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Representing Weather in Travel Behaviour Models: A Case Study from Sydney, AUS

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Abstract

In the transportation literature in general and the travel behaviour literature specifically, there is no consensus on the representation of weather in behavioural models, ranging from studies that use direct meteorological measurements, such a continuous variable for inches of rainfall or temperature, to indicator variables (which themselves are often subjectively derived) for qualitative weather assessments. To explore the representation of weather, this paper develops constructs of weather based upon cluster analysis of various daily weather characteristics and test the validity of these weather representations against two dimensions of travel behaviour: mode share and trip generation. Using Sydney, AUS as a case study, ten years of hourly weather data for the region are reduced using a two-stage cluster analysis technique, resulting in 17 meteorologically distinct weather types. These weather types are then tested for their correlation with one way of data from the Sydney area Household Travel Survey. Initial results comparing mode shares with weather types indicate that the weather types can be further reduced into fewer types. The inclusion of these weather types into models of trip generation show improved model performance; however, the results are weak with respect to contributing to a final valid set of weather constructs. More work needs to be done to explore the representation of weather in travel behaviour models and the overall effect of weather on travel choices.

1. Introduction and Background

Weather is often omitted in studies of travel behaviour or at a minimum, incorporated as a simple instrument. Although the impact of weather on behaviour may seem obvious at first, incorporation of the multiple dimensions of weather into models of travel behaviour is not a straightforward endeavour. Research on travel and weather has developed primarily from work on active transportation options, such as walking and biking, and their role in promoting and achieving sustainable transportation goals. Weather is commonly incorporated through indicator variables in active transportation studies (Dill and Carr 2003; Winters et al 2007; and Saneinejad et al. 2010). The representation of weather and climate vary, from aggregate representations on one side, typically with annual average temperatures and total rainfall, to more disaggregate scales, using temperature, wind, relative humidity and precipitation conditions. These studies also vary in terms of geographic scales, with some studies looking at national level data, which are rich in socio-demographic data, but weak in weather data, and local level studies characterized by “count” data that provide more opportunities for obtaining detailed day-to-day weather information, but are weak in traveler attribute, travel alternative and trip data.

Studies show that weather conditions are significant in travel decisions, even after controlling for more primary factors. Dill and Carr (2003) analyzed bicycling in forty-three US cities, and bike-related variables, such as bike facilities, but examined few socio-demographic variables. Weather was included on an aggregate level through the annual number of rain days and inches of rainfall. They suggest that temperature would matter and that precipitation has a stronger impact than indicated, but did not capture these since the data were at an aggregate level and socio-demographic variables limited. Similarly, Winters et al. (2007) looked at cycling in fifty-three Canadian cities and the relationship with climate and socio-demographic characteristics. Climate data were aggregated and included the number of days annually with freezing temperatures or precipitation. In a recent study in Toronto, Saneinejad et al. (2010) examined the impact of weather on active transportation using a disaggregate mode choice model estimated using travel activity data and corresponding historical hourly weather condition in Toronto. This study addressed many of the gaps with previous studies by considering travel and weather at disaggregate level in terms of representation of weather and travel demand modeling. However, Saneinejad et al. (2010) used indicator variables to represent different ranges of weather based of arbitrarily chosen cutoffs. One example of the impact of weather on walking is a study done by Aultman-Hall et al. (2009). They counted pedestrian traffic and also collected temperature, wind, relative humidity and precipitation data. They conclude that the weather is an important factor in travel in downtown areas, justifying policy making for walking during adverse weather.

The actual representation of weather in studies of travel behaviour needs to be considered more carefully. Understanding and modelling the relationship between travel and weather is important for developing strategies that rely on behavioural change, such as shifting current travel choices to incorporate more walking, cycling and transit. Furthermore, in the context of sustainability and climate change, modelling this relationship may provide insights regarding the impacts of transportation and related climate policies that rely on interventions to transportation systems.

Several different approaches to representing weather within travel behavioural models are available. One method is to include the various dimensions of weather directly as continuous explanatory variables. A second approach is to construct binary indicators (or dummy variables) that represent weather conditions and include these in the models. For example, indicators have been used to represent presence of rain, fair weather, or temperatures within a specific range. A third possible method is to use a data reduction technique that examines how the various dimensions of weather are covariant. In this approach, a factor analysis or similar statistical data reduction technique is used develop groupings or categories of weather characteristics and then these categories are employed as independent variables in the models. It is this third approach that is the subject of this paper.

To further explore the representation of weather, this study has the following objectives:

1) Explore data reduction techniques for better representation of weather: A cluster analysis is used as a methodology for organizing weather station data into types that represent the variation in weather across and between seasons. The daily weather variables used are hourly and from weather stations: (a) air temperature; (b) precipitation; (c) relative humidity; and (d) wind speed. These are aggregated to daily: (i) minimum temperature; (ii) maximum temperature; (iii) total precipitation; (iv) average relative humidity; and (v) maximum wind speeds.

2) Validate the weather constructs using travel data
    a. The weather representations developed previously will be tested against aggregate daily mode shares to determine whether the constructs have distinct relationships to travel.
    b. Similar to the analysis in a., models of household daily trip generation by mode will be developed based upon socio-economic characteristics and weather information.

The Sydney Greater Metropolitan Area (GMA) in New South Wales, Australia is the location for this case study. The meteorological and travel data for this region are available at spatially and temporally disaggregate units over long periods in time, making it an ideal location for an integrated analysis.

2. Representation of Weather

The representation of weather variables within travel behaviour data has not been given much explicit attention. One issue that arises is how to incorporate the various aspects of weather – temperature, humidity, precipitation, wind – into theoretical frameworks for travel behaviour and represent these aspects in statistical analysis. Each of these characteristics of weather is likely to have different effects when taken individually and these individual aspects may interact with one other, such as the combined effect of temperature and humidity. Some characteristics, like temperature, are likely to have non-linear relationships with travel decisions. For walking and cycling, high and low temperatures are likely to have a negative association with being out of doors while some temperate range will be positively associated with more active travel. Using seasons as a proxy for average, aggregate weather conditions is a commonly used method for integrating weather into behavioural models. But seasonal proxies mask daily variations in the weather and these seasonal outliers may actually have a greater impact on decisions than the normal conditions. This section describes the effort to better represent weather.

Weather data are obtained from the Commonwealth of Australia Bureau of Meteorology. At Automatic Weather Stations (AWSs), data on temperature, humidity, pressure and wind are recorded hourly from Automatic Weather Stations (AWS) for the GMA geographic area (Bureau of Meteorology 2011). There were 32 AWS stations in the GMA and weather data are available hourly for each station for the years 1998 to 2008. The distribution of these stations across the Sydney GMA is shown in Figure 1.

One hypothesis is that within a given climatic region, people will understand “types” of weather conditions within a given season (weather day types) and respond accordingly with their travel decisions. To identify these weather day types, a two-step cluster analysis is performed on the weather variables available, aggregated daily to include: Minimum temperature, maximum temperature, total precipitation, average relative humidity and maximum wind speed.

The two-step cluster analysis procedure is used as an exploratory tool for revealing the natural groupings (or clusters) within a dataset that would otherwise not be apparent. A likelihood measure for distance was used, which assumes a probability distribution on the variables used for clustering, in this case the weather data. Continuous variables are assumed to be normally distributed, while categorical variables are assumed to be multinomial. All variables are assumed to be independent. Clusters are only unique within each austral seasonal group: Summer (Dec, Jan., Feb), Fall (March, April, May), Winter (June, July, Aug.) and Spring (Sept, Oct. Nov.). Observations were first segmented by season (summer, autumn, winter and spring)[1] and the two-step cluster procedure done within each season. This resulted in a total seventeen weather clusters. The results of the cluster analysis are shown below in Figure 2.

Figure 2 shows the mean and standard deviation for the five derived weather variables across all seventeen weather clusters. The plots show several interesting trends with regard to weather and its variability. First, all of the weather clusters are distinctly different from each other. Inspecting all seventeen weather clusters across all five dimensions, the clusters appear distinct from each other, although these clusters are very similar for relative humidity (the shape is less distorted towards one cluster, or axis, relative to the other clusters). Second, in general the standard deviation is lower than the mean, which suggests that all clusters exhibit the same amount of variability. However, Winter 1 (Very Rainy) constantly shows the greatest variability with the highest standard deviation value across most of the weather dimensions. For total rain, Winter 1 has a standard deviation (8.149 mm) that exceeds its mean (6.428 mm). This suggests that more than just differing in absolute weather conditions, these clusters may also represent the variability in weather across different weather days.

The cluster analysis of the weather data resulted in 17 distinct weather phenomena. However, humans may not respond to each of these weather days in distinct or unique ways. Travel behaviour responses in each weather cluster may not necessarily be a response to the weather experienced, but the variability or reliability in the weather. In addition, 17 weather day types add more complexity to travel models, not less. The next steps, then, are to validate these various weather constructs using travel data. This effort is described in the next section.

[1] Initial cluster analysis on the pooled data revealed only four clusters, which aligned roughly with the seasons. Segmenting the data into austral seasons for the analysis revealed more variation of weather within season.

Figure 1 Distribution of AWS weather stations in the Sydney GMA

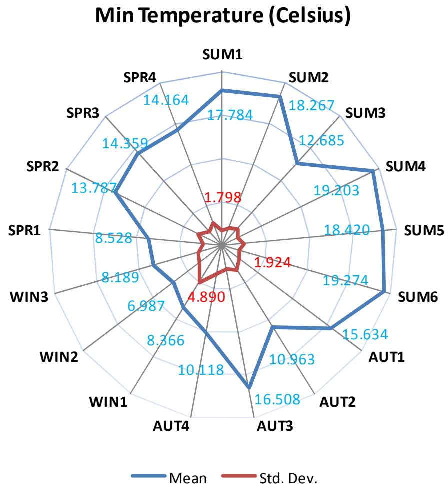
3. Validating Weather Constructs with Travel Data

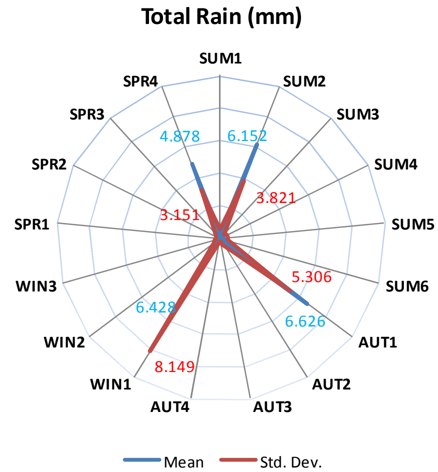
This section describes the travel data used to validate weather constructs and then discusses the methods and results of statistical analysis of weather and travel behaviour. Two types of travel dimensions are examined: mode share and trip generation. The first analysis attempts to determine differences in choice probabilities across different weather clusters for travel mode shares. A trip generation model which incorporates the weather clusters is also presented and discussed with regards to how weather is represented in the model.

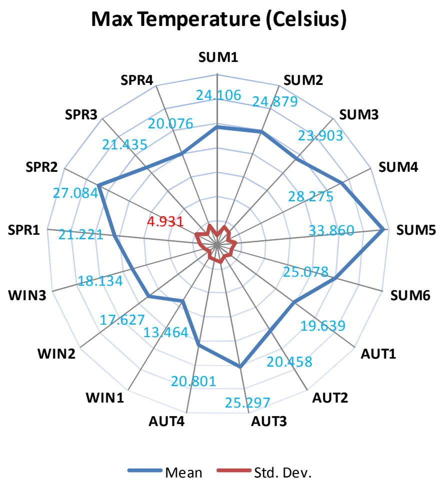
3.1 Travel Data

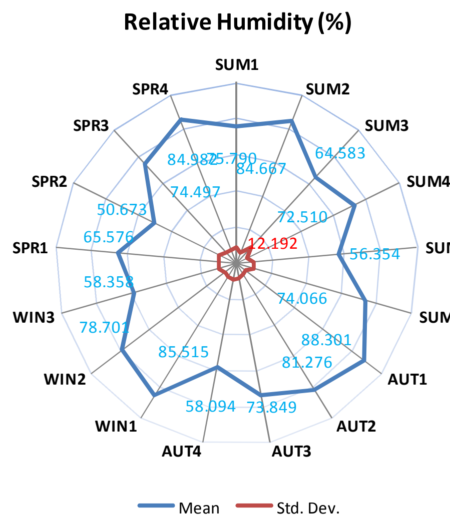
The travel and activity data for the analysis in this paper are sourced from the Sydney Household Travel Survey (HTS)[2]. The Sydney HTS provides personal travel data for the Sydney Greater Metropolitan Area. Initiated in 1997, the survey is the longest running continuous household travel survey in Australia. The HTS is carried out every day from July to June of each financial year and data are collected across all days of the week, for every week of the year. Households are sampled from private dwellings and information is collected from each resident of the household. A simple travel diary is used by each householder to record the details of all travel undertaken for their nominated 24-hour period. An interviewer then interviews each householder to collect the details of the travel made on the assigned day. The interviewer records the mode of travel, trip purpose, start and end location, and time of departure and arrival. Vehicle occupancy, toll roads used and parking are recorded for private vehicle trips and fare type and cost for public transport trips. Detailed socio-demographic information is also

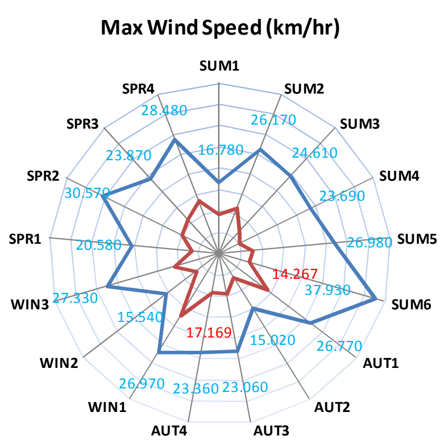
[2] Transport and Population Data Centre (2004) 2002 Household Travel Survey Summary Report 2004 Release, New South Wales Department of Infrastructure, Planning and Natural Resources, Sydney, AUS. Available online: http://www.bts.nsw.gov.au/ArticleDocuments/79/hts-report-2004.pdf.aspx.











SUM1 (Cool w/ Light Rain)
SUM2 (Very Rainy & Humid)
SUM3 (Chilly & Dry)
SUM4 (Warm & Dry)
SUM5 (Very Hot & Dry)
SUM6 (Very Windy)
AUT1 (Very Rainy)
AUT2 (Cool & Rainy)
AUT3 (Hot)
AUT4 (Cool & Dry)

WIN1 (Very Rainy)
WIN2 (Chilly)
WIN3 (Warmer, Dry, & Windy)
SPR1 (Chilly & Dry)
SPR2 (Warm & Dry)
SPR3 (Light Rain)
SPR4 (Very Rainy)

Figure 2: Weather Clusters

collected on the household. This includes dwelling type, household structure and vehicle details, as well as age, gender, employment status, occupation and income of individual household members.

For this analysis testing the validity of the weather constructs with travel data, data are sampled from the 2002 wave of the Sydney Household Travel Survey (HTS). Although several waves are available, the sample is limited to 2002 to allow ease with handling the data and to allow for future analysis of weather and travel using other waves of the HTS.

This study analyses the behaviour of individuals who have relatively easy access to motorized and non-motorized modes of transportation and who are not captive to specific travel modes or choice sets of modes. To obtain the sample for analysis, a set of constraints were applied:

1) Households with at least one individual with a **valid** driver's license to ensure that driving was feasible;
2) Households with at least one vehicle to ensure that the auto driver or passenger modes are feasible;
3) Trips with both origin and destination within Sydney boundaries to ensure that some form of reliable public transit is available to the trip maker.

These constraints resulted in a trip-based data set with 719 households, 2,950 persons, and 13,686 trips over the 2002 time frame in the Sydney GMA.

For the purpose of analysis, trip ends (or destinations) from the HTS data linked to the nearest AWS station in the Sydney GMA. For each of the 32 weather stations, the cluster analysis assigned one of the 17 weather day types for each day of the year. These weather day types were then linked to individual trip origins. One limitation is that distances to the nearest weather station does vary across the travel data, raising questions about the degree to which weather conditions experienced at the AWS station are the same as those at the trip origin. However, given that this analysis is based upon aggregate daily weather conditions, the effect of this limitation is likely to be small.

3.2 Mode Share

To determine whether these 17 different weather constructs are distinct with respect to travel outcomes, this paper examines statistical differences in observed travel patterns, characterized by travel mode shares (walk, bike, auto and transit), across the various weather day types. To statistically test the differences, non-parametric statistical tests were conducted between different pairs of clusters to determine if the differences in mode shares were statistically significant. Although a reasonably sized sample was obtained, non-parametric statistical tests were used because of the difficulty in establishing independence between samples (different clusters of weather) and to free us from any distributional assumptions required. To examine statistical differences in mode choices, the chi-squared test was used. To evaluate the differences in observed mode shares across these clusters, the following procedure was used:

1) First, statistical differences in mode shares across the four seasons were tested on the basis of observed mode choices. One motivation for this initial effort was to ensure that

across a more aggregate level relative to the weather clusters, differences in travel characteristics were indeed statistically significant. A second motivation was to reduce the number of tests done on the disaggregated weather clusters. If test were conducted on all seventeen clusters, as opposed to just clusters within each season, there would be potentially 136 cluster pairs to test. Seasons were tested by pairs, and those pairs for which the null hypothesis that the, were grouped in the later analysis on the weather clusters.

2) Second, based on the grouping of seasons, the clusters within each grouping were tested by pairs on the basis of observed mode choices. If test results indicated that two clusters were not statistically distinct, they were consolidated into one cluster. This was continued until all clusters tested statistically different on the basis of travel mode choice.

Chi-square tests for differences in mode shares evoke the following assumptions: (1) each sample is random; that is each sample from each weather cluster is randomly selected; (2) the samples are mutually independent; this may not hold since each sample may be related by season (i.e. summer dry, summer wet) or related by time; and (3) Each observation is in only 1 category (weather-mode or weather-trip purpose combination). All chi-square tests were conducted at a significance level of 0.05.

Chi-square tests on aggregate mode choices across pairs of seasons revealed that summer and autumn have statistically distinct mode shares from all other seasons. A test between the winter and spring seasons, and the remaining two seasons, showed that their mode choice probabilities were distinct from summer and autumn, but not each other. Based on these results, three groups of seasons were considered when testing pairs of weather clusters, each statistically distinct from each other: (i) summer; (ii) autumn; (iii) winter/spring. Within each of these statistically distinct season groupings, tests on mode choice probabilities between pairs of weather clusters revealed that some clusters were not statistically distinct in terms of mode choice probabilities, and could be combined and regarded as equivalent. The final taxonomy between statistically significant seasons and weather clusters, based on statistical tests of mode choice probability differences across clusters, is shown below in Table 1. With this analysis, the 17 weather day types are reduced to 11 types with distinct observable differences in mode share.

The results in Table 1 show that varying weather conditions does have some relationship with travel mode choice probabilities within different clusters. The highest shares of auto trips occurs during “very rainy,” “chilly and dry or very hot and dry” and “very rainy, humid or very windy” in the spring and summer seasons, while the highest shares of bike trips occur during “cool with light rain” during the summer season. Both of these trends are intuitive from the perspective of exposure to weather. Biking, since it exposes riders directly to the environment is most favourable when the weather is not too extreme. Compared to other modes, such as biking and walking, driving provides more protection. The majority of driving occurs during extreme weather conditions, under high precipitation or extreme temperatures. The results suggest that mode choices do vary across weather clusters, but do not necessarily advocate that mode shifts occur. For example, although "cool with light rain" shows a higher percentage of walk trips, whether these are travellers who shifted from other modes is questionable.

Table 1: Mode Choice Probabilities across Weather Clusters

Cluster	Description	Travel Mode			
		Auto	Transit	Bike	Walk
Summer 1	Cool w/ Light Rain	0.6396	0.0790	0.0070	0.2744
Summer 2 + 6	Very Rainy & Humid or Very Windy	0.7184	0.0555	0.0098	0.2163
Summer 3 + 5	Chilly & Dry of Very Hot & Dry	0.7327	0.0558	0.0045	0.2070
Summer 4	Warm & Dry	0.6983	0.0625	0.0062	0.2330
Autumn 1	Very Rainy	0.6593	0.0801	0.0083	0.2523
Autumn 2 + 4	Cool & Rainy or Cool & Dry	0.6901	0.0692	0.0073	0.2334
Autumn 3	Hot	0.7019	0.0697	0.0083	0.2202
Winter 1 + Spring 1 + Spring 2	Very Rainy or Chilly & Dry or Warm & Dry	0.6828	0.0727	0.0085	0.2361
Winter 2 + Spring 3	Chilly or Light Rain	0.6672	0.0749	0.0069	0.2510
Winter 3	Warmer, Dry, Windy	0.6815	0.0693	0.0063	0.2430
Spring 4	Very Rainy	0.7395	0.0568	0.0044	0.1993

3.3 Trip Generation

To further validate the weather constructs against observed travel behaviour, models of daily household trip generation rates are estimated using weather day types as explanatory variables. This analysis was done at the household level strictly to validate the weather concepts. Future work will analyse these weather concepts at the individual level. Regression models of household trip rates for car trips and biking trips are estimated to examine how the representation of weather would differ across those types of trips. Incorporating the results from the cluster analysis into the trip generation models can occur at different aggregation levels. On one end of the spectrum the clusters can be represented individually as seventeen distinct clusters. On the other end, these clusters can be merged based on the type of weather independent of season. For example, instead of having "very rainy" represented by Winter 1, Spring 4, Autumn 1 and Summer 2, an alternative option is having them represented by one variable “very rainy.” Furthermore, the representation may be mixed where some clusters remain distinct, while others are aggregated together. The estimation results are shown below in Table 2a and b (in the Appendix). Each model was tested against the previous model using an F test at a 0.05 rejection level. The final specification preferred is the last model specification at the right side of each table. Different models estimated for driving trips and biking trips generated, since one mode (biking) is likely to show different trip decisions with respect to weather. The estimation results illustrate several points related to weather representation and travel:

1) Including weather variables improves the explanatory power of the model relative to a specification which only includes socio-demographic and trip related variables. Conducting an F test between the model with only socio-demographic variables and models that include weather variables show that the latter is preferred over the former.

2) The level of representation of weather varies with the mode under consideration. According to the estimation results, automobile trips are sensitive to a more aggregate level of representation, relative to biking trips. This is shown comparing Tables 2a and 2b where the statistically preferred model for auto trips only represents weather at the level of rain intensity. For biking trips, the representation preferred is at the level of seasons as well.

3) However, the estimation results show that having all seventeen distinct clusters in the model was not preferred for either driving or biking trips. For driving trips, the final specification did not include any of the seventeen weather clusters. For biking trips, only one distinct cluster (Summer 1) was included in the final specification. For the biking trips, including one variable for “very rainy” (Winter 1, Spring 4, Autumn 1 and Summer 2) was statistically insignificant, but combining only Winter 1 and Summer 2 was significant so these clusters were combined.

The results from the trip generation models show that weather does impact trip-making, which is similar to other studies. More importantly, the estimation results show that the representation of weather matters both statistically and from a conceptual or behavioural standpoint. However, the results do not show as clear a distinction in the representation of weather as originally hoped. Table 2 suggests that for biking trips representing weather by seasons as well as type is required, relative to driving. This is consistent with the assumption that biking exposes individuals to weather more directly and thus, should have greater sensitivity to seasonal differences. For drivers, it may be that rain, regardless of season, is rain so they do not perceive them differently. However, this was not exhibited statistically, possible due to inability to control for the sampling of weather days.

4. Conclusion and Future Directions

This brief paper documents the exploration of alternative representations of weather and tests these constructs against aspects of travel behaviour. This exploratory analysis provides some preliminary direction and initiates some discussion about how weather might be included in travel behaviour models. With respect to these tests, several interesting conclusions regarding the nature of weather and travel decisions were made:

1) Over all the tests conducted between the weather clusters for both mode choice probabilities, some clusters remained statistically significant from other clusters having being tested on the basis of travel mode and trip purpose: Summer 1 (cool, light rain), Autumn 1 (very rainy), Spring 4 (very rainy), Winter 3 (warmer, dry, windy). This suggests that some weather cluster evoke different travel patterns from individuals, regardless of the travel decision considered.

2) The level of representation of weather varies according to the travel dimension under consideration. When considering mode choice, walking trips are more sensitive to not only the weather, but time of year. Auto trips seem less sensitive to seasonal effects, relative to walking trips.

3) The non-random occurrence of weather suggests that adjustments may need to be made to any conventional statistical analysis of weather related to travel decisions to ensure that a large enough sample for each type of weather obtained for robust results.

These preliminary findings are relatively weak to support a complex weather construct based upon cluster analysis. However the contribution of this analysis is to attempt to reduce weather data in ways that explain the meteorological variations between and across the seasons and account for the interaction and correlation between various aspects of weather. Attempts to incorporate weather into behavioural frameworks should consider how humans respond to weather conditions. For example, the literature on outdoor apparel design considers the concepts of comfort/discomfort as the condition motivating outdoor experiences. Identifying this comfort zone for various weather conditions may prove to be a useful framework for future studies.

Furthermore, weather conditions vary widely in different geographic regions. Tropical and continental climates have a larger temperature range, than more humid and colder climatic regions (Evans, 2003), making generalizations about the relationship to human behaviour difficult and location specific. The cultural acclamation that residents have to their local weather conditions only compounds the issue and limits the ability to extend results beyond the study area. Future studies should further consider more behavioural and socio-cultural responses to weather and the methodologies for incorporating these effects parsimoniously into existing travel demand and activity-based models. In the case of this work, the additional data available for the Sydney region can be used to examine disaggregate travel behaviour in more depth with these validated weather concepts.

Biking Trips per Household												
Variable	**Coeff.**	**Std. Er**	**t**	**Coeff.**	**Std. Er**	**t**	**Coeff.**	**Std. Er**	**t**	**Coeff.**	**Std. Er**	**t**
Constant	2.824	0.836	3.377	2.942	0.88	3.344	2.99	0.884	3.381	2.926	0.835	3.502
Num. Adult Bikes per Household Veh	1.231	0.439	2.802	1.216	0.443	2.742	1.173	0.446	2.631	1.189	0.44	2.701
Number of Vehicles	0.242	0.164	1.475	0.242	0.165	1.472	0.259	0.167	1.552	0.263	0.165	1.596
Num. Driver's Licence Holders per HH	-2.954	1.12	-2.636	-2.892	1.128	-2.564	-2.835	1.131	-2.507	-2.809	1.12	-2.507
Household Income (Aus$)	5.08E-06	0	1.259	5.35E-06	0	1.32	4.6E-06	0	1.128	4.7E-06	0	1.149
Hot (0/1)	---	---	---	-0.827	0.641	-1.29	-0.821	0.642	-1.279	-0.793	0.6	-1.323
Rain (0/1)	---	---	---	0.154	0.615	0.25	---	---	---	---	---	---
Sum 1: Cool w/Light Rain (0/1)	---	---	---	---	---	---	1.662	1.346	1.234	1.686	1.319	1.278
Spr 3: Light Rain (0/1)	---	---	---	---	---	---	0.275	0.746	0.369	---	---	---
Summer 2 + Winter 1 (0/1)	---	---	---	---	---	---	---	---	---	-2.164	1.573	-1.376
Sum 2: Humid and Very Rainy (0/1)	---	---	---	---	---	---	-2.075	2.137	-0.971	---	---	---
Win 1: Very Rainy (0/1)	---	---	---	---	---	---	-2.335	2.353	-0.992	---	---	---
Aut 1: Very Rainy (0/1)	---	---	---	---	---	---	0.041	1.595	0.026	---	---	---
Spr 4: Very Rainy (0/1)	---	---	---	---	---	---	-0.753	2.708	-0.278	---	---	---
Chilly (0/1)	---	---	---	-0.245	0.595	-0.412	-0.24	0.596	-0.403	---	---	---
Number of Households	438			438			438			438		
R-Squared	0.036			0.041			0.049			0.048		
SSE	9312.823			9266.79			9185.941			9196.535		
SSR	347.141			393.173			474.023			463.429		
SST	9659.963			9659.963			9659.963			9659.963		

Table 2a: Trip Generation Models: Biking Trips

Automobile Trips (Driver) per Household												
Variable	**Coeff.**	**Std. Er**	**t**	**Coeff.**	**Std. Er**	**t**	**Coeff.**	**Std. Er**	**t**	**Coeff.**	**Std. Er**	**t**
Constant	1.8800	1.1640	1.6150	1.6940	1.1720	1.4460	1.5330	1.1650	1.3160	1.4010	1.1650	1.2030
Num. Adult Bikes per Household Veh	-0.8070	0.3990	-2.0220	-0.9120	0.3980	-2.2910	-0.9120	0.3990	-2.2850	-0.9430	0.3950	-2.3880
Number of Workers	1.7610	0.3470	5.0690	1.6700	0.3460	4.8300	1.6910	0.3470	4.8780	1.7040	0.3440	4.9550
Household Income per Worker (Aus$)	9.79E-06	0.0000	1.4730	9.00E-06	0.0000	1.3670	8.75E-06	0.0000	1.3140	8.68E-06	0.0000	1.3200
Household Size	0.7910	0.2080	3.7990	0.8050	0.2080	3.8780	0.7980	0.2080	3.8310	0.7980	0.2060	3.8680
Hot (0/1)	---	---	---	1.2850	0.6520	1.9710	1.4530	0.6240	2.3300	1.5900	0.6280	2.5340
Rain (0/1)	---	---	---	1.5800	0.6250	2.5270	---	---	---	1.0090	0.7160	1.4090
Light Rain (0/1)	---	---	---	---	---	---	---	---	---	1.3240	0.8880	1.4910
Sum 1: Cool w/Light Rain (0/1)	---	---	---	---	---	---	1.1850	1.3240	0.8950	---	---	---
Spr 3: Light Rain (0/1)	---	---	---	---	---	---	2.4670	0.7350	3.3570	---	---	---
Sum 2: Humid and Very Rainy (0/1)	---	---	---	---	---	---	2.0080	2.2370	0.8970	---	---	---
Aut 1: Very Rainy (0/1)	---	---	---	---	---	---	0.1960	1.5990	0.1220	---	---	---
Win 1: Very Rainy (0/1)	---	---	---	---	---	---	-0.3950	2.2470	-0.1760	---	---	---
Spr 4: Very Rainy (0/1)	---	---	---	---	---	---	0.4740	2.5760	0.1840	---	---	---
Chilly (0/1)	---	---	---	-0.5140	0.5990	-0.8590	---	---	---	---	---	---
Number of Households	387			387			387			387		
R-Squared	0.125			0.153			0.159			0.160		
SSE	7654.245			7407.319			7353.141			7347.04		
SSR	1092.008			1338.934			1393.113			1399.213		
SST	8746.253			8746.253			8746.253			8746.253		

Table 2b: Trip Generation Models: Auto Trips

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