The Effects of Weather on the Current and Future Ridership of Urban Cycling in North American Cities Considering a Changing Climate

By

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Abstract

The presented work analyzes the influence of weather on urban cycling demand following two objectives: 1) to investigate the impact of weather conditions and bicycle demand using time-series models and 2) to carry out a climate analysis to estimate the cycling demand for 2050 under different climate model projections.

For the first objective, the proposed methodology characterized the temporal dynamics of the daily and weekly ridership profiles, identified the trends of utilitarian patterns, and determined the ridership trends across years while controlling for the influence of weather variations. Historical data of cyclist counts, and registered weather conditions for 12 years are used to calibrate models. In the second objective, the author estimated the annual profile of cyclist demand for 2050 based on the future climate projections following different emissions scenarios. For this purpose, an Extreme Gradient Boost (XGBoost) model was trained using historical counts and measured weather conditions to predict expected daily counts for the future year.

The results show a significant sensitivity to weather conditions and a constantly growing trend in cyclist volumes for Montreal that surged during the COVID-19 pandemic as new users adopted the bike for commuting or recreational uses. Regarding the future, predictions using different climate scenarios show a rise in bicycle demand in March, April, and November. However, the forecasts showed decreasing counts during the summer months due to extremely high temperatures drawing an annual reduction of cyclist demand in the high-emission scenarios. The results of this work could help plan and adapt better bicycle infrastructure and services considering a changing climate.

Abrégé

Le travail présenté analyse l'influence des conditions météorologiques sur la demande de cyclisme urbain en suivant deux objectifs : 1) étudier l'impact des conditions météorologiques et de la demande de vélos à l'aide de modèles de séries temporelles et 2) effectuer une analyse climatique pour estimer la demande de vélos en 2050 selon différentes projections de modèles climatiques.

Pour le premier objectif, la méthodologie proposée a caractérisé la dynamique temporelle des profils de fréquentation quotidiens et hebdomadaires, identifié les tendances des modèles utilitaires et déterminé les tendances de la fréquentation d'une année sur l'autre tout en contrôlant l'influence des variations météorologiques. Les données historiques des comptages de cyclistes et des conditions météorologiques enregistrées pendant 12 ans sont utilisées pour calibrer les modèles. Dans le deuxième objectif, l'auteur a estimé le profil annuel de la demande de cyclistes pour 2050 sur la base des projections climatiques futures suivant différents scénarios d'émissions. À cette fin, un modèle Extreme Gradient Boost (XGBoost) a été entraîné à l'aide des comptages historiques et des conditions météorologiques mesurées afin de prédire les comptages quotidiens attendus pour l'année à venir.

Les résultats montrent une sensibilité significative aux conditions météorologiques et une tendance à l'augmentation constante du nombre de cyclistes à Montréal, qui a bondi pendant la pandémie de COVID-19, de nouveaux utilisateurs ayant adopté le vélo pour leurs déplacements quotidiens ou leurs loisirs. En ce qui concerne l'avenir, les prévisions utilisant différents scénarios climatiques produisent une augmentation de la demande de bicyclettes au cours des mois de mars, avril et novembre. Cependant, les prévisions ont montré une diminution des comptages pendant les mois d'été en raison des températures extrêmement élevées, dessinant une réduction annuelle de la demande de cyclistes dans les scénarios à fortes émissions. Les résultats de ce travail pourraient aider à planifier et à adapter de meilleures infrastructures et de meilleurs services pour les cyclistes en tenant compte du changement climatique.

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Contribution of the Authors

The author’s contribution to the first paper is as follows: study conception and design: D. Beitel, L.F. Miranda Moreno, V.T. Van-Nguyen; data collection: E. Adame Valenzuela, P. Barban; analysis and interpretation of results: E. Adame Valenzuela, P. Barban, D. Beitel, L.F. Miranda Moreno; draft manuscript preparation: E. Adame Valenzuela, D. Beitel, L.F. Miranda Moreno. All authors reviewed the results and approved the final version of the manuscript.

The contribution of the authors to the second paper is as follows: study conception and design: E. Adame Valenzuela, L.F. Miranda Moreno, V.T. Van-Nguyen; data collection: E. Adame Valenzuela, Chenglong, You; analysis and interpretation of results: E. Adame Valenzuela, L.F. Miranda Moreno; draft manuscript preparation: E. Adame Valenzuela, L.F. Miranda Moreno. All authors reviewed the results and approved the last version of the manuscript.

Introduction, literature review, Bridge, Discussion of the Finding, as well as the Conclusions and Summary of the thesis was written by the author, Eduardo Adame Valenzuela, under the supervision of Luis Fernando Miranda-Moreno and Van Than Van-Nguyen.

1. Chapter I: Introduction.

1.1 Context

Cities are spaces where people can access opportunities, and interact with each other in the search to improve their lives (1). Considering the exponential growth of cities in the past decades and their expected expansion in the future (2), investments in these regions provide a great opportunity to improve the well-being of a great number of people. In the last decades, this well-being has been challenged by problems related to air and noise pollution, safety, healthcare, and poor accessibility (3,4) that derive from the car-centric urban sprawl seen in most North American cities since the end of the second world war (5).

For these reasons, several cities have shifted their plans to include the promotion of more sustainable transportation modes. This transformation has caused a resurgence of the bicycle thanks to the vast investments to improve the infrastructure and the policies aimed at its promotion (6) which has derived economic, and sustainable benefits from bicycle use not only limited to the individual (7) but are also enjoyed by the community in general (7–10).

Nonetheless, cycling as a mode of transport does have some deterrents, one of them being its exposure to adverse weather conditions (e.g., high or low temperatures, precipitation, high humidity, and combinations of those weather factors). The literature agrees that there is a significant relationship between weather factors and cyclist demand (11–13) which only confirms what is evident for anybody who rides a bike. Generally, people do not bike on days that are too cold, too hot, raining, snowing etc. In the North American context, cities with cold winters such as Montreal have very noticeable bike seasons with demand peaking in the summer months and decreasing almost to a stop during the winter. Additionally, weather might offset the decline in cyclist trends (14) which could lead planners and researchers to formulate wrong conclusions when studying the impacts of certain policies or investments.

Although researchers and city authorities might have a good understanding of the seasonality and behaviour of the cyclist demand, global warming is expected to disrupt the measured values of different weather variables in the future. Research seems to agree that, for the Canadian context, it is likely that the temperature will rise while the number of rainy days will decrease in the coming years (15–17). Additionally, the frequency of extreme weather events, such as heatwaves and flash floods, is expected to increase in the following decades. However, the effects of these changes on cyclist demand can not be generalized for different cities across the globe. This is because the direction and magnitude of the weather changes will vary for different regions and cyclists in every city will have dissimilar resilience to weather factors (18).

Hence, understanding the climate's effects on cyclist demand and how it might change in the future will help plan and design more sustainable and resilient transportation systems. This also includes the temporal impact assessment of strategies, projects and policies while controlling for the effects of weather or the identification of new infrastructure designs that allow people to cycle in adverse weather events (e.g., heat waves, winter, and high precipitation).

Despite the long literature on the impact of adverse weather on urban cycling, only a few works have looked at the long-term trends of cycling ridership while controlling for the variations caused by the weather conditions across seasons and years. Additionally, with the uncertainty in weather brought by climate change, there is no study, to the best of the author's knowledge, that tries to evaluate the changes in the cyclist demand in Canadian cities like Montreal under different climate-change scenarios. The motivation of this research is then to accurately understand the current and future trends of urban cycling considering the impact of climate and the expected variations under various climate scenarios.

1.2 Objective of the Thesis

Considering the past research on the relationship between weather and urban cycling, this work aims to investigate the temporal trends and relationship between historical climate conditions and urban cycling to better understand the present and future trends of cycling under alternative climate scenarios.

More specifically, the objectives of this work are:

1) To propose a methodology that characterizes the historical temporal dynamics of utilitarian and recreational cycling across the years before and after the COVID-19 pandemic while controlling for weather factors. The weather-controlled cycling volume growth trends are determined for four North American cities as a case study.
2) To propose a methodology to predict future cycling ridership under alternative climate scenarios combining cycling demand models as a function of weather conditions and climate-model outcomes. Projections of cyclist demand for the year 2050 are made using the city of Montreal as a case study.

1.3 Structure of the Thesis

Chapter II presents a general literature review of the context of urban cycling, its relationship to the weather, and the challenges of climate change. Chapter III contains the research following the first specific objectives, which resulted in an issued article and is presented as it was published in the Transportation Research Record 2023. Chapter IV provides a general review of the first objective and links the discoveries made with the second objective. Chapter V presents the research that followed the second specific objective, which will be presented to be published as a second article and is shown as the author intends to submit it. Chapter VI encompasses a general discussion of the findings regarding the previous chapters. Chapter VII provides the conclusion and a general summary of the thesis.

2. Chapter II: Literature Review.

2.1 Cycling as a Transportation Mode

Cycling as a transportation mode is no novelty at all. A cycling boom ploughed the American cities of the 1890s as people started using bicycles more and more for commuting and leisure trips, in part thanks to their characteristic as private vehicles that could take you wherever they wanted without the limitations of timetables and fixed routes of the streetcars (19). Nonetheless, after walking in any city in the United States or Canada it is easy to realize this is not the case anymore. Since the 1950's high levels of motorization, city sprawl, car-centric infrastructure, and government policies that promote the automobile have caused a high adoption of private motorized vehicles and a sharp decline in cyclists (20). Even so, if the bicycle does not have the same modal share as before, there is still a percentage of the population that continues to cycle in several North American cities.

2.2 Benefits of Cycling

This continuous use of the bicycle by individuals is due to the many benefits it provides to them. First, due to the low skill required to bike, it is a transportation mode available to a large segment of the population (21). In 2013, 82% of Canadians aged between 12 to 14 years old reported cycling in the previous year (22). Second, it can be competitive against the use of cars for short trips. Ellison and Greaves (23) compared trips from 178 motorists in Sydney, Australia and concluded that 90% of the trips below 5 km would only take up to 10 minutes more for an inexperienced cyclist. Third, it provides economic benefits to the individual being less expensive compared to a private vehicle and even to public transport (24), having a private cost per kilometer 6 times lower than the car (25). Fourth, commuting using a bicycle provides several health benefits. Following a literature review, de Hartog et al. (26) concluded that shifting the commuting mode from car to bicycle would gain 3 to 14 months in life expectancy and concluded that the benefits from the activity outweighed the negativities of exposure to pollution and the risk of accidents. The moderate 30-minute physical, which can be achieved by travelling to work daily on a bike, can lead to a 19% reduction in the mortality risk (21). People who frequently cycle have reported lower levels of psychological distress and higher levels of life satisfaction (27), which remarks the additional mental health benefits of commuting by bike.

The use of the bicycle as a transportation mode does not only provide benefits for individuals but also the cities. First, it requires a lower amount of public space dedicated to that mode. For example, cyclists in Rajkot City, India, consumed 12.5% of the space-time required by a car (28) while, in France, a cyclist needs 19% of the space-time consumed by a car-driver (29). Both results confirm that bicycles are more space efficient than private cars implying that a modal shift from a significant part of the population would liberate public areas that could be used for other functions such as greenery, urban furniture or increasing development. The lower space consumption can also be related to congestion levels. This is reflected in Copenhagen, where cyclists are presumed to represent a lower cost for congestion to the city (30). This is in line with the findings in Washington D.C. where bike-sharing stations were negatively related to congestion levels (31). In regards to health, Bassett et al. (32) found a negative relationship between active mobility modal share and obesity levels. Gotschi estimated that, for Portland, Oregon, 30 minutes of daily biking saved $544 annually per person to the healthcare system (33). In general, the promotion of active mobility networks has beneficial effects on society when considering road safety, parking, and health costs (34) along with congestion, infrastructure maintenance, pollution, and quality of life (25). In Norway, Lanus et al. (35) deemed that a Cycle Investment Model would be highly cost-effective based on the gains of quality-adjusted life years (in monetary terms) it would achieve. The literature confirms that investing in cycling produces benefits for the cities, giving a strong argument for the expansion of bike facilities and the promotion of this mode.

Although the literature has given plenty of reasons to invest in cycling, in the last decades there is another one that has spurred into debate. The concept of sustainability has gained significant momentum within the research, political and community agenda (36). With the commitment of countries to reduce humanity's impact on the environment, cities have been identified as strategic locations for the reduction of greenhouse gases in the world, since they host a significant proportion of the population and enterprises with major world production contributions, which would be at significant risk from the effects of climate change (37). These factors place the urban areas as key players in the mitigation of emissions and transition to a low-carbon lifestyle (38). In recognition of the situation, cities have designed plans that will help guide their development, in which cycling and walking could work as zero-carbon sustainable solutions for urban transportation (39). For example, a study in Adelaide, Australia, found that a 5 to 40% shift in Vehicle Kilometer Travelled (VKT) from private vehicles to alternative transportation modes such as cycling, would result in 0.15 to 0.95 million fewer tons of CO_2 in 2023 compared to a business-as-usual scenario (40). Because of these results along with a desire to fulfil their sustainability mode, urban areas have started to adopt cycling-related strategies such as the installation of bike-sharing systems to reduce greenhouse-gas emissions, although the magnitude of the reduction will depend on the modal shift (41–44).

2.3 Cycling and its Promotion

For all the benefits and reasons stated above, cities across the globe are promoting the use of bicycles through investment in infrastructure and the passing of policies even before state or national legislatures (45). In 2016, bike-sharing systems had expanded to 850 from a handful in the 1990s, which shows the refocusing of urban transport planning towards more sustainable modes (46). In American cities, bike trips doubled from 1977 to 1995 (6) while in Canadian cities, a study found a ten percent growth from 1996 to 2016 (47). This interest in cycling shows a need to further the research for its promotion, regarding the valid strategies, the impact and, maybe more importantly, the challenges it will face.

2.4 Cycling and Weather

One of the main challenges related to the use of the bicycle for commuting trips is the exposure of the mode to weather factors which has been identified as one of the discouraging factors(48), having an important impact on the overall travel experience (49). Due to its major influence, the weather has been proven to be an important predictor that can improve the estimations of the Annual Average Daily Bicyclists Traffic (AADBT) (50).

The research regarding the relationship between daily travel behaviours and weather conditions is quite extensive. Böcker et al. (51) carried out a systematic literature review of 54 published articles and concluded that warm and dry weather favours the use of active transportation modes while rain, snow, and hot weather conditions cause a shift of users to sheltered modes and can also lead to the cancellation of trips with outdoor destinations. From the review, they concluded that warm and dry days affected active traveler volumes positively while rain, wind, and hot days affected them negatively however the relationship does not seem to be linear. The magnitude of the effects also depended on the region the paper was carried out suggesting that people living in different climates will present different levels of resilience against the specific weather factors. In their overview of the literature focusing on the main factors affecting urban cycling Heinen et al. (52) dedicated a whole section to the effects of weather, acknowledging that variations in the day-to-day conditions could affect cyclists' daily decisions. Their overview showed that precipitation harmed cyclist counts, however, there was no clear consensus regarding its magnitude while temperature was deemed to affect cyclist counts positively. They also noted that commuters seem to be less affected by the weather conditions compared to other riders since they can not cancel nor modify their trip. Regarding the Canadian context, the highest levels of activity in Toronto's Bike Sharing system were associated with perceived temperatures between 20 and 30°C, while rain, snow, and humidity harmed cycling activity (53). In Montreal, Miranda-Moreno and Nosal (54) concluded that temperature increases will result in greater bicycle ridership up to a certain point, while humidity reduces them. As expected, rain reduced the cyclist in the same hour but also presented lagged effects up to three hours. Additionally, they noticed that users will respond differently to the weather depending on the season, for example, extreme increases in temperature would promote cycling in winter and reduce them in summer.

2.5 Cycling and Climate Change

In the present decade, cities have recognized the new challenges brought by global warming and its effects can already be felt in the world, with more frequent and greater weather events already causing losses in nature and human societies (55). It is expected that the number of hot days, heatwaves, and intense precipitation events are very likely to increase, while decreases in very cold days are likely to occur (56). In the Canadian context the number of days with a maximum temperature greater than 25°C, 30°C, and nights with maximum temperatures greater than 22°C has already increased from 1946 to 2016 in the southern regions, which is derived in warmer winters and summers (57). Canada’s Changing Climate Report (58) estimates an increase in temperature during the last and in the coming years at double the mean of the projected global average. Regarding precipitation, the report estimates an increase in precipitation during the winter and a decrease during the summer with an overall annual growth.

Regarding transportation, climate change will likely impact the sector. In 2008, Koetse and Rietveld (59) carried out a literature review to understand the impact climate change would have on transportation and concluded that the topics had received little attention in research, however, one could expect the transportation systems to perform worse under extreme conditions. Considering the impacts of climate change on transportation systems is critical since projects could fail to meet their objectives due to a shortening of their useful lifespan caused by evolving travel patterns or because of disruptions from extreme climate events (60). While some authors argue that the extreme events brought by the warming climate may interrupt the functionality of urban transportation networks (61) others have suggested that climate change will modify the annual patterns of cyclists and pedestrians, with cities with colder climates, such as Montreal, possibly gaining active mobility users (51). The exact impacts of climate change are unknown and whether these experiences are positive or negative for urban cycling will likely vary for each city.

2.6 Conclusions

Although the literature review has confirmed the relationship between the weather and cyclist demands, there are a few gaps in the literature:

- Few studies have analyzed the growth of cyclist volumes in North American Cities while controlling for the effects of climate and the impacts brought by the COVID-19 pandemic.
- There are few studies regarding the possible variation in future cyclist demand in Canadian cities considering the effects of climate change under different emissions scenarios.

Chapters three and five showcase two methodologies that tackle these gaps in the literature and provide empirical evidence by applying them to data from cities in North America as case studies.

3. Chapter III: Analyzing the Behavior and Growth of Cycling in Four North American Cities Before, During and After the COVID Pandemic

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Data Statement: The cyclist counts data used for this study is property of the city of New York, the city of Montreal, the city of Ottawa, and the city of Vancouver. Any request for the cycling counts data must be submitted to the corresponding authorities or information portals of each city. All the weather measurement data were acquired from World Weather Online.

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3.1 Abstract

The paper highlights the changes in cycling patterns and ridership trends across 12 years (including the COVID-19 pandemic) in Montreal, Vancouver, Ottawa, and New York. Using data from 17 bicycle counting stations, changes in the dynamics of daily and weekly profiles before and during the pandemic were determined. Additionally, the ridership demand evolution across the years is explored using models that control for the variations in the weather. All the studied bicycle facilities experienced a change in the daily and hourly patterns in 2020 (the first year of the pandemic), tending towards recreational purposes. Buehler and Pucher (62) had previously found a significant growth in bicycle activity during the first year of the pandemic, but the trends for the following years (2021 and 2022) have not been studied. This paper found that all counting sites located on cycling facilities primarily used for utilitarian purposes experienced a growth in ridership during 2020. Ridership on utilitarian corridors in Montreal and New York City grew considerably during the pandemic before stabilizing in 2021 and 2022. The same counting sites returned quickly to utilitarian hourly and daily patterns in 2021. The mixed-utilitarian bicycle facilities in Ottawa and Montreal shifted towards more recreational uses during the pandemic, though ridership did not grow in 2021 and 2022. All the counting sites in Vancouver shifted towards mixed-use during the first year of the pandemic and have not shown any clear sign of returning to utilitarian patterns.

3.2 Introduction

During the last decades, many North American cities have seen an increase in bicycle ridership, which in part can be related to the investment in cycling infrastructure (6). With the energy and climate change concerns, cycling is seen as one of the most sustainable transportation modes. Cycling not only reduces fossil fuel consumption and related emissions but also helps improve public health and well-being (63). Bicycle trips represent a relatively small modal share compared to automobiles in North American cities; however, an important increase has been observed in many cities. The COVID-19 pandemic in 2020, had a major impact on transportation demand. While public transportation mode share reduced significantly, bicycle mode share growth became more pronounced (62).

During the pandemic, bicycle infrastructure played a critical role in cities, offering an alternative transportation mode for commuters with public health and safety concerns related to public transit systems. A positive correlation between bicycling sharing system (BSS) trips and the number of new daily COVID cases in New York City, as shown by Teixeira and Lopes (64), suggests a possible modal shift from the subway system toward the CityBike system. Bicycle infrastructure also provided the general population the opportunity to safely participate in recreational activities during the pandemic (65). Bicycle infrastructure helped ensure access to destinations and activities during the pandemic with minimum economic and environmental impacts. Accordingly, cycling has emerged not only as a sustainable but also as a resilient mode of transportation (66,67).

Given the important role of cycling as a sustainable mode of transportation, an important body of literature has been published in the last few years. A large body of research has documented key issues that limit cycling participation such as road safety, the lack of infrastructure, or the impact of weather (68,69). A few papers have also looked at the cycling ridership evolution before and during the pandemic (70,71). Most research explored the impact of weather before the pandemic or the challenges that the pandemic posed to bike-sharing systems – with significant changes in the usage patterns of share-mobility bicycle services (64,66,72–76).

These works are important in that they study the resilience of bike share systems. However, they do not reflect the entire picture of the bicycle infrastructure usage and bicycle demand during these critical pandemic years. Buehler and Pucher investigated the impact of the pandemic on cycling in various cities and countries in Europe, North America and Australia (62). Using data from 2019 and 2020, they attempt to establish the overall trends as well as the variations over time.

Despite the significant amount of work in the last years, to our knowledge, very little work has explored the long-term trends and detailed patterns before and during the pandemic in various cities in North America. As reported by Buehler and Pucher, a significant growth in bicycle activity was observed in the first year of the pandemic, but there is less knowledge of trends in 2021 and 2022. Additionally, past research on cycling trends has not controlled for the potential impact that weather may have in the seasonal-yearly variations, leading to results that under- or over-estimate cycling growth.

This paper illustrates the long-term bicycle patterns and trends before and during the pandemic across four major cities in North America (Montreal, Vancouver, Ottawa in Canada, and New York City in the United States) during the 2010-2022 period. The specific objectives are: i) to propose a methodology to characterize the temporal dynamics of the daily and weekly ridership profiles to identify the trends of utilitarian patterns and ii) to investigate the ridership trends across seasons and years in four cities while controlling for weather variations. Understanding the behaviour and the growth trends occurring in each city may provide city planners and authorities with greater knowledge of current and future cyclist demand. This knowledge can be used to inform modifications to existing facilities and the creation of new active transportation routes. Additionally, controlling for weather allows for a fair comparison of cities located in different climates.

The following sections in this paper will provide a review of the existing literature, a summary of the methodology, a description of the cities and the data, and an analysis of the results to better understand the temporal variations of cyclist behavior and demand in the different cities.

3.3 Literature Review

Trying to understand the changes in travel behavior by analyzing the census data in Seoul's Metropolitan area, Choi et al. discovered that bike trips increased in duration and frequency from 2002 to 2006 (77). Pucher, Buehler, Merom, et al. stated that cycling levels stagnated in the United States from 2001 to 2009 based on the results of the National Household Travel Surveys (78). When analyzing the trends in demand for London's bike-sharing system Chibwe et al. found that the number of trips increased throughout the years as the unemployment rate decreased, which could mean that most of the scheme's trips are of a utilitarian nature (71). Ledsham et al. analyzed the results of surveys by using generalized structural equation models to better understand the factors influencing the amount of utilitarian and recreational trips in the suburbs of Toronto (79). Stinson et al. created statistical models capable of estimating the amount of utilitarian and recreational trips in the city of Los Angeles. Nonetheless, the author of this paper could not find any research regarding temporal changes in usage patterns of bike activity throughout the years (80).

Nankervis, in 1995 compared the daily counts of cyclists in an Australian university to a weather condition index, which was made up of the force of the wind, the maximum daily temperature, and the presence of rain (11). Although he did find a relationship between the variables, the magnitude of the influence was weaker than first assumed. However, the author mentions the study focused on the behavior of students which may not be representative of the general population. This change in commuting behavior may be explained by the change in the perception of safety cyclists experience in adverse weather conditions (12). On an interesting note, the behavior could be affected not only by the present meteorological conditions but also by the weather forecast (81). By applying a log-linear regression model on automatic bike counts, Thomas et al. stated that temperature had the greatest influence on the counts while wind speed, hours of sunshine and precipitation did have a significant effect and also found that favorable weather could hide a downward trend in bicycle usage (24). Miranda-Moreno and Nosal noted that temperature had an important positive effect and humidity harmed bike counts, while precipitation could have a significant lagged negative effect of up to three hours on the observed counts. They also discovered that above a certain threshold cyclists' desire to bike starts to decline with higher temperatures. The threshold was calculated at 28C, 28C, 30C and 27C in Montreal, NYC, Seattle, and Austin, respectively (54,82–84). This indicates that the magnitude of the effects of the weather conditions on cyclist demand will vary from city to city, as also noted by Goldmann and Wessel (18). The magnitude of the effect also varies depending on the use of the bike route. Zhao et al. found that weekday users of a bike train in Seattle were more resilient to weather conditions than their weekend counterparts (27). Also in Seattle, Niemeier discovered a greater variability of counts in the afternoon peak (from 3:30 pm to 6:00 pm) and stated that this could be partially attributed to the presence of non-utility cycling trips (85). Miranda-Moreno and Nosal in their study of the data from automatic counters in Montreal found that recreational locations were more sensitive to weather (25). Wessel also found that the effect of lighting conditions differs between utilitarian, recreational, and mixed-type users (31). Pazdan et al. also carried out the classification of nine different bicycle corridors in the city of Krakow (32). Then they added the site's classification as an independent categorical variable in a regression model of the bike counts which turned out to be not significant. When determining the influence of weather variables, studies have used regression models such as linear and log-linear (14,18), square root (87), log-linear in absolute and relative models (54) and Negative Binomial with log identity (81,88). While those models dealt with the non-linear relationship of temperature and by using squared terms and of precipitation by categorizing that variable, other studies have opted for the use of General Additive Models (82,84,88) which, instead of assigning a constant coefficient, the influence of each variable is determined by a function. When dealing with time series data, it is important to control for the autoregressive temporal effects (83). Some studies have addressed this issue by using auto-lagged effects (13,82) and by transforming the data using a 9-term average of the counts (83,89). Others have studied the use of Auto-Regressive Integrated Moving Average (ARIMA) models to account for this temporal correlation between observations (87,90).

Regarding the effects of the pandemic on cycling demand, Buehler & Pucher investigated the overall trends in different cities across, Europe, the Americas, as well as Australia by using automatic counter data. The authors concluded that cycling increased from 2019 to 2020 in most of the studied cities (3). Nikiforiadis et al. investigated the impacts of the pandemic on the perception of bike-sharing systems (BSS) in the city of Thessaloniki in Greece. A field survey found that the pandemic made the city's BSS a more attractive option and could become the preferred commuting mode for current car passengers and users already registered in the system (76). In London, Heydari et al. compared the observed cycle hires in the city's BSS with the estimated counts if the pandemic had not occurred. They found that, although counts initially dropped in the first months, they rapidly bounced back to the expected levels which is a strong indication of the system's resiliency (75). The authors also noticed an increase in the duration of trips which could be caused by a shift from public transit users to the BSS. Similarly, Shang et al. also discovered an increase in the average duration of bike-shared trips in Beijing during the pandemic (91). Wang & Noland, analyzed data from New York City's subway and bike-sharing systems, comparing the daily counts from 2019 to 2020 while controlling the effect of weather. They concluded that both systems saw an initial decrease in riders during the first months of the pandemic. However, by September 2020, the BSS had nearly recovered to pre-pandemic levels while the subway's rider counts remained low (67). Nguyen & Pojani found, through a face-to-face survey, an increase in recreational cycling in the city of Hanoi, Vietnam. They also stated that income and age were not significant in the choice of taking up more recreational trips and that most people adopted cycling as a way to increase or maintain their level of physical activity and to socialize in an infection-safe environment (92).

3.4 Methodology

The proposed methodology consists of six steps as shown in Figure 1:

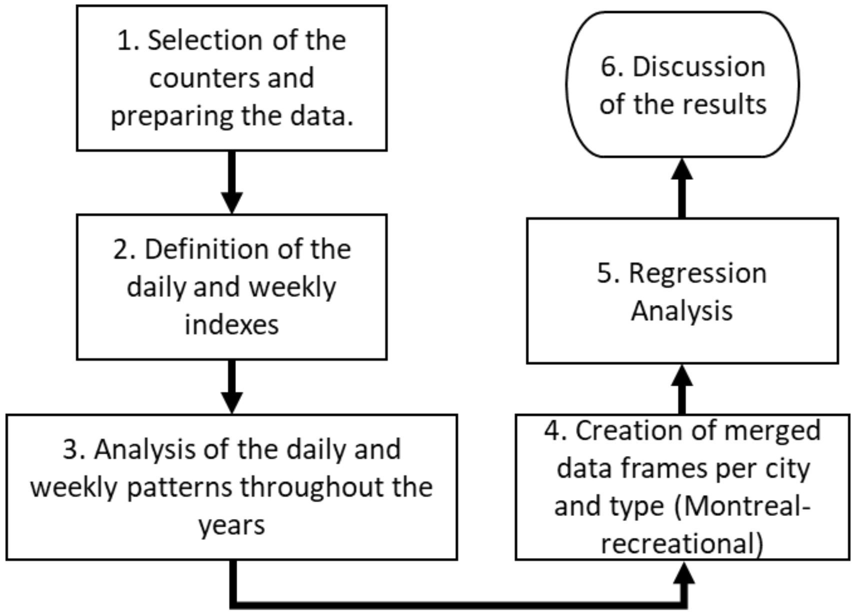

Figure 1: Methodology flow chart

The first step is the selection of bicycle counting sites to be used in this research. The selection process is based on the following criteria: i) the counters should be located on main corridors with few, or no alternative routes; ii) the counters should have historic long-term data of at least 8 years of relatively complete counts; iii) the facilities should exhibit a mainly utilitarian pattern in the years preceding the pandemic; iv) the counter should be located on corridors with high annual average daily counts.

As a second step, each counting site was classified per day as utilitarian, recreational or mixed based on their daily and weekly patterns by using the indexes defined in [1] and [2], which were developed in a similar way to the ones presented by Miranda-Moreno et al. (93). The hourly index is defined as follow:

$$I_{AM/Noon} = \frac{V_{peak}}{V_{out}} = \frac{\frac{1}{2}\sum_{i=7}^{8} V_i}{\frac{1}{2}\sum_{i=11}^{12} V_i} \ldots [1]$$

Where $I_{AM/Noon}$ is the hourly index computed as the ratio of the V_{peak} or the average peak-hour volume from 7:00 a.m. to 9:00 a.m. and V_{out}, the average off-peak volume from 11:00 a.m. to 1:00 p.m. Here, V_i stands for the number of counts at the hour i, and *n* is the number of hours in the period (2 hours for the AM peak from 7:00 a.m. to 9:00 a.m. and 2 hours for the noon peak going from 11:00 am to 1:00 p.m.).

The weekday versus weekend is defined as:

$$I_{wd/we} = \frac{D_{wday}}{D_{weekend}} = \frac{\frac{1}{5}\sum_{i=1}^{5} D_i}{\frac{1}{2}\sum_{i=6}^{7} D_i} \ldots [2]$$

Where $I_{wd/we}$ is the daily index computed as the ratio of the D_{wday} or the average daily volume from Monday to Friday (i = 1 on Monday, i = 2 on Tuesday, etc.), and $D_{weekend}$, which is the average daily volume from Saturday to Sunday. These formulas would give a unique am/noon index for each day on the historic data, excluding weekends, and the same weekday/weekend index for every day on the same week.

As a third step, the days were classified using a similar process to the one presented by Wessel (81). If both indexes were greater than one, the day would be considered to have a utilitarian pattern, if both indexes were less than one it would be considered as recreational, and as mixed for every other case, that is:

If $I_{AM/Noon} > 1$ and $I_{wd/we} > 1$ then *day type* = Utilitarian.

If $I_{AM/Noon} < 1$ and $I_{wd/we} < 1$ then *day type* = Recreational.

Else *day type* = Mixed

Then, for every year, the percentage of utilitarian, recreational, and mixed days was calculated to create the line graphs presented in the Results section.

In the fourth step, all counting sites are classified into four possible groups, the same classifications used by Miranda-Moreno et al. (93). If the counting site has 60% or more of its days classified as utilitarian, then the site is considered to be used for purely utilitarian purposes. If 60% or more of the days are recreational, then the site is classified as purely recreational. All the rest are classified as mixed and divided into two groups: mixed-utilitarian when the number of utilitarian days is greater than the number of recreational days, or mixed-recreational in the inverse case, that is:

If *utilitarian days* >= 60% of all days in the year, then *site type* = Utilitarian.

If *recreational days* >= 60% of all days in the year, then *site type* = Recreational.

Else:

If *utilitarian days* > *recreational days,* then *site type* = Mixed - Utilitarian

If *utilitarian days* < *recreational days,* then *site type* = Mixed - Recreational

Afterwards, for all counting data from the same city and of the same type (for example Montreal-Utilitarian, Montreal-Mixed, etc.) their total daily counts were paired with the daily measured weather factors, the daily stringency index, a holiday dummy variable (1 if the day is a national holiday, 0 if not), a bridge dummy variable (1 if the day was a Friday after a holiday or a Monday before a holiday, 0 if not), as well as with a location variable (site id), and to the year the count was taken. Similar weather variables, such as maximum daily temperature and average daily temperature, were compared and those with the highest correlation to the counts, or with the greater explanatory power, were kept for future analysis. Afterwards, another correlation analysis was carried out to ensure the independence of the explanatory variables. If there was a high correlation between the two of them (equal or greater than 0.5), the variable with the greater correlation to the counts was kept.

In the fifth step, a regression analysis was carried out by fitting each data-frame, optimized to eliminate any correlated or nonsignificant variables, to two different regression models wildly used in similar studies: log-linear and the negative binomial with log identity.

In the last step, the yearly coefficients of the models were analyzed to determine if the cities were experiencing an overall growth in cycling demand independent of weather conditions.

3.5 Data

3.5.1 Counters

The study used bike counts from counters manufactured by Eco-Counter and installed in cities with an open data access policy. The study only used counts classified as “bike” by the counter algorithm. A first selection was made by identifying the counting locations on cycling routes with few (or no) alternatives. Therefore, counting locations on bridges, underpasses and major cycling routes were prioritized. This reduced the likelihood that pop-up bike lanes, or new infrastructure in general, would impact growth trends at each counting location. From the locations selected in the first stage, only the counters that showed a small number of outliers in their historical data were selected. Additionally, all locations with a low mean daily count compared to the other sites of the same city were dropped. This generated a total of 17 sites to be used in the study. The extreme values from these sites were identified using a visual time-series analysis and manually replaced by a null value. For the cases where three consecutive days or less had null values, the counts were linearly interpolated. All other null values were deleted from the analysis. Additionally, there were some additional deletions of data for specific counters which will be explained in the following paragraphs.

The data spans from the installation of the counter until June 30, 2022. Table 1 shows the summary statistics for all the daily cyclist counts collected at each of the studied counters. Although the number of total sites per city might be smaller than the ideal, this allowed a more relevant dataset and a careful inspection of the counts. However, the low number of studied sites remains a limitation of this paper.

3.5.1.1 New York City

New York is the most populous city in this paper with a population of 8,550,405 in 2015 and a density of 10,474.7 people per square kilometer (94). The city experiences warm and humid summers followed by mild to cold winters (95). By 2018 the city had installed 1,240 miles of bike lanes and had a daily average of 490,000 cycling trips. In 2022 the borough of Manhattan scored 54 over 100 according to the City Rating made by the People for Bikes Organization (96), giving the area the 11th place within the ranking of large cities. The selected counters were the Williamsburg Bridge Path (NY1), the Ed Koch Queensboro Bridge Shared Path (NY2), and the Manhattan Bridge Display Bike Counter (NY3). The bike counts from the Manhattan Bridge pedestrian path were added to the NY3 site to account for any bikers that may have changed routes because of the partial or total closure of the cycling path.

3.5.1.2 Montreal

In 2021 Montreal had a population of 4,291,732 and a density of 919 residents per square kilometre (97). Currently, there are 889 kilometers of bike lanes in the city (98). In City Ratings, Montreal scored 65 points over 100, making it 1st place among the large cities of North America (96). The selected counters are located on the Jacques-Cartier Bridge (MT1), Rue Rachel near the Papineau intersection (MT2), Boulevard Maisonneuve near the intersection with Rue Peel (MT3), Côte Sainte-Catherine near the intersection with Rue Stuart (MT4), Avenue du Parc near the intersection with Rue Duluth (MT5), and Rue Berri near the intersection with Rue Ontario (MT6). The 2020 counts of the MT6 site were deleted due to a construction project that reduced access to Rue Berri.

3.5.1.3 Ottawa

The Ottawa metropolitan area had an estimated population of 1,135,014 and a population density per square kilometre of 243.3 in 2021 (97) which makes it the smallest and least dense city of this study. The city scored 51 over 100 in the People for Bikes City Rankings of 2022, placing it as the 13th best place to bike between the large cities of North America (96). The selected counters were the NCC Eastern Canal Pathway Colonel By (OT1), one on Avenue Laurier near the intersection with Metcalfe (OT2), the Trillium Bayview (OT3), the Trillium Gladstone (OT4), and the NCC Alexandra Bridge Cycle Track (OT5).

3.5.1.4 Vancouver

The metropolitan area of Vancouver had a population of 2,642,825 and a population density per square kilometre of 918 in 2021 (97). With a cycling network of 325 kilometers in 2018 (46) the city scored 56 points out of 100 in the 2022 City Rankings (96), which gave it the 6th place of all large cities. The selected counters are located on the Seawall path near Science World (VN1), on the Seawall path near the Creekside Community Centre (VN2), and Burrard Street near the intersection with Cornwall Avenue (VN3). Due to the presence of abnormal counts during 2012, that year of data was deleted from the VN1 site.

Table 1: Summary statistics of the daily cyclist counts for each counter (units in cyclists per day).

Site	Mean	Median	Maximum	Minimum	Standard deviation
New York City					
NY1	4830	4820	10940	162	2461
NY2	3702	3689	8295	21	1793
NY3	3953	3907	9466	117	2083
Montreal					
MT1	1138	835	5857	0	1123
MT2	2725	2325	9772	0	2200
MT3	2696	2174	11092	0	2358
MT4	1133	930	5337	0	1015
MT5	1451	1147	5305	0	1315
MT6	2347	1805	8812	0	2101
Ottawa					
OT1	831	619	3340	0	774
OT2	994	650	4128	2	948
OT3	427	272	2350	0	471
OT4	528	390	2724	0	495
OT5	931	751	3284	0	866
Vancouver					
VN1	3622	3151	10187	0	2272
VN2	1973	1440	8823	0	1716
VN3	3585	3245	10129	56	2084

3.5.2 General Analysis

Analyzing the boxplots presented in *Figure 2,* the New York sites' median values for daily cyclist counts do seem to have increased slightly in the last years. Looking at the Montreal counters, there is no visible trend citywide, which is a similar case in Vancouver. Most of the counters in Ottawa seem to show a downward trend in the last years, even before the start of the lockdown measures. However, it would be wrong to assume, based on these plots, that cycling demand in the cities has decreased in the last years. As noted in the literature, it is important to control for any external variables, such as the general weather and the lockdown measures that could hide the inherent trend of cycling demand before making any assessment about future investments.

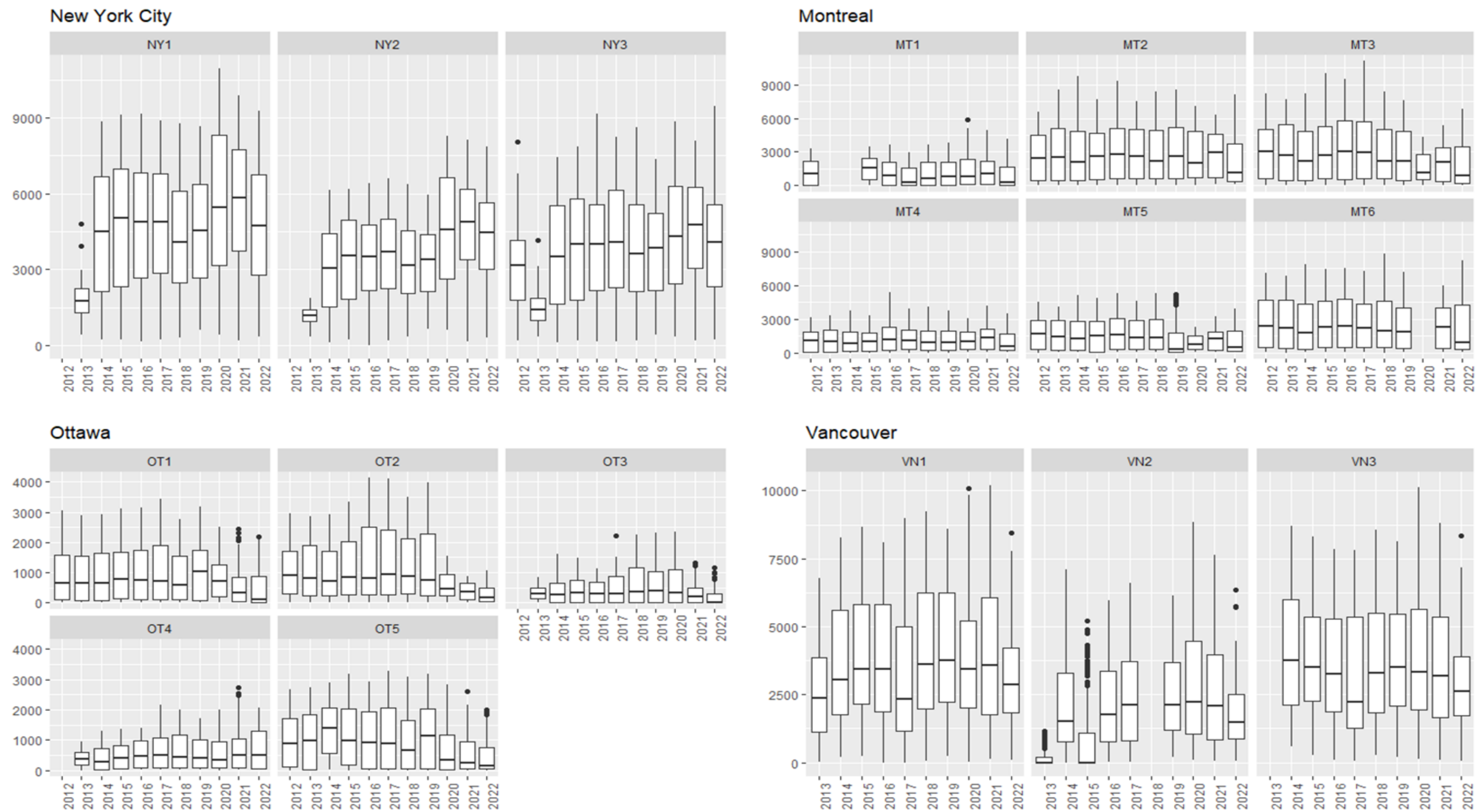

Figure 2: Boxplot of the daily cyclist counts from each of the studied sites (units in cyclist per day)

3.5.3 Weather Variables

The weather data was obtained through the *World Weather Online*'s API. For each city, the measured weather data was recovered from the station closest to the centroid of all the counters in that city. The initial weather variables extracted for analysis were daily maximum and average temperature (degrees Celsius), daily average and maximum wind speed (kilometers per hour), daily total precipitation (millimetres), daily average and maximum precipitation intensity (millimetres per hour), daily average and maximum humidity (percentage), as well as the daily percentage of the sky that was obscured by clouds, also known as cloud cover.

3.5.4 COVID Variable

Ritchie et al. (2020) calculated per day a *stringency index* which is the mean score of nine different metrics: school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movements, and international travel controls. The possible values have a range from 0 to 100 (where 0 means there are no restrictive measures in place and 100 means the strictest response by the authorities).

3.6 Results

3.6.1 Descriptive Analysis: Behavioral Patterns by Indexes

From *Figure 3* it is observed that most of the selected bicycle corridors show a utilitarian pattern before the start of the pandemic. During the pandemic (2019-2022), the studied facilities experienced a shift towards more mixed or even fully recreational patterns. This is expected as the lockdown measures required people to work from home, which diminished the number of commuter trips. The biggest impact can be seen in 2020 when six of the seventeen sites shifted from utilitarian to mixed and three others shifted from utilitarian to recreational. However, the last two years (2021 and 2022) show a recovery trend toward mixed-utilitarian or purely utilitarian patterns in most cases, which could suggest an eventual return to previous uses in most of the study corridors.

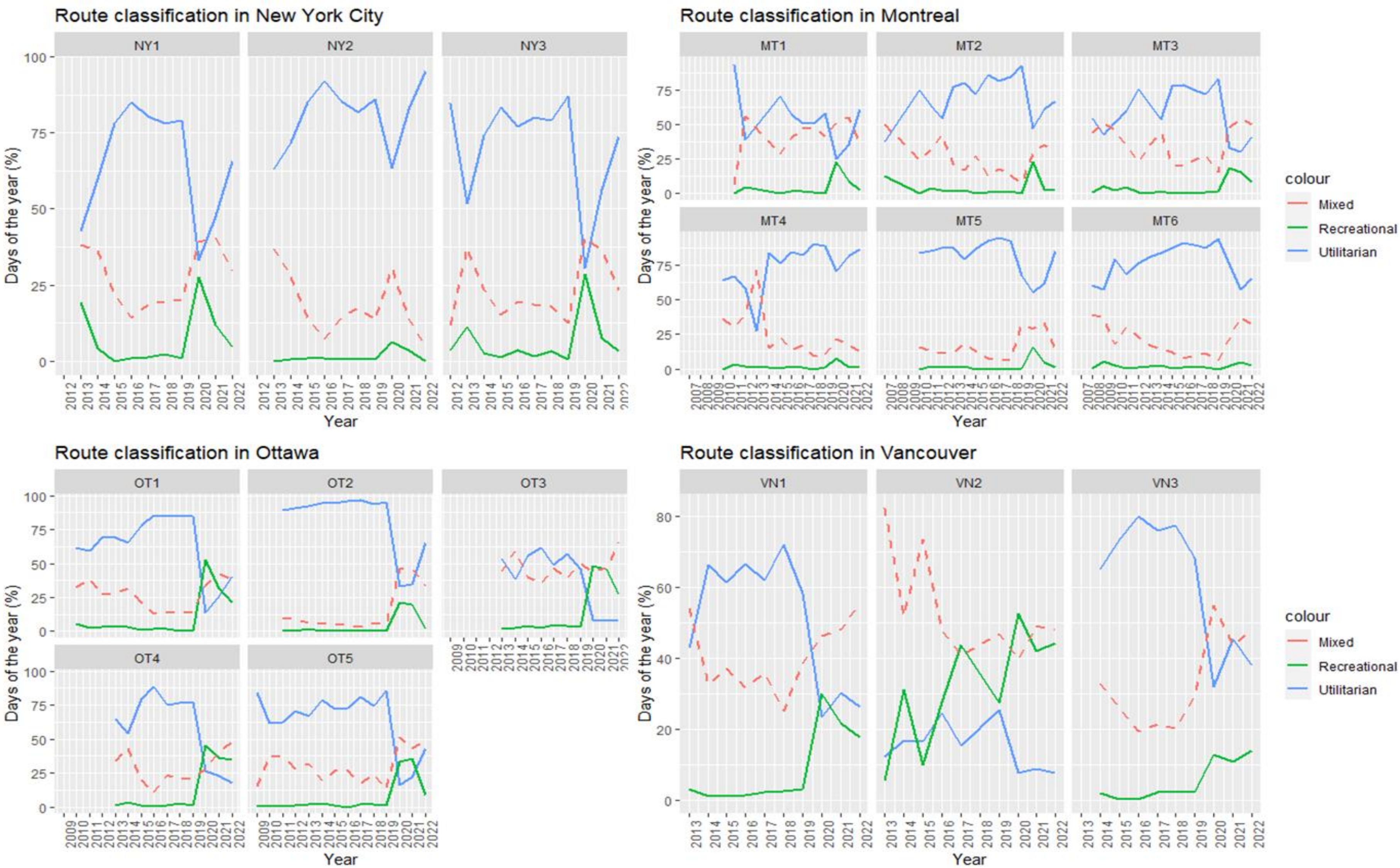

Figure 3: Temporal changes in the usage of the facilities

Two of the New York counting sites had some of the biggest declines in utilitarian days during 2020. Nonetheless, all three of them showed a fast recovery towards the patterns observed before the start of the lockdown measures. Ottawa was another city with sharp declines in utilitarian days during the pandemic. However, unlike New York City, the recovery towards past patterns occurs more slowly in three of the sites. In the other two, both located on the Trillium path, the change toward mixed patterns seems to be permanent as the number of utilitarian days stagnated after 2020. Ottawa also registered the highest percentage of recreational days compared to the other study cities.

Montreal was the city with the most consistent patterns throughout the pandemic. Although all the locations showed a dip in 2020, most of the locations still mainly experienced utilitarian days. Only two of them had an important shift in 2020 towards mixed patterns. These graphs are more closely related to those from New York City, although with less sharp 2020 dips as seen in *Figure 4*.

Vancouver showed a different behavior, being the only city with more mixed pattern days in all its counting sites. It is important to note that the VN2 location showed a general trend towards more recreational use before the start of the pandemic. The other two sites were like the ones seen in Ottawa, where utilitarian patterns shifted towards mixed and did not show any sign of shifting back. In both, there is a significant decline of utilitarian days in 2020, then a small increase in 2021, followed by a smaller dip in 2022. It is interesting to see the indexes in this case, as shown in *Figure 5*, Vancouver is the only city where the weekday/weekend ratio continued to decline in 2022 even though the AM/noon peaks ratio is increasing slightly. This mismatch in tendencies explains the mixed classification.

Figure 4: Yearly variation of the indexes in New York and Montreal

Figure 5: Yearly variation of the indexes in Ottawa and Vancouver

3.6.2 Regression Analysis: Yearly Trends After Controlling for Weather

A regression analysis was carried out for every type of route in the four cities. Each data frame was optimized by eliminating all correlated variables and by only keeping significant variables at a 95% confidence level. Due to space limitations, only the coefficients and results for the Negative Binomial models of the utilitarian facilities are shown in *Table 2* since their R^2 score showed a lower variability. The coefficients calculated by the models, which were built with R functions, were graphed as the percentage change in counts through time compared to a base year, which was the first year of available data for every individual dataset.

The utilitarian bike facilities located in the cities of New York (NY1, NY2, and NY3) and Montreal (MT2, MT3, MT4, MT5, and MT6) show a consistent growth throughout the years, which increased in the first year of the pandemic. This could be attributed to the implementation of “pop-up” bike lanes, the closure of streets, or the shift of public transport users towards biking due to the loss in the level of transit service and greater concern of infection in crowded vehicles. The trend seems to stabilize in 2021 and 2022 for both cities which could be a sign of the general recovery of service in the main public transport services in those cities. Ottawa’s utilitarian facilities (OT1, OT2, OT4, and OT5) have also experienced consistent growth throughout the years. However, for the first half of the timeframe they showed lower levels of demand compared to the base year.

The Mixed-Utilitarian cycling corridors in Ottawa (OT3) and Montreal (MT1) show a different story with a more erratic growth pattern than their utilitarian counterparts. Both show a downward trend in demand which was magnified during the first year of the pandemic. In the last years, the decrease seems to have stagnated in Ottawa and even reversed in Montreal. It must be noted that the data analyzed came from one counter for both cases which means that this behavior represents only a local situation and cannot be assumed for the rest of mixed-utilitarian sites in the cities. Future research should be carried out to confirm if this is a city-wide or simply a local trend.

All of Vancouver’s locations were classified as a different type. Site VN3 was the only utilitarian route in the analysis and showed a stagnated growth except in 2017 when it suffered a decrease in counts. As with the other utilitarian sites, the growth increased in 2020. Nonetheless, it was not capable of retaining the higher demand in the following years. The site VN1 was classified as Mixed-Utilitarian and shows a similar trend to the one observed in the utilitarian facilities with constant growth throughout the years, except for 2017, and stagnation in the last two years. As with the mixed utilitarian corridors, these results may be only representative of the location of the counter and may not be assumed as the general situation of the city.

It is important to note that the models of the mixed-patterns corridors showed in most cases lower R^2 scores than the utilitarian ones, because of greater variability in the counts. These models are based on data from a single counter rather than a group of them, which may explain the lower scores. Beyond the scope of this paper, it is interesting to note that all utilitarian facilities across the four cities seem to have stagnated or even suffered a decrease in counts during the years 2018-2019, just before the growth in counts caused by the pandemic.

The graph of the utilitarian facilities in the four cities is shown in *Figure 6* and the ones for the Mixed-Utilitarian facilities are shown in *Figure 7*.

Table 2: Coefficients of the Negative Binomial models

City	New York City			Montreal			Ottawa			Vancouver		
Coefficients	**Estimate**	**Std. Error**	**S.L.**	**Estimate**	**Std. Error**	**S.L.**	**Estimate**	**Std. Error**	**S.L.**	**Estimate**	**Std. Error**	S.L.
(Intercept)	7.68	0.03	***	6.43	0.05	***	5.53	0.06	***	8.25	0.07	***
site_cat2	-0.25	0.01	***	-0.05	0.01	***	0.44	0.02	***	-	-	-
site_cat3	-0.20	0.01	***	-1.02	0.01	***	-0.35	0.02	***	-	-	-
site_cat5	-	-	-	-0.73	0.01	***	0.00	0.02		-	-	-
site_cat6	-	-	-	-0.20	0.01	***	-	-	-	-	-	-
maximum daily temperature	0.09	0.00	***	0.08	0.00	***	0.08	0.00	***	0.11	0.00	***
sqaured maximum daily temperature	0.00	0.00	***	0.00	0.00	***	0.00	0.00	***	0.00	0.00	***
maximum wind speed	-0.01	0.00	***	-0.01	0.00	***	-0.01	0.00	***	-	-	-
average wind speed	-	-	-	-	-	-	-	-	-	-0.03	0.00	***
precip_cat2	-	-	-	-0.09	0.01	***	-0.07	0.02	***	-	-	-
precip_cat3	-	-	-	-0.51	0.03	***	-0.50	0.04	***	-	-	-
precip_cat4	-	-	-	-0.45	0.12	***	-0.36	0.09	***	-	-	-
precip_cat5	-	-	-	-0.63	0.30	*	-0.83	0.21	***	-	-	-
average daily precipitation	-0.08	0.00	***	-	-	-	-	-	-	-	-	-
average humidity	-	-	-	-	-	-	-	-	-	-0.01	0.00	***
average cloudcover	0.00	0.00	***	-0.01	0.00	***	-0.01	0.00	***	-0.03	0.00	***
total cm of Snow	-0.03	0.00	***	-0.05	0.00	***	-0.02	0.00	***	-	-	-
stringency index	0.00	0.00	**	-0.01	0.00	***	-0.01	0.00	***	-0.18	0.05	***
holiday dummy 1	-0.45	0.02	***	-0.75	0.05	***	-0.40	0.04	***	-0.21	0.09	*
bridge dummy 1	0.12	0.03	***	0.23	0.06	***	-	-	-	0.06	0.03	*
day of the week 2 (Tuesday)	0.04	0.01	***	0.04	0.02	**	-	-	-	0.05	0.03	.
day of the week 3 (Wednesday)	0.07	0.01	***	0.04	0.02	**	-	-	-	0.01	0.03	
day of the week 4 (Thursday)	0.03	0.01	**	0.04	0.02	*	-	-	-	-0.06	0.03	*
day of the week 5 (Friday)	-0.01	0.01		-0.05	0.02	**	-	-	-	-0.18	0.03	***
day of the week 6 (Saturday)	-0.20	0.01	***	-0.56	0.02	***	-	-	-	-0.24	0.03	***
day of the week (Sunday)	-0.33	0.01	***	-0.64	0.02	***	-	-	-	-	-	-
weekend_dummy 1	-	-	-	-	-	-	-0.49	0.01	***	-	-	-
season_dummy (spring)	0.10	0.01	***	0.60	0.02	***	0.76	0.02	***	0.35	0.02	***
season_dummy (summer)	0.15	0.01	***	0.71	0.02	***	0.80	0.03	***	0.37	0.03	***
season_dummy (autumn)	0.15	0.01	***	0.89	0.02	***	0.82	0.02	***	0.07	0.02	**
year 2009	-	-	-	0.16	0.05	***	-	-	-	-	-	-
year 2010	-	-	-	0.41	0.04	***	-0.40	0.06	***	-	-	-
year 2011	-	-	-	0.38	0.04	***	-0.09	0.06		-	-	-
year 2012	-	-	-	0.40	0.04	***	-0.01	0.06		-	-	-
year 2013	-0.06	0.04	.	0.47	0.04	***	-0.06	0.06		-	-	-
year 2014	0.05	0.03	.	0.46	0.04	***	-0.04	0.06		-	-	-
year 2015	0.14	0.03	***	0.54	0.04	***	0.10	0.06	.	-0.01	0.03	
year 2016	0.19	0.03	***	0.63	0.04	***	0.03	0.06		0.01	0.03	
year 2017	0.20	0.03	***	0.66	0.04	***	0.18	0.06	**	-0.16	0.03	***
year 2018	0.15	0.03	***	0.54	0.04	***	0.10	0.06		-0.06	0.03	.
year 2019	0.16	0.03	***	0.53	0.04	***	0.10	0.06		-0.04	0.03	
year 2020	0.33	0.03	***	0.97	0.05	***	0.60	0.09	***	0.04	0.03	
year 2021	0.37	0.03	***	1.15	0.06	***	0.40	0.09	***	-0.02	0.03	
year 2022	0.36	0.03	***	1.10	0.06	***	0.17	0.08	*	-0.12	0.04	**
2 x log-likelihood:	-157726.231			-40893.404			-226507.317			-49342.23		
AIC:	157790			40945			226573			49394		

Significance level (S.L.) codes: '***' 0.001 *' 0.01 0.05 '.' 0.1 ' ' 1 '- ' Unused variable

Site_cat = variable representing the different counters in the analysis (example MT2, MT3)

Precip_cat: groups of the average daily preciptation. Precip_cat base = no precipitation

Precip_cat2 = precipitation values in the 25% quantile

Precip_cat3 = precipitation values between the 25% the 50% quantiles

Precip_cat4 = precipitation values between the 50% and 75% quantiles

Precip_cat5 = precipitation values above the 75% quantiles

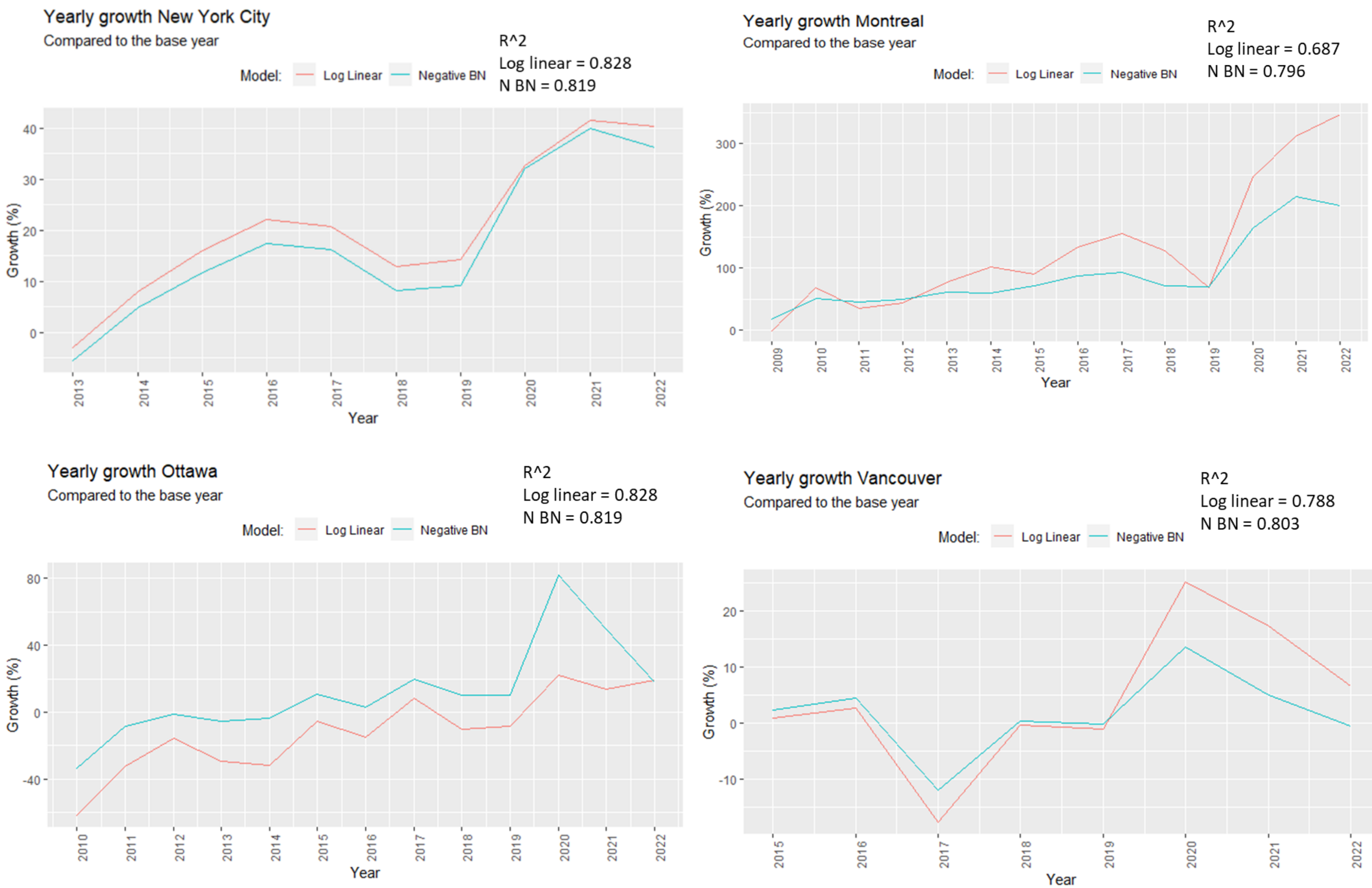

Figure 6: Growth of Utilitarian bicycle facilities

Figure 7: Growth in Mixed-Utilitarian bicycle facilities

3.7 Conclusions

This paper investigates the long-term trends across cycling seasons before and after the pandemic using data from counting stations in four cities. Among other things, it was observed that most of the study utilitarian facilities in the four cities suffered a change in the daily and hourly patterns during the first year of the pandemic (2020), which saw a greater mixed and recreational usage of the facilities. This is related to the lockdown and work-from-home measures implemented in the study cities. Despite that, there is no generalized pattern.

Most of the utilitarian facilities have experienced growth in the years before the start of the pandemic; the magnitude of the growth increased in 2020 even after controlling for weather variations across years. This is perhaps related to the shift of public transport users to other modes including cycling during the pandemic. In the year 2022, it seems that the magnitude of the growth as well as the hourly and daily patterns are converging to the pre-pandemic years. The utilitarian cycling corridors in Montreal and New York City grew considerably during the pandemic before stabilizing in the last two years and also returned more quickly to mostly utilitarian patterns after 2020. This could be explained by the fact that both places have the biggest bike infrastructure networks among the studied cities and may have a greater commuter cycling culture. Although the utilitarian facilities in these cities did suffer a sudden change during the pandemic, they do not seem to have been affected by it. They may have even benefited from it.

The mixed-utilitarian bicycle facilities shifted towards more recreational usage during the pandemic. One could attribute this to an increase in recreational riders during the pandemic. However, they do not seem to have experienced any growth in the last years, so it seems that these corridors lost commuters rather than gained recreational users. The changes in the patterns after the pandemic vary between the different cities. While the facility in Montreal shows a tendency towards more utilitarian patterns and a small growth in 2021 and 2022, the growth in the mixed facilities of Ottawa and Vancouver stagnated in the same years and showed a tendency to stay mostly utilitarian or even shift to a more recreational use respectively. In a general sense, these facilities lost commuters during and after the pandemic. Future research analyzing more counting sites of the same type is necessary to confirm this finding.

Ottawa presents a slower recovery to pre-pandemic patterns in most of its sites. Vancouver presented a different situation than the other three cities, where its utilitarian routes have not shown any major growth during the last years, except for 2020. However, the Mixed-Utilitarian routes have grown constantly throughout the years. Also, all the studied sites in this city shifted towards mixed-use during the first year of the pandemic and all three of them do not show any clear sign of changing towards more utilitarian patterns. In general, the studied biking facilities in Vancouver seem to have increased in recreational users. Further studies with data from more counters may be necessary to confirm this finding.

The next steps for this investigation will be to conduct the same methodology with the data from the second half of 2022 and incorporate a greater number of counting sites from other cities in North America. Furthermore, more advanced modelling settings (general additive and dynamic ARIMA regression models) will be tested to account for serial autocorrelation.

3.8 Acknowledgments

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4. Chapter IV: Bridge

As seen in Chapter III, the cycling demand in big North American cities with significant bicycle networks has grown over the last 10 years. Even with the challenges brought by the COVID-19 pandemic, cycling demand in Montreal grew considerably during those years due to the influx of users shifting from public transit. Although it’s not an ideal situation having both modes fighting for the same users, it does show that there is a potential share of people willing to commute using bicycles and that it could be used as a complement to urban public transport. The growth also justifies the future expansion of the cycling network to supply the increasing demand.

Nonetheless, as shown by the literature review, cycling is significantly affected by weather conditions. For example, warmer temperatures increase biking demand and rainy days reduce it. While it is important to control for these variables when evaluating current policies and infrastructure, since favourable weather may hide a decreasing trend in cycling counts (14), city authorities need to acknowledge its effects to ensure that the planned cycling infrastructure continues to meet the needs of its residents in the future. This requires them to understand the growth trends and anticipate the expected demand for cycling facilities in the coming years. Planners should consider the potential impact the changing weather patterns due to climate change will have on future cyclist volumes.

As extreme weather events become more frequent, cities that wish to preserve and grow their cycling commuters will need to adapt the infrastructure to ensure that the bicycle remains a viable mode of transportation throughout the year such as tree-shaded bike lanes, cool pavements, rain-protected facilities, and storm-water drainage. This will require a comprehensive understanding of what weather could be expected in the future to design climate-resilient infrastructure that will protect potential users.

Chapter three showed a methodology that considers the effects of weather on the cycling counts and analyzes the behavioural changes of cyclists in the face of the COVID-19 Pandemic which provides a diagnosis of the present cyclist volumes in North America. The next step is to take this diagnosis into the future to understand what cities might face in terms of cyclist infrastructure demand and how can they prepare for it.

Unfortunately, the prediction of the forthcoming weather is a tricky task due to all the uncertainties found not only in the interaction between the natural systems but also in possible climate mitigation actions of the nations. Because of this, the expected demand should be estimated across different scenarios and climate models to cover a wide range of feasible outcomes in the middle of all the uncertainty.

Chapter five provides a methodology capable of predicting cyclist counts into any future year of the XXI century by combining historical data from counting sites with the projections given by climate models following different emission scenarios. This framework can calculate a range of expected demands cities must consider when planning the construction of new infrastructure.

5. Chapter V: Effects of Climate Change on Future Yearly Cycling Demand for the City of Montreal

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Data Statement: The cyclist counts data used for this study is the property of Ville de Montreal. Any request for the cycling counts data must be submitted to the corresponding authorities or information portals of each city All the weather measurements data were acquired from the Government of Canada.

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5.1 Abstract

In the context of a changing climate, the bike infrastructure requires understanding future needs (demand) under the most probable climate conditions to ensure resilient infrastructure capable of promoting and meeting the expectations of the urban bicycle demand in Canadian cities. The objective of this work is to propose a methodology capable of predicting cycling ridership under alternative climate scenarios by combining models that simulate the relationship between bicycle counts and weather along with climate-model outcomes. Cycling demand projections for 2050 are made using Montreal as a case study. For this purpose, six years of data from nine locations with automatic cyclist counters are used to train a ridership-weather model based on the Extreme Gradient Boost (XGBoost) technique. The predictions of that model are validated by comparing them to known cyclist counts. In parallel, climate predictions for the year 2050 are obtained using the statistically downscaled projected weather conditions from different climate models and scenarios. These climate predictions are inputted into the ridership-weather models to estimate bicycle demand for 2050. From the various scenarios, the results show a change in cyclist counts between -4.77% and 27.22% in cyclist ridership during March, April, and November depending on the scenario considered, with an average increase of 11.21%. During the summer, the change in ridership goes from 9.77% to -11.53%, with an average decrease of 0.88%. Most scenarios predict a slight increase in counts during winter, which can go from 14.55% to -12.02% with an average increase of 1.27%. Depending on the climate scenario, the overall growth in winter, spring, and fall can be offset by the high temperatures during summer. Therefore, results show the need to build infrastructure that considers heat mitigation strategies.

5.2 Introduction

Since the middle of the nineteenth century, the bike has become one of the most recognizable modes of transportation in many cities. The low cost to acquire and maintain a bicycle as well as the several health and mental benefits its usage can provide (26,100–103) makes it appealing for individuals to use. The benefits of the bike are not limited to the user. Higher cycling levels bring many economic benefits to cities (104–106) and reduce air pollution levels in urban areas (107–110). For these reasons, cities have started promoting its use through campaigns, investments in infrastructure, and general policies. An example is Paris, where authorities have developed a plan to transform the city into one of the most bike-friendly environments in the world (111). The "biking renaissance" has also made its way into the North American theatre in the past two decades (6) and Montreal is not an exception. By 2022, the city had built a bike network of 889 km across the whole island (98) and still has plans for future expansion. These efforts resulted in Montreal achieving 18th place in the world according to the Copenhagen Index, making it the only North American city to appear consistent in the index since 2011 (112). However, if authorities wish to continue promoting cycling, they need to plan for the long term.

The problem is that the future hides many challenges, especially in the face of climate change. Therefore, cities need to plan and design more resilient infrastructure. Accordingly, they need to understand better the influence of local weather conditions on cycling demand and the variations (in temperature and precipitation, for instance) that climate change might bring.

The study aims to propose a methodology that helps predict bicycle demand under alternative climate scenarios by combining cycling ridership models and climate-model outcomes. It consists of three steps; development of ridership-weather models based on historical data, generation of climate projections based on downscaling climate models, and predictions of future bicycle ridership according to the alternative climate scenarios for 2050. The methodology is developed using Montreal as a case study. The results of this paper give insights to the cities about what the future might look like and what features should be considered when planning the bicycle network in the long term.

The paper consists of five sections: 1) a literature review regarding the relationship between the weather variables and cycling demand, estimating cycling demand considering future weather, the expected effects of climate change around the Montreal area, and the use of machine learning models in the prediction of cyclist volumes; 2) the methodology used in this paper; 3) the predictions obtained from the models; and 4) the conclusion of the research, its limitations, possible future research routes, and its implications for future actions regarding infrastructure and transport policy for the city.

5.3 Literature Review

5.3.1 Relationship Between Weather and Cycling

In 1995 Nankervis (11) compared the number of bikes parked inside an Australian university with a daily weather index made up of the maximum temperature, the wind speed and the presence of rain during the day. He found a relationship between the index and bike counts but noted that students are less sensitive to weather variables. Thomas et al. (14) merged daily counts from automatic counters in rural areas of the Netherlands with the daily weather measurements and concluded that the bike counts were mostly affected by the measured temperature as well by precipitation, wind speed and hours of sunshine to a lesser but significant degree. Bean et al. concluded that the hour of the day and precipitation were the most significant variables affecting bike-sharing systems usage in their study across 40 cities (72). For the city of Toronto, Saneinejad et al. concluded that chilly weather, precipitation, and wind speed had a significant impact on active transport modes (113). Wessel found out that even weather forecasts can have a considerable influence on cyclist counts (81). Böcker et al. carried out a literature review on the link between weather and transport and concluded that warm and dry weather increase the use of active transportation modes while rain, snow, clouds, cold weather, and windy days reduce their use. They also noted that bike counts do not have a linear relationship with temperature (114). This idea follows the research of Miranda-Moreno & Nosal (54) who found a maximum temperature threshold in which, cyclist counts would go down as those variables increase. Nonetheless, this threshold varies by city. The value found by Heaney et al. (82) for the city of New York was similar but not equal to the one found by Miranda-Moreno & Nosal for the city of Montreal. Other cities such as Austin (84) and Seattle (83) also had a threshold value that differed from their eastern North American counterparts. These results reinforce the idea of Goldman & Wessel that cyclists of different cities will have a unique sensitivity to the weather factors depending on the climate of the region or other unseen factors such as the biking culture present (18).

5.3.2 Climate Change Models and Projections Downscaling

As shown, a significant relationship exists between the weather variables (especially temperature and precipitation) and cyclist volumes. While this relationship can be expected to continue, the weather cities will face in the future will not be the same as the present conditions. Climate change is expected to alter the variance and distributions of the weather variables which, as seen in the previous sector, will modify cyclist behaviour. The question that arises is, how will cyclist demand react to the future changing climate and what will this mean for the design of future cyclist infrastructure?

Predicting the weather is a difficult task, especially with a complex system such as the global environment. For this purpose, researchers have developed powerful climate models. These theory-based representations have evolved from conceptual to analogue to mathematical and finally to computational simulations of the atmospheric flow capable of giving projections of possible future weather conditions (115). Nonetheless trying to predict the weather in the years to come is more difficult since the influence of human activity has been proven to alter the climate and induce warming of global temperatures (116). For this reason, various models have been run considering different scenarios of human activity to cover a wide range of possible future climates.

Although these models represent powerful tools, their output cannot be used at a local level due to its coarse spatial resolution of about 200 km (117). That cell size is unable to capture the variations at a lower scale, which is needed when studying the future weather in smaller spaces such as urban areas. Downscaling allows establishing links between the climate model outputs with the surface temperature in an area. This can be done in two ways: The first strategy is called dynamical downscaling (DD) which follows the rules of conservation of mass-energy and momentum by creating a smaller model spanning across the desired area and using the outputs of the larger models as boundary conditions. Although they allow for more complete physics, they require high amounts of computational power. Statistical Downscaling is a second, less computationally intense strategy that provides faster results by using statistical regression techniques to model the relationships between the model projections and the surface temperature (118). Statistical downscaling techniques can be divided into three groups: Regression models that linearly represent the relationship directly between the outputs of the climate model with the conditions at the point for each weather factor, Stochastic Weather Generators that simulate weather data based on the characteristics of the variable, and weather typing that groups days into weather condition types and the bigger climate models are used to determine the frequency and variance of these types (119).

The models and downscaling methods have been used in the literature to provide insight into what the weather might look like in the future for a city like Montreal. In a general review of the effects of climate change on the weather conditions of the United States, Huber and Gulledge (120) concluded that there is a statistical trend towards more frequent and intense extreme weather events in the future and an increase in the risk of heatwaves over time. The authors also mentioned that cold events will become less frequent but will not disappear and noticed that the models tend to under-predict maximum temperatures. Berardi and Jafarpur (15) statistically downscaled a General Circulation Model (GMC) to obtain future weather values for the city of Toronto. They projected an increase in the mean temperature of 0.8 °C and a decrease in the humidity values and concluded that the combination of multiple

GMCs along with Regional Climate Models (RCM) had the best prediction accuracy of the climate in the region. Wang et al. (121) developed high-resolution climate projections for the province of Ontario using the HadCM3 model and the Providing Regional Climate for Impact Studies (PRECIS) regional modelling system to downscale the weather projections. Their results showed a province-wide increase of the average temperature of 2.6 to 2.7 °C for 2030, 4 to 4.7°C in 2050, and 5.9 to 7.4 in 2080. They also projected a slight increase in the annual sum of rainfall, a greater number of precipitation events during the winter and spring months, as well as a province-wide increase in rainfall intensity. Cheng et al. (122) used a synoptic weather typing method's capability to analyze the impact of climate change on extreme events in the south-central region of Canada. They estimated an increase in heat-related mortality, freezing rain as well as the frequency and intensity of future daily extreme weather events. For Montreal, Gaitán (123) downscaled the CGCM3.1 and CRCM4.2 models and found an increase of 7°C in the maximum temperature for a 30-year return period. Dickau et al. (124) used a MarkSim Weather Generator to obtain future temperature projections and estimated a reduction in the number of days of the outdoor skating season due to the projected increases in temperature and the shortening of the freezing season.

5.3.3 Climate and Cyclists

These studies confirm a growing trend in the number of warm days and a shortening of the typical winter season which suggests an annual increase of cyclist counts with more equally distributed volumes across the seasons. This might cause an extension at both ends of the biking season in Montreal, which has historically taken place from mid-April to mid-November. Nonetheless, the models also predict an increase in total precipitation and frequency throughout the year as well as an increase in the number of heat wave events during the summer which could counteract the positive effects of a warmer shoulder season (spring and fall) and a milder winter.

Böcker et al. (114) studied the potential effects of climate change in modal choice and distance travelled by mode for the year 2050 in the region of Randstad in the Netherlands using extreme observed weather values to represent the expected weather for 2050. Their results showed an increase in the modal share of active transport during the winter and a loss during the summer caused by high temperatures and greater precipitation volumes. Wadud calculated the effects of climate change on cycling levels in London for 2041 with negative binomial models and data from the HadCM3 general climate model. He predicted an overall marginal annual increase in counts due to the counteracting effects of temperature and precipitation with cyclist volumes increasing during the summer and winter and decreasing in the spring and autumn (125). One major difference with the work of Böcker et al. is the use of data from future projections made by a climate model and from automatic bike counters instead of survey data, which is the standard in the following papers. Heany et al. (82) estimated the future number of trips and their length for the Bike Sharing System (BSS) of New York City using a general additive model. When inputting future weather conditions into the model, the results showed an annual increase in the number of trips and their length. On a seasonal level, they predicted a decrease in the summer counts due to extremely hot days, which was offset by the gains in spring, autumn, and especially winter. Similarly, Galich et al. (126) predicted the bicycle counts in Berlin for 2050 while adjusting for climate change with four different models: a statistical one and 3 machine learning based. The authors concluded that the city would experience a small annual increase in bike counts between 1 and 4% compared to 2020, with greater gains being made during the winter season. Additionally, they concluded that the machine learning models had a greater predictability accuracy. Sharafi (127) predicted trip counts for the BSS in Montreal using statistical regression models and future weather projections derived from a Global Environmental Multiscale model. She concluded that future weather would increase the demand for the BSS in April, September, and October. She did not study the winter months since the BSS closes during that season and did not consider non-BSS cyclists. Chan and Wichman (128) quantified the monetary impacts of climate change on leisure cycling in 16 cities across North America with the use of a regression model. On the seasonal scale, they predicted greater cyclist volumes throughout the year with a marginal change in summer, greater in the shoulder months and the greatest during the winter. Nonetheless, it is important to notice that their analysis across multiple cities and climate zones may have not accurately projected the responses of the citizens from each city to the changing climate since it is not the same to have warmer days in a cold city than in one with already extremely hot days. As a comparison, Mathisen et al. (129) estimated the bike usage in the city of Bodo, located in the Arctic region of Norway for low, middle, and high emissions climate projections. The authors found a small increase in bike usage in all the scenarios. On the other hand, Lanza et al. (84) carried out similar research to the previous papers on an urban trail located in the city of Austin, United States, which is in a humid sub-tropical area. The authors imputed the expected climate condition obtained from downscaled climate model predictions for the 4.5 and 8.5 emission pathways of the IPCC. They estimated a decrease in urban trail usage due to the loss in counts due to the extremely hot temperatures of the summer offsetting the gains during warmer days in the winter.

The revised papers seem to agree that in cities with continental or colder climates, like Montreal, the annual bike usage will slightly increase due to climate change with the greatest gains during the winter. Nonetheless, the impact of climate change on counts from one city cannot be assumed to be true for another since the variation in the climate and climate resilience of the citizens will be different. The magnitude of the effect also varies throughout the year, which shows the importance of carrying out separate analyses for each season, as noted by Böcker et al. (114). Additionally, it is important to consider the observation of Mathisen et al. (129) that their model had a bias toward overestimating low counts, which are more likely to occur during the winter. If all the models had a similar problem and the predicted values were compared to the observed values rather than to the fitted values, there would be an overestimation of the impact during the low-counts seasons, which could explain the great increase during the winter season reported by the articles. The literature proves that the weather conditions in the region and its variations due to climate change can influence the prediction of future annual counts. This information confirms that cyclist counts are likely to change in the future and supports the need to carry out this type of analysis for Montreal.

5.3.4 Machine Learning Methods and Cyclist Predictions

Researchers have started to explore the capabilities of newer models based on machine learning methods to predict cyclist demand. A study used bicycle renting data from Washington D.C. and compared the prediction capabilities of linear regression (LR), random forest (RF), and extreme gradient boosting (XGBoost) models, with the latter one outperforming the others (130). Another study also compared different models trained on data from Brussels, Belgium along with measured weather factors. The authors mentioned that models' prediction capabilities increased after adding the weather variables with the Fully Connected Neural Network (FNN) performed the best, followed by the XGBoost model (131). A different study paired a database of bicycle trips in Washington D.C. with weather variables and found that the XGBoost model had the best RMSLE compared to LM, RF, Support Vector Regression (SVR), Adaboost, and bagging models (132). Cui et al. developed an XGBoost prediction model of cyclist demand at the exits of subway stations in Beijing, China, which performed better than other statistical models. They also mentioned that special weather events had a noticeable impact on cyclist counts, and concluded that adding these factors to the model will increase its prediction capabilities (133). In Seoul, South Korea, researchers compared different models trained on hourly bike data while controlling for weather effects and concluded that gradient boosting, followed by XGBoost, performed better than LM, SVR, and boosted trees. They also found that the temperature and hour of the day attributes had the greatest prediction capability (134). A study using bike rental data from Thessaloniki, Greece, included the measured weather in the analysis and compared different machine learning models (Random Forest, Gradient Boosting, Extreme Gradient Boosting and Neural Networks). They concluded that gradient boosting and XGBoost had the best prediction capabilities (135).

5.4 Methodology

5.4.1 Definition of the Periods

The study defines three distinct periods. The first one is *The Training Period*, (from 2015 to 2018) used to fit the models. The second is *The Validation Period* (2019), used to evaluate the model and to compare the changes with the year 2050. These two periods compose *Historical Data* (from the 1st of January 2015 to the 31st of December 2019) whose years were selected to maximize the amount of data. The years 2020 and 2021 were excluded due to the lockdown measures of the COVID-19 pandemic. The third one is *The Prediction Period*, which goes from the 1st of January 2050 to the 31st of December 2050 in which future cyclist volumes were estimated.

5.4.2 Selection of the Sites and Cleaning the Data

The data information from the 53 automated bicycle counters owned by the City of Montreal and fabricated by Eco-Counters were downloaded. Each site was classified according to its daily and weekly profiles with the same methodology as a previous study (136). The data were cleaned following two processes. First, all zero counts observed outside of the winter period were considered non-representative and replaced with an NA value. Secondly, for each counter, the observations were compared to an upper and lower threshold that was calculated per season as shown in *Equations 1* and *2*:

$$Upper\ threshold = Q_{75} + 1.5 * IQR \ \ [eq. 1]$$

$$Lower\ threshold = Q_{25} - 1.5 * IQR \ [eq. 2]$$

Where Q_{75} is the 75th quantile of the counts, Q_{25} is the 25th quantile, and IQR is the Inter-Quantile Range which is equal to the difference between Q75 and Q25. This method was chosen because it does not assume any distribution of the data. Any daily counts outside their corresponding seasonal thresholds were replaced by an NA value. Afterwards, a linear interpolation was made in cases where the number of consecutive days with NA values was less or equal to three. All other NA values were eliminated leading to a deletion of 4.69% of the data. Two rules were followed to select the final list of counters to be used in the study:

1) The counter should have more than 90% of the data from the year 2015 to 2019.
2) The counter should be used mostly for utilitarian purposes.

In the end, the data from nine counters were selected. The counter with the lowest amount of non-missing data accounted for 90.7% of the counts of the historical period and the highest for 99.54% with an average of 96.3% and a total of 18,986 observations, 15,962 in the Training Period and 3,024 in the Validation Period.

The cleaned historic counts were paired with the measured weather variables registered by the station located at the Montreal-Trudeau International Airport. Afterwards, the data sets were divided into *Training Period* and *Validation Period* based on the periods defined above. To account for the seasonality, variables such as the week, month of the year, holiday, and bridge day (if the day was a Friday that followed a holiday on Thursday or a Monday followed by a holiday on Tuesday) were added, as well as the longitude and latitude coordinates of each site to control for spatial correlations.

5.4.3 Ridership-Weather Model

Based on the literature, machine learning methods have shown a greater predictability capacity compared to statistical ones. However, the fitting process is more complex, and the results cannot be easily translated to establish the elasticities of the dependent variable with the independent variable. Furthermore, they have a higher risk of overfitting the sample data (137), which means that the input of different data would not alter by much the result given by the model. The XGBoost algorithm already implements strategies such as the regulating objective, scaling of the weights for each step, and the subsampling of independent variables (or features) for each step of the model (138). The last two can be tuned as hyperparameters to optimize the results and reduce overfitting. The hyperparameters for this study were estimated using a randomized grid search by first selecting 100 random hyperparameter combinations. Each combination was used within a stratified five k-fold cross-validation (*xgb.cv* function from the *xgboost* package for R). In other words, the training data were split into 5 groups with more or less the same distribution. Afterwards, a model was trained with 4 of those 5 groups considering the combination to set the model's hyperparameters and established a *train RSME* as a measure of how well the model fitted the training data.

Then the newly trained model predicted the counts using the independent variable values stored in the fifth group of data and was compared to the observed counts to set the *test RSME*. This process was repeated four times more so each group of data would be excluded at least once from the training process and used as testing data. A final test-train ratio was calculated by dividing the Average *Test RMSE* by the Average *Train RMSE* of the five folds. The same process was carried out with all the other 99 combinations. Then the 5% combinations with the worst (highest) *Average Train RMSE* were eliminated due to underfitting. After, the 25% with the best ratio (those closer to 1) were kept to avoid overfitting. Finally, the combination with the best *Average Test RSME* of that group was selected. A new random set of 99 combinations was created with values close to the ones selected in the previous round and joined together to get a total of 100 combinations. The process was repeated two times to get a final selection after the third round. Although the random grid search may select a local best combination instead of the absolute best, it is considerably less computationally expensive and still yields models with good results.

The final hyper-parameters selected obtained an *Average Train RMSE* of 407.18 and an *Average Test RMSE* of 417.47. These were: maximum levels per tree (*max_depth*) equal to 1, the percentage of features used per tree (*colsample_bytree*) equal to 0.6, the percentage of observations used to train each tree (subsample) equal to 0.85, minimum weight per node (*min_child_weight*) of 3, a learning rate (eta) of 0.6, a gamma value of 4, and a total number of iterations (*n_rounds*) equal to 850. The Training Data were separated into four different seasons: winter, spring, summer, and autumn which were used to fit four different models.

Afterwards, the four seasonal models predicted the 2019 counts using the independent variables of the *Validation Period*. The results obtained a Mean Average Percentage Error (MAPE) of 42%, a Median Average Percentage Error (MDAPE) of 19% and a coefficient of determination (R^2) of 0.93 when compared to the observed counts for the same period.

5.4.4 Selection of the Climate Models and Downscaling

The CanESM2 (Canada) and the HadCM3 (U.K.) Global Climate Models were selected because they provide values for different emissions scenarios and have been validated for a longer period than newer models and by multiple researchers. The projections made by the two models consider different emission scenarios.

Model	Scenario	Description
HadCM3	A2	Storyline of a heterogeneous world with countries working on regional and local solutions with a policy focused on economic growth (139).
	B2	Storyline of a heterogeneous world with countries working on regional and local solutions with a policy focused on environmentally sustainable growth and slower population growth (139).
CanESM2	RCP 2.6	Strong emission mitigation strategies were implemented with an average radiative forcing level of 2.6 W/m^2 by 2100(46).
	RCP 4.6	Intermediate emission mitigation strategies implemented with an average radiative forcing level of 4.5 W/m^2 by 2100 (46).
	RCP 8.5	Weak emission mitigation strategies were implemented with an average radiative forcing level of 8.5 W/m^2 by 2100 (46).

While one could classify the models into low emissions (CanESM2 RCP 2.6 and HadCM3 B2) and high emissions (CanESM2 RCP 4.5, RCP 8.5 as well as HadCM3 A2) it would be a mistake to assume them equal since they are based on different assumptions, so all comparisons must be made between scenarios from the same model.

The projections of all the scenarios for both models are available in resolution 50 km^2 grids. For the study, the projections were needed on a smaller scale to cover the island of Montreal. The climate values were statistically downscaled using SDSM software. This required that the climate projections along with their historic validation values be compared and regressed to the historic measured weather in Montreal.

The historic weather data were obtained from the Dorval Weather Station, located in the Montreal–Trudeau International Airport from 1941 to 2019. Weather data from the same weather station was used to train and validate the cycling demand prediction model. Five datasets with the downscaled weather measurements for each scenario from both climate models were created for the *Future Data* by paring the projected daily maximum temperature and daily precipitation accumulation for the year 2050 were matched to the additional regressors for 2019 data by day of the year.

5.4.5 Prediction and Comparison

The future data sets were divided into four subsets, one for each season and input into the validated models to predict the cycling counts for every day of the year 2050 with the four future datasets. The predictions were compared against three sets of 2019 counts. First, the observed as registered by the automatic counters which are the true values. Second, against the counts predicted by the validated models using the measured weather to eliminate the cyclist prediction models' error while still evaluating close to the real situation. Third, against the predictions made by the cyclist demand models using the weather projections for 2019 from the same climate model and scenario to correct not only for any error in the cyclist models but also for the bias present in the climate model. The percent changes were calculated at the annual and monthly levels.

5.5 Results

5.5.1 Climate Projections Comparison

Compared to the measured weather in 2019, we can see that all the models do a good job capturing the seasonality of the maximum daily temperature, as shown in *Figure 8 (*validation refers to the projected weather for and prediction of the projected weather for 2050*).*

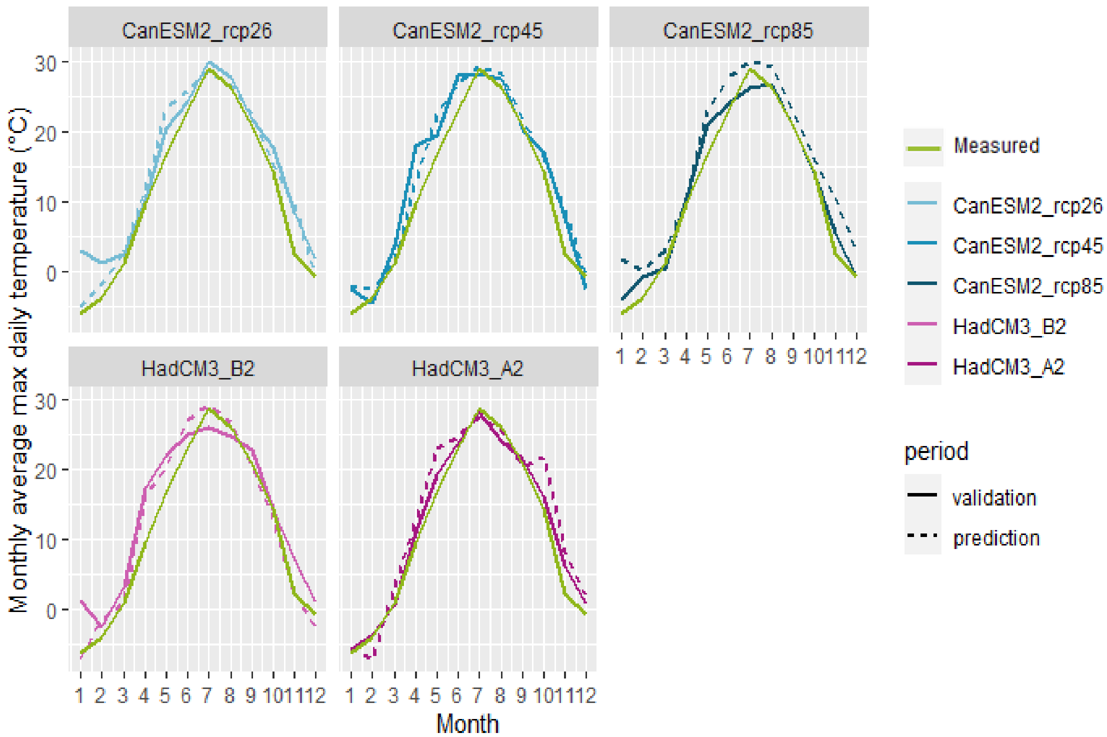

Figure 8: Average max daily temperatures per month.

Regarding the daily accumulated precipitation, the values for the 25th, 50th, and 75th percentiles are shown in *Table 3*.

Table 3: Percentiles of the daily precipitation distribution.

Source	Period	Q 25th	Q 50th	Q 75th
Measured	2019	0.00	0.00	2.80
CanESM2_rcp26	2019	0.00	0.06	4.06
CanESM2_rcp45	2019	0.00	0.00	2.91
CanESM2_rcp85	2019	0.00	0.00	1.56
HadCAM3_B2	2019	0.00	0.00	3.30
HadCAM3_A2	2019	0.00	0.00	2.33
CanESM2_rcp26	2050	0.00	0.00	2.83
CanESM2_rcp45	2050	0.00	0.00	3.30
CanESM2_rcp85	2050	0.00	0.31	3.74
HadCAM3_B2	2050	0.00	0.00	2.43
HadCAM3_A2	2050	0.00	0.00	4.00

5.5.2 Validation of the Daily Cyclist Counts Model

The information from those six datasets (measured weather in 2019 and the downscaled projections from each of the five climate models for the same year) was used as input to generate six sets of predictions for the 2019 daily counts, with all other variables staying the same. *Figure 9* shows the time series of the predictions made by the model using the 2019 weather data.

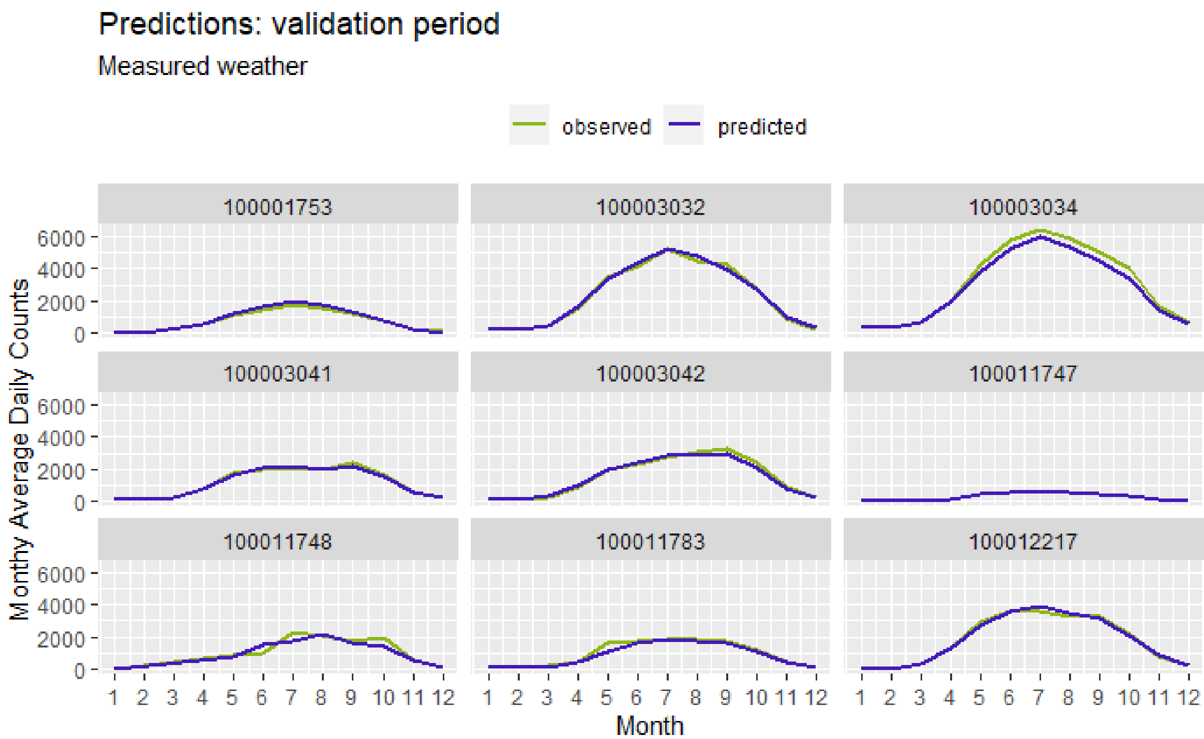

Figure 9: Model validation time series and metrics.

Table 4: Validations' R squared values.

2019 Weather source	R2	MAPE	MDAPE
Measured	0.93	0.42	0.19
Projections CanESM2_rcp26	0.79	0.66	0.31
Projections CanESM2_rcp45	0.79	0.67	0.29
Projections CanESM2_rcp85	0.83	0.58	0.26

Projections HadCAM3_A2	0.82	0.62	0.28
Projections HadCAM3_B2	0.79	0.67	0.31

From the values presented in *Table 4*, we can see that the predictions given by the model using the measured weather have a high coefficient of determination (R2) to the observed counts and follow the seasonality of the cyclist demand throughout the year in the different sites. As expected, the different weather projections produced by the models yielded different results; however, all R2 values remained equal to or above 0.78 and the highest median percentage error (MDAPE) was 30 %. *Figure 10* shows the boxplots of the daily counts observed and predicted in all the sites using the six weather data sets for the year 2019.

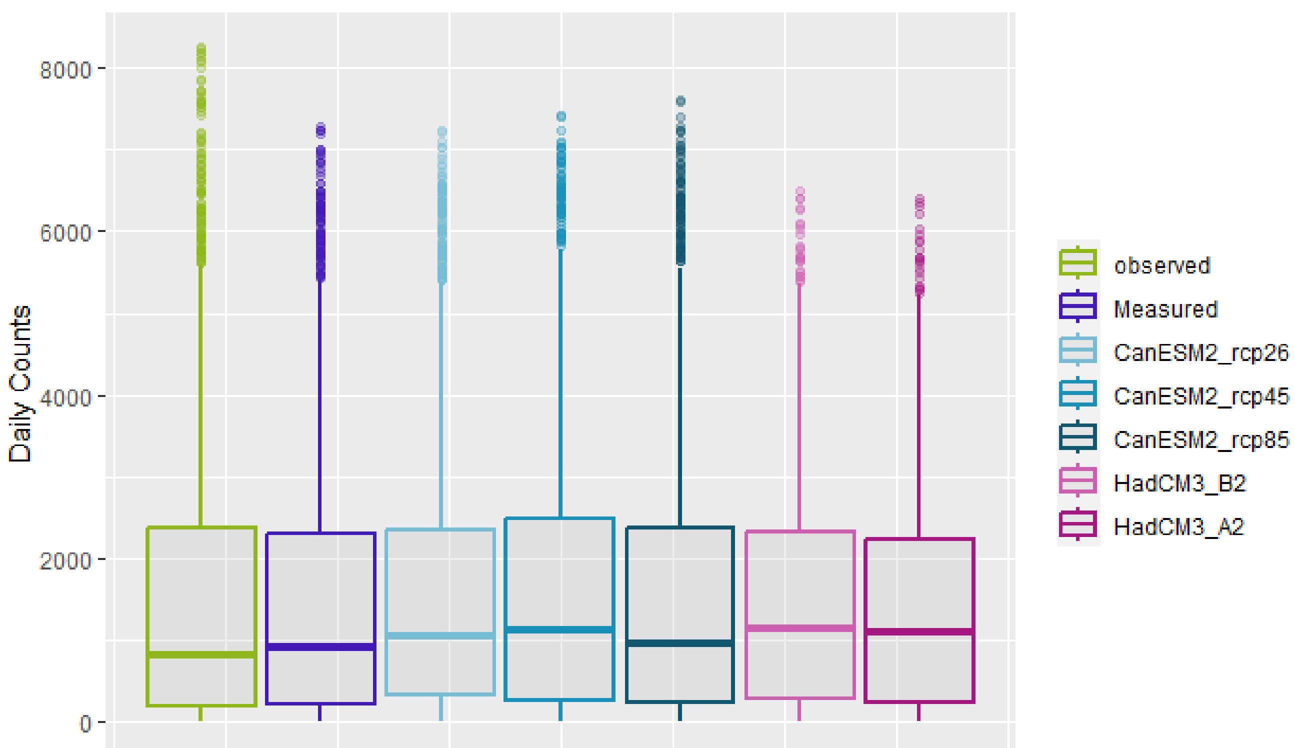

Figure 10: Boxplots for the 2019 daily counts.

5.5.3 Predictions for 2050.

The five different 2050 weather projections from the downscaled climate models were input into the 2019 regressors dataset. This means that the models predicted the counts as if the year 2019 had the weather of 2050, similar to the method followed by Galich et al. (126). *Figure 11* shows the boxplots of the daily counts observed in 2019 and those predicted for the year 2050 in all the sites.

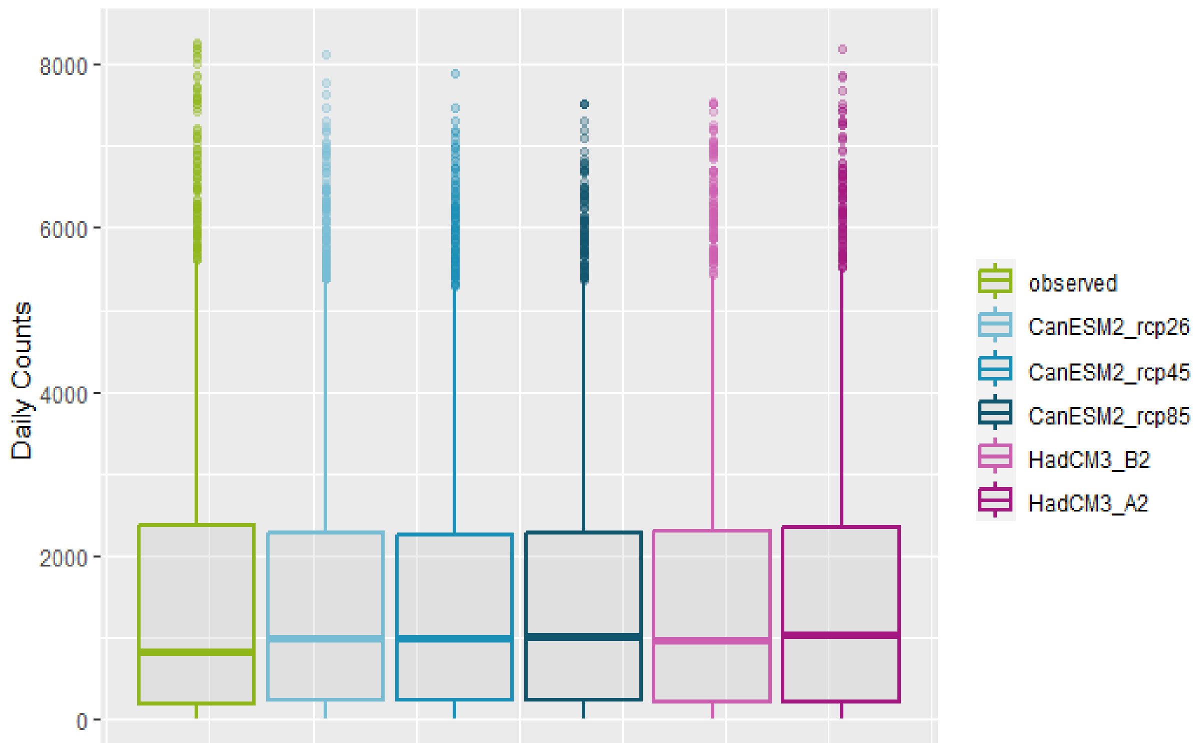

Figure 11: Boxplots for the 2050 daily counts.

In *Figure 11* the boxplots show a small decrease between 3 to 4% of the 75th quartile, an increase between 15% and 19% for the 25th quantile and an increase between 20 to 23% of the median for the CanESM2 scenarios compared to the 2019 observed counts. In the HadCM3 scenarios, one can see that the quantiles for the A2 scenario changed by 11%, 25% and -1% (25th, 50th, and 75th quantiles respectively) while for the B2 scenario, the count's quantiles changed by 6%, 11%, and -3% (25th, 50th, and 75th quantiles respectively) for the year 2050.

5.5.4 Comparison Between 2019 and 2050

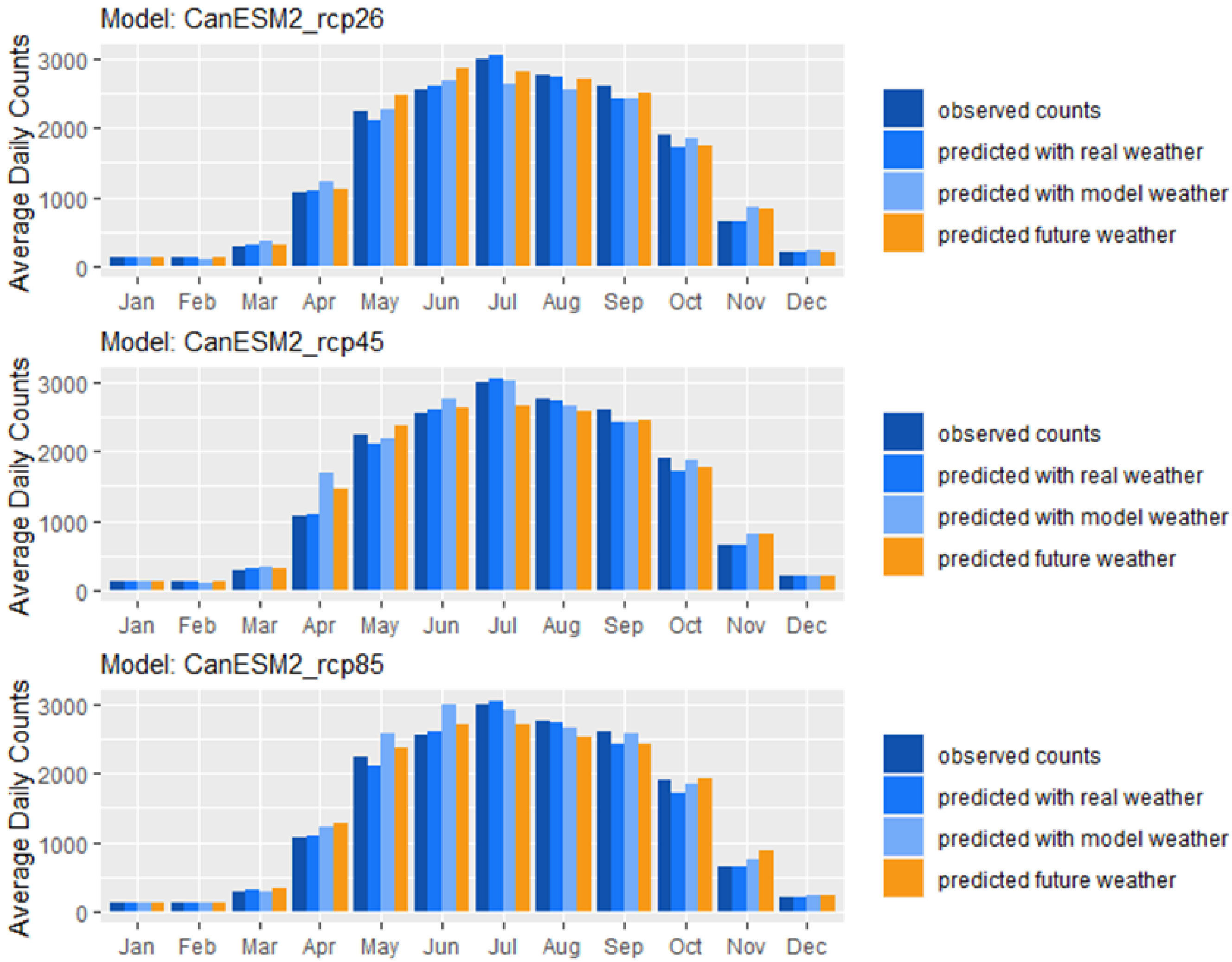

Figure 12: Average daily counts predicted for 2019 and 2050 for the three CanESM2 scenarios.

Figure 12 shows the time-series bar graphs with the monthly average daily counts for the three CanESM2 scenarios. One can see that the weather projected in the low emission scenarios causes higher counts in the future for May and June, while the other two scenarios show lower expected counts in June, July and August compared to 2019 while having higher counts in November.

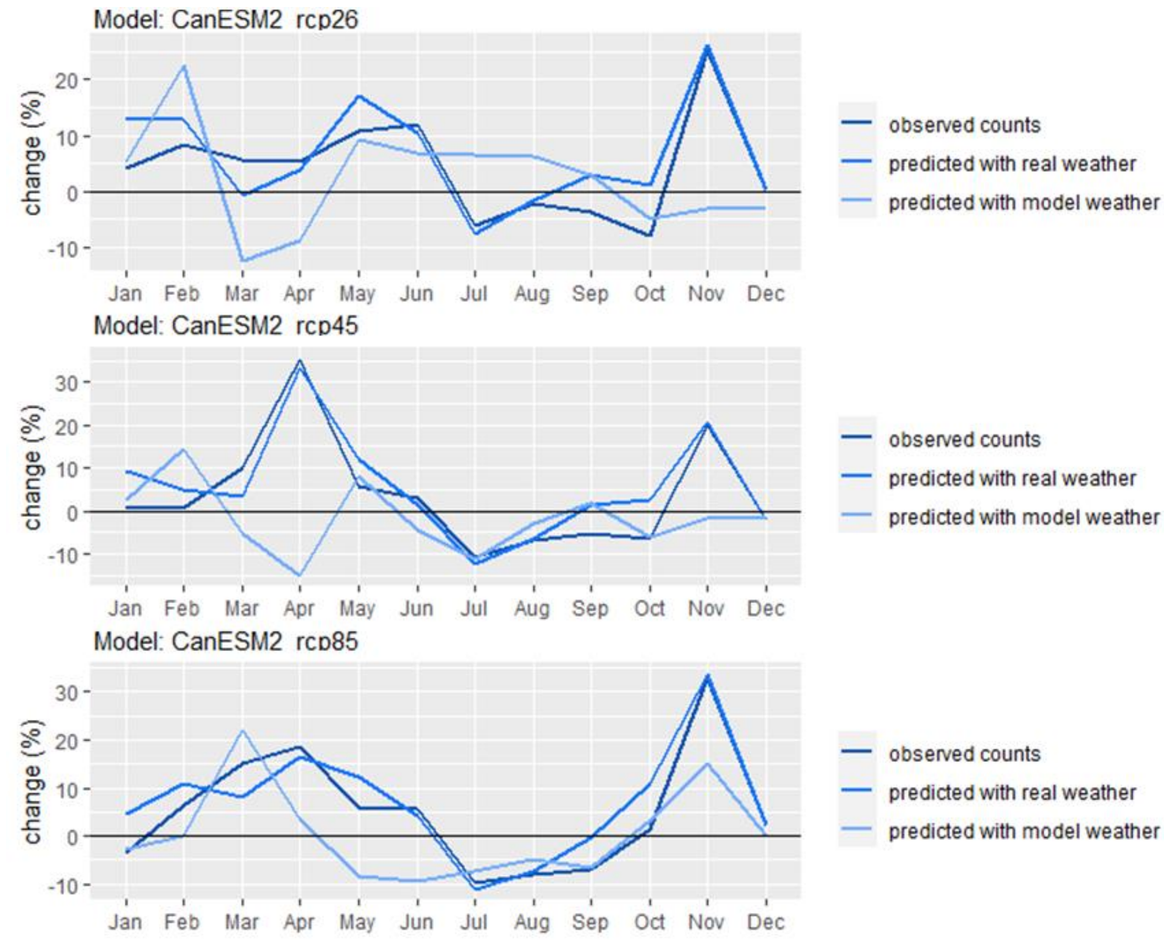

Figure 13: Percent change between 2019 and 2050 counts for the CanESM2 scenarios.

Figure 13 shows the percent change per month between the 2019 counts and those predicted with the projected 2050 weather. In a general sense we can see that for the first scenario, the percent change around the summer stays closer with positive changes in May and June, while the other scenarios show a more consistent growth in February, March, and May.

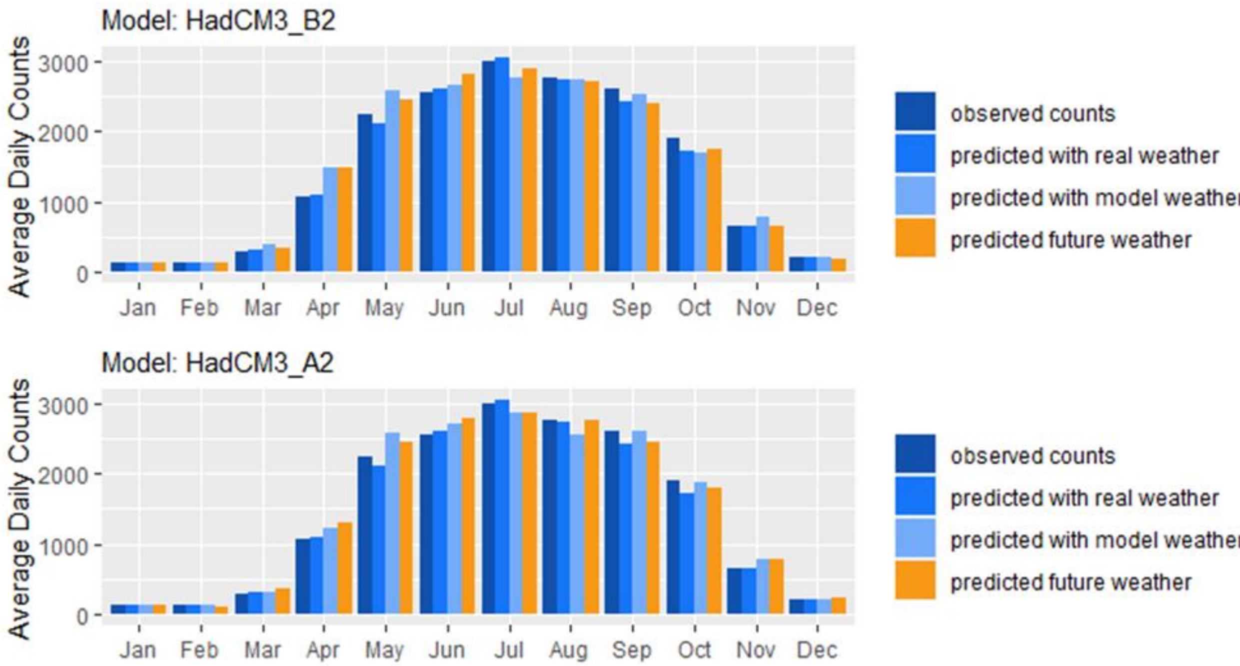

Figure 14: Average daily counts predicted for 2019 and 2050 for the two HadCAM3 scenarios.

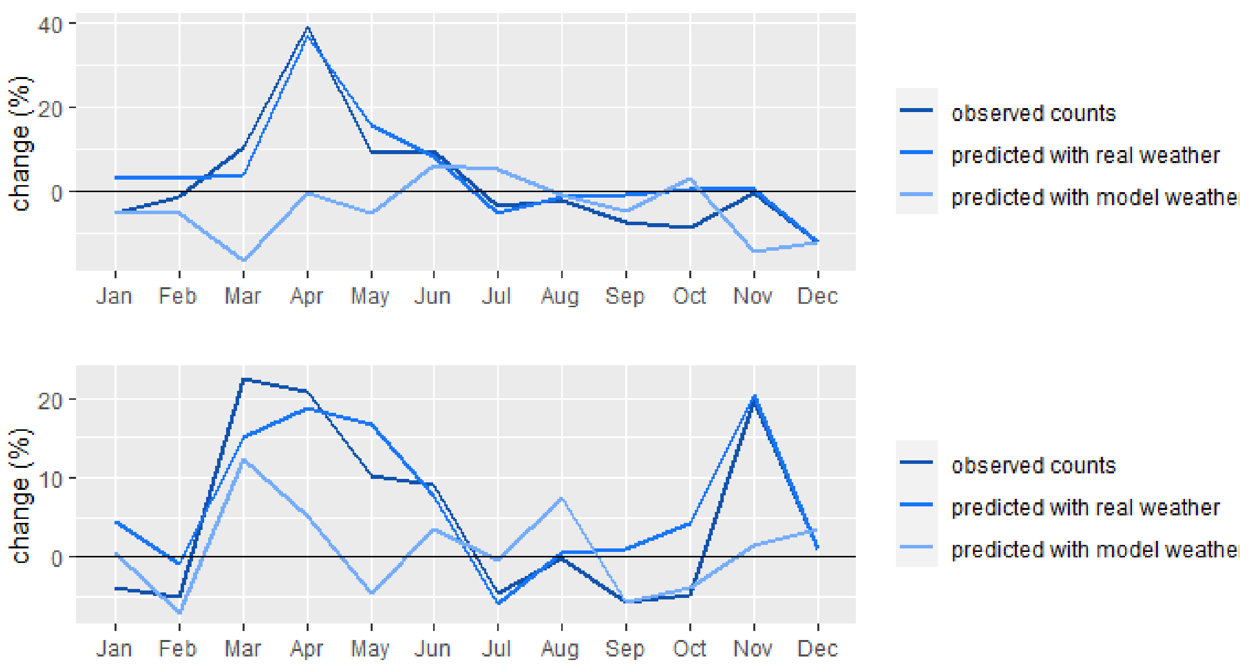

Figure 15: Percentage change between 2019 and 2050 counts for the HadCAM3 B2 (top) and A2 (bottom) scenarios.

As shown in *Figures 14* and *15*, the high emission scenario (A2) causes greater cyclist volume gains in the shoulder months of March, May, and November, while the low emission (B2) scenario has smaller negative changes during the summer. Nonetheless, both scenarios show a reduction in counts during the summer months, especially in July and August.

Table 5: Observed and predicted counts for each model.

Model	Observed 2019	2019 Predictions with Measured weather	2019 Predictions with Projected Weather	2050 Prediction with Projected Weather	Compared to Observed	Compared to Measured	Compared to Projected
CanESM2_rcp26	1506	1472	1479	1528	1.46%	3.81%	3.30%
CanESM2_rcp45	1506	1472	1551	1492	-0.94%	1.36%	-3.79%
CanESM2_rcp85	1506	1472	1570	1505	-0.07%	2.24%	-4.13%
HadCM3_B2	1506	1472	1534	1526	1.31%	3.66%	-0.51%
HadCM3_A2	1506	1472	1536	1539	2.21%	4.57%	0.21%

Table 5 shows in numbers the average daily counts for 2019 observed at the counting sites as well as those predicted by the Cyclist Counts Model using the measured weather data and the projected data from the same climate model and scenario. The fifth column shows the predicted counts using the 2050 projected weather. The final three columns show the percent changes when comparing the counts in the fifth column with those of the second, third and fourth columns respectively. One should notice that, for the CanESM2 climate model, only the RCO 2.6 scenarios expect a general increase of count ranging from 1.45% to 3.30% while the other higher emission scenarios show, in general, a reduction of count into the future. For the HadCAM3 models, the “higher emission” scenario causes greater growth compared to the B2 one. This could be explained that, in this climate model, temperatures during the summer are not expected to increase as much as in the CanESM2 model, so the gains in the shoulder month are enough to offset the losses in summer. However, it is a very marginal gain. In general, rising temperatures will not necessarily lead to an annual growth of cyclist numbers in the future at these counting sites since the summer might become too warm to bike.

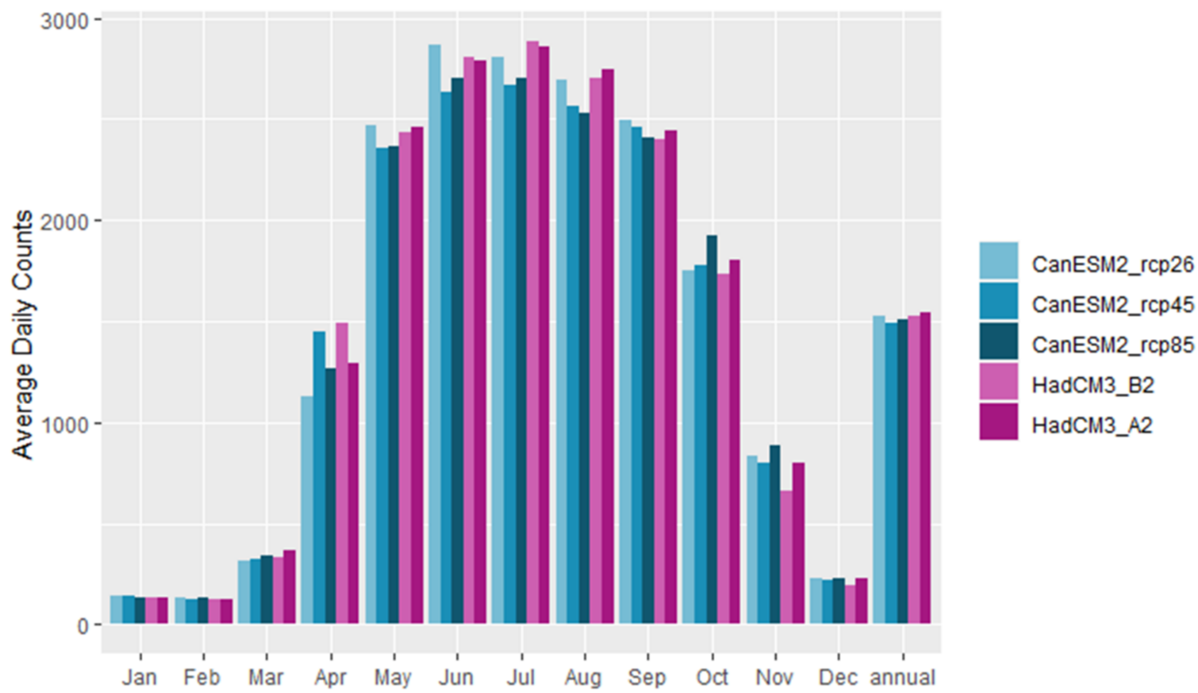

Figure 16: Daily average cyclist volumes per month for each climate model.

Figure 16 also shows the predictions calculated for the year 2050 using the weather projections from the different models and scenarios. During the summer months of June and July, the low-emission scenarios (represented in the lighter colours) predict higher average daily counts than their high-emission counterparts, while the inverse is generally true for the shoulder months. Another similarity is the average daily counts during the winter months through the different models do not represent the greatest gains which differs from the findings reported in other studies (82,126,128). However, none of those studies were carried out in the same region as Montreal, so the winter experience in those cities may not be as cold as those experienced in Québec. On the other hand, the study's finding of the reduction in counts during the summer months does align with the findings of similar studies (82,84,114,128) and the finding of the greatest increases occurring during the shoulder months also agrees with the conclusion drawn by Sharafi for Montreal (127).

5.6 Conclusion

The results suggest that, when considering the projections of the CanESM2 model, the weather in the high-emissions scenarios increases the counts of cyclists in March, April, and November, while the lower-emission one shows a higher number of cyclists in June and July. Given that the cycling demand is much higher during the summer months in Montreal, the annual ridership is expected to decrease between 0.65% and 1.12% compared to the reference period in the higher emission scenarios.

The predictions under the HadCAM3 models show an expected annual cycling increase of 2.33% for the A2 scenario and 1.49% for the B2 scenario. Both scenarios estimate an increase in counts during April, May, and June going from 6.71% to 25.4%, and a mostly negative change in August and September between 2.59% and -4.33%. Only the A2 scenario estimates a growth during winter between 0.38% to 13.82%, which can be explained by the higher temperature expected for that scenario.

For both climate models, the greatest increase in cycling volumes occurs during the shoulder months of the cycling season (March, April, and November). However, in the CanESM2 high emissions scenarios these gains are not enough to offset the percentage loss in ridership during the summer. This loss of counts during the summer months in the high emissions scenarios can be explained by a considerable number of days that are expected with maximum temperatures greater than the threshold found by Miranda-Moreno and Nosal (54). Additionally, heavier precipitation events will also decrease counts even if the days are warmer.

These results suggest that cities can expect a stretch of the cycling season in the shoulder months. Nonetheless, the increased temperatures in the summer seem to decrease counts which is explained by the significant relationship between cyclist volumes and Universal Thermal Comfort Index (140). Accordingly, if cities like Montreal wish to maintain a higher number of cyclists throughout the year, cities must adapt the infrastructure to offset the effect of expected higher temperatures during the summer and higher frequency of heavier rain events. One possible improvement is the use of green cover, which could eliminate between half and one-third of the extra-urban heat island effect for the year 2050 (141). Other strategies are to change the asphalt pavement for lower heat-absorbing infrastructure such as interlocked bricks (142) or other cool pavement strategies capable of mitigating urban heat discomfort (143). The use of permeable and high albedo surfaces can reduce urban temperatures. Multiple strategies can be incorporated beyond the bike lanes such as white cool roofs, water bodies, and green pavements (144) to reduce the land coverage of artificial heat-absorbing materials. It should be noted that, in any scenario, the change in annual cyclists is marginal with a maximum of 4.13%, which is smaller than the accuracy of the models. The results show that the estimated impact of climate change on cycling can be smaller than the prediction error of the model.

While this study has tried to provide results as accurately as possible, it is important to note the current limitation of the climate models to accurately predict long-term climate changes, especially when considering precipitation. The results shown here are based on the available data and models and best estimates up to date. However, caution must always be taken when dealing with weather estimates. This study does not consider any inherent increases in bicycle ridership that might result from other urban design and land use policies, investments in bicycle infrastructure that could accelerate bicycle urban mobility, actions to improve road safety of active modes, etc. Also, this study assumes that the relationship between the cyclist number and the weather will remain the same from 2019 up to 2050. Yet, this may not be the case since the citizens may acclimatize to the future weather, an idea discussed by Goldman & Wessel (18).

Other lines of research could focus on determining the cold "threshold", how warm a day must be before one can observe a substantial increase in the counts. Future research will need to be carried out as newer and better versions of the climate models and machine learning technique models are made available to the research community.

5.7 Acknowledgements

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6. Chapter VI: Discussion of the Findings

This thesis presents a framework to investigate the historical bicycle patterns in North American cities and the impact of weather conditions on urban cycling to predict the potential effects of climate change. For this purpose, the methodological contributions of this work are divided into two components: i) improvement of the understanding of bicycle trends and the effect of weather in the years before and after the COVID-19 pandemic, and ii) the prediction of bicycle demand changes under different climate scenarios for the year 2050. Using data from several counting stations in the Cities of Montreal, New York, Ottawa, and Vancouver, along with weather measurements from nearby stations, this method can determine the accurate trends in cyclist demand regardless of the effect of weather. This work requires the integration of different sources of data, modelling techniques and downscaling climate models.

In the first part of this thesis, the proposed methodology proved cyclist volumes in the counting stations analyzed in the study are increasing in Montreal regardless of the weather conditions and lockdown measures, with significant growth in 2021 compared to 2009 volumes when controlling for weather factors. The demand increased noticeably in 2020 at the height of the COVID-19 pandemic, which is explained by a modal shift of public transport users towards an individual, but still cheap, transportation alternative. This phenomenon shows a potential group willing to incorporate cycling into their commute. Another finding was that, even at the height of the pandemic in 2020 when work-from-home policies were in place, most of the analyzed cycling facilities retained a mainly utilitarian use and those who shifted towards recreational purposes showed signs of reverting to pre-pandemic patterns in 2021 which confirms a strong commuting culture within the city. These two points proved the existence of a strong and growing commuter cyclist group in Montreal that will require the provision of safe and reliable cycling infrastructure in the coming years. If the city wishes to continue serving this population, the facilities will need to be expanded to accommodate a constantly growing population in the next few years. However, climate change will introduce variations in the weather that could alter the annual bike-use behaviours in the medium and long term. Any longlasting infrastructure will need to be designed with these changes in mind to expand the project's useful lifetime.

It should be noted that the classification method used, based on the temporal distribution of cyclists has some limitations. First, it is biased towards jobs with more traditional 9 to 5 schedules which does not encapsulate all labour positions. This could leave trips made by population groups that work on a different schedule outside of the analysis, which could lead to ignoring the trip behaviour of a sector of the population. Additionally, the pandemic could have shifted the traditional working hours in the last few years, as more flexible schedules are adopted thanks to work-from-home or hybrid work schemes. This would require other sources of data such as surveys to validate de classification of the counting sites and the behavioiral patterns of the employed population. Nonetheless, due to the available data, it was deemed the best classification method available for most of the trips.

Either way, one can assume that the classification shows which used is most likely given by the cyclist based on traditional work schedules. For the Vancouver results, insights from the locations have noted the existence of a bypass used by commuters to avoid leisure traffic at the VN1 and VN2 counter sites, which would explain why they showed the biggest recreational use compared to all the other sites in the study. Furthermore, both sides are close together, which could have influenced the analysis. These observations support the need to repeat the methodology in the city with different sites and more precise knowledge of the area to reach better conclusions.

In the second part of this thesis, the proposed methodology helps describe the future changes in the cycling demand considering the expected variations in the weather factors under critical climate change scenarios. The results from the different scenarios show a major percentage increase in counts during the shoulder month which suggests that, in the future, the biking season in the city will start earlier and finish later in the year. Although it would be logical to assume that the winter season would see the greatest increment in counts due to rising daily temperatures, the analysis shows a smaller percentage change compared to the gains observed in

November and April. One possible explanation is that, even if the days' maximum temperatures are warmer compared to the present, most days will still be too cold to bike, and precipitation will play a bigger role in those freezing days. The increase in temperature during the spring and autumn might bring most days into an optimal cycling season into the “Goldilocks” range. Nonetheless, the results also show that, with higher global average temperatures, counts during the summer months are predicted to decrease. As discussed in the literature review, the relationship between the temperature and cycling number is not linear and, after reaching a threshold, counts will start to decline as the temperature rises. The increase in daily maximum temperature would cause greater heat discomfort to the potential cyclists, pushing these days out of the ideal weather conditions for cycling. The combination of these factors could lead to a reduction in annual counts in the future since the percent gain of cyclists in the shoulder months is not enough to offset the losses during the summer, which currently has the highest number of daily counts.

7. Chapter VII: Conclusion and Summary

The thesis highlights a bicycle commuting segment of the Montreal cyclist population that has consistently grown during the last decade. The growing trends reinforce the positive impacts of the current strategies to expand the cycling network to promote and accommodate additional cycling demand in the coming years.

The results of this research can be valuable to authorities in their infrastructure planning endeavours. By considering the trends observed in recent years and projecting them into the future, cities can better anticipate the demand changes and needs of infrastructure development. Furthermore, accounting for the changing weather patterns in these projections increases the accuracy of the analysis and ensures that infrastructure plans are well-suited to meet future challenges in a changing climate context.

The methodologies used in this thesis can serve as a guideline for analyzing current growth trends in cycling ridership while accounting for weather conditions in other cities. By incorporating these methodologies, authorities can gain a deeper understanding of how weather and other factors influence cyclist ridership in the present and make more accurate predictions about future demand.

Regarding the future, different scenarios suggest an expansion of the biking season beyond the current time frame, currently from April 1st to November 15th (145). City authorities should keep promoting the maintenance of cycling infrastructure across seasons to ensure they remain open and in optimal condition for an extended period of the year to accommodate for a possible increase in demand. More importantly, to promote cycling as a viable transportation mode throughout the year, planners will need to incorporate strategies into the existing and current facilities, such as heat-mitigating strategies during summer. As temperatures rise due to climate change and natural weather cycles, it is essential to consider designs that enhance thermal comfort for cyclists. Approaches like green shading and cool pavements can help mitigate the heat, making cycling more comfortable even during those hotter months. These strategies would retain a greater volume of cyclists during summer and lead to an overall gain in annual cyclist counts.

Overall, the research presented in this thesis expects to provide valuable insights that can promote cycling as a key element in sustainable urban mobility solutions. By effectively designing infrastructure to meet the expected demand and considering the impacts of changing weather patterns, authorities can continue to support and encourage the use of bicycles as a viable mode of transportation in Montreal. Greater adoption of this mode year-round will bring multiple benefits to the city, like the reduction in healthcare costs, lower inner-city emissions and congestion levels, as well as smaller land consumption dedicated to the transportation of people.

Future lines of research would include the evaluation of the growth trends in the post-pandemic years of 2022 to 2024 to confirm if the observed trends remained as expected or turned out to just be a short-phase phenomenon. The same methodology of the first paper could be expanded to include more counting sites in Vancouver and New York as more of the data are cleaned and reconstructed to confirm the observed trends in those cities. In the same way, the methodology could be used to carry out the analysis in different cities around the world to estimate the growth trends while controlling for the effects of the weather. Regarding prediction into the future, the methodology of the second objective could be repeated for different future years to estimate an annual time series and variations in counts to understand the temporal trends expected due to climate change under different scenarios. Additionally, the research should be repeated whenever more accurate climate projections are made available and as the models' prediction capabilities increase with the adoption of new technology. The proposed methodologies could also be automated and integrated into a decision-support toolbox that could make the data, models, and outcomes easily accessible to decision-makers.

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