

Demand Prediction and Influencing Factors Analysis of Shared Bicycles near Public Transportation Stations based on GCN

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Abstract. Traffic prediction is a pivotal technology in the development of intelligent transportation systems. Real-time and accurate traffic prediction holds significance in route planning, resource allocation, and improving travel efficiency. To enhance the convenience of shared bicycle travel near public transportation hubs and optimize shared bicycle deployment strategies, this paper proposes the utilization of a graph convolutional neural network prediction model. Initially, shared bicycle travel data is scrutinized for spatiotemporal characteristics. Subsequently, an adjacency matrix is constructed based on the spatial attributes of the data to establish the graph convolutional network. Lastly, global spatial autocorrelation analysis and a coupled coordination model are integrated for validation and augmentation. This model is employed to predict shared bicycle travel patterns near public transportation hubs in the Xiamen Island area. Experimental results demonstrate a high level of precision, underscoring the model's effectiveness in providing valuable guidance for shared bicycle travel. The effectiveness of this method can be further verified in subsequent empirical studies.

Keywords: Shared bikes, smart traffic, GCN, time-space analysis.

1. Introduction

Amid the global challenges posed by climate change and worsening pollution, the principles of green transportation and environmental preservation have become deeply ingrained in the collective consciousness. Since the advent of bike-sharing services, shared bicycles have gained widespread popularity worldwide owing to their flexible mobility options. Currently, hundreds of cities across the globe have implemented public bike-sharing systems [1]. On one hand, public bicycles, as a mode of transportation, generate no exhaust emissions and consume no energy. On the other hand, the utilization of public bikes can, to some extent, reduce the dependence on traditional car travel, thus further mitigating urban traffic congestion, promoting public health, and lowering urban carbon emissions [2-3]. The deployment of public bike-sharing systems is highly adaptable and complements existing urban public transportation modes such as buses and subways. Passengers have the flexibility to rent bicycles from any self-service bike station and return them to any station after completing their journeys. In contrast to conventional public bicycles, shared bikes offer users greater flexibility in choosing routes and travel modes at their destinations, thanks to their inherent mobility and free parking features [4]. This accessibility has led to their widespread adoption and garnered significant attention from the public. Consequently, since the introduction of shared bikes in cities, their growth rate has been exceptionally rapid.

Nonetheless, merely increasing the quantity of deployment does not automatically translate to an improved urban transportation service capacity. In fact, it often gives rise to a range of urban challenges, including widespread indiscriminate parking and management difficulties. Currently, there is a growing interest in harnessing scientific methodologies from academia to effectively manage shared bike systems.

Predicting the demand for shared bicycles is a key research area aimed at addressing the challenges associated with shared bicycle systems. Borgnat, for instance, leveraged historical data from Lyon's bike-sharing system to forecast hourly demand on a daily basis, employing a combination of models

[5]. Bo utilized LSTM and GRU to predict shared bicycle trips in Suzhou, with results indicating that GRU exhibited advantages in training time, whereas LSTM proved more suitable for long-term time series predictions [6]. Chen employed a BP neural network to predict the dispatch demand of public bicycle single stations and uncovered the temporal distribution patterns of bicycle flow [7]. In recent times, numerous scholars have applied machine learning techniques to forecast demand [8, 9]. However, there is currently limited research within the academic community on free-floating, stationless shared bicycles with real-time availability, necessitating consideration of both spatial and non-spatial travel attributes.

Hence, this paper aims to initiate the prediction of shared bike demand by harnessing the capabilities of advanced deep learning models, particularly Graph Convolutional Networks (GCN), to forecast the demand for shared bikes in proximity to public transportation stations. Graph Convolutional Networks (GCN) represent a category of neural networks meticulously designed for handling graph-structured data, where data points are depicted as nodes within a graph, and their interconnections are represented as edges. GCNs have garnered significant acclaim for their efficacy in a wide range of tasks involving graph data, including node classification, link prediction, recommendation systems, and social network analysis. Given that traffic volume forecasting data can be effectively captured through the traffic network's graph structure, GCN can directly harness this structural information to extract local features and process interconnected irregular data, thereby facilitating the task of traffic prediction.

2. Area and Data Sources

2.1. Study Area

This article centers its focus on a case study of Xiamen, a highly urbanized city situated in the southern region of China as depicted in Fig. 1 (a) and (b). Xiamen boasts a substantial population, attracts a considerable number of tourists, and possesses a predominantly flat topography. These factors contribute to an immense market potential for shared bicycles. Simultaneously, the adaptability, accessibility, and affordability of bike-sharing have solidified its status as a successful component of Xiamen's multi-modal public transportation system. It serves as a last-mile commuting solution and seamlessly integrates with other public transportation options. According to the "2021 Xiamen Urban Resident Travel and Transportation Survey," Xiamen has maintained a stable proportion of green commuting, with 65.2% to 76.5% of island residents opting for environmentally friendly transportation modes. Notably, the use of slow transportation modes, including walking, electric bicycles, and traditional bicycles, has steadily increased, establishing them as the dominant means of travel within the city. Collectively, these slow modes now account for 47.5% of all transportation methods employed by city residents.

The thriving shared bicycle market and active bicycle usage present promising research opportunities for the integration of shared bicycles with public transportation. Xiamen serves as an ideal case study for examining the synergy between "shared bicycles + public transportation" in multi-modal integration. This research offers valuable insights into the development of more efficient multi-modal transportation models and deepens our understanding of their relationships with urban demographics, built environments, and other pertinent factors. It's worth noting that this research narrows its geographic scope to focus on the most densely populated districts, namely HuLi and SiMing, collectively known as Xiamen Island.

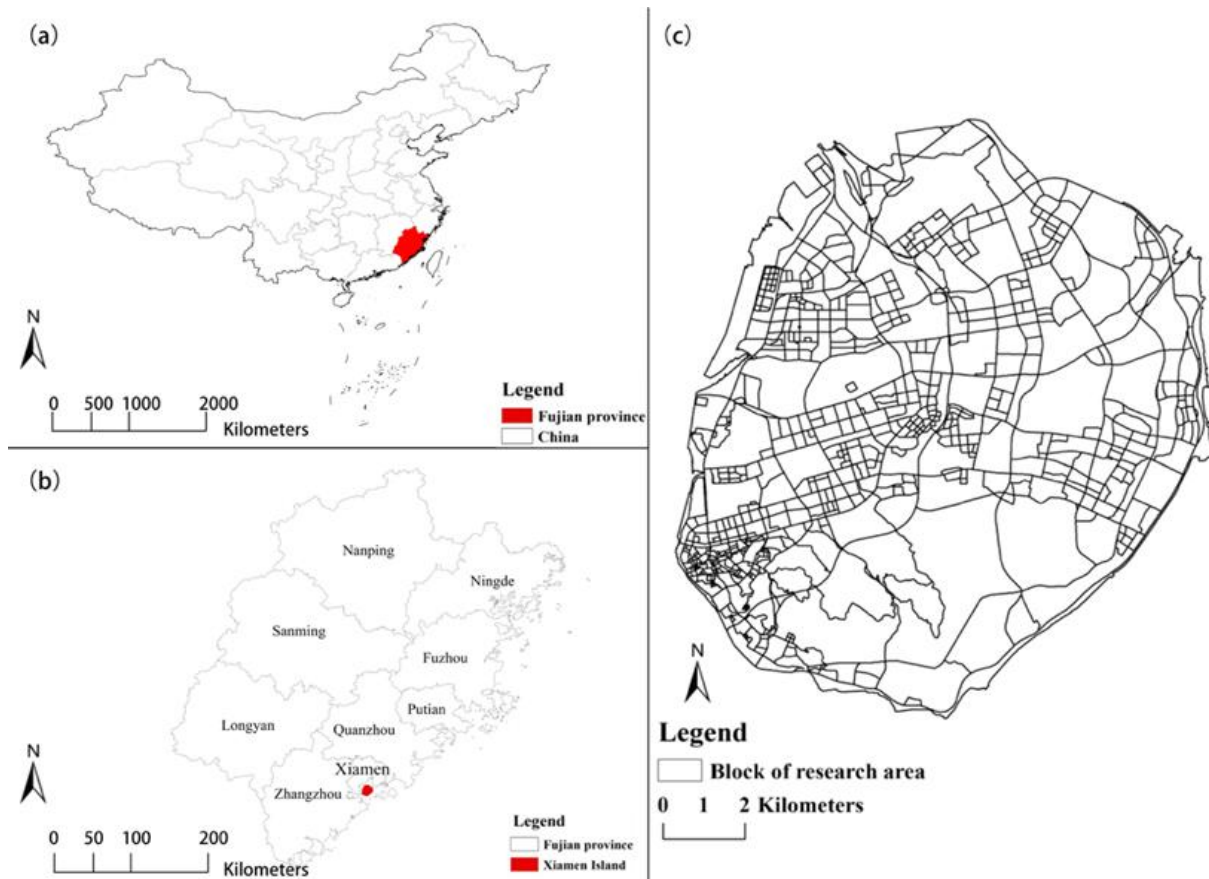


Fig. 1 Site selection (a), (b) and road network (c)

2.2. Data Sources

The data utilized in this study primarily comprises: 1) Shared Bike Trajectory Data: The study relies on shared bike trajectory data collected between December 21 and December 25, 2020, during the hours of 6:00 AM to 10:00 AM, sourced from Xiamen City. This dataset was provided by the 2021 Digital China Innovation Contest and includes attribute fields like vehicle ID, timestamp, latitude, longitude, and date. Further details and statistics regarding the collected data can be found in Fig. 3. 2) Points of Interest (POI) Data: The study incorporates Points of Interest (POI) data for Xiamen Island, gathered using Python through the Baidu Map Open Platform. The POI data encompasses various types, including transportation-related stations such as MRT (Mass Rapid Transit) stations and bus stations, along with other relevant categories.

3. Methods

3.1. GCN

The Graph Convolutional Network (GCN) is a neural network architecture that has garnered increasing popularity in recent years. What sets GCNs apart from traditional network models like LSTM and CNN is their exceptional capability to handle non-Euclidean structured data and effectively extract deep feature information. In practical scenarios, shared bicycle transportation displays irregular patterns, which can be viewed as a form of non-Euclidean structure. By leveraging graph convolutional neural networks to analyze road networks, we can effectively capture spatial correlations present in traffic data. This, in turn, enhances our ability to make more accurate predictions.

Maximizing the utility of limited data, this paper endeavors to create an efficient predictive model for shared bicycle journeys near public transportation stations. The database encompasses both pickup

and drop-off locations for shared bicycles, collectively referred to as "travel points," and the objective is to forecast the connection between the positions of public transportation stations and the overall volume of shared bicycle trips. In this investigation, we adopt a graph-based methodology, employing spectral domain graph convolution [10]. Within the framework of spectral domain graph convolution, the graph is depicted by its corresponding Laplacian matrix, denoted as " L ."

$$L = D^{-\frac{1}{2}}(D - A)D^{-\frac{1}{2}} = I_N - D^{-\frac{1}{2}}AD^{-\frac{1}{2}} \quad (1)$$

Where D is the degree matrix, defined as $D_{ii} = \sum_j A_{ij}$, I_N is the identity matrix of size $N \times N$. Performing eigenvalue decomposition on L :

$$L = U\Lambda U^T \quad (2)$$

Where Λ is a diagonal matrix composed of the eigenvalues of L . $U = \{u_1, u_2, \dots, u_N\}$ consists of the eigenvectors of L corresponding to a set of orthogonal bases in the space $\mathbf{R}^N$.

Graph convolution is an equivalent replacement of classical convolution operators by linear operators defined diagonalization in the Fourier domain. The graph G is convolved with the convolution kernel $g\theta$.

$$g_\theta^* x = U g_\theta U^T x \quad (3)$$

In this paper, the interlayer propagation formula of spectral domain convolution is adopted:

$$H^{l+1} = \sigma(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^l W^l) \quad (4)$$

Where σ represents the activation function; $\tilde{A} = A + I_N$ means that the adjacency matrix is self-looped, and the features of the center node can participate in the convolution by adding the identity matrix. $\tilde{D} = \sum_i \tilde{A}_{ij}$ and $H^l \in \mathbf{R}^{N \times F}$ represent the activation value of the first layer. And $H^{(0)} = X$, where X is the starting input value. $W^l \in \mathbf{R}^{F \times F}$ represents the learning parameter of the first layer.

Since the research goal of this paper is to travel by shared bicycles, the travel points of shared bicycles are defined as nodes, the connection relationship between travel points and public transport stations is defined as edges, and the overall road network is abstracted as an undirected graph. This paper defines the traffic network as $G(V, E, A)$. Where, $V \in \mathbf{R}^N$ is the vertex, that is, the section in the road network; $E \in \mathbf{R}^{N \times N}$ is the edge, that is, the link between the sections in the traffic network; $A \in \mathbf{R}^{N \times N}$ is the adjacency matrix, that is, the adjacency relationship between every 2 sections in the traffic network. For the construction of adjacency matrix, the method used by most scholars is to determine the element value corresponding to the adjacency matrix based on the Euclidean distance or Mahalanobis distance between nodes [11]. In order to avoid the problem of limiting the model parameter updating due to the constant construction of the adjacency matrix, the gradient updating method is chosen to make the model dynamically update the lead matrix according to the loss function during the training process, so that the graph structure is closer to the reality (Figure 2).

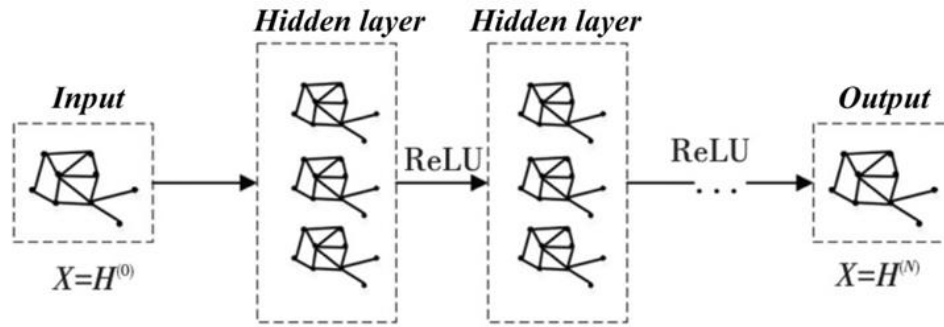


Fig. 2 Convolution structure

3.2. Spatial Autocorrelation

To determine if there exists spatial autocorrelation among shared bicycle journeys near public transportation stations in various regions, this paper investigates whether these journeys display any systematic clustering tendencies in their spatial arrangement. Moran's Index is utilized to assess the spatial autocorrelation of shared bike journeys around public transportation stations. The formula for Moran's Index is as follows:

$$I = \frac{n}{\sum_{i=1}^n \sum_{j=1}^n w_{i,j}} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n w_{i,j} z_i z_j}{\sum_{i=1}^n z_i^2} \quad (5)$$

Here, z_i is the deviation between the vibrancy of i th Area and the mean value of vibrancy of all Area, $w_{i,j}$ is the spatial weight between i th and j th Area, which is measured by the reciprocal distance between the centers of these two Area. The above spatial autocorrelation analysis can be completed in the spatial statistics toolbox of ArcGIS version 10.2.2. ArcGIS is a software produce of ESRI company, which is located in California, USA.

3.3. Coupling Coordination Degree

The coupling coordination degree can serve as an indicator to evaluate the demand for shared bicycles near public transportation stations and the degree of coordination with other subsystems. It helps in understanding the interactions and interdependencies between different regions. The specific steps for its calculation are as follows:

Step1: Normalize the shared bicycle travel data and POI (Point of Interest) data.

$$y = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (6)$$

Step 2: Gridize the shared bicycle travel data and POI data in 100m*100m.

Step 3: Calculate the coupling coordination degree between the two [12,13].

$$C = \frac{2\sqrt{U_1 U_2}}{U_1 + U_2} \quad (7)$$

$$T = \sum_{i=1}^n \alpha_i \times u_i, \sum_{i=1}^n \alpha_i = 1 \quad (8)$$

$$D = \sqrt{C \times T} \quad (9)$$

Where, C is the coupling degree, T is the evaluation comprehensive index, and D is the coupling coordination degree.

4. Results and Discussion

This study focuses on the shared bicycle trip data in the Xiamen Island area from December 21st to 25th, 2020, during the time period of 6:00 AM to 10:00 AM. An overview of the data volume is shown in Figure X. On December 21st, the total number of shared bicycle trip orders was 103,920 (52,473 unlock orders and 51,447 lock orders). On December 22nd, the total number of shared bicycle

trip orders was 109,518 (55,251 unlock orders and 54,267 lock orders). On December 23rd, the total number of shared bicycle trip orders was 38,879 (19,566 unlock orders and 19,313 lock orders). On December 24th, the total number of shared bicycle trip orders was 100,169 (50,636 unlock orders and 49,533 lock orders). On December 25th, the total number of shared bicycle trip orders was 232,806 (182,399 unlock orders and 50,407 lock orders). In terms of trip times, the number of trip orders from 6:00 AM to 7:00 AM was 42635, from 7:00 AM to 8:00 AM was 168299, from 8:00 AM to 9:00 AM was 269416, and from 9:00 AM to 10:00 AM was 104942 (Figure 3).

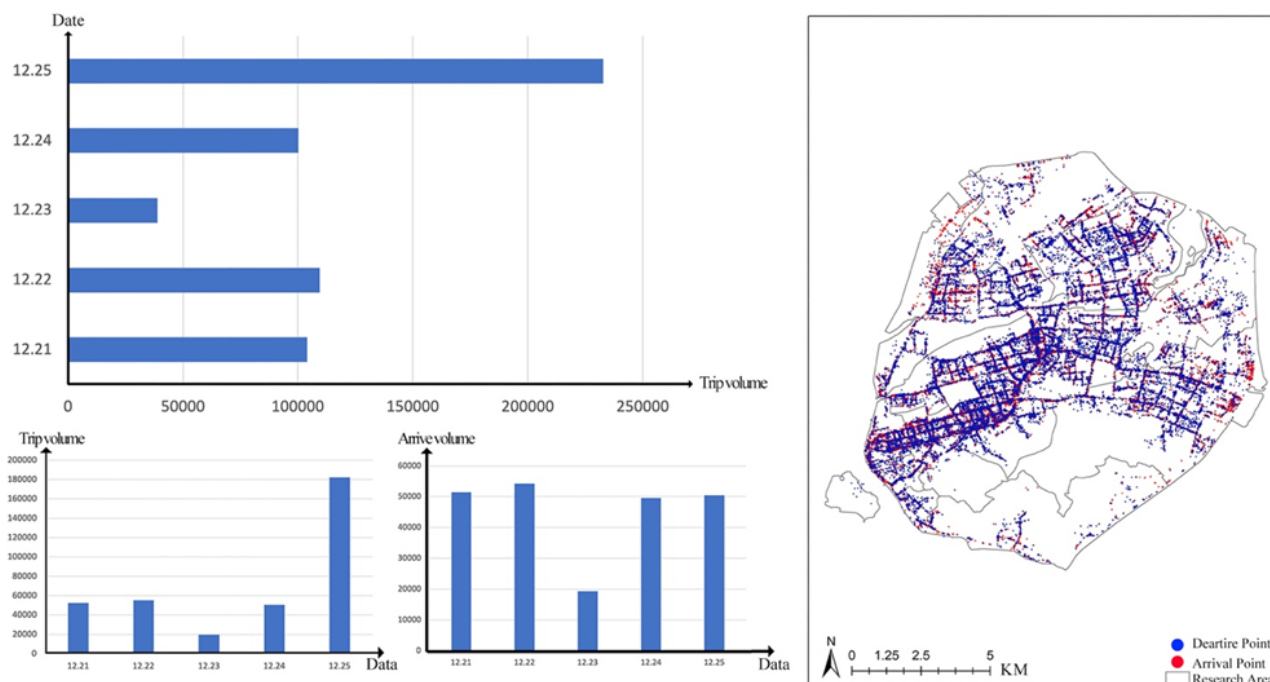


Fig. 3 Data summary

The travel origins and destinations were subjected to kernel density analysis in ArcGIS, resulting in the map shown below. Within the Xiamen Island area, the weekday shared bike trips exhibit a pattern of "large aggregation, small dispersion." For this study, data from the unlocking of shared bikes on five weekdays and the unlocking and locking data during the morning peak hours (7:00 AM - 8:00 AM and 8:00 AM - 9:00 AM) were selected for hotspot analysis of shared bike travel. Analyzing the density of all shared bike unlocks from 6:00 AM to 10:00 AM on weekdays, the hotspot areas for travel are observed around areas such as Hubin South Road, Luling Road, Xian Yue Road, and the Ring Road. Specific travel concentrations are observed at metro Line 1 stations like Wenzao, Lianban, Hubin East Road, and Wushi Pu stations; and metro Line 2 stations like Hubin Middle Road, Lücuo, Gudi Stone, and Houpu stations. Considering different time periods, during the peak travel hours of 7:00 AM - 8:00 AM, the high-density distribution areas for travel are around Xahe Road and Hubin South Road near Wenzao station; Luling Road and Jiahe Road near Lücuo station; areas near Jiangtuo and Houpu stations; areas near Gudi Stone station; and areas near Huli Innovation Park station. From 8:00 AM - 9:00 AM, the high-density distribution areas for travel are similar to the aforementioned locations, but the heat map is notably smaller than during 7:00 AM - 8:00 AM (Figure 4).

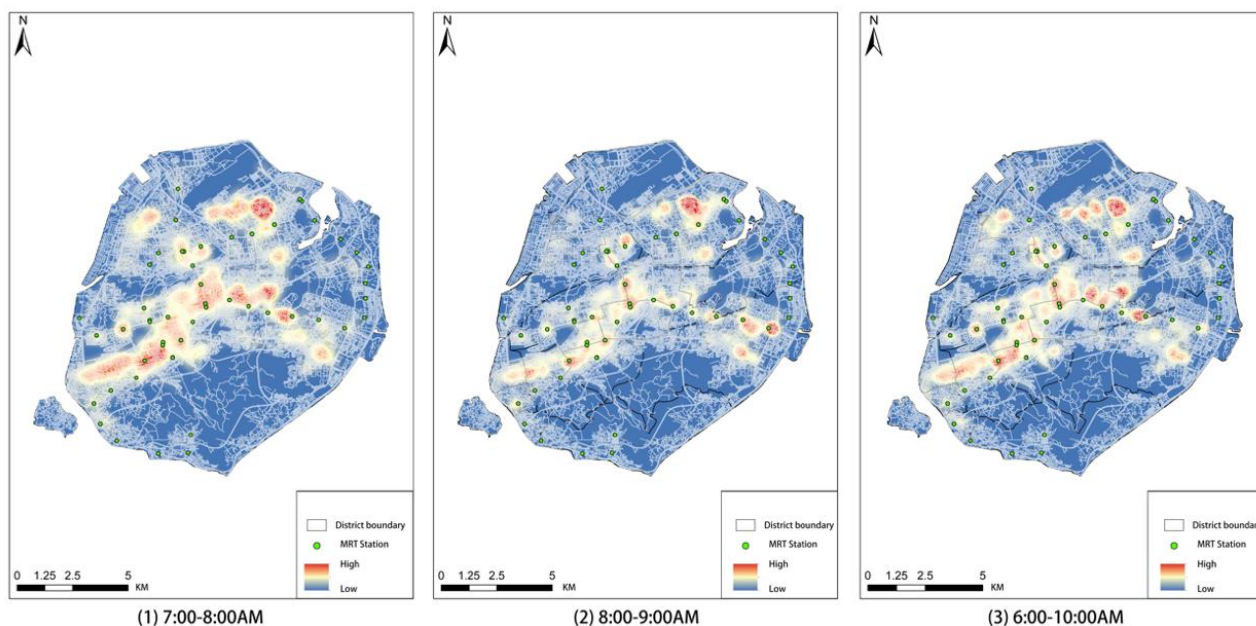


Fig. 4 Travel point heat map

Looking at the density analysis of all shared bike locking data from 6:00 AM to 10:00 AM on weekdays, the hotspot areas for arrivals are the Jiahe Road and Luling Road areas near Lücuo and Wushi Pu stations; the Luling Road area near Cai Tang station; the Luling Road and Huizhan Road areas near Software Park Phase II station; and the Huli Innovation Park area. Considering different time periods, during the peak travel hours of 7:00 AM - 8:00 AM, the arrival hotspot areas are distributed around the Eastern Paris Square, Tianhong Shopping Mall, and Zhongmin Baihui Shopping Mall areas near Lücuo and Wushi Pu stations; the Hexiang Commercial Center area near Wenzao station; the Wanhe Plaza area near Lianban station; the Cai Tang Square area near Cai Tang station; and the Software Park Phase II and Huli Innovation Park areas. For the 8:00 AM - 9:00 AM period, the prominent high-density arrival areas include the Huli Innovation Park area and the Software Park Phase II area, as well as the Eastern Paris Square, Tianhong Shopping Mall, and Zhongmin Baihui Shopping Mall areas near Lücuo and Wushi Pu stations, Lücuo and Wushi Pu stations' vicinity (Figure 5).

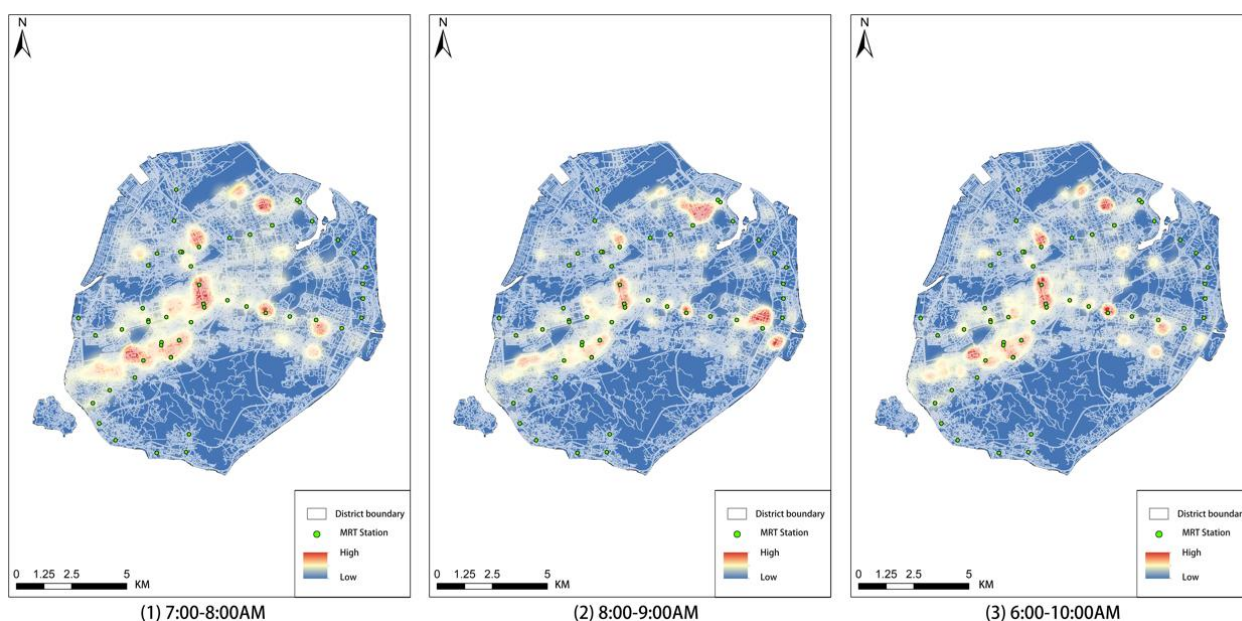


Fig. 5 Arrival point heat map

4.1. Demand Prediction

We initially filtered the shared bicycle trip and arrival order data within a 200-meter radius of BUS stations and a 500-meter radius of MRT stations, as illustrated in the density plot shown in Figure 6.

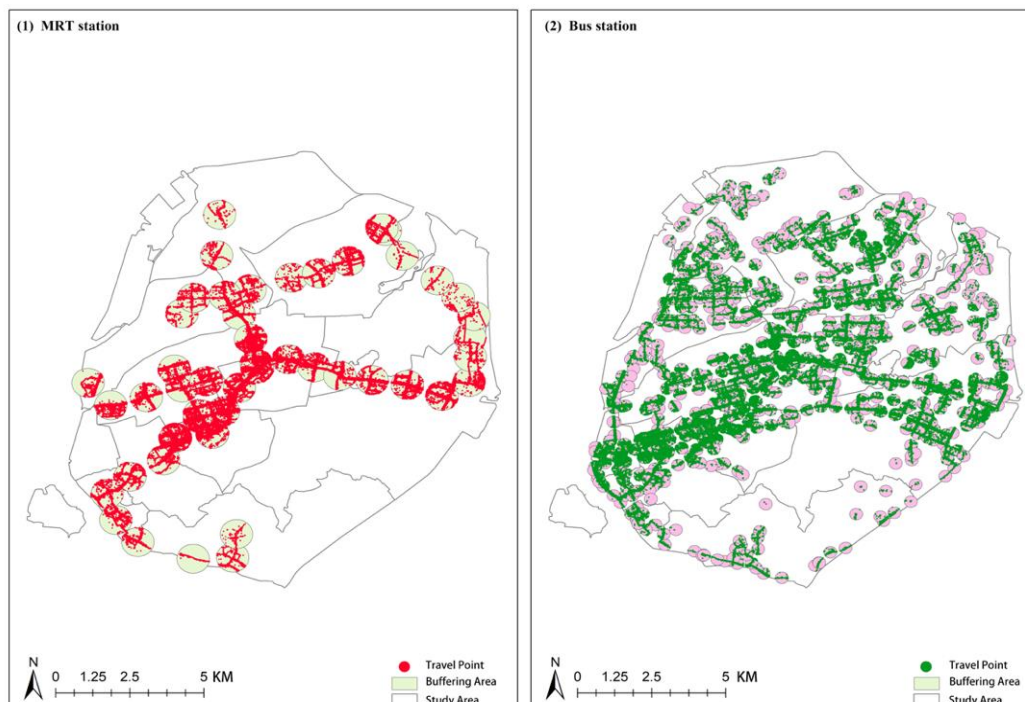


Fig. 6 Travel points near the station near the transportation station

The dataset comprises shared bicycle travel trajectories and order data within the Xiamen Island area, recorded from December 21st to December 25th, 2020. The primary focus of this study centers on the Xiamen Island area as the research region for shared bicycles. To process the experimental data, we determine the largest area encompassed by all shared bicycles as the training scope. Within this scope, we calculate the count of shared bicycles and the active count of shared bicycles (where the lock status is equal to 1) for each coordinate point. The coordinate precision is maintained at three decimal places. Moreover, we ascertain the distances from different coordinate points to the nearest subway station and bus stop, incorporating these as training parameters. Python is employed for data retrieval, categorization, and normalization. Linear normalization is applied to standardize the collected data. This process yields coordinate plots and shared bicycle density maps. Subsequently, the gathered data is input into a neural network for training. For data validation, we randomly generate 5,000 coordinate data points and input them into the prediction model. This generates a new prediction graph, which is then compared with real data for validation and assessment.

4.1.1 Prediction of the public transportation location and total number of shared bikes

The GCN model was applied to this training set for training purposes. In this study, 80% of the total dataset was used as the input for the training dataset, while the remaining 20% was used as the input for the testing dataset. The fitness of the GCN model's predictions is illustrated in Figure 7, depicting the relationship between predicted values and actual values as shown in Figure 8. The relationship between the number of shared bicycles and map coordinates, along with the prediction results based on random coordinate inputs, is demonstrated in Figure 9. The neural network training results yielded an RMSE (Root Mean Squared Error) of 0.058861, an R^2 (R-squared) value of 0.89, a Mean Squared Error (MSE) of 0.0034646, and a Mean Absolute Error (MAE) of 0.044566. From these outcomes, it can be observed that the model's predictions throughout the day closely align with the actual data values. This suggests that the GCN model, through training, is capable of achieving favorable predictive results in forecasting the quantity of shared bicycle trips. This reflects a certain level of predictive performance.

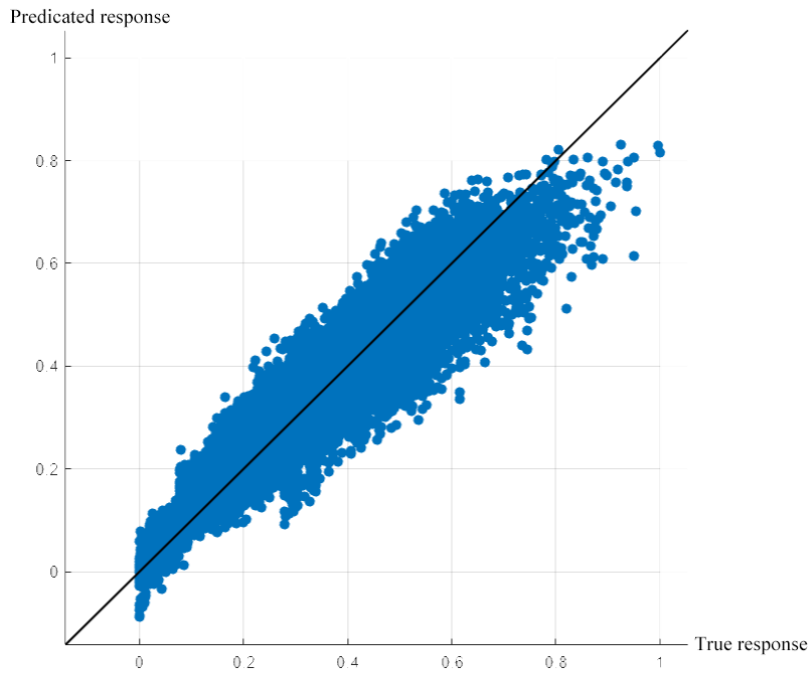


Fig. 7 Test of Goodness for Fit

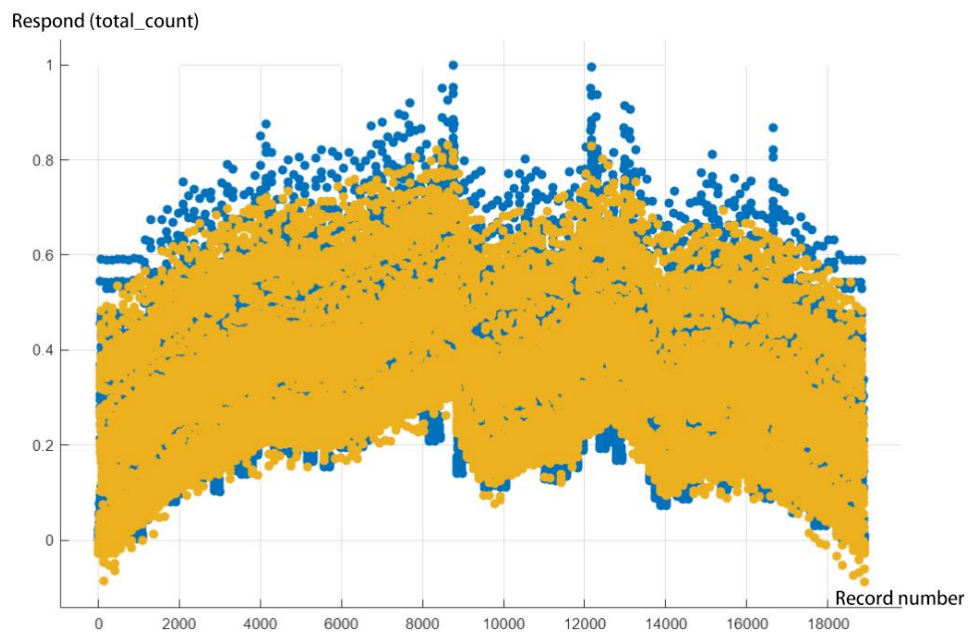
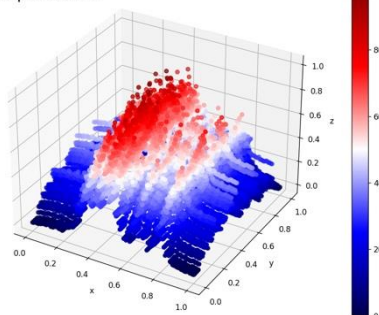
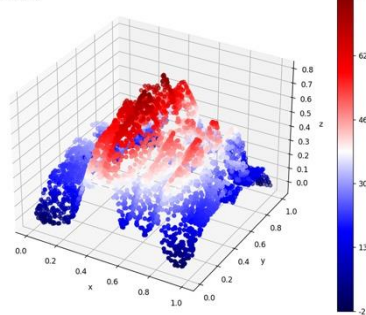


Fig. 8 Predicted value and true value

(1) Relationship between the number of shared bicycles and map coordinates



(2) Random coordinate input predicts the number of shared bikes



(3) Real data and random predicted data overlap graph

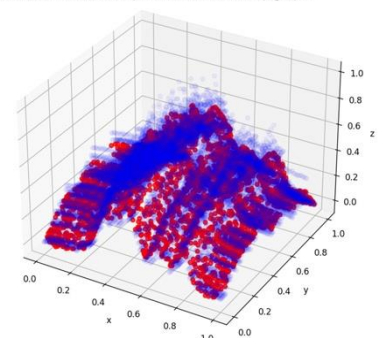


Fig. 9 Predict results

4.1.2 Location of public transport stations and prediction of the "active" shared bikes

The fitness of the GCN model's predictions is demonstrated in Figure 10, showing the relationship between predicted and actual values as depicted in Figure 11. The relationship between the quantity of "active" shared bicycles and map coordinates, along with the prediction results based on random coordinate inputs, is illustrated in Figure 12. The neural network training outcomes yielded an RMSE (Root Mean Squared Error) of 0.059961, an R^2 (R-squared) value of 0.88, a Mean Squared Error (MSE) of 0.0035953, and a Mean Absolute Error (MAE) of 0.045254. These results indicate that the model's predictions throughout the day closely approximate the actual data values. This indicates that the GCN model, through training, is capable of achieving favorable predictive results in forecasting the quantity of "active" shared bicycle trips near public transportation sites. This underscores a certain level of predictive performance.

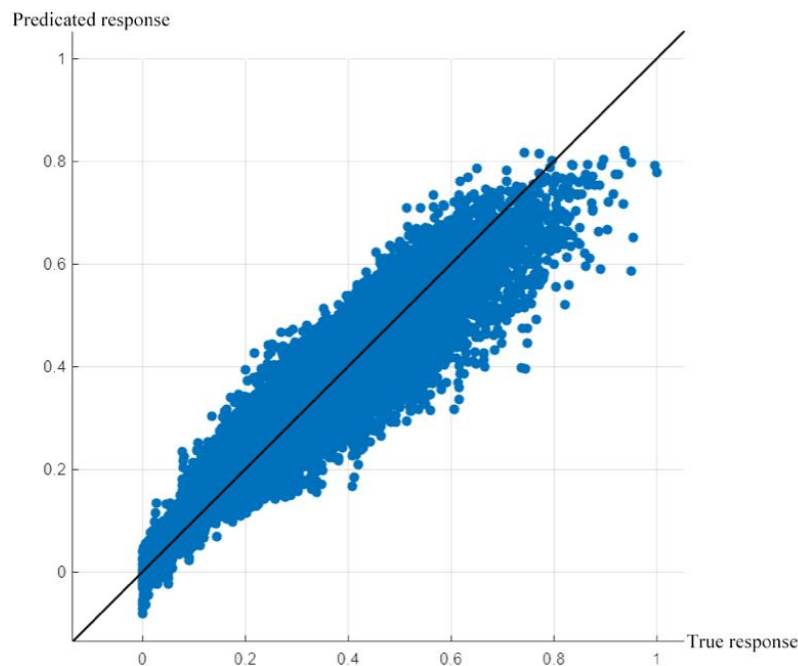


Fig. 10 Test of Goodness for Fit

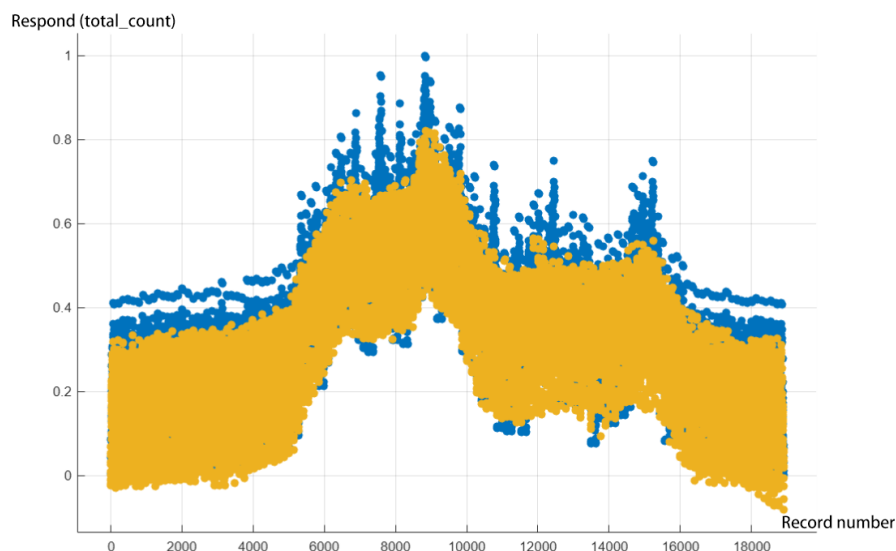


Fig. 11 Predicted value and true value

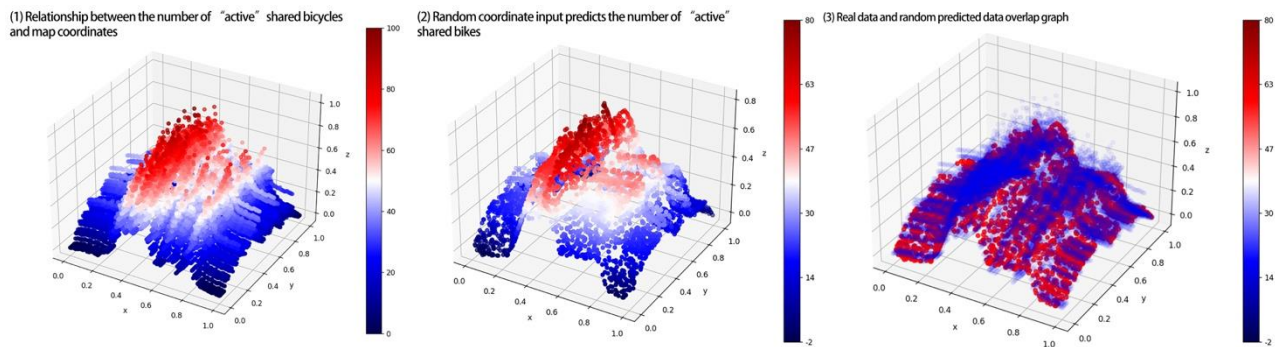


Fig. 12 Predict results

4.2. Spatial Autocorrelation Test

Treating the bike-sharing order data as travel points, global spatial autocorrelation analysis of various street travel patterns was conducted using ArcGIS 10.2.2. The results are as follows: The Global Moran's I index is -0.110787, Z score is -0.686669, and the P value is 0.492291. The Moran's I index approaching 0 suggests weak spatial correlation among the data, indicating the absence of distinct clustering or dispersion patterns. The practical implication is that the number of bike-sharing trips within different street blocks on Xiamen Island is relatively balanced, indicating an overall even distribution of bike-sharing travel areas within Xiamen Island.

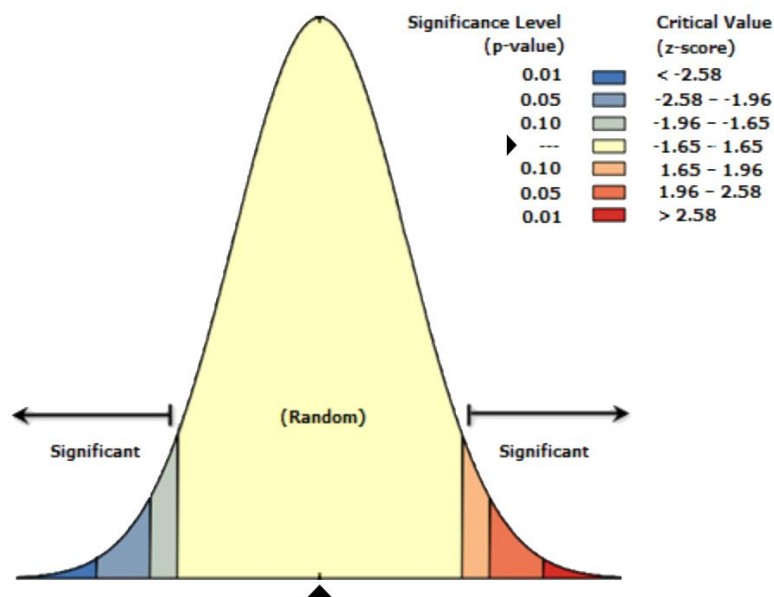


Fig. 13 Spatial autocorrelation test

4.3. Coupling and Coordination of Travel and Business Facilities

Regarding the factors influencing bike-sharing travel, we primarily selected Points of Interest (POI) related to commercial establishments and residential areas, including dining, leisure, residential, and shopping categories. The specific collected POI data are as follows (Table 1).

The density zoning of different POI facilities is shown in the diagram below. Through kernel density analysis, it can be observed that streets with a higher concentration of dining facilities are Heshan Street, Lianqian Street, and Jiangtou Street; streets with a higher concentration of leisure and entertainment facilities are Lianqian Street, Heshan Street, and Yundong Street; streets with a higher concentration of shopping facilities are Jiangtou Street, Heshan Street, and Lianqian Street; streets with a higher concentration of residential areas are Heshan Street, Lianqian Street, and Huli Street.

Table 1. POI statistics table

Type	Amount
Dining	21464
Leisure	2207
Residential	3738
Shopping	27072

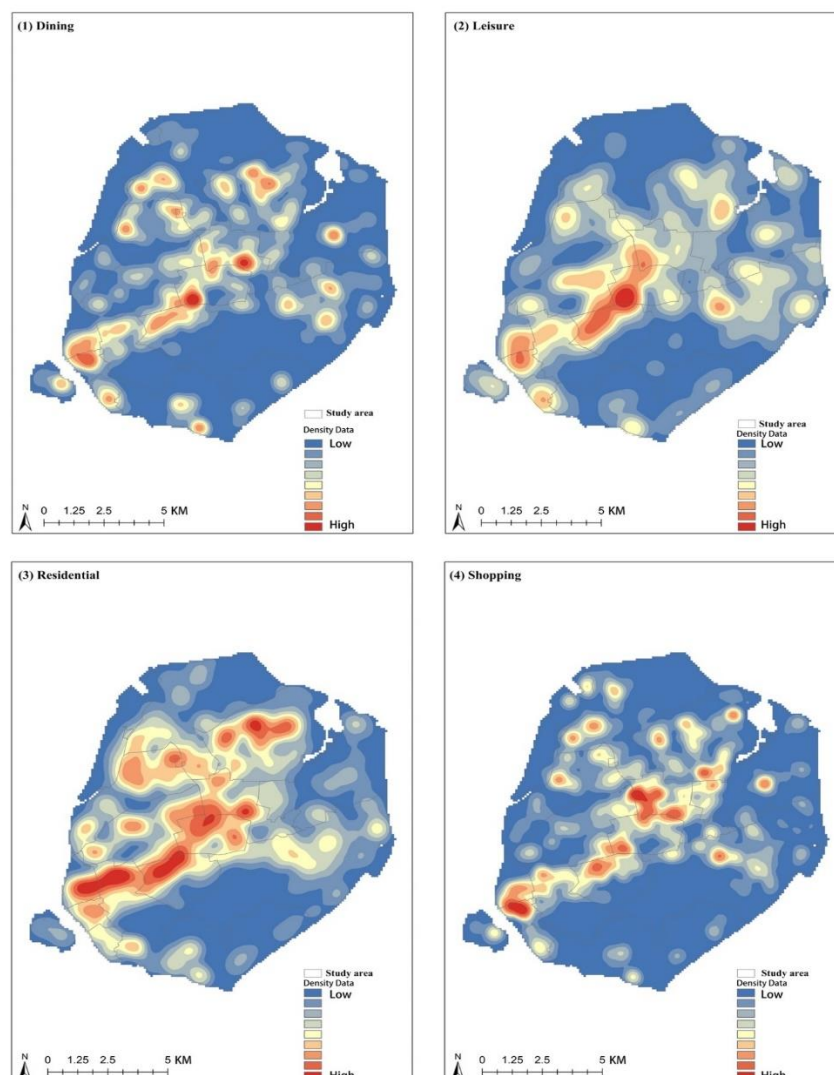


Fig. 14 POI facility nuclear density results

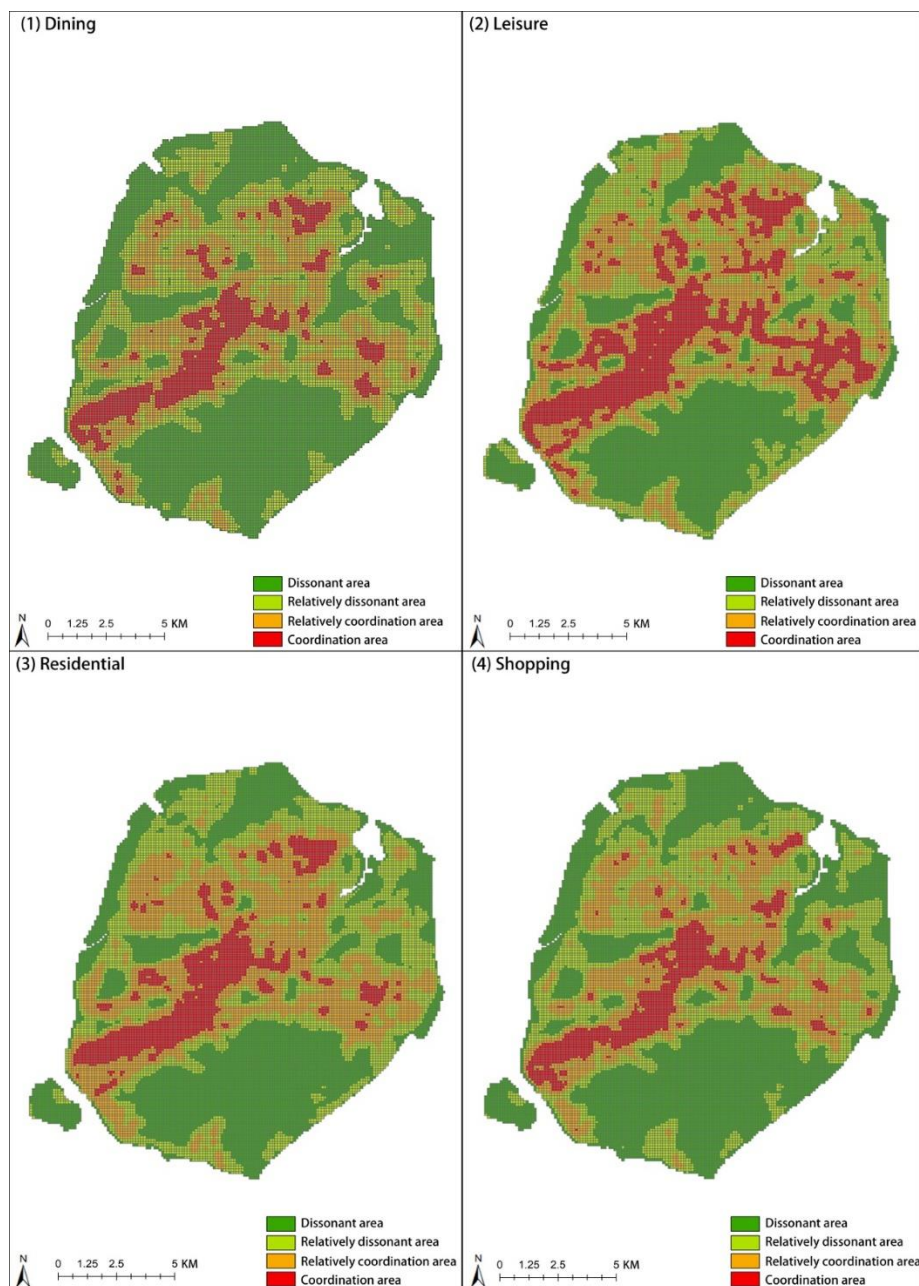


Fig. 15 Coupling coordination results

The coupling coordination analysis of shared bicycle trips within the Xiamen Island area concerning dining, shopping, leisure, entertainment, and residential facilities is presented in Figure 14 and 15. In terms of the coordination between shared bicycle trip points and shopping facility Points of Interest (POI) points, the highest coordination is observed around the Xiamen Island metro Line 1 (Zhenhai Road - Yan Nei) and Line 2 (Tian Zhu Shan - Wu Yuan Wan). This suggests a strong relationship between the quantity of shared bicycle trips near subway stations along these lines and the surrounding shopping areas. The placement of shared bicycle pickup and drop-off points appears to align with the proximity of shopping facilities near these metro stations. When examining the coordination between shared bicycle trip points and residential facility POI points, notable coordination is observed not only in the core areas within Xiamen Island (such as Bin Hai Road, Xian Yue Road, and both sides of Cheng Gong Avenue) but also in the northeastern part of Xiamen Island, including Hu Li Innovation Park, and the eastern part containing Xiamen Software Park. This indicates a higher demand for shared bicycle trips in these regions, especially in industrial innovation parks. In the context of coordination between shared bicycle trip points and leisure and entertainment facility POI points, the areas with higher coordination are more dispersed. This suggests that shared

bicycles located near leisure and entertainment facilities generally meet travel demands across various regions. Finally, when analyzing the coordination between shared bicycle trip points and dining facility POI points, the spatial distribution closely resembles that of shopping facilities. This similarity may be attributed to the co-location of dining and shopping within the same commercial complexes or streets, highlighting a potential synergy between these two factors.

5. Conclusion

Building upon an existing neural network framework, this study leverages shared bicycle travel order data from the Xiamen Island area within Xiamen city. The research employs a Graph Convolutional Network (GCN) to forecast the volume of shared bicycle trips near public transportation hubs, including subway and bus stations, in the Xiamen Island region. The experimental results highlight the effectiveness of the graph convolutional network, especially when it comes to automatically updating adjacency matrices during model training. This capability allows the network to delve deeper into the intricate features of transportation data, ultimately resulting in improved predictive accuracy and more precise results. Conclusively, the network successfully predicts the volume of shared bicycle trips near public transportation hubs, ultimately contributing to the improved distribution of shared bicycles around urban public transportation nodes.

Furthermore, this research integrates different types of Points of Interest (POI) facilities for coordinated analysis. By factoring in commercial, residential, and public transportation-associated trips, the study enhances the convenience of shared bicycle usage. The findings can be valuable for government authorities and businesses to regulate shared bicycles appropriately and optimize deployment strategies. This promotes the healthy development of shared bicycles and addresses the "last mile" challenge in public transportation comprehensively.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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