Exploratory Spatial Analysis:

The Distribution Change of Electric Vehicle Charge Points in London between 2019 and 2020

MSc Spatial Data Science and Visualisation

The Bartlett Centre for Advanced Spatial Analysis

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Online tutorial bookdown: http://zeqiang.fun/_book/

1. Introduction

Electric vehicle (EV) infrastructure is of importance for sustainable urban development. "UK e-charging market is recognised as one of the most advanced in Europe," said Martin Lucas. He is a partner of Watson Farley & Williams LLP, an international law firm (2020). "Solve both the problems experienced within cities and the problems caused by cities" is used to define the term of urban sustainability (European Commission, 2006). Compared with traditional energy cars, EVs have significant advantages in terms of carbon emissions. However, urban residents who purchase new energy vehicles have to face range anxiety, which has become a constraint on developing the EV market. EVs' sales are lower than expected because of the potential users' anxiety range (Bonges and Lusk, 2016).

For urban sustainability, the government has also put forward initiatives to construct supporting infrastructure for EVs in the past and present. For instance, the Office for Low EVs demonstrates that there will be approximately £30 million in funds to invest in charging infrastructure in the next five years (Office for Low Emission Vehicles, 2014). Apart from that, the briefing published in House of Commons Library point that "in the Road to Zero Strategy, the Government has committed £400m to the public-private Charging Infrastructure Investment Fund" (Dempsey et al., 2020).

R, a programming language, has been widely used in spatial analysis with multiple R packages such as "spat stat," "GISTools," etc. For instance, urban spatial data analysis has been used in Geographical Information Systems (GIS) to support the local authority policy (Pedro, Silva, and Pinheiro, 2019). There are cases where researchers combined R tools and GIS to analyse urban spatial research topics. For example, researchers from the University of Texas at Dallas utilised R language tools to integrate spatial analysis in a GIS environment to the Texas Census (Koo, Chun, and Griffith, 2018). However, the challenge of representing data via spatial analysis remains.

In this report, the research question will be investigated and discussed --- How do the distribution and density of EV charge change in London between 2019 and 2020? The aim is to apply theories from GIS, especially the spatial analysis method, to explore the distribution and density in these two years. Firstly, the big data of charge points, from the UK government official website, is pre-processed and cleaned. One of the analysis methods is to apply spatial pattern analysis. It is based on the number of samples in two years. It compares their distribution and density to obtain the corresponding objective value. Besides, a reproducible analysis process is established using open source spatial analysis software RStudio, which applies the advanced spatial analysis methods in clean energy and explores spatial value content to contribute to urban sustainability.

2. Literature Review

There are valuable findings can be obtained in the distribution of EV infrastructures. On the topic of spatial analysis, there is some corresponding research in regions outside the UK, such as North America and China. Based on GIS technology (the correlation of spatial density), a team analysed the functions and performance of electric vehicle charging infrastructure from eight indicators: charger's intensity. According to the research conclusions, it was proposed that the free parking policy should be restricted to increase the rate of EV adoption (Lucas et al., 2018)

Moreover, some researchers also used an analytic hierarchy process approach for electric vehicle charging stations in Amsterdam. It is based on a geographical information system to select ideal locations for fast EV charging stations. Which helped Fastned, a Dutch innovation company, optimise the layout charge point (Ward, 2016).

Spatial autocorrelation plays an important part in spatial analysis of EV infrastructure. In 2018, a team conducted this study on the registration volume of UK electric vehicles and charging points' location distribution. It found that the local government's charging facilities, such as charging stations, positively correlate with the demand for electric vehicles. However, the electric vehicle market is differentiated because they found that the adoption rate of EVs in neighbouring regions is also positively correlated (Morton et al., 2018).

Besides, the distribution of EV charge points and their usage habits are also related to urban planning. Some researchers have found that commuters need to charge their EVs during the morning peak hours. On the one hand, the charging facilities are located in public places where they work. On the other hand, facilities are located at transportation hubs such as railway stations (Element Energy, 2021).

The limitation of some spatial analysis still exists. The Delft University of Technology's research team constructed a dynamic space model to develop an electric vehicle-charging infrastructure in a metropolitan area. After testing different charging stations' usage scenarios, they pointed out that the demand for charge points in the city's centre is less than the supply (Wirges, Linder, and Kessler, 2012). However, this simulation was executed in 2012. With the increase in EV production, and the decrease in the cost, the demand for charge points in urban areas will differ from the past situation.

3. Methodology

This exploratory analysis mainly applies R language with multiple packages to this spatial research topic. The following contents are data source, data pre-processing, spatial analysis method, and visualisation.

3.1 Data Source

The NCR, a database of charge points for electric vehicles in the UK, is available for individuals and business data developers without charge (GOV.UK, 2020). Following the UK government website's guidance, the National Chargepoint Registry (NCR) dataset was collected in CSV format.

Spatial data is available on the London Datastore official website. The shape format file called Statistical GIS Boundary is the original geographic boundaries data, which is based on our spatial analysis (London Datastore, 2020). One of the variables called "GSS_CODE" can be identified via "sf," an R package, to present the London borough polygons in multiple types.

3.2 Data Pre-processing

As shown in Figure 1, NCR, the original dataset, is filtered by a rule. Those rows, which contain "London" string value such as "London Borough of Islington," remain when it comes to the variable "county." In the next step, 11 columns such as "postcode" worthy of being utilised are selected into a new data frame called London_NCR. Before dplyr, an R package, count the frequency for each GSS_CODE in this processed dataset. The postcode_lookup method from the PostcodesioR package is applied to look up GSS_CODE by identifying each row's postcode. Finally, the data join method is used to merge two datasets (The shapefile and London NCR) based on two standard variables GSS_CODE, which contributes to the visualization of the distribution and density.

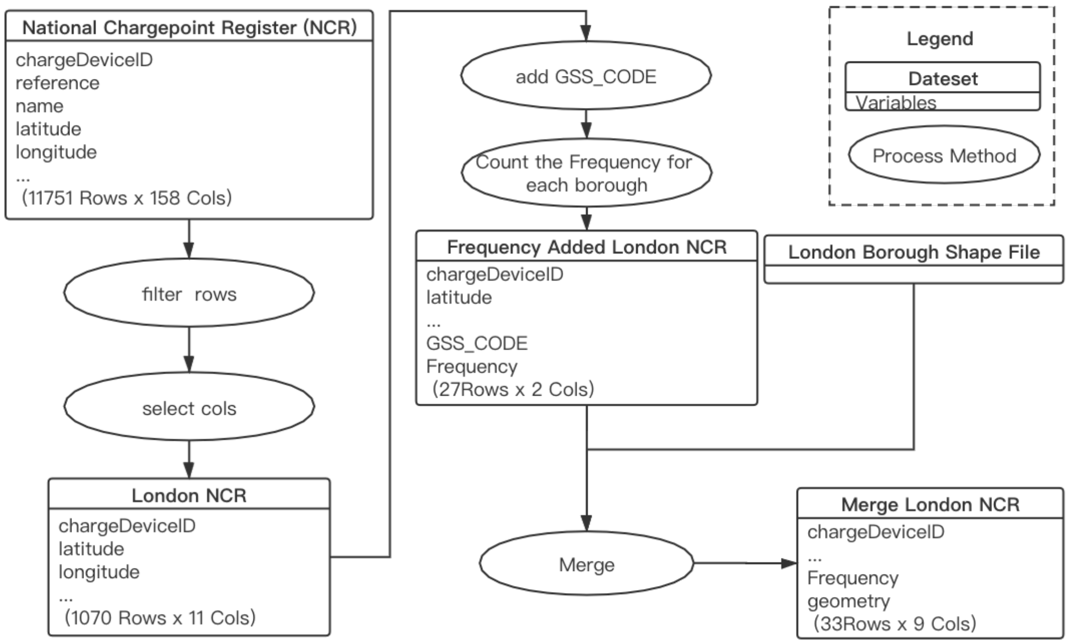

Figure 1. The flow diagram of data cleaning and processing in Rstudio

3.3 Spatial Analysis

In descriptive statistics section, the R language tool table format is utilised to indicate the distribution of these samples in each borough in 2019 and 2020. In other words, the sample size and proportion of each borough in two years are presented in the form of a table. The last column of it uses a total to indicate the overall number and proportion of every borough in all data.

For density Calculation, the Merged London NCR dataset is divided into two data sets in the Analysis of density, one is the charge point data set created in 2019, and the other is the one in 2020. These two data are merged respectively with the London Borough dataset to ensure the integrity of the drawn map. The necessary spatial variables such as GSS_CODE is selected for further research. In the next step, the number of charge points for each borough is counted. After obtaining the area (the unit is square kilometre) for each borough, the below formula is applied to compute the density of EV charge points for each borough in 2019 and 2020 datasets.

$$\boldsymbol{Density} = \frac{\boldsymbol{Num} * 1000{,}000}{\boldsymbol{Area}}$$

Where *Num* is the number of newly created EV charge points in a borough of London; *Area* is the area of the borough which is presented in square kilometre.

Generating the neighbour list is essential. For the following local Moran's I test, it is of importance to get the number of neighbours for each borough. Under this circumstance, the centroids of all boroughs are found and visualised. Then the neighbours for each borough is stored in a list, which contributes to the Moran's I test.

When it comes to Moran's I Test Method, to analyse the spatial autocorrelation of London charge points, both the global and local Moran's I are tested by following the standard formula of Moran's I. One of the R packages called "spdep" is imported and integrate the Moran test function to test the global and local test. What might be worthy to notice is that the sample of 2019 is too small to obtain an appropriate test result. Therefore, the charge point dataset which contains 2019 and 2020 is the main test objective.

3.4 Map and Visualisation

In the density analysis section, the tmap (an R package for map-making) is applied to execute multiple functions. In the density visualisation map, the lighter the colour of the borough is, the larger density of charge point for each borough is. Regarding the visualisation of centroids and neighbours of London boroughs, scatter plots were first used to describe the visualisation of the geometric centre distribution of London boroughs.

In the next step, "plot" method and "st_geometry" method are used to present the neighbours list on the geometric map. As for the final local Moran's I test, in order to prevent the legend from obscuring the map colour, we used the "leaflet" package to draw interactive maps. According to the maximum, minimum, and average values of the result of Moran's I test, the scale and colour distribution of Legend are specified.

4. Result

4.1 Descriptive Statistics

As shown in the table1, in spite of fuzzy value London, it is obvious that EV charge points in Camden make up the largest part in the dataset. It is worth noting that there are many charge stations in the EV charge point account for the largest proportion in the Lambeth area in 2019, Camden and Ealing. On the contrary to the statistics in 2019, Charge points in the Camden area is the largest one while the amount of charge points in other areas is quite small in 2020.

Table 1. The distribution of all London boroughs in 2019 and 2020

	2019 (N=696)	2020 (N=362)	Overall (N=1058)
county			
London	150 (21.6%)	150 (41.4%)	300 (28.4%)
London Borough of Camden	87 (12.5%)	179 (49.4%)	266 (25.1%)
London Borough of Ealing	65 (9.3%)	1 (0.3%)	66 (6.2%)
London Borough of Greenwich	2 (0.3%)	0 (0%)	2 (0.2%)
London Borough of Hackney	62 (8.9%)	0 (0%)	62 (5.9%)
London Borough of Hammersmith and Fulham	2 (0.3%)	3 (0.8%)	5 (0.5%)
London Borough of Hounslow	78 (11.2%)	0 (0%)	78 (7.4%)
London Borough of Islington	3 (0.4%)	15 (4.1%)	18 (1.7%)
London Borough of Lambeth	118 (17.0%)	2 (0.6%)	120 (11.3%)
London Borough of Richmond upon Thames	8 (1.1%)	9 (2.5%)	17 (1.6%)
London Borough of Southwark	1 (0.1%)	0 (0%)	1 (0.1%)
London Borough Of Southwark	57 (8.2%)	0 (0%)	57 (5.4%)
London Borough of Waltham Forest	60 (8.6%)	2 (0.6%)	62 (5.9%)
London Borough of Wandsworth	3 (0.4%)	1 (0.3%)	4 (0.4%)

4.2 Visualisation and Maps

In 2019, as presented in figure 2, it is easy to find from the map that the density of charge points is the highest in Camden and Lambeth, while Hackney and Southwark have similarly larger densities. Judging from the several areas on the map, adjacent areas tend to have similar density.

In other words, areas with a relatively high density of charge points form an aggregated distribution, such as Brent, Ealing and Hounslow areas. The areas where the EV charge point density is relatively large are relatively close in distance. However, as shown in figure 3, it is not difficult to find that the areas with higher EV charge points density are less and relatively concentrated, such as Camden, Islington and Southwark areas in 2020. The density of new EV charge in other regions is more average.

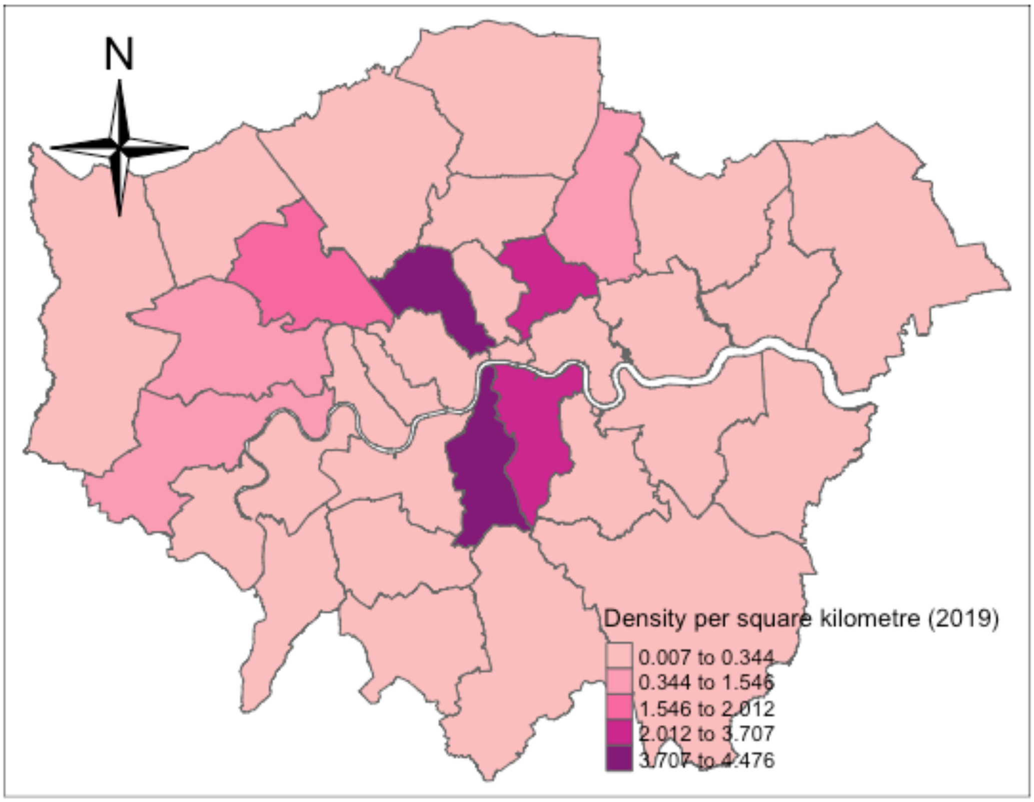

Figure 2. The density of EV charge points for each borough of London in 2019

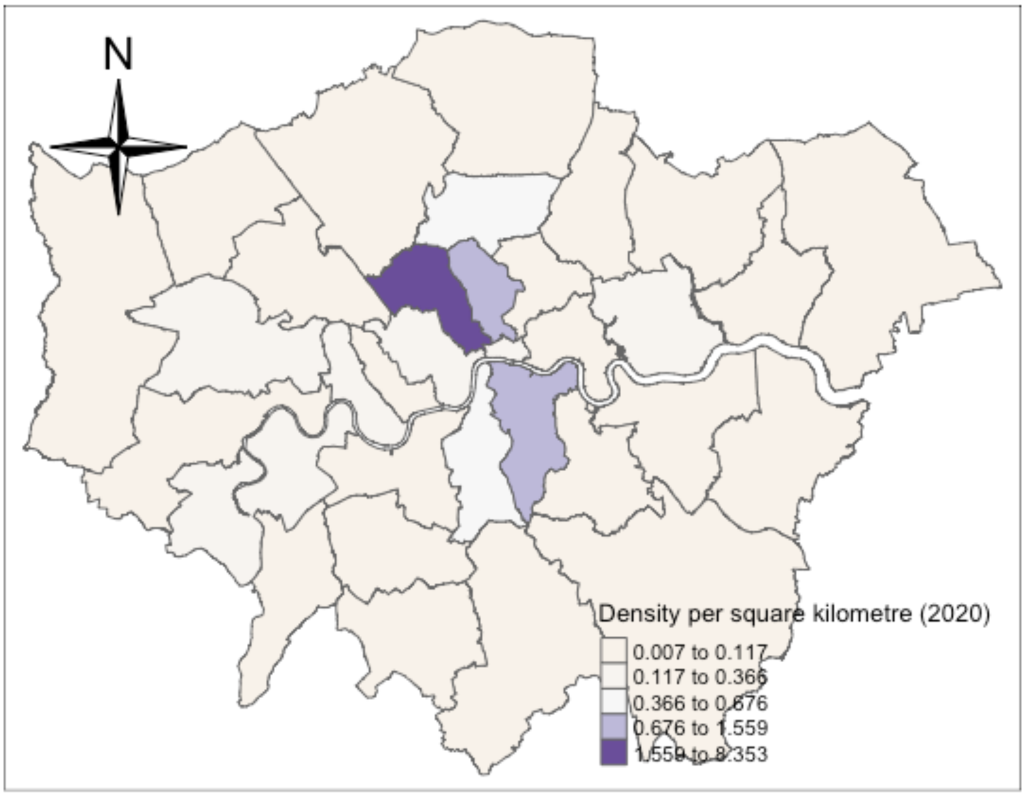

Figure 3. The density of EV charge points for each borough of London in 2020

As shown in Figure 4, we found that the spatial effect of Moran's I higher than 0 might be significant in some areas, especially in the dark red areas. These regions with high local Moran's I values are mainly distributed on the east and west, while the Barnet and Camden regional indexes are low and basically negative. They might be related to the lack of relevant data in 2019 and 2020, indicating that there are few new charge points in these regions. The areas may not have added EV charge points in the past two years because of some characteristics.

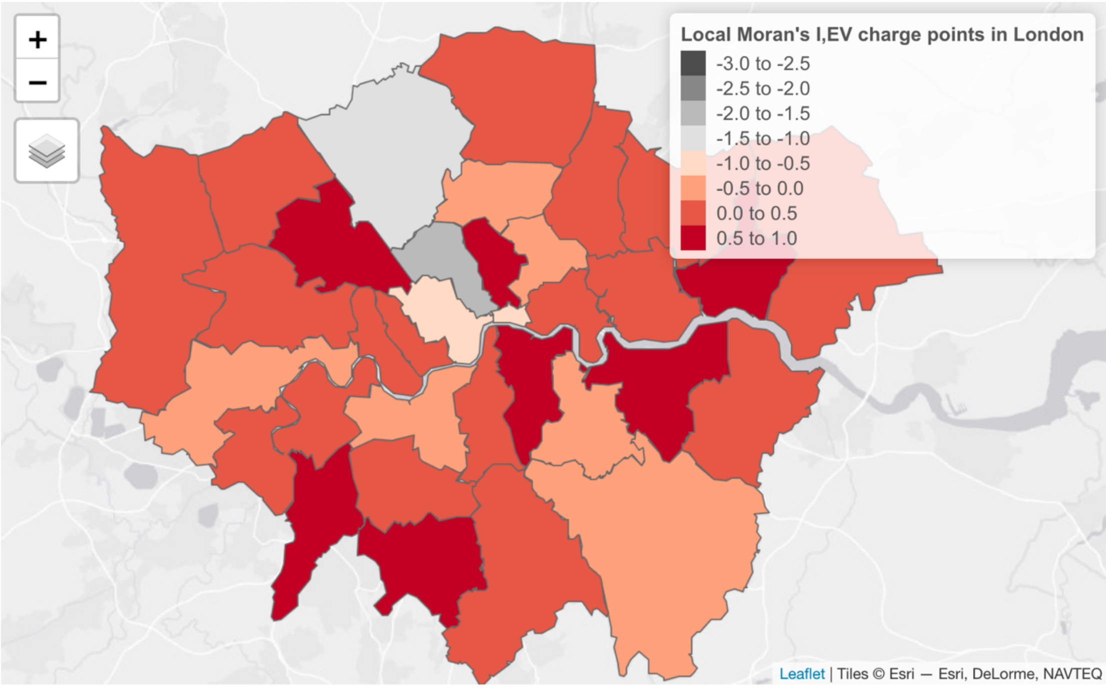

Figure 4. Local Moran's I test result in all boroughs of London in 2019 and 2020

5. Discussion

5.1 Reflection on results

The results of this analysis mainly found the clustering phenomenon in space and the different manifestations of this phenomenon in different years. From the above results, we can see that a lot of EV charge points have been added in various boroughs in 2019 because it is found that the new charge points in 2019 have a great density in several areas.

Simultaneously, it is not difficult to find that adjacent areas have a certain clustering pattern, such as Waltham Forest and Hackney. The number of newly created EV charge infrastructure in 2019 is mainly concentrated in central and western London.

Combining the sample distribution table in the result, it is not difficult to see that the size of the newly added number and the size of the density are related. Basically, the number of charge points on a borough determines the density of newly created charge points in the corresponding year. In 2020, the new EV charge points are more concentrated, mainly in certain boroughs in the middle such as Islington and Camden. The number of newly created charge points has significantly changed in many Boroughs in 2020. The reason might be the change of policy, market demand, covid-19 pandemic and etc.

5.2 Limitations

In terms of the NCR dataset, it might not be particular for London's completeness of charge points if the suppliers or individuals did not register their details of EV charge points on the UK government website. Besides, the accuracy of charge points is not quite perfect since the people, who had registered their charge stations, might forget to or be late to update their status or other information.

In the data processing section, there are several rows whose values are missing. To successfully and smoothly continue this spatial research, there is a likelihood that those rows with missing values are removed from the dataset. It can affect the data analysis result and conclusion.

It is an exam challenge what extend can map and visualisation represent EV charge point data. The frequency of charge points in every borough is not always equal to the density. The size of the area also plays an essential role in the spatial analysis of density.

6. Conclusion

When it comes to choosing a topic, it is hard to find a dataset that contains environmental sustainability factors. It is also challenging to get a static location dataset from the EVs dataset. Fortunately, the EV charge point becomes a good analysis objective because of its static spatial data. Challenges can also be found in the data processing. It was a tricky problem of how to identify which boroughs each charge point belongs to. Through long hours of effort, the solution was found that one of the R packages could add GSS_CODE to every row via applying a custom function in the loop.

Considering the analysis reproducibility, the data format is one of the essential parts. Furthermore, more variables can be contained in spatial analysis of charge points, such as EV chargers' energy efficiency. It is appropriate for choosing map tools to choose the interactive map that can be manipulated in a simple GUI. This method can present more data visualisation in only one window.

In the future development of this analysis, there is a tendency to combine more dimensions, such as temporal data. It is likely to collect more data in different years to analyse EV infrastructure development and obtain more valuable insights from temporal and spatial data.

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Declaration of Authorship

I, Zeqiang FANG, confirm that the work presented in this assessment is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

Date of signature: 10/Jan/2021

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