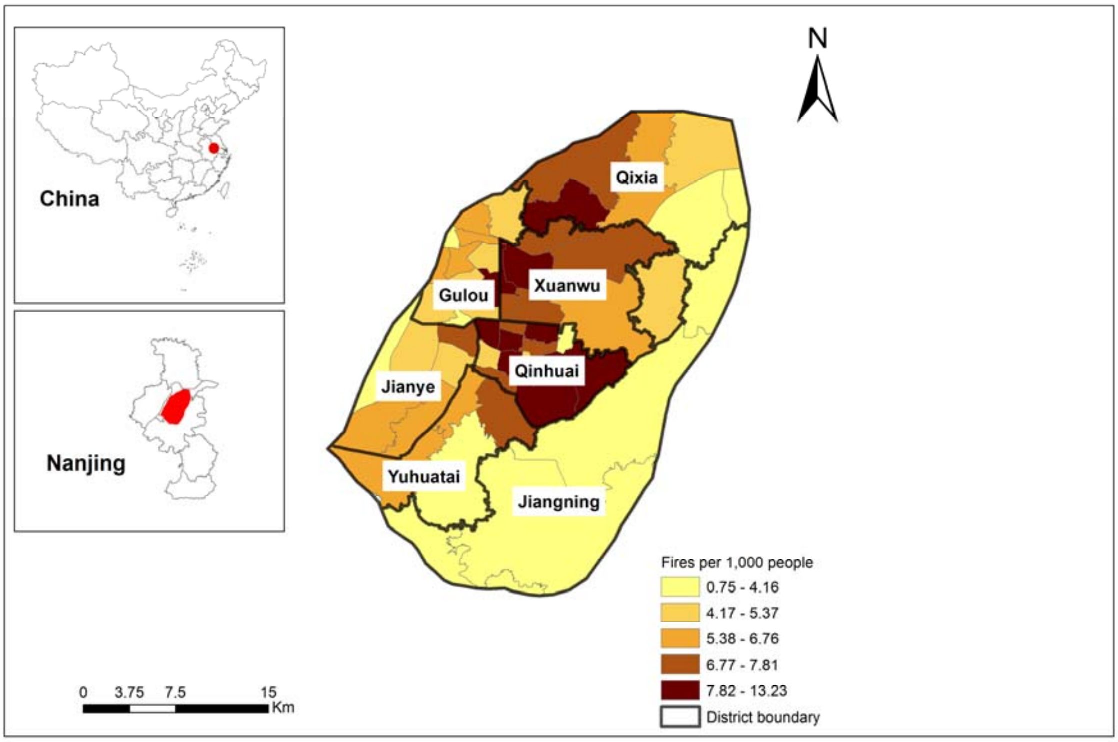
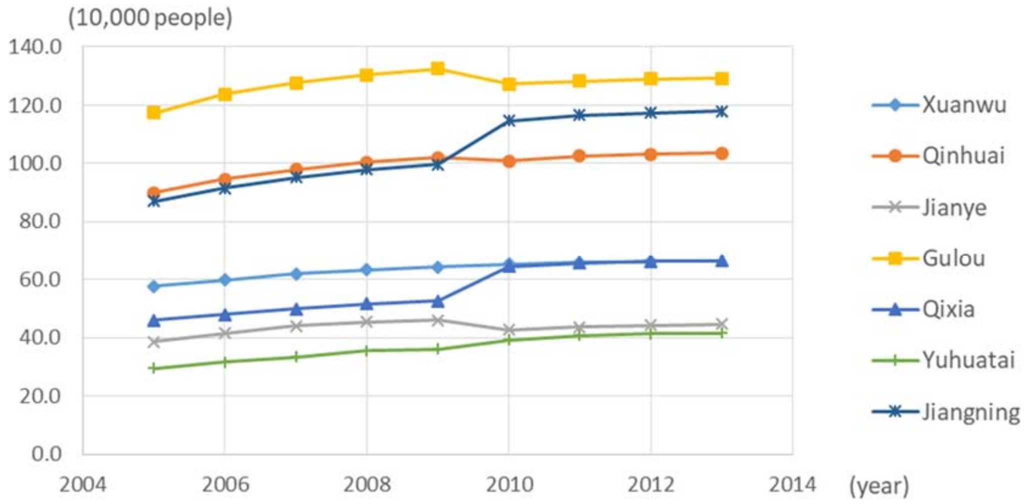


Figure 1. Fire incident rates in Nanjing by Jiedao (2002–2013).

Like many other Chinese cities, Nanjing has experienced rapid urbanization in the last three decades with the primary goal of promoting economic growth. In 2013, the urban land area was about 1833.6 km^2, with an increase of 58.1% compared to that of 2001 [18]. Meanwhile, the gross domestic product (GDP) of Nanjing in 2013 was $121.4 billion, increased by 357.8% compared to that of 2001 [19]. An important outcome of fast urban expansion is the rapid increase in urban population. According to the sixth Population Census of China, the population in Nanjing has increased about 28.3% during 2000–2010 [17]. Figure 2 shows the population information of the seven urban districts for years 2005–2013 [19] (the information on permanent residents for each urban district is only available from 2005 onwards). The population density at the city core has been consistently higher than those in the other three districts, where Gulou and Qinhuai are ranked top in both population and its density. Both Jiangning and Qixia have seen an obvious population growth in 2010 but their population densities have been lower than those of other districts, possibly due to the large area they occupy. The overall population growth has led to comprehensive urban transformation reshaping both urban landscapes and socioeconomic activities. For example, in order to connect the city core, new urban districts and suburban areas, seven subway lines with a total length about 258 km have been planned and built in Nanjing since 2000, and Line 1 entered into operation in 2005 (http://www.njmetro.com.cn). The changes in the built environment as well as the increased population have brought new characteristics to urban fire risks, raising new concerns and challenges to the fire and rescue services such as high-rise firefighting.



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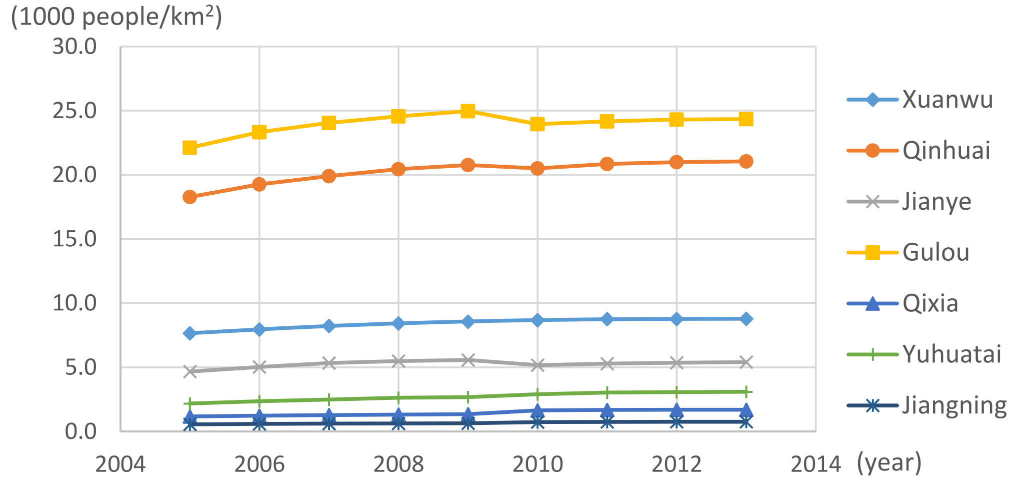


(**b**)

Figure 2. Population information for years 2005–2013: (**a**) population of permanent residents; (**b**) population density.

The data used in this research were provided by the Fire Department of Ministry of Public Security (FDMPS), Nanjing, containing twelve-year (2002–2013) urban fire incidents for the seven districts in central Nanjing. In order to make the fire incidents comparable over space and time, we excluded the major events attended by more than 40 firemen, and a total of 28,383 urban fires are included in the analysis. The information attached to each fire incident includes its type (such as dwelling fires, vehicle fires or false alarm, etc.) and geographic location recorded by longitude and latitude. Using the 2010 Census data, the population-based fire risks are calculated as the total number of fires per 1000 people for each Jiedao within the study area. The results are shown in Figure 1 using the quintile classification. It can be seen that the higher incident rates are largely located in the city core (mainly covering Gulou, Xuanwu and Qinhuai) and the west of Qixia. It is not surprising because those areas have relatively higher densities of population (see Figure 2) and socioeconomic activities than the rest of the city [19].

The incidents have been classified into ten categories: vehicles (VH), non-residential buildings (NRB) (e.g., restaurants and hotels), industrial (IN), retail stores (RS), refuse (RF), dwellings (DW), grassland (GL), facilities (FL) (e.g., transformer and high-tension power lines), false alarm (FA) and others (OT) (e.g., construction sites). The proportions of each type of fire are as follows: 10.3% (VH), 2.8% (NRB), 2.1% (IN), 2.8% (RS), 13.8% (RF), 34.1% (DW), 10.2% (GL), 15.5% (FL), 4.1% (FA) and 4.4% (OT). During 2002–2013, dwelling fires and fires involving facilities together amount to almost half of the total incidents. The following descriptions and analyses will particularly focus on those two types of fires as they have a significant impact on human life and daily activities.

2.2. Spatial Analyses

This research employs a variety of spatial, temporal and spatiotemporal analytical techniques, including both basic descriptive statistics and more advanced exploratory spatial data analysis (ESDA) approaches. First, spatial distribution of fire events is explored by spatial clustering analysis. Further, temporal patterns of fires are examined using circular statistics. Finally, spatial-temporal variations of fire incidents are investigated by space-time scan statistics (STSS) [20].

In this research, spatial clustering analysis is used to identify the places with significantly high concentrations of fire events, which is implemented on point and lattice data, respectively. First, using the point data representing discrete fire events, continuous surfaces of fire densities are generated by spatial KDE [21]—a spatial smoothing technique, through which the spatial variations of fire distribution can be observed. A key parameter for KDE is the bandwidth, which controls the smoothness of the generated density surfaces. Although many techniques have been developed to seek the optimum bandwidth, Corcoran et al. [7] argued that "trial and error" is usually a simple yet effective method which is employed in this research. Also, a single bandwidth is chosen here to ensure the comparability between different types of fire. As a result, a bandwidth of 1.0 km was selected in order to achieve a good visual representation of the fire distribution geographically.

Further, since the areas of the Jeidao are quite large (for example, there are a total of 53 Jiedao within the study area and the largest one covers an area of 80.2 km^2), the study area is discretized using a set of regular grid cells (1.0 km $\times$ 1.0 km, in total 587 cells) as the basis for areal data analysis, which ensures the identifiability of potential incident clusters while avoiding too many zero-event grid cells. Based on the total fire events within each grid cell, the local clusters of high relative DW or FL fire risks are identified using the Getis-Ord G^* statistic, a common spatial modelling technique for hot spot analysis [22]. Specifically, each grid cell has an associated attribute defined as the proportion of a particular type of fire to all the fires within that grid cell, which is involved in the calculation of the Getis-Ord G^*.

The temporal variations of fire events are examined using rose diagrams on a daily, weekly and monthly basis, respectively. Rose diagrams are graphic tools originally designed to describe wind speed and direction, but also have been adapted for describing the temporal distribution of fire events, such as the work by Corcoran et al. [9] and Asgary et al. [10]. Specifically, two associated attributes are considered: one is the proportion of fire incidents to the overall amount of the same type of fire, and the other is the proportion of each type of fire to all the fire incidents. In addition, as the fire incidents can be considered circular data when summarized by rose diagrams, circular statistical analysis is utilized to test the temporal uniformity of each type of fire as well as to test the temporal homogeneity on two types of fire events. In this research, the Watson's U^2 one-sample test [23], a method to test circular uniform distribution, is employed to test whether each type of fire is uniformly distributed over time. The Watson's U^2 two-sample test [23], a method to compare the distribution of two sets of circular data, is adopted to compare two rose diagrams to see whether the two types of fires represented by them have similar temporal patterns.

Finally, spatiotemporal patterns of fire incidents are explored by space-time scan statistics using the retrospective space-time model [20], which have been widely applied in many domains for spatiotemporal clustering analysis such as detection of disease or crime clusters [24,25]. In this case, a cylindrical scanning window with varying sizes in both space-radius and temporal height moves over the study area and study time period, seeking clusters of events across both space and time. The statistical significance (p value) of the identified clusters is obtained using a Monte Carlo simulation. Based on the potential spatial clusters observed in Figures 2 and 3, the maximum cluster size in this research is set to 1.0 km radius and 6 years (50% of the study time period) to avoid generating very large clusters which provide little insight for policy intervention. As the fire incidents are spatial count data, the Poisson model is applied to both DW and FL fires using the same set of lattice data that is used for the Getis-Ord G^* statistic calculation, with the total fires in each grid cell as the underlying population. Therefore, the spatiotemporal clusters of interest here represent the relative risks of DW or FL fires over space and time compared with other types of urban fires.

The above analyses are implemented using several software tools. All the statistical analyses are carried out in the *R* environment (https://www.r-project.org/), an open source software framework for statistical computing. Spatial data processing, manipulation and all the other spatial analyses are implemented in ArcGIS 10 (ESRI, Redlands, CA, USA). The STSS is calculated with SaTScan (https://www.satscan.org)—free software for spatial, temporal and space-time scan statistics.

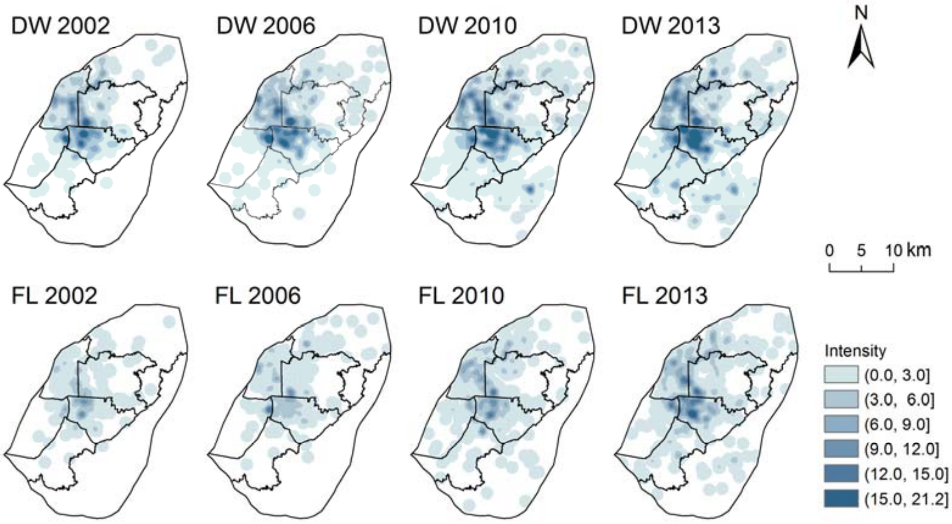


Figure 3. Kernel density estimation (KDE) of dwellings (DW) and facilities (FL) fires in 2002, 2006, 2010 and 2013.

3. Results

3.1. Spatial Distribution

First, kernel densities are estimated for the dwelling and facility fires, respectively. Figure 3 shows the kernel density surfaces for the years 2002, 2006, 2010 and 2013, representing the beginning, middle and end of the study time period. It can be seen that both DW and FL fires have expanded from the central three urban areas—Gulou, Xuanwu and Qinhuai, towards the surrounding areas, especially the districts Qixia on the north and Jiangning on the southeast. However, the FL fires are, in general, less dense than the DW fires around the city core. As to the DW fires, the higher intensity of incidents has consistently clustered around the central three districts mentioned before, especially Qinhuai, sprawling towards the north across Gulou, Xuanwu and Qixia. With regard to the FL fires, the intensity of events is much higher around the city core in 2013 than those in the other years.

Again, considering the same four representative years, 2002, 2006, 2010 and 2013, the hot spot analysis results are presented in Figure 4, which shows the areas with significantly (p-value < 0.05) higher risks (z-score > 1.96) of DW and FL fires, respectively. It can be observed that the spatial patterns of relative fire risks are very different from those of fire intensities shown in Figure 3. For the DW fires, both higher intensity and higher risk of incidents are largely concentrated in the central three districts in 2002 and 2006, but the latter has been moving towards the surrounding area in 2010 and 2013 with its share in the central areas greatly decreased. As to the FL fires, higher risks are mainly located in Gulou and Qinhuai in 2002. Since 2006, they have been moving towards the intersection of the central three districts. Meanwhile, the other districts have also seen emerging higher risks of FL fires, particularly the south of Qixia.

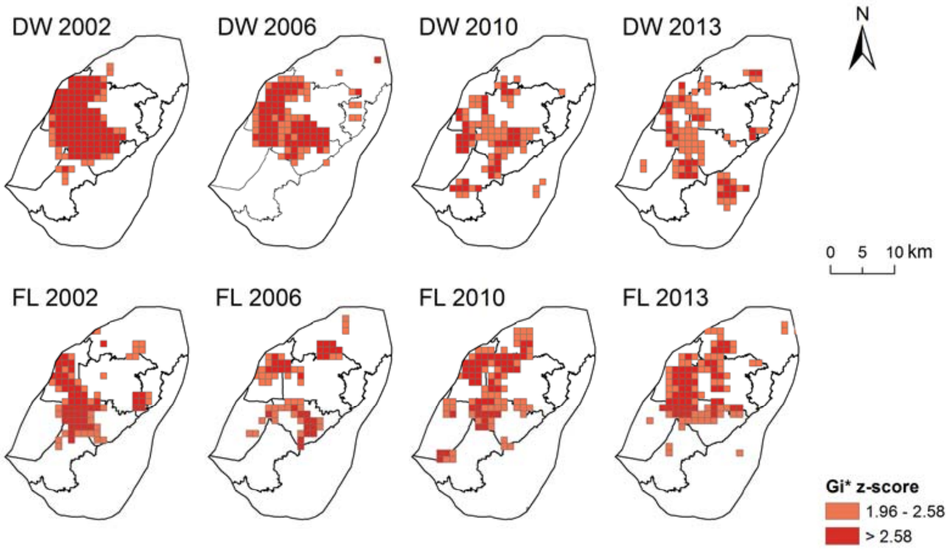


Figure 4. Spatial clusters of relative DW and FL fire risks in 2002, 2006, 2010 and 2013.

3.2. Temporal Variations

Figure 5 shows the annual variations (in percentage) of DW, FL and all fires compared to the corresponding amount in year 2002, respectively. It can be seen that in general the three lines demonstrate similar temporal trends. That is, the annual variations in urban fires have kept within 50% until 2008 but then have experienced rapid growth, except for a slight drop in 2012 (for all types and FL) and in 2011 (for DW). Also, the temporal pattern of DW fires is more similar to that of all fires, especially during 2002–2008 when the absolute average variations are about 16.8% (all types) and 15.8% (DW), while the value for FL fires in the same period of time is about 29.5%. The difference after 2008 becomes more prominent, with the absolute average variations being about 103.4% (all types), 68.2% (DW) and 136.1% (FL), respectively.

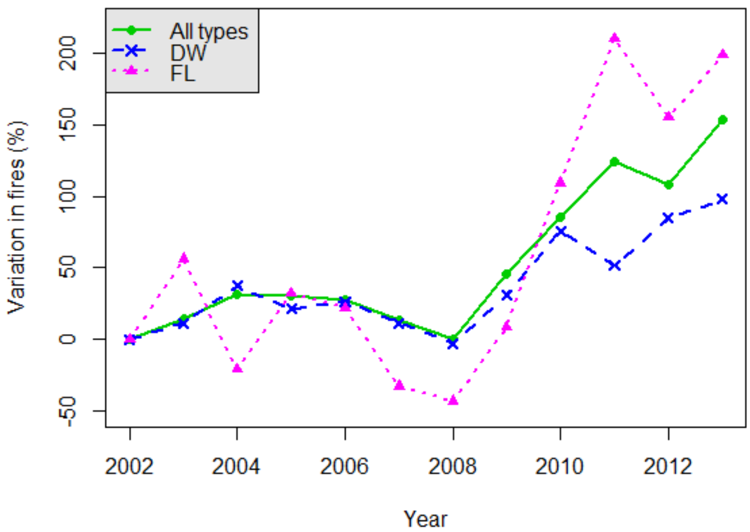
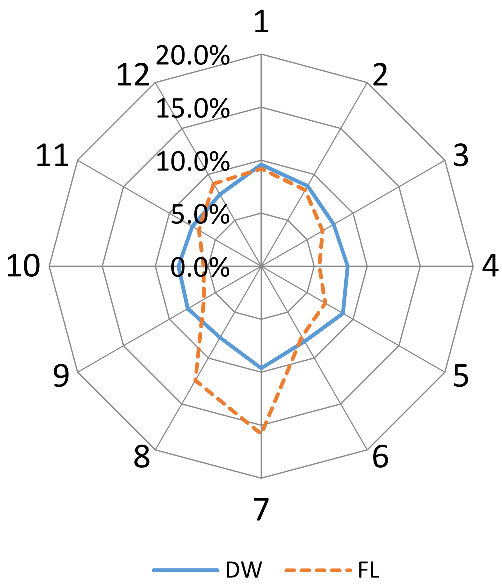


Figure 5. Annual variations of fire incidents (2002–2013).

The temporal variations of both DW and FL fires across the study time period are further examined on a monthly, weekly and daily basis using rose diagrams. Specifically, two associated attributes are considered: one is the proportion of fire incidents to the overall amount of the same type of fire, and the other is the proportion of each type of fire to all the fire incidents. The results are shown in Figures 6–8.

In terms of monthly distribution, the highest proportions of DW and FL fires both occur in July as shown in Figure 6a. But, there is much more variation in FL fires with a standard deviation of 3.1% (compared to 0.7% for DW fires), largely due to the higher rates in July (15.8%) and August (12.4%). A similar pattern also can be observed in Figure 6b which accounts for the contributions of DW or FL fires to all the incidents. Again, the distribution of FL fires is similar to that in Figure 6a, with proportions in July and August being much higher than those in the other months. For the DW fires, the highest proportion is in September (39.7%) and the lowest is in December (29.4%), with a variation of 3.5% across the year. Overall, for each month, DW fire has a larger share of all urban fires than FL fire, and on average the monthly fire incidents contain about 34.4% of DW fires and 15.5% FL fires.



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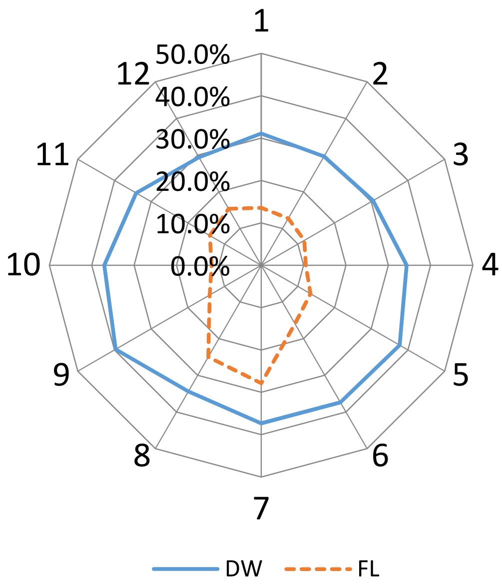
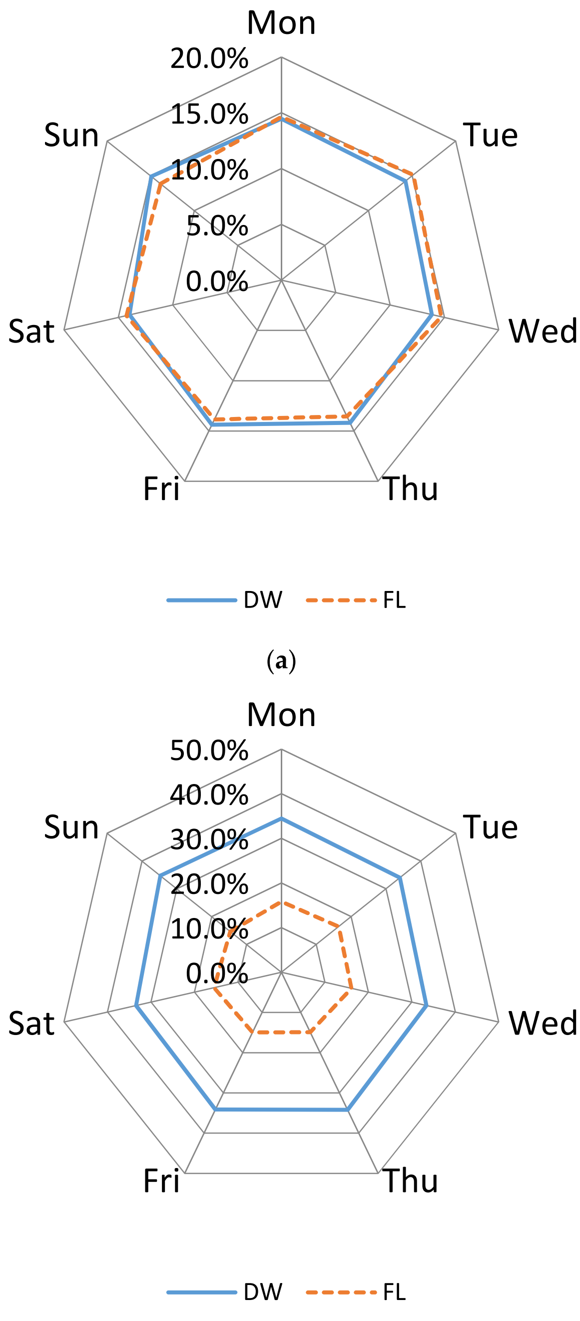


(**b**)

Figure 6. Monthly variations: (**a**) proportions to each type of fire; (**b**) proportions to all fires.

As shown in Figure 7a, most of the DW fires occurred on Sunday (14.9%) and the lowest proportion on Wednesday (13.8%). For the FL fires, Tuesday has the highest proportion (15.1%) while Thursday has the least (13.5%). In fact, the average variations in the weekly distribution for both DW and FL fires are very small, with the standard deviations about 0.3% and 0.5%, respectively. On average, the incidents on each day of the week contain about 34.1% DW fires and 15.5% FL fires, which is similar to their monthly proportions. Further, it is indicated by Figure 7b that the variations of contributions to all fires are quite small as well, with the standard deviations around 0.5% (DW) and 0.6% (FL).



(**b**)

Figure 7. Weekly variations: (**a**) proportions to each type of fire; (**b**) proportions to all fires.

Compared to Figures 6 and 7, Figure 8 shows the fire distribution on a finer temporal scale. Figure 8a indicates that most of the DW fires (about 80.5%) occurred during the hours 8 a.m.–9 p.m. FL fires largely occurred in the period 9 a.m.–11 p.m. (about 80.0%), among which actually more than half (43.6%) happened during 5 p.m.–10 p.m. In terms of their contributions to all the fires on one day, Figure 8b shows that the average hourly proportion of DW fires is about 32.2%, almost twice that of FL fires (15.5%). Also, except for the time between 9 p.m.–10 p.m., the former has a larger proportion than the latter for the remaining hours of the day. In particular, the hourly rate of DW fires during 8 a.m.–5 p.m. is as high as 40.6%. As to the FL fires, only for the time intervals 6 a.m.–7 a.m. and 7 p.m.–11 p.m., it comprised more than 20% (21.9–28.5%) of the total fires having occurred during that time.

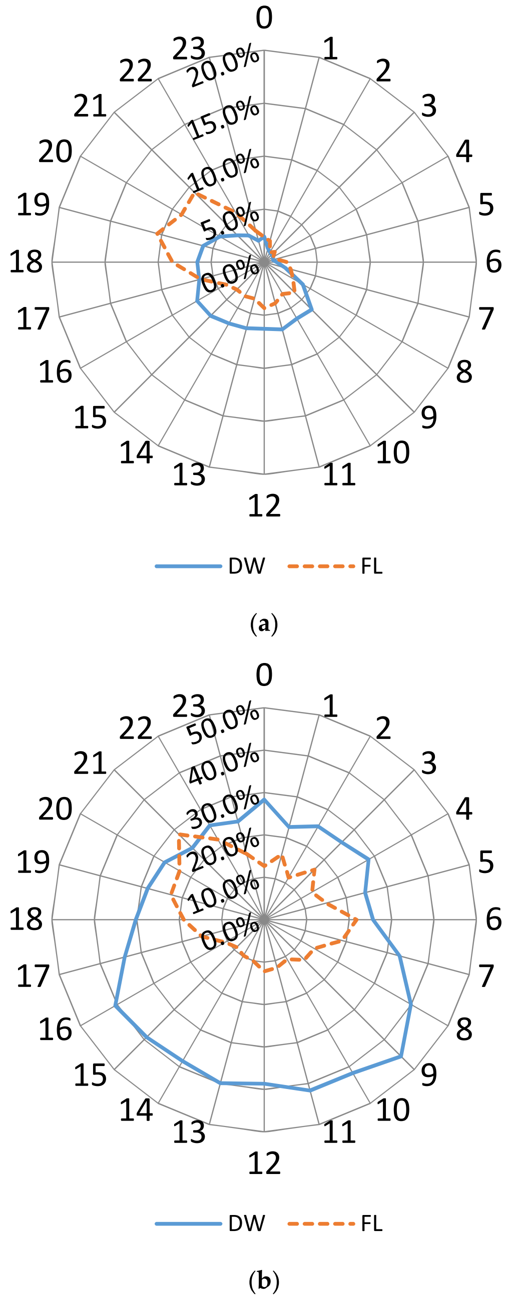


Figure 8. Daily variations: (**a**) proportions to each type of fire; (**b**) proportions to all fires.

Finally, the Watson's one-sample U^2 test suggests only monthly (Figure 6a) and daily (Figure 8a) distribution of the FL fire are significantly different from circular uniform distribution, with the test statistic 101.0 (p-value < 0.05) and 31.1 (p-value), respectively. Further, the Watson's two-sample U^2 test indicates that the temporal patterns of DW and FL fires, in terms of month of year (Figure 6a) and hour of day (Figure 8a), are significantly different from each other, with the test statistic 4.5 (p-value < 0.05) and 15.6 (p-value < 0.05), respectively, which is consistent with the observations above.

3.3. Spatiotemporal Dynamics

There is a total of five spatiotemporal clusters for DW fires and six for FL fires at the 10% significance level (p-value < 0.10) based on 999 Monte Carlo replications. The spatiotemporal clusters are depicted by space-time cubes, as shown in Figure 9 where the bottom of the cubes represents the spatial extent, which is also shown by the shaded grid cells in the underlying layer of the study area, and the height indicates the corresponding time period.

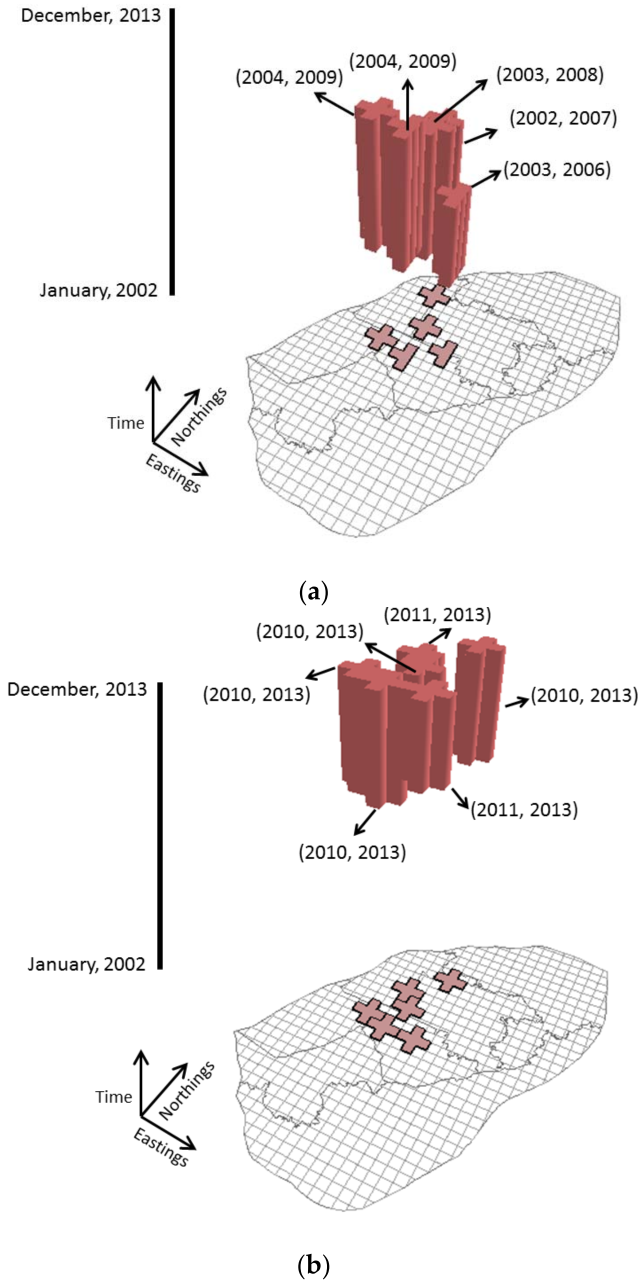


Figure 9. Spatiotemporal clusters of fire incidents: (**a**) DW fires; (**b**) FL fires.

It can be observed that the clusters of DW and FL fires span quite different time periods but are located at similar geographical areas. That is, the high risks of DW fires are largely found between years 2002–2009, whereas FL fires in contrast are between 2010 and 2013. Further, the temporal size of the clusters for the former ranges from four to six years, while for the latter, it varies from three to four years, which is noted for each cluster in Figure 9. In terms of the geographic locations, the high risks of DW and FL fires are both concentrated in the city core, with each cluster covering an area about 4 or 5 km^2. Those clusters primarily involve 17 Jiedao that are close to the common borders of Gulou–Xuanwu, Xuanwu–Qinhuai, and Qinhuai–Jianye.

4. Discussion and Conclusions

Urban fire has long been a great threat to properties, lives and the physical environment. A good understanding of the occurrences of fire incidents can offer insights into the underlying driving factors and assist with decision-making in relation to fire services and management. Using GIS-based spatial analytics, this research has explored the spatiotemporal dynamics of urban fires in Nanjing (2002–2013), China. In particular, the variations of DW and FL fires, which constitute about 50% of total fire incidents, have been investigated from three perspectives: space, time and space-time. The results can help identify disadvantaged populations and communities at higher fire risk, assisting future fire protection and prevention planning.

In general, the amount of urban fire has greatly increased since 2008 and DW fires remain a major threat to urban safety, which account for about one third of all fires. The city core has higher population-based fire risks than the other districts. Similarly, the intensities of DW and FL fires have been decreasing from the city core towards the surrounding areas, with emerging risks in the south, particularly in Jiangning. However, the relative high risks considering all fires are very different for DW and FL fires, which have a pattern of dispersing from the city core over time for the former but a pattern of concentration towards the city core for the latter. In terms of the temporal dimension, the rose diagrams suggest that for every month, each day of the week and every hour during one day, about one third fires are related to dwellings. Regarding the spatiotemporal distribution, both high concentrations of DW and FL fires are at the city core but the former covers a time interval before 2010 and the latter is the opposite.

In addition to human and stochastic factors, considering the urban development in Nanjing in recent years, there might be two types of associated influencing forces of the identified urban fire patterns: inner city growth and urban expansion. First, the three districts, Gulou, Qinhuai and Xuanwu, have relatively larger populations and higher population densities. As suggested by Figure 2, the population densities of Gulou and Qinhuai are much higher (more than ten times) than those in Qixia and Jiangning. Also, they occupy the majority of the city core, where high-quality public resources (e.g., health and education) and good job opportunities are concentrated. For example, by the end of 2013, over 90% of Jiangsu provincial authorities and more than 70% of the high-quality Pre-tertiary education resources of Nanjing are located in Gulou [19]. As a result, they remain the most active areas of socioeconomic activities [26,27]. Further, most residential buildings in those districts are quite old with a crowded population. In 2013, within the city core, Qinhuai had the most urban villages (74) and Jianye has the least (11) [19], which were mainly occupied by rural migrants and urban poor. Such dwellings are usually not equipped with modern safety devices like smoke detectors [19] and thus more vulnerable to fires. The continuing growth of population and job opportunities in the inner city might be one reason for the consistently higher densities of DW and FL fires in those areas (see Figures 3 and 9).

However, with the progress of constructions in newly developed urban districts and new towns since 2000, Nanjing has transitioned to a polycentric city, and the changing urban landscape and spatial distribution of population might also have affected the risks and occurrence of urban fires. For example, since 2001, urban land expansion has been largely driven by the new urban district/towns and development zones such as the Hexi Area (in Jianye), Banqiao New City (in Yuhuatai) and Jiangning Economic and Technical Development Zone (in Jiangning) [18]. The fast development has been guided by the urban planning strategy that new urban districts would be sub-centers mainly accommodating new housing and commercial growth [26]. For example, in 2013, Jianye had the biggest investment, about $2.3 billion, in real estate development, and Jiangning had the highest GDP of $15.8 billion among the seven districts [19]. Many people have been moving to the periphery of the city, largely towards the south, for a better living environment with newly deployed or improved public services and amenities [27]. Figure 2 indicates that both Qixia and Jiangning had a sharp population increase in 2010 while Gulou and Jianye both had a decrease. All the above consequences of urban expansion might be one reason for the increasing fire intensities in the south (Jianye, Yuhuatai and Jiangning) across the years (see Figure 3), as well as why the clusters of high DW fire risks located at the city core have a temporal window ending before or in 2010 (see Figure 9a).

Due to limited availability of the socioeconomic data at a fine spatial scale and a lack of concrete analyses, the discussion above essentially proposed several hypotheses with regard to the association between the spatiotemporal dynamics of urban fires and urban development. In order to verify the aforementioned assumptions there are several areas worthy of further investigation. First, based on the identified spatiotemporal patterns of urban fires, the impact of potential socioeconomic and environmental factors such as population density, conditions of dwellings and industrial agglomeration can be examined using spatial regression analysis, and thus various intervention measures targeting different causal factors can be implemented. Further, the actual causes of various fires can be analyzed to offer valuable insights into the occurrence of fire incidents, which can assist with future urban fire safety planning. Finally, in addition to DW and FL fires, the other types of fires are also important to urban safety and need further analyses. For example, refuse fires can cause air pollution and improving refuse monitoring and management can reduce the potential threat to the urban environment.

Given the continuing urbanization and on-going social-spatial urban transformation in China, the challenges presented by urban fires must be addressed if a safe and sustainable urban environment is to be achieved. This research has demonstrated that GIS-based spatiotemporal analytics can be powerful tools to help improve fire services and management.

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References

1. Department for Communities and Local Government (DCLG). Fire Statistics: Great Britain April 2013 to March 2014. Available online: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/456652/Fire_Statistics_Great_Britain_2013-14___PDF_Version_.pdf (accessed on 28 December 2017).
2. Karter, M.J. *Fire Loss in the United States during 2003*; National Fire Protection Association: Quincy, MA, USA, 2004.
3. Jennings, C.R. Social and economic characteristics as determinants of residential fire risk in urban neighborhoods: A review of the literature. *Fire Saf. J.* **2013**, *62*, 13–19. [CrossRef]
4. Xinhua News. Investigation Report: The Massive Explosions at Ruihai Warehouses for Hazardous Goods at Tianjin Port on 12 August 2015. 2016. Available online: http://news.xinhuanet.com/politics/2016-02/05/c_1118005206.htm (accessed on 2 May 2017).
5. Department of Economic and Social Affairs, the United Nations (UN-DESA). Challenges and Way Forward in the Urban Sector. 2012. Available online: https://sustainabledevelopment.un.org/content/documents/challenges_and_way_forward_in_the_urban_sector_web.pdf (accessed on 2 May 2017).
6. Špatenková, O.; Virrantaus, K. Discovering spatio-temporal relationships in the distribution of building fires. *Fire Saf. J.* **2013**, *62*, 49–63. [CrossRef]

7. Corcoran, J.; Higgs, G.; Brunsdon, C.; Ware, A.; Norman, P. The use of spatial analytical techniques to explore patterns of fire incidence: A South Wales case study. *Comput. Environ. Urban Syst.* **2007**, *31*, 623–647. [CrossRef]
8. Brunsdon, C. The comap: Exploring spatial pattern via conditional distributions. *Comput. Environ. Urban Syst.* **2001**, *25*, 53–68. [CrossRef]
9. Corcoran, J.; Higgs, G.; Brunsdon, C.; Ware, A. The Use of Comaps to Explore the Spatial and Temporal Dynamics of Fire Incidents: A Case Study in South Wales, United Kingdom. *Prof. Geogr.* **2007**, *59*, 521–536. [CrossRef]
10. Asgary, A.; Ghaffari, A.; Levy, J. Spatial and temporal analyses of structural fire incidents and their causes: A case of Toronto, Canada. *Fire Saf. J.* **2010**, *45*, 44–57. [CrossRef]
11. Corcoran, J.; Higgs, G.; Higginson, A. Fire incidence in metropolitan areas: A comparative study of Brisbane (Australia) and Cardiff (United Kingdom). *Appl. Geogr.* **2011**, *31*, 65–75. [CrossRef]
12. Corcoran, J.; Higgs, G.; Rohde, D.; Chhetri, P. Investigating the association between weather conditions, calendar events and socio-economic patterns with trends in fire incidence: An Australian case study. *J. Geogr. Syst.* **2011**, *13*, 193–226. [CrossRef]
13. Guldåker, N.; Hallin, P.O. Spatio-temporal patterns of intentional fires, social stress and socio-economic determinants: A case study of Malmö, Sweden. *Fire Saf. J.* **2014**, *70*, 71–80. [CrossRef]
14. Fire Department of Ministry of Public Security (FDMPS). *China Fire Services 2014*; Yunnan People's Publishing House: Kunming, China, 2014. (In Chinese)
15. Fire Department of Ministry of Public Security (FDMPS). *China Fire Services 2011*; Yunnan People's Publishing House: Kunming, China, 2011. (In Chinese)
16. National Bureau of Statistics of China (NBSC). *China Statistical Yearbook 2015*; China Statistics Press: Beijing, China, 2015. (In Chinese)
17. National Bureau of Statistics of China (NBSC). *Tabulation on the 2010 Population Census of the People's Republic of China*; China Statistics Press: Beijing, China, 2012. (In Chinese)
18. Chen, J.; Gao, J.; Chen, W. Urban land expansion and the transitional mechanisms in Nanjing, China. *Habitat Int.* **2016**, *53*, 274–283. [CrossRef]
19. Nanjing Municipal Bureau Statistics (NMBS). *Statistical Yearbook of Nanjing 2014*; China Statistics Press: Beijing, China, 2014. (In Chinese)
20. Kulldorff, M.; Athas, W.F.; Feurer, E.J.; Miller, B.A.; Key, C.R. Evaluating cluster alarms: A space-time scan statistic and brain cancer in Los Alamos, New Mexico. *Am. J. Public Health* **1998**, *88*, 1377–1380. [CrossRef] [PubMed]
21. Silverman, B.W. *Density Estimation for Statistics and Data Analysis*; Chapman and Hall: London, UK, 1986.
22. Getis, A.; Ord, J.K. The analysis of spatial association by use of distance statistics. *Geogr. Anal.* **1992**, *24*, 189–206. [CrossRef]
23. Fisher, N.I. *Statistical Analysis of Circular Data*; Cambridge University Press: Cambridge, UK, 1995.
24. Lian, M.; Warner, R.D.; Alexander, J.L.; Dixon, K.R. Using geographic information systems and spatial and space-time scan statistics for a population-based risk analysis of the 2002 equine West Nile epidemic in six contiguous regions of Texas. *Int. J. Health Geogr.* **2007**, *6*, 42. [CrossRef] [PubMed]
25. Nakaya, T.; Yano, K. Visualising Crime Clusters in a Space-time Cube: An Exploratory Data-analysis Approach Using Space-time Kernel Density Estimation and Scan Statistics. *Trans. GIS* **2010**, *14*, 223–239. [CrossRef]
26. Qian, Z. Master plan, plan adjustment and urban development reality under China's market transition: A case study of Nanjing. *Cities* **2013**, *30*, 77–88. [CrossRef]
27. Zeng, W.; Zhang, X.; Xiang, L.; Wang, Y. The Features of Population Redistribution of Nanjing Metropolitan Area in 2000–2010. *Sci. Geogr. Sin.* **2016**, *36*, 81–89. (In Chinese)