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Effects of Regional Temperature on Electric Vehicle Efficiency, Range, and Emissions in the United States

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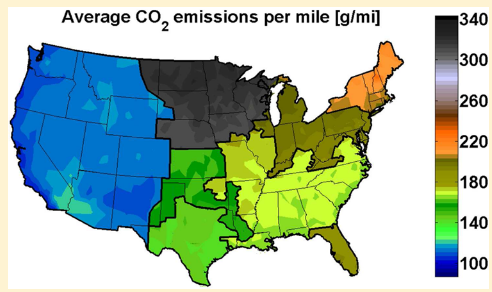
Supporting Information

ABSTRACT: We characterize the effect of regional temperature differences on battery electric vehicle (BEV) efficiency, range, and use-phase power plant CO_2 emissions in the U.S. The efficiency of a BEV varies with ambient temperature due to battery efficiency and cabin climate control. We find that annual energy consumption of BEVs can increase by an average of 15% in the Upper Midwest or in the Southwest compared to the Pacific Coast due to temperature differences. Greenhouse gas (GHG) emissions from BEVs vary primarily with marginal regional grid mix, which has three times the GHG intensity in the Upper Midwest as on the Pacific Coast. However, even within a grid region, BEV emissions vary by up to 22% due to spatial and temporal ambient temperature variation and its implications for vehicle efficiency and charging duration and timing. Cold climate regions also encounter days with substantial reduction in EV range: the average range of a Nissan Leaf on the coldest day of the year drops from 70 miles on the Pacific Coast to less than 45 miles in the Upper Midwest. These regional differences are large enough to affect adoption patterns and energy and environmental implications of BEVs relative to alternatives.



INTRODUCTION

The transportation sector is responsible for 32% of U.S. CO_2 emissions and 28% of U.S. greenhouse gas emissions.[1] In addition, 70% of U.S. petroleum demand is consumed by the transportation sector.[2] Battery electric vehicles (BEVs), which are powered by electricity alone, have the potential to reduce transportation related greenhouse gas emissions as well as petroleum consumption by replacing gasoline with electricity as the energy source. However, there are some barriers to large scale adoption of these vehicles. Range anxiety is a key factor affecting consumer willingness to adopt BEVs.[3,4] The driving range of a BEV depends on the energy capacity of the battery and vehicle efficiency, which are affected by design characteristics as well as some use-phase factors, such as driving conditions[5,6] and temperature.[7]

Battery performance depends strongly on temperature. At cold temperatures, battery efficiency, discharge capability, and available energy decrease. In addition, battery internal resistance increases, decreasing the power that can be drawn from the battery. Battery performance increases with temperature rise, but batteries also degrade faster at high temperatures,[8] increasing thermal management requirements.

Ambient temperature determines initial battery temperature and thermal management loading (if the vehicle is parked outside, the battery is not thermally preconditioned, and solar radiation is negligible) as well as battery temperature and thermal management load during use. Weather conditions, therefore, have a direct impact on battery efficiency. Ambient temperature also drives the use of cabin air conditioning to either heat or cool the cabin on cold and hot days, respectively.[9,10] The net effect of these factors causes customers to report up to a 40% decrease in their driving range on cold winter and/or hot summer days compared to the maximum range they achieve.[7] The cold temperature effect is generally larger for two main reasons: electric cabin heating consumes more power compared to cooling,[11] and batteries have poorer performance at low temperatures.

Air conditioning (A/C) use during hot days is an important factor affecting the fuel economy in all types of vehicles, since A/C is the largest auxiliary load in many vehicles.[12] Cold temperatures, on the other hand, are particularly disadvantageous for BEVs, since vehicles with internal combustion engines can use engine waste heat for cabin heating, whereas in BEVs heat must be generated using limited onboard stored electrical energy. Reduced efficiency results in increased energy consumption and increased emissions from the electricity grid when BEVs charge.[13,14] The net effect on emissions varies across the country due to the source of electricity generation[15] as well as the regional differences in marginal electricity grid mix.[16]

Prior studies investigating the regional differences in energy consumption and emissions of electrified vehicles do not account for efficiency losses with temperature change: A 2012

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report by Union of Concerned Scientists (UCS) investigates the greenhouse gas (GHG) emissions of gasoline vehicles, gasoline hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and BEVs in different regions of the US using constant efficiency assumptions and average electricity generation emissions in each eGRID subregion.[17] They find that about 45% of the U.S. population lives in a region where BEVs have lower use-phase GHG emissions than the most efficient gasoline vehicle: The Toyota Prius. Another report by Climate Central performs a similar analysis but also includes the carbon emissions from vehicle manufacturing and uses average emissions factors for electricity generation by state.[18] They conclude that in 40 states a high-efficiency hybrid vehicle like the Toyota Prius is better for the climate than a BEV over the first 50,000 miles driven. However, Graff Zivin et al. point out that such average emissions factors are not appropriate for estimating the net effect of new electric vehicle load due to differences between average and marginal generation mix and substantial trade among regions. They estimate marginal emission factors in each of the eight North American Electric Reliability Corporation (NERC) regions and use results to evaluate emissions of a Chevy Volt type plug-in hybrid electric vehicle.[16] They find that in some regions, such as the upper Midwest, charging from midnight to 4 am will generate more CO_2 emissions than even an average gasoline vehicle. Tamayao[19] uses the marginal emission factors proposed by Graff Zivin et al.[16] and by Siler-Evans et al.[20] to compare various gasoline and electrified vehicle types while accounting for regional driving patterns. She finds that today's BEVs and PHEVs reduce GHG emissions relative to their gasoline counterparts in most urban regions, but they may increase GHG emissions in the Northern Midwest; the comparison is inconclusive in much of the country due to uncertainty in marginal grid mix estimates.

All of the analyses mentioned above assume constant efficiency for each of the vehicles they analyze, and none of them consider the ambient temperature effect. Neubauer and Wood analyze the impact of various factors, including climate, on electric vehicle miles traveled.[10] They use a vehicle performance model to estimate the change of vehicle efficiency with temperature by including a temperature dependent battery internal resistance term in their model, and they perform the analysis at three selected locations with different climates: hot, cold, and mild. Their battery model (based on a nickel manganese cobalt oxide (NCA) Li-ion battery) suggests that battery resistance effects are negligible in their case, but cabin thermal conditioning can increase the per mile energy consumption by 24% percent in cold climates compared to the case when there is no heating or cooling. Kambly and Bradley also show that heating, ventilation, and air conditioning (HVAC) systems can decrease BEV range depending on the region and time of day.[9,21] Their analyses, based on a thermal comfort model of a hypothetical BEV, suggest that the vehicle range is lowest at noon when the solar load is highest, and thermally preconditioning the cabin before the trip can improve the range by about 10%.[21] According to their estimates, annual HVAC energy consumption is 50% higher in Arizona than in West Virginia.[9]

To the authors' knowledge, there is no study focusing on the regional benefits of BEVs due to spatial and temporal ambient temperature differences. The studies investigating regional emissions do not include the effect of ambient temperature in their analysis, and studies that examine the effect of climate do not assess regional environmental benefits. We aim to fill this gap in the literature. In this paper, we quantify the variance in driving range, electricity consumption, and related emissions due to regional ambient temperature using real world energy efficiency, climate, and driving pattern data. In the following sections, the data used in the analysis are introduced, and the analysis method is described. Results of the regional analyses are presented, and a discussion of comparisons between different regions is provided.

■ DATA AND ANALYSIS

To estimate regional effects of temperature on electric vehicle efficiency, range, and emissions, we construct models of vehicle energy consumption vs temperature; U.S. temporal and spatial temperature variation; vehicle driving and charging patterns; and U.S. regional grid emission factors. In the following sections, we explain the data used for each aspect and our analysis approach.

Energy Consumption Versus Temperature. To find a relationship between energy consumption and ambient temperature, we use the publicly available data collected by Canadian company FleetCarma.[7] FleetCarma provides vehicle monitoring services for fleet owners, and they collect and analyze vehicle data to determine performance under various conditions. We adopt the aggregated results from Nissan Leaf users for more than 7000 trips across North America reported as average driving range versus ambient temperature. The use of these real world data has two key advantages over the prior literature: (1) our results are based on results experienced by real drivers in actual driving conditions instead of simulation models, and (2) we include the net effect of both cabin conditioning and battery efficiency implications of ambient temperature in the analysis (as well as any other factors that may vary with temperature, such as road and driving conditions). Although these data were collected from locations across North America, we use only information about the average effect of temperature on vehicle efficiency in order to isolate the temperature effect from other location-specific factors, such as driving conditions. We convert range to energy consumption using the Nissan Leaf usable battery capacity of 21 kWh[22] applied to every data point provided in the FleetCarma data set, and we obtain new data points for energy consumption, as given in Figure 1. We then fit a curve to these

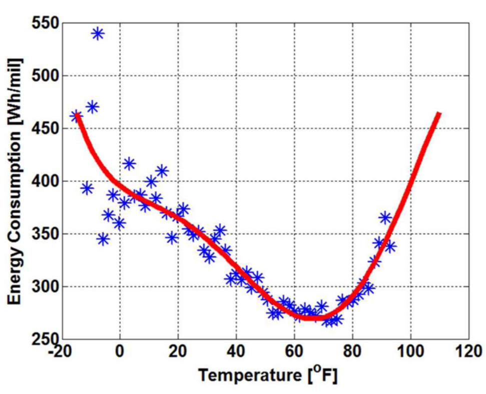

Figure 1. Nissan Leaf energy consumption per mile versus ambient temperature. The blue stars correspond to data points obtained by converting FleetCarma range data to energy consumption. The red curve is the polynomial fit given by eq 1.

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new data points by least-squares regression using the lowest order polynomial that follows the trend of the data qualitatively, and we obtain a generic functional relationship between the vehicle energy consumption per unit distance c and ambient temperature T as

$$c(T) = \left(\sum_{n=0}^{5} a_n T^n\right) \tag{1}$$

where a_n's are the coefficients of the polynomial given in kWh/mi/°F^n

$$a = [0.3950 \quad -0.0022 \quad 9.1978 \times 10^{-5} \quad -3.9249 \times 10^{-6} \quad 5.2918 \times 10^{-8} \quad -2.0659 \times 10^{-10}]$$

Spatial and Temporal Temperature Data. We use the Typical Meteorological Year (TMY) Database from the National Renewable Energy Laboratory (NREL)[23] to obtain time- and location-dependent ambient temperature data. The latest database, TMY3, provides hourly values of meteorological data, including ambient temperature. These data are given for 1020 different locations in United States,[24] including Guam, Puerto Rico, and US Virgin Islands, but we filter the data and exclude the latter regions, which reduces the total number of locations in our study to 1011. The temperature data in this database represent typical hourly temperatures rather than extreme cases, based on 1976 to 2005 records wherever available and 1991−2005 records for other locations.

Driving and Charging Patterns. To obtain driving patterns, we use the National Household Travel Survey (NHTS) 2009 data set.[25] NHTS is conducted by the US Department of Transportation and is an inventory for daily household travel. It contains information on all kinds of transportation activity of a household, including walking, public transport, biking, etc. To obtain a subset of data for the purposes of this study, we filter this data set to obtain the trips completed by private light-duty vehicles only. We also exclude the data points that are reported by the members of the household other than the driver to avoid counting the same trip by the same vehicle more than once. This reduces the total number of vehicles we include in the analysis to 87 777. The NHTS data set has only 1 day of data for each vehicle. Therefore, NHTS does not provide information on day to day variability for a single vehicle. By averaging over each vehicle driving profile and each day of the year, we thus estimate fleet average effects, and individual vehicle owners may experience higher or lower efficiency in a given climate. In addition, we treat the full distribution of driving patterns in the NHTS data as representative of every location in the country, and we ignore any systematic regional variation in daily driving patterns in order to isolate the effect of temperature.

The data set provides start time, end time, and distance of every trip made by each vehicle on the day surveyed. We use this information to determine what time of the day and how far the vehicle is driven, and we assume charging begins upon arrival at home after the last trip of each day and continues until the battery is fully charged.

Grid Emission Factors. To estimate the grid emissions related to increased load with BEV electricity consumption, we need to know the marginal emissions from the power plants that are utilized to meet the extra demand. The mix of the power plants that operate on the margin, and the resulting emissions, show significant variation across regions.[16,20] Graff Zivin et al.[16] estimate the marginal CO_2 emission factors by regressing the emissions in the corresponding interconnect as a function of electricity consumption in each NERC region. In our analysis, we use their expected values of the seasonal time of day marginal emission factors (MEFs) for each NERC region (see Supporting Information). Since estimates of day to day variation of MEFs within one season are not available, we use the same MEFs for each day of the season. These MEFs estimate power plant emissions and exclude upstream emissions from feedstock supply.

Analysis. We start our analysis by estimating energy consumption per mile traveled every day and every hour at each location provided in the TMY3 data set and for each vehicle driving profile in the data obtained from NHTS using the temperature-efficiency relationship extracted from the FleetCarma data. In this calculation, we apply some boundaries to the temperature values that can be used in the computation. The lower bound is equal to the minimum temperature recorded in the FleetCarma data set. For the upper bound (i.e., high temperatures), we extrapolate the curve to the point at which the energy consumption is equal to the maximum value recorded, as shown with the curve fit in Figure 1b. This results in the lower and upper ambient temperature boundaries of −15 °F and 110 °F, respectively. The extrapolation is necessary for fair comparison of hot vs cold regions. The regional hourly electricity consumption per distance traveled can thus be estimated for each vehicle as follows:

$$c_{ldh}^{\mathrm{HOUR}} = \begin{cases} \sum_{n=0}^{5} a_n \cdot (T_{ldh})^n, & -15°\mathrm{F} < T_{ldh} < 110°\mathrm{F} \\ \sum_{n=0}^{5} a_n \cdot (-15)^n, & T_{ldh} \le -15°\mathrm{F} \\ \sum_{n=0}^{5} a_n \cdot (110)^n, & T_{ldh} \ge 110°\mathrm{F} \end{cases} \tag{2}$$

where c_{ldh}^{HOUR} is the Nissan Leaf's electricity consumption per unit distance (Wh/mi) and T_{ldh} is the ambient temperature (°F) at location $l \in \{1,2,..., N_L\}$, day $d \in \{1,2,..., N_D\}$, and hour $h \in \{1,2,..., N_H\}$, where $N_L = 1011$, $N_D = 365$, and $N_H = 24$. In our base case, whenever the temperature is lower or higher than the given boundaries, we assume the energy consumption will be equal to the value calculated at the boundaries.

To estimate the daily average electricity consumption per mile, we need to know how much each vehicle is driven at each hour of the day. We estimate this using the national driving patterns from the NHTS data set. For all the vehicle driving profiles in the subset of data we are using, we distribute the driving durations into hourly bins throughout the day by looking at the start and end time of each trip, and we compute $\Delta_{hv}^{\mathrm{DRV}}$, the amount of time (hours) each vehicle driving profile $v \in \{1,2,..., N_V\}$ spent driving during the corresponding 1 h bin h (where N_V = 87 777 vehicle driving profiles):

$$\Delta_{hv}^{\mathrm{DRV}} = \sum_{\tau \in T_v} \begin{cases} 1 & \text{if } t_\tau^{\mathrm{S}} \le h - 1 \text{ and } t_\tau^{\mathrm{E}} \ge h \\ 0 & \text{if } t_\tau^{\mathrm{S}} \ge h \text{ or } t_\tau^{\mathrm{E}} \le h - 1 \\ \min(h, t_\tau^{\mathrm{E}}) - \max(h - 1, t_\tau^{\mathrm{S}}) & \text{otherwise} \end{cases} \tag{3}$$

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where t_τ^S and t_τ^E are the start and end times of each trip τ, respectively, and T_v is the set of trips for vehicle driving profile v in the data set.

We then use Δ_{hv}^{DRV} to obtain the weighted daily average energy consumption per unit distance for each vehicle driving profile v as follows:

$$c_{ldv}^{VEH} = \frac{\sum_h \Delta_{hv}^{DRV} c_{ldh}^{HOUR}}{\sum_h \Delta_{hv}^{DRV}}, \qquad l = 1, 2, .., N_L, \quad d = 1, 2, .., N_D \tag{4}$$

where c_{ldv}^{VEH} is the daily average energy consumption per mile for vehicle driving profile v in location l and at day d (in Wh/mi).

The expected daily range in each region can be found by first calculating the range for each vehicle driving profile and then averaging over all the profiles in the data set.

$$s_{ld} = \frac{1}{N_V} \sum_v \frac{C^{BAT}}{c_{ldv}^{VEH}} \tag{5}$$

where s_{ld} is the regional expected daily range averaged over all vehicle driving profiles used in the analysis and C^{BAT} is the battery usable energy capacity, taken as 21 kWh for Nissan Leaf battery.[22]

The distance driven by each vehicle profile on each day in each location is computed as

$$s_{ldv} = \min\left(s_v^{NHTS}, \frac{C^{BAT}}{c_{ldv}^{VEH}}\right) \tag{6}$$

where s_v^{NHTS} is the distance traveled by vehicle driving profile v in the NHTS data set. Here, we assume that if the distance driven in a vehicle profile is longer than the all-electric range (AER) of the vehicle, the vehicle shortens travel on those days. We test robustness via sensitivity cases that include a larger battery (to reduce truncated trips) and a slower recharging rate (to shift charge timing).

The regional average electricity consumption per mile c_l^{REG} averaged over all vehicle profiles and days of the year can then be estimated as

$$c_l^{REG} = \frac{\sum_v \sum_d s_{ldv} c_{ldv}^{VEH}}{\sum_v \sum_d s_{ldv}} \tag{7}$$

Greenhouse gas emissions vary depending on charge timing. We first determine the total charging duration for each vehicle profile as

$$t_{ldv} = \frac{s_{ldv} c_{ldv}^{VEH}}{r} \tag{8}$$

where s_{ldv} is total daily distance traveled by vehicle profile v, t_{ldv} is the total charging duration in hours, and r is the constant battery charging rate, which is 6.6 kW for Nissan Leaf battery.[26] Then, we distribute the total charging duration into hourly bins assuming charging starts right after the last trip of the day ends:

$$\Delta_{ldhv}^{CHG} = \sum_{\tau \in L_v} \begin{cases} 1 & \text{if } t_\tau^E \le h - 1 \text{ and } t_\tau^E + t_{ldv} \ge h \\ 0 & \text{if } t_\tau^E \ge h \text{ or } t_\tau^E + t_{ldv} \le h - 1 \\ \min(h, t_\tau^E + t_{ldv}) - \max(h - 1, t_\tau^E) & \text{otherwise} \end{cases} \tag{9}$$

where L_v is the last trip of the day for vehicle profile v, and we obtain Δ_{ldhv}^{CHG} which gives the charging duration that falls into hourly bin h. Using this information, CO_2 emissions can be estimated as

$$\Gamma_{ldhv} = \frac{r \Delta_{ldhv}^{CHG} M_{ldh}^{MEF}}{\eta}, \qquad v = 1, ..., N_V \tag{10}$$

where Γ_{ldhv} is the CO_2 emissions in grams from charging vehicle v at hour h of day d in location l, M_{ldh}^{MEF} is the expected value of the regional seasonal time of day marginal emission factors in grams/kWh, and η is the charging efficiency, taken as 87%.[27] Note that 87% represents the on-board charger + electric vehicle supply equipment (EVSE) efficiency. In other words, 87% of the energy delivered from the grid can be charged into the battery. We neglect any losses that might occur between the onboard charger and the battery; therefore, the efficiency value used here does not affect charging duration. We account here only for power plant emissions and ignore upstream emissions associated with feedstock supply.

Regional average CO_2 emissions in grams/mile, γ_l (averaged over all vehicle profiles and days of the year), are then found by

$$\gamma_l = \frac{\sum_d \sum_h \sum_v \Gamma_{ldhv}}{\sum_v \sum_d s_{ldv}} \tag{11}$$

■ RESULTS AND DISCUSSION

The variation of daily average driving range in selected cities is shown in Figure 2. In three of the cities shown in Figure 2, the median of the daily averages is around 70 miles (112 km). In San Francisco, the median is 76 miles (122 km) and the driving range is greater than 70 miles 99% of the time. As the location changes to cities where more hot or cold extremes might be observed, we see a wider spread of vehicle range throughout the year. In Phoenix, where the daily average temperature can be as high as 105 °F (41 °C), the range can drop as low as 49 miles (78 km), a 29% decrease from the median value of 69 miles(111 km). In cold climates, such as Rochester, MN, the decrease in the range compared to the median can be as high as 36%.

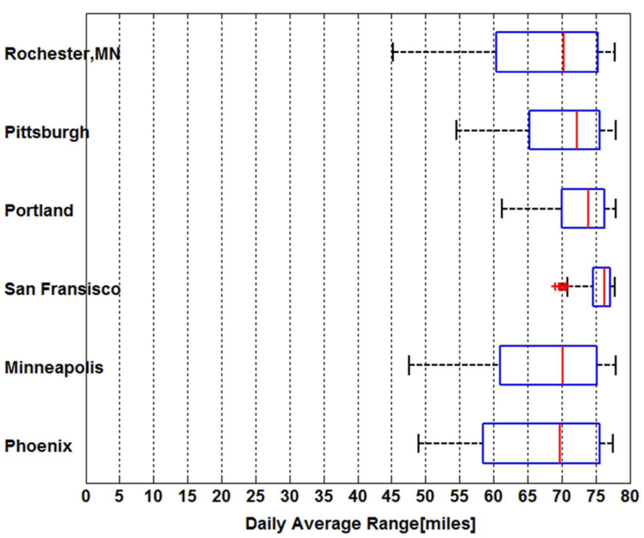

Figure 2. Box plot of daily driving range distributions for selected cities. Red lines indicate median range; blue boxes capture the 2nd and 3rd quartiles across days of the year; the whiskers extend to the most extreme data points that are not considered outliers, and the red + symbols indicate outlier days.

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As mentioned before, the temperature limits used in computations are −15 and 110 °F (−26 and 43 °C), and we do not know exactly how the range or vehicle efficiency changes in excess of these values. In Figure 3, the locations

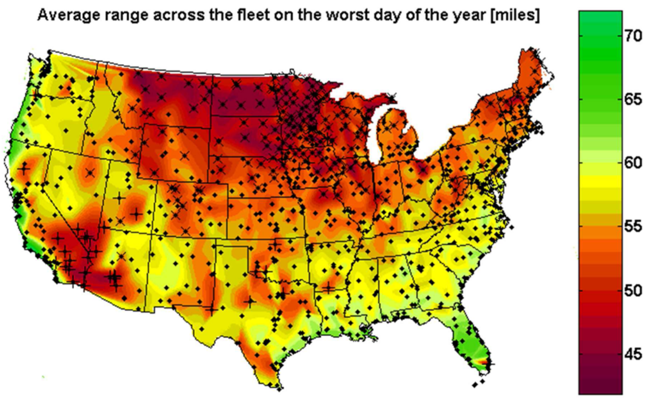

Figure 3. Average range across the fleet on the worst day of the year (day with the lowest predicted EV range). In the figure, dots (•) represent the locations given in the TMY3 data set, crosses (×) represent locations with temperatures colder than the minimum data point at least one time during the year, and plus signs (+) represent locations with temperature warmer than our imposed upper limit of extrapolation at least one time during the year.

where the temperature is outside the limits at least 1 h on the worst day of the year are marked, indicating that actual range on the worst day of the year may be lower than estimated here. For comparison, we also make the same calculation by extrapolating the curve for a wider range of temperature values in the Supporting Information, and overall trends are robust.

Similar to the change in driving range, Figure 4 shows that the average energy consumption per mile can increase by 15%

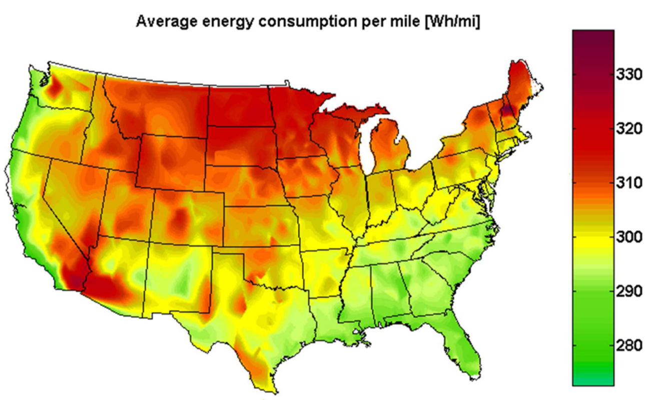

Figure 4. Energy consumption per mile averaged across the fleet over a full year (Wh/mi).

from 273 Wh/mi (170 Wh/km) along the Pacific Coast or in certain parts of South Florida to 315 Wh/mi (196 Wh/km) in the Upper Midwest. It is also possible to observe that the energy consumption can vary inside the same state because of the temperature differences of different locations. In Southeast California, the average energy consumption is 323 Wh/mi (201 Wh/km), 18% higher than the coast.

As depicted in Figure 5, the most significant factor affecting the regional differences in emissions is the grid mix. The worst region in terms of CO_2 emissions is MRO, where both the

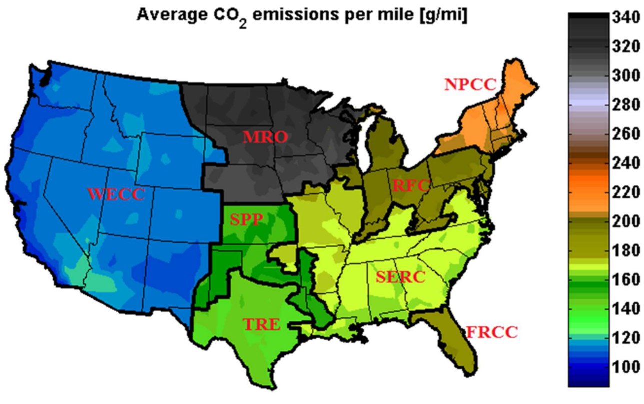

Figure 5. CO_2 emissions per mile in eight NERC regions averaged across the fleet and over the year (g/mi).

marginal emission factors and the energy consumption per mile are high. WECC, with the cleanest grid, has the lowest emissions, especially on the coast where energy consumption is the lowest. When the mean value of average emissions in MRO is compared to the mean value in WECC, there is a 186% increase due primarily to grid mix. Within the WECC region, the emission rates can increase from 100 g/mi (62 g/km) up to 122 g/mi (76 g/km), a 22% increase inside the same NERC region due to ambient temperature. Note that this happens mainly because of two reasons: energy consumption changes with temperature, but also as energy consumption changes so does the charging duration. This creates an impact on emissions, too, since marginal emission factors vary depending on the time of the day when the vehicle is being charged. For reference, tailpipe CO_2 emissions for a Toyota Prius hybrid electric vehicle is reported as 179 g/mi (111 g/km);[28] however, gasoline vehicle emissions rates also vary with temperature.

Since the main source of difference in the regional emissions is the grid mix, as the grid becomes cleaner for most of the country, as targeted by the Environmental Protection Agency's Clean Power Plan,[29] the impact of location on the environmental benefits of electric vehicles will be reduced. However, ambient temperature will remain a source of variation in EV benefits across the US.

To see the sensitivity of these results to some of our assumptions, such as battery capacity and charging rate, we ran two other cases: (1) with an increased battery capacity of 85 kWh and (2) with a lower charge rate of 3.3 kW. Both of these assumptions can change emissions estimates up to 4%. Details are available in the Supporting Information.

Limitations and Assumptions. In this study, we use data only for a particular electric vehicle, the Nissan Leaf. Other electric vehicles differ in vehicle efficiency, HVAC efficiency, battery technology, and thermal management and may therefore have different temperature-specific range and emissions implications. Nevertheless, the trends observed here are fairly general because (1) heater and A/C use increases BEV energy consumption and (2) electrochemical reactions in batteries are temperature dependent. With improvements in battery technology and with the use of more energy efficient vehicle thermal conditioning systems, it might be possible to see a reduced effect of ambient temperature in the future.

The driving range versus temperature data set we use in this study is collected from real world trips. It therefore contains some effects due to different driving styles, trip conditions such

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as congestion on the road, driver preferences on climate control, technology differences due to different model years, and other weather elements, such as precipitation and humidity. We attribute the entire efficiency effect to temperature, which could introduce bias if temperature is correlated but not perfectly correlated with these other factors. In addition, the FleetCarma data set reports average driving range observed across the fleet. Therefore, the results shown in Figure 2 do not show the worst range that can be experienced but rather the fleet average range on the worst day of the year. Some drivers may experience shorter range. In particular, the Nissan Leaf drivers observed in the data are early adopters and may have different behaviors than mainstream consumers (for example, with respect to HVAC use or driving style). Also, we assume the range at temperatures below −15 °F or above 110 °F are equal to the estimated range at the corresponding limit. The results using extended extrapolation are also provided in the Supporting Information, resulting in similar trends but increased magnitude in the hottest and coldest regions.

The NHTS data set provides information on the trips taken by each surveyed U.S. vehicle on a single survey day and does not include day to day variability for each vehicle. In this study, we average over the vehicle profiles to assess implications for average driving distances and assume these daily distances are identical spatially and seasonally. Individual drivers may experience different range and efficiency, and any correlations between driving distance and location or weather could influence results.

We only consider convenience charging in this study. However, time of charging could have a significant effect on emissions. For example, delayed nighttime charging may avoid adding demand during peak times and reduce costs while increasing marginal emission rates in many areas because coal fired power plants tend to be on the margin at times of low demand.[16] In addition, we assume charging rate is constant during charging, and we neglect the effect of temperature on charging efficiency and duration.

Finally, we use point estimates for marginal emission factors and for the curve fit in eq 1. Uncertainty in marginal emission factors and vehicle efficiency implies uncertainty in implications of electric vehicle charging. Further, we attribute the estimated marginal emissions within each NERC region to every location in that NERC region. In practice, marginal emissions vary by location within each NERC region, but due to substantial interregional trade, differences of marginal emission rates at sub-NERC-region resolution are not known. Large penetration of electric vehicles could also have grid effects that are beyond marginal. Additionally, we estimate only power plant emissions associated with electric vehicle charging and do not consider the full life cycle (e.g., including upstream emissions from feedstock supply or temperature-specific repair and maintenance), and we characterize only CO_2 emissions and do not estimate implications of other air emissions from electric vehicle charging.

■ ASSOCIATED CONTENT

Ⓢ Supporting Information

Additional details on data and analysis, sensitivity analyses using full extrapolation on the range versus temperature data, sensitivity analyses for battery capacity, charging efficiency and charging rate, comparison of overall time of day marginal emission factor estimates from Graff Zivin[16] and Siler-Evans et al.,[20] comparison of emissions obtained by using overall time of day and seasonal time of day marginal emission factor estimates from Graff Zivin[16] and Siler-Evans et al.,[20] extended limitations and assumptions section, and all marginal emission factors used in the study in tabulated form. This material is available free of charge via the Internet at http://pubs.acs.org.

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Author Contributions

The manuscript was written through contributions of all authors. All authors have given approval to the final version of the manuscript.

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Notes

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■ ABBREVIATIONS

EV	electric vehicle
BEV	battery electric vehicle
A/C	air conditioning
GHG	greenhouse gas
UCS	Union of Concerned Scientists
NERC	North American Electric Reliability Corporation
TMY	Typical Meteorological Year
NREL	National Renewable Energy Laboratory
NHTS	National Household Travel Survey
EPA	Environmental Protection Agency
AER	all-electric range

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