

Research Article

Optimized ST-Moran's I Model for Characterizing the Dynamic Evolution of Terminal Airspace Congestion

Honghao Chen D, Xinping Zhu D, Yajun Zou, Zhongkun Li, and Tianxiong Zhang

Air Traffic Management College, Civil Aviation Flight University of China, Guanghan 618307, China

Correspondence should be addressed to Xinping Zhu; zxp@cafuc.edu.cn

Received 16 May 2023; Revised 17 February 2024; Accepted 21 February 2024; Published 6 March 2024

Academic Editor: Indrajit Ghosh

Copyright © 2024 Honghao Chen et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This study aims to unveil the spatiotemporal evolution of congestion within terminal airspace, offering an in-depth analysis of congestion concerns to effectively utilize airspace resources and devise targeted control strategies, thereby enhancing airspace operation safety and efficiency. Initially, converting segment flow rates into equivalent speeds serves as a quantitative benchmark for operational status. Subsequently, an enhanced version of the ST-Moran's I index model, specifically tailored to terminal airspace, is developed by incorporating improvements across spatial weight matrices, standard state parameters, and temporal dimensions. Validating this model with actual operational data from Chengdu's terminal airspace, the research demonstrates significant advancements. Compared to conventional models, the proposed model enhances recognition rates for congestion in spatial and temporal dimensions by 62.5% and 43.61%, respectively. Congestion within terminal airspace predominantly occurs at the intersection of departure-climb and approach-departure segments, exhibiting evident spatiotemporal migration behavior. The proposed model accurately delineates the spatiotemporal characteristics of segment congestion, offering support for tailored congestion management strategies.

1. Introduction

Terminal airspace serves as a vital nexus for the arrival and departure activities of multiple airports, bridging towercontrolled airspace and regional-controlled airspace. With dense traffic flow and intricate route structures, it is prone to becoming a bottleneck in air traffic operations [1]. When airspace resources are strained and capacities reach saturation, the escalating conflict between terminal airspace capacity and flight volumes leads to congestion, manifesting as flight delays [2, 3]. A comprehensive understanding of congestion's dynamic evolution in terminal airspace is pivotal for formulating effective air traffic control measures, optimizing airspace resources, and alleviating operational pressures within the airspace.

In aviation research, terminal airspace congestion has received increasing attention, evolving from a macrolevel perspective encompassing airspace demand, capacity, and flow rates [4, 5], to a microlevel understanding rooted in fundamental traffic flow parameters [6, 7]. This evolution has led to diverse research approaches: (1) quantitative indicators for congestion. Establishing a robust quantitative index system is imperative for comprehending the complexities of congestion. The evaluation methodology has evolved from unidimensional approaches focusing on flight delay [8, 9], airspace capacity [10, 11], and traffic flow parameters [12, 13], to multidimensional analyses that delve into the multifaceted aspects of congestion. (2) Prediction of congestion. Despite the inherent uncertainties in airspace operations, efforts towards congestion prediction [14] have gained momentum. Research in this domain explores trends and peaks in congestion through the analysis of airspace system parameters [15], dynamic density metrics in urban air traffic [16], and sophisticated spatiotemporal neural network models [17]. (3) Congestion relief. Addressing terminal airspace congestion necessitates effective mitigation and management strategies. The integration of heuristic algorithms has facilitated the development of measures to alleviate congestion [18-20], ranging from optimizing departure times to minimizing various factors impacting

airspace efficiency. However, traditional methods often overlook airspace resource constraints, exacerbating challenges for air controllers. Novel approaches, integrating simulation [21, 22], airspace operation mode adjustments [23, 24], and resource analysis [25–27], offer promising avenues for exploring mitigation strategies within resource limitations, thus enhancing the efficacy of congestion management efforts.

Examining the evolutionary traits of terminal airspace congestion provides significant advantages. Firstly, it furnishes valuable insights for policy formulation and strategic planning by comprehensively understanding congestion's long-term evolution. Secondly, unlike singular approaches, exploring evolutionary traits involves a holistic multifactor analysis, considering historical changes, developmental patterns, influencing factors, and various elements within the airspace environment. This approach fosters a systematic understanding of congestion issues, guiding effective intervention strategies. Despite the importance of analyzing the evolutionary characteristics of congestion in terminal airspace, there remains a scarcity of studies in this area, with methodologies often singular in approach. For instance, while Jiang et al. [28] and Yang et al. [29] studied congestion evolution patterns using simulation, their analyses lacked integration of both spatial and temporal dimensions. Additionally, Jiang et al. [30] introduced a congestion propagation network, but it somewhat overlooked dynamic traffic flow evolution. Building upon these studies, some scholars have outlined prospects for analyzing the evolutionary traits of congestion in terminal airspace. They emphasize the importance of comprehensive spatiotemporal analysis and the pivotal role played by traffic flow complexity in the evolution of congestion [31]. Moreover, they highlight the need to integrate historical trajectory data with standard procedures to optimize airspace utilization. These perspectives offer valuable guidance for future in-depth explorations into the evolutionary characteristics of airspace congestion [32].

In this context, digital technology enables real-time monitoring of various parameters within the research subject, empowering researchers to respond promptly and implement necessary adjustments or interventions [33, 34]. Similarly, in road transportation, spatial econometric models [35–37] have proven effective in analyzing congestion dynamics within transportation networks. For example, Fu et al. [38] utilized the Moran Index model to scrutinize spatial clustering features within traffic networks, while Chen et al. [39] proposed the ST-Moran exponential model for spatiotemporal object state analysis. These models offer valuable insights for understanding the dynamic evolutionary traits of congestion.

In this paper, we enhance the traditional ST-Moran's I model by incorporating the operational dynamics of traffic flow within the airspace network structure and accounting for the unique operational characteristics of terminal airspace. Our objective is to establish a dynamic and evolving characterization model for congestion in terminal airspace, based on a comprehensive analysis of time and spatial integration.

This paper is structured as follows: Section 2 provides an analysis and summary of the operational characteristics of terminal airspace traffic flow. Section 3 introduces the traditional Moran Index and identifies its shortcomings. Subsequently, Section 3.1 delves into the application method of the Moran Index in road traffic analysis, while Section 3.2 analyzes its limitations within the context of terminal airspace operations. In Section 4, we establish a spatiotemporal Moran Index model for terminal airspace. Section 4.1 presents the enhanced design of the base parameters in the model, while Section 4.2 outlines the complete spatiotemporal Moran Index model. Additionally, Section 4.3 introduces the analytical method of the Moran scatter plot. In Section 5, utilizing actual operational data from Chengdu terminal airspace, we conduct example analyses. Section 5.1 describes the process and steps of data processing, Section 5.2 validates the model's effectiveness, and Section 5.3 analyzes the experimental results. Section 6 synthesizes and analyzes the actual operational process of Chengdu terminal airspace based on the analysis results. Finally, Section 7 summarizes the main work and results of this paper, while Section 8 delineates the practical significance of this study.

2. Terminal Airspace Traffic Flow Characteristics

As the primary airspace hub for takeoffs and landings across multiple airports [40], the traffic flow dynamics within terminal airspace showcase several defining features.

2.1. Heightened Density of Terminal Airspace Traffic Flow. With the escalating number of flights, there has been a concurrent expansion in airport scales and approach and departure segments within terminal airspace [41]. Despite endeavors like diverting approaches and departures and optimizing flight procedures to facilitate a well-organized traffic flow, the overall density of traffic continues to escalate.

2.2. Enhanced Flexibility in Flight Operations within Terminal Airspace. Traffic flow within terminal airspace generally adheres to fixed distribution patterns, where aircraft ascend or descend along established approach and departure segments or flight procedures [42] (as illustrated in Figure 1). However, uncertainties within the airspace, such as weather conditions and potential conflicts, necessitate aircraft to navigate, wait, or modify maneuvers accordingly. Simultaneously, owing to established operational interval control, aircraft may execute controlled maneuvering flights as directed by controllers (depicted in Figure 2). This underscores the considerable latitude in managing flight activities within terminal airspace.

2.3. Complex Congestion Scenarios in Terminal Airspace Traffic Flow. The concentrated influx of approach and departure flights in terminal airspace manifests in diverse congestion scenarios. Common congestion instances encompass





FIGURE 2: Schematic diagram of aircraft maneuvering flight. (a) Guide aircraft into holding procedure; (b) altitude and speed management; (c) radar vector.

- Increased flight delays. During high traffic flow periods in terminal airspace, controllers must coordinate flight takeoff and landing times to prevent airspace saturation, often resulting in flight delays;
- (2) Reduced flight intervals. In congested terminal airspace, controllers may adjust takeoff or landing intervals to optimize airspace resource utilization without compromising safety intervals and complying with outer area flow control intervals;
- (3) Augmented airborne holding. In instances of high traffic volume, flights may be instructed to conduct airborne holding procedures to ensure safe and orderly operations within terminal airspace.

3. Traditional Moran's I Model and Its Deficiencies for Terminal Airspace Operations

3.1. Traditional Moran's I Model. The traditional Moran's I model serves as a fundamental tool for spatial correlation analysis among objects and finds extensive application in assessing the spatial distribution patterns of road traffic accidents within the transportation domain [43, 44]. This model utilizes the flow velocity within the traffic network as the state parameter for each road section [38, 39], employing the connectivity between these sections to formulate a spatial

weight matrix. Subsequently, it conducts an in-depth analysis to delineate and characterize congestion attributes. The global Moran's I assesses the overarching congestion status of the road network, while the local Moran's I delves into the specific congestion disparities among individual sections. The mathematical formulations for both indices are outlined as follows:

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (X_{i} - \bar{X}) (X_{j} - \bar{X})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \sum_{i=1}^{n} (X_{i} - \bar{X})},$$

$$I_{\text{local}} = \frac{(X_{i} - \bar{X}) \sum_{j=1}^{n} W_{ij} (X_{j} - \bar{X})}{(1/n) \sum_{i=1}^{n} (X_{i} - \bar{X})^{2}},$$
(1)

where X_i and X_j are the state parameter values of spatial objects *i* and *j*, respectively; *n* is the total number of spatial objects; \overline{X} is the mean value of state parameters of all objects; W_{ij} is the adjacency matrix among all objects.

The ST-Moran's I model [39] is an extension of the traditional Moran's I model into the temporal dimension, allowing for a comprehensive analysis across both time and space. Specifically, the global ST-Moran's I index enables an examination of holistic spatiotemporal entities, such as the analysis of congestion clustering characteristics within traffic systems. Its expression is shown as

$$I_{\rm ST} = \frac{\mathrm{NT}\sum_{p=0}^{N}\sum_{t_p=0}^{T}\sum_{q=0}^{N}\sum_{t_q=0}^{T}w_{(p,t_p)(q,t_q)}(y_{(p,t_p)} - \bar{y})(y_{(q,t_q)} - \bar{y})}{\sum_{p=0}^{N}\sum_{t_p=0}^{T}\sum_{t_p=0}^{T}\sum_{p=0}^{N}\sum_{t_p=0}^{T}\sum_{p=0}^{N}\sum_{t_q=0}^{T}w_{(p,t_p)(q,t_q)}},$$
(2)

where N is the total number of objects, T is the length of the research period, $w_{(p,t_p)(q,t_q)}$ is the adjacency state of object p at t_p time, and object q at t_q time (when the spatial-temporal objects are adjacent, the value is 1, otherwise it is 0), $y_{(p,t)}$ is the state attribute value of object p at t time, and \bar{y} is the average attribute value of all spatial-temporal objects whose expression is shown as

$$\bar{y} = \frac{\sum_{p=0}^{N} \sum_{t=0}^{T} y_{(p,t)}}{NT}.$$
(3)

The local ST-Moran's I model facilitates a localized analysis of spatiotemporal objects (e.g., the specific congestion characteristics within the traffic system at distinct moments), represented by its expression as follows:

$$I_{(p,t)} = Z_{(p,t)} \times W_{Z_{(p,t)}},$$
(4)

where

$$Z_{(p,t)} = \frac{y_{(p,t)} - \bar{y}}{\sqrt{\left(\sum_{p=0}^{N} \sum_{t=0}^{T} \left(y_{(p,t)} - \bar{y}\right)^{2} / \text{NT}\right)}},$$

$$W_{Z(p,t)} = \frac{\sum_{q=0}^{N} \sum_{t_{q}=0}^{T} w_{(p,t)} \left(q,t_{q}\right) Z_{(p,t)}}{\sum_{q=0}^{N} \sum_{t_{q}=0}^{T} w_{(p,t)} \left(q,t_{q}\right)}.$$
(5)

Notice that $Z_{(p,t)}$ is the normalized attribute value of the spatial-temporal object; $W_{Z(p,t)}$ is the weighted value of the normalized attribute values of all spatial-temporal objects in the spatial-temporal range.

3.2. Deficiencies of the Traditional Moran Index Model in the Context of Terminal Airspace Operations. Upon closer scrutiny in Sections 2 and 3.1, while the ST-Moran's I model adeptly captures the spatial-temporal dynamic characteristics of traffic network congestion, there exists a need for refinement to better align with the operational characteristics specific to terminal airspace. This improvement should emphasize the following aspects.

3.2.1. Transformation of Spatial-Temporal Freedom. Given the high spatial-temporal degrees of freedom within terminal airspace, conducting a transformation of these degrees of freedom allows for a more comprehensive analysis when designing state parameters. This transformation unifies the spatial-temporal data into a standardized form of degrees of freedom, enhancing the ability to capture and illustrate the dynamic changes and operational states within the airspace more effectively. 3.2.2. Refinement of the Spatial Weight Matrix. During actual operations, longer flight segments are more likely to serve as evacuation routes for aircraft. When these segments experience congestion, it significantly impacts the normal operation of adjacent segments. However, the conventional model, which uses an adjacency matrix as the spatial weight matrix, merely describes connectivity between segments [45] and fails to effectively quantify the impact of varying segment lengths on congestion levels.

3.2.3. Temporal Constraints in Transmission. In contrast to congestion in road traffic, congestion in airspace tends to exhibit relatively weaker manifestations and transmission effects. To precisely depict the microdynamic evolution of airspace congestion, it becomes necessary, in the temporal dimension, to further restrict the propagation cycle of its congestive effects.

4. Methodology

Building upon the shortcomings outlined in Section 2, this section enhances the conventional ST-Moran Index model by integrating the operational specifics of terminal airspace. Initially, the methodology for refining certain parameters within the model is devised. Subsequently, the temporal dimension expansion technique is optimized by aligning with the model's characteristics. The following delineates the specifics of these enhancements.

4.1. Parameter Design and Enhancement in the Model

4.1.1. The Segment State Parameters. Combined with Section 2, congestion in airspace can directly or indirectly cause variations in aircraft speed [46]. Therefore, this paper adopts the segment equivalent flow rate, representing the effective flight speed per unit time for an aircraft within a segment after accounting for comprehensive space-time deployment degrees of freedom, as the state parameter in the model. Its calculation formula is expressed as follows:

$$y_{(\text{type},i,t)} = \frac{1}{M} \sum_{m=1}^{M} \left\| v_{i(\text{type},m,t)} \right\| * \zeta_{(m,t)}, \begin{pmatrix} i = 1, 2 \dots N \\ t = 1, 2 \dots T \end{pmatrix},$$
(6)

where $y_{(type,i,t)}$ is the state parameter of aircraft *type* (including *A*, *B*, *C*, *D*, and E) in segment *i* at time *t*, *N* is the total number of segments, *M* is the number of aircraft in segment *i*, $v_{i(type,m,t)}$ is the flight speed (ground speed) of the corresponding category of aircraft *m* in segment *i* at time *t*, and $\zeta_{(m,t)}$ is the speed gain coefficient of aircraft *m* in the

segment, which is the ratio of the nominal segment length L to the actual flight distance $D_{(m,t)}$ of aircraft m at time t. It can be defined as

$$\zeta_{(m,t)} = \frac{L}{D_{(m,t)}}.$$
(7)

4.1.2. The Standard Parameters for the Segment. The standard state covariate \bar{y} in the ST-Moran's I model represents the normal state value of the studied object within the system under investigation. In the context of researching terminal airspace, \bar{y} serves as a crucial indicator for assessing the segment's operational status. Its value significantly influences the model's precision in identifying segment congestion states.

As depicted in Figure 1, noticeable speed fluctuations occur in various stages of aircraft operations. Utilizing equation (3) uniformly for each stage might induce disparities \bar{y} , thereby diminishing the model's precision in evaluating congestion. Additionally, distinct aircraft categories have varying speed requisites within the segment. Consequently, building upon the state parameter calculations from the traditional model, the standard segment parameters are categorized into two scenarios: identical category combinations and diverse category combinations, each calculated separately.

- (1) Homogeneous aircraft combination scenario. As depicted in Figure 3(a), Aircraft 1 encounters no interference from other aircraft in the segment's forward direction. Hence, it can be considered a freely operating aircraft within the segment, establishing the standard state parameter for each aircraft between waypoints C1 and C2.
- (2) Heterogeneous aircraft combination scenario. As depicted in Figure 3(b), if the segment involves various aircraft categories, each category's aircraft encounters differing speed and operational requirements due to distinct aircraft performance. Consequently, the standard state parameter for each aircraft category is derived from the free-state aircraft within a specific temporal vicinity within this segment.

Based on the above analysis, the formulae for calculating the standard state parameters can be summarized as follows:

$$\bar{y}_{(\text{type},i,t)} = \begin{cases} y_{1(\text{type},i,t)}, \text{ aircraft in the segment are of the same class,} \\ y_{1(\text{type},i,t-\Delta t)}, \text{ aircraft in the segment are of different class,} \end{cases}$$
(8)

where *i* denotes the segment number, *t* denotes the time at which it is located, $\bar{y}_{(type,i,t)}$ denotes the standard state parameter of the aircraft *type* at moment *t* in segment *i*, y_1 denotes the speed of the aircraft numbered 1, $y_{1(type,i,t)}$ denotes the speed of the aircraft *type* which is numbered 1 at moment *t* in segment *i*, Δt denotes the time interval, and $y_{1(type,i,t-\Delta t)}$ denotes the speed of the aircraft *type* at moment *t* in segment *i* as number 1 in the past moments.

4.1.3. Enhancement of Spatial Weighting Matrices. To gauge the varying impact of segment lengths on congestion levels, this paper introduces the Hadamard product of the adjacency matrix w_s and the standardized physical length matrix D for each segment, serving as the spatial weight matrix. Illustrated in Figure 4, this matrix encapsulates the directional adjacency traits between segments, factoring in the length attribute of each segment and its influence on neighboring segments. Its mathematical representation is shown as

$$W_{SG(i,j)} = w_{s(i,j)} \odot D_{(i,j)}, \qquad (9)$$

where *i* and *j* denote the number of segments, respectively; $w_{s(i,j)}$ is the adjacency state of segment *i* and segment *j*. If the aircraft can reach segment *j* directly from segment *i*, then $w_{s(i,j)} = 1$, otherwise $w_{s(i,j)} = 0$; $D_{(i,j)}$ is the weight value of the standardized length of segment *i*, and its calculation formula is

$$D_{(i,j)} = \frac{\text{len}_i}{\sum_{i=1}^{N} \text{len}_i}, (j = 1, 2...N),$$
(10)

where *N* denotes the total number of segments and len_i is the length of segment *i*.

4.2. Development of the Improved ST-Moran's I Model

4.2.1. Improved Global ST-Moran's I Model. The global ST-Moran Index model characterizes the spatial-temporal dynamics across all terminal locations throughout the study period. To further refine its applicability within dynamic



FIGURE 3: Schematic diagram of the combination form of flight segment models (taking class A and class B as examples). (a) The situation of the same type of aircraft combination; (b) the situation of different aircraft type combinations.



FIGURE 4: Schematic diagram of the calculation form of the spatial weight matrix.

analysis, this paper introduces a specialized model designed to analyze the evolving spatial-temporal congestion patterns within terminal airspace. This adaptation involves modifying the temporal interval constraints within the traditional model, as elaborated below:

$$I_{\text{Global_ST}} = \frac{N \sum_{i=0}^{N} \sum_{j=0}^{T} \sum_{j=0}^{N} \sum_{tj=0}^{t} W_{SG(i,j)} (y_{(type,i,t)} - \bar{y}_{(type,i,t)}) (y_{(type,j,tj)} - \bar{y}_{(type,j,tj)})}{2 \times \sum_{i=0}^{N} \sum_{t_j=0}^{T} (y_{(type,i,t)} - \bar{y}_{(type,i,t)})^2 \times \sum_{i=0}^{N} \sum_{j=0}^{N} W_{SG(i,j)}},$$
(11)

where N is the total number of segments, T is the length of time, and the meanings and parameters of $W_{\text{SG}(i,j)}$ and $\bar{y}_{(\text{type},i,t)}$ are consistent with equations (8) and (9).

Table 1 displays the values of the upgraded global Moran index, elucidating their corresponding implications within the context of terminal airspace.

4.2.2. Improved Local ST-Moran's I Model. The Local ST-Moran Index focuses on discerning congestion patterns across segments at various times and spaces, demanding detailed time calculation specifications. To refine the Local ST-Moran Index, this study incorporates the sliding window method and supplements it with an intermediary matrix layer, establishing Algorithm 1. This layer is designed to encapsulate the temporal influence of preceding moments on the present, while also considering time transfer effects and the inverse correlation between periods and their influence. Throughout the sliding window process, the algorithm retains the weighted average of past moments' impact at each specific moment. This retained information is then utilized to calculate the weighted average for subsequent moments, gradually diminishing the influence of prior time points to align more accurately with the current moment. By integrating the influence of previous moments at each time point, the refinement process enhances the precision of the Local ST-Moran Index. Refer to Table 2 for the detailed calculation process, and its corresponding calculations are shown in equations (14) and (15).

In summary, the formula of the improved Local ST-Moran Index is shown as

$$I_{\text{Local_ST}(i,t)} = Z_{(i,t)} \times W_{ZSW(i,t)}.$$
 (12)

Notice that $Z_{(i,t)}$ is the standardized attribute value of the spatial-temporal object, and $W_{\text{ZSW}(i,t)}$ is the weighted value for the normalized attribute value of the spatial-temporal object after optimization by the sliding window method.

Variable name	Value range	Interval	Meaning of state
I _{Global_ST}	(-1, 1)	(0, 1) 0 (-1, 0)	The segments with similar attributes are clustered in spatial and temporal distribution. The larger the value, the more obvious the aggregation The segments with similar attributes are random in time and space distribution The segments with similar attributes are discrete in spatial and temporal distribution. The smaller the value, the more obvious the dispersion

TABLE 1: Global ST-Moran index range and corresponding meaning.

TABLE 2: Pseudocode for the optimization process of the sliding window method.

Algorithm 1: Sliding window method for local ST-Moran's index optimization
Input : <i>wz0</i> , the initial matrix obtained according to the formula of W_z
width, matrix columns of wz0
length, matrix rows of wz0
c, window size in the sliding window method
Output: wzo, matrix after optimization by the sliding window method
1: for $i \leftarrow 1$ to width do
2: $wz1 \leftarrow wz0$ [i, 1: width]
3: for $ii \leftarrow 1$ to length do
4: if $ii \le c-1$ then
5: $wzo [i, ii] \leftarrow wz1 [ii]$
6: else
7: $wz2 \leftarrow [wz0[i, ii-(c-1)], wz1[ii]]$
8: $wzo [i, ii] \leftarrow sum (wz2)/length (wz2)$
9: end
10: end
11: $i \leftarrow i + 1$
12: end
13: return wzo

Both can be calculated based on the following (the meaning of the parameters is the same as before):

$$Z_{(i,t)} = \frac{y_{(\text{type},i,t)} - \bar{y}_{(\text{type},i,t)}}{\sqrt{\left(\sum_{i=0}^{N} \sum_{t=0}^{T} \left(y_{(\text{type},i,t)} - \bar{y}_{(\text{type},i,t)}\right)^{2} / \text{NT}\right)}},$$
 (13)

$$W_{ZSW(i,t)} = \begin{cases} \frac{W_{ZSW(i,t-1)} + W_{Z(i,t)}}{2}, t \ge 2, \\ W_{Z(i,t)}, t = 1, \end{cases}$$
(14)

where

$$W_{Z(i,t)} = \frac{\sum_{j=0}^{N} W_{\text{SG}(i,j)} Z_{(i,t)}}{\sum_{j=0}^{N} W_{\text{SG}(i,j)}}.$$
 (15)

The refined Local ST-Moran Index serves to depict the localized spatial-temporal state characteristics of each segment, showcasing their values and corresponding interpretations in Table 3.

4.3. ST-Moran Scatter Plot. Moran scatter diagrams are employed to depict the dynamics of congestion evolution by showcasing the correlation distribution between z (normalized attribute values of segments) and W_{ZSW} (weighted normalized attribute values), facilitating the exploration of local spatial instability. Figure 5 illustrates the specific interpretation of each quadrant concerning the traffic state after application.

Based on the operational status of the segment and its adjacent segments depicted in each quadrant of Figure 5, the spatial-temporal relationship between them can be categorized into two types: positive and negative correlation. As depicted in Figure 6, the positively correlated regions encompass sample points in quadrants one and three of the Moran scatter plot, while the negatively correlated regions comprise sample points in quadrants two and four of the Moran scatter diagrams.

5. Empirical Study

5.1. Data Description and Processing. Utilizing the terminal airspace of Chengdu, Sichuan Province, China, as the focal point, this study collected ADS-B data from Vari Flight Ltd. pertaining to flight operations between 0000 and 0100 (UTC) on November 11, 2019. The dataset, comprising flight numbers, departure and landing airfields, altitude, speed, heading, track coordinates, and timestamps, totaled over 28,000 records. Figure 7 displays the sector arrangement, 108 approach segments (Figure 7(a)), and 93 departure segments (Figure 7(b)), along with two runways and 12 sectors, based on November 2019's navigation information.

After refining the flight data related to the approach and departure to the destination airport, we plotted the real flight paths observed during the study's duration using latitude

Variable name	Value range	Interval	Meaning of state
I _{Local_ST}	(-∞, +∞)	$(0, +\infty)$ 0 $(-\infty, 0)$	 At a certain moment, the operating state of the segment has abnormal fluctuations and tends to be consistent with the operating state of its adjacent segment. The larger the value, the more obvious the consistency At a certain moment, the operating state of the flight segment fluctuates within the normal range and does not correlate with the state of its adjacent flight segment At a certain time, the operating state of the segment has abnormal fluctuations and is opposite to the running state of its adjacent segment. The larger the value, the more obvious the reverse difference

TABLE 3: The range of values for Local ST-Moran Index and the corresponding meanings.



and temporal state at the segment is characterized by smooth dissipation

When a segment is congested at a certain time, its adjacent segments also tend to be congested; the spatial and temporal state at the segment is characterized by congestion accumulation

When a segment is smooth at a certain time, its adjacent segments tend to be congested; the spatial and temporal state at the segment is characterized by congestion dissipation





FIGURE 6: Correlation distribution in the Moran scatter plot. (a) Positive correlation property quadrant in the Moran scatter plot; (b) negative correlation property quadrant in the Moran scatter plot.

and longitude coordinates extracted from the aircraft data. Additionally, integrating the obtained Aeronautical Information Publication (AIP), we visually represented the approach and departure procedure details utilized by the flights throughout the study window, showcased in Figure 8.

With the obtained data processing outcomes, this study proceeds to derive the operational status of each flight segment by segmenting the actual operational trajectories and correcting the speeds of flights exhibiting congestion behavior. Figure 9 illustrates the principle behind the track



FIGURE 7: Schematic diagram of the Chengdu terminal airspace sector with approach and departure section structure. (a) Approach procedure structure; (b) departure procedure structure.



FIGURE 8: Actual trajectory of flights during the study period with the use of approach and departure procedures.

segmentation process: utilizing the coordinates of a flight's initial and final track points to calculate its overall operating heading. If the heading angle falls within the range of 315° to 45° or 135° to 225°, the flight trajectory is cut based on the latitude coordinates of each waypoint in its approach and departure program. Conversely, if the heading angle lies within 45° to 135° or 225° to 315°, the trajectory is segmented using the longitude coordinates of each waypoint in the approach and departure program. Following the segmentation, the aircraft's heading angle within each segment and the directional angle of the segment itself are determined. Congestion appearance is identified when the heading angle deviates from the segment's directional angle. In such

instances, the aircraft's operational data are recorded, and its speed is recalculated using equation (6) to replace the recorded ADS-B data.

Following the aforementioned processing steps, a total of 35 segments were identified during the study period, comprising 21 approach procedure segments and 14 departure procedure segments. As the experimental data lack information regarding aircraft type and wake class, this paper's data processing and analysis consider all aircraft as similar for analytical purposes.

The flow rates in the congested segments underwent correction using the analytical model outlined in Section 4. Figure 10 portrays the evolution of state fluctuations in each



FIGURE 9: Schematic diagram of the flight operation data segmentation principle.

segment, specifically in the approach and departure procedures, denoted as Figures 10(a) and 10(b), respectively, across different time intervals during the study period. Vertical coordinates within the plots represent the corrected flow rates for individual segments, while the horizontal axis denotes time. Following the determination of these segments' dynamic operational states, they were employed as input data for calculating subsequent state parameters and standard state parameter values.

Following this procedure, the paper will proceed to compute both the global and local ST-Moran's I indices and conduct a comparative validation of the model. An empirical analysis will revolve around the calculation results to validate the model's efficacy.

5.2. Comparative Validation of the Model. In Table 3, the variability in the local ST-Moran's I values reflects the fluctuation in the equivalent flow rate of each segment and its neighboring segments, aiding in the identification of congestion occurrences within a segment. Since the local ST-Moran's I value represents the combined impact of the segment and its immediate surroundings, a nonzero value suggests congestion in the segment and its neighboring areas.

Upon analyzing the operational segments exhibiting congestion behavior, Table 4 summarizes the count of segments displaying nonzero local ST-Moran Index values in both the enhanced ST-Moran Index model and the traditional ST-Moran Index model, alongside their respective adjacent segments.

Table 4 indicates that the proposed enhanced ST-Moran's I model successfully identifies 12 congested segments, achieving a recognition rate of 75% for terminal airspace congestion in comparison to the congested segments observed during actual operations. Furthermore, the traditional ST-Moran's I model demonstrates an improved congestion identification rate of 62.5% in the spatial dimension.

Moreover, as illustrated in Table 5, to evaluate the enhanced ST-Moran's I model's efficacy in the temporal dimension, this study extracted the durations of nonzero local ST-Moran's I values for each segment in both the improved and conventional models. Additionally, the paper tallied the durations of simultaneous congestion across adjacent segments observed during actual operations.

As per Table 5, the enhanced ST-Moran's I model presented in this paper achieves a recognition rate exceeding 70% for congestion at each nonzero local ST-Moran's I value of the segment. Overall, its recognition rate in the temporal dimension reaches 78.2%, marking a notable improvement of 43.61% compared to the traditional ST-Moran's I model.

Considering the analysis outcomes from Tables 4 and 5, the congestion recognition rate of the model proposed in this paper surpasses that of the traditional ST-Moran's I model in both temporal and spatial dimensions. However, given that ADS-B data are recorded at 10-second intervals, certain flights might exhibit short-term state fluctuations or minor fluctuations that do not trigger changes in the model's indices.

5.3. Empirical Analysis. Postvalidation in Section 5.2 revealed a global ST-Moran's I value of 0.47804 upon data integration into the model. This indicates that segments with akin state attributes within Chengdu's terminal airspace cluster in a spatial-temporal distribution during the studied period. In this section, a deeper analysis of the segment structure's operational characteristics within Chengdu's terminal airspace is derived from the local ST-Moran's I value, reflecting the correlation between segments sharing similar

Journal of Advanced Transportation



FIGURE 10: Flow rate correction results for each segment of the approach and departure procedure. (a) Schematic diagram of the corrected speed of flow in each segment of the approach procedure; (b) schematic diagram of the corrected speed of flow in each segment of the departure procedure.

TABLE 4: Statistics of the spatial extent of the congested segments.

	Spatial extent of congestion phenotype				
	Actual number of segments	The number of segments in the traditional model	Number of segments in the improvement model	Accuracy of improvement model (%)	
Main segments	7	1	5	71.43	
Adjacent segments	9	1	7	77.78	
Total	16	2	12	75.00	

state attributes. Herein, we delve into the spatial-temporal distribution characteristics and dynamic evolution of segments exhibiting positive and negative correlation attributes.

According to the spatial and temporal distribution figures of the positively correlated segments shown in Figure 11, their spatial and temporal distribution patterns are as follows:

- Spatially, the positively correlated segments are concentrated predominantly in climbing segments post-takeoff (e.g., RW20L-BHS, RW20R-UU411, and RW20R-UU402 segments) and at the intersections of articulated approach and departure segments (e.g., UU403-UU410 segments);
- (2) Temporally, within time intervals of about 430s to 980s and 2600s to 3130s, the positively correlated segments are mainly concentrated in the climb

segment area post-takeoff. After intervals of roughly 4 to 6 minutes, these segments then shift towards the downstream segment area.

The spatial and temporal distribution pattern of the negatively correlated segments in Chengdu terminal airspace is similar to the positively correlated segments but slightly different, as shown in Figure 12, and the regional spatial and temporal distribution pattern of each segment and its adjacent segments whose operational status exhibits negative correlation characteristics can be summarized as follows:

 In the analyzed spatial domain, negatively correlated segments primarily cluster in climbing segments post-takeoff (e.g., RW20L-BHS and RW20R-UU402 segments) and at intersections of approach and departure segments (e.g., BHS-WFX segment);

RW20R-UU411 and its adjacent segments RW20L-BHS and its adjacent segments (include WFX-BHS segment)	Actual time length (s) 730	Duration Time length in the traditional model (s) 0 460	of congestion phenotype Time length in improvement model (s) 60 560	Accuracy of improvemen model (%) 85.71 76.71
UU403-410 and its adjacent segments	260	0	230	88.46
RW20R-UU402 and its adjacent segments	270	0	190	70.37
Total	1330	460	1040	78.20

TABLE 5: Summary of the duration of congestion phenotypes.



FIGURE 11: Spatial and temporal distribution of positive correlation segments.



FIGURE 12: Spatial and temporal distribution of negative correlation segments.



FIGURE 13: Schematic diagram of the evolution of the local ST-Moran's I for each segment with fluctuations in state attributes. (a) WFX-BHS segment; (b) RW20R-UU411 segment; (c) UU403-UU410 segment; (d) RW20L-BHS segment; (e) RW20R-UU402 segment.



FIGURE 14: Moran scatter plot at the RW20L-BHS segment.



FIGURE 15: Schematic diagram of the state description under each period of the RW20L-BHS segment. (a) The evolution of spatial and temporal characteristics between the RW20L-BHS segment and the BHS-ZYG segment; (b) the evolution of Moran scatter between RW20L-BHS and BHS-ZYG segments.

(2) Regarding the temporal aspect of the study, the negatively correlated segments displayed shorter durations and lacked the pronounced diffusion transfer behavior observed in the positively correlated segments. The analysis reveals that correlated segments within the spatial and temporal boundaries of Chengdu terminal airspace are primarily concentrated in climbing segments posttakeoff and at the intersections of approach and departure procedures. Positive correlation, indicating similar status

TABLE 6: Congestion evolution process under each period in each phase.

Stage	Period	Evolutionary process
	(540s~580s)	The RW20L-BHS segment and its adjacent segments are in a state of congestion, and congestion is accumulating
1	(580s~630s)	The RW20L-BHS segment and its adjacent segments are in congestion, and the accumulation of congestion continues to diminish
	(660s~700s)	The RW20L-BHS segment and its adjacent segments are in congestion, while congestion is accumulating in both segments
	(700s~750s)	The RW20L-BHS segment and its adjacent segments are in congestion, and the accumulation of congestion in both segments continues to diminish
2	(750s~830s)	As the accumulation of congestion continues to diminish, the adjacent segment of the RW20L-BHS segment evolves from congestion to a smooth state with control diversion
	(830s~860s)	As the RW20L-BHS segment is in congestion, its adjacent segment is transformed from smooth to congested due to its congestion influence after a short period of smooth operation
	(860s~980s)	The RW20L-BHS segment and its adjacent segments are in congestion, and the congestion remains stable



FIGURE 16: Schematic diagram of the proposed changes to the PANKO approach scheme.

attributes among segments and their adjacent counterparts at the same time, notably spreads to downstream segments, displaying a discernible time interval for this propagation. Conversely, segments with negatively correlated status attributes, denoting opposite attributes between the segment and its adjacent counterparts simultaneously, effectively mitigate the spreading phenomenon through control measures and guidance from neighboring segments.

Building upon the spatial and temporal analysis, we gain deeper insights into the dynamic evolution of segment characteristics. As depicted in Figure 13, among the segments, only the RW20L-BHS segment exhibits a significant spatial correlation, while the others demonstrate a weaker spatial correlation. This discrepancy primarily arises due to the spatial-temporal adjustments initiated by the segment's aircraft, resulting in fluctuations that do not significantly impact its adjacent segments.

Combining the above results, this paper analyzes the spatial and temporal operational characteristics of the RW20L-BHS segment and its adjacent segments, which have a strong spatial correlation. To commence, the Moran scatter plot of the RW20L-BHS segment is depicted in Figure 14. As per the quadrant index definitions in Figure 5, the sample points of the local ST-Moran's I pertaining to the RW20L-BHS segment are predominantly distributed in the third quadrant, with some sample points located in the second quadrant. This distribution signifies that the RW20L-BHS segment experienced congestion throughout the study period, exerting a pronounced influence on its adjacent segments, which were also notably congested under its impact.

Given the aforementioned characteristics, this paper further dissects the evolution process at the RW20L-BHS segment by scrutinizing temporal correlation changes and state evolution. Observing Figure 13(d), the segment's state fluctuations are notably concentrated in the 0~1000stimeframe, preceding the actual operational period. Considering its correlation alterations, the segment's evolution can be bifurcated into four phases, outlined in Figure 15(a). In A1 and A2, the correlation between the segments is positive, showing an ascending and descending trend. Subsequently, in A3, the correlation turns negative, following a similar ascending and descending pattern. Finally, in A4, the correlation becomes positive and maintains stability. Moreover, Figure 15(b) illustrates the sample points of the local ST-Moran's I in each period's quadrant. As per the quadrant's implications from Figure 5, both segments experience congestion accumulation in the B1 and B2 periods, signifying congestion at the RW20L-BHS segment and its adjacent segments. However, in the B3 period, RW20L-BHS experiences a smoother operational flow while its adjacent segments alleviate and transition toward smooth operations. Eventually, in the B4 period, both segments return to congestion accumulation, indicating sustained congestion at RW20L-BHS with its adjacent segments reverting to a congested state.

Ultimately, the dynamic evolution at the RW20L-BHS segment can be delineated into two principal stages, correlating to the relationship between the two segments as shown in Figures 15(a) and 15(b) during each moment. These stages correspond to A1 (B1) and A2, A3, and A4 (B2, B3, and B4). The specific evolution process is detailed in Table 6.

6. Discussion

Based on the analysis and operational considerations, here are proposed enhancements for refining control measures within Chengdu's terminal airspace:

(1) Figures 11 and 12 delineate a positive correlation observed among flights originating from CDX, NOBIK, and OGOMO departure points, converging in the RW20R-UU402 segment. This observed correlation indicates a trend where congestion in this specific segment tends to influence adjacent segments, amplifying congestion downstream. The implications of such a pattern suggest a cascading effect on the airspace traffic flow.

Considering this correlation, it becomes evident that congestion in the RW20R-UU402 segment has repercussions on the broader traffic dynamics, particularly during periods of heightened departure traffic. Therefore, an operational consideration arises for controllers to evaluate the feasibility of diverting flights departing from CDX, NOBIK, and OGOMO departure points towards Runway 02R.

Redirecting flights from these specific departure points to an alternative runway during peak traffic periods could potentially alleviate congestion in the RW20R-UU402 segment and prevent its propagation downstream. Such proactive measures align with the need for adaptable traffic management strategies to optimize airspace utilization and mitigate congestion hotspots.

(2) Considering the distinct phases identified in the evolution of the segment's correlations, depicted in Figure 15(a), it is evident that the RW20L-BHS segment undergoes dynamic changes. The segmentation into A1 to A4 phases demonstrates the fluctuations in correlation, showcasing distinct trends in segment behavior over time. Furthermore, the quadrant analysis in Figure 15(b) reveals local ST-Moran's I sample points in each period's quadrant, reinforcing the varying congestion states experienced by both RW20L-BHS and its neighboring

The fluctuations and correlations observed in the BHS waypoint, particularly in proximity to the PANKO approach point to the UU702 initial approach positioning point and the route from Runway 02R to ZYG departure point, underscore the susceptibility of this waypoint to operational challenges. The intricate spatial correlations and state fluctuations, as illustrated in Figures 13, 15, and Table 6, accentuate the vulnerability of this area to congestion and operational disruptions.

Consequently, the distinct departure procedure from Runway 02R to the ZYG departure point raises the suggestion of relocating the flight segment between the PANKO approach point and UU702 initial approach positioning point to the PANKO approach point to HLC initial approach positioning point during navigation (as shown in Figure 16). Such an adjustment could potentially mitigate congestion and operational challenges in this critical airspace area, promoting smoother operations and reducing vulnerability to state fluctuations observed in this region.

Indeed, this study has certain limitations. Firstly, the covariate design of terminal airspace's operational state only incorporates congestion's impact on segment flow rates, lacking a comprehensive multiscale quantification index construction. Secondly, the research primarily centers on terminal airspace congestion dynamics, neglecting the influence of the airport surface system.

7. Conclusions

segments.

This paper enhances the traditional Moran's Index model by dissecting the operational characteristics of terminal airspace concerning state parameters, spatial weight matrices, and the temporal dimension. This improved model, termed the ST-Moran Index, is tailored to capture the dynamic evolution of congestion within terminal airspace. To validate its efficacy, flight operation data from Chengdu Shuangliu International Airport's controlled terminal area were employed. Given the absence of aircraft type information in the ADS-B data, all flights were assumed to belong to the same aircraft type for analysis purposes in this study. The ensuing conclusions are as follows:

(1) The enhanced ST-Moran's I model exhibits evident effectiveness in analyzing terminal airspace congestion, as highlighted by the results. This paper demonstrates that compared to the traditional ST-Moran's I model, the improved version significantly enhances the recognition rate of congestion in both spatial and temporal dimensions. Specifically, it increases recognition rates by 62.5% for spatial dimensions and by 43.61% for temporal dimensions, surpassing conventional models.

(2) Analyzing the congestion dynamics in Chengdu terminal airspace revealed spatial correlation primarily in the ascent segment after takeoff and at the juncture of approach and departure segments. Additionally, the impact of positively correlated segment combinations spreading to their downstream counterparts was observed.

Future studies might emphasize indicator design across multiple scales and analyze air-ground integration concerning congestion.

8. Practical Implications

This paper introduces a model designed to analyze the spatiotemporal dynamics of congestion within terminal airspace. Through case studies, it has been demonstrated that this model effectively assesses the evolution and state of congestion in terminal airspace. The practical implications of this work can be highlighted as follows:

- Operational optimization: understanding congestion patterns across different timeframes and locations can significantly enhance flight planning and traffic management. This understanding facilitates better route adjustments, landing/departure procedure optimization, and overall flight efficiency improvement, thereby reducing congestion.
- (2) Airspace planning: improved insights into airspace structure and routes enable more efficient planning and design. This aspect is crucial for establishing more streamlined control areas, increasing flight capacity, and mitigating congestion.
- (3) Decision support: this model aids airlines, regulatory authorities, and airport managers in making more informed decisions. It optimizes resource allocation, refines operational processes, and enhances overall efficiency.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This research was funded by the Fundamental Research Funds for the Central Universities (ZHMH2022-008), the Subproject of the National Key Research and Development Program (2021YFB2601704), the Sichuan Science and Technology Plan Project (2021YFS0319), and Funding for Graduate Student Research and Innovation at Civil Aviation Flight University of China (X2023-34).

References

- CAAC, China, Air Traffic Management Rules for Civil Aviation, Civil Aviation Administration of China, Beijing, China, 2023.
- [2] W. L. Cheung, "Data-driven integrated approach to airport demand management," Doctoral thesis, Nanyang Technological University, Singapore, 2021.
- [3] Y. Zhao and M. Wang, "Important theories and critical scientific technology of air traffic engineering," Acta Aeronautica et Astronautica Sinica, vol. 43, no. 12, pp. 122–163, 2022.
- [4] T. Xu, J. Ding, B. Gu, and J. Wang, "Forecast warning level of flight delays based on incremental ranking support vector machine," *Acta Aeronautica et Astronautica Sinica*, vol. 30, no. 7, pp. 1256–1263, 2009.
- [5] L. Ma, W. Liu, and H. Wang, "Optimization of airspace capacity based on intersection complexity," *Science Technology and Engineering*, vol. 22, no. 24, pp. 10796–10804, 2022.
- [6] C. F. Daganzo, "The cell transmission model, part II: network traffic," *Transportation Research Part B: Methodological*, vol. 29, no. 2, pp. 79–93, 1995.
- [7] C. F. Daganzo, "The cell transmission model: a dynamic representation of highway traffic consistent with the hydrodynamic theory," *Transportation Research Part B: Methodological*, vol. 28, no. 4, pp. 269–287, 1994.
- [8] V. Attwooll, "The costs of terminal area delays," Journal of Navigation, vol. 21, no. 1, pp. 66–80, 1968.
- [9] Y. Lin, L. Li, P. Ren, Y. Wang, and W. Szeto, "From aircraft tracking data to network delay model: a data-driven approach considering en-route congestion," *Transportation Research Part C: Emerging Technologies*, vol. 131, Article ID 103329, 2021.
- [10] P. D. Vascik, J. Cho, V. Bulusu, and V. Polishchuk, "Geometric approach towards airspace assessment for emerging operations," *Journal of Air Transportation*, vol. 28, no. 3, pp. 124–133, 2020.
- [11] V. Bulusu and V. Polishchuk, "A threshold based airspace capacity estimation method for UAS traffic management," in 2017 Annual IEEE International Systems Conference (SysCon), Montreal, Canada, April 2017.
- [12] L. Gui-Yi, H. Ming-Hua, and Z. Zhe, "Multi-sector traffic congestion identification method based on FCM-rough sets," *Journal of Transportation Systems Engineering and Information Technology*, vol. 17, no. 6, p. 141, 2017.
- [13] F. Sun, X. Xu, H. Zhang, D. Shen, Y. Mu, and Y. Chen, "Evolution mechanism and optimisation of traffic congestion," *Aeronautical Journal*, vol. 128, no. 1321, pp. 598–630, 2023.
- [14] Q. Gao, J. Chu, and Y. Li, "Prediction of congestion level in airport terminal area based on BP neural network," *Aeronautical Computing Technique*, vol. 49, no. 6, pp. 57–61, 2019.
- [15] W. Tian, X. Dai, and M. Hu, "Systemic congestion propagation in the airspace network," *Mathematical Problems in Engineering*, vol. 2018, pp. 1–12, 2018.
- [16] L. Spirkovska, C. S. Kulkarni, J. Watkins, and L. Martin, "Urban air mobility airspace dynamic density," in AIAA AVIATION 2022 Forum, Chicago, IL, USA, June 2022.
- [17] Z. Yang, R. Tang, W. Zeng, J. Lu, and Z. Zhang, "Short-term prediction of airway congestion index using machine learning methods," *Transportation Research Part C: Emerging Technologies*, vol. 125, Article ID 103040, 2021.

- [18] J. Lavandier, A. Islami, D. Delahaye, S. Chaimatanan, and A. Abecassis, "Selective simulated annealing for large scale airspace congestion mitigation," *Aerospace*, vol. 8, no. 10, p. 288, 2021.
- [19] J. Ren, S. Qu, L. Wang, and Y. Wang, "An en route capacity optimization model based on air traffic control process," *Mathematical Biosciences and Engineering*, vol. 19, no. 4, pp. 4277–4299, 2022.
- [20] K.-Q. Cai, J. Zhang, M.-M. Xiao, K. Tang, and W.-B. Du, "Simultaneous optimization of airspace congestion and flight delay in air traffic network flow management," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 11, pp. 3072–3082, 2017.
- [21] C. Chin, K. Gopalakrishnan, H. Balakrishnan, M. Egorov, and A. Evans, "Protocol-Based congestion management for advanced air mobility," *Journal of Air Transportation*, vol. 31, no. 1, pp. 35–44, 2023.
- [22] S. Badrinath, M. Z. Li, and H. Balakrishnan, "Integrated surface-airspace model of airport departures," *Journal of Guidance, Control, and Dynamics*, vol. 42, no. 5, pp. 1049– 1063, 2019.
- [23] M. Sergeeva, D. Delahaye, C. Mancel, and A. Vidosavljevic, "Dynamic airspace configuration by genetic algorithm," *Journal of Traffic and Transportation Engineering*, vol. 4, no. 3, pp. 300–314, 2017.
- [24] Y. Dong, Z. Lu, Y. Liu, Q. Zhang, and D. Wu, "China's corridors-in-the-sky design and space-time congestion identification and the influence of air routes' traffic flow," *Journal of Geographical Sciences*, vol. 29, no. 12, pp. 1999– 2014, 2019.
- [25] Z. Wang, D. Delahaye, J.-L. Farges, and S. Alam, "A quasidynamic air traffic assignment model for mitigating air traffic complexity and congestion for high-density UAM operations," *Transportation Research Part C: Emerging Technologies*, vol. 154, Article ID 104279, 2023.
- [26] Y. Han and X. Huang, "Traffic flow modeling and optimization control in the approach airspace," *Journal of Industrial and Management Optimization*, vol. 19, no. 5, pp. 3784–3793, 2023.
- [27] B. Wang, Z. Deng, X. Ni, K. B. Smith, M. Z. Li, and R. Saigal, "Learning-Driven airspace congestion pricing for advanced air mobility," in *AIAA SCITECH 2023 Forum*, National Harbor, MD, USA, January 2023.
- [28] J. Jiang, H. Zhang, and Q. Qiu, "Evaluating method of air traffic congestion state of approaching traffic flow in terminal areas," *Journal of Wuhan University of Technology*, vol. 40, no. 6, pp. 1043–1049, 2016.
- [29] L. Yang, S. Yin, and M. Hu, "Network flow dynamics modeling and analysis of arrival traffic in terminal airspace," *IEEE Access*, vol. 7, pp. 73993–74016, 2019.
- [30] F. Jiang, Z. Zhang, and X. Dai, "Ground-Air traffic congestion propagation model based on hierarchical control interdependent network," *Journal of Advanced Transportation*, vol. 2023, Article ID 4602148, 22 pages, 2023.
- [31] Y. Zhang, Z. Lu, X. Du, Y. Dong, and Q. Zhang, "Research on airspace resource allocation supported by spatiotemporal continuous data: review and prospect," *Advances in Earth Science*, vol. 34, no. 9, pp. 912–921, 2019.
- [32] M. Z. Li and M. S. Ryerson, "A data-driven approach to modeling high-density terminal areas: a scenario analysis of the new Beijing, China airspace," *Chinese Journal of Aeronautics*, vol. 30, no. 2, pp. 538–553, 2017.
- [33] T. Dong, S. Yin, and N. Zhang, "The interaction mechanism and dynamic evolution of digital green innovation in the

- [34] S. Yin, Y. Wang, and J. Xu, "Developing a conceptual partner matching framework for digital green innovation of agricultural high-end equipment manufacturing system toward agriculture 5.0: a Novel Niche Field Model Combined with Fuzzy VIKOR," *Frontiers in Psychology*, vol. 13, Article ID 924109, 2022.
- [35] J. P. Lesage and R. K. Pace, "Spatial econometric models," Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications, Springer, pp. 355–376,Berlin, Germany, 2009.
- [36] J. P. Lesage and R. K. Pace, "Interpreting spatial econometric models," *Handbook of Regional Science*, Springer, pp. 2201–2218,Berlin, Germany, 2021.
- [37] S. Glaser, A Review of Spatial Econometric Models for Count Data, University of Hohenheim, Stuttgart, Germany, 2017.
- [38] X. Fu, C. Xu, Y. Liu, C.-H. Chen, F. Hwang, and J. Wang, "Spatial heterogeneity and migration characteristics of traffic congestion—a quantitative identification method based on taxi trajectory data," *Physica A: Statistical Mechanics and Its Applications*, vol. 588, Article ID 126482, 2022.
- [39] S. Chen, W. Wei, B. Mao, and W. Guan, "Analysis on urban traffic status based on improved spatio-temporal Moran's I," *Acta Physica Sinica*, vol. 14, pp. 519–525, 2013.
- [40] S. Sidiropoulos, A. Majumdar, and K. Han, "A framework for the optimization of terminal airspace operations in Multi-Airport Systems," *Transportation Research Part B: Methodological*, vol. 110, pp. 160–187, 2018.
- [41] CAAC, Guidance of CAAC on Accelerating the Construction of Chengdu-Chongqing World Class Airport Cluste, Civil Aviation Administration of China, Beijing, China, 2022.
- [42] X. Dong, Z. Zhao, and H. Zhang, Fundamentals of Air Traffic Management, Science Press, Beijing, China, 2011.
- [43] A. L. Achu, C. Aju, V. Suresh, T. P. Manoharan, and R. Reghunath, "Spatio-temporal analysis of road accident incidents and delineation of hotspots using geospatial tools in Thrissur District, Kerala, India," *KN-Journal of Cartography* and Geographic Information, vol. 69, no. 4, pp. 255–265, 2019.
- [44] V. Prasannakumar, H. Vijith, R. Charutha, and N. Geetha, "Spatio-temporal clustering of road accidents: GIS based analysis and assessment," *Procedia-social and behavioral sciences*, vol. 21, pp. 317–325, 2011.
- [45] H. Singh and R. Sharma, "Role of adjacency matrix and adjacency list in graph theory," *International Journal of Computers and Technology*, vol. 3, no. 1, pp. 179–183, 2012.
- [46] L. Yang, Studies on Complex Dynamics and Congestion Mitigation Methods of Air Traffic Flow in Terminal Airspace, Nanjing University of Aeronautics and Astronautics, Nanjing, China.