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Impacts of Area-Wide Air Pollution on Multimodal Traffic: Comparing Pedestrian, Motor Vehicle, and Transit Volumes in Utah

Prachanda Tiwari
Utah State University, prachanda.tiwari@usu.edu

IMPACTS OF AREA-WIDE AIR POLLUTION ON MULTIMODAL TRAFFIC:

COMPARING PEDESTRIAN, MOTOR VEHICLE,

AND TRANSIT VOLUMES IN UTAH

by

Prachanda Tiwari

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Approved:

Patrick Singleton, Ph.D. Major Professor	Ziqi Song, Ph.D. Committee Member
Michelle Mekker, Ph.D. Committee Member	Soukaina Filali Boubrahimi, Ph.D. Committee Member

D. Richard Cutler, Ph.D.
Vice Provost for Graduate Studies

UTAH STATE UNIVERSITY
Logan, Utah

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ABSTRACT

Impacts of area-wide air pollution on multimodal traffic:
Comparing pedestrian, motor vehicle, and transit volumes in Utah

by

Prachanda Tiwari, Master of Science

Utah State University, 2023

Major Professor: Dr. Patrick Singleton
Department: Civil and Environmental Engineering

During area-wide episodes of poor air quality, people may want to: 1) reduce their transportation-related emissions by driving less, 2) reduce their exposure to emissions by walking/bicycling less, or 3) go about their activities as usual. These three reactions have different consequences for travel behaviors and impacts on traffic volumes and the environment. This study investigates the effects of area-wide air pollution on multimodal traffic volumes by comparing associations of daily air quality with pedestrian, motor vehicle, and transit volumes over a two-year period in Utah, US. We used multilevel modeling to measure how this relationship differs by mode and across locations. The study region consisted of the Wasatch Front and Cache County in Northern Utah. The results revealed that, on days with poor air quality in Cache County, there was a decrease in pedestrian volumes accompanied by an increase in motor vehicle volumes; however, in the Wasatch Front, there was a decrease in pedestrian volumes, but a non-linear relationship was found out for motor vehicle volumes: i.e., motor volumes increased during yellow air quality days while it decreased during orange air quality days. Similarly, an increase in transit ridership was observed during moderate levels of air pollution.

We found that in Cache County, in areas with high street connectivity, pedestrian volumes did not decrease as much on poor quality days, whereas in neighborhoods with higher vehicle ownership, pedestrian volumes decreased more on poor air quality days. In the Wasatch Front, neighborhoods with higher median income saw amplified decrease in both pedestrian and motor vehicle volumes. Our findings suggest policy implications (air quality alerts and voluntary behavior change encouragements) for various locations and the scope of future research to better understand the relationships between air quality and multimodal traffic volumes.

(132 pages)

PUBLIC ABSTRACT

Impacts of area-wide air pollution on multimodal traffic:
Comparing pedestrian, motor vehicle, and transit volumes in Utah

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The impact of area-wide air pollution on multimodal traffic volumes has been underexplored. Thus, this research investigates the effect of area-wide air pollution on pedestrian volumes, motor volumes, and transit ridership across two urban areas in Utah for two years (2018 and 2019). The research employed multilevel modeling to study this effect. The model results showed an overall decrease in pedestrian volumes in both study areas, while driving volumes saw both increases and decreases in different locations. Transit ridership saw an increase during days with moderate air quality in one particular study area. Median income, vehicle ownership, and higher street connectivity were significant players in defining variations in the relationships between air quality and multimodal traffic volumes across different locations. Our findings suggest policy implications (air quality alerts and voluntary behavior change encouragements) for various locations and the scope of future research to better understand the relationships between air quality and multimodal traffic volumes.

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1. BACKGROUND

1.1 Introduction

In many parts of the world, air pollution can frequently reach unhealthy levels, affecting both urban and rural downwind communities and negatively impacting public health, out-of-home and outdoor activities, recreation, and tourism. The transportation system is the major cause of pollutants like fine particulate matter (PM2.5) and ground-level ozone (Climate Watch, 2019). Road traffic exhaust emissions have been the major concern as they are associated with the production of PM2.5 and tropospheric ozone (Colvile et al., 2001). During area-wide air pollution events (smog, haze, dust, and wildfire smoke), governments often resort to hard and soft policies to induce behavior change in people (Teague et al., 2015; Cummings & Walker, 2010). For example, air quality alerts are often issued to spread awareness regarding the high pollution levels and to encourage (discourage) travel behaviors that would contribute to reduced (greater) transportation emissions: e.g., carpooling, trip chaining, teleworking, postponing trips, or using public and active transportation modes (UDOT, 2022).

However, without detailed study of the link between air pollution and travel behavior, the design of policies is far from effective. Although research on effects of the transportation system on air quality and air pollution is plentiful (e.g., Caiazzo et al., 2013; Kryzanowski et al, 2005), research emphasizing the reverse link—i.e., how measurements of air pollution impact multimodal traffic volumes and other aggregate outcomes of individuals' travel behaviors and transportation choices—is comparatively limited. In order to improve public health as well as manage the public's responses to such air pollution events, it is important to know how people's travel behaviors are affected by area-wide air pollution.

Theoretically, there are a variety of ways in which traveler behaviors may be affected by area-wide air pollution events, associated information, and any policy actions. First, people may exhibit no behavioral response, especially if the pollution event is minor or few options for alternative behaviors or activity schedules exist. Second, people may reduce their automobile travel or their use of other polluting modes of travel, in order to minimize their contribution to the air pollution issue. Third, people may increase their use of encapsulated motorized modes, switching from exposed active modes in an attempt to reduce their exposure and inhalation of air pollution. One might call the second option the *altruistic* while the third option is a *risk averse* response (Noonan, 2014). The altruistic response prioritizes the overall good of the society even if it comes at one's individual benefit (forgoing automobile usage to reduce air pollution even if it increases one's exposure to emission), while the risk averse response prioritizes one's individual benefit over the overall good of society (taking up automobile usage to decrease one's exposure to emission even if it contributes to more air pollution). The conflict between these two responses highlights the challenge of information dissemination and soft/hard policies that seek to mitigate episodes of area-wide air pollution through travel behavior change.

In addition to the severity of the air pollution event, the population-wide response depends on the interplay of various factors, including (but not limited to) the existing transportation and built environment structures. Thus, an investigation into the relationship of air quality and multimodal traffic volumes—with consideration for varying responses across built environment contexts—is needed to effectively manage the travel behavior response during episodes of poor air quality. This study addresses the need by employing multilevel modeling to study the aggregate effects of air quality on both motor vehicle and pedestrian volumes in different locations.

It is to be noted that we could have taken a disaggregate approach to study the impact of air quality on traffic volumes, by studying people's behavior at an individual-level, so that we could consider awareness, psychological, and other personal factors (Zhao et al., 2018; Li et al., 2017). But for this study, we chose an aggregate approach, as it allows us to analyze the overall impact of air quality on traffic volumes across different modes. This approach provides a broader perspective and helps identify general trends in population-level travel behavior response during periods of bad air quality. The aggregate approach helps us overcome one of the major disadvantages of individual-level approach: probable selection of a non-representative sample of the population. Also, people's self-reported behavior in surveys might not match their actual behavior, and to track those individual behaviors over long periods of time is demanding. Furthermore, an aggregate approach would be more relevant in exploring the interplay between air quality's effect on traffic volumes and the built environment.

1.2 Literature Review

As active transportation (walking and cycling), automobile, and transit involve different levels of exposure to air pollutants (both the total exposure and exposure/inhalation rate) (Chaney et al., 2017; Morabia et al., 2009; Good et al., 2016) and different levels of contribution to emissions (Colvile et al., 2001), people's response in terms of the use of each mode might be different. Thus, we have streamlined our literature review into three sections. Separate sections review literature on active transportation, driving, and transit, to highlight potential similarities and differences in modal reactions to increased levels of area-wide air pollution.

1.2.1 Active Transportation

In the domain of exploring the relationship between air pollution and active transportation, a few studies have been conducted in different locations around the world. Doubleday et al. (2021) examined the impact of wildfire smoke events on pedestrian and bicycle counts at eight city counters in Seattle, WA. They calculated the difference between pre-, during-, and post-wildfire smoke periods for two smoke events in the summers of 2017 and 2018 and found that wildfire smoke event decreased daily average bicycle counts by 15–36% across the eight counters, and 32–45% across the two pedestrian counters. Similarly, Saberian et al. (2017) analyzed cyclist counts at 31 points across different cycle-paths in the city of Sydney, Australia. The authors concluded that when an air quality alert was issued, the amount of cycling was reduced by 14–35%. Holmes et al. (2009) analyzed the traffic count at 30 multi-use trail points from May 2004 through August 2006 in Indianapolis, USA. They employed fixed effects regression and found that both high levels of ozone and fine particulate matters were significantly associated with lower levels of trail traffic. Kim (2020) investigated how $PM_{2.5}$ and PM_{10} affect bike sharing in different seasons in Seoul, South Korea. The study concluded high PM levels in spring and winter negatively affected bike sharing but showed no significant association with bike sharing during summer. Chung et al. (2019) examined the effect of PM_{10} for different air quality grades (good, moderate, and bad) on pedestrian volume data collected from 1,223 street locations in Seoul, South Korea, in October 2015. They used multiple regression and concluded that when PM increased by 1%, pedestrian volume decreased by 0.121%. Acharya & Singleton (2022) studied the non-motorized trail volumes in Logan, Utah, and found a measurable but small deterring impact of air pollution events on utilitarian active transportation.

Although the above-mentioned studies were conducted in different settings at different time-points, all reached similar conclusions: walking/cycling activities decrease during the episodes of poor air quality. However, it is interesting to note the different approaches and control variables employed by the studies. Saberian et al. (2017) subdivided trips by purpose and stratified the effects of air pollution for leisure and commuter trips. This allowed the authors to deduce that cycling for leisure was reduced more (38%) than cycling to work (20%). These studies have included a mix of explanatory variables to control for the effect of time and weather. However, we see no consistency in the addition of controls. For example, seasonal control was lacking in all except Kim (2020). Kim (2020) addressed this by creating different models for different seasons. On the other hand, Holmes et al. (2009) explored the distinction of effects due to air pollution itself and that of air quality alerts. They isolated the effect of public alerts by estimating the probability of a public announcement being made as a function of the level of air quality parameters. However, the study did not find the coefficient on the corrected air pollution advisory variable to be significant.

1.2.2 Driving

Another stream of research focuses on the effect of air quality/alerts on encapsulated and motorized modes such as automobiles. Using driving data from the Atlanta Regional Commission in central Atlanta, Noonan (2014) studied the relationship of household-level daily vehicle miles traveled (VMT) and regional ozone. The author hypothesized that daily VMT would fall on ozone alert days. However, there was no significant discontinuity at the ozone cutoff point of 85ppb. In another study in Salt Lake and Davis counties in Utah, Tribby et al. (2013) analyzed motor vehicle traffic data to examine the relation between daily traffic and air quality alerts. They ran ANOVA and multiple regression methods for summer and winter traffic separately. The authors found that there was no significant reduction in daily motor vehicle traffic during yellow and red days of air pollution. They concluded the ineffectiveness of air quality alerts on reducing traffic volume on days of poor air quality. The authors found similar reactions to alerts for both $PM_{2.5}$ and Ozone. They also noted an unintended consequence of the alerts, as they found an increase in the average traffic volume for yellow and red days which was significant for traffic counters near the mountain regions. The authors attributed the increase in traffic to the presence of mountains nearby that provide an easy escape for Salt Lake residents from the air quality problem.

1.2.3 Public Transit

Welch et al. (2005) studied the effects of ozone action day public advisories on train ridership in Chicago. For the study they used fixed effects regression model to analyze the effect of ozone action days on hourly Chicago Transit Authority (CTA) train ridership. The effect was found out to be significant and even sizable during some parts of the day, but the overall effect of ozone action days on ridership was not significant. Cutter & Neidell (2009) studied the response of traffic to Spare the Air (STA) Program in the San Francisco Bay Area and found that total daily traffic is reduced by 2.5–3.5%. This is accompanied by two largest increases in BART (Bay Area Rapid Transit) at 9am and 6pm. The results suggested that STA Advisories reduced traffic volume and slightly increase the use of public transit, which supported a role of voluntary information programs on change in traffic volumes.

1.2.4 Research Gaps

To conclude, the most pronounced changes in traffic volumes in response to area-wide poor air quality are reductions for open and active modes, especially for discretionary trips. This conclusion, however, does not clarify if the decrease in pedestrian/cyclist volume is accompanied by an increase in other modes such as driving and transit. Since the existing studies on driving (Noonan, 2014; Tribby et al., 2013) show insignificant changes in volume during days of bad air quality, it leads us towards a gap in the literature: the lack of research about traffic volume changes for different modes, measured in the same location. As the response to air quality depends on the available substitute mode options, demographics, and other built environment characteristics, any conclusions about modal shifts are potentially inappropriate if made by comparing studies from different sites (e.g., active mode studies from Seoul, Sydney, and Seattle vs. motorized mode studies from Atlanta and Salt Lake vs. transit studies in Chicago and Bay Area). Thus, there is a need for research exploring traffic volume changes for different modes in the same location.

Also, the reaction to changes in air quality is likely affected by characteristics of a place, such as the availability of transit, the built environment, and the sociodemographic characteristics of the location. Most studies have not explored spatial variations in the relationships between air quality and traffic volumes. Although Tribby et al. (2013) concluded that stations near mountains react differently to stations near downtown, their conclusion was derived by calculating differences between the mean values of traffic for different air quality categories for individual stations. Their approach does not allow us to explore the variation of the air quality–traffic volume relationship according to different locational characteristics. Chung et al. (2019) also controlled for spatial units, but they did so for weather parameters and calculated a single defining relationship between air quality and traffic volume for the whole area. Thus, a methodological gap to be filled is modeling variations in the relationship between air quality and traffic volume for different locations.

Furthermore, during air pollution, some trips might be shifted to a future day in response to the air pollution, also known as trip shifting. The presence of trip shifting could be studied by the introduction of time-lag variables in the model, but current literature has not investigated into the time lag effects of air pollution. Cutter & Neidell (2009) implement hourly levels in the model to study the effects of scheduling the trip for another time within a day, but we do not find any effort to study the effect of trips shifted to another day. Also, a discussion about substitution and shifting of trips have been lacking in the literature until now.

1.3 Research Objectives

The above-mentioned gaps point us towards a need for this study to explore the relationships between air quality and traffic volume for different modes in the same area, and allowing for the possibility that each count location could have a different reaction to air pollution. Thus, this thesis will address these needs by focusing on the following objectives:

1. To measure the effects of area-wide air pollution on multimodal traffic volumes and study how these effects differ by mode, by building separate models for walking, driving, and transit to observe the difference in effects across mode.
2. To explore locational variations in the effects of area-wide air pollution on multimodal traffic volumes, by using multilevel modeling to represent the locational variations in each mode-specific model.

3. To identify any occurrences of trip shifting, by introducing time lag effects of air pollution on multimodal traffic volumes.

2. DATA AND METHODS

2.1 Setting and Study Areas

To meet the objective of the thesis, we approached the study by defining two study areas in the state of Utah in the western US. The first study area includes Cache County, which lies in the northernmost part of Utah. The second area includes the counties of the Wasatch Front region (Weber, Davis, Salt Lake, and Utah). All of the counties involved in the study are listed in Table 2-1 along with their 2020 Census population.

Table 2-1

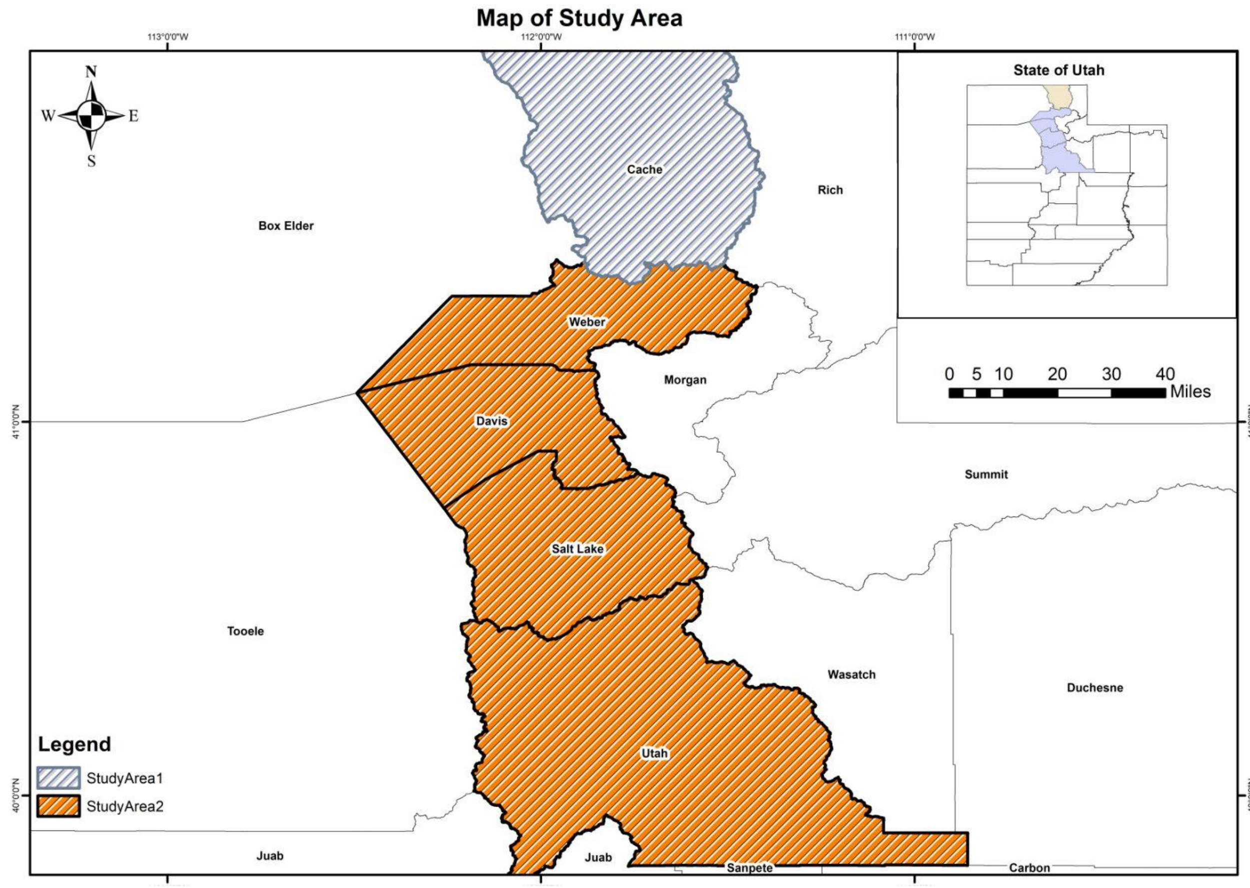
Counties in study areas

Study Area	County	2020 Census Population
Study area 1	Cache	133,154
Study area 2	Salt Lake	1,158,238
	Utah	659,399
	Davis	362,679
	Weber	262,223

The reasons behind the demarcation of our geographical scope into two areas are transit accessibility and area coverage of the regions. Cache County (study area 1) is not served by the Utah Transit Authority (UTA) service; instead it has its own local transit system: Cache Valley Transit District (CVTD). Thus, the transit accessibility is not as robust as in the study area 2. Also, the lack of data availability from the Smart Location Database, which used pre-2020 Census data and transit information from General Transit Feed Specification (GTFS) feeds meant some of the built environment variables related to transit service were not available in this study area. Secondly, study area 1 served is a smaller region with small dataset which allowed us the leverage to build a model which explained the spatial distribution of effect of air quality on multimodal traffic volumes. This model then, efficiently, was replicated for study area 2.

Figure 2-1

Division of counties into study areas



Study area 1 includes a university town in an agricultural area. Logan is the biggest town in study area 1 and also home to Utah State University. Study area 2 includes the majority of the state's population in one long and narrow urban area. The region is fast-growing and home to the state's largest city and the capital, Salt Lake City. The second largest metro area in the state, Provo, also lies in study area 2. Besides, the prominent universities in the area are University of Utah, Brigham Young University, Weber State University, and Utah Valley University.

Both study areas experience summertime wildfire smoke (mostly from California and the Pacific Northwest) as well as wintertime inversions that trap pollutants from transportation, agriculture, and industry in snow-covered urban valleys adjacent to recreational mountain areas. During summer, ozone levels get high in Utah as vehicle emissions and industrial sources mix with sunlight and heat. Smoke from various western North American wildfires (Dollar Ridge Fire in July 2018 is one notable example) also contribute to the pollution in summer. An ozone concentration of 70 parts per billion (ppb)—the 8-hour National Ambient Air Quality Standard (NAAQS) standard—is often exceeded in the Wasatch Front (DEQ Utah, 2022).

During winter months, areas in the Wasatch Front experience high levels of particulate matter $PM_{2.5}$ with daily average values reaching up to 60–80 μgm^{-3}. The $PM_{2.5}$ pollution is related with the formation of persistent cold air pools in Utah's bowl-shaped basins. These conditions are related to stratification and capping inversion of air, which in turn leads to pollutants being trapped near the surface (Baasandorj et al., 2017). Study area 1 is also similar as high particle concentration is resulted from severe cold temperature- inversion, a mix of rural and urban sources, and confined geographical area (Silva et al., 2007). Due to these pollutants, the $PM_{2.5}$ concentration of 35μgm^{-3}—the 24-hour National Ambient Air Quality Standard (NAAQS) standard—is often exceeded in the region, leading to some of the worst non-fire-related air quality within the state of Utah and sometimes the entire US (Wang et al., 2015). The counties comprising study area 2 are designated as serious non-attainment areas for $PM_{2.5}$, and Cache County in study area 1 was only redesigned as a maintenance area in 2021 (DEQ Utah, 2022).

2.2 Data and Variables

In line with our objective of measuring changes in daily multimodal traffic volumes in response to area-wide air pollution for multiple modes across various locations, we assembled a variety of data. In the following sections, we describe how we obtained multimodal traffic volumes—daily motor vehicles volume from traffic count stations, daily pedestrian volumes from traffic signals, and public transit ridership (across whole service-area) from transit agencies—assembled data on air quality and weather from atmospheric sensors; and combined these data with locational information about the built environment around each count location. A two-year period from January 2018 through December 2019 was selected for this study. Extending the timeframe to include the COVID-19 pandemic could lead to erroneous conclusion of the relationship between air quality and multimodal traffic volumes because of inadequate control for COVID. Thus, this analysis did not consider timeframe during COVID-19.

2.2.1 Multimodal Traffic Volumes

Motor vehicle traffic volume counts on various streets and highways are taken from continuous count stations (CCSs) maintained by the Utah Department of Transportation (UDOT). The stations record the number of vehicles passing a given station by using sensor devices such as inductive loops and overhead microwave radar sensors. The UDOT counts provide the number of vehicles crossing each location per day for CCSs distributed throughout Utah. The motor vehicle traffic volume data had some missing observations spread across locations and times. To minimize the effect of missing data on our analysis, we set a threshold of 600 days (out of a possible 730 days). After the use of thresholds to filter out stations, six stations located in Cache County were selected for the analysis of study area 1. Similarly, 34 stations spread across study area 2 were selected for the second set of analysis. The remaining missing data from the filtered stations were omitted from the model.

Pedestrian volumes come from a novel big data source: pedestrian push-button data obtained from high-resolution traffic signal controller logs. In Utah, such real-time and archived data are available from nearly all traffic signals throughout the state. A recent research project compared push-button data with ground-truth pedestrian volumes collected from over 10,000 hours of video at 90 signalized intersections throughout Utah, and developed a set of simple regression models to convert push-button data to estimated pedestrian crossing volumes. Details of these methods are provided elsewhere (Singleton et al., 2020), but the methods had good accuracy (correlation of 0.84, mean absolute error of 3.0 pedestrians per hour). The pedestrian signals estimate, though, had a large number of observations with zero in it. Most common reasons could be faulty stations, power outage, weekends, and low users in an area. To deal with the missing observations, first, we only picked the stations with an average daily estimated volume of more than 10. This would eliminate the signals with huge number of missing data and also, the signals in area with sparse pedestrian traffic. Then, we picked stations which had less than 20 zero counts for a total of 730-day counts. (We kept the limit at 20 as some of the zeros could be true zeros as they were observed in weekends only.) After the use of thresholds to filter out signals (we had a total of 1,845 signals at start of the process), we used daily estimates of pedestrian volumes at 38 signals in study area 1, and 871 signals for the remaining counties in study area 2.

Daily transit ridership was obtained from the transit service provider operating in each study area. For the study area 1, the Cache Valley Transit District (CVTD) provided the total daily transit ridership across all of their bus routes for each day throughout the study period. For study area 2, the Utah Transit Authority (UTA) provided the total daily transit ridership across each of their commuter rail (FrontRunner) and light rail (TRAX) routes for each day during the 2-year study period. We also attempted to get bus ridership data from UTA, but they were not confident of the accuracy of the day-to-day daily bus ridership statistics.

It is important to note that the transit data has a different structure than the pedestrian/motor data, as it captures the area-wide ridership rather than location-specific ridership. We are using system-wide data for transit rather than location-specific/route-specific data because we would have to use boarding/alighting data to be location/route specific. But, boarding/alighting data would capture only the trips starting or ending on that particular point, whereas the pedestrian/motor count data capture every trip passing through the point. Thus, to maintain the consistency in the nature of data used for analysis across each mode, we opted for system-wide data for transit even if it meant forgoing locational analysis for transit system.

2.2.2 Air Pollution, Weather, and Control Variables

Daily air quality information (air quality index, concentrations of particulate matter and ozone) is collected from sensors and was obtained from the US Environmental Protection Agency (EPA). In 2012, the Utah Division of Air Quality (UDAQ) revamped its air quality categorization in line with the EPA standard and created six categories. The categories are described in Table 2-2. The Air Quality Index (AQI) is representative of the pollution due to ozone, particulate matter, and oxides of nitrogen, sulfur, and carbon. At most of the air quality monitoring stations in Utah, only ozone and particulate matter were tracked.

During the study period (2018–2019), the highest daily AQI value was 160. However, only a few observations in Utah county were in the range of 150-160. Adding a new color-coded category to our analysis for few samples would weaken the statistical potency of our model. Thus, only three-color categories (green, yellow, and orange) were considered in our analysis as the limited observations in the range of 150-160 AQI were put under orange category.

Table 2-2

Air Quality Index (EPA, 2018)

Air Quality Index (AQI) Values	Health Concern	Colors
0-50	Good	Green
51-100	Moderate	Yellow
101-150	Unhealthy for Sensitive Groups	Orange
151-200	Unhealthy	Red
201-300	Very Unhealthy	Purple
301-500	Hazardous	Maroon

Travel activity is also influenced by weather and climatic factors (Bocker et al., 2013; Runa & Singleton, 2021). Therefore, to control for atmospheric environmental impacts on travel behaviors, daily weather data (about precipitation, snow, temperature, etc.) were obtained for various stations throughout the study areas from the National Oceanic and Atmospheric Administration's National Centers for Environmental Information (NCEI). To account for seasonal differences and behavioral adaptation to weather expectations, a maximum temperature difference variable was created as a measure of how much warmer the maximum temperature observed in a day was compared to the 30-year average of daily maximum temperature on the same day. Since the study areas experience both rain and snow throughout the year, a combined precipitation variable was created with following categories: no rain and no snow, light rain (1–25mm), light snow (1–50mm), heavy rain (>25mm), and heavy snow (>50mm).

Study Area 1: Air Quality and Weather Stations: For our initial investigation in study area 1, air quality data from a single monitoring station in Smithfield (a suburb of Logan) was used. The air quality station was 15.4 km and 21.5 km apart from the furthest pedestrian signal and motor count station respectively. Also, weather data were obtained from two weather stations: one located at Utah State University in Logan that reported daily precipitation (in mm), snowfall (in mm), and maximum and minimum temperature (in °C), and another located at the Logan–Cache Airport, where a dataset containing historical temperature for the last 30 years was obtained. The weather station in university was 6.2 km and 28.1 km apart from the furthest pedestrian signal and motor count station respectively.

Study Area 2: Air Quality and Weather Station Matching: Since the air quality and weather stations were not in the same location as the traffic station (and we had a large number of available air quality and weather station to choose from), we had to match stations with each other. The minimum distance approach for each attribute was employed to match stations. For example, assume a traffic station (T1) had two weather stations (W1 and W2) at a distance of 5 km and 9 km respectively. (The threshold distance between weather station and traffic station was set at 15 km for the analysis). Ideally, we would take all the weather data from W1. But, if W1 only recorded temperature data, then for other missing weather records (such as snow, precipitation) we matched it to next nearest weather station (W2). If W2 didn't contain such records, the record would be registered as missing. Similarly, if the same traffic station (T1) had three air quality stations (A1, A2, and A3) at distances of 10, 16, and 25 km, respectively (our threshold for air quality stations was set at 30 km), we would choose air quality data from A1. Only if A1 had missing air quality data, the next nearest air quality station A2 would be considered. This individual attribute matching helped us to decrease the number of missing records. After the matching was completed, traffic signals where a single weather and air quality attribute was missing on more than 20 occasions were left out.

Besides the weather controls, three additional control variables were introduced to account for temporal variations in traffic volumes and travel patterns. A seasonal categorical variable was created which distributed the 12 months into four seasons. Days-of-the-week were categorized into Saturday, Sunday, and weekdays to control for the effects of weekends on traffic. Also, holidays in the state of Utah during the study period were identified (Office Holidays, n.d.). As schools and universities have a significant say in the pedestrian counts, we identified the presence of schools and universities near a pedestrian signal. For universities, a logical variable was created which would be true for signals near university during the time of university breaks. This variable accounted for the low pedestrian volumes in signals near university during the breaks.

2.2.3 Count Station-Level Variables

Recall our second objective to measure variations in the air quality–traffic volume relationship across locations. We also collected built and social environment variables at each traffic count location. A quarter-mile buffer was created around each location and information regarding population and employment density, commercial and residential land uses, transit stops, park coverage, schools, and places of worship were calculated from the EPA’s Smart Location Database (US EPA, 2021). Similarly, sociodemographic attributes like average household size, average household income, and median household income were obtained from the American Community Survey (ACS) 2016-2020.

Since we had built and social environment variables for each traffic analysis zones and census block group, we had to transform those variables into our spatial unit of analysis: traffic count stations. For that, we used area-weighted averaging process. First, we created a 400m circular buffer around pedestrian signal and took the area-weighted average of the traffic zones/ census group included in that buffer. Then, thus-obtained result was used as the built and social environment variable for a particular signal. A similar approach with a buffer of 2000m was used for the motor signal.

2.2.4 Descriptive Statistics and Maps

A map of pedestrian count stations, motor volume count stations, weather station, and air quality station for study area 1 is shown in Figure 2-2. Similarly, a map of pedestrian count stations, motor volume station, and air quality station in the study area 2 are shown for each individual county in Figure 2-3 for better representation. The summary of descriptive statistics of the associated variables is shown in

Table 2-3 for study area 1, while the summary of descriptive statistics of the associated variable for study area 2 is shown for each mode (driving, walking, and transit) in Table 2-4, Table 2-5, and Table 2-6, respectively.

Figure 2-2

Distribution of stations in study area 1 (Cache County)

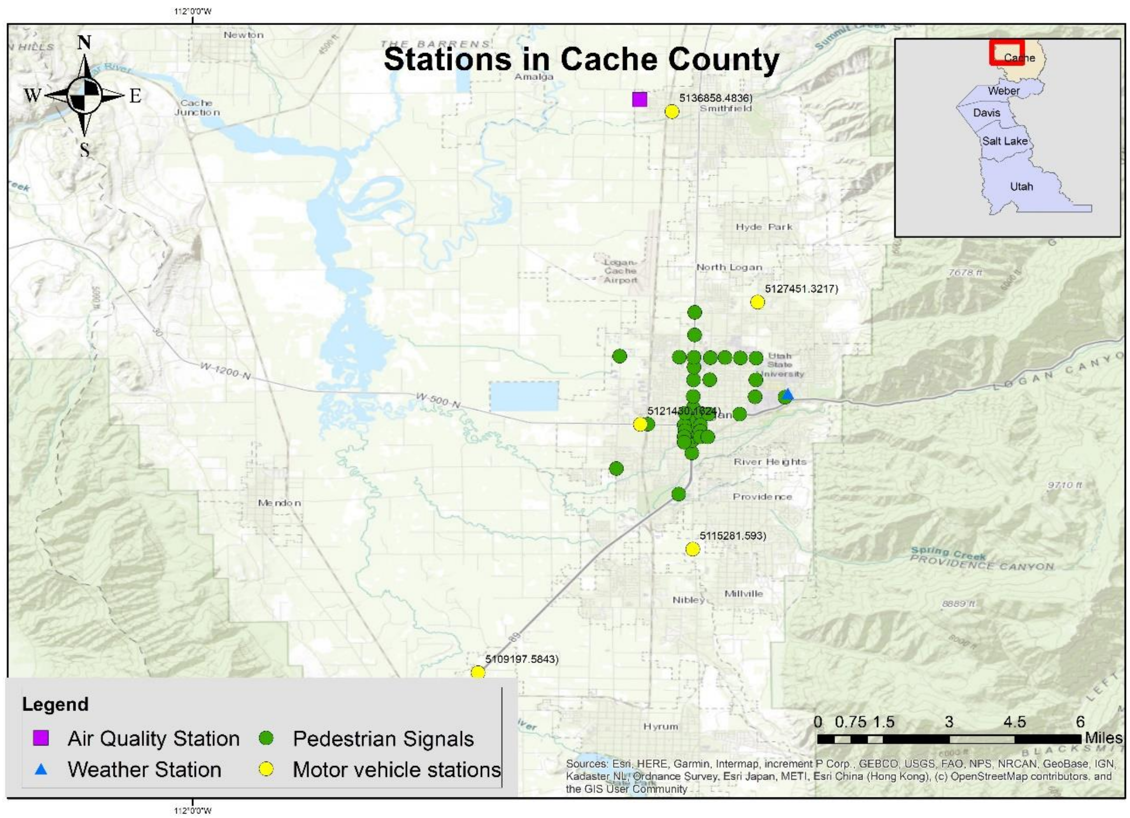
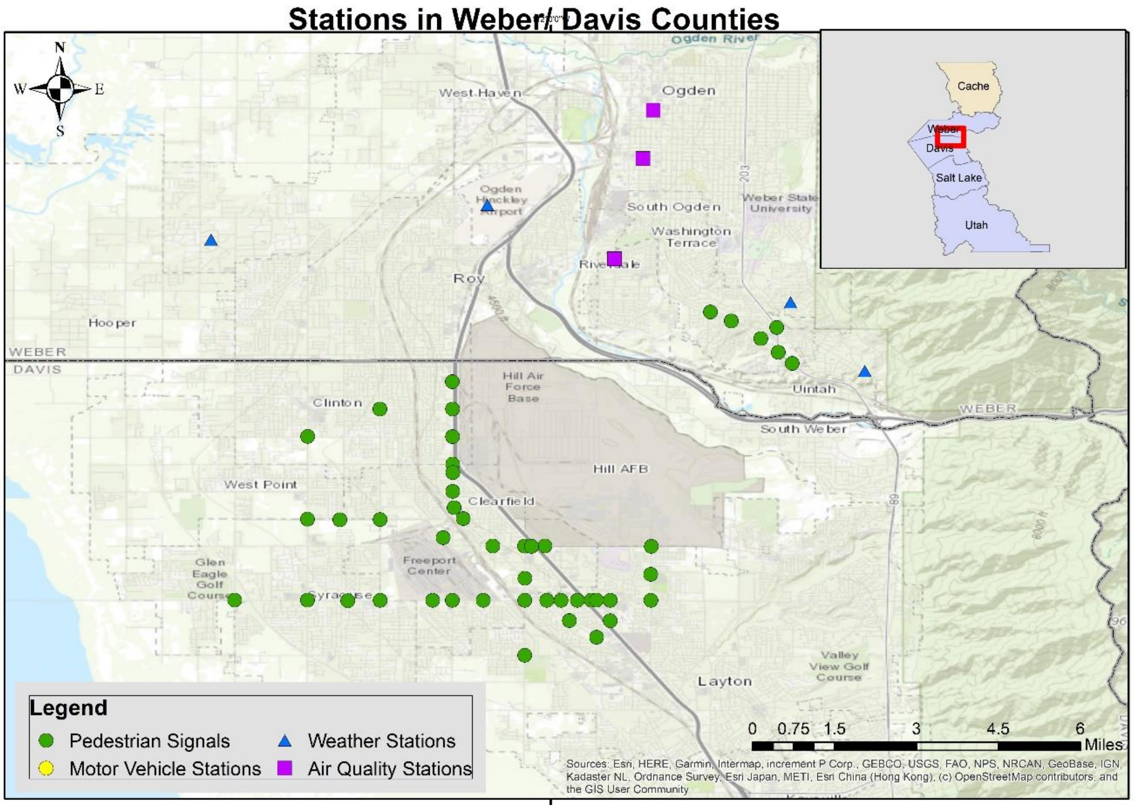
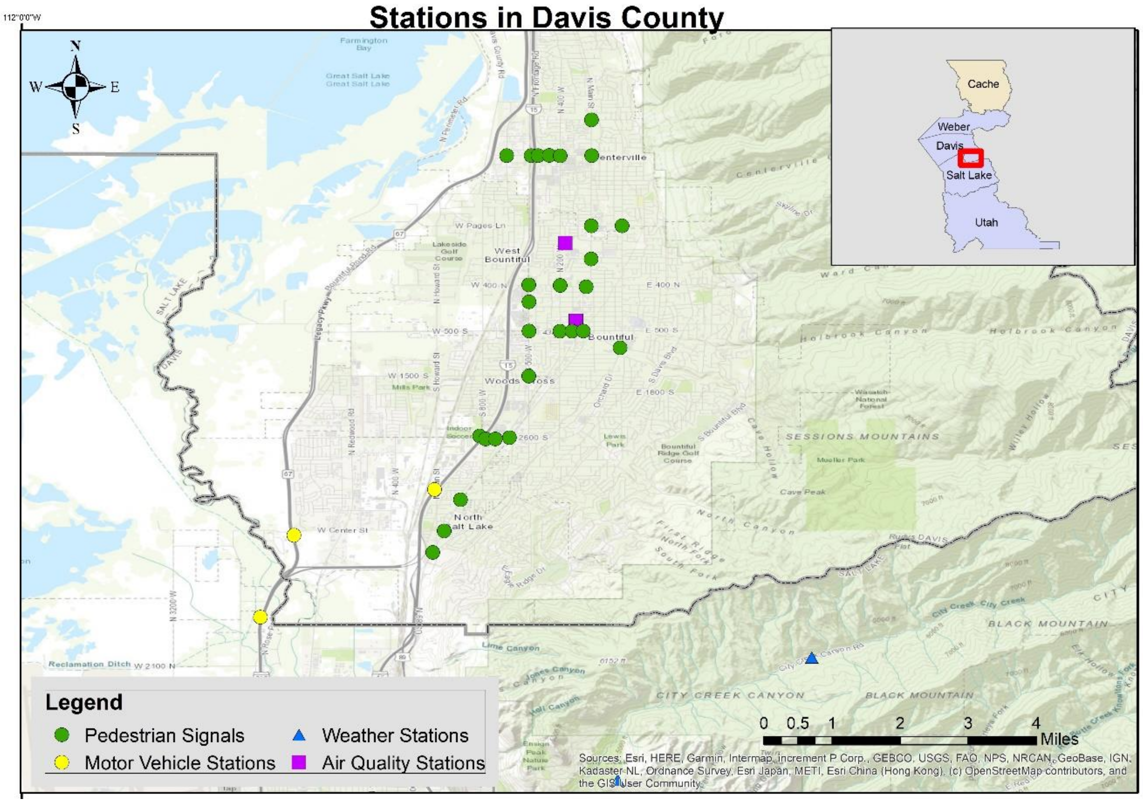
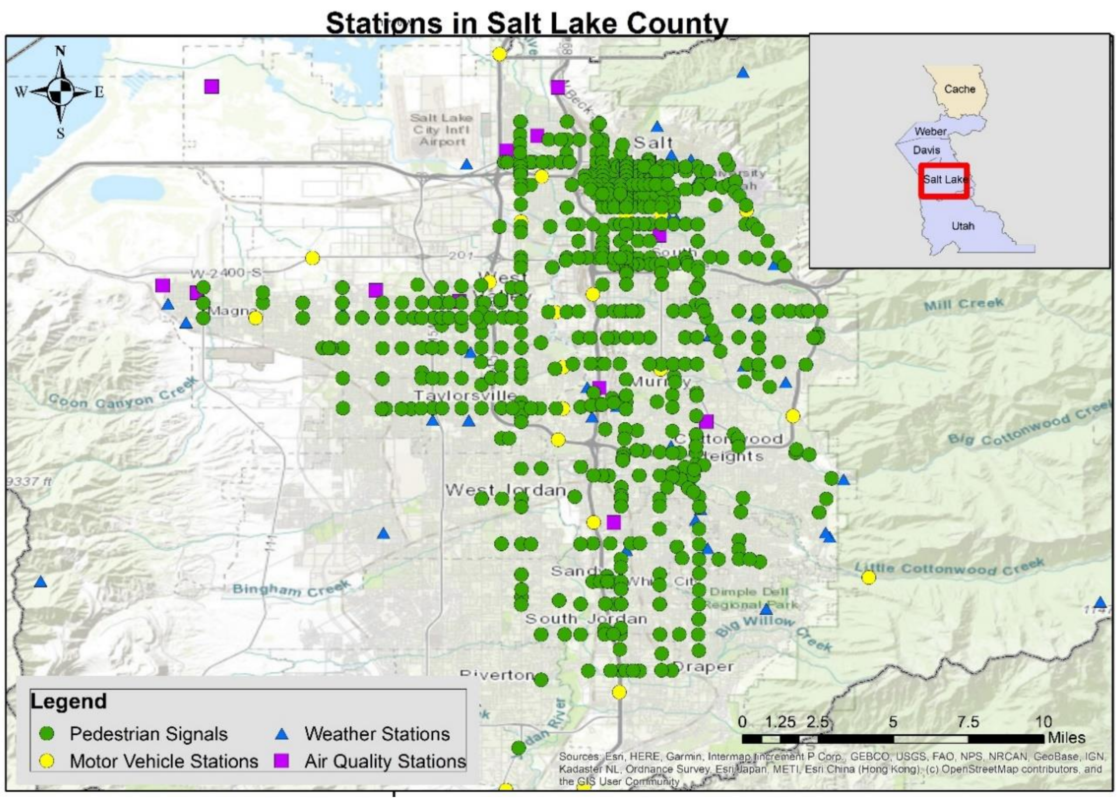


Figure 2-3

Distribution of stations in study area 2: geographically arranged north to south




Stations in Davis County
Cache
Weber
Davis
Salt Lake
Utah
Legend
Pedestrian Signals
Motor Vehicle Stations
Weather Stations
Air Quality Stations
0 0.5 1 2 3 4
Miles
Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), (c) OpenStreetMap contributors, and the GIS User Community


Stations in Salt Lake County
Cache
Weber
Davis
Salt Lake
Utah
Legend
Pedestrian Signals
Motor Vehicle Stations
Weather Stations
Air Quality Stations
0 1.25 2.5 5 7.5 10
Miles
Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), (c) OpenStreetMap contributors, and the GIS User Community

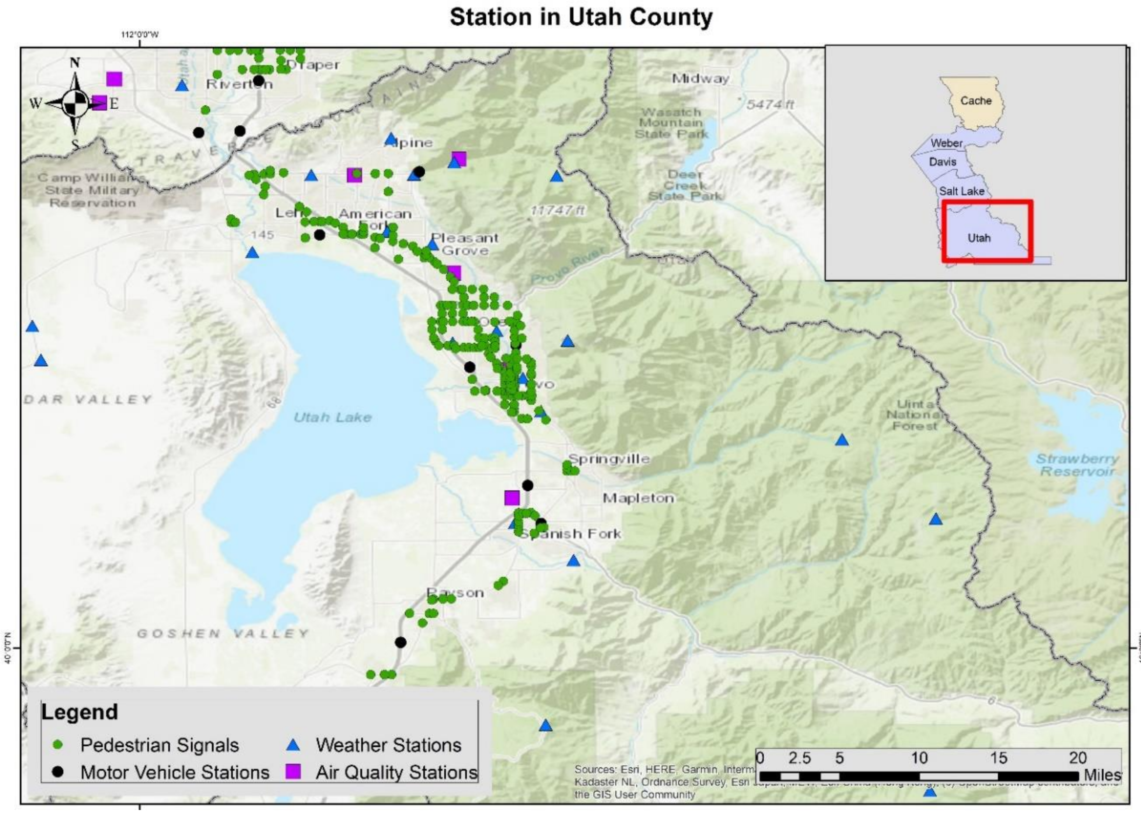

Station in Utah County
Legend
Pedestrian Signals
Weather Stations
Motor Vehicle Stations
Air Quality Stations
Cache
Weber
Davis
Salt Lake
Utah
0 2.5 5 10 15 20 Miles
Utah Lake
Springville
Mapleton
Spanish Fork
Pleasant Grove
American Fork
Riverton
Draper
Midway
Strawberry Reservoir
Uinta National Forest
GOSHEN VALLEY
Camp Williams State Military Reservation
Wasatch Mountain State Park
Deer Creek State Park
11747 ft
5474 ft
Provo River

Table 2-3

Descriptive statistics, study area 1

Variable	Mean	SD	#	%
Motor vehicle traffic volume	12,502	8,413		
(*N* = 3,963 = 6 stations × 730 days – missing data)				
Pedestrian traffic volume	379	1,035		
(*N* = 27,053 = 38 stations × 730 days – missing data)				
Daily Transit Ridership	4715	1971.9		
(*N* = 730 – holidays - Sundays)				
Temporal variables (730 days)				
Day of week: Weekday			522	71.5
Saturday			104	14.2
Sunday			104	14.2
Holiday: False			706	96.7
True			24	3.3
Season: Winter			180	24.7
Spring			184	25.2
Summer			184	25.2
Fall			182	24.9
Precipitation: No rain / no snow			532	73.0
Light rain (1–25mm)			117	16.0
Light snow (1–50mm)			57	7.8
Heavy rain (>25mm)			2	0.3
Heavy snow (>50mm)			21	2.9
Max temperature (°C) difference from average	0.04	4.73		
Air quality index: Green (AQI = 0–50)			626	85.7
Yellow (AQI = 51–100)			88	12.1
Orange (AQI = 101–150)			16	2.2
Built and social environment variables (38 pedestrian count stations)				
Percentage of residential parcels	18.6	13.7		
Percentage of commercial parcels	33.8	16.8		
Percentage of vacant land	6.9	4.6		
Population density (1,000 people/mi^2)	4.7	2.2		
Employment density (1,000 jobs/mi^2)	9.1	6.3		
Intersection density (#/mi^2)	83.5	39.4		
% 4-way intersections	44.6	21.4		
Number of transit stops	5.9	3.8		
Number of schools	0.2	0.5		
Park acreage	1.2	2.8		
Household income (median, $1,000)	38.2	9.2		
Vehicle ownership (mean)	1.6	0.3		

Table 2-4

Descriptive statistics (motor vehicle volumes), study area 2

Variable	**Mean**	**SD**	**#**	**%**
Motor vehicle traffic volumes (*N* = 23,064 = 34 stations × 730 days – missing data)	70,081	70,696		
Temporal variables (730 days)				
Day of week: Weekday			522	71.5
Saturday			104	14.2
Sunday			104	14.2
Holiday: False			706	96.7
True			24	3.3
Season: Winter			180	24.7
Spring			184	25.2
Summer			184	25.2
Fall			182	24.9
Spatial-temporal variables (N = 23,064)				
Precipitation: No rain / no snow			16,642	72.2
Light rain (1–25mm)			4,432	19.2
Light snow (1–50mm)			1,330	5.8
Heavy rain (>25mm)			46	0.2
Heavy snow (>50mm)			609	2.6
Max temperature (°F) difference from average	0.68	8.6		
Air quality index: Green (AQI = 0–50)			19,632	85.2
Yellow (AQI = 51–100)			3,251	14.1
Orange (AQI = 101–150)			157	0.6
Built and social environment variables (34 motor count stations)				
Percentage of zero-car households in CBG, 2018	0.04	0.04		
Gross employment density (people/acre) on unprotected land	4.73	3.31		
Jobs per household	4.71	5		
Total road network density	13.11	6.72		
Distance from population-weighted centroid to transit stop (m)	606.1	194.6		
Jobs within 45 minutes auto travel time, network travel time weighted	78,341	37,609		
Park acreage	31.39	45.5		
Number of schools	5	4.97		
Household income (median, $1,000)	80.66	26.88		
Number of transit stops	47.24	51.6		

Table 2-5

Descriptive statistics (pedestrian volumes), study area 2

Variable	Mean	SD	#	%
Pedestrian traffic volumes (N = 635,830 = 871 stations × 730 days – missing data)	330	693		
Temporal variables (730 days)				
Day of week: Weekday			522	71.5
Saturday			104	14.2
Sunday			104	14.2
Holiday: False			706	96.7
True			24	3.3
Season: Winter			180	24.7
Spring			184	25.2
Summer			184	25.2
Fall			182	24.9
Spatial-temporal variables (N = 635,830)				
Precipitation: No rain / no snow			464,661	73
Light rain (1–25mm)			120,001	18.8
Light snow (1–50mm)			34,543	5.4
Heavy rain (>25mm)			772	0.1
Heavy snow (>50mm)			15,853	0.2
Max temperature (°F) difference from average	0.86	8.4		
Air quality index: Green (AQI = 0–50)			544,985	85.7
Yellow (AQI = 51–100)			86,774	13.6
Orange (AQI = 101–150)			3,915	0.6
Built and social environment variables (871 pedestrian count stations)				
Percentage of zero-car households in CBG, 2018	0.07	0.076		
Gross employment density (people/acre) on unprotected land	8.2	4.5		
Jobs per household	5.5	8.6		
Total road network density	20.1	4.5		
Distance from population-weighted centroid to transit stop (m)	525.8	228.5		
Jobs within 45 minutes auto travel time, network travel time weighted	84,555	33,422		
Park acreage	10.9	48.9		
Number of schools	0.07	0.076		
Household income (median, $1,000)	67.6	24.5		
Number of transit stops	5.2	3.8		
Signal near university: False			825	94.7
True			46	5.3
Signals near university and on break: False			623,096	98.0
True			12,734	2.0

Table 2-6

Descriptive statistics (transit ridership), study area 2

Variable	**Mean**	**SD**	**#**	**%**
Daily Transit Ridership (UTA Trax) (*N* = 730 – holidays)	4715	1971.9		
Daily Transit Ridership (UTA Frontrunner) (*N* = 730 – holidays - Sundays)	16548	4793.6		
Temporal variables (730 days)				
Day of week: Weekday			522	71.5
Saturday			104	14.2
Sunday			104	14.2
Holiday: False			706	96.7
True			24	3.3
Season: Winter			180	24.7
Spring			184	25.2
Summer			184	25.2
Fall			182	24.9
Precipitation: No rain / no snow			538	74.8
Light rain (1–25mm)			120	16.6
Light snow (1–50mm)			46	6.4
Heavy rain (>25mm)			-	-
Heavy snow (>50mm)			15	2.1
Max temperature (°F) difference from average	1.26	8.3		
Air quality index: Green (AQI = 0–50)			626	87.1
Yellow (AQI = 51–100)			90	12.5
Orange (AQI = 101–150)			3	0.4

2.3 Analysis Methods

The three different modes (driving, pedestrian, and transit) under analysis had datasets that were distinct in their locational representation: driving and pedestrian data covered multiple locations across two years, while transit ridership had a single regional aggregate for two years. Because of this difference in the nature of datasets, we employed general regression modeling for transit volumes and multilevel modeling for driving and pedestrian volumes.

For transit ridership, in line with the first objective to examine the relationship of air quality and traffic volumes, for each study area we estimated a simple regression model as represented by Eq. 1. The dependent variable (Y_{ij}) was the natural log of the daily total transit ridership in each study area (only bus in study area 1, only rail in study area 2), and the independent variables (x_i) were air quality, weather, and temporal controls.

$$Y_i = \beta_0 + \beta_1 x_i + R_i \quad (1)$$

Since the datasets for motor vehicle and pedestrian volumes covered multiple locations and across a span of two years, multilevel modeling was an appropriate approach for our analyses. Multilevel models can adequately represent the two-level nature of our data: daily counts Y_{ij} (level one), nested within locations (level two). Such models also allow clear specifications of variations in model coefficients at level one (across level two units j), including fixed and random intercepts (β_{0j}), slopes (β_{hj}) for h level-one variables (x_{ij}), and cross-level interactions in which level-two variables (z_j) affect level-one slopes. In other words, multilevel models can represent variations in the air quality–traffic volume relationship (slope) across locations and due to locational characteristics. A simple multilevel model with one level-one variable and level-one residuals R_{ij} is represented in the following Eq. 2:

$$Y_{ij} = \beta_{0j} + \beta_{1j}x_{ij} + R_{ij} \qquad (2)$$

In line with the first objective to examine the relationship of air quality and traffic volume for each mode, we estimated separate multilevel models for motor vehicle traffic volumes and for pedestrian volumes. The dependent variable (Y_{ij}) was the natural log of the daily (motor vehicle or pedestrian) traffic count in each study area, and independent (level one) variables (x_{hij}) were air quality, weather, and temporal controls. Different specifications for air quality were considered, but the best-fitting and most intuitive results were found for dummy variables representing the green, yellow, and orange AQI categories (Table 2-2). For driving and walking, we allowed the intercept (but not the slopes) to vary across locations. (Recall, for transit, we resorted to general linear regression as we had aggregate transit ridership data, not for particular locations.) For pedestrian volumes (38 locations in study area 1 and 868 locations in study area 2), we used a random effects intercept model (Eq. 3), in which the intercept coefficient (β_{0j}) varied randomly following a normal distribution for level-two residuals (U_{0j}). For motor vehicle volumes in study area 1 (6 locations), the few sites meant we used a fixed effects intercept model (Eq. 4), in which a different intercept coefficient was estimated for each station k. But the increased number of motor stations in study area 2 (34 locations) allowed us to use the random effects intercept model (Eq. 3).

$$Y_{ij} = \beta_{0j} + \sum_h \beta_h x_{hij} + R_{ij}$$ (3a), where

$$\beta_{0j} = \gamma_{00} + U_{0j} \quad \text{(3b).}$$

$$Y_{ij} = \beta_{0j} + \sum_h \beta_h x_{hij} + R_{ij} \quad \text{(4a), where}$$

$$\beta_{0j} = \sum_k \gamma_{0k} D_k \quad \text{(4b), and}$$

D_k is a dummy variable equal to 1 for station k and 0 otherwise.

To address the study's second objective—exploring variations across locations in the effect of area-wide air pollution on multimodal traffic volumes—we first modified the first objective models and allowed slopes for the air quality dummy variables to vary across count stations. Again, for pedestrian volumes in both of the study areas, this was a random effects slope model (Eq. 5), in which the random coefficients were normally distributed. For motor vehicle volumes in study area 1, this was a fixed effects slope model (Eq. 6), in which different coefficients were estimated for each station. For motor vehicle volumes in study area 2, this was a random effects slope model (Eq. 5) similar to that employed for pedestrian volumes. If the slopes were found to vary across locations—measured using likelihood-ratio tests versus the models for the first objective—we then tested whether g level-two location characteristics (z_{gj}) were significant in predicting the intercept and air quality slope variations across locations. In the terminology of multilevel modeling, these effects are called cross-level interactions (γ_{gh}), because they result in an interaction of a level-two variable (built or social environment) with a level-one variable (air quality). Only variables with significant interaction coefficients were retained in the final models. Due to the lack of transit data across multiple locations, we could not employ the second objective models for transit volumes.

$Y_{ij} = \beta_{0j} + \sum_h \beta_{hj} x_{hij} + R_{ij}$ (5a), where

$\beta_{0j} = \gamma_{00} + \sum_g \gamma_{g0}\, z_{gj} + U_{0j}$ (5b), and

$\beta_{hj} = \gamma_{h0} + \sum_g \gamma_{gh}\, z_{gj} + U_{hj}$ (5c).

$Y_{ij} = \beta_{0j} + \sum_h \beta_{hj} x_{hij} + R_{ij}$ (6a), where

$\beta_{0j} = \sum_k \gamma_{0k} D_k$ (6b),

$\beta_{hj} = \sum_k \gamma_{hk} D_k$ (6c), and

D_k is a dummy variable equal to 1 for station k and 0 otherwise.

Model estimation was performed using the “lme4” package in R (Bates et al., 2015).

3. RESULTS, STUDY AREA 1

As defined in Chapter 2, we demarcated our study area into two regions. This chapter explains the model results for different modes in study area 1. First, we built a model for each mode (walking/cycling, driving, and transit) without locational parameters to meet our objective 1. Then, two additional models were created to explain the locational variation of relationships between air quality and both pedestrian and motor vehicle traffic volumes. Since we had the overall transit ridership for the region (not for specific stops or routes), we could not explain locational variations of the air quality and transit ridership relationship. Models specific to each mode are discussed in the sections below.

3.1 Driving

Table 3-1 reports results of the fixed intercept model for motor vehicle traffic volumes. One of the air quality variables (orange) was positively and significantly associated with traffic volumes (β = 0.048, *SE* = 0.016, t = 3.053, p = 0.002). The positive association implies that driving increased during unhealthy (orange) air quality days by 4.9% when compared to days with good (green) air quality. The coefficient for yellow air quality was not significant, implying no significant difference in traffic volumes on yellow (moderate) versus green air quality days.

Table 3-1

Motor vehicle traffic volumes, fixed intercept model

Coefficient	Estimate	SE	t-statistic	p-value
Intercept (station 301)	8.909	0.041	217.961	<0.001
Difference for station 363	1.084	0.008	143.615	<0.001
Difference for station 510	-0.662	0.007	-89.283	<0.001
Difference for station 511	-0.398	0.007	-53.463	<0.001
Difference for station 620	0.221	0.008	29.067	<0.001
Difference for station 622	0.948	0.008	126.064	<0.001
Day of week (ref. = Weekday)				
Saturday	-0.116	0.006	-18.209	<0.001
Sunday	-0.609	0.006	-95.359	<0.001
Holiday (ref. = No holiday)	-0.268	0.012	-22.245	<0.001
Season (ref. = Winter)				
Spring	0.101	0.007	14.393	<0.001
Summer	0.135	0.007	19.142	<0.001
Fall	0.113	0.007	16.210	<0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.026	0.009	-4.213	<0.001
Light snow	-0.071	0.041	-8.226	<0.001
Heavy rain	-0.030	0.040	-0.758	0.449
Heavy snow	-0.145	0.013	-11.288	<0.001
Max temperature difference from average	-0.001	0.000	-1.228	0.220
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.004	0.007	0.489	0.625
Orange (AQI = 100+)	0.048	0.016	3.053	0.002

Notes: N = 3,963; adjusted R-squared = 0.961.

Table 3-2 reports results of the fixed intercept and fixed slope model for motor vehicle traffic volumes, which involved interaction terms included between the air quality categories and each station. None of the air quality–station interaction terms were significant ($p > 0.10$), which implies that there was no significant difference in the relationship between air quality and motor vehicle traffic volumes across the six count stations. Because no significant slope variation was detected, we did not estimate a subsequent model to predict this variation from built and social environment variables.

Table 3-2

Motor vehicle traffic volumes, fixed intercept and fixed slope model

Coefficients	Estimate	SE	t-statistic	p-value
Intercept (Station 301)	9.056	0.007	1137.596	<0.001
Difference for Station 363	1.083	0.008	132.976	<0.001
Difference for Station 510	-0.659	0.008	-82.432	<0.001
Difference for Station 511	-0.398	0.008	-49.547	<0.001
Difference for Station 620	0.218	0.008	26.587	<0.001
Difference for Station 622	0.943	0.008	116.956	<0.001
Day of week (ref. = Weekday)				
Saturday	-0.116	0.006	-18.198	<0.001
Sunday	-0.609	0.006	-95.323	<0.001
Holiday (ref. = No holiday)	-0.268	0.012	-22.247	<0.001
Season (ref. = Winter)				
Spring	0.100	0.006	14.425	<0.001
Summer	0.135	0.007	19.171	<0.001
Fall	0.112	0.006	16.24	<0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.026	0.006	-4.202	<0.001
Light snow	-0.070	0.008	-8.191	<0.001
Heavy rain	-0.030	0.039	-0.756	0.449
Heavy snow	-0.145	0.012	-11.277	<0.001
Max temperature difference from average	-0.0005	0.000	-1.216	0.224
Air quality index (ref. = Green)				
Yellow (AQI = 50–99) (Station 301)	-0.006	0.016	-0.391	0.695
Difference for Station 363	0.006	0.023	0.283	0.777
Difference for Station 510	-0.006	0.022	-0.264	0.791
Difference for Station 511	0.007	0.022	0.312	0.754
Difference for Station 620	0.021	0.023	0.931	0.351
Difference for Station 622	0.035	0.024	1.492	0.135
Orange (AQI = 100+) (Station 301)	0.076	0.038	1.963	0.049
Difference for Station 363	-0.027	0.054	-0.510	0.610
Difference for Station 510	-0.072	0.052	-1.372	0.170
Difference for Station 511	-0.052	0.053	-0.986	0.324
Difference for Station 620	-0.021	0.053	-0.401	0.688
Difference for Station 622	0.009	0.052	0.180	0.857

Notes: N = 3,693; adjusted R-squared = 0.961.

3.2 Pedestrian

Table 3-3 reports results of the random intercept model for pedestrian volumes. The coefficient estimates for both the yellow (β = -0.023, *SE* = 0.023, *t* = -1.691, *p* = 0.091) and orange air quality days (β = -0.093, *SE* = 0.029, *t* = -3.204, *p* = 0.001) were negative and at least marginally significant. This implies that pedestrian volumes decreased during episodes of poor air quality (compared to green days), especially on orange days (unhealthy for sensitive groups). The magnitude of decrease during orange days was significantly higher (8.8%) than that on yellow days (2.3%).

Table 3-3

Pedestrian volumes, random intercept model

Coefficients	Estimate	SE	df	t-statistic	p-value
Intercept	4.989	0.162	37.310	30.738	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.357	0.012	27000	-30.403	<0.001
Sunday	-1.008	0.012	27000	-86.497	<0.001
Holiday (ref. = No holiday)	-0.674	0.023	27000	-29.905	<0.001
Season (ref. = Winter)					
Spring	0.380	0.013	27000	29.004	<0.001
Summer	0.483	0.013	27000	38.158	<0.001
Fall	0.473	0.013	27000	36.371	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.083	0.012	27000	-7.150	0.000
Light snow	-0.282	0.016	27000	-17.405	<0.001
Heavy rain	-0.220	0.076	27000	-2.876	0.004
Heavy snow	-0.421	0.024	27000	-17.197	<0.001
Max temperature difference from average	0.004	0.001	27000	4.335	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	-0.023	0.013	27000	-1.691	0.091
Orange (AQI = 100+)	-0.093	0.029	27000	-3.204	0.001

Notes: N = 27,053; # groups = 38; log-likelihood = -27,141; between-group variance = 0.99; residual variance = 0.43.

Table 3-4 reports results of the random intercept and random slope model for pedestrian volumes. By estimating an earlier model (not shown), we found that there were significant random slopes for the air quality variables: a likelihood-ratio test found that the random intercept and slope model (log-likelihood = -27,124) was significantly better-fitting than the random intercept only model (log-likelihood = -27,141). Therefore, we estimated several models, each testing cross-level interactions with air quality involving built and social environment variables. As shown in Table 3-4, there were significant interaction effects for two variables: the percentage of 4-way intersections and average vehicle ownership. For the intersection variable, there was a positive and significant interaction term with orange days (β = 0.005, *SE* = 0.02, *t* = 2.736, *p* = 0.01) but not yellow days. This implies that the negative effect of orange air quality days on pedestrian volumes (see Table 3-3) was attenuated in places with a greater share of 4-way intersections. For the vehicle ownership variable, there was a negative and significant interaction term with yellow days (β = -0.161, *SE* = 0.055, *t* = -2.942, *p* = 0.01) and a negative but not statistically significant interaction term with orange days (β = -0.200, *SE* = 0.125, *t* = -1.600, *p* = 0.117). This implies that the negative effects of yellow and perhaps orange air quality days on pedestrian volumes (see Table 3-3) were enhanced in places with greater average household vehicle ownership.

Table 3-4

Pedestrian volumes, random intercept and random slope model

Coefficients	Estimate	SE	df	t-statistic	p-value
Intercept	0.069	1.229	31.590	0.056	0.956
Day of week (ref. = Weekday)					
Saturday	-0.357	0.012	26960	-30.448	<0.001
Sunday	-1.008	0.012	26960	-86.620	<0.001
Holiday (ref. = No holiday)	-0.674	0.022	26960	-29.947	<0.001
Season (ref. = Winter)					
Spring	0.380	0.013	26960	29.044	<0.001
Summer	0.483	0.013	26960	38.221	<0.001
Fall	0.473	0.013	26960	36.427	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.083	0.012	26960	-7.166	<0.001
Light snow	-0.282	0.016	26960	-17.433	<0.001
Heavy rain	-0.220	0.076	26960	-2.881	0.004
Heavy snow	-0.421	0.024	26960	-17.211	<0.001
Max temperature difference from average	0.004	0.001	26960	4.348	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	0.227	0.108	44.400	2.106	0.041
Orange (AQI = 100+)	0.005	0.247	41.080	0.022	0.983
Built and social environment variables					
Percentage of commercial parcels	0.005	0.007	31.030	0.750	0.459
Household income (median, $1,000)	0.044	0.018	31.050	2.419	0.022
Population density (1,000 people/mi^2)	0.390	0.079	31.020	4.910	0.000
Vehicle ownership (mean)	0.423	0.431	31.400	0.981	0.334
% 4-way intersections	-0.004	0.007	31.510	-0.669	0.509
Number of transit stops	0.110	0.037	31.050	2.974	0.006
Cross-level interactions					
Yellow AQI with % 4-way intersections	0.000	0.001	44.280	0.292	0.772
Orange AQI with % 4-way intersections	0.005	0.002	40.970	2.737	0.009
Yellow AQI with Vehicle ownership	-0.161	0.055	44.410	-2.944	0.005
Orange AQI with Vehicle ownership	-0.200	0.125	41.430	-1.600	0.117

Notes: N = 27,053; # groups = 38; log-likelihood = -27,095; between-group variance = 0.45; residual variance = 0.43; random coefficient variance for yellow AQI = 0.003; random coefficient variance for orange AQI = 0.020.

3.2.1 Posterior Slopes

Because cross-level interaction terms are difficult to interpret in any type of regression model and even more difficult when they affect random slope coefficients, we also calculated what are called “posterior slopes” (Snijders & Bosker, 2012). Since the random air quality coefficients are not estimated by the model (just their mean and standard deviation), we used empirical Bayes estimation to let the model and data give us the “best” estimate of each location's slope coefficients. See a multilevel modeling textbook (Snijders & Bosker, 2012) for details on this calculation. Since the air quality coefficients were also interacted with built and social environment variables, we then multiplied each location's values for these level-two variables with their respective coefficients, and added them to the random portion obtained through empirical Bayes estimation to get the total value of the posterior slopes for yellow and orange air quality days (vs. green days).

Figure 3-1 plots these posterior slopes, first in a scatterplot (yellow vs. orange) and second in a combined plot vs. AQI. The left portion of the figure shows how most locations had a more negative orange coefficient than yellow coefficient, and how the posterior slopes were positively correlated (which is expected, since they are both conditional on the same data at each location). The right portion of the figure shows how air quality coefficients in the orange range (AQI = 101–150) were typically more extreme (mostly more negative, some are more positive) than coefficients in the yellow range (AQI = 51–100). In both portions of Figure 3-1, it appears one location had a much more negative orange coefficient than did all other locations.

Figure 3-1

Figures showing pedestrian model posterior slopes for yellow and orange air quality levels (left: scatterplot; right: plot vs. AQI)

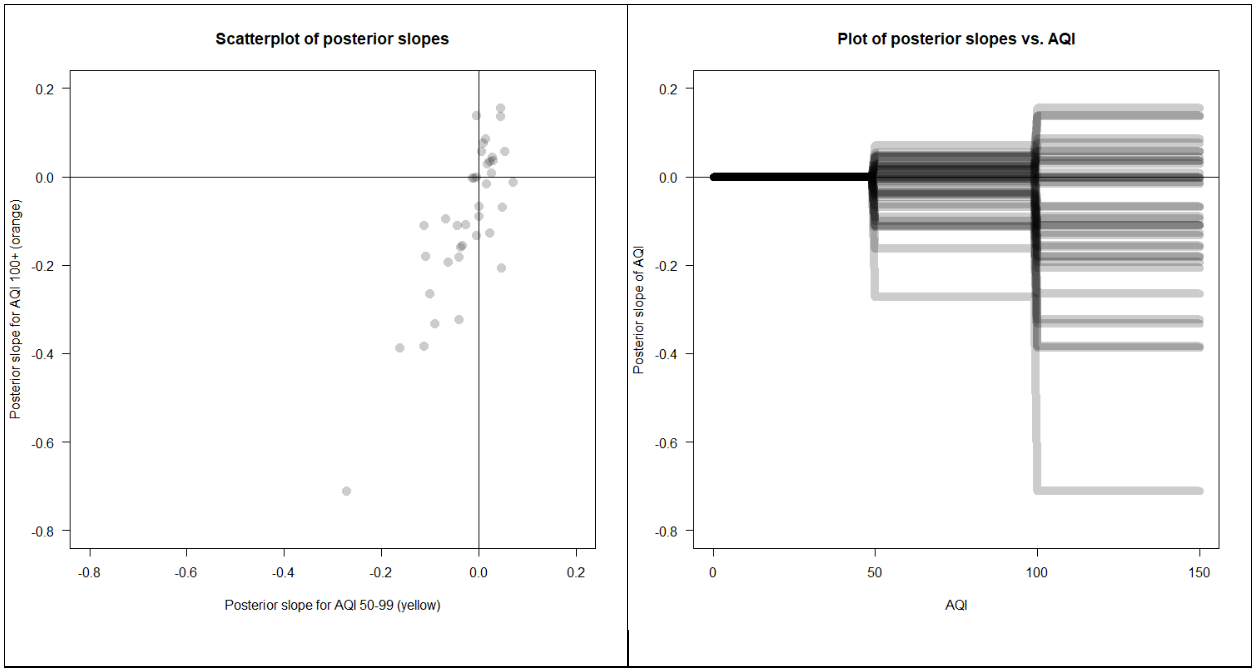
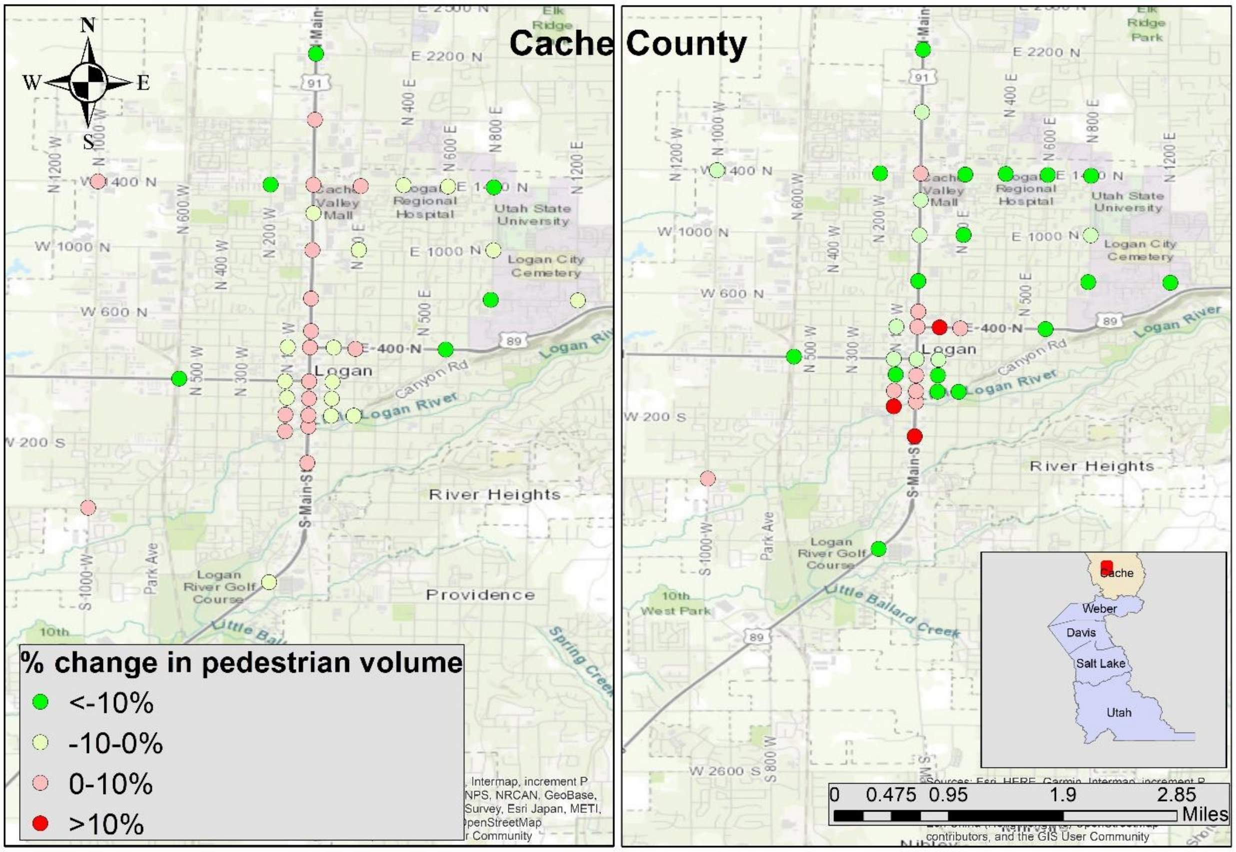


Figure 3-1 plots these posterior slopes on a map for yellow (left) and orange (right) air quality days. In both cases, it appears that locations with positive coefficients tend to be concentrated along Main Street (running north–south) and in downtown Logan. Locations with more negative coefficients (including the location with the most negative coefficient) seem to be concentrated in the northeast portion of the city, near to the Utah State University campus.

Figure 3-2

Maps showing pedestrian model posterior slopes for yellow (left) and orange (right) air quality levels



3.3 Transit

Table 3-5 reports results of the ordinary regression model for transit ridership in Cache County. It should be noted that we did not run a multilevel model for our transit data because we did not have location-specific data in the case of transit. Since, the transit service did not operate during Sundays and holidays in study area 1, their estimates are missing from the model. The estimates for both the yellow and orange air quality days were found to be negative but were not statistically significant.

Table 3-5

CVTD bus transit ridership, ordinary regression model

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	8.654	0.028	305.698	<0.001
Day of week (ref. = Weekday)				
Saturday	-1.228	0.027	-45.856	<0.001
Sunday	-	-	-	-
Holiday (ref. = No holiday)	-	-	-	-
Season (ref. = Winter)				
Spring	-0.041	0.033	-1.240	0.215
Summer	-0.360	0.032	-11.167	<0.001
Fall	0.070	0.033	2.100	0.036
Precipitation (ref. = No rain / no snow)				
Light rain	-0.044	0.029	-1.548	0.122
Light snow	-0.101	0.041	-2.459	0.014
Heavy rain	0.142	0.247	0.573	0.567
Heavy snow	-0.125	0.064	-1.954	0.051
Max temperature difference from average	-0.002	0.002	-0.732	0.464
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.013	0.034	-0.395	0.693
Orange (AQI = 100+)	-0.044	0.067	-0.650	0.516

Notes: N = 580; adjusted R-squared = 0.961.

4. RESULTS, STUDY AREA 2: WASATCH FRONT

Building from the models tested for study area 1, we refined them (by adding some location-specific variables) for study area 2. The approach taken was similar in approach to that of study area 1: first we estimated a model for each mode (motor vehicle, pedestrian, and transit), then added locational attributes to the available mode (motor vehicle and pedestrian), and finally graphically analyzed the locational distribution of relationships between air quality and traffic volumes (motor vehicle and pedestrian). Since we had the overall transit ridership for the region (not for specific stops or routes), we could not explain locational variations of the air quality and transit ridership relationship.

4.1 Driving

Table 4-1 reports results of the random intercept model for motor vehicle traffic volumes across the Wasatch Front. One of the air quality variables (yellow) was positively and (marginally) significantly associated with traffic volumes ($\beta = 0.009$, $SE = 0.005$, $t = 1.858$, $p = 0.063$). The positive association implies that driving increased during moderate (yellow) air quality days when compared to days with good (green) air quality. The coefficient for orange air quality was negative and significantly associated with traffic volumes ($\beta = -0.068$, $SE = 0.019$, $t = -3.652$, $p < 0.001$), implying a decrease in traffic volumes on orange (unhealthy) versus green air quality days. There is a slight increase in yellow days (0.9%), compared to the much larger 6.6% decrease in the orange days; this indicates a presence of a non-linear relationship between air quality and motor volumes in study area 2.

Table 4-1

Motor vehicle traffic volumes, random intercept model

Coefficients	Estimate	SE	df	t-statistic	p-value
Intercept	10.680	0.185	33	57.680	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.130	0.004	22950	-29.298	<0.001
Sunday	-0.442	0.004	22950	-99.293	<0.001
Holiday (ref. = No holiday)	-0.266	0.008	22950	-31.323	<0.001
Season (ref. = Winter)					
Spring	0.077	0.004	22950	0.077	<0.001
Summer	0.131	0.005	22950	28.647	<0.001
Fall	0.071	0.004	22950	16.018	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.019	0.004	22950	-4.610	0.014
Light snow	-0.070	0.007	22950	-10.030	<0.001
Heavy rain	-0.226	0.034	22950	-6.600	<0.001
Heavy snow	-0.164	0.010	22950	-16.551	<0.001
Max temperature difference from average	-0.001	0.000	22950	-3.868	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	0.009	0.005	22950	1.858	0.063
Orange (AQI = 100+)	-0.068	0.019	22950	-3.652	<0.001

Notes: N = 23,001 # groups = 34; log-likelihood = 1018.7; between-group variance = 1.16; residual variance = 0.052.

Table 4-2 reports results of the random intercept and random slope model for motor vehicle volumes along the Wasatch Front. By estimating a model (not shown), we found that there were significant random slopes for the air quality variables: a likelihood-ratio test found that the random intercept and slope model (log-likelihood = 1074.5) was significantly better-fitting than the random intercept only model (log-likelihood = 1018.7). Therefore, we estimated several models, each testing cross-level interactions with air quality involving built and social environment variables. As shown in Table 4-2, there were significant interaction effects for median income. For the median income, there was a positive and significant interaction term with yellow days (β = 0.0004, SE = 0.000, t = 2.37, p = 0.03) and also a similar but stronger interaction on orange days (β = 0.003, SE = 0.001, t = 3.24, p = 0.002). This implies that the positive effect of yellow air quality days on motor volumes (see Table 4-1) was enhanced in places with higher median income;

whereas, the negative effect of orange air quality days on motor volumes was attenuated in places with higher median income.

Table 4-2

Motor vehicle traffic volumes, random intercept and random slope model

Coefficients	**Estimate**	**SE**	**df**	**t-statistic**	**p-value**
Intercept	13.690	1.050	22	13.037	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.156	0.004	20940	-34.736	<0.001
Sunday	-0.473	0.005	20970	-104.792	<0.001
Holiday (ref. = No holiday)	-0.281	0.009	20980	-32.727	<0.001
Season (ref. = Winter)					
Spring	0.074	0.005	20940	16.323	<0.001
Summer	0.112	0.005	20760	0.112	<0.001
Fall	0.067	0.005	20880	14.781	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.015	0.004	20990	-3.701	<0.001
Light snow	-0.065	0.007	20980	-9.206	<0.001
Heavy rain	13.690	0.037	20980	-6.549	<0.001
Heavy snow	-0.245	0.010	20980	-15.669	<0.001
Max temperature difference from average	-0.001	0.000	20980	-3.213	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	-0.053	0.019	24	-2.833	0.009
Orange (AQI = 100+)	-0.178	0.078	46	-2.282	0.027
Built and social environment variables					
Gross residential density	-0.987	0.323	22	-3.053	0.006
Household income (median, $1,000)	-0.014	0.008	22	-1.825	0.081
Jobs per household	-0.090	0.041	22	-2.205	0.038
Percent of zero car households	-10.870	7.534	22	-1.443	0.163
Distance from population-weighted centroid to transit stop (m)	-0.003	0.001	22	-3.622	0.001
Jobs within 45 minutes auto travel time, network travel time weighted	0.000	0.000	22	3.253	0.003
Number of schools	0.186	0.067	22	2.801	0.010
Cross-level interactions					
Yellow AQI with median income	0.0004	0.000	18	2.37	0.029
Orange AQI with median income	0.003	0.001	49	3.241	0.002

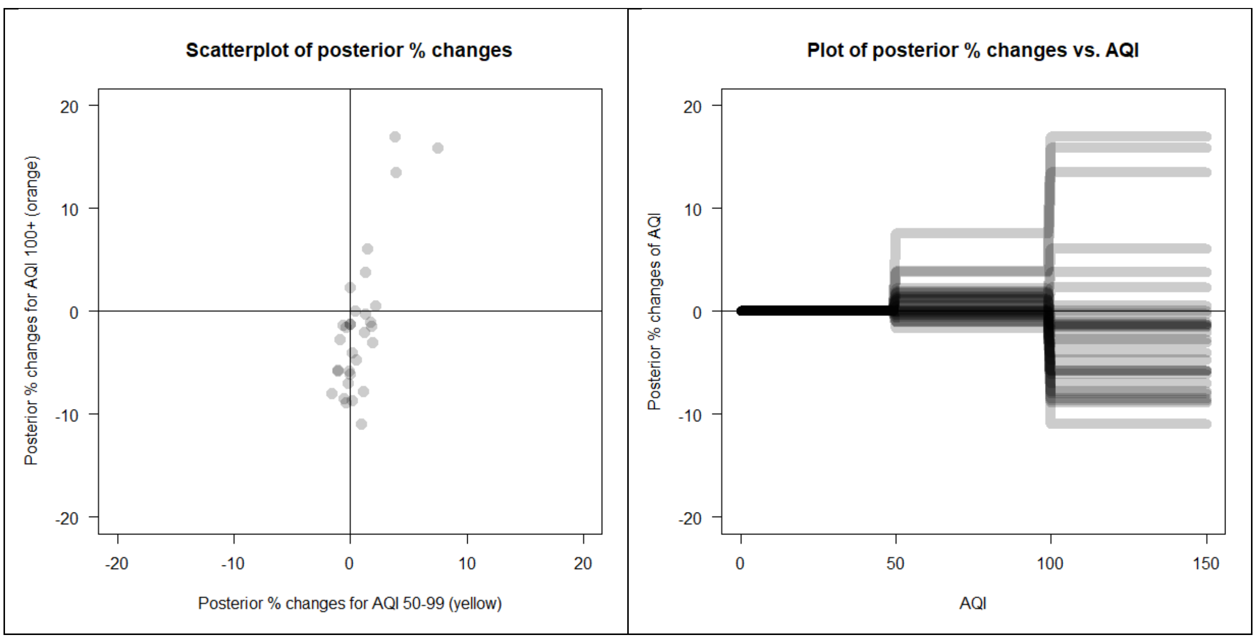
Notes: N = 21,040; # groups = 31; log-likelihood = 1495.3, between-group variance = 0.68; residual variance = 0.049; random coefficient variance for yellow AQI = 0.0001; random coefficient variance for orange AQI = 0.001.

4.1.1 Posterior Slopes

We calculated posterior slopes for the motor vehicle model for study area 2 in a similar approach as discussed in Pedestrian results section of Chapter 3. Then, we plotted these posterior slopes in Figure 4-1 first in a scatterplot (yellow vs. orange) and second in a combined plot vs. AQI. The left portion of the figure shows how most locations had a more positive yellow coefficient than orange coefficient for motor vehicle volumes, and how the posterior slopes were positively correlated (which is expected, since they are both conditional on the same data at each location). The right portion of the figure shows how air quality coefficients in the orange range (AQI = 101–150) were typically more extreme (mostly more negative, some were more positive) than coefficients in the yellow range (AQI = 51–100).

Figure 4-1

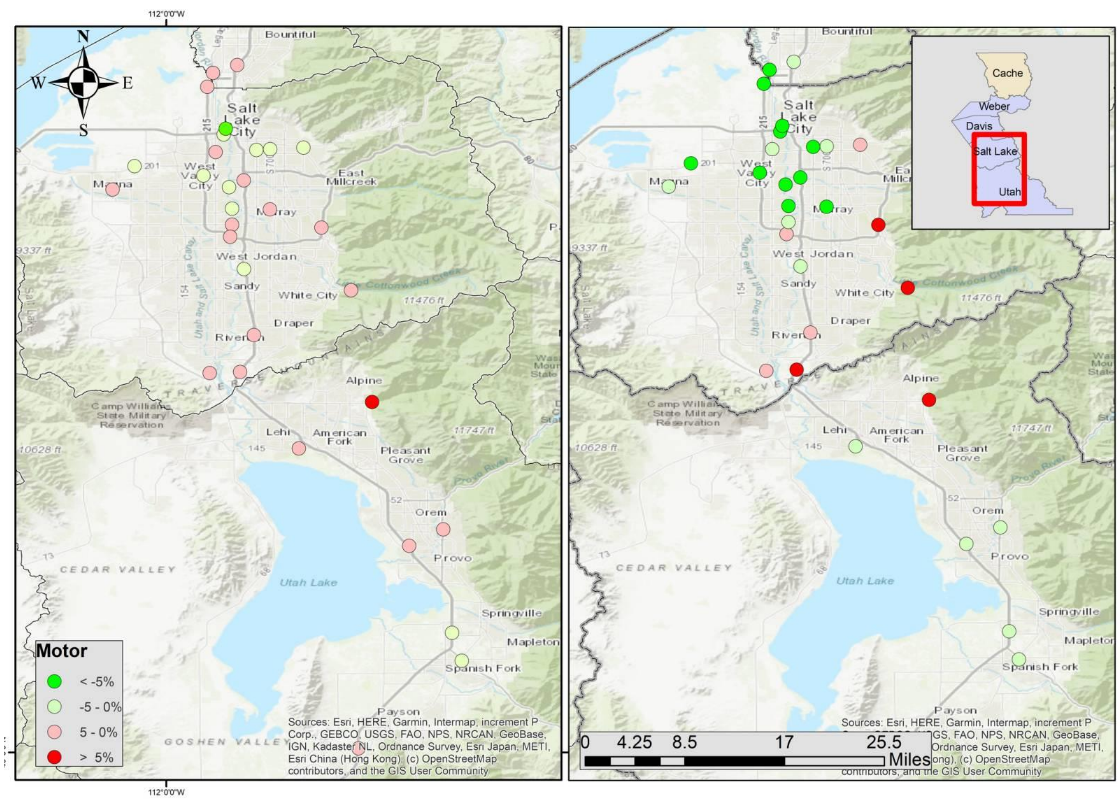
Figures showing motor vehicle model posterior slopes for yellow and orange air quality levels (left: scatterplot; right: plot vs. AQI)



The posterior slopes for yellow and orange air quality levels for motor vehicle volumes are mapped in the figures below. Figure 4-2 plots motor vehicle model posterior slopes on a map for yellow (left) and orange (right) air quality days. In both cases, it appears that locations with positive coefficients tend to be concentrated along the areas near the mountains: i.e. there is increase in motor vehicle volume near mountains. This might indicate to the increase in number of trips to escape the air pollution. Also, we can see more negative relationship during orange days. Especially, in areas closer to downtown SLC, we can see the increase observed on yellow days transform into a decrease during orange days. In overall, we see a decreasing trend on orange days, although it comes with more spatial variation, compared to the increasing trend on yellow days.

Figure 4-2

Maps showing motor vehicle model posterior slopes for yellow (left) and orange (right) air quality levels



4.2 Pedestrian

Table 4-3 reports results of the random intercept model for pedestrian volumes in study area 2. The coefficient estimates for both the yellow (β = -0.058, *SE* = 0.002, *t* = -27.044, *p* <0.001) and orange air quality days (β = -0.061, *SE* = 0.007, *t* = -10.237, *p* < 0.001) were negative and significant. This implies that pedestrian volumes decreased during episodes of poor air quality (decrease of 5.6% on yellow days and decrease of 5.9% on orange days, when compared to green days). The results indicate an existence of similar pattern as that in study area 1: i.e. pedestrian volumes tend to go down on days with poor air quality.

Table 4-3

Pedestrian volumes, random intercept model

Coefficients	Estimate	SE	df	t-statistic	p-value
Intercept	4.910	0.039	869	125.33	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.354	0.002	627900	-194.856	<0.001
Sunday	-0.809	0.002	627900	-445.482	<0.001
Holiday (ref. = No holiday)	-0.499	0.004	627900	-140.556	<0.001
Season (ref. = Winter)					
Spring	0.275	0.002	627900	146.318	<0.001
Summer	0.280	0.002	627900	151.760	<0.001
Fall	0.273	0.002	627900	147.231	<0.001
Precipitation (ref. = No rain / no snow)			630100		
Light rain	-0.062	0.002	627900	-36.456	<0.000
Light snow	-0.277	0.003	627900	-93.689	<0.001
Heavy rain	-0.088	0.018	627900	-4.947	0.004
Heavy snow	-0.484	0.004	627900	-114.899	<0.001
Max temperature difference from average	0.004	0.000	628000	46.760	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	-0.058	0.002	628000	-30.351	<0.001
Orange (AQI = 100+)	-0.061	0.008	627900	-7.604	<0.001

Notes: N = 628,826; # groups = 868; log-likelihood = -451,018; between-group variance = 1.32 residual variance = 0.24.

Table 4-4 reports results of the random intercept and random slope model for pedestrian volumes in the Wasatch Front. By estimating a model (not shown), we found that there were significant random slopes for the air quality variables: a likelihood-ratio test found that the random intercept and slope model (log-likelihood = -450,241) was significantly better-fitting than the random intercept only model (log-likelihood = -451,018). Therefore, we estimated several models, each testing cross-level interactions with air quality involving built and social environment variables. As shown in Table 4-4, there were significant interaction effects for two variables: household median income and the percent of zero-car households. For the median income variable, there was a negative and significant interaction term with orange days (β = -0.002, $SE = 0.000$, t = -3.963, p < 0.001) but the estimate was very small on yellow days. This implies that the negative effect of orange air quality days on pedestrian volumes (see Table 4-3) was amplified in places with higher median incomes. For the percent of zero-car household variable, there was a negative and significant interaction term with yellow days (β = -0.199, SE = 0.056, t = -3.518, p < 0.001) and a negative but not statistically significant interaction term with orange days. This implies that the negative effects of yellow and perhaps orange air quality days on pedestrian volumes (see Table 4-3) were enhanced in places with more zero-car households.

Table 4-4

Pedestrian volumes, random intercept and random slope model

Coefficients	Estimate	SE	df	t-statistic	p-value
Intercept	4.202	0.219	833	19.211	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.358	0.002	607600	-196.364	<0.001
Sunday	-0.810	0.002	607000	-445.707	<0.001
Holiday (ref. = No holiday)	-0.496	0.004	607400	-139.452	<0.001
Season (ref. = Winter)					
Spring	0.274	0.002	607200	145.501	<0.001
Summer	0.289	0.002	605300	154.943	<0.001
Fall	0.266	0.002	599100	142.954	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.059	0.002	607400	-34.350	<0.001
Light snow	-0.270	0.003	607600	-91.325	<0.001
Heavy rain	-0.108	0.018	607200	-6.012	0.004
Heavy snow	-0.480	0.004	607600	-114.117	<0.001
Max temperature difference from average	0.004	0.000	607900	45.048	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	-0.007	0.015	879	-0.442	0.658
Orange (AQI = 100+)	0.070	0.038	622	1.839	0.066
Built and social environment variables					
Gross employment density (jobs/acre)	0.031	0.004	830	7.227	<0.001
Household income (median, $1,000)	-0.008	0.001	831	-5.751	<0.001
Jobs per household	-0.009	0.004	830	-2.410	0.016
Percent of zero car households	2.268	0.586	834	3.868	<0.001
Total road network density	0.031	0.007	829	4.157	<0.001
Jobs within 45 minutes auto travel time	0.000	0.000	829	-1.647	0.003
Park area	0.001	0.001	827	0.922	0.356
Number of schools	0.086	0.038	829	2.292	0.022
Transit bus stops	0.077	0.008	829	9.221	<0.001
Near a university	0.848	0.131	831	6.489	<0.001
University break	-0.480	0.006	607800	-86.452	<0.001
Cross-level interactions					
Yellow AQI with median income	0.0005	0.000	865	-2.649	0.008
Orange AQI with median income	-0.002	0.000	685	-3.963	<0.001
Yellow AQI with % zero-car household	-0.199	0.056	855	-3.518	<0.001
Orange AQI with % zero-car household	-0.131	0.150	876	-0.878	0.380

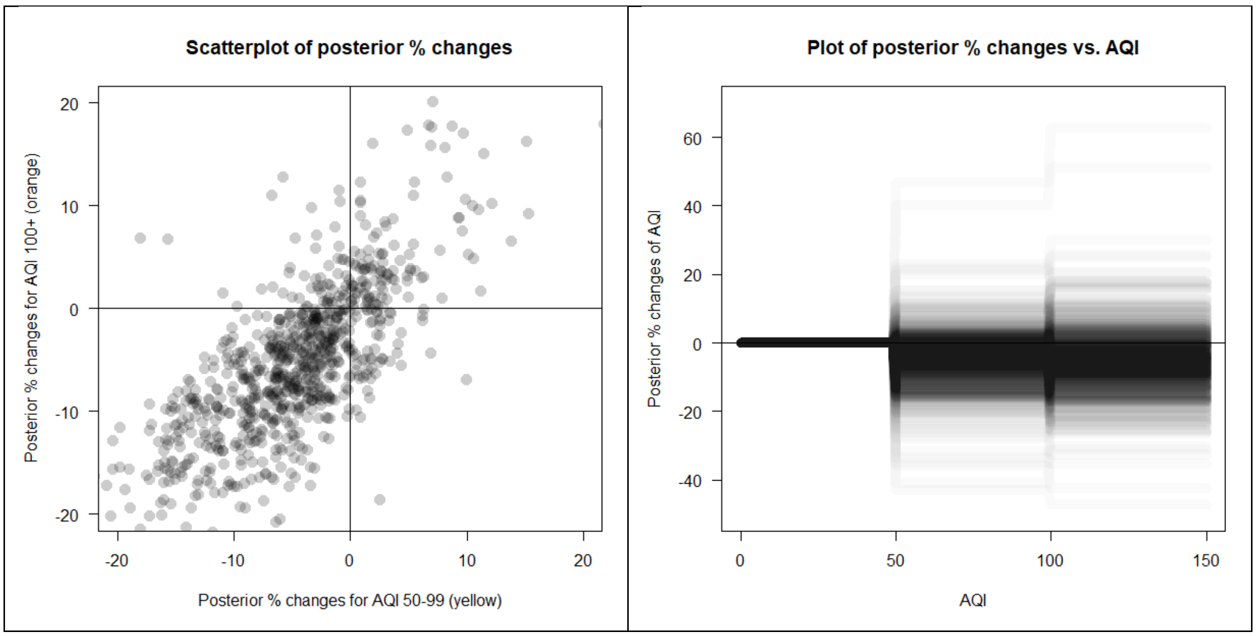
Notes: N = 609,255; # groups = 841; log-likelihood = -428,155; between-group variance = 0.622; residual variance = 0.235; random coefficient variance for yellow AQI = 0.008; random coefficient variance for orange AQI = 0.017.

4.2.1 Posterior Slopes

Similarly, the distribution of posterior slopes for pedestrian volumes in study area 2 is shown in Figure 4-3. The left portion of the figure shows how most locations had negative yellow and orange coefficients and how the posterior slopes were positively correlated. The right portion of the figure shows how air quality coefficients in the orange range (AQI = 101–150) are distributed quite similar to the coefficients in the yellow range (AQI = 51–100), except for a few extreme cases.

Figure 4-3

Figures showing pedestrian model posterior slopes for yellow and orange air quality levels (left: scatterplot; right: plot vs. AQI)



The posterior slopes for yellow and orange air quality levels for pedestrian volumes are mapped in the figures below. Since, the number of signals in pedestrian models was high, the map is divided into counties, and for two of the counties (Salt Lake and Utah), the downtown area is shown in a different map.

Figure 4-4

Maps showing pedestrian model posterior slopes for yellow (left) and orange (right) air quality levels in Weber (top) and Davis (bottom) counties

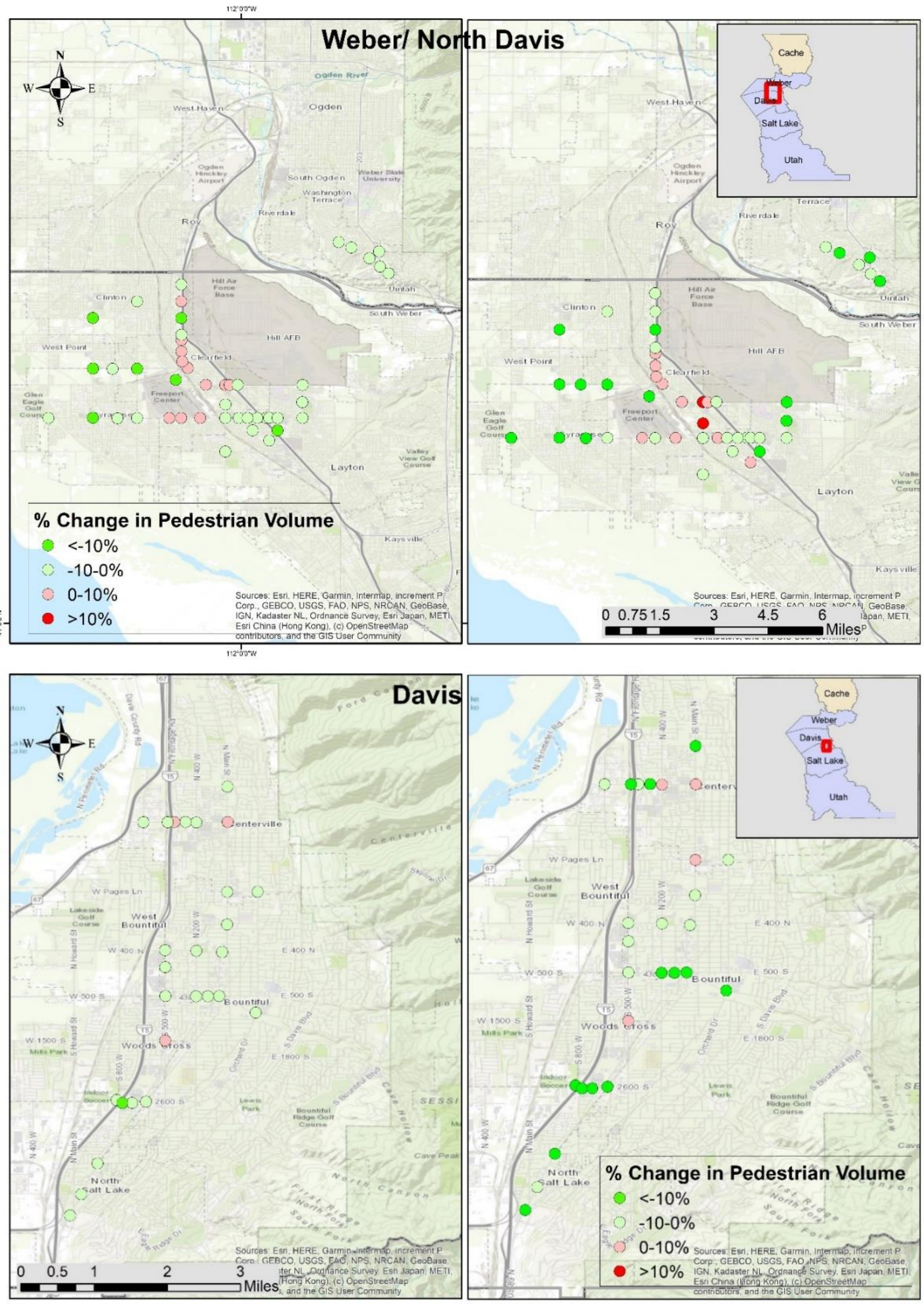


Figure 4-4 plots pedestrian model posterior slopes on a map for yellow (left) and orange (right) air quality days in Davis and Weber counties. We can see a pattern where in orange days the change in pedestrian slope mostly decrease from yellow days. In places near Clearfield, the increase in yellow days reduces in magnitude and in places near Bountiful, the decrease in yellow days increases in magnitude. In both cases, it appears that red days seem to decrease the number of pedestrians in these counties.

Figure 4-5 plots pedestrian model posterior slopes on a map for yellow (left) and orange (right) air quality days in Salt Lake county and Salt Lake downtown. We see a similar pattern for both yellow and red days in both the maps. During orange days, we can observe fewer locations with increases in pedestrian volumes. The magnitude of increase also decreases during the orange days. In general, the higher decreases are in the area near downtown and to the east of the downtown. The higher median income in the downtown area might have contributed to the higher decrease. The east area includes University of Utah and recreational parks (golf courses). This can explain the higher decrease as recreational trips could be forgone and students might opt in for online mode of learning.

Figure 4-5

Maps showing pedestrian model posterior slopes for yellow (left) and orange (right) air quality levels in Salt Lake county (top) and Salt Lake downtown (bottom)

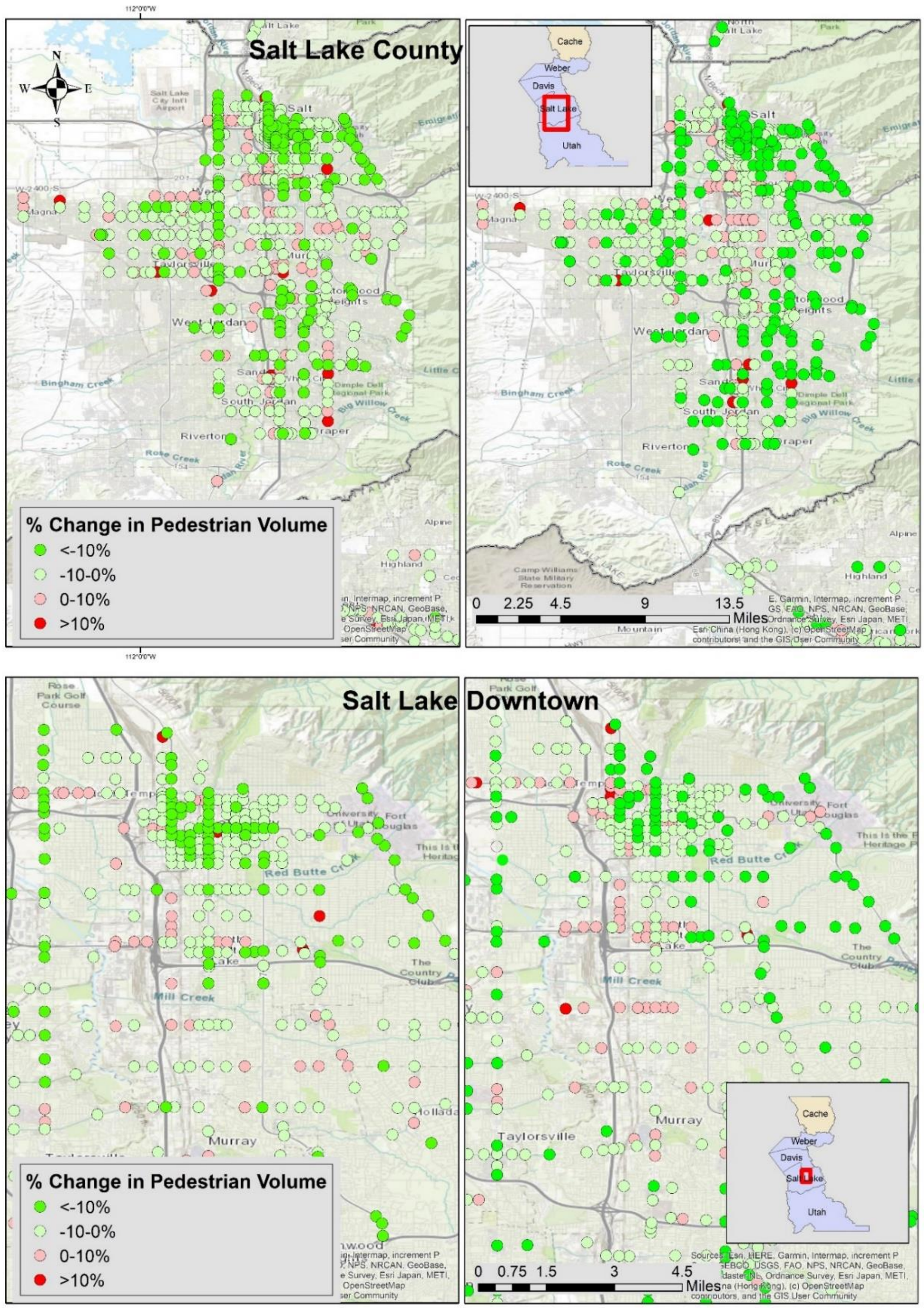


Figure 4-6

Maps showing pedestrian model posterior slopes for yellow (left) and orange (right) air quality levels in Utah county (top) and Provo downtown (bottom)

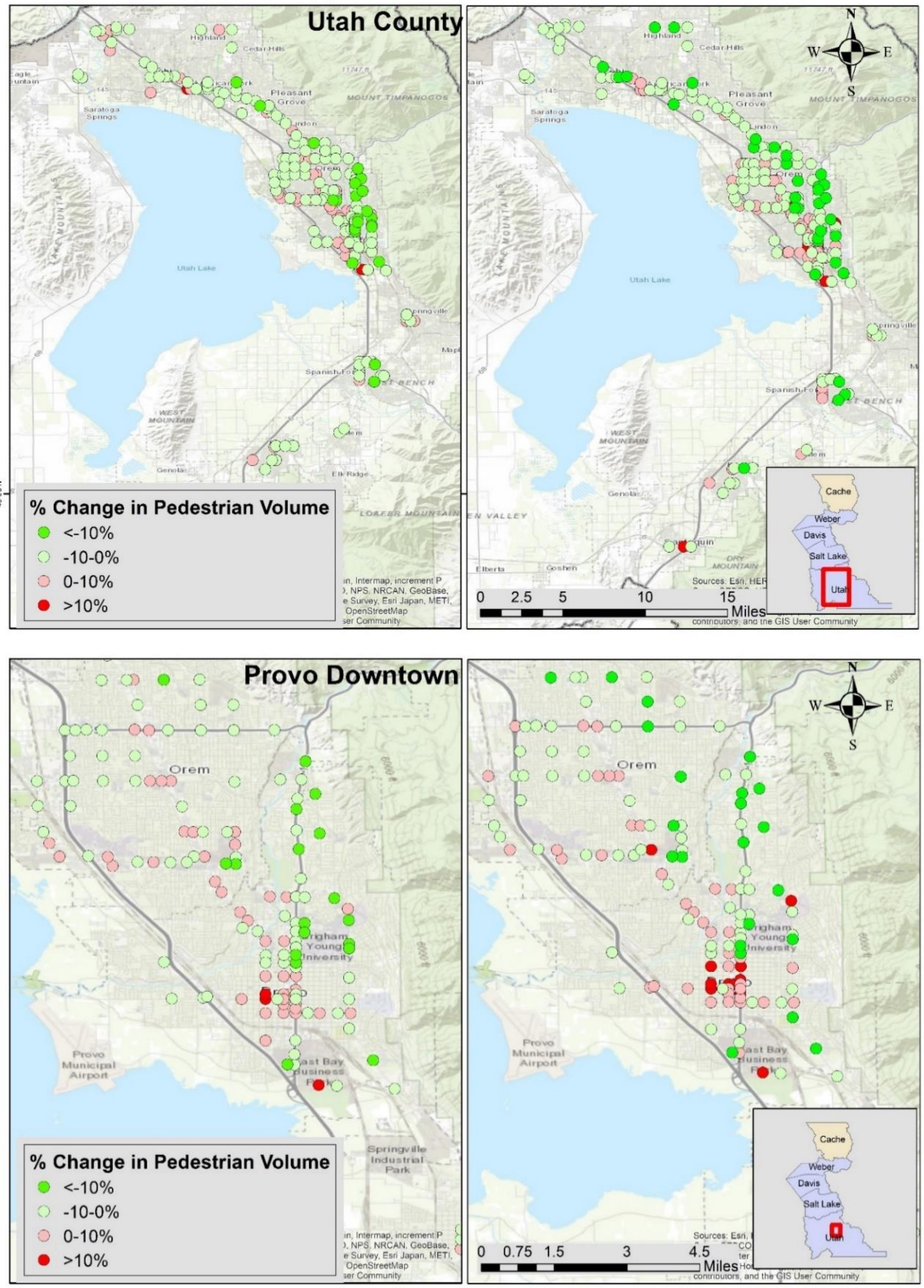


Figure 4-6 plots pedestrian model posterior slopes on a map for yellow (left) and orange (right) air quality days in Utah county and Provo downtown area. On orange days, the pedestrian volumes seem to decrease from yellow days, but it is interesting to note that there are lots of stations which record an increase in pedestrian volumes (when compared to green days) as air pollution levels increase. This might indicate to a presence of altruistic response in the area as travelers might have shifted from automobiles to walking or walking plus transit.

4.3 Transit

Table 4-5 reports results of the model for UTA TRAX light-rail ridership. The coefficient estimates for the yellow ($\beta = 0.084$, $SE = 0.04$, $t = 2.094$, $p = 0.037$) was positive and significant. This implies that rail transit volumes increased during episodes of poor air quality (compared to green days), especially on yellow days (unhealthy for sensitive groups). The model suggests a slight decrease overall in orange days, but it is not statistically distinguishable from zero. Similarly, Table 4-6 reports results of the model for UTA FrontRunner commuter rail ridership. The coefficient estimates for the yellow ($\beta = 0.035$, $SE = 0.025$, $t = 1.402$, $p = 0.161$) was positive and insignificant, whereas the coefficient estimates for the red ($\beta = -0.050$, $SE = 0.118$, $t = -0.428$, $p = 0.668$) was negative and not significant. We can observe the negative direction of coefficient estimates for poor air quality days although they were not statistically significant. Due to the regional nature of transit data, we could not study variations in these relationship across different locations.

Table 4-5

UTA TRAX transit ridership, ordinary regression model

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	10.846	0.061	177.498	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.474	0.037	-12.774	< 0.001
Sunday	-1.092	0.037	-29.567	< 0.001
Holiday (ref. = No holiday)	-0.406	0.090	-4.497	0.000
Season (ref. = Winter)				
Spring	-0.018	0.045	-0.409	0.682
Summer	-0.220	0.065	-3.396	0.001
Fall	0.030	0.044	0.687	0.492
Precipitation (ref. = No rain / no snow)				
Light rain	-0.042	0.036	-1.188	0.235
Light snow	0.002	0.056	0.039	0.969
Heavy rain	-	-		
Heavy snow	-0.101	0.092	-1.093	0.275
Max temperature difference from average	0.002	0.001	1.323	0.186
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.084	0.040	2.094	0.037
Orange (AQI = 100+)	-0.026	0.201	-0.130	0.897

Notes: N = 706; adjusted R-squared = 0.575.

Table 4-6

UTA FrontRunner transit ridership, ordinary regression model

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	9.809	0.020	486.144	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.851	0.022	-38.986	< 0.001
Sunday	-2.020	0.202	-10.007	< 0.001
Holiday (ref. = No holiday)	-0.927	0.049	-19.056	0.000
Season (ref. = Winter)				
Spring	-0.027	0.024	-1.083	0.279
Summer	-0.048	0.024	-1.994	0.047
Fall	0.130	0.024	5.311	0.000
Precipitation (ref. = No rain / no snow)				
Light rain	-0.026	0.022	-1.156	0.248
Light snow	0.049	0.036	1.358	0.175
Heavy rain	-	-		
Heavy snow	-0.164	0.060	-2.731	0.007
Max temperature difference from average	0.001	0.001	0.523	0.601
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.035	0.025	1.402	0.161
Orange (AQI = 100+)	-0.050	0.118	-0.428	0.668

Notes: N = 595; adjusted R-squared = 0.759.

5. MODEL ENHANCEMENTS

5.1 Introduction

In chapters 3 and 4, we have addressed the first and second objectives of the study. Specifically, we quantified the effects of area-wide air pollution on multimodal traffic volumes and also explored locational variations in those effect (for motor vehicle and pedestrian traffic). However, the models used in those chapter were limited in following aspects:

- During episodes of air pollution, people might want to postpone some out-of-home activities and shift some of their trips to a later day. The decreases seen in walking (both study area 1 and study area 2) and driving (study area 2) might involve trips shifting to another day. However, the current models could not explain any time lag effects that air pollution could have on the scheduling of trips.
- Multilevel models used in Chapter 3 and 4 addressed within-station correlation of traffic volumes, but they did not account for spatial autocorrelation between traffic stations. Although the addition of social/built environment variables in the second level accounted for some spatial autocorrelation, the multilevel models used in both chapters indicated spatial autocorrelation (tested through Moran's I). Addressing the spatial autocorrelation would give us better coefficient estimates for the air quality–traffic volume relationship, which would help us achieve the objectives of our study.
- We studied multimodal volumes each in a different model wherein, they do not have relationship with one another. However, this is contrary to the real-life situation where unobserved factors affecting multimodal traffic volumes are likely correlated with each other. Addressing the relationships between the three traffic volume estimates (driving, pedestrian, and transit) would help us find better coefficient estimates in the model.

Thus, to address these limitations, in this model enhancement chapter, we mainly make changes to our previous model to achieve better coefficient estimates, and explain the time lag effects of air pollution to find any occurrences of trip shifting by introducing lagged variables.

5.2 Methodology

5.2.1 Time Lags

In order to potentially capture the effects of air pollution on trip shifting, we introduced a new variable for air quality with a time lag of 1: i.e., lagged air quality would represent the preceding day's air quality. This allowed us to study the effect of the preceding day's air quality on a particular day alongside the effect of that day's air quality. We added lagged air quality variables to the models in the following ways:

- Equation 7 shows how the addition of time lag variables in the transit models across both study areas was represented.
- Equation 8 represents the addition of time lag variables in the random intercept models: pedestrian volumes in study area 1, and both pedestrian and motor vehicle volumes in study area 2.
- Equation 9 shows the addition of time lag variables in the fixed intercept model, for motor vehicle volumes in study area 1.

Equations 7, 8, and 9 are modifications of Equations 1, 3, and 4, as explained in the Analysis section of Chapter 2.

$$Y_i = \beta_0 + \beta_1 x_i + \lambda_1 AQI_{i-1} + R_i \quad (7)$$, where

AQI_{i-1} = Air quality variable lagged by a day

λ_1 = Time Lag Estimate

$Y_{ij} = \beta_{0j} + \sum_h \beta_h x_{hij} + \lambda_1 AQI_{i-1} + R_{ij}$ (8a), where

$\beta_{0j} = \gamma_{00} + U_{0j}$ (8b).

AQI_{i-1} = Air quality variable lagged by a day

λ_1 = Time Lag Estimate

$Y_{ij} = \beta_{0j} + \sum_h \beta_h x_{hij} + \lambda_1 AQI_{i-1} + R_{ij}$ (9a), where

$\beta_{0j} = \sum_k \gamma_{0k} D_k$ (9b), and

D_k is a dummy variable equal to 1 for station k and 0 otherwise,

AQI_{i-1} = Air quality variable lagged by a day

λ_1 = Time Lag Estimate

5.2.2 Spatial Filters

Multilevel models used for the random intercept model of pedestrian volumes in both study areas and motor vehicle volumes in study area 1 represent the within-group correlation but do not address the spatial autocorrelation present in the model itself. In order to address the spatial autocorrelation within the dataset and that remaining in the model, we implemented an eigenvector spatial filtered multilevel model (Chung & Griffith, 2011). A spatial filter—obtained through iterative reduction of spatial error (Park et al., 2022; Park & Kim, 2014)—was included in the random intercept models used for analysis in Chapter 3 and Chapter 4. Equation 10 represents the addition of spatial lag variables in the random intercept models (used in both study areas) and equation 11 represents the addition of spatial lag variable in random slope and intercept model with level 2 variables (locational attributes for each station).

$Y_{ij} = \beta_{0j} + \sum_h \beta_h x_{hij} + \lambda_1 E + R_{ij}$ (10a), where

$\beta_{0j} = \gamma_{00} + U_{0j}$ (10b).

$E =$ Eigen Vector selected through iteration

$\lambda_1 =$ Spatial Lag Estimate

$Y_{ij} = \beta_{0j} + \sum_h \beta_{hj} x_{hij} + \lambda_1 E + R_{ij}$ (11a), where

$\beta_{0j} = \gamma_{00} + \sum_g \gamma_{g0}\, z_{gj} + U_{0j}$ (11b), and

$\beta_{hj} = \gamma_{h0} + \sum_g \gamma_{gh}\, z_{gj} + U_{hj}$ (11c).

$E =$ Eigenvector selected through iteration

$\lambda_1 =$ Spatial Lag Estimate

Selection of Eigenvector

The basic multilevel model was tested for residual autocorrelation using Moran’s I. If there was significant autocorrelation in the model (tested by the Moran’s I test: details in Table 5-5), we created a spatial filter (eigenvector E) to whiten the model residuals. Doing so makes the residuals independent and identically distributed with a mean of zero: i.e., the residuals are not predictable anymore. For that, a set of spatial eigenvectors were created for each traffic count station (level 2 units) from eigen-decomposition of the following matrix (Griffith, 2003).

$\left(I - 1 \cdot \frac{1^T}{n}\right) \cdot W \cdot \left(I - 1 \cdot \frac{1^T}{n}\right)$ (12), where

W is a spatial weight matrix of size $n \times n$, and n is the number of traffic count locations.

The spatial weight matrix quantified spatial connectivity between two locations: the non-zero entries in the weight matrix implied spatial connectivity between two locations. With the help of the weight matrix, a series of n candidate eigenvectors were produced. An iterative procedure was then applied where each eigenvector was added to the model and the change in AIC was noted. The eigenvector yielding the largest reduction in AIC was selected for the final model. Thus, a final model with added eigenvector was tested for Moran's I to see if the spatial autocorrelation existing in the model was removed or not.

5.2.3 Seemingly Unrelated Regression (SUR)

In the case when there are multiple dependent variables that are correlated, and the residuals of the equations are correlated, one can use Seemingly Unrelated Regression (SUR) to help account for some of the errors. There could be some unexplained factors that might be affecting all the equations, for example in our case, economic conditions in a particular time might have affected the traffic volumes for each mode. This would yield a correlation between residuals of the equations and accounting for this residual would help us obtain a better coefficient estimates for the traffic-air quality relationship. SUR models are based on the Generalized Least Squares (GLS) principle, which considers the covariance structure of the error terms (Hennigsen & Hamann, 2007). The explicit consideration of covariance structure allows us to move beyond assuming independence of the error terms as in the Ordinary Least Squares (OLS) principle.

For the SUR models, natural log of the multimodal traffic volumes were the dependent variables. The independent variables were the temporal and weather controls used in the multilevel models: holiday, temperature, precipitation category, holidays, season, day of week, and air quality index. (For more details, see the Data and Variables section in Chapter 3). To simplify the analysis, the study areas were split into three regions: 1) Cache County, 2) Salt Lake County, and 3) Salt Lake City. Instead of using the daily count for each signal, we calculated the average daily count for all traffic count stations in each region. Then, we used that average as the daily traffic count for each region for each mode. (This was done to allow for there to be a clear linkage between modes for the same place and time, and to make the model estimation computationally feasible.) The same weather station and air quality station used in the multilevel models of study area 1 was used for Cache County. For the Salt Lake region (both the county and city), weather station (Station = USW0002417) was used and air quality station (Site ID = 490353006) was used.

The equations used in the SUR model are:

$$Y_{motor_i} = \beta_0 + \sum_h \beta_h x_{motor_i} + R_{motor_i} \tag{12}$$

$$Y_{ped_i} = \beta_0 + \sum_h \beta_h x_{ped_i} + R_{ped_i} \tag{13}$$

$$Y_{transit_i} = \beta_0 + \sum_h \beta_h x_{transit_i} + R_{transit_i} \tag{14}$$

However, we allow for correlation between the residuals which are represented by the non-zero entries in the non-diagonal elements of the correlation matrix of residuals in Table 5-1.

Table 5-1

Correlation matrix of residuals of equations in SUR

	$\boldsymbol{R_{motor}}$	$\boldsymbol{R_{ped}}$	$\boldsymbol{R_{transit}}$
$\boldsymbol{R_{motor}}$	1	$\rho(motor, ped)$	$\rho(motor, transit)$
$\boldsymbol{R_{ped}}$	$\rho(ped, motor)$	1	$\rho(ped, transit)$
$\boldsymbol{R_{transit}}$	$\rho(transit, motor)$	$\rho(transit, ped)$	1

5.3 Results

5.3.1 Time Lags

We introduced the time lagged air quality variable in the base models for driving, pedestrian, and transit to study the effect of time lag in each mode. In this section, we only discuss the air quality coefficients from the model. For complete model results, see Appendix A.

For motor vehicle volumes (Table 8-1), there was a negative and significant association between lagged air quality variables and driving. The coefficient estimates of both yellow (β = -0.031, p < 0.001) and orange days (β = -0.033, p = 0.062) were negative and significant for lagged air quality index. It is interesting to note the positive and higher coefficient estimates for regular air quality index for same mode. This suggests that people are unable to quickly shift from automobiles to alternative modes. For the pedestrian volumes, the coefficient estimates for the lagged air quality variables in the time lag model were not significant (Table 8-2), which implies an absence of significant association between lagged air quality variables and pedestrian count. In the case of transit volumes, similar to the model in Table 3-5, the coefficient estimates for both lagged and unlagged air quality variable were not significant.

Table 5-2

Time lag model results, study area 1

	Without Time lag		With Time Lag	
Coefficients	**Estimate**	**p-value**	**Estimate**	**p-value**
Motor vehicle traffic volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.004	0.625	0.025	0.004
Orange (AQI = 100+)	0.048	0.002	0.073	<0.001
Lagged Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-	-	-0.031	<0.001
Orange (AQI = 100+)	-	-	-0.033	0.062
Pedestrian volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.023	0.091	-0.023	0.091
Orange (AQI = 100+)	-0.093	0.001	-0.093	0.001
Lagged Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-	-	0.007	0.550
Orange (AQI = 100+)	-	-	-0.045	0.108
Transit ridership (CVTD bus)				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.013	0.693	-0.019	0.643
Orange (AQI = 100+)	-0.044	0.516	-0.036	0.639
Lagged Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-	-	0.035	0.388
Orange (AQI = 100+)	-	-	-0.075	0.322

A random intercept model with the introduction of time lagged air quality variable was run for motor volumes in study area 2 (

Table 8-4). The coefficient estimates for time lagged air quality variable for motor vehicle volumes were found to be significant. The estimate for orange days (β = -0.056, p = 0.004) was negative and significant. Similarly, the coefficient estimates for lagged yellow days (β = 0.004, p = 0.027) was significant in the pedestrian model, but the magnitude of change was only 0.4%. Thus, the major time lag effect of air quality was observed on motor vehicle volumes during orange days. This hints at the inability of automobile users to quickly change their trip to alternative modes such as walking or walking plus transit. All of the transit model yielded insignificant lagged air quality coefficient estimates.

Table 5-3

Time lag model results, study area 2

	Without Time lag		With Time Lag	
Coefficients	**Estimate**	**p-value**	**Estimate**	**p-value**
Motor vehicle traffic volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.009	0.063	0.016	0.004
Orange (AQI = 100+)	-0.068	<0.001	-0.049	0.012
Lagged Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-	-	-0.007	0.157
Orange (AQI = 100+)	-	-	-0.056	0.004
Pedestrian volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.058	<0.001	-0.058	<0.001
Orange (AQI = 100+)	-0.061	<0.001	-0.061	<0.001
Lagged Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-	-	0.004	0.027
Orange (AQI = 100+)	-	-	-0.006	0.404
Transit ridership (UTA TRAX)				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.084	0.037	0.070	0.159
Orange (AQI = 100+)	-0.026	0.897	-0.049	0.814
Lagged Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-	-	0.022	0.647
Orange (AQI = 100+)	-	-	-0.078	0.701
Transit ridership (UTA FrontRunner)				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.037	0.135	0.035	0.260
Orange (AQI = 100+)	-0.048	0.683	-0.053	0.665
Lagged Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-	-	0.003	0.917
Orange (AQI = 100+)	-	-	0.070	0.553

5.3.2 Spatial Filters

In this section, we discuss about how the addition of spatial filter changed the goodness of fit and coefficient estimates of our models in Chapter 3 and 4. We only report the Moran's test result, AIC, between-station variance, air quality variable and other related variables that changed. For full model results, see Appendix B.

In the case of pedestrian volumes in study area 1, the addition of a spatial filter could address spatial autocorrelation in the model with level 2 variables (model in Table 3-4). We can see the reduction of Moran's I statistic from 0.145 to -0.031. Given the non-significant p-value in the model with spatial filter, we can conclude the spatial distribution of feature values in the model to be random. Similarly, the AIC values of the model with spatial filter decreases to 54,390 from 54,405, which indicates improvement in performance of the model. However, for random intercept model (model in Table 3-3) the addition of spatial filter manages only to reduce the AIC without significantly changing the presence of spatial autocorrelation.

However, we did not see any changes in the air quality-pedestrian volume relationship in random intercept model. For the random intercept and random slope model, the noticeable changes were observed in the built and social environment variables. The variables that had significant interaction with air quality (vehicle ownership and percentage of 4-way intersections) both increased in magnitude by 0.282 and 0.003 respectively. This would lead to changes in the posterior slopes for poor air quality days at different locations which were calculated in Chapter 3 and Chapter 4.

Table 5-4

Spatial filter model results (Pedestrian volumes), study area 1

	Without Spatial Filter	With Spatial Filter
Random Intercept Model		
Moran's I	0.427	0.454
p-value	<0.001	<0.001
AIC	54,404	54,392
Between-group variance	0.9962	0.7372
Air quality coefficient (ref. = Green)		
Yellow (AQI = 50–99)	-0.023	-0.023
Orange (AQI = 100+)	-0.093	-0.093
Random Intercept and Random Slope with locational variables		
Moran's I	0.145	-0.031
p-value	0.11	0.513
AIC	54,405	54,390
Between-group variance	0.446	0.267
Air quality coefficient (ref. = Green)		
Yellow (AQI = 50–99)	0.227	0.227
Orange (AQI = 100+)	0.005	0.005
Built and Social Environment Variables with Significant Interaction		
Vehicle ownership (mean)	0.423	0.705
% 4-way intersections	-0.004	-0.001

For the motor vehicle model in study area 2, the presence of spatial autocorrelation in the random intercept model (model in Table 4-1) is addressed by the addition of spatial filter (eigenvector) as we can see the reduction of Moran's I statistic from 0.188 to 0.069. Given the non-significant p-value (0.25) in the model with spatial filter, we can conclude the spatial distribution of feature values in the model to be random. Similarly, the AIC values of the model with spatial filter decreases to -1896 from -1890 which indicates improvement in performance of the model. Similarly, for random intercept and random slope model with cross level interactions, a similar pattern follows. The addition of spatial filter reduces the AIC value. It is to be noted that addition of level 2 variables has already addressed for significant amount of spatial autocorrelation (Moran's I: 0.126, p-value = 0.168) in the model without the spatial filter to begin with.

Similar to analysis in study area 1, we did not see any changes in the air quality-motor vehicle volume relationship in random intercept model for study area 2. For the random intercept and random slope model, a slight change was observed in the built and social environment variables. The variable that had significant interaction with air quality (household median income) changed in magnitude by 0.001. This would lead to change in the posterior slopes for poor air quality days at different locations which were calculated in Chapter 3 and Chapter 4.

Table 5-5

Spatial filter model results (Motor vehicle volumes), study area 2

	Without Spatial Filter	**With Spatial Filter**
Random Intercept Model		
Moran's I	0.188	0.069
p-value	0.076	0.25
AIC	-1,890	-1,896
Between-group variance	1.166	1.002
Air quality coefficient (ref. = Green)		
Yellow (AQI = 50–99)	0.009	0.009
Orange (AQI = 100+)	-0.068	-0.068
Random Intercept with locational variables		
Moran's I	0.126	-0.012
p-value	0.167	0.45
AIC	-2,924	-2,927
Between-group variance	0.68	0.621
Air quality coefficient (ref. = Green)		
Yellow (AQI = 50–99)	-0.053	-0.053
Orange (AQI = 100+)	-0.178	-0.178
Built and Social Environment Variables with Significant Interaction		
Household income (median, $1,000)	-0.014	-0.013

For the pedestrian model in study area 2, the addition of spatial filter manages only to reduce the AIC slightly without significantly changing the presence of spatial autocorrelation. Given the significant p-value (<0.001) in the model with spatial filter, we can conclude the spatial distribution of feature values in the model is not random: i.e., spatial autocorrelation is still present. Similarly, the AIC values of the random intercept model with spatial filter decreases to 902202 from 902208 which indicates a slight improvement in performance of the model;

however, for random intercept and random slope model with cross level interactions, no change in AIC was observed. A computationally extensive model limited us from finding a set of best spatial filters to reduce the spatial autocorrelation in our model.

Similar to preceding analysis with spatial filters, we did not see any changes in the air quality-pedestrian volume relationship in random intercept model for study area 2. For the random intercept and random slope model, a slight change was observed in the built and social environment variables (All of the changes are reported in Appendix B,

Table 8-13). The variable that had significant interaction with air quality (percent of zero car households) changed in magnitude by 0.007. This would lead to change in the posterior slopes for poor air quality days at different locations which were calculated in Chapter 3 and Chapter 4.

Table 5-6

Spatial filter model results (Pedestrian volumes), study area 2

	Without Spatial Filter	With Spatial Filter
Random Intercept Model		
Moran's I	0.647	0.64
p-value	<0.001	<0.001
AIC	902208	902202
Between-group variance	1.321	1.328
Air quality coefficient (ref. = Green)		
Yellow (AQI = 50–99)	-0.058	-0.058
Orange (AQI = 100+)	-0.061	-0.061
Random Intercept with locational variables		
Moran's I	0.623	0.623
p-value	<0.001	<0.001
AIC	856384	856384
Between-group variance	0.446	0.446
Air quality coefficient (ref. = Green)		
Yellow (AQI = 50–99)	-0.007	-0.007
Orange (AQI = 100+)	0.070	0.070
Built and Social Environment Variables		
Household income (median, $1,000)	-0.008	-0.008
Percent of zero car households	2.268	2.275

5.3.3 Seemingly Unrelated Regression (SUR)

In this section, we compare the results from general linear models for each mode with Seemingly Unrelated Regression (SUR) for three regions: Cache County, Salt Lake Downtown, and Salt Lake City. In line with the scope of this thesis, we only report the coefficient estimates of air quality variables. For full model results, see Appendix C.

As shown in Table 5-7, in the model for Cache County, pedestrian volume estimates for orange days and motor vehicle volume estimates are significant. The yellow day coefficient for motor vehicle volumes in negative in both General Linear Model (GLM) (β = -0.023, p = 0.088) and Seemingly Unrelated Regression (SUR) (β = -0.021, p = 0.108). For orange days, the estimates are positive and significant (GLM: β = 0.058, p = 0.039; SUR: β = 0.063, p = 0.025). For pedestrian volumes, orange day estimates are negative and significant (GLM: β = -0.212, p = 0.047; SUR: β = -0.182, p = 0.089); while yellow days estimate were found negative but statistically insignificant. The transit volumes were positive for poor air quality days in both of the models but were statistically indistinguishable from zero.

In the case of motor vehicle volumes, SUR indicate a lower magnitude of decrease (compared to GLM) in motor vehicle volumes during yellow days; while they show an increased number of motor volumes (compared to GLM) during orange air quality days. Also, SUR indicates a lower magnitude of decrease in pedestrian volumes (compared to GLM) during orange days. Overall, we see a similar pattern of decrease in pedestrian volumes and an increase in driving volumes during poor air quality days as that observed in Chapter 3.

It is interesting to note that the correlation of residuals between the motor and pedestrian is quite low, which indicates an appropriate capture of the relationship between dependent variables and traffic count in the model. The highest correlation is between pedestrian and transit, which is reasonable as most transit riders are pedestrians at the start and end of their trip.

Table 5-7

SUR model results, Cache County

	GLM		SUR	
Coefficients	**Estimate**	**p-val**	**Estimate**	**p-val**
Motor Volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.023	0.088	-0.021	0.108
Orange (AQI = 100+)	0.058	0.039	0.063	0.025
Pedestrian Volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.079	0.120	-0.070	0.164
Orange (AQI = 100+)	-0.212	0.047	-0.182	0.089
Transit Volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.061	0.658	0.061	0.658
Orange (AQI = 100+)	0.166	0.567	0.166	0.567
Correlation of the Residuals				
Motor and Pedestrian 0.175				
Motor and Transit 0.299				
Transit and Pedestrian 0.321				

In the model for Salt Lake City, as shown in Table 5-8, only pedestrian volume estimates are significant during yellow air quality days. We observed a similar coefficient for both GLM and SUR models. (β = -0.108, p <0.001). This indicates an overall decrease in the pedestrian volumes during days with bad air quality. The limited number of observations during red days might have contributed to the insignificant coefficient estimates in both of the model. We see a decrease in both motor vehicle volumes and pedestrian volumes during days of poor quality, although the negative estimates for motor vehicle volumes (yellow: -0.002; red = -0.052) were statistically indistinguishable from zero.

The SUR results do not differ from the results that we get from GLM. Nevertheless, the direction of estimates—i.e. decreases in motor vehicle and pedestrian volumes and increase in transit—is similar to the pattern observed in Chapter 4. It is interesting to note that the correlation of residuals between the motor vehicle and pedestrian models is quite high which might be indicating to the presence of some unobserved factor affecting both the models (for example, economical pattern in the area).

Table 5-8

SUR model results, Salt Lake City

	GLM		SUR	
Coefficients	**Estimate**	**p-val**	**Estimate**	**p-val**
Motor Volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.002	0.845	-0.002	0.845
Orange (AQI = 100+)	-0.052	0.316	-0.052	0.316
Pedestrian Volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.108	<0.001	-0.108	<0.001
Orange (AQI = 100+)	-0.061	0.564	-0.061	0.564
Transit Volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.071	0.596	-0.071	0.596
Orange (AQI = 100+)	0.062	0.927	0.062	0.927
Correlation of the Residuals				
Motor and Pedestrian 0.553				
Motor and Transit 0.477				
Transit and Pedestrian 0.253				

We see a similar pattern of results for Salt Lake County to that of core Salt Lake City. In the model for Salt Lake county, as shown in Table 5-9, only pedestrian volume estimates are significant during yellow air quality days. We observed a similar coefficient for both GLM and SUR models (β = -0.045, p =0.015). This indicates an overall decrease in the pedestrian volumes during days with bad air quality. The limited number of observations during red days might have contributed to the insignificant coefficient estimates in both of the model. We see an increase in motor vehicle volumes during days of poor quality, although the positive estimates for motor vehicle volumes (yellow: 0.005; red = 0.020) were statistically indistinguishable from zero.

The SUR results do not differ from the results that we get from GLM. It is interesting to note that the correlation of residuals between the motor and pedestrian is quite high which might be indicating to the presence of some unobserved factor affecting both the models (for example, economical pattern in the area).

Table 5-9

SUR results, Salt Lake County (omitting Salt Lake City)

		GLM		SUR
Coefficients	**Estimate**	**p-val**	**Estimate**	**p-val**
Motor Volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.005	0.505	0.005	0.505
Orange (AQI = 100+)	0.020	0.634	0.020	0.634
Pedestrian Volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.045	0.015	-0.045	0.015
Orange (AQI = 100+)	0.039	0.676	0.039	0.676
Transit Volumes				
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.071	0.596	-0.071	0.596
Orange (AQI = 100+)	0.062	0.927	0.062	0.927
Correlation of the Residuals				
Motor and Pedestrian 0.406				
Motor and Transit 0.353				
Transit and Pedestrian 0.248				

6. DISCUSSION

6.1 Objective 1: Modal differences in the effects of area-wide air pollution on traffic volumes

In line with the first objective of our study—to measure the effects of area-wide air pollution on multimodal traffic volumes and study how these effects differ by mode, by building separate models for walking, driving, and transit to observe the difference in effects across mode—we ran multilevel model for motor volume, pedestrian volume and transit ridership. The models are discussed in two different sections, one for each study area.

6.1.1 Study Area 1: Cache County

The results obtained from our models shed light on the effects of area-wide air quality on motor vehicle, pedestrian, and transit volumes. Table 3-1 and Table 3-3 inform us of the general increase in driving and decrease in walking on days with higher levels of air pollution. For orange days (AQI = 101–150, unhealthy for sensitive groups), an increase of 4.9% in driving volumes and a decrease of 8.8% in walking volumes were observed, compared to green days. Table 3-5Table 3-5 suggests that there were no significant changes in the transit volumes in study area 1.

These findings could possibly be explained by a tendency of active commuters to avoid exposing themselves to outdoor air pollution by switching from walking (or walking plus public transit) to driving (an encapsulated mode of travel with sometimes lower exposure to air pollution, at least in terms of minutes). In addition, there could be a reduction of recreational trips made by active modes such as running or visiting parks.

6.1.2 Study Area 2: Wasatch Front

In the case of study area 2, Table 4-1 and Table 4-3 inform us of the general increase in driving and walking on days with higher levels of air pollution in the area. For yellow days, an increase in 0.9% in driving volumes and a decrease of 5.6% in walking volumes were observed, compared to the green days. For orange days, we saw a change in pattern as a decrease of 6.6% in driving volumes and a decrease of 5.9% in walking volumes are expected, compared to green days. Similarly, an increase in transit ridership (only for UTA's TRAX light-rail system) by 8.8% was observed during yellow days.

A non-linear effect of air quality on traffic volumes is observed in study area 2 during poor air quality days. There was an increase in the traffic volume slightly during yellow air quality days, but the driving volume went down much more during orange days. The pattern seen in yellow days was similar to that in study area 1 and could possibly be explained by a similar reasoning (switching from walking or walking plus transit to driving to avoid exposure). Alternatively, on orange days we saw a reduction in driving, which might be explained by the effectiveness of air quality alerts in circulation: i.e., people seem to be reducing their number of automobile trips.

In general, the trend to use more automobile seemed to diminish in study area 2. The rise seen in yellow days was small compared to the 4.9% increase observed in study area 1, and in red days the pattern reversed i.e. there was a decrease in driving volumes. Better circulation of air quality alerts (there are a lot more Variable Message Signs (VMS) that show messages related to driving less on bad air quality days in study area 2) and options of teleworking (presence of more developed business areas in study area 2) could be potential explanations. Also, the availability of more public transit options could lead to the decrease in the driving volumes. The simultaneous decrease in volumes of walking and driving during red days indicate a possibility of people forgoing their trips in study area 2; whereas, during yellow days, the significant change in transit ridership (plus its better accessibility) indicates possibility of walking/cycling trips shifting to transit.

The combined increase and decrease in motor vehicle and pedestrian volumes in study area 1 suggest a strong probability of mode shifting. In study area 2, decrease in driving volumes along with pedestrian volumes indicate cases of people forgoing their trips. The urban nature of the Wasatch Front (study area 2) could probably explain the results obtained. In addition to people forgoing their trips, we can observe cases of mode shifts in some regions of study area 2 like downtown Provo, where the driving volume might have shifted to walking or walking plus transit (increase in walking in maps of downtown Provo).

6.2 Objective 2: Locational variations in relationships of air pollution with traffic volumes

In line with the second objective of our study—to explore locational variations in the effects of area-wide air pollution on multimodal traffic volumes, by using multilevel modeling to represent the locational variations in each mode-specific model—we introduced cross-level interaction variables in the multilevel models discussed in Chapter 3. As transit ridership was not available for specific locations within the region (only aggregated for each study area), we could not look at the effect of location on the relationship between air quality and transit ridership. Again, we discuss findings for study area 1 first, followed by study area 2.

6.2.1 Study Area 1: Cache County

For pedestrian volumes, as shown in Table 3-4, we found significant associations of the percentage of four-way intersections and average vehicle ownership with the slope of the air quality coefficients.

The positive interaction between orange days and the percent of 4-way intersections (a measure of street network connectivity), informs us that in areas with high street connectivity, pedestrian volumes do not decrease as much on poor air quality days. Areas with more connected street grids allow more direct walking trips (Tal & Handy, 2012), which can shorten time exposed to air pollution and thus may make people walking in these areas less sensitive to polluted air. Also, good street network connectivity implies a business area—in Figure 3-2, notice how coefficients were less negative and more positive in downtown—which might involve mostly non-discretionary and work-related walk trips, which we expect to be less sensitive to poor air quality.

On the other hand, there was a significant negative interaction for yellow (and almost significant for orange) days with average vehicle ownership. In other words, in neighborhoods with higher vehicle ownership, pedestrian volumes tend to decrease more on poor air quality days. One likely explanation is that greater vehicle ownership provides more opportunities (modal options) for escaping air pollution and shifting from higher-exposure modes like walking to less-exposed modes like driving a personal automobile. Conversely, neighborhoods with limited private vehicle access may not have such flexibility of modal shift.

Compared to walking, we did not find any significant variations across locations for the relationship between air quality and motor vehicle volumes. This may be attributed to the small number of stations (six) that were available for motor vehicle counts. Another explanation could be the different spatial scales at which walking and driving take place. Let us assume that the travel behavioral differences in air quality responses are mostly due to who people are and where they live. If this is the case, then the shorter nature of walk trips will average these differences over a small spatial area, perhaps within one mile. Since automobile trips tend to be longer, then individual or neighborhood differences will be averaged over a larger scale, perhaps 5–10 miles. Thus, the differences that appear when comparing air quality relationships with traffic volumes across locations will be diminished for motor vehicle traffic compared to pedestrian traffic. Given the sparseness of our motor vehicle volume count locations, we could not test this hypothesis, but future work should try to see if this is happening.

6.2.2 Study Area 2: Wasatch Front

For pedestrian volumes, as shown in Table 4-4, we found significant associations of the median income with the slope of the air quality coefficients.

The negative interaction between orange days (small estimate for yellow days) and the median income (indication of rich neighborhoods, higher vehicle ownership (Dargay & Gately, 1999)), informs us that in areas with high average median income, pedestrian volume tends to decrease more on poor air quality days. One likely explanation is that areas with higher median income might provide more opportunities for escaping air pollution and shifting from higher-exposure modes; higher number of vehicles in household provides options to switch from walking. Also, since higher median incomes are associated with tech-jobs, a significant portion of that demographics might have the option to work remotely in the case of days with bad air pollution.

The negative interaction between yellow days and percentage of zero-car households (indicating the demographics of an area), informs us that in areas with high percentage of zero-car households, walking volume tend to decrease more on yellow days. Though low vehicle ownership contributing to the decrease in walking volume contrasts with the findings in study area 1 (in study area 1, higher vehicle ownership contributed to decrease in walking volumes), this could be explained by the locational attributes represented by percentage of zero-car households. For example, an area near university with students might have a higher number of zero-car households, but the composition of the area also means that the students might forgo a trip by shifting to online modes of learning. The number of people going out for recreational walks near those areas might significantly go down (Figure 4-5).

For motor volumes, as shown in Table 4-2, we found significant associations of the median income with the slope of air quality coefficients. The positive interaction between orange days (small estimate for yellow days) and the median income (indication of rich neighborhoods, higher vehicle ownership), informs us that in areas with high average median income, motor volumes tend to decrease less on poor air quality days. Whereas, on yellow days, in areas with higher average median income, motor volumes tend to increase more. The positive interaction might have been produced by the relation of higher median income with vehicle ownership which allows for the trips made by walking, cycling to shift into automobiles. This aligns with the finding of pedestrian volume’s interaction with median income where pedestrian volume decreased in area with higher median income. The decreased volume of pedestrian might have accounted for the increase in motor volumes.

6.3 Time Lag

In both of the study areas, we observed significant estimates for time-lagged air quality variables for motor vehicle volumes only. In study area 1, there was 0.7% decrease in motor vehicle volumes if the preceding days' air quality was yellow. Similarly, there was 4.9% decrease in motor vehicle volumes if the preceding day's air quality was orange. In study area 2, a similar pattern followed as there was decrease of 5.6% in motor vehicle volumes if the preceding day's air quality was orange. This indicates the slow assimilation of air quality alerts or people's inability to make quick changes to their mode, especially if their mode-in-use is driving. This finding suggests that there may be barriers or constraints preventing people from making immediate changes to their transportation choices when faced with air quality concerns.

6.4 Policy Implications

This study informs stakeholders in air quality and transportation by highlighting the aggregate behavior of travelers during periods of area-wide air pollution, such as due to wintertime inversions or summertime ozone or wildfire smoke. These findings are especially relevant for efforts to affect changes in travel and other health-related behaviors through air quality alerts. The Utah Division of Air Quality issues alerts that are directly linked to the color-coded AQI levels (Utah DEQ, 2022). For example, on orange days, the recommendation for sensitive groups is to: "Reduce prolonged or heavy exertion. It's OK to be active outside, but take more breaks and do less intense activities. Watch for symptoms such as coughing or shortness of breath." Also, the Utah Department of Transportation encourages people to "TravelWise" (UDOT, 2022) and reduce driving during poor air quality days through the use of travel behavior change strategies such as carpooling, riding public transit, trip chaining, trip shifting, and teleworking. Many employers (including the State of Utah) have mandatory (mostly vehicle) trip reduction programs that they can deploy on severe air pollution days.

From our study's results in study area 1—Cache County, Utah—it appears that people are walking less, which could be an active response to the air quality alerts or to seeing (or breathing) the air pollution. However, we find that people do not seem to be driving less on poor air quality days; instead, motor vehicle traffic volumes were actually higher on orange air quality days, all else equal. This implies that air quality and travel behavior alerts are not effective at reducing driving, at least in study area 1. More and different strategies may be needed, including wider use of mandatory employer-based programs. Organizations should be encouraged to provide arrangement for telecommuting and flexible work arrangements which can reduce the number of trips in each mode during episodes of bad air quality (Giovanis, 2018; Kitou & Horvath, 2008). In cases of severe air quality, hard policies such as road pricing schemes could be introduced to decrease the number of motor vehicle volumes (Isaksen & Johansen, 2021; Simeonova et al., 2021).

In contrast, in the Wasatch Front (study area 2), the number of people walking seems to have gone down along with the number of cars during orange days, which indicates an active response to the air quality alerts and/or air pollution. However, the results from time lag study suggests that if yesterday's air quality was orange, then the reduction in motor volume is higher. This indicates the efficacy of air quality alerts increases after a certain period of time; perhaps people need some leeway to make a change in their travel practices. Policies could work in disseminating information on air quality prediction before the air quality worsens to consider the time required for travelers to change their behavior. This might appeal to the trend of using less automobiles which is manifested in study area 2. Policies and communication campaign can emphasize the health benefits of reducing motor vehicle usage during poor air quality days, highlighting the collective impact of individual actions on air pollution reduction and public health. Furthermore, to amplify the magnitude of decrease, UTA could consider implementing free public transit during periods of bad air quality. If necessary, transportation agencies could also look at hard policies as suggested for study area 1.

6.5 Limitations & Future Work

This thesis has several shortcomings that could be remedied through future work. First, though this research explored changes in motor vehicle traffic volumes, pedestrian volumes, and transit ridership, it could not explain how the change in volume in different modes could have interlinked (due to the aggregate nature of the data). Precisely, it could not explain why driving increased and walking decreased on poor air quality days in study area 1 or why driving and walking both decreased on poor air quality days in study area 2. Other works could supplement this aggregate traffic volume analysis with more disaggregate analysis of travel diaries, travel behaviors derived from location-based services data, and/or travel surveys to understand how and why individuals change their travel patterns in response to poor air quality. Such studies could be better able to capture behavioral responses such as shifting modes or forgoing or rescheduling trips.

Secondly, all of the models did not account for temporal autocorrelation, although we did attempt to structurally model the temporal patterns through the use of temporal control variables representing day-of-week and season. Future work could look into time series modeling to better address the impact of temporal autocorrelation. Thirdly, a lack of robust data for transit led to several limitations: it did not allow us to build multilevel model for transit ridership; we could not examine bus ridership in study area 2; and we could not investigate locational variations in the relationship between air quality and transit ridership. For example, were there some areas which were more/less significantly affected by air quality? In the case of pedestrians, we could see that different regions within study area 2 had a varied response to air quality; the lack of locational data for transit did not allow us to study this possibility.

Fourthly, this study did not account for the period during and since the COVID-19 pandemic. After COVID-19, people's ability and adaptation to teleworking has changed drastically (Belostecinic et al., 2021). Employees have been more flexible in the policy of teleworking, which means that during the periods of poor air quality, more travelers could respond by opting for teleworking. However, our study does not include the timeline during COVID-19, as it would complicate the inference of relationship between air quality and traffic volumes. There were lots of travel impacts during early phases of COVID which might not truly reflect the relationship between air quality and traffic volumes. Further studies could look into the relationship between air quality and multimodal traffic volumes during and after COVID by including adequate controls for COVID spread and response.

Though the study defines the air quality impacts on traffic volume, it does not distinguish the different impact that might be present during different seasons i.e. winter and summer. Owing to the different types of air pollution (source/causes) and different travel options available during each season, we might see a different response in each season. For example, the escaping of air pollution by going to the mountains might be more common in summertime than during wintertime. Also, the shift from automobiles to walking is convenient in summer than during the cold winter. However, the study does not segregate the air quality impacts into different seasons.

Furthermore, the effect air pollution has on travel behavior depends on the nature of trip i.e. if a trip is of recreational type rather than a work trip it has an increased chance of being affected by air pollution (Saberian et al., 2017). However, the study does not distinguish the trip into their types. Future studies could try to distinguish between trip purposes, either by location, or data source (e.g. Strava for recreational cycling), or some new data (e.g., Streetlight O/D) or proxies (e.g., roadway facility type). Moreover, the study could use an addition of control variables such as fuel cost which might have led to the changes in traffic volumes for each mode.

In the time lag analysis, we considered the effects of yesterday's air quality by adding lagged air quality variables. Though this approach allowed us to individually study yesterday's air quality's effect on today's traffic volume, it did not address the correlation between yesterday's air quality and today's air quality. Incorporating the correlation between air quality of different days would help us address the issue. Furthermore, including time lag variable representing the number of recent days with poor air quality would help us study the change in behavior during prolonged periods of air quality.

For the model enhancement part, we could not completely remove spatial autocorrelation from the random intercept and random slope model for pedestrian volumes in study area 2. The computationally intensive model that was used limited us from finding the best set of eigenvectors that could remove the spatial autocorrelation existing in the dataset. Similarly, for a combined study of all three modes in the seemingly unrelated regression models, we were limited by lack of data at the same level of spatial unit. We could not obtain traffic volumes for all mode from a single location, because count stations were not perfectly aligned in space. This meant we had to calculate a regional aggregate for our study areas, which might have been greater in geographical scope than what we wanted.

Despite these limitations, this thesis has been successful in addressing the limitations prominent in the field of research. The individual chapters have been built up from the limitations of the previous chapters. Firstly, the pedestrian models did not account for any similarity in unobserved factors affecting counts for stations that are located closer to each other; i.e., it ignored the spatial structure of the data. Accounting for potential spatial autocorrelation—such as the use of a spatial lag term—in the model addressed this limitation in the model enhancement chapter. Also, the study prior to this had been done in a particular location (an approach similar to one taken in study area 1), so its findings may be limited to this or similar locations (e.g., small urban areas, university towns, and/or mountain valleys). But the incorporation of study area 2 examining larger urban areas with more non-automobile transportation options (and greater availability of frequent public transit, larger downtowns, more demographic diversity, etc.) allowed us to explore significant impacts of air pollution on multimodal traffic volumes.

To conclude, our study made several contributions to the limited literature on how air pollution affects travel behaviors. First, it examined air quality effects on multiple transportation modes in the same general study area, finding differences in how much driving and walking changed (and, importantly, in which direction). Such modal findings within the same region are more comparable in our study than between other unimodal studies conducted in different regions. Second, we used more robust multilevel models to find and explain locational variations in how (pedestrian) volumes changed on poor air quality days. Third, we used time lag study to find the effect of preceding day's air quality on today's traffic volumes. Such information gives insights that help to understand why travel behavior changes in response to air pollution.

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8. APPENDICES

A. Time Lag

Table 8-1

Time Lag Model (Motor volumes), study area 1

Coefficient	Estimate	SE	t-statistic	p-value
Intercept (station 301)	8.909	0.041	217.961	<0.001
Difference for station 363	1.084	0.008	143.615	<0.001
Difference for station 510	-0.662	0.007	-89.283	<0.001
Difference for station 511	-0.398	0.007	-53.463	<0.001
Difference for station 620	0.221	0.008	29.067	<0.001
Difference for station 622	0.948	0.008	126.064	<0.001
Day of week (ref. = Weekday)				
Saturday	-0.116	0.006	-18.209	<0.001
Sunday	-0.609	0.006	-95.359	<0.001
Holiday (ref. = No holiday)	-0.258	0.012	-22.245	<0.001
Season (ref. = Winter)				
Spring	0.101	0.007	14.393	<0.001
Summer	0.135	0.007	19.142	<0.001
Fall	0.113	0.007	16.210	<0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.026	0.009	-4.213	<0.001
Light snow	-0.071	0.041	-8.226	<0.001
Heavy rain	-0.030	0.040	-0.758	0.449
Heavy snow	-0.145	0.013	-11.288	<0.001
Max temperature difference from average	-0.001	0.000	-1.228	0.220
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.025	0.008	2.819	0.004
Orange (AQI = 100+)	0.073	0.018	4.119	<0.001
Lagged Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.031	0.008	-3.551	<0.001
Orange (AQI = 100+)	-0.033	0.177	-1.868	0.062

Notes: N = 3,936; adjusted R-squared = 0.961.

Table 8-2

Time Lag Model (Pedestrian volumes), study area 1

Coefficients	Estimate	SE	df	t-statistic	p-value
Intercept	4.988	0.162	37.3	30.739	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.358	0.012	26960	-30.418	<0.001
Sunday	-1.008	0.012	26960	-86.410	<0.001
Holiday (ref. = No holiday)	-0.673	0.023	26960	-29.884	<0.001
Season (ref. = Winter)					
Spring	0.380	0.013	26960	28.991	<0.001
Summer	0.483	0.013	26960	38.157	<0.001
Fall	0.473	0.013	26960	36.345	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.083	0.012	26960	-7.159	0.000
Light snow	-0.282	0.016	26960	-17.383	< 2e-16
Heavy rain	-0.218	0.077	26960	-2.838	0.005
Heavy snow	-0.425	0.025	26960	-17.311	< 2e-16
Max temperature difference from average	0.004	0.001	26960	4.279	0.000
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	-0.023	0.013	26960	-1.687	0.092
Orange (AQI = 100+)	-0.093	0.029	26960	-3.215	0.001
Lagged Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	0.007	0.013	26960	0.588	0.557
Orange (AQI = 100+)	-0.045	0.028	26960	-1.606	0.108

Notes: N = 27,015; # groups = 38; log-likelihood = -27,162; between-group variance = 0.99; residual variance = 0.43.

Table 8-3

Time Lag Model (Transit volumes), study area 1

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	8.657	0.029	302.167	<0.001
Day of week (ref. = Weekday)				
Saturday	-1.224	0.027	-45.456	<0.001
Sunday	-	-	-	-
Holiday (ref. = No holiday)	-	-	-	-
Season (ref. = Winter)				
Spring	-0.045	0.033	-1.329	0.184
Summer	-0.367	0.032	-11.342	<0.001
Fall	0.066	0.034	1.947	0.052
Precipitation (ref. = No rain / no snow)				
Light rain	-0.047	0.029	-1.639	0.102
Light snow	-0.107	0.041	-2.609	0.009
Heavy rain	0.142	0.246	0.575	0.566
Heavy snow	-0.127	0.064	-1.988	0.047
Max temperature difference from average	-0.002	0.002	-0.720	0.472
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.019	0.041	-0.464	0.643
Orange (AQI = 100+)	-0.037	0.078	-0.469	0.639
Lagged air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.035	0.041	0.863	0.388
Orange (AQI = 100+)	-0.076	0.077	-0.990	0.323

Notes: N = 580; adjusted R-squared = 0.802.

Table 8-4

Time Lag Model (Motor volumes), study area 2

Coefficients	**Estimate**	**SE**	**df**	**t-statistic**	**p-value**
Intercept	10.690	0.185	33	57.688	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.130	0.004	22910	-29.363	<0.001
Sunday	-0.441	0.004	22910	-98.645	<0.001
Holiday (ref. = No holiday)	-0.257	0.009	22910	-29.632	<0.001
Season (ref. = Winter)					
Spring	0.075	0.005	22910	16.660	<0.001
Summer	0.129	0.005	22910	28.231	<0.001
Fall	0.069	0.004	22910	15.528	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.018	0.004	22910	-4.480	<0.001
Light snow	-0.070	0.007	22910	-10.077	<0.001
Heavy rain	-0.226	0.034	22910	-6.613	<0.001
Heavy snow	-0.165	0.010	22910	-16.668	<0.001
Max temperature difference from average	-0.001	0.000	22910	-3.586	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	0.016	0.005	22910	2.853	0.004
Orange (AQI = 100+)	-0.049	0.020	22910	-2.516	0.012
Lagged Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	-0.008	0.005	22910	-1.414	0.157
Orange (AQI = 100+)	-0.056	0.020	22910	-2.844	0.004

Notes: N = 22,955 # groups = 34; log-likelihood = 980.3; between-group variance = 1.16; residual variance = 0.052.

Table 8-5

Time Lag Model (Pedestrian volumes), study area 2

Coefficients	**Estimate**	**SE**	**df**	**t-statistic**	**p-value**
Intercept	4.906	0.039	869	125.315	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.354	0.002	626900	-194.694	<0.001
Sunday	-0.809	0.002	626900	-444.988	<0.001
Holiday (ref. = No holiday)	-0.499	0.004	626900	-140.421	<0.001
Season (ref. = Winter)					
Spring	0.275	0.002	626900	146.225	<0.001
Summer	0.280	0.002	626900	151.643	<0.001
Fall	0.273	0.002	626900	147.117	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.062	0.002	626900	-36.407	<0.000
Light snow	-0.277	0.003	626900	-93.583	<0.001
Heavy rain	-0.088	0.018	626900	-4.943	0.004
Heavy snow	-0.484	0.004	626900	-114.768	<0.001
Max temperature difference from average	0.004	0.000	627000	46.719	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	-0.058	0.002	626900	-30.295	<0.001
Orange (AQI = 100+)	-0.061	0.008	626900	-7.590	<0.001
Lagged air quality index (ref. = Green)					
Yellow (AQI = 50–99)	0.004	0.002	626900	2.203	0.028
Orange (AQI = 100+)	-0.007	0.008	626900	-0.835	0.404

Notes: N = 627,816; # groups = 868; log-likelihood = -450,426; between-group variance = 1.32 residual variance = 0.24.

Table 8-6
Time Lag Model (UTA Trax), study area 2

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	10.905	0.033	329.107	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.475	0.037	-12.755	< 0.001
Sunday	-1.090	0.037	-29.301	< 0.001
Holiday (ref. = No holiday)	-0.397	0.091	-4.388	0.000
Season (ref. = Winter)				
Spring	0.015	0.039	0.392	0.695
Summer	-0.148	0.039	-3.823	0.001
Fall	0.068	0.039	1.743	0.492
Precipitation (ref. = No rain / no snow)				
Light rain	-0.038	0.036	-1.033	0.302
Light snow	0.001	0.056	0.017	0.986
Heavy rain	-	-		
Heavy snow	-0.106	0.092	-1.155	0.248
Max temperature difference from average	0.002	0.002	1.214	0.225
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.070	0.050	1.409	0.159
Orange (AQI = 100+)	-0.049	0.206	-0.236	0.814
Lagged air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.023	0.050	0.457	0.648
Orange (AQI = 100+)	-0.078	0.205	-0.383	0.702

Notes: N = 706; adjusted R-squared = 0.575.

Table 8-7
Time Lag Model (UTA Frontrunner), study area 2

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	9.809	0.021	478.168	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.851	0.022	-38.937	< 0.001
Sunday	-2.020	0.202	-9.996	< 0.001
Holiday (ref. = No holiday)	-0.926	0.049	-18.971	0.000
Season (ref. = Winter)				
Spring	-0.026	0.025	-1.053	0.293
Summer	-0.048	0.024	-1.997	0.046
Fall	0.129	0.025	5.268	0.000
Precipitation (ref. = No rain / no snow)				
Light rain	-0.027	0.022	-1.200	0.231
Light snow	0.046	0.036	1.287	0.199
Heavy rain	-	-		
Heavy snow	-0.165	0.060	-2.735	0.006
Max temperature difference from average	0.001	0.001	0.527	0.598
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.035	0.031	1.126	0.261
Orange (AQI = 100+)	-0.053	0.122	-0.433	0.665
Lagged air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.003	0.031	0.104	0.917
Orange (AQI = 100+)	0.071	0.119	0.593	0.553

Notes: N = 620; adjusted R-squared = 0.759.

B. Spatial Filters

Table 8-8

Study Area 1: Ped Volumes Random Intercept Model with Spatial Filters

Coefficients	**Estimate**	**SE**	**df**	**t-statistic**	**p-value**
Intercept	4.989	0.162	37.310	30.738	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.357	0.012	27000	-30.403	<0.001
Sunday	-1.008	0.012	27000	-86.497	<0.001
Holiday (ref. = No holiday)	-0.674	0.023	27000	-29.905	<0.001
Season (ref. = Winter)					
Spring	0.380	0.013	27000	29.004	<0.001
Summer	0.483	0.013	27000	38.158	<0.001
Fall	0.473	0.013	27000	36.371	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.083	0.012	27000	-7.150	0.000
Light snow	-0.282	0.016	27000	-17.405	<0.001
Heavy rain	-0.220	0.076	27000	-2.876	0.004
Heavy snow	-0.421	0.024	27000	-17.197	<0.001
Max temperature difference from average	0.004	0.001	27000	4.335	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	-0.023	0.013	27000	-1.691	0.091
Orange (AQI = 100+)	-0.093	0.029	27000	-3.204	0.001
Spatial Filter (E12)	-3.213	0.859	36	-3.471	0.001

Notes: N = 27,053; # groups = 38; log-likelihood = -27,179; between-group variance = 0.737; residual variance = 0.43.

Table 8-9

Study Area 1: Ped Volumes Random Intercept and Random Slope Model with Spatial Filters

Coefficients	**Estimate**	**SE**	**df**	**t-statistic**	**p-value**
Intercept	0.069	1.229	31.590	0.056	0.956
Day of week (ref. = Weekday)					
Saturday	-0.357	0.012	26960	-30.448	<0.001
Sunday	-1.008	0.012	26960	-86.620	<0.001
Holiday (ref. = No holiday)	-0.674	0.022	26960	-29.947	<0.001
Season (ref. = Winter)					
Spring	0.380	0.013	26960	29.044	<0.001
Summer	0.483	0.013	26960	38.221	<0.001
Fall	0.473	0.013	26960	36.427	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.083	0.012	26960	-7.166	<0.001
Light snow	-0.282	0.016	26960	-17.433	<0.001
Heavy rain	-0.220	0.076	26960	-2.881	0.004
Heavy snow	-0.421	0.024	26960	-17.211	<0.001
Max temperature difference from average	0.004	0.001	26960	4.348	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	0.227	0.108	44.400	2.106	0.040
Orange (AQI = 100+)	0.005	0.247	41.080	0.022	0.984
Built and social environment variables					
Percentage of commercial parcels	0.005	0.005	30	1.027	0.313
Household income (median, $1,000)	0.031	0.014	30	2.169	0.038
Population density (1,000 people/mi^2)	0.310	0.064	30	4.861	0.000
Vehicle ownership (mean)	0.705	0.338	30	2.084	0.046
% 4-way intersections	-0.001	0.005	30	-0.225	0.824
Number of transit stops	0.107	0.029	30	3.696	0.001
E12	-2.541	0.534	30	-4.727	<0.001
Cross-level interactions					
Yellow AQI with % 4-way intersections	0.000	0.001	44.280	0.292	0.772
Orange AQI with % 4-way intersections	0.005	0.002	40.970	2.737	0.009
Yellow AQI with Vehicle ownership	-0.161	0.055	44.410	-2.966	0.005
Orange AQI with Vehicle ownership	-0.200	0.125	41.430	-1.597	0.118

Notes: N = 27,053; # groups = 38; log-likelihood = -27,163; between-group variance = 0.267; residual variance = 0.43; random coefficient variance for yellow AQI = 0.003; random coefficient variance for orange AQI = 0.020.

Table 8-10

Study Area 2: Motor Volumes Random Intercept Model with Spatial Filters

Coefficients	Estimate	SE	df	t-statistic	p-value
Intercept	10.680	0.172	32	62.220	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.130	0.004	22950	-29.298	<0.001
Sunday	-0.442	0.004	22950	-99.293	<0.001
Holiday (ref. = No holiday)	-0.266	0.008	22950	-31.323	<0.001
Season (ref. = Winter)					
Spring	0.077	0.004	22950	17.234	<0.001
Summer	0.131	0.005	22950	28.647	<0.001
Fall	0.071	0.004	22950	16.018	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.019	0.004	22950	-4.610	0.014
Light snow	-0.070	0.007	22950	-10.030	<0.001
Heavy rain	-0.226	0.034	22950	-6.600	<0.001
Heavy snow	-0.164	0.010	22950	-16.551	<0.001
Max temperature difference from average	-0.001	0.000	22950	-3.868	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	0.009	0.005	22950	1.858	0.063
Orange (AQI = 100+)	-0.068	0.019	22950	-3.652	<0.001
Spatial Filter (E11)	-2.533	1.001	32	-2.53	0.017

Notes: N = 23,001 # groups = 34; log-likelihood = 965; between-group variance = 1.001; residual variance = 0.052.

Table 8-11

Study Area 2: Motor Volumes Random Intercept and Random Slope Model with Spatial Filters

Coefficients	**Estimate**	**SE**	**df**	**t-statistic**	**p-value**
Intercept	13.690	1.050	22	13.037	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.156	0.004	20940	-34.736	<0.001
Sunday	-0.473	0.005	20970	-104.792	<0.001
Holiday (ref. = No holiday)	-0.281	0.009	20980	-32.727	<0.001
Season (ref. = Winter)					
Spring	0.074	0.005	20940	16.323	<0.001
Summer	0.112	0.005	20760	0.112	<0.001
Fall	0.067	0.005	20880	14.781	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.015	0.004	20990	-3.701	<0.001
Light snow	-0.065	0.007	20980	-9.206	<0.001
Heavy rain	-0.245	0.037	20980	-6.548	<0.001
Heavy snow	-0.157	0.010	20980	-15.669	<0.001
Max temperature difference from average	-0.001	0.000	20980	-3.213	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	-0.053	0.019	24	-2.833	0.009
Orange (AQI = 100+)	-0.178	0.078	46	-2.282	0.027
Spatial Filter (E11)	-1.834	1.025	21	-1.790	0.088
Built and social environment variables					
Gross residential density	-1.004	0.309	21	-3.250	0.004
Household income (median, $1,000)	-0.013	0.008	21	-1.765	0.092
Jobs per household	-0.123	0.043	21	-2.873	0.009
Percent of zero car households	-6.460	7.649	21	-0.845	0.408
Distance from population-weighted centroid to transit stop (m)	-0.003	0.001	21	-3.355	0.003
Jobs within 45 minutes auto travel time, network travel time weighted	0.000	0.000	21	3.287	0.004
Number of schools	0.182	0.064	21	2.862	0.009
Cross-level interactions					
Yellow AQI with median income	0.0004	0.000	18	2.370	0.029
Orange AQI with median income	0.003	0.001	51	3.244	0.002

Notes: N = 21,040; # groups = 31; log-likelihood = 1497.8, between-group variance = 0.62; residual variance = 0.049; random coefficient variance for yellow AQI = 0.0001; random coefficient variance for orange AQI = 0.001.

Table 8-12

Study Area 2: Ped Volumes Random Intercept Model with Spatial Filters

Coefficients	Estimate	SE	df	t-statistic	p-value
Intercept	4.464	0.043	1271	103.963	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.354	0.002	627900	-194.856	<0.001
Sunday	-0.809	0.002	627900	-445.482	<0.001
Holiday (ref. = No holiday)	-0.499	0.004	627900	-140.556	<0.001
Season (ref. = Winter)					
Spring	0.275	0.002	627900	146.318	<0.001
Summer	0.280	0.002	627900	151.760	<0.001
Fall	0.273	0.002	627900	147.231	<0.001
Precipitation (ref. = No rain / no snow)			630100		
Light rain	-0.062	0.002	627900	-36.456	<0.000
Light snow	-0.277	0.003	627900	-93.689	<0.001
Heavy rain	-0.088	0.018	627900	-4.947	0.004
Heavy snow	-0.484	0.004	627900	-114.899	<0.001
Max temperature difference from average	0.004	0.000	628000	46.760	<0.001
Spatial Filter (E8)	-2.816	1.149	866	-2.450	0.015
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	-0.058	0.002	628000	-30.351	<0.001
Orange (AQI = 100+)	-0.061	0.008	627900	-7.604	<0.001

Notes: N = 628,826; # groups = 868; log-likelihood = -451,084; between-group variance = 1.32 residual variance = 0.24.

Table 8-13

Study Area 2: Ped Volumes Random Intercept and Random Slope Model with Spatial Filters

Coefficients	**Estimate**	**SE**	**df**	**t-statistic**	**p-value**
Intercept	4.184	0.221	832	18.965	<0.001
Day of week (ref. = Weekday)					
Saturday	-0.358	0.002	607600	-196.364	<0.001
Sunday	-0.810	0.002	607000	-445.707	<0.001
Holiday (ref. = No holiday)	-0.496	0.004	607400	-139.452	<0.001
Season (ref. = Winter)					
Spring	0.274	0.002	607200	145.501	<0.001
Summer	0.289	0.002	605300	154.943	<0.001
Fall	0.266	0.002	599100	142.954	<0.001
Precipitation (ref. = No rain / no snow)					
Light rain	-0.059	0.002	607400	-34.350	<0.001
Light snow	-0.270	0.003	607600	-91.325	<0.001
Heavy rain	-0.108	0.018	607200	-6.012	0.004
Heavy snow	-0.480	0.004	607600	-114.117	<0.001
Max temperature difference from average	0.004	0.000	607900	45.048	<0.001
Air quality index (ref. = Green)					
Yellow (AQI = 50–99)	-0.007	0.015	879	-0.441	0.659
Orange (AQI = 100+)	0.070	0.038	622	1.838	0.067
Spatial Filter (E8)	-0.527	0.827	828	-0.637	0.524
Built and social environment variables					
Gross employment density (jobs/acre)	0.031	0.004	829	7.206	<0.001
Household income (median, $1,000)	-0.008	0.001	831	-5.541	<0.001
Jobs per household	-0.009	0.004	829	-2.428	0.015
Percent of zero car households	2.275	0.587	833	3.879	<0.001
Total road network density	0.032	0.008	828	4.202	<0.001
Jobs within 45 minutes auto travel time	0.000	0.000	828	-1.738	0.083
Park area	0.001	0.001	826	0.937	0.349
Number of schools	0.085	0.038	828	2.24	0.025
Transit bus stops	0.077	0.008	828	9.208	< 2e-16
Near a university	0.845	0.131	830	6.458	0.000
University break	-0.480	0.006	607800	-86.452	< 2e-16
Cross-level interactions					
Yellow AQI with median income	0.0005	0.000	865	-2.649	0.008
Orange AQI with median income	-0.002	0.000	685	-3.963	<0.001
Yellow AQI with % zero-car household	-0.199	0.056	855	-3.518	<0.001
Orange AQI with % zero-car household	-0.131	0.150	876	-0.878	0.380

Notes: N = 609,255; # groups = 841; log-likelihood = -428,155; between-group variance = 0.622; residual variance = 0.235; random coefficient variance for yellow AQI = 0.008; random coefficient variance for orange AQI = 0.017.

C. Seemingly Unrelated Regression (SURs)

Table 8-14

Salt Lake City (Downtown): Motor Vehicle Volumes General Linear Model

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	10.614	0.008	1264.317	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.284	0.010	-28.790	< 0.001
Sunday	-0.539	0.010	-54.952	< 0.001
Holiday (ref. = No holiday)	-0.437	0.019	-23.212	< 0.001
Season (ref. = Winter)				
Spring	0.079	0.010	7.944	< 0.001
Summer	0.060	0.010	5.918	< 0.001
Fall	0.060	0.010	6.054	< 0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.018	0.009	-1.931	0.054
Light snow	-0.060	0.014	-4.141	0.000
Heavy rain	-	-		
Heavy snow	-0.228	0.023	-9.793	< 0.001
Max temperature difference from average	0.001	0.000	1.738	0.083
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.002	0.010	-0.195	0.846
Orange (AQI = 100+)	-0.052	0.052	-1.002	0.317

Notes: N = 700; adjusted R-squared = 0.856.

Table 8-15

Salt Lake City (Downtown): Pedestrian Vehicle Volumes General Linear Model

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	6.638	0.017	386.895	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.267	0.020	-13.258	< 0.001
Sunday	-0.702	0.020	-35.037	< 0.001
Holiday (ref. = No holiday)	-0.553	0.038	-14.394	< 0.001
Season (ref. = Winter)				
Spring	0.160	0.020	7.842	< 0.001
Summer	0.119	0.021	5.713	< 0.001
Fall	0.148	0.020	7.288	< 0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.066	0.019	-3.427	0.001
Light snow	-0.184	0.029	-6.268	0.000
Heavy rain	-	-		
Heavy snow	-0.486	0.048	-10.204	< 0.001
Max temperature difference from average	0.004	0.001	4.110	0.000
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.109	0.021	-5.178	0.000
Orange (AQI = 100+)	-0.061	0.106	-0.577	0.564

Notes: N = 700; adjusted R-squared = 0.723.

Table 8-16

Salt Lake City (Downtown): Transit Ridership General Linear Model

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	10.886	0.109	99.442	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.438	0.129	-3.407	< 0.001
Sunday	-1.037	0.128	-8.112	< 0.001
Holiday (ref. = No holiday)	-4.219	0.245	-17.203	< 0.001
Season (ref. = Winter)				
Spring	0.001	0.130	0.010	0.992
Summer	-0.155	0.133	-1.167	0.243
Fall	0.181	0.130	1.398	0.162
Precipitation (ref. = No rain / no snow)				
Light rain	-0.188	0.122	-1.543	0.123
Light snow	-0.033	0.187	-0.177	0.860
Heavy rain	-	-		
Heavy snow	-0.698	0.304	-2.300	0.022
Max temperature difference from average	0.008	0.005	1.536	0.125
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.071	0.134	-0.530	0.597
Orange (AQI = 100+)	0.062	0.679	0.091	0.927

Notes: N = 700; adjusted R-squared = 0.343.

Table 8-17

Salt Lake City (Downtown): Seemingly Unrelated Regression (SURs) for Motor, Pedestrian, and Transit Volumes

Coefficients	Estimate	SE	t-statistic	p-value
Motor				
Intercept	10.614	0.008	1264.317	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.284	0.010	-28.790	< 0.001
Sunday	-0.539	0.010	-54.952	< 0.001
Holiday (ref. = No holiday)	-0.437	0.019	-23.212	< 0.001
Season (ref. = Winter)				
Spring	0.079	0.010	7.944	< 0.001
Summer	0.060	0.010	5.918	< 0.001
Fall	0.060	0.010	6.054	< 0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.018	0.009	-1.931	0.054
Light snow	-0.060	0.014	-4.141	0.000
Heavy rain	-	-		
Heavy snow	-0.228	0.023	-9.793	< 0.001
Max temperature difference from average	0.001	0.000	1.738	0.083
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.002	0.010	-0.195	0.846
Orange (AQI = 100+)	-0.052	0.052	-1.002	0.317
Pedestrian				
Intercept	6.638	0.017	386.895	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.267	0.020	-13.258	< 0.001
Sunday	-0.702	0.020	-35.037	< 0.001
Holiday (ref. = No holiday)	-0.553	0.038	-14.394	< 0.001
Season (ref. = Winter)				
Spring	0.160	0.020	7.842	< 0.001
Summer	0.119	0.021	5.713	< 0.001
Fall	0.148	0.020	7.288	< 0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.066	0.019	-3.427	0.001
Light snow	-0.184	0.029	-6.268	0.000
Heavy rain	-	-		
Heavy snow	-0.486	0.048	-10.204	< 0.001
Max temperature difference from average	0.004	0.001	4.110	0.000
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.109	0.021	-5.178	0.000
Orange (AQI = 100+)	-0.061	0.106	-0.577	0.564
Transit				
Intercept	10.886	0.109	99.442	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.438	0.129	-3.407	< 0.001
Sunday	-1.037	0.128	-8.112	< 0.001
Holiday (ref. = No holiday)	-4.219	0.245	-17.203	< 0.001
Season (ref. = Winter)				
Spring	0.001	0.130	0.010	0.992
Summer	-0.155	0.133	-1.167	0.243
Fall	0.181	0.130	1.398	0.162
Precipitation (ref. = No rain / no snow)				

Light rain	-0.188	0.122	-1.543	0.123
Light snow	-0.033	0.187	-0.177	0.860
Heavy rain	-	-		
Heavy snow	-0.698	0.304	-2.300	0.022
Max temperature difference from average	0.008	0.005	1.536	0.125
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.071	0.134	-0.530	0.597
Orange (AQI = 100+)	0.062	0.679	0.091	0.927

Table 8-18

Correlation of Residuals

	Motor	**Ped**	**Transit**
Motor	1.000	0.553	0.477
Ped	0.553	1.000	0.253
Transit	0.477	0.253	1.000

Table 8-19

Model Metrics for SUR Salt Lake City (Downtown)

	N	**DF**	**SSR**	**MSE**	**RMSE**	**R2**	**Adj R2**
Motor	700	687	5.393	0.007	0.088	0.855	0.853
Ped	700	687	22.529	0.032	0.181	0.727	0.723
Transit	700	687	917.085	1.334	1.155	0.354	0.343

Table 8-20

Salt Lake County: Motor Vehicle Volumes General Linear Model

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	11.453	0.007	1628.333	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.175	0.008	-21.215	< 0.001
Sunday	-0.513	0.008	-62.661	< 0.001
Holiday (ref. = No holiday)	-0.279	0.016	-17.703	< 0.001
Season (ref. = Winter)				
Spring	0.046	0.008	5.508	< 0.001
Summer	0.070	0.009	8.189	< 0.001
Fall	0.061	0.008	7.338	< 0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.016	0.008	-2.005	0.045
Light snow	-0.074	0.012	-6.138	0.000
Heavy rain	-	-		
Heavy snow	-0.229	0.020	-11.746	< 0.001
Max temperature difference from average	< 0.001	0.000	0.982	0.326
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.006	0.009	0.666	0.506
Orange (AQI = 100+)	0.021	0.044	0.477	0.634

Notes: N = 701 ; adjusted R-squared = 0.868.

Table 8-21

Salt Lake County: Pedestrian Volumes General Linear Model

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	5.170	0.015	338.232	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.357	0.018	-19.882	< 0.001
Sunday	-0.686	0.018	-38.595	< 0.001
Holiday (ref. = No holiday)	-0.415	0.034	-12.114	< 0.001
Season (ref. = Winter)				
Spring	0.182	0.018	10.048	< 0.001
Summer	0.116	0.019	6.286	< 0.001
Fall	0.206	0.018	11.409	< 0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.061	0.017	-3.581	0.001
Light snow	-0.203	0.026	-7.743	0.000
Heavy rain	-	-		
Heavy snow	-0.498	0.042	-11.755	< 0.001
Max temperature difference from average	0.004	0.001	4.597	0.000
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.045	0.019	-2.432	0.015
Orange (AQI = 100+)	0.040	0.095	0.417	0.677

Notes: N = 701; adjusted R-squared = 0.767.

Table 8-22

Salt Lake County: Transit Volumes General Linear Model

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	10.886	0.109	99.442	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.438	0.129	-3.407	< 0.001
Sunday	-1.037	0.128	-8.112	< 0.001
Holiday (ref. = No holiday)	-4.219	0.245	-17.203	< 0.001
Season (ref. = Winter)				
Spring	0.001	0.130	0.010	0.992
Summer	-0.155	0.133	-1.167	0.243
Fall	0.181	0.130	1.398	0.162
Precipitation (ref. = No rain / no snow)				
Light rain	-0.188	0.122	-1.543	0.123
Light snow	-0.033	0.187	-0.177	0.860
Heavy rain	-	-		
Heavy snow	-0.698	0.304	-2.300	0.022
Max temperature difference from average	0.008	0.005	1.536	0.125
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.071	0.134	-0.530	0.597
Orange (AQI = 100+)	0.062	0.679	0.091	0.927

Notes: N = 701; adjusted R-squared = 0.343.

Table 8-23

Salt Lake County: Seemingly Unrelated Regression (SURs) for Motor, Pedestrian, and Transit Volumes

Coefficients	Estimate	SE	t-statistic	p-value
Motor				
Intercept	11.453	0.007	1628.333	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.175	0.008	-21.215	< 0.001
Sunday	-0.513	0.008	-62.661	< 0.001
Holiday (ref. = No holiday)	-0.279	0.016	-17.703	< 0.001
Season (ref. = Winter)				
Spring	0.046	0.008	5.508	< 0.001
Summer	0.070	0.009	8.189	< 0.001
Fall	0.061	0.008	7.338	< 0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.016	0.008	-2.005	0.045
Light snow	-0.074	0.012	-6.138	0.000
Heavy rain	-	-		
Heavy snow	-0.229	0.020	-11.746	< 0.001
Max temperature difference from average	< 0.001	0.000	0.982	0.326
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.006	0.009	0.666	0.506
Orange (AQI = 100+)	0.021	0.044	0.477	0.634
Pedestrian				
Intercept	5.170	0.015	338.232	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.357	0.018	-19.882	< 0.001
Sunday	-0.686	0.018	-38.595	< 0.001
Holiday (ref. = No holiday)	-0.415	0.034	-12.114	< 0.001
Season (ref. = Winter)				
Spring	0.182	0.018	10.048	< 0.001
Summer	0.116	0.019	6.286	< 0.001
Fall	0.206	0.018	11.409	< 0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.061	0.017	-3.581	0.001
Light snow	-0.203	0.026	-7.743	0.000
Heavy rain	-	-		
Heavy snow	-0.498	0.042	-11.755	< 0.001
Max temperature difference from average	0.004	0.001	4.597	0.000
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.045	0.019	-2.432	0.015
Orange (AQI = 100+)	0.040	0.095	0.417	0.677
Transit				
Intercept	10.886	0.109	99.442	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.438	0.129	-3.407	< 0.001
Sunday	-1.037	0.128	-8.112	< 0.001
Holiday (ref. = No holiday)	-4.219	0.245	-17.203	< 0.001
Season (ref. = Winter)				
Spring	0.001	0.130	0.010	0.992
Summer	-0.155	0.133	-1.167	0.243
Fall	0.181	0.130	1.398	0.162
Precipitation (ref. = No rain / no snow)				

Light rain	-0.188	0.122	-1.543	0.123
Light snow	-0.033	0.187	-0.177	0.860
Heavy rain	-	-		
Heavy snow	-0.698	0.304	-2.300	0.022
Max temperature difference from average	0.008	0.005	1.536	0.125
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.071	0.134	-0.530	0.597
Orange (AQI = 100+)	0.062	0.679	0.091	0.927

Table 8-24

Correlation of Residuals: SUR Salt Lake County

	Motor	Ped	Transit
Motor	1.000	0.405	0.353
Ped	0.405	1.000	0.248
Transit	0.353	0.248	1.000

Table 8-25

Model Metrics for SUR Salt Lake County

	N	DF	SSR	MSE	RMSE	R2	Adj R2
Motor	701	688	3.792	0.006	0.074	0.871	0.869
Ped	701	688	17.910	0.026	0.161	0.771	0.767
Transit	701	688	917.129	1.333	1.155	0.355	0.344

Table 8-26

Cache County: Motor Volumes General Linear Model

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	9.445	0.011	837.821	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.069	0.012	-5.817	< 0.001
Sunday	-0.553	0.012	-46.357	< 0.001
Holiday (ref. = No holiday)	-0.232	0.023	-10.253	< 0.001
Season (ref. = Winter)				
Spring	0.091	0.013	6.923	< 0.001
Summer	0.115	0.013	8.834	< 0.001
Fall	0.100	0.013	7.656	< 0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.027	0.012	-2.242	0.025
Light snow	-0.058	0.016	-3.615	0.000
Heavy rain	-0.033	0.076	-0.432	0.666
Heavy snow	-0.168	0.024	-6.858	0.000
Max temperature difference from average	-0.001	0.001	-0.833	0.405
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.023	0.013	-1.711	0.088
Orange (AQI = 100+)	0.058	0.028	2.065	0.039

Notes: N = 701; adjusted R-squared = 0.78.

Table 8-27

Cache County: Pedestrian Volumes General Linear Model

Coefficients	Estimate	SE	t-statistic	p-value
Intercept	5.871	0.043	137.275	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.613	0.045	-13.575	< 0.001
Sunday	-1.296	0.045	-28.655	< 0.001
Holiday (ref. = No holiday)	-1.013	0.086	-11.797	< 0.001
Season (ref. = Winter)				
Spring	0.106	0.050	2.131	0.033
Summer	0.029	0.049	0.579	0.563
Fall	0.458	0.049	9.280	< 0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.046	0.045	-1.033	0.302
Light snow	-0.321	0.061	-5.238	0.000
Heavy rain	-0.008	0.290	-0.029	0.977
Heavy snow	-0.327	0.093	-3.525	< 0.001
Max temperature difference from average	0.000	0.003	-0.119	0.905
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.079	0.051	-1.556	0.120
Orange (AQI = 100+)	-0.213	0.107	-1.984	0.048

Notes: N = 694; adjusted R-squared = 0.63.

Table 8-28

Cache County: Transit Volumes General Linear Model

Coefficients	**Estimate**	**SE**	**t-statistic**	**p-value**
Intercept	8.403	0.115	73.126	< 0.001
Day of week (ref. = Weekday)				
Saturday	-1.028	0.122	-8.411	< 0.001
Sunday	-8.351	0.122	-68.227	< 0.001
Holiday (ref. = No holiday)	-	-	-	-
Season (ref. = Winter)				
Spring	0.085	0.135	0.629	0.530
Summer	-0.238	0.134	-1.776	0.076
Fall	0.062	0.134	0.464	0.643
Precipitation (ref. = No rain / no snow)				
Light rain	-0.095	0.122	-0.777	0.438
Light snow	-0.261	0.167	-1.565	0.118
Heavy rain	0.043	0.788	0.055	0.956
Heavy snow	-0.435	0.252	-1.729	0.084
Max temperature difference from average	-0.006	0.009	-0.701	0.484
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.061	0.138	0.443	0.658
Orange (AQI = 100+)	0.167	0.291	0.572	0.567

Notes: N = 694; adjusted R-squared = 0.87.

Table 8-29

Cache County: Seemingly Unrelated Regression (SURs) for Motor, Pedestrian, and Transit Volumes

Coefficients	Estimate	SE	t-statistic	p-value
Motor				
Intercept	9.439	0.011	837.644	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.065	0.012	-5.468	< 0.001
Sunday	-0.548	0.012	-46.009	< 0.001
Holiday (ref. = No holiday)	-0.148	0.022	-6.664	< 0.001
Season (ref. = Winter)				
Spring	0.095	0.013	7.239	< 0.001
Summer	0.117	0.013	9.035	< 0.001
Fall	0.101	0.013	7.765	< 0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.026	0.012	-2.167	0.031
Light snow	-0.059	0.016	-3.627	0.000
Heavy rain	-0.032	0.076	-0.412	0.680
Heavy snow	-0.172	0.024	-7.049	0.000
Max temperature difference from average	-0.001	0.001	-0.842	0.400
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.022	0.013	-1.609	0.108
Orange (AQI = 100+)	0.063	0.028	2.241	0.025
Pedestrian				
Intercept	5.832	0.043	136.525	< 0.001
Day of week (ref. = Weekday)				
Saturday	-0.587	0.045	-13.018	< 0.001
Sunday	-1.270	0.045	-28.097	< 0.001
Holiday (ref. = No holiday)	-0.499	0.081	-6.136	< 0.001
Season (ref. = Winter)				
Spring	0.131	0.050	2.638	0.009
Summer	0.044	0.049	0.901	0.368
Fall	0.467	0.049	9.456	< 0.001
Precipitation (ref. = No rain / no snow)				
Light rain	-0.041	0.045	-0.912	0.362
Light snow	-0.322	0.061	-5.258	0.000
Heavy rain	0.001	0.290	0.003	0.998
Heavy snow	-0.355	0.093	-3.832	0.000
Max temperature difference from average	0.000	0.003	-0.134	0.894
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	-0.071	0.051	-1.393	0.164
Orange (AQI = 100+)	-0.183	0.107	-1.702	0.089
Transit				
Intercept	8.403	0.115	73.126	< 0.001
Day of week (ref. = Weekday)				
Saturday	-1.028	0.122	-8.411	< 0.001
Sunday	-8.351	0.122	-68.227	< 0.001
Holiday (ref. = No holiday)	-	-	-	-
Season (ref. = Winter)				
Spring	0.085	0.135	0.629	0.530
Summer	-0.238	0.134	-1.776	0.076

Fall	0.062	0.134	0.464	0.643
Precipitation (ref. = No rain / no snow)				
Light rain	-0.095	0.122	-0.777	0.438
Light snow	-0.261	0.167	-1.565	0.118
Heavy rain	0.043	0.788	0.055	0.956
Heavy snow	-0.435	0.252	-1.729	0.084
Max temperature difference from average	-0.006	0.009	-0.701	0.484
Air quality index (ref. = Green)				
Yellow (AQI = 50–99)	0.061	0.138	0.443	0.658
Orange (AQI = 100+)	0.167	0.291	0.572	0.567

Table 8-30

Correlation of Residuals: SUR Cache County

	Motor	**Ped**	**Transit**
Motor	1.000	0.321	0.299
Ped	0.321	1.000	0.473
Transit	0.299	0.473	1.000

Table 8-31

Model Metrics: SUR Cache County

	N	**DF**	**SSR**	**MSE**	**RMSE**	**R2**	**Adj R2**
Motor	701	688	3.792	0.006	0.074	0.871	0.869
Ped	694	680	118.727	0.175	0.418	0.619	0.612
Transit	694	681	834.881	1.226	1.107	0.874	0.872