Cycling in a Changing Climate: An Examination of the Effects of Weather and Climate Change on Cycling Frequencies in Southern Ontario

by
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Author’s Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

This thesis contributes to the knowledge-base of how commuter cycling frequencies are impacted by current weather conditions, and what effects climate change will have on them by mid-century. Numerous studies have focused on the effects of climate change on passive modes of travel (e.g. automotive, locomotive, aviation), with less attention devoted to active transportation, such as cycling. As the climate changes through the 21st century, it is important to develop an understanding of how commuter cyclists are affected by weather and what these impacts will look like under future conditions when planning for modern and accessible cities. This research applies this reasoning to contribute to filling-in a geographic void in southern Ontario where there is a current lack of knowledge on this topic. Publicly available weather and cycling count data for Waterloo, Ontario, is used to analyze the effects of several weather variables on commuter cyclists at present and predicted at mid-century using a generalized linear regression model. The model results for present-day impacts were consistent with findings in other research: that adverse conditions (e.g. rain and snow) negatively affect cycling frequencies, while increased temperatures and a lack of precipitation generally result in a positive change, however the rates of change varied depending on the trail location in the City of Waterloo. Under the climate change analysis, the results contest the numerous studies conducted outside of southern Ontario that indicate cycling frequencies will increase under a changed climate by suggesting that they will decrease as the effects of climate change intensify. The findings of this research may contribute to the understanding of the numerous factors that influence cycling frequencies and provide planners with a tool to effectively apply investments in infrastructure and to programs that will seek to encourage adaptation to the impacts of weather and climate change identified here.

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List of Abbreviations

AADT	Average Annual Daily Traffic
AMDT	Average Monthly Daily Traffic
CFM	Change-Field Method
CMIP5	Coupled Model Intercomparison Project Phase 5
ECCC	Environment and Climate Change Canada
EDU	Ontario Ministry of Education
FHWA	Federal Highway Authority
GCM	Global Climate Model
GLM	Generalized Linear Model
GRCA	Grand River Conservation Authority
GTA	Greater Toronto Area
HCA	Hamilton Conservation Authority
IHT	Iron Horse Trail
IPCC	International Panel on Climate Change
LTC	Laurel Trail at Columbia St. W.
LTE	Laurel Trail at Erb St. E.
LTSL	Laurel Trail at Silver Lake
LTW	Laurel Trail at Weber St. N.
KNMI	The Royal Netherlands Meteorological Institute
MLR	Multiple Linear Regression
MMAH	Ontario Ministry of Municipal Affairs and Housing
MOECC	Ontario Ministry of the Environment and Climate Change
MOHLTC	Ontario Ministry of Health and Long Term Care
MOI	Ontario Ministry of Infrastructure
MTCS	Ontario Ministry of Tourism, Culture and Sport
MTO	Ontario Ministry of Transportation
NCAR	National Center for Atmospheric Research
NGO	Non-Governmental Organization
PET	Physiological Equivalent Temperature
RCM	Regional Climate Model
RMSE	Root Mean Square Error
TCAT	Toronto Centre for Active Transportation
TTS	Transportation Tomorrow Survey
USAID	United States Agency for International Development
WCRP	World Climate Research Programme

1.0 Introduction and Background Research

1.1 Introduction

Cycling has become a major trend in cities throughout Ontario. Citizens and all levels of government are realizing the benefits of cycling through its ability to increase public and environmental health, help drive sustainable initiatives, further economic development, and promote an enhanced quality of life (Transport Canada, 2012; Hooqzaad et al., 2013). Many citizens in Canada have been in support of cycling and its related infrastructure. A 2014 opinion poll commissioned by Share the Road, a provincial cycling advocacy group, reported that more than half of Ontarians wish to cycle more often and over two-thirds state they would cycle more if infrastructure was improved (Share the Road, 2014). Share the Road Cycling Coalition estimates that approximately 600,000 Ontarians cycle on Ontario's roadways daily, while 3.8 million cycle on a weekly or monthly basis within the province for recreation[1], utilitarian[2], and commuter[3] trips (Share the Road, 2014). Data collected by the Transportation Tomorrow Survey (TTS), a transportation research group at the University of Toronto, shows that the number of trip-starts in the survey area[4] by walking or cycling, during both morning rush-hour and over a 24-hour period, have increased over time, nearly doubling in the period between 1996 and 2011 (TTS, 2011).

Despite increasing trends in cycling rates, a number of barriers inhibit people from cycling more frequently or at all. The perception of safety while cycling on roads, lack of cycling infrastructure, and perceived inconveniences all play a role in deterring individuals from cycling (Bidordinova, 2010). While the aforementioned factors influence cycling frequencies in Ontario, none are as significant as weather (Stinson & Bhat, 2004; Mullan, 2013; Bidordinova, 2010). With cycling rates increasing in Ontario, and cyclists largely deterred by the perceived negative impacts

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[1] Recreational cycling includes cycling for leisure, health and wellness, among other reasons, but does not include travelling for transportation or to complete a task, e.g. shopping.
[2] This includes cycling as a mode of transportation to reach a destination to perform a task, such as shopping, or travelling to school or work (i.e. commuting).
[3] Commuter cycling is a form of utilitarian cycling; however it strictly refers to travelling by bicycle to and from an individual's place of work or school.
[4] The municipalities surveyed in the TTS include: the cities of Barrie, Brantford, Guelph, Hamilton, Kawartha Lakes, Peterborough, and Toronto; the counties of Brant, Dufferin, Peterborough, Simcoe, and Wellington; the regional municipalities of Durham, Halton, Niagara, Peel, Waterloo, and York; and the Town of Orangeville.

of riding in ‘bad’ weather conditions, Ontario has considerable room for improvement to match the rates found in cycling-dominant regions such as Vancouver, BC, and Minneapolis-St. Paul, USA in North America; along with Germany and Denmark, in Europe (Pucher & Buehler, 2007; Pucher et al., 2011; Behan & Lea, 2010).

Weather conditions are an important influence on active transportation activity, particularly cycling. Positive weather conditions are considered the most suitable for all cyclists and are when the greatest number of cyclists are reported to ride, such as periods of warm temperature, low winds and the absence of precipitation (Lewin, 2011; Moreno-Miranda & Nosal, 2011; Saneinejad, Roorda & Kennedy, 2012; Böcker, Prilwitz & Dijst, 2013a). This is important as it allows less committed utilitarian cyclists to cycle comfortably and as confidently as the “strong and fearless” cyclists who ride in most conditions (Patterson & Steiger, 2013). Alternatively, negative or adverse conditions may include the presence of rain, fog, snow, extreme temperatures (hot and cold), humidity, wind, and atmospheric cover (Pucher & Buehler, 2006; Behan & Lea, 2010; Saneinejad et al., 2012; Böcker et al., 2013a). The presence of these conditions in isolation or combination may adversely affect cycling frequency and volume.

In addition to weather, there are a range of infrastructure and policy elements that are associated with increasing cycling activity. The Government of Ontario has put forth a number of policies, guidelines and related articles supporting cycling programs at the municipal level. The Ministries of Infrastructure (MOI); Environment and Climate Change (MOECC); Transportation (MTO); Municipal Affairs and Housing (MMAH); Tourism, Culture and Sport (MTCS); Health and Long Term Care (MOHLTC); and Education (EDU), along with government agencies such as Metrolinx, and non-governmental organizations (NGOs) such as Share the Road and the Toronto Centre for Active Transportation (TCAT) have expressed support through increased funding, education, advocacy and improvements towards cycling within Ontario (Ontario, 2014). The Ontario government introduced the *Ontario Municipal Cycling Infrastructure Program* where additional funding opportunities are made available to municipalities (Ontario, 2015). Within the program, $10 million is allocated to municipal cycling improvements, while $15 million is available to expand and improve cycling infrastructure along provincial highways, lands and trails (Ontario, 2015).

Ontario’s cities are allocating more money and resources into cycling than ever before; increased infrastructure installations, year-round bike route maintenance and bike sharing services have been initiated. More municipalities are commissioning cycling master plans and active transportation master plans to guide future development, objectives and planning for cycling and active transportation routes, infrastructures, policies and programs. The City of Waterloo's *Transportation Master Plan* (2011) lists a number of objectives for cycling, including reduced dependency on non-renewable energy, increased multi-modality, and to establish a network of cycling trails and routes.

Although ambitious objectives and considerable resources have been presented, there is no accepted understanding of how factors, such as weather, influence cycling in Ontario. Without comprehensive evidence of how weather influences cycling, municipalities cannot optimize their investments. This is a key consideration when planning for and evaluating the effectiveness of infrastructure and initiatives due to the influence weather has on utilitarian cycling. Additionally, there is an absence in understanding how climate change will alter the weather conditions that cyclists experience in future years. It is important that consideration is given to how utilitarian cycling in Ontario will be impacted by climate change and what these implications mean for long-range transportation planning within the province, especially with regards to active transportation infrastructure investment.

Weather is arguably the most influential deterrent preventing individuals from cycling. In a 2010 study on barriers to utilitarian cycling in Toronto, weather is identified as the largest deterrent to utilitarian cycling (Bidordinova, 2010). While lack of infrastructure and dangerous driving were also identified as significant deterrents, the perception of decreased safety and comfort as a result of 'bad' weather has a greater effect on utilitarian cyclists' willingness to travel by bicycle (Bidordinova, 2010). Additionally, a study on cycling deterrents in Canada and the United States found that 60% of respondents selected unpleasant weather as the greatest barrier to commuting by bicycle (Stinson & Bhat, 2004). Notably, cyclists who identified as frequent bicycle commuters chose unpleasant weather as their greatest deterrent 64% of the time, followed by personal reasons (33%), and lack of daylight to ride safely (26%) (Stinson & Bhat, 2004). A study on commuter cycling behaviour in Ireland echoes these results as interviewees noted weather as the biggest obstacle to cycling for transportation (Mullan, 2013). Developing a thorough understanding of how cyclists respond to different weather events (i.e. sensitivity and perception of weather) is integral to ensuring continued and effective use of cycling infrastructure.

Beyond present-day weather, trends of increasing average annual temperatures and greater precipitation variability across Canada have led to further attention towards climate change and how it will impact society (Lemmen et al., 2008; Hamilton Conservation Authority [HCA], 2012; Warren & Lemmen, 2014).To avoid negative outcomes from the inevitable climatic shift, municipalities must develop greater resiliency through infrastructure, policy and program adaptation that incorporate cycling (Giodana et al., 2013). Distinguishing between adaptation and other strategies such as coping is an important component. The Intergovernmental Panel on Climate Change (IPCC) states that "coping focuses on the moment, constraint, and survival", while "adapting focuses on the future, where learning and reinvention are key features" (2012). Similarly, CARE International defines coping as a "lack of alternatives", and a "short-term and immediate response"; and that adaptation "involves planning", "finding alternatives" and is oriented towards a longer-term strategy (2009). Therefore, by proactively introducing climate change into active transportation, cycling and/or transportation master plans, municipalities will be prepared to adapt cycling policies, programs and infrastructure according to current and future climate conditions rather than retroactively coping with the impacts.

The purpose of this research is to establish an understanding of how weather impacts cyclists and how cycling will be impacted by climate change in Ontario using weather and cycling count data collected in the City of Waterloo to facilitate this exploration. While research into active transportation modes is becoming more popular within transportation literature (e.g. Behan & Lea, 2010; Pucher, 2011; Ahmed et al., 2012; Tin Tin, 2012; Böcker et al., 2013a; Spencer et al., 2013; Wadud, 2014), the impacts of various climate and weather events on cyclists remain narrowly focused on several specific weather conditions and geographic locations (e.g. north and western European nations). Further, the importance of incorporating climate change into planning for cycling is often not considered despite its acknowledgement and looming presence. Although there is research within the field on the impacts of weather on cycling, few studies have sought to provide an understanding of how future climate conditions will impact cycling. Casello and Towns (in press), and Koetse and Rietveld (2009) identify the need for localized analysis of "consequences of climate change and weather for the transport sector", which have received little attention. Heinen et al. (2010) state that there has been little discussion on the effects of climate change on cycling, warranting further research.

1.2 Research Relevance

Cycling is very sensitive to weather conditions, with the degree of sensitivity to a given weather variable known to vary throughout locations. Research has been conducted in large volumes on the correlation between cycling frequencies and weather conditions in northern Europe (e.g. Mathisen et al., 2015; Brandenberg et al., 2007), Belgium (e.g. Cools et al., 2009; Cools et al., 2010; Cools & Creemers, 2013; Creemers et al., 2013; Khattak & de Palma, 1997), the Netherlands (e.g. Böcker et al., 2013a; Böcker et al., 2013b; Koetse & Rietveld, 2009; Thomas et al., 2012) and Australia (e.g. Ahmed et al., 2012; Measham et al., 2011; Nankervis, 1999). Findings from these studies provide an integral glimpse into the importance of identifying the degree to which weather impacts a utilitarian cyclist's decision to commute via bicycle in different regions. However, there is not a similar abundance of material in the Ontario, or even Canadian contexts. Therefore, studying Waterloo cyclists will contribute to the sparse research on the effects of weather on cyclists in Canada. A local analysis of weather sensitivities and cycling frequencies can further the discussion on appropriate policy development for the continued growth of cycling in Canada and offer an opportunity to compare against other jurisdictions with high cycling mode share for future development.

Research on the implications of future climatic changes on cyclists will be of utmost interest to transportation engineers, planners and policy analysts who must ultimately implement new cycling policies or programs. Additionally, provincial planners and policy analysts in Ontario ministries including the MTO, MMAH, and MOECC, as well as federal ministries and agencies that benefit through increased knowledge during discussions on provincial and federal roads, lands and interests, and in climate change and active transportation plans, strategies or guide lines. This information will provide these individuals an opportunity to explore policy and infrastructure adaptations in advance by gauging weather, cycling frequencies and sensitivities, and population change to implement adaptation strategies at the most appropriate time. The findings of this research will be relevant to most of southern and eastern Ontario (i.e. the very populated regions in the province), according to the Köppen-Geiger Climate Classification. Cities such as Toronto, Waterloo, Barrie, Ottawa, and St. Catharines are found within the same climate classification (Dfb: warm-humid continental climate) (Kottek, et al. 2006). Therefore, this research will be applicable to a large region home to millions of people. This research, therefore, can be seen as the proactive development of a tool for governments and agencies to use and offer effective and appropriate means to continue cycling growth during years of climatic variability.

1.3 Research Questions

This study will be oriented around the following two research questions:

1. How is commuter cycling impacted by weather conditions?
2. How will climate change potentially impact commuter cycling?

The purpose of the first research question is to develop an understanding of how Waterloo cyclists are currently affected by weather variables during their daily commutes. This will establish a baseline from which future cycling frequencies and weather conditions or climate projections can be compared against to identify trends in cycling throughout the temporal scale of the study. This question will be investigated using several datasets: Environment and Climate Change Canada's (ECCC) Waterloo weather data (collected at the Waterloo International Airport); the City of Waterloo's cycling count data; and the University of Waterloo's weather data, for the years 2015 and 2016.

The second research question looks directly at identifying the impact of climate change on cycling behaviour in Waterloo over various time periods, using different climate models and projections. The scenarios explored in this exercise will allow insight into the potential impacts of climate change on cycling frequencies and provide a platform through which the discussion, found later in this report, will offer adaptation strategies and recommendations for the City of Waterloo.

The City of Waterloo was selected as the location for this study for a number of reasons. Firstly, it has unparalleled data availability on cycling frequencies throughout the city compared to other Ontario municipalities. The city employs eleven automatic cycling counters at ten locations that report the frequency at which cyclists travel past the stationary instrument on an hourly basis year-round (data is available through the City of Waterloo's Open Data portal). Cycling counters have been installed on most of Waterloo's multi-use trails that travel into, or out of the central urban area, as well as along both directions of an on-road bike lane. These sensors provide opportunities to further study commuter cyclist travel behaviour during the morning and afternoon commutes (German Institute of Urban Affairs, 2012). Next, weather data is easily attainable within the region due to the presence of an ECCC weather station at the Region of Waterloo International Airport, with over 30 years of archived weather data. This is supplemented by a weather station located at the Laurel Creek Conservation Area, operated by the Grand River Conservation Authority. Finally, the City of Waterloo has a strong cycling community that is supported by a political drive to invest in further infrastructural and community improvements to enhance cyclist safety and accessibility (City of Waterloo, 2011).

The structure of this thesis is as follows: chapter two contains the literature review, which will outline the relevant research others have conducted on the importance of evaluating weather's impacts on cyclists, cyclist sensitivities to weather, and impacts of climate change on cyclists' behaviour and frequencies; a review of methods that researchers have used to examine the relationship between weather and cycling, along with methods to determine the impact of climate change on cyclists under future climate change projections. Chapter three will consist of the methodology section, which will state and describe the methods used to study the relationships presented in this thesis. Chapter four will present the preliminary results of the study, which will include general statistics such as frequency of extreme weather events in a year, cycling and weather trends at various time scales, and outlines the variables and model that will be used in this thesis. Chapter five will present the study's findings including the impacts of present-day weather on cycling frequencies and the expected effects of climate change on cycling frequencies at mid-century. Finally, Chapter six is the discussion and conclusion section, which will discuss uses and potential actions for the City of Waterloo based on a summary of the findings from Chapter five, in addition to study limitations and future research opportunities.

2.0 Literature Review

2.1 Introduction

Literature on the effects of weather and climate change within the transportation sector thus far is predominantly oriented towards motorized vehicles (Petersen et al., 2008), and is comparatively lacking in research on cycling and its influencers (Koetse & Rietveld, 2009; Böcker et al., 2013b). The push for alternative personal transportation, and cycling's exposure to meteorological factors is leading researchers to better understand the influences that impact cyclists travel behaviour (Ahmed et al., 2012). Hanson and Hanson (1977) published one of the first studies on cyclists' responses to specific weather events; 40 years later there remains little literature relative to motorized transportation analyzing cycling frequency in response to weather and climate change (Behan & Lea, 2010). As such, a need for future exploration to address the known spatial variation in cycling travel behaviour and the uncertainties regarding the effects of climate change on cycling frequencies and travel behaviours has been identified by researchers such as Ahmed et al. (2010). Studies that have been completed examine a range of factors that impact travel behaviour from a cyclist's perspective, including mode choice, travelled distance, and current and forecasted weather conditions, and, of interest to this study, the relationship between cycling frequencies and weather (e.g. Cools et al., 2010; Gallop et al., 2012; Böcker & Thorsson, 2013). This literature review presents current research and knowledge on the effects that weather and climate change may have on cycling frequencies. This section is presented in the following order: objectives of past studies, type and scale of cycling and meteorological data, overview of research methodologies, results and findings across the literature, and a summary of the reviewed literature.

2.2 Types of Study Objectives

Researchers studying the impacts of weather on cycling travel behaviour approach the relationship by analyzing certain aspects of cycling that are affected by weather variables. Four types of study objectives that seek to analyze the relationship between cycling travel behaviour and weather are found in the literature, including preferred transportation mode choice, trip purpose, trip distance or duration, and frequency of cycling activities under various combinations of weather conditions. Similar study objectives are present regarding the impacts of future weather conditions and cycling frequencies, or cycling frequencies under a changed climate, however the focus of these studies is on cycling frequencies rather than a variety of cycling travel behaviours. Below, an overview of the study objectives found within the literature on the impacts of weather and climate change on cycling travel behaviour will be presented.

Meteorological impacts on cycling are amplified by its exposure to weather conditions. Due to the exposed nature of cycling to weather, scholars show substantial interest in understanding how cyclists adjust their travel behaviour based on a variety of weather conditions. Studies seek to identify when individuals are more likely to choose a bicycle for utilitarian travel (i.e. commuting) versus other modes of transport (e.g. public transit, personal automobile, or car-pooling) based on current weather conditions (Saneinejad et al., 2012; Flynn et al., 2013; Böcker et al., 2013a). Cools and Creemers (2013) believe that commuters refer to weather forecasts to identify days where the weather may not be ideal and therefore choose not to cycle, while Gallop et al. (2012) state that cyclists form their decision on whether to cycle based on current weather. Other weather-related studies focus on the relationship between trip purpose and an individual's choice to cycle (e.g. Cools et al., 2010; Creemers et al., 2013; Mathisen et al., 2015). Researchers are also interested in whether individuals are more likely to cycle depending on their destination (e.g. shopping, leisure, recreation, or commuting) or motive for travelling (recreation or utilitarian) during various weather conditions (Cools et al., 2010; Creemers et al., 2013). Next, there is an interest in studying the distances or durations that cyclists will travel based on current weather conditions. Sears et al. (2012) study the relationship between cycling frequency, weather, and distance to work, focusing on how far cyclists are willing to travel in weather conditions (considering one or more conditions at a time), while Böcker and Thorsson (2013) orient their study towards trip duration within specific weather conditions. Ultimately, these studies are designed to identify how far or how long a cyclist is willing to travel under certain weather conditions. Finally, several scholars direct their studies towards how weather conditions alter cycling frequencies or rates, excluding considerations on the amount of time spent cycling, mode choice, and trip purpose as noted above (e.g. Miranda-Moreno et al., 2013, Wadud, 2014; Mathisen et al., 2015). More specifically, Gallop et al. (2012) state that the objective is to "determine the significance and magnitude effect of select weather variables on bicycle traffic… and devise a time series model that can be used to forecast future bicycle traffic". Studies of this nature have the advantage of generating accurate, directly comparable results that explicitly identify the relationship between cycling and a variety of meteorological factors, but lack personal perspectives on weather conditions or consider socioeconomic factors that deter or incentivize cyclists (Böcker et al., 2013b). Understanding the relationship between cycling and weather is a study objective of this thesis research.

As jurisdictions around the world are increasing cycling infrastructure, resources, and funding, studies are continually seeking to understand what promotes or deters cycling as a form of transportation to underline where improvements may be made. While an abundance of research outlines conditions that enable or deter cycling, some studies focus on the factors that deter people from considering cycling as a viable alternative transportation mode altogether (Bidordinova, 2010; Spencer et al., 2013; Fisher, 2014; Manaugh et al., 2016). These studies consider factors ranging from the presence of end-of-trip facilities (e.g. change rooms, showers, and secure bicycle storage) to an individual's perception of safety while cycling. The dominant theme, however, is the connection between an individual not commuting by bicycle as a result of weather (Bidordinova, 2010; Manaugh et al., 2016). Other research is specific to cold climatic conditions that may be experienced in North America (Spencer et al., 2013; Fisher, 2014). Conversely, though there are many articles identifying deterrents to utilitarian cycling, Fisher (2014) identifies methods used by other regions (e.g. better winter maintenance, and installing infrastructure more suitable to regional climates) that promote cycling during adverse weather, namely the winter season.

While the above studies generally focus on a single region, several authors perform a comparative analysis of trends, policies, or weather sensitivities amongst a range of jurisdictions. Each comparative study seeks to understand different aspects of cycling's relationship to weather around the world, such as whether climatic conditions influence cycling rates differently in North American and European cities (Behan & Lea, 2010); how commuter cyclists in a number of cold climate regions respond to the winter season (Fisher, 2014); how several of North America's most cycle-friendly cities compare with regards to weather sensitivities (Miranda-Moreno et al., 2013); and, why Canada reports a higher average cycling rate than the United States despite a climate that is considered to be less conducive to cycling (Pucher & Buehler, 2006).

More research is extending the scope of studies beyond identifying the impacts of current weather on cycling to forecasting the role that climate change will have in altering future cycling frequencies. International examples of local and regional studies on climate change impacts on cycling are numerous. Studies on climate change as it relates to cycling travel behaviours in the municipalities of Bodø, Norway, Sutherland Shire, Australia, and Copenhagen, Denmark, are used to determine if a revised approach and adaptation measures are necessary to prepare for future weather (Fletcher, 2011; Measham et al., 2011; Mathisen et al., 2015). The aforementioned research seeks further information on whether seasonal weather, rising sea-levels, increased precipitation, and extreme temperatures will prove detrimental to the respective cycling communities and related infrastructure. These few studies are unique in that they are designed to provide a basis for policy- and decision-makers to make informed decisions with respect to cycling policies, programs, and infrastructure by considering future implications of climate change. Impacts on cycling frequency derived from projected climate change within a Canadian context is a research objective of this thesis research.

2.3 Types of Data

Throughout the reviewed literature there is an array of data used to analyze the relationships between weather and climate change on cycling. To model these relationships, researchers collect data on cycling travel behaviours (e.g. frequency count data, distance travelled, and trip duration), weather events, and climate projections. Cycling travel behaviour data collection shows the greatest variability of methods used across the reviewed data types, with a strong presence of automated count data. Data used within research on the impact of weather on cycling travel behaviour may be placed into three categories based on the reviewed literature: cycling count data and activity information (e.g. frequency, travelled distances, and trip durations), local weather data, and climate projections. Data collection and obtainment methods used within the reviewed literature are discussed below, including the spatial and temporal variations within different datasets.

2.3.1 Cycling Data Collection Methods

While there are many different types of studies using an array of methods, the types of data used remains consistent. Each study uses similar types of data to conduct research on meteorological impacts on cyclists' travel behaviour. Studies that seek to identify cyclists' sensitivities to weather (e.g. Brandenburg et al., 2007; Böcker et al., 2013a) use a combination of cycling travel data (e.g. frequency count data, or duration or distance of travel) and actual weather data (e.g. hourly temperatures, daily precipitation), while those studying climate change (e.g. Saneinejad et al., 2012; Waded, 2014; Matheson et al., 2015) substitute weather data for climate projections. To gather these data, researchers employ a variety of collection methods which differ based on the objectives and required data in a study. While weather and climate projections are usually obtained from public agencies (e.g. ECCC, Royal Netherlands Meteorological Institute [KNMI]) sources of cycling frequency data and information on cyclists' sensitivities to weather may be further categorized. The categories are as follows: interviews and focus groups, censuses, and surveys, and automatically collected cycling data. Each of the aforementioned data collection methods have inherent strengths and weaknesses that will be outlined below.

Interviews and focus groups are used to develop an intimate understanding of cyclists' preferences, behaviours, and thought processes, as well as to what degree their choice of transport mode is affected by certain weather variables (Cools et al., 2010; Sears et al., 2012). Interviews are generally limited to smaller geographic areas and sample populations, such as university faculty, students, and staff members (Bidordinova, 2010); cyclists within recreation areas (Brandenburg et al., 2007); and commuter cyclists in urban cities (Spencer et al., 2013). Interviews and focus groups offer researchers a more personal and in depth understanding of the driving or deterring factors that influence cycling rates. Examples include specific reasons behind choosing a mode of transport during adverse weather conditions as a result of safety or comfort concerns (Bidordinova, 2010), and personal adaptation strategies for cycling in adverse weather (Spencer et al., 2013). Due to limited sample sizes, these approaches may not represent a larger population, and lack the ability to identify general trends and patterns in cycling rates and behaviour (Spencer et al., 2013), however they may provide insight into the individualized behaviours of cyclists experiencing a variety of weather conditions (Jacobson, 2010; Flynn et al., 2012; Spencer et al., 2013).

Censuses and surveys are commonly employed as an alternative, less costly method to collect information on the behaviour and preferences of cyclists (Böcker & Thorsson, 2013). This may also enable jurisdictional comparison (Behan, 2010; Fisher, 2014), and may be used within regions where higher resolution data (i.e. automated counter data) are not available (Böcker et al., 2013b). Generally, census data is presented at the national (e.g. The Netherlands National Household Travel Survey) or state/provincial level, however several jurisdictions in North America and Europe routinely collect regional and municipal data (e.g. the Transportation Tomorrow Survey in southern Ontario). Censuses and surveys have the advantage of reaching a greater number of potential participants than interviews and focus groups, however the predetermined questionnaire design may limit the amount of information available to researchers for analysis (Saneinejad, 2010).

The above data collection methods are very common within cycling literature due to a lack of automated and technological alternatives in past studies. Recently, however, cities around the world are installing automated cycle counters, which use inductive loop and infrared sensor technology to measure the number of cyclists, cars, and pedestrians at a specific location (US Depart of Transportation, Federal Highway Administration [FHWA], 2013). This data collection method generates data at an hourly or daily resolution on the number of travellers passing by the location, and may include the direction of travel and type of transport mode they are using (FHWA, 2013). Automated counter data is heavily used within recent research on cycling and pedestrian travel (e.g. Aultman-Hall et al., 2009; Ahmed et al., 2010; Nosal & Miranda-Moreno, 2014). Due to automated counters being tied to a specific location they may not capture all travelers when unpredictable movements occur next to or near a facility, such as using 'short cuts' that effectively bypass the counter, and may over or undercount (FHWA, 2013). However, automated counters provide the unrivaled ability to continuously count and collect data on cycling frequencies at high temporal resolutions, addressing the lack of continuous, non-motorized vehicle data collection (Zhao, 2016). In the face of the conventional limitations of automated counters, new technologies have been emerging that seeks to more dynamically monitor traffic counts, including cycling. Examples include a new mobile application employed by the City of Toronto, Ontario, developed by Brisk Synergies. This free application "allows cyclists to record their cycling routes [using GPS enabled smartphones] and provide this data to the City" that can then be used by the City of Toronto to inform "data collection and analysis when developing cycling network plans" without the need for physical infrastructure installations (City of Toronto, n.d.). Another example includes the Ontario-based company MioVision that utilizes video technology to differentiate between and count different modes of traffic, including active travellers (MioVision, 2017).

2.3.2 Weather Data Collection Methods

Weather data within most of the studies reviewed in this thesis rely on data that is collected and made available by meteorological agencies or independent weather stations (i.e. ECCC or KNMI). Alternatively, Cools and Creemers (2013) use cyclists' perceptions of weather, rather than actual weather data, to study the relationship between weather and cycling. The authors argue that the perception of weather is as important as the measured conditions themselves.

While many researchers agree on the use of quantitative weather data to analyze temporal fluctuations in cycling, there is a great deal of discussion oriented around which weather variables are necessary within an analysis. Common weather variables used within analyses include: precipitation (mm), temperature (°C), wind speed (km/h), amount of sunshine (h/day), and relative humidity (%). A number of authors argue the necessity of further dividing these variables into subcategories to represent different conditions and degrees of severity. Precipitation may be categorized into rain (Gallop et al., 2012; Tin Tin et al., 2012; Wadud, 2014) and snow (Winters et al., 2007; Sears et a., 2012), while authors also consider the variable impact of different amounts of rain per hour on cyclists, commonly citing a non-linear relationship (Ahmed et al., 2012; Mathisen et al., 2015). Similarly, varying wind speeds are hypothesized to have differing effects on cycling, therefore studies include the full range of wind speeds to identify thresholds (Ahmed et al., 2010; Creemers et al., 2013), or a severity index is developed to categorize wind speeds (Nosal & Miranda-Moreno, 2014). Next, ambient air temperature values are commonly used within weather sensitivity models (Miranda-Moreno & Nosal, 2011; Saneinejad et al., 2012; Thomas et al., 2013). However, examples exist of ambient air temperature being combined with other weather variables (e.g. relative humidity, solar radiation, wind speed) to develop apparent temperature values (e.g. physiological equivalent temperature [PET], HUMIDEX), which consider how comfortable an individual may feel under a combination of atmospheric conditions (e.g. Brandenburg et al., 2007). Others argue that the amount of sunshine plays a significant role and should be included, as cyclists may feel unsafe cycling in low-light or dark environments, therefore greater amounts of sunshine (i.e. summer months) will result in greater cycling frequency (Brandenburg et al., 2007; Phung & Rose, 2007; Behan & Lea, 2010). Further, several authors state that certain weather variables have lagged effects, meaning that even when they are no longer occurring they continue to impact cycling frequencies for a period of time, such as after rain or snowstorms (Miranda-Moreno & Nosal, 2011; Ahmed et al., 2012).

2.3.3 Climate Change Data Collection Methods

Forecasts of the impacts of future weather conditions on cycling use climate projections or scenarios in models of future effects. Their use in research has been limited thus far to several examples within transportation literature focused on active travellers, which will be discussed below. The most common source of climate projection data appears to be from regional models on climate change (Saneinejad et al., 2012; Böcker et al., 2013a; Mathisen et al., 2015). These studies use seasonal projection averages (Böcker et al., 2013a), or a range of projection values (Saneinejad et al., 2012; Mathisen et al., 2015) that are noted within studies on climate change to then be used in cycling research. Some studies use regional climate models (RCMs) or outputs from these models as generated by other research (Böcker et al., 2013a; Mathisen et al., 2015), while others use global climate models (GCMs) (Wadud, 2014). Slight differences exist in the application of RCMs and GCMs. GCMs typically have poor spatial and temporal resolutions in comparison to RCMs, which have greater resolution and are better able to represent regional weather patterns, but are not available for every region and rely heavily on information derived from GCMs (Takle, 2005). Therefore, an RCM does not replace a GCM, rather it provides climate information at a finer resolution (Takle, 2005). When RCMs are not available or are not desired, alternative methods may be used to downscale GCM projections to smaller temporal and spatial resolutions, as seen in Wadud (2014). In some cases (Mathisen et al., 2015), authors use a single report on climate change projections to guide their research and develop cycling forecasts, which raise questions over the degree of uncertainty surrounding cycling frequency modelling (Mathisen et al., 2015). In contrast, others use multiple reports or entire climate model projections to generate cycling forecasts based on current weather data and produce more robust findings (Saneinejad et al., 2012; Wadud, 2014).

2.3.4 Temporal and Spatial Scale of Collected Data

With such a variety of geographic areas represented in the literature, ranging from case studies of a single transport corridor (Saneinejad et al., 2012; Mathisen et al., 2015), to regional (Cools et al., 2010; Ahmed et al., 2012; Wadud, 2014) to nation-wide (Pucher & Buehler, 2006; Creemers et al., 2013), there are debates regarding the appropriate scale of data collection required for a study area that will provide useful results without overly generalizing the findings. Studies performed at a municipal level are said to be capable of considering demographic differences within a city or region, as well as providing localized weather and cycling data for more refined outcomes than at larger scales (assuming localized data is available) (Saneinejad, 2010). Conversely, studies using larger scales (e.g. national) are able to consider broader weather pattern, climate, and geographical differences, as well as provide further analysis from an inter-city perspective (Saneinejad, 2010).

In addition to the variety of locations and the size of geographic areas under study, there are considerable differences in the temporal scale of weather and cycling data used within research. In some instances, researchers are constrained to shorter time periods as automated counters may have been recently activated (e.g. Phung & Rose, 2007). However, researchers offer a variety of hours or days that they believe are the most appropriate to study. Examples include only using hours that correspond to the morning rush hour (Brandenburg et al., 2007; Ahmed et al., 2010; Sears et al., 2012; Flynn et al., 2012), while others opt to utilize a continuous stretch of time throughout the day to include both morning and afternoon rush hour periods, and travel occurring outside these periods, such as 06:00 to 20:00 (Phung & Rose, 2007; Miranda-Moreno & Nosal, 2011; Tin Tin et al., 2012; Nosal & Miranda-Moreno, 2014). This method omits night time hours due to low cycling frequencies and low representation of utilitarian cycling after nightfall (Miranda-Moreno & Nosal, 2011; Nosal & Miranda-Moreno, 2014). Authors also consider the weekly fluctuations in cycling frequencies, and therefore must identify days of the week that are to be included or excluded from study. Thomas et al. (2013) exclude weekends, statutory, and school holidays from utilitarian cycling travel behaviour modelling, while Saneinejad et al. (2012) and Ahmed et al. (2010) include all days of the week to identify differences between utilitarian and recreational cyclists. Finally, months of the year are considered when determining the appropriate time periods to study, with specific months being preferred over others. Authors argue that the majority of commuter cyclists travel by bicycle during the spring, summer, and fall (i.e. April to November), with few cyclists continuing throughout the winter (Miranda-Moreno & Nosal, 2011; Miranda-Moreno et al., 2013; Nosal & Miranda-Moreno, 2014). However, this omission does not consider cyclists who travel year-round, and also limits one's ability to model the relationship between cycling frequency and climate change for a full year. Despite this, examples exist of research on the impacts of weather on cycling for all twelve months (Creemers et al., 2013; Wadud, 2014; Mathisen et al., 2015).

There are differing opinions on what resolution of weather and cycling data should be used. Authors generally show support for using hourly data when it is available (Saneinejad et al., 2012; Tin Tin et al., 2012; Böcker et al., 2013b; Miranda-Moreno et al., 2013), however several researchers prefer the use of daily summaries or aggregates of data (Aaheim & Hauge, 2005;

Creemers et al., 2013). Though hourly data provides greater resolution and detail, some researchers argue that daily averages or aggregates are more appropriate due to uncertainties regarding the hourly measurement of certain conditions (Thomas et al., 2013), or modelling routine activities such as work or school commuting trips (Sabir, 2011; Böcker & Thorsson, 2013). Böcker et al. (2013b) conversely state that "daily weather data [does] not always reflect actual weather at the moment a trip or activity takes place", and that many past studies have used daily data because it was the highest resolution that was publicly available.

2.4 A Review of Methods Used within the Literature

A variety of methods are used by authors to quantify the relationship between cycling travel behaviour and weather or climate change. Models and analyses may be used to statistically represent the expected changes in cycling rates as a function of weather or future climate conditions. As noted above, there are several types of data that are used to study these relationships, which are analyzed using different methods. The types of modelling and measurement throughout the reviewed literature are listed below for both weather and climate change.

2.4.1 Methods of Cycling Travel Behaviour Analysis

Prior to modeling the relationship of weather effects on cyclists, cycling frequencies must first be analyzed to identify any underlying temporal influences and to demonstrate the temporal variation in cycling frequencies across a study area. The dominant method used to assess temporal effects on cycling frequencies is to sort the cycling count data into time-based categories, which are commonly based on the hour of day, day of the week, and month of the year (Miranda-Moreno & Nosal, 2011, uses the term "absolute approach" to reference this method). Variations include considering weekends and weekdays separately, as well as seasonal summaries of cycling count data (e.g. Tin Tin et al., 2012; Böcker et al., 2013a). These time scales provide a cursory glance at the temporal effects on cycling. The advantage of this approach is its ability to identify long-term trends in cycling frequencies (Miranda-Moreno & Nosal, 2011). However, it fails to adequately model short-term trends over long time periods in response to an independent variable (i.e. weather). An absolute approach possesses the potential to be impacted by systematic changes in cycling rates that are not a result of weather, such as the influx of students, a social group that has a high reliance on bicycles, in regions with post-secondary institutions every fall (Miranda-Moreno

& Nosal, 2011). This occurrence will register higher cycling frequencies not as a result of positive weather conditions, but through a simple increase in volume.

While cycling count data may be analyzed at varying time scales, Miranda-Moreno and Nosal (2011) find that count data may be analyzed using an alternative approach. Rather than relating weather conditions with the sheer volume of cyclists, as is the case with an absolute approach, a relative approach compares average cycling volumes for a given day of the week at a given time of day, indicating changes relative to the mean (Miranda-Moreno & Nosal, 2011). Miranda-Moreno and Nosal (2011) state that this approach is better at analyzing short term trends and directly examining the impact of weather on cycling as it accounts for systematic seasonal non-weather impacts (e.g. post-secondary students, individuals who are frequent cyclists, returning to school in September resulting in an absolute increase in cycling volumes). However, it is important to note that this approach is limited in its application, first being used in Miranda-Moreno and Nosal (2011), and again by Miranda-Moreno et al. (2013) and Nosal and Miranda-Moreno (2014), lacking use by alternative research groups. Additionally, several years of time-series data is required to produce representative means to compare current cycling count data against.

Aside from the absolute and relative approaches outlined above, alternative methods are found in a variety of studies. Studies using travel diaries, logs, or surveys to collect cycling travel data may analyze cycling frequencies as a binary distribution (e.g. did a participant cycle: yes or no), using whichever time scale is provided by the participant or required within the study, such as the time of day or day of the week that the cycling activity began, finished, or occurred (Flynn et al., 2012; Sears et al., 2012). A binary distribution is useful when the aforementioned data collection methods are employed, however it cannot be applied to all studies, such as those that use automated cycling count data, as individuals that do not cycle and an individual's cycling trips are not registered at automated count locations.

2.4.2 Weather and Cycling Modelling Methods

Understanding how weather influences cycling is a common theme within the reviewed literature, as researchers seek to understand how different geographic areas respond to a variety of weather conditions. A common method used to study the relationship is to combine cycling frequency or travel data and weather data, termed the "revealed accounts of weather approach" (Böcker et al., 2013b). This approach seeks to reveal travel behaviour by combining the two types of data to identify the relationship. Each publication that studies the impact of weather on cycling travel behaviour uses this approach with their respective cycling and weather datasets. Due to the variety of data researchers use to model the relationship, as well as varying research objectives, there are a number of notable methods authors use within studies to analyze the relationship. Below, a review of quantitative and qualitative analyses within the literature are provided.

Statistical analysis of cycling and weather data is a common approach within the literature to quantify the relationship between cycling frequency and weather variables. There is a range of approaches that researchers use to quantitatively analyze the relationship, however all methods use a form of regression analysis. Amongst multivariate regressions are two approaches to modeling explanatory variables: linear (e.g. a constant change in a weather variable will result in a constant change in cycling frequency) and non-linear (e.g. a change in a weather variable does not result in a similar change in cycling frequency) models. A common practice amongst the reviewed literature is to predetermine the linearity of the model based on past findings (Nosal & Miranda-Moreno, 2014; Wadud, 2014; Mathisen et al., 2015). Thomas et al. (2013) argue that this is a dangerous approach, as the use of non-linear variables inappropriately included in a linear regression model violates the linearity assumption of a multiple linear regression (as cited in Phung & Rose, 2007, and Ahmed et al., 2010). Wooldridge (2012), conversely states that the use of a linear or non-linear model should be determined by the linearity of the included weather parameters, which is exhibited in select publications (e.g. Thomas et al., 2013). The use of a linear or non-linear model is not a binary decision, rather authors (e.g. Nosal & Miranda-Moreno, 2014; Wadud, 2014) show that non-linear variables (e.g. wind speed, precipitation, and temperature) may be included into a linear regression model. This is achieved by using categorical variables to represent non-linear weather variables in linear models. A categorical variable is divided into a number of segments (e.g. precipitation values of <1 mm, 1 mm to 4.9 mm, and >5 mm) to coarsely capture a non-linear relationship, while still meeting the necessary assumptions and conditions of an MLR. This non-linear approach has been applied to the weather variables rain, temperature, and wind, with the added benefit of being able to represent variables found to have a linear relationship with cycling frequencies (e.g. hours of sunlight, wind speed, and temperature).

There are a variety of regression models used throughout the literature to statistically analyze the relationship between weather and cycling. A common approach is to use a log-linear model (a linear regression model with a logarithmic transformation applied to the explanatory variables) to reduce the positive skew of the cycling data, producing a normal distribution, as required within linear regression (Brandenburg et al., 2007; Phung & Rose, 2007; Ahmed et al., 2010; Miranda-Moreno & Nosal, 2011; Nosal & Miranda-Moreno, 2014). A noted benefit of using a log-linear model is that the interpretability of the coefficients is made simple as they are listed as a percentage change in the response variable (i.e. cycling frequencies) relative to the reference case (Phung & Rose, 2007). However, interpreting categorical coefficients is not as simple, as Halvorsen and Palmquist (1980) "suggest taking the anti-log of the coefficient and subtracting one to obtain the percentage effect", reversing the effects of the previously applied logarithmic transformation (as cited in Phung & Rose, 2007). An alternative to using an ordinary linear model, Sears et al. (2012), Creemers et al. (2013), and Thomas et al. (2013) use a generalized or generic regression due to the flexibility of the model. Authors using this approach indicate their preference for allowing the data to determine the appropriate model form (i.e. linear or non-linear), which is an inherent benefit of this regression. This is in contrast to Wadud (2014) and Mathisen et al. (2015) who follow an econometric approach. The authors point to the advantages of using an econometric model over logarithmic transformations of explanatory variables, as they argue this method is unable to handle valid zeroes, which are common in precipitation data (Mathisen et al., 2015). Wadud (2014) also states that log-linear ordinary least squares models, though common in the literature, are inappropriate for weather and cycling data analysis due to the presence of non-normal and heteroskedastic error values, producing biased estimates, indicating preference for the use of a Poisson and Negative Binomial regression approach in its place. Another type of quantitative analysis can be found with authors choosing to use a multinomial logistic (MNL) regression, as seen in Saneinejad, et al. (2012). An MNL regression models nominal outcome variables, "in which the log odds of the outcomes are modeled as a linear combination of the predictor variables" (University of California, Los Angeles [UCLA], n.d.). This method differs from the above by not attempting to predict a count, but the probability of an outcome occurring, and is beneficial for studies on mode choice, as well as those that employ large numbers of categorical variables (e.g. Saneinejad et al., 2012). Finally, Bidordinova (2010) uses non-parametric regression to rank mean values for the collected responses, after coding each response using a Likert scale. The mean values are also used to measure the average response to each question as well as the variance around the mean (Bidordinova, 2010).

Outside quantitative analysis, there are a few examples of qualitative analyses on the impacts of weather on cycling travel behaviour. Approaches in qualitative analysis of cycling frequencies include identifying the frequency at which common themes and topics arise in interviews and focus groups, and interpreting the results using the mean of select weather variables, as seen in Spencer et al. (2013). Spencer et al. (2013) identifies the frequency of themes, determining the proportions for how frequently a topic is mentioned by focus groups or based on a characteristic shared amongst the participants (e.g. gender). Identifying and analyzing common topics in focus groups and interviews is benefitted by being a simple means to determine potential effects of weather on cyclists based on the sample population. While this form of analysis provides unparalleled insight into the thought processes, feelings, and decision-making processes of utilitarian cyclists' travel behaviours, it lacks the ability to extrapolate to larger populations due to the individualized nature of the responses (Spencer et al., 2013). Additionally, there is no objective analysis of the relationship between cyclists' travel behaviours and weather. Rather, qualitative studies on weather's effects on cycling frequencies analyze subjective statements by participants, later, in the case of Spencer et al. (2013), relating them to mean weather values.

2.4.3 Climate Change and Cycling Modelling Methods

Among the few publications that statistically forecast and analyze the impacts of climate change (or future weather conditions) on cycling frequency there are two notable methods of analysis. The most common approach found in cycling and climate change literature is to use the delta or change-factor method, whereby projected changes in future weather are applied to present-day values to project actual weather conditions. Values representing weather conditions in future climates are entered into a regression model (usually the same one used to model weather sensitivities as discussed above) to model cyclists' weather sensitivities in future climates. Mathisen et al. (2015) uses the most simplistic approach by referring to a Norwegian national climate change study and using the projected values for temperature and precipitation for 2050 in their cycling and climate change model. Saneinejad et al. (2012) continues the use of the change-field method in a study on climate change impacts on Toronto, Ontario cyclists with an increase in the range of conditions being modelled compared to Mathisen et al. (2015). The authors use a range of projections from four climate change reports to determine the expected change in temperature and precipitation in mid-century climates. For temperature, the expected increases (between 1°C to 6°C) are individually applied to a dataset of past temperature values used within the initial study to model the changes in cycling travel behaviour per each 1°C increase in temperature. Precipitation is modelled in a similar fashion, by applying the expected 0-20% increase in precipitation to past precipitation data. Changes in precipitation are applied by randomly changing 10% or 20% of hours from rain events to clear or cloudy conditions (decreased occurrence of rain), or by changing hours from clear or cloudy conditions to rain (increase in occurrence of rain). The change-field method is advantageous due to the simplicity of the approach and its ability to generate robust results, especially when using weather sensitivities generated with current weather conditions that may then be applied to forecasting climate change impacts (Anandhi et al., 2011; USAID, 2014). This method is also beneficial when comparing the impacts of current to future climate conditions, as the output values share the same units by using the same regression model, albeit with modified values. USAID (2014) identifies that the previously mentioned benefits exist, however there are assumptions within the change-field method that must be acknowledged. This method requires that normally distributed data are used (e.g. monthly precipitation as opposed to daily precipitation values, which is positively skewed), and is also noted as not being an appropriate method for modelling extreme events or changes in weather variability (Matthews, 2014; USAID, 2014). Therefore, the change-field method is a simple approach to model future weather conditions at coarse temporal resolutions, although important limitations in the type of data and its distribution must be considered.

To work around coarse temporal resolutions within climate projections, Wadud (2014) employs a weather generator to synthetically downscale the data to hourly and daily time scales. A GCM is used within their study, which features coarse spatial and temporal resolutions that make representation of future hourly and daily weather conditions problematic, justifying the use of a weather generator to produce values similar in scale to the previously inputted weather variables. The weather generator produces a large volume of projections which may then be applied to a model in similar fashion to the change-field method noted above. Each projected change in a weather variable is applied and the model is rerun to model the relationship between future weather through climate change on cycling frequencies. Unlike the change-field method which can model the change in precipitation severity, a weather generator is able to calculate how long a period of precipitation or drought may occur (USAID, 2014). This approach is identified by the Intergovernmental Panel on Climate Change (IPCC) as an inexpensive and robust method of generating regional climate information (Giorgi et al., 2001), while USAID (2014) finds that it is better able to model non-normally distributed weather variables such as precipitation and wind speed than the more commonly used change-field method. Additionally, weather generators produce large volumes of data series within a range of climate projections (USAID, 2014; Wadud, 2014). While this is beneficial in some scenarios, it also requires a large and exhaustive review of the outputs and is "computationally more cumbersome" than alternatives, such as the change-field method (Matthews, 2014; USAID, 2014). Additionally, USAID (2014) reports that weather generators' outputs require post-processing, in contrast to the straightforward interpretation and use of change-field method outputs.

An alternative approach to the change-field method and weather generator, Böcker et al. (2013a) simulates climate change impacts on transportation using a different method. A key difference from this study and the above is that Böcker et al. (2013a) does not seek to simulate the effects of current weather on cycling frequencies, and therefore does not develop a statistical model for current conditions. Rather, Böcker et al. (2013a) focuses strictly on climate change analysis. Seasonal weather data from 2004-2009 are used, with seasons categorized as being representative of normal or unusual weather conditions (based on average temperature and precipitation values for a given season compared to the historical record). Cases categorized as normal represent current weather conditions, while those categorized as unusual closely exhibit projected conditions under a changed climate in 2050. Transportation data is then combined with temperature and precipitation data collected from the previously categorized seasons into a multivariate regression. To model future mode choice, Böcker et al. (2013a) employs a multinomial LOGIT model that can categorically represent each mode based on utility maximization, using personal automobiles as the reference case, while travelled distances are modelled with a TOBIT model due to the abundance of valid zeroes and lack of non-negative values. This approach enables the researcher to use past, non-simulated examples of how Dutch cyclists respond to conditions projected to occur in 2050. The use of past seasonal cycling frequencies to determine future responses appears to be a novel approach amongst the literature. A disadvantage to this approach is that the relationship between weather, travelled distances and mode choice is performed solely at a seasonal level, with another being that it does not attempt to model adaptation, rather focusing on how cyclists have coped with past weather conditions. Böcker et al. (2013a) identifies that this method does not model at higher temporal resolutions, or consider the impacts that individual hourly, daily, or monthly weather conditions have on mode choice and travelled distances (including cycling), focusing instead on the overall seasonal impact.

2.5 Discussion of Findings and Results within the Literature

The literature uses a variety of methods, datasets, and variables amongst each of the analyses, and as such the reported findings show degrees of variation from one study to another. However, despite this variability, consistencies appear across a number of the findings. Cycling travel patterns, select weather variables and climate projections are identified in the literature as having similar effects on cycling travel behaviours, while other variables appear to show greater variability. Findings within the literature are reported in this paper by the following categories: temporal variations in cycling frequencies; the degrees of impacts of weather on cycling frequencies, mode choices, and travelled distances; and projected impacts of climate change on cycling.

2.5.1 Cycling Travel Behaviour Patterns

As the basis for modelling the relationship between weather and climate change on cycling travel behaviours, many authors report descriptive statistics for each facility to acknowledge temporal variations in cycling frequencies. The consistency in global cycling travel behaviour can be identified here, where similarities in weekday versus weekend cycling distributions (both at time of day and day of the week) are seen in study areas ranging from Vancouver, BC (Gallop et al., 2012), to Melbourne, Australia (Phung & Rose, 2007; Ahmed et al., 2010). Along commuter cycling routes, workday (weekdays that are not a holiday) hourly variations consist of a bimodal distribution, with a clear AM peak (between 7:00 – 9:00 am) and a clear PM peak (between 4:00 – 6:00 pm) (Ahmed et al., 2010; Gallop et al., 2012). This is in contrast to weekend and holiday patterns, where a unimodal peak is found in the afternoon hours as a result of recreational and non-commuting utilitarian cycling activities (Miranda-Moreno et al., 2013; Mathisen et al., 2015). Further, weekly patterns are shared across all study areas, with Monday representing the lowest average cycling frequencies, and Tuesday or Wednesday holding the highest rates amongst workdays, and Saturday and Sunday having the overall lowest cycling frequencies of the week (Nosal & Miranda-Moreno, 2014; Mathisen et al., 2015). Differences emerge when comparing monthly or seasonal variations in cycling frequencies commonly resulting from current climates and pre-existing travel behaviours in each of the study areas. While summer months (May to July in the northern hemisphere, and January to February in the southern hemisphere) commonly experience peak annual cycling (Ahmed et al., 2010; Flynn et al., 2012; Miranda-Moreno & Nosal, 2011), some regions have higher spring and fall cycling frequencies, such as in Texas, US, where high summer temperatures prove detrimental to cycling (Sener, Eluru & Bhat, 2009). In addition, winter months appear be the least popular time for cycling (Sener et al., 2009; Fisher, 2014), also showing varying impacts depending on the locations under study. Miranda-Moreno et al. (2013) notes that across Canada, Vancouver, BC, does not experience a significant decline in winter ridership when compared to the cities of Ottawa, ON, and Montreal, QC, likely due to the mild climate that is found in Vancouver, BC. Overall, clear temporal patterns exist that are exemplified by numerous studies around the world.

2.5.2 Results of Modelling Weather and Cycling

Each weather variable has a differing impact on cycling, which may be influenced by differences in time (e.g. time of day, day of the week, or month of the year) and in space (e.g. by region or continent). This section will provide an overview of the reported findings on the relationship between current weather and cycling frequencies, identifying variability and limitations in the findings where possible.

Temperature is one of the most studied weather variables for its potential influence on cycling rates. The literature suggests that temperature generally effects cycling frequencies, however these effects can range from negative to positive, with some researchers arguing that the effects are linear. There is a general theme that an increase in temperature will result in higher cycling frequencies, when holding all other variables constant, and that the influence is relatively strong or significant (Böcker & Thorsson, 2013). Examples of the increases range from a 3% increase in cycling frequencies for every 1 °F (0.56 °C) increase in temperature in Vermont, US (Flynn et al., 2012); a 1.65% increase in cycling frequencies for every 1 °C increase in temperature in Vancouver, BC (Gallop et al., 2012); to a 3.2% increase in cycling frequencies for every 1 °C increase in temperature in Auckland, New Zealand (Tin Tin et al., 2012). Alternatively, some authors express the relationship by finding the optimum temperature or range of temperatures that increase cycling, indicating a non-linear pattern as both extreme heat and cold temperatures may negatively impact cycling frequencies. Optimum maximum temperatures are predominantly reported between 24 °C and 28 °C (Phung & Rose, 2007; Ahmed et al., 2010; Böcker & Thorsson, 2013; Wadud, 2014), however Phung and Rose (2007) also report that the optimal riding range (where the effect of temperature on cycling is positive) is between 14 °C to 41 °C. Additionally, Saneinejad et al. (2012) finds that 15 °C is a key temperature: above 15 °C cyclists become insensitive to temperature, while below 15 °C the utility of cycling is found to decrease. Conversely, Behan and Lea (2010) and Cools et al. (2010) both find that temperature has a minimal or insignificant impact on cycling and active transportation. An important note must be made that both Behan and Lea (2010) and Cools et al. (2010) use average temperatures rather than hourly temperature readings, which may lead to underestimating the impact of temperature on cycling. Additionally, neither Behan and Lea (2010) or Cools et al. (2010) report any advantage of using mean, maximum, and minimum temperatures over the more widely used hourly temperature data found in other studies.

Precipitation is another weather variable that is commonly under study for its supposed negative effects on cycling frequencies. It may also prove hazardous to cyclists depending on the type of precipitate a study area experiences (e.g. rain, hail, snow, sleet, and freezing rain). Rain is the most common precipitate included in publications due to its presence during the cycling season (this varies by season and location, but generally includes spring, summer, and fall). Researchers commonly identify the non-linear effects of rain on cycling frequencies, finding light rain (e.g. <10 mm) has a more dramatic impact than heavy rain (e.g. >10 mm) on cycling frequencies and travel behaviour (Phung & Rose, 2007; Ahmed et al., 2010; Wadud, 2014). Other authors find rain has a linear effect on cycling frequencies, such as a 10.6% decrease in cycling rates for every 1 mm of rain during a given hour (Tin Tin et al., 2012). The lagged effect of precipitation is also considered, with numerous publications indicating a significant effect up to three hours after a rain event (Wadud, 2014), with cycling frequency decreases ranging from -8.86% (one hour after a rain event) in Vancouver, BC (Gallop et al., 2012) to an extreme of -36% in Montreal, QC (Miranda-Moreno & Nosal, 2011). Saneinejad et al. (2012) also identify a lagged effect, as they mention that many cycling trips are postponed rather than cancelled due to rain. Despite the general consensus that rain negatively impacts cycling rates, Behan and Lea (2010) find no meaningful results by comparing the levels of precipitation across eight cities in Europe and North America based on annual precipitation values, rather than hourly or daily values used in the studies mentioned above. Their use of annual volumes cannot consider variations in the severity of precipitation, identify the number of precipitation days, or the duration of precipitation events and their impacts on cycling, all of which are available when using hourly weather data.

The final weather variable that is heavily researched is wind speed. There appears to be a large degree of variability in cyclists' responses to varying degrees of wind speed. Flynn et al. (2012) find that wind has a significant negative effect on cycling rates, stating for every 1 mph (1.6 km/h) increase in wind speed, there is a 5% decrease in cycling frequency, while Ahmed et al. (2010) identify a 15% decrease in frequency during peak hours. When presented, authors indicate that wind may have either a linear or non-linear relationship with cycling frequency. Thomas et al. (2013) finds that wind negatively affects cycling up to a specific point, whereby the effects of stronger winds become disproportionately larger indicating a non-linear effect, while Phung & Rose (2007) are supportive, finding that cyclists only respond to strong winds (above 40 km/h). Conversely, some research points to a linear or nearly linear effect; as wind speeds increase there is a proportional decline in cycling frequencies (Wadud, 2014). In contrast, there is evidence in research that wind does not significantly and wholly impact cycling. Böcker and Thorsson (2013) find that average daily wind speed has a negative effect on cycling durations (at a 90% confidence interval), however it does not significantly affect cycling frequencies. Finally, Spencer et al. (2013) report alternative responses to the impacts of wind throughout focus groups and interviews of Vermont cyclists. Spencer et al. (2013) share cyclists' perspectives that wind can be dealt with and is not a significant factor in its own right, however its ability to influence apparent air temperatures can be a deterrent. Conversely, one participant stated that the impact of wind depends on its direction: head winds (riding into the wind) can be uncomfortable, while tail winds (riding with the wind to one's back) can make cycling easier (Spencer et al., 2013).

Aside from the main three weather variables reviewed above an additional three are discussed in the literature. The influence of daylight hours is studied due to the perception that a lack of daylight may be less safe and comfortable and may exacerbate the effects of adverse weather conditions. There is a divide in research outcomes, with some indicating that there is a clear impact on cycling frequency with a lack of daylight hours (Ahmed et al., 2010; Tin Tin et al., 2012; Böcker & Thorsson, 2013), while others find the effect to be statistically insignificant or have minimal impact (Phung & Rose, 2007; Behan & Lea, 2010; Flynn et al., 2012; Wadud, 2014). A common concern identified with using this parameter is that daylight hours are generally found to be highly correlated with temperature and visibility, which all benefit cycling frequencies and are unlikely to occur individually from the other two parameters (Thomas et al., 2013). Next, humidity is considered with varying impacts, ultimately dependent on the geography of the study area. Such is the case in Ottawa and Montreal, where Nosal and Miranda-Moreno (2014) finds that these regions experience greater negative impacts by humidity than other study areas, such as Portland, Oregon. Gallop et al. (2012) provide further evidence of this regional variation as the effect of humidity in Vancouver, BC, has a minimal impact on cycling, with a 0.08% decrease in bicycle traffic per 1% increase in humidity from the mean. Finally, a condition that is not experienced across all study areas, snow appears to generally have a negative impact on cycling frequencies. Flynn et al. (2012) are the only authors to quantify the impact that snow depth has on cycling, stating that one inch (2.5 cm) on the ground reduces the likelihood of cycling by roughly 10%. Flynn et al. (2012) subsequently state that the majority of the respondents within their study did not cycle during the winter, and that these values are generated off of a small sample group that continued cycling. The remainder of the studies that include snow use qualitatively collected data, simply indicating the presence of snow on the ground or of precipitation in the form of snow (Spencer et al., 2013; Wadud, 2014), continuing to support the negative effect of snow on cycling frequencies. Gallop et al. (2012) finds that its effect is insignificant, however the study area did not experience many hours with snow during the data collection period, limiting the application of their findings.

Researchers identify that although their results appear accurate there are limitations in what may be extrapolated from them. A common concern is that the temporal range of weather data may not truly represent the weather patterns within a study location. Tin Tin et al. (2012) state that their use of continuous data is a clear strength, however their study uses weather data from a single location with a “reasonably narrow range of weather conditions”. Additionally, the spatial context of a study’s findings is found to potentially limit their applicability to other environments. Thomas et al. (2013) point out that their research is focused around a small number of rural cycle paths, with uncertainties for how their model and findings may be applied in regions with different levels of urbanization; while Flynn et al. (2012) identify that the broad spatial distribution of study participants lacks local detail and could weaken the studied relationships. Therefore, despite the similarities in findings across studies, a number of limitations are identified by authors that may reduce the ability of their findings for the relationship between weather and cycling travel behaviours to be generalized to a larger population.

2.5.3 Results of Modelling Climate Change and Cycling

Amongst the publications that consider the impact of climate change on cycling travel behaviours, there is a broad range in reported results, in part due to the differing study objectives, study areas, and methods through which the studies are generated. Additionally, not all publications project climate impacts to the year 2050 (mid-century). Wadud (2014) uses 2041 as the forecasting year, Mathisen et al. (2015) uses both mid (2050) and end of century (2100) depending on the effect being examined, while Saneinejad et al. (2012) and Böcker et al. (2013a) exclusively use 2050 projections.

Commonalities exist across the literature: by mid-century, there is an agreement that precipitation events will become more severe and occur over fewer days (Böcker et al., 2013a; Mathisen et al., 2015) and that mean annual air temperatures in each of the study areas are expected to increase (Wadud, 2014; Mathisen et al., 2015). These two factors are expected to extend the cycling season due to the reduction of winter conditions (Mathisen et al., 2015). Similarities in findings continue when reviewing the results only at an annual scale, with the general theme being minimal, but significant (at a 99% confidence interval) annual increases in cycling rates (Böcker et al., 2013a), with a projected net annual increase in cycling of 0.5% (Wadud, 2014). Mathisen et al. (2015) go so far as to state that, when excluding consideration of seasonal variations in climate and cycling impacts, increases in the cycling rate of Bodø, Norway, in 2050 is expected to increase predominantly due to population growth. This finding is counterintuitive given Mathisen et al. (2015) report increases of 1.2°C, 6.8% increase in the amount of rain, with reductions in the duration of the winter season, no expected change in average wind speeds, and a greater number of days above 5°C.

Researchers explain that the minimal expected annual increase in cycling frequencies by mid-century is a function of counteracting seasonal impacts (Böcker et al., 2013a). Due to the high degree of variability between each season, it is therefore not advisable to consider expected annual impacts as the final figures. Böcker et al. (2013a) find that each of the four seasons in 2050 in The Netherlands will impact transportation usage across all modes, including cycling, differently. A rise in temperatures (from 3.6°C to 5.1°C) and precipitation (from 173 to 212 mm), along with fewer wet days (from 50 to 47) are forecasted for the winter season, which Böcker et al. (2013a) find to have a significant positive effect on active transportation mode choice, and a substantial increase in cycling travel distances (at 99% and 95% confidence intervals respectively). Winter increases in cycling rates are supported by others, with Wadud (2014) forecasting a 1.5% increase (in 2041), and explanations including the expected reduction in the duration of winter by as much as two months in northern climates (Mathisen et al., 2015). However, Böcker et al. (2013a) expect differing impacts on mode choice and travelled distances for cyclists in each of the remaining seasons. Spring shows a non-significant increase in cycling mode share, with a significant negative effect on travelled distances (at 95% confidence interval) (Böcker et al., 2013a). Summer sees a significant, negative impact on cycling mode share (at 99% confidence interval), with no significant impact on travelled distances (Böcker et al., 2013a). Finally, Böcker et al. (2013a) find a non-significant decrease in cycling mode share, and non-significant increase in travelled distances during fall, 2050. Conversely, Wadud (2014) expects a 2.5% increase in the summer, with reductions of 2.0% and 0.1% in the spring and fall, respectively. Potential explanations for this seasonal variability include warmer winter weather with fewer occurrences of winter conditions that benefit cycling; and decreases in summer cycling mode share and travelled distances from potential negative effects of increased temperature. Contrary to the above results, Saneinejad et al. (2012) do not find seasonal variations in cycling rates, but that there is a linear effect in the percentage increase in number of trips made between 0°C and temperatures above 20°C, not allowing for considerations of extreme heat or reductions in cold temperatures. Similarly, Saneinejad et al. (2012) find a negative linear association in the percentage change in number of cycling trips depending on the amount of precipitation (ranging from -20% to 20% change in the number of hours with precipitation).

A key consideration found within some research is that base year selection has a significant impact on the forecasted values for the respective projection years. Wadud (2014) finds that when the base year of 2011 is changed to 2009 (which was cooler and wetter than 2011), climate projections have a greater positive impact on cycling rates in 2041. Similarly, Böcker et al. (2013a) also perform a number of sensitivity analyses to determine how the chosen base years and seasons impact mode choice and travelled distances per mode. Examples include switching the base season and year of spring 2008 to spring 2007 (which was warmer and wetter, but over fewer days) where cycling mode share projections for 2050 change from a positive, but non-significant increase, to a positive and highly significant effect (Böcker et al., 2013a). Therefore, selection of which base year to use when projecting the relationship between future weather and cycling is of utmost important, as the findings may largely change as a result.

2.6 Summary of the Literature

This literature review presents an overview of the available study objectives, data collection methods and sources, the quantitative and qualitative methods used to analyze the relationship between weather or climate change on cycling travel behaviour, and the associated findings from the respective researchers. Although there are several approaches identified above, the research points to the common use of observed weather and cycling count data using quantitative methods to analyze this relationship.

Several study objectives are identified above, such as how cycling is included in a commuter's decision on mode choice due to weather, whether trip purpose or trip destination impacts the selection of cycling as the preferred transport mode, and if cycling trip distance or duration is affected by weather. However, the most common objective is to examine the influence that weather has on cycling frequencies, omitting considerations of trip distance, specific destinations, and trip purpose (aside from commuter or recreational trips), among others. This objective proves advantageous in its ability to explicitly identify the relationships between cycling and weather variables, as well as the significance of these relationships.

There are few types of collection methods or sources of data used within the literature. Surveys, interviews, and focus groups are found in many articles seeking to study how travel behaviours such as mode choice, travelled distances or durations, and trip purpose are impacted by weather variables. It may be seen that while these studies provide very descriptive findings due to the personal nature of their data inputs, they are generally limited to small geographic areas, few study participants, and are commonly unable to apply their findings outside of their study area. Alternative data include measured weather conditions and cycling counts from facilities positioned throughout a city or region. This type of data provides high temporal resolution and objective accounts of weather and cycling occurrences. Additionally, the frequent availability of these data enables easy comparison between jurisdictions and studies due to consistencies in data collection methods.

An array of methods, both quantitative and qualitative, are used to analyze the relationship between weather variables and cycling travel behaviour. Qualitative methods, although present in the literature are not commonly used, especially within the recent decade due to the ubiquity of available observational datasets. Therefore, quantitative methods are frequently used with the analyses. Within these methods, a regression analysis, most notably a multiple regression, is used to identify the impacts of several independent variables (e.g. temporal, meteorological, and socioeconomic) on a dependent variable (e.g. cycling count at a given time and location). Further considerations are made by the researchers based on the linearity of the variables used. While Thomas et al. (2013) argues that there are several weather variables that are non-linear and should not be used in a traditional multiple regression model (e.g. precipitation, temperature, and wind speed), researchers such as Phung & Rose (2007) and Ahmed et al. (2010) have found that by segmenting a non-linear variable into categories based on a range of values and inputting it as a dummy variable, both linear and non-linear variables are able to be entered into a single multiple linear regression model. This approach allows for a much more simple and robust method of analyzing the relationship while continuing to the meet the assumptions of a multiple linear regression.

To model future weather conditions or the effects of climate change on cycling travel behaviour, three methods are presented above, including the change-field or delta method (Saneinejad et al, 2012; Mathisen et al., 2015), a weather generator (Wadud, 2014), and a custom approach whereby weather observations are used to estimate how cyclists will react in a future climate (Böcker et al., 2013a). Each approach has its merits; however, the change-field method and weather generator are methods that are supported by the IPCC (Giorgi et al., 2001) and climate scientists (Anandhi et al., 2011) as tools that generate robust results.

The reviewed literature offers a plethora of methods to approach studying the relationship between weather or climate change and cycling travel behaviour, collecting data, and analyzing the relationship. However, after reviewing the literature certain approaches have been selected based on being the best methods to tackle the research questions presented in Section 1.3. To model the relationship posed in the first research question, this research will employ the methods used by Phung & Rose (2007) and Ahmed et al. (2010), whose model is specific to weather and cycling frequencies and enables simple modelling of linear and non-linear variables. To address the second research question, the change-field method, as used by Saneinejad et al. (2010) and Mathisen et al. (2015), will be used to model the impacts of climate change on cycling frequencies. Therefore, this research will borrow proven methods used by researchers to conduct analyses on the impacts of weather and climate change on cycling frequencies in the City of Waterloo, Ontario.

3.0 Methodology

3.1 Introduction

In order to model the effects of meteorological variables on cycling frequencies, this study uses a quantitative methodology. By using quantitative methods, this research will be able to both identify the impacts that observed weather has on utilitarian cycling frequencies, and to predict how cyclists will be impacted under future weather conditions due to climate change. Data, collected at hourly temporal resolutions by federal government agencies as well as non-governmental organizations and institutions, are used to quantitatively evaluate and identify meteorological impacts on cycling frequencies within the City of Waterloo. To quantitatively analyze the relationship between weather and cycling and climate change and cycling, this research borrows from past studies on the impacts of weather on cycling frequencies by Phung and Rose (2007) and Ahmed et al. (2010), who model the impacts of weather on cycling frequencies in Melbourne, Australia, using a log-linear regression, a variant of a multiple linear regression (MLR). The methods used in Phung and Rose (2007) and Ahmed et al. (2010) are presented and used later in this chapter, with adaptations that will make the model better able to represent cycling count data and the meteorological conditions found in Canada and make predictions on cycling counts under a changed climate. For this research, a Quasi-Poisson regression will be used within the model in place of the log-linear model used by Phung and Rose (2007) and Ahmed et a. (2010) for reasons explained later in Section 3.6.

To model the relationships between utilitarian cycling, weather, and climate change, daytime, weekday hours within the AM and PM peak periods are selected, with mid-day, nighttime, and weekend hours excluded, in keeping with similar studies as discussed in the literature review (Section 2.5.1). Further information on the selection and application of these hours is discussed in Section 3.3.3. By restricting the hours under study to those that coincide with peak travel periods this research is able to focus on impacts due to weather on cycling travel behaviour during significant commuter travel periods.

This chapter focuses on the methods that will be used in analyzing the impacts of weather and climate change on cycling frequencies. Section 3.2 introduces the study area and relevant initiatives undertaken within the municipality. Section 3.3 discusses the study data, including the methods through which the data were collected, cleaned, prepared for analysis, and any additional data inputs that were calculated and inputted for consideration in the final model. Section 3.4

discusses the means through which variables will be selected and assessed for input into the model. Section 3.5 describes the assessment and validation procedures that are used to verify the final model form prior to its use. Finally, Section 3.6 specifies the basic model form that will be used within this study.

3.2 Study Area

This section provides context about the study area, including general information regarding the location and characteristics of the City of Waterloo and the justification for selecting this municipality as the study area. Additionally, an overview of the study data is provided, as well as the methods that were undertaken by this research to prepare the data for analysis.

3.2.1 Characteristics of the City of Waterloo

The City of Waterloo is located in southwestern Ontario, less than 100 km west of the City of Toronto and the Greater Toronto Area (GTA) and is 150 km west of the City of Buffalo, New York, near the Canada-USA border (see Figure 3.1). The city is a landlocked municipality, situated approximately in the middle of three Great Lakes: Lake Erie to the south, Lake Huron to the west and north, and Lake Ontario to the east. Waterloo is a geographically small city, comprising a total land area of 64 km^2, with approximately 105,000 inhabitants (Statistics Canada, 2017). Despite a geographically small municipality and moderate population size, Waterloo's population density of 1,634 persons per km^2 is similar to or larger than neighbouring urban centres and the GTA, but remains significantly lesser than the City of Toronto, making for a small yet densely populated municipality. The City of Waterloo is a single-tier municipality within the Region of Waterloo, which also includes the cities of Cambridge and Kitchener, and the townships of North Dumfries, Wellesley, Wilmot, and Woolwich. Several post-secondary institutions are located in the City of Waterloo, with additional campuses found in adjacent municipalities. The University of Waterloo, Wilfrid Laurier University, and Conestoga College are all located a short distance apart in central Waterloo, close to Waterloo Park and the city's central business area known as Uptown Waterloo.

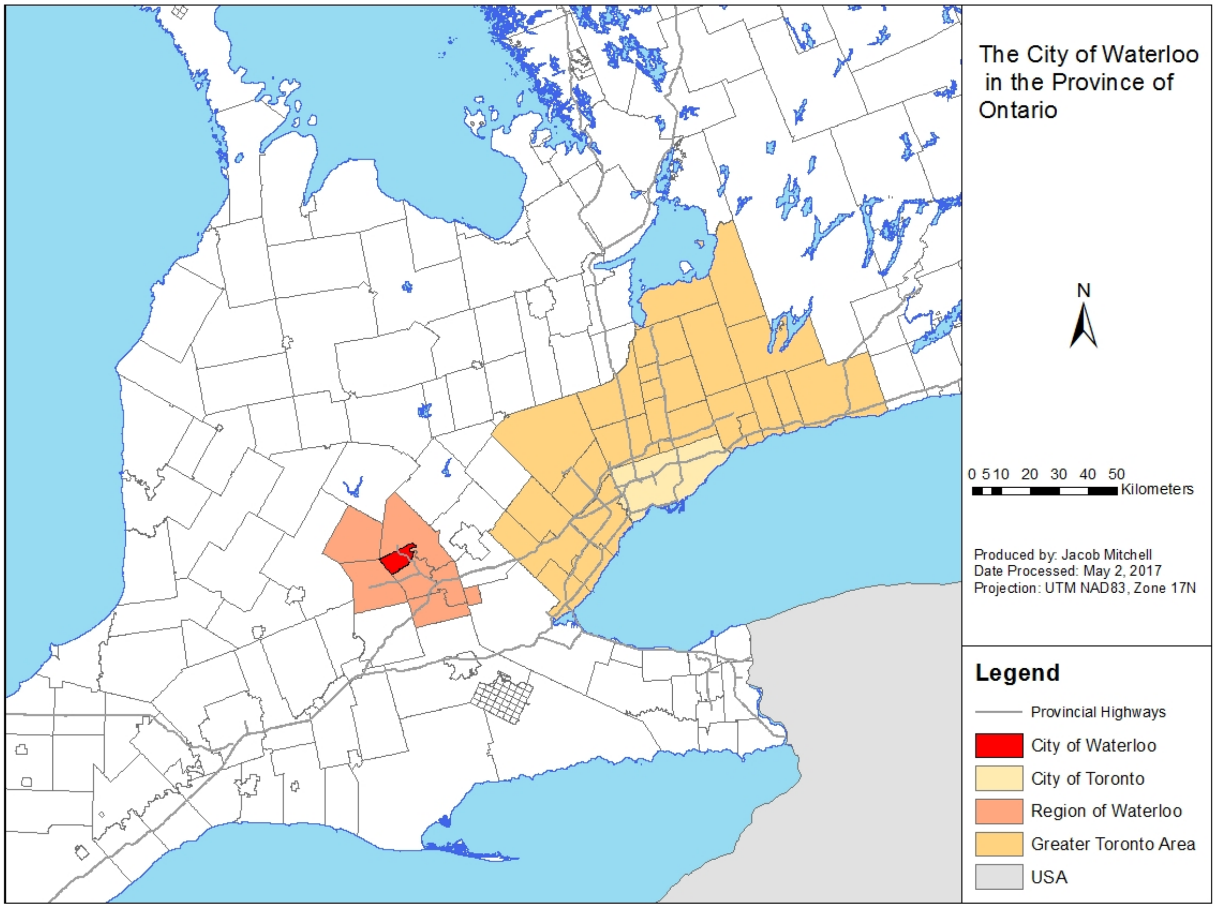


Figure 3.1 - Location of the City of Waterloo in the Province of Ontario.

3.2.2 Cycling and Active Transportation Initiatives in the City of Waterloo

The City of Waterloo has frequently invested lands and resources to continue its strong cycling initiatives within the municipality. The City of Waterloo, to date, has installed 150 km of off-road multiuse trails and 60 km of on-road bicycle lanes to promote accessible transportation for all modes, earning it the Bike Friendly Communities Award by Share the Road Cycling Coalition in 2011 (WeAre_Waterloo, 2013). Recent road improvements have furthered the city's accessible travel initiatives, with Davenport Road receiving a "complete-street" makeover that facilitates safe and easy travel for cyclists, pedestrians, motorists, and everyone in between (WeAre_Waterloo, 2013). Additionally, the City of Waterloo continues to increase cycling infrastructure by installing, improving, or extending current multi-use trails; installing new cycling lanes, introducing new active transportation technology, such as the "cross-ride" at Erb Street East and Peppler Road; and installing covered and secured bicycle storage boxes in public places. These investments are aided by the continual funding, improvement, and expansion of the current active transportation monitoring program (City of Waterloo, 2015). Waterloo's past efforts are also being aided by a recent announcement of increased provincial funding for cycling initiatives. Through joint funding by the Province of Ontario and the City of Waterloo, $650,000 was allocated to cycling infrastructure improvements in the City of Waterloo, which is being used on trail improvements in Waterloo Park, the location of the most frequented multi-use trail in the municipality (CTV Kitchener, 2016).

3.3 Study Data

For this study, detailed hourly weather and cycling count data were required to quantify weather sensitivities for cyclists in the City of Waterloo. Weather data used within this research is provided by several sources, all of which record data at daily, hourly, or quarter-hourly resolutions depending on the nature of the weather variable. While bicycle count data is provided by a single source, the City of Waterloo, observed weather data is made available by several organizations, including ECCC, the Grand River Conservation Authority (GRCA), and the University of Waterloo.

The study period for this research is dictated by the dataset with the smallest data collection period. In this research, the study period is based on the available bicycle count data. This dataset contains hourly observations from August 2014 to December 2016, with each count facility possessing different amounts of time series data based on the date of installation of the given facility. This is complemented by regional weather data, which is available from the three aforementioned sources for the length of the study period. In the cases of the recorded observations from the University of Waterloo and ECCC, quarter-hourly and hourly data are available from the 1990s and 2000s, respectively, to present.

This section will discuss the data that is used within this research to model the effects of weather and climate change on cycling frequencies. Methods of data collection by the City of Waterloo, the University of Waterloo, ECCC, and the GRCA are discussed, in addition to data cleaning methods. Finally, data preparation tasks are discussed to ensure that the data is accurate and valid.

3.3.1 Data Collection

This section discusses the methods through which each organization collected the respective data, in addition to the means through which this research obtained the information.

Cycling Count Data Collection

The City of Waterloo has installed eleven automated counters along priority active transportation routes throughout the municipality. These counters are employed to collect data on the frequency of use of an active transportation corridor by pedestrians and cyclists. Counters have been periodically installed by the company Eco-Counter since 2014, with active counter data available since August 26, 2014 at the Trans Canada Trail/Laurel Trail at Silver Lake Bridge facility in Waterloo Park. Since August 2014 eight additional multi-use trail locations have been activated, along with two counters located in an on-road bicycle lane, one on each side of the roadway (see Figure 3.2 for the location of automated counters and cycling lanes in the City of Waterloo).

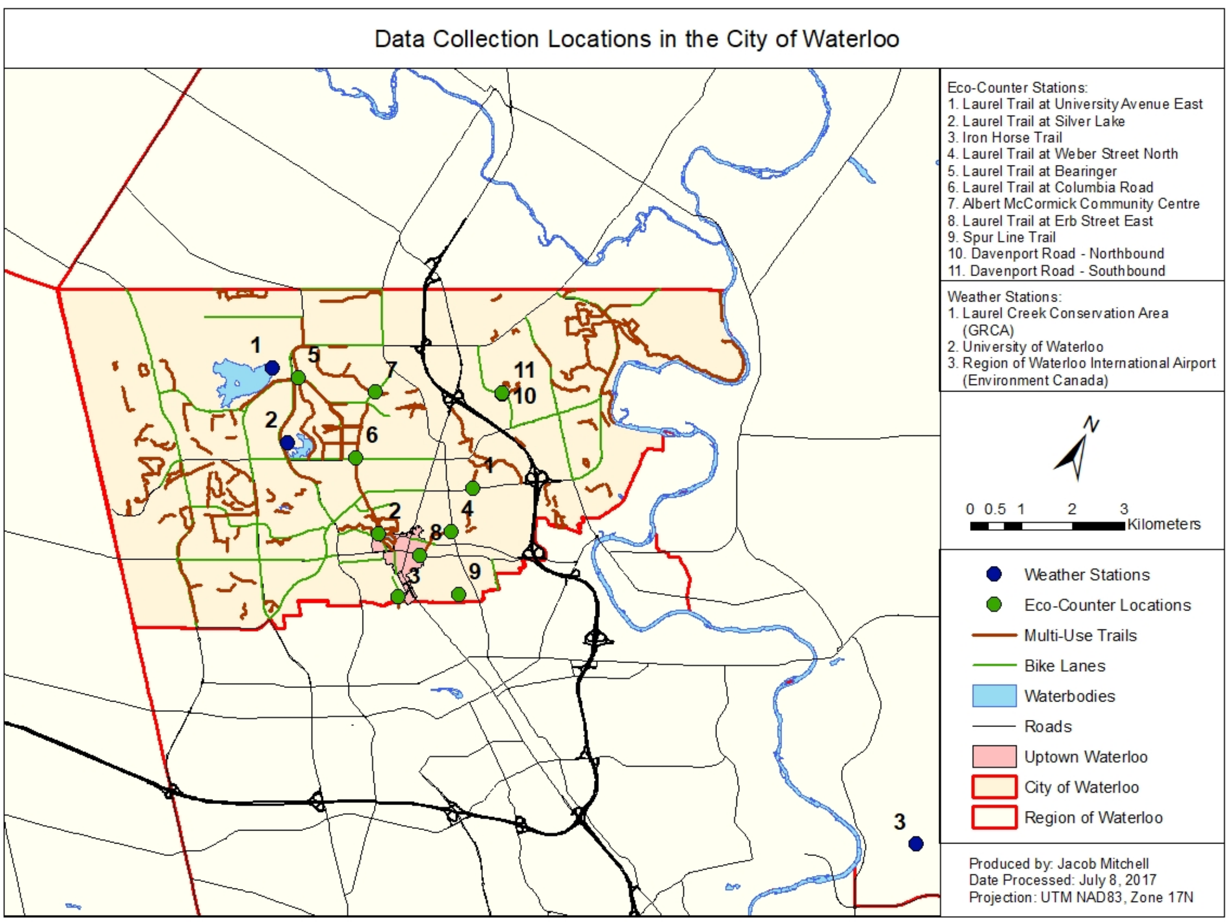


Figure 3.2 - Locations of cycling counter facilities in Waterloo, Ontario.

Automated counters on active transportation routes in Waterloo are permanently installed systems found at trail or pathway entrance points, collecting cyclist and pedestrian counts 24 hours a day, 7 days a week, year-round. Each system uses inductive loop technology, a common method for counting vehicles along roadways, that is embedded in the ground to count passing cyclists, combined with infrared sensors to measure passing pedestrians (FHWA, 2013). For the purpose of this thesis, only cycling data collected by inductive loop counters will be studied, omitting pedestrian counts from infrared sensors. Inductive loop detectors utilize an electrical current that circulates through a wire coil installed in the pavement or pathway that is triggered by conductive, but not necessarily ferrous, materials such as those found on a bicycle (FHWA, 2013). Any disruption in the electromagnetic field that is produced by the inductive loop detector is registered as a count (FHWA, 2013). Necessary modifications are made to inductive loop detectors to count cyclists. As this is a technology that was initially designed to detect motor vehicles with large amounts of ferrous and non-ferrous materials, cycling specific counters are more sensitive and have additional criteria to detect and register the passing of a bicycle, which has far less material, ferrous or non-ferrous to disrupt the detector (see FHWA, 2013 for greater detail on the workings of inductive loop detectors) (FHWA, 2013; Gunst, 2017).

Weather Observation Data Collection

Weather data for the City of Waterloo is made available from three sources located across the Region of Waterloo. The first is from ECCC, which operates a weather station at the Region of Waterloo International Airport 11 km to the east of Uptown Waterloo, in the City of Kitchener. This weather station offers decades of historical results as observed at the airport, and has the advantage of being recorded and reviewed by a large meteorological and federal agency. The second source of weather data is from the Grand River Conservation Authority (GRCA), located 4.5 km to the northwest of Uptown Waterloo at the Laurel Creek Conservation Area. The third and final weather station is on the University of Waterloo's North Campus, 3.4 km to the northwest of Uptown Waterloo. All weather stations within the Region of Waterloo publish data at an hourly resolution or less.

A range of weather observations are provided at each weather station noted above. A key point is that not all observations are collected and/or reported as quantitative or continuous data, which may be the result of the type of data collected or the weather station not having the means to collect the information in a quantitative format. As such, there are some instances of qualitative data that must be accommodated, such as current atmospheric conditions being reported as “rain”, “fog”, “snow”, etc., among others.

Climate Projection Data Collection

To model the effects of future weather conditions on cycling travel behaviour, use of climate predictions is necessary. To achieve this, climate projection data is obtained from the CMIP5 climate model. CMIP5 is the most current and extensive model of the Coupled Model Intercomparison Project (CMIP), a coordinated climate model experiment agreed upon by the World Climate Research Programme (WCRP), which was partly designed to project future climate change at both near term (around 2035) and long term (2100 and beyond) scales (CMIP, n.d.; National Center for Atmospheric Research [NCAR], 2016). To generate climate projections, CMIP5 uses the years 1981-2005 as the reference period to establish the mean temperature and precipitation values. Data found within this dataset consists of “change-fields”. Change-fields (discussed in Section 2.4.3) are expected changes in precipitation or temperature from the mean, calculated using weather observations during the above reference period that may be presented as actual changes in a variable, or as a relative change (i.e. percentage change).

CMIP5 Emissions Scenarios	RCP26	RCP45	RCP85
Time Periods	2011-2040 2041-2070 2071-2100	2011-2040 2041-2070 2071-2100	2011-2040 2041-2070 2071-2100
Weather Variables	Temperature (°C) Precipitation (mm)	Temperature (°C) Precipitation (mm)	Temperature (°C) Precipitation (mm)
Model Outputs	Mean 25th Percentile 50th Percentile 75th Percentile	Mean 25th Percentile 50th Percentile 75th Percentile	Mean 25th Percentile 50th Percentile 75th Percentile

Table 3.1 - Available predictive weather information and emission scenarios of CMIP5.

Specific values for use in the forthcoming analysis of the effects of future weather conditions on cyclists were provided by Dr. Chris Fletcher at the University of Waterloo. Monthly values representing the changes in temperature and precipitation throughout the 21st century were provided. Change-fields are provided at a monthly resolution for three emissions scenarios (RCP26, RCP45, and RCP85) at three time periods: near (2011-2040), mid (2041-2070), and far (2071-2100). A list of available data and scenarios is shown in Table 3.1.

3.3.2 Data Cleaning

This section outlines the methods used to clean and verify individual data points within each dataset to ensure that the data were valid and accurate observations of the respective variables. Despite the differences between each the cycling, weather observation, and climate change datasets, all datasets were screened and cleaned using the same procedure that will be discussed below.

Each dataset was initially screened based on time of day, day of week, and date to identify missing rows or data entries as well as the areas of concern. Upon doing so, discrepancies were identified amongst the time entries, in the cycling and weather observation datasets where numerous data entries were either not included in the datasets or in some cases multiples of one data entry were found. To ensure each hour of each year was accounted to allow the dataset to be truly representative of all hours of the year and identify where missing data occurred, empty rows were inputted in place of a missing entry. Missing entries were further validated by reviewing that the data ID numbers increased sequentially at a constant rate. In select cases missing data was replaced through the assistance of staff at the City of Waterloo who provided raw data. At this point several cycling counter facilities were identified as having significant gaps several months long due to malfunctions at the cycle counters (see Table 3.2).

After reviewing the temporal data of each dataset attention was shifted towards the actual observations or data entries. Here, focus was placed on identifying blatantly erroneous data and missing data entries. During this process a few inconsistencies were identified across both weather and cycling datasets. The University of Waterloo's weather data proved to be riddled with missing and erroneous data for select weather variables (see Table 3.3), while one cycling counter facility was found to have results that were highly erroneous due to its proximity to a streetlamp (see Figure 3.3) which persisted for several months (Personal Communications, 2017).

Once data cleaning concluded a series of decisions were made to omit certain data from the study due to highly erroneous or large numbers of missing data. Five of the eleven cycling counter facilities were excluded due to large amounts of missing data and one site with erroneous data (refer to Table 3.2), while a number of variables from the University of Waterloo weather station were excluded for similar reasons. The remaining weather stations (GRCA and ECCC) showed few missing data and no obvious errors in the data entries, and therefore were included in full for use in this study. Finally, the CMIP5 climate change data does not show any signs of missing or erroneous data and therefore will remain unchanged.

Facility Name	Nearest Intersection	Distance from Uptown Waterloo	Activation Date	Direction of Travel	Dataset Errors/ Inconsistencies/ Missing Data	Included in Study?
Albert McCormick Community Centre	Parkside Drive at Cedarbrae Avenue	3.3	April 29, 2015	N-S	- Erroneous count data (10 months) - Less than one full year of data	No
Davenport Road – Northbound	Davenport Road at Hallmark Drive	3.8	May 1, 2016	N-S	- Missing count data (4 months) - Less than one full year of data	No
Davenport Road – Southbound	Davenport Road at Hallmark Drive	3.8	May 1, 2016	N-S	- Missing count data (4 months) - Less than one full year of data	No
Iron Hose Trail at John Street West	Park Street at John Street West	0.8	July 15, 2015	N-S	N/A	Yes
Laurel Trail at Erb Street East	Peppler Road at Erb Street East	0.3	July 17, 2015	N-S	N/A	Yes
Laurel Trail at University Avenue East	Carter Avenue at University Avenue East	2.0	July 17, 2015	N-S	- Missing count data (8 months) - Less than one full year of data	No
Laurel Trail at Weber Street North	Weber Street North at Bridgeport Road East	1.0	April 28, 2015	E-W	N/A	Yes
Laurel Trail/ Trans Canada Trail at Bearinger Road	Westmount Road North at Bearinger Road	4.1	April 29, 2015	N-S	Missing count data (7 months)	No
Laurel Trail/ Trans Canada Trail at Columbia Street West	Hagey Boulevard at Columbia Street West	2.2	April 29, 2015	N-S	N/A	Yes
Laurel Trail/ Trans Canada Trail at Silver Lake Bridge	Father David Bauer Drive at Erb Street West	0.7	August 26, 2014	N-S	Missing count data (2 weeks)	Yes
Spur Line Trail at Roger Street	Waterloo Street at Roger Street	1.2	July 27, 2016	N-S	Less than one full year of data	No

Table 3.2 - Basic information regarding location and time of activation of each counter facility.

Weather Station	Year	Number of Observations	Number of Removed Entries	Percentage of Entries Removed
Environment Climate Change Canada (ECCC)	2016	8784	4	0.0%
	2015	8762	94	1.0%
	2014	6600	54	0.0%
University of Waterloo	2016	35,136	2,388	6.8%
	2015	35,040	10,512	30.0%
	2014	34,748	34,748	100.0%
Grand River Conservation Authority (GRCA)	2016	8,232	0	0.0%
	2015	8,760	0	0.0%
	2014	8,736	0	0.0%

Table 3.3 - Number of erroneous or missing data removed from each weather dataset.

Figure 3.3 - Image of the Albert McCormick cycling counter potentially impacted by radiation (photo courtesy of Google Street View).

3.3.3 Data Preparation

This section outlines the final steps that were required to be conducted following data collection and cleaning, such as preparing the datasets for analysis by removing erroneous and missing data entries. In addition, this section also mentions the inclusion of additional variables that have been calculated and are derived from the original datasets.

In order to generate the final dataset that will be used to answer the first research question regarding the impacts of weather on cycling frequencies select data entries must be removed. As this research seeks to study the impacts of weather on utilitarian travel, weekends, statutory holidays, and select hours of the day were removed. For the purpose of this research two periods of time are used to model commuter cyclist travel behaviour: the AM peak travel period (07:00 to 09:00) and the PM peak travel period (16:00 to 18:00 pm). Cycling counts within these time periods are aggregated to create a daily commuter cycling frequency for both the AM and PM peak periods. The time periods are similar to those found in Ahmed et al.'s (2010) research, however this study will include the PM peak period as well to assist in explaining commuter cyclists' travel behaviours and cover both in and outbound travels. Any data entries between 00:00 and 06:59, 10:00 and 15:59, and 19:00 to 23:59 were removed as they represent hours that are not widely used by commuter cyclists (e.g. mid-day and nighttime hours).

The final step was to remove all entries that had previously been flagged as erroneous or missing during the above data cleaning exercise. Once all irrelevant or erroneous data entries were removed, the datasets were ready for analysis and now shared the following form: data entries between Monday and Friday (not including statutory holidays) with two entries per day representing the morning and afternoon peak travel periods (07:00 – 09:00, and 16:00 – 18:00), excluding all instances of missing or erroneous data as stated above. To create the final datasets, cycling count and weather observation data are merged around the temporal variables to align the cycling and weather data to their corresponding rows. At this point, five datasets have been created, each of which contains its own cycling count data, as well as the corresponding weather observation data from the combined ECCC, University of Waterloo, and GRCA weather datasets.

3.3.4 Additional Data Inputs

Following the data preparation stages, additional variables are required to be inputted into each dataset. These variables were not provided by the City of Waterloo, the University of Waterloo, ECCC, or the GRCA. This section will outline the variables that have been identified by the literature as being necessary, including newly calculated variables and qualitative variants of previously recorded quantitative variables.

The first variable that is to be calculated and included is "apparent temperature". This variable is presented in both Phung and Rose (2007) and Ahmed et al. (2010) (originally presented by the Australian Bureau of Meteorology, 2010), and is calculated using the following expression:

$$ATEMP = T + 0.33\ [6.105^{\,(17.27\ \mathrm{T}\ /\ 237.7\ +\ \mathrm{T})} \times 0.01\ \mathrm{H}] - 0.7\ \mathrm{W} - 4.0$$

Equation 3.1 - Equation used to calculate apparent temperature (Australian Bureau of Meteorology, 2010)

where, T is the air temperature in degrees Celsius, H is relative humidity (%), and W is wind speed (m/s). The use of an apparent temperature rather than observed air temperature is discussed in Sections 2.3.2 and 2.5.2. As none of the three weather datasets contained apparent temperature values, these were required to be calculated and entered for each entry in the recently cleaned and prepared datasets. It should be noted, however, that ECCC weather data includes entries for HUMIDEX and Wind Chill, which are calculated using relative humidity and temperature, and temperature and wind speed, respectively (Equation 3.1). However, observations of temperature, relative humidity, and wind speed are not included in a single variable as seen in the above apparent temperature calculation.

Scenario	Wind Speed (km/h)	Relative Humidity (%)
LOW-LOW	0	40
LOW-HIGH	0	40
HIGH-LOW	40	100
HIGH-HIGH	40	100

Table 3.4 - Values used in the hypothetical scenarios used to illustrate changes in apparent temperatures.

To explain how variations in relative humidity and wind speed alter the values of apparent temperature, a simple graph illustrating the relationship is used (Figure 3.4). In this graph four hypothetical scenarios are presented that display how changes to the wind speed or relative humidity, while using pre-set temperature values, can alter the effects of apparent temperature. Table 3.4 defines the values used in the four scenarios. In Figure 3.4 it becomes evident that relative humidity does not play a large role in influencing apparent temperatures at the colder end of the temperature spectrum, while it appears to have a greater effect at higher temperatures, suggesting greater apparent temperatures. The effect of wind speed appears to indicate a constant cooling effect when comparing the low to high scenarios, providing a cooling effect during high temperatures, while similarly contributing to colder-feeling temperatures (i.e. wind chill) during the colder times of the year (i.e. winter season).

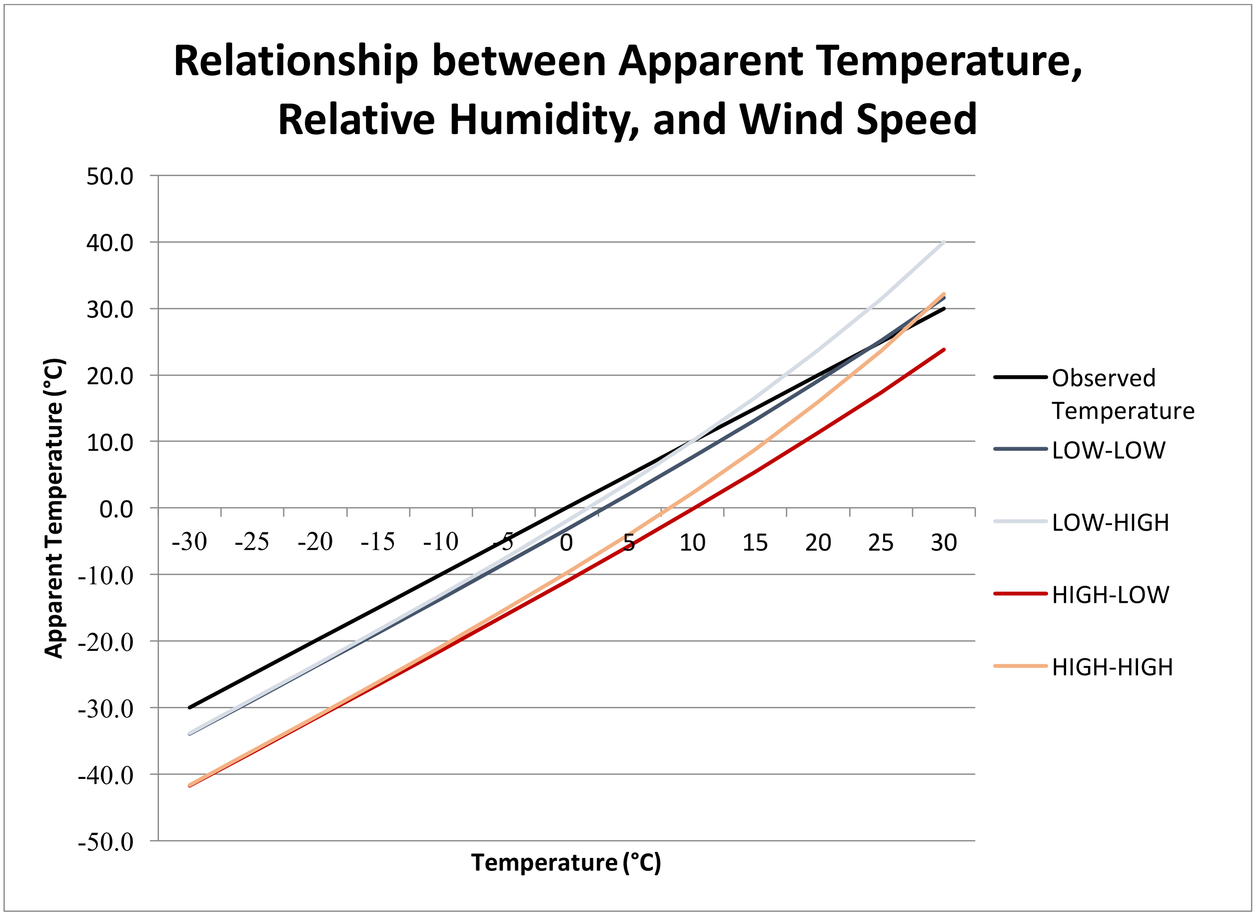


Figure 3.4 - Illustration of the effects of relative humidity and wind speed on apparent temperature.

To complement the aggregated cycling counts during the AM and PM peak periods, the weather data listed above must be representative of these time periods at each of the five facilities. To accommodate this, several weather variables were used to create additional variables to be used to find the most representative variable to use in the analysis. These variables include: precipitation, wind speed, temperature, apparent temperature, snowfall, and relative humidity. A list of the additional variables can be found in Table 3.4. These variables are calculated using hourly weather observation data during the three hours of each AM and PM peak travel period. Additionally, it is worth noting the inclusion of lagged variables in this list, which are discussed at length in Section 2.3.2. The inclusion of a lag variable into this study enables the monitoring of the delayed effects of precipitation on cycling frequencies. Any occurrence of precipitation during or three hours before the AM or PM peak period is coded 'TRUE' for the presence of precipitation, with all other entries assigned a value of 'FALSE'. A lagged variable is also created for snowfall, however rather than identifying if snow has fallen in the previous three hours, this variable will identify if snow has fallen within the past 24 hours, with the lagged effect applied to the full day. The reason for the change in approach is due to the different characteristics of snow versus rain and other precipitates. Unlike non-frozen precipitation, snow must usually be removed from a cycling pathway, or in the event that it melts it may lead to significantly wet or ice-covered routes for an extended period of time.

Next, to ensure that the best form of the data is being used during the analysis select quantitative variables were converted into qualitative variables based around categories that correspond to intensity levels. The variables selected for this conversion and their corresponding intensity levels were derived from previous studies which are extensively discussed in Section 2.3.2. Additionally, Section 2.3.2 discusses the advantages and disadvantages of including quantitative versus qualitative variables within a regression analysis. The general consensus amongst researchers is that the use of categorical variables in a regression may be used to overcome issues surrounding the inclusion of non-linear variables. Categorical variables, therefore, are able to represent non-linear and linear variables, albeit at a coarser resolution than through the use of variables with continuous data. All variables that have been selected for this process are outlined in Table 3.5, which also identifies the corresponding categories for each variable. These three variables will be considered alongside their quantitative alternatives for use within this study. For this research, rainfall and wind speed have categorical variables that are categorized based on the bins presented in Phung and Rose (2007) and Ahmed et al. (2010), while temperature and apparent temperature are included as categorical variables due to arguments over the non-linear effects of temperature on cycling, as present in Wadud (2014), among others. Each of the variables identified in Table 3.4 are used to produce the additional qualitative variables listed in Table 3.5 above.

Observed Variable	Newly Created Variable	Description of the Newly Created Variable
Temperature	Maximum Temperature	The maximum temperature observed during the AM or PM peak period
	Minimum Temperature	The minimum temperature observed during the AM or PM peak period
	Average Temperature	The average temperature observed during the AM or PM peak period
Apparent Temperature	Maximum Apparent Temperature	The maximum apparent temperature observed during the AM or PM peak period
	Minimum Apparent Temperature	The minimum apparent temperature observed during the AM or PM peak period
	Average Apparent Temperature	The average apparent temperature observed during the AM or PM peak period
Wind Speed	Maximum Wind Speed	The maximum wind speed observed during the AM or PM peak period
	Minimum Wind Speed	The minimum wind speed observed during the AM or PM peak period
	Average Wind Speed	The average wind speed observed during the AM or PM peak period
Relative Humidity	Maximum Relative Humidity	The maximum relative humidity observed during the AM or PM peak period
	Minimum Relative Humidity	The minimum relative humidity observed during the AM or PM peak period
	Average Relative Humidity	The average relative humidity observed during the AM or PM peak period
Rainfall	Average Rainfall	The average rainfall observed during the AM or PM peak period
	Maximum Hourly Rainfall	The maximum hourly rainfall observed during the AM or PM peak period
	Total Rainfall	The total rainfall observed during the AM or PM peak period
	Rainfall Lag	If rainfall was observed during the AM or PM peak period or three hours prior, this variable is given the value of “TRUE”
Snowfall	Snow Presence	If snow was observed during the AM or PM peak period
	Snow Lag	If snow was observed within the past 24 hours, this variable is given the value of “TRUE”

Table 3.5 – A list of newly created variables generated from observed weather variables.

Quantitative Variable	Qualitative Categories	Range of Values for Each Category
Rainfall	No Rain Light Rain Moderate Rain Heavy Rain	< 0.2 mm 0.2 – 0.9 mm 1.0 – 2.9 mm ≥ 3.0 mm
Wind Speed	No Wind Light Wind Moderate Wind Fresh Wind Strong Wind	0.0 km/h 1.0 – 19.0 km/h 20.0 – 29.0 km/h 30.0 – 39.0 km/h ≥ 40.0 km/h
Temperature; Apparent Temperature	Extreme Cold Very Cold Cold Freezing Near Freezing Cool Mild Warm Very Warm Hot Very Hot	< -15.0 -15.0 – -10.1 -10.0 -- -5.1 -5.0 – 0.1 0.0 – 4.9 5.0 – 9.9 10.0 – 14.9 15.0 – 19.9 20.0 – 24.9 25.0 – 29.9 ≥ 30.0

Table 3.6 - Selected quantitative variables converted to qualitative variables, with range of values per qualitative category.

Finally, in keeping with Phung and Rose (2007) and Ahmed et al. (2010), a variable identifying the number of hours of daylight has been included to explore whether the amount of sunshine in a day has an impact on cycling frequencies. Each entry is coded with the number of daylight hours that were observed during a given day in half hour increments.

In addition to further data inputs based on weather observations, modifications must be made to account for climate change data. In past sections this research has stated that in addition to modelling the impacts of the effects of weather on cycling frequencies, the effects of climate change on cycling frequencies are also under study. To achieve this, the change-field method (CFM) will be used, which provides estimated changes for both precipitation and temperature at a monthly resolution. Temperature values are provided as actual changes in temperature (per degree Celsius), while precipitation uses percentage changes to represent either an increase or decrease in monthly precipitation. An important note about the precipitation data is that it does not indicate changes in the distribution of precipitation days, rather it provides an indication on whether there will be a change in precipitation intensity or volume during a given period. This method assumes that the number of precipitation days remains the same. This approach certainly is a deviation from the consideration of changing number of precipitation days under a changing climate, and therefore needs to be interpreted differently. Where this approach is beneficial is that it allows this study to understand how varying effects on precipitation will ultimately impact cycling frequencies within a peak period, or how it impacts the use of cycling by commuters at trip-level. This approach considers the impacts of precipitation variations at a smaller temporal scale rather than estimating the effects of changing precipitation across the entire month, season, or year.

3.4 Variable Selection

Due to the number of variables that are under consideration for inclusion in this study a regimented procedure in which variable selection occurs is required. First, descriptively analyzing the data will be necessary to provide a cursory glimpse of the patterns and trends found within the variables at each counter location. By analyzing the data at different temporal scales (e.g. year, month, week, day, hour) an understanding will be developed of when variations in cycling frequencies and each weather variable occur and how time may play a role.

Second, further analysis of the data will be used to delve into not only the temporal patterns of each variable, but also the relationship between the variables. Due to the nature of the data, which includes both quantitative and qualitative data, different means are used to visually represent and analyze it. For quantitative data, such as count and continuous variables, scatterplot matrices will be used to identify correlations between each of the variables to assess the strengths of their relationships, while the scatterplots will show the distribution of the data points in the relationships. Next, qualitative variables, such as temporal and binary variables, are displayed using boxplots to show the distribution of data points within each level of a variable, as well as the range and median values of the distributions. Exploratory analysis is a key component and greatly assists in the variable selection process.

The final step is to select the variables. First, the relationships between the response and explanatory variables will be identified to determine whether to include the variable in a quantitative/continuous or in a categorical form. To select the variables that will be included in this study those that have the strongest relationships (larger correlations) will be selected to explain changes in the response variable. As the relationships between the response and explanatory variables are determined at each of the five counter locations the largest correlation for each variable group at each dataset will be considered, as well as the mean correlation for each variable group. It is also important to note that will be employed to ensure effective, intuitive, and sensible variables are chosen for inclusion in the model. Finally, findings from relevant literature, as well as a degree of common-sense will also be used to select explanatory variables to ensure that they are effective, intuitive, and sensible.

3.5 Model Assessments

Once variables are selected for consideration in the model a series of assessments are required to ensure that the model meets the requirements to be both a Quasi-Poisson regression and a predictive model. It is important to test the foundations of the Quasi-Poisson regression and ensure that the results of the predictive model are accurate relative to the observed values and can generate meaningful results.

The assumptions and conditions of a Quasi-Poisson regression will be checked using the statistical modelling software R (R Core Team, 2016). There are four assumptions and conditions that are necessary to check prior to modelling with a Quasi-Poisson regression, which include: the dependent variable consists of count data; one or more independent variables can be measured on a continuous, ordinal, or dichotomous scale; observations are independent of one another; and, the distribution of counts follows a Poisson distribution (positively skewed). Use of a standard Poisson regression would requite a fifth assumption, that that variance is equal to the mean. This assumption is not applied when using a Quasi-Poisson regression as this type of regression does not restrict the dispersion parameter to a value of 1 (or, where the variance is equal to the mean) as is seen in a Poisson regression. Rather a Quasi-Poisson regression provides flexibility to account for overdispersion, a common problem within regression models using count data. To assess these conditions, a scatterplot of the predicted versus residuals will be produced and interpreted for each counter location.

After the Quasi-Poisson regression has been proven to be appropriate for continued use, the model's predictive abilities will be tested. To achieve this, a method called 'cross-validation' is used. Cross-validation is a method which seeks to build and test predictive models by using a researcher's own data to train and test the predictive abilities of a model. Typically, a dataset is partitioned into two new, randomly assigned sets: a training set and a test set. The training set holds approximately 80% of the original data, while the test set holds the remaining 20%. A model is built around the training set and measured for its ability to model the provided values. To determine whether a model is able to predict new values, it is then applied to the test set (data that it has never seen or used for training). By comparing the test metrics between the training and test sets, a researcher may be able to determine whether the model is able to predict new values (the desired outcome), or if the model is 'overfit', where the model may represent the training set perfectly, but fails to predict the test set as it has not been trained to accept new values properly (James et al., 2013). For this research, k-fold cross-validation will be used to validate that the model is able to predict new values. For this research, the Caret package in the statistical program R will be used to perform repeated 10-fold cross-validation to validate the predictive abilities of the model (Kuhn, 2016; R Core Team, 2016; Kuhn, 2017).

3.6 Model Specification

Following the assessment and verification of the model its form may be identified. At this point it is important to understand the models that this research is using as a baseline for refining the count model. Phung and Rose (2007) and Ahmed et al. (2011) both use a similar log-linear model based on a multiple linear regression (MLR). MLR models make use of the "ordinary least squares" approach to determine the best fit of the regression line; that is, the regression line is oriented to make the sum of the squared residuals (the difference between the observed and predicted y-values) as small as possible (De Veaux, et al., 2005). The basic form of an MLR can be seen below in Equation 3.2:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \epsilon_i$$

Equation 3.2 - Basic form of a multiple linear regression model.

Where Y is the response variable (quantitative/continuous), β_0 is the intercept, the point at which the regression line intersects the Y-axis, β_1 is the coefficient for the ith explanatory variable (where i = 1, 2, 3, …, k), X_{i1} is the observed value or value representing a categorical variable, and ϵ_i is the residual or error term.

The model form that is used by Phung and Rose (2007) and Ahmed et al. (2011) is the log-linear model, displayed in Equation 3.3:

$$logY_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \epsilon_i$$

Equation 3.3 - Basic form of a multiple linear regression model with a logarithmic transformation applied to the response variable (log-linear MLR).

Where β_0 remains as the intercept, β_1 is the coefficient, X_{i1} is the observed value, and ϵ_i is the residual term. The difference between Equation 3.2 and 3.3 is that a logarithmic transformation is applied to the response variable. The purpose of a logarithmic transformation is to transform positively-skewed, non-negative data towards a normal distribution, which is applicable for count data. Challenges with this approach for count data are that it cannot easily generate predicted count data, cannot handle overdispersion within the data, a common problem with count data, and can over or underestimate the coefficient standard errors, ultimately impacting inference (Fox, 2016).

To refine the model that was created by the aforementioned authors, a commonly used alternative distribution is used in this model. Generalized linear models (GLM), specifically Poisson or Negative Binomial models are commonly used in literature on transportation count modelling as they are able to appropriately handle positively-skewed count data. This research will be modifying the equation presented by Phung and Rose (2007) and Ahmed et al. (2010) by using a Quasi-Poisson regression, similar to the methods seen in Wadud (2014) and Mathisen et al. (2015) where a Poisson regression is used. Quasi-Poisson regression models are a GLM, however they make use of a least-squares algorithm when fitting the model to data, similar to simple linear regressions, and the variance is defined as a linear function of the mean offering greater flexibility over Poisson models (Ver Hoef & Boveng, 2007). The form of a Quasi-Poisson regression can be seen below in Equation 3.4:

$$logE[\mu_i] = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \varepsilon$$

Equation 3.4 - Basic form of a generalized linear regression model (GLM) with a Poisson distribution.

Where *LogE* is the logarithm of the expectation of the count, μ_i is the mean response variable (expected count), β_0 is the intercept, β_1 is the coefficient for the *i*th explanatory variable, X_{i1} is the observed value or value representing a categorical variable, and ε is the residual or error term, similar to a simple or multiple linear regression.

There are notable differences between the log-linear model used by Phung and Rose (2007) and Ahmed et al., (2011) as presented in Equation 3.3. Most notably a log-linear regression uses a logarithmically transformed dependent variable modeling the dependent variable as a linear function of the regression coefficients, while the Quasi-Poisson regression in Equation 3.4 applies a natural logarithmic transformation on the expectation of the count (Gardiner, Mulvey & Shaw, 1995). Use of a logarithmically-transformed linear regression proves problematic as count data frequently contains valid zero counts. A common approach by researchers using a logarithmically-transformed linear regression is to apply log(X + 1), where X is the count with a value of zero. This enables the use of a log transformation, however it does so through inappropriate manipulation of count data that can lead to less than desirable results (Feng, Wang, Lu, Chen, He, Lu & Tu, 2014).

Therefore, to accommodate the potential implications of using a log-linear regression to model count data, and the restrictive dispersion parameter of a Poisson regression, a Quasi-Poisson model is used in their place. This method is well suited to handling count data, producing predictive results using count data, is easily interpretable, and can manage the common issue surrounding overdispersion of count data, unlike that of a traditional Poisson regression (Ver Hoef & Boveng, 2007).

4.0 Preliminary Results and Analysis

4.1 Introduction

As discussed in Chapter 2, weather plays an important role in changing cycling frequencies. Conditions considered to be pleasant (e.g. sunny, warm, and dry) are thought to encourage cycling counts, while adverse conditions (e.g. the presence of snow or rain, and extreme temperatures) may negatively influence cycling counts. In order to correctly model the effects that weather has on cycling counts, it is important to identify the key variables, such as those previously mentioned, that play an important role in explaining variability in cycling counts to include them within the model. Through descriptive and exploratory analyses, a better understanding of the data and the relationships between variables will be identified and used to guide variable selection as well as the final steps of model building in this study.

This chapter details the preliminary analysis that has been performed. The preliminary analysis includes an overview of the general trends and patterns within the data which is used to display valuable information within the data, and provides the foundation for informed and systematic variable selection (Section 4.2). Additionally, the variable selection process is outlined in Section 4.3 along with brief descriptions of the variables that are included. In Section 4.4, the model is assessed using several tests to confirm its validity and predictive modelling abilities. This chapter concludes with the model specification in Section 4.5, whereby the final model is outlined and described prior to discussing the modeling results in Chapter 5.

4.2 Data Analysis

An overview of the data trends and patterns may be found in Section 4.2.1, while a more extensive analysis of the relationship between the response and explanatory variables will be conducted within Section 4.2.2.

4.2.1 Descriptive Analysis

This section will provide basic insight into the data, such as the range and temporal variations in cycling counts and weather observations. By reviewing this information temporal and geographic patterns may be identified across the study period and area.

Cycling Counts

Despite the location of each cycling counter within the City of Waterloo and their close proximity to Uptown Waterloo, each facility exhibits different cycling counts over the year. However, similar patterns emerge between cycling facilities regardless of where they are located within the city due to temporal influences. Using the same method of explaining the variability in cycle path usage in Waterloo as Ahmed et al. (2010), temporal variations in cycling frequencies will be identified in this section through the use of several time scales.

Although the five count facilities are located centrally around Uptown Waterloo, as seen in Figure 3.2 and Table 3.2, overall use of the facilities can greatly differ across the municipality. During the study period, only one count facility was active from August 2014 to December 2016 with the remaining facilities installed at later dates. To explain the variability in cycling frequencies across each site, a variety of measures are used, including average annual daily traffic (AADT), as seen in Table 4.1. The AADT is a measure that displays the average daily cycling rate across the entire year. Upon examination of Table 4.1, it is clear that there are stark differences in cycling frequencies between each facility. The count facility located along the Laurel Trail at Silver Lake has the highest AADT, and largest range between its maximum and minimum hourly cycling rates. The remaining four facilities appear to align to two groups. The Laurel Trail at Columbia Avenue and the Iron Horse Trail both have similar mean cycling values, and are both located along centrally located routes around Uptown Waterloo and the city's post-secondary campuses. The last grouping consists of the Laurel Trail at Weber, and the Laurel Trail at Erb, which both show lower AADTs, and lower numbers of cyclists over the course of a year. Both of these sites may be found along the same contiguous segment of pathway, which may explain the similarly low cycling frequencies.

Counter Location	Cycling Counts				
	Total Number of Observations (hourly)	Total Cyclists Observed	AADT	Max. hourly Cyclists	Min. hourly Cyclists
Iron Horse Trail	5,290	82,028	232.37	94.00	0.00
LT at Columbia	6,097	95,350	234.56	90.00	0.00
LT at Erb	5,288	32,200	91.48	47.00	0.00
LT at Silver Lake	8,477	203,477	360.14	178.00	0.00
LT at Weber	6,107	37,313	91.65	30.00	0.00

Table 4.1 - Descriptive statistics of cycling counts by facility location during the study period.

In addition to the effects of geography on cycling rate variability, seasonal and monthly time scales show separate degrees of variation. The below figures better represent the overall changes in cycling rates throughout the course of the year based on aggregate monthly values. Figure 4.1 shows the average monthly daily traffic (AMDT) variations by month throughout the year, with individual seasons identified for comparison. Two distinct peaks are present at about half of the counter facilities. The first occurs between April and June, when the weather warms and both public and post-secondary schools are still in session, which may increase the number of student commuters. This peak declines after June, which corresponds with the end of the public

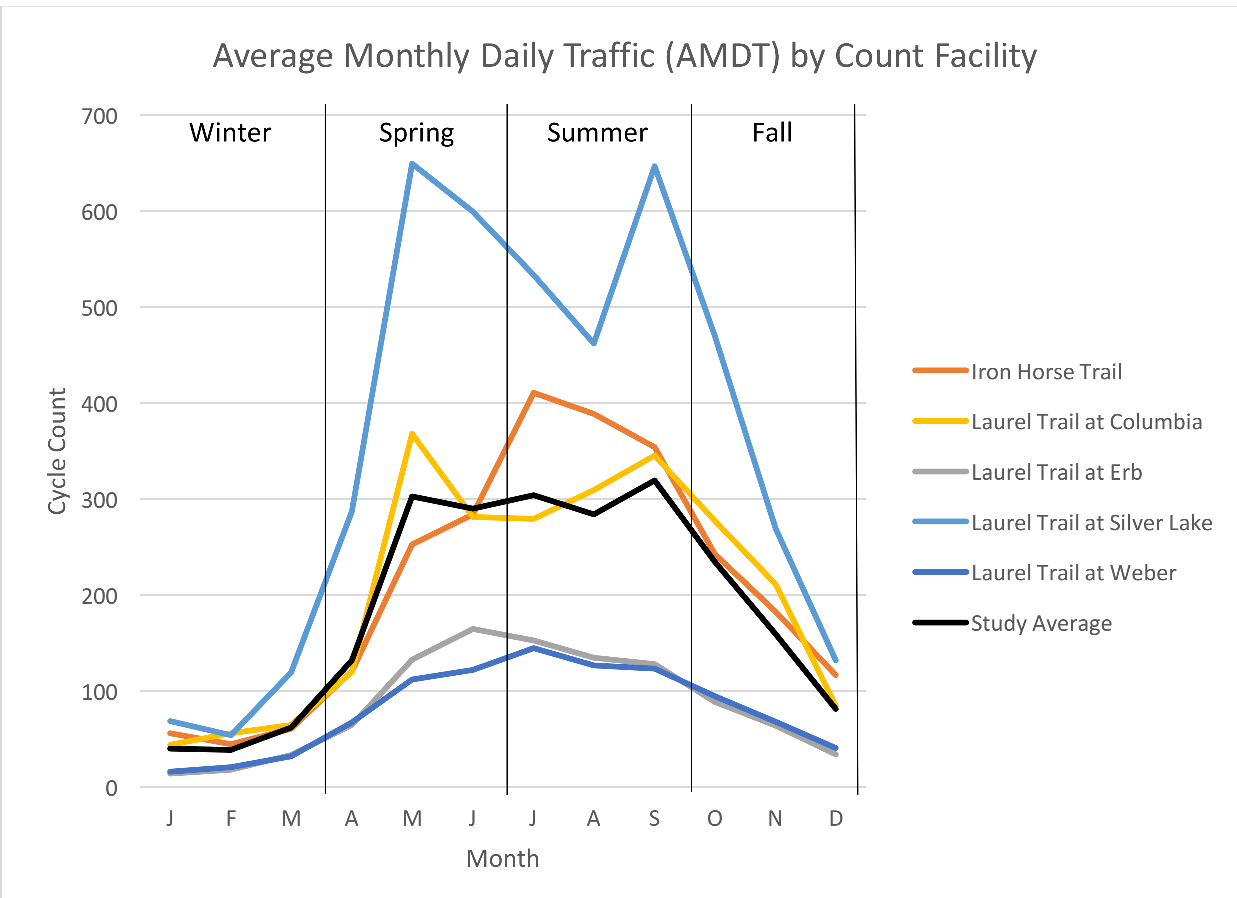


Figure 4.1 - Average monthly daily traffic (AMDT) by count facility.

school year. On average, July and August both experience a decline in cycling rates across the city, which is most prominent at the Laurel Trail at Silver Lake and Laurel Trail at Columbia facilities, which are situated along common routes for students and staff travelling to nearby post-secondary institutions. A second peak occurs in September at these facilities which may be attributed to the return of both public school and post-secondary students. These trends, however, are not found at all facilities. The Iron Horse Trail experiences a surge of cyclists during the summer months with a unimodal distribution, while the Laurel Trail at Erb and Laurel Trail at Weber both experience lower rates and a unimodal distribution peaking in the late spring/early summer.

It is also important to understand the variations in cycling rates throughout the week. While many publications make the distinction between weekends and weekdays and their corresponding cycling rates, this research focuses solely on commuter cycling, and therefore excludes weekends from analysis. Nonetheless, variations throughout the work week do occur with certain days experiencing greater rates of cycling than others, as is exhibited in Figure 4.2. Below, in Figure 4.2, slight variations throughout the week are evident, typically with Tuesday or Wednesday experiencing the greatest weekday cycling rate, with lower rates experienced on Mondays and Fridays. Comparing facilities, three locations along the Laurel Trail (Columbia, Erb, Weber) have similar patterns throughout the week despite differences in cycling rates. The pattern deviates at the most popular route, the Laurel Trail at Silver Lake.

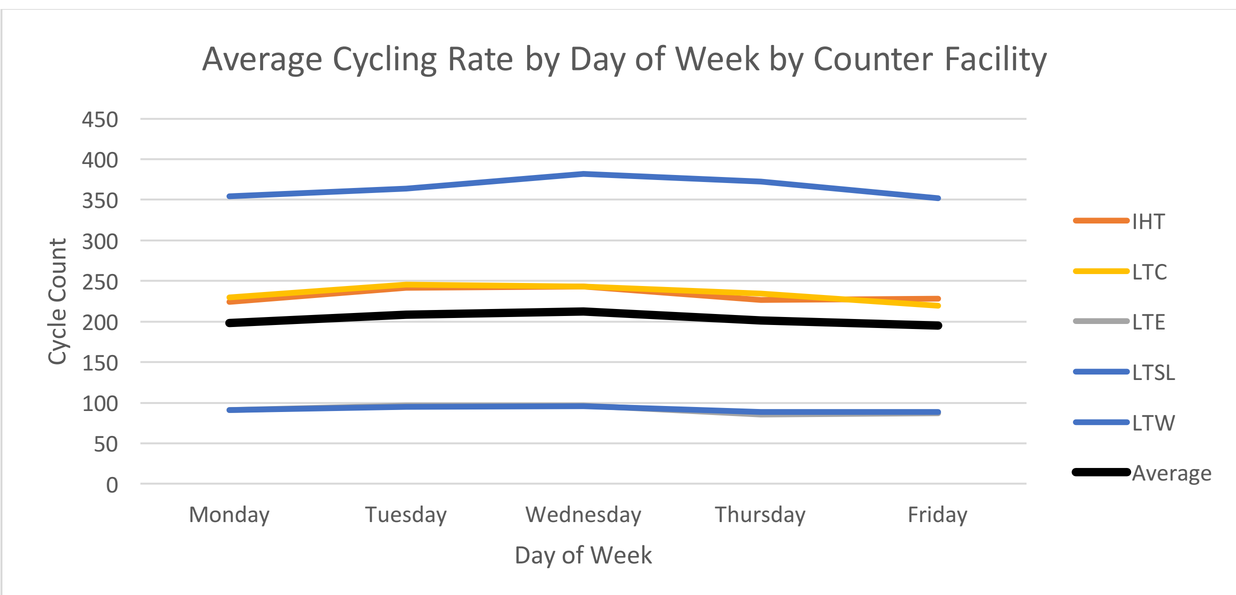


Figure 4.2 - Average cycling rate by day of the week by counter facility.

Finally, fluctuations in cycling frequencies occur throughout the day on an hourly basis. Between 06:00 and 20:00 a pattern emerges for the distribution of cycling frequencies throughout the day. Beginning at approximately 07:00, a peak in the cycling rate emerges as cyclists begin traveling to their respective places of work during the morning peak travel period, which extends to approximately 09:00. A similar peaked-pattern emerges around 16:00 with the beginning of the afternoon rush hours, which extends in the evening until approximately 18:00. The final important portion of this pattern are the mid-day cycling rates (i.e. approximately 10:00 to 15:00). Typically, on routes that are identified solely as utilitarian and not recreational, mid-day cycling rates decrease dramatically as most cyclists that have travelled to work are at work and are no longer cycling. The "Study Area Average" and the three most frequented sites all show a pronounced bimodal distribution throughout the day common with commuting routes. The Laurel Trail at Erb and Laurel Trail at Weber, however, exhibit less diurnal variation which may be in part a result of the typically low cycling frequencies observed at these facilities. As previously stated, this research is focusing on two periods during the day that represent the AM and PM peak travel periods. In addition to the daily cycling count trends identified in Figure 4.3, the AM (07:00 – 09:00) and PM (16:00 – 18:00) peak travel periods that are being used within this study are outlined for easy visualization of the patterns.

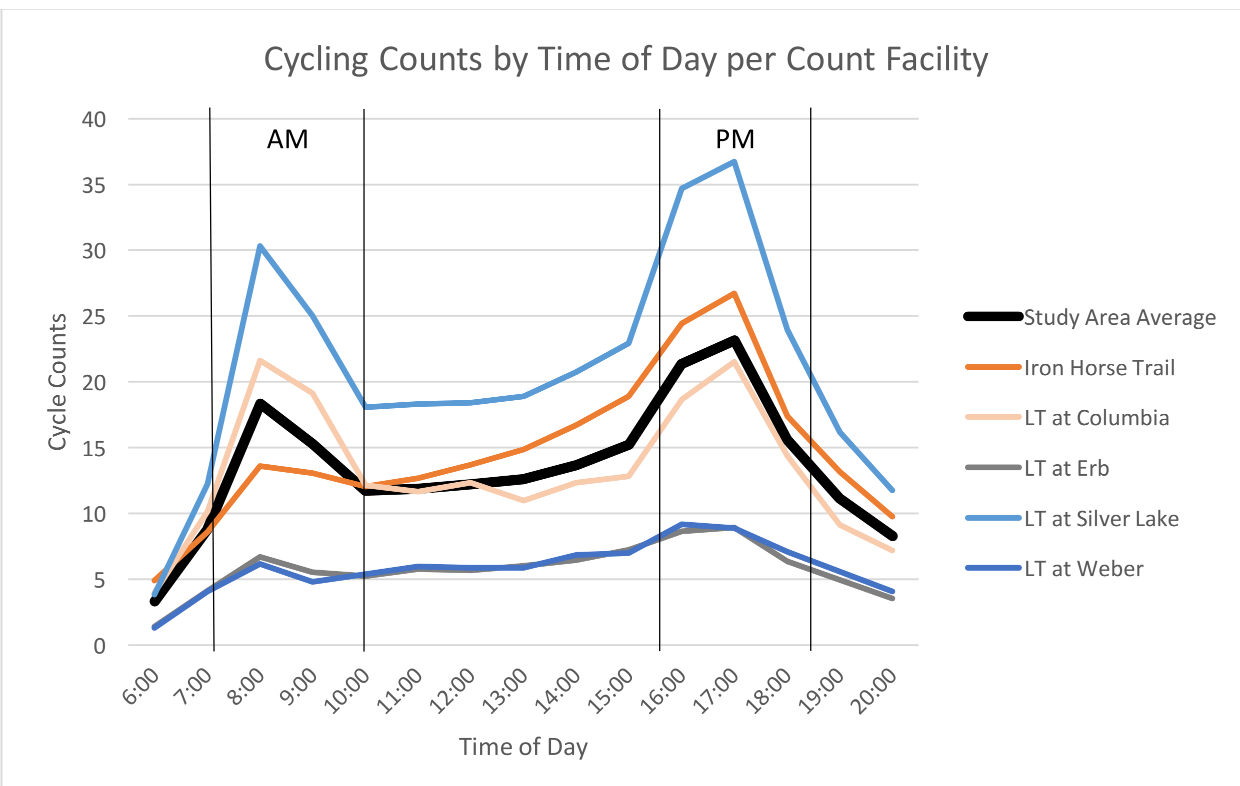


Figure 4.3 - Cycling counts by time of day by count facility with peak travel periods included in study identified.

Weather Observation Data

Weather variables considered for use within this research include those that are discussed at length in Section 3.3.1 and 3.3.4. Upon creation and formation of the cycle counter facility datasets, weather data is descriptively analyzed to provide a basic understanding of the individual variables that may be used within the final analysis. Meteorological data for the dates between August 26, 2014, and December 8, 2016, were analyzed to provide a range of data regarding the overall weather conditions observed throughout the study period, as well as annual, seasonal, and monthly descriptions.

The City of Waterloo and the remainder of southern Ontario experience a variety of weather conditions with large variations month-to-month as a result of the continental climate and lake-effect weather events throughout the year (Bourdage & Huard, 2010). Table 4.2 shows the mean, maximum, and minimum values for each of the continuous weather variables during the length of the study period. Here, basic statistics on the observed weather variables are found. It is apparent that weather conditions in southern Ontario have significant ranges. Examples include the nearly 60 degree Celsius range between the maximum and minimum temperatures that were observed in the summer and winter months, respectively. Rain and snowfall are experienced relatively infrequently, shown with very low mean values (note: snowfall values are based on the period between October and April, not the full year) Finally, wind speeds have an average value of approximately 16 km/h throughout the year, although during storm-like events, the maximum wind speed can be significantly greater, as is identified by the maximum wind speed of 54 km/h during the study period.

	Temperature (C)	Apparent Temperature (C)	Relative Humidity (%)	Rain (mm)	Snow Fall (cm)	Wind Speed (km/h)
Mean	8.56	4.75	74.28	0.08	0.18	15.58
Max	33.90	32.78	100.00	19.20	19.00	54.00
Min	-27.60	-32.35	20.00	0.00	0.00	0.00
Std. Dev.	8.98	13.64	17.14	0.60	1.83	8.73
Skewness	-0.17	-0.16	-0.81	19.07	5.60	0.48

Table 4.2 - Descriptive statistics of continuous weather variables throughout the study period (August 2014 to December 2016).

Apart from the annual statistics of key weather variables, shown above in Table 4.2, there are a number of seasonal variations to consider when addressing variability in weather. In Figure

4.4, six key weather variables are graphed to display how they change throughout the year. Firstly, average monthly wind speeds show some degree of variation across the year, with the main pattern being an increase in wind speeds during the late fall, winter, and early spring months (October – March), with a decrease in wind speeds during the late spring, summer, and early fall (April – September). Next, relative humidity, a variable with a strong relationship with temperature and precipitation, appears to show a similar pattern to wind speeds, in that it exhibits an annual decrease in values during the summer, with a peak during the winter months. Next, precipitation within southern Ontario consists of two predominant precipitates: rain and snow, both of which are graphed together in the lower-left panel of Figure 4.4. Here, it can be seen that snowfall is dominant through the winter months, which is expected due to the presence of temperatues below 0 degrees Celsius, while rain becomes the sole precipitate during the spring, summer, and fall months where temperatures are typically above the freezing point. It is important to note that despite the colder temperatures that characterize a winter in Ontario, there has been an increasing prevalence of temperatures rising near or above 0 degrees Celsius, resulting in the increased presence of rainfall throughout the entire year. Temperature variations follow a normal pattern, where temperatures reach their peak during the summer months, and the lowest temperatures during the winter season. Due to the large range in annual maximum and minimum temperatures in Ontario, the spring and fall seasons are characterized by a steep increase or decrease in temperatures. Additionally, while Figure 4.4 shows that the summer and winter averages appear to be around 20 and -10 degrees Celsius, the summer may be dramatically impacted by humidity and wind speeds, while the winter can be similarly affected by wind speeds, resulting in significantly more extreme apparent temperatures. Finally, due to the location of Waterloo and southern Ontario, there is a noticeable difference in the number of daylight hours throughout the year, with a high of 15.5 hours of daylight on June 21, and a low of nine hours of daylight on December 21 of each year.

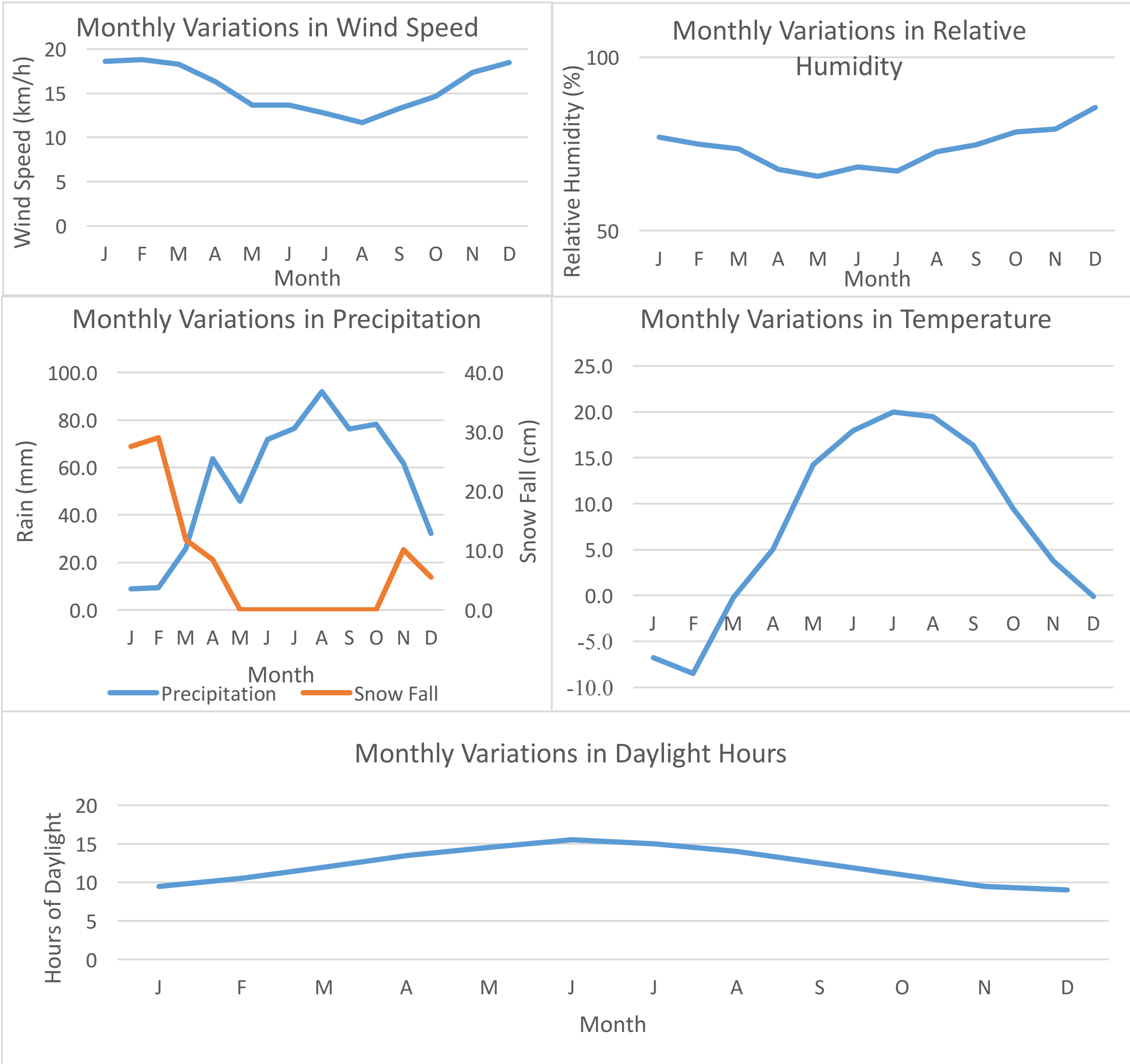


Figure 4.4 - Monthly variations in wind speed, relative humidity, precipitation, temperature, and daylight hours in Waterloo, Ontario.

Climate Change Data

The final dataset to be discussed is the climate change data generated by the CMIP5 climate model. Table 4.3 displays the average monthly predicted changes to temperature and precipitation at mid-century in three emissions scenarios and at three levels of climate change predictions: the mean prediction, and the outer bounds of the 50% inter-model range (25% and 75%). This table illustrates the variations that exist between the three emission scenarios and the three levels of climate change predictions, which speaks in part to the uncertainty that surrounds the expected changes to Ontario's climate at mid-century. Two similar trends are present within Table 4.3: the average effects intensify across the three levels of climate change predictions (25%, mean, 75%); and, the average effects intensify as the emission scenarios intensify from RCP26 to RCP85.

Mid-Century (C. 2050)	Temperature (°C)			Precipitation (%)		
	25%	Mean	75%	25%	Mean	75%
RCP26	1.113	1.765	2.331	0.973	1.055	1.125
RCP45	1.636	2.352	2.874	1.002	1.077	1.152
RCP85	2.484	3.175	3.713	1.007	1.083	1.163

Table 4.3 - Summary of average CMIP5 inter-model climate projections for each emission scenario at mid-century.

4.2.2 Exploratory Analysis

To complement Section 4.2.1, where patterns are identified for both cycling frequencies and weather observations, this section will further seek to explain some of the underlying relationships found within the data that is being used for this study. This section will begin to uncover the relationships between the response variable (cycling counts) and the explanatory variables (temporal and weather), as well as where relationships exist between explanatory variables.

Quantitative Variables

To further explore the quantitative variables, the extent of the relationships between each pair of variables are assessed. The purpose of this procedure is to identify which variables are strongly or weakly correlated, such as key variables identified in the literature that impact cycling frequencies as well as which explanatory variables show large correlations with each other, as seen in Table 4.3. Additionally, the distribution of the points between two variables can be assessed to determine if the relationship is linear or non-linear.

Across the five count facilities there are similarities in the relationships between the response and explanatory variables, as well as amongst the explanatory variables. Apparent temperature and daylight hours demonstrate strong positive correlations (see Table 4.3) with the response variable, however Figure 4.5 indicates that apparent temperature shows a non-linear relationship with the response variable due to the variable effects of temperatures that range from approximately -20 degrees to 30 degrees Celsius. Both of these findings are in line with those found by existing literature on the impacts of weather on cycling frequencies (Ahmed et al., 2010). Conversely, relative humidity, precipitation, and wind speed indicate a negative correlation when measured against the response variable. What is notable is that each of these variables has a fairly weak correlation with the response variable (see Table 4.3). While the sign of the correlation of these three variables is similar to the literature (Wadud, 2014; Mathisen et al., 2015) the distribution of the points differs. Through these preliminary findings, precipitation and relative humidity show a non-linear relationship as per the literature. However, wind speeds, though negatively correlated with cycling counts, do not show a non-linear distribution which is consistent with Wadud (2014), who finds that wind speed has a negative linear relationship with cycling counts.

In addition to the general findings from the correlation matrices noted above, one remaining note must be detailed. Daylight hours is described in the literature as a potential key variable in the explanation of seasonal cycling frequency variations. However, while it does show a strong positive correlation with cycling frequencies it does also show stronger correlations with other explanatory variables (i.e. apparent temperature), introducing the potential for collinearity.

Iron Horse Trail													
Count	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	Count	<0.01	<0.01	<0.01	0.041	0.042	0.074
0.640	ATempAVG	<0.01	<0.01	<0.01	<0.01	<0.01	-0.130	PrecipSUM	<0.01	<0.01	0.044	0.057	0.040
0.640	1.000	ATempMAX	<0.01	<0.01	<0.01	<0.01	-0.110	0.960	PrecipMAX	<0.01	0.120	0.160	0.110
0.640	1.000	0.990	ATempMIN	<0.01	<0.01	<0.01	-0.130	1.000	0.960	PrecipAVG	0.044	0.057	0.040
-0.480	-0.320	-0.300	-0.340	RHMAX	<0.01	<0.01	-0.077	0.076	0.059	0.076	WindAVG	<0.01	<0.01
-0.510	-0.380	-0.360	-0.390	0.970	RHAVG	<0.01	-0.077	0.072	0.053	0.072	0.970	WindMAX	<0.01
0.430	0.700	0.700	0.690	-0.450	-0.510	Daylight	-0.067	0.077	0.061	0.077	0.960	0.880	WindMIN
Laurel Trail at Columbia													
Count	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	Count	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
0.600	ATempAVG	<0.01	<0.01	<0.01	<0.01	<0.01	-0.140	PrecipSUM	<0.01	<0.01	<0.01	<0.01	<0.01
0.610	1.000	ATempMAX	<0.01	<0.01	<0.01	<0.01	-0.120	0.980	PrecipMAX	<0.01	<0.01	0.012	<0.01
0.580	1.000	0.990	ATempMIN	<0.01	<0.01	<0.01	-0.140	1.000	0.980	PrecipAVG	<0.01	<0.01	<0.01
-0.330	-0.320	-0.300	-0.340	RHMAX	<0.01	<0.01	-0.190	0.110	0.094	0.110	WindAVG	<0.01	<0.01
-0.390	-0.370	-0.360	-0.380	0.970	RHAVG	<0.01	-0.160	0.100	0.088	0.100	0.970	WindMAX	<0.01
0.430	0.690	0.630	0.690	-0.420	-0.470	Daylight	-0.200	0.100	0.091	0.100	0.960	0.880	WindMIN
Laurel Trail at Erb													
Count	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	Count	<0.01	0.011	<0.01	<0.01	<0.01	<0.01
0.730	ATempAVG	<0.01	<0.01	<0.01	<0.01	<0.01	-0.120	PrecipSUM	<0.01	<0.01	0.044	0.057	0.040
0.730	1.000	ATempMAX	<0.01	<0.01	<0.01	<0.01	-0.095	0.960	PrecipMAX	<0.01	0.120	0.160	0.110
0.720	1.000	0.990	ATempMIN	<0.01	<0.01	<0.01	-0.120	1.000	0.960	PrecipAVG	0.044	0.057	0.040
-0.510	-0.620	-0.300	-0.340	RHMAX	<0.01	<0.01	-0.170	0.076	0.059	0.076	WindAVG	<0.01	<0.01
-0.580	-0.380	-0.360	-0.390	0.970	RHAVG	<0.01	-0.160	0.072	0.053	0.072	0.970	WindMAX	<0.01
0.630	0.700	0.700	0.690	-0.450	-0.510	Daylight	-0.180	0.077	0.061	0.077	0.960	0.880	WindMIN
Laurel Trail at Silver Lake													
Count	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	Count	0.140	0.380	0.140	<0.01	<0.01	<0.01
0.630	ATempAVG	<0.01	<0.01	<0.01	<0.01	<0.01	-0.044	PrecipSUM	<0.01	<0.01	0.310	0.340	0.350
0.630	1.000	ATempMAX	<0.01	<0.01	<0.01	<0.01	-0.026	0.980	PrecipMAX	<0.01	0.270	0.280	0.340
0.630	1.000	0.990	ATempMIN	<0.01	<0.01	<0.01	-0.044	1.000	0.980	PrecipAVG	0.310	0.340	0.350
-0.130	-0.200	-0.200	-0.210	RHMAX	<0.01	<0.01	-0.230	0.030	0.033	0.030	WindAVG	<0.01	<0.01
-0.150	-0.240	-0.240	-0.240	0.970	RHAVG	<0.01	-0.210	0.028	0.032	0.028	0.970	WindMAX	<0.01
0.530	0.700	0.700	0.690	-0.290	-0.310	Daylight	-0.230	0.028	0.029	0.028	0.970	0.890	WindMIN
Laurel Trail at Weber													
Count	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	Count	0.014	<0.01	<0.01	<0.01	<0.01	<0.01
0.730	ATempAVG	<0.01	<0.01	<0.01	<0.01	<0.01	-0.086	PrecipSUM	<0.01	<0.01	0.190	0.210	0.160
0.730	1.000	ATempMAX	<0.01	<0.01	<0.01	<0.01	-0.110	0.980	PrecipMAX	<0.01	0.090	0.093	0.076
0.730	1.000	0.990	ATempMIN	<0.01	<0.01	<0.01	-0.110	0.980	1.000	PrecipAVG	0.090	0.093	0.076
-0.560	-0.310	-0.290	-0.330	RHMAX	<0.01	<0.01	-0.120	0.046	0.059	0.059	WindAVG	<0.01	<0.01
-0.610	-0.370	-0.360	-0.380	0.970	RHAVG	<0.01	-0.110	0.044	0.059	0.059	0.970	WindMAX	<0.01
0.560	0.700	0.700	0.690	-0.420	-0.480	Daylight	-0.130	0.049	0.062	0.062	0.960	0.880	WindMIN

Table 4.4 – Bivariate matrices showing the Pearson correlations of each variable pairing (lower-left) and associated p-values (upper-left).

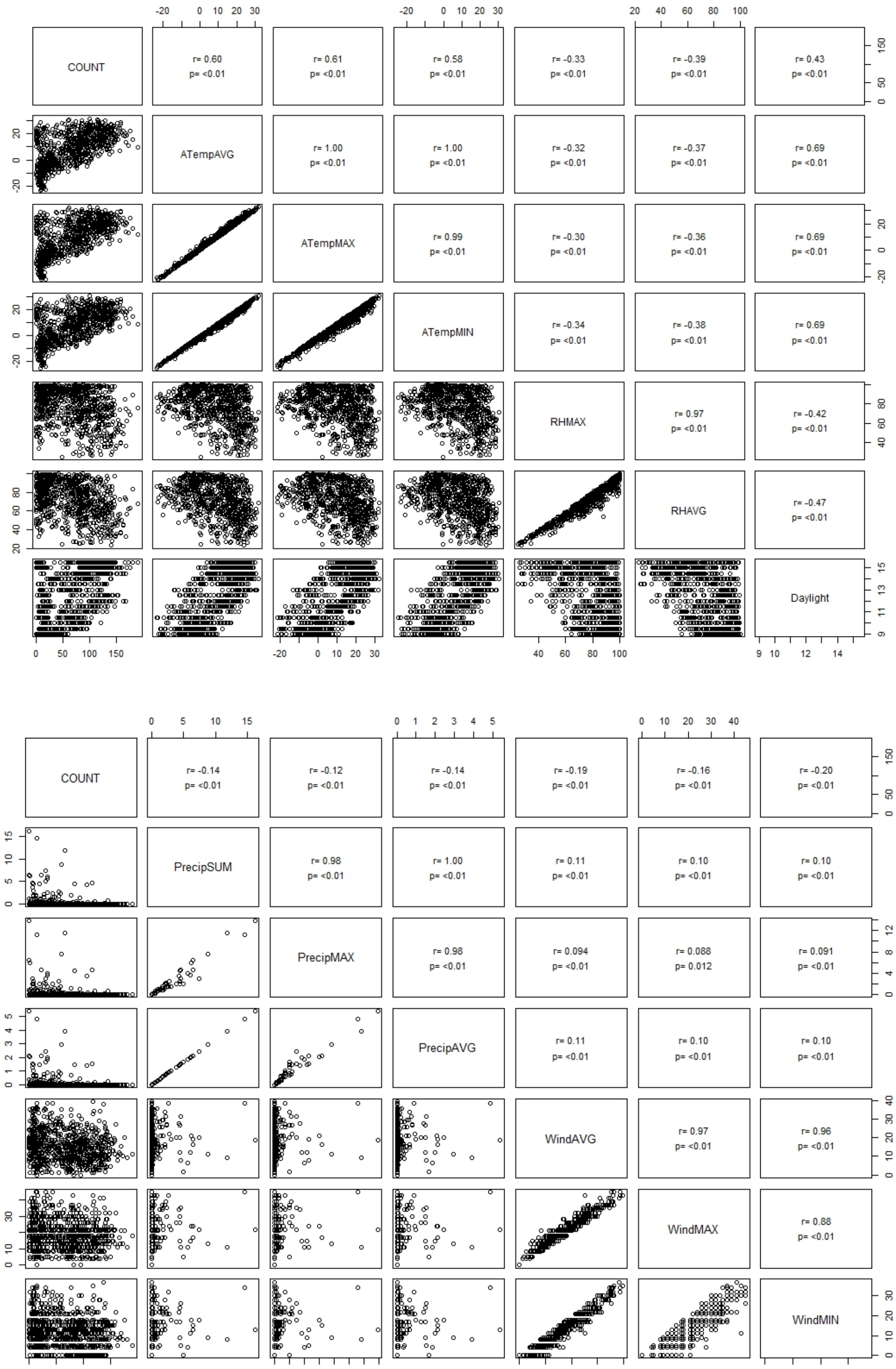


Figure 4.5 – A representative example of the scatterplot matrices of the considered variables from the Laurel Trail at Columbia counter location.

Categorical Variables

Not all variables used in this study are continuous and/or quantitative in nature. As such, not all variables were included in the discussion or correlation matrices provided above due to the nature of the data. By analyzing the qualitative data using boxplots, as shown in Figure 4.6. First, seasonality is reviewed. Seasonality indicates considerable variation in the number of cycling counts across the year, with the winter months experiencing the least, while the summer months experience the highest counts. Additionally, there is a much larger range in daily cycling counts during the summer, potentially due to the variation in temperatures and presence or absence of precipitation. Second, the presence of snow in the current hour has a significant effect on cycling frequencies, resulting in a dramatic reduction of cycling observations. This is also true for the lagged variants of rain and snow, which show that cycling rates remain affected up to three hours after rainfall, as well as 24 hours after snowfall.

4.3 Variable Selection

Due to the number of variables that have been presented in Section 4.2.2, a structured approach is necessary to identify the variables that will be used. To achieve this, correlation matrices are used to identify the variables that are strongly correlated with the response variable (COUNT), as well as other explanatory variables. In this case, explanatory variables that are highly correlated with the response variable are preferred (numbers nearer 1 or -1), while correlations between explanatory variables are ideally, but not exclusively, closer to 0 to avoid complications with collinearity. Table 4.3 shows the correlation matrices used for variable selection. In the bottom-left corner are the correlations of one variable against another, while the upper-right corner shows the corresponding p-values.

For simplicity, all correlations between the response and explanatory variables are presented in Table 4.4. Values that are shaded in grey identify the highest correlated variable with the COUNT response variable, while variables with bolded text represent those that have the most number of strongest correlations within the variable grouping, and therefore are selected for use within this study. The findings in Table 4.4 indicate that the maximum apparent temperature observed during the AM or PM peak travel period has the most number of highest correlations out of the two other alternatives: the average and the minimum observed apparent temperatures. Similarly, Table 4.4 identifies relative humidity (where the average values are selected), rain (average rainfall is selected), and wind speed (minimum wind speed is selected) as variables that should be included in this study. Daylight has no alternative variable form, therefore it remains unchanged as the number of hours of daylight in a day. Where deviation from the previously mentioned variable selection method occurs is with regards to rainfall. While the average rainfall during the AM or PM peak period is identified as being the best variable to represent rain within the analysis based on the results of Table 4.4, this author believes that the sum of rainfall during peak periods is the most intuitive and suitable form. The sum of rainfall during a period of time is also supported and used by Ahmed et al. (2010). In addition, there is very little reported difference between the correlations of the two values against the response variable, therefore there should not be any appreciable negative effects from using the sum over the average rainfall values. With suitable candidate variables identified for use in this study, a review of the variables' characteristics was undertaken to determine if any should be excluded. Hours of daylight was identified as a variable that should be excluded due to the strong correlation between it and the apparent temperature variable. To mitigate concerns over multicollinearity, this variable was removed from further consideration and inclusion in this study. Despite increasing hours of daylight suspected of being linked with increased safety and security of cyclists (e.g. Tin Tin et al., 2012; Thomas et al., 2013; Wadud, 2014), several other authors have identified that daylight has only marginal positive effects on cycling frequencies (e.g. Phung & Rose, 2007; Behan & Lea, 2010; Flynn et al., 2012), further supporting this variable's omission. The last variable to be excluded is relative humidity. While it may play a crucial role in comfort levels of cyclists during warmer months, the effects of this variable are already included within the apparent temperature variable (see Section 3.3.4 for details), making a separate relative humidity variable redundant.

Next, as this study is borrowing from a past study, it is important to consider the meteorological differences between the two study areas. Ahmed et al. (2010) performed a study on the effects of weather on cycling frequencies in Melbourne, Australia, which experiences warm temperatures and no snow, among other differences. Given Waterloo's location in a region that receives annual snowfall and a full range of temperatures from well-below to well-above the freezing point, considerations must be made to accommodate their effects. Therefore, this research which has been inspired by the work of Phung and Rose (2007) and Ahmed et al. (2010) aims to better represent typical Canadian weather conditions and cycling frequencies by including weather variables that are able to represent both winter and summer weather conditions.

Additionally, assessments were undertaken to identify whether select variables (i.e. apparent temperature, precipitation, and wind speed) should be included as continuous/quantitative or categorical variables. By interpreting added-variable plots (also known as partial regression plots) for the proposed variables, the effects of the three aforementioned variables were assessed. It was determined that apparent temperature and precipitation exhibit non-linear relationships with the response variable (cycling counts), while wind speed displays a linear relationship (see Appendix for results). Therefore, apparent temperature and precipitation will henceforth be included as categorical variables, while wind speed will remain as a continuous variable. This selection is supported by the literature as temperature and apparent temperature (e.g., Ahmed et al., 2010; Saneinejad et al., 2012; Böcker & Thorsson, 2013), as well as precipitation (e.g., Phung & Rose, 2007; Wadud, 2014) are commonly found to be non-linear with cycling counts, while wind speed is commonly found to have a linear relationship with cycling counts (e.g., Flynn et al., 2012; Wadud, 2014).

	ATempAVG	**ATempMAX**	ATempMIN	**RHAVG**	RHMAX	**PrecipAVG**	PrecipMAX	PrecipSUM	WindAVG	WindMAX	**WindMIN**	**Daylight**
Iron Horse Trail	0.64	0.64	0.64	-0.51	-0.48	-0.13	-0.11	-0.13	-0.077	-0.077	-0.067	0.43
Laurel Trail at Columbia	0.60	0.61	0.58	-0.39	-0.33	-0.14	-0.12	-0.14	-0.19	-0.16	-0.20	0.43
Laurel Trail at Erb	0.73	0.73	0.72	-0.58	-0.51	-0.12	-0.095	-0.12	-0.17	-0.16	-0.18	0.63
Laurel Trail at Silver Lake	0.63	0.63	0.63	-0.15	-0.13	-0.044	-0.026	-0.044	-0.23	-0.21	-0.23	0.53
Laurel Trail at Weber	0.73	0.73	0.73	-0.61	-0.56	-0.11	-0.11	-0.086	-0.12	-0.11	-0.13	0.56

Table 4.5 - Correlations calculated in R of each continuous explanatory variable against the response variable (COUNT). Cells shaded in grey represent the variant of that variable that has the highest correlation with the response variable.

After considering the origin of the model initially produced by Phung and Rose (2007) and the application of the model in a northern climate several adaptations have been made, notably the inclusion of snowfall and lagged snowfall variables to account for precipitation during the winter months. A full list of variables that have been selected for inclusion in the model are identified in Table 4.5, including a description and identification of the type of variable being used.

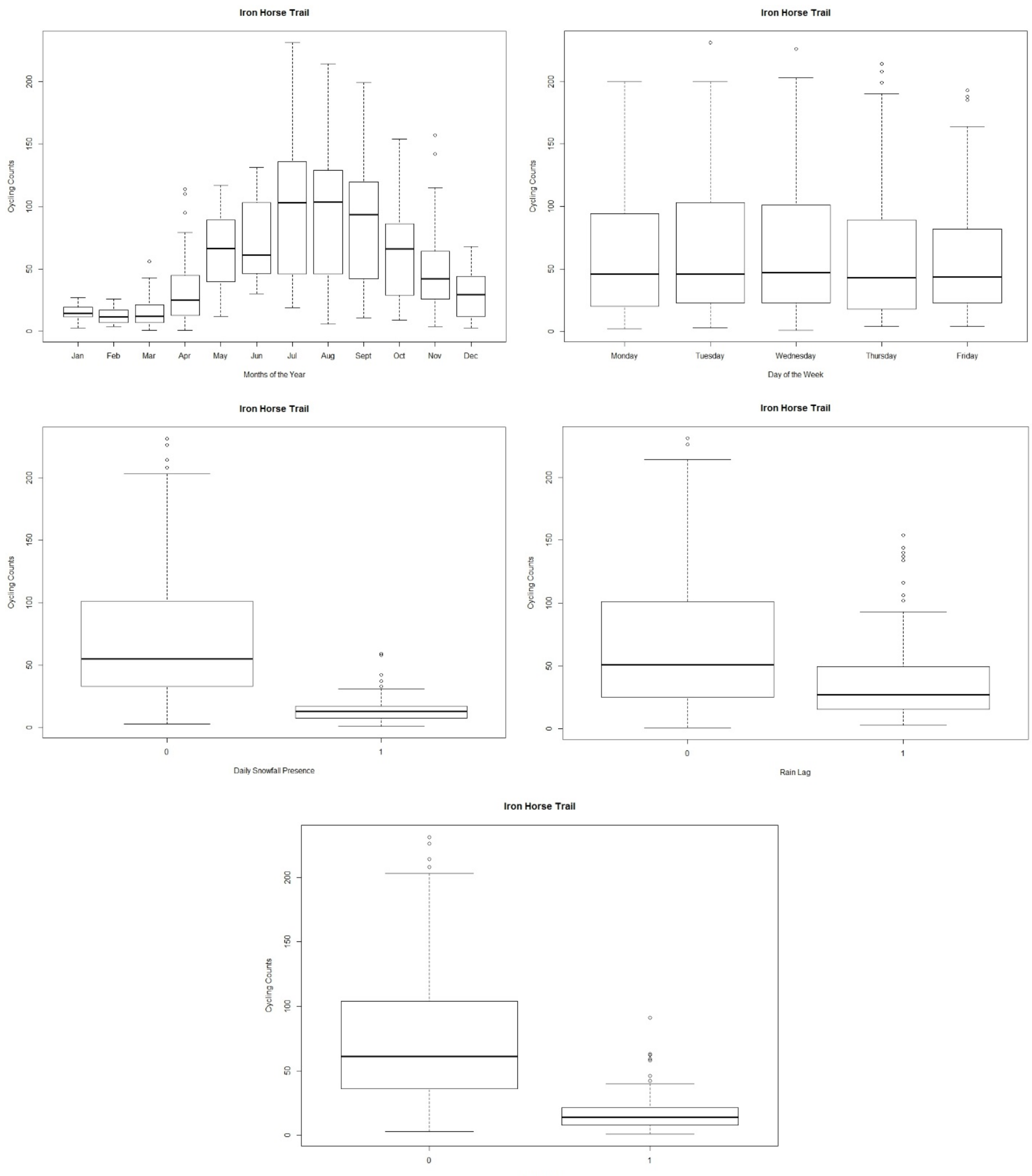


Figure 4.6 - Boxplots of the categorical variables that are considered for inclusion within this study, from the Iron Horse Trail counter location.

Variable	Variable Name	Description
Cycling Counts	COUNT	Response variable - Number of cyclists detected during the AM and PM peak travel periods
Maximum Apparent Temperature	ATempMAX_D	Categorical variable for the maximum calculated apparent temperature during the AM and PM peak travel periods
Total Rainfall	PrecipSUM_D	Categorical variable for the total rainfall during the AM and PM peak travel periods
Snow Presence	SnowPresence	Binary variable for the presence of snow during the AM and PM peak travel periods (0 or 1)
Lagged Rain	RainLag	Binary variable for the presence of rain during the AM and PM peak travel periods, or up to three hours prior (0 or 1)
Lagged Snowfall	SnowLag	Binary variable for the presence of snow during the AM and PM peak travel periods, or up to 24 hours prior (0 or 1)
Minimum Wind Speed	WindMIN	Continuous variable for the minimum wind speed observed during the AM and PM peak travel periods
Month of the Year	MONTH	Categorical variable for the month of the year

Table 4.6 - List of variables under consideration for inclusion in final model.

Following variable selection, it is important to outline the expectations for the findings the variables identified in Table 4.5 may produce based on prior knowledge of the weather that is experienced in southern Ontario. Given the general understanding that cycling is greater in the summer than the winter, it is expected that there would be a generally strong positive correlation between maximum apparent temperature and cycling counts, however this would change depending on the temperature level and count facility. Total rainfall and the presence of snow would be expected to have strong negative correlations with cycling counts, as the presence of rain and snow can be assumed to result in a decreased desire to cycle. Similar expectations exist for the lagged variables for rain and snowfall, due to the presence of wet and muddy, or slippery and treacherous trail conditions. The relationship between minimum wind speed and cycling counts is expected to be a weak negative correlation. Section 2.5.2 of the literature review discusses the range of findings relating to wind speed and the difficulties that researchers have in identifying whether it is beneficial or detrimental to overall cycling frequencies, however it is generally suggested there is a negative effect on cycling frequencies. Finally, month of the year is expected to have varying results depending on the time of year in question: spring, summer, and fall months should all exhibit strong positive correlations, while the winter months should display a strong negative correlation due to the combination of freezing temperatures, icy and snowy conditions.

4.4 Model Assessments

With variable selection completed it is important to assess the validity of the proposed model. The model assessment procedure is a two-stage process. The first stage is to check that the model meets all assumptions and conditions of a Quasi-Poisson regression. Next, due to this research requiring the ability to predict the effects of future weather conditions on cycling frequencies, the second stage assesses the predictive capabilities of the model through the use of a process called "cross-validation".

Assumptions and Conditions of a Quasi-Poisson Regression

Based on the assessment procedures outlined in Section 3.5 the model has been assessed on its fit within a Quasi-Poisson Regression. Figure 4.7 is used to assess the assumptions and conditions of a Quasi-Poisson Regression. Figure 4.7 indicates that the variables are independently observed and are not influencing one another through the generally even distribution of points with no apparent patterns. Other assumptions to mention are that the mean and variance of the model must be identical, and a Poisson distribution (positive-skew) must be present through the use of count data. Typically, a Poisson regress requires that the variance equals the mean (dispersion parameter equals a value of 1). It has been identified through testing that this model experiences overdispersion, which resulted in the use of a Quasi-Poisson model which accommodates overdispersion of data in the model. Therefore, this assumption is not relevant for this approach (Laerd Statistics, 2017). At this point, all assumptions and conditions have been satisfied.

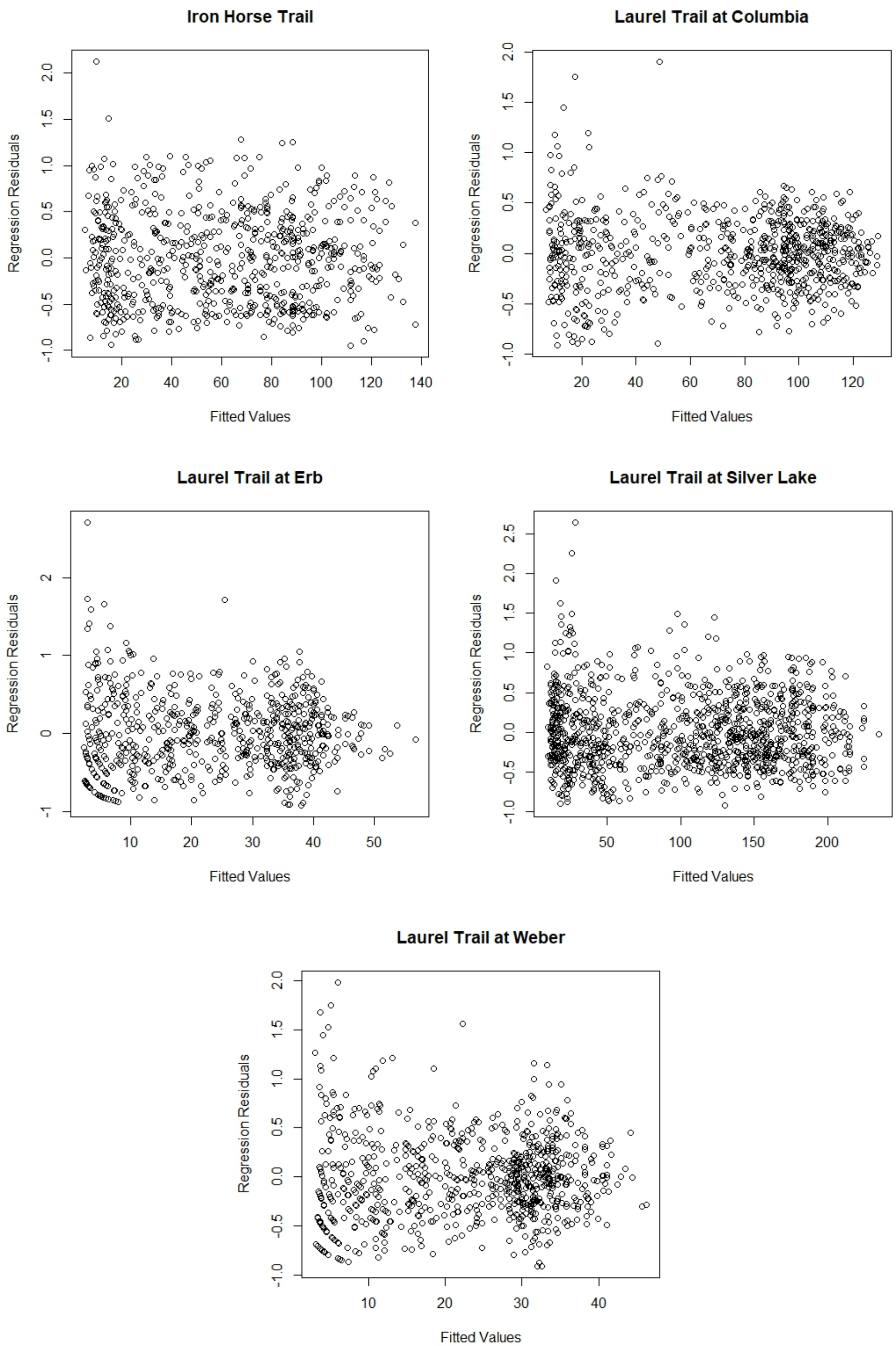


Figure 4.7 - Plots of regression residuals versus fitted (predicted) values used to assess the assumptions and conditions.

Cross-Validation

The last assessment required is to verify the model's predictive abilities. As stated in Section 3.5, a repeated 10-fold cross validation on a Quasi-Poisson GLM using the *caret* package in the program R was used (R Core Team, 2016; Kuhn, 2017). The original datasets were randomized and partitioned into a training and test set, with the model calibrated using the 'train' function in the *caret* package with the data found in the training set for each counter facility. All models were trained and tested using this function and assessed by comparing the root mean square error (RMSE) and R^2 metrics that were produced by the *train* function. The predictive abilities of the models were then tested by introducing the testing sets from the originally partitioned datasets, using the *predict* function in R, comparing the observed and predicted values using the *Metrics* package (Hammer, 2017). Table 4.6 summarizes the outcome of the training and test sets, which exhibits low RMSE's and low variations between training and test sets, as well as moderate R^2 values. Through the use of this function, it may be concluded that the current model is adequate for predictions and may be used to analyze the effects of weather and climate change on cycling frequencies.

Site		Iron Horse Trail	Laurel Trail at Columbia	Laurel Trail at Erb	Laurel Trail at Silver Lake	Laurel Trail at Weber
Training Set	R^2	42.70 %	37.42 %	45.18 %	51.51 %	46.25 %
	RMSE	35.99	36.16	12.58	55.87	10.17
Test Set	R^2	39.21 %	34.70 %	43.99 %	46.05 %	44.88 %
	RMSE	38.32	37.29	13.68	57.83	10.55

Table 4.7 - Summary of the model cross-validation processes.

4.5 Model Specification

After proving the predictive abilities of the model it is now appropriate to detail the model that has been extensively verified and assessed. The model continues to follow the functional form that was displayed in Equation 3.4, which is a Quasi-Poisson Regression. With this form in mind, the following regression equation (Equation 4.1) has been developed with descriptions of the variables presented in Table 4.7:

$$
\begin{aligned}
&logE[COUNT_{it}] \\
&\quad = \beta_0 + \sum_{j=1}^{11} \beta_{iMonth,j} Month_{jt} + \sum_{k=1}^{10} \beta_{iATempMAX,k} ATempMAX_{kt} \\
&\quad + \sum_{m=1}^{3} \beta_{iRainSUM,m} RainSUM_{mt} + \beta_{iWindMIN} WindMIN_t \\
&\quad + \beta_{iSnowPresence} SnowPresence_t + \beta_{iRainLag} RainLag_t + \beta_{iSnowLag} SnowLag_t \\
&\quad + \varepsilon
\end{aligned}
$$

Equation 4.1 - Proposed Quasi-Poisson Regression model form for use in this research.

By using the model presented in Equation 4.1, the descriptive statistics of the model are produced, which are shown below in Table 4.8. Table 4.8 identifies that when the model is applied to each of the five counters it is expected to perform reasonably well. Each model shows a moderately-high R^2 value (calculated by using: $1 - \frac{deviance}{null\ deviance}$), identifying that the regression line fits well with the observed data. A value for the dispersion parameter is also presented in Table 4.8 to demonstrate the application of a Quasi-Poisson model to correct for overdispersion of a traditional Poisson regression (which would assign a restrictive value of 1). Overall, the model presented in Equation 4.1 shows promise as proven by the assessments that were conducted in Section 4.4 and the preliminary results presented in Table 4.8.

Variable	Variable Name	Variable Type	Levels
Daily AM (07:00 – 09:00) and PM (16:00 to 18:00) Bicycle Counts	COUNT	Response	N/A
Month of the Year	Month (*j*)	Categorical	January *** February March April May June July August September October November December
Maximum Apparent Temperature (°C)	ATempMAX (*k*)	Categorical	Extreme Cold (< -15.1°C) Very Cold (-15.0°C – -10.1°C) Cold (-10.0°C – -5.1°C) Freezing (-5.0°C – 0.1°C) Near Freezing (0.0°C – 4.9°C) *** Cool (5.0°C – 9.9°C) Mild (10.0°C – 14.9°C) Warm (15.0°C – 19.9°C) Very Warm (20.0°C – 24.9°C) Hot (25.0°C – 29.9°C) Very Hot (≥ 30.0°C)
Total Rainfall (mm)	PrecipSUM (*m*)	Categorical	No Rain (< 0.2 mm)*** Light Rain (0.2 – 0.9 mm) Moderate Rain (1.0 – 2.9 mm) Heavy Rain (≥ 3 mm)
Minimum Wind Speed (km/h)	WindMIN	Continuous	N/A
SnowPresence	SnowPresence	Binary	False*** True
RainLag	RainLag	Binary	False*** True
SnowLag	SnowLag	Binary	False*** True

*Table 4.8 - List of key explanatory variables used in preliminary regression equation (*** denotes the base case of a categorical or binary variable).*

Location	Iron Horse Trail	Laurel Trail at Columbia	Laurel Trail at Erb	Laurel Trail at Silver Lake	Laurel Trail at Weber
R^2	61.26%	76.70%	69.08%	71.31%	66.76%
Dispersion Parameter	14.40	7.25	4.04	18.38	3.15
P-Value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Table 4.9 - Regression statistics for each counter facility using the model presented in Equation 4.1.

4.6 Summary of Preliminary Findings

The findings presented in the above sections provide an overview of the data and brief insights into the relationships between the variables. While this information is not as in depth and explanatory as the findings that will be presented in Chapter 5, it is of use in this research. Preliminary data analysis allows for a better understanding of the data and its inherent qualities, as well as identifies where relationships exist, expected or unexpected, between different variable pairings. All of this information ultimately culminates into a more informed and decisive variable selection process, as discussed above in Section 4.3. Additionally, preliminary data analysis offers the first opportunity to compare findings with other researchers. Typically, cycling is more frequent during periods of warm, dry, and low wind conditions, and less frequent when adverse conditions (e.g. snowfall, rain, high winds) are present. Both of these generalizations are well supported in the literature with this research proving to be consistent with these findings, as seen in Figure 4.5 and Table 4.3, which show the correlation between cycling counts and weather variables.

Finally, this chapter has detailed the model that will be used within the analysis of the impacts of weather and climate change on cycling frequencies. The model form has seen several major changes from the base log-linear model used by Phung and Rose (2007) and Ahmed et al. (2010) shown in Equation 3.3. Their models, log-transformed multiple linear regressions (discussed in Section 3.6), have a number of limitations when used to model count data. A Quasi-Poisson regression, used in this research, in place of a log-linear model is better able to model count data that does not follow a nearly normal distribution and linear dispersion, required components in linear regression and Poisson regression, respectively. Additionally, the inputted variables have been altered to better represent the conditions found within southern Ontario, Canada. Variables were selected based on findings from the literature, preliminary data analysis, and inherent knowledge on the impacts of cyclists in the specified region. Finally, this model was assessed using the assumptions and conditions of a Quasi-Poisson regression, as well as cross-validation to ensure that it holds predictive capabilities, which will be an important feature in Chapter 5.

5.0 Results & Discussion

5.1 Introduction

After detailing the methods used to conduct this study in Chapter 3, and presenting results from the preliminary analysis in Chapter 4, the regression results may now be identified and discussed. The findings presented within this chapter are calculated from the Quasi-Poisson regression model displayed in Equation 4.1. This model was determined to have predictive abilities using the cross-validation procedure outlined in Section 3.5, and verified through the procedure outputs as seen in Section 4.5. A separate set of results have been produced for each of the five counter facilities for both current weather (Section 5.2) and future weather (i.e., the effects of climate change; Section 5.3) cycling frequency analyses.

This chapter reports the findings from the statistical analysis that was conducted using the aforementioned methods. Section 5.2 shares the model results for the current weather and cycling frequency analysis, including interpretation and a discussion on the model outputs and their application in daily life. Section 5.3 reports the model outputs from the future weather (climate change) and cycling frequency analysis. This section will be oriented in a similar format as Section 5.2, in addition to a comparison between emissions scenarios displaying the potential impacts of different emission levels in a mid-century climate. Finally, Section 5.4 is the culmination of this research, whereby the effects of weather on cycling will be assessed both at present and at mid-century providing a glimpse as to how cycling may be impacted due to a changing climate.

5.2 Weather and Cycling Results

The basis for this section revolves around the first research question presented in Section 1.3, which asks "how is utilitarian cycling impacted by weather conditions?" In order to answer this question each counter facility has its cycling counts regressed against weather and temporal variables (shown in Section 4.6) to effectively model the sensitivity of Waterloo utilitarian cyclists in current weather conditions. The findings, therefore, identify the degree to which cycling is affected by various weather conditions or different levels (i.e., temperatures or amounts of precipitation), as will be discussed in further detail below. It is important to recall that this research uses an absolute model that does not take into effect systematic seasonal

Locations		IHT		LTC		LTE		LTSL		LTW	
Variables		Coef.	% Δ	Coef.	% Δ	Coef.	% Δ	Coef.	% Δ	Coef.	% Δ
Month	January	BASE		BASE		BASE		BASE		BASE	
	February	-0.291	-25.237	0.104	10.971	-0.074	-7.102	-0.300	-25.916	0.066	6.848
	March	-0.467	-37.343	-0.001	-0.121	0.170	18.563	0.202	22.390	0.031	3.197
	April	0.106	11.214	0.632	88.125	0.768	115.613	0.859	136.037	0.493	63.650
	May	0.279	32.244	1.440	322.147	0.959	160.893	1.401	305.805	0.583	79.167
	June	0.285	32.928	1.140	212.662	1.101	200.693	1.271	256.416	0.601	82.447
	July	0.546	72.702	1.002	172.434	0.873	139.302	1.166	220.956	0.632	88.134
	August	0.607	83.402	1.167	221.346	0.864	137.241	1.036	181.762	0.556	74.351
	September	0.564	75.747	1.303	267.855	0.841	131.800	1.427	316.687	0.592	80.808
	October	0.449	56.696	1.290	263.203	0.824	127.985	1.235	243.812	0.632	88.075
	November	0.351	42.013	1.110	203.346	0.640	89.700	0.829	129.141	0.447	56.403
	December	0.119	12.692	0.367	44.281	0.194	21.441	0.176	19.210	0.147	15.861
Apparent Temperature	Extreme Cold	-0.591	-44.621	-0.305	-26.289	-0.827	-56.275	-0.514	-40.170	-0.714	-51.026
	Very Cold	-0.616	-45.966	-0.456	-36.640	-0.657	-48.139	-0.459	-36.783	-0.607	-45.515
	Cold	-0.347	-29.331	-0.150	-13.941	-0.345	-29.154	-0.236	-20.998	-0.379	-31.560
	Freezing	-0.155	-14.334	-0.016	-1.602	-0.101	-9.581	-0.216	-19.438	-0.111	-10.540
	Near Freezing	BASE		BASE		BASE		BASE		BASE	
	Cool	0.131	14.009	0.099	10.428	0.209	23.247	0.107	11.324	0.223	25.040
	Mild	0.342	40.706	0.232	26.056	0.405	49.993	0.142	15.308	0.399	49.030
	Warm	0.517	67.646	0.242	27.425	0.525	69.080	0.242	27.349	0.476	60.978
	Very Warm	0.470	59.958	0.263	30.076	0.596	81.509	0.180	19.678	0.497	64.449
	Hot	0.396	48.620	0.435	54.514	0.665	94.392	0.049	5.060	0.638	89.260
	Very Hot	0.567	76.287	0.331	39.229	0.688	98.886	0.266	30.442	0.733	108.106
Precipitation	No Rain	BASE		BASE		BASE		BASE		BASE	
	Light Rain	-0.040	-3.931	-0.036	-3.537	-0.111	-10.505	-0.002	-0.241	-0.155	-14.375
	Moderate Rain	-0.465	-37.186	-0.348	-29.397	-0.388	-32.173	-0.102	-9.671	-0.371	-30.990
	Heavy Rain	-0.664	-48.519	-0.279	-24.354	-0.534	-41.387	0.112	11.850	-0.486	-38.514
Wind Speed		0.018	1.853	-0.002	-0.200	0.004	0.425	0.002	0.152	0.008	0.806
Snow Presence		-0.021	-2.123	-0.441	-35.641	-0.314	-26.947	-0.066	-6.381	-0.338	-28.677
Precipitation Lag		-0.260	-22.872	-0.113	-10.727	-0.207	-18.731	-0.215	-19.366	-0.142	-13.259
Snow Lag		-0.594	-44.803	-0.068	-6.585	-0.019	-1.880	-0.380	-31.624	-0.144	-13.390
Intercept		3.399		3.064		2.119		3.644		2.311	
R^2		61.26%		76.70%		69.08%		71.31%		66.76%	

Table 5.1 - Regression coefficients and percentage changes in cycling frequencies derived from the current weather and cycling analysis. All shaded values are significant at the 95% level[5].

changes in cycling frequencies, therefore annual events, such as the end of a school term may report a reduction in cycling frequencies, which may not be a result of a weather or temporal variable. As these systematic seasonal changes will affect all counter facilities at the same time, it

[5] The first row of the table lists the counter facilities by their short form. The following is a list of the location names: Iron Horse Trail at John St. (IHT), Laurel Trail at Columbia Ave. (LTC), Laurel Trail at Erb St. E. (LTE), Laurel Trail at Silver Lake (LTSL), and Laurel Trail at Weber St. N. (LTW). These short forms are used throughout this chapter.

is expected that this will not be a concern when reporting the regression results. The results of the regression may be found in Table 5.1, where all shaded cells indicate variables or levels that are significant at the 95% level or greater.

Prior to further discussing the results of the weather and cycling analysis it is important to identify what the most influential variables are within the model outlined in Equation 4.1 to aid in interpretation of the model results. Through use of a simplified model each variable was individually assessed to determine the impact on the model's R^2 value, or goodness-of-fit. Through this process the most influential variable used in the overall model was determined to be maximum apparent temperature, with the variable month of year appearing to also be largely influential, which coincides with the larger estimated coefficients listed in Table 5.1. The least influential variables were determined to be the variables minimum wind speed and rain lag, which are generally reflected in the lower regression coefficients of these two variables. With this information in mind it is easier to understand the variable magnitudes of the effects of the presented variables and how they alter the overall regression results.

The remainder of this subsection will be used to discuss the resultant regression coefficients. The table displays two values for each variable or variable level: the left is the regression coefficient, or the estimated parameter value calculated by the regression model; the right is the proportional effect of Y with a one-unit change in X or a percentage change relative to the respective base case for categorical variables, which is identified in Table 5.1. All counter locations show moderately-strong goodness-of-fit with R^2 values ranging from about 61% to 77%, with all models having been found to be statistically significant at the 95% level.

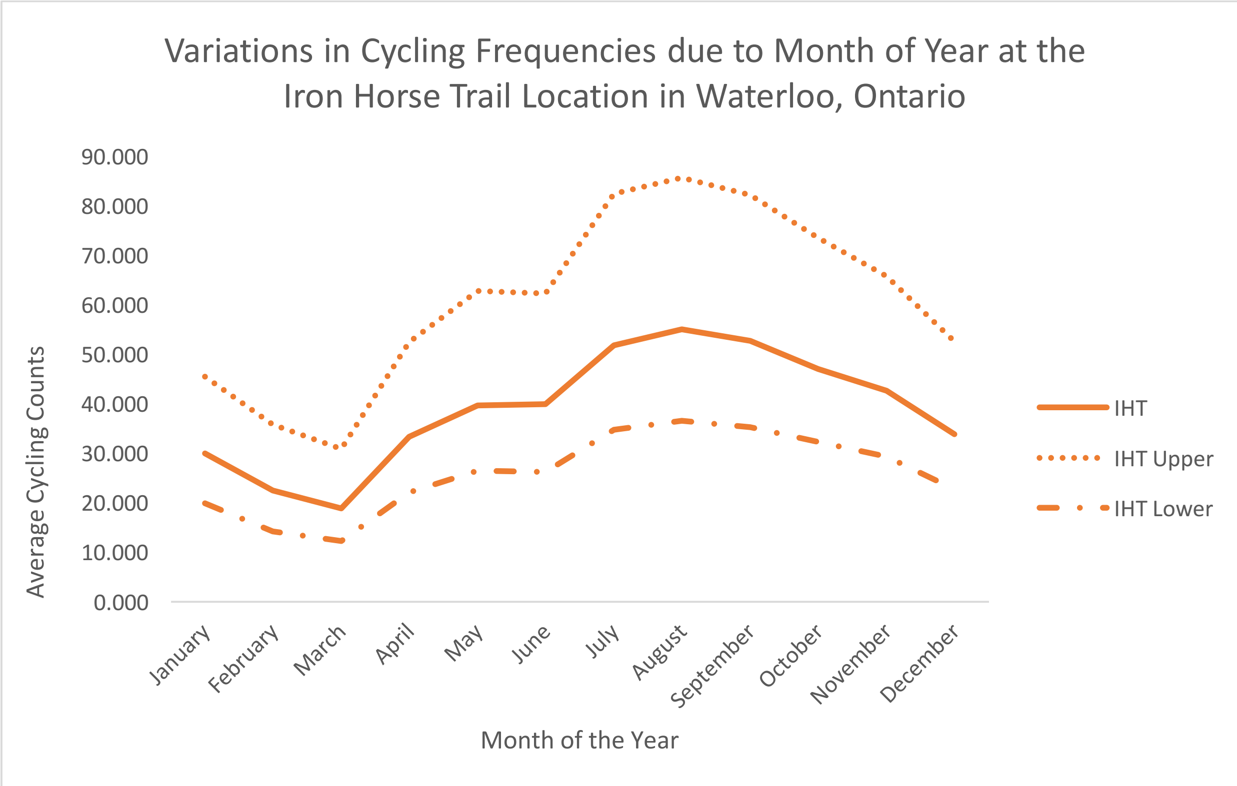
5.2.1 Seasonal Effects on Cycling Frequencies

Beginning with the 'Month' variable, January was used as the base case for which all other levels (i.e. months) are compared against. The month parameter suggests that as the year progresses from January (winter) to June (summer) cycling frequencies increase dramatically, with some sites experiencing as much as a 322% increase in June cycling rates over January (see Table 5.1). Proceeding beyond the month of June, there is an expected general decline in cycling rates which is likely due to decreasing temperatures and shortened daylight hours as the year progresses towards the winter season. This shows the expected trend that cycling rates are lowest during the winter season and greatest during the summer season. An interesting dip in cycling rates occurs between May and September across some sites (see Figure 5.1 – Laurel Trail at Silver Lake). This is likely due to the absence of students and staff traveling to the post-secondary institutions and public school systems in April and June, respectively, later returning in September when the cycling rates return to higher levels. These findings are similar to those reported in other publications (e.g. Miranda-Moreno & Nosal, 2011) as seasonal variations in cycling appear to be consistent throughout most northern regions with four distinct seasons, and school systems that do not operate or run less frequently during the summer months.

The effects of seasonality appear to also have different impacts on cycling rates across Waterloo. The Laurel Trail at Silver Lake (Figure 5.1) and Laurel Trail at Columbia show a very high degree of seasonal variations, with the period of late spring to early fall clearly exhibiting much larger cycling rates than other times of the year. Conversely, the Laurel Trail at Weber and Iron Horse Trail (Figure 5.1) show less variation over the course of the year, with greater consistency across the spring, summer, and fall seasons, with winter having an obvious effect on cycling rates at these and all other counter locations.

Also notable are the levels of significance at each counter facility. Four of the five facilities are significant from April to November, while the winter months are not significant. These months experience low cycling rates, but the response variable can vary dramatically depending on the conditions of a given winter season (e.g. warm and wet versus cold and snowy). Also notable is that, unlike the other facilities, the Iron Horse Trail is not significant at the 95% level through most of the year despite demonstrating a similar unimodal pattern as other sites, albeit at a much smaller magnitude.

Finally, Figure 5.1 illustrates an important consideration when modelling the impact of month of year on cycling frequencies: uncertainty surrounding the estimated outputs. The hashed lines of Figure 5.1 for both the Iron Horse Trail and Laurel Trail at Silver Lake indicate the degree of uncertainty that surrounds the estimated effects (the solid line) through the use of 95% confidence intervals. It is apparent within Figure 5.1 that a large degree of variation exists in the estimated effects around the summer months, which may be caused by variable weather conditions that deter individuals from cycling, while more favourable days (e.g., warm, no rain) may encourage significantly greater number of cyclists, leading to a wide range of effects depending on the weather conditions, among other factors. These results are therefore viewed as the estimated average effects on cycling frequencies.



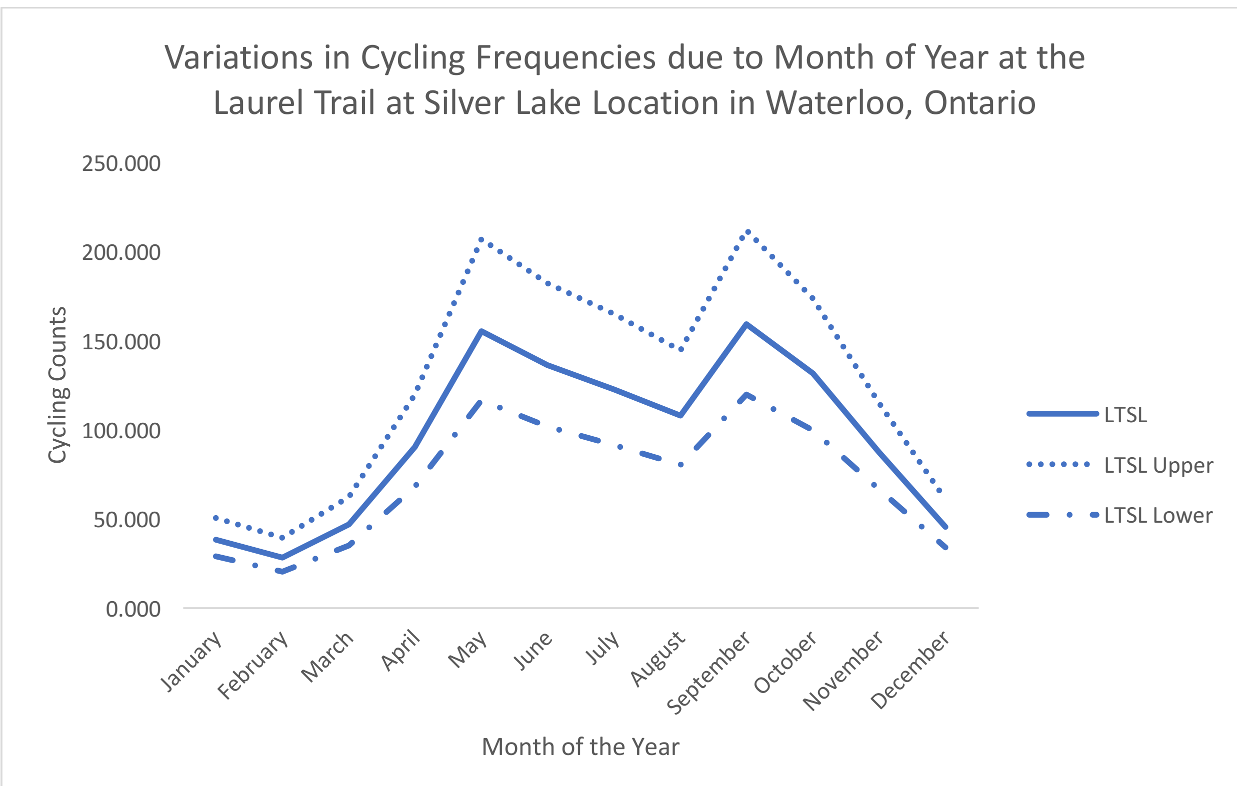
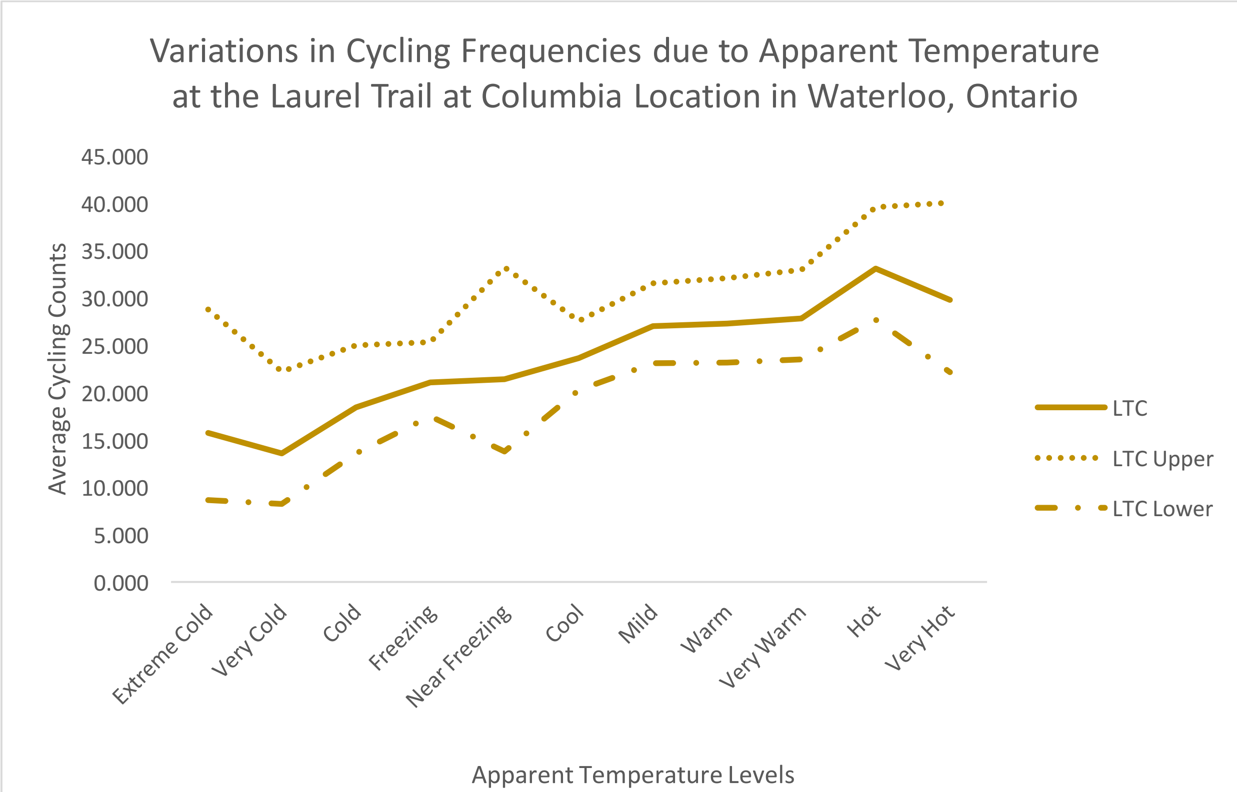


Figure 5.1 – Representative examples of the variations in cycling frequencies as a function of month of year relative to the base case (January), with upper and lower confidence intervals to display the range of estimation uncertainty.

5.2.2 Effects of Maximum Apparent Temperatures on Cycling Frequencies

The apparent temperature variable suggests strong results in that most parameter estimates are significant at the 95% level. General trends are present across most counter facilities, reporting that colder temperatures are less conducive to cycling represented by the negative and progressively decreasing regression coefficients (see Table 5.1), while warmer temperatures encourage cycling due to similar, but positive trends in the regression coefficients. Apparent temperature also shows differing relationships with cycling counts (see Figure 5.2). Facilities like the Laurel Trail at Erb indicate a more linear relationship between cycling rates and apparent temperature, while the Laurel Trail at Silver Lake and the Laurel Trail at Columbia show that this relationship deviates from linearity towards a more erratic pattern. Additionally, the manner in which cyclists respond to extreme temperatures varies by counter location. Whereas all counter locations share similar decreases in cycling rates as the apparent temperature decreases, the changes in cycling rates during warmer weather varies significantly between sites, with the Iron Horse Trail, Laurel Trail at Erb and Laurel Trail at Weber indicating greater rates of change at warmer temperatures. The remaining counter locations show conflicting results, in that a decrease is reported at very high maximum apparent temperatures at the Laurel Trail at Columbia and Laurel Trail at Silver Lake. It is likely that, due to the assumed high volume of student cyclists on these two corridors the decrease in temperatures of 'Hot" and 'Very Hot' maximum apparent temperature conditions may be influenced by the lack of students and staff members cycling along these trails during the summer months, influencing the magnitude of the regression coefficients.

The example graphs presented in Figure 5.2 suggest a general trend in the results seen in Table 5.1. The results for the Laurel Trail at Columbia and Laurel Trail at Erb indicate a deviation from the trend at extreme hot and cold temperatures, while also exhibiting greater variation in the estimated effects of extreme temperatures on cycling counts, as illustrated by the upper and lower confidence intervals. It is at these extremes that it is necessary to consider both the variation in cycling frequencies during extreme temperatures, as well as the model's ability to effectively estimate the effects. While the results displayed in Table 5.1 and Figure 5.2 are based on a wealth of data and robust methods, there remains a need to consider uncertainty when interpreting the estimated effects of the apparent temperature variable on cycling frequencies.



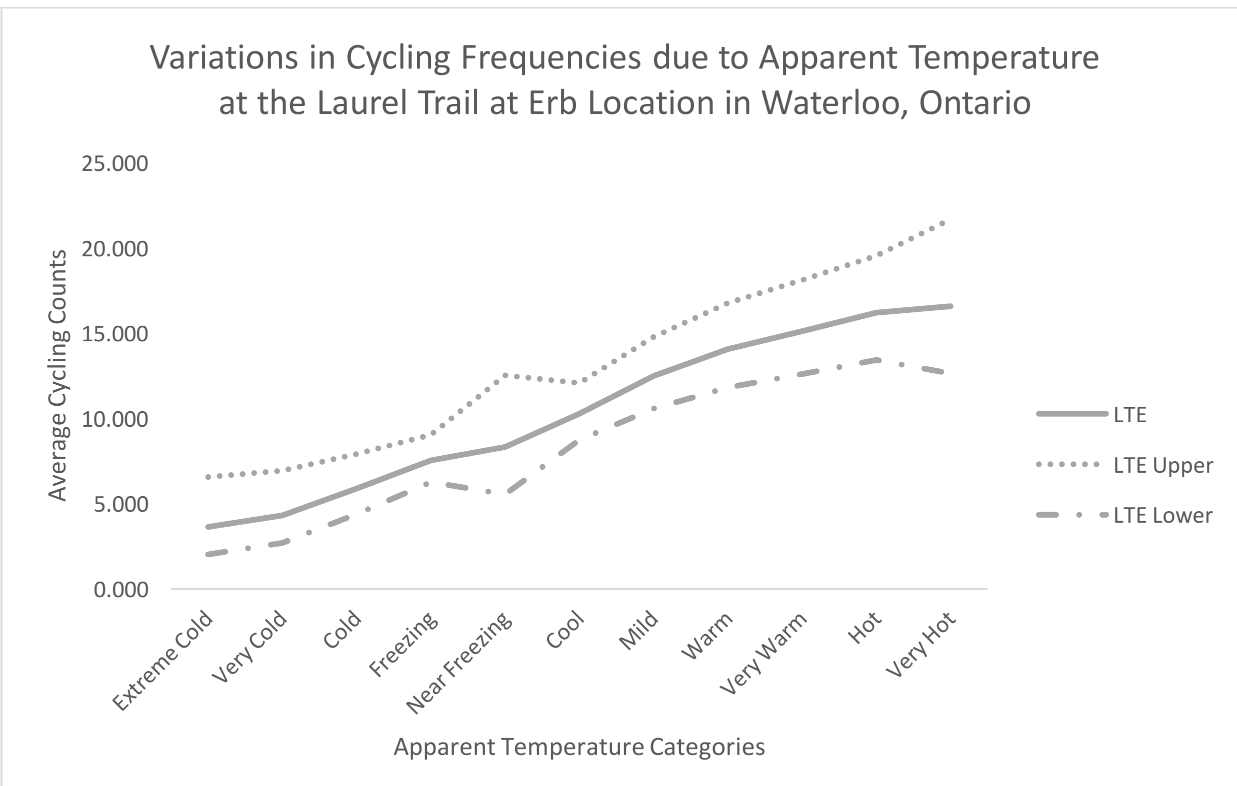
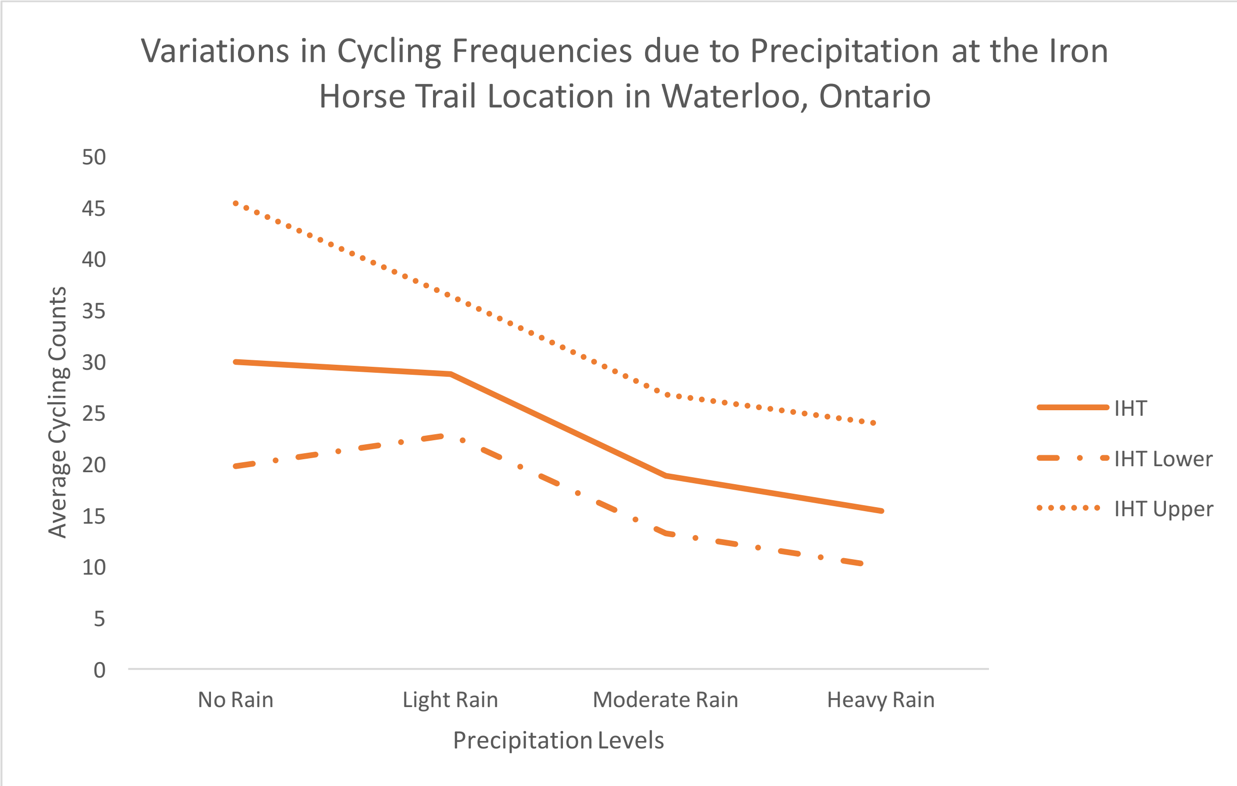


Figure 5.2 - Representative examples of the variations in cycling frequencies as a function of apparent temperature relative to the base case (Near Freezing), with upper and lower confidence intervals to display the range of estimation uncertainty.

These findings are generally similar to many other relevant publications (e.g., Böcker & Thorsson, 2013). Past research has indicated that cycling is strongly correlated with temperature, which is again proven here. Where some reports (e.g.; Wadud, 2014) deviate is with regards to the effects of extreme heat with suggestions that temperature and apparent temperature have a negative effect on cycling frequencies beyond a certain point. In several studies (e.g., Phung & Rose, 2007; Ahmed et al., 2010; Saneinejad et al., 2012) researchers have been able to identify the point at which cycling frequencies will decrease due to extreme heat, or the optimal temperature range where cycling rates are at their maximum. Using the above chart it is not obvious at which point cycling rates achieve their peak or even begin to taper off as each facility demonstrates fairly erratic results.

5.2.3 Effects of Rainfall on Cycling Frequencies

The regression coefficients for the four levels of the categorical variable 'total rainfall' revealed generally consistent results. Prior to the analysis it was hypothesized, based on the findings of other studies, that as rainfall increases in volume cycling frequencies will decrease non-linearly, as reported in Ahmed et al. (2010) and Wadud (2014). The findings of this study are generally similar to those of others mentioned above. Three of the five facilities show a non-linear response to varying levels of rainfall during the AM or PM peak travel period, shown in Table 5.1 and illustrated in part in Figure 5.3. The Laurel Trail at Columbia shows mild deviation, where the negative effects of 'Heavy Rain' on cycling appears to be slightly less impactful than 'Moderate Rain', contrary to the majority of sites. The pattern deviates greatly at the Laurel Trail at Silver Lake, where Table 5.1 suggests that 'Moderate Rain' has a mild negative impact on cycling rates, while 'Heavy Rain' has a positive effect, increasing the number of cyclists rather than decreasing. Upon inspection there were several peak travel periods that had very large cycling counts (greater than 100), which experienced large amounts of rainfall during the three-hour period that were skewing the results. Plausible explanations for this occurrence include cyclists travelling along the trail unbeknownst of the impending heavy rainfall; cyclists travelling via the trail to work or school just before or after a large rainfall within the same hour or three-hour peak period; differing rates of rainfall during the peak travel period(s) that encouraged greater cycling rates; or, a result of local variations in precipitation and the distance between the count facility and the weather station. It should also be noted that this trail is not significant at the 95% level at any level of the



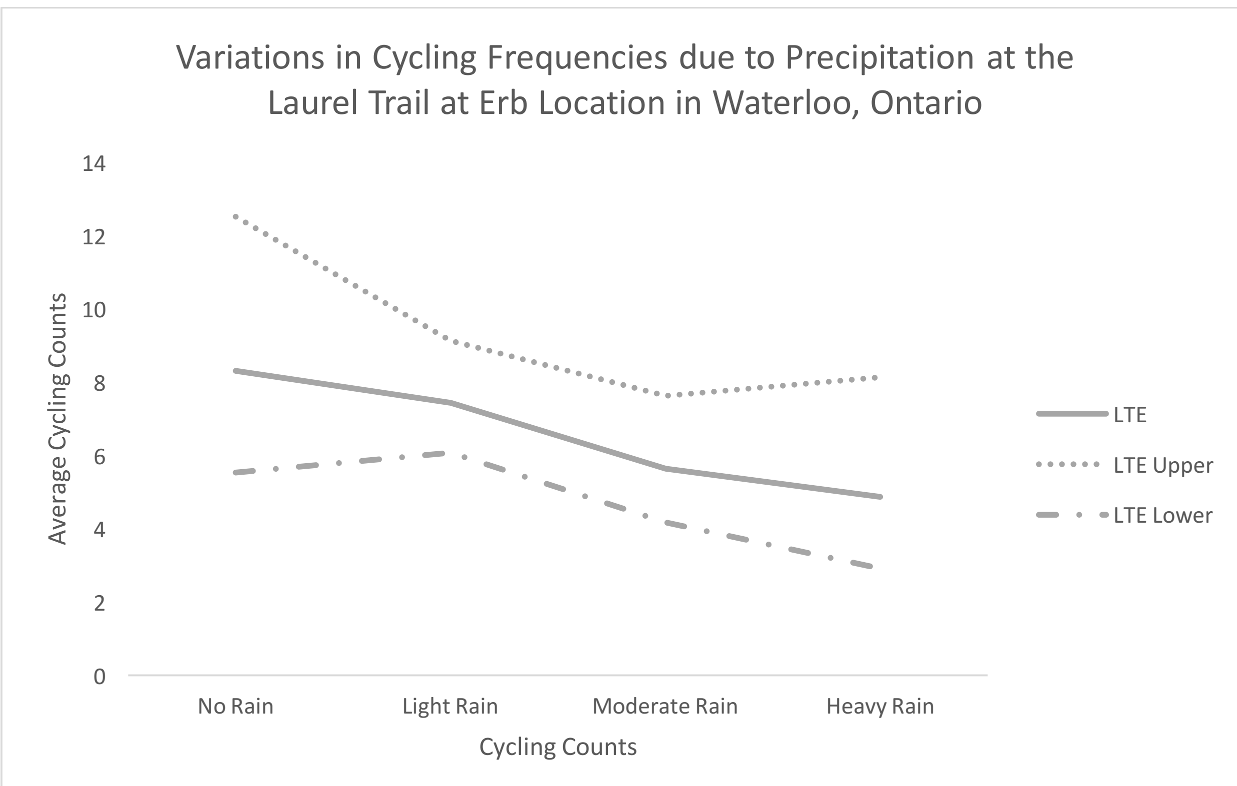


Figure 5.3 - Representative examples of the variations in cycling frequencies as a function of precipitation relative to the base case (No Rain), with upper and lower confidence intervals to display the range of estimation uncertainty.

precipitation variable, likely caused by the wide range of atypical cycling rates per level of rainfall. The Laurel Trail at Silver Lake is the most used multiuse trail in the City of Waterloo connecting key destinations such as two universities and UpTown Waterloo with residential neighbourhoods. Because of its large-scale use there is much greater potential for varying results than along the other four trails. These variations in the estimated effect of precipitation on cycling frequencies are attempted to be captured by the confidence intervals included in Figure 5.3, which seek to display the variations at a 95% confidence level. The area between the upper and lower bounds therefore identifies the range in which this research is 95% confident the estimated effects on cycling frequencies exist.

The lagged effect of rain is also considered in addition to its effects during the current hour. The common results are that rain has a unanimously significant negative effect on cycling frequencies up to three hours after rain is observed, similar to findings by Gallop et al. (2012) and Saneinejad et al. (2012). Despite the consensus across facilities that the lagged effect of rain has a negative impact on cycling frequencies, the degree to which it affects cycling varies, with the Laurel Trail at Columbia, the facility nearest the University of Waterloo, indicates that there is a decrease of about 10%, while the other facilities report between a 13% and 23% decline in cycling frequencies up to three hours after rainfall. It may be speculated that an individual's decision to cycle may be negatively influenced by the prospect of rainfall during the day or the presence of wet roads and cycling paths, some of which are gravel or dirt-covered which may also act as a deterrent to cycling after rainfall.

5.2.4 Effects of Minimum Wind Speed on Cycling Frequencies

Unlike apparent temperature and rainfall, the 'minimum wind speed' variable is the only continuous variable used in this study, and as such the reported results indicate a linear effect. Across all counter facilities there is no consensus on the effects of minimum wind speeds on cycling frequencies. The Iron Horse Trail, Laurel Trail at Erb, Laurel Trail at Silver Lake, and Laurel Trail at Weber report a slight positive linear effect of wind speed on cycling frequencies (1.9%, 0.4%, 0.2%, and 0.8%, respectively, increases in cycling frequency per 1 km/h increase in minimum wind speed, when holding all other variables constant), while the Laurel Trail at Columbia indicates a very small negative linear effect, with a reported reduction in cycling frequency by 0.2% with every 1 km/h increase in minimum wind speed (holding all other variables constant). Despite these generally small effects on cycling frequencies, they are not uncommon as seen in Phung and Rose (2007) and Böcker and Thorsson (2013).

The lack of consensus and small regression coefficients indicate that wind speed does not have a consistent or large impact on cycling frequencies, and that cycling rates appear to change independently of wind speeds. At the Iron Horse Trail location, each 10 km/h increase in minimum average wind speed suggests an increase in cycling frequencies by 18.5% contrary to findings in relevant literature (e.g. Flynn et al., 2012), which suggests that wind speed has a consistent negative effect. The Laurel Trail at Columbia shows a more common slight decrease in cycling rates as wind speeds increase, however it is marginal at -2% with every 10 km/h increase in minimum average wind speed. Of the five counter locations, only the Iron Horse Trail and Laurel Trail at Weber are reported as having statistically significant minimum wind speeds, while the remaining three are statistically non-significant at the 95% level.

5.2.5 Effects of Snowfall on Cycling Frequencies

The presence of snowfall during the current hour is significant at the 95% level three of the five locations where a strong negative effect is reported (a reduction of between 27% and 36%). The remaining two facilities are not significant at the 95% level, but also indicate that there is little effect on cycling frequencies, contrary to findings at other sites. The results from the statistically significant sites suggest that the presence of snowfall which may or may not remain on the ground and accumulate has a fairly strong negative effect on cycling. The statistical insignificance at some sites could be impacted by the rapidity of the snow clearing response by municipal or University of Waterloo maintenance crews, local conditions as well as the transportation choices of individuals using said routes (i.e. continuing to cycle despite the presence of snowfall). If trails are well maintained during winter months they may prompt greater cycling frequencies due to a reduction in the perception of hazardous conditions. It is not known at this point when snow clearing or winter maintenance has occurred within the study area in relation to snowfalls.

Continuing with the effects of snowfall on cycling, the variable ‘Snow Lag’ again shows a large mixture of results across counter facilities. While all reported parameter estimates are negative, only the Iron Horse Trail and Laurel Trail at Silver Lake are significant at the 95% level and show large negative lagged effects of snowfall of about 32% and 45%, respectively. The remaining three facilities are statistically non-significant and show much smaller negative lagged effects of the presence of snow up to 24 hours after snowfall, with one site reporting a marginally negative effect of 1.8% on cycling frequencies.

Both current and lagged effects of snowfall on cycling frequencies are generally consistent with those found in published literature on this topic. Spencer et al. (2013) identifies a significant decrease in cycling rates during snowfall, while Miranda-Moreno and Nosal (2011) find a similar impact due to the lagged effect of snowfall. Current and lagged effects of snowfall may have a negative impact on cycling frequencies due to the perceived safety and comfort implications by cycling in wet, slippery, and cold conditions with potential for reduced visibility, as found by Bidordinova (2010) and Spencer et al. (2013), however the interpretation and statistical significance (or lack thereof) of the results presented in Table 5.1 suggest that further analysis may be required.

5.2.6 Summary of Results of the Effects of Weather on Cycling Frequencies

Above, the findings of the effects of each variable on cycling frequencies at the five counter locations are reported and discussed. Each reported finding provides an opportunity to better understand the impacts of current weather on cycling frequencies in the City of Waterloo, as well as weather conditions where less expected effects may occur. Generally, it may be seen that the findings are similar to those found throughout other literature on this topic: month of year plays a significant role in cycling frequencies; cyclists are more active during warmer temperatures, and less so during cooler temperatures; wind is estimated to have a very minor, if any, and albeit generally statistically non-significant impact on cyclists; and, rainfall and snowfall lead to sharp estimated decreases in cycling rates both during and after their occurrence, although this is not well supported by the corresponding p-values and is subject to a degree of uncertainty. Despite the results aligning with those of relevant literature, there are some discrepancies when comparing the results of Table 5.1 with the a priori expectations outlined in Section 4.3. Examples include the uncertainty surrounding the results during winter months despite consistently low cycling frequencies, and the inconsistent effects of rainfall and snowfall across all counter facilities, when considering either the regression coefficients or their respective significance levels. While general patterns may have been preserved at each counter location discrepancies emerged regarding the accuracy of some regression coefficients, most notably the ‘Heavy Rain’ level of the rainfall variable in one instance. While this is an outlier amongst the other reported findings it is a result that is based on accurate and valid weather observations and must be considered when reviewing the findings in this analysis. Aside from these few cases each set of results were reported as being statistically significant, and all reported moderately-high R^2 values suggesting that the regression model fit the distribution of the data well.

5.3 Climate Change and Cycling Results

The results presented in this section are in response to the second and final research question presented in Section 1.3, which asks "how will climate change potentially impact utilitarian cycling?" CMIP5 Climate change data was provided by Dr. Chris Fletcher at the University of Waterloo. This data specifies the estimated expected changes in temperature and precipitation at mid-century using the multi-model mean for three different emissions scenarios, with other model predictions used to provide a degree of consideration for uncertainties in estimating effects under a changing climate. Therefore, to respond to this question several sets of results are presented for each counter facility. This is to compensate for the uncertainty surrounding which emission scenario is most likely to occur at mid-century. To produce the results that will be discussed below, the same model presented in Equation 4.1 and used above to produce the results in Section 5.2 is used, albeit with updated values for select variables to account for changes in future weather due to climate change. Below, the results will be displayed and discussed, with comparisons made between the findings presented here and in relevant literature.

Using the climate change data generated by the CMIP5 climate model predictions are made on how changes in future climate will impact cycling frequencies. Climate change will ultimately impact all aspects of future weather conditions (to which degree remains uncertain), however due to the limitations and available data of climate change models, only key variables will be discussed below. Changes in cycling frequencies based on month of year, maximum apparent temperature and total rainfall during peak travel periods will be discussed in detail. Variables that are not predicted in the CMIP5 climate model (i.e. relative humidity, wind speed, snowfall, snow lag, and rain lag) are held constant at present day observations during this exercise due to unavailable or uncertain predictions. The presence of snowfall, and by association the lagged effects of snowfall, are not provided by the CMIP5 climate model. However, the variables are altered to accommodate changes in future weather by reclassifying any snowfall event as false once the maximum apparent temperature during that period reaches above 2°C (the highest maximum apparent temperature at which snowfall was reported during this study).

	IHT	LTC	LTE	LTSL	LTW	Average
Observed	38.9	57.7	16.2	95.8	15.4	44.8
RCP26	35.0	57.1	17.4	88.8	14.5	42.6
RCP45	36.8	58.2	17.8	86.1	15.1	42.8
RCP85	33.3	56.9	17.5	81.6	14.2	40.7

Table 5.2 - Predicted average annual peak period bicycle counts by location and CMIP5 emission scenario using the inter-model mean.

Using the cycling count model displayed in Equation 4.1, future weather data was inputted into the model to generate predicted counts for three emission scenarios (RCP26, RCP45, RCP85) during the mid-century period using the inter-model mean set of predictions. The 25% and 75% predictions from the inter-model range are also used to provide a degree of consideration surrounding the uncertainty of climate change predictions, effectively providing alternative perspectives of the predicted effects of climate change on cycling frequencies. Average predicted cycling counts are calculated using the average model results for each emission scenario and are displayed in Table 5.2, which displays an average cycling count across all counter facilities at mid-century of 42.6, 42.8, and 40.7 for RCP26, RCP45, and RCP85, respectively. Based on these results, it appears that as the effects of climate change intensify the average number of cyclists may decrease. However, as these numbers are only based on the inter-model mean of the CMIP5 climate model uncertainty surrounding these predictions must be considered. Table 5.2 should therefore be read as an example of the effects of climate change on cycling frequencies under a very specific set of climate change predictions, and is a representation of the one of the sets of predicted cycling counts amongst a range of potential future outcomes.

Below, Table 5.3 displays the predicted regression coefficients for each emission scenario using the inter-model mean set of climate change predictions at each counter facility. The results located in this table will be further discussed in the following sections broken down by variable type. Table 5.4 builds on Table 5.3 by displaying the effects of climate change on cycling as rendered using the aforementioned model in Equation 4.1 by including two additional sets of climate change predictions to offer a wider range of predicted effects, using the Iron Horse Trail location as a representative example. Full regression results are available in the Appendix B.

Location		IHT			LTC			LTE			LTSL			LTW		
Variable		RCP26	RCP45	RCP85	RCP26	RCP45	RCP85	RCP26	RCP45	RCP85	RCP26	RCP45	RCP85	RCP26	RCP45	RCP85
Month	January	BASE			BASE			BASE			BASE			BASE		
	February	20.6	20.9	18.0	23.2	23.1	22.5	7.5	7.4	7.4	26.7	24.1	24.2	9.3	9.7	9.0
	March	17.5	18.4	15.7	21.4	21.9	21.3	10.1	10.4	10.3	43.4	41.9	39.6	9.9	10.5	9.6
	April	28.8	29.3	27.1	39.9	40.3	39.8	18.8	19.3	18.9	83.3	79.6	76.4	15.7	15.9	15.2
	May	36.0	38.3	35.2	89.7	91.9	90.2	24.1	24.7	24.2	145.7	142.8	134.3	17.0	18.0	17.2
	June	35.7	38.0	34.4	90.2	92.2	89.9	28.3	29.1	28.5	127.9	125.9	117.2	17.6	18.4	17.4
	July	45.9	49.2	45.4	82.2	84.5	82.1	22.0	22.5	22.2	114.2	110.9	105.3	17.8	18.8	17.8
	August	48.4	51.7	47.4	69.1	71.0	68.9	21.7	22.2	21.8	98.4	95.7	90.8	16.6	17.5	16.5
	September	46.0	49.1	45.9	78.0	79.1	77.4	21.7	22.2	21.5	146.7	143.2	135.7	17.5	18.2	17.3
	October	42.8	44.9	40.3	76.3	77.6	75.9	20.8	21.4	20.5	120.4	118.0	110.9	18.2	19.0	17.7
	November	39.6	41.3	37.3	64.5	65.2	64.4	16.7	16.9	16.6	81.9	80.1	74.7	15.0	15.4	14.6
	December	30.9	30.5	27.2	30.0	30.9	29.2	10.2	10.2	10.0	41.7	39.8	37.7	11.2	11.1	10.3
Temperature	Extreme Cold	15.3	15.4	16.5	17.5	17.5	18.3	3.7	3.4	3.1	20.1	18.8	20.9	5.1	5.0	5.6
	Very Cold	13.0	12.8	13.6	12.1	11.3	11.1	3.8	4.2	4.2	23.9	18.7	23.8	4.6	4.7	4.0
	Cold	17.1	16.7	16.5	18.3	16.5	16.1	6.0	6.2	5.4	29.0	24.7	25.1	7.5	6.5	6.7
	Freezing	21.9	20.3	21.1	20.7	19.0	18.6	7.4	7.4	6.8	28.9	26.0	31.0	8.1	7.5	7.3
	Near Freezing	BASE			BASE			BASE			BASE			BASE		
	Cool	34.3	33.2	31.8	23.4	22.0	22.1	9.5	9.3	9.4	39.7	35.2	39.5	10.0	10.0	9.7
	Mild	38.4	38.4	35.4	23.6	22.8	22.9	10.2	10.2	10.4	43.3	39.8	42.6	12.3	12.4	11.6
	Warm	50.1	47.8	40.6	28.3	27.2	27.1	12.1	12.0	11.6	47.7	41.9	45.0	13.5	13.5	12.9
	Very Warm	53.1	53.0	52.1	27.8	27.8	28.4	12.3	12.1	13.4	47.1	44.1	49.4	14.0	14.5	14.2
	Hot	48.6	48.6	45.3	31.2	28.5	29.1	14.0	14.1	13.2	42.1	39.9	45.6	16.5	16.1	14.7
	Very Hot	56.5	56.1	52.5	28.8	28.5	29.9	14.4	14.2	15.0	43.2	40.3	41.3	16.3	16.7	16.7
Precipitation	No Rain	BASE			BASE			BASE			BASE			BASE		
	Light Rain	27.2	28.6	25.5	19.7	19.2	19.2	6.6	6.7	6.8	33.3	31.2	31.9	7.1	7.5	7.3
	Moderate Rain	18.2	19.6	16.7	17.7	17.6	17.3	5.3	5.3	5.2	37.4	27.5	29.2	6.0	6.4	5.8
	Heavy Rain	14.3	14.8	13.5	16.7	16.7	16.4	5.5	5.5	5.5	45.1	33.1	33.7	5.3	5.6	5.4
Intercept		28.4	29.9	25.7	21.0	20.8	20.9	7.5	7.7	7.8	34.9	31.6	32.5	8.4	9.0	8.3

Table 5.3 – Predicted cycling frequencies of key variables for all emission scenarios using the CMIP5 inter-model mean. All shaded values are significant at the 95% level.

Iron Horse Trail		RCP26			RCP45			RCP85		
		25%	Mean	75%	25%	Mean	75%	25%	Mean	75%
Month	January	31.5	28.4	29.0	25.6	29.9	23.9	23.5	25.7	20.9
	February	22.0	20.6	20.8	20.9	20.9	19.1	20.4	18.0	16.7
	March	18.7	17.5	17.0	18.4	18.4	16.5	17.8	15.7	14.4
	April	30.1	28.8	30.7	29.8	29.3	28.1	28.6	27.1	25.5
	May	38.5	36.0	37.1	37.5	38.3	36.8	36.7	35.2	32.8
	June	38.6	35.7	37.2	37.2	38.0	35.8	34.8	34.4	32.8
	July	49.8	45.9	47.4	47.8	49.2	47.3	45.9	45.4	43.9
	August	52.0	48.4	49.9	50.5	51.7	49.8	48.1	47.4	45.9
	September	49.9	46.0	47.7	48.4	49.1	47.6	46.4	45.9	43.7
	October	45.4	42.8	42.8	45.0	44.9	42.3	42.0	40.3	37.7
	November	41.9	39.6	40.6	41.2	41.3	39.0	39.5	37.3	34.9
	December	33.0	30.9	29.8	31.5	30.5	28.9	29.4	27.2	25.6
Apparent Temperature	Extreme Cold	15.1	15.4	14.4	14.9	15.4	15.7	14.1	16.5	13.9
	Very Cold	12.6	12.9	12.5	12.6	12.8	13.3	12.8	13.6	16.2
	Cold	17.3	17.2	15.1	17.3	16.7	17.0	15.3	16.5	15.8
	Freezing	23.6	21.7	19.7	21.1	20.3	20.6	20.0	21.1	21.2
	Near Freezing	31.5	28.4	29.0	25.6	29.9	23.9	23.5	25.7	20.9
	Cool	36.1	34.7	34.7	34.5	33.2	33.4	33.6	31.8	30.5
	Mild	44.7	38.3	38.0	39.4	38.4	36.1	36.9	35.4	37.3
	Warm	53.1	50.2	48.1	49.4	47.8	44.1	45.3	40.6	38.3
	Very Warm	53.4	53.4	52.7	52.5	53.0	53.2	54.6	52.1	49.8
	Hot	49.5	49.1	48.4	49.5	48.6	47.0	49.6	45.3	44.9
	Very Hot	55.5	57.0	51.3	49.8	56.1	47.7	48.0	52.5	43.0
Precipitation	No Rain	31.5	28.4	29.0	25.6	29.9	23.9	23.5	25.7	20.9
	Light Rain	30.0	27.2	27.9	28.4	28.6	26.9	27.3	25.5	23.7
	Moderate Rain	17.1	18.2	19.0	16.0	19.6	18.6	15.6	16.7	16.9
	Heavy Rain	16.6	14.3	14.7	15.3	14.8	14.1	14.3	13.5	12.6

Table 5.4 - Representative example of the variations in predicted cycling counts as a function month of year, maximum apparent temperature, and precipitation at the Iron Horse Trail location using the 25%, 75%, and mean CMIP5 model predictions.

5.3.1 Temporal Effects Under a Changing Climate

The temporal effects of weather on cycling frequency have been identified in publications on this topic as well as in Section 5.2.1 to generally be a significant factor in affecting cycling counts throughout the year. It is no surprise that the time of year will continue to play a role in influencing cycling counts under a changed climate at mid-century. The results displayed in Table 5.3 identify that trends exist with regards to cycling count frequencies at each counter facility and within each emission scenario. Within the results using the CMIP5 inter-model mean set of predictions, it is typically seen that the RCP45 emission scenario (mid-intensity) has the greatest average positive effect on cycling counts across four of the five locations. The Laurel Trail at Silver Lake location stands out as indicating that the more severe the emission scenario, the greater the negative effects on cycling frequencies. The RCP45 emission scenario appears to have the most positive influence on cycling frequencies in Waterloo at most facilities, while the most extreme scenario, RCP85, is reported as generally being the most detrimental of the three scenarios. When reviewing the results of Table 5.4, however, the effects are less distinguishable and decisive across each emission scenario. While the high-intensity emission scenario (RCP85) continues to appear to be the most detrimental to cycling rates throughout the year, the low-, mid-, and high-intensity emission scenarios (RCP26, RCP45, RCP85) appear to significantly overlap and are not able to definitively indicate how they rank against each other in terms of their effects on cycling rates. As a result of the overlapping range of predictions at the Iron Horse Trail, it is not appropriate to identify that one emission scenario will definitively result in a positive or negative change over another due to uncertainties surrounding the predicted effects.

Aside from the emission scenarios, it is apparent that the winter months show the least variation in predicted cycling frequencies, with the late spring and early fall showing the greatest amount of variation, exemplified by the Laurel Trail at Silver Lake where there are reductions as great as 11 cyclists (-7.5%) between the most and least positive emission scenario. The significance levels across counter facilities remain similar to those reported during the weather and cycling frequency analysis in Section 5.2.1, with four of the five facilities reporting statistically significant values between April and November, while the winter months are consistently non-significant at the 95% level.

Despite similar methods and data inputs to other studies, the findings presented above deviate from those found by other researchers. Wadud (2014) suggests that weekday commuter cyclists in the U.K. will cycle more during the winter and summer, while the spring and fall show reductions in cycling under a changed, mid-century climate. This analysis shows that cycling rates in Waterloo may experience decreases in all months of the year, contrary to Wadud (2014), with the most dramatic reductions occurring under the more severe RCP85 emission scenario. However, as exemplified by Table 5.4, there is uncertainty surrounding how dramatic a decrease in cycling rates could be expected throughout the year as well as which emission scenario will ultimately be represented at mid-century.

5.3.2 Effects of Maximum Apparent Temperature Under a Changed Climate

The effects of the maximum apparent temperature experienced during the AM or PM peak travel periods under a changed climate display similar patterns to those found during the current weather and cycling frequencies analysis in Section 5.2, where cycling frequencies increase non-linearly from cooler to warmer temperatures. Individual patterns at each counter facility have also been preserved, with the Laurel Trail at Columbia and Laurel Trail at Silver Lake experiencing a reduced percentage change in cycling rates at higher apparent temperatures than the other three sites. Additionally, these sites continue to experience a decrease in cycling rates during the warmest of temperatures (i.e., ‘Hot’ and ‘Very Hot’ apparent temperature levels), in contrast to the other counter facilities. When comparing these results with those of relevant publications, there is some degree of discrepancy. Böcker et al. (2013a) and Mathisen et al. (2015) both suggest that increased bicycle use will occur under a changed climate (in northern European nations) due to warmer temperatures affecting year-round travel. This research suggests that this may not be the case, as no discernible trend can be established amongst the regression results, leading to variable impacts on cycling rates depending on the emission scenario, cycling facility, and observed maximum apparent temperature. This is more in line with the findings of Saneinejad et al. (2012), who state that cycling trips are expected to experience greater variation in the number of trips made under a changed climate. Table 5.4 further illustrates the predicted general decline across all apparent temperature levels, emission scenarios, and CMIP5 model predictions, however it does identify the large range in predicted cycling rates between emission scenarios and across model prediction sets.

5.3.3 Effects of Rainfall Under a Changed Climate

The final variable that will be covered within this section is the effect of total rainfall during peak travel periods on future cycling rates. On a whole, the change in rainfall has a positive relationship with the predicted severity of climate change: the more severe the emission scenario the greater the amount of predicted annual rainfall and the fewer predicted cyclists. This trend is seen at the Iron Horse Trail, Laurel Trail at Columbia, Laurel Trail at Erb, and is vaguely present at the Laurel Trail at Silver Lake and Laurel Trail at Weber. This is in line with the findings in Section 5.2.3, that as rainfall increases the number of cyclists decrease, and that rainfall will generally increase at an annual scale under more severe effects of climate change. Additionally, the significance of the results is consistent with those presented in Table 5.3, where ‘Light Rain’ is generally statistically non-significant, with the other two levels reported as statistically significant at most locations and emission scenarios with the exception of the Laurel Trail at Silver Lake, which is entirely non-significant.

The patterns presented in Section 5.2.3 remain consistent during this analysis, with most counter facilities indicating that fewer cyclists are predicted under greater amounts of precipitation. These findings are consistent with those reported by researchers describing the effects of rainfall on cyclists either at present (e.g., Ahmed et al., 2010; Gallop et al., 2012; Böcker et al., 2013b) or under future climates (e.g., Böcker et al., 2013a; Wadud, 2014; Mathisen et al., 2015). Exceptions to this remains the Laurel Trail at Silver Lake which continues to suggest that more cyclists will be present during ‘Heavy Rain’ ($\geq$ 3 mm of rainfall in three hours) conditions. Again, this is a unique finding that may not be representative of actual cyclist responses to varying amounts of rainfall. As this is the most popular cycling trail in Waterloo located between several key destinations, there are number of potential explanations for this unintuitive result, some of which are outlined in Section 5.2.3. Overall, the findings discussed within this section identify that greater levels of rainfall will continue to negatively affect cycling rates, and that this may be exacerbated under the presence of more severe climate change conditions.

5.3.4 Summary of the Effects of Future Weather on Cycling Frequencies

This section provides insight into the potential effects that future weather conditions may hold on cycling frequencies under a changed climate. Three key variables that will be impacted due to climate change are discussed in Section 5.3, detailing the predicted effects they will have on cycling frequencies under three emission scenarios at mid-century. The findings identify general trends within the data that suggest that cycling frequencies may decrease under more severe changes in the local climate, such as the negative impacts that may be present throughout the year (Section 5.3.1) and under different maximum apparent temperatures during the AM and PM peak travel periods (Section 5.3.2), however uncertainties regarding the intensity and the ultimate impact of climate change must be acknowledged and considered. Both of these variables suggest a decrease in cycling frequencies that is not consistent with other publications on this topic, but are based on valid observations using robust methods. The effects of rainfall under a future climate (Section 5.3.3) again suggest decreasing cycling frequencies are possible under more severe changes in climate, however these findings are consistent with other research. In summary, these findings suggest that, when considering the range of climate change predictions available and the inherent uncertainties that frame climate change modelling, cycling frequencies may be negatively impacted as more severe climate change conditions develop.

5.4 Comparison of the effects of Current and Future Weather Conditions on Cycling Frequencies

Presenting the results found above is only the first step to understanding how cycling frequencies will be affected due to climate change. This section will combine the results from Sections 5.2 and 5.3 to provide a more inclusive overview of how cycling frequencies will be impacted by weather between the 2014-2016 study period and a mid-century climate under three emission scenarios using the CMIP5 inter-model mean, 25%, and 75% sets of predictions. It is important to note that the climate change analysis does not take into account population growth, changes in cycling infrastructure, socioeconomic variables, behavioural changes due to the presence of alternative transportation options, equipment adaptations made by cyclists to reduce the effects of weather, or the perception of the safety or utility of cycling; rather, these variables continue to be assumed to be constant from the point at which the data was collected. Changes in these variables may lead to different outcomes when comparing present-day to predicted cycling frequencies. The following comparison of results is based solely on the differing levels of impact that month of year, rainfall, and temperature will have on cyclists using present-day observations as the baseline. In addition, as this section compares the differences between present-day and future predicted cycling rates, it is important to acknowledge the range of predictions presented as well as the uncertainties that surround climate change modelling when interpreting the following findings.

5.4.1 Temporal Variations

As discussed above in Section 5.3.1 the mid-intensity emission scenario is identified as potentially having the most positive effect on cycling frequencies under a changed climate. When comparing the cycling counts during the 2014-2016 study period with the predicted counts under each emission scenario the predicted positive effects become clearer. In Figure 5.4, the percentage change is calculated for each emission scenario relative to the observed, present-day cycling counts (used as the baseline) at the Iron Horse Trail (this site is used as a representative example for the rest of the dataset). When graphed it becomes apparent that RCP85 remains the most likely scenario in which cycling counts will be negatively impacted, however the prediction sets used for RCP26 and RCP45 both suggest a negative effect on cycling rates, but it is not possible to distinguish which emission scenario may have the greater impact due to the range of predictions.

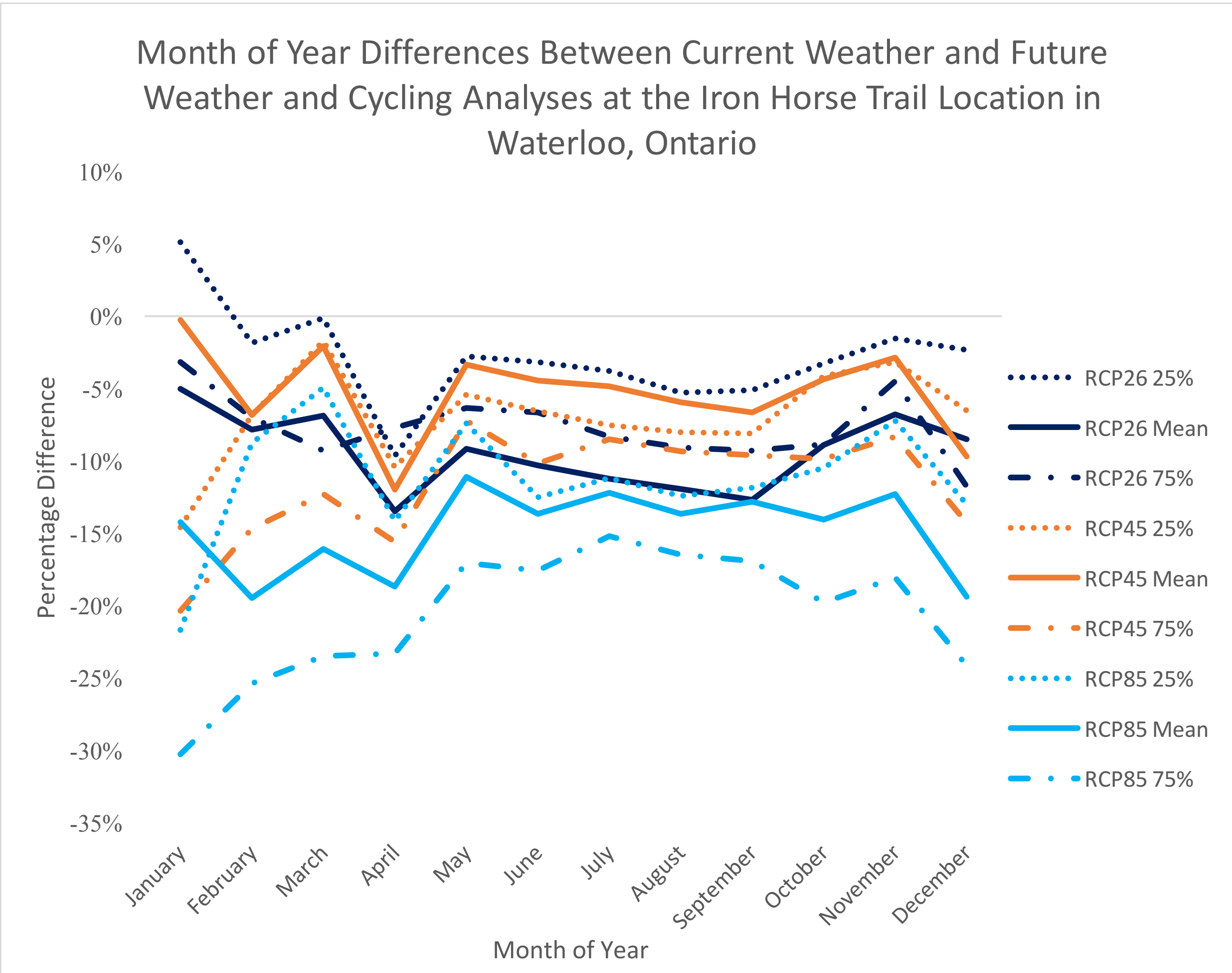


Figure 5.4 – Month of year differences between the current weather and future weather and cycling analyses at the Iron Horse Trail. 25%, 75%, and mean predictions generated from the CMIP5 climate model are presented to display the varying predicted effects and uncertainties regarding the predicted outcomes under each emission scenario.

5.4.2 Maximum Apparent Temperature Variations

Arguably one of the most expected impacts of climate change is the predicted increases in apparent temperature. This variable is also one of the most studied by researchers seeking to quantify the effects of climate change on cycling frequencies. As a result, it is no surprise that apparent temperature remains a high-profile variable within this study. To showcase the predicted increases in apparent temperature, Figure 5.5 graphs the average maximum apparent temperatures during the study period ("Observed"), along with the average maximum apparent temperatures for each emission scenario by month. It becomes clear that a well-defined increase in temperature will occur between present-day and mid-century, which may be exacerbated by the development of more severe climate conditions, represented by the three emission scenarios (using CMIP5 inter-model mean).

The results of the predicted changes in temperature by emission scenario are represented below in Figure 5.6, which again uses data generated for the Iron Horse Trail as a representative example. It can be seen that the overall warming of Waterloo's climate may have an overall negative effect on cycling frequencies when compared to the observed data collected during the study period, however an increase in cycling rates relative to present-day data may be observed within the apparent temperature levels that correspond with warmer temperatures. RCP85 appears to again be the most impactful across most maximum apparent temperature levels with the less severe emission scenarios indicating generally balanced effects relative to the present-day baseline across all apparent temperature levels. Considering the obvious, ubiquitous, and progressively increasing apparent temperature at mid-century it may be assumed from this study that cyclists in Waterloo, Ontario, and potentially southern Ontario as a whole may be negatively impacted by future increases in apparent temperature, when holding all other variables constant. However, when considering the full range of predictions (i.e. RCP26 25%) it may be suggested that a definitive decrease in cycling rates may not occur, and that there remains a potential for conditions to exist which will support and encourage cycling rates. An important consideration for this discussion is how wind speed and relative humidity, two of the three variables included in the apparent temperature calculation, will be affected under a changed climate. Due to the inconsistency of findings on how these two variables will be altered by climate change, they have remained constant during this analysis, however they both play important roles in determining apparent temperature. Relative humidity is considered a negative influencer on cycling frequencies

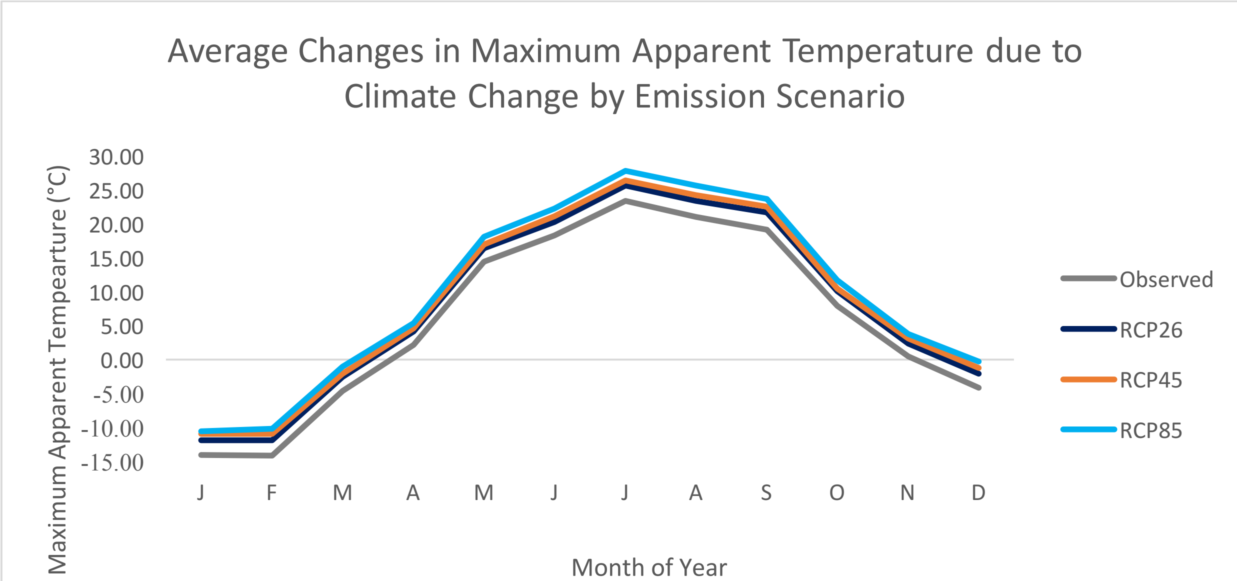


Figure 5.5 - Average Changes in Maximum Apparent Temperature due to Climate Change by Emission Scenario

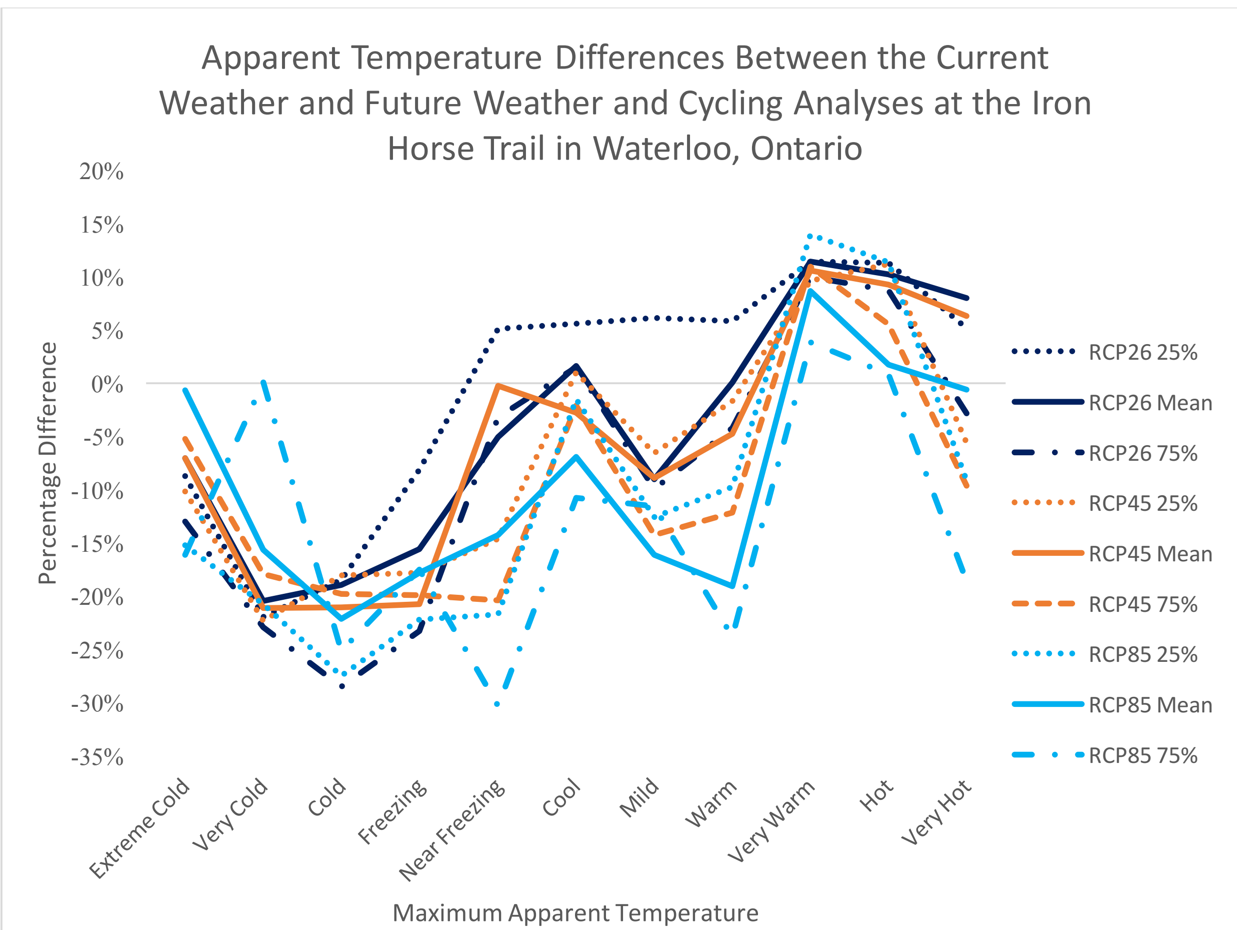


Figure 5.6 - Apparent Temperature differences between the current weather and future weather and cycling analyses at the Iron Horse Trail. 25%, 75%, and mean predictions generated from the CMIP5 climate model are presented to display the varying predicted effects and uncertainties regarding the predicted outcomes under each emission scenario

during warm weather, while wind speeds have a positive effect in warm weather and a negative effect during cold weather, resulting in 'wind chill'. It raises the question of: would apparent temperature have a different effect on cycling frequencies if there were adequate predictions for wind speeds and relative humidity at mid-century?

5.4.3 Total Rainfall variations

The final variable that will be compared between the weather and cycling and climate change and cycling analyses is the effects of total rainfall. For this analysis, the data for the Iron Horse Trail will again be used as a representative example for all analyses. Using the baseline present-day observations for reference, the relative effects of rainfall under each emission scenario are seen in Figure 5.7. As with the above sections a clear distinction between which emission scenario is the most or least impactful is difficult. While RCP85 appears to be the most negative scenario on cycling rates relative to present-day, there remains sets of predictions under RCP45 that also suggest largely negative effects, particularly under the variable level 'Moderate Rain'. In addition there are a full range of results that should also be considered, such as RCP45 Mean, RCP26 25%, and RCP26 75% which all suggest marginal increases, decreases, or the possibility of no detectable change in cycling rates relative to present-day results. Despite the full range of climate predictions indicating a negative-bias to the future effects of precipitation on cycling rates, the potential for positive or status quo outcomes remains a possibility, and therefore makes it difficult to definitively state that the effects of precipitation will negatively affect cycling frequencies under a changed climate.

Due to the findings within this section regarding the effects of total rainfall on cycling frequencies, it is important to note the actual changes in predicted rainfall depends on the baseline quantities. For seasonal or annual changes in rainfall the amount of rain will likely be noticeably greater due to the larger baseline values and the effects of a multiplicative approach when applying the rate of change of precipitation to observations. However, for much smaller temporal resolutions, such as within this study, where there is much less time to accumulate precipitation, the baseline values are much smaller and therefore do not show great levels of change when the predicted percentage changes are applied.

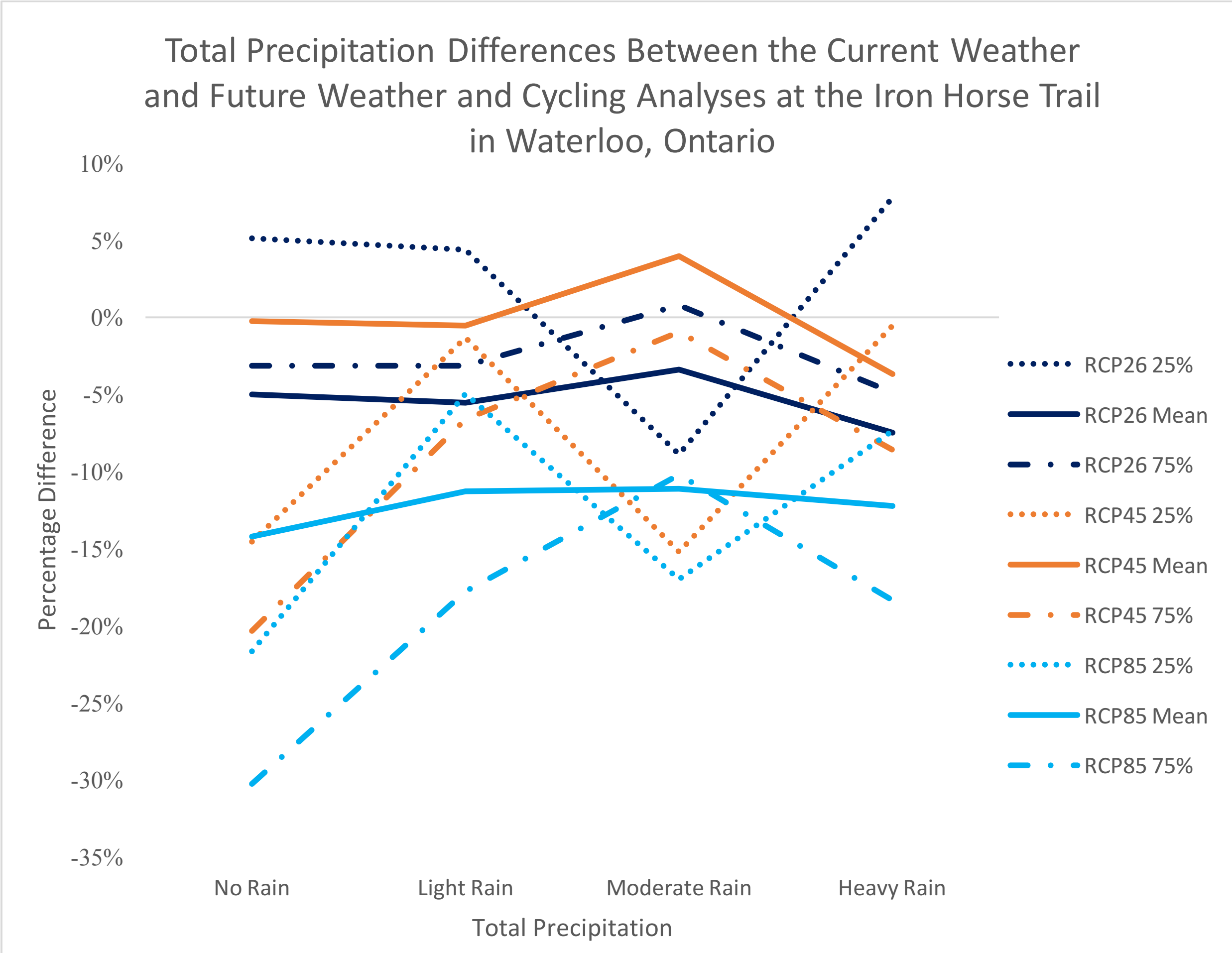


Figure 5.7 - Precipitation differences between the current weather and future weather and cycling analyses at the Iron Horse Trail. 25%, 75%, and mean predictions generated from the CMIP5 climate model are presented to display the varying predicted effects and uncertainties regarding the predicted outcomes under each emission scenario.

6.0 Conclusion

The purpose of this research was to quantify the impact of weather conditions, and to predict the effects of future weather conditions under a changed climate on commuter cyclists in southern Ontario, Canada. To conduct this research, quantitative methodologies were employed using cycling count data from the City of Waterloo. A multilinear regression model developed by Phung and Rose (2007) and refined by Ahmed et al. (2010) was used as a base model (Equation 3.3) to analyze the data. Revisions were made to the regression to develop a more appropriate model (Equation 4.1) given the inherent constraints of the cycling count data and the required outputs of the two analyses discussed in Chapter 3. Chapters 4 and 5 identified the current impacts of several weather conditions on commuter cycling frequencies, which were then used to predict commuter cycling frequencies under a future, changed climate. The latter analysis used three emission scenarios calculated from the CMIP5 climate model ranging from low- to high-degrees of change in temperature and precipitation. The findings of these two analyses were then compared against each other to identify expected trends in cycling frequencies between current and predicted counts at mid-century, which included several additional sets of climate change predictions to further the discussion regarding the possible range of outcomes and the uncertainty that frames discussions on predicted climate change impacts. To conclude this research, the key findings of the weather and climate change analyses will be summarized below (Section 6.1), in addition to sections detailing research contributions (Section 6.2), study limitations (Section 6.3), and opportunities for future research (Section 6.4).

6.1 Summary of Findings

Weather and Cycling Count Analysis

The first research question pertained to developing an understanding of the impacts that weather conditions have on cycling frequencies. The responses to this question have generally been straight forward, as stated in Section 5.2. Across most counter facilities it was determined that the month of the year plays a significant role in cycling frequencies, displaying a distinct unimodal pattern; cycling peaks during the summer months (June, July and August) reaching a low-point during the winter months (December, January, and February). The only deviation from this general trend is that counter facilities nearer post-secondary institutions show a marked decline in cycling counts during the months of July and August, likely due to a lack of students and staff traveling to school. These facilities show more of a bimodal distribution with peaks corresponding to the end and beginning of the winter and fall school terms (May and September, respectively).

The effect of maximum apparent temperature during peak travel periods also shows expected patterns; cycling counts decrease as it gets colder (less than 0 degrees Celsius) and increase as it becomes warmer (greater than 0 degrees Celsius). Differences in the magnitude of the effect of maximum apparent temperature appear when comparing counter locations, with the facilities nearest post-secondary institutions experiencing a lesser effect than those located elsewhere. The effects of total rainfall during peak travel periods also show expected patterns, with a non-linear relationship present; the effect of moderate rain has the most impact, with decreasing effects under heavier amounts of rain (as seen at the Iron Horse Trail, Laurel Trail at Erb, and Laurel Trail at Weber locations). This is likely caused by individuals opting not to cycle during periods of sustained or moderate rain, while feeling less deterred by light rain, and if already cycling, are more likely to continue to travel during heavier amounts of rain. It was also found that the lagged effect of rain was a deterrent to cycling, as up to a quarter fewer cyclists were counted during a three-hour period following rainfall. The minimum wind speed during each peak travel period was used to assess the effect of wind on cycling rates at each counter facility, which were found to be negligible and inconsistent, with facilities experiencing either a marginally positive or negative impact due to increased wind speeds. Finally, snowfall was a variable included in this study due to its seasonal, albeit variable, presence across southern Ontario and its typically deterring characteristics with regards to cycling. In statistically significant cases it was found that the presence of snowfall has a sizeable negative effect on cycling frequencies. This is furthered by the presence of the negative effects that snow has up to 24 hours after snowfall, which was analyzed using the snow lag variable noted in Section 5.2. Conflicting findings were identified amongst the results that were reported as being statistically non-significant. Approximately half of the findings for the variables “snow presence” and “snow lag” were reported as non-significant, and with much smaller regression coefficients, bordering on negligible effects. The lack of snowfall data available during the study period may have contributed to this. This is certainly an area that could be improved upon in the future for more reliable results.

It is important to note that the results were not always consistent across all counter facilities. Counters located nearest to the University of Waterloo and Wilfrid Laurier University (i.e. Laurel

Trail at Columbia and Laurel Trail at Silver Lake) experienced different impacts than the remaining three locations, such as smaller magnitudes of change due to extreme temperatures and contradictory impacts from increases in precipitation amounts, with a wide-range of estimated impacts as exemplified by the confidence intervals included in Figures 5.1 – 5.3. It is assumed that these differences may be the result of fewer students traveling to school during the summer months impacting the effects of temperature and precipitation. Another plausible explanation is that cycling along these trails is a necessary means for individuals travelling between school and their dwelling. Alternative forms of transportation such as transit, walking, or driving may not be available due to proximity to transit routes, distance from school, and financial burdens causing an individual to be more likely to travel through adverse weather conditions. These assumptions will remain unverified at present due to a lack of information or data on the topic of mode choices and socioeconomic status as it pertains to cycling frequencies in Waterloo.

Climate Change and Cycling Count Analysis

Following the weather and cycling count analysis, a second analysis was run using the same model with new data obtained from the CMIP5 climate model representing the impacts of climate change at three levels of severity in addition to several other sets of CMIP5 inter-model predictions. Due to data limitations (lack of predicted values for select variables used in the regression model such as snowfall data) several variables used the same observed values as found in the weather and cycling count analysis, while updated values were provided for maximum apparent temperature and total rainfall.

Similar patterns were observed throughout the climate change and cycling frequency analysis as seen in the initial analysis using observed weather data. As apparent temperature increases, so to do cycling counts; and as rainfall increases, cycling counts sharply decline. Section 5.3 suggests that the more severe the predicted effects of climate change, the fewer cyclists are predicted under the CMIP5 inter-model mean set of predictions (this is also depicted in Table 5.2). This was true for the variables month of year, maximum apparent temperature, and total rainfall; however, a number of points were identified suggesting uncertainty over the definitive negative impact of future apparent temperature and rainfall on cycling rates given the presence of several slightly positive predictions. This is interesting because research on the impacts of climate change on cycling generally suggests that cycling counts will experience an increase due to warmer year-round temperatures that effectively shorten the winter season which is largely viewed as hazardous due to a number of reasons previously listed. However, in a study on the effects of climate change on cycling rates in Norway, Mathisen et al. (2015) found that climate change will only result in marginal increases in cycling rates, and that the biggest positive contributor is likely to be population growth, a variable that was not included in this research, but is still a plausible source of future rate increases. Overall, this research finds that, generally, the more severe the effects of apparent temperature and rainfall under climate change, the greater the potential for negative effects on cycling counts in southern Ontario, when holding all other variables constant.

Comparison of the Effects of Current and Future Weather Conditions on Cycling Counts

The predicted effects of weather under a changed climate were compared to results from the observed weather and cycling count analysis to better understand how climate change will impact cycling counts relative to the study period. The comparison highlighted expected differences between current weather and future weather under a changed climate. Apparent temperatures are expected to increase year-round, although the percentage change will vary by season and trail location, and cycling may generally experience greater negative effects under warmer apparent temperatures than during the values observed during the study period, however several sets of predictions suggest that a generally positive effect may also exist, leading to a degree of uncertainty over the future effects of apparent temperature on cycling frequencies. Additionally, cycling rates are likely to be lesser during each month of the year. Finally, the total rainfall variable indicated interesting results, notably that a generally negative effect will occur, with the potential for positive or status quo effects when considering the full range of predictions. It is also worth noting that the range of predictive impacts of rainfall on cycling rates is quite wide when considering all counter locations studied in the City of Waterloo.

Therefore, it can be suggested that, when holding all other variables constant, the climate predictions generally point to declining cycling rates under a changed climate when accounting for changes in apparent temperature and rainfall throughout the year. However, due to the presence of few predictions indicating a positive or neutral effect on cycling frequencies within the studied variables, the uncertainty of these findings must be acknowledged and considered.

6.2 Research Contributions

Research on the impacts of weather and climate change on cycling frequencies has been performed in a number of locations using a variety of data, making this study a replication of past efforts by researchers with similar objectives. A key point, however, is that cycling analyses are often limited to small geographic areas that may or may not be representative of the larger population. Additionally, a large portion of studies have targeted European communities, particularly the Benelux countries, U.K., and Denmark (e.g., Böcker et al., 2013; Mathisen et al., 2015). Where this research provides new insights on the effects of weather and climate change on cycling frequencies is in the relatively sparsely studied region of southern Ontario, Canada. Despite this region being home to millions of Canadians and many cyclists, past work has been limited, and has focused on mode choice (e.g. Saneinejad et al., 2012) and rider perceptions (e.g. Bidordinova, 2010) within a small, single study location. Therefore, this research contributes by filling the knowledge gaps that currently exist on cycling research as it pertains to the effects of weather and climate change on cycling frequencies outside of Europe and other prominent areas of study. This study may also be viewed as a response to the identification of the need for further research to identify the effects of weather and climate change and contribute to the understanding of geographic variations in cycling frequencies, as suggested by researchers such as Ahmed et al. (2010).

It is important to further understand and consider these effects on cycling frequencies, especially as jurisdictions across Ontario continue to push for and invest in cycling and active transportation infrastructure and programs to align with climate change mitigation and adaptation goals, objectives, and strategies. By contributing to this knowledge-base, municipalities will be better able to effectively invest in appropriate infrastructure and programs to enhance and incentivize commuter cycling. In doing so, municipalities will better align their operations to conform with municipal and provincial policies and programs, such as the City of Waterloo's *Transportation Master Plan* (2011), and *Ontario's Climate Change Action Plan* (Ontario, 2017) through evidence-based decision making. Understanding the deterrents and incentives that drive cycling rates may prove beneficial when identifying priorities in cycling investments. For example, if snowfall results in significant reductions to cycling frequencies, as identified in this study, it may be beneficial to install and implement relevant infrastructure and programs. Examples may include increasing segregated cycling infrastructure that removes the hazards or perception of hazards associated with cycling near vehicles in adverse, slippery conditions; ensuring rapid-responses during and after snowfall to keep trails and cycling routes devoid of snow and ice; or, initiate educational programs that teach cyclists recommended techniques when riding in winter conditions, and provide advice on appropriate clothing and equipment that will make cycling more comfortable and safe.

6.3 Limitations of Study

This research has highlighted several important and unique findings on the topic of the effects of weather and climate change on cycling frequencies. Like most studies limitations have been identified that must be noted and considered when reading and interpreting the findings found in Chapter 5. Below, key limitations are discussed based on their impact to this research, as well as how they may be addressed to have lesser effects on future research.

While concluding this study it is important to remember the intent of this research was to investigate the effects of weather and climate change on cycling frequencies. As such, variables that are also associated with cycling frequencies (e.g., socioeconomic and demographic data, information on mode choices, routes taken, and perceptions associated with commuter cycling) have been omitted from this study to ensure that the two research objectives were met and scope creep was avoided. Additionally, regression models are most effective when the number of variables included in the model are kept to a minimum. Therefore, it is recommended to reduce the number of variables to only those that are deemed important for the research. This was accomplished by limiting the objectives of this research to pertain strictly to weather, climate change and cycling counts, as well as using only relevant variables, and avoiding the inclusion of alternative influencers on cycling frequencies, ultimately narrowing the scope but generating better results.

The data used within this study also has several limitations or points to consider when interpreting these findings. As discussed at length in Chapter 2, data originated from several sources and were collected at many locations around and outside of the City of Waterloo. Immaturity of the cycling counter facilities in Waterloo limited the inclusion of some facilities as they had yet to compile even a year's worth of cycling counts. Weather data collected at the Waterloo Region International Airport by ECCC, though extensive, lacked a number of key variables that could have furthered the understanding of this study, such as quantitative measurements of snowfall or snow depth, and consistent and reliable precipitation measurements (these were substituted by rainfall data made available by GRCA). Finally, the CMIP5 climate model, though a complete and reliable source of current climate change predictions, only included estimations on changes to temperature and the intensity of rainfall events. This dataset does not include any predictions for variables such as wind speed, humidity, snowfall, or snow depth at mid-century. It is important that these data availability concerns are addressed in future research to ensure that complete analyses can be conducted and that no missing or unavailable data is a cause of limitations.

Similarly, the accuracy of the data was a barrier that had to be overcome throughout this research. Despite the number of cycling counter facilities, a number of them had issues around data accuracy and completeness which is highlighted by this research only using five of the twelve available counter facilities. Several facilities suffered from suspected mechanical problems, such as water ingress or empty batteries that impacted their ability to provide accurate counts. Another was suspected to be negatively impacted by the radiation produced by a nearby streetlight or utility line. These facilities were omitted to mitigate concerns surrounding data accuracy. Beyond cycling counters, a common problem associated with using regional weather stations, such as the one at the Waterloo Region International Airport, is that the localized variations in weather are not captured. Local wind patterns or shifts that are generated by the physical environment (e.g., buildings and wooded areas) are not registered, nor are localized precipitation events. For a more complete picture of local weather conditions more weather stations should be installed to provide data representative of current conditions, rather than those at an airport with flat terrain devoid of many built or natural features such as those found in urban areas.

Considering the above limitations, this study could be enhanced under a number of different approaches. The first is through using more cycling counter facilities to provide deeper insight into the geographic variation in cycling rates across the city, especially as there were notable differences between routes centred around the universities versus those nearest the city-centre. This could be complemented by extending cycling counters into the neighbouring City of Kitchener to capture commuter cycling rates across the contiguous Kitchener-Waterloo area. Additionally, more data from each counter facility would enhance the study by providing more observations to overcome any fluctuations in counts that may have been impacted by external factors or even by unseasonable weather patterns. Having access to more quantitative measurements of weather variables such as rainfall and snowfall would also benefit this study. While the qualitative identification of snowfall was used, it would be beneficial to use a method similar to the rainfall variable and quantify how different levels of snowfall or snow depth impact an individual's choice to cycle during the winter months. Finally, installing more reliable counters around the city would have significant benefits. The cycling counters currently used by the City of Waterloo appear to offer fairly accurate measurements of counts, however as noted by this research as well as a staff member at the City of Waterloo, they are not perfect (Personal Communication, 2017). Over the few years that the counters have been installed, they have been prone to mechanical failures, which is compounded by the fact that they run on batteries rather than the municipal power-grid, wind turbines, or photovoltaic systems, and are not watertight. This all proves detrimental to the city's ability to continually collect data for evidence-based decision making on investments in active transportation and providing reliable data for use by researchers.

6.4 Opportunities for Future Research

While this study and its outputs are new to the region and have resulted in important results, there are areas where this research may improve through future exploration on the topic to bolster the understanding of weather and climate change impacts on cycling frequencies in southern Ontario. Future research should seek to understand the qualitative impacts of weather and climate change on commuter cycling to offer an alternative perspective to the presented findings. An example of this work would be similar to Bidordinova's (2010) research on University of Toronto faculty and staff, however it is important to be more inclusive by including university students and staff as well as the general public. The findings of this research have suggested that there are differences between individuals travelling to universities for school or work versus those travelling elsewhere during peak travel periods, making it important for future research to explore these differences in travel behaviours. This is especially true in cities with large post-secondary student populations.

Another source of future research would be to complement this study with an understanding of socioeconomic and demographic variables that impact cycling frequencies and potentially mode choice. This topic is identified as an important consideration when reviewing future investments in cycling infrastructure. By understanding who cycles and where they live, work, or otherwise travel in a city a municipality can ensure that they create effective and useful infrastructure, with a transportation system to match.

Finally, due to the data limitations identified in Section 6.3 and the expected changes in cycling infrastructure, investment, and cycling rates through population and climate change, this research should be conducted again in five or more years. This will provide time for cycling infrastructure and programs to come to fruition, as well as associated schemes that could result in changes to cycling frequencies such as infilling and density increases in targeted corridors (such as University Avenue, Columbia Avenue, and King Street in Waterloo). Most importantly, this will allow for either new cycling counters to be installed or at least more data to be collected.

References

Aaheim, H.A., Hauge, K.E. (2005). Impacts of climate change on travel habits: a national assessment based on individual choices. *CICERO Report 07 Oslo: Centre for International Climate and Environmental Research.*

Adapting to Climate Change in Time [ACT] (2013). Planning for Adaptation to Climate Change: Guidelines for Municipalities. *LIFE Program on Environmental Policy and Governance.*

Ahmed, F., Rose, G., Jacob, C. (2010, September). Impact of weather on commuter cyclist behaviour and implications for climate change adaptation. In *Australasian Transport Research Forum (ATRF), 33rd, 2010, Canberra, ACT, Australia* (Vol. 33).

Ahmed, F., Rose, G., Jakob, C. (2012). Examining the impact of changes in weather on commuter cyclist's travel behavior. In *On the 92nd Transportation Research Board Annual Meeting, Washington DC*.

Anandhi, A., Frei, A., Pierson, D.C., Schneiderman, E.M., Zion, M.S., Lounsbury, D., Matonse, A.H. (2011). Examination of change factor methodologies for climate change impact assessment. *Water Resources Research,* 47.

Aultman-Hall, L., Lane, D., Lambert, R.R. (2009). Assessing the impact of weather and season on pedestrian traffic volumes. *Transportation Research Board, 88th Annual Meeting*.

Australian Bureau of Meteorology (2010). Thermal Comfort Observations. Retrieved from: http://www.bom.gov.au/info/thermal_stress/#using.

Behan, K., Lea, N.S. (2010). Benchmarking active transportation in Canadian cities. *Clean Air Partnership,* Toronto, ON.

Bidordinova, A. (2010). Motivators and Barriers to Utilitarian Cycling in Downtown Toronto. CTRF 45th Annual Conference – Transportation and Logistics Trends and Policies: Successes and Failures.

Böcker, L., Prillwitz, J., Dijst, M. (2013a). Climate change impacts on mode choices and travelled distances: A comparison of present with 2050 weather conditions for the Randstad Holland. *Journal of Transport Geography*, 28(2013): 176-185.

Böcker, L., Prilwitz J., Dijst, M. (2013b). Impact of Everyday Weather on Individual Daily Travel Behaviours in Perspective: A Literature Review. *Transport Reviews,* 33(1): 71-91.

Böcker, L., Thorsson, S. (2013). Integrated weather effects on cycling shares, frequencies, and durations in Rotterdam, the Netherlands. *Weather, climate, and society*, *6*(4), 468-481.

Bourdage, L., Huard, D. (2010). Climate Change Scenarios over Ontario Based on the Canadian Regional Climate Model (CRCM4.2). *Ouranos: Consortium on Regional Climatology and Adaptation to Climate Change*.

Brandenburg, C., Matzarakis, A., Arnberger, A. (2007). Weather and cycling: A first approach to the effects of weather conditions on cycling. *Meteorological Applications*, 14: 61-67

CARE International (2009). Climate vulnerability and capacity analysis handbook.

Casello, J., Towns, W. (in press). Assessment of Climate Risks and Adaptation Practices for the Urban Transportation Sector in Canada.

City of Halifax. (2014). Making Connections: 2014-19 Halifax Active Transportation Priorities Plan, Halifax, NS.

City of Toronto (n.d.). Bike counts: Toronto Cycling App. Retrieved from: https://www1.toronto.ca/wps/portal/contentonly?vgnextoid=5c555cb1e7506410VgnVCM10000071d60f89RCRD.

City of Waterloo (2011). Transportation Master Plan, Waterloo, ON.

CMIP (2013). CMIP5 – Coupled Model Intercomparison Project Phase 5 – Overview. Retrieved from: http://cmip-pcmdi.llnl.gov/cmip5/index.html.

CMIP (2013). CMIP5 – Coupled Model Intercomparison Project Phase 5 – Overview. Retrieved from: http://cmip-pcmdi.llnl.gov/cmip5/index.html.

Cools, M., Moons, E., Janssens, B., Wets, G. (2009). Shifting towards environment-friendly modes: profiling travelers using q-methodology. *Transportation*, 36(4): 437-453.

Cools, M., Moons, E., Creemers, L., Wets, G. (2010). Changes in travel behavior in response to weather conditions: Whether type of weather and trip purpose matter? *Transportation Research Board 2010 Annual Meeting*.

Cools, M., Creemers, L. (2013). The dual role of weather forecasts on changes in activity-travel behavior. *Journal of Transport Geography*, 28(2015): 167-175.

Cragg, S., Cameron, C., Craig, C.L. (2006). 2004 National Transportation Survey. *Canadian Fitness and Lifestyle Research Institute*.

Creemers, L., Wets, G., Cools, M. (2013). Meteorological variation in daily travel behaviour: Evidence from revealed-preference data from the Netherlands. *Theoretical and Applied* Climatology, 120(1): 183-194.

CTV Kitchener (2016). Province pledges nearly $1M for cycling initiatives in Waterloo Region. Retrieved from: http://kitchener.ctvnews.ca/province-pledges-nearly-1m-for-cycling-initiatives-in-waterloo-region-1.2814151?autoPlay=true.

De Veaux, R.D., Velleman, P.F., Bock, D.E. (2005). Stats: Data and Models. Michigan, US. Pearson/Addison Wesley.

El Faouzi, N., Billot, R., Nurmi, P.,Heilmann, B. (2010). Effects of adverse weather on traffic and safety: State-of-the-art and a European initiative. *SIRWEC 2010: 15th International Road Weather Conference*.

Federal Highway Administration [FHWA] (2013). Traffic Monitoring Guide. US Department of Transportation, Federal Highway Administration, Office of Highway Policy Information.

Feng, C., Wang, H., Lu, N., Chen, T., He, H., Lu, Y., Tu, X.M. (2014). Log-Transformation and its Implications for Data Analysis. *Shanghai Archives of Psychiatry*, 26(2): 105-109.

Fisher, C. (2014). Cycling through winter. Plan Canada (winter).

Fletcher, A. (2011). City of Copenhagen: Adaptation case study. *Sustainability Solutions Group*.

Flynn, B. S., Dana, G. S., Sears, J., Aultman-Hall, L. (2012). Weather factor impacts on commuting to work by bicycle. *Preventive medicine*, *54*(2), 122-124.

Fox, J. (2016). *Applied Regression Analysis and Generalized Linear Models*. Third Edition. Sage Publications

Gallop, C., Tse, C., Zhao, J. (2012). A seasonal autoregressive model of Vancouver bicycle traffic using weather variables. *Transportation Research Board Annual Meeting*.

Gardiner, W., Mulvey, E.P., Shaw, E.C. (1995). Regression analyses of Counts and Rates: Poisson, Overdispered Poisson, and Negative Binomial Models. *Psychological Bulletin*, 118: 392-404.

German Institute of Urban Affairs (2012). Cycling Expertise: The Cycling Mode Share in Cities.

Giodana, F., Mascolo, R. A.,Capriolo, A. (2013). Chapter 2: Review the available knowledge and establish a baseline. *Planning for Adaptation to Climate Change: Guidelines for Municipalities*.

Giorgi, F., Hewitson, B., Christensen, J., Hulme, M., Von Storch, H., Whetton, P., Jones, R., Mearns, L., Fu, C. (2001). Regional Climate Information – Evaluations and Projections. In *Climate Change 2001: Working Group 1 – The scientific basis.* Intergovernmental Panel on Climate Change.

Global News (2017). Census 2016: Population of Toronto outpaced national growth rate. Retrieved from: http://globalnews.ca/news/3235236/census-2016-population-of-toronto-outpaced-national-growth-rate/.

Government of Ontario (2015). #CycleON: Ontario's Cycling Strategy, Toronto, ON

Gunst, J. (2017). Ask a tech: Are specialty bikes accurately counted? Retrieved from: https://www.eco-compteur.com/blog/2017/03/28/ask-tech-specialty-bikes-counted/#more-1721.

Halvorsen, R., Palmquist, R. (1980). The interpretation of dummy variables in semilogarithmic equations. *American Economic Review, 70*(3). 474-475.

Hamilton Conservation Authority [HCA] (2012). Hamilton Conservation Authority climate change strategy: Case Study. *Ontario Centre for Climate Impacts and Adaptation Resources*. Hamilton, ON.

Hammer, B. (2017). Metrics: Evaluation Metrics for Machine Learning. R package version 0.1.2. https://CRAN.R-project.org/package=Metrics.

Hanson, S., Hanson, P. (1977). Evaluating the impact of weather on bicycle use. *Transportation Research Record*, *629*, 43-48.

Hooqzaad, J., Lee, A., Greiner, S. (2013). MRV of cycling: Measuring the carbon impact of bicycle policy and infrastructure. *Climate Focus*, Amsterdam, NL.

Intergovernmental Panel on Climate Change [IPCC] (2012). Managing the risks of extreme events and disasters to advance climate change adaptation. A special report of working groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, USA

Jacobson, M. (2010). Data collection methods. *ServeMontana Symposium*.

James, G., Witten, D., Hastie, T., Tibshirani, R. (2013). Resampling Methods in *An Introduction to Statistical Learnng: With Applications in R* (175-201). New York, NY: Springer Texts in Statistics.

Khattak, A. J., De Palma, A. (1997). The impact of adverse weather conditions on the propensity to change travel decisions: a survey of Brussels commuters. *Transportation Research Part A: Policy and Practice*, *31*(3), 181-203.

Koetse, M. J., Rietveld, P. (2009). The impact of climate change and weather on transport: An overview of empirical findings. *Transportation Research Part D: Transport and Environment*, *14*(3), 205-221.

Kottek, M., Grieser, J., Beck, C., Rudolf, B., Rubel, F. (2006). World Map of Köppen-Geiger Climate Classification, Updated. *MeteorologischeZeitschrift, 15*: 259-263.

Kuhn, M. (2016). A Short Introduction to the Caret Package. 2-10. Retrieved from: https://cran.r-project.org/web/packages/caret/vignettes/caret.pdf.

Kuhn, M. (2017). caret: Classification and Regression Training. R package version 6.0-76. https://CRAN.R-project.org/package=caret.

Laerd Statistics (2017). Poisson Regression Analysis using SPSS Statistics. Retrieved from: https://statistics.laerd.com/spss-tutorials/poisson-regression-using-spss-statistics.php

Lemmen, D.S., Warren, F.J., Lacroix, J., Bush, E. (2008). From impacts to adaptation: Canada in a changing climate 2007; Government of Canada, Ottawa, ON.

Lewin, A. (2011). Temporal and weather impacts on bicycle volumes. *Transportation Research Board of the National Academies*, Washington, DC.

McInnes, K.L., Erwin, T.A., Bathols, J.M. (2011). Global Climate Model Projected Changes in 10 m Wind Speed and Direction due to Anthropogenic Climate Change. *Atmospheric Science Letters, October 2011*, 12(4): 325-333.

Maindonald, J.H., Braun, W.J. (2015). DAAG: Data Analysis and Graphics Data and Functions. R package version 1.22. https:CRAN.R-project.org/package=DAAG.

Manaugh, K., Boisjoly, G. & El-Geneidy, A. (2016). Overcoming barriers to cycling: Understanding frequency of cycling in a university setting and the factors preventing commuters from cycling on a regular basis. *Transportation*.

Mathisen, T.A., Annema, J.A., Kroesen, M. (2015). The effects of weather and climate change on cycling in northern Norway. *EJTIR*, 15(2): 261-273.

Matthews, L.C. (2014). Climate change and winter road maintenance: Planning for change in the City of Prince George, British Columbia (Master's thesis, University of Waterloo).

Measham, T.G., Preston, B.L., Smith, T.F., Brooke, C., Gorddard, R., Withycombe, G., Morrison, C. (2011). Adapting to climate change through local municipal planning: Barriers and challenges. *Mitigation and Adaptation Strategies for Global Change*, 16(8): 889-909.

MioVision (2017). MioVision DataLink: Smart cities start with data you can trust. Retrieved from: http://miovision.com/.

Miranda-Moreno, L., Nosal, T. (2011). Weather or not to cycle: Temporal trends and impact of weather on cycling in an urban environment. *Transportation Research Record: Journal of the Transportation Research Board*, (2247): 42-52.

Miranda-Moreno, L., Nosal, T., Schneider, R., & Proulx, F. (2013). Classification of bicycle traffic patterns in five North American Cities. *Transportation Research Record: Journal of the Transportation Research Board*, (2339), 68-79.

Mullan, E. (2013). Exercise, weather, safety, and public attitudes: A qualitative exploration of leisure cyclists' views on cycling for transport. *SAGE Open*. Waterford, IR.

Nankervis, M. (1999). The effect of weather and climate on bicycle commuting. *Transportation Research Part A: Policy and Practice*, 33(6): 417-431.

National Centre for Atmospheric Research (2016). The Climate Data Guide: CMIP (Climate Model Intercomparison Project) Overview. Retrieved from: https://climatedataguide.ucar.edu/climate-model-evaluation/cmip-climate-model-intercomparison-project-overview.

Nosal, T., Miranda-Moreno, L. (2014). The effect of weather on the use of North American bicycle facilities: A multi-city analysis using automatic counts. *Transportation Research Part A 66*(2014): 213-225.

Ontario (2014). *#CycleON Action Plan 1.0*. Retrieved October 4, 2016, from: http://www.mto.gov.on.ca/english/publications/pdfs/ontario-cycle-action-plan.pdf.

Ontario (2015). *Ontario Investing $25 Million in Cycling Infrastructure*. Retrieved October 4, 2016, from https://news.ontario.ca/mto/en/2015/04/ontario-investing-25-million-in-cycling-infrastructure.html

Patterson, B., Steiger, H. (2013). Shifting gears: The emergence of cycle tracks in the Canadian urban landscape. *Plan Canada*: 32-39.

Peterson, T.C., McGuirk, M., Houston, T.G., Horvitz, A.H., Wehner, M.F. (2008). Climate Variability and Change with Implications for Transportation. *Transportation Research Board*.

Pucher, J., Buehler, R. (2006). Why Canadians cycle more than Americans: a comparative analysis of bicycling trends and policies. *Transport Policy*,*13*(3), 265-279.

Pucher, J., Buehler, R. (2007). At the Frontiers of Cycling: Policy Innovations in the Netherlands, Denmark, and Germany. *World Transport Policy and Practice*, *13*(3), 8-57.

Pucher, J., Buehler, R., Seinen, M. (2011). Bicycling renaissance in North America? An update and re-appraisal of cycling trends and policies. *Transportation Research Part A*, 45(2011): 451-457.

R Core Team (2016). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

Region of Waterloo (2014). Walk Cycle Waterloo Region: Region of Waterloo active transportation master plan,Waterloo, ON.

Sabir, M., Koetse, M. J., & Rietveld, P. (2008). The impact of weather conditions on mode choice: empirical evidence for the Netherlands. *Department of Spatial Economics, VU University, Amsterdam*.

Sabir, M. (2011). Weather and travel behaviour (Doctoral dissertation, Vrije Universiteit).

Saneinejad, S. (2010). Modelling the impact of weather conditions on active transportation travel behaviour (Master's thesis, University of Toronto).

Saneinejad, S., Roorda, M. J., Kennedy, C. (2012). Modelling the impact of weather conditions on active transportation travel behaviour. *Transportation research part D: transport and environment*, 17(2): 129-137.

Sears, J., Flynn, B., Aultman-Hall, L., Dana, G. (2012). To bike or not to bike: seasonal factors for bicycle commuting. *Transportation Research Record: Journal of the Transportation Research Board*, (2314), 105-111.

Sener, I.N., Eluru, N., Bhat, C.R. (2009). An analysis of bicyclists and bicycling characteristics: Who, why, and how much are they bicycling? *Transportation Research Record: Journal of the Transportation Research Board* (2134), 63-72.

Share the Road (2014). 2014 Survey Research Summary. *2014 Ontario Bike Summit*: Toronto, ON.

Spencer, P., Watts, R., Vivanco, L., Flynn, B. (2013). The effect of environmental factors on bicycle commuters in Vermont: influences of a northern climate. *Journal of Transport Geography*, *31*, 11-17.

Statistics Canada (2017). Waterloo, CY [Census Subdivision], Ontario (table). *Census Profile*. 2016 Census. Statistics Canada Catalogue no. 98-316-X2016001. Ottawa. Released May 3, 2017. Retrieved from: http://www12.statcan.gc.ca/census-recensement/2016/dp-pd/prof/index.cfm?Lang=E

Stinson, M.A., Bhat, C.R. (2004). Frequency of Bicycle Commuting: Internet-Based Survey Analysis. *Transportation Research Board*. Chicago, USA.

Takle, E.S. (2005). Regional Climate Modelling. Iowa State University. Retrieved from: http://www.meteor.iastate.edu/gccourse/model/regional/regional_lecture_new.html

Thomas, T., Jaarsma, R., Tutert (2013). Exploring temporal fluctuations of daily cycling demand on Dutch cycle paths: The influence of weather on cycling. *Transportation*, 40: 1-22.

Tin Tin, S., Woodward, A., Robinson, E., Ameratunga, S. (2012). Temporal, seasonal and weather effects on cycle volume: An ecological study. *Environmental Health*, 11(12): 1-9.

Transport Canada (2011). Active transportation in Canada: A resource and planning guide. *Transport Canada – Environmental Initiatives Group, Ottawa, ON*

Transportation Tomorrow Survey [TTS] (2011). 2011 Survey Area Summary. Department of Civil Engineering, University of Toronto. Toronto, ON.

USAID (2014). A review of downscaling methods for climate change projections. Retrieved from: http://www.ciesin.org/documents/Downscaling_CLEARED_000.pdf

Wadud, Z. (2014). Cycling in a changed climate. *Journal of Transport Geography*, 35(2014): 12-20.

Ward, J. (2012). A tale of two suburbs: The physical plan and its implications for active transportation. *Plan Canada*.

Warren, F.J., Lemmen, D.S. (2014). Canada in a changing climate: Sector perspectives on impacts and adaptation; Government of Canada, Ottawa, ON.

WeAre_Waterloo (2013). Why Waterloo: Bike Friendly City. Retrieved from: http://www.wearewaterloo.ca/en/community/bike-friendly-city.asp.

Winters, M., Friesen, M.C., Koehoorn, M., Teschke, K. (2007). Utilitarian Bicycling: A multilevel analysis of climate and personal influences. *American Journal of Preventative Medicines 32*(1): 52-58.

Wooldridge, J.M. (2012). Introductory Econometrics: A modern approach, 5th ed. Mason, OH. Cengage Learning.

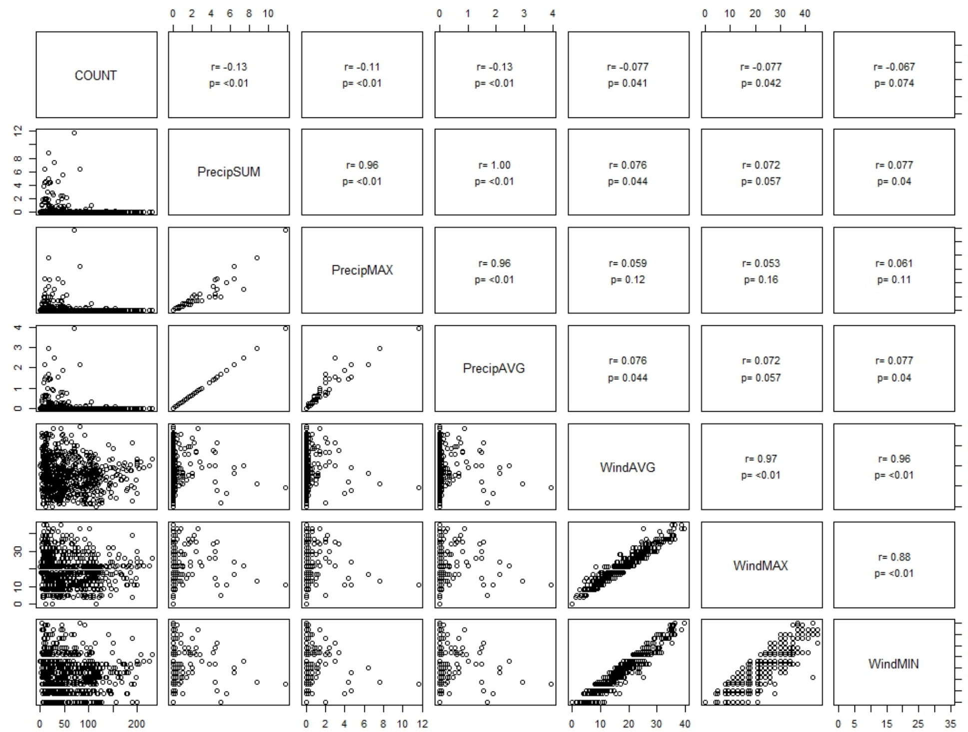
Wu, C., Wu, J., Luo, Y. (2011). Spatial Interpolation of Severely Skewed Data with Several Peak Values by the Approach Integrating Kriging and Triangular Irregular Network Interpolation. *Environmental and Earth Sciences, 2011*(63): 1093-1103.

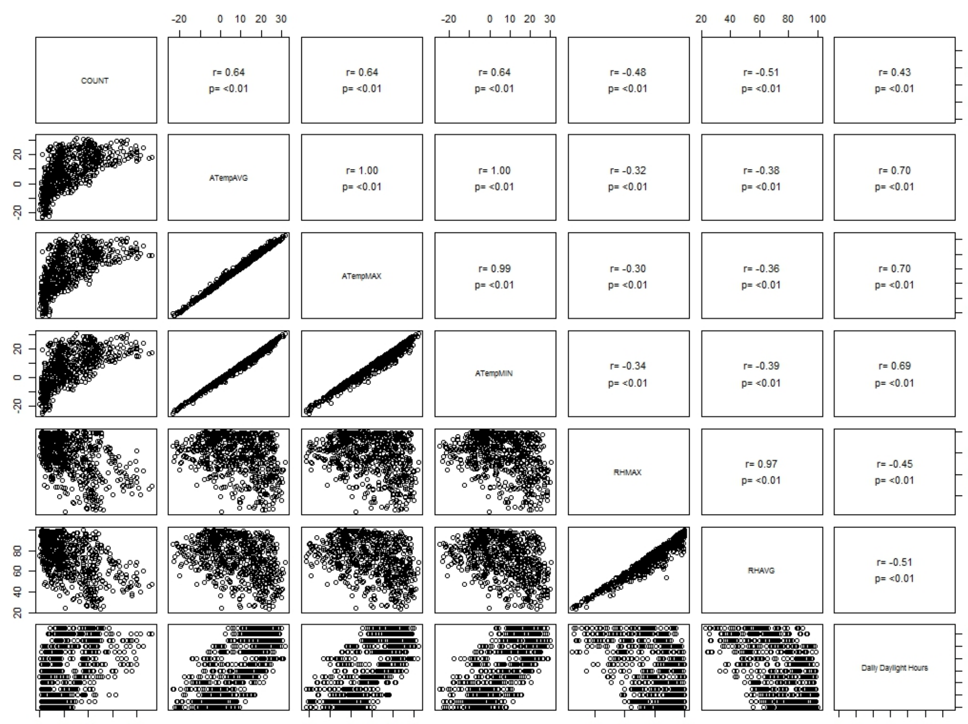
Young, I.R., Zieger, S., Babanin, A. (2011). Global Trends in Wind Speeds and Wave Height. *Science (Washington)*, 332(6028): 451-455.

Zhao, W. (2016). Modelling seasonal and weather impacts on cycling count (Master's thesis, University of Washington).

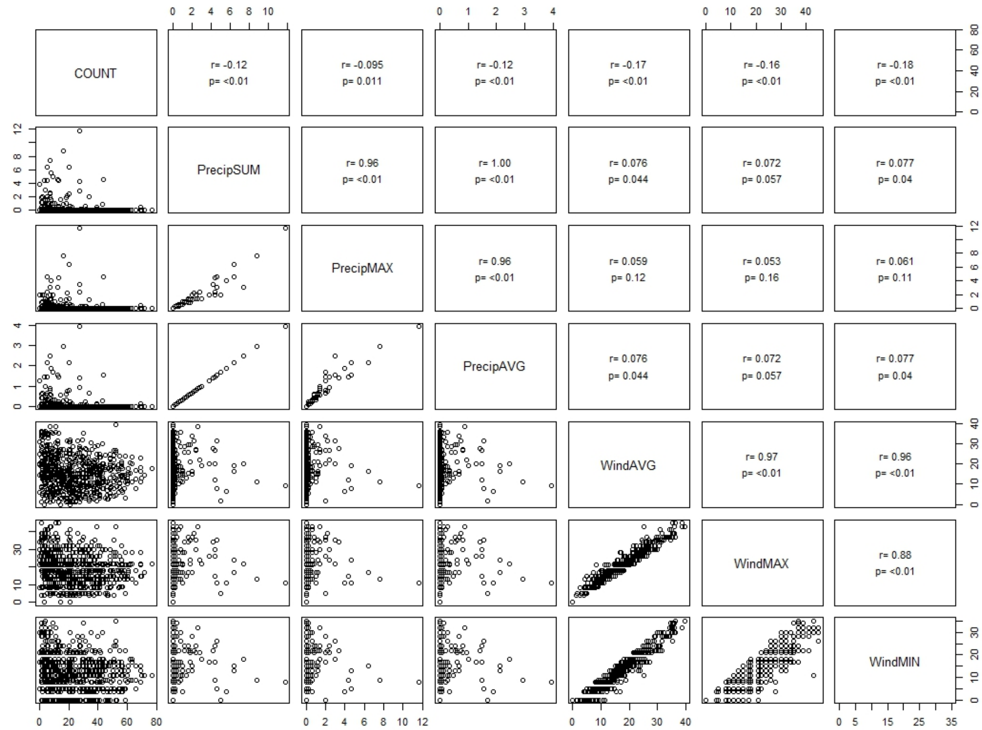
Appendix

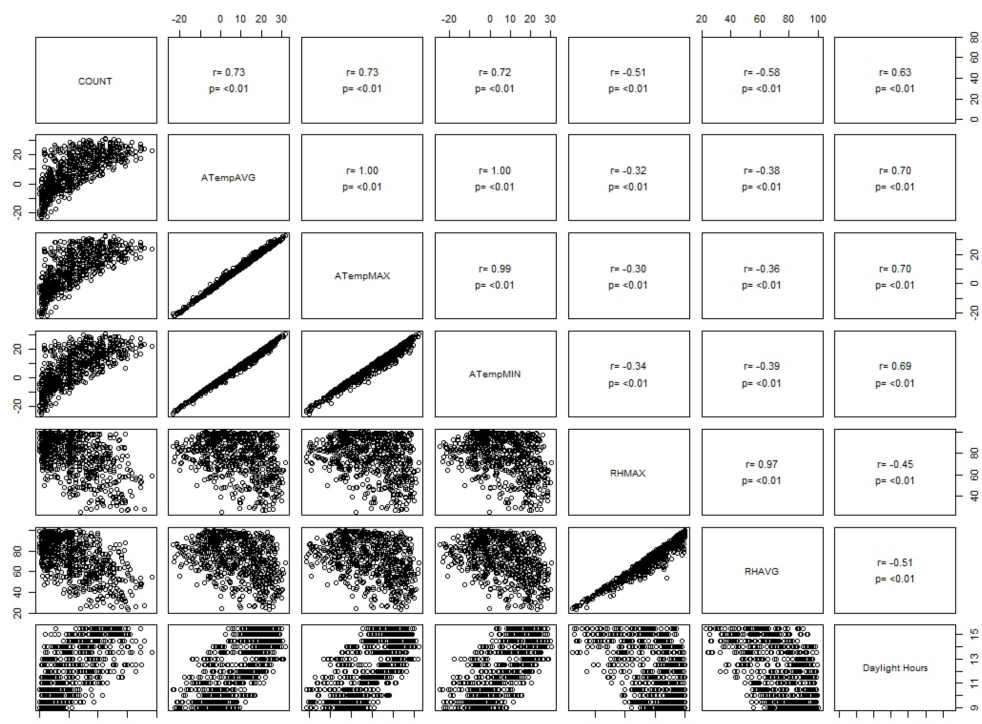
Scatterplot Matrix – Iron Horse Trail



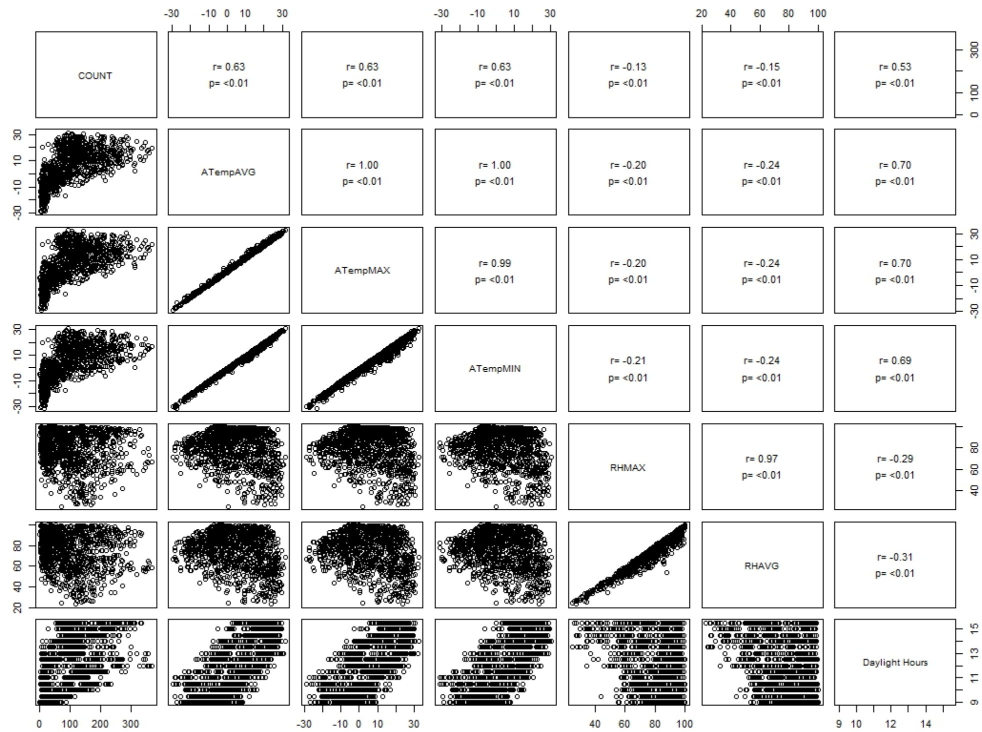


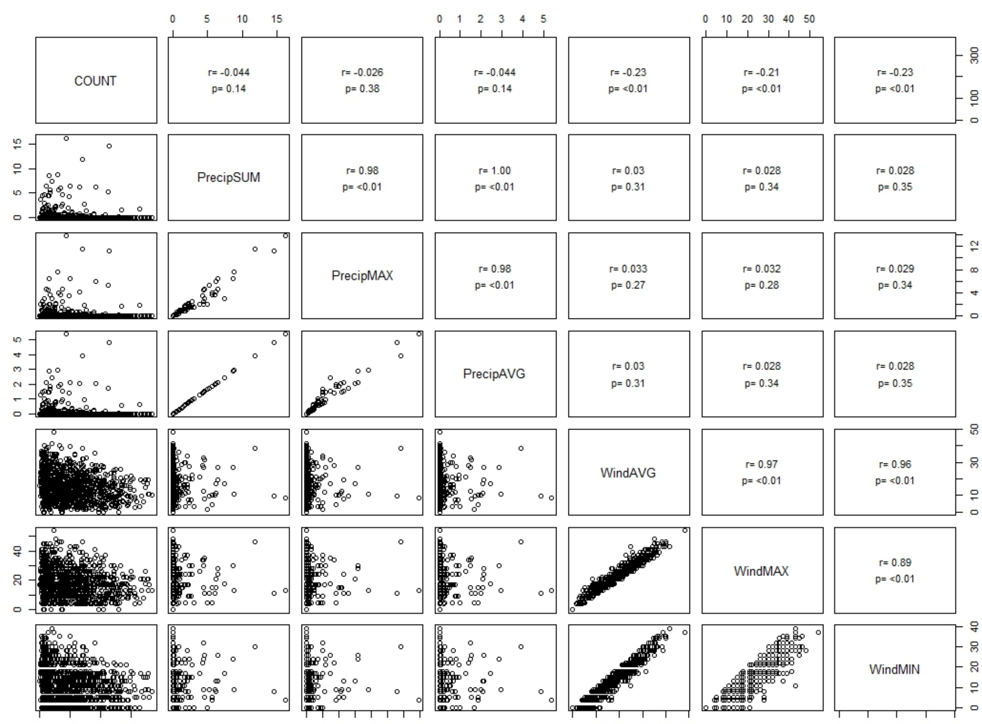
Scatterplot Matrix – Laurel Trail at Erb St. E.



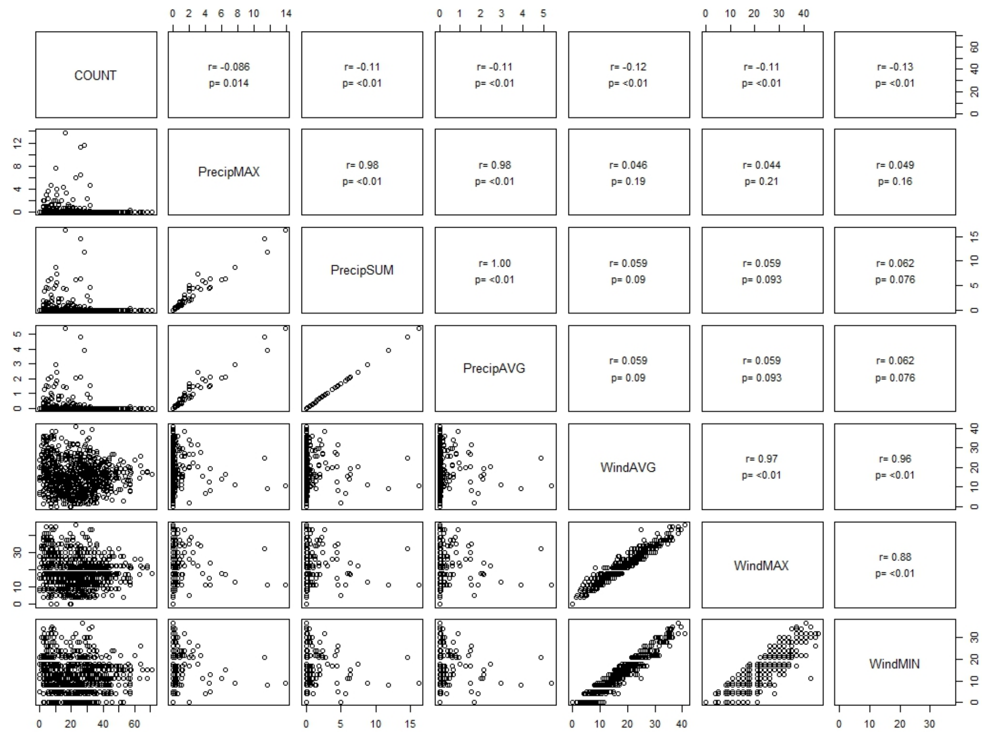


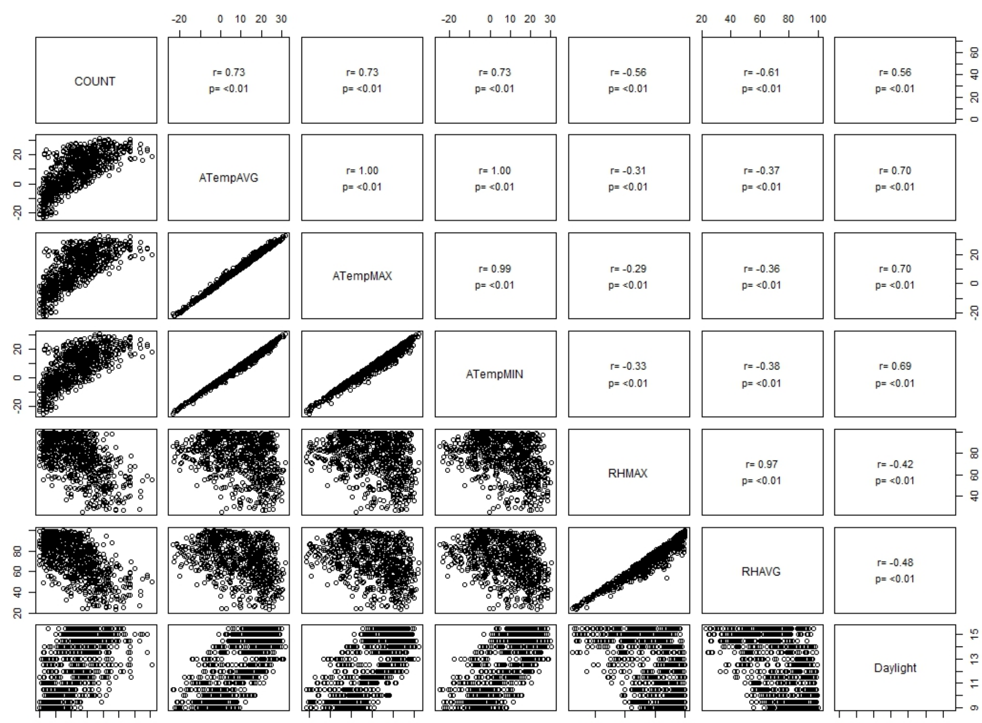
Scatterplot Matrix – Laurel Trail at Silver Lake



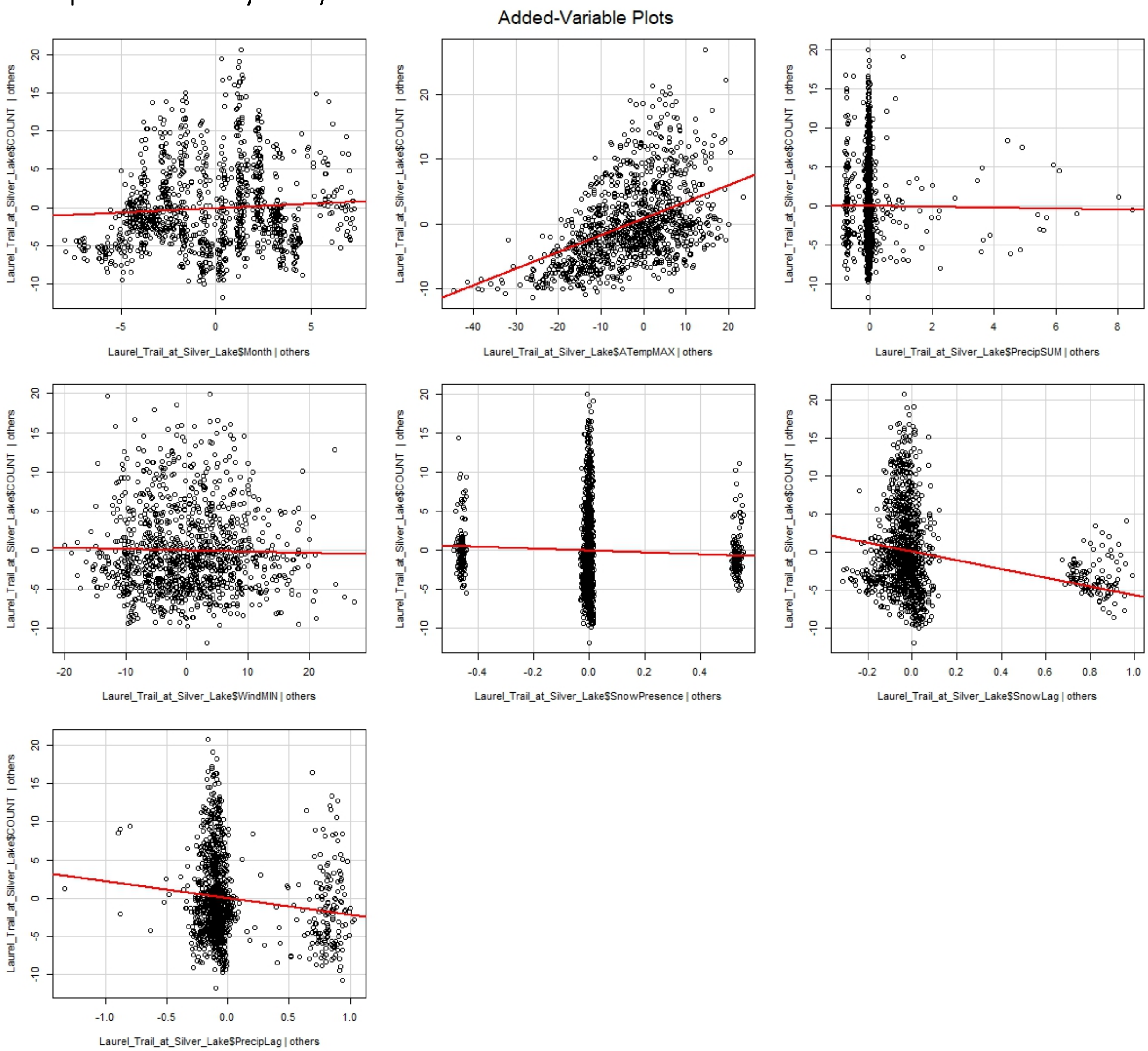


Scatterplot Matrix – Laurel Trail at Weber St. N.

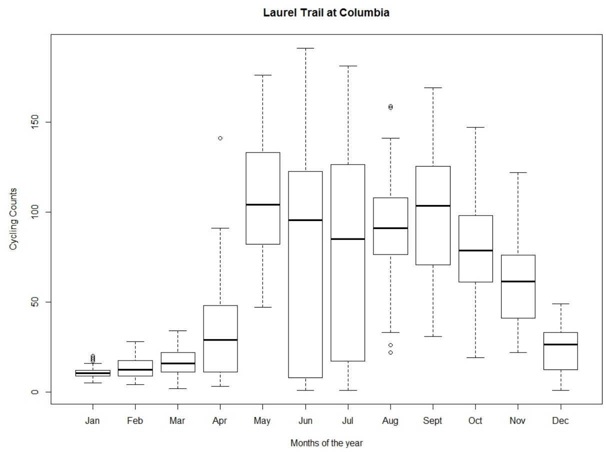


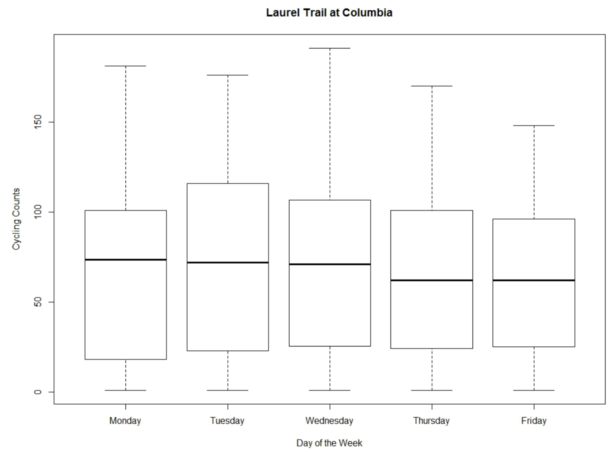


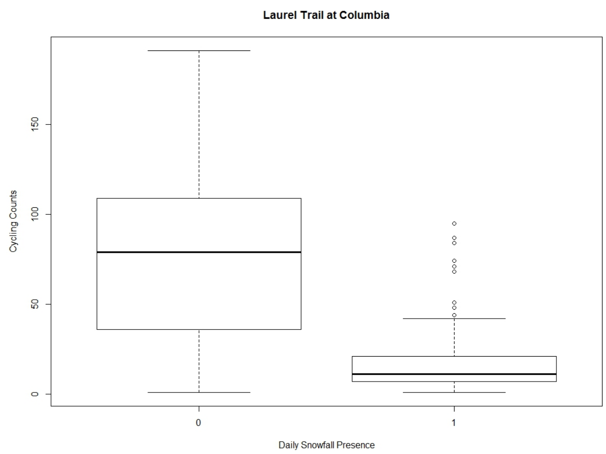
Added-Variable Plots (Partial Regression Plots) – Laurel Trail at Silver Lake (representative example for all study data)

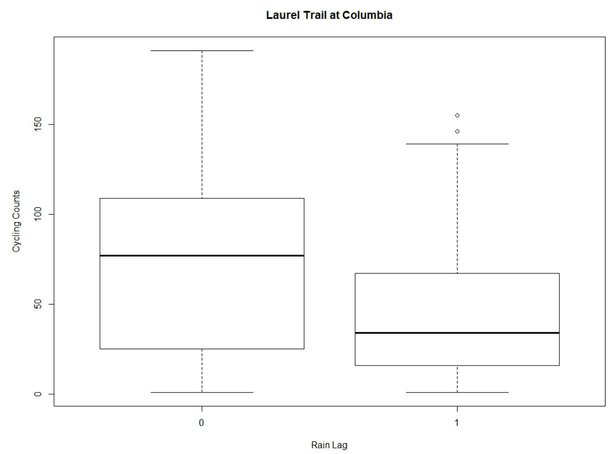


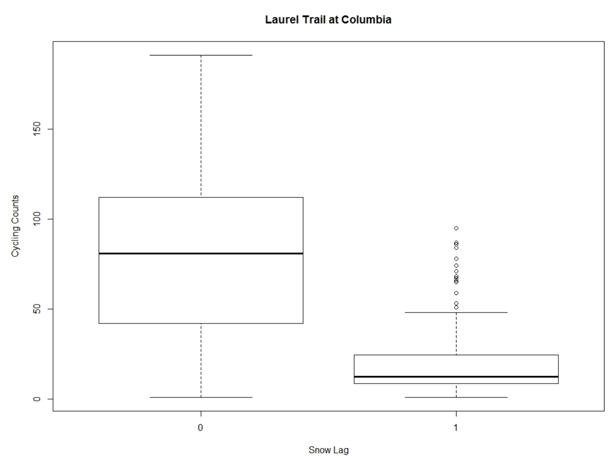
Boxplots – Laurel Trail at Columbia St. W.



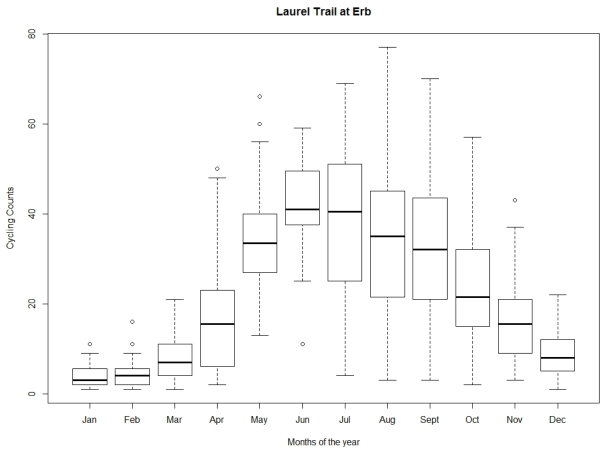


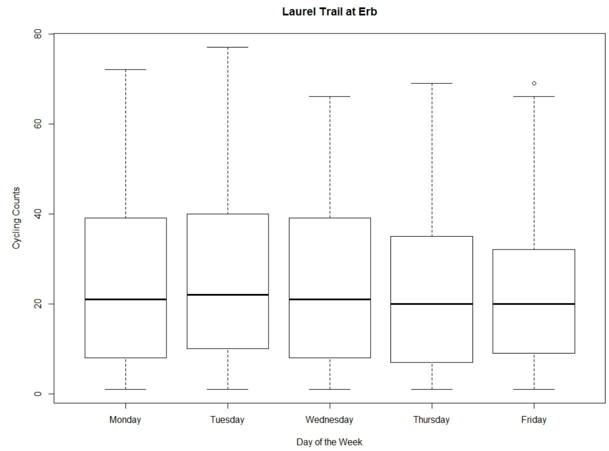


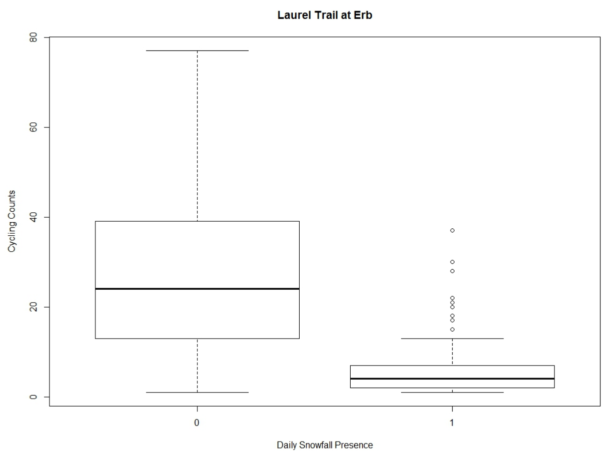


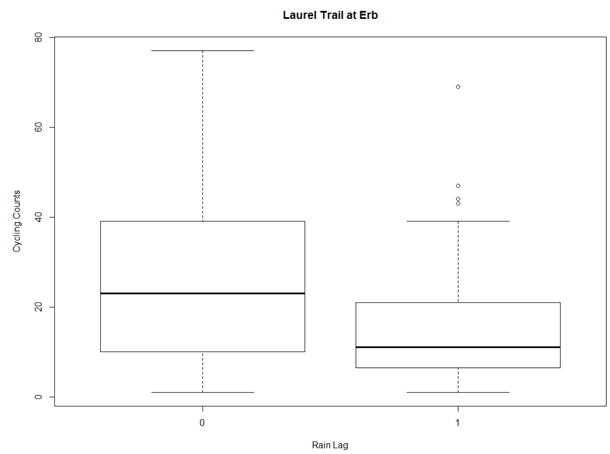


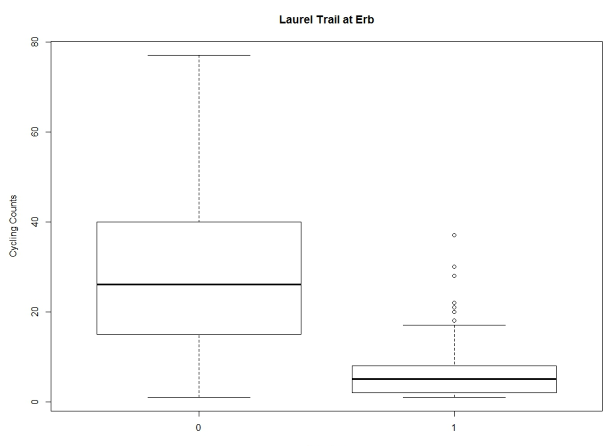
Boxplots – Laurel Trail at Weber St. N.



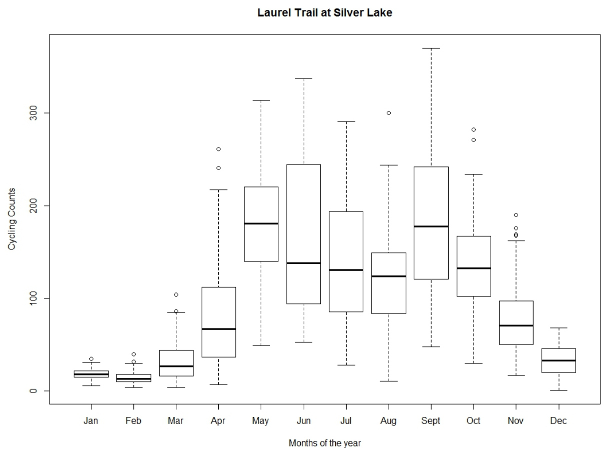


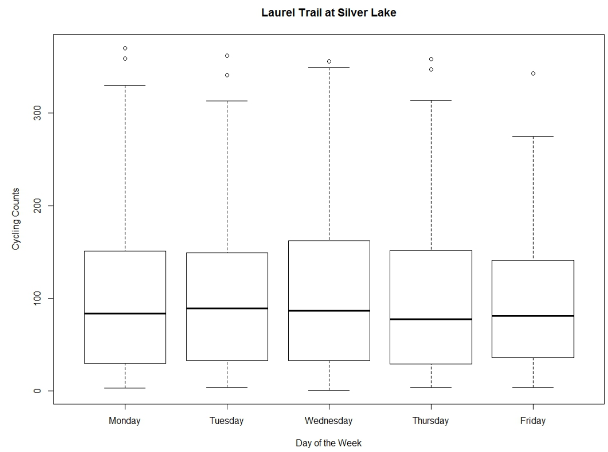


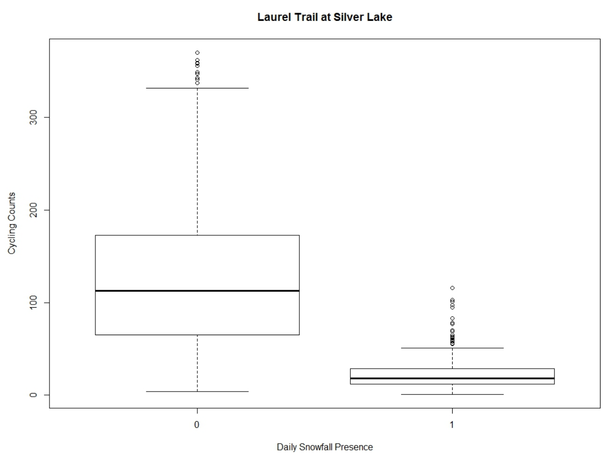


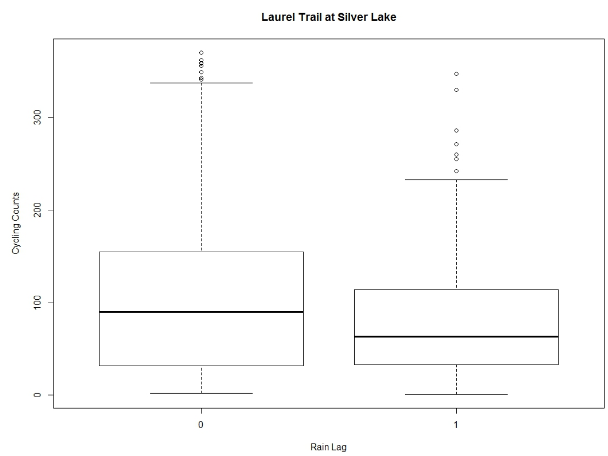


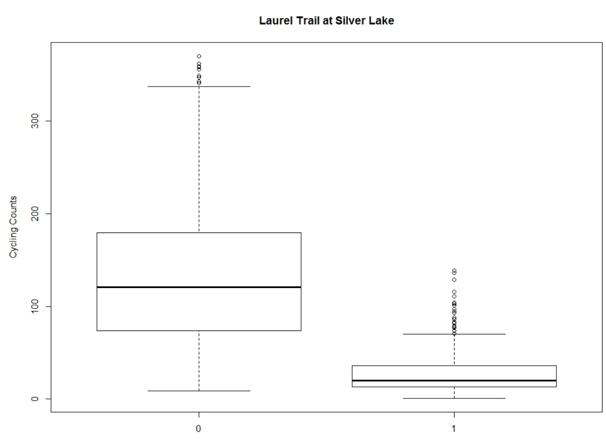
Boxplots – Laurel Trail at Silver Lake



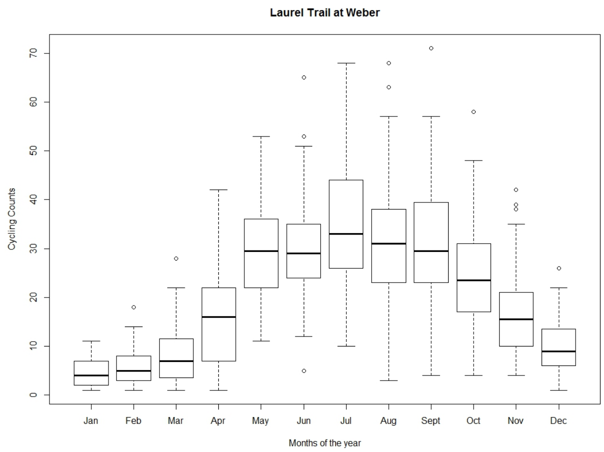


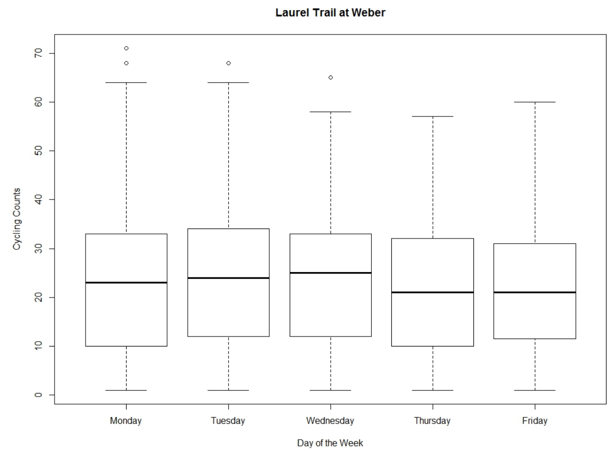


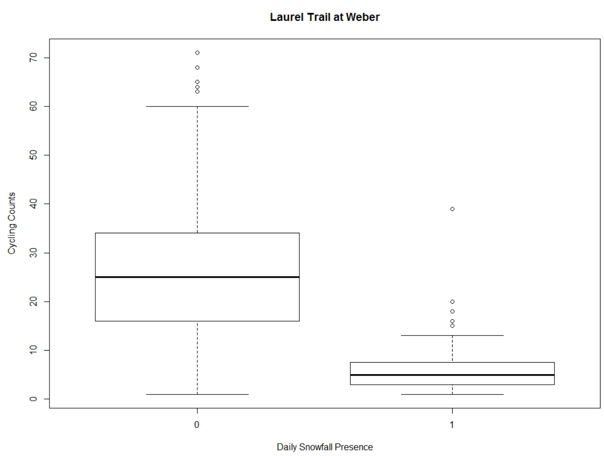


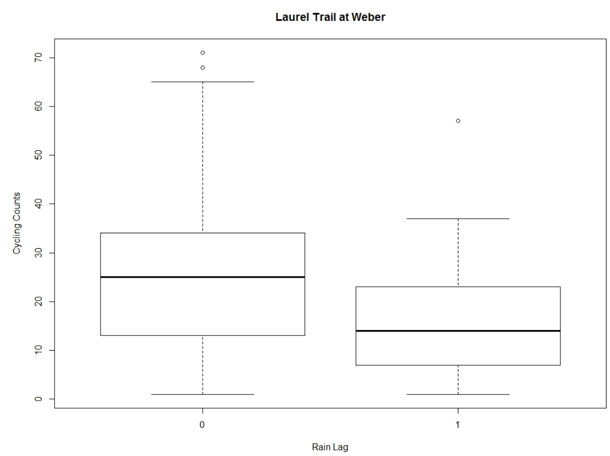


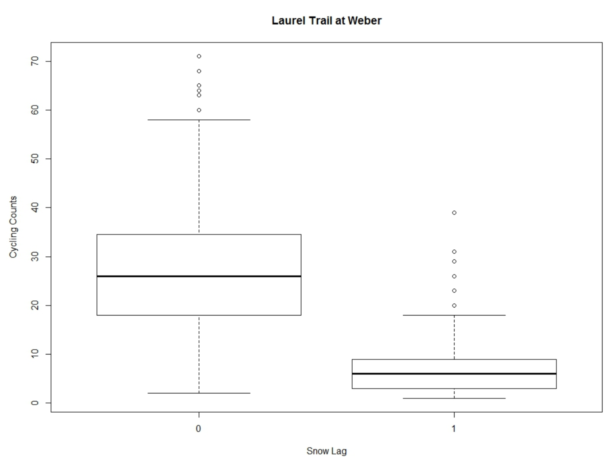
Boxplots – Laurel Trail at Weber St. N.











Weather and Cycling Regression Result Table – Iron Horse Trail

IHT		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	-0.291	0.234801	-1.211	0.226	-0.751	0.169
	March	-0.467	0.236765	-1.855	0.064	-0.932	-0.003
	April	0.106	0.220725	0.535	0.593	-0.326	0.539
	May	0.279	0.219876	1.359	0.175	-0.151	0.710
	June	0.285	0.221259	1.303	0.193	-0.149	0.718
	July	0.546	0.22044	2.583	0.010	0.114	0.978
	August	0.607	0.217235	2.83	0.005	0.181	1.032
	September	0.564	0.215832	2.665	0.008	0.141	0.987
	October	0.449	0.210026	2.255	0.024	0.037	0.861
	November	0.351	0.205579	1.801	0.072	-0.052	0.754
	December	0.119	0.213326	0.623	0.534	-0.299	0.538
Apparent Temperature	Extreme Cold	-0.591	0.303895	-2.056	0.040	-1.187	0.005
	Very Cold	-0.616	0.272149	-2.434	0.015	-1.149	-0.082
	Cold	-0.347	0.165405	-2.335	0.020	-0.671	-0.023
	Freezing	-0.155	0.10662	-1.721	0.086	-0.364	0.054
	Near Freezing	BASE					
	Cool	0.131	0.093806	1.245	0.213	-0.053	0.315
	Mild	0.342	0.096388	3.459	0.001	0.153	0.530
	Warm	0.517	0.099819	5.046	0.000	0.321	0.712
	Very Warm	0.470	0.105397	4.402	0.000	0.263	0.676
	Hot	0.396	0.110237	3.496	0.001	0.180	0.612
	Very Hot	0.567	0.153223	3.651	0.000	0.267	0.867
Precipitation	No Rain	BASE					
	Light Rain	-0.040	0.11892	-0.337	0.736	-0.273	0.193
	Moderate Rain	-0.465	0.179831	-2.586	0.010	-0.817	-0.113
	Heavy Rain	-0.664	0.223039	-2.977	0.003	-1.101	-0.227
Wind Speed		0.018	0.002596	7.106	0.000	0.013	0.023
Snow Presence		-0.021	0.191393	0.117	0.907	-0.397	0.354
Precipitation Lag		-0.260	0.091604	-2.809	0.005	-0.439	-0.080
Snow Lag		-0.594	0.147175	-4.063	0.000	-0.883	-0.306
Intercept		3.399	0.211752	16.026	0.000	2.984	3.814
R^2		61.26%					

Weather and Cycling Regression Result Table – Laurel Trail at Columbia

LTC		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	0.104	0.241408	0.494	0.621	-0.369	0.577
	March	-0.001	0.246483	-0.017	0.986	-0.484	0.482
	April	0.632	0.230098	2.861	0.004	0.181	1.083
	May	1.440	0.223317	6.528	0.000	1.002	1.878
	June	1.140	0.226408	5.096	0.000	0.696	1.584
	July	1.002	0.228421	4.472	0.000	0.555	1.450
	August	1.167	0.22757	5.24	0.000	0.721	1.613
	September	1.303	0.225836	5.898	0.000	0.860	1.745
	October	1.290	0.221323	5.892	0.000	0.856	1.724
	November	1.110	0.21792	5.171	0.000	0.683	1.537
	December	0.367	0.231599	1.606	0.109	-0.087	0.821
Apparent Temperature	Extreme Cold	-0.305	0.306237	-1.016	0.310	-0.905	0.295
	Very Cold	-0.456	0.252452	-1.81	0.071	-0.951	0.038
	Cold	-0.150	0.155605	-1.026	0.305	-0.455	0.155
	Freezing	-0.016	0.093968	-0.208	0.836	-0.200	0.168
	Near Freezing	BASE					
	Cool	0.099	0.078169	1.271	0.204	-0.054	0.252
	Mild	0.232	0.079886	2.73	0.006	0.075	0.388
	Warm	0.242	0.082707	2.896	0.004	0.080	0.404
	Very Warm	0.263	0.085916	2.953	0.003	0.095	0.431
	Hot	0.435	0.091232	4.704	0.000	0.256	0.614
	Very Hot	0.331	0.150908	2.116	0.035	0.035	0.627
Precipitation	No Rain	BASE					
	Light Rain	-0.036	0.066538	-0.541	0.589	-0.166	0.094
	Moderate Rain	-0.348	0.115615	-3.011	0.003	-0.575	-0.121
	Heavy Rain	-0.279	0.146386	-1.907	0.057	-0.566	0.008
Wind Speed		-0.002	0.002194	-0.833	0.405	-0.006	0.002
Snow Presence		-0.441	0.136329	-3.279	0.001	-0.708	-0.173
Precipitation Lag		-0.113	0.049001	-2.317	0.021	-0.210	-0.017
Snow Lag		-0.068	0.099655	-0.553	0.580	-0.263	0.127
Intercept		3.064	0.224032	13.608	0.000	2.625	3.504
R^2		76.70%					

Weather and Cycling Regression Result Table – Laurel Trail at Erb

LTE		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	-0.074	0.227125	-0.316	0.752	-0.519	0.371
	March	0.170	0.215964	0.866	0.387	-0.253	0.594
	April	0.768	0.206973	3.722	0.000	0.363	1.174
	May	0.959	0.209989	4.578	0.000	0.547	1.371
	June	1.101	0.210748	5.183	0.000	0.688	1.514
	July	0.873	0.212345	4.075	0.000	0.456	1.289
	August	0.864	0.21028	4.067	0.000	0.452	1.276
	September	0.841	0.209217	3.946	0.000	0.431	1.251
	October	0.824	0.204772	4.057	0.000	0.423	1.225
	November	0.640	0.201659	3.209	0.001	0.245	1.036
	December	0.194	0.212117	0.922	0.357	-0.221	0.610
Apparent Temperature	Extreme Cold	-0.827	0.300871	-2.811	0.005	-1.417	-0.238
	Very Cold	-0.657	0.241256	-2.828	0.005	-1.129	-0.184
	Cold	-0.345	0.150112	-2.412	0.016	-0.639	-0.050
	Freezing	-0.101	0.09385	-1.202	0.230	-0.285	0.083
	Near Freezing	BASE					
	Cool	0.209	0.083212	2.368	0.018	0.046	0.372
	Mild	0.405	0.085655	4.686	0.000	0.238	0.573
	Warm	0.525	0.088834	5.938	0.000	0.351	0.699
	Very Warm	0.596	0.092939	6.477	0.000	0.414	0.778
	Hot	0.665	0.096085	6.987	0.000	0.476	0.853
	Very Hot	0.688	0.137705	5.05	0.000	0.418	0.957
Precipitation	No Rain	BASE					
	Light Rain	-0.111	0.104091	-1.066	0.287	-0.315	0.093
	Moderate Rain	-0.388	0.154591	-2.511	0.012	-0.691	-0.085
	Heavy Rain	-0.534	0.261419	-2.044	0.041	-1.047	-0.022
Wind Speed		0.004	0.00224	1.978	0.048	0.000	0.009
Snow Presence		-0.314	0.150635	-1.939	0.053	-0.609	-0.019
Precipitation Lag		-0.207	0.077896	-2.838	0.005	-0.360	-0.055
Snow Lag		-0.019	0.114336	-0.217	0.828	-0.243	0.205
Intercept		2.119	0.208367	10.17	0.000	1.710	2.527
R^2		69.08%					

Weather and Cycling Regression Result Table – Laurel Trail at Silver Lake

LTSL		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	-0.300	0.168	-1.781	0.075	-0.629	0.029
	March	0.202	0.147	1.403	0.161	-0.087	0.491
	April	0.859	0.144	5.992	0.000	0.577	1.141
	May	1.401	0.147	9.576	0.000	1.113	1.688
	June	1.271	0.148	8.594	0.000	0.981	1.561
	July	1.166	0.151	7.782	0.000	0.871	1.461
	August	1.036	0.150	6.925	0.000	0.742	1.329
	September	1.427	0.145	9.832	0.000	1.142	1.712
	October	1.235	0.142	8.725	0.000	0.957	1.513
	November	0.829	0.139	5.991	0.000	0.557	1.101
	December	0.176	0.149	1.213	0.225	-0.116	0.468
Apparent Temperature	Extreme Cold	-0.514	0.159	-3.204	0.001	-0.826	-0.202
	Very Cold	-0.459	0.139	-3.293	0.001	-0.731	-0.187
	Cold	-0.236	0.094	-2.52	0.012	-0.419	-0.052
	Freezing	-0.216	0.708	-3.061	0.002	-1.603	1.171
	Near Freezing	BASE					
	Cool	0.107	0.059	1.841	0.066	-0.007	0.222
	Mild	0.142	0.060	2.388	0.017	0.025	0.260
	Warm	0.242	0.063	3.849	0.000	0.118	0.365
	Very Warm	0.180	0.068	2.668	0.008	0.046	0.313
	Hot	0.049	0.074	0.689	0.491	-0.097	0.195
	Very Hot	0.266	0.094	2.813	0.005	0.082	0.450
Precipitation	No Rain	BASE					
	Light Rain	-0.002	0.057	-0.043	0.966	-0.113	0.108
	Moderate Rain	-0.102	0.096	-1.059	0.290	-0.290	0.087
	Heavy Rain	0.112	0.124	0.904	0.366	-0.131	0.355
Wind Speed		0.002	0.002	0.888	0.375	-0.002	0.005
Snow Presence		-0.066	0.114	-0.585	0.559	-0.289	0.157
Precipitation Lag		-0.215	0.043	-4.905	0.000	-0.299	-0.131
Snow Lag		-0.380	0.086	-4.407	0.000	-0.549	-0.211
Intercept		3.644	0.144	25.338	0.000	3.363	3.926
R^2		71.31%					

Weather and Cycling Regression Result Table – Laurel Trail at Weber

LTW		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	0.066	0.180123	0.385	0.700	-0.287	0.419
	March	0.031	0.179389	0.267	0.790	-0.320	0.383
	April	0.493	0.172163	2.885	0.004	0.155	0.830
	May	0.583	0.171991	3.418	0.001	0.246	0.920
	June	0.601	0.173374	3.482	0.001	0.261	0.941
	July	0.632	0.174606	3.67	0.000	0.290	0.974
	August	0.556	0.174405	3.202	0.001	0.214	0.898
	September	0.592	0.1734	3.44	0.001	0.252	0.932
	October	0.632	0.169675	3.787	0.000	0.299	0.964
	November	0.447	0.167337	2.706	0.007	0.119	0.775
	December	0.147	0.174245	0.876	0.381	-0.194	0.489
Apparent Temperature	Extreme Cold	-0.714	0.238892	-3.061	0.002	-1.182	-0.246
	Very Cold	-0.607	0.203252	-3.108	0.002	-1.006	-0.209
	Cold	-0.379	0.12824	-3.099	0.002	-0.631	-0.128
	Freezing	-0.111	0.078806	-1.586	0.113	-0.266	0.043
	Near Freezing	BASE					
	Cool	0.223	0.067636	3.199	0.001	0.091	0.356
	Mild	0.399	0.069696	5.654	0.000	0.262	0.536
	Warm	0.476	0.071624	6.558	0.000	0.336	0.616
	Very Warm	0.497	0.074211	6.624	0.000	0.352	0.643
	Hot	0.638	0.078227	8.075	0.000	0.485	0.791
	Very Hot	0.733	0.116713	6.235	0.000	0.504	0.962
Precipitation	No Rain	BASE					
	Light Rain	-0.155	0.083674	-1.855	0.064	-0.319	0.009
	Moderate Rain	-0.371	0.119598	-3.101	0.002	-0.605	-0.137
	Heavy Rain	-0.486	0.140465	-3.463	0.001	-0.762	-0.211
Wind Speed		0.008	0.001812	4.47	0.000	0.004	0.012
Snow Presence		-0.338	0.130849	-2.371	0.018	-0.594	-0.081
Precipitation Lag		-0.142	0.061714	-2.296	0.022	-0.263	-0.021
Snow Lag		-0.144	0.10028	-1.529	0.127	-0.340	0.053
Intercept		2.311	0.172379	13.402	0.000	1.973	2.648
R^2		66.76%					

Climate Change and Cycling Regression Result Table – Iron Horse Trail

IHT RCP26		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	-0.321	0.233	-1.375	0.170	-0.778	0.136
	March	-0.487	0.234	-2.078	0.038	-0.947	-0.028
	April	0.013	0.218	0.06	0.952	-0.414	0.441
	May	0.235	0.218	1.077	0.282	-0.193	0.663
	June	0.227	0.220	1.036	0.301	-0.203	0.658
	July	0.479	0.219	2.185	0.029	0.049	0.908
	August	0.531	0.216	2.46	0.014	0.108	0.954
	September	0.480	0.215	2.237	0.026	0.059	0.900
	October	0.408	0.208	1.961	0.050	0.000	0.815
	November	0.332	0.204	1.632	0.103	-0.067	0.731
	December	0.082	0.210	0.392	0.695	-0.329	0.494
Apparent Temperature	Extreme Cold	-0.612	0.332	-1.843	0.066	-1.264	0.039
	Very Cold	-0.792	0.336	-2.362	0.018	-1.450	-0.135
	Cold	-0.506	0.221	-2.292	0.022	-0.938	-0.073
	Freezing	-0.272	0.121	-2.247	0.025	-0.509	-0.035
	Near Freezing	BASE					
	Cool	0.199	0.094	2.121	0.034	0.015	0.383
	Mild	0.299	0.097	3.065	0.002	0.108	0.489
	Warm	0.569	0.100	5.677	0.000	0.373	0.765
	Very Warm	0.630	0.105	5.99	0.000	0.424	0.836
	Hot	0.545	0.109	5.015	0.000	0.332	0.758
	Very Hot	0.696	0.155	4.488	0.000	0.392	1.000
Precipitation	No Rain	BASE					
	Light Rain	-0.046	0.120	-0.381	0.703	-0.280	0.189
	Moderate Rain	-0.448	0.180	-2.488	0.013	-0.801	-0.095
	Heavy Rain	-0.690	0.223	-3.09	0.002	-1.128	-0.252
Wind Speed		0.018	0.003	7.069	0.000	0.013	0.023
Snow Presence		-0.252	0.092	-2.738	0.006	-0.433	-0.072
Precipitation Lag		-0.250	0.179	-1.395	0.163	-0.601	0.101
Snow Lag		-0.246	0.136	-1.808	0.071	-0.513	0.021
Intercept		3.348	0.208	16.075	0.000	2.940	3.756
R^2		61.33%					

IHT RCP45		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	-0.359	0.235	-1.528	0.127	-0.820	0.102
	March	-0.486	0.235	-2.067	0.039	-0.947	-0.025
	April	-0.019	0.219	-0.086	0.932	-0.447	0.410
	May	0.248	0.218	1.135	0.257	-0.180	0.676
	June	0.241	0.219	1.101	0.271	-0.188	0.671
	July	0.499	0.219	2.283	0.023	0.071	0.928
	August	0.547	0.216	2.539	0.011	0.125	0.970
	September	0.497	0.214	2.32	0.021	0.077	0.918
	October	0.407	0.208	1.957	0.051	-0.001	0.814
	November	0.324	0.204	1.588	0.113	-0.076	0.724
	December	0.020	0.212	0.095	0.924	-0.395	0.435
Apparent Temperature	Extreme Cold	-0.662	0.343	-1.931	0.054	-1.333	0.010
	Very Cold	-0.850	0.348	-2.445	0.015	-1.532	-0.169
	Cold	-0.581	0.219	-2.647	0.008	-1.011	-0.151
	Freezing	-0.385	0.127	-3.027	0.003	-0.634	-0.136
	Near Freezing	BASE					
	Cool	0.105	0.094	1.12	0.263	-0.079	0.290
	Mild	0.251	0.096	2.599	0.010	0.062	0.440
	Warm	0.471	0.102	4.628	0.000	0.271	0.670
	Very Warm	0.573	0.103	5.575	0.000	0.371	0.774
	Hot	0.487	0.107	4.549	0.000	0.277	0.697
	Very Hot	0.631	0.155	4.077	0.000	0.328	0.934
Precipitation	No Rain	BASE					
	Light Rain	-0.043	0.120	-0.362	0.718	-0.278	0.192
	Moderate Rain	-0.424	0.180	-2.358	0.019	-0.776	-0.072
	Heavy Rain	-0.699	0.224	-3.128	0.002	-1.137	-0.261
Wind Speed		0.018	0.003	6.971	0.000	0.013	0.023
Snow Presence		-0.255	0.092	-2.775	0.006	-0.436	-0.075
Precipitation Lag		-0.247	0.180	-1.37	0.171	-0.600	0.106
Snow Lag		-0.243	0.140	-1.735	0.083	-0.518	0.032
Intercept		3.397	0.207	16.376	0.000	2.991	3.804
R^2		61.26%					

IHT RCP85		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	-0.354	0.235	-1.503	0.133	-0.815	0.108
	March	-0.489	0.236	-2.075	0.038	-0.951	-0.027
	April	0.053	0.218	0.244	0.807	-0.374	0.480
	May	0.315	0.218	1.448	0.148	-0.112	0.743
	June	0.291	0.219	1.33	0.184	-0.138	0.721
	July	0.570	0.218	2.609	0.009	0.142	0.998
	August	0.613	0.215	2.846	0.005	0.191	1.036
	September	0.580	0.214	2.711	0.007	0.161	0.999
	October	0.451	0.208	2.17	0.030	0.044	0.859
	November	0.373	0.203	1.836	0.067	-0.025	0.772
	December	0.058	0.212	0.272	0.785	-0.358	0.474
Apparent Temperature	Extreme Cold	-0.444	0.362	-1.226	0.221	-1.154	0.266
	Very Cold	-0.632	0.368	-1.719	0.086	-1.353	0.089
	Cold	-0.443	0.229	-1.936	0.053	-0.892	0.005
	Freezing	-0.197	0.140	-1.405	0.161	-0.472	0.078
	Near Freezing	BASE					
	Cool	0.213	0.099	2.155	0.032	0.019	0.407
	Mild	0.320	0.101	3.169	0.002	0.122	0.518
	Warm	0.459	0.107	4.287	0.000	0.249	0.669
	Very Warm	0.706	0.107	6.596	0.000	0.496	0.916
	Hot	0.567	0.111	5.112	0.000	0.350	0.785
	Very Hot	0.715	0.159	4.496	0.000	0.403	1.026
Precipitation	No Rain	BASE					
	Light Rain	-0.006	0.120	-0.052	0.959	-0.240	0.228
	Moderate Rain	-0.430	0.191	-2.251	0.025	-0.804	-0.056
	Heavy Rain	-0.641	0.225	-2.856	0.004	-1.081	-0.201
Wind Speed		0.018	0.003	6.779	0.000	0.013	0.023
Snow Presence		-0.283	0.093	-3.056	0.002	-0.465	-0.102
Precipitation Lag		-0.298	0.182	-1.633	0.103	-0.655	0.060
Snow Lag		-0.230	0.142	-1.624	0.105	-0.507	0.048
Intercept		3.246	0.208	15.6	0.000	2.838	3.654
R^2		61.12%					

Climate Change and Cycling Regression Results Table – Laurel Trail at Columbia

	LTC RCP26	Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	0.103	0.176	0.587	0.557	-0.242	0.448
	March	0.022	0.177	0.126	0.900	-0.324	0.368
	April	0.644	0.164	3.915	0.000	0.322	0.966
	May	1.453	0.160	9.100	0.000	1.140	1.766
	June	1.459	0.161	9.036	0.000	1.142	1.775
	July	1.367	0.164	8.345	0.000	1.046	1.688
	August	1.194	0.163	7.332	0.000	0.874	1.513
	September	1.314	0.162	8.132	0.000	0.997	1.631
	October	1.292	0.158	8.175	0.000	0.982	1.601
	November	1.124	0.156	7.228	0.000	0.819	1.429
	December	0.360	0.165	2.182	0.029	0.037	0.684
Apparent Temperature	Extreme Cold	-0.182	0.247	-0.740	0.460	-0.666	0.301
	Very Cold	-0.550	0.237	-2.319	0.021	-1.015	-0.085
	Cold	-0.137	0.137	-1.000	0.318	-0.406	0.132
	Freezing	-0.012	0.075	-0.154	0.877	-0.160	0.136
	Near Freezing	BASE					
	Cool	0.109	0.059	1.848	0.065	-0.007	0.225
	Mild	0.120	0.060	1.994	0.046	0.002	0.237
	Warm	0.302	0.061	4.973	0.000	0.183	0.421
	Very Warm	0.283	0.064	4.425	0.000	0.158	0.408
	Hot	0.399	0.066	6.000	0.000	0.268	0.529
	Very Hot	0.318	0.076	4.203	0.000	0.170	0.467
Precipitation	No Rain	BASE					
	Light Rain	-0.061	0.049	-1.242	0.215	-0.156	0.035
	Moderate Rain	-0.166	0.085	-1.962	0.050	-0.333	0.000
	Heavy Rain	-0.230	0.093	-2.475	0.014	-0.412	-0.048
Wind Speed		-0.003	0.002	-1.957	0.051	-0.006	0.000
Snow Presence		-0.076	0.036	-2.101	0.036	-0.146	-0.005
Precipitation Lag		-0.333	0.112	-2.986	0.003	-0.552	-0.114
Snow Lag		-0.224	0.084	-2.676	0.008	-0.388	-0.060
Intercept		3.043	0.159	19.098	0.000	2.730	3.355
R^2		77.32%					

LTC RCP45		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	0.103	0.179	0.577	0.564	-0.248	0.454
	March	0.051	0.181	0.281	0.779	-0.303	0.405
	April	0.659	0.168	3.919	0.000	0.329	0.988
	May	1.484	0.163	9.127	0.000	1.165	1.803
	June	1.487	0.164	9.044	0.000	1.165	1.809
	July	1.400	0.167	8.395	0.000	1.073	1.727
	August	1.226	0.166	7.397	0.000	0.901	1.550
	September	1.335	0.165	8.110	0.000	1.012	1.657
	October	1.316	0.161	8.173	0.000	1.000	1.631
	November	1.141	0.159	7.178	0.000	0.829	1.453
	December	0.396	0.169	2.341	0.020	0.064	0.727
Apparent Temperature	Extreme Cold	-0.173	0.257	-0.673	0.501	-0.677	0.331
	Very Cold	-0.610	0.268	-2.276	0.023	-1.136	-0.085
	Cold	-0.232	0.143	-1.629	0.104	-0.512	0.047
	Freezing	-0.081	0.086	-0.940	0.347	-0.250	0.088
	Near Freezing	BASE					
	Cool	0.052	0.061	0.864	0.388	-0.067	0.171
	Mild	0.088	0.061	1.448	0.148	-0.031	0.208
	Warm	0.265	0.063	4.240	0.000	0.143	0.388
	Very Warm	0.289	0.064	4.519	0.000	0.164	0.415
	Hot	0.315	0.067	4.682	0.000	0.183	0.447
	Very Hot	0.314	0.075	4.178	0.000	0.167	0.461
Precipitation	No Rain	BASE					
	Light Rain	-0.079	0.050	-1.602	0.109	-0.177	0.018
	Moderate Rain	-0.167	0.086	-1.953	0.051	-0.335	0.001
	Heavy Rain	-0.224	0.094	-2.384	0.017	-0.408	-0.040
Wind Speed		-0.003	0.002	-1.624	0.105	-0.006	0.001
Snow Presence		-0.081	0.036	-2.233	0.026	-0.151	-0.010
Precipitation Lag		-0.354	0.106	-3.341	0.001	-0.561	-0.146
Snow Lag		-0.144	0.078	-1.861	0.063	-0.296	0.008
Intercept		3.037	0.162	18.794	0.000	2.720	3.353
R^2		76.65%					

LTC RCP85		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	0.074	0.178	0.414	0.679	-0.275	0.423
	March	0.022	0.180	0.122	0.903	-0.331	0.375
	April	0.645	0.167	3.857	0.000	0.317	0.973
	May	1.463	0.162	9.009	0.000	1.145	1.782
	June	1.460	0.164	8.882	0.000	1.138	1.782
	July	1.369	0.167	8.217	0.000	1.043	1.696
	August	1.193	0.166	7.208	0.000	0.869	1.518
	September	1.310	0.164	7.975	0.000	0.988	1.632
	October	1.291	0.161	8.019	0.000	0.975	1.606
	November	1.127	0.158	7.112	0.000	0.816	1.437
	December	0.337	0.169	1.996	0.046	0.006	0.668
Apparent Temperature	Extreme Cold	-0.132	0.263	-0.501	0.616	-0.647	0.383
	Very Cold	-0.634	0.284	-2.234	0.026	-1.190	-0.078
	Cold	-0.262	0.150	-1.743	0.082	-0.556	0.032
	Freezing	-0.113	0.093	-1.217	0.224	-0.295	0.069
	Near Freezing	BASE					
	Cool	0.059	0.063	0.935	0.350	-0.064	0.182
	Mild	0.091	0.062	1.454	0.146	-0.032	0.213
	Warm	0.263	0.064	4.101	0.000	0.137	0.388
	Very Warm	0.309	0.065	4.743	0.000	0.181	0.437
	Hot	0.331	0.068	4.853	0.000	0.197	0.464
	Very Hot	0.361	0.072	4.983	0.000	0.219	0.502
Precipitation	No Rain	BASE					
	Light Rain	-0.086	0.049	-1.746	0.081	-0.183	0.011
	Moderate Rain	-0.186	0.088	-2.121	0.034	-0.358	-0.014
	Heavy Rain	-0.240	0.093	-2.573	0.010	-0.423	-0.057
Wind Speed		-0.003	0.002	-1.742	0.082	-0.006	0.000
Snow Presence		-0.072	0.036	-1.985	0.047	-0.143	-0.001
Precipitation Lag		-0.269	0.119	-2.262	0.024	-0.503	-0.036
Snow Lag		-0.198	0.084	-2.349	0.019	-0.363	-0.033
Intercept		3.039	0.162	18.771	0.000	2.722	3.356
R^2		76.74%					

Climate Change and Cycling Regression Result Table – Laurel Trail at Erb

LTE RCP26		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	0.006	0.227	0.025	0.980	-0.439	0.450
	March	0.299	0.211	1.417	0.157	-0.114	0.712
	April	0.921	0.200	4.604	0.000	0.529	1.313
	May	1.170	0.203	5.762	0.000	0.772	1.568
	June	1.330	0.203	6.539	0.000	0.931	1.728
	July	1.078	0.205	5.256	0.000	0.676	1.480
	August	1.064	0.203	5.239	0.000	0.666	1.463
	September	1.063	0.202	5.273	0.000	0.668	1.458
	October	1.022	0.197	5.186	0.000	0.636	1.409
	November	0.802	0.194	4.136	0.000	0.422	1.183
	December	0.306	0.206	1.489	0.137	-0.097	0.709
Apparent Temperature	Extreme Cold	-0.703	0.287	-2.451	0.014	-1.265	-0.141
	Very Cold	-0.669	0.263	-2.546	0.011	-1.184	-0.154
	Cold	-0.227	0.135	-1.683	0.093	-0.492	0.037
	Freezing	-0.017	0.088	-0.198	0.843	-0.190	0.156
	Near Freezing	BASE					
	Cool	0.242	0.078	3.101	0.002	0.089	0.396
	Mild	0.308	0.079	3.901	0.000	0.153	0.463
	Warm	0.481	0.082	5.872	0.000	0.320	0.641
	Very Warm	0.496	0.086	5.739	0.000	0.327	0.666
	Hot	0.629	0.090	6.984	0.000	0.452	0.805
	Very Hot	0.654	0.120	5.467	0.000	0.419	0.888
Precipitation	No Rain	BASE					
	Light Rain	-0.120	0.105	-1.136	0.256	-0.327	0.087
	Moderate Rain	-0.354	0.156	-2.268	0.024	-0.659	-0.048
	Heavy Rain	-0.314	0.163	-1.922	0.055	-0.634	0.006
Wind Speed		0.001	0.002	0.490	0.624	-0.003	0.006
Snow Presence		-0.236	0.079	-2.998	0.003	-0.391	-0.082
Precipitation Lag		-0.294	0.147	-2.001	0.046	-0.582	-0.006
Snow Lag		-0.066	0.114	-0.579	0.563	-0.291	0.158
Intercept		2.013	0.201	10.023	0.000	1.619	2.407
R^2		68.41%					

LTE RCP45		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	-0.043	0.227	-0.188	0.851	-0.487	0.401
	March	0.297	0.209	1.423	0.155	-0.112	0.706
	April	0.916	0.199	4.601	0.000	0.526	1.307
	May	1.164	0.200	5.820	0.000	0.772	1.556
	June	1.328	0.200	6.633	0.000	0.935	1.720
	July	1.071	0.202	5.300	0.000	0.675	1.468
	August	1.058	0.200	5.285	0.000	0.666	1.450
	September	1.059	0.199	5.330	0.000	0.670	1.448
	October	1.021	0.194	5.258	0.000	0.641	1.402
	November	0.787	0.192	4.097	0.000	0.410	1.163
	December	0.282	0.204	1.385	0.167	-0.117	0.682
Apparent Temperature	Extreme Cold	-0.819	0.320	-2.564	0.011	-1.445	-0.193
	Very Cold	-0.598	0.255	-2.347	0.019	-1.097	-0.099
	Cold	-0.213	0.161	-1.324	0.186	-0.530	0.103
	Freezing	-0.046	0.101	-0.458	0.647	-0.243	0.151
	Near Freezing	BASE					
	Cool	0.185	0.078	2.388	0.017	0.033	0.337
	Mild	0.279	0.079	3.518	0.000	0.124	0.435
	Warm	0.442	0.082	5.393	0.000	0.281	0.602
	Very Warm	0.452	0.087	5.220	0.000	0.283	0.622
	Hot	0.602	0.090	6.656	0.000	0.425	0.779
	Very Hot	0.609	0.106	5.716	0.000	0.400	0.817
Precipitation	No Rain	BASE					
	Light Rain	-0.146	0.106	-1.379	0.168	-0.352	0.061
	Moderate Rain	-0.375	0.156	-2.411	0.016	-0.680	-0.070
	Heavy Rain	-0.331	0.163	-2.038	0.042	-0.650	-0.013
Wind Speed		0.001	0.002	0.543	0.587	-0.003	0.006
Snow Presence		-0.220	0.079	-2.788	0.005	-0.374	-0.065
Precipitation Lag		-0.292	0.125	-2.330	0.020	-0.537	-0.046
Snow Lag		-0.099	0.104	-0.952	0.341	-0.303	0.105
Intercept		2.041	0.197	10.366	0.000	1.655	2.427
R^2		68.37%					

LTE RCP85		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	-0.057	0.229	-0.248	0.804	-0.506	0.392
	March	0.279	0.213	1.311	0.190	-0.138	0.695
	April	0.887	0.202	4.401	0.000	0.492	1.282
	May	1.135	0.204	5.569	0.000	0.735	1.534
	June	1.295	0.204	6.341	0.000	0.895	1.695
	July	1.048	0.206	5.078	0.000	0.643	1.452
	August	1.028	0.204	5.030	0.000	0.627	1.428
	September	1.012	0.203	4.991	0.000	0.615	1.410
	October	0.967	0.199	4.872	0.000	0.578	1.357
	November	0.758	0.196	3.869	0.000	0.374	1.142
	December	0.251	0.209	1.206	0.228	-0.157	0.660
Apparent Temperature	Extreme Cold	-0.931	0.361	-2.577	0.010	-1.640	-0.223
	Very Cold	-0.610	0.257	-2.370	0.018	-1.114	-0.106
	Cold	-0.344	0.177	-1.942	0.053	-0.690	0.003
	Freezing	-0.143	0.108	-1.325	0.186	-0.355	0.069
	Near Freezing	BASE					
	Cool	0.185	0.081	2.287	0.023	0.026	0.344
	Mild	0.289	0.084	3.425	0.001	0.123	0.454
	Warm	0.397	0.087	4.563	0.000	0.227	0.568
	Very Warm	0.541	0.089	6.058	0.000	0.366	0.716
	Hot	0.530	0.094	5.625	0.000	0.345	0.714
	Very Hot	0.657	0.105	6.264	0.000	0.451	0.862
Precipitation	No Rain	BASE					
	Light Rain	-0.136	0.105	-1.292	0.197	-0.341	0.070
	Moderate Rain	-0.399	0.164	-2.428	0.015	-0.720	-0.077
	Heavy Rain	-0.349	0.163	-2.134	0.033	-0.669	-0.029
Wind Speed		0.001	0.002	0.572	0.568	-0.003	0.006
Snow Presence		-0.216	0.079	-2.734	0.006	-0.371	-0.061
Precipitation Lag		-0.329	0.126	-2.620	0.009	-0.575	-0.083
Snow Lag		-0.005	0.102	-0.051	0.960	-0.205	0.195
Intercept		2.053	0.200	10.267	0.000	1.661	2.445
R^2		68.23%					

Climate Change and Cycling Regression Result Table – Laurel Trail at Silver Lake

LTSL RCP26		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	-0.270	0.169	-1.592	0.112	-0.602	0.062
	March	0.217	0.147	1.483	0.138	-0.070	0.505
	April	0.869	0.141	6.176	0.000	0.593	1.145
	May	1.428	0.144	9.933	0.000	1.146	1.710
	June	1.298	0.145	8.952	0.000	1.014	1.582
	July	1.185	0.147	8.034	0.000	0.896	1.474
	August	1.036	0.147	7.045	0.000	0.748	1.324
	September	1.434	0.143	10.060	0.000	1.155	1.714
	October	1.237	0.139	8.886	0.000	0.964	1.510
	November	0.852	0.136	6.268	0.000	0.586	1.118
	December	0.178	0.147	1.208	0.227	-0.111	0.466
Apparent Temperature	Extreme Cold	-0.552	0.176	-3.138	0.002	-0.897	-0.207
	Very Cold	-0.379	0.160	-2.366	0.018	-0.694	-0.065
	Cold	-0.186	0.110	-1.693	0.091	-0.402	0.029
	Freezing	-0.191	0.079	-2.428	0.015	-0.345	-0.037
	Near Freezing	BASE					
	Cool	0.127	0.063	2.000	0.046	0.003	0.251
	Mild	0.214	0.062	3.439	0.001	0.092	0.337
	Warm	0.310	0.065	4.752	0.000	0.182	0.438
	Very Warm	0.298	0.069	4.291	0.000	0.162	0.434
	Hot	0.186	0.074	2.504	0.012	0.040	0.332
	Very Hot	0.213	0.080	2.648	0.008	0.055	0.370
Precipitation	No Rain	BASE					
	Light Rain	-0.048	0.051	-0.945	0.345	-0.147	0.051
	Moderate Rain	0.068	0.123	0.556	0.578	-0.173	0.310
	Heavy Rain	0.255	0.183	1.390	0.165	-0.105	0.614
Wind Speed		0.001	0.002	0.755	0.450	-0.002	0.005
Snow Presence		-0.189	0.042	-4.528	0.000	-0.270	-0.107
Precipitation Lag		-0.077	0.113	-0.683	0.495	-0.299	0.144
Snow Lag		-0.345	0.088	-3.920	0.000	-0.517	-0.172
Intercept		3.554	0.141	25.225	0.000	3.278	3.830
R^2		70.89%					

LTSL RCP45		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	-0.273	0.171	-1.595	0.111	-0.609	0.063
	March	0.282	0.147	1.920	0.055	-0.006	0.570
	April	0.923	0.141	6.528	0.000	0.646	1.200
	May	1.507	0.144	10.463	0.000	1.225	1.790
	June	1.381	0.145	9.500	0.000	1.096	1.666
	July	1.254	0.148	8.471	0.000	0.964	1.544
	August	1.107	0.148	7.499	0.000	0.817	1.396
	September	1.510	0.143	10.545	0.000	1.229	1.790
	October	1.317	0.139	9.447	0.000	1.043	1.590
	November	0.929	0.136	6.831	0.000	0.663	1.196
	December	0.230	0.148	1.546	0.122	-0.061	0.520
Apparent Temperature	Extreme Cold	-0.522	0.175	-2.980	0.003	-0.866	-0.179
	Very Cold	-0.525	0.173	-3.033	0.002	-0.864	-0.186
	Cold	-0.250	0.114	-2.194	0.028	-0.473	-0.027
	Freezing	-0.195	0.085	-2.303	0.021	-0.361	-0.029
	Near Freezing	BASE					
	Cool	0.106	0.065	1.631	0.103	-0.021	0.233
	Mild	0.230	0.064	3.604	0.000	0.105	0.355
	Warm	0.282	0.068	4.164	0.000	0.149	0.414
	Very Warm	0.331	0.070	4.723	0.000	0.194	0.469
	Hot	0.232	0.075	3.092	0.002	0.085	0.379
	Very Hot	0.243	0.081	3.002	0.003	0.084	0.401
Precipitation	No Rain	BASE					
	Light Rain	-0.013	0.057	-0.228	0.820	-0.126	0.100
	Moderate Rain	-0.139	0.101	-1.385	0.166	-0.337	0.058
	Heavy Rain	0.046	0.093	0.495	0.621	-0.136	0.228
Wind Speed		0.002	0.002	1.020	0.308	-0.002	0.005
Snow Presence		-0.179	0.042	-4.233	0.000	-0.262	-0.096
Precipitation Lag		-0.243	0.110	-2.210	0.027	-0.459	-0.027
Snow Lag		-0.106	0.086	-1.230	0.219	-0.274	0.063
Intercept		3.454	0.140	24.707	0.000	3.180	3.728
R^2		70.30%					

LTSL RCP85		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	-0.298	0.170	-1.751	0.080	-0.631	0.036
	March	0.197	0.147	1.343	0.180	-0.091	0.485
	April	0.854	0.142	6.001	0.000	0.575	1.133
	May	1.418	0.145	9.781	0.000	1.134	1.702
	June	1.282	0.146	8.758	0.000	0.995	1.568
	July	1.175	0.149	7.891	0.000	0.883	1.467
	August	1.027	0.149	6.912	0.000	0.735	1.318
	September	1.428	0.144	9.905	0.000	1.145	1.710
	October	1.226	0.141	8.725	0.000	0.951	1.502
	November	0.831	0.137	6.056	0.000	0.562	1.100
	December	0.147	0.148	0.988	0.324	-0.144	0.437
Apparent Temperature	Extreme Cold	-0.443	0.188	-2.353	0.019	-0.813	-0.074
	Very Cold	-0.312	0.159	-1.958	0.050	-0.624	0.000
	Cold	-0.261	0.134	-1.944	0.052	-0.524	0.002
	Freezing	-0.047	0.086	-0.548	0.584	-0.216	0.122
	Near Freezing	BASE					
	Cool	0.195	0.067	2.921	0.004	0.064	0.326
	Mild	0.270	0.068	3.981	0.000	0.137	0.403
	Warm	0.324	0.070	4.602	0.000	0.186	0.462
	Very Warm	0.417	0.073	5.711	0.000	0.274	0.560
	Hot	0.337	0.077	4.377	0.000	0.186	0.488
	Very Hot	0.238	0.081	2.956	0.003	0.080	0.396
Precipitation	No Rain	BASE					
	Light Rain	-0.018	0.056	-0.327	0.744	-0.129	0.092
	Moderate Rain	-0.109	0.100	-1.091	0.275	-0.305	0.087
	Heavy Rain	0.036	0.095	0.385	0.701	-0.149	0.222
Wind Speed		0.001	0.002	0.793	0.428	-0.002	0.005
Snow Presence		-0.181	0.042	-4.312	0.000	-0.263	-0.099
Precipitation Lag		-0.074	0.117	-0.635	0.525	-0.303	0.155
Snow Lag		-0.359	0.088	-4.099	0.000	-0.531	-0.187
Intercept		3.482	0.142	24.542	0.000	3.204	3.760
R^2		70.99%					

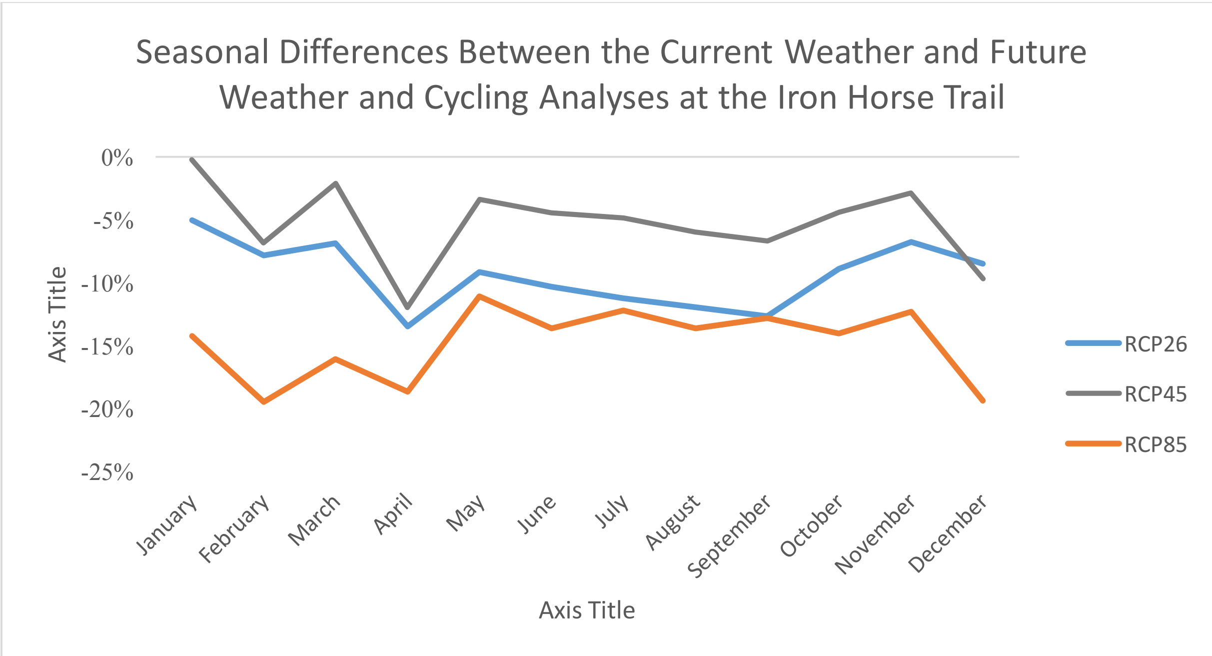
Climate Change and Cycling Regression Results – Laurel Trail at Weber

LTW RCP26		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	0.097	0.178	0.544	0.587	-0.253	0.447
	March	0.155	0.174	0.887	0.376	-0.187	0.496
	April	0.622	0.167	3.728	0.000	0.295	0.949
	May	0.697	0.166	4.190	0.000	0.371	1.022
	June	0.732	0.168	4.368	0.000	0.404	1.061
	July	0.741	0.169	4.381	0.000	0.409	1.073
	August	0.679	0.169	4.020	0.000	0.348	1.011
	September	0.727	0.168	4.326	0.000	0.398	1.056
	October	0.759	0.164	4.631	0.000	0.438	1.081
	November	0.574	0.162	3.549	0.000	0.257	0.891
	December	0.277	0.169	1.641	0.101	-0.054	0.608
Apparent Temperature	Extreme Cold	-0.487	0.283	-1.719	0.086	-1.042	0.068
	Very Cold	-0.590	0.268	-2.202	0.028	-1.115	-0.065
	Cold	-0.101	0.169	-0.596	0.551	-0.433	0.231
	Freezing	-0.023	0.108	-0.216	0.829	-0.236	0.189
	Near Freezing	BASE					
	Cool	0.167	0.070	2.390	0.017	0.030	0.304
	Mild	0.384	0.070	5.475	0.000	0.247	0.522
	Warm	0.475	0.072	6.560	0.000	0.333	0.617
	Very Warm	0.508	0.075	6.734	0.000	0.360	0.656
	Hot	0.672	0.078	8.643	0.000	0.520	0.825
	Very Hot	0.657	0.087	7.535	0.000	0.486	0.828
Precipitation	No Rain	BASE					
	Light Rain	-0.233	0.077	-3.015	0.003	-0.385	-0.082
	Moderate Rain	-0.592	0.181	-3.264	0.001	-0.947	-0.237
	Heavy Rain	-0.236	0.219	-1.076	0.282	-0.666	0.194
Wind Speed		0.009	0.002	4.890	0.000	0.005	0.012
Snow Presence		-0.155	0.062	-2.512	0.012	-0.276	-0.034
Precipitation Lag		-0.437	0.116	-3.778	0.000	-0.663	-0.210
Snow Lag		-0.205	0.106	-1.935	0.053	-0.412	0.003
Intercept		2.139	0.163	13.119	0.000	1.820	2.459
R^2		66.99%					

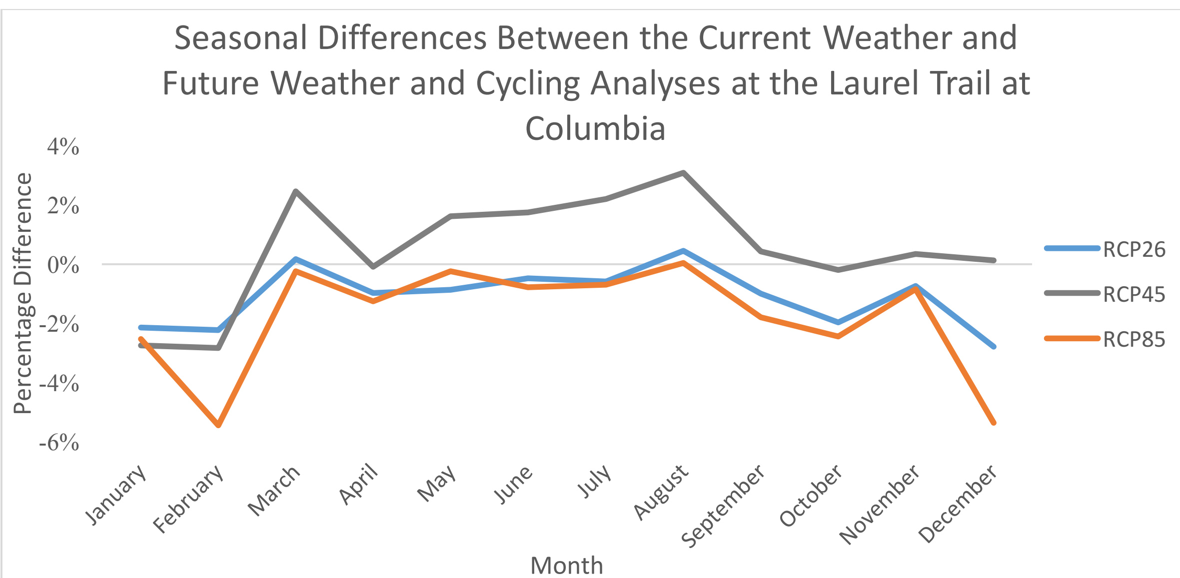
LTW RCP45		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	0.070	0.181	0.390	0.697	-0.284	0.425
	March	0.149	0.177	0.843	0.399	-0.197	0.495
	April	0.572	0.169	3.392	0.001	0.241	0.902
	May	0.689	0.167	4.111	0.000	0.360	1.017
	June	0.712	0.169	4.213	0.000	0.381	1.043
	July	0.729	0.170	4.282	0.000	0.396	1.063
	August	0.665	0.170	3.903	0.000	0.331	0.998
	September	0.701	0.169	4.139	0.000	0.369	1.033
	October	0.740	0.165	4.480	0.000	0.416	1.064
	November	0.540	0.163	3.305	0.001	0.220	0.860
	December	0.209	0.171	1.223	0.222	-0.126	0.544
Apparent Temperature	Extreme Cold	-0.586	0.285	-2.058	0.040	-1.145	-0.028
	Very Cold	-0.652	0.266	-2.449	0.015	-1.173	-0.130
	Cold	-0.325	0.160	-2.034	0.042	-0.639	-0.012
	Freezing	-0.172	0.101	-1.711	0.088	-0.370	0.025
	Near Freezing	BASE					
	Cool	0.098	0.074	1.329	0.184	-0.047	0.243
	Mild	0.321	0.073	4.390	0.000	0.178	0.464
	Warm	0.404	0.077	5.273	0.000	0.254	0.555
	Very Warm	0.483	0.078	6.208	0.000	0.331	0.636
	Hot	0.578	0.080	7.197	0.000	0.420	0.735
	Very Hot	0.621	0.088	7.019	0.000	0.447	0.794
Precipitation	No Rain	BASE					
	Light Rain	-0.237	0.078	-3.032	0.003	-0.391	-0.084
	Moderate Rain	-0.596	0.179	-3.339	0.001	-0.946	-0.246
	Heavy Rain	-0.264	0.221	-1.196	0.232	-0.697	0.169
Wind Speed		0.009	0.002	4.719	0.000	0.005	0.012
Snow Presence		-0.140	0.062	-2.255	0.024	-0.262	-0.018
Precipitation Lag		-0.433	0.115	-3.774	0.000	-0.659	-0.208
Snow Lag		-0.120	0.092	-1.307	0.192	-0.301	0.060
Intercept		2.204	0.165	13.338	0.000	1.880	2.528
R^2		66.56%					

LTW RCP85		Estimated Coef.	Std. Error	t-value	p-value	Lower Conf. Int.	Upper Conf. Int.
Month	January	BASE					
	February	0.081	0.182	0.449	0.654	-0.274	0.437
	March	0.138	0.178	0.774	0.439	-0.211	0.487
	April	0.611	0.170	3.605	0.000	0.279	0.944
	May	0.727	0.169	4.293	0.000	0.395	1.059
	June	0.743	0.171	4.346	0.000	0.408	1.077
	July	0.760	0.172	4.414	0.000	0.423	1.098
	August	0.692	0.172	4.017	0.000	0.354	1.029
	September	0.735	0.171	4.297	0.000	0.400	1.070
	October	0.752	0.167	4.495	0.000	0.424	1.079
	November	0.565	0.165	3.433	0.001	0.243	0.888
	December	0.212	0.173	1.226	0.221	-0.127	0.551
Apparent Temperature	Extreme Cold	-0.391	0.290	-1.346	0.179	-0.959	0.178
	Very Cold	-0.726	0.305	-2.385	0.017	-1.323	-0.129
	Cold	-0.214	0.163	-1.309	0.191	-0.533	0.106
	Freezing	-0.124	0.106	-1.169	0.243	-0.331	0.084
	Near Freezing	BASE					
	Cool	0.146	0.074	1.973	0.049	0.001	0.291
	Mild	0.336	0.073	4.584	0.000	0.192	0.479
	Warm	0.440	0.077	5.726	0.000	0.290	0.591
	Very Warm	0.538	0.078	6.920	0.000	0.386	0.690
	Hot	0.571	0.080	7.100	0.000	0.414	0.729
	Very Hot	0.697	0.085	8.237	0.000	0.531	0.863
Precipitation	No Rain	BASE					
	Light Rain	-0.199	0.079	-2.530	0.012	-0.353	-0.045
	Moderate Rain	-0.553	0.180	-3.073	0.002	-0.905	-0.200
	Heavy Rain	-0.221	0.223	-0.990	0.323	-0.657	0.216
Wind Speed		0.008	0.002	4.441	0.000	0.005	0.012
Snow Presence		-0.162	0.063	-2.595	0.010	-0.285	-0.040
Precipitation Lag		-0.365	0.136	-2.684	0.007	-0.632	-0.098
Snow Lag		-0.189	0.106	-1.776	0.076	-0.397	0.020
Intercept		2.121	0.167	12.673	0.000	1.793	2.449
R^2		66.14%					

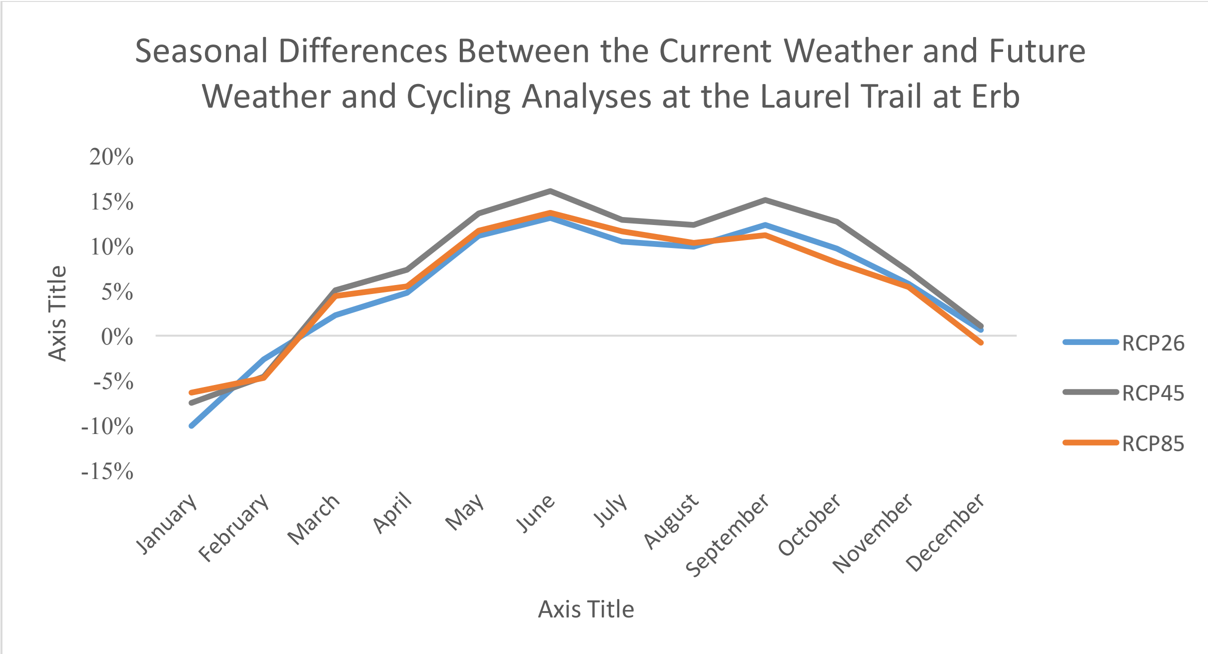
Seasonal Differences – Iron Horse Trail (CMIP5 inter-model mean prediction set only)



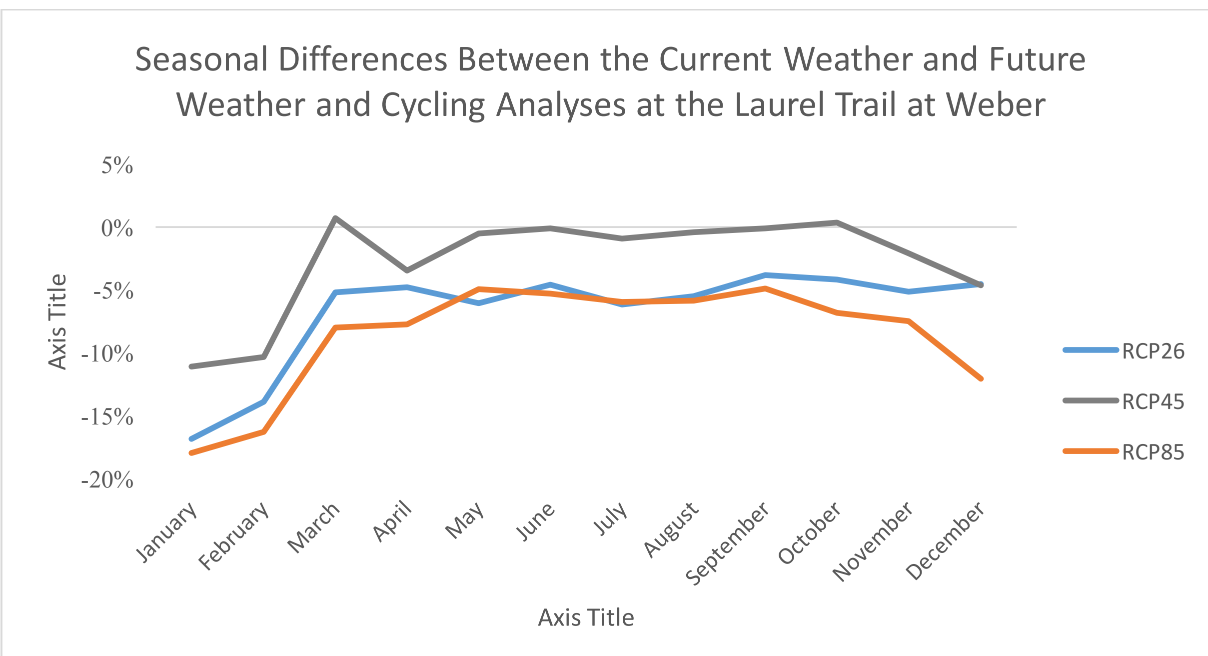
Seasonal Differences – Laurel Trail at Columbia (CMIP5 inter-model mean prediction set only)



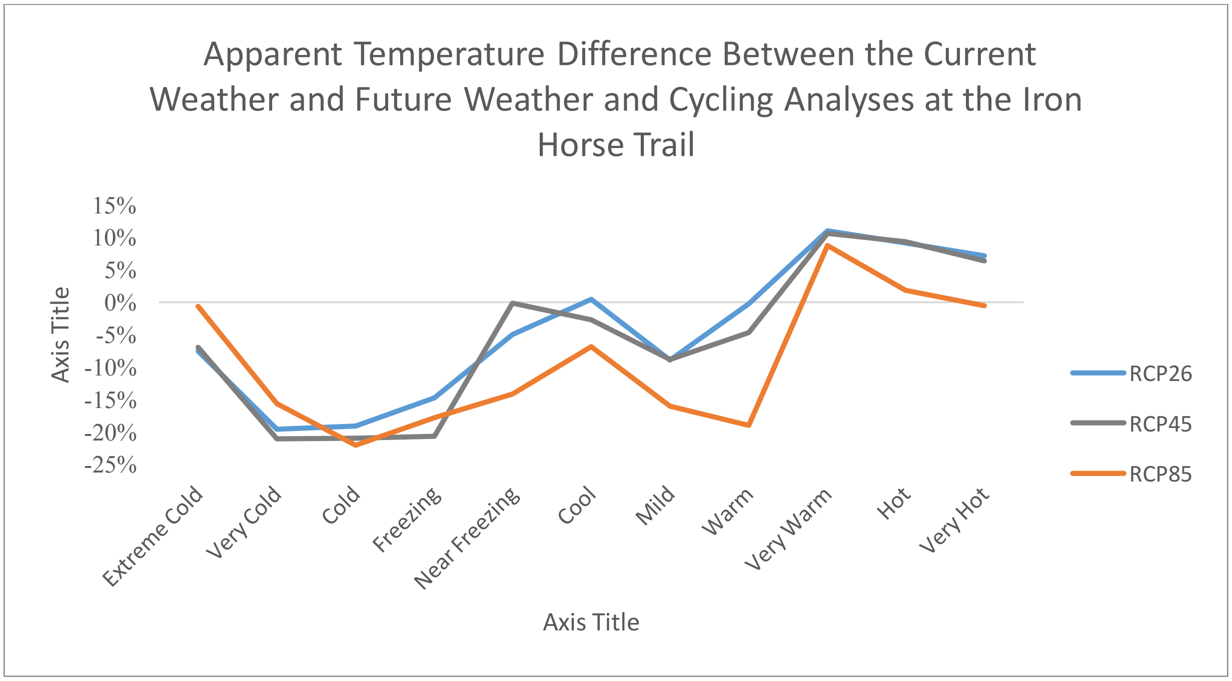
Seasonal Differences – Laurel Trail at Erb St. E. (CMIP5 inter-model mean prediction set only)



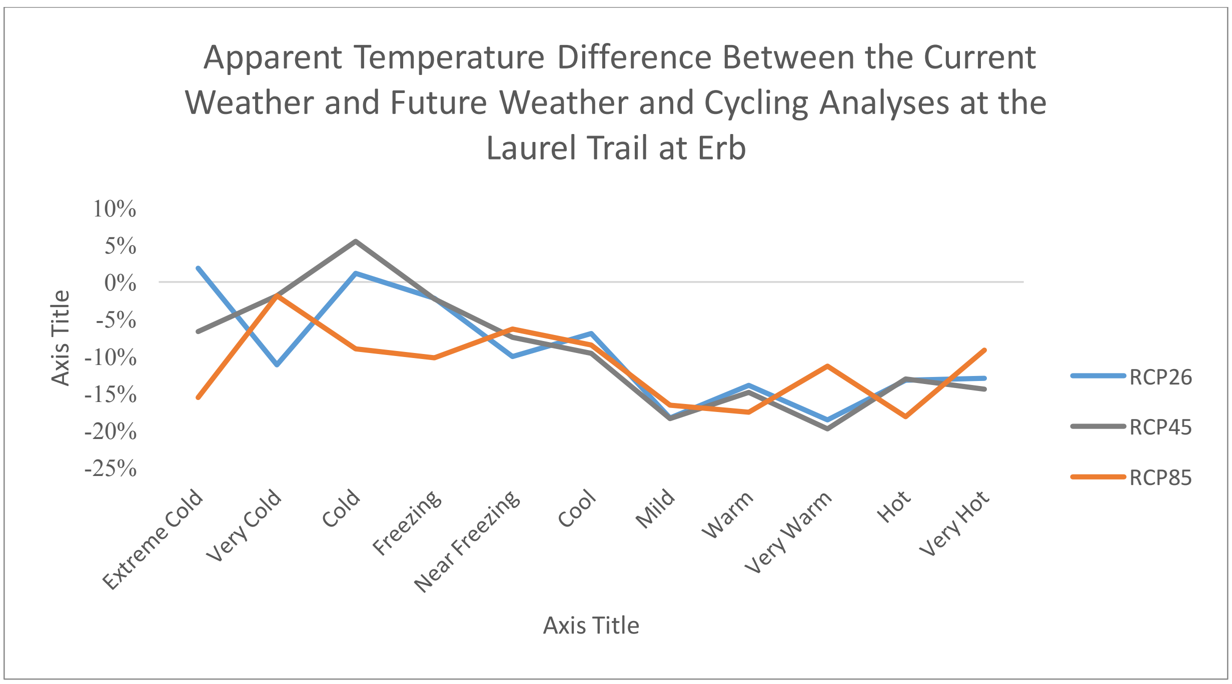
Seasonal Differences – Laurel Trail at Weber St. N. (CMIP5 inter-model mean prediction set only)



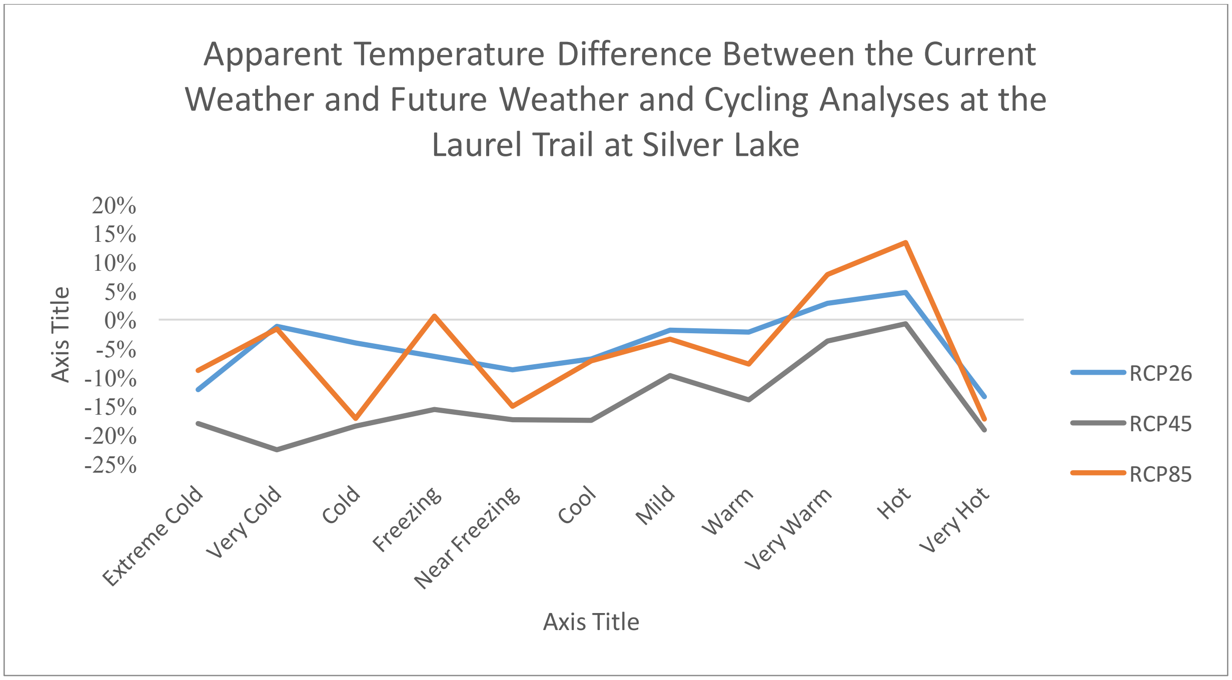
Apparent Temperature – Iron Horse Trail (CMIP5 inter-model mean prediction set only)



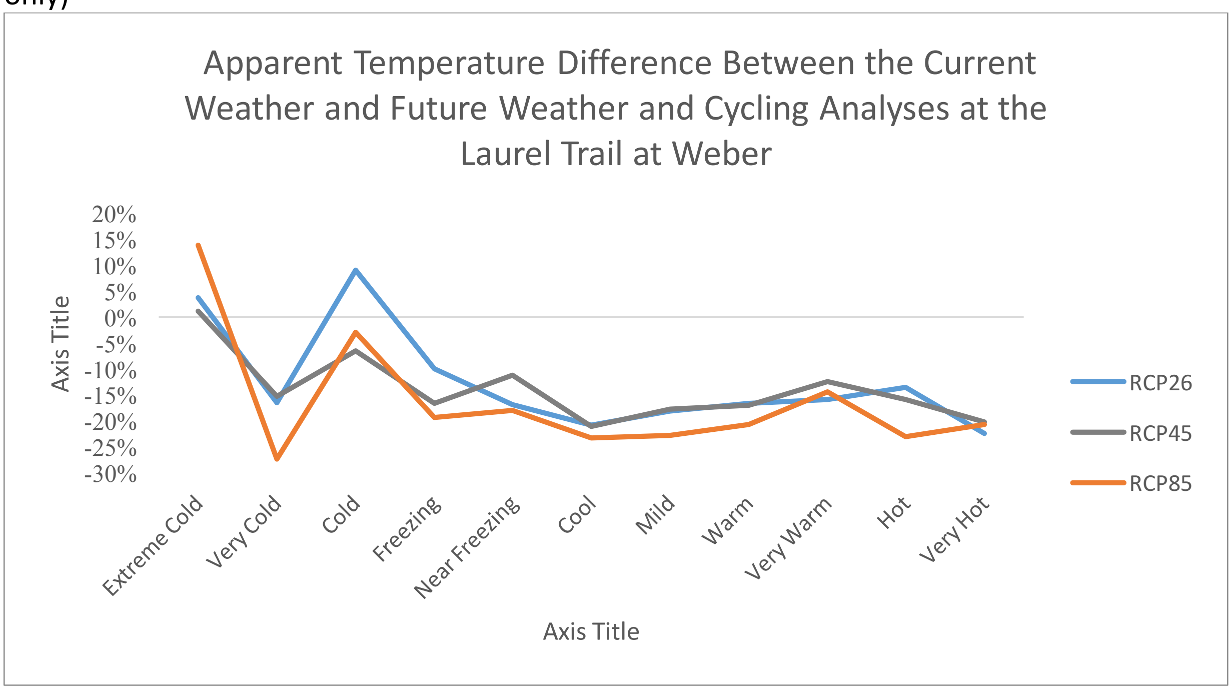
Apparent Temperature – Laurel Trail at Erb St. E. (CMIP5 inter-model mean prediction set only)



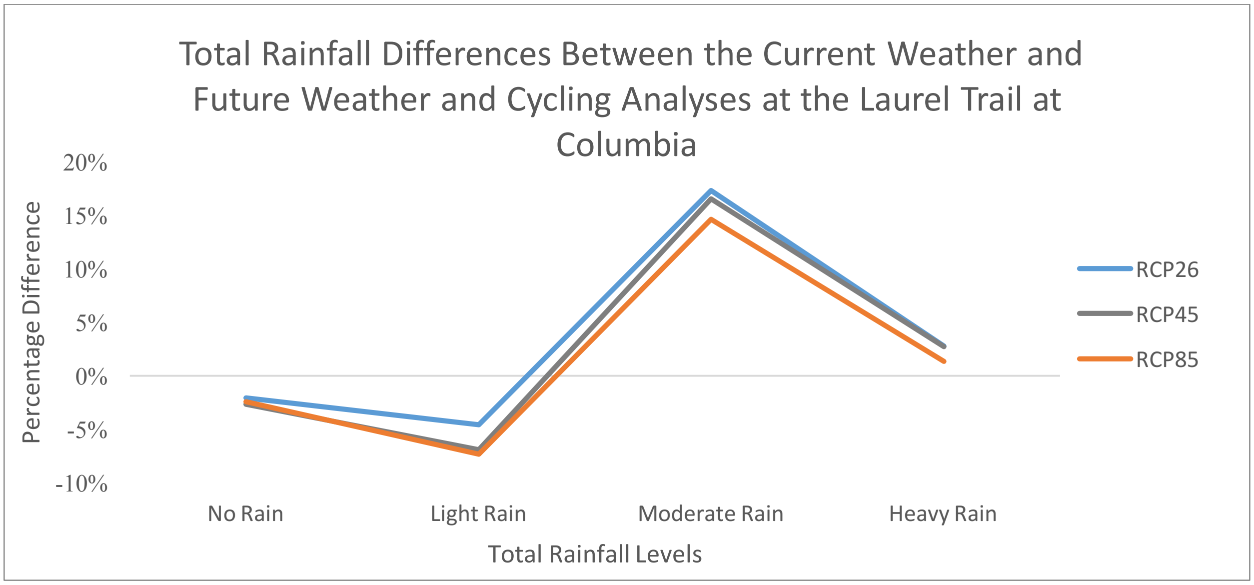
Apparent Temperature – Laurel Trail at Silver Lake (CMIP5 inter-model mean prediction set only)



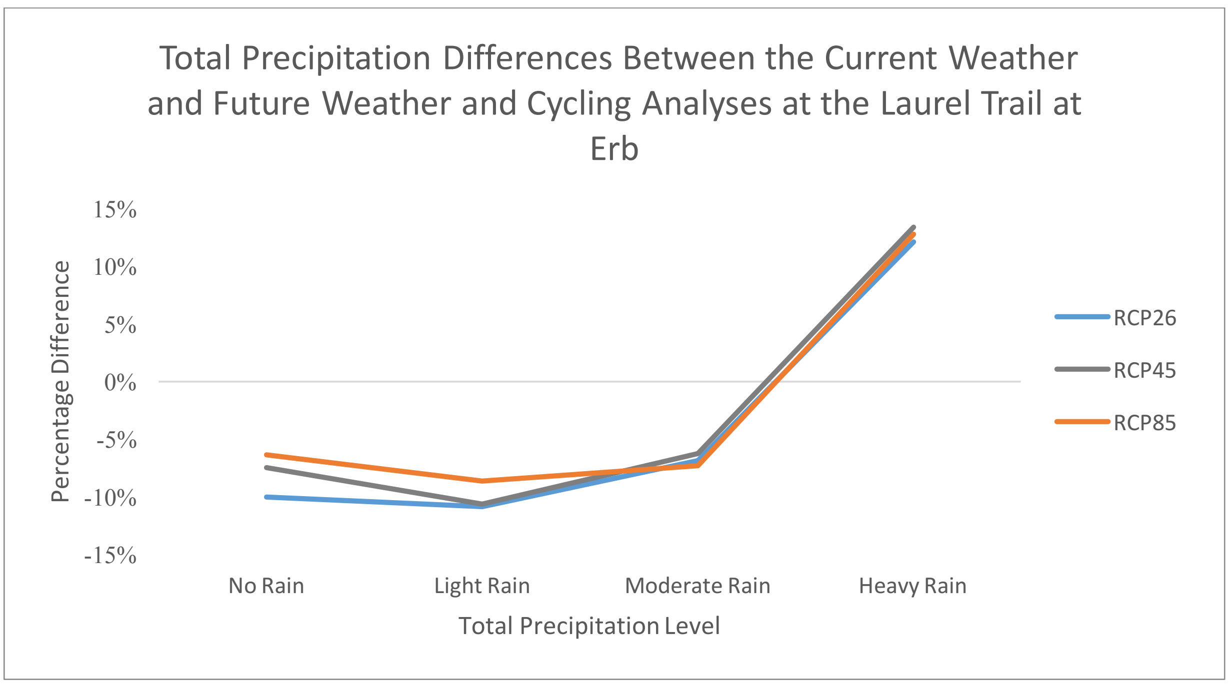
Apparent Temperature – Laurel Trail at Weber St. N. (CMIP5 inter-model mean prediction set only)



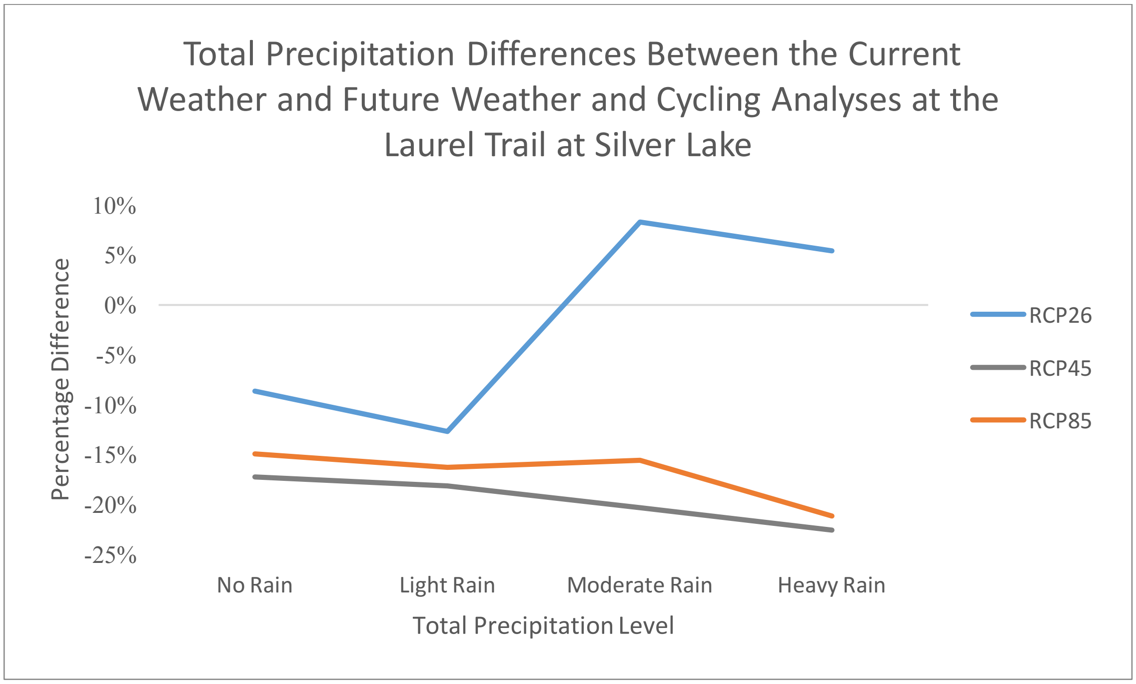
Total Rainfall – Laurel Trail at Columbia (CMIP5 inter-model mean prediction set only)



Total Rainfall – Laurel Trail at Erb St. E. (CMIP5 inter-model mean prediction set only)



Total Rainfall – Laurel Trail at Silver Lake (CMIP5 inter-model mean prediction set only)



Total Rainfall – Laurel Trail at Weber St. N. (CMIP5 inter-model mean prediction set only)