A Geospatial analysis of Charging Station Infrastructure in the Dallas-Fort Worth Area

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Abstract

Gasoline powered vehicles continue to stand the test of time, but industry changing technology has paved the way for electric vehicles to challenge the dependence on gasoline powered travel. To cut carbon emissions globally, law makers continue to push for an eco-friendlier way of travel. The most recent effort encompasses transitioning from gasoline to electric powered transportation by implementing deadlines or a pashed out approaches to gasoline powered vehicles in large metropolitan areas. The success of electric vehicle market growth relies heavily on the ability for people to transition from gas powered to electric powered transportation. While there are multiple metropolitan cities, Dallas-Fort Worth is one of the leaders in charging station infrastructure according to (Nicholas et al., 2019). However, given significantly more charging infrastructure will be needed to sustain the transition to electric vehicles by 2025. While there is sufficient availability of charging stations throughout the Dallas and Fort Worth areas, the surrounding metroplex may lack enough charging stations for those wanting to make the transition to electric powered transportation. Furthermore, electric vehicle companies and legislators should consider addressing certain social and economic barriers throughout the DFW Metroplex. This study provides a geospatial analysis of the current charging station infrastructure by learning how they are clustered and determining if there is some sort of spatial process present. Additionally, by analyzing how certain physical and socioeconomic barriers influence the current charging station infrastructure, engineers and law makers will be able to assess future needs to meet the increasing demand.

Introduction

Electric Vehicles (EV's) have had a long history within the United States dating back to the early 1900s. However, EV's at the time couldn't gain significant traction due to better performing gasoline powered vehicles. Additionally, there were substantial barriers plaguing the development of a sustainable electric vehicle market. Throughout the last decade, data from the U.S. Department of Energy shows that electric vehicle sales have increased and are on track to continue.

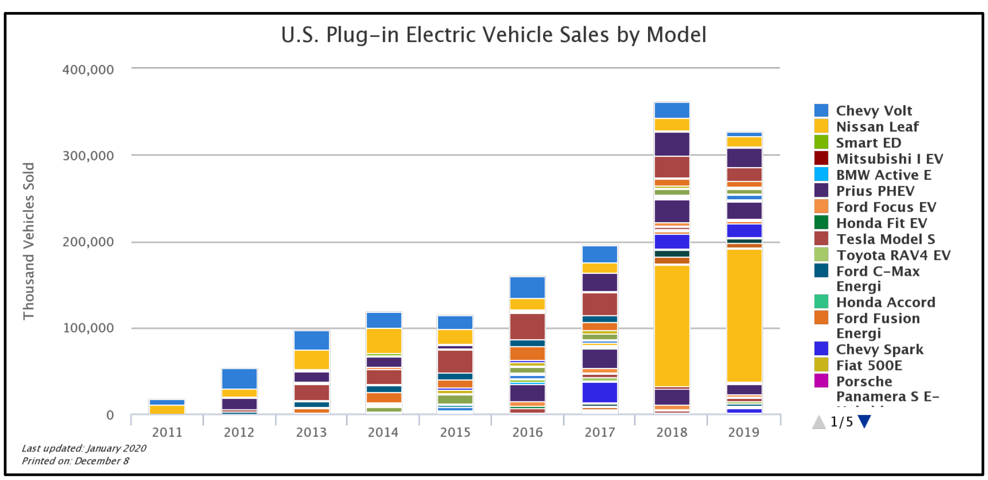

Figure 1. Sales of plug-in electric vehicles (PEVs) grew rapidly from 2011 to 2018. Technology improvements, cost reduction, increasing model choice, maturing charging infrastructure, and economic recovery have continued to influence and support increased sales. Source: Transportation Research Center at Argonne National Laboratory

This study focuses on the electric vehicle charging station infrastructure across the Dallas-Fort Worth metropolitan area. As electric vehicle sales have risen in recent years the demand for more charging stations may become essential to the longevity of electric vehicles. Research has highlighted the lack of charging station locations and poor status of current charging station infrastructure across the United States. As the climate continues to change, state legislators and engineers are continuously discussing ways to cut into carbon emissions, hence the ongoing mission to transition from gas to electric powered vehicles. However, the need to improve charging station infrastructure stems from economic and social barriers. According to (Nicholas et al., 2019), the current charging station infrastructure in Dallas-Fort Worth as of 2017 is 21-30% short of the percentage needed to be sustainable by 2025.

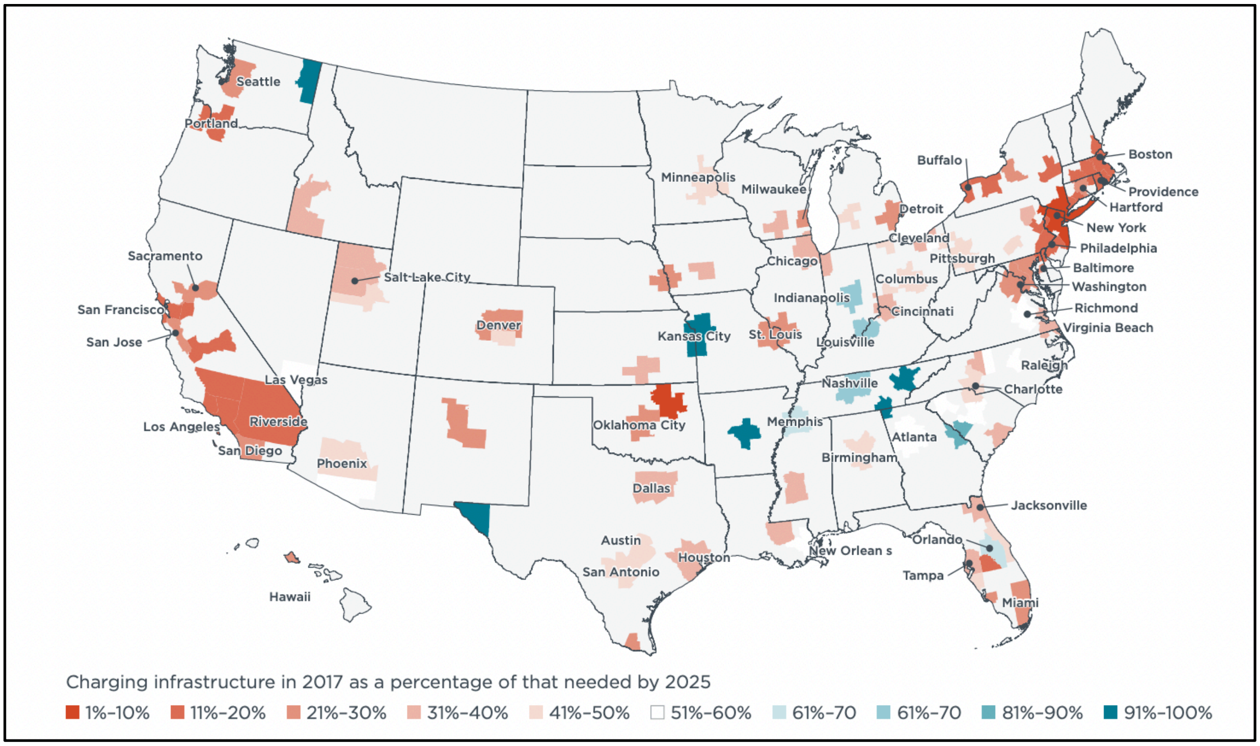

Figure 2. Public and workplace charging infrastructure in place in 2017 as a percentage of infrastructure needed by 2025 by metropolitan area. Source: Nicholas et al, 2019.

In markets where electric vehicle uptake will grow more rapidly that's where the largest charging gaps will be located. However, in places like Dallas-Fort Worth government and industry development to deploy future charging station infrastructure are either absent or lack enough resources to close the charging gaps (Nicholas et al., 2019). According to a report by the Center for Public Policy Priorities and data from the United States Census Bureau the average poverty threshold for a family of four is approximately $25,000 annual income (Center for Public Policy Priorities, 2014 and U.S. Census Bureau, 2019). While the electric vehicle market offers incentives that may benefit the owner, owning a car cab become difficult for the average American to afford. Researchers found that the average vehicle-owning U.S. households earning less than $25,000 spend 50% of their income on vehicle ownership and operation annually (Bauer et al., 2021). Additionally, households earning an annual income of $75,000-$100,000 on average own a total of two new cars and spend on average $34,000 for the purchase of a new vehicle, according to data found in the Bauer et al., 2021 study. Since April of 2020, the average cost of an electric vehicle was estimated to be $51,000, with smaller and cheaper options available (Murillo, 2021).

To close the charging gaps, researchers have analyzed how certain physical and socioeconomic factors influence the behavior surrounding the development of electric charging station infrastructure. There have been multiple studies conducted that aim to solve this problem. Among one of the problems is charging station location and can be a key to expanding the current charging station infrastructure. While charging time could be something that is widely considered in similar research, impacts such as milage and passenger priority are among some of the main influencers of charging station location (Tang et al., 2017). There are many different types of charging stations out there. Perhaps the most well-known is the Tesla Super Charger which is higher voltage than many of the other chargers out there. In fact, there are many differently owned chargers across the Dallas-Fort Worth metropolitan area. As a result, there can be some disadvantages of these different charging stations, more specifically, the low density and inconsistent nature of the energy input, which leads to an increase in the cost of the produced electric energy in comparison to the traditional alternative fuel sources (Gorbunova et al., 2020). Dallas-Fort Worth is a very busy and traffic heavy metropolitan area. There have been efforts to encourage car-pooling and other various options to reduce carbon emissions and traveling costs. However, the willingness to travel via another transportation mode other than gasoline powered is dependent upon destination choices (Liu et al., 2017). Additionally, studying the behavior of electric vehicle drivers can be an important factor that can contribute to charging station capacity (Fotouhi et al., 2019). Research and analysis highlight the need for governmental incentives to keep the electric vehicle market cost competitive (Breetz and Salon, 2018). Furthermore, to persuade the public to be more receptive of the electric vehicle market, there remains a need for a wide variety of different types of charging stations (Anderson et al., 2018).

There are multiple studies that address the need for charging station infrastructure, however, there is limited analysis on the distribution of current charging station locations and the influence of economic factors. This study specifically looks at the clustering of charging station locations across the Dallas-Fort Worth area to determine if there is any spatial relationship. Median Income at the census tract level is also analyzed and identifies hotspots and cold spots. Through the illustration of hotspots and cold spots I'm able to determine if there is any statistical significance to the distribution of median income and charging station location. Results will answer the following:

- Whether the charging station footprint in DFW is random?
- Do certain socioeconomic factors influence the placement of charging stations?
- Is there a difference in the distribution of alternative fuel stations and charging stations?
- Is there a correlation based off access type?

Data and Methods

The data I chose to use in this study is an Alternative Fuel Station dataset from the United States Department of Energy which is a point shapefile. I will use the TIGER/line shapefiles for both

Dallas-Fort Worth counties and census tracts. For the last dataset, I will pull median income at the census tract level which comes from the U.S. Census Bureau.

For this study, I will use a statistical approach. Since this study is focused on the charging infrastructure and median income in the Dallas-Fort Worth Metroplex, the unit of analysis for this project will be at the census tract level. To account for both, the geographically small scale, and the number of charging stations, it will be easier to use census tract data rather than county level data given the sample size.

The data was downloaded into a local folder and ingested into R Studio. Before I can start performing a statistical analysis, I first have to select the proper R Studio packages, or the script won't run properly. The R Studio packages I will be using are: sp, stats, rgeos, rgdal, raster, spatstat, and maptools. The shapefiles then have to be read into R Studio and stored as a vector. All the data then has to be cleaned up and organized properly. The Median Income data was downloaded as a CSV in Excel. I first deleted all columns in that dataset that were not Median Income. I then manipulated the GEO_ID column to exclude everything but the numeric code. Once imported into R Studio, I had to delete the "NAME" column and rename the GEO_ID column to "GEOID". The county dataset included a total of 16 counties which needed to be trimmed down to five counties. A list was created to contain the five counties I wanted to obtain and turned into DFWCounties. The census tracts and median income CSV were merged via the GEOID attribute and stored as a vector called DFWTracts.

The next step involved project all the layers in the same project coordinate system so a spatial analysis could be conducted properly. I found the DFWChargingStations dataset had the correct projected coordinate system, therefore, I transformed the DFWCounties, fuelingstations, and DFWTracts datasets into the same projected coordinate system as the DFWChargingStations. After that, I perfomed a clip on the DFWChargingStations and fuelingstations datasets to include only charging stations and fueling stations within the five counties I determined to be the DFW area. I also clipped the fuelingstations dataset to include everything but fuel_type "ELEC" so that it would only overlay alternative fueling stations.

To visualize the data, I plotted a series of maps to show the charging station locations, alternative fueling stations, and median income across the DFW metroplex. For the median income dataset, I chose to show areas that earn an annual median income of $75,000 based off what the research suggested.

The first method chosen was the Point Pattern Analysis which is useful for determining if a point pattern produces clustering. The point pattern has an associated intensity that explains the point density among a study region. From there, my DFWChargingStations dataset can be run through a Monte Carlo Simulation to determine the mean nearest neighbor distances. The observed mean nearest neighbor distance can be analyzed versus the simulated mean nearest neighbor distances to determine whether the point pattern is more clustered than what would expect under an Complete Spatial Randomness Null Hypothesis. I also analyze the p-values associated with the simulated mean nearest neighbor distances to determine if the clustering is statistically significant.

The second method I have chosen is spatial autocorrelation which is useful in determining the degree to which spatial data from nearby locations are more likely to be similar than data from distant locations. I can then determine if there is any spatial autocorrelation between median income across neighboring census tracts. Additionally, I can analyze the p-values based of the spatial autocorrelation analysis to determine statistical significance.

Lastly, I can run a geographically weighted regression model to examine percentage of publicly accessible charging stations and whether they vary spatially. I can calculate the residuals based of the County code and analyze if the model overpredicts or underpredicts in both Fort Worth and Dallas.

Results

The charging stations in Dallas-Fort Worth provide a few patterns to examine. The first pattern seen below is a clustered pattern. Those clusters are located where you would expect a city center which can be identified by the smaller and closer census tracts. Those city centers include Fort-Worth, Dallas, Denton, and Plano. Another pattern we see here is that most charging stations are lined along major interstates and highways from north to south and west to east.

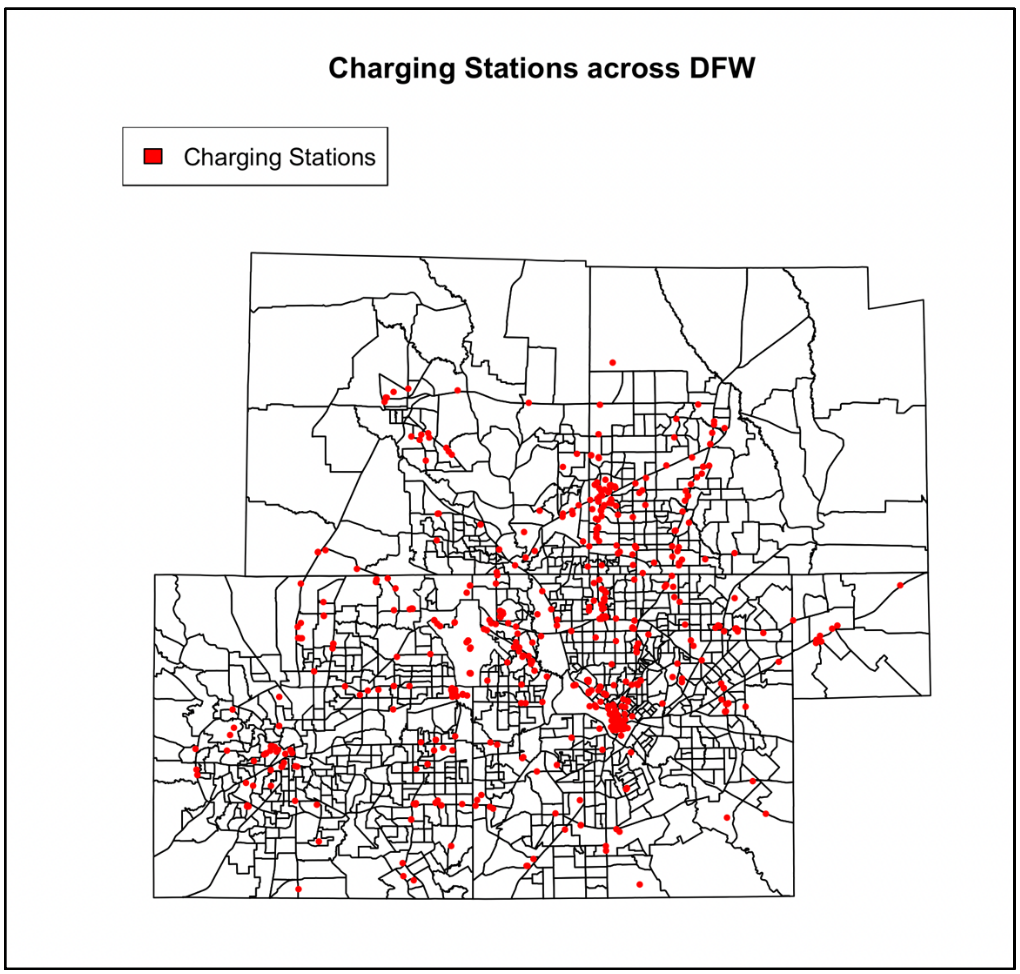

Figure 3. Map of Charging stations across the DFW area. Source: U.S. Department of Energy and U.S. Census Bureau.

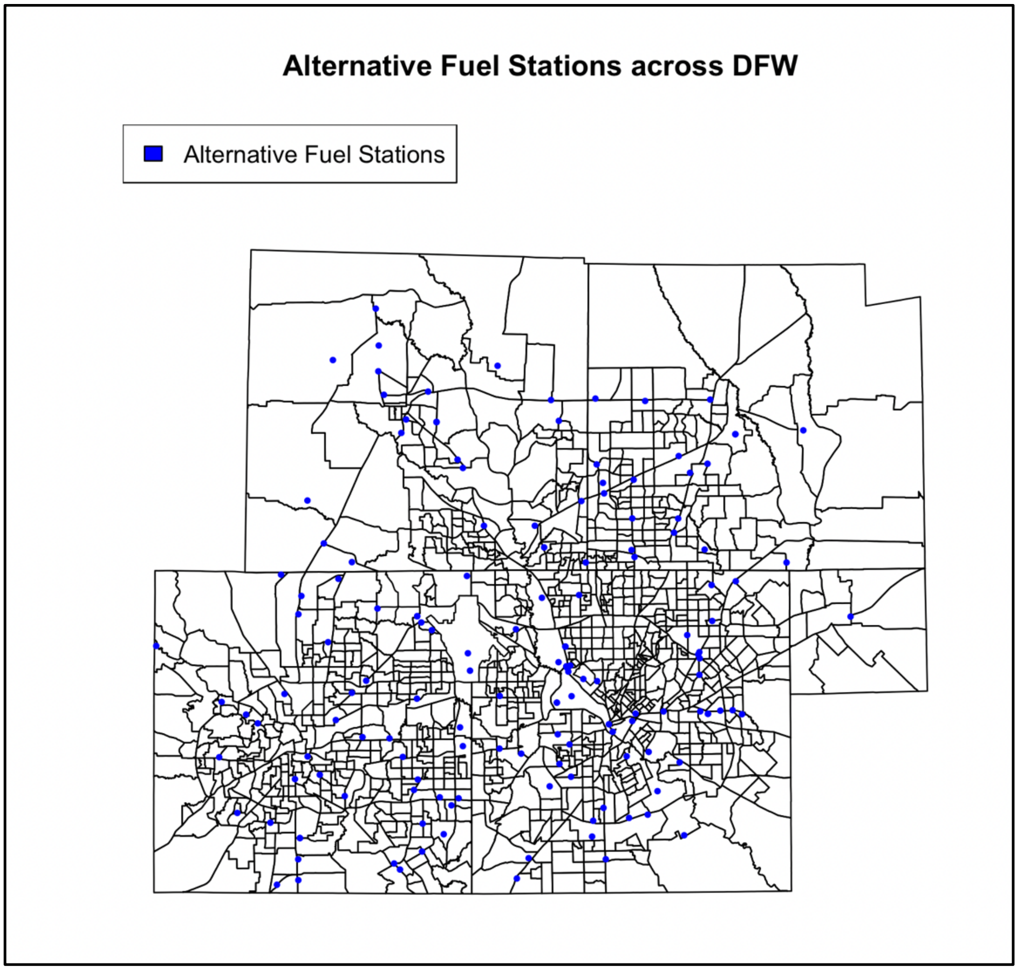

Figure 4. Map of alternative fueling stations across the DFW area. Source: U.S. Department of Energy and U.S. Census Bureau.

The alternative fuel station dataset is not quite as like the charging station dataset. The patterns we observe here don't show clustering and are spaced out further than the charging stations.

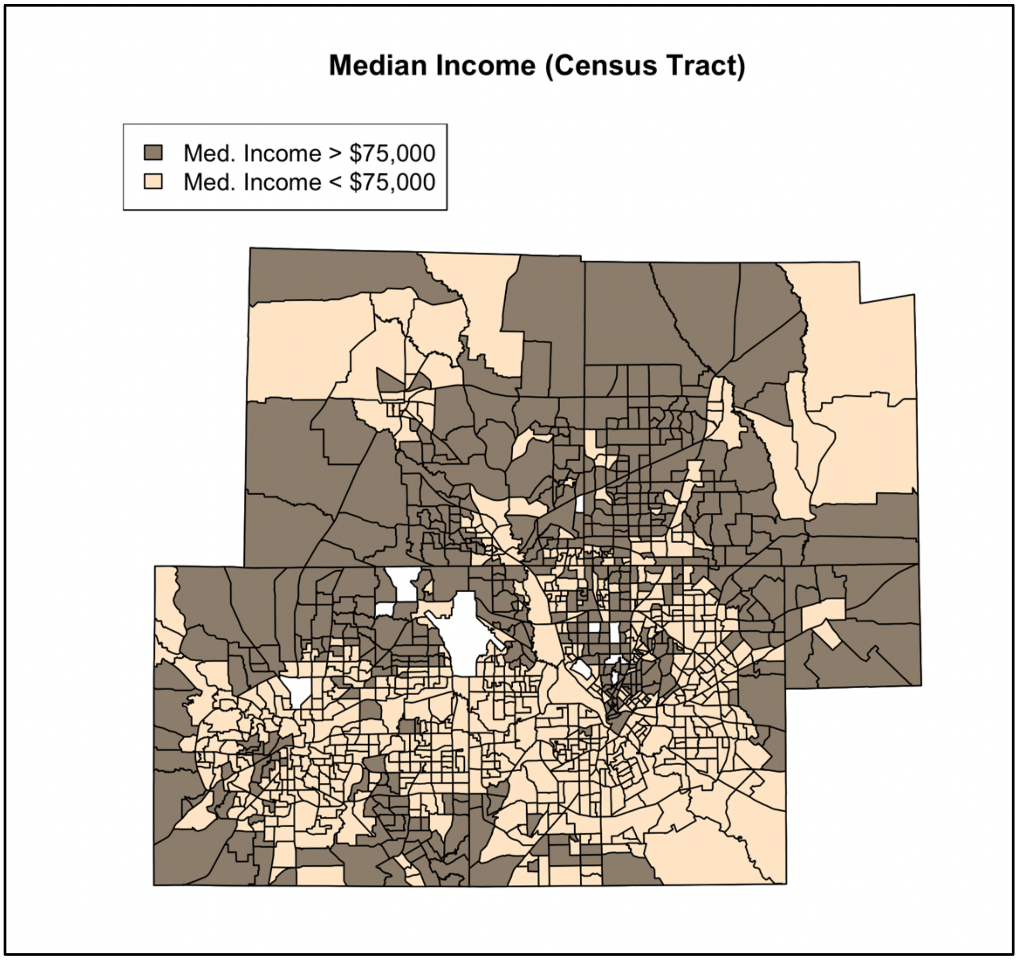

Figure 5. Map of annual median income across the DFW area at the census tract level. Source: U.S. Census Bureau.

The annual median income distribution is about how I would expect. Most households earning a median annual income of less than $75,000 can be found in and around Dallas proper and to the south of Dallas. There is another hotspot of median annual income of less than $75,000 located between Dallas and Fort-Worth near Arlington and around Fort-Worth as well. Whereas households earning a median income more than $75,000 can be found in less urban areas out in the suburbs. This is an interesting outcome based off the thresholds for owning cars and amount of money made you would expect more charging stations outwards of the city center given the median income. Additionally, there are more clusters of charging stations in and around where median income is less than $75,000 highlighting the economic barrier to charging station infrastructure.

From the Monte Carlo simulation I ran we found an observed mean nearest neighbor distance of 2657 and a simulated mean nearest neighbor distance of 6697. There is a point density or intensity of 0.06 per km^2.

```
> observed
[1] 2657.838
> simulated
[1] 6697.919
> intensity
[1] 0.0626997
```

```
> summary(MNNDs)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   6121    6592    6704    6698    6800    7165 
```

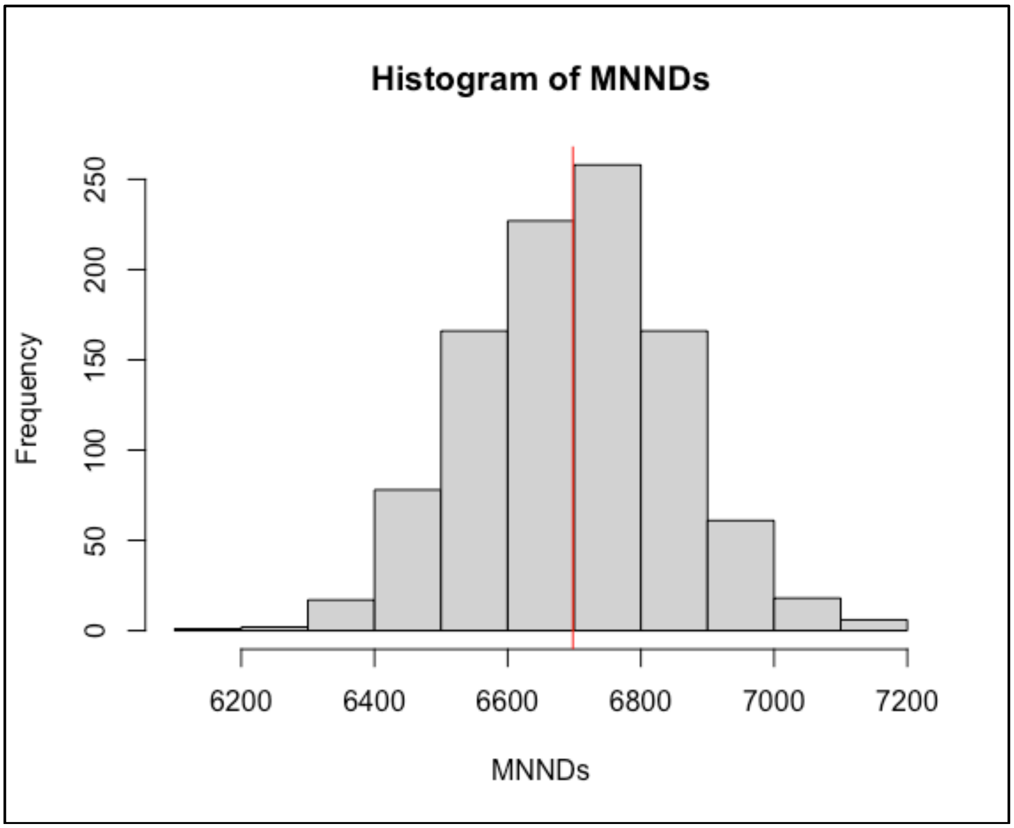

Figure 6. Histogram of MNNDs.

```
> p.value
[1] 0.001
```

If we consider, the summary of simulated mean nearest neighbor distances we see that the smallest simulated mean nearest neighbor distance of 6121 is still much bigger than my observed mean nearest neighbor distance 2657. Given this outcome we can infer that the point patter under the Complete Spatial Randomness null hypothesis is more clustered than we could expect it to be. Additionally, the p-values associated with the simulated mean nearest neighbor distances is less than 0.05 therefore it is statistically significant.

I wanted to find out if there was any spatial autocorrelation of median income in the DFW census tracts. Given the lagged means plot below we see that there is a strong positive spatial autocorrelation between median income per spatial unit and the mean of median income in the neighboring spatial unit.

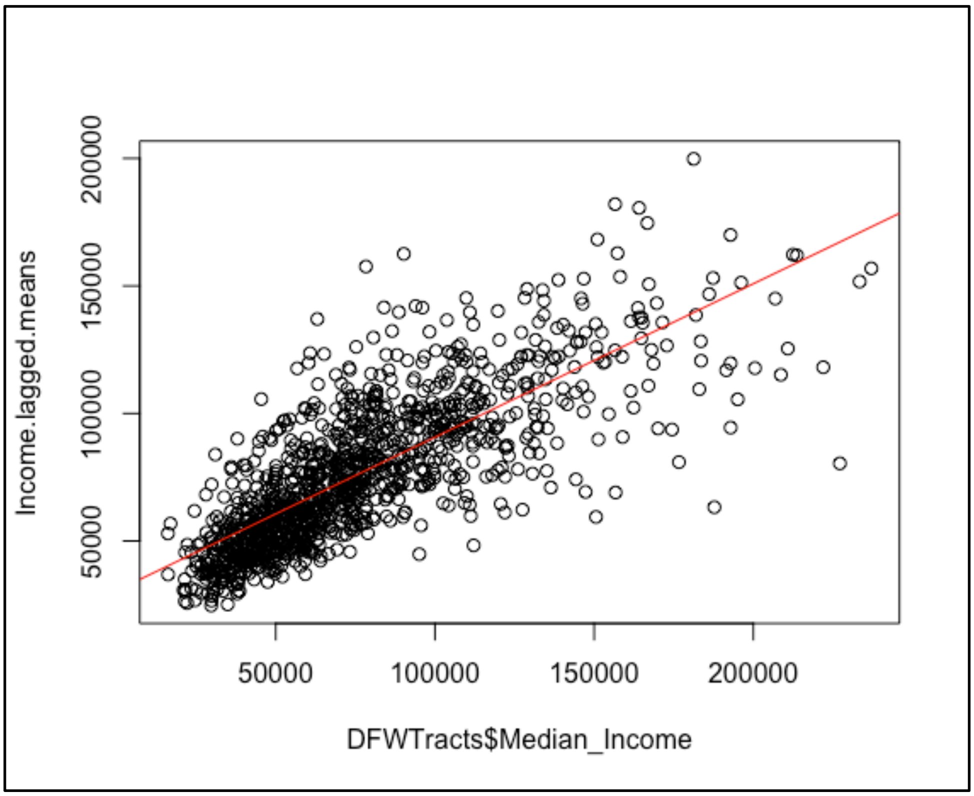

Figure 7. Plot of fitted linear model to analyze spatial autocorrelation.

```
Call:
lm(formula = Income.lagged.means ~ DFWTracts$Median_Income)

Residuals:
   Min     1Q Median     3Q    Max 
-86774 -11626  -1962   9471  79968 

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)             3.052e+04  1.186e+03   25.74   <2e-16 ***
DFWTracts$Median_Income 6.015e-01  1.409e-02   42.69   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 18030 on 1171 degrees of freedom
Multiple R-squared:  0.6088,	Adjusted R-squared:  0.6085 
F-statistic:  1823 on 1 and 1171 DF,  p-value: < 2.2e-16
```

In the fitted linear regression model we see that there is a strong relationship to the median income and mean of the median income of those in the neighboring spatial unit. The R-value of 0.6 suggests a strong positive spatial relationship and the p-value that is less than 0.05 indicates that this is statistically significant.

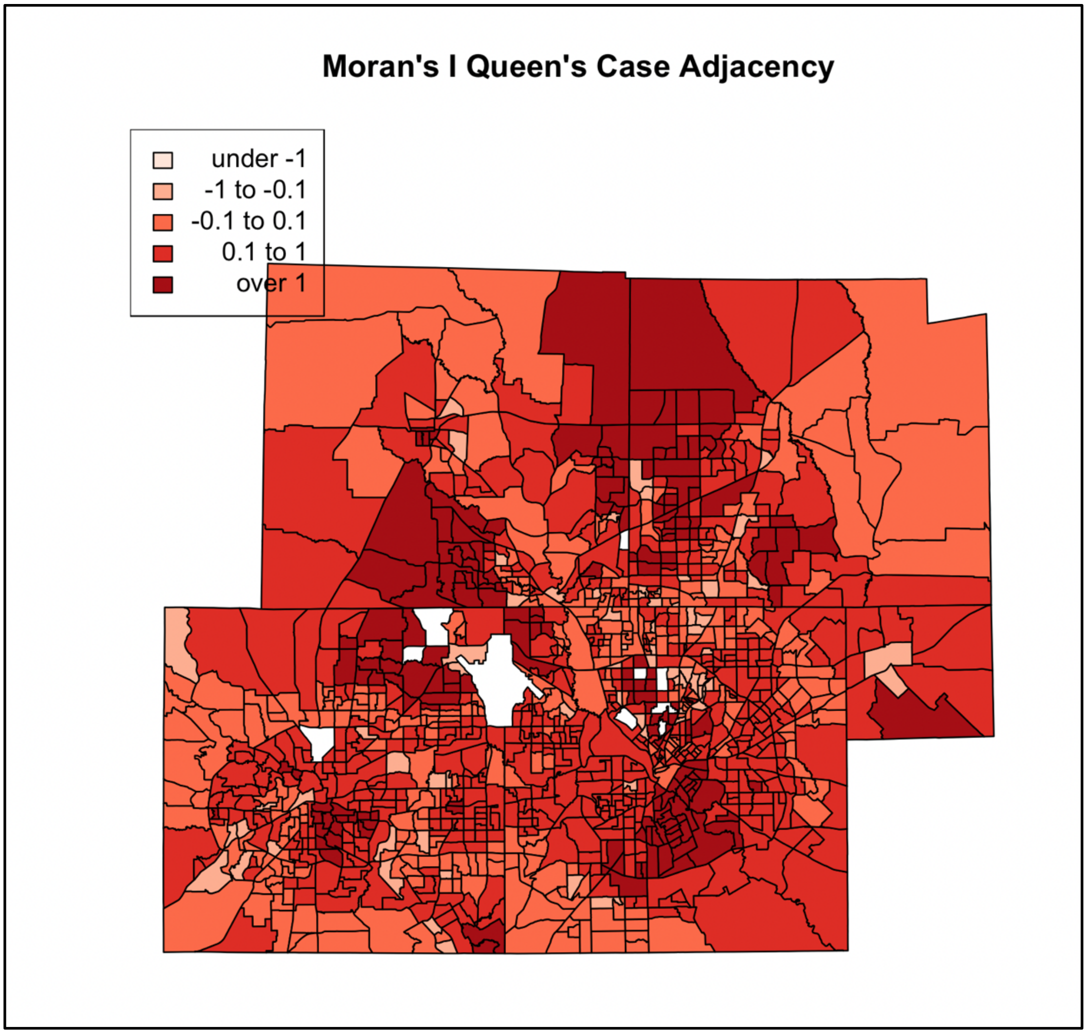

Figure 8. Plot of Moran's I values from the geographically weighted regression model. Source: U.S. Census Bureau

```
Call:
lm(formula = DFWTracts$PCTpubilc ~ DFWTracts$Median_Income)

Residuals:
     Min       1Q   Median       3Q      Max 
-101.615    3.761    8.998   11.384   15.534 

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)             8.215e+01  3.749e+00  21.912   <2e-16 ***
DFWTracts$Median_Income 1.074e-04  4.181e-05   2.568   0.0108 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 24.45 on 244 degrees of freedom
Multiple R-squared:  0.02632,	Adjusted R-squared:  0.02233 
F-statistic: 6.596 on 1 and 244 DF,  p-value: 0.01082
```

```
> mean(Dallas$Residuals)
[1] -2.463314
> mean(FortWorth$Residuals)
[1] -0.8257517
```

Lastly, I fit a geographically weighted regression model to examine access type of charging stations in Dallas and Fort-Worth to see if there is an spatial relationship. I find that there is a significant but small spatial autocorrelation in the residuals from the geographically weighted regression model given a p-value that is less than 0.05. In the case of this model, we see that the residuals are negative indicating an overprediction. Additionally, in the map above where the Moran's I values are mapped we can see that there is perfect clustering of the percentage of publicly accessed charging stations where we would expect most of those charging stations to be. As you move out towards the suburbs and beyond, we see that there is less clustering or more dispersion and rightfully so.

Discussion

The results of this study carefully answered the questions about the clustering of the charging station infrastructure in the Dallas-Fort Worth area. I strategically focused on certain factors that other studies didn't consider in analyzing charging station infrastructure across a large metropolitan city. To minimize the challenges engineers and policy makers face in pushing the electric vehicle market forward, this study analyzed certain physical and economic factors. I found that the current charging station infrastructure is more clustered than expected. Therefore, there is no random spatial process in determining where to place charging stations. In addition, median income will continue to be a challenge or barrier for future development and expansion. Given the strong spatial autocorrelation of median income within the DFW census tracts, policy makers should consider targeting the areas in the suburbs and beyond where the correlation of median income negative and less significant. In future research and given the time I would like to look at different socioeconomic factors and expand this analysis.

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