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ESTIMATING THE USAGE OF CYCLING INFRASTRUCTURE IN CITIES WITH COLD CLIMATE

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Abstract: Cycling has gained increased attention among both researchers and public planners in the last two decades as a sustainable means of transportation. Compared to users of other modes of transportation, cyclists are more exposed to weather conditions. For example, harsh weather conditions such as cold temperatures or rain negatively affect an individual's decision to use a bicycle for transportation. As a result, cycling infrastructure usage changes throughout the year because of highly variable weather conditions. On the other hand, in recent years North American cities try to encourage cycling through the development of cycling infrastructure networks. For that, municipalities require estimates of infrastructure network usage throughout the entire year to make decisions about investments and maintenance costs. However, collecting data for all cycling infrastructure throughout the year is not economically feasible. The objective of this paper is to develop a model capable of estimating changes in cycling infrastructure usage for different months of the year based on observations from only one month. An estimation model will be developed using Generalized Estimating Equations (GEE). Changes in cycling frequency for each month will be estimated relative to a reference month. The usage change will be estimated based on weather variables, namely temperature, precipitation (i.e. rain, snow, hail), collected snow on the ground, wind speed and the number of sunlight hours in a day. As the model was developed, it was noticed that the effect of weather conditions on commuter cyclists and reactional cyclists is not the same. As a result, two separate sub-models will be developed. The first sub-model will be based on weekday usage data which will evaluate the impact of weather conditions on commuter cyclists. The second sub-model will be based on weekend usage to evaluate the impact of weather condition on utilitarian (non-commuter) cyclists. Additionally, it will be examined to what extent the above-mentioned weather variables are accountable for estimating cycling infrastructure usage. The developed model can help Cities and municipalities in decision making on investments, maintenance and modifications to the cycling infrastructure.

1 INTRODUCTION

In the last few decades, transportation planning efforts in North America has aimed to increase the share of active modes of transportation such as cycling and walking due to its benefits over the vehicular mode of transportation. While walking is limited to only close destinations, cycling offers a greater access range to users. Cycling is also an environmentally friendly mode of transportation, is cost-efficient, and increase in cycling will lead to higher social interaction and livelihood on streets. Since environment, social and economic are the three pillars of sustainability (Bell and Morse, 2008), increasing the share of cycling can help cities to move toward more sustainable transportation system (Buehler and Pucher 2012). To encourage cycling, it is important to improve infrastructure network (i.e. providing better conditions for cycling infrastructures) and expanding the infrastructure network (i.e. building new road sections).

Due to limited budget available within municipalities, planners and decision makers use infrastructure usage data as an evidence for identifying the optimal place to spend the money to improve the infrastructure network more efficiently. While using annual infrastructure usage is more reliable for decision making, currently municipalities use short count usage (partial data) which is collected for a limited period of the year (i.e. one month). Collecting infrastructure usage for an entire city throughout the year is not economically feasible. Since data collection requires either numerous bicycle counters installed on every road section or manpower assigned to each road section for the entire year. Hence, currently, short count usage data is used and it implement limitations for decision making since short count data does not provide any information about the usage variation throughout the year. Infrastructure usage variation throughout the year is needed especially in cities with cold climate such as most Canadian cities. There is a debate on whether keeping or removing cycling infrastructure during cold months of the year. It is assumed that cycling infrastructure will remain unused or will have a low usage during cold months.

The objective of this study is to develop a model with the goal of estimating cycling infrastructure usage through the year using observations from only one month. Literature suggests that many variables affect cycling. These variables can be categorized into five main group namely, cyclists' characteristics, attitudes toward cycling, cycling infrastructure, network connectivity and built environment and weather conditions. This study will focus on variables from the last group referred to as weather conditions. All the variables that affect infrastructure usage are constant for a specific infrastructure during a year except weather variables. Hence the variation in usage is attributed to weather variables. The weather variables examined in this study are temperature, precipitation (i.e. rain, snow, hail), snow on the ground, wind speed and sunlight hours in a day. This study first evaluates the impact of above-mentioned weather variables on cycling infrastructure usage and then estimates the change in usage during a year using weather variables. Generalized Estimated Equation (GEE) is used to develop the model since data used in this study was correlated over time. The model presented in this study estimates usage throughout the year and consequently the annual usage and can be used as a guide for decision making about funding allocation in municipalities.

2 LITERATURE REVIEW

In recent years, two studies in particular investigated cycling infrastructure usage trends and a number of studies developed estimation models to estimate infrastructure usage. Investigating cycling infrastructure usage trends helps us to better understand usage variation and the possible causes of the variation. A better understanding of cycling usage trends enables us to develop more accurate estimation models.

2.1 Infrastructure Usage Trends

Studies have shown that cycling infrastructure usage varies throughout the year and showed that cycling infrastructure usage during a year was affected by weather conditions (Lindsey et al., 2013; Miranda-Moreno et al. 2013). One study from Minneapolis found that traffic volumes for cyclists and pedestrians (non-motorized usage) varied over time. The usage varied depending on the month and day of the week. Usage variation trends were similar for different locations with different magnitudes. (Lindsey et al., 2012). Another research studied cycling patterns in five North-American cities namely, Montreal, Ottawa, Portland, San Francisco, and Vancouver. It was found that that monthly usage in cities with cold climates decreased more compared to usage in warmer cities. Cycling usage pattern was categorized into commuter, mixed commuter, recreational, and mixed recreational. The study showed that the impact of weather on recreational and commuter cyclists was not the same; infrastructure usage used by recreational cyclists decreased more compared to the usage of infrastructure used by commuter cyclists (Miranda-Moreno et al. 2013).

2.2 Weather Impact on Usage

Several studies have been published on the impact of weather conditions on cycling. These studies indicated that weather variables significantly impacted cycling infrastructure usage. Harsh weather conditions, such as days with extremely low or high temperatures and high precipitation, reduced the number of cyclists.

Temperature: Temperature was positively correlated with cycling frequency according to relevant studies. Different studies have confirmed that days with higher temperatures caused more people to cycle (Bergström and Magnusson, 2003; Buehler 2012; Flynn et al., 2012; Saneinejad et al., 2012; Brandenburg et al. 2007). A study surveyed employees of four companies in two Swedish cities showed a difference in mode choice between seasons. People cycled more during summer compared to winter. Instead of cycling, the majority of people used their cars in winter. Moreover, distance became a more important factor when choosing the mode of transportation during winter. For long distances, the number of cyclists remarkably dropped as distance increased in winter. The study showed that people almost never used bicycle for trips of more than 10 km in winter (Bergström and Magnusson, 2003). Similarly, Buehler (2012) showed that the likelihood of commuting to work by bicycle in summer was 73% more than the likelihood of using a bicycle to commute in winter. Another study from Vermont showed that people tended to cycle more on warmer days. The regression likelihood model presented in the study showed that an increase in one degree of Fahrenheit resulted in a 3% increase in the likelihood of cycling (Flynn et al., 2012). Similarly, another study from Toronto showed that cold temperatures negatively affected people's tendencies to cycle. In that study, it was found that using a bicycle was only sensitive to temperatures below 15° C (Saneinejad et al., 2012). Another study investigated the impact of weather conditions on different types of cyclists. With, using data from a suburban recreation area in Vienna, the study found that recreational cyclists were more affected by weather conditions compared to commuter cyclists. Consequently, it is possible that recreational cyclists checked the weather conditions beforehand, and as a result, they avoided cycling in harsh weather (Brandenburg et al. 2007).

Sunlight: Studies have shown that individuals tended to cycle during daylight hours rather than in the dark (Osberg et al., 1998; Rodgers, 1995; Spencer et al., 2013). A study that observed cyclists in Paris and Boston showed that the majority of cyclists, cycle during daylight hours. 65% and 76% of cyclists were observed during daylight hours in Paris and Boston, respectively (Osberg et al., 1998). Respondents in another study mentioned that during some parts of the year, they could not cycle safely due to insufficient daylight hours. Also, some respondents indicated that the effect of weather variables, such as rain, could compound the negative effects of cycling in the dark, which further prevented them from cycling (Spencer et al., 2013).

Wind: Wind speed was found to have a negative impact on a cycling infrastructure usage. Researchers believe that the main reason for the negative impact is that wind makes the temperature feel colder. A study from Toronto found that wind speed negatively affected cyclists and pedestrians. The magnitude of the impact of wind was twice on cyclists compared to pedestrians (Saneinejad et al., 2012). Another study surveyed 24 adult bicycle commuters from Vermont, and the results showed that wind could also have a positive impact on cycling when it was at a cyclist's back (Spencer et al., 2013).

Precipitation: According to relevant studies, precipitation is one of the preventing factors for cyclists; the number of cyclists drops on days with precipitation (Flynn et al., 2012; Nankervis, 1999; Saneinejad et al. 2012). A case study in Vermont found that people cycle less during rainy days. Among the weather variables considered in the study, rain was found to have the most negative effect on cycling. Days without rain had usage nearly doubled compared to rainy days. Each inch of snow resulted in a 10 % decrease in the likelihood of bicycle commuting (Flynn et al., 2012). Another study from Melbourne showed that rain was the most important preventing factor for cyclists as it caused more than half of the people surveyed (50.7%) to choose not to ride a bicycle on rainy days. Similarly, according to Saneinejad et al. (2012), precipitation in the form of rain and showers negatively impacted cyclists. However, rain was not always considered a negative factor for cyclists. Some respondents in Vermont described rain as refreshing and helpful (Spencer et al., 2013).

Snow on the ground: Snow on the ground also considered being one of the factors that prevented cyclists from cycling. According to Bergstrom and Magnusson (2003), road surfaces that were not cleared of snow was the most important road condition for mode choice according to the opinion of the surveyed cyclists.

2.3 Usage Estimation Models

Studies estimated cycling infrastructure usage by developing models using short count data (Nordback et al., 2013; El-Esawey, 2014; El-Esawey et al., 2013; El-Esawey and Mosa, 2017). These studies estimated cycling infrastructure usage by creating daily, monthly, and seasonal factors. Cycling infrastructure usage was estimated by multiplying the known short-term count by those factors.

Recent studies estimated cycling infrastructure usage using short count duration factors. The factors were calculated by dividing year usage to short-term count usage. However when estimating the usage for years other than the year in which factors were developed on, their estimation accuracy significantly drops since the variation in weather conditions is different in each year. While using short count factors is limited for only one year, this study estimates cycling infrastructure usage with considering the effect of weather variables on usage which estimates the usage with better accuracy and can be used for any year with known weather data.

3 METHODOLOGY

The objective of this study is to develop a model capable of estimating cycling infrastructure usage variation using short count data. To develop the model, potential variables that impact usage over a year were identified. Previous studies suggested that weather variables had a significant impact on cycling infrastructure usage variation (Lindsey et al., 2012; Miranda-Moreno et al. 2013). Investigating the association between temperature and one infrastructure section usage, confirmed the speculation about the effect of weather conditions on infrastructure usage. The magnitude of the impact of weather variables on cycling infrastructure usage was determined, and the usage was estimated based on those variables. To develop the model cycling infrastructure usage data from the city of Calgary was used. The Transportation Department at the City of Calgary provided daily cycling infrastructure usage throughout the year from 25 counters mainly located in downtown area. This source of data included 15750 data points; each data point represented specific road section usage for a specific day of the year. Weather data was provided by Canadian Government and (http://www.sunrise-and-sunset.com). Weather data included mean temperature, precipitation, cumulated snow on the ground, wind speed and sunlight hours in the day. Data was split into two sections. The majority of the collected data (90%) was used to develop the model, and a small portion (10%) was used as test data to validate the model and to determine the model accuracy for estimating cycling infrastructure usage.

3.1 Model Design

This study estimated the usage of cycling infrastructure compared to a reference month with known usage (the month with observation). The estimation was conducted with evaluating the change in usage as a result of a change in weather variables. The usage change contained five components. Each component represented the impact of one weather variable on usage. Total change in usage was computed by adding up the changes in usage resulted from the effect of each weather variables on usage. The equation can be written as follows where *ΔF* represents the usage change.

[1] $\Delta F = \beta_1 (\Delta\ Temp) + \beta_2 (\Delta\ Prec) + \beta_3 (\Delta\ Wind) + \beta_4 (\Delta\ Snow) + \beta_5 (\Delta\ Sunh) + E$

Where β_1 to β_5 represent the coefficients of weather variables, weather variables (i.e. Temp, Prec, Wind, Snow, Sunh) represent the mean value of each weather variable for each month and *E* represents estimation error. Generalized Linear Model (GLM) is a general statistical approach that generally is used to estimate β. This study uses data that was collected with counters installed on cycling infrastructure sections. Each infrastructure section is a part of infrastructure with different characteristics from other parts of infrastructure which is separated from other sections by intersections. Cycling infrastructure usage was measured at successive times throughout the year. When data was collected from the same units at successive points over time, repeated observations are correlated. Since GEE is capable to estimate the coefficients when observations are correlated, Generalized Estimating Equations (GEE) was chosen over GLM analysis methods such as multiple regression, to analyze the data.

In GEE, quasi-likelihood estimates of β*'s* are computed from the maximization of the normality-based log likelihood without assuming that the observations are normally distributed. In this study, the parameters β are coefficients for the weather variables, which are estimated by solving the following equation:

[2] $\sum_{i=1}^{M} (\frac{\partial \mu_i}{\partial \beta})\ V_i^{-1} (Y_i - \mu_i) = 0$

where M is the number of infrastructure sections, Y_i represent the vector of observations for each infrastructure section throughout the time, μ_i called the mean vector of Y_i which is the estimated value of Y_i as a function of input variables (observations) and β parameters, and *V* is the covariance matrix of observations, which takes into the account how changes in one variable is associated with the changes in other variables. The covariance matrix includes three elements:

[3] $V_i^{-1} = \phi\, A_i^{1/2}\, R_i\, A_i^{1/2}$

where ϕ is an overdispersion parameter which takes into the account the difference in variability of dataset and model estimation; $A_i^{1/2}$ is an *n* × *n* diagonal matrix with the square root of variances of observation where *n* represents the number of observations; and R_i is an *n* × *n* correlation matrix. The correlation between observations is carried out by using a correlation matrix in GEE. Different types of correlation matrixes exist such as independent, exchangeable, auto-regressive and unstructured. Independent matrix is used when observations are independent. Exchangeable is used when all observations are equally correlated. Auto regressive is used when the correlation is known to decline through time and unstructured is used when there is no specific correlation between observations.

The GEE model is first fitted with computing initial estimates of β's, for example, using a naive linear regression. After computing initial β estimates, GEE estimates the dispersion parameter from residuals and computes the correlation matrix based on residuals. Then, the working covariance matrix is computed and β's are estimated again. These steps are continued until convergence of β's is obtained.

3.2 Model Development

The model estimated the change in usage of infrastructure for different months of the year relative to a reference month (a month with available usage count data), which in this study is September. A closer look at the daily usage revealed that there was a difference in usage during weekdays and weekends. Figure 1 shows daily usage of one cycling infrastructure section during weekdays and weekends. For example, as it can be seen in Figure 1, during three different periods of the year 2016 (early in the year, middle of the year and end of the year) weekend and weekday usages were different in values (A, B and C).

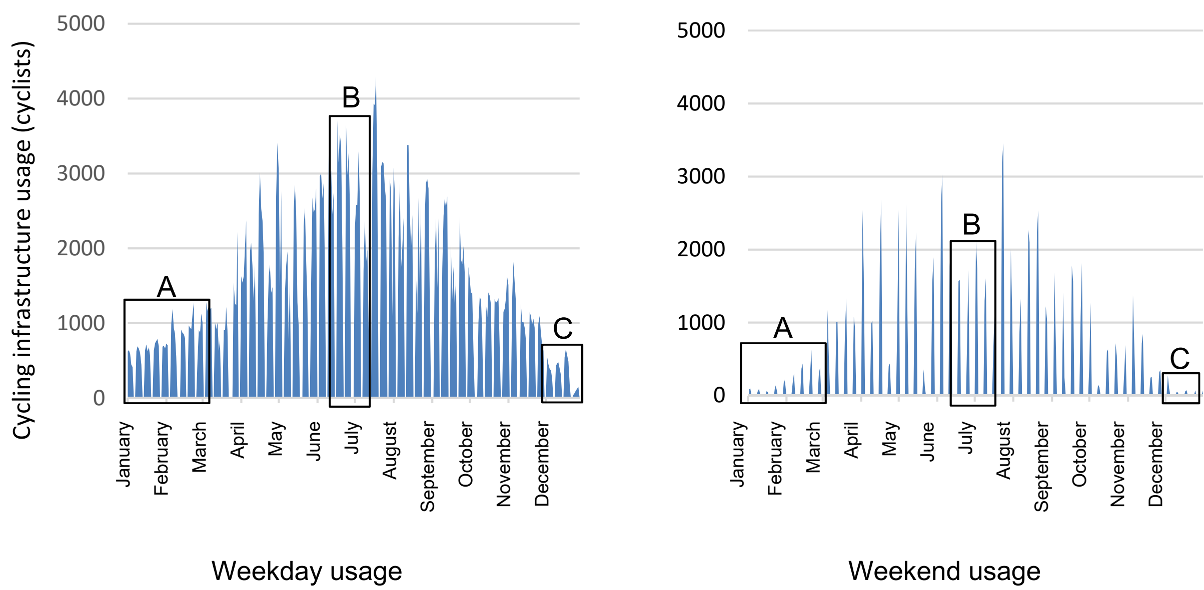


Figure 1: Daily infrastructure usage trends during weekdays and weekends

Due to differences in weekday and weekend usage, two separate models were developed. The first model (Commuter Model) was developed based on weekday usage, and the second model (Utilitarian Model) was developed based on weekend usage. Since cyclists who cycle on weekdays are generally commuter cyclists combined with utilitarian cyclists, commuter model evaluates the impact of weather conditions on a combination of commuters and utilitarian cyclists. The utilitarian model focuses on only utilitarian cyclists since in general, cyclists who cycle during weekends have only utilitarian purposes. They cycle for purposes such as shopping, going to restaurants, or for exercise, all of which fall into the category of utilitarian purposes. This study used auto regressive structure for both models since it showed the best fit on data compared to other correlation structures.

The model estimates usage based on only weather variable, hence other factors that affect cycling were removed to increase model accuracy. For example, national holidays were excluded from the database. To analyze data, the change in usage for each day of the week in each month was compared to the same day of the week in September to eliminate the impact of the day of the week. Also, since cycling infrastructure usages collected in this study had different standard deviations for different infrastructure sections, logarithmic data transformation was applied. Consequently, the logarithmic value of cycling infrastructure usage was used to develop the model.

Effect of weather variables on people's decision to cycle is not constant over a year. The effect of preventing factors, such as precipitation, are assumed to be greater in cold months due to the compounding effect of rain and cold temperatures. The variation in the magnitude of the effect of the variables makes it necessary to have separate models for different time periods. (Miranda-Moreno et al. 2013) found that hourly and weekly usage patterns were consistent in different cities with different characteristics while monthly usage patterns were different due to the impact of weather variables. Hence, monthly periods were selected for developing sub-models. Therefore, 11 sub-models were developed. Each sub-model evaluated the effect of weather conditions on changes in cycling frequency for each month of the year compared to September.

The commuter model was developed using weekday usage and weather data. Table 1 provides the results of the 11 sub-models of the commuter model. The coefficients represent the impact of each weather variable on the log value of infrastructure usage. Some of the coefficients were not significant nor rational. For example, Snow on the ground in winter can not positively impact cycling infrastructure usage. Therefore, those coefficients were removed from the model.

Table 1: Commuter model coefficients

Month	Temp	Total Precipitation	Snow on Ground	Wind Speed	Hours of Sunlight
January	0.021	-0.019		-0.003	0.097
February	0.020	-0.029		-0.005	0.026
March	0.017	-0.032	-0.008	-0.006	
April	0.025	-0.017	-0.012	-0.009	
May	0.020	-0.033		-0.006	
June	0.018	-0.011		-0.005	
July	0.027	-0.009		-0.006	
August	0.022	-0.013		-0.007	
September	-	-	-	-	-
October	0.015	-0.026	-0.052	-0.003	
November	0.014	-0.017	-0.021	-0.006	
December	0.017	-0.018	-0.035	-0.004	

All the coefficients presented are significant at p-value <0.05.

Table 2**Error! Reference source not found.** provides the results obtained from the analysis on weekend usage for the 11 sub-models. The utilitarian model had fewer significant coefficients compared to the weekday model because it had a smaller sample size.

Table 2: Utilitarian model coefficients

Month	Temp	Total Precipitation	Snow on Ground	Wind Speed	Hours of Sunlight
January	0.034	-0.023		-0.006	
February	0.032	-0.014		-0.015	0.016
March	0.032	-0.046	-0.016		0.08
April	0.040	-0.015	-0.597	-0.009	
May	0.030	-0.023		-0.012	
June	0.023	-0.033		-0.002	
July	0.027	-0.028		-0.002	
August	0.028	-0.016		-0.01	
September	-	-	-	-	-
October	0.025	-0.015	-0.092	-0.001	
November	0.039	-0.044			
December	0.023	-0.023	-0.017	-0.012	

All the coefficients presented are significant at p-value <0.05.

3.3 Model applicability

To find which model had the best goodness of fit for estimating usage, both models were applied to estimate infrastructure usage during weekends and weekdays. To evaluate models accuracy, the usage for each month was estimated using September usage and weather variables. The mean value of percentage error (MAPE) was calculated as:

[4] MAPE=$\frac{1}{N}\sum_{i=1}^{N}\left|\frac{Actal\ cycling\ frequency - Estimated\ cycling\ frequency}{Actal\ cycling\ frequency}\right|$

Where *N* represents the number of observations used for validation which in this case is the number of months used for validation for each infrastructure section. The value of MAPE was calculated for both models. Months with an average usage of below 100 cyclists/month were excluded from the model. The small difference between the estimated and actual usage in those months led to a large MAPE value because of the small actual usage. This increased total MAPE value unrealistically. For example, for an infrastructure section with actual usage of 5 cyclists in a month and the estimated usage of 9 cyclists in month, the difference of model estimation and actual usage was only 4 cyclists while the estimation error was 80%.

Infrastructures usage during weekends was estimated with both models and the results were compared with actual usage. The utilitarian model showed a lower MAPE value compared to commuter model for estimating weekends usage for all infrastructure sections. Hence utilitarian model was selected to estimate infrastructure usage on weekends. Both models were applied to estimate weekday usage. By calculating MAPE values for two models it was noticed that for some infrastructure sections the commuter model had a better estimation result while for some other sections the utilitarian model better estimated the weekday usage.

In general, each infrastructure section has different types of users during weekdays and weekends. Weekend cyclists are mainly utilitarian cyclists, while weekday cyclists are a combination of commuter and utilitarian cyclists. The portion of commuter and utilitarian cyclists is different for different infrastructure sections. To discover more about the characteristics of infrastructure section users, a user type ratio (UTR) was defined as follows:

[5] UTR= $\frac{Average\ number\ of\ cyclists\ on\ weekends}{Total\ number\ of\ cyclins\ t\ on\ weekdays\ and\ weekends}$

A high UTR for an infrastructure section represents high usage on weekends compared to total usage. Usage on weekends is mainly attributed to utilitarian cyclists. Hence, infrastructure section with a high UTR contains a high portion of utilitarian cyclists among their users and mainly used for utilitarian purposes. By calculating UTR for different infrastructure sections, it was noted that sections with high UTR were mainly located at recreational locations. Also, looking at hourly trends of infrastructure sections usage, we noticed that usage trends of different sections were not the same. Sections with mainly commuter users (low UTR) had higher peak usage in the morning and afternoon and lower usage at midday during weekdays compared to infrastructure sections with utilitarian users (high UTR). While sections with utilitarian users had higher midday usage compared to sections with mainly commuter users during weekends. For the next step, we sorted infrastructure sections based on their UTR value. The result showed that for sections with UTR value more than 0.1,1 the utilitarian model gave a better fit while for sections with UTR value lower than 0.11 the commuter model gave a better estimation result. Figure 2 shows model selection procedure.

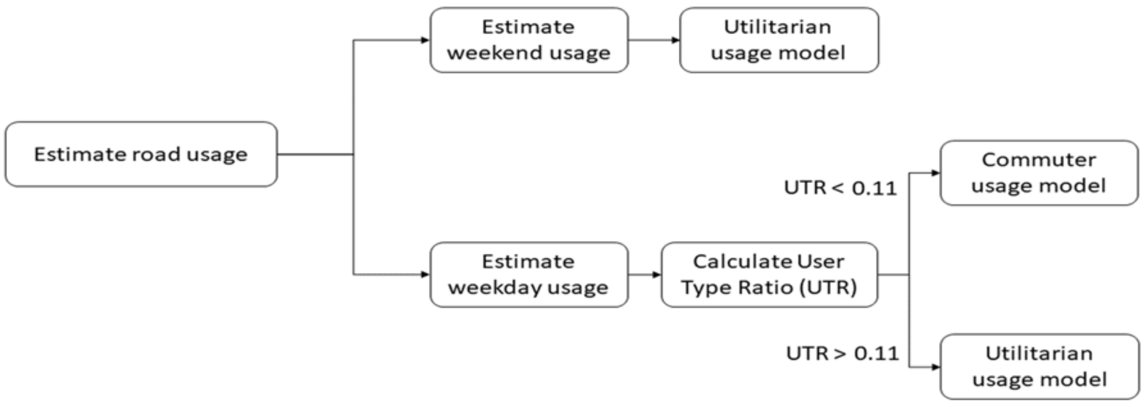


Figure 2: The model selection process

4 VALIDATION

To validate the model, the estimation model was used to estimate usage in 2017 for two infrastructure sections based on their September usage. Selected infrastructure sections had different infrastructure types and different locations that covered a variety of infrastructure sections with different characteristics. The results were compared with actual usage counted by bicycle counters. Table 3 provides details about selected infrastructure sections.

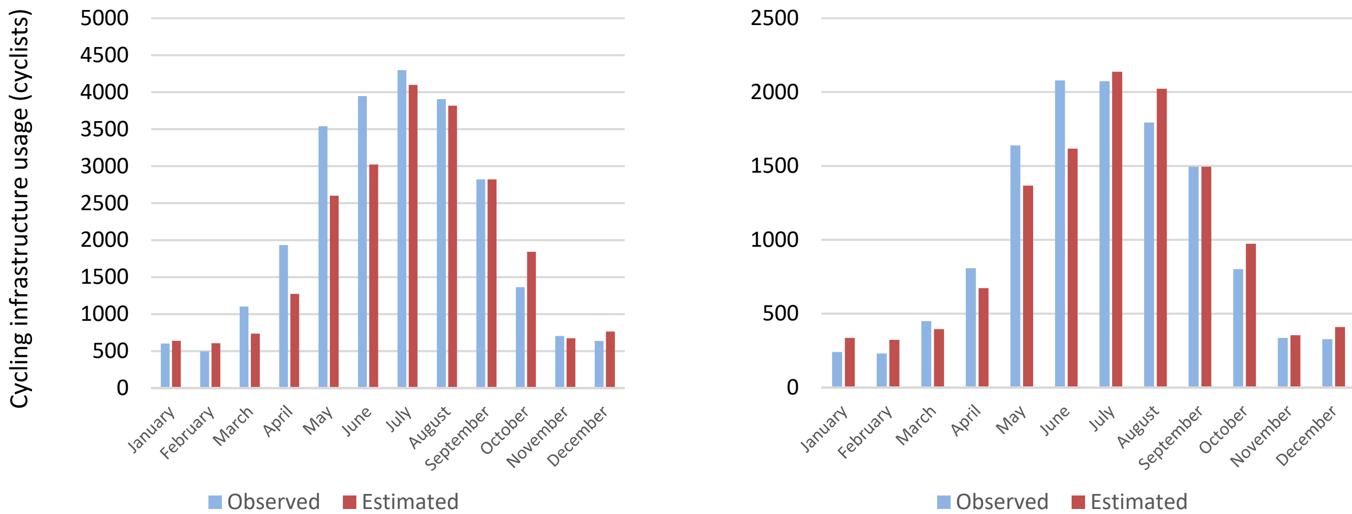
Table 3: Overview of selected infrastructure sections characteristics

Infrastructure section	Type of Infrastructure	Location	UTR	Infrastructure Neighbourhood
Parkdale	Off-road pathways	Outside downtown	0.1592	Recreational
5 Street North of 15 Ave	On-road Sep. physically	Downtown	0.1814	Commercial

Usage on weekends and weekdays were estimated separately based on September weekend and weekday usage. Since UTR values for selected infrastructure sections were higher than 0.11, the utilitarian model was used to estimate both weekend and weekday usage. The total monthly usage was calculated by adding the weekend and weekday usage together. Table 4 shows the observed and estimated annual usage and the estimation error. The estimated cycling frequency and actual cycling frequency are shown in Figure 3.

Table 4: Model result

Infrastructure section	Actual Annual Usage	Estimated Annual Usage	Annual Estimation Error	MAPE
Parkdale	25344	22894	0.096	0.192
5 St and 15 Ave SW	12265	12094	0.013	0.195



a) Parkdale

b) 5 St and 15 Ave SW

Figure 3: Comparison of the model result and observed usage

5 CONCLUSION

This study presented a framework for developing a model capable of estimating cycling infrastructure usage throughout the year. The results of this study showed the effect of different weather variables on cycling infrastructure usage. Among the weather variables, temperature and sunlight hours showed a positive impact on cycling infrastructure usage, while precipitation, collected snow on the ground, and wind speed showed a negative impact on cycling infrastructure usage. Also, the results indicated that the magnitude of the impact of these variables was not constant during the year. The impact of the variables with a negative impact, such as collected snow on the ground and precipitation, was generally higher during cold months of the year compared warm months. Temperature and precipitation were found as the two main weather variables that impact cycling as they showed higher impact on usage compared to other variables and their impact was significant for all months of the year.

The impact of the weather variables was evaluated separately for weekday and weekend usage because usage in weekends and weekdays were different in values. While in general weekday usage is attributed to commuter cyclists, usage on weekends is attributed to utilitarian cyclists. As the results of the model showed, the impact of weather variables was generally higher for weekend usage compared to weekday usage. The higher magnitude of the impact of weather variables on weekend usage indicated that utilitarian cyclists were more affected by weather conditions than commuter cyclists which is in line with (Miranda-Moreno et al. 2013; Brandenburg et al. 2007). The validation showed that when estimating usage for different months of the year, the model had an average error of 19.35%. This error represented the accuracy of the model in terms of estimating usage variation for different months of the year. When estimating the annual usage of infrastructure, the model had an average error value of 5%.

The developed estimation model in this study allows the usage throughout a year to be estimated based on the effect of weather conditions on cyclists. According to Köppen climate classification, climate can be classified into 5 groups namely, tropical, arid, temperate, cold, and polar. Calgary is a city with a cold climate. The effect of weather conditions on cyclists is not the same for people who live in different climate types. For example, people who live in cold cities are more resistant to cold weather compared to people who live in warmer cities; hence, the effect of temperature on cycling is not the same in different climate types. As a result, since the model presented in this study used data from a city with a cold climate, the model can be used to estimate cycling infrastructure usage for cities with a similar climate to Calgary.

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