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Associations of inclement weather and poor air quality with non-motorized trail volumes

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ABSTRACT

Inclement weather and poor air quality present unfavorable conditions for active transportation. This study investigated associations of area-wide air pollution and inclement weather with non-motorized travel at two trail locations in northern Utah (one recreational, one utilitarian). Rainfall, snowfall, high/low temperatures, and high wind speed were measures of inclement weather, and overall air quality index (AQI) measured air pollution. This study fit time-series (ARIMA) regression models for the utilitarian and recreational sites (separately), using multiple years of daily non-motorized counts. Non-motorized travel was reduced significantly during inclement weather, and the effects of rainfall and cold temperatures were smaller for the utilitarian site than for the recreational site. Counts at the recreational site were higher on holidays, weekends, and days with greater snow depth. Although non-motorized counts were lower on days with worse air quality at the utilitarian location, they were higher at the recreational location. Results are interpreted in terms of the discretionary nature of recreational travel, particulars of the location and elevation of the recreational site, and a desire to escape pollution through outdoor recreation in a natural area.

1. Introduction

Unprecedented growth of automobiles in the US and the world has resulted in several negative externalities such as air pollution, noise pollution, and traffic congestion (Parry et al., 2007). Transportation agencies and professionals are challenged to find possible solutions to reduce such negative externalities. Among the plethora of alternative solutions, promoting active modes of travel is considered as a promising one. The choice of active transportation modes (walking, bicycling, etc.) over automobiles has benefits in terms of reducing air and noise pollution, reducing congestion, and improving health in several ways: from reducing obesity to lowering the risks of chronic diseases such as diabetes and cardiovascular disease (Rabl & De Nazelle, 2012; Wanner et al., 2012). In order to increase the attraction of active modes, a favorable environment is necessary (although not sufficient). A favorable environment for active modes often includes flat terrain, a mild climate, decent built-up areas (with sidewalks, bike lanes, etc.), accessibility (via active modes) to jobs and other destinations, safe corridors, etc. (Wang et al., 2015a). This study focuses on the atmospheric elements of the environment, specifically exploring behavioral changes in non-motorized travel in response to changes in weather and air quality.

Understanding how active transportation behaviors and volumes change coincident with time periods of inclement weather and

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poor air quality is important for a number of reasons. First, such knowledge could be useful for the promotion of environmentally sustainable transportation modes and the evaluation of transportation or recreational policies. Knowing the degree to which specific types of adverse weather deter walking and bicycling could inform the timing and messaging of marketing strategies (e.g., "don't let the weather get you down," "physical activity can help improve your mood"), and the specific content and necessary intensity of educational and other non-infrastructural interventions (e.g., winter bicycling workshops, hand-outs of lights and gloves) to promote active travel. Many regions and states discourage automobile use during periods of elevated area-wide air pollution levels through policies and recommendations (e.g., UDOT, n.d.) such as telework, using active modes, and using public transit. These policies—which likely affect engagement in utilitarian and/or recreational active transportation—require continued evaluation.

Second, knowing the sensitivity of active travelers to air pollution, quantified by the marginal effect that air pollution contributes to the temporal variations in active transportation levels, is important for quantifying the human health effects of the transportation system. Increasingly, urban regions around the globe are interested in applying transportation–health impact tools (e.g, Woodcock et al., 2009, 2013) to evaluate the health effects of transportation policies and suites of projects, including those that increase active travel (Mueller et al., 2015). While increased active transportation in most places has the potential for large and widespread health benefits, increased exposure to very high levels of air pollution for long time periods can be detrimental (Tainio et al., 2016). Most of these transportation–health impact models decouple active transportation use from air quality levels; i.e., there is no risk aversion to air pollution. Knowledge of the degree to which people may avoid active travel during episodes of poor air quality can help to calibrate and improve the accuracy of such transportation–health models.

Third, quantifying the associations between non-motorized trail use and weather and air quality helps to address some unanswered questions in these research areas. As the subsequent Literature Review section will detail, only a handful of studies have analyzed the impacts of air pollution on active transportation use (activity, volume, etc.) using revealed/observed data; research like this can help illuminate the degree to which health concerns affect traveler behaviors. Also, by comparing how non-motorized volumes are affected by weather and air quality in different locations with more utilitarian vs. mostly recreational travel, additional insights could be gained about active transportation behavior that may be useful for transportation and recreation managers.

This study uses time-series (ARIMA) regression models and multiple years of daily data at two trail locations in northern Utah (one recreational, one utilitarian) to analyze the impacts of inclement weather and poor air quality on non-motorized trail volumes. The following sections of the paper: summarize the literature and note the study objectives, describe the data and analysis method, present the model results, and discuss the study's findings, implications, and limitations.

2. Literature review

2.1. Inclement weather

Many studies have investigated the impacts of inclement weather on walking, bicycling, and/or non-motorized counts or volumes. Therefore, this brief review summarizes other systematic reviews as well as research with particular relevance to the present study: focusing on non-motorized trail usage at US locations, and differences by location type and/or user profile (utilitarian vs. recreational).

Two fairly-recent review papers summarized evidence regarding the impacts of weather on traveler behaviors (Böcker et al., 2013; Liu et al., 2017). In general, many studies have found that precipitation (especially snow) negatively affects cycling, whether through lower bicycle counts on days or in locations with more rain, or mode switching from active-to-motorized modes on rainy days; however, this effect may be stronger for discretionary travel than for utilitarian travel, for women than for men, and at smaller amounts of precipitation (Böcker et al., 2013; Liu et al., 2017). Warmer temperatures seem to increase active transportation levels, but only up to a certain amount: above 25–30 °C (77–86°F), outdoor activity was less favorable (Böcker et al., 2013). Wind seemed to mostly affect cycling levels, negatively (Böcker et al., 2013), but not walking levels (Liu et al., 2017). Other weather characteristics—humidity, fog, sunshine, cloud-cover—have less often been investigated (Liu et al., 2017). Authors have noted that weather impacts are relative and may depend on climate (larger variations in continental vs. temperate climates) as well as exposure sensitivity (Böcker et al., 2013; Liu et al., 2017): e.g., residents of wet or hot regions may be less affected by rain or warm temperatures, respectively.

Many of the studies cited in the literature reviews involve modeling weather impacts on active transportation volumes, measured along non-motorized trails, since managed trail locations may be easier to count than on-street or sidewalk locations (Ryus et al., 2014). A non-exhaustive but illustrative sample of studies are summarized in this paragraph, most of which find similar impacts of adverse weather. Lindsey et al. (2007) assessed the impacts of weather on multiple-years of trail counts at 30 locations in Indianapolis, IN, US. They found significantly lower levels of trail traffic on days with (compared to average weather conditions): colder temperatures (but non-linear effects), more precipitation, more snow, and fewer hours of sunshine (Lindsey et al., 2007). Nosal and Miranda-Moreno (2014) compared weather impacts on bicycle ridership in four North American cities. They found positive (but non-linear, concave-down) relationships with temperature, negative effects of humidity, and negative impacts of rainfall (Nosal & Miranda-Moreno, 2014). Wang et al. (2014) modeled trail counts at six locations in Minneapolis, MN, US, as a function of weather and other variables. They found that trail counts increased on days with warmer temperatures, and decreased on days with more precipitation, stronger winds, and greater deviation from seasonally-normal temperature (Wang et al., 2014). Ermagun et al. (2018) studied 32 multi-use trail locations in 13 US cities (within different climate zones) and the different impacts of weather on bicycle/pedestrian volumes. Across all locations, they found several associations: positive (but non-linear) with temperature, negative (but non-linear) with precipitation, and positive with dew point for both modes; although, cycling was more sensitive to weather than walking, including to wind and snow, and results differed across regions (Ermagun et al., 2018).

Given that weather is such an important driver of temporal variations in non-motorized trail volumes, much research has identified

Table 1
Summary of studies about the impacts of area-wide air pollution on observed non-motorized travel.

Study	*Units*	*Method*	*Results*
Zahran et al., 2008	Census Bureau estimates (2000?) of walk and bicycle commuters in 2,974 counties in US	Negative binomial regression models, controlling for built and natural environment, socioeconomics, other variables	County-level counts of walk and bicycle commuters were lower in counties with more hazardous air pollution emissions per capita.
Holmes et al., 2009	853 days (2004–2006) of non-motorized counts at 30 multi-use trail locations in Indianapolis, IN, US	Log-linear panel regression model with fixed effects, controlling for weather	Higher levels of ground-level ozone (O_3) and fine particulate matter ($PM_{2.5}$) were associated with significantly less trail traffic. Elasticities: −0.126 for O_3, −0.179 for $PM_{2.5}$.
Li & Kamargianni, 2017	Two days (2015–2016) and 3,519 trips from travel diary surveys of 492 residents in Taiyuan, China	Multinomial logit mode choice models, controlling for weather, travel time and cost, socioeconomics	During winter (worse air quality), people were less likely to walk, bicycle, or use bike-share. During summer (better air quality), people were more likely to bicycle or use bike-share. The authors speculate that air pollution was less important than other factors unless severe.
Chung et al., 2019	A couple of days (2015) of pedestrian counts at 1,207 street segments in Seoul, South Korea	Log-linear spatial error regression model, controlling for weather, built environment	Pedestrian volumes were less on days with higher concentrations of particulate matter (PM_{10}), but only (statistically significant) when measured at a borough spatial level. Elasticity: −0.121 for PM_{10}.
Kim, 2020	365 days (2018) of bike-share usage (trips, travel distances, travel times) in Seoul, South Korea	Negative binomial regression models, controlling for weather, calendar events	Bike-share usage (trips, traveled distances, traveled times) was less on days with higher concentrations of particulate matter (PM_{10}, or $PM_{2.5}$), especially in winter.
Doubleday et al., 2021	105 summer days (2017–2018) of counts at 8 bicycle and 2 pedestrian roadway/trail locations in Seattle, WA, US	Tukey's tests (pairwise comparisons) of pre/during/post-wildfire events, after time series decomposition	There were significant decreases in bicycle/pedestrian volumes during the wildfire smoke events at 1 location in 2017 and at all 10 locations in 2018. The authors speculate that improved public health messaging may have affected the results.
This study	1,004 days (2017–2020) of non-motorized counts at 2 trail locations in Logan, UT, US	Log-linear time series (ARIMA) regression, controlling for weather, calendar events	Days with higher air pollution (overall AQI) saw less trail traffic at the utilitarian site, but more trail traffic (marginally significant) at the recreational site. Elasticities: −0.056 for AQI at utilitarian site, +0.090 for AQI at recreational site.

common patterns in bicycle/pedestrian traffic volumes, relating those patterns to characteristics of trail users, surrounding environments, and weather/climate. Again, only a selection of studies are summarized here. Miranda-Moreno et al. (2013) considered bicycle volumes at 40 locations in 5 North American cities. Using hourly/weekday patterns, they classified sites into four categories ranging from "primarily utilitarian" (AM/PM weekday peaks, lower on weekends, less decrease in winter) to "primarily recreational" (midday peak, higher on weekends, more decrease in winter). In a follow-up study, Nosal and Miranda-Moreno (2014) found that bicycle counts at utilitarian locations were less affected by adverse weather than cycling at recreational locations. Nordback et al. (2013) studied bicycle/pedestrian count data in Colorado and identified three groups of patterns: "commute" (high weekdays, low monthly variation), "non-commute front-range" (high weekends, low monthly variation), and "non-commute mountain" (high weekends, high monthly variation). Many of these studies are motivated by a desire to construct factor groups with similar patterns, in order to extrapolate short-duration counts to longer-term average volumes (Ryus et al., 2014).

2.2. Poor air quality

Most of the existing studies (e.g., Engström & Forsberg, 2019; Zakaria et al., 2019) related to air quality focus on the negative effects of poor air quality on the health conditions of pedestrians and cyclists, whereas a few studies (e.g., Giallouros et al., 2020) focus on tradeoffs between the positive effects of physical activity resulting from walking and bicycling and the negative health effects as a result of exposure to air pollution. However, understanding behavioral changes in walking and bicycling during periods of poor air quality is still lacking.

There exist only a few studies that explore the impacts of air quality on non-motorized travel; many of them are based on stated (rather than revealed) behaviors. A stated preference survey conducted by Anowar et al. (2017) found that cyclists are willing to travel an extra four minutes if they can reduce the air pollution exposure level by five parts per billion. Badland and Duncan (2009) found that most active travelers are aware of negative health consequences of exposure to air pollution, but very few of them consider air pollution as a barrier to walking and cycling or change their commute routes to minimize exposure to poor air quality. Bigazzi and Gehrke (2018) reported that around half of sampled cyclists in Vancouver, Canada, considered air quality while choosing a cycling route. Based on a survey of US residents, Bunds et al. (2019) asserted air pollution level as the foremost barrier of walking among the list of seven (air pollution level, air pollution source, noise level, noise source, natural environment, traffic, and walking time/distance).

Only a few studies analyze the effects of air quality on observed non-motorized travel behaviors or volumes; see Table 1 for a summary. Researchers have taken a variety of approaches to investigating this topic, including analyzing county-level estimates of walk/bicycle commuters (Zahran et al., 2008), mode choices from travel diary surveys (Li & Kamargianni, 2017), and bike-share usage across a city (Kim, 2020). The more relevant studies (for the present paper) model pedestrian, bicycle, and/or non-motorized counts across multiple locations and for multiple days, although even these studies vary considerably: Chung et al. (2019) modeled just a couple of days of counts across>1,000 locations, while Doubleday et al. (2021) analyzed just over 100 days of counts at 10 locations. The most similar study (to the present one) was by Holmes et al. (2009), who used 850 + days of counts at 30 trail locations in their model.

The analysis methodologies used in previous research reflect these differences in scope. Studies using longer time durations can potentially account for more variability in air pollution levels, but need to account for other time-varying factors (like weather, calendar events, etc.) that also affect non-motorized volumes. On the other hand, studies analyzing many locations can (and may need to) include built environment and neighborhood socioeconomic factors that are related to spatial differences in walking and bicycling activity. Most studies address the nature of traffic count data (non-negative, positive skewness) by using non-linear regression methods, including log-linear or negative binomial regression (both of which use a natural log of the dependent variable).

Overall, most studies have found that poor air quality reduces walking and bicycling. Days and/or places with poorer air quality—higher concentrations of particulate matter (PM_{10} or $PM_{2.5}$), ground-level ozone (O_3), and/or wildfire smoke—had fewer walk/bicycle commuters (Zahran et al., 2008), lower odds of choosing active transportation modes (Li & Kamargianni, 2017), less bike-share usage (Kim, 2020), and lower bicycle/pedestrian/non-motorized volumes (Holmes et al., 2009; Chung et al., 2019; Doubleday et al., 2021). However, the effects were fairly modest—elasticities of around −0.12 to −0.18 (Holmes et al., 2009; Doubleday et al., 2021)—and stronger for more severe air pollution events or winter (Li & Kamargianni, 2017; Chung et al., 2019; Kim, 2020; Doubleday et al., 2021).

2.3. Summary and study objectives

In summary, many studies provide evidence to show how inclement weather affects walking and bicycling. Due to their exposure nature, active transportation modes seem to be more greatly influenced by weather conditions than enclosed modes. Temperature seems to have the strongest role, followed by precipitation (rain, snow), and finally other factors (e.g., wind, humidity); although, temperature and perhaps precipitation have non-linear impacts on non-motorized volumes. Bicycling may be more strongly influenced by the weather than walking, perhaps because more clothing or equipment is required to protect oneself from rain and cold, and greater physical activity/exertion makes one more sensitive to sun and heat. Relatedly, most research on (hourly, daily, and seasonal) temporal variations in activity identifies different utilitarian vs. recreational patterns (Nordback et al., 2019).

However, most studies of non-motorized shared-use trails have occurred in urban areas. Some evidence suggests that trail volume patterns differ in recreational areas compared to locations with more utilitarian traffic, everyday trip-making, and commuters. Specifically, utilitarian sites tend to have less monthly variation, while recreational sites may vary more month-to-month (Nordback et al.,

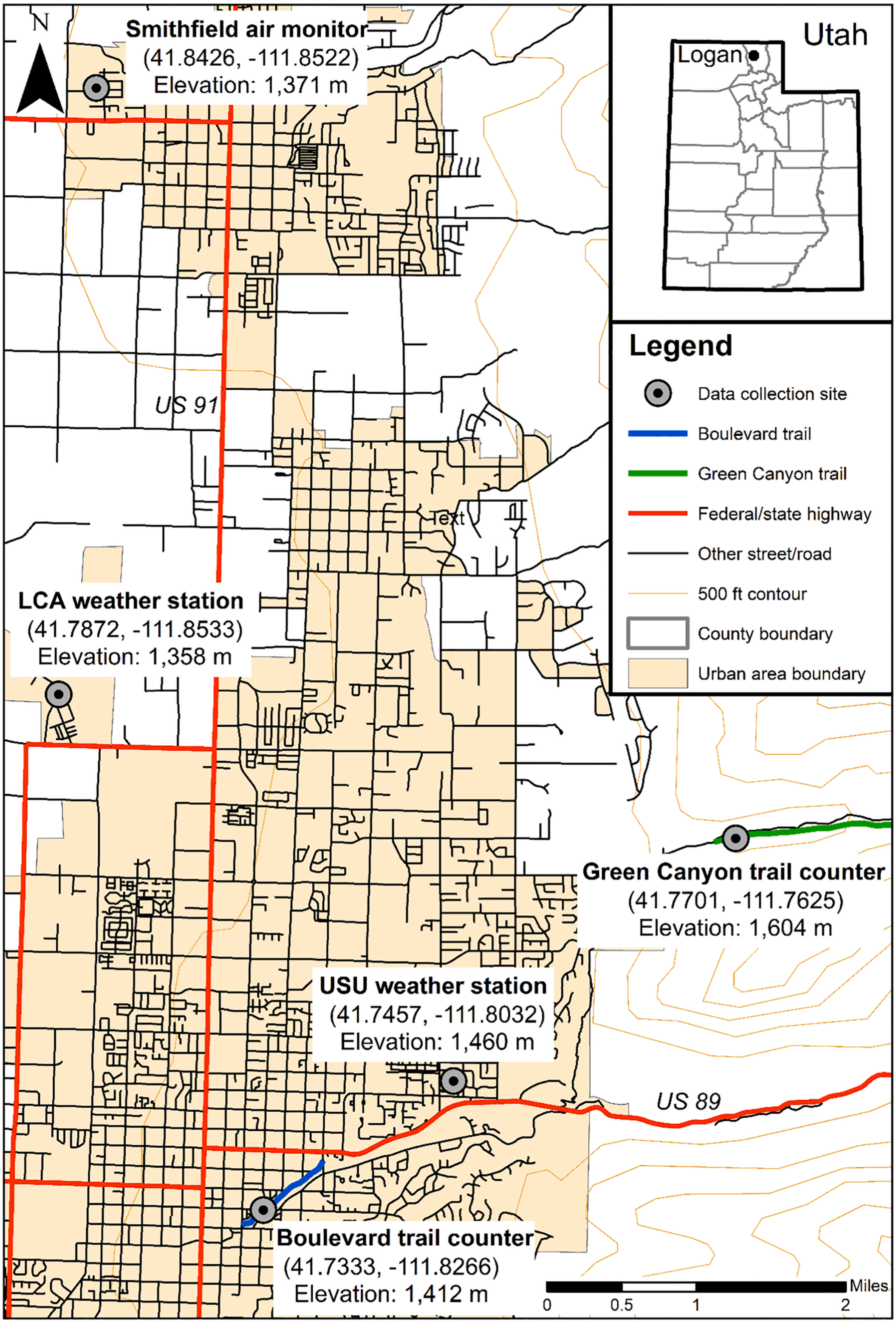

Fig. 1. Map of data collection sites.

2013). Similarly, a few studies have found that adverse weather seems to affect recreational travel/locations more than it does for utilitarian travel/locations (Nosal & Miranda-Moreno, 2014). This is likely due to the kinds of users each site experiences and the motivations for that travel. Trips in more urban locations are more likely to be for mandatory (work, school) purposes or errands, so they are less likely to be able to be rescheduled for days/times with more favorable weather. Also, because the journey-to-work is a more frequent (and sometimes habitual) activity, active commuters can better prepare for (and thus be less deterred by) adverse weather, such as through the use of protective clothing and equipment (e.g., rain jacket, boots, sun hat, umbrella). Conversely, trails in recreational areas are likely used for more discretionary purposes, such as leisure, sport, exercise, and other recreational active transportation. As the motivation for this kind of undirected travel is usually internal, and thus the travel experience is more central, inclement weather can adversely affect that experience and be a bigger deterrent to recreational trip-making. To improve our understanding of these relationships, more studies of how weather impacts non-motorized travel in both utilitarian and recreational locations are needed.

Turning now to air quality, only a handful of studies have measured the impact of area-wide air pollution on observed non-motorized travel behavior. Several look at aggregate behaviors across a region, including number of commuters (Zahran et al., 2008), bike-share usage (Kim, 2020), or mode choices (Li & Kamargianni, 2017). Those that focus on traffic counts have usually (with the exception of Holmes et al., 2009) studied only a few days at a time (Chung et al., 2019) or only tracked changes over the course of a few months (Doubleday et al., 2021). While most studies have found that non-motorized volumes are lower on days with poor air quality, the effects are fairly modest (elasticities of around −0.12 to −0.18) and may only appear when air pollution levels are very high (Doubleday et al., 2021) and attention is noted through public alerts to reduce or avoid strenuous outdoor activities (Air Now, 2020). More in-depth empirical evidence and analysis is required to validate these results about the impacts of air pollution on non-motorized travel in other locations.

Furthermore, additional research is needed to investigate whether the effects of area-wide air pollution affect non-motorized volumes in different trail locations. One might assume that (like for weather), utilitarian travel would be less affected by poor air quality than recreational travel, due to the latter's more discretionary nature. However, a study of motorized traffic volumes in Salt Lake City, Utah, US found a significant decrease within the core of the city (mostly utilitarian areas) and a significant increase within the edges of the city (mostly recreational areas) during days of poor air quality (Tribby et al., 2013), which the authors attributed to people "escaping" polluted mountain valleys for recreational opportunities in the mountains. Also, travelers in utilitarian locations may have more modal options (including public transit) to switch to (than travelers in recreational areas) in order to reduce their personal exposure to (actual or perceived) polluted air (Humagain & Singleton, 2021). Studying differences between utilitarian and recreational areas would increase knowledge in this area and potentially inform policy measures, as mentioned in the Introduction.

Based on this information, the specific objectives of this study are: (1) to identify associations of (a) inclement weather and (b) area-wide poor air quality with non-motorized traffic volumes, measured on shared-use trails; and (2) to compare the impacts of these factors on non-motorized travel in utilitarian vs. recreational areas. Informed by the literature review, we hypothesize that there is a reduction in non-motorized traffic volumes during both periods of poor air quality and inclement weather, and that the reductions are greater for recreational areas (at least for weather) due to a greater share of discretionary travel.

3. Data and methods

3.1. Data

Multiple time series were used to explore the associations of weather and air quality on non-motorized traffic volumes. Data were collected in and near the City of Logan, Utah, the largest city within Cache Valley, located in northern Utah and southern Idaho. Logan's weather is characterized by a continental climate with warm and dry summers and cold winters with moderate to heavy snowfall. The overall rainfall is low with highest values during spring, whereas the average wind speed is moderate to high. As Cache Valley is surrounded by tall steep mountains and is usually covered by snow in winter, temperature inversions are often experienced

Fig. 2. Images of typical sections of the two non-motorized trail locations.

during winter, creating favorable conditions for the accumulation of particulate matter (air pollutants) of size less than or equal to 2.5 μm (i.e. $PM_{2.5}$). The $PM_{2.5}$ concentration of 35μgm^{-3}, 24-hour National Ambient Air Quality Standard (NAAQS) standard, is often exceeded in the valley, leading to some of the worst non-fire-related air quality within the state of Utah and sometimes even in the nation too (Wang et al., 2015b). In addition to meteorological factors, gasoline and diesel motor vehicles, wood burning, and ammonia from agriculture (e.g., animal waste) are major local emissions sources of primary and secondary air pollutants forming $PM_{2.5}$ in winter (Malek et al., 2006). Like other parts of the western US, Cache Valley also experiences high pollution events from wildfire smoke. Thus, due to the varied climate and conditions for air pollution, Cache Valley offers a good opportunity to study these topics.

Three datasets used in this study were daily non-motorized traffic counts data, weather data, and air quality data. See Fig. 1 for a map depicting the data locations.

Two sites selected in this study with non-motorized travel data were the Boulevard Trail and Green Canyon locations. The Boulevard Trail is an approximately 0.8-mi (1.3-km) paved shared-use path. Located within the core of city, it connects downtown Logan with the main campus of Utah State University and is most commonly used for utilitarian travel. The Green Canyon location is a narrow natural surface trail located on National Forest land, and is used for year-round recreation (e.g., hiking, mountain biking, snowshoeing). Fig. 2 illustrates the urban and natural contexts of the two different sites. Non-motorized traffic count data for the Boulevard Trail and Green Canyon locations were obtained from permanent infrared counters, maintained by Cache County. The infrared counters are not able to distinguish modes, simply tabulating all trail users. While perhaps not entirely representative of the area's modest but growing trail network, data collection at these locations had been occurring for several years longer than at other sites in the region. The hourly counts of non-motorized traffic along the trails were aggregated into daily counts for use in the analysis.

In order to justify the selection and classification of the two non-motorized traffic count locations into utilitarian and recreational sites, Fig. 3 depicts the temporal variations in volumes across a typical week. Specifically, the figure plots the average proportion of total weekly volumes by hour and weekday. The Boulevard Trail exhibits clear AM and PM peaks on weekdays, with slightly lower traffic on weekends, indicating that it is likely used more for every-day utilitarian trips, including commuting. Conversely, the Green Canyon trail location experiences dramatically more Saturday activity, with Sundays being busier than weekdays, which is a common pattern of recreational travel. Similar methods and criteria were used by Nosal and Miranda-Moreno (2014) to identify the primary travel purpose of trails.

Weather data were obtained from the National Oceanic and Atmospheric Administration (NOAA) website for a weather station located at Utah State University (USU) and a local climatological data station located at the Logan-Cache Airport (LCA) (NOAA, 2020). The weather data used in the analysis were daily maximum and minimum temperatures, wind speed, snowfall amounts, snow depth, and rainfall. Air quality data were obtained from the US Environmental Protection Agency (EPA) website for a station located at an elementary school in Smithfield, Utah (US EPA, 2020). The air quality data considered in this study were daily mean $PM_{2.5}$ concentrations (μg/m^3), daily maximum 8-hour ozone concentrations (parts per million (ppm)) within a day, daily mean PM_{10} concentrations (μg/m^3), and daily maximum 1-hour NO_2 concentrations (parts per billion (ppb)) within a day, as well as the air quality index (AQI) values for $PM_{2.5}$, ozone, PM_{10}, and NO_2 separately and overall AQI (Air Now, 2020). All the datasets were prepared for the time

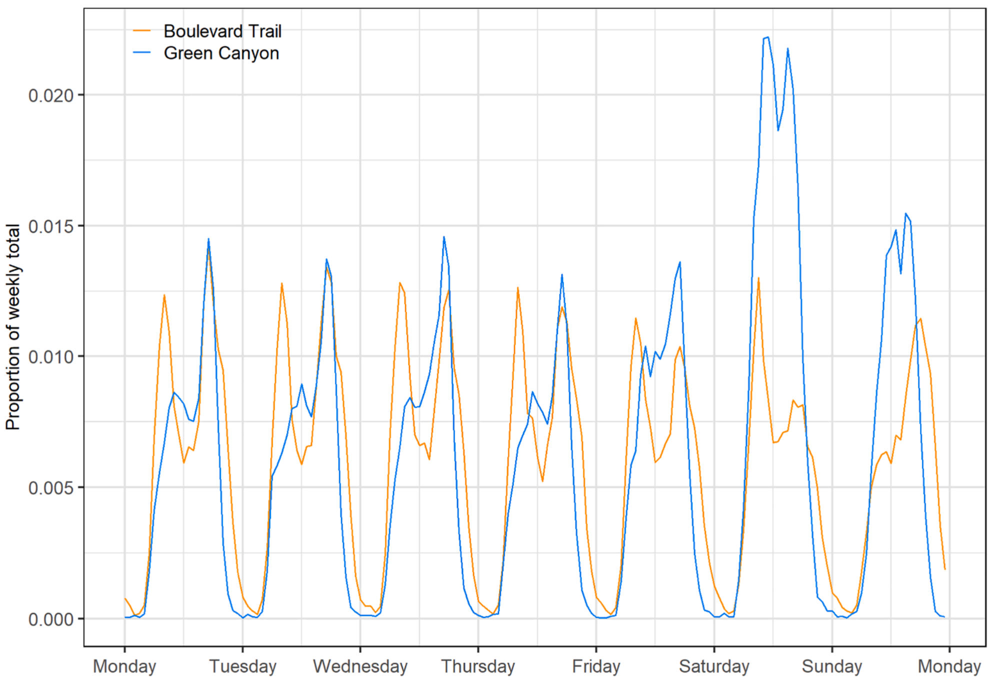

Fig. 3. Distribution of trail volumes by hour and day of the week.

period of June 2017 to February 2020 (as per the availability of non-motorized traffic counts); thus, the analysis period ends immediately prior to the COVID-19 pandemic (when worldwide changes in travel patterns were observed). The trail counters and the weather stations were all within 4-mi (6.4-km) of each other, while the air quality station was up to 7.5-mi (12.0-km) away from the furthest trail count location.

Before modeling, missing time series data had to be imputed. There were 33 and 6 missing observations in the Boulevard Trail and Green Canyon count datasets, respectively. Kalman smoothing was adopted to impute the missing time series data. The method utilizes linear quadratic estimation to estimate the missing values based on available observations and is considered a superior method for the imputation of univariate time-series data having strong seasonality (Moritz & Bartz-Beielstein, 2017). Similarly, the missing observations on snowfall (2), snow depth (6), maximum temperature (6), minimum temperature (8), daily maximum 8-hour ozone (concentration/air quality index (AQI)) (6), daily mean PM_{10} (concentration/AQI) (95), and daily maximum 1-hour NO_2 (concentration/AQI) (21) were also imputed by using Kalman smoothing. These imputations were carried out using the “imputeTS” package in R (Moritz & Bartz-Beielstein, 2017).

A description of the variables and their descriptive statistics are summarized in Table 2, while plots of the time series variables used in the analysis are shown in Fig. 4.

Other than the above mentioned dependent and explanatory variables, three sets of control variables were added to the analysis to account for other temporal variations in traffic. Months were converted into four seasons (spring, summer, fall, and winter), creating a “Season” categorical variable. In addition, days of the week were converted into a logical variable called “Weekend” where true represents weekends (Saturday and Sunday) and false represents traditional working days (Monday through Friday). Similarly, the list of holidays from June 2017 through February 2020 in the state of Utah were searched (Office Holidays, n.d.) and imputed as a new logical variable called “Holiday,” where true represents a holiday. In total, there were 35 holidays during the analysis period.

To avoid the issue of multicollinearity in the models, correlations between the explanatory variables were calculated and are presented in Table 3. High correlation between maximum temperature and minimum temperature was observed; including both variables directly into the model would cause statistical issues. But, instead of excluding one, both variables were included in the model by converting them into logical variables. Maximum thermal comfort temperature of 86°F and freezing temperature of 32°F were used to convert the continuous temperature variables into logical variables (maximum temperature > 86°F and minimum temperature < 32°F). Other than this, no strong correlations (>0.80) between other explanatory variables were observed. Yet, even though snowfall and snow depth were not highly correlated, they are related to each other by definition, and so only one variable was used in each analysis.

Then, different sorts of representations of air quality variables were tested for modeling. First, the concentrations of $PM_{2.5}$, ozone, and NO_2 were used as the continuous independent variables. Second, air quality index (AQI) values based on $PM_{2.5}$, ozone, and NO_2 concentration values were used. Concentration and AQI for PM_{10} were not considered in these two tests because they were strongly correlated with of $PM_{2.5}$ concentration and AQI. And lastly, overall AQI (worst among $PM_{2.5}$ AQI, ozone AQI, PM_{10} AQI, and NO_2 AQI) was used as a continuous independent variable representing the air quality of the day. The use of overall AQI was found to have good model fits, and some insightful relationships with dependent variable was observed, hence it was used in the final models. Over the analysis period of 1,004 days, ozone was the main pollutant contributing to overall AQI on 717 days, followed by $PM_{2.5}$ on 283 days; PM_{10}, and NO_2 were the worst pollutants on only 3 days and 1 day, respectively.

Finally, before fitting the models, the values of the dependent variables (counts at utilitarian and recreational sites) were inserted as the natural logarithm of non-motorized counts, where a unit change in weather or air quality was associated with some proportional

Table 2
Explanation of the variables and descriptive statistics (N = 1,004).

Variables	Explanation	Mean	Std. Dev.	Min.	Max.
Non-motorized counts					
Boulevard Trail	daily non-motorized counts on the Boulevard Trail	162.11	61.11	27.00	329.00
Green Canyon	daily non-motorized counts at Green Canyon	102.50	68.27	4.00	407.00
Weather related variables					
Rainfall	daily rainfall (inch)	0.05	0.14	0.00	1.70
Snowfall	daily snowfall (inch)	0.17	0.76	0.00	9.80
Snow depth	accumulated depth of snow (inch)	1.38	2.71	0.00	13.00
Maximum temperature	maximum temperature (°F)	59.84	22.15	15.00	99.00
Minimum temperature	minimum temperature (°F)	38.62	16.95	1.00	72.00
Wind speed	average wind speed (miles/hour)	4.47	2.54	0.38	18.29
Air quality related variables					
$PM_{2.5}$ [a]	daily mean $PM_{2.5}$ concentration (μg/m^3)	7.92	7.59	0.47	51.54
Ozone [a]	daily maximum 8-hour ozone concentration (ppm)	0.04	0.01	0.01	0.07
PM_{10} [a]	daily mean PM_{10} concentration (μg/m^3)	18.07	13.03	0.00	80.00
NO_2 [a]	daily maximum 1-hour NO_2 concentration (ppb)	12.22	7.90	0.70	40.00
$PM_{2.5}$ AQI [a]	AQI based on daily mean $PM_{2.5}$ concentration	33.96	23.82	3.00	147.00
Ozone AQI [a]	AQI based on daily maximum 8-hour ozone concentration	42.57	13.00	12.00	101.00
PM_{10} AQI [a]	AQI based on daily mean PM_{10} concentration	16.77	11.79	0.00	63.00
NO_2 AQI [a]	AQI based on daily maximum 1-hour NO_2 concentration (ppb)	11.43	7.38	0.00	38.00
Overall AQI	worst AQI index among $PM_{2.5}$ AQI, Ozone AQI, PM_{10} AQI, and NO_2 AQI	49.55	18.12	18.00	147.00

[a] Not included in final models.

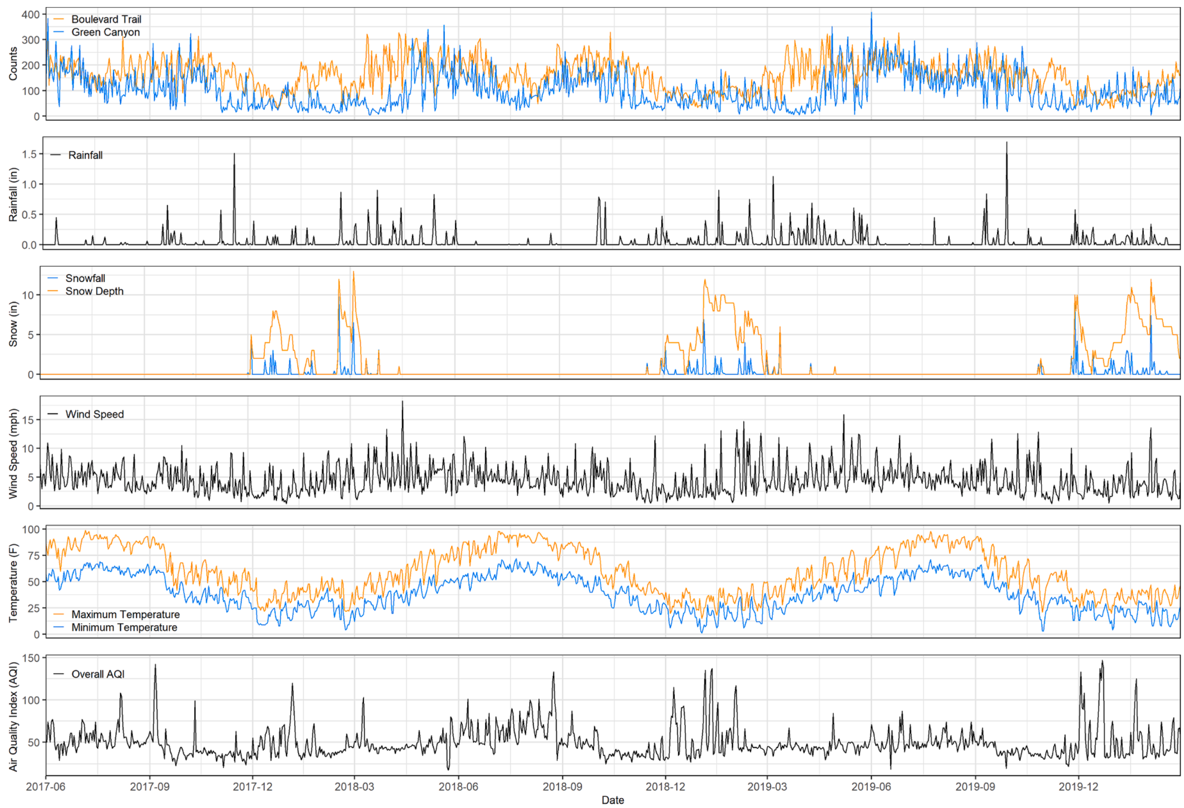

Fig. 4. Daily time series of non-motorized traffic, weather, and air quality.

Table 3
Correlations of independent variables.

#	Variable	1	2	3	4	5	6	7	8	9	10	11
1	Rainfall	1.00										
2	Snowfall	0.37	1.00									
3	Snow depth	0.11	0.46	1.00								
4	Maximum temperature	−0.12	−0.23	−0.59	1.00							
5	Minimum temperature	−0.08	−0.23	−0.60	0.97	1.00						
6	Wind speed	0.17	0.08	−0.14	0.29	0.31	1.00					
7	$PM_{2.5}$ AQI	−0.07	−0.08	−0.30	0.67	0.65	−0.30	1.00				
8	Ozone AQI	−0.29	−0.15	−0.07	0.45	0.41	0.25	0.00	1.00			
9	PM_{10} AQI	−0.15	0.03	0.41	−0.54	−0.57	−0.07	0.76	0.32	1.00		
10	NO_2 AQI	−0.14	−0.07	0.13	0.15	0.13	−0.49	0.46	−0.47	0.15	1.00	
11	Overall AQI	0.37	0.46	−0.59	0.97	0.31	−0.10	0.83	0.34	0.69	0.22	1.00

change in non-motorized counts. Not only did this improve the fit of models, but it is also more appropriate given that the traffic counts were non-negative and positively skewed.

3.2. ARIMA model with regression

The autoregressive integrated moving average (ARIMA) model is a broadly used statistical model for the analysis and forecasting of time series data (Shumway et al., 2000). An ARIMA model consists of three parts: an autoregressive part AR(p) of order p, a differencing part I(d) of order d, and a moving average part MA(q) of order q (Brockwell & Davis, 2002; Shumway et al., 2000). Two assumptions of time series data, stationary and non-autocorrelation, must be met before proceeding to any time series analysis (Brockwell & Davis, 2002; Shumway et al., 2000). Stationarity in non-stationary time series data can be attained by differencing the time series data by order d. Autocorrelation among the time series data can be handled by identifying the optimal number of terms for AR(p) and MA(q) using the partial autocorrelation function (PACF) and autocorrelation function (ACF) plots, respectively.

A typical ARIMA model of order (p, d, q) is shown in equation (1).

$$Y_t = \mu + \sum_{i=1}^{p} (\rho_i y_{t-i}) + \sum_{i=1}^{q} (\theta_i y_{t-i}) \quad (1)$$

A linear regression model can be developed based on the following equation (2).

$$Y_t = \beta_0 + \beta_i X_{i,t} + \in \quad (2)$$

Equations (1) and (2) can be combined and simplified to give equation (3), which is the equation for an ARIMA model with regression.

$$Y_t = \emptyset + \sum_{i=1}^{p} (\rho_i y_{t-i}) + \sum_{i=1}^{q} (\theta_i y_{t-i}) + \beta_i X_{i,t} + \in \quad (3)$$

A structural model with ARIMA disturbances can be used to fit the time series data under an ARIMA framework, where:
Y_t = time series of non-motorized counts.
$y_t = d^{th}$ difference of order Y_t. If d = 0, $y_t = Y_t$; if d = 1, $y_t = Y_t - Y_{t-1}$; and so on.
$\emptyset$ = constant term which combines the intercept terms of ARIMA model (μ) and linear regression model (β_0).
ρ_i = vectors of coefficients of autoregression parts.
θ_i = vectors of coefficients of moving average parts.
$X_{i,t}$ = vectors of time series of weather and air quality index variables.
β_i = vectors of regression coefficients.
β_0 = intercept term.
$\in$ = error term.

Time series regression analysis (using an ARIMA model with regression) was carried out with natural log of non-motorized counts as the dependent variables, and temporal, weather, and air quality related variables as the independent variables. Before this, the stationarity of the time series data (dependent variables) was accessed, and suitable transformations (by introducing a differentiating *d* term) were made. Moreover, the autocorrelation of the time series data was also diagnosed, and suitable remedies (by introducing the *p* and *q* terms) were applied. The modeling was done using the "forecast" package in R (Hyndman et al., 2020).

4. Results

The models were estimated separately for the two locations: utilitarian site (the Boulevard Trail) and recreational site (Green Canyon). As described earlier, non-stationarity and autocorrelation in the time series data were checked and rectified first. A trial-and-error approach was used to identify the best orders of (p, d, q), where the order yielding the ARIMA model with the lowest value of

Table 4
Results of ARIMA with regression model.

ARIMA with regression model	Utilitarian site (Boulevard Trail)				Recreational site (Green Canyon)			
	B	SE	z	p	B	SE	z	p
Dependent variable:	ln(counts at the Boulevard Trail)				ln(counts at Green Canyon)			
ARIMA(p,d,q)	(1, 0, 1)				(2, 0, 1)			
ρ_1	0.943	0.020	47.928	<0.001*	1.092	0.044	24.921	<0.001*
ρ_2	–	–	–	–	−0.109	0.041	−2.629	<0.009*
θ_1	−0.612	0.040	−15.117	<0.001*	−0.799	0.027	−29.600	<0.001*
Intercept	5.137	0.096	53.466	<0.001*	4.336	0.223	19.480	<0.001*
Temporal variables								
Season (base: Winter)								
Spring	0.249	0.122	2.049	0.040*	0.052	0.184	0.284	0.776
Summer	0.279	0.117	2.375	0.018*	0.219	0.206	1.064	0.287
Fall	0.151	0.103	1.467	0.142	0.126	0.164	0.768	0.443
Weekend	−0.200	0.016	−12.823	<0.001*	0.376	0.032	11.854	<0.001*
Holiday	−0.107	0.040	−2.652	0.008*	0.424	0.078	5.402	<0.001*
Weather related variables								
Rainfall	−0.270	0.057	−4.756	<0.001*	−1.035	0.108	−9.555	<0.001*
Snowfall	−0.026	0.011	−2.323	0.020*	–	–	–	–
Snow depth	–	–	–	–	0.054	0.014	3.746	<0.001*
Maximum temperature > 86°F	−0.043	0.033	−1.317	0.188	−0.035	0.063	−0.552	0.581
Minimum temperature < 32°F	−0.100	0.030	−3.298	0.001*	−0.125	0.058	−2.152	0.031*
Wind speed	−0.043	0.033	−1.317	<0.001*	0.054	0.014	3.746	<0.001*
Air quality related variables								
Overall AQI	−0.001	0.001	−2.141	0.032*	0.002	0.001	1.788	0.074~
# of observations	1,004				1,004			
σ^2	0.062				0.228			
Log-likelihood	−21.20				−675.01			
AIC	72.40				1382.02			
AICc	72.89				1382.57			
BIC	146.08				1460.61			

Notes: * indicates statistically significant at 95% confidence interval, ~ at 90% confidence interval (marginally significant), – not applicable.

sample-corrected Akaike Information Criteria (AICc) was considered as the best order. As a result, the best orders of (p, d, q) were identified as (1, 0, 1) and (2, 0, 1) for the utilitarian and recreational sites, respectively. Then, for these orders, ARIMA models with regression were fitted using the set of explanatory variables.

The results of the coefficient estimates of the log-linear models of trail counts for the utilitarian and recreational sites are presented in Table 4. To aid in the interpretation of the absolute and relative magnitudes of the estimated relationships, several other values were calculated and are shown in Table 5. The marginal effect at the mean ($B\bullet\overline{Y}$) represents the unit change in the dependent variable when the independent variable is changed by one unit, evaluated at the mean value of the dependent variable (162.1 for Boulevard Trail, 102.5 for Green Canyon). To avoid having to specify a value at which to evaluate this change, another calculation ($100\bullet(e^{B}-1)$) represents the percentage change in the dependent variable when the independent variable is increased by one unit; for categorical variables, this represents moving from the base category to the category of interest. For continuous variables, the point elasticity ($B\bullet\overline{X}$) represents the percentage change in the dependent variable when the independent variable is changed by one percent, evaluated at the mean value of the independent variable. (These calculations assume all other independent variables remain the same.).

The results of the time series regression models of non-motorized counts at the two sites, utilitarian and recreational, were found to be different in terms of statistical significance, coefficient estimates, and estimated effects of temporal, weather, and air quality related variables. While all seasons had more traffic than winter months, the differences were only statistically significant for spring and summer at the utilitarian site. Spring and summer months on the Boulevard Trail experienced 28% and 32% more traffic than winter months, on average. Summer days were also 24% busier than winter days at the Green Canyon site, but the different was not statistically significant. Weekends and holidays were found to have statistically significant but differing effects on non-motorized counts at the two locations. At the utilitarian site, weekends had 18% less and holidays had 10% less traffic than weekdays, while at the recreational site, weekends had 46% more and holidays had 53% more traffic than weekdays, on average.

The impacts of weather at the two locations differed depending on the location and the weather variable. Rainfall was a deterrent to non-motorized traffic at both sites, but the effect was stronger at the recreational site than at the utilitarian site. At mean values of rainfall (0.05 in.), trail use was fairly inelastic: −0.013 for the Boulevard Trail and −0.050 for the Green Canyon location. However, sensitivity to rain increased with rainfall: at 0.5 in. (experienced a few times per year), the elasticities were −0.135 for the utilitarian site and −0.518 for the recreational site. Going from no rain to 1 in., the models predict that trail traffic would decrease by 24% for the Boulevard Trail and by 64% for the Green Canyon location. Snowfall appeared to decrease non-motorized traffic at the utilitarian site: the elasticity was −0.004 (at mean 0.17 in.), and there was 2.6% less traffic for each additional inch of snowfall. However, higher depths of snow seemed to increase non-motorized traffic at the recreational site: the elasticity was +0.009 (at mean 1.38 in.), and there was 5.5% more traffic for each additional inch of snow depth. Days with very warm and very cold temperatures saw less trail traffic, but the differences were not statistically significant for warm high temperatures. When low temperatures were below 32°F, the Boulevard Trail saw 10% less traffic, while the Green Canyon location had 12% less traffic. Elasticities of non-motorized trail traffic to wind speed (at mean 4.5 miles/hour) were negative (−0.056) for the utilitarian site but positive (+0.090) for the recreational site.

Different effects were also observed for the impacts of air quality. Non-motorized traffic was generally inelastic to overall AQI (at mean 49.6, right at the border between “Good” and “Moderate” air quality); however, a 1% increase in AQI would decrease traffic at the utilitarian site by 0.06% (elasticity −0.056) but increase traffic at the recreational site by 0.09% (elasticity +0.090). At an AQI of 100 (the border between “Moderate” and “Unhealthy for Sensitive Groups”), elasticities were greater but still fairly inelastic: −0.11 for the utilitarian site and +0.18 for the recreational site. The model predicts that a 50-point increase in AQI (equivalent to moving between each category/color) might decrease traffic for the Boulevard Trail by 5.5% but increase traffic for the Green Canyon location by 9.6%. It should be noted that the coefficient on AQI at the recreational site was only marginally significant ($p < 0.10$).

Table 5
Results of elasticity and marginal effects for both sites.

Variables	*Utilitarian site (Boulevard Trail)*			*Recreational site (Green Canyon)*		
	Marginal effect at the mean ($B\bullet\overline{Y}$)	*% change* ($100\bullet(e^{B}-1)$)	*Elasticity* ($B\bullet\overline{X}$)	*Marginal effect at the mean* ($B\bullet\overline{Y}$)	*% change* ($100\bullet(e^{B}-1)$)	*Elasticity* ($B\bullet\overline{X}$)
Season (base: Winter)						
Spring	40.4*	28.3*	–	5.3	5.4	–
Fall	24.4	16.3	–	12.9	13.4	–
Summer	45.2*	32.1*	–	22.4	24.5	–
Weekend	–32.4*	−18.1*	–	38.5*	45.6*	–
Holiday	−17.4*	−10.2*	–	43.4*	52.8*	–
Rainfall	−43.7*	−23.6*	−0.013*	−106.1*	−64.5*	−0.050*
Snowfall	−4.3*	−2.6*	−0.004*	–	–	–
Snow depth	–	–	–	5.5*	5.5*	0.009*
Max. temperature > 86°F	−7.0	−4.2	–	−3.6	−3.4	–
Min. temperature < 32°F	−16.2*	−9.5*	–	−12.8*	−11.7*	–
Wind speed	−3.9*	−2.4*	−0.109*	−5.2*	−4.9*	−0.227*
Overall AQI	−0.2*	−0.1*	−0.056*	0.2~	0.2~	0.090~

Notes: * indicates statistically significant at 95% confidence interval, ~ at 90% confidence interval (marginally significant), – not applicable.

5. Discussion

The results offer insights into the utilization of non-motorized trails and the behavioral responses of active transportation mode users to inclement weather, poor air quality, and other temporal variables. As expected, on weekends and holidays there was less non-motorized traffic at the utilitarian site, and more non-motorized traffic at the recreational site. The more natural recreational site seems to attract users on their days off. Summer was the busiest seasons (and winter the quietest) at both locations—in keeping with the climate of northern Utah (warm and dry summers, cold and snowy winters)—although the lack of significance could also be explained by significant weather effects which comprise much of the otherwise seasonal effects.

In keeping with most past research (e.g., Böcker et al., 2013; Liu et al., 2017), inclement weather was found to reduce non-motorized traffic volumes, especially at the more utilitarian location in the city. As expected by the exposed nature of active transportation modes, non-motorized traffic was lower at both locations on days with more rainfall and freezing low temperatures. Active travel was also deterred by greater snowfall and higher wind speeds, at the utilitarian site only. This could indicate a behavioral shift towards motorized modes (car and transit) when conditions make walking/bicycling treacherous (like snow) and less enjoyable (like rain).

It is also notable that non-motorized traffic at the recreational site was more greatly affected than at the utilitarian site (larger negative coefficients) by low temperatures and especially by rainfall. This is consistent with the Green Canyon location accommodating recreational travel, which is more discretionary in nature and can be more easily cancelled or rescheduled (than less-discretionary or mandatory travel like commuting) due to adverse weather conditions. At first, it was surprising to see higher non-motorized counts during days with greater snow depth and stronger winds at the recreational site. Upon reflection, the impact of snow might be due to the increased interest of people to ski, snowshoe, fat-tire bike, or play snow games in winter at recreational sites like Green Canyon. Also, the trail there is fairly sheltered by trees and the canyon walls, which might make it relatively more attractive for recreation during high wind events.

In terms of air quality related variables, as the overall AQI increased, non-motorized traffic at the utilitarian site was reduced, although the response—at an AQI of 50, the border between "good" and "moderate"—was fairly inelastic: −0.056, less than half of what has been found in previous research (Holmes et al., 2009; Doubleday et al., 2021). This may be a result of the more substantial air pollution observed in other locations, such as wildfire smoke (Doubleday et al., 2021); when considering an AQI of 100 (between "moderate" and "unhealthy for sensitive groups"), the elasticity (−0.11) was more comparable. Still, this study's finding suggest that air pollution has a measurable but small impact on utilitarian active transportation.

Interestingly, non-motorized traffic at the recreational site actually increased with greater air pollution levels (elasticity +0.090), albeit the modeled sensitivity was also inelastic and only marginally statistically significant. It is possible that people seeking active outdoor recreation were attracted to the Green Canyon natural forest location to escape air pollution in the city. Also, wintertime inversions can trap pollutants at lower elevations in the mountain valleys, so the Green Canyon trail can be (but is not always) above the inversion layer. While perhaps very specific to the unique conditions and locations examined in this study, this intriguing difference has been corroborated in a study of motor vehicle traffic volumes in urban Salt Lake City, Utah: Tribby et al. (2013) saw volumes increase at the urban edge near recreational areas during poor air quality days, which they attributed to people escaping pollution and seeking higher-elevation outdoor recreation opportunities.

Altogether, the varying findings regarding weather and air quality at the two locations support this study's contribution of studying differences between utilitarian and recreational areas. Knowledge of the degree of sensitivity of utilitarian non-motorized travel to inclement weather—rainfall, snowfall, wind speed, and cold temperatures—could suggest a need for programs and policies that could encourage and support wintertime walking and cycling. For instance, workshops offering equipment and tips for winter bicycling, or policies prioritizing snow clearance of non-motorized pathways, could help to sustain utilitarian active transportation through the winter season. Alternatively, providing increased transit services during dates of inclement weather might help active commuters to ease their travel. Recreational area managers could also use the knowledge that trail users seek snow in winter and are more likely to visit on weekends and holidays to prioritize maintenance efforts (e.g., parking, restrooms, trails).

Regarding air quality, several soft policy measures—e.g. programs such as TravelWise (UDOT, n.d.), Breathe Utah (Breathe Utah, 2020)—have already been implemented within Utah to reduce air pollution. These programs raise awareness of air quality issues, alert the public about days with poor air quality, and encourage travelers to reduce their exposure (and contribution) to air pollution. Reduction in non-motorized travel at the utilitarian site on days with higher AQI could be an indicator of the relative effectiveness of existing soft policy measures in encouraging travel behavior change and mitigating air pollution's negative impacts. However, the relatively inelastic nature of non-motorized traffic suggests that existing policy measures may not able to substantially reduce active transportation mode users' air pollution exposure, especially in recreational areas. Policymakers and public health/transportation agencies should continue studying the effectiveness of existing policy measures and consider additional actions.

That said, there are many health benefits to physical activity and active transportation that may mitigate or even outweigh the negative health impacts of increased air pollution exposure. In fact, in studies evaluating scenarios of even modest increases in population active transportation levels, the disability adjusted life years gained from increased physical activity are often orders of magnitude more than those lost from greater air pollution exposure (Mueller et al., 2015; Taino et al., 2016), except in the most extreme cases. In fact, the AQI guidelines (Air Now, 2020) recommend reduced outdoor exercise for everyone (outside of sensitive groups) only when the AQI reaches the "unhealthy for everyone" level (AQI > 150). Thus, policies should be implemented with care to avoid messaging that discourages healthful active transportation when the air quality is only "moderate" (AQI 51–100).

This study had number of shortcomings that could be addressed through additional research. First, only one utilitarian and one recreational site was studied due to the unavailability of data. Although the findings were generally consistent with the literature, some effects were likely specific to this study's particular locations. Additionally, the utilitarian site was likely used partially for recreation as well, thus obscuring greater differences between types of trails. Studying more sites, including those outside of Utah, could strengthen the correlations and improve the generalizability of the results.

Second, by relying on automated counts, this study could not measure individual or trip characteristics, so it could not determine who may be more or less sensitive to adverse weather or air pollution. There may be differences by age, gender, income, education, attitudes towards air quality, and/or awareness of air pollution that underlie the aggregate trends observed in this study. Future work should consider multiple methods of data collection, including surveys and/or interviews, in order to better understand these variations in the population. Third, by relying on total counts of all trail users, this study could not distinguish bicyclists from pedestrians. In reality, it is likely that walking and bicycling are affected differently by weather and perhaps air quality conditions. As noted in the earlier literature review, bicycling may be more strongly influenced by inclement weather and air pollution than walking, given higher speeds, greater activity, and increased inhalation; however, this is an important area for future research to investigate.

Fourth, the impacts of weather and air quality on active transportation may occur on a time scale different than that used in this study (a particular day). If rain or snow is periodic during a day, people may be able to shift their walk or bicycle trips to a different time-of-day, although such time shifting may be more possible for recreational than utilitarian travel. Also, the impacts may be different before vs. during vs. after a snowfall, for example. There may be forecast effects, where forecasts of rainfall or high levels of area-wide air pollution may depress active transportation even if those conditions fail to materialize. All of these possibilities suggest the use of shorter time durations (e.g., hourly data) as well as testing time lags in the models. Fifth, not a single day during the study period surpassed the "unhealthy" limits of $PM_{2.5}$ and ozone concentrations (AQI $>$ 150), so the impacts of extreme air pollution could not be captured. Replicating this study for a longer time period or in a location unfortunate enough to have experienced high levels of air pollution (such as from nearby wildfire smoke) might find increased sensitivity of non-motorized travelers. It was also not possible in this study to determine exactly how and why non-motorized trail counts decreased (or increased) on days with poor air quality. Additional research into behaviors and perceptions may be able to tell if people notice pollutant concentrations or AQI levels or if they simply detect air pollution visibly (or through smell), and to determine the effectiveness of air quality information (e.g., websites, smartphone apps, news/radio messages) and awareness campaigns. It is hoped that this initial study into the effects of weather and air quality on non-motorized trail usage in Logan, Utah, offers additional understanding and insights into improving the health and well-being of active travelers.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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