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Electric Vehicle Infrastructure Plan in Illinois

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16. Abstract

We study the allocation of dynamic electric vehicle charging investments from the policymaker's perspective, which aims to meet statewide emission-reduction targets for the Illinois passenger vehicle sector. We determine statewide charging deployment trajectories over a 30-year planning horizon and estimate their emission reduction. Electric vehicle demand functions model the electrified vehicle market growth and capture network externalities and spatial heterogeneity. Our analysis indicates that most chargers need to be deployed in the first 10 to 15 years of the transition to allow benefits to accrue for electric vehicle drivers, availability of home charging influences consumers' choice and drivers' electrified travel distance, charging stations should be prioritized for frequent long-distance drivers, and spatial effects are crucial in accurately capturing the demand for electric vehicles in Illinois. We also develop a multi-criteria suitability map to site charging stations for electric vehicles based on economic, societal, and environmental justice indicators. We identify census tracts that should be prioritized during Illinois' statewide deployment of charging infrastructure along with interstates and major highways that traverse them. Major interstates and highways I-90, I-80, I-55, and I-57 are identified as having high siting suitability scores for charging stations. Last, a novel location model was developed for equitable electric vehicle charging infrastructure placement in the Illinois interstate and major highway network. Two objectives were set to reduce detours and improve the ability to complete long-distance trips for low-income electric vehicle travelers and multi-unit dwelling residents. Our analysis indicates that if the system's efficiency is the only consideration, low-income/multi-unit housing resident travelers are most likely to fail to complete their trips, while an equitable charging siting could mitigate this issue.

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EXECUTIVE SUMMARY

The objective of this research was to provide a comprehensive plan for charging infrastructure deployment that supports the adoption and use of electric vehicles in Illinois based on the latest historical data, research, and practice. The research was guided by forming a statewide electric vehicle infrastructure committee that identified priorities for sustainable passenger vehicle electrification pathways and provided feedback on research outcomes. The models and data analytics tools developed enabled the Illinois Department of Transportation and the State of Illinois to identify timelines for electric vehicle charging infrastructure deployment to support electric vehicle travel across Illinois interstates and highways. The questions that guided this research are listed below:

- What is the number and timeline for deploying fast charging stations across clustered regions in Illinois to meet carbon dioxide reduction goals while transitioning away from fossil-fueled vehicles and facilitating the adoption and use of passenger electric vehicles?
- Which are the most suitable census tracts for charging infrastructure across the State of Illinois when accounting for a diverse set of economic, societal, and environmental justice criteria aligned with enabling greater benefits from passenger vehicle electrification in disadvantaged communities?
- Which charging hubs are critical to serving low-income households and multi-unit dwelling residents who conduct intercity trips along the Illinois interstates' network?

The goal of enabling the adoption and travel of one million electric vehicles by 2030 on Illinois roads is achieved when charging infrastructure investments increase gradually, following an S-shaped curve and reaching a maximum level of coverage during the first 10 to 15 years of the transition horizon from fossil-fueled to electric vehicles. The maximum number of charging stations depends on the emission-reduction goal set; the more ambitious the environmental goal, the greater the number of charging stations that should be deployed. For example, consider a goal of reducing carbon dioxide emissions from the operation of light-duty vehicles (based on the transition from fossil-fueled and electric vehicle mix) by 3.95 10^7 metric tons of CO_2. The deployment of electric vehicle charging stations should be greater than 2,400 public fast charging station locations and be built in 10 to 15 years (initial year of analysis 2020) to enable electric vehicle users and adopters to accrue greater benefits from electrifying their vehicle miles traveled. Market considerations like the availability of home charging influence consumers' choices and drivers' electrified travel distance, charging stations should be prioritized for frequent long-distance drivers, and spatial effects are crucial in accurately capturing the demand for electric vehicles in Illinois.

A multi-criteria suitability map for siting electric vehicle charging stations is proposed using the analytical hierarchy process. The mapping is based on economic, societal, and environmental justice indicators. We identify census tracts that should be prioritized during Illinois' statewide deployment of charging infrastructure along with interstates and major highways that traverse them. Major interstates and highways I-90, I-80, I-55, and I-57 are identified as having high siting suitability scores for charging stations and could be prioritized under the assumption of equally weighting the diverse set of siting criteria.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION

ELECTRIC VEHICLE CHARGING INFRASTRUCTURE PLANNING

Transportation is one of the primary energy consumers in the United States and the only sector depending almost exclusively on petroleum (U.S. Energy Information Administration, 2021a). The entry of electric vehicles into the transportation market promises diversification of this sector's fuel sources. Plug-in electric vehicles have zero tailpipe emissions due to operating solely on electricity. Hence, substituting conventional gasoline vehicles with electric ones can reduce carbon dioxide and greenhouse gas emissions (depending on the source of electricity used for charging) and gasoline consumption for the transportation sector (Rietmann et al., 2020). The U.S. Energy Information Administration's (2021b) outlook of net electricity generation by fuel type shows that the proportion of renewable energy is estimated to increase over time, which implies that the emissions associated with electric vehicle charging will also decrease. However, due to the higher purchase price of electric vehicles than comparable conventional vehicle products, lack of dense charging station infrastructure, and induced range anxiety, consumers have little intention to purchase electric vehicles (Canepa et al., 2019; Carley et al., 2013). Countries with higher electric vehicle penetration rates implement various policies to stimulate demand and accelerate environmental gains from their use. Such policies and incentives include rebates, tax credits, charging station deployment, etc. (Zhou et al., 2015). Monetary incentives, like rebates, discount an electric vehicle's capital cost, and investments in a dense charging network result in driver savings that are accrued from lower operating costs. Electric vehicles are promoted by policymakers through tax credits and other incentives partly because of their potential to reduce tailpipe emissions (Kontou et al., 2017) and gradually improve regional air quality (Brady & O'Mahony, 2011).

To design an effective incentives and infrastructure investment allocation program, we need to understand how different policies might influence electric vehicle adoption and which programs play a crucial role in accelerating the electrification transition. Hardman et al. (2017) find that 91% of pertinent studies indicate that electric vehicle rebates play a significant role in increasing electric vehicle adoption. Hardman et al. (2017) and Narassimhan and Johnson (2018) also point out that rebates are usually more effective in driving ownership decisions than tax credits. Charging availability is another important electric vehicle demand determinant. Hardman et al. (2018) conclude that access to electric vehicle charging at home, work, or public locations increases consumers' willingness to purchase electric vehicles. Kontou et al. (2019) show the importance of charging availability on electric vehicle daily trip feasibility and coverage. Recognizing that rebates and charging infrastructure provision promote the electrification of personal mobility, we provide a framework to determine priorities for incentives investments that mathematically captures electric vehicle market penetration. Monetary incentives, such as rebates, discount significant capital costs associated with purchasing electric vehicles in the introductory years of this new technology when economies of scale are not yet achieved (Helveston et al., 2015). At the same time, investing in public charging infrastructure placement contributes to reducing the operational costs of electric vehicle drivers and decreases environmental externalities associated with conducting daily trips by electrifying more miles.

Equity in the siting of electric vehicle charging infrastructure is multifaceted and increasingly valued by public agencies. Equity could be aligned with environmental externalities reduction and justice objectives. Distributive equity assessment studies reveal that housing type and income level significantly impact home charging installation and availability; communities with fewer resources have little intention to adopt clean energy technologies. In addition, high-income population groups are usually able to charge their electric vehicles in privately owned parking, which might not be an option for lower-income renters and apartment complex residents. Therefore, public charging infrastructure should not only be prioritized in high-income communities, whose members tend to be early electric vehicle adopters, but also in low-income areas where residents need reliable access to charging infrastructure and incentives to adopt zero-tailpipe emission technology. To achieve equitable electric vehicle adoption, public charging infrastructure investments should be allocated in communities designated as disadvantaged. Few studies use data-driven models to address equity, even though distributive equity is elevated as the primary scope of local, regional, and federal decision-makers. We, thus, develop a data-driven charging infrastructure suitability map through an analytical hierarchy process leveraging economic, societal, and environmental justice considerations, with a focus on prioritizing census tracks for charging infrastructure placement in the state of Illinois.

OBJECTIVES

The main objective of this research project is to assess public charging infrastructure requirements over time and space to facilitate electrified intercity travel through major interstate highways in Illinois. We develop and extend state-of-the-art literature approaches to achieve the following goals:

- Estimate electric vehicle adoption over a 30-year planning horizon to achieve greenhouse gas reduction goals.
- Determine electric vehicle charging infrastructure investment allocation and deployment across the state of Illinois to support projected levels of passenger vehicle electrification.
- Assess the environmental benefits and operational costs associated with passenger vehicle electrification.
- Coordinate a statewide electric vehicle steering committee that identifies priorities for sustainable electrification pathways.

The analysis enables decision-makers to have a blueprint that quantifies electric vehicle charging deployment pathways and the environmental benefits of the transition from fossil-fueled to electrified mobility.

We study the problem of dynamic electric vehicle infrastructure investment allocation from the perspective of public decision-makers, who aim to meet statewide emission-reduction targets for Illinois' light-duty vehicle sector and provide policy recommendations. Our research contributes to the transportation planning and policy literature in the following ways: (i) we introduce a new and dynamic electric vehicle incentive design problem with emission-reduction targets and demand functions that capture network externalities; (ii) we present a simulated annealing algorithm to solve the highly nonlinear problem; and (iii) we provide a plethora of policy and planning recommendations from a real-world case study focusing on the State of Illinois. By evaluating diverse electric vehicle investment portfolio outcomes, we aim to comprehensively describe the decision-making mechanism and provide suggestions for governmental policies that incentivize electric vehicle growth and transportation decarbonization.

We also develop a suitability map to site charging stations for electric vehicles based on economic, societal, and environmental justice indicators. Using the analytic hierarchy process (AHP), commonly applied in multi-criteria decision-making for geographic information system applications, we identify Illinois census tracts and regions that could be prioritized for the statewide deployment of electric vehicle charging stations in Illinois.

Coordinating a statewide electric vehicle steering committee identifies priorities for sustainable electrification pathways (Kócs, 2021). A series of meetings were held involving academics, public agencies, private stakeholders, and nongovernmental organizations, while research and state-of-practice webinars promoted discussion on the following topics: (i) electric vehicle infrastructure and technology needs, (ii) utility service coordination, and (iii) environmental justice and equity considerations. A summary list of the events and committee members' agencies involved in these discussions is highlighted in Table 1.

Table 1. Electric Vehicle Steering Committee Participants and Events Overview

Committee	Stakeholders	Session Types
Electric vehicle steering committee	a) Illinois Department of Transportation b) Stakeholders from Illinois academic institutions (UIUC, UIC, Northwestern University, etc.) c) Automakers d) Charging infrastructure providers e) Utility service providers f) Nongovernmental organizations g) Environmental protection agencies h) National laboratory researchers (e.g., Argonne National Laboratory) i) Equity and environmental justice groups	Three webinars providing summaries of research progress. Q&A sessions and feedback during the 1.5 hours of fast-paced meetings to receive feedback on: (i) criteria for charging infrastructure planning and placement in highways, and (ii) relative weighting of the importance of a diverse set of criteria for charging infrastructure placement.

CHAPTER 2: DYNAMIC CHARGING INFRASTRUCTURE PLANNING

Light-duty electric vehicle cumulative sales reached 1.8 million during the final quarter of 2020 in the United States. Electric vehicles have zero tailpipe emissions and substantially lower life-cycle emissions compared to conventional ones, particularly when charging with low carbon intensity electricity (Tessum et al., 2014). Electrification of light-duty and portions of medium- and heavy-duty transportation is a necessary step to put the United States on the path to achieve goals to reduce carbon dioxide and other pollutants over the next 30 years (National Academy of Sciences, Engineering, and Medicine, 2021). In addition, electric vehicles benefit drivers by significantly decreasing their operational costs and energy consumption (Kontou et al., 2015, 2017). Due to such advantages, transportation electrification can be a major contributor toward reaching national energy security goals (Kelly et al., 2012; Ogden et al., 2004). However, existing barriers to widespread electric vehicle adoption include short driving ranges of plug-in vehicles that induce range anxiety (i.e., the fear of exhausting the driving range before reaching a destination or charging infrastructure) and a sparse network of charging infrastructure inadequate to fully support daily short- and long-distance travel needs.

To promote and densify the interstate charging infrastructure network, the Federal Highway Administration (FHWA, 2021) designates interstate segments as “electric vehicle charging corridor ready” when the sited public direct-current (DC) fast charging stations are separated by less than 50 miles and located no greater than 5 miles off the highway. Fast charging stations are essential to the conduct of long-distance habitual and nonhabitual trips and will be the backbone of commercial fleets’ electrification, which will rely primarily on depot and highway charging outlet deployment (Davis & Figliozzi, 2013; Lee et al., 2013).

In September 2022, there are 50,994 electric vehicle registrations in Illinois and more than 900 charging station locations of all levels available to support electrified transportation operations. Figure 1 (left) presents the 2020 status of passenger vehicle electrification in Illinois, portraying the ratio of electric vehicles to total registrations per county. The share of electric vehicles in 2020 was 0.36% compared to 0.25% during 2019. Cook, DuPage and Lake counties lead the electric vehicle transition, while Chicago suburb counties as well as McLean, Champaign, St. Clair, and Madison counties have growing electric vehicle numbers. Figure 1 (right) portrays the locations of charging stations and the number of charging outlets in 2020. According to the latest 2022 U.S. Department of Energy data (2022c), there are 642 DC fast charging station ports in Illinois.

Through the Climate and Equitable Jobs Act, the State of Illinois has set the goal of increasing electric vehicle registrations to one million by 2030. Strategically planning public charging infrastructure deployment that can facilitate the movement of passenger electric vehicles is necessary to meet these ambitious electric vehicle adoption targets.

In the existing literature, state-of-the-art methods for electric vehicle charging infrastructure investment allocation, siting, and value include macroscopic models and network facility location mathematical frameworks (e.g., Greene et al., 2020; He et al., 2013; Nie et al., 2016; Shahraki et al., 2015). However, there is limited literature studying the optimal rollout of charging station infrastructure (Kontou et al., 2017); such a roadmap is necessary for meeting passenger travel demand and allocating appropriate investments. Our research amends research gaps by developing a macroscopic optimization framework to determine the number of electric vehicle chargers to meet carbon dioxide emission-reduction targets over a 30-year planning horizon (i.e., 2020–2050).

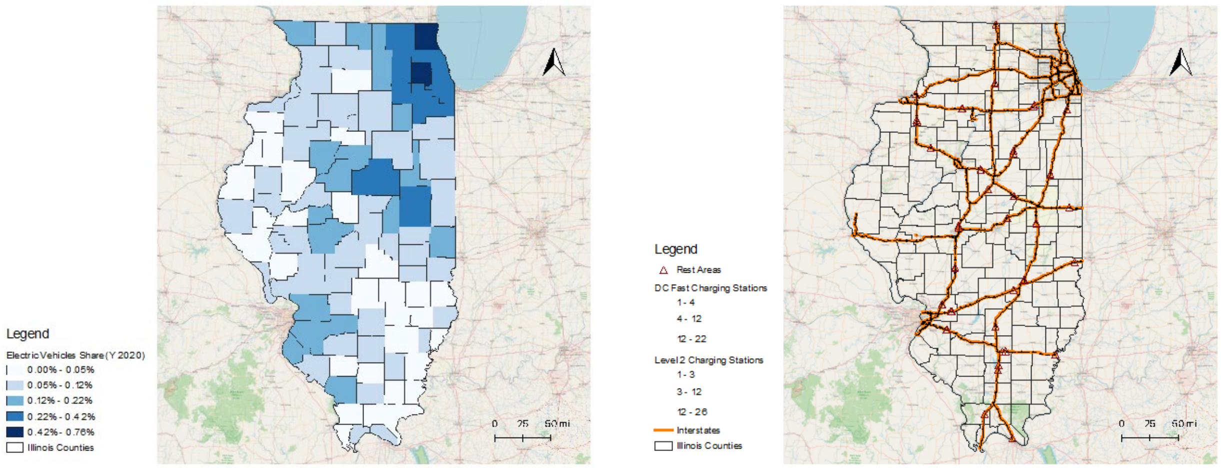


Figure 1. Graph. Electric vehicle registration share and charging infrastructure in Illinois (in 2020).

METHODOLOGY

Our model's objective is to conserve investment resources for the deployment of public charging infrastructure (i.e., minimizing deployment costs) while meeting policymaking goals related to achieving passenger transportation emission-reduction targets.

We assume that the planning horizon for the decision-maker is $t \in T = \{1,2,\ldots,Y\}$. During this period, investments will be allocated annually to deploy charging infrastructure, which will impact electric vehicle adoption and electrify more miles on the Illinois network. Variables x_k^t denote the vehicle stock type $k \in \{\, g$: gasoline, e: electric$\}$ by year t. The consumers' demand each year t, q_k^t, is a function of the rebate r^t provided at year t to the adopters of electric vehicles and the charging infrastructure deployed at year t, u^t. All vehicles have an average lifespan of l years and are replaced with new vehicles after reaching that year. The existing vehicle stock x_k^t is a discrete-time system and is updated by the number of vehicles of each technology k sold each t and $t-l$, as shown in Figure 2.

$$x_k^{t+1} = x_k^t + q_k^t(r^t, u^t) - q_k^{t-l}$$

Figure 2. Equation. Discrete time system of vehicle stock.

The state transition function in Figure 3 captures the dynamic nature of the charging infrastructure placement on the transportation network.

$$v^{t+1} = v^t + u^t$$

Figure 3. Equation. State transition function of electric vehicle charging infrastructure.

Note that v^t is the number of chargers in place up to year t and u^t is the number of chargers installed in year t. The decision variable in this case is u^t, which has an upper bound of $\bar{v}$. This constraint ensures realistic density of the charging network.

Demand q_k^t for the vehicle technologies is a control variable. A logistic function denotes the sales of each vehicle technology k in t, and the demand is a function of utility U_k^t. The perceived utility of an average consumer is the sum of the indirect utility and an error component, as $U_k^t(r^t, u^t) = V_k^t(r^t, u^t) + \epsilon_k^t$ (Ben-Akiva & Lerman, 1985). We assume that all consumers are utility maximizers, aligned with literature on electric vehicle adoption studies (Javid & Nejat, 2017; Nie et al., 2016). Their logistic demand functions are shown in Figures 4 and 5.

$$q_e^t(r^t, u^t) = \left(m^t + q_e^{t-l} + q_g^{t-l}\right) \cdot \frac{e^{V_e^t(r^t, u^t)}}{e^{V_g^t} + e^{V_e^t(r^t, u^t)}}$$

Figure 4. Equation. Electric vehicle logistic demand function.

$$q_g^t(r^t, u^t) = \left(m^t + q_e^{t-l} + q_g^{t-l}\right) \cdot \frac{e^{V_g^t(r^t, u^t)}}{e^{V_g^t} + e^{V_e^t(r^t, u^t)}}$$

Figure 5. Equation. Gasoline vehicle logistic demand function.

The incremental market size of new vehicle registrations is m^t, and q_e^{t-l} and q_g^{t-l} are the number of vehicles purchased l years ago that need to be replaced due to vehicle turnover. The probability of a consumer choosing an electric or a gasoline vehicle is $\frac{e^{V_e^t(r^t, u^t)}}{e^{V_g^t} + e^{V_e^t(r^t, u^t)}}$ and $\frac{e^{V_g^t(r^t, u^t)}}{e^{V_g^t} + e^{V_e^t(r^t, u^t)}}$, respectively.

Total cost, including capital and operational costs, and network externalities enter the utility functions of electric and gasoline vehicles, as in Figure 6 and Figure 7, respectively. The network externalities play an important role in explaining a portion of the utility of innovative products by describing purchasing choice learning-by-doing effects and the impact of information spread. Information spreading by existing adopters is a factor that is accounted for in alternative-fuel vehicle-choice modeling studies: a portion of the electric vehicle market penetration is assumed to be explained by the positive impact of "neighborhood effects" (Eppstein et al., 2011). Neighborhood or word-of-mouth effects can drive electric vehicle social exposure (Shepherd et al., 2012). The electric vehicle indirect utility function could capture the impact of information spreading under the assumption that the probability of choosing this vehicle type is more likely to increase as the number of vehicles adopted increases in a certain region. A logarithmic function is used to capture such effects, penalizing low electric vehicle adoption or low charging infrastructure availability: when the electric vehicle stock or charging infrastructure approaches zero, the function goes to $-\infty$; as their levels increase, it becomes zero (Cohen et al., 2016).

$$V_e^t(r^t, u^t) = \beta_1 \cdot \left(B_e^t(\mathrm{R}) - r^t + O_e^t(u^t)\right) + \beta_2 \cdot ln\left(\frac{x_e^t}{x_e^t + x_g^t}\right) + \beta_3 \cdot ln\left(\frac{v^t}{\bar{v}}\right) + \beta_4 + \omega^t$$

Figure 6. Equation. Electric vehicle utility function.

$$V_g^t = \beta_1 \cdot \left(B_g^t + O_g^t\right) + \omega^t$$

Figure 7. Equation. Gasoline vehicle utility function.

Note that $O_e^t(u^t)$ and O_g^t are the annual vehicle operating costs for the corresponding type of vehicles, and ω^t is the random demand. Electric vehicles with different driving ranges, R, correspond to different retail prices.

The logit model captures the consumers' choice and behavior, which accounts for features like vehicle capital cost, operational cost, and network externalities. The utility shows consumers' attitudes and how they consider purchasing different vehicle technologies. Their decisions are based on the utility they perceive. Because we are planning for vehicle electrification at a macroscopic level, we hypothesize that charging infrastructure will be optimally located and provide adequate service, but we do not track network-level impacts of such infrastructure that might be associated with exact siting locations and their waiting times. Operational costs for each vehicle type k are presented in Figures 8 and 9.

$$O_e^t(u^t) = (d_1^t + d_2^t) \cdot \frac{P_e^t}{n_e^t} + d_3^t \cdot \left(\left(\frac{P_g^t}{n_g^t}\right) + f\right)$$

Figure 8. Equation. Electric vehicle operating cost function.

$$O_g^t = d_t^t \cdot \frac{P_g^t}{n_g^t}$$

Figure 9. Equation. Gasoline vehicle operating cost function.

where d_1^t is the average distance traveled on electricity depleting the battery charged at home, d_2^t is the average distance traveled on electricity depleting the battery charged at public charging stations, d_3^t is the average distance traveled with a backup gasoline vehicle, while d_t^t denotes the average annual miles traveled as the sum of d_1^t, d_2^t, and d_3^t in year t. P_e^t is the cost of electricity for charging, n_e^t is the onboard electricity efficiency, P_g^t is the gasoline cost, n_g^t is the gasoline efficiency, and f is the fixed cost to own or rent a backup gasoline vehicle. Note that d_t^t, d_1^t, d_2^t, and d_3^t are calculated as $d_t^t = \int_0^\infty p^t(x)xdx \cdot 312$, while $d_1^t = \gamma \cdot \int_0^R p^t(x)xdx \cdot 312$ and $\left(d_t^t - d_1^t - \left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t\right) \leq M(1-y^t)$ as well as $\left(d_t^t - d_1^t - \left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t\right) \geq -My^t$ hold. Electrified distance due to access to public charging stations is calculated from $d_2^t = (d_t^t - d_1^t) \cdot y^t + \left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t \cdot\ (1-y^t)$ and the remaining distance covered by a backup vehicle is $d_3^t = d_t^t - d_1^t - d_2^t$. The probability density function of the daily vehicle miles traveled (VMT) in year t is $p^t(x)$, and γ is the percentage of availability of home charging for electric vehicle drivers.

The average daily VMT is calculated as the integration from 0 to ∞, and the average distance that can be traveled with electricity charged at home is calculated as the integration from 0 to the vehicle driving range boundary denoted by R (Lin, 2014). The probability density function is the distribution of the daily vehicle miles traveled. To calculate the annual distance, the daily travel distance is multiplied by 312, as vehicles are assumed to be used on average 312 days per year (Melaina et al., 2016). Based on a Weibull distribution of daily travel, Greene et al. (2020) find that a logarithmic function of charging availability can describe well the proportion of annual miles traveled that can be electrified. Thus, the product $\left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t$ calculates the annual enabled electrified miles that could be traveled with the corresponding number of charging stations v^t. Parameters α_0^t and α_1^t are estimated based on the fitted logarithmic function, according to the daily VMT distribution and the vehicle's average driving range. If the electric vehicle's driving range is long enough and the number of charging stations is adequate (i.e., the enabled electrified distance by the number of public charging stations is long enough to cover all travel distances when the driver cannot charge at home), drivers would not need backup vehicles to complete nonhabitual trips. Thus, binary variables y^t and a big M are introduced. If the potential enabled electrified miles are greater than all travel distances covered without charging at home, y^t will become 1 due to constraints (11a) and (11b), otherwise y^t will be 0. When y^t equals 1, d_2^t will be equal to $d_t^t - d_1^t$ instead of $\left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t$, and d_3^t will be zero.

Figures 10 and 11 represent the carbon emissions of each technology that have a similar form as the operational costs.

$$E_{\mathrm{e}}^t(v^t) = (d_1^t + d_2^t) \cdot C_e^t + d_3^t \cdot C_g^t$$

Figure 10. Equation. Carbon dioxide emissions function related to electric vehicle operation.

$$E_{\mathrm{g}}^t = d_t^t \cdot C_g^t$$

Figure 11. Equation. Carbon dioxide emissions function related to gasoline vehicle operation.

C_e^t and C_g^t are carbon dioxide emissions in grams per mile for each vehicle technology. Although electric vehicles have zero tailpipe emissions, there are carbon emissions from the electricity generation that is consumed while charging. Thus, to calculate C_e^t, we convert the electricity generation carbon emission rate (gCO_2/kWh) into gCO_2/mile with the electric vehicle efficiency. Table 2 summarizes the mathematical notations used in the optimization model.

Table 2. Summary of Mathematical Notation

$t \in T$	The set of years that policymakers allocate incentives
$k \in \{g, e\}$	g: conventional vehicle, e: electric vehicle
r^t	Rebate offered per electric vehicle in year t
q_k^t	Consumers demand of vehicle type k in year t
u^t	Number of charging infrastructures installed in year t
τ	Charging infrastructure's cost
δ	Discount factor
x_k^t	Vehicle stock of vehicle type k in year t
l	Vehicle's life expectance
v^t	Number of charging infrastructures in place up to year t
m^t	The incremental market size of new vehicle registrations in year t
V_k^t	Utility of vehicle type k in year t
B_k^t	Purchase price of vehicle type k in year t
O_k^t	The operational cost of vehicle type k in year t
d_1^t	Average distance traveled on electricity charged at home in year t
d_2^t	Average distance traveled on electricity charged at public chargers in year t
d_3^t	Average distance traveled with a backup vehicle in year t
d_t^t	Average annual miles traveled in year t
P_e^t	Cost (\$/kWh) of electricity for charging the vehicle in year t
P_g^t	Gasoline cost (\$/gal) in year t
n_e^t	On-board electricity efficiency (mi/kWh) in year t
n_g^t	Gasoline efficiency (mi/gal) in year t
f	Fixed cost (\$/mi) for the backup gasoline vehicle
γ	The ratio of people having access to home charging
R	Electric vehicle driving range (mi)
$p^t(x)$	The probability density function of daily miles driven in year t
α_0^t, α_1^t	Parameters for the annual enabled electrified miles in year t
y^t	Binary variable in year t to ensure the annual enabled electrified miles do not exceed the total annual driving distance.
E_k^t	Carbon dioxide emissions (gCO_2) of vehicle type k in year t
C_e^t	Carbon dioxide emission (gCO_2/mi) rate of electricity generation in year t
C_g^t	Carbon dioxide emission (gCO_2/mi) rate of gasoline vehicle in year t
$\bar{r}$	Upper bound of rebate
$\bar{v}$	Upper bound of the number of charging infrastructures in place

The complete nonlinear mixed-integer programming framework proposed for modeling the dynamic charging infrastructure investment problem is presented below.

$$min\ z = \sum\nolimits_{t \in T} (r^t \cdot q_e^t(r^t, u^t) + \tau \cdot u^t)/(1+\delta)^t$$

Figure 12. Equation. Objective function.

subject to

$$x_k^{t+1} = x_k^t + q_k^t(r^t, v^t) - q_k^{t-l}, \forall k \in \{e, g\}, \forall t \in T$$

Figure 13. Equation. Discrete time vehicle stock constraints.

$$v^{t+1} = v^t + u^t, \forall t \in T$$

Figure 14. Equation. Discrete time charging infrastructure constraints.

$$q_e^t(r^t, u^t) = \left(m^t + q_e^{t-l} + q_g^{t-l}\right) \cdot \frac{e^{V_e^t(r^t, u^t)}}{e^{V_g^t} + e^{V_e^t(r^t, u^t)}}\ , \forall t \in T$$

Figure 15. Equation. Electric vehicle demand constraints.

$$q_g^t(r^t, u^t) = \left(m^t + q_e^{t-l} + q_g^{t-l}\right) \cdot \frac{e^{V_g^t(r^t, u^t)}}{e^{V_g^t} + e^{V_e^t(r^t, u^t)}}\ , \forall t \in T$$

Figure 16. Equation. Gasoline vehicle demand constraints.

$$V_e^t(r^t, u^t) = \beta_1 \cdot \left(B_e^t(\mathrm{R}) - r^t + O_e^t(u^t)\right) + \beta_2 \cdot ln\left(\frac{x_e^t}{x_e^t + x_g^t}\right) + \beta_3 \cdot ln\left(\frac{v^t}{\bar{v}}\right) + \beta_4 + \omega^t, \forall t \in T$$

Figure 17. Equation. Electric vehicle utility constraints.

$$V_g^t = \beta_1 \cdot \left(B_g^t + O_g^t\right) + \omega^t, \forall t \in T$$

Figure 18. Equation. Gasoline vehicle utility constraints.

$$O_e^t(u^t) = (d_1^t + d_2^t) \cdot \frac{P_e^t}{n_e^t} + d_3^t \cdot \left(\left(\frac{P_g^t}{n_g^t}\right) + f\right), \forall t \in T$$

Figure 19. Equation. Operating cost of electric vehicle constraints.

$$O_g^t = d_t^t \cdot \frac{P_g^t}{n_g^t}, \forall t \in T$$

Figure 20. Equation. Operating cost of gasoline vehicle constraints.

$$d_t^t = \int_0^\infty p^t(x) x dx \cdot 312, \forall t \in T$$

Figure 21. Equation. Operating cost of electric vehicle constraints.

$$d_1^t = \gamma \cdot \int_0^R p^t(x) x dx \cdot 312, \forall t \in T$$

$$\left(d_t^t - d_1^t - \left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t\right) \leq M(1 - y^t), \forall t \in T$$

$$\left(d_t^t - d_1^t - \left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t\right) \geq -My^t, \forall t \in T$$

$$d_2^t = (d_t^t - d_1^t) \cdot y^t + \left(\alpha_0^t + \alpha_1^t ln\left(\frac{v^t}{\bar{v}}\right)\right) \cdot d_t^t \cdot \ (1 - y^t), \forall t \in T$$

$$d_3^t = d_t^t - d_1^t - d_2^t, \forall t \in T$$

Figure 22. Equation. Distance constraints.

$$E_{\mathrm{e}}^t(v^t) = (d_1^t + d_2^t) \cdot C_e^t + d_3^t \cdot C_g^t, \forall t \in T$$

Figure 23. Equation. Electric vehicle emission constraints.

$$E_{\mathrm{g}}^t = d_t^t \cdot C_g^t, \forall t \in T$$

Figure 24. Equation. Gasoline vehicle emission constraints.

$$\sum_{t \in T} x_e^t \cdot \left(E_g^t - E_e^t(v^t)\right) \geq target$$

Figure 25. Equation. Exogenous emission-reduction target constraint.

$$x_k^t, v^t \geq 0, \forall k \in \{e, g\}, \forall t \in T$$

$$v^1 = \zeta, u^t \geq 0, v^t \leq \bar{v}, \forall t \in T$$

$$x_k^1 = \theta_k, \forall k \in \{e, g\}$$

$$y^t \in \{0,1\}, \forall t \in T$$

Figure 26. Equation. Decision variable domain constraints.

The decision variable of this model is the number of chargers built each year, i.e., u^t. In Figure 12, we present the objective function, which is the government's cumulative expenditure for the electric vehicle incentives allocation over the years. Our goal is to minimize the total expenditure. Note that τ is the cost of charging infrastructure, and δ is the discount factor. The constraint in Figure 25 enforces the target of emission-reduction savings due to electric vehicles substituting gasoline vehicles over a set planning horizon. A variety of potential incentive investment paths can achieve the cumulative emission-reduction target, and we aim to find and analyze the incentive portfolio with the least expenditure among these pathways. Figure 26 shows non-negativity and variable restriction constraints, setting feasibility intervals for the decision variables.

The optimization framework is solved using the simulated annealing algorithm (Wu & Kontou, 2022).

ILLINOIS CASE STUDY

The developed optimization framework can be applied to different spatial scales. We focus on Illinois as the area of our case study. According to the Climate and Equitable Jobs Act (CEJA, SB2408), Illinois plans to provide a $4,000 rebate starting July 1, 2022, $2,000 starting July 1, 2026, and $1,000 starting July 1, 2028, for the purchase of an electric vehicle and aims to meet the adoption goal of 1,000,000 electric vehicles by 2030 (*Public Act 102-0662*, 2021). We aim to determine the number of charging stations needed to induce adoption levels aligned with CEJA goals.

Data

Vehicle adoption data and parameter values need to be collected and analyzed to accurately estimate the utility function coefficients of a higher-resolution vehicle ownership model and capture consumers' behavior. National-level data like vehicle range, vehicle lifespan, vehicle efficiency, etc. can be adopted directly to a state-level analysis. However, different values for the data of the number of vehicles, fuel prices, emission rates, and daily VMT need to be included in the study to realistically represent the Illinois vehicle market. Table 3 presents the pertinent Illinois scalar parameters and Table 4 the dynamic parameters.

Table 3. Input Scalar Parameters of the Illinois Vehicle Market

Constant Parameters	Unit	Value
Vehicle range, R	mi	150
Access to home charging, γ	–	84%
Vehicle's lifespan, l	year	12
Chargers upper bound, $\bar{v}$	–	4,113
No. of chargers in the first year, ζ	–	637
No. of electric vehicles in the first year, θ_e	–	26,153
No. of gas vehicles in the first year, θ_g	–	6,997,674
Cost to build a charging station, τ	$	150,000
Discount factor, δ	–	0.1

Due to a lack of Illinois or nationwide data, the home charging accessibility percentage is based on survey data from California (Tal et al., 2018). The upper bound of the number of charging stations is set to the number of existing gas stations to ensure a realistic density of the charging network. Gasoline station data for Illinois are collected from the Office of the Illinois State Fire Marshal (2022). Historical data of electric vehicle registration in Illinois are from the Office of the Illinois Secretary of State (2022).

Table 4. Input Parameters of the Illinois Vehicle Market

Dynamic Parameters	Unit	Y 2021	Y 2030	Y 2040	Y 2050
Incremental market size, m^t	–	0	0	0	0
Electric vehicle retail price, B_e^t	$	25,347	28,180	31,328	34,476
Gas vehicle retail price, B_g^t	$	30,101	29,042	27,865	26,689
Electricity cost, P_e^t	$/kWh	0.105	0.110	0.108	0.094
Electricity efficiency, n_e^t	mi/kWh	2.924	2.932	2.931	2.931
Gasoline cost, P_g^t	$/gal	2.326	2.723	3.038	3.587
Gasoline efficiency, n_g^t	mi/gal	48.908	50.860	50.253	49.563
Emission rate of electricity, C_e^t	gCO_2/mi	72.725	61.670	67.690	85.976
Emission rate of gasoline, C_g^t	gCO_2/mi	177.199	153.542	127.256	100.970
Mean of daily VMT	mi	72.725	61.670	67.690	85.976
Median of daily VMT	mi	72.725	61.670	67.690	85.976

After using linear regression to track the incremental vehicle market increase over time, R square is found close to 0. Thus, we assume there is no growth in vehicle registrations over time. We fit a linear function using historical data of the most popular vehicle of each fuel technology to predict their future retail price trend. For the electric vehicle, we use Nissan Leaf, and for the gasoline vehicle Toyota Camry. Data on gasoline fuel and electricity pricing trends are collected directly from the outlook data of the U.S. Energy Information Administration (2018). We use the mid-case outlook data of the CO_2 from electricity generation [kg/MWh] (equivalent to gCO_2/kWh) for the State of Illinois (National Renewable Energy Laboratory, 2020). We then convert the emission rate of the electricity generation into gCO_2/mi, by using the electricity efficiency data. We select the Illinois trip data from the National Household Travel Survey to predict the mean and median daily VMT (U.S. Department of Transportation, 2021).

Model Modification

The Climate and Equitable Jobs Act (CEJA, SB2408) (*Public Act 102-0662*, 2021) specifically sets the Illinois plan for the electric vehicle rebates allocation. We consider rebates given as parameters. We fit the logit demand model with the state-level data to estimate the coefficients of each variable and run the simulation. However, due to the huge difference in the magnitude of historical data on the number of electric vehicles and the number of gasoline vehicles, we get a β_2 (1304.19) much larger than β_1 (-0.000259) and β_4 (-4.512) in the equation of Figure 17. In later years, when the number of electric vehicles becomes greater, $\beta_2 \cdot \left(\frac{x_e^t}{x_e^t+x_g^t}\right)$ and V_e^t becomes too large, the value of $e^{V_e^t(r^t,u^t)}$ approaches infinity. To capture spatial heterogeneity and dependence and other intangible factors such as views on new technologies that may vary continuously in space, we consider spatial effects, which could be significant in capturing the relative tendency of people to choose electric vehicles in different regions (Florax & Rey, 1995).

Considering the accuracy and computation time for the solution by our optimization model and heuristic algorithm, we divide the state of Illinois into five clusters based on current electric vehicle adoption trends. The equation in Figure 17 is substituted by the equation in Figure 27, where y_1, y_2, y_3, and y_4 is set to one for cluster 1, cluster 2, cluster 3, and cluster 4, respectively, and zero otherwise.

$$V_e^t(r^t,u^t) = \beta_1 \cdot \left(B_e^t(\mathrm{R}) - r^t + O_e^t(u^t)\right) + \beta_4 + \omega^t + \beta_5 y_1 + \beta_6 y_2 + \beta_7 y_3 + \beta_8 y_4$$

Figure 27. Equation. Utility function from electric vehicle, capturing spatial effects.

Electric Vehicle Adoption Clusters

We leverage the Jenks natural breaks (Jenks, 1967) classification method to divide Illinois into five clusters based on their electric vehicle share heterogeneity to account for regional demand differences. Figure 28(a) shows the county-level electric vehicle share in January 2021. The five clusters, based on current year 2021 adoption trends in Illinois, are shown in Figure 28(b), where cluster 5 is characterized by the highest electric vehicle adoption share and cluster 1 by the lowest. Table 5 demonstrates the number of gas stations, charging stations, and the number of gasoline and electric vehicles in the first year of our analysis for the five clusters.

We assume that the upper bound of the number of charging stations should be the same as the gasoline stations to achieve maximum coverage. Cluster 1 has the lowest electric vehicle share. It consists of rural counties in Illinois with the highest current availability of gas stations but the fewest charging ones. Counties in clusters 4 and 5 are mostly concentrated in the greater Chicago area, where electric vehicle adoption share and charging station coverage are higher.

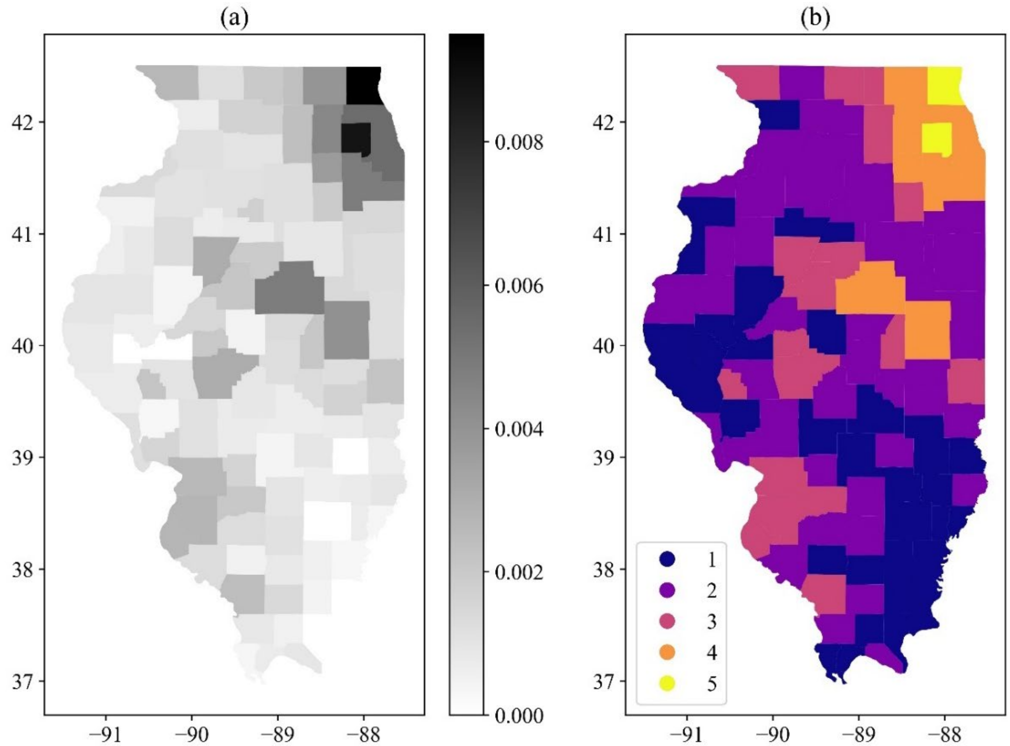


Figure 28. Graph. (a) Electric vehicle registrations share (Y 2021); (b) electric vehicle adoption clusters (1 corresponds to laggers and 5 to early electric vehicle adopters).

Table 5. Clusters of Electric Vehicle Ownership in Illinois and Charging Infrastructure

Cluster	No. of gas stations	No. of charging stations	No. of gasoline vehicles in the first year (2021)	No. of electric vehicles in the first year (2021)
Cluster 1	1,672	9	266,300	113
Cluster 2	879	32	815,717	713
Cluster 3	751	50	979,246	1,803
Cluster 4	459	417	3,862,688	15,497
Cluster 5	352	129	1,073,723	8,027

Illinois Charging Infrastructure Deployment Results

Base Case

We optimize the number of charging infrastructures for each cluster, compared to the do-nothing scenario and the maximum emission-reduction scenario for each cluster. The emission reduction for the do-nothing scenario is $3.76 \cdot 10^7$ metric tons of CO_2 and the maximum emission reduction is $4.14 \cdot 10^7$ metric tons of CO_2. We set the emission-reduction target for the base case to $3.76 \cdot 10^7 + 0.5 \times (4.14 \cdot 10^7 - 3.76 \cdot 10^7) = 3.95 \cdot 10^7$ metric tons of CO_2. Tables 6, 7, and 8 demonstrate the predicted number of electric and gasoline vehicles for each cluster in different years under the do-nothing scenario, base case, and maximum emission-reduction scenario, respectively. If no charging station investments are provided, 997,212 electric vehicles will be adopted in 2030, which is close to the goal of the State of Illinois; while for the base case and maximum emission-reduction targets, CEJA's goal of one million vehicles is reached. The growth of the electric vehicle share in each cluster is presented in Figure 29. The relationship between the do-nothing case, maximum emission reduction, and the target is shown in Figure 30(a). Figure 30(b) shows the predicted trajectory of the total number of electric vehicles; it indicates that the number of electric vehicles will greatly increase after 2040. Figure 30(c) shows that the investments in charging station installation should increase to provide around 2,200 stations by 2037 and remain at this level to support electric vehicle operation. We know that the earlier the charging stations are built, the more effective they are in electrifying driving distance; however, the later the charging stations are built, the lower the installation expenditure. Therefore, the required number of charging stations will keep increasing at first until reaching a critical coverage level and then remain at that same level until the end of the planning horizon.

Figure 31 breaks down the electric vehicle share per cluster and the number of charging stations per cluster for the base case. From Figure 31(a), we see that the electric vehicle share for every cluster will greatly increase after 2040, which is also shown in Figure 30, where the electric vehicle share is much higher in 2050 compared to 2030 and 2040. Moreover, the result shows that cluster 5 will always have the highest electric vehicle share and lead the electrification transition, reaching 100% in 2050; cluster 1 remains the lowest but can gradually reach about 60% in 2050; and clusters 2, 3, and 4 will reach more than 80% electric vehicle share at the end of the planning horizon. These electric vehicle trajectories meet the set emission-reduction target with increasing investments in charging infrastructure in the first 15 to 18 years of the transition. Figure 31(b) shows the required number of charging stations for each cluster; it indicates that charging stations should be invested in the earliest and the most in cluster 1, which currently has the fewest charging stations. This result demonstrates the pressing need for allocating investments for rural electrification to accelerate electric vehicle adoption in such lagger regions. Electric vehicle transitions of lagger regions are very important for accruing emission savings for the state. Charging stations in clusters 2, 3, 4, and 5 should be installed and reach peak levels within the next 15 to 18 years.

Table 6. Results of the Do-Nothing Scenario

Scenario	Cluster	Vehicle Type	2030	2040	2050	Emission reduction ($mtCO_2$)
Do-nothing	Cluster 1	EV	5,758	25,457	160,775	$3.78 \cdot 10^5$
		GV	260,655	240,956	105,638	
	Cluster 2	EV	53,032	193,018	682,193	$2.57 \cdot 10^6$
		GV	763,398	623,412	134,237	
	Cluster 3	EV	74,748	256,113	827,107	$3.45 \cdot 10^6$
		GV	906,301	724,936	153,942	
	Cluster 4	EV	567,291	1,507,540	3,510,779	$2.18 \cdot 10^7$
		GV	3,310,894	2,370,645	367,406	
	Cluster 5	EV	296,382	638,745	1,081,750	$9.39 \cdot 10^6$
		GV	785,368	443,005	0	
	Total	EV	997,212	2,620,873	6,262,604	$3.76 \cdot 10^7$
		GV	6,026,615	4,402,954	761,223	

Note: GV stands for gasoline vehicle, and EV stands for electric vehicle.

Table 7. Results of the Base Scenario

Scenario	Cluster	Vehicle Type	2030	2040	2050	Emission reduction ($mtCO_2$)
Base	Cluster 1	EV	6,860	33,269	182,266	$4.86 \cdot 10^5$
		GV	259,553	233,144	84,147	
	Cluster 2	EV	58,999	238,941	754,193	$3.16 \cdot 10^6$
		GV	757,431	577,489	62,237	
	Cluster 3	EV	80,992	303,583	898,243	$4.06 \cdot 10^6$
		GV	900,057	677,466	82,806	
	Cluster 4	EV	567,985	1,515,974	3,521,819	$2.19 \cdot 10^7$
		GV	3,310,200	2,362,211	356,366	
	Cluster 5	EV	302,546	667,884	1,081,750	$9.87 \cdot 10^6$
		GV	779,204	413,866	0	
	Total	EV	1,017,382	2,759,651	6,438,270	$3.95 \cdot 10^7$
		GV	6,006,445	4,264,176	585,557	

Table 8. Results of the Maximum Emission-Reduction Scenario

Scenario	Cluster	Vehicle Type	2030	2040	2050	Emission reduction ($mtCO_2$)
Max	Cluster 1	EV	9,531	39,943	194,260	$5.94 \cdot 10^5$
		GV	256,882	226,470	72,153	
	Cluster 2	EV	79,985	270,086	790,483	$3.75 \cdot 10^6$
		GV	736,445	546,344	25,947	
	Cluster 3	EV	103,813	335,591	934,402	$4.68 \cdot 10^6$
		GV	877,236	645,458	46,647	
	Cluster 4	EV	573,276	1,521,265	3,527,110	$2.20 \cdot 10^7$
		GV	3,304,909	2,356,920	351,075	
	Cluster 5	EV	323,581	689,593	1,081,750	$1.04 \cdot 10^7$
		GV	758,169	392,157	0	
	Total	EV	1,090,186	2,856,478	6,528,005	$4.14 \cdot 10^7$
		GV	5,933,641	4,167,349	495,822	

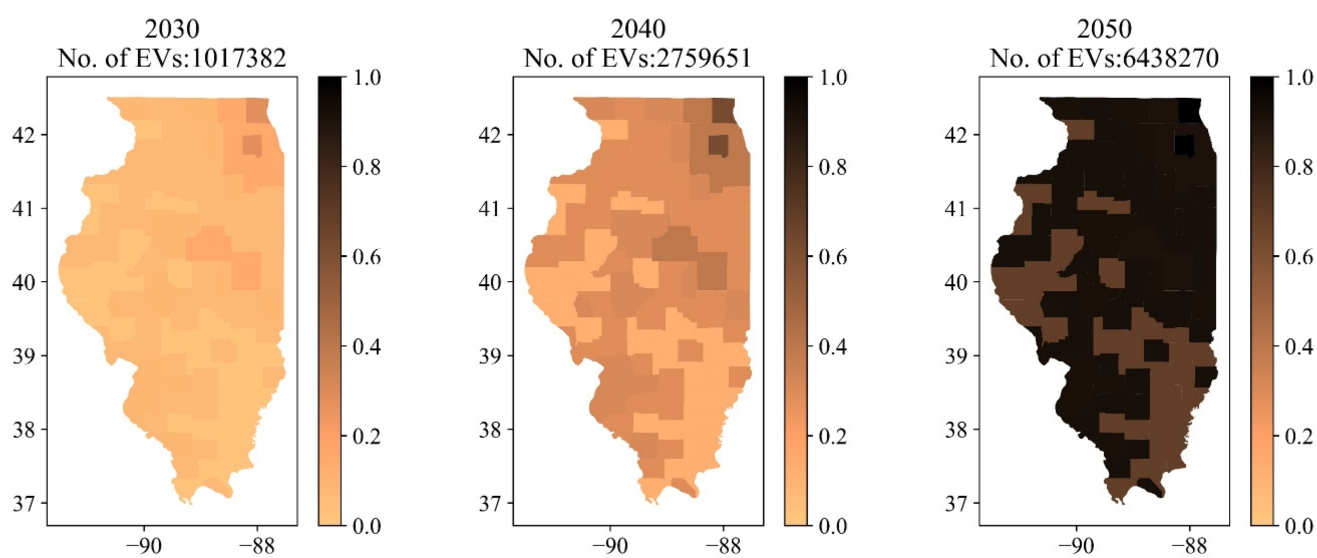


Figure 29. Graph. Growth of electric vehicle adoption share in Illinois.

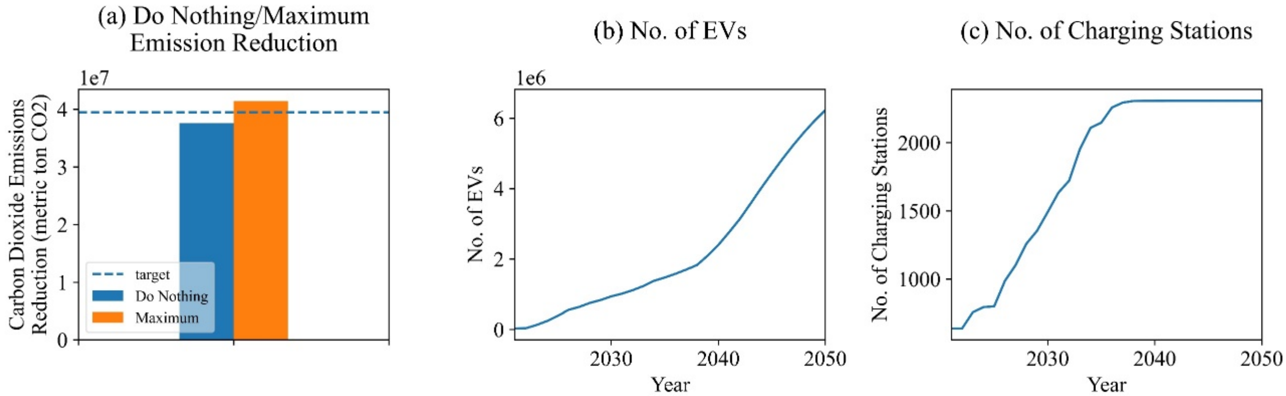


Figure 30. Graph. Optimization results: (a) emission reduction, (b) expected electric vehicle adoption, and (c) optimal number of charging stations to invest.

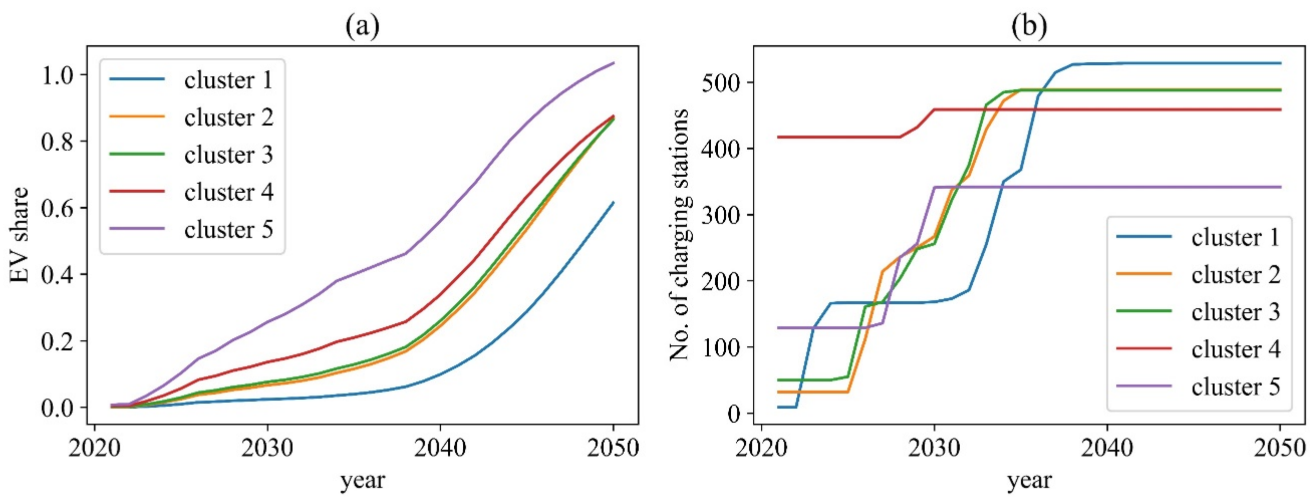


Figure 31. Graph. (a) Electric vehicle registration shares per cluster and (b) number of charging stations to be deployed per cluster.

Sensitivity Analyses

We conduct sensitivity analyses for the state of Illinois case study. The analyses include evaluation of the impact of different parameters that denote home charging availability, electricity generation mixes to infer charging carbon intensity, traveler type distances, fuel price outlooks, and alternate planning horizons.

The optimization results are shown in Figure 32 and Figure 33. The main findings are summarized as follows. Home charging levels have a great impact on emissions reduction. Figure 32(1-a) shows that the set emission-reduction target cannot be reached if home charging availability is 0%, 25%, 50%, and 75%. From Figure 32(1-c), we observe that when home charging availability is 100%, no charging stations are needed to achieve the emission-reduction target. This is because the electrified distances are longer and enabled by universal and reliable home charging access, and the operational cost of drivers is lower since fewer backup gasoline vehicles are needed. In addition, lower operational costs also drive more electric vehicle adoption, as shown in Figure 32(1-b).

Low renewable energy cost corresponds to a future where more renewable energy is integrated and used for electricity generation and, thus, a lower emission rate is associated with electricity production. Figure 32(2-a) demonstrates the huge differences in emission reductions for different electricity generation mixes: a less carbon-intensive electricity generation sector can lead to light-duty vehicle electrification emission reduction that is much greater than the base scenario. Therefore, as shown in Figure 32(2-b) and Figure 32(2-c), even though the number of electric vehicles in the transition trajectories is similar for the two cases, no significant additional investment in charging stations would be required to reach the target in the low renewable energy cost case.

Three types of travelers are tested based on their daily vehicle miles traveled: modest, average, and frequent. From Figure 32(3-c), we uncover that for modest drivers, their travel distance is, on average, short, and the demand for charging stations is lower. On the contrary, charging infrastructure extends the electrified distance of frequent drivers, who can effectively reduce operational costs.

We also examine scenarios with low gas prices and high electricity prices as well as high gas prices and low electricity prices. From Figure 33(4-c), we learn that with high gas prices and low electricity prices, people will be more willing to purchase electric vehicles, and therefore, to meet the same emission-reduction target, fewer additional charging stations need to be provided. When experiencing high gas prices and low electricity prices, the emission reduction for the do-nothing scenario is higher than the target, as shown in Figure 33(4-a), and charging stations are still needed, as shown in Figure 33(4-c). This is because the emission reduction in Figure 33(4-a) is the summation of emission reductions for five clusters, and it does not mean that for every cluster the do-nothing scenario has a higher emission reduction than the target. In fact, additional charging station investments are still needed in counties in clusters 1, 2, and 3.

Similar to the analysis of different fuel prices, if the planning horizon is 35 years, although the total emission reduction for the do-nothing scenario is higher than the target, charging stations are still required to meet the target. Figure 33(5-c) shows that to meet the same environmental quality target, having a longer planning horizon to achieve this reduction requires fewer chargers to be deployed.

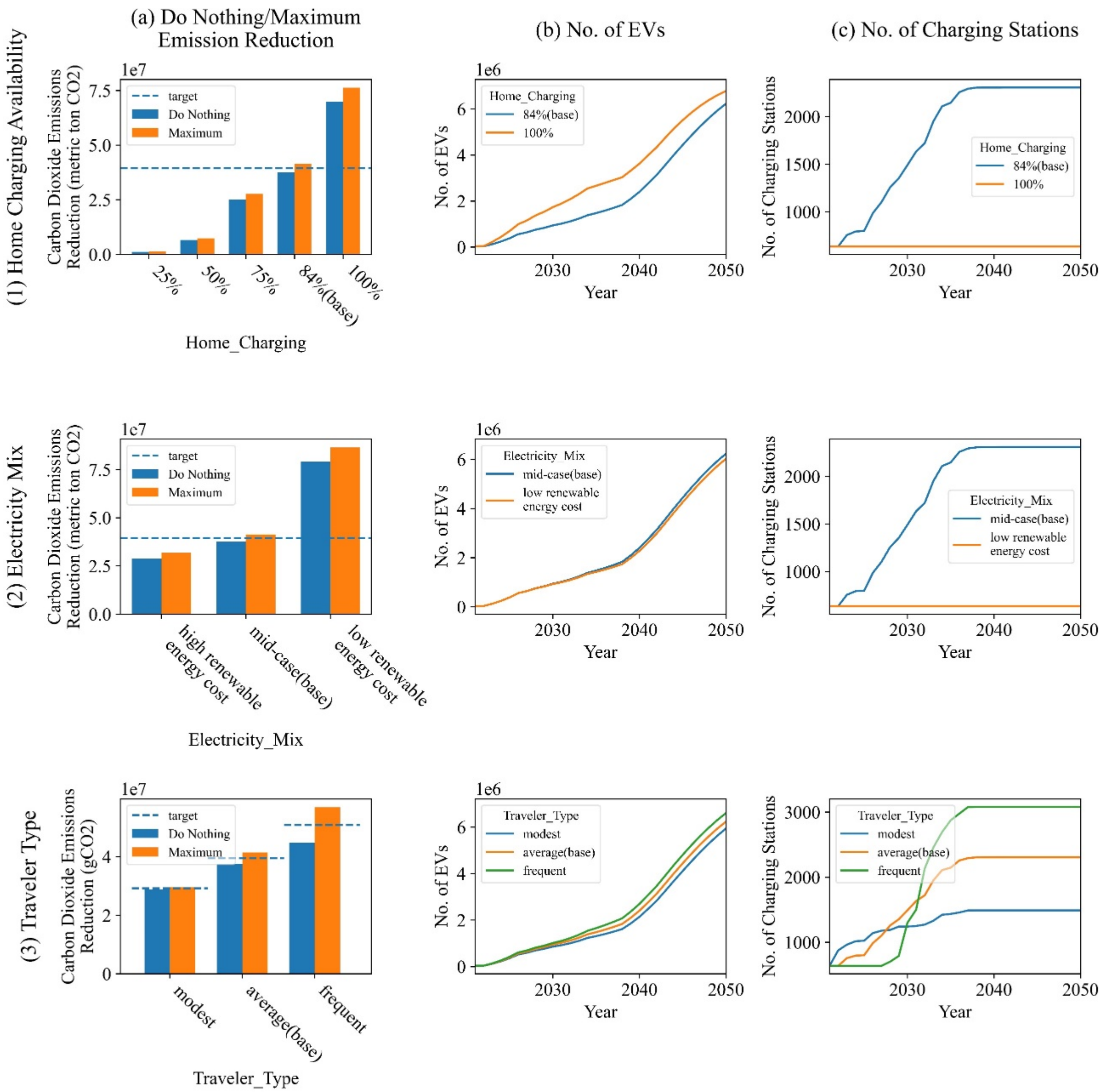


Figure 32. Graph. Optimization results for sensitivity analysis scenarios, including (1) different home charging availabilities, (2) electricity generation mixes, and (3) traveler types.

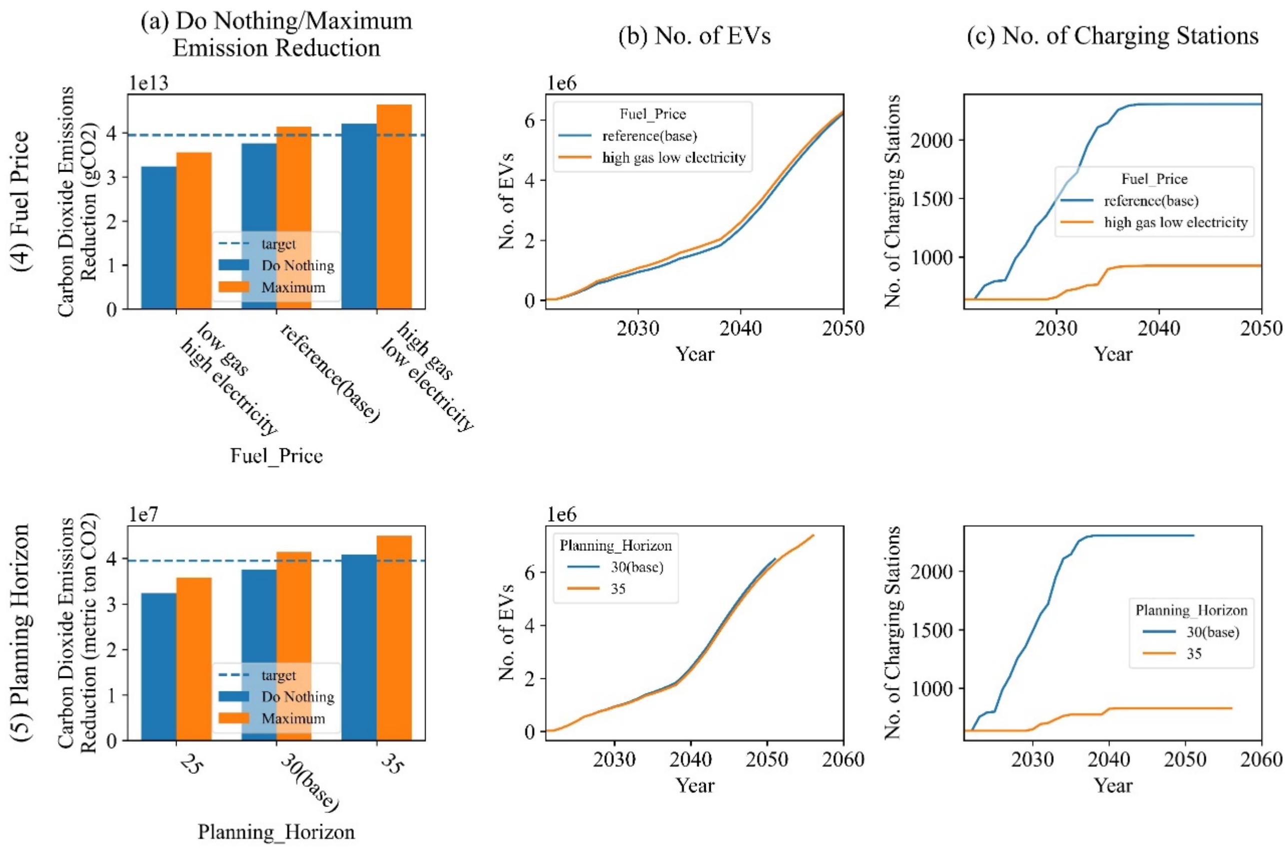


Figure 33. Graph. Optimization results for sensitivity analysis scenarios, including (4) different fuel pricing outlooks and (5) alternative lengths of planning horizons.

CONCLUSION

We study the problem of dynamic electric vehicle charging investment allocation from the policymaker's perspective, which aims to meet statewide emission-reduction targets for Illinois' light-duty vehicle sector. Our research introduces a new and dynamic electric vehicle charging deployment problem with emission-reduction targets and electric vehicle demand functions that capture network externalities, presents a simulated annealing algorithm to solve the highly nonlinear problem, and provides a plethora of policy and planning recommendations from real-world numerical experiments in Illinois. By evaluating diverse electric vehicle charging investment outcomes, we aim to comprehensively describe the decision-making mechanism and provide suggestions for infrastructure placement that incentivizes electric vehicle growth and transportation decarbonization.

CHAPTER 3: SUITABILITY MAPPING OF CHARGING INFRASTRUCTURE DEPLOYMENT

The goal of this analysis is to develop a suitability map for siting of electric vehicle charging stations based on economic, societal, and environmental justice indicators. Using the analytic hierarchy process (AHP), commonly applied in multi-criteria decision-making for geographic information system applications, we provide information for an Illinois statewide deployment of charging infrastructure.

SUITABILITY FEATURES

There are numerous studies that aim to identify suitable regions for charging placement; AHP is a commonly employed approach to meet this objective. For instance, to select the suitable location for charging stations in Istanbul, Guler and Yomralioglu (2020) use AHP to weigh environmental and accessibility indices and fuzzy AHP for outcomes accuracy, underlining the importance of the process of determining weights. Similarly, Erbas et al. (2018) used fuzzy AHP and identified regions suitable to install new chargers in Ankara. Guo and Zhao (2015) use the same approach for new charging infrastructure placement in Beijing, including three indicators (economic, societal, environmental) and 11 features (ranging from land costs to construction noise impacts). Few studies incorporate justice criteria into the suitability mapping process. Our analysis considers the economic and social indicators that are expected to affect chargers' siting but also evaluates Illinois census tract locations against quantitative environmental justice metrics, addressing environmental externalities concerns of disadvantaged communities in Illinois. Table 9 denotes features included in our charging suitability mapping process and their appearance in similar studies.

Table 9. Charging Placement Criteria in Literature

Features	Literature sources
Inaccessibility of current charging	Erbas et al. (2018)
Service capabilities	Guo and Zhao (2015); Erbas et al. (2018); Zhang et al. (2016); Zhai and Li (2016)
Service radius	Zhang et al. (2016); Zhai and Li (2016)
Distance from the substations	Erbas et al. (2018); Zhang et al. (2016); Zhai and Li (2016)
Traffic convenience	Zhai and Li (2016)
Income rates	Guler and Yomralioglu (2020)
Traffic volume	Guo and Zhao (2015); Erbas et al. (2018)
Particulate matter concentration	Guo and Zhao (2015)

The application of the AHP method to charging infrastructure siting suitability in Illinois stems from Al Garni and Awasthi (2017). First, we compare the relative importance of each n feature to the rest in a judgment matrix $M = (m_{i,j})_{n \times n}$; the comparison scores should be obtained through expert elicitation and diverse stakeholders' engagement. The relative importance of feature i compared to feature j is $m_{i,j}$. Table 10 presents the comparison scores and their scales. Also, $m_{i,j}$ has the reciprocal value of $m_{j,i}$, with $m_{i,j} \times m_{j,i} = 1$ and $m_{i,i} = 0$.

Then, we normalize the judgment matrix based on the equation in Figure 34.

$$\overline{m_{i,j}} = \frac{m_{i,j}}{\sum_1^n m_{i,j}}$$

Figure 34. Equation. Normalization function for judgment matrix.

Each weight P_i can be estimated from the cumulative $\overline{m_{i,j}}$ of each row, based on the equation shown in Figure 35.

$$P_i = \frac{\sum_{j=1}^n \overline{m_{i,j}}}{n}$$

Figure 35. Equation. Criteria weight equation.

We perform a consistency check by following the equations in Figure 36.

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^{n} \frac{(M \times P)_i}{P_i}$$

$$CI = \frac{\lambda_{max} - n}{n - 1}$$

$$CR = \frac{CI}{RI}$$

Figure 36. Equation. Consistency check equations.

In Figure 36, λ_{max} is the maximum characteristic root, CI is the consistency check factor, RI is the average random consistency factor, and CR is the consistency ratio. The consistency of the weight should meet the requirement of $CR < 0.1$. Otherwise, the judgment matrix needs to be adjusted (Ruan et al., 2014).

The features we consider are aligned with existing literature in this field, and we provide their pertinent data sources in Table 11. We use openly accessible data, available at the census tract group level, and we present the analysis outcomes for 3,116 Illinois census tracts. We compare the mean and standard deviation of the variables in Table 12. These variables can be grouped into three indicators, representing economic, societal, and environmental justice drivers of electric vehicle charging station placement, integrating indicators that serve as a proxy for supply and social welfare policymaking priorities. The schematic of the indicators' structure and the datasets that comprise the suitability metric are shown in Figure 37. Plotting the spatial distribution of these features is conducted via natural breaks, which minimize the sum of squared deviation within classes and maximize the differences between each class, commonly used in the classification of continuous features.

Table 10. Comparison Scores and Their Scale

Scale	Definition
1	Equal importance of i and j
3	Moderate importance of i over j
5	Essential or strong importance of i over j
7	Very strong importance of i over j
9	Extreme importance of i over j
2,4,6,8	Intermediate values in between

Table 11. Features Integrated in Charging Suitability Mapping for Illinois

Parameters	Data Source
Total population (people per census tract)	2017 LATCH data (2012–2016 American Community Survey 5-year estimate tract data)
Average vehicle miles traveled per person in a weekday (VMT)	2017 LATCH data
Average household income (US $)	2017 LATCH data (2012–2016 American Community Survey 5-year estimate tract data)
No. of vehicles that level 2 charging plugs could serve	Calculated using Alternative Fuels Data Center data, accessed in 2022
No. of vehicles that level 3 charging plugs could serve	Calculated using Alternative Fuels Data Center data, accessed in 2022
Locations of substations	U.S. Department of Energy, accessed in 2022
Disadvantaged community indicator (binary)	U.S. Department of Energy, accessed in 2022
No. of vehicle registrations (vehicles)	2012–2016 American Community Survey 5-year estimate tract data
Levels of PM2.5 in the air $\left(\frac{ug}{m^3}\right)$	EPA's Environmental Justice Screening and Mapping Tool, accessed in 2022
AADT on major roads	EPA's Environmental Justice Screening and Mapping Tool, accessed in 2022
Share of racial minorities (%)	EPA's Environmental Justice Screening and Mapping Tool, accessed in 2022

Table 12. Descriptive Statistics of Features That Compose Suitability Indicators

Variables	Mean	Standard Deviation	Min	Max	Unit
Inaccessibility of EVCS	0.807	0.120	0.00	1.00	%
Substation proximity	0.232	0.135	0.00	1.00	%
Traffic proximity	818.320	1601.541	0.003	22,114.272	No. of vehicles
Household income	61,178.487	29,750.901	5,736.00	240,000.00	US Dollars ($)
PM 2.5 Concentration	9.941	0.631	8.363	10.974	ug/m^3
Minorities share	0.402	0.321	0.00	1.00	%
Disadvantaged communities	0.200	0.400	0.00	1.00	Binary

Note: EVCS stands for electric vehicle charging station, and PM stands for particulate matter.

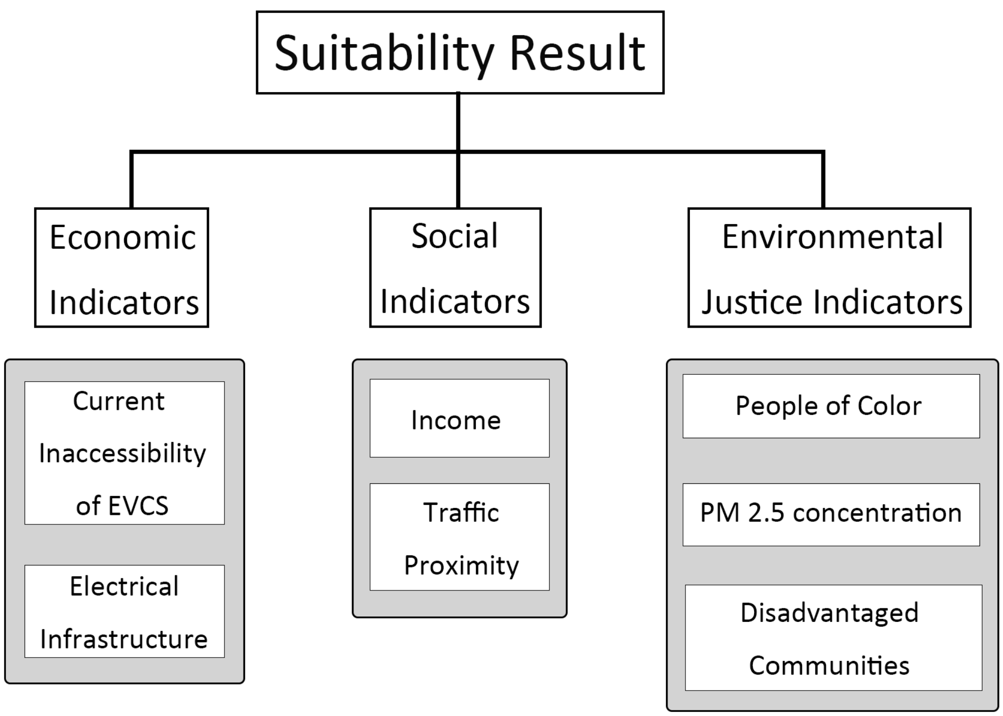


Figure 37. Graph. Indicators and features used in charging suitability mapping for Illinois.

Economic Indicators

One of the key considerations for charging station installation and its investors is cost-effectiveness (Kchaou-Boujelben, 2021). We consider the economics when proposing suitable locations for electric vehicle charging stations' siting. Two economic criteria are used that are aligned with prospective investors' objectives for coverage of demand and installation cost minimization. We measure the inaccessibility of charging based on current vehicle adoption and charging infrastructure levels since gaps in inaccessibility will need to be filled by additional charger deployment. We also report the distance from the electrical infrastructure since it is cost-effective to place new charging stations near existing substations to reduce the costs of electrical infrastructure upgrades for sufficient electrical capacity.

Current Inaccessibility of Charging Stations in Illinois

To quantify charging inaccessibility in Illinois, we measure accessibility and the level of service that is currently provided by level 2 (L2) and level 3 (L3) charging stations, as proposed by Traut and Wolfinbarger (2021). We assume a different radius of influence for each charging power level. We choose 15 miles and 50 miles for L2 and L3 stations, respectively, to enable people who are pursuing various activities within these driving mileages during the day to recharge in specific destinations or en-route. We assume that each charging station can be used by all the vehicles in its buffer of influence uniformly.

We calculate the number of vehicles (under a universal electrification scenario) that could be charged by one level 2 and one level 3 plug per unit of area. The input parameters for the calculation are the average charging rate of each charger's power level, the utilization rate of the charger—i.e., the average number of hours a current charger is used over a day (FreeWire Technologies, 2022), and the average daily driving distance per vehicle in each spatial unit of analysis, as shown in Figure 38.

$$E2_j = \frac{C_2 U_2}{D_j A_k}$$

$$E3_j = \frac{C_3 U_3}{D_j A_k}$$

Figure 38. Equation. Charger capability.

For each census tract j, D_j are the average daily vehicle miles traveled that will need to be recharged. We set $C_2 = 23$ miles per hour, $C_3 = 6.667$ miles per minute, while $U_2 = 8$ hours and $U_3 = 3$ hours, representative of the charging rate and utilization rate for L2 and L3 charging ports, respectively. A_K is the sum population of the number of vehicles in station k's service area. $E2_j$ and $E3_j$ are the average numbers of vehicles that could be served by one level 2 and one level 3 charging plug divided by the population in the census tract respectively.

We sum up the total number of vehicles that could be served based on the number and the level of charging ports in each census tract as T_j, shown in Figure 39. For each census tract j, there are $N_{2,j}$ numbers of level 2 charging ports and $N_{3,j}$ numbers of level 3 charging ports. Pop_j is the total population in j.

$$T_j = Pop_j \left(\sum_{i1=1}^{N_{2,j}} E2_j + \sum_{i2=1}^{N_{3,j}} E3_j \right)$$

Figure 39. Equation. Total number of vehicles served by current charging infrastructure.

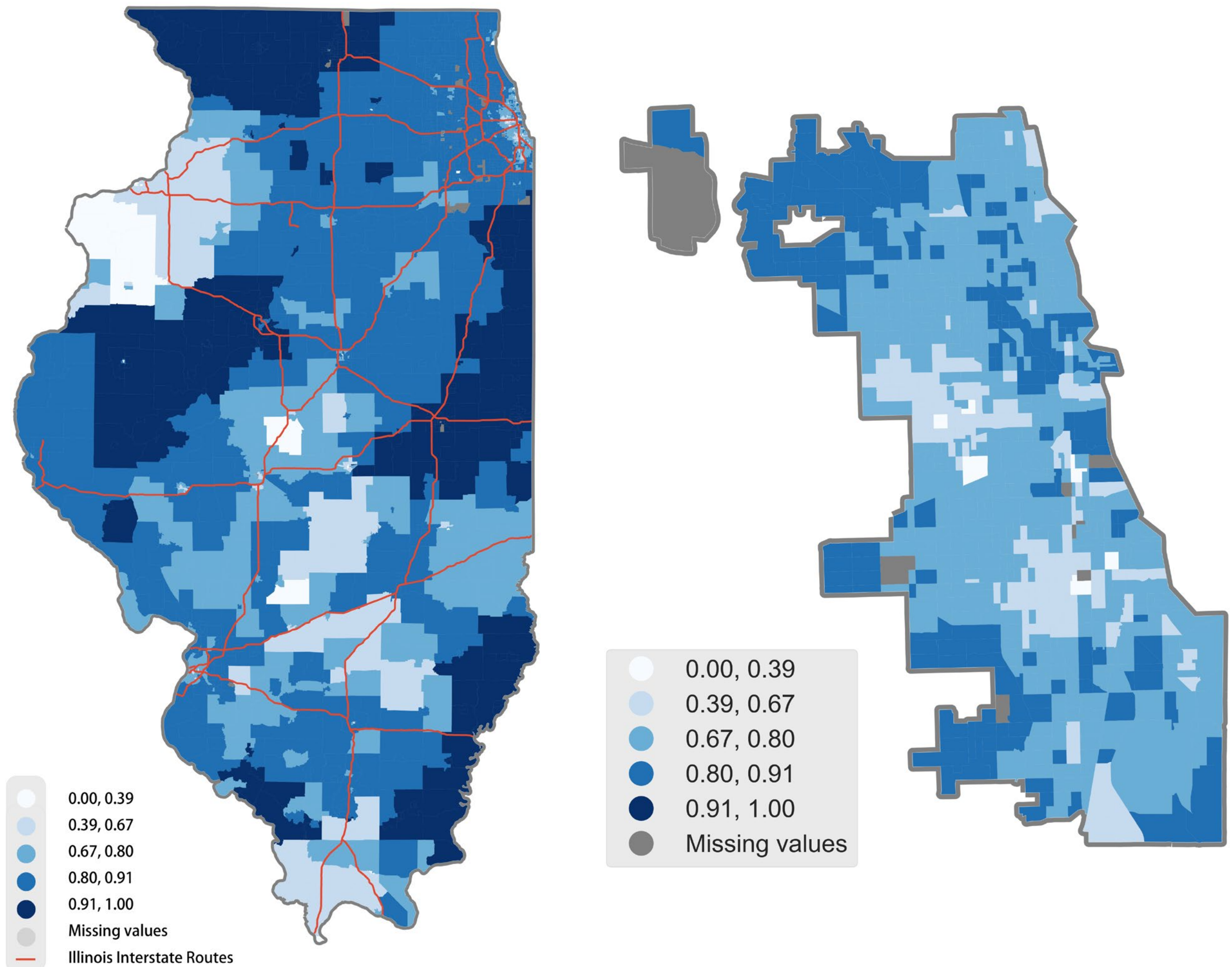
We compare the number of vehicles that can be served, T_j, with the total number of vehicles, V_j, in each census tract, as in shown in the equation in Figure 40.

$$IA_j = \left(1 - \frac{T_j}{V_j}\right) \times 100$$

Figure 40. Equation. Inaccessibility of charging stations at each census tract.

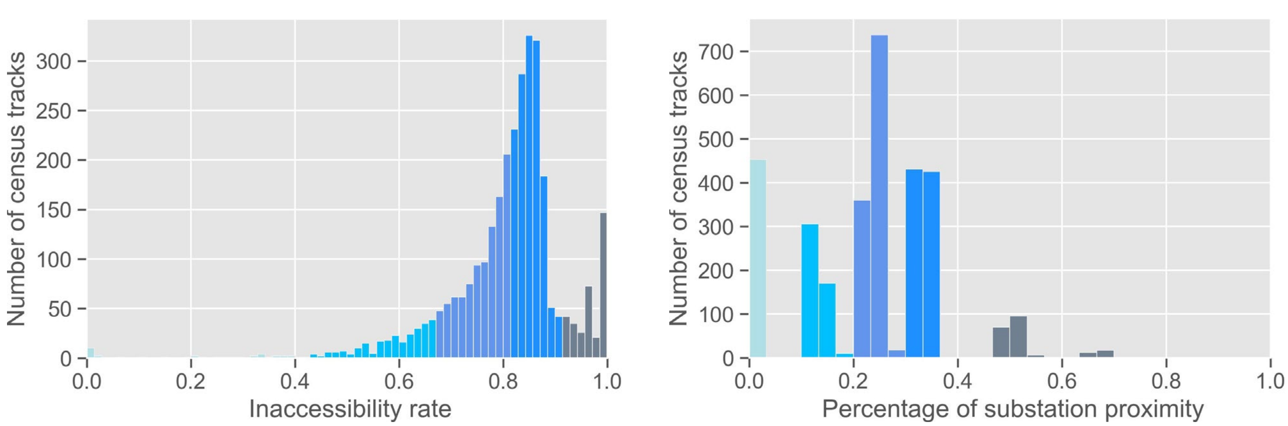
The inaccessibility map requires frequent updates of the location and the power level of the current charging infrastructure, as well as the current distribution of vehicle registrations, to be accurately measured. Electric vehicle charging station inaccessibility measures how many vehicles cannot be accommodated by the current charging stations and points out the areas that lack such infrastructure investments.

Figure 41 displays the current levels of charging inaccessibility map for (a) Illinois and (b) the city of Chicago, respectively. The distribution of inaccessibility values is shown in Figure 42(a). The inaccessibility value is calculated for 3,080 tracts, while the missing values are because the aggregate number of vehicles for the rest of the tracts is not available. In Illinois, 353 tracts endure extreme charging station inaccessibility, having a value greater value than 91%. None of those tracts are in the Chicago region. Extreme charging station inaccessibility regions are mostly in Illinois rural areas, such as Hardin, Carroll, and Fulton counties. More than half of the census tracts are characterized by high charging inaccessibility (1,639 tracts under 80% of inaccessibility). The mean inaccessibility rate is 73.3% in the Chicago region while 22.7% of tracts in this metropolis are characterized by high inaccessibility. Highly unreachable areas for charging stations are in Garfield Ridge, Clearing, Ashburn, Beverly, Mount Greenwood, Hegewisch, and around O’Hare.



(a) State of Illinois (b) City of Chicago

Figure 41. Graph. Maps of current level of charging inaccessibility (%).



(a) Inaccessibility rate of charging (b) Substation proximity

Figure 42. Graph. Distributions of (a) charging inaccessibility and (b) charging proximity.

Electrical Infrastructure

The locations of all substations in Illinois stem from data available through the Energy Zones Mapping Tool (U.S. Department of Energy, 2022a). We depict the number of transmission lines. We use the inverse distance weighted method to weight the number of transmission lines by the distance from the nearby substations (ArcGIS Pro 3.0, 2022), as shown in Figure 43. We choose $p = 2$ and assign greater weight to the number of transmission lines that connect to each substation, which can serve as a proxy of the transmission lines' capacity. We plot a raster spatial heat map that portrays the number of transmission lines per unit area. By converting the raster map to a vector one and by summing up the average proximity value, we obtain the substation proximity map, as in Figure 44. The values distribution in the map is based on percentiles of the weighted distance from transmission lines capacity.

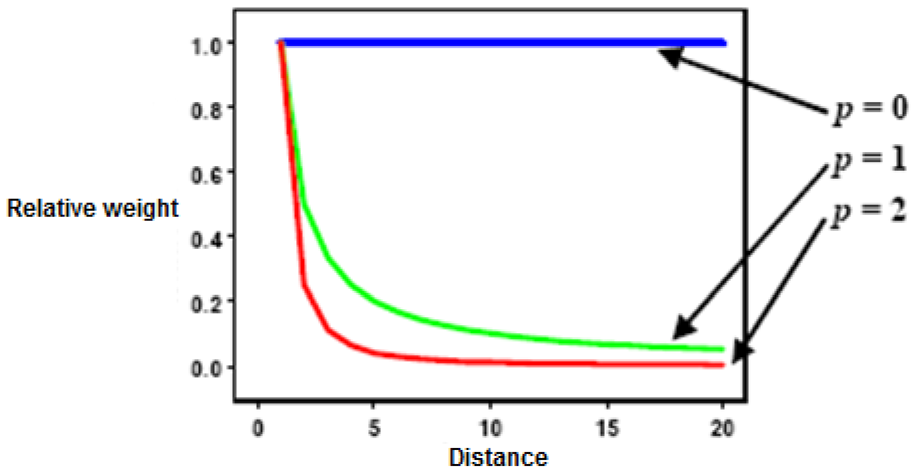
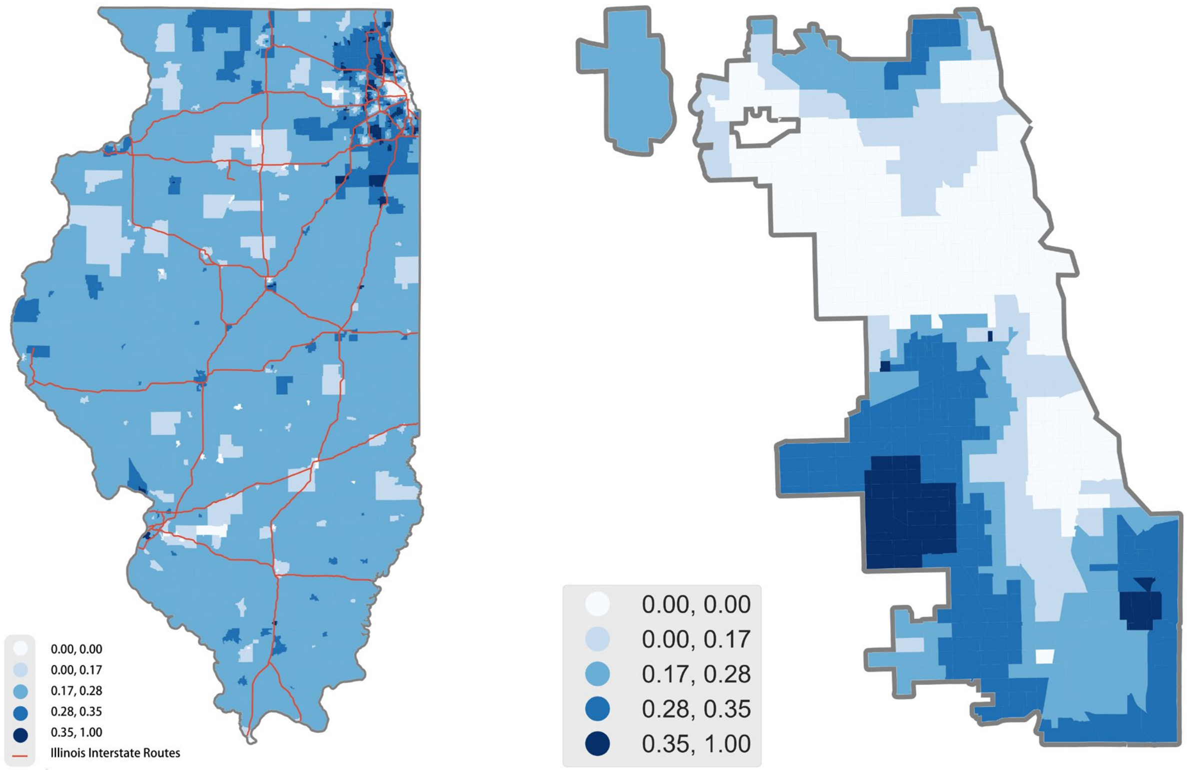


Figure 43. Graph. Decrease of relative weight with distance, under different p values.

Source: ArcGIS 10.3 (2022)

The color represents the average number of transmission lines in each census tract. Darker colors indicate higher proximity to substations, where it is more economical to install a charger. The distribution of the proximity to substations is shown in Figure 42(b). Regarding the statewide map in Figure 44(a), 27.2% of census tracts have high charging suitability (0.28–0.35) and 7.0% of tracts have a very high charging suitability (> 0.35), due to their proximity to substations. The major high suitability areas are in the suburban and collar counties. In Chicago, West Lawn, Chicago Lawn, Ashburn, and South Deering are closer to electrical infrastructure. The Chicago region has a relative low mean value (13.9%) of electric infrastructure proximity compared to the Illinois region, which might pose a barrier to installation of high-power charging hubs.



(a) State of Illinois (b) City of Chicago

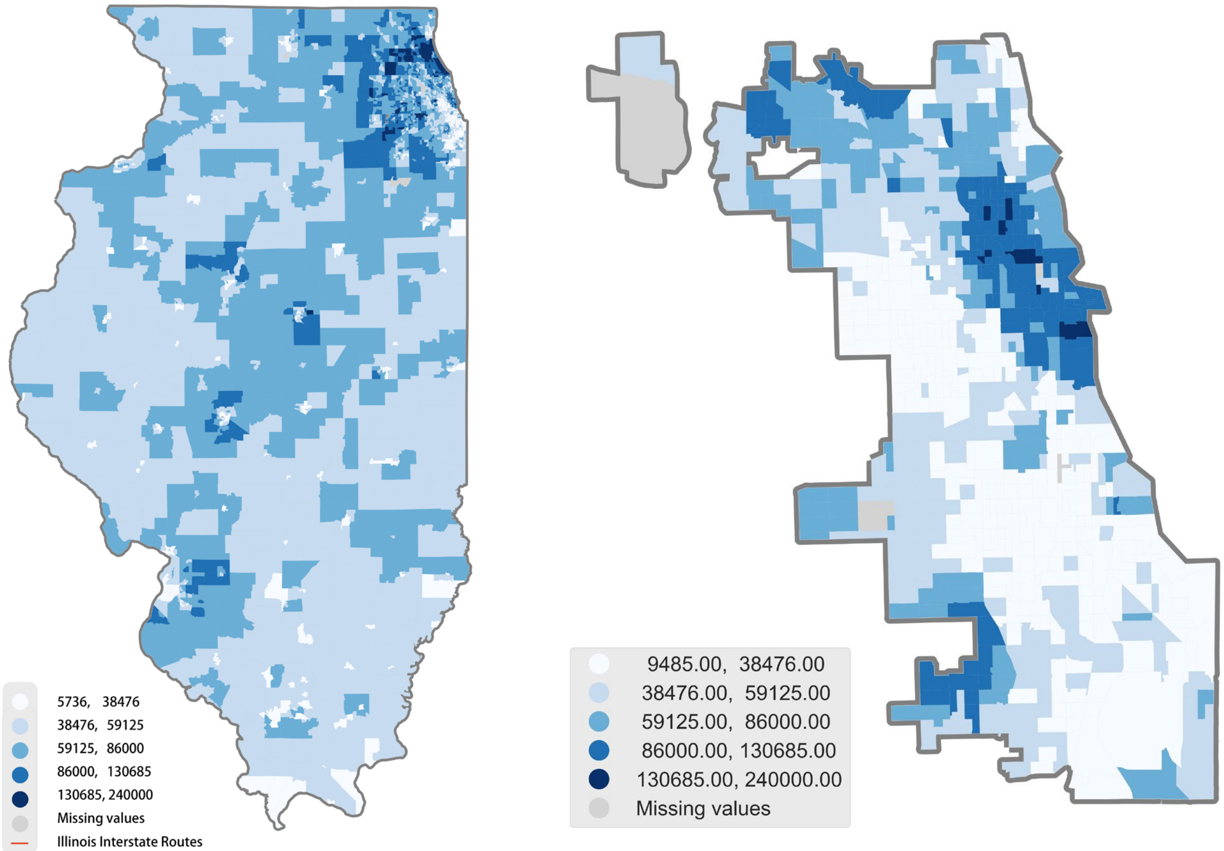
Figure 44. Graph. Substation proximity maps.

Social Indicators

Besides economic indicators, identifying regions for charging deployment also needs to be driven by socioeconomic indicators to ensure greater utilization of the sited infrastructure. Census tracts are evaluated based on two societal criteria: income and traffic proximity.

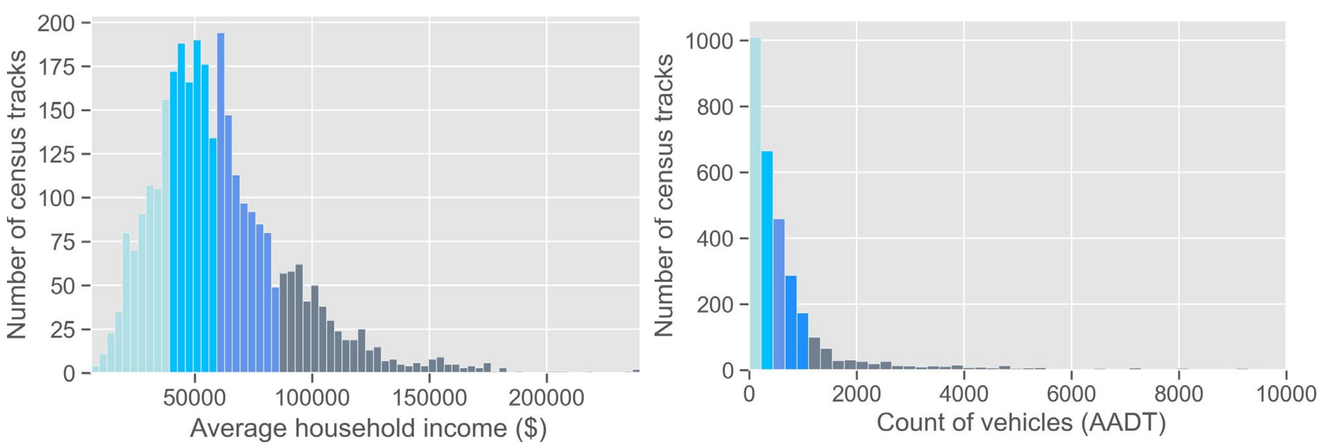
Income

We account for the average household income in each census tract (Jansson et al., 2018); there are 11 tracts with a missing average household income value, due to not having residents. Populations of greater income are currently leading the electrification transition (Noel et al., 2020; Mukherjee & Ryan, 2020). As shown in Figure 45, darker areas represent areas with higher income, which are currently more likely to host a population that, in the short run, is more likely to purchase and operate an electric vehicle; accessibility consideration for different socioeconomic groups will be mitigated when introducing environmental justice factors. The distribution of the income map is shown in Figure 46(a), where 2.8% of tracts are highlighted as leaders and 14.6% of tracts are considered moderate candidates to lead the transition to passenger vehicle electrification. Leader groups are mostly located in suburban collar counties in Illinois. Figure 45(b) shows prospective regions to lead the transition to electric vehicles are in central Chicago. Fewer high-income households live in the Chicago region than in other places in Illinois (only 1.3% of tracts are considered very high-income regions).



(a) State of Illinois (b) City of Chicago

Figure 45. Graph. Income distribution maps.

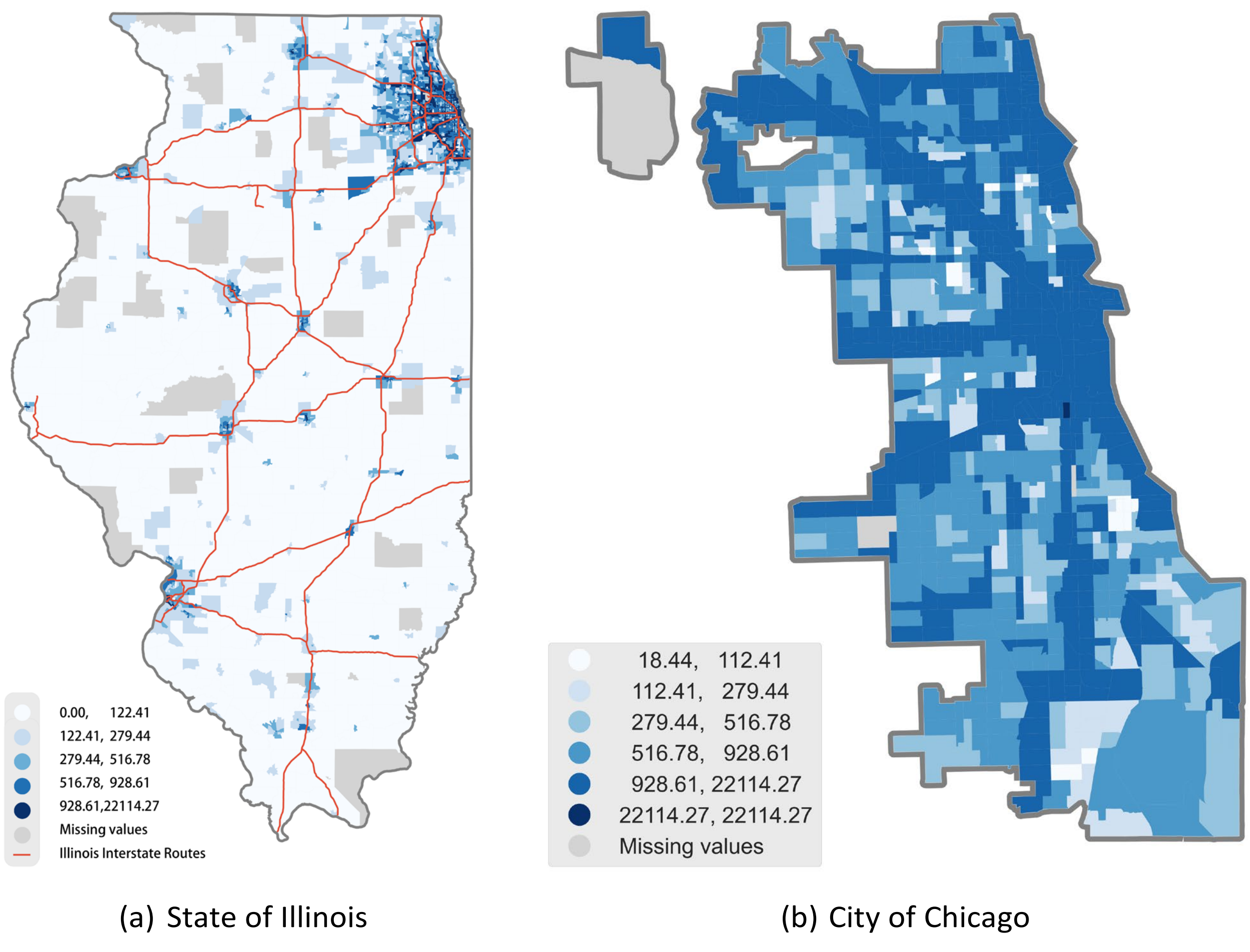


(a) Income (b) Traffic proximity

Figure 46. Graph. Distributions of income and traffic proximity.

Traffic Proximity

We use the traffic volume data as a proxy of electric vehicle charging demand since the growth of the electric vehicle penetration level will result in the substitution of fossil-fueled vehicles on the road (Arias & Bae, 2016; Harris & Webber, 2014). The traffic proximity map represents the average annual daily traffic (AADT) on major roads (within 500 meters). Figure 46(b) reveals the distribution of the traffic proximity map values. The darker color shows higher suitability for building electric vehicle charging stations. A subset of 3,066 tracts has an available estimated traffic proximity value for the Illinois region. We use the quantiles classification scheme to measure traffic proximity. There are a few tracts that are highlighted, like Blackhawk Township in Rock Island, St. Clair near St. Louis, Dekalb, Tazewell, and Menard. Figure 47(a) reveals that the traffic proximity could be associated with Illinois interstate routes, and high-suitability electric vehicle charging sites can be found at the intersections of interstate routes. Despite that, more than half of the high traffic proximity (greater than 930 vehicles) tracts are in Chicago (359 of 611 census tracts) urban and suburban regions and are distributed in a radial pattern. Likewise, the four darker color lines in Figure 47(b) are consistent with the four interstate lines. The area close to Lake Michigan has high traffic proximity and, thus, charging station deployment suitability.



(a) State of Illinois (b) City of Chicago

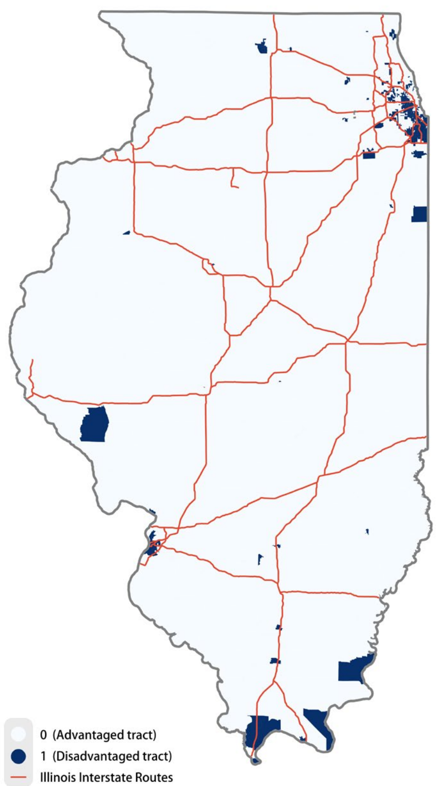
Figure 47. Graph. Traffic proximity (AADT) distribution maps.

Environmental Justice Indicators

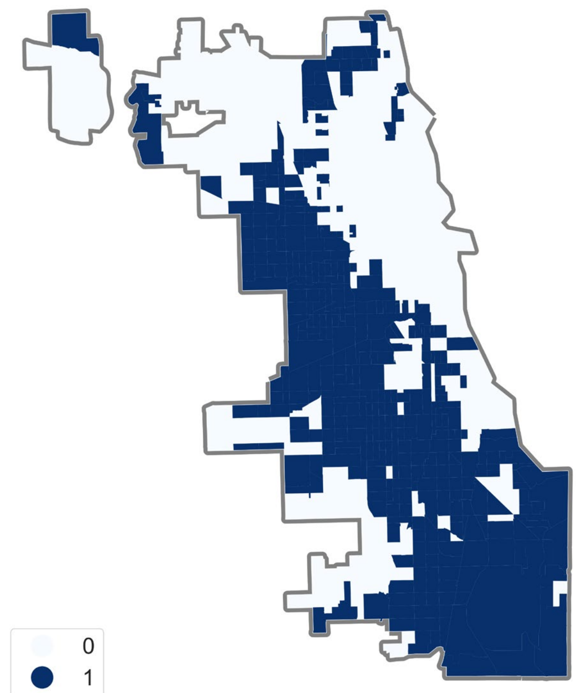
The Justice40 initiative directs 40% of overall benefits of certain federal investments to flow into disadvantaged communities. A major goal of establishing an environmental justice indicator in this suitability analysis is to mitigate environmental injustices and enable better accessibility to charge for marginalized and disadvantaged communities (White House, 2021a, 2021b). Three features were selected to represent environmental and distributive charging access proxies.

Disadvantaged Communities

Disadvantaged communities are communities that are impacted by compounded burdens related to transportation access and health, environmental, economic, resilience, and social disadvantages (U.S. Department of Energy, 2022). The disadvantaged regions designated in Illinois are highlighted in Figure 48. Note that 610 communities are considered disadvantaged communities, and 405 of them are found in the Chicago region. Most of the disadvantaged census tracts are in Chicago's south and western regions.



(a) State of Illinois



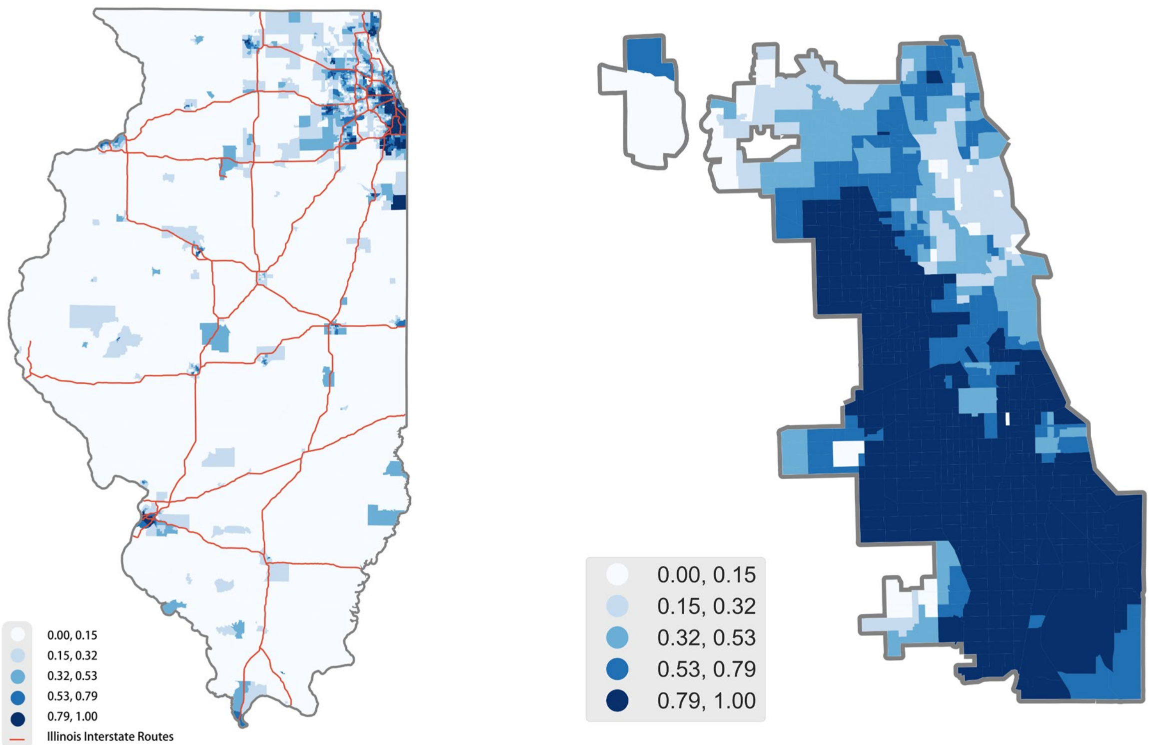
(b) City of Chicago

Figure 48. Graph. Disadvantaged communities (binary) maps.

Minorities Share

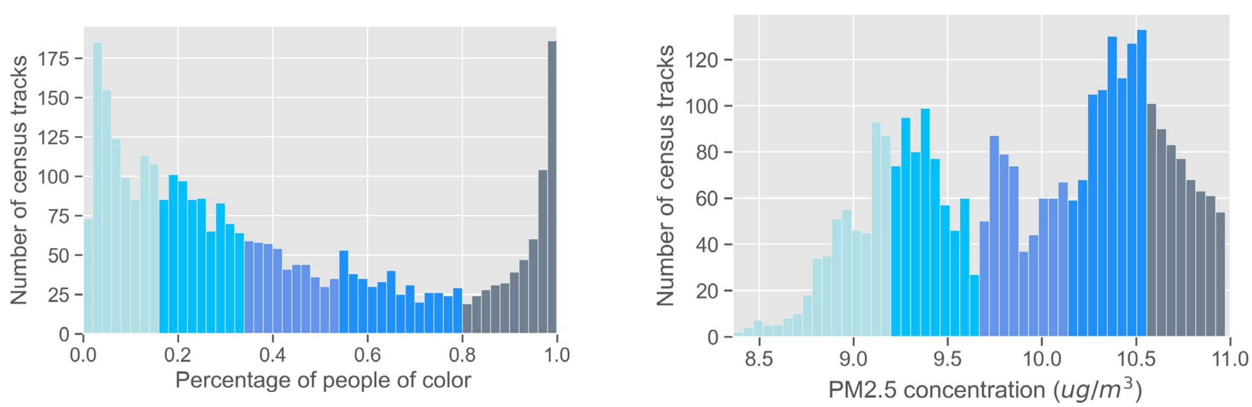
This feature represents the percentage of racial minorities; people of color experience greater energy burdens and compound energy vulnerability while being disproportionately affected by pollutants

(Chambliss et al., 2021; Price et al., 2021; Hsu & Fingerman, 2021). The distribution map is found in Figure 50(a). Figure 49 reveals the regions with a high share of minorities that can be selected to improve accessibility to charging for these underserved populations. The Chicago region has a high concentration of minorities located in the southwest; 398 disadvantaged tracts are in Chicago while 586 tracts are in Illinois regions. Besides the Chicago region, tracts like St. Clair, Pulaski, Ogle, and Iroquois counties are highlighted.



(a) State of Illinois (b) City of Chicago

Figure 49. Graph. Minorities share (%) distribution maps.

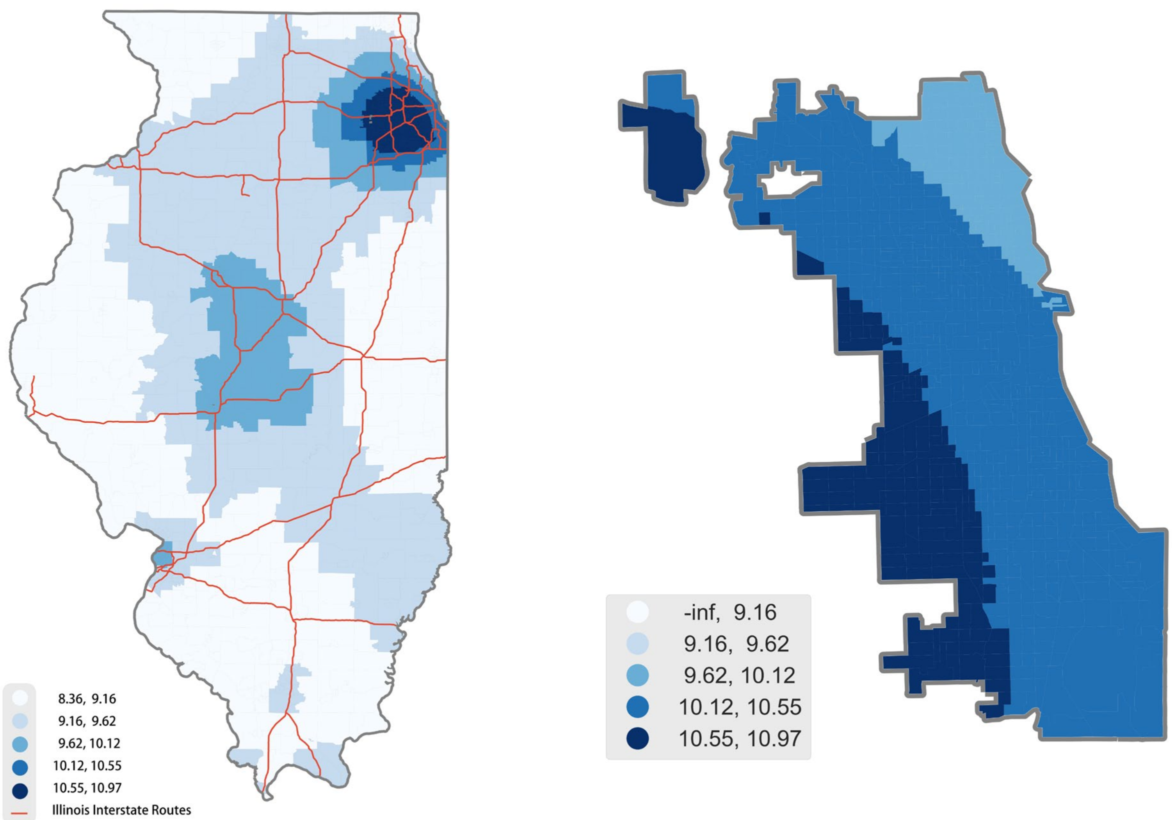


(a) Minorities share (b) PM 2.5 concentration

Figure 50. Graph. Distributions of (a) minorities share and (b) PM 2.5 concentration.

Particulate Matter 2.5 Concentration

Particulate matter (PM) 2.5 is an air pollutant that can severely impact health, particularly for vulnerable populations suffering from respiratory and heart diseases (Chambliss et al., 2021; Monaco et al., 2015). PM 2.5 levels in the air are a proxy to evaluate environmental justice among different communities. The distribution of PM 2.5 concentration values is shown in Figure 51(b). As shown in Figure 50, there are high PM 2.5 concentration values in Chicago and the collar counties region, which could be more suitable for charging station siting. Charging station siting can accelerate ownership and use of electric vehicles, which can reduce environmental externalities of passenger transportation and improve local air quality.



(a) State of Illinois (b) City of Chicago

Figure 51. Graph. PM 2.5 concentration $\left(\frac{\mu g}{m^3}\right)$ distribution maps.

ILLINOIS CHARGING SUITABILITY MAPPING RESULTS

We weight the features that comprise the suitability indicators based on the rank scores shown in Table 13. Alternative ranking approaches would significantly impact the result for charging station siting suitability. Under weight assignments W1, W2, and W3, we are only considering the individual effect of economic, social, and environmental justice indicators, respectively, on charging suitability. Weight assignment W4 reflects equal weighting of the three indicators, while W5 assigns a higher weight to the economic indicator. The resulting weight values (W6) for expert elicitation and stakeholder feedback data collection are found in Table 14. This is obtained by calculating the main value of weights assigned to the criteria by a diverse set of stakeholders in Illinois who represent various sectors (25% from the public sector, 25% from the nonprofit sector, 37.5% from industry, and 12.5% from academia). Using the derived judgment matrix from the AHP method, as in Table 15 we have $RI = 1.32$ (Hassan et al., 2017) and $CR = 0.08$, showing that the result is satisfactory.

Table 13. Example Weights of Charging Suitability Indicators

Ranking approach	W1	W2	W3	W4	W5	W6
Inaccessibility of EVCS	1/2	0	0	1/7	3/11	0.138
Substation proximity	1/2	0	0	1/7	3/11	0.114
Household income	0	1/2	0	1/7	1/11	0.132
Traffic proximity	0	1/2	0	1/7	1/11	0.150
Minorities share	0	0	1/3	1/7	1/11	0.122
PM 2.5 concentration	0	0	1/3	1/7	1/11	0.526
Disadvantaged communities	0	0	1/3	1/7	1/6	0.192

Table 14. Features Evaluation Form, Used to Derive W6 Weighting Assignment

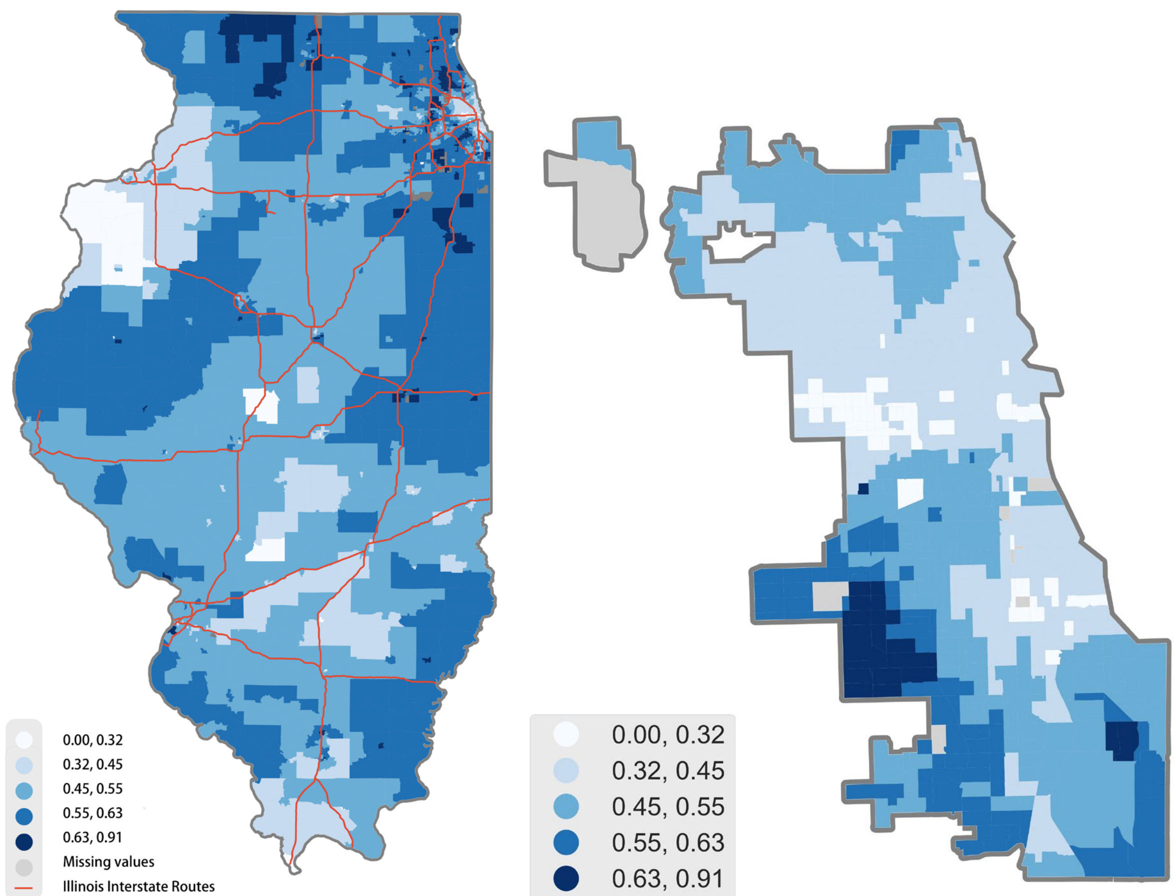
Indicators	I1	I2	I3	I4	I5	I6	I7
Inaccessibility of EVCS (I1)	1	4	0.33	3	3	1	1
Electrical Infrastructure (I2)	0.25	1	0.33	3	0.33	1	0.33
Income (I3)	3	3	1	5	1	3	1
Traffic Proximity (I4)	0.33	0.33	0.2	1	0.2	0.33	0.33
People of Color (I5)	0.33	3	1	5	1	1	0.20
PM 2.5 Concentration (I6)	1	1	0.33	3	1	1	1/3
Disadvantaged Region (I7)	1	3	1	3	5	3	1

Table 15. AHP Weighting Results

Indicators	Weight
Inaccessibility of EVCS (I1)	0.1729
Electrical Infrastructure (I2)	0.0737
Income (I3)	0.2429
Traffic Proximity (I4)	0.0414
People of Color (I5)	0.1329
PM2.5 concentration (I6)	0.0975
Disadvantaged Region (I7)	0.2387

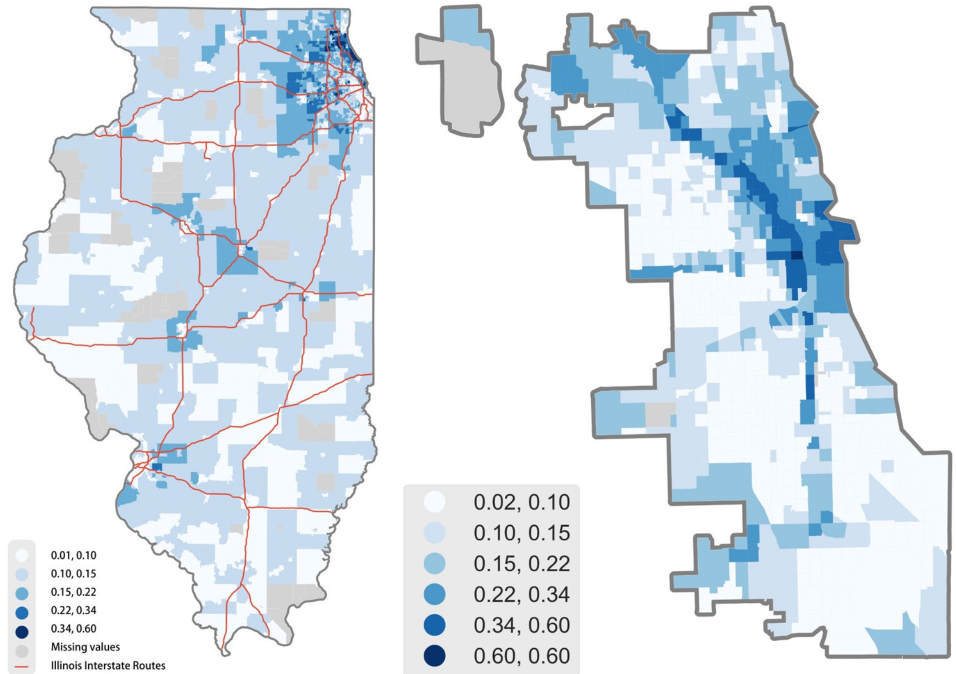
Charging Station Siting Suitability Maps

The suitability mapping that accounts only for the social indicator (Figure 53) stands out since it highlights different regions than the rest of the maps in Figures 52 and 54 (i.e., economic and justice ones), compared with the other two single-weighted indicator maps. This is expected since the social indicator reinforces the need for charging deployment in affluent and busy in terms of traffic regions, while the rest of the indicators highlight charging siting needs in charging underserved and historically disadvantaged regions. Figure 53(b) reveals that the northwest parts of Chicago are suitable regions for charging deployment, but Figure 52(b) and Figure 54(b) show the southeast part of Chicago to be preferable for charger installation. From the economic perspective in Figure 52(a), 256 tracts are highlighted for new charging infrastructure placement, mainly in Stephenson, Winnebago, and Ford counties. While considering the environmental justice perspective in Figure 54(a), there are 504 tracts suitable as charging locations, primarily in St. Clair and Cook counties (378 of them are in the Chicago region).



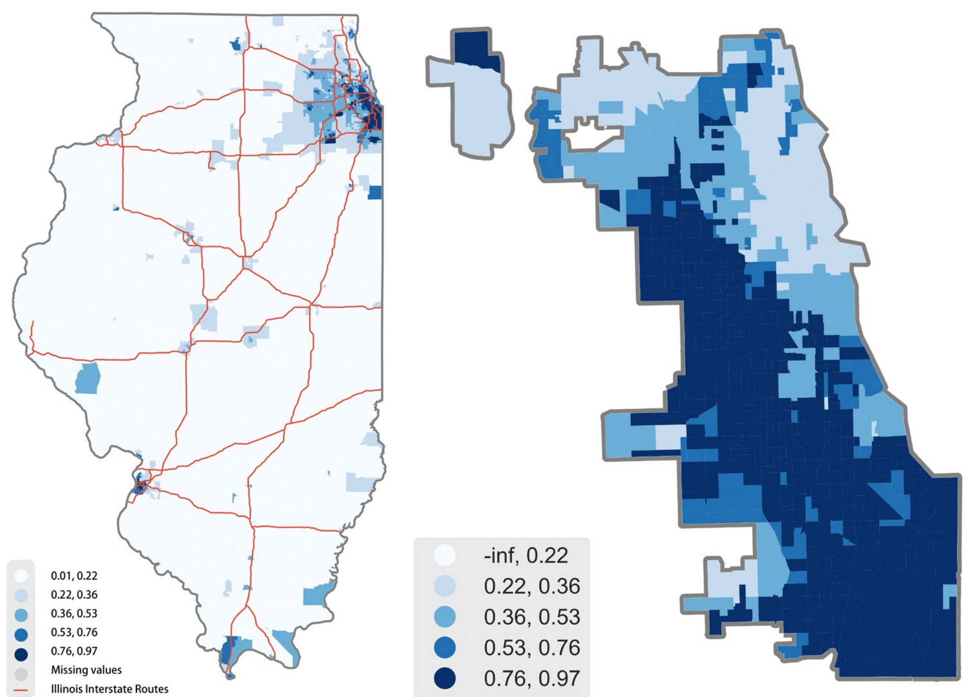
(a) State of Illinois (b) City of Chicago

Figure 52. Graph. Charging suitability mapping including only economic indicators (W1).



(a) State of Illinois (b) City of Chicago

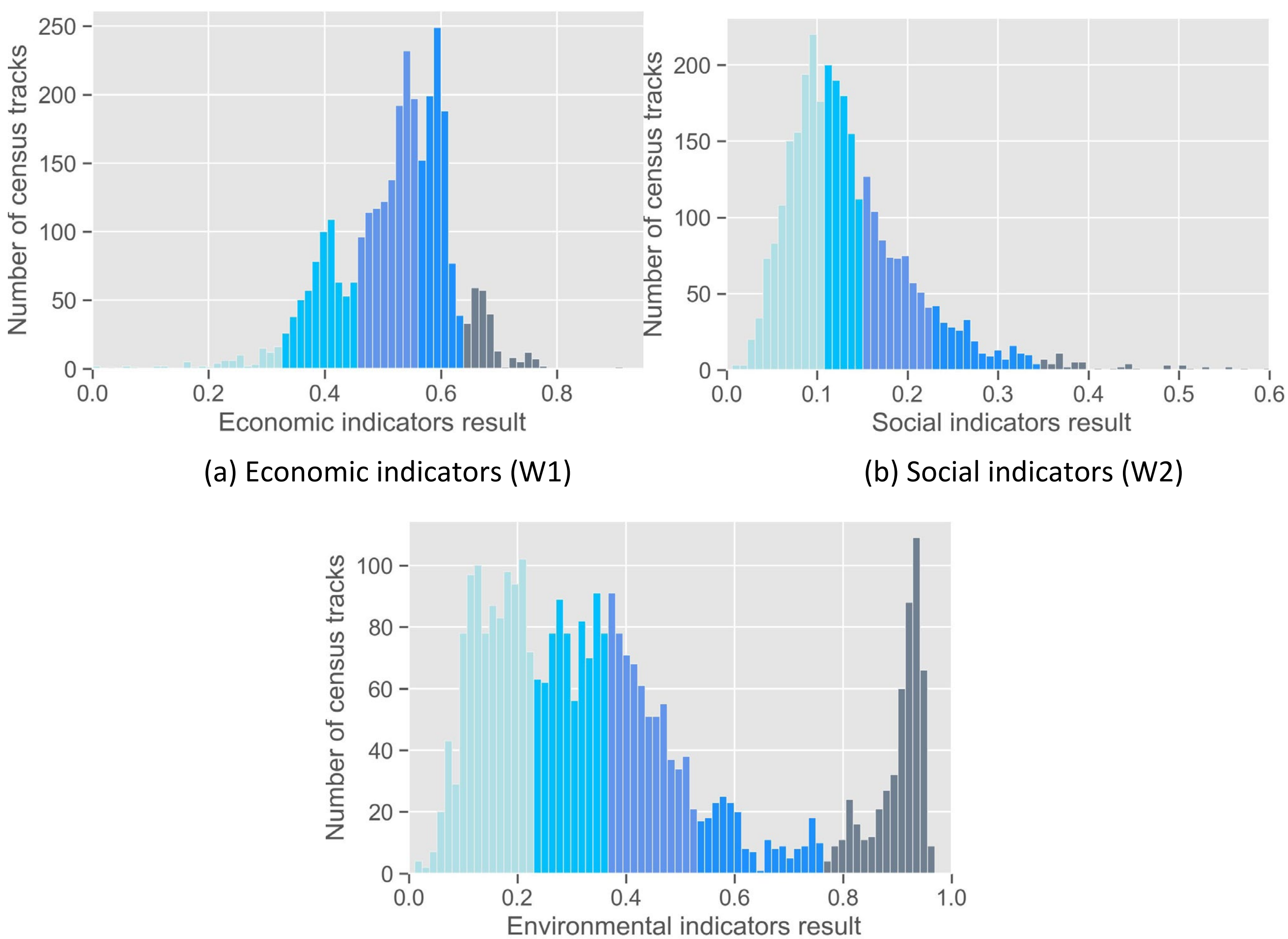
Figure 53. Graph. Charging suitability mapping including only societal indicators (W2).



(a) State of Illinois (b) City of Chicago

Figure 54. Graph. Charging suitability mapping including only environmental justice indicators (W3).

Figure 56 presents the distribution of the suitability metric among different weighting assignments for urban and rural regions in the state of Illinois. Urban regions differ from rural regions based on the population density in each census tract. If the density is greater than 1,500 people per square kilometer, then the census tract is classified as an urban area; otherwise, it is a rural one (Dijkstra et al., 2020). The heavily economic-weighted suitability map has a mean value of 51.91%, with rural regions slightly more suitable for charger deployment than urban regions. The heavily social-weighted perspective has a lower suitability outcome (mean value of 13.72%). Compared with rural areas, the median suitability of urban areas is relatively larger with smaller variance. There is a notable suitability difference between rural and urban areas. We can observe that rural areas are more suitable for charging placement when the environmental justice indicator is the sole one in the suitability analysis.



(a) Economic indicators (W1)

(b) Social indicators (W2)

(c) Environmental justice indicators (W3)

Figure 55. Graph. Distributions of suitability metrics, under W1, W2, and W3 weighting schemes.

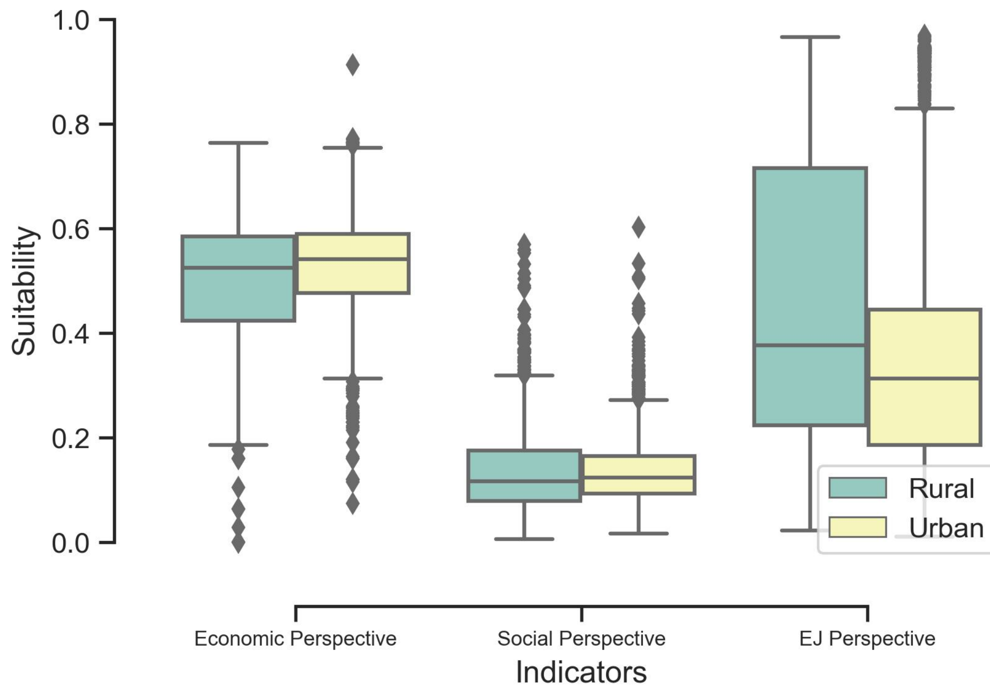
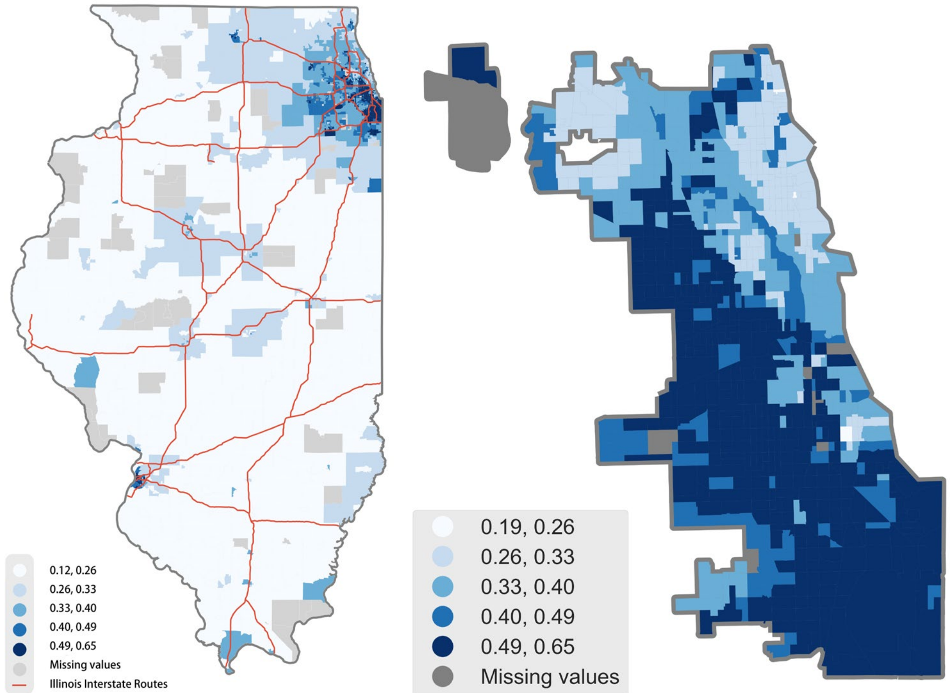


Figure 56. Graph. Box plot of the three indicators and their individual impact on charging station siting suitability.

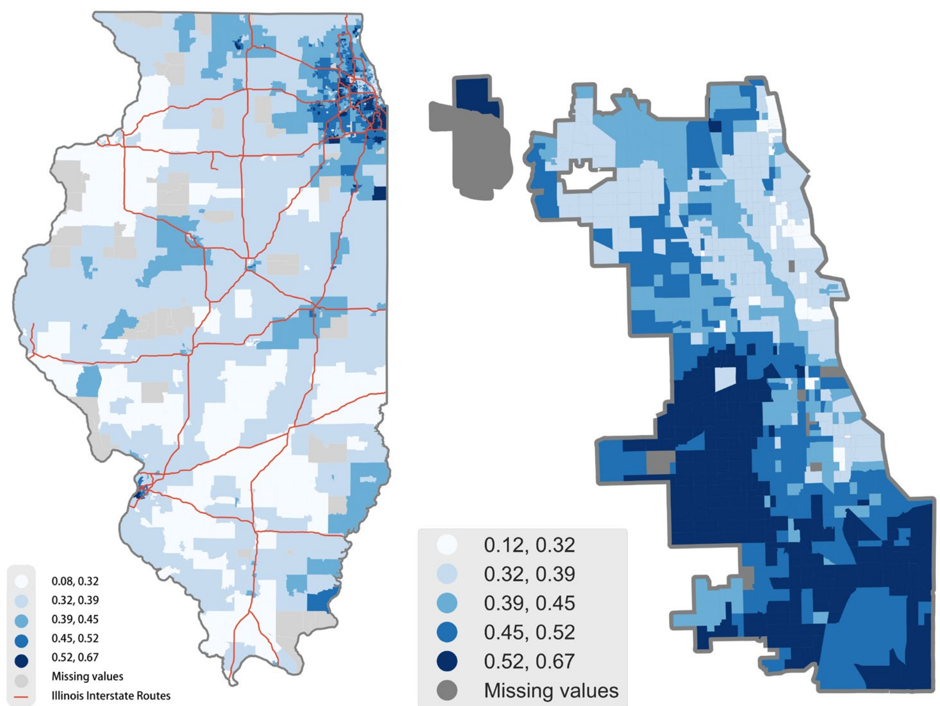
Multi-Criteria Charging Station Siting Suitability Maps

Similarly, we evaluate the outcome of the assignment of weights w_4, w_5, and w_6, as shown in Figures 57, 58, and 59, respectively. The suitability maps obtained by the three weighting methods have similarities. We observe that the diverse stakeholders' elicitation weighting result is approximately equal to the equal weights mapping. Both maps emphasize the same tracts, both in Illinois and Chicago. Moreover, the suitability values follow a similar distribution. Therefore, we can use the equal weights map to identify potential electric vehicle placement locations. Then, we compare the equal weights map and the higher economic value siting results. There is high suitability in the south and east regions of Chicago on the equal weights map, while the economic preference map has a few areas of high suitability in southeast Chicago (e.g., Ashburn, West Lawn, Chicago Lawn, Gage Park, Archer Heights, and the east side).



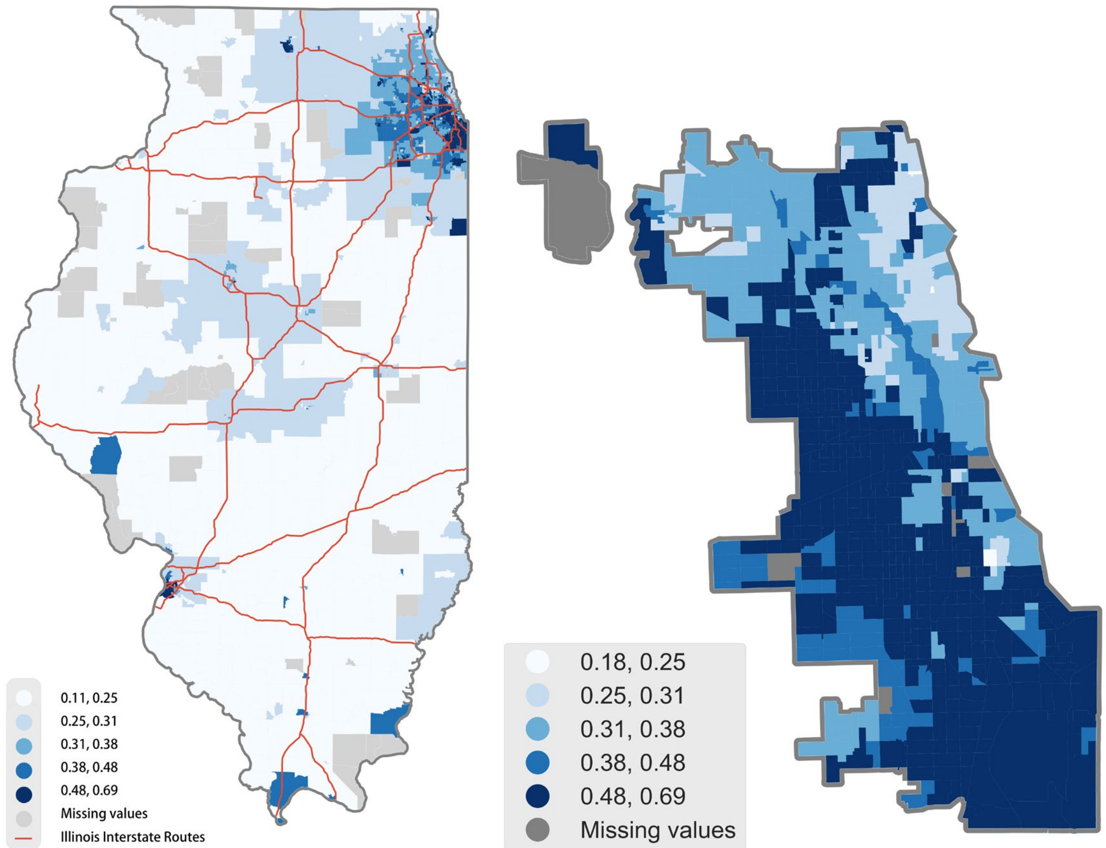
(a) State of Illinois (b) City of Chicago

Figure 57. Graph. Multi-criteria charging siting suitability maps with equal weights (W4).



(a) State of Illinois (b) City of Chicago

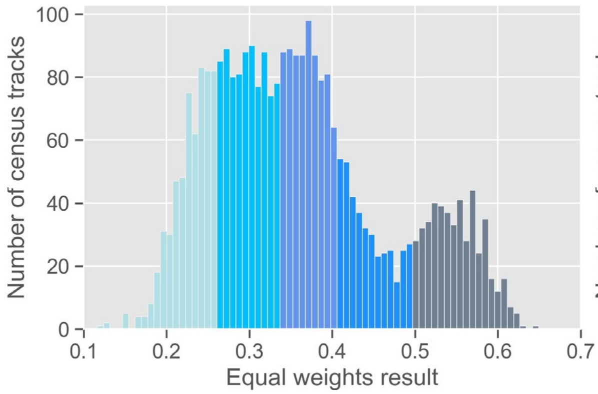
Figure 58. Graph. Multi-criteria charging siting suitability maps with highly valued economic weights (W5).



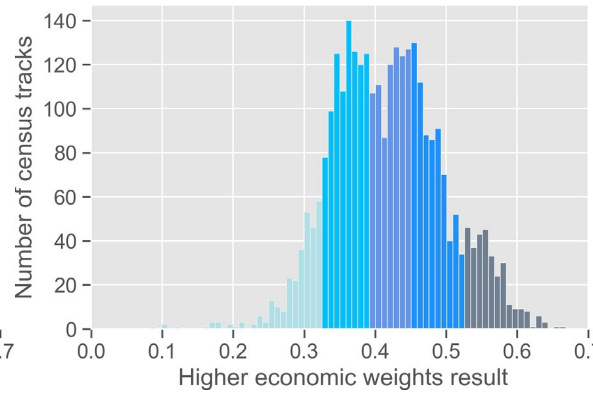
(a) State of Illinois (b) City of Chicago

Figure 59. Graph. Multi-criteria charging siting suitability maps with AHP weights (W6) from diverse stakeholders' feedback elicitation process.

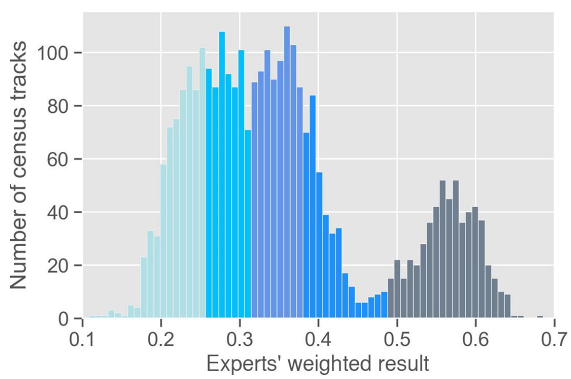
As shown in Figure 61, the trend of charging suitability is the same for the three weighting assignments, with rural areas having a higher suitability score than urban ones. However, the economic preferences option has higher suitability than the outcome of the equal weight for rural and urban regions, and the median suitability difference between cities and rural regions is larger. Considering all three factors simultaneously significantly reduces the number of outliers compared to the single-factor suitability results, owing to a more comprehensive consideration that makes the charging siting recommendation results more robust and the values more reliable.



(a) W4 suitability values distribution



(b) W5 suitability values distribution



(c) W6 suitability values distribution

Figure 60. Graph. Distributions of charging siting suitability values for equal weights, higher economic weights, and AHP weights from stakeholders' elicitation.

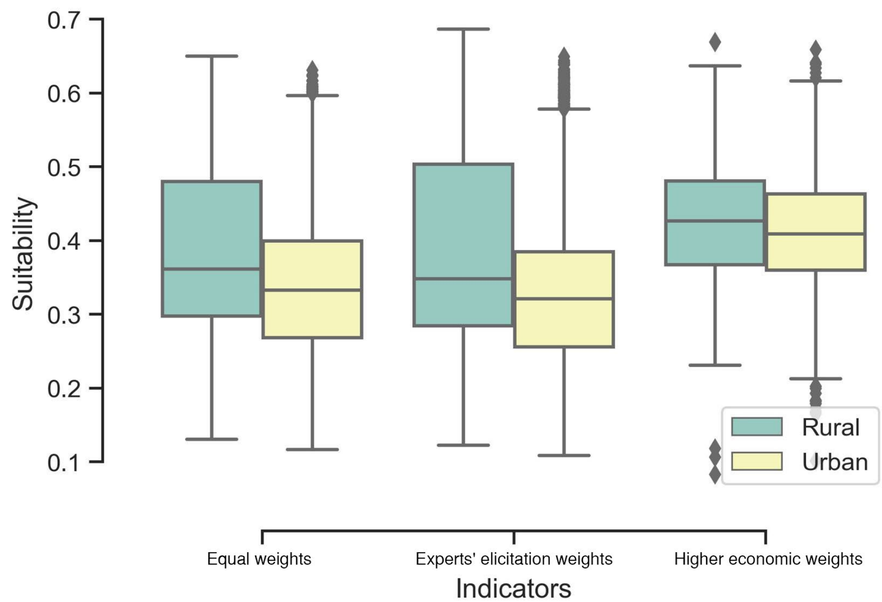
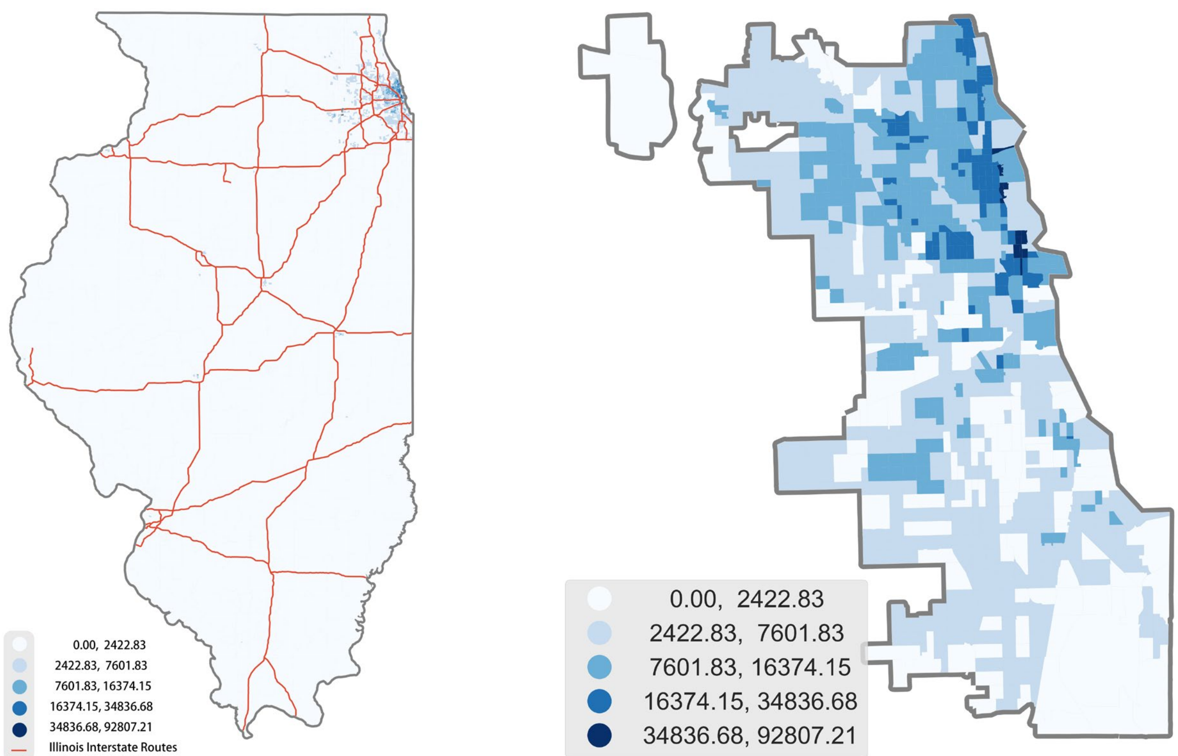


Figure 61. Graph. Box plot of the three types of weighting results for charging siting suitability: equal weights, stakeholders' elicitation weights, and higher economic weights.

Integrating Commercial Activity Indicator into Charging Suitability Maps

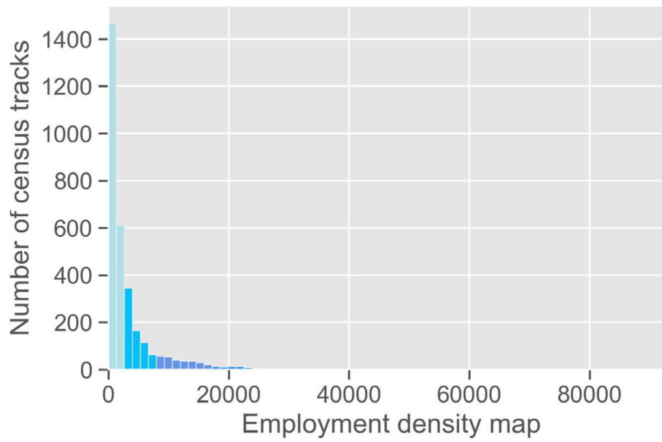
The employment density indicator is computed using employment per square miles (leveraging census data) as a commercial activity indicator. The darker the color, the more commercial activity is generated, which means more travelers will pass through/stay in the area, leading to more demand for electric vehicle charging in the current tract. Strong active areas are concentrated in Cook County, as shown in Figure 62. There are 14 extremely active census tracts and 83 highly active tracts, all of which are in the northwest Chicago region.

We integrated the commercial activity indicator into the economic siting criteria under the equal weights assumption for charging suitability mapping. The result is shown in Figure 64. Compared to the original map, the overall mean suitability value was reduced from 36.10% to 32.04%. The number of high-charging suitability census tracks dropped from 500 to 479 in Illinois, which includes reducing 358 highly recommended tracks for siting to 352. The integration of the employee's density did not produce a change in the distribution of the equal weights suitability values, indicating that the employee density map can reflect the suitability of charging placement to some extent.

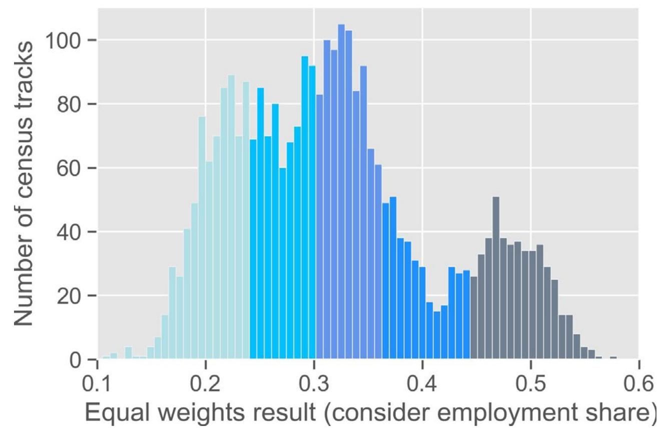


(a) State of Illinois (b) City of Chicago

Figure 62. Graph. Employment density (employees per square mile) maps.

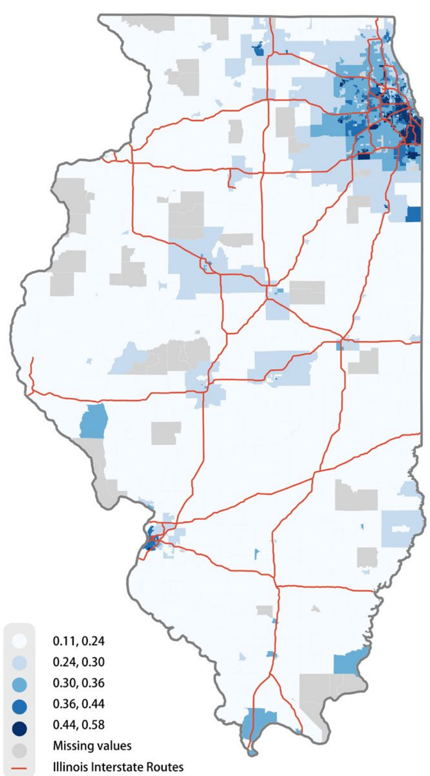


(a) Employment density

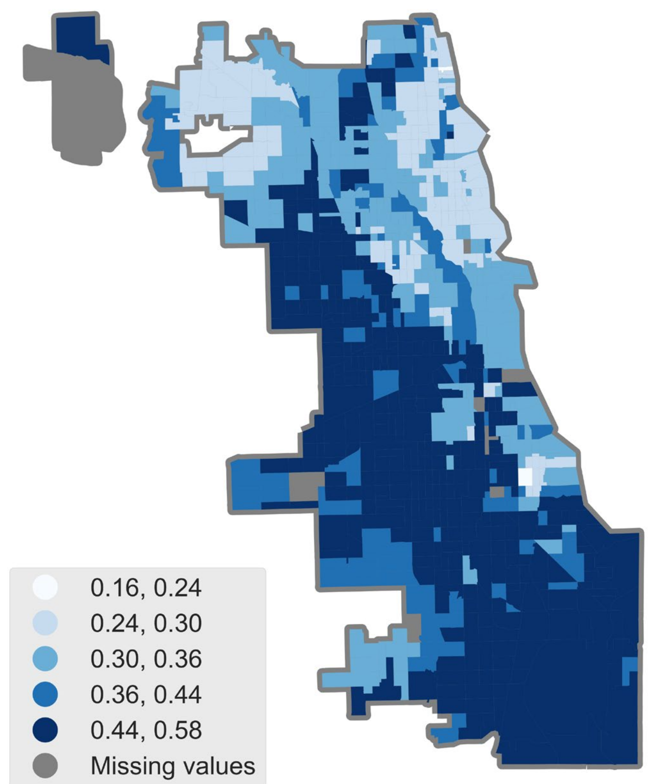


(b) Equal weights map with employment share feature added

Figure 63. Graph. Distributions of (a) employment density and (b) charging siting suitability values with employment density integration.



(a) State of Illinois



(b) City of Chicago

Figure 64. Graph. Equal weights charging siting suitability map with employment share.

Interstate charging infrastructure deployment is critical in enabling electric vehicle corridors (according to the FHWA definition). Note that 27 interstates and major highways traverse the Illinois region. I-57 passes through the greatest number of the state of Illinois census tracts (99 tracts). What is more, I-55 (94 tracts) and I-90 (81 tracts) go through multiple census tracts. We identify interstate and highway sections that should be prioritized based on the Illinois census tracts with a larger mean electric vehicle charging siting suitability. The suitability result underscores two interstates as priorities: I-90 and I-80, which have average suitability of 52.7% and 48.5%, respectively. Most of the interstates' tracts mentioned earlier are in the vicinity of Chicago. According to the geographical distribution of the suitability scores, east–west highways are traversing tracts that have higher charging station siting suitability than north–south highways. The north–south interstates and major highways, such as I-55 and I-57, should also be prioritized to meet the need for long-distance travel facilitated by en-route charging.

DISCUSSION

While eliciting feedback from diverse stakeholders during the second electric vehicle steering committee meeting, we collected feedback on the prioritization of the criteria to determine the charging station siting location. The weighting of the criteria revealed uniform preferences of weights among economic, societal, and environmental indicators. Some useful suggestions were also provided during these meetings. For example, stakeholders suggest evaluating the timeline for workforce development and recruitment in the suitability of charging siting. Charging infrastructure investments could lead to the growth of workforce development in disadvantaged regions, which is an additional benefit attributed to the advent of the electric vehicle market. Other comments underscore the trade-offs between installing charging stations in charging deserts to drive demand and adding more charging where electric vehicle adoption is growing to serve those drivers.

Our analysis considers the economic and social indicators expected to affect electric vehicle charging station siting but also evaluates Illinois census tract locations against quantitative environmental justice metrics, addressing environmental externalities concerns of disadvantaged communities in our state. The charging suitability mapping results highlight the southwest side of Chicago, which poses high suitability for future charging station placement. Multiple factors contribute to this outcome, including the high traffic proximity, substation proximity, high minorities share, high PM 2.5 concentration, and disadvantaged communities. Note that changing the weights of this process will result in different suitability outcomes. The weights provided are indicative, while University of Illinois researchers elicited feedback from diverse stakeholders and uncovered uniform weight assignment for the multiple economic, societal, and environmental justice criteria. In the future, insights into the priorities of decision-makers and stakeholders invested in passenger vehicle electrification should be further investigated as electric vehicle registrations rise. While our analysis demonstrated the criteria and applied algorithms to guide future electric vehicle charging station placement, the results should be interpreted with an understanding of the limitations of the data and the need for continuous updates of the data inputs that change annually or even monthly. A range of programs (federal, state, and local) are underway to promote electric vehicle adoption and use. At the same time, investments in transportation electrification are expected to affect demand and priorities for electric vehicle charging station placement.

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