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Investigating the influence of spatial characteristics on cycling volume: A multi-scale geographic weighted regression approach

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A R T I C L E I N F O

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A B S T R A C T

Cycling has seen a remarkable rise, signifying a paradigmatic move towards sustainable, eco-friendly, and efficient commuting alternatives in the contemporary urban setting. Cities also encourage this trend by establishing cycle lanes, bike-sharing programs, and incentives for frequent riders. To enhance these motivations from an urbanistic perspective, it is essential to comprehend the influence of urban characteristics on cycling volume and to incorporate this understanding into data-driven decision-making processes.

This research examines the Bicification project data from Istanbul with a spatial perspective. Utilising a comprehensive array of spatial big data, the study explores the impact of urban land use, transport services, land morphology, and sociodemographic factors on cycling volume through a Multi-scale Geographically Weighted Regression (MGWR). With an Adj R^2 value of 0.68, the model demonstrates a strong relation between cycling volume and several factors, including biking park stations, park and ride points, pier stops, rail stops, transfer points, main roads, elevation, population, industrial facilities, health facilities, sports areas, and residential areas. The findings will serve to develop a data-driven strategic approach to promote cycling in Istanbul.

1. Introduction

During the last decades of the 20th century, the contemporary urban planning and design agenda has been discussing strategies and concepts that will enable the cities to overcome the problems in the future. However, the scale and structure of cities have grown to such an extent that conventional urban planning and management systems are no longer feasible. Correspondingly, cities are utilizing technological advancements presented by the information age and data, which is the fuel of our era (Al Nuaimi et al, 2015). Enhanced smart city technologies and systems produce big-data flow, providing possibilities to formulate evidence-based decisions for urban environments. The notion of big data and data-driven decision-making, in this sense, is gaining attention in the urbanism context in both practice and research as an emerging solution to contemporary problems (Kitchin, 2014a,b, 2017; Bibri and Krogstie, 2021; Batty et al., 2012). It enables experts to control the process proactively by providing adaptive, reflexive, and responsive approaches. Furthermore, utilizing urban big data presents a practical opportunity to understand its citizens, predict their present and future requirements, identify the underlying reasons for current issues, and produce diverse projections to estimate the social, environmental, and economic advantages before initiating city projects.

Such an emerging approach offers an opportunity to provide sustainable solutions for diverse urban planning agendas, including urban transport. The urban transport discipline draws advantage from the data-centric approaches (Zhu et al., 2018) by having a direct impact on the daily activities of urban flow. Data-driven decision-making provides practical insights into understanding the transport patterns of cities to increase the efficacy of urban decision-making by collecting, monitoring, and processing real-time big data (Welch and Widita, 2019). It also enables the planning of well-connected, and sustainable transport systems in cities. Cycling, one of the most prominent modes of sustainable transport, comes to the fore in the contemporary research agenda, leveraging big-data-related approaches. The substantial growth in big data related to cycling in recent years has spurred numerous approaches in the fields of transportation and urban planning. A large track concentrated on employing large spatial–temporal trajectory data for shared bike demand prediction (Hua et al., 2020; Wang et al., 2023). There is also other significant research on the location optimization of biking systems (Yang et al., 2020a,b, Caggiani et al., 2020; Frade and

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Ribeiro, 2015). Several studies have been conducted to characterize the spatial effects of the built environment on bike ridership (Chen et al., 2017; Lyu et al., 2020; Yang et al., 2020a,b; Dai et al., 2023; Zhou et al., 2023a,b). With such a broad perspective being developed in the context of cycling, there is an emerging research track on the big data-informed strategy development for cycling (Duran-Rodas et al., 2019; Gao et al., 2023; Nelson et al., 2023; Xie and Wang, 2018; Yuan et al., 2023) and room for further research.

From this perspective, in this research, we examine the spatial relationship between different variables and cycling volume to develop a framework for data-driven urbanism. We used twenty-four independent variables listed as religious facilities, green areas, commercial facilities, sports areas, industrial facilities, health facilities, cultural facilities, public spaces, financial facilities, educational facilities, residential areas, transfer points, park and ride points, pier stops, minibus stops, bus stops, rail stops, bicycle parking stops, main roads, pedestrian roads, car parks, vehicle flow, elevation, and population to investigate the impact of urban variables on route choice. For this purpose, we employed the cycling trip data from the Bicification project which is funded by the European Institute for Innovation and Technology (EIT) Urban Mobility, an organization of the European Union. Istanbul Metropolitan Municipality (IMM) supports decision-making with a data-driven approach by providing high-quality data and data governance studies based on global best practices. Herein, we also aim to provide a mapping of cycling use patterns by highlighting the strategies for data-driven decision-making.

The article consists of six consecutive sections. In the first section, the introduction, we explain the general content of the research by setting the contextual frame, the objectives, and the scope of the study. Following this, in the second part, the literature review, the joint literature review is formulated to reveal the current research agenda and identify research gaps in the context of data-driven decision-making and cycling. In the methodology, we present Istanbul as a study area and explain the data collection, validation, computation, and modeling approaches of the research. In the fourth section, the results, we deliver the model results by referring to the theoretical foundation of the research. In the discussion, we propose critical inferences for Istanbul in the context of data-driven decision-making and cycling. We also acknowledge the limitations of our research and suggest future directions for further investigation. In the conclusion, we generalize the results and contextualize the discussion by exploring the potential applications of the research approach in Istanbul.

2. Theoretical background

2.1. Data-driven urbanism and decision-making in the context of cycling

Technological developments have made revolutionary changes possible among different professions in the last two decades. The digital methods and new techniques that arise with the increasing usage of computers affect professional practices. The use of computers has enabled faster performance of complex operations and simplified the solution of computational problems. In the field of urbanism, the most significant recent development has been the integration of technology into planning and design processes. It enabled the creation of adaptable solutions that are responsive to specific contexts and provide a relational framework for discovering new ways of decision-making, as well as enhancing the complexity of planning and design processes (Aish & Woodbury, 2005, p. 1; Marshall, 2012). In this context, the notion of big data paves the way to generate the necessary approach to relate technology and urbanism (Al Nuaimi et al., 2015; Batty, 2013, 2018; Kitchin, 2014a,b, 2015; Bibri, 2019a).

In the urbanism agenda, with the increasing importance of big data, data-informed decision-making is becoming prominent as the main catalyst of smart city systems and technologies (Bibri, 2019b; Batty, 2013; Kitchin, 2014a,b). Although there is a diverse utilization pattern of big data for urban services, urban transportation systems increasingly rely on data-informed decision-making. As argued by Bibri and Krogstie (2021), this approach prioritizes the use of data analytics to guide policy and operational decisions, ensuring efficient, sustainable, and user-friendly urban transport solutions. Leveraging data for informed decision-making and tactical management, data-driven approaches involve collecting, analyzing, and utilizing data to guide decisions and strategies (Rosa et al., 2020). It stands in contrast to traditional approaches, which often rely more on heuristic or experience-based decision-making. The adoption of a data-driven approach in urban transportation is crucial for the development of efficient, sustainable, and responsive city transit systems (Olaniyi et al., 2023). To provide such an integrated approach, big data collection is an important process that involves gathering a wide array of data, including traffic sensor readings, GPS data from public transportation systems, user feedback, and insights derived from social media analytics (Zha et al., 2023). This extensive data collection is crucial in painting an accurate picture of the urban mobility landscape. As presented by Yin et al. (2023), following collection, the data undergoes thorough analysis, where advanced analytics, incorporating AI and machine learning algorithms, are employed to process and interpret this vast amount of information. The analysis stage is pivotal in extracting meaningful insights about traffic patterns, user preferences, and potential inefficiencies within the system. Lastly, modeling plays a critical role, as it leverages data to forecast future trends in urban transportation (Alessandretti et al., 2023). Such predictive capability is instrumental in proactive planning, ensuring that cities can effectively manage traffic, maintain their infrastructure, and develop it further to meet future demands. In essence, a data-driven methodology transforms urban transportation into a dynamic, adaptive system, capable of meeting the evolving demands of growing urban populations while promoting environmental sustainability and improving the quality of urban life.

By relying on the existing research agenda, for this study, we focused on the studies that discuss, particularly, the relationship between data-driven decision-making and cycling. Although there has been numerous data-driven research on cycling (Romanillos et al., 2016), the potential use of big data for decision-making in cycling remains to be explored. Correspondingly, Xie and Wang (2018) analyzed trip history data from the Capital Bikeshare system in Washington to investigate the connection between data-driven decision support and bike-sharing systems. Similarly, Gao et al. (2023), by utilizing a machine learning model, assessed the impact of built environment factors on the mode substitution patterns of the dockless bike-sharing system, providing an analytical foundation for decision-making systems. Also, Yuan et al. (2023) developed a data-driven decision-making framework for greenway planning through the examination of how various built environment factors influence cycling behavior. Nelson et al. (2023) highlighted the importance of data-driven decision-making and classified the streets with a k-means clustering algorithm based on bicycle usage by utilizing diverse spatial data on the built environment, communities, and bicycling. By focusing on the correlation between the arrivals and departures of station-based bike-sharing systems and built environment factors, Duran-Rodas et al. (2019) formulated a decision-making approach as a strategy for executing or extending bicycle-sharing systems. From a qualitative perspective, Marquart et al. (2020) investigated the awareness of decision-makers regarding cyclists' needs and perceptions, aiming to develop a bottom-up decision-making perspective.

2.2. Spatial parameters influencing cycling volume

The influence of the urban built environment on the cycling volume has been thoroughly documented in many research. For instance, there exists a positive correlation between the mixture of land use and the density of commercial usage with the volume of cycling (Pucher & Buehler, 2006; Griswold et al., 2011; Chen et al., 2017; Hankey et al.

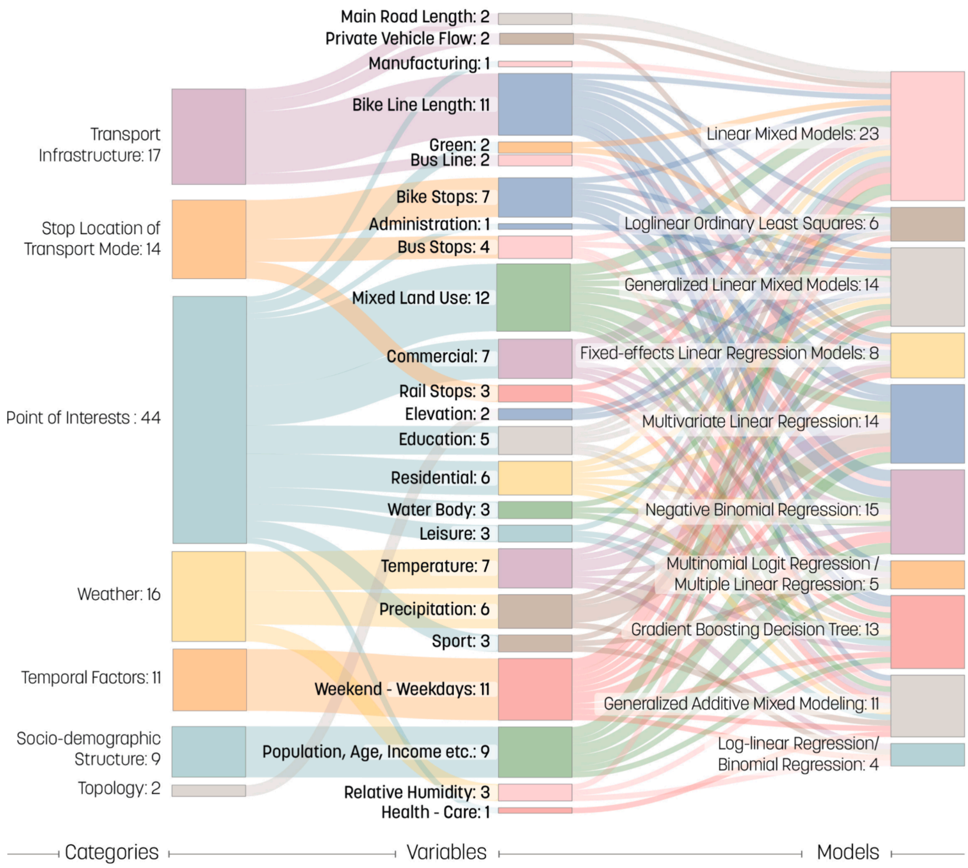

Fig. 1. Distribution of variables and models in current discussions.

2012). When urban facilities have mixed land uses, such as residential and commercial, destinations become closer to each other. This reduces the need for long-distance travel and makes cycling a convenient and practical mode of transportation for short trips. (Heinen et al., 2010; Moudon et al., 2005; Zhou et al., 2023a,b). Furthermore, while there exists a positive correlation between residential density and bicycle volume (Noland et al., 2016; Zhou et al., 2023a,b), some studies indicate that there is no statistically significant correlation with cycling volume (Sun et al., 2017; Chen et al., 2017). In addition, the implementation of cycling infrastructure, such as bike lanes and bike racks, not only enhances safety but also fosters increased participation in cycling (Buck and Buehler, 2012; Reynolds et al., 2009; Griswold et al., 2011; Xing et al., 2010).

Several studies have emphasized the impact of temporal attributes and weather conditions on the volume of cycling (Tin Tin et al., 2012; El Esawey et al., 2013; Gosse & Clarens, 2014; Zhou et al., 2023a,b). Some of the results exhibit that there are more significant decreases in cycling volume on routes during rainy, cold, and windy days (Miranda-Moreno and Nosal, 2011). Upon deeper examination, Hong et al. (2020), and Chen et al. (2017) state that the frequency of cycling activities is higher in spring, summer, and autumn compared to winter, indicating that the peak cycling activity occurs during the summer months. Moreover, Sun et al. (2017) and Tin Tin et al. (2012) emphasize that bicycle usage is higher during peak hours in the morning and evening compared to other times of the day.

2.3. Model approaches

Various regression-based models have been utilized to identify the relation between the spatial elements in urban areas and the cycling volume. Tin Tin et al. (2012), Dill and Carr (2003), and Pucher and Buehler (2006) applied multivariate regression models to demonstrate the relation. Hankey et al. (2012) yielded negative binomial models to provide reasonable relative estimates of volumes for non-motorized traffic. Similarly, Miranda-Moreno and Nosal (2011) utilized log-linear models and regression models for count data, encompassing conventional negative binomial models as well as multilevel count data regression models designed for repeated measures to show the correlation between weather conditions and cycling ridership. Hong et al. (2020) utilized a fixed-effect regression model to measure the influence of rainy conditions on cycling safety using crowd-sourced cycling data. Faghih-Imani et al. (2014) and Sun et al. (2017) employed a linear mixed model to identify the dependencies linked with the movement of bicycles.

In the context of Poisson distribution, Jestico et al. (2016), and Chen et al. (2017) employed a generalized linear mixed model to capture the temporal changes in bicycle volume while accounting for temporal autocorrelations. Similarly, Hankey et al. (2012) and Noland et al. (2016) utilized negative binomial regression, which is another type of Poisson regression. They analyze the impacts of bicycle infrastructure, population and employment, land use mix, and transit access individually, considering different seasons of the year and distinguishing between weekdays and weekends.

Alternatively, an increasing number of studies have investigated the presence of nonlinearity in the relationship between the built environment and cycling behavior (Ji et al., 2023). A generalized additive model, incorporating marginal nonlinear interactions, was applied to investigate the associations between spatial characteristics of urban areas and cycling (Hu et al., 2022).

2.4. Identifying gaps in the literature and novel aspects of the research

This research contributes to the ongoing research agenda from a practical and methodological perspective in three ways by identifying

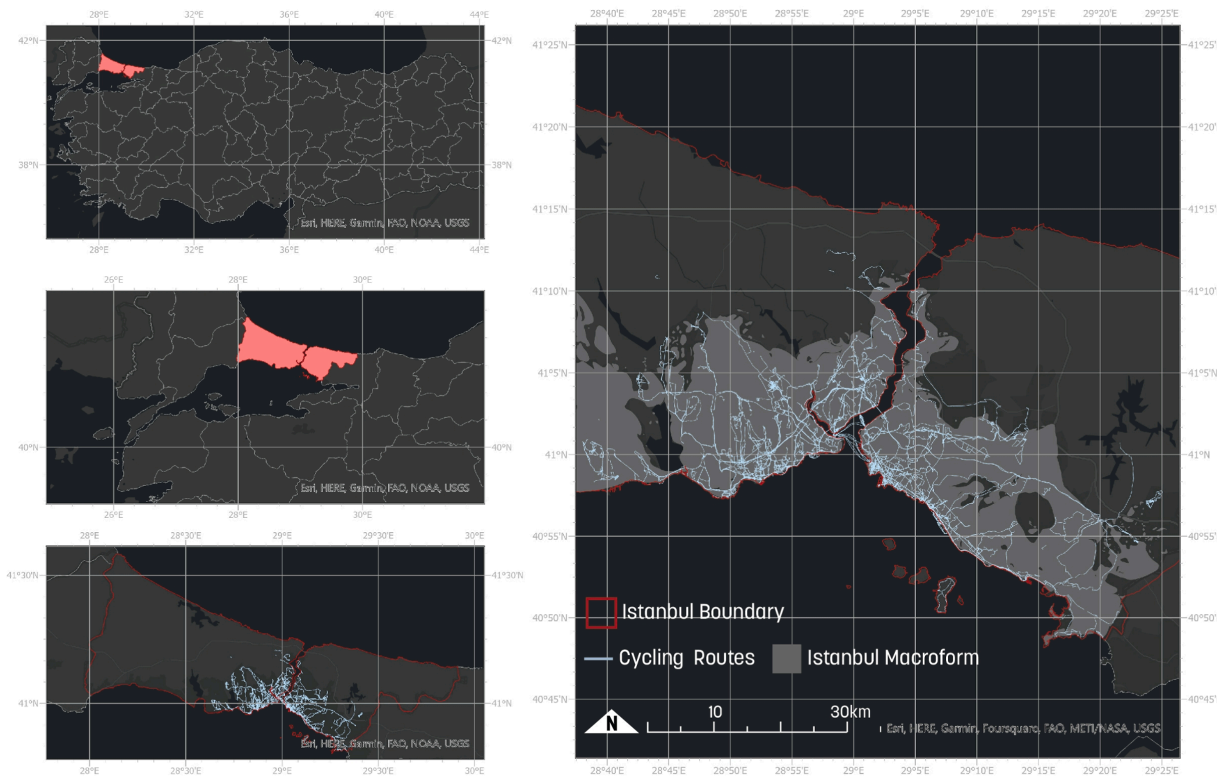

Fig. 2. Study area and Bicification project cycling route data.

gaps identified through the review of the current literature.

Most studies tend to focus on a single scale within the built environment, such as streets or neighborhoods with a limited set of variables. It makes it challenging to ensure a comprehensive understanding of the impact of the built environment on cycling. Our research aims to investigate the correlation between the built environment and cycling volume, addressing a research gap. The research identifies the influential factors and comprehensively analyzes the spatial characteristics of cycling at different scales. For this objective, we utilize numerous variables in the research that cover the urban facilities through points of interest (POIs), transportation services, land morphology, and socio-demographic structure.

In the literature, while most studies utilize linear regression models; some of them examine the non-linear and threshold effects of the built environment on cycling volume. The utilization of these models limits the incorporation of variables exhibiting spatial characteristics within the study area. As Anselin (2010) states linear models are negatively impacted by spatial data due to spatial heterogeneity and autocorrelation. To overcome this gap, this research employs the MGWR model which enables the variation of scales for the coefficients of each covariate. It permits the spatially variable adjustment of scales in the relationship between variables, providing a comprehensive understanding of the connection between spatial dynamics and cycling volume. Although a few studies (Lyu et al., 2020; Zhou et al., 2023a,b) employ the MGWR model, the elaborative evaluation of the impacts of spatial variables within the urban areas has been limited by the small set of variables. This study contributes to ongoing discussions by employing a distinctive geographic regression method to model the relationship between comprehensive spatial variables (Fig. 1).

Another conclusion from the literature is that existing studies offer limited interpretations of the results derived from calculating the relationship between urban characteristics and cycling. In contrast, the research not only evaluates the results of the analyses but also examines them in the context of strategic planning and data-driven urbanism. We believe that the results will provide urban planners, experts, and decision-makers with valuable insights on how to optimize the urban built environment to encourage cycling behavior.

3. Methodology

3.1. Study area

Istanbul, Türkiye's largest metropolis, is a dynamic and culturally rich city that serves as a bridge between Europe and Asia. With a population of over 16 million, it stands as a true melting pot of cultures and traditions. In particular, the city contributes significantly to the economy of Türkiye, accounting for approximately 30 % of the country's GDP (TÜİK, 2023).

To accommodate the needs of its population, Istanbul has various modes of transportation. Approximately 630 public transport routes crisscross the city, providing around 9 million daily boardings. A significant portion of the population engages in intercontinental trips, amounting to around 2.2 million per day. The city operates an extensive bus fleet of 6546 and has a maritime presence with 396 ferries (IMM Smart City Directorate, 2021). Rail transport includes 11 metro lines and 4 tram lines, indicating a well-developed infrastructure. In addition, a push towards green transport is evident, reflecting Istanbul's commitment to sustainable urban mobility. In addition to such a developed and integrated use of transport facilities, pedestrian activity is also notable with a high pedestrian rate of 40.5, however, bicycle usage remains below 1 % (Istanbul Planning Agency, 2021).

Istanbul aims to promote sustainable transport solutions, including cycling, to achieve carbon neutrality soon. To reduce traffic congestion and pollution, Istanbul aims for 35 % of trips to be made by public transport. Additionally, there is a strong emphasis on active mobility, with a goal for 50 % of daily journeys to be conducted by walking and cycling, promoting both environmental and health benefits (Istanbul Planning Agency, 2021).

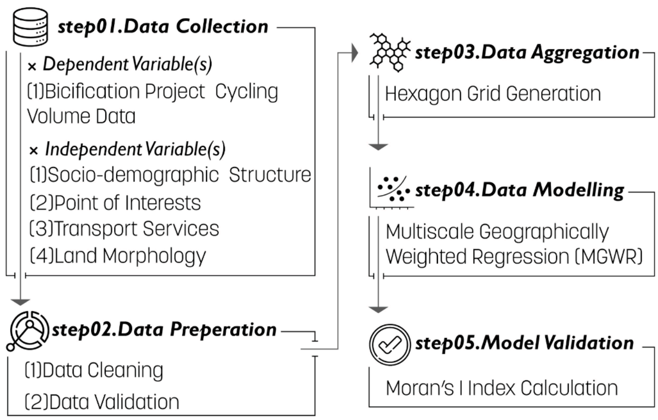

Fig. 3. The general framework of the research.

3.2. The Bicification project

Istanbul Metropolitan Municipality (IMM) engaged in a Bicification project to provide practical solutions for promoting cycling in Istanbul. Bicification is a project funded by EIT Urban Mobility, an initiative of the European Institute for Innovation and Technology (EIT), an organization of the European Union. The project aims to encourage the use of sustainable and healthy mobility options by raising citizens' awareness of the quality of their urban environment, rather than focusing on infrastructure (EIT Urban Mobility, 2022). Bicification proposes a reward-based gamification system that includes patented hardware and software to reliably track cycling trips and reward cyclists. It offers a high-TRL (TRL9) technological solution that includes patented hardware and software to track bike journeys. This system not only promotes cycling but also provides Istanbul with valuable data on cycling volumes.

The data set of the Bicification project comprises spatial and temporal patterns of cycling volume, rider demographics, and route preferences. The project's novel approach to data collection enables a comprehensive understanding of cycling volume and behavior/patterns. By utilizing GPS and motion sensors, the project gathers spatial big data, providing insights into the most frequently used routes, peak cycling times, and underutilized paths (IMM Open Data Portal, 2023).

In this sense, we used Bicification data in this research to develop a data-driven decision-making framework for cycling in Istanbul, aiming to reveal further spatial correlations with relevant urban parameters (Fig. 2).

3.3. Data collection

In the research, we collected 25 different variables by categorizing (a) dependent variables (1) 'Bicification' Project Cycling Volume Data and (b) independent variables (2) Point of Interest (POI), (3) Transportation Services, (4) Land Morphology, and (5) Socio-demographic Structure (Fig. 3). Respectively, we employed the following dataset in the research:

'Bicification' Project Cycling Volume Data: We obtained the cycling volume data from the Open Data Platform of Istanbul Metropolitan Municipality (IMM) (https://data.ibb.gov.tr/en/). The dataset includes trip route, starting latitude, longitude, and time, ending latitude, longitude, and time, and driving ID. The data was collected by IMM for 7 months between June and December 2022. Before utilizing the data, we removed several trips from the dataset due to errors that arose during the data collection process. After cleaning the data, we aggregated all trips into a single dataset. In this stage, we used the Driving ID as a unique attribute to create the database. This allowed us to structure a database for analysis, containing 2033 individual trip routes.

Point of Interests: Considering all relevant land use services with cycling in an urban setting, we utilized eleven POIs listed as Religion Facilities, Green Areas, Commercial Facilities, Sports Areas, Industrial Facilities, Health Facilities, Cultural Facilities, Public Spaces, Financial Facilities, Educational Facilities, Residential Areas. We gathered the data from the Open Data Platform of IMM (https://data.ibb.gov.tr/en/) with latitude and longitude attributes. We also conducted cleaning for the POIs by removing duplicates. Finally, there are 374,306 POIs within the data set.

Transportation Services: As a complementary data set for the cycling volume studies, we gathered eleven different variables for transportation services as follows: Transfer Points, Park, and Ride Points, Pier Stops, Minibus Stops, Bus Stops, Rail Stops, Bicycle Parking Stops, Main Roads, Pedestrian Roads, Carparks, Vehicle Flow. For the pedestrian roads, we obtained the road data from OpenStreetMap (OSM) (https://www.openstreetmap.org), an open-source spatial data platform. We cleaned road data and structured a filtered data set to use only pedestrian roads. We also procured other variables through the Open Data Platform of IMM (https://data.ibb.gov.tr/en/).

Land Morphology: To determine the elevation within the study area, we used the Digital Elevation Model (DEM) from the United States Geological Survey (USGS) Raster Dataset (https://www.usgs.gov/). Employing ArcGIS Pro software, we also obtained contour lines from the DEM to calculate the average slope.

Socio-demographic Structure: As the only variable for socio-demographic structure, we obtained population data from the Global Human Settlement Layer (GHSL) generated by the European Commission JRC (https://ghsl.jrc.ec.europa.eu/ghs_pop2023.php). The dataset comprised 250-meter resolution grids. As the research employs a 1 km hexagonal grid for the analysis scale, we aggregated the population data using ArcGIS Pro software.

3.4. Modeling approaches of the research

3.4.1. Global vs. local regression models

Spatial regression analysis enables modeling, examination, and investigation of spatial relationships providing a means to clarify the factors contributing to observed spatial patterns. Conventional or traditional regression methods are classified as global statistics, assuming a consistent relationship throughout space, so the parameter is estimated to be uniform across the entire study area (Tu and Xia, 2008). Within the global model, the parameters are estimated globally and, as a result, do not exhibit spatial variability (Pu et al., 2017). Global models represent the associations between the explanatory and response variables as follows:

$$y_i = \beta_0 \sum_{j=0}^{m} \beta_j x_{ij} + \varepsilon_i \tag{1}$$

where y_i represents the target variable, x_{ij} denotes the value of the j-th predictor variable, m is the number of predictor variables, β_0 is the intercept term, β_j is the regression coefficient for the j-th predictor variable, and ε_i is the random error term.

While the estimates of global regression coefficients can capture the overall relationships, they fall short of representing local variations; the information regarding local dynamics remains insufficient (Chi and Zhu, 2020). Liu et al. (2020) argued that global models operate under the assumption that the geographical environment is spatially homogeneous across regions, potentially obscuring local features in real-world applications. In the modeling of the relationship between dependent and explanatory variables, where these relationships do not vary over space, global models assume spatial stationery (Reda et al., 2023). To enable the variation of variables across space, local models expand the general

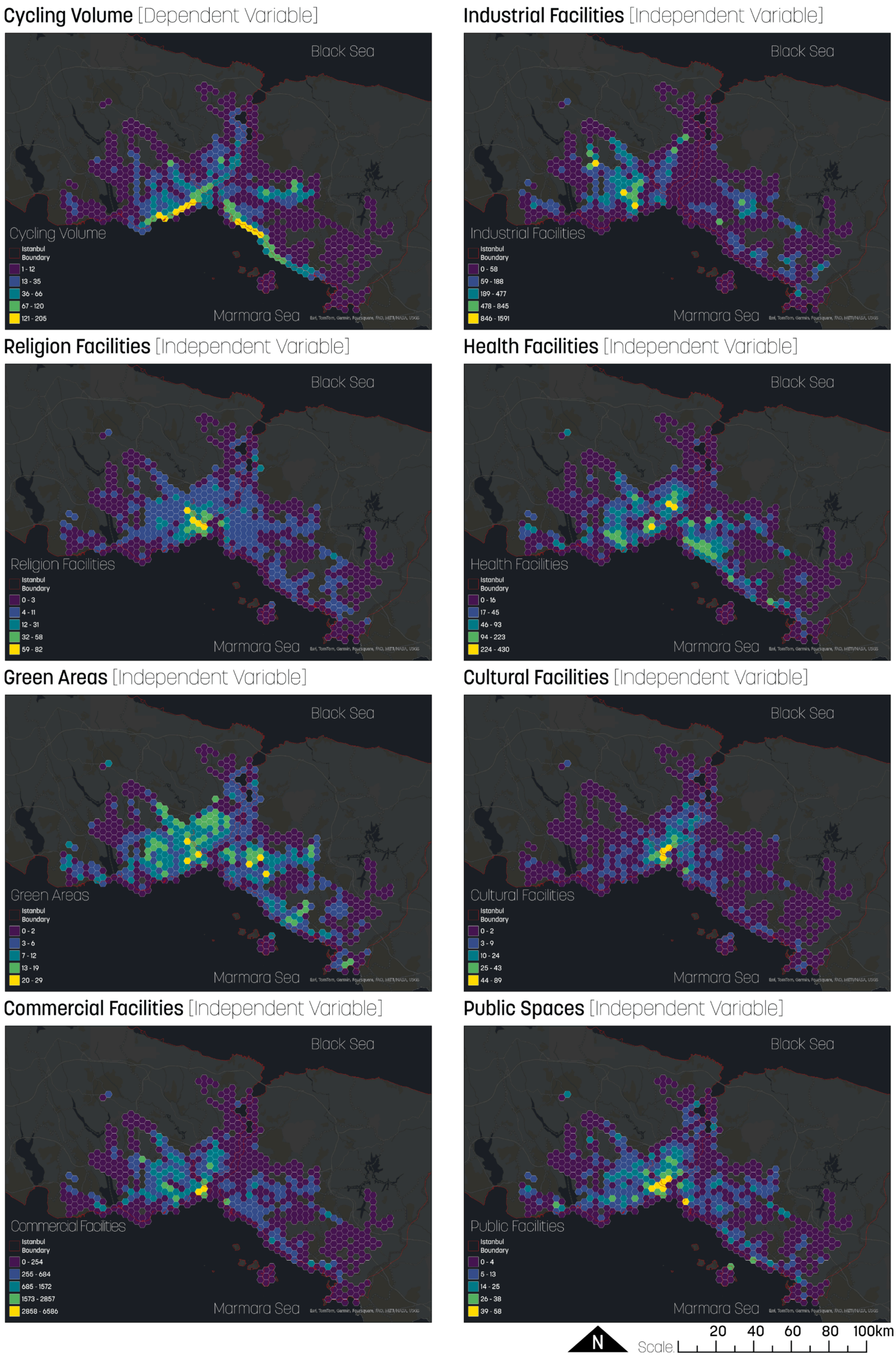

Fig. 4. Spatial distribution of model variables-1.

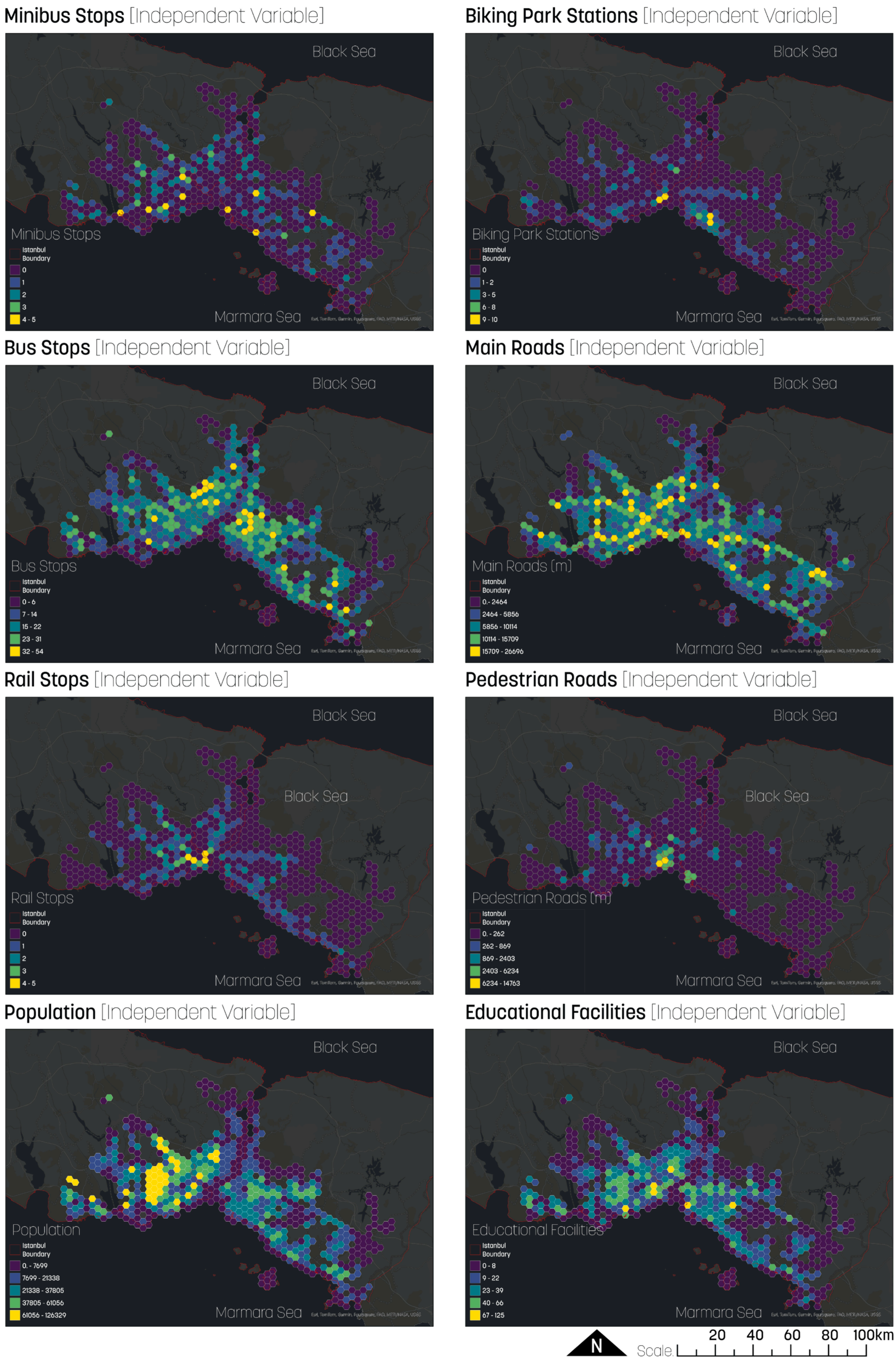

Fig. 5. Spatial distribution of model variables-2.

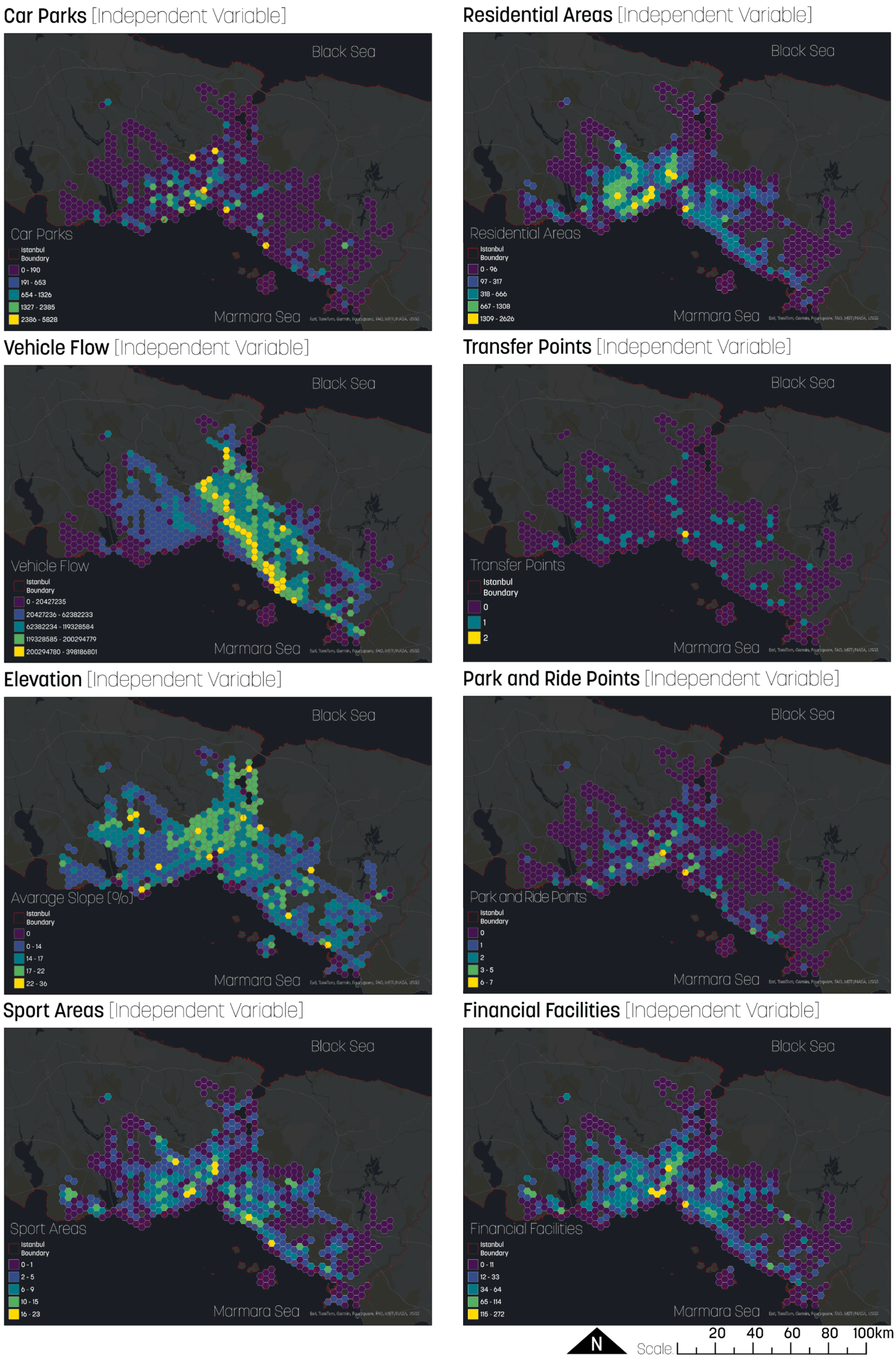

Fig. 6. Spatial distribution of model variables-3.

Table 1
Descriptive statistics of the variables.

Variables (n = 604)	Description	Mean	SD	Min	Max
Dependent Variable(s)					
Cycling Volume	Number of cycling journeys	17.05	28.94	1	205.
Independent Variable(s)					
Point of Interests					
Religious Facilities	Number of religious facilities	5.07	8.84	0.00	82
Green Areas	Number of green areas	4.70	5.05	0.00	29
Commercial Facilities	Number of commercial facilities	277.99	524.67	0.00	6586
Sport Areas	Number of sport areas	3	3.70	0.00	23
Industrial Facilities	Number of industrial facilities	71	156.61	0.00	1591
Health Facilities	Number of health facilities	22.19	38.04	0.00	430
Cultural Facilities	Number of cultural facilities	2.45	6.73	0.00	89
Public Space Facilities	Number of public space facilities	5.88	8.23	0.00	58
Financial Facilities	Number of financial facilities	18.26	26.20	0.00	272
Educational Facilities	Number of educational facilities	15.09	16.90	0.00	125
Residential Areas	Number of residential areas	194.07	330.16	0.00	2626
Transportation					
Transfer Points	Number of transfer points	0.07	0.27	0.00	2
Park and Ride Points	Number of park and ride points	0.35	0.83	0.00	7
Pier Stops	Number of piers stops	0.08	0.39	0.00	5
Minibus Stops	Number of minibuses stops	0.42	0.82	0.00	5
Bus Stops	Number of bus stops	13.66	9.98	0.00	54
Rail Stops	Number of rails stops	0.35	0.77	0.00	5
Bicycle Parking Stops	Number of bicycle parking stops	0.39	1.14	0.00	10
Main Roads	Length of main roads	6635.50	5213.69	0.00	26696.79
Pedestrian Roads	Length of pedestrian roads	195.11	953.65	0.00	14763.68
Car parks	Number of car parks	178.59	518.81	0.00	5828.00
Vehicle Flow	Number of cars	64557835.37	69747562.41	0.00	398,186,801
Land Morphology					
Elevation	Average slope	13.91	5.16	0.00	36.20
Socio-demographic					
Population	Number of people	19644.82	21759.23	0.00	126,329

regression model whilst reducing the spatial stationary assumption (Brunsdon et al., 2002). While spatial non-stationarity and spatial autocorrelation frequently manifest jointly as attributes of geographic data, the application of local models, a prevalent local regression technique, offers a means to mitigate issues associated with both within the conventional framework of global models (Qiu and Wu, 2011).

Furthermore, in spatial analysis, there exist two fundamental factors that have negative influences on global models, especially in OLS: spatial heterogeneity and spatial autocorrelation of observation (Anselin, 2010). Distinctly, local models such as GWR and MGWR overcome these impacts by operating based on Tobler's (1970) first law of geography: "*Everything is related to everything else, but near things are more related than distant things*" (Oshan et al., 2019; Zhou et al., 2023a,b). They consider both the spatial autocorrelation and spatial heterogeneity of observations, making it a widely employed method for investigating spatial non-stationary regression models (Soltani et al., 2018; Zhao et al., 2020).

GWR, one of the prevalently utilized local models, bears similarity to linear regression, differing in that it computes a set of local linear regressions instead of a global one (Chang Chien et al., 2020). It expands upon the conventional regression model or local model by relaxing the assumption of spatial stationarity, thereby permitting spatial variations in the variables across different geographical locations (Brunsdon et al., 2002). The mathematical representation of the GWR model is formalized by Fotheringham et al. (2003):

$$y_i = \sum_{j=0}^{m} \beta_j(ui, vi)x_{ij} + \varepsilon_i \tag{2}$$

where x_{ij} denotes the j-th predictor variable, b_j (u_i, vi) represents the j-th coefficient, ε_i is the error term, and y_i is the response variable.

3.4.2. Multi-scale geographically weighted regression

While GWR represents a notable improvement, the utilization of a uniform bandwidth in a standard GWR may not be suitable in scenarios where diverse independent variables operate across varying spatial scales, thereby possessing distinct spatial relationships with the dependent variable (Zhou et al., 2023a,b). As a result, MGWR undergoes additional improvement. MGWR models address the challenge of varying variable scales and bandwidths by employing the optimal bandwidth specific to each independent variable (Chen et al., 2023). The basic formulation of MGWR can be expressed as (Fotheringham et al., 2017):

$$y_i = \beta_{bw0}(u_i, v_i) + \sum_{j=0}^{m} \beta_{bwj}(ui, vi)x_{ij} + \varepsilon_i \tag{3}$$

where $\beta_{bw0}(u_i, vi)$ denotes the local intercept of the i-th observation, β_{bwj} (u_i, v_i) represents the parameter associated with the j-th independent variable x_{ij}, the term bwj in β_{bwj} denotes the bandwidth utilized for the calibration of the conditional relationship associated with the j-th independent variable, ε_i signifies the random error term, and (u_i, v_i) indicates the spatial coordinates of the i-th observation.

We utilized MGWR in the research since it offers a more flexible and advanced structure than GWR by analyzing the spatial relationship between dependent and independent variables at different spatial scales (Zafri and Khan, 2022). Analyzing relationships at various spatial scales offers flexibility that can help minimize over-fitting, decrease bias in parameter estimates, and alleviate issues related to collinearity (Fotheringham et al., 2017; Oshan et al., 2019).

3.4.3. Model factors for multi-scale geographically weighted regression

A variety of parameters and model options are required to run MGWR. Correspondingly, the selection of the optimal bandwidth represents a crucial stage in the entire process. MGWR employs a distinctive bandwidth for each explanatory variable, thereby accounting for the diverse spatial scales of the coefficients (Lyu et al., 2020). In this research, we employed the adaptive bi-square as the spatial weighted (kernel) approach for estimating the kernel bandwidth. This approach enables the model to effectively capture and analyze spatially varying relationships. It provides more accurate and reliable local estimates by adapting to local data density and it is more flexible in the handling of data density variations.

Another parameter that must be considered when employing MGWR is the searching method. The Golden Section method was employed to identify uniform and locally varying bandwidths. The optimal bandwidth value is identified by successively narrowing the range of values within which the optimal value exists and comparing the optimization score of the model for each. The Gaussian model type for calibrating MGWR ensures a comprehensive understanding of the spatial heterogeneity of relationships between a continuous dependent variable and multiple predictors. This method is employed when the dependent variable is continuous and follows a normal distribution. Moreover, it provides a more localized perception than global regression models. Lastly, the Corrected Akaike Information Criterion (AICc) was employed to optimize the model. The model with the lowest AICc is considered to represent the optimal fit (Fotheringham et al., 2017). Besides, it is useful for the selection of bandwidth in adaptive kernels.

3.5. Computation of the variables

For the spatial aggregation of the variables, we used Hexagon within the scope of the research. Correspondingly, the study area was divided into a grid of hexagons, with 1 km cells. Although the majority of the research in spatial analysis uses square grids (Polisciuc et al.,2016), we preferred to conduct our analyses with hexagons since they reduce sampling bias caused by edge effects of grid shapes (Chien et al., 2020; Duan et al.,2023). This is because hexagons are the closest shape to a circle that can tessellate to form an evenly spaced grid. Furthermore, we preferred hexagons over administrative boundaries because administrative boundaries usually have a limited capacity to exhibit spatial variation. Additionally, administrative boundaries are subject to change over time and spatial dynamics do not necessarily follow the boundaries drawn with a ruler (McKenzie, 2022).

In particular, we employed H3 Hexagons in our research, by utilizing ArcGIS Pro Software. Developed by Uber, H3 is a hierarchical indexing system that uses hexagons to tile the surface of the Earth (Uber Technologies, 2023). H3 hexagons are practical since they are built over a model of the Earth, ensuring their position remains consistent at each resolution. This makes them an ideal standardized grid for use across multiple scales of spatial analysis. Correspondingly, we created 9928 hexagonal cells for Istanbul to be used within the MGWR analysis by utilizing ArcGIS Pro Software. Out of these, 604 cells were used for the analysis as they intersected with cycling volume data.

To spatially aggregate the variables within hexagons we followed several operations aligned with the characteristics of the variables (Figs. 4–6). In this sense, we counted the total number of POI per cell. We also followed the same operations for transport services except for main roads, pedestrian routes, car parks, and vehicle flows. For main roads and pedestrian roads, we calculated a sum of lengths for each cell. Car parks and vehicle flows have been computed as an aggregated sum. As the only variable from socio-demographic data, the population was also figured with the same approach. As a final variable, we overwritten the average slope of the contour lines for each cell. Additionally, we computed the descriptive statistics through R Studio to have a further understanding of the variables (Table 1).

Table 2
Evaluation indices for GWR and MGWR models.

Statistic	GWR	MGWR
R-Squared	0.472	0.756
Adjusted R-Squared	0.372	0.682
AICc	1558.950	1229.685
Sigma-Squared	0.792	0.317
Residual Sum of Square	319.151	163.756

4. Results

4.1. Evaluation index and model comparison

We employed five evaluation indices to assess the comparative performance of the two models by computing R-squared value (R2), adjusted R-squared value (Adjusted R2), corrected Akaike information criterion (AICc), sigma-squared (SS) and residual sum of square (RSS) (Chien et al., 2020; Fotheringham et al., 2017; Shi et al., 2023; Senyel Kurkcuoglu, 2023; Zhou et al., 2023a,b). The R-squared value is a commonly preferred indicator as the measure of the model's goodness of fit. Higher values indicate that the model explains a larger portion of the variability in the dependent variable. AICc serves as a metric for evaluating model performance and can be employed to compare different regression models. A lower value is indicative of a better fit when regarding model complexity. SS is the least-squares estimate of the variance and represents the square of the standard deviation for the residuals. RSS denotes the sum of squared residuals within the model. Smaller values of this statistic for SS and RSS are considered more favourable (Table 2).

The model results demonstrate that the MGWR model outperforms the GWR model. This is evidenced by its lower AICc and RSS, as well as its higher log-likelihood or R-squared values, indicating that the MGWR has a better model fit. The adjusted R-squared value of the model was 0.68, pointing out that 68 % of the variation in cycling volume can be explained by the variables in the model. Additionally, the AICc value of 1229.685 further supports the model's fit to the data. The AICc value for MGWR is 21 % lower, and the R-squared value is 28 % higher.

4.2. Local multicollinearity tests

The presence of multicollinearity among independent variables constitutes a significant concern, as it introduces bias into the outcomes of the model. The Variance Inflation Factor (VIF) serves as a tool for detecting multicollinearity, evaluating the increased variance of an estimated regression coefficient when variables exhibit correlation (Wen et al., 2018). An instance in which the VIF value exceeds 7.5 signifies redundancy within the explanatory variables, while a VIF surpassing 10 indicates a high degree of multicollinearity (Chen et al., 2023). As shown in Table 4 no statistically significant collinearity was detected among the independent variables. So, they are suitable for constructing a regression model and there is no necessity for additional processing. In addition to VIF, the Pearson Correlation Coefficient (PCC) serves as an alternative approach to assessing the impact of multicollinearity, and variables with coefficients exceeding 0.7 are eliminated. (Tang et al., 2019; Li et al., 2023).

4.3. Spatial heterogeneity and autocorrelation tests

The study of spatial heterogeneity and spatial autocorrelation is of significant importance as it allows us to comprehend the robustness and accuracy of model application. Spatial heterogeneity, evident in the diverse characteristics observed at local and global levels, informs our understanding of spatial patterns. This intricate variation across space lays the foundation for exploring the phenomenon of spatial autocorrelation, where nearby observations tend to exhibit similarities. While

Table 3
Summary of independent variables and neighborhoods.

Dependent Variables	Neighbors* (% of Features)	Significance** (% of Features)
Point of Interests		
Religion Facilities	604 (100.00)	0 (0.00)
Green Areas	604 (100.00)	0 (0.00)
Commercial Facilities	604 (100.00)	0 (0.00)
Sport Areas ***	114 (18.87)	147 (24.34)
Industrial Facilities ***	249 (41.23)	94 (15.56)
Health Facilities ***	468 (77.48)	197 (32.62)
Cultural Facilities ***	604 (100.00)	604 (100.00)
Public Space Facilities	604 (100.00)	0 (0.00)
Financial Facilities	604 (100.00)	0 (0.00)
Educational Facilities	604 (100.00)	0 (0.00)
Residential Areas ***	604 (100.00)	604 (100.00)
Transportation		
Transfer Points ***	84 (13.91)	34 (5.63)
Park and Ride Points ***	385 (63.74)	144 (23.84)
Pier Stops ***	385 (63.74)	192 (31.79)
Minibus Stops	520 (86.09)	0 (0.00)
Bus Stops	604 (100.00)	0 (0.00)
Rail Stops ***	468 (77.48)	204 (33.77)
Bicycle Parking Stops ***	604 (100.00)	604 (100.00)
Main Roads ***	190 (31.46)	64 (10.60)
Pedestrian Roads	604 (100.00)	0 (0.00)
Car parks	604 (100.00)	0 (0.00)
Vehicle Flow	604 (100.00)	0 (0.00)
Land Morphology		
Elevation ***	333 (55.13)	101 (16.72)
Socio-demographic		
Population ***	33 (5.46)	73 (12.09)

* The number in the parenthesis ranges from 0 to 100% and can be interpreted local, regional, and global scale based on the geographical context from low to high.
** In the parenthesis, the percentage of features that have significant coefficients of an explanatory variable.
*** Statistically significant independent parameters.

spatial autocorrelation can challenge statistical tests due to its violation of independence assumptions, it also offers valuable insights into spatial clustering and biases within the data.

The spatial heterogeneity analysis results show that the bandwidths associated with population, transfer points, sports facilities, and park-and-ride points can be considered micro-scale, indicating higher spatial heterogeneity. Elevation, industrial areas, and the length of main traffic axes are global-scale variables, thus exhibiting low spatial heterogeneity. Variables with bandwidths between 358 and 603 do not demonstrate spatial heterogeneity (Table 4).

On the other hand, we utilized Moran's I index (Lyu et al., 2020) to investigate spatial autocorrelation. Moran's I values range from -1, indicating perfect dispersion, to $+1$, indicating perfect correlation, with a value of zero interpreted as a random spatial pattern (Pu et al., 2017). Regarding the MGWR models, the global Moran's I of their residuals is much lower (0.037), indicating the successful incorporation of spatial heterogeneity. The insignificant p-value indicates that the null hypothesis, suggesting the absence of autocorrelation, cannot be rejected. The strong model fit (0.756) with weak and statistically insignificant levels of spatial autocorrelation (0.037) in the residuals, implies the suitability of employing this model (Table 4).

4.4. Coefficient analysis of spatial pattern

The population variable demonstrates statistical significance in about 12 % of the observations, indicating its impact on a local scale with 33 neighborhoods (Table 3). The coefficients show variations in regions with significant values, influenced by the demographic structure of Istanbul. In densely populated areas of the Asian continent (central-southern), the coefficients are both significant and low. On the European side, in certain regions with the average population (central-southern), the coefficients are significant and moderate. Additionally, in the northern part of the Asian continent with a relatively lower population, the coefficients are both significant and high.

The variable of sports facilities/areas is significant in 24 % of neighborhoods. The coefficients exhibit statistically significant values in the coastal areas of the Asian side bordering the Sea of Marmara and in the central-eastern sector of the European side. Notably, their influence on bicycle volume is exclusively positive in the regions situated on the Asian side. Health facilities are significant in 32 % of all neighborhoods. The coefficients demonstrate statistical significance across the eastern part of the Asian continent and a substantial area of the European continent where the number and distribution of health facilities are quite high. The residential density variable is insignificant in all observations, while its impact on a global scale with 604 neighborhoods. In the central part of the European side, characterized by high building density, the coefficient values are lower compared to the eastern part of the Asian side, where density is low. Nevertheless, it's noteworthy that the residential density variable shows limited diversity, indicated by its low standard deviation value. The variable of industrial facilities is significant 15 % of observations and it operates at a regional scale with 249 neighborhoods (Table 3). In Istanbul, there exist two primary large-scale organized industrial zones (OIZ): Dudullu OIZ, located in the central part of the Asian continent, and İkitelli OIZ located in the central-eastern part of the European side. The coefficient values are both significant and low on the Asian side, whereas on the European side, they are high but lack statistical significance.

The variable of stop location of urban rail systems is significant in 33 % of observations (Table 3), indicating its impact on a global scale with 468 neighbors. In the eastern part of the Asian region, the coefficients demonstrate statistically significant and higher values. The pier stop variable is significant in 31 % of observations while operating at a regional scale with 385 neighbors. The coefficients show high values in the southern part of the Bosporus on both the east and west sides, as well as in the central-southern part of the European and Asian continents. However, they are statistically significant only in the central-southern part of the European side. The main road length variable has significance in 10 % of the observations, indicating its influence on a local scale with 190 neighborhoods. The observation reveals a concentration of access roads within the city center, particularly in the central region of the European side. In these areas, the coefficients display a significant and high value. Furthermore, notable coefficients are also observed in the central-northern and central-western regions. However, on the Asian side, specifically in areas with bridge connection roads (central west), although a relatively high value is present, it lacks statistical significance. The transfer point variable shows statistical significance in approximately 5 % of the observations, suggesting its impact at a local scale with 84 neighborhoods. Upon analyzing points that facilitate transfers between different modes of transportation, a specific distribution pattern is observed across certain areas of the city. Notably, the coefficients are significant and high in the central-southern region of the European side. The park and ride points variable demonstrates statistical significance in about 24 % of the observations, operating at a regional scale with 385 neighbors. The coefficients are positive across the entire study area but achieve significance only in the eastern part of the Asian continent, where bus and rail stop density is at a relatively moderate level (Fig. 5). The bike park variable displays significance in all observations, with its impact expanding globally across 604 neighborhoods. Notably, the coefficients show positive and higher values in the central part of Istanbul, encompassing two continents and the Bosporus line.

The average slope variable is significant in 16 % of observations while operating at a regional scale with 333 neighbors. In the central-

Table 4
Coefficient values of the variables.

Variable	Mean	STD	Min	Median	Max	VIF	Bandwidth*	ACV of Pseudo-t Statistics**
Intercept	0.028	0.382	−0.396	−0.079	1.758	–	30	3.287
Point of Interests								
Religion Facilities	0.077	0.001	0.076	0.077	0.079	3.117	604	1.975
Green Areas	0.016	0.005	0.010	0.014	0.024	2.810	604	2.016
Commercial Facilities	0.042	0.001	0.040	0.042	0.044	7.188	604	1.980
Sport Areas	0.005	0.185	−0.285	−0.004	0.553	3.438	114	2.779
Industrial Facilities	−0.057	0.107	−0.286	−0.025	0.058	1.651	249	2.466
Health Facilities	0.114	0.021	0.092	0.101	0.156	5.536	468	2.041
Cultural Facilities	0.134	0.001	0.133	0.134	0.135	3.313	604	1.974
Public Spaces	−0.086	0.005	−0.096	−0.085	−0.079	4.406	604	2.019
Financial Facilities	−0.075	0.003	−0.080	−0.075	−0.069	6.912	604	2.006
Residential Areas	0.294	0.004	0.289	0.292	0.302	6.457	604	1.975
Educational Facilities	−0.051	0.004	−0.056	−0.051	−0.046	4.500	604	2.019
Transportation Services								
Transfer Points	0.011	0.105	−0.123	−0.009	0.565	1.241	84	2.911
Park and Ride Points	0.060	0.036	0.011	0.049	0.121	2.667	385	2.190
Pedestrian Roads	−0.039	0.000	−0.040	−0.039	−0.038	4.912	604	1.972
Main Roads	0.032	0.080	−0.125	0.037	0.236	1.380	190	2.646
Pier Stops	−0.060	0.020	−0.094	−0.061	−0.017	1.520	385	2.106
Minibus Stops	−0.001	0.023	−0.029	−0.005	0.034	1.182	520	2.186
Carparks	0.031	0.002	0.027	0.031	0.035	2.044	604	2.022
Bus Stops	−0.005	0.006	−0.012	−0.009	0.008	2.256	604	2.055
Bicycle Parking Stops	0.128	0.002	0.123	0.128	0.132	1.684	604	2.019
Rail Stops	0.063	0.025	0.027	0.060	0.100	1.956	468	2.130
Vehicle Flow	0.001	0.005	−0.005	−0.002	0.009	1.304	604	2.021
Land Morphology								
Elevation	0.034	0.059	−0.066	0.023	0.139	1.198	333	2.458
Socio-demographic								
Population	−0.250	0.529	−3.325	−0.120	0.640	4.068	33	3.225

* Bandwidth for GWR is constant: 344.
** Adjusted Critical Values (ACV) of Pseudo-t Statistics: This value is utilized for assessing the statistical significance of coefficients in a two-sided *t*-test at a 95% confidence level. The value corresponds to a significance level (alpha) of 0.05 divided by the effective degrees of freedom.

southern parts of the European continent, where the average slope is comparatively lower than the northern and eastern sides, the coefficient values are both higher and statistically significant.

5. Discussion

5.1. Implications of model results for data-driven cycling strategies in Istanbul

Numerous studies (Faghih-Imani et al., 2014; Noland et al., 2016; Lyu et al., 2020; Zhou et al., 2023a,b) identified that the size of the population has a positive impact on cycling. They indicated that in areas with a high population density, the prevalence of facilities and services increases accessibility, rendering cycling a convenient mode of transportation for a variety of purposes. In contrast, in the findings, there exists a negative correlation between population and cycling volume. Among the regions exhibiting significant values, a negative relationship is observed in particular in the southern part of the Asian continent. The most significant factor contributing to this situation is the extensive use of a long recreational coastline with bike lanes. As illustrated in Fig. 5, the population along the coastline is notably lower than in nearby regions. Conversely, some densely populated areas on the European side also exhibit low levels of cycling. The primary factor causing the low cycling rates observed in these areas is the lack of adequate infrastructure, which is a consequence of the high housing density (Fig. 7). To increase cycling volume in these areas, there is a necessity to strengthen connectivity between key cycle routes within the city and optimize bike-sharing services in high-demand areas. It is also crucial to integrate cycling into daily routines and to create a continuous cycle network from the city center to the coast, complementing the implementation of coastal strategies.

Elevation, as a natural factor, plays a significant role in influencing the cycling volume among individuals. A high percentage of slope discourages people from using bicycles and directs them to explore different alternatives in route selection. Cyclists generally exhibit a preference for avoiding terrain with significant elevation or hills (Griswold et al., 2011; Chen et al., 2017). The research conducted by Menghini et al. (2010) shows that cyclists tend to prefer routes with lower inclines, avoiding steep gradients. Nevertheless, this observation stands in contrast to the findings of Sener et al. (2009) who identified a stated preference for moderate hills, especially in the context of recreational cycling when compared to flat terrain. An alternative perspective in the literature proposes that regions with steep slopes may serve as a positive motivator for bicycle users, potentially attributed to the wide range of visual perspectives they offer. On the street level, the slope is identified as the most crucial factor, with the green and sky view indexes following in importance (Zhou et al., 2023a,b). In this context, the model results provide parallels with the existing literature. It is evident in the central-southern part of the European side, characterized by a moderate slope (Fig. 7). The region's cultural richness and its elevated position, which affords panoramic views of the Bosporus, have positively influenced the volume of bicycle usage.

Sports areas, as a part of the green ecosystem in the urban environments, are identified as being positively associated with cycling (Fraser and Lock, 2011; Nawrath et al., 2019). The research findings indicate that on the Asian side of Istanbul, the results are consistent with previous studies. The positive and statistically significant impact of sports facilities on cycling volume in the Asian continent can be attributed to the

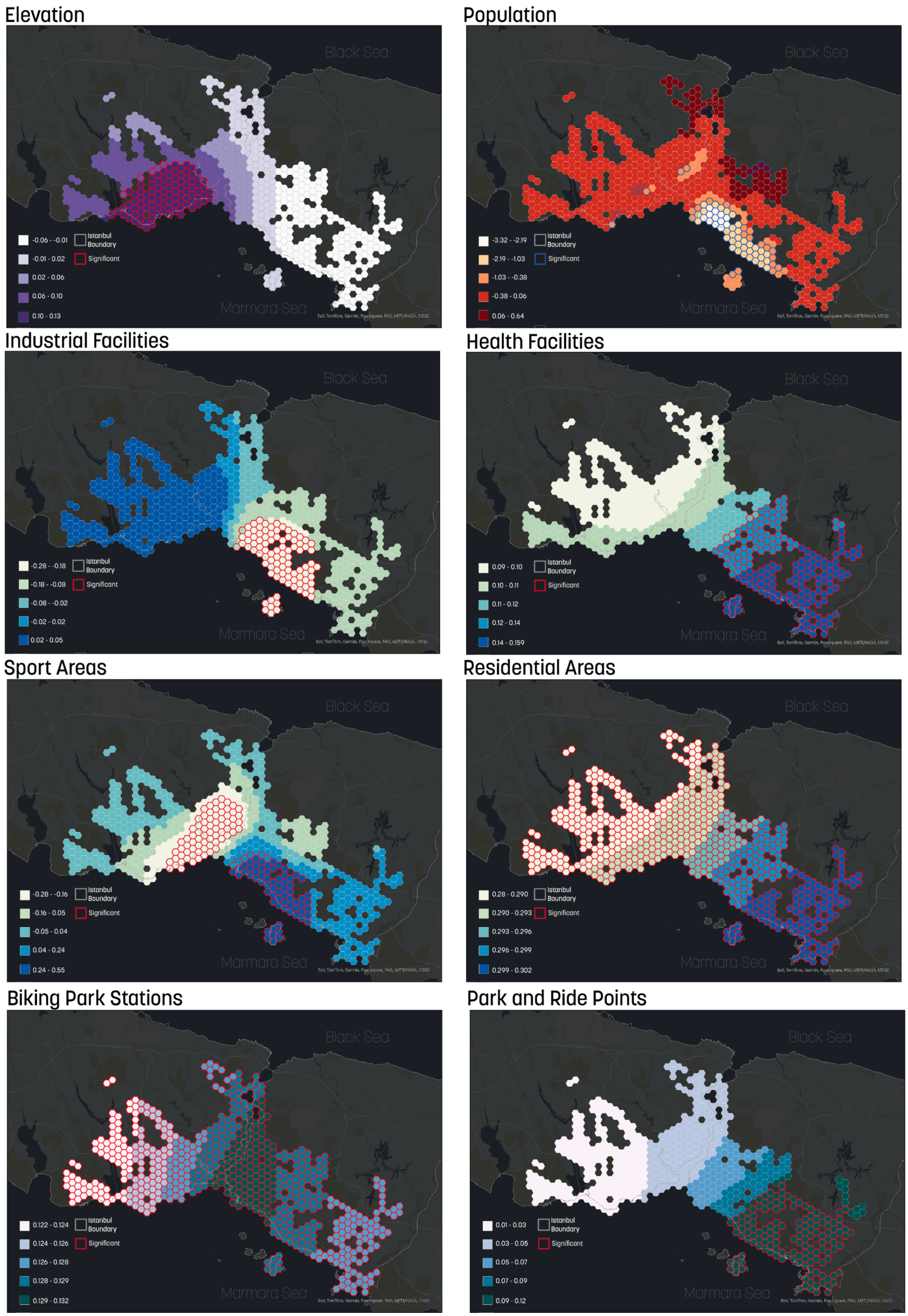

Fig. 7. Spatial distribution of significant parameter coefficients for MGWR-1.

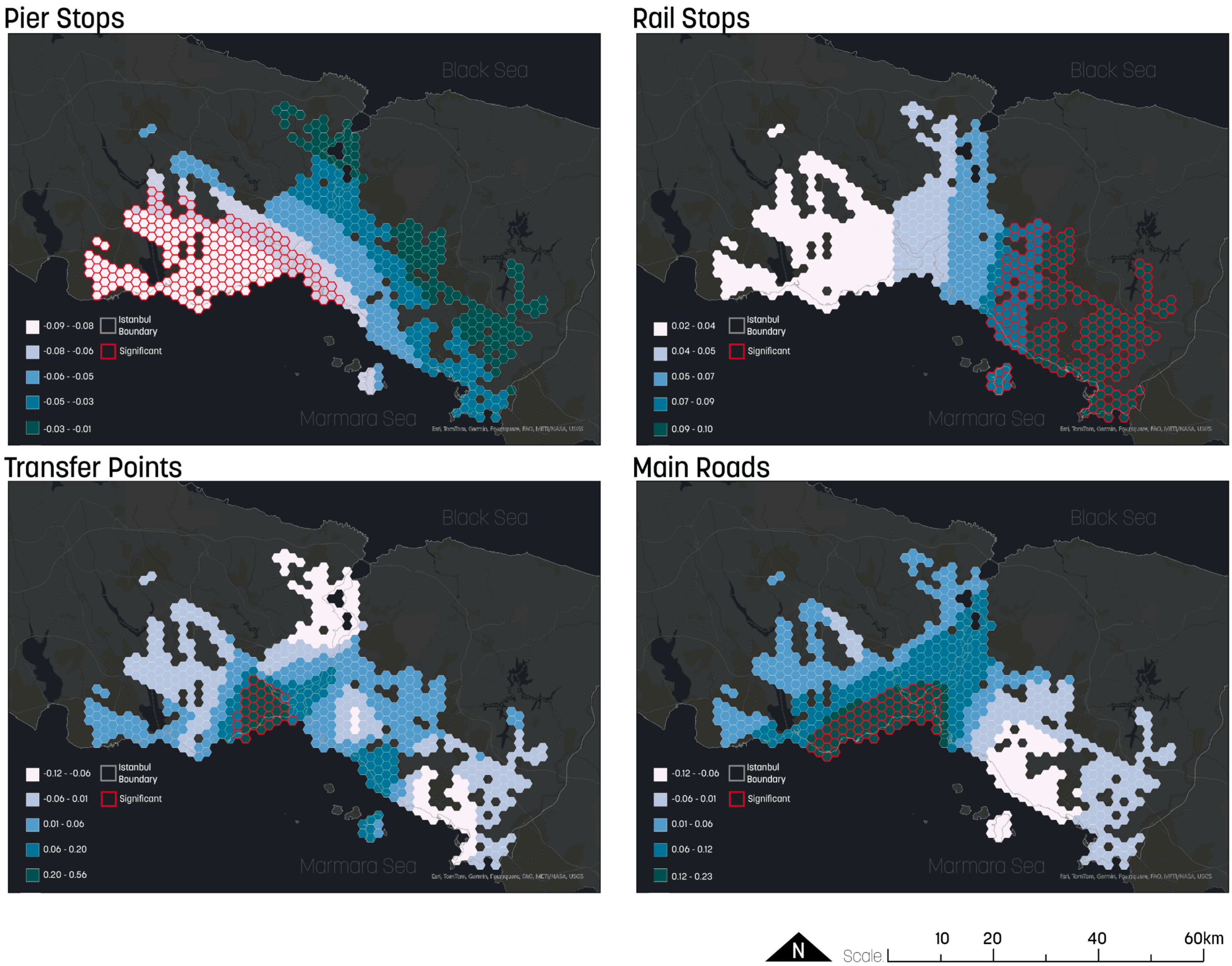

Fig. 8. Spatial distribution of significant parameter coefficients for MGWR-2.

extensive, public, and mixed-use characteristics of the coastal areas. This enables urban residents to prioritize their preference for cycling in these specific regions. On the other hand, on the European side, it is observed that the statistically significant areas have a negative impact on cycling volume. The primary cause of this phenomenon is the high residential density, which has resulted in the distribution of sports facilities in a small and fragmented manner. This case has the effect of discouraging people from utilizing their bicycles in sports areas.

The impact of housing density on cycling volume shares several characteristics with the population variable in many aspects. Extensive residential areas encompass various built environment elements within proximity, such as commercial establishments, schools, and green spaces, and individuals are likely to prefer cycling for short distances (Zhou et al., 2023a,b). In contrast, Cheng et al. (2022) observe that regions characterized by high residential density often signify a large population. In densely populated areas, there might be a discouragement for cycling due to factors like traffic congestion and road safety. The spatial organization of the built environment has a significant influence on cycling volume in a city. Cycling may primarily depend on the arrangement of the residential neighborhood, ensuring that destinations and activities are conveniently situated within a suitable cycling distance (Xing et al., 2010). The results reveal that in all observed grids of Istanbul, residential density has a statistically significant and positive impact on cycling volume (Fig. 7). This positive correlation suggests that higher residential densities contribute to increased cycling activity. The findings underscore the importance of considering residential density in urban planning and policy-making to promote cycling. Strategies to increase residential density, such as mixed-use developments and cycling-friendly living environments, could be effective in boosting cycling rates in Istanbul. In light of the findings regarding population parameters, targeted investments in cycling infrastructure in high-density areas could serve to amplify the positive impact of residential density on cycling volume.

Transfer points play a critical role in providing interchange facilities for urban rail systems, maritime routes, and rubber-wheeled transportation modes. Public transport systems cannot ensure door-to-door service due to constraints of limited station accessibility; thereby they need to be consolidated by different modes. Integrating different modes of public transport with cycling has a great impact on providing urban accessibility and route flexibility of public transport by easing first- and last-mile connectivity (Fu et al., 2023). This integration increases the traveling efficiency of individuals as well as the service level of the public transport system (Ma et al., 2023). The availability of diverse transportation options in these areas may positively influence the volume of cycling, as individuals favoring these transportation modes may opt for bicycles to access the region. The central areas of the European side and western part of the Asia side of Istanbul provide crucial transfer points for various modes of public transport such as bus, bus-rapid transit, metro, tram, and ferry. In parallel, the model results present a positive influence on the central area of both sides of the city, with statistical significance observed in central Europe, including the Historic Peninsula. It is noticeable that one of the most prominent tourist attractions of Istanbul could be enhanced through the implementation of active cycling initiatives, which would require the development of comprehensive and inclusive public transport strategies.

The distribution of urban facilities and services directly related with the planning of urban transport systems and preferences of individual mode choices. In explaining the relationship between the urban amenities and levels of cycling, several studies (Griswold et al., 2011; Chen et al., 2017; Sun et al., 2017; Ji et al., 2023; Zhou et al., 2023a,b) have relied on land-use mix. In alignment with the existing discussions, we analyzed the urban facilities. Furthermore, we explore all the facilities independently to ensure more accurate results in terms of explaining the relationship with cycling volume. Correspondingly, for health facilities, it is observed that they are concentrated in the central and eastern regions of the European side and the western part of the Asian side (Fig. 4). In addition to the model results indicating a positive effect on Istanbul as a whole, there is also a statistically significant result on the Asian side. Although there is a high density of health facilities on the European side, the intensity of bicycle routes and usage on the Asian side, especially along the coast, is the main reason for the importance of these regions. From this perspective, strategies to enhance the utilization of bicycles, particularly for accessing healthcare facilities, appear to be highly relevant and practical on the European side. The distribution of workplaces in the city and their proximity to residential areas is a crucial factor influencing the utilization of bicycles (Dai et al., 2023). The significant and positive impact of the coefficients in these regions indicates that for accessing work and urban services, individual preferences are concentrated around cycling, particularly for short distances. In this regard, industrial facilities present relevant results with the literature. They have a negative influence on both the Asian and the parts of the European side close to the Bosporus. However, they represent a positive influence on the central and western European sides. Notably, the model results show a statistically significant negative effect in the central and southern regions of the Asian side. The fundamental reason underlying this is that the residential zones are predominantly situated on the Asian side, while industrial zones are mostly on the European side. In contrast, the central areas of the European side, which concentrate industrial facilities, experience a positive effect. It provides an opportunity to support the transition towards cycling as an active commuting mode, attributable to the investment in cycling infrastructure in these regions.

Several studies (Sun et al., 2017; Zhou et al., 2023a,b) have proved that there is a negative correlation between vehicle (road) density and bicycle usage volume. However, as is common practice in Türkiye, the bicycle lanes are typically integrated into main road axes and share the same infrastructure and routes with vehicles. This configuration may facilitate increased cycling activity, particularly in areas where the length of vehicle routes is extensive. In contrast to the findings of previous studies, the density of main roads in Istanbul has a positive effect on cycling, except for the eastern part of the city. This parameter, which is statistically significant in particular in the coastal part of the Anatolian side and the central and southern part of the European side, demonstrates the importance of route selection for bicycle road networks. Therefore, it is of great importance that the strategies to be developed for the new construction of new bicycle lanes are informed by this understanding (Fig. 8).

Stop density of different modes have the potential to encourage individuals to utilize cycling as a mode of transportation (Ji et al., 2023; Zhou et al., 2023a,b). One strategy for enhancing the appeal of cycling is to integrate it with alternative modes of public transportation, such as ferries and metro systems. This integration can facilitate the transition from one mode of transportation to another, making cycling a more viable option for commuters. Concerning marine transportation in urban areas, the coefficient tends to exhibit positive values in regions along the Bosporus coasts where the piers are concentrated. This suggests that formulating policies to encourage bicycle users to utilize ferries has the potential to enhance bicycle usage between the two continents. The same principle can be applied to the Marmaray suburban rail line, which connects the Asia and Europe sides of Istanbul. The provision of access on the east–west axis enables bicycle users to engage with a broader array of built environment elements, thereby contributing to an increase in the volume of cycling. (Fig. 8).

Integrating bicycles as feeders into the park-and-ride system can enhance accessibility at different spatial scales such as street level or neighborhood level. As an example, the Netherlands Ministry of Transport initiated the "Space for the Bicycle" project to enhance the efficiency of bike parking facilities around metro stations. The enhancements have shown some impact on the use of cycling, with approximately 11 % of the respondents indicating that improved bicycle parking facilities were a motivating factor to travel more frequently by bicycle to the train station (Martens, 2007). Park-and-ride facilities can attract individuals who may not prefer cycling as their main mode of transportation but are willing to use it for part of their journey. This could result in an overall increase in cycling volume, even if it is not the primary mode of transportation. In this research, the Park and Ride parameter has a positive influence on all observation grids within Istanbul. The statistical significance of this parameter, particularly in the eastern part of the city, where residential areas are dense, provides a foundation for further discussions on the potential of bicycles as an effective means of transport for accessing residential and work areas. Furthermore, the positive effect observed on the European and Asian coasts can be utilized as a valuable input for the formulation of policies, creating a potential for effective bicycle usage on the north–south axis in addition to the east–west direction.

5.2. Limitations of the research and further directions

As is the case with the majority of studies addressing comparable issues, this study is subject to some limitations. The first of these relates to the type of variable included in the study. Including climatic conditions in the research on bicycle use can provide a more comprehensive understanding of the dynamics involved. Climate can significantly influence people's willingness and ability to use bicycles for transportation. As was mentioned in Section 2.1, many of the studies covered climatic factors (Tin Tin et al., 2012; El Esawey et al., 2013; Gosse & Clarens, 2014; Chen et al., 2017; Hong et al., 2020; Zhou et al., 2023a,b). Further research can establish a broader framework by incorporating climatic factors into a comprehensive analysis of spatial variables. The second limitation is about methodology. A substantial body of literature, including the present research, employs a methodological approach that predominantly focuses on linear relationships between variables. However, there is limited research exploring non-linear relationships (Sun et al., 2018; Cheng et al., 2022; Ji et al., 2023). In further studies, it is possible to conduct comparative analyses of linear and non-linear relationships between various spatial variables, thereby providing a comprehensive perspective on the existing literature.

6. Conclusions

This study employs multi-scale geographically weighted regression to investigate the effects of different spatial dynamics on cycling volume under the local scale. Upon assessing the benefits of local models in contrast to global models, the study identified the most suitable model through a comparative analysis of two distinct local models using performance criteria. A comprehensive data set was created by categorizing 24 different variables related to the built environment, transport services, land morphology, and socio-demographic structure as independent variables and bicycle volume data were determined as the dependent variable. It is observed that POIs, including sport, health, and industrial facilities, along with residential density; transportation

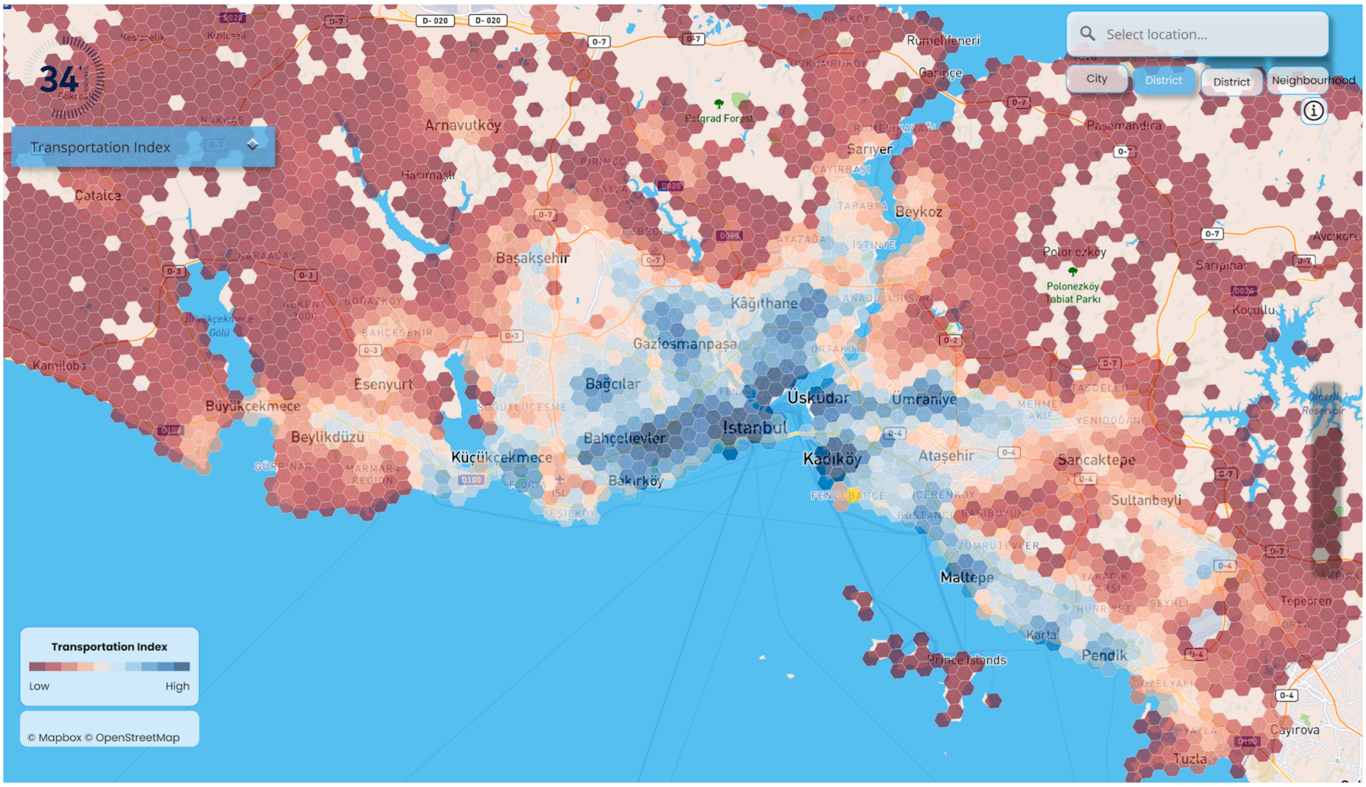

Fig. 9. Transportation index for the 34-Minute Istanbul project.

services encompassing transfer points, park and ride points, piers, railway stops, road length, and bike parks; as well as land morphology represented by slope, and socio-demographic variables such as population, significantly influence cycling volume. Furthermore, the impacts of these distinctive variables on cycling volume exhibit diversity in various regions. The results provide a comprehensive perspective on the understanding of the impact of spatial characteristics on the volume of cycling. The findings hold significance for the advancement of data-driven methodologies and the implementation of developed strategies at both micro (local) and macro (urban) levels.

By considering the current practice of data-driven decision-making in Istanbul, one could argue that the research approach is also highly relevant given IMM's recent work in the context of data-driven decision-making. Most recently, IMM launched a project called *34-minute Istanbul*, an interactive, dynamic, and data-driven planning tool for accessibility planning. The project uses hexagonal grids for analysis and displays areas where daily needs can be met by walking on different themes. One of these categories is transport (Fig. 9), and our research provides a practical basis for further exploring the transport theme of cycling.

By integrating the analytical methodology and significant variables as an extra layer for the platform, further indices can be developed for citizens in the context of cycling accessibility. IMM also recently declared the Istanbul Sustainable Urban Mobility Plan (SUMP). The plan has nine key objectives, including stimulating the modal shift to active modes – walking and cycling – (IMM, 2022, p.18). Furthermore, data-driven decision-making is one of the critical principles of the governance framework of the project. Herein, the model approach of this research has the potential to enable decision-makers to prioritize the allocation of resources to areas in need of cycling investment, promote carbon-free transport, and improve the overall cycling experience by providing a cycling-friendly urban environment in Istanbul.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Google Gemini and ChatGPT to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Seçkin Çiriş: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mert Akay:** Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ece Tümer:** Writing – original draft, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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