Assessing Electric Vehicle's Impact on Megaregion Expansion: Spatial Analysis of Beijing's Metropolitan Growth Based on Mobility Data

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16. Abstract

Electric vehicles have been proliferating in large cities across the world, and we increasingly face challenges in estimating charging demand and in planning EV infrastructure. Focusing on Beijing as a case study, this research uses a novel data-driven method to measure the Charging Demand Indicators (CDI) derived from location-based service big data. Analyses through kernel density function reveal dynamic relations between the spatial patterns of CDI and the distribution of Public Charging Stations (PCS). Spatial match examination is conducted to discover areas of mismatch between charging demand and infrastructure supply. The results expose a CDI pattern which, although largely complies with the city's centripetal structure, demonstrates variations between weekdays and weekends and by EV travel distances. A spatial regression model confirms the influence of urban structure and distribution of amenities on EV charging behavior and

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suggests that particular land uses and location features have a significant association with EV charging demand. These findings shed light on the understanding of the spatial disparity between the CDI pattern and the current PCS distribution, which could inform future urban policies and planning of EV infrastructure with an emphasis on its coordination with land use, physical layout, and transit.

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Executive Summary

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Chapter 1. Background

The market of electric vehicles (EVs) has been growing rapidly worldwide, as this new type of mobility is promoted as a solution of clean energy and reduction of carbon emission (Liang et al., 2019). With more and more vehicles powered by the battery on the road, the networks of public charging stations (PCS) are also expanding rapidly to meet the growing charging demands (Pardo-Bosch, Pujadas, Morton & Cervera, 2021). A question, therefore, arises in terms of how to estimate charging demand and what strategy is available for deploying this new urban infrastructure. Answering this question requires a better understanding of the relationship between the charging infrastructure network and the urban spatial structure, with considerable implications in transportation system, urban life quality, and social and environmental sustainability (Orsi, 2021; Zhang et al., 2021).

Existing research employs various types of data to study charging behavior and estimate potential needs, including questionnaire-based survey, demographic and vehicle registration data, Origin-Destination (OD) analysis, charging session data, and GPS trajectory data (Erbaş, Kabak, Özceylan & Çetinkaya, 2018; Frade, Ribeiro, Gonçalves & Pais Antunes, 2011; Kontou, Liu, Xie, Wu & Lin, 2019; Labeye, Hugot, Brusque & Regan, 2016; Liu, 2012; Namdeo, Tiwary & Dziurla, 2014; Tu et al., 2019). These studies explore the relation between EV travel behavior and charging demand and develop some demand-based models that could inform infrastructure planning (Pagany, Ramirez Camargo & Dorner, 2019). With the advance of Information and Communication Technologies (ICT), location-based service (LBS) data from drivers' mobile or GPS devices become increasingly accessible, pointing to a new direction to analyze drivers' travel patterns at a finer grain Yang & Fang. (2018) . This method, however, has not seen substantial usage in studying EV travel and charging activities, despite its great potential to reveal the spatio-temporal relation of the new mobility.

To capture this highly dynamic dataset, our research initiates a new index called the "Charging Demand Indicator" (CDI), which measures the potential charging demand derived from EV drivers' LBS search for public charging station (PCS). This method not only enables us to map EV drivers' travel patterns but also facilitates observation of the interaction between EV behaviors and the spatial attributes of the city. In addition, compared to the comparable existing studies that focus on static consumption data at PCS (e.g. billing records, charging records, etc.), this novel data-mining method takes into consideration both the completed charging activities as well as the "unmet" charging demands, enabling us to uncover and analyze the disparity within the supply-demand relationship. This means LBS data is more suitable considering the scope and purpose of this research. By shifting the attention from actual charging consumption to the intention-based demand, this research offers an alternative approach to evaluating EV growth and infrastructure planning with research and practical values not represented by traditional methods. In practice, understanding the interrelations among EV drivers' CDI, the distribution of PCS, and the urban spatial structure is crucial for harnessing traffic, planning infrastructure, and managing urban growth. Few attempts have been made to investigate the association between a city's spatial attributes (e.g. land use, amenity, road network, and neighborhood characters) and the pattern of growing EV travel. To address this gap, we develop a model to evaluate the extent to which a series of spatial variables influence the dynamics between the CDI and the current PCS.

In short, this paper tries to answer three research questions: (1) How to map the spatial pattern of EV charging demand based on drivers' LBS requests? (2) How well does the provision of PCS match the EV drivers' charging demand? (3) To what extent is the CDI pattern associated with the urban spatial structure? To address these questions, we conduct a case study in Beijing, the city boosting the most EVs in the world. The methods and findings, however, are potentially applicable in other large cities in different countries.

Chapter 2. Research design and methodology

2.1. What can we learn from existing studies?

2.1.1. PCS and charging demand estimation

The charging behavior of EV is a concern of multiple disciplines including transport planning, data science, GIS, and physical planning, leading to different methods. Early research relies on questionnaire-based surveys and empirical data to understand EV owners' charging preferences (Smart & Schey (2012)). Some investigate the utility data at different types of charging facilities (home, workplace, and public-charging) to compare their respective demands and usage patterns, which helps with decisions of concentrating limited resources upon the more effective areas to stimulate EV growth (Morrissey, Weldon & O'Mahony, 2016; Neubauer & Wood, 2014; Sedighizadeh, Mohammadpour & Alavi, 2019). Others try to gain insights into these issues by classifying different types of EV users, namely residents, commuters, and visitors, and by simulating scenarios of their charging needs (Helmus, Lees & van den Hoed, 2020; Khoo, Wang, Paevere & Higgins, 2014; Xydas et al., 2016).

Among the different charging options, PCS has been the challenging part for quantitative study and spatial analysis as it involves different types of users whose activities tend to be more random in temporal and spatial terms. Its significance related to the growth of EV market has nonetheless been recognized (Funke, Sprei, Gnann & Plötz, 2019; Pardo-Bosch et al., 2021). Research has demonstrated that a large number of EV owners use PCS for charging (Plötz, Schneider, Globisch & Dütschke, 2014; Smart & Schey, 2012), and the accessibility to PCS is a crucial factor for EV market growth as it influences EV owners' level of mileage anxiety (Kester, Sovacool, Noel & Zarazua de Rubens, 2020; Pan, Yao, Yang & Zhang, 2020). The demand for PCS will keep increasing with EV's rapid growth, even taking into account the concurrent improvement of battery performance (Schmidt, Staudt & Weinhardt, 2020; Xu, Meng, Liu & Yamamoto, 2017).

Some researchers zoom in to individual charging stations to model EV drivers' charging activities (Kara et al., 2015; Khoo et al., 2014; Morrissey et al., 2016; Xydas et al., 2016). Although the PCS consumption dataset (such as number of charge and daily electric consumption) represents valuable information for studying the quantitative pattern of public charging behavior, there are some limitations. First of all, accessibility to and accuracy of the PCS consumption data vary by suppliers and cities (Funke et al., 2019). In many cities (including Beijing), PCS is operated by a number of individual suppliers, which means a challenge for collecting valid PCS consumption data with sufficient and consistent samples. Therefore, the methods that use PCS consumption data become impractical or flawed in many cities. Second, this method is incapable of capturing the unmet demands and visualizing the dynamics of EV travel behaviors in a large city with diverse geographic features (Helmus et al., 2020). Third, PCS charging data seldom engages "driver behaviors" such as where drivers have the need to charge their vehicles (the location that drivers search for the charging stations) and where drivers actually charge their vehicles (the charging station that drivers search for), which is important for some studies in terms of the behaviors and preferences of EV drivers including travel purpose, distance, and timing (weekdays and weekend) associated with their charging activities.

This justifies an alternative approach, which is the LBS service requests for PCS charging. This user-based data enables the documentation of "unmet" demands and drivers' travel behaviors, and matches the objective of this study. Admittedly, this data source also has its limitations as it does not capture the charging activities of EV drivers without using LBS in their smartphones. Our research indicates that the smartphone service requests data still represents a considerable proportion of the charging demand and provides a lens to the whole picture; and since this paper focuses on EV drivers' charging behavior and its relation to urban spatial attributes, EV drivers' service requests represents a better tool than the static consumption data.

2.1.2. Spatial match between PCS and charging demand

The need of recharging is a fundamental characteristic of the EV apart from the conventional petroleum vehicle. Researchers explore different aspects of this technical feature, including travel range, operation cost, and charging time (De Gennaro,et al., 2015; Schmidt et al., 2020). EV drivers tend to take into account travel range, charging time, and availability of charging pile on their way to a destination when planning a trip, thus rely more on navigation and path optimization than non-EV drivers (Azadfar et al., 2015; Bac & Erdem, 2021). Due to the substantially longer time required for electric charging than refueling at a gas station, EV drivers are more likely to choose a PCS closer to the origin or the destination of their trips than somewhere in the middle of the route (Schmidt et al., 2020; Yang et al., 2016). Therefore, the spatial match between charging demand and PCS locations are worthy of in-depth study.

Spatial analysis based on Geographic Information Systems (GIS), including point-based methods (Csiszár et al., 2019; Frade et al., 2011; He, Wuet al. 2013; Liu, 2012), spatial clustering analysis (Ip et al., 2010), polygon overlay analysis (Csiszár et al., 2019), and geospatial modeling method (Namdeo et al., 2014), is often used to map the distribution of EV charging supply and demand. Such analytics are leading toward visualizing the spatial patterns of EV charging behaviors. As the majority of data is derived from statistics, however, the spatial properties and environmental factors presented in these estimations are not directly connected to individual EV users. Only a small number of studies utilize big data in examing some special groups of EVs, such as electric taxis or ride-sharing vehicles, of which the GPS data is easier to attain Jia et al., (2017); Pagany et al. (2019); Tu et al. (2019); Yang et al., (2017). A gap therefore exists in estimating the charging need of the private EV owners who utilize PCS, mapping how the distribution of PCS influences their travel behavior, and using actual user data to bring such research to a higher level of accuracy. This paper thus addresses this gap by recognizing "match" and "mismatch" areas between EV charging demand and supply by comparing the spatial pattern between the CDI of private EV drivers and the current PCS.

2.1.3. Association between EV charging and urban spatial structure

Some research has combined regression models with GIS-based methods to evaluate EV travel behaviors and charging demands. Psychological and sociodemographic factors are considered to help understand the charging preferences of different EV user groups. (Franke & Krems, 2013; Li et al., 2017; Pan et al., 2020). Others focus on such technical specifics as battery power level, charging cost, and travel distance (Daina et al., 2017; Yang et al., 2016; Zoepf et al., 2013). These studies address different aspects that influence EV drivers' charging decisions and trip planning.

Successive studies have established some common dependent variables including choice of charging location, charging time, and charging mode for modeling (Daina et al., 2017; Morrissey et al., 2016; Sun et al., 2015; Xu et al., 2017; Xu et al., 2020). Some introduce multi-source datasets to analyze charging behaviors. Wolbertus, Kroesen, van den Hoed & Chorus (2018) use multinomial logistic regression to evaluate factors that affect the charging time at PCS based on 2.6 million charging sessions. Li et al. (2018) collect search and navigation data from charging-service apps, and combine it with PCS records to model the distribution of charging activities. Their research indicates the potential of LBS for modeling EV user behaviors and assessing infrastructure deployment. Carrying on this method, this paper expands the effort of measuring EV drivers' charging demand through more extensive investigation of smartphone searching records, and through a new model incorporating urban spatial variables to examine their association with EV charging behaviors.

With all available findings and progressing methods, what remains relatively opaque in the current studies is the way in which urban spatial conditions influence the charging behaviors and the resultant travel patterns of EV drivers. In other words, can geo-spatial research move beyond the abstract coordinates to offer a picture of the dynamics between EV activities, charging demands, and the spatial properties of the PCS locations and their surrounding? This study looks into the association between a set of urban physical environment factors (e.g. land use, neighborhood character, amenity, and transportation network) with the EV charging demand pattern, in order to provide new insights into the relationship between urban built environment and individual behaviors and to offer advice for future EV infrastructure development.

2.2. Electric mobility in Beijing

We chose Beijing, the capital of China, as the city to study EV for several reasons. First and foremost, Beijing is the city with the most battery-electric cars in the world. The number of EVs in Beijing in 2020 has reached 388,000, with a successive increase of 60,000 new registrations of EVs per year(Beijing Transport Annual Report, 2021). It is more than three times of the number in Los Angeles that has the second largest number of EVs in the world (Hall et al., 2017), at about 100,000 EVs in 2020 (Bui et al.,2021). Second, Beijing has been rapidly expanding into its metropolitan peripheries, causing the transformation of its urban structure. The urban expansion and transformation have involved building many PCS, both in the inner city and the new districts, yet the effectiveness has never been thoroughly examined. An in-depth investigation of Beijing thus represents a condensed, pilot study of issues confronting cities in the world, many of which are following suit in EV development.

Beijing consists of 16 administrative districts (six of which are considered central city districts) with a total area of 16,410 km2 and a total permanent residential population of more than 21 million(Beijing Transport Annual Report, 2019) . A concentric pattern characterizes the city's spatial structure with a series of ring roads (Fig. 1). The ring roads are a dominant geographic feature as they frame Beijing's urban growth pattern and transportation structure in a more powerful and direct way than the administrative divisions. Traffic condition continues to deteriorate due to urban sprawl, arising from this unicentric structure and causing increasing home-work separation. Such urban structure contributes to the city's environmental degradation, particularly severe air polution, 20% of which is attributed to transportation (Pan et al., 2016). Nevertheless, Beijing is decisively moving towards transport electrification, thanks to the tremendous support from the central and local governments committed to improving the city's environment. With the exponential growth of EVs, the charging stations networks are also expanding rapidly, including home-charging, commercial-charging, and public charging, as indicated in table 2.1. This study collected data from 3,075 PCSs across the city.

Table 2.1. Overview of the numbers and types of charging stations in Beijing[1].

Type	**Number (2019)**	**Location**
Open Public	2358 public stations (with about 24,300 charging piles)	Shopping centers, business centers, agricultural wholesale markets, tourist attractions, freight hubs, public parking lots, other public amenities
Partially open	2382 charging stations (with about 17,900 charging piles)	Internal parking lots of administrative complexes, corporate buildings, and institutions, some of which are partially open to public.
Public dedicated charging stations	534 charging stations (with approximately 5400 charging piles)	Electric-taxi parking lots, public transit nodes.
Private charging	145,500 fixed charging piles	Private parking spaces for personal usage in residential neighborhoods.

[1] Xinhuanet report: Over 190,000 electric vehicle charging piles in Beijing. 2019. Available at http://www.xinhuanet.com/fortune/2019–12/25/c_1125384489.htm

Table 2.2 and Figure 2.1 show the distribution of the registered EVs as well as the distribution of PCS by district for initial analysis. The statistics indicate that 21% of EVs are registered within the urban core (Xicheng and Dongcheng districts) where only 8% of PCS are deployed; and 47% of EVs are registered in the other inner-city districts (Chaoyang, Haidian, Fengtai and Shijingshan) where 44% of PCS are deployed. Totally 76% of PCS is located within the Sixth Ring Road (inclusive of its 5 km buffer zone). The ratio of EV per PCS decreases as it moves further out to the suburban areas, and reaches the lowest number in the outer suburbs of the metropolitan region. This provides some basic info of EV usage within the entire metropolitan region. Such statistical data, however, only reflects a general and inaccurate spatial pattern of the EV-PCS relation. For example, there are many specific situations affecting the owners' registration including quota availability, financial incentive, and ownership of multiple properties. It is common for an owner living in one district to register the EV in another under Beijing's quota and lottery system for vehicle license. In addition, the dynamic pattern of EV trips is far more complex than the static distribution by registration. The level of heterogeneity can only be revealed with a closer examination of EV usage at a finer grain. This hypothesis has informed our research in exploring the spatial patterns of EV charging demand and evaluating to what degree they match the PCS supplies.

Table 2.2 Statistics of EV registrations and PCS locations.

Empty Cell	**Location Type**	**District**	**Number of registered EVs**	**Proportion%**	**Total**	**Number of PCS**	**Proportion%**	**Total percentage**
Main Urban Districts	Central area	Dongcheng	21,118	13%	**22%**	94	3%	**8%**
		Xicheng	14,378	9%		142	5%	
	Inner Urban	Chaoyang	23,356	14%	**47%**	588	19%	**44%**
		Fengtai	13,435	8%		242	8%	
		Haidian	36,497	22%		416	14%	
		Shijingshan	4204	3%		90	3%	
Suburb Districts		Changping	9475	6%	**25%**	175	6%	**33%**
		Daxing	13,821	8%		249	8%	
		Fangshan	3745	2%		182	6%	
		Shunyi	4913	3%		157	5%	
		Tongzhou	9838	6%		254	8%	

Empty Cell	**Location Type**	**District**	**Number of registered EVs**	**Proportion%**	**Total**	**Number of PCS**	**Proportion%**	**Total percentage**
Rural Districts		Huairou	3992	2%	**6%**	151	5%	**15%**
		Miyun	2193	1%		96	3%	
		Pinggu	1983	1%		80	2%	
		Yanqing	1406	1%		90	3%	
		Mentougou	1452	1%		69	2%	

2.3. CDI estimation and spatial analysis

2.3.1. Data collection and cleaning

LBS has been widely used in local trips and generated enormous amount of observed data, offering a new lens through which travel behaviors could be examined. The frequency of people's request for LBS reflects the level of interaction between drivers and urban space. In this study, we collected the data from Baidu, the leading map service provider and big data operator in China, to collect EV trip data and PCS distribution data.

The inquiry of PCS distinguishes the EV from other vehicles. When an EV driver finds a PCS through the smartphone app and requests direction to travel to the PCS, this record represents a potential charging demand, constituting a unit of Charging Demand Indicator (CDI). This index enables quantitative measurement of charging demand, which also carries spatial attributes.

Data cleaning workflow includes three steps (Figure 2.2). First, we use the keyword “charging station” as the indicator to identify EV users, assuming that non-EV drivers have no need for charging. The location data of each valid search is then extracted, including both the origin and the destination. We then process the raw data to protect privacy by resampling all location records to a grid of 100 by 100 m and grouping them by the generic square unit (spatial aggregation). The resulted datasets thus contain OD pairs by clustering the EV visit data without any individual information. The number of logs within each 100 m × 100 m unit is recorded as a geographical attribute to indicate the demand. We then use ESRI ArcGIS software to translate the records into a point shapefile. Finally, if the origin of EV trip in a dataset is located outside Beijing, the record is categorized as a non-local user and removed from the dataset.

We attain 186,297records of LBS dataset through this process during a full month of observation with spatial aggregation, from the 1st through the 30th of November 2019. Ultimately, 175,123 records (41,347 OD pairs) are harvested after data screening that removes about 6% of invalid records (Table 2.3). Admittedly, some specific charging demand cannot be captured by the LBS records (e.g. home-charging and commercial-charging). However, since the objective of this research is to focus on analysis of public-charging supply and demand, it is reasonable to exclude the home-charging and commercial-charging demands, which follow a quite different logic.

Table 2.3. Overview of cumulative observation data from smartphone app.

Accumulative Observation Data (100 × 100 m)	**All days (30)**	**Weekdays (21)**	**Weekend (9)**
Original records units			
Number of OD pairs	43,977	29,143	14,834
Total visit frequencies	186,297	122,203	64,094
Selected EV users records			
Number of OD pairs	41,347	27,411	13,936
Total visit frequencies	175,123	114,992	60,131
Overview of the data structure			
ID	The unique ID of each data		
PCS_X	Longitude of the destination searched by smartphone app		
PCS_Y	Latitude of the destination searched by smartphone app		
SO_X	Longitude of the location where the EV driver search for charging		
SO_Y	Latitude of the location where the EV driver search for charging		
Number	Number of users' records in this unit		

To calculate CDI, we need to identify locations where the charging demand occurs. Therefore, we employ OD distance (Euclidean distance to be exact) to examine the Origins and Destinations in order to analyze different scenarios of travel behavior. We use the Euclidean distance of 1.5 km as a threshold value, which is defined for two reasons: 1) statistic indicates that 54% of the OD distances fall within 1.5 km; and 2) Beijing's planning guidelines use 1.5 km as the benchmark for walking and cycling, meaning people generally do not need a car to get around within this radius. When the OD distance is within 1.5 km, we assume that the driver is looking for charging near the origin, and thus use the Origin as the location where the charging demand occurs. When the OD distance is farther than 1.5 km, it often means that the charging inquiry is associated with a trip to a particular destination. The GPS inquiry is usually presented like "(public) charging station near XXX." In this scenario, we regard the Destination as the location where the charging demand occurs. We incorporate these two scenarios in our statistics and modeling.

2.3.2. Spatial analysis

Kernel density analysis is employed to create a continuous surface based on the inputs of CDI and PCS data in our study. It produces a smooth curved surface with the input points, which allows researchers to visualize both the general trend as well as instances of spatial heterogeneity, and to better understand the spatial distribution pattern of charging activities and infrastructure Gerber (2014). The point-based kernel density function is shown as followed:

$$Density = \frac{1}{(radius)^2}\sum_{i=1}^{n}\left[\frac{3}{\pi}\cdot pop_i(1-(\frac{dist_i}{radius})^2)^2\right]$$

$$dist_i < radius$$

where i represents the point of PCS location and the point of PCS that accumulative visits of EV users search for charging from smartphone; pop_i represents a weighted value to perform a higher weight during the generation of a rasterized topography—the number of charging service requests of each PCS point (The default value is 1); $dist_i$ represents the distance between the input point i and the predict location point of (x,y).

The selection of radius (also known as bandwidth) has significant impact on the outcome of computing. The bandwidth estimation is conducted based on Silverman empirical rule (Silverman (1986), as the following formula shown.

$$Radius = 0.9 * \min(SD_\omega, \sqrt{\underline{1} * D_m}) * n^{-0.2}$$

$$SD_\omega = \sqrt{\frac{\sum_{i=1}^{n}\omega_i(x_i - \overline{X}_\omega)^2}{\sum_{i=1}^{n}\omega_i}} + \sqrt{\frac{\sum_{i=1}^{n}\omega_i(y_i - \overline{Y}_\omega)^2}{\sum_{i=1}^{n}\omega_i}} + \sqrt{\frac{\sum_{i=1}^{n}\omega_i(z_i - \overline{Z}_\omega)^2}{\sum_{i=1}^{n}\omega_i}}$$

Where x_i, y_i, z_i are the coordinates of point i; SD_ω is the weighted standard distance; D_m is the median of the weighted average center distance of all points. Based on Silverman empirical radius, experiments with different values is conducted to identify the optimal radius to comply with the actual conditions. The optimal threshold value of search radius is set at 1,500 m with the suggested output grid size of 300–500 m. This process is completed with ESRI's ArcMap software using its Spatial Analyst Tools.

In application, the setting of radius mostly relies on the scale of research as well as geographic context. In most radius estimation methods, the radius is positively correlated with the dispersion degree of the input points–a more sparse point will hold a larger radius. Adaptive radius estimation methods is proposed in recent years that will use different positions and adaptive scales. Here, PCS points are sparse points relative to CDI; in order to facilitate spatial visualization and analysis, we used the same parameter setting and operation for the current PCS to generate overlay comparison.

This process reveals areas of "match" and "mismatch" between actual charging needs and the current infrastructural deployment. Based on the kernel density analysis (dimensionless), we compare the cumulative visit frequencies from EV users with PCS deployment density by spatial overlay, which exposes if the CDI density spatially matches the density of PCS. Four categories can be identified: High-High (HH), High-Low (HL), Low-High (LH), and Low-Low (LL), defined by the relation between the level of CDI (first letter) and the level of PCS supply (second letter). HL and LH indicate areas where spatial incompatibility exists and the issues should be addressed in planning. HL refers to an area where there is high charging demand but insufficient PCS, while LH refers to the opposite condition. In contrast, HH and LL indicate the areas where the PCS distribution matches the CDI. HH refers to an area where there is high charging demand and also sufficient PCS, and LL sees low charging demand and low supply of PCS.

2.4. Spatial regression modeling

We proceed with the Spatial Regression model (Anselin, Syabri & Kho, 2010) to investigate the potential influences of land use and physical environmental factors (as independent variables) on the CDI (as dependent variable). Multi-source data is used to analyze these geographic variables (Table 3). We then conduct regression of CDI and built-environment modeling at the scale of Jiedao (meaning "street"), China's primary unit of neighborhood administration, as the statistical unit for this spatial analysis. A total of 325 Jiedaos in Beijing are included in this research. As EV drivers' travel behaviors and charging needs vary by time and trip distance, we conduct regressions separately for weekdays and weekends as well as for short-distance trips and long-distance trips (using 1.5 km as threshold value).

We carry out regression diagnostics to compare the Spatial Regression models (Spatial Error and Spatial Lag regression) with the Ordinary Least Squares (OLS) models. The diagnostic results indicate that spatial lag model is most suitable in the case of Jiedao-scale regression of CDI and built-environment, and spatial error model performs better for regression of the CDI assigned with residential community, which takes the following form:

$$Spatial\ lag\colon\ y_1 = \rho W_y + \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + \varepsilon$$

$$Spatial\ error\colon\ y_2 = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + \lambda W_\varepsilon + u$$

Where y_1 represents the dependent variable—the CDI, y_2 represents the CDI assigned with different community locations; β_0 is constant; $\beta_1 \dots \beta_n$ represents the coefficient for independent variable; $X_1 \dots X_n$ — the dependent variables that represent different factors of urban built environment and residential attributes; ε is the unobserved error term; ρW_y is lag of y, where ρ is the spatial lag coefficient, λW_ε is spatially lagged residuals, u is random noise; W is the spatial weights matrix defined by Queen contiguity neighborhoods.

Table 2. 4. Description of variable data.

Data source	Data type	Description	
Charging demands indicator (CDI)	.txt	Identify EV owners, and mine their information associated with charging behavior; Used as dependent variables for regression modeling	
Urban Geographic data	.shp	The basic geographic information data of Beijing, including urban administrative districts, blocks and road network, etc; used for GIS-based spatial analysis and mapping, and regression modeling.	
POI Density	.shp	Tourist attraction	Independent variables in the regression model, representing different land uses and amenities.
		Shopping mall	
		Residential community	
		Medical service	

Data source	Data type	Description
		Education
		Business center
		Metro station

Points of interest (POI) data is introduced as independent variables. It contains detailed geographic information for studying travel behaviors, and complements land use designations. The POI dataset includes seven categories—tourist attraction, shopping mall, residential community, medical service, educational institution, business center, and metro station (Table 4). The POIs represent different travel purposes that generate charging demand, and the density (the numbers of POI in each Jiedao unit) are independent variables. Since each variable holds different dimension, and the POI is non-normal distribution and non-negative integer, the Min-Max normalization method is used for data normalization.

2.5. Results and Discussion

2.5.1. Spatial distribution of PCS and CDI

Kernel density analysis generates continuous surface for the distribution of PCS (Figure 2.3a) and CDI (Figure 2. 3b). Shown in Figure 2. 3a, the density of existing PCS is high within the Sixth Ring Road, largely consistent with the city's radial urban layout and centralized population pattern. The mapping of CDI distribution, however, reveals remarkable spatial heterogeneity, showing clustering of high-CDI zones in the center city while leaning toward the northern areas (Figure 2. 3b). In general, the high CDI density areas are located within the fifth ring road, usually considered the center city. Between the Fifth and the Sixth Ring Roads, however, there are isolated hotspots that coincide with some of the large-scale high-density residential neighborhoods. This leads to deeper examination of potential factors associated with the spatial heterogeneity of CDI.

When we study the OD distances pertaining to PCS search records, the outcome indicates that over 53% of the trips are within 1.5 km distance, and 73% of them are within 5 km. It is a clear indication of trip preference when charging is needed. To represent the trip distance factor, we distinguish the short OD distances within 1.5 km and those larger than 1.5 km (Figure 2. 4c and 4d). The result demonstrates that the high-density CDI areas associated with short-distance trips tend to be located along the urban areas in the north from the urban center toward the sixth ring roads, while the long-distance trips scattered more widely, with relative clustering in the west and the north. Particularly, the suburban zones between the 5th and 6th ring roads and the areas around Beijing's two airports exhibit high density patterns of CDI associated with long-distance trips.

2.5.2. Spatial mismatch patterns

We then conducted spatial match analysis to examine the areas of "mismatch" between CDI and PCS. The mismatched areas (HL1 – HL5, LH1 – LH4) are identified in Fig. 5. When we overlay the mismatched areas with the spatial density map of PCS (the base map) as well as the "hotspots" with high CDI (whose boundaries are marked with green lines), interesting patterns appear. The areas with high demand but low supply, labelled HL1~HL5, coincide with most of the high-density CDI zones within the Sixth Ring Road. The LH areas, including LH1~LH4, are primarily located on the outskirt with spots of high-density PCS deployment (Figure 2.5).

Combining the descriptive statistics with the results of macro-scale spatial analysis, we zoom into the incompatible areas for further investigation in order to provide planners and decision-makers with applicable guidance. Using satellite images as the basemap to examine the zones at the neighborhood scale, the HL and LH zones help understand the extent to which the urban conditions cause the mismatch in charging demand and provision. These results reveal a heterogeneous pattern with hints for future planning, investment, and management of EV infrastructure.

Five representative areas—HL1 through HL5—stand out with significant mismatch. Among them, HL1 through HL4 are located in the suburban areas between the Fifth and Sixth Ring Roads, forming a loop where demands for PCS are growing rapidly as it absorbs a large portion of urbanization; only HL5 is located within the center city. They can be roughly categorized with three different scenarios. The first category encompasses some large-scale high-density residential communities (HL1, HL3) which were built in recent years, yet PCS deployment has not caught up with the pace of urbanization. The second category mainly involves the transport hubs within the regional or national networks (HL2, HL4), including airports and high-speed rail stations, as well as the intersections of highways and metro lines. It appears that the overlap of inter-urban and inner-urban transportations generates high demand for PCS. HL5, representing the last category, is associated with a bustling business and shopping district in the western side of the center city between the Third and Fourth Ring Roads, which demonstrates geographic characteristics of the HL zones located in the inner ring (Figure 2.6).

Out of the 3,075 public charging stations we examined in November 2019, 45.1% received less than 1 search request per day, and 13.6% received no inquiry during the entire month. Although this does not mean no or minimum operation at these PCS because some other EV drivers may use them without searching for it, the low service frequency from LBS nevertheless indicates underutilization of these facilities either due to their locations or other urban conditions.

Our mapping indicates that Shijingshan (LH1), Tongzhou New Town (LH2), and Yizhuang Economic and Technological Development Zone (LH3 and LH4) are equipped with PCS at a high density, most of which, however, are underutilized. These areas are also located within the loop between the Fifth and the Sixth Ring Roads, yet they do not belong to any of the center city districts. This suggests that the deployment of PCS has been influenced by the municipal government's developmental policies to promote these new towns and economic development zones. For instance, Tongzhou was made the new administrative seat of Beijing Municipal Government in 2015 and has since grown rapidly around the administrative programs and business centers. Despite the state-of-the-art infrastructure in this new district, many high-end residential estates remain underpopulated (Figure 2. 6). Similarly, Yizhuang Economic and Technological Development Zone in southeast Beijing also show some signs of real estate bubble with low housing occupancy, relative to its job provision, leading to the (temporary) oversupply of EV infrastructure (Figure 2. 6). These conditions suggest that decisions for additional PCS facilities should be made in caution.

2.5.3. Spatial match patterns

We also examine the areas where PCS density matches the CDI density (Figure 2. 3. HH areas are analyzed and compared with HL zones to discover additional geographic attributes of EV charging activities. It is worth noting that while the high CDI areas, illustrated with green circles in mapping (Figure 2. 5), have sufficient supply of charging stations, this “match” condition is accompanied by a certain degree of over-deployment of infrastructure. The level of redundancy is probably necessary due to the prospect of continuous growth in the near future.

Most major HH areas are located within the Fifth Ring Road, the main urban areas, exemplified by two categories of urban zones, namely mixed-used commercial and residential areas in the inner city, and high-tech industrial zones in the more established new districts just outside the urban core (Figure 2. 7). HH1, an example of the first category, is a high-density neighborhood characterized by a great variety of uses and serviced by three major transit stations. It also enjoys several parks, many historic and cultural attractions, a few shopping centers as well as Business Centers. HH2, or Wangjing, exemplifies the second category, and has grown upon high-tech industries that provide many employment opportunities. Residential population has been growing rapidly in tandem with the development of the business sector in the district, leading to strong demand for PCS.

2.5.4. Relationship between charging demand and built-environment

Consistent with the spatial and temporal pattern of charging demand revealed by the GIS spatial analysis, the results of spatial lag model confirm correspondence between CDI and the independent variables (Table 5). When different combinations of the weekday/weekend factor and OD distance are modeled, some patterns are revealed, suggesting that the effect of built environment on charging demand and preference might vary over time and change by OD-distance band.

Table 2.5. Correlation of built environment variables with CDI.

Dependent variable= CDI density	**Weekdays (21days)**		**Weekends (9 days)**	
Independent variables POI density with time and OD band	**od < =1.5km**	**od >1.5km**	**od < =1.5km**	**od >1.5km**
Metro Station	9.049***	22.780***	3.299*	7.393**
Shopping Mall	1.197	7.520***	1.411***	3.550***
Business Center	0.722***	1.387***	0.0866	0.263
Residential Community	0.523***	0.791***	0.416***	0.396***
Education	−0.078	−1.307	0.369	−0.207
Medical Service	−0.374	4.075	−1.342*	0.695
Tourist Attraction	−0.759	−2.076	−0.359	−0.672

Dependent variable= CDI density	Weekdays (21days)		Weekends (9 days)	
Independent variables POI density with time and OD band	**od < =1.5km**	**od >1.5km**	**od < =1.5km**	**od >1.5km**
Constant	1.207	3.294	0.563	1.174
ρW_y (Spatial Lag of CDI)	0.408***	0.086	0.391***	0.343***

Note: Signif. codes: *** = 0.001; ** = 0.01; * = 0.05. We examine spatial autocorrelation in residuals, comparing the extents to which OLS, Spatial Lag, and Spatial Error models fit statistics. The extensive comparison suggests that spatial lag model performs better in this research.

Metro station represents the highest positive correlation with CDI in all categories of trip distance and in all time. This verifies a phenomon, common in a large metropolis like Beijing, that many drivers use EV (and other vehicles) in conjunction with public transit to commute to work or for leisure. Another reason for this high correlation is that most metro stations are located within high-density mixed-used zones, which also draw large amount of traffic. Both possibilities deserve further investigation.

Shopping mall also demonstrates a positive correlation with CDI in all scenarios. This effect, however, is more prominent for long-distance travelers than those coming from nearby, regardless of weekends or weekdays. This suggests that shopping remains a major activity generating EV trips, and shoppers often take advantage of the PCS near the mall due to their long stay there. Residential community shows a different pattern from shopping mall although both zones foster CDI. The correlation is higher for trips above 1.5 km on weekdays and for trips within 1.5 km on weekends, suggesting that residents prefer to charge near their living locations. Therefore, the correlation is higher for long-distance commuting trips on weekdays, but on weekends residents don't need to commute long distances so they just look for PCS nearby. Business center shows a modest positive correlation with CDI on weekdays, but has almost no effect during weekends for understandable reasons. This confirms the assumption of weekday/weekend variation, and suggests the weekday charging demand should be considered not only for the needs of office workers but also for visitors who might linger around the area for business or other affairs.

When we consider the impact of large-scale facilities like education, medical center and tourist attractions, only medical center has negative correlation with CDI for short-distance trips on weekends. The insignificant correlations may due to the very few PCS in the parking lots of these facilities.

A particularly important insight from the findings is that residential areas have strong correlation with high charging demand in general, regardless of time and types of charging need. In reality, neighborhoods are not the priority in deploying PCS, particularly in the early stage. Regarding this finding, comparison between different residential attributes is conducted to investigate the factors of residential community that may affect high CDI occurred. We examine two categories of residential attributes, namely the physical characteristics of the residential community and the public facilities within the 1 km buffer zone of each community. In total 10 variables were examined as shown in Table 5. We run a regression of the CDI on the 10 variables. The dependent variable is measured by the distance-weighted CDI of the nearest PCS to each community. The coefficients of each of the variable is shown in Table 2.6.

Table 2.6. Correlation of different residential attributes with CDI.

Dependent variable= CDI distributed close to residential community		**Correlation**
Independent variables=Residential Attributes		
The physical characteristics of the residential community	Built_year	−0.028**
	Average price (/m^2)	0.007
	Number of households	0.077***
	To city center (km)	−0.083***
Public service facilities (within 1 km buffer zone of each community)	Public transportation	−0.032**
	Shopping Mall	0.001
	Business Center	−0.052***
	Educational resource	−0.027**
	Medical Service	−0.031
	Cultural Tourism	−0.018
Lambda		0.529***
Constant		0.122***

Note: Signif. codes: *** = 0.001; ** = 0.01; * = 0.05. The extensive comparison suggests that spatial error model performs better in this research.

The physical characteristics of the residential community is derived from the China's official real-estate transactions website, and 8.842 residential communities are used in the model. Four variables in this category are fitted into the model. “Built-year” represents the construction year of the community building. This variable is selected based on the hypothesis that it is more difficult to renovate the circuits and install charging facilities in the older buildings, thus may have a higher demand for the public charging facilities. This may affect the consideration when residents purchase an EV. The variable shows a negative correlation with CDI, indicating that newer neighborhoods tend to become EV owners' choices and may have a higher demand of charging. The number of households in the community has a positive correlation with CDI, indicating that the larger population is associated with higher charging demand. The distance between the community and city center is used to differentiate the location of the community, in an urban or a suburban area, which has a negative correlation with CDI, meaning that the communities located further away from the city center have higher CDI. Housing price approximately represents the income level of the residents in the neighborhood, which sees no significant correlation in the result.

The second category of variables, namely public service facilities, reflects the quality of living environment of the community, and is measured by the number of each type of facility within the 1 km buffer zone of each community normalized with the min-max approach. Public transportation, educational resource and business center show negative correlation with CDI, indicating that the communities with imperfect public service facilities tend to be more reliant on PCS. This oversight should be corrected in future infrastructure planning. The residents who do not have access to private parking space rely on the PCS either within the neighborhood or in the facilities nearby. The emerging working-class neighborhoods along North Fifth Ring Road (HL1) typify this situation. Their relatively affordable housing price and the employment opportunities in adjacent areas encourage the continuing influx of residents to settle in these high-density condominium neighborhoods. Yet amenities haven't caught up to support this growth. Such dynamics should be considered in the next phase of planning of PCS and other infrastructure.

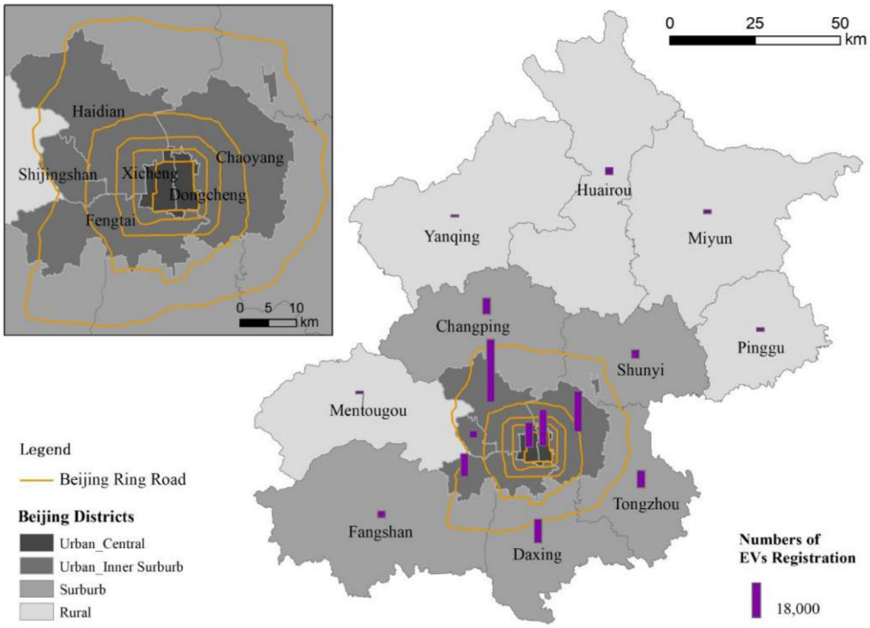

Figure 2.1. Distribution of registered EVs in Beijing. The histogram represents the numbers of EVs registered in each district, corresponding to Table 2.

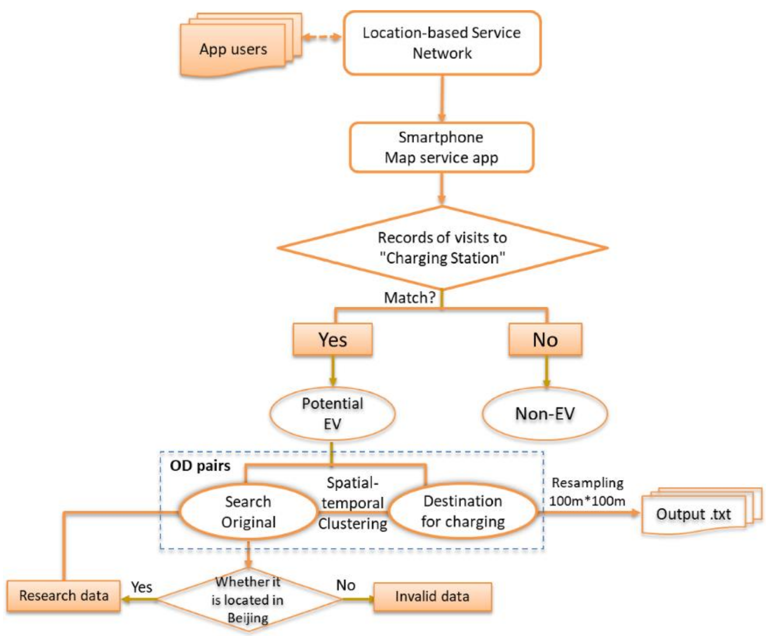

Figure 2.2 Workflow of identifying CDI from EV drivers based on GPS data processing.

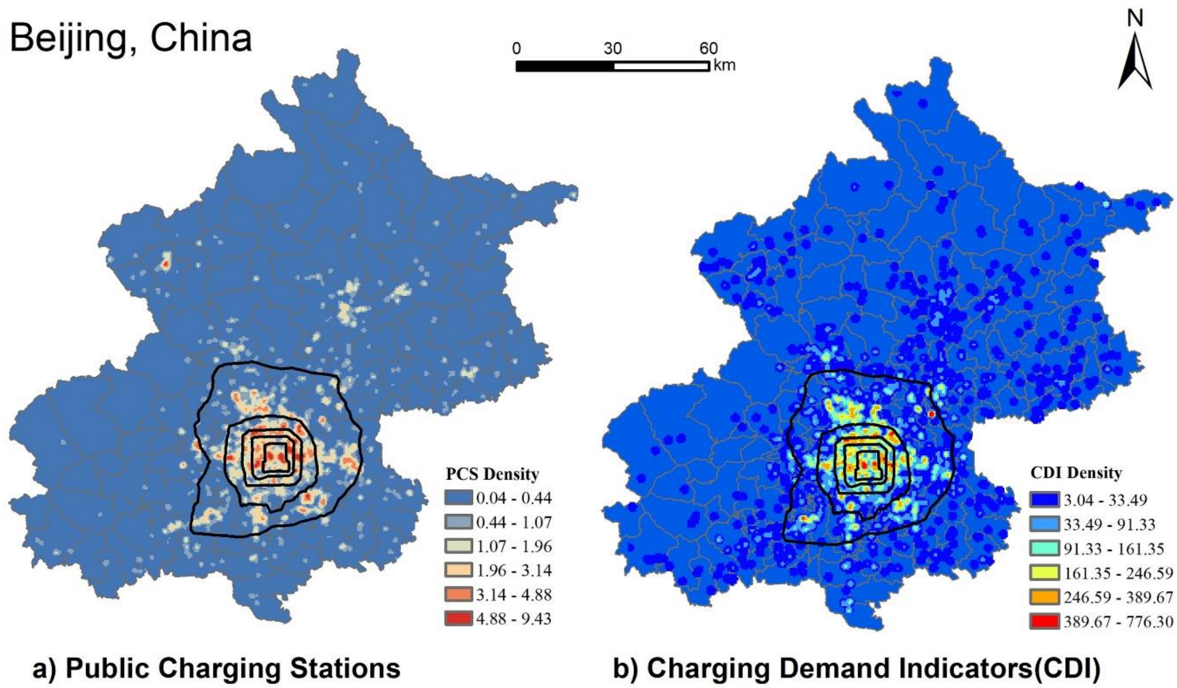

Figure 2.3 Kernel density analysis map. a) PCS density map; b) CDI density representing EV drivers' charging demand from navigation data

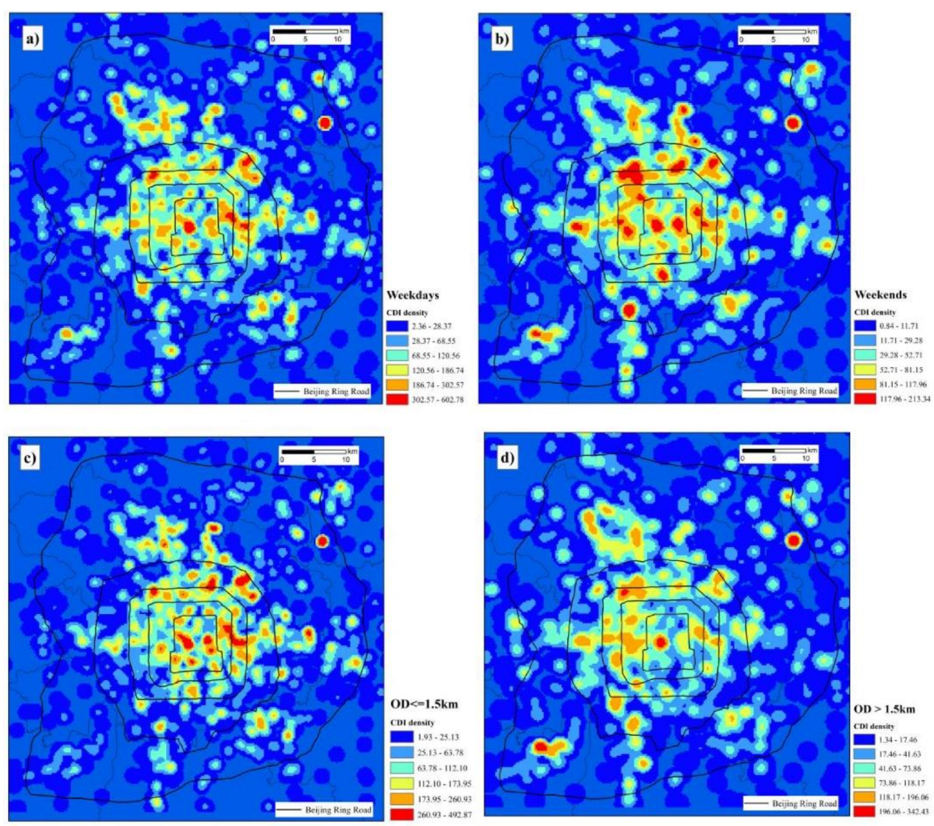

Figure 2.4 Mapping of CDI density on a) weekdays; b) weekends; c) when OD<=1.5 km; and d) OD>1.5 km

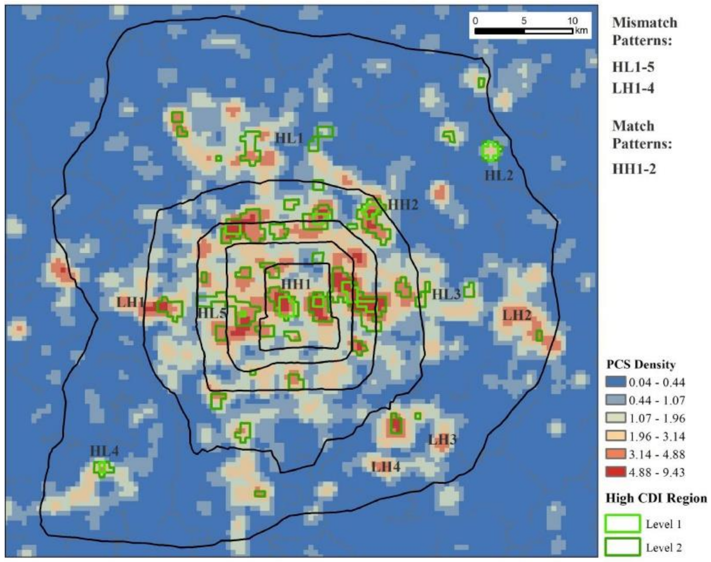

Figure 2.5. Spatial consistency map between CDI density and PCS density, showing locations of match and mismatch. The green circles represent the boundaries of the areas with high-density CDI, and are divided into two categories, Level 1 (highest) and Level 2(high)

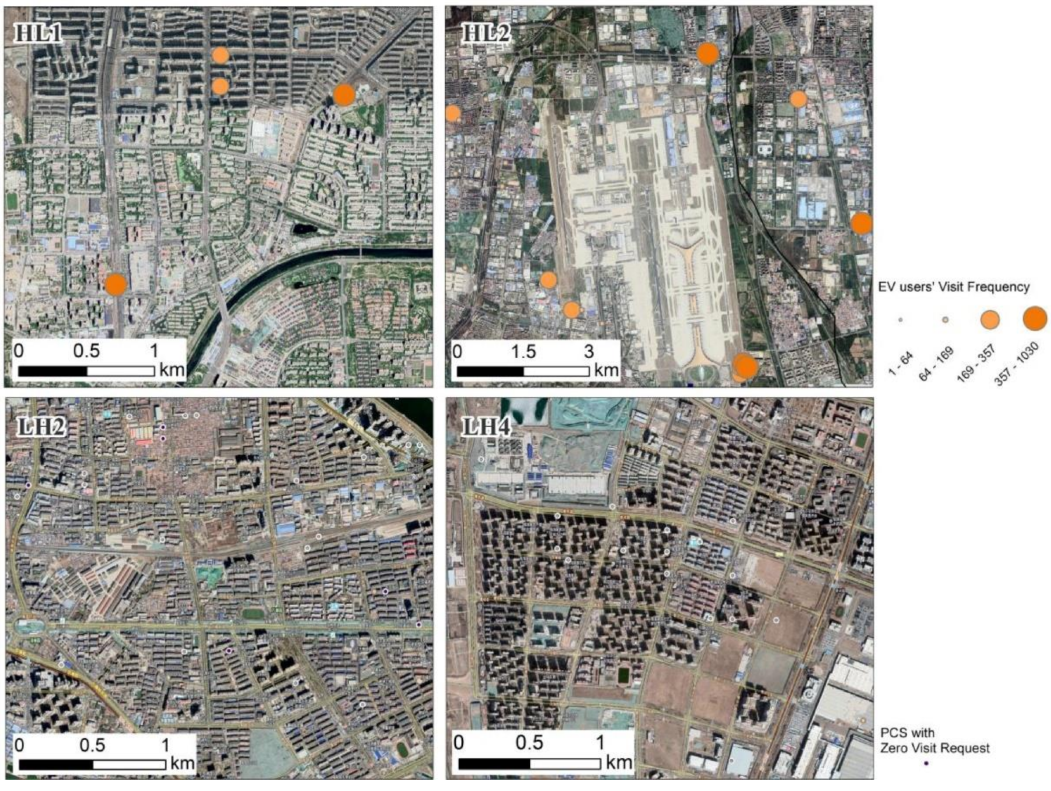

Figure 2.6 Examples of mismatch areas, including HL and LH. Zoomed in and overlay on Google Earth satellite images. HL1: Tiantongyuan residential neighborhood; HL2: Beijing Capital Airport; LH2: Tongzhou New Town, an administrative district; LH4: Yizhuang Economic and Technological Development Zone.

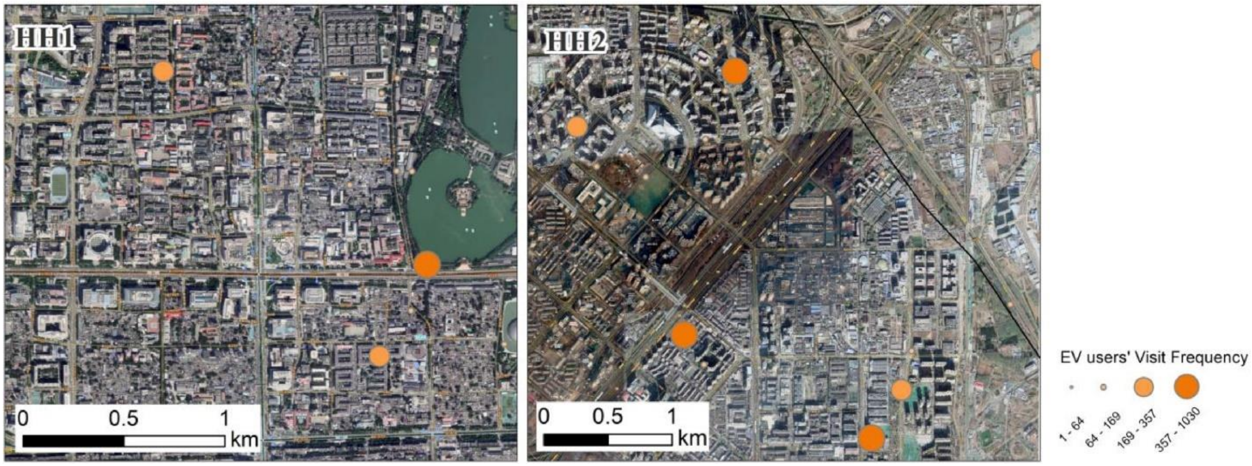

Figure 2.7 Examples of HH match areas. EV visit frequency on Google Earth satellite images. HH1: West Changan Street Area; and HH2: Wangjing business center

Chapter 3. Conclusion and Recommendations

Beijing exemplifies many contemporary metropolises across the globe, which have seen rapid growth of EV. To build a sustainable infrastructure to support the development of electric mobility becomes a pressing issue of these cities. It is crucial to understand the dynamics of EVs charging demand within the context of contemporary urbanization in order to optimize this significant public investment. This paper employs a novel data-driven method to engage smartphone navigation data in mapping EV owners' public charging activities by location and time. It allows us to investigate how well the current PCS network meets the demand of EV drivers citywide, and where there are shortage of supply, over-investments or advanced deployments. This method offers new insights into infrastructure planning for the future. The GIS analytics is further combined with spatial regression modeling to explore the correlation between a series of urban spatial variables and the EV charging behavior measured by CDI. The research also incorporates other spatial factors characterized by OD distance and the temporal factor of weekday/weekend to reveal at a finer grain the relationship between urban spatial characters and EV driver behaviors.

The navigation data offers an enhanced tool in this research to visualize the spatial pattern of EV charging demands, which complements traditional statistical approaches in evaluating the impacts of various urban factors. A focus on charging demands instead of realized charging activities leads to a different strategy of data-mining and investigation and offers an alternative lens to examine EV drivers' demand of public charging through capturing the interaction between PCS locations and EV drivers' travel and charging preferences. By tracking the dynamics of charging demands, the conception and visualization of CDI explore the potential of informing future infrastructural deployment.

While this research focuses on Beijing, the findings reveal general dynamics between the urban spatial property and the density of EV usage, and suggest practical and policy implications for cities worldwide. Nevertheless, more samples and further investigation in other cities should be engaged in order to produce more accurate results. Different urban layouts in other cities also mean varying conditions for EVs and PCS, leading to other forms of equilibrium, thus more local tests should be carried out. Furthermore, the navigation data does not capture the activities and charging demands of EV users who have established a routine of location and time of charging and thus do not rely on LBS. Therefore, the model generated by this method represents a proportional indicator rather than concrete numbers. Should the PCS data become more accessible, researchers should combine both types of data in order to reach a higher level of precision in mapping and assessing the EV charging demand and behavior.

In order to better prepare our cities for the upcoming age of electric mobility and to achieve a higher level of urban sustainability, further research should be encouraged on the growth of EV system and its reciprocal relationship with urban space. Two fundamental changes are influencing the spatial pattern of many large cities, and thus require adjustment in the way in which we plan and develop EV infrastructure. On the one hand, the centralized spatial structure of many cities is gradually dissolved as populations and employments are increasingly redistributed to the previous peripheries, forming a multimodal metropolitan network. The spatial heterogeneity we discover in this study will become stronger and thus require more in-depth analyses of the actual demand-supply dynamics that spread across the wider territory. On the other hand, the world of electric mobility is moving toward a higher level of automation as the driverless technology is advancing. It makes possible the rapid development of ride-sharing and reduces the dependence on car ownership. This implies not only a more decentralized distribution of EV infrastructure but also a greater role that PCS has to play in contemporary urbanization.

The progression in research of EV charging demand is anticipated to inform the future policies and planning of EV infrastructure. The building of a system to support transport electrification is a significant public investment, especially considering the rate of growth in a city like Beijing. Therefore, decisions should be made based on concrete investigation of the demands related to urban growth. The current PCS network in Beijing gathers most resources in the urban center. Our spatial study, however, suggests an asymmetrical and less centralized pattern of demand. For example, greater attention should be paid to the high-density condominium neighborhoods in the inner ring of the metropolitan area. This kind of neighborhood often sees high numbers of EV users who rely on public charging facilities as few residents can afford private parking spaces. In another category encompassing shopping districts and business centers, charging activities fluctuate more significantly between weekdays and weekends, which would require consideration of flexibility in the deployment of charging stations. Our research finds robust charging hotspots around the metro stations as well as airport terminals, suggesting high-level correlation between EV travel and other transport modes. Metro stations deserve particular priority in EV infrastructure deployment as the connectivity becomes very important even cities expand to such a scale as Beijing. For airports, further investigation should incorporate mobile data with charging pile utility data in order to gain a higher-resolution picture due to the heterogeneous spatial domains within and around such enormous field.

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