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Examining spatial disparities in electric vehicle charging station placements using machine learning

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ABSTRACT

Electric vehicles (EV) are an emerging mode of transportation that has the potential to reshape the transportation sector by significantly reducing carbon emissions thereby promoting a cleaner environment and pushing the boundaries of climate progress. Nevertheless, there remain significant hurdles to the widespread adoption of electric vehicles in the United States ranging from the high cost of EVs to the inequitable placement of EV charging stations (EVCS). A deeper understanding of the underlying complex interactions of social, economic, and demographic factors which may lead to such emerging disparities in EVCS placements is, therefore, necessary to mitigate accessibility issues and improve EV usage among people of all ages and abilities. In this study, we develop a machine learning framework to examine spatial disparities in EVCS placements by using a predictive approach. We first identify the essential socioeconomic factors that may contribute to spatial disparities in EVCS access. Second, using these factors along with ground truth data from existing EVCS placements we predict future ECVS density at multiple spatial scales using machine learning algorithms and compare their predictive accuracy to identify the most optimal spatial resolution for our predictions. Finally, we compare the most accurately predicted EVCS placement density with a spatial inequity indicator to quantify how equitably these placements would be for Orange County, California. Our method achieved the highest predictive accuracy (94.9%) of EVCS placement density at a spatial resolution of 3 km using Random Forests. Our results indicate that a total of 11.04% of predicted EVCS placements in Orange County will lie within a high spatial inequity zone – indicating populations with the lowest accessibility may require the greater investments in EVCS placements. 69.52% of the study area experience moderate accessibility issues and the remaining 19.11% face least accessibility issues w.r.t EV charging stations. Within least accessible areas, 7.8% of the area will require low density of predicted EVCS placements, 3.4% will require a medium density of predicted EVCS placements, and 0.55% will require high density of EVCS placements. The moderately accessible areas would require the highest placements of EVCS but mostly with low density placements covering 54.42% of the area. The findings from this study highlight a generalizable framework to quantify inequities in EVCS placements that will enable policymakers to identify underserved communities and facilitate targeted infrastructure investments for widespread EV usage and adoption for all. The findings from this study highlight a generalizable framework to quantify inequities in EVCS placements that will enable policymakers to identify underserved communities and facilitate targeted infrastructure investments for widespread EV usage and adoption for all.

1. Introduction

Adoption of emerging alternative transportation modes like EVs has been identified as a primary requirement to meet California's climate mitigation goal (Williams et al., 2012). EVs provide the opportunity to reduce localized air pollution (Brady & O'Mahony, 2011) as well as reduce traffic noise (Hawkins et al., 2013) in cities. As part of the U.S government's EV charging action plan (The United States Government, 2021), the state of California and many of its cities have aggressive goals for achieving high EV penetration by 2030. For example, the City of Los Angeles aims to have 80% of its vehicle fleet electrified by 2035 (Bui, Slowik, & Lutsey, 2021). The City of San Francisco has a 2030 goal to

Abbreviations: EV, Electric Vehicle(s); EVCS, Electric Vehicle Charging Station; EVCI, Electric Vehicle Charging Equity Index; KDE, Kernel Density Estimate.

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make EVs 100% of all new vehicle sales (Hsu et al., 2020) . However, California currently has less than 40% of the charging infrastructure needed by 2025 to support the projected EV fleet (Lutsey & Nicholas, 2019) . The steps taken to deploy charging infrastructure by local authorities will therefore tend to determine who would benefit most from such investments.

Access to current EV charging stations is extremely inequitable throughout the United States, leaving large percentages of the population without affordable access to electric vehicles necessary for employment opportunities and access to essential goods and services. Low-income populations, which comprise people of color and people with disabilities suffer from the largest barriers to access (Marcantonio et al. 2017) and are therefore disproportionately vulnerable to EV adoption. Some of the primary barriers to extensive electric vehicle (EV) adoption in urban areas are the high purchase cost (Adepetu & Keshav, 2017), the vehicle travel range which often leads to range anxiety among drivers, and the lack of sufficient amount of charging infrastructure availability (Bakker & Jacob Trip, 2013; Egbue & Long, 2012; She et al., 2017) distributed uniformly across an entire geographic region (E.g.: country/state/city). The socioeconomic barriers have limited the demographics of early and current EV owners with populations from higher-income neighborhoods, with high levels of education and living in single-family households (Carley, Krause, Lane, & Graham, 2013; Farkas, Shin, & Nickkar, 2018; Rubin & St-Louis, 2016). Some studies have shown that lower-income or minority communities are still lagging in terms of access to EV usage due to cost barriers, lower availability of the technology (Brockway, Sorrell, Semieniuk, Heun, & Court, 2021; Dailey, Bryne, Powell, Karaganis, & Chung, 2010; Judge, Puckett, & Cabuk, 2004), and fewer programs facilitating technology uptake (Warschauer, Knobel, & Stone, 2004). However, further research is needed to identify the explicit factors contributing to spatial inequities in EVCS access across different cities as they are still not very well understood by planners and policymakers.

Factors like purchase cost and battery range are similar across markets and present the overall barriers to EV usage and mass adoption across a larger scale (Hsu & Fingerman, 2021). Some studies have used machine learning algorithms to coordinate EV chargers (Shibl et. Al., 2020) while others have looked at profit-maximization approaches to EVCS placements (Huang & Kockelman, 2020) and the charging demand of EV users from public charging stations based on previous charging behavior (Almaghrebi et al., 2020). However, these studies did not investigate the differential access of public charging infrastructure between different sociodemographic groups at finer spatial scales.

More recently, U.S. cities are focusing on equity issues related to EV and charger access (Loosen, 2019; Evolve, 2019). To our knowledge, no extensive systematic analyses have yet been considered on how to equitably place EVCS in cities based on their underlying socioeconomic characteristics. Addressing such equity issues related to EV charging stations has been limited owing to a lack of good quality data. Previously, solar panel data (Sunter, Castellanos, & Kammen, 2019) have been used to understand charging availability in disadvantaged communities (Canepa et al., 2019), but further research is needed to examine spatial disparities in EVCS placements and access.

In this study, we aim to answer the following research questions around equitable EVCS placements: (a) What are the social, economic, and demographic factors that can quantify spatial inequity in EVCS access? (b) Which is the most appropriate spatial scale at which EVCS placements can be predicted accurately after accounting for these factors? (c) How would future EVCS placements distribution vary spatially with existing inequities in place? The overall spatial distribution and availability of charging infrastructure can highlight the inequities in EV usage at smaller spatial scales depending upon the frequency and densities of local deployment.

Our study aims to bridge this gap using a machine learning approach. By combining disparate data sources from EV charging stations and solar panels (which act as a proxy for EV usage) along with social, economic, and demographic factors this study highlights existing disparities and barriers to access to EV charging infrastructure. Machine learning algorithms are then used to generate predictive maps of EVCS placements which are compared with different levels of spatial inequity to quantify the accessibility issues related to these EVCS placements.

The method developed in this study is open and reproducible and can be used in other counties and states for conducting similar analyses. The results generated from this study will enable policymakers to make informed decisions by visually examining the spatial distributions of EV charging infrastructure and identifying areas that may need more targeted infrastructure planning and management in the future to ensure equitable access among all populations.

2. Related works

Previously, researchers have examined the application of mobile charging stations in energy systems to feed the batteries of EVs often optimizing operational costs and charging capacity (Raboaca et al., 2020; Held et al., 2018). Others have discussed ways of integrating stationary and mobile charging stations into energy systems (Pelzer, 2019) and prioritized time management in terms of charge scheduling across the electrical energy distribution systems (Saboori & Jadid, 2020). However, these studies have not included the socioeconomic aspects to address equity concerns in EVCS placements.

More recently, the focus has shifted to examining the disparities in EVCS placements which is a primary factor in reduced utilization of EVs and plug-in EVs among the socially disadvantaged communities across the United States (Hardman et al., 2021). Fair distribution of transportation infrastructure across populations requires a holistic understanding of several contextual factors involving politics, environment, and economics (Guo et al., 2020). In the case of EV charging stations, it has been noted in earlier studies that EVCS placements are typically dense in high-income neighborhoods (Guo et al., 2020). Even in California, where the number of charging stations is comparatively higher than rest of the United States, public EV charging stations are not equitably distributed with respect to race and income levels (Hsu & Fingerman, 2021) thereby, widening the gap in access and adding to the sociodemographic and economic disparities in the region. Some EV owners with a lack of access to public EVCS, have resorted to installing residential EV chargers but these installations correlate with the economic conditions and housing type of the EV owners and highlight social equity issues based on uneven distributions of EVCS (Min & Lee, 2020). Therefore, addressing the socio-economic aspects that lead to such disparities in EVCS access is crucial to enhancing EV usage in the future.

Addressing the social equity issues also requires advanced analytical approaches to quantify and highlight the causal links that determine the accessibility of EVCS among all. Some studies have looked at station-level optimization approaches in plug-in EVs (Zeng et al., 2021) in terms of pricing and charge scheduling while others have focused on user behavior using an agent-based modeling approach to highlight decision-making in terms of charging effectively (Pagani et al., 2019); developed a multi-objective approach with hierarchical clustering for EVCS location optimization by planning horizons (Bitencourt et al., 2021); or used game-theoretic deep learning approaches (Xiong, Gan, An, Miao, & Bazzan, 2017) to plan long-term EV infrastructure investments. However, these studies have not touched upon the socio-economic aspects of EVCS access in their analysis.

Previous research focusing on social aspects of EVs has highlighted the safety and noise implications Cocron & Krems (2013), social cost-benefit analysis of battery-operated cars in the Carlsson & Johansson-Stenman (2003) and impact of political classes on EV purchase (Sovacool et al., 2019) in the European context. Most commonly found associations w.r.t EV purchase and early adoption were that of having full-time employment (Sovacool et al., 2019), high-income level (Higueras-Castillo et al., 2020), age below 30 (Sovacool et al., 2019) and long-distance commuters (Mukherjee & Ryan, 2020) which exacerbates the issues of social inequality and thereby demands a more nuanced understanding of social issues which can ease the process of equitable EV infrastructure planning across all sections of society.

3. Study area

We selected Orange County in Southern California as our study area to understand the spatial inequities of EV charging access. Orange County is one of the highest density regions in the country in terms of EV ownership and charging infrastructures in the state of California (California Energy Commission, 2022). The county is immensely heterogeneous in terms of income and population characteristics (Fig. 1), thereby making it an ideal place to study EV charging access and equity issues. As of 2021, the county has over 78,000 registered EVs with only 5852 existing public and private EVCS (Table 1), therefore, the current service coverage of existing EVCS is worth investigating as well as crucial for future infrastructure planning in this highly car-dependent county.

The central part of the county has the highest discrepancies in terms of population density and income levels (Fig. 1) with cities like Santa Ana, Orange, Garden Grove, Tustin and Costa Mesa. Also in the southern part of the county cities like Laguna Niguel, San Clemente, and San Juan Capistrano are mostly underserved where the coverage of EVCS is much lower compared to population density. However, the comparatively wealthier neighborhoods near Irvine, Newport Beach and some parts of Huntington Beach have higher numbers of existing charging stations well distributed throughout the cities. The data applied in our models and analysis are collected from open data portals provided by the Orange County, California Energy Commission, Department of Energy, and the U.S. Census Bureau (Table 1).

4. Problem formulation

The overall methodology of this study combines machine learning along with quantitative spatial analysis as described in the workflow diagram in Fig. 2. We first evaluated the existing EVCS placements using kernel density estimation (KDE) and classified three levels of intensities based of the KDE results. Then, we extracted relevant variables from

Table 1
Summary of the socioeconomic statistics in Orange County.

Socioeconomic characteristics	Estimate **
Total Population	3,175,692
Median Age	38.6
Median Household Income	$90,234
Median Home Value (Owner-occupied)	$679,300
Population below poverty level (Percent)	9.5%
Mean Travel Time to Work (Workers age 16 years+)	28 min
Zero Emission Vehicle Population (as of end of 2020)	78,256
Cumulative Battery Electric Vehicle Sales (as of 2021 Q3)	73,046
Total Number of EV Chargers (Public and shared private Lv1, Lv2, and DC Fast)	5657

** Source: 2019 ACS 5-year estimates, California Energy Commission.

chosen sources and spatially joined the features into different sizes of the fishnet grids . Using the extracted variables and KDE classes, the next step is to apply machine learning model fitting to predict the EVCS grids.

This procedure includes testing the model accuracy using different training methods, confusion matrix comparison, and tuning the model performance repeatedly. After that, the model with the highest accuracy will then be summarized into our spatial analysis with other relevant features to determine whether communities have equitable access to EVCS. Lastly, we develop an equity index using a raster weighted overlay to demonstrate the access disparities and compare them with current infrastructure coverage. Each step is discussed elaborately in Sections 3.1 through 3.6.

4.1. *Kernel density estimation to categorize EV placements along spatial grids of varying scales*

In the data preparation phase, we combined data on existing EVCS, socioeconomic characteristics of neighborhoods at the census block group level, and information on housing density as well as summarized the spatial relationship among the collected datasets. These variables were meaningfully chosen for quantifying EVCS access based on previous work (Law & Roy, 2021; Shahriar et al., 2021), and preprocessed in

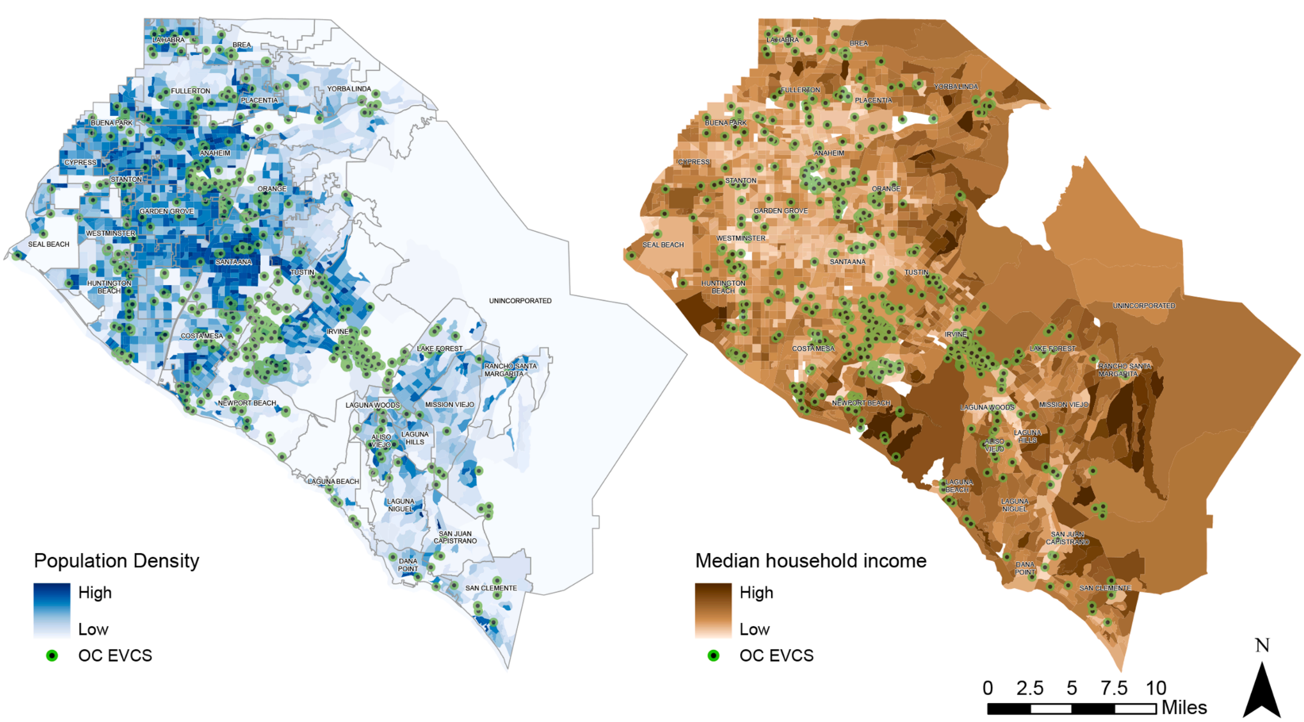

Fig. 1. Spatial distribution of existing EV charging stations across Orange County w.r.t to (a) population density and (b) median household income distribution.

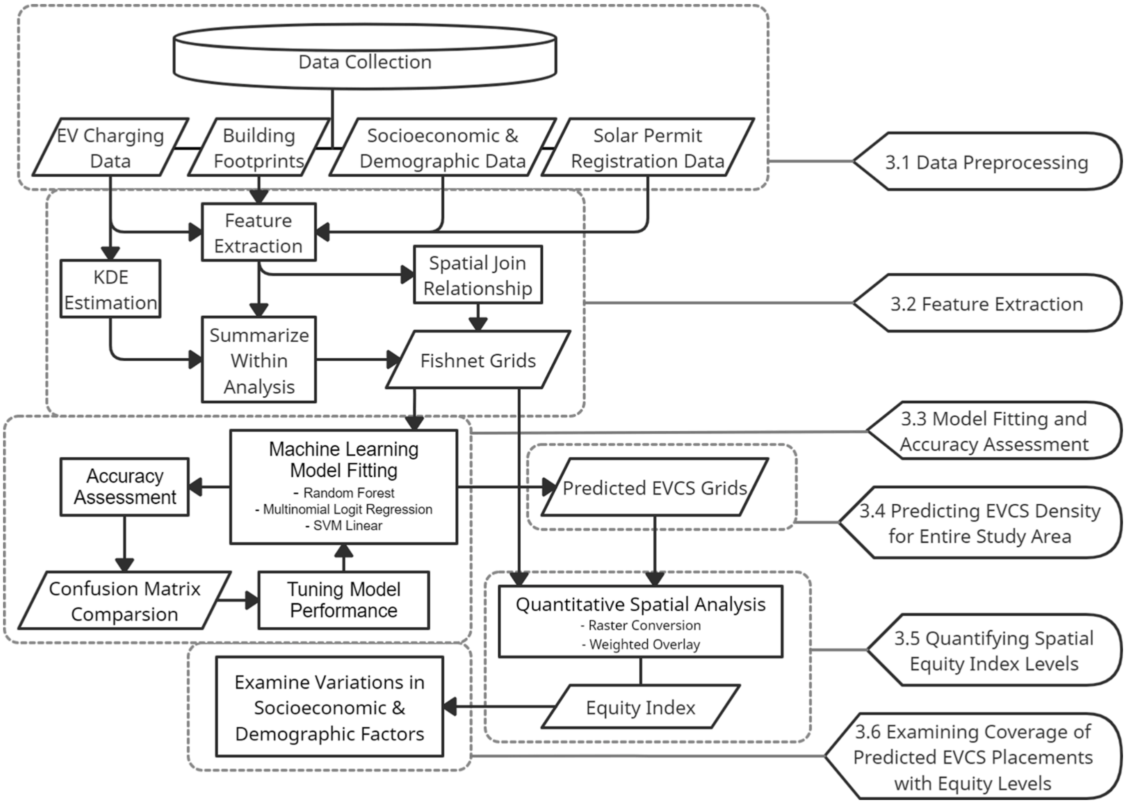

Fig. 2. Spatial distribution of existing EV charging stations across Orange County w.r.t to (a) population density and (b) median household income distribution.

ArcGIS and converted to raster format ensuring the spatial resolution of all data layers was matched. We addressed multicollinearity by ensuring that Pearson's correlation coefficient among all variables was below 0.4. The feature classes are listed in Table 2 and demonstrate the open data resources used for this analysis. The EVCS locations collected from several sources were converted to a raster format using KDE for matching it with the other data layers and smoothing out the density distributions. The KDE results were then categorized into three levels high, medium and low using a natural Jenks classification. These categories of EVCS density were used as ground truth for training the machine learning models.

The three different classes of low/medium/high were derived by applying a distance-based kernel function to generate a raster surface from raw latitude and longitude values. Often, vector point data from latitude and longitude suffer from the well-known modifiable areal unit problem in GIS, which does not scale well geographically and increases the overall uncertainties in the model, hence we created a raster surface that is still geographically relevant and can be used for modeling purposes once the spatial unit of the raster grids has been specified. This is typically a popular spatial analysis approach often undertaken in remote sensing studies where each cell from the image data represents a spatial grid containing latitude and longitude values - in this case, we used point density values by fitting a spatial kernel using the nearest neighbors approach in ArcGIS Pro.

Table 2
List of variables included in our study which influences social inequality in Orange County, CA.

Feature Category	Data Resolution	Features Extracted	Data Source	Relevance
EV Charging Data	Points	KDE of EVCS (Mean & Std. Dev) EVCS Count	Alternative Fuels data center	Service Coverage (Luo, 2015)
Building footprints	Parcel	Percentage of Built-up Area (Mean & Std. Dev) Building Count	County of Orange	Building density (Hsu, 2019)
Solar Panel Permit Registration	Zip Code	PV System Size (Mean & Std. Dev) Total Solar User Count	California Distributed Generation Statistics	Solar Energy Charging (Good, 2019)
Socioeconomic & Demographic	Census Block Group Level	Total Population Population Density (Mean & Std. Dev) Household Size Median Age (Mean & Std. Dev) Census Block Group Count Median Household Income (Mean & Std. Dev) Total Households Population Below Poverty Level Minority Population Population with College Education Transportation Modes (Drive along, carpool, public transit) Vehicle Ownership	U.S. Census Bureau, American Community Survey	Demographic characteristics (Westin, 2018, Chakraborty, 2019), Socioeconomic characteristics (Li, 2017, Hsu & Fingerman, 2021, Javid & Nejat, 2017), Transportation & commuting factors (Chakraborty, 2019)

The KDE is calculated based on latitudes and longitudes of EVCS which are converted into raster grids by applying the kernel density tool in ArcGIS. Rather than choosing raw coordinates to present the geographic locations, we use grids to equally divide communities into the same scale, thereby enhancing the reliability of the model fitting outcomes. This approach offers greater flexibility on various scales by avoiding using sharp features to assess point concentration. The use of different grid sizes also presents variability between finer and coarser extent, which ensures the optimal model fitting is selected for further analysis.

4.2. Feature extraction from independent variables

We divided our study area into grids to better represent the spatial distribution of EV charging infrastructures and associated the relevant variables from Section 3.1 to each grid for a joint investigation of the spatial variations in socioeconomic attributes along with EVCS distributions. Using the fishnet tool in ArcGIS, we divided the study area into spatial grids. We varied the scale of our analysis using different grid sizes ranging from 1×1 km to 5×5 km to estimate the prediction accuracies of the models at multiple scales. The preprocessed data from socioeconomic and built environment variables extracted in Section 3.1 were then spatially joined to the grid features for all grid sizes. Finally, the summary statistics of the extracted features for each grid cell were calculated using mean and standard deviation from the joined dataset. We repeated this process by varying the grid sizes from 1 km up to 5 km.

4.3. Model fitting and accuracy assessment using machine learning models

Our machine learning model predicts the EVCS grid density levels within Orange County. We used the caret (Classification and Regression Training) 'R' package to train three different machine learning models by varying the spatial grid sizes from 1 km to 5 km. The algorithms used for training the three different models were - random forests, multinomial logistic regression, and support vector machines . We used 80% of the data for training our models and used the held out 20% of the data for testing the accuracy of the models. To ensure the training data are randomized and the models do not overfit, we implemented a control mechanism called repeated 'k' fold cross-validation, such that the training data were split into ten folds and models were repeatedly fitted in each fold with a new dataset. The process was repeated three times for each algorithm. Eventually, we generated a total of 15 models which were compared among each other for the best fit by comparing the accuracies of each model with a total of 30 iterations.

4.4. Predicting EVCS placements for the entire Orange County, CA

After model training, we computed the mean cross-validation accuracy among three algorithms and five grid sizes to determine the most accurate model for prediction among all fifteen models. Based on the training data, we also calculated the precision, recall, and F1 scores for each model. The most accurate model was then used to predict EVCS density classes from the test data. The predicted and actual class labels were also used to generate confusion matrices that highlighted how accurately each EVCS density class was predicted at different spatial scales. Finally, we selected the model with the highest cross-validated accuracy, maximum F1 score, and lowest misclassification rates to predict the EVCS placement density classes for the entire Orange County at the most appropriate spatial grid size. A map of the predicted EVCS placements at the chosen spatial scale was then generated for the entire study area.

4.5. Quantifying spatial equity levels for EVCS placements across spatial grids

Since the key objective of this study is to understand equity access of EVCS placements, we computed a weighted equity index to demonstrate the spatial variations in overall accessibility of the predicted EVCS placements. Raster layers constructed from the socioeconomic and demographic features listed in Table 2 and were used to generate a weighted index called the Electric Vehicle Charging Inequity (EVCI) index using a multicriteria decision analysis approach developed by Roy & Kar (2022). The outcome was a weighted equity index map (at the chosen spatial resolution from Section 3.4) was generated to highlight the levels of spatial equity throughout Orange County for the spatial grid size chosen in Section 3.4.

4.6. Quantifying spatial equity levels for EVCS placements

The weighted index map generated in Section 3.5 was overlaid with the predicted EVCS placements map to visually compare how equitably the future EVCS would be placed. The spatial coverage of the EVCS placements was computed from the percentage of area covered by the predicted EVCS placements that overlapped with each spatial grid and aggregated using overall mean for each equity level. We also calculated the local Moran's I for each 3 km grid to statistically assess how well the high and low EVCS placement densities varied spatially with existing socioeconomic inequalities.

5. Analysis of results

5.1. Feature extraction from preprocessed data

In total we calculated 28 features from the four sources listed in Table 2 for each grid resolution by summarizing the variables using mean and standard deviation for each spatial grid. These features were used as predictor variables to train the machine learning models.The KDE of the existing EVCS placements are shown in Fig. 3. These are categorized into three classes – low, medium and high and overlaid with the spatial grids at each resolution and used as the response variable for training machine learning models.

Based on the available data, the kernel density estimate was able to categorize the existing EV charging station placements into three categories low, medium and high which varied by the size of the spatial grid chosen for our analysis as shown in Table 3.

5.2. Model accuracy assessment by varying spatial scales

The cross-validation accuracy of the machine learning models varied based on the spatial grid sizes and training methods. Table 4 lists the 10-fold cross validation accuracy with 3 repeats for random forests, multinomial logit and support vector machines for varying grid sizes from 1 to 5 km. The trend plots of overall model accuracy for Random Forest, Support Vector Machines and Multinomial Logit for varying grid sizes are shown in Fig. 4.

The Random Forest model outperformed both Support Vector Machines and Multinomial Logit in terms of mean cross-validation accuracy for the grids ranging from 1 to 3 km (Table 4). The models become more uncertain in their predictions as we kept increasing the grid size and the variance in the accuracy became large for grid sizes 4 and 5 km (Table 4). The underlying socioeconomic factors were not sufficient to predict placements at these scales as the populations modeled became more heterogeneous as we increased the resolution of our analysis.

5.3. Confusion matrices for EVCS placement predictions

The random forests at 3 km grid sizes had the highest accuracy with the lowest variance (Fig. 5) and were chosen as the best model for EVCS

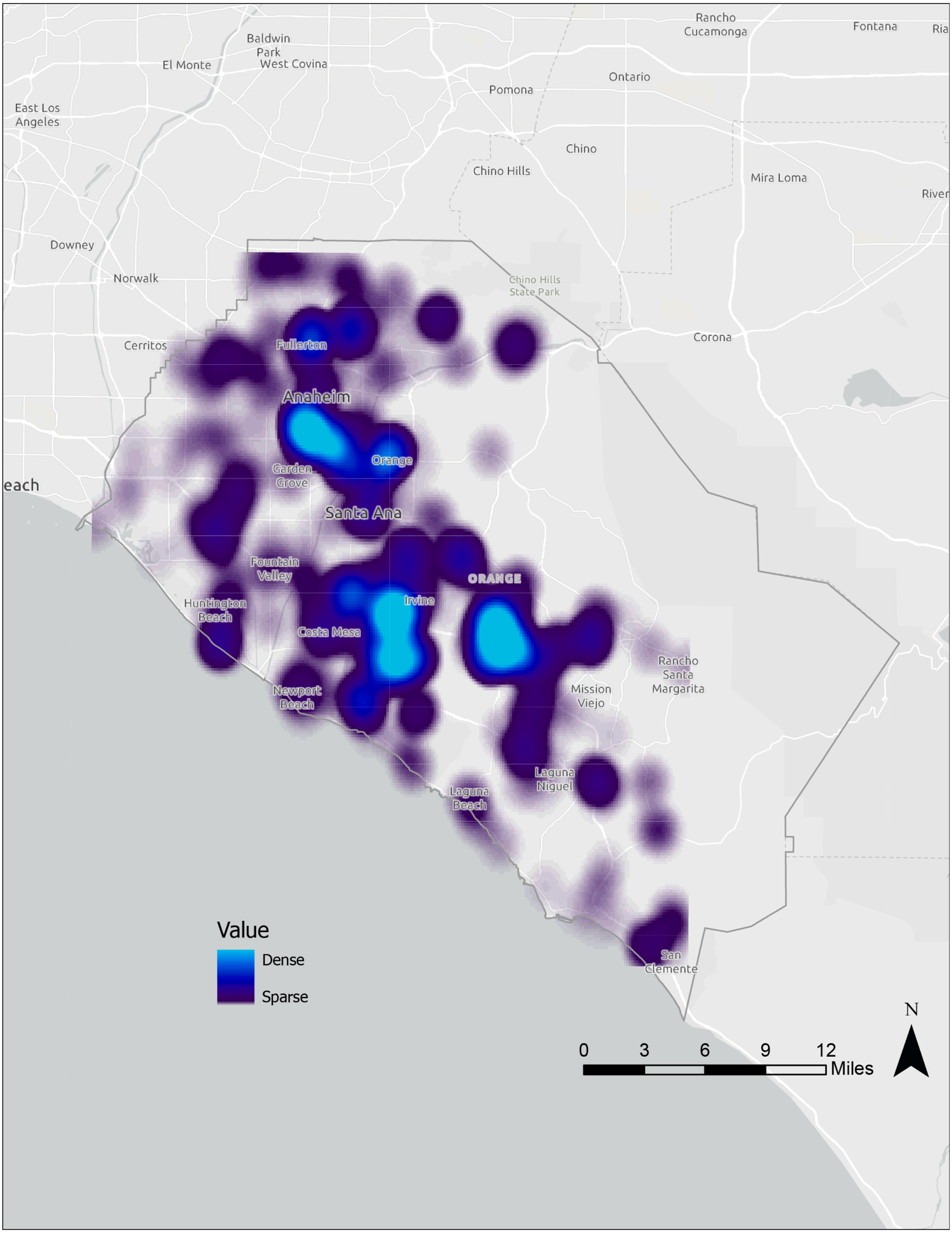

Fig. 3. A heatmap showing the kernel density estimate of existing electric vehicle charging station placements in Orange County, California.

placement predictions. Additionally, we generated confusion matrices (Fig. 6) to distinguish the misclassification rates among EVCS placement density classes across the five grid sizes using Random Forests to further gauge the class level accuracy in predictions as the spatial scale varied.

The 'Low' density EVCS placements are most accurately classified for 3 km grids, whereas the 'Medium' and 'High' density EVCS placements are most accurately classified at the 5 km resolution, however, these results have a high variance as the uncertainties around the predictions increase as we increase the grid sizes as well (Fig. 5). Hence, we chose the 3 km grids as the most optimal scale for our analysis. Based on

Table 3
Categories of existing EVCS density derived using Kernel density estimation.

Grid Size	Low EVCS density	Medium EVCS density	High EVCS density
1 km	0-11483	11483-36587	>36587
2 km	0-10894	10894-35584	>35584
3 km	0-13263	13263-39246	>39246
4 km	0-11074	11074-32995	>32995
5 km	0-5344	5344-17403	>17403

existing data the highest number of grids were pre-labelled as low density areas – but a resampling technique was used to reduce overfitting of the models.

5.4. Examining spatial equity levels of predicted EVCS placements for Orange County

We examined the spatial accessibility of predicted EVCS placements throughout Orange County using the weighted equity index and categorized the region into three classes based on low, medium and high level of inequities that exist in each 3 km grid. The EV charging inequity index (EVCI) demonstrated areas with low vehicle ownership, high population density, high percentage of minority population, high percentage of people living below poverty levels, with less access to education, low median household income were categorized as high inequity areas.

Table 4a lists all the variables used to estimate the EVCI across Orange County. These variables were derived and quantified based on existing literature and by consulting local authorities about the current determinants of charging accessibility issues in our study area.

By mapping out the equity indicators (Fig. 7a), it was further revealed that the central part of Orange County near the cities of Santa Ana, some parts of Costa Mesa and Garden Grove appear to have a highest inequity in EVCS access compared to the rest of the county. Cities like Newport Beach, Irvine and Huntington Beach experienced very low inequities as the underlying populations are homogeneous in terms of income levels, education levels as well as vehicle access. We have ensured that most of the contextual factors that influence decision-making by planners in EV infrastructure investments are accounted for.

We have added more variables in Table 4a to account for social inequality factors related to EVCS. Since this is a pilot study conducted with existing data, we have selected the most impactful variables based on previous literature in the Southern California context and by means of gathering local knowledge by speaking with local authorities from Orange County. Table 2 is not an exhaustive list but our model is flexible and robust enough to support the addition or removal of confounding variables relevant to a city's design, policy regulations, and availability of data of comparable resolution.

The variables listed in Table 4a will be available from most U.S cities' open data portals and can be normalized to derive the equity index for any city. Even in cases where such an exhaustive list of confounding variables for equity analysis may not be available, practitioners can rely on standard measures of income, ethnicity, traffic volumes, or a meaningful subset of the indicators used in this study to perform the analysis. However, if lesser variables are added it may lead to higher uncertainties in the measure of the EVCI index for the study.

The final EVCI layer shown in Fig. 7b was derived from the normalized values shown in Table 5 for each of the variables listed in Fig. 7a and combining then using a weighted linear sum approach using the raster analysis toolbox in ArcGIS Pro. The overall cost of access based upon all contributing factors listed in Table 4a was used to generate a single EVCI layer ranging from 1-10 (labelled as Low-High) in Fig. 7b.

We also estimated generated maps for predicted EVCS placements along with the weighted equity indicator (Fig. 7) and computed the percentage of spatial overlap of the EVCS grids with the categorized equity classes from Table 4a We found that the spatial coverage of the high inequity area w.r.t EV charging access spans across 11.04% of the total area of Orange County indicating very low access to nearby EV charging stations. 69.52% of the area experiences medium inequity levels thereby having only moderate access to EV charging stations and 19.11% experience low inequity or higher access to charging stations throughout Orange County (Table 5a).

As per our model predictions the low-density EV charging stations placements would be the most common with about 76.83% of the entire county will see experience very few EVCS placements with only 7.8% of

Table 4
Mean cross-validation accuracy scores of different models with varying spatial resolution.

Grid Size	Random Forest	Multinomial Logit Regression	SVM Linear
1 × 1 km	0.9281	0.9230	0.9260
2 × 2 km	0.9297	0.9182	0.9394
3 × 3 km	0.9499	0.9219	0.9487
4 × 4 km	0.9208	0.9146	0.9479
5 × 5 km	0.8930	0.7920	0.8807

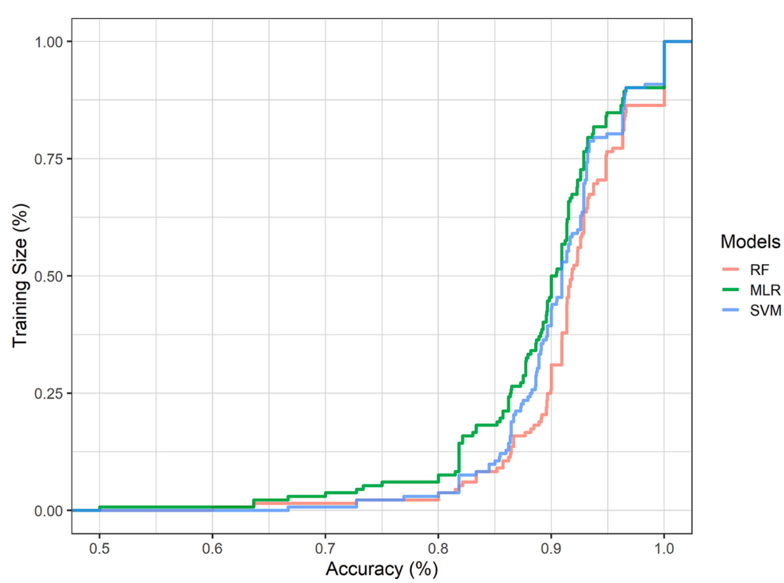

Fig. 4. Trend plots showing the model accuracy for different machine learning classifiers.

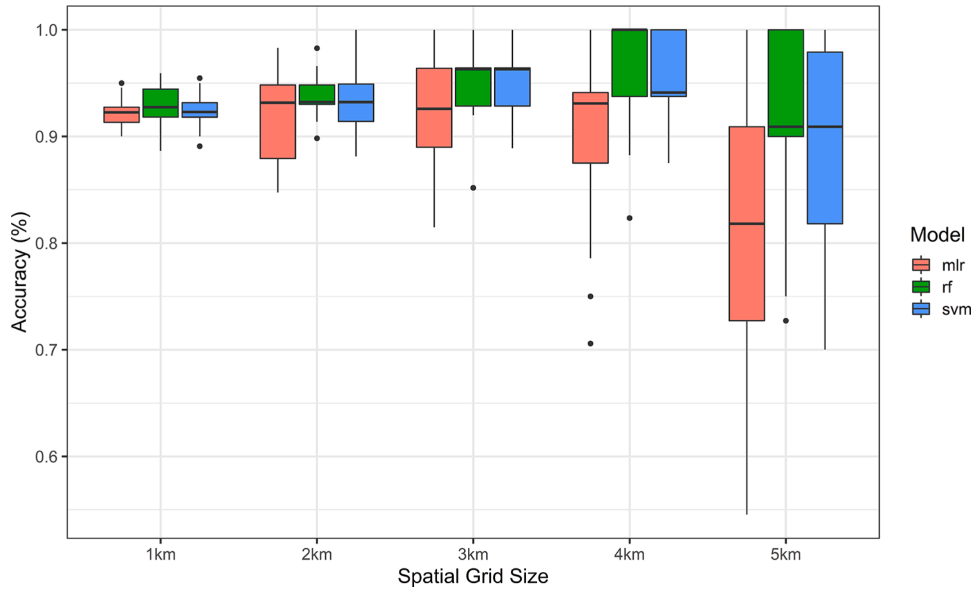

Fig. 5. Prediction accuracy of Random Forest, Multinomial Logit and Support vector Machines at varying spatial resolutions.

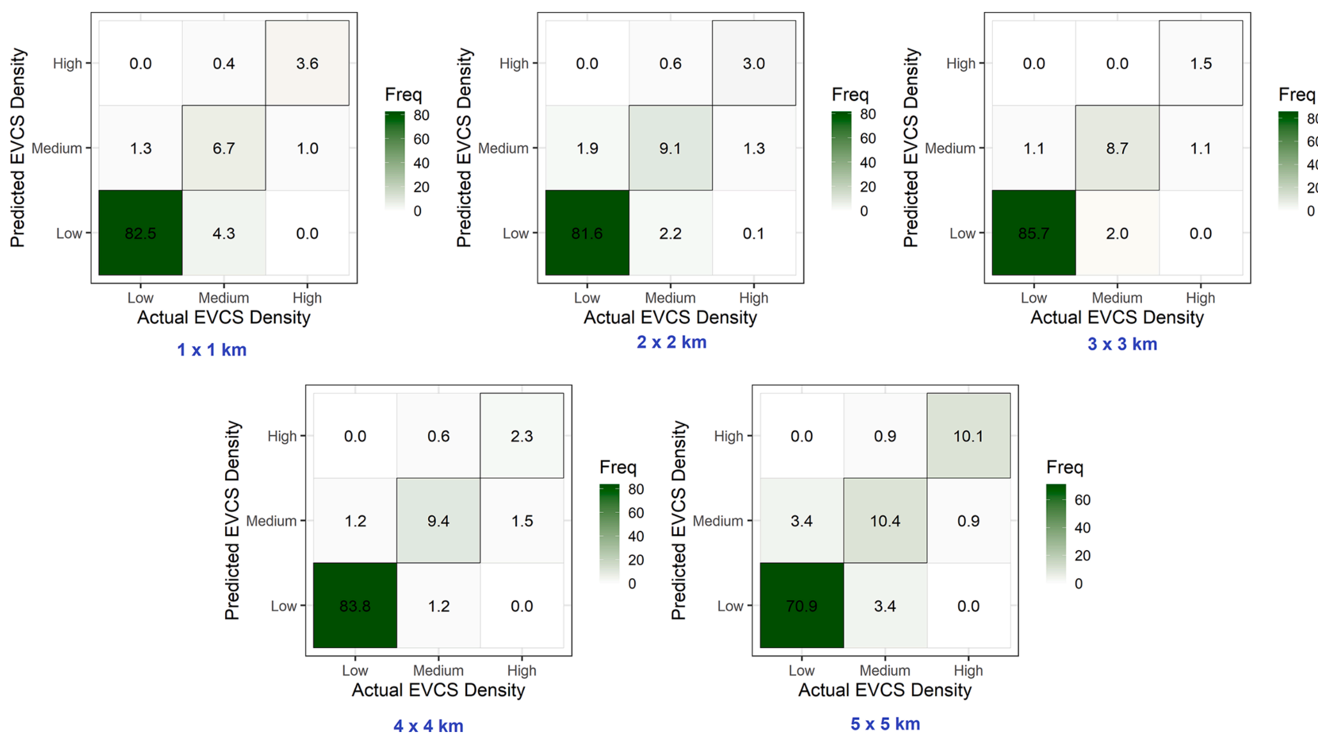

Fig. 6. Confusion matrices of Random Forest models at varying spatial resolutions for Orange County, CA.

medium density placements and 0.78% of high-density EVCS placements. The central part of Orange County still shows a high density of future EVCS placements based on our predictions. However, the small pockets of high inequity regions within the central part of the county do seem to have a medium density of predicted EVCS placements. The area with high inequity in the southern parts of the county continues to show a low density of EVCS placements based on the socioeconomic factors used in our model predictions.

6. Discussion

Our study incorporates machine learning along with spatial accessibility measurement to highlight the spatial disparities in EVCS placements based on the socioeconomic composition of cities in Orange County, California. Since the methodology developed in this study uses a data-driven approach, the model performance and predictions depend upon the availability of good quality data. The spatial inequality indicator (Fig. 7) was derived by combining multiple factors at play like – vehicle ownership, poverty levels, educational access, income levels and housing affordability (Table 4a) which was a step forward in terms of capturing some of the complex interactions among the underlying social, economic and demographic characteristics at play.

The least EVCS access occur in the cities of Santa Ana, some parts of Costa Mesa, Anaheim, La Habra, Seal Beach and San Juan Capistrano

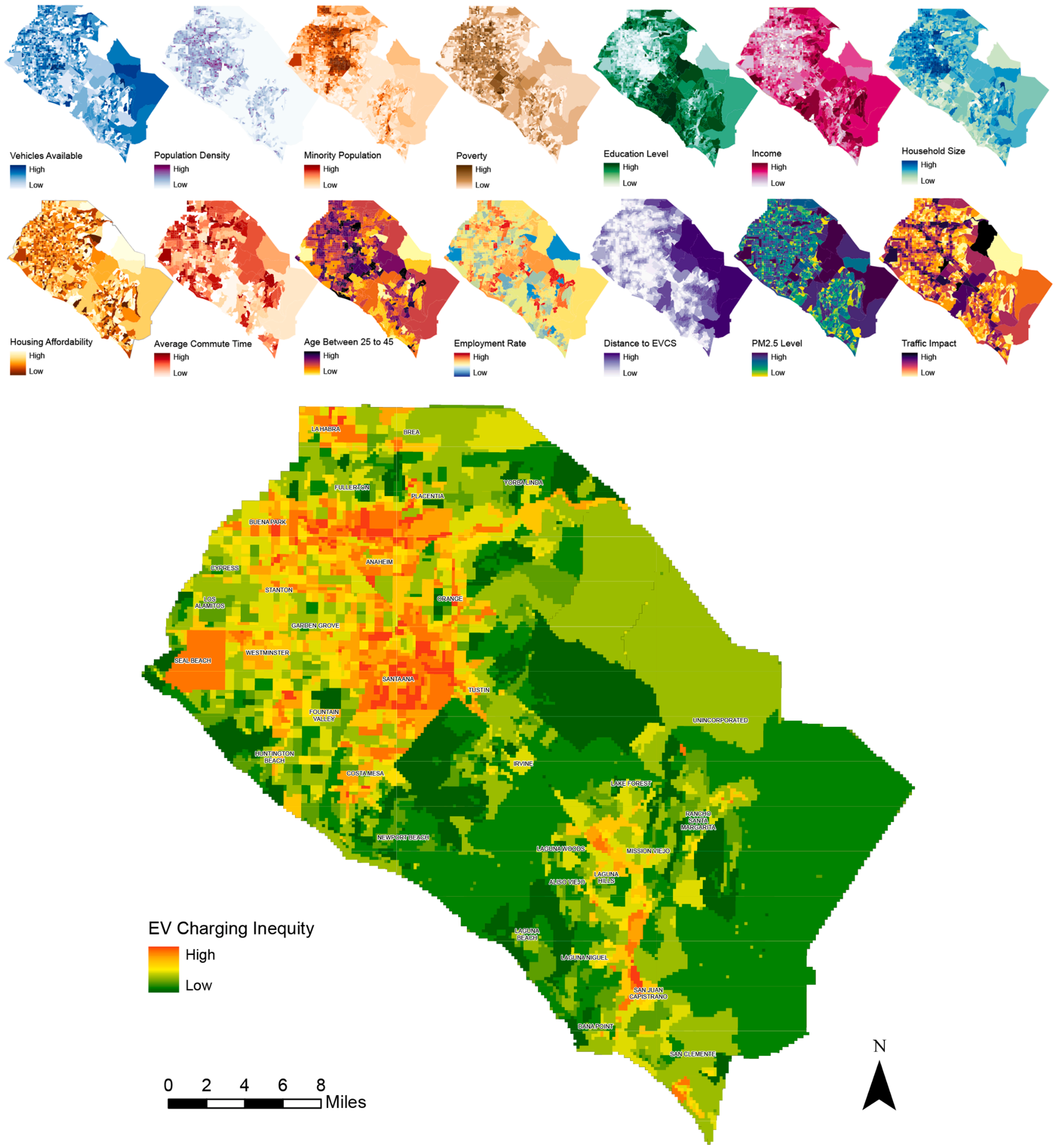

Fig. 7. Fig. 7(a): Spatial distribution of socioeconomic composition of populations residing in Orange County, CA used for equity level calculation. Fig. 7(b): The weighted EVCI layer showing different levels of access to EV charging stations throughout Orange County, CA.

(Fig. 7b). These areas have high population density, higher percentage of minority populations, high percentage of population living below poverty level, lower education levels but also have younger populations between 25–45 years residing in these cities who could be potential and/or existing users of EVs (Fig. 7a). These areas also encounter high volume of motorized traffic and are typically in the lower spectrum of environmental quality in terms of PM 2.5 concentrations (Fig. 7a) and might need to move to EV adoption in the near future.

Some parts of Seal Beach, Orange, Santa Ana, La Habra also have high average commute times (Fig. 7a) which would mean people would be able to reduce fuel usage if EV adoption becomes popular in these areas, but that would also need significant investments in terms of EVCS placements in and around these locations to account for such change. Currently, the EV market is moving towards more affordable cars for the middle to low income communities and the high inequity areas suggested in our study could provide an assessment of the major hotspots for EVCS demand in the future.

Based on our model predictions, some parts of Anaheim, Santa Ana, Orange and Tustin would experience medium to high EVCS placements in the future (Fig. 8), but other cities that are currently deprived of

Table 4a
List of variables used to create equity indicators for Orange County.

Variable	Description	Relevance
Vehicles Available	Average number of vehicles available in each household	Mobility indicator (Hanke et al., 2014, Luo et al., 2015, Javid & Nejat, 2017)
Population Density	Spatial distribution of population, calculated by total population/Land area	Demographic indicator (Plötz et al., 2014, Chakraborty, 2019)
Poverty	Percentage of population that lives under the poverty line	Socioeconomic indicator (Li, 2017, Hsu & Fingerman, 2021, Javid & Nejat, 2017)
Education	Percentage of population that holds a bachelor's degree or higher	Socioeconomic indicator (Hanke et al., 2014, Nayum et al., 2016, Javid & Nejat, 2017)
Income	Average median household income	Socioeconomic indicator (Hanke et al., 2014, Nayum et al., 2016)
Household Size	Average number of persons living in a household	Demographic indicator (Plötz et al., 2014, Chakraborty, 2019)
Housing Affordability	Percentage of population that spend more than 30% of monthly income on housing	Socioeconomic indicator (Westin et al., 2018, Hanke et al., 2014, Nayum et al., 2016)
Average Commute Time	Average one-way travel time to work	Mobility indicator (Luo et al., 2015, Javid & Nejat, 2017)
Age Between 25 to 45	Percentage of population that are between age 25 to 45	Demographic indicator (Westin, 2018, Chakraborty, 2019)
Employment Rate	Percentage of employment for population over age of 16	Socioeconomic indicator (Li, 2017, Hsu & Fingerman, 2021, Javid & Nejat, 2017)
Distance to EVCS	Distance between centroid of Census block group and the closest EVCS	Mobility indicator (Luo et al., 2015, Javid & Nejat, 2017)
PM 2.5 Level	Annual mean concentration particulate matter level	Environmental indicator ((Nayum, Klöckner and Mehmetoglu, 2016), Nordlund et al., 2016; Zeise & Blumenfeld, 2022)
Traffic Impact	Sum of traffic volumes (vehicle-kilometers per hour) divided by total road length (kilometers) within 150 meters of the census tract	Mobility and environmental indicator (Luo et al., 2015, Nordlund et al., 2016, Javid & Nejat, 2017)

charging stations like San Juan Capistrano, Brea, La Habra will still see low investments in EVCS placements (Fig. 8) which may need to improve over time to provide better accessibility to the lower-middle income populations residing in these cities. The spatial accessibility measure we derived based on previous studies (Roy & Kar, 2022) can be catered towards addressing issues of social, economic and demographic factors that limit access to EV infrastructure. But with addition of more factors that quantify EV demand the inequity estimates could be further improved in the future. We used only open data available from the US. Department of Energy on Level 1 and Level 2 chargers for our analysis but if cities start collecting and curating housing level charging information about EVCS more accurate predictions could be made in the future.

The random forest algorithm reaches the highest predictive accuracy for the models compared to support vector machines and multinomial logit (Table 4). The model accuracies are also affected by the scale of analysis as shown in Fig. 4. The accuracy of the models keep increasing as we increase the spatial resolution of the grids from 1 km up to 3 km but sharply declines after that. A possible reason could be that the uncertainties in prediction amplify as we make the spatial units of analysis much larger and there is more spatial heterogeneity at scales of 4 km or above which are not captured completely by the models. The current study also limits us in terms of EVCS data as we have a sparse coverage of

Table 5
Levels of spatial inequity calculated using the MCDA approach for Orange County.

Level	1	2	3	4	5	6	7	8	9	10
Categories	High Inequity			Medium Inequity				Low Inequity		
Vehicles Available (per household)	0 – 0.01	0.02–1.40	1.41–1.68	1.69–1.92	1.93–2.17	2.18–2.41	2.42–2.64	2.65–2.97	2.98–3.59	3.60–4.16
Population Density (Per square mile)	35671–16926	16925–12869	12868–10071	10070–7553	7552–5455	5454–4056	4055–2797	2796–1538	1537–559	558–0
Underrepresented Minority Population (%)	1–0.88	0.87–0.78	0.77–0.69	0.68–0.58	0.57–0.46	0.45–0.33	0.32–0.24	0.23–0.16	0.15–0.07	0.06–0
Population Below Poverty (%)	0.82–0.74	0.73–0.65	0.64–0.57	0.56–0.49	0.48–0.41	0.40–0.32	0.31–0.24	0.23–0.16	0.15–0.08	0.07–0
Education Level (Bachelor's or higher for pop over 25)	0–0.06	0.07–0.16	0.17–0.24	0.25–0.32	0.33–0.41	0.42–0.51	0.52–0.60	0.61–0.69	0.70–0.77	0.78–1
Median Household Income ($)	0–20589	20590–50446	50447–65521	65522–80729	80730–96641	96642–114647	114648–132321	132322–159267	159268–207019	207020–250001
Household Size	7.51–5.36	5.35–4.65	4.64–4.12	4.11–3.68	3.67–3.32	3.31–3.00	2.99–2.65	2.64–2.18	2.17–0.02	0.01–0
Housing Affordability, pop Spending > 30% of income (%)	1–0.91	0.90–0.77	0.76–0.66	.65–0.57	0.56–0.49	0.48–0.41	0.40–0.32	0.31–0.22	0.21–0.09	0.08–0
Average Commute Time	24.8–20.6	20.5–17.2	17.1–15.4	15.3–14.3	14.2–13.6	13.5–12.7	12.6–11.7	11.6–11.0	10.9–10.0	9.9–7.0
Population between Age 25–45 (%)	0.76–0.56	0.55–0.47	0.46–0.41	0.40–0.36	0.35–0.32	0.31–0.27	0.26–0.22	0.21–0.17	0.16–0.05	0.04–0
Employment Rate	0–0.28	0.29–0.43	0.44–0.51	0.51–0.56	0.57–0.60	0.61–0.64	0.65–0.67	0.68–0.71	0.72–0.77	0.78–0.89
Distance to nearest EVCS (meters)	10773–6221	6220–4038	4037–2812	2011–2137	2136–1678	1677–1309	1308–996	995–705	704–423	422–16
$PM_{2.5}$ concentration	12.1–9.1	9.0–6.7	6.6–5.4	5.3–4.4	4.3–3.5	3.4–2.8	2.7–2.2	2.1–1.6	1.5–1.0	0.9–0
Traffic Impact	4502–2450	2449–1665	1664–1224	1223–914	913–686	685–503	502–370	369–262	261–152	151–6

Table 5a
Proportion of spatial coverage of predicted EVCS placements categorized by equity levels.

Predicted EVCS Placements Density	Area covered across 3km grids by different equity levels (%)			
	Low Spatial Inequity	Medium Spatial Inequity	High Spatial Inequity	Total
Low	15.32%	54.42%	7.8%	76.83%
Medium	3.68%	14.00%	3.40%	21.09%
High	0.11%	1.10%	0.55%	1.76%
Total	19.11%	69.52%	11.04%	99.67% **

** 0.33% have no EVCS grid coverage.

existing EVCS locations on the southeast corner of the county and large portions of the eastern part also do not have any ground truth to compare model predictions with. But it is quite evident that the optimal choice of the grid size can distinctively change the predictive accuracy of the models. Hence, this study further validates the fact that scale effects in transportation planning is crucial in determining service areas and choosing suitable sites for future infrastructure investments.

Previous studies (Li et al., 2022) have not accounted for scale issues in equity analysis. We address this concern specifically through our scale-based machine learning approach for EVCS equity analysis. Our approach is a generalized version of the spatial accessibility analysis considering additional covariates like housing affordability, built environment characteristics, and socioeconomic factors that contribute to the overall differences in lack of accessibility among different population groups. Previous studies have either considered distance-based approaches to spatial autocorrelation without accounting for contextual information about the geography and surroundings of the neighborhoods. Moreover, our study highlights scalability issues in machine learning models - which is an issue in traditional urban studies - as a model for one city at a specific resolution will never fit exactly in other cities and consequently, the parameters which define accessibility and equity at a specific scale will vary widely across cities at large. We provide a possible workaround to capture and adapt scale issues in

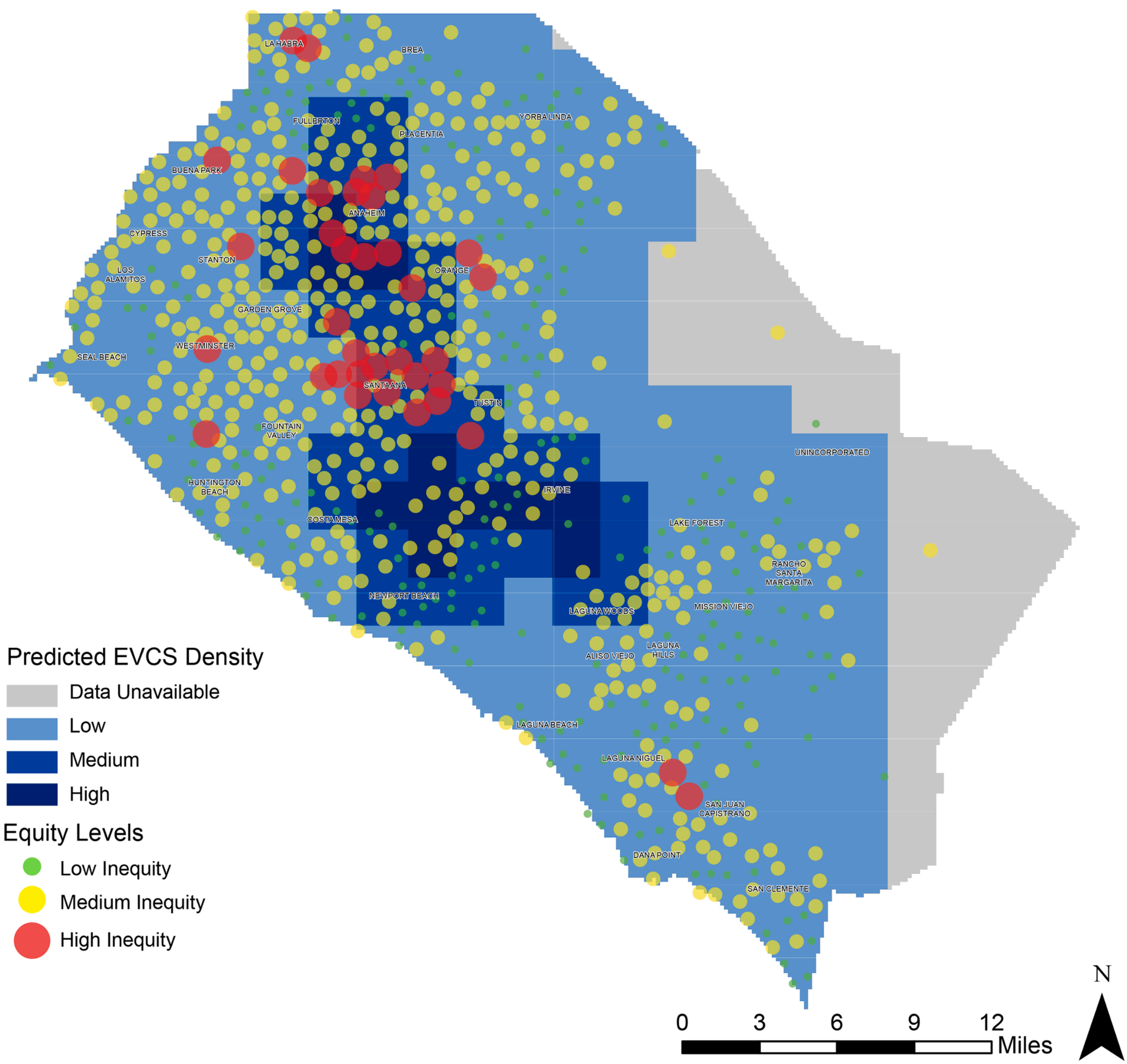

Fig. 8. Map showing the predicted EVCS placements in Orange County along with spatial inequity levels.

equity analysis using machine learning models by combining it with multicriteria decision analysis using varying grid sizes. Our methodology is easily replicable provided practitioners and policymakers have access to suitable datasets that quantify accessibility measures within the context of the city of their choice.

Better decision-making on infrastructure allocation could be facilitated by our conceptual framework. As shown by our results, the spatial inequity measurement can be summarized into three different categories namely – high inequity, medium inequity and low inequity. Considering that people in low income densely populated neighborhoods with low job accessibility tend to have least access to public EV charging stations, it is recommended to place new and supplementary EV charging stations with extended operating hours in the central part of the Orange County area. The cold spots which have lower inequity levels could be less prioritized, given that they are located in green belts and have lower population density.

The framework developed in this study is generalizable and can be applied to any type of study area. With the improved availability of sufficient amount of data with high spatial and temporal granularity the inequity index can be expanded to include diverse infrastructure, such as healthcare resources (Chen et al. 2020, Wang et al. 2020) and food outlets (Chen et al. 2017, Wang et al. 2018). The inequity levels help in identifying a particular region within the study area that has limited access to EVCS and proposing locations to place additional EV charging infrastructure.

7. Conclusion

In this work, we presented a machine learning framework for the prediction of EV charging station placements to address issues of spatial accessibility. Unlike previous work, we utilized social, economic, and demographic data along with the historical charging data to characterize future placements of new EV charging infrastructure. We trained three popular machine learning models along with social inequity levels at various spatial scales for the prediction of charging stations placements. The results obtained in terms of prediction performance is superior to the results in the previous works. Although several existing approaches address cost benefits to optimize EV charging access, out study is one of the first to address and account for spatial inequality to EVCS placements by combining socioeconomic characteristics of underlying populations in multiple cities within a study area.

We believe that a combination of scalable machine learning approaches and decision-making tools has not been fully explored in equity analysis studies - especially in the context of EV charging access, since it is an emerging area of research. Previous studies have found that MCDA is suitable for modeling causal relationships among confounding variables in the context of public health (Roy and Kar, 2022)- hence we have tried applying it to the context of transportation equity as well. Although MCDA is a new relatively new approach in equity analysis, it has not been applied to EVCS problem before, it's a pretty well-established GIS method for site suitability applied to both public health issues and engineering problems - previous studies on EVCS equity have used spatial autocorrelation techniques to quantify access disparities, but we introduced a machine learning approach to predict the level of disparities in EV access across different spatial scales. Cities are complex entities and having very rigid models at a specific resolution makes it difficult for researchers to compare and contrast the behavior of these models across multiple study areas. Policymakers are especially interested in generalized and scale-independent models to replicate regional studies at the national level. The approach developed in our research is a stepping stone in this direction.

Our framework can be improved further by including additional measures that contribute to low spatial accessibility like job density and updated EVCS density data from future counts conducted by federal agencies. The scale effects can also be further tuned by testing model behavior at finer spatial grids based upon the availability of more ground truth data on EV charging stations. The primary advantage of our method is that it is generalizable - we provide a reliable framework for EVCS placement equity assessment. Irrespective of the actual location of EV stations, planners/policymakers can still use the model even if there is sparse data by generating a KDE. For cities with very few charging stations and with no prior analytical tool for site suitability of future EVCS placements, our method is a step forward in generating predictive maps that can be used as a baseline for planners to place new charging stations. This would reduce the cost and effort required in determining where and how many stations to place aat the same time adhering to the needs of low-income and socially disadvantaged neighborhoods.

CRediT authorship contribution statement

Avipsa Roy: Visualization, Conceptualization, Writing – review & editing. **Mankin Law:** Data curation, Formal analysis.

Declaration of Competing Interest

None.

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