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Research Article

The Analysis of Spatial Pattern and Hotspots of Aviation Accident and Ranking the Potential Risk Airports Based on GIS Platform

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Aviation accident analysis is an important task to ensure aviation safety. The existing researches mainly focus on the analysis of aviation accident time characteristics and accident causes and less analysis of the spatial characteristics of aviation accidents. The spatial characteristics analysis of aviation accidents can identify hot spots of aviation accidents, improve the accuracy of aviation accident emergency management, and provide decision support for airport route planning. This study established the severity index of aviation accident based on aviation accident data, using GIS spatial analysis methods to study the spatial distribution characteristics of aviation accidents. The hot spots were identified in the aviation accidents. Finally, airports around the accident hot spots were ranked to obtain the airports with high potential aviation risks based on RI, taking Florida as an example. It was found that in the Florida aviation accident, general aviation accidents accounted for the majority, but the aviation accident severity index for air route flight was far greater than general aviation accidents. From the spatial distribution point of view, accidents with high severity index were distributed around large international airports. The Density Center for Aviation Accidents was located in Tampa, Miami, and some airports link areas in Florida. In terms of the Moran's I index, the distribution of aviation accidents tended to aggregate in the region as a whole. However, aviation accident severity index was randomly distributed for each year separately. At the level of significance of 0.01, there were a total of 75 accident hotspots in the Florida region, mainly in the north and southwest. Airports with high RI in the Florida area were mainly concentrated in the Miami area and the Tampa Bay area, and Orlando Airport was ranked outside the top 10.

1. Introduction

Aviation safety is the most important aspect of civil aviation transportation. Only by ensuring safety can we achieve high benefits with high efficiency. Therefore, aviation safety research has always been one of the key research topics of researchers [1, 2]. Aviation accident analysis is an important method to ensure aviation safety. Statistical analysis of aviation accidents is a passive risk identification method. However, by analyzing these actual aviation accidents, the law can be found to identify potential causes or sources of hazards and then effectively manage them to improve safety. Compared with other modes of transportation, civil aviation transportation is the safest mode of transportation [2]. But there are still many aviation accidents every year, especially in general aviation. Aviation accidents can be divided into two types, general aviation accidents and airline flight accidents. General aviation has a large amount of flight, mainly small aircraft, and the frequency of accidents is high, but the degree of damage and the number of casualties is small; the amount of airline flight is relatively small, the aircraft is mainly large, and the frequency of accidents is low, but the degree of damage is large, and there are many casualties. In the United States, there were 1,332 aviation accidents in the United States in 2017. Although the frequency of aviation accidents is relatively low, the consequences are so serious to cause serious casualties, property losses, and social impacts.

In previous studies, many researchers have analyzed the characteristics of aviation accidents. After a series of statistical analysis, Bazargan M found that the probability of accidents caused by pilot errors is not related to the pilot's gender, but experienced male pilots are more likely to cause fatal accidents [3]. Baker S P analyzed the crash accidents of General Aviation in the United States and found that the types of misoperations of pilots were very different in gender. The improper handling of aircraft dynamics, errors in decision-making systems, and negligence were the most common causes of pilot errors, which should be focused on the pilot training [4]. Salvatore S found that aviation accidents were most likely to occur in summer and early autumn [5]. Sun Ruishan found that the occurrence time of global aviation accidents was different in different periods. 11:00-12:00 and 15:00-16:00 are high accident periods [6]. The research on aviation accident characteristics analysis also includes the analysis of accident phases, the impact of weather conditions on aviation accidents, and the ranking of factors affecting general aviation accidents [7–11].

At present, the statistical analysis of aviation accidents mainly focuses on the types of accidents and their causes. Most of the studies on accidents happen from the perspective of year or month. There is a less statistical analysis of the time interval. The analysis of the spatial characteristics of aviation accidents mostly considers the flight phase [7, 12–14]. At present, there is less research on the spatial pattern characteristics of aviation accidents. The authors studied the relationship between aircraft collision risk and mortality in different geographical regions and showed that sector aviation safety should be focused [15]. The authors used geographic information systems and spatial analysis tools to study the geographic characteristics of the general aviation pilot's death rate and plotted the crash site. GIS was a valuable tool for aviation accidents and aviation safety research [16].

In other areas of transportation, Geographic Information System (GIS) is an effective tool for spatial analysis and is often used to study the temporal and spatial characteristics of traffic accidents. Based on pedestrian accident data, the authors used the method of spatial statistical analysis to identify seven areas with high pedestrian accidents and analyzed the time characteristics of pedestrian accidents on the road [17]; the authors used the cyberspace analysis framework and kernel density function to identify traffic accident hotspots in the road network based on the road traffic accidents that have occurred and discussed the social background of road traffic accidents [18]; the authors investigated daily and weekly time characteristics of vehicle accidents in Western Australia from 1999 to 2008 and used the kernel density function to analyze the spatial clustering characteristics of vehicle accidents on three spatial scales [19]. The authors proposed a vehicle-pedestrian accident data analysis model based on spatial autocorrelation analysis to identify and sort unsafe bus stops and generate hot spots map for vehicles and pedestrian accidents [20]. In the field of road traffic, there are many similar research results [21–24].

The spatial characteristics analysis of aviation accidents can identify the hot spots where aviation accidents occur frequently in the study area and analyze the spatial distribution characteristics of existing aviation accidents. It has important practical significance for reducing accidents. However, there are few studies in this area currently [16]. Therefore, based on the existing aviation accident data, this paper used GIS spatial analysis model, including nuclear density analysis, hotspot analysis, and spatial autocorrelation analysis, to study the temporal and spatial characteristics of aviation accidents and rank the potential accidents airports around the hot spots. The research results can provide decision support tools for aviation accident emergency management and airport route planning. It also can provide a new perspective for aviation accident analysis.

The goal of this research is to identify the hot spots where aviation accidents occurred. The research of other traffic areas has extensively used the kernel density function to analyze the hot spots of traffic accidents. Another goal is to analyze the spatial autocorrelation characteristics of aviation accidents and to determine whether aviation accidents have spatial aggregation trends. On this basis, the severity index of existing aviation accidents has been calculated to study which airports have high potential aviation accident risks in the past 15 years.

2. Study Area and Data Collection

Florida is selected as a case research area. There are 481 airports in Florida (2017). The major international airports include Miami Airport, Orlando Airport, Fort Lauderdale Airport, and Tampa Airport (Figure 1). Among them, Orlando International Airport is one of the busiest airports in the world. The total number of passengers was 44,611,265 in 2017, and the global ranking was 38th. Miami Airport's total passengers in 2017 were 44,171,313, ranking 40th in the world. Florida has a population of 20.98 million in the state, ranking third in the United States, with a population density of 6.57 people/acre (data from the Florida Geographic Data Library https://www.fgdl.org/).

2.1. Data Collection. The study employed the data provided by the National Transportation Safety Board (NTSB) (https://www.ntsb.gov/_layouts/ntsb.aviation/index.aspx), which maintains a database with all aviation accidents that occur in the world. Among many aviation accidents that arose in Florida between 2002 and 2017, 1182 were successfully geocoded in the ArcGIS environment, as shown in Figure 4. This research focused on accidents that involve nonfatal and fatal. This data also included the number of casualties in different situations

The data used in the study also included Florida State border and county boundary and the spatial location data of existing airports in Florida.

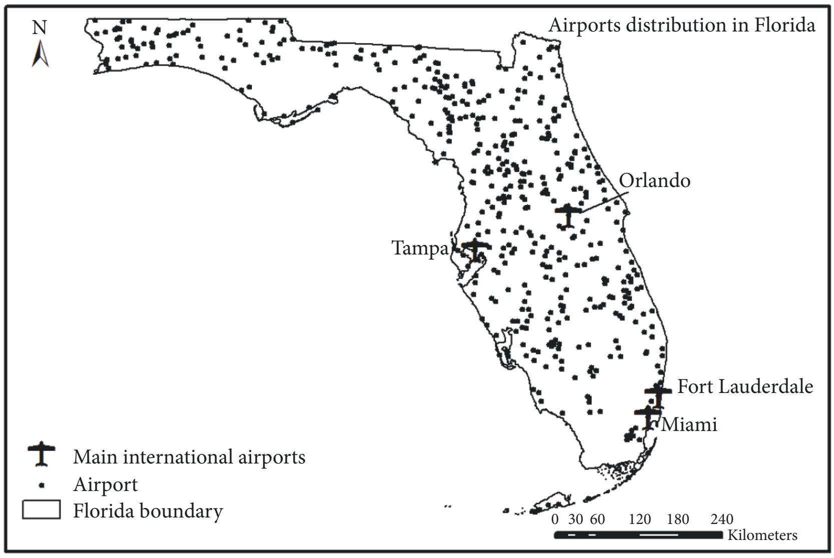

Figure 1: The map of airports distribution in Florida.

3. Methodology

The main task of this study was to analyze the spatial and temporal distribution characteristics of aviation accidents in the Florida region from 2002 to 2017 and to determine the airports that have potential aviation accident risks and rank these airports according to the severity of aviation accidents. Therefore, the research method of this study can be divided into the following steps:

(1) According to the space information of aviation accidents, the aviation accident data of Florida was imported into the ArcGIS platform to determine the spatial location of each aviation accident; (2) the severity index of aviation accidents was calculated by using information on the number of casualties in aviation accidents; (3) the spatial and temporal distribution characteristics of aviation accidents were studied based on various spatial analysis models; (4) the hot spot distribution map of aviation accidents was made to obtain typical hot spots in the study area; (5) combine the spatial distribution data of airports with the distribution map of aviation accident hotspots to determine the airports around the typical hot spots of aviation accidents; (6) calculate the severity index of these typical airports and rank them to determine which airports have higher aviation accident severity in 2002-2017, that is, which airports have potential aviation accident risks.

The platform used for the research was ArcGIS 10.3, especially the spatial analysis module of ArcGIS. All data processing was performed on this platform.

3.1. Severity Index of Aviation Accidents. The severity degree of disasters caused by aviation accidents is different. The number of aviation accidents can only be used to assess the frequency of occurrence of aviation accidents and cannot reflect the severity degree of aviation accidents. Serious aviation accidents should receive more attention. This study refers to weights of the road traffic severity index [25] and establishes the severity index model of aviation accidents. It is calculated by the formula [25]:

$$\mathrm{SI} = 3.0 * X_1 + 1.8 * X_2 + 1.3 * X_3 + X_4 \quad (1)$$

where X_1 is total number of fatal injuries, X_2 is total number of serious injuries, X_3 is total number of minor injuries, and X_4 is total number of uninjured.

This severity index is used as the criterion for spatial analysis in this research.

3.2. Kernel Density Function. Kernel density (KDE) is a nonparametric method that involves introducing the symmetrical surface over each point feature, assessing the distance from the point to a reference location based on a mathematical function, and subsequently adding the value of all the surfaces for that reference location [26]. It is a nonparametric method for estimating the probability density function. It is n sample points with independent and identically distribution F. Let its probability density function be f and the core density estimate be the following, calculated by the formula [26]:

$$\widehat{f_h}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \quad (2)$$

where x_i is the value of the variable x at the location i, n is the total number of locations, h is the bandwidth or smoothing parameter, and K is the kernel function. This research employed a normal distribution as a kernel function that weighs all points in the study area with near points having more weight than distant points. The outcome of the KDE depends significantly on the bandwidth and the cell size.

3.3. Spatial Autocorrelation. To examine spatial patterns, this research makes use of the Moran's I Index to measure spatial autocorrelation. The spatial patterns of crash data take into account simultaneously crash locations and their attribute values by measuring for attribute similarity and location proximity into one single index named Moran's I. The index is formally expressed according to [20]:

$$\mathrm{I} = \frac{N\sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{S_0 \sum_{i=1}^{N}\left(x_i - \overline{x}\right)^2} \tag{3}$$

$$\forall_i = 1,\ldots,n;\ \forall_j = 1,\ldots,n$$

where w_{ij} are the elements of a spatial binary contiguity matrix with weights representing proximity relationships between location i and neighboring location j, S_0 is the summation of all elements, x_i is the variable value at a particular location i, x_j is the variable value at another location (i≠j), $\overline{x}$ is the mean of the variable, and N N is the total number of locations. The values of Moran's I index range from −1 to 1, where the former represents a strong negative autocorrelation (i.e., perfect dispersion or clusterization of dissimilar values) and the latter represents a strong positive autocorrelation (i.e., perfect concentration or clusterization of similar values). A value of Moran's I near zero indicates a spatially random pattern [17].

The results from the spatial autocorrelation are always interpreted within the context of its null hypothesis, which states that the attribute being analyzed is randomly distributed among the features in the study area [27]. The statistical significance for Moran's I can be calculated using z-score methods. Based on the expected values ($E(I)$) for a random pattern and the variances ($\mathrm{var}(I)$), the standardized z-score can be mathematically represented as follows [27]:

$$\mathrm{Z} = \frac{I - E(I)}{\sqrt{\mathrm{var}(I)}} \tag{4}$$

In this research, the Spatial Autocorrelation tool was used to compute Moran's I statistics and z-scores. Since each data point is analyzed in terms of its neighboring data points defined by a distance threshold, it is necessary to find an appropriate distance threshold where spatial autocorrelation is maximized. The Spatial Autocorrelation tool was run multiple times with different distance thresholds to find the distance with the maximum z-score.

In this study, these aviation accident points are projection points on the ground where aviation accidents have occurred. The main objective of spatial autocorrelation is to analyze the spatial clusters of these aviation accident points. Although the cause of aviation accidents mostly comes from the air condition, it is possible to study whether there are clusters characteristics of aviation accidents in space, and which areas are more likely to have aviation accidents, such as around the airport or intensive air route areas. Then, the hot spot location of aviation accidents will be determined.

3.4. Hot Spot Analysis (Getis-Ord Gi∗). Getis-Ord statistic is used to identify aviation accidents hot spots. The Gi∗ statistic returned for each feature in the dataset is a z-score. For statistically significant positive z-scores, the larger the z-score is, the more intense the clustering of high values (hot spot) is. For statistically significant negative z-scores, the smaller the z-score is, the more intense the clustering of low values (cold spot) is. The Getis-Ord local statistic is calculated by the formulas [23]:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \overline{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right] / (n-1)}} \tag{5}$$

where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features and

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{6}$$

$$\mathrm{S} = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\overline{X}\right)^2} \tag{7}$$

The G_i^* statistic is a z-score so no further calculations are required.

4. Results and Discussion

4.1. Aviation Accident Spatial Distribution in Florida. From 2002 to 2017, a total of 1812 aviation accidents occurred in the Florida area. Most of the aviation accidents were general aviation accidents (Part 91, a Part 91 operator has regulations defined by the US Federal Aviation Administration (FAA) for operations of small noncommercial aircraft within the United States), accounting for more than 95% of the accidents. The aviation accident severity index was low, with an average value of 3 or so. The number of air route transportation accidents (Part 121, a Part 121 operator has regulations defined by the FAA for operations of scheduled air carriers (regional and major airlines)) is relatively small, but the number of people affected is large, and the aviation accident severity index is above 50.

The spatial distribution of aviation accidents is shown in Figure 2. From the point of view of location information alone, the distribution of aviation accidents in the Florida area is relatively fragmented, there is no obvious aggregate feature, and aviation accidents have occurred in almost every county, which may be related to the distribution of airports. According to aviation accident statistics, 60% of serious aviation accidents occurred at take-off, climb or approach, and landing phases closer to the airport. Due to the scattered distribution of airports in the Florida region, the occurrence of aviation accidents has no obvious aggregate characteristics.

From the aviation accident severity index, as shown in Figure 3, most of the serious aviation accidents (severity index greater than 100) occurred around the large international airports in the Florida area. Among them, there are 3 airports around Miami and Fort, 2 around Tampa Airport, and 2 around Orlando Airport, accounting for 60% of all serious accidents, and all of them are part 121 accidents.

4.2. Kernel Density Analysis of Aviation Accident. Based on the location of the aviation accidents in the Florida region

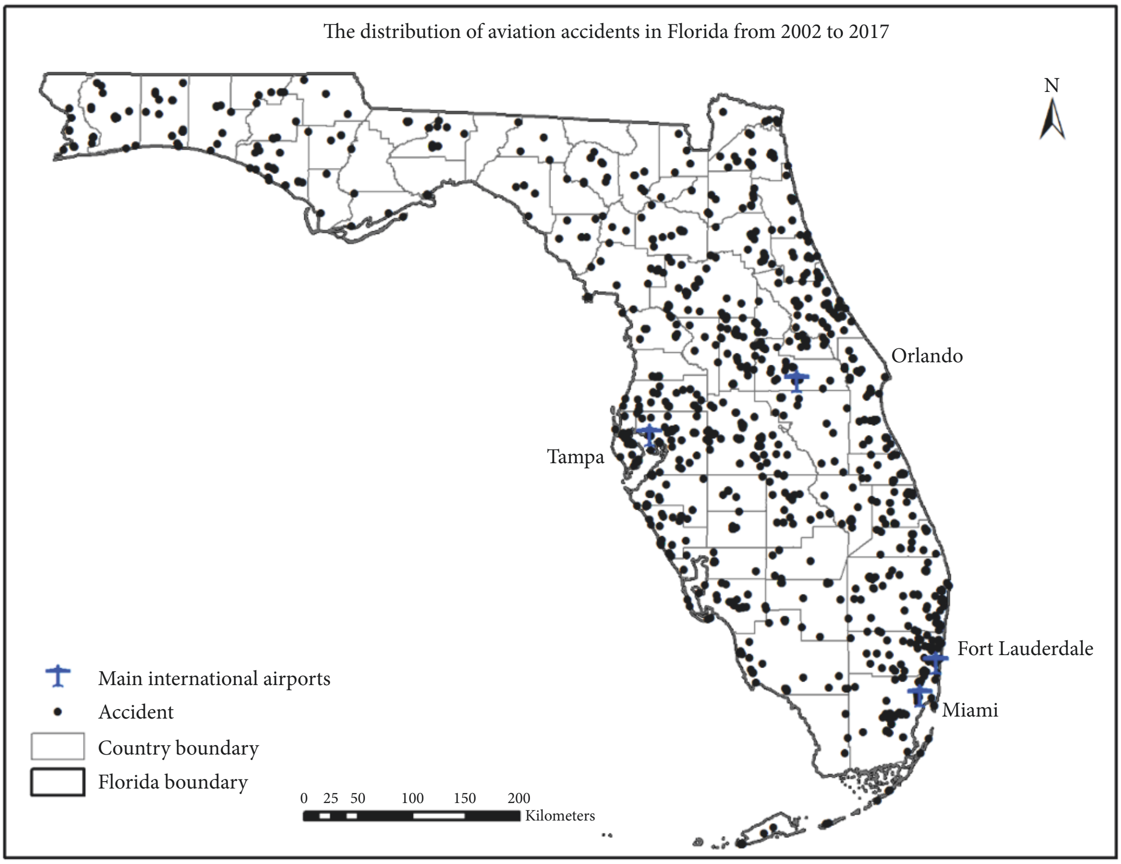

Figure 2: The distribution map of aviation accidents in Florida from 2002 to 2017.

from 2002 to 2017 and the severity index of each location, the kernel density maps were obtained by the methods of kernel density analysis tool of GIS. The bandwidth was the Silverman's rule of thumb algorithm, and the pixel size cell size was 0.025 degrees.

Figure 4 only considers the location of aviation accidents. Figure 5 considers the severity index of aviation accidents at each location. As shown in Figure 4, Florida's aviation accident density center is mainly located in the Tampa area on the west coast of Florida, the area between Tampa Airport and Orlando Airport, the Miami and Fort area on the east coast of Florida, the northeastern area of Orlando Airport, and the entire east coast.

As shown in Figure 5, if the severity index of aviation accidents is taken into account, the density center of Florida aviation accidents is mainly concentrated around Tampa Airport, around Fort Lauderdale Airport, and in the northeast direction of Orlando Airport.

This was because aviation accidents considered in this study did not distinguish between general aviation accidents and airline flight accidents, while flight accidents had more casualties and severe severity indices. Therefore, considering the severity index, aviation accident density center is around the state's large international airport in Florida.

4.3. Spatial Autocorrelation. Based on the spatial autocorrelation formula, the spatial autocorrelation index of the aviation accident severity index in Florida was calculated, and the spatial characteristics of the aviation accident severity index in the region were analyzed.

In this research, the Spatial Autocorrelation tool was used to compute Moran's I statistics and z-scores. Since each data point is analyzed in terms of its neighboring data points defined by a distance threshold, it is necessary to find an appropriate distance threshold where spatial autocorrelation is maximized. The Spatial Autocorrelation tool was run multiple times with different distance thresholds to find the distance with the maximum z-score. Table 1 shows that, with a distance threshold of 130 kilometers, the z-score reaches the highest value of 14.432, which means the aviation accident data is clustered until having a distance threshold of 130 kilometers with a statistical significance level of 0.01.

Only 1% of the aviation accident severity data distribution may be randomly distributed, the probability of data aggregation was greater than the probability of random distribution, and the null hypothesis can be significantly rejected. This result showed that the spatial distribution of the severity index of aviation accidents in Florida had a certain aggregation characteristic and positive spatial correlation pattern. That is, the severity index of each aviation accident point was completely positively correlated with the severity index of the surrounding aviation accidents. Where there was a large aggregate degree of spatial distribution, the severity index of aviation accidents also was high.

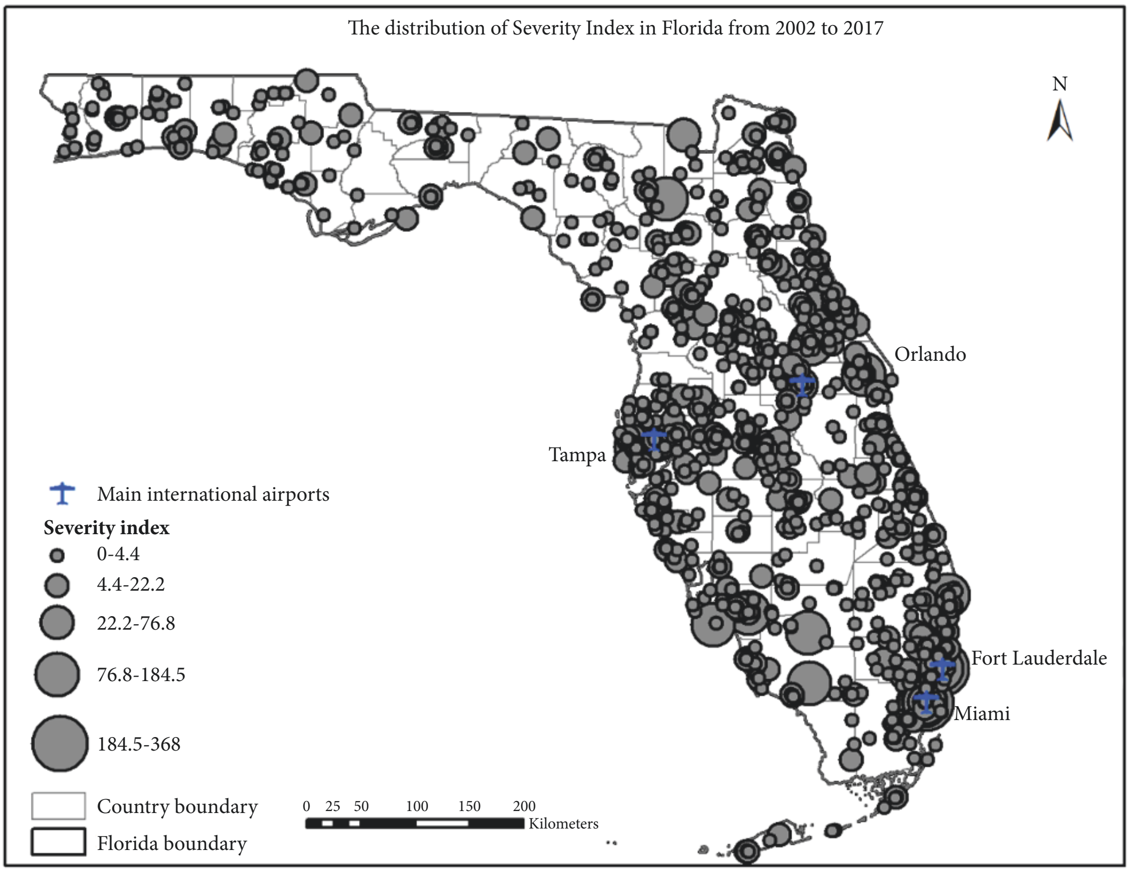

Figure 3: The distribution map of the severity index in Florida from 2002 to 2017.

Table 1: Spatial autocorrelation (Moran's Index) by distance thresholds.

Distance (km)	10	50	90	130	170	210	250	300
Moran's Index	0.266	0.214	0.209	0.208	0.206	0.205	0.203	0.202
z-score	13.816	14.225	14.352	14.432	14.408	14.395	14.381	14.316
p-value	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Spatial Autocorrelation	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered

From the perspective of annual changes, Moran's Index was calculated by the same method, considering the severity index of Aviation Accidents from 2002 to 2017. The annual variation characteristics of the spatial autocorrelation of aviation accident severity index were analyzed. As shown in Table 2, from 2002 to 2017, the spatial autocorrelation characteristics of aviation accident severity index were quite different. In 2003, 2005, 2006, 2007, and 2011, the spatial distribution of aviation accident severity data showed a certain aggregation characteristic. It had a spatial positive correlation patter, which had the same spatial autocorrelation characteristics as the total aviation accident severity index. Among them, the severity index aggregate characteristics in 2006 and 2007 were higher than the overall level (high z-score), indicating that the correlation between severity index and spatial distribution of aviation accidents was higher than the overall level of the study time.

In other years, the aviation accident severity index was randomly distributed, and there was no correlation between the severity of aviation accidents and spatial distribution, reflecting the randomness and unpredictability of aviation accidents. However, from the long-term sequence analysis (2002 to 2017), as described above, there was a strong positive correlation between the severity index of aviation accidents and their spatial distribution. It was possible to identify hot spots where aviation accidents may occur frequently.

4.4. Hot Spots Analysis. According to the spatial autocorrelation analysis, the distance threshold of 130 kilometers associated with maximum z-score in the previous step was chosen for the Getis-Ord Gi$*$ analysis. The hot spot analysis map of aviation accident severity index was shown in Figure 6. From 2002 to 2017, there were 45 hot spots of aviation accidents, marked in red. These points not only had a high value of their

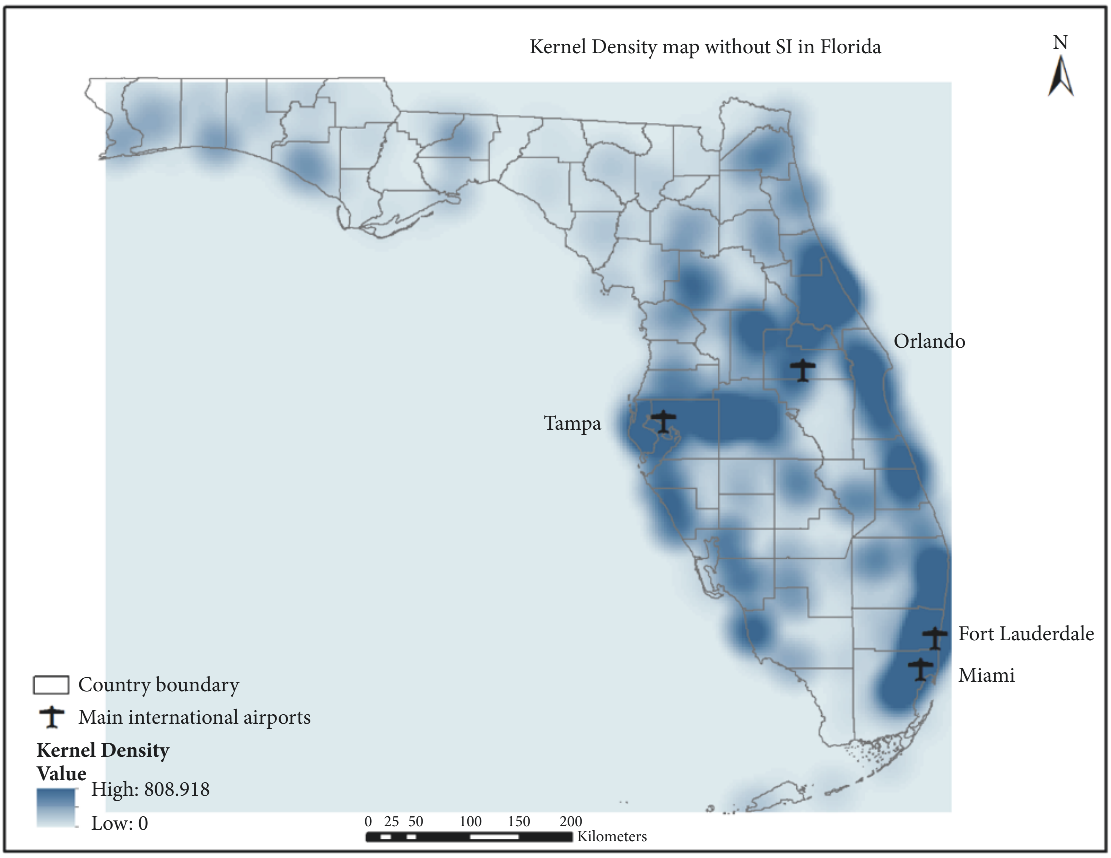

FIGURE 4: The Kernel density map without SI in Florida.

TABLE 2: Spatial autocorrelation (Moran's Index) from 2002 to 2017.

Year	Moran's Index	z-score	p-value	Spatial Autocorrelation
2002	0.009	0.268	0.788	Random
2003	0.367	5.676	0	Clustered
2004	-0.007	0.136	0.892	Random
2005	0.143	2.221	0.026	Clustered
2006	0.56	18.548	0	Clustered
2007	0.839	15.098	0	Clustered
2008	-0.028	-0.346	0.729	Random
2009	0.038	2.571	0.01	Clustered
2010	-0.026	-0.264	0.792	Random
2011	0.255	3.678	0	Clustered
2012	-0.024	-0.593	0.553	Random
2013	-0.074	-0.742	0.457	Random
2014	-0.032	-0.247	0.805	Random
2015	-0.029	-1.016	0.309	Random
2016	-0.045	-0.337	0.735	Random
2017	0.088	1.187	0.235	Random

own severity index, but also had high values around them, which were high-value and high-value areas.

It can be seen that the location of large international airports was a hot spot where the severity of aviation accidents was high in Florida. This is due to a large number of people on the air route flight. If an accident occurs, the severity index is relatively high. Therefore, the area where the large international airport is located was a hot spot of the aviation accident severity index normally. In addition, there were several hot spots in the north and southwest of Florida.

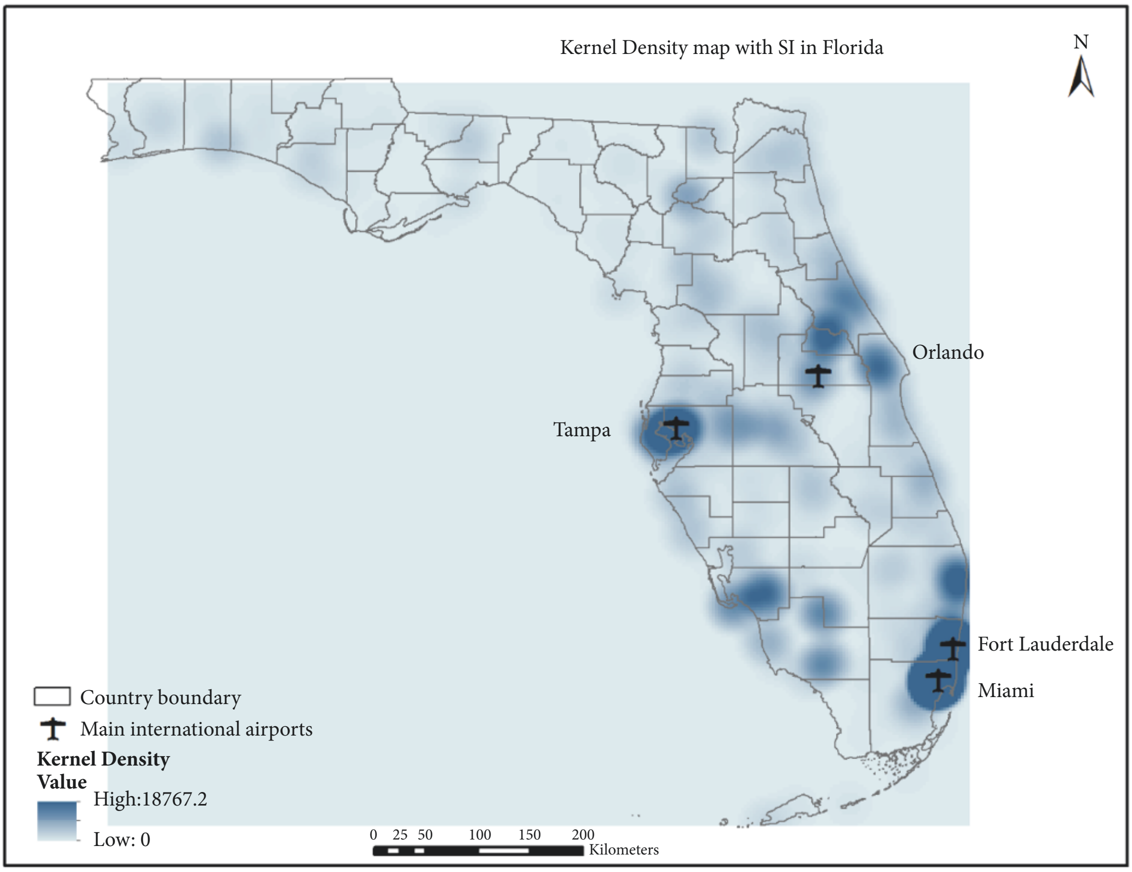

Figure 5: The Kernel density map with SI in Florida.

This next step made use of the aviation accident hot spots map to identify airports in the vicinities of the aviation accident hot spot. Taking the hotspot as the center and using the radius of 30km (the effective service area of the airport), it determined the buffer for the hotspot impact of the aviation accident. The airport data was overlaid on the hot spots map to identify the airport that was within 30km of each aviation accident hot spot. As shown in Figure 7, there were 76 airports in the potential aviation accident area, accounting for 15.8% of the number of airports in Florida.

4.5. Ranking the Potential Risk Airport. In this step, potential risk airports, identified in the previous step, were ranked based on the severity of aviation accidents in their vicinities. The goal of this step was to compute an appropriate severity index for each potential risk airport. It can be argued that aviation accidents that occurred closer to an airport more likely could be related to that airport than others. Therefore, they should be given greater weights in computing severity index for that airport.

Taking the airport as a center, a buffer zone was established with a radius of 15km and 30km, respectively, and the severity index of aviation accidents in the buffer zone was calculated. A weight of 1.5 was given to those within 15 km as they were more likely to be related to the airport. According to the following formula, the risk index was calculated:

$$\mathrm{RI}_{airpot} = 1.5 \times SI_{15} + SI_{15-30} \tag{8}$$

where SI_{15} and SI_{15-30} were computed using (1); SI_{15}= severity index of all aviation accidents within a 15 kilometers buffer of the airport; SI_{15-30}= severity index of all aviation accidents within a 30 kilometers buffer, but outside a 15km buffer of the airport.

The potential risk airports were ranked based on their risk indexes. The calculation results were shown in Table 3.

As shown in Table 3, when studying the severity index of aviation accidents around the airports, route flights and general aviation flights were considered. Among the 76 potential risk airports, the top 10 airports with potential risks were ranked according to the risk index. As can be seen, among the four major international airports in Florida, three airports had high aviation accident risk, including Miami, Fort Lauderdale, and Tampa airports, while Orlando Airport, as the world's busiest airport, was not in the top ten. These risk airports were mainly concentrated in the Miami area about 8 and in the Tampa Bay area about 2. It showed that from 2002 to 2017, the number of aviation accidents in these two regions occurred more frequently, and the number of aviation

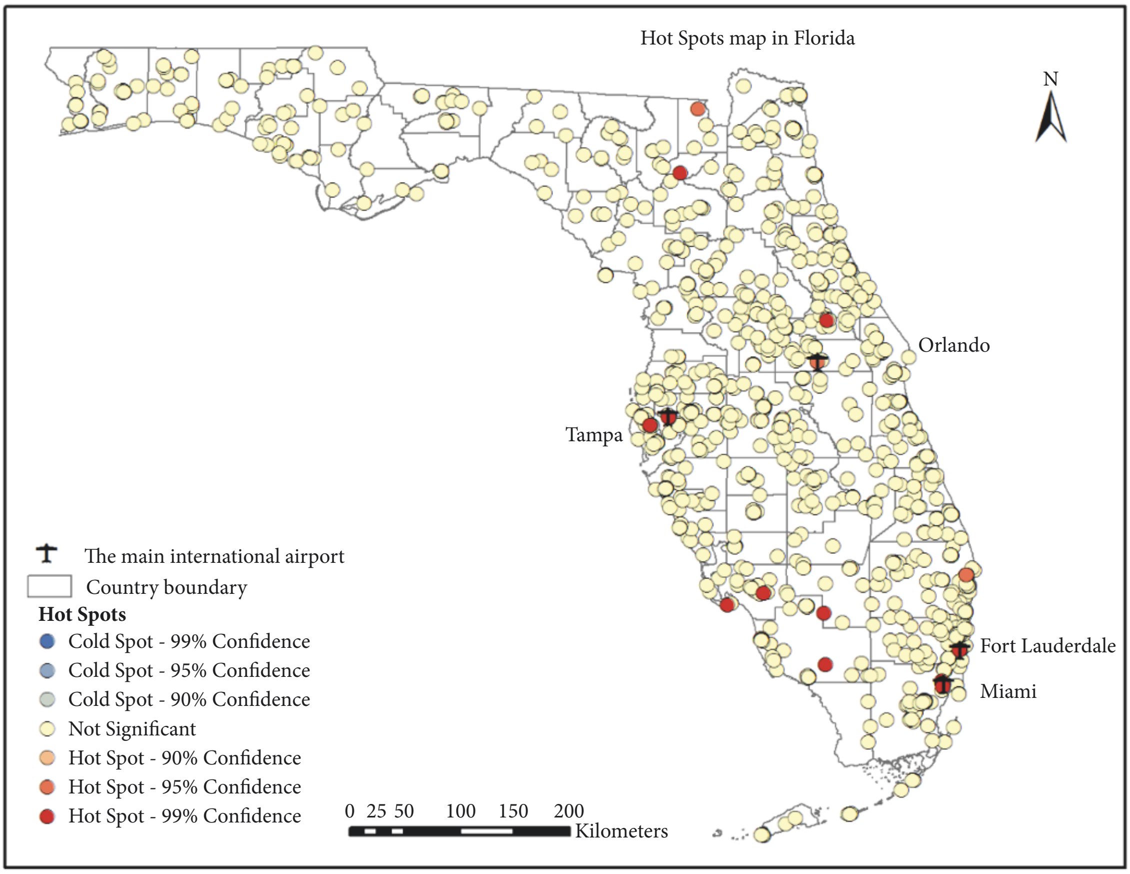

FIGURE 6: Aviation accidents hotspots map in Florida.

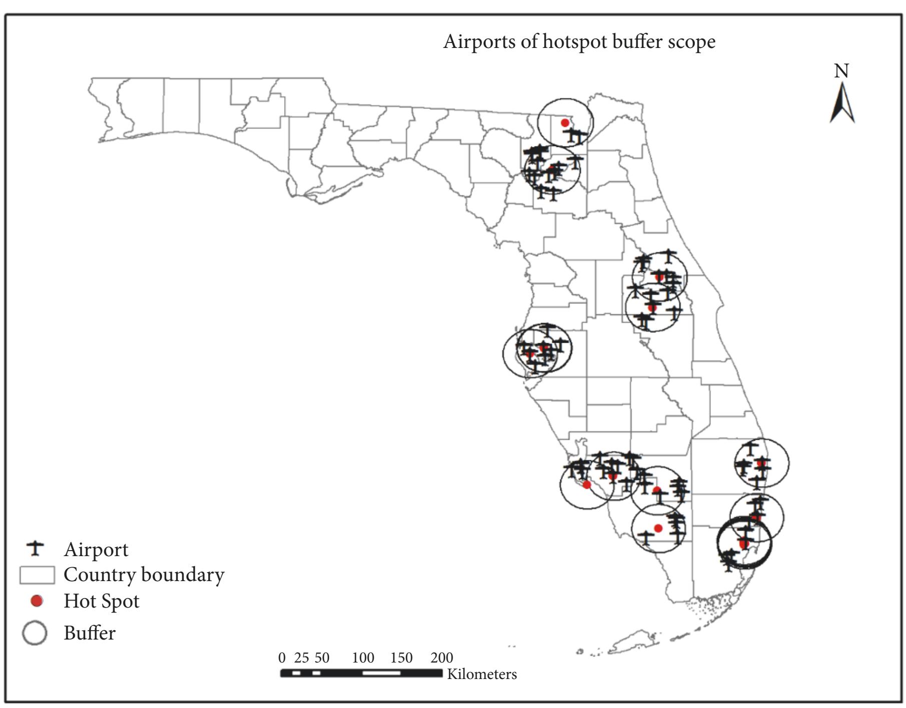

FIGURE 7: The map of airports of hotspot buffer scope.

Table 3: Ranking potential risk airports.

Rank	Name	RI
1	Opa-Locka Executive Airport	3431
2	North Perry Airport	3255.4
3	Miami International Airport	2700.4
4	Lindbergh's Landing	1841.5
5	Miami Executive Airport	1839.85
6	Fort Lauderdale Executive Airport	1637.8
7	Fort Lauderdale/Hollywood International Airport	1589.6
8	Pompano Beach Airpark	1219.5
9	MacDill Air Force Base	939.5
10	Tampa International Airport	913.7

casualties was the largest, and the management of aviation safety needs to be strengthened.

5. Conclusions and Discussion

5.1. Conclusion. Aviation accident analysis is an important part of aviation safety research. Although the spatial location of aviation accidents is difficult to predict, aviation accidents that have occurred in the past can be analyzed to obtain some of the spatial characteristics. It may provide decision support for aviation accident risk management. In the current study, there are many studies on the analysis of aviation accident time characteristics, but less research on spatial characteristics.

Based on the Florida aviation accident data and airport distribution data from 2002 to 2017, this paper calculated the severity index of aviation accidents. Using GIS spatial analysis methods, the spatial and temporal distribution characteristics of aviation accidents were studied in Florida. Combined with the airport distribution data, the airports that may have aviation accident potential risk were ranked.

Judging from the number of aviation accidents, Florida aviation accidents were mainly general aviation accidents, and transport aviation accidents are less. However, judging from the severity index of aviation accidents, the severity of aviation accidents in air route flight is much higher than that of general aviation accidents. The average severity index of general aviation accidents was about 3, and the severity index of aviation accidents on route flight was above 50. Most aviation accidents with a high severity index occurred around large international airports (Figure 3).

The kernel density function calculated the density center of the aviation accident distribution in the study area. The density center of Florida aviation accidents was mainly located in the Tampa area on the west coast of Florida, the area between Tampa Airport and Orlando Airport, the Miami and Fort Lauderdale on the east coast of Florida, and the northeastern area of Orlando Airport, across the entire east coast (Figure 4).

The Moran's I analysis indicated a statistically significant clustering pattern of aviation accident data for the Florida area (Table 1), with a distance threshold of 130 kilometers, the z-score reaches the highest value of 14.432. At the same time, the annual change characteristics of the Moran's I index of aviation accidents in the Florida region were analyzed (Table 2). It was found that the severity index was randomly distributed each year, reflecting the random occurrence of aviation accidents in space. There were no obvious aggregation characteristics.

The Getis-Ord Gi$*$ analysis also detected the aviation accident hot spots with 0.01 level of significance. Most of these hotspots were located around large international airports. In addition, there were several hotspots in the north and southwest of Florida (Figure 6). There were 45 hotspots in total.

Most aviation accidents occurred during the aircraft take-off climb and approach landing stage, which were closer to the airports. Therefore, the study focused on aviation accident hotspots and identified airports with potential aviation accident risks within a range of 30 km. There were 76 airports in total. Using buffer analysis and severity index of each accident point, the potential aviation accident risk around the airport was calculated to rank typical airports based on potential risk index (Equation (8)). Table 2 showed the top 10 potential risk airports. According to the aviation accident data in the past 15 years, these airports had a high potential risk.

It was found that aviation accidents were mainly general aviation accidents in Florida; the accidents had obvious spatial cluster characteristics, mainly around international airports and airport connection areas. The top 10 potential risk airports were also identified through the severity index. In order to improve the regional aviation safety level, the focus should be on strengthening the safety management of general aviation, renewing the equipment of general aviation, and increasing the training of flight personnel. In the density centers and hotspot areas where aviation accidents occurred frequently, aviation accident emergency response centers should be established according to actual conditions to provide rescue for accidents. In the top 10 potential risk airports, it should strengthen aviation accident risk management at airports and surrounding areas, and the flight schedules and procedures should be optimized to improve the safety level of these airports.

5.2. Discussion. Air transport is relatively safe compared to other modes of transport. However, with the rapid development of general aviation, the frequency of aviation accidents has increased. But the number of general aviation participants is small, and the loss of personnel and property and social impacts are small. The frequency of aviation accidents of air route flight is relatively low, but the number is large, and the loss of personnel and social impacts are relatively large. Therefore, they should be considered when analyzing aviation accidents. This study used the aviation accident severity index to combine the two kinds of aviation accidents, which has certain scientific significance.

Compared with other modes of transportation, aviation accidents are more random, and it is difficult to predict the time and location of aviation accidents with the existing technology. However, aviation accident analysis is still of great significance. It can not only avoid similar accidents from happening again, but also help managers formulate corresponding emergency management strategies. At present, most studies focus on the analysis of the causes and time series of aviation accidents. There are few studies on the spatial distribution characteristics of aviation accidents. However, in other areas of transportation, a large amount of research has been carried out, especially in the area of public transport, identifying hot spots for pedestrians and vehicle accidents in order to improve the transportation facilities in these streets and avoid frequent accidents. Similarly, since the starting point and the end point of air transportation are both located in the airport, the airport is the most active area for air transportation and also the area where aviation accidents frequently occur. Through determining the location of potential risk airports in the research, relevant departments can improve the accident emergency management level of these sensitive airports and their surrounding areas in order to reduce the occurrence of aviation accidents.

Data is very significant for research to obtain accurate results, and the collection of aviation accident data is also important for improving the safety of aviation safety. The data used in the study is from 2002 to 2017. The time span is only 15 years, and the amount of data is still relatively small. In the future, we will gradually increase the number of data and improve the accuracy of the research results.

According to the distribution of accidents in a given year, the spatial aggregation of aviation accidents was not significant and belonged to the randomly distributed. However, when using multiyear accident data, it can be clearly seen that aviation accidents had a significant aggregate feature in space, indicating that the location of aviation accidents still followed a certain rule in space.

In the future, based on more data accumulation, we consider applying the research method to other regions for comparative verification. Further research should include a multicriterion ranking method and sensitivity analysis of buffer sizes. Such improvements could improve the accuracy and reliability of the prioritization of potential risk airports. In terms of emergency management strategies, the location of the emergency management center can be determined based on hot spots and flight volume to raise the efficiency of rescue.

Data Availability

The aviation accidents data used to support the findings of this study may be released upon application to the National Transportation Safety Board (NTSB), who can be contacted at (https://www.ntsb.gov/layouts/ntsb.aviation/index.aspx).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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