The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-4/W19-2025
The 10th International Conference on Smart City Applications (SCA2025), 10–13 November 2025, Tangier, Morocco

From Data to Map: Geospatial Visualization of Istanbul's Daily Traffic

[1]Enishan Sardoğan, [2]Hacer Kübra Sevinç, [1]İsmail Rakıp Karaş, [3]Abdul Nurunnabi

[1] Dep. Of Computer Engineering, Karabük University, Karabük, Turkiye
2210213004@ogrenci.karabuk.edu.tr, ismail.karas@karabuk.edu.tr
[2]Vocational School of Information Technology, Karabük University, Karabük, Turkiye
kubrasevinc@karabuk.edu.tr
[3]Independent researcher, Luxembourg. pyal1471@yahoo.com

Keywords: Geospatial Visualization, Interactive Mapping, Data-Driven Mapping, Smart City, Geographic Information Systems.

Abstract

Urban mobility challenges in megacities such as Istanbul require advanced approaches to effectively analyse and interpret traffic flow data. This study focuses on the visualization of spatial attribute data, specifically the number of vehicles recorded by location-based sensors across the city. Rather than relying solely on traditional visualization platforms, the proposed approach emphasizes coding-based solutions to enhance flexibility, reproducibility, and integration with artificial intelligence technologies. To achieve this, multiple visualization tools, including Folium, Mapbox, and Power BI, were applied to the same dataset, enabling a comparative evaluation of their capabilities in representing daily traffic patterns.
The results highlight the advantages and limitations of each platform in terms of interactivity, spatial accuracy, and scalability. Beyond technical comparisons, the study demonstrates the potential of spatial data visualization through coding as a bridge between raw sensor data and actionable insights for urban mobility planning. This approach is particularly significant in the era of AI-driven smart city applications, where spatial data can be dynamically integrated into decision-making processes. Ultimately, the study aims to guide researchers and practitioners working with web technologies, geospatial tools, and coding frameworks by providing a methodological reference for processing, mapping, and visualizing spatial traffic data.

1. Introduction

Data visualisation involves converting complex datasets into visual formats, such as charts, graphs and maps, to improve understanding and interpretation of information. This technique plays a crucial role in various fields as it makes data more comprehensible to a broader audience, thereby enhancing decision-making processes and facilitating the extraction of insights beyond mere numbers and statistics.

Data visualization can be defined as a graphical representation of information and data using visual elements like charts, graphs, and maps to represent data sets. This approach allows users to identify patterns, trends, and anomalies quickly, thereby facilitating a data-driven understanding of complex phenomena. By leveraging visual elements, data visualization converts raw data into understandable formats, significantly enhancing human cognition in the process (Shinde and Shivthare 2024).

The significance of data visualization can be encapsulated under several key aspects. One of the primary advantages is its ability to simplify complex datasets, making them easier to understand and analyze. This becomes particularly beneficial when interpreting patterns in large datasets, as visual representations can reveal insights that might not be immediately apparent through textual or numerical data alone (Austin et al., 2022). Another important contribution of data visualization lies in the identification of trends and patterns. Visual tools are instrumental in recognizing developments over time or between variables. For example, in healthcare, the visual representation of patient data can help identify patterns that inform better health decisions and interventions (Abudiyab and Alanazi, 2022; Ofori et al., 2025). Similarly, in machine learning, data visualization aids practitioners in understanding data distribution and relationships, which are vital for improving model accuracy and decision making (Shinde and Shivthare, 2024).

Data visualization also plays a crucial role in facilitating communication. It serves as a universal language, enabling the effective transfer of insights to stakeholders who may lack technical expertise. For instance, dashboards populated with visual elements allow management teams to quickly grasp complex information, leading to informed decision-making without requiring extensive analytical backgrounds (Uddin, Ullah, and Moniruzzaman 2024). With advances in technology, modern data visualization tools further support interactive exploration of data. Users can zoom in on details, filter information, and manipulate datasets in real time, providing a dynamic way to explore vast amounts of data. This interactivity enhances engagement and enables users to uncover actionable insights more effectively (Bheekya et al., 2020). Moreover, the integration of data visualization into business intelligence strategies significantly impacts decision-making processes. Decision-makers rely on visualized data to guide strategic planning and operational efficiency, as effective visual representations can illustrate how different variables correlate, thereby enabling better forecasting and planning (Singh, 2023).

The applications of data visualization extend across multiple domains. In business intelligence, organizations utilize visualization techniques to analyze sales performance, market trends, and customer insights, thereby enabling more strategic business decisions (Uddin et al., 2024). In the healthcare sector, visualization supports the tracking of patient outcomes, demographic trends, and epidemic monitoring, contributing to improved public health responses (Abudiyab and Alanazi 2022; Ofori et al. 2025). In education, educators employ data visualization to represent and teach complex subjects, with interactive visualizations enhancing learning experiences by making academic content more engaging (Austin et al., 2022). Finally, geospatial analysis is another domain where visualization techniques prove critical. They allow for a better understanding of geographic patterns and trends through mapping tools and techniques, which play a central role in

This contribution has been peer-reviewed.
https://doi.org/10.5194/isprs-archives-XLVIII-4-W19-2025-111-2026

urban planning and disaster management (Balla et al. 2020; Heinzlef et al., 2020).

In consideration of these facts, it is evident that visualization of geographical data through the implementation of data visualization techniques is of paramount importance within the context of Geographic Information Systems (GIS). Geospatial visualization is a process that integrates GIS with dynamic data analytics. The result is interactive maps and visual outputs suitable for various applications.

This study utilizes Istanbul's daily vehicle count data as a case study to illustrate the significance of geographic visualization. The present study will address the role and importance of the techniques employed in the visualization of geographic data. In addition, the study will introduce the functionalities of different visualization tools and present a comparative evaluation. Consequently, the contribution of geographic data visualization methods to spatial analysis processes and decision support mechanisms will be emphasized.

2. Literature Review

Daily traffic data captures important metrics critical to understanding urban mobility, infrastructure planning, and traffic management. Applying geospatial visualization techniques to this data significantly aids in transforming it into insightful, actionable information. Integrating daily traffic data with geospatial visualization techniques establishes a paradigm for advancing urban traffic management and infrastructure optimization. Visualization enhances stakeholder understanding and empowers data-driven decision-making, promoting more sustainable and efficient urban mobility. As urbanization escalates, adopting sophisticated visualization tools will be vital to addressing traffic data complexities and enabling intelligent, responsive and efficient urban planning.

Daily traffic data typically involves metrics such as the Annual Average Daily Traffic (AADT), Average Daily Traffic (ADT), and real-time traffic flow data. These datasets provide insights into vehicle counts and patterns of movement on roadways over specified timeframes, which is essential for various applications. For infrastructure planning, estimating AADT is crucial for both state and local agencies to prioritize road maintenance and upgrades (Baffoe-Twum et al., 2022). Accurate predictions help optimize resource allocation for infrastructure development, supporting long-term planning (Limantara et al. 2021). In terms of traffic management, the analysis of traffic patterns aids in congestion alleviation, route planning, and understanding traffic dynamics across different times, such as weekdays versus weekends, as demonstrated in detailed assessments of traffic flow phases (Koliou and Spyropoulou, 2023). Additionally, traffic data play a significant role in safety analysis, contributing to accident evaluation and safety improvements by examining correlations between traffic volume and incidents, thereby providing insights for enhancing road safety measures (Al-Nuaimi and Jameel 2023; Zhang et al. 2022).

Geospatial visualization is a powerful tool that enables stakeholders to interpret traffic data effectively, and a variety of techniques are employed to enhance this process. One such technique is the use of heatmaps, which display traffic density across both temporal and spatial dimensions, providing immediate visual cues regarding areas of high traffic and congestion. Wang et al. (2020) demonstrate, their application of geospatial analytics through heatmaps can play a critical role in optimizing traffic management in urban environments (Wang et al., 2020). In addition to heatmaps, interactive dashboards have become increasingly significant in traffic data visualization. Tools such as Tableau and Microsoft Power BI allow for the development of dynamic, interactive dashboards that showcase traffic information in real time. These dashboards enable users to filter data by parameters such as geographic region, time of day, or vehicle type, thereby enriching the exploratory and analytical dimensions of visualization (Hasan and Oh 2020). Another advanced technique is three-dimensional modeling and simulation, which facilitates the creation of detailed representations of road networks and supports the illustration of dynamic traffic flow. Beil et al. (2022) highlight the effectiveness of such interactive models in visualizing traffic data in real time, offering stakeholders a more tangible and immersive understanding of traffic dynamics (Beil et al. 2022). Collectively, these diverse visualization techniques underscore the transformative potential of geospatial visualization in advancing traffic analysis and management.

Urban traffic analysis has increasingly emphasized the importance of geospatial visualization as a means of interpreting and managing mobility patterns in cities. Research highlights that data collected from Automatic Number Plate Recognition (ANPR) systems and GPS devices can be effectively utilized to generate detailed urban mobility maps, thereby enabling city planners to identify critical behavior patterns that emerge during different times of the day (Afrin et al. 2023; de Vyvere and Colpaert 2022). Beyond mobility management, the visual representation of traffic data also has significant implications for public health. For instance, Soares et al. (2021) demonstrate how urban air quality trends, which are strongly influenced by traffic-related emissions, can be visualized in relation to traffic conditions to provide insights into their impacts on public health outcomes(Soares et al. 2021). This integration of traffic and health data through visualization techniques allows for a more holistic understanding of how urban mobility directly and indirectly shapes environmental and health indicators.

Collectively, these studies illustrate how geospatial visualization not only enhances the analytical scope of urban traffic analysis but also establishes meaningful intersections with public health and adaptive, technology-driven traffic management systems.

Çavdaroğlu (2016) conducted a study that aimed to extract traffic data by processing screenshots of traffic density maps through image processing methods. By capturing screenshots from the Google Maps application, traffic density information was derived in textual form according to the color scale represented in the road visuals (Çavdaroğlu 2017). Likewise, Çetin Taş and Müngen (2021) employed weather and traffic data collected from 75 different locations via the Istanbul Metropolitan Municipality Open Data Portal to estimate regional traffic density(ÇetiN Taş and Müngen 2021). In this research, the data obtained through web services from the Open Data Portal were transferred to a MySQL database for preprocessing, converted into CSV format, and subsequently utilized in MATLAB for training and testing. The model proposed by the authors demonstrated a 90% success rate in accurately predicting traffic density. In addition, Polat et al. (2017) investigated the relationship between the increase in the number of residential areas due to urban growth and the resulting traffic density in Istanbul. Their analysis focused on regions experiencing rapid urbanization in close proximity to major transportation corridors.

3. Methodology

3.1 Study Area

As the study area, Istanbul, the most densely populated city in Turkey, we selected. Istanbul is one of the cities where transportation problems are most evident due to both its population density and the increase in the number of motor vehicles. According to the data of the Turkish Statistical Institute (TUİK n.d.), the population density of Istanbul is shown in Figure 1. In addition, Figure 2 presents a graphical representation of the change in the number of motor vehicles in Istanbul from 2016 to 2024. This data was obtained from the statistics titled “Number of Motor Land Vehicles in Istanbul by Years” published by TUIK. These indicators reveal that Istanbul constitutes a suitable laboratory for traffic density studies in both spatial and temporal dimensions.

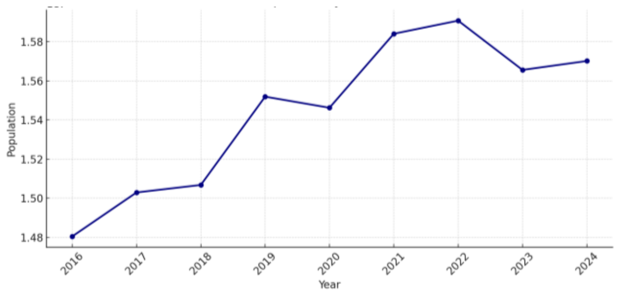


Figure 1. Istanbul Population by Year (2016–2024)

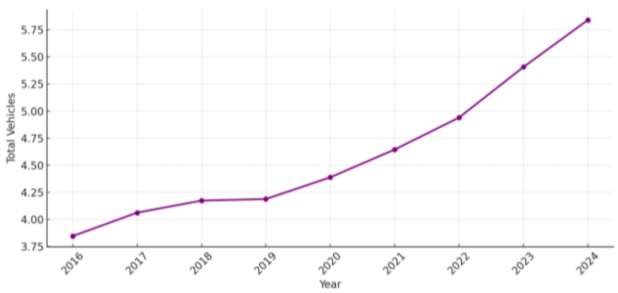


Figure 2. Total Number of Motor Vehicles in Istanbul (2016–2024)

3.2 Data Source

This research obtained daily vehicle count data from the Istanbul Metropolitan Municipality (IMM) Open Data Portal covering the years 2016–2024. The dataset includes the data collection date (day-month-year), the name of the traffic sensor, the sensor's geographical coordinates (latitude-longitude), and the total daily vehicle count recorded by each sensor. During the study period, the number of unique sensors ranged from 397 in 2016 to 251 in 2024, and the total number of detected vehicles exceeded 85 billion. To illustrate the scope and temporal distribution of the dataset, two visualizations were created: one showing the total number of vehicles detected by sensors between 2016 and 2024 (Figure 3), and Figure 4 showing the number of unique sensors by year. The IMM Information Technology Department (IMM, 2024) provided the dataset in CSV format and published it as open data, forming the basis for this study.

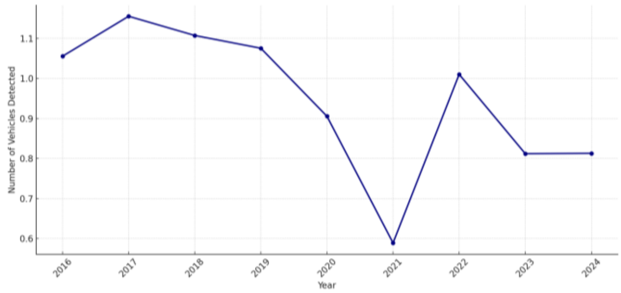


Figure 3. Number of Vehicles Detected by Sensors (2016–2024)

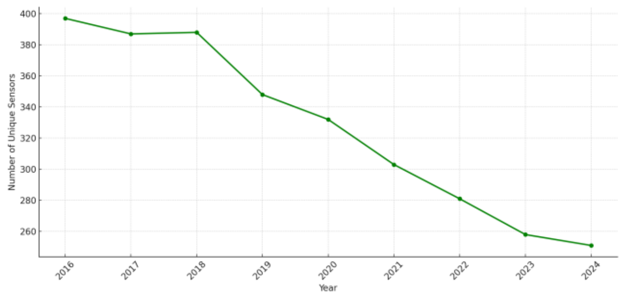


Figure 4. Number of Unique Sensors by Year (2016–2024)

3.3 Data Preprocessing

Prior to data analysis, several preprocessing steps were performed on the dataset. First, rows containing null values were removed and excluded from the analysis. Since the data used in the study were obtained from the IMM Open Data Portal, detailed technical information regarding the sensors was considered beyond the scope of this article.
The data were processed using different software and platforms. In this context, map-based visualizations were carried out via Mapbox, dynamic dashboards were created with Power BI, and interactive maps were produced using the Folium library in Python. In this way, the same dataset was processed with different techniques, and the visualization methods were comparatively evaluated.

3.3 Geospatial Data Visualization

The development of interactive and dynamic visualizations has transformed the way of geospatial and data-driven information is communicated. Among the wide range of tools available, Mapbox, Microsoft Power BI, Folium, and Tableau represent some of the most prominent platforms capable of generating insightful visualizations. This section discusses these tools, emphasizing their functionalities, strengths, and applications in various fields, including urban planning, health, and data analytics.

Mapbox is a versatile mapping platform that supports the creation of custom maps for web and mobile applications. It is particularly notable for its ability to handle large-scale geospatial data and provide high-quality visualizations. One of its key features is in-depth customization, as users can extensively style maps using Mapbox Studio, offering multiple basemaps that can be tailored to specific needs, which is crucial for branding and thematic representation (Allheeib et al., 2022). Another significant advantage lies in its use of vector tiles. Unlike traditional raster maps, Mapbox employs vector tiles, which allow for detailed, interactive graphic elements that improve load times and interactivity (Zhou et al. 2019).

https://doi.org/10.5194/isprs-archives-XLVIII-4-W19-2025-111-2026 | © Author(s) 2026. CC BY 4.0 License.

Furthermore, Mapbox provides strong integration capabilities through its APIs, which facilitate connections with numerous programming languages and frameworks, making it highly adaptable for developers seeking to implement interactive map functionalities (Walker, 2024). It is widely employed in applications requiring advanced geolocation services, such as logistics, urban planning, and public engagement platforms.

Microsoft Power BI is a robust business intelligence tool that excels in data visualization, reporting, and analytics. One of its key strengths is its user-friendly interface, which allows users to create interactive dashboards with drag-and-drop ease, making it accessible for both technical and non-technical audiences (Akhtar et al., 2020). In terms of data connectivity, Power BI can link to a diverse array of data sources, including cloud services, databases, and spreadsheets, thereby facilitating comprehensive data integration. Another central feature is its capacity for real-time dashboards, allowing for immediate updates that combine visualization with instantaneous analysis, an essential function in dynamic environments such as public health and finance (Orji et al., 2022). The tool is often used in corporate environments, where it supports decision-making through data insights that visualize sales trends, market analyses, and operational metrics (George-Sankoh et al., 2024).

Folium is a Python library that provides tools for creating interactive maps using the Leaflet.js framework, and it is particularly favored in data science and analytics communities. Its simplicity and ease of use allow users to create complex maps with minimal code, enabling quick visualizations well suited for exploratory data analysis (Nagel et al., 2012). Folium also integrates effectively with Pandas, allowing efficient workflows for researchers who seek to manipulate and visualize geospatial data simultaneously. In addition, it offers interactive capabilities such as marker clustering and popups, which enrich user experience and improve data presentation. Folium is widely employed in environmental monitoring, health data visualization, and educational contexts, where it enhances data storytelling through geospatial representation (Allegri et al., 2022).

Tableau is a leading data visualization platform recognized for its strong analytical capabilities and wide variety of visualization options. One of its core strengths lies in powerful analytics, as it allows users to perform complex analyses, including predictive modeling and trend detection, with intuitive visual outputs. Tableau is particularly acclaimed for its interactive dashboards, which can incorporate data from multiple sources and allow users to perform deep dives through drill-down functionalities (Batt et al. 2020). In addition, Tableau benefits from a large and active user community, offering extensive resources that make it easier to share visualizations and learn from peer-driven projects (Datig and Whiting 2018). Its applications span multiple industries, including healthcare for monitoring epidemic outbreaks, business for sales analytics, and education for interactive classroom engagement (Orner 2023)

A comparison of the four visualization platforms is presented in Table 1, highlighting their primary use cases, ease of use, supported data sources, interactivity, and deployment environments. This comparison provides a concise overview of the distinctive strengths of Mapbox, Microsoft Power BI, Folium and Tableau, thus assisting researchers and practitioners in selecting the most suitable tool for their specific needs.

Table 1. Comparison of Visualization Tools

Feature	**Mapbox**	**Microsoft Power BI**	**Folium**	**Tableau**
Primary Use Case	Custom mapping solutions	Business intelligence and reporting	Geospatial maps with Python	Data visualization and analytics
Ease of Use	Moderate; requires coding	User-friendly, intuitive GUI	Simple; Python-based	Requires training & knowledge
Data Sources	Web APIs, vector data	Diverse data sources, including cloud services	Pandas DataFrames, GeoJSON	Multiple sources, including databases
Interactivity	Highly interactive with rich visuals	Interactive dashboards with real-time updates	Interactive maps with HTML interfaces	Interactive dashboards and reports
Deployment	Web and mobile applications	Web-based, cloud-enabled	Python applications	Desktop and web applications

4. Results

The results of this study are presented through geospatial and temporal visualisations generated using Mapbox, Folium, and Microsoft Power BI. The utilisation of Tableau was precluded by the constraints imposed by licensing restrictions. Each platform offered unique capabilities for exploring Istanbul's daily traffic data, and representative screenshots are presented below.

4.1 Mapbox Visualizations

The creation of interactive and customised visualisations of the traffic dataset was primarily facilitated by the utilisation of Mapbox. As illustrated in Figure 5, the project's general interface is presented.

Figure 5. General interface of the Mapbox-based project

As illustrated in Figures 6, sensor-based geospatial representations are provided, with traffic sensors displayed across Istanbul, some of which are accompanied by their associated data values. Figure 7, present the five busiest sensors for a selected year and month.

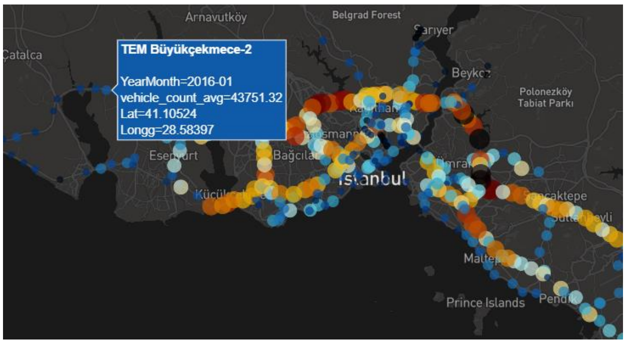
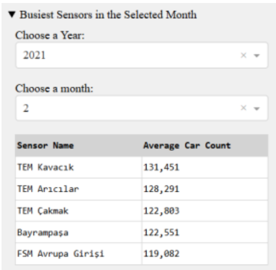


Figure 6. Geospatial representation of traffic sensors on the map, including selected sensor data values



Sensor Name	Average Car Count
TEM Kavacık	131,451
TEM Arıcılar	128,291
TEM Çakmak	122,803
Bayrampaşa	122,551
FSM Avrupa Girişi	119,082

Figure 7. Top five busiest sensors in a selected month

Figures 8(a) illustrates percentage change analyses, while Figure 8(b) presents the overall trend of traffic volume across the study period. An anomaly detection output is demonstrated in Figure 9.

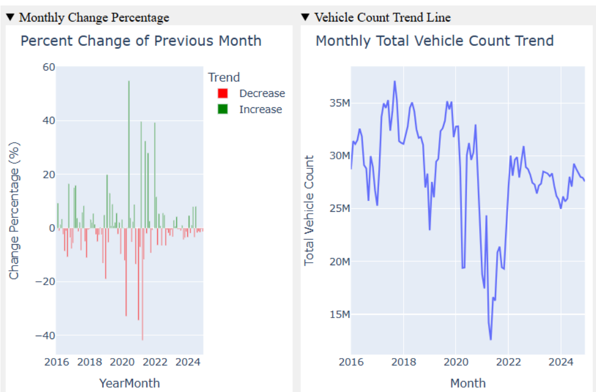


Figure 8. (a). Percentage change analysis of vehicle counts across selected time periods, **(b).** Overall trend of traffic volume across the study period

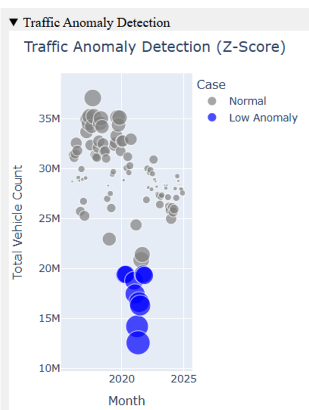


Figure 9. Anomaly detection visualization showing unusual traffic fluctuations

Further temporal and regional comparisons are illustrated in Figure 10. As illustrated in Figure 10(a) provides an average daily traffic volume across days of the week. Figure 10(b) presents a comparative analysis between the European and Asian sides of Istanbul through the utilisation of pie charts. Finally, Figure 11 compare weekday and weekend traffic volumes.

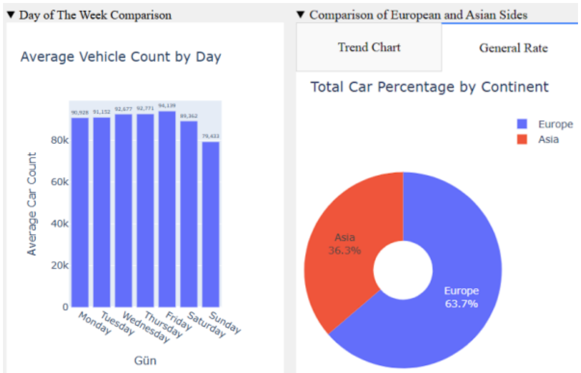


Figure 10. (a). Average daily traffic counts for each day of the week, **(b).** Comparative traffic distribution between the European and Asian sides of Istanbul

Figure 11. (a). Comparison of weekday traffic volume against weekend traffic volume, **(b).** Alternative visualization of weekday versus weekend traffic dynamics

4.2 Folium Visualizations

The Folium library in Python was utilised to generate heatmaps and time-series visualisations, facilitating the exploration of spatial and temporal variations concurrently. Figure 12 presents a heatmap illustrating daily vehicle counts across Istanbul, while Figure 13 offers an interactive time-series view that facilitates dynamic exploration of traffic fluctuations. These outputs demonstrate Folium's capacity to facilitate rapid and effective exploratory geospatial visualisations with negligible coding effort.

Figure 12. Heatmap visualization of daily vehicle counts across Istanbul using Folium

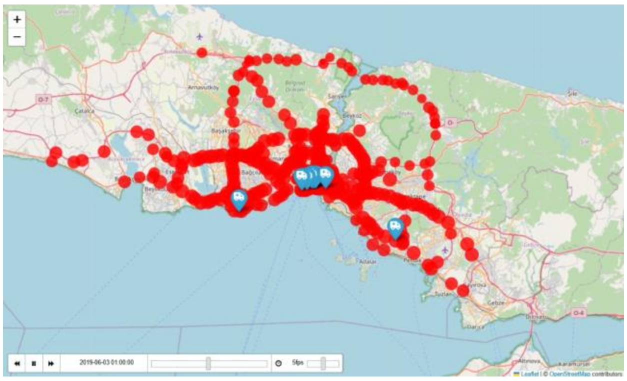


Figure 13. Interactive time-series visualization of traffic fluctuations with Folium

4.3 Power BI Visualizations

Power BI was utilised to generate dynamic dashboards and interactive maps. The tool facilitated the integration of traffic data with spatial coordinates, thereby producing map-based visualisations enriched with pie charts for each sensor location. Figure 14 presents examples of these output, where each pie chart reflects the proportional distribution of vehicle counts across different categories. This feature provided a clear visual overview of sensor-based traffic patterns and allowed for interactive filtering by year, month, or location.

Figure 14. Power BI dashboard showing traffic data mapped to sensor locations with pie charts

5. Discussions

This study examined Istanbul's traffic data from 2016–2024 using geospatial visualization methods. Visualisations produced with Mapbox, Folium and Power BI demonstrated the respective advantages of these tools in interpreting traffic data.

The results demonstrated a precipitous decline in 2020–2021, corresponding to the pandemic period, followed by a recovery trend in 2022 and subsequent years (see Figure 8(b)). The application of anomaly detection algorithms revealed anomalous fluctuations (see Figure 9). A comparison of traffic density revealed that it was consistently higher on the European side than on the Asian side (see Figure 10(b)). As demonstrated in Figure 10(a), weekday traffic was found to be more substantial in comparison to weekend traffic. Furthermore, seasonal variations, as well as the busiest months and days, were also clearly observed (see Figures 10(a)).

Mapbox provided a robust environment conducive to detailed and interactive spatial analysis (see Figure 5). Folium offered fast and practical Python-based solutions (see Figures 12–13). Power BI has been demonstrated to facilitate effective decision-making through the provision of dynamic dashboards and sensor-based charts (see Figure 14). The utilisation of Tableau was precluded due to restrictions imposed by licensing agreements.

6. Conclusion and Future Work

The dataset utilised in this study is derived from sensor-based measurements provided by the Istanbul Metropolitan Municipality Open Data Portal. The presence of data gaps may be attributed to malfunctions in the sensors or an uneven spatial coverage. Despite the implementation of preprocessing steps, including the elimination of null values and the standardisation of the data, the employment of interpolation or more sophisticated methods for addressing missing data could yield more reliable results in subsequent studies. Moreover, the present study concentrated principally on descriptive visualisations; predictive modelling or advanced statistical analyses were not conducted.

The current data series has been used to conduct forecasting experiments with AI algorithms. However, more parameters are required to accurately predict traffic density. Therefore, combining this dataset with others and applying AI-based methods in future research could produce stronger, more robust results.

It is recommended that future research endeavours incorporate traffic data along with additional datasets, including but not limited to weather conditions, socioeconomic indicators, and public transport usage. This integrated approach will facilitate a more comprehensive understanding of mobility patterns in Istanbul. Moreover, the development of real-time adaptive traffic systems has the potential to significantly enhance congestion management. Conducting comparative analyses with other metropolitan areas is the most effective method of evaluating Istanbul's traffic dynamics within a broader global context.

The selection of a particular geospatial data visualization platform, such as Mapbox, Microsoft Power BI, Folium, or Tableau, should be informed by a comprehensive evaluation of the project's specific requirements, the proficiency of the intended users, and the desired outcomes. The Mapbox is distinguished by its web mapping applications, Power BI for business analytics, Folium for rapid map development in Python, and Tableau for comprehensive data visualisation tasks. The effective utilisation of these tools has the potential to markedly improve data comprehension and decision-making processes across a range of sectors.

Acknowledgements

This study was supported by Scientific and Technological Research Council of Türkiye (TUBITAK) under Grant Number 124N109. The authors thank TUBITAK for their support.

References

Abudiyab, Nehad A., and Abdullah T. Alanazi. 2022. "Visualization Techniques in Healthcare Applications: A Narrative Review." *Cureus*. doi:10.7759/cureus.31355.

Afrin, Tanzina, Lucy G. Aragon, Zhibin Lin, and Nita Yodo. 2023. "An Integrated Data-Driven Predictive Resilience Framework for Disaster Evacuation Traffic Management." *Applied Sciences* 13(11):6850. doi:10.3390/app13116850.

Akhtar, Nikhat, Nazia Tabassum, Asif Perwej, and Yusuf Perwej. 2020. "Data Analytics and Visualization Using Tableau Utilitarian for COVID-19 (Coronavirus)." *Global Journal of Engineering and Technology Advances*. doi:10.30574/gjeta.2020.3.2.0029.

Allegri, Stephen A., Kevin McCoy, and Cassie S. Mitchell. 2022. "CompositeView: A Network-Based Visualization Tool." *Big Data and Cognitive Computing* 6(2):66. doi:10.3390/bdcc6020066.

Allheeib, Nasser, Marine Alraqdi, and Mohammed Almukaynizi. 2022. "Data Warehouse and Interactive Map for Promoting Cultural Heritage in Saudi Arabia Using GIS:" *International Journal of Data Warehousing and Mining* 18(1):1–18. doi:10.4018/IJDWM.314236.

Al-Nuaimi, Atheer, and Abeer K. Jameel. 2023. "An Impact of Traffic Characteristics on Crash Frequency" edited by M. Karkush. *E3S Web of Conferences* 427:03040. doi:10.1051/e3sconf/202342703040.

Austin, Robin R., Michelle A. Mathiason, and Karen A. Monsen. 2022. "Using Data Visualization to Detect Patterns in Whole-person Health Data." *Research in Nursing & Health* 45(4):466–76. doi:10.1002/nur.22248.

Baffoe-Twum, Edmund, Eric Asa, and Bright Awuku. 2022. "Estimation of Annual Average Daily Traffic (AADT) Data for Low-Volume Roads: A Systematic Literature Review and Meta-Analysis." *Emerald Open Research*. doi:10.35241/emeraldopenres.14515.1.

Balla, Dániel, Marianna Zichar, Róbert Tóth, Emőke Kiss, Gergő Karancsi, and Tamás Mester. 2020. "Geovisualization Techniques of Spatial Environmental Data Using Different Visualization Tools." *Applied Sciences* 10(19):6701. doi:10.3390/app10196701.

Batt, Steven, Tara Grealis, Oskar Harmon, and Paul Tomolonis. 2020. "Learning Tableau: A Data Visualization Tool." *The Journal of Economic Education* 51(3–4):317–28. doi:10.1080/00220485.2020.1804503.

Beil, C., M. Kendir, R. Ruhdorfer, and T. H. Kolbe. 2022. "DYNAMIC AND WEB-BASED 4D VISUALIZATION OF STREETSPACE ACTIVITIES DERIVED FROM TRAFFIC SIMULATIONS AND SEMANTIC 3D CITY MODELS." *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* X-4/W2-2022:29–36. doi:10.5194/isprs-annals-X-4-W2-2022-29-2022.

Bheekya, Dharamsotu, Kanakapodi Swarupa Rani, Salman Abdul Moiz, and Chillarige Raghavendra Rao. 2020. "A Novel Representative K-NN Sampling-Based Clustering Approach for an Effective Dimensionality Reduction-Based Visualization of Dynamic Data." *Advances in Science, Technology and Engineering Systems Journal* 5(4):08–23. doi:10.25046/aj050402.

Çavdaroğlu, G. Çiğdem. 2017. "Trafik Yoğunluk Harita Görüntülerinin Görüntü İşleme Yöntemleriyle İşlenmesi." *Academic Platform-Journal of Engineering and Science* 22–22. doi:10.21541/apjes.289448.

ÇetiN Taş, İclal, and Ahmet Anıl Müngen. 2021. "YAPAY SİNİR AĞLARI ve DESTEK VEKTÖR MAKİNELERİ YÖNTEMLERİ Ile BÖLGESEL TRAFİK YOĞUNLUK TAHMİNİ." *Adıyaman Üniversitesi Mühendislik Bilimleri Dergisi*. doi:10.54365/adyumbd.971461.

Datig, Ilka, and Paul J. Whiting. 2018. "Telling Your Library Story: Tableau Public for Data Visualization." *Library Hi Tech News*. doi:10.1108/lhtn-02-2018-0008.

George-Sankoh, Ibrahim, Laura E. MacMullen, Asif T. Chinwalla, Deanne Taylor, Rebecca D. Ganetzky, Katelynn Stanley, Elizabeth M. McCormick, Zarazuela Zolkipli-Cunningham, and Marni J. Falk. 2024. "MMFP-Tableau: Enabling Precision Mitochondrial Medicine through Integration, Visualization, and Analytics of Clinical and Research Health System Electronic Data."

Govind Shinde, Ms. Bhakti, and Dr. Sunayana Shivthare. 2024. "Impact Of Data Visualization In Data Analysis To Improve The Efficiency Of Machine Learning Models." *Journal of Advanced Zoology* 107–12. doi:10.53555/jaz.v45iS4.4161.

Hasan, Md Mehedi, and Jun-Seok Oh. 2020. "GIS-Based Multivariate Spatial Clustering for Traffic Pattern Recognition Using Continuous Counting Data." *Transportation Research Record: Journal of the Transportation Research Board* 2674(10):583–98. doi:10.1177/0361198120937019.

Heinzlef, Charlotte, Vincent Becue, and Damien Serre. 2020. "A Spatial Decision Support System for Enhancing Resilience to Floods: Bridging Resilience Modelling and Geovisualization Techniques." *Natural Hazards* *and Earth System Science*. doi:10.5194/nhess-20-1049-2020.

Koliou, Katerina, and Ioanna Spyropoulou. 2023. "Analyzing Motorway Operator Data for Spatiotemporal Insights Into Speed Dynamics." doi:10.20944/preprints202312.2204.v1.

Limantara, Arthur Daniel, Tjahjaning Tingastuti Surjosuseno, Bambang Subiyanto, Fauzie Nursandah, Sri Wiwoho Mudjanarko, Muhammad Ikhsan Setiawan, and Nawir Rasidi. 2021. "Smart Survey Model of Average Daily Traffic (ADT) for Pavement Planning and Monitoring." doi:10.2991/aer.k.210810.001.

Nagel, Till, Erik Duval, and Andrew Vande Moere. 2012. "Interactive Exploration of Geospatial Network Visualization." doi:10.1145/2212776.2212830.

Ofori, Michael Arthur, Stella T. Lartey, Polina Durneva, Niharika Jha, Nidhi Mittal, Shongkour Roy, Zebunnesa Zeba, Stella Chirwa, Nichole Saulsberry-Scarboro, Michelle L. Taylor, and Ashish Joshi. 2025. "Visual Communication of Public Health Data: A Scoping Review." *Frontiers in Digital Health*. doi:10.3389/fdgth.2025.1555231.

Orji, Ugochukwu, Elochukwu Ukwandu, Ezugwu Obianuju, Modesta Ezema, Chikaodili Helen Ugwuıshıwu, and Malachi. C. Egbugha. 2022. "Visual Exploratory Data Analysis of the Covid-19 Pandemic in Nigeria: Two Years After the Outbreak." doi:10.1109/ited56637.2022.10051529.

Orner, Sylvia. 2023. "Data Visualization for Collection Analysis." *Pennsylvania Libraries Research & Practice*. doi:10.5195/palrap.2023.278.

Shahab Uddin, Md Kazi, Rahmat Ullah, and Mohammad Moniruzzaman. 2024. "Data Visualization in Annual Reports – Impacting Investment Decisions." *International Journal for Multidisciplinary Research*. doi:10.36948/ijfmr.2024.v06i05.29149.

Singh, Kamred Udham. 2023. "Visualization and Exploration of Complex Scientific Data." doi:10.52783/tojqi.v11i3.10004.

Soares, Angelo Roldão, Ricardo Deus, Carla Barroso, and Carla Silva. 2021. "Urban Ground-Level O3 Trends: Lessons From Portuguese Cities, 2010–2018." *Atmosphere*. doi:10.3390/atmos12020183.

TUIK. (2024, 5 3). *Merkezi Dağıtım Sistemi.* TUIK: https://biruni.tuik.gov.tr/ adresinden alındı

de Vyvere, Brecht Van, and Pieter Colpaert. 2022. "Using ANPR Data to Create an Anonymized Linked Open Dataset on Urban Bustle." *European Transport Research Review*. doi:10.1186/s12544-022-00538-1.

Walker, Kyle E. 2024. "Mapgl: Interactive Maps With 'Mapbox GL JS' and 'MapLibre GL JS.'" doi:10.32614/cran.package.mapgl.

Wang, Qi, Min Lü, and Qingquan Li. 2020. "Interactive, Multiscale Urban-Traffic Pattern Exploration Leveraging Massive GPS Trajectories." *Sensors*. doi:10.3390/s20041084.

Zhang, Liyan, Min Zhang, Jiazhen Tang, Jian Ma, Xiaoke Duan, Juan Sun, Xiaofei Hu, and Suchuan Xu. 2022. "Analysis of Traffic Accident Based on Knowledge Graph." *Journal of Advanced Transportation*. doi:10.1155/2022/3915467.

Zhou, Xiaodong, Tinghua Ai, Nina Meng, and Peng Xie. 2019. "A PDF Tile Model for Geographic Map Data." *Isprs International Journal of Geo-Information*. doi:10.3390/ijgi8090373.