Urban Mobility Responses to Wildfire Smoke-Related Air Quality Advisories in Montréal, Canada

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Abstract

Wildfire smoke events are increasing in frequency and severity, yet evidence on how urban populations modify their mobility in response to air quality advisories remains limited. In this work we apply time-series forecasting modelling to four mobility datasets (bike-share, metro rail, bus, and recreational running). We examine changes to daily activity counts in Montréal, Canada during wildfire smoke-related air quality advisory days from 2022 through 2025. Controlling for seasonality, weather, holidays, and major events, we find that advisories are associated with a shift from active to enclosed transportation modes. Bike-share usage declined while bus and metro ridership significantly increased. Recreational running showed no significant response. Further analysis revealed within-city heterogeneity in these effects. These findings contribute to an emerging literature on urban mobility responses to wildfire smoke and carry implications for public health communication and transportation planning under increasing climate risk.

Keywords: air quality, mobility, transportation, wild fire, smoke

1. Introduction

With the potential increase in the frequency of wildfires due to climate change (Shi et al., 2025), and the well-established relationship between exposure to wildfire smoke and adverse health outcomes (Gould et al., 2024),

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a vital question is *to what extent people adopt protective health measures in response to smoke events*, especially in terms of adherence to public health messaging (Vien et al., 2024). Wildfire smoke exposure has been found to negatively affect all-cause mortality, respiratory morbidity, and a range of other negative health outcomes (Gould et al., 2024; Reid et al., 2016; Lei et al., 2024), with evidence that air pollution from a wildfire source is especially bad for respiratory health (Aguilera et al., 2021), and potentially also for cerebrovascular health (Milton and White, 2020). More vulnerable populations include older adults, children, those pregnant, and people with existing respiratory or cardiovascular diseases (Rizzo and Rizzo, 2025). Wildfire smoke increasingly affects air pollution levels in the United States (Burke et al., 2023), with 71,000 attributable excess deaths predicted by 2050, making wildfire smoke among the more costly and dangerous risks of climate change (Qiu et al., 2025). With these risks, there is a need for evidence on the effectiveness of strategies to mitigate the risk of smoke exposure (Gould et al., 2024).

In recent years, Canadian wildfire seasons have surpassed previous records in terms of area burnt, with the 2023 season being, by far, the worst in recorded history (17,347,637 hectares burnt), and the 2025 season following as the second worst year on record (8,920,803 hectares burnt) (Canadian Interagency Forest Fire Centre, 2026). A study attributes 5,400 acute, and 64,300 chronic deaths in North America and Europe to exposure to pollution from smoke from the 2023 Canadian wildfires alone (Zhang et al., 2025). Wildfire smoke in these seasons was widespread across Canada, the United States, and Europe, and media attention was substantial (Matza, 2023; Kitching, 2025; Amatulli, 2023). Cities which typically do not experience substantial pollution from wildfire smoke were affected, such as Montréal (Lepage, 2025), where public agencies issued warnings to residents to limit exposure to wildfire smoke. The extent of wildfires in Canada has increased in recent years, and this pattern is expected to continue (Hanes et al., 2025).

During wildfire smoke events, public health agencies publish warnings to communicate the health risks of smoke exposure, and warn the public to limit unnecessary movement outside, especially for vulnerable populations, and an open question is how a population's mobility changes during wildfire smoke events. Existing research has studied changes in mobility around natural disasters (Gong et al., 2025) and in response to air pollution (Xu et al., 2025), though few studies have explored how wildfires affect local-scale mobility patterns (Noi et al., 2025), and fewer still have looked at the effects on mobility of wildfire smoke in particular. The existence of spatially and temporally high-resolution mobility data offers opportunities to investigate this topic. In this work we ask the following research questions in the context of Montréal, Québec, Canada and restricted to the temporal periods of 2022 through 2025, a period with unusually intense wildfire activity in North America.

`RQ1` *Does population mobility change during air quality advisory events associated with wildfire smoke?* To address this question, we examine differences in multiple mobility datasets between days when air quality advisories are in effect and days without advisories.

`RQ2` *Do air quality advisory–related changes in mobility vary by transportation mode?* We compare bus, metro rail, bike-share, and recreational running mobility patterns to assess how air quality advisories differentially impact travel behaviour across modes.

`RQ3` *Do air quality advisory–related changes in mobility vary spatially within a city?* Focusing on Montréal boroughs, we investigate spatial variation in advisory-related mobility changes across two of our focal mobility modes.

Using a range of mobility data sources, this study explores how mobility patterns change in relation to ambient air pollution from wildfire smoke, during which public agencies have issued warnings advising the public, particularly vulnerable populations, to limit movement outdoors.

2. Literature Review

2.1. Air Pollution and Human Mobility

While fewer studies have investigated the effect of wildfire smoke on human mobility in particular, researchers have explored myriad avenues to examine the effects of air pollution in general on human mobility. The presence and extent of air pollution generally has been sourced from secondary data from weather stations reporting on particulate matter levels (PM2.5, PM10), the levels of particular pollutants (NO_2, SO_2, CO), or values on scales designed for public communication, such as the Air Quality Index (AQI). These data are typically public and widely available. Most often, air pollution values are then placed against mobility data from various sources. Some researchers have opted for collecting primary data, such as surveys (Kim et al., 2024; López-Gil et al., 2022; Mandolakani et al., 2024; Dabirinejad et al., 2024), while others have instead employed secondary data sources, such as vehicle counter data (Acharya and Singleton, 2022), micromobility vehicle sharing records (Liang et al., 2023; Morton, 2020; Park et al., 2022), or mobile phone location records (Xia and Yeh, 2025; Xu et al., 2021). These data vary in their representativeness, with survey data of course reflecting a limited sample, but instead allowing for the simultaneous collection of demographic and socioeconomic data, reports on protective behaviours, and other data specific to a study's research questions. Meanwhile, mobile phone records are much more representative, but often lack any demographic data, preventing analyses of how different population segments respond to pollution.

Different methodologies have been used, but all essentially compare mobility during periods with higher air pollution to periods with lower pollution. Within these parameters, studies have used time-series regression models (Acharya and Singleton, 2022), fixed effects models (Cheng et al., 2024), integrated choice and latent variable models (Kim et al., 2024), autoregressive distributed lag models (Morton, 2020), generalized additive models (Park et al., 2022), and geographically weighted regressions (Gong et al., 2024). Studies range geographically, with a concentration of research in China (An et al., 2019; Yu and Zhang, 2023; Yu et al., 2017; Liang et al., 2023) and the United States (Xu et al., 2025; Gong et al., 2024; Acharya and Singleton, 2022; Tribby et al., 2013), and while findings of course vary by geographical context, there is now a robust body of evidence that demonstrates that human mobility does change in response to air pollution.

Most studies have found that air pollution reduces outdoor mobility with high exposure pathways, such as walking, cycling, jogging, and other forms of outdoor moderate-to-vigorous physical activity (An et al., 2019; Cheng et al., 2024; Liang et al., 2023; López-Gil et al., 2022; Mandolakani et al., 2024; Tainio et al., 2021; Xia and Yeh, 2025; Xu et al., 2021; Yu et al., 2017; Yu and Zhang, 2023; Yoo et al., 2025); though, some studies have instead found no or limited effect of air pollution on levels of mobility (Gong et al., 2024; Kim et al., 2021; Lee et al., 2025; Morton, 2020). The use of other travel modes with lower exposure may also be effected, such as public transit (Dabirinejad et al., 2024). One study has suggested that air pollution-induced reduction in mobility may even extend to reduced levels of travel the next day (Yoo et al., 2024). The effect of pollution on mobility may be nonlinear, with thresholds beyond which activity sharply decreases (Park et al., 2022). The purpose of travel matters, with some studies having found that cycling decreases more for commuter cyclists rather than for recreational cyclists during periods of pollution (Park et al., 2022; Acharya and Singleton, 2022). The perception of risk from air pollution moderates the relationship between air pollution exposure and changes to mobility, with greater perceived risk corresponding with a greater likelihood to change travel behaviour (Kim et al., 2024; Dabirinejad et al., 2024).

2.2. Natural Disasters and Human Mobility

The relationship between natural disasters and mobility has also been studied through evacuations. To understand evacuation adherence, dynamics, and challenges, the analysis of mobility data is crucial (Zehra and Wong, 2024), and mobile phone location data has commonly been used (Borody and Wong, 2025; Cova et al., 2024; Liao et al., 2024; Ha and Long, 2025), though some studies have also used data from location-based services such as point of interest (POI) visitations from Baidu Maps (Chen et al., 2020; Noi et al., 2025). Noi et al. (2025) examined wildfire evacuations in California using human movement flows and POI visitations through generalized additive models, pursuing a high-spatiotemporal resolution to identify nuanced responses in mobility responses to wildfires. The authors note that most related studies focus on evacuation strategies and their effectiveness, while a research gap remains around how wildfires affect "localized, fine-scale human mobility patterns" (p. 3). Beyond evacuations, Shen et al. (2025) identified a research gap of the effect of wildfire smoke on non-evacuated communities.

2.3. Wildfire Smoke and Human Mobility

Studies that have investigated mobility responses to wildfire smoke, aside from evacuations, have largely used qualitative methods, such as surveys and interviews. For example, an in-depth study of 20 households in Montana found that moderate-to-vigorous outdoor activities decreased during periods of wildfire smoke (Stewart et al., 2025), a questionnaire study found that respondents reduced physical activity during wildfire smoke in British Columbia (Giles et al., 2024), and another interviewed low-income residents in Los Angeles to understand adaptation behaviours (Palinkas et al., 2023). Of the studies that use quantitative methods, a common source is smartphone movement data, typically collected by a third-party provider (e.g., SafeGraph, Near Vista) (Shen et al., 2025; Burke et al., 2022; Mullan et al., 2024), though others have used bike or pedestrian counts from counter stations (Doubleday et al., 2021), metro ridership figures (Han et al., 2024), or wearable fitness monitor data (e.g., Fitbit) (Rosenthal et al., 2020). These studies have largely examined cases in western states in the U.S. (Doubleday et al., 2021; Mullan et al., 2024; Rosenthal et al., 2020; Shen et al., 2025), though there exists a U.S. nation-wide study (Burke et al., 2022) and another in Washington D.C. (Han et al., 2024).

The methodological approach is similar to that of other research evaluating the effect of air pollution on mobility: contrasting mobility patterns during period of high pollution with periods with lower pollution. Metrics of mobility, such as resident outflow, distance travelled, and length of stay at home, can be compared between time periods (Shen et al., 2025). Multiple methods have been used to assess changes in mobility, including panel fixed effects estimators (Burke et al., 2022), fixed effects pseudo Poisson models (Mullan et al., 2024), seasonal-trend decomposition models (Doubleday et al., 2021), and forms of regressions (Shen et al., 2025; Han et al., 2024). Studies have found that mobility outside of the home decreases with the presence of wildfire smoke (Shen et al., 2025; Burke et al., 2022), including on a metro system (Han et al., 2024), a bike-share system (Doubleday et al., 2021), and to parks and playgrounds (Mullan et al., 2024). This effect may be nonlinear, and the severity of pollution matters to the extent of the reduction in mobility (Burke et al., 2022; Rosenthal et al., 2020), according with work on the relationship of mobility to air pollution in general (Park et al., 2022).

While this research often has used data such as mobile phone locations records which lack demographic information, where studies have been able to attach this information to mobility patterns, for example through census data of the areas from which travel originates, there are demographic-related differences in mobility responses. Shen et al. (2025) found that lower-income, elderly, and minority ethnic groups tended to be more affected by wildfire smoke, and Burke et al. (2022) found that people in wealthier areas were more likely to stay home during wildfire smoke events, perhaps because of more latitude available to change their mobility in response. Mullan et al. (2024) found that people from areas with higher average levels of education or incomes reduce their mobility when pollution is moderately poor, and only when pollution reaches more hazardous levels do all population groups reduce their mobility, indicating that the threshold of mobility response to smoke is demographically variant.

Much of this research has used actual pollution levels, though some studies have focused on the effect of public alerts around air pollution, emphasizing the aspect of public health communication. Air quality alerts have been found in some contexts to reduce mobility (Castro Pérez and Flores, 2025; Saberian et al., 2017; Wen et al., 2009), though others have suggested that alerts may not have an effect, even while actual pollution levels do (Xu et al., 2025, 2022; Tribby et al., 2013). A systematic review found that adherence to air pollution warning health advice was low, and demographics did not consistently predict adherence, though psychosocial factors do, including knowledge around air pollution and its effects, perceived severity of pollution, understanding of indices, etc. (D'Antoni et al., 2017). A general awareness and knowledge of air pollution, its health risks, and effective adaptive actions may improve the adherence to public health alerts (McCarron et al., 2023; Ciarloni and Newbold, 2023; Kim et al., 2024; Meena and Goswami, 2024). Providing actual actionable information is important in addressing feelings of powerlessness that might otherwise reduce adherence (Riley et al., 2021; Santana et al., 2021).

Communication is an intervening factor between air pollution and mobility response. A scoping review on gaps in human behaviour in fires research found that there exists limited evidence on the effectiveness of smoke-related messaging, and more research is needed to know how mobility changes in response to wildfire smoke events (Kinkel et al., 2025). Studies of public health agency warnings during these events finds that adherence to this messaging varies by message style, content, and delivery method (Heaney et al., 2021; Keegan and Rahman, 2021; Vien et al., 2024). Marginalized communities may demonstrate less adherence to messaging, indicating that they may be poorly prepared to take protective action (Sandoval et al., 2025); older adults, who are at increased risk of averse health effects, may also have poorer knowledge of the health risks of exposure (Buchanan et al., 2024). There are few studies that investigate behaviour change to reduce smoke exposure (Vien et al., 2024), and most existing studies of the effectiveness of public health messaging related to wildfire smoke are qualitative (Sandoval et al., 2025). This study contributes towards filling the critical research gap of the mobility response to wildfire smoke, in the context of severe and unprecedented smoke events in Montréal in 2023 and 2025.

3. Data

Three categories of data were used for this analysis: air quality warnings, mobility datasets, and control variables. The relationship of interest was between the air quality warnings and individual mobility datasets, with control variables used in modelling.

3.1. Study Context: Montréal

In 2021, the City of Montréal had a population of 1.8 million over 387 km^2, with the Greater Montréal Area having a population of 4.3 million over 4670 km^2 (Canada, 2023). The City is on the Island of Montréal, which also has areas that are not administratively part of the city, and are incorporated as separate municipalities. For this work, we include those activities that took place on the Island of Montréal (see Figure 1). The modal share in the Montréal metropolitan region is split 67% car, 13% public transport, 16% active transport (walking and bicycling), and 4% other modes (Autorité Régionale de Transport Métropolitain, 2023).

3.2. Air Quality Warnings

The record of public alerts related to air quality between 2022 and 2025 was provided directly from Environment and Climate Change Canada (ECCC), the national agency responsible for issuing environmental alerts and advisories. In Québec, the *Info-Smog* program monitors air quality, and if air quality is poor, ECCC issues an alert (smog alerts or special air quality (SAQ) statements) that is broadcast on their website, to the media and partner organizations, and to external platforms (e.g., weather apps) (ECCC). Alerts are issued with an accompanying informational bulletin that identifies at-risk populations and measures for reducing harmful exposure to pollution (see Listing A1 for an example warning message). We used OpenAI's GPT-5.1 Code Interpreter to assist in developing and executing a deterministic Python workflow for parsing the unstructured alert data and identifying fire-related events. Independent execution in Visual Studio Code reproduced all alert classifications and aggregate counts. This natural language processing pipeline systematically extracted metadata, including issuance date, local time, time zone, alert type, operational status, and geographic regions. Dates and times were parsed from standardized issuance lines; alert types and statuses were identified from bulletin headings; and locations were extracted from regional blocks preceding the discussion sections.

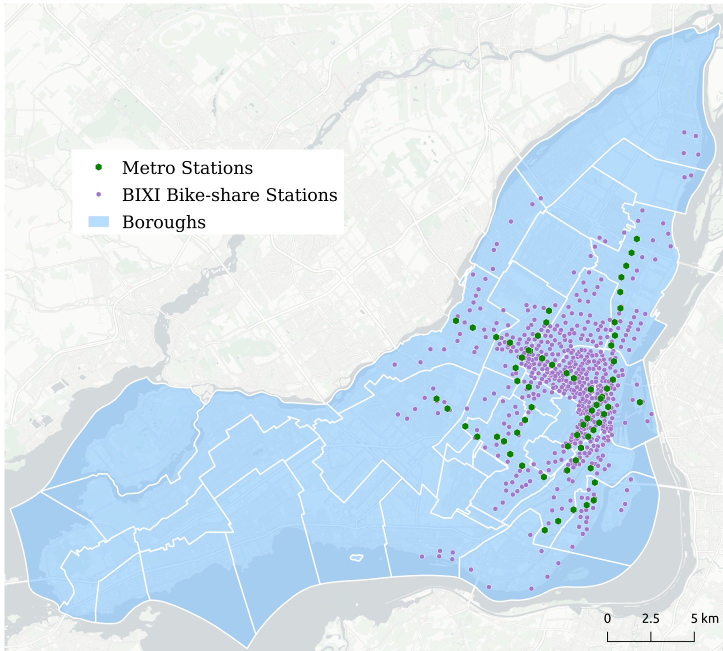


Figure 1: Montréal boroughs shown along with metro stations and BIXI bike-share stations. Stations are restricted to those associated with a Montréal boroughs. Bus stations are not shown as data were provided in aggregate rather than at the stop level. Recreational running origins are not shown for privacy reasons.

A bulletin was classified as fire-related when its normalized text contained an explicit wildland fire term or an expression directly connecting smoke to fires. Informed through discussion with officials at ECCC, English search terms included "wildfire", "wild fire", "forest fire", "forest fires", "smoke from fire", "smoke from fires", and "from fires in". French terms included "feu de forêt", "feux de forêt", "incendie", "incendies" and "fumée provenant de feux". Singular, plural, accented, and unaccented variants were recognized. The terms "smoke", "haze", "fumée" and "brume", together with transport terms such as "transport", "carried", "wind", "winds", "souffl" and "vent", were used to identify relevant contextual evidence. Generic smoke or haze language without an explicit connection to fire was not sufficient for inclusion.

The complete raw dataset comprised 188 bulletins issued between 2021 and 2025. Restricting the analytical period to 2022–2025 yielded a final sample of 157 bulletins. Validation of the automated pipeline against a thorough manual review of the structured audit dataset (by the authorship team) showed complete agreement. Finally, bulletin updates separated by more than 96 hours were temporally clustered into discrete advisory episodes. The final analysis included 86 fire-related bulletins from eight episodes, covering 27 air quality advisory dates: 15 in 2023 and 12 in 2025.

3.3. Mobility Datasets

Four different modes of mobility were used in this analysis. Specifically, we accessed daily activity counts for Metro rail, bus service, bike-share, and recreational running on the Island of Montréal. This analysis is limited to the summer months of May-September of each year, to encompass wildfire smoke events, all of which occurred during summer months, and nearby months, for context. Mobility patterns during the winter months will be different but not in response to smoke events. Trips and activity counts for these data are provided in Table 1.

Table 1: Number of activities (trips or runs) per mobility mode and year of analysis. The numbers reflect activities between May and September (inclusive) for each year.

Dataset	**Mobility Activities**			
	2022	*2023*	*2024*	*2025*
Metro	75,000,873	89,714,969	96,709,025	91,060,204
Bus	66,098,364	76,945,469	85,214,198	75,305,766
Bike-Share	7,054,899	8,912,082	9,693,073	10,685,811
Running	34,415	48,353	88,591	39,379*

*Running data for 2025 include observations for May–June only.

3.3.1. Metro Rail

Montréal's *Metro* is a rail-based underground public transit system that serves the Island of Montréal and surrounding regions. The system is operated by the Société de transport de Montréal (STM) and reported an average of almost 1 million trips per weekday in 2024 (Société de transport de Montréal, 2025). The data were provided directly by STM. Daily trip counts, per station, were analyzed for the period from 2022 to 2025. For our purposes, a trip is identified as someone using their public transit card (pass or single ticket) to enter a station. Station egress is not recorded.

3.3.2. Bus Service

The STM also operates a bus network in the greater Montréal region with 165 daytime and 20 nighttime service routes. An average of 686,000 trips per workday were reported in 2023 (American Public Transportation Association, 2025). Data were again provided directly by STM. Although STM collects ridership data at the individual stop level, data were provided to us for 2022–2025 in aggregate form due to privacy concerns around sparse counts at many stops. Accordingly, bus ridership was analyzed at the city level only. The bus network operates on the same payment system as the Metro, so again, trips are identified as someone using their public transit card when getting on the bus at a stop.

3.3.3. Bicycle Share

Montréal has a popular public bike-sharing system, BIXI[2] that operates in the greater Montréal region. As one of the most widely used bike-sharing systems in the world, BIXI reported 13 million trips in 2024 (BIXI Montréal, 2024). The BIXI system uses docking stations, meaning that trips are reported as a bike leaving a particular station and being returned to a station. Daily trip records are publicly available via the BIXI website and were accessed for 2022 through 2025.

3.3.4. Recreational Running

Recreational running activities were accessed through the geosocial fitness application, *Strava*[3]. Specifically, a series of 100 *segments* (sections of road/-trail) were identified programmatically through the application programming interface (API). Each segment provides a list of all the Strava running activities that have traversed the segment, as well as the day that the activity took place. We counted all unique activities per day on the Island of Montréal for 2022 through 2025.

3.4. Control Variables

Additional datasets were used in the time-series modelling and are presented below.

[2] `https://bixi.com/en/open-data/`
[3] `https://www.strava.com/`

3.4.1. Climate Data

Daily meteorological data for Montréal over the period 2022–2025 were obtained from the ECCC[4] climate database. Automated shell scripts were used to retrieve the bulk records as CSV files. The dataset includes geographic metadata as well as variables related to air temperature, precipitation, snowfall, snow cover, and wind characteristics, along with associated data quality flags.

3.4.2. Events & Holidays

Major events were accessed through the online event portal, *La Vitrine*[5], a non-profit cultural organization that aggregates major events in the greater Montréal region. For each of our focal years, we identified major events published through the website. We identified an event as being *major* by conducting manual searches related to each of the events posted on La Vitrine. Specifically, we identified the number of *followers* for an event's Instagram social media profile, used online search engines to identify official websites, blog posts, news articles, Facebook events, and other event aggregator postings. In many cases, we were able to find attendance numbers or estimates. The research team discussed each event and recorded those that we felt met the criteria for a major public event. In total, 202 event dates were identified over the analysis period. In addition to events, all provincial and federal holidays were noted in our models.

In addition to general cultural and public events, we separately considered popular running events (marathons and half-marathons). Similar to other events, we conducted manual verification using official race websites, registration platforms, and media coverage to assess their scale and prominence. Only events with substantial participation were retained. For multi-day race events, only the primary race days (typically weekend dates) were included in the analysis. Our final analysis included three running events taking place over four days.

3.4.3. Microscopic airborne particles ($PM_{2.5}$)

Average daily microscopic airborne particles, referred to as *particulate matter* at less than or equal to 2.5 micrometers in diameter ($PM_{2.5}$) were accessed from the Montreal Air Quality Monitoring Network, *Réseau de*

[4] `https://climate.weather.gc.ca/`

[5] `https://www.lavitrine.com`

surveillance de la qualité de l'air.[6] The median $PM_{2.5}$ from all stations across Montréal were calculated for each day in our focal study range. These data were used as a regressor in separate time-series forecasting models to determine whether estimated changes in mobility on advisory days persisted after controlling for smoke levels.

4. Analysis

The impact of air quality advisories on daily urban mobility ($RQ1$) was assessed using time-series forecasting models applied to our four mobility modes of metro, bus, bike-share, and recreational running. Specifically, we estimated counterfactual mobility activities (i.e., trips, runs) using *Prophet*[7], a time-series forecasting model appropriate for mobility datasets with strong seasonal patterns (Taylor and Letham, 2018). This method has previously been used for air pollution-related research (Nath et al., 2021; Nugraha et al., 2025; Hasnain et al., 2022; Samal et al., 2019; Zhao et al., 2018).

The Prophet model is commonly represented as:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{1}$$

where $y(t)$ represents the predicted value at a point in time t, $g(t)$ represents the trend component modelled as a piecewise linear function that allows the underlying rate of change to vary over the study period, $s(t)$ captures seasonal effects through Fourier series, including recurring patterns such as yearly and weekly seasonality, $h(t)$ captures the effects of holidays and events that may cause deviations from expected patterns, and ϵ_t represents the error term (Taylor and Letham, 2018).

A predictive, as opposed to an inference-based model is well-suited for this analysis given the limitation of only 27 advisory days in the study period. Time-series models, such as Prophet, have distinct advantages versus fixed-effects regression models when handling continuous temporal data. As advisory days are likely to cluster temporally (i.e., not occur randomly throughout the year), and are results of both weather and seasonal variations across scales, time-series models are better suited. In our example, Prophet models a continuous Fourier series and considers each advisory day as separate events. In addition, mobility patterns exhibit strong seasonal

[6] `https://open.canada.ca/data/en/dataset/3e9f7b96-3f25-4404-a5ad-22d9a31060e6/resource/45caef37-2cc3-4e81-9040-095d2119d198`

[7] `https://facebook.github.io/prophet/docs/quick_start.html`

and temporal variations. In the Prophet model, these patterns are explicitly modelled through the trend and seasonal components, allowing expected mobility to be predicted for a given date.

The presence of advisories was included as a regressor in the Prophet model, with advisory days assigned a value of 1 and non-advisory days assigned a value of 0. The time-series model for each mobility mode also included regressors for weather conditions (i.e., daily mean temperature and precipitation), along with controls for major events, public holidays, weekends, and annual baseline shifts in trip volume. Temperature was categorized into four bins ($\leq$ 15°C, 15–20°C, 20–25°C, and $>$ 25°C) and included as regressors in the bike-share and recreational running models, following the approach of Chan and Wichman (2020), to account for the non-linear relationship between temperature and outdoor activity (Tucker and Gilliland, 2007). Finally, for the recreational running mode, we also controlled for days when popular running events were held. Prophet's seasonality components were used to account for recurring weekly and yearly temporal patterns in the underlying data. The models used multiplicative seasonality as it provided a better fit for this data. By controlling for these factors, the models generated counterfactual estimates of expected trip volumes for each mode on advisory days, had no advisory been in effect. Observed trip counts were then compared to these counterfactual predictions to isolate the effect of advisories on each mobility mode. One model was constructed for each of the mobility modes independently, allowing us to identify differences between the mobility modes and address $RQ2$.

After assessing temporal mobility patterns between the four mobility modes across the entire city of Montréal, we further examined variation in mobility between boroughs and metro stations on the Island of Montréal (addressing $RQ3$). This was done for two of the most popular mobility modes in the city, namely BIXI bike-share trips and Metro ridership trips. We restricted our analysis to these two modes because we did not have enough recreational running data to meaningfully split by borough, and the bus ridership data is only publicly available at the city level.

The BIXI ridership data were aggregated to the borough level and then separate time-series models were developed for each borough. In all cases, we controlled for the same covariates as the city-level models. For Metro ridership, we developed separate time-series models for each individual station, with daily ridership per station as the dependent variable. We elected not to aggregate to the borough level for these data as metro stations are more concentrated in a small number of boroughs, and given the volume of ridership per station, we determined that analysis at the station level would be more appropriate.

5. Results

The results of our city-level time-series analysis are reported in Table 2. The 95% confidence intervals (CI) and p-values were calculated using a t-test to determine whether the mean advisory day effect differs significantly from zero. Significance, in this case, means advisories are associated with a significant change in travel, when all other factors are controlled for. Notably, all but the running mode show statistically significant differences in trips on days with air quality advisories, answering our first research question, $RQ1$.

Table 2: Estimated effects of air quality advisories on daily trip counts by transportation mode. Changes in trips represent mean differences between observed ridership and counterfactual model predictions on advisory days.

Mode	**Trips/day**	**% Change**	$\mathbf{R^2}$	**(95% CI)**
Metro	+25,448*	+4.7%	0.86	[+1,128, +49,769]
Bus	+30,270*	+6.7%	0.91	[+6,253, +54,286]
Bike-share	−3,644**	−5.8%	0.74	[-5,362, -1,926]
Running	−17	−5.4%	0.58	[-73, +38]

$^{**}p < 0.01$, $^{*}p < 0.05$

Interestingly, the presence of air quality advisories led to an increase in activity for some modes and a decrease for others, answering $RQ2$. Specifically, we found that bus ridership showed the largest positive change in ridership, with an average increase of 6.7% per day on days when an air quality advisory was issued. Similarly, metro ridership significantly increased by 4.7% on days with air quality warnings. The active transportation option of using a shared bicycle (BIXI) saw an average statistically significant decrease of 5.8% on days with air quality advisories. The results of the recreational running analysis did not produce significant results. Figure 2 shows a plot of the time-series analysis results for metro ridership over two time periods (2023 and 2025). The grey lines indicates actual daily ridership. Red indicates periods where air quality advisories were issued, and the green lines indicate the expected ridership volume based on the time-series models. Time-series plots for the three other mobility modes are provided in the Appendix.

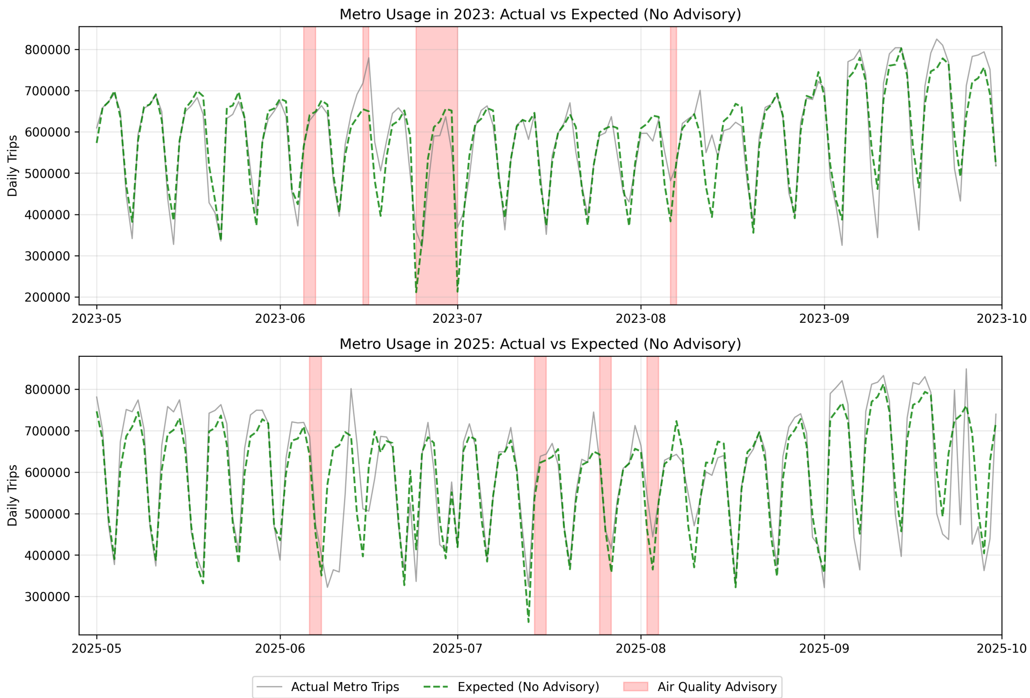
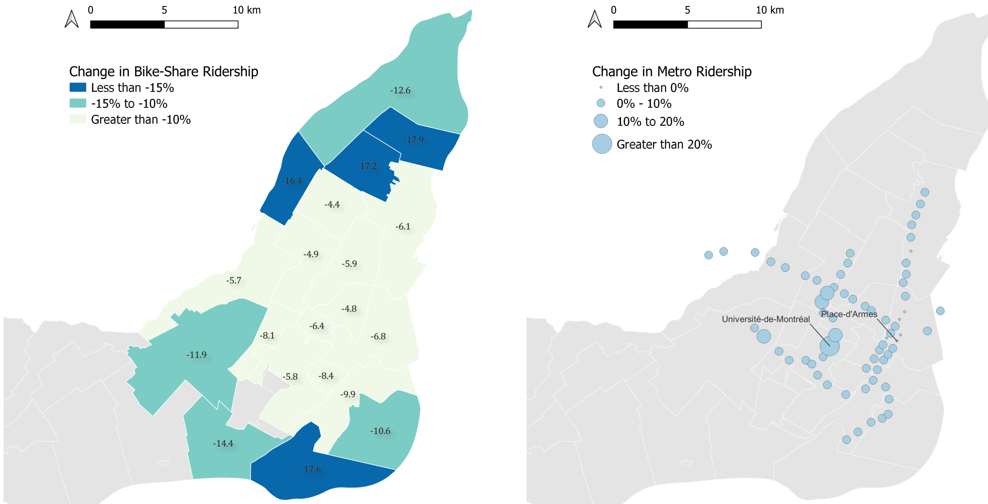


Figure 2: Plots showing the outputs from the time series model for Metro station ridership. The results for 2023 are shown on top with the 2025 results shown below. Gray lines indicate actual ridership volume, red lines show periods where advisories were issued, and green lines show the expected ridership volume as output from the time-series model.

Separate models were estimated for each mobility mode with daily $PM_{2.5}$ concentrations included as an additional regressor. Results from these models are presented in Table A1. After accounting for pollution levels, shifts in mobility remained generally consistent with the original models. Metro and bus trips continued to increase during air quality advisory periods, with estimated changes of +5.9% and +8.4%, respectively, compared with +4.7% and +6.7% in the models without $PM_{2.5}$. Bike-share trips continued to decline, with a similar estimated change of -6.0% compared with -5.8% without $PM_{2.5}$. In contrast, the estimated decline in running trips was reduced from -5.4% to -2.1% after including $PM_{2.5}$, although the effect remains statistically non-significant. These results indicate that the observed changes in metro, bus, and bike-share activity during advisory periods are largely consistent, even after accounting for pollution severity.

Figure 3 shows the results of the *within* Montréal borough analysis for



(a) Bike-share trips by borough

(b) Metro ridership by station

Figure 3: Observed change in activities due to air quality advisories for bike-share and metro trips within Montréal.

bike-sharing and metro mobility modes. These show that the changes in trips attributed to air quality advisories are not uniform across the city (addressing *RQ*3) and that the largest decreases are found outside the downtown core of the city. Specifically, regions to the North and Southeast report the largest decreases in bike-share activity. We see that in almost all cases these changes are statistically significant.

Metro ridership data were analyzed at the station-level, and the results are shown in Figure 3b. The majority of stations saw an increase in ridership on days with air quality advisories. This mirrors the city-level analysis reported earlier. We do find that while the general trend is an increase, it is not uniform across the city, further addressing *RQ*3. Specifically, we find that stations near the downtown core (e.g., *Place d'Armes*) reported a decrease in trips, whereas one station, *University de Montréal*, reported an exceptionally high increase of 24.8%. All of this supports the finding that people in different regions of the city responded differently to air quality advisories.

6. Discussion

The mobility response to wildfire smoke events carries important implications for public health; insufficient adherence to warnings and bulletins introduces public health risk and may indicate problems with communication around the health risks of wildfire smoke exposure. By investigating changes in mobility patterns during wildfire smoke events, we have a window into the effectiveness of public alerts in modifying population mobility behaviours. Our findings suggest that while there is a mobility response to wildfire smoke events, the magnitude of this change is small and spatially variable, indicating insufficient adherence to public bulletins. This poses a risk to public health and suggests that more needs to be done to communicate to and convince travellers of the risks of exposure to wildfire smoke and protective actions, and ensure that travel alternatives are available. Considering the well-established adverse health effects of wildfire smoke exposure (Gould et al., 2024), the public health consequence of low levels of adherence to warnings may be significant. Policy options such as temporarily reducing transit fares or encouraging remote work during these pollution events may encourage adherence.

6.1. Changes in Bike-Share, Metro, and Bus Mobility Patterns

We found a -5.8% change in bike-share trips, and 4.7% and 6.7% increases in metro and bus trips, respectively, during wildfire smoke events. It is important to note that because these mobility datasets are independent and cannot be linked at the individual level, the observed opposing trends are consistent with but do not directly demonstrate a substitution effect, whereby the same travellers shifted from active to enclosed modes. Further, the different travel modes analyzed vary in their demographic representativeness and use for trip purposes, meaning that changes in mobility patterns across modes may not reflect uniform changes in travel behaviour across the population, and may instead reflect varied responsiveness to advisories across demographics, though this is not possible to ascertain with available data.

Our finding on the magnitude of the reduction of bike-share trips is substantially less than related studies. Doubleday et al. (2021) found a 14-36% reduction in bicycle trips across automatic counters in Seattle, Washington, and, similarly, Saberian et al. (2017) found that air quality alerts were associated with a 14-35% reduction in bicycle trips from automatic counters in Sydney, Australia. The difference in data collection may be partially accountable, as our study used bike-share trip records provided by the sharing system operator rather than vehicle counters, devices measuring the number of passing vehicles at a given location. Alternatively, it may be that travellers in Seattle and Sydney are more responsive to wildfire smoke than in

Montréal, perhaps because they are more experienced with the phenomenon; or, it may be that more bicycle trips are recreational than in Montréal, and hence more discretionary. For metro trips, Han et al. (2024) found that ridership in Washington D.C. during a wildfire smoke event increased by 0.8% on weekdays, and 3.7% on weekends. Our finding of a 4.7% increase in metro traffic follows this pattern, but to a greater magnitude, perhaps because more trips in Montréal originate from active modes and can be diverted to public transit. Further research is needed to investigate possible explanations of differences across geographical contexts.

Spatially, we found that bike-share use outside of the downtown core saw a greater decrease in trips than in more central areas. A possible explanation is that these trips are more likely to be recreational, and thus discretionary, compared to a heavier use of the bike-share system for utilitarian purposes. We found that metro stations near the downtown core saw a decrease in trips, which may suggest avoided travel to work or recreational travel (i.e., shopping, tourism), while the increase of travel at the *University of Montréal* station may indicate that travellers who might normally bicycle to the campus adopted other transport modes. Existing research has found that trip purpose is important in conditioning the mobility response to air pollution (Park et al., 2022; Acharya and Singleton, 2022), which offers credence to these possible explanations.

6.2. Changes in Recreational Running Mobility Patterns

Interestingly, the recreational running data did not show any significant change due to air quality advisories. This was counterintuitive to us, as we expected there to be a significant decrease in running on advisory days. There are a number of possible explanations for these results. First, the data collected from *Strava* samples segment leader-boards which are specifically biased towards faster athletes that compete against each other over specific segments. Faster athletes tend to be more serious runners and could therefore be less likely to respond to advisories related to air quality. Either they chose to ignore the advisories or prioritized fitness over pollution risk. Second, while we were able to access municipally-sanctioned running events (e.g., marathons) there are many community running events and regular running groups of which we were likely unaware. Without being able to control for *fun runs* and other events, the sparsity of the data has a larger impact on the results. Additional work is currently underway to investigate issues related to modelling recreational running.

Considering changes to recreational running is a valuable contribution to the literature, as this form of discretionary mobility (vigorous physical activity) is specifically cautioned against, but has typically been studied through qualitative methods or small-scale primary data collection (López-Gil et al., 2022; Cheng et al., 2024; Yu and Zhang, 2023), due to the difficulty of sourcing large-scale data on this type of mobility. A limitation is that *Strava* data is not necessarily representative of the wider population, introducing possible bias to the sample and related ethical concerns (Williams and Behrendt, 2025; Venter et al., 2023). Given the lack of alternative large-scale data sources on recreational outdoor activities, however, this data remains valuable and has been used often in mobility analyses (Battiston et al., 2023; McKenzie et al., 2025; Jean-Louis et al., 2024).

6.3. Limitations

This analysis evaluated mobility data against air quality warning data, rather than direct measures of air quality (e.g., AQI, PM2.5), due to an analytical focus on the effectiveness of public health alerts. However, existing research has shown a difference in the adoption of protective behaviours, between exposure to advisories and a personal perception of air pollution and its risks (D'Antoni et al., 2017; Kim et al., 2024). While air quality alerts are issued whenever air quality is low, the severity of pollution might be expected to affect mobility response, independent from public alerts. Future research can further explore the relationship between the effect of advisories and the effect of actual pollution levels on mobility response. When considering the adherence to alerts recommending avoiding outdoor activity, it is also important to note that staying indoors to reduce exposure depends on sufficient filtration to prevent poor air quality from infiltrating indoor environments (Liang et al., 2021; Walker et al., 2023). The effectiveness of the prevention of indoor infiltration may be correlated with socioeconomic variables (Walker et al., 2023), and so this introduces a key equity dimension.

Our work faced a number of other limitations. While the mobility data used enabled a mode-specific analysis, the coverage of this data is limited relative to other datasets (e.g., mobile phone records) which are sometimes used in air pollution mobility research (Shen et al., 2025; Burke et al., 2022; Mullan et al., 2024). It is possible to derive travel mode from mobile phone records based on trajectories and speed, but this may introduce some uncertainty that was avoided by using mode-specific datasets. Conversely, because of the limited coverage of this data, it was not possible to assess whether there were significant differences in mobility response across demographic and socioeconomic groups, though previous research has indicated this is likely (Shen et al., 2025; Burke et al., 2022; Mullan et al., 2024). Different demographics are differently at risk of health effects resulting from air pollution (Rizzo and Rizzo, 2025), and so the ability to differentiate travellers by age, for example, is important for considering the possible costs resulting from a lack of adherence to air quality advisories. However, this was not possible with our mobility data. It is also not possible with existing data to conclusively establish the rate of mode substitution from open-air modes to enclosed modes, as this mobility data is not linked at the individual level. Future research that supplements large-scale mobility data with individual-level assessment, such as with questionnaires, may be useful in evaluating mode shift.

6.4. Future Research

Our future efforts in this domain will focus on conducting similar analyses in other cities and comparing the results. We anticipate that responses to air quality advisories vary substantially between cities with some differences being explained through political, social, and cultural factors. For instance, some cities (e.g., Edmonton) experience the impacts of wildfire smoke far more than Montréal. Does constant exposure influence response to advisories? In the same vein, the mobility response for wildfire smoke events may be different than for other air pollution events, due to their increased visibility (on the media and sometimes literally), which merits further exploration. In addition, we aim to improve the robustness of our analysis by accessing additional mobility datasets, representing longer periods of time. Future research should also attempt to draw concrete health implications from changes in mobility patterns, to better understand the consequences of the lack of adherence to public health bulletins and the urgency of improving communication strategies.

7. Conclusion

In this study, we investigated how mobility patterns associated with the issuance of wildfire-related public health alerts, changed in Montréal. Given the anticipated increase in severe wildfires globally due to climate change, and mounting evidence of the public health consequences of wildfire smoke, this research is prescient and responds to an identified gap in the literature (Kinkel et al., 2025; Vien et al., 2024). With data on bike-share, bus, metro, and recreational running activities, we employ a set of time-series forecasting models, accounting for seasonality, weather, holidays, and major events, to answer our research questions.

In response to *RQ*1 (*Does population mobility change during air quality advisory events associated with wildfire smoke?*) and *RQ*2 (*Do air quality advisory–related changes in mobility vary by transportation mode?*), we find significant changes in bike-share (-5.8%), metro (+4.7%), and bus (+6.7%) trips, though no significant change to recreational running. In response to *RQ*3 (*Do air quality advisory–related changes in mobility vary spatially within a city?*), we find spatial variance in bike-sharing and metro trips, for which we had sufficient spatial data, with larger decreases in bike-sharing in non-central areas and variable changes to metro station trip counts depending on location. Our methodology was effective in addressing these research questions and holds promise for future, planned analyses of the mobility response to exogenous events. Our findings indicate potentially low levels of adherence to public health bulletins advising reduced outdoor travel during smoke events, suggesting that current communication strategies may be inadequate.

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Appendix

Listing A1: Example smog warning.

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WLCN41 CWUL 010220
SMOG WARNING
FOR QUEBEC
UPDATED BY ENVIRONMENT CANADA, THE MINISTERE DE L'ENVIRONNEMENT ET
DE LA LUTTE CONTRE LES CHANGEMENTS CLIMATIQUES, THE MINISTERE DE LA
SANTE ET DES SERVICES SOCIAUX, THE DIRECTION REGIONALE DE SANTE
PUBLIQUE DE MONTREAL AND THE CITY OF MONTREAL
AT 10:20 P.M. EDT FRIDAY 30 JUNE 2023.
------------------------------------------------------------------
SMOG WARNING FOR:
        GATINEAU
        METRO MONTREAL - LAVAL
        VAUDREUIL - SOULANGES - HUNTINGDON
        RICHELIEU VALLEY - SAINT-HYACINTHE
        LANAUDIERE
        LACHUTE - SAINT-JEROME
        LAURENTIANS
        MONT-LAURIER
        UPPER GATINEAU - LIEVRE - PAPINEAU
        TEMISCAMINGUE
        EASTERN TOWNSHIPS
        DRUMMONDVILLE - BOIS-FRANCS
        MAURICIE
        LA TUQUE.

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==DISCUSSION==

HIGH CONCENTRATIONS OF FINE PARTICULATE MATTER ARE CAUSING POOR AIR
QUALITY AND REDUCED VISIBILITIES. THESE CONDITIONS MAY PERSIST UNTIL
SUNDAY.

SMOG ESPECIALLY AFFECTS ASTHMATIC CHILDREN AND PEOPLE WITH
RESPIRATORY AILMENTS OR HEART DISEASE. IT IS THEREFORE RECOMMENDED
THAT THESE INDIVIDUALS AVOID INTENSE PHYSICAL ACTIVITY OUTDOORS
UNTIL THE SMOG WARNING IS LIFTED.

WE CAN ALL HELP IMPROVE AIR QUALITY BY DOING SIMPLE THINGS, SUCH AS
USING PUBLIC TRANSIT, REDUCING OUR DRIVING SPEED AND NOT LETTING OUR
CAR ENGINES IDLE UNNECESSARILY.

ADDITIONAL INFORMATION:

TO LEARN MORE ABOUT THE INFO-SMOG PROGRAM, GO TO ENVIRONMENT
CANADA'S WEBSITE AT WWW.CANADA.CA/INFO-SMOG-PROGRAM.

FOR AIR QUALITY INDEXES IN QUEBEC, VISIT THE WEBSITE OF THE
MINISTERE DE L'ENVIRONNEMENT ET DE LA LUTTE CONTRE LES CHANGEMENTS
CLIMATIQUES AT
WWW.IQA.ENVIRONNEMENT.GOUV.QC.CA/CONTENU/INDEX(UNDERSCORE)EN.ASP.
```

FOR THE AIR QUALITY INDEX IN MONTREAL, VISIT THE RESEAU DE SURVEILLANCE DE LA QUALITE DE L'AIR DE LA VILLE DE MONTREAL'S WEBSITE AT WWW.RSQA.QC.CA (FRENCH ONLY).

TO LEARN MORE ABOUT THE EFFECTS OF SMOG ON YOUR HEALTH IN QUEBEC, VISIT THE MINISTERE DE LA SANTE ET DES SERVICES SOCIAUX'S WEBSITE AT WWW.QUEBEC.CA/EN/HEALTH. YOU CAN ALSO VISIT THE DIRECTION REGIONALE DE SANTE PUBLIQUE DE MONTREAL AT WWW.SANTEMONTREAL.QC.CA/EN/PUBLIC.

PLEASE CONTINUE TO MONITOR ALERTS AND FORECASTS ISSUED BY ENVIRONMENT CANADA.

HTTP://WEATHER.GC.CA

END/QSPC

Table A1: Estimated effects of air quality advisories on daily trip counts by transportation mode, while controlling for $PM_{2.5}$. Changes in trips represent mean differences between observed ridership and counterfactual model predictions on advisory days.

Mode	**Trips/day**	**% Change**	**R^2**	**(95% CI)**
Metro	+31,973*	+5.9%	0.85	[+7,636, +56,310]
Bus	+37,861**	+8.4%	0.91	[+13,727, +61,995]
Bike-share	−3,773**	−6.0%	0.74	[-5,486, -2,060]
Running	−7	−2.1%	0.57	[-66, +53]

$^{**}p < 0.01$, $^{*}p < 0.05$

Table A2: Estimated change in bike-share ridership by borough during air quality advisories. * indicates $p < 0.05$.

Borough	Trips/day	% Change	R^2	95% CI
Ahuntsic-Cartierville	-102*	-5.7%	0.73	[-196, -9]
Anjou	-23*	-17.2%	0.73	[-32, -14]
Côte-des-Neiges-Notre-Dame-de-Grâce	-263*	-5.8%	0.72	[-452, -74]
L'Île-Bizard-Sainte-Geneviève	1	25.7%	0.35	[-0, 3]
LaSalle	-97*	-17.6%	0.59	[-149, -44]
Lachine	-61*	-14.4%	0.55	[-121, -1]
Le Plateau-Mont-Royal	-1,761*	-4.8%	0.75	[-3011, -510]
Le Sud-Ouest	-947*	-9.9%	0.72	[-1424, -469]
Mercier-Hochelaga-Maisonneuve	-326*	-6.1%	0.76	[-563, -89]
Mont-Royal	-28*	-8.1%	0.70	[-48, -8]
Montréal-Est	-4	-17.9%	0.38	[-9, 1]
Montréal-Nord	-28*	-16.4%	0.66	[-40, -15]
Outremont	-113*	-6.4%	0.70	[-194, -32]
Pierrefonds-Roxboro	-3	-4.3%	0.65	[-19, 12]
Rivière-des-Prairies-Pointe-aux-Trembles	-9*	-12.6%	0.55	[-17, -2]
Rosemont-La Petite-Patrie	-854*	-5.9%	0.73	[-1388, -320]
Saint-Laurent	-56*	-11.9%	0.68	[-84, -28]
Saint-Léonard	-13	-4.4%	0.62	[-34, 8]
Verdun	-335*	-10.6%	0.64	[-509, -161]
Ville-Marie	-2,121*	-6.8%	0.71	[-3272, -970]
Villeray-Saint-Michel-Parc-Extension	-287*	-4.9%	0.72	[-549, -26]
Westmount	-83*	-8.4%	0.68	[-145, -21]

Table A3: Estimated change in metro ridership by station during air quality advisories. * indicates $p < 0.05$.

Station	Trips/day	% Change	R^2	95% CI
Acadie	+171*	+6.2%	0.88	[+10, +333]
Angrignon	+434	+4.2%	0.85	[-10, +877]
Assomption	+135	+4.6%	0.83	[-30, +299]
Atwater	+991*	+8.2%	0.83	[+26, +1,956]
Beaubien	+310*	+4.2%	0.86	[+72, +548]
Beaudry	-77	-2.5%	0.37	[-261, +106]
Berri-Uqam	+1,272*	+6.0%	0.67	[+298, +2,247]

Station	Trips/day	% Change	R^2	95% CI
Bonaventure	+399	+2.8%	0.85	[-506, +1,304]
Cadillac	+267*	+5.2%	0.88	[+22, +512]
Cartier	+339	+5.5%	0.86	[-41, +719]
Champ-de-Mars	-223	-2.0%	0.64	[-662, +216]
Charlevoix	+247*	+6.1%	0.87	[+43, +451]
Crémazie	+625*	+8.3%	0.90	[+106, +1,143]
Côte-Sainte-Catherine	+247*	+5.0%	0.91	[+42, +452]
Côte-Vertu	+1,070*	+6.3%	0.92	[+13, +2,127]
Côte-des-Neiges	+696*	+9.8%	0.85	[+45, +1,347]
D'Iberville	+176*	+6.2%	0.88	[+54, +299]
De Castelnau	+402*	+12.9%	0.58	[+133, +671]
De l'Église	+89	+1.3%	0.82	[-97, +276]
De la Concorde	+219	+7.4%	0.88	[-13, +451]
De la Savane	+248*	+6.7%	0.82	[+32, +465]
Du Collège	+561*	+10.0%	0.89	[+69, +1,052]
Fabre	+212*	+5.1%	0.89	[+70, +354]
Frontenac	+386*	+6.3%	0.80	[+115, +657]
Georges-Vanier	+134*	+5.8%	0.81	[+3, +265]
Guy-Concordia	+969*	+6.0%	0.79	[+98, +1,840]
Henri-Bourassa	+519*	+4.6%	0.89	[+0, +1,038]
Honoré-Beaugrand	+532	+4.7%	0.91	[-53, +1,117]
Jarry	+401*	+5.9%	0.84	[+164, +637]
Jean-Drapeau	+1,282	+9.3%	0.41	[-3,674, +6,239]
Jean-Talon	+267*	+2.3%	0.81	[+40, +494]
Jolicoeur	+259*	+6.0%	0.90	[+43, +475]
Joliette	+148	+2.3%	0.84	[-48, +344]
LaSalle	+129*	+4.2%	0.84	[+4, +255]
Langelier	+246	+4.2%	0.88	[-1, +493]
Laurier	+420*	+4.6%	0.84	[+100, +739]
Lionel-Groulx	+648*	+5.2%	0.84	[+228, +1,067]
Longueuil	+1,000	+6.3%	0.67	[-212, +2,212]
Lucien-L'Allier	+58	+1.1%	0.60	[-348, +464]
McGill	+1,233*	+6.9%	0.89	[+493, +1,972]
Monk	+165*	+4.8%	0.88	[+43, +286]
Mont-Royal	+312	+2.5%	0.76	[-106, +730]
Montmorency	+566	+5.3%	0.77	[-128, +1,260]
Namur	+216	+3.4%	0.84	[-28, +461]
Outremont	+245	+9.1%	0.85	[-5, +496]
Papineau	-152	-2.2%	0.52	[-567, +263]
Parc	+686*	+12.0%	0.84	[+322, +1,050]
Peel	+604	+5.1%	0.69	[-131, +1,339]
Pie-IX	+199	+1.9%	0.54	[-693, +1,092]
Place-Saint-Henri	+434*	+7.9%	0.88	[+159, +709]
Place-d'Armes	-886*	-6.2%	0.52	[-1,444, -328]
Place-des-Arts	-317	-2.2%	0.62	[-1,565, +931]
Plamondon	+426*	+4.6%	0.90	[+85, +767]
Préfontaine	+183	+4.1%	0.90	[-20, +385]
Radisson	+251	+3.2%	0.84	[-265, +768]
Rosemont	+316*	+5.2%	0.89	[+59, +573]
Saint-Laurent	+16	+0.3%	0.56	[-438, +471]
Saint-Michel	+402	+4.2%	0.91	[-67, +870]
Sauvé	+377	+4.8%	0.90	[-42, +796]
Sherbrooke	+557*	+6.4%	0.82	[+238, +877]
Snowdon	+415*	+4.6%	0.89	[+15, +815]
Square-Victoria	+909*	+8.6%	0.95	[+276, +1,542]
Université-de-Montréal	+870*	+24.8%	0.81	[+27, +1,712]

Station	Trips/day	% Change	R^2	95% CI
Vendôme	+837	+6.6%	0.92	[-12, +1,685]
Verdun	+129	+3.4%	0.89	[-10, +267]
Viau	-30	-0.4%	0.52	[-400, +339]
Villa-Maria	+482*	+7.8%	0.86	[+76, +888]
Édouard-Montpetit	+306*	+15.1%	0.82	[+51, +562]

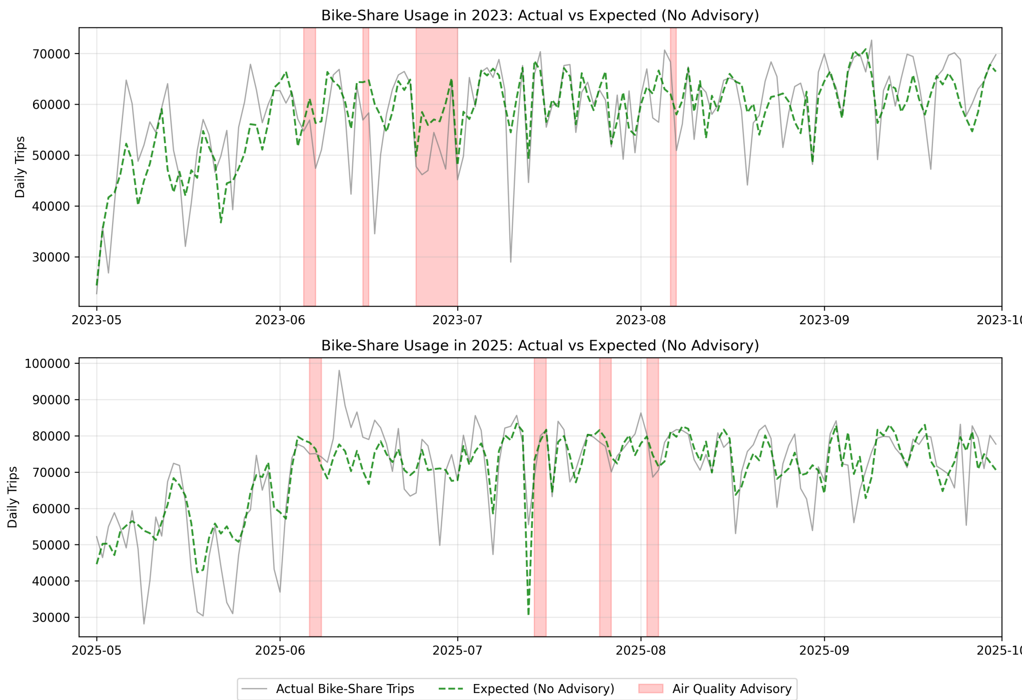

Figure A1: BIXI time-series model.

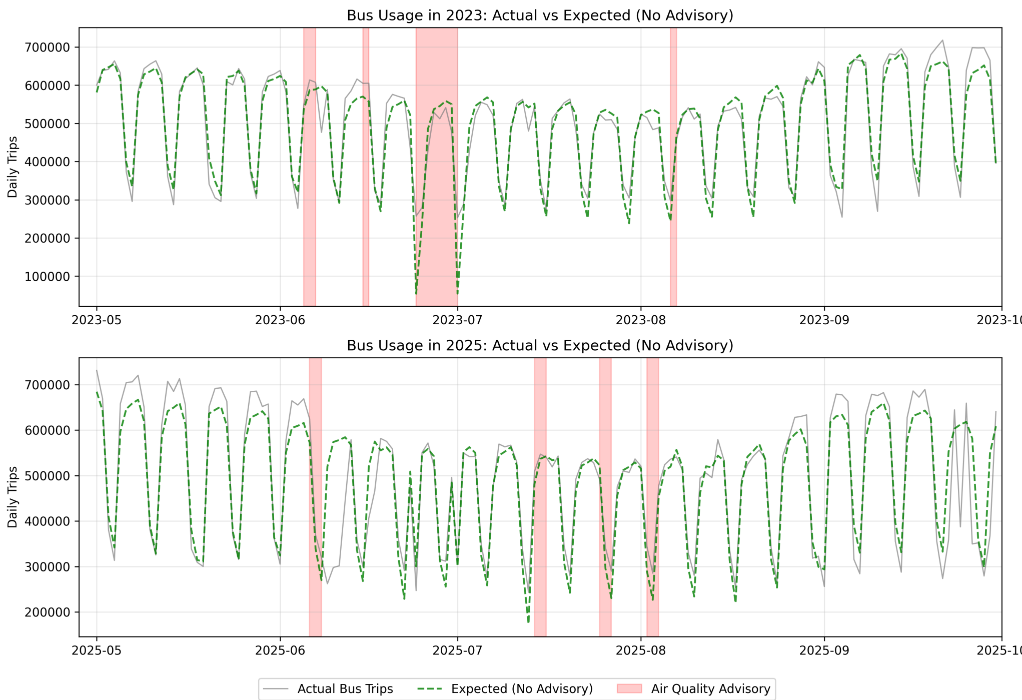

Figure A2: Bus time-series model.

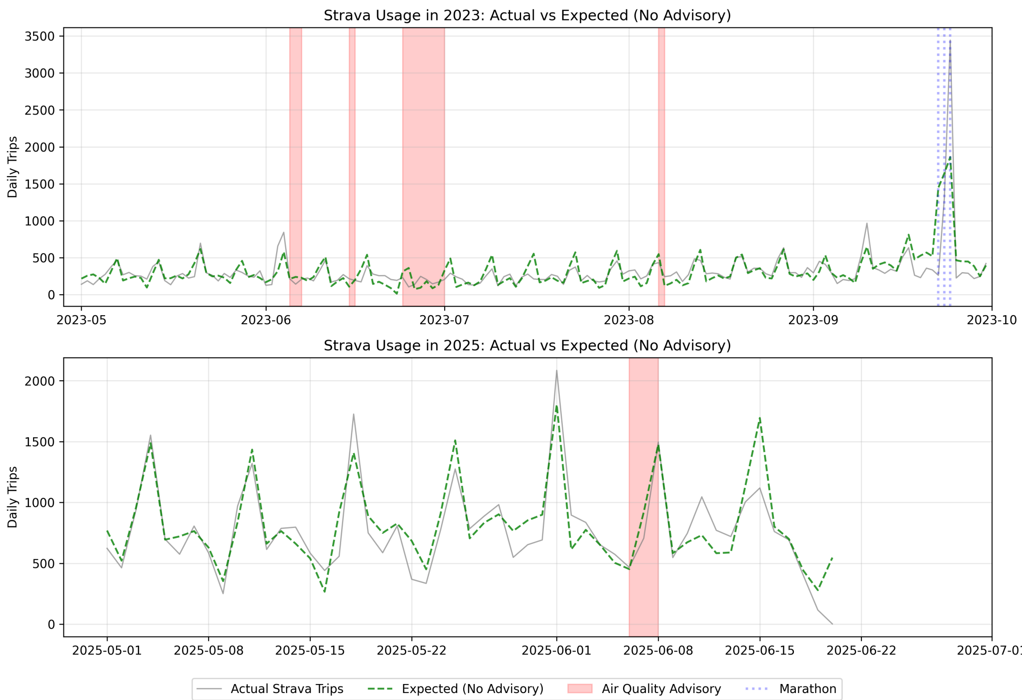

Figure A3: Recreational running time series model.