Impact of weather on commuter cyclist behaviour and implications for climate change adaptation

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Abstract

Within the transport sector, much of the climate change research conducted to date has focussed on mitigation. This includes for example, strategies to reduce emissions from our transport system that is heavily dependent on carbon based fuels. Adaptation research is now expanding in the transport sector with most effort addressing issues such as the vulnerability of infrastructure to higher sea levels or more frequent and severe storms. An area of adaptation that has received little attention in the literature relates to how individuals will adjust their travel behaviour in the face of changes in weather and climate. This paper examines the relationship between weather and travel behaviour with an emphasis on bicycling. Evidence from the literature is used to highlight how weather and climate affect active transport users. Examination of result from an aggregate bicycle demand model, developed using Melbourne data, confirms that around half of the variations in bicyclist volume can be explained by the changes in weather parameters. A non-linear effect on ridership of key weather parameters, specifically rainfall and temperature, is identified. This paper assesses adaptation behaviour in face of weather and climate change and it has important implications for government strategies that seek to increase the role of active transport in urban areas.

Key Words: Weather, Climate change, Travel behaviour, Active transport

1. Introduction

Weather and climate change are high on the agenda for most cities around the world today. Current climate projections (CSIRO and Bureau of Meteorology, 2007, p. 8-11) point to potentially substantial impacts on many areas of the economy including transport. In the transport context, the bulk of existing research is directed at mitigation. That is aiming to reduce future emissions to minimise climate change impacts. Climate change effects which have been detected to date are a result of emissions that have already accumulated in the atmosphere (CSIRO and Bureau of Meteorology, 2007). Consequently adaptation to climate change is an issue regardless of progress on emission mitigation. In the context of sustainable transport, adaptation research is of growing importance particularly if emissions are not reduced and the accelerated climate changes which have been predicted eventuate. An area of adaptation which has received relatively little attention in the literature relates to how individuals adjust their travel behaviour in the face of changes in weather and climate.

While changes in weather and climate have the potential to affect the travel behaviour of all transport users they are particularly relevant to active transport users (walking, bicycling and public transport). There has been some research that has looked generally at the effects of

weather on the transport sector (Koetse and Rietveld, 2009) but less has focussed on the effects on bicyclists.

In an effort to improve the sustainability of the transport system, State, Federal and Local Governments have been promoting cycling (Austroads, 2005). Apart from investing in infrastructure such as off-road paths and bicycle lanes, governments have regularly sponsored the national 'Ride to Work Day' event (Bicycle Victoria, 2009). That event, which attracts thousand of participants, actively promotes riding to and from work (Rose and Marfurt, 2007). State and local governments are also supporting public bike hire schemes in Melbourne (Department of Transport, 2008) and Brisbane (Brisbane City Council, 2010).

Against that backdrop of government support, there is growing body of literature which seeks the understand the many factors that affect the demand for bicycling. While prior research has highlighted the importance of infrastructure (Dill and Voros, 2007) consideration has also been given to the effects of weather on bicycling (Phung and Rose, 2008). The consequence of climate change for active transport users in general and cyclists, in particular, is unclear. Will government policies to increase cycling be undermined by user response to the changing climate? This paper focuses directly on providing enhanced understanding of the impact of weather on cyclists. From that base, the paper highlights issues of relevance the implications for cycling of human induced changes in weather (i.e. climate change) which are predicted to eventuate over a longer time scale.

Cyclists riding for fitness, recreation or utilitarian purposes are likely to react differently to changes in weather and climate. Given its relevance to transport policy, the focus of this paper is on utilitarian cycling specifically commuter journeys.

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 behaviour. The following section focuses on quantitative analysis of bicycle ridership and weather data to both explore and explain the variation in cyclist volumes. The results of that analysis are then considered in the context of adaptation under climate change. The final section presents the conclusions of the research and identifies research priorities.

2. Insight from the literature

There is relatively little research which explores how travel behaviour is influenced by weather. This is perhaps surprising given that weather data is routinely collected and stored by government departments responsible for meteorology and transport agencies routinely collect a wide range of travel related data. While the weather data are commonly collected on an hourly basis 365 days per year, it is perhaps less common for data on active transport users to be collected at such fine granularity.

Researchers who have explored the link between weather and travel behaviour have relied on either travel surveys or observational data to quantify the latter. The travel surveys have been either specifically designed to suit the purpose of the study (Khattak and Palma, 1997) or were broad based travel surveys where data on all travel activity was collected using a successive samples approach over an extended period of time (Richardson, 2000). Observational travel data is generally of two types. It is either collected specifically for the purposes of the study (Nankervis, 1999) or is routinely collected via automatic data collection equipment. The latter category includes both ticket sales (Rose, 1986) or automatic fare collection systems (Guo et al, 2007) in the context of public transport ridership as well as automatic equipment for counting pedestrians (Aultman-Hall et al, 2009) or cyclists (Phung and Rose, 2007; Thomas et al, 2009). One obvious advantage of the automatic data collection systems is that they usually provide a longer time series of data which will then correspond to a period of greater variation in weather parameters. Special purpose surveys

are likely to either be of short duration or rely on respondents' recall of their behaviour in the past (Khattak and Palma, 1997).

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 (Nankervis, 1999; Richardson, 2000; Aultman-Hall et al, 2009). 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 which have been employed include time series models (Rose, 1986), linear and non-linear regression models (Phung and Rose, 2007; Thomas et al, 2009) and ordered Probit models (Khattak and Palma, 1997). The ordered Probit model used by Khattak and Palma (1997) suited the response categories provided to participants in their special purpose survey which examined changes in automobile user's departure time, model and route choice decisions in response to adverse weather.

Khattak and Palma (1997) found that just over half (54 %) of the surveyed automobile users in Brussels, Belgium, changed their travel decisions (mode choice, departure time choice and/or route choice) because of changes in weather conditions. They also identified that the majority of drivers were mainly flexible to change mode between automobile and transit and departure time.

Transit ridership can be affected by weather. Rose (1986) examined the impact of fare changes on transit ridership in Chicago and included weather variables (rain and snowfall) in his time series model. While the weather variables did not have significant coefficients in the final model, the snow variable was close to being significant. Guo et al (2007) examined the impact of five weather elements (temperature, rain, snow, wind and fog) on daily bus and rail ridership and variation across modes, days and seasons in Chicago, Illinois, USA. Those researchers found that warmer weather led to higher ridership in all seasons. Specifically, each 0.6^0C (1^0F) rise in temperature resulted in increased weekday ridership of between 0.04% and 0.07% for the bus network and 0.06% and 0.1% for the rail network. Rain led to reduced ridership in all seasons for both bus and rail. A 25 mm increase in daily rainfall decreased weekday ridership by between 1.6% and 2.2% for the bus network and between 1% and 1.2% for the rail network. Similarly, increasing wind speed caused reduced ridership. An increase of 1.85 kph in wind speed caused weekday bus ridership to reduce by between 0.08% and 0.13% but there was negligible effect on rail ridership.

Aultman-Hall et al (2009) found that season and weather have an effect on levels of pedestrian activity in downtown Montpelier, Vermont. During the peak noon hour, weather accounts for 30% of the overall variation in pedestrian volume. Precipitation reduces the average hourly volume by approximately 13% and winter weather reduces it by 16%. Both humidity and temperature were found to have a statistically significant effect on pedestrian volumes. Very cold and very hot temperatures reduced pedestrian volumes the most, suggesting a non-linear effect.

Bicycle riders are directly exposed to changing weather and climate and a limited number of researchers have sought to quantify the impact of changes in weather on rider travel behaviour. Nankervis (1999) 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 percent 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. Likewise, Keay (1992) found that higher rainfall caused a decline in cyclist volume with 50% decline of women cyclists in slight rain. Temperatures greater than 30^0 C and less than 10^0 C decreased the cyclist volume indicating a non-linear relationship between temperature and cyclist volume. Thomas et al (2009) identified that temperature

caused greatest variation and wind caused the least variation in bicycling demand in Netherlands. Winters et al (2007) examined the association of utilitarian cycling with precipitation and temperature in Canadian cities and found that more days of precipitation per year and more days of freezing temperature per year resulted lower utilitarian cycling.

Both Richardson (2000) and Phung and Rose (2007) 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 (2000) 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 (2007) 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 with commuter cyclist volume whereby the volume of riders decreases after the 'ideal riding temperature' is reached (Richardson, 2000; Phung and Rose, 2007). Phung and Rose (2007) identified the ideal riding air temperature to be about 28^0C whereas Richardson's (2000) analysis identified the optimal air temperature to be 25°C. In Phung and Rose's (2007) analysis, ridership on the Bay Trail, which runs along the exposed coast of Port Phillip Bay, was the most sensitive to wind change. Strong wind (defined as 40-62 kph) reduced the volume of commuter cyclist by between 11 and 23%.

Apart from trying to directly relate weather to levels of travel demand, there has been a small amount of research which has focused on either the conceptualization or quantification of an indicator of riding comfort. On a day-to-day basis, cyclists may make their travel decisions depending on how comfortable they feel to ride. Understanding whether riders perceive the weather to be comfortable for riding on a specific day may provide insight into the likelihood that they would ride.

The notion of 'comfort' in the cycling literature is often interpreted in relation to the perceptions of the physical environment and in particular to different forms of bicycle infrastructure. For example, Harkey et al (1998) developed a compatibility index for bicyclists while other studies have explored the perception of bicyclists about their comfort level when riding through intersections (Wadhwa, 2003). Studies like these typically focus on only geometric and operational traffic system factors and do not consider impacts of weather or climatic influences on behaviour.

In a slightly different context, Yu et al (2009) considered perceived temperature (a combination of air temperature, relative humidity and wind elements), wind speed, visibility and significant weather (a combination of rain, lighting, hail and snow) to represent how comfortable the climate was for tourism. That research developed a climatic comfort index for tourism which categorized the prevailing conditions into three categories: unsuitable, marginal and ideal.

In examining the relationship between weather and riding comfort, Nankervis (1999) considered three weather elements: wind, rain and temperature. He classified these elements into categories based on a four-point scale ranging from very good to good, poor and very poor. The relationship between daily bike count numbers and the categorization and scoring of those three elements was then tested. The results indicated that his comfort ratings for the different weather variables were statistically related to bicycle ridership numbers. It is appropriate to note that in Nankervis's analysis, the break points used to define the comfort categories for each variable were judgements made by the author rather than being based on information provided by riders.

Having identified the relationships in the literature between weather and travel behaviour we now turn to analysis which relates variations in cyclist volumes to changes in weather.

3. Exploring and explaining variations in cyclist volumes

This section focuses on quantitative analysis of cycling and weather data. The nature of the ridership and weather data are explained in the following section. Variability in the key variables is then quantified before statistical models are developed to relate variations in weather to the observed variations in cyclist volumes.

3.1. Ridership and weather data

The analysis presented here focused on aggregate data analysis and modelling. To correlate bicyclist volume with a range of explanatory variables, hourly bicyclist volume data for the period of Dec 2005- Sep 2009 has been compiled. In terms of weather variables, which can influence the cyclist volume, rain, hours of sunshine, temperature, wind and humidity have previously been found to be significant (Phung and Rose, 2007). The weather data has been collected for 2005 through to 2009. The analysis reported here extends the earlier research of Phung and Rose (2007) since their work was based on only one year of data while the results reported here relate to a four year analysis period. In addition, Phung and Rose (2007) considered daily ridership which would have reflected a combination of commuting and recreational riding. The modelling undertaken here focuses on a time period in the day which would be expected to be dominated by commuter cycling.

In Melbourne, Vic Roads has installed inductive loop bicycle counters at 17 locations. Permanent recording equipment has been installed at a subset of these sites as shown in Figure 3.1. An installed inductive loop bicycle loop counter is shown in Figure 3.2.

Figure 3.1: Location of automatic loop counters with permanent recording equipment

Site	Trail Name	Distance to Melbourne Town Hall (km)
1	Anniversary Trail	8.3
3	Main Yarra Trail No. 1	6.2
4	Koonung Trail	12.2
5	North Bank	2.0
6	South Bank	2.0
7	Canning Street	2.6
8	Upfield Railway	4.2
9	Capital City Trail	3.7
10	Footscray Road "Capital City Trail"	3.7
11	St. Georges Road	5.4
13	Gardiners Creek	5.0
16	Tram 109 Trail	2.5
17	Bay Trail	5.4

Source: Vic Roads

Figure 3.2: Automatic loop counter installation on a bike path

Source: Vic Roads

Since the focus of this analysis is on utilitarian travel behaviour, the data for four locations are considered: Canning street, Capital city trail, South Bank and St. Georges road. Those locations were identified in previous research (Phung and Rose, 2007) to have usage profiles which suggested higher utilitarian use compared to other locations which are dominated by recreational riding. The sites considered in this analysis are highlighted with black circles in Figure 3.1.

3.2. Exploring variability in key variables

Table 3.1 summarizes average daily ridership across the four sites over the four years for which data are available. Canning Street is clearly the busiest while St. Georges Road has experienced the highest annual growth in ridership.

Table 3.1: Average daily ridership across the sites

	Average daily ridership				
Bike path	2006	2007	2008	2009	Growth (2006-2009)
Canning street	1560.9	1704.6	1958.3	2280.3	46.1%
Capital city	659.3	745.0	851.9	878.7	33.3%
South bank	929.0	943.1	969.2	1082.1	16.5%
St. Georges road	800.7	940.1	1184.8	1393.9	74.1%

The heavier flows on Canning Street are also evident when hourly variations in cyclist volumes are considered for each of the sites (Figure 3.3). Bicyclist volume varies by time of day with similar but not identical patterns across the sites. There are clear AM peak (7 to 9 AM) and PM peak (4 to 6 PM) periods with the morning peaks corresponding to higher flows than the afternoon peaks. The peaks on Canning Street are much sharper than at the other locations, particularly in the AM.

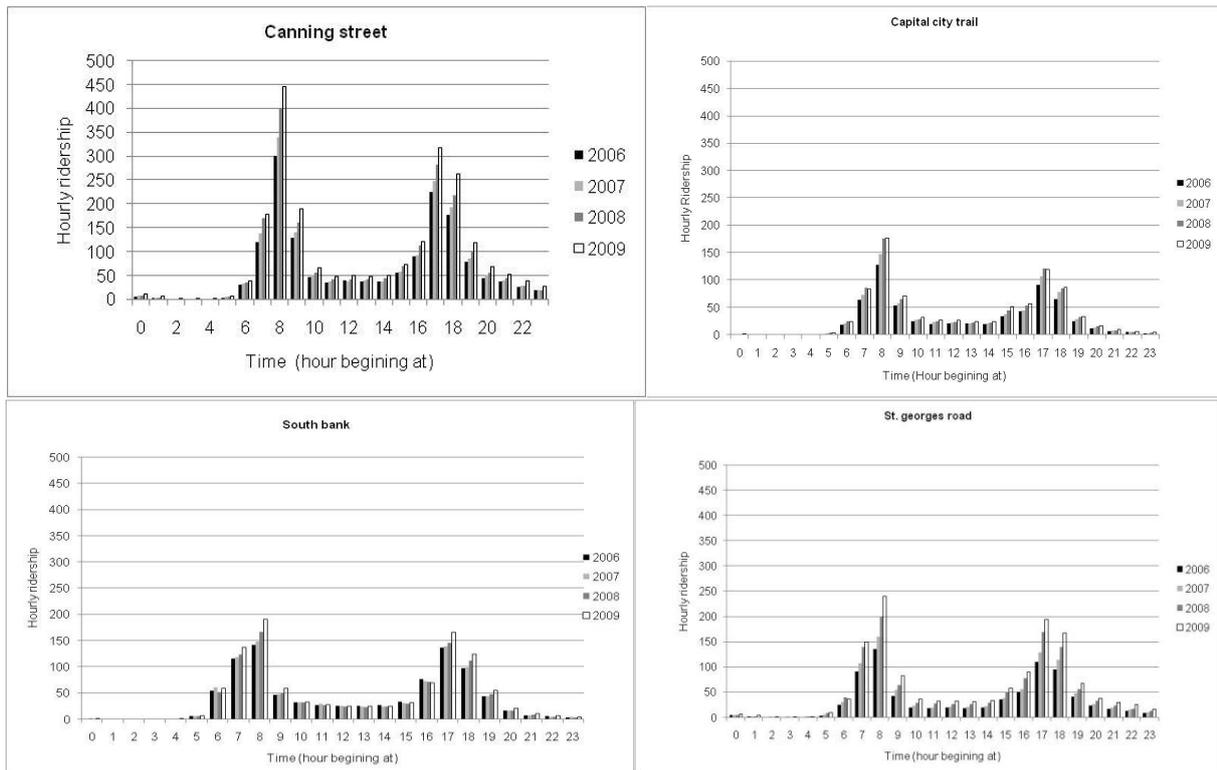**Figure 3.3: Average bicyclist volume across sites**

Figure 3.4 shows the monthly variations in average daily ridership recorded at each site. Here the monthly average is converted to a ratio of the July figure which at each site corresponded to the lowest average daily ridership. There is a peak ridership period during the summer (January – February) and late spring (October – November). During winter (June – July), ridership is at its lowest. This is consistent with the finding of Sener et al (2009) who examined ridership data in Texas and identified the winter season as corresponding to lowest volumes of commuter cyclists. In the current Melbourne analysis, three of the trails exhibit a similar profile of monthly ridership while the South Bank location appears different – it has a much higher variation in summer relative to winter ridership. That could be due to differences in demographics, underlying travel patterns or attitudes to riding in different weather conditions in the catchment areas for each of these paths.

Figure 3.4: Monthly variation in indexed average daily bicycle ridership
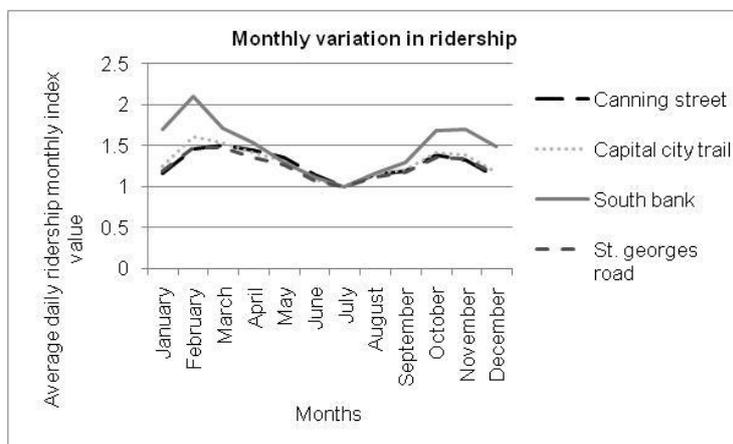
3.3. Variation in weather parameters

Variability is considered in the following weather parameters:

- Wind speed = Arithmetic mean of the 9am and 3pm wind speeds in kph

- Daily Precipitation

- Hours of sunshine over the day

- Humidity

- Apparent temperature in degree Celsius,

Here, the variable 'Apparent temperature' is considered as people's perception is different to the measured air temperature (Phung and Rose, 2007). Apparent temperature is calculated as:

$ATEMP = T + 0.33\ [6.105\ e^{(17.27\ T\ /\ 237.7\ +\ T)} \times 0.01\ H] - 0.7\ W - 4.0$…………… (3.1)

(Bureau of Meteorology, 2007)

where,

- T = Air temperature in degrees Celsius. 'T' is the arithmetic mean of the maximum, 9am and 3pm daily temperatures.

- H = Relative humidity (%)

- W = Wind speed (m/s), Here, it is the arithmetic mean of the 9am and 3pm wind speeds.

Figure 3.5 shows the monthly variation in the key weather variables. The values reflect the average over the four years (2006, 2007, 2008 and 2009). The average apparent temperature falls from a high of around 25^{0}c in summer to about 10^{0}c in winter. Higher wind speeds are observed in summer (January) and the wind gradually declines till the middle of the year and then picks up in the latter half of the year. Precipitation generally increases as the year progresses. The wettest months are October and November. The winter months are generally drier. The number of hours of sunshine appears to be primarily associated with long term seasonal changes. Over the course of the year, the average daily hours of sunshine falls from a high of around 14 hours in summer to about 10 hours in winter months.

Figure 3.5: Monthly variation in weather parameters
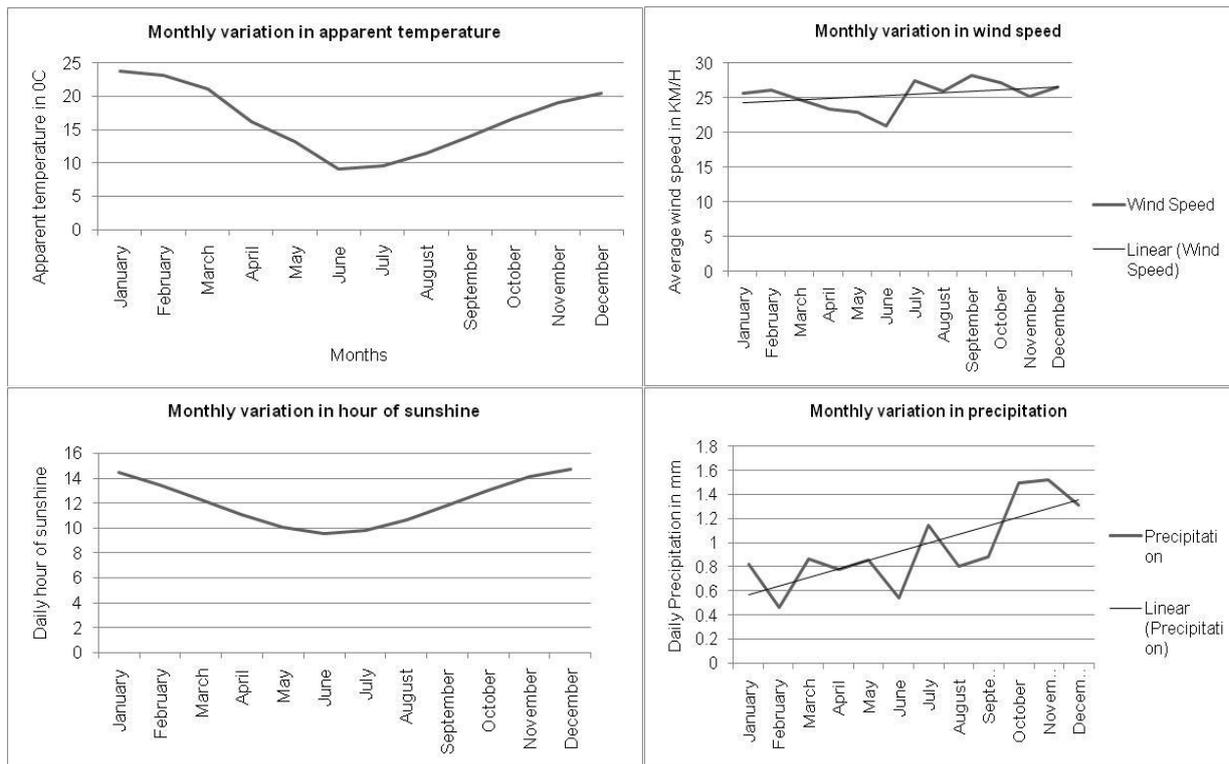
4. Explaining variability in commuter cyclist volumes

To examine the variation in bicycle usage and the factors contributing to those variations, Phung and Rose (2007) developed a log linear model which incorporated the following explanatory variables:

- time based growth

- public holidays

- rainfall

- the hours of sunshine over the day

- temperature

- humidity

- wind speed and

- the day of week.

In this analysis, the same model specification has been adopted. However the dependent variable reflects only the AM peak period flows (7 to 9 AM) which are expected to correspond primarily to commuting journeys. As the focus here is on commuting, public holidays, Saturdays and Sundays are excluded from the analysis.

The model calibrated in this research takes the following form:

$$log_e(Q_{it}) = \alpha_i + \beta_{iTIME}TIME_t + \sum_{j=1}^{2} \beta_{iRAIN,j}RAIN_{jt} + \beta_{iSUN}SUN_t + \sum_{m=1}^{2} \beta_{iATEMP,m}ATEMP_t^m$$

$$+ \sum_{k=1}^{3} \beta_{iWIND,k}WIND_{kt} + \sum_{n=1}^{4} \beta_{iDOW,n}DOW_n + \varepsilon_{it} \forall_{i,t}$$

………………………………………………………………………………………… (4.1)

Where;

Q = Daily AM peak period bicycle volume (7 AM to 9 AM)

i = Site index

t = Time index

TIME = Time based growth, an index variable that increments over the analysis period

RAIN = Rainfall, categorized as

no rain (rain fall < 0.2 mm) ,

light rain (0.2 mm<= rain fall < 10.0 mm) and

heavy rain (rainfall => 10.0 mm) (Phung and Rose, 2007)

The RAIN variable is coded as two dummy variables for light and heavy rain with the base case corresponding to "no rain".

SUN = Hours of sunshine

ATEMP = Apparent temperature in degree Celsius.

WIND = Arithmetic mean of the 9am and 3pm wind speeds

Wind is categorized as

Calm or no wind (wind speed = 0 kph)

Light wind (wind speed <=19 kph)

Moderate wind (wind speed 20 – 29 kph)

Fresh wind (wind speed 30 -39 kph)

Strong wind (wind speed 40 -62 kph)

The WIND variable is coded as four dummy variables for light, moderate, fresh and strong wind with the base case (i.e. all WIND dummies equal to zero) corresponding to "calm".

DOW = day of week

The DOW variable is coded using four dummy variables (Monday through Thursday) with the base case corresponding to Friday.

As Equation 4.1 is in log-linear formulation, the coefficients of the continuous variables are directly interpreted as the percentage change in the dependent variable (daily AM peak bicycle volume) as a function of a change in the explanatory variable. For example, a coefficient of 0.06 on the hours of sunlight variable would imply that an additional hour of sunlight would cause 6 % increase in daily bicycle volume. The effect of the dummy variables is measured as $effect = e^{\beta} - 1$, where β = co-efficient of the explanatory variable (Halvorsen and Palmquist, 1980, as cited by Phung and Rose, 2007). The interpretation is relative to the base case. For example, coefficient of 0.33 for Tuesday would be interpreted as the volume on a Tuesday is 39.09% higher than that of Friday (since Friday is the reference day for the analysis).

Correlation coefficients were calculated across the explanatory variables but no significant correlations were observed.

4.1. Modelling results

The modelling results are presented in Table 4.1. The estimated coefficients and the Coefficient of Determination (R^2), a measure of 'Goodness of fit' for OLS regression, are also given in this table. Statistically significant parameters are shown shaded in Table 4.1.

The R^2 value ranges from 0.3 to 0.6 across the four sites. Thus, around 50% of the variation in daily peak period bicycle volume on weekdays has been explained by the model. While these R^2 values are slightly lower than these reported by Phung and Rose (2007), who analysed daily rather that peak period ridership, they are still adequate to support robust interpretation of the results. There is scope for further research to either segment the data or use broader time series to get a better fit. While we need to be cautious in interpreting the results, it is reassuring that most of the coefficients are statistically significant.

All four sites experienced statistically significant growth during the analysis period. St. Georges Road experienced highest growth (19.89% per annum). For the other three sites, the growth ranges between 7% and 13%. The annual growth has been calculated as Growth per annum = Coefficient* 365.

Figure 4.1 shows how the bicyclist volume changes across different working days where the reference day is Friday. It is possible that use of flex time or rostered days off, or changes in activity patterns before or after work, result in lower cyclist volumes on Friday.

Table 4.1: Regression model results

Bike path		Canning Ctreet	Capital City	South Bank	St. Georges Road
Intercept		6.30 (46.44)	5.26 (45.44)	5.13 (54.49)	5.23 (48.67)
Time based growth		3.8×10^{-4} (13.32)	3.2×10^{-4} (14.04)	2×10^{-4} (10.5)	5.5×10^{-4} (25.79)
Rain	Light	-0.14 (-5.74)	-0.13 (-6.56)	-0.12 (-6.97)	-0.13 (-6.53)
	Heavy	-0.41 (-4.79)	-0.50 (-6.74)	-0.47 (-7.34)	-0.56 (-8.20)
Wind	Light	-0.08 (-0.80)	-0.04 (-0.54)	-0.03 (-0.39)	-0.02 (-0.22)
	Moderate	-0.08 (-0.79)	-0.06 (-0.72)	-0.03 (-0.51)	-0.02 (-0.32)
	Fresh	-0.11 (-1.12)	-0.11 (-1.29)	-0.07 (-1.01)	-0.08 (-1.03)
	Strong	-0.21 (-2.05)	-0.22 (-2.63)	-0.13 (-1.83)	-0.18 (-2.31)
Sunshine		-0.04 (-4.99)	-0.02 (-2.85)	7×10^{-3} (1.26)	-0.02 (-3.00)
Apparent temperature	Atemp	0.03 (5.05)	0.03 (6.53)	0.02 (5.17)	0.03 (6.83)
	Atemp^2	5.6×10^{-4} (-3.50)	6.6×10^{-4} (-4.92)	1.4×10^{-4} (-1.25)	6.0×10^{-4} (-4.87)
Day of week	Mon	0.16 (4.55)	0.17 (6.06)	0.20 (8.52)	0.18 (6.75)
	Tue	0.27 (8.03)	0.25 (8.93)	0.28 (12.17)	0.27 (10.24)
	Wed	0.24 (7.19)	0.19 (6.68)	0.24 (10.54)	0.24 (9.00)
	Thu	0.20 (5.95)	0.17 (6.09)	0.17 (7.33)	0.18 (6.84)
R^2		0.32	0.37	0.47	0.55

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

**Figure 4.1: Variation in bicyclist volume on different days**
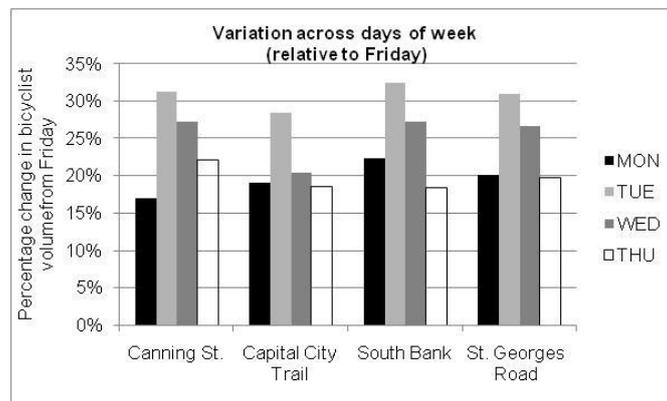
It is clear from Figure 4.1, that the highest volumes occur on Tuesdays while Friday (the reference day in this analysis) has the lowest volumes (corresponds to a 0 % result in the context of Figure 4.1). In case of South Bank, the volume on Tuesday is around 34% higher than that of a Friday. There is a sharp jump observed from Monday to Tuesday and over the remainder of the week, the volume declines.

From the analysis, a significant effect of sunshine (at a 5% significant level) is found for three of the four sites indicating extra hours of sunshine decrease the peak period commuter cyclist volumes. For the Canning Street location the ffect is strongest and, an additional one hour of sunshine decreases the bicyclist volume by 4%. For the other sites, the effect is around 1%. The sunshine variable was not significant for the South Bank location.

The modelling results highlight that ridership drops when there is rain as demonstrated in Figure 4.2. The greatest impact is for heavy rain (daily rainfall above 10 mm) which produces decrease in volume of more than twice that which results from light rain fall (defined as 0.2 to 10 mm).

**Figure 4.2: Effect of rain on bicyclist volume**
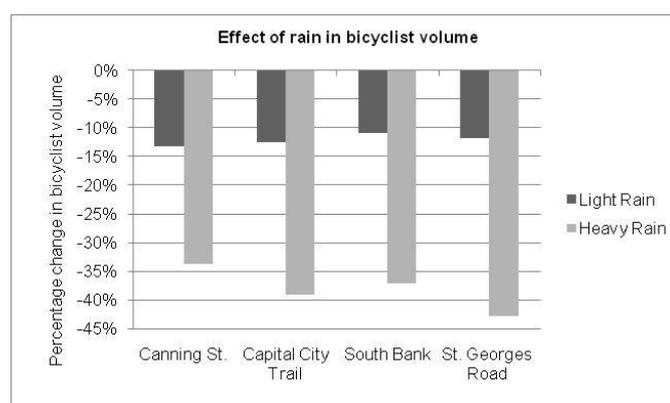
As shown in Figure 4.2, across the four sites, light rain decreased ridership by around 13%. While when heavy rain occurs the bicyclist volumes drop by about 40%.

The modelling results only indicated statistically significant coefficients in the case of strong wind (defined as wind speed 40-62 kph). The effect of strong wind is shown in Figure 4.3 where it is indicated that Capital city trail experiences the largest effect of 20% reduction in

ridership. The effects across the rest of the sites are similar with high winds producing a reduction of about 15 % in peak hour cyclist volumes.

Figure 4.3: Effect of strong wind on bicyclist volume
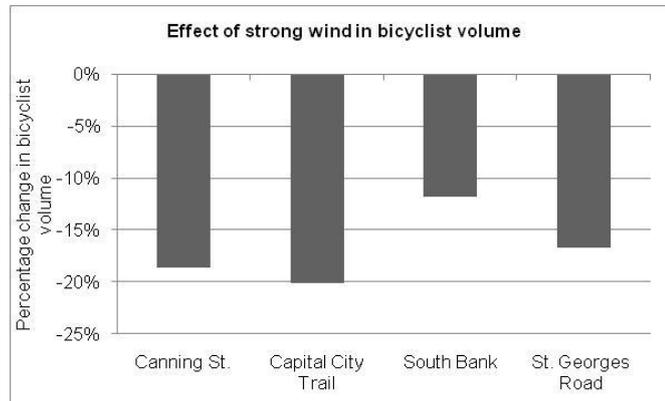
When considered overall, it appears that the Capital City Trail volumes are more sensitive to both rain and wind compared to other sites. Further research would be required to help understand what factors might explain that difference.

Temperature has a non-linear effect on bicyclist volume. This is consistent with other thermal comfort research which highlights non linear temperature effect (Fanger, 1970). The non-linear effect is captured here by different signs on the coefficients of ATEMP and $ATEMP^2$. Figure 4.4 shows the non-linear effect of increasing apparent temperature across the three sites where a significant non-linear effect was detected (the $ATEMP^2$ variable did not have a significant coefficient in the case of the South Bank location. In that figure, the percentage change in volume is compared relative to a reference point of 0^0 C.

Figure 4.4: Effect of apparent temperature on bicyclist volume
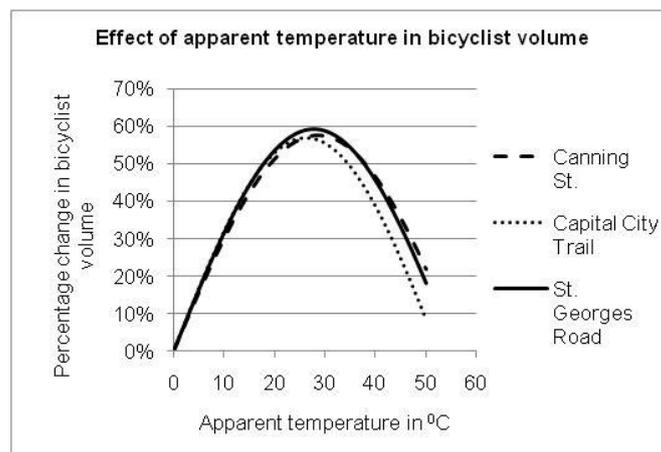
Up to a certain optimum riding temperature, the volume increases with temperature. Beyond the optimum temperature, the volume declines with increasing temperature. The optimum temperature, corresponding to maximum ridership, varies across sites with highest being around 28^0 C for Canning street. In the case of Capital city trail and St. Georges road, the optimum temperature is around 25^0 C. Relative to the 0^0 C reference point, volumes are around 60% higher at the optimum riding temperature.

5. Implications for adaptation of cyclist travel behaviour under climate change

Weather and climate have a profound influence on life on Earth. While sometimes used interchangeably, the terms "weather" and "climate" have distinct meanings. The "weather" reflects the atmospheric conditions over a small area for a short period of time and is characterized by the temperature, wind, precipitation, clouds and other parameters. "Climate" on the other hand, refers to the atmospheric conditions over a large area for a long period of time. Climate can be measured by differences in the mean or variability in the weather variables mentioned above (IPCC, 2001).

Climate change is high on the agenda for most cities around the world today. The intergovernmental Panel on Climate Change (IPCC) defines 'Climate change' as a change in the state of the climate that can be identified (e.g. using statistical tests) by changes in the mean and/or the variability of parameters such as temperature, wind speed and precipitation. The change in climate persists for an extended period, typically decades or longer (CSIRO and Bureau of Meteorology, 2007, p. 14).

The following summary is based on the evidence presented in technical reports released by the CSIRO and Bureau of Meteorology (2007) and the Department of Climate Change, Australia (2009).

Australian average temperatures have increased by 0.9° C since 1950. There has been an increase in the frequency of warm days and warm nights and a decrease in the frequency of cool days and cool nights (CSIRO and Bureau of Meteorology, 2007, p. 8-11 and Department of Climate Change, 2009). It is projected that, in Melbourne, temperature will increase by 70-190% (resulting in 20 hot days ($>35^{0}$ C)), relative to 1990 level (considering high emission scenario) (CSIRO and Bureau of Meteorology, 2007, p. 60-61). While there has been little change to total Australian rainfall since 1900, rainfall patterns have changed significantly. The east coast, Victoria, and southwest Australia have all experienced substantial rainfall declines since 1950 with some areas receiving a reduction of 50mm/10 years. In stark contrast, north-west Australia has experienced an increase in rainfall over this period with some areas receiving 50mm/10 years more rainfall.

The climate changes already observed have raised concerns over what lies ahead particularly if green house gas emissions are not abated (CSIRO and Bureau of Meteorology, 2007, p. 14). Table 5.1 summarizes Australia wide projections for 2030, 2050 and 2070 relative to 1990 levels (CSIRO and Bureau of Meteorology, 2007).

Under climate change, Australia can expect higher temperatures, more variability in precipitation, coupled with more intense storms when it does rain, and increases in wind speed. The analysis presented in the previous section demonstrated that each of those effects would be expected to reduce peak period commuter cyclist volumes. Of course it is not possible to know how, or if, people will adapt their own behaviour in the face of changes in climate. The results from the pervious section suggest that there are already differences in the way that commuter cyclists in different parts of Melbourne respond to changes in weather. Further research is required to understand the reasons for those differences.

Table 5.1: Climate change projections for Australia[1]

Weather parameter	2030	2050		2070	
	Moderate emission[1]	Low emission	High emission	Low emission	High emission
Temperature	1^{0}c	1.2^{0}c	2.2^{0}c	1.8^{0}c (Median emission)	3.4^{0}c (High emission)
Precipitation	-2% to -5%	-15% to +7.5% in the central, eastern and northern areas and around -5% in southern areas	-20% to +10% in central, eastern and northern areas and around -7.5% in southern areas	Comparable with high emission scenario by 2050	-30% to +20% in central, eastern and northern areas and -10% in southern areas
Wind speed	+2% to +5%	Around +5%	Around +5% to +8%	Around +10%	More than +15%

Source: CSIRO AND Bureau of Meteorology, 2007

Given that governments are seeking to increase the role that cycling plays in commuting there is a need for further thought about the influence that weather and changes in weather, have on cyclist volumes. Clearly the data employed in this study provides no insight into what the commuters did when they did not cycle in the face of adverse weather. Did they delay their journey till after the peak period, work from home or change mode? The extent of those changes has implications for the degree of resilience that the transportation system needs to provide to support commuter cyclists. It is also not clear whether those who continue to ride in adverse weather have access to better end of trip facilities, or have invested in wet weather protective clothing for themselves, or equipment for their bicycle (e.g. mud guards, all weather panniers) which makes them less sensitive to adverse weather. Understanding those dimensions could have implications for the need to expand end of trip facilities or provide information to support informed rider equipment purchases which would encourage growth in all year round commuter cycling.

6. Conclusion

This paper has provided insight into how weather affects commuter bicyclist volumes. The existing literature provides only limited insight into the impact of weather and what is happening at the disaggregate level in terms of decisions about trip timing or mode choice.

Analysis of the impact of weather variations on aggregate bicyclist volume confirms that around half of the variations in bicyclist volume can be explained by changes in weather. The following weather variables were found to be statistically significant.
- Light and heavy rain
- Strong wind
- Hours of sunshine and
- Apparent temperature

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[1] 1: For simplicity the terminology used here, low, moderate and high emission scenarios refer to scenarios B1, A1B and A1F1 from the technical reports released by the CSIRO and Bureau of Meteorology (2007)

Heavy rain and strong wind produce the most noticeable reductions in ridership. Temperature affects ridership in a nonlinear way. The optimum temperature appears to be between 25^0 C and 28^0 C.

Further research is required to extend the analysis of the aggregate changes in travel behaviour to other locations and to deepen the research to consider the causes for those changes at an individual level. Research of this nature will enhance understanding of travel behaviour and provide an important contribution to understand the adaptation in utilitarian cyclist behaviour which may result from climatic change. Clearly the results presented in this paper must be interpreted very cautiously from the perspective of what insight they might provide into cyclists' behavioural adaptation under climate change. Further research is needed to understand the effects of global warming on the propensity of people to cycle as well as implications for people who do not currently cycle. Research of this nature does however, have implications for the types of policy settings pursued by governments. Or particular relevance in that context is developing end of trip facilities and providing information to cyclists about the equipment they purchase, to ensure that weather and climate effects do not undermine the often ambitious targets set for growth in utilitarian cycling in the years ahead.

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Acknowledgements