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The effect of weather on the use of North American bicycle facilities: A multi-city analysis using automatic counts

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A B S T R A C T

This study investigates the impact of weather on the use of urban bicycle facilities in Montreal, Ottawa, Vancouver and Portland, as well as on the Green Route in Quebec. This research makes use of long-term hourly and daily counts collected automatically using inductive loop detectors. The count data locations are organized into two groups – utilitarian and recreational. Using regression models with autoregressive and moving average (ARMA) errors, the direct impact and lagged effects of weather variables on hourly and daily bicycle counts are investigated. Among the main findings, temperature and humidity are positively and negatively associated with cycling, respectively, with a non-linear association in most cases. Precipitation has a significant negative impact on cycling flows, and its effect was observed to increase with rain intensity. Lagged effects of rain were also observed, such as the effect of rain in the previous three hours, rain in the morning only, and rain in the afternoon only. Furthermore, urban bicycle flows are more sensitive to weather on weekends than on weekdays, and recreational facilities are more sensitive than utilitarian facilities.

1. Introduction

In order to promote cycling and to accommodate the growing number of cyclists, many North American cities are investing in bicycle infrastructure (e.g., cycle tracks, bicycle lanes, bicycle parking) and implementing new policies and programs (e.g., bike sharing programs, traffic calming, bicycle integration with transit) (Pucher and Beuhler, 2011). As cities continue to invest and the number of cyclists grows, it is becoming increasingly necessary to study the safety, operations and planning of cycling facilities. This requires identifying the determinants of cycling activity across different cities and types of facilities. One topic that has been attracting more attention as of late is the relationship between weather and cycling.

Understanding the effect of weather on cycling ridership across different facilities is important for several reasons, as highlighted by Miranda-Moreno and Nosal (2011) and Thomas et al. (2012), among others. For instance, it will be essential for the development of methods to adjust brief cyclist data counts for weather, which is expected to increase the accuracy of cyclist exposure estimates, also known as the average annual daily bicyclists (AADB). AADB is used in a wide range of bicycle analyses (Sprinkle Consulting, 2011).

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Although several recent studies have been published on this topic (Lewin, 2011; Miranda-Moreno and Kho, 2012; Miranda-Moreno and Nosal, 2011; Rose et al., 2011; Thomas et al., 2012), there are several shortcomings in the literature. Most studies have used survey data, brief manual counts, or daily (aggregate) data, which cannot capture the effects of hourly (disaggregate) weather conditions, such as the effect of rain in the morning versus rain in the evening. Most past studies have either focused on one specific geographical area or a particular type of bicycle facility; few works have examined how the relationship between cycling and weather differs across cities or across different types of facilities. Very little research has examined the difference between the impact of weather on weekdays and the weekend, including lagged effects of weather.

This study will help address these shortcomings by using data from four North American cities – Montreal, Ottawa, Vancouver and Portland – and from a recreational bike network in Quebec, to develop hourly and daily cyclist ridership models. Regression with autoregressive moving-average (ARMA) errors is used to account for autocorrelation. In short, this work has the following two objectives: (i) to investigate the relationship between weather and hourly and daily cyclist volumes on utilitarian bicycle facilities, as well as how that relationship differs across cities, and (ii) to investigate the relationship between weather and hourly cyclist volumes on recreational facilities, as well as how that relationship differs from that of utilitarian facilities.

The following section presents a short literature review. Section 3 presents the methodology, including the data used and the analysis method. Section 4 presents the results, Section 5 presents a brief discussion, and Section 6 presents the conclusions.

2. Literature review

Though the relationship between cycling and weather has been studied directly as early as 1977 (Hanson and Hanson, 1977), there has more recently been an increase in research regarding the impact of weather on bicycle usage, and a wide range of data collection methods and statistical analyses have been utilized. Data collection methods include surveys as well as manual and automatic count data. For instance, Nankervis (1999a,b) used survey data and counts of parked bicycles on a university campus, Hanson and Hanson (1977) used travel survey data to estimate the daily cycling modal share, and more recently, Lewin (2011), Rose et al. (2011), and Thomas et al. (2012) used automatic long-term counts. Most studies incorporate data aggregated at the daily level, but more studies are emerging that use hourly cycle counts (Gallop and Tse, 2012; Miranda-Moreno and Nosal, 2011; Tin Tin et al., 2012). Regression models, with bicycle counts or the logarithm of bicycle counts modeled as a function of weather variables and various temporal fixed effects, make up the bulk of the statistical analyses (Brandenberg et al., 2007; Jaarsma and Wijnstra, 1995; Lewin, 2011; Miranda-Moreno and Nosal, 2011; Nankervis, 1999a,b; Rose et al., 2011; Thomas et al., 2012; Tin Tin et al., 2012).

In the literature, the two main weather determinants are temperature and rain, but others such as humidity and wind speed have been identified. In general, cycle counts increase with temperature. Though varying specifications make it difficult to compare directly across studies, an increase in temperature of one degree Celsius is generally associated with an increase in cycle counts of less than five percent (Tin Tin et al., 2012; Miranda-Moreno and Nosal, 2011). Two studies found the square of temperature to be insignificant when entered into a model with temperature, suggesting that the effect of temperature is linear (Tin Tin et al., 2012; Rose et al., 2011). However, Lewin (2011) and Miranda-Moreno and Nosal (2011) used binary variables to show that high temperatures are associated with a decrease in cycle counts, and Richardson (2000) observed a non-linear effect. Miranda-Moreno and Nosal (2011) found that increases in humidity are associated with decreases in cycling. Only one known study has utilized a thermal index to describe the perception of weather by cyclists (Brandenberg et al., 2007). Other variables that have been examined include hours of sunshine and wind speed (Thomas et al., 2012), and cloud coverage (Hanson and Hanson, 1977).

Regression models generally incorporate precipitation as a continuous variable, as the duration of precipitation (in hours), or simply as a binary variable. The effect of precipitation varies across locations, but in general, it was shown to have a smaller effect than temperature. Lewin (2011) found that rainfall in a day decreases the count by about 10% of the annual daily average, and Tin Tin et al. (2012) found that cycle counts decrease by 1.5% and 10.6% per millimeter of rain in a day and hour, respectively. Gallop and Tse (2012) found that rain one of the previous three hours can have an effect on cycle counts in the current hour comparable to or greater than rain in the current hour. Miranda-Moreno and Nosal (2011) confirm this, and found that rain in the morning can reduce cycling counts in the afternoon. These results suggest that lagged effects of precipitation can improve model fit, but they have been considered by no other known studies. Lagged effects of other weather variables have been examined, such as in the work by Jaarsma and Wijnstra (1995) which noted among other things that contiguous stretches of poor weather can lead to an extra boost in cycling when a day with good weather finally occurs.

In terms of the geographical areas, many of these studies are based in European, Australian, and recently, North American locations. Studies have typically only considered one region or city, with very few exceptions, such as the work of Rose et al. (2011)that included data from Portland, Oregon, USA and Melbourne, Australia. This study presents an aggregate (daily) ridership model to study the effects of weather on bicyclist volumes. As one of the main results, it is found that cyclists in the two cities (Melbourne and Portland) exhibit different sensitivities to weather.

While some studies make no distinction, several have examined the effects of weather on utilitarian and recreational cycling separately (Brandenburg et al., 2007; Hanson and Hanson, 1977; Richardson, 2000; Thomas et al., 2012). Brandenburg et al.

(2007) observed that commuting occurs more in cooler weather than recreational cycling, and that commuters are less sensitive to rain than recreational cyclists. Hanson and Hanson (1977) found that the effect of weather was greater on discretionary trips than trips reportedly for work. Richardson's (2000) study looked at the effects of weather on cycle trips in Australia using travel survey data, observing that cycling recreational users are more affected by extreme temperatures and rainfall than utilitarian users are. Thomas et al. (2012) also noted that different user groups respond differently to weather; recreational cycling is much more sensitive to weather than utilitarian cycling. In other words, discretionary trips can be more easily put off than trips to work. Though he did not look at utilitarian vs. recreational cyclists, Nankervis (1999a,b) conclude that certain cyclist groups, like students, may respond to weather differently from others. Thomas et al. (2012) also examined weekend and weekday cycling separately and concluded that cycling on utilitarian facilities is more sensitive to weather conditions on weekends, suggesting that decisions to make non-obligatory trips are more heavily affected by weather. Finally, as documented in a recent work (Miranda-Moreno et al., 2014), "pure" utilitarian or recreational facilities do rarely exist. Facilities in urban areas are predominantly utilitarian during weekdays but they often present a mixed traffic during weekends. Moreover, facilities connecting urban areas with recreational areas may show predominantly recreational traffic during weekends but this can be mixed with utilitarian ridership in particular during the weekdays.

From this literature, we can identify that comparative studies are missing, in particular studies involving different North American cities, with different weathers, urban form characteristics and cyclist culture. Comparative studies across cities could help distinguish between the absolute level of cycling and day-to-day variations. The urban form, topography and/or cyclist culture can effect absolute levels, but not necessary the temporal patterns of cycling. Also, the influences of the weather on cycling could be observed everywhere, but people may react differently. Although, Rose et al. (2011) involved two cities, they only involved data for two counting stations and only one North America city. One study looked at the impact of weather on recreational versus utilitarian in Australia, but there have been none in North America. Although, one can anticipate that weather affects cycling across user types differently, little empirical evidences exist. Due to a wide range of factors, cyclists in some cities may exhibit a different response to weather conditions, and it has been suggested that utilitarian cyclist trips are less sensitive to weather than recreational trips, but no studies have confirmed this at the disaggregate level. In addition, there is little evidence regarding the differences between weekend and weekday cycling.

3. Methodology

This section describes the locations and data used, and then outlines the two main steps in achieving the objectives of this research: first, the classification of bicycle counting stations according to their temporal patterns, and second, the combination and analysis of weather and bicycle counts at the hourly and daily level.

3.1. Study areas

This study utilizes cyclist count data from 10 automatic counting stations in four North American cities – one in Portland, OR, USA; four in Vancouver, BC, Canada; four in Montreal, QC, Canada; and one in Ottawa, ON, Canada – and from 3 counting stations along the Green Route (GR) in the Province of Quebec. A brief description of each location is provided in Table 1. For the purposes of this study, cycle-tracks are on-street, but physically separated, bi-directional bicycle facilities; separated paths are off-road facilities that may or may not be shared with pedestrians; sidewalk bike facilities are sidewalks that permit use by cyclists, generally over bridges; and bicycle boulevards are quiet streets optimized for cycling with traffic calming and markings.

Table 1
Summary of the urban and Green Route counting stations.

City	Name	Location	Type	ADV* (standard deviation)
Montreal	Mon1	Maisonneuve Blvd.	Cycle track	1896 (1024)
	Mon2	Maisonneuve Blvd.	Cycle track	3575 (1627)
	Mon3	Brebeuf St.	Cycle track	3456 (1626)
	Mon4	Berri St.	Cycle track	3735 (1972)
Ottawa	Ott1	Ottawa R. Path	Separated path	1721 (813)
	Ott2	Colonel By Pathway	Separated path	890 (396)
Vancouver	Van1	Cambie St Bridge	Sidewalk bike facility	909 (451)
	Van2	CV Greenway at Rupert	Separated path	525 (234)
	Van3	CV Greenway at Victoria	Separated path	779 (334)
	Van4	Ontario &11th St.	Bicycle boulevard	859 (349)
Portland	Port1	Hawthorne Bridge	Sidewalk bike facility	4367 (1677)
Velo Quebec	VQ1	Métabéchouan, QC	Separated path	316 (286)
	VQ2	Duschesnay, QC	Separated path	210 (191)
	VQ3	Quebec City, QC	Separated path	943 (1013)

* Average seasonal daily volumes corresponding to April 01–November 30.

All of the used counter locations in the four cities exhibit utilitarian traffic patterns and all of the GR counters exhibit recreational patterns, as defined later. Both Portland and Vancouver have temperate climates with mild, wet winters and warm, dry summers. Average winter temperatures are above freezing and total rainfall is roughly 1000 mm per year. Montreal and Ottawa experience warm, often humid summers and cold, snowy winters. Both cities average roughly 1000 mm of precipitation per year, roughly 200 mm of which is snow. Finally, the GR is an extensive bike network, covering Quebec with over 4000 km of bike trails, multi-use paths, and shared roadways. The GR locations all have a similar climate to Montreal. (EC, 2011).

3.2. Bicycle count data

All bicycle data in cities was collected using inductive loop bicycle counters, which count bicycles by detecting changes in the electric current in sub-pavement loops of cable. For the GR, data was collected with pneumatic tubes. These technologies can distinguish cyclists from automobiles in mixed traffic, making them suitable for both segregated and non-segregated facilities. The data are continuously logged in 15-min intervals and for the purpose of this research were aggregated into hourly and daily totals. The performance of this inductive-loop technology has been studied and documented by Nordback et al. (2011), who reported that, on separated facilities, the absolute error between the true number of cyclists and the counted number is generally less than 3% when the counters are operating properly.

Both Montreal and Vancouver have data available for 2008–2010, but Ottawa has data for only 2009–2010, and Portland and most Green Route counters have data for only 2010. Some locations had data available for only a portion of a given year. Given the considerable differences in winter weather across these four cities, and to reduce the scope of this paper, data from December to March (inclusive) were excluded. The relationship between cycling and weather differs between the winter and summer, and therefore a separate analysis was conducted by Miranda-Moreno and Kho (2012). The data were closely examined for missing values.

3.3. Weather data

Weather data, consisting of hourly values for temperature, relative humidity, and precipitation, were obtained from weather stations maintained by Environment Canada, the *Ministère du Développement durable*, *de l'Environnement et des Parcs*, and the National Oceanic and Atmospheric Administration. The bicycle count data locations in Montreal, Vancouver, Portland and Ottawa were all matched with data from four respective weather stations, while each "Route Verte" location was matched to a separate station. The weather stations are typically located within 2–6 km of the bicycle counters.

3.4. Data processing

The bicycle and weather datasets were joined by date (and time, when applicable), and were screened for missing or erroneous data. Data were discarded on holidays, when improbably large sections of contiguous hours with zero cyclists were discovered, and when graphical inspection revealed irregular behavior characteristics of counter malfunction, such as days with very low counts in the midst of very busy days. Also discarded were days with missing weather data, as they could not be used in the models. Even if a day was missing only one or two hours of weather or bike data, it was discarded in full, as observed maximum/minimum temperatures, precipitation totals, and so on could be erroneous. In general, such holes made up less than 5% of the given dataset. However, Montreal and the Green Route locations were missing roughly 15% and 13% of their data. In addition, roughly 2% of the Vancouver hourly weather dataset was missing. If three or less values in a row for temperature or humidity were missing, the missing values were replaced by linear interpolation. If more than three were missing then that day's data were discarded. After interpolation, only 0.3% of the dataset was excluded due to missing weather data.

3.5. Counter location classification according to temporal patterns

The bicycle traffic data from each counter were classified as either utilitarian or recreational according to their hourly, daily and monthly patterns. This analysis provided the basis for the organization of the data locations in the modeling section, and was based on the method developed by Miranda-Moreno et al. (2014). The method involves calculating standardized indices, which express the annual average ridership for a given time period (for all Mondays, for example) as a percentage of the overall AADT, and then plotting the values to identify how the facilities are used temporally. For this analysis, it was assumed that primarily utilitarian locations exhibit AM and PM traffic peaks on weekdays, and have higher ridership on weekdays than over the weekend; conversely, primarily recreational locations exhibit only one PM peak and have higher ridership on the weekend than on weekdays. The indices, which are sometimes referred to as expansion factors for their use in estimating AADT, are defined as follows:

$$I_h = (\bar{v}_h / \overline{V}_{24}) \tag{1a}$$

$$I_d = (\bar{v}_d / \overline{V}_{24}) \tag{1b}$$

$$I_m = (\bar{v}_m / \bar{V}_{24}) \tag{1c}$$

$$\bar{v}_{24} = \frac{\sum_{j=1}^{D} V_j}{D} \tag{1d}$$

Where

I_h, I_d and I_m – hourly, daily and monthly standardized indices, respectively;
$\bar{v}_h$ – average hourly volume for hour h, with $h = 0, 1 \ldots 23$;
$\bar{v}_d$ – average daily volume for a given day of the week, with d = Mon, Tue… Sun;
$\bar{v}_m$ - average daily volume for a given month, with m = April, May… November (including only the bicycle season)
$\bar{V}_{24}$ - average daily volume during the whole season (from April to November), with $V_j = \sum_{i=1}^{24} v_{ij}$
v_{ij} – hourly volume for hour i and day j, and
D = number of available days of data within the cycling season.

Note that formulae (1a)–(1d)are restricted to data from within the cycling season (April 01–November 30) and may exclude holidays and missing or erroneous data. Further description of the calculation and use of such indices can be found in the Federal Highway Administrations Traffic Monitoring Guide (2001). The advantage of classifying user groups in this manner, as opposed to relying upon functional classification or local experience, is the assurance that all of the count data locations included in each category exhibit the same temporal patterns. This increases the likelihood that those locations along bike facilities in each category are being used in a similar manner. As demonstrated by Miranda-Moreno et al. (2014), both urban cycling facilities and facilities on the green route can exhibit mixed patterns; including those in the utilitarian and recreational groups would be erroneous. Of those used in the weather analysis, all of the count data locations in Montreal, Ottawa, Vancouver and Portland exhibit utilitarian patterns and all of those along the green route exhibit recreational patterns. A summary of the temporal characteristics of utilitarian and recreational facilities is presented in Fig. 1.

3.6. Bicycle ridership modeling

The relationship between weather and both hourly and daily cyclist volumes was analyzed using log-linear regression models. Daily-level models were incorporated in the analysis to validate the results of the hourly-level models, and as a potential solution to significant auto-correlation in the residual errors of the hourly models. Counting stations from the same city were used to calibrate one general model per city. After verifying that they exhibited similar results when calibrated separately, all of the Green Route count data locations were used to calibrate one general model. All of the models have the following functional form:

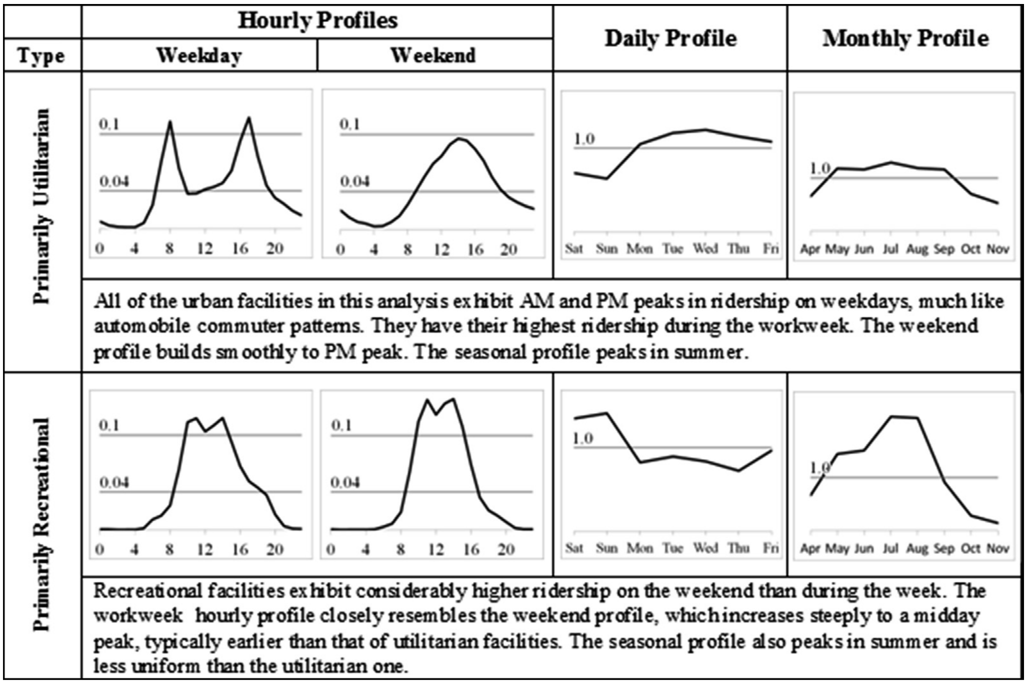

Fig. 1. Typical utilitarian and recreational bicycle ridership profiles.

$$\ln(N_{k,h,d,m,y}) = \alpha + \beta X_{h,d,m,y} + \upsilon W_{h,d,m,y} + \gamma_k + \delta_h + \eta_d + \lambda_m + \varphi_y + \omega_{h,k,d,m,y}, \quad (2)$$

where:

$N_{k,h,d,m,y}$ is the number of bicycle counts on path k, in an hour h, during day of the week d, month m, and year y;
$X_{h,k,d,m,y}$ are hourly weather variables during the same date and time as $N_{k,h,d,m,y}$ (h, d, m and y); These include continuous variables, discrete variables, and non-linear transformations of weather variables;
$W_{h,d,m,y}$ are variables that incorporate weather conditions from hours other than hour h, such as a binary variable set to one if it has rained in the three hours prior to h;
$\gamma_k, \delta_h, \eta_d, \lambda_m, \varphi_y$ are fixed parameters for path k, hour period h, day of the week d, month m, and year y;
$\omega_{h,k,d,m,y}$ is either an independent error term, or when accounting for serial autocorrelation, is equivalent to $\phi_1 e_{h-1,k,d,m,y} + \cdots + \phi_p e_{h-p,k,d,m,y} - \theta_1 z_{h-1,k,d,m,y} - \cdots - \theta_q z_{h-q,k,d,m,y}$, where e_h is the error in hour h and z_h is a white noise process, and ϕ and θ are parameters to be estimated from the data;
α, β, υ are parameters to be estimated from the data.

In the case of daily level models, the subscript h is removed from all variables above, δ_h is not included, and in the error and white noise terms, ϕ and θ, respectively, h is replaced with d. All models incorporate fixed effects to account for temporal patterns (months, days of the week, hours of the day) and locations.

Due to a high presence of non-missing zeroes in the overnight hours, data from 20:00 to 06:00 were excluded from the analysis. Because the log of cycle counts was used as the dependent variable, remaining non-missing 0 counts were changed to one. For all of the urban locations, less than 1 percent of the data needed to be changed. Due to lower demand, particularly in the colder months, 15% of the Green Route observations were changed.

Both continuous and binary variables were used to incorporate weather conditions into the models. Weather variables that were available across all cities were tested, and those that had a significant effect on bicycle ridership were retained. Non-linear (such as second-order polynomial function) effects of temperature and humidity were tested; for instance, both temperature and the square of temperature were entered into the models. Binary variables were used to relate precipitation from previous hours to a given hour (hourly models), or to specific in which portion of the day rainfall occurred (daily models). The Akaike Information Criterion (AIC) was used to evaluate different model specifications and aid with model selection.[2]

Correlation between independent variables was evaluated. If two weather variables had a correlation coefficient greater than 0.5, whichever variable had a weaker correlation with cyclist ridership was excluded. For example, both Vancouver and Portland exhibited a strong negative correlation between temperature and relative humidity. Therefore, only the models for Ottawa and Montreal incorporate humidity.

In addition to the model coefficients, elasticity values are computed in the following sections to facilitate comparisons between variables with different units. Elasticity is generally defined as proportional change in the dependent variable relative to proportional changes in a given independent variable. The combined elasticity of a continuous variable represented as a quadratic function is $(\beta_k \cdot \overline{X}_k + 2 \cdot \beta_{k+1} \cdot \overline{X}_k^2)$, where $\overline{X}_k$ is the mean value of variable k and β_k is the estimated coefficient for variable k. This value is the change in the cyclist count for an hour (or day) corresponding to a 1% change in the independent weather variable. If one of the terms, β_k or β_{k+1}, is insignificant, then it is excluded from the equation. The elasticity of a binary variable is $100 \times [\exp(\beta_k) - 1]$, which is the percent change in the cyclist count expected when the conditions described by the variable are present.

4. Results

The results of the hourly and daily models are presented in the following two subsections, in Tables 2 and 3, respectively. Variables are significant at the five percent level if the t-statistic is greater than 1.96 in absolute value. The model coefficients, t-statistic values, and elasticity values, are presented in each table. In order to conserve space, the fixed effects for month, day of the week, hour, and facility are not presented. To see an example of similar modeling results that include all parameters, refer to Miranda-Moreno and Nosal (2011).

4.1. Hourly model results

The hourly modeling results for the utilitarian and recreational counting stations are presented in Table 2. With the exception of the second-order terms in the Ottawa and Green Route models, both the temperature and square of the temperature have a significant effect on hourly cycle counts. To illustrate this effect and the differences across the cities, the elasticity of ridership with respect to temperature is plotted in Fig. 2. The effect is similar across the Montreal, Vancouver, and Portland models: elasticity increases until reaching a peak value, and stays positive over the full range of temperature

[2] AIC is equal to $[2k - 2\ln(L)]$ where k is the number of parameters in the model and L maximum likelihood value for the calibrated model. The AIC value reflects goodness of fit and because it includes the number of parameters, discourages over-fitting the model. The model with the lowest AIC is generally preferred.

Table 2
Hourly modeling results – effects of temperature, humidity and precipitation.

	Montreal			Ottawa			Vancouver			Portland			Green Route		
	Coef.	*t*-Stat	Elast.[1]	Coef.	*t*-Stat	Elast.	Coef.	*t*-Stat	Elast.	Coef.	*t*-Stat	Elast.	Coef.	*t*-Stat	Elast.
$Temp^2$	−0.00026	−6.7	0.12	−0.00027	−1.3*	0.35	−0.0010	−5.0	0.56	−0.00079	−5.1	0.32	0.00048	1.8*	0.96
Temp	0.018	13	–	0.033	4.3	–	0.072	13	–	0.050	8.3	–	0.047	5.1	–
$Humidity^2$	-7.9×10^{-5}	−18	−0.39	-3.3×10^{-5}	−1.3*	−0.89	–	–	–	–	–	–	1.4×10^{-4}	−4.2	−1.61
Humidity	0.0049	8.2	–	−0.0082	−2.2	–	–	–	–	–	–	–	−0.0044	−1.0*	–
Rain1	−0.040	−6.8	−0.039	−0.096	−3.0	−0.092	−0.28	−15	−0.24	−0.034	−3.3	−0.033	−0.19	−3.5	−0.18
Rain2	−0.046	−7.6	−0.045	−0.10	−2.5	−0.10	−0.26	−19	−0.23	−0.042	−2.7	−0.042	−0.24	−4.9	−0.21
Rain3	−0.071	−6.1	−0.068	−0.11	−1.8*	−0.11	−0.38	−15	−0.31	−0.081	−2.4	−0.077	−0.22	−4.6	−0.20
RainPrev3	−0.062	−12	−0.060	−0.12	−3.6	−0.12	−0.23	−14	−0.20	−0.014	−0.78	−0.013	−0.16	−3.7	−0.15
AMrain	−0.034	−3.8	−0.033	−0.090	−1.3*	−0.086	−0.087	−3.3	−0.083	0.0044	0.13*	0.0044	0.17	2.2	0.19
PMrain	0.018	2.3	0.018	0.16	3.3	0.17	0.040	1.5*	0.040	0.017	0.59*	0.017	0.077	1.2*	0.08
AR	1, 8, 9, 11, 15	–	–	1, 4, 15	–	–	1–3, 5–10, 15	–	–	1, 2, 4, 7, 9, 10, 15	–	–	1, 15	–	–
MA	1, 15	–	–	15	–	–	1, 15	–	–	1, 15	–	–	1, 15	–	–
AIC	−25839	–	–	3118	–	–	13,608	–	–	−1927	–	–	12335	–	–
obs	20130	–	–	4110	–	–	18,225	–	–	2550	–	–	6570	–	–

[1] Elast., elasticity values (at the mean values, in the case of continuous variables).
* Not significant at 95% confidence level.

Table 3
Weekday and weekend daily-level model results – effects of temperature, humidity and precipitation.

	Montreal			Ottawa			Vancouverr			Portland			Green Route		
	Coef.	*t*-Stat	Elast.[1]	Coef.	*t*-Stat	Elast.	Coef.	*t*-Stat	Elast.	Coef.	*t*-Stat	Elast.	Coef.	*t*-Stat	Elast.
Weekday															
$Temp^2$	−0.0010	−10	0.25	−0.00072	−2.5	0.19	−0.0017	−8.5	0.48	−0.0012	−12	0.35	−0.0052	−10.4	0.99
Temp	0.058	16	–	0.042	4.5	–	0.093	11	–	0.070	14	–	0.28	13.1	–
$Humidity^2$	0.000021	1.3*	−0.39	0.00013	3.8	−0.40	–	–	–	–	–	–	−0.00026	−3.8	−1.17
Humidity	−0.010	−5.7	–	−0.023	−5.4	–	–	–	–	–	–	–	0.0063	0.75*	–
Rain_hrs1	−0.14	−8.1	−0.13	−0.18	−4.2	−0.16	−0.22	−8.9	−0.20	−0.076	−2.3	−0.073	−0.35	−3.4	−0.30
Rain_hrs2	−0.32	−16	−0.27	−0.33	−6.8	−0.28	−0.37	−12	−0.31	−0.12	−3.7	−0.11	−0.74	−5.9	−0.53
Rain_hrs3	−0.62	−29	−0.46	−0.54	−11	−0.42	−0.64	−27	−0.47	−0.26	−10	−0.23	−1.2	−12	−0.70
AMrain	−0.096	−4.8	−0.092	−0.21	−3.9	−0.19	0.014	0.46*	0.014	−0.032	−0.9*	−0.032	0.21	1.7*	0.23
PMrain	0.15	7.7	0.16	0.071	1.6*	0.073	0.061	2.0	0.063	0.035	1.3*	0.036	0.50	4.7	0.64
AR	1–3	–	–	1	–	–	1	–	–	2	–	–	1	–	–
MA	1	–	–	1	–	–	1, 2	–	–	–	–	–	1	–	–
AIC	−810	–	–	979	–	–	−410	–	–	−266	–	–	609	–	–
obs	1537	–	–	213	–	–	904	–	–	164	–	–	402	–	–
Weekend															
$Temp^2$	−0.00124	−5.4	0.59	−0.0032	−4.6	0.89	−0.0027	−5.4	0.66	−0.0023	−4.6	0.21	−0.0047	−6.7	1.1
Temp	0.085	10.8	–	0.19	6.8	–	0.14	7.6	0.00	0.11	6.0	–	0.26	8.6	–
$Humidity^2$	0.000040	1.1*	−0.41	−0.00022	−1.5*	−0.88	–	–	–	–	–	–	−0.00016	−2.1	−.61
Humidity	−0.013	−3.0	–	0.0071	0.61*	–	–	–	–	–	–	–	0.0065	0.47	–
Rain_hrs1	−0.13	−3.1	−0.12	−0.31	−2.6	−0.27	−0.19	−3.6	−0.17	−0.40	−4.4	−0.33	−0.45	−2.5	−0.36
Rain_hrs2	−0.42	−8.6	−0.35	−0.29	−1.8*	−0.25	−0.51	−7.8	−0.40	−0.37	−3.8	−0.31	−0.41	−2.0	−0.34
Rain_hrs3	−0.71	−14.9	−0.51	−1.0	−9.8	−0.65	−0.82	−19.2	−0.56	−0.54	−6.5	−0.42	−1.2	−5.8	−0.69
AMrain	0.008	0.14*	0.008	0.11	0.65*	0.11	0.012	0.22*	0.012	0.13	1.2*	0.14	−0.19	−1.1*	−0.17
PMrain	0.055	1.2*	0.057	0.14	1.0*	0.15	0.11	1.8*	0.12	0.14	1.7*	0.16	−0.098	−0.53*	−0.093
AR	1,2,6,10,11	–	–	–	–	–	1	–	–	7	–	–	1	–	–
MA	1	–	–	–	–	–	1	–	–	–	–	–	1	–	–
AIC	339	–	–	53	–	–	78	–	–	−5.6	–	–	310	–	–
obs	563	–	–	94	–	–	369	–	–	67	–	–	178	–	–

[1] Elast., elasticity values (at the mean values, in the case of continuous variables).
* Not significant at 95% confidence level.

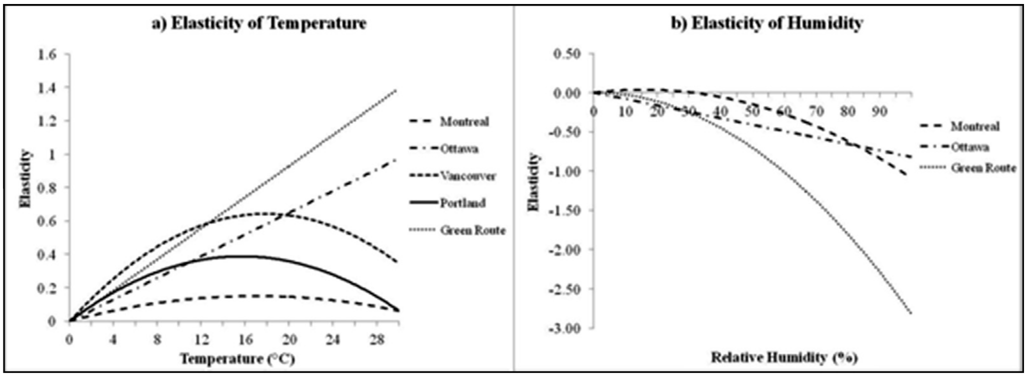

Fig. 2. Elasticity of temperature and humidity – hourly models.

values. Elasticity increases linearly with temperature for both Ottawa and the Green Route, as the squared terms for temperature are insignificant. Overall, the utilitarian locations exhibit lower elasticity than the Green Route locations; a 10% increase in temperature from the mean for each dataset results in an increase in ridership of 3.4% and 9.6% for the average utilitarian location and the Green Route locations, respectively.

Again, humidity was excluded from the Vancouver and Portland models due to the strong negative correlation between it and temperature. However, for the Montreal, Ottawa, and Green Route, as was done for temperature, variables for both humidity and the square of humidity were entered into the models. Both variables were significant for Montreal, but only first order term was significant in the Ottawa model, and only the second-order term was in the Green Route model. The elasticity values are plotted over a range of humidity in Fig. 2. For all three locations, increases in humidity result in decreases in cycling counts at all or nearly all values of humidity. For the Montreal and Green Route models, the magnitude of this effect increases more rapidly at higher humidity. Again, utilitarian locations appear less sensitive; a 10% increase from the average humidity of roughly 65% results in an average decrease in cycling of 6.4% in Ottawa and Montreal, and of 16% at Green Route locations.

After testing several different methods, it was determined that the best representation for direct precipitation was a three level factor, corresponding to low (*rain1*), moderate (*rain2*), and heavy (*rain3*) precipitation. While the intervals for low, moderate and high correspond roughly to the National Weather Service's convention of .25–2.5 mm/h, 2.5–7.6 mm/h, and greater than 7.6 mm/h, respectively, the intervals were tweaked to provide the best fit for each city. Intuitively, the presence of rain in a given hour has a negative impact on ridership that increases in magnitude with precipitation intensity. With the exception of Vancouver, the recreational locations are more sensitive to direct precipitation than the utilitarian ones.

Three other binary variables were entered into the models to account for lagged effects of precipitation. For a given hour, *RainPrev3Hrs* is set equal to one if it is not raining in the current hour and if it has rained in any of the previous three. It is significant in all models except for Portland's, and it results in a decrease in cycling that is comparable to direct precipitation. *AMrain* is set to one in the hours of 15:00–19:00 if it rained between 05:00 and 10:00, but did not rain at any other point in the day. It was significant in all of the utilitarian locations except Portland, and exhibited a negative effect on cycling, again comparable to the effect of direct precipitation. This suggests that, even if it does not rain in the afternoon, rain in the morning can result in lower cycling at utilitarian locations due to those who have switched modes or abandoned trips for the day. However, on the Green Route locations, *AMrain* has a positive effect, suggesting that rain in the morning shifts a higher concentration of recreational trips to the afternoon and evening. Finally, *PMrain* is set to one in the hours of 15:00–19:00 if it rains during that period, but at no other point in the day. It is significant in the Montreal and Ottawa models, and has a positive effect on cycling counts, which would serve to counteract the effect of the direct precipitation variables. This suggests that if it rains only in the afternoon or evening, a number of cyclists who would have otherwise changed modes are caught out with no choice but to cycle.

As noted earlier, the hourly models calibrated using OLS produced error series with significant autocorrelation. Incorporating ARMA error structures greatly reduced autocorrelation in the residual errors. Autoregressive error terms up to the 11th lag, first-order moving average terms, and moving average terms at the 15th lag were tested for each model, and terms which were significant at the 95% confidence level were retained. For each model, the lags at which significant AR and MA terms were obtained are identified in Table 2. The actual AR and MA coefficients are not presented in order to conserve space, and because they are of lesser interest than the weather variable coefficients. In some cases, significant correlation persisted at several lags. For example, the autocorrelation plots for the residual errors from both the OLS and regression with ARMA errors are presented in Fig. 3. Previous research has demonstrated that complex ARIMA models are capable of producing hourly models with no correlation in the residuals errors (Gallop and Tse, 2012). However, these models included lagged values of the dependent variable, cycle counts, as well as roughly 40 autoregressive error terms. Explaining variation in bicycle counts using lagged count values limits the practical applications of the model, and including a high number of lagged error terms increases the computational difficulty. Therefore, as an alternative solution to the correlation problem, and to

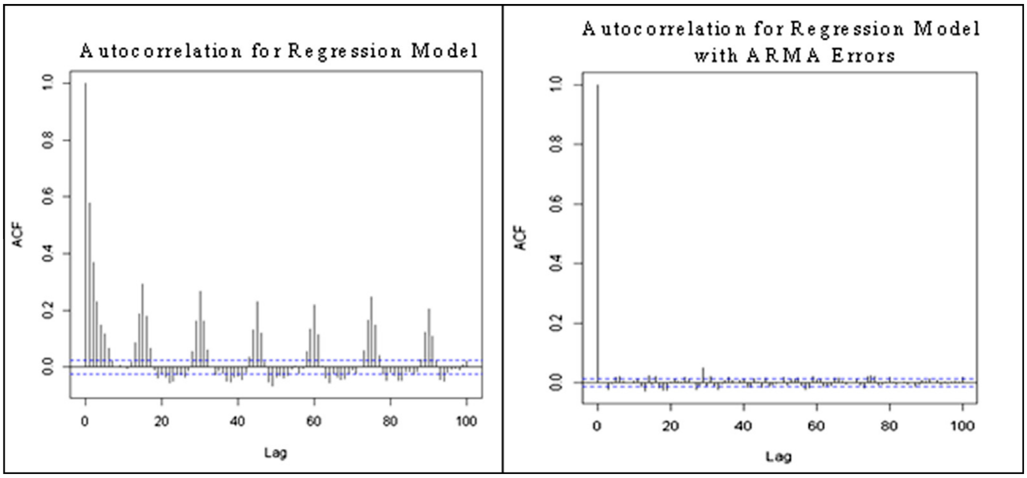

Fig. 3. Autocorrelation plots for regression model with and without ARMA errors.

verify the results obtained from the hourly data, daily models were also calibrated, the results of which are presented in the next section.

4.2. Daily model results

Residual errors from the daily OLS models exhibited far less autocorrelation than those from the hourly models; in general, fewer AR and MA terms were necessary to reduce autocorrelation, and in all cases it was possible to eliminate it fully. Again, the lags at which significant AR and MA terms were obtained are identified in Table 3. To save space, and because the results agreed, the analysis of the effect of weather on weekdays vs. weekends is undertaken using only daily models. The weekend and weekday results of the daily models for both utilitarian and recreational locations are presented in Table 3.

The behavior of the elasticity values of temperature and humidity is similar in the weekday daily models to that of the hourly ones. The maximum daily temperature and the minimum daily humidity were found to provide the best fit in general. Again, the elasticity of temperature on weekdays increases to a maximum value for all locations (Fig. 4a). However, in the daily models, all of elasticity values decrease more rapidly, crossing the y-axis between roughly 27 °C and 30 °C. Again, like in the hourly models, the elasticity values of humidity on weekdays are mostly negative (Fig. 4c). However, Ottawa's elasticity plot is concave-up, crossing the y-axis at roughly 80% humidity. This could be due to the lower amount of data used in the daily models, or due to the fact that only roughly 10% of the minimum humidity values fall above 80% humidity. As with the hourly models, the magnitudes of the elasticity values are generally higher for the Green Route locations, suggesting that recreational locations are more sensitive to weather.

Slight modifications were made to adapt the precipitation variables to the daily models. The three discrete precipitation variables in Table 3, *Rain_hrs1–Rain_hrs3*, relate the duration of rainfall between 06:00 and 20:00 to cycling counts, and correspond to 1 h, 2–3 h, and greater than 3 h, respectively. In Montreal, Ottawa and Vancouver, the effect of rain on weekday cycle counts ranges from −13% to −47%, while the effect in Portland ranges only from −7% to −23%. The Green Route locations are more sensitive, with a reduction as high as 70% due to prolonged rain. In the daily models, *AMrain* is set to 1 if the day's rainfall occurred only between 05:00 and 10:00, and though it is only significant for Montreal and Ottawa, the signs and magnitudes are consistent with the hourly models. Finally, *PMrain* is set to 1 if the day's rainfall occurred only between 15:00 and 19:00, and again, the signs and magnitudes are consistent with the hourly models. *PMrain* in the Green Route models has a large magnitude relative to that of the utilitarian models. This is perhaps because a much larger proportion of cyclists rides in the afternoon at recreational locations and so, should it rain only in the afternoon, a large proportion would be caught out. Note that the *AMrain* and *PMrain* rain variables occur in conjunction with the *Rainhrs* variables; for instance, the positive effect of *PMrain* counteracts and reduces the magnitude of the negative effect of *Rainhrs*.

In general, cycle counts at utilitarian locations are more sensitive to weather on weekends than on weekday; the magnitudes of the elasticity of cycle counts with respect to temperature and humidity are greater (Fig. 4b and d). Furthermore, precipitation appears to have a larger negative effect on cycle counts on the weekends than during the week at utilitarian locations (Table 3). This is not true in a few cases, such as for *Rain_hrs1* for Montreal, but this may be due to the smaller amount of data available for the weekend models. The *AMrain* and *PMrain* variables are not significant in the weekend models. As for recreational locations, cycle counts exhibit similar elasticity values across weekends and weekdays. This is likely because recreational locations serve similar trip purposes on both weekends and weekdays, while utilitarian locations generally serve markedly different ones: trips for commuting and other obligatory purposes on weekdays, and trips for more recreational or leisurely purposes on weekends.

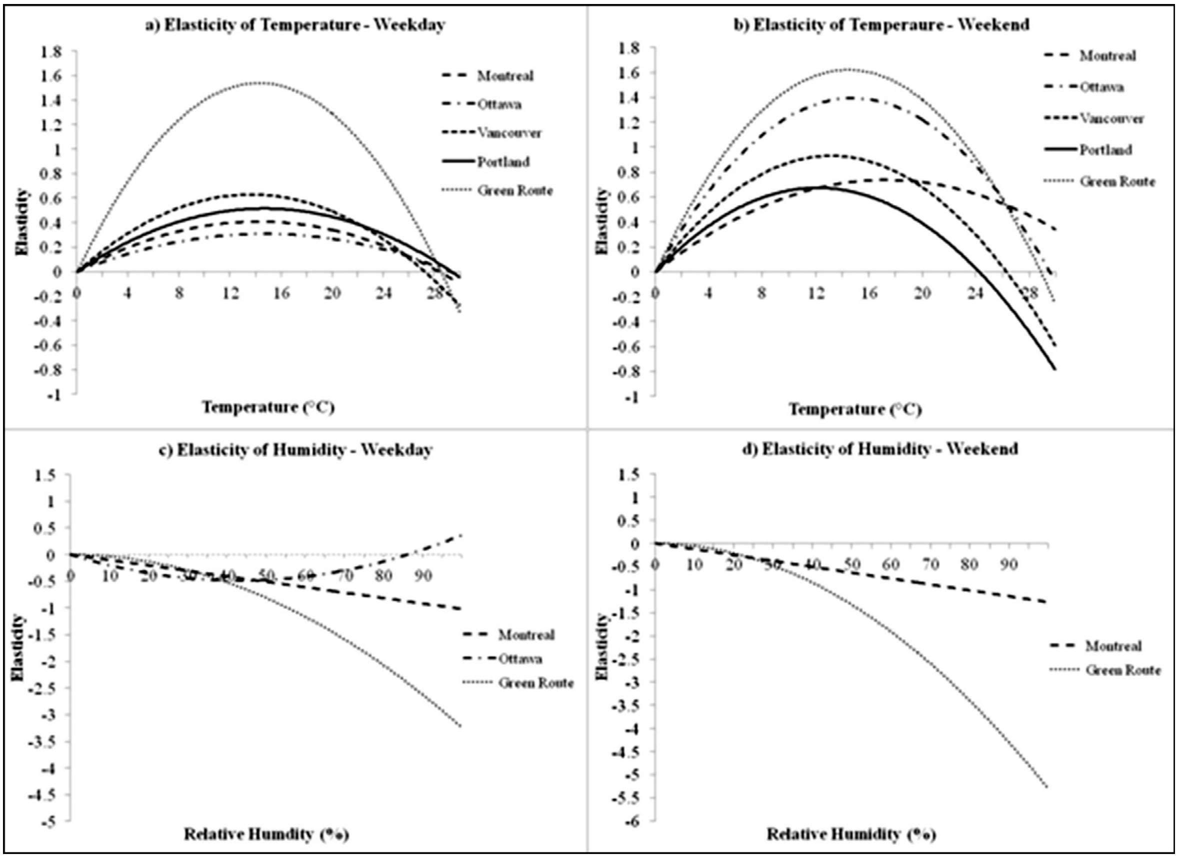

Fig. 4. Elasticity of temperature and humidity – daily models.

5. Discussion

This work found that temperature, humidity, and precipitation, in addition to temporal and location fixed effects, can be used to model hourly and daily bicycle counts. Results obtained at the two data aggression levels are consistent. Though two previous studies have found no or little evidence to support a non-linear effect of temperature (Rose et al., 2011; Tin Tin et al., 2012), it was found here that both temperature and the square of temperature were generally significant. In nearly all cases, this resulted in a positive relationship between cycling and temperature, the magnitude of which at higher temperatures. Humidity was also found to have a significant, non-linear effect on cycle counts for some paths. However, increases in humidity generally result in decreases in cycle counts, and the non-linear effect was less found less consistently than it was for temperature. Previously, only Gallop and Tse (2012) found a significant relationship between cycle counts and humidity.

Precipitation was found to have a negative effect on cycle counts that increases in magnitude with precipitation intensity. This is consistent with all prior literature. However, it was further demonstrated in this work that greater specificity with regards to when rainfall occurred over the course of the day can have a significant effect in models. If rainfall only occurs in the morning or evening, as opposed to throughout the course of day, cycle counts in a given hour or day can be affected differently. Furthermore, cycle counts in a given hour can be affected by rainfall that occurred in a previous hour, as was reported by Gallop and Tse (2012).

Utilitarian locations were shown to be less sensitive to weather conditions than recreational locations, as has been reported in prior research (Brandenburg et al., 2007; Richardson, 2000; Thomas et al.; 2012). Furthermore, this research showed that not only do the magnitudes of precipitation variables differ between the two groups, but the dynamics of the effect can differ as well. For instance, rain in just the morning appears to have a negative effect on cycling in the afternoon at utilitarian locations, presumably because commuter cyclists have already switched modes for the day. However, rain in just the morning can increase cycling in the afternoon on recreational locations, presumably because cyclists delay their departure or exercise until later in the day. Recreational/leisure trips are less constrained by time.

For utilitarian locations, cycle counts on weekends were shown to be more sensitive to weather than cycle counts on weekdays, presumably because trips are more recreational or leisurely in nature on the weekend. This is consistent with the findings of Thomas et al. (2012).

This work confirms that the sensitivity of bicycle flows to weather conditions should be taken into account when collecting bicycle count data to estimate AADB. This is particularly true when data are collected over relatively short periods, such as for manual counts or brief automatic counter installations. For example, if weather conditions happened to be worse than average conditions during a brief data collection period, then an AADB estimated with that count data would under-represent the true AADB. The quality of these models and those presented by others suggests that methods may be developed to model weather and account for weather-related variation when estimating AADB. Furthermore, the effect of weather should be also considered when collecting and studying bicycle travel behavior using survey data methods. For instance, data based on "previous day" surveys, such as origin–destination surveys, will be influenced by the weather conditions of the day for which the survey asks respondents to describe their travel choices. Such data are usually collected at the end of October or beginning of November in Montreal. This means that in addition to the bias introduced by the daily weather conditions, trips could be underestimated due to the seasonal effect (bicycle flows dramatically decline in this period), if they are not adjusted.

This work can lead to the development of methods to estimate changes in bicycle usage due to climate change. Municipalities can estimate how cycling rates would be affected by increases or decreases in average temperature, humidity and rainfall.

In addition to the log-linear models, count data regression models were attempted with and without serial correlation. Time-series models for count data using more complex estimation methods (such as full Bayes and copula modeling) are promising; however, the use of more complex methods is beyond the scope of this paper.

6. Conclusion

This study utilized a rich hourly and daily bicycle count dataset, comprised of data from 10 counting stations, to investigate the temporal patterns and the effect of weather across bicycle facilities in four North American cities – Montreal, Portland, Ottawa and Vancouver – and on a recreational network across Quebec. This represents a considerable expansion of the evidence on the effects of weather on cycling counts in North America. Results were generally in accordance with prior research. However, this work observed non-linear effects of temperature and humidity while prior research was inconclusive or failed to identify such. Furthermore, this work identified the effects of more nuanced representations of precipitation, such as rain in the morning or afternoon, or rain in previous hours. Finally this work confirms limited research regarding the differences between weather's impact on weekday and weekend cycling.

Significant auto-correlation was identified in hourly cyclist count models, and was addressed using regression models with ARMA errors. Correlation in hourly models is a more serious problem than daily models which had considerably less auto-correlation. However, consistent results were obtained in both models. The agreement between the hourly and daily models should serve as some validation for the hourly models.

The results of this research help with the understanding of how the effect of weather varies across cities and types of bicycle facilities. This work highlights the importance of understanding and accounting for the characteristics of bicycle facilities under analysis, and will help to form methodologies to correct bicycle volumes and count data for weather conditions.

In the future, this study will be extended, using the same methodology, to involve more North American cities and to compare them with European cities. Generic models could be developed among cities with relatively similar weather conditions. More data and research are needed to reach more general conclusions. More count data will be incorporated for the same cities. Relative models, which relate deviations from average cycling counts to deviations from average weather conditions, will also be developed. These models will be extended to develop methods for adjusting short-term counts for weather, which is expected to improve AADT estimates.

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