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Using Connected Vehicle Data to Evaluate National Trip Trends

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Abstract: The National Household Travel Survey (NHTS), conducted by the Federal Highway Administration, has historically been used for documenting personal mobility trends. Current techniques using surveys to collect this data are labor-intensive and difficult to scale. Emerging connected vehicle (CV) data can provide an alternative data source to potentially provide a more scalable method to measure the temporal and spatial usage of passenger vehicles in near real-time. With an impending shift in the automobile industry towards alternative fuel vehicles (AFV), agile monitoring of trip trends is important to help guide state and national investments in AFV infrastructure. This study presents methodologies and visualizations summarizing observed trip characteristics using a sample of more than 500 billion CV records and nearly 1 billion CV trips for December 2022 in the United States. The analysis found very close agreement between trip lengths for internal combustion engine vehicles (ICEV) for CVs and those reported by the 2017 NHTS. Mean trip lengths and trip durations from CVs and NHTS for ICEVs are within 7.8% and 6.6% of each other. The 85th percentile comparison was similarly close, within 0.7% and 8.3%. A comparison of trip trends among states for ICEVs and AFVs as well as US census places and temporal trends for a selection of states, including Indiana, Texas, Wyoming, and California, is provided. The paper concludes that CV data is an important source to monitor trip characteristics across ICEVs and AFVs in near real-time, which will be particularly important to track during the anticipated change to AFVs.

Keywords: connected vehicles; big data; trip trends; travel patterns

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1. Introduction

Travel behavior in the United States has been evolving continuously, most recently with the emergence of electric vehicles (EV) and micro-mobility. It is critical to understand travel patterns and activities to guide transportation policy, planning, investments, and operations. The National Household Travel Survey (NHTS), conducted approximately every 5–8 years by the Federal Highway Administration, has been historically used for documenting mobility trends at the household, personal, trip, and vehicle levels. This NHTS data has provided important information for decision-makers to plan infrastructure improvements and funding allocations [1,2]. This dataset includes the demographic and socioeconomic attributes of households and individuals, as well as trips made by all modes of travel. This data is used to model travel behavior, traffic safety trends, congestion, demographic trends, and transit usage trends. Past NHTSs and follow-up studies have provided insights on the growth of taxi use and ride-hailing in mid-sized to larger cities to specific demographics, an increase in walking and cycling due to improved infrastructure and integrated policies, and have documented trends on the mobility of transportation-disadvantaged groups [3–5]. Additionally, agencies and researchers have leveraged automatic traffic recorders [6], traffic count stations [7], and mobile phone data [8] to observe trends in vehicle volumes and human mobility. These techniques, however, are fairly infrastructure-intensive, requiring the installation of recording equipment, detectors, or cellular connectivity to accurately capture relevant data. The following sections briefly document current survey practices with a focus on the well-founded NHTS and some potential limitations and present the applications, benefits, and emerging opportunities for using connected vehicle data to augment the current state of the practice in this domain.

1.1. Current Survey Practices

Although the comprehensive dataset collected by the NHTS and other such surveys is valuable for a variety of applications, the current data collection techniques are labor-intensive, difficult to scale, and take substantial time to process and obtain results. The 2017 survey alone recruited more than 252,000 households, and the final dataset containing information from more than 129,000 households was published in 2018.

A major challenge with survey-based approaches is the cost of acquisition. For example, when the 2001 survey was conducted, the cost was expected to exceed $10 million [9]. Recruitment surveys with cash incentives for participation over mail, online, and telephone were conducted between March 2016 and May 2017. State and regional agencies often tend to offer monetary rewards for the public to respond to, as the data is invaluable to them, and the derived insights help determine follow-up survey requirements at a regional level [10–12].

Additionally, there are opportunities to introduce biases due to the use of estimations and proxy interviews. For example, the trip distance attribute in the 2017 survey was estimated using the shortest distance recommended by Google Maps between the user's reported origin and destinations [13]. The relative infrequency of conducting these surveys (years 2001, 2008, and 2017) also makes it difficult to understand current trends and patterns [14] associated with fuel prices and new technologies such as micro-mobility. Finally, a rising concern with current practices is the standard use of mail-in diary methods for recording household surveys. These methods are receiving lower than desired response rates, leading to the data becoming less representative. The NHTS is supplementing and even replacing these mail-in methods with phone interviews, internet surveys, and mobile applications in an attempt to improve response rates and accuracy [15].

1.2. Emerging Connected Vehicle Data Opportunities

Emerging connected vehicle (CV) data can act as an alternative data source to potentially deliver a more scalable method to measure temporal and spatial usage of passenger vehicles in near real-time for a variety of applications, including trip origin-destinations, quantifying traffic congestion, travel mode choice, traffic safety, and infrastructure planning [16–20]. Early studies have shown that these CV datasets capture around 500 billion vehicle records in a month nationwide [21] for the United States, with a rough market penetration of 5–7% [22].

Although the 2022 NextGen NHTS has incorporated raw mobile device location data to document national mobility, this still lacks information on the type of vehicle being used and will be reliant on cellular connectivity. CV data offers highly accurate trip statistics owing to the data being recorded directly by the vehicle with limited scope for errors, unlike the aforementioned methods, and provides additional detailed insights at the vehicular level, which may be difficult to capture with traditional survey-based methods.

This data has already shown wide-ranging applicability to prioritize traffic signal retiming, monitor mobility in varying weather conditions, and assess work zone mobility [20,23,24]. Including additional probe, CV data sources provide unique opportunities to evaluate transportation infrastructure and prioritize investments, including pavement markings, pavement quality, and the deterioration of roadway conditions during winter storms using friction data [21,25]. Combining all of these emerging CV data attributes can provide stakeholders and planning commissions with a holistic view of the transportation network and present opportunities to invest in infrastructure improvements, including electric vehicle charging. Previous studies have looked at the use of CV data to assess interstate exit utilization to aid in charging infrastructure site selection and to monitor EV and hybrid vehicle (HV) usage patterns, including operational performance measures such as vehicle miles traveled and charger utilization [17,18].

Thus, as outlined in the preceding text, current survey practices for collecting trip data face multiple concerns in terms of the cost and time of acquisition, low response rates, accuracy of self-reported trip data, and data representativeness, among others. CV Data, already in extensive use by multiple agencies as outlined above, has the potential to fill in these gaps and report accurate trip statistics recorded directly onboard vehicles at representative levels. It is widely available without the need for any fixed infrastructure installations to record the data. This paper uses a one-month CV dataset to demonstrate the applicability of this data in documenting national trip trends.

2. Objectives and Scope

With an impending shift in the automobile industry towards alternative fuel vehicles, agile monitoring of trip trends for both ICEV, as well as HV and EV, is important to help guide state and national investments in alternative fuel infrastructure.

The objective of this paper is to estimate national trip trends by passenger vehicle type, specifically trip length and trip duration, using CV data for the month of December 2022 and to compare the estimations with results from the NHTS 2017 trends. This CV data is also used to visualize inter-state spatial travel patterns among US census places and cities. The final objective is to evaluate daily trip trends and patterns by vehicle type for four states (one in each time zone)—Indiana (Eastern), Texas (Central), Wyoming (Mountain), and California (Pacific).

3. CV Data

Approximately 500 billion records of December 2022 CV trajectory data for the United States were used for this study. This data was available at 1–3 s frequency and approximately 3-m spatial accuracy. Each CV waypoint had an associated anonymized journey identifier, geolocation, timestamp, speed, heading, ignition status, and vehicle classification code attribute, enabling the identification of a waypoint as an EV, HV, or ICEV waypoint. These attributes together help generate aggregated records, one per CV journey, as outlined by the procedures in the following section. CV waypoints with a missing vehicle classification code value were excluded from the analysis for consistency.

4. Methodology

For each CV journey, the chronological first and last waypoints are identified. These waypoints are treated as the origin and destination for the journey, respectively, and are referred to as such in the text that follows. The corresponding origin and destination geolocations are spatially joined to a publicly available dataset of census blockgroups. CV journeys whose origin has an associated ignition status of 'key on' and a destination that has a corresponding ignition status of 'key off' are selected to ensure only complete journeys are analyzed. Gaps in time between consecutive waypoints along a journey, beginning with the origin and ending at the destination, are recorded with their summation representing the trip duration and maximum value documented. The minimum time gap between waypoints was observed to be 1 s. Only journeys with a maximum time gap of 10 s between consecutive waypoints are considered. Similarly, great-circle distances between consecutive waypoints along a journey, beginning with the origin and ending at the destination, are recorded with the sum representing the estimated trip length and maximum value documented. Journeys with a maximum distance gap of 0.75 miles between consecutive waypoints are considered for this analysis. These spatial and temporal thresholds for filtering journeys may be modified as needed per the demands of the analysis and were selected to account for a reasonable tolerance of GPS errors as well as missed data points due to connectivity issues. Finally, only those CV trips that included at least two waypoints over a non-zero time period were selected. Insights into trip trends with very short or near-zero estimated lengths, enabled by these thresholds and waypoint level granularity, are valuable for policymakers in tracking emissions due to idling vehicles, a traditionally unattainable performance measure using survey methods, and especially important to longitudinally monitor the industry's shift towards alternative fuel vehicles. This methodology was utilized to reduce nearly 500 billion CV waypoint records into an aggregated set of nearly 1 billion CV trip records. The attributes derived for each trip and a short corresponding description for each are summarized in Table 1.

Table 1. CV Trip Attributes Derived from Raw CV Trajectory Data.

Attribute	Description
Anonymized Journey Identifier	Allows classification of CV records into journeys
Vehicle Classification Code	Allows classification of CV journeys by fuel type—EV, HV or ICEV
Estimated Trip Length	Cumulative sum of pairwise consecutive waypoint distances
Trip Duration	Cumulative sum of pairwise gaps in consecutive waypoint timestamps
Origin Census Blockgroup ID	Census Blockgroup ID within which a journey's first waypoint lies
Destination Census Blockgroup ID	Census Blockgroup ID within which a journey's final waypoint lies
Origin Ignition Status	Ignition Status at journey's first waypoint
Destination Ignition Status	Ignition Status at journey's final waypoint
Origin Timestamp	Timestamp recorded by journey's first waypoint
Destination Timestamp	Timestamp recorded by journey's final waypoint
Maximum Distance	Maximum value of shortest great-circle distance between two consecutive waypoints on a journey
Maximum Time Gap	Maximum gap in time observed between two consecutive waypoints on a journey

5. National Trip Trends Summary Statistics

Table 2 shows the summary statistics for the estimated trip length (ETL) and trip duration (TD) using December 2022 CV data. The table provides estimates of the mean, 85th, and 95th percentiles by vehicle type (ICEV, HV, and EV). Data from nearly 947 million combined vehicle trips is used to estimate these trip statistics. Table 3 shows a similar table with only the mean and 85th percentile results from a follow-up analysis of the 2017 NHTS [26].

Table 2. Summary Statistics using December 2022 CV Data.

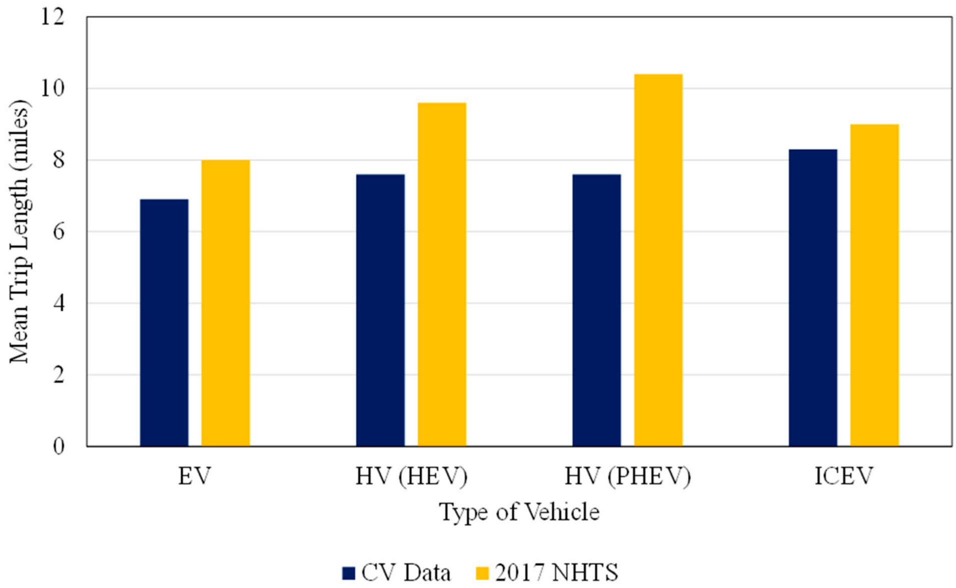
Vehicle Type	Trips	Mean		85th Percentile		95th Percentile	
		ETL (mi)	TD (min)	ETL (mi)	TD (min)	ETL (mi)	TD (min)
ICEV	937,912,748	8.3	18.5	14.6	32.5	30.6	57.8
HV	2,056,404	7.6	16.7	13.7	30.0	29.3	52.6
EV	6,940,148	6.9	16.6	13.0	29.5	27.7	51.9

Table 3. Summary Statistics using 2017 NHTS [26].

Vehicle	Mean		85th Percentile	
	ETL (mi)	TD (min)	ETL (mi)	TD (min)
ICEV	9.0	19.8	14.7	30
HEV	9.6	20.7	16.0	31
PHEV	10.4	21.6	17.8	35
EV	8.0	19.1	14.8	30

In general, both the trip length and duration estimates from CV data match very closely with the NHTS. A side-by-side bar plot comparing the mean and 85th percentile trip lengths is presented in Figure 1 for visualization purposes. The mean trip length for ICEV differs by only 0.7 mi (Figure 1a), whereas the 85th percentile differs by only 0.1 mi (Figure 1b). The estimations using CV data are slightly higher for EV—1.1 and 1.8 mi difference in mean and 85th percentile trip length, respectively. This is likely due to the higher penetration of both vehicles and charging infrastructure in 2022 compared with 2017.

There are slight variations among the HV estimations, which could be due to the CV data using a single category for hybrid vehicles and the NHTS separating hybrids and plug-in hybrids, as well as a change in HV market penetration rates. Mean ICEV trip lengths and trip durations for CV data and NHTS are within 7.8% and 6.6% of each other, respectively. Similarly, 85th percentile ICEV trip lengths and trip durations are within 0.7% and 8.3%, respectively. Figure 2 compares the percentage of trips by estimated trip length between CV and NHTS [1]. The trip lengths are classified into six bins, ranging from less than 6 miles to more than 30 miles. As seen, there is a close correlation between the two estimates across all trip lengths, and on average, the estimates are within 1.2% of each other.



(a)

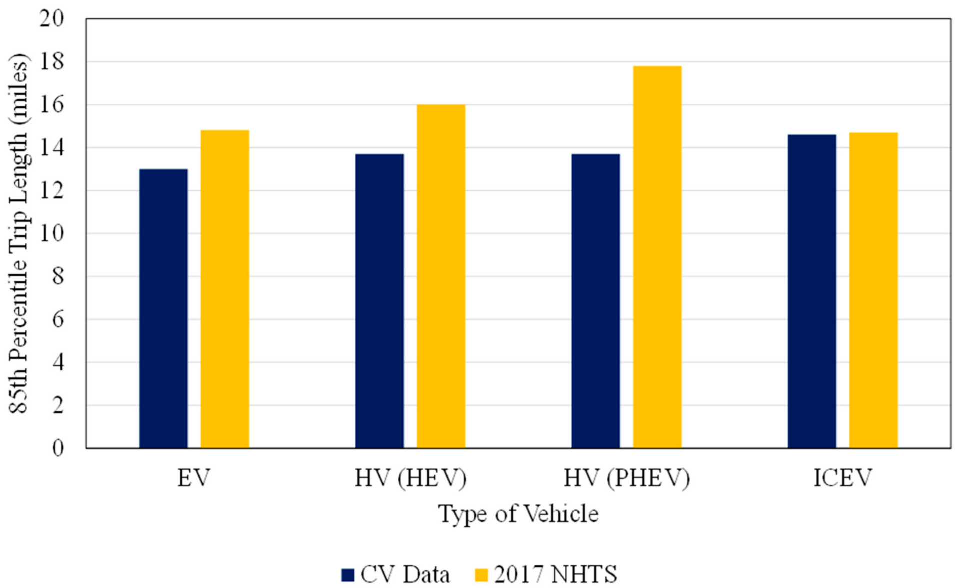


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Figure 1. Trip Length by Vehicle Type using December 2022 CV Data and 2017 NHTS (**a**) Mean Trip Length (**b**) 85th Percentile Trip Length.

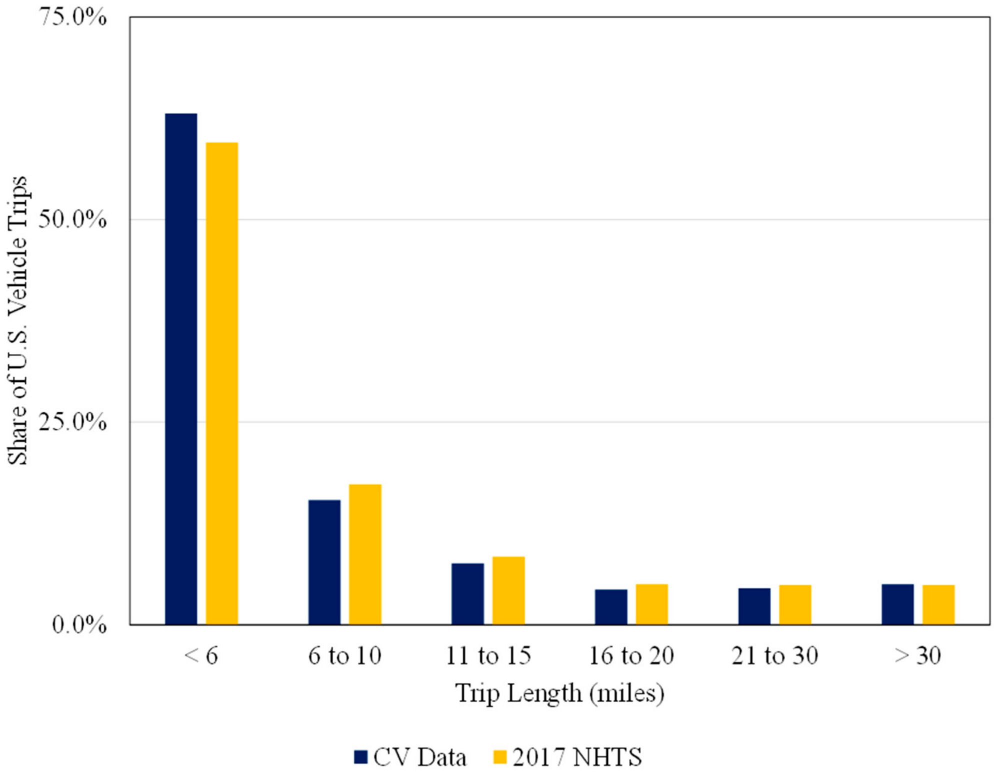


Figure 2. Share of Vehicle Trips by Length.

6. Inter-State Trip Trends between US Census Places

CV trip origins and destinations and the corresponding census blockgroup attributes identified in Table 1 were used to spatially aggregate trip counts and thus travel trends at the national level. A census place representing a named and locally recognized concentration of population as defined by the US Census Bureau [27] was chosen as the aggregation level for this analysis as an example. However, due to the granular census blockgroup level at which each CV trip origin and destination is recorded, alternative visualizations for any chosen census geographic entity, for example, state, county, census tract, zip code, or even core-based statistical areas, may be easily generated. CV trip origin and destination records were spatially joined to 8421 nationwide census places covering 118,067 census blockgroups (about half of the national tally) to formulate aggregate trip count numbers originating and ending in these census places. Following this, only those trips where the US state that the CV trip origin lies in did not match the destination's US state were selected to ensure only inter-state travel was visualized.

To illustrate how CV trip patterns can be visualized, CV trips beginning and ending on 2 December 2022 Coordinated Universal Time (UTC) are plotted in Figure 3. This figure represents approximately 33 million trips that occurred that day. Figure 3a shows a spatial representation of trip counts among all census places, while Figure 3b depicts a similar visualization but only among census places with the keyword 'city' in their assigned legal/statistical area description (LSAD) name, thus being more indicative of inter-city travel at the national level.

Trip counts shown are bidirectional in nature—for example, trips from Hammond, Indiana, ending in Chicago, Illinois, and those originating in Chicago, Illinois, ending in Hammond, Indiana, are represented by a single line segment. Solid blue dots on each figure indicate a census place location, while solid red lines indicate connecting links among the same, with trip counts directly proportional to the line segment's opacity. A significant concentration of trips is visible in census places along the East Coast as well as in major cities including Chicago, Omaha, Fargo, Memphis, New York, and Jersey City, to name a few. The highest trip count nationwide was seen for travel between Kansas City, Missouri, and Kansas City, Kansas, at the Kansas-Missouri state border.

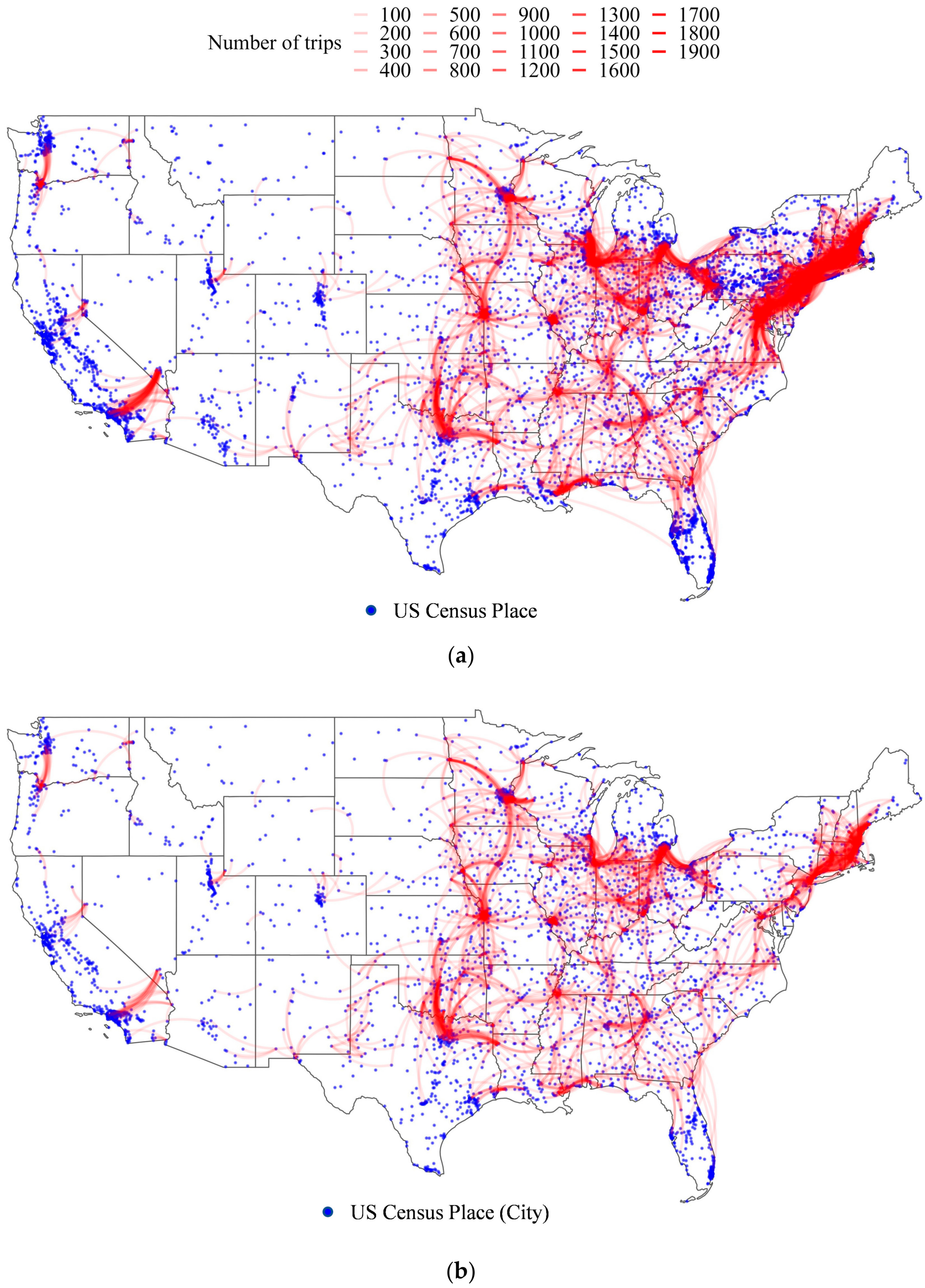


Figure 3. Inter-state Trip Counts between US Census Places (2 December 2022 UTC) (**a**) Trip counts between all US Census Places (**b**) Trip counts between US Census Places marked Cities.

These visualizations depict how CV trip data can be easily scaled to observe trip trends at any geographic level, aided in part by the geolocation accuracy associated with this data, which may not have been reportable using traditional survey-based methods of trip documentation. Such visualizations present insights into trip trends that may be useful for stakeholders in the decision-making process when allocating infrastructure improvement funds by providing quantitative real-world performance measures of corridor travel both inter- and intra-state.

7. Trip Lengths by Vehicle Type

Using the vehicle classification code attribute from Table 1, each CV trip was classified as an EV, HV, or ICEV trip. Correspondingly, summary trip statistics by vehicle type for December 2022 were computed at the state level. Figure 4 shows an alphabetically sorted two-column view of mean trip lengths categorized by vehicle type and US state for December 2022 with states from Alabama to Mississippi shown in Figure 4a and Missouri through Wyoming depicted in Figure 4b. Individual pareto-sorted visuals of these mean trip lengths by vehicle type are shown in Figure 5 for easier comparisons among the various states.

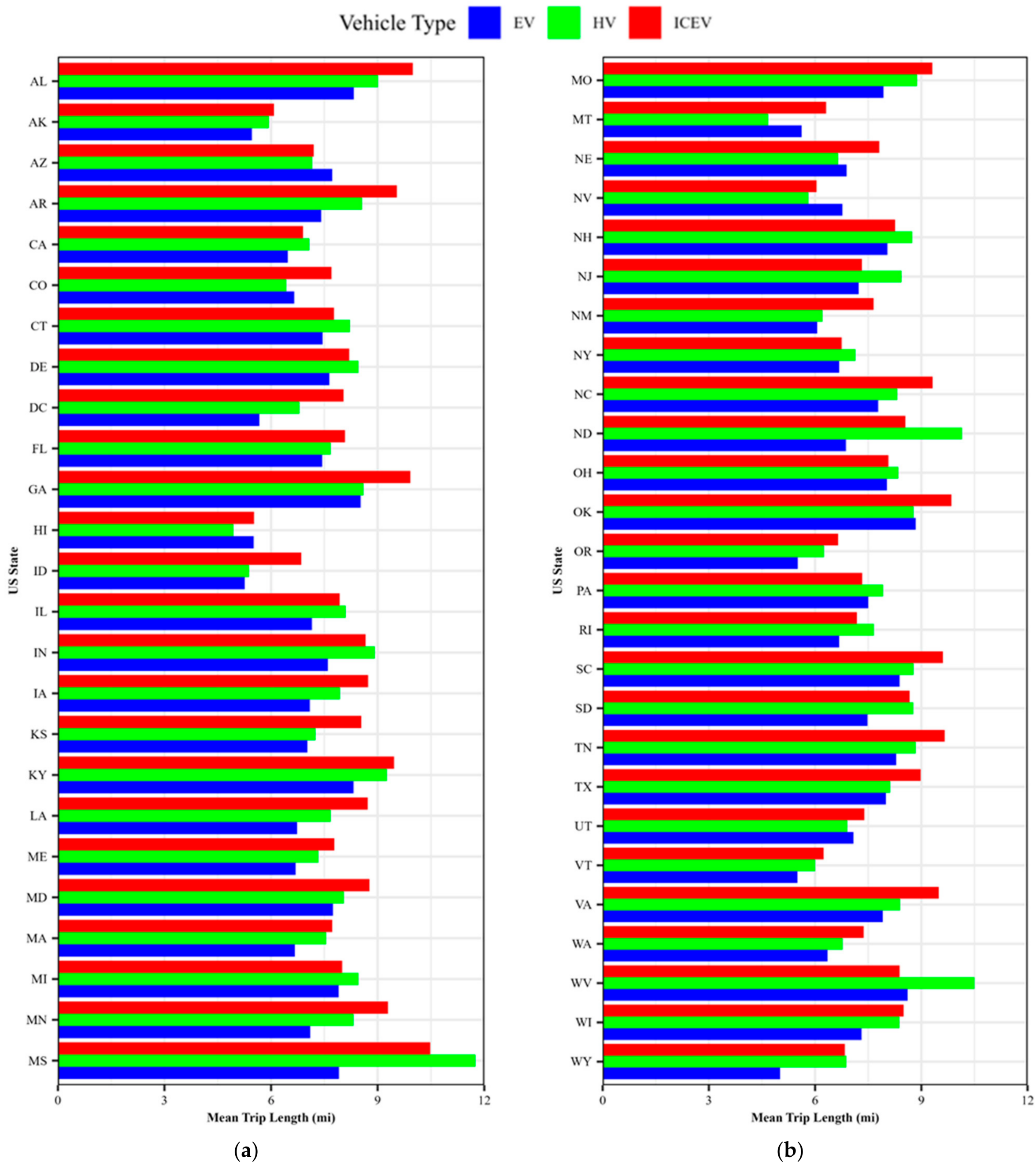
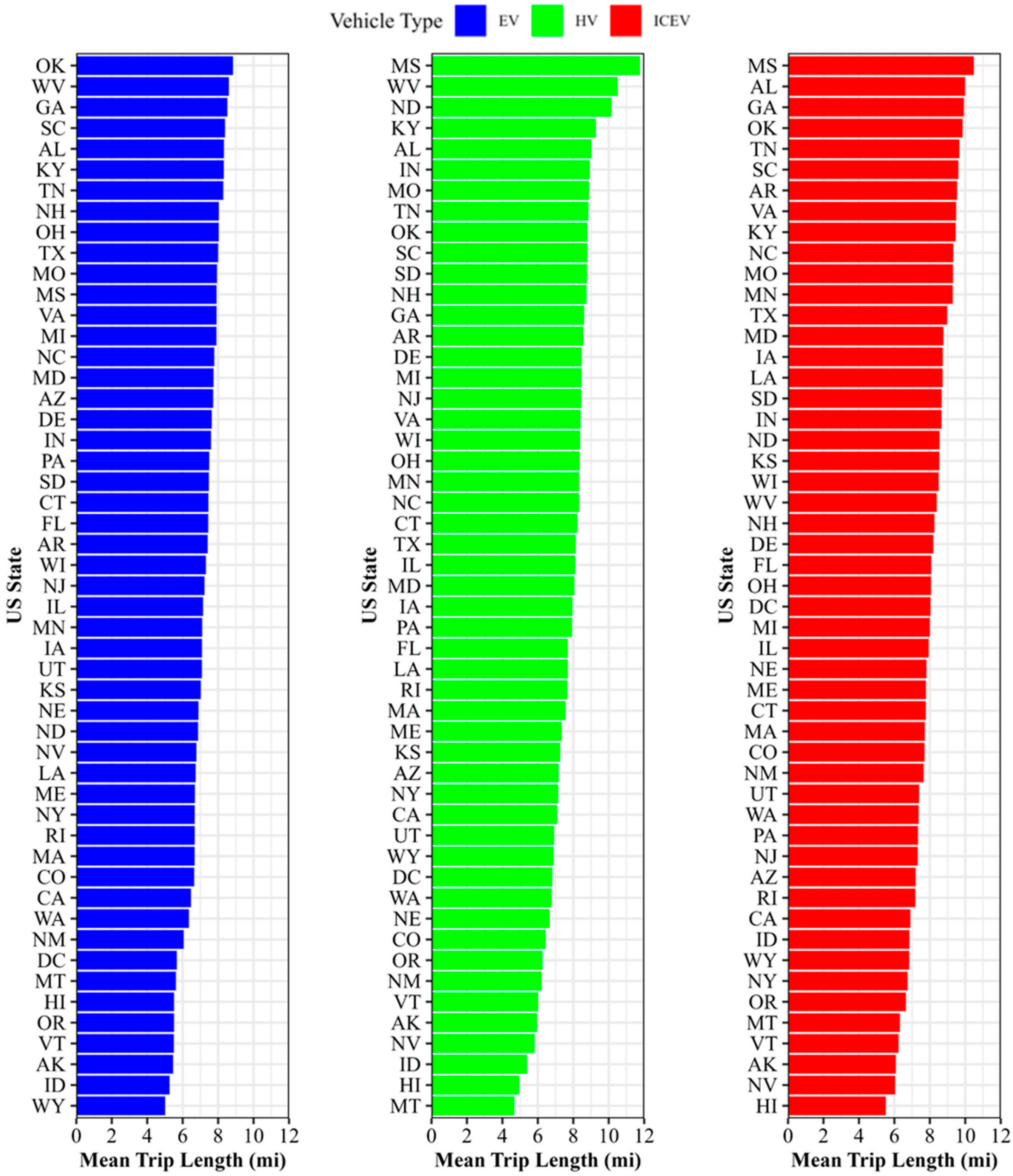


Figure 4. Mean Trip Lengths Measured from CV data by Vehicle Type for December 2022 (alphabetically sorted) (**a**) States AL through MS (**b**) States MO through WY.



(**a**) (**b**) (**c**)

Figure 5. Mean Trip Lengths by Vehicle Type for December 2022 (pareto sorted) (**a**) EV (**b**) HV (**c**) ICEV.

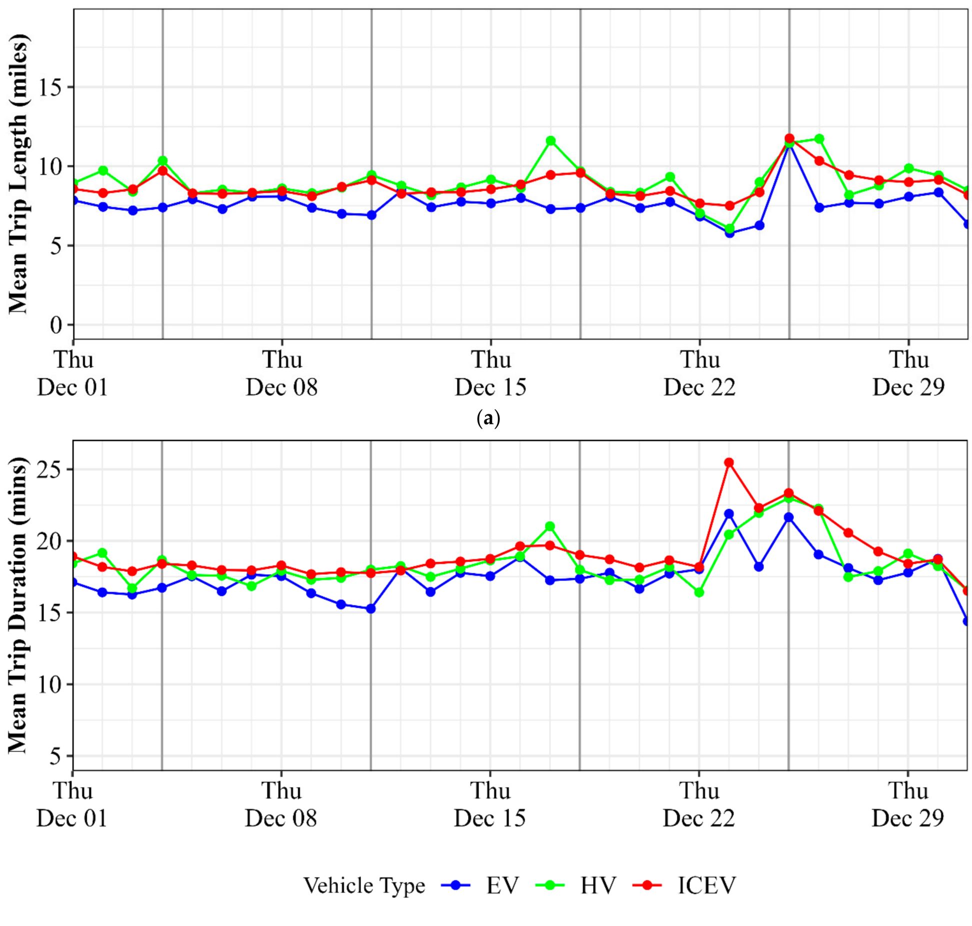
CV trips in Mississippi show the highest mean trip length among HVs and ICEVs, while Oklahoma depicts the highest mean trip length among EVs. Wyoming, Montana, and Hawaii depict the lowest mean trip lengths for EVs, HVs, and ICEVs, respectively. Overall, HVs show higher mean trip lengths, followed by ICEVs and EVs.

These trends can potentially be explained by Mississippi being a primarily rural and low population density state, resulting in driving being the preferred mode of travel and thus leading to higher mean trip lengths. Correspondingly, the states of Alaska, Idaho, and Wyoming have two of the three lowest counts of alternative fueling stations nationwide [28], which may potentially help explain the low mean trip lengths for EVs in these states (Figure 5a), owing to range anxiety among motorists due to a lack of charging infrastructure resulting in shorter EV travel.

8. Daily Mean Trip Lengths for Selected States

Daily trip statistics provide visibility into how day-of-week travel patterns differ across the country as well as by time of year. As a reference, one state from each of the four major time zones in the United States has been selected for the visualizations in this section; however, these graphics can easily be reproduced for any state or another geographic aggregation level of choice (county, census tract, census blockgroup, for example). For the visualizations presented in this section, CV trips are spatially and temporally assigned based on the state they originated from and the date on which they began, respectively. Solid gray vertical lines on each of the graphics in this section represent Sundays for the month of December.

About 23 million CV trips were recorded to be originating in Indiana in December 2022, and the corresponding daily mean values of trip length and trip duration are shown in Figure 6a,b, respectively. The highest mean trip length observed for Indiana was 11.76 mi for Christmas Day and the highest mean trip duration observed was 25.47 min for 23 December, one of the days when Indiana was severely impacted by a winter storm event characterized by an arctic cold front [29]. On average, Indiana recorded mean trip lengths of 8.93 mi for HVs, 8.66 mi for ICEVs, and 7.59 mi for EVs. ICEVs were observed to be driven for the longest time on average, with a mean trip duration of 18.82 min for the month. Weekday trip length and trip duration trends are fairly repetitive, while most higher trip lengths are visible over the weekends.



(b)

Figure 6. Daily Trip Statistics for Indiana (December 2022) (**a**) Mean Estimated Trip Length (**b**) Mean Trip Duration.

The state of Texas observed ICEVs being driven the longest in terms of distance and time, both for the month, with mean values of 8.99 mi and 19.62 min, respectively. On a daily fidelity, Christmas Day exhibited the highest mean trip length across all three types of vehicles, at 12.80 mi, 11.90 mi, and 10.65 mi, respectively, for HVs, ICEVs, and EVs. Nearly 114 million CV trips are represented by the daily aggregated graphics for mean trip length and mean trip duration shown in Figure 7.

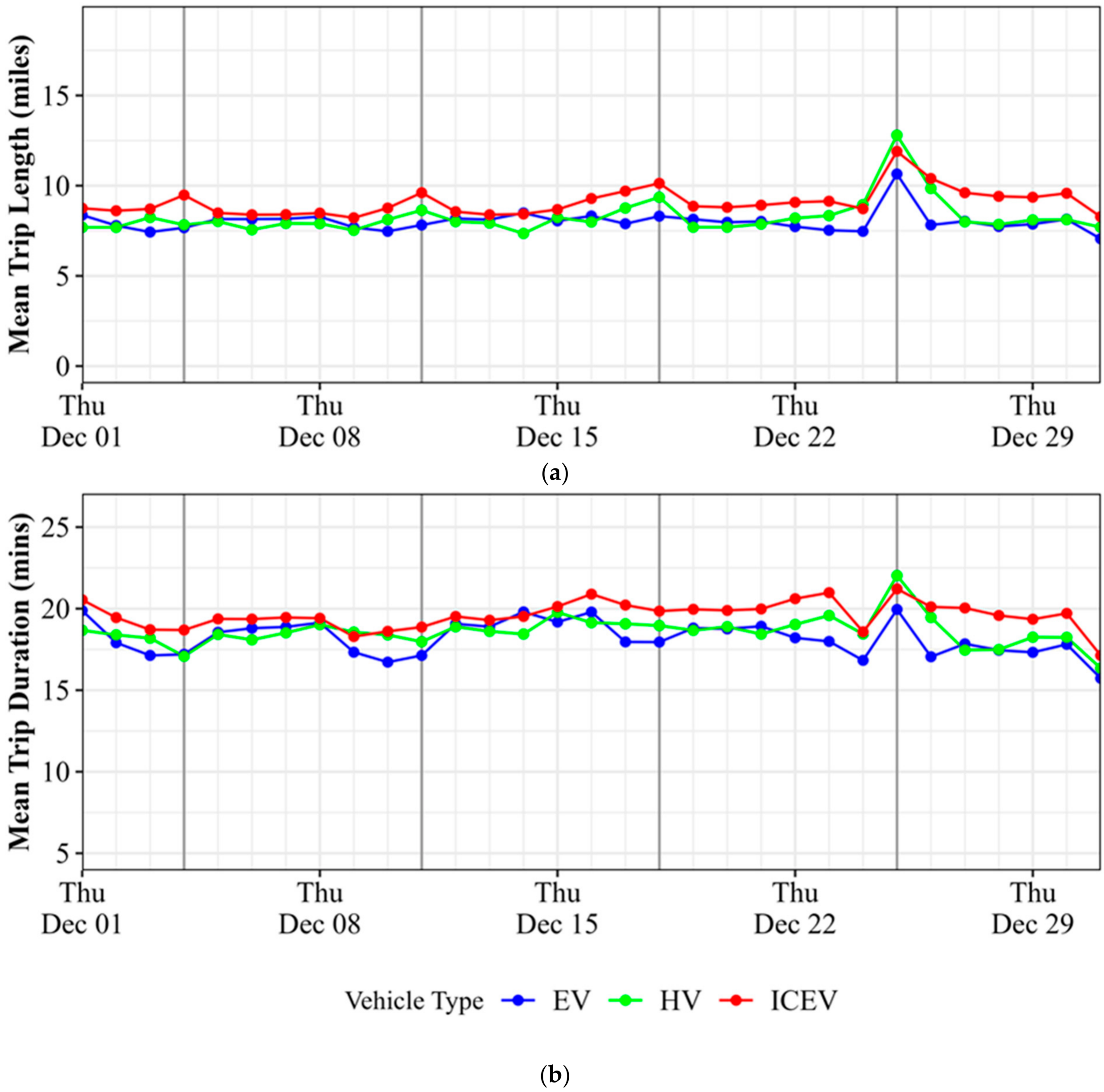
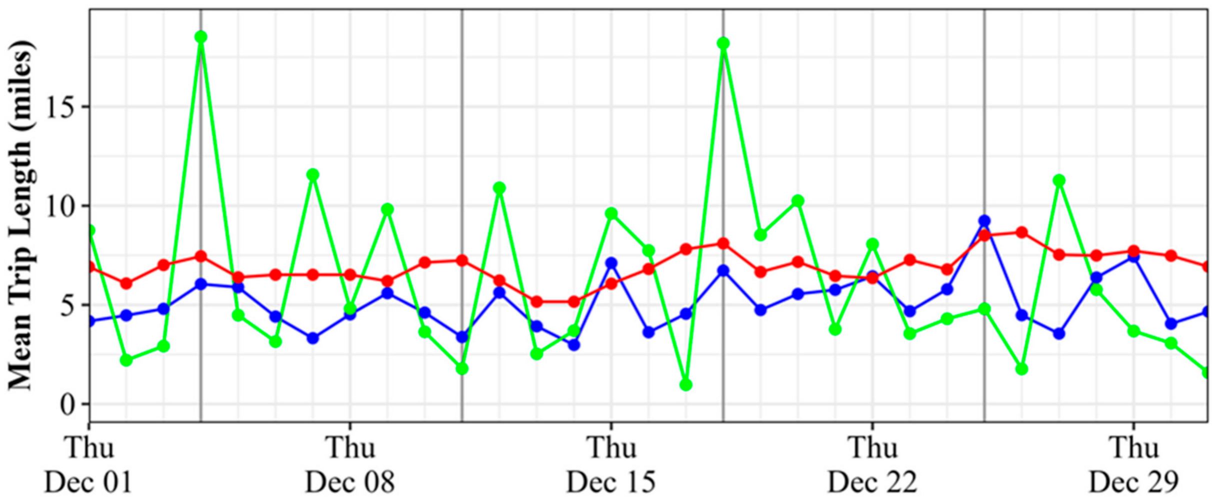
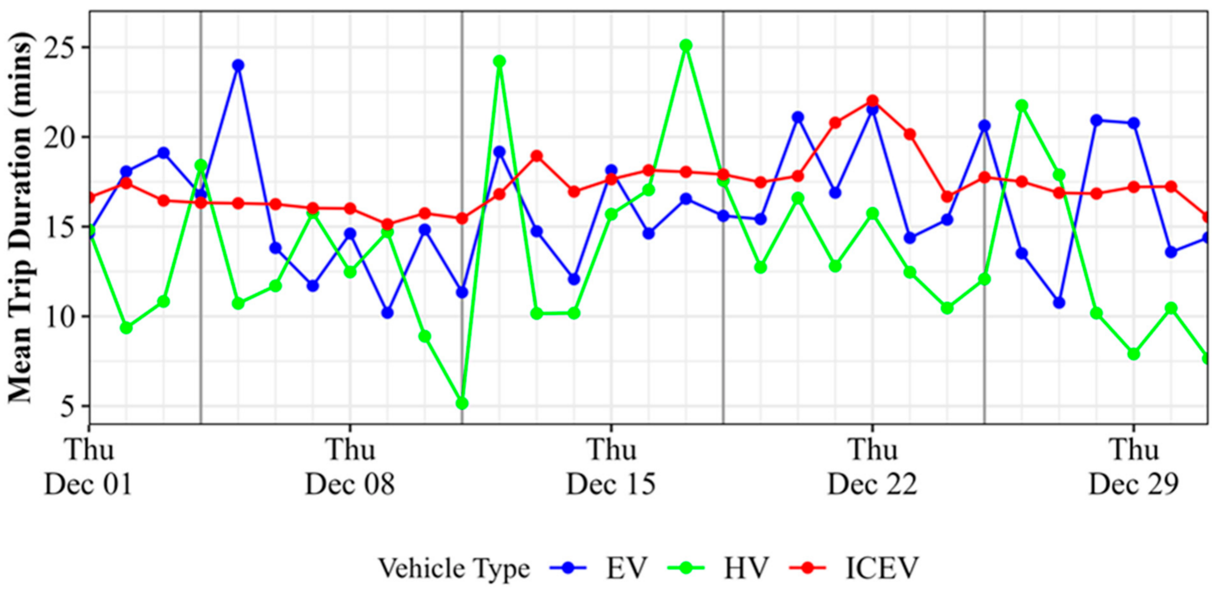


Figure 7. Daily Trip Statistics for Texas (December 2022) (**a**) Mean Estimated Trip Length (**b**) Mean Trip Duration.

Wyoming recorded about 1.7 million CV trips for the month of December, with HVs and ICEVs on average being driven nearly the same distance of about 6.9 mi, with the mean trip length for EVs nearly 2 miles lower at 4.99 mi. The high variation seen in HV trip lengths and trip durations over the month (Figure 8) can be attributed to a low sample size (730 trips).



(**a**)



(**b**)

Figure 8. Daily Trip Statistics for Wyoming (December 2022) (**a**) Mean Estimated Trip Length (**b**) Mean Trip Duration.

California observed approximately 75 million CV trips for the month, including about 3 million EV trips and 0.75 million HV trips. On average, mean trip lengths were lower in California than in Indiana and Texas, with mean trip lengths of 7.08 mi, 6.91 mi, and 6.47 mi for HVs, ICEVs, and EVs, respectively. Expectedly, weekday patterns across the month are fairly repetitive, with longer trips in terms of duration and distance seen to be taken on the Sundays of the month, as shown in Figure 9. Across all the days and irrespective of vehicle type, Christmas Day (Sunday 25 December 2022) observed the highest mean trip distance of 8.96 mi, nearly 1.5 miles higher than any other day of the month. Long-distance travel rising on Christmas Day has historically been documented by the American Travel Survey [30], and the CV data analyzed by this study confirms this largely anecdotal and survey-based observation with quantitative statistics.

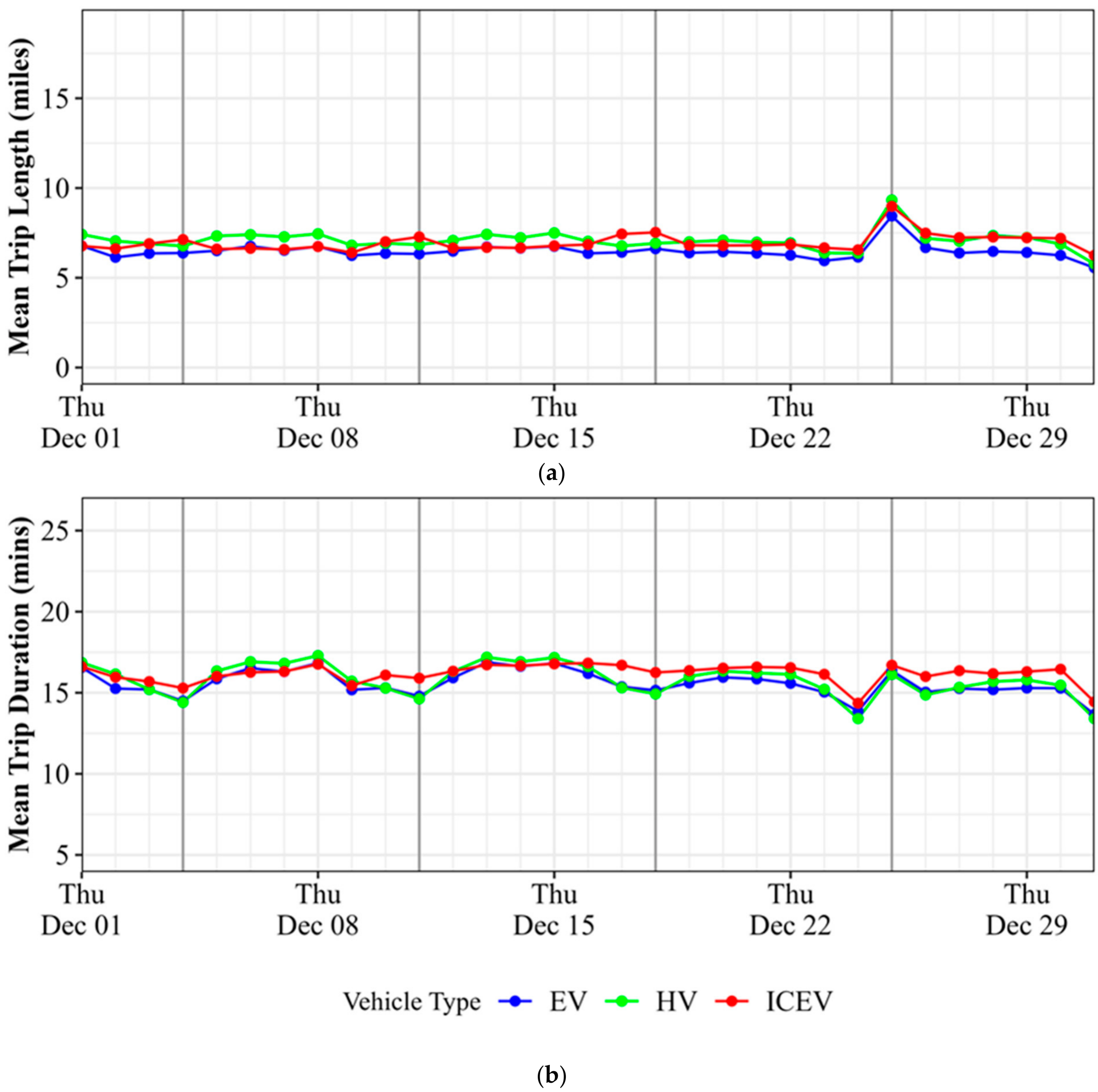


Figure 9. Daily Trip Statistics for California (December 2022) (**a**) Mean Estimated Trip Length (**b**) Mean Trip Duration.

The methodologies and corresponding visualizations demonstrated by this study highlight the versatility and scalability of CV data towards monitoring national trip trends in a cost-, labor-, and time-effective manner to analyze trip trends at the national, state, and local levels. Traditionally reported observations and trends documented by survey-based methods, including the NHTS and American Travel Survey, are confirmed by the quantitative statistics generated by this analysis and point to the ease with which such CV data analysis can be repeated to spatially and temporally monitor trip trends.

9. Conclusions

The current state of the practice of using travel surveys may suffer from inaccuracies and underreporting based on how well each respondent documents their trip length and duration and how the data is collected (telephone, online, or mail surveys). In fact, our CV data analysis may suggest that survey techniques overestimate actual trip length and duration (Figures 1 and 2). This is not surprising, since NHTS trip length is based upon the shortest path estimated by the Google Maps API between self-reported trip origins and destinations.

This paper proposes scalable methodologies to monitor national trip trends using emerging CV trajectory data. Approximately 500 billion anonymized CV waypoint records for the month of December 2022 were aggregated into nearly 1 billion CV trip records for the entire United States. This data represents approximately 5% of the trips in the United States [22].

Trip characteristics such as duration, length, and vehicle type were estimated from the aggregated data (Figures 1 and 4, Table 2). Trip origins and destinations were linked to their respective census blockgroups to allow for efficient geographic aggregation. Summary CV trip statistics for the month were then compared with results obtained by the 2017 NHTS, which collected data from nearly 130,000 households between April 2016 and April 2017.

- All ICEV trip length and trip duration statistics computed with CV data showed close agreement with the 2017 NHTS values (Tables 2 and 3, Figure 1). The mean values were within 7.8% and 6.6% of each other, respectively, while the 85th percentile values were within 0.7% and 8.3%.
- The share of trips by length (Figure 2) showed a close alignment between the two independent techniques, with values agreeing within 1.2% on average.
- Visualizations demonstrating observed inter-state trip counts between US census places at the national level illustrated an expectedly high concentration of trips on the eastern seaboard (Figure 3).

The methodologies and visualizations (Figures 6–9) presented by this analysis are scalable to any state or local level and offer substantial efficiency improvements in comparison to traditional survey-based methods.

Future research in this space will involve a comparative analysis of results obtained from current survey methods at the national, state, and local levels with CV data to identify emerging opportunities for public sector stakeholders to work together with automotive OEMs and third-party commercial data providers toward more efficient and scalable techniques to document passenger vehicle travel patterns. Researchers may potentially find widespread and diverse uses of these methodologies and results in estimating travel demand, planning tourism and hospitality developments, planning transit systems, prioritizing locations when allocating funds for infrastructure improvements, and tracking vehicular emissions as well as energy consumption as the United States and countries around the world work actively towards a transition to electric vehicles in the near future.

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Conflicts of Interest: The authors declare no conflict of interest.

References

1. Federal Highway Administration 2017 National Household Travel Survey. U.S. Department of Transportation, Washington, DC. Available online: https://nhts.ornl.gov/ (accessed on 28 July 2023).
2. Hu, P. *Summary of Travel Trends 2009 National Household Travel Survey*; ORNL/TM-2004/297; Oak Ridge National Laboratory: Oak Ridge, TN, USA, 2005. [CrossRef]
3. Conway, M.; Salon, D.; King, D. Trends in Taxi Use and the Advent of Ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. *Urban Sci.* **2018**, *2*, 79. [CrossRef]
4. Pucher, J.; Buehler, R.; Merom, D.; Bauman, A. Walking and Cycling in the United States, 2001–2009: Evidence from the National Household Travel Surveys. *Am. J. Public Health* **2011**, *101*, S310–S317. [CrossRef] [PubMed]
5. Mattson, J. *Travel Behavior and Mobility of Transportation-Disadvantaged Populations: Evidence from the National Household Travel Survey*; Upper Great Plains Transportation Institute: Fargo, ND, USA, 2012; p. DP-258.
6. Festin, S.M.; United States. Federal Highway Administration. Office of Highway Information Management. Summary of National and Regional Travel Trends: 1970–1995. 1996. Available online: https://rosap.ntl.bts.gov/view/dot/4574 (accessed on 29 August 2023).
7. Leduc, G. Road Traffic Data: Collection Methods and Applications. *Work. Pap. Energy Transp. Clim. Chang.* **2008**, *1*, 1–55.
8. Alexander, L.; Jiang, S.; Murga, M.; González, M.C. Origin–destination trips by purpose and time of day inferred from mobile phone data. *Transp. Res. Part C Emerg. Technol.* **2015**, *58*, 240–250. [CrossRef]
9. Schofer, J. *Letter Report: National Household Travel Survey (NHTS)*; Bureau of Transportation Statistics: Washington, DC, USA, 2002; Available online: https://www.trb.org/publications/reports/nhts.pdf (accessed on 23 July 2023).
10. Frequently Asked Questions. New York State Department of Transportation. Available online: https://www.dot.ny.gov/programs/nhts/faq (accessed on 28 July 2023).
11. Brown, E.; You, D.; Maneva, P.; Hong, S.; Vladimir, L.; Copperman, R.; Kuppam, A.; Selby, B.; DeBoer, K.; Stephanie, A.; et al. *2017 MAG Household Travel Survey*; Maricopa Association of Governments: Phoenix, AZ, USA, 2018.
12. VIRGINIA RESIDENTS ENCOURAGED TO PROVIDE FEEDBACK THROUGH TWO SURVEYS. Virginia Department of Transportation. 2023. Available online: https://www.virginiadot.org/newsroom/statewide/2022/virginia-residents-encouraged-to-provide-feedback-through-two-surveys7-7-2022.asp (accessed on 28 July 2023).
13. Federal Highway Administration. 2017 NHTS Data User Guide. Available online: https://nhts.ornl.gov/assets/NHTS2017_UsersGuide_04232019_1.pdf (accessed on 28 July 2023).
14. Martin, E.W.; Shaheen, S.A.; Zohdy, I.H. *Understanding Travel Behavior: Research Scan*; FHWA-PL 17-025; Federal Highway Administration: Washington, DC, USA, 2016. [CrossRef]
15. Stopher, P.R.; Greaves, S.P. Household travel surveys: Where are we going? *Transp. Res. Part A Policy Pract.* **2007**, *41*, 367–381. [CrossRef]
16. Mathew, J.K.; Desai, J.C.; Sakhare, R.S.; Kim, W.; Li, H.; Bullock, D.M. Big Data Applications for Managing Roadways. *Inst. Transp. Eng. ITE J.* **2021**, *91*, 28–35.
17. Desai, J.; Mathew, J.K.; Li, H.; Bullock, D.M. Analysis of Electric and Hybrid Vehicle Usage in Proximity to Charging Infrastructure in Indiana. *J. Transp. Technol.* **2021**, *11*, 577–596. [CrossRef]
18. Desai, J.; Mathew, J.K.; Li, H.; Bullock, D.M. Leveraging Connected Vehicle Data to Assess Interstate Exit Utilization and Identify Charging Infrastructure Investment Allocation Opportunities. *World Electr. Veh. J.* **2022**, *13*, 167. [CrossRef]
19. Desai, J.; Li, H.; Mathew, J.K.; Cheng, Y.-T.; Habib, A.; Bullock, D.M. Correlating Hard-Braking Activity with Crash Occurrences on Interstate Construction Projects in Indiana. *J. Big Data Anal. Transp.* **2021**, *3*, 27–41. [CrossRef]
20. Saldivar-Carranza, E.D.; Li, H.; Mathew, J.K.; Desai, J.; Platte, T.; Gayen, S.; Sturdevant, J.; Taylor, M.; Fisher, C.; Bullock, D.M. *Next Generation Traffic Signal Performance Measures: Leveraging Connected Vehicle Data*; Purdue University Press: West Lafayette, IN, USA, 2023. [CrossRef]
21. Desai, J.; Mathew, J.; Li, H.; Sakhare, R.S.; Horton, D.; Bullock, D. National Mobility Analysis for All Interstate Routes in the United States: December 2022. In *Indiana Mobility Reports*; Purdue University: West Lafayette, IN, USA, 2022. [CrossRef]
22. Sakhare, R.S.; Hunter, M.; Mukai, J.; Li, H.; Bullock, D.M. Truck and Passenger Car Connected Vehicle Penetration on Indiana Roadways. *J. Transp. Technol.* **2022**, *12*, 578–599. [CrossRef]
23. Zheng, J.; Liu, H.X. Estimating traffic volumes for signalized intersections using connected vehicle data. *Transp. Res. Part C Emerg. Technol.* **2017**, *79*, 347–362. [CrossRef]
24. Sakhare, R.S.; Desai, J.; Li, H.; Kachler, M.A.; Bullock, D.M. Methodology for Monitoring Work Zones Traffic Operations Using Connected Vehicle Data. *Safety* **2022**, *8*, 41. [CrossRef]
25. Mahlberg, J.A.; Li, H.; Zachrisson, B.; Leslie, D.K.; Bullock, D.M. Pavement Quality Evaluation Using Connected Vehicle Data. *Sensors* **2022**, *22*, 9109. [CrossRef]

26. Li, X.; Liu, C.; Jia, J. Ownership and Usage Analysis of Alternative Fuel Vehicles in the United States with the 2017 National Household Travel Survey Data. *Sustainability* **2019**, *11*, 2262. [CrossRef]
27. United States. Bureau of the Census. *Geographic Areas Reference Manual*; United States: Washington, DC, USA, 1994. Available online: http://catalog.gpo.gov/F/?func=direct&doc_number=000565256&format=999 (accessed on 30 July 2023).
28. Alternative Fuels Data Center: Alternative Fueling Station Counts by State. Available online: https://afdc.energy.gov/stations/states (accessed on 28 July 2023).
29. US Department of Commerce. Dec 23–24, 2022 Winter Storm and Arctic Blast. Available online: https://www.weather.gov/iwx/20221223_WinterStorm (accessed on 28 July 2023).
30. United States; Department of Transportation; Bureau of Transportation Statistics. *Home for the Holidays*; United States; Department of Transportation; Bureau of Transportation Statistics: Washington, DC, USA, 1997. [CrossRef]