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Spatio-temporal analysis of urban traffic patterns in metropolitan areas applying the emerging hot spot analysis (EHSA) algorithm: A short-term (one-week) analysis of online data from Tehran

Hassanali Faraji Sabokbar[1*]

1. Human Geography and Planning Department, Faculty of Geography, University of Tehran, Tehran, Iran

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Abstract

Objective: To identify, analyze, and model the spatio-temporal patterns of traffic congestion in the Tehran metropolitan area using the emerging hot spot analysis (EHSA) approach based on a space-time cube framework. This study seeks to answer the question of what the spatio-temporal structure of traffic congestion in Tehran is and how high- and low-congestion hotspots are distributed across space and time.
Methodology: Online traffic data for Tehran's road network were collected over the period from April 22 to April 29, 2026 (comprising 259 observation intervals with 30-minute time steps). The resulting dataset included more than 7.9 million records. After preprocessing and constructing a space-time cube, three levels of analysis were conducted: calculation of spatial autocorrelation (Moran's I), high/low clustering analysis, and implementation of the emerging hot spot analysis (EHSA) in ArcGIS Pro.
Results: The analyses revealed a statistically significant positive spatial autocorrelation (z-score = 212.41) at the 99% confidence level. The EHSA identified eight distinct patterns. Among hot spots, a "persistent hot spot" was detected in District 10 and its surrounding areas, representing the most critical congestion zone. An "intensifying hot spot" was observed in Districts 21 and 22, indicating a transition toward worsening congestion conditions. Additional oscillating and sporadic patterns were identified in the middle urban rings. Regarding cold spots, the most extensive pattern was "dispersed cold spots" in Districts 22, 20, and 4. Furthermore, "intensifying cold spots" and "diminishing cold spots" were detected in peripheral areas of the city. Overall, Tehran's traffic exhibits a concentric four-ring structure, in which congestion intensity decreases from the urban core toward the periphery.
Conclusion: The integration of real-time traffic data with the EHSA method provides an efficient and robust framework for traffic monitoring and spatio-temporal congestion analysis.

Keywords

Spatio-temporal analysis
urban traffic congestion
Emerging Hot Spot Analysis (EHSA)
Space-Time Cube

* Corresponding Author: hfaraji@ut.ac.ir

1. Introduction

Urban traffic is recognized as one of the most complex urban phenomena and has consistently remained at the center of academic attention. In recent years, with the increasing complexity of urban transportation problems and the challenges associated with them, it has attracted interest from multiple academic disciplines, including transportation engineering, urban planning, social sciences, urban geography, and data science. Understanding traffic patterns requires the simultaneous analysis of two fundamental geographic dimensions: the temporal dimension, which reflects traffic variations across different hours of the day, days of the week, months, seasons, years, and special events; and the spatial dimension, which reveals the spatial distribution of traffic density and flows across the city.

The city of Tehran, with a population of over 9 million, has one of the most dense and complex traffic systems, making its study of particular scientific and applied importance. Travel demand in Tehran is shaped by its distinctive administrative, educational, and financial-economic centrality, as well as by the concentration of a large proportion of Iran's urban population. The population moves dynamically across different parts of the city through various transportation systems. In addition, Tehran not only accommodates its resident population but also receives a substantial influx of commuters from surrounding areas toward the city center, which functions as the economic and financial core. At the end of the working day, commercial, administrative, and economic activities largely shift from the central areas toward the outskirts, generating a distinct pattern of mobility dynamics.

Traffic patterns in Tehran are highly time-dependent, and these patterns may change significantly across different time intervals. Traffic management policies such as congestion pricing zones and odd–even traffic restrictions act as regulatory mechanisms that influence urban mobility patterns. Furthermore, special events such as public holidays and, in recent contexts, mass social gatherings (e.g., during Ramadan-related events) have also affected traffic dynamics. Night-time gatherings, in particular, generate additional travel flows within the city. On the other hand, Tehran's traffic system is associated with significant environmental consequences, including air pollution, noise pollution, and the emission of various urban pollutants, while also exerting substantial impacts on both the urban and national economy. Therefore, understanding traffic patterns is crucial for effective urban management and for guiding sustainable development and traffic planning policies in Tehran.

In this study, using novel methods of collecting non-official recorded data, traffic data were gathered over an extended period, resulting in a large-scale dataset. Accordingly, traffic congestion data from April 22 to April 29, 2026 (2/2/1405 to 9/2/1405 in the Iranian calendar) were selected and processed as a sample for this research. The study aims to address the following questions: What spatio-temporal patterns characterize traffic in Tehran? Is it possible to identify underlying structures in these patterns? Moreover, based on these patterns, is the prediction feasible? To answer these questions, the collected data were processed, and the patterns were identified using space-time cube modeling techniques.

2. Theory

Urban traffic is a multifaceted, dynamic, and non-linear phenomenon whose understanding requires the simultaneous analysis of two fundamental dimensions: space and time. In recent decades, the rapid expansion of remote sensing technologies, mobile phone data, human location tracking systems, urban traffic cameras, and a wide range of sensors has provided researchers with vast amounts of spatio-temporal data. This data-driven transformation has necessitated the development of advanced spatial data mining and pattern recognition methods capable of revealing hidden structures, interrelationships, and the dynamic behavior of traffic flows. Spatio-temporal traffic pattern analysis acts as a bridge between geographic sciences, transportation engineering, spatial econometrics, and data science, offering a powerful framework for planning, managing, and controlling traffic in metropolitan areas.

Mobility lies at the heart of many challenges faced by cities (den Hoed, 2024). The term "mobility" carries multiple meanings; in this context, it refers to the movement of vehicles through space and time, while implicitly also encompassing human mobility (Barbosa et al., 2018). Mobility generates population movement dynamics and leads to trip production. In an urban system, as a result of continuous urban processes, certain areas act as trip generators, while others function as trip attractors. Between these two types of spaces, a continuous flow of movement is maintained. However, the pattern, intensity, and volume of this mobility are not constant and are influenced by various factors, leading to temporal and spatial fluctuations. These mobility structures, often referred to as the sources of urban traffic, shape overall urban traffic patterns.

There are various perspectives and theoretical approaches in the study of urban traffic. In line with the focus of this article, these can be broadly categorized into several groups, including studies on traffic flow dynamics and models related to spatio-temporal analysis, which will be discussed in the following sections in accordance with the objectives of this research.

2.1. Fundamental traffic flow models

Traffic flow models have been developed since the early 19th century to understand, explain, and predict traffic dynamics (van Wageningen-Kessels, van Lint, Vuik, & Hoogendoorn, 2015). Traffic flow theory represents one of the most fundamental frameworks for interpreting traffic behavior. Greenshields (1935) introduced the first mathematical relationship between speed (v), density (k), and flow (q), demonstrating that this relationship can be expressed in a linear form: $q = k \times v$. In this formulation, flow (q) is defined as the number of vehicles passing a point per unit time, density (k) as the number of vehicles per unit length, and speed (v) as the average vehicle speed.

2.2. Fundamental diagram of traffic

Another key perspective in urban traffic modeling is the fundamental diagram of traffic, which graphically represents the relationship between flow and density. Daganzo (1994), through the cell transmission model (CTM), approximated this diagram using a trapezoidal form, enabling more accurate simulation of traffic wave propagation. Later, Geroliminis and Daganzo (2008) introduced the concept of the macroscopic fundamental diagram (MFD), which describes the relationship between density and flow at the scale of an entire urban network. This concept represented a major advancement in urban traffic management, as it enabled the control and optimization of traffic at the city scale.

2.3. Three-phase traffic theory

The three-phase traffic theory, developed by Boris S. Kerner in 2004 (Boris S. Kerner, Rehborn, Aleksic, & Haug, 2004), provides a modern framework for describing roadway traffic behavior. This theory is based on empirical observations of real-world traffic data (including extensive measurements from German highways). It classifies traffic into three main phases: free flow, synchronized flow, and wide moving jams. A key contribution of this theory is its explanation of traffic waves (such as wide moving jams), which account for the primary mechanisms of congestion formation on roads (Treiber, 2013).

The free flow phase is defined as a state in which vehicles move at high speeds with minimal constraints, and the relationship between flow (q) and density (ρ) is approximately linear. In this phase, average speeds are typically above 80 km/h, and density is below 15 vehicles per kilometer. This regime is based on empirical observations from uncongested highways, and a spontaneous transition from free flow to synchronized flow (F → S) occurs when density exceeds a critical threshold. This transition is often observed at bottlenecks and leads to a reduction in highway performance (Kerner, 2004). In mathematical formulations and fundamental diagrams, the maximum flow (q_{max}) in this phase is approximately 2000–2500 vehicles per hour per lane, while local instabilities may trigger phase transitions (Treiber & Kesting, 2013).

The synchronized flow phase is described as an intermediate state in which vehicles travel at moderate speeds (approximately 40–80 km/h) and exhibit synchronization across lanes. Unlike free flow, this phase does not show a simple functional relationship between flow and density. Instead, flow can vary within a two-dimensional region of the fundamental diagram, typically corresponding to densities of 20–50 vehicles per kilometer. This phase, first identified by Kerner applying empirical data from the German A5 motorway, often serves as a precursor to the formation of traffic waves. It is widely regarded as a key factor behind the capacity drop phenomenon in traffic systems, and microscopic models are often applied to simulate its behavior (Kerner, 2004; Treiber & Kesting, 2013).

The wide moving jam phase is characterized by stable, self-sustaining traffic waves with high density (typically above 50 vehicles per kilometer) and near-zero speeds within the jam. These waves propagate backward through traffic at an approximately constant speed of about 15 km/h and can persist without external disturbances. Kerner describes this phase as a self-sustaining phenomenon that typically emerges from synchronized flow. In macroscopic models, it is explained using shockwave equations, where wave stability is supported by empirical evidence (Kerner, 2004). This phase significantly reduces overall highway capacity and is widely used in simulations to predict long-term congestion patterns (Kerner, 2002).

2.4. Space–time cube theory

The space–time cube theory, introduced by Hägerstrand (1970), is based on the idea that every human event—and consequently every behavioral pattern at the urban scale—can be analyzed simultaneously across two spatial dimensions and one temporal dimension. Within this conceptual framework, movement trajectories in the city are not merely represented as occurring "in a place" or "at a time." However, they are instead conceptualized as three-dimensional entities, where temporal change is structurally organized along the time axis, while spatial positions are recorded along the spatial axes (Hägerstrand, 1970).

From this theoretical perspective, urban traffic can be understood as a collection of spatio-temporal movements and interactions. Vehicles, groups of drivers, passengers, and even flows associated with specific temporal conditions (such as peak hours or urban events) all occur within a defined geographic space and over specific time intervals (Hägerstrand, 1970). Accordingly, accurate traffic modeling is only possible when spatial and temporal patterns are represented simultaneously in an integrated framework.

Recent studies have demonstrated that the integration of spatio-temporal data with advanced computational models provides an efficient and scalable framework for urban traffic prediction and analysis (Boris S. Kerner et al., 2004; Mohammed, Alkhereibi, Abulibdeh, Jawarneh, & Balakrishnan, 2023; Soltani & Roohani Qadikolaei, 2024). In particular, spatio-temporal structures based on graph convolutional networks and temporal neural networks exhibit strong capabilities in capturing complex spatial and temporal dependencies in traffic systems (Komarovsky & Haddad, 2025; Zhang et al., 2025; Zhu, Zhang, Jian, & Yang, 2025).

Given the focus of this study, it is necessary to provide a clear and scientific definition of both "pattern" and "spatio-temporal pattern mining." In data science, a pattern refers to a recurring, regular, or meaningful structure within data. Han et al. define a pattern as "a set of relationships among variables that appears repeatedly and with significant probability in data" (Han, Kamber, & Pei, 2011). This definition is particularly useful for understanding traffic patterns, as urban traffic itself consists of repetitive and partially predictable behavioral structures.

In the context of urban traffic, patterns can be classified into three main levels: temporal patterns, which describe traffic variations across hours of the day, days of the week, or seasons; spatial patterns, which represent the distribution of traffic density across different locations in the road network; and spatio-temporal patterns, which capture the dynamic interaction between spatial locations and temporal changes in traffic conditions (Cheng, Haworth, Anbaroglu, Tanaksaranond, & Wang, 2014). Based on this understanding, spatio-temporal pattern mining can be defined as "the process of discovering novel, non-trivial, and potentially useful knowledge from large datasets that contain both spatial and temporal attributes." In the context of urban traffic analysis, this process involves the identification of (Shekhar et al., 2015):

- Spatial clusters: grouping regions with similar traffic behavior
- Hotspots: areas exhibiting abnormal or extreme traffic density
- Association rules: relationships among different traffic phenomena
- Similar time series: identifying road segments with similar temporal patterns
- Anomalies: deviations from expected or normal patterns
- Traffic waves: propagation of congestion through the road network

Based on the above discussion, it can be concluded that spatio-temporal traffic pattern mining is not a unidimensional approach but rather the result of the convergence and gradual evolution of multiple theoretical and methodological streams. From Greenshields' fundamental equation, which provided the first mathematical representation of the relationship between speed, density, and flow, to the macroscopic fundamental diagram that enabled network-level traffic analysis, and Kerner's three-phase traffic theory that explained traffic complexity through free, synchronized, and congested phases, all have contributed to a robust theoretical foundation for understanding the nonlinear and dynamic nature of traffic flow.

Alongside these quantitative frameworks, Hägerstrand's space-time cube theory (1970), which established the simultaneous analysis of space and time as a fundamental requirement, and precise definitions of pattern and spatio-temporal pattern mining in data science collectively form a coherent and multi-layered theoretical framework. Within this framework, urban traffic is not merely a physical flow but a spatio-temporal phenomenon characterized by hidden structures, recurring patterns, and detectable anomalies, which constitute the conceptual basis of this study.

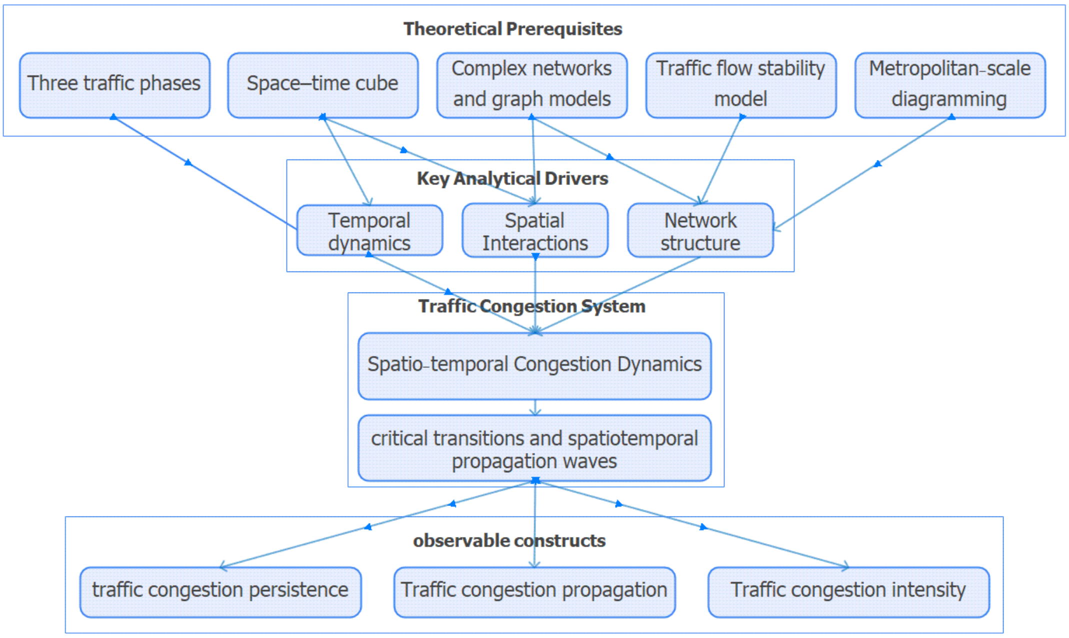


Figure 1. Theoretical framework of urban traffic congestion pattern mining in Tehran

The theoretical framework illustrated in Figure 1 is based on the assumption that traffic density or congestion is not a simple outcome of increased travel demand, but rather the result of a multi-layered interaction among network structure, temporal dynamics, and spatial interactions. At the first layer, the fundamental theories of traffic flow—including Greenshields' classical speed–density–flow relationship, the macroscopic fundamental diagram, and Kerner's three-phase traffic theory—provide the conceptual foundation for describing traffic behavior in terms of capacity, instability, phase transitions, and the formation of congestion waves.

Within this framework, congestion is interpreted as an emergent phenomenon arising from nonlinear interactions among network components rather than being solely driven by traffic demand. Simultaneously, Hägerstrand's space–time cube theory provides a spatio-temporal formalization of this phenomenon, demonstrating that traffic flows must be analyzed as dynamic trajectories within a continuous space–time continuum rather than as static events.

In addition, the incorporation of complex network theory and graph-based models enables the consideration of topological dependencies within the network, including the effects of bottlenecks, critical pathways, and the cascading propagation of disruptions.

Based on this theoretical foundation, the diagram introduces three primary analytical constructs—network structure, temporal dynamics, and spatial interaction—as latent dimensions generating the dynamics of traffic congestion. Network structure represents the topological properties of road networks, including node centrality and link capacity. Temporal dynamics refer to temporal cycles, daily and weekly rhythms, and critical system transitions. Spatial interaction reflects the spatial propagation of congestion, proximity effects, and spatial dependencies among network segments.

In continuation, these dynamics may lead to critical transitions and congestion propagation waves, which can be explained within the literature of complexity theory, percolation theory, and network cascade dynamics.

At the final layer, these mechanisms are operationalized through three measurable constructs: traffic congestion intensity, congestion extent and persistence, and network-based congestion propagation. Congestion intensity reflects the magnitude or severity of traffic disruption; congestion extent and persistence capture the temporal continuity of traffic conditions; and congestion propagation represents the diffusion dynamics of disruptions across the network.

The significance of this conceptual structure lies in its ability to integrate classical traffic flow theory, the spatio-temporal paradigm, and complex network approaches. In doing so, it provides a theoretical foundation for analyzing high-resolution vector–network data from Tehran with fine temporal granularity. In essence, this diagram presents an integrative framework in which urban traffic is modeled not merely as a flow process, but as a complex spatio-temporal system. This approach offers a robust theoretical and operational basis for analyzing Tehran's road network, particularly using half-hourly and link-based traffic data.

3. Literature review

Urban traffic in metropolitan areas such as Tehran is recognized as one of the most complex spatio-temporal phenomena. It has consistently attracted the attention of researchers across transportation engineering, urban planning, and artificial intelligence. A systematic review of the literature indicates that existing studies in this domain can be broadly classified into two distinct methodological streams: the first stream is based on time series modeling for traffic behavior prediction. In contrast, the second focuses on descriptive spatial analysis and clustering approaches for identifying congestion hotspots. A critical examination of these approaches reveals methodological gaps that the present study aims to address through the use of the emerging hot spot analysis (EHSA) algorithm and the space–time cube framework.

In the first stream, researchers have primarily focused on extracting dynamic data and modeling temporal patterns. Rezaei et al. (2024), using online data from the MapBox platform, collected key traffic variables such as traffic volume, speed, and travel time across Tehran's road network and applied ARIMA and SARIMA models for forecasting. Their findings demonstrated the strong capability of these models in capturing periodic and temporal trends, with statistically significant moving average coefficients. Similarly, Nouri and Masghari (2026) utilized Google imagery and traffic-related visual data to predict traffic conditions for route optimization purposes. Although these studies are effective in modeling temporal patterns and short-term prediction, they inherently neglect the spatial dimension and the interactions between different urban areas. Time series models are typically single-location approaches and are therefore unable to capture complex phenomena such as the spatial diffusion or dissipation of traffic between regions in an integrated manner.

In the second stream, research has mainly focused on identifying traffic hotspots at specific temporal snapshots. Shariat-Mahmoudi (2023) used Google Maps services to calculate traffic congestion indices across 117 districts of Tehran. By applying the Getis-Ord Gi* statistic and the Kruskal–Wallis test, the study identified high-density clusters during morning peak hours in the western parts of the city with 90% confidence. While this approach is effective for producing static maps of congestion, the inherently static nature of the Getis-Ord method does not allow for the analysis of temporal evolution and the dynamics of hotspot formation over time. In other words, this approach is limited to identifying "hotspots". It cannot distinguish between persistent, intensifying, or emerging hotspots—distinctions that are critical for proactive urban traffic management and policy design.

A comparative analysis of previous studies reveals three major research gaps: first, the separation of spatial and temporal dimensions in existing models; second, the inability to identify emerging patterns and dynamic transitions (e.g., increasing or decreasing trends in congestion hotspots); and third, limitations in handling large-scale vector-based spatio-temporal datasets.

The present study addresses these gaps by employing a space–time cube framework. This data structure integrates large-scale vector datasets (comprising more than 7.9 million records) into a unified three-dimensional representation, providing the necessary foundation for applying the EHSA algorithm. Unlike static methods, EHSA captures temporal evolution over time and identifies eight distinct spatio-temporal patterns, including persistence, intensification, decline, and oscillation.

This analytical approach provides a powerful tool for understanding not only the "where" and "when" of traffic congestion, but also the "how" and "why" behind its evolution. It enables urban managers to move beyond reactive strategies and instead develop proactive policies targeting areas that are at risk of becoming critical congestion zones. Consequently, the contribution of this study lies in shifting the literature from descriptive-static analyses toward dynamic-predictive frameworks, offering a novel foundation for intelligent urban traffic monitoring and management.

4. Methodology

4.1. Emerging hot spot analysis (EHSA)

In the final stage of spatio-temporal analysis, the emerging hot spot analysis (EHSA) algorithm was employed. This method integrates two complementary approaches: the Getis-Ord Gi* spatial statistic for measuring spatial clustering at each time step, and the non-parametric Mann–Kendall test for identifying statistically significant trends in the time series of Gi* values for each spatial cell (Ord & Getis, 1995). The Getis-Ord Gi* statistic for each spatial unit i is computed using the following equation (Lanorte, Nolè, & Cillis, 2024):

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2}{n-1}}}$$

where (x_j) denotes the value of attribute (j), (w_{i,j}) represents the spatial weight between features (i) and (j), and (n) is the total number of spatial units. (\bar{X}) is the global mean of the variable, and (S) is the sample standard deviation. A positive and statistically significant Gi* value indicates clustering of high values (a hot spot), whereas a negative and statistically significant value indicates clustering of low values (a cold spot) (Getis & Ord, 1992; Mitchell, 2009).

In the next step, the Mann–Kendall test is applied to evaluate the temporal trend of the Gi* time series for each spatial cell over 245 time steps. This non-parametric test, whose null hypothesis assumes the absence of a monotonic trend, is based on the S statistic, which is computed as follows:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_j - x_k)$$

where sgn denotes the sign function, and (x_j) and (x_k) represent the Gi* values at time steps (j) and (k), respectively. By combining the significance status of the Gi* statistic at each time step (i.e., whether a location is identified as a statistically significant hotspot or cold spot) with the results of the Mann–Kendall trend test (indicating the presence, absence, and direction of temporal trends), each spatial unit can be classified into one of the 17 standard categories defined within the emerging hot spot analysis (EHSA) framework. In this study, eight of these categories were identified in the traffic dataset of Tehran. The significance threshold for all analyses was set at the 95% confidence level (< 0.05) (Peng, Shen, Cui, Cheng, & Li, 2019). Spatial relationships were modeled using a rook-contiguity spatial weights matrix, a specification that is methodologically consistent with the network-based structure of urban street data (Anselin, 1995).

4.2. Research workflow

The methodology of this study follows a multi-stage workflow designed to extract, organize, preprocess, represent, and analyze spatiotemporal traffic data in Tehran. In the first stage, raw traffic data were collected from web-based traffic monitoring platforms and online traffic information services. The collected dataset included road network segments, street types, traffic congestion levels, and timestamps recorded at approximately 30-minute intervals over seven days, spanning from April 22 to April 29, 2026 (02/02/1405–09/02/1405 Solar Hijri). Data were collected daily between 06:30 and 24:00. Records corresponding to nighttime hours (00:00–06:30) were intentionally removed during the preprocessing stage prior to the construction of the space–time cube. This exclusion was a deliberate structural decision rather than a consequence of missing observations. Consequently, the resulting space–time cube contained 245 active temporal intervals and no null cells associated with nighttime periods. This stage provided the foundation for generating the large-scale traffic dataset used in the study.

In the second stage, the extracted data were stored and organized within a structured GeoPackage database. Subsequently, the dataset was converted into a geodatabase format to facilitate further processing and analysis within ArcGIS Pro.

The third stage focused on data quality control and preprocessing. Given the nature of online traffic data, issues such as missing values, outliers, recording errors, incomplete observations, and temporal inconsistencies were expected. Therefore, a comprehensive data-cleaning procedure was implemented, including error detection and correction, removal or reconstruction of missing observations, logical range validation, and temporal standardization. These procedures enhanced the reliability and analytical validity of the dataset.

In the fourth stage, the linear road network data were transformed into point features to enable space–time cube construction and spatiotemporal analysis. This transformation was performed by extracting the centroid of each road segment. Each point was then enriched with spatial coordinates, temporal attributes, traffic conditions, and road-type information. The resulting point dataset was subsequently used to construct the space–time cube.

In the fifth stage, spatiotemporal traffic analysis was conducted using the space–time cube framework. The analysis focused on identifying patterns of traffic congestion intensity, spatial extent, temporal persistence, and network diffusion dynamics. To achieve this objective, spatiotemporal clustering techniques, emerging hot spot analysis (EHSA), and critical transition analysis were employed. The outputs of this stage provided insights into the spatiotemporal structure of traffic congestion and the dynamic behavior of Tehran's urban transportation network.

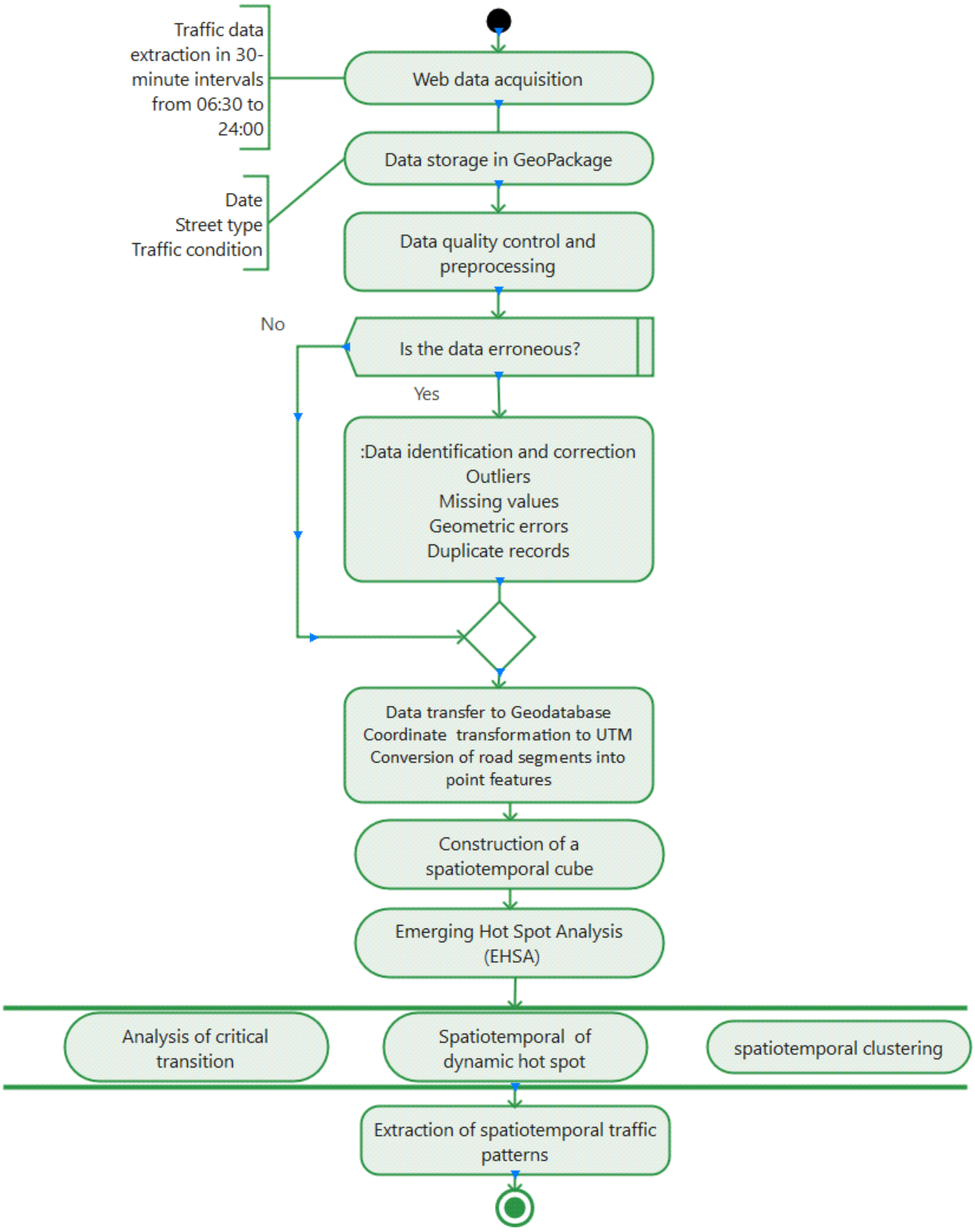


Figure 2. Research workflow

5. Result

In this study, a total of 259 traffic observations were recorded at approximately 30-minute intervals throughout the period from February 21 to February 28, 2026 (02/02/1405–09/02/1405 Solar Hijri). At each time step, an average of 30,667 road segments was recorded. In total, 7,945,396 traffic observations were obtained. Given the number of study days, an average of 984,000 observations per day was recorded, with a standard deviation of 325,000. Table 1 presents the distribution of observations across the study period.

Variations in the number of recorded traffic observations are influenced by both internet quality and traffic volume. In periods of higher traffic congestion, a greater number of road segments are successfully captured, reaching more than 32,000 observations per recording instance.

Table 1. Distribution of traffic records collected during the study period (22–29 April 2026)

Category	Missing data	22 Apr 2026	23 Apr 2026	24 Apr 2026	25 Apr 2026	26 Apr 2026	27 Apr 2026	28 Apr 2026	29 Apr 2026
Frequency	70,166	980,243	1,102,811	1,174,821	1,258,110	1,173,121	913,511	1,044,403	228,210

As shown in Table 1, a total of 7,945,396 traffic records were collected during the study period. The highest number of observations was recorded on 25 April 2026 (1,258,110 records), while the lowest number was associated with 29 April 2026 (228,210 records), reflecting the incomplete coverage of the final day of data collection. Missing records accounted for 70,166 observations, representing less than 1% of the total dataset. Overall, the dataset demonstrates substantial temporal coverage and provides a robust basis for subsequent spatiotemporal traffic analysis.

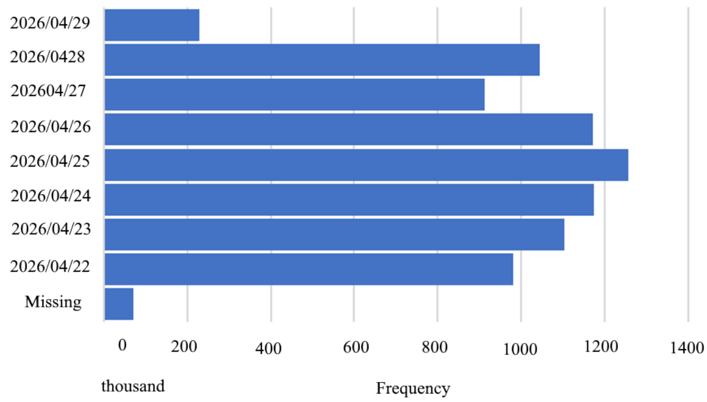


Figure 3. Number of traffic records collected during the study period (22–29 April 2026)

Figure 3 illustrates the temporal distribution of traffic records collected throughout the study period. Although the overall volume of observations remained relatively stable across most days, moderate fluctuations are evident. These variations can be attributed to differences in data retrieval performance as well as temporal changes in traffic activity across the urban road network. The noticeably lower number of observations on the final day reflects the partial coverage of the data collection period rather than an actual reduction in traffic activity.

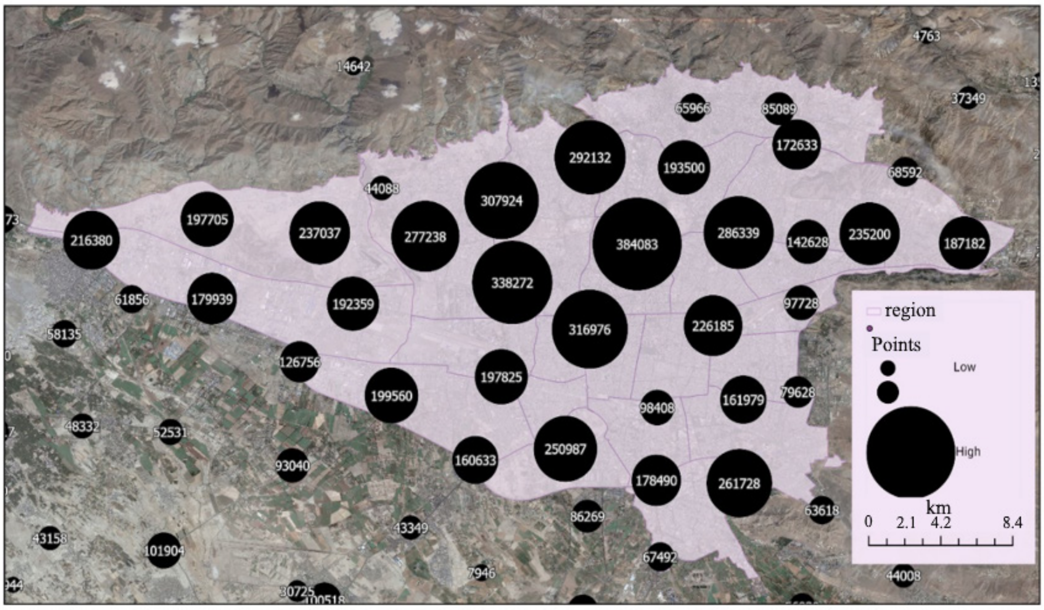


Figure 4. Spatial distribution of traffic observation points in Tehran during the study period (22–29 April 2026)

To facilitate spatial analysis and modeling, the linear road network data were converted into point features. Figure 4 illustrates the spatial distribution of the generated points across the city of Tehran. The highest concentration of points is observed in the central areas. It extends toward the northern parts of the city, indicating a denser road network and greater data availability in these areas.

Table 2. Traffic conditions of Tehran Road segments during the study period (22–29 April 2026).

Traffic	Number of roads	Percentage (%)
Closed	146,952	1.85
Severe	103,642	1.30
Heavy	423,173	5.33
Moderate	1,795,248	22.59
Free	5,476,381	68.93
Total	7,945,396	100

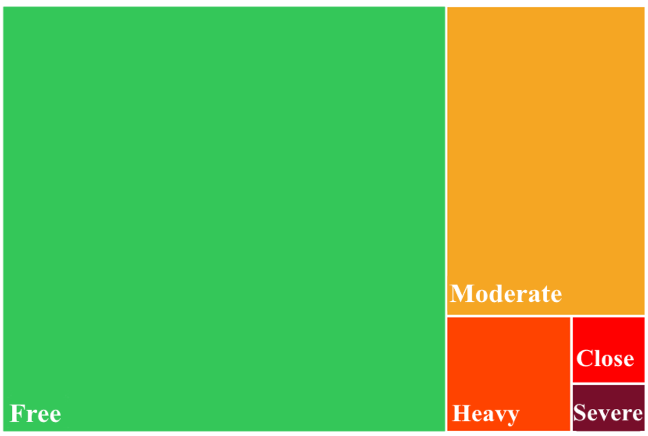
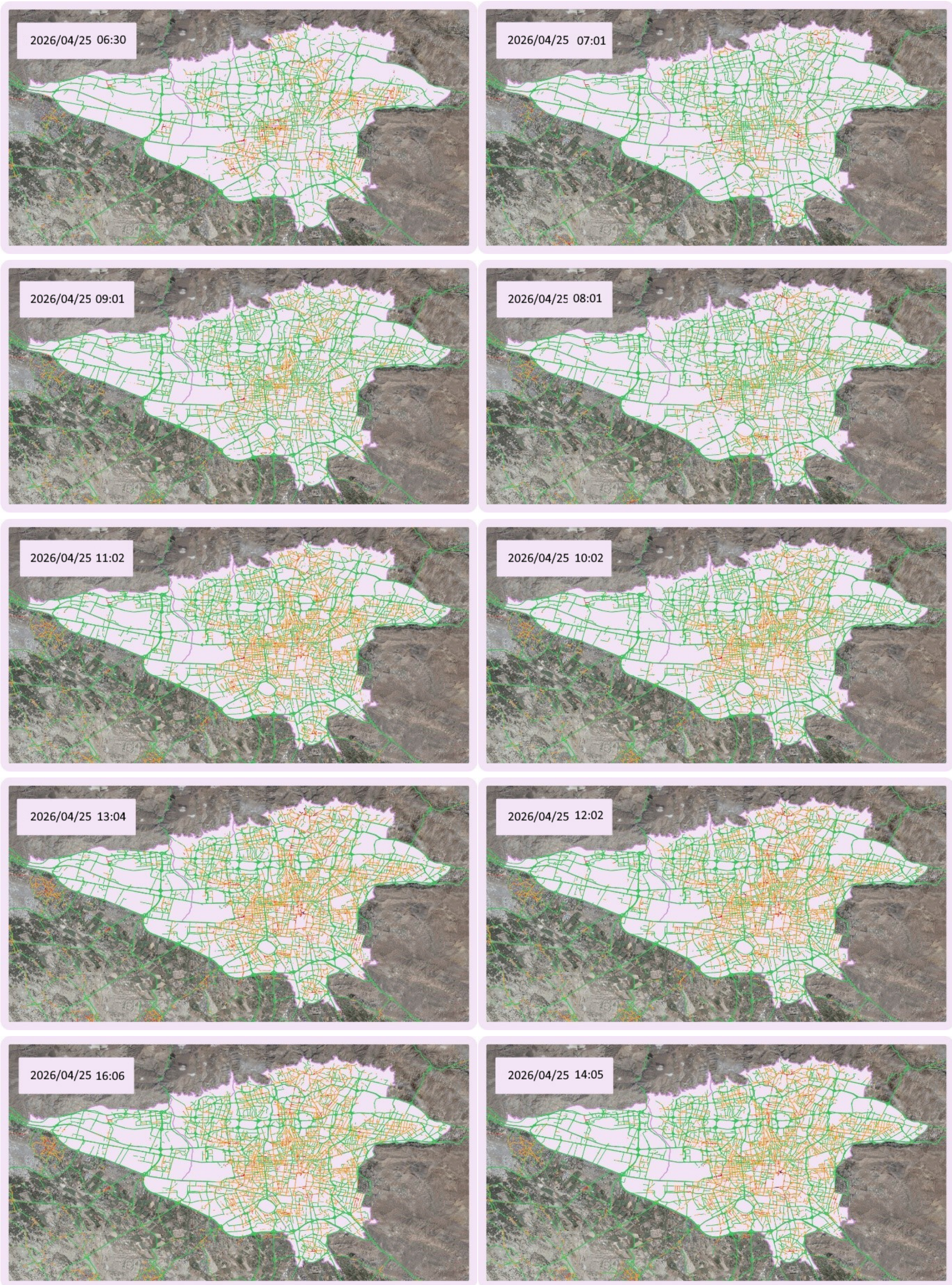


Figure 3. Number of traffic records collected during the study period (22–29 April 2026)

Traffic conditions across Tehran's road network exhibit substantial heterogeneity. According to the analysis, 68.93% of road segments operated under free-flow conditions during the study period, while 22.59% experienced relatively uncongested traffic. In contrast, 5.33% of road segments were classified as heavily congested and 1.30% as severely congested. These results indicate marked spatial and functional differences in traffic conditions across the urban road network. The spatial distribution of these traffic patterns is further explored in the following sections (Table 2).



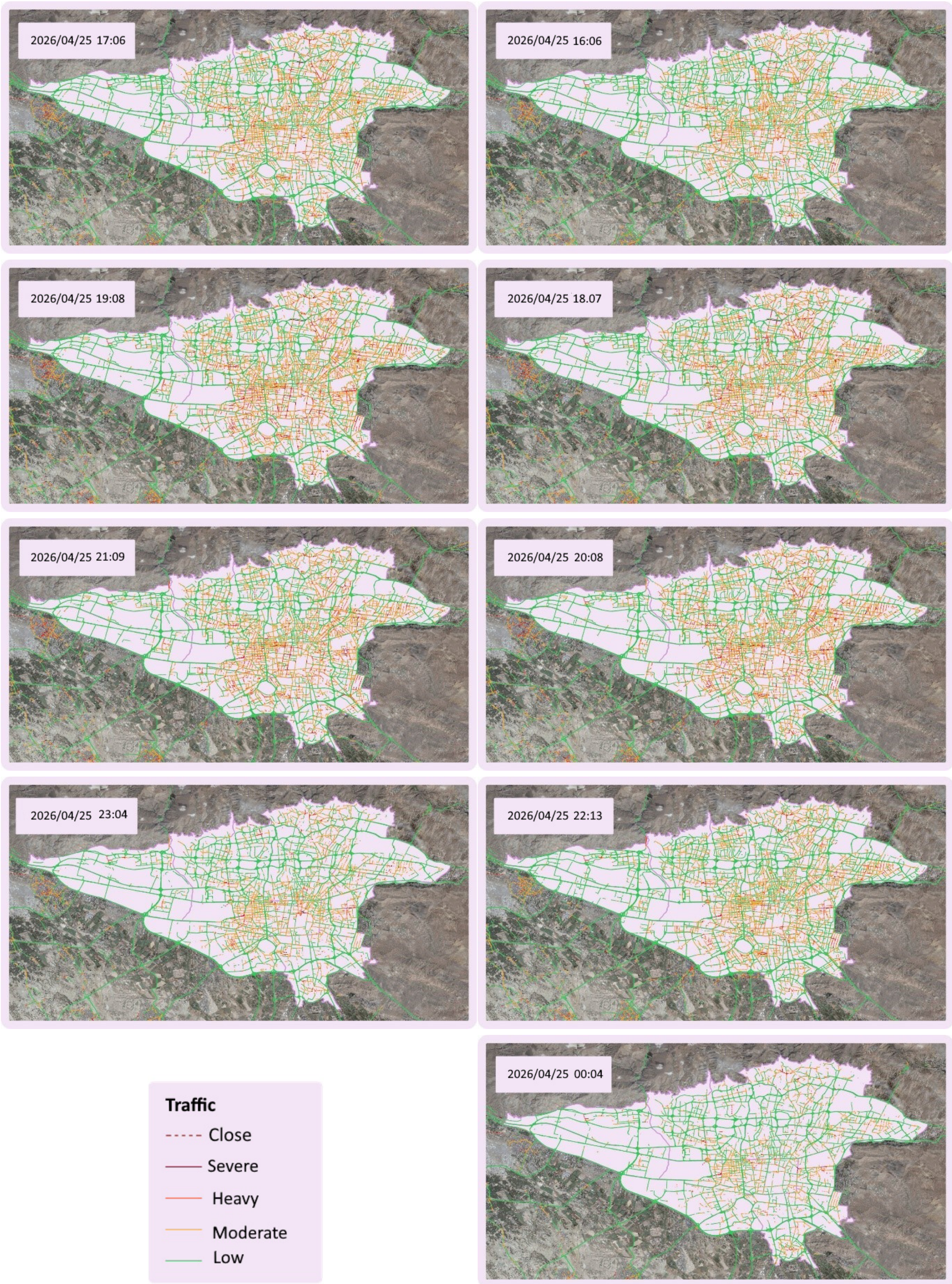


Figure 6. Traffic conditions of the Tehran road network on Saturday, 25 April 2026 (sample day)

Traffic congestion is a highly dynamic phenomenon that varies continuously over time. Accordingly, traffic conditions across the city fluctuate throughout the day. To better capture this temporal variability, a representative sample day (Saturday, 25 2026) was selected for detailed analysis. Figure 6 illustrates traffic conditions from 06:30 AM—coinciding with the activation of the traffic control scheme through to midnight (24:00), thereby capturing the full daily evolution of urban traffic patterns.

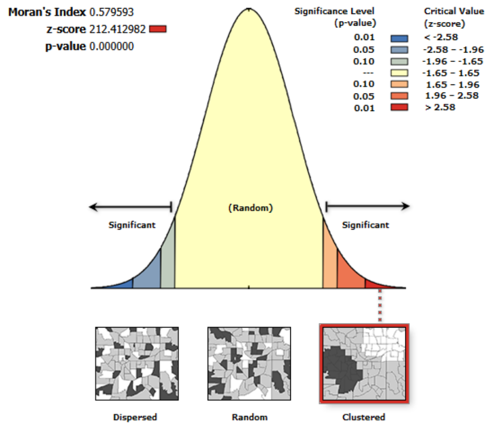


Figure 7. Moran's I scatter plot of traffic congestion in Tehran

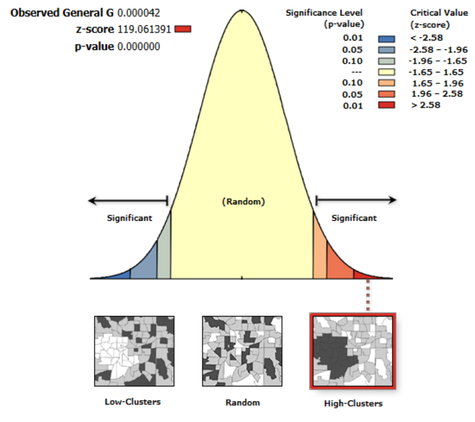


Figure 8. High–low traffic congestion clusters in Tehran

The raw traffic data presented in Figure 6 reveal clear temporal fluctuations in congestion intensity across the urban road network. To assess whether these spatial variations exhibit statistically significant clustering or are randomly distributed, Global Moran's I was applied as a measure of spatial autocorrelation. The results indicate a z-score of 41.212, which is substantially higher than the critical value of 2.58 at the 99% confidence level. This confirms the presence of strong positive spatial autocorrelation in traffic congestion, suggesting that similar traffic conditions tend to cluster spatially rather than being randomly distributed across the network (Figure 7).

To further investigate the nature of these clusters, a global Getis-Ord general G (high/low clustering) analysis was performed. The positive and significant z-score indicates a dominance of high-value clustering, meaning that locations with high traffic congestion tend to form statistically significant spatial clusters (Figure 8).

However, while global statistics confirm the existence of clustering, they do not identify its spatial location. Therefore, local Getis-Ord Gi* hotspot analysis was employed to detect localized spatial patterns. The results reveal three main categories of spatial patterns: (i) hotspots representing areas with high and very high traffic congestion, (ii) cold spots corresponding to areas with relatively smooth traffic conditions, and (iii) transitional zones characterized by moderate or mixed traffic behavior. These patterns provide a detailed spatial understanding of congestion structure within Tehran's road network.

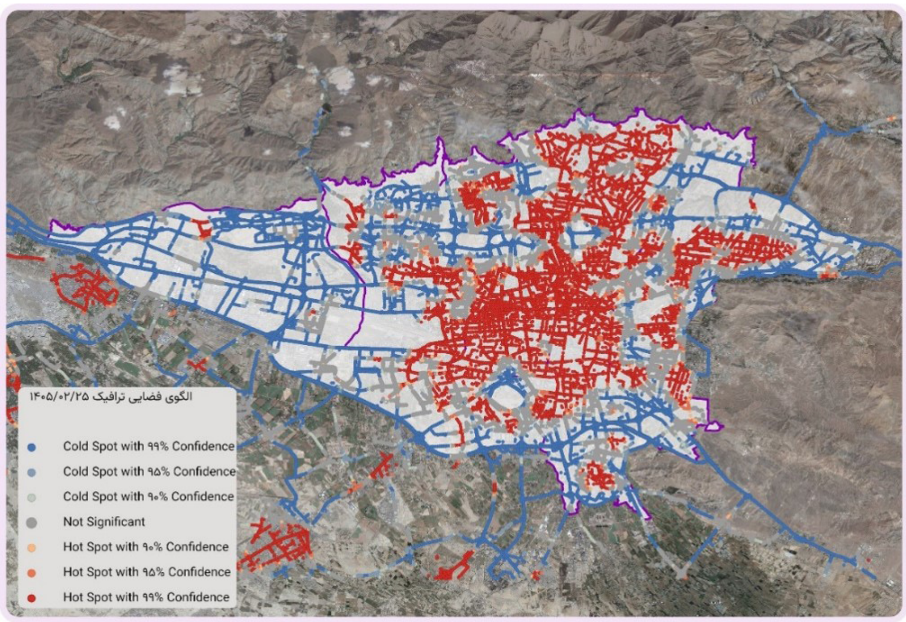


Figure 9. Spatial distribution of traffic congestion in Tehran

The exploration of spatiotemporal patterns in urban phenomena represents a fundamental approach in contemporary urban planning and metropolitan management studies. In this context, emerging hot spot analysis (EHSA) is recognized as one of the most advanced and powerful spatial data mining techniques, as it integrates both spatial and temporal dimensions to identify hidden patterns, intensifying trends, and evolving hotspot dynamics.

EHSA further classifies the temporal trajectories of hotspots into distinct conceptual categories, including persistent, oscillating, intensifying, diminishing, and sporadic patterns. Identifying such patterns across Tehran provides a critical foundation for targeted interventions, efficient resource allocation, and evidence-based urban policy-making.

To achieve this objective, point-based traffic congestion data were applied to construct a space–time cube. Based on this structure, EHSA was applied to investigate spatiotemporal patterns of traffic dynamics. The final output of this analysis is presented as a spatial classification map consisting of eight distinct categories. This map provides a comprehensive and multi-layered representation of current conditions, historical evolution, and potential future trajectories of traffic congestion across the city.

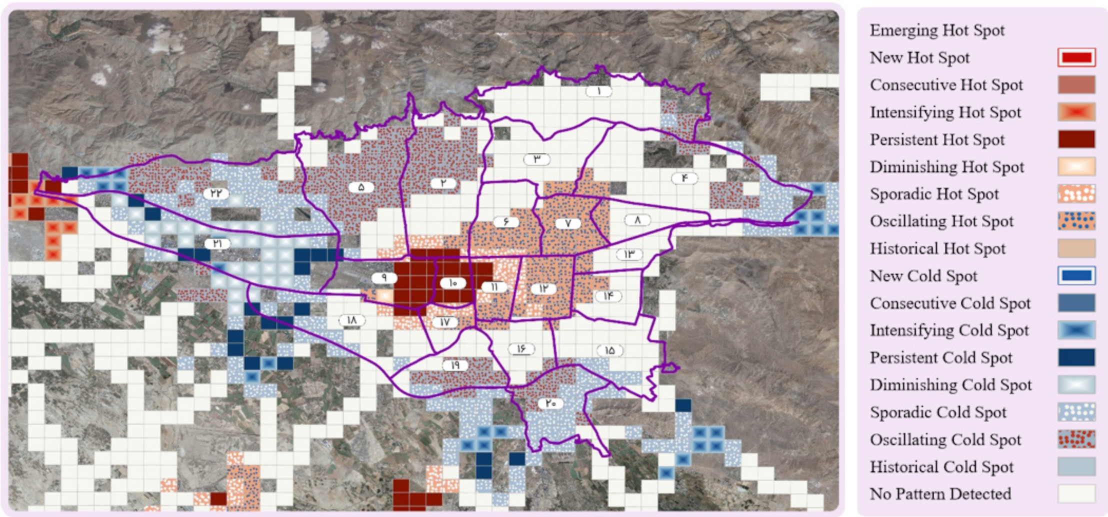


Figure 10. Spatiotemporal pattern of traffic hotspots in Tehran

Figure 10 illustrates the emerging hot spot analysis (EHSA) results for traffic congestion across Tehran. The map reveals a variety of spatiotemporal patterns, highlighting the dynamic spatial behavior of the phenomenon across the 22 municipal districts of the metropolitan area. The identified patterns are broadly categorized into two main groups: hot spots and cold spots.

Hot spots: Hot spots refer to spatial configurations in which a statistically significant positive relationship exists between a location and its neighboring units, resulting in values that are consistently higher than the overall mean. These areas form clusters of high traffic congestion, representing persistent or emerging centers of traffic intensity across the city.

In the present study, the hot spot patterns reflect zones of traffic congestion that exceed the global average, indicating spatial concentration of high traffic intensity. These patterns can be further classified into several subcategories based on their temporal behavior, including persistent, intensifying, emerging, and sporadic hotspots, each of which reflects different dynamics of traffic evolution over time.

Cold spots: Cold spots, in contrast, represent areas characterized by significantly lower-than-average traffic congestion, forming clusters of relatively smooth traffic flow conditions. Together, these spatial structures provide a comprehensive representation of the spatiotemporal organization of traffic dynamics in Tehran and serve as a basis for interpreting urban mobility patterns and congestion processes.

The emerging cold spot refers to spatial units that have recently experienced a loss in traffic congestion intensity and were not previously identified as statistically significant cold spots. This pattern was not observed in the study period within Tehran.

The consecutive cold spot pattern represents areas that have remained significantly cold (i.e., low congestion conditions) over multiple consecutive time periods. This pattern was not detected within the study area. Another pattern, the intensifying cold spot, refers to areas where coldness has strengthened over time, indicating increasingly smoother traffic conditions. This pattern covers approximately 98.2% of the traffic spatial units. It is predominantly located in the peripheral areas of Tehran, including the easternmost part of District 4, the Shariati neighborhood in western Tehran, and the Shahrak Resalat area in southern Tehran. The persistent cold spot pattern represents spatial units that have remained consistently and significantly cold throughout most or the entire study period. This pattern accounts for approximately 2.32% of the spatial units. It is mainly observed in limited parts of western Tehran, particularly in District 21, and in neighborhoods such as Vileshahr, Shahrak-e Ghazali, parts of the University of Tehran area, Pasdaran, and Shahrak-e Farhangian–Azadi. The diminishing cold spot pattern refers to areas where previously smooth traffic conditions have weakened over time, indicating a transition toward moderately congested conditions. This pattern covers approximately 3.64% of the study area and is almost entirely concentrated in District 21 of Tehran Municipality. The sporadic cold spot pattern accounts for approximately 13.34% of Tehran's traffic space. It includes District 22, District 20, the eastern part of District 4 (notably Hakimieh), Mashiriyeh in District 15, and parts of District 18. Finally, the oscillating cold spot pattern represents areas where traffic conditions fluctuate between relatively smooth and moderately congested states over time, showing no stable temporal trend. This pattern covers approximately 11.58% of Tehran. It is mainly located in peripheral urban areas, including parts of Districts 5 and 2, Sero-Azad, the Chitgar Lake neighborhoods in District 22, Ghasemabad–Deh Narak, Kohsar, Golshan, East Tehranpars, Javadiyeh neighborhoods in District 4, Javanmard-e Qassab and Dowlatabad neighborhoods in District 20, and the southern parts of District 19.

6. Discussion and interpretation of findings

The findings of this study, based on more than 7.9 million traffic observations recorded across 259 half-hour intervals in Tehran over one week, provide a multi-layered and dynamic representation of the spatiotemporal structure of urban traffic. This section interprets the results along four main dimensions: the overall traffic structure, spatial autocorrelation patterns, emerging hotspot and cold spot dynamics (EHSA), and implications for urban planning and traffic management.

Overall traffic structure and distribution: Descriptive analysis indicates that 68.93% of road segments in Tehran were characterized by free-flow traffic conditions during the study period. Approximately 22.59% of segments experienced moderate traffic conditions, while only a small proportion was classified as congested, including heavy (5.33%), severe (1.30%), and closed (1.85%) conditions.

Although the dominance of free-flow conditions may initially suggest an efficient urban traffic system, this interpretation requires caution. Traffic demand and mobility flows are highly concentrated within a limited number of arterial and strategic corridors. In other words, a large proportion of the urban road network operates under low utilization conditions, while a smaller subset of critical links carries the majority of the traffic load. This observation is consistent with the Pareto principle in transportation networks, where approximately 20% of road segments accommodate nearly 80% of total traffic flow (Zhao, Wu, Ren, Ji, & Qian, 2019).

Spatial autocorrelation analysis: The results of Moran's I analysis, with a z-score of 41.212 (substantially exceeding the critical value of 2.58 at the 95% confidence level), provide strong evidence that the spatial distribution of traffic congestion in Tehran is not random. Instead, it exhibits a statistically significant pattern of positive spatial autocorrelation and pronounced clustering.

This finding indicates that similar traffic conditions tend to occur in spatial proximity, forming coherent clusters of high congestion rather than being randomly distributed across the urban road network. The results are consistent with previous studies conducted in other large metropolitan areas, including Beijing (Liu, Sun, Sun, & Gao, 2017) and Istanbul (Kaygisiz, Düzgün, Yildiz, & Senbil, 2015), which similarly report that urban traffic congestion is inherently spatially autocorrelated.

Furthermore, the positive and significant z-score obtained from the high/low clustering (Getis-Ord General G) analysis confirms that the observed clustering is primarily driven by the aggregation of high traffic values. In other words, high-congestion road segments tend to co-locate, forming spatially concentrated hotspots rather than being dispersed throughout the network.

From a theoretical perspective, this spatial configuration can be interpreted through the lens of central place theory (Christaller, 1933) and monocentric urban models (Alonso, 1964). Tehran's urban structure, characterized by a strong centrality and radial expansion pattern, promotes the convergence of daily commuting flows toward central areas. This spatial organization facilitates the formation of dense congestion clusters, particularly in central and highly accessible urban corridors.

Spatiotemporal emerging patterns analysis (EHSA): The most significant analytical findings of this study are derived from the emerging hot spot analysis (EHSA), which reveals that persistent hot spot conditions characterize 4.08% of Tehran's road network. This pattern is primarily concentrated in the central–western core of the city, encompassing a substantial portion of District 10, the eastern part of District 9, and the western part of District 11. This spatial configuration corresponds closely to Tehran's historical urban core.

From an urban morphology perspective, this area is characterized by a compact and historically developed fabric, often associated with narrow street layouts and limited road capacity. In terms of land use, the zone exhibits a highly mixed and intensive configuration of residential, commercial, and administrative functions. Moreover, its strategic accessibility is reinforced by the convergence of major highways and arterial roads, making it one of the most critical nodes within the city's transportation network.

In addition to the resident population, this area experiences a high level of floating population due to the concentration of commercial centers, governmental institutions, and service activities. These conditions generate substantial daily commuting flows toward the central district, followed by systematic outbound movements in the afternoon and evening. It is also noteworthy that part of the traffic activity observed after 20:00 in central Tehran may be influenced by social gatherings and nighttime urban activities, which further intensify congestion in key corridors.

Another important finding relates to the intensifying hot spot pattern, which accounts for approximately 3.1% of spatial units and is primarily observed in the western edge of Districts 21 and 22. Although the one-week observation period limits the extent to which long-term trends can be inferred, the presence of this pattern suggests a transition from stable conditions toward increasing congestion intensity. This trend can be associated with rapid urban expansion in western Tehran over the past two decades, particularly the development of large-scale residential complexes such as Chitgar City and the Lake of the Martyrs of the Persian Gulf, as well as the broader growth of District 22. These developments have significantly increased population density and traffic demand along major highways and arterial corridors in western Tehran.

The oscillating (7.61%) and sporadic (3.64%) hot spot patterns collectively account for approximately 11.25% of the urban area. These patterns are predominantly distributed in ring-like formations around the persistent central hot spot core, indicating transitional zones between the urban center and peripheral areas. The oscillatory behavior of traffic intensity in these zones reflects high sensitivity to temporal variations, including peak and off-peak hours as well as weekday–weekend dynamics. This highlights the critical role of temporal variability in shaping spatiotemporal traffic structures and emphasizes the transitional function of these peripheral-central interface zones within the urban mobility system of Tehran.

7. Conclusion

This study aimed to identify and analyze the spatiotemporal patterns of traffic congestion in the metropolitan area of Tehran using the emerging hot spot analysis (EHSA) framework, based on a space–time cube

constructed from web-based traffic data. A total of more than 7.9 million traffic records were analyzed across 259 half-hour intervals over one week, providing a comprehensive, multi-layered, and dynamic representation of urban traffic structure in Tehran.

The main findings can be summarized in six key points. First, descriptive analysis revealed a strong spatial concentration of traffic congestion within specific urban corridors. In contrast, temporal analysis indicated significant load accumulation during peak hours, reflecting a clear manifestation of the Pareto principle in urban traffic systems.

Second, Global Moran's I results confirmed that traffic distribution in Tehran is not random but exhibits strong positive spatial autocorrelation and clustering behavior. The positive z-score in the high/low clustering analysis further demonstrated that congestion operates as a spatial diffusion process, where high-traffic segments exert spillover effects on adjacent road segments.

Third, EHSA results identified eight distinct spatiotemporal traffic patterns, highlighting the heterogeneous and dynamic nature of congestion across the urban network.

Fourth, a critical and policy-relevant finding is the presence of intensifying hot spot patterns in western Tehran (Districts 21 and 22), indicating a statistically significant upward trend in congestion intensity. This suggests that these areas are transitioning toward future congestion hotspots and may require proactive transportation planning interventions.

Fifth, the integration of EHSA results reveals a concentric, multi-ring spatial structure of traffic congestion in Tehran, characterized by a dominant central core surrounded by transitional and peripheral zones with varying temporal stability.

Sixth, the consistency of these findings with previous studies conducted in major global cities such as London and Beijing supports the methodological robustness of the EHSA framework. It confirms its applicability for urban traffic analysis in rapidly growing metropolitan contexts.

Despite these contributions, it is essential to acknowledge the limitations of the study. The dataset covers a relatively short time window (seven days) of web-based traffic observations. From a methodological perspective, this temporal span is insufficient for capturing seasonal variations or long-term structural trends in urban traffic behavior. Therefore, the results should not be interpreted as fully representative of annual traffic dynamics in Tehran.

Accordingly, this study should be considered a pilot and cross-sectional analysis aimed at demonstrating the methodological applicability of EHSA and capturing short-term, transient, and emerging traffic patterns that are often obscured in long-term averaged datasets. Future research should extend the temporal scope of analysis to longer periods to capture more stable and reliable long-term spatiotemporal traffic structures and improve the generalizability of the findings.

Authors' Contributions

The author's contribution is 100%.

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No cases reported by the authors.

Conflict of Interest

The author declares no conflict of interest.

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