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Evaluation of bicycle sharing scheme data as a proxy for cycling mobility – How COVID-19 measures influenced cycling in Paris

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ABSTRACT

The use of bicycles can provide myriad benefits to society, especially in crowded urban centres where other modes of transport are at or near capacity. However, integrating cycling into policy and planning requires more comprehensive data about their use in space and time. Current approaches, using sparse networks of counters provide one possible route to more comprehensive data. In this paper we investigate another, using data collected from Paris' bicycle sharing system to explore use during 2020. We chose 2020 as a test year because the use of bicycles was strongly influenced by the COVID-19 pandemic, allowing us to explore how bicycle use adapted to both legal and environmental influences. We used interactive visualization to allow hypothesis generation and data exploration, before analysing bicycle use as a function of weather and COVID-19 restrictions. Our results show that bicycle sharing system data and Paris' counters both capture very similar behaviour patterns, and therefore bicycle sharing system data are a reliable proxy for overall cycling behaviour, providing finer spatial granularity than existing sparse counter networks. Seasonally, precipitation influenced bicycle use more strongly in 2020 than COVID-19 measures.

1. Introduction

The use of bicycles as a potentially safe, sustainable, non-polluting, space-saving and healthy model of transport in urban centres has been promoted across the globe in recent years. During the COVID-19 pandemic, many populations saw a modal shift from crowded public transport to bicycles, and cities worldwide made efforts to promote the use of bicycles. However, collecting data on bicycle use, and understanding the factors that influence changes of use in time and space remain challenging and lag studies of other modes of transport. Many cities have relatively sparse networks of bicycle-specific counters, and while crowdsourced data such as Strava receive increasing attention (Fischer et al., 2022), especially in North America, collecting representative data about bicycle use for short, everyday journeys within cities remains challenging.

In this paper, we address this shortcoming by comparing data from a bicycle sharing system (BSS) in Paris to a relatively sparse network of bicycle counters. We use interactive visualization for data exploration and hypothesis generation, before analysing bicycle use captured by both the BSS and bicycle counters. We do so in the context of the COVID-19 pandemic, and explore cycling behaviour with respect to COVID-19 restrictions and weather using both data sources. Paris was selected as a test area because it has both a mature bicycle sharing system and a network of bicycle counters, and was subject to a wide range of restrictions during 2020. The city also has a long-standing interest in promoting cycling as a mode of transport for short journeys within the city, which was accelerated during the COVID-19 pandemic.

In addition to describing the context of bicycle use in Paris during the first year of the Covid pandemic, our work offers three generalisable contributions:

- We evaluate the reliability of public bicycle sharing scheme data as a proxy for all urban cycling behaviour demonstrating it consistently reflects dedicated cycle counter data.
- We propose a visual analytic approach for capturing both long-term and real-time patterns in cycling behaviour that can be used to guide subsequent statistical analysis.
- We uncover empirical evidence that even in the context of an extreme exogenous shock to transport systems, cycling behaviour remains highly responsive to local environmental conditions.

Bicycle sharing systems have increasingly emerged as a way for large

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urban centres to encourage cycling. As of August 2021, there were nearly 10 million shared bicycles and 3,000 BSS across the world. The Paris BSS, Vélib, has been in operation since 2007 and consists of more than 1,400 stations from which about 20,000 bicycles can be borrowed. The existing network of stations is densest in central Paris, while the network is being continually expanded toward the suburbs. According to Vélib, the number of registered users increased from about 85,000 in January 2019 to 270,000 in December 2019,[1] and in 2020 an estimated 210,000 daily trips took place with 40,000 subscribed users.

Data produced by BSS have been considered a useful data source for various mobility analyses by the scientific community over the past decade. In many BSS the most accessible public information recorded with respect to mobility are the number of bicycles checked in and out at a given station within a given time period. These two values can be used to derive a count (the difference between checked in and checked out bicycles), a proxy of ridership or bicycle demand at a BSS station level (e.g. Gebhart and Noland, 2014; El-Assi et al., 2017). While most BSS provide this basic information, some systems provide additional information such as origin–destination data indicating start and end station of individual journeys. This enables not only analyses based on ridership, but also more complex questions, for example determining bicycle trip's commuting or recreational purpose (Li et al., 2020; Chen et al., 2020), group cycling motivation (Beecham and Wood, 2014a) and gender-related behaviour (Beecham and Wood, 2014b). However, few studies (e.g. Pazdan et al., 2021) have combined BSS data with bicycle traffic counters, leaving open questions about the representativeness of studies focussing only on BSS.

Besides analyses of trip purpose, other mobility analyses performed using bicycle sharing data, include socio-demographic studies (Wang et al., 2018), impacts of external factors on bicycle sharing use e.g., weather or built environment (El-Assi et al., 2017), and more recently, modelling the impact of the COVID-19 pandemic on cycling (Teixeira and Lopes, 2020). Studies exploring the impact of weather on cycling, via, for example, temperature, precipitation and humidity (Gallop et al., 2011; Gebhart and Noland, 2014; Kim, 2018) are common as journeys can often be discretionary and therefore responsive to environmental conditions. Linking weather parameters to cycling behaviour means choosing a temporal interval over which to summarise weather conditions. Most typical are hourly or daily values of either directly measured weather conditions such as average temperature, rainfall totals, average wind speed or insolation hours. Alternatives include indicators thought to capture likely responses to weather (e.g. the temperature-humidity index (THI) (Kim, 2018) or lagged effects of rain and snow (Gebhart and Noland, 2014). The selected temporal resolution can have important consequences for the results - higher temporal resolutions will capture more and shorter trips, which are especially common in BSS, and thus may lead to different results. For example, De Chardon et al (2017) did not identify a negative impact of humidity on BSS ridership counts, most likely due to monthly aggregation of data, while studies with much finer (hourly) temporal resolutions (Gebhart and Noland, 2014; Nosal and Miranda-Moreno, 2014, Pazdan et al., 2021) all reported that increased humidity reduced the propensity to cycle. Both De Chardon et al (2017) and El-Assi et al (2017) identified optimum cycling temperatures of between around 20 and 30C, with temperatures below freezing, rain and high humidity decreasing the number of trips and their duration (Gebhart and Noland, 2014).

An additional strong external factor affecting human mobility generally, and in particular cycling in 2020 was the COVID-19 pandemic. The crisis impacted many aspects of everyday life provoking huge challenges in supply (Guan et al., 2020) and human mobility (Hu et al., 2021; Chinazzi et al., 2020; Teixeira and Lopes, 2020; Linka et al., 2020). To reduce the rate of spread of the virus, governments worldwide imposed travel bans on international transport followed by more local mobility restrictions and lockdowns. This caused an immediate and strong decline in human mobility during the first wave of the pandemic (Hu et al., 2021; Chinazzi et al., 2020; Teixeira and Lopes, 2020; Linka et al., 2020). Studies exploring the effects of the COVID-19 pandemic on cycling represent a growing body of research. Many have used BSS data as a baseline for cycling mobility patterns (Shang et al., 2021; Hu et al., 2021; Kim, 2021; Kubaľák et al., 2021), with very few using counters capturing total bicycle traffic at specific locations (Doubleday et al., 2021; Büchel et al., 2022). Most authors considered BSS data to be representative of overall cycling patterns in cities, despite rapid changes in potential ridership, for example due to travel bans, and few studies considered the additional impact of weather on patterns of use.

To our knowledge no study has been published that has a) explored variation in cycling mobility using both counter data and the proxy of BSS and b) has controlled for effects of weather on variation in these patterns. Both of these effects are important since counter data nominally capture all bicycle use but only at selected locations, while BSS typically have more extensive spatial coverage but only indirectly measure actual cycle use.

Thus, we define our research questions as follows:

- How did the COVID-19 pandemic and three weather parameters (temperature, precipitation and insolation) impact bicycle-sharing mobility patterns during the first year of the COVID-19 outbreak in Paris?
- Are the patterns of mobility and their relationships to weather and lockdown measures captured in bicycle-sharing data replicated in data captured by a network of bicycle counters?

2. Materials and methods

2.1. Study area

Paris is the most populated urban region of France with some 2.2 million inhabitants in the city of Paris, and more than 12 million in the adjoining urban agglomeration. The public transport service RATP operates an integrated public transport system in the Paris region (Ile de France) including metros, trams, buses, and RER trains, recording around 3.3 billion trips per year. Its infrastructure includes 206 km and 302 stations belonging to 16 metro lines, 117 km of regional train lines (RER) with 66 stations, a tramway network of 105 km and 4,700 buses. Paris was the sixth most visited city in the world in 2018 with 17.5 million tourists. Bicycle infrastructure is also highly developed with more than 1,000 km of cycle paths by the end of 2020.

Paris has a typical Western European climate, affected by its proximity to the Atlantic. The overall climate throughout the year is mild and moderately wet. Average annual precipitation is 641 mm with relatively light rainfall distributed evenly throughout the year. However, the city is also known for intermittent, abrupt, heavy showers. Summer days are warm and pleasant with average temperatures ranging between 15 and 25C and with a fair amount of sunshine. Spring and autumn usually have mild days and fresh nights but are often subject to unsettled weather. During winter, sunshine is scarce; days are cool, and nights are cold but generally above freezing with low temperatures around 3C. Icy roads, a significant hazard to winter cycling, are unusual.

2.2. Data

2.2.1. Bicycle sharing system

We use data collected from the Vélib fixed docking station BSS that has been in operation since 2007. The system includes 1,400 stations in the Paris region (Ile-de-France), 20,000 bicycles of which 35 % are e-bicycles, and had 400,000 registered users in 2020. Despite (or perhaps

[1] Retrieved from https://www.smovengo.fr/wp-content/uploads/2020/08/Smovengo_Rapport-annuel_2019.pdf, October 28, 2021.

because of) the COVID-19 pandemic, 2020 was a record-breaking year in terms of use, including a monthly record of 5.5 million trips (September 2020) and a daily trip record of 215,000 trips was set on 11th September 2020.[2]

Our Vélib raw dataset contains information about station locations and capacity, together with temporal information on changes in the number of available bicycles at individual stations over time. The resolution of registered changes is 5 min. Thus, every record in the dataset represents a change in the number of available bicycles at a station within 5 min. Paris' urban area is covered by a total of 1,004 Vélib stations (Fig. 1). Bicycle IDs are not stored, so origin–destination journeys cannot be extracted directly.

Since the information available to us is the number of bicycles available at an individual station at any given time, we define bicycle ridership as the difference between the number of available bicycles at the start and at the end of a given time interval at a station. This measure is sensitive to temporal resolution - lower temporal resolutions may miss throughput of bicycles as they are docked and then removed within the temporal bins. We defined temporal resolution as one hour - a compromise between capturing all possible changes to the system and a useful temporal granularity over which to aggregate.

Paris is administratively structured into 20 *arrondissements*, each of which is further sub-divided into 4 *quartiers*. Since spatial aggregation reduces the effects of individual station errors or biases and many aspects of Parisian life are adapted to local quartiers, including transportation, education, shopping, health, and policing, we spatially aggregated BSS counts to quartiers, with on average 13 stations assigned to each quartier.

2.2.2. Bicycle counters

A network of bicycle traffic counters has been developed over Paris since 2010 (Fig. 1). The counters are distributed across the city and designed to capture important bicycle flows throughout Paris. The company 'Ecocompteur' that runs the Paris counters claim an accuracy of more than 95%[3] and counters are rarely out of order so provide a reliable record of bicycle flows throughout the year. Counter data are published as hourly counts of bicycles at counter locations, and in 2020, 50 counters were in operation for the whole year.

However, as is visible in Fig. 1, some counters are placed very close to one another. It is not unusual for these counters to be paired, measuring unidirectional flows of traffic, where for example separated bicycle lanes are found on opposite sides of wide streets. In such cases we summed counts to create a single counter measurement, reducing the total number of count locations to 40.

Since we have a well distributed set of counters across the whole city of Paris, which nominally captures all bicycle movements, we consider the counter data to be representative of behaviour as a whole in Paris in 2020, albeit with reduced spatial granularity in comparison to the 1,004 BSS stations, even when aggregated to 80 quartiers. The temporal granularity of one hour is fine enough to capture lagged responses to weather conditions, and allows us to compare BSS and counter data across all of 2020.

2.2.3. Weather data

We consider three aspects of weather in this study: precipitation, insolation and temperature. These capture the conditions in Paris most likely to influence discretionary bicycle travel. For example, we expect bicycle use to decrease on rainy days, increase on sunny days, and be generally positively correlated with temperature (Nosal and Miranda-Moreno, 2014; De Chardon et al., 2017; Kim, 2018; Wang et al., 2018). High winds and icy conditions are rare in Paris, and therefore not considered. We chose an interval of one hour for weather data, aligned to the bicycle counter temporal resolution, since this has been found sufficient to capture responses of cyclists to weather (Gebhart and Noland, 2014; Nosal and Miranda-Moreno, 2014, Pazdan et al., 2021). Although most trips are shorter than an hour, we expect to see a lagged effect from weather events on hourly counts.

The weather dataset was obtained from Météo-France, France's national weather service, and data were collected at the Paris-Montsouris meteorological station in the south of Paris (Fig. 1). Given Paris' relatively compact size and topography, we assume this station to be broadly representative of temperature and precipitation in the city as a whole (Fig. 2).

2.3.4. COVID-19 lockdown in Paris

To represent the effects of the COVID-19 pandemic on cycling behaviour we created a dataset capturing important events related to the outbreak in France in 2020. We included three types of events – imposition of restrictions (e.g. lockdowns), their relaxation and public holidays likely to influence behaviour. We selected events from the official French government chronology of the COVID-19 outbreak and governmental responses.[4] We additionally linked these events to the stringency index – a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to values between 0 and 100 created by the Our World in Data team.[5] We used stringency values with a daily temporal resolution in our statistical analysis.

2.4. Analysis

We used a combination of visual and statistical analytical methods to explore spatial and temporal patterns in the use of Vélib and general bicycle usage in Paris in 2020. Table 1 catalogues the raw data used in our analysis and analytical approaches taken, as well as the independent variables used to represent both weather and the effects of COVID-19 on bicycle-related mobility in Paris.

We initially constructed a series of visualizations to explore patterns in bicycle counts. Firstly, we created dynamic plots to visualise the anomaly in use of individual stations, by plotting signed χ-scores (Wood et al., 2010) calculated with respect to baselines of average daily system use between January 6th and March 1st 2020.

$$\chi = \frac{count - baseline}{\sqrt{baseline}} \tag{1}$$

This baseline represents counts with respect to observed data prior to the effects of COVID-19 in Paris, and explicitly excludes the Christmas holiday period. As with any calculation of anomalies, changing the baseline period would result in changes with respect to the anomaly.

Two graphical representations were used to plot anomalies - line plots of individual station anomalies, and heatmaps vertically ordered by absolute counts of station use. Both representations were annotated with important events related to the COVID-19 pandemic, as illustrated in Fig. 3. The visualizations were implemented dynamically, allowing individual stations to be selected and viewed in conjunction with a representation of their locations in Paris,.

A third heat map-based representation plotted average hourly absolute counts across Paris over monthly periods, with the aim of capturing changes in absolute mobility at hourly intervals on individual days of the week during the pandemic.

We carried out a statistical analysis of average daily counts to explore the influence of both the COVID-19 pandemic and weather-related

[2] Retrieved from https://www.velib-metropole.fr/service, November 5, 2021.

[3] Retrieved from https://www.eco-compteur.com/expertise/compter-les-velos/, November 8, 2021.

[4] https://www.gouvernement.fr/info-coronavirus/les-actions-du-gouvernement.

[5] https://ourworldindata.org/grapher/covid-stringency-index.

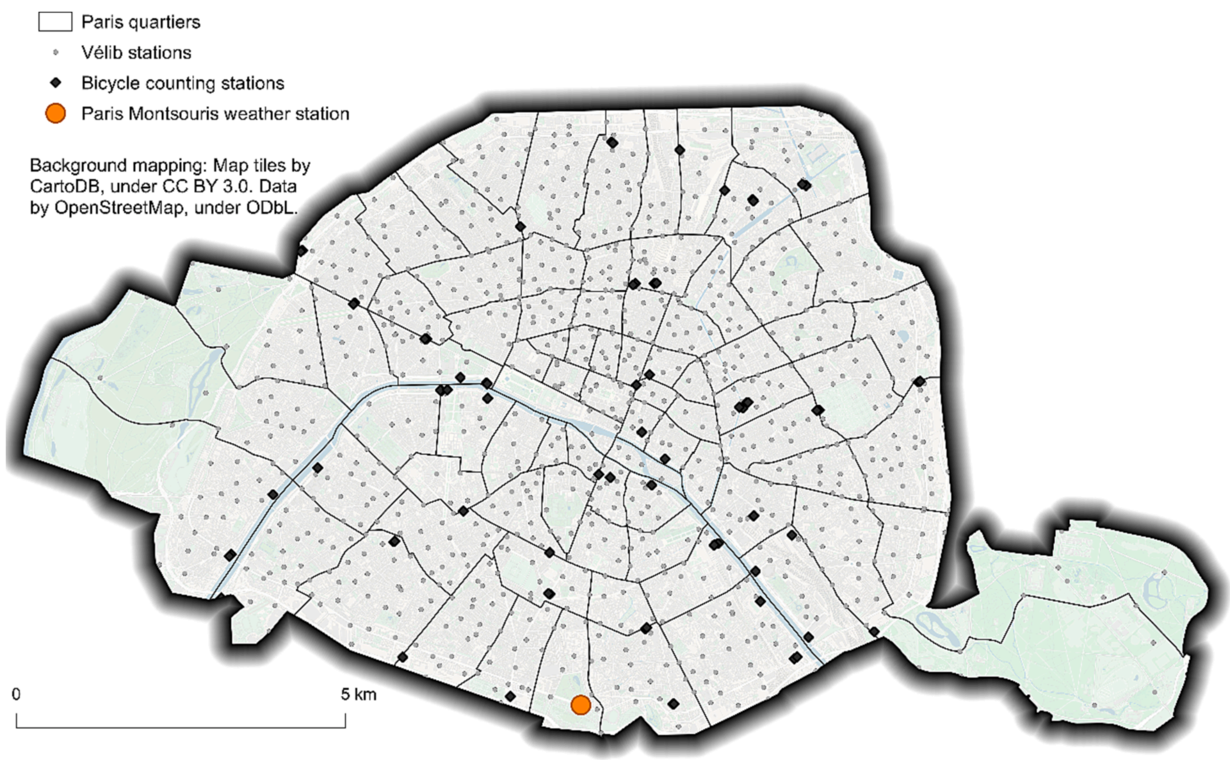

Fig. 1. Locations of Vélib docking stations and bicycle counting stations in the quarters of Paris.

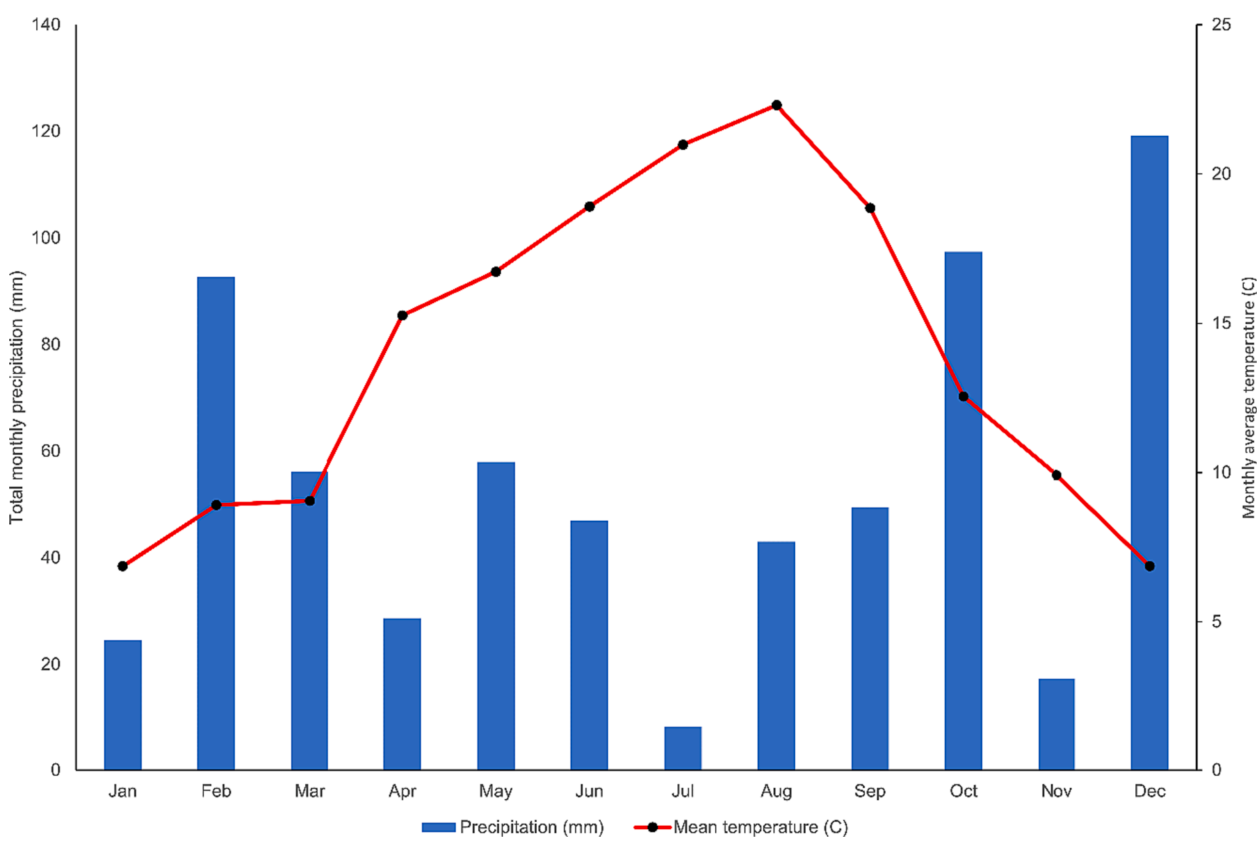

Fig. 2. Monthly total precipitation and mean temperature at Paris-Montsouris in 2020.

Table 1
Overview of the analytical process and data aggregation.

Dataset	Raw data	Visual analytics			Statistical analysis
Vélib BSS	1004 stations recording changes in bicycle availability every 5 min	Daily line plots of anomaly in count per quartier	Heatmaps of anomaly in count per quartier	Monthly summary of average hourly docking station count per day	Negative binomial regression of hourly docking station counts
Bike counters	50 locations, hourly counts	Daily line plots of anomaly in count	Heatmaps of anomaly in count per count station	Monthly summary of average hourly count per day	Negative binomial regression of hourly docking station counts
Weather data	Hourly mean temperature, total insolation and precipitation	NA	NA	NA	Hourly temperature, insolation and precipitation used as independent variables
COVID-19	Key events and daily stringency index	Events indicated on plots	Events indicated on plots	NA	Daily stringency index
Aggregation		Hourly counts aggregated to calculate daily anomalies; BSS stations aggregated per quartier; unidirectional counters aggregated	Hourly counts aggregated to calculate daily anomalies; BSS stations aggregated per quartier; unidirectional counters aggregated	Hourly counts averaged over month and week day for the city of Paris	Counts aggregated over Paris as a whole; separate models for whole year and quarters

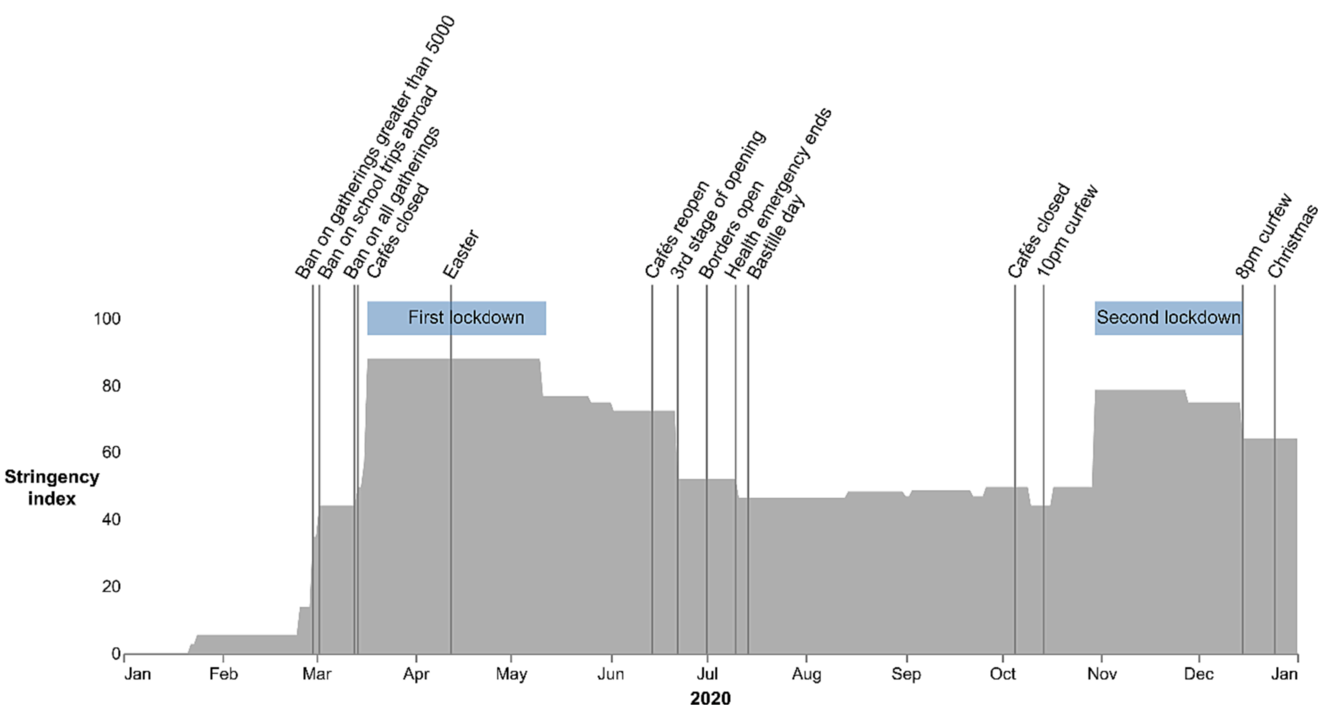

Fig. 3. Significant events COVID-19 related events and the stringency index in Paris in 2020.

influences on both the Vélib system and overall bicycle use as captured by counters in 2020. Consistent with prior approaches (e.g. Kim, 2018; Gebhard and Noland, 2014; De Chardon et al., 2017) we modelled bicycle counts using negative binomial regression. This allows us to relate the relative contribution and significance of weather and stringency measurements to changes in the overall count of bicycle trips. The influence of weather was represented using hourly average temperature, hourly total precipitation and hourly total insolation. To capture the effects of the COVID-19 pandemic, we used the daily stringency index as an additional independent variable.

3. Findings

The effects of COVID-19 lockdown on bicycle sharing use in Paris were first analysed at a daily level. Daily cycling activity for each 80 quartiers for BSS data and 40 counter locations for overall cycling activity recorded in the city were plotted with respect to COVID-19 events (Fig. 4)[6].

The first large anomaly is observed at the start of March, shortly before lockdown where a sudden peak is visible, especially in the BSS data. We interpret this as a shift to bicycles as people sought to avoid public transport before the first lockdowns. The initial lockdown is visible in both datasets, though more strongly in the BSS data, suggesting strong compliance with the measures introduced. As measures are relaxed, we see greater use of both BSS and bicycles overall, with variations suggesting leisure use, for example at weekends and over the Easter break. A dip in usage in the summer holiday period is apparent, before increased usage as people returned to work onsite in late August. Later in autumn usage decreases, with a sharp drop as a second lockdown was introduced in October, and a curfew in December. Both

[6] Interactive visualizations of Figs. 4, 5 and 6 can be viewed at https://jwolondon.github.io/tripParisVis/.

Fig. 4. Line plots of anomaly in BSS use per quartier (top) and counter locations in 2020 (bottom).

datasets show considerable variance between stations, which make the plots more difficult to interpret. Nonetheless, it is clear that the overall pattern of use in the longer term reflects stringency measures and that similar patterns are visible in both datasets.

To observe patterns of use in more detail, we used heatmaps of signed anomalies, ranked by magnitude of usage (Fig. 5). These representations allow us to not only capture the broad pattern of usage described above - for example the sudden peak of usage of the BSS for a few days before the major dip during lockdown, with a slight upturn over Easter, but also allow us to compare stations more reliably. Most notable here are the differences during the second lockdown, where in both BSS and counter data we observe that the downturn of the system varies in space, with some quartiers and locations (presumably linked to permitted commuting for essential workers for example) subject to much less of a downturn (c.f. pale orange strips and pale blue strips from late October until shortly before Christmas).

Fig. 6 shows absolute average counts over quartiers (for BSS) and over counter locations. Since we are observing systems of different natures - in the case of BSS we count all usage of the Vélib system, which makes up a proportion of total bicycle use in Paris, while counters count bicycles of all types at specific locations - then the absolute values are not directly comparable. Nonetheless, we see strong correspondences between both systems. Pre-pandemic, clear commuter use with diurnal peaks is visible, while during the first lockdown usage decreases globally. However, some use of bicycles remains visible, especially in the morning/ evening for counters, potentially reflecting travel of essential workers. As measures are relaxed and then reimposed over the summer and autumn we note that the strength of the commuter peaks decreases (e.g. in June) and that some new behaviours become visible - for instance a peak in use of both BSS and other bicycles on Saturday afternoons in November.

Combining the three visualization approaches allows us to effectively describe many patterns of cycling behaviour in Paris qualitatively at differing spatial and temporal scales. Thus, in Fig. 4 we gain insights as to overall behaviour in time, and can identify possible outliers to this behaviour. In Fig. 5 patterns of use in individual quartiers is visualized, and it is possible to qualitatively compare anomalies and their timing between quartiers. Finally, Fig. 6 summarises daily temporal patterns of

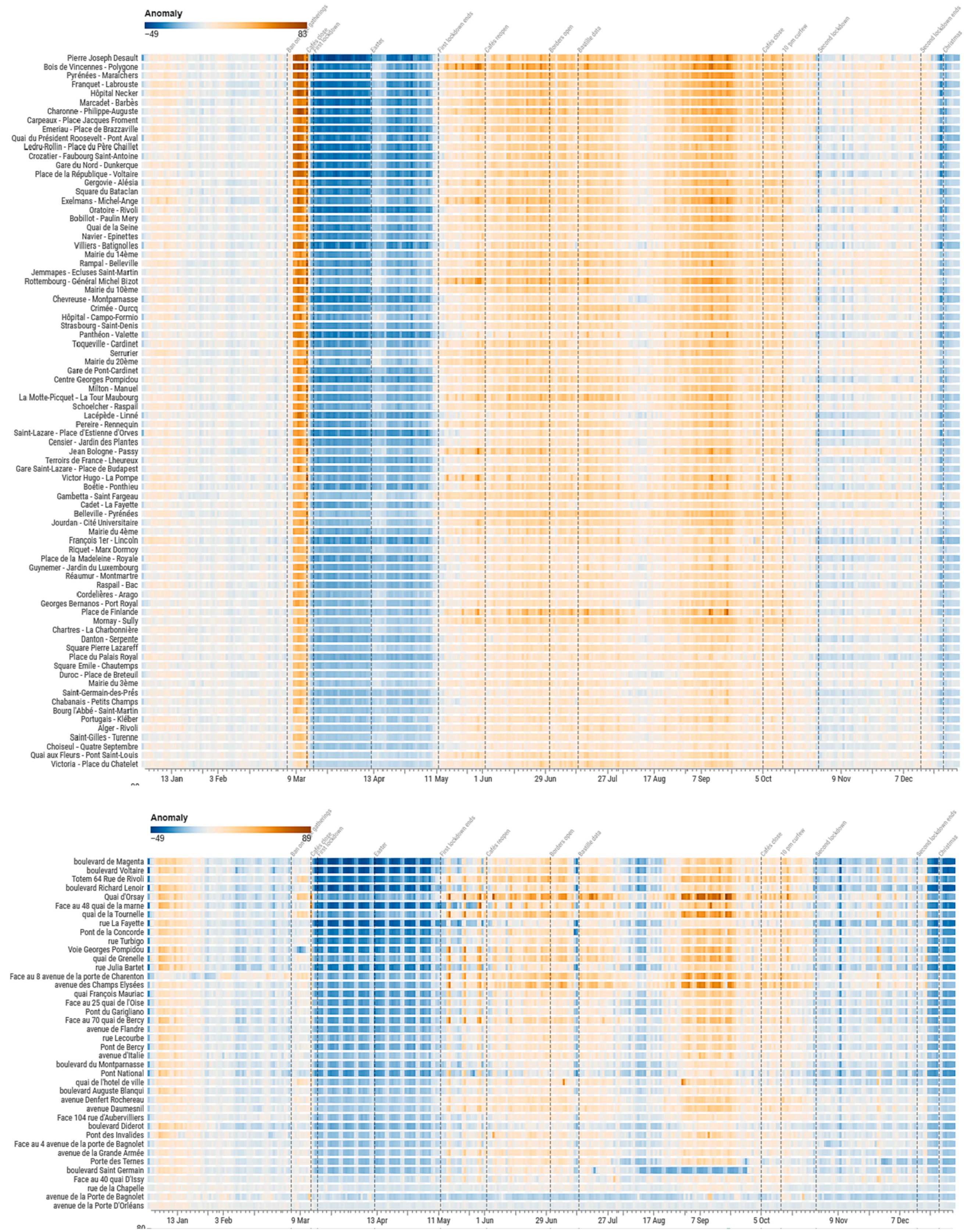

Fig. 5. Heat maps of signed anomaly vertically ordered by use for BSS per quartier (top) and counter locations (bottom).

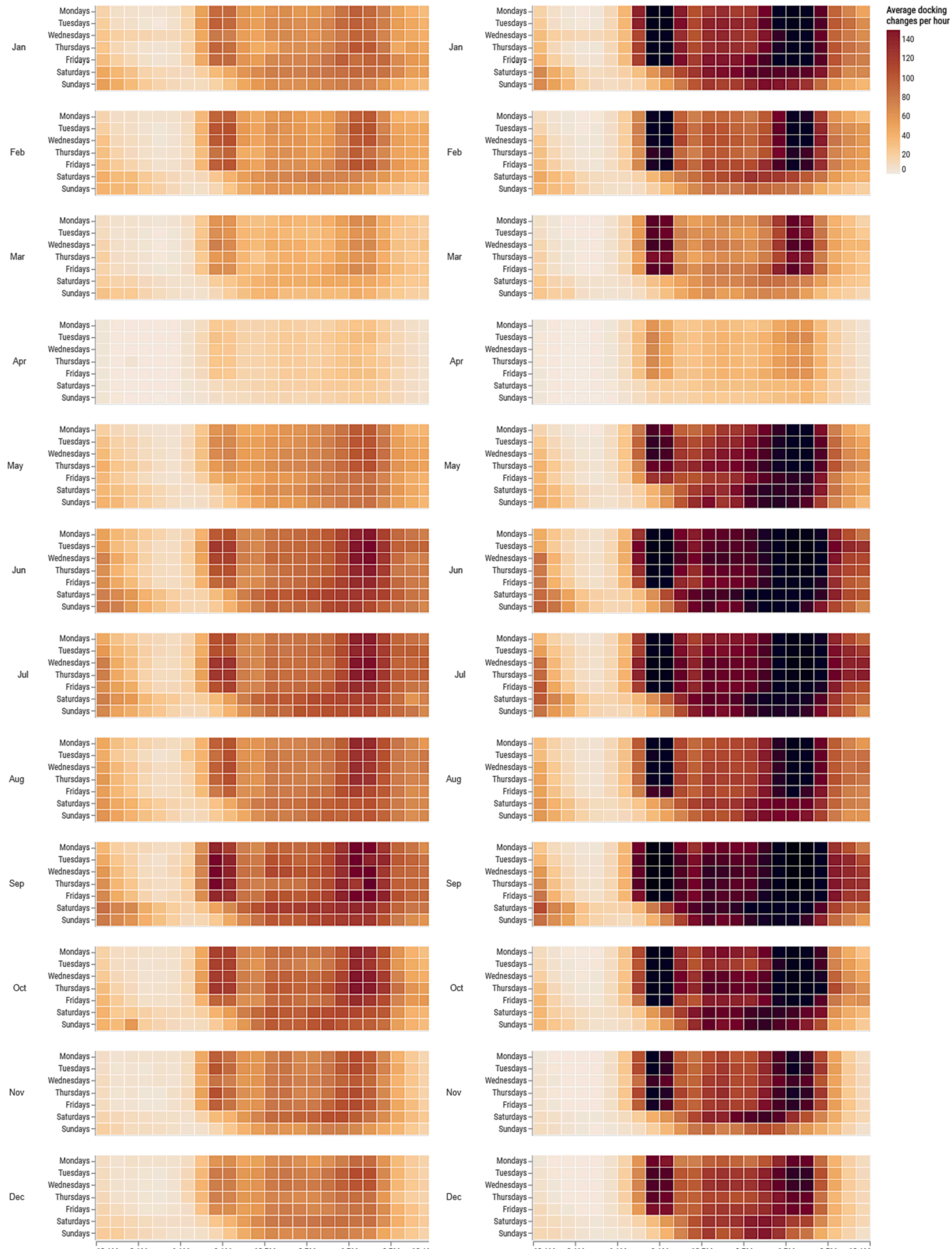

Fig. 6. Daily and hourly variation in average use of bicycles per month per quarter for BSS (left) and counter data (right).

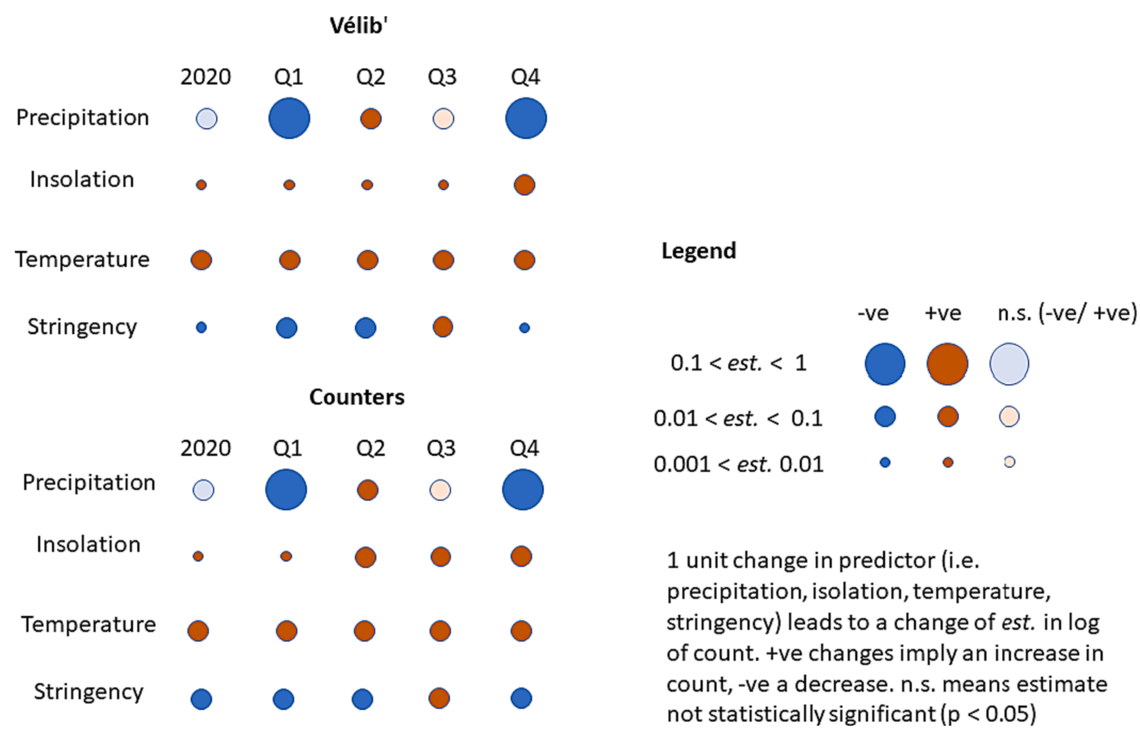

Fig. 7. Visual summary of the results of negative binomial regression on bicycle counts for BSS and counters. Circle size indicates effect size; hue indicates direction of relationship; colour lightness indicates statistical significance.

use across the whole city for the BSS and counter networks, giving a higher temporal but coarse spatial resolution to the results.

However, robust interpretation also requires us to understand how bicycle use is influenced by other factors, especially weather. To pick apart the influence of stringency and weather we carried out a negative binomial regression. The results of this analysis are visually summarised in Fig. 7.

The statistical analysis is useful in a number of ways. Firstly, it confirms that both bicycle counter and BSS data exhibit very similar behaviour. For example, Fig. 7 reveals that both measures of cycling volume respond to precipitation and temperature identically. This result is important, since it confirms that BSS data are a reliable proxy for overall cycling behaviour, in a study using a large number of counter locations (40). Indeed, direction and significance of all variables predicting count are identical, while small variations in the magnitude of the estimates are present. Precipitation leads to a decrease in bicycle use in Q1 and Q4, during the colder months of the year. Increases in insolation and temperature are always predictors of increased usage of bicycles. Finally, bicycle use generally decreased where stringency increased, except during Q3 where we observe the opposite effect for both systems. The results for Q1, Q2 and Q4 again suggest general conformity with stronger measures (lockdowns and stay at home orders were in force during all of these periods). Q3 was the period of the pandemic with the lowest stringency and also coincides with the French holiday period, which as we observed above led to a general decline of bicycle use, coincident with a decrease in stringency.

4. Discussion

This paper has considered the use of BSS and counter data to explore cycling behaviour in the city of Paris. We used a combination of visualization and statistical analysis to explore the comparability of these two data sources, and the influences on cycling behaviour in 2020. Since behaviour generally in 2020 was strongly influenced by restrictions imposed as a result of the COVID-19 pandemic, it is an ideal test year to explore both the sensitivity of bicycle use to major mobility shocks and how aligned BSS use is with direct bicycle counts. The impacts of COVID-19 provide a non-weather-related control over behaviour that allow us to both assess and account for weather-related measurements. In the following, we explore the key results found, comment on the strengths and weaknesses of the methodological approaches taken and relate our results to previous work.

The proposed visual analytics methods revealed behavioural changes at hourly, daily and monthly levels. The visualizations allowed us to see fluctuations in cycling activity at different temporal scales in Paris over the first pandemic year. The immediate signal resulting from the first wave of the pandemic was rapid and obvious, and of particular note was the rapid increase in use of bicycles across all of Paris immediately before the first lockdown. This suggests bicycle travel and BSS have a potentially important role in acting as a 'buffer' in response to external mobility shocks. More generally, the visualization suggested a strong link between lockdown events and use of bicycles, with easing of measures resulting in increased demand. By changing temporal scales, we observed ways in which demand shifted through the day, flattening morning and evening rush hours, while maintaining overall demand during the day.

The visualization also prompted questions, since peaks and troughs in usage were visible at different spatial scales which did not appear to be driven by COVID-19. We used a negative binomial regression model to link the effects of COVID-19 (stringency index) and weather (precipitation, insolation and temperature) effects on cycling in Paris for bike sharing and counter data. The results were remarkably consistent for both datasets, with both temperature and insolation effects significantly positively correlated with cycling over the whole year and during all quarters. On the other hand, the effects of precipitation on cycling demand were negative over the year as a whole, but vary consistently between the two datasets over calendar quarters. This suggests that despite an obvious utility function, bicycle use is significantly discretionary in character, even in the presence of strong external constraints such as lockdown and pandemic-induced reluctance to use public transport. Unlike most existing work (e.g., De Chardon et al., 2017; Hyland et al., 2018), increased precipitation was not associated with a decrease in cycling in two quarters (Q2 & Q3). In these quarters we also note a switch in the influence of stringency measures, from a negative to a positive correlation. We suggest that these results demonstrate that the abrupt and sharp increase in bicycling induced by the end of 'stay at home' order in Paris, that lasted until the imposition of a new lockdown in October was broadly resistant to weather influences. Given the extreme nature of COVID-19 impacts on behaviour in France (with relatively strict stay at home orders and restrictions) our results point to the importance more generally of considering environmental factors in modelling disruptive events such as transport strikes (Saberi et al., 2018).

Regarding weather effects in cycling more generally, our findings are broadly in line with the results of others (e.g., De Chardon et al., 2017, Hyland et al., 2018) when it comes to temperature and insolation effects. Positive precipitation effects on cycling were not reported in any of reviewed studies. However, few authors have compared the combined effects of weather and COVID-19 measures, with the notable exception of Büchel et al. (2022) who used weather as input data to model baseline behaviours in Switzerland. Our results point to the importance of disentangling multiple factors on behaviour. Even after aggregation to quartiers we had 80 data points per hour for Vélib data and 40 for counter data, allowing us to perform robust regressions.

Our analyses of COVID-19 impact on cycling showed similar results to existing studies. The changes in cycling traffic induced by the pandemic – reduced during strict restrictions, but recovering quickly, had similar trends to other studies using BSS (Shang et al., 2021; Hu et al., 2021; Kim, 2021) and counter data (Doubleday et al., 2021; Büchel et al., 2022). Our comparative study shows clearly that BSS and counter data show very similar patterns and relationships in both our qualitative and quantitative analysis. Since these two datasets are independent, this is good evidence that BSS data capture well the overall pattern of bicycle usage in Paris. Furthermore, these data have finer spatial granularity than counter data due to their much denser network of stations. Since BSS data exist in many cities, and basic counter data are often available through APIs, this result is encouraging, because it suggests a possible route to fine-grained spatial and temporal studies of bicycle use, without resorting to expensive counter networks.

The methods and data sources we have adopted here provide a useful approach for establishing detailed baseline behaviour for those analysing post-pandemic mobility responses. It could be productively combined with other methods for understanding demographics and behaviour (e.g. the survey-based investigation of cyclists' motivation explored by Adam et al., 2023). Paris, like several other major cities, has retained new infrastructure that was built to support cycling during the pandemic (Buehler and Pucher, 2021). Our approach, which reveals spatial detail in behaviour change, could inform planning of further infrastructure as well as inform city managers of changes in behaviour during major disruptions to the system. Our interactive visualizations are resolved to individual quartiers in Paris, allowing exploration of geographic variations in behaviour in time.

Nonetheless, our approach has several important limitations. First, our results are clearly sensitive to the spatial and temporal aggregations we chose. In particular, the choice of quartiers for counts may mask important local spatial variation. Second, the stringency index we used to explore the impacts of COVID-19 in our statistical analysis integrates multiple measures which influence different sorts of cycling behaviour in different ways. For example, during lockdowns people were encourage to work from home, while exercise by bicycle was still permitted or even encouraged – thus commuting cycling likely decreased at high stringency index values while some recreational cycling probably increased as has been observed in other studies (Hu et al., 2021; Doubleday et al., 2021). Third, no information about individual cyclists is available that would allow deeper mobility change analyse, for example, based on social stratification or gender, both known to be important predictors of some forms of cycling behaviour (Hu et al., 2021, Beecham and Wood, 2014b). Finally, the network of bicycle counters in Paris is underdeveloped compared to the BSS network with respect to density and therefore spatial analyses with finer granularity are not possible using counter data.

5. Conclusions and further work

In this paper we set out to explore and compare cycling behaviour captured through two sources: counts of activity at 1,004 fixed stations of the Vélib bicycle sharing system in the city of Paris, aggregated to 80 quartiers, and bicycle counts captured on the Paris street network at 40 locations.

Our results demonstrate that:

- Bicycle sharing station data are an effective and reliable proxy for both qualitative (as captured in a range of dynamic visualization) and quantitative (comparing bicycle use to weather and COVID-19 stringency) patterns of overall bicycle use as captured by bicycle counters.
- Cycling behaviour responded rapidly to specific events during the COVID-19 pandemic in Paris, and behaviour patterns (e.g. use of bicycle at different times of day and reduced commuter peaks) are visible.
- Overall bicycle use in Paris was influenced more strongly over the year as a whole by precipitation than COVID-19 stringency, while temperature and insolation have influences of a similar magnitude.

Our approach, which combines dynamic visualization with more traditional statistical analysis is flexible, and indeed we have already produced visualizations for other cities using both BSS and counter data. In future work we plan to explore in more depth the spatial pattern of responses to other forms of disruption on the network through events such as strikes, holidays and festivals.

CRediT authorship contribution statement

Stefan S. Ivanovic: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft. **Jo Wood:** Conceptualization, Methodology, Software, Writing – review & editing, Visualization. **Ross S. Purves:** Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – review & editing, Visualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data and code related to this paper are available on FigShare at https://doi.org/10.6084/m9.figshare.24231706.

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