A geospatial data fusion framework to quantify variations in electric vehicle charging demand

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Abstract

Electric vehicles (EV) are an emerging mode of transportation, and big cities in the United States have witnessed an ever-growing demand for EV usage. The primary benefit of EVs is the high fuel efficiency by using only electricity, and hence lowers the dependency on fossil fuels and significantly reduces greenhouse gas emissions. Although the number of EVs has increased, the availability of EV charging stations for public use has been disproportionate to its demand. More recently, populations residing in the Southern California region have been faced with challenges such as range anxiety owing to the uneven spatial distribution of charging stations throughout the region. As the EV population continues to expand, identifying hotspots of EV charging and barriers to the equitable access of charging stations have gained much importance. Our study uses a geospatial data fusion approach with spatial statistics to combine EV charging station data, land use information, and American Community Survey (ACS) data at the census block group level in Orange County, California to discover optimal locations to broaden the EV charging network and identify potential equity issues surrounding charging station placements.

Keywords: data fusion, electric vehicle, KDE, least cost path, charging demand

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1 Introduction

The sales of EVs have been growing exponentially since the last decade as California is set to have 100% all-electric new cars by 2035 [1]. Notably, the number of light-duty BEVs has increased from 82,686 in 2015 to 369,364 in 2020, and there are 74,459 total EV chargers in California as of July 2021 [2]. 18 out of the 20 largest original equipment manufacturers (OEM) have set goals to develop and sell more battery electric vehicles (BEV) to embrace electric mobility worldwide [3]. There will be more BEV models available from various car brands in the upcoming years. However, the charging demand has also been rising simultaneously, and the charging networks are overcapacity in many places. The EV charging Infrastructure Assessment from CEC have shown that California will need nearly 1.2 million chargers to meet the fueling demands of the 7.5 million EVs by 2030 [4]. In Orange County, eight cities have not fully complied with AB1236, which requires the city to implement a streamlined process in obtaining permits to install EV charging stations [5]. Thus, Orange county needs a comprehensive evaluation of the existing infrastructures to understand the changing demands. Quantifying EV charging demand depends upon a combination of factors including availability of charging stations, access to EVs, economic levels as well as sociodemographic composition of resident populations within our study area. Using a geospatial data fusion approach we develop a mechanism to quantify and visualize the spatial variation in EV charging demand and assess how the demand various contingent about social, economic and demographic composition of the study area. The following sections highlight the study area, different data preprocessing, fusion analysis and visualization of charging demand within the Orange county area (Figure 1) in southern California.

2 Data & Study Area

Our study area is the Orange County (OC) in Southern California. As of 2021, OC has a population of 3.175 million across its 34 cities [6]. The population density in the central part of the county is notably higher in cities such as Santa Ana and Garden Grove (Figure 1). The EV charging demand in those regions has also been increasing as the EV population continues to grow. In 2020, there were 44,441 light-duty BEV and 32,265 PHEV in Orange County, but the total number of EV chargers is currently at 5,477 [2]. The uneven distribution of EV charging stations within OC (Figure 1), highlights the growing divide in EV usage between urban and suburban areas which needs further examination of underlying socioeconomic factors that lead to such inequalities. We collect data from various sources as highlighted in (Table 1)

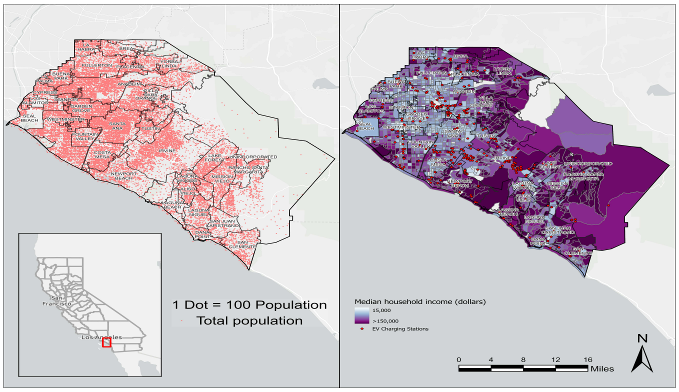

Figure 1. Population density of the anticipated study region (left) and median household income (right) in census block group level

3 Methods

We combine data from various sources as highlighted in Table 1 using data fusion and apply spatial statistics to capture the spatial variation of EV charging demand within Orange County, CA.

Data Layer	Source	Spatial Resolution	Reference
OC DEM	USGS	30x30m	Topography
Street Centerlines	SCAG	Parcels	High/Low Cost
EV Charging Stations	Alternative Fueling Station, Dept of Energy	Points	Destination
Census Demographic	ACS, Census Bureau	Census Block Group Level	Origin/ Source Point

Table 1. Sources for Weighted Cost Raster and Least-CostPath Model

3.1 Geospatial data fusion

To achieve data fusion approach, we developed a model to preprocess layers for LCP analysis using ArcGIS model builder (Figure 2). Slope, land use, and street centerlines were the three components used to created weighted raster. To merge the cost raster layer, A Digital Elevation Model (DEM) imagery was converted to a slope raster. The slope is one crucial component to consider when calculating cost distance because of the geographical barriers from point to point, as steeper terrain might result in a higher cost of traveling. The Land-use layer was converted to a raster by reclassifying the zoning designation to an applicable scale, which involves residential, commercial, office, open space, government buildings, and other infrastructures. The street centerlines shapefile was also converted to a raster by using polyline to raster tool. Last, all three layers were merged as 20% slope, 40% land use, and 40% Street centerlines using the raster calculator.

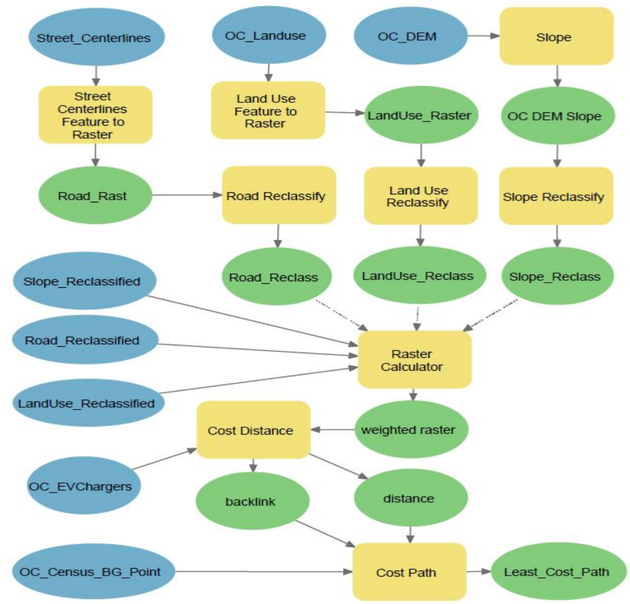

Figure 2. Workflow of least-cost path model, blue indicates sources, yellow indicates geoprocessing tools, and green indicates the outputs

3.2 Charging demand analysis

First, we used the weighted raster for the LCP analysis by determining the distance from an EV charging station to the centroid of census block group. The fused raster layer was weighted by the factors listed in Table 1 and EV charging station data, to estimate the least cost distance and backlink rasters.

Second, we conducted a kernel density analysis to identify the spatial hotspots of the LCP of charging stations. The regions were classified based on the LCP values and converted to a line shapefile using the raster to polyline tool. The output vectors were then used as a population field to generate the kernel density.

Finally, based on the 2019 ACS census block group data, we created a cluster and outlier analysis of the LCPs using the Local Moran's I statistic for two specific attributes - the median age and the median household income (Based on a

4-person household) using the inverse distance technique. The local Moran's I highlights the high and low clusters of LCP variations at the census block group level.

4 Results

4.1 Quantifying public EV charging demand using LCP analysis

The LCP statistics for OC subdivisions are summarized in Table 2, where the cost unit indicates the high/low cost of traveling from point to point, it's a result of different unit/scale calculated from multiple raster layers, not in geographic units. It appears the highly urbanized regions in North and central of Orange County have the lowest cost unit, and this value increases towards the suburban/rural areas. This illustrates the denser cities might have flatter surfaces, more road access, or less blockage for people traveling from point to point. Furthermore, the kernel density estimate further quantified the spatial hotspots based on overall charging demands (Figure 3) across Orange County. Irvine has the highest EV charging demands, followed by Fullerton, Santa Ana, Orange, Southern Costa Mesa, and Laguna Niguel. These cities have significantly higher demands because the LCP are very close to each other, which means more people will be seeking to charge their EV in these regions.

Orange County Subdivisions	Mean (Cost Unit)	Min	Max	Std.Dev
North Coast	6155	1195	12313	3886
Anaheim-Santa Ana-Garden Grove	9153	1686	18029	5202
Central Coast	7507	380	19822	5548
Irvine-Lake-Fores	17708	791	36810	10095
South Coast	9909	1678	20054	5142
Mission-Viejo	16189	1321	27356	7614
Sliverado	19575	1484	43437	13834

Table 2. Least-cost path statistics in the order of population density (North Coast is highest, Sliverado is the lowest)

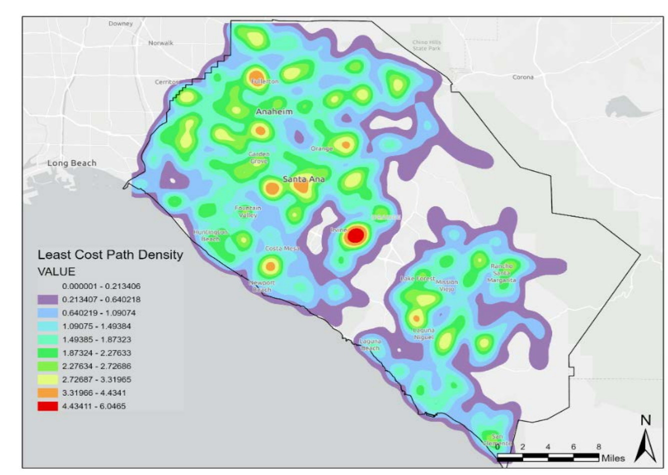

Figure 3. LCP Kernel Density shows the charging demand in Orange County, CA

4.2 Evaluating the variation between socioeconomic factors based on cluster and outlier analysis

The current public EV charger distribution in California has clear socioeconomic disparities between the outlier regions with much higher or lower charger deployment than the population would suggest [7]. Using Anselin Moran's I, the result of the cluster analysis with median age and household income (Figure 5) shows the high-high cluster correlation is well separated from the low-low clusters. The boxplot demonstrated the similarity of range between the four cluster groups in terms of age and income. As higher age people (HH) are more likely to have higher income (HH). In comparison, the median household income clusters in denser city centers in Anaheim, Garden Grove, and Santa Ana are mostly low-low clusters (Figure 4). The high-high income clusters are thoroughly distributed in the suburban regions, and the majority of the low-high outliers are near Irvine and Southeastern Orange County. In addition, the P-Value is an indicator whether the cluster analysis are considered as significant, and the income cluster shows a more significant P-value and lower standard deviations than the age cluster. This aligns with our clustering results and shows median household income is a more reliable factor to compare with charging demands.

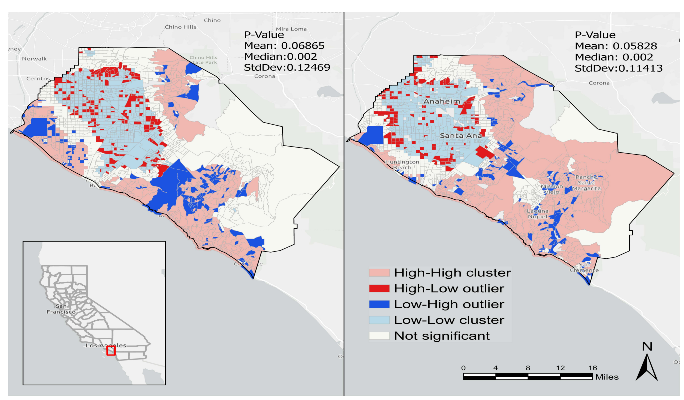

Figure 4. Spatial distribution of median age clusters (left) and median household income clusters(right)

5 Discussion

Our study quantified the EV charging demand and assessed the spatial autocorrelation among population, median age and household income in Orange County, California. The LCP value and population density are not necessarily the

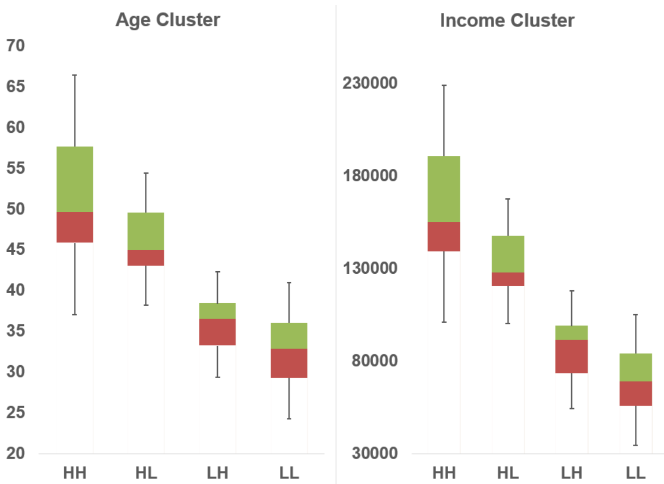

Figure 5. Boxplot summary of the age (left) and income (right) clusters in HH, HL, LH, LL.

dominant impact of charging demand. Instead, the age and income clusters shows a spatial correlation with our kernel density analysis (Figure 3). For instance, Irvine has 88 EV charging stations within its jurisdictions, but the city still have extremely high demands. The lower income regions in Irvine (Figure 1) are not benefited by the distribution of charging stations, and there are lack of services in the poorer neighborhoods. Similar circumstances have appears in high-demand cities such as Santa Ana, Tustin, and Fullerton. In Santa Ana, it has significantly higher demands than the surrounding regions, but there are only 20 EV charging stations within the city. Majority of the block groups in Santa Ana are low-low clusters with a few high-low outliers (Figure 4). This indicates the low income regions are having higher charging demands, but more charging stations were deployed in the high-low outlier areas. The age clusters also demonstrated the high demand cities tend to be in the younger neighborhoods. Thus, it appears EV is not only a premium to the high-incomes anymore as they are becoming more affordable and efficient. In the U.S., the average annual household income for PEV buyers is $125-150k, and average age is 40-55 in 2019 [8]. However, California have approximately 425,300 EV registrations, which is 25% share nationwide[9]. The EV buyers in California is in transition from high-medium income to middle-low income households, and for lower income families that owns an EV, their average age is 30.7 [10]. Hence, what makes Orange county cities have higher charging demands is the income diversity and the trend of younger EV owners in the region. The low-income neighborhoods does not have equitable access of EV charging, which resulted overcapacity near poor neighborhoods. This matches our findings that the high EV charging demand regions are usually medium-low income and younger neighborhoods that have lack of charging access.

6 Conclusion

The LCP charging demand analysis shows a spatial correlation with the median household income clusters. From a transportation equity perspective, the EV charging demands are underestimated based on the income outlier clusters (Figure 4). The existing EV charging station placements tend to focus on providing the most geographic coverage [11]. Thus, deploying more EV charging stations in the high-demand regions will benefit current EV owners and potential buyers. As California is transitioning to an emission-free state, the EV population is expecting to grow more quickly, so increasing EV charging access will improve the current capacity and reduce range anxiety. In the future work we aim to focus on improving the metrics for transportation equity around EVs, thereby helping policymakers in local governments to help fulfill the disparities of charging demands for underserved populations.

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