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Weather and cycling in New York: The case of Citibike

Ran An[a], Renee Zahnow[b], Dorina Pojani[a], Jonathan Corcoran[a,*]

[a] School of Earth and Environmental Sciences, The University of Queensland, Brisbane, Australia
[b] School of Social Sciences, The University of Queensland, Brisbane, Australia

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ABSTRACT

This study maps and models the effect of weather on cycling in New York whilst controlling for several built *and* natural environment characteristics *and* temporal factors. To this end, we draw on 12 months of disaggregate trip data from the Citibike public bicycle sharing scheme (PBSP) in New York, currently the largest public bicycle sharing system in the United States, and spatially integrate these data with information on land use, bicycle infrastructure, topography, calendar events and weather. Overall, we find that weather impacts cycling rates more than topography, infrastructure, land use mix, calendar events, and peaks. The policy implication is that, in northern latitudes which experience inclement weather for extended periods, creating state-of-the-art cycling infrastructure - sheltered, promptly cleared from snow, and potentially heated - may be much more important than in warm and sunny places if planners are to succeed in “getting people out of their cars.”

1. Introduction

Weather and the propensity to cycle are inextricably linked (Nankervis, 1999; Corcoran et al., 2014). Extensive empirical evidence demonstrates that inclement weather conditions act to supress cycling trips (more than other travel modes) because cyclists are exposed to the elements and thus vulnerable to their full effects (Nahal and Mitra, 2018). This suppression of trips during bad weather is shown to be especially pronounced for non-utilitarian cycling trips where travellers are likely to have greater flexibility to re-schedule or cancel a planned trip to better suit shifts in prevailing conditions (Heinen et al., 2010). With climate change, extreme weather conditions are predicted to become more frequent and intense which goes to underscore the importance of developing a comprehensive empirical understanding of the weather-cycling relationship (Heaney et al., 2019). Developing this understanding will go some way to generating the necessary evidence from which tailored weather resilient cycling infrastructure can be better conceived and integrated into existing transit systems.

Existing weather-cycling studies have begun to unpack the way in which certain observed weather conditions, such as rain, temperature, wind, and humidity, as well as season or human-perceived variables, such as the heat index, explain variations in bicycle ridership (Schmiedeskamp and Zhao, 2016). This empirical literature, which is based across a variety of situational and climatic contexts has, however, painted a somewhat varied picture. To this end, some studies have found that weather exerts an important impact explaining variations in ridership (Pucher and Buehler, 2006) whilst others suggest that its effects are less prevalent (Dill and Carr, 2003; Winters et al., 2007).

Despite increasing interest and a growing weather-cycling literature, further research is needed to bring greater clarity on the intricacies of the relationship in various contexts. In this paper we draw particular attention to one element of the weather-cycling relationship that is currently underdeveloped. More specifically, we seek to shed new light on the way in which weather conditions interact with characteristics of the built and natural environment, alongside temporal variations, to explain increases or decreases in cycling ridership. For example, a state-of-the-art bike lane network, a high land use mix, or a flat topography might act to moderate the effects of inclement weather. Understanding such interactions will unveil important and previously unexplored subtleties in the weather-cycling relationship that we hope will begin to help eliminate apparent contradictions in the literature that include: high cycling rates in rainy Copenhagen, snowy Montreal, and scorching Seville and low cycling rates in balmy Sydney and Johannesburg (Pojani et al., 2018); or high cycling rates in hilly San Francisco and low cycling rates in flat East Anglian towns in the United Kingdom. Identifying environmental factors, built or natural, that in combination produce situations that support high bicycle ridership, regardless of weather conditions, can inform smarter cycling infrastructure design and implementation to navigate the potential effects of future climate changes on weather and resultant implications for bicycle ridership (Böcker et al., 2013).

The present study draws on mapping and modelling techniques to

* Corresponding author.
E-mail address: jj.corcoran@uq.edu.au (J. Corcoran).

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reveal the effect of weather on cycling in New York whilst controlling for a suite of built *and* natural environment characteristics *and* temporal factors. In particular we explore a series of interaction effects, which each capture the extent to which two characteristics occurring simultaneously exert a combinatorial effect on cycling ridership – for example how is cycling impacted when it is both wet and a weekend day or humid day in the hilliest parts of the cycling network. To this end, we draw on 12 months of disaggregate trip data from the Citibike public bicycle sharing scheme (PBSP) in New York, currently the largest public bicycle sharing system in the United States, and spatially integrate these data with information on land use, bicycle infrastructure, topography, calendar events and weather.

The remainder of the article is organised as follows: The next section provides an overview of the current scholarship on the determinants of cycling and develops a conceptual framework. This serves to guide the analytical approach delineated in the third section. Section four presents the results before discussing their consequences and proposing a set of policy recommendations.

2. Background: cycling determinants

We next review empirical scholarship to unpack the key determinants of cycling in order to inform the development of our conceptual model and guide the empirical analysis. To this end, we draw on existing reviews by Butterworth and Pojani (2018), Willis et al. (2015) and Heinen et al. (2010).

2.1. Natural environment factors

2.1.1. Weather

The transport-weather relationship is complex for all modes. Research has determined that inclement weather conditions can lead to trip re-scheduling, re-routing, and cancellation (de Palma and Rochat, 1999; Sabir et al., 2010; Cools et al., 2010; Zanni and Ryley, 2015). Cycling is particularly vulnerable to weather (Miranda-Moreno and Nosal, 2011). Temperature variations have a major effect on decisions to cycle. Both excessively high and excessively low temperatures can deter cycling, in particular among recreational cyclists who engage in the activity by choice rather than for utilitarian purposes (Pucher and Buehler, 2006; Brandenburg et al., 2007; Heaney et al., 2019; Helbich et al., 2014). Sensitivity to weather varies among geographic regions but generally cyclists perceive cold temperatures to be more unpleasant than hot temperatures (Heinen et al., 2010; Nankervis, 1999). Cities with continental climates and distinct seasons see major variations in cycling rates between summer and winter, with fewer people cycling during the colder and darker months. In fact, more days of freezing temperatures per year are associated with lower levels of utilitarian cycling (Winters et al., 2007). The 'ideal' cycling temperature range appears to be between 17 °C and 33 °C; although in cities with continental climates cycling occurs in much wider temperature ranges, e.g., −4 °C to 40 °C (Heinen et al., 2010; de Chardon et al., 2017; Brandenburg et al., 2007). Precipitation, including rain and/or snow, or even the chance of precipitation, are among the most influential weather variables for determining decisions to cycle. Precipitation is a particularly strong deterrent for women, recreational cyclists, and winter commuters (Nosal and Miranda-Moreno, 2012; Heinen et al., 2010; Winters et al., 2007; Nankervis, 1999; Gebhart and Noland, 2014; Corcoran et al., 2014). Strong wind and high humidity are also well documented deterrents to cycling (Rietveld and Daniel, 2004; Nankervis, 1999; de Chardon et al., 2017; Corcoran et al., 2014).

2.1.2. Topography

Hilliness has a negative effect on cycling rates, especially among inexperienced cyclists (Heinen et al., 2010; Rietveld and Daniel, 2004; Mateo-Babiano et al., 2016). Cyclists tend to choose routes with flat or gentle gradients. Uninterrupted topography - for example, by harbours, bays, and rivers – has also been found to favour cycling as it enables more direct routes to a destination (Buehler and Pucher, 2011; Pucher et al., 2011; Vandenbulcke et al., 2011).

2.2. Built environment factors

2.2.1. Infrastructure

The availability and quality of cycling infrastructure is a key factor in cycling rates, especially among women, children, and inexperienced cyclists (Krizek et al., 2009; Dill and Carr, 2003; Nelson and Allen, 1997; Mateo-Babiano et al., 2016; El-Assi et al., 2017). Cyclists prefer higher levels of separation from other traffic, especially on major roads with higher traffic intensity and on intersections or roundabouts, as this imparts much higher levels of safety, both objectively and subjectively (Heinen et al., 2010; Reynolds et al., 2009; Krizek et al., 2009; Pucher and Buehler, 2006). For example, continuous and segregated paths are preferred to (patchy) curb side lanes, and their presence leads to higher cycling rates (Dill and Carr, 2003; Nelson and Allen, 1997; Pucher et al., 2010a; Pucher and Buehler, 2006; de Chardon et al., 2017; Vandenbulcke et al., 2011). One cross-sectional study of 43 cities in the US found that each additional mile of bicycle lane per square mile produced an increase of 1% in the share of cycling commuters (Dill and Carr, 2003). Narrower roads with fewer crossings and more pavement markings such as coloured lanes and bike boxes (advanced stop lines) are also preferred (Pucher et al., 2010a; Reynolds et al., 2009). In addition to 'hard' cycling infrastructure, there is some evidence that visually appealing urban settings attract higher cycling rates (Heinen et al., 2010). Exceptionally, some older US-based studies find that cycling rates are only moderately associated with infrastructure but this likely reflects the limited bicycle infrastructure in the case study settings (Moudon et al., 2005).

2.2.2. Land-use mix

A mix of land uses is linked to smaller distances between destinations, which generally results in higher shares of cycling as a commute mode (Heinen et al., 2010). Given that both distance and land-use mix are key factors in decisions to cycle, cycling rates are higher in (a) smaller and medium-sized cities, (b) cities with denser population and street network patterns, (c) inner city areas, as opposed to suburbs, and (d) fine-grained neighbourhoods (Heinen et al., 2010; Pucher and Buehler, 2006; Pucher et al., 2011; Vandenbulcke et al., 2011; Saelens et al., 2003). The maximum acceptable cycling distance varies by place and by gender, with women willing to cycle shorter distances than men. But generally, there is a strong market for trips shorter than 2.5 km and cycling rates decline after about 4 km (Krizek et al., 2009). Regular cyclists tend to live closer to their work compared to commuters who employ other transport modes (Heinen et al., 2010).

2.3. Temporal factors

2.3.1. Calendar events

Public holidays and weekends, have been identified as a factor influencing ridership patterns (Corcoran et al., 2014; Borgnat et al., 2011; Brandenburg et al., 2007). Such periods reflect changes in the routine activities of individuals and households, which, in turn, can encourage or suppress bicycle trips. Some studies suggest that weekend trips are shorter and slower than weekday trips (Mateo-Babiano et al., 2016).

2.3.2. Peaks

During regular weekdays, patterns of bicycle trips change during peak travel periods. Peak travel periods are times of the day when commuting is highest. These periods tend to align with socially prescribed activities such as the 9-5 pm work day or school hours. For example, in Lyon, France and Brisbane, Australia, a trimodal weekday peak is evident, reflecting commute trips in the morning and evening peak periods and a smaller peak around lunchtime (Borgnat et al., 2011; Mateo-Babiano et al., 2016). Studies point to how weather exerts a larger effect during off-peak periods (Zhou et al., 2017) and weekends (Al Hassan and Barker, 1999) where travellers are likely to have greater flexibility to adjust travel plans according to shifts in prevailing conditions (or weather predictions).

2.4. Other factors

In addition to the abovementioned factors, the propensity to cycle is also known to be influenced by a series of other factors including socioeconomic characteristics, household structure, gender and ethnicity, attitudes and perceptions, social norms, cultural traditions, image and identity, habits and routines, transportation costs, urban composition (e.g., a high percentage of college students), physical fitness, fear of crime, and traffic law enforcement levels (Willis et al., 2015; Heinen et al., 2010; Pucher and Buehler, 2006; Pucher et al., 2010a; Pojani et al., 2017). These mostly *internal* factors fall outside of our study scope given the nature of the data we employed Bikeshare trip data do not contain characteristics of the individual riders, and as such, do not permit us to examine of the effect of socioeconomic or psychological factors on cycling in New York. Further, there is little that can be done by transport planners to *change* these internal, individual factors to enhance cycling propensity. Therefore, we focus on *external* factors, such as the natural and built environment and temporal factors. It is these external factors that are amenable to modification through the manipulation of environmental conditions using smart transport infrastructure and planning strategies.

2.5. Conceptual framework: cycling determinants

Based on the review of the empirical literature concerning the determinants of cycling we have constructed a three-point conceptual framework, which has guided our analytical approach (Fig. 1).

Existing scholarship has tended to place a particular emphasis on a subset of, rather than consider all of, the variables included in our framework. For example, Schmiedeskamp and Zhao (2016) examined the weather-cycling interaction in relation to temporal factors (such as holidays or day of the week). Zhao et al. (2018) examined the same interaction in relation to cycling infrastructure and temporal factors, such as day of week and time of day combinations. Nahal and Mitra (2018) assembled a comprehensive model, which examined the effect of commute distances, cycling infrastructure, land use mix, and age of housing in neighbourhoods, in addition to socio-demographic factors, on the weather-cycling relationship. However, their empirical analysis was limited to cyclists who commute to the University in Toronto; thus, the findings might not be widely applicable. The study by El-Assi et al. (2017) presented arguably the most inclusive conceptual and empirical model to date by drawing on bikeshare ridership data for Toronto and incorporating hourly weather information, population and employment data, and bicycle and other transport infrastructure data. In combination, these studies indicate that there is no single, silver-bullet factor that determines cycling rates but rather a complex web of forces (see Cervero et al., 2019). Our framework recognises this complexity. Furthermore, we embrace this complexity through the introduction of interactions into our modelling framework. More specifically, we capture how combinations of our independent variables, when simultaneously present, exert significant effects on cycling. To this end, we are now able to explore the extent to which a weekend day that is wet or a humid day in a hilly district are important factors in explaining variations in the number of cycling trips.

3. Methodology

3.1. Case study context

At 8.5 million inhabitants, New York City (NYC) is the most populous urban conurbation in the United States. It comprises five boroughs (Brooklyn, Queens, Manhattan, The Bronx, and Staten Island). The city experienced a doubling in cycling over the decade leading to 2010 (Pucher et al., 2010b). The Citibike public bicycle sharing system is located across Brooklyn, Queens and Manhattan (Figs. 2a and b).[1] Beginning operations in 2012, it is now the largest is the United States, comprising 12,000 bicycles, 750 stations, 130,000 registered members, and 450,000 daily bicycle trips (Citibike, 2017).

The NYC climate is classified as *humid continental* by the Köppen classification (Köppen, 1900; Kottek et al., 2006). As such, it is characterised by cold and snowy winters, with January and February having average daily temperatures below −3 degrees Celsius. Summers are hot and humid, with temperatures averaging around 29 degrees Celsius in July, but relatively short (Fig. 3). The topography of NYC is relatively flat. There is only a 30.5 m variation in height across our study area and a mean slope of 4.7 degrees; the steepest gradient on a cycle path is 24% (West End Avenue).

3.2. Data and analysis

To explore system-wide ridership patterns we drew on trip data from Citibike (Citibike, 2018) and a publically available weather database (Weather Underground, 2018). The choice to employ Citibike rather than population survey data owes to the coverage of the dataset. Population surveys tend to be problematic in that response rates are often low. Additionally, surveys rely on participants' travel diaries, and human memory is notoriously fallible (Stopher, 1992; Wolf et al., 2001; Stopher and Shen, 2011). By contrast, the Citibike dataset captures every trip within a determined period, rather than just a sample of trips and therefore for our study design that is concerned with metropolitan-wide cycling ridership patterns is best suited. As we highlight in the discussion, much opportunity exists to develop methods to integrate bikeshare data with population surveys to extend our understanding of ‘objective’ characteristics via bikeshare data [along with other datasets describing the physical environment] allied with information on individuals, households and ‘subjective’ characteristics via survey data.

While rental bicycle systems have existed for nearly half a century, the specificity of modern bike-sharing is that stations are fully automated and computerised. This allows for system-wide management allied with the capacity to monitor and record the state of the system in real-time. In some cases, the implementation of a bikeshare system in itself leads to slight increases in bicycle use and also in private bicycle ownership (Castillo-Manzano et al., 2015; Fishman, 2016; Nadal, 2007). As such, the findings of this study have the potential to inform design and planning of PBSPs, in addition to supporting planning for cycling transport more broadly.

Our Citibike data includes 622 cycle stations situated across 17 NYC Community Districts. Constructed as early as 1975, Community Districts (59 in total) are administrative units used by the City of New York for the planning and administration of public services. Each district has a community board which advises on matters such as land use and zoning, and participates in the NYC budget process (Berg, 2007). The ‘statements of needs’ in New York (e.g., requests for new cycle lanes, bus stops, parks, and other amenities and services) are issued by Community Districts. The Community Districts within our study area vary in both physical size (from less than 243 ha to almost 1600 ha) and in population (from 51,700 residents to over 219,900). Given their diversity and distinctiveness along with their importance in city planning, Community Districts were considered as an appropriate unit of analysis. The selection of this unit of analysis is further informed by an

[1] Citibike is also located in New Jersey. However the New Jersey portion of the PBSP is excluded from this study given that the system's expansion outside of NYC is relatively recent (2016) and has a comparatively limited number of docking stations (50).

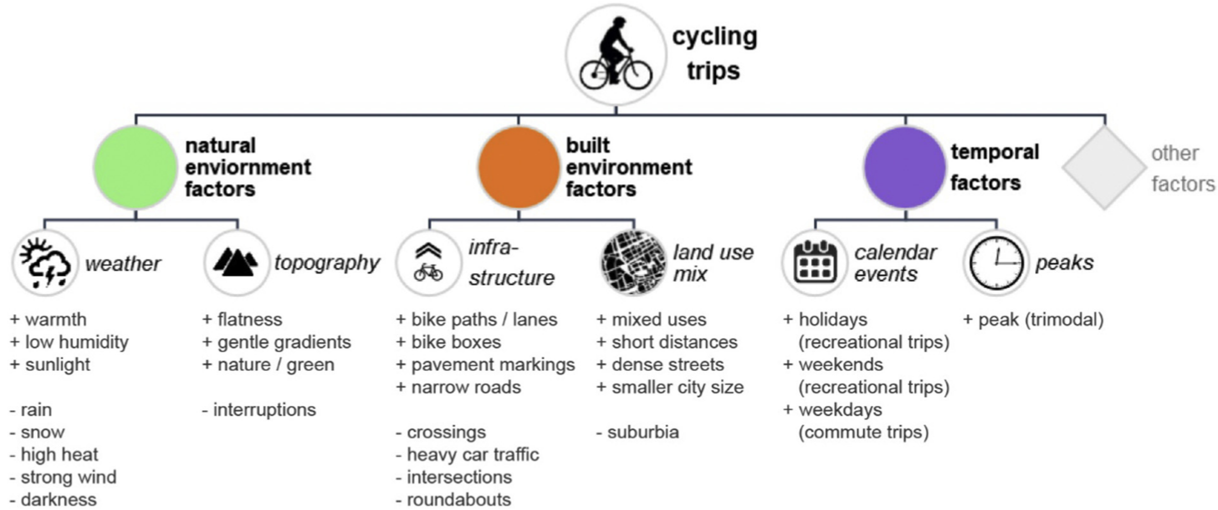


Fig. 1. Conceptual framework: cycling determinants.

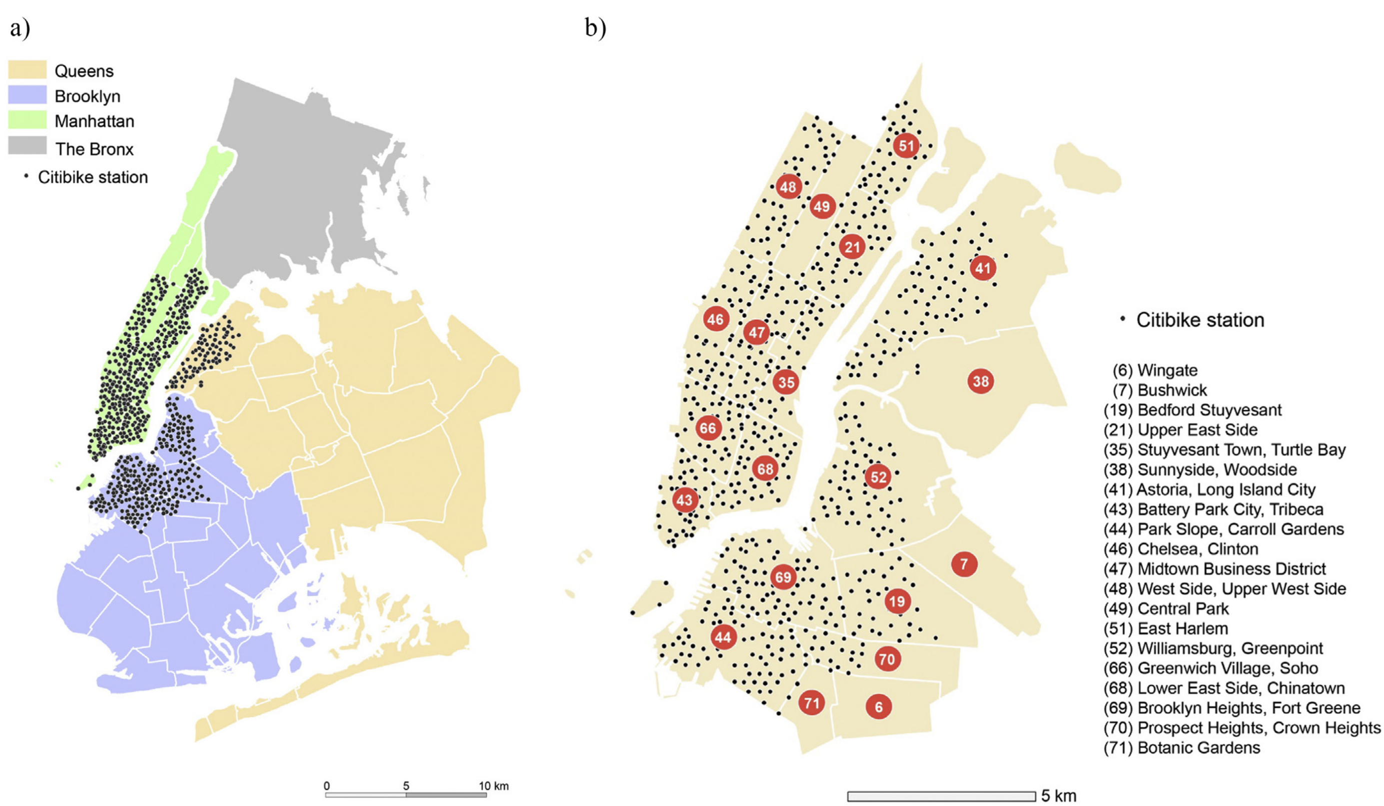


Fig. 2. a. Case study context. b. Community districts in the study area.

examination of all bicycle trips highlighting that on average 37% of trips begin and end in the same Community District and 72% end in a neighbouring Community District. In lieu of GPS-based data that captures the actual path of a given bike trip, we consider that Community Districts (and their neighbouring districts) offer an appropriate scale that acknowledges their distinctive planning function along with broadly reflecting the underlying distribution of bikeshare trips. In sum, we argue that this unit enables us to capture the way in which natural and built environment features vary across the study space whilst simultaneously unpacking the role played by weather on the cycling ridership (New York City Planning, 2018).

The study proceeded in two steps.

First, to visually explore sub-system ridership patterns we employed flow-comaps (Tao et al., 2014). Flow-comaps reveal the way in which weather and temporal factors exert an influence on the spatial patterns of cycling across a set of locations. The flow-comap is an augmentation of two well established mapping techniques to visually depict spatial movement patterns, namely the flow map (Tobler, 1987) and the comap (Brunsdon, 2001). Flow maps have long been employed by geographers to visualise the movement of populations and commodities between a point of origin and destination using arrows to symbolise direction and varying the width of the line to indicate the volume of the flow. The comap introduces the capacity to visually explore multivariate spatial data by segmenting the data into a panel of maps. Each of these depicts the relationship between a pair of variables that are conditioned on a third variable. Flow-comaps have already been used in

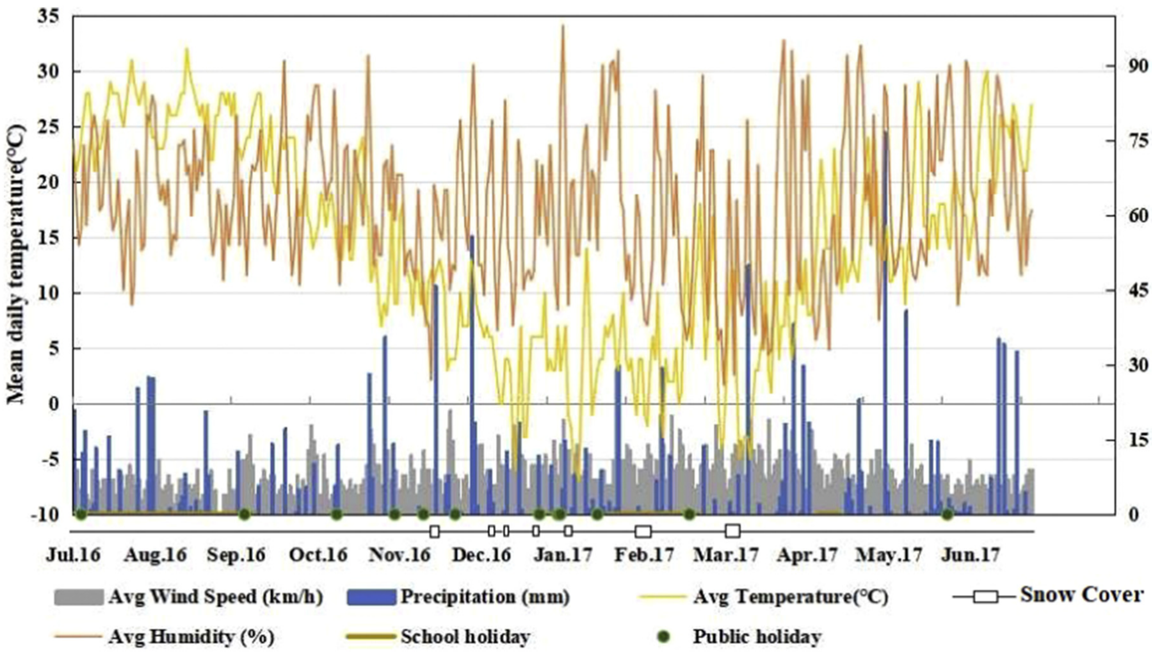


Fig. 3. Weather conditions and calendar events in NYC.

various urban planning sub-disciplines, in addition to transport. For example, Corcoran et al. (2007) have employed comaps to explore the relationship between the locations of fire incidents and their variation by different aggregations of time (i.e., month, day, and hour).

Second, we examined the impact of weather features and cycle station characteristics on ridership in NYC Community Districts. We use the log-normalized count of cycling trips in panel regression models that take into account clustering on time (level one) and Community District (level two) variables. Independent (predictor) variables represent the key components of the natural, built, and temporal environment around a cycle station, among which the principal is weather. The weather variables are included in the model at level one (time variant) while elements of the built and natural environment, measured at the level of the Community District, are included in the model at level two (time stable). Community District variables are also included as spatially lagged terms to estimate the influence of the physical characteristics of the surrounding Community Districts. Spatially lagged terms were computed using Stata software with first-order rook contiguity. For the focal community district, the spatially lagged measure of land mix for example, indicates the average land use mix among contiguous districts. The list of independent variables is presented in Table 1. The multilevel regression analysis tests the relationship between weather and cycle trips whilst accounting for the physical characteristics of the bikeshare station environment.

Existing transport research suggests that the strength of the relationship between weather and people's activities may vary dependent on whether the activity is ‘obligatory’ or ‘discretionary’ (Böcker et al., 2013; Nosal and Miranda-Moreno, 2012). Therefore, we explicitly tested whether the link between weather and cycling trips differs on weekends and public holidays, when people are more likely to be engaging in discretionary activities, compared to days of working/school week (i.e., Monday through to Friday). We also estimated the moderating effects of each of the weather variables on the influence of the physical environment of the bike station on cycling trips. In total we examined 20 interactions between the weather characteristics: temperature; rainfall; humidity; wind; snow, and four separate variables (1) weekend/weekday; (2) elevation; (3) infrastructure; and, (4) land use mix. Here we report the results of four interaction effects that were both statistically significant and meaningful.

4. Results

4.1. Sub-system analysis

The flow co-maps shown in Fig. 4 (a to h) visually depict the intra- and inter-community spatial patterns of Citibike ridership. Fig. 4a provides an overall summary of these spatial patterns. It reveals that the Manhattan portion of the Citibike scheme accounts for the majority of both intra- and inter-community trips, with communities 46 (Chelsea, Clinton) and 47 (Midtown Business District) being especially popular. The two communities located in Queens (38: Sunnyside, Woodside and 41: Astoria, Long Island City) recorded the fewest number of trips.

Fig. 4b examines the variation in spatial patterns over a 24 h period. Most trips occur between the afternoon and evening (1 pm and 7 pm); the fewest number of trips is recorded during the morning period (5 am to 10 am). Communities 46 and 47 are major locales for trips during all periods; however 66 (Greenwich Village, Soho), 68 (Lower East Side, Chinatown) and 43 (Battery Park City, Tribeca) also display relatively high numbers of inflows and outflows across each time period. That is especially the case for 66 and 68 between 6 pm and 11 pm.

Next, Fig. 4c visualises how Citibike trips vary over a 24 h period by weekdays and weekends. Common to patterns captured in Fig. 4b, communities 46 and 57 remain key in terms of trip origins and destinations. That is especially the case during 1 pm to 7 pm on weekdays; however, communities 66 and 68 surpass this number during weekends between both 9 am to 2 pm and 1 pm to 7 pm. Fig. 4d examines differences in trip patterns during public and school holidays revealing that, spatially, trip patterns for these two holiday periods are broadly alike. The principal differences are in the number of trips, wherein more trips take place during school holidays than public holidays.

The effect of rain across weekdays and weekends is depicted in Fig. 4e. Rain appears to exhibit a suppressing effect that is consistent across both weekdays and weekends. All inter- and intra-community trips are equally reduced during rainfall. With regard to temperature, Fig. 4f provides some evidence to suggest that cooler temperatures (down to minus 7 degree Celsius) are associated with a reduction in ridership. That is especially the case for weekends.

Wind speed, examined in Fig. 4g, appears to exert a rather dramatic effect on ridership on weekends where winds are in excess of 6 km/h.

Table 1
List of variables used in modelling.

	Category	Variable	Description	Data source
	Dependent variable			
	Cycling trips		Number of cycle trips per day from community district i	Citibike data for a 12 month period (1st July 2016 to 30th June 2017) was procured from the operators' website (Citibike, 2017) and included a total of 14,985,889 individual trips.
	Independent variables			
Natural environment factors	Weather	Temperature	Average daily temperature in degrees Celsius	Climate and weather data was procured from Weather Underground history data and included hourly observations for temperature, humidity, wind speed, precipitation and snow cover. (Weather Underground, 2018)
		Rainfall	Total daily rainfall in mm	
		Humidity	Average daily humidity (percentage)	
		Wind	Average daily wind speed in km per hour	
		Snow	1 if there is snow cover during the day 0 if no snow cover during the day	
	Topography	Elevation	SD of elevation in community district i	Topographic data was sourced from NYC OpenData. (NYC Planning, 2018)
Built environment factors	Infrastructure	Cycle paths	Total length of cycle path in km in community district i	Bicycle infrastructure was sourced from Open Street Map revealing a total of 1823 km of cycle paths across NYC of which around 684 km are protected bicycle lanes (Hu, 2018).
	Land use mix	Land use mix	Shannon entropy index	Land use data was sourced from NYC Government Website New York City Planning, 2018). The spatial unit of analysis were the community districts i.
Temporal factors	Calendar events	Weekend	1 if a weekend 0 if a weekday	Sourced from https://publicholidays.us/ Included 11 days of public holiday, 52 weekends and 105 days of school holiday for the study period.
		School holiday	1 if a school holiday 0 if not a school holiday	
		Public holiday	1 if a public holiday 0 if not a public holiday	
	Peaks	Peak	Percentage of journeys started during peak periods	Citibike System Data included trip-duration (seconds), start time and date, stop time and date, start station, end station.
		Trip duration	Trip duration in minutes for all trips in one day	

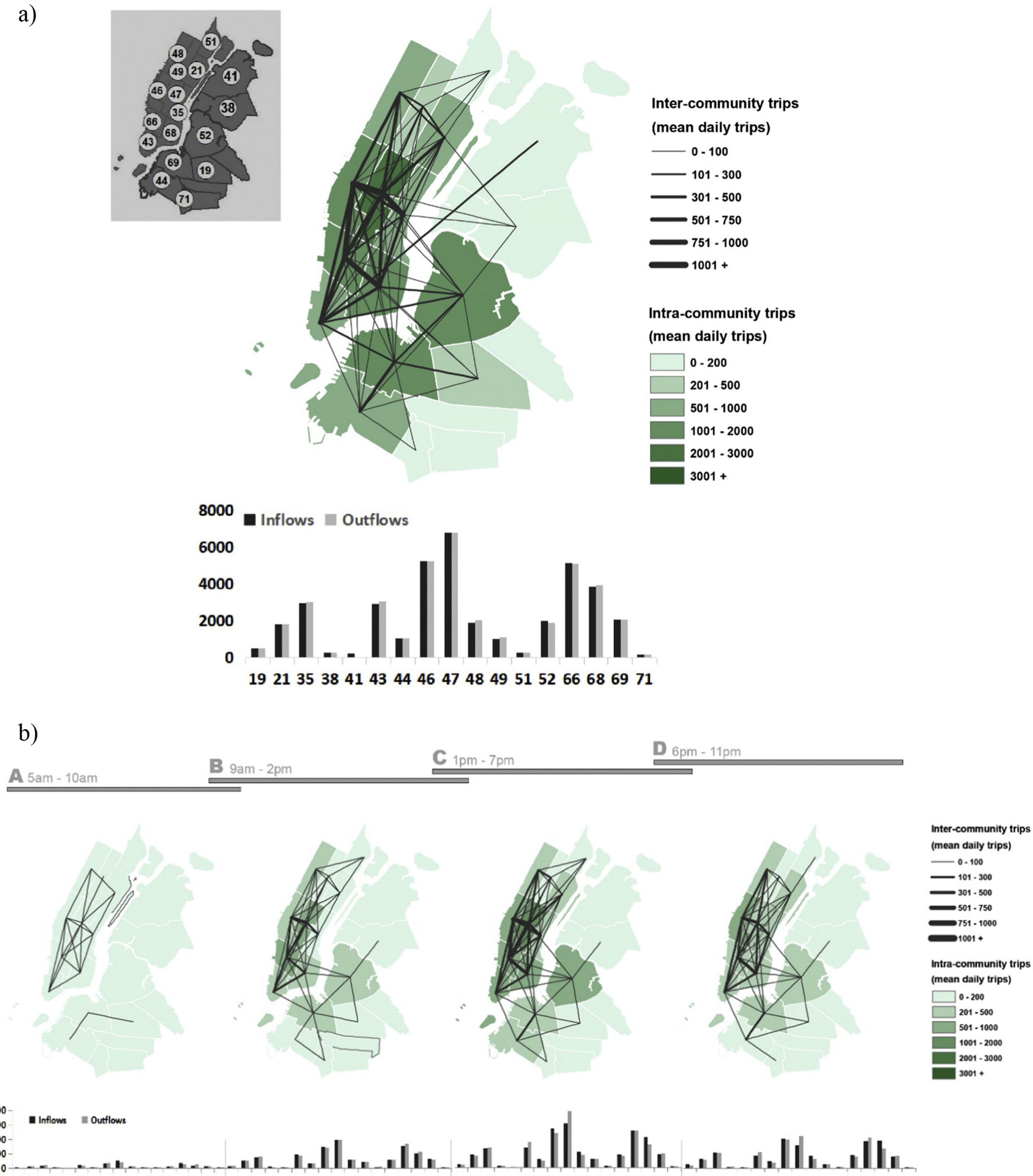


Fig. 4. a. Average daily Citibike trips. b. Univariate flow-comap for Citibike trips (by hour). c. Bivariate flow-comap for Citibike trips (by hour of day and for calendar events [weekday/weekend]). d. Bivariate flow-comap for Citibike trips (by hour of day and for calendar events [public holiday/school holiday]). e. Bivariate flow-comap for Citibike trips (rainfall and calendar events [weekday/weekend]). f. Bivariate flow-comap for Citibike trips (temperature and calendar events [weekday/weekend]). g. Bivariate flow-comap for Citibike trips (wind speed and calendar events [weekday/weekend]). h. Bivariate flow-comap for Citibike trips (snow and calendar events [weekday/weekend]).

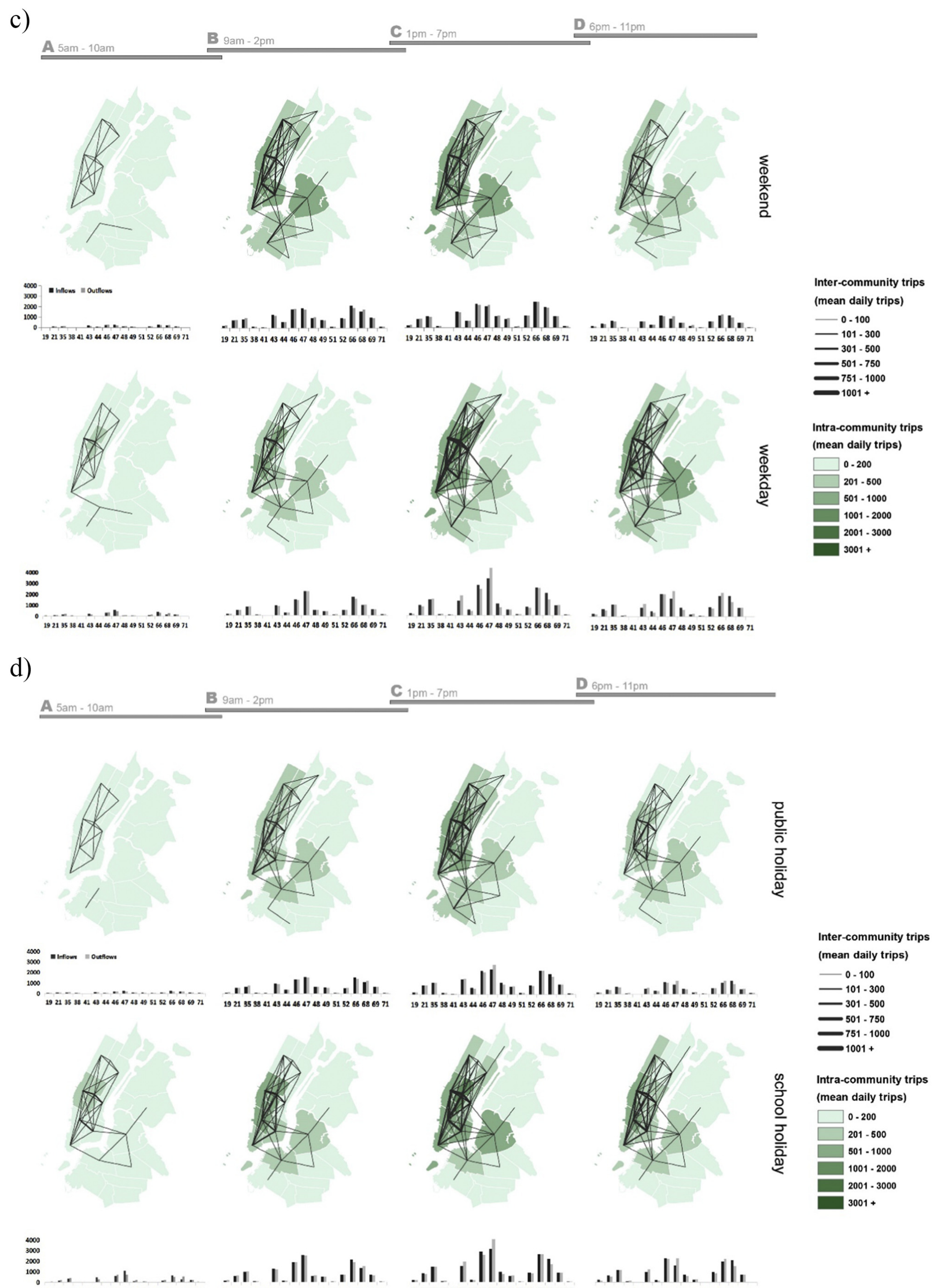


Fig. 4. (*continued*)

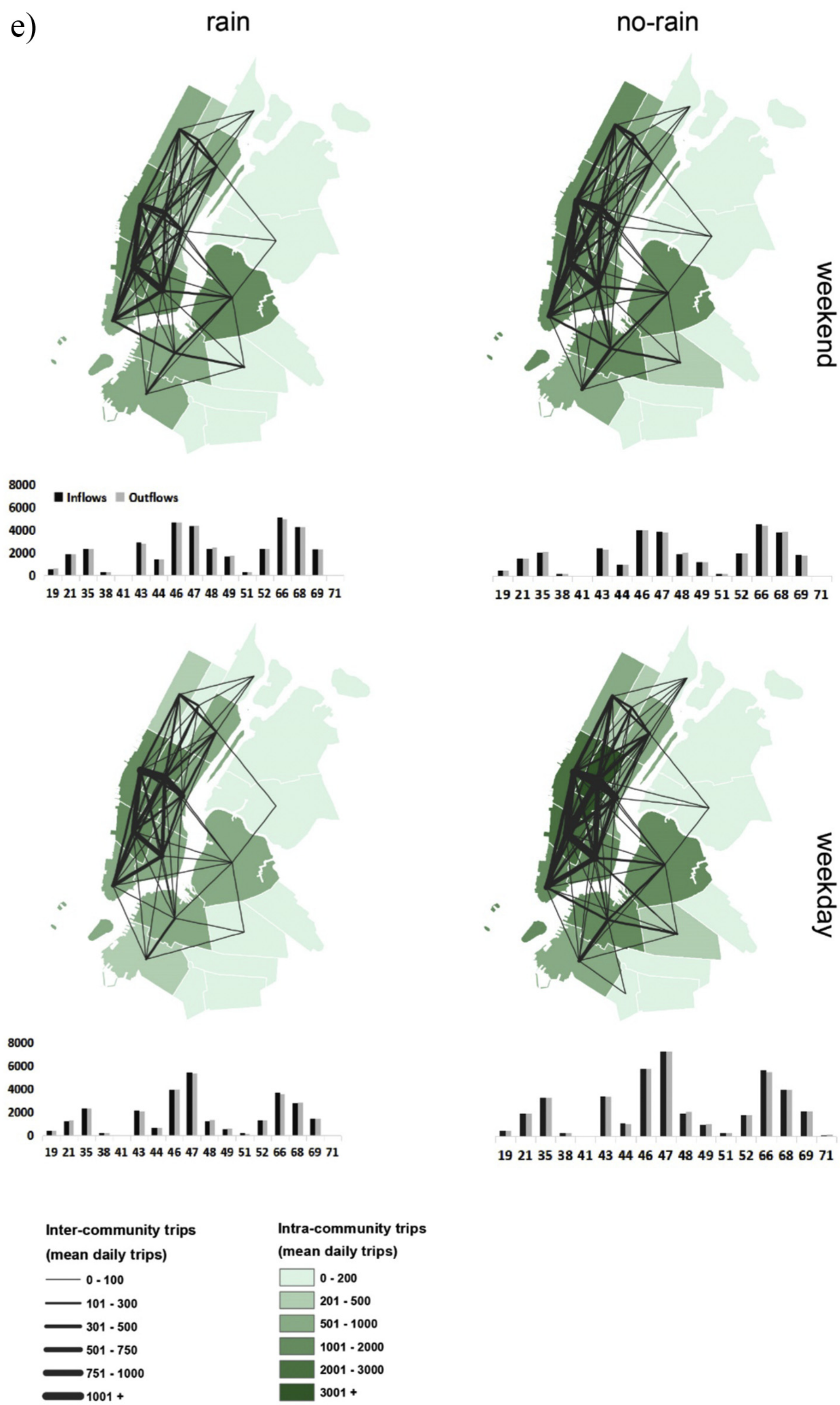
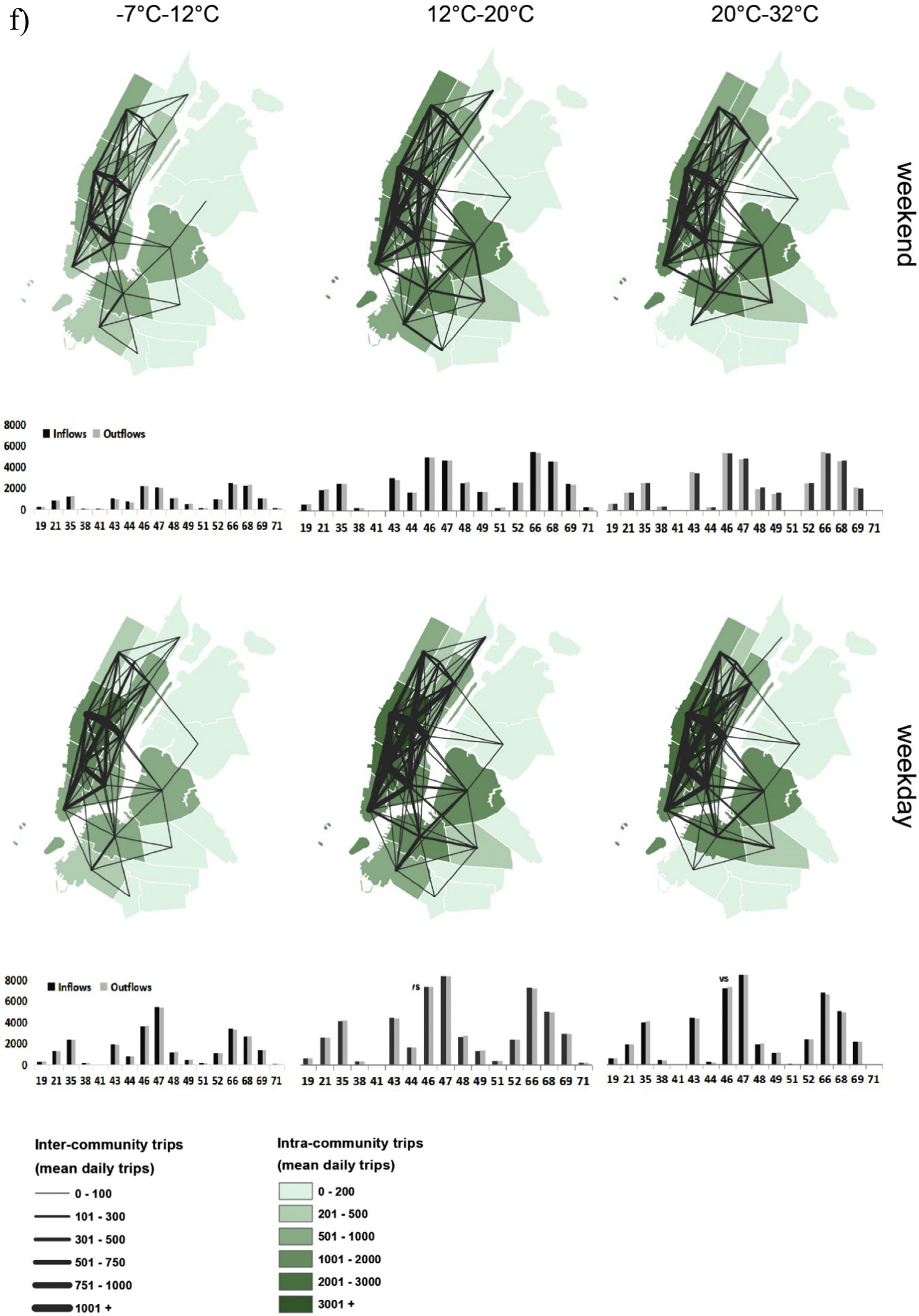


Fig. 4. (*continued*)

Strong winds suppress inter- and intra-community trips equally. The same effect is not visible in weekday travel. The latter appears largely unaffected by wind. Finally, Fig. 4h reports the effect of snow on ridership across weekends and weekdays. It shows that, compared to all other weather parameters, the presence of snow on the ground has the most dramatic effect on ridership, especially during the weekend.

4.2. System-wide analysis

Summary statistics for all variables included in the analysis are reported in Table 2. The correlations between the variables were considered and are presented in Table 3. The magnitude of the correlations between the independent variables suggested that multicollinearity would not be problematic; all independent variables had variance inflation factors less than 3.0. There was no evidence that the simultaneous inclusion of these variables impacted analytic results.



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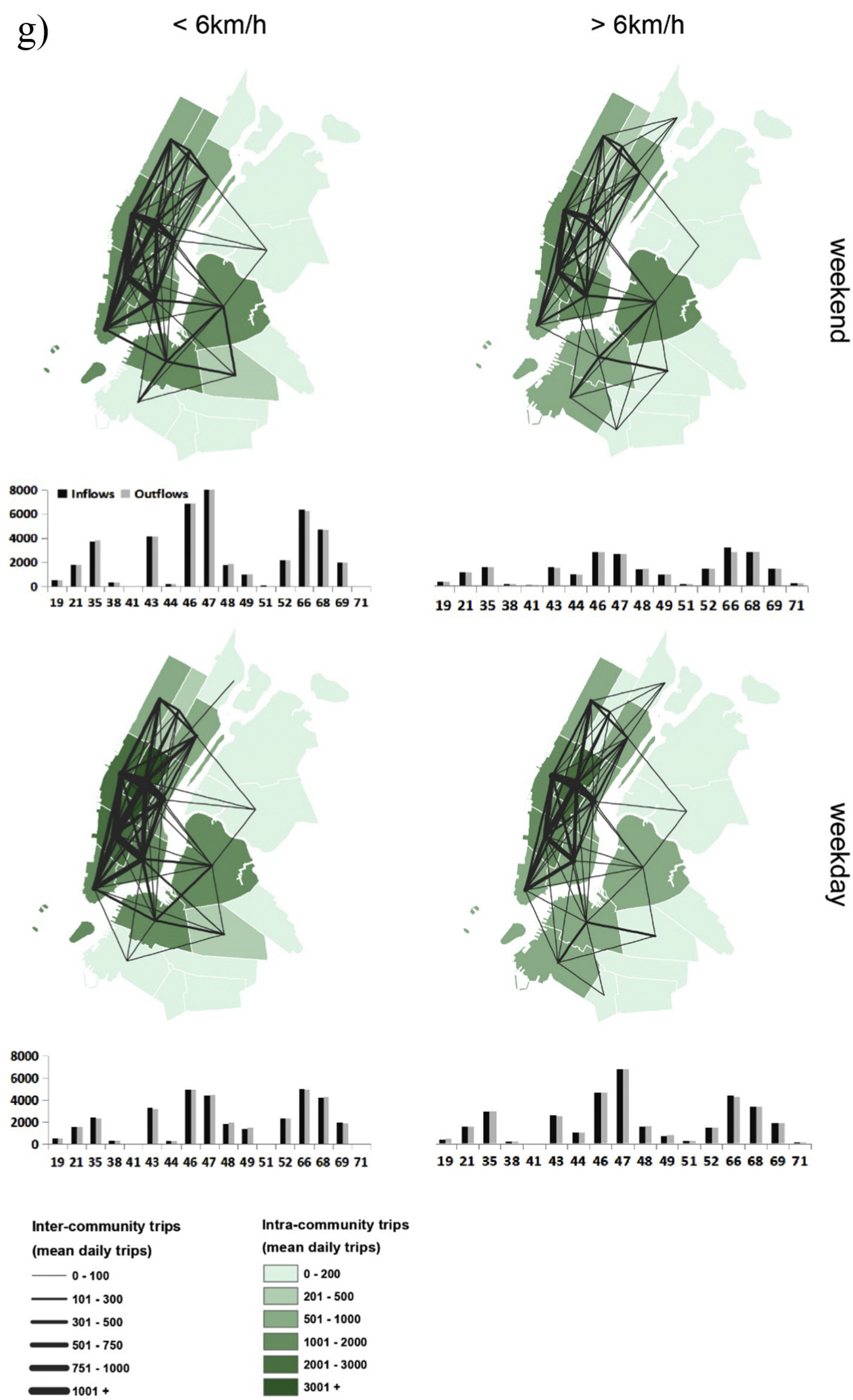

Fig. 4. (*continued*)

The results of the five regression models are presented in Table 4. Model 1 examines the direct relationship between average daily weather indicators and daily number of cycling trips initiated from NYC community districts while controlling for natural and built environment characteristics. The results demonstrate a significant relationship between weather and cycling in NYC across all weather parameters.

Consistent with existing scholarship, higher temperature predicted more cycling trips ($\beta = 0.154$, $p < .001$), regardless of the natural and built environment characteristic in which those trips took place. On the other hand, higher rainfall ($\beta = -0.153$, $p < .001$); higher humidity ($\beta = -0.037$, $p < .01$); higher wind speed ($\beta = -0.057$, $p < .001$) and the presence of snow ($\beta = -0.790$, $p < .001$) predicted fewer cycling trips. There was also evidence of fewer cycling trips on weekends and public holidays when compared to workdays (i.e., Monday through Friday) ($\beta = -0.127$, $p < .001$). The average daily temperature had a greater influence on cycling trips during weekends compared to weekdays ($\beta = 0.070$, $p < .01$). While there was no significant relationship between the physical characteristics of the origin Community

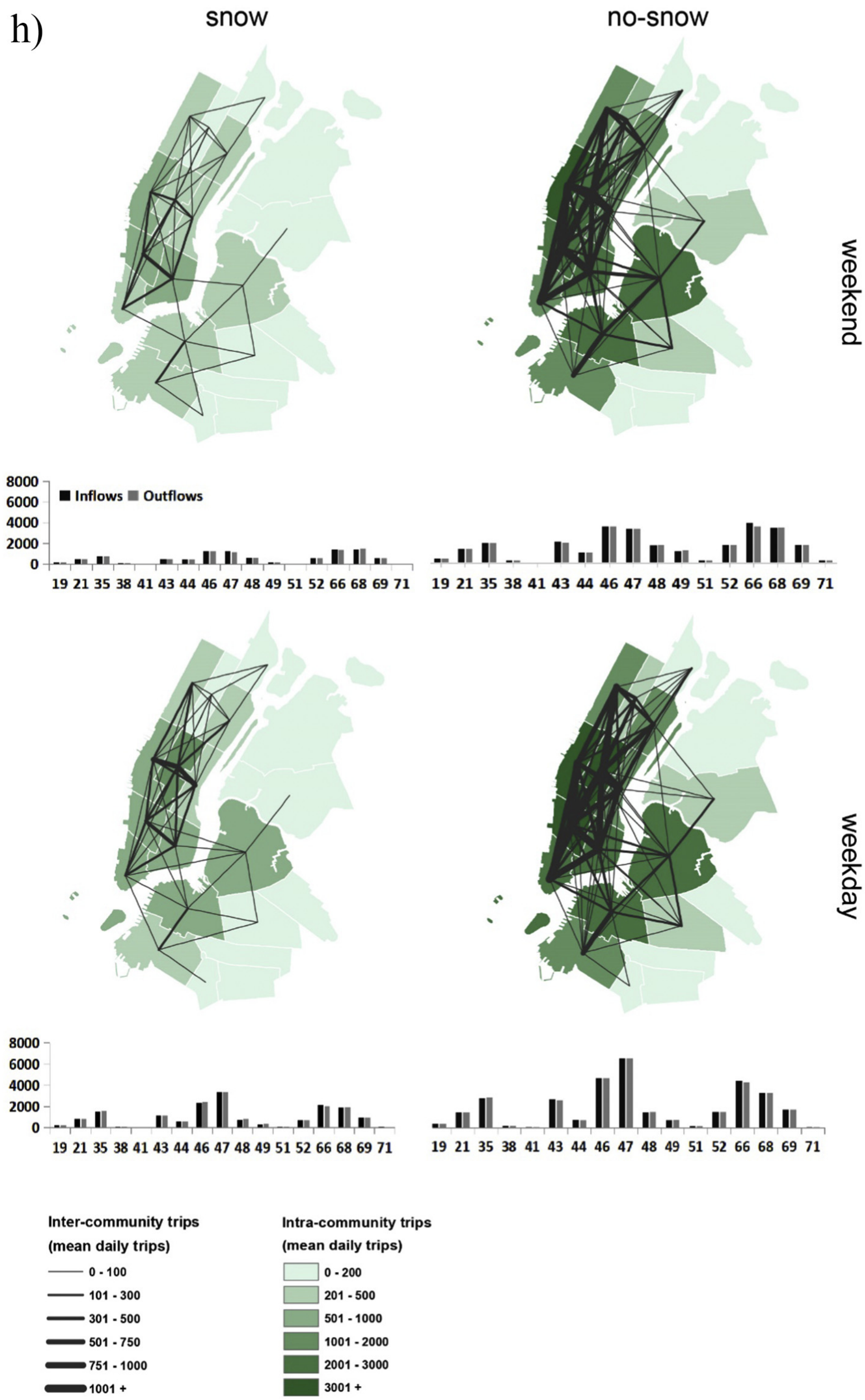

Fig. 4. (*continued*)

District and cycling trips, level of elevation in the spatially contiguous Community Districts was significantly and negatively associated with cycling trips ($\beta = -2.262$, $p < .001$).

Of the twenty interactions effects tested, four were statistically significant. The average daily temperature had a greater influence on cycling trips during weekends compared to weekdays ($\beta = 0.070$, $p < .01$); in Community Districts where the topography is flatter compared to areas with greater elevation ($\beta = -0.136$, $p < .001$); and in Community Districts with poorer cycle infrastructure ($\beta = -0.105$, $p < .001$). Similar to temperature, average daily humidity had a greater influence on cycling trips during weekends compared to weekdays ($\beta = 0.048$, $p < .05$). There was no evidence that the association between other weather parameters (i.e., rainfall, wind speed, snow) and cycling trips was contingent upon the day of the week or physical characteristics of the bike station (see Figs. 5 to 8).

5. Discussion and conclusion

The decision to cycle is a complex interplay of personal, situational, and natural- and built-environmental factors. Identifying the key

Table 2
Summary statistics (n = 6102; N = 17).

	Min	Max	Mean/%	SD
Cycling trips (total n)	0	12,710	2326.054	2438.348
Average daily temperature (degrees C)	−7	32	14.107	9.393
Precipitation (mm)	0	76.71	3.602	9.220
Average daily humidity (%)	26	98	62.126	14.882
Average daily wind speed (km/h)	2	29	8.642	3.858
Snow (0 = no snow; 1 = snow)	0	1	Snow 3.84%	
Weekend (0 = work day; 1 = weekend)	0	1	Weekend 30.41%	
Environmental controls				
Elevation (m)	8.844	39.300	20.203	9.112
Cycle path (length km)	16.535	49.647	33.863	8.985
Land use mix	0.172	0.813	0.560	0.150

factors that influence cycling across a metropolitan area is a non-trivial task. In this paper, we have sought to focus on the way in which weather influences cycling in NYC, whilst accounting for other well-known determinants of cycling, namely land-use, bicycle infrastructure, topography, and calendar events. Through the use of both mapping and modelling, we have identified a number of important findings, which, taken together, elucidate the cycling-weather relationship.

Weather and cycling are related across each of the weather parameters investigated in the context of NYC. Overall, we find that the weather impacts the number of cycling trips more than the topography, infrastructure, land-use mix, calendar events, and travel peaks. Consistent with existing scholarship, a higher temperature (up to 28 °C) predicts more cycling trips (Heaney et al., 2019), regardless of the natural- and built-environment characteristics in which those trips take place. In good weather, characterised by temperate conditions and an absence of strong winds, humidity and/or precipitation, people cycle more. This relationship remains present after accounting for land-use mix, topography and bicycle path availability.

On the other hand, rainy, humid, windy and especially snowy weather leads to fewer cycling trips – which is also consistent with existing studies (Heaney et al., 2019). The presence of bicycle paths, a high land-use mix, and a flat topography moderate the effects of inclement weather but not in a marked manner. However, this finding may be an artefact of the spatial unit of analysis used in this study, allied to the fact that we employed an area-based model rather than a trip-based model. This finding may also be due to a lack of high quality and dense cycling networks in New York City – which is a problem throughout the United States (see Pucher et al., 2011). A useful follow-up study could draw on Citibike GPS tracking data to identify the spatial circuits taken by riders and the extent to which the latter seek to use bicycle paths and avoid other parts of the road network. This GPS-based data would also be helpful to identify locations where riders have lingered during a given trip such that we can better understand how particular types of land-use and topography interact to inhibit or facilitate trip-making and route choices (Heesch and Langdon, 2017).

With regard to temporal factors, fewer cycling trips are taken during weekends and public holidays compared to weekdays - especially in colder temperatures. Likely, weekday trips are ostensibly utilitarian in nature (work-related); thus there is less opportunity to cancel or postpone even when the weather is inclement. Existing research (see for example, Brandenburg et al., 2007) also suggests that calendar events help to explain trip variations as they disrupt the routines of individuals and families. The effect of wind and snow is dramatic on weekends but not during weekdays. Most cycling trips occur between the afternoon and early evening when temperatures are typically the warmest rather than being closely aligned with the two commute peaks.

Bikesharing data (such as that used in this study) provide excellent coverage of cycling patterns, and can be linked, relatively easily, to 'objective', physical characteristics of the cycling environment, such as topography, bicycle infrastructure, traffic conditions, access and linkage, and transportation alternatives. However data lack information on 'subjective' characteristics (safety and danger, convenience, cost and income, valuation of time, valuation of exercise, health condition, family circumstances, habits, attitudes and values, public image, and peer group acceptance) – all of which are known to influence cycling (Federal Highway Administration, 1992; Pucher et al., 1999; Pojani et al., 2017). To further unpack the effect of these important subjective factors, the use of additional datasets is needed. One fruitful future avenue of research could explore ways to integrate traditional travel survey/diary data with bikesharing databases, to potentially provide a more complete empirical foundation through which to explain cycling patterns and behaviours.

Taken together, our findings hold a number of important policy implications. Clearly, urban planners and transport policy makers must be much more mindful of the role of weather when planning, designing or retrofitting active travel spaces. As Susan Joy Hassol, director of Climate Communication, a non-profit organisation devoted to science outreach, said in a press interview: "*Weather, and especially extreme weather, is how most people will experience climate change…You don't experience the slow change in average temperature. What you experience are the changes in extreme weather that are brought about*" (Plumer, 2019). In practical terms, predicted shifts in the patterns and intensity of severe weather might mean that in creating state-of-the-art cycling infrastructure – that is, sheltered, promptly cleared of snow, and potentially heated or cooled - may become the key to 'getting people out of their cars.' In cold, northern latitudes this may be more important than in warm, sunny places.

There is some evidence that climate and weather sensitive cycling infrastructure is already being both considered and implemented. For example, the Netherlands is building the longest heated bicycle path in western Europe (totalling 1.7 km in length) to connect Wageningen and Arnhem, which will be kept snow-free (Boffey, 2018). Meanwhile, Qatar has proposed to build a shaded, solar-powered, mist-cooled bicycle path of 30 km (Naparstek, 2006), while Berlin is planning on converting an elevated rail line (9 km) into a covered cycle path

Table 3
Pairwise correlations.

Variables	1	2	3	4	5	6	7	8	9
1. Average daily temperature	1.00								
2. Precipitation	**−0.031**	1.00							
3. Average daily humidity	**0.187**	**0.459**	1.00						
4. Average daily wind speed	**−0.492**	**0.167**	**−0.056**	1.00					
5. Snow	**−0.303**	**0.142**	**0.070**	**0.189**	1.00				
6. Elevation	0.000	0.000	0.000	0.000	0.000	1.00			
7. Cycle path (length km)	0.000	0.000	0.000	0.000	0.000	**0.221**	1.00		
8. Land use mix	0.000	0.000	0.000	0.000	0.000	**−0.227**	**0.626**	1.00	
9. Weekend	**−0.052**	**−0.030**	**−0.040**	0.015	**0.085**	0.000	0.000	0.000	1.00

NOTES: bold face $p < 0.05$; collinearity diagnostics show all VIFs are below 2.0 with exception of cycle paths (2.15) and land use mix (2.14).

Table 4
Multilevel regression†.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Cycling trips		Interaction: temperature × weekend		Interaction: temperature × elevation		Interaction: temperature × infrastructure		Interaction: humidity × weekend	
	β	SE	β	SE	β	SE	β	SE	β	SE
Natural environment variables										
Temperature	0.154	0.013***	0.132	0.015***	0.154	0.013***	0.153	0.013***	0.153	0.013***
Rainfall	−0.153	0.013***	−0.154	0.013**	−0.152	0.013***	−0.153	0.013***	−0.151	0.013***
Humidity	−0.037	0.012**	−0.038	0.012***	−0.035	0.012**	−0.037	0.012**	−0.053	0.015***
Wind	−0.057	0.013***	−0.057	0.013***	−0.058	0.013***	−0.057	0.013***	−0.056	0.012***
Snow	−0.790	0.063***	−0.763	0.064***	−0.825	0.062***	−0.790	0.062***	−0.806	0.064***
Elevation	0.634	0.378	0.634	0.378	0.635	0.378	0.634	0.377	0.634	0.378
Built environment variables										
Infrastructure (cycle paths)	0.120	0.434	0.120	0.434	0.120	0.434	0.121	0.434	0.120	0.434
Land use mix	0.89	0.419	0.189	0.420	0.188	0.420	0.189	0.419	0.189	0.419
Temporal variables										
Weekend	−0.127	0.024***	−0.125	0.024***	−0.126	0.023***	−0.127	0.023***	−0.124	0.024***
Spatial lags										
Elevation	−2.262	0.648***	−2.262	0.648***	−2.262	0.648***	−2.262	0.648***	−2.262	0.648
Infrastructure (cycle paths)	0.071	0.748	0.071	0.748	0.071	0.748	0.070	0.747	0.070	0.748
Land use mix	−0.078	0.810	−0.078	0.810	−0.077	0.810	−0.077	0.810	−0.078	0.810
Interactions										
Interaction: temperature × weekend			0.070	0.024**						
Interaction: temperature × elevation					−0.136	0.011***				
Interaction: temperature × infrastructure							−0.105	0.011***		
Interaction: humidity × weekend									−0.125	0.023*
Constant	6.926	0.270***	6.926	0.270***	6.926	0.270***	6.926	0.270***	6.927	0.270***
R^2 overall	0.4576		0.4578		0.4609		0.4600		0.4577	
Wald chi^2	914.72***		924.81***		1060.44***		1021.86***		919.40***	

Significance: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. † n = 6102; N = 17; standardised coefficients.

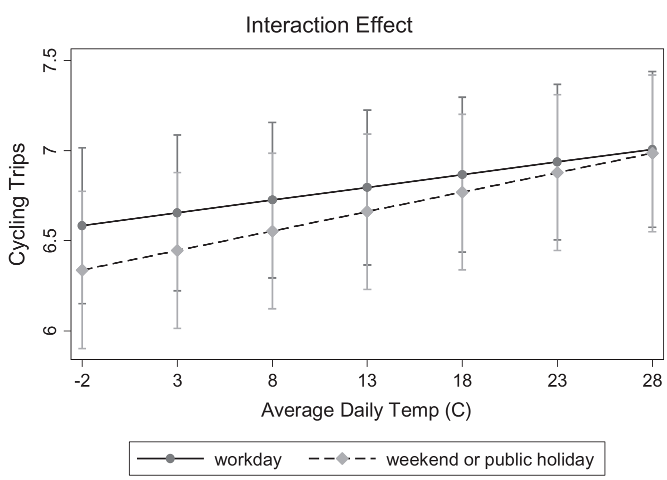

Fig. 5. Interaction term weekend/weekday and average daily temperature on number of cycle trips.

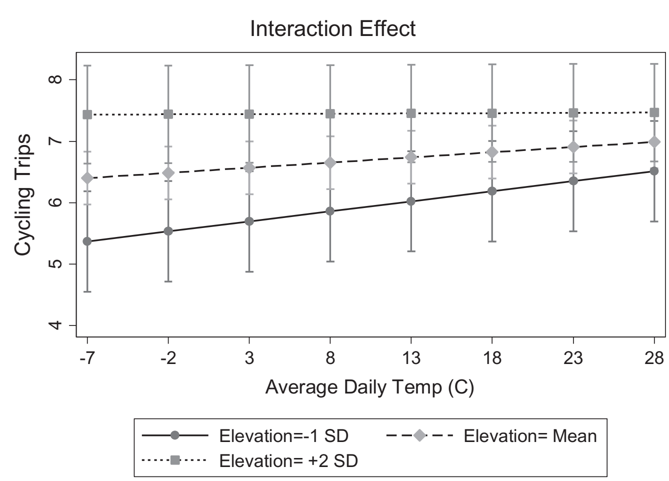

Fig. 6. Interaction term elevation and average daily temperature on number of cycle trips.

(Finger, 2017). Similarly, Singapore has recommended the creation of covered and/or shaded cycling paths in its new Walking and Cycling Design Guide (Urban Redevelopment Authority and Land Transport Authority, 2018).

Weather intrinsically influences our everyday behaviours. The decision to cycle is far from exempt from the influences of weather that together with walking, cycling are the most vulnerable modes of travel to variations in prevailing conditions. Climate change is set to place a growing and disproportionate influence [compared to motorised modes] on such methods of travel underscoring the urgency for us to develop a rigorous understanding of the weather-cycling relationship. Indeed, if cities are to increase cycling patronage there is a compelling need to expand the cross-national research on cycling determinants, and understand how these determinants vary across space, time, climatic and cultural contexts. Once this evidence base on cycling is assembled, urban planners will be far better equipped to (re)design urban environments in a manner that best protects citizens and offers the most conducive conditions for active travel.

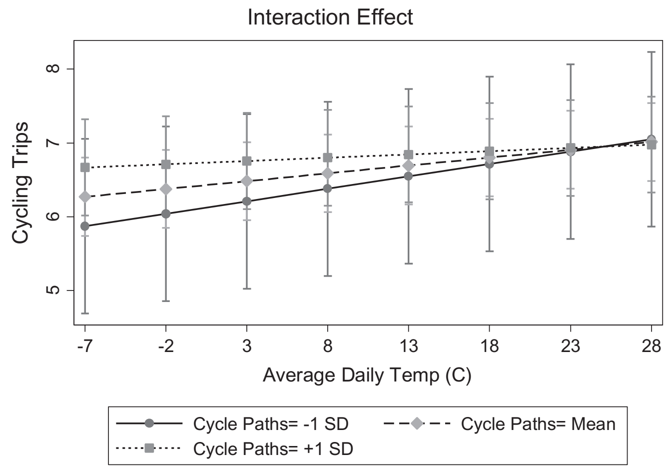

Fig. 7. Interaction term infrastructure and average daily temperature on number of cycle trips.

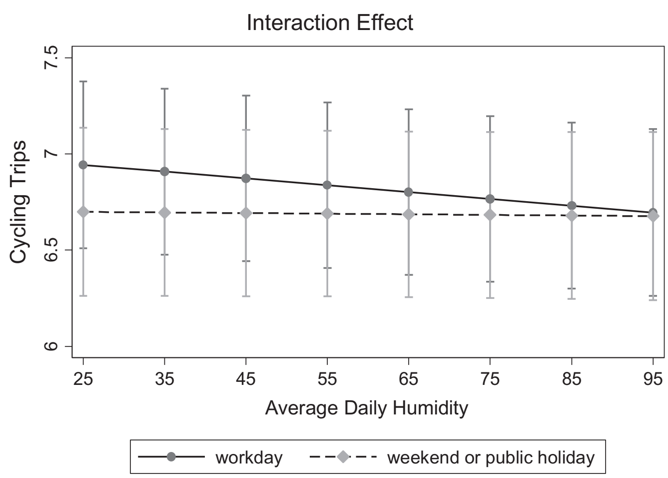

Fig. 8. Interaction term weekend/weekday and average daily humidity on number of cycle trips.

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