Assessing the Impacts of Electric Vehicle on the Transition of Urban Energy Structure: A Geospatial Machine Learning Study in Beijing

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Abstract: The electric vehicle (EV) has been regarded as a promising tool for decarbonizing urban transportation and mitigating climate change. As EV's market share continues to increase worldwide, it starts to influence the patterns of electrical power usage and human behavior, particularly in the urban areas, which might eventually lead to significant change in urban structure and energy policy. Some particular questions arise in urban layout and infrastructure: does changing to an EV affect people's preference of home location? Will the increasing popularity of EV lead to further suburbanization or help promote a more compact urban form? How should the deployment of new urban infrastructure including the energy system guide this transition toward a sustainable future? This study of the rapidly expanding metropolis of Beijing is conducted to address these questions by combining geo-spatial big data analysis, machine learning, and theories of urbanization to examine the relationship between the trajectory of EV users' home location and the changing pattern of energy infrastructure. Gradient Boost Decision Tree model is used to investigate the nonlinear associations between the spatial distribution of

EV residents and a series of variables related to neighborhood attributes including land use mix, building coverage ratio, accessibility to public charging, accessibility to public transit, and employment density, as well as GDP. The results indicate that the majority of EV users live in the near suburban areas, especially the areas around the 10 km radius away from the city center. The discovery that most public charging activities occur within a 1.5 km radius from home suggests an optimal threshold for public charging station deployment. These findings can inform energy management and infrastructure planning at the local and regional levels to promote sustainable urbanization and smarter energy planning.

Key words: electric vehicle, spatial analytics, machine learning, Gradient Boost Decision Tree, urban sustainability, energy transition

Highlights

- The nonlinear relationship between the EV users' home location and series neighborhood attributes is examined.
- The majority of EV users live in the near-suburban areas around 10 km away from the city center.
- Most public charging activities occur within a 1.5 km radius of home, indicating an optimal threshold for public charging station deployment.
- Results suggest that the residents in the suburban areas represent the primary beneficiary of the electric mobility.
- The findings provide useful hints for future urban layout and infrastructure planning.

Word Count: 7680

List of abbreviations:

EV: Electric Vehicle

PEV: Plug-in Electric Vehicle

PCS: Public Charging Station

LBS: Location-based Service

GDP: Gross Domestic Product

1. Introduction

The increasing number of cars, coupled with the rapid urbanization worldwide, has led to challenges related to environmental pollution and human health. When it comes to the pathway of decarbonization, which is necessary to address increasingly severe climate change problems, the electric vehicle (EV) have been promoted as an essential choice of urban transportation [1]. As an alternative to traditional fuel vehicle options, EVs are growing rapidly in cities around the world. The total number of Plug-in EVs (PEV) has reached 11 million worldwide in 2021[2], and continues upward. This trend has accelerated as more governments are implementing policies and using incentives to encourage EV production and consumption, while limiting the growth of gasoline vehicles. For example, the United Kingdom plans to stop selling new diesel and petrol gasoline cars by 2030, and only issue new licenses for EVs; Denmark and France aim to eliminate gasoline vehicles by 2030 and 2050 respectively [3]. The United States has also set an ambitious goal for EVs to make up 50 percent of all vehicles sold by 2030 to combat climate change and promote environmental justice [4]. Currently, China boasts the largest EV market, with over 3.3 million EV sold in 2021, more than all other countries combined [2].

It is believed that the increasing penetration of EVs will have a significant impact on the future form of cities, yet the scope remains unclear. This shift in energy and transportation will certainly stimulate further urban transformation, from infrastructure for power system on a macro-scale to travel behavior and home location choice on a micro-scale. However, there are debates among scholars and policy makers about in which way the EV will influence the urban form and density. Some argue that EVs will become more prevalent in urban centers for their potential of improving air quality and reducing traffic congestion[5]. The limitations in travel range and charging time also make EVs more suitable for short-distance commuting in large cities[6]. These characteristics are expected to contribute to a more compact urban form, characterized by high-density development, mixed land uses, and shorter live-work distance. Others contend that due to significant lower energy costs driving an EV, people may be more inclined to live in the suburb. With the anticipated advancements in battery technology, expansion of charging networks, and improvement of road network, EVs may benefit long-distance travelers even more [7]. The growing business model of ride-sharing and the forthcoming autonomous driving technologies might offer greater comfort and flexibility for travels and passengers and potentially encourage people to spend more time in a car. However, current studies have not provided concrete evidence as to how the EV will impact urban growth. This remains a crucial question as it will affect the demand of new infrastructure and influence the deployment of energy networks.

Previous studies have discovered the mutual influence between spatial attributes of neighborhood environmental and car ownership [8-11]. For example, people who live in suburbs with inadequate public transportation have a higher dependence on cars, while a compact city form with higher public transport accessibility tend to discourage car ownership [10]. In general, home location has a larger impact on car dependency than workplace [11]. When we compare EVs and gasoline vehicles, their different ways of operation, such as location, time, and frequency of charging or refueling, means that they likely have different influences on the built environment including home location choice, live-work pattern, as well as urban layout and infrastructure. However, a gap remains in the study of EV owners' residential preference and the relationship between the built-environment attributes and EV ownership.

Understanding the above-mentioned issues is crucial for transportation planning, energy management, and urban sustainability, as well as for policies promoting EV, green energy, and sustainable urban development. To address the research gap, this study focuses on the distribution pattern of EV users' home locations and its association with the built environment, and tries to answer two primary questions:

(1) Do EV users tend to live in the city or in the outskirts; in other words, will the rapidly growing EV penetration lead to further expansion of large cities or contribute to consolidation of urban density?

(2) To what extent are the major attributes of urban layout compatible to the EV's characteristics and playing a role in EV users' home location choice?

This study focuses on the non-linear effects related to the built environment. It uses multi-source geospatial big data, specifically the anonymous active EV users' residential distribution data, from location-based services, and employs geospatial analytics and machine learning models for analyses. GIS-based spatial analytics are first used to visualize EV users' residential patterns in relation to such built-environment variables as land use mix, building coverage ratio, accessibility to public charging, accessibility to public transit, employment density, and the corresponding economic productivity (GDP) in the same area. We then use a Gradient Boost Decision Tree (GBDT) model to measure the non-linear effects of correlations between the rate of EV owners within the residents and the selected built-environmental variables.

2. Literature review

Many researchers and planners argue that EV technology will primarily benefit city dwellers due to the limited travel range of battery power. It is also believed that EVs, with their environmental attributes such as low pollution and noise, will make an ideal alternative to conventional vehicles for inner-city commuters. As a result, public charging facilities tend to be deployed in urban centers [12]. Until recently, car registration data in Europe does indicate that EV owners tend to cluster around downtowns [7]. This conclusion, however, might depend on location and social context. In the same time, the growing popularity of EVs has slowly shifted the perspectives of the relationship between EV usage and urban transport infrastructure. A 2019 research and development agenda by the U.S. Renewable Energy Laboratory, for example, urges a more in-depth re-evaluation of the dynamics [13]. Some data suggests that EVs may grow faster in suburbs or rural areas than in urban centers. In the UK, surveys show that 70% of households have garages or off-street parking, indicating potential for high residential charging demand, but only 30% in urban areas [14]. High-density urban areas may not be the best places for EVs due to traffic congestion, which can cause issues with battery limits and space constraints for building charging stations. On the contrary, people living in the urban outskirts may benefit more from EVs' lower operational costs [5]. Other researchers observe that with less options of public transportation, suburban lifestyle makes residents more reliant on an efficient vehicle [15]. Even some surveys in Europe indicates a stronger motivation by suburban or rural residents to switch to an EV than urban residents [16]. Other researchers try to look into the variations related to residential location that might affect the willingness to purchase an EV [17].

Many studies have been conducted to understand the specific characteristics of EV in order to promote their acceptance as an alternative to traditional fuel vehicles. Researchers have found that most EV trips are short distance, but the average total mileage over a period of time is considerably higher than that of a gasoline vehicle, suggesting that EV users tend to travel more frequently [18, 19]. While the limited driving distance is still a common concern for EV owners [20], some studies suggest that EV drivers prioritize energy efficiency by optimizing their routes more often than non-EV drivers [21]. Additionally, due to the long charging time required, EV users are more likely to charge their vehicles near their departure point (home-charging) or at the end of a trip (destination charging) [22]. While charging at home is the best solution, it is not a common condition for everyone in large cities, as private parking is often not available [23]. An empirical study from Germany indicates that 40 percent of drivers do not have a dedicated parking spot, and many EV owners depend on public charging facilities [16, 24]. Another survey from Northern Europe shows that more than 75 percent of respondents emphasize their dependence on public charging stations (PCS) [7]. deployment of PCS is seen as a crucial factor in promoting the EV market [25].

Given the distinctions between EVs and gasoline vehicles, it is important to understand how this emerging mode of transportation may interact with the built environment. Many studies have explored the factors that influence car ownership, assuming linear correlations. Some common findings suggest that higher residential density [9], higher level of mixed land use [26], and higher density of bus stops all have the effect of contain private car ownership or usage when other policies are implemented properly. In contrast, poor accessibility to or planning of public transportation services force car purchase and use [27, 28]. However, findings also vary by countries and social contexts. For example, the case studies in New York City [29] and in Washington DC [8] confirm that adjacency to the city's Central Business District (CBD), high employment density, and convenient bus system substantially reduce car ownership. In Shanghai, however, the accessibility to public transit does not show a clear correlation [8].

In recent years, machine learning models have become increasingly popular for exploring the non-linear relationship between the residential environment, social-economic variables, and car ownership. For example, Zhang et al. 2020 [10] used a GBDT model to measure the non-linear impact of household car ownership and multivariate accessibility measures in Beijing and found that local accessibility indicators, such as retail and service density and employment density, have more important influences than public transport accessibility in reducing car ownership. Wang et al 2021 [11] discussed the non-linear effects of the built environment of residential neighborhood versus workplace on car dependence. The use of non-linear models can connect variables effectively and better articulate policy implications for planning. Although these previous studies have explored the impacts of urban planning variables on car ownership, it is unclear whether the same holds true for EVs. There remains a gap in exploring the relationships of the increasing EV penetration with the trajectory of urban expansion and with the traditional forms of public transportation. No research has focused on EV owners' residential pattern, and explore the effects of essential built-environmental factors.

3. Data and Methodology

3.1 Study area

Beijing has become a pioneer among cities worldwide in promoting EVs. Due to the serious air pollution, the city has implemented strict policies to control car ownership since the 2008 Olympic Games, including a lottery system for purchasing a car and alternate dates of permitting car usage based on license plate number. It also incentivizes EV ownership through direct subsidies and waiver of those restrictions placed on gasoline cars.

There are entirely 40,000 more EVs in Beijing in a single year of 2020. The rapid proliferation of EV in Beijing is changing the city's urban layout, infrastructure strategies, and environment. It is estimated that CO_2 emission could decrease by 38,280 tons per day with the transport electrification [30]. In the meantime, Beijing has been undergoing dynamic urbanization, with a substantial increase of density in existing urban areas as well as continued expansion into its peripheries. In general, the growth pattern of Beijing has been radial one centered at the historic core, the Forbidden City, and expanding by building circular ring roads. Figure 1 indicates this centripetal structure and the distribution of population densities. How does this spatial pattern match the charging demands of EV users, and how does the growing number of EVs influence the continuing development of the city? With the predicted dominance of EVs in the near future, this mutual influence is critical for the planning and management of the city.

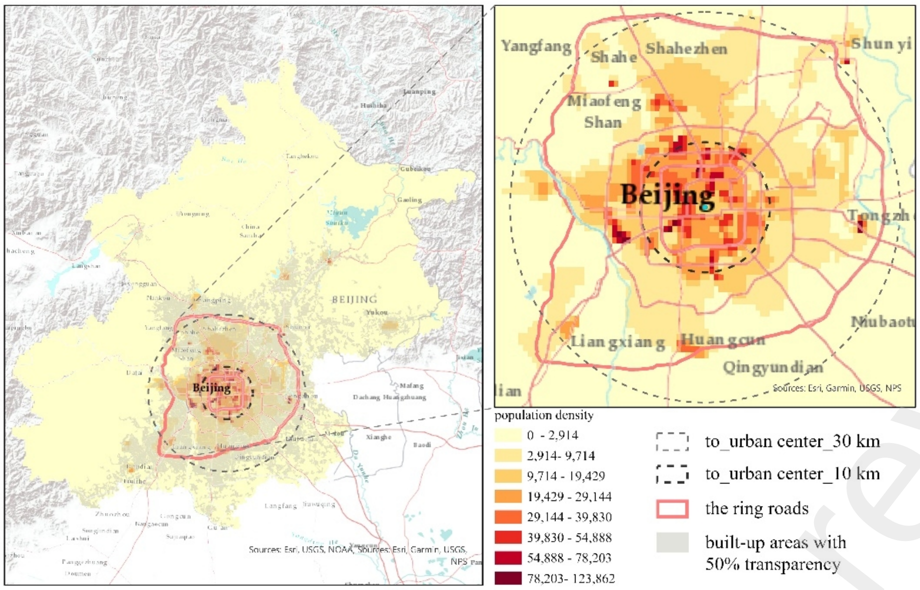


Figure 1. Map of study area overlay with parcels of built-up areas (50% transparency display), population density[31], urban ring roads, radiation circle from the city center (10 km and 30 km).

3.2 Data collection and processing

The datasets for this study are derived from multiple sources, as listed in Table 1. The built-up areas consist of urban parcels, used as the basic units of spatial analysis and modeling [32]. We collected 24,778 EV charging records (using public charging stations during November 2019), and the EV owners' home locations were derived from location-based services (LBS) data. In the data cleaning process, EV residential locations outside of Beijing were excluded, resulting in 20,387 valid EV users. In addition, the invalid parcels of only non-residential use were removed. EV users were then aggregated into urban parcels and spatially combined with other variables in ArcGIS Pro. The final dataset consists of 2,970 parcels with active 20,387 EV residents (with public charging activities) used for analysis and modeling. The LBS data was provided by Baidu Maps, China's largest mobile map service and big data provider [33].

Table 1. Overview of variables and descriptions

Category	Name	description	Mean	SD	Min	Max
Y	EV resident rate	$= \log\left(\frac{EV_{resident}}{Total\ residents} \times 100\right)$ (each parcel)	0.16	0.27	0.00	2.00
X1	Employment density	Working population density of each parcel (counts/km^2)	7.01	1.48	0.00	11.15
	Surrounding amenities/ Landuse mix	To measure the service capacity and convenience of each parcel	0.18	0.32	0.00	2.40
	The proportion of building areas	The ratio of total building areas and parcel areas (range between 0 and 1)	0.20	0.10	0.00	0.72
X2	Density of bus station	The density of bus stops from POI (counts/km^2)	0.00	0.00	0.00	0.02
	Metro accessibility	To measure public transport service capability,	1.39	1.93	0.00	12.37
	PCS accessibility	based on formula (1) ~ (2)	0.33	0.25	0.00	0.98
X3	Charging distance (from home to PCS)	The distance between home location and the charging station they visited (km)	0.95	0.42	-2.30	1.61
X4	Distance to urban center	The distance between each parcel (center point) and Beijing Tiananmen (km)	2.73	0.66	0.44	4.43
X5	GDP	1 km grided raster data through spatial zonal statistics	1.58	0.10	0.00	0.72

*PCS represent public charging stations; for the ML model, logarithmic transformation of these datasets are performed. Y represents the dependent variable; X1~X4 represents the independent variables that in four categories. According to the distribution of each variable, log transformation were conducted to make the variance as constant as possible for modelling. Y represents the dependent variable; X1 represents the economic variables, X2 represents the indicator to measure the relationship with public transport system, X3 represents the indicators developed to measure charging distance and relationship with the infrastructure; X4 represents the indicators designed to measure the relationship between EV distribution and urban space/decentralization.

We use EV Residential Rate as the dependent variable, representing the ratio of active EV residents to the total resident population in each parcel. The selected independent variables were divided into five categories:

1) X1 (urban development): indicators that reflect urban development, including building coverage ratio, employment density and land use mix.

2) X2 (public transport): indicators related to public transportation and infrastructure, including density of bus stops, and accessibility to metro station and public charging station.

3) X3 (charging behavior): indicators reflecting accessibility to charging, such as distance to public charging stations.

4) X4 (location): an indicator reflecting EV owners' home location in the city, measured with distance to the urban center.

5) X5 (economic factor): the grided GDP data reflects economic vitality over urban space.

In Table 1, list of all variables, the distance metric uses Euclidean distance. The grided GDP data is retrieved from remote sensing calibrated nighttime light data [34]. The accessibility to metro stations and to public charging stations are measured by public transportation service capabilities. The population density and employment density are derived from Baidu heat map big data, which has been used and verified in several studies [35, 36]. The densities of public transportation service, including metro stations, bus stops, and public charging stations, and other land use categories (surrounding amenities) are measured using point of interests (POI) data. The service capacity and convenience of surrounding amenities are calculated using the land use mix entropy approach, including supermarkets, commercial buildings, educational places (primary and middle schools), universities, hospitals, and entertainment. The formula reads:

$$S = \frac{-\sum_{i=1}^{N} c_i \ln(c_i)}{\ln N} \tag{1}$$

Where c_i represents the ratio of each surrounding amenities categories in each parcel, and N stands for the total number of amenities categories, namely six in this study.

We calculate the accessibility by using cumulative opportunity method to evaluate the spatial separation effects [37]

$$A_{ij} = \sum f(d_{ij})$$

$$f(d_{ij}) = \begin{cases} 1 - \frac{d_{ij}}{R}, & d_{ij} < R \\ 0, & d_{ij} \geq R \end{cases} \quad (2)$$

Where A_{ij} represents the accessibility index which summarizes the surrounding amenities' service capacity and convenience for people living in each parcel; where d_{ij} is the Euclidean distance from the parcel center *i* to amenity *j*; R is the threshold distance that is set with 1.5 km as it has been used as a walkable distance for normal life circles in many studies.

3.3 GIS-based mapping

The kernel density estimation (KDE) method in ArcGIS was used to visualize the selected variables, using the parcel as the unit of spatial analysis. As a popular spatial analysis technique, KDE can produce a smooth density surface of point features over space by computing the feature intensity as density estimation[38]. These mappings can help to show the spatial patterns and characteristics of different variables over urban areas, taking into account distance decay effects. In addition, bivariate categorical mapping was used to represent the distribution of EV residents in relation to resident population and metro accessibility. By visually interpreting information from these maps, initial spatial associations between independent and dependent variables can be interpreted. These maps will be further combined with the machine learning model results to improve interpretability.

3.4 GBDT model

This study applied the Gradient Boost Decision Tree (GBDT) method to examine the nonlinear associations between the rate of EV residents and the built environment attributes in the vicinity of their home location. GBDT is a data-driven machine learning method, proposed by Friedman[39], which is well-suited for dealing with heterogeneous data (e.g., features measured on different scales) and can automatically detect non-linear feature interactions. GBDT has some advantages compared to other ML models when dealing with various challenges. For example, compared to Random Forest, the tree in GBDT is fit to the residual of the previous tree, allowing GBDT to reduce bias, while RF tries to reduce variance. Compared to traditional Boosting methods, GBDT can better eliminate residual errors.

As a result, GBDT has been widely used to evaluate the non-linear effects of built-environmental factors on various transportation issues such as conventional driving distances[40], conventional car ownership/dependence[11], and transport-induced carbon emissions[41], etc. It has been demonstrated as an efficient machine learning model with optimal performance, yet few studies have applied it in exploring the relationship between built-environment factors and the rate of EV adoption.

Mathematically, in this study, GBDT sets y as the dependent variable or predicted variable (i.e., the rate of EV residents in the urban parcel), and sets x as the independent variables (i.e., built environment variables $x1 \sim x9$, into four categories); and the datasets were split into 80% for training and 20% for testing sets. The algorithm targets to a predicted expected function $f(x)$ as a linear combination of *N* addictive decision trees $\sum_{n=1}^{N} \alpha_n \beta(x,\theta_n)$ with minimizing a specific loss function $L(y, f(x))$ (i.e., Gaussian loss function, in general, for a continuous dependent variable). *N* represents the number of trees; α_n and θ_n represent the weight and a set of parameters of the *n-th* tree $\beta(x,\theta_n)$, respectively.

The squared error for regression is used for Loss function:

$$L(y, f(x)) = (y - f(x))^2 \tag{3}$$

The GBDT iteratively approximates $f(x)$ using a gradient-descent method, which targets to fit the *n-th* decision tree $\beta(x,\theta_n)$; given the estimated tree, the optimal gradient can be estimated and derived, $\aleph$ is set as a learning rate ($0 < \aleph < 1$) to moderate the under- or over- fitting, and thus the iterative equation for the loop from 1 to *N* can be expressed as:

$$f_n(x) = f_{n-1}(x) + \aleph \alpha_n \beta(x,\theta_n) \tag{4}$$

The 5-fold cross-validation was used to tune parameters until the mean square error (MSE) of approximation reached the minimum value. The final model here sets the learning rate at 0.01, with 1,000 trees and a depth of 4.

The results of the model provide insight into the relative importance of each independent variable on the dependent variable, the rate of EV residents. However, the outcome of GBDT alone cannot provide significance tests or address the spatial hierarchies. To address this, GIS spatial analysis was integrated with the partial dependence plot (PDP) to improve the interpretation of the results. PDP can show whether the relationship between the dependent variable and a selected feature is linear, monotonic, or more complex and non-linear. In this research, PDP was used to enhance the interpretability of the model results by demonstrating the non-linear relationship between the rate of EV residents and each explanatory variable. The PDP function for regression is defined as:

$$\hat{f}_s(x_s) = E_{Xc}\left[\hat{f}(x_s, Xc)\right] = \int \hat{f}(x_s, Xc)d\mathbb{R}(Xc) \quad (5)$$

$$\hat{f}_s(x_s) = \frac{1}{n}\sum_{i=1}^{n} \hat{f}(x_s, x_c^{(i)}) \quad (6)$$

where the x_s represents the specific explanatory variable that the PDP should be plotted and Xc are the other variables together used in GBDT model. The feature x_s and Xc make up the total features (explanatory variables). By marginalizing over other features Xc, the effects of x_s on the prediction (here is EV rate) will be plotted. $\hat{f}_s$ is estimated by Monte Cario method in function (5) by calculating averages based on the training data.

4. Results

4.1 Interpretations from geospatial analysis

Figure 2 plots the kernel density mapping of the EV residential rate and that of the other relevant variables that might be associated with EV residential patterns. As can be seen from Figure 2(a), the places where EV residents are densely located are neither in the urban center (within the second or third ring road), nor in the suburbs (e.g., outside the sixth ring road), but located in some specific areas between the fourth ring road and the fifth ring road. Moreover, it did not increase or decrease with the distance to the urban center (that we used to measure the urban extent), which indicated a nonlinear relationship between these locations and the urbanized space. Combined with the bivariate mapping in Figure 3, the distribution of EV users and resident users is consistent in the yellow parcel; Noted that the areas between the fourth and fifth ring roads especially in the northern part are ‘both high’. In contrast, the parcels in blue show there is higher density of EV residents, relatively, and the red parcel represents a relatively small

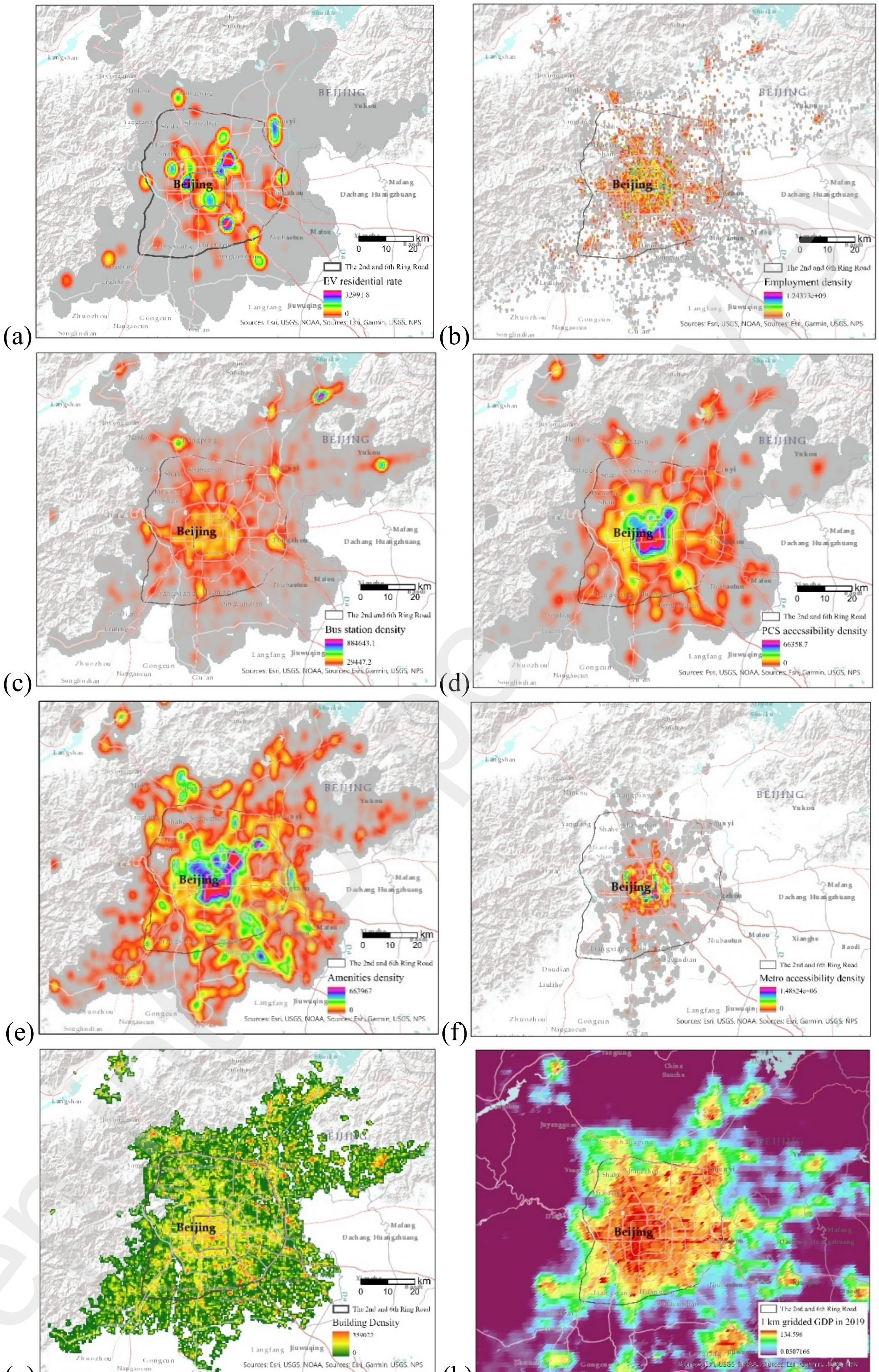
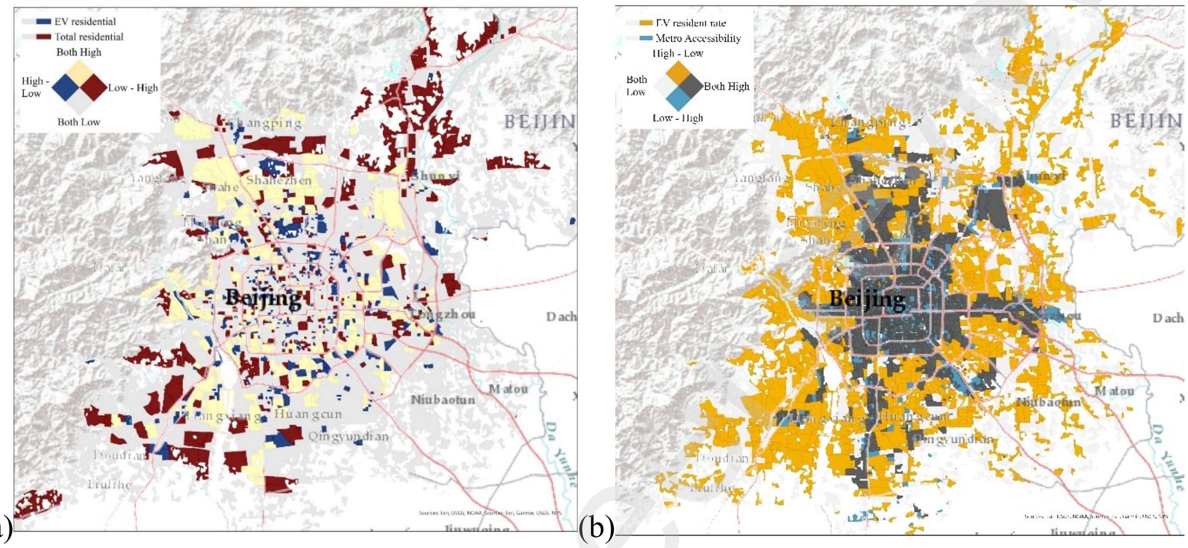


Figure 2. Mapping the variables with GIS. (a) is the density map of EV residential rate. (b) is the

employment population density map. (c) is the bus stations density map. (d) is the density of PCS accessibility index. (e) is the density map of service capacity and convenience based on each parcel. (f) is the density of Metro accessibility. (g) is the density map of building areas. (h) is the 1km grided calibrated GDP level from nighttime light data.



(a) (b)

Figure 3. The bivariate mapping, showing the distributions of both high, high-low, low-high and both low. (a) shows the EV resident vs the total residents. (b) shows the EV residents vs metro accessibility index.

number of EV residents. Specifically, the southwestern and northeastern areas have a relatively small proportion of EV users, particularly outside the sixth ring road. This spatially adjacent but differential distribution further indicated that EV residents' location might be related to surrounding built environmental variables, for example, the metro accessibility (Figure 3. b) etc. An interesting pattern is that, the accessibility characteristics of the metro stations are concentrated in the area within the fourth ring road in Figure 3, and the areas outside the fourth ring road continue in the north and south directions respectively; however, in the suburban areas (here is between the fourth and fifth ring road), there is still a relatively high proportion of EV residents while the metro accessibility is low, indicating that EV has the potential to provide mobility alternatives at areas with low metro accessibility.

Table 3. Relative contributions of explanatory variables on the EV residential rate

Explanatory Variables	Category	Rank	Importance (%)
Employment density	X1: urban development	1	60.0
Land use mix		4	4.6
Building coverage ratio		2	12.0
Density of Bus stop	X2: public transport	3	5.0
Metro Accessibility		9	2.3
PCS Accessibility	X3: charging behavior	7	3.9
Charging distance		5	4.5
Distance to urban center	X4: deurbanization	8	3.4
GDP	X5: economic factor	6	4.3

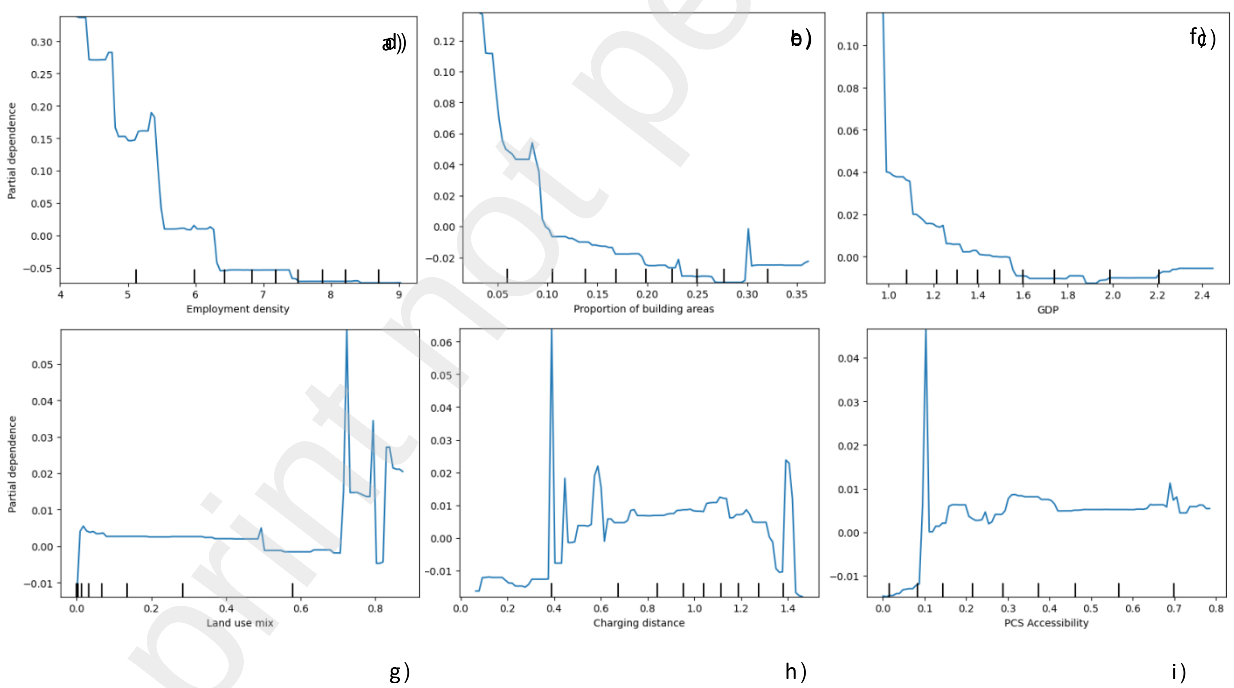
4.2 Results from GBDT model

4.2.1 Relative significance of explanatory variables

The importance and rank of selected explanatory variables on the EV rate was showed in table 3. The importance of employment density ranked first, accounting for nearly 65% of the explanatory variables; it indicated that EV rate is significantly affected by employment distributions. The second important variable was the proportion of building areas, with a relative contribution of 11.6%; the impact of this variable was easy to follow because the EV infrastructure layout has certain requirements for the available space, especially for the renovation of existing facilities; and the building area proportion reflected the development of the parcel and the occupancy of building in space. The influence of the density of public transportation and the accessibility of subway stations were relatively small (though the former is more important than the latter), considering private EVs were used usually as supplement for the places where public transportation system was not sufficient. Ranked fourth was the distance to public charging stations from residential point, assuming some people' dependence on the public charging facilities. While the accessibility of public charging stations was also with relative small influences, suggesting potential mismatch between supply and demand; it has also been discussed in [33]: most of the current charging stations in Beijing are located in commercial land, while the layout of residential land is deployed less, particularly the suburbs is relatively lower. The level of GDP representing economic activity, the land mix representing surrounding convenience, and the indicator representing de-urbanization—the distance from the center—showed relatively lower effects on EV rate.

4.2.2 Nonlinear impacts of explanatory variables

Most of the built-environment factors have non-linear and threshold effects on EV residential rate (i.e., Partial dependence) as shown in the figure 4. The interpretation from the results is given from four aspects as follow.



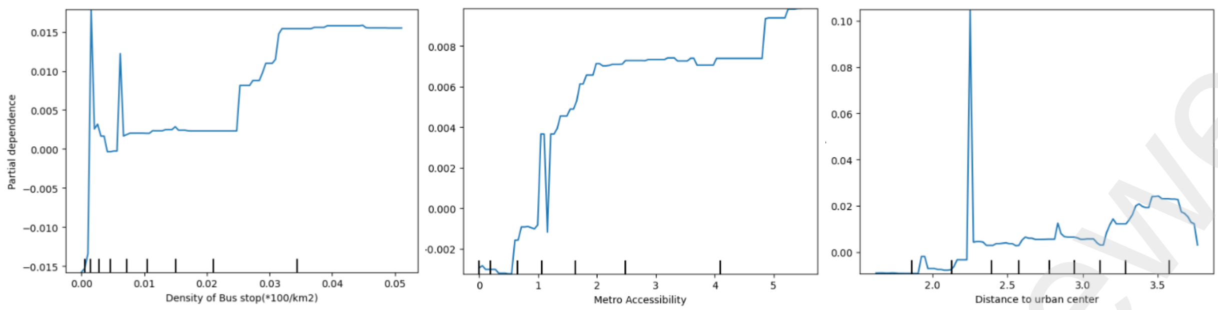


Figure 4. Non-linear effects of explanatory variables on EV residential rate

Regarding the relationship between EV residential rate (EVrate) and some economically-related variables figure 4 a)~d), we explore how EV residential rates change with the increase of a). employment density, b).proportion of build area, c).GDP and d).landuse mix. In general, the employment density, the proportion of build areas and GDP have a negative effect on EVrate. From economically perspective, it indicated that developing regions in the city are more likely to favor EV. It is consistent with the conclusion from previous studies [8, 29]) that employment density has a negative impact on car ownership (conventional vehicles); it also applies to EV. Empirically, workplace accessibility from home may reduce human's car depends, while high employment density is usually associated with high GDP and well-developed levels of public transport system. The high proportion of build areas refers to the available space is relatively limited; it indicated that EV users may be more likely to live in areas with a lower density of buildings, such as suburban areas or in the newly built communities. Landuse mix has a positive effect on EVrate, and the significant threshold effects showed that first with a relative flat line between 0.025 and 0.71, then increasing sharply and peaking around 0.73.

PCS accessibility and charging distance have significant non-linear effects on EVrate (positive in general), as shown in figure 4 e) and f). When it comes to the threshold effects the relationship varies across the whole range of such two variables that related to charging behavior and infrastructure deployment. When the charging distance below 0.39, it nearly showed no effects on EVrate but then sharply increasing and peaking around 0.4 (the logarithm corresponds to 1.5 km in reality); and then decreased to a short flat line and start increasing again with two peaks at 0.45 and 0.58; between 0.61 and 1.3, it showed a relative steady and non-effects on EV rate; then it reached another peak at 1.4 (the logarithm corresponds to 4.0 km in reality). Regarding the PCS accessibility, it has very limited effects below 0.09 but then increased sharply and reached the peak around 0.1; after the peak, it decreased and the trend is leveling stable after 0.12. The peaks also indicated that EV users prefer to charging not far from home (i.e., within 4 km); Insufficient deployment of PCS will have a negative impact on EVrate. Some previous study pointed out that current PCS has not been fully used [33]. These threshold effects indicated the implications the appropriate level of public charging deployment around residential neighborhoods (i.e., 1.5 km living-circles, according to the peaking threshold above) for increasing EVrate.

In terms of the non-linear and threshold effects of public transport system—metro accessibility and bus stop density, the results in general, showed they have positive impacts on EVrate. Specifically, when the bus stop density is below 0.000012, the rate of EV residents increases dramatically and reaches the first peak when the bus stop density is 0.000021; as the bus stop density reaches 0.000063, the EV residents rate increases significantly again and then the EV residents rate remain steady when the bus stop density is between 0.000075 and 0.00025; and then keep increasing and remain steady at 0.00032 stops/km^2. These findings have two implications regarding the relationship between EV residential patterns and bus stop density. Firstly, when the bus stop density is low, residents usually have to rely on private cars and thus

EV is a preferred mode for these groups of residents. Secondly, EV users tend to live in areas with relatively high bus coverage (more than 0.00032 stops per square kilometer according to our results). Therefore, when considering the implementation of public charging stations to benefit EV residents, the areas with no or very little bus coverage or very high bus coverage should be given priority to.

The distance to urban center was used that characterize urban decentralization to explore whether EV popularization will lead to urban expansion. The non-linear and threshold effects showed that the further away from the city has a positive impact on the increase of EV rate. However, it is noted that the distance from the city center is peaking about 10 km (corresponding to 2.25 after taking the logarithmic value in figure 4), which is the favorite place for EV users. This is consistent with the spatial distribution in figure 2-3. Through spatial measurement, such 10 km threshold reflected by radiation circle in figure 1 is around the fourth ring road of Beijing, which is far away from the city center and between the center and the suburbs. After the peak, it decreased sharply and showed a relative low effect on EV rate until 3.5 (refers to 30 km radiation circle) to reach another peak; it partially indicated some EV users choose to live around the sixth ring road but distributed with significant spatial heterogeneity.

5. Discussion and Conclusion

EV technology is driving a new transition in energy and transportation worldwide. While this trend is unavoidable and is supported by policies everywhere, EV's penetration rate is still dependent on some external factors. Through geospatial analysis using machine learning GBDT model, this research examines the non-linear effects of different neighborhood built-environment variables on the rate of EV residents in Beijing. Based on the observation data of active EV users' datasets, this study reveals a verifiable linkage between EV ownership and the suburbanization of the city. In the case of Beijing, this indicates that EV users in general are leaning towards living in areas that are neither too far away from nor too close to the city center, and they tend to cluster around the areas about 10 km from the city center. In general, employment density, building coverage ratio, and GDP have negative effects on EVrate; while accessibility to public transportations and public charging stations have positive effects on EVrate.

This local context provided here should help with understanding the non-linear results. The finding that EV rates are higher outside urban centers and that most EV residents require public charging around their home locations are to some degree related to Beijing's local conditions. The increasing EV ownerships pose challenges to existing power system and demand updates of infrastructure deployment. There are many old neighborhoods in Beijing, where renovations are both difficult and costly. This represents another challenge for the historic center of Beijing, where building density is high, streets are narrow, electric infrastructure is dated, and historic landmarks and traditional Hutong neighborhoods have to be preserved. Even in the newer residential areas, the high-density high-rise housing typology also means a shortage of parking space. A private parking space typically costs multiple times the price of an EV. It is reported that 64 percent of car owners in the center city choose to rent a parking space[42]. It means most people do not have access to home charging and rely more on public charging stations.

In regard of the EV's effect on the urban structure, namely, whether it tends to foster a compact urban form or encourage further decentralization, the results suggest that the residents in the suburban areas represent the primary beneficiary of the electric mobility. This effect is reflected in a reciprocal relationship, that is, people living in the suburb tend to choose EV as a primary means of travel, and existing EV users tend to choose a suburban location when looking for a new home. For the former effect, the lower operational cost of the EV makes it favorable for the long-distance commute, and the environmental benefits are also more obvious. At the same time, the relative shortage of public transportation options prompts suburban residents to choose a personal vehicle. Beijing's incentives for the EV also play a major role in these dynamics, but their impact is the same for people living in the center city and those in the suburban areas. For the latter effect, the lower building density proportion in the suburb also means that the capacity to install charging facilities (ratio of charging station per capita) is higher, and the prospect of future infrastructural expansion and upgrade is also better.

6. Policy implications

These findings, along with the thresholds for PCS and distance to urban centers, could provide useful hints for future urban layout and infrastructure planning, and contribute to efforts of urban sustainability. First, provided that the majority of PCS were currently deployed in urban center, increasing the density of PCS network in the suburban areas is recommended, using the principle of 1.5 km radius from major residential areas to better serve the existing and prospective EV users. This strategy should also reduce the pressure on infrastructural development in the high-density building parcels in the inner city as more EV drivers can charge near their suburban homes. Priority should be given to the large residential neighborhoods around the fifth Ring Road, with a priority of the areas around 10km radius from the urban centers.

Understanding the EV owners' residential rate and its relationship with urban environmental variables helps assess the impact of this new transport mode on urban forms. The study of these correlations can inform decision making in response to transport electrification and urbanization, including the coordination of EV infrastructure with electric network, the layout for urban expansion as related to transit planning and community building, and the redesign of streets and open spaces to enhance human interaction in conjunction with the emerging modes of transportation. It is critical to incorporate the EV's benefits of energy and carbon reduction with proper urban plans and design strategies in order to improve the human environment and lifestyle and to optimize urban resources.

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