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Spatial and Temporal Analysis of Location and Usage of Public Electric Vehicle Charging Infrastructure in the United States

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Abstract

Switching to electric vehicles (EVs) has increased rapidly over recent years. This paradigm change provides an important pillar in the United States transport sector to reach sustainability goals. EVs rely on a network of charging locations to operate. This study analyses the spatial distribution, accessibility and usage patterns of the public EV infrastructure in the US. First, using a negative binomial regression model, the influence of socio-economic and other factors on the abundance of EV charging locations in a state is investigated. Second, analysis of the network's use and of service areas generated around charging locations provides insight into the accessibility of these stations to populations living in urban and rural areas. Third, the study compares publicly available datasets on the EV charging infrastructure provided by different companies in the Miami urbanized area, and lastly, it analyses real-time data from the SemaConnect charging network. Results indicate increased access of residents to the EV charging infrastructure over the years. Economic activity, highway density and political preference were statistically associated with the number of charging stations. Charging behaviour was found to follow the patterns of a regular workday, indicating that EV owners rely primarily on the public infrastructure as opposed to charging their vehicles only at home.

Keywords:

Mobility, electric vehicle, EV, charger, network analysis, sustainability

1   Introduction and Motivation

Electric cars are an important part of meeting global goals on climate change (Helmers et al., 2017; Pero et al., 2018). Just as cars with an internal combustion engine rely on gas stations, EVs rely on a network of charging locations to recharge batteries. While home charging is one of the most convenient ways to keep EVs running, charging at workplaces or in public places is also a crucial component of transport infrastructure (Hardman et al., 2018; Tal et al., 2020). Not having access to public charging has been identified as one of the barriers to adopting EVs for people without the means to charge at home, as in high-density urban areas (Ajanovic

& Haas, 2016). As a result, public locations such as carparks were favoured by EV users (Morrissey et al., 2016).

In 2021, the Biden-Harris Administration released the Electric Vehicle Charging Action Plan to outline steps that federal agencies are taking to support the installation of chargers in communities in the US (White House, 2021). In addition, the Bipartisan Infrastructure Law (2022) includes $5 billion in funding, with the goal of building a national network of 500,000 electric vehicle chargers (Osborne, 2022). Since the number of development projects aiming to increase EV charging capabilities is likely to increase, it is important that decision makers have access to reliable information about the current state of the infrastructure. Limited evidence suggests that there are inequalities based on race and income in the distribution of the public charging network (Hsu & Fingerman, 2021). A detailed analysis in New York City showed that the availability of charging locations is heavily skewed against low-income, black-identifying and disadvantaged neighbourhoods (Khan et al., 2022). Likewise, economic incentives (e.g., tax rebates) are distributed predominantly to rich neighbourhoods (Guo & Kontou, 2021).

To achieve the widespread adoption of EVs, marginalized communities must be included in the revolution. This study aims to increase our understanding of the current state of the public EV charging infrastructure, including its spatial distribution and accessibility. While multiple data sources about charging stations are available in the US, differences in their spatial distribution are unknown. To address some of these limitations in the literature and the challenges, this study set four aims:

- Aim 1: Use regression to identify factors associated with the relative abundance or paucity of charging locations in the contiguous US.
- Aim 2: Conduct a network analysis to assess the US population's level of access to the public EV charging infrastructure and its evolution over time.
- Aim 3: Compare the spatial distribution of charging locations in three publicly available EV charger datasets for the Miami urbanized area (UA).
- Aim 4: Describe spatial and temporal patterns of EV charging locations.

The remainder of this paper is structured as follows. Section 2 describes the study area and data used. Section 3 provides a detailed overview of analysis methods for each of the four aims. Section 4 reports analysis results for each aim. Section 5 summarizes and discusses major outcomes and provides directions for future research.

2 Study Setup

2.1 Study area

The study area comprises the contiguous US for the analysis of the spatial distribution of charging stations, and the Miami UA for comparison of EV charging location datasets and

analysing charging behaviour. While the locations of charging stations were available for the entire US, charging behaviour has been tracked for the Miami UA only. Figure 1 shows the location of 49,817 public EV charging stations with Level 2 or DC Fast chargers installed in the contiguous US (as at 15 January 2023). Data were obtained from the US Department of Energy (DoE). Highway geometries are based on US Census Bureau TIGER/Line Primary Roads national file data.
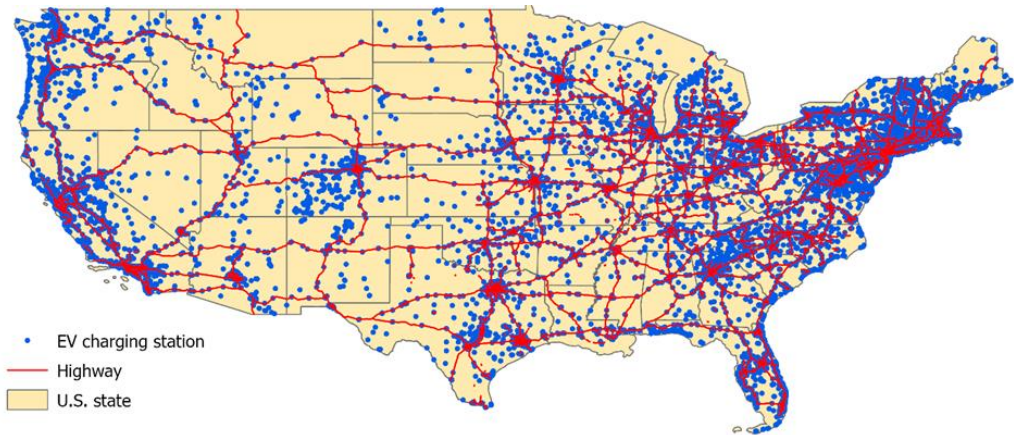
Figure 1: Locations of public EV charging stations

The Miami UA spans approximately 3,300 km² in southeast Florida (grey area in Figure 2a). 476 hexagons with sides of approximately 2 km were superimposed on the area and used as the unit of spatial aggregation. The spatial distributions of different EV charger datasets analysed are shown in Figures 2b–2e.
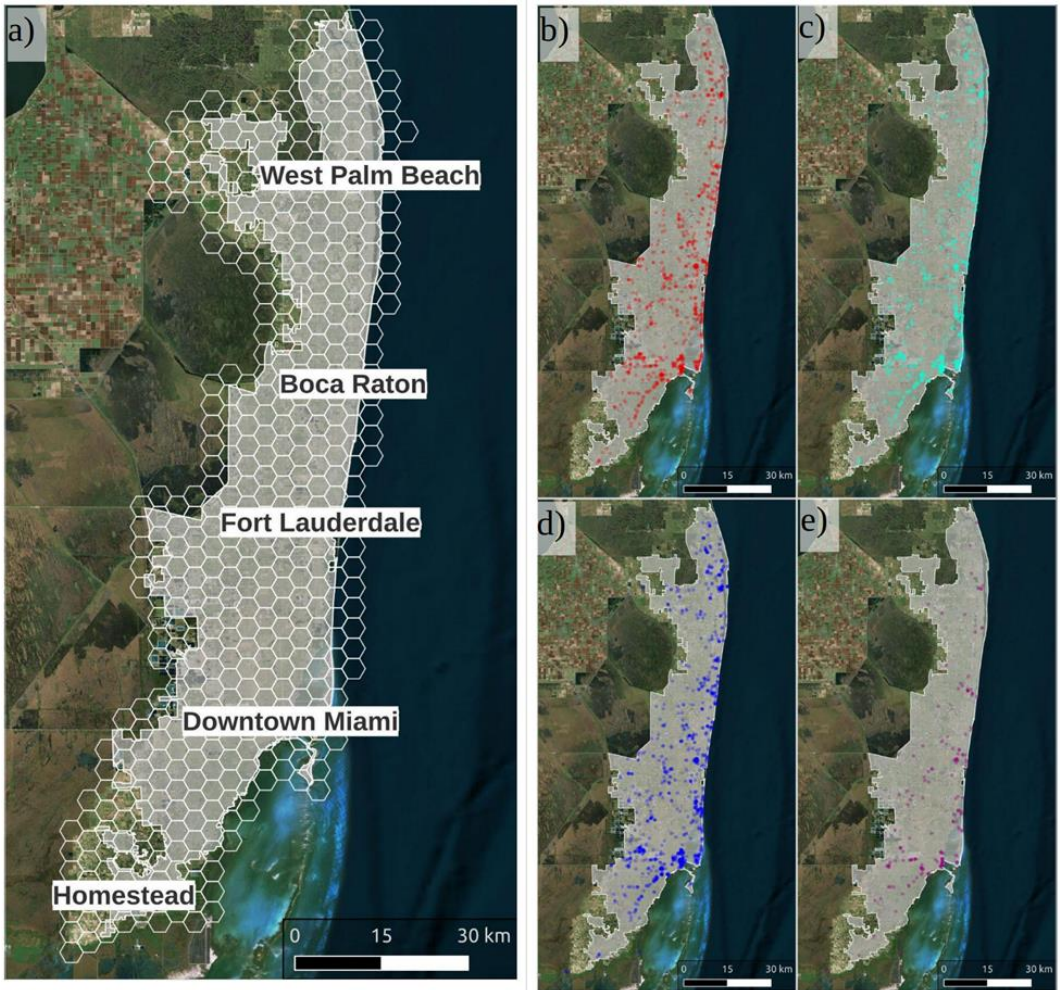
Figure 2: (a) Analysis grid (hexagons) superimposed on the spatial distribution in the Miami UA of EV charger point datasets for: **(b)** PlugShare, **(c)** ChargePoint, **(d)** DoE, **(e)** SemaConnect

2.2 Data collection and preparation

EV charging station data to be used in various analyses were obtained as a csv file from the DoE Alternative Fuels Data Center website. The data come with a wide range of attributes, including geographic coordinates, geocode status, last update, owner type, date the station became operational, connector type, facility type, and pricing. Census data for regression analysis (race, income, voting behaviour) was obtained from the US Census Bureau and the Federal Election Commission. US-wide population grid data, as well as road and urban area geometries, were used for network analysis to measure the access of the US population to EV charging stations over the years.

We extracted other charger location datasets in addition to DoE data in order to allow comparison of datasets related to the public EV charging infrastructure. Both PlugShare (https://www.plugshare.com/) and ChargePoint (https://driver.chargepoint.com/stations/) have implemented crowdsourcing to enable users to add missing charger locations. These companies offer freely available web map interfaces that allow filtering based on various criteria (e.g., plug type, power, nearby amenities). Although both companies provide commercial APIs and data products, these resources are not available for academic research. We therefore extracted the underlying JSON data used by the web browser to reproduce the maps on these websites. These point locations were then inserted into a spatially enabled PostgreSQL database. For the point pattern analysis comparing the PlugShare (Figure 2b), ChargePoint (Figure 2c) and DoE (Figure 2d) datasets in southeast Florida, only a unique location ID and the point geometry of charger locations were retained.

The SemaConnect network (https://network.semaconnect.com) provides both mobile and web applications that display the real-time availability of charger ports at each location. To obtain data, all charging locations were first extracted (Figure 2e). Next, a custom Python script queried and saved the real-time status of each charger location every 5 minutes from 1 June 2022 to 31 August 2022.

The types of data used for the different analyses are listed in Table 1.

Table 1: Data used in the different analyses and their sources

Content	Variable description	Data source	Analysis
Census			
Population	30 arc-second population grid	Global Human Settlement Layer (GHSL) 2015	A
Race	% African American population	US Census Bureau – 2020 Census at state level	R
Income	Median household income	US Census Bureau – American Community Survey (ACS) – 5-year estimates (2017–2021) at state level	R
Voting behaviour	Number of wins for Republican party candidate in a given state in the 2016 and 2020 presidential elections	Federal Election Commission	R
Urban Areas	Urban Areas with > 50,000 people and urban clusters with > 2,500 people	US Census Bureau TIGER/Line 2022	A

Transportation			
Highways	Divided (dual-carriageway), limited-access primary road	US Census Bureau TIGER/Line 2022	R
All roads	Primary, secondary and lower-order roads		A
EV charging stations			
DoE	Location and first day of operation of Level 2/DC Fast charging stations	US Department of Energy	A, R, C
PlugShare	Location and number of available ports of Level2/DC Fast charging stations	PlugShare	C
ChargeHub	Location and number of available ports of Level2/DC Fast charging stations	ChargeHub	C
Sema	Location and number of available ports of charging stations; charger usage statistics	SemaConnect charging network	U

A: accessibility analysis; R: negative binomial regression; C: point pattern comparison; U: charger usage analysis

3   Analysis methods

3.1   Spatial distribution of EV station locations

Using aggregated EV charging station counts in the 48 conterminous states and the District of Columbia as predicted variable, the influence of socio-economic, road infrastructure and political preference on the abundance of EV charging stations was determined using regression. The Poisson model can be applied to the counts occurring within a specific area if mean and variance of the count data are equal. However, the given station data was over-dispersed (mean = 1,014.7, variance = 4,030,563). Therefore, a negative binomial model was developed instead. To express the left-hand side of the equation as a rate of events per areal unit exposure, an offset variable was introduced to the right side of the equation and set to the natural logarithm of the state area in km². The regression model was developed in a manual stepwise approach by adding and removing variables in an exploratory manner to improve model fit, as measured by the Akaike information criterion (AIC). As part of data preparation, Spearman's rho correlation coefficient was computed between all candidate explanatory variables. Since population's density and highway density were highly correlated (Pearson's r =

0.94), and highway density provided a consistently better model fit in the different models tested than population density, the latter was excluded as a predictor candidate. The mean of state median household incomes decreased with the number of Republican wins at state level as follows: 0 wins: M = $77,565 (SD = 10,258); 1 win: M = $65,762 (SD = 1,745); 2 wins: M = $61,002 (SD = 6,675). A one-way ANOVA (unequal variance assumed) suggested a link between the number of Republican wins at state level and household income ($F_{(2, 28.3)}$ = 18.88, $p < 0.0001$). Therefore, Republican wins and median household income were not used together as predictors in the same regression model. Residuals were tested for spatial autocorrelation, since ignoring spatial dependence in spatial data can lead to coefficient estimation bias and biased standard errors (Anselin, 1988).

3.2 Accessibility of charging stations

The use of EVs requires a dense network of public EV charging stations, especially for residents who own an EV but have no charging station at home. For the analysis of accessibility to EV charging stations, a network dataset, based on US TIGER/Line road data, was built using vertex connectivity in ArcGIS Pro Network Analyst. Road data were downloaded in 3,233 folders with shapefiles from the TIGER/Line ftp archive, appended in ArcGIS Pro 3.0, and clipped to the contiguous US, which resulted in a road feature class with over 18 million edges. This was used to build a network dataset with distance as the cost variable. In addition, population 30 arc-second (~ 900 m) GHSL grid points were aggregated to 3 arc-minute grid points, converted to polygons, and intersected with the US Census Bureau TIGER/Line Urban Area feature layer to enhance each population polygon with a binary urban/rural attribute that describes whether the grid cell is within an urban or a rural area.

The distance threshold, assuming a two-way trip from home to the charging station and back, is half the driving range of the EV. Using an average distance of 250 miles on one charge (Kempton, 2016), the maximum feasible distance between home and station is therefore 125 miles (200 km). To estimate the population that lives more than this distance from an EV charging station, 200-km service areas were constructed around EV charging stations for a given year on the US-wide road network dataset. Next, the population numbers for US population grid polygons that do not intersect with these areas (representing areas without charging points) are summed up for each year; a distinction between urban and rural populations is made.

As an example, Figure 3 illustrates the service areas around EV charging stations for the years 2010 and 2014. Comparison shows that 2014 provides a higher service coverage, which leads to a reduction in the under-served population with regards to EV charging (2010: 145.5 million; 2014: 1.8 million).
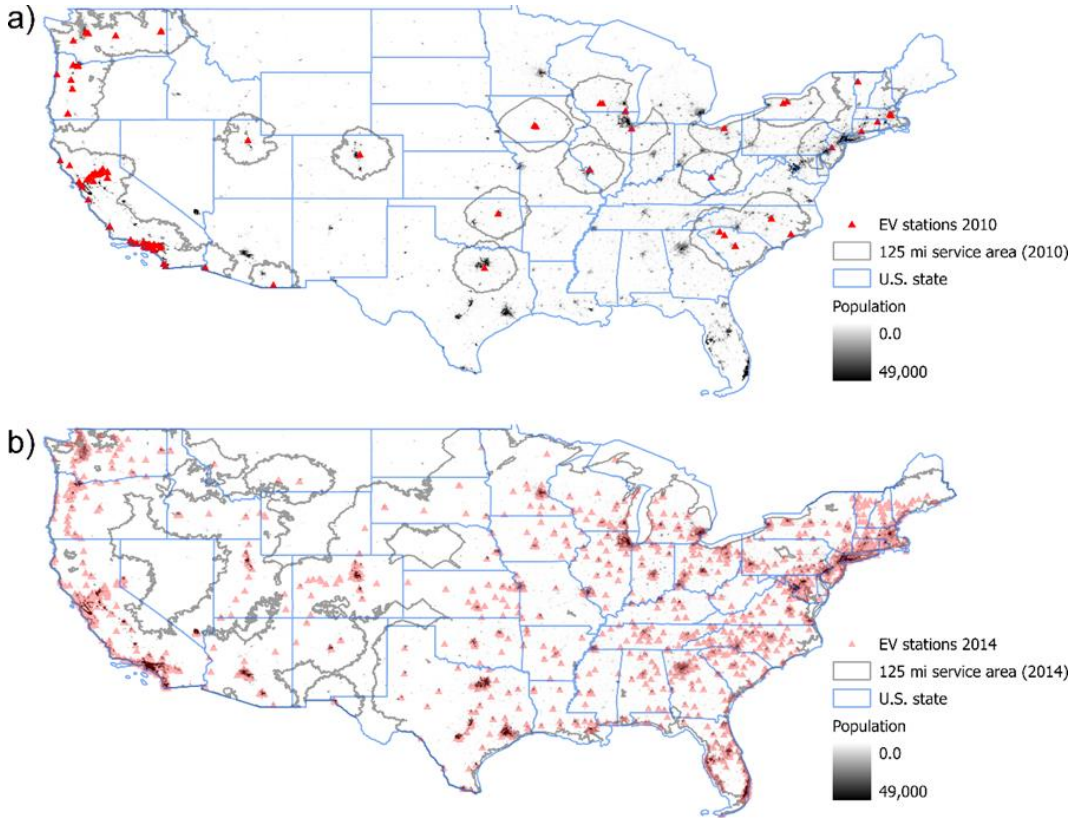
Figure 3: 125-mile (200-km) service areas around EV charging stations: (a) 2010, (b) 2014.

3.3 Localized station analysis

To compare the spatial distribution of EV charger locations on a more refined scale, point datasets of DoE, PlugShare and ChargeHub were aggregated into a hexagon grid superimposed on the Miami UA (Figure 3a). The total point counts were recorded for each hexagon. To identify where each dataset clusters spatially, the Gi* local statistic (de Smith et al., 2018) was calculated for each hexagon feature in each point dataset. The Gi* statistic allows the extraction of hotspots and indicates where charger locations cluster spatially. Clusters at the 0.01 and 0.05 levels of significance were retained for visualization.

To measure the similarity of point datasets, a similarity metric based on hexagon grids was used (Juhász & Hochmair, 2018; Lenormand et al., 2014). First, raw count values were normalized by dividing them by the total number of EV charger locations in the Miami UA, for each point dataset separately. Then, pairwise Pearson-correlation coefficients for all pairs of variables were calculated. A higher correlation for a variable pair indicates that EV charger locations from those sources are located primarily within the same hexagon grids.

To assess the influence of the modifiable areal unit problem (Wong 2004) on the results, the approaches described above were conducted on three sets of hexagon grids with hexagon side-lengths of 1, 2 and 3 km. Results did not change significantly. We therefore retained a hexagon grid with 2km-long sides. This balances computational efficiency and spatial resolution, still making it possible to distinguish between urban forms (e.g., downtown and suburban areas).

3.4 EV Charging patterns

Figure 2e shows the EV charger locations of the SemaConnect network, for which we collected the availability in 5-minute intervals. Each row in the dataset denotes a charger location at a specific point in time. Data points contain the number of available charger ports at the location at that point in time. The total number of available ports in the location is also known. Charger availability was expressed as a percentage and calculated as $U_{l,h} = \frac{T-M}{T} x100$, where $U_{l,h}$ is the average use during a one-hour time slot h (e.g. 12:00–13:00) on a specific day at location l; T is the total number of charging ports at location l, and M is the geometric mean of available charging ports (i.e., ports not in use) recorded during that hour. Note that the calculation of $U_{l,h}$ is independent of the number of times our data collector software was able to extract availability information during an hour. This fault tolerance is useful to avoid issues introduced by network timeout and other errors. This metric was used for describing individual charging patterns. Charger use was also aggregated by the day of the week (Monday, Tuesday, etc.) so that general weekly patterns during the study period (1 June 2023 to 31 August 2023) could be explored.

Charger locations were aggregated to the hexagon grid described in Section 2.1. A similar use metric was calculated for each individual cell, which combines the total number of ports across all charger locations in a cell and their availability. This step allowed us to compare charging behaviour in different parts of the Miami UA (i.e., downtown vs. other areas).

4   Analysis results

4.1 Spatial distribution of EV stations

Table 2 presents the results of the two best-fitting negative binomial regression models for the prediction of the number of EV charging stations in 49 states. The two models have a similar model fit and comparable AIC values. One model focuses on household income, the other on election results. The generalized variance inflation factor was below 2 for all predictors in both models, which indicates that multicollinearity did not pose a problem. The low Moran's I coefficients and p-values above 0.05, based on Queen contiguity, indicate absence of spatial autocorrelation in residuals. Both models show that a denser highway network comes with more EV charging stations, indicating that highways are important corridors for such services. These findings are also in line with what has been found when investigating EV charging access at zip-code level in New York City (Khan et al., 2022). Model 1 shows that states with a higher household income tend to provide more charging stations. This points to mobility-related social exclusion for states with lower incomes (i.e. access to relevant transportation

infrastructure), as has been shown, for example, when analysing access to public transport for disadvantaged sociodemographic groups (Hochmair et al., 2022). Lastly, results show that the dominant political presence in a state (Democratic or Republican), with all this implies about beliefs, values and governance, also plays a role. In Model 2, the majority for the Democratic candidate in the presidential elections of 2016 and 2020 is the base category of that predictor.

Table 2: EV charging station negative binomial model results; ln (area in km2) used as offset

	Model 1			Model 2		
Facility type	**Coeff.**	**z**		**Coeff.**	**z**	
Intercept	**-9.55**	**-11.92**	*	**-4.88**	**-22.66**	*
Median household income (US $)	**6.01E-5**	**4.92**	*	–	–	
Highway density (km/km^2)	**7.75**	**6.78**	*	**9.46**	**9.39**	*
Factor (Republican 2016/2020) 1	–	–		-0.76	-1.90	
Factor (Republican 2016/2020) 2	–	–		**-1.30**	**-5.13**	*
Moran's I (*p* value)	0.06(.09)			-0.08 (.84)		
Null log likelihood	-387.6			-387.6		
Full log likelihood	-368.64			-367.2		
AIC	745.28			744.44		
Adjusted McFadden's pseudo R^2	0.044			0.045		
N	49			49		

*p<.001

States where the Republican candidate won most votes in both elections provide fewer EV charging stations. This suggests that these states tend to support policies which foster the use of traditional cars rather than EVs more strongly than Democratic states. Figure 4 shows the spatial distribution of the election variable, where a value of 1 indicates a state where the party of the winning candidate changed between 2016 and 2020. Value 0 indicates a Democratic win in both elections (blue states), and value 2 a Republican win in both elections (red states). This is overlaid with the location of EV charging stations, shown as grey dots. While regression results hint at the differing roles of Republican/Democratic states as well as of household income in EV charging station distribution, further investigation is necessary to determine whether one or other of the two variables can be considered the more dominant factor.
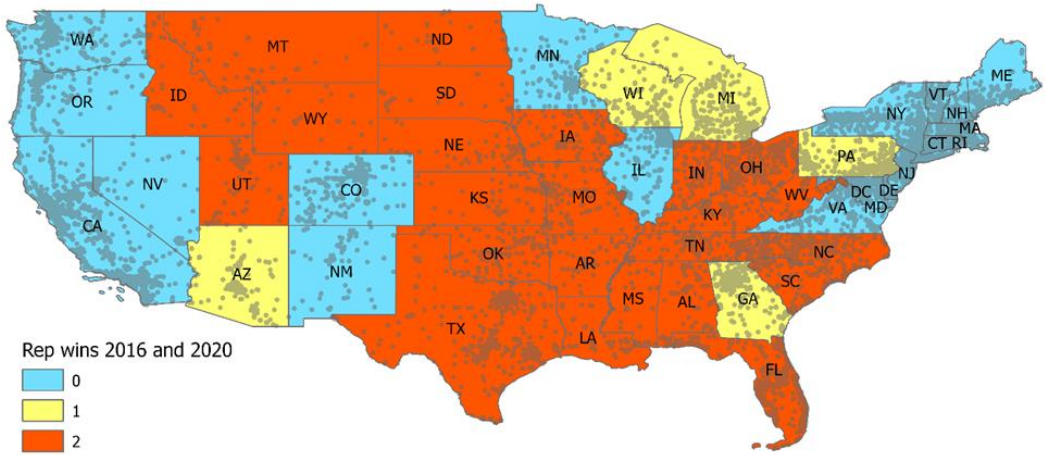
Figure 4: Number of wins of Republican candidate in 2016 and 2020 presidential elections combined

The DoE EV charging station table demonstrates a wide range of fee models for EV-charging. We simplified these to two classes, namely free (i.e., no parking or EV charging fees mentioned), and payment required. Pricing information is available for 14,154 EV charging stations in the contiguous US. For frequently mentioned types of facilities, Table 3 lists the percentage of free stations. Car dealers, hotels and hospitals are among those with the highest proportion of free charging stations. As opposed to this, gas stations and convenience/grocery stores most often require payment for EV charging. A chi-square test of independence showed that the relation between facility type and fee level is significant: X^2 (26, N = 8580) = 2414.8, $p < 0.0001$, and that therefore the facility type does play a role in the provision of free (or paying) charging services.

Table 3: Facility types and associated fee levels for EV charging stationsan hour

Facility type	Total	% Free	Facility type	Total	% Free
Hotel	2310	94.7	Park	168	88.7
Car dealer	1141	98.4	Gas station	163	6.7
Shopping center	694	61.1	Entertainment	134	86.6
Pay garage	363	80.7	Convenience store	132	12.1
Municipal government	362	88.7	Utility	129	89.1
Inn	340	95.6	Sports facility	99	87.9
Grocery	295	52.9	Library	85	87.1
Restaurant	277	57.0	Bed and breakfast	80	78.8
Shopping mall	276	79.7	Hospital	79	100.0
Parking lot	269	56.5	Airport	69	82.6
College campus	267	75.3	Travel center	65	23.1
Brewery/winery	234	67.1	Museum	63	85.7
Parking garage	229	99.1	School	55	69.1
Office building	202	84.7			

4.2 Accessibility of EV charging stations

Figure 5 shows two curves, for the years 2010 to 2022. The green curve shows the number of EV charging stations available in a given year, which demonstrates a particularly rapid growth since 2019. The decreasing curves with a log scale on the ordinate indicate the population (urban and rural) in millions that lives more than 125 miles (~ 200 km) from the nearest EV charging station in a given year. Assuming a 250-mile radius per battery charge and reliance on public EV charging stations, about 121 million urban and 24 million rural residents could not rely solely on battery-driven cars in 2010. A steep drop in the curves for the first few years shows that strategically adding EV charging stations to the infrastructure significantly improved EV station accessibility across the country. From about 2018 onwards, accessibility is complete, except for a few remote locations, such as on islands. Any further stations will therefore facilitate access to charging locations for EVs with smaller battery capacities in particular.
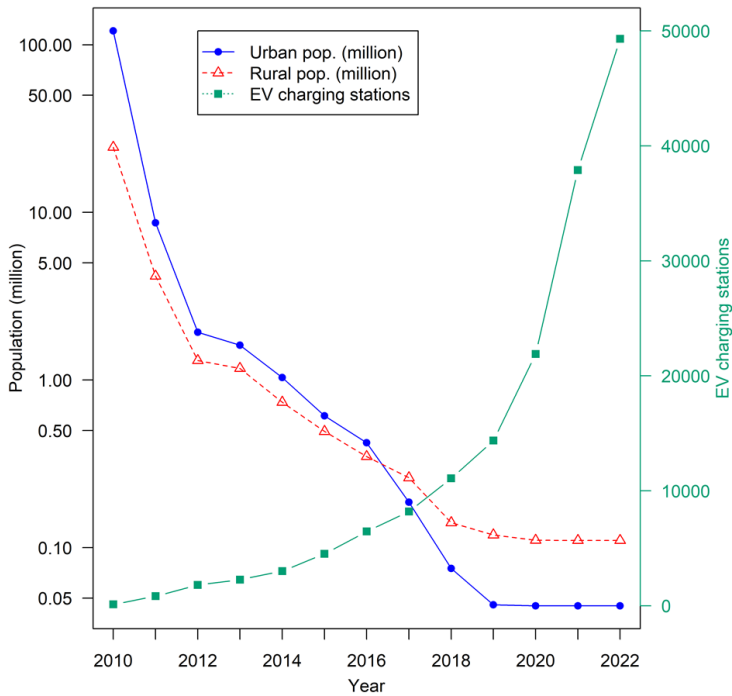
Figure 5: Population, in urban and rural environments, in the contiguous US, living more than 200 km from the nearest public EV charging station

4.3 Localized station analysis

Table 4 provides information about the different EV charger datasets in the Miami UA. PlugShare and ChargeHub reveal similar station numbers; the DoE dataset provides approximately 27% and 34% more stations than PlugShare and ChargeHub, respectively. The

spatial distributions of all three dataset shows similar patterns (Figures 2b–2d). All datasets have their highest number of charging locations per hexagon grid within the same cell, in and near Downtown Miami. This neighbourhood consists of many commercial and residential high-rise buildings. Another indication of the similar distribution of EV charging stations provided by the different companies (PlugShare etc.) is the small variation between the number of hexagon cells without any charger locations (Table 4).

**Table 4:** Number of EV charging locations in the Miami UA in different datasets

Dataset	Total no. of locations	Max no. of locations in a hexagon	Hexagons without charger locations
PlugShare	807	36	280
ChargePoint	763	35	271
DoE	1,022	47	273

To confirm the spatial similarity of EV charging datasets statistically, Gi* statistic were calculated. Figure 6 shows the identified hotspots for the three datasets, which are located in the same areas. Hotspots correspond well to major cities in the UA. With the exception of Homestead, all highlighted areas in Figure 2a show up as significant clusters. So, too, does Sunny Isles Beach, which has the second highest skyline in Florida and the fourteenth highest in the US (The Skyscraper Center, 2023) and therefore provides a high density of EV charging stations.
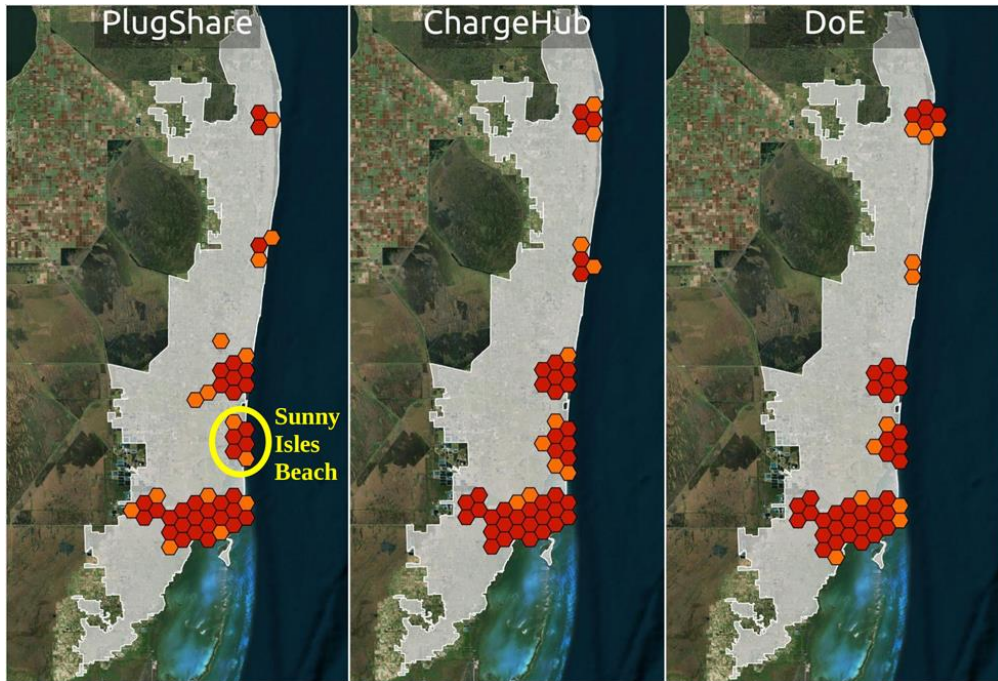
Figure 6: Hotspots of EV charging locations on the 99% (red) and 95% (orange) confidence levels

Figure 7 shows the results of the calculation for the hexagon cell-based pairwise Pearson correlation coefficient, which quantifies similarity between point datasets. The high correlation coefficients of r > 0.91 ($p < 0.001$) for all analysed pairs indicate that most EV chargers are located in the same areas. The lower half of Figure 7 shows scatterplots of normalized cell-based count values. The main diagonal elements in Figure 7 show the frequency histogram of charger raw count values using the same axis scales for all datasets. The histograms show long-tailed distributions, with only a few cells having high count values. This confirms the strong spatial clustering previously shown by the Gi* statistic.
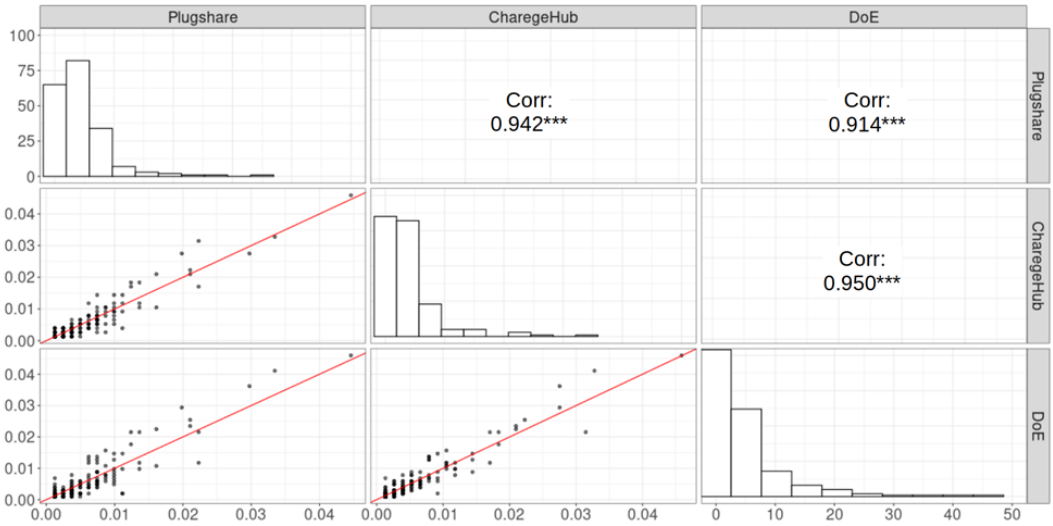

Figure 7: Spatial similarity of EV charger point datasets demonstrated through scatterplots, Pearson correlation coefficients, and frequency histograms of raw charger count values in hexagon grids.

Figure 8 provides another visual overview of charger locations in the Miami UA for the same three charger platforms. It suggests that urban centres provide the best availability of chargers, whereas rural and agricultural areas, as around Homestead, lack EV charging stations.

4.4 EV charging patterns

The SemaConnect network is the only data source to allow the retrieval of temporal usage information. It consists of 161 charger locations in the Miami UA (Figure 2e). 19 chargers were excluded from further analysis as they had an offline status during the study period (1 June 2022 to 31 August 2022). All but one location were used at least once during this period. 13 locations (9%) had an average hourly use value of over 70%, meaning that on average at any point in time (including at night) at least 70% of their available ports were being used. These locations are scattered throughout the Miami UA, but none of them are located in downtown areas. At the lower usage end, 85 locations (60%) were used, on average, to less than 30% of their capacity (Figure 9a).
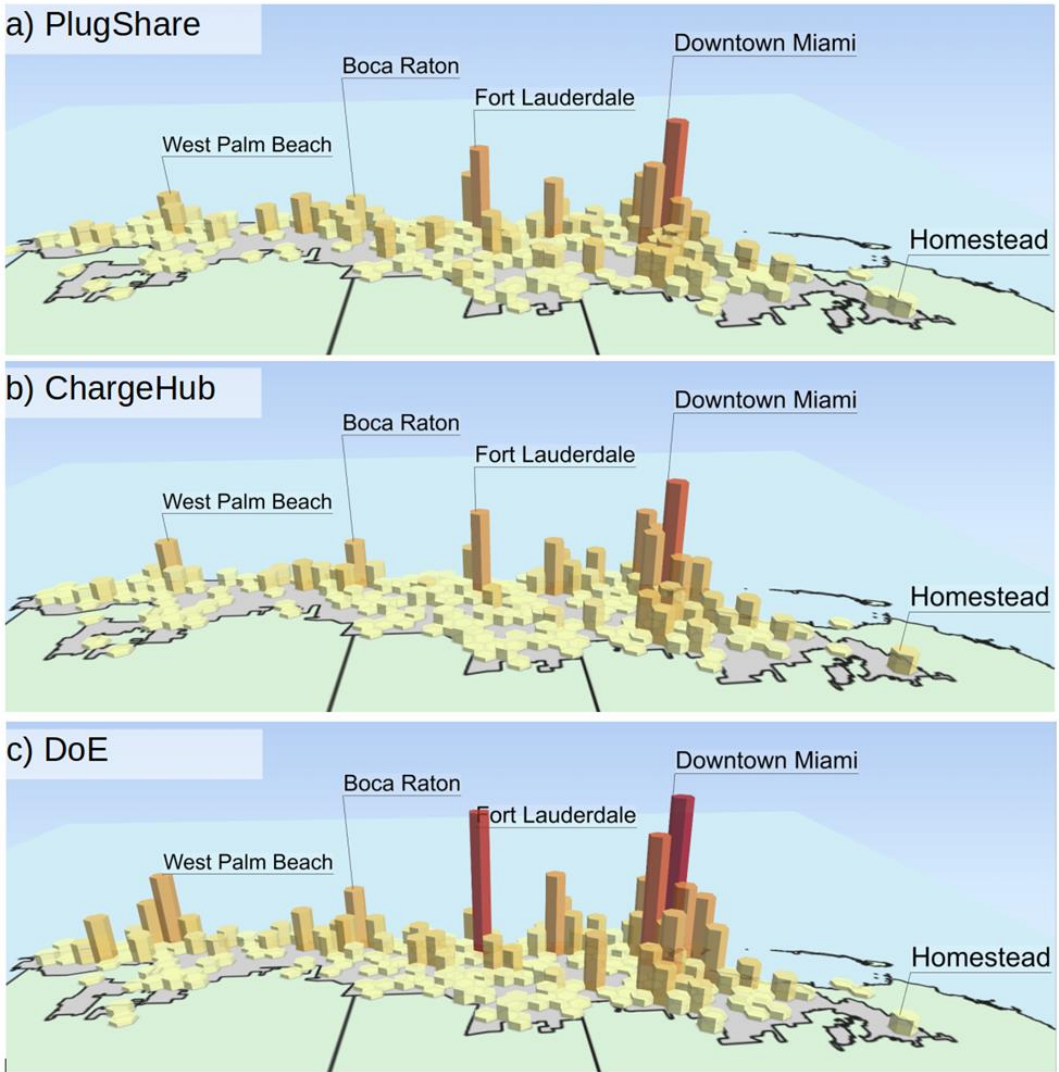
Figure 8: Spatial distribution of publicly available EV chargers in the Miami UA in three different datasets. Hexagons are extruded based on raw count values.

Figure 9b plots the average hourly use (percentage of their capacity) for all days of the week, averaged from the entire study period, and separated into downtown and other areas. Downtown areas consist of charger locations in Downtown Miami, Brickell (slightly south of Miami), and Downtown Fort Lauderdale. The time-series suggests that charging usage exhibits the same pattern regardless of location. There is a clear distinction between weekday and weekend patterns. During weekdays, charging patterns demonstrate daily local maximum peaks in the early afternoon and lowest charger usage around 8–9am. This closely follows the pattern of a standard working day, suggesting that EV owners use the public EV charger infrastructure during their daily activities. In contrast, weekend usage shows no distinct peaks,

and demand at publicly available sites appears to be more steady. Charging patterns follow similar patterns in downtown areas and elsewhere (Pearson's r = 0.92, $p < 0.001$).

However, some differences can be observed. For example, despite almost identical charging peaks especially on weekdays, low-demand times at night are more pronounced in downtown areas. This can be explained by the high number of chargers located in workplaces that are empty after regular working hours.
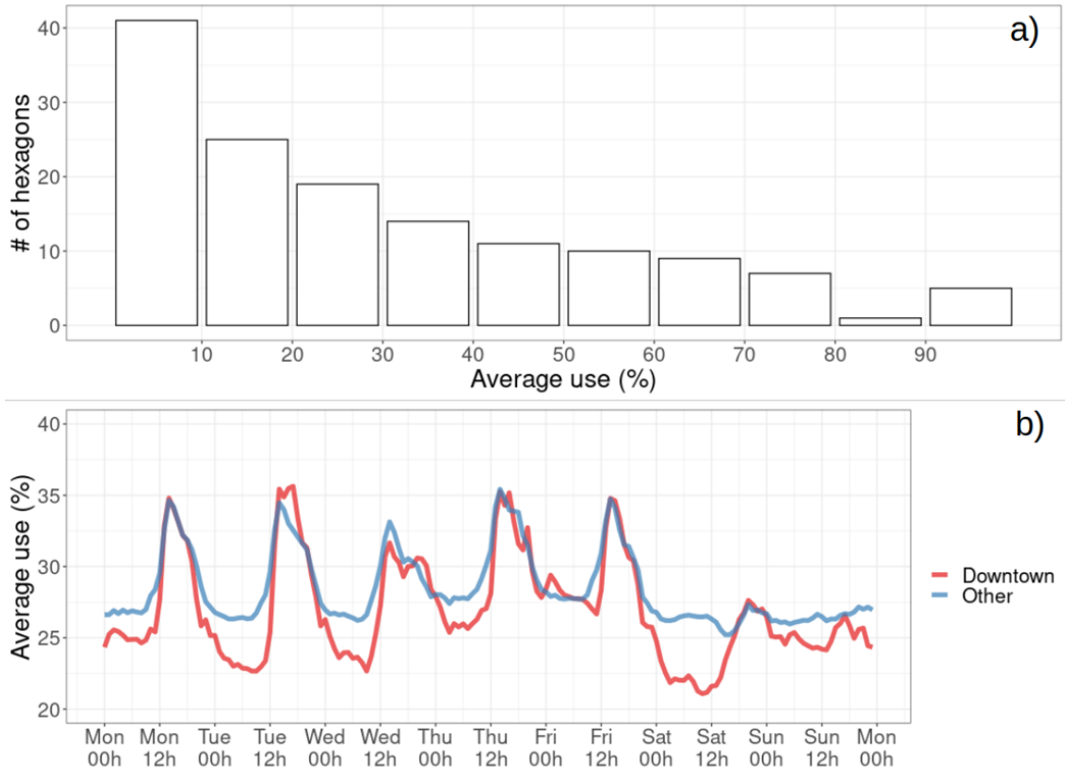
Figure 9: (a) Histogram and (b) time-series plot for charging behaviour

5 Summary and Conclusions

This research demonstrated the evolution of the public EV charging infrastructure and access to it along the urban–rural spectrum. It also showed that at the US state level, social, economic, transport- and politics-related variables influence the numbers of charging locations. Our findings are in line with the limited evidence suggested by the current literature on EV charging accessibility. Whether use of the chargers was free or not was found to be dependent on the facility type (supermarket, carpark etc.) where they are installed. Using the Miami UA as an example, the spatial distribution of different providers' EV charging stations was seen to be similar, with a focus on downtown areas. Exploration of temporal usage patterns of EV

charging stations in Miami revealed daytime peaks on workdays, which can be ascribed to people charging their EVs during their working hours. In contrast, weekend peaks are considerably less pronounced.

In summary, spatial and temporal analysis of EV charging locations and usage provides informative insights for planning the future of the public charging infrastructure – for example, providing free charging facilities to facilitate access in low-income areas. More research is needed to identify areas that currently lack EV charging resources, a lack which could prevent other populations from joining the EV revolution. Future research will consider a more refined set of socio-economic variables, as well as finer spatial scales of aggregation, such as counties and US Census tracts to explore social equity in terms of access to EV charging locations.

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