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Weather and cycling: Mining big data to have an in-depth understanding of the association of weather variability with cycling on an off-road trail and an on-road bike lane

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ABSTRACT

Although cycling is an easy and popular form of physical activity and urban travel, barriers exist. In particular, cycling is more likely and more severely to be affected by inclement weather than the motorized modes as the cyclists are entirely exposed to outdoor environment. Understanding the weather-cycling relationship is of great importance to academics and practitioners for cycling activity analysis and promotion. This study contributes to an in-depth understanding of how the changes in weather conditions affect cycling on an off-road trail and an on-road (bridge) bike lane at both daily and hourly scales across four seasons. The paper compares the weather-cycling relationship based on day of week and time of day combinations. The autocorrelation effect of cycling itself and the lagging effect of weather elements are also examined. The findings indicate that cycling is significantly self-dependent especially at the finer temporal scales. Weather have a very different influence on bicycle usage of off-road trails versus on-road bike lanes. When it rains its negative impact not only continues but also significantly affects the cycling within previous one hour. At the daily level, weekend cycling on the trail is less likely to be affected by weather as compared to cycling on the bike lane, whilst inverse is true for weekday cycling. Cycling is most likely to be affected by weather conditions in spring and least likely to be affected in winter. Cycling pattern which is more unrelated to weather at the aggregated level tends to be more flexibly adjusted according to the real-time weather conditions at the disaggregated level. Cyclists on weekends especially during the weekend peak hours (11 AM–4 PM) tend to have more flexibility to adjust their cycling schedule before or after the adverse weather conditions than on weekdays. In addition, cyclists with utilitarian purposes are more likely to shift from cycling to other modes (e.g., transit) due to real-time bad weather conditions in weekdays than in weekends, especially during weekday peak hours (7–9 AM and 4–6 PM). The results provide weather officials, transport agencies and research institutions with valuable information for cycling activity analysis and promotion by considering the effects of weather events especially rainfall.

1. Introduction

In urban transit management and active transport promotion, weather as a major defining factor has received increasing

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attentions (e.g., Burchfield et al., 2012; Guo et al. 2007; Liu et al., 2015a; Miranda-Moreno and Nosal, 2011; Singhal et al., 2014; Thomas et al., 2013). In particular, compared with other travel modes, cycling is more likely and more severely to be affected by weather as the cyclists are entirely exposed to outdoor environment. Although cycling has a number of social and environmental benefits and has enjoyed a continuous boom in cities throughout Europe as well as a remarkable rebirth in some North American and Chinese cities (Pucher et al., 1999; Pucher and Buehler, 2006; Zahabi et al., 2016; Zhao et al., 2014), barriers in bicycle usage and promotion still exist. Previous studies suggested that cyclists are more sensitive to adverse weather conditions than car users and transit passengers (Liu et al., 2015a; Sabir, 2011). As such it is particularly important to understand to what extent and how the changes in weather conditions affect cycling so that the potential reduction in bicycle usage due to bad weather can be ameliorated.

Indeed, a growing number of studies have sought to investigate the impacts of weather on cycling from both survey data analysis and big data mining (e.g., Burchfield et al., 2012; Creemers et al., 2015; Gebhart and Noland, 2014; Liu et al., 2015a, 2015b; Thomas et al., 2013). Findings from survey data analysis indicated that weather could significantly affect travel mode choices on cycling and other modes at the individual level, whilst big data mining exclusively focused on investigating the impacts of various bad weather conditions (e.g., low temperature, strong wind, heavy rainfall, etc.) on bicycle usage at different spatial and temporal levels. These existing studies highlighted the negative influence of inclement weather conditions on cycling and suggested academics and practitioners to address weather as a determinant in affecting cycling is worthwhile.

Although the evidence of weather impacts on cycling is accumulating and strengthening, an in-depth understanding of the relationship between weather and cycling is still one of the major challenges of our time in terms of health and green transport promotion. In particular, at least three research gaps can be identified. First, previous studies utilizing absolute values of big data to examine weather-cycling relationship did not control for the temporal variation of cycling due to non-weather effects, nor did they take into account the autoregressive effect of cycling itself (Burchfield et al., 2012; Gebhart and Noland, 2014). The inherent flaw hinders an accurate understanding of weather impacts on cycling. Second, few, if any, studies have performed time of day models to distinguish peak hours from non-peak hours. Therefore, the weather impacts on cycling with respect to different trip purposes has been rarely explored. Third, although a few studies (Miranda-Moreno and Nosal, 2011; Tao et al., 2018) have examined the lagging effect of rainfall on cycling or transit ridership, no study to our best of knowledge has examined the advance effect of weather conditions on cycling. Furthermore, a close scrutiny of the existing literature reveals that very few studies have explored cycling big data to compare the weather-cycling relationships between off-road trails and on-road bike lanes. Given that people cycling on off-road trails and on-road bike lanes tend to have different cycling characteristics and trip purposes, the influence differences of weather on cycling usage on the two typical cycling facilities are worthwhile to be examined.

This study aims to fill these research gaps and enrich the existing literature through exploring the impacts of weather on cycling on both an off-road trail and an on-road bike lane at both daily and hourly scales across four seasons. To achieve this, we have collected smart counter data for cycling on the Burke-Gilman Trail and the Fremont Bridge in Seattle, Unites States together with the detailed weather meteorological records to form an integrated database. Using an autoregressive model allied with 9-term moving average residual, dozens of regression models were estimated to examine how the weather-cycling relationships vary depending on cycling facilities, seasons, days of week, time of day, and purposes. The finer temporal data at hourly scale also allowed us to understand the advance and lagging effects of some weather events on cycling. Findings from this study will provide weather officials, transport agencies, and research institutions with valuable information for analysis of cycling behavior and promotion of cycling activity by considering the effects of weather elements especially rainfall.

The remainder of this paper is organized as follows. Section 2 provides a literature review on the relationship between weather and cycling. Section 3 introduces the study context and data source. Analytical models are presented in Section 4. Section 5 presents the analysis results and research findings. Finally, Section 6 discussed the findings and concludes the paper with potential directions for future research.

2. Literature review

Given the renaissance of cycling in recent years and the vulnerability of cyclists against inclement weather conditions, a growing number of studies have sought to investigate the weather-cycling relationship (e.g., Burchfield et al., 2012; Creemers et al., 2015; Gebhart and Noland, 2014; Liu et al., 2015a, 2015b; Thomas et al., 2013). According to the data source used for analysis, previous studies examining weather–cycling association could be categorized into two main streams. The first group of studies investigated the self-reported survey data (Creemers et al., 2015; Liu et al., 2015a, 2015b, 2016), and the second stream of studies explored naturalistic cycling data from smart counters or smart cards (Burchfield et al., 2012; Gebhart and Noland, 2014; Miranda-Moreno and Nosal, 2011; Thomas et al., 2013).

2.1. Survey data analysis

Accumulating evidence from survey data analysis indicates that weather related factors have a mild effect on individual travel behavior, and bicycle users are affected by adverse weather conditions more seriously compared to other travelers (Bergström and Magnusson, 2003; Liu et al., 2015a, 2015b; Müller et al., 2008; Sabir, 2011; Winters et al., 2007). As bicycle users are less protected against the bad weather compared to motorized travelers (Liu et al., 2015b), cyclists are more likely to reduce cycling trips due to cold or hot temperature (Ahmed et al., 2012; Richardson, 2000), rainfall (Bergström and Magnusson, 2003; Winters et al., 2007), and strong wind (Aaheim and Hauge, 2005; Flynn et al., 2012).

Previous studies indicated that cyclists' travel behavior vary significantly depending on seasons, especially the cyclists with leisure purposes (Bergström and Magnusson, 2003; Richardson, 2000). A study on the survey of the employees at four major companies in two Swedish cities indicated that bicycle choice decreases by 47% from summer to winter (Bergström and Magnusson, 2003). The analysis on an ongoing household travel survey in Melbourne, Australia indicated that cycling for recreational purposes is influenced by weather more dramatically than for utilitarian purposes such as commuting to work, school or going shopping (Richardson, 2000).

Several existing studies (Liu et al., 2015a, 2015b, 2016) showed that the impacts of weather on bicycle choice not only depend on seasons but also depend on regions and travel purposes. For instance, cyclists in northern Sweden are more aware of temperature variation than cyclists in the central and southern Sweden (Liu et al., 2015a). The impacts of weather on non-commuters are much more significant than on commuters. In addition, rising temperature in a “colder than normal” day encourages non-commuters to ride in warm months, but it is not the case in cold winter (Liu et al., 2015b). These studies provide a solid foundation for analysis of associations of weather and the use of bicycles.

Weather also plays an important role in traveler’s mode choice between bicycle and other modes. Utilizing GIS to disaggregate travel-to-school survey data in Dresden, Germany, Müller et al. (2008) found that the number of cycling trips increase in summer compared to winter at the expense of car and transit trips. In Netherlands, Sabir (2011) found the similar conclusion that part of car and transit trips are replaced by cycling trips during warm weather, whilst travelers tend to switch from cycling to walking and transit in extreme cold weather.

From the perspective of survey data analysis, weather variability acts as an important complement to other conditions (e.g. individual characteristics, travel distance, car availability) in affecting cycling mode choice. The increase in cycling trips and the switch from other modes to cycling can also be verified by the fact that there are more active physical activities in warm or dry weather conditions than in cold or high humidity weather conditions (Chan and Ryan, 2009). In many cases, self-reported survey is difficult and costly to be implemented for a long period of time due to the low response rate (Ma et al., 2013; Zhao et al., 2015). In addition, the impacts of weather elements such as temperature and rainfall on cycling are difficult to be quantitatively estimated from survey data due to small sample. By using the emerging technology of smart counters or cards, the bicycle usage can be recorded automatically (Zhao et al., 2015), which enables us to examine weather-cycling relationship at finer temporal scales to complement the self-reported survey results.

2.2. Big data mining

Compared to survey data analysis, the research efforts on big data mining in terms of the weather influence on bicycle usage is relatively less. One of the plausible reasons is the lack of big data. To investigate the weather-cycling relationship, it is necessary to control for the impacts of day of week or time of day on bicycle usage, and thus large amounts of data are needed within each period of interest. However, automatic data collection for cycling have become available only in recent years with the installation of smart cycling counters and the usage of smart cards. Another reason is that the influence of weather on cycling is more complex than on motorized trips. Cyclists are often directly subject to weather and thus respond more complicatedly to the changes in weather conditions as compared to car users or transit passengers. In addition, different from trips by transit and walking that are generally made for utilitarian and leisure purposes, respectively, cycling can be used for both utilitarian and leisure purposes. Thereby, to analyze the weather-cycling relationship, both direct and indirect effects of trip purposes have to be controlled.

Exploring infrared trail counter data from an urban greenway in Knoxville, United States Burchfield et al. (2012) found that temperature, precipitation and relative humidity are significantly correlated with trail-based cycling and walking travel activities during daylight time. Temperature alone accountes for 18% of the variance in daily trail trips. The amount of variance increases to 42% in more detailed model by including factors related to weather and seasonality. Interestingly, they found that the number of trail trips increase with temperature up to 76 °F (24.4 °C), at which point it begins to slightly decrease. The finding is indirectly consistent with Richardson (2000) who found that cyclists are less likely to ride in very cold or very hot weather. This study, however, is limited to 3 seasons between August 1, 2005 and April 30, 2006, neither separates cycling from walking nor compares the weather-cycling relationships between trails and bike lanes.

In a larger-scale study, Thomas et al. (2013) explored the impacts of weather on daily bicycle flows on 16 cycle paths near two cities in the Netherlands. They found that up to 80% of the variation in cycling demand could be attributed to weather related elements. The detailed multiple regression analysis improves the goodness of model fit. However, the linear regression modeling absolute values of cycling could not control for the temporal variation of cycling due to day of week by season, or other non-weather effects.

Smart card data are also used to analyze the influence of weather on the usage of bicycle (Gebhart and Noland, 2014). The analysis on the smart card data of Capital Bike Sharing indicated that cold temperatures, rain and high humidity reduce the likelihood of shared bicycles’ usage. By modeling the spatial usage features, Gebhart and Noland (2014) also found that trips taken from bike sharing stations proximate to Metro stations are affected more by rain than trips not proximate to Metro stations. Given that Capital Bike Sharing is not used for free, shared bicycles users’ response to weather conditions might be different from the ordinary cyclists due to charging policy of bike sharing. Thus, it is still necessary to explore the more representative bicycle usage data to analyze the weather-cycling relationship.

To sum up, most of the mentioned above studies are conducted either by using traditional survey data with relatively small sample or using the big cycling data have arguably yet to fully explored weather-cycling relationship. There is still lack of evidence on the real-time weather-cycling relationship at a finer hourly temporal scale. The advance and lagging effects of weather on cycling are still need to be fully understood. In addition, given what we know of both bicycle facilities and cycling purposes, it is likely that cycling on different facilities with different purposes may also respond differently to the changes in weather conditions. This study is designed to contribute uniquely and enrich the understanding of how the weather impacts on cycling vary depending by facilities, time, and purposes.

3. Study context and data sources

3.1. Study context

Cycling on the off-road Burke-Gilman Trail and protected bike lanes on the Fremont Bridge in Seattle, United States is the study context. Seattle is the seat of King County, Washington State located on the west coast of the United States. With a land area about 217.3 km^2, and population over 650 thousand, Seattle is the largest city in both the state of Washington and the Pacific Northwest region of North America (U.S. Census Bureau, 2017; Seattle Department of Transportation, 2016).

Seattle is situated in the temperate marine climate region. The winter is cool and wet whilst the summer is sunny, dry and warm (Kottek et al., 2007). In cool winter, the temperature is generally above −7 °C, whereas the warm summer generally has high temperatures averaging 24.5 °C but rarely reaches 32 °C. Whilst winter in Seattle is cold, heavy snow is rare. However, with the average annual precipitation of about 950 mm, the rain is common in this city, especially in fall and winter seasons (the National Oceanic and Atmospheric Administration, NOAA, 2017). Conversely, Seattle goes through some of a lower precipitation in summer.

Whilst the Seattle locates in a hilly area and its climate is changeable, it is impressive that the commute mode share of bicycle in this city was 4% in 2015 (SDOT, 2016). Thanks to the Seattle Bicycle Master Plan (SBMP) and other cycling promotion programs, bicycle volumes continue to climb in recent years (SDOT, 2016, 2017a). The sustained investment efforts on planning, designing, and building bicycle facilities have accommodated and attracted more people to ride bicycles. These bicycle facilities with safe and comfortable separation from motor vehicle include off-road trails, protected bicycle lanes, and neighborhood greenways, which nurture the Seattle's bicycle in a manner that purposefully benefit the city's livability, affordability, public health, economic competitiveness, and natural environment (SDOT, 2017a).

3.2. Cycling data

Since the late 2012, SDOT strategically installed automated bicycle counters to evaluate bicycle usage and the effects of weather and other factors on cycling. Using wires in a diamond formation in the concrete, the smart counters are very accurate in counting bicycle usage on cycling facilities (SDOT, 2017a). These counts show both hourly and daily cycling patterns on typical facilities such as off-road trails and on-road bike lanes.

From this big dataset, we selected hourly cycling data from January, 1 2014 to December 31, 2014 for two popularly used and representative cycling facilities of Burke-Gilman Trail and Fremont Bridge for analysis (SDOT, 2017b). Fig. 1 presents some key information about the two cycling facilities, including their locations, landscapes, daily cycling statistic, and the average value of daily cycling by days of week in 2014. As can be seen, the two facilities represent two entirely different cycling patterns of leisure (Burke-Gilman Trail) and utilitarian (Fremont Bridge). The bike lanes on Fremont Bridge are used more heavily by cyclists on weekdays than on weekends for utilitarian purpose such as working, schooling or shopping, whilst the Burke-Gilman Trail is used more popularly used by residents on weekends than on weekdays for recreational purposes such as outdoor physical activity or exercise.

3.3. Weather data

The 2014 weather data for Seattle were obtained from three sources: (1) the National Oceanic and Atmospheric Administration (NOAA), (2) the World Weather Online (WWO), and (3) Weather Underground. The three data sources, especially the NOAA and Weather Underground, have been extensively used by researchers for examining the impacts of weather on cycling or transit ridership (Burchfield et al., 2012; Gebhart and Noland, 2014; Singhal et al., 2014).

Whilst NOAA is believed to be more reliable for providing weather information, the weather dataset we downloaded from its official website only contains weather events of daily maximum temperature, minimum temperature and precipitation. WWO provides other daily weather events such as humidity and wind speed. The daily weather information provided by NOAA and WWO are highly consistent as the Pearson correlation coefficient of the maximum temperature provided by the two data sources is as high as 0.950. The hourly weather events of temperature, precipitation, humidity and wind speed could be acquired from the Weather Underground.

NOAA records Seattle's weather at Seattle–Tacoma International Airport and is assumed to be representative of weather conditions across the city. We could not get the weather station information from WWO. For hourly weather information acquired from Weather Underground, we used the weather data recorded by the weather station of Phinney Ridge in Seattle (see Fig. 1). This station is about 1.8 km from Fremont Bridge and 7.1 km from Burke-Gilman Trail. Thus, the weather recorded by this station is suitable to be representative of the weather conditions around both Burke-Gilman Trail and Fremont Bridge. The weather data were then allied with cycling data to form an integrated database for the daily and hourly weather-cycling relationship analysis by employing an autoregressive model integrated with 9-term moving average residual.

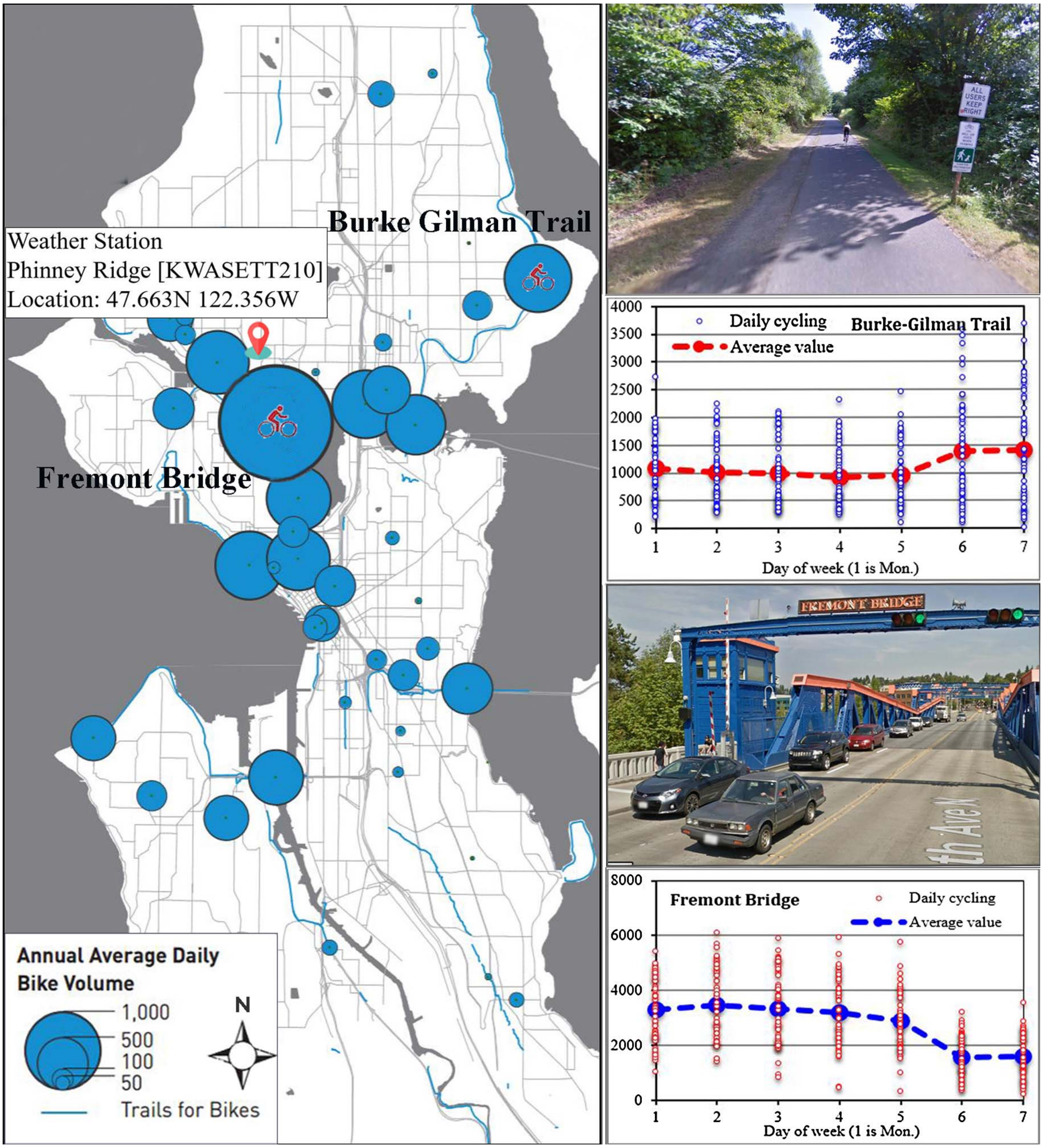

Fig. 1. Outline of the study context for Burke-Gilman Trail and Fremont Bridge.
Sources: SDOT (2014, 2017b), redraw by the authors.

4. Methodology

This section first defines the dependent variable and independent variables used in this study. We then introduce the model used in this study, which combines the 9-term moving average residual with autoregressive model.

4.1. Dependent variable

To control the inherent time series variations of cycling by day of week, time of day and other non-weather effects, the percentage difference between the actual daily/hourly cycling during a particular day/hour and the 9-term moving average for that day/hour is defined as the dependent variable. The readers are encouraged to refer to Kalstein et al. (2009) for details regarding why 9-term moving average residual and percentage terms are chosen. The 9-term moving average residual cycling is defined by the following

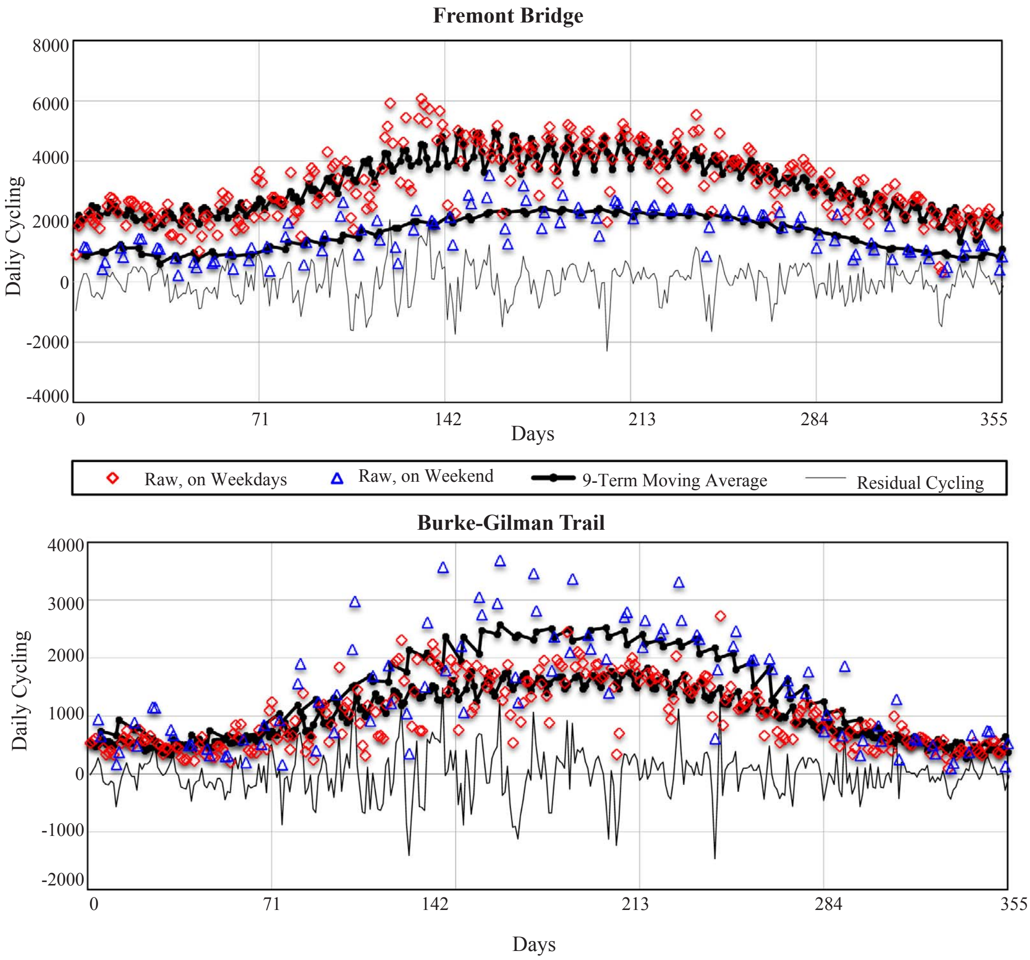

Fig. 2. Daily raw, 9-term average, and residual cycling on Fremont Bridge and Burke-Gilman Trail in 2014 (10 federal holidays were excluded for analysis).

equation:

$$\Delta C_t = \frac{C_t - \overline{C}_t^{\mathrm{MA}\pm4}}{\overline{C}_t^{\mathrm{MA}\pm4}} \tag{1}$$

with

$$\overline{C}_t^{\mathrm{MA}\pm4} = \frac{\sum_{\tau=-4}^{4} C_{t+7\tau}}{9} \tag{2}$$

where ΔC_t is cycling residuals at daily level or hourly level; the C_t represents cycling during a particular day t or hour t; $\overline{C}_t^{MA\pm4}$ is the 9-term moving average value for the day t or hour t; The index τ represents weeks, $(t + 7\tau)$ goes from 28 days before to 28 days after, by sevens.

Fig. 2 shows the time series for daily raw cycling, 9-term moving average, and residual cycling on Fremont Bridge and Burke-Gilman Trail of year 2014 (10 federal holidays were excluded for analysis). For demonstration purpose, the residual cycling is shown in absolute value rather than percentage terms. It can be seen that on Fremont Bridge, cycling on weekdays is more than on weekends, whereas the weekday cycling on Burke-Gilman Trail is generally less than weekend cycling. The absolute residual cycling during the warm summer is higher than it is during cold winter, but the variation would be less evident in percentage terms, as the absolute cycling is also higher in warm summer than in cold winter.

Fig. 3 shows the hourly raw cycling, 9-term average, and residual cycling in absolute value for weekdays, Saturday, and Sunday during one-week period (Sep. 29–Oct. 5, 2014). On both Fremont Bridge and Burke-Gilman Trail, weekday cycling demonstrates a double-peak nature (7–9 AM and 4–6 PM) whilst weekend cycling shows a single-peak property (11 AM–4 PM). In addition, the utilitarian use pattern of cycling on Fremont Bridge is more obvious than on Burke-Gilman Trail, as its weekday double-peak are more pointed. However, compared to Fremont Bridge, Burke-Gilman Trail is more heavily used for leisure purposes, especially on weekends. The distinctly different cycling patterns on the two cycling facilities enable us to examine how weather-cycling

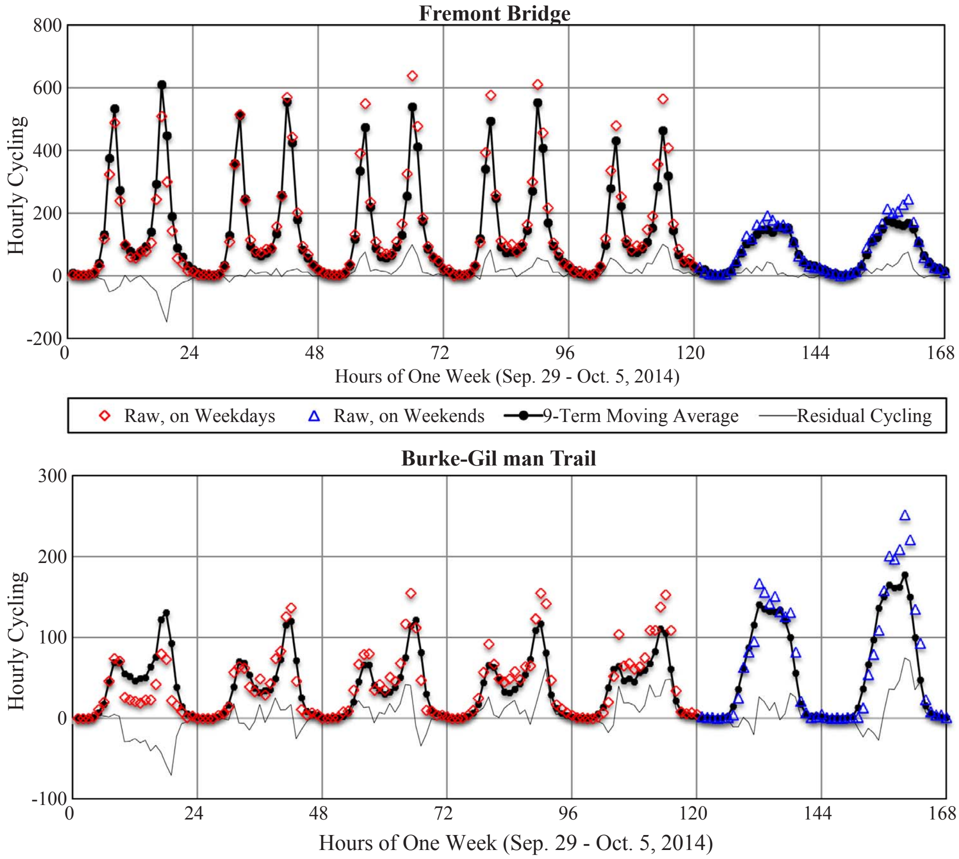

Fig. 3. Hourly raw, 9-term moving average, and residual cycling over days of one week (between Sep. 29 and Oct. 5, 2014).

relationships vary depending on trip purposes. In addition, the hourly cycling patterns over days of week in Seattle compared with that in Nanjing, China indicate that the major cycling activities on weekends in Untied States are made for leisure purpose whilst some people in China still have to bike for utilitarian purposes on weekends (Zhao et al., 2015).

4.2. Independent variables

Similar to the time series cycling, some weather variables have inherent time series variations resulted from diurnal cycles, especially the temperature, humidity and wind speed, whilst rain and snow are relatively independent from day of week and time of day. To control the temporal variation of temperature, humidity and wind speed, the residual weather equation is formulated as:

$$\Delta W_t = \frac{W_t - \overline{W}_t^{\mathrm{MA}\pm 4}}{\overline{W}_t^{\mathrm{MA}\pm 4}} \tag{3}$$

with

$$\overline{W}_t^{\mathrm{MA}\pm 4} = \frac{\sum_{\tau=-4}^{4} W_{t+7\tau}}{9} \tag{4}$$

where ΔW_t is the residual weather conditions of temperature, humidity and wind speed; W_t is the observed weather conditions at a particular day t or hour t; $\overline{W}_t^{\mathrm{MA}\pm 4}$ is the 9-term moving average for day t or hour t.

To distinguish the weather elements of rainfall and snowfall, three dummy variables are defined: rainfall, heavy rainfall, and snowfall. For daily and hourly models, rain precipitation exceeding 1.0 in./d and 0.2 in./h are considered as heavy rainfall at the daily level and hourly level in this study, respectively. Otherwise, the rainfall would be recorded as light rainfall. For dummy snow variable, only two snowing days in 2014 were recorded. Thus, the two days and each hour slot during that two days are defined as snowfall. In addition, for daily models, wind speed is represented by the average value, whilst the wind speed is represented by the highest value observed during a given hour for hourly models (Singhal et al., 2014).

4.3. Autoregressive model

Whilst the 9-term moving average residual performs well in controlling for cycling fluctuation associated with non-weather reasons, the residual itself still demonstrates a time series nature as shown by Figs. 2 and 3. That is, cycling in a day or an hour tend to be associated with cycling in the previous day or hour. Failing to take the temporal autocorrelation or such self-dependency into account is likely to generate biased estimations concerning the effects of weather on cycling. In addition, cycling may not only vary with the concurrent weather conditions, but also the previous weather conditions (Miranda-Moreno and Nosal, 2011; Tao et al., 2018). To verify these hypotheses, the analytical model used in this study takes the general form of:

$$\Delta C_t = \beta_0 + \beta_1 \Delta C_{t-1} + \beta_2 \Delta T_t + \beta_3 \Delta H_t + \beta_4 \Delta W_t + \beta_5 Rain_t + \beta_6 Rain_{t-n} + \beta_7 Heavy\ rain_t + \beta_8 Heavy\ rain_{t-n} + \beta_9 Snow_t + \beta_{10} Snow_{t-n} \tag{5}$$

where ΔC_t denotes cycling residuals in day t or at hour t; ΔC_{t-1} is the cycling residuals in day $t-1$ or at hour $t-1$; ΔT_t, ΔH_t and ΔW_t are the daily/hourly residuals of temperature, relative humidity and wind speed, respectively; $Rain_t$, $Heavy\ rain_t$ and $Snow_t$ denote rainfall, heavy rainfall and snowfall indicators at concurrent time t, respectively; $Rain_{t-n}$, $Heavy\ rain_{t-n}$, and $Snow_{t-n}$ indicate the corresponding weather conditions n day(s)/hour(s) earlier.

Daily and hourly models are developed for estimation of cycling at different time periods including all days, weekdays only, weekends only, and four seasons. Ten days of federal holidays in 2014 are excluded for analysis (OPM, 2014), when cycling activity is impacted by major events unrelated to the weather. In addition, hourly models are developed at finer temporal scale that considers the peak hours (7–9 AM and 4–6 PM for weekdays, and 11 AM–4 PM for weekends) and non-peak hours of weekdays and weekends, respectively. We exclude the data collected between 9 PM and 6 AM of the following day for hourly analysis due to many zero cycling observations are recorded during this period as Fig. 3 shows. Thus, the sample size for daily and hourly models are 355 days and 5325 h, respectively. Furthermore, for seasonal analysis, the December, January and February are defined as winter season. March through May is defined as the spring. The summer season extends from June to August, and September through November is defined as the fall season.

5. Results

5.1. Descriptive statistics

Table 1 lists the descriptive statistics of daily and hourly cycling on Burke-Gilman Trail and Fremont Bridge by seasonality and day of week. For seasonal variation of daily cycling, average daily cycling on Burke-Gilman Trail and Fremont Bridge in summer are 3.7 times and 2.1 times of the average daily cycling in winter, respectively. As for variation of daily cycling due to day of week, the average weekend cycling on Burke-Gilman Trail is 1.4 times of the average weekday cycling, whilst the average daily cycling on Fremont Bridge Trail on weekdays is 2.1 times of it is on weekends. These results are reasonable as the Burke-Gilman Trail and Fremont Bridge are mainly used for leisure and utilitarian purposes, respectively. The hourly statistics reveal similar results with daily statistics. The cycling patterns varied by facilities, seasonality and day of week motivate the current study to model weather-cycling association at more disaggregated levels considering seasonality and day of week.

Fig. 4 compares the average daily cycling on weekdays and weekends on Fremont Bridge and Burke-Gilman Trail under different

Table 1
Descriptive statistics by seasonality and day of week.

Daily Statistics	Burke-Gilman Trail				Fremont Bridge				No. of records
	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	
Spring	160	3573	1203.6	695.2	375	6088	2930.8	1457.9	91
Summer	341	3688	**1811.8**	616.5	859	5551	**3744.9**	1144.8	91
Fall	100	2469	892.6	495.3	324	4940	2629.1	1060.9	87
Winter	15	1152	485.5	202.0	221	2960	1757.4	698.1	86
Weekdays	100	2316	991.0	558.4	324	6088	**3284.7**	1179.6	251
Weekends	15	3688	**1394.9**	963.3	221	3547	1566.3	770.6	104
Overall	15	3688	1109.3	724.0	221	6088	2781.3	1330.0	355
Hourly Statistics	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	No. of records
Spring	0	735	78.1	72.3	4	946	184.1	163.4	1365
Summer	0	571	**117.1**	75.8	10	877	**232.6**	168.7	1365
Fall	0	303	57.8	51.3	3	778	164.9	142.8	1305
Winter	0	209	31.2	26.9	2	451	110.2	90.1	1290
Weekdays	0	565	63.4	51.5	8	946	**206.2**	164.2	3765
Weekends	0	735	**91.8**	93.7	2	432	95.9	70.1	1560
Overall	0	735	71.8	67.9	2	946	173.9	151.7	5325

Abbreviations: SD, Standard deviation.
Note: Bold numbers denote the maximums of mean for seasons or day of week, whilst shaded numbers denote the minimums of mean.

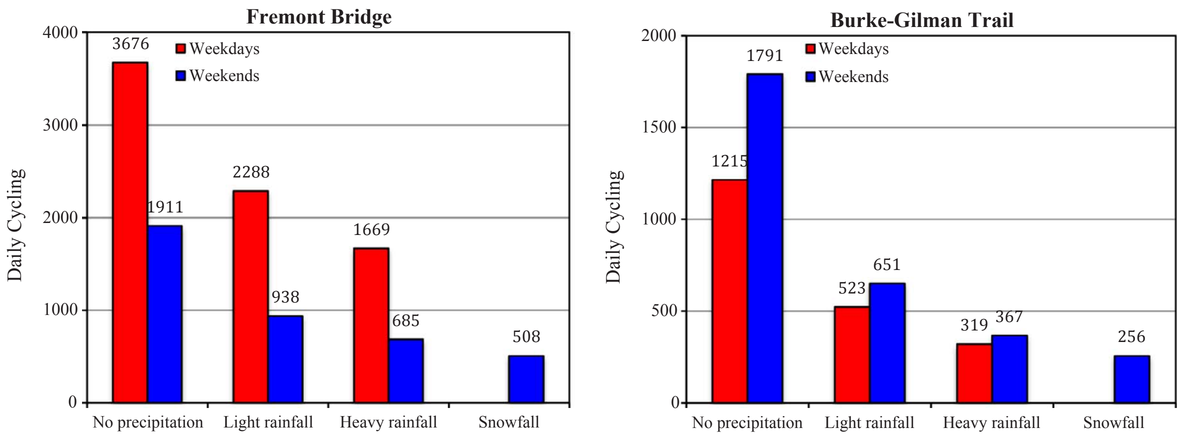

Fig. 4. Average daily cycling on Fremont Bridge and Burke-Gilman Trail categorized by dry, light rainfall, heavy rainfall, and snowfall weather conditions.

weather conditions of no rainfall, light rainfall, heavy rainfall and snowfall. As can be seen, rainfall and snowfall have significantly negative impacts on cycling on both Fremont Bridge and Burke-Gilman Trail in both weekdays and weekends. For instance, the average daily cycling on Fremont Bridge in weekdays with no precipitation is 1.6 times and 2.2 times of it is with light rainfall and heavy rainfall, respectively. These figures could be compared to the counterparts of 2.0 times and 2.8 times for weekend statistics for Fremont Bridge. Daily cycling on Burke-Gilman Trail is more severely affected by rainfall than on Fremont Bridge, as the average daily cycling on Burke-Gilman Trail in weekends with precipitation is 2.7 times and 4.8 times as it is under light rainfall and heavy rainfall, respectively. The most severe impact on cycling is observed from snowfall. Coupled with cold temperature in winter, daily cycling on Fremont Bridge and Burke-Gilman Trail in snow is only about one quarter and one seventh as it is under dry weather conditions, respectively.

Fig. 5 shows the temporal distribution of average hourly cycling across 24 h, comparing the average hourly cycling between dry and rainfall conditions (as heavy rainfall and snowfall is rare and not observed in some hours, average hourly cycling under the two weather conditions is integrated with light rainfall as the 'rainfall' condition). The average hourly cycling in weekdays and weekends on Fremont Bridge during rainy hours is 58% and 47% as it is during dry hours, respectively, compared to the counterparts (42% and 33%) on Burke-Gilman Trail.

5.2. Co-linearity diagnostics

Prior to regressions analysis, the degree of co-linearity among weather variables has to be examined. If the degree of co-linearity is high, the joint effect of different weather elements such as the physiologically equivalent temperature or the universal thermal climate index would be better in reflecting weather-cycling relationship (Creemers et al., 2015). Table 2 reports the level of co-linearity measured by Eigenvalue, Condition Index, and Variance Proportions, taking residual cycling on Burke-Gilman Trail in all days of 2014 as the dependent variable. Serious co-linearity exists among variables if the eigenvalue approaches 0, or the condition index exceeds 10, or the variance proportions approaches 1. As can be seen, all co-linearity diagnostics are well below the thresholds. Thus, the effects of weather indicators on number of cycling are independent and could be included into the regression models.

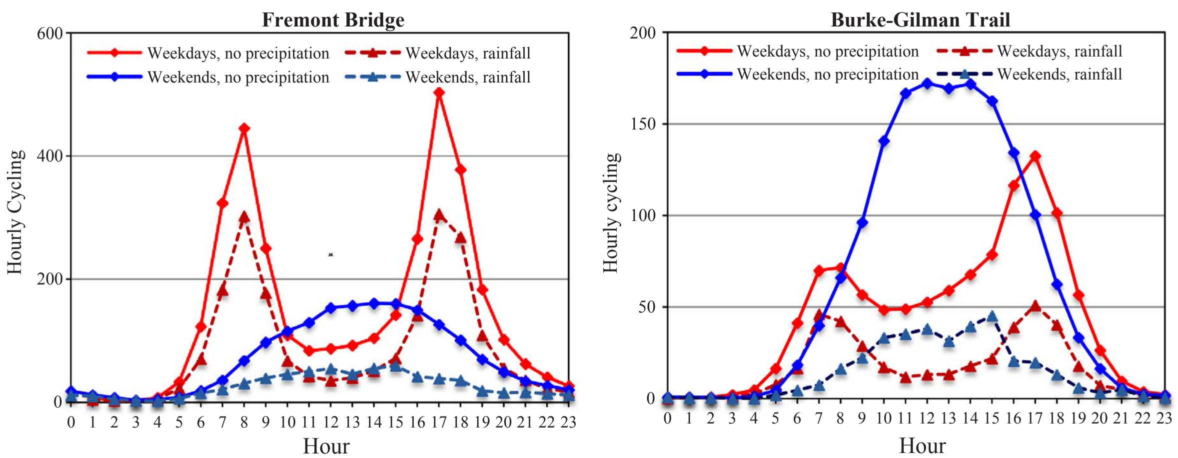

Fig. 5. Temporal distribution of average hourly cycling across 24 h.

Table 2
Co-linearity diagnostics.

Dimension	Eigenvalue	Condition Index	Variance proportions[a]						
			(Constant)	ΔT	ΔH	ΔW	*Rain*	*Heavy rain*	*Snow*
1	1.865	1.000	0.01	0.06	0.11	0.11	0.05	0.03	0.01
1	1.530	1.000	0.14	0.00	0.11	0.00	0.22	0.09	0.01
2	1.563	1.092	0.17	0.07	0.02	0.01	0.10	0.00	0.06
2	1.131	1.163	0.12	0.00	0.18	0.40	0.00	0.00	0.13
3	0.992	1.371	0.00	0.00	0.01	0.00	0.05	0.79	0.02
3	1.011	1.230	0.03	0.59	0.05	0.00	0.00	0.02	0.28
4	0.963	1.391	0.07	0.02	0.03	0.05	0.00	0.02	0.74
4	0.984	1.247	0.03	0.39	0.08	0.00	0.00	0.12	0.37
5	0.770	1.556	0.04	0.59	0.00	0.27	0.00	0.00	0.16
5	0.937	1.277	0.19	0.01	0.10	0.20	0.03	0.45	0.00
6	0.536	1.865	0.01	0.21	0.64	0.46	0.00	0.03	0.02
6	0.850	1.341	0.01	0.00	0.12	0.39	0.09	0.32	0.19
7	0.310	2.454	0.71	0.04	0.19	0.11	0.79	0.14	0.00
7	0.557	1.658	0.47	0.00	0.36	0.00	0.66	0.01	0.01

Note 1: Numbers without shade denote the co-linearity diagnostics for daily weather elements, and the shaded numbers denote co-linearity diagnostics for hourly weather elements.
Note 2: Co-linearity exists among variables if the eigenvalue approaches 0, or the condition index exceeds 10, or the variance proportions approaches 1.
[a] Dependent variable: Residual cycling on Burke-Gilman Trail in 355 days.

5.3. Model comparisons

We then compared the model performance by considering the autocorrelation effect of cycling itself and the lagging effects of rainfall and snowfall. The estimated models for cycling on both Burke-Gilman Trail and Fremont Bridge are presented in Table 3. In

Table 3
Comparison of modeling results.

Comparison of modeling results.

	Daily Model				Hourly Model					
	Model 1		Model 2 ($n = 1$)[a]		Model 3		Model 4 ($n = 1$)[b]		Model 5 ($n = 2$)[c]	
	β	t	β	t	β	t	β	t	β	t
Intercept	0.057	3.610	0.036	1.978	0.056	6.234	0.022	3.921	0.019	3.333
	(0.049)	(4.326)	(0.037)	(2.853)	(0.054)	(7.386)	(0.015)	(3.333)	(0.015)	(3.402)
ΔC_{t-1}	/[d]	/	0.149	3.321	/	/	0.781	92.578	0.782	92.83
	/	/	(0.244)	(5.321)	/	/	(0.806)	(100.25)	(0.805)	(100.206)
ΔT	0.546	11.967	0.493	10.128	0.021	3.488	~~0.003~~	~~0.901~~	~~0.003~~	~~0.894~~
	(0.349)	(10.699)	(0.282)	(8.298)	~~(0.006)~~	~~(1.261)~~	~~(-0.001)~~	~~(-0.495)~~	~~(-0.001)~~	~~(-0.486)~~
ΔH	-0.627	-7.257	-0.580	-6.187	-0.959	-18.701	-0.181	-5.495	-0.193	-5.874
	(-0.432)	(-6.983)	(-0.338)	(-5.182)	(-0.805)	(-19.087)	(-0.144)	(-5.555)	(-0.144)	(-5.610)
ΔW	-0.316	-8.059	-0.288	-7.527	-0.062	-5.116	~~-0.007~~	~~-0.958~~	~~-0.009~~	~~-1.170~~
	(-0.204)	(-7.258)	(-0.173)	(-6.223)	(0.031)	(3.071)	(0.014)	(2.331)	(0.014)	(2.298)
$Rain$	-0.216	-7.158	-0.185	-5.721	-0.273	-9.515	-0.130	-7.148	-0.120	-6.684
	(-0.149)	(-6.898)	(-0.133)	(-5.859)	(-0.159)	(-6.761)	(-0.071)	(-4.970)	(-0.066)	(-4.668)
$Rain_{t-n}$	/	/	0.102	2.494	/	/	-0.060	-2.194	~~-0.016~~	~~-0.601~~
	/	/	(0.054)	(1.879)	/	/	~~(-0.004)~~	~~(-0.178)~~	~~(-0.002)~~	~~(-0.080)~~
$Heavy\ rain$	-0.402	-4.718	-0.435	-5.145	-0.456	-7.081	-0.170	-4.197	-0.168	-4.114
	(-0.345)	(-5.669)	(-0.372)	(-6.292)	(-0.315)	(-5.893)	(-0.116)	(-3.663)	(-0.106)	(-3.333)
$Heavy\ rain_{t-n}$	/	/	~~0.009~~	~~0.105~~	/	/	-0.103	-1.914	~~-0.016~~	~~-0.301~~
	/	/	~~(0.042)~~	~~(0.696)~~	/	/	~~(-0.073)~~	~~(-1.035)~~	~~(-0.004)~~	~~(-0.088)~~
$Snow$	-0.353	-2.134	-0.367	-2.236	~~-0.150~~	~~-1.347~~	~~-0.043~~	~~-0.630~~	~~-0.041~~	~~-0.601~~
	(-0.284)	(-2.404)	(-0.282)	(-2.454)	(-0.535)	(-5.855)	(-0.125)	(-2.321)	(-0.127)	(2.203)
$Snow_{t-n}$	/	/	~~0.028~~	~~0.120~~	/	/	~~0.054~~	~~0.145~~	~~0.157~~	~~0.418~~
	/	/	~~(0.139)~~	~~(0.859)~~	/	/	~~(0.859)~~	~~(0.926)~~	~~(0.427)~~	~~(0.860)~~
No. of records	355				5325		5325			
R^2	0.574		0.589		0.124		0.667		0.666	
	(0.549)		(0.583)		(0.108)		(0.692)		(0.691)	
Adjusted R^2	0.566		0.577		0.123		0.667		0.666	
	(0.541)		(0.571)		(0.107)		(0.692)		(0.691)	
Model F	78.03		49.37		125.37		1064.959		1059.98	
	(70.52)		(48.16)		(107.75)		(1196.63)		(1192.86)	

[a] The effects of rainfall and snowfall lag for 1 day.
[b] The effects of rainfall and snowfall lag for 1 hour.
[c] The effects of rainfall and snowfall lag for 2 hours.
[d] "/" indicates the variable is not included into estimation.
Note: Numbers in parentheses are estimated for cycling on Fremont Bridge. ~~Numbers~~ indicate a significance level of less than 90%.

this table, Model 1 and Model 2 are estimated without and with considering daily cycling autocorrelation and the lagging weather effects by one day, respectively. Model 3 is estimated hourly cycling without considering any effect, and Model 4 and Model 5 are estimated by examining the lagging weather effects for one hour and two hours, respectively.

The model comparisons confirm that in addition to concurrent weather conditions, the cycling autoregressive effect and the lagging weather effect also significantly affect the cycling activities, and especially at the hourly level. Interestingly, the lagging effect of rainfall on daily cycling is estimated with a significantly positive sign for both Burke-Gilman Trail and Fremont Bridge. A plausible reason is that daily cycling in Seattle tends to increase in a dry day after a few rainy days, especially considering the fact that Seattle is characterized by frequently rainy days especially in winter. Whilst the lagging effect of heavy rainfall and snowfall on daily cycling is not estimated to significant, this could mainly due to the small sample rather than the insignificantly lagging effect of heavy rainfall or snowfall itself.

As for the estimated models for hourly cycling, the estimated R-square for Burke-Gilman Trail and Fremont Bridge increase significantly from 0.124 and 0.108 to 0.667 and 0.692, respectively by including the cycling autoregressive effect and lagging weather effect. This result indicates that hourly cycling has a higher autocorrelation compared to daily cycling. Whilst the autocorrelation dilutes the impacts of weather elements on hourly cycling, the lagging rainfall effect on cycling on Burke-Gilman Trail is still significant within one hour yet becomes absent for a loner time. In addition, the lagging effect of rainfall on hourly cycling on Fremont Bridge is insignificant when considering the hourly cycling autoregressive effect at the same time. Due to the better estimation performance, Model 2 and Model 4 in Table 3 would be used to examine the impacts of weather variability on cycling at daily level and hourly level, respectively.

By incorporating the hourly cycling autocorrelation, the Model 4 in Table 3 improves the models' goodness of fit significantly. However, the strong autocorrelation may hinder an in-depth understanding of the advance and lagging weather effects on cycling. Thus, before utilizing Model 4 to investigate hourly weather-cycling relationship, several models are estimated to evaluate the advance and lagging effects of weather conditions on cycling. Table 4 shows to what extent the advance and lagging rainfall affect the cycling. As can be seen, when it rains its negative impact not only continues but also significantly affects cycling within previous 1 h. As 95% of cyclists could finish their cycling trips within half an hour (Zhao et al., 2015), the concurrent rainfall does not show a significantly negative impact on cycling of previous two hours. The significantly negative impact of rainfall on cycling on Fremont Bridge could last for at least 3 h, a finding consistent with Miranda-Moreno and Nosal (2011), and its significantly negative impact on cycling on Burke-Gilman Trail tends to last for a longer time.

5.4. Daily estimation results

After comparing the model performance and examining the advance and lagging effects of rainfall on cycling, Model 2 in Table 3 is used to explore the weather-cycling relationship at the daily level. The results are reported in Table 5. Both the F statistics and goodness-of-fit of R-square demonstrate that all estimated models are statistically significant. The estimated weekday models explain

Table 4
Advance effect and lagging effect of rainfall on hourly cycling.

Advance effect and lagging effect of rainfall on hourly cycling.

	Advance Effect				Lagging Effect							
	$n=-1$		$n=-2$		$n=2$		$n=3$		$n=4$		$n=5$	
	β	t	β	t	β	t	β	t	β	t	β	t
Intercept	0.062	6.750	0.057	6.276	0.061	6.750	0.061	6.707	0.060	6.558	0.057	6.243
	(0.058)	(7.689)	(0.055)	(7.393)	(0.057)	(7.677)	(0.057)	(7.627)	(0.056)	(7.521)	(0.056)	(7.460)
ΔT	0.021	3.493	0.021	3.478	0.021	3.504	0.021	3.499	0.021	3.495	0.021	3.488
	~~(0.006)~~	~~(1.269)~~	~~(0.006)~~	~~(1.257)~~	~~(0.006)~~	~~(1.271)~~	~~(0.006)~~	~~(1.266)~~	~~(0.006)~~	~~(1.262)~~	~~(0.006)~~	~~(1.260)~~
ΔH	-0.938	-18.13	-0.956	-18.58	-0.942	-18.30	-0.943	-18.31	-0.949	-18.45	-0.957	-18.63
	(-0.792)	(-18.61)	(-0.802)	(-18.97)	(-0.796)	(-18.79)	(-0.796)	(-18.80)	(-0.800)	(-18.91)	(-0.802)	(-19.00)
ΔW	-0.061	-5.007	-0.062	-5.122	-0.059	-4.833	-0.059	-4.867	-0.060	-4.931	-0.062	-5.068
	(0.031)	(3.150)	(0.031)	(3.070)	(0.032)	(3.251)	(0.032)	(3.220)	(0.032)	(3.186)	(0.031)	(3.140)
$Rain$	-0.282	-9.791	-0.271	-9.430	-0.262	-9.068	-0.267	-9.302	-0.279	-9.679	-0.273	-9.501
	(-0.165)	(-6.963)	(-0.158)	(-6.694)	(-0.153)	(-6.407)	(-0.157)	(-6.626)	(-0.163)	(-6.877)	(-0.160)	(-6.783)
$Rain_{t-n}$	-0.117	-2.689	~~-0.024~~	~~-0.565~~	-0.144	-3.247	-0.142	-3.206	-0.117	-2.196	~~-0.038~~	~~-0.723~~
	(-0.071)	(-1.975)	~~(-0.020)~~	~~(-0.574)~~	(-0.075)	(-2.074)	(-0.074)	(-2.030)	~~(-0.065)~~	~~(-1.476)~~	~~(-0.055)~~	~~(-1.269)~~
$Heavy\ rain$	-0.465	-7.157	-0.456	-7.023	-0.448	-6.815	-0.460	-7.056	-0.461	-7.094	-0.457	-7.031
	(-0.320)	(-5.992)	(-0.315)	(-5.892)	(-0.311)	(-5.741)	(-0.320)	(-5.963)	(-0.317)	(-5.936)	(-0.316)	(-5.919)
$Heavy\ rain_{t-n}$	-0.486	-1.797	~~-0.362~~	~~-1.338~~	~~-0.125~~	~~-1.446~~	~~-0.089~~	~~-0.507~~	~~-0.140~~	~~-0.729~~	~~0.084~~	~~0.437~~
	~~(-0.315)~~	~~(-1.417)~~	~~(-0.153)~~	~~(-0.687)~~	~~(-0.098)~~	~~(-1.378)~~	~~(-0.028)~~	~~(-0.194)~~	~~(-0.021)~~	~~(-0.102)~~	~~(0.093)~~	~~(0.593)~~
$Snow$	~~-0.152~~	~~-1.368~~	~~-0.151~~	~~-1.356~~	~~-0.157~~	~~-1.411~~	~~-0.156~~	~~-1.401~~	~~-0.152~~	~~-1.371~~	~~-0.150~~	~~-1.354~~
	(-0.536)	(-5.872)	(-0.536)	(-5.861)	(-0.539)	(-5.900)	(-0.538)	(-5.889)	(-0.536)	(-5.867)	(-0.536)	(-5.865)
$Snow_{t-n}$	~~-0.189~~	~~-0.312~~	~~-0.373~~	~~-0.616~~	~~0.048~~	~~0.079~~	~~0.060~~	~~0.099~~	~~0.166~~	~~0.275~~	~~-0.256~~	~~-0.423~~
	~~(-0.002)~~	~~(-0.003)~~	~~(-0.135)~~	~~(-0.271)~~	~~(0.298)~~	~~(0.595)~~	~~(0.307)~~	~~(0.615)~~	~~(0.355)~~	~~(0.713)~~	~~(0.114)~~	~~(0.230)~~
R^2	0.126		0.124		0.126		0.126		0.125		0.124	
	(0.109)		(0.109)		(0.109)		(0.109)		(0.109)		(0.109)	
Adjusted R^2	0.124		0.123		0.124		0.124		0.123		0.123	
	(0.108)		(0.107)		(0.108)		(0.108)		(0.107)		(0.107)	
Model F	84.85		83.85		85.10		84.87		84.21		83.64	
	(72.52)		(71.90)		(72.59)		(72.35)		(72.12)		(72.04)	

Note: Numbers in parentheses are estimated for cycling on Fremont Bridge. ~~Numbers~~ indicate a significance level of less than 90%.

Table 5
Daily cycling estimation results for weekdays and weekends.
Daily cycling estimation results for weekdays and weekends.

	Weekday Model				Weekend Model			
	Burke-Gilman Trail		Fremont Bridge		Burke-Gilman Trail		Fremont Bridge	
	β	t	β	t	β	t	β	t
Intercept	~~0.025~~	~~1.488~~	0.036	3.041	~~0.065~~	~~1.307~~	~~0.044~~	~~1.248~~
ΔC_{t-1}	0.077	1.684	0.176	3.796	0.282	2.671	0.318	3.014
ΔT	0.517	11.231	0.267	8.628	0.434	3.168	0.333	3.321
ΔH	-0.628	-6.845	-0.321	-5.168	-0.530	-2.297	-0.402	-2.445
ΔW	-0.308	-8.015	-0.165	-6.23	-0.197	-1.951	-0.167	-2.358
$Rain$	-0.160	-5.341	-0.121	-5.884	-0.256	-2.907	-0.171	-2.735
$Rain_{t-1}$	0.116	2.747	~~0.037~~	~~1.277~~	~~0.066~~	~~0.684~~	~~0.073~~	~~1.063~~
$Heavy\ rain$	-0.443	-4.756	-0.359	-5.614	-0.471	-2.700	-0.404	-3.271
$Heavy\ rain_{t-1}$	~~0.013~~	~~0.152~~	~~0.039~~	~~0.674~~	~~0.018~~	~~0.093~~	~~0.058~~	~~0.406~~
$Snow$	NA	NA	NA	NA	~~-0.300~~	~~-1.226~~	~~-0.241~~	~~-1.387~~
$Snow_{t-1}$	~~-0.042~~	~~-0.230~~	~~0.074~~	~~0.584~~	NA	NA	NA	NA
No. of records	251				104			
R^2	0.661		0.621		0.531		0.572	
Adjusted R^2	0.649		0.607		0.486		0.531	
Model F	52.267		43.981		11.839		13.938	

Note: ~~Numbers~~ indicate a significance level of less than 90%. NA: not available.

higher variation (66.1% and 62.1% for daily cycling on Burke-Gilman Trail and Fremont Bridge respectively) compared to their weekend counterparts (53.1% and 57.2%). Thus, weekend cycling is less likely to be affected by inclement weather than weekday cycling at the daily level. This finding is inconsistent with the findings on weather-ridership relationship (e.g., Guo et al., 2007; Singhal et al., 2014). One plausible explanation for the contrary results is that transit is more preferred for commuting trips whilst cycling is more preferred for leisure trips. This explanation is further confirmed by the finding that weekend cycling on recreational Burke-Gilman Trail (53.1%) is less related to weather than on Fremont Bridge (57.2%). These findings indicate that at the daily level, weekend cycling with leisure purpose tends to be more stable on Burke-Gilman Trail than on Fremont Bridge, whilst commuting cycling in weekdays tends to be more regular on Fremont Bridge than on Burke-Gilman Trail, regardless of the adverse weather.

For daily cycling activity, the sign of the estimated coefficients for different weather indicator is generally the same. It should be noted that the cycling activity on weekends on Burke-Gilman Trail tends to be more severely affected by bad weather than on Fremont Bridge. For instance, the rainfall is estimated with a beta coefficient of -0.256 for weekend cycling on Burke-Gilman Trail compared to -0.171 for weekend cycling on Fremont Bridge. Thus, the term of 'more severely' is different from the 'more likely'. The 'more likely' is judged from the R-square reflecting the overall model goodness-of-fit, whilst the 'more severely' is reflected by the magnitude of beta coefficient for a specific weather indicator. Generally, daily cycling increases significantly with increase of temperature, especially on Burke-Gilman Trail. Adverse weather conditions of high humidity, strong speed, rainfall and snowfall have strong negative influence on daily cycling.

Table 6 demonstrates the daily weather-cycling relationship for each season. Whilst all the models are statistically significant, the estimated coefficients and significance for weather indicators vary in the specific season. The estimated models for cycling in spring accounts for the highest variation (76.7% and 74.4% for daily cycling on Burke-Gilman Trail and Fremont Bridge respectively) compared with the models estimated for winter which have the lowest counterparts (58.3% and 55.5%). This finding indicates that cycling is most likely to be impacted by weather conditions in spring partly due to the capricious weather conditions in spring, but least likely to be affected in winter. This gives us an impression that cyclists in winter are the cycling enthusiasts regardless of the cold temperature and rainfall.

Table 6
Daily cycling estimation results for four seasons.
Daily cycling estimation results for four seasons.

	Spring				Summer				Fall				Winter			
	Burke-Gilman Trail		Fremont Bridge		Burke-Gilman Trail		Fremont Bridge		Burke-Gilman Trail		Fremont Bridge		Burke-Gilman Trail		Fremont Bridge	
	β	t	β	t	β	t	β	t	β	t	β	t	β	t	β	t
Intercept	0.146	3.867	0.111	4.094	~~0.030~~	~~1.439~~	0.025	1.84	~~0.005~~	~~0.115~~	~~0.046~~	~~1.524~~	~~0.005~~	~~0.088~~	~~0.025~~	~~0.614~~
ΔC_{t-1}	~~0.013~~	~~0.174~~	~~0.079~~	~~0.98~~	~~0.069~~	~~0.670~~	~~0.08~~	~~0.909~~	~~0.026~~	~~0.271~~	~~0.122~~	~~1.165~~	0.303	3.069	0.473	4.905
ΔT	0.490	4.425	0.315	3.998	~~0.303~~	~~1.426~~	~~0.087~~	~~0.646~~	0.430	3.783	0.267	3.224	0.432	4.192	0.183	2.524
ΔH	-1.138	-3.989	-0.533	-2.691	-0.768	-3.714	-0.765	-5.556	-0.409	-2.373	-0.206	-1.71	-0.441	-1.724	~~-0.121~~	~~-0.654~~
ΔW	-0.154	-1.966	-0.150	-2.697	~~-0.080~~	~~-1.095~~	~~-0.061~~	~~-1.282~~	-0.399	-4.773	-0.216	-3.662	-0.347	-3.855	-0.178	-2.759
$Rain$	-0.395	-6.110	-0.260	-5.627	-0.210	-2.662	-0.123	-2.503	-0.157	-2.105	-0.140	-2.687	~~-0.073~~	~~-1.03~~	~~-0.075~~	~~-1.435~~
$Rain_{t-1}$	~~-0.062~~	~~-0.826~~	~~-0.073~~	~~-1.361~~	~~-0.076~~	~~-0.808~~	~~-0.019~~	~~-0.328~~	0.211	2.453	0.105	1.716	~~0.095~~	~~1.036~~	~~0.037~~	~~0.534~~
$Heavy\ rain$	-0.552	-4.607	-0.457	-5.36	NA	NA	NA	NA	-0.354	-2.431	-0.347	-3.452	~~0.269~~	~~0.900~~	~~0.019~~	~~0.088~~
$Heavy\ rain_{t-1}$	~~-0.020~~	~~-0.171~~	~~0.017~~	~~0.195~~	NA	NA	NA	NA	~~-0.074~~	~~-0.502~~	~~-0.032~~	~~-0.311~~	~~0.002~~	~~0.006~~	~~-0.002~~	~~-0.009~~
$Snow$	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	-0.372	-1.922	-0.280	-1.965
$Snow_{t-1}$	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	~~0.089~~	~~0.327~~	~~0.223~~	~~1.103~~
No. of records	91				91				87				86			
R^2	0.767		0.744		0.588		0.657		0.607		0.594		0.583		0.555	
Adjusted R^2	0.744		0.719		0.559		0.633		0.567		0.553		0.527		0.496	
Model F	33.71		29.84		19.98		26.87		15.08		14.28		10.48		9.35	

Note: ~~Numbers~~ indicate a significance level of less than 90%. NA: not available.

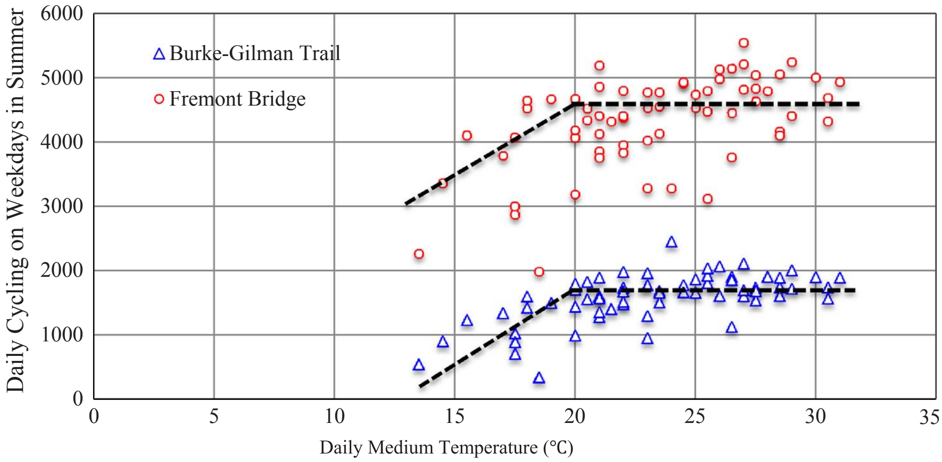

Fig. 6. Daily temperature-cycling relationship on weekdays in summer in Seattle.

Cycling on Burke-Gilman Trail is more likely to be affected by weather than cycling on Fremont Bridge in seasons of spring, autumn and winter, and especially on weekdays. However, people tend to bike for leisure purposes most regularly in summer, as the estimated models for summer season explain a lower variation (58.8%) in daily cycling on recreational Burke-Gilman Trail than on Fremont Bridge (65.7%).

The explanatory power of each weather indicator varies in models estimated for different seasons. Interestingly, temperature deviation is estimated with the highest beta coefficients in the spring models, but its impact is absent in the summer models. Fig. 6 shows that the number of daily cycling in summer in Seattle fluctuates up and down when the average daily temperature exceeds 20 °C, which is different from the observations in some previous studies (e.g., Ahmed et al., 2012; Burchfield et al., 2012).

As for other weather indicators, wind deviation is absent in the summer models, but significant in other seasonal models and estimated with the highest negative beta coefficients in the fall models. Rainfall is estimated with the highest negative beta coefficients in the models estimated for cycling in spring, but unexpectedly, its impact is absent in the winter models. This may be due to the fact that the winter in Seattle is rainy, and cyclists have been get used to rainfall or generally biked very few in winter. In addition, on both Burke-Gilman Trail and Fremont Bridge, the snowfall indicator is estimated with a strongly negative impact on daily cycling in winter.

Table 7
Hourly cycling estimation results for weekdays and weekends.

Hourly cycling estimation results for weekdays and weekends.

	Weekdays				Weekends			
	Burke-Gilman Trail		Fremont Bridge		Burke-Gilman Trail		Fremont Bridge	
	β	t	β	t	β	t	β	t
Intercept	~~0.001~~	~~0.252~~	0.056	10.756	0.056	3.988	-0.055	-5.495
ΔC_{t-1}	0.703	62.002	0.736	69.573	0.821	50.530	0.798	52.415
ΔT	~~0.004~~	~~1.287~~	~~-0.002~~	~~-0.731~~	~~0.010~~	~~0.396~~	~~0.006~~	~~0.319~~
ΔH	-0.253	-7.631	-0.172	-6.203	~~-0.115~~	~~-1.347~~	-0.100	-1.713
ΔW	~~-0.006~~	~~-0.830~~	~~0.009~~	~~1.366~~	~~-0.008~~	~~-0.423~~	~~0.009~~	~~0.649~~
$Rain$	-0.093	-5.148	-0.076	-4.975	-0.221	-5.075	-0.101	-3.354
$Rain_{t-1}$	-0.056	-2.070	~~-0.013~~	~~-0.548~~	-0.149	-2.330	~~-0.029~~	~~-0.657~~
$Heavy\ rain$	-0.072	-1.706	-0.094	-2.620	-0.185	-2.036	-0.102	-1.626
$Heavy\ rain_{t-1}$	-0.074	-2.154	~~-0.088~~	~~-1.191~~	~~-0.043~~	~~0.308~~	~~-0.080~~	~~-0.827~~
$Snow$	NA	NA	NA	NA	~~-0.063~~	~~-0.717~~	~~-0.064~~	~~-1.040~~
$Snow_{t-1}$	~~0.001~~	~~0.003~~	~~0.150~~	~~0.751~~	NA	NA	NA	NA
No. of records	3765				1560			
R^2	0.578		0.614		0.727		0.678	
Adjusted R^2	0.577		0.613		0.726		0.676	
Model F	571.32		664.49		459.04		362.13	

Note: ~~Numbers~~ indicate a significance level of less than 90%. NA: not available.

Table 8
.Hourly cycling estimation results of four seasonal models.
Hourly cycling estimation results of four seasonal models.

	Spring				Summer				Fall				Winter			
	Burke-Gilman Trail		Fremont Bridge		Burke-Gilman Trail		Fremont Bridge		Burke-Gilman Trail		Fremont Bridge		Burke-Gilman Trail		Fremont Bridge	
	β	t	β	t	β	t	β	t	β	t	β	t	β	t	β	t
Intercept	0.020	1.807	~~0.008~~	~~1.089~~	~~0.009~~	~~1.029~~	~~0.006~~	~~0.906~~	0.030	2.524	0.02	2.28	0.042	2.862	0.036	2.931
ΔC_{t-1}	0.791	49.983	0.808	51.762	0.796	49.283	0.795	49.631	0.788	45.611	0.807	49.235	0.739	39.442	0.781	45.000
ΔT	~~-0.027~~	~~-0.467~~	~~0.044~~	~~1.077~~	~~0.028~~	~~0.257~~	0.244	2.731	0.093	2.704	0.080	3.041	~~0.002~~	~~0.425~~	~~-0.003~~	~~-0.817~~
ΔH	-0.314	-3.814	-0.18	-3.12	~~-0.132~~	~~-1.491~~	~~-0.016~~	~~-0.222~~	~~-0.043~~	~~-0.668~~	~~0.024~~	~~0.499~~	~~-0.125~~	~~-1.300~~	-0.149	-1.821
ΔW	~~-0.004~~	~~-0.228~~	~~-0.01~~	~~-0.854~~	~~-0.022~~	~~-1.564~~	0.028	2.482	~~-0.016~~	~~-1.049~~	~~-0.006~~	~~-0.492~~	~~0.015~~	~~0.939~~	0.041	3.126
$Rain$	-0.115	-3.368	-0.049	-2.057	-0.250	-4.403	-0.109	-2.373	-0.134	-4.026	-0.089	-3.538	-0.127	-3.373	-0.084	-2.679
$Rain_{t-1}$	~~-0.074~~	~~-1.513~~	~~0.002~~	~~0.073~~	~~-0.058~~	~~-0.829~~	~~-0.014~~	~~-0.254~~	~~-0.073~~	~~-1.492~~	~~0.01~~	~~0.281~~	-0.118	-2.011	~~-0.05~~	~~-1.023~~
$Heavy\ rain$	-0.211	-2.013	-0.097	-1.82	~~0.062~~	~~0.379~~	~~-0.050~~	~~-0.381~~	-0.111	-1.653	-0.121	-2.338	-0.141	-1.649	~~-0.085~~	~~-1.193~~
$Heavy\ rain_{t-1}$	~~-0.191~~	~~-1.345~~	~~0.177~~	~~1.382~~	~~-0.083~~	~~-0.367~~	~~-0.106~~	~~-0.582~~	~~-0.024~~	~~-0.281~~	~~-0.055~~	~~-0.847~~	~~0.185~~	~~1.624~~	~~0.151~~	~~1.597~~
$Snow$	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	~~-0.064~~	~~-0.771~~	-0.141	-2.024
$Snow_{t-1}$	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	~~0.098~~	~~0.217~~	~~0.146~~	~~1.249~~
No. of records	1365				1365				1305				1290			
R^2	0.730		0.750		0.679		0.680		0.684		0.693		0.586		0.669	
Adjusted R^2	0.728		0.748		0.677		0.678		0.682		0.691		0.583		0.666	
Model F	457.80		507.26		358.3		359.75		350.5		365.20		180.95		258.05	

Note: ~~Numbers~~ indicate a significance level of less than 90%. NA: not available.

5.5. Hourly estimation results

Table 7 reports the estimation results for hourly cycling on weekdays and weekends separately. All models are statistically significant. However, different from the estimation results for daily cycling, the model for hourly weekend cycling on Burke-Gilman Trail explains a higher variation of (72.7%) than it is for Fremont Bridge (67.8%). For hourly weekday cycling, again, the results are opposite to that at the daily level. Compared to the estimation results for daily cycling in Table 5, findings from this study indicate that whilst the habit of weekend cycling on a leisure trail is more unrelated to weather at the daily level, cyclists in weekends with leisure purposes tend to be more flexible to adjust their cycling trips according to the real-time weather conditions. This is reasonable since for instance, a person may regularly bike on weekends for exercise, but have more flexibility to adjust the cycling schedule before or after the rain in a weekend. Thereby, it is also reasonable to understand that hourly weekday cycling on Fremont Bridge is more likely to be affected by adverse weather than on Burke-Gilman Trail, as commuters in inclement weather conditions are more likely to shift from cycling to other modes such as car or transit to finish utilitarian trips.

Cycling autocorrelation on both weekdays and weekends at the hourly is much stronger and more significant than at the daily level. Relatively few weather indicators are found to be significant in the estimated models for cycling at the hourly level partly due to this strong autocorrelation effect. In particular, the impacts of temperature deviation and wind deviation become less significant in hourly models. Like the 'boiling frog', cyclists tend to response mildly to the continuous variation of weather elements such as temperature and wind speed at a finer temporal scale, whilst could respond aggressively to weather emergencies such as rainfall and snowfall. In addition, rainfall has a negatively lagging effect on recreational cycling, but this effect is absent in utilitarian cycling after controlling for the hourly cycling autocorrelation.

Table 8 shows the hourly weather-cycling relationship for the four seasons. Based on the estimated models, the number of hourly cycling on Burke-Gilman Trail is less likely to be influenced by adverse weather than on Fremont Bridge, but may only in weekdays. Similar to weather-cycling relationship at the daily level, the estimated models for number of cycling in spring explain the highest variations (73.0% and 75.0% for daily cycling on Burke-Gilman Trail and Fremont Bridge respectively) compared to the lowest counterparts (58.6% and 66.9%) in the models for winter. This finding reinforces the impression that cyclists in the winter tend to the loyal fans of cycling regardless of the relatively bad weather conditions such as low temperature and cold rainfall in winter.

As for the impacts of weather elements, it is interesting to note that temperature deviation is significantly and positively associated with hourly cycling on both Burke-Gilman Trail and Fremont Bridge in autumn, even after controlling for the cycling autocorrelation. This finding indicates that the warm hours in autumn could be seen with a surge of cycling. This result is useful for urban traffic agencies to design effective cycling management plan during the warmer than general hours in autumn. It is surprised to find that the estimated coefficient for wind deviation is positive sign in the winter model. This occurs may because of the error terms. The estimated results for other weather indicators are reasonable. Rainfall is the only one weather indicator that has a significantly negative impact on hourly cycling across four seasons.

Table 9 summarizes the estimation results reflecting weather-cycling relationship in peak hours and non-peak hours of weekdays and weekends. Note that cycling in weekday peak hours on Fremont Bridge is more likely to be affected by bad weather than on Burke-Gilman Trail, whilst weekend peak models indicate the opposite results. These findings further indicate that travelers with utilitarian purposes during peak hours in weekdays are more likely to shift from cycling to other modes such as car and transit due to bad weather conditions. This is reasonable since they have to go working or schooling during weekday peak hours and car or transit provides they with a more comfortable alternative in inclement weather conditions. Weekend models explain higher variations (75.4% and 49.4% for weekend peak hours and non-peak hours respectively) in hourly cycling on Burke-Gilman Trail as compared to the counterparts (61.6% and 13.9%) on Fremont Bridge. This finding indicates that cyclists on Burke-Gilman Trail tend to be more flexible to adjust cycling schedule than cyclists on Fremont Bridge, especially during weekend peak hours (11 AM–4 PM). These results also highlight the necessity to protect the cyclists on Fremont Bridge on weekends from adverse weather conditions as they are more likely to keep on cycling even in bad weather conditions.

Table 9
Hourly cycling estimation results of time of day models.
Hourly cycling estimation results of time of day models.

	Weekdays								Weekends							
	Peak hours				Off-peak hours				Peak hours				Off-peak hours			
	Burke-Gilman Trail		Fremont Bridge		Burke-Gilman Trail		Fremont Bridge		Burke-Gilman Trail		Fremont Bridge		Burke-Gilman Trail		Fremont Bridge	
	β	t	β	t	β	t	β	t	β	t	β	t	β	t	β	t
Intercept	0.047	5.496	0.111	12.457	-0.026	-3.25	0.020	3.21	~~0.055~~	~~1.627~~	~~0.030~~	~~1.525~~	0.070	3.578	-0.406	-15.025
ΔC_{t-1}	0.655	35.565	0.781	51.816	0.694	45.98	0.601	40.345	0.815	31.212	0.724	20.268	0.858	25.396	0.302	7.626
ΔT	~~-0.004~~	~~-0.277~~	~~-0.001~~	~~-0.109~~	~~0.004~~	~~1.085~~	~~-0.003~~	~~-1.216~~	~~0.114~~	~~1.534~~	~~0.091~~	~~1.561~~	~~-0.005~~	~~-0.171~~	~~0.019~~	~~1.179~~
ΔH	-0.390	-8.020	-0.231	-5.54	-0.188	-4.263	-0.195	-5.614	~~-0.094~~	~~-0.814~~	~~-0.148~~	~~-1.656~~	~~-0.052~~	~~-0.404~~	-0.207	-2.825
ΔW	~~0.015~~	~~1.507~~	~~0.039~~	~~1.430~~	-0.028	-2.671	-0.018	-2.229	~~-0.024~~	~~-0.702~~	~~-0.027~~	~~-1.015~~	~~-0.001~~	~~-0.043~~	~~-0.001~~	~~-0.013~~
$Rain$	-0.056	-2.280	-0.017	-2.450	-0.135	-5.381	-0.139	-7.049	-0.283	-4.375	-0.182	-3.642	-0.167	-2.769	-0.106	-3.011
$Rain_{t-1}$	-0.082	-2.054	-0.024	-1.704	~~-0.044~~	~~-1.205~~	~~-0.004~~	~~-0.128~~	~~-0.070~~	~~-0.740~~	~~-0.007~~	~~-0.093~~	-0.177	-2.045	-0.099	-1.963
$Heavy\ rain$	~~0.029~~	~~0.437~~	~~-0.027~~	~~-0.463~~	-0.124	-2.273	-0.137	-3.197	-0.310	-2.324	-0.257	-2.505	~~-0.094~~	~~-0.763~~	~~-0.105~~	~~-1.452~~
$Heavy\ rain_{t-1}$	~~0.055~~	~~0.668~~	~~0.003~~	~~0.039~~	~~0.151~~	~~0.220~~	~~0.129~~	~~0.402~~	~~0.305~~	~~1.341~~	~~-0.001~~	~~-0.008~~	~~-0.052~~	~~-0.290~~	~~-0.116~~	~~-1.110~~
$Snow$	NA	NA	NA	NA	NA	NA	NA	NA	~~-0.013~~	~~-0.095~~	~~-0.071~~	~~-0.696~~	~~-0.066~~	~~-0.546~~	-0.141	-2.001
$Snow_{t-1}$	NA	NA	NA	NA	~~0.045~~	~~0.132~~	~~0.095~~	~~0.608~~	NA	NA	NA	NA	NA	NA	NA	NA
No. of records	1506				2259				624				936			
R^2	0.560		0.687		0.558		0.510		0.754		0.616		0.494		0.139	
Adjusted R^2	0.557		0.685		0.556		0.508		0.750		0.611		0.489		0.131	
Model F	237.69		410.04		315.46		259.70		208.57		109.61		100.32		16.60	

Note: ~~Numbers~~ indicate a significance level of less than 90%. NA: not available due to snowfall was not observed on weekdays.

5.6. Expanding the findings

Results from this study can be compared to that from previous studies examining the weather impacts on other travel modes. For instance, academics and practitioners can refer to the results from the present study and Singhal et al. (2014) for better understanding of travel behavior of cyclists and transit users under different weather conditions. We should remind that including autocorrelation and lagging weather impact into time series cycling, ridership and other travel demand analysis can significantly improve the analysis accuracy, especially at the hourly level. Whilst Singhal et al. (2014) did not consider the ridership autocorrelation and lagging weather effects in weather-ridership analysis, comparing the estimation results from Tables 3, 5 and 7 in this paper to Table 1 in Singhal et al. (2014) could obtain some useful findings.

Compared to subway ridership, cycling is more likely and more severely to be affected by weather conditions. Daily weather conditions explain obviously higher variation (more than 50% from both weekday and weekend models) in cycling compared with subway ridership (17.7% from the weekday model and 24.1% from the weekend model) (Singhal et al. (2014). Although the independent variables examined in the two studies are different, the obvious difference in models' goodness-of-fit could be mainly ascribed to cyclists are more vulnerable to adverse weather than transit users. In addition, findings from the two studies are generally consistent with the demographic profile indicating that adverse weather could reduce the desire to travel in general and divert the travel demand from cycling to transit as noted by Khattak (1991).

Weekend subway ridership is more likely to be affected by inclement weather than weekday ridership at the daily level (Singhal et al., 2014), which has also been highlighted by other previous studies (e.g., Guo et al., 2007; Kalstein et al., 2009). However, completely opposite to weather-ridership relationship, findings from this study indicate that daily weekend cycling is less likely to be affected by bad weather than daily weekday cycling. The main reason for the opposite results verified by the present study is that cyclists on weekends have more flexibility to adjust their cycling schedule according to the real-time weather conditions, especially during weekend cycling peak hours (11 AM-4 PM).

In addition, it should be noted that the impacts of some weather events on travel demand are contextual and work in two ways. For instance, the negative effect of wind could be coupled with cold temperature, whilst a gentle breeze may reduce the feeling of unpleasantness and thus show a positive effect in the hot climate (Kashfi et al., 2016). When temperature exceeds a specific value such as 24.4 °C in Knoxville, United States and 20 °C in Brisbane, Australia cycling shows significantly decline trend in the two cities, respectively (Ahmed et al., 2012; Burchfield et al., 2012), whilst cycling fluctuates up and down when the temperature exceeds 20 °C in Seattle (Fig. 6). However, the impact of weather emergencies such as rainfall on travel demand seems always noticeable. Synthesizing the existing findings, the impact of rainfall on cycling is significantly negative without exception, whilst its impact on transit ridership and car users still leaves room for future research.

6. Discussion and conclusions

This literature at the outset intends to give insights into the association of weather with cycling at both daily and hourly levels, whilst the findings from this paper are far beyond the association itself. In this study, two main types of cycling facilities are distinguished: recreational trails and utilitarian bike lanes. Three temporal scales are compared: seasonal, day of week, and time of day. The cycling autocorrelation effect as well as the advance and the lagging effects of rainfall on cycling are also investigated. In addition, autoregressive model allied with 9-term moving average residual is used to estimate relationship between weather and cycling, which provides an in-depth, sophisticated statistical analysis of a typical cycling dataset from two typical cycling facilities.

Mining a valuable dataset including daily/hourly meteorological data for the enter year of 2014 and the contemporaneous cycling on Burke-Gilman Trail and Fremont Bridge in the city of Seattle, United States the descriptive statistics indicate that the trail is more popularly used by cyclists for leisure purposes than the bike lane, especially on weekends, whilst bike lane is more heavily used for utilitarian cycling than the trail, especially on weekdays. Comparing the hourly cycling pattern over days of week in Seattle with that in Nanjing, China (Zhao et al., 2015), we find when the American people cycling for leisure on weekends whilst some Chinese people still have to cycling for survival. The underlying causes of the cycling differences in the two countries still need future research.

The comparisons between models with and without considering cycling autocorrelation as well as the advance and lagging weather effects indicate that cycling is significantly autocorrelated, and especially at the hourly level. This finding is consistent with Tobler's first law of geography indicating that "everything is related to everything else, but near things are more related to each other" (Tobler, 1970). Thus, in time series travel demand analysis such as for cycling, transit ridership, or car usage, it is important to take the temporal autocorrelation into consideration. In addition, model comparisons indicate that incorporating 9-term moving average residual with autocorrelation would be a useful and an effective methodology for time series travel demand analysis.

Equally important, this study confirms the advance and lagging effects of rainfall on cycling. The concurrent cycling is not only affected by the concurrent rainfall, but also the rainfall one hour later. As more than 95% of cycling trips finish within half an hour (Zhao et al., 2015), it is important and necessary to let the cyclists know the weather conditions in advance to bet their outdoor cycling on weather. The accurate short-term weather prediction and a real-time weather display screen installed near the cycling facilities can play a role in improving the odds for enjoying a better cycling experience. In addition, when it rains its negative impact on cycling could be last for 3 h for the bike lane and even a longer time for the trail. The significant lagging impact of weather is also found in Miranda-Moreno and Nosal (2011) and Tao et al. (2018). As when it rains its negative impact continues, transport agencies should continually focus on transport operation and management after rainfall rather than limiting within a short time period. Furthermore, although without being examined, slippery surface and gathered water could amplify the negative effect of the rainfall, a detailed evaluation of the whole cycling network after rainfall would be helpful to derive recommendations for cycling practice design and policy making.

Unlike weather-ridership relationship variation due to day of week (e.g., Guo et al., 2007; Kalstein et al., 2009; Singhal et al., 2014), weekend cycling is less likely to the affected by weather than weekday cycling at the daily level. In addition, daily cycling weekends on the trail is less likely to be affected by weather than on the bike lane. These findings indicate that daily active travel of cycling is more stable on weekends than on weekdays, especially the cycling with leisure purposes on trails. The daily weather-cycling relationship can be compared to weather-ridership relationship estimated by Singhal et al. (2014). Findings from the present study and Singhal et al. (2014) confirm that whilst bad weather tends to reduce travel demand in general, cycling is more likely and more severely to be affected by adverse weather than subway ridership.

By developing models at hourly scale and comparing weather-cycling relationship variation due to seasonality (spring, summer, autumn and winter), day of week (weekdays and weekends), and time of day (peak hours and non-peak hours), findings from the finer temporal scale analysis help to understand of the impacts of weather on cycling in-depth. Contrary to modeling results at the daily level, cyclists with utilitarian purposes are more likely to transfer from cycling to other modes at the hourly level in weekdays, especially during the weekday peak hours of 7–9 AM and 4–6 PM. In addition, cyclists with leisure purposes are more likely to adjust their cycling schedule according to real-time weather conditions in weekends, especially during the weekend peak hours of 11 AM–4 PM. As for seasonal weather-cycling relationship, there are more weather conditions that affect cycling in spring than those suggested by other seasonal models. Cyclists in winter tend to be the tough cycling enthusiasts regardless of adverse weather conditions such as cold temperature and rainfall. In addition, warm hours in autumn may be seen with a surge of cycling. These findings provide academics and practitioners with valuable information for cycling behavior analysis and cycling management.

The paper also highlights the significantly negative impact of rainfall on cycling on both trail and bike lane at both daily and hourly scales across all four seasons. Weather officials, transport agencies, and research institutions should work together to predict and announce weather conditions accurately in advance, install real-time weather display screen and public rain shelters near popularly used cycling facilities, and generalize personally convenient wearable devices for cyclists so as to protect cyclists from rainfall thus to improve the active travel level of cycling. The concurrent rainfall not only impact the concurrent cycling but also has a significantly negative influence on cycling within previous 1 h. Weather officials should announce accurately hourly or even shorter-time weather forecasting, thus cyclists could prepare to shift to other modes or adjust their cycling schedule in advance. In addition, as when it rains its negative impact on cycling continues, transport agencies should appropriately extend the particular transport management model to cope with weather emergencies such as rainfall rather than focusing within a short-time period.

To conclude, this study has examined to what extent the changes in weather conditions impact cycling, and how the impacts vary depending on facilities (off-road trail and on-road (bridge) bike lane), time (weekdays, weekends, peak hours, and non-peak hours), and purposes (utilitarian purposes and recreational purposes). The advance and lagging rain effects on cycling have also been examined at a level of detail previously uninvestigated. Findings contribute to meaningful implications for academics and practitioners in cycling activity analysis and promotion. Limitations of this study are the small sample of some weather conditions especially the snowfall, the incapacity of directly comparing the weather effect on cycling with that on other modes such as transit or cars, and the powerlessness of amalgamating with demographic profile, which hinder a finer understanding of mechanisms of cyclists' responses toward weather variability. However, the methodology employed in this study, the advance and lagging rain effects, and the temporal responses of cyclists with different trip purposes toward changes in weather conditions could be used for cycling activity analysis and promotion for other areas

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