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Authors
Clark, Callie
Ozturk, Ayse Tugba
Hong, Preston
et al.

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RESEARCH REPORT

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EEZ Mobility: A Tool for Modeling Equitable Installation of Electric Vehicle Charging Stations

Callie Clark, Graduate Student Researcher, New York University
Ayse Tug Ozturk, Graduate Student Researcher, Department of Civil and Environmental Engineering, University of California, Berkeley
Preston Hong, Department of Mechanical Engineering, University of California, Berkeley
Marta Gonzalez, Ph.D., Associate Professor, Department of City and Regional Planning, University of California, Berkeley
Scott Moura, Ph.D., Professor, Department of Civil and Environmental Engineering, University of California, Berkeley

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16. Abstract

Public electric vehicle (EV) chargers are unevenly distributed in California with respect to income, race and education-levels. This creates inequitable access to electric mobility especially for low-income communities of color, which. are less likely to have access to home charging stations. These vulnerable communities are also more likely to be located in areas with poor air quality and would therefore benefit from EV adoption. Currently programs exist in California that fund incentives for public EV chargers in "Disadvantaged Communities" but the process for identifying these communities does not consider key characteristics such as housing type, potential for local emission reduction, and the degree of access to private chargers that would maximize economic benefits to these areas and the state. This study develops a model-based tool that incorporates key additional information to predict economic benefits and health impacts to local communities to guide the location of public charging infrastructure. This tool will improve the equitable distribution of public funds by identifying three types of expected benefits: economic benefit to EV owners/users, economic benefit to infrastructure operators, and greenhouse gas and PM2.5 emission reductions.

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EEZ Mobility: A Tool for Modeling Equitable Installation of Electric Vehicle Charging Stations

Callie Clark, Graduate Student Researcher, New York University
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Executive Summary

Executive Summary

Electric vehicles (EVs) can provide economic benefits to vehicle owners and drivers. However, the ability to realize these benefits depends on owners having convenient access to public charging stations. California has a goal of 1.5 million zero-emission vehicles on the road by 2025 and 5-8 million by 2030. To achieve these ambitious goals, former Governor Edmund G. Brown, Jr. issued Executive Order B-48-18, which encouraged the installation of 10,000 direct current fast chargers (DCFCs) by 2025.

Currently, EV ownership is lower in communities of color and low-income communities. These communities also have less access to public chargers. Studies have demonstrated a feedback loop between ownership of electric vehicles and access to public charging infrastructure; where access to chargers is low, fewer residents are likely to purchase them, which results in fewer chargers being located in those places (Vergis and Chen, 2015; Haidar and Rojas, 2022; Hsu and Fingerman, 2021).

Many areas of the state are disproportionately burdened by multiple sources of pollution. Various state environmental programs have adopted funding goals for low-income and disadvantaged communities (DACs). Under SB 535 the CalEPA has designated 25 percent of the census tracts in California as DACs using the California Communities Environmental Health Screening Tool: CalEnviroScreen 4.0 (CES 4.0), in addition to census tracts that meet other requirements. Many of these communities would benefit from having more access to EV charging stations, which could encourage more residents to purchase EVs. The California Energy Commission is committed to seeing more chargers installed in these areas and has set a goal of allocating 50 percent of its budget to DACs. However, the current method for identifying these tracts — CES 4.0 — fails to incorporate certain factors that could help to optimize the placement of EV chargers in areas where they could provide more economic benefits to local residents and the state. The missing factors include means of predicting EV adoption and use, such as housing types, particularly multi-family housing units (MFH) whose occupants rely more heavily on public charging, access to private chargers, and potential for local emissions reduction. Furthermore, it ignores important differences within large census tracts which can result in charging stations not being placed in the most beneficial locations.

We propose three key performance indicators (KPIs) to use to locate and evaluate appropriate sites for EV chargers to address these equity concerns: 1) economic benefits to the individual (KPI 1), 2) economic benefits to charging station operators (KPI 2), and 3) reduction in local and greenhouse gas emissions (KPI 3).

KPI 1 separately calculates the economic benefit for existing EV owners and current owners of internal combustion engine (ICE) vehicles if a public charger is installed near their home. We consider two economic benefits: (i) improved access to a charging/fueling station quantified in terms of travel time and converted to a monetary equivalent using a value of time calculated from the average median income in the study area, and (ii) lower transportation costs per mile quantified by average vehicle miles traveled (VMT) and electricity/gas prices.

KPI 2 calculates the potential operating revenue increase from servicing new EV charging demand with a local DC charging station. These could create local business opportunities and jobs that are currently monopolized by oil and gas companies. For example, local businesses with parking can add charging to their revenue stream, thereby putting local money back into communities. Additionally, this metric can be used to determine where placing new chargers would be an economically viable investment.

KPI 3 assesses the potential that EVs have to improve local air quality and reduce greenhouse gas (GHG) emissions. This metric quantifies the resulting PM2.5 and carbon dioxide equivalent (CO2e) emissions reduction if a public charger were to be added within a given area. Air pollution has various negative short and long-term health impacts that can vary by local environment and demographics. Quantifying the environmental and health benefits of charging infrastructure installation would allow public agencies to better evaluate the potential effects on disadvantaged communities.

Our study area consists of nine counties in the San Francisco Bay Area: San Francisco, Alameda, Contra Costa, Marin, Napa, San Mateo, Santa Clara, Solano, Sonoma, which contain a total of 1,497 census tracts of which 144 are in DACs. To assess the utility of the KPIs we adopted a spatial unit of analysis consisting of 5.16 square-kilometers hexagons about half the size of an average census tract to better identify optimal locations at a finer scale. Four different scenarios were evaluated for each KPI using different combinations of our proposed KPIs and random placement, both with and without constraints on placement in DACs. These scenarios represent the application of the current DAC definition, two implementations of our model and baseline considering market forces alone.

The main results of the analyses of the modelling showed that:

1. Current DAC definition has disparities in types of economic benefits created.

   The results indicate a tradeoff between economics and equity: DACs get fewer chargers when economic benefit is optimized. The current DAC definition has the lowest individual health benefit and the highest community health benefit (in terms of air pollution reduction).

2. Economic benefits increase when chargers are placed using the three KPIs.

   The results show that, compared to current policies, when DCFC placement is optimized within DACs the estimated economic benefits increase by 74% for current EV owners, 76% for owners of gasoline powered vehicles, and 172% for station owners, and result in a 222% increase in value for the study area from PM2.5 particulate matter reduction. Chargers are also better located within large census tracts based on the model's KPIs due to the use of a smaller spatial unit of analysis.

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Introduction

Studies have shown spatial inequality in public charger access across California, and current State funded programs have introduced goals and earmarked funds for "disadvantaged communities" Hsu and Fingerman, 2021. The currently implemented definition of disadvantaged communities is based on the CalEPA definition created by SB 535. This definition uses 21 statewide indicators that fall under two categories: Pollution Burden and Population Characteristics (OEHHA, 2021). CES 4.0 does not consider key characteristics that are specific to EV vehicle benefits like housing type, commute patterns and private charger likelihood. We propose that this generic and broad definition of DACs is in itself inequitable and that the economic benefits of charger infrastructure access are not being fully realized with the current definition of DACs.

Charger access has a high amount of spatial variation in California due to factors that make access more difficult like housing types and current infrastructure. These factors are systemic and stem from historical inequitable practices like redlining, and as a result are intrinsically linked to demographics. In a situation with limited resources (public charger installations), an equitable distribution would place chargers in areas that have the greatest need and would benefit the most. The benefits include economic (individual and business owners) and environmental (local health and overall climate). To evaluate these benefits, we propose three KPIs. Then we evaluate what benefits the current definition of DACs is providing compared to our model that uses EV-specific data to locate chargers. Our model calculates the missed economic benefit due to an inappropriately broad definition of "disadvantaged community" for individuals, infrastructure operators and the community.

Current EV Infrastructure Access and Goals

The transition from internal combustion engine (ICE) vehicles to electric vehicles (EVs) has the potential to reduce California's greenhouse gas (GHG) emissions and provide local benefits, including improved air quality and transportation access. In 2018, former Governor Edmund G. Brown, Jr. issued Executive Order B-48-18, which established a goal of having at least 5 million vehicles on the road by 2030 and mandated that state agencies work to install 250,000 public and private zero-emission vehicle chargers, including 10,000 direct current fast chargers (DCFCs) by 2025.[1] Although by January 2021 the state had already installed more than 70,000 public and shared private chargers and 6,000 DC fast chargers, with plans to add more, the California Energy Commission (CEC) estimated there would still be a gap of over 57,000 chargers overall and 430 fast chargers by 2025 (CEC, 2021).

[1] A DC fast charger can provide an EV with an 80 percent charge in about an hour, compared to several hours or overnight using most common Level 2 AC chargers found in homes, workplaces, or shopping areas. . https://evsafecharge.com/dc-fast-charging-explained/

Subsequently, the state has banned the sale of new gasoline-powered vehicles beginning in 2035 (California Air Resources Board, Advanced Clean Cars II Regulations, August 25, 2022), which could increase the number of EVs on the road by 2030 to 8 million, making installing additional chargers a high priority. To facilitate this, extensive investments in EV charging infrastructure will be required across the state. Currently, there are 8,528 DCFCs in the state with funding allocated for an additional 10,323, more than enough to meet the 2025 goal early.[2] The CEC estimates that by the year 2030 approximately 700,000 public and shared private chargers will be needed to meet the original 5 million vehicle goal and 1.2 million chargers to meet the expanded 8 million goal (CEC, 2023a).

Overall, the current pattern of EV ownership and distribution of charging infrastructure exclude low-income and disadvantaged communities from participating in the benefits of transitioning to EVs. Chargers tend to be located in higher income areas where EV ownership is greatest. Even when controlling for other factors like highway proximity, there are fewer public chargers in low-income and majority Black and Hispanic areas (Hsu and Fingerman, 2021) where EV ownership is low (Canepa, Hardman and Tal, 2019). While single family homeowners may have access to a private charger, residents of multi-unit housing tend to rely more heavily on public chargers. As a result, public charger availability tends to be higher where multi-unit housing is concentrated, but access increases at a slower rate in low-income areas (Hsu and Fingerman, 2021)..

Studies have demonstrated a feedback loop between access to public charging infrastructure and electric vehicle ownership: Where access to chargers is low, fewer residents are likely to purchase them, which leads to fewer chargers being located in those areas (Vergis and Chen, 2015; Haidar and Rojas, 2022; Hsu and Fingerman, 2021). Addressing these needs depends on the private EV charging market to make the necessary investments, but in many places EV charging is not seen as profitable. While it may become self-sustaining in the future, at present, infrastructure implementation is heavily reliant on public funding.

Clean Transportation Program and CALeVIP

The CEC's Clean Transportation Program (also known as the Alternative and Renewable Fuel and Vehicle Technology Program) provides funding to support innovation and accelerate the development and deployment of advanced transportation and fuel technologies throughout the state. Using funds collected from vehicle and vessel registration, vehicle identification plates, and smog abatement fees, and leveraging public and private investments, the program expedites development of conveniently located fueling and charging infrastructure for low-and zero-emission vehicles. It provides opportunities to participate in and benefit from clean transportation projects for diverse, underrepresented, underserved, and disadvantaged communities throughout the state (CEC, 2023b). The CEC is committed to providing more than 50 percent of Clean Transportation Funds to projects that benefit low-income and disadvantaged communities. Since the inception

[2] There would, however, still be a gap of 37,461 to meet the 2030 goal.

of the Clean Transportation Program over $1,229.4 million has been invested with 49 percent ($601.1 million) allocated to disadvantaged and low-income communities (CEC, 2023a).

The CEC created the California Electric Vehicle Infrastructure Project (CALeVIP) in 2017 to provide Clean Transportation Program incentives for light-duty EV charging infrastructure. The program makes block grants available to provide incentives for the purchase and installation of light-duty EV chargers. The rebates are intended to spur development of the EV charger industry especially in areas where demand for charging is currently low with the aim to encourage greater EV adoption. Initially funded by $200 million from the Clean Transportation Program with an additional $40 million from community partners,

CALeVIP has a goal of at least 50 percent of these incentives reaching low-income and/or disadvantaged communities. The program provides substantial rebates to private investors and non-profit organizations installing publicly available chargers to meet current and future EV drivers' needs. CALeVIP 1.0's 13 county-based block grants, administered by the Center for Sustainable Energy (CSE), allocated $186 million for rebates on a first-come, first-served basis to cover up to 75 percent of EV charger installation costs. Most of these incentive projects earmarked at least 25 percent for disadvantaged or low-income communities. Applicants could receive up to $80,000 for DCFCs.[3] Higher incentives were also available for projects within disadvantaged communities (CEC, 2023a). So far, the program has provided $171 million toward rebates, of which $83 million (48 percent) went to low-income and disadvantaged communities. The CEC's 2022-2023 Investment Plan Update increases funding for the Clean Transportation Program with at least 50 percent targeted to benefit priority populations, with $900 million set aside for light-duty EV charging infrastructure. CEC staff estimates the plan will result in 90,000 new EV chargers across the state, more than double the 80,000 chargers (L2 and DCFC) installed today. Combined with funding from utilities and other programs, these investments are expected to ensure the state achieves its goal to deploy 250,000 chargers by 2025.

In 2021, CSE was awarded a $250 million grant to administer the CALeVIP 2.0 program, which emphasizes installing high-speed chargers only and directs 50 percent of funding for equitably installing DCFCs in low-income and disadvantaged communities. As part of this program, the Golden State Priority Project, begun in January 2023, makes $30 million in rebates available for up to 50 percent of total approved costs up to $100,000 per connector and is exclusively for low income and disadvantaged communities in the eastern and central regions of the state (CSE, 2023). To identify these areas the CEC relies on a mapping tool known as CalEnviroScreen developed by the California Environmental Protection Agency (CalEPA) for purposes of allocating California Climate Investment program funds, 25 percent of which must go to projects that provide a benefit to disadvantaged communities.[4] The targeted range for percent investment in disadvantaged

[3] The program provided rebates for four of the counties in the study area for Level 2 and DCFCs: Alameda, San Mateo, Santa Clara, and Sonoma.

[4] Senate Bill (SB) 535 (2012) allocates California Climate Investment program funds from the proceeds of the state's Cap-and-Trade Program.

communities varies, for the purposes of our study we adopt the lower bound of 25% when we evaluate scenarios.

Defining Disadvantage Communities

Senate Bill (SB) 535 charges CalEPA with defining disadvantaged communities (DACs) as areas which are disproportionately burdened by multiple sources of pollution based on “geographic, socioeconomic, public health, and environmental hazard criteria” (CalEPA, 2023). CalEnviroScreen analyzes data on environmental, public health and socioeconomic indicators in California’s 8,000 census tracts to provide a clear picture of cumulative pollution burdens and vulnerabilities in disadvantaged communities throughout the state. It uses 21 statewide indicators to characterize both pollution burdens and population characteristics and combines the individual component scores to create a composite score for any tract (Zeise and Blumenfeld, 2023).

The first designation of DACs appeared in 2017. CalEPA recently released CalEnviroScreen version 4.0 (CES 4.0) which designated 2,130 census tracts in state as DACs for 2020, consisting of (i) those tracts in the top 25 percent of the overall CES 4.0 scores (1,984 tracts); (ii) those with no overall score due to data gaps but in the top 5 percent of cumulative pollution burden scores (19 tracts); and (iii) tracts identified as disadvantaged in the previous 2017 designation regardless of CES 4.0 score (307), along with certain tribal areas (CalEPA, 2023).

There are a several problems in relying on CES 4.0 to determine public EV charger infrastructure funding, primarily it was not designed with this specific objective in mind. The pollution burden indicators and population characteristics have varying levels of relevancy to EV benefits, and CES 4.0 evaluates all these metrics with different weights to rank individual census tracts as DACs (Eng et al., 2018). However, the model ignores several factors related to predicting EV adoption and use, such as type of housing, particularly the number of multi-family housing units (MFH) whose residents rely more heavily on public charging facilities, as well as local vehicle miles traveled, and current public charger access. While the program permits users to filter out existing metrics and add outside metrics, there is no documentation of this occurring in connection with EV infrastructure placement. Both CES 4.0 and my model do not site the chargers at a specific location but flags areas that qualify for rebates. The granularity of the areas flagged differ, CES 4.0 produces scores at the census tract level and my model uses hexagons. The larger granularity of census tracts does not guarantee that infrastructure will be placed in the most beneficial location within a tract because some are fairly large in area and can be highly heterogeneous (Hsu and Fingerman, 2021).

Clearly, it is vital that disadvantaged communities are not left out during the transition to EVs. However, identifying these communities and understanding how they may be impacted by EV charger installation needs to be addressed. A number of factors can affect how communities will benefit from access to EV charging stations, including: racial make-up of an area, income levels, housing type, tenure, and public transit access. These factors should be considered in choosing where best to place chargers to increase overall benefits but understanding the interaction between demographics, EV vehicle ownership and public charger access is challenging.

Proposed Key Performance Indicators

We propose an alternative model, *EEZ Mobility*, that relies on three key performance indicators (KPIs) to locate appropriate sites for EV chargers to maximize their benefits while addressing equity concerns:

KPI 1 measures economic benefits to residents

KPI 2 measures economic benefits to charging station operators, and

KPI 3 measures the value of the health benefits from reducing local pollution and greenhouse gas emissions.

These three key performance indicators are represented graphically in **Figure 1** below and described in the following sections. We specifically focus on DC fast charging stations because they are essential for encouraging EV adoption, especially for Californians who drive long distances or can't charge their vehicles at home or work. Evaluating the tradeoffs in a quantitative way between multiple benefits is difficult especially when the relevant inputs vary by location and affect various social processes.

Case Study of the Bay Area

We tested our proposed methodology on data from nine counties in the San Francisco Bay Area: San Francisco, Alameda, Contra Costa, Marin, Napa, San Mateo, Santa Clara, Solano, Sonoma. The census tracts in the study area are a subset of the total across the nine counties due to data limitations. Our study area contains a total of 1,497 census tracts of which 144 are in DACs based on the 2020 CES 4.0 designation (see **Figure 1**).

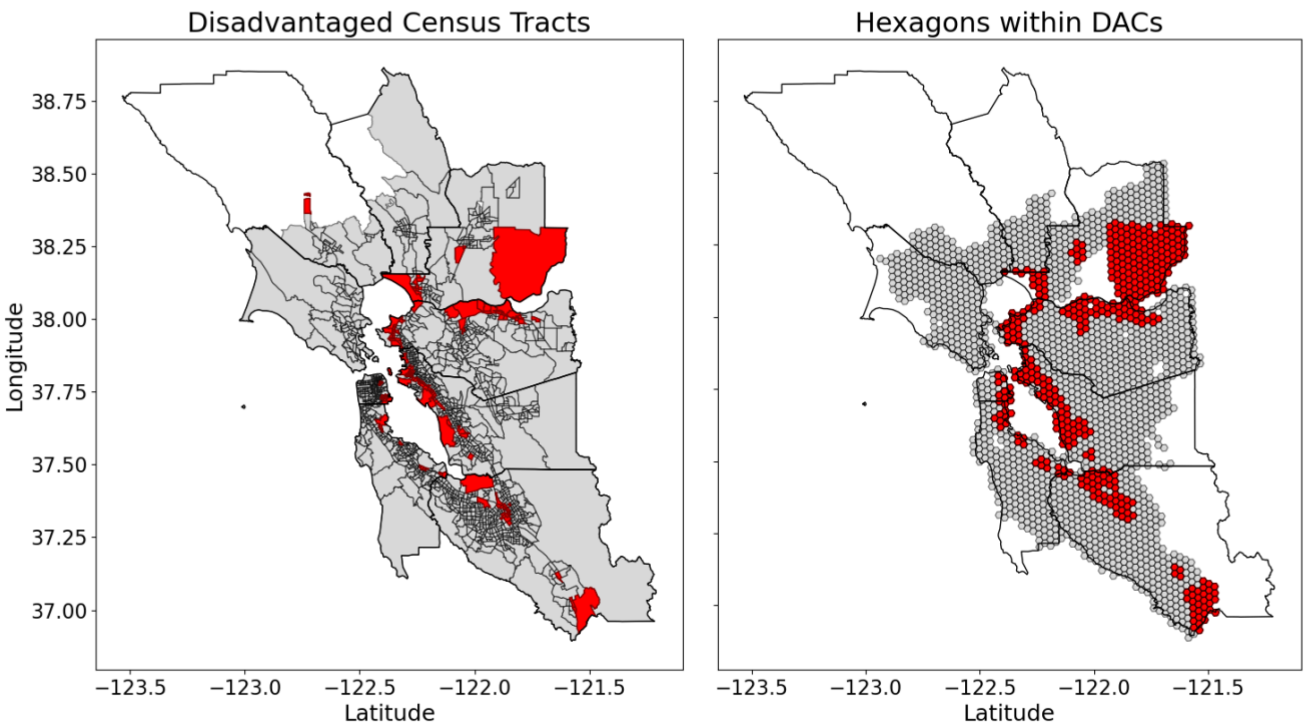

Figure 1. Disadvantaged Census Tracts in Study Area

In 2021 California had 79,023 installed chargers with 35,594 of those being public chargers 6,695 of which were DC fast chargers (CEC 2023d).[5] Based on the Governor's 2018 goal of installing 10,000 chargers across the state (Executive Order B-48-18), there would have been a gap of 3,305 DC fast chargers in California, with approximately 992 of those in our study area based on historical charger density. Assuming four plugs at each station, 248 stations would have been needed to supply all the fast chargers required to meet the state's goal at that time.

We designed four scenarios to identify possible locations for those charging stations based on their economic benefits at large. One scenario models the benefit of adding the KPIs in conjunction with the current definition of CES 4.0 and another evaluates using the KPIs with no constraints related to their DAC status. We also evaluate two baseline scenarios with the current DAC definition and a scenario with no DAC requirement that relies on private investor decisions alone. The next section describes our three KPIs and how they could be employed to identify appropriate locations for these chargers in our hypothetical case study.

[5] The state currently has 13,799 public electric charging stations (37,311 EVSE ports) of which 1737 have fast DC chargers (8,564 ports) (https://afdc.energy.gov/fuels/electricity_locations.html#/analyze).

Proposed Key Performance Indicators

The KPIs are designed to identify locations for DCFC installation that would have a positive impact on disadvantaged communities. The three KPIs provide information on various aspects of economic benefit due to charger installation. **Figure 2** shows recipient of the economic benefits due to a charger installation for each KPI; KPI 1 focuses on the individual (ICE or EV owner), KPI 2 evaluates the owner of the charging infrastructure, and KPI 3 addresses community health and global carbon level. Our spatial unit of analysis consists of a grid of hexagons which were overlayed on our study area (see following section for details) The three KPIs were calculated for each hexagon and those which demonstrated the highest benefits were selected to receive chargers, up to the total of 248. A detailed description of the inputs used for the each of the calculations and the process is contained in the Appendix.

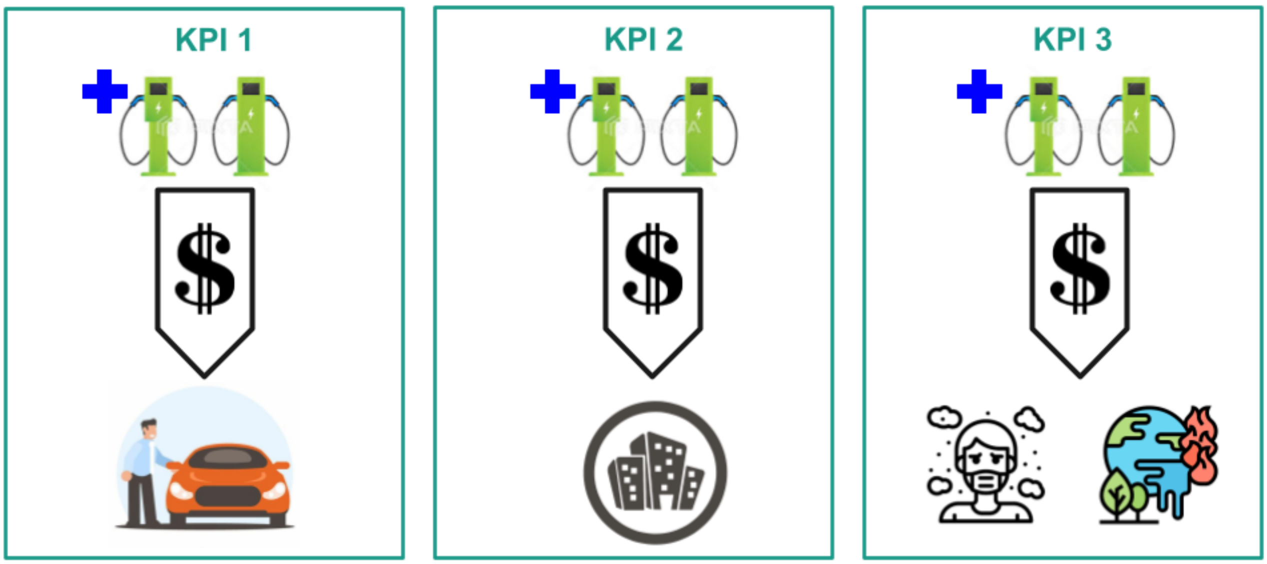

Figure 2. Diagrammatic Representation of the Three KPIs

KPI 1

KPI 1 separately calculates the economic benefit for both existing EV owners and current owners of internal combustion engine (ICE) vehicles if a public fast charger is installed near their homes. KPI 1 combines the two calculations to an average individual economic benefit for each hexagon by applying the proportion of EV owners and ICE owners in each hexagon. This is important because it identifies areas with the potential for increased EV adoption if appropriate infrastructure could be supplied.

We consider two economic benefits: (i) change in access to a charging/fueling station quantified in terms of travel time and converted to a monetary equivalent using a value of time calculated from the median income in the study area, (ii) change in transportation costs ($/mile) quantified by average vehicle mile traveled (VMT) and electricity/gas prices. EVs can provide economic benefits to vehicle owners and drivers because they typically have lower long-term operating and maintenance costs, however, the ability to realize these benefits depends on having convenient access to charging infrastructure.

The calculation depends on inputs that vary depending on the travel time to the next nearest charger. A charger installation in one hexagon affects the travel time to the nearest charger of all neighboring hexagons, as far as the newly installed charger is closer than the previous closest charger Therefore, the process of identifying the optimal charger placement of chargers for KPI 1 requires an iterative calculation of the benefits associated with the placement of each charger. First, we calculated the cumulative benefit across the entire study area for all 1,986 cases where one charging station was placed in each hexagon. Then we determined the optimal placement of the first charger, the one providing the maximum benefit. Next, we identified the hexagons whose travel time would be affected by this installation and recalculated the benefits across the remaining hexagons. We then selected a second hexagon with the next highest benefit, and so on until all 248 chargers were placed, and then calculated the cumulative benefit of installing the selected chargers.

KPI 2

KPI 2 calculates the potential revenue from servicing new EV charging demand with a local DC fast charging station. This is important as it could help jump start the EV charging industry by identifying potentially profitable charger locations. This could create local business opportunities and jobs that are currently monopolized by oil and gas companies. For example, local businesses with parking can add charging to their revenue stream, thereby putting local revenue back into communities. KPI 2 calculates the increase in charging revenue in a hexagon if a DC fast charger is installed in that hexagon assuming that all current demand is met by existing infrastructure.

KPI 3

KPI 3 assesses the potential that EVs have to both improve local air quality and reduce greenhouse gas (GHG) emissions. The transportation sector is responsible for 41 percent of GHG emissions (California Air Resources Board, 2022) making vehicle electrification an essential component in achieving California's emissions reduction goals. This metric quantifies the resulting PM2.5 air pollution that has various negative short and long-term health effects that vary by environment and local demographics. Unlike ICE vehicles, EVs do not produce tailpipe emissions, a particularly important issue in urban areas due to the urban heat island effect. The urban heat island effect causes higher temperatures in urban areas due to higher concentrations of surfaces that reflect and re-emit heat compared to natural landscapes. Higher temperatures and increased sun exposure increase the rate of formation of ground-level ozone and tailpipe emissions produce emissions that contribute to the formation of ground-level ozone (U.S. EPA, 2008). PM2.5 is one of the five tailpipe emissions and smog precursors that is federally regulated (EPA 2023). Quantifying the environmental and health benefits of charging infrastructure installation would allow public agencies to better evaluate the potential impact on disadvantaged communities.

KPI 3 has two parts. KPI 3a calculates the value of local health benefits from reducing PM2.5 emissions[6] in the atmosphere by installing a charging station in the area. PM2.5 was chosen as our local health indicator due to its significant health impacts and data availability (Shwartz et al., 2021). This has very important equity implications as communities of color tend to have poorer air quality (Shonkoff et al., 2010). KPI 3b calculates the wider environmental benefits of lowering GHG pollution by reducing tailpipe emissions in general. Specifically, it measures the carbon dioxide equivalent (CO2e) emissions reduction if a public charger were to be added within a given area.

KPI 2 and KPI 3 were both calculated for each hexagon independent of its proximity to chargers in neighboring hexagons, with those receiving the highest values placed first, up to the total of 248.

[6] PM2.5 refers to pollution (dust, soot, dirt, and smoke) due to fine inhalable particles less than 2.5 micrometers in size, from vehicle exhaust and other sources, which can produce severe respiratory illness. They are considered local sources of pollutions and generally affect air quality in the immediate area.

Method of Analysis

We incorporated a large variety of spatial data into our model at varying geographic scales, shown in **Table 1** below. Some of our data is organized by location (point coordinates), some by census blocks, some by zip code areas, and some by census tracts. In order to consolidate it all into standard units, we overlayed our study area with a hexagonal grid to serve as our spatial unit of analysis. As a result, our model is also more fine-grained than CES 4.0.

Table 1. Spatial Data Used in Model

Spatial Data	Data source	Geographic Scale	Use	Aggregation Method
Fast DC Charger Locations	Alternative Fuels Data Center (AFDC)	Point Coordinates	All KPIs	Summation
Number of Vehicles by fuel type (including BEV, PHEV)	California DMV	Zip code	KPI 1	Spatial Assignment
Vehicles Miles Traveled	Call Detail Records (Xu et al, 2018)	Distance between Origin and Destination Coordinates	All KPIs	Average
Average Traffic Speed	Uber Movement Speeds	Point Coordinates	KPI 1	Average
Home Ownership Rates	2019 American Community Survey	Census Block Group	Calculating likelihood of using a charger	Spatial Assignment
2021 BEV Adoption	California Energy Commission (CEC) dashboard	County	EV Adoption Rate	N/A
2021 Public DC Charger Installation	Alternative Fuels Data Center (AFDC)	County	EV Adoption Rate	N/A

Spatial Data	Data source	Geographic Scale	Use	Aggregation Method
Disadvantage Census Tracts	CalEnviroScreen 4.0	Census Tract	Scenario Analysis	N/A

The area of each hexagon is approximately 5.16 square-kilometers or a bit less than half the size of the average census tract, which is 12.14 square-kilometers. However, it is important to note that census tracts vary in size as they have an approximately normalized population where the hexagons are uniform in size so the ratio between census tracts in the study and hexagons is not two to one. There are 1,986 hexagons in our study area and 1,497 census tracts. **Figure 3**, shows the boundaries of census block groups (the unit used for demographic data) and zip code boundaries with respect to hexagon size. Due to the smaller geographic size of our analysis units, our results can serve as a tool to locate chargers more precisely within census tracts using CES 4.0 or as a stand-alone tool to place chargers based on different equity tradeoffs.

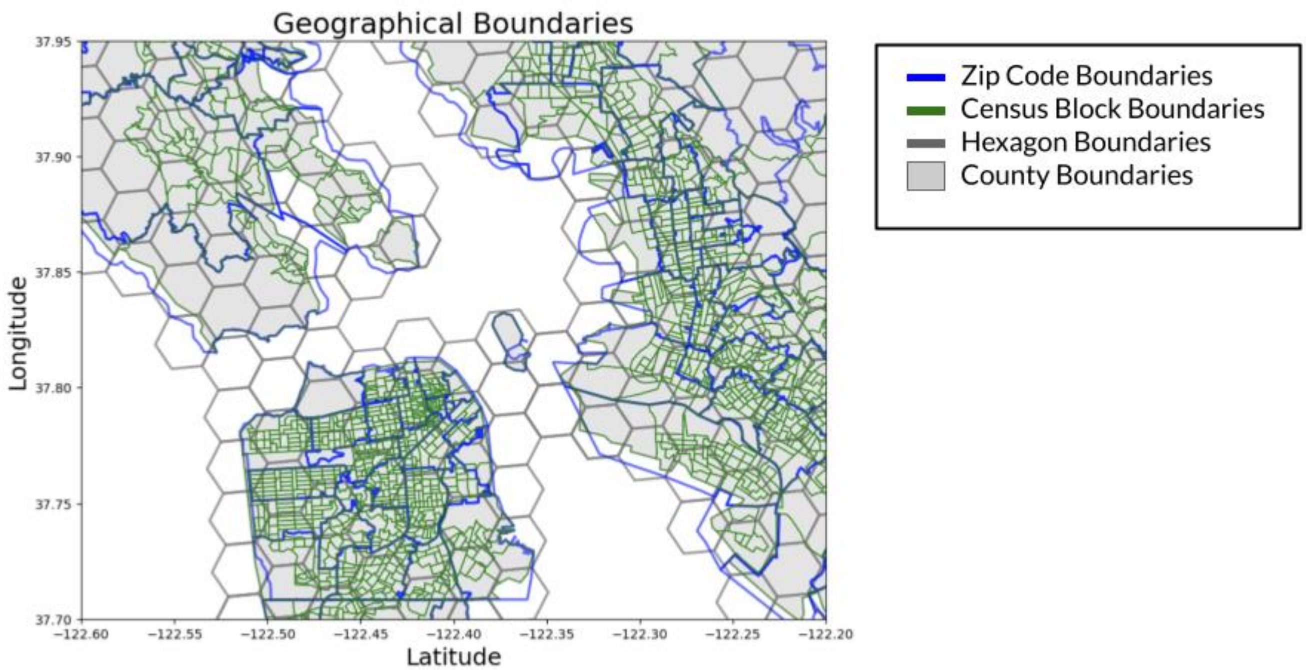

Figure 3. Geographic Comparison of Spatial Analysis Units

For point data, we either summed or averaged the values of the features contained in each hexagon, as appropriate. We used a spatial function to assign data from census and postal areas to individual hexagons based on their overlapping geographical boundaries. Details are contained in the Appendix. We calculated values for each KPI for all hexagons in the study area. We used the results to determine optimal locations for EV charging stations, for various scenarios with different constraints.

Scenario Analysis

We designed four scenarios to evaluate the potential economic benefit of using our model to site chargers and the current economic benefit of implemented methods. The four scenarios apply different definitions of “disadvantaged communities” to place the 62 chargers to meet the 25% funding requirement that we adopted in this study. The scenarios quantify the economic and compare the current approach to defining disadvantaged communities with other approaches that incorporate our model in various forms. The results of the scenario analysis allow us to evaluate if and how our model should be implemented. In the following scenarios, the DAC requirement refers to the CES 4.0 definition as shown in Figure 1 and when the requirement is applied the selected hexagons must be in a DAC census tract. The four scenarios are as follows:

1. 25 percent using KPIs (no DAC requirement)
2. 25 percent using KPIs (DAC requirement)
3. 25 percent random (DAC requirement)
4. 25 percent random (No DAC requirement)

In the first scenario, the locations of all 62 stations are based solely on the optimization criteria in the three KPIs. In other words, the stations are placed in those hexagons scoring highest on each indicator. This represents the most complete use of the model and would replace any reliance on the CES 4.0. In Scenario 3, there is no reliance on CES 4.0, but the selection of locations is random, representing a scenario with no consideration for DACs. In scenario 2 through 4, 62 stations are constrained to being located in DACs, as currently defined by CES 4.0, but scenario 2 uses the model and scenario 4 randomly places the chargers within the constraints.

Scenario 1: 25 Percent of Chargers Assigned Based on KPIs (No DAC Requirement)

Scenario 1 models a situation where 62 chargers are placed to achieve an optimal distribution for each KPI and there is no guarantee of placing any number of chargers in DACs. Some DAC hexagons may nevertheless score high enough to be included, and this percent varies across the KPIs based on how much overlap there is between the KPIs and the CES 4.0 definition of disadvantaged community. This model illustrates a situation where the current definition of DACs is not used, and evaluates the potential economic benefit being missed with those restrictions that the current definition may be not capturing.

Scenario 2: 25 Percent of Chargers Assigned Based on KPIs (With DAC Requirement)

Scenario 2 models a situation where all chargers are optimally located for each KPI but with 25 percent of the chargers (62) being placed in disadvantaged census tracts. Comparing to scenario 1, allows the economic benefit of our model without constraints to be quantified. The range of difference across KPIs shows the type of economic benefits that utilizing DACs as a constraint provides.

Scenario 3: 25 Percent of Chargers Assigned Randomly (With DAC Constraint)

Scenario 3 models a situation where 25 percent of chargers are allocated randomly to hexagons in DACs. In other words, the installation of the 25 percent of chargers set aside for DACs is not optimized using the KPIs. This scenario can be interpreted as our current baseline and the results show the potential economic benefit of using DACs as a requirement without including any other factor in the placement within DACs. Comparing scenario 3 and 2 shows the potential economic benefit of our model while using the CES DAC constraint.

Scenario 4: 25 Percent of Chargers Assigned Randomly (No DAC Constraint)

Scenario 4 models a situation where private entities are responsible for installing chargers and there is no 25% requirement. This scenario acts as a baseline for the case that there is no DAC requirement. We assume a random distribution to model this situation, but it is important to note that the actual distribution of chargers is not random and tends to skew towards higher concentration in wealthier areas. Comparison between 3 and 4 shows the economic benefit (or detriment) of the 25% DAC requirement with the current DAC definition.

Results

As would be expected the highest economic benefit occurs when charger locations are governed solely by the key performance and that benefit decreases when constraints are introduced. The change in benefit varied across the economic, environmental and health KPIs. These differences provide important information on what benefits are well represented in the DAC definition and what ones may be lacking. These results can be applied either in the context of amending the DAC definition for the purposes of EV infrastructure decisions or utilizing our model to guide placement decisions for certain economic benefit goals.

The Model Does Not Place 25 Percent of Chargers in Disadvantaged Communities

As shown in **Table 2**, when 25% of charger locations are determined by the economic benefit (KPI total, KP! 2, KPI 3a, KPI 3b) 25.5% (compared to the expected 100%) of chargers are placed in DACs. The results indicate a tradeoff between economics and equity: DACs get fewer chargers when economic benefit is optimized. When the placement criterion is the economic benefit to the charger station operators alone, 29% are placed in DACs. Considering only environmental and health benefits, between 33% and 52% are placed in DACs. When considering the economic benefit to EV owners, the percentage is almost 23%. However, for ICE owners, the percentage is much lower at 6.5%, and since the combined KPI is weighted by the vehicle ownership in each hexagon the total percentage is low at 8.1% (since ICE ownership is dominant in most hexagons). This demonstrates that DACs are a more advantageous place to site chargers to achieve pollution reduction, but the other KPIs result in a below average level of DAC placements. The modeling shows that certain economic benefits are better represented by the current DAC definition, and we explore the extent of the disparity below.

Table 2. Percent of Chargers in DACs

Scenarios	KPI 1	KPI 1_ICE	KPI 1_EV	KPI 2	KPI 3a: PM2.5	KPI 3b: GHG
Scenario 1	8.1%	6.5%	22.6%	29.0%	51.6%	33.1%
Scenario 2	100%	100%	100%	100%	100%	100%
Scenario 3	100%	100%	100%	100%	100%	100%
Scenario 4	29.0%	29.0%	29.0%	29.0%	29.0%	29.0%

Table 3. Scenario KPI Benefits ($/Day)

Scenarios @ 25%	KPI 1 Total	KPI 1_ICE	KPI 1_EV	KPI 2	KPI 3a: PM2.5	KPI3b: GHG
1. KPIs (no DAC requirement)	$12,472	$12,673	$1,220	$12,437	$492	$3,072
2.KPIs (DAC requirement)	$5,838	$5,961	$639	$8,134	$354	$2,066
3. Random (DAC requirement)	$3,334	$3,395	$367	$2,989	$110	$469
4. Random (no DAC requirement)	$7,582	$7,891	$598	$2,845	$51	$446

DACs and Individual Economic Benefits

The percentage of DACs in Scenario one is lowest for KPI 1, indicating that there is the least overlap in criteria for DAC selection and individual economic benefit. The total economic benefit from installing the chargers in the selected hexagons is shown in Table 2. Applying the optimization model with DAC constraints produces a 75% increase in economic benefit as compared to Scenario 3 (Table 3). Optimizing with with no constraints produces an increase of 274% compared to Scenario 3, and we discuss below whether scenario 1 or 2 is most equitable.

Figure 4 shows model results for KPI 1 and the proposed spatial allocation of chargers in all scenarios. The 62 hexagons selected to receive a charging station are shown in blue and selected based on optimizing individual economic benefits of both ICE and EV owners. The hexagons with the green outlines are disadvantaged census tracts as identified by CalEnviroScreen 4.0. The red hexagons indicate hexagons with at least one public fast DC charger available. The same legend is used for Figures 4-6.

Comparing Scenario 3 and 4, it is apparent that the economic benefit for random hexagons is higher when there is no DAC constraint applied, meaning that the overall economic benefit appears higher in non-DAC hexagons. KPI 1 has several inputs: proximity to nearest charger, housing type, vehicle miles travelled, average vehicle fuel efficiency, percent ICE ownership and percent EV ownership. Studies have determined that public charger infrastructure is less available in DACs than non-DACs across California (Hsu and Fingerman, 2021). However, public charger frequency increases near major roadways and in urban areas, referring to **Figure 4** we can see the overlap between DACs (shown in green outlines) and hexagons with fast DC charger access (shown in red) in our study area. Traffic volumes and pollution are CES 4.0 inputs, and these may correlate with charger availability causing this disconnect between DACs and individual economic benefit. As a result, there may be some interference between areas being designated as DACs due to high pollution exposure but having high access to chargers. KPI 1 also utilizes data on housing type and EV ownership which are not captured in CES 4.0.

KPI 1 has a higher percentage of hexagons in DACs for existing EV owners as compared to existing ICE owners. The calculation for the EV owners only considers the benefit of shorter travel time to the nearest charger, but it assumes one's driving patterns remain the same. The ICE to EV transition factors the reduction in cost per distance of charging versus gas, and it incorporates VMT and average MPG of cars in that hexagon. A key advantage of this proposed approach is that it captures the unique travel behavior in each of the census tracts. Higher VMT results in proportionately higher individual economic benefits, when switching from a gasoline powered vehicle to an EV (it also results in lower tailpipe emissions and more charger use). This demonstrates the usefulness of optimizing charger placement by taking travel behavior into account as it accurately indicates places where there is more driving, and an EV may have a bigger economic impact.

The average VMT for DACs is 26.7 compared to 30.1 miles per day for non-DACs. However, a significant portion of the DACs are in urban areas where commutes are shorter compared to rural areas and public transit is an option. At the scale of our study, the variation in VMT may be more of a reflection of differences in rural versus urban driving patterns. However, the correlation between high VMT and a demographic is not clear. Generally, residents of some DACs suffer from longer commute times due to limited access to employment centers or lack of access to efficient public transit. In that sense, they are in a more disadvantaged situation due to high transportation costs. In urban areas, high income may be associated with efficient public transit access and low VMT (due to the design of BART), or it also may be associated with high VMT due to the ability to drive into work and pay for parking. These relations and the demographic associations may change in rural areas or based on the local public transit design. As a result, VMT is useful in determining the economic benefits, but may not provide the most consistent indication of need.

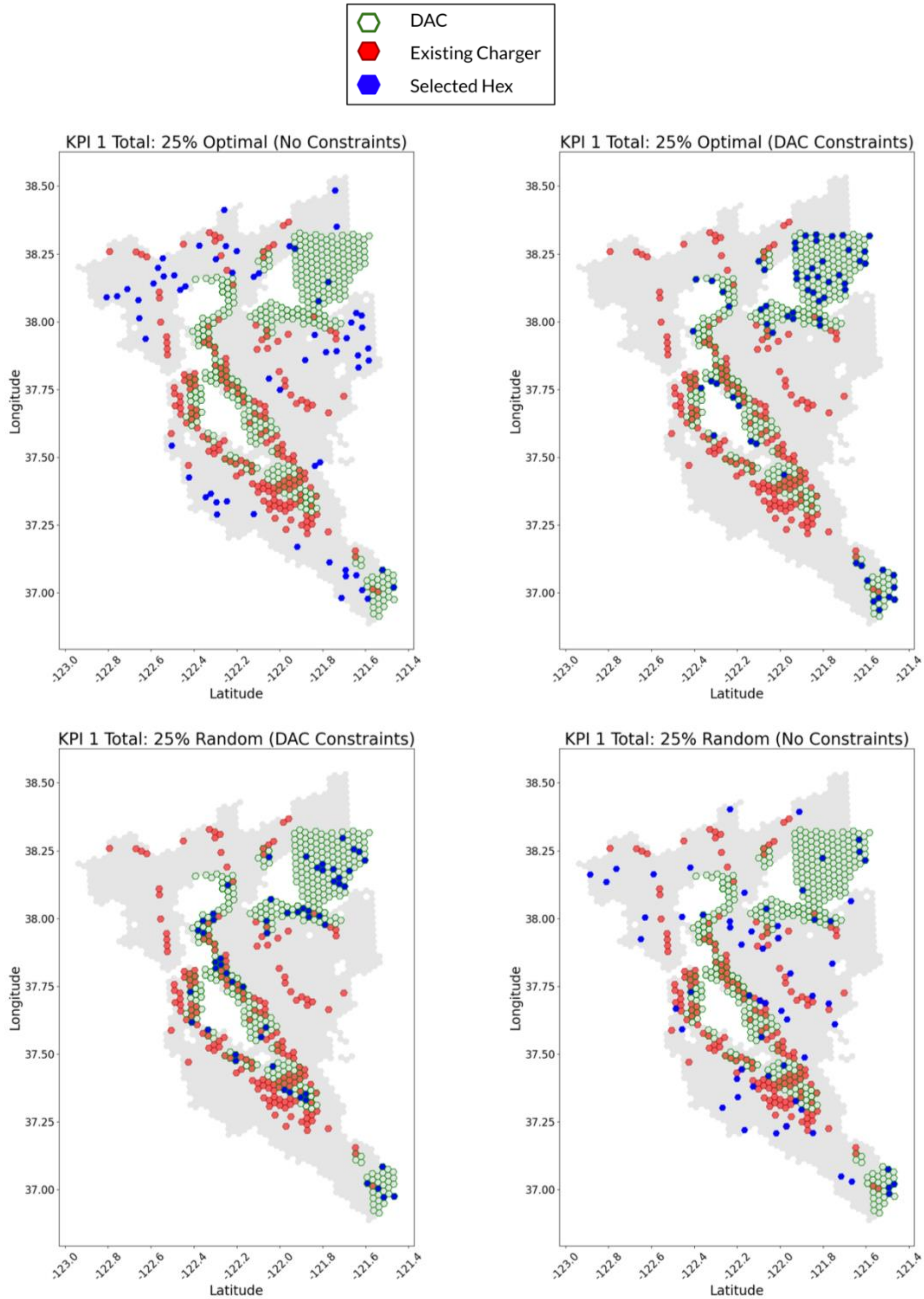

Figure 4. Charger Locations Based on Individual Economic Benefit

DACS and Operator Economic Benefits

KPI 2 locates 29% of its chargers in DACs (Scenario 1) which is the same as the random case (Scenario 4) and slightly below the actual average (32.7%). This indicates a lack of correlation between economic benefit to charger operators and the DAC definition. Scenario 3 and 4, only differ by 5% further indicating that the difference in DACs and non-DAC hexagons is minimal. KPI 2 looks at average VMT, county EV adoption rates and housing type. Multi-family housing (MFH) percentage has a correlation with income and race due to redlining practices, so we originally expected to see DAC selection above average. However, the MFH data is available at census block level which allows more heterogeneity than the census tract level. For example, Marin is not a DAC but it has areas with high percentage MFH. As shown in Figure 5, this model selects those areas and scenario 1 places multiple chargers in Marin. Refer to the case study in the appendix for further information. In Scenario 2, the model still selects areas with higher MFH housing which helps improve the granularity of the location selection by identifying optimal locations within census tracts. Comparing Scenario 2 to Scenario 4, there is a 172% increase by implementing our model with the DAC constraints. There is a further increase of 53% if we implemented our model with no constraints.

Maximizing the model's benefits to vehicle owners relies heavily on taking into account housing type and current public charger location. Due to redlining and other discriminatory zoning practices, single family homes are more abundant in areas with higher income and majority white households (Nardone, Chiang and Corburn, 2020). While it is also true that both public charger availability and the likelihood of using a public charger increases in areas with multifamily housing, public charger availability increases more slowly in areas with lower income (Hsu and Fingerman, 2021). In theory, taking into account the likelihood of using a public charger, as done in our model, should increase the economic benefit of installing public chargers in areas with a high percentage of multifamily housing units and help correct this problem. However, there are many luxury apartments in cities and the housing market in the Bay Area has been significantly affected by gentrification, and as a result the housing type metric alone may not provide a clear correlation with redlining practices. As a result, like VMT, the correlation between demographics and MFH may not be consistent across urban areas, and between rural and urban areas. This could account for the not seeing more chargers allocated to DACs. This means that the model may optimize the economic benefit, but it may not accurately capture need. To address the complex relationship between historical and current practices, additional demographic data captured by CES 4.0, such as race and income, may need to be considered to boost the economic benefit score high enough to justify placing chargers in more DACs in our model.

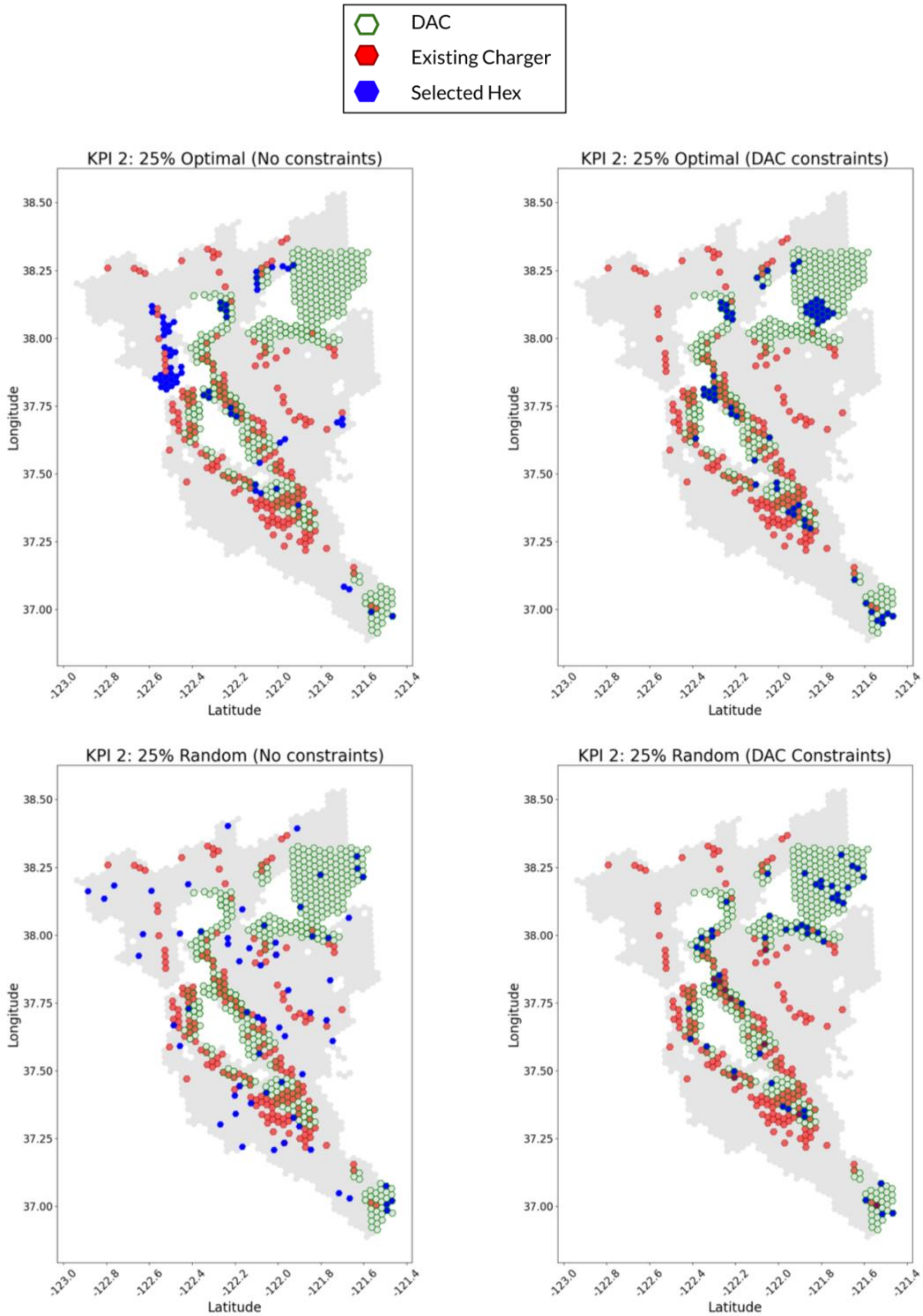

Figure 5. Charger Locations Based on Operator Economic Benefit

DACs and Health and Environmental Economic Benefits

KPI 3 has the highest percentage of DACs in the unconstrained optimization simulation for both community health and environmental benefits (Table 2). Comparing the economic benefit from Scenario 2 to 4, we see a 222% and 341% increase for KPI 3A and 3B respectively.

Both KPI 3a and 3b considers the change in ICE to EV VMT based on charger installation. KPI 3b applies two non-spatially varying variables, the grams carbon dioxide equivalent per VMT and the social cost of carbon. As a result, KPI3b is very similar to KPI 2, both in distribution and percent in DACs. KPI 3a however applies to spatially varying components, that we modeled using EMFAC and EAUSIUR. Both these models apply the physical characteristics of the landscape to understand the creation and impact that PM2.5 will have on the local environment. Additionally, the social impact calculator looks at the county-level income when producing social cost, which is why we see a higher percentage of DACS. Our model does not consider current sensitive populations for 3a and KPI 3b does not account for local resiliency. Even though this KPI has the highest overlap with DACs, our model still does not consider current sensitive populations for 3a and KPI 3b does not account for local resiliency and the use of DACs or some other input to simulate need seems apparent from an equity perspective.

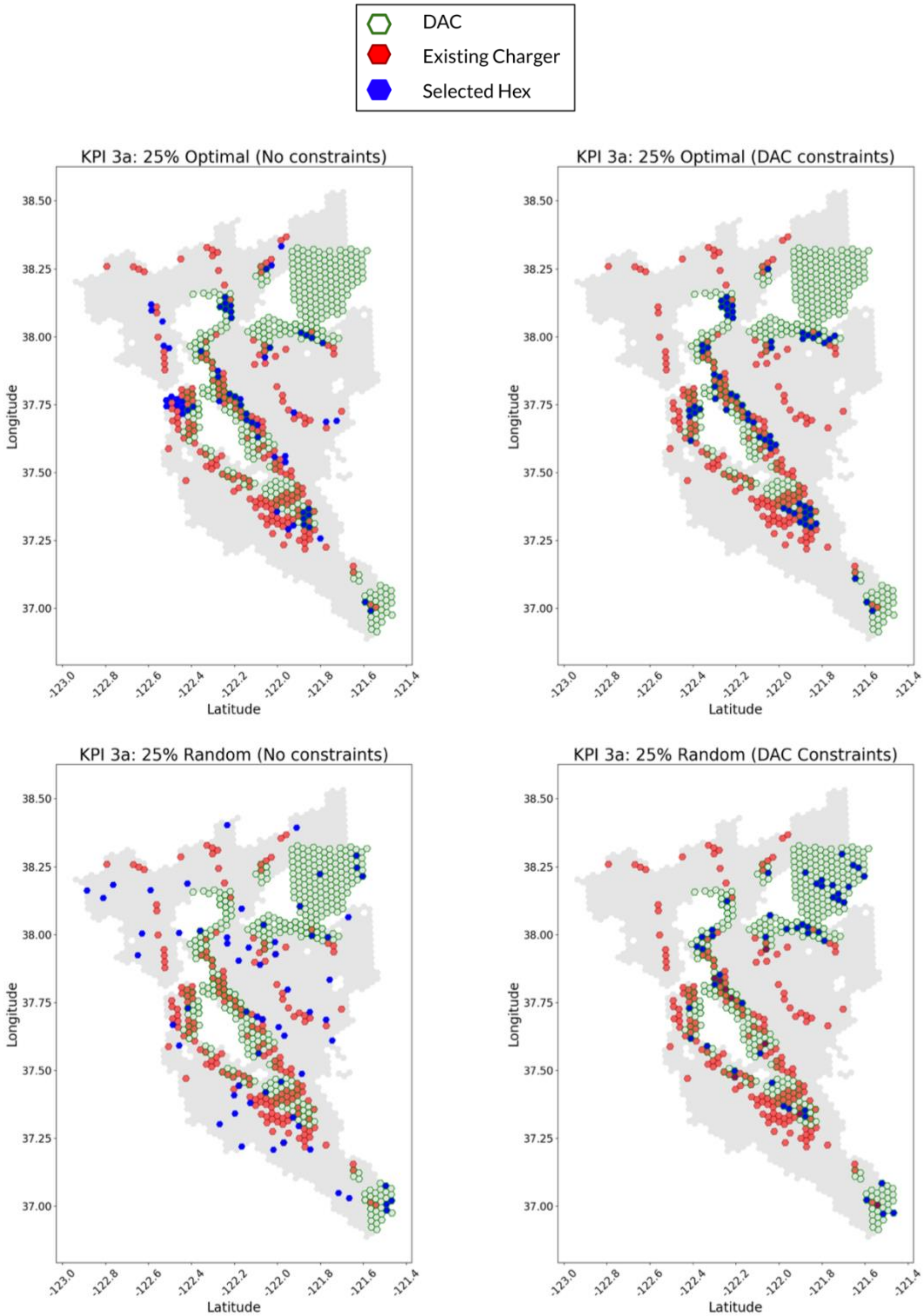

Figure 6. Charger Locations Based on Economic Health Benefit

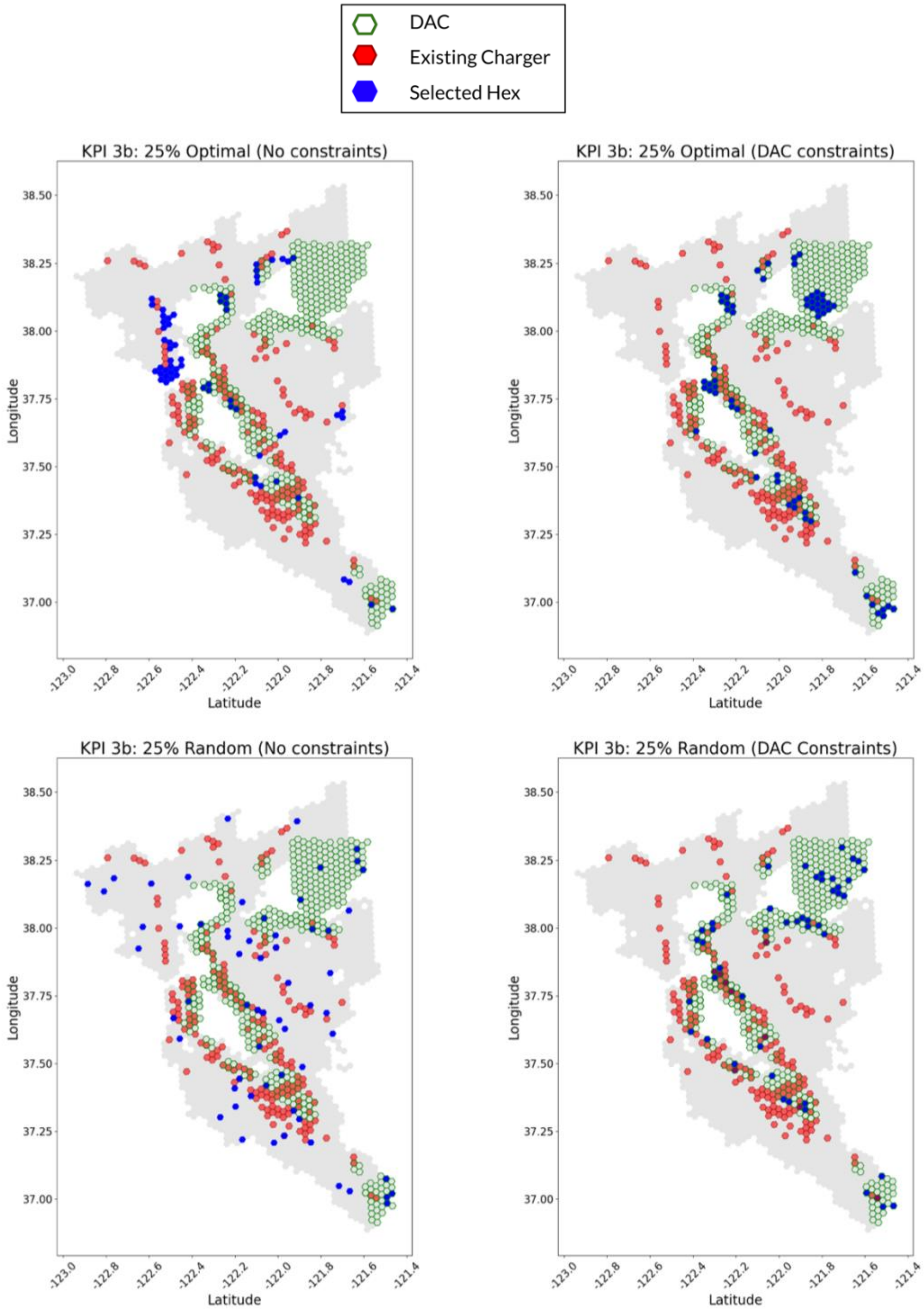

Figure 7. Charger Locations Based on Environmental Economic Benefit

Table 4. Percent Increase of Economic Benefit

Scenarios	KPI 1	KPI 1_ICE	KPI 1_EV	KPI 2	KPI 3a: PM2.5	KPI 3b: GHG
% Increase between Scenarios 1 & 2	114.0	113%	91%	53%	39%	49%
% Increase between Scenarios 2 & 3	75%	76%	74%	172%	222%	341%
% Increase between Scenarios 1 & 4	64%	61%	104%	337.%	865%	589%
% Increase between 3 and 4	-56%	-57%	-39%	5%	116%	5%

Percent increase between Scenarios 2 and 4, represents the case where the proposed optimization model is applied within the current definition of DACs. The percent increase is the economic benefit that could be achieved from our model compared to the currently implemented approach. The % increase between scenario 1 and 2, shows the potential increase to economic benefits that could be achieved if DAC constraints were removed and only the model was applied. However, as discussed above, we are not recommending that as a solution due to the complicated muli-dimensional layers that contribute to disadvantaged communities. Our model applies an EV-specific lens and higher granularity to identify better locations within Census Tracts, but it does not have enough demographic data to capture all the dynamics at play. As a result, we think the % increase between scenarios 1 and 3 better represent a potential implementation of best prioritizing the use of government funds to optimize the economic output of the charger location. In conclusion, the % increase between scenarios 2 and 4 are the increase in economic benefits we think can be captured without compromising the current definition of DACs. As explored in the discussion above, disadvantaged communities have many layers and quantifying the impact demographics have can be very difficult and simplifying the benefit to an economic number without applying demographic context is risky. In future research, we either suggest the addition of resiliency considerations and public transit access into our model or into the CES score.

Additionally, we assert that our model is useful outside of the DAC context as well as shown in the % increase between scenarios 1 and 3.

Conclusions and Recommendations

We Recommend the use of CES in conjunction with model due to the impact of demographics that are not captured in the model. The CES DAC definition prioritizes community health and environmental benefits over individual benefits. Individual economic benefit is the only benefit that had a greater percent increase between scenario 1 and 2 than scenario 2 and 4. As a result, we recommend either weighting the importance of KPI 1 higher when viewing a combined score or adding housing data to CES.

Percent increase between Scenarios 2 and 4, represents the case where the proposed optimization model is applied within the current definition of DACs. The percent increase is the economic benefit that could be achieved from our model compared to the currently implemented approach. The percent increase between scenario 1 and 2, shows the potential increase to economic benefits that could be achieved if DAC constraints were removed and only the model was applied. However, as discussed above, we are not recommending that as a solution due to the complicated multi-dimensional layers that contribute to disadvantaged communities. Our model applies an EV-specific lens and higher granularity to identify better locations within Census Tracts, but it does not have enough demographic data to capture all the dynamics at play. As a result, we think the % increase between scenarios 1 and 3 better represent a potential implementation of best prioritizing the use of government funds to optimize the economic output of the charger location. In conclusion, the percent increase between scenarios 2 and 4 are the increase in economic benefits we think can be captured without compromising the current definition of DACs. As explored in the discussion above, disadvantaged communities have many layers and quantifying the impact demographics have can be very difficult and simplifying the benefit to an economic number without applying demographic context is risky. In future research, we either suggest the addition of resiliency considerations and public transit access into our model or into the CES score.

Additionally, we assert that our model is useful outside of the DAC context as well as shown in the percent increase between scenarios 1 and 3. This model could be useful to place chargers separate from DAC constraint, to find gaps in service. There is a potential economic benefit ranging from $492 to $12,673, with a range of 232% to 555% increase from random placement based on market-demands.

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Appendix

Constructed Data

Data was not available on the likelihood of using a public charger and the likelihood of purchasing an EV based on distance to a DC charger from one's residence. We used available data and existing studies to construct two variables, lambda (likelihood of using public charger) and alpha (likelihood of purchasing an EV), to represent these factors. In addition to the constructed data, we used various other data sources in the calculation of each KPI (see **Table A-1).** KPI 1 measures the economic benefit of installing a fast DC charger in closer proximity than the current closest charger, and it consists of two parts (KPI_EV and KPI_ICE) since the benefit of a charger is different for EV owners and ICE owners. KPI_EV refers to the economic benefit for existing EV owners and KPI_ICE refers to the economic benefit for existing ICE that would switch to an EV.

Table A-1. Parameters considered in the calculation of each KPI

KPI	Parameter
KPI 1_EV	Change in travel time to access nearest charger
	Value of time
	Percentage of EV owners
KPI 1_ICE	Travel time to access charger
	Travel time to access gas station
	Value of time
	Charging cost ($/mile)
	Fueling cost ($/mile)
	Vehicle miles traveled
	Percentage of ICE owners
KPI 2	Alpha: EV adoption rate
	Lambda: Likelihood of using public charger
	Vehicle miles traveled
	Charging rate
KPI 3	Alpha: EV adoption rate
	Lambda: Likelihood of using public charger

KPI	Parameter
	Vehicle miles traveled
	Social cost of PM2.5
	PM2.5 intensity (grams PM2.5 / VMT)
	Social cost of CO2
	CO2 intensity in grams CO2 / VMT

Lambda: Likelihood of Using a Public Charger

A key factor in choosing whether to purchase an EV is access to a home charger. Single family homeowners can install a private charger but those living in apartments and attached single family homes may have to depend on a landlord to install a charger, or use a nearby public charger. Since many low income communities and communities of color have a higher percentage of renters, the residents may be at a disadvantage in access to EV chargers (Tal, Lee, and Nicholas, 2018).

The study reports public charger use, level 1 home charging use and level 2 home charging use for residents in apartment buildings, attached single family homes, and detached single family houses. The study reports the data on charger uses for two types of EV owners: Low-range EV owners and high-range EV owners. We used the 2021 CEC classification of high-range EV as an EV with greater than or equal to a 200-mile range per charge and the associated data for the nine counties in the study area. The likelihood of not having home charger access (lambda), was calculated for each hexagon, as the inverse at the hex-level to create a spatially varying likelihood of using a public charger. The results can be seen in Figure A-1 (left).

Alpha: EV Adoption Rate

The relationship between public charger installation with charger demand and pollution reduction depends on how local public charger installation impacts EV adoption. The relationship between charger accessibility and EV adoption is extremely complicated and there is a whole body of research attempting to model this relationship (Vergis and Chen, 2015; Haidar and Rojas, 2022). After reviewing the literature, we determined that it was not feasible to create our own model or apply a model that was not designed in the context of our study area with sufficient accuracy. As a result, we used a data-driven approach to create a coefficient for EV adoption (alpha) per DC fast charger installations.

We define alpha as the number of new EVs adopted per new charger installed. We use the Alternative Fuels Data Center (AFDC) public DC fast charger location data and the associated installation date to calculate the number of chargers installed in 2021 by county. We then combined this with the CEC dashboard (California Energy Commission, 2023c) and its EV sales for 2021 (based on DMV data) to get the EV adoption rate based on charger installation for the nine counties in our study area for 2021 (see **Table A-2**). We intentionally utilized county-level data to get general trends because at the zip code or hexagon level there are many places with zero EVs or zero public chargers and an adoption rate of zero would not provide useful insight into potential future trends. Additionally, we acknowledge that this method neglects other factors that affect EV adoption, like income, public transit availability and likelihood of home charger access. As a result, we multiply alpha by the likelihood of using a public charger (lambda) to create an alpha lower bound that takes into account other factors that contribute to EV adoption at a smaller spatial scale, see the right panel of Figure A-1. With this application, if the area has a higher likelihood of using a public charger, then the EV adoption rate will be higher per charger.

Table A-2. 2021 County-level Data Used to Calculate Alpha

County (FIP #)	2021 New chargers	2021 EV Adoption	Adoption Rate (EVs/Charger)
Alameda (1)	90	11,690	129.9
Contra Costa (13)	102	7,225	70.8
Marin (41)	12	2,602	216.8
Napa (55)	9	704	78.2
San Francisco (75)	69	1,990	72.4
San Mateo (81)	128	4,998	51.0
Santa Clara (85)	136	6,528	132.8
Solano (95)	11	18,062	141.7
Sonoma (97)	43	1,559	46.3
Study Area	600	55,358	92.3

The alpha value for a hexagon with an existing charger is set to zero (shown as dark purple). Since this model focuses on siting new stations (not the actual number of plugs), once a hexagon is determined to have a charging station the additional plugs from adding a new station will not produce any additional benefit in our model, so the tool will not recommend installing a charger in any hexagon where a station already exists. This can be seen alongside the formulated data in .

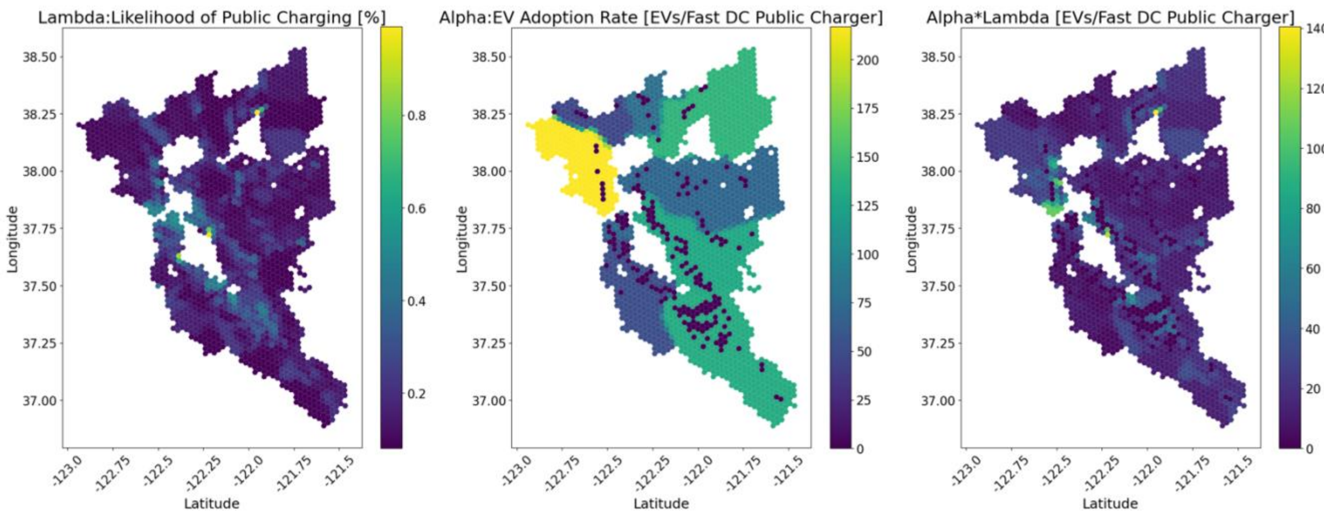

Figure A-1. Geographic Representation of Constructed Data

Case Study: Marin County

We performed a case study on Marin County to verify our alpha and lambda coefficients and to demonstrate how they capture the spatial variation in EV adoption behaviors. We chose Marin County due to its high alpha value (#EVs adopted/chargers installed) and its spatial variation in the lambda value due to housing type (Figure A-1). This study verifies if our constructed Alpha value can effectively represent the EV adoption behavior. The high alpha value is due to a high amount of new EVs purchased in 2021 coupled with a lower number of public DC chargers installed. This shows the importance of applying lambda to account for the use of home charging in encouraging EV adoption, as applying lambda creates spatial variation based on housing types to show which areas have a high alpha due to private charging access. Figure A-2 (left) shows the percentage of MFH units out of all housing types (left), the EV adoption rate per public DC fast charger installed (middle), and the EV adoption rate adjusted for the likelihood that public charger access affects the adoption rate (right). As can be seen, the southeast portion of Marin County maintains a high EV adoption rate due to a high percentage of MFH units, but the adoption rate for the area with a majority of single-family homes (SFH) decreases to reflect the lower EV adoption rate with respect to public chargers due to the availability of at-home chargers in that area.

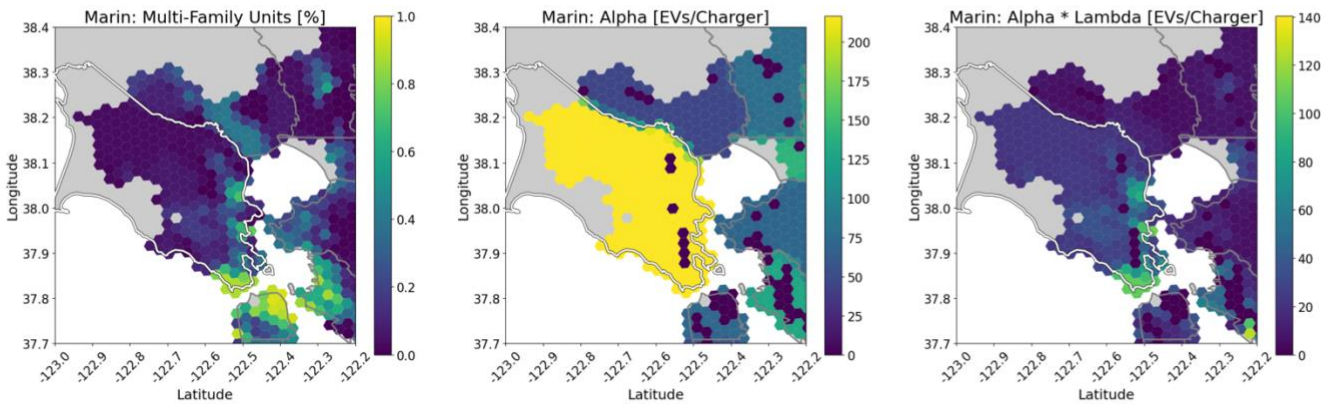

Figure A-2. Case Study for Marin County

KPI 1

The following data was utilized in the KPI 1 calculation: lambda, car type (EV, ICE), average vehicle miles traveled (VMT), car age, charger location, average speed. As a result, KPI 1 captures unique driving patterns, demographic data like housing type, and current proximity to a charging station. There are three parts to the calculation: benefit to existing EV owners, potential benefit to current ICE owners, and total benefit.

The monetary benefit to current EV owners of installing a new public charger in closer proximity than current infrastructure is calculated by evaluating the change in travel time from the hexagon centroid to the new charger compared to the travel time to the previous closest charger. We multiplied the change in travel time by a value of time of $62.61 per hour (which was calculated using the average median income across the entire study area, assuming a 40-hour work week).

The benefit to potential EV owners is a bit more involved. It is based on a change in travel time from the closest gas station (assumed to be 10 minutes) to the closest charger, and the difference in the cost of fueling the vehicle. The cost of fueling the vehicle is based on the average weekly vehicle miles travelled (VMT) in the hexagon determined by the vehicle trajectories mapped from cellular data, the average miles per gallon or kilowatt-hour of the vehicle, the average historical cost of gas and representative charging rates. We only considered hexagons where there was a change in the travel time to the closest EV charger, in order to capture the increase in economic benefit due to charger installation. Combining the economic benefit calculated for each group, the total economic benefit is calculated using the percent of EV and ICE vehicle owners in the hexagon.

Figure A-3 shows the economic benefit to the potential EV owner (left), current EV owner (middle) and the combined total benefit (right) when 62 charging stations are placed in the optimal locations with no DAC restrictions (Scenario 1).

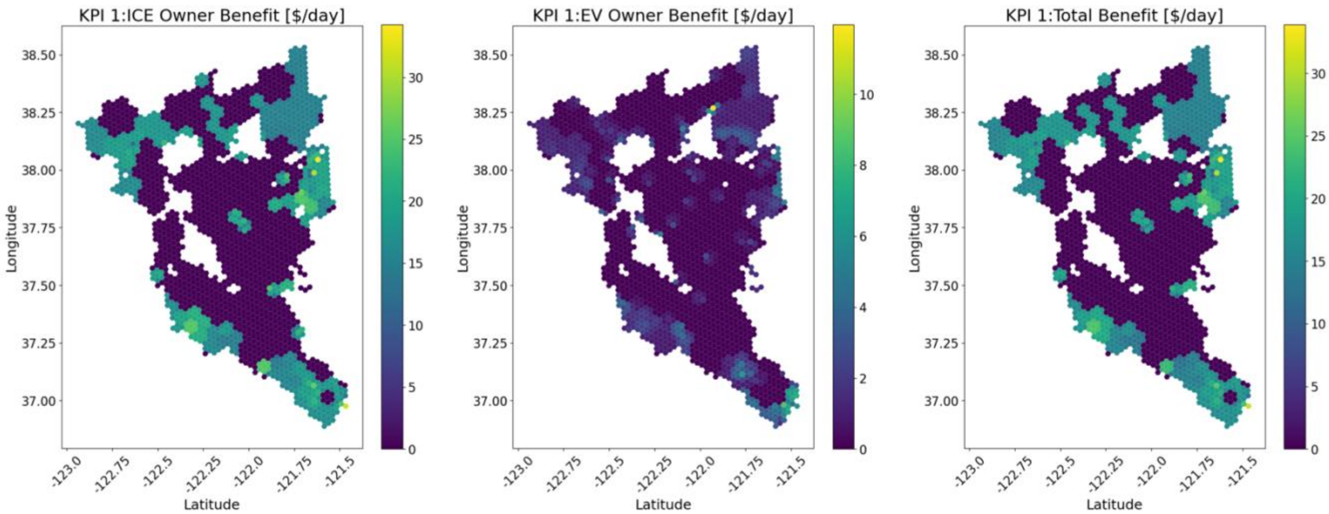

Figure A-3. KPI 1 Economic Benefits to EV Owners, ICE Owners, and Combined

KPI 2

The calculation of KPI 2 utilizes lambda (home charger likelihood), alpha (2021 EV adoption / public DC charger installation), VMT, and the representative charge rate. KPI 2 assumes that all current demand is met by existing infrastructure and only calculates the increase in demand that would be generated upon the installation of a fast DC charger in the hexagon. Figure A-4 shows the spatial variation of the VMT across the study area (left) and the total economic benefit for each hexagon resulting from increased demand for EV charging due to public charger availability (right). The coefficients lambda and alpha map the installation of a new charger to the appropriate EV adoption for each hexagon. Combining the number of EVs adopted with the VMT travelled in each hexagon we can determine the increase in charging demand. We apply a representative charge rate to convert to income.

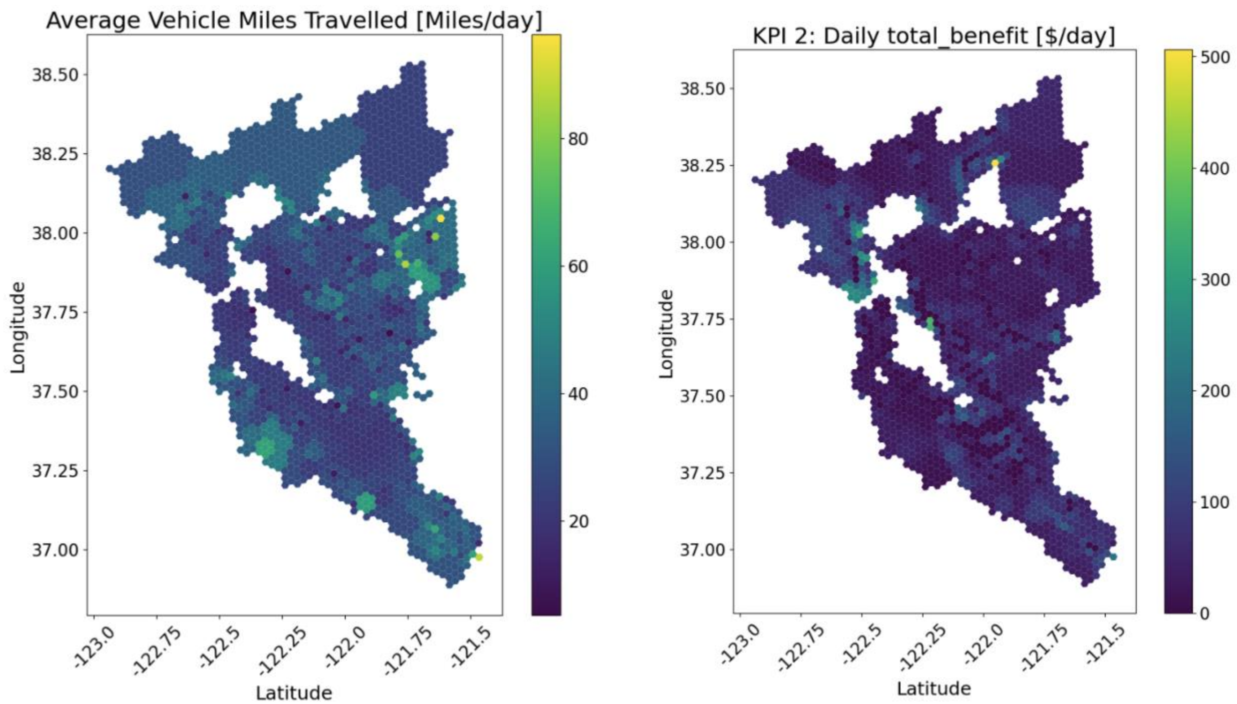

Figure A-4. KPI 2 Economic Benefit to Charger Operators from Increased Demand for EV Charging

KPI 3

KPI 3a: Local Health impacts: PM2.5 Emission Reduction

The local health benefits of EVs have very important equity implications as areas with majority racial minorities which tend to have poorer air quality (Shonkoff et al., 2010). The level of PM2.5[7] in the atmosphere is our local health indicator and was selected due to its significant health impacts and data availability (Shwartz et al., 2021).

To construct this indicator, we calculated the potential reduction of ICE vehicle miles travelled per hexagon using alpha and average current VMT. Then we used the EMFAC model developed by the California Air Resources Board to estimate the PM2.5 reduction per VMT at the county level. Next, we used the Estimating Air pollution Social Impact Using Regression (EASIUR) model to calculate the social cost of a given amount of PM2.5 reduction at the county level. Finally, we obtained a value representing the economic benefit of local PM2.5 reduction in each hexagon. Figure A5 shows the social value of reduced PM2.5 pollution due to EV adoption induced through an increase in public charging infrastructure.

[7] Particulate matter less than 2.5 millimeters in size, which have severe respiratory health effects.

KPI 3b: Global Health Impacts: Greenhouse Gas Emission Reduction

We quantified the potential reduction in greenhouse gas emissions based on the placement of a DC fast charger in each hexagon, and then selected the 62 hexagons with the highest benefit. First, we consider alpha to determine the BEV adoption rate, and then we looked at VMT and applied average GHG emissions per VMT (Xu et al, 2018). Finally, we took the average grams of reduced GHG emissions per hexagon and applied the social cost of carbon emissions, $51 per ton, set by the Biden administration (Joselow, 2022). Figure A-5 shows the social value of reduced greenhouse gas emissions due to EV adoption induced by increasing public charging infrastructure.

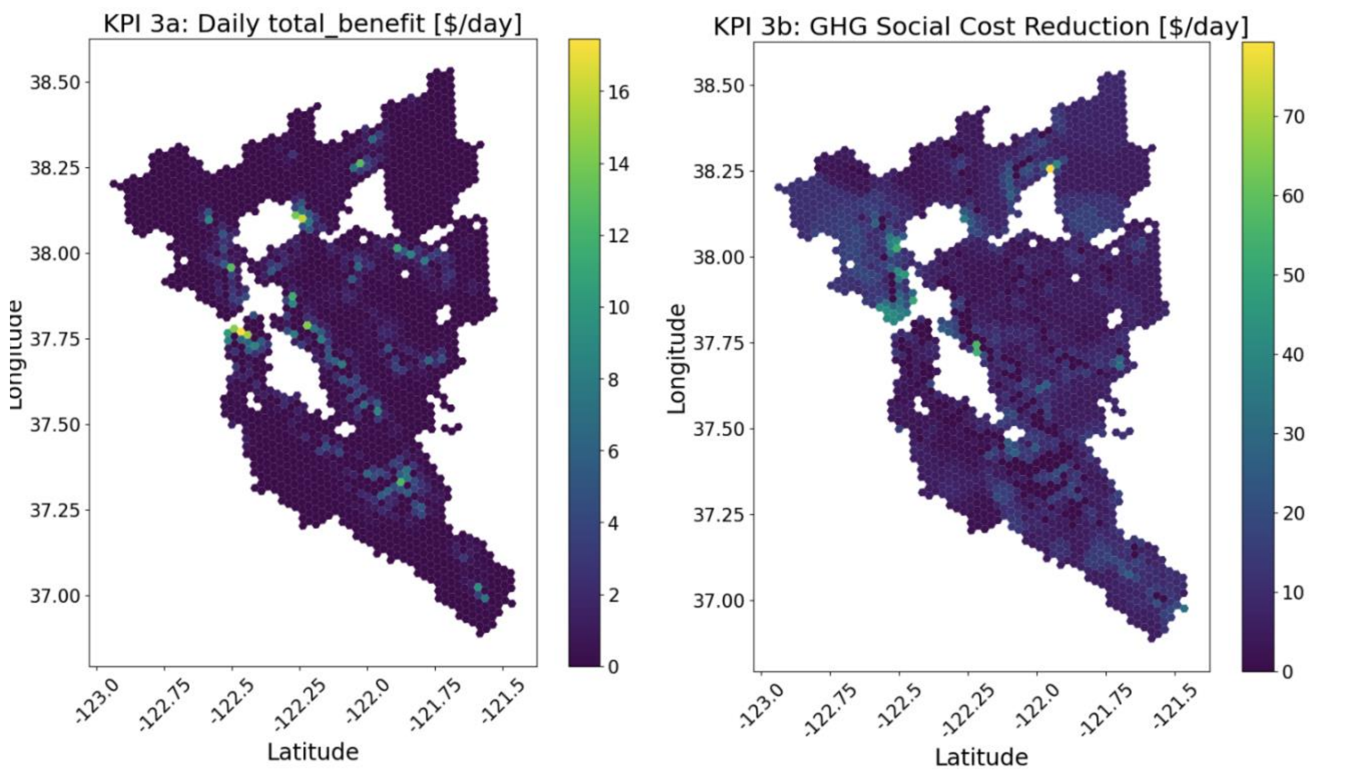

Figure A-5. KPI 3 Value of Reduced PM2.5 Pollution from Increase in Public Charging Infrastructure.

Method for Determining Optimal Charging Station Placement

The optimal allocation of a fixed number of chargers can be determined by two different approaches depending on the inputs to the KPI calculation: (i) calculating the benefit based on inputs that are independent of the proximity to chargers in neighboring hexagons, or (ii) calculating the benefit based on inputs that vary depending on the travel time to the next nearest charger. For example, a charger placed in a hexagon can help decrease the travel times of all neighboring hexagons. Hence, the travel time benefit of installing a charger must be quantified considering the impact of the neighboring hexagons with approach (ii). On the other hand, GHG reduction impacts depend on local EV adoption and are calculated with approach (i).

In KPI 1, a charger installation in a hexagon affects the travel time to the nearest charger of all neighboring hexagons, as far as the newly installed charger is closer than the previous closest charger. Therefore, the process of identifying optimal charger placement for KPI 1 requires an iterative calculation of the benefits associated with the placement of each charger. First, we calculated the cumulative benefit across the entire study area for all 1,986 cases where one charging station was placed in each hexagon. Then we determined the optimal placement of the first charger to achieve the maximum benefit. Next, we adjusted the public charger location data to account for the new charger installation, and then identified the hexagons whose travel time would be affected by this installation and updated the cumulative benefit data frame. We then selected the next hexagon with the highest benefit and proceeded to adjust the public charger placement data. This process continued until all the 62 chargers were placed, and then we calculated the cumulative benefit of installing the selected chargers. Please note, in the scenario with DAC constraints, only the DAC hexagons are evaluated. KPI 2 and KPI 3 were calculated with approach (i) since the factors calculating the benefits are assumed to be internal to each hexagon and independent of neighboring hexagons. As a result, the optimal charger location for KPI 2 and KPI 3 was determined by calculating the benefit within all hexagons internally when a charger is placed there. Then, the hexagons with the highest benefit were selected both with and without applying DAC constraints.