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Can infrastructure, built environment, and geographic factor negate weather impact on Strava cyclists?

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Abstract: Cycling participation is context-sensitive and weather condition is reportedly a significant factor. How weather affects cyclists with different demographics, trip purposes, and in the context of cycling infrastructure, built environment and geographic factors is less well understood by existing literature. This paper applies autoregressive models to explain difference in Strava cycling volume from the same hour of the previous day as a function of change in weather conditions, and day of the week; the contextual effect of cycling infrastructure, built environment and geographic factors is accounted for using interaction terms. We use Strava crowdsourced cycling data in Sydney, Australia, as a case study; commute and leisure cyclists, male and female, young and older cyclists are modeled separately. We find weather conditions have a statistically significant effect on cycling participation; rain, rainfall in the last 2 hours and wind are general deterrents to cycling. Physically separated cycling lanes reduce the adverse effect of precipitation on leisure cyclists and male cyclists but have little effect in retaining commute cyclists and female cyclists. The adverse effect of precipitation and wind on commute cycling is amplified in areas with good access to jobs, possibly due to the availability of better alternative modes of transport. Inland locations generally attenuate effects of windy conditions, except for young adults. This paper sheds light on factors attenuating adverse weather effects on cycling participation and provides useful guidance for future cycling infrastructure.

Keywords: Crowdsourced data, weather, bicycling, Strava, climate, Australia

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1 Introduction

Cycling is a sustainable mode of transport, and is particularity suited for urban areas where the average travel distance is reduced by compact land use and a job-rich environment (Levinson, 1998). In major metropolitan areas across the world, cycling can typically reach more job locations than by public transport within the same amount of travel time, making cycling an efficient mode of transport both by itself (Wu et al., 2021), and by

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complementing public transport (Zhang & Lee, 2023). In addition, cycling activities have well documented health (Celis-Morales et al., 2017) and environmental benefits (Abduljabbar et.al, 2021; Woodcock et al., 2018). Traffic congestion imposes significant financial cost on society, and the cost is projected to further increase due to population growth (BITRE, 2015). Congestion reduction is a major benefit of cycling infrastructure investment (Li & Faghri, 2014). Mode shift towards cycling reduces the number of automobiles on the road and thus traffic congestion, which can have significant economic benefits through increased productivity.

Yet there is a dichotomy between the convenience and benefits afforded by cycling, and the number of people who actually use cycling as a day-to-day means of transport. Cycling mode share is generally below 2% in most cities in North America, U.K. and Australia (Buehler & Pucher, 2021). The literature identified barriers to cycling including safety, terrain, lack of cycling infrastructure, weather condition, and a combination of these factors. Cyclists prefer flat terrain (Buehler & Pucher, 2012); steep slopes are disfavored, especially among female and commute cyclists (Hood et al., 2011). There is a general preference among cyclists for a safe cycling environment with dedicated cycling infrastructure (Heesch et al., 2012), and being physically separated from the traffic (Larsen & El-Geneidy, 2011).

Weather has been identified as a major factor affecting daily cycling activities. Adverse weather conditions such as rainfall, snow, or uncomfortable temperature are common deterrents for cycling (Bean et al., 2021; Rose et al., 2011). The volume of recreational cyclists is sensitive to both rainfall and temperature (Dunlap et. al., 2014). Wind is also identified to negatively affect cycling participation (Helbich et al., 2014). While wind and precipitation are widely identified as deterrents for cycling, temperature has a bell-shaped effect on cycling where warm temperature up until a certain degree increases cycling usage, but excessively cold or hot temperature reduces cycling (Phung & Rose, 2007). Cyclists are directly exposed to weather elements, and adverse weather conditions affect cycling participation more than other modes of transport (Yang et al., 2018). Cyclists often switch to other modes of transport during adverse weather (Böcker et. al, 2013; Hyland et. al, 2018). However, there are exceptions that suggest other elements overriding or having combined effects with weather that affect cycling rate. For instance, European cities with mature cycling infrastructure, such as the Netherlands and Denmark have high cycling rates despite rainy climates; Finland, Canada, and Minneapolis in the US have high cycling rates despite cold winter temperatures; Canada also has higher cycling rates than US (Buehler & Pucher, 2021) despite being further north and have colder climates. These exceptions shed light on the possibility of providing proper cycling infrastructure in the right place and for the right type of cyclists in order to attenuate the adverse effect of weather on cycling participation. Research is needed to understand the complex interaction between weather and cycling, and to understand whether cycling infrastructure would be effective in retaining cyclists against weather.

The literature reports varying degrees of weather impacts by population demographics and trip purposes. Cycling involves people from diverse demographic backgrounds, and varying trip purposes, and the effect of weather on cycling may differ depending on who and why people cycle. Adverse weather conditions affect certain demographic groups more than others in cycling participation. Students in high school, college, or university are less affected by precipitation than other demographic groups (Winters et al., 2007). Precipitation reduces cycling among females more than males (Bean et al., 2021). A study in New York samples bike sharing trips and suggests that female and the elderly are more vulnerable to rainfall than other population groups (Zhou et al., 2019). Females are generally more risk averse than male cyclists, preferring separated cycling lanes and having a higher stated aversion to rain or windy conditions (Heesch et al., 2012). Leisure cycling trips tend to be affected by weather conditions more than commute trips, which was attributed to the higher flexibility with leisure trips (Helbich et al., 2014; Thomas et al., 2013). Studies linking weather effects with demographics are mostly based on surveys, including self-reported cycling trips and stated preferences; in this paper we supplement and verify these survey results using actual road-segment level cycling volume and hourly weather data.

Cycling infrastructure (or the lack thereof) at route or facility level can affect local bike usage, as a study of 43 cities in the US affirms that new bike lanes will increase bike usage (Broach et.al., 2012; Dill & Carr, 2003); the percentage of roads with separated bike infrastructure has a positive effect on bike usage (El-Assi et al., 2017). However, there has been mixed evidence on how safer cycling infrastructure reinforces or attenuates effects from adverse weather. A study in Glasgow, UK found rainfall reduces cyclist numbers by a larger amount in streets with better cycling infrastructure, suggesting that people using these streets might be more sensitive to weather conditions (Hong et al., 2020). Other studies in the Netherlands (Helbich et al. 2014) and in the U.S. (Dill & Voros, 2007) suggest that the built environment and infrastructure might reduce negative effects from weather. Better understanding of the combined effect of weather and environment on cycling participation would shed light on cycling behavior, and provide design guidance on alleviating the effect of adverse weather on cycling.

The literature suggests that cycling participation is affected by weather in conjunction with environmental factors. For example, wind has a stronger deterrent effect on cycling participation in coastal areas than inland areas (Phung & Rose, 2007). The effect of adverse weather appears to be weaker in built-up urban areas than suburbs (Helbich et al., 2014). Temperature and wind conditions reportedly play a less significant role for cycling in dense and compact urban areas compared to low-density suburbs, which could be attributable to tall buildings protecting cyclists from adverse weather (Helbich et al., 2014). The spatial variations in weather factors has also been partially attributed to the urban heat island effect (Stewart & Oke, 2012) and urban canyons sheltering adverse weather elements (Blocken & Carmeliet, 2004). However, there is a gap in existing literature in modeling variations in cycling participation as a function of variations in weather conditions that include contextual effects of cycling infrastructure, build environment and geographic factors. To the best of our knowledge, this paper is the first attempt in directly modeling the combined effect of weather and cycling environment for different types of cyclists. Such an attempt is only possible until recently with the widespread use of GPS enabled smartphones and health tracking apps.

Although it has been well established by the literature that adverse weather conditions reduce cycling participation, the extent to which weather affects cycling participation in different cycling infrastructure, built environment and geographic factors, and for different types of cyclists and cycling trip purposes are not well understood. This paper connects hourly weather conditions including temperature, precipitation, humidity, and wind speed with detailed environmental factors including accessibility to jobs, distance from the coast, presence of separated cycling lane, urbanized environment, and attempts to explain and quantify their joint effects on cycling participation for different demographics and trip purposes. This paper is the first in cycling research to match cycling data with spatially closest weather stations (13 weather stations in Greater Sydney), which should improve the accuracy of hourly weather data. The average cycling travel distance in dense and job-rich urban areas are generally shorter than in suburban areas (Levinson, 1998), and this shorter travel distance may reduce cyclists' exposure to weather elements and contribute to the resilience of cycling rates to adverse weather conditions; this hypothesis has never before been tested with real data. This paper will also be the first in the literature to examine if cycling access to jobs can actually attenuate the effect of weather on cycling participation.

The effect of weather on cycling participation will be examined separately for leisure and commute cycling, male and female, and young and old cyclists. Female and older cyclists are generally more risk averse (Boufous et. al, 2021), and might to be more sensitive to the combination of weather and environmental factors; leisure trips should be more sensitive to weather conditions. In particular, we formulate and examine the following hypotheses in this paper:

1. ***Both rainfall and wind adversely affect cycling participation.***

   In this paper we aim to verify the adverse effect of precipitation, past rainfall, and windy conditions on cycling participation by using high resolution (hourly) weather and cycling volume data. We specifically test the effect from past rainfall.

2. ***Physically separated cycling infrastructure attenuates adverse weather effects on cycling participation.***

   Cycling infrastructure providing separation from vehicular traffic should make it safer for cyclists during adverse weather. We examine whether such an attenuation effect is detectable from crowdsourced Strava cycling data, and if cycling infrastructure attenuates weather effect for both commute and leisure cycling.

3. ***Access to jobs may either attenuate or reinforce the effect of adverse weather on commute cycling.***

   Places with good access to jobs generally have shorter commute distances, which in theory reduces the effect of adverse weather. On the other hand, places with good cycling access to jobs often overlap with places with good transit service, providing alternative methods of travel for cyclists during adverse weather events. Cyclists switching to alternative modes of transport due to weather would suggest insufficient cycling infrastructure to shelter cyclists, and end-of-trip facilities.

The next section of the paper will provide an overview of data sources, followed by a discussion on autoregressive models and interaction terms, and how the combined effect of weather and contextual cycling infrastructure, built environment and geographic factors are modeled. Cycling participation rates are modeled separately for commute and leisure cyclists, and for male and female, young and old cyclists. This paper also discusses how certain factors, such as separated cycling lanes, or having good access to jobs either reinforces or attenuates the effects of adverse weather condition on cycling participation, and differences between cycling purposes and among cyclist groups.

2 Data

This study uses crowdsourced cyclist count data to measure cycling participation. Road-segment level hourly cyclists count data is obtained from Strava[1]. Hourly cyclists count data has been rounded up by Strava to the nearest multiple of 5 for privacy reasons. Cyclist counts are broken down by trip purposes (commute vs. leisure), age group and gender of the cyclists; trip purposes are manually labelled by cyclists themselves. There is no cross-tabulation between trip purposes and cyclist demographics, so the relation between weather and different types of cycling trips are examined separately in this paper.

Cyclists count data is based on a version of OpenStreetMap (OSM) customized by Strava, in which links are broken-up at intersections; the median segment length is about 60 meters with a standard deviation of 146 meters. It is possible that longer segments are more likely to "capture" more cyclists than shorter segments, but since links are broken-up at intersections, cyclists will still have to travel through the entire length before they can reach other segments, therefore each segment can be treated effectively as a cross-section.

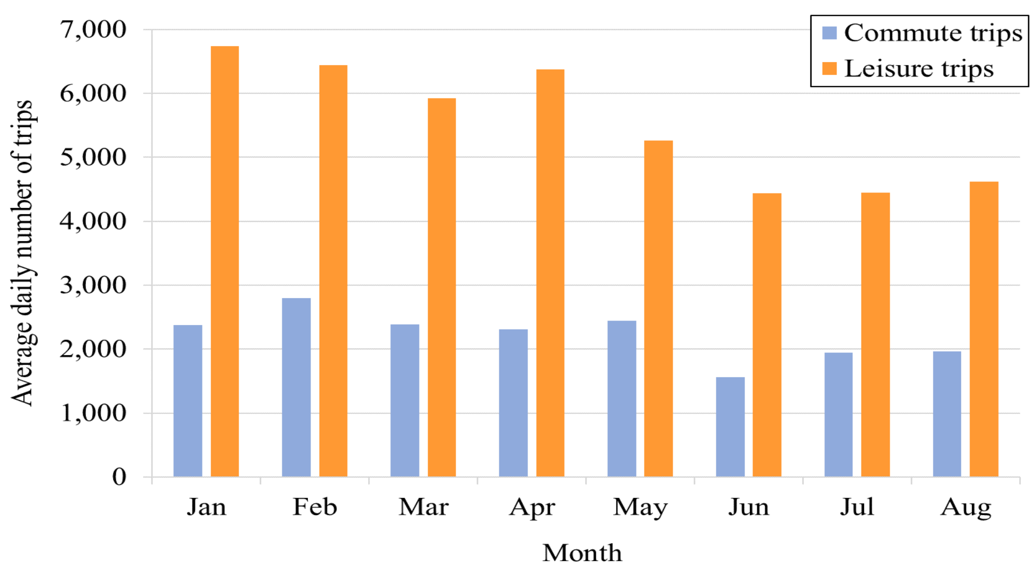

Figure 1. Average daily number of cycling trips by month, as recorded by Strava between January and August 2019 in Sydney, Australia

Factors such as the haze from Australian wildfire from September 2019 to March 2020, and the COVID-19 pandemic-related restrictions beginning in March 2020 may have caused irregular travel patterns; to study the effect of weather and cyclists' behavior in the absence of such irregularities, this paper uses Strava count data from every hour between January and August 2019. The data used in this paper includes 2581 road segments in Sydney, and around 1.2 million observations of hourly cyclists' volumes on these segments between 6 AM and 9 PM. We focus on road segments in the Greater Sydney area that are categorized by Transport for New South Wales (TfNSW) and includes classification of

[1] Strava is a company that provides activity tracking apps for active transport users.

facility types (e.g., separated, mixed traffic). In Sydney, cyclists on painted bike lanes and on roads with only bike markings often have to cycle in mixed traffic, making the effect of these types of cycling infrastructure to be less pronounced. Therefore this paper only considers the effect of cycling infrastructure where cyclists have exclusive right-of-way, or if cyclists are physically separated from vehicle traffic. Links with low cyclist volume[2] are excluded from analysis; the purpose of excluding links with low cyclist volume is to reduce noise in the data, and to reduce the effect of binned cyclists count data, so that differences in cycling volume between the same hour of two consecutive day will be less due to random fluctuations. Segments with sufficient number of cyclists represent links that are frequently used by cyclists, which makes results from this paper more useful. Average daily number of commute and leisure cyclists are shown in Figure 1.

It should be noted that Strava data represents only a part of overall cyclists. For instance, a review found that Strava data typically represent between 1% to 5% of cyclists count from either manual or video counting in various cities. The correlation between Strava and actual cycling traffic is also high, and a study in Sydney, Australia compared manual count data with Strava monthly cycling volume data, and found a correlation coefficient of 0.79 between Strava and manual count data (Conrow et al., 2018). In light of the representativeness of Strava data, and a lack of cycling data from other sources, Strava data is used in this paper to model the effect of weather on cycling participation. Strava collapses link level count with low cyclist volume to "0" for privacy reasons, and cyclists count data are in increments of "5."

Cycling infrastructure data is based on the NSW Bicycle Network dataset from Transport for New South Wales (TfNSW). This inventory data of existing cycling infrastructure includes categorization for each segment. We differentiate cycling lanes between those having physical or grade separation with traffic, and those in mixed traffic, or having only marked bike lanes. The rationale is that marked bike lanes with no physical barrier are frequently ignored by drivers, which makes them less effective. The geographical boundary of Greater Sydney, and NSW Bicycle Network is shown in Figure 2.

Table 1. Average daily weather conditions by month, between January and August 2019 in Sydney, Australia. Average of all weather stations

	Precipitation (mm)		Temperature (℃)		Relative Humidity (%)		Wind Speed (km/h)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
January	2.34	6.74	24.26	2.78	76.62	10.05	11.83	5.14
February	1.56	4.68	21.93	2.68	70.37	11.51	13.00	5.77
March	5.06	11.41	20.91	2.80	74.84	11.34	11.94	5.83
April	0.56	2.44	17.92	2.56	76.21	10.09	9.00	4.62
May	0.33	1.68	14.57	2.84	69.40	13.12	11.03	7.69
June	3.09	8.04	11.95	2.57	75.69	12.15	10.77	6.60
July	0.67	2.40	11.72	2.24	66.69	14.56	11.84	8.09
August	1.20	6.15	11.77	2.25	62.29	14.74	14.26	9.29

[2] Cycling links with low volume is defined as links that never exceeded 20 cyclists/hour for the entire duration. About 85% of all links are excluded. Sensitivity test show little effect from this threshold on modeling results.

Hourly weather data for Greater Sydney is obtained from the Australian Bureau of Meteorology, including hourly precipitation (mm), temperature (C), wind speed (km/h), relative humidity (%). There are a total of 20 weather stations with valid data in New South Wales (13 in Greater Sydney) for the study period, and hourly cyclists count data is matched with hourly weather data from the spatially nearest weather station. Table 1 provides an overview of weather conditions during the study period. The locations of weather stations are shown in Figure 2. Sydney, Australia has subtropical climate and mild winters, so cold temperature is unlikely to be a deterrence to cycling. Extreme weather events are very rare in Sydney, and there is no recorded extreme weather event[3] during the study period.

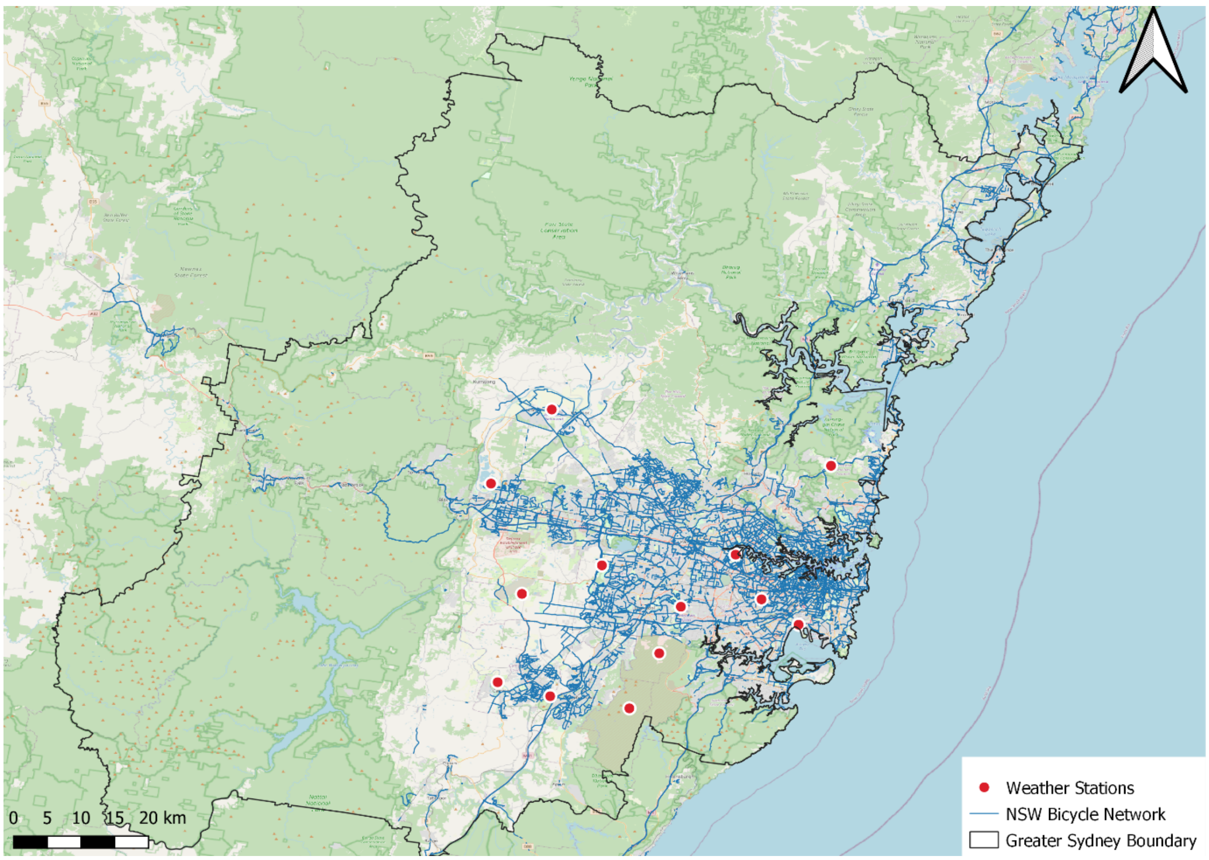

Figure 2. Geographical boundary of Greater Sydney, NSW bicycle network and weather station locations

Accessibility refers to the ease of reaching desired destinations, and is measured by the number of jobs or urban amenities reachable within a travel time threshold. There has been evidence that for a mode of transport, the level of accessibility is a significant predictor of its mode share and patronage (Owen & Levinson, 2015; Wu et. al, 2019). Cycling access to jobs has a positive effect on shared bike usage (Wang et. al, 2016). The average commute cycling distance is lower in a job-rich environment with good cycling access to jobs

[3] Extreme weather events include extreme temperature, flood, hurricane, wildfire and haze. These events are absent for the study period.

(Levinson, 1998), which might better retain cyclists against adverse weather. Cycling access to jobs is calculated as the cumulative number of jobs reachable within 30 minutes using all streets where cycling is allowed. Figure 3 shows cycling access to jobs in Sydney. On the other hand, places with good access to jobs tend to have good transit services providing an alternative to cycling under adverse weather conditions. This paper tests the possibility that good cycling access to jobs attenuates effects from adverse weather conditions.

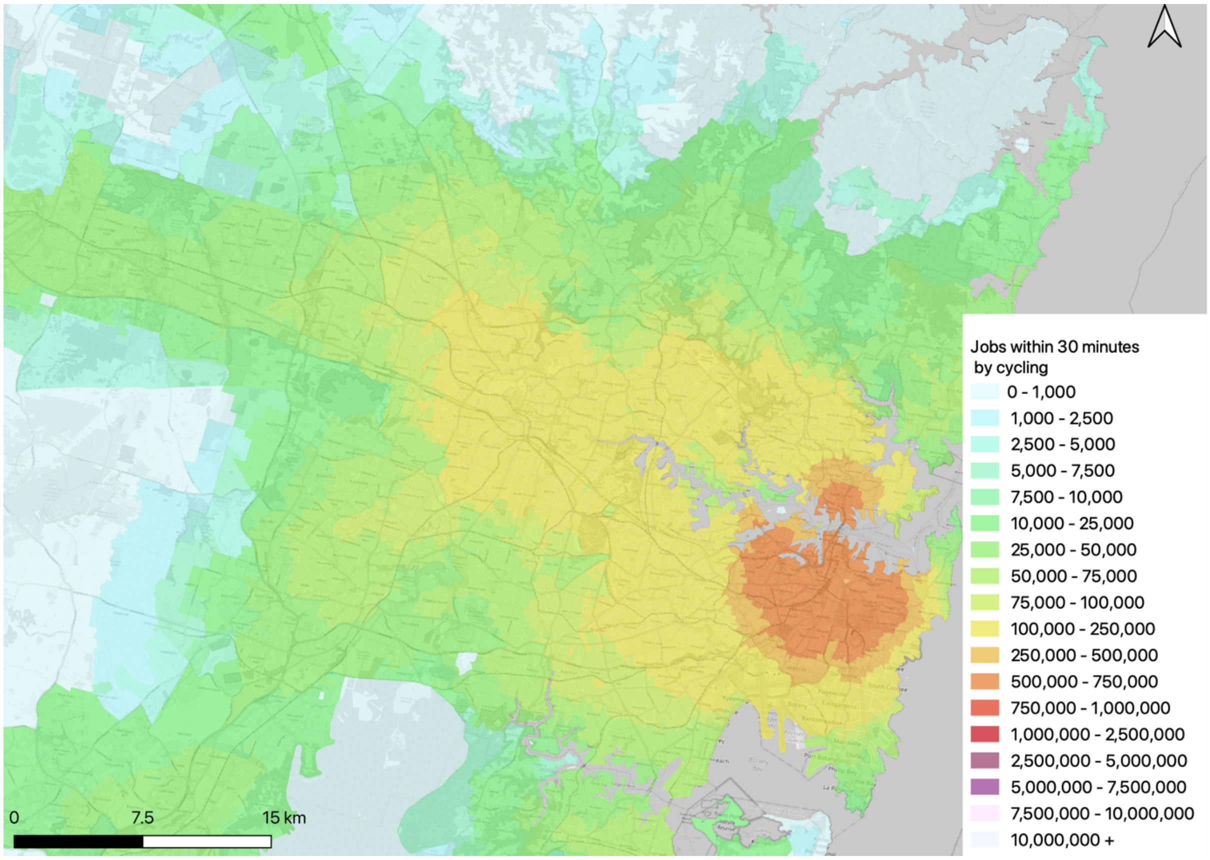

Figure 3. Cycling accessibility to jobs; number of jobs reachable within 30 minutes by cycling

3 Method

Autoregressive (AR) model is a time-series modeling method which assumes model output to depend linearly both on its own previous values, and a disturbance term which is responsible for the difference between its present and previous values. This study applies an autoregressive (AR) model, and predicts the amount of cycling traffic during a particular hour as a function of cycling traffic in the same hour of the previous day, and changes in hourly weather conditions. The idea is to model how cycling traffic volumes respond to shifting weather conditions. Other factors such as cycling infrastructure, built environment and geographic factors are accounted for using interaction terms with weather conditions. Autoregressive model has been used previously to study the effect of weather on cycling on two cycling trails using counter data (Zhao et. al, 2018); this study expands the application of autoregressive model in cycling research by using crowdsourced Strava cycling data in Sydney, and with the addition of demographic, cycling purpose data, and interaction terms in order to examine how the weather effect is reinforced or attenuated at different locations in Sydney.

Our modeling method focuses on explaining the hour-to-hour (comparing to the same hour of the previous day) "*variation*" in cycling traffic volume as a result of changing weather, rather than the "*base*" level cycling traffic. Each road segment has a base level of cycling traffic, which depends on its location, level of cycling infrastructure, and other attributes, so that some roads have more cyclists per hour than others. The reasons why some roads have more cyclists than others is assumed to be an intrinsic attribute of the road itself and its location, and therefore outside of the scope of this paper. Although it can be difficult to include all relevant variables affecting cycling traffic, the AR model includes its past value as an explanatory variable, allowing the model to focus on explaining variations in cycling traffic that result from changes in weather. Interaction terms amongst explanatory variables are aimed at examining the contextual effect of weather conditions; wind and precipitation might be negated by elements of the cycling environment, such as separated cycling infrastructure, and in a more urbanized environment. We focus on the interaction between precipitation, windy conditions, and environmental factors of access to jobs, and the presence of cycling infrastructure.

In order to model this variation in cycling traffic volumes, hourly cycling volume on road segment (k) on day (t) is paired with the cycling volume on the same road segment (k) during the same hour but from the previous day (t-1), whenever such data record exists in our data. In our data there are about 1.2 million observations of consecutive cycling traffic spread over 2,548 road segments during the study period. Based on these observed cycling traffic data, the hourly cycling traffic on a road segment ($V_{k,t}$) is used in autoregressive modeling as the dependent variable, and is modeled as a function of cycling traffic on the same road segment from the same hour of the previous day ($V_{k,t-1}$), plus disturbance factors from changing weather conditions, and interaction terms between weather and other factors. The effect from day of the week is accounted for using a dummy variable. This model formulation is shown in Equation 1. Explanatory variables with a delta (Δ) sign measure changes in weather conditions.

$$V_{k,t} = \beta_0 \cdot V_{k,t-1} + \beta_1 \cdot I_{k,t} \cdot \Delta T_{k,t,t-1} + \beta_2 \cdot \Delta P_{k,t,t-1} + \beta_3 \cdot \Delta U_{k,t,t-1} + \beta_4 \cdot \Delta W_{k,t,t-1} + \beta_5 \cdot \Delta P_{k,t,t-1} \cdot D_k + \beta_6 \cdot \Delta P_{k,t,t-1} \cdot A_k + \beta_7 \cdot \Delta W_{k,t,t-1} \cdot C_k + \beta_8 \cdot \Delta W_{k,t,t-1} \cdot A_k + \beta_9 \cdot \Delta W_{k,t,t-1} \cdot D_k + \beta_{10} \cdot E_k + \beta_{11} \cdot F + c \quad \text{(Eq. 1)}$$

$V_{k,t}$: Cycling traffic on link k, on day t
$V_{k,t-1}$: Cycling traffic on link k, on the same hour from day t - 1
$\Delta T_{k,t,t-1}$: Change in temperature between the same hour of day t and t-1
$\Delta P_{k,t,t-1}$: Change in precipitation between the same hour of day t and t-1
$\Delta U_{k,t,t-1}$: Change in humidity between the same hour of day t and t-1
$\Delta W_{k,t,t-1}$: Change in wind speed between the same hour of day t and t-1
D_k: Dummy variable for the presence of separated cycle lane
$I_{k,t-1}$: Dummy variable for the temperature range from a previous day
F: Dummy variable for day of the week (Sunday as ref.)
E_k: Dummy variable for rainfall in the last 2 hours (day t)
C_k: Euclidean distance to coastline from link k
A_k: 30-minute cycling accessibility to jobs (Num. jobs reachable by cycling within 30 minutes)

β_i: Coefficients
c: Constant

The autoregressive model assumes that variations in cycling traffic of the same hour between two consecutive days is caused by external changes in weather conditions, and day of the week. Factors such as the presence of separated cycling lane, cycling access to jobs can either reinforce or attenuate external weather effects, and this effect is included in modeling using interaction terms with weather variables. Interaction terms are constructed as the product of a dummy variable representing the existence of certain built environment or geographic attributes, and weather variables. For instance, increase in precipitation ($\Delta P_{t,t-1}$) during the same hour between two consecutive days is expected to have a negative effect on cycling participation, meaning that if it rained more during the same hour of day "t" than the previous day "t-1," then the "$\Delta P_{t,t-1}$" variable would have a negative sign since an increase in precipitation reduces cycling traffic from the previous day. If this particular road segment happens to have separated cycling lane, then a positive coefficient with the interaction term (i.e., Change in precipitation $\Delta P_{k,t,t-1}$ ::: Physically separated cycling lane) would suggest that the presence of cycling infrastructure offsets the effects from precipitation. Different positive/negative coefficients between weather variables and their interaction terms would indicate whether certain factors offsets or reinforces the effect of weather; the magnitude in the coefficients can be interpreted for how much of the weather effect is offset/reinforced. By interpreting the coefficients of interaction terms, this research attempts to address the research question: *can the provision of good cycling infrastructure and good access to jobs attenuate the effects of adverse weather on cycling participation?*

Both past and present rainfall are included in modeling. Precipitation in previous hours may still have a lasting effect on cycling participation (Nosal & Miranda-Moreno, 2014; Zhao et al., 2018). To account for the effect of past rainfall, we include a dummy variable for the presence of rainfall within the previous 2 hours on day (t). It should be noted that this dummy variable for past rainfall does not conflict with the changing precipitation variable ($\Delta P_{t,t-1}$), since the $\Delta P_{t,t-1}$ measures whether rainfall increases or decreases based on the same hour of the previous day, and the dummy variable measure if any precipitation happened in the last 2 hours of the present day.

We use temperature between 13 C and 26 C as Neutral PET (Physiologically Equivalent Temperature) for Sydney (Brandenburg et. al, 2007; Shooshtarian et. al., 2020), and the temperature at which a person would feel comfortable outdoors. These two threshold values divides the temperature spectrum into three sections: cold – below 13 C; neutral – between 13 and 26 C; and hot – above 26 C. A dummy variable ($I_{k,t}$) denoting the current temperature, and a continuous variable for the change in temperature are used to construct an interaction term. This interaction term is intended to study if temperature changes would have different effects on cycling participation, if the change resulted in different temperatures. For example, a rise to comfortable temperature may have different effects compared to rising to uncomfortable temperatures.

4 Results

Modeling results suggest that autoregressive (AR) models for link level cycling traffic have a good fit; hourly cycling traffic by Strava cyclists can be well explained by cycling traffic from the same hour of the previous day, plus adjustment from day of the week, variations in weather conditions, interactions between weather and elements of cycling infrastructure, built environment and geographic factors. Overall, weather condition and its interaction terms have a small but statistically significant effect on cycling participation. There are notable differences in how the combination of weather and environment affects commute and leisure trips, and trips by male and female, young and old cyclists.

4.1 Commute and leisure trips

Model coefficients for predicting commute and leisure trips are shown in Table 2. Precipitation has a negative effect on cycling participation for both commute and leisure trips. The variable for change in precipitation ($\Delta P_{k,t,t-1}$) has a negative sign, confirming the effect of rainfall on reducing cycling participation, which is also consistent with the literature. Rainfall in the past 2 hours (of the present day) has a notable effect on reducing cycling trips and affects leisure cyclists more than commute cyclists.

Overall, precipitation has a greater effect in reducing leisure trips compared to commute trip. Model coefficients for wind and humidity variables also have negative signs, identifying these factors as having a negative effect on both leisure and commute cycling trips. The correlation coefficient between precipitation and humidity variables are low (0.07), so these two variables likely have separate effects on cycling participation.

One notable finding is that cycling infrastructure, built environment and geographic factors do have an effect in either attenuating or reinforcing the effects of weather on cycling participation, so the effect from weather is contextual. For the leisure trips model, the interaction term between precipitation and the dummy variable for physically separated cycling lane has a positive sign (0.455), suggesting that physically separated cycling lane offsets the negative effect of precipitation on leisure cycling trips. Considering that the coefficient for precipitation ($\Delta P_{k,t,t-1}$) is -0.383, it appears that the negative effect from rainfall is offset. However, since rainfall in Sydney often don't last long, it is more likely that leisure cyclists switched routes to use separated cycling lanes, which makes separated cycling lanes appear to have offset the effects from rainfall. On the other hand, physically separated cycling lane has a statistically significant effect in reducing commute cycling trips during rainy conditions. This result is echoed by another study in Glasgow, UK, where the presence of physically separated cycle lanes further reduced cyclist numbers (all trip purposes) during rain; this was attributed to cyclists using physically separated cycling paths being less experienced and more sensitive of weather compared to other cyclists (Hong et al., 2020). The lack of end-of-trip facilities may have contributed to this phenomenon, as commute cyclists need to change into work attire using change rooms and shower facilities, while leisure cyclists have no such requirement.

Having good cycling access to jobs further reduces commute cyclists during rainfall, and offsets negative effects from precipitation on leisure cyclists. The interaction term between precipitation and cycling access to jobs is negative and statistically significant for commute trips, meaning that the negative effect of precipitation is reinforced in job-rich, more urbanized areas. This finding is unexpected, since better access to jobs tend to reduce travel distance and offset adverse weather effects. In addition to end of trip facilities, it is highly likely that commute cyclists in a job-rich area find it easier to substitute transit for cycling trips during adverse weather events, so the effect of job-rich environment may appear to further reduce commute cyclists.

Wind is identified as a deterrence to cycling participation for both commute and leisure trips by Strava cyclists, and its adverse effect is partially offset by distance to coastline. Places further inland have a higher chance of reduced wind speed from ground obstructions, and thus reduced deterrence effect to cycling participation. The negative effect of windy conditions on commute cycling is reinforced with the presence of cycling infrastructure, and in more job-rich areas; for leisure cyclists, cycling infrastructure and job-rich aeras attenuates the effects of windy conditions.

Table 2. Coefficients from models predicting commute and leisure trips; all changes in cycling volume and in weather conditions are based on the same hour from the previous day

	Variable Name	Model 1 – Commute Trips	Model 2- Leisure Trips
Non-interaction Terms	Cycling traffic from the same hour of the previous day $V_{k,t-1}$	0.743***	0.630***
	Change in precipitation $\Delta P_{k,t,t-1}$	-0.078***	-0.383***
	Change in wind $\Delta W_{k,t,t-1}$	-0.011***	-0.087***
	Change in humidity $\Delta U_{k,t,t-1}$	-0.012***	-0.036***
	Day of the week T(dummy, Sunday as ref.)	/	/
	Rain in the last 2 hours of the present day E_k (dummy)	-0.611***	-2.515***
Interaction Terms	Change in precipitation $\Delta P_{k,t,t-1}$ ::: Physically separated cycling lane	0.022	0.455***
	Change in precipitation $\Delta P_{k,t,t-1}$ ::: Cycling accessibility to jobs A_k	$-9.3 \cdot 10^{-7}$***	$9.0 \cdot 10^{-7}$ **
	Change in wind $\Delta W_{k,t,t-1}$ ::: Distance to coastline C_k	$8.2 \cdot 10^{-7}$***	$3.9 \cdot 10^{-6}$***
	Change in wind $\Delta W_{k,t,t-1}$ ::: Physically separated cycling lane	-0.018 ***	0.056 ***
	Change in wind $\Delta W_{k,t,t-1}$ ::: Cycling accessibility to jobs A_k	$-1.1 \cdot 10^{-7}$***	$1.1 \cdot 10^{-7}$**
	Change in temperature $\Delta WT_{k,t,t-1}$ ::: Current temperature range $I_{k,t}$ (dummy – below 13 C)	-0.084***	-0.232***
	Change in temperature $\Delta WT_{k,t,t-1}$ ::: Current temperature range $I_{k,t}$ (dummy – 13 - 26 C)	-0.020***	0.042***
	Change in temperature $\Delta WT_{k,t,t-1}$ ::: Current temperature range $I_{k,t}$ (dummy – over 26 C)	-0.023***	-0.389***
Model Fit (Adj.R^2)		0.619	0.391
Significance levels: 0.001 ***; 0.01 **; 0.05 *; 0.1 ·			

Overall, adverse weather conditions including precipitation, precipitation in the past 2 hours, wind and humidity reduces both commute and leisure cycling trips, and leisure trips are affected more than commute trips. Physically separated cycling infrastructure is able to retain cyclists for leisure purposes; this can be caused either by more cyclists retained on separated cycling infrastructure compared to in mixed traffic, or by leisure cycling trips shifting from mixed traffic towards separated cycling infrastructure during adverse weather events. However, despite previous hypotheses, physically separated cycling infrastructure, good cycling access to jobs do not appear to retain commute cyclists against adverse weather conditions.

4.2 Gender

Model coefficients for predicting male and female cyclists are shown in Table 3. Autoregressive model better predicts male than female cyclist volumes. The model predicts cyclist volumes based on cycling traffic from the same hour of the previous day. For male cyclists, the coefficient for cycling traffic from the previous day is 0.603, meaning that on average, about 60.3% of male cyclist volume are repetitive from day to day. The same coefficient for female is 0.273, suggesting that that female cycling trips are more occasional, and male cyclists have more consistent cycling travel patterns which makes their overall cycling traffic easier to predict.

Table 3. Coefficients from models predicting male and female cyclists; all changes in cycling volume and in weather conditions are based on the same hour from the previous day

	Variable Name	Model 3 – Male Count	Model 4- Female Count
Non-interaction Terms	Cycling traffic from the same hour of the previous day $V_{k,t-1}$	0.603***	0.273***
	Change in precipitation $\Delta P_{k,t,t-1}$	-0.288***	-0.016***
	Change in wind $\Delta W_{k,t,t-1}$	-0.052***	-0.013***
	Change in humidity $\Delta H_{k,t,t-1}$	-0.033***	-0.002***
	Day of the week (dummy, Sunday as ref.)	/	/
	Rain in the last 2 hours of the present day (dummy)	-2.507***	-0.232***
Interaction Terms	Change in precipitation $\Delta P_{k,t,t-1}$ ::: Physically separated cycling lane	0.194***	0.014
	Change in precipitation $\Delta P_{k,t,t-1}$ ::: Cycling accessibility to jobs A_k	$-4.6 \cdot 10^{-8}$	$-3.4 \cdot 10^{-9}$
	Change in wind $\Delta W_{k,t,t-1}$ ::: Distance to coastline D_k	$3.7 \cdot 10^{-6}$***	$3.7 \cdot 10^{-7}$***
	Change in wind $\Delta W_{k,t,t-1}$ ::: Physically separated cycling lane	$-2.3 \cdot 10^{-3}$	0.005 ***
	Change in wind $\Delta W_{k,t,t-1}$ ::: Cycling accessibility to jobs A_k	$-6.0 \cdot 10^{-8}$ **	$2.6 \cdot 10^{-8}$ **
	Change in temperature $\Delta WT_{k,t,t-1}$ ::: Current temperature range $I_{k,t}$ (dummy – below 13 C)	-0.268***	-0.023***
	Change in temperature $\Delta WT_{k,t,t-1}$ ::: Current temperature range $I_{k,t}$ (dummy – 13 - 26 C)	0.031***	0.010***
	Change in temperature $\Delta WT_{k,t,t-1}$ ::: Current temperature range $I_{k,t}$ (dummy – over 26 C)	-0.296***	-0.061***
Model Fit (Adj.R^2)		0.346	0.090

Significance levels: 0.001 ***; 0.01 **; 0.05 *; 0.1 ·

Both male and female cyclists have reduced cycling participation due to precipitation and windy conditions. Male and female cyclists have different responses to the combination of precipitation and cycling infrastructure. For male cyclists, the presence of separated cycling lane offsets the negative effect of precipitation by about 67% (0.194/0.288). For female cyclists, the offsetting effect of physically separated cycling paths against precipitation is not statistically significant.

Wind is identified as a deterrent to cycling participation for both male and female cyclists, and its effect is offset by increasing distance to coastline. Being in a job-rich urban area has a statistically significant effect in offsetting the effect of windy conditions for females, but urban locations reinforces the negative effect from winds on male cycling participation. Cycling infrastructure attenuates the effect of windy conditions for female cyclists but has no measure effect on cycling participation of male cyclists. It is possible than male and female cyclists ride for different purposes, which may explain, in part, why infrastructure and built environment factors would have different effects on male and female cyclists during adverse weather.

4.3 Age groups

Table 4 shows model coefficients for different age groups. Cyclists are separated into two groups using 35-year-old as threshold; this is both due to a data constraint in how Strava binned cycling traffic from different age groups, and this age being a life milestone for career advancement and family development. Older adults (35+) in general have more consistent day-to-day travel patterns compared to younger adults. Precipitation (both past and current), wind and humidity are universal deterrents to cycling participation for all age groups. The presence of physically separated cycling infrastructure offsets to a great extent the adverse effect of precipitation for both young (77%) and old (85%) cyclists. The interaction term between precipitation and cycling access to jobs and is not significant for either age group (or either gender group).

Wind is a deterrent to cycling for both age groups, inland locations provide some offset for the adverse effect of wind on cycling participation only for older adults (35+); this offsetting effect is not statistically significant among younger adults (20 - 34). It should be noted that young adults is the only demographic group in this study that is not sensitive to this offsetting effect of inland locations. This might be due to the difference in physical strength between age groups, and that a reduction in wind speed is valued more by older cyclists. It is also possible that older adults are more consciousness in their decisions (Horn & Cattell, 1967) and therefore more sensitive to the offsetting effect provided by inland locations. The presence of cycling infrastructure and more urbanized job-rich locations attenuates the effect of windy conditions for cyclists aged below 35; no measurable effect is found for cyclists aged over 35.

Table 4. Coefficients from models predicting young and old; all changes in cycling volume and in weather conditions are based on the same hour from the previous day

	Variable Name	Model 5 - Young (20 - 34)	Model 6- Old (35+)
Non-interaction Terms	Cycling traffic from the same hour of the previous day $V_{k,t-1}$	0.445***	0.577***
	Change in precipitation $\Delta P_{k,t,t-1}$	-0.031***	-0.247***
	Change in wind $\Delta W_{k,t,t-1}$	-0.008***	-0.055***
	Change in humidity $\Delta H_{k,t,t-1}$	-0.004***	-0.029***
	Day of the week (dummy, Sunday as ref.)	/	/
	Rain in the last 2 hours of the present day (dummy)	-0.283***	-2.307***
Interaction Terms	Change in precipitation $\Delta P_{k,t,t-1}$ ::: Physically separated cycling lane	0.024**	0.209***
	Change in precipitation $\Delta P_{k,t,t-1}$ ::: Cycling accessibility to jobs A_k	$1.8 \cdot 10^{-8}$	$4.2 \cdot 10^{-8}$
	Change in wind $\Delta W_{k,t,t-1}$ ::: Distance to coastline D_k	$-2.1 \cdot 10^{-8}$	$4.3 \cdot 10^{-6}$***
	Change in wind $\Delta W_{k,t,t-1}$ ::: Physically separated cycling lane	0.003 *	-0.001
	Change in wind $\Delta W_{k,t,t-1}$ ::: Cycling accessibility to jobs A_k	$-1.3 \cdot 10^{-8}$ **	$1.2 \cdot 10^{-8}$
	Change in temperature $\Delta WT_{k,t,t-1}$ ::: Current temperature range $I_{k,t}$ (dummy – below 13 C)	-0.023***	-0.252***
	Change in temperature $\Delta WT_{k,t,t-1}$ ::: Current temperature range $I_{k,t}$ (dummy – 13 - 26 C)	$-2.2 \cdot 10^{-5}$	0.041***
	Change in temperature $\Delta WT_{k,t,t-1}$ ::: Current temperature range $I_{k,t}$ (dummy – over 26 C)	-0.038***	-0.316***
Model Fit (Adj. R^2)		0.201	0.319

Significance levels: 0.001 ***; 0.01 **; 0.05 *; 0.1 ·

5 Discussion and conclusion

Cycling is a sustainable mode of transport with a wide range of social, environmental, economic, and public health benefits. Compared to other modes of transport, cycling is especially susceptible to adverse weather conditions. Climate change increases the frequency of extreme weather events, causing widespread intensification of precipitation (Stott, 2016). Therefore, it is necessary to incorporate weather-aware cycling planning and design to ensure that cyclists are not exposed to risk such as accidents due to weather conditions and can adapt to future weather conditions. An important first step is to understand whether, and which cycling infrastructure, built environment and geographic factors will be effective in retaining cyclists against adverse weather.

This paper examines the effect of adverse weather conditions on cycling participation of Strava cyclists using autoregressive models; the combined effects of weather conditions and cycling infrastructure and built environment factors are included in modeling using interaction terms. We verified the first and second hypotheses, namely that weather conditions have a small, albeit statistically significant effect on cycling participation of Strava cyclists in Sydney, Australia. Elements such as current and past (2 hours) rainfall and humidity and windy conditions are identified as universal deterrents for both leisure and commute cycling, and for both male and female cyclists and cyclists of different age groups. Distance away from the coast reduces the negative effect of wind, which is consistent with the literature (Nikolopoulou & Lykoudis, 2007; Phung & Rose, 2007).

We find that the effect of weather on cycling participation of Strava cyclists is contextual, and cyclists for leisure purposes can be retained against rainfall and windy conditions by providing separated cycling lanes, and under specific geographic and built environments such as inland (distanced from coast) and densely built-up areas. The presence of separated cycling lane almost completely negates the effect of precipitation for leisure cyclists. While it is possible that this may have resulted from leisure cyclists shifting from mixed traffic to separated cycling lanes during adverse weather events, this offsetting effect is nonetheless significant in showing that leisure cyclists are indeed sensitive to the combination of weather and cycling infrastructure and prefer sheltered cycling environment against weather elements. Therefore, weather-aware cycling infrastructure and provision of better sheltered and segregated cycling lanes can be effective for promoting leisure-purpose cycling regardless of weather conditions.

The effect of temperature change is examined in the context of the current temperature. We find that in Sydney, a rise in temperature is generally a deterrent for cycling participation of Strava cyclists, unless this rise in temperature brings the current temperature into a comfortable range (defined as 13 C–26 C). For commute cycling, any increase in temperature has a deterrent effect on cycling. Naturally the effect of temperature on cycling participation is bell-shaped where neither cold nor hot temperatures is preferrable (Phung & Rose, 2007); however, it should be noted that temperature preference per se is outside the scope of this paper; by using AR models, findings of this paper only applies to day-to-day changes in temperature. In much colder climates such as in Canada, increase in temperature is associated with more cycling traffic (Gallop et al., 2011).

We also find that separated cycling infrastructure cannot retain commute Strava cyclists against precipitation, or windy conditions. Good cycling access to jobs further reinforces adverse weather effects in reducing commute cycling. Better quality of transit services makes it easier for cyclists to switch to transit alternatives. Based on our calculation[4], areas adjacent to separated cycling lanes have on average 3.8 times more jobs reachable by transit within 30 minutes, when compared to areas with no physical separation. A job-rich environment, and better transit services in these areas (Levine et. al, 2012) might have provided better transit alternatives to substitute for bike commute trips during adverse weather events.

Commute Strava cyclists in Sydney are sensitive to weather conditions, and current cycling infrastructure appears inadequate for retaining commute cyclists against weather. There are different possible explanations for why infrastructure and accessibility factors cannot retain commute cyclists in adverse weather conditions. Commuter cyclists often choose to travel along busy routes during peak hours, making them more susceptible to safety risks caused by unfavorable weather conditions, whereas leisure cyclists have the option to ride on quieter streets during non-peak hours. This highlights the need for greater investment in cycling infrastructure to support commuter cyclists who require safer and more efficient routes. Another explanation is the lack of end-of-trip facilities; commute cyclists also need to maintain their attire and appearance at workplaces, so end-of-trip cycling facilities such as shower and changing rooms are important consideration for mode choice of commute cyclists (Heinen, et. al., 2013). In cities with a mature cycling culture such as the Netherlands, cyclists are more resilient to weather conditions, which might be due to people starting to cycle at a younger age, and the widespread availability of showers and change rooms at workplaces (Haas & Hamersma, 2020).

In light of our findings, direct physical protection against weather might be necessary in order to retain commute cyclists against adverse weather conditions. This can be accomplished in an urban area through overhanging eaves from adjacent buildings, street trees, underground passage for cyclists, and overhead canopies at signalized intersections. Providing such urban canopies will benefit both cyclists and pedestrians, and requires a built environment friendly to active transport, such as in a CBD or other densely built-up areas; these measures may not be feasible in low density neighborhoods with vast distance between buildings, and buildings and stores fronted by parking lots. In addition to physically separated cycling lanes that have been shown in this paper to be effective for retaining leisure cyclists against weather, more and better end-of-trip cycling facilities near workplaces, including bike storage, shower and clothes changing room will be instrumental for protecting and retaining commute cyclists against weather.

Limitations of this paper include the data available for measuring accurate cycling activities. The use of binned Strava count data reduces the resolution of link level cyclists count and may potentially impact model outcomes (Raturi, et. al., 2021). While we do not expect this to affect the validity of this research, precaution has been taken to remove links with low cyclists' volume from modeling. Strava data is also inherently biased and represent a segment of the entire population; it is widely considered that Strava users are more fitness-focus compared to other cyclists. Strava cyclists count data may differ substantially from actual bike counter data (Jestico et al., 2016). In the absence of data on general cyclists, it remains an open question whether Strava users would have similar responses to changing weather conditions compared to cyclists in general. Correcting for this bias may produce better measurement of cycling activities. For future research, it is recommended that individual level or stated preference data be used to incorporate in the modeling to better

[4] Calculation for transit access to jobs is based on a typical Wednesday transit schedule in Feb. 2019, 8 AM departure time

understand and explain the individual level response to adverse weather conditions. This paper uses road segments as the subject of analysis, and there could be spatial correlation involved.

This paper sheds light on how cyclists of different demographics and trip purposes respond to weather conditions. We show that the effect of weather is contextual upon cycling infrastructure, built environment and geographic factors, and that it is possible to shelter and retain cyclists against weather using appropriate cycling infrastructure at the right places. As a starter cycling city, the level of cycling participation and cycling infrast››ructure in Sydney, Australia lags behind many of its European counterparts. With climate change and an intensification of precipitation (Stott, 2016), making cycling a viable day-to-day travel option despite adverse weather is instrumental for reducing vehicle ownership, and for moving towards sustainable transport. It is hoped that this paper would help better understand the relationship between weather, infrastructure, and cycling participation, and lead to more informed decisions on cycling infrastructure investment.

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