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ABSTRACT

The purpose of this paper is to model the current and potential future distribution of electric vehicles in California. Because of the current growth of the plug-in electric vehicle (PEV) market, there is a need for charging infrastructure planning and analysis of electricity system demand. The primary goal of this work is to demonstrate a flexible geographic information system (GIS) scenario planning tool developed by the PH&EV center at UC Davis and soon available to the public, that can aid the PEV readiness planning process. This paper covers the development of the GIS tool, conducts a simple tool validation through comparison with the Clean Vehicle Rebate Project (CVRP), and tests two planning scenarios to explore the potential future changes in the distribution of PEV buyers. Validation results indicate that the tool structure may be improved by considering alternative empirical model structures, and new data from current vehicle owners. The results from two future scenarios, one where prices for PEVs drop and another where range for BEVs increases, indicate that the distribution of PEV buyers will likely continue to be clustered in current areas, but become more dispersed with drops in price. However, results suggest the distribution of BEV buyers will stay tightly clustered, even with increases in range.

INTRODUCTION

With increasing concerns regarding greenhouse gas (GHG) emission impacts on global climate change, and considering that the transport sector accounts for more than 20% of the global anthropogenic CO_2 emissions, there is a growing desire for governments to encourage the adoption of plug-in electric vehicles (PEVs) as a substitute for internal combustion engine (ICE) vehicles. Recent efforts from governments around the world have generated substantial growth in the PEV market. Currently the US has far and away the largest EV market (almost half the world's PEVs) *(1)*, and within the US, California has a unique subset of this market due to various policies and technological innovation.

With the current growth in PEVs, comes added complexity to the already complicated statewide, regional, and local transportation planning process. Since 2011, the U.S. Department of Energy (DOE), and the California Energy Commission (CEC) have released numerous competitively bid grants to fund PEV readiness planning at the regional planning level in California which has resulted in numerous planning documents attempting to predict and respond to the new PEV market (see *(2)* for a consolidation of regional reports). However, the state of the PEV market is highly variable and uncertain, making the creation of meaningful planning documents extremely difficult. It is important that within the PEV planning context we have flexible planning tools and communication strategies to react to the changes in PEV adoption and use.

It is the primary goal of this paper to offer a flexible tool that can be used to aid the PEV infrastructure planning process. This tool is one of a suite of tools that have been developed for analysis of possible PEV futures in the state of California and it can be used to model the home locations of future PEV buyers. In this paper we will: [1] explain the development of a geographic information system (GIS) tool to study the potential distribution of PEV households for further analysis of charging station placement and electricity management, [2] validate the PEV tool's estimated household distribution with existing vehicle rebate data, and [3] test various scenarios to determine the tool's effectiveness and responsiveness to various policies and buying behaviors.

BACKGROUND

There has been a recent rise in PEV manufacturing and purchasing across Europe, US, and Asia, largely due the involvement of governments incentivizing PEVs. With this recent growth of PEV markets, data indicate that there are general factors that promote the growth of a PEV market, although they vary by region. A recent study suggested that at a national scale, financial incentives, charging infrastructure, and local presence of production facilities have a positive correlation with a country's electric vehicle market share *(3)*. The prevalence of charging infrastructure seems to be the strongest correlate with national PEV markets, although there are exceptions (e.g. the Netherlands) *(3)*. In the U.S., the California market has recently experienced significant growth in PEV sales to around 5% of the California passenger vehicle market in the first quarter of 2014 *(1)*. Much of the reason why California has become an outlier in the US PEV market is due to the aggressive political incentives such as the Governor issued Executive Order B-16-2012 to put 1.5 million zero-emission vehicles (ZEVs) in California by year 2025 to help meet the greenhouse gas reduction goals set forth in Assembly Bill 32 (AB32) *(4)*. With this mandate came the major goal that “charging infrastructure must expand as the market grows…and rely on strategically deployed charging stations in a variety of locations” (*(4)*, p.8).

Of the many considerations in deciding where to place charging infrastructure, the most salient may be the needs and desires of consumers—to ensure use of the system—and the management of the electricity loads for this emerging fleet of vehicles. Because there is a gap in the literature about the spatial distribution of PEV buying, modeling PEV impacts on electric utilities and planning for charging stations is difficult. In a recent paper on the potential utility impacts from PEV charging, a model was specified to randomly assign PEVs to households because there was no other basis for knowing where future PEV buyers might be located *(5)*. However, we know that PEV buyers are not a purely random occurrence, because they can be clustered geographically, and may partially be explained by socio-economic data. This should be taken into account for future utility modeling as well as charging infrastructure planning.

People that are buying PEVs generally have higher incomes, education, and occupy housing units that have attached garages *(6)*. Importantly, women only account for a small percentage of PEV buyers in California even though they account for roughly half of the new car buyers *(7)*. However, socio-demographics are not good predictors of PEV adoption at the national scale; this has been attributed to the relatively small PEV market *(3)*. Individual attitudes and preferences about travel are known to have an influence on car buying in general *(8)* and environmental concerns have been correlated with intention of buying a PEV *(9, 10)*. In a study of potential BEV buyers in Portugal, it was concluded that financial incentives were critical for making BEVs a viable choice, and that the high price of BEVs were a barrier for most would be buyers *(11)*. In a study in San Diego, California, the most common concerns people had with BEVs were limited range, charger availability, and purchase price *(12)*. The concern about range has been well noted in California before the current surge in PEV ownership (see the stated preference study by Bunch et. al., 1993 *(13)*).

Traditionally vehicle buying is modeled as a function of vehicular attributes such as price, size, power, operating cost, and reliability *(14)*. However, as shown above, the process of determining plausible PEV buyers may be limited by unique constraints (e.g. need to charge), and personal preferences (e.g. concern about the environment) *(11)*. What is most clear is that the dynamic nature of the current PEV market makes it difficult to establish conclusive links between socio-demographics and PEV buyers. Given this uncertainty and the need for planners and utility managers’ to predict the distribution of PEVs, flexible tools are needed to establish geographic predictions, even when causal links are unknown. The following paper demonstrates a first step at understating the spatial distribution of PEV households through the construction of a flexible scenario planning tool.

METHODS

The process of generating the map of PEV households can be seen through the flow diagram in Figure 1. It begins with the estimation of empirical models from disaggregate survey data. The odds ratios from those models are used together with aggregate socio-demographic data and analyst specified parameters to generate a map of PEV households. Each of these steps will be discussed independently from A through D as illustrated by Figure 1.

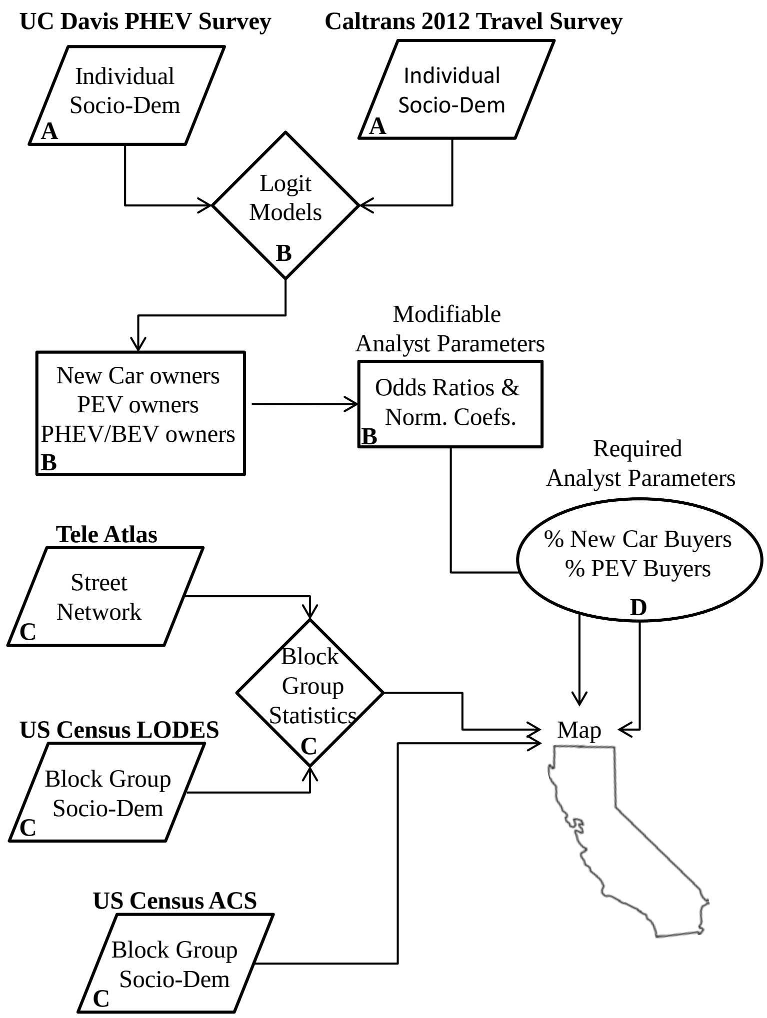

FIGURE 1 Methodological flow chart for the estimation of disaggregate logit models, processing of aggregate socio-economic data, and mapping of PEV households from the PEV Buyers GIS tool.

Empirical Models

Data (Step A)

We extracted a subset of the 2012 CALTRANS travel survey (households that purchased new vehicles from 2012). This sample included new car buyers, hybrid buyers, and PEV buyers totaling over 9,000 households. In addition to this subset from the statewide travel survey, the UC Davis PH&EV 2012 survey—conducted with the Center for Sustainable Energy (CCSE), in coordination with the California Air Resources Board (CARB)—yielded 3,200 households (a 31% response rate) of only PEV buyers through a web-based survey. The sample frame for this survey included all PEV buyers in California who applied for the Clean Vehicle Rebate Project (CVRP). The combined CALTRANS and UC Davis dataset is summarized by Tal & Nicholas, 2013 *(15)*. Due to over sampling, the combined data contain a total of 9,001 PEV households' demographics and information about their vehicles and travel behavior. The location of each household was used to enrich the knowledge on each household using census data, GIS network analysis of commute traveling, and secondary data on block level property values as presented in Table 1.

TABLE 1 Descriptive Statistics of the New Car Buyers Sample

	New ICE	Hybrid	Non-Tesla S BEV	PHEV
Sample Size (*n*)	4815	681	2211	1285
Number of drivers in the HH	2.15	2.21	2.15	2.15
Cars to drivers ratio	1.05	1.04	1.16	1.14
Commute distance	20.04	19.92	14.94	21.58
Share of commuters	78%	83%	82%	83%
Number of vehicles in HH	2.18	2.22	2.28	2.18
Home ownership	0.87	0.92	0.95	0.90
Homes up to 4 units	0.91	0.93	0.96	0.93
Average HH income	110330	136961	166428	171878
Upper 75%tile property value	608089	741515	809798	792787
Population density (ppl/sq mile)	5894	6102	5891	5967
Share live in urbanized area	83%	91%	97%	97%
Share live in urban cluster	10%	6%	2%	2%
Share live in rural area	7%	3%	1%	1%

Model Structures (Step B)

The choice to buy a new non-PEV, plug-in hybrid vehicle (PHEV), or battery electric vehicle (BEV) are estimated through a series of three binary logit models based on the above combined disaggregate socio-economic data. The resulting odds ratios for each of these models are used as the default weights in the stochastic sampling of the market scenario PEV buyers GIS tool. Additionally, the normalized coefficients are used as additional weights when the model specification is a function of more than one predictor variable. The three models include: *New*

Car buyers = f(Income), PEV buyers = f(Income, Number of HH vehicles, detached/attached unit), and BEV buyers = f(commute distance).

Market Scenario PEV Buyers GIS Tool

The GIS tool was created to address the need to better understand the future PEV market. While the initial data compilation and analysis covers the state of California as reflected by the 2012 and 2013 surveys, the tool can easily be extended to other regions as long as the data is compiled for the region of interest. The PEV Buyers tool can be used to simulate the geographic dispersion of various new car buying and PEV buying scenarios. The current tool estimates the number of vehicles per census block group, given the constraints of the scenario defined by the analyst. The output from this tool should not be considered a forecast because the analyst directly limits the number of vehicles that will be bought for a given scenario. This tool should be used to explore possible geographic distributions of vehicles given various scenarios of new car and PEV buying. The tool is implemented in the *python* programming language as an ArcGIS python toolbox, with use of the *python* library *numpy* for stochastic sampling (see Figure 2 for an image of the user interface).

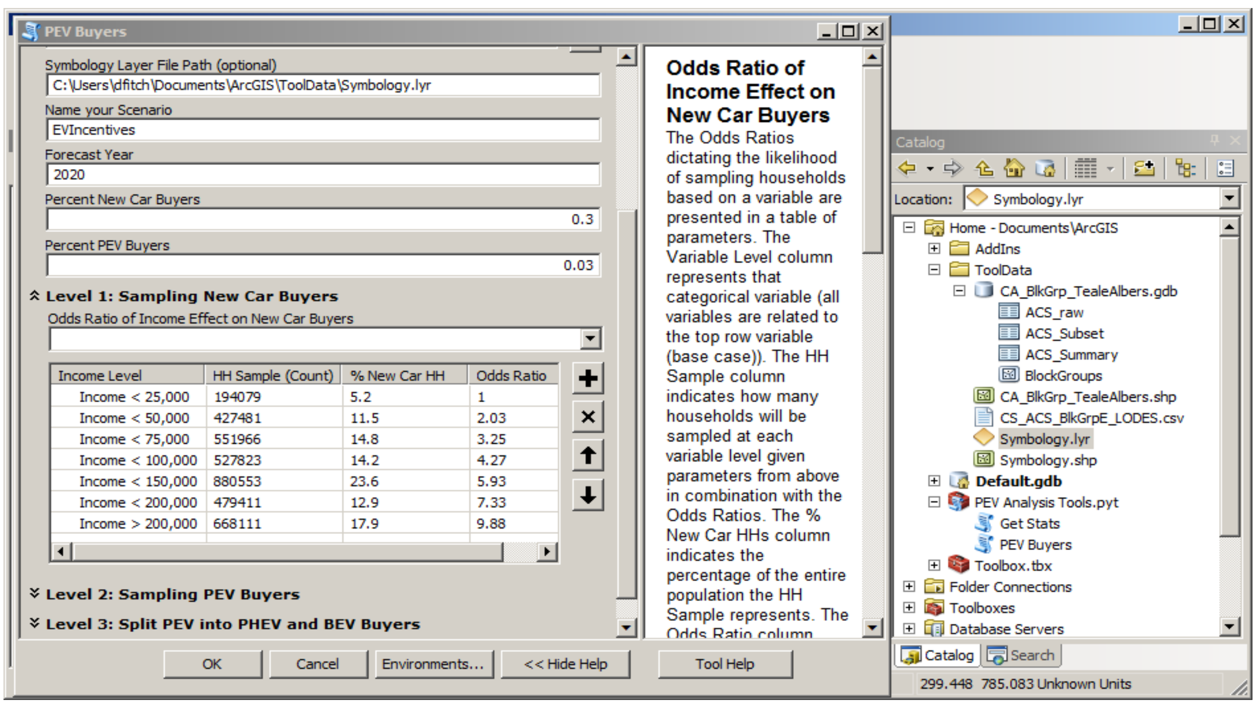

Figure 2 Image of the PEV Buyers tool in the PEV Analysis Tools ArcGIS python toolbox. The main dialog shows how the user has the ability to alter the main parameters (e.g. percent of new car and PEV buyers), and to alter the default odds ratios for sampling.

Data (Step C)

The tool uses two datasets that are publicly available: the 2011 5-year American Community Survey (ASC) and Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES version 7). These datasets were consolidated into variables that were determined to most effectively predict the ownership of PEVs at an individual level, as specified in the logit models. All the variables derived from the ACS data were generated from simple addition and/or subtraction of raw ACS variables; however the LODES variables were generated based on network distance calculations from the raw data.

The LODES version 7 data contains 2010 block enumerated counts of origin-destination (OD) pairs for work travel. This data was used in order to estimate commute distances. The data is composed of a combination of confidential census bureau data sources combined with public census data. Noise is added to personal data to protect privacy, and synthetic data methods are used to project total numbers of workers to each block (see *(16)* for details). This data *does not* include military or self-employed workers, and so is systematically biased to under-represent total worker travel. Unlike the ACS data, the LODES data had to be processed in order to be used by the tools. Only the in-state LODES data were processed, meaning all out of state workers/residents are not considered in this analysis.

The processing of the LODES data involved the following steps: First, the LODES employment totals for each origin-destination (OD) pair were summed at the block group level in order to match the spatial enumerations of the ACS data. Once the OD data were aggregated to the block group, commute distances between all OD pairs were calculated based on the shortest time network distance using ESRI's ArcGIS network analyst and the 2011 Tele Atlas StreetMap network dataset. An average Wednesday at 8am was used as the basis for calculating the shortest time commute path. The associated commute distance was calculated from the generated paths such that the final dataset was composed of individual OD pair commute distances. The final LODES variables were created by summing up the counts of OD pairs for each block group and classifying them into distance categories representative of the various PEV ranges available on the market.

Tool Structure (Step D)

The PEV buyers tool is structured hierarchically whereby household decisions to buy a new vehicle are made in a stepwise manner. This structure allows the tool to operationalize various aspects of PEV buying that have been observed through past empirical modeling *(6)*. Each buying decision in the hierarchy is based on the odds ratios and normalized coefficients of the empirical models (Step B). The following parameters and variables are used in each level of the decision hierarchy: The scenario constraints include the parameters *percentage of new car households*, and *percentage of PEV households* for a given scenario/horizon. These parameters are analyst defined, and act as constants for a given scenario. The new car buyer households are sampled as function of *income*. The PEV buyer households are sampled from the new car buyer households as a function of *income*, *number of household vehicles*, and *housing unit type* (detached vs. attached). The PHEV/BEV buyer households are divided from the PEV buyer households as a function of *commute distance*.

The selection of households is operationalized as a stochastic sample of households constrained by the analyst defined scenario and weighted by the odds ratios and normalized coefficients from the empirical logit models. For both the New Car buyer and PEV buyer steps, households are disaggregated from the block group level and randomly sampled based on the distribution of the explanatory variables and their associated weights. In the PHEV/BEV step, households are divided into the two categories based on the odds ratios with no further stochasticity added. The result of this procedure is a sample of households where PEV buyers are a subset of New Car buyers, and the sum of PHEV and BEV buyers equal the number of PEV buyers.

Tool Validation and Test Analysis Scenarios

Validation of the tool was conducted by simulating the actual total number of vehicles and PEVs purchased in California from 2010-2013. Records from the California New Car Dealers Association (CNCDA) outlook reports and from the Clean Vehicle Rebate program (CVRP) were used as the basis for the validation and indicated that an estimated 5.88 million new vehicles of which 70,000 were PEVs were sold between 2010 and 2013. Using these estimates as control totals in the PEV buyers tool, the distribution of vehicles was modeled and compared to the CVRP data for the entire state of California.

Along with a validation of the model, two policy/economic scenarios were analyzed to demonstrate the scenario effect on the future PEV market in California. We selected two extreme scenarios where PEVs price drops to that of ICEs, and where BEVs range increases that of ICEs. With both scenarios, our hypothesis is that the spatial distribution of new PEV buyers will shift to new areas that currently have low share of PEVs. This hypothesis is based on the theory that the high cost of PEVs, or the limited range of BEVs, are a barrier to households in certain regions. Alternatively we may see that the spatial distribution will stay relatively stable even with price drops and range extends, which would require explanations beyond price and range. Both price and range have been demonstrated as uniquely difficult hurdles to PEV adoption *(12)*, but as government policies begin to weaken these barriers, the impacts on the distribution of PEV buying is unclear. In order to test the effect of reduced vehicular cost on PEV buying, we kept all original parameters at their default level, and then set the odds ratios for income to 1 for all income classes in the second step of the hierarchy (PEV buying), and called this the *price equalization* scenario (i.e. we are simulating income has no effect on buying PEV). In the *range equalization* scenario, we again kept all original parameters at their default level, and then set the odds ratios for commute distance to 1 for all commute ranges in the third step of the hierarchy (BEV buying) (i.e. we are simulating no effect of commute distance on the choice between BEV and PHEV).

We conducted these two scenarios in combination with a *base* scenario—leaving all parameters at their default levels—and just like in the model validation above, we matched the total number of new cars and PEVs bought between 2010-2013. The scenario model runs were then added to the *base* case and then compared back to the *base*. This approach helps answer the following questions: [1] How will the spatial distribution of PEVs differ if—when the market has doubled—the income of households do not affect the decision to buy a PEV vs. a non-PEV? And [2] How will the spatial distribution of BEVs differ if—when the market has doubled— the commute distance of households do not affect the decision to buy a BEV vs. a non-BEV?

These scenarios were run in two subsets of California, the Sacramento Area Council of Governments (SACOG) and the San Diego Association of Governments (SANDAG). These regions were selected because they have similar population (SANDAG = 3 million, SACOG = 2.2 million), and because they offer unique geographical and economic contrasts.

RESULTS AND DISCUSSION

Tool Validation

The PEV buyers GIS tool was specified using the default odds ratios from the binary logit models and the percentage of homes buying PEVs to exactly replicate the total number of PEVs on the Clean Vehicle Rebate record from 2010-2013. The model estimated PEVs at each block group were aggregated to the ZIP code level—currently the most detailed geographic enumeration of the CVRP data available—and compared to the observed number of PEVs requesting a rebate (Figure 3). The lesser slope of the regression line compared to the 1:1 line in Figure 3 indicates that the model has a systematic bias to under-predict in more zipcodes than over-predict. However, the magnitude of the over-prediction in the fewer zipcodes is greater on average.

The spatial distribution of the model errors are not constant, and instead show considerable clustering. Most small cities around the Monterey Bay, Santa Barbara coast, and in the Central Valley are well predicted by the model as evident in their white color in Figure 3. However, the major urban areas of California (i.e. San Francisco Bay Area, greater Los Angeles and greater San Diego) have the most errors. The San Francisco Bay Area has a particular pattern of extreme over-estimation in downtown San Francisco and extreme underestimation in the more peripheral urban areas of the Silicon Valley and East Bay (i.e. Pleasanton, San Ramon, Redwood City, Cupertino, and Los Gatos).

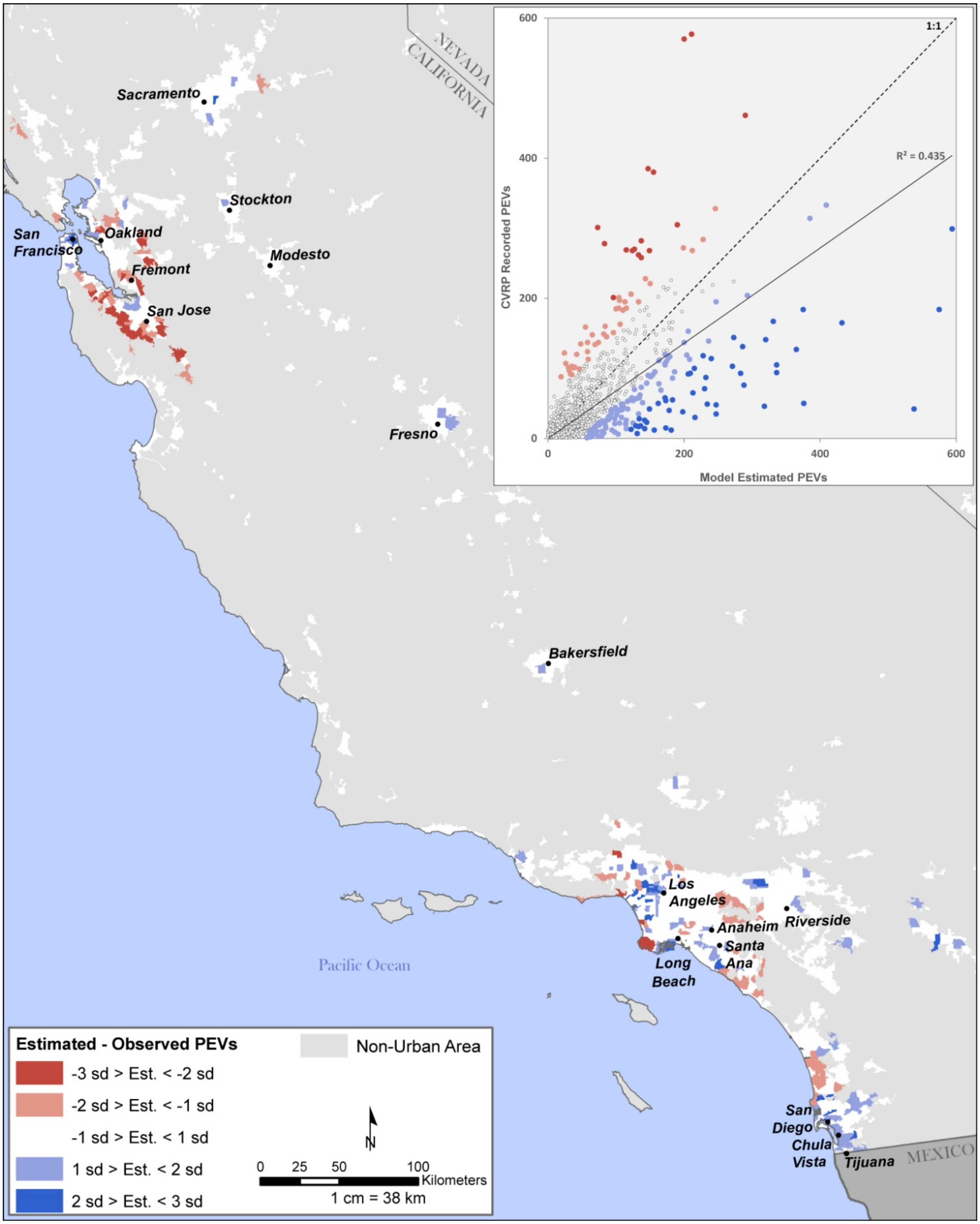

FIGURE 3 Map and scatter plot of the difference between CVRP and model estimated PEVs in California. Darker red colors indicate model under-estimation in standard deviations from 0, and darker blue colors indicate model over-estimation in standard deviations from 0. The US census defined Non-Urban Areas are excluded from the visualization and noted instead symbolized in grey.

In the greater Los Angeles area the model over-estimates PEV ownership in Long Beach, and central to north Los Angeles, while under-estimates in inland and coastal areas including Malibu, Palos Verde, Chino Hills, Yorba Linda, and southern Orange County. In the San Fernando Valley there is a combination of over and under estimation which makes it difficult to hypothesize any systematic bias.

San Diego has a clear divide much like the San Francisco Bay Area, where the model over-estimates in southern and eastern cities like Chula Vista and El Cajon, and under-estimates in northern coastal cities such as Del Mar and Encinitas. However, the magnitude of the errors in San Diego are not as great as they are in the San Francisco Bay Area and the greater Los Angeles region. This may be because San Diego already has a clearly defined PEV buying region (i.e. the North Coast) which is fairly well captured by the model, whereas the other major urban areas have much more dispersion in PEV buying.

There are numerous possible explanations for the model validation results; we present four possible reasons why the model behaves in the above summarized fashion: [1] Types of PEVs have changed from 2010-2013 (i.e. addition of long range BEVs like Tesla model S, and the 20 mile PHEVs like Fords Fusion and C-Max). The individual survey data was collected in 2013 before these types of vehicles were available, making the odds ratios from the models not reflective of the owners of these new vehicles. [2] We are limited by the available income data in the ACS. Because the ACS does not collect categories of income above 200,000, all households with high incomes are getting treated equally. This might partially explain the combination of the overly optimistic and pessimistic estimates in the San Francisco Bay Area. [3] There is no explicit factor in the models to account for the proximity to high occupancy vehicle (HOV) lanes for commuting. It is likely that by including a variable such as "distance of commute on freeway with HOV", the model might be able to better reflect known local motivations for wanting a PEV *(17)*. [4] Because PEVs are a new technology, their adoption is subject to *diffusion of innovation* (i.e. theoretical basis for the complex process of buying and selling new products). There is no part of our model that takes this into account (the clustering effect of the new innovation) as the model is based directly on the socio-demographic data. Although it may be difficult to model processes related to *diffusion of innovation*, future use of multi-level empirical models (e.g. varying intercepts and slopes) may be able to better account for the clustering of data across numerous variables which might represent social processes.

Test Scenarios

Results

In the SACOG region, results from the *price equalization* scenario show an increase in the dispersion of PEV owners, but the primary growth in ownership occurs where current ownership is already high. This can be seen in Figure 4 where areas of high PEV ownership in the *price equalization* case were often already high in the *base* case. There are two areas which show a unique increase in PEV ownership: south of downtown Sacramento near Florin Rd., and in the city of Auburn, a foothill town that is disconnected from the Sacramento Valley. In the *range equalization* scenario, increases in BEV ownership again closely correspond to the *base* scenario hotspots but also show some limited evidence of sporadic dispersion with no new localized hotspots of BEV buying (Figure 5).

In the SANDAG region, results from the *price equalization* scenario show continued buying in the North Coast regions which are existing PEV buying areas, but also increases in lower PEV buying areas such as Kearney Mesa, El Cajon, Mission Valley, and downtown San Diego areas (Figure 6). BEV ownership growth from the *range equalization* scenario show consistent growth in the same areas of the inland North Coast (e.g. Carmel Valley, Fairbanks Ranch, Torrey Highlands, and Black Mountain Ranch) (Figure 7). The only new hotspot of BEV buying from this scenario was in the Otay Lakes area in south San Diego, although this is one of the areas in which the model was shown to significantly over-estimate PEVs.

Inter-Regional Comparison

SACOG and SANDAG exhibit very similar trends for both the *price equalization* and *range equalization scenarios*, however the effect of each scenario manifests differently on the distribution of vehicles. By effectively reducing the price of PEVs to the equivalent of ICEs, we observe a spreading of PEV buyers beyond the current areas of high PEV ownership in both SACOG and SANDAG regions (Figures 3, 5). This is expected, because by reducing the price of the vehicle, areas of the region with lower incomes will begin to consider PEVs as a viable option. However, by effectively creating a BEV with an unlimited range for commuting purposes (i.e. commuting with a BEV would be as easy as commuting with a non-BEV), we observe the distribution of BEV buying will stay primarily isolated to the current areas in both SACOG and SANDAG (Figures 4, 6). It is expected that increasing the range of BEVs would make them more viable for those with longer commutes. These results do not contradict that expectation, but instead suggest that areas with longer commutes already own BEVs at high rates. There may be numerous explanations for this result, one of which may simply be that the BEV is not often the car used for daily commute in the households, which is consistent with the fact that BEV households have on average more household vehicles than non-BEV households (Table 1). It may also be that since there are so few BEV owners, even with dramatic changes in range capability—as specified in the scenario—the next round of BEV owners are just more likely to be where there is the highest potential demand (i.e. same place where current BEV owners live). Another explanation—of a methodological nature—is that the tool may be missing would-be BEV buyers because it is restricting the decision to buy a BEV as a subset of the decision to buy a PEV. It may be that people consider a BEV without directly ever considering a PHEV. Further research is needed to determine the decision *process* by which buyers approach purchasing a PEV so as to alter the model structure we adopted for the current PEV buyer GIS tool.

Scenario results seem to indicate that minor changes in the distribution of PEVs are likely in the near future, and even less likely is any change in the distribution of BEVs in both SANDAG and SACOG. However, while both regions have similar responses to each of the scenarios, their differences in their *base* case distribution of PEVs may indicate different planning strategies. SACOG has a fairly widespread distribution of PEVs with hotspots on the opposite sides of the region ranging from Davis in the west, to Rocklin and Folsom in the east. Alternatively, the spread of PEV owners in SANDAG are primarily located in one major region, the North Coast. How these *base case* and scenario results should effect the decision of where to put public charging stations remains to be seen, and will be a focus of future scenario tool development.

FIGURE 4 Maps of base case (A) and price equalization scenario (B) for the major urban areas of SACOG. Darker red areas indicate more PEV ownership per household.

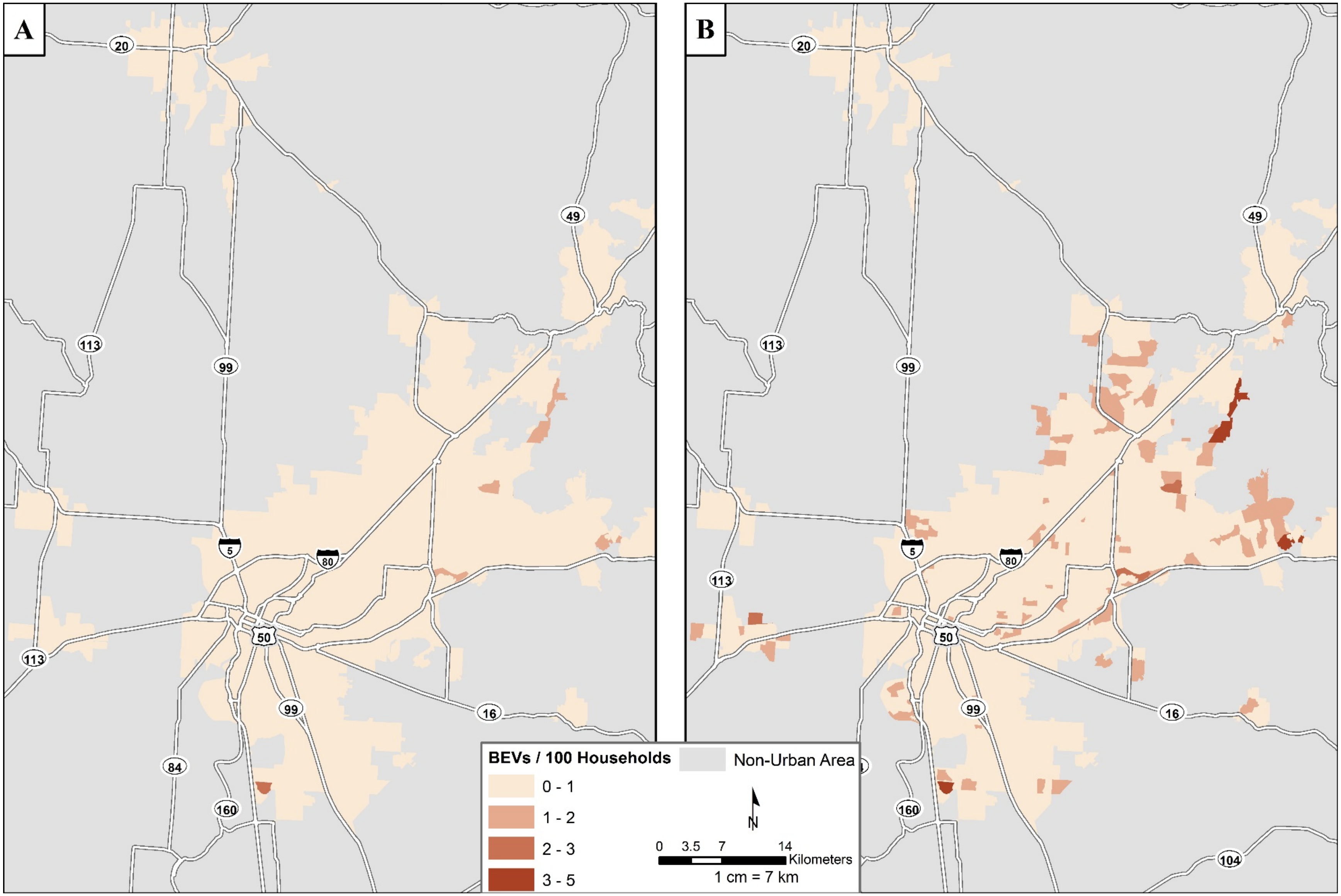

FIGURE 5 Maps of base case (A) and range equalization scenario (B) for the major urban areas of SACOG. Darker red areas indicate more BEV ownership per household.

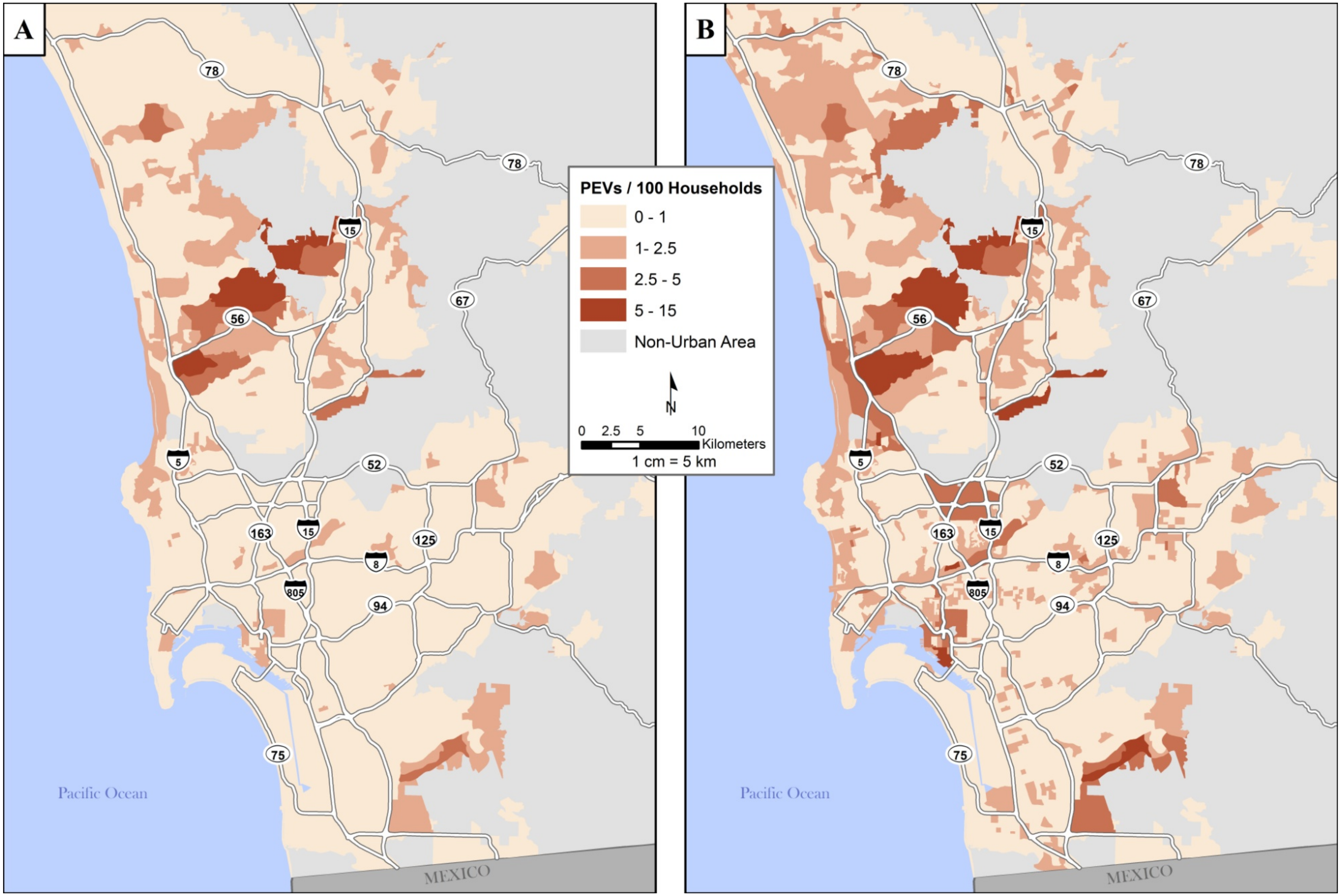

FIGURE 6 Maps of base case (A) and price equalization scenario (B) for the major urban areas of SANDAG. Darker red areas indicate more PEV ownership per household.

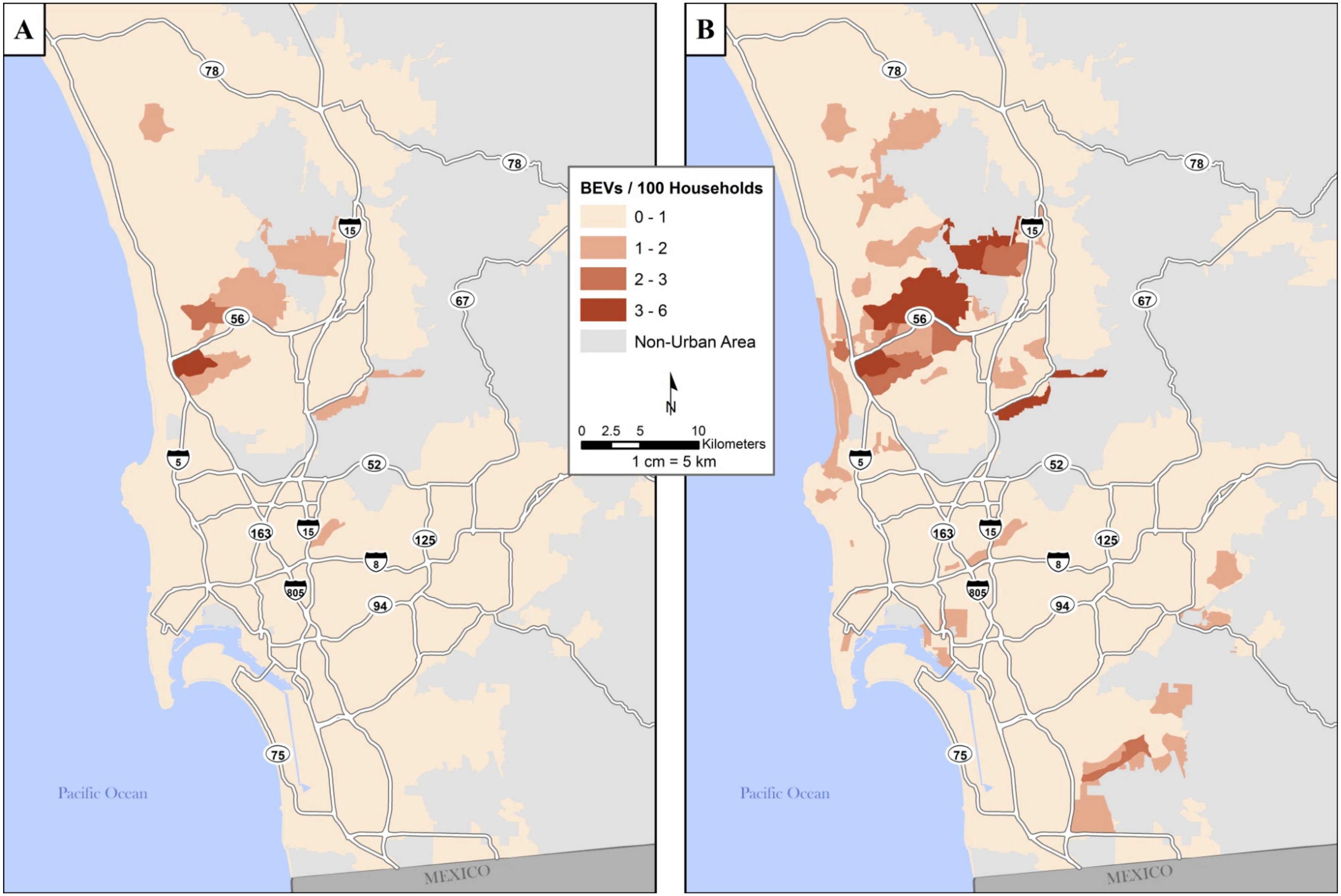

FIGURE 7 Maps of base case (A) and range equalization scenario (B) for the major urban areas of SANDAG. Darker red areas indicate more BEV ownership per household.

CONCLUSIONS

We have constructed and demonstrated a novel GIS tool for scenario analysis of PEV ownership that is soon going to be available to planners, policy makers, consultants, utility companies and others who are interested in forecasting the home location of PEV owners. Currently the tool includes data from California's PEV market but can be extended to other regions by processing the same publicly available data. Although there is still considerable research needed to improve the accuracy of the PEV buyers GIS tool, this analysis has demonstrated that with reduced prices of PEVs we expect to see slightly more geographically dispersed ownership in both SANDAG and SACOG regions. However, with added range to BEVs we expect new BEV buyers to generally be located in areas which currently have high BEV ownership in the same two regions. We believe that the current tool can be improved by incorporating new data on factors important for PEV adoption such as HOV lane availability and charging availability, together with methodological improvements such as multi-level models to account for clustering of data. Furthermore, to maximize the benefit of a flexible planning tool we need continued data collection on new car buyers and PEV buyers through web-based surveys to account for the dynamic nature of the PEV market.

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