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The Effect of Weather on Pedestrian Activity at Signalized Intersections in Utah

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THE EFFECT OF WEATHER ON PEDESTRIAN ACTIVITY AT SIGNALIZED INTERSECTIONS IN UTAH

by

Ferdousy Runa

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ABSTRACT

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Utah State University, 2020

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A deeper understanding of how weather variables impact pedestrian volumes is important, as active travelers (pedestrians and bicyclists) are an essential part of a sustainable transportation system. Pedestrian data are limited for investigating the impacts of weather on walking levels, with most studies having data at only a couple of locations. Pedestrian actuation data (from push-buttons at traffic signals) overcomes this limitation. The Utah Department of Transportation (UDOT) archives pedestrian push button press data for use in its Automated Traffic Signal Performance Measures (ATSPM) system.

In this study, pedestrian actuation data was used as a proxy for pedestrian signal activity and weather data was collected from the National Oceanic and Atmosphere Administration (NOAA). Using 15 months of daily time series data in Cache County, Utah, the impacts of weather on pedestrian signal activity were examined at 49 signalized intersections, using a log-linear time series regression analysis with categorical step-wise weather variables. The findings revealed that snow depth had the most frequent negative effect on pedestrian activity. Snowfall (> 0.6 inches) also tended to have negative impacts when significant. Very hot maximum temperatures (≥ 90ºF) were associated with lower

pedestrian activity at around one-third of signals. Very low minimum temperatures (< 20ºF) were also associated with lower pedestrian activity. Precipitation had a negative effect on pedestrian activity levels, but at only a few signals. The study's key findings offer implications for multimodal transportation planning (winter maintenance, shade trees, etc.) and traffic signal operations.

(106 pages)

PUBLIC ABSTRACT

The Effect of Weather on Pedestrian Activity at Signalized Intersections in Utah

Ferdousy Runa

The weather has a significant influence on pedestrian activity. Profound knowledge and research can identify *how* weather variables impact and *why* people change their travel patterns. This study aims to assess the relationship of weather (snowfalls, snow depth, precipitation, maximum and minimum temperature) with pedestrian activity at 49 signalized intersections in Cache County, Utah. This study uses pedestrian actuation (push-button) data as a proxy for pedestrian activity and collects weather data from the National Oceanic and Atmosphere Administration (NOAA).

Using 15 months of daily time-series data, this study applied log-linear time series models in the analysis. To account for non-linear effects, categorical step-wise weather variables were used. The findings reveal most of the signals have significant effects on the weather on pedestrian activity. Snow depth, snowfalls, and the maximum temperature had the largest effects at most of the locations. Besides, very cold temperatures (< 10ºF) were negatively associated with pedestrian activity at some locations. Precipitation had a negative effect on walking levels, but at only a few signals. The relationship between weather and walking is non-linear rather than linear. Also, pedestrian activity is affected more by weather in urban areas compared to suburban areas. These findings have implications in multimodal transportation planning (winter maintenance, shade trees, etc.) and traffic signal operations.

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Ferdousy Runa

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LIST OF SYMBOLS AND NOTATION

ATSPM	Automated Traffic Signal Performance Measures
UDOT	Utah Department of Transportation
NEMA	National Electrical Manufacturers Association
NOAA	National Oceanic and Atmosphere Administration.
USU	Utah State University

CHAPTER 1

INTRODUCTION

1.1 Problem Statement

Weather is expected to have a greater impact on active mode users than motorized users as people walking and bicycling are completely exposed to the outdoor environment and simultaneous weather events. Active travelers are also exposed to the elements for a comparatively longer time due to their slower travel speeds. After a big snowstorm, pedestrians may stop walking because of icy surfaces or even shift to another mode (automobile or public transit). Warmer weather may encourage walking, but extremely hot weather may discourage it. A deeper understanding of *how* weather variables impact active modes is important. Active modes are the key elements of a sustainable transportation system that can reduce traffic congestion and motor vehicle emissions, including initiatives to reduce driving and promote the use of public transit.

A profound knowledge of how weather influences walking levels can provide insights for planners concerning ways to alleviate the negative impacts of adverse weather. Understanding which weather variables force pedestrians to forego walking is crucial to know for redesigning or developing pedestrian infrastructure and prioritizing pedestrian investments. People may still make decisions to walk on extreme days if they are given sufficient pedestrian facilities (e.g., providing shade over the sidewalk) for overcoming the adverse effects of weather.

As will be discussed in the Background section below, some research has been done to identify the weather impacts on non-motorized activity: for example, walking activity at

a single location (Aultman-Hall et al., 2009; Attaset et al., 2010), cycle ridership at five automatic counting stations (Mirando-Moreno & Nosal, 2013) or both active modes on two trails (Zhao et al., 2019; Singleton et al., 2019). Most previous studies collected pedestrian data either a single location or only few locations. It might not be reasonable to apply the results of weather impacts from one or some particular locations to other places. Also, a different weather impact may be revealed if pedestrian volumes are collected at multiple locations or over a longer time period.

Research on weather variables and pedestrian activity are limited by pedestrian data collection methods. There are ways methods of obtaining pedestrian count data that can be classified into manual and automated methods. Manual counts can effectively collect data at many locations but are most appropriate for relatively short durations (FHWA, 2016). Automated methods are best for long-duration counts (FHWA, 2016; Ryus et al., 2014), but their larger up-front costs make it difficult to study many locations. Due to a deficiency of existing methods, the impacts of weather on pedestrian volumes were not explored in many places over long periods. A thorough understanding of how weather influences walking levels at multiples locations is needed.

To fill this gap, this study uses a novel big data source that is available at many intersections over long time periods: pedestrian push button data from traffic signals. Traffic signal controllers manage the safe operation of signalized intersections and their signal control infrastructure, such as vehicle and pedestrian indications/displays. Smaglik et al (2007) developed a general method and module for automatically logging time-stamped event data from traffic signal controllers. These data can then be archived and

turned into useful signal performance metrics through the Automated Traffic Signal Performance Measure (ATSPM) system.

In summary, to our knowledge, only one study has investigated the influence of weather on pedestrian signal activity (from an ATSPM system) in a time-series framework (Day et. al., 2016), and only at a single intersection. While the study of weather and its impact on pedestrian movement is not new, the use of this unique data set is helpful to develop a profound understanding of pedestrian behaviors and travel patterns.

1.2 Research Questions

The study aims to answer the following questions to quantify the impacts of weather on pedestrian activity:

- Does the weather (snowfall, snow depth, precipitation, maximum and minimum air temperature) affect levels of pedestrian activity?
- Which weather variables have the strongest influence on walking?
- Are relationships between weather and walking linear or non-linear?
- Do the weather variables have different effects on walking in urban and suburban areas?

These research questions are addressed through an approach involving novel data collection and different modeling methods. The conceptual diagram shown in Figure 2.1 provides the overall approach.

1.3 Document Organization

This thesis contains six chapters. Chapter 1 contains a brief introduction and presents the motivation, scope, and objectives of the research program. Chapter 2 gives an overview of previous research works. Chapter 3 presents the required data and data collection method for this study. Chapter 4 discusses the methodology used to carry out the analyses presented in this thesis. Chapter 5 presents the study results. Finally, Chapter 6 draws conclusions from this research and discusses future work on this topic. The details of pedestrian data collection locations and results at individual intersections are included in the appendices.

CHAPTER 2

LITERATURE REVIEW

Some work has been done to identify the impacts of weather on walking and bicycling behavior. This chapter reviews relevant literature to summarize existing works, and notes that data collection has been a limitation.

A literature search was performed using a few search terms (e.g., "pedestrians" or "walking", "bicycling", and "weather") on Google Scholar. The filtering of results involved reviewing relevant titles, reading abstracts, then finally downloading and reading papers in detail. Besides, when I found that a paper was relevant, I looked at the reference lists and figured out relevant papers (Google Scolar or Goolge) those were cited. This process was helpful to get an appropiate number of papers to review. Continuing this process, I found 20 relevant papers (Table 2.1). Finally, I reviewed only those relevant papers in this section.

2.1 Impacts of Specific Weather Variables on Pedestrians and Cyclist Activity

2.1.1 Air Temperature

Air temperature, an easily and frequently measured weather variable, was evaluated to identify some impacts on active modes. The effects of temperature are different for walking and cycling and vary based on locations. For instance, temperature above 80ºF decreased pedestrian activity (Attaset et al., 2010; Singleton et al., 2019); however, in terms of minimum temperature, temperature (< 30ºF) in Utah and California (< 50ºF) were seen as negatively associated with the walking activity. In Doha, Qatar, temperature between

20-50ºC (Shaaban & Muley, 2016) and above 30ºC – below 20ºC tended to reduce pedestrian activity in Montreal (Miranda-Moreno & Fernandes, 2011). It may not be always true that cold temperature reduces walking activity. In Doha, walking activity increased in winter and decreased in summer (Shaaban et al., 2018) where the exact opposite relationship was found in Toronto (Li & Fernie, 2010). A plausible explanation for this may be that Doha experiences a very hot summer (May-Sep) with average daily temperature above 37°C but mild cold winter (average daily temperature below 25°C). As the winter season stays only December to March, people feel comfortable walking particularly during that season.

In summary, the effects of temperature on walking and cycling are nonlinear. Although it is hard to identify a specific threshold, extremely hot and cold temperatures are seen to decrease and moderate temperatures to increase active transportation.

2.1.2 Rain

Most studies identified a negative relationship between precipitation and active transportation. Looking at the differences among different study locations, precipitation of any amount tended to yield lower walking activity in the USA (Attaset et al., 2010; Aultman-Hall et al., 2009), Canada (Miranda-Moreno & Lathi, 2013) and a few cities in Europe (Minting et al., 2012), and bicycle commuting in Vermont (Flynn et al., 2012) and Austria (Brandenburg et al., 2007).

Some previous works quantified the impacts of rainfall on non-motorized counts on trails (Zhao et al., 2019; Singleton et al., 2019); bike share (Lieshout & Strijkstra, 2015; Gebhart & Noland, 2014) and bike commuting (Spencer et al., 2013). Bicycle commuters

found to be affected more by rainfall than pedestrians (Miranda-Moreno & Lathi, 2013). Even, precipitation in the form of showers reduced bicycle commuting twice than walking (Saneinejad, 2012). Besides, bicycle commuters shifted to another mode after the morning rain (Mirando-Moreno & Nosal, 2011). The impacts of shower and rainfall appeared different on active transportation. Zhao et al. (2019) found that walking was more sensitive than cycling on Elliott bay trails in Seattle, Washington.

Some studies investigated the difference in precipitation impacts on weekdays vs. weekends. Rainfall had a greater effect on pedestrian volumes (Attaset et al., 2010) and bike trips (Lieshout & Strijkstra, 2015) on weekends (especially on Sundays for bike trips). Pedestrians may make more discretionary trips on weekends. This may mean that the weekday is less affected by the weather. Moreover, moderate rainfall (5.0 mm/h) was adversely connected with weekend trips (Vanky et al., 2017). In Vermont, precipitation was seen to have negative associations with pedestrian volumes on weekdays and Saturdays except for Sunday (Aultman-Hall et al., 2009). Precipitation reduced average pedestrian volumes by 13% on weekdays and Saturday (except Sundays or holidays). Also, the lagged effects of rainfall had a significant influence on active transportation. Significant negative anticipatory effects of rainfall were found cycling and walking off the previous 1h (Zhao et al., 2019).

Overall, precipitation reduces walking activity and bicycling commuting at different locations. Some contrasting results reveal the difference in active transportation on weekdays vs weekends. Also, people change their modes (maybe cycling to walking) on a rainy day.

2.1.3 Humidity

When investigated, most of the previous studies found that humidity (or relative humidity) was negatively associated with walking activity (Zhao et al., 2019) or bicycling (Gebhart & Noland, 2014). In most cases, the relationship was linear; however, non-linear effects were found on bike share with stronger effects on weekends (Lieshout & Strijkstra, 2015). Besides, Miranda-Moreno & Lathi (2013) showed a non-linear effect on pedestrian flows during both the week and weekend in Montreal. However, some studies didn't find any significant effect of humidity on active modes (Shaaban & Muley, 2016; Flynn et al., 2012). Humidity also had stronger effects on weekends. Looking at the differences, the impacts of humidity appear to have either linear or non-linear with a negative association most of the time at different locations.

2.1.4 Wind Speed

Similar to other weather variables, wind speed has been reported to play an important role in active modes. Wind speed negatively affected pedestrian volumes (Miranda-Moreno & Lathi, 2013; Attaset et al., 2010). Also, the wind has been found to negatively affect bicycle commuting and decrease the number of trips in Vermont (Flynn et al., 2012; Spencer et al., 2013), Washington, D.C. (Gebhart & Noland, 2014), London (Lieshout & Strijkstra, 2015), and Melbourne (Nankervis, 1999). The relationship was not linear always; however, Zhao et al. (2019) found a non-linear relationship on active modes (walking and cycling) with wind flow up (0-1 km/h). Then active transportation gradually declined with a gentle breeze (2-6 km/h) and increased when wind speeds at 7-8 km/h. Lieshout & Strijkstra (2015) confirmed the non-linear relationship of wind speed with the

number of bike trips in their study in London. Besides, they found that if the wind speed was stronger than 15 km/h, the negative marginal effect was less strong. Cyclists with faster travel tend to be more sensitive to higher wind speed than pedestrians. On the contrary, some studies in Vermont (Aultman-Hall et al.,2009), Doha, Qatar (Shaaban & Muley, 2016), Montreal (Mirando-Moreno & Nosal, 2011) found no significant relationship of wind speed on active travel. Overall, wind speed may effect (either linearly or non-linearly) walking activity and bike commuting.

2.1.5 Snow/Ice

Snow only occurs in a subset of the regions evaluated in the previously mentioned studies. A few studies showed that snow/ice decreased pedestrian activity in Toronto, Canada (Li et al., 2013; Li & Fernie 2010). Snowfall also reduced cycling activity in Vermont, USA (Spencer et al., 2013; Flynn et al., 2012) and Washington, DC (Gebhart & Noland, 2014). Li et al. (2013) found differences between young, middle-aged, and older respondents in winter. Snowy and/or icy ground surface kept older aged people at home. Older adults may be more concerned about icy sidewalk and crosswalks. It is clear that snowy/icy road surface makes some people decide not to walk or cycle.

2.2 Limitations of Existing Research

The above-mentioned studies identified the effects of weather at a single location (specific one sidewalk) (Aultman et al., 2009), a few sidewalks (Attaset et al., 2010; Miranda-Moreno & Lathi, 2013), a few streets (Shaaban & Muley, 2016; Shaaban et al., 2018), or one intersection (Li & Fernie, 2010). However, one or a few locations cannot

fully explain the weather effects on either pedestrian or cyclist, and results many not be generalizable.

Various data collection methods — video cameras (Shaaban & Muley, 2016; Montigny et al, 2016; Li & Fernie, 2010; Brandenburg et al., 2007), manual and infrared counters (Aultman-Hall et al., 2009; Miranda-Moreno & Lathi, 2013; Attaset et al., 2010), inductive loops (Mirando- Moreno & Nosal, 2011), Mobile app (Vanky et al., 2017), and interviews or questionnaire surveys (Li et al., 2013; Spencer et al., 2013) — were used by most of the researchers. However, video cameras and manual counts need more human effort to watch and count pedestrians. Inductive loops or infrared counters are expensive for the long-term period. Getting big data is not possible from an interview or questionnaire survey. To identify the impact of the weather on pedestrian volume, it is important to collect data over longer time periods. Manual count and video recording are not possible for a longer period at many different locations.

This study attempts to address these limitations (especially data/location) by using a relatively big data source that is relatively ubiquitous in both time and space (available 24/7 at many intersections), pedestrian push button data from traffic signals—contained within one state's (Utah's) ATSPM system—as a proxy measure of pedestrian activity. Every time a person presses a push-button or makes a pedestrian call to cross the street, this activity is recorded, and the Utah Department of Transportation (UDOT) archives these traffic signal pedestrian actuation data for use in its ATSPM system. The use of pedestrian signal actuation data is a potentially rich source of information about levels of pedestrian activity.

Table 2.1 Summary of previous works

Studies	*Geography*	**Number/ type of locations**	*Data Source*	*N (valid response)*	*Mode*	*Time/duration*	*Weather variables*	*Methods*
Singleton et al., 2019	Logan, Utah	1 shared path, two trails	Infrared detector	542	ped	Jan 2017- Jun 2018	Temp [70°F –80°F (+); low (-)], prcp (-)	TSR, LTR
Vanky et al., 2017	Massachusetts & California	Boston & San Francisco	Mobile app application	2,47,814 trips (Boston),2,57,697 trips (SF)	Ped	May 15, 2014- May 1, 2015	**Temp (+),** humidity (-), wind [SF (+); Boston (-)], prcp (-), cloud cover (+)	LLR
Shaaban et al., 2018	Doha, Qatar	Different streets of Al Sadd neighborhood	VC	1454(winter) 630(summer) 960(spring)	ped	2 days in Mar, jul and Aug (2014)	Winter **temp** (+), summer **temp** (-)	BLR
Shaaban & Muley, 2016	Doha, Qatar	Al Sadd neighborhood	VC	1454 (winter) 630 (summer) 960 (spring)	ped	2 days in Mar, jul and Aug (2014)	Temp [20- 50ºC, (-)], humidity (~), wind (~), cloud cover (~)	LR
Miranda-Moreno & Lathi, 2013	Montreal, Canada	Sidewalk, Five location	AC	767	ped	Jun 2010 – Jun 2011	**Temp** (+/-), humidity (+/-), wind (-), prcp (-)	LTR, LR
Li et al., 2013	Toronto, Canada	??	QS	183	ped	March-April, 2008	Snow/ice (-)	Non parametric tests
Montigny et al., 2012	Nine cities*	Single location	Web based cameras	6,255	ped	Over 7 months (Nov 2007-May 2008)	Temp [5ºC↑ (+)], sunlit (+), prcp (-)	PR
Miranda-Moreno & Fernandes, 2011	Montreal, Canada	1,018 signalized intersections	MC	45,844	ped	2008-2009	Temp [> 30ºC (-); < 20°C (-)], prcp (-), humidity (-)	LR, NB
Attaset et al., 2010	California, US	13 sidewalk locations	AC	29,680	ped	1 year	Temp [> 80ºF (-); < 50ºF (-)], prcp (-), wind (-), cloud cover (~)	LR
Li & Fernie 2010	Toronto, Canada	One intersection (south side crosswalk)	VC	654	ped	Mar 2007- Feb 2008	Cold **temp (-),** warm **temp (+),** dry weather (no prcp +), snow (-)	One-way ANOVA
Aultman-Hall et al., 2009	Downtown, Vermont	Single Location	MC and infrared sensor	8,664	ped, bike	2006-2007	Cold & hot **temp** (-), prcp (-), humidity (-), wind (~)	LR
Zhao et al., 2019	Seattle, Washington, USA	Burke-Gilman & Elliott bay trails	SDOT	Daily (N=350), Hourly (N= 5250)	ped, bike	Jan- Dec, 2014	Temp [> 20ºC (+)], rainfall (-), humidity (-), wind (-)	LR
Saneinejad et al., 2012	Toronto, Canada	??	Transportation Tomorrow Survey (TTS)	??	ped, bike	Sep- Dec, 2001; May- Jun, 2002	Temp [cyclists: < 15℃ (-) & > 15°C (+); ped: 1ºC-5ºC (-)], wind (-), prcp / shower (-), rainfall [ped (+), cyclists (-)]	MNL

Lieshout & Strijkstra, 2015	London	London	Barclays Cycle Hire	24.8 million trips	bike share	Jan 4, 2012- Oct 11, 2014	Temp [> 25ºC (+); < 0ºC (+)], rain (-), humidity (-), wind (-)	NB, LLR
Gebhart & Noland, 2014	Washington, D.C	??	Capital bike share website	Around 1,350k	bike share	2015 to 2011(15 months)	Temp [32-38ºC (+), 10-15ºC(-)], rain (-), snow, wind (-), humidity (-)	NB
Spencer et al., 2013	Vermont	NA	Interview	24 commuters	bike	2008-2009	Cold **temp** (-), rain (-), snow (-), wind (-)	??
Flynn et al., 2012	Vermont, U.S.A	Five counties	QS	163	bike	~ 10 months	**Temp** (+), wind (-), snow (-), prcp (-), humidity (~)	LLR
Mirando-Moreno & Nosal, 2011	Montreal, Canada	5 automatic counting locations	Induction loop counters	47,560	bike	Apr 2008- Jul 2010	Temp [> 28ºC (-), ~5- 25ºC (+)], humidity (-), prcp (-), wind speed (~)	LLR, NB
Brandenburg et al., 2007	Vienna, Austria	Wienerberg' recreation area	VC	55,824(weekdays) 20,886 (weekend)	bike	Jan- Dec, 2002	Temp [> 5℃ (+)], prcp (-)	LR
Nankervis, 1999	Melbourne, Australia	Three Melbourne institutions	Systematic check parked bikes & group survey	??	bike	1990-1991	**Temp** (high + /low -), rain (-), wind (-)	Pearson's

Notes: ?? = unknown. *= Significant; ~ = not significant,

Method: AC = automatic counts, MC = manual counts, QS= questionnaire survey, VC= video camera

Type: LR= Linear Regression; MNL= Multinomial logit; BL= Binomial Logit; PR= Quasi-Poisson regression; LTR= Log linear time series Regression; NB= Negative Binomial Regression; LLR= Log Linear Regression; BLR= Binary Logistic Regression; TSR= Time Series regression

Others: Temp= temperature, **temp =** unknown exact temperature**,** Prcp= precipitation, Ped= pedestrian, SDOT= Seattle Department of Transportation (wire for bicyclist; infrared sensor for ped), SF= San Francis

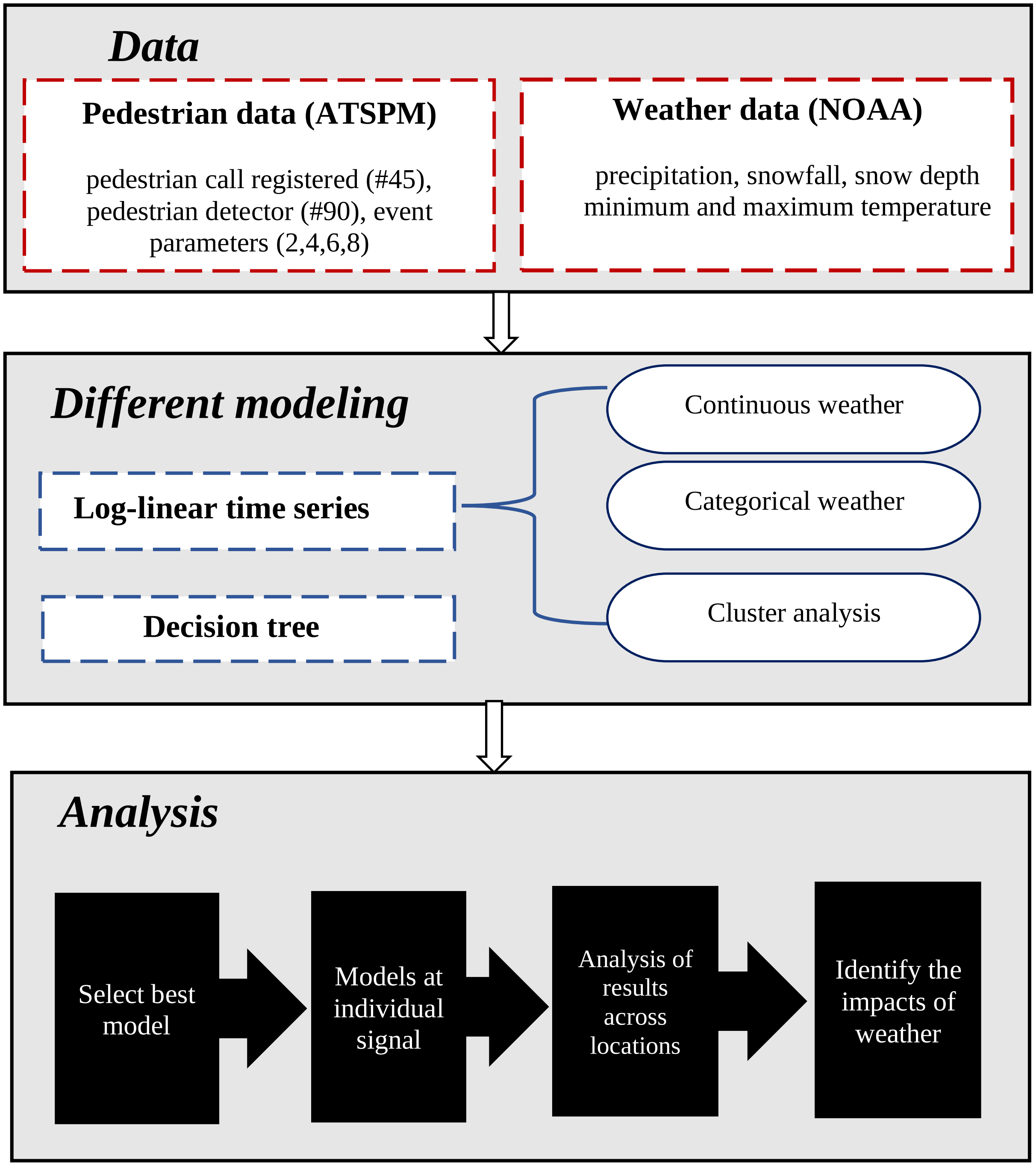


Figure 2.1 Conceptual framework for assessing the weather impacts on pedestrian activity

CHAPTER 3

DATA COLLECTION

3.1 Overview

This chapter summarizes the process of initial data collection, assembly, and processing. First, I introduce the raw pedestrian data that can be obtained from the traffic signal controller logs through the ATSPM system at 49 different signalized intersections in Cache County, Utah. Then, I document the validation of ATSPM data and data processing process used to generate the inputs for the analysis. Second, I discuss details about the weather data that can be downloaded from the National Oceanic and Atmosphere Administration (NOAA). Next, I present the descriptive statistics relating pedestrian data to different weather variables. Finally, this chapter ends up by discussing the merged pedestrian and weather data.

3.2 Traffic Signal Pedestrian Data

3.2.1 Traffic Signal Controller Logs

Traffic signal controllers manage the safe operation of signalized intersections and their signal control infrastructure, such as vehicle and pedestrian indications/displays. This role includes interpreting and responding to external information about user demand through vehicle and pedestrian detectors (Urbanik et al., 2015). As a result, controllers deal with up to hundreds of events per minute, from phase changes to detector events. Such second-by-second event information—which can be as fine-grained as specific cycles and

individual approaches—is useful for traffic signal operations management and for calculating signal performance measures.

Until recently, this set of signal event data was not being systematically logged. These high-resolution data loggers record many types of traffic signal events, including active phase changes, barrier/ring events, phase control and overlap events, vehicle and pedestrian detection events, and preemption and coordination events. Each record includes a timestamp, an event code, and an event parameter representing a phase or overlap number, detector channel, or other information about the event (Sturdevant et al., 2012). Several pedestrian-relevant events are commonly logged (Sturdevant, et al. 2012) as shown in Table 3.1 below:

Table 3.1 Pedestrian-related event codes and parameters

Event Code	*Event Description*	*Description*
0	Phase On	This event occurs with the activation of the NEMA phase on, such as the start of green or the start of the walk interval
21	Pedestrian Begin Walk	This event occurs with the activation of the walk indication for a particular phase
22	Pedestrian Begin Clearance	This event occurs with the activation of the flashing don't walk indication for a particular phase.
23	Pedestrian Begin Solid Don't walk	This event occurs when the don't walk indication becomes solid, with the termination of the pedestrian clearance interval.
45	Pedestrian Call Registered	This event occurs when a call to service for a particular phase is registered from pedestrian demand. Note that this event may not occur if pedestrian recall is set for the phase.
89 & 90	Ped Detector Off and On	These events occur when the signal from the pedestrian push-button is deactivated or activated, after any delay or extension is processed, for a particular pedestrian detector channel. Multiple pedestrian detection events may occur for a single pedestrian call registered.

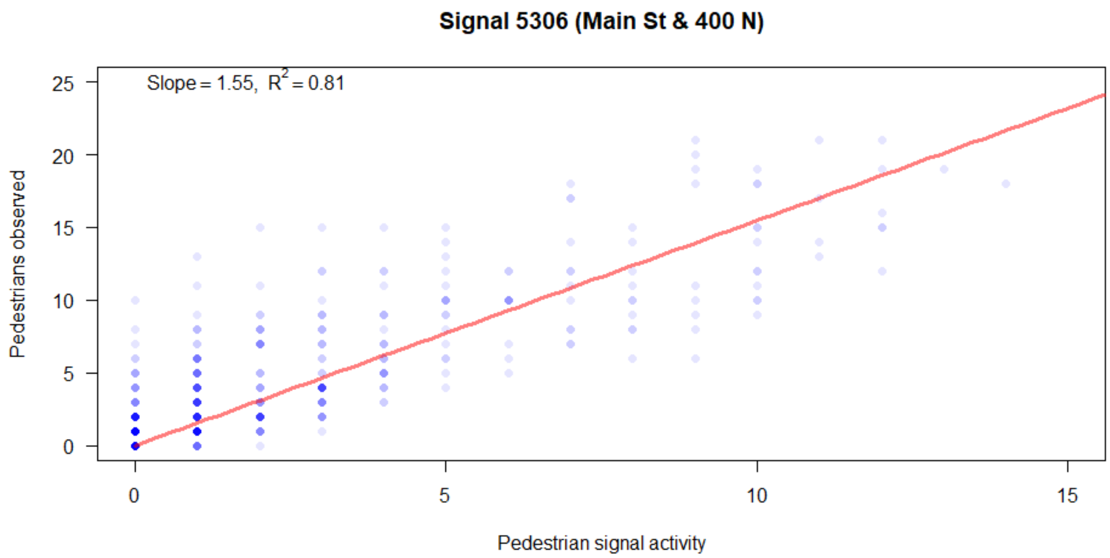
The two most-relevant pedestrian event codes are #45 and #90. Whenever a pedestrian push-button is activated (pressed), which could happen multiple times per cycle, event code #90 (pedestrian detector on) occurs. Event code #45 (pedestrian call registered) happens when a call to service a walk phase is registered, which usually happens just once per cycle for each crossing. Pedestrian recall means that a call is placed automatically every time without having to press the push-button.

3.3 Validity of ATSPM Data

Pedestrian traffic signal data may not be a perfect measure of pedestrian activity at signals. However, prior research at one intersection in Oregon found correlations of around 0.80 or greater between pedestrian actuations and crossing volumes (Blanc et al., 2015; Kothuri et al., 2017). Similar ongoing research by Singleton and Runa (2020) at 90 signalized intersections in Utah also finds strong correlations of 0.70 or better between signal data and observed counts.

To ensure the accuracy of ATSPM data, the preliminary results at two intersections—signal ID 5306 (Main St & 400N, Logan) & signal ID 5311 (Main St & 1400 N, Logan) — from an ongoing research (Singleton and Runa, 2020) are presented here. Figure 3.1 represents the actual pedestrian crossing counts (manually counted from recorded video) vs. pedestrian signal activity (ATSPM system) for all phases by the hour. The r-squared value of both examples was 0.81 and 0.86. This means pedestrian calls registered could be a better predictor of actual pedestrian signal activity as it explains 80-85% of the variance in the actual pedestrian crossing volumes. Overall, ATSPM data

provides a valid estimate of pedestrian signal activity (details can be found in Singleton, et. al., 2020).



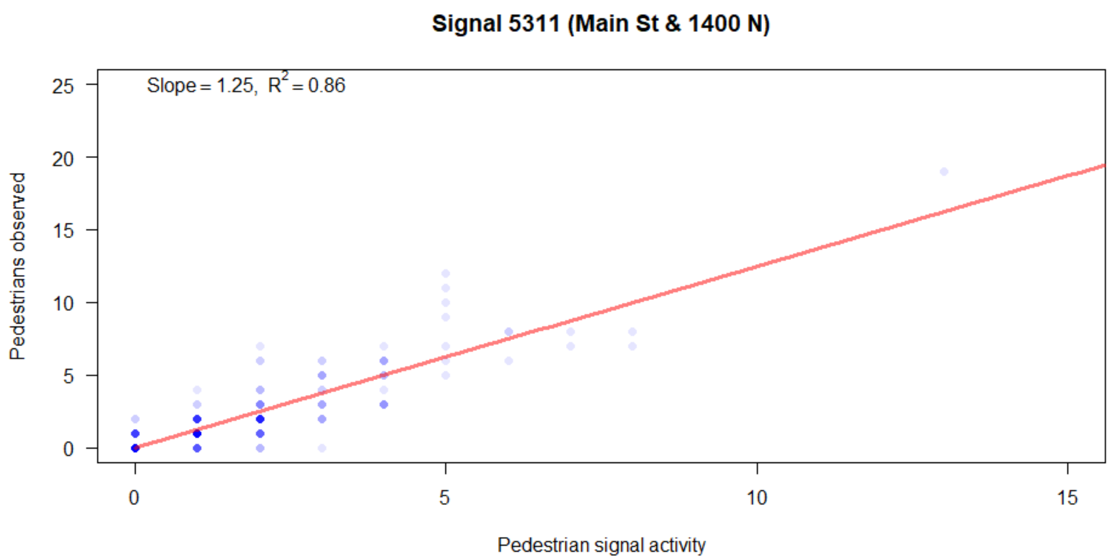


Figure 3.1 The relationship between observed and ATSPM data

3.4 Traffic Signal Pedestrian Data Processing

3.4.1 Study Location

The analysis of this study was done in Cache County, located in northwestern Utah, United States. Cache County has an area of 1,173 mi^2 with approximately 129,000 people (Census Bureau, 2020). Logan is the largest city in the county, with a population of approximately 53,000 (Census Bureau, 2020). The summers are hot, dry (low humidity & rainfall), and mostly clear (no clouds in the sky); the winters are cold, snowy, and partly cloudy, and it is dry year-round. The average annual high and low temperature are 60°F and 32°F. The average annual precipitation and snowfall 18.58 and 55 inches (US Climate, 2019). There are in total 57 signalized intersections in Cache County (see Figure 3.2). Most of the signals (48) are located in Logan. A few signals are located in North Logan, Hyde Park, Providence, Smithfield, Hyrum, Wellsville, and Richmond. However, ATSPM data was missing for a few signals during the study period. Excluding those signals, a total of 49 signals were included in this study (see Appendix A for the lists).

3.4.1 Data Processing

The processing of traffic signal pedestrian data includes several steps. First, the high-resolution traffic signal controller log data from the ATSPM website was downloaded from July 1, 2017 to October 1, 2018 for each signal. The raw ATSPM data contained only pedestrian related event codes (#45 & #90) and parameters of interest.

However, some traffic signal controllers sometimes did not record a pedestrian call registered (#45) (such as when the phase was in pedestrian recall), or recorded multiple

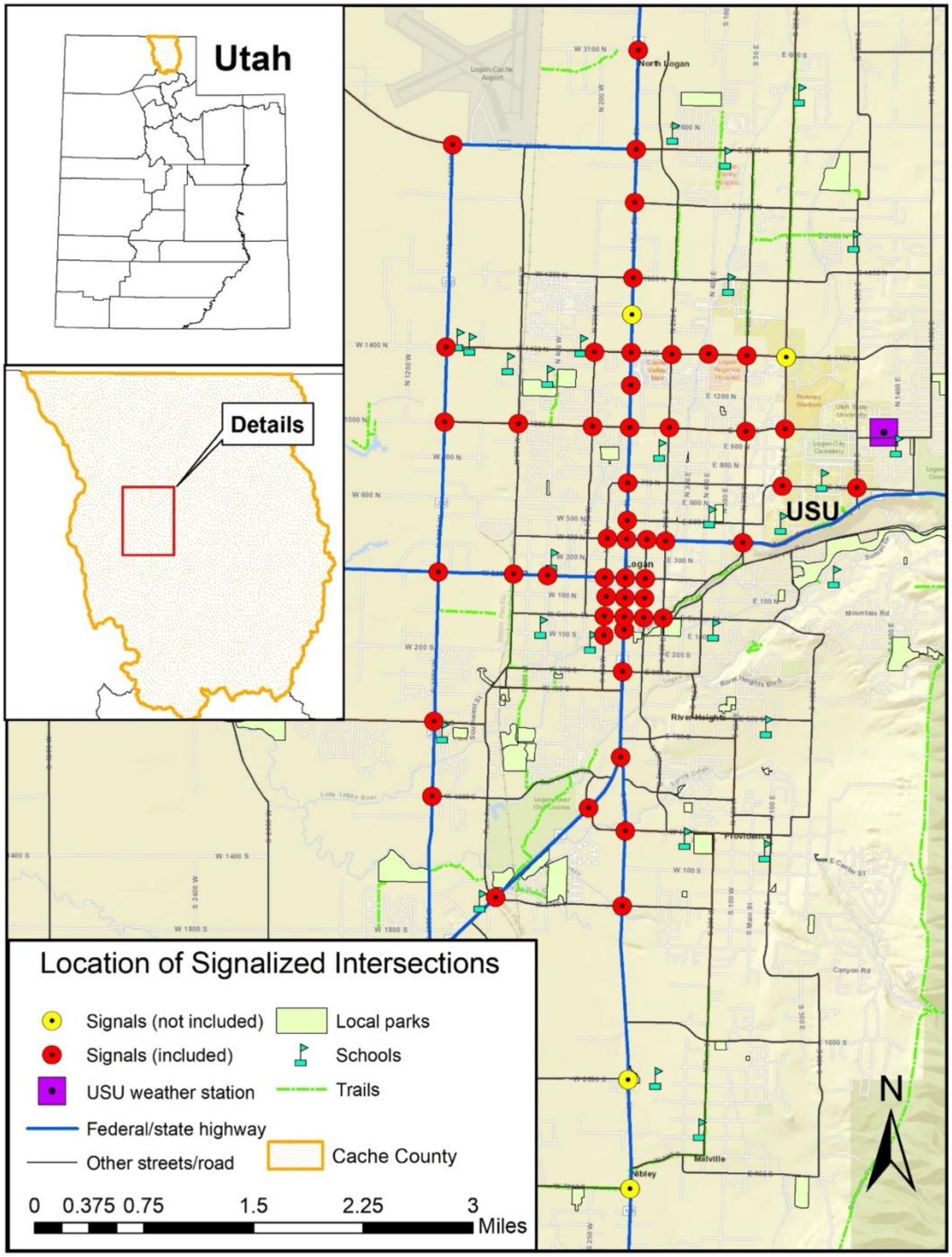


Figure 3.2 Map showing study locations

pedestrian calls registered (if the pedestrian push-button was pressed while the walk indication was on (between event codes #21 and #22)). Moreover, people may press the push-button multiple times in quick succession, which may hinder the ability to predict pedestrian volumes from traffic signal pedestrian data. Therefore, a new measure of pedestrian signal activity (#45A) was constructed by Singleton and Runa (2020). Specifically, it is the number of times in an hour that a push-button associated with a particular phase was pressed after the start of the phase (or the walk indication on that phase):

- #45A: imputed pedestrian calls registered, with some variations. In a sequence of event codes with just {0, 21, 22, 90}, this is the number of 90 events immediately preceded by a 0 or 22 event.

The preliminary analysis (Singleton and Runa, 2020) revealed that #45A seemed to be a better predictor than the original measures of #45 (number of push-button presses) and other metric #90 (highest correlation). In this study, the newly constructed measure of pedestrian actuations (#45A) was used as a proxy measure of pedestrian activity.

Second, for each signal, new pedestrian actuations (#45A) were tabulated for each hour in the entire year. The hourly pedestrian actuations were aggregated into daily counts; see Figure 3.3 for a time series. Note that people walking, bicycling or on e-scooters, skateboards, wheelchairs, who were pressing the push-button for crossing the crosswalk or sidewalk are included as “pedestrian signal activity”. Table 3.2 shows the example of daily pedestrian data for signal ID 5808 (1200 E & 700 N).

Table 3.2 Example of summarizing pedestrian actuation (#45A) data

Signal ID	*Date*	*Total Ped*	*Year*	*Month*	*Weekday*
5808	7/1/2017	67	2017	July	Saturday
5808	7/2/2017	72	2017	July	Sunday
5808	7/3/2017	288	2017	July	Monday
5808	7/4/2017	139	2017	July	Tuesday
5808	7/5/2017	405	2017	July	Wednesday
5808	7/6/2017	489	2017	July	Thursday
5808	7/7/2017	415	2017	July	Friday
5808	7/8/2017	114	2017	July	Saturday
5808	7/9/2017	55	2017	July	Sunday
5808	7/10/2017	409	2017	July	Monday

3.4.2 Data Cleaning

Before finalizing the pedestrian signal activity data, checking for missing data was done. The stage of checking involved manual inspection of the following:

- Are the day, time, and location correct?
- Are there any missing pedestrian signal activities?
- Which day, year, and month did "zero pedestrian activity" happen?
- Did it continue for more than seven days?
- Did it happen to a consecutive signal? (for example: 5801,5802,5803?)
- Was there any school break?

After observing carefully all these missing values and "zero pedestrian activity", a total of 332 (2%) daily observations were removed from 18 signals. For instance, it seems that a road construction project was being done and pedestrian facilities were removed or not accessible. See Table 3.3 for the details. In total, there were 448 daily records for each signal (except a few with missing data) and 21,808 daily observations for all signals.

Table 3.3 Signals with missing observations

Signal	*# missing*	*N*	*Time/ duration*	*Summer Break?*
5301	7	441	Jul 23 - Jul 29, 2017	Yes
5302	8	440	Jul 11 & Jul 23-Jul 29, 2017	Yes
5303	8	440	Aug 6- Aug 13, 2018	Yes
5315	6	442	Jul 11- Jul 16, 2017	Yes
5316	6	442	Jul 11- Jul 16, 2017	Yes
5317	6	442	Jul 11- Jul 16, 2017	Yes
5321	8	440	Aug 19-Aug 26, 2017	Yes
5322	8	440	Aug 18- Aug 26, 2017	Yes
5800	8	440	Oct 4- Oct 11, 2017	No
5801	12	436	Oct 4- Oct 11, 2017 & Feb 8- Feb 11, 2018	No
5802	8	440	Oct 4- Oct 11, 2017	No
5803	11	437	Oct 4- Oct 11, 2017 & Feb 9- Feb 11, 2018	No
5806	50	398	Aug 9- Aug 30 & Sep 1-Sep 27, 2017	No
5810	27	413	Jul 20- Jul 31 & Aug 1- Aug 21, 2017	Yes
5811	134	314	19 Oct- 31 Dec, 2017 & Jan 1- 26 Feb, 2018 & 6 Aug-13 Aug, 2018	No
5812	7	441	Jul 23 - Jul 29, 2017	Yes
5814	14	434	Apr 14 & Aug 31- Sep 24, 2017	No
5817	8	440	Aug 6- Aug 13, 2018	Yes

3.4.3 Descriptive Statistics of Pedestrian Data

Using clustering analysis over 1-year data (2017-2018) at different signalized intersections in Utah, Humagain et al. (2019) developed three categories: high, medium and low (pedestrian) volume intersections. All three types of intersections are present in the study area. Figure 3.3 shows the daily time series of pedestrian count at three different locations. Low volume signal 5812 is located in 100 W & 100 S, Logan; medium volume

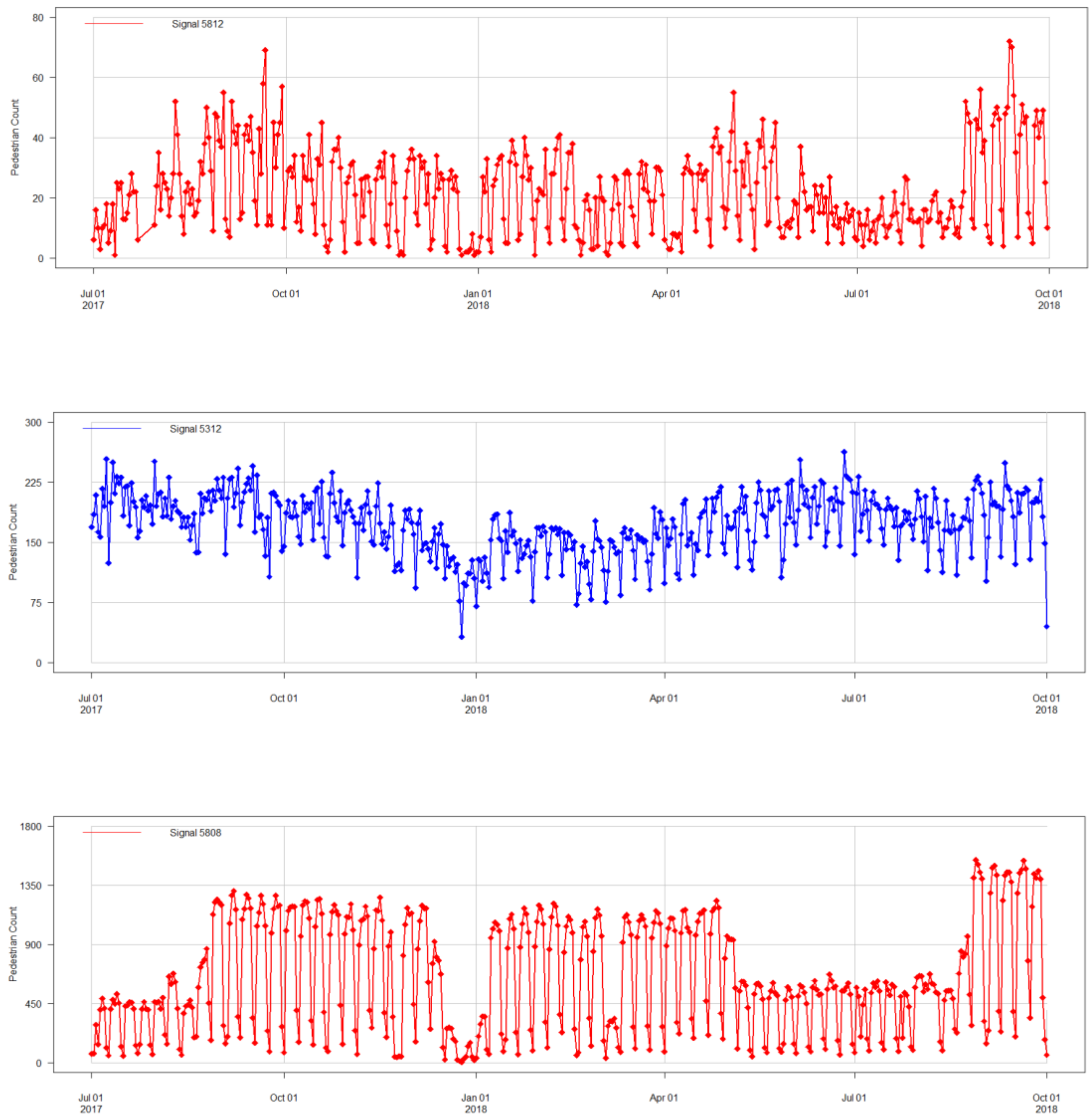


Figure 3.3 Low (signal 5812, medium (5312) and high (5808)) volume intersections

signal 5312 is located in 100 E & 400 N, Logan; and high-volume signal 5808 (1200 E & 700 N, Logan) is located near USU. All three examples show low pedestrian activity in mid-December to January first, and moderate to high activity in August to October. Signal 5808 shows low pedestrian activity in May-July because of USU's summer break.

In this study, the skewness, kurtosis, mean and standard deviation of daily pedestrian signal activity were not consistent across locations as the signals conveyed different characteristics based on pedestrian activity and locations (see details in the appendix). For some statistical analysis, it is required that the residuals will be normally distributed or nearly normal.

Skewness and kurtosis can be used to assess the normality of a variable. A normally distributed curve has skewness of zero and kurtosis of three. Distribution with kurtosis less than 3 are said to be platykurtic, and distributions with kurtosis greater than 3 are leptokurtic. This distribution is important as they can measure normality. The distribution is highly skewed if skewness is less than -1 or greater than 1. For example, the pedestrian signal activities at signal 5309 had a skewness of 11 and kurtosis of 181.1 (see Figure 3.4), suggesting that the dependent variable was leptokurtic and positively skewed. Simultaneously, signal 5807 showed an approximately normal distribution with skewness of 0.03 and kurtosis of 1.59 (see appendix A).

In addition, not all pedestrians pressed the push button while crossing the streets, especially when pedestrian phases are on recall. Figure 3.1 shows the slopes (1.55, 1.25) of the line corresponds to the conversion factor. Larger conversion factors (> 1) mean there are more people per pedestrian push-button press. In other words, people are "using" push-buttons less on a per-person basis. Therefore, a natural log transformation was performed, which has the beneficial side-effect of making the dependent variable (DV) more normally distributed before using it in the model (see equation 3.1). In addition, it seems more reasonable to determine the impacts of meteorological conditions on the relative proportion

of counts rather than the raw number: note that a log transformation didn't change the raw values into proportion.

$$Y(DV) = log(Pedestrian\ activity) \tag{3.1}$$

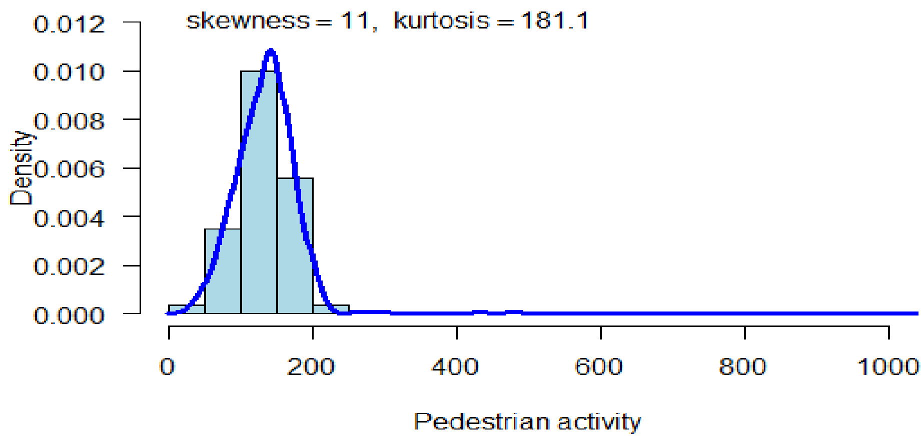


Figure 3.4 Histogram of pedestrian activity at signal 5309

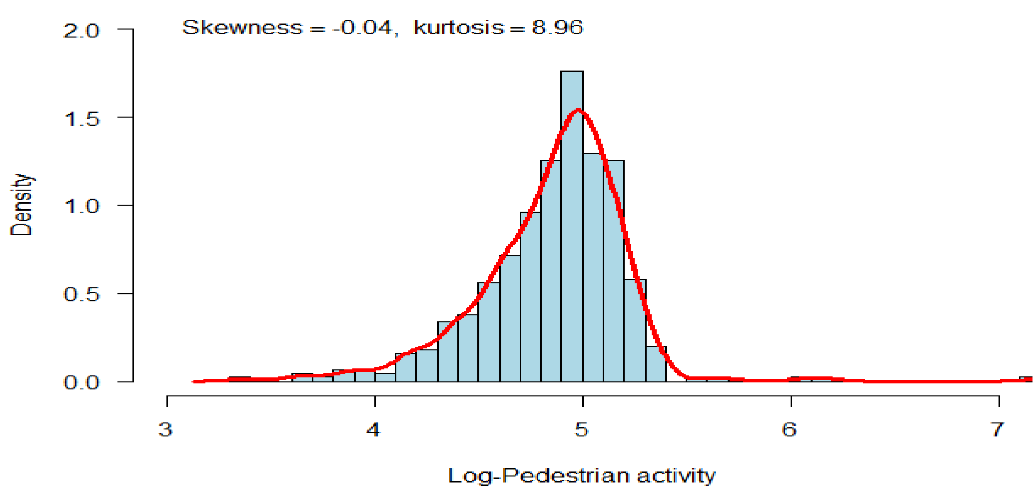


Figure 3.5 Histogram of log transformed pedestrian activity at signal 5309

The proportion mainly came from the interpretation of parameter estimates or beta value. The interpretation of regression coefficient (for the equation 3.1) is a unit change in X yields a $100(e^{\beta} - 1)$ percentage change in Y. Figure 3.5 shows the distribution of signal 5309 located at Main St a& 1000 N. The log-pedestrian activity had a skewness of -0.4 and kurtosis of 8.96 that makes the dependent variable more normally distributed.

3.4.4 Weather Data

The weather data was downloaded from the NOAA website from July 1, 2017 to October 1, 2018 (NOAA, 2020). A weather station located on the Utah State University campus was used that is approximately three miles from the farthest signal 5322 (Main St & 2200 N). Daily summaries of minimum and maximum temperature (°F), precipitation (in), snowfall amount (in), and snow depth (in) were found from the weather station; see Figure 3.6 for plots of the time series. According to NOAA, precipitation is the weather equivalent for the day which includes all types of precipitation (melted and frozen); snowfall is the daily amount of snowfall (snow, ice pellets) since previous snowfall, and snow depth is the depth of new and old snow remaining on the ground at the observation time.

The weather variables were very complete with few missing values. Among a total of 458 observations (number of days), 14 observations were missing: 6 for min/max temperature, 2 for snowfall, and 6 for snow depth. The min, max, mean, and standard deviation, skewness, and kurtosis for precipitation, snowfall, snow depth, min, and max temperatures are presented in Table 3.4.

Table 3.4 Descriptive statistics of weather data

Variable	*Min*	*Max*	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*N*
Precipitation (in)	0	1.51	0.04	0.14	5.74	42.65	448
Snowfall (in)	0	9.8	0.13	0.75	8.57	88.55	448
Snow depth (in)	0	13	0.82	2.09	2.96	9.09	448
Min temperature (°F)	4	72	41.03	16.45	-0.14	-1.00	448
Max temperature (°F)	22	98	63.05	21.42	-0.07	-1.25	448

Table 3.5 Correlation matrix for weather variables

Weather variables	*Correlations*				
	Precipitation	*Snow fall*	*Snow Depth*	*Max Temp*	*Min Temp*
Precipitation	1				
Snowfall	0.43	1			
Snow Depth	0.17	0.56	1		
Max Temp	-0.15	-0.19	-0.54	1	
Min Temp	-0.15	-0.20	-0.55	0.97	1

An important step in a multiple regression analysis is to ensure that the assumption of no multicollinearity has been met. Multicollinearity occurs when two or more predictor variables are highly correlated to each other (here 0.80 used as a threshold), such that they don’t provide unique information in a multiple regression model. Pearson correlations were calculated among the five weather variables. Min/max temperatures were strongly correlated with each other (+0.97) and snow depth was moderately correlated with min/max temperatures (−0.54, −0.55) and snowfall (+0.56). Precipitation was very weakly correlated with min/max temperatures (−0.15, −0.15) and low to moderately correlated with snow depth (+0.17) and snowfall (+0.43). Table 3.5 shows the correlation and collinearity statistics for the independent variables.

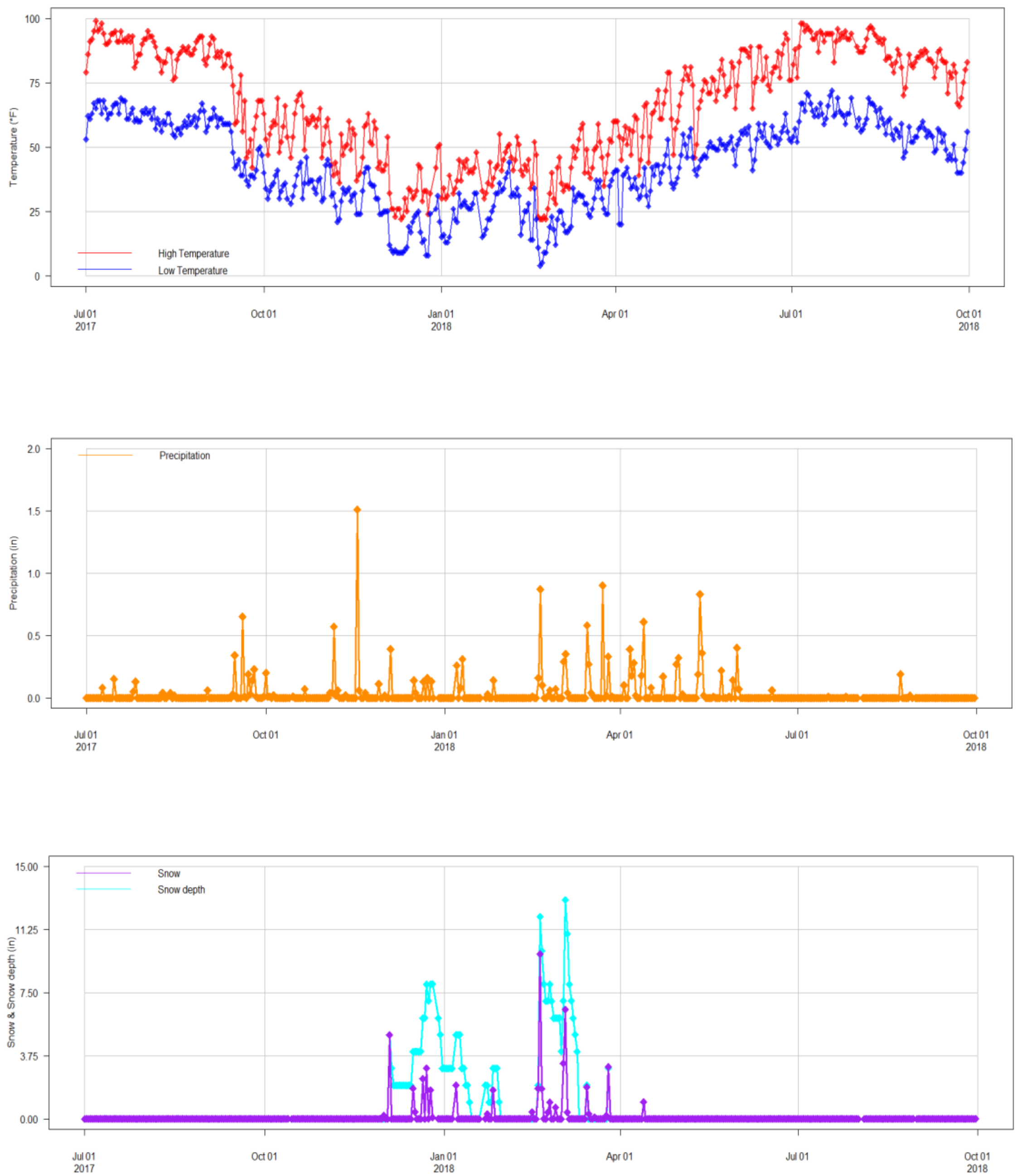


Figure 3.6 Daily time series of weather variables, including (a) temperature, (b) precipitation, and (c) snowfall and snow depth.

CHAPTER 4

METHODOLOGY

4.1 Overview

This chapter presents a brief review of different methods to represent weather variables and model their relationships with pedestrian activity. This chapter describes the details of linear regression methods and two machine learning methods, cluster analysis and decision trees, considered in this study to find the effect of weather on the pedestrian signal activity at different signalized intersections.

4.2 Log-linear Time Series Regression (LTR) of Representing Weather Variables

Log-linear Time Series Regression (LTR) was applied in this study to identify the weather impacts on pedestrian signal activity. A natural log transformation makes the DV nearly normal and helps interpreting results of independent variables as relative vs absolute impact on DV (details have been discussed in chapter 3). Also, the data used in this study are time dependent. It is reasonable to use time series regression. In LTR, multiple independent variables (X) are used to predict the value of a dependent variable (Y). Equation 4.1 shows a natural log transformed DV.

$$\log{(Y)_i} = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \dots\dots\dots\dots + \varepsilon_i \qquad (4.1)$$

4.2.1 Autocorrelation and Stationarity

As autocorrelation and non-stationarity are the foremost issues for time series (TS) data analysis, this study checked these for the model residuals using plots of the

autocorrelation (or partial autocorrelation) coefficients for the DV and residuals. For example, in Figure 4.1, the peaked autocorrelation coefficients are at lags of 7, 14, and 21 days, which shows the weekly patterns of pedestrian activity. If the autocorrelation coefficients reduce to near zero, datasets will be weakly stationary, while a non-stationary time series would have high values for several time periods.

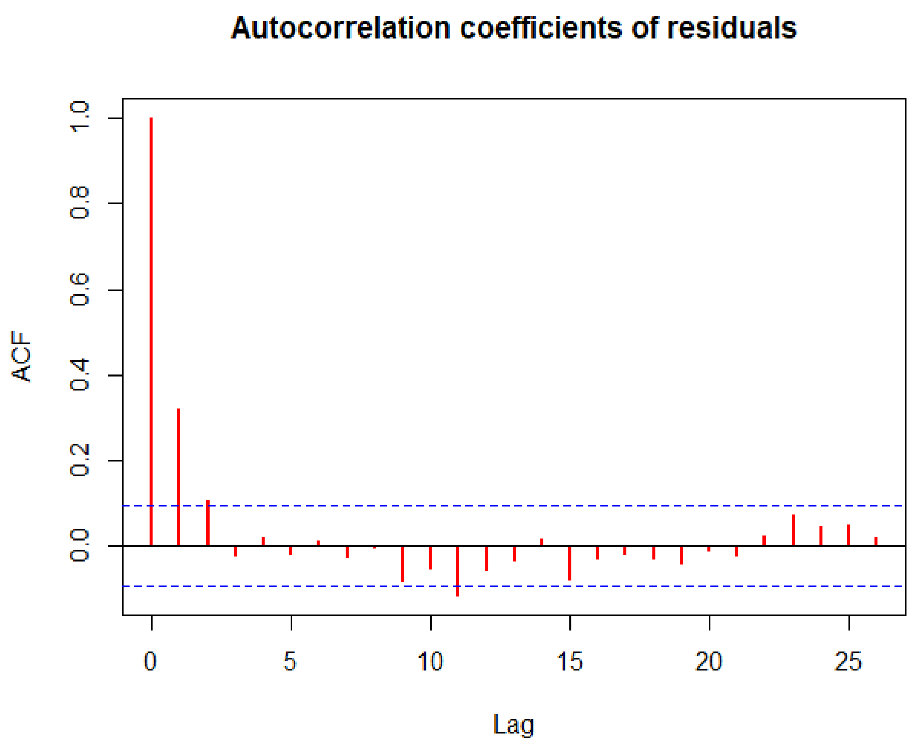


Figure 4.1 Autocorrelation check for signal 5303

If these issues appeared, we used the common first-order autoregressive model known as AR(1)—using the Prais-Winston function (Cochrane-Orcutt) from the *"orcutt"* package (Stefano, et.al., 2018) in R—to address serial correlation by transforming the time series variables in the model. This transformation basically subtracts a portion of the previous observation, depending on the strength of the autocorrelation coefficient.

4.3 Different Ways of Representing Weather Variables

This study examined four different ways of representing weather variables: continuous weather variables, categorical weather variables, and cluster analysis groupings, all used in a log-linear regression model; I also considered using a decision tree. The reason behind testing different representations of weather variables is to get a better fit model ($R^2, RMSE$) but more importantly to account for linear or non-linear effects of weather.

4.3.1 Continuous Weather Variables (Model A)

In this model, continuous weather variables were used as control variables. As min/max temperature were highly correlated with each other, only one variable was used to address the multicollinearity issue.

$$\begin{aligned} log(Y_i) = \beta_0 + \beta_1 snow_i + \beta_2 snwd_{\ i} + \beta_3 prcp_{\ i} + \beta_4 tmax_{\ i} \\ + \beta_{5-15} month_{(1-11)i} + \beta_{16-21} weekdays_{(16-21)i} \end{aligned} \quad (4.2)$$

4.3.2 Categorical Weather (Step-wise) Variables (Model B)

This study used the categorical weather variables for min/max temperature, precipitation, snowfall, and snow depth (see Table 4.1). A categorical variable takes on the values 0 and 1 to identify the mutually exclusive classes of the explanatory variables.

For example:

$$Temperature_{10°\mathrm{F}} = \begin{cases} 1\ if\ temperature\ is\ less\ than\ 10°\mathrm{F} \\ 0\ \ otherwise \end{cases} \quad (4.3)$$

$$Snow\ Depth_{\geq 0.1\ in} = \begin{cases} 1\ if\ snow\ depth\ is \geq 1\ inch \\ 0\ \ otherwise \end{cases} \tag{4.4}$$

For each weather variable, several different sets of threshold values were tested. For example, the category of temperature was started with 10°F with an increment of 10°F (10°F, 20°F, 30°F and so on). Next, a different combination of each variable was added in the model and I selected the best combinations for each variable. The best combination was selected based on goodness-of-fit of the model (R^2, root mean square error (RMSE), mean square error (MSE), chi-square likelihood ratio tests). After several trials, temperature below 10-30°F was considered as min temperature and above 60-90°F as max temperature based on goodness-of-fit. This procedure was applied for other weather variables.

$$\begin{aligned} log(Y_i) = \ & \beta_0 + \beta_1 Snow_{\geq 0.1i} + \beta_2 snow_{\geq 0.6i} + \beta_3 snwd_{\ \geq 0.1\ i} \\ & + \beta_4 snwd_{\ \geq 0.1\ i} + \beta_5 prcp_{\geq 0.01\ i} + \beta_6 prcp_{\geq 0.05\ i} \\ & + \beta_7 prcp_{\geq 0.25\ i} + \beta_8 tmin_{< 30\mathrm{F}\ i} + \beta_9 tmin_{< 20\mathrm{F}\ i} \\ & + \beta_{10} tmin_{< 10\mathrm{F}\ i} + \beta_{11} tmax_{\geq 60\mathrm{F\ i}} + \beta_{12} tmax_{\geq 70\mathrm{F\ i}} \\ & + \beta_{13} tmax_{\geq 80\mathrm{F\ i}} + \beta_{14} tmax_{\geq 90\mathrm{F\ i}} \\ & + \beta_{15-25} month_{(15-25)i} + \beta_{26-31} weekdays_{(26-31)i} \end{aligned} \tag{4.5}$$

First, to identify the major difference between model A and B, a comparison of results among few intersections was made. For example: for signal 5309, model B gives a better prediction (R^2 = 0.64) than the model A (R^2 = 0.45) with statistically significant improvements in model fits as determined by chi-square likelihood ratio tests. Overall, the LTR model with categorical variables had a better performance (lowest RMSE, good fit, non-linearities) than with continuous weather variables.

Table 4.1 Frequencies (percentages) of categorical weather variables

Variable names		*# (%)*	*Variable names*		*# (%)*
Snow Depth:	≥ 0.1 in	16 (3.5)	Breaks:	USU, winter	18 (4)
	≥ 0.6 in	2 (0.4)		USU, spring	7 (1.6)
Snowfall:	≥ 0.1 in	71 (15.8)		LSD, spring	7 (1.6)
	≥ 0.6 in	24 (5.4)		USU, summer	167 (37.3)
Precipitation:	≥ 0.01 in	92 (20.5)		LSD, fall	3 (0.7)
	≥ 0.05 in	56 (12.5)	Holidays:	New Year's Day	1 (0.2)
	≥ 0.25 in	22 (4.9)		—day after	1 (0.2)
Min Temperature:	< 10ºF	11 (2.5)		Memorial Day	1 (0.2)
	< 20ºF	41 (9.2)		Independence Day	2 (0.4)
	< 30ºF	99 (22.1)		Pioneer Day	2 (0.4)
Max Temperature:	≥ 60ºF	268 (59.8)		Labor Day	2 (0.4)
	≥ 70ºF	221 (49.3)		Thanksgiving Day	1 (0.2)
	≥ 80ºF	170 (37.9)		—day after	1 (0.2)
	≥ 90ºF	75 (16.7)		Christmas Eve	1 (0.2)
Events:	USU, commencement	7 (1.6)		Christmas Day	1 (0.2)
	USU, Football	2 (0.4)		—day after	1 (0.2)
				New Year's Eve	1 (0.2)

USU = Utah State University, LSD = Logan School District,

4.3.3 Cluster Analysis (CA)

Cluster analysis (CA) is powerful tool to identify common weather types (Hidalgo, et al., 2018). CA was performed using two different sets of weather data: 1-year data (2017-2018) and 10-year data (2010-2020). 10-year weather data was examined to accommodate a wider array of weather conditions.

This study estimated four different cluster models (C vs D x 1-year vs 10-year) using two different datasets:

- Model C: CA using all continuous weather variables (min/max temperature, snowfall, snow depth, and precipitation) for 1-year data.
- Model C_1: CA using all continuous weather variables for 10-year data.
- Model D: CA was done using three weather variables (min/max temperature, snow depth) and separately other two continuous variables (precipitation and snowfall). Max/min temperature were highly correlated with each other and moderately correlated with snow depth. To address the multicollinearity issue, only three variables were used in CA for 1-year data.
- Model D_1: same as model D except using 10-year data.

4.3.3.1. Number of Local Weather Types

One important task of CA is to find a reasonable number of clusters. Different methods (silhouette method, elbow method, gap statistic method, etc.) can determine the number of clusters. First, an elbow curve was formed by plotting the within sum of squares for each number of clusters. The number of clusters can be found where there is sharp turning like an elbow or a large change in the slope of the plot. These four models found the number of clusters to be either two or three (see Figure 4.2 and 4.3).

Second, some other methods (silhouette method suggested two and gap statistic method nine clusters) to confirm this number of clusters. However, five clusters seemed to be reasonable compromise between distinctiveness and interpretability, although one could have selected three or nine clusters instead (see Figure 4.4).

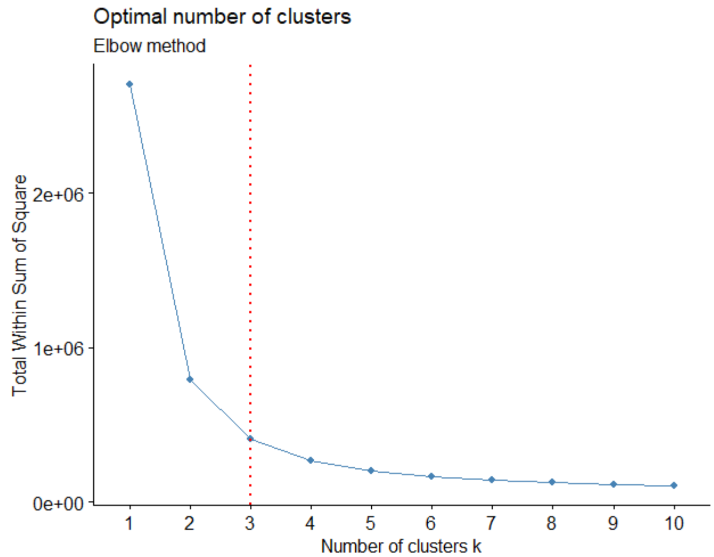


Figure 4.2 Number of clusters (Elbow method)

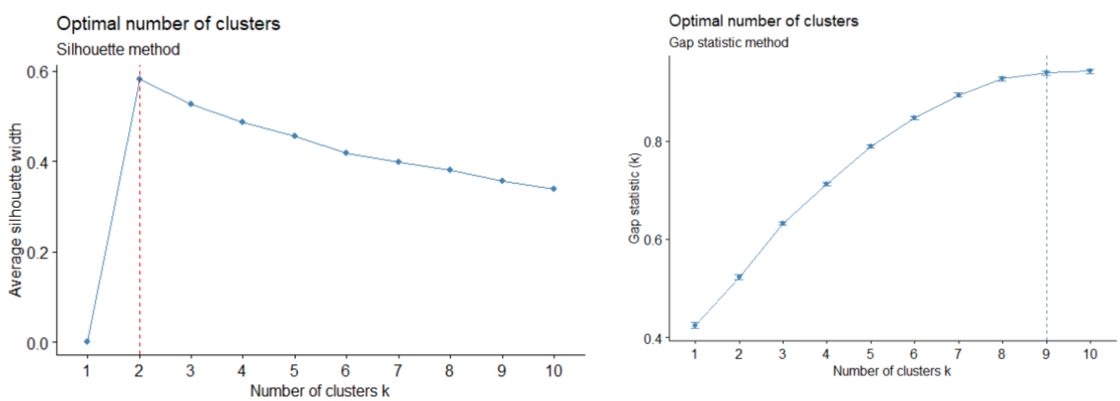


Figure 4.3 Number of clusters (Silhouette (left) & Gap Statistic(right) method)

Next, the k-means cluster algorithm was applied to get five sets of weather types for both data sets (1-year and 10-year data). Table 4.2 shows the mean values of each cluster. Based on the mean value of each cluster, weather types were described. For instance, cluster 2 (1-year data) with T_{min} 27ºF, T_{max} 43ºF with 1.3 in snow depth can be said to be a "very cold snowy and shower (in form of precipitation) day". Cluster 5 (1-year

data) and cluster 4 (10-year data) are very similar which can be said to be "very hot sunny summer days" with T_{max} 90ºF.

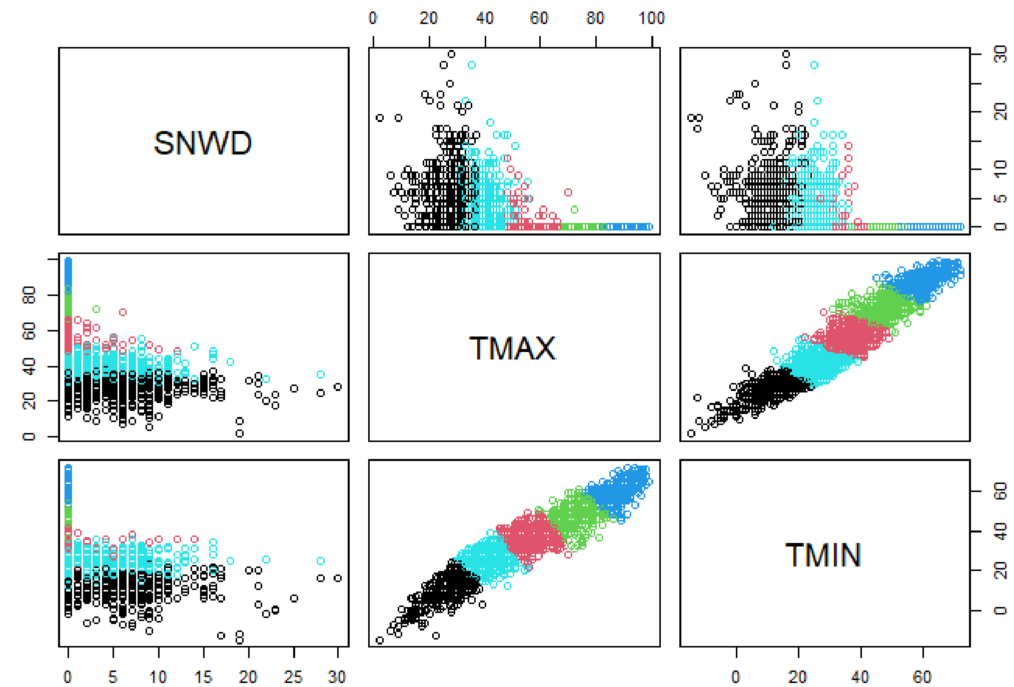


Figure 4.4 Clusters of min/max temperature and snow depth

Next, log-linear time series analysis was preformed using these five weather types for all four models at few signalized intersections. Model C and C_1 follow equation 4.7 whereas Model D and D_1 follow equation 4.8 (reference: cluster 5):

$$\begin{aligned} log(Y_i) = {} & \beta_0 + \beta_1 cluster_{1i} + \beta_2 cluster_{2i} + \beta_3 cluster_{3i} \\ & + \beta_4 cluster_{4i} + \beta_{5-15} month_{(1-11)i} \\ & + \beta_{16-21} weekdays_{(16-21)i} \end{aligned} \tag{4.6}$$

$$\begin{aligned} log(Y_i) = {} & \beta_0 + \beta_1 snow_i + \beta_2 prcp_{\,i} + \beta_3 cluster_{1i} + \beta_4 cluster_{2\,i} \\ & + \beta_5 cluster_{3i} + \beta_6 cluster_{4\,i} + \beta_{7-17} month_{(1-11)i} \\ & + \beta_{18-23} weekdays_{(18-23)i} \end{aligned} \tag{4.7}$$

Preliminary results revealed that there was no difference between using 1-year and 10-year weather data. For example: for signal 5306, model C ($R^2 = 0.83$) and C_1 ($R^2 = 0.83$) give similar with no significant difference in model fits as determined by chi-square likelihood ratio tests. Concurrently, model D gives a little improvement in model fit ($R^2 = 0.83$) than model C ($R^2 = 0.80$). However, chi-square likelihood ratio tests found no statistically significant improvements in model fits.

Table 4.2 Weather types according to cluster data

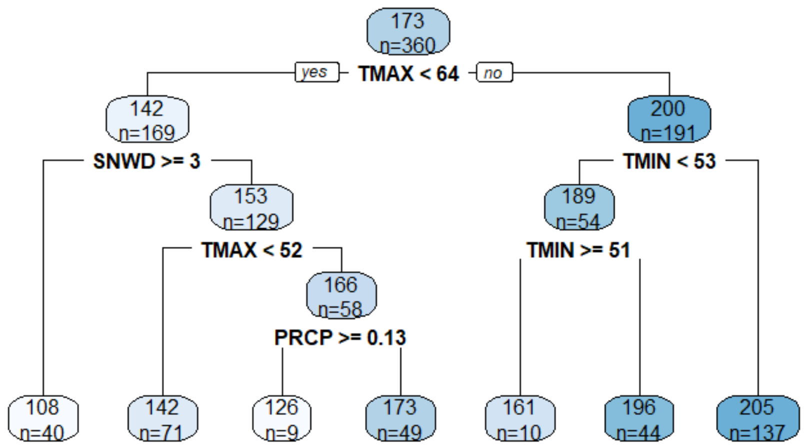
	1-year data						*10-year data*			
Cluster	*Prcp*	*Snow falls*	*Snow depth*	*Tmax*	*Tmin*	*Weather types*	*Snow depth*	*Tmax*	*Tmin*	*Weather types*
1	0.02	0.25	4.50	29.5	13.9	Very cold, snowy, and rainy days	6.29	27.1	11.5	Very cold snowy day
2	0.05	0.43	1.32	43.3	27.3	Cold, snowy, shower	2.27	41.4	26.6	Cold snowy day
3	0.07	0.04	0.09	57.7	37.1	Sunny with snow and shower	0.16	56.4	36.8	Sunny snowy winter day
4	0.04	0.00	0.00	75.0	49.7	Hot, dry, rainy	0.01	72.4	47.4	warm sunny day with shower
5	0.01	0.00	0.00	89.5	60.9	Very hot sunny day with rain	0.00	87.7	59.8	Very hot , sunny summer day

Notes: prcp= precipitation, Tmax= maximum temperature, Tmin= minimum temperature

4.3.4 Decision Tree

As an alternative to cluster analysis, a decision tree was applied to few signalized intersections. This method fitted the pedestrian data by classifying days based on weather variables. For example (see Figure 4.5), every tree has the root at the top and the leaves at the bottom. The most important variable according to the models can be found in the root. For both signals, temperature is the most important variable to predict walking activity. For signals 5306, the root of tree is “Is max temperature less than 64ºF?” → if yes, then go to

Decision Tree for Signal 5306



Decision Tree for Signal 5808

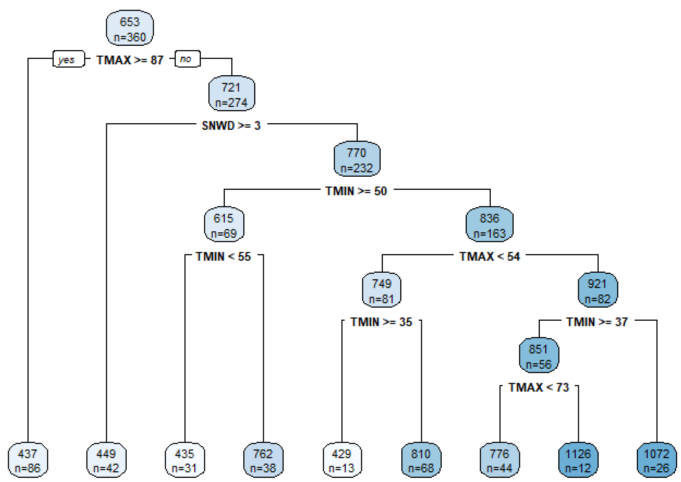


Figure 4.5 Decision tree for signal 5306 and 5808

min temperature (< 53ºF), otherwise go to snow depth (≥ 3 in). Similarly, for signal 5808, the root of the tree is "Is max temperature greater than 87 ºF?". The results of these two trees are different. It can be expected that for every signal, it will give different types of trees. This is the main limitation of this method.

4.4 Final Model

To select a best model, overall goodness of fit is an important criterion. However, this study also desired to represent complex relationships like non-linear effects of weather to get a better interpretation so that this result can be applied to get knowledge about how weather might affect walking activity in future.

It is clear from the above-mentioned models that every method has pros and cons. The LTR model with continuous weather variables is easy to interpret and seems to give overall better goodness of fit (R^2), but non-linear effects cannot be accounted for. Also, as min/max temperature are highly correlated, only one temperature variable can be used in the model because of multicollinearity. LTR model with categorical weather variable can address this multicollinearity issues. It also accounts for more fine-grained non-linearities; interpretation is fairly easy too.

Cluster analysis is a solution for considering multicollinearity issues. This is also fairly easy to interpret and can account for some amount of non-linear relationships. Fit is not much worse than the previous method. However, it is clear from the Figure 4.4 that clusters are constructed primarily based on min/max temperature which are the most dominating variables, thus obscuring effects of precipitation and snow. Another limitation of CA is scaling or normalization. Normalization should be done before performing CA when variables are in different units (Hidalgo, et al., 2018). Since clustering techniques use Euclidean Distance to form the cohorts, it will be important to re-scale the variables (e.g., having temperature in degree Fahrenheit and snow depth in inch) before calculating the distance. However, scaling makes the prediction difficult and unintuitive. Interpretation is

more difficult (you cannot say that a 10ºF increase in temperature is associated with a percentage change in the DV). It is also harder to apply to other situations, since it depends on local weather patterns.

Decision tree can address multicollinearity issues. It is a simple method with easy explanation. However, interpreting, predicting, and comparing across signals would be difficult in this model. For each location, one needs a separate model with different decision criteria. Results of one signal cannot be applied to another location as each signal hold different features.

Looking into the pros and cons of every model and systematically eliminating the least significant models yielded the best models for this study. Based on model goodness-of-fit, interpretability, and representing non-linear effects, this study decided to use log-linear time series model with categorical weather variables (see equation 4.9).

$$\begin{aligned} log(Y_i) = \beta_0 + &\beta_1 Snow_{\geq 0.1 i} + \beta_2 snow_{\geq 0.6 i} + \beta_3 snwd_{\geq 0.1\, i} \\ &+ \beta_4 snwd_{\geq 0.1\, i} + \beta_5 prcp_{\geq 0.01\, i} + \beta_6 prcp_{\geq 0.05\, i} \\ &+ \beta_7 prcp_{\geq 0.25\, i} + \beta_8 tmin_{< 30\mathrm{F}\, i} + \beta_9 tmin_{< 20\mathrm{F}\, i} \\ &+ \beta_{10} tmin_{< 10\mathrm{F}\, i} + \beta_{11} tmax_{\geq 60\mathrm{F\,i}} + \beta_{12} tmax_{\geq 70\mathrm{F\,i}} \\ &+ \beta_{13} tmax_{\geq 80\mathrm{F\,i}} + \beta_{14} tmax_{\geq 90\mathrm{F\,i}} \\ &+ \beta_{15-25} month_{(15-25)i} + \beta_{26-31} weekdays_{(26-31)i} \\ &+ \beta_{32-33} events_{(32-33)i} + \beta_{34-38} breaks_{(34-38)i} \\ &+ \beta_{34-38} holidays_{(39-50)i} \end{aligned} \tag{4.8}$$

In the final model, a few other time-related categorical variables were added to address some other sources of non-weather variability. For example, time-related categorical variables were created for the national holidays, USU fall/spring breaks, and major events (commencement and football games) to capture temporal trends and address some other sources of non-weather variability.

4.5 Detail of the Log-Linear Time Series (LTR) Analysis

A log-linear time series analysis with categorical variables was performed for all signals separately. Most of the models used 448 observations, one per day from July 1, 2017, to October 1, 2018. However, few signals had some missing values that made observations lower than 448 ($314 \leq N < 448$, details in chapter 3). The models were estimated sequentially (only the final model is presented in the next section). A detailed procedure is presented for signal 5306 (randomly selected as an example) in the following paragraph (all signals follow the same procedure).

Signal 5306 is a low volume intersection located in 400N and Main Street, Logan. First, the merged pedestrian signal activity and weather data were checked for missing values. Second, reference levels were changed to be May for month and Wednesday for weekdays. Third, temporal variables (month and weekdays) were included and a model was estimated ($R^2= 0.78$). Fourth, the categorical events, holiday and school breaks variables were added in the model ($R^2= 0.83$). Finally, the categorical weather variables entered the model. This addition slightly improved the goodness-of-fit ($R^2= 0.83$ to $R^2= 0.87$), with statistically significant improvements in model fits as determined by chi-square likelihood ratio tests ($\Delta df = 14$, $p < 0.001$).

4.5.1 Checking Assumptions of LTR Model

Next, key assumptions were checked: linearity (linear of the mean), heteroscedasticity (constant variance of residuals), exogeneity (zero mean of residuals), normality (normally distributed residuals), and non-autocorrelation (temporal independence of residuals). Figure 4.6 and 4.7 show that all assumptions are met for signal

5306. However, this was not true for all signals. Concurrently, there are no quick and easy solutions to violations of assumptions. This study took account of the violation of non-autocorrelation because of time series data and performed remedial measures (details are presented in section 4.2.1) if autocorrelation was present.

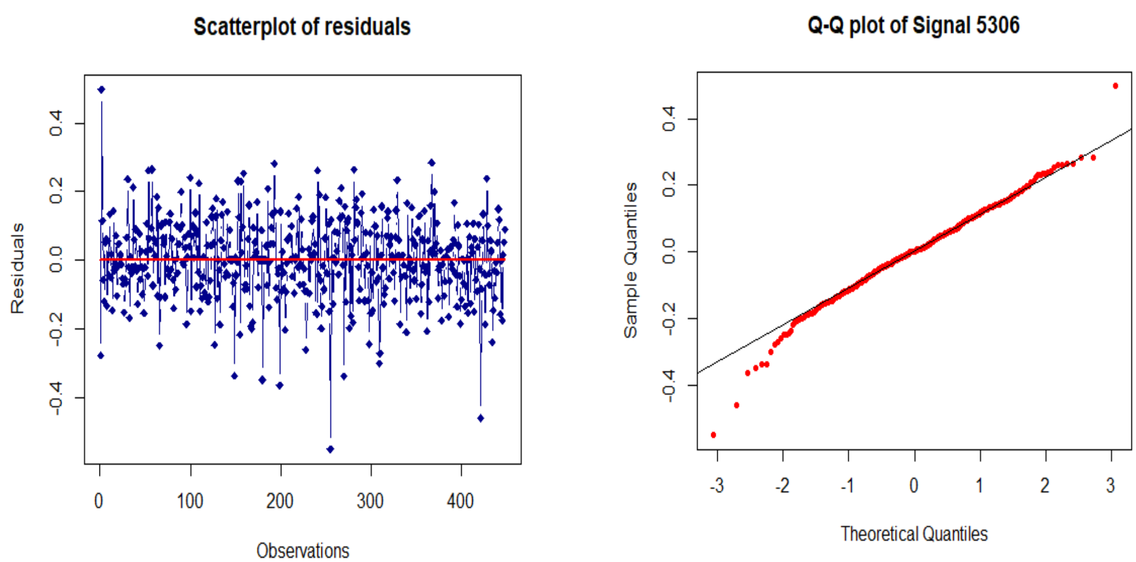


Figure 4.6 Scatter and Q-Q plot for signal 5306

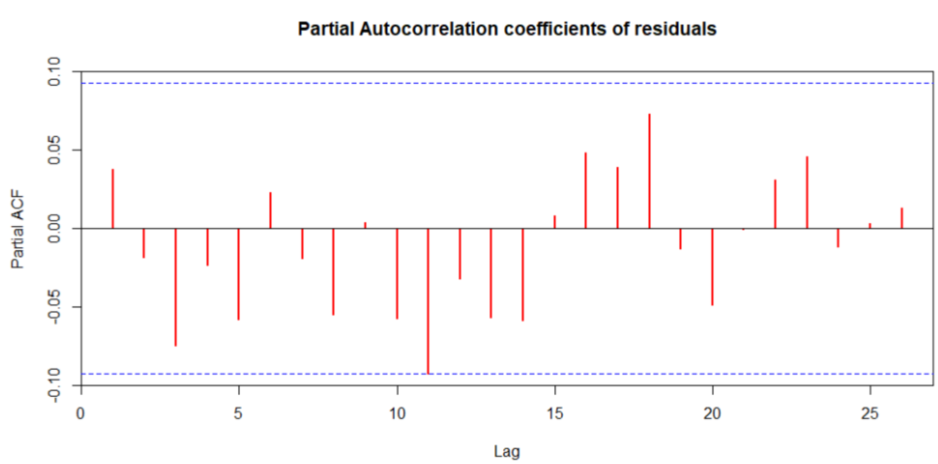


Figure 4.7 Scatter and Q-Q plot for signal 5306

CHAPTER 5

RESULTS

5.1 Overview

This chapter reports the detailed results of the log-linear time series analysis with categorical variables at 49 signalized intersections according to the methodology outlined in Chapter 4. A detailed comparison among different signals based on regression coefficients for weather variables is presented. This chapter also represents the final results in sophisticated ways adopting several methods: tables with frequencies/percentages of significant results, boxplots, histograms, maps, and t-tests of model parameters. Finally, this chapter ends by summarizing how the effects of weather vary at different signals.

5.2 Comparison Among Three Signals

The log linear time series results of three signals — signal 5306, a low pedestrian signal activity intersection located at 400N and main street; signal 5816, a medium pedestrian signal activity intersection located at 600 E & 1000 N; and signal 5808, a high pedestrian signal activity intersection located at 1200 E & 700 N— are presented in Table 5.1 (all results are presented in the appendix). Note that this comparison was done for all 49 signals. The comparison among three signals are presented here only to show how the comparison was made.

The overall goodness of fits of these three models was good (R^2 between 0.80-0.90 and low RMSE). To interpret the impacts of weather variables, the model coefficients (βs) were exponentiated to get the effects on pedestrian signal activity. The interpretation of

β for categorical variables is different as weather variables are cumulative categories whose effects add on to each other. For example: if the β value of temperature higher than 60ºF is 0.02 and 70ºF is 0.05, then the interpretation is that for an average day with temperature higher than 70ºF, we can expect a 7% [$100\left(e^{(0.02+0.05)}-1\right)$] increase in pedestrian signal activity. Several weather variables were significantly associated with pedestrian signal activity. Days with a snow depth of any amount tended to have lower pedestrian signal activity (marginally significant: signal 5306 & 5816). The additional amounts of snow depth (above 0.6 inches) were linked to further decreases in pedestrian activities. Even so, days with snowfall amount above 0.6 inches further reduce pedestrians. Precipitation (> 0.25 in) was found to be negatively associated with pedestrian signal activity at signal 5306.

An average day with low temperature below 10°F had 35% higher pedestrian activity at signal 5808 (marginally significant), 5% higher at 5815, and 13% lower at 5306, though the associations were not significant for last two signals. A day with a temperature below 20°F had 8% fewer pedestrians at signal 5306. Warmer temperatures (between 70-80°F) increased pedestrian activity by 11% at signal 5816. However, extreme temperatures negatively affected pedestrian signal activity. Very hot summer days (above 90°F) decreased pedestrian activity by 3% at signal 5306, 1% at signal 5816, and 15% at signal 5808.

Several temporal variables were also significant though they worked as control variables (address some other sources of non-weather variability). After controlling for other factors, the highest pedestrian signal activity was found for July at signal 5306, June

at signal 5816, and August at signal 5808, while the lowest were in December (signal 5808, 5816) and January (5306). Similarly, pedestrian signal activity was highest on Friday at signal 5306 and Thursday at signal 5808 and 5816. The lowest activity was found on weekend days.

Table 5.1 Results of log linear time series models

		Signal 5306 (N=448)			***Signal 5816 (N=448)***			***Signal 5808 (N=448)***		
Variable		*β*	*SE*	*P*	*β*	*SE*	*P*	*β*	*SE*	*P*
Weather Variables										
Snow Depth	≥ 0.1 in	-0.069	0.039	~	-0.113	0.059	~	0.055	0.099	
	≥ 0.6 in	-0.127	0.046	*	-0.298	0.071	*	-0.302	0.126	*
Snowfall	≥ 0.1 in	0.015	0.037		-0.004	0.053		-0.098	0.078	
	≥ 0.6 in	-0.268	0.106	*	-0.234	0.147		-0.913	0.209	*
Precipitation	≥ 0.01 in	-0.013	0.025		-0.034	0.035		0.005	0.051	
	≥ 0.05 in	-0.044	0.032		-0.061	0.045		-0.071	0.064	
	≥ 0.25 in	-0.098	0.039	*	-0.058	0.055		-0.045	0.078	
Min Temperature	< 30ºF	-0.012	0.027		0.008	0.040		-0.025	0.064	
	< 20ºF	-0.065	0.036	~	0.016	0.055		0.088	0.091	
	< 10ºF	-0.055	0.053		0.027	0.081		0.240	0.134	~
Max Temperature	≥ 60ºF	-0.022	0.028		-0.014	0.040		0.019	0.060	
	≥ 70ºF	0.037	0.031		0.117	0.047	*	0.050	0.076	
	≥ 80ºF	0.007	0.026		0.019	0.038		0.029	0.059	
	≥ 90ºF	-0.049	0.025	*	-0.115	0.039	*	-0.239	0.072	*
Temporal Variables										
Month:	January	-0.274	0.062	*	-0.251	0.100	*	-0.004	0.204	
	February	-0.234	0.058	*	-0.298	0.093	*	0.120	0.194	
	March	-0.184	0.056	*	-0.328	0.091	*	0.090	0.191	
	April	-0.015	0.052		-0.204	0.085	*	0.263	0.178	
	May	–	–	–	–	–	–	–	–	–
	June	0.165	0.036	*	0.103	0.060	~	0.037	0.140	
	July	0.186	0.039	*	0.048	0.064		0.126	0.141	
	August	0.081	0.035	*	0.022	0.058		0.292	0.131	*
	September	0.037	0.048		-0.035	0.078		0.247	0.164	
	October	-0.004	0.053		-0.205	0.086	*	0.130	0.182	
	November	-0.215	0.054	*	-0.391	0.087	*	-0.027	0.184	
	December	-0.248	0.067	*	-0.434	0.107	*	-0.115	0.215	
Weekday:	Sunday	-0.597	0.023	*	-0.205	0.034	*	-1.978	0.055	*
	Monday	-0.171	0.023	*	-0.131	0.034	*	-0.246	0.052	*
	Tuesday	0.005	0.023		0.014	0.031		-0.002	0.043	
	Wednesday	–	–	–	–	–	–	–	–	–
	Thursday	-0.001	0.023		-0.035	0.031		0.001	0.043	
	Friday	0.022	0.023		-0.093	0.034	*	-0.077	0.052	
	Saturday	-0.106	0.024	*	-0.478	0.035	*	-1.268	0.056	*

Events:	USU[a], commencement	0.141	0.102		-0.337	0.156	*	0.274	0.255	
	USU, Football	0.045	0.052		0.233	0.073	*	0.126	0.102	
Breaks:	USU, winter	-0.142	0.049	*	-0.728	0.078	*	-1.236	0.159	*
	USU, spring	0.076	0.065		-0.379	0.105	*	-0.621	0.209	*
	LSD[b], spring	-0.118	0.057	*	-0.367	0.094	*	-0.294	0.199	
	USU, summer	0.004	0.039		-0.626	0.064	*	-0.586	0.130	*
	LSD, fall	-0.075	0.082		-0.376	0.129	*	-0.442	0.230	~
Holidays:	New Year's Day	-0.449	0.142	*	-0.559	0.208	*	-1.764	0.343	*
	—day after	-0.015	0.141		-0.492	0.201	*	-0.356	0.303	
	Memorial Day	0.014	0.134		0.057	0.188		-0.400	0.265	
	Independence Day	-0.319	0.094	*	0.190	0.133		-0.990	0.187	*
	Pioneer Day[c]	-0.201	0.093	*	-0.378	0.132	*	-1.007	0.186	*
	Labor Day	0.115	0.095		-0.137	0.134		-0.205	0.191	
	Thanksgiving Day	-0.627	0.132	*	-1.410	0.189	*	-2.233	0.286	*
	—day after	-0.282	0.134	*	-0.971	0.192	*	-2.067	0.292	*
	Christmas Eve	-0.063	0.146		-0.795	0.210	*	-0.584	0.327	~
	Christmas Day	-0.640	0.149	*	-1.661	0.218	*	-3.010	0.356	*
	—day after	-0.276	0.143	~	-0.691	0.203	*	-1.605	0.306	*
	New Year's Eve	0.384	0.137	*	-0.182	0.196		-0.245	0.301	
Assumptions:										
	Normality		yes			no			no	
	Non-autocorrelation		yes			no			no	
	Exogeneity		yes			yes			yes	
	Homoscedasticity		yes			no			yes	
Goodness of fits:										
	R^2		**0.87**			**0.80**			**0.89**	
	RMSE		0.13			0.18			0.28	

Notes: * $p < 0.05$, ~ $p< 0.1$, – reference case; [a]USU = Utah State University, [b]LSD = Logan School District, [c] Pioneer Day is an official Utah State holiday celebrated on July 24

Some major events also impacted pedestrian signal activity. The date of USU's commencement saw lower use of signal 5816, located near USU. However, pedestrian activity was positively associated with football games, which saw 27% increased pedestrian activity compared to an average day at the same intersection, while the other two signals were found to have no association. All school breaks reduced pedestrian activity at all three signals. The breaks associated with USU were found to be more significant at signal 5808 and 5816 as these signals are located near campus.

Several holidays appeared to be negatively associated with the pedestrian signal activity. Among all holidays, Christmas and Thanksgiving Day saw lower use of intersection crossings. For example, Christmas and Thanksgiving Days were expected to see 95% and 90% fewer pedestrian activity at signal 5808.

5.3 The Overall Effects of Weather Variables on Pedestrian Activity

This section summarizes the estimated effects of weather variables on pedestrian signal activity across all signals in Cache County in several ways. First, I tabulate the number (and share) of significant coefficients. Then, among statistically significant coefficients, I tabulate the frequency (and percentage) that have negative or positive associations with pedestrian signal activity. Table 5.2 summarizes these tabulations. I also visually represent the distribution of all estimated coefficients using boxplots, histograms and maps. Finally, I pool the coefficients for each weather variable together and perform a one-sample t-test (see table 5.3) with the null hypothesis of no association with pedestrian signal activity ($\beta = 0$). The impacts of weather on pedestrian signal activity, detailed in the sections below, are divided into three parts: effects of snowfalls and snow depth, min/max temperatures, and precipitation.

5.3.1 Snowfalls and Snow Depth

Among all 49 signals, snow depth appeared to have a significant association with pedestrian activity at 18 signals (37%) when snow depth $\geq$ 0.1 inch, and at 25 signals (51%) when snow depth $\geq$ 0.6 inch.

Table 5.2 Frequencies (percentages) of significant results with weather over one year

Weather variables		All signals (N=49)		Only Significant signals*	
		Not Sig (%)	Sig (%)	(-) sig* factor (%)	(+) sig* factor (%)
Snow Depth	≥ 0.1 in	31 (63%)	18 (37%)	18 (100%)	0 (0%)
	≥ 0.6 in	24 (49%)	25 (51%)	25 (100%)	0 (0%)
Snowfall	≥ 0.1 in	44 (90%)	5 (10%)	3 (60%)	2 (40%)
	≥ 0.6 in	28 (57%)	21 (43%)	20 (95%)	1 (5%)
Min Temperature	< 10ºF	45 (92%)	4 (8%)	4 (100%)	0 (0%)
	< 20ºF	41 (84%)	8 (16%)	5 (62%)	3 (38%)
	< 30ºF	41 (84%)	8 (16%)	4 (50%)	4 (50%)
Max Temperature	≥ 60ºF	45 (92%)	4 (8%)	1 (25%)	3 (75%)
	≥ 70ºF	41 (84%)	8 (16%)	1 (13%)	7 (87%)
	≥ 80ºF	43 (88%)	6(12%)	1 (17%)	5 (83%)
	≥ 90ºF	35 (71%)	14 (29%)	14 (100%)	0 (0%)
Precipitation	≥ 0.01 in	41 (84%)	8 (16%)	7 (87%)	1 (13%)
	≥ 0.05 in	46 (94%)	3 (6%)	3 (100%)	0 (0%)
	≥ 0.25 in	41 (84%)	8 (16%)	7 (87%)	1 (13%)

Note: Sig= significant, Factor= β value, *= the positive and negative factors were calculated from significant from significant factors (sig %). Percentage were added for those factors holding 100%

Table 5.3 Results of one sample t-test

Variables		*t-statistics*	*P*	*CI*	*Mean of variable*	*Reject Null?*
Snow Depth	≥ 0.1 in	-5.37	*	[-0.159, -0.072]	-0.12	yes
	≥ 0.6 in	-6.83	*	[-0.272, -0.148]	-0.21	yes
Snowfall	≥ 0.1 in	-0.45	≈	[-0.042, 0.027]	-0.01	no
	≥ 0.6 in	-7.39	*	[-0.382, -0.217]	-0.30	yes
Precipitation	≥ 0.01 in	-3.37	*	[-0.042, -0.011]	-0.03	yes
	≥ 0.05 in	-6.74	*	[-0.080, -0.043]	-0.06	yes
	≥ 0.25 in	-5.04	*	[-0.088, -0.036]	-0.06	yes
Min Temperature	< 10ºF	-2.52	*	[-0.086, -0.009]	-0.05	yes
	< 20ºF	-1.48	≈	[-0.051, 0.008]	-0.02	no
	< 30ºF	-0.52	≈	[-0.038, 0.022]	-0.01	no
Max Temperature	≥ 60ºF	0.13	≈	[-0.028, 0.029]	0.00	no
	≥ 70ºF	1.31	≈	[-0.015, 0.068]	0.03	no
	≥ 80ºF	2.99	*	[0.009, 0.049]	0.03	yes
	≥ 90ºF	-6.02	*	[-0.102, -0.051]	-0.07	yes

Notes: CI= confidence interval, * = p < 0.05, ≈ = p > 0.05

When significant, coefficients were all negative, implying that on average days with any amount of snow depth (≥ 0.1 in & ≥ 0.6 in), reduced pedestrian activity was seen. A boxplot of coefficients (Figure 5.1) and histogram (Figure 5.2) shows that the median value was less than zero and around 75% of coefficient were negative.

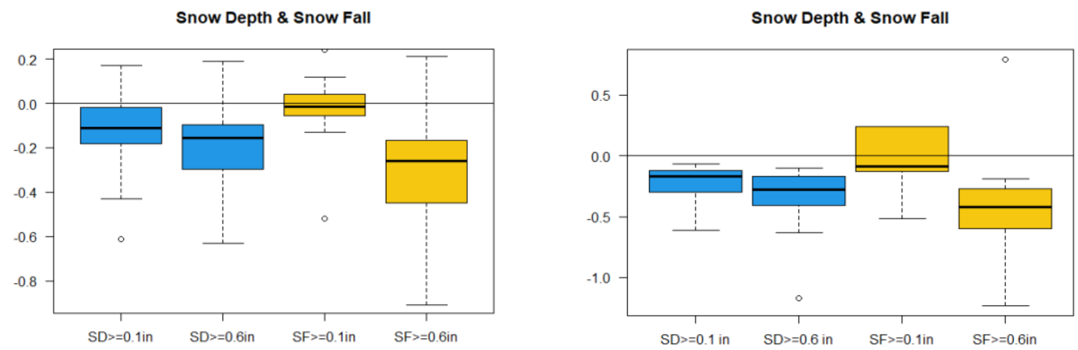


Figure 5.1 Box plot showing factors of snow depth & snowfalls (Left= all signals, Right= only significant)

Similarly, snowfall tended to have significant association with pedestrian activity at only 5 signals (10%) when snow ≥ 0.1 in falls and 21 signals (43%) when snow ≥ 0.6 in falls. The majority of significant signals showed negative (60% for ≥ 0.1 in; 95% for ≥ 0.6 in) and a few positive (40% for ≥ 0.1 in; 5% for ≥0.6 in) associations on pedestrian activity. The boxplot shows that the greatest impact was for larger snowfalls ≥ 0.6 in.

On average, snow depth had a significant negative impact on pedestrian activity at signals. Days with snow depth amounts above 0.6 in saw 26% reduced pedestrian activity. Compared to normal condition, days with snow falls above 0.6 in tended to have a significant negative impact with 20% reduction in pedestrian activity.

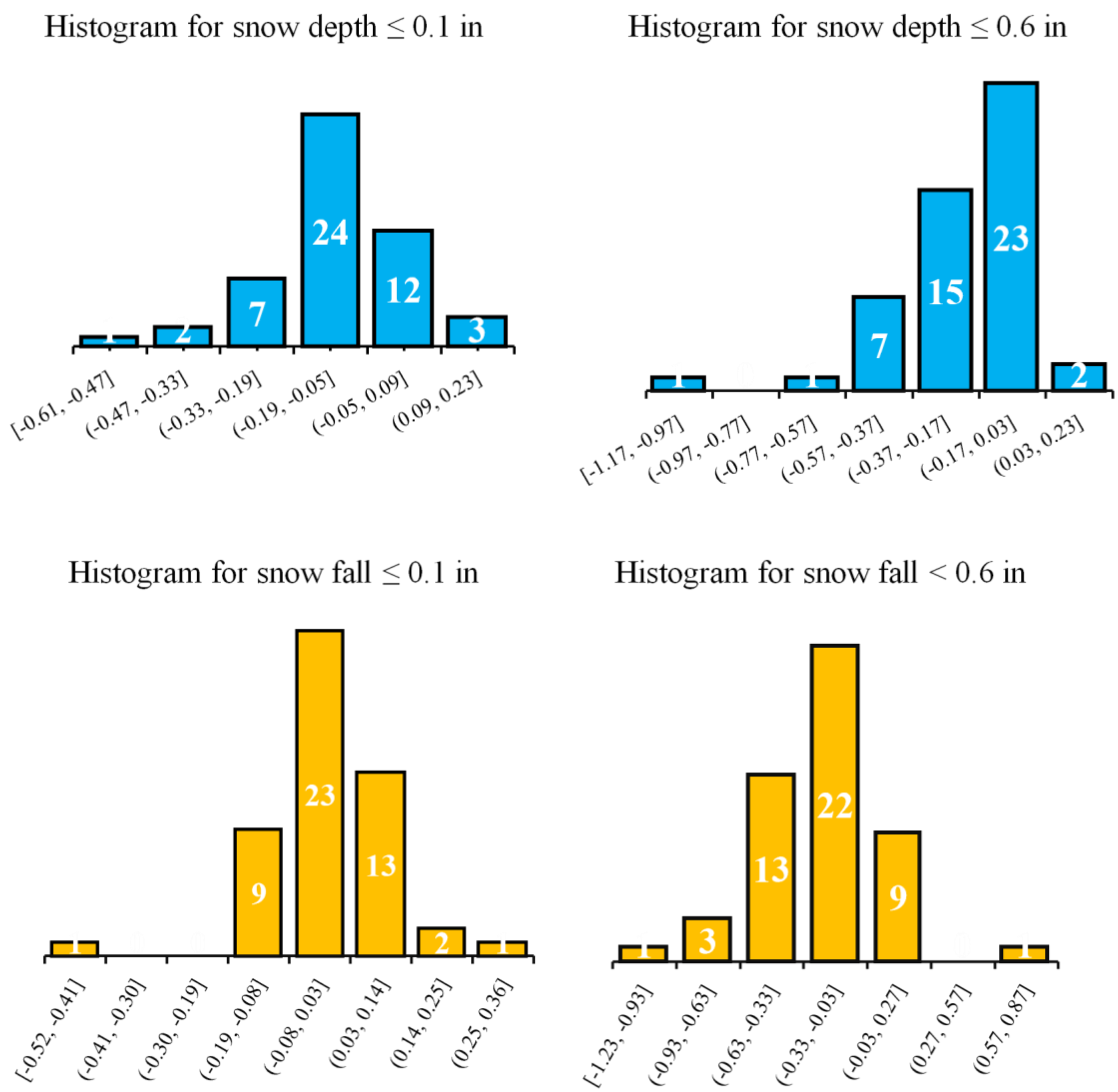
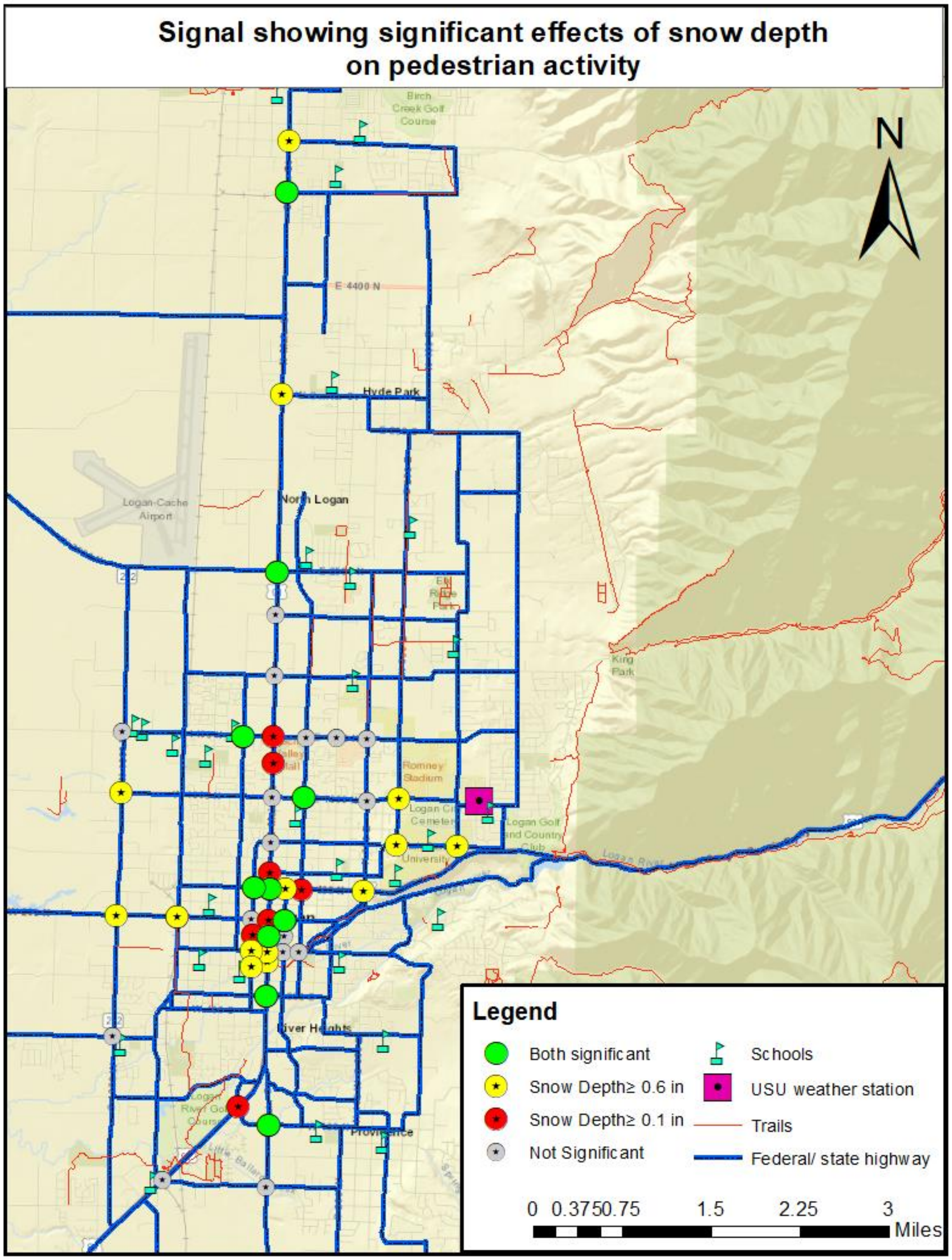


Figure 5.2 Histrogram showing frequency of snow depth and snowfalls

Figure 5.3 shows the location of the signals where snow depth and snowfalls found significant effects on pedestrian activity. Snow depth and snowfall reduce pedestrian activity near downtown and USU campus areas but not as much in suburban areas. As pedestrian activities are high near campus and downtown, any amount of snowfall and snow depth are expected to have significant negative impacts on activity.


Signal showing significant effects of snow depth on pedestrian activity
N
Legend
Both significant
Snow Depth≥ 0.6 in
Snow Depth≥ 0.1 in
Not Significant
Schools
USU weather station
Trails
Federal/ state highway
0 0.3750.75 1.5 2.25 3
Miles
Hyde Park
North Logan
River Heights
Providence
Logan-Cache Airport
E 4400 N

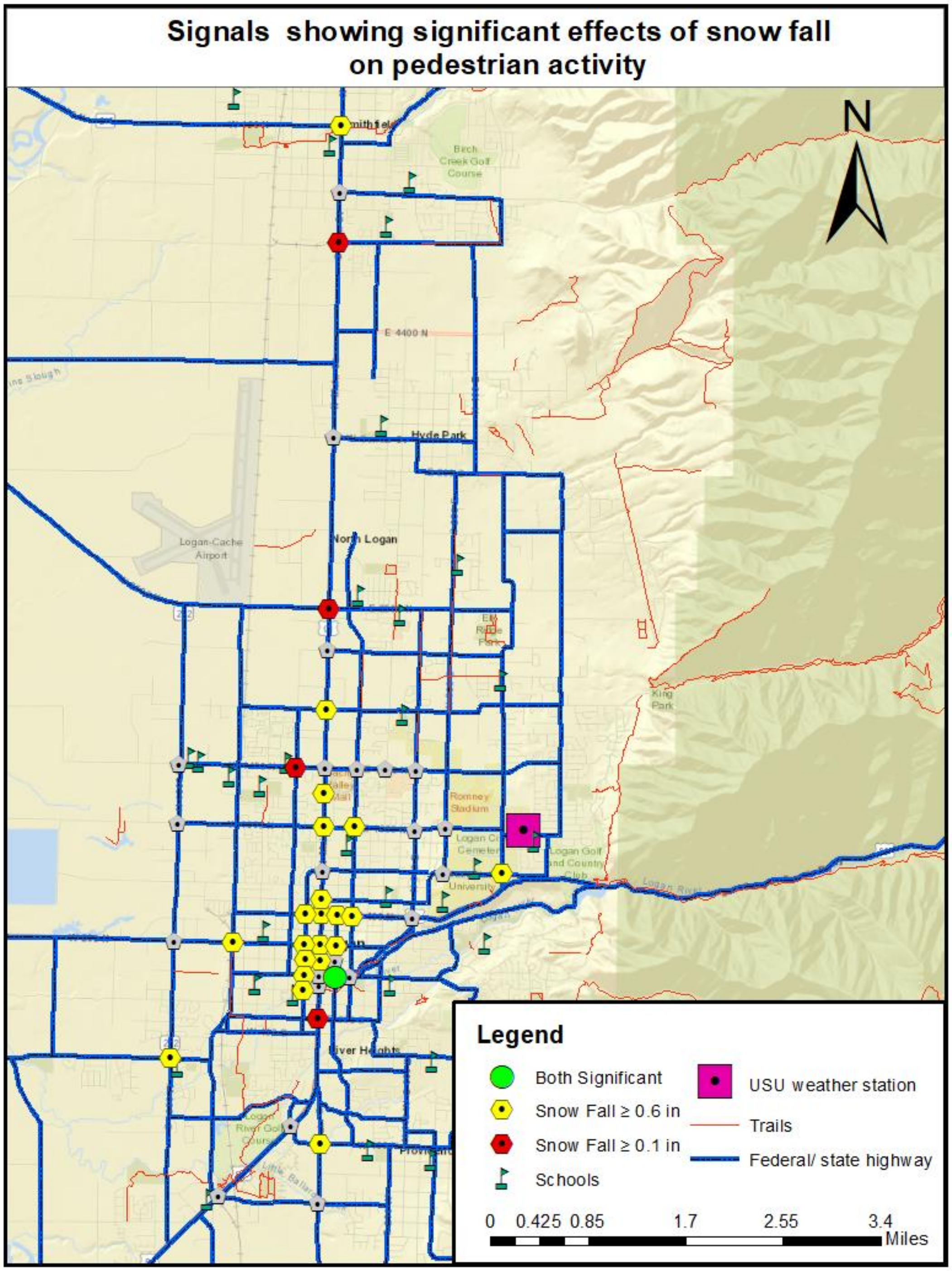


Figure 5.3 Maps showing the significant effects of snow depth and snowfalls

5.3.2 Temperature

Temperature seems to play an important role in affecting pedestrian activity, at least in some locations. At 8% signals there was a significant association with pedestrian activity when the low temperature was below 10ºF, and all of these signals (100%) showed a negative association. When the low temperature was below 30ºF, 16% of signals found a significant effect, where half of them were positive.

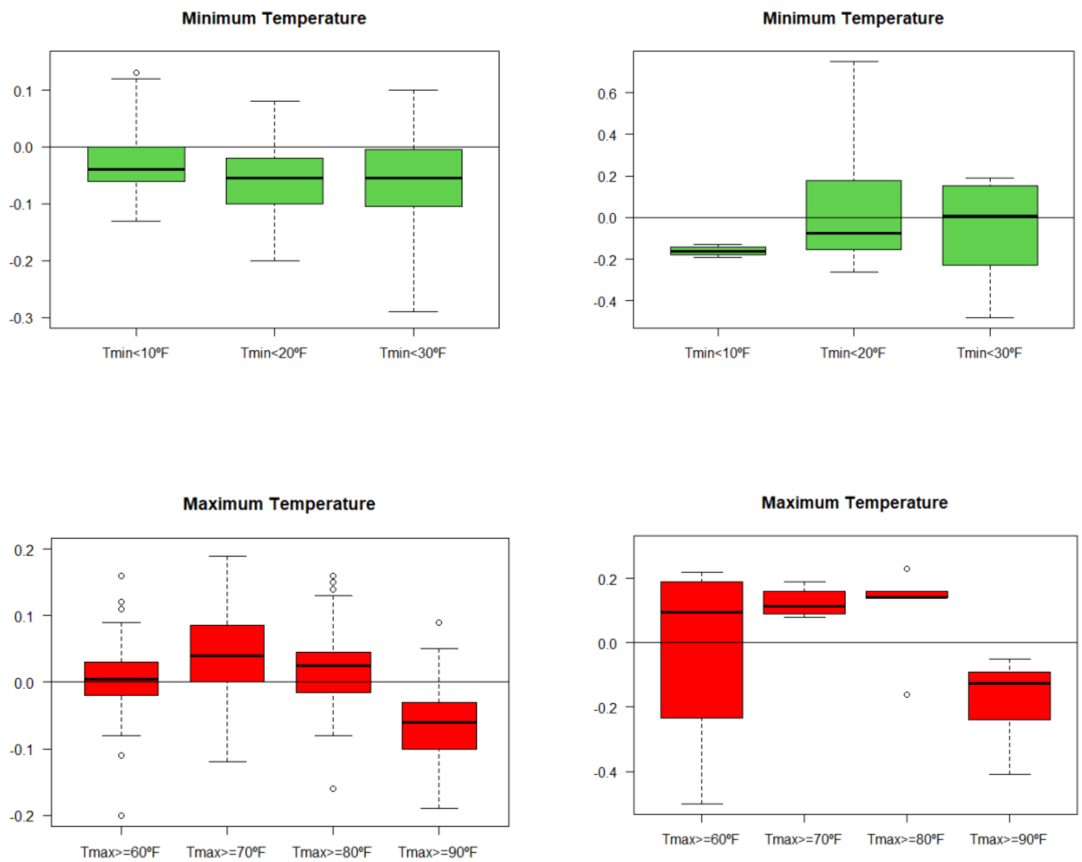


Figure 5.4 Box plot showing factors of min/max temperature (Left= all signals, Right= only significant)

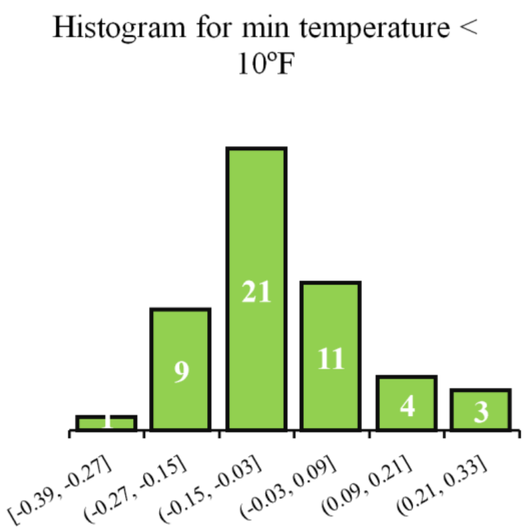
The effect of temperature lower than 10ºF was significantly different from zero, but the other two (< 20ºF and < 30ºF) were not (see Figure 5.4).

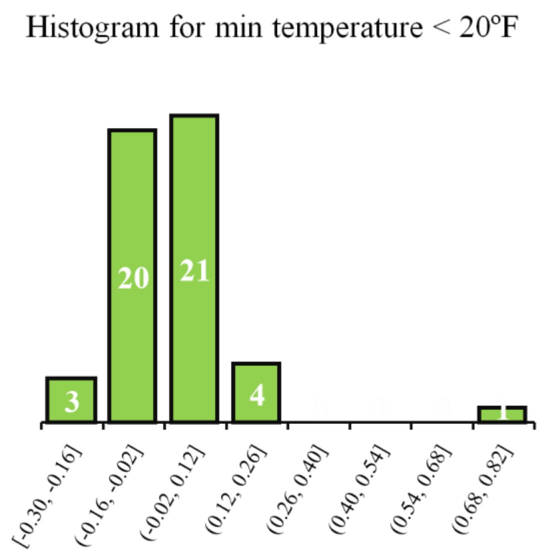
High temperatures higher than 60ºF but lower than 90ºF showed a positive association (70-85%) with pedestrian activity at 8-12% signals. The negative significant association started when the temperature went beyond 90ºF. About 30% of the signal had significant negative effects on pedestrian activity on extremely hot days. The effect of temperature higher than 90ºF was negative and different from zero (Figure 5.4).

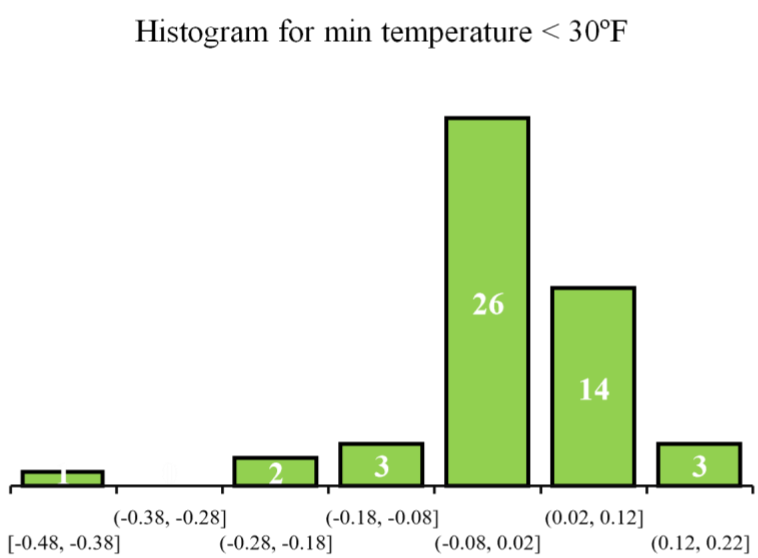
Overall, temperatures also had a significant association with pedestrian activity. Extreme hot days (≥ 90ºF) saw 7% decreased pedestrian activity (over +80-degree days), whereas warmer high temperatures (≥ 80ºF) found 3% increased pedestrian activity above that seen on +70-degree days. Minimum temperature (< 20ºF) had around 2% additional decreased in walking levels over that seen on days below 30 degrees. Subfreezing low temperatures negatively affected pedestrian activity. Days with temperatures lower than 10ºF saw 5% reduced pedestrian activity (below < 20-degree days). The histogram (Figure 5.5) plots show the same thing graphically. The mean temperature higher than 90ºF is negative and different from zero.

Figure 5.6 shows the location of the signals where maximum and minimum temperature show significant effects on pedestrian activity. Following a similar trend as snowfall and snow depth, pedestrian activities are seen to have negative associations near downtown and USU campus areas when the temperature goes above 90ºF. Surprisingly, temperature (70-90ºF) also has significant effects in suburban areas. In winter season, only one intersection near the USU campus tends to have lower pedestrian activity when

temperature is below 20ºF. Students of USU may still walk to reach in the campus. Compare to maximum temperature, a few signals show sigificant associations with pedestrian activity in the downtown areas when temperature is below 20ºF or 30ºF. Besides, some signals towards the main street and North Logan finds significant associations. People may be getting used to adopting cold temperatures (as winter stays longer than summer).







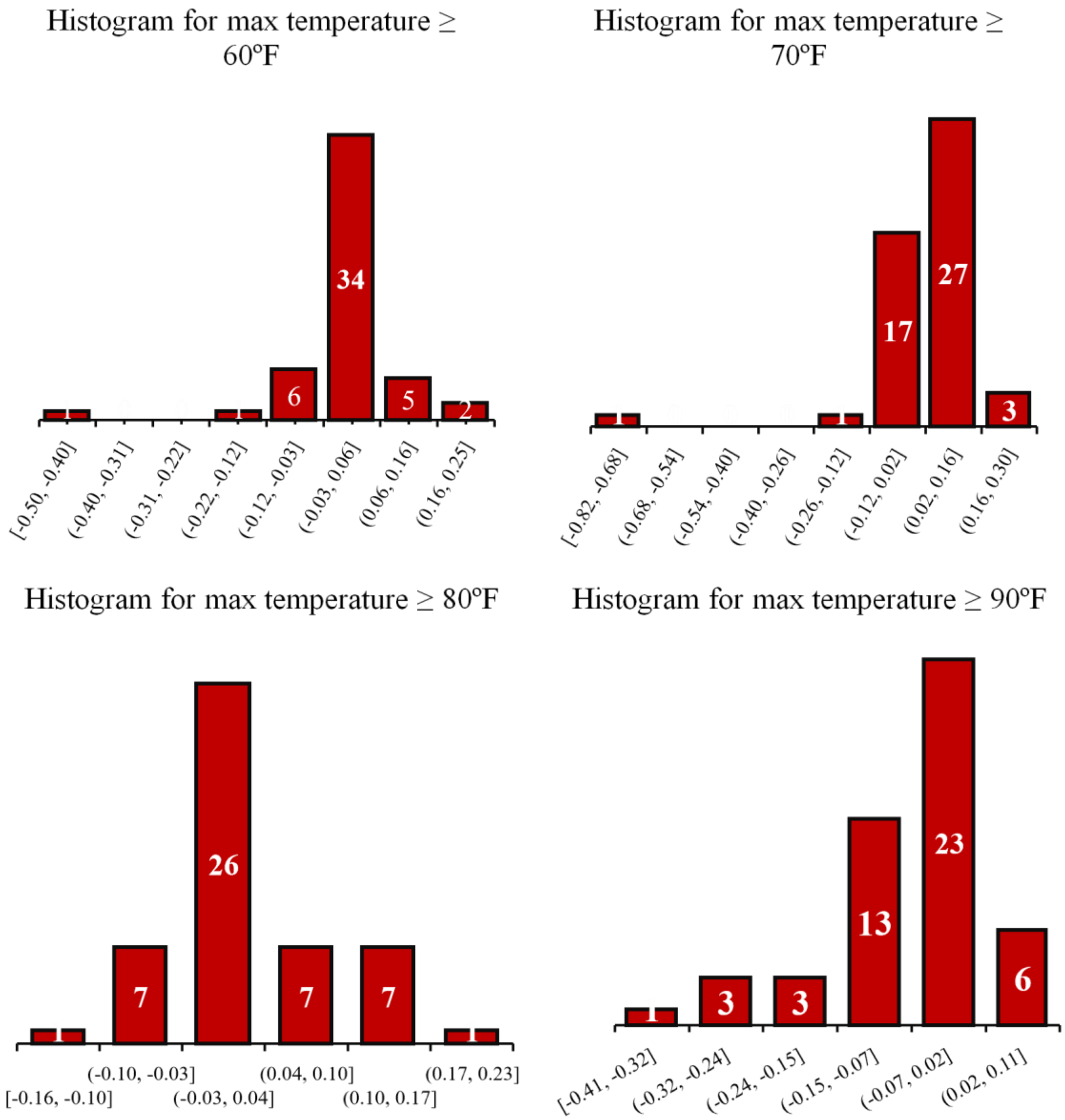
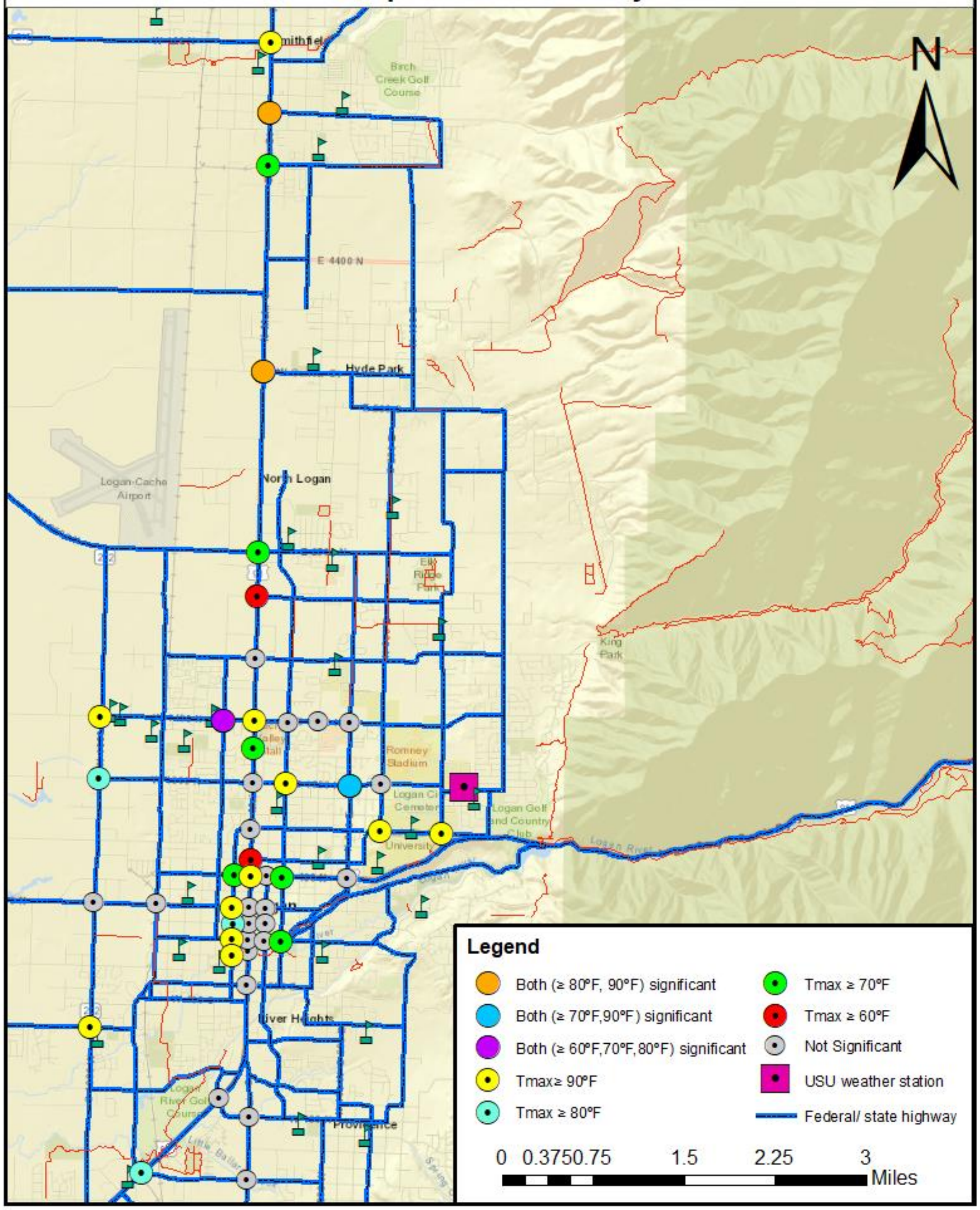


Figure 5.5 Histrogram showing frequency of max/min temperature

Signals showing significant effects of maximum temperature on pedestrian activity



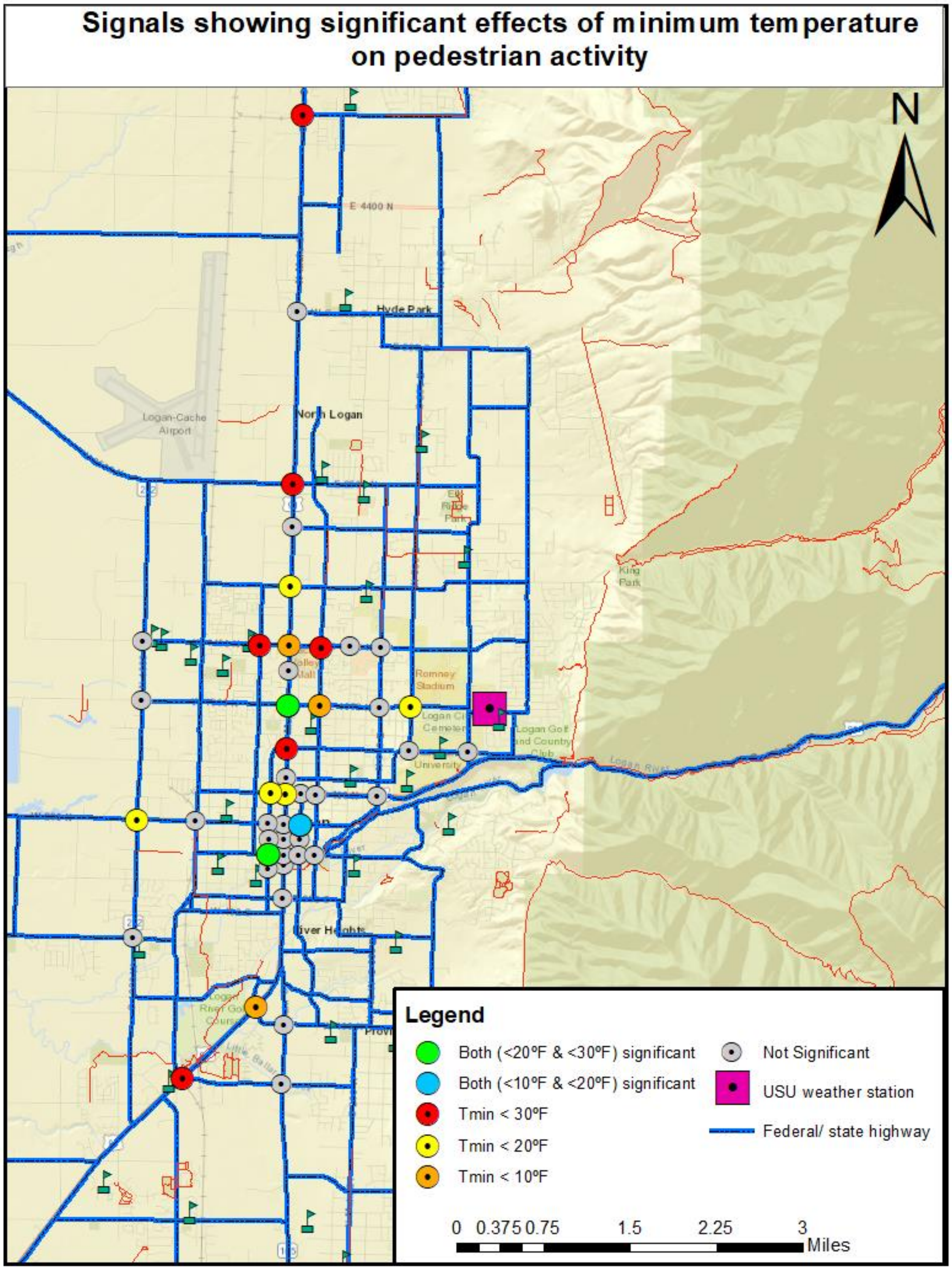


Figure 5.6 Maps showing the significant effects of max/min temperature

5.3.3 Precipitation

Any amount of precipitation had statistically significant impacts at less than 20% of the signals. At around 80% of these locations, precipitation was a deterrent to pedestrian activity while the rest had a positive association. The median of regression coefficients for precipitation is under zero (Figure 5.7). The deterring effect of precipitation increased as daily levels of precipitation increased. The histogram shows the frequency of positive and negative factors (see Figure 5.8). Maximum values at signals fall between 0.00 to -0.30. A few signals show a positive association of pedestrian activity during precipitation.

On average, precipitation had a significant negative impact on pedestrian activity at signals. Compared to dry conditions, days with precipitation > 0.01 in tended to have 3% reduced pedestrian activity. Increasing precipitation amount (> 0.25 in) appeared to have double (6%) the reduction in pedestrian activity.

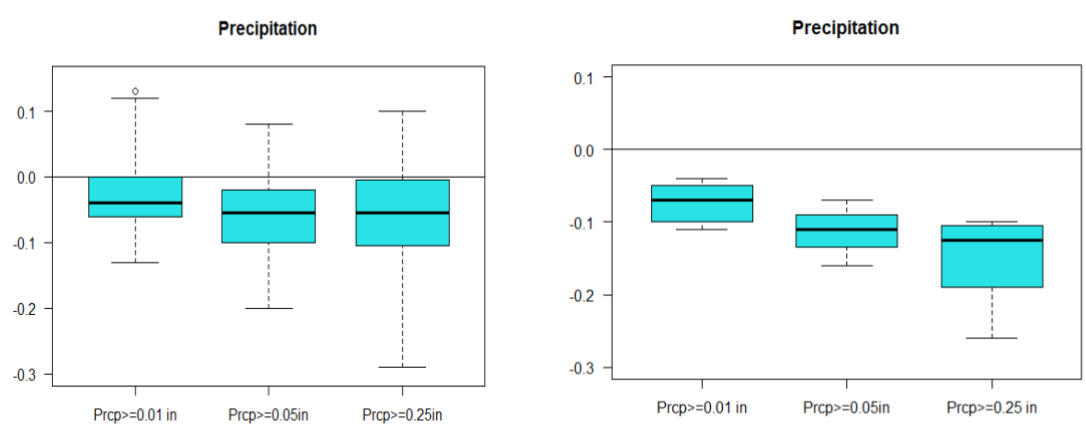


Figure 5.7 Box plot showing factors of precipitation (Left= all signals, Right= only significant signals)

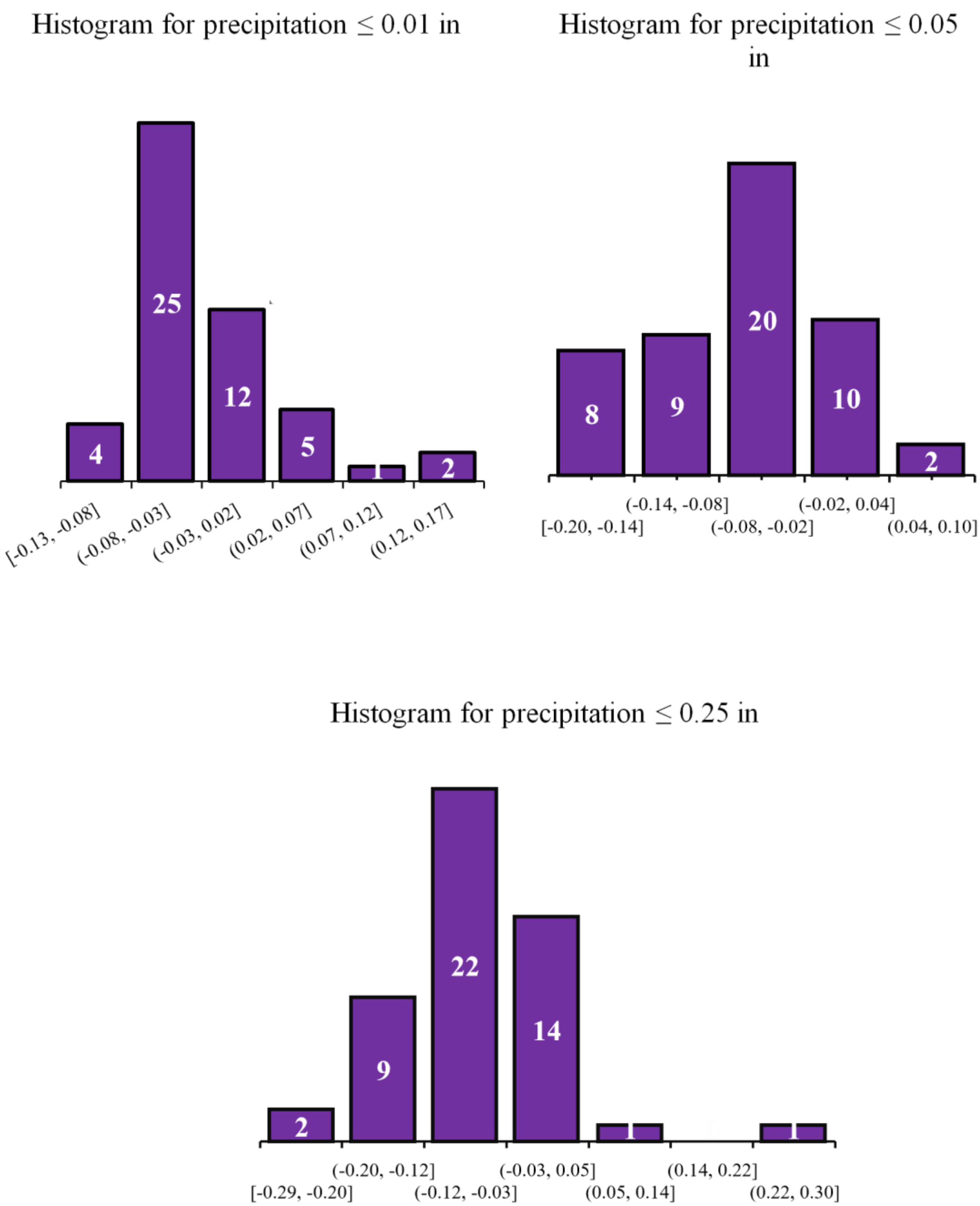


Figure 5.8 Histogram showing frequency of precipitation

Figure 5.9 shows the location of the signals where precipitation show significant effects on pedestrian activity. Precipitation appears to have least significant effects

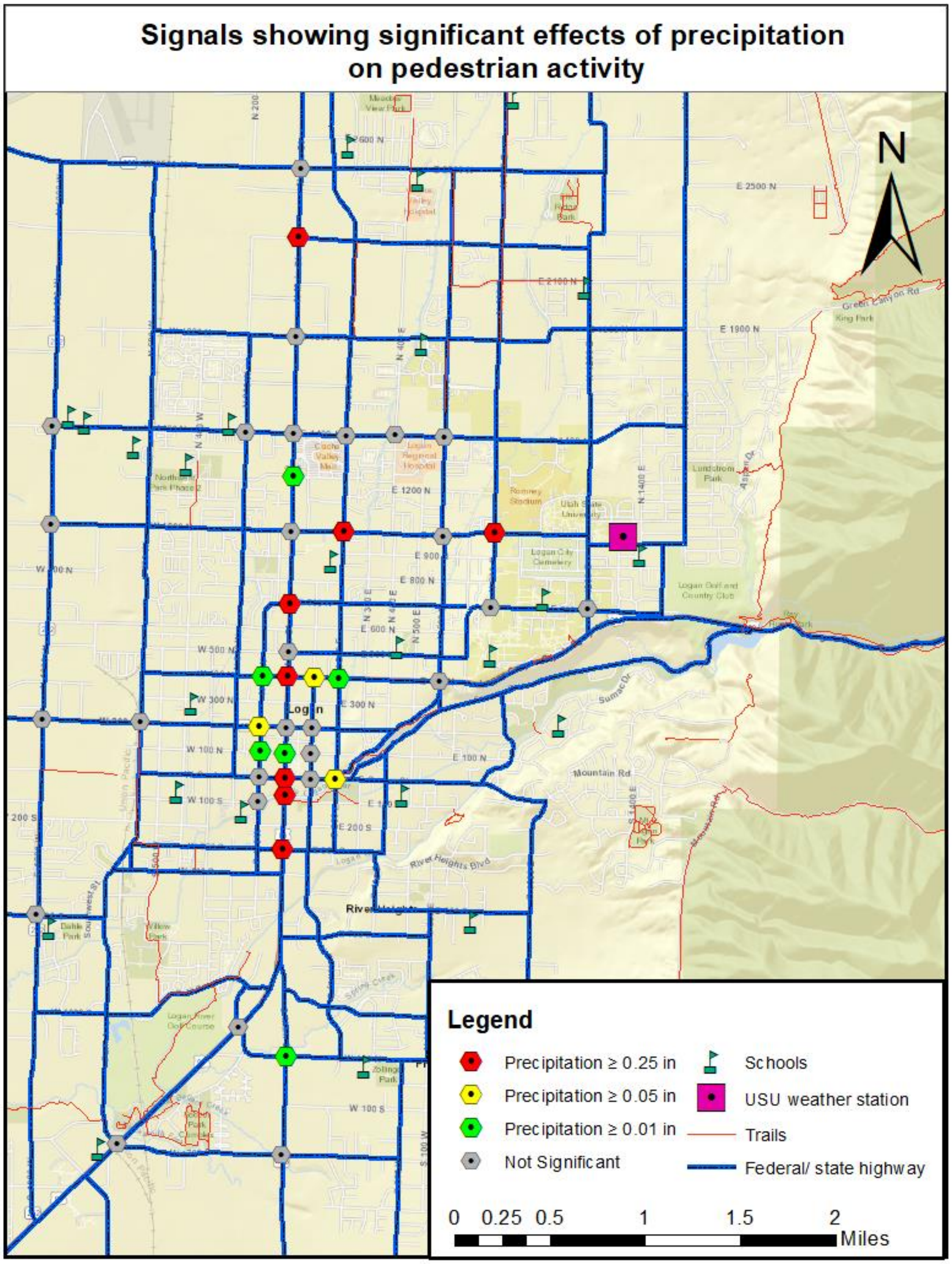


Figure 5.9 Map showing the significant effects of precipitation

compared to other weather variables on pedestrian activity. One signal near USU shows lower pedestrian activity when precipitation amount goes above quarter-inch. Though some significant associations were seen in the downtown area, less were found in the suburban areas. These findings seem reasonable as precipitation is less common in Cache County than snowfalls and snow depth.

5.4 Goodness of Fit and R-Squared

In this study, R^2 values for half of the signals fall between 0.7-0.9. This indicates that many of the models explain 70% to 90% of the variation in the pedestrian signal activity around its mean. The other half lies between 0.5 to 0.7. See Figure 5.10.

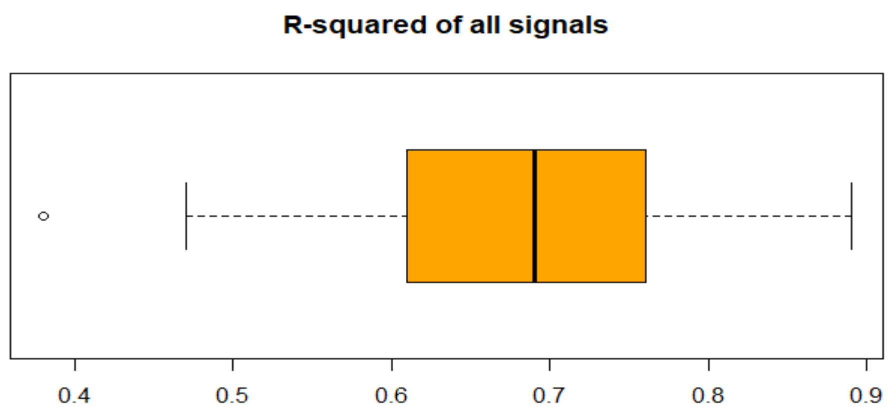


Figure 5.10 Box-plot showing R^2 value for all signals

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Key Findings

This concluding section first highlights the major findings of this study. Next, it summarizes the major contributions of this work, and policy implications are then discussed. This section concludes by noting some limitations and potential future work. Overall, the findings of log-linear time series analysis suggest that weather variables have significant effects on pedestrian signal activity in Cache County, Utah. This subsection summarizes the key findings of this study.

Snow depth was the most frequently significant factor, and it had a negative impact on pedestrian walking levels. This significant association was greater than the effect of snowfalls (≥ 0.1 in). Snowfall above 0.6 inches was also frequently significant with pedestrian signal activity. When significant, it had a negative impact.

Maximum temperature above 90ºF was significant fairly often. When significant, it had a negative (lower pedestrian activity at around 30% of signals) association. This suggests that people choose not to walk as much on very hot days.

Other weather variables were significant at only a few (< 20%) locations. But when significant, some had consistent findings. Minimum temperatures below < 20ºF and especially < 10ºF had negative effects on walking activity. Cold temperatures were associated with lower pedestrian activity at 5-10% of signals. On average, the strength of this association was similar to a quarter-inch of precipitation and half the impact of snow depth (≥ 0.1 in). Maximum temperatures above 60ºF, 70ºF, and 80ºF had a positive effect.

Any amount of precipitation had a negative effect on walking levels. The effect of a quarter-inch of precipitation resulted in a 6% depletion in walking activity, which was half the impact of snow depth at or above 0.1 inches.

Overall findings suggest that most of the signals showed a significant effect of the weather on pedestrian activity. The direction of the results is consistent with previous studies and expectations. Findings show that weather variables and walking activity have non-linear relationships. Urban walking activity is more affected by weather in urban areas compared to suburban areas.

6.2 Contributions

Multimodal transportation planning, traffic safety analyses, and health impact assessments require information on how many people are walking in various locations throughout the day. However, traditional data collection methods for levels of pedestrian activity are insufficient for these purposes. Similarly, a small sample size cannot properly find out a variation in weather variables.

The major contribution of this study is the use of unique pedestrian data. This study uses one promising pedestrian actuation data source as a proxy measure of pedestrian signal activity (this data was taken from the ongoing project by Singleton and Runa, 2020). UDOT archives these traffic signal pedestrian actuation data for use in its Automated Traffic Signal Performance Measures (ATSPM) system. The use of pedestrian signal actuation data is a potentially rich source of information about levels of pedestrian activity at little additional cost.

Second, this study used more than 1-year pedestrian signal data at 49 different locations where the previous studies looked at only a few locations. The analyses and results of Chapter 5 confirmed several relatively well-established findings of associations between walking activity and weather variables. This study also finds non-linear relationships between weather variables and walking.

Finally, the results of this study support findings from previous studies. The finding that very hot and cold temperatures reduce walking activity is consistent with prior research (Attaset et al., 2010; Singleton et al., 2019; Li & Fernie 2010). Besides, some previous studies found negative associations of snowfall or ice on bicyclist and pedestrian levels (Li & Fernie 2010; Spencer et al., 2013) that is confirmed by this study.

Previous findings revealed that any amount of precipitation tended to have lower walking activity (Attaset et al.,2010; Aultman-Hall et al., 2009), however, our find is inconsistent with this finding. The results find no apparent effect of precipitation on walking levels. Besides, negative association depends on the amount of precipitation. It may be because of dry climate, low frequency of precipitation or precipitation occurs in short period, so people can avoid it within the day.

6.3 Policy Implications

This work and its findings have several implications for multimodal transportation planning. For instance, snowfall and snow depth are the most influential factors and reduce walking levels. This means that pedestrians seem to be averse to walking/crossing the sidewalks with snow on the ground or on the day of a big snowstorm (that makes few inches of snow depth). The question is why they do not walk as much on those snowy

days? Of course, it is not possible to identify exactly why pedestrians are changing their transportation behavior using aggregate observational data. It could be because of road and sidewalk conditions including snow/ice or poor snow treatment measures (snow clearance, ice treatment, road salting, or sanding). Spencer et al. (2010) concluded that travelers stopped walking/cycling after a big snowstorm because they were concerned about the plowing of snow: “plowing pushes snow toward the sides of roads, narrowing them and often covering over shoulders or bike lanes” or crossing areas. This makes it very inconvenient for walking on the sidewalks or crossings streets. Sometimes, snow clearance takes a few days, and snowplowing may be delayed on weekends or major holidays. Walking in the sidewalks can sometimes be impossible, which forces pedestrians to walk through the shoulder (maybe because of walking fast) that is extremely dangerous on snowy days. Travelers are also concerned about their safety as inclement conditions cause road accidents. Though the transportation policy cannot change the weather conditions, however, they can provide the highest pedestrian facilities (efforts for snow removal on sidewalks; making crosswalks, corners) through proper infrastructure development and maintenance in the winter for making active travelers comfortable and safe.

As extreme hot temperature reduces walking activity, it may be worth planting more trees which will provide shade in the sidewalk. The presence of trees and vegetation can limit the solar radiation from sidewalk surface through reducing the air temperature. Travelers can get relief from hot summer sun even from the shade of one single tree.

Another policy implication may be to set all crosswalks to pedestrian recall (note that pedestrian recall means that the walk sign will come on automatically in all crosswalks

and there is no need to press the push-button). It is difficult to wait a longer period at the intersection during very snowy or cold temperatures. Li & Fernie (2010) found that inclement weather adversely influenced pedestrian behavior at signalized intersections with a two-stage crossing. Their findings showed that pedestrians increased walking speeds in the very cold temperature and were more likely to walk against a “Pedestrian begin clearance (#22)” or “Don’t Walk” signal (#23)”. Though this work was done at a two-stage refuse island, however, it may be true for a single crossing as well. Traffic engineers and planners should pay attention to optimize signal timing especially in the winter that minimizes both vehicular and pedestrian delays. We know that signalized intersections are the most vulnerable places for pedestrian crashes with left-turning vehicles. Policymakers could increase “pedestrian begin walk (#21)” time to decrease the possibilities of crashes.

It is hard to find out how and why active travelers change their travel patterns. Perhaps, they take a different route where they find more shade on the sidewalk and or maybe cleaned road surface. Active travelers may change their modes to enclosed motorized means of transportation (public transit or driving an automobile) in very hot and cold temperatures. This would imply that the policy makers should improve public transit services, for example, increasing route frequencies, number of stoppage and routes; operating longer hours.

6.4 Limitations and Future Work

One major limitation of this study is that the underlying traffic signal controller log data may not capture all of the pedestrian activity. Another challenge related to this study is that the traffic signal pedestrian data used as a proxy measure of pedestrian activity are

historical time series data. The pedestrian activity could differ in the future with a growing population.

Furthermore, this study used weather data from one station (USU weather station) to identify the effect of weather on pedestrian activity. The station is approximately 3 mi from the farthest signal. Though it is not unreasonably distant from the farthest signal, the levels of snowfall, snow depth, and precipitation may differ from the closest station which may affect the results. Besides, the station is on the bench, so it is elevated from most signals in the valley, which may mean weather effects are slightly different. Furthermore, this study only looked at only few weather variables. Like other studies, this study couldn't examine the effect of wind, cloud cover, and humidity.

This study didn't provide more discussion of the intersection (classification of intersections), sociodemographic characteristics and their effects on walking or on the relationship between walking and weather (as this was not a primary research question). As land use and sociodemographic characteristics, intersection types play an important role on how many people will walk at intersections, this may be other limitations of this study.

Future tasks could use a slightly better measure of pedestrian activity. Singleton and Runa (2020) collected observed pedestrian counts (from video recordings) to validate the signal actuations, and developed factoring methods to estimate pedestrian intersection volumes. Future work could use factors to convert the constructed measure pedestrian signal activity (#45A) into estimated pedestrian crossing volumes; however, we wouldn't expect this to change our results significantly. Last but not least, more sophisticated modeling techniques could be analyzed to consider the probable effects of temporal and

spatial correlation in a future study with additional weather variables, such as cloud cover, wind speed, and humidity.

The time series analysis of this study depended on only 16 months of data. Future works should use larger sample sizes (several years of data) because of few reasons: it could increase the power of the analysis, and it might yield more statistically significant associations.

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APPENDICES

APPENDIX A. DESCRIPTISC STATISTICS OF PEDESTRIAN

Signal ID	*Location*	*City*	*Min*	*Max*	*Mean*	*SD*	*Skewness*	*Kurtosis*
5294	*Main St & 1600 N*	*North Logan/Logan*	—	—	—	—	—	—
5295	*US-89 & 1000 W*	*Logan*	—	—	—	—	—	—
5297	Main St & 1700 S	Logan/ Providence	0	80	3.32	4.61	10.55	172.34
5298	*Main St & 2600 S*	*Nibley*	—	—	—	—	—	—
5299	200 W & Main St	Richmond	3	145	36.27	17.08	1.23	7.79
5301	Main St & 100S	Logan	0	226	87.96	29.70	-0.14	3.90
5302	Main St & 300S	Logan	0	211	60.67	29.02	1.32	6.98
5303	Main St & Center St	Logan	0	659	158.92	78.70	2.02	11.39
5304	Main St & 100 N	Logan	11	534	105.52	54.25	3.19	20.91
5305	Main St & 200 N	Logan	4	377	128.53	56.93	0.90	4.32
5306	Main St & 400 N	Logan	41	291	173.29	50.17	-0.31	2.33
5307	Main St & 500 N	Logan	11	119	69.28	19.74	-0.45	2.76
5308	Main St & 700 N	Logan	1	115	60.32	16.52	-0.03	3.23
5309	Main St & 1000 N	Logan	28	1338	136.48	71.48	11.00	181.10
5310	Main St & 1250 N	Logan	6	89	43.30	14.08	0.27	2.83
5311	Main St & 1400 N	Logan	34	294	192.26	44.83	-0.34	2.90
5312	100 E & 400 N	Logan	35	258	168.29	46.27	-0.54	2.52
5313	200 E & 400 N	Logan	32	263	173.34	37.68	-0.44	2.98
5314	600 E & 400 N	Logan	6	405	160.72	77.05	0.59	3.02
5315	1000 W & 600 S	Logan	0	142	50.73	33.34	0.53	2.28
5316	1000 W & 1000 N	Logan	0	25	6.17	4.68	0.61	3.12
5317	1000 W & 1400 N	Logan	0	31	8.14	6.34	0.48	2.73
5318	100 W & 200 N	Logan	6	252	122.83	51.38	-0.25	2.26
5319	600 W & 200 N	Logan	0	57	18.14	7.96	0.70	4.29
5320	1000 W & 200 N	Logan	0	46	14.23	8.84	0.65	2.87
5321	Main St & 1800 N	Logan	0	44	19.19	9.20	0.18	2.64
5322	Main St & 2200 N	Logan	0	113	11.54	7.33	5.93	83.36
5323	Main St & 2500 N	North Logan	0	48	18.41	9.39	0.58	2.88
5324	Main St & Hyde Park Ln (Center St)	Hyde Park	0	47	5.66	4.43	2.50	19.69
5325	Main St & 600 S	Smithfield	0	39	8.99	5.88	1.15	5.27
5326	Main St & 300 S	Smithfield	1	49	18.15	8.72	0.48	2.83
5327	Main St & 100 N	Smithfield	3	111	50.18	20.43	-0.11	2.47
5330	US-89/US-91 1700 S / 800 W	Logan	0	344	11.76	34.00	8.08	72.08
5331	100 W & Main St	Logan	3	110	54.92	19.24	0.10	2.57
5332	Main St & 1200 S	Logan/Providence	2	82	39.94	17.04	0.15	2.31
5333	*Main St & 3200 S*	*Nibley*	—	—	—	—	—	—
5341	*Main St & 800 E*	*Hyrum*	—	—	—	—	—	—
5342	*US-89 / US-91 & SR-101*	*Wellsville*	—	—	—	—	—	—
5800	200 W & 1400 N	Logan	0	154	71.29	27.11	-0.46	3.08
5801	200 E & 1400 N	Logan	0	256	144.34	50.42	-0.69	3.55
5802	400 E & 1400 N	Logan	0	132	61.16	24.37	-0.28	2.76
5803	600 E & 1400 N	Logan	0	261	67.70	32.67	0.62	6.14
5805	200 E & 1000 N	Logan	18	277	155.21	49.06	-0.04	2.44
5804	*800E & 1400 N*	*Logan*	—	—	—	—	—	—
5806	800 E & 1000 N	Logan	0	1311	394.11	340.61	0.67	2.36
5807	800 E & 700 N	Logan	13	1655	860.12	498.39	0.03	1.59
5808	1200 E & 700 N	Logan	6	1544	648.46	426.90	0.21	1.73
5809	100 W & 400 N	Logan	24	148	86.92	25.30	-0.13	2.52
5810	100 W & 100 N	Logan	0	96	24.73	14.36	0.51	3.77

5811	100 W & Center St	Logan	0	136	39.82	32.98	0.21	1.95
5812	100 W & 100 S	Logan	0	72	21.46	14.39	0.60	2.89
5813	100 E & 200 N	Logan	4	267	60.29	26.83	1.97	16.74
5814	100 E & 100 N	Logan	0	553	36.96	42.08	9.19	105.14
5815	100 E & Center St	Logan	0	1033	108.73	75.17	8.47	98.45
5816	600 E & 1000 N	Logan	8	395	169.49	64.26	0.49	3.43
5817	200 E & Center St	Logan	0	595	99.84	48.24	3.33	33.11

APPENDIX B. RESULTS OF LOG-LINEAR TIME SERIES ANALYSIS

Variable		***Signal 5297 (N=448)***			***Signal 5299 (N= 448)***			***Signal 5301 (N= 441)***			***Signal 5302 (N=440)***			***Signal 5303 (N= 440)***		
		β	*SE*	*P*	*β*	*β*	*SE*	*P*	*SE*	*P*	*β*	*SE*	*P*	*β*	*SE*	*P*
Weather Variables																
	β_0	1.428	0.221	*	3.829	0.164	*	4.804	0.075	*	4.141	0.135	*	4.962	0.107	*
Snow Depth	≥ 0.1 in	-0.303	0.198		-0.125	0.111		-0.098	0.057	~	-0.024	0.097		-0.111	0.072	
	≥ 0.6 in	-0.247	0.214		-0.152	0.138		-0.164	0.067	*	-0.487	0.118	*	-0.268	0.089	*
Snowfall	≥ 0.1 in	0.097	0.160		-0.092	0.093		-0.091	0.055	~	-0.013	0.087		0.007	0.059	
	≥ 0.6 in	0.012	0.457		-0.003	0.250		-0.211	0.155		-0.249	0.240		-0.188	0.159	
Precipitation	≥ 0.01 in	0.061	0.107		0.080	0.061		-0.038	0.037		-0.003	0.058		-0.037	0.039	
	≥ 0.05 in	-0.143	0.140		-0.105	0.077		-0.010	0.048		0.002	0.075		0.078	0.049	
	≥ 0.25 in	0.099	0.169		-0.043	0.094		-0.109	0.058	~	-0.258	0.090	*	-0.175	0.060	*
Min Temperature	< 30ºF	0.022	0.116		0.053	0.074		-0.013	0.039		-0.026	0.066		0.033	0.047	
	< 20ºF	0.144	0.161		-0.065	0.103		-0.005	0.053		-0.032	0.091		-0.072	0.066	
	< 10ºF	-0.009	0.231		-0.210	0.153		-0.052	0.078		0.114	0.135		0.048	0.098	
Max Temperature	≥ 60ºF	0.113	0.121		0.164	0.071	*	0.026	0.041		-0.010	0.066		0.003	0.045	
	≥ 70ºF	-0.043	0.135		0.009	0.087		0.071	0.046		0.023	0.077		0.056	0.056	
	≥ 80ºF	0.148	0.110		0.001	0.069		0.054	0.038		-0.004	0.063		0.026	0.044	
	≥ 90ºF	-0.029	0.106		0.025	0.079		-0.062	0.038		-0.046	0.070		-0.005	0.053	
Temporal Variables																
Month:	January	-0.313	0.269		-0.225	0.208		-0.391	0.092	*	-0.270	0.167		-0.199	0.136	
	February	-0.450	0.251	~	-0.507	0.197	*	-0.387	0.085	*	-0.131	0.157		-0.162	0.129	
	March	-1.229	0.243	*	-0.302	0.192		-0.300	0.083	*	-0.215	0.153		-0.110	0.126	
	April	0.024	0.223		-0.127	0.180		-0.114	0.076		-0.032	0.142		-0.032	0.118	
	June	0.075	0.155		-0.048	0.135		-0.025	0.053		0.067	0.101		0.237	0.088	*
	July	0.108	0.166		-0.272	0.139	~	-0.044	0.059		0.316	0.112	*	0.297	0.092	*
	August	0.014	0.150		-0.288	0.127	*	0.036	0.051		0.146	0.097		0.064	0.085	
	September	-0.027	0.206		-0.213	0.166		-0.116	0.070	~	-0.001	0.131		0.046	0.109	
	October	-0.011	0.227		-0.054	0.183		-0.177	0.077	*	0.095	0.144		0.145	0.120	
	November	-0.247	0.231		-0.430	0.185	*	-0.383	0.079	*	-0.236	0.146		-0.161	0.121	
	December	-0.811	0.289	*	-0.457	0.221	*	-0.476	0.098	*	-0.174	0.179		0.027	0.144	
Weekday:	Sunday	-0.771	0.100	*	-0.601	0.062	*	-0.407	0.035	*	-0.173	0.056	*	-0.279	0.040	*
	Monday	-0.150	0.100		-0.091	0.060		-0.232	0.034	*	-0.222	0.055	*	-0.285	0.039	*
	Tuesday	-0.022	0.100		0.014	0.052		-0.080	0.034	*	0.001	0.051		-0.018	0.033	
	Thursday	0.034	0.101		0.017	0.052		0.023	0.035		0.122	0.051	*	0.046	0.033	
	Friday	-0.252	0.101	*	-0.006	0.060		-0.054	0.035		0.072	0.056		0.069	0.039	~

	Saturday	-0.171	0.104		-0.283	0.064	*	-0.148	0.036	*	0.238	0.058	*	0.292	0.041	*
Events[a]:	USU, commencement	-0.268	0.440		-0.317	0.292		0.054	0.150		0.039	0.258		0.098	0.188	
	USU, Football	0.025	0.224		0.037	0.123		0.076	0.076		0.173	0.119		0.026	0.079	
Breaks:	USU, winter	0.262	0.233		-0.067	0.164		-0.071	0.071		-0.318	0.131	*	-0.110	0.107	
	USU, spring	0.110	0.284		0.115	0.219		0.114	0.095		0.039	0.176		0.110	0.142	
	LSD[b], spring	0.089	0.244		-0.319	0.202		-0.285	0.083	*	-0.371	0.158	*	-0.183	0.132	
	USU, summer	0.108	0.170		0.026	0.135		-0.155	0.058	*	-0.034	0.108		0.126	0.089	
	LSD, fall	-0.210	0.355		-0.577	0.255	*	-0.269	0.121	*	-0.341	0.216		-0.198	0.164	
Holidays:	New Year's Day	-0.210	0.610		-0.803	0.387	*	-0.165	0.207		0.676	0.343	*	0.060	0.249	
	—day after	-0.743	0.610		-0.202	0.355		-0.068	0.207		-0.355	0.329		-0.255	0.227	
	Memorial Day	-0.196	0.575		-0.136	0.320		-0.098	0.196		-0.072	0.307		-0.058	0.204	
	Independence Day	-0.442	0.404		-0.343	0.226		-0.354	0.138	*	-0.592	0.217	*	-0.305	0.144	*
	Pioneer Day	-0.224	0.401		-0.232	0.224		0.048	0.192		0.044	0.303		-0.021	0.143	
	Labor Day	0.845	0.408	*	0.075	0.229		-0.012	0.139		-0.352	0.219		-0.159	0.146	
	Thanksgiving Day	0.394	0.569		-0.877	0.336	*	-0.551	0.194	*	-0.497	0.311		-0.443	0.215	*
	—day after	-1.041	0.577	~	-0.808	0.342	*	-0.333	0.196	~	-0.026	0.315		0.028	0.219	
	Christmas Eve	0.066	0.628		-0.463	0.378		0.093	0.214		-0.839	0.346	*	-0.440	0.242	~
	Christmas Day	-0.570	0.640		-1.006	0.404	*	-0.664	0.218	*	-0.848	0.360	*	-1.071	0.260	*
	—day after	-0.644	0.617		-0.298	0.358		-0.256	0.209		-0.197	0.333		-0.243	0.229	
	New Year's Eve	-0.046	0.592		-1.301	0.350	*	0.213	0.201		-0.762	0.322	*	-0.182	0.224	
Assumptions:																
	Normality		no			no			no			yes			no	
	Non-autocorrelation		yes			yes			yes			no			no	
	Exogeneity		yes			yes			yes			yes			yes	
	Homoscedasticity		no			no			yes			yes			yes	
Goodness of fits:																
	R^2		**0.52**			**0.47**			**0.74**			**0.53**			**0.66**	
	RMSE					0.33			0.19			0.29			0.21	

Variable		*Signal 5304 (N=448)*			*Signal 5305 (N=448)*			*Signal 5306 (N=448)*			*Signal 5307 (N=448)*			*Signal 5308 (N=448)*		
		β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*
Weather Variables																
	β_0	4.562	0.109	*	4.903	0.098	*	5.309	0.051	*	4.494	0.068	*	4.448	0.077	*
Snow Depth	≥ 0.1 in	-0.160	0.076	*	-0.236	0.067	*	-0.069	0.039	~	-0.137	0.051	*	-0.064	0.057	
	≥ 0.6 in	-0.170	0.093	~	-0.109	0.083		-0.127	0.046	*	-0.093	0.061		-0.048	0.068	
Snowfall	≥ 0.1 in	0.074	0.065		-0.042	0.057		0.015	0.037		0.040	0.049		-0.056	0.051	
	≥ 0.6 in	-0.897	0.176	*	-0.326	0.153	*	-0.268	0.106	*	-0.280	0.140	*	0.011	0.142	
Precipitation	≥ 0.01 in	-0.077	0.043	~	-0.003	0.037		-0.013	0.025		-0.044	0.033		-0.047	0.034	
	≥ 0.05 in	0.024	0.054		-0.071	0.047		-0.044	0.032		-0.042	0.043		-0.047	0.044	
	≥ 0.25 in	-0.101	0.066		-0.011	0.058		-0.098	0.039	*	-0.051	0.052		-0.116	0.053	*
Min Temperature	< 30ºF	0.049	0.051		0.021	0.045		-0.012	0.027		0.007	0.035		-0.066	0.038	~
	< 20ºF	-0.026	0.071		-0.006	0.063		-0.065	0.036	~	0.005	0.048		-0.016	0.053	
	< 10ºF	0.033	0.104		-0.064	0.092		-0.055	0.053		-0.099	0.071		-0.104	0.078	
Max Temperature	≥ 60ºF	0.037	0.049		-0.026	0.043		-0.022	0.028		0.029	0.037	~	-0.050	0.039	
	≥ 70ºF	0.066	0.059		-0.019	0.052		0.037	0.031		0.032	0.042		0.032	0.045	
	≥ 80ºF	-0.005	0.048		0.016	0.042		0.007	0.026		-0.037	0.034		0.022	0.037	
	≥ 90ºF	-0.045	0.053		-0.064	0.047		-0.049	0.025	*	-0.059	0.033		-0.029	0.038	
Temporal Variables																
Month:	January	-0.271	0.137	*	-0.175	0.123		-0.274	0.062	*	-0.269	0.083	*	-0.325	0.096	*
	February	-0.264	0.129	*	-0.290	0.116	*	-0.234	0.058	*	-0.254	0.077	*	-0.316	0.090	*
	March	-0.175	0.126		-0.196	0.114	~	-0.184	0.056	*	-0.200	0.075	*	-0.281	0.087	*
	April	-0.063	0.118		-0.050	0.107		-0.015	0.052		-0.115	0.069	~	-0.225	0.081	*
	June	0.243	0.086	*	0.204	0.079	*	0.165	0.036	*	0.137	0.048	*	-0.005	0.058	
	July	0.335	0.090	*	0.331	0.082	*	0.186	0.039	*	0.169	0.051	*	0.034	0.062	
	August	0.120	0.082		0.206	0.074	*	0.081	0.035	*	0.109	0.046	*	-0.019	0.055	
	September	0.063	0.109		0.161	0.098		0.037	0.048		0.009	0.064		-0.069	0.075	
	October	0.078	0.119		-0.002	0.108		-0.004	0.053		-0.052	0.070		-0.076	0.082	
	November	-0.226	0.121	~	-0.359	0.109	*	-0.215	0.054	*	-0.196	0.071	*	-0.254	0.084	*
	December	-0.093	0.146		-0.260	0.131	*	-0.248	0.067	*	-0.243	0.089	*	-0.245	0.103	*
Weekday:	Sunday	-0.386	0.043	*	-0.683	0.038	*	-0.597	0.023	*	-0.629	0.031	*	-0.451	0.033	*
	Monday	-0.150	0.041	*	-0.169	0.036	*	-0.171	0.023	*	-0.175	0.031	*	-0.220	0.032	*
	Tuesday	-0.010	0.036		-0.018	0.032		0.005	0.023		-0.029	0.031		-0.044	0.030	
	Thursday	0.004	0.037		0.018	0.032		-0.001	0.023		-0.013	0.031		-0.089	0.030	*
	Friday	0.094	0.042	*	-0.001	0.037		0.022	0.023		-0.038	0.031		-0.009	0.033	
	Saturday	0.287	0.044	*	0.041	0.039		-0.106	0.024	*	-0.160	0.032	*	-0.140	0.034	*
Events[a]:	USU, commencement	0.050	0.200		0.065	0.177		0.141	0.102		0.025	0.136				
	USU, Football	0.158	0.087	~	0.065	0.076		0.045	0.052		0.071	0.069		0.094	0.071	
Breaks:	USU, winter	-0.109	0.108		-0.065	0.097		-0.142	0.049	*	-0.125	0.065	~	-0.048	0.075	
	USU, spring	0.148	0.144		0.119	0.130		0.076	0.065		-0.068	0.086		-0.191	0.101	~

		β	SE	P	β	SE	P	β	SE	P	β	SE	P	β	SE	P
	LSD[b], spring	0.082	0.132		-0.059	0.119		-0.118	0.057	*	-0.128	0.075	~	-0.171	0.090	~
	USU, summer	0.057	0.089		0.141	0.080	~	0.004	0.039		-0.134	0.052	*	-0.093	0.062	
	LSD, fall	-0.200	0.171		-0.042	0.153		-0.075	0.082		-0.115	0.109		-0.143	0.125	
Holidays:	New Year's Day	-0.409	0.264		-0.832	0.234	*	-0.449	0.142	*	-0.665	0.188	*	-0.041	0.201	
	—day after	0.148	0.246		-0.013	0.216		-0.015	0.141		-0.095	0.188		-0.296	0.195	
	Memorial Day	0.052	0.225		0.154	0.196		0.014	0.134		0.218	0.178		0.285	0.182	
	Independence Day	-0.642	0.159	*	-0.885	0.138	*	-0.319	0.094	*	-0.468	0.125	*	-0.228	0.128	~
	Pioneer Day	-0.424	0.158	*	-0.306	0.137	*	-0.201	0.093	*	-0.253	0.124	*	0.030	0.127	
	Labor Day	0.068	0.161		0.194	0.140		0.115	0.095		-0.044	0.126		0.088	0.130	
	Thanksgiving Day	-0.613	0.233	*	-0.563	0.204	*	-0.627	0.132	*	-0.414	0.176	*	-0.520	0.183	*
	—day after	-0.324	0.237		-0.576	0.208	*	-0.282	0.134	*	-0.763	0.178	*	-0.171	0.186	
	Christmas Eve	-0.668	0.261	*	-0.035	0.230		-0.063	0.146		0.116	0.194		-0.036	0.203	
	Christmas Day	-1.007	0.276	*	-2.227	0.244	*	-0.640	0.149	*	-1.103	0.197	*	-2.790	0.211	*
	—day after	-0.067	0.249		-0.121	0.218		-0.276	0.143	~	-0.655	0.189	*	-0.111	0.196	
	New Year's Eve	-0.025	0.242		0.379	0.212	~	0.384	0.137	*	-0.232	0.183		-0.025	0.190	
Assumptions:																
	Normality		no			yes			yes			yes			no	
	Non-autocorrelation		no			no			yes			yes			no	
	Exogeneity		yes			yes			yes			yes			yes	
	Homoscedasticity		yes			no			no			yes			yes	
Goodness of fits:	**R^2**		**0.69**			**0.79**			**0.87**			**0.78**			**0.71**	
	RMSE		0.22			0.19			0.13			0.17			0.17	

Variable		***Signal 5309 (N=448)***			***Signal 5310 (N=448)***			***Signal 5311 (N=448)***			***Signal 5312 (N=448)***			***Signal 5313 (N=448)***		
		β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*
Weather Variables																
	β_0	5.094	0.105	*	3.901	0.082	*	5.30	0.06	*	5.347	0.051	*	5.288	0.053	*
Snow Depth	≥ 0.1 in	-0.008	0.071		-0.181	0.062	*	-0.21	0.04	*	-0.058	0.039		-0.069	0.038	~
	≥ 0.6 in	-0.045	0.088		-0.109	0.073		0.00	0.05		-0.120	0.046	*	-0.062	0.046	
Snowfall	≥ 0.1 in	-0.034	0.058		0.065	0.059		-0.03	0.04		-0.032	0.037		0.033	0.034	
	≥ 0.6 in	-0.506	0.157	*	-0.521	0.168	*	0.00	0.11		-0.258	0.106	*	-0.225	0.092	*
Precipitation	≥ 0.01 in	-0.038	0.038		-0.097	0.040	*	-0.01	0.03		-0.003	0.025		-0.040	0.022	~
	≥ 0.05 in	-0.028	0.048		-0.002	0.052		-0.04	0.03		-0.071	0.033	*	-0.046	0.028	
	≥ 0.25 in	0.033	0.059		-0.071	0.062		-0.04	0.04		-0.024	0.039		0.008	0.035	
Min Temperature	< 30ºF	0.086	0.046	~	0.012	0.042		0.00	0.03		-0.034	0.027		0.006	0.026	
	< 20ºF	-0.111	0.065	~	-0.063	0.058		0.01	0.04		-0.046	0.037		-0.030	0.036	
	< 10ºF	-0.071	0.097		-0.078	0.085		-0.13	0.06	*	-0.071	0.054		-0.001	0.053	

Max Temperature	≥ 60ºF	0.007	0.044		-0.029	0.044		-0.03	0.03		0.003	0.028		0.015	0.026	
	≥ 70ºF	0.000	0.055		0.109	0.050	*	0.03	0.03		0.021	0.031		0.095	0.030	*
	≥ 80ºF	0.055	0.044		-0.020	0.041		0.04	0.03		0.024	0.026		0.001	0.025	
	≥ 90ºF	-0.074	0.050		-0.031	0.039		-0.06	0.03	*	-0.028	0.025		-0.008	0.026	
Temporal Variables																
Month:	January	-0.099	0.133		-0.292	0.099	*	-0.06	0.07		-0.242	0.063	*	-0.186	0.067	*
	February	-0.260	0.126	*	-0.267	0.092	*	-0.13	0.07	~	-0.228	0.058	*	-0.226	0.062	*
	March	-0.249	0.124	*	-0.174	0.090	~	-0.08	0.07		-0.234	0.057	*	-0.213	0.061	*
	April	-0.031	0.116		-0.098	0.083		0.09	0.06		-0.125	0.052	*	-0.090	0.057	
	June	0.220	0.087	*	0.085	0.057		0.06	0.04		0.125	0.036	*	0.109	0.041	*
	July	0.191	0.090	*	0.031	0.061		0.12	0.05	*	0.122	0.039	*	0.080	0.043	~
	August	0.156	0.082	~	-0.026	0.056		0.09	0.04	*	0.059	0.035	~	-0.014	0.039	
	September	0.057	0.107		-0.068	0.076		0.11	0.06	~	-0.027	0.048		-0.040	0.052	
	October	-0.022	0.117		-0.153	0.084	~	-0.02	0.06		-0.018	0.053		0.013	0.057	
	November	-0.214	0.119	~	-0.208	0.085	*	-0.14	0.06	*	-0.179	0.054	*	-0.065	0.058	
	December	-0.240	0.142	~	-0.258	0.106	*	-0.14	0.08	~	-0.258	0.067	*	-0.133	0.071	~
Weekday:	Sunday	-0.552	0.039	*	-0.331	0.037	*	-0.34	0.02	*	-0.630	0.023	*	-0.379	0.022	*
	Monday	-0.164	0.038	*	-0.209	0.037	*	-0.07	0.02	*	-0.109	0.023	*	-0.060	0.021	*
	Tuesday	-0.025	0.032		0.003	0.037		0.03	0.02		0.022	0.023		0.039	0.019	*
	Thursday	-0.009	0.033		0.047	0.037		0.02	0.02		0.012	0.023		-0.002	0.019	
	Friday	-0.005	0.038		0.099	0.037	*	0.09	0.02	*	0.014	0.024		-0.013	0.021	
	Saturday	-0.096	0.040	*	0.214	0.038	*	0.05	0.03	*	-0.101	0.024	*	-0.056	0.022	*
Events[a]:	USU, commencement	0.008	0.185		0.085	0.163		0.15	0.11		0.096	0.103		-0.094	0.101	
	USU, Football	0.102	0.077		0.007	0.083		0.03	0.05		0.069	0.052		0.007	0.046	
Breaks:	USU, winter	-0.312	0.105	*	0.080	0.077		0.03	0.06		-0.200	0.049	*	-0.173	0.052	*
	USU, spring	-0.090	0.140		0.113	0.103		0.06	0.08		0.004	0.065		0.030	0.070	
	LSD[b], spring	-0.256	0.130	*	-0.106	0.090		-0.16	0.07	*	-0.152	0.057	*	-0.144	0.063	*
	USU, summer	-0.263	0.087	*	-0.008	0.063		0.01	0.05		-0.134	0.040	*	-0.125	0.043	*
	LSD, fall	-0.107	0.162		-0.104	0.131		-0.04	0.09		-0.232	0.083	*	-0.167	0.085	~
Holidays:	New Year’s Day	1.571	0.245	*	-0.203	0.225		-0.46	0.15	*	-0.288	0.142	*	-0.514	0.134	*
	—day after	-0.199	0.223		-0.202	0.225		0.08	0.15		-0.235	0.142	~	-0.011	0.128	
	Memorial Day	-0.364	0.201	~	0.137	0.213		0.03	0.14		0.138	0.134		0.104	0.118	
	Independence Day	0.167	0.141		-0.205	0.150		-0.19	0.10	~	-0.229	0.094	*	-0.235	0.083	*
	Pioneer Day	-0.073	0.141		0.104	0.148		-0.22	0.10	*	-0.183	0.094	~	-0.188	0.083	*
	Labor Day	-0.052	0.144		0.027	0.151		0.02	0.10		0.162	0.095	~	0.069	0.084	
	Thanksgiving Day	-0.893	0.211	*	-0.483	0.211	*	-0.34	0.14	*	-0.565	0.133	*	-0.446	0.120	*
	—day after	0.220	0.215		0.540	0.214	*	0.15	0.14		-0.663	0.135	*	-0.342	0.122	*
	Christmas Eve	-0.273	0.239		0.118	0.232		-0.09	0.15		-0.079	0.147		-0.109	0.134	
	Christmas Day	-0.813	0.255	*	-1.115	0.237	*	-1.16	0.16	*	-0.761	0.149	*	-1.215	0.141	*
	—day after	1.071	0.226	*	-0.295	0.227		0.19	0.15		-0.113	0.143		-0.297	0.129	*
	New Year’s Eve	1.508	0.220	*	-0.132	0.219		-0.31	0.14	*	-0.073	0.138		0.123	0.125	

Assumptions:						
	Normality	no	yes	yes	yes	yes
	Non-autocorrelation	yes	yes	no	yes	no
	Exogeneity	yes	yes	yes	yes	yes
	Homoscedasticity	yes	yes	yes	no	yes
Goodness of fits:	R^2	**0.61**	**0.70**	**0.74**	**0.86**	**0.75**
	RMSE	0.20	0.20	0.13	0.13	0.13

Variable		***Signal 5314 (N=448)***			***Signal 5315 (N=442)***			***Signal 5316 (N=442)***			***Signal 5317 (N=448)***			***Signal 5318(N=448)***		
		β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*
Weather Variables																
	β_0	5.786	0.117	*	4.815	0.196	*	2.672	0.188	*	2.607	0.210	*	5.188	0.093	*
Snow Depth	≥ 0.1 in	0.008	0.076		0.174	0.140		-0.018	0.142		0.074	0.158		-0.113	0.070	
	≥ 0.6 in	-0.433	0.096	*	-0.197	0.170		-0.284	0.168	~	-0.115	0.188		-0.106	0.083	
Snowfall	≥ 0.1 in	-0.039	0.062		-0.084	0.123		0.114	0.136		-0.019	0.151		0.006	0.067	
	≥ 0.6 in	-0.260	0.165		-0.612	0.335	~	-0.505	0.387		0.035	0.428		-0.417	0.191	*
Precipitation	≥ 0.01 in	-0.003	0.040		-0.036	0.081		0.127	0.092		0.028	0.102		-0.062	0.045	
	≥ 0.05 in	-0.077	0.051		-0.151	0.104		-0.158	0.120		-0.197	0.133		-0.158	0.059	*
	≥ 0.25 in	-0.038	0.062		-0.162	0.126		-0.013	0.144		0.016	0.160		0.016	0.071	
Min Temperature	< 30ºF	-0.073	0.050		-0.102	0.094		0.047	0.097		-0.138	0.108		-0.033	0.048	
	< 20ºF	-0.046	0.070		0.094	0.131		-0.002	0.134		0.067	0.149		-0.060	0.066	
	< 10ºF	0.052	0.104		-0.178	0.193		-0.084	0.196		-0.054	0.219		-0.130	0.097	
Max Temperature	≥ 60ºF	-0.004	0.047		0.072	0.093		0.043	0.102		0.008	0.114		-0.023	0.051	
	≥ 70ºF	0.083	0.059		0.111	0.111		-0.002	0.115		-0.121	0.128		0.076	0.057	
	≥ 80ºF	-0.034	0.047		-0.075	0.090		0.163	0.094	~	-0.039	0.106		-0.005	0.046	
	≥ 90ºF	-0.090	0.055		-0.284	0.096	*	0.024	0.091		-0.264	0.102	*	-0.109	0.045	*
Temporal Variables																
Month:	January	-0.549	0.150	*	-0.844	0.244	*	-0.671	0.229	*	-0.038	0.256		-0.293	0.113	*
	February	-0.476	0.142	*	-0.728	0.230	*	-0.473	0.213	*	-0.221	0.238		-0.280	0.105	*
	March	-0.553	0.140	*	-0.547	0.224	*	-0.536	0.207	*	-0.299	0.231		-0.236	0.102	*
	April	-0.366	0.131	*	-0.296	0.209		-0.568	0.190	*	-0.059	0.213		-0.057	0.094	
	June	-0.060	0.100		-0.393	0.151	*	-0.147	0.132		0.097	0.148		0.148	0.065	*
	July	-0.158	0.102		-0.424	0.160	*	-0.464	0.142	*	0.206	0.162		0.042	0.070	
	August	-0.234	0.094	*	-0.277	0.144	~	-0.369	0.128	*	0.132	0.144		-0.074	0.063	
	September	-0.197	0.120		-0.431	0.193	*	-0.501	0.176	*	0.065	0.197		-0.160	0.087	~
	October	-0.269	0.133	*	-0.555	0.212	*	-0.081	0.193		0.066	0.216		-0.296	0.095	*
	November	-0.528	0.134	*	-0.742	0.215	*	-0.449	0.197	*	-0.163	0.220		-0.454	0.097	*
	December	-0.678	0.159	*	-0.933	0.261	*	-0.640	0.245	*	-0.162	0.274		-0.425	0.121	*
Weekday:	Sunday	-0.738	0.042	*	-1.386	0.080	*	-1.757	0.086	*	-1.963	0.096	*	-1.216	0.042	*
	Monday	-0.107	0.040	*	-0.166	0.078	*	-0.404	0.086	*	-0.109	0.095		-0.184	0.042	*
	Tuesday	0.018	0.034		0.033	0.070		0.006	0.086		0.076	0.094		0.071	0.042	~
	Thursday	-0.030	0.034		0.007	0.071		-0.024	0.086		0.066	0.095		-0.056	0.042	

	Friday	-0.049	0.041		-0.070	0.079		-0.361	0.087	*	-0.308	0.096	*	-0.075	0.042	~
	Saturday	-0.417	0.043	*	-0.971	0.082	*	-1.451	0.089	*	-1.684	0.099	*	-0.375	0.044	*
Events[a]:	USU, commencement	-0.056	0.199		-0.159	0.369		0.407	0.374		-0.401	0.418		-0.095	0.185	
	USU, Football	0.065	0.081		0.058	0.166		0.347	0.191	~	-0.020	0.211		0.177	0.094	~
Breaks:	USU, winter	-0.869	0.118	*	-0.220	0.192		-0.078	0.178		0.014	0.199		-0.070	0.088	
	USU, spring	-0.351	0.156	*	0.069	0.258		0.305	0.238		-0.056	0.266		0.112	0.118	
	LSD[b], spring	-0.158	0.147		-0.778	0.233	*	-0.003	0.208		-0.178	0.233		-0.146	0.103	
	USU, summer	-0.613	0.097	*	-0.512	0.159	*	-0.174	0.145		0.037	0.162		0.022	0.071	
	LSD, fall	-0.353	0.176	*	-0.815	0.313	*	-0.765	0.302	*	-0.192	0.338		-0.070	0.149	
Holidays:	New Year’s Day	-0.668	0.265	*	-1.764	0.490	*	-1.546	0.519	*	-2.477	0.576	*	-1.034	0.257	*
	—day after	-0.484	0.238	*	-1.381	0.465	*	-1.263	0.519	*	-1.275	0.575	*	0.106	0.256	
	Memorial Day	-0.045	0.211		-0.507	0.430		0.357	0.490		0.789	0.543		0.478	0.242	*
	Independence Day	-0.050	0.149		-0.774	0.303	*	-1.276	0.345	*	-1.922	0.383	*	-1.152	0.170	
	Pioneer Day	-0.167	0.148		-0.257	0.301		0.075	0.342		-1.327	0.379	*	-0.467	0.169	*
	Labor Day	-0.196	0.152		-0.129	0.307		0.115	0.348		0.255	0.385		0.191	0.172	
	Thanksgiving Day	-1.248	0.225	*	-1.175	0.439	*	-0.813	0.485	~	-2.487	0.538	*	-0.806	0.240	*
	—day after	-0.972	0.229	*	-1.021	0.446	*	-1.213	0.492	*	-2.143	0.545	*	-0.999	0.243	*
	Christmas Eve	-0.616	0.255	*	-0.427	0.490		0.144	0.535		0.765	0.593		-0.638	0.264	*
	Christmas Day	-1.544	0.275	*	-1.173	0.513	*	-1.292	0.545	*	-1.303	0.605	*	-1.908	0.269	*
	—day after	-0.780	0.240	*	-0.650	0.469		-0.720	0.523		-2.338	0.579	*	-0.758	0.258	*
	New Year’s Eve	0.052	0.235		-0.489	0.455		-0.226	0.504		-0.430	0.558		0.195	0.249	
Assumptions:																
	Normality		no			no			yes			yes			no	
	Non-autocorrelation		yes			no			yes			no			yes	
	Exogeneity		yes			yes			yes			yes			yes	
	Homoscedasticity		no			no			yes			yes			yes	
Goodness of fits:	**R^2**		**0.74**			**0.68**			**0.73**			**0.74**			**0.85**	
	RMSE		0.22			0.42			0.47			0.51			0.23	

Variable		*Signal 5319 (N=445)*			*Signal 5320 (N=315)*			*Signal 5321(N=440)*			*Signal 5322 (N=439)*			*Signal 5323 (N=448)*		
		β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*
Weather Variables																
	β_0	3.187	0.145	*	3.336	0.221	*	3.039	0.134	*	2.650	0.152	*	2.450	0.169	*
Snow Depth	≥ 0.1 in	-0.306	0.110	*	-0.182	0.137		0.074	0.101		-0.106	0.115		-0.431	0.128	*
	≥ 0.6 in	-0.330	0.130	*	-0.479	0.161	*	-0.007	0.120		-0.023	0.136		-0.394	0.152	*
Snowfall	≥ 0.1 in	0.124	0.105		0.009	0.139		-0.080	0.097		0.080	0.110		0.240	0.123	~
	≥ 0.6 in	-1.226	0.299	*	-0.167	0.374		-0.597	0.276	*	-0.316	0.313		-0.453	0.349	
Precipitation	≥ 0.01 in	-0.005	0.071		-0.050	0.123		-0.044	0.065		0.049	0.074		-0.056	0.083	
	≥ 0.05 in	-0.005	0.092		-0.023	0.151		0.000	0.086		-0.151	0.098		-0.031	0.107	
	≥ 0.25 in	-0.145	0.111		-0.190	0.162		-0.099	0.103		0.230	0.117	*	-0.104	0.130	
Min Temperature	< 30ºF	0.005	0.075		0.044	0.103		-0.021	0.069		-0.003	0.079		0.187	0.088	*
	< 20ºF	0.084	0.103		-0.262	0.129	*	-0.198	0.095	*	0.092	0.108		-0.017	0.121	
	< 10ºF	-0.167	0.151		-0.127	0.187		-0.064	0.140		-0.165	0.158		0.230	0.177	
Max Temperature	≥ 60ºF	0.008	0.079		-0.196	0.141		-0.007	0.073		0.219	0.083	*	0.118	0.092	
	≥ 70ºF	0.136	0.089		-0.104	0.135		0.019	0.082		-0.035	0.093		0.189	0.104	~
	≥ 80ºF	-0.038	0.074		0.126	0.107		0.089	0.067		0.044	0.076		0.032	0.085	
	≥ 90ºF	-0.102	0.071		0.048	0.126		0.027	0.066		-0.077	0.074		-0.097	0.082	
Temporal Variables																
Month:	January	-0.330	0.177	~	-0.536	0.252	*	-0.214	0.163		-0.359	0.185	~	-0.671	0.206	*
	February	-0.296	0.164	~	-0.451	0.240	~	-0.143	0.152		-0.188	0.172		-0.450	0.192	*
	March	-0.315	0.159	*	-0.757	0.230	*	-0.045	0.147		-0.023	0.167		-0.561	0.186	*
	April	-0.010	0.147		-0.403	0.211	~	0.052	0.136		-0.119	0.154		-0.178	0.172	
	June	-0.113	0.102		0.127	0.131		0.023	0.094		0.031	0.106		0.176	0.119	
	July	0.041	0.112		-0.095	0.170		0.107	0.102		-0.100	0.116		-0.019	0.128	
	August	-0.078	0.099		-0.267	0.154	~	0.032	0.092		-0.183	0.104	~	-0.124	0.116	
	September	-0.145	0.136		-0.171	0.225		0.022	0.125		-0.277	0.142	~	-0.292	0.159	~
	October	-0.033	0.149		NA	NA		0.292	0.138	*	-0.300	0.156	~	-0.501	0.174	*
	November	-0.353	0.152	*	-0.441	0.234	~	0.065	0.140		-0.409	0.159	*	-0.678	0.178	*
	December	-0.228	0.189		-0.452	0.266	~	0.104	0.175		-0.260	0.198		-0.677	0.221	*
Weekday:	Sunday	-0.430	0.066	*	-1.052	0.099	*	-0.923	0.062	*	-0.925	0.070	*	-0.896	0.077	*
	Monday	-0.105	0.066		0.062	0.099		-0.075	0.062		-0.149	0.070	*	-0.085	0.077	
	Tuesday	-0.004	0.066		0.010	0.098		0.124	0.062	*	0.108	0.070		0.180	0.077	*
	Thursday	-0.012	0.066		0.028	0.098		0.061	0.062		0.066	0.070		0.091	0.077	
	Friday	0.009	0.066		-0.212	0.099	*	0.099	0.062		0.154	0.070	*	0.077	0.078	
	Saturday	-0.256	0.068	*	-0.895	0.101	*	-0.280	0.064	*	-0.272	0.072	*	-0.098	0.080	
Events[a]:	USU, commencement	-0.032	0.289		0.537	0.376		0.168	0.267		-0.028	0.302		0.054	0.338	
	USU, Football	0.090	0.147		0.318	0.248		0.034	0.136		0.021	0.154		0.281	0.172	
Breaks:	USU, winter	0.140	0.138		0.130	0.170		-0.409	0.127	*	-0.024	0.144		0.051	0.161	

	USU, spring	0.157	0.184		0.598	0.228	*	-0.169	0.170		-0.072	0.192		0.563	0.215	*
	LSD[b], spring	-0.158	0.161		0.005	0.202		-0.303	0.149	*	0.175	0.168		-0.469	0.188	*
	USU, summer	-0.111	0.112		0.027	0.184		0.025	0.103		-0.008	0.117		-0.141	0.130	
	LSD, fall	-0.031	0.233		NA	NA		-0.149	0.216		0.044	0.244		-0.254	0.272	
Holidays:	New Year's Day	-1.288	0.401	*	-0.394	0.497		-0.405	0.370		-0.715	0.419	~	-0.791	0.468	~
	—day after	0.058	0.401		-0.236	0.497		0.650	0.370	~	-0.412	0.419		0.197	0.468	
	Memorial Day	-0.153	0.378		0.008	0.472		-0.176	0.350		-0.296	0.396		0.158	0.442	
	Independence Day	-2.149	0.266	*	-0.888	0.480	~	-0.869	0.246	*	-0.245	0.279		-0.039	0.311	
	Pioneer Day	-0.256	0.264		-0.754	0.463		-0.533	0.343		0.143	0.388		0.126	0.308	
	Labor Day	-0.474	0.268	~	-0.998	0.464	*	0.073	0.248		0.068	0.281		-0.077	0.314	
	Thanksgiving Day	-0.876	0.374	*	-1.537	0.469	*	-0.768	0.346	*	-0.921	0.392	*	-0.477	0.437	
	—day after	-0.366	0.380		-0.877	0.484	~	-0.424	0.351		-0.129	0.397		-0.176	0.443	
	Christmas Eve	0.348	0.413		0.431	0.512		0.484	0.381		0.150	0.432		-0.502	0.482	
	Christmas Day	-2.395	0.421	*	-0.906	0.524	~	-1.627	0.389	*	-0.892	0.440	*	-1.467	0.492	*
	—day after	-0.190	0.404		-0.113	0.503		-0.746	0.373	*	-0.477	0.422		0.187	0.472	
	New Year's Eve	-0.758	0.389	~	0.373	0.482		-0.073	0.360		-0.639	0.407		-0.799	0.366	*
Assumptions:																
	Normality		yes			no			no			no			yes	
	Non-autocorrelation		yes			NA			yes			yes			yes	
	Exogeneity		yes			yes			yes			yes			yes	
	Homoscedasticity		no			yes			yes			no			yes	
Goodness of fits:	**R^2**		**0.53**			**0.65**			**0.64**			**0.58**			**0.63**	
	RMSE		0.37			0.45			0.34			0.38			0.36	

Variable		*Signal 5324 (N=448)*			*Signal 5325 (N=448)*			*Signal 5326 (N=448)*			*Signal 5327 (N=448)*			*Signal 5330 (N=448)*		
		β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*
Weather Variables																
	β_0	3.580	0.136	*	2.450	0.169	*	3.580	0.136	*	4.106	0.098	*	2.366	0.256	*
Snow Depth	≥ 0.1 in	-0.034	0.103		-0.431	0.128	*	-0.034	0.103		-0.121	0.074		-0.276	0.194	
	≥ 0.6 in	-0.240	0.122	*	-0.394	0.152	*	-0.240	0.122	*	-0.151	0.088	~	-0.285	0.229	
Snowfall	≥ 0.1 in	-0.108	0.099		0.240	0.123	~	-0.108	0.099		-0.049	0.072		0.286	0.186	
	≥ 0.6 in	0.067	0.281		-0.453	0.349		0.067	0.281		-0.520	0.207	*	0.205	0.529	
Precipitation	≥ 0.01 in	-0.067	0.066		-0.056	0.083		-0.067	0.066		-0.036	0.049		-0.132	0.125	
	≥ 0.05 in	-0.085	0.086		-0.031	0.107		-0.085	0.086		-0.172	0.063		-0.025	0.162	
	≥ 0.25 in	0.006	0.104		-0.104	0.130		0.006	0.104		-0.060	0.077		-0.285	0.196	
Min Temperature	< 30ºF	0.032	0.071		0.187	0.088	*	0.032	0.071		0.043	0.051		-0.264	0.133	*
	< 20ºF	-0.113	0.097		-0.017	0.121		-0.113	0.097		-0.073	0.070		-0.012	0.183	
	< 10ºF	-0.070	0.142		0.230	0.177		-0.070	0.142		0.073	0.103		-0.150	0.268	
Max Temperature	≥ 60ºF	0.025	0.074		0.118	0.092		0.025	0.074		0.004	0.054		-0.112	0.140	
	≥ 70ºF	0.000	0.083		0.189	0.104	~	0.000	0.083		0.090	0.060		0.163	0.157	
	≥ 80ºF	0.142	0.068	*	0.032	0.085		0.142	0.068	*	0.013	0.050		0.228	0.128	~
	≥ 90ºF	-0.193	0.066	*	-0.097	0.082		-0.193	0.066	*	-0.091	0.047	~	-0.059	0.124	

Temporal Variables																
Month:	January	-0.833	0.166	*	-0.671	0.206	*	-0.833	0.166	*	-0.341	0.119	*	-0.858	0.312	*
	February	-0.663	0.155	*	-0.450	0.192	*	-0.663	0.155	*	-0.308	0.110	*	-0.987	0.291	*
	March	-0.659	0.150	*	-0.561	0.186	*	-0.659	0.150	*	-0.266	0.107	*	-0.606	0.282	*
	April	-0.318	0.138	*	-0.178	0.172		-0.318	0.138	*	-0.078	0.098		-0.211	0.260	
	June	-0.515	0.096	*	0.176	0.119		-0.515	0.096	*	0.073	0.068		0.152	0.180	
	July	-0.392	0.103	*	-0.019	0.128		-0.392	0.103	*	0.039	0.074		0.546	0.193	*
	August	-0.361	0.093	*	-0.124	0.116		-0.361	0.093	*	0.039	0.066		-0.028	0.175	
	September	-0.378	0.128	*	-0.292	0.159	~	-0.378	0.128	*	0.098	0.091		-0.270	0.240	
	October	-0.410	0.140	*	-0.501	0.174	*	-0.410	0.140	*	-0.078	0.100		-0.208	0.264	
	November	-0.647	0.143	*	-0.678	0.178	*	-0.647	0.143	*	-0.277	0.102	*	-0.608	0.269	*
	December	-0.916	0.178	*	-0.677	0.221	*	-0.916	0.178	*	-0.433	0.127	*	-0.943	0.334	*
Weekday:	Sunday	-0.818	0.062	*	-0.896	0.077	*	-0.818	0.062	*	-0.967	0.046	*	-0.573	0.117	*
	Monday	-0.088	0.062		-0.085	0.077		-0.088	0.062		-0.132	0.045	*	-0.142	0.117	
	Tuesday	0.057	0.062		0.180	0.077	*	0.057	0.062		0.054	0.046		-0.092	0.116	
	Thursday	0.062	0.062		0.091	0.077		0.062	0.062		0.036	0.047		-0.026	0.117	
	Friday	-0.018	0.062		0.077	0.078		-0.018	0.062		0.009	0.046		-0.074	0.117	
	Saturday	-0.253	0.064	*	-0.098	0.080		-0.253	0.064	*	-0.298	0.047	*	-0.316	0.120	*
Events[a]:	USU, commencement	-0.033	0.272		0.054	0.338		-0.033	0.272		0.159	0.196		-0.002	0.511	
	USU, Football	0.114	0.138		0.281	0.172		0.114	0.138		0.101	0.102		0.173	0.260	
Breaks:	USU, winter	0.053	0.129		0.051	0.161		0.053	0.129		0.211	0.092	*	-0.128	0.243	
	USU, spring	0.069	0.173		0.563	0.215	*	0.069	0.173		0.228	0.123	~	-0.175	0.325	
	LSD[b], spring	-0.490	0.151	*	-0.469	0.188	*	-0.490	0.151	*	-0.274	0.107	*	-0.074	0.284	
	USU, summer	-0.216	0.105	*	-0.141	0.130		-0.216	0.105	*	0.062	0.075		0.028	0.197	
	LSD, fall	-0.529	0.219	*	-0.254	0.272		-0.529	0.219	*	0.092	0.157		-0.181	0.412	
Holidays:	New Year’s Day	-1.211	0.377	*	-0.791	0.468	~	-1.211	0.377	*	-1.128	0.275	*	0.414	0.708	
	—day after	-0.177	0.377		0.197	0.468		-0.177	0.377		-0.513	0.277	~	-0.041	0.708	
	Memorial Day	-0.142	0.356		0.158	0.442		-0.142	0.356		0.002	0.261		0.207	0.669	
	Independence Day	-0.384	0.250		-0.039	0.311		-0.384	0.250		-0.602	0.184	*	-1.508	0.470	*
	Pioneer Day	0.110	0.248		0.126	0.308		0.110	0.248		0.030	0.182		-0.559	0.466	
	Labor Day	-0.298	0.252		-0.077	0.314		-0.298	0.252		0.243	0.185		0.281	0.475	
	Thanksgiving Day	-1.897	0.352	*	-0.477	0.437		-1.897	0.352	*	-1.145	0.258	*	-1.731	0.662	*
	—day after	-0.994	0.357	*	-0.176	0.443		-0.994	0.357	*	-0.133	0.262		-0.879	0.671	
	Christmas Eve	-0.780	0.388	*	-0.502	0.482		-0.780	0.388	*	-0.390	0.284		0.267	0.729	
	Christmas Day	-0.558	0.396		-1.467	0.492	*	-0.558	0.396		-1.878	0.289	*	0.805	0.744	
	—day after	0.215	0.379		0.187	0.472		0.215	0.379		-0.676	0.279	*	0.031	0.713	
	New Year’s Eve	0.195	0.249		-0.799	0.366	*	0.195	0.249		-0.350	0.269		0.918	0.688	
Assumptions:																
	Normality		no			no			yes			yes			no	
	Non-autocorrelation		yes			yes			yes			no			yes	
	Exogeneity		yes			yes			yes			yes			yes	
	Homoscedasticity		yes			yes			no			no			yes	
Goodness of fits:	**R^2**		**0.47**			**0.65**			**0.64**			**0.81**			**0.61**	
	RMSE		0.54			0.43			0.34			0.25			0.64	

Variable		*Signal 5331 (N=448)*			*Signal 5332 (N=448)*			*Signal 5800 (N=440)*			*Signal 5801 (N=436)*			*Signal 5802 (N=440)*		
		β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*
Weather Variables																
	β_0	4.159	0.087	*	3.756	0.102	*	4.703	0.185	*	5.231	0.149	*	4.445	0.162	*
Snow Depth	≥ 0.1 in	-0.255	0.066	*	-0.134	0.077	~	-0.606	0.233	*	-0.145	0.104		0.112	0.114	
	≥ 0.6 in	-0.096	0.078		-0.365	0.092	*	-1.167	0.221	*	0.076	0.128		0.192	0.139	
Snowfall	≥ 0.1 in	0.035	0.063		-0.041	0.074		-0.521	0.216	*	0.032	0.088		0.047	0.100	
	≥ 0.6 in	-0.160	0.179		-0.383	0.211	~	-0.263	0.202		-0.065	0.240		-0.148	0.272	
Precipitation	≥ 0.01 in	-0.039	0.042		-0.110	0.050	*	-0.025	0.150		-0.034	0.059		-0.051	0.067	
	≥ 0.05 in	-0.063	0.055		0.082	0.065		-0.003	0.156		-0.091	0.074		-0.017	0.084	
	≥ 0.25 in	-0.060	0.066		-0.099	0.078		0.014	0.142		-0.001	0.090		-0.122	0.102	
Min Temperature	< 30ºF	-0.033	0.045		0.006	0.053		-0.481	0.207	*	0.117	0.069	~	0.082	0.077	
	< 20ºF	0.023	0.062		-0.035	0.073		-0.299	0.214		0.050	0.100		-0.145	0.107	
	< 10ºF	-0.170	0.091	~	-0.169	0.107		-0.165	0.186		0.006	0.142		-0.091	0.158	
Max Temperature	≥ 60ºF	0.042	0.047		-0.035	0.056		-0.495	0.248	*	-0.022	0.071		0.001	0.080	
	≥ 70ºF	0.084	0.053		0.064	0.063		-0.819	0.071	*	0.035	0.081		-0.024	0.091	
	≥ 80ºF	0.030	0.043		-0.020	0.051		-0.160	0.068	*	-0.015	0.065		0.032	0.073	
	≥ 90ºF	-0.045	0.042		-0.013	0.049		0.044	0.059		-0.081	0.072		-0.054	0.078	
Temporal Variables																
Month:	January	-0.152	0.106		-0.446	0.125	*	0.000	0.059		-0.457	0.186	*	-0.483	0.201	*
	February	-0.240	0.098	*	-0.152	0.116		0.039	0.069		-0.861	0.181	*	-1.077	0.189	*
	March	-0.288	0.095	*	-0.386	0.113	*	-0.111	0.073		-0.310	0.171	~	-0.311	0.185	~
	April	-0.040	0.088		-0.013	0.104		-0.169	0.183		-0.079	0.160		-0.047	0.172	
	June	-0.016	0.061		0.228	0.072	*	-0.096	0.245		0.127	0.117		0.136	0.125	
	July	-0.033	0.065		0.134	0.077	~	-0.278	0.226		0.123	0.123		0.216	0.132	
	August	-0.029	0.059		0.132	0.070	~	-0.059	0.152		0.083	0.111		0.198	0.119	~
	September	-0.073	0.081		0.138	0.096		0.074	0.288		-0.023	0.147		0.048	0.159	
	October	-0.145	0.089		0.062	0.105		0.050	0.328		-0.186	0.169		-0.085	0.182	
	November	-0.388	0.091	*	-0.082	0.107		0.108	0.150		-0.318	0.164	~	-0.116	0.177	
	December	-0.298	0.113	*	-0.283	0.134	*	-0.530	0.435		-0.403	0.199	*	-0.453	0.215	*
Weekday:	Sunday	-0.439	0.039	*	-0.734	0.047	*	0.356	0.399		-0.632	0.059	*	-0.900	0.066	*
	Monday	-0.094	0.039	*	-0.148	0.047	*	-0.253	0.361		-0.097	0.057	~	-0.143	0.064	*
	Tuesday	0.022	0.039		0.085	0.046	~	-0.416	0.254		0.069	0.050		0.019	0.057	
	Thursday	-0.030	0.040		0.083	0.047	~	-0.327	0.252		0.000	0.051		-0.050	0.058	
	Friday	0.007	0.040		0.062	0.047		-1.985	0.258	*	0.060	0.058		-0.054	0.064	
	Saturday	-0.176	0.041	*	-0.117	0.048	*	-0.449	0.378		-0.073	0.061		-0.468	0.067	*
Events[a]:	USU, commencement	-0.017	0.173		0.245	0.204		0.280	0.385		0.043	0.272		-0.103	0.302	
	USU, Football	0.188	0.088	*	0.137	0.104		-0.264	0.425		0.076	0.128		0.030	0.145	
Breaks:	USU, winter	0.160	0.082	~	0.139	0.097		-2.100	0.454	*	-0.044	0.146		-0.269	0.158	~
	USU, spring	0.052	0.110		0.187	0.130		0.046	0.403		-0.184	0.197		-0.164	0.212	
	LSD[b], spring	0.013	0.096		-0.236	0.114	*	-0.486	0.393		-0.143	0.179		-0.194	0.192	

	USU, summer	0.051	0.067		0.112	0.079		0.094	0.125		-0.058	0.121		-0.132	0.131	
	LSD, fall	-0.075	0.139		-0.039	0.165		0.112	0.155		0.141	0.236		0.087	0.259	
Holidays:	New Year’s Day	-0.673	0.240	*	-0.248	0.283		-0.040	0.104		-0.551	0.361		-0.525	0.400	
	—day after	-0.118	0.240		0.367	0.283		-0.150	0.282		0.178	0.336		-0.021	0.378	
	Memorial Day	0.029	0.226		0.623	0.267	*	0.012	0.070		0.128	0.307		-0.026	0.349	
	Independence Day	-0.447	0.159	*	-0.473	0.188	*	-0.114	0.087		-0.253	0.216		0.394	0.246	
	Pioneer Day	0.025	0.158		-0.159	0.186		-0.110	0.106		-0.326	0.215		-0.580	0.244	*
	Labor Day	0.533	0.161	*	0.204	0.190		0.163	0.172		-2.438	0.219	*	-1.885	0.249	*
	Thanksgiving Day	-0.409	0.224	~	-0.579	0.265	*	-0.208	0.116	~	-0.705	0.317	*	-0.489	0.357	
	—day after	-0.563	0.227	*	-0.333	0.268		0.059	0.083		0.107	0.323		-0.770	0.364	*
	Christmas Eve	-0.487	0.247	*	-0.572	0.292	~	-0.015	0.084		-0.485	0.356		0.225	0.399	
	Christmas Day	-1.943	0.252	*	-1.598	0.297	*	-0.031	0.098		-1.852	0.376	*	-2.085	0.419	*
	—day after	-0.261	0.242		0.238	0.285		-0.001	0.078		-0.428	0.339		-0.838	0.382	*
	New Year’s Eve	0.140	0.233		-0.266	0.275		-0.057	0.088		0.128	0.330		0.287	0.370	
Assumptions:																
	Normality		yes			no			no			no			no	
	Non-autocorrelation		yes			yes			no			no			no	
	Exogeneity		yes			yes			yes			yes			yes	
	Homoscedasticity		no			yes			no			no			no	
Goodness of fits:	**R^2**		**0.73**			**0.77**			**0.56**			**0.58**			**0.61**	
	RMSE					0.26			0.37			0.31			0.34	

Variable		***Signal 5803 (N=439)***			***Signal 5805(N=448)***			***Signal 5806 (N=448)***			***Signal 5807 (N=448)***		
		β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*
Weather Variables													
	β_0	4.734	0.192	*	5.514	0.055	*	6.505	0.247	*	7.125	0.145	*
Snow Depth	≥ 0.1 in	0.044	0.124		-0.156	0.042	*	0.031	0.129		0.014	0.085	
	≥ 0.6 in	-0.039	0.156		-0.116	0.049	*	-0.625	0.167	*	-0.272	0.111	*
Snowfall	≥ 0.1 in	0.017	0.100		0.004	0.040		-0.031	0.099		-0.106	0.065	
	≥ 0.6 in	-0.351	0.267		-0.272	0.114	*	0.156	0.263		-0.193	0.174	
Precipitation	≥ 0.01 in	-0.057	0.066		-0.057	0.027	*	0.124	0.072	~	0.051	0.042	
	≥ 0.05 in	-0.122	0.082		0.010	0.035		-0.041	0.088		-0.076	0.052	
	≥ 0.25 in	-0.090	0.100		-0.131	0.042	*	-0.195	0.106	~	-0.075	0.065	
Min Temperature	< 30ºF	0.132	0.081		-0.018	0.029		-0.115	0.082		-0.018	0.054	
	< 20ºF	-0.150	0.114		-0.009	0.039		0.206	0.116	~	0.065	0.077	
	< 10ºF	0.047	0.169		-0.145	0.058	*	0.142	0.172		0.185	0.114	
Max Temperature	≥ 60ºF	-0.075	0.080		0.010	0.030		0.030	0.082		-0.001	0.050	
	≥ 70ºF	0.074	0.095		0.045	0.034		0.091	0.105		0.020	0.064	
	≥ 80ºF	0.035	0.075		0.015	0.028		0.104	0.082		0.066	0.050	

	≥ 90ºF	-0.147	0.089		-0.049	0.027	~	-0.166	0.108		-0.131	0.063	*
Temporal Variables													
Month:	January	-0.668	0.245	*	-0.441	0.067	*	0.052	0.308		0.150	0.190	
	February	-1.232	0.235	*	-0.484	0.063	*	0.178	0.297		0.200	0.182	
	March	-0.565	0.228	*	-0.459	0.061	*	0.096	0.292		0.151	0.178	
	April	-0.292	0.213		-0.226	0.056		0.069	0.268		0.172	0.165	
	June	0.208	0.165		-0.033	0.039		0.139	0.206		0.028	0.136	
	July	0.292	0.167	~	-0.089	0.042	*	0.158	0.210		0.018	0.135	
	August	0.203	0.154		-0.088	0.038	*	0.204	0.212		0.150	0.127	
	September	-0.053	0.196		-0.159	0.052	*	0.332	0.277		0.225	0.153	
	October	-0.283	0.228		-0.293	0.057	*	-0.108	0.283		0.113	0.171	
	November	-0.382	0.220	~	-0.451	0.058	*	-0.212	0.284		-0.019	0.173	
	December	-0.716	0.260	*	-0.390	0.072	*	-0.299	0.322		-0.136	0.199	
Weekday:	Sunday	-1.040	0.069	*	-0.682	0.025	*	-1.390	0.075	*	-1.491	0.047	*
	Monday	-0.177	0.066	*	-0.116	0.025	*	-0.194	0.070	*	-0.258	0.044	*
	Tuesday	0.042	0.055		0.023	0.025		-0.013	0.057		0.001	0.035	
	Thursday	-0.111	0.056	*	-0.015	0.025		-0.001	0.057		-0.016	0.036	
	Friday	-0.132	0.067	*	-0.061	0.025	*	-0.063	0.070		-0.061	0.044	
	Saturday	-0.371	0.071	*	-0.233	0.026	*	-0.890	0.076	*	-0.962	0.048	*
Events[a]:	USU, commencement	-0.114	0.321		-0.150	0.110		0.125	0.336		0.085	0.216	
	USU, Football	0.065	0.141		0.102	0.056	~	0.551	0.138	*	0.186	0.084	*
Breaks:	USU, winter	-0.299	0.192		-0.111	0.052	*	-1.229	0.220	*	-1.135	0.146	*
	USU, spring	-0.181	0.255		0.066	0.070		-0.735	0.284	*	-0.666	0.188	*
	LSD[b], spring	-0.296	0.240		-0.458	0.061	*	-0.018	0.278		-0.074	0.184	
	USU, summer	-0.293	0.158	~	-0.229	0.042	*	-1.123	0.227	*	-0.618	0.118	*
	LSD, fall	0.118	0.288		-0.333	0.089		-0.566	0.301	~	-0.182	0.199	
Holidays:	New Year’s Day	-0.370	0.429		-0.693	0.152	*	-1.692	0.444	*	-1.565	0.295	*
	—day after	0.008	0.384		-0.158	0.152		-0.620	0.385		-0.371	0.256	
	Memorial Day	0.067	0.340		0.024	0.144		-0.020	0.330		-0.288	0.219	
	Independence Day	0.936	0.239	*	-0.029	0.101		0.525	0.232	*	-0.693	0.154	*
	Pioneer Day	-0.426	0.238	~	-0.307	0.100	*	-0.551	0.231	*	-0.928	0.153	*
	Labor Day	-1.952	0.244	*	0.061	0.102		0.157	0.347		0.227	0.158	
	Thanksgiving Day	-0.807	0.364	*	-0.571	0.142	*	-1.625	0.362	*	-1.934	0.240	*
	—day after	-0.669	0.371	~	-0.217	0.144		-1.596	0.369	*	-1.970	0.244	*
	Christmas Eve	-0.203	0.412		-0.174	0.157		-1.037	0.416	*	-1.306	0.276	*
	Christmas Day	-1.870	0.446	*	-1.467	0.160	*	-2.001	0.459	*	-2.491	0.305	*
	—day after	-0.754	0.388	~	-0.502	0.154	*	-0.327	0.388		-1.413	0.257	*
	New Year’s Eve	0.260	0.380		-0.063	0.148		-0.087	0.384		-0.219	0.255	
Assumptions:													
	Normality		no			yes			no			no	
	Non-autocorrelation		no			yes			no			no	

	Exogeneity	yes	yes	yes	yes
	Homoscedasticity	no	no	yes	no
Goodness of fits:	**R^2**	**0.63**	**0.87**	**0.74**	**0.87**
	RMSE	0.36	0.14	0.36	0.24

Variable		***Signal 5808 (N=448)***			***Signal 5809 (N=448)***			***Signal 5810 (N=413)***			***Signal 5811***			***Signal 5812***		
		β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*
Weather Variables																
	β_0	6.854	0.158	*	4.713	0.065	*	3.541	0.136	*	4.349	0.124	*	3.928	0.202	*
Snow Depth	≥ 0.1 in	0.055	0.099		-0.088	0.049	~	-0.298	0.099	*	-0.131	0.178		-0.129	0.147	
	≥ 0.6 in	-0.302	0.126	*	-0.104	0.058	~	-0.039	0.118		-0.413	0.208	*	-0.452	0.178	*
Snowfall	≥ 0.1 in	-0.098	0.078		-0.038	0.047		0.111	0.092		0.045	0.162		-0.121	0.133	
	≥ 0.6 in	-0.913	0.209	*	-0.486	0.134	*	-0.423	0.254	~	0.785	0.378	*	-0.757	0.367	*
Precipitation	≥ 0.01 in	0.005	0.051		-0.059	0.032	~	-0.104	0.063	~	-0.021	0.068		0.021	0.089	
	≥ 0.05 in	-0.071	0.064		-0.036	0.041		0.000	0.081		-0.096	0.093		-0.111	0.115	
	≥ 0.25 in	-0.045	0.078		-0.038	0.050		-0.050	0.096		-0.155	0.114		-0.132	0.138	
Min Temperature	< 10ºF	0.240	0.134	~	-0.035	0.068		0.008	0.136		NA	NA		-0.217	0.204	
	< 20ºF	0.088	0.091		-0.081	0.046	~	-0.131	0.093		0.753	0.240	*	0.198	0.138	
	< 30ºF	-0.025	0.064		-0.051	0.034		-0.002	0.067		-0.198	0.104	~	-0.054	0.100	
Max Temperature	≥ 60ºF	0.019	0.060		-0.033	0.036		-0.024	0.069		0.062	0.076		-0.059	0.101	
	≥ 70ºF	0.050	0.076		0.083	0.040	*	-0.095	0.081		0.018	0.076		-0.038	0.117	
	≥ 80ºF	0.029	0.059		0.039	0.033		0.136	0.068	*	0.009	0.060		0.025	0.096	
	≥ 90ºF	-0.239	0.072	*	-0.030	0.031		-0.023	0.075		-0.121	0.061	*	-0.409	0.105	*
Temporal Variables																
Month:	January	-0.004	0.204		-0.332	0.079	*	-0.431	0.167	*	-1.259	0.314	*	-0.450	0.250	~
	February	0.120	0.194		-0.262	0.074	*	-0.418	0.156	*	-0.334	0.140	*	-0.530	0.234	*
	March	0.090	0.191		-0.200	0.072	*	-0.449	0.152	*	-0.281	0.122	*	-0.554	0.228	*
	April	0.263	0.178		-0.113	0.066		-0.144	0.141		0.143	0.084	~	-0.331	0.212	
	June	0.037	0.140		0.040	0.046		0.225	0.104	*	0.023	0.091		-0.157	0.151	
	July	0.126	0.141		0.012	0.049		0.093	0.120		-0.302	0.083	*	-0.035	0.167	
	August	0.292	0.131	*	-0.081	0.044	~	0.091	0.102		-0.320	0.113	*	0.143	0.145	
	September	0.247	0.164		-0.087	0.061		0.016	0.132		-0.359	0.132	*	-0.066	0.196	
	October	0.130	0.182		-0.157	0.067	*	0.175	0.143		-0.935	0.064	*	-0.479	0.215	*
	November	-0.027	0.184		-0.313	0.068	*	-0.073	0.145		-0.162	0.065	*	-0.662	0.218	*
	December	-0.115	0.215		-0.291	0.085	*	-0.254	0.178		-0.041	0.063		-0.496	0.268	~
Weekday:	Sunday	-1.978	0.055	*	-0.447	0.030	*	-0.871	0.060	*	0.025	0.065		-1.426	0.086	*
	Monday	-0.246	0.052	*	-0.133	0.030	*	-0.175	0.060	*	-0.014	0.066		-0.229	0.084	*
	Tuesday	-0.002	0.043		0.025	0.029		0.088	0.057		-0.270	0.067	*	-0.133	0.078	~
	Thursday	0.001	0.043		-0.015	0.030		0.033	0.057		NA	NA		0.033	0.079	
	Friday	-0.077	0.052		0.043	0.030		-0.029	0.060		-0.188	0.207		-0.124	0.085	

	Saturday	-1.268	0.056	*	-0.157	0.031	*	-0.149	0.062	*	-0.380	0.134	*	-0.897	0.088	*
Events[a]:	USU, commencement	0.274	0.255		0.018	0.130		0.050	0.263		-0.209	0.240		-0.295	0.390	
	USU, Football	0.126	0.102		0.123	0.066	~	0.140	0.126		0.267	0.131	*	0.142	0.182	
Breaks:	USU, winter	-1.236	0.159	*	-0.084	0.062		-0.046	0.129		NA	NA		-0.214	0.196	
	USU, spring	-0.621	0.209	*	-0.032	0.082		0.179	0.172		NA	NA		-0.016	0.263	
	LSD[b], spring	-0.294	0.199		-0.104	0.072		-0.388	0.153	*	NA	NA		-1.420	0.235	*
	USU, summer	-0.586	0.130	*	-0.040	0.050		-0.072	0.107		-0.008	0.093		-0.470	0.161	*
	LSD, fall	-0.442	0.230	~	-0.175	0.105	~	-0.023	0.215		NA	NA		-1.275	0.325	*
Holidays:	New Year's Day	-1.764	0.343	*	-0.114	0.180		-0.256	0.352		NA	NA		-1.911	0.521	*
	—day after	-0.356	0.303		0.073	0.180		-0.250	0.344		NA	NA		-1.069	0.503	*
	Memorial Day	-0.400	0.265		0.031	0.170		0.412	0.325		0.015	0.312		-0.290	0.470	
	Independence Day	-0.990	0.187	*	-0.572	0.119	*	-0.640	0.327	~	-1.030	0.219	*	-1.368	0.332	*
	Pioneer Day	-1.007	0.186	*	-0.248	0.118	*	0.434	0.319		0.323	0.217		0.494	0.463	
	Labor Day	-0.205	0.191		0.102	0.121		0.470	0.231	*	-0.100	0.222		-0.358	0.335	
	Thanksgiving Day	-2.233	0.286	*	-0.579	0.168	*	-0.373	0.324		NA	NA		-0.961	0.473	*
	—day after	-2.067	0.292	*	-0.773	0.170	*	-0.804	0.328	*	NA	NA		-2.178	0.481	*
	Christmas Eve	-0.584	0.327	~	-0.164	0.185		-0.783	0.359	*	NA	NA		-0.397	0.526	
	Christmas Day	-3.010	0.356	*	-0.493	0.189	*	-1.218	0.370	*	NA	NA		-2.109	0.546	*
	—day after	-1.605	0.306	*	-0.497	0.181	*	-1.130	0.348	*	NA	NA		-1.186	0.507	*
	New Year's Eve	-0.245	0.301		0.162	0.175		0.276	0.336		NA	NA		-0.262	0.491	
Assumptions:																
	Normality		no			yes			yes			yes			no	
	Non-autocorrelation		no			yes			no			NA			no	
	Exogeneity		yes			yes			yes			yes			yes	
	Homoscedasticity		yes			yes			yes			yes			yes	
Goodness of fits:	**R^2**		**0.89**			**0.78**			**0.69**			**0.69**			**0.67**	
	RMSE		0.28			0.16			0.31			0.29			0.45	

Variable		*Signal 5813 (N=434)*			*Signal 5814 (N=439)*			*Signal 5815 (N=439)*			*Signal 5816 (N=448)*			*Signal 5817 (N=440)*		
		β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*	β	*SE*	*P*
Weather Variables																
	β_0	4.376	0.103	*	3.410	0.222	*	4.866	0.123	*	5.618	0.081	*	4.894	0.089	*
Snow Depth	≥ 0.1 in	-0.124	0.075	~	-0.068	0.149		-0.077	0.082	~	-0.113	0.059	~	-0.175	0.065	*
	≥ 0.6 in	-0.204	0.090	*	-0.127	0.185		-0.052	0.102		-0.298	0.071	*	-0.172	0.078	*
Snowfall	≥ 0.1 in	-0.046	0.067		-0.085	0.126		-0.125	0.067	~	-0.004	0.053		-0.005	0.059	
	≥ 0.6 in	-0.241	0.186		-0.197	0.340		-0.192	0.181	~	-0.234	0.147		-0.184	0.162	
Precipitation	≥ 0.01 in	-0.014	0.045		-0.111	0.084		-0.076	0.044		-0.034	0.035		-0.059	0.039	
	≥ 0.05 in	-0.082	0.057		0.023	0.108		-0.062	0.055		-0.061	0.045		-0.111	0.050	*
	≥ 0.25 in	-0.017	0.070		-0.149	0.130		0.015	0.068		-0.058	0.055		-0.037	0.061	

Min Temperature	< 10ºF	-0.187	0.103	~	0.140	0.205		-0.391	0.112		0.027	0.081		-0.110	0.090	
	< 20ºF	0.153	0.070	*	-0.069	0.139		0.011	0.076		0.016	0.055		0.010	0.061	
	< 30ºF	-0.028	0.051		-0.010	0.099		0.069	0.054		0.008	0.040		-0.033	0.044	
Max Temperature	≥ 60ºF	0.030	0.051		0.028	0.099		0.018	0.051		-0.014	0.040		0.010	0.045	
	≥ 70ºF	0.023	0.060		0.033	0.119		-0.030	0.063		0.117	0.047	*	0.133	0.052	*
	≥ 80ºF	-0.031	0.049		-0.015	0.095		-0.017	0.051		0.019	0.038		-0.048	0.043	
	≥ 90ºF	-0.047	0.050		-0.077	0.112		-0.053	0.060		-0.115	0.039	*	-0.063	0.046	
Temporal Variables																
Month:	January	-0.361	0.127	*	0.012	0.278		-0.372	0.155	*	-0.251	0.100	*	-0.323	0.110	*
	February	-0.429	0.119	*	-0.075	0.263		-0.493	0.147	*	-0.298	0.093	*	-0.380	0.103	*
	March	-0.314	0.116	*	0.020	0.258		-0.362	0.144	*	-0.328	0.091	*	-0.235	0.101	*
	April	-0.202	0.108	~	0.181	0.242		-0.071	0.135		-0.204	0.085	*	-0.068	0.094	
	June	0.324	0.077	*	0.589	0.177	*	0.358	0.101	*	0.103	0.060	~	0.256	0.066	*
	July	0.103	0.082		0.142	0.187		0.064	0.105		0.048	0.064		0.015	0.072	
	August	0.044	0.074		0.084	0.169		0.050	0.097		0.022	0.058		-0.057	0.065	
	September	-0.051	0.100		0.059	0.226		0.001	0.124		-0.035	0.078		-0.094	0.087	
	October	-0.149	0.109		0.152	0.244		-0.075	0.137		-0.205	0.086	*	-0.218	0.095	*
	November	-0.338	0.111	*	0.037	0.247		-0.368	0.139	*	-0.391	0.087	*	-0.443	0.096	*
	December	-0.439	0.136	*	-0.112	0.296		-0.243	0.165		-0.434	0.107	*	-0.455	0.118	*
Weekday:	Sunday	-0.763	0.043	*	0.019	0.084		-0.291	0.046	*	-0.205	0.034	*	-0.560	0.038	*
	Monday	-0.131	0.042	*	-0.032	0.082		-0.079	0.044		-0.131	0.034	*	-0.146	0.038	*
	Tuesday	0.076	0.039	~	-0.001	0.071		0.010	0.038		0.014	0.031		0.018	0.035	
	Thursday	0.005	0.039		0.029	0.072		0.039	0.038		-0.035	0.031		-0.020	0.035	
	Friday	-0.020	0.043		0.101	0.083		0.027	0.044		-0.093	0.034	*	-0.034	0.038	
	Saturday	-0.411	0.044	*	-0.019	0.087		-0.073	0.047		-0.478	0.035	*	-0.134	0.039	*
Events[a]:	USU, commencement	-0.040	0.198		0.114	0.394		-0.231	0.214		-0.337	0.156	*	-0.128	0.172	
	USU, Football	0.106	0.092		0.287	0.182		0.001	0.089		0.233	0.073	*	0.025	0.081	
Breaks:	USU, winter	-0.096	0.100		-0.106	0.216		-0.346	0.122	*	-0.728	0.078	*	-0.115	0.086	
	USU, spring	0.144	0.134		0.016	0.290		-0.102	0.163		-0.379	0.105	*	-0.084	0.116	
	LSD[b], spring	-0.126	0.119		-0.262	0.268		-0.363	0.151	*	-0.367	0.094	*	-0.281	0.103	*
	USU, summer	-0.039	0.082		0.115	0.184		-0.020	0.102		-0.626	0.064	*	-0.067	0.072	
	LSD, fall	-0.112	0.165		-0.047	0.340		-0.034	0.187		-0.376	0.129	*	-0.315	0.143	*
Holidays:	New Year’s Day	-1.382	0.264	*	-1.157	0.520	*	-0.004	0.283		-0.559	0.208	*	-0.378	0.230	
	—day after	-0.269	0.255		-1.068	0.479	*	-0.077	0.258		-0.492	0.201	*	-0.551	0.222	*
	Memorial Day	-0.092	0.238		0.315	0.435		0.183	0.231		0.057	0.188		0.088	0.208	
	Independence Day	-0.902	0.167	*	-0.560	0.306	~	-0.372	0.163	*	0.190	0.133		-0.305	0.146	*
	Pioneer Day	-0.448	0.166	*	-0.334	0.305		-0.260	0.162		-0.378	0.132	*	-0.131	0.145	
	Labor Day	0.289	0.169	~	-0.047	0.437		-0.156	0.166		-0.137	0.134		-0.213	0.148	
	Thanksgiving Day	-1.019	0.240	*	-1.446	0.454	*	-0.497	0.244	~	-1.410	0.189	*	-0.703	0.209	*
	—day after	-0.996	0.244	*	-0.779	0.462	~	-0.625	0.248	*	-0.971	0.192	*	-0.580	0.212	*
	Christmas Eve	-1.055	0.267	*	-1.325	0.510	*	-0.132	0.275		-0.795	0.210	*	-0.258	0.232	
	Christmas Day	-1.382	0.277	*	-1.197	0.542	*	-0.094	0.295		-1.661	0.218	*	-0.473	0.241	~

	—day after	-0.798	0.257	*	-0.942	0.484	~	-0.688	0.260	*	-0.691	0.203	*	-0.666	0.224	*
	New Year's Eve	-0.149	0.249		-0.962	0.472	*	-0.197	0.254		-0.182	0.196		0.280	0.217	
Assumptions:																
	Normality		no			no			no			no			yes	
	Non-autocorrelation		no			no			no			no			no	
	Exogeneity		yes			yes			yes			yes			yes	
	Homoscedasticity		no			no			no			no			yes	
Goodness of fits:	**R^2**		**0.73**			**0.38**			**0.48**			**0.80**			**0.75**	
	RMSE		0.23			0.47			0.23			0.18			0.20	