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The Relationships between Adverse Weather, Traffic Mobility, and Driver Behavior

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Abstract: Adverse weather conditions impact mobility, safety, and the behavior of drivers on roads. In an average year, approximately 21% of U.S. highway crashes are weather-related. Collectively, these crashes result in over 5300 fatalities each year. As a proof-of-concept, analyzing weather information in the context of traffic mobility data can provide unique insights into driver behavior and actions transportation agencies can pursue to promote safety and efficiency. Using 2019 weather and traffic data along Colorado Highway 119 between Boulder and Longmont, this research analyzed the relationship between adverse weather and traffic conditions. The data were classified into distinct weather types, day of the week, and the direction of travel to capture commuter traffic flows. Novel traffic information crowdsourced from smartphones provided metrics such as volume, speed, trip length, trip duration, and the purpose of travel. The data showed that snow days had a smaller traffic volume than clear and rainy days, with an All Times volume of approximately 18,000 vehicles for each direction of travel, as opposed to 21,000 vehicles for both clear and wet conditions. From a trip purpose perspective, the data showed that the percentage of travel between home and work locations was 21.4% during a snow day compared to 20.6% for rain and 19.6% for clear days. The overall traffic volume reduction during snow days is likely due to drivers deciding to avoid commuting; however, the relative increase in the home–work travel percentage is likely attributable to less discretionary travel in lieu of essential work travel. In comparison, the increase in traffic volume during rainy days may be due to commuters being less likely to walk, bike, or take public transit during inclement weather. This study demonstrates the insight into human behavior by analyzing impact on traffic parameters during adverse weather travel.

Keywords: adverse weather; traffic conditions; travel behavior; trip purpose; road weather; weather-related crashes; weather-related travel disruption

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1. Introduction

This study analyzes the relationship between inclement weather and road conditions for an example locale: Boulder, Colorado. According to the Federal Highway Administration's (FHWA) Road Weather Management Program, approximately four-fifths of all fatal weather-related crashes were due to wet pavements [1], which lead to reduced friction between a vehicle's tires and the road surface. Many previous studies have shown that crash risk increases during rainfall [2–15] and winter weather [4,7,11,16–21]. Increased crash risk results from both meteorological and non-meteorological factors beyond the loss of friction. Weather factors such as the intensity, accumulation, and time since the last precipitation event have all been found to increase risk [4,10]. Non-weather factors such as ambient light conditions, road design, driver training and experience, and changes in traffic volume/flow can contribute to or mitigate crash risk depending on the event.

Past studies [22] have explored the reduction in traffic volume that may result from inclement weather. For example, reductions in weekday travel due to snowfall range from 7% to 34% while weekend travel is reduced by 19% to 47% [23], with larger reductions related to higher snowfall totals. Knapp and Smithson [24] found similar reductions in travel volume of 16% to 47%, and the FHWA estimates that heavy snow may reduce traffic volume by as much as 44% [1]. Rainfall also leads to reduction in traffic volume [10,25], and those reductions may be as much as 15% during heavy rainfall [1]. In addition, Keay and Simmonds [9] found that daily traffic volume decreases 0.08% for each 1.0 mm of rainfall. More recent work [26,27] took observational and modeling approaches to demonstrate how traffic volumes during adverse weather conditions can vary with vehicle classifications; noting reductions in personal passenger vehicles paired with increases in commercial vehicles, suggesting the more discretionary nature of passenger vehicle trips.

Research [22] suggests that motorists do alter their behavior during inclement weather conditions. In general, the behavioral changes made by those who do travel are not enough to offset the increased crash risk of driving during these conditions [4,18,19,21], leading to the previously mentioned increase in crash risk. An example of this is that many drivers will make minor adjustments to their speed during inclement weather by slowing down [28]. However, Edwards [28] argues that this decrement in speed is not enough to offset the increased risk associated with stormy weather conditions. Beyond decreasing speed, many people choose not to travel, as reflected in the traffic volume reductions. For example, an individual's ability to engage in self-regulation influences their decisions related to driving [29]. Self-regulation is an individual's ability to understand and manage their behavior in the context of their emotions and the surrounding environment. Additionally, other factors (e.g., age, gender, driving strategies, and views on the utility of driving) interact with a person's ability to self-regulate their driving behavior [29]. In addition to the aforementioned variables, there are a wide range of other factors that influence a person's driving habits and abilities, such as experience, visual attention ability, visuo-spatial scanning abilities, and the environmental cues that the person perceives [30,31].

In addition to changes in driving behavior, adverse weather conditions also contribute to modifications in trip purpose and occurrence [32–37]. The most common self-reported modifications included changes in mode of travel, departure time, and travel route [32]. Snow was consistently found to have the greatest impact on trip purposes [33]. Moreover, commuting trips to work or school were more resistant to change than shopping or leisure trips [33]. Some studies [37] consider a longer-term climate change lens relative to changes in trip purpose and subsequent travel patterns. An important limitation of these previous studies is that they often rely on survey data and methods to understand and quantify changes in trip purpose. The use of crowdsourced and artificial intelligence applications would yield a more robust dataset with greater efficiency in data collection, as well as mitigating potential survey biases.

The aim of this study is to assess the feasibility and potential insights of using crowd-sourced, smartphone-based traffic mobility data to understand the context of motorist travel behavior and decision-making during inclement weather. Given the proliferation of smartphones and various location-tracking applications, these data offer new and potentially rich insights into motorist behavior and travel decision-making beyond conventional techniques. Moreover, these insights can integrate a database of conventional traffic mobility information such as speeds and volumes in conjunction with the demographics of those who are traveling and the purpose of these trips. This information has the potential to expand our understanding of motorist travel behavior and decision making during inclement weather with the broader goal of improving safety and efficiency. This study represents a proof-of-concept analysis incorporating a novel, proprietary database on a case study.

2. Methods and Data

To examine the relationship between adverse weather events and traffic conditions, data were obtained for three different weather stations for 2019 from the National Centers for Environmental Information [38]. These weather stations are located near Colorado Highway 119, which is a favored commuting route that connects the cities of Boulder, Longmont, and Niwot (Figure 1). This corridor was selected given the personal familiarity of the research team with traffic patterns and conditions during the study period. The locations of the weather stations are indicated by the red circles and the location of the "virtual traffic data logger" is indicated by the blue circle in Figure 1. The distance between the weather stations and the corridor varies between 7–14 km. This "virtual traffic data logger" is a polygon that can be drawn as small as a singular directional road segment and as large as a four-square kilometer area. All vehicular movements within the bounds of the polygon are considered and incorporated into the analysis.

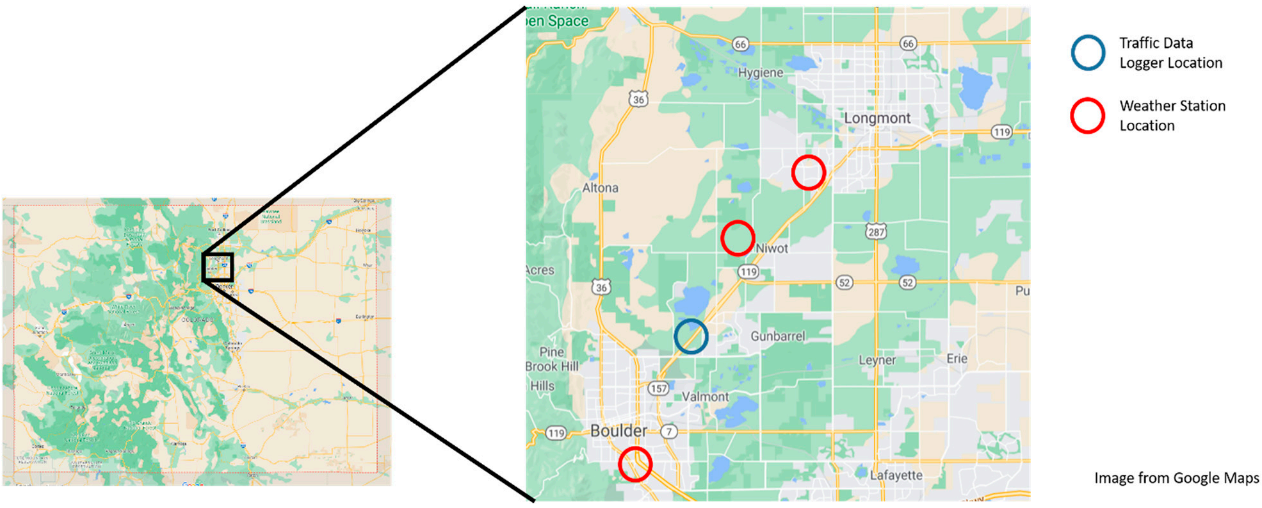

Figure 1. Study area in north-central Colorado for traffic data (blue) and weather station data (red) information.

The traffic data were retrieved from a company called StreetLight Data. Their platform records data by using smartphone applications to measure vehicle motion on most roads [39]. StreetLight provides anonymized, crowdsourced traffic mobility data that includes information relevant to this analysis such as traffic volume, traffic speed, trip classification (i.e., school/work-related commute versus short or long-distance personal travel), trip duration, trip length, and traveler attributes. In addition to smartphone movement and location information, census tract and parcel zoning information are integrated to define the residential locations in which a particular smartphone "resides" (typically overnight) as the "home" location. Proprietary artificial intelligence algorithms have been trained on the dataset to make these reasonably accurate classifications; however, it is important to acknowledge that there may still be classification errors. Additionally, a trip begins when a smartphone moves greater than 20 m at "reasonable vehicular speeds" from any given location. This criterion is implemented to ensure that walking, running, or cycling around a home or neighborhood is not classified as a trip. The trip ends once the device has been stationary for at least five minutes. These data can be used as a proxy to help understand driver behavior at a given place and time, as well as how external factors may disrupt behavior relative to "normal" conditions. Additional work leveraging these data have assessed impacts of flooding on the number of trips taken in a given community [40] and air pollution and greenhouse gas emissions [41].

To better understand the variation in the traffic parameters, the data were divided into three main weather classifications: "Clear", "Rain", and "Snow". Days that contain both rain and snow precipitation are automatically labeled as "Snow" if the snow measurement is greater than or equal to 0.1 in. (0.25 cm). If snow is absent but rain exceeded 0.01 in. (0.025 cm), then the day is labeled as "Rain". If neither type of precipitation meets the criteria, then the day is labeled as "Clear". Rainfall or snowfall was required at any point within a 24 h period of given day. Although the weather station data gathered were of high quality, there were some missing data. As a quality control measure, three weather stations were compared to determine which location had the most complete data, as seen in Table 1. Because the Boulder station contained only one missing value (Table 1), this location was used to draw conclusions for this research.

Table 1. Daily weather type day classifications for the 2019 year in Boulder, Longmont, and Niwot.

Weather Types	Number of Days			
	Boulder	Niwot	Longmont	Total
Clear	263	256	249	768
Rain	55	19	63	137
Snow	46	40	40	126
Missing	1	50	13	64

The traffic data were divided into four periods for analysis: (1) All Times (12 a.m.–12 a.m. local time [LT]), (2) Peak Morning (6 a.m.–10 a.m. LT), (3) Mid-Day (10 a.m.–3 p.m. LT), and (4) Peak Afternoon (3 p.m.–7 p.m. LT). LT for this region is either Mountain Daylight (UTC-6) or Mountain Standard Time (UTC-7). For each of these periods, the yearly averages of the following traffic parameters were calculated: (1) Traffic Volume, (2) Trip Speed, (3) Trip Length, and (4) Trip Duration. StreetLight Data and its partners anonymously monitor smartphone device movement over a period of at least one month to develop a profile for a particular device and classify its trip purposes. As an example, suppose an individual leaves a residential zoned parcel at the same time every weekday morning during a one-month period and concludes a trip at a commercial zoned parcel where the device does not depart until several hours later. The algorithms would reasonably assume that this would be a trip between a home and work location. The percentages for the following trip purposes are calculated: (1) Home-Based Work, (2) Home-Based Other, and (3) Non-Home-Based. Home-Based Work was defined for trips in between home and work locations, while Home-Based Other applies for trips that are between home and non-work locations such as dropping off children at school or picking up coffee. Non-Home-Based travel accounts for trips that do not involve travel to or from home, such as picking up food during a lunch break at work or returning home from work at the end of a day. All these variables were calculated separately for eastbound and westbound traffic, weekdays versus weekends, and then calculated again with respect to weather class. A multivariate general linear model assessed the influence of several variables on a variety of trip purposes. The independent variables in the model were traffic volume, day of week (weekday versus weekend), time of day, and type of weather. The three trip types that were entered into the model as the dependent variables were "percent of home-to-work" trips (Home-Based Work), "percent of home to non-work locations" (Home-Based Other), and "percent of non-home-based trips" (Non-Home-Based). The pairwise comparisons utilized Bonferroni's Correction.

To consider finer temporal resolution weather data, thrice-hourly (i.e., every 20 min) automated weather observations from the Boulder, CO station was obtained from the Iowa Environmental Mesonet (IEM) archive [42] for each day during the study period. The number of observations with snow, rain, or clear conditions were then tabulated for the four time periods available from StreetLight Data: All Times, Peak Morning, Mid-Day, and Peak Afternoon. It is important to note that there are a variety of classification techniques that could be used to define sub-daily weather types such as the most frequent observation during the period and/or the more "severe" weather event.

For example, during the four-hour peak morning period, there are 12 total observations available (i.e., thrice-hourly). There are numerous instances in the data where six of the observations could be snow, three of the observations rain, and three of the observations are clear. This presents a classification challenge for the period as there are several possibilities: (1) classify the period as snow, as this is the most frequent observation; (2) classify the period as snow, as this is the most "severe" weather observation; (3) consider a new classification of "mixed", as the period is not a homogeneous weather type; (4) consider a new classification of "wet snow", as it is unlikely that snow coincident with rain and clear conditions during the same four-hour period would be substantially impactful; (5) classify the period as "clear", as it is the least "severe" weather type; or (6) classify the period as "rain", as it is the intermediate "severity" of weather type. There would be benefits and caveats with all of these methods; however, the greater challenge was the desire to be both objective and consistent. There also exists the case where all 12 observations could be split evenly among the categories. Moreover, observed precipitation does not necessarily provide context for how that precipitation may or may not be accumulating on the surface of the road in particular. There could be observed snow that is simply leaving the road pavement wet instead of icy, slushy, or snow-covered. Similarly, there could be observed extremely light rain that is only making the road surface damp instead of soaking wet. In summary, there is a precipitation "intensity" component that is unavailable for further scrutiny in the current analysis.

The traffic mobility data was not available at any finer temporal resolution than these three sub-daily periods. The overall number of days defined as a particular weather type changed very little when using sub-daily data compared to daily data, with ten or fewer days changing classification between the two methods. Given the non-homogenous distribution of sub-daily weather information, the increased subjectivity in selecting a classification strategy shown by the example, and the relatively small differences from the daily weather types, the original daily classifications were used for the remainder of the analysis. This decision is supported by previous studies that have found similar results when comparing the utility of daily versus sub-daily data when examining weather-related crash risk [43]. In most cases, the use of sub-daily weather data does not result in risk estimates that vary significantly from those calculated from daily weather data [43]. To best understand the variability of the parameters by weather type, it is crucial to analyze every single day for Boulder in 2019, rather than just the year as a whole. Thus, we provide plots to reveal the variation in these parameters along with their relationship with different weather classes.

3. Results and Discussion

The methodology described in the previous section was applied to all 365 days of 2019 for Boulder, to determine differences in the parameter values that imply a link to human behavior with weather class. The averages for these parameters were calculated separately for each time period and weather type (Tables 2–5). Table 2 shows the All Times aggregation, while Tables 3–5 break Peak Morning, Mid-Day, and Peak Afternoon periods.

These tables indicate that eastbound traffic (leaving Boulder) is overall more congested than westbound traffic (toward Boulder) during the entire day (Table 2) and Peak Afternoon (Table 5), while westbound travel is more common during the Peak Morning (Table 3) and Mid-Day (Table 4). One can argue that the westbound volume is higher in the morning because most people on the road are either traveling to work or dropping their children off at school, both of which are primarily in that direction of travel. This should also be expected as Highway 119 is often used by people living in Longmont and points farther north or east who commute to Boulder, and beyond, for work. Similarly, traffic volumes in general are higher on weekdays associated with commuters, compared to more recreational and leisure travel on weekends.

Table 2. Average All Times weather-related traffic parameters based on Boulder weather. Percentage change relative to clear conditions are shown in brackets for the rain and snow weather type traffic parameters.

Day of Week	Travel Direction	Weather Type	Traffic Parameters			
			Volume (Number of Vehicles)	Speed (mph [km/h])	Length (miles [km])	Duration (min)
All Days	*Eastbound*	Clear	20,850	28.0 (45.1)	24.4 (39.3)	52.7
		Rain	21,593 [3.6]	28.2 (45.4) [0.7]	23.5 (37.8) [−3.7]	53.0 [0.6]
		Snow	18,429 [−11.6]	27.5 (44.2) [−1.8]	23.5 (37.9) [−3.7]	52.3 [−0.8]
	Westbound	Clear	19,004	28.4 (45.6)	23.8 (38.3)	50.5
		Rain	19,489 [2.6]	28.2 (45.4) [−0.7]	22.3 (35.9) [−6.3]	50.7 [0.4]
		Snow	16,780 [−11.7]	27.6 (44.4) [−2.8]	22.8 (36.7) [−4.2]	50.3 [−0.4]
Weekdays	*Eastbound*	Clear	22,356	27.5 (44.2)	23.5 (37.9)	52.1
		Rain	22,435 [0.4]	27.8 (44.7) [1.1]	23.9 (38.4) [1.7]	52.3 [0.4]
		Snow	20,133 [−9.9]	26.8 (43.1) [−2.5]	22.7 (36.5) [−3.4]	51.9 [−0.4]
	Westbound	Clear	20,426	27.8 (44.8)	23.1 (37.2)	50.1
		Rain	20,234 [−0.9]	27.9 (44.9) [0.4]	23.2 (37.4) [0.4]	50.1 [0.0]
		Snow	18,300 [−10.4]	26.9 (43.2) [−3.2]	22.2 (35.7) [−3.9]	50.4 [0.6]
Weekends	*Eastbound*	Clear	17,076	29.6 (47.6)	26.7 (43.0)	54.3
		Rain	19,125 [12.0]	29.4 (47.3) [−0.7]	26.7 (43.0) [0.0]	54.9 [1.1]
		Snow	14,532 [−14.9]	29.0 (46.7) [−2.0]	25.5 (41.0) [−4.5]	53.1 [−2.2]
	Westbound	Clear	15,440	29.7 (47.8)	25.6 (41.2)	51.5
		Rain	17,160 [11.1]	29.1 (46.8) [−2.0]	25.7 (41.4) [0.4]	52.6 [2.1]
		Snow	13,307 [−13.8]	29.2 (47.0) [−1.7]	24.2 (38.9) [−5.5]	50.2 [−2.5]

Table 3. Average Peak Morning weather-related traffic parameters based on Boulder weather. Percentage change relative to clear conditions are shown in brackets for the rain and snow weather type traffic parameters.

Day of Week	Travel Direction	Weather Type	Traffic Parameters			
			Volume (Number of Vehicles)	Speed (mph [km/h])	Length (miles [km])	Duration (min)
All Days	*Eastbound*	Clear	2680	29.6 (47.6)	25.5 (41.0)	50.7
		Rain	2856 [6.6]	29.6 (47.7) [0.0]	26.2 (42.1) [2.7]	52.1 [2.8]
		Snow	2368 [−11.6]	27.4 (44.1) [−7.4]	24.6 (39.5) [−3.5]	53.1 [4.7]
	Westbound	Clear	5823	29.1 (46.8)	24.1 (38.8)	49.7
		Rain	5938 [2.0]	29.0 (46.6) [−0.3]	24.2 (38.9) [0.4]	49.9 [0.4]
		Snow	5254 [−9.8]	27.3 (43.9) [−6.2]	23.0 (37.0) [−4.6]	51.6 [3.8]
Weekdays	*Eastbound*	Clear	3216	28.8 (46.4)	24.3 (39.1)	49.7
		Rain	3258 [1.3]	29.1 (46.8) [1.0]	24.8 (39.8) [2.1]	50.6 [1.8]
		Snow	2881 [−10.4]	26.4 (42.6) [−8.3]	23.0 (37.0) [−5.3]	52.7 [6.0]
	Westbound	Clear	7068	28.2 (45.4)	23.4 (37.6)	49.9
		Rain	6969 [−1.4]	28.4 (45.7) [0.7]	23.5 (37.8) [0.4]	49.9 [0.0]
		Snow	6497 [−8.1]	25.9 (41.6) [−8.2]	22.6 (36.3) [−3.4]	53.2 [6.6]
Weekends	*Eastbound*	Clear	1336	31.4 (50.5)	28.4 (45.7)	53.1
		Rain	1680 [25.7]	31.3 (50.4) [−0.3]	30.2 (48.7) [6.3]	56.4 [6.2]
		Snow	1165 [−12.8]	29.6 (47.7) [−5.7]	28.1 (45.2) [−1.1]	53.8 [1.3]
	Westbound	Clear	2701	31.1 (50.1)	25.9 (41.6)	49.2
		Rain	2919 [8.1]	30.6 (49.3) [−1.6]	26.2 (42.1) [1.2]	50.1 [1.8]
		Snow	2412 [−10.7]	30.5 (49.1) [−1.9]	23.9 (38.5) [−7.7]	47.9 [−2.6]

To understand the extent to which adverse weather affects these traffic parameters, average traffic parameters were again calculated by time of day but broken into the weather classes. It is important to note that while differences in values may seem small, they were found to be statistically significant ($p < 0.05$). Tables 2–5 all indicate that traffic volume during snow is substantially smaller than during rainy or clear weather. This result aligns with recent work by Call and Flynt [16], who found that daily snowfall had a substantial impact on passenger vehicle counts whereas commercial vehicle counts were less affected. It is important to note that the metrics used in the current study did not segment traffic volume by vehicle type due to data limitations. Overall, this decrease in traffic volume during snow may be due to individuals cancelling trips, as they may believe that it will be too dangerous to commute. It is also important to note the variability of the average all trip duration for snow. Tables 4 and 5 indicate that trip duration during Mid-Day and Peak Afternoon is shortest during snow, while Table 3 indicates that trip duration during Peak Morning is longest for snowy conditions. Individuals may still commute to work, but it may take longer to get to their destination. Additionally, longer-distance trips are more likely to be canceled in lieu of shorter, commuter-type trips for potentially more essential activities. There are no substantial differences when considering day of week, beyond the differences in traffic volumes.

Table 4. Average Mid-Day weather-related traffic parameters based on Boulder weather. Percentage change relative to clear conditions are shown in brackets for the rain and snow weather type traffic parameters.

Day of Week	Travel Direction	Weather Type	Traffic Parameters			
			Volume (Number of Vehicles)	Speed (mph [km/h])	Length (miles [km])	Duration (min)
All Days	*Eastbound*	Clear	6608	27.9 (44.8)	24.0 (38.7)	52.1
		Rain	6928 [4.8]	27.8 (44.7) [−0.4]	24.1 (38.8) [0.4]	52.4 [0.6]
		Snow	5739 [−13.2]	27.6 (44.4) [−1.1]	23.1 (37.2) [−3.7]	50.9 [−2.3]
	Westbound	Clear	6213	27.8 (44.7)	23.4 (37.6)	50.6
		Rain	6377 [2.6]	27.6 (44.4) [−0.7]	23.8 (38.3) [1.7]	51.4 [1.6]
		Snow	5326 [−14.3]	27.7 (44.6) [−0.4]	22.4 (36.1) [−4.3]	49.1 [−3.0]
Weekdays	*Eastbound*	Clear	6769	27.5 (44.2)	23.5 (37.9)	51.9
		Rain	7013 [3.6]	27.6 (44.5) [0.4]	23.8 (38.2) [1.3]	52.1 [0.4]
		Snow	5998 [−11.4]	27.0 (43.4) [−1.8]	22.7 (36.5) [−3.4]	51.5 [−0.8]
	Westbound	Clear	6049	27.4 (44.2)	22.8 (36.8)	50.2
		Rain	6169 [2.0]	27.3 (43.9) [−0.4]	23.1 (37.2) [1.3]	50.5 [0.6]
		Snow	5318 [−12.1]	27.3 (44.0) [−0.4]	22.0 (35.4) [−3.5]	48.9 [−2.6]
Weekends	*Eastbound*	Clear	6203	28.8 (46.4)	25.3 (40.7)	52.4
		Rain	6675 [7.6]	28.2 (45.4) [−2.1]	25.1 (40.4) [−0.8]	53.2 [1.5]
		Snow	5147 [−17.0]	29.1 (46.8) [1.0]	24.1 (38.8) [−4.7]	49.5 [−5.5]
	Westbound	Clear	6625	26.7 (42.9)	24.7 (39.8)	51.8
		Rain	6982 [5.4]	28.4 (45.8) [6.4]	25.8 (41.4) [4.5]	53.8 [3.9]
		Snow	5345 [−19.3]	28.6 (46.0) [7.1]	23.4 (37.7) [−5.3]	49.4 [−4.6]

Table 5. Average Peak Afternoon weather-related traffic parameters based on Boulder weather. Percentage change relative to clear conditions are shown in brackets for the rain and snow weather type traffic parameters.

Day of Week	Travel Direction	Weather Type	Traffic Parameters			
			Volume (Number of Vehicles)	Speed (mph [km/h])	Length (miles [km])	Duration (min)
All Days	*Eastbound*	Clear	7624	26.7 (42.9)	23.5 (37.8)	53.3
		Rain	7591 [−0.4]	26.8 (43.1) [0.4]	23.7 (38.1) [0.9]	53.6 [0.6]
		Snow	6898 [−9.5]	26.5 (42.6) [−0.7]	22.3 (35.9) [−5.1]	51.5 [−3.4]
	Westbound	Clear	4607	27.1 (43.5)	23.3 (37.5)	51.6
		Rain	4657 [1.1]	27.0 (43.4) [−0.4]	23.3 (37.5) [0.0]	52.2 [1.2]
		Snow	4139 [−10.2]	26.9 (43.2) [−0.7]	22.1 (35.5) [−5.2]	49.6 [−3.9]
Weekdays	*Eastbound*	Clear	8403	25.7 (41.3)	22.6 (36.4)	53.4
		Rain	8147 [−3.0]	26.1 (42.0) [1.6]	23.0 (37.0) [1.8]	53.6 [0.4]
		Snow	7829 [−6.8]	25.8 (41.6) [0.4]	21.7 (34.8) [−4.0]	51.3 [−3.9]
	Westbound	Clear	4878	26.2 (42.1)	22.4 (36.0)	51.5
		Rain	4690 [−3.9]	26.4 (42.5) [0.8]	22.6 (36.4) [0.9]	51.8 [0.6]
		Snow	4337 [−11.1]	26.2 (42.1) [0.0]	21.3 (34.3) [−4.9]	49.2 [−4.5]
Weekends	*Eastbound*	Clear	5673	29.1 (46.8)	25.8 (41.4)	53.1
		Rain	5961 [5.1]	28.8 (46.3) [−1.0]	25.5 (41.1) [−1.2]	53.9 [1.5]
		Snow	4769 [−15.9]	28.0 (45.1) [−3.8]	23.8 (38.3) [−7.8]	51.8 [−2.4]
	Westbound	Clear	3928	29.3 (47.1)	25.6 (41.2)	52.0
		Rain	4561 [16.1]	28.5 (45.9) [−2.7]	25.3 (40.7) [−1.2]	53.4 [2.7]
		Snow	3686 [−6.2]	28.4 (45.8) [−3.1]	23.8 (38.4) [−7.0]	50.6 [−2.7]

A comparison of traffic parameters relative to one another in the context of weather, day of week, and time period can provide further insight into the nature of adverse weather travel. To illustrate this, four combinations of the traffic parameters were plotted based on weather type and day of week.

The first combination of traffic parameters was traffic volume and trip duration. The figures show two clusters of points during the Peak Mornings and the Peak Afternoons for traffic volume during All Days and Weekdays, with the rightmost cluster illustrating westbound traffic for the morning and eastbound traffic for the afternoon (Figures 2 and 3). This commuter clustering is not apparent during weekends. This is because many commuters travel westward to Boulder for work. Eastbound traffic is more common during the Peak Afternoon, as many commuters leave work and travel home during this time.

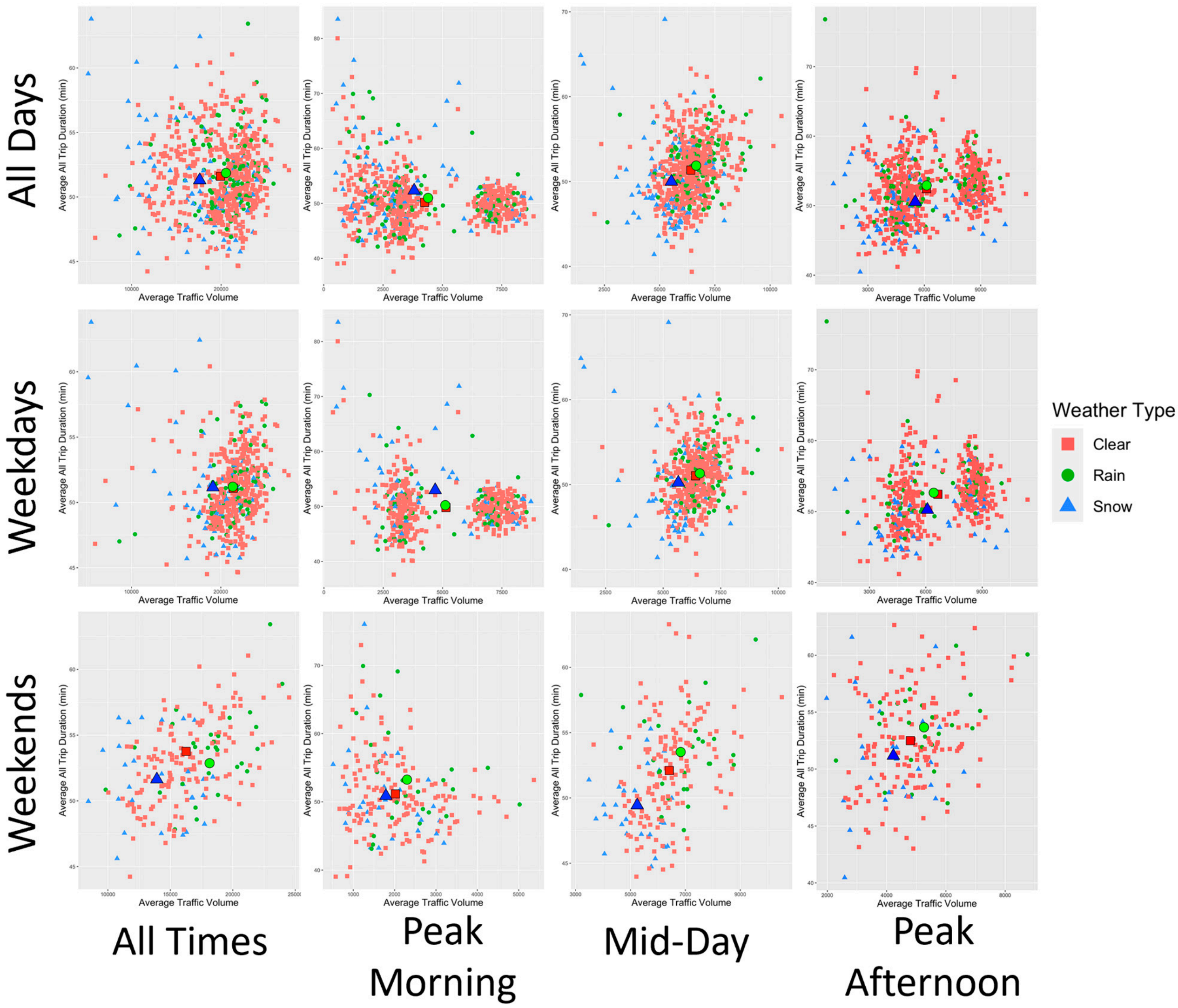

Figure 2. Mean traffic volume and mean trip duration for significant weather types during the study period. From top to bottom, the rows represent All Days (top row), Weekdays (middle row), and Weekends (bottom row). From left to right, the columns represent All Times (leftmost column), Peak Morning (second column), Mid-Day (third column), and Peak Afternoon (rightmost column).

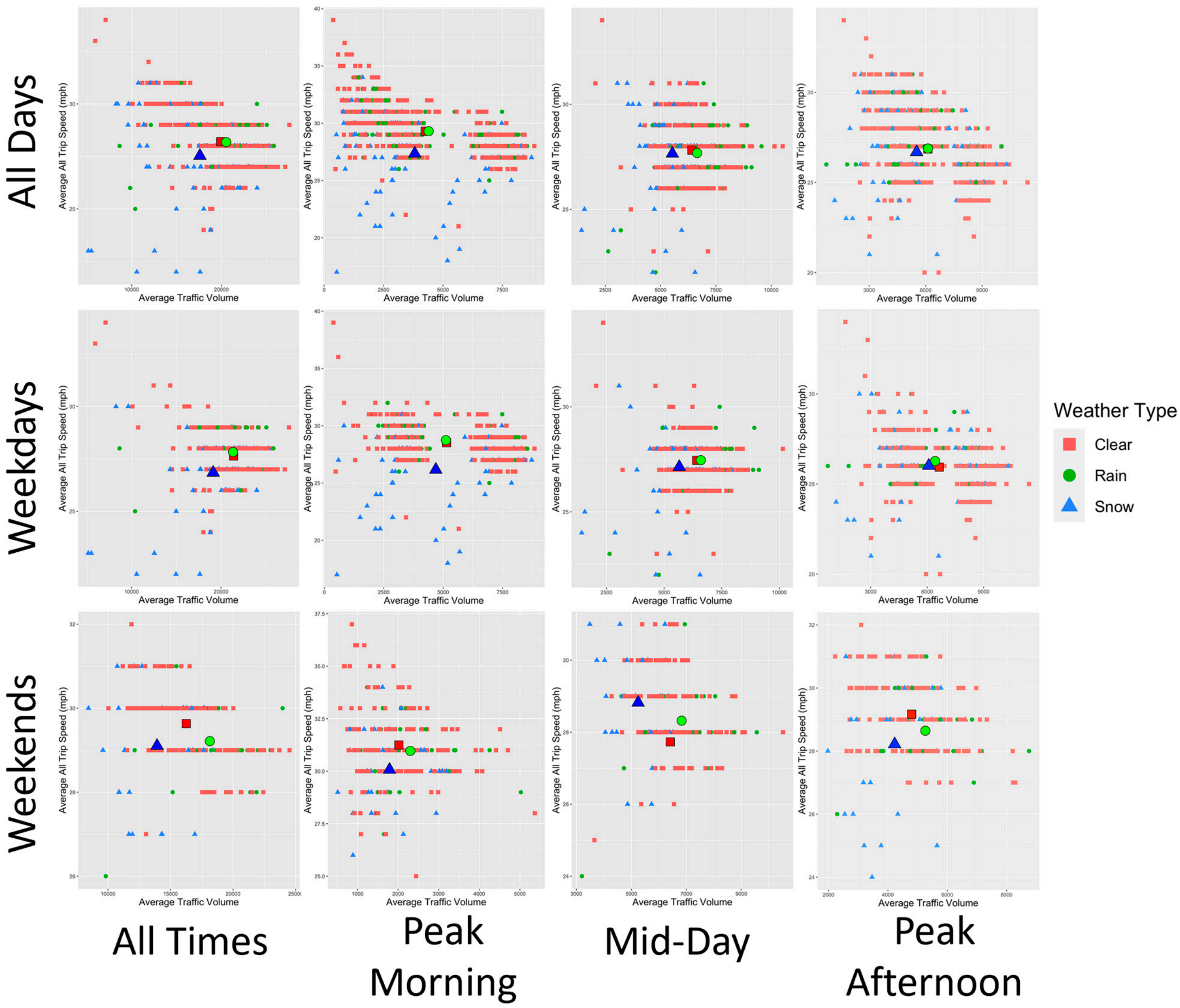

Figure 3. Mean traffic volume and mean trip speed for significant weather types during the study period. From top to bottom, the rows represent All Days (top row), Weekdays (middle row), and Weekends (bottom row). From left to right, the columns represent All Times (leftmost column), Peak Morning (second column), Mid-Day (third column), and Peak Afternoon (rightmost column).

Traffic parameters show the greatest variability during snow (Figures 2–5). The higher duration values are likely due to people who continue commuting, but take longer to get to their destination as the snow slows down their average speed, while the lower values are due to people who choose to commute a shorter distance due to the inclement weather (Figures 2–4). This is highlighted in Figure 3, where the average trip speeds were generally the lowest for snow. It is important to emphasize that these observed changes in speed are averaged over the entire study period, so it is likely that speed during a specific weather event, such as a snowstorm, may be even lower than what these averages alone suggest. The average trip length contains the lowest variability out of the four parameters (Figures 4 and 5). This is to be expected, as inclement weather has no effect on the distance that it takes to travel from one location to another. An exception to this would be possible closure of certain roads due to icy pavements or weather-related traffic incidents. Such closures may be one source of the variability in trip length during snowy conditions.

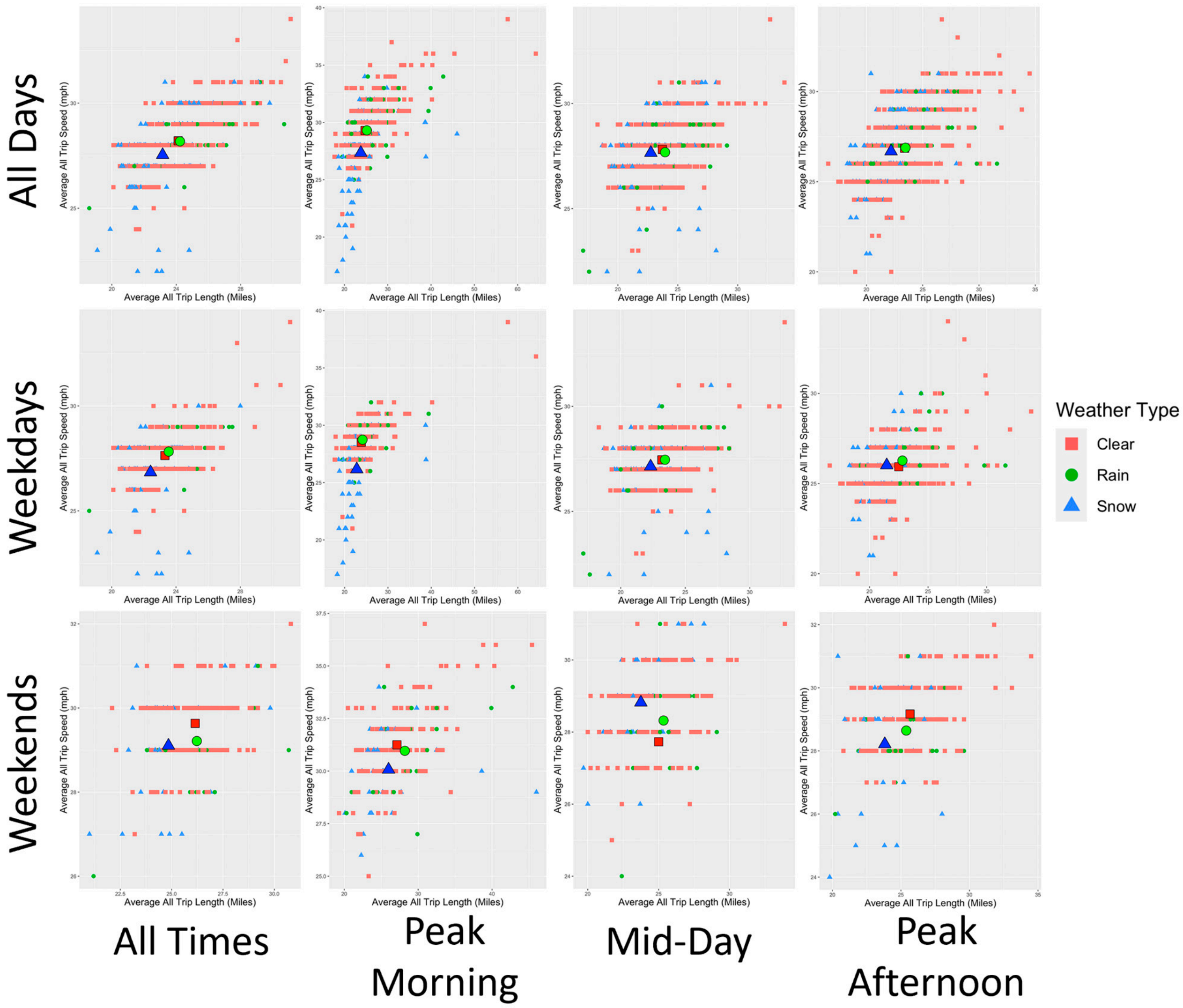

Figure 4. Mean trip speed and mean trip length for significant weather types during the study period. From top to bottom, the rows represent All Days (top row), Weekdays (middle row), and Weekends (bottom row). From left to right, the columns represent All Times (leftmost column), Peak Morning (second column), Mid-Day (third column), and Peak Afternoon (rightmost column).

Unlike snow, the parameters for rainy weather are not substantially different from clear weather (Figures 2–5). This similarity between rain and clear conditions suggests that people are not modifying their travel behavior or driving to accommodate the change in road conditions. Moreover, this implication agrees with Pisano et al. [44] that most weather-related crashes occur due to rain, as motorists are not slowing down for the changed weather conditions. Overall, snowy conditions indicate a departure from "normal" conditions, whereas there is substantial overlap between clear and rainy conditions irrespective of the day of the week.

To understand the nature of travel for the individuals on the road, the percentages for the main three trip purposes were calculated (Tables 6–9). Recall that these results are salient, as the trip purposes vary within each period, day of week, and with weather type. Overall, home-based work values are highest on the weekdays (associated with commuter travel), while home-based other values are highest on weekends (associated with more leisure, shopping/errands travel). One will note that the home-based work percentages are the highest during snowy weather (Table 6). This is likely due to the overall reduced volume caused by people who choose not to commute in favor of more essential, work-related travel.

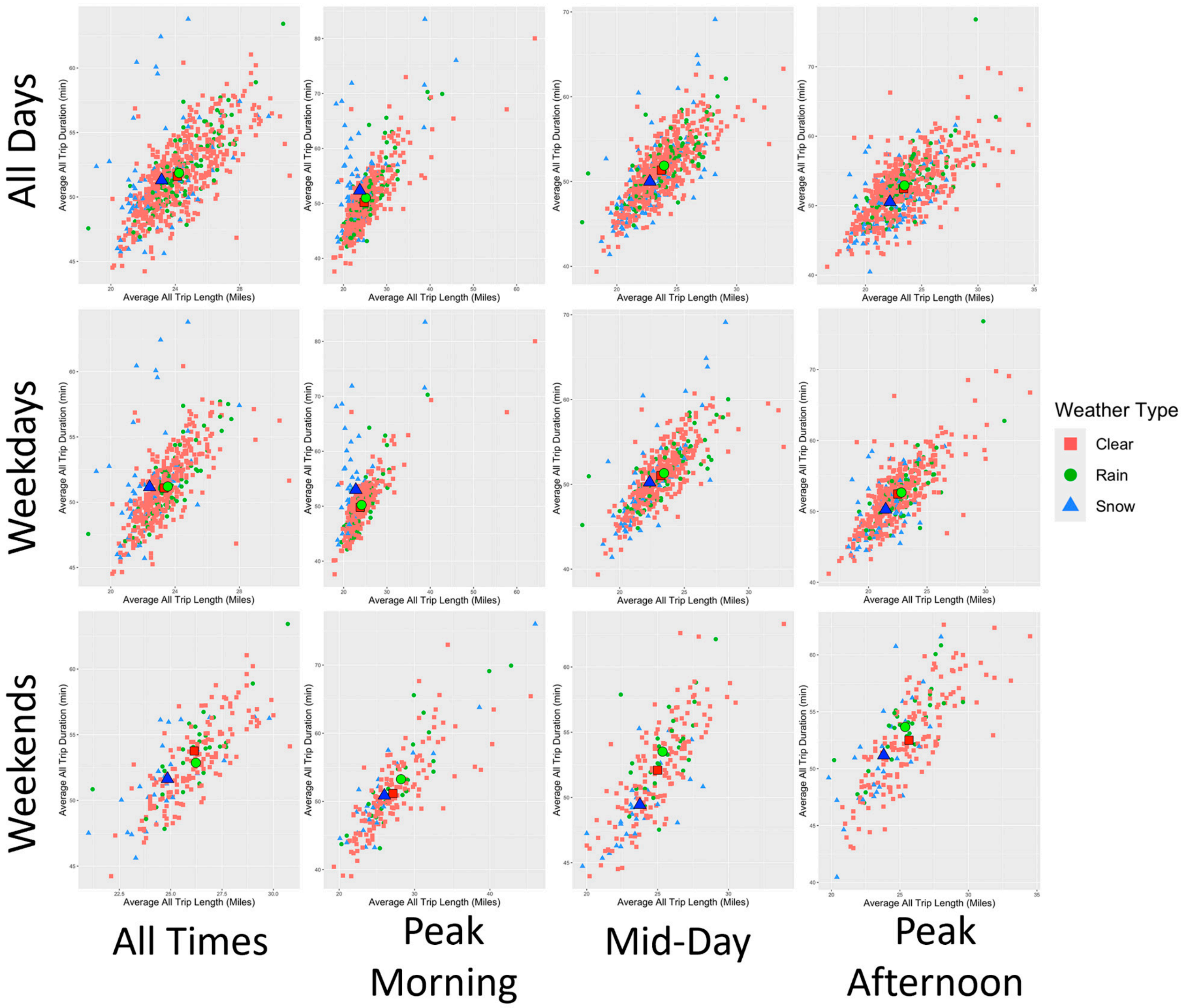

Figure 5. Mean trip length and mean trip duration for significant weather types during the study period. From top to bottom, the rows represent All Days (top row), Weekdays (middle row), and Weekends (bottom row). From left to right, the columns represent All Times (leftmost column), Peak Morning (second column), Mid-Day (third column), and Peak Afternoon (rightmost column).

The results for the peak morning period align with most of the working population in Boulder beginning their workday (Table 7). It is also possible that some of the working population may be labeled as "Home-Based Other" if those that are traveling to work make a stop for other errands during their commute (e.g., dropping off children, picking up coffee).

The mid-day results are not surprising either, since this is typically the time where people may go out for lunch or to run errands, which results in a higher "Home-Based Other" volume (Table 8). Additionally, workers are usually on their lunch break during this time. This gives time for workers to make a short trip for lunch, which is responsible for the large "Non-Home-Based" percentage (Table 8). One will note that the "Home-Based Other" percentage elevates a bit during the evening (Table 9). This may be due to commuters returning home from work and families picking up their children from school or childcare.

Based on this information, adverse weather does not seem to affect the trip purposes of commuters as much as time of the day or day of week do. While snow has affected the Home-Based Work and Non-Home-Based percentages by as much as 2.9% in the morning (Table 7), the Mid-Day trip purposes had a percentage difference of up to 25% from the morning parameters (Table 8). Therefore, changes in human behavior due to weather does little compared to the influence of time of day.

Table 6. Average All Times weather-related trip purpose based on Boulder weather.

Day of Week	Direction of Travel	Weather Type	Traffic Parameters			
			Volume (Number of Cars)	Home-Based Work Percentage (Volume)	Home-Based Other Percentage (Volume)	Non-Home-Based Percentage (Volume)
All Days	*Eastbound*	Clear	20,850	18.7% (3899)	44.7% (9320)	36.6% (7631)
		Rain	21,593	18.5% (3995)	43.6% (9415)	37.9% (8184)
		Snow	18,429	20.3% (3741)	44.3% (8164)	35.4% (6524)
	Westbound	Clear	19,004	20.6% (3915)	42.1% (8001)	37.3% (7088)
		Rain	19,489	20.9% (4073)	40.6% (7913)	38.6% (7523)
		Snow	16,780	22.5% (3776)	42.5% (7132)	35.0% (5873)
Weekdays	*Eastbound*	Clear	22,356	22.9% (5120)	39.7% (8875)	37.4% (8361)
		Rain	22,435	22.0% (4936)	40.0% (8974)	38.0% (8525)
		Snow	20,133	25.0% (5033)	39.0% (7852)	36.0% (7248)
	Westbound	Clear	20,426	25.5% (5209)	36.8% (7517)	37.7% (7701)
		Rain	20,234	25.2% (5099)	36.6% (7406)	38.2% (7729)
		Snow	18,300	28.2% (5161)	36.5% (6680)	35.3% (6460)
Weekends	*Eastbound*	Clear	17,076	8.0% (1366)	57.4% (9802)	34.6% (5908)
		Rain	19,125	8.1% (1549)	54.1% (10,347)	37.9% (7248)
		Snow	14,532	9.6% (1395)	56.4% (8196)	34.0% (4941)
	Westbound	Clear	15,440	8.3% (1282)	55.5% (8569)	36.2% (5589)
		Rain	17,160	8.1% (1390)	52.2% (8958)	39.7% (6813)
		Snow	13,307	9.5% (1264)	56.1% (7465)	34.4% (4578)

Table 7. Average Peak Morning weather-related trip purpose based on Boulder weather.

Day of Week	Direction of Travel	Weather Type	Traffic Parameters			
			Volume (Number of Cars)	Home-Based Work Percentage (Volume)	Home-Based Other Percentage (Volume)	Non-Home-Based Percentage (Volume)
All Days	*Eastbound*	Clear	2680	29.5% (791)	36.4% (976)	34.0% (911)
		Rain	2856	28.7% (820)	36.6% (1045)	34.7% (991)
		Snow	2368	32.4% (767)	35.1% (831)	32.5% (770)
	Westbound	Clear	5823	35.6% (2073)	36.2% (2108)	28.1% (1636)
		Rain	5938	36.3% (2155)	33.6% (1995)	30.0% (1781)
		Snow	5254	37.6% (1976)	34.9% (1834)	27.5% (1445)
Weekdays	*Eastbound*	Clear	3216	37.0%(1190)	28.1%(904)	34.9% (1122)
		Rain	3258	34.8% (1134)	30.6% (997)	34.6% (1127)
		Snow	2881	40.2% (1158)	28.6% (824)	31.2% (899)
	Westbound	Clear	7068	44.0% (3110)	28.3% (2000)	27.7% (1958)
		Rain	6969	43.0% (2997)	28.4% (1979)	28.7% (2000)
		Snow	6497	46.4% (3015)	27.0% (1754)	26.7% (1735)
Weekends	*Eastbound*	Clear	1336	10.9% (146)	57.3% (766)	31.8% (425)
		Rain	1680	10.9% (183)	54.1% (909)	35.0% (588)
		Snow	1165	14.6% (170)	50.0% (583)	35.4% (412)
	Westbound	Clear	2701	14.7% (397)	56.1% (1515)	29.2% (789)
		Rain	2919	16.8% (490)	49.1% (1433)	34.1% (995)
		Snow	2412	17.6% (425)	53.2% (1283)	29.2% (704)

A multivariate general linear model assessed the influence of several variables on a variety of trip purposes. The independent variables in the model were traffic volume, day of week (weekday versus weekend), time of day, and type of weather. The three trip types that were entered into the model as the dependent variables were "percent of home-to-work" trips (Home-Based Work), "percent of home to non-work locations" (Home-Based Other), and "percent of non-home-based trips" (Non-Home-Based). The pairwise comparisons utilized Bonferroni's Correction.

Table 8. Average Mid-Day weather-related trip purpose based on Boulder weather.

Day of Week	Direction of Travel	Weather Type	Traffic Parameters			
			Volume (Number of Cars)	Home-Based Work Percentage (Volume)	Home-Based Other Percentage (Volume)	Non-Home-Based Percentage (Volume)
All Days	*Eastbound*	Clear	6608	10.8% (714)	40.8% (2696)	48.5% (3205)
		Rain	6928	11.3% (783)	39.9% (2764)	48.8% (3381)
		Snow	5739	11.9% (683)	40.8% (2342)	47.4% (2720)
	Westbound	Clear	6213	11.4% (708)	40.6% (2522)	47.9% (2976)
		Rain	6377	11.4% (727)	40.0% (2551)	48.5% (3093)
		Snow	5326	13.3% (708)	42.2% (2248)	44.5% (2370)
Weekdays	*Eastbound*	Clear	6769	12.8% (866)	35.6% (2410)	51.6% (3493)
		Rain	7013	13.0% (912)	36.4% (2553)	50.6% (3549)
		Snow	5998	13.7% (822)	35.7% (2141)	50.6% (3035)
	Westbound	Clear	6049	13.8% (835)	35.6% (2153)	50.6% (3061)
		Rain	6169	13.5% (833)	36.5% (2252)	50.0% (3085)
		Snow	5318	16.2% (862)	36.6% (1946)	47.2% (2510)
Weekends	*Eastbound*	Clear	6203	5.6% (347)	53.6% (3325)	40.8% (2531)
		Rain	6675	6.4% (427)	50.1% (3344)	43.5% (2904)
		Snow	5147	7.6% (391)	52.7% (2712)	39.8% (2049)
	Westbound	Clear	6625	5.5% (364)	53.2% (3525)	41.3% (2736)
		Rain	6982	5.4% (377)	50.3% (3512)	44.3% (3093)
		Snow	5345	6.7% (358)	54.9% (2934)	38.4% (2052)

Table 9. Average Peak Afternoon weather-related trip purpose based on Boulder weather.

Day of Week	Direction of Travel	Weather Type	Traffic Parameters			
			Volume (Number of Cars)	Home-Based Work Percentage (Volume)	Home-Based Other Percentage (Volume)	Non-Home-Based Percentage (Volume)
All Days	*Eastbound*	Clear	7624	21.4% (1632)	43.4% (3309)	35.2% (2684)
		Rain	7591	20.9% (1587)	42.4% (3219)	36.7% (2786)
		Snow	6898	23.0% (1587)	43.1% (2973)	34.0% (2345)
	Westbound	Clear	4607	13.4% (617)	46.0% (2119)	40.6% (1870)
		Rain	4657	13.9% (647)	43.8% (2040)	42.3% (1970)
		Snow	4139	14.9% (617)	47.4% (1962)	37.7% (1560)
Weekdays	*Eastbound*	Clear	8403	27.1%(2277)	38.0% (3193)	34.8% (2924)
		Rain	8147	25.6% (2086)	38.8% (3161)	35.6% (2900)
		Snow	7829	29.4% (2302)	37.1% (2905)	33.5% (2623)
	Westbound	Clear	4878	16.7% (815)	41.8% (2039)	41.5% (2024)
		Rain	4690	17.1% (802)	40.8% (1914)	42.1% (1974)
		Snow	4337	18.9% (820)	42.6% (1848)	38.5% (1670)
Weekends	*Eastbound*	Clear	5673	7.1% (403)	57.0% (3234)	35.9% (2037)
		Rain	5961	7.4% (441)	52.7% (3141)	39.9% (2378)
		Snow	4769	8.2% (391)	56.7% (2704)	35.1% (1674)
	Westbound	Clear	3928	5.3% (208)	56.6% (2223)	38.1% (1497)
		Rain	4561	4.8% (219)	52.5% (2395)	42.7% (1948)
		Snow	3686	5.9% (217)	58.3% (2149)	35.9% (1323)

We found a significant multivariate effect of weather type (Pillai's Trace = 0.041, $F(4, 5726) = 29.678$, $p < 0.001$, partial $\eta^2 = 0.02$). There was a significant impact of weather when the trips were from home to work, $F(2, 2863) = 39.056$, $p < 0.001$, partial $\eta^2 = 0.027$. For the pairwise comparison of marginal means, there was no significant difference in trips from home to work when the weather was clear ($M = 0.167$, $S.E. = 0.001$) versus rainy ($M = 0.164$, $S.E. = 0.002$) ($p = 0.81$). However, drivers were significantly more likely to make the trip from home to work when it was snowy ($M = 0.189$, $S.E. = 0.002$) than when it was clear ($p < 0.001$) or rainy ($p < 0.001$). For the significant impact of weather on home-based trips to other locations ($F(2, 2863) = 19.684$, $p < 0.001$, partial $\eta^2 = 0.014$), drivers were significantly more likely to make these trips when it was clear ($M = 0.453$, $S.E. = 0.001$) than when it was rainy ($M = 0.439$, $S.E. = 0.003$), $p < 0.001$, or snowy ($M = 0.438$, $S.E. = 0.003$), $p < 0.001$. There was no significant difference in marginal means for home-based trips to other locations when comparing snowy and rainy days (p = 1.00). Weather also had a significant influence on trips that were not home-based, $F(2, 2863) = 26.802$, $p < 0.001$, partial $\eta^2 = 0.018$). People were more likely to make these trips when it was rainy (M = 0.397, $S.E.$ = 0.002) than clear (M = 0.381, $S.E.$ = 0.001) or when it was snowy (M = 0.373, $S.E.$ = 0.003), $p < 0.001$. People were also significantly more likely to make these trips when it was clear than when it was snowy, p = 0.022.

Within this model, there was also a significant multivariate impact of the day of the week (weekday versus weekend) on trip purpose, (Pillai's Trace = 0.614, $F(2, 2862) = 2274.385$, $p < 0.001$, partial $\eta^2 = 0.614$). The day of the week significantly influenced the percent of trips that were from home to work $F(1, 2863) = 4017.582$, $p < 0.001$, partial $\eta^2 = 0.584$. People were more likely to travel from home to work on weekdays (M = 0.254, $S.E.$ = 0.001) than on weekends (M = 0.082, $S.E.$ = 0.002). The day of the week also significantly influenced trips from home to non-work locations, ($F(1, 2863) = 2954.921$, $p < 0.001$, partial $\eta^2 = 0.508$). On the weekend, people were significantly more likely to go from home to non-work locations (M = 0.525, $S.E.$ = 0.003) than to work locations (M = 0.361, $S.E.$ = 0.001. However, the day of the week did not significantly influence non-home-based trips, $F(1, 2863) = 1.400$, p = 0.237, partial η^2 = 0.000.

The type of weather and day of the week significantly interacted to influence the purpose of the trip, (Pillai's Trace = 0.017, $F(4, 5726) = 12.076$, $p < 0.001$, partial $\eta^2 = 0.008$). Figure 6 display the marginal means of the home-to-work trips and the comparison of these means found that drivers made significantly more trips to work during the week than on the weekend during clear weather, rainy weather, and snowy weather (ps < 0.001). Figure 7 displays the marginal means for home-to non-work trips and the comparison of marginal means estimates found that drivers were more likely to make non-work trips from home one the weekend during clear weather, rainy weather, and snowy weather (ps < 0.001). Figure 8 displays the marginal means for non-home-based trips. The pairwise comparison found that during clear weather, drivers were significantly more likely to make non-home-based trips during the weekdays than on the weekend ($p < 0.001$), were less likely to make these trips during the weekday than on the weekend if the weather was rainy (p = 0.02), and they showed a similar pattern of behavior for both types of days when it snowed (p = 0.566).

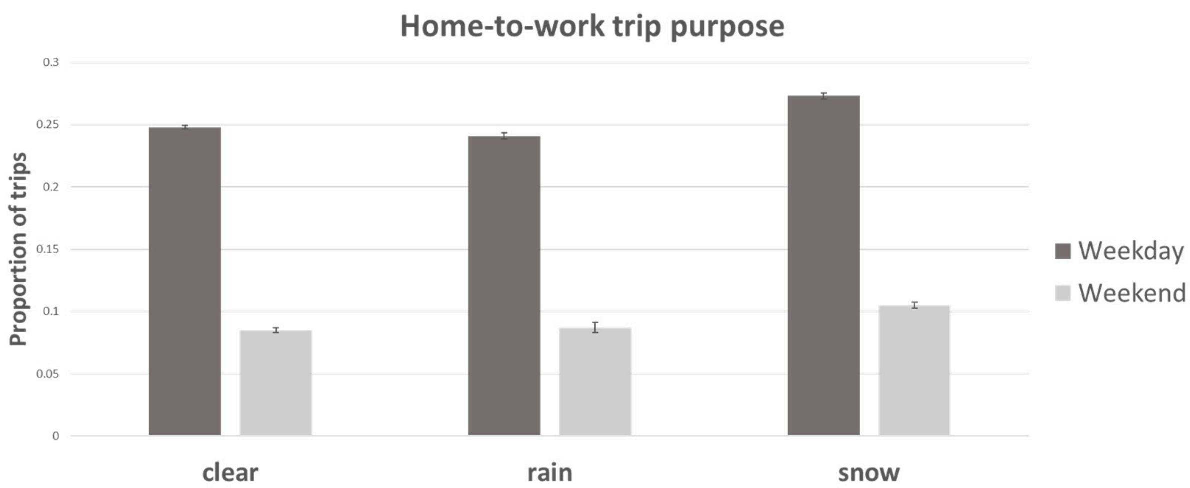

Figure 6. Influence of weather and day of the week on trips from home to work. The left (dark gray) bar in each group represents weekday trips. The right bar (light gray) in each group represents weekend trips.

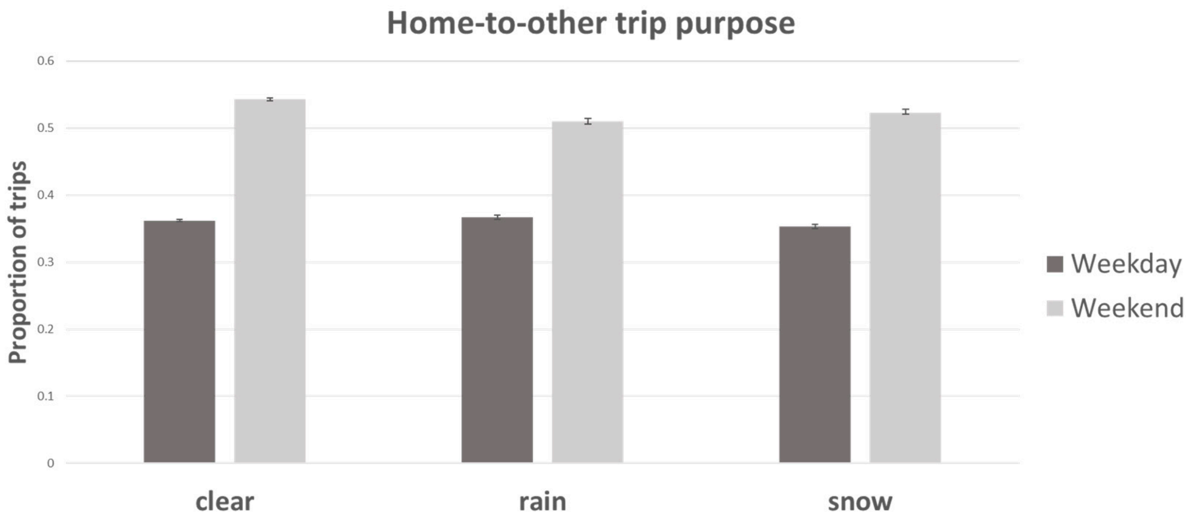

Figure 7. Influence of weather and day of the week on trips from home to non-work sites. The left (dark gray) bar in each group represents weekday trips. The right bar (light gray) in each group represents weekend trips.

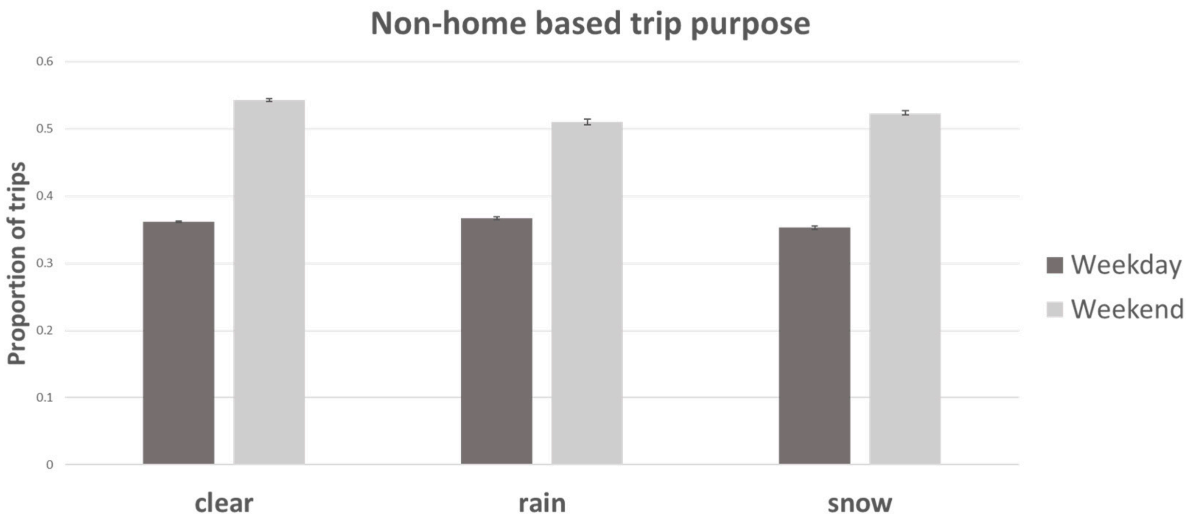

Figure 8. Influence of weather and day of the week on trips from non-home sites. The left (dark gray) bar in each group represents weekday trips. The right bar (light gray) in each group represents weekend trips.

One particularly noteworthy finding is that while the multivariate interaction between the day of the week, the time of day, and weather type did not significantly influence the overall purpose of trip (Pillai's Trace = 0.007, $F(12, 5726) = 1.589$, $p = 0.087$), the between-subjects univariate analysis of each type of trip purpose found that this interaction impacted each specific trip purposes differently. While this interaction did not have a significant influence on home-based trips to work ($F(6, 2863) = 0.883$, $p = 0.506$.) and non-home-based trips ($F(6, 2863) = 1.615$, $p = 0.139$.), it significantly impacted home-based trips to non-work locations ($F(6, 2863) = 2.668$, $p = 0.014$.). See Figures 9 and 10 for the estimated marginal means. Pairwise comparisons of the estimated marginal means found that during the Peak Mornings on weekdays, drivers made significantly more trips from home to non-work locations when the weather was rainy than when it was snowy ($p = 0.04$). These comparisons also found that on the weekends, drivers were significantly more likely to make morning trips when it was clear than when it was rainy ($p < 0.001$) or snowy rainy ($p < 0.001$). In the weekend Mid-Day period, drivers were more likely to make trips when it was rainy than snowy ($p < 0.001$). During the weekend Peak Afternoon, drivers were more likely to make trips when it was clear than when it was rainy ($p = 0.01$) and more likely to make trips when it was rainy than when it was snowy ($p = 0.01$).

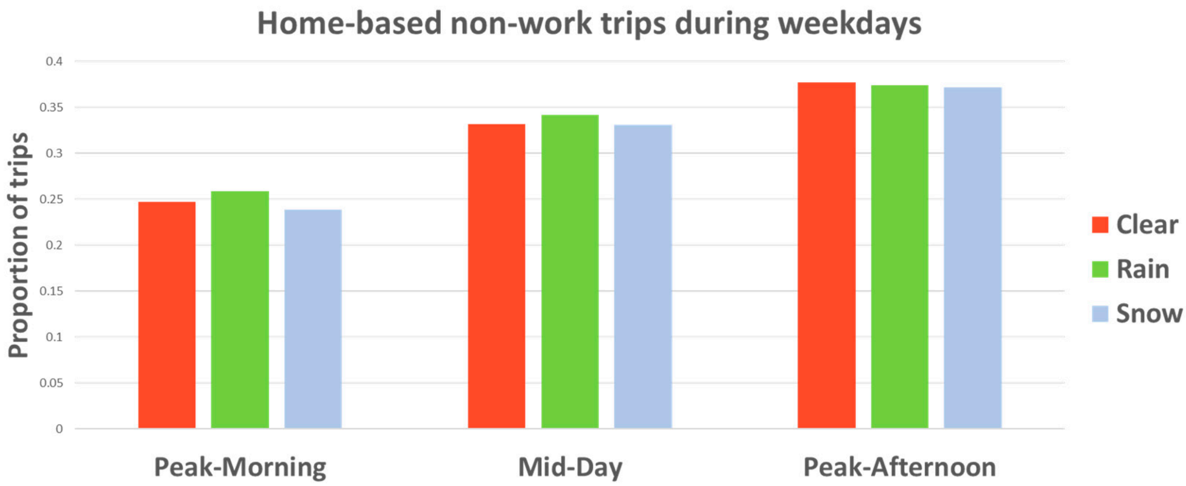

Figure 9. Marginal means of home-based non-work trips for significant interaction between weekdays, time of day, and weather. The left (red) bar in each group represents clear weather trips, the middle (green) bar in each group represents rainy weather trips, and the right (blue) bar in each group represents snowy weather trips.

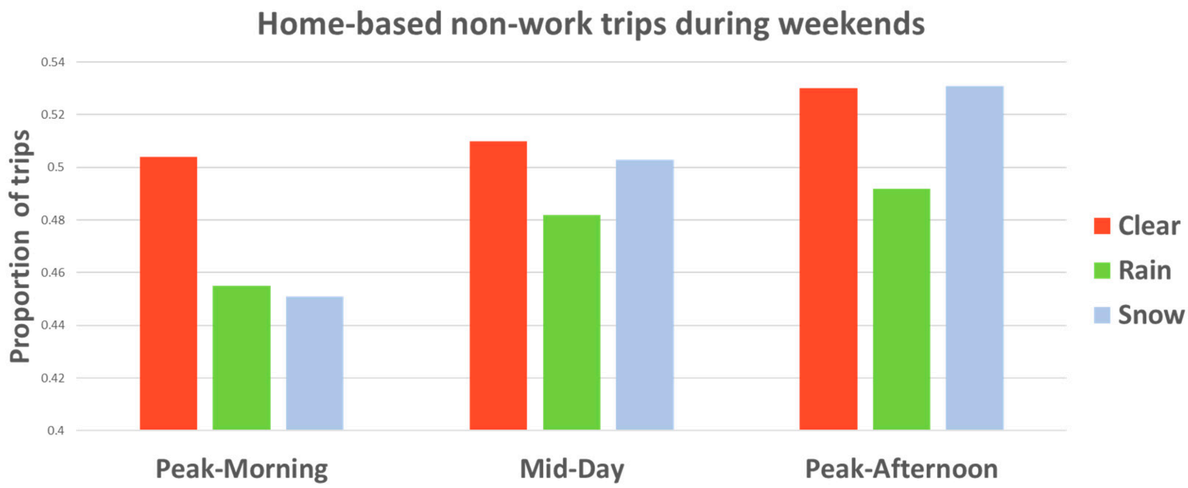

Figure 10. Marginal means of home-based non-work trips for significant interaction between weekends, time of day, and weather. The left (red) bar in each group represents clear weather trips, the middle (green) bar in each group represents rainy weather trips, and the right (blue) bar in each group represents snowy weather trips.

Overall, these findings suggest that weekday trips are somewhat less responsive to weather conditions than weekend trips. One possible explanation is that the nature of weekday trips tend to be more essential or mandatory (e.g., commuting to work, traveling to school, other personal/business obligations such as health appointments). Weekend trips tend to be more discretionary for a greater portion of drivers (e.g., leisure, errands such as shopping, more personal travel). These discretionary trips are more likely to be influenced, and either canceled or modified, during adverse weather conditions if drivers have an easier choice in doing so. As observed in the traffic volume and trip purpose data, regardless of weekday versus weekend, volumes and the number of trips generally appear to peak during the afternoon time frame. During the commuting weekday period, this may be attributable to more eastbound traffic to communities north and east of the study corridor. Similarly, during the weekend period, this may be attributable to drivers returning from weekend leisure trips into Colorado's famous mountainous terrain.

4. Summary and Conclusions

This work has investigated the relationship between adverse weather and traffic conditions, and suggests how human behavior is likely to play a role. Traffic statistics between rainy and clear weather seldom differed, while the impact of snow conditions revealed the most variability as well as an overall reduction in both the average traffic volume and trip speeds over a yearly basis. This observation aligns with the literature that documents that the most common weather-related traffic crashes are due to wet pavements [44]. Moreover, the current study suggests that the trip purpose was most influenced by weather conditions. The results show that home to work trips are a larger proportion of trips during snow days due to overall traffic volume reduction. The findings in this study indicate that not only does weather play a significant role in traffic conditions, but it also affects the actions that humans take during these events.

An important limitation of this study is that, as a proof-of-concept incorporating a novel, proprietary database on a trial basis [39], data represented a single year and were analyzed for an individual location. A more robust analysis exploring traffic mobility and driver behavior across multiple roadways and over a longer duration would provide further insights. Vehicle type classifications would provide another layer to assess changes in behavior among passenger vehicles and freight/commercial vehicles. Additionally, the temporal resolution of the weather and traffic mobility data should be explored to consider a time series analysis of the two datasets on a sub-daily and perhaps even sub-hourly basis. With a longer period of record spanning multiple years and multiple corridors, an expanded comparison of the influence of day of week and holidays will be possible. Moreover, consideration of global disruptions such as the COVID-19 pandemic could provide additional insights into potentially forever changed commuter patterns as well.

While an annual analysis of the effects of weather on roads is useful for grasping a general idea of what happens during a typical day in Boulder, it is important to analyze each day of the year and other years to understand the interannual variability of the traffic parameters. Future studies will involve repeating these analyses using Boulder data from 2020 and 2021, as it is important to understand how human behavior changed on roads during the COVID-19 pandemic. The results from these future studies may be compared with 2019 to analyze the significance of these changes, especially for trip purpose. Because most workplaces have either laid off workers or temporarily closed during the pandemic, we would expect a significant impact on the home-based work percentage. This future study can help quantify the extent trip purpose is influenced by the pandemic versus adverse weather. Additional future work may corroborate the more traditional survey-based approaches to understanding weather-related modifications in trip purpose in conjunction with these novel mobility dataset to inform decision-risk paradigms and hazard communication practices.

The previous body of literature [1–28] considers the impacts of weather on mobility and safety (i.e., vehicle crashes). However, many of these studies are unable to provide additional context into the potential human factor contributions. Indeed, it is known and corroborates this study's results that precipitation, most notably snow, leads to decreases in vehicle speeds, traffic volume reductions, and increases in crash risk, e.g., [1,4,18]. Further, it is highlighted that rain and wet roads are associated with the greatest crash and fatality risks, e.g., [1–3,9,13]. However, it is the results presented in this study that provide confirmation into the driver behavior factor, given the overlap between clear and rain weather conditions. Past studies have only been able to infer such relationships, while this novel crowdsourced data provides further benefit and validation of those previous conclusions. Additionally, the trip purpose classifications are a means for transportation, meteorological, emergency management, public safety, and other agencies to develop actionable solutions to improve road safety and mobility during adverse weather. All of the other studies highlight the known and documented danger which, by itself, is insufficient to change the paradigm of weather-related vehicle crashes, fatalities, and disruption to the transportation system. The crowdsourced data provides awareness of where and why drivers were traveling during adverse weather events which is pivotal for encouraging desired protective-action behaviors, such as slowing down, changing routes, or canceling travel entirely.

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Data Availability Statement: Weather information used in this study is publicly available from the National Centers for Environmental Information [38] and the Iowa Environmental Mesonet [42] as cited in the methods section. The traffic mobility data from StreetLight Data [39] used in this study is subject to access restrictions and is therefore only available upon request directly from the corresponding author. All computer programs written to perform the data analysis are available from the corresponding author upon request.

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