A traffic big data analysis on relationships between urban planning and traffic noise level——taking Dongguan Demonstration Area, China as an example

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ABSTRACT

With the promotion of smart city research, traffic big data has become a new way to study urban traffic noise. Taking Dongguan Demonstration Area, China as an example, this research discussed the relationships between traffic noise levels and urban plannings using Geographic information system (GIS), global positioning system (GPS) techniques and OpenITS Organization OpenData. The results showed that, for the whole area, some planning factors, say global integration, local integration (R=500m), global betweenness, local betweenness (R=500m) and number of points of interest (POIs) had significant positive correlations with the daytime traffic noise levels. Among them, the number of POIs had the strongest correlation with the traffic noise levels (r=0.560 p<0.01). However, the degree of influence of each variable on traffic noise levels can be changed with geographical

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locations. This research also identified specific areas where traffic noise levels were negatively correlated with local integration, which had great potential to provide a recreational and peaceful place for people to walk. Therefore, traffic noise can be effectively controlled by making changes in urban planning.

Keywords: Big data; Traffic noise level; Urban planning

1. INTRODUCTION

Traffic big data has been widely applied to smart city construction due to its enormous potentials for long-term city planning, such as the planning of public transportation and parking spaces [1]. For example, studies have found that, in terms of traffic conditions, traffic big data can be used to predict traffic congestion using machine learning. Aristeidis and Christos demonstrated that data quality and size were the most critical factors towards algorithmic accuracy and decision trees were more accurate than logistic regression in the prediction of traffic congestion [2]. In addition, studies also discussed big data applications in the aspects of traffic flow research and jam real-time evaluation [3]. Furthermore, applying big data and machine learning analysis was able to forecast the real time traffic accurately [4]. For the traffic management aspect, a framework was proposed for visual big data analytics for automatic detection of bike-riders without helmets in city traffic [5]. Sustainable management could proceed by overseeing or redirecting traffic along different, less blocked routes to lessen carbon outflows in a specific territory [6]. Besides, traffic big data was applied to smart parking which could provide government managers with effective, accurate, and real-time data support, thereby improving the efficiency of managers' planning and management of parking lots[7]. However, most research focuses on the mobility management level, which ignores the ability of traffic big data to improve the acoustic environment.

The term “urban planning” has extensive meanings, referring to urban morphological factors, network structure, land use type et al. The relationships between the acoustic environment and urban planning have been proven. Research indicated that there were significant correlations among the spatiotemporal patterns in soundscape, acoustic and urban morphological factors that represented buildings, roads, open public space, and water feature components [8]. Moreover, a recent study has shown that regional road network structure, land use type, urban built-up area morphology, and street block morphology can affect noise-induced health problems[9]. Space syntax, which is a method of quantifying road network structure, shows its capacity for big data technique. Furthermore, integration and betweenness, which were widely used in existing research, are important concepts in space syntax. Integration represents the accessibility within a network and determines whether pedestrians can travel to a given space quickly. Betweenness measures the probability that a spatial element is located along the shortest path between any two elements in the system [10]. Some research has discussed their influence on the urban sound environment. For instance, Nabil and Sara found an obvious indication of a link between the noise level and the spatial configuration (integration and choice) of the street network. Although the correlation was not highly significant, the outcomes might still shed light on the type of relationship between noise and places [11]. Another study suggested that space syntax might have a potential for predicting traffic noise exposure by improving models for noise simulations using specialized software or actual traffic counts [12]. It can be seen that integration, betweenness and land use type are important components of urban planning. Although the above-mentioned studies focused on the effects of urban planning on the sound environment, little attention was given to the abundant existing traffic big data of cities. Therefore, based on the traffic big data from OpenITS Organization OpenData, geographic information science（GIS）and global positioning system (GPS) techniques.This paper explores the relationship between traffic noise levels and urban planning factors such as global integration, local integration (R=500m), global betweenness, local betweenness (R = 500m) and the number of points of interest (POIs) which represent land use type.

Specifically, two research questions are addressed in this study: (1) What will the correlations between urban planning and daytime traffic noise level be like when traffic big data gets involved? (2) What are the effects of geographic factors on the results?

2. METHODOLOGY

2.1. Study Area and Datasets

As we expected that results from traffic noise research in a city area would be the most generalizable, a typical area of Dongguan Demonstration Area, China with abundant road networks was selected as the study area. This study used open datasets for GPS floating cars in Dongguan demonstration area of China from OpenITS Organization OpenData (OpenITS Org. OpenData V5.0-Introduction of open data for GPS floating cars in Dongguan demonstration area https://www.openits.cn/openData2/604.jhtml (2021). Accessed: 2022-01-03), which covered a study area between east longitude 113°702' to 113°825' and northern latitudes 22°994' to 23°070' in the World Geodetic System 1984 (WGS 84). Figure 1 (a) shows the location of Dongguan City in Guangdong Province, China and Figure 1 (b) indicates that the study area contains Guancheng, the main urban district, Dongcheng, Nancheng and Wanjiang, as well as the western part of Liaobu Town, which can be seen as the urban fringe districts. Guancheng is the main city district of Dongguan which is the center of the study area. There are 217 roads, including 1 motorway, 68 urban trunk roads, 46 urban secondary roads and 102 urban feeder roads in the study area. Public facilities such as supermarkets, hospitals and gymnasiums are mainly situated in the center of the study area, while the fringes of the area includes more industrial zones as shown in Figure 1 (c). After downloading the satellite image of the study area, we vectored the roads and buildings in ArcGIS by extracting the road centerlines and the polygons of the building plans with their height that would be used in parametric computation and acoustic simulation for the following steps. The vectoring area was with an extra space of 4.5 km on each side to avoid edge effect.

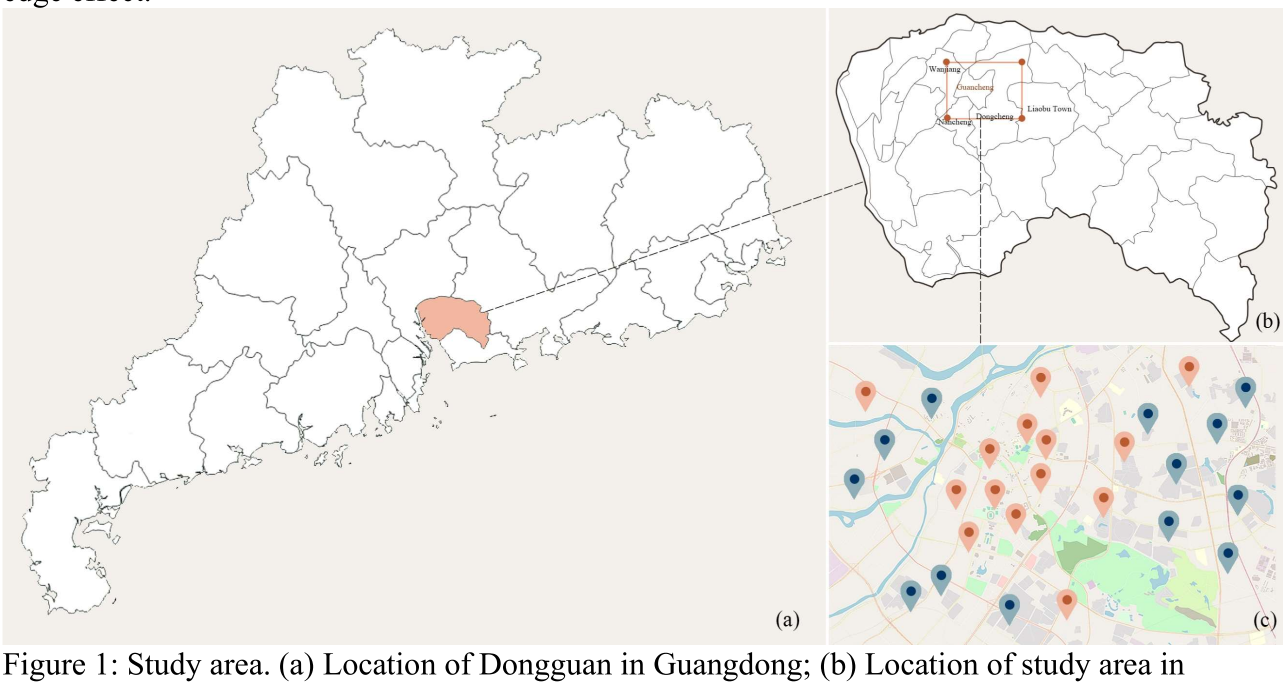


Figure 1: Study area. (a) Location of Dongguan in Guangdong; (b) Location of study area in Dongguan; (c) Red marks represent services, blue marks represent industries.

Table 1: Description of the traffic big data.

Field Name	Data Type	Field Description
CARID	Number	Vehicle number (each vehicle has a unique number)
SIGNALTIME	Date Time	Time to receive GPS signal (year/month/day hour: minute: second)

Table 1 (*continued*)

Field Name	Data Type	Field Description
LATITUDE	Number	Latitude, the coordinate system for vehicle latitude is WGS84 earth coordinates
SPEED	Number	Instantaneous speed of vehicle (km/h)
DIRECTION	Number	Direction of travel. For example, DIRECRION=93 means that the vehicle is travelling in a direction of 93 degrees northeast

The datasets recorded all day information about Car ID, signal time, longitude, latitude, speed and direction for every floating car that passed through this study area on November 1st, 2nd and 3rd in the year of 2015. The description of each field is listed in Table 1. The key of the research is to count the number of suitable Car IDs. Signal time is the basis for screening proper data; longitude and latitude are the foundation for data visualization. In preparing for this research, we organized the data by Excel in order to calculate the daytime traffic flow of each road. According to the *Emission Standard for Community Noise GB22337-2008*, daytime is stipulated as the period from 6:00am to 22:00pm. Firstly, we selected the traffic data of nine day time points for each day (6am, 8am, 10am, 12pm, 2pm, 4pm, 6pm, 8pm, 10pm) and converted them to shapefiles so that the cars were able to fall on the roads in ArcGIS at the specific points according to their unique latitude and longitude coordinates. Subsequently, the points that represented the cars were joined with the road centerlines in ArcGIS, which meant the number of cars at each moment on every single road could be figured out automatically. Then, we exported Excel tables with the fields of road ID, road length and point counts per road. Afterwards, we calculated the arithmetical mean of the point counts by 27 different times (3×9) at each road, which represented the average car counts at any daytime point from 6am to 10pm per road. Meanwhile, we have calculated the average speed of the selected floating cars at the 27 time points over three days, which came up with an average daytime speed of 16.086 km/h. Finally, we estimated the daytime traffic flow of each road using Equation 1, which is:

$$F = \frac{vn}{L} \quad , \tag{1}$$

where the F is daytime traffic flow, v is the average daytime speed of 16.086 km/h, n is the average car counts at any daytime point from 6am to 10pm, and L is the length of the road.

2.2. Simulation of Traffic Noise Level

Traffic noise levels were simulated by Computer Aided Noise Abatement (Cadna/A) which was the leading software for the calculation, presentation, assessment and prediction of environmental noise. Besides traffic flow, road width and car speed are also important parameter valuations in the simulation. Roads were classified into three different levels: main roads with a width of 50 meters where the car speed was thought to be 70 km/h, 30-meter-width secondary roads with cars of 40 km/h, and other branch roads with a width of 16 meters where the cars were 30 km/h. In addition, based on practical experience, the vehicle model proportion was evaluated as 20% large vehicles, 30% middle-sized vehicles and 50% small vehicles. Then, the daytime traffic flows which were obtained in 2.1 section, the widths, car speeds and vehicle model proportions were imported into Cadna/A as the attributes of a specific road. In this way, Cadna/A was able to simulate the daytime traffic noise levels of the study area. Then, the simulated traffic noise level values were exported into ArcGIS for the next statistical analysis.

2.3. Calculation of Urban Planning Factors

This research calculated space syntax parameters which represent road network morphology by Spatial Design Network Analysis (sDNA), a plug-in tool based on ArcGIS, and chose 500 meters (pedestrian area) as the searching radius for local integration and local betweenness. Therefore, four space syntax parameters that were NetQuantPD Ang Rn, TPBetweenness Ang Rn, NetQuantPD Ang

R500, TPBetweenness Ang R500 were obtained. NetQuantPD Ang (NQPDA) is the indicator calculated by sDNA referring to the integration of road networks. It's calculation formula is shown in Equation 2[13]:

$$NQPDA(x) = \sum_{y \in Rx} \frac{P(y)}{d(x,y)} \ , \tag{2}$$

Where P(y) is the proportion of link y within the radius of R, d(x,y) is the shortest topological distance from link x to link y; Rx is the set of links in the network Euclidean radius R from link x; NQPDA(x) is the integration of the road network within searching radius of R.

Besides, TPBetweenness Ang (TPBtA) is the indicator computed by sDNA, which means the betweenness of the roads network. Its formulation is [13]:

$$OD(y,z,x) = \begin{cases} 1, if\ x\ is\ on\ the\ goedesic\ from\ y\ to\ z \\ 1/2, if\ x\ \equiv y \not\equiv z \\ 1/2, if\ x \equiv z \not\equiv y \\ 1/3, if\ x \equiv y \equiv z \\ 0, otherwise \end{cases} \ , \tag{3}$$

$$TPBtA(x) = \sum\nolimits_{y \in N} \sum\nolimits_{z \in Ry} OD(y,z,x) \frac{P(z)}{Links(y)} \ , \tag{4}$$

where OD(y,z,x) is the shortest topological distance through link x between link y and z within searching radius of R; P(z) is the proportion of link z within the radius of R; Links(y) is the number of links in radius of R from each link y; Ry is the set of links in the network Euclidean radius R from link y; N is the set of links in the global spatial system; TPBtA(x) is the betweenness of the road network within the searching radius of R.

Figure 2 shows the visualization of those four space syntax parameters. The locations of high-global-integration and high-global-betweenness are mainly on those main trunk roads as shown in Figure 2 (a) and (b). While Figure 2 (c) and (d) show that the places of high-local-integration and high-local-betweenness dispersedly distribute on the main junctions of the road network.

In this paper points of interest (POI) with a higher resolution were used instead of land use type data [10]. We crawled POI data which had a close connection with population mobility and traffic distribution in the year 2015 located in the study area from Open Street Map (OSM). In general, the POI data were classified as follows: traffic travel, financial service, scientific education, bus station, parking lot, leisure, medical services, and accommodation services.

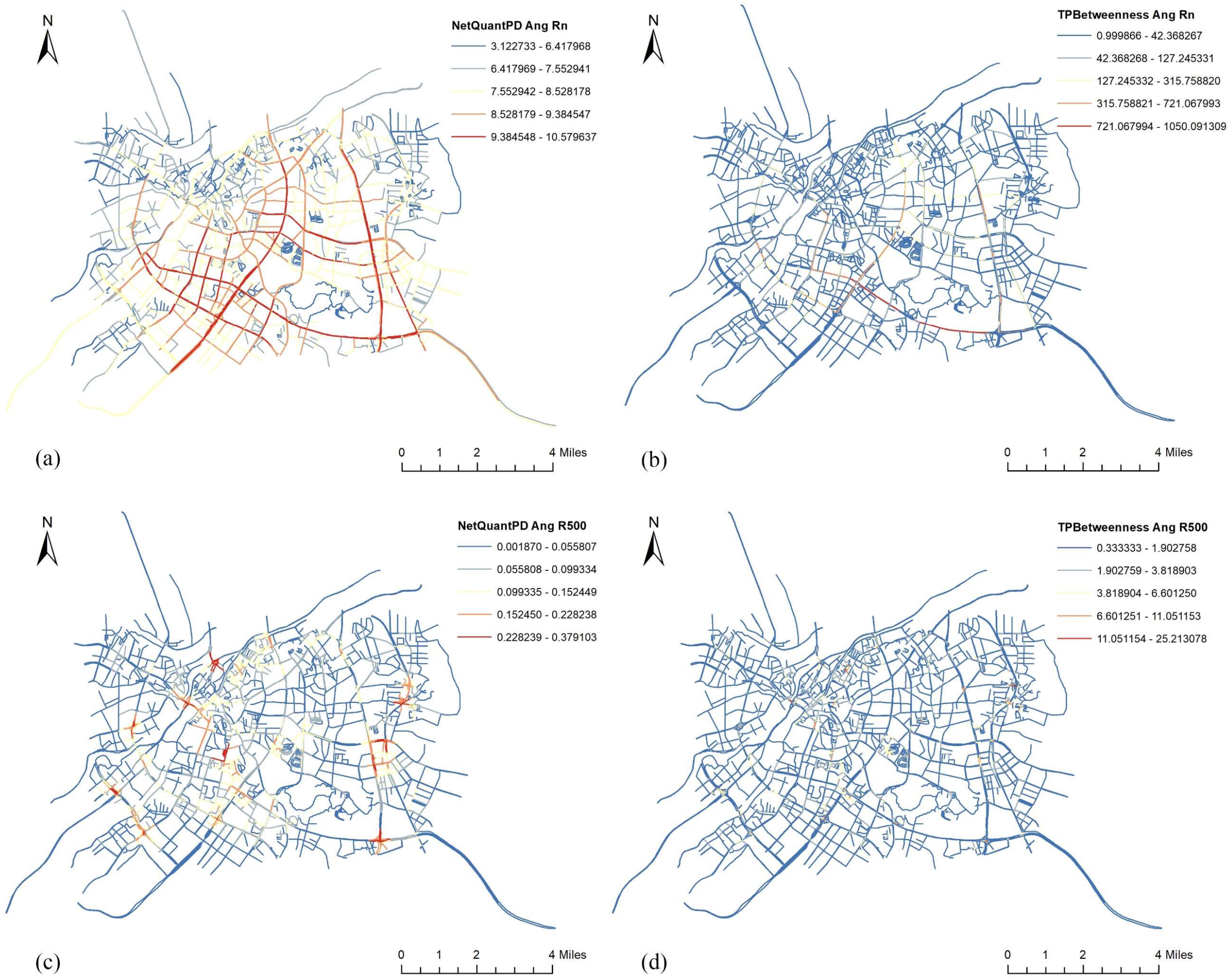


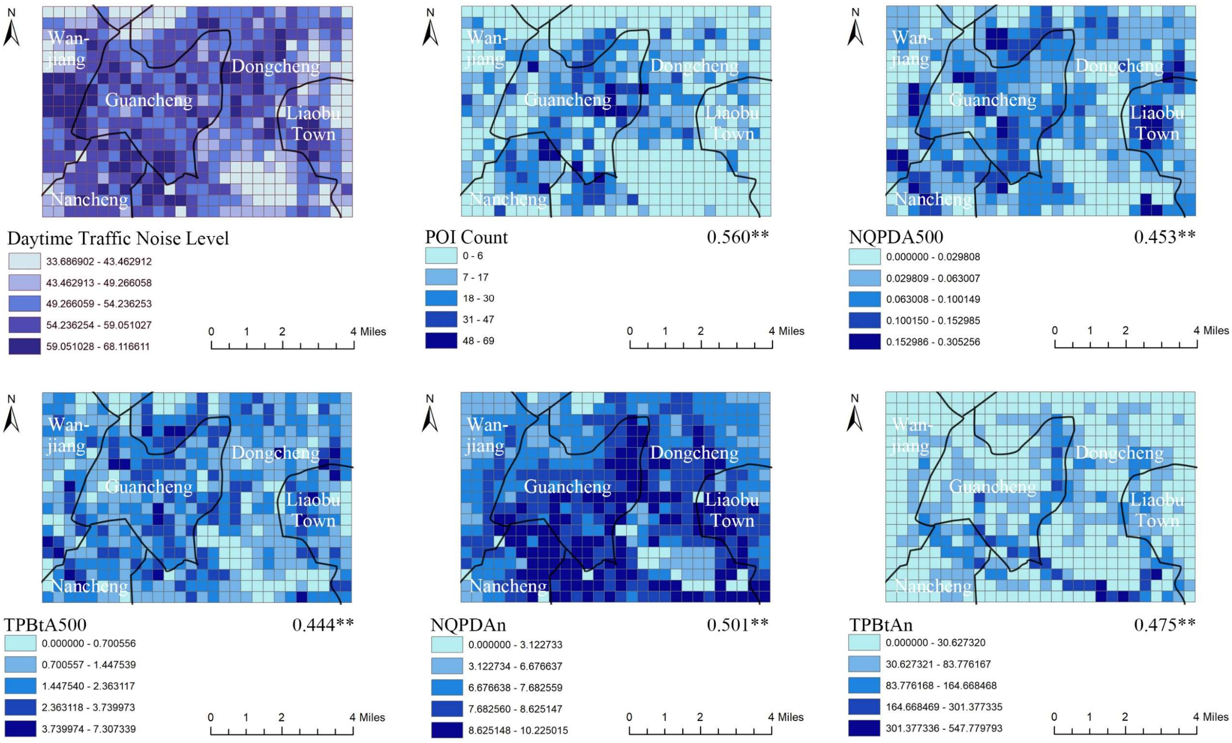
Figure 2: The results of space syntax: (a) Global integration; (b) Global betweenness; (c) Local integration; (d) Local betweenness.

3. RESULT AND DISSCUSSION

3.1. Effect of Urban Planning Factors on Daytime Traffic Noise Levels

The grid method divides the study area into several cells and regards the cells as individual cases where the variable values can be summarized and calculated. Therefore, the cases with variables of different values are able to be got so as to statistical analysis. This research created a fishnet of 500m ×500m for each cell by ArcGIS and respectively computed the average daytime traffic noise level, average global integration, average global betweenness, average local integration (500m), average local betweenness (500m), and sum of the POI counts, for every cell as shown in Figure 3. The study area was divided into 532 grids of 500m×500m.

The professional statistics commercial software SPSS 24.0 (Statistical Product and Service Solutions, IBM, America) was used to conduct statistical analysis based on the data obtained above. Initially, the Spearman correlation analysis method was used to analyze the correlation between daytime traffic noise level and the four urban planning factors. As listed in Figure 3, the results show that all of the four indicators have a positive correlation with daytime traffic noise level. Furthermore, the Spearman correlation coefficient (r=0.560) between traffic noise level and POI counts is higher than that between traffic noise level and any space syntax parameter (r=0.453 with local integration, r=0.444 with local betweenness, r=0.501 with global integration, r=0.475 with global betweenness). Which indicates that for the whole study area, daytime traffic noise level is more dependent on the number of land use types than road network structure.



**indicates $p < 0.01$.

Figure 3: Overlayed mappings for the variables and the results of the Spearman correlation analysis between daytime traffic noise level and the other independent variables.

3.2. Effect of Geographical Locations on the Influence Degree

Studies have proven that spatial factors played a key role in urban soundscape[8], which means, in this study, the values of dependent variable (daytime traffic noise level) were interact with each other. Therefore, in consideration of spatial non-stationarity, the GWR (Geographically Weighted Regression) model was adopted to investigate the local relationships. Before the GWR analysis, Ordinary Least Squares (OLS) should be used to examine significances of the independent variables. Table 2 shows the results of the OLS model. It can be seen that the F-statistic test is significant ($p<0.01$) which means the OLS model is able to estimate the population. VIFs of the variables are all below 7.5, it indicates that there is no multicollinearity among these variables. However, p-values of local betweenness ($p=0.632$) and global betweenness ($p=0.162$) are both above 0.1. In other words, the independent variables of 500m local betweenness and global betweenness are insignificant. Therefore, we need to eliminate local and global betweennesses for the following GWR analysis.

The GWR model has a better fitting degree than OLS. According to the results shown in Table 3, the GWR model can explain 69.88% of the variations in local noise level, which increases by 25.72 percentage points compared to OLS model. Besides, the AICc of GWR decreases by 233.908 than that in OLS model, which means GWR model performance is better than OLS. In the GWR model, every single cell would have its own local R^2 and regression coefficients. For the varying regression coefficients of GWR, it is necessary to show the coefficients of the minimum (Min), the median (Median), the maximum (Max), the mean value (Mean) and standard deviation (SD) to reflect the variations in the regression coefficients. As shown in Table 3, the regression coefficients of POI count and global integration are all positive. This means that POI count and global integration can increase traffic noise levels. The coefficients of 500m local integration are positive or negative in various places. In addition, the influence degree of local integration is much higher than the POI count and global integration as its average regression coefficient is larger than the others. Interestingly, in the GWR results, the average coefficient of POI count is smaller than the others, which is reverse to the Spearman result in section 3.1. Therefore, for the global influence, the number of land use types (POI count) is a more important variable than road network structure (space syntax parameter) affecting traffic noise level. However, for the local influence, daytime traffic noise levels are more dependent on road network structure than the number of land use types. This indicates that a global predictive model for traffic noise levels is not applicable for local research. Thus, the study area should be further divided and discussed to consider the diversity of factors influencing locations.

Table 2: Statistical results of Ordinary Least Squares (OLS).

Variable	Coefficient	t-Statistic	P-Value	VIF
POI Count	0.157**	9.317	0.000	1.096
NQPDA500	22.233**	2.673	0.008	3.541
TPBtA500	0.184	0.479	0.632	3.518
NQPDAn	1.433**	10.242	0.000	1.553
TPBtAn	-0.005	-1.402	0.162	1.288
		R^2=44.16%		
		AICc=3206.467		
		F-Statistic=83.193**		

**indicates $p < 0.01$.

Table 3: Statistical results of the regression coefficients based on GWR.

Variable	Min	Median	Max	Mean	SD
POI Count	0.048	0.150	0.535	0.183	0.109
NQPDA500	-32.693	18.378	77.720	20.162	22.339
NQPDAn	0.386	1.419	6.279	1.601	0.865
			R^2=69.88%		
			AICc=2972.559		

Figure 4 shows the spatial distributions of the regression coefficients of the independent variables from GWR model. These figures show that the value of the regression coefficient of the same independent variable may have positive or negative differences to varying degrees among the different cells. In addition, these figures indicate that the effects of the same factors exhibit significant spatial variations that cannot be generalized in this research.

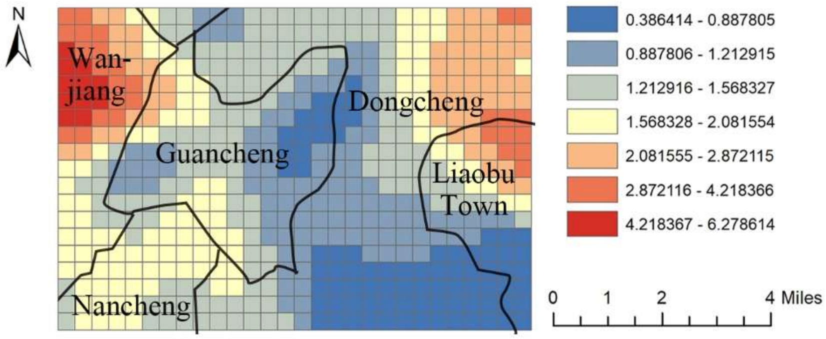
In terms of distribution of the influencing degrees of independent variables, Figure 4 (a) and Figure 4 (c) show that global integration (with 2.08~6.28 of the coefficients in fringes, 0.39~1.21 in center) and POI count (with 0.23~0.53 of the coefficients in fringes, 0.05~0.14 in center) exhibit greater influences on the urban fringes, but have fewer influences on the urban center. Figure 4 (b) reflects that 500m local integration has the largest influencing degree on the southern fringe where its coefficients are in the range of 24.13~77.72, and in the neighborhood of the main district Guancheng, it has the lowest influencing degree. The influence degree of local integration becomes larger in the northern fringes, but it is negatively correlated with the traffic noise level (with -32.69~-14.76 of the coefficients).

For the main district Guancheng, all these three independent variables have comparatively small influences on noise levels. This illustrates that the factors affecting noise levels in urban centers are complex, there should be other important factors such as density of building, greening rate, width of the road, etc. However, among the three independent variables in this research, the influence degree of local integration is still the most in urban center. The coefficients of global integration is in the scope of 0.39~2.08, POI count coefficients are 0.05~0.30, and local integration coefficients are mostly in 12.44~24.13. Therefore, in the urban center, the traffic noise level is more dependent on the local accessibility than the global accessibility and the number of land use types.

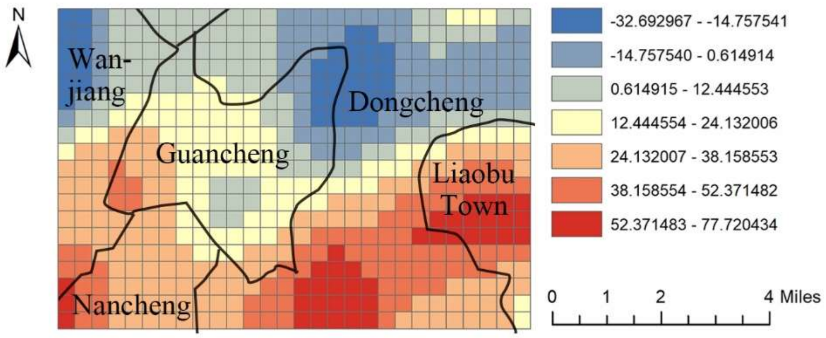
Similar tendencies can be found in the south of Wanjiang, the north of Nancheng, the south of Dongcheng, and the southwest of Liaobu Town, all of which are located on the south of Guancheng.

Global integration and POI counts have small effects on the noise levels in these places as their coefficients are respectively in 0.39~2.08 and 0.05~0.54. Whereas, the influence degree of local integration reaches the most, which ranges from 24.13~77.72. This indicates that, in terms of the urban fringe to the south of the main district, the local accessibility of roads has a nearly decisive effect on the traffic noise level. The higher the local accessibility is, the higher the traffic noise level is.

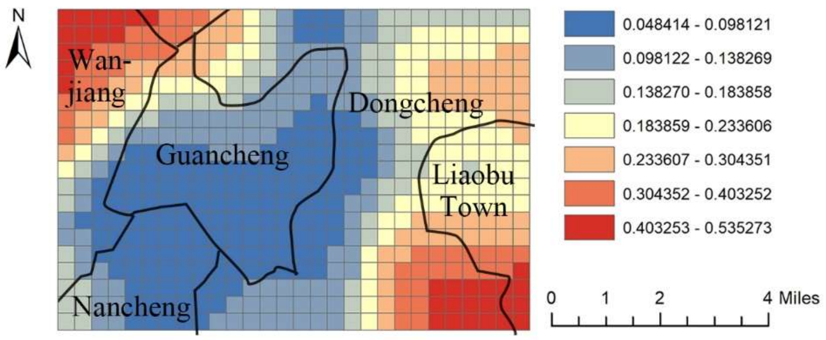
Moreover, as for the fringe areas to the north of Guancheng, which are northern Wanjiang and northern Dongcheng, their effect tendencies are also similar. The coefficients of global integration in these places range from 0.89 to 6.28, and are higher in the east and west of the area (2.87~6.28). POI count coefficients are in the range of 0.05~0.54 and is higher in the west where they are in the scope of 0.40~0.54. However, their influence degrees are still much less than local integration whose coefficient range is -32.69~-14.76. This means that the local road accessibility has a large influence on the traffic noise level of the urban fringe in northern Guancheng. In this area, road accessibility has a negative correlation with the noise levels. This may be because there are many types of blocks of enclosure at the junctions of roads. They lower the noise levels in the blocks. These kinds of enclosure type blocks are suitable for people to walk and relax, as well as offer restful acoustic environments.



(a) The regression coefficients of global integration affecting on daytime traffic noise level.



(b) The regression coefficients of 500m local integration affecting on daytime traffic noise level.



(c) The regression coefficients of POI counts affecting on daytime traffic noise level.
Figure 4: Visualization of the results of GWR model.

4. CONCLUSIONS

This research is based on the open datasets for GPS floating cars in Dongguan demonstration area of China, analyzes the influences of urban planning factors on urban daytime traffic noise levels. The urban planning factors include global integration, global betweenness, 500m local integration, 500m local betweenness, and POI counts. The first four are indicators explaining road network structure and the last one indicates the number of land use types.

The study reflects that, in the global perspective of the study area, POI count is the most important factor affecting traffic noise level. In terms of the local model, global and local betweenness have no correlation with noise level. Nevertheless, global integration and POI count both have positive correlation with noise level in any local area. As for the main district, Guancheng, the traffic noise levels more dependent on local integration than global integration and POI count. But because of the complex effects of these three variables in main district, the influence degrees of these three variables are not high. Thus, for the future prediction model, we should add more independent variables such as building density, greening rate, width of the road, etc. for the urban central areas. While for urban fringe areas, the influence degree of local integration on noise level is extremely high. Usually, the higher the local integrations of fringes are, the higher the traffic noise levels are. However, it is able to reduce the noise levels by setting blocks of enclosure types at the junctions of roads, which produces a quiet and friendly acoustic environment.

In conclusion, urban centers and urban fringes should be treated separately when we establish forecasting models in the future, and it is necessary to add more affecting factors for urban centers. This research proves that changing urban planning can effectively control traffic noise.

5. ACKNOWLEDGEMENTS

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