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# GEOVISUALIZATION OF TRAJECTORY DATA USING SPACE-TIME CUBES: A CASE STUDY OF CROWDSOURCED TRAFFIC CONGESTION DATA

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**Abstract.** Traffic congestion is a common issue, particularly during peak hours, holiday seasons, and religious holidays, with cities like Yogyakarta experiencing significant traffic challenges. According to INRIX Research, Yogyakarta ranks 60th among the most congested cities globally, with drivers spending an average of 45 hours annually in traffic. Traditional methods for monitoring congestion, such as CCTV, are limited in coverage, leading to gaps in traffic data. Alternatively, crowdsourced data from Twitter, gathered via the Twitter API, offers an effective solution by providing real-time traffic updates, including reports on congestion, accidents, and road closures. This research leverages Twitter data to analyze congestion patterns and uses geovisualization through the Space-Time Cube (STC) method to present a comprehensive 3D representation of congestion. STC allows for the visualization of spatial and temporal patterns, enhancing the analysis of congestion dynamics. The study demonstrates that Twitter data provides accurate congestion information, validated through a t-test with a 95% confidence level. By combining crowdsourced data and STC, this approach offers a more dynamic, detailed, and informative method for understanding and analyzing traffic congestion, which can support traffic planning and decision-making in large urban areas.

**Keywords:** traffic congestion, crowdsourced data, Twitter, Space-Time Cube (STC), geovisualization, urban traffic planning, spatial and temporal analysis.

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## 1. Introduction

The phenomenon of traffic congestion can occur during peak hours, holiday seasons, and religious holidays. This condition is common in many places, especially in large cities like Yogyakarta. According to a survey conducted by INRIX Research in 2017, Yogyakarta ranked 60th among the most congested cities in the world and 4th in Indonesia, following Jakarta, Bandung, and Malang (Prastiti & Wildan, 2018). Based on INRIX Research statistics, drivers in Yogyakarta spend an average of 45 hours per year in traffic. The percentage of congestion during peak hours reaches 27%, compared to 26% during normal conditions, indicating that traffic intensity in Yogyakarta is relatively high, with only a 1% difference between peak and normal traffic conditions.

One way to identify congestion data is by combining remote sensing technology with CCTV video utilization. This approach enables real-time monitoring and visual analysis of traffic conditions, providing more accurate information to better understand congestion patterns in an area (Prabandaka

& Farda, 2014). Urban traffic monitoring through CCTV is widely used, but it has significant limitations, particularly in terms of coverage. CCTV cameras are typically installed at specific locations, such as major intersections or high-traffic areas, and therefore cannot offer a comprehensive view of the entire city road network. As a result, gaps in traffic data emerge, posing a challenge when analyzing congestion patterns in large urban areas (Peppas et al., 2021).

Alternatively, crowdsourced data collection through Twitter API technology has proven highly effective. By utilizing data shared by Twitter users, such as reports of congestion, accidents, or road closures, this information can be automatically processed to provide more comprehensive and up-to-date traffic data. Research indicates that crowdsourced data from social media platforms like Twitter can complement CCTV data by covering areas not captured by cameras and providing faster updates on road conditions (Peppas et al., 2021). This makes Twitter APIs a valuable data source for congestion analysis in large cities, especially in enhancing the coverage and timeliness of traffic information (Peppas et al., 2021).

Geovisualization and visual analytics provide interactive insights into the factors and impacts of traffic congestion. One common tool for congestion geovisualization is heat maps, which depict congestion locations. Heat maps help identify and compare congestion patterns using color gradations that reflect varying congestion levels (Campbell, 2011). They are particularly useful for pinpointing areas with high traffic concentrations (He et al., 2019). However, heat maps have limitations, as they cannot represent the time dimension in three-dimensional form, where the Z-axis would indicate time. This research aims to present a 3D congestion model using the Space-Time Cube (STC) method. STC allows for the geovisualization of movement and reveals temporal patterns in traffic analysis (Andrienko et al., 2010). This technique is effective in representing spatially dispersed objects within a cube volume or grouped into clusters, enabling congestion analysis from both spatial and temporal perspectives (Sibolla et al., 2018).

## 2. Materials and methods

### 2.1. Research area

The research area, as shown in Figure 1, is Yogyakarta City, which serves as the center of government and the Central Business District (CBD) in the Special Region of Yogyakarta. This location plays an important role in various sectors, acting as a hub for high office and economic activity. In addition, tourism attractions such as Malioboro Street and

the Keraton contribute to its vibrancy as a center of urban life (Putro & Putri, 2020). However, the potential for congestion during peak vehicle hours remains a significant urban issue (Munawar & Kamulya, 2021).

### 2.2. Data and methods

This research utilizes crowdsourced data, which is obtained through collective contributions from a large group of individuals (Andriansyah et al., 2009). Crowdsourcing refers to activities or tasks traditionally carried out by employees within a company or institution, which are instead openly distributed to a broad audience connected via the internet. One prominent application of location-based crowdsourced data is social media, specifically Twitter. This research focuses on leveraging Twitter to gather traffic congestion information, using data from 2012 to 2020.

The research method employs a social media data analysis approach, particularly Twitter data, to map the spatial and temporal distribution of traffic congestion. Additionally, the distribution of congestion is visualized and analyzed using the STC method. A detailed overview of the research method is presented in Figure 2.

The descriptions of the workflows are as follows:

#### 1. Twitter data collection.

The research began by accessing Twitter's Streaming API to collect data based on keywords relevant to traffic congestion. The API is designed to help developers build applications that integrate with Twitter's services,

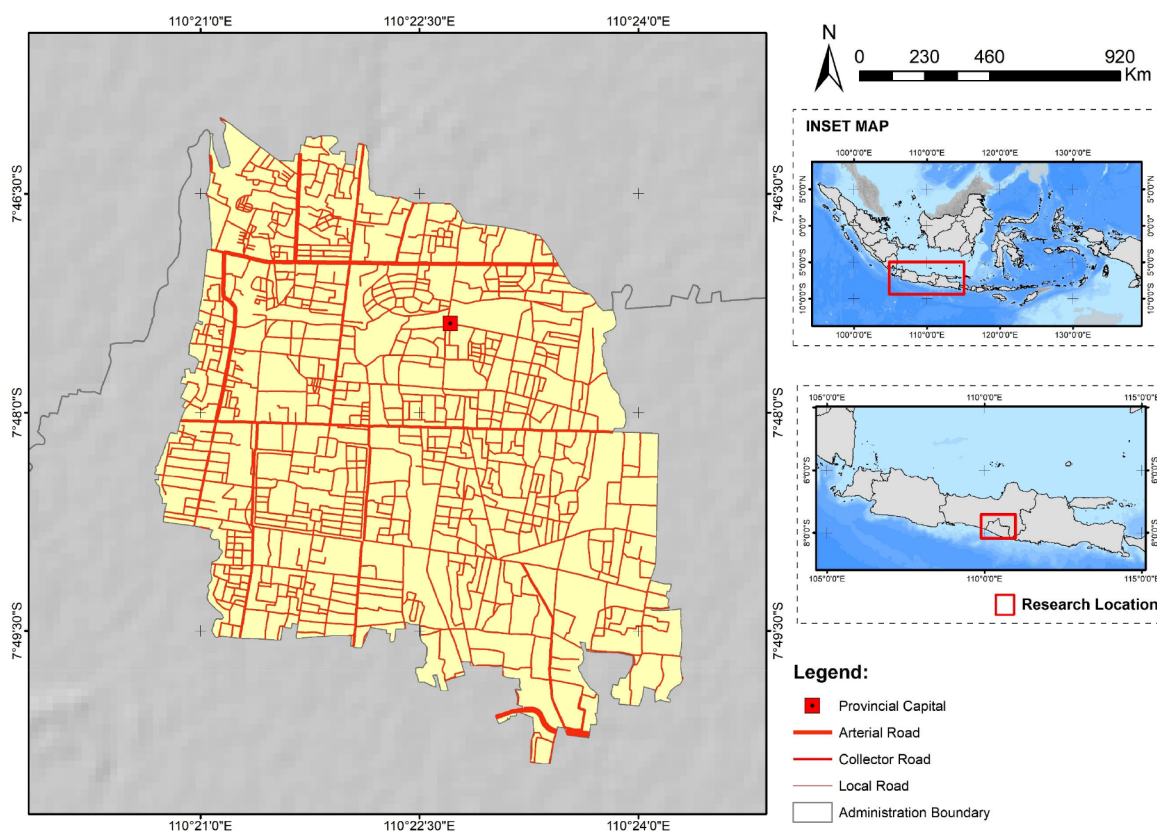


Figure 1. Map of research location

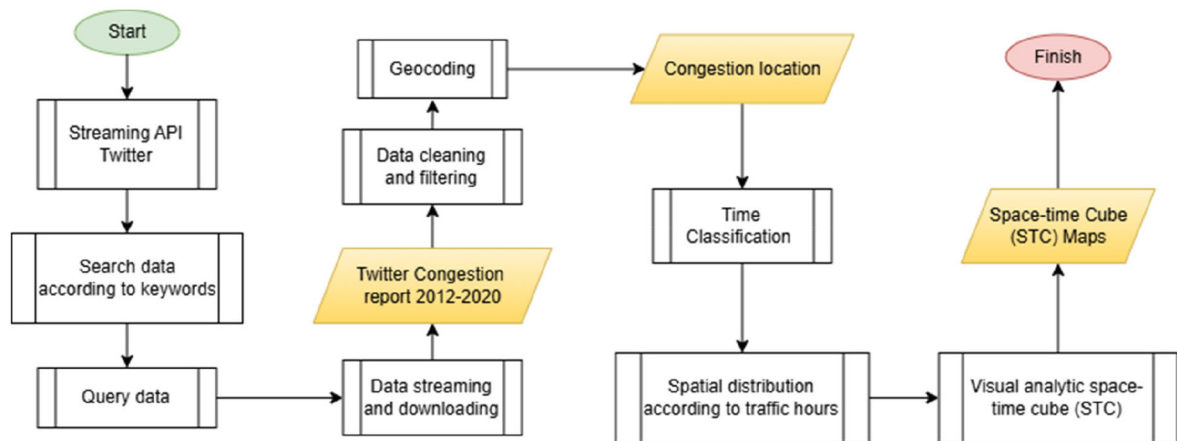


**Figure 2.** Research flowchart

allowing easy access to retrieve tweet data through keyword searches, user accounts, and geolocation (Atmini et al., 2019). This process involves querying the API to obtain the relevant information.

#### 2. Streaming and downloading data.

The streaming and data download stage involves collecting raw data from Twitter using the Streaming API. This API allows data retrieval in real-time or from a specific historical period, depending on the research needs. This phase includes gathering traffic congestion-related reports from Twitter users, spanning from 2012 to 2020. The streaming process involves monitoring Twitter activity using specific keyword filters related to traffic congestion.

#### 3. Data cleaning and filtering.

The next step is data cleaning and filtering, where irrelevant data or noise is removed to ensure the quality of the information used in the analysis. In the case of Twitter, the cleaning process involves eliminating noise in the form of hashtags (words beginning with the symbol "#"), mentions using the "@" symbol, retweet markers ("RT"), and URLs (e.g., "[pic.twitter.com/abc](https://pic.twitter.com/abc)"). The cleansing process can be performed by replacing these characters with space characters (" ").

#### 4. Geocoding.

The geo-located feature extends the existing manual search process by enabling the interpretation of key messages contained in the data (Thom et al., 2012). The geocoding stage is a process in spatial data analysis where location information from cleaned tweets is converted into geographic coordinates (latitude and longitude). This location information can include addresses, place names, or location metadata provided by Twitter users. Location metadata, such as street names, regions, or landmarks, is identified through keyword pattern recognition. The result is a dataset enriched with geographic information, ready for further analysis, such as time classification and spatial distribution. To ensure the accuracy of the location data, a statistical t-test using data from the Department of Transportation is required.

#### 5. Time classification.

In the time classification stage, congestion locations identified through the geocoding process are categorized based on specific time parameters to analyze the temporal pattern of congestion. These time parameters include divisions of the day, such as morning rush hours, midday, evening rush hours, and other relevant periods. Time classification helps identify when congestion occurs most frequently and how this pattern changes throughout the day or during specific periods, such as weekdays, weekends, or holidays. The resulting temporal data allows researchers to analyze the relationship between specific times of day and the intensity of congestion at various locations.

#### 6. Spatial distribution.

At the spatial distribution stage, the traffic congestion data, which has already undergone time classification, is further analyzed to understand its geographical distribution pattern. This analysis aims to identify specific congestion hotspots and examine how congestion is distributed across the study area. By integrating location data obtained through geocoding, the information was mapped spatially to provide a visual representation of areas with high congestion.

7. Geovisualization and visual analytics using the Space-Time Cube (STC).

In the STC geovisualization and visual analytics stage, the results of the traffic congestion data analysis are presented as a three-dimensional (3D) visual representation. STC is a visualization method that integrates three key elements: spatial data (geographic location), temporal data (time dimension), and the volume or intensity of traffic congestion. Each point in the STC represents a congestion event at a specific location and time, allowing for the observation of patterns and trends in traffic congestion over time.

## 3. Results and discussion

### 3.1. Twitter crowd data

Crowd data is a collection of information gathered from a wide range of sources, providing specific insights through

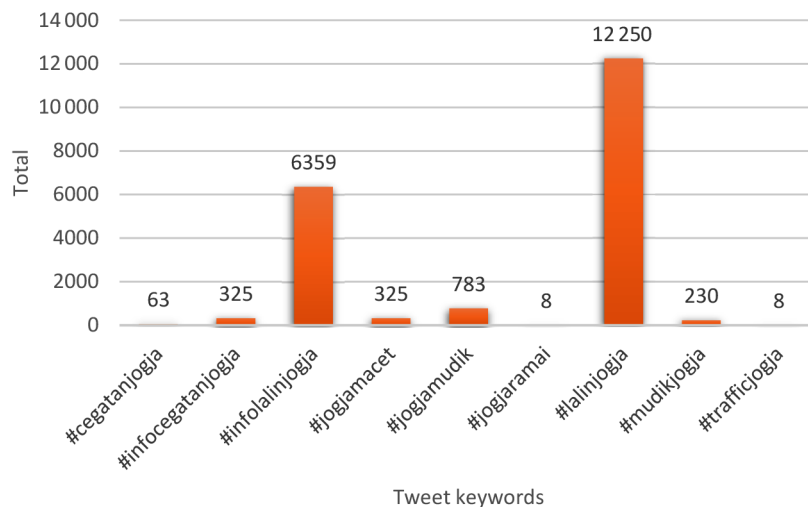


**Figure 3.** Number of primary data scraping traffic jams

groups or social media (Supriyanto, 2023). In this study, Twitter was used as one of the primary data sources, where information is disseminated through tweets containing textual content, images, geolocation data, and hyperlinks to other information sources. The research focused on collecting Twitter data related to traffic congestion. Data were gathered by searching for tweets using specific keywords and hashtags associated with traffic conditions, including #cegatanjogja, #infocegatanjogja, #infoalalinjogja, #jogjamacet, #jogjamudik, #jogjaramai, #lalinjogja, #mudikjogja, and #trafficjogja. These keywords were selected to capture a wide range of traffic congestion reports shared directly by users within the study area.

Figure 3 shows that the highest number of tweets was obtained using the keyword "lalinjogja," with a total of 12,250 tweets, while the lowest number was found for the keywords "jogjamacet" and "trafficjogja," each with only 8 tweets. This suggests that Twitter users prefer hashtags that are practical, short, concise, and clear. For example, hashtags like #lalinjogja and #infoalalinjogja are more popular because the word "lalin" directly represents traffic, while "jogja" refers to the location. As a result, Twitter users reporting traffic conditions in the area tend to choose #lalin over #macet or #traffic. This difference in preference explains the significant variation in the amount of data between the keywords used in Figure 3.

From the collected data, a cleaning and filtering process was necessary to ensure the quality and relevance of the information. Of the total 20,351 tweets, only 320 relevant data points remained after cleaning and filtering, meeting the required criteria. The large volume of irrelevant data was caused by factors such as content unrelated to the research topic, absence of identifiable location information, data redundancy (duplicate information), and data from locations outside the scope of the research area.

The results of congestion data collection are shown in Figure 4, which represents traffic congestion by temporal time/hour from 2012 to 2020. From the visual representation in dark blue, the highest traffic congestion events

occurred in 2013 and 2019. The bar chart further indicates that the peak congestion occurs between 16:00 and 17:00 hours. In addition to these peak hours, the Figure 4 shows that traffic congestion with high intensity is most prevalent between 15:00 and 18:00. This time range coincides with office hours, which leads to increased vehicle volume on several roads in Yogyakarta, resulting in congestion.

### 3.2. Statistical test of data

Verification is carried out to determine whether the data used comes from a valid source or has reliable proof of accuracy. Good data and information are trustworthy, valid, and accountable, ensuring there is no bias. However, data that cannot be verified does not necessarily contain biased information. The data being tested is sourced from crowdsourced Twitter data, with comparison data obtained from the Yogyakarta City Transportation Agency's congestion reports. Since the data

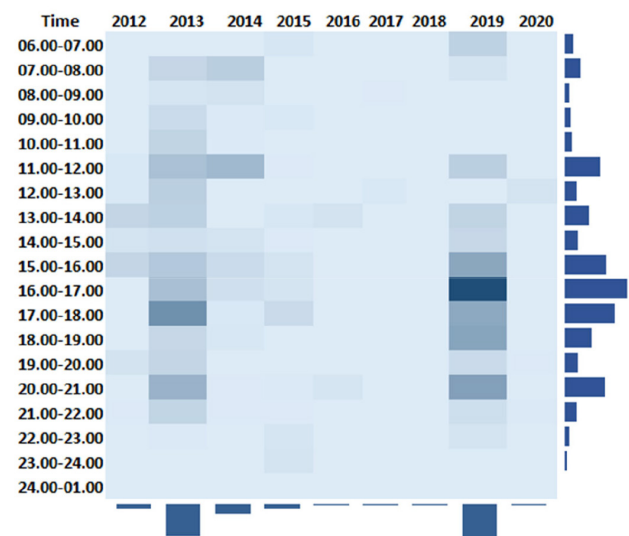


**Figure 4.** Heat-map of traffic congestion table by temporal hour 2012–2020

originates from social media, where information delivery may be less formal, and Twitter users often do not forward information to government accounts or authorities, statistical testing is essential.

The data verification process is carried out by cross-checking field events with data from relevant institutions, namely the DIY Transportation Office. The data used consists of traffic congestion information monitored through the Area Traffic Control System (ATCS) and CCTV. The following is a summary of the congestion reports and the data verification results, as shown in Table 1.

Based on Table 1, the number of tweets reporting traffic jams is 106. This number represents the tweets associated with locations that can be monitored and verified by the relevant authority, namely the Transportation Agency. Furthermore, a paired t-test is performed, comparing the estimated values using the average weight between two sample categories for the same object, as shown in Table 2. The hypothesis is constructed where  $H_0$  assumes that the traffic jam tweet data accurately represents the incidents.

Table 2 presents the results of the statistical test, which is conducted with a confidence level of 95% and a significance level of 5%. The test is performed as a two-tailed test, meaning the significance value is divided into two parts, each at 2.5% (0.025), resulting in a t-table value of 2.060.

The results of the t-test show that the t-count value is 0.534, based on 26 samples representing traffic congestion locations. Since the t-count value (0.534) is less than the t-table value (2.060) and the negative t-count value (−0.534) is greater than the negative t-table value (−2.060), we fail to reject  $H_0$ . This indicates that the traffic jam reports obtained from the tweets can be considered to accurately represent the actual occurrences on the ground, with a 95% confidence level and 5% significance level.

### 3.3. Space-Time Cube geovisualization

Cartography and visualization graphics are realized through the application of cartographic design theories

**Table 1.** Verified congestion data

| No.   | Sample area                          | Number of tweets | Verified | Not verified | Report weight |                   |
|-------|--------------------------------------|------------------|----------|--------------|---------------|-------------------|
|       |                                      |                  |          |              | Verified (Xi) | Not verified (Yi) |
| 1     | ATCS Giwangan                        | 2                | 1        | 1            | 5             | 5                 |
| 2     | ATCS Druwo Junction                  | 2                | 1        | 1            | 5             | 5                 |
| 3     | ATCS Gamping Junction                | 1                | 1        | 0            | 5             | 0                 |
| 4     | ATCS Pelem Gurih Junction            | 2                | 1        | 1            | 5             | 5                 |
| 5     | ATCS Serengan Junction               | 2                | 1        | 1            | 5             | 5                 |
| 6     | CCTV PKU Muh                         | 1                | 1        | 1            | 5             | 5                 |
| 7     | CCTV Km Nol                          | 1                | 1        | 1            | 5             | 5                 |
| 8     | ATCS Ketandan Junction               | 0                | 0        | 0            | 0             | 0                 |
| 9     | ATCS SGM Junction                    | 1                | 1        | 1            | 5             | 5                 |
| 10    | ATCS Bandara Adi Sucipto Junction    | 14               | 10       | 8            | 50            | 40                |
| 11    | ATCS Maguwoharjo Junction            | 5                | 3        | 2            | 15            | 10                |
| 12    | ATCS Janti Junction                  | 3                | 3        | 0            | 15            | 0                 |
| 13    | ATCS UIN Junction                    | 6                | 5        | 1            | 25            | 5                 |
| 14    | ATCS Demangan Junction               | 2                | 2        | 1            | 10            | 5                 |
| 15    | ATCS Galeria Junction                | 1                | 1        | 0            | 5             | 0                 |
| 16    | ATCS Gramedia Junction               | 1                | 1        | 1            | 5             | 5                 |
| 17    | ATCS Tugu Junction                   | 13               | 9        | 4            | 45            | 20                |
| 18    | ATCS Jati Kencana Junction           | 1                | 0        | 1            | 0             | 5                 |
| 19    | ATCS Patran Junction                 | 3                | 1        | 2            | 5             | 10                |
| 20    | ATCS Demak Ijo Junction              | 4                | 1        | 3            | 5             | 15                |
| 21    | ATCS Borobudur Plaza Junction        | 1                | 1        | 1            | 5             | 5                 |
| 22    | ATCS Selokan (St. Magelang) Junction | 1                | 1        | 0            | 5             | 0                 |
| 23    | ATCS Monjali Junction                | 2                | 1        | 1            | 5             | 5                 |
| 24    | ATCS Kentungan Junction              | 25               | 15       | 10           | 75            | 50                |
| 25    | ATCS Condongcatur Junction           | 10               | 6        | 4            | 30            | 20                |
| 26    | ATCS Seturan (UPN) Junction          | 2                | 2        | 1            | 10            | 5                 |
| Total |                                      | 106              | 70       | 47           | 350           | 235               |

**Table 2.** Paired sample T-Test for traffic jam locations

| No      | Report weight |                   | $(X1-X')^2$ | $(X-Y')^2$ | x.y  | x2    | y2   |
|---------|---------------|-------------------|-------------|------------|------|-------|------|
|         | Verified (Xi) | Not verified (Yi) |             |            |      |       |      |
| 1       | 5             | 5                 | 71.59763    | 16.30917   | 25   | 25    | 25   |
| 2       | 5             | 5                 | 71.59763    | 16.30917   | 25   | 25    | 25   |
| 3       | 5             | 0                 | 71.59763    | 81.69379   | 0    | 25    | 0    |
| 4       | 5             | 5                 | 71.59763    | 16.30917   | 25   | 25    | 25   |
| 5       | 5             | 5                 | 71.59763    | 16.30917   | 25   | 25    | 25   |
| 6       | 5             | 5                 | 71.59763    | 16.30917   | 25   | 25    | 25   |
| 7       | 5             | 5                 | 71.59763    | 16.30917   | 25   | 25    | 25   |
| 8       | 0             | 0                 | 181.213     | 81.69379   | 0    | 0     | 0    |
| 9       | 5             | 5                 | 71.59763    | 16.30917   | 25   | 25    | 25   |
| 10      | 50            | 40                | 1335.059    | 958.6169   | 2000 | 2500  | 1600 |
| 11      | 15            | 10                | 2.366864    | 0.924556   | 150  | 225   | 100  |
| 12      | 15            | 0                 | 2.366864    | 81.69379   | 0    | 225   | 0    |
| 13      | 25            | 5                 | 133.1361    | 16.30917   | 125  | 625   | 25   |
| 14      | 10            | 5                 | 11.98225    | 16.30917   | 50   | 100   | 25   |
| 15      | 5             | 0                 | 71.59763    | 81.69379   | 0    | 25    | 0    |
| 16      | 5             | 5                 | 71.59763    | 16.30917   | 25   | 25    | 25   |
| 17      | 45            | 20                | 994.6746    | 120.1553   | 900  | 2025  | 400  |
| 18      | 0             | 5                 | 181.213     | 16.30917   | 0    | 0     | 25   |
| 19      | 5             | 10                | 71.59763    | 0.924556   | 50   | 25    | 100  |
| 20      | 5             | 15                | 71.59763    | 35.53994   | 75   | 25    | 225  |
| 21      | 5             | 5                 | 71.59763    | 16.30917   | 25   | 25    | 25   |
| 22      | 5             | 0                 | 71.59763    | 81.69379   | 0    | 25    | 0    |
| 23      | 5             | 5                 | 71.59763    | 16.30917   | 25   | 25    | 25   |
| 24      | 75            | 50                | 3786.982    | 1677.848   | 3750 | 5625  | 2500 |
| 25      | 30            | 20                | 273.5207    | 120.1553   | 600  | 900   | 400  |
| 26      | 10            | 5                 | 11.98225    | 16.30917   | 50   | 100   | 25   |
| Total   | 350           | 235               | 7988.462    | 3550.962   | 8000 | 12700 | 5675 |
| Average | 13.46153846   | 9.038461538       |             |            |      |       |      |
| SD X    | 17.87563877   |                   |             |            |      |       |      |
| SD Y    | 11.91798899   |                   |             |            |      |       |      |
| t count | 0.533503957   |                   |             |            |      |       |      |

Note: tTable significance level  $\alpha = 5\%$  (two-tailed,  $df = 25$ );  $t(0.025;25) = 2.060$ ; conclusion:  $H_0$  accepted ( $t \text{ count} = 0.534 < t \text{ table} = 2.060$ ).

that have evolved over time, one of which is geovisualization. This research alters the characteristics of congestion geodata through visual perception by emphasizing the spatiotemporal aspects – time, day, and year. The geovisualization technique used to present congestion geodata is STC. STC is a significant geovisualization method that enhances information perception by integrating both location and time variables, leading to a more comprehensive understanding of the data (Kveladze et al., 2019). The results of the geovisualization are presented below:

Figure 5 illustrates that the selection and application of visual variable design significantly influence the interpretation of information. Color variables are used to classify

the level of traffic congestion, with high congestion levels indicated by a deep brown hue and low congestion levels indicated by a lighter brown hue. The Space-Time Cube (STC) results shown in Figure 5 represent Twitter data on traffic congestion events from 2012 to 2020. However, data from 2016 to 2018 and 2019 to 2020 are merged due to a lack of sufficient congestion reports for those periods. This merging was done to create more informative and understandable visualizations.

Additionally, visualization through the STC provides insights into the trajectory of congestion events based on intensity levels, represented by color variables. The long time span allows for the analysis of historical changes and

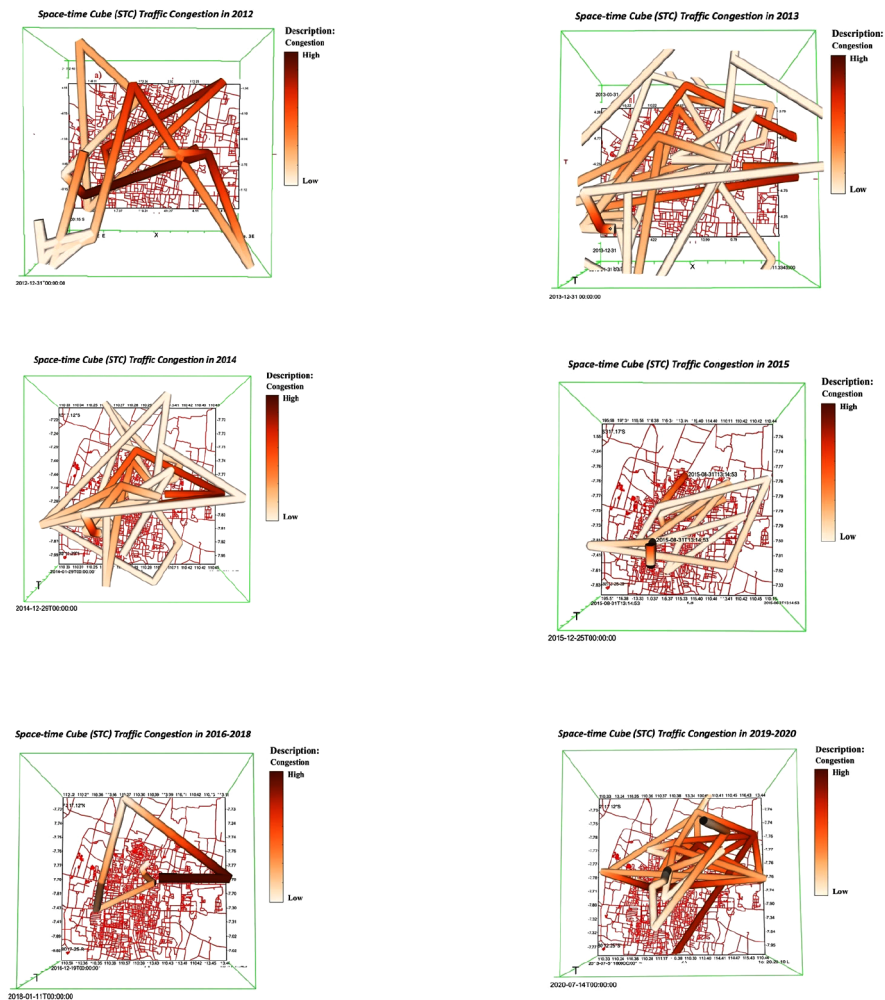


**Figure 5.** Space-time Cube Traffic congestion 2012–2020

helps identify trends in the phenomenon. For example, Figure 6 displays the congestion trajectory by hour and date of occurrence. In the figure, areas marked with black boxes and arrows highlight key information regarding the timing of congestion events, supporting a more comprehensive temporal and spatial interpretation.

The image above provides information about the trajectory of traffic jams based on their time and date of occurrence. This visualization uses the STC, which enables an in-depth analysis of traffic congestion patterns across both temporal and spatial dimensions. As shown in the figure, the black boxes and arrows highlight specific instances, providing detailed information about the timing of congestion events. For example, in the STC geovisualization results for traffic congestion in 2012, a time trajectory is labeled as *2012-12-27 T15:30:14*. This indicates that a traffic jam occurred on December 27, 2012, at 3:30:14 PM. Such precise information helps identify the peak congestion time at specific locations.

In addition, the visualization results provide a consistent historical overview for subsequent years. With the same time format, users can easily map and analyze the

trajectory of congestion over a given period. Such visualizations are highly useful for understanding congestion dynamics, both for transportation planning and strategic decision-making. STC geovisualizations offer the advantage of mapping the overall congestion pattern, which can help identify trends or seasonal variations, such as increased congestion during holidays or at specific times. The information generated from these visualizations supports the development of data-driven recommendations to mitigate the impact of future congestion.

## 4. Conclusions

Through crowdsourced data, Twitter provides an alternative method for mapping, especially in cases of traffic congestion. This study demonstrates that Twitter data can offer congestion information with a high level of accuracy. The results of the t-test indicate that congestion reports obtained from tweets can be considered an accurate representation of actual events on the ground, with a 95% confidence level and a 5% significance level. The geovisualization design using STC enhances the value of

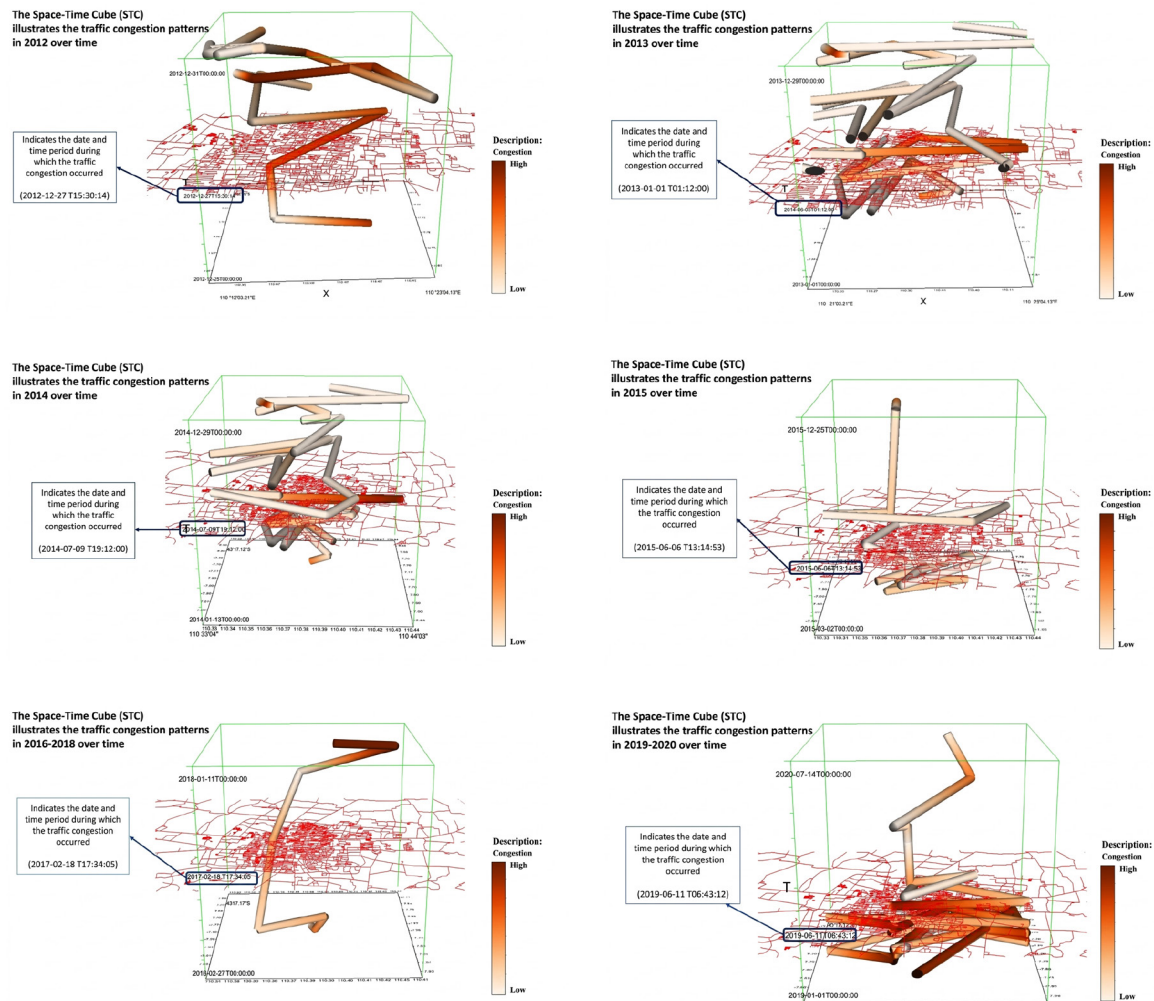


**Figure 6.** The temporal period of traffic congestion data from 2012 to 2020 is represented using a Space-Time Cube visualization

traffic congestion data presentation. STC can illustrate the distribution of congestion through incident trends, visualized using color variables. Additionally, STC enables the presentation of information in 3D form, incorporating the time dimension, allowing for more in-depth and detailed congestion analysis. This study demonstrates that crowdsourced data from Twitter can serve as an effective alternative for high-accuracy traffic congestion mapping. The use of STC as a geovisualization method enhances the quality of the analysis, providing a more comprehensive spatial and temporal representation of congestion. As a result, this approach offers a more informative and dynamic way to understand congestion patterns, which can be valuable for decision-making in traffic planning for large cities.

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