Commuter Cyclist's Sensitivity to Changes in Weather: Insight from Two Cities with Different Climatic Conditions

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ABSTRACT
This study examines the relationship between various weather conditions and commuter bicyclist volume in two cities (Portland, USA and Brisbane, Australia), which fall into different climatic zones. Investigating the variation in day-to-day bicycle ridership can help to understand factors influencing demand and in particular how base climatic conditions may condition bicyclist's responsiveness to changes in weather and climate. Temporal variations in bicycle usage and key weather parameters (temperature and rainfall) are analyzed. Ridership counts and weather data are then used to develop an aggregate demand model that provides quantitative insight into the effects of weather on bicyclist volumes. The results indicate that daily bicyclist volume varies across hours of the day as well as days of the week. Both temperature and rainfall are found to have a significant influence on daily bicyclist volume but with different degrees of sensitivity in these two cities which correspond to their base climates. The results are discussed in view of their implications for government strategies that seek to increase the role of bicycle in urban areas.

INTRODUCTION

Policy makers are promoting bicycling as a mode of transportation since it reduces traffic congestion, energy consumption and greenhouse gas emissions and enhances health outcomes (*1, 2, 3*) and therefore offers sustainable economic, environmental and social benefits (*4*). At the same time, changes in weather are high on the agenda in cities around the world today because the intensity and frequency of extreme weather conditions are expected to increase as a result of climate changes (*5*). Since cyclists are directly exposed to the weather this paper seeks to quantify the impact of changes in weather on bicyclist's travel behavior.

There are many factors that affect demand for bicycling although research consistently highlights the importance of adequate infrastructure (*6*). Apart from investing in infrastructure, such as off-road paths and bicycle lanes to accommodate the growing number of cyclists and to facilitate even more growth, governments have regularly sponsored events to encourage bicycle commuting (e.g. 'Ride to Work Day' (*7*)). Seasonal variations in ridership (*8*, *9*) suggest that there are many fair weather utilitarian cyclists and this presents a challenge from the perspective of gaining the maximum benefit from the investments in bicycle infrastructure targeted on promoting this mode of transport. Policies could be undermined by the influence of weather; particularly where the target is to increase women's cycling (*2*), if women are more likely to be deterred from riding in adverse weather.

Following global policy, Portland, Oregon and Brisbane, Queensland has been encouraging bicycling. Portland is well known for being one of the most bicycle friendly cities in the USA. In 2008 Portland became the first major city in the USA designated as a Platinum-level Bicycle Friendly Community by the League of American Bicyclists (*10, 11*). Likewise, in Queensland, cycling has been encouraged by allocating funds to develop cycle networks, through supporting various cycle events (*12*) and developing world-class end-of-trip facilities to promote commuter cycling (*13*). While bicycle count data has been complied for more than ten years (*14*), little research has explored the temporal variability in bicycle volume and in particular, how commuter cyclists of Portland and Brisbane are influenced by weather conditions.

Portland and Brisbane fall into different climatic zones; Portland's climate is more temperate mediterranean climate whereas Brisbane experiences a tropical climate (*15*). As noted earlier, weather and climate has the potential to influence cycling. Thus, this paper seeks to quantify the influence of day to day changes in weather on bicyclist volume in these two cities whose base climatic condition are different. This analysis can also provide insight into weather corrections which could be useful in adjusting counts made at one point in time (e.g. census journey to work data) to account for regional differences in weather/climate.

The structure of this paper is as follows. Section two provides a review of the relevant literature. The review focuses on the effect of changing weather conditions on travel behavior and identifies the sources of data and the methodologies which have been used to develop understanding of those relationships. The following section examines temporal variation of bicyclist volume in Portland and Brisbane. It also explores how various weather parameters specifically, temperature and rainfall, vary over the year. Data from Portland and Brisbane are then used to calibrate aggregate bicycle demand models that incorporate a range of explanatory variables including weather. The final section presents the conclusions of the research and identifies future research needs and directions.

INSIGHT FROM THE LITERATURE

There is limited research which explores how travel behavior is influenced by weather. Nankervis (*16*) examined how weather and climate affects bicycle commuters in Melbourne, Australia. He identified a decrease in cycling over the winter months. Heavy rain was the biggest deterrent for the cyclists to ride with 67% of the respondents indicating they would be deterred from riding in heavy rain. Among these respondents who did not ride (67%), almost all of them (90%) indicated that they still made the trip but used an alternative mode. Thomas et al (*17*) identified that temperature caused greatest variation and wind caused the least variation in bicycling demand in Netherlands. More recently, Lewin (*18*) confirmed that the impact of temperature on daily bicyclist volume in Boulder, CO was non linear with the optimum riding temperature estimated to be 32.2^{0}C. Moreno and Nosal (*1*) investigated how bicycle usage in Montreal, Canada is impacted by various weather conditions. Their analyses found that precipitation, temperature and humidity influence bicycle ridership. When other factors are controlled, a 100% increase in temperature increases the ridership by 43-50%. However, temperature greater than 28^{0}C and humidity greater than 60%, reduced the ridership which confirms a non- linear effect. Precipitation was also found to have both a direct and a lagged effect on ridership. As a result, bicyclist volume in a particular hour is not only affected by the presence of rain in that hour but also affected if there was rain in previous hours. Other research (*19*) examined ridership sensitivity to weather in Portland, Oregon, USA. Analyses of six months of data from Portland, Oregon indicated that a 1^{0}C rise in temperature increases the volume of daily bicyclists by between 3% to 6% whereas each1mm increase of precipitation decreases the volume by around 4%.

Both Richardson (*20*) and Phung and Rose (*21*) explored how weather variations affect bicycle ridership in Melbourne, Australia. Rain was identified as the most influential weather parameter which significantly decreased commuting cyclist volumes. Both of these studies found that rainfall has a non-linear effect. Richardson (*20*) identified that daily rainfall of around 8 mm, reduces cyclist volumes by about 50% compared to days when there is no rain. In contrast, Phung and Rose (*21*) found that light rain (defined as daily rainfall less than 10 mm) deterred between 8 and 19% of all cyclists while heavy rain (defined as daily rainfall greater than 10 mm) deterred about one-third more (13 to 25%). Air temperature has been identified to have a non-linear and non-symmetrical relationship on commuter cyclist volume with the volume of riders decreasing immediately after the ideal riding temperature (*20, 21*). Phung and Rose (*21*) identified the ideal riding air temperature to be about 28^{0}C whereas Richardson's (*20*) analysis identified the optimal air temperature for riding to be 25^{0}C. Wind effects were detected for most of the sites in Melbourne studied by Phung and Rose (*21*), but ridership on the Bay Trail, which runs along the exposed coast of Port Phillip Bay, was the most sensitive to wind change.

Table 1 summarizes the general nature of the conclusions reached from studies focused on different geographic locations which have a range of background climatic conditions. The literature suggests that across the locations which have been examined, cyclists have been found to be sensitive to weather although that sensitivity varies across different weather parameters. Temperature and precipitation are the most important influences on bicyclist volume. Wind was found to be deterrent in some places but mostly identified as being less influential.

TABLE 1 Different Location's Sensitivity to Weather Parameters

Location	Weather parameter			Climate	Reference
	Temperature	Precipitation	Wind		
Melbourne, Australia	✓	✓ Highly influential	✓ Least influential	Temperate oceanic climate	Nankervis (*16*)
Netherlands	✓ Highly influential	✓	✓	Temperate oceanic climate	Thomas et al (*17*)
Boulder, CO	✓ Highly influential	✓		Warm oceanic climate	Lewin (*18*)
City of Montreal, Canada	✓	✓	✓	Warm Continental climate	Moreno and Nosal (*1*)
Portland, Oregon	✓ Highly influential	✓		Temperate Mediterranean climate	Rose et al (*19*)
Melbourne, Australia	✓	✓ Highly influential		Temperate oceanic climate	Richardson (*20*)
Melbourne, Australia	✓	✓ Highly influential	✓	Temperate oceanic climate	Phung and Rose (*21*)
Melbourne, Australia	✓	✓	✓	Temperate oceanic climate	Ahmed et al (*9*)

Researchers have drawn on a range of data types and sources to explore how travel behavior is related with weather. Table 2 summarizes some of the widely used data sources. It is found that travel behavior data is exclusively collected by questionnaire surveys but in the case of ridership data, it has been collected both automatically and through observational surveys.

TABLE 2 Different Data Types and Sources

Data	Data Sources		References
Travel behavior data	Questionnaire Survey		Khattak and Palma (*22*)
Ridership data	Automatic Counting System	Pneumatic tube	Thomas et al (*17*), Rose et al (*19*)
		Detector loops	Moreno and Nosal (*1*), Ahmed et al (*9*), Lewin (*18*), Rose et al (*19*), Phung and Rose (*21*),
	Observational Survey		Nankervis (*16*)
Weather data	Usually the weather data is provided by the relevant local meteorological organizations		Ahmed et al (*9*), Nankervis (*16*), Thomas et al (*17*), Lewin (*18*), Rose et al (*19*), Phung and Rose (*21*),

In recent years, most of the research has relied on automatically counted hourly ridership data. The advantage of an automatically counting approach is that it gives the data for a continuous period whereas manually collected data may represent a specific period of a year, or at the very least a much more limited time period. The local Bureau of Meteorology is usually a rich source of weather data with information available in either an hourly or 24 hour aggregate format. Depending on the requirement of the research, both hourly and daily data have been analyzed in different studies.

When seeking to understand weather or seasonal patterns in ridership data, a first level of analysis often involves use of plots or descriptive statistics to understand patterns in the data (*16, 20, 23*). Higher level analysis usually focuses on development of a statistical model to explore the relationship between a range of explanatory variables and a dependent variable (usually ridership volume). Models that have been employed include time series models (*24*), linear and non-linear regression models (*17, 21*) and ordered probit models (*22*).

The research described above is expanding understanding of how travel behavior is influenced by changing weather and climate. This paper adds to that knowledge base by combining weather effects in two cities with differing base climatic scenarios.

TEMPORAL VARIATION IN RIDERSHIP AND WEATHER

We now turn attention to the two cities considered in the analysis: Portland, Oregon (USA) and Brisbane, Queensland (Australia). The data available from those two locations is described, and then the day to day variability in key parameters is quantified.

Data

Portland's bridges act as feeders to carry commuters and students from the neighborhoods of the east into the downtown area and beyond. Bicycle volumes have been monitored on these bridges since the early 1990’s through automatic hose counts. However, the data utilized in this research was collected using state of the art bicycle sensors of high accuracy (*25*) which were installed in August 2009. Among the bridges that carry pedestrian and cyclists to the downtown area, the Hawthorne Bridge has the greatest use and carries more bicycle traffic than all other Portland bridges combined. Because of its importance in the network, and the availability of quality data, the Hawthorne Bridge is considered in the analysis reported here. Previous research (*19*) which examined the impact of weather on Portland cyclists could only draw on data covering a six month period. As a result of additional data becoming available, the analysis reported here considers a total period in excess of twelve months.

Automatic bicycle counts have been conducted in Queensland for more than ten years (*14*) and they provide continuous, directional data at 15 min to 1 hour intervals (varies from site to site). The site considered here for analysis is located on a dedicated bicycle path as it passes through Mowbray Park, Brisbane (an inner suburb) which was found to be predominantly a commuter trail in earlier research (*26*). Moreover, it is a permanent count location and had less missing data compared to other candidate locations in Brisbane.

Overall, the data used here to analyze the variation in ridership covered the period September 2009 to December 2010 and thus, the seasonal variation for both sites is captured. The corresponding weather data for the two sites was also obtained from the relevant meteorological organizations.

Variation in Ridership

The Average Annual Daily Traffic (AADT) values, computed separately for weekdays and weekends and public holidays, for the two sites are summarized in Table 3. The table indicates the variability in usage. Ratios of AADT of weekday to weekend and public holiday are also shown to identify the predominant functionality of each site.

TABLE 3 Average Annual Daily Traffic (AADT) By Weekday/Weekend and Public Holiday

Site name	AADT		Ratio*	Predominant type of trail**
	Week day	Weekend and public holiday		
Hawthorne Bridge	4478	2023	2.21	Commuter
Mowbray Park	488	165	2.95	Commuter

*Ratio = Weekday AADT/ Weekend and public holidays AADT
**Type of trail: Commuter trail, ratio >1

As shown in the above table, both sites have higher bicyclist volume on weekdays than weekends and public holidays. For both sites the ratio of weekday/weekend is above 1. Considering the magnitude of the ratios it can be concluded that both sites are predominantly catering for commuter cyclists (*21*).

Figure 1 shows the average weekday hourly bicycle volume for each site. Bicyclist volume varies by time of day with similar patterns across the sites. On the basis of AADT, Hawthorne Bridge serves an order of magnitude more commuter cyclists than the Mowbray Park location however peak hour counts only differ by a factor of three to four. As highlighted in Figure 1, here is clearly more inter-peak bicycle traffic on the Hawthorne Bridge than at the Mowbray Park site.

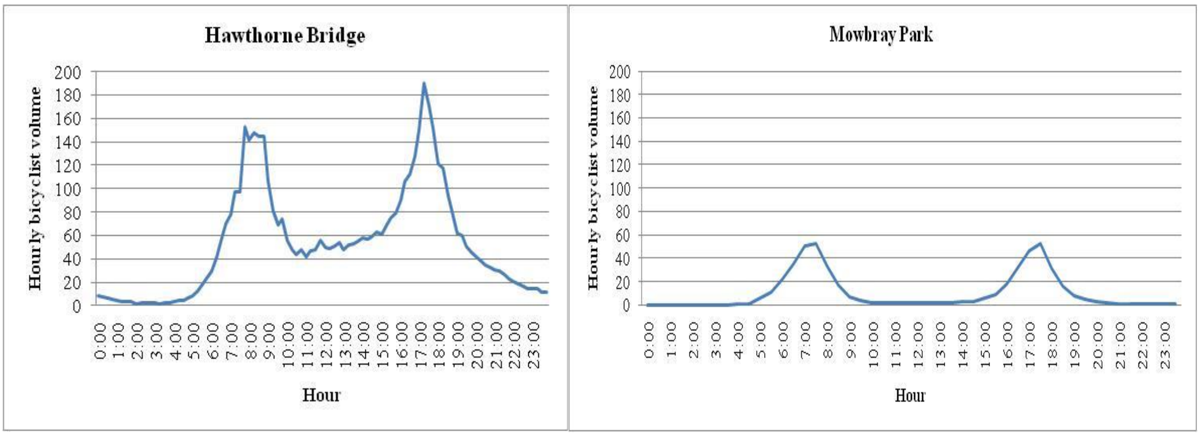

FIGURE 1 Average hourly bicyclist volume across sites

At both sites, ridership predictably peaks twice per day, in morning (6:00 to 9:00) and in evening (16:00 to 19:00). The identified peak periods again confirm that the sites are primarily used by commuters.

Variation in Key Weather Parameters

Monthly variation in the key weather variables, temperature and rainfall (*18*), is illustrated in Figures 2 and 3 respectively. The values in the figures reflect the average over two years (2009 and 2010) for Portland and three years (2008, 2009 and 2010) for Brisbane. A clear contrast in temperature range between Portland and Brisbane can be seen in Figure 2. During summer in Portland, temperature ranges from around 15^{0}C to 27^{0}C whereas it is 23^{0}C to 28^{0}C in Brisbane. The variation is more pronounced during winter. Temperature ranges from 12^{0}C to 22^{0}C in winter in Brisbane whereas Portland experiences lower temperatures and a wider temperature range of -4^{0}C to 11^{0}C during the same season. The plots of average monthly temperature highlight that temperature peaks in August in Portland, whereas in Brisbane, reflecting its southern hemisphere location, experiences its lowest temperatures at that time of year.

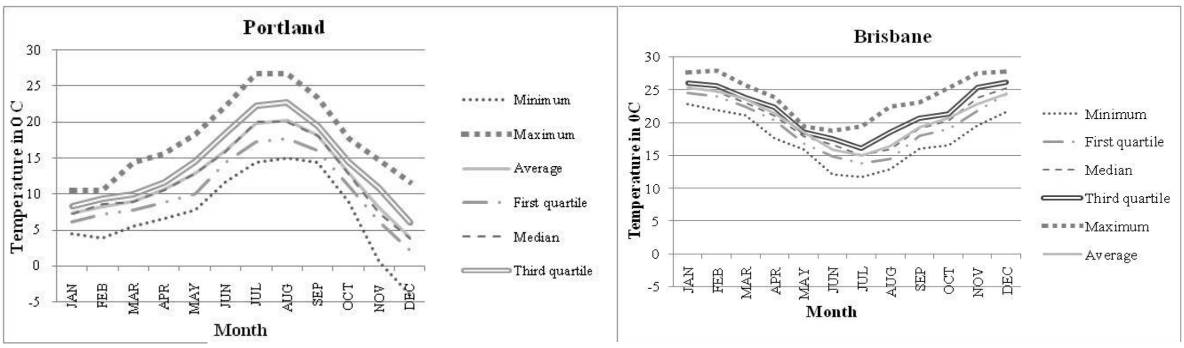

FIGURE 2 Monthly variation of average daily temperature

Figure 3 depicts the variation in rainfall over the year where daily rainfall averaged on a monthly basis is plotted. The upper plots show actual level of rainfall in Portland and Brisbane whereas the lower plots indicate indexed values. To calculate the indexed value, the average rainfall is normalized with respect to the December average since the highest amount of rainfall in both cities falls in December. The value in each month therefore reflects the average daily rainfall in that month relative to the December base. For example, July rainfall in Portland is about 10 % of that which falls in December.

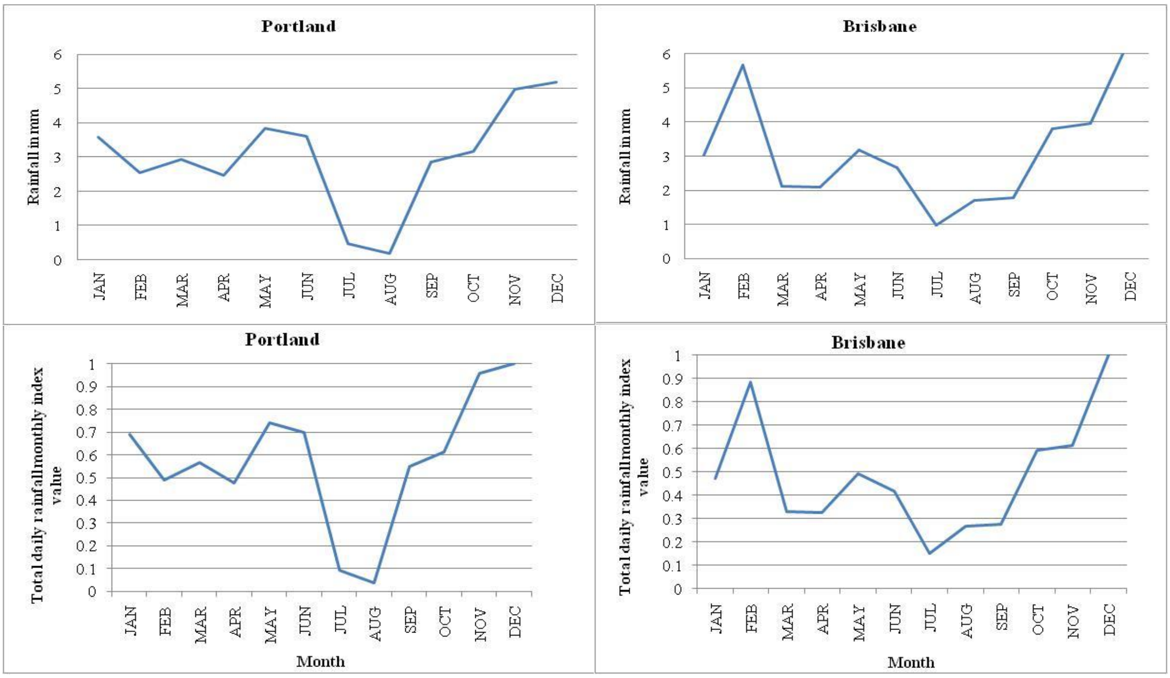

FIGURE 3 Monthly variation of total daily rainfall

Maximum rainfall of around 5 mm is observed during winter months in Portland. In Brisbane, rainfall peaks during summer months when the maximum average daily rainfall is about 6mm. In both cities, the driest months are July-August when Portland gets only about 5% of the maximum rainfall in December whereas for Brisbane it is around 25%.

The variation in temperature and rainfall are measured by the Coefficient of Variation (COV) and summarized in Table 4 for both locations. The COV for temperature is much higher in Portland but the two cities experience a similar degree of variation in rainfall.

TABLE 4 Degree of Variation in Temperature and Rainfall

Location	**Coefficient of Variation**	
	Temperature	Rainfall
Portland	.43	.50
Brisbane	.18	.52

MODELING COMMUTER CYCLIST BEHAVIOR

To estimate the effect of weather and other potential factors into bicyclist volume a regression modeling approach is adopted in this study as this approach has previously provided valuable insight (*1*, *9*, *18*, *19, 21*). As the analysis reported here focuses on commuter cyclist behavior, Saturdays and Sundays are excluded from the analysis. Public holidays are included in order to estimate how much public holidays influence the weekday ridership.

To examine the variation in bicycle usage and the factors contributing to those variations, a log linear model is employed. Different combinations of explanatory variables have been used in the model to identify which combination yield the best fit to the ridership data. Equation 1 summarizes the formulation of the underlying model.

Model

$$log_e\,(Q_{it}) = \alpha_i + \sum_{n=1}^{6} \beta_{iDOW,n} DOW_n + \beta_{iTIME} TIME_t + F_T(TEMP_{mt}) + F_R(RAIN_{jt}) + \beta_{iPUB} PUB_t + \varepsilon_{it} \forall_{i,t} \quad (1)$$

Where;

Q = Daily total (24 hour) bicycle volume

i = Site index

t = Time index

DOW = DOW variable is coded using four dummy variables (Monday through Thursday) with the base case corresponding to Friday (when the Day of Week dummies for Monday through Thursday are equal to zero).

TIME = a variable which increments to reflect the day when the data was collected (incrementing from the start to the end of the series of data). This variable is used to capture any time based growth effect.

PUB = Public holiday, coded as a dummy variable (1 for a public holiday and 0 otherwise)

TEMP = Average daily (24 hour) temperature (Celsius).

RAIN = Daily total (24 hour) rainfall (mm)

Three alternative functional forms are used for TEMP and RAIN variable:

1. Continuous variable – linear effect

$$F_{T1} = \beta_{iTEMP} TEMP_t$$

$$F_{R1} = \beta_{iRAIN} RAIN_t$$

2. Continuous variable – non-linear effect

$$F_{T2} = \sum_{m=1}^{2} \beta_{iTEMP,m} TEMP_t^m$$

$$F_{R2} = \sum_{j=1}^{2} \beta_{iRAIN,j} RAIN_t^J$$

3. Categorical representation

$$F_{T3} = \sum_{m=1}^{3} \beta_{iTEMP,m}\, TEMP_{mt}$$

$$F_{R3} = \sum_{j=1}^{2} \beta_{iRAIN,j}\, RAIN_{jt}$$

The third functional form (categorical representation) is considered to reflect differences in the underlying climate of the cities. In this representation,

TEMP variable is coded using three dummy variables corresponding to a 'Cool Day', a 'Warm Day' and a 'Mild Day' with the base case (all temperature dummies set to zero) corresponding to a 'Very Warm Day'. The RAIN variable is coded using two dummy variables for 'Light rain' and 'Heavy rain' with the base case corresponding to 'No rain'.

The categorization of both 'TEMP' and 'RAIN', shown in Table 5, is based on analysis of quartiles from the respective distributions. Each quartile is given a linguistic interpretation for temperature (i.e. Cool, Mild, Warm or Very Warm Day) while the fourth quartile (i.e. the highest 25% of the daily rainfall totals) is used for defining heavy rain days. The categorization of the variables 'TEMP' and 'RAIN' corresponds to how each area experiences the variation in temperature and rain and so, therefore reflects differences in the base climatic conditions of the two cities.

TABLE 5 Categorization of Variables 'TEMP' and 'RAIN'

Weather parameter	Category	Portland	Brisbane
Temperature	Cool day (First quartile)	< 7.2^{0}C	< 18.2^{0}C
	Mild day (Second quartile)	7.2^{0}C to 10.6^{0}C	18.2^{0}C to 21.7^{0}C
	Warm day (Third quartile)	10.6^{0}C to 16.1^{0}C	21.7^{0}C to 24.3^{0}C
	Very warm day (Fourth quartile)	>16.1^{0}C	> 24.3^{0}C
Rainfall	No rain	0 mm	0 mm
	Light rain (up to the third quartile)	Up to 3.8 mm	Up to 1.4 mm
	Heavy rain (Fourth quartile)	> 3.8 mm	> 1.4 mm

As Equations 1 is a log-linear formulation, the coefficients of the continuous variables are directly interpreted as the percentage change in the dependent variable (daily bicycle volume) as a function of a change in the explanatory variable. For example, a coefficient of 0.08 on the 'TEMP' variable in functional form 1 would imply that an additional 1^{0}C of temperature would cause an 8% increase in daily bicycle volume. In contrast, the effect of the dummy variables is measured as effect= e^{β}– 1, where β = co-efficient of the explanatory variable (*21*). The interpretation is relative to the base case. For example, coefficient of 0.13 for Tuesday would be interpreted as the volume of a Tuesday is 14% ($e^{0.13}$-1) higher than that of Friday (since Friday is the reference day for coding the data). The analysis focuses on the effects of temperature and rainfall since those weather variables were found to be the most important in explaining variations in ridership in earlier studies (*16*, *18*, *21*). Correlation among the explanatory variables was examined but no significant correlations were observed. The highest correlation of -0.37 was observed between 'TIME' and 'Mild Day'.

MODELLING RESULTS AND DISCUSSIONS

The modeling results for Portland and Brisbane are presented in Table 6 and Table 7 respectively. The estimated coefficients and the Coefficient of Determination (R^2), a measure of 'Goodness of fit' for OLS regression, are also given in these tables. The shaded boxes correspond to significant variables at a 95% confidence level.

Portland Results

For Portland models, the R^2 value ranges from 0.67 to 0.74 across the models. Thus, around 70% of the variation in daily bicyclist volume has been explained by these models. The poorest fit is for model number 3 where temperature and rain are both included as categorical variables.

TABLE 6 Regression Model Results for Portland

Explanatory Variable		Model Number			
		1	2	3	4
Time based growth		-0.00019 (-1.58)	-0.00018 (-1.6)	-0.0001 (-0.74)	-0.0002 (-1.74)
Day of week	Mon	.14 (3.09)	.13 (3.09)	0.13 (2.77)	0.12 (2.83)
	Tue	.16 (3.38)	.15 (3.36)	0.12 (2.51)	0.13 (3.04)
	Wed	.17 (3.66)	.16 (3.80)	0.15 (3.02)	0.15 (3.42)
	Thu	.13 (2.78)	.12 (2.74)	0.10 (2.09)	0.10 (2.21)
Public holiday		-.9 (-12.6)	-.9 (-13.25)	-0.99 (-13.08)	-0.94 (-13.85)
Cool day				-0.66 (-13.69)	
Mild day				-0.36 (-6.85)	
Warm day				-0.16 (-3.49)	
TEMP		.045 (17.76)	.08 (11.87)		0.08 (11.63)
$TEMP^2$			-0.002 (-5.44)		-0.002 (-5.51)
RAIN		-.02 (-7.73)	-0.04 (-7.50)		
$RAIN^2$			0.0008 (4.11)		
Light rain				-0.02 (-0.60)	-0.10 (-2.69)
Heavy rain				-0.26 (-6.45)	-0.35 (-9.31)
R^2		.71	.74	.67	.74

KEY: The associated t stats are presented in parenthesis. The critical values for t stats are for a 95% confidence interval. Variables which are significant at a 95%confidence level are lightly shaded.

Time based growth is not found to be statistically significant in any model. The changes in volume across different days of the week show the same trend for all the models. In each case the reference day is Friday. Bicyclist volume reaches its peak in the middle of the week with Wednesday recording the highest volume which is around 17% ($e^{(.16)}$ -1) higher than that on Friday. Volume declines as the week progresses with lowest volume on Friday. On Public holidays, the daily bicyclist volume decreases by around 60% ($e^{(-.94)}$ -1).

Temperature was found to have significant effect on bicyclist volume in all models. From model 3 where temperature is specified as a dummy variable, it is estimated that very warm days (those in the top quartile of temperatures >16.1^{0}C) correspond to the highest bicyclist volume. Warmer weather increases bicyclist volume. However, when temperature is specified as continuous variable, a non- linear effect is identified in model 2 and 4which is illustrated in Figure 4.

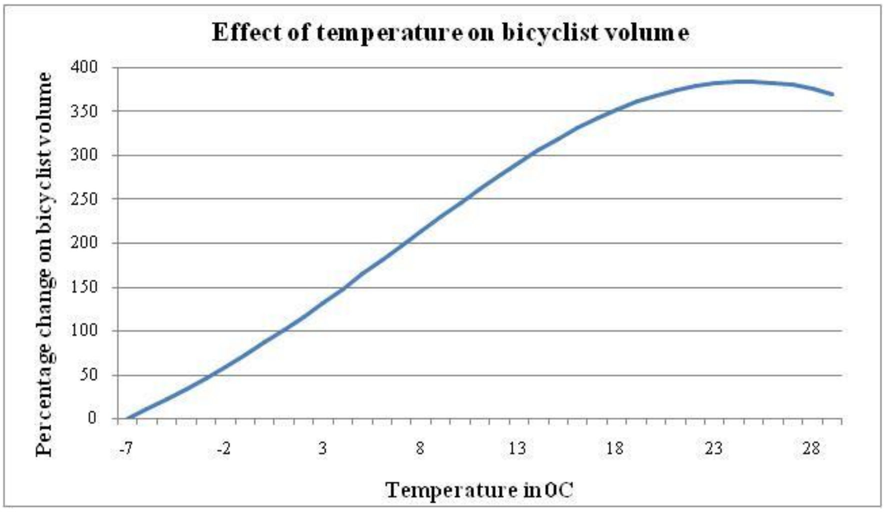

FIGURE 4 Effect of temperature on bicyclist volume

An optimum riding temperature of 24^{0}C is indicated by Figure 4. The result shows that when the temperature reaches to the optimum level, volume increases by around 400% from that at -7^{0}C (the recorded minimum temperature). However, the effect of temperature drops off when it is greater than 24^{0}C

The effect of heavy rain is found to be statistically significant in models 3 and 4 though the effect of light rain is found to be statistically significant only in model 4. The greatest impact comes from heavy rain which decreases volume by 29% which is about three times higher than the effect of light rain. When the effect of rain is treated as continuous variable, it is observed that each 1 mm increase of rain reduces the bicyclist volume by around 3%.

Brisbane Results

The Brisbane model results are presented in Table 7. The first four models have the same specifications as for Portland. Model 5 considers a different rainfall effect. The availability of hourly rainfall data for Brisbane made it possible to examine the impact of early morning rain on daily ridership. The dummy variable 'Presence of rain_5am-8am' in model number 5 indicates days when there was rain during 5am to 8am period.

The R^2 value ranges from 0.56 to 0.61 across the models. Thus, around 60% of the variation in daily bicyclist volume has been explained by these models. The discussion focuses first on models1 to 4 and then returns to consider model 5.

The negative and statistically significant (in all except model 4) time based growth coefficients highlight that ridership at the Mowbray Park site is declining over time. Over the analysis period, the site has experienced a reduction of about 10 % (-.0003*365) per annum in daily bicycle volume.

TABLE 7 Regression Model Results for Brisbane

Explanatory Variable		**Model Number**				
		1	2	3	4	5
Time based growth		-0.0003 (-2.4)	-0.0003 (-2.16)	-0.0003 (-2.09)	-0.0002 (-1.86)	-0.0003 (-2.86)
Day of week	Mon	.24 (4.55)	.25 (5.14)	0.23 (4.49)	0.24 (4.60)	0.29 (5.85)
	Tue	.33 (6.42)	.34 (6.87)	0.34 (6.61)	0.34 (6.65)	0.33 (6.72)
	Wed	.30 (5.8)	.30 (6.15)	0.30 (5.87)	0.31 (5.93)	0.31 (6.16)
	Thu	.25 (4.88)	.25 (5.10)	0.22 (4.32)	0.22 (4.31)	0.26 (5.30)
Public holiday		-1.25 (-13.91)	-1.22 (-14.29)	-1.28 (-14.49)	-1.29 (-14.50)	-1.23 (-14.33)
Cool day				0.02 (0.29)		
Mild day				0.10 (2.20)		
Warm day				0.06 (1.39)		
TEMP		-0.0035 (-.67)	.08 (1.51)		0.07 (1.37)	-0.01 (-1.63)
$TEMP^2$			-0.002 (-1.57)		-0.002 (-1.37)	
RAIN		-0.012 (-9.36)	-0.03 (-9.75)			
$RAIN^2$			0.0002 (6.11)			
Light rain				-0.08 (-1.84)	-0.09 (-1.94)	
Heavy rain				-0.41 (-9.83)	-0.40 (-9.84)	
Presence of rain_5am-8am						-1.21 (-11.28)
R^2		.56	.61	.58	.58	.61

KEY: The associated t stats are presented in parenthesis. The critical values for t stats are for a 95% confidence interval. Variables which are significant at a 95%confidence level are lightly shaded.

Although ridership varies relatively little across weekdays, Tuesday appears to have the highest volume. Ridership decreases as the week progresses. On Public holidays, the daily bicyclist volume decreases by around 70%.

Model 1 which includes only a linear, continuous temperature and rainfall effect produces the lowest R^2 value. Temperature is insignificant in all except model number 3 where only the effect of mild days (18.2 ^{0}C to 21.6^{0}C) is found to be statistically significant. Model number 2 produces an optimum riding temperature of 20 ^{0}C which falls into the mild temperature category for Brisbane. While not statistically significant this result is constant with model number 3 which shows that on days with mild temperature the ridership is around 10% higher than that on very warm days (temperature >24.3^{0}C).

When the effect of light rain is significant (in model number 4) it produces a 9% decrease in ridership. Heavy rain has an effect four times greater than that of light rain. When rain enters as a continuous variable (model 1 and 2), each 1mm of increase in rainfall reduces the bicyclist volume by 1 to 3%.

The positive co-efficient on the variable $RAIN^2$ which was found in case of both Portland and Brisbane, means the relationship between rainfall and ridership is 'U' shaped. It implies that ridership would initially decrease with increasing rainfall before reaching a minimum and then increase as rainfall gets heavier. The priori expectation would be that ridership would continue to decline with increasing rainfall. So, the positive coefficient on $RAIN^2$ is counter to expectations. To explore the rainfall effect further it was coded categorically into Light and Heavy rain (models 3 and 4) which as discussed above, demonstrate the greatest impact of heavy rain.

Previous research conducted in Montreal identified that the bicyclist volume in an hour is not only affected by the presence of rain in that hour but it also affected if there was rain in previous hours (*1*). To examine how presence of rainfall during the morning peak period (5am-8am) affects daily bicyclist volume in Brisbane, the variable, 'Presence of rain_5am-8am', is included in model 5. Here, rain fall is categorized as 'No rain' (total rain fall during 5am to 8am = 0mm) and 'Presence of rain_5am-8am' (minimum total rainfall during 5am to 8am > 0 mm). The variable is coded as a dummy variable with the base case corresponding to 'No rain'. A high statistically significant effect is found which indicates that if rainfall occurs within the specified period it reduces the daily bicyclist volume by 70%, compared to when there is no rain. That model also produced the highest R^2 values and thus explained the greatest variation in the ridership data. As the hourly data were not available for Portland, it was not possible to report results for a comparable model for Portland.

COMPARISON BETWEEN PORTLAND AND BRISBANE MODEL RESULTS

The models for both cities explain a high proportion of the variation in bicyclist volume. Across the different model specifications, most of the explanatory variables are found to be statistically significant. The comparisons discussed below between these two cities are based on the results from model 3 as most of the explanatory variables for model 3 are statistically significant across the two locations and the identified effects of weather variables reflect each location's base climatic conditions.

Day of the Week Effect

The pattern of ridership across working days is similar in Portland and Brisbane where Friday is associated with lowest volume in both cases. However, it is noticeable that Friday gets much lower volume compared to other weekdays in Brisbane (coefficients of the days in Brisbane models are larger than that for Portland). The results indicate that commuters in Brisbane are less likely to ride to work in Friday compared to the commuters in Portland.

Effect of Public Holiday

Public holidays influence commuter bicyclists nearly in the same manner across the cities though the effect is slightly higher in Brisbane. When it is a public holiday daily bicyclist volume decreases by 72% in Brisbane compared to 63% in Portland.

Weather Effect

There is evidence of a difference in the sensitivity with respect to temperature across the two cities. Ridership in Portland reaches its peak on very warm days. On days with other temperature ranges (cool day, mild day and warm day), estimated ridership is much lower compared to that on very warm days. The optimum riding temperature in Portland is 24 ^{0}C, which is in the 'very warm' category for its local climate. On mild days, daily ridership is 30% lower than that on very warm days. In Brisbane the optimum riding temperature is 20 ^{0}C, which is in the 'mild' category for its local condition. Bicyclist volume is 10% higher on mild days than on very warm days in Brisbane. Thus, very warm days in Portland stimulate ridership. However, in Brisbane, ridership is much lower on very warm days compared to other days.

The effect of light rain was not found to be statistically significant for either city. However, heavy rain is found have significant effect in both cities, though the sensitivity in the two cities is different. Heavy rain produces a 23% decrease in ridership in Portland whereas it is 33% in Brisbane.

CONCLUSIONS AND RESEARCH DIRECTIONS

This paper has investigated weather impacts on bicycle ridership in Portland and Brisbane using a regression modeling approach. Temperature and rainfall, which were previously identified as two important weather parameters, were again found to significantly influence ridership.

The models are able to explain a high proportion of variability in daily bicyclist volume. The study confirms the sensitivity of ridership to weather with different extents across the cities. Temperature affects ridership both in Portland and Brisbane but with different degrees which correspond to their base climatic conditions. Moreover, a non liner effect of temperature is captured in Portland where 24^{0}C is appeared to be ideal for riding. Heavy rain has the greatest impact on ridership in both cities. Furthermore, presence of rainfall during morning peak period influences daily ridership in Brisbane.

In the future, hourly variations in ridership as a result of changes in weather will be investigated. Other variables which have the potentiality to influence cyclist volume but were not incorporated in this analysis will be considered in future work such as effect of humidity. More sites from both Portland and Brisbane will be analyzed as an extension of this study. Moreover, disaggregate travel data will be analyzed to examine how bicycle riders adapt their day to day travel behavior in response to changes in weather. Exploring disaggregate data will facilitate an understanding of the relative effects of weather on male versus female riders and the extent to which riders who have invested in appropriate equipment (mud guards, weather proof panniers) are less sensitive to changes in weather. From a transport policy perspective, it would be useful for future research to provide insight into whether riders who have access to end of trip facilities (change rooms, showers, lockers, airing closets etc) are less sensitive to changes in weather. Furthermore, the modal shift of bicycle riders as a result of weather changes will be quantified which will provide insight into whether increases in public transportation ridership or additional pressure on the road system through increased use of private motorized transport might be expected when weather is not favorable for riding.

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