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Evacuation patterns and socioeconomic stratification in the context of wildfires

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Abstract

Wildfires are becoming more frequent and intense, leading to increased evacuation events that disrupt mobility and socioeconomic structures, impacting access to resources, employment, and housing. Understanding the interplay between these factors is crucial for developing effective mitigation and adaptation strategies. We analyse evacuation patterns during the wildfires that occurred in Valparaíso, Chile, on February 2-3, 2024, using high-definition mobile phone records. Applying a causal inference approach combining regression discontinuity and difference-in-differences, we focus on socioeconomic stratification to isolate the wildfire impact on different groups. We find that many people spent nights away from home, with the lowest socioeconomic group staying away the longest. Overall, people reduced their mean and median night-to-night travel distances during the evacuation. Movements initially became irregular but later concentrated in areas of similar socioeconomic status. Finally, we demonstrate a comparability potential of the mobile phone records to the Facebook Disaster Maps, although the latter have a coarse time resolution and are generated only after the wildfire onset. Our results highlight the role of socioeconomic differences in evacuation dynamics, offering valuable insights for response planning.

Keywords: Computational social science; Natural disasters; Wildfires; Emergency response; Human displacement; Socioeconomic inequalities; Evacuation patterns; Mobile phone data; Social media data

1 Introduction

The increasing frequency and severity of natural disasters are part of a broader trend related to climate change that has become evident in recent years [1–3]. As global temperatures rise, the incidence of wildfires is expected to increase, forcing governments and international organisations to reassess and improve their response strategies. Beyond changing weather conditions, human activities, such as the construction of settlements and infrastructure near flammable vegetation, have also intensified the frequency of wildfires [4]. The impact of wildfires extends beyond immediate physical and economic damage. It also leads to increased exposure to air pollution, which affects the health of people, especially those in the low-income strata [1], and contributes to the significant release of greenhouse gases, with the potential to further accelerate global warming [5]. Therefore, response plans should not only enhance the adaptive capacities of communities, especially in areas prone to climate-related disasters, but also address broader challenges related to health and forest management.

Such an event unfolded on the night of February 2-3, 2024, when severe wildfires ravaged the well-known and touristic area of Valparaíso, Chile. This was the country's worst natural disaster since the earthquakes in 2010, and the most devastating wildfire in the past 30 years. The disaster resulted in 137 deaths, left 1600 people homeless, and directly affected more than 16,000 people [6]. In response, the Chilean Government declared a State of Emergency and Catastrophe, and the Health Ministry issued a Sanitarian Alert, leading to curfews and the deployment of additional firefighting and rescue teams. Further, the Ministry of Health responded by hiring medical students to alleviate pressure on the healthcare system [7]. Despite all these efforts, the emergency response faced numerous challenges; the wildfire caused extensive damage to drinking water supply systems and severely affected the health situation. A UNICEF humanitarian report highlighted the importance of delivering the necessary supplies and services to the most affected population, the majority of whom were children and adolescents [8]. Many residents were forced to evacuate from their homes, seeking shelter elsewhere. These challenges highlighted vulnerable points in actual response policies and underscored the need for improved emergency strategies.

Telecommunication and GPS data are invaluable tools to follow-up on such rapid behavioural changes, enabling real-time, high-resolution observations for a large number of individuals. For instance, in the 2019 Sonoma wildfires evacuation process, researchers used GPS data to systematically analyse and identify different groups of evacuees [9]. Similar data have been used to develop a knowledge database to store evacuation plans for typical population distributions, significantly accelerating the process of finding near-optimal evacuation plans for urban emergency management [10]. Estimation of real-time population movements during large disasters has been carried out using various kinds of mobile phone data and data assimilation techniques, combined with simulation of population movement and observation data, to estimate prediction accuracy and find ways to improve it [11]. GPS data was used in a study conducted on evacuation behaviours during four earthquakes in Japan to show that an individual's evacuation probability depends on the intensity of the seismic they experience [12]. At the same time, the distance travelled during evacuation does not appear to depend on the intensity of the seismic event itself.

In addition to telecommunication and GPS data, social media data have become valuable tools for disaster monitoring. Facebook Disaster Maps (FBDM) have been used to study evacuation mobility patterns during the two mega-fires in California, USA, in 2018 [13]. In that study, the FBDM was found to be representative of the California population, and analysis indicated three stages in evacuation mobility dynamics: a drastic decrease after the evacuation order, a significant increase near open shelters or nearby towns, and a gradual return to baseline after the lifting of the evacuation order.

Diverse adaptation capacities to emergency scenarios following a natural disaster due to living, employment, and financial conditions can affect groups with divergent socioeconomic characteristics differently. Through understanding of such inequalities, effective response strategies can be developed to compensate for the various impact effects during emergencies. Social vulnerabilities have been found to significantly impact evacuation decisions during wildfires, with notable differences between geographic areas [14]. In the same study, by analysing individual characteristics, unemployment emerged as a critical factor that negatively influences both the timing of evacuation and the distance traveled to their evacuation destinations. However, the impact of social vulnerabilities (such as being impoverished or non-white) on evacuation rates varied significantly across different census block groups, and their effects on departure delays and destination distances were found to be more uniform. Furthermore, evacuees with higher income were found to be more likely to evacuate from affected areas and reach safer locations with less damage to housing and infrastructure [15]. These differences were common among evacuees within and outside mandatory evacuation zones. Meanwhile the trends of population recovery after a displacement were found to be quite homogeneous among different socioeconomic groups [16]. Similarly, community resilience, defined as a function of the magnitude of impact and recovery time, was assessed from GPS data during Hurricane Harvey, uncovering pronounced socioeconomic and racial disparities in evacuation and recovery patterns [17]. Racial and wealth disparities have been found to be important in evacuation patterns, with disadvantaged minorities being less likely to evacuate than wealthier Caucasian residents [18].

In this paper, we investigate the impact of natural disasters on post-crisis human behaviour in the context of Chile. This country has long experienced severe socioeconomic inequality and spatial segregation, which exacerbate the potential impact of natural disasters on vulnerable populations [19, 20]. By analysing the Valparaíso wildfire as a case study, our aim was to understand its implications on the behaviour of different socioeconomic groups of the population to observe adoption capacity differences. We demonstrate how lower socioeconomic groups exhibited longer displacement durations and delayed departures. We also compare our observations to similar data collected by FBDM to validate aggregated disaster maps when confronted with more precise individual-level data from mobile phone records. By comparing these datasets, we offer a novel analysis of human mobility during disasters, revealing their complementary strengths. Additionally, we address methodological challenges, such as identifying home locations and socioeconomic status, while acknowledging the broader applicability of our findings to other natural disasters. Finally, we outline prospects for future research and emphasise the importance of industry partnerships in disaster management for effective resource allocation.

2 Methods

For our investigations, we use anonymised data provided by a major mobile phone operator in South America (Telefónica Movistar[1]), with a market share of 27% in 2023 [21]. The observed mobile phone population moderately correlates with the official population at the census zone level ($\rho = 0.36$, see Supplementary Fig. 1), a fine-grained intermediate area between the block and the census district.[2]

The original XDR dataset records activity around telecommunication towers at 15-minute intervals throughout the day. However, the aggregated XDR dataset specifically captures information about unique phone IDs and the telecommunication towers to which they are connected most frequently each night (from 12:00 am to 05:00 am) during the

[1]Hereafter mainly referred to as the mobile data provider.

[2]User manual for the database of the 2017 population and housing census, Department of Demography and Censuses, National Institute of Statistics of Chile, September 2018 (file in Spanish). Available at: this link.

specified periods (see [22]), providing a more reliable indicator of relocation patterns. The Valparaíso region, where the analysis is conducted, includes 594 telecommunication towers.

The analysis encompasses two periods: November 11-17, 2023 and January 19-February 19, 2024. The intervals from November 11-17 and January 19-February 1 represent baseline mobility patterns. These baseline periods, taken together, enable precise identification of local residents, with the November interval accounting for seasonal tourism fluctuations in the Valparaíso region, typical of January and February, the summer holidays period in the Southern Hemisphere. The February 2-19 interval captures mobility patterns during and after the wildfire event.

To determine socioeconomic status in the context of the lack of accurate self-reported socioeconomic attributes, we assign an approximate socioeconomic profile to the individual according to their inferred home location. However, in the literature, there is little consensus on the optimal criteria to implement when creating decision rules for home detection methods [23]. Pappalardo et al. having thoroughly evaluated 37 home location algorithms, concluded that the most efficient approach based on XDR records is the TC-WK-19-7 [24] which considers as home the most frequent antenna between 7 pm and 7 am during weekdays for approximately two weeks [25]. Thus, we adopt the TC-WK for our analysis with added restrictions and validations, which we detail below, to account for factors proper to the area and time under analysis (i.e., a popular tourist destination during summer).

We infer individuals' home locations by estimating for each of them their most visited tower during the night (from 12.00 am to 05.00 am), a much more conservative measure than usual [25]. We assume that the tower is an individual's home location if (1) it is their most visited tower for at least six nights between 19 January and 1 February 2024, and (2) it is their most visited tower for at least five nights during a "business-as-usual" week, between 11 and 17 November 2023. These conditions help to ensure that the individuals included in our sample are part of a local population that can be seriously affected by the wildfire. Using this approach, we successfully assigned home locations to 126,129 unique phone IDs out of the 282,118 unique phone IDs in our dataset. Among these, 115,600 (91.65%) retained the same home location assignment across both baseline periods: 11-17 November 2023 and 19 January - 1 February 2024. These individuals are the focus of our further analysis on relocation patterns.

During the analysis of changes in human behaviour, we differentiate among three groups of individuals.

- *Potentially affected* are those who spent one night from January 31 to February 2 near towers within a 5-kilometre radius around the areas warned (143 towers that received a warning about the wildfire and a need to evacuate).
- *Likely evacuated* is a subgroup of potentially affected with a home location within the affected area and who were away from their home tower at least once during the nights from January 31 to February 4.
- *Not affected* are individuals observed outside the 5 km warned areas on the corresponding nights and used as a control group for comparison.

Following our definition of potentially affected, likely evacuated and not affected, we have 156,896 potentially affected unique phone IDs and 200,851 not affected ones. Of them, we could identify stable home locations for 47,487 and 54,637 unique phone IDs,

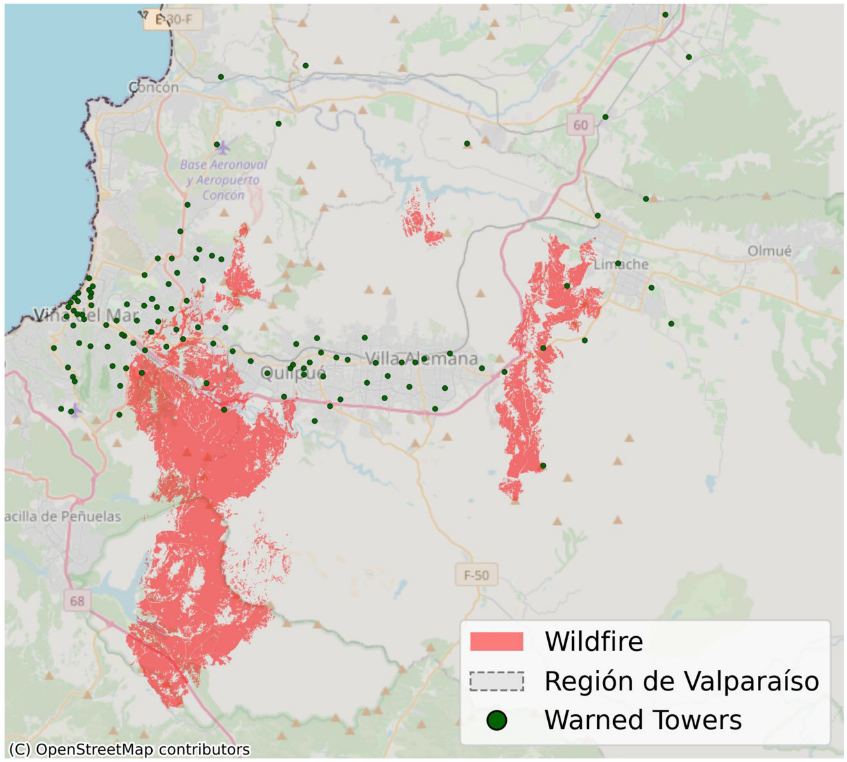

Figure 1 *Map of the areas affected by the wildfire and spatial distribution of the warned towers.* Overall, users around 143 telecommunication towers received a warning message

accordingly. Potentially affected people include 28,676 unique IDs of likely evacuated people (60.38% of potentially affected with inferred home locations). Figure 1 presents a map of the areas affected by the wildfire, along with the spatial distribution of the warned towers. Some of the wildfire-affected areas lack telecommunication towers, as they are largely unpopulated regions within a national park.

Having inferred the home locations of individuals in the dataset, we assign each person an estimated socioeconomic status based on the socioeconomic status of their home tower. The socioeconomic status of the home tower, in turn, is determined by the census zone in which the tower is located. In our dataset, the Valparaíso region includes 674 census zones, 94 of which are in areas affected by the wildfire. On average, each census zone covers 1.36 square kilometres, contains 1.53 telecommunication towers, and has a total population of nearly 2436 people. More detailed statistics and distributions for census zones can be found in the Supplementary Sect. 3.

Based on this census data, we use the percentage of people with higher education as a proxy for socioeconomic status and divide districts into three socioeconomic groups: Low, Medium, and High. We consider a socioeconomic division based on population quantiles: each socioeconomic quantile (bin) contains the same number of individuals, determined based on the population sizes of the corresponding census zones. Table 1 shows the distribution of identified mobile phone users in each sociodemographic group according to their home location. More detailed explanation for different socioeconomic groups and spatial distribution of telecommunication towers according to the inferred socioeconomic class can be found in the Supplementary Sect. 4.

Table 1 *Socioeconomic Distribution of Unique Mobile Devices Among Affected Groups.* Number of unique Phone IDs

Group	Low	Medium	High
Potentially Affected	12,334	18,929	16,224
Likely Evacuated	7059	11,226	10,391
Not Affected	19,646	17,549	17,442

The interference of some biasing events required additional preprocessing of our data. We addressed some outliers by removing movements that did not match typical travel patterns one week prior. For instance, an unexpected increase in movement within the 'not affected' group, particularly among those in the medium socioeconomic group, was found to be linked to a local festival in the broader area. Additionally, anomalies observed in the low socioeconomic group on specific dates were attributed to a likely communication tower malfunction. To account for this, we excluded users affected by the tower issue when it did not interfere with our main wildfire analysis. These changes helped smooth out irregularities and provided a more accurate representation of user behaviour. At the same time, more caution must be exercised when describing the results, particularly regarding the socioeconomic differences.

As demonstrated later in this paper, we also use the Facebook Population in Crisis Data as a robustness check for our analysis [26]. After aligning the two datasets in terms of spatial and temporal resolution, we observe strong correlations between the baseline populations in these areas, as computed from both datasets. Additionally, we find moderately strong correlations in the changes observed during the post-crisis period. These findings validate the connections between the two datasets and support the robustness of our subsequent analysis. A detailed comparison is provided in Sect. 3.4.

2.1 Causal modelling

2.1.1 Regression discontinuity in time

We applied a Regression Discontinuity in Time (RDiT) design to assess the causal effects of people's travel patterns before and after the wildfires [27]. In this context, treatment refers to compensating for the impact of wildfires that affected the local population and potentially forced people to relocate. Our RDiT design is based on the assumption that, in the absence of treatment, evacuated people would continue their daily routine movement and there would be no noticeable discontinuity. Since time cannot be assigned randomly, another traditional Regression Discontinuity Design's assumption of local randomisation cannot work in this scenario. In our modelling, we place greater emphasis on controlling for variables that could obscure the effect of wildfires on human displacement patterns, such as weekday mobility trends. To account for heteroskedasticity and autocorrelation, the Newey-West variance estimator is used. Our model is defined as:

$$\mathrm{Y}_t = \alpha + \beta \cdot \Delta_t + \gamma \cdot \mathrm{threshold}_t + \delta(\Delta_t \times \mathrm{threshold}_t) + \theta \cdot \mathrm{Controls}_t + \epsilon_t,$$

where Y_t is the dependent variable of choice, typically representing either the fraction of people who leave their home towers or the average distance travelled (in km) at time t. Δ_t represents time (in days) relative to the threshold, which is defined as the wildfire event that provoked evacuation, occurring during the night from February 2 to February

3. The term threshold_t is an indicator variable that equals 1 if time t is after the threshold. The coefficient β captures the effect of time on the dependent variable of choice, while γ represents the immediate effect of the wildfire event (threshold) on the dependent variable. The coefficient δ indicates how the effect of time changes after the threshold. The term $\theta \cdot \text{controls}_t$ represents control variables, specifically accounting for weekday effects, which capture differences in the dependent variable based on the day of the week, from Monday to Sunday. Finally, ϵ_t is the error term.

Further modifications include socioeconomic classes and their interaction with the threshold value. This interaction term indicates changes in a dependent variable of choice corresponding to a particular socioeconomic class after the beginning of the wildfire.

To further assess the robustness of our results, we test alternative model specifications by including time polynomials in the model. This allows us to capture potential non-linear trends in the data that a linear time variable might miss. Our analysis shows that including time polynomials does not change the main findings, indicating that the results are robust to different functional forms of time (see Supplementary Sect. 9, Tables 2, 3).

2.1.2 Difference-in-differences

The second approach we employ is the Difference-in-Differences (DiD) method, which is used to estimate causal effects by comparing changes in outcomes over time between a treatment group and a control group, before and after an intervention [28]. In our case, the treatment group are those people who were evacuated due to wildfires, while the control group is the non-affected population, according to our definitions above.

The DiD design relies on the parallel trend assumption, which is key in identifying the causal effect. The parallel trend assumption implies that, in the absence of intervention (in our case - wildfires), both the treatment and control groups would behave the same. Our further analysis reveals that the treatment and control groups exhibit parallel trends in their pre-wildfire behaviour, supporting the assumption that, in the absence of the intervention, both groups would have followed similar trajectories. We also assume that there are no spillover effects: the treatment effect is confined to the treated group and does not affect the control group, which is reasonable taking into account our earlier definitions of evacuated, affected, and non-affected populations. This assumption is supported by the geographic and temporal scope of the wildfire, which was largely contained within specific areas.

DiD analysis helps control for factors that change over time but are not related to treatment, assuming that these factors affect both the treatment and control groups in the same way. Our model is defined as:

$$\mathrm{Y}_t = \alpha + \beta \cdot \text{threshold}_t + \gamma \cdot \text{treatment}_t + \delta(\text{threshold}_t \times \text{treatment}_t) + \theta \cdot \text{Controls}_t + \epsilon_t,$$

where Y_t represents the dependent variable of choice, usually the fraction of people away from their home towers or the average distance travelled (in km) at time t. The term threshold_t is an indicator variable equal to 1 if time t is after the threshold event. treatment_t is an indicator variable equal to 1 for evacuated people (treatment group) and 0 for non-affected people (control group). The coefficient β captures the effect of time on the dependent variable of choice, while γ represents the difference in the dependent variable between the treatment and control groups before the wildfire. The term δ is the

Difference-in-Differences estimator, showing the differential effect of the wildfire on the treatment group relative to the control group. The $\theta \cdot \text{Controls}_t$ term represents control variables, including weekday effects (which capture the differences in the dependent variable based on the day of the week) and Δ_t (which represents time in days relative to the threshold). Finally, ϵ_t is the error term.

As in the case with RDiT, additional modifications also include socioeconomic classes and their interactions with the treatment and threshold variables. This "triple" difference-in-differences indicates changes in a dependent variable of choice corresponding to a particular socioeconomic class of the likely affected people after the beginning of the wildfire compared to those not affected. We also add time polynomials for robustness check and see that they do not alter the main findings, ensuring results' robustness to the different functional forms of time.

Using RDiT and DiD together, we show how wildfire (intervention) affected population groups differently based on socioeconomic status, providing insight into the effectiveness of emergency responses and the disparities in impacts on different populations. Using the coefficient γ near the threshold term in the RDiT design, we can capture changes in displacement patterns exclusively for likely evacuated individuals. In DiD, the main coefficient of interest is δ near the difference-in-differences interaction term, as it additionally compares changes in displacement patterns relative to the control group of not affected people. Our dual approach provides insight into both the overall effect of the wildfire and the differential impact on various population subgroups.

3 Results

3.1 Measuring evacuation rates and travelled distances

To assess behavioural differences between affected and unaffected groups, we analyse aggregated patterns of human behaviour after the onset of wildfires in Chile. Initially, we look at the fraction of people who evacuated from their home[3] on the night of the fire. The "fraction of residents" metric represents the fraction of individuals who spent the corresponding night away from their home tower location. Figure 2a shows a clear difference between the three types of population observed. Before the wildfire, the percentage of people away from home rarely exceeded 20% among all the groups analysed. However, after the night when the wildfires struck (2-3 February), this percentage increased for likely evacuated people to more than 60%, while the trend for non-affected people remained more or less the same. This difference remains clear between the three groups for the weeks following the natural disaster.

Both regression discontinuity (Supplementary Table 2) and difference-in-differences (Supplementary Table 3) models showed a statistically significant increase in the fraction of likely evacuated people who had to spend nights away from their home, especially compared to unaffected people. For example, after the onset of the wildfires, the fraction of evacuated individuals spending a night away increased by an average of 0.269, compared to the same set of people before the wildfire (all else being equal), or an average of 0.116, when compared to the control group of non-affected (all else being equal). This result highlights the substantial impact of the wildfires on the displacement patterns of the affected population, which, in turn, supports the validity and precision of our methodology

[3] Hereinafter, "home" refers to the inferred home tower.

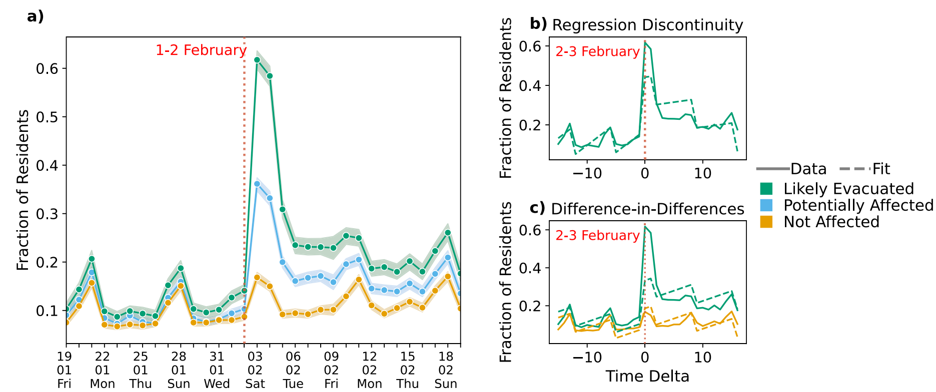

Figure 2 *Fraction of individuals whose night location was different from their home location. a)* Fractions of individuals by three group types (Not Affected, Potentially Affected, and Likely Evacuated), with a 95% confidence interval. 95% CI obtained through bootstrapping the fraction of moved people by iteratively resampling the original dataset (1000 times) with replacement, each time generating a sample representing around 10% of the population. *b)* Fractions of likely evacuated people as observed in the data and inferred with the regression discontinuity in time model. *c)* Fractions of likely evacuated and not affected people as observed in the data and inferred with the difference in differences model

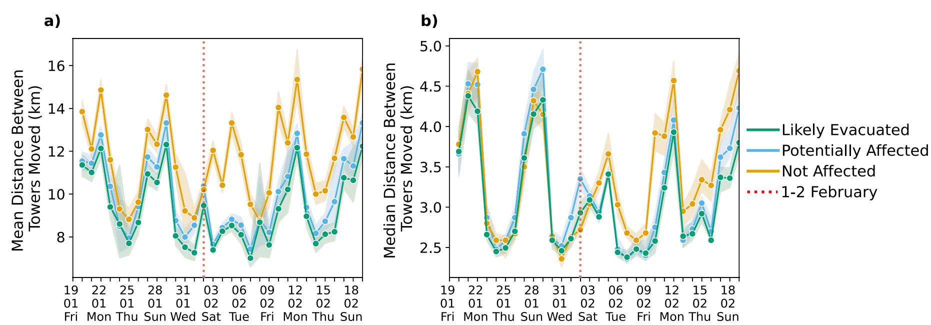

Figure 3 *Travelled distances between the towers (only for individuals who moved to another tower). a)* Mean travel distances by three group types (Not Affected, Potentially Affected, and Likely Evacuated), with a 95% confidence interval. *b)* Median travel distances by three group types (Not Affected, Potentially Affected, and Likely Evacuated), with a 95% confidence interval

in identifying target populations. Figures 2b and 2c compare the fitted models against the observed data.

In addition, we explore the distances between the most visited towers every night for each individual before and after the beginning of the wildfire. Figure 3 shows the mean (3a) and median (3b) travel distances for those individuals who moved to a different tower at night. Despite seeing before that the fraction of evacuated people who spent a night away noticeably increased, both mean and median travelling distances of the evacuated people in kilometres rather decreased compared to the previous weeks. This suggests that, although more people having moved due to the wildfire, they did not go that far from their home, rather choosing relatively close areas (e.g. shelters, relatives, and friends) for relocation.

For those not directly affected, the mean distance moved showed little change compared to the previous week. However, the median distance travelled exhibited a drop similar to that of the evacuated people at the onset of the wildfires, with subsequent movement patterns returning closer to pre-wildfire levels. These differences in behavioural patterns may reflect an interesting dynamic. When wildfires impact a region, even those unaffected may alter their travel behaviour (e.g., avoiding certain areas or staying closer to home), which could result in a reduction in median displacement. In this case, although most people may still travel long distances, a shift in the distribution (with more people staying near home) could cause the median to decrease. However, the mean would remain relatively stable if the longer-distance movements in other areas of Valparaíso continued as before.

When applying regression discontinuity and difference-in-differences, we observe a statistically significant decrease of 0.47 km in the median travel distances for evacuated individuals, compared to their pre-wildfire median distances (Supplementary Table 6), and a reduction of 1.71 km in their average travel distances (Supplementary Table 4). In comparison to the non-affected population, the overall drop in the median distance in the post-wildfire period was approximately 0.46 km (Supplementary Table 7), and around 1.15 km in the average (Supplementary Table 5). These findings suggest that a greater proportion of evacuated individuals sought refuge in relatively nearby locations, rather than travelling long distances.

3.2 Socioeconomic differences in displacement patterns

After identifying general trends and differences between likely evacuated and not affected populations, we can examine further variations in the behaviours of different socioeconomic groups. Due to a lack of accurate self-reported socioeconomic attributes, we assign an approximate socioeconomic profile to the individual according to their inferred home location. As the inferred home location corresponds to a census zone, we divided available census zones into three socioeconomic groups (Low, Medium, and High) using the percentage of people with higher education as a socioeconomic proxy. Each socioeconomic group contains a similar number of individuals.

Figure 4 illustrates the differences in trends among the three socioeconomic groups. Although there are no noticeable differences between these groups for the unaffected population before or after the wildfires, the variations for the potentially affected and likely evacuated populations are significant. Firstly, the people in the lowest socioeconomic group stayed away from their homes for a longer period. The same is true for the medium socioeconomic class compared to the richest, although this difference is considerably smaller. Secondly, the highest proportion of the lowest socioeconomic class was reached the day after similar peaks occurred for people of medium and high socioeconomic classes. This may imply that certain people from lower socioeconomic areas needed more time to adapt to the crisis.

Regression models confirmed significant statistical differences in behavioural responses between different socioeconomic groups after the onset of wildfires. For example, compared to previous time periods, the fraction of evacuated individuals from the medium and high socioeconomic classes who had to spend a night away from their home towers was lower by 0.058 and 0.086, respectively, compared to the low socioeconomic class (Supplementary Table 2). This difference between socioeconomic groups was not statistically significant before the natural disaster occurred. Compared to the control group of non-affected individuals, only the fraction for the high socioeconomic class was significant, being 0.085 lower (Supplementary Table 3). Figures 4d and 4e compare the fitted models against the observed data.

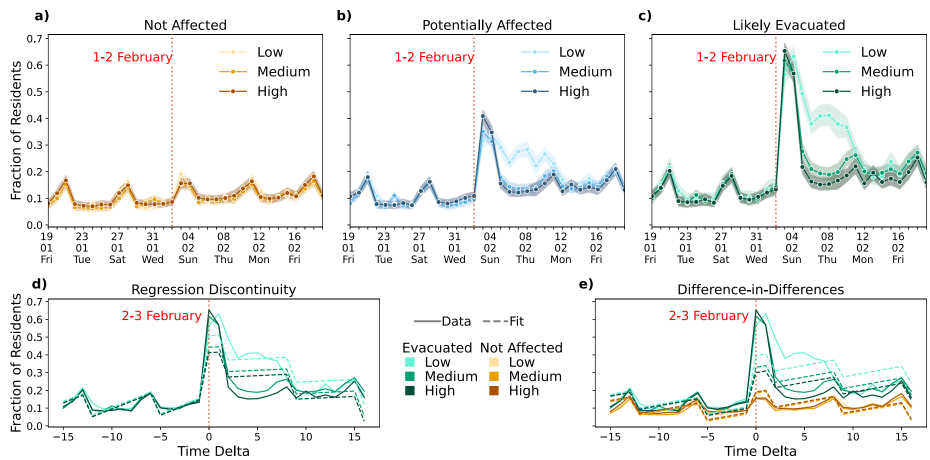

Figure 4 *Fraction of individuals whose night location was different from their home location by socioeconomic status. a)-c)* Fractions of individuals by three group types (Not Affected, Potentially Affected, and Likely Evacuated) and by socioeconomic status (Low, Medium, High), with a 95% confidence interval. 95% CI obtained through bootstrapping the fraction of moved people by iteratively resampling the original dataset (1000 times) with replacement, each time generating a sample representing around 10% of the population. *d)* Fractions of likely evacuated people (by socioeconomic status) as observed in the data and inferred with the regression discontinuity in the time model. *e)* Fractions of likely evacuated and not affected people (by socioeconomic status) as observed in the data and inferred with the difference-in-differences model

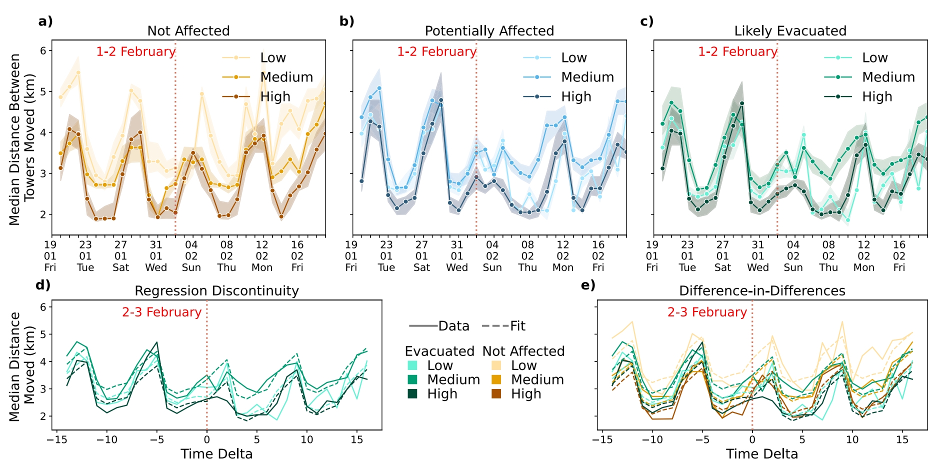

Figure 5 *Median travel distance between the towers by socioeconomic status (only for individuals who moved to another tower). a)-c)* Median travel distances of individuals by three group types (Not Affected, Potentially Affected, and Likely Evacuated) and by socioeconomic status (Low, Medium, High), with a 95% confidence interval. *d)* Median travel distances of likely evacuated people (by socioeconomic status) as observed in the data and inferred with the regression discontinuity in time model. *e)* Median travel distances of likely evacuated and not affected people (by socioeconomic status) as observed in the data and inferred with the difference-in-differences model

When we look at the median kilometres travelled by individuals from different socioeconomic classes (Fig. 5), it appears that there is a greater variation between socioeconomic classes even within the non-affected sample. Regressions confirm this statistically significant difference, showing that, compared to people of lower socioeconomic status, people of the rich and middle classes move on average a shorter distance, by 1.153 and 0.857 km, respectively (Supplementary Table 7) .[4] However, once we focus on the impact of the wildfire on mobility, we still see a significant decrease in travel distances for the likely evacuated people. Nevertheless, in this case, there are no statistically significant variations between the socioeconomic groups in the likely-evacuated group compared to the control group. After the beginning of the natural disaster, people from all socioeconomic groups experienced a similar decrease in their median travel distances, moving from one tower to another. When focusing solely on the median movement of those likely evacuated before the wildfire, we observe similar results, with no statistically significant differences between the socioeconomic groups (Supplementary Table 6). A comparable analysis of the mean movement also showed no statistically significant differences between the socioeconomic groups after the beginning of the wildfire (see Supplementary Sect. 6).

While describing these differences between socioeconomic classes, it is important to emphasise that our data enables us to picture general trends and behavioural patterns. However, the dataset does not offer enough detail to fully explore the underlying reasons behind these differences. Future research with more granular data could help to uncover the specific factors driving these variations in movement behaviour.

3.3 Investigating socioeconomic segregation in displacement

In this study, we define socioeconomic segregation as the stratification of individuals or groups based on socioeconomic characteristics, as reflected in spatial (residential) and mobility patterns. Previous research has found significant differences in daily routine mobility behaviours between different socioeconomic groups [29, 30], as well as socioeconomic biases towards specific areas within cities [31]. Building on this foundation, this section aims to investigate how socioeconomic status influences displacement patterns, providing new insights into the relationship between mobility behaviours and socioeconomic inequalities.

To understand the effect of socioeconomic segregation on displacement patterns, we use the assortativity coefficient. The assortativity coefficient represents the correlation coefficient of stratification matrices, which is widely used in the study of human mobility patterns [32]. The stratification matrix illustrates the aggregated movement of individuals between areas of different or similar socioeconomic classes. Given the normalised matrix $\tilde{X}$, where the trips between i and j are normalised over the total trips that occur in the system, we calculate the *assortativity* ρ with the Pearson correlation coefficient of the matrix entries, across all income groups.

$$\rho = \frac{\sum_{i,j} ij\tilde{X}_{ij} - \sum_{i,j} i\tilde{X}_{ij} \sum_{i,j} j\tilde{X}_{ij}}{\sqrt{\sum_{i,j} i^2\tilde{X}_{ij} - (\sum_{i,j} i\tilde{X}_{ij})^2}\sqrt{\sum_{i,j} j^2\tilde{X}_{ij} - (\Sigma_{i,j} j\tilde{X}_{ij})^2}}$$

Researchers have already shown that, in the context of urban mobility, people tend to visit places of the same socioeconomic class more often [32, 33]. We use the assortativity coefficient to determine whether displacement patterns during wildfires exhibit similar segregation. A completely assortative matrix will have an assortativity value of $\rho = 1$, indicating that displacement is highly segregated, with individuals from similar socioeconomic backgrounds moving to the areas of the same socioeconomic status. In contrast,

[4]Given that the wildfire occurred near the city of Valparaíso, and the entire affected area is quite urbanised, a distance difference of 1.1 km is substantial in this context.

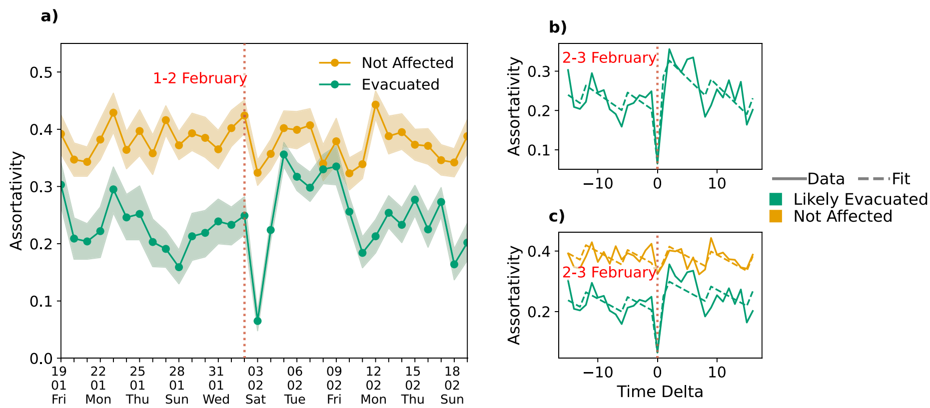

Figure 6 *Assortativity of people who changed night towers. a)* Assortativity over time for two groups of people (Not Affected and Likely Evacuated), with a 95% confidence interval. The 95% CI was obtained through bootstrapping the assortativity values of moved individuals by iteratively resampling the original dataset (1000 times) with replacement. For each resample, an assortativity measure was computed using a heatmap representing movement patterns between socioeconomic categories, capturing the variability in assortativity over time. *b)* Assortativity of likely evacuated people as observed in the data and inferred with the regression discontinuity in time model. *c)* Assortativity of likely evacuated and not affected people as observed in the data and inferred with the difference-in-differences model

a completely disassortative matrix will have $\rho = -1$, suggesting that displacement is characterised by individuals from different socioeconomic groups moving to areas with completely different statuses. Figure 6 helps compare the differences in the assortativity values between evacuated and non-affected people.

After the beginning of the wildfire, there was a noticeable drop in assortativity for evacuated people, which is mainly due to the fact that people had to leave their home locations in haste (see Supplementary Fig. 15). If we focus only on the assortativity of those who moved (Fig. 6a), these values also showed a slight drop the first day after, but then reached higher values compared to previous weeks. For the non-affected people, these changes were not differentiable from the previous two weeks. Supplementary Sect. 5 presents further figures and a description of the spatial patterns of movement.

Regression modelling confirms the statistical significance of these changes. Compared to the control group, the assortativity of the likely evacuated people decreased by 0.143 on the first night of forced mobility changes (2-3 February), and their overall assortativity after the beginning of wildfires increased by 0.04 (all else being equal) (Supplementary Table 9). Compared with its time trend before the crisis, assortativity decreased by 0.236 on the first night of forced mobility changes but generally increased by 0.108 during the crisis (Supplementary Table 8). Figures 6b and 6c compare the fitted models against the observed data.

These results suggest that people likely forced to evacuate due to the wildfire initially relocated to areas with varying socioeconomic statuses, indicating that socioeconomic factors were not a significant determinant in their immediate choice of destination (see [34] for a similar phenomenon in long-term relocation). However, after a few days, their movement assortativity increased. This pattern may indicate that evacuees eventually moved to stay with friends or family members, who are more likely to share a similar socioeconomic status.

3.4 Comparing mobile and social media data

As a final step of this analysis, we compare Telefónica data with Facebook Population in Crisis Data [26]. Meta collects crisis data for different types of disasters. These datasets show the number of Facebook users with geolocation enabled on a grid of approximately 2.4×2.4 km, in a time window of 8 hours, correcting for a baseline of Facebook usage before and after emergencies. A particularity of these datasets is that data collection begins after a disaster occurs, and hence the behaviour of the people prior to or during the disaster is not observed, unlike our data. The motivation behind our comparison is to cross-validate the use of Facebook and mobile phone data sets to analyse human displacement patterns during natural disasters and similar crises. This analysis is especially crucial because Meta's crisis data are readily accessible to practitioners and policymakers, providing them with valuable insights into population mobility and displacement.

To create a dataset comparable to that of Facebook's Population in Crisis, we calculated the number of unique mobile devices connected to each tower at 15-minute intervals. These data were also temporally aggregated into 8-hour intervals and spatially by the size of cells in the Facebook grid. A tower belongs to a particular Facebook cell if it is located inside this cell. If a tower does not belong to any cell, it is assigned to the nearest grid, provided the distance is no more than 10 km. Since Facebook data are available from February 4 to February 19, we use the same time frame for our dataset derived from mobile phone data. For the baseline values that indicate the number of people connected to each tower before the crisis, we use the average values from January 19 to February 1. These values were aggregated by weekday and 8-hour time intervals.

After transformation, we compare the Facebook and Telefónica datasets. First, we compare the correlations of different indicators in the two datasets: the average number of people during the pre-crisis period, the percentage changes in the number of people in the post-crisis period compared to the baseline, and the z-scores of these changes. Supplementary Fig. 16 shows the correlations for a specific time and date (Thursday, February 8, 13:00), and Fig. 7 presents the Pearson correlation throughout the observation period. As can be seen, the highest correlation between both datasets is achieved when comparing population baselines, which are calculated as the number of geolocated Facebook users or the number of active phone IDs in the areas under investigation.

Additionally, both percentage change and z-score reflect changes in the number of people present in these areas compared to the pre-crisis period. We observe relatively strong correlations for percentage changes, although there are some periods, particularly on Sundays, when correlation values drop. The correlations of the z-score tend to be lower. In general, the correlation of both measurements tends to be variable; sometimes it is around 0.6, while at other times it drops below 0.1.

After analysing general correlations, we categorised each measurement (percentage change and z-score) into three groups and compared these categories between the Meta and mobile data datasets. These categories represent whether human activity around each tower increased, remained stable, or decreased during the crisis period. The three categories are: Increase (percentage change ≥ 20 or z-score ≥ 2), Stable (percentage change from -20 to 20 or z-score from -2 to 2, excluding border values), and Decrease (percentage change ≤ -20 or z-score ≤ -2). Figure 8a shows an example of a confusion matrix for February 8, 13:00 [35]. To compare classes between data from the two data providers, the

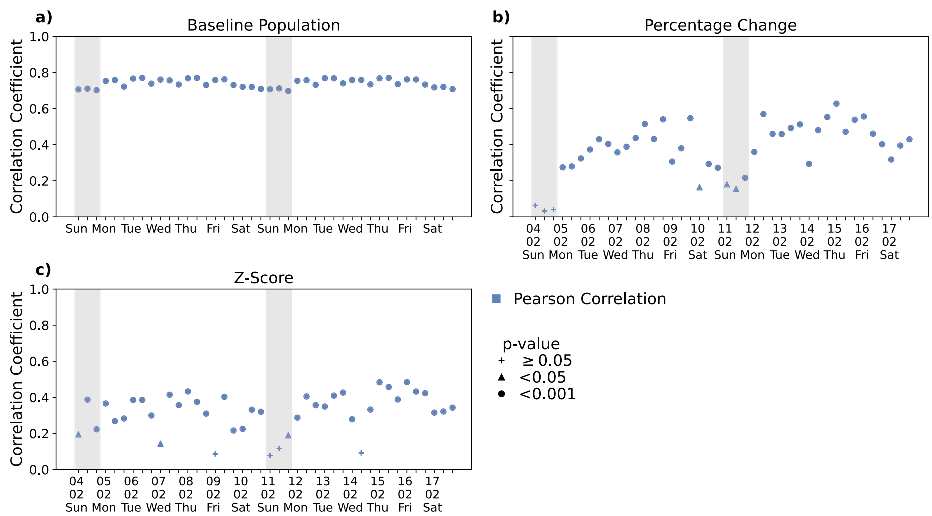

Figure 7 *Pearson correlations between three indicators in Telefónica and Meta datasets across geolocated cells over time. a)* Comparing recorded number of users between two datasets in pre-crisis period over time. Sundays coloured grey. *b)* Comparing percentage changes of users activity before and after the crisis between two datasets over time. Sundays coloured grey. *c)* Comparing changes in z-scores of users activity before and after the crisis between two datasets over time. Sundays coloured grey

following accuracy formula is used:

$$\text{Accuracy} = \frac{1}{N}\sum_{i=1}^{N} \mathbb{I}(y_i = x_i), \tag{1}$$

where N represents the total number of geotiles, y_i is the Meta label for the i-th geotile, and x_i is the Telefónica label for the i-th geotile. The term $\mathbb{I}$ is the indicator function, which takes the value 1 if the condition inside is true (i.e., $y_i = x_i$) and 0 otherwise.

The accuracy score varies from 0 (when there is no overlap between two datasets) to 1 (complete overlap). The confusion matrix score in Fig. 8a is equal to 0.52, indicating that more than half of the geolocated tiles showed similar mobility patterns in both datasets. Figure 8b shows the accuracy score of categorised percentage change over time (for changes in z-score, see Supplementary Figs. 17 and 18). The lowest accuracy typically occurs on Sundays and around 5 am. However, apart from these times, the accuracy scores tend to be relatively high, which means that both datasets reflect mobility changes in a similar way.

4 Discussion and conclusions

Natural disasters, such as wildfires, have a significant impact on communities in affected areas, with some vulnerable populations more exposed to the consequences of the emergency than others [36, 37]. In this paper, we show how wildfires disproportionately affect poorer populations in the Valparaíso region of Chile. We show that individuals from the lower socioeconomic strata left their homes with a one-day time lag and remained displaced for a longer period of time. Additionally, the night-to-night travel distances for evacuated individuals overall decreased, with no statistically significant differences observed between the socioeconomic groups. Furthermore, we identify distinct patterns of

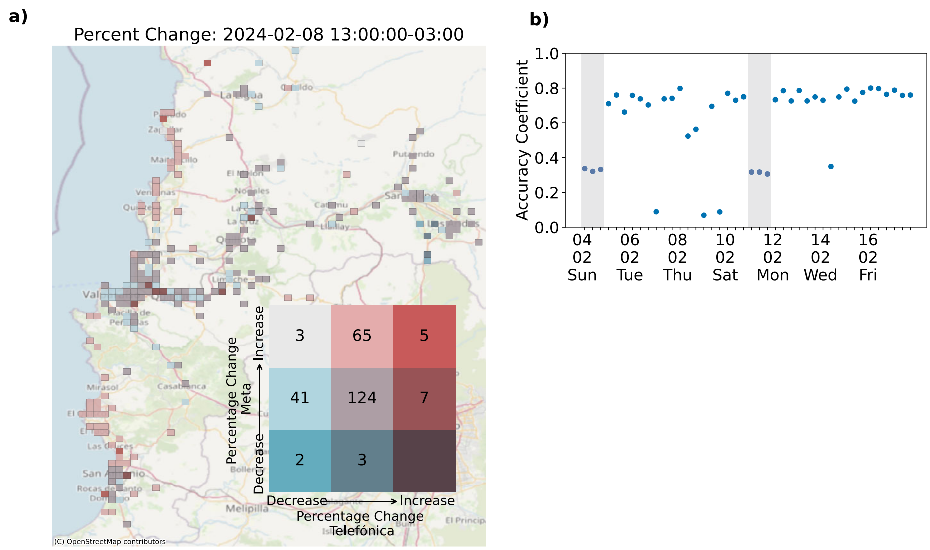

Figure 8 *Percentage changes by geotiles split into categories. a)* Confusion matrix of recorded percentage changes for Thursday, February 8, at 13:00 (GMT-4). Accuracy equals 0.52. The plotted geotiles represent areas that were successfully matched between the XDR Telefónica and Facebook datasets. Since not all areas are populated, the tiles are not uniformly distributed across the entire territory. *b)* Accuracy scores for the percentage change in different time periods. Sundays coloured grey

mobility segregation among evacuated populations, with irregular displacement patterns observed on the first night of the wildfire, followed by more structured movement toward areas of similar socioeconomic status for at least five subsequent nights.

One of the key contributions of our work is the comparative analysis of human mobility using both mobile phone data and Facebook's crisis mobility data provided by Meta. This comparison is important because while mobile phone data offers real-time, continuous monitoring of individuals' movements during the event, the Facebook dataset provides broader population-level insights, albeit with higher temporal and spatial aggregation. Our results show that, while the datasets are inherently different, they exhibit some degree of comparability in recording activity changes over the overlapping period. This finding is significant because it highlights the potential for combining both data sources to create a more comprehensive understanding of displacement during natural disasters.

One limitation in this article is that we analyse the consequences of one single natural disaster: the Valparaíso wildfire. However, the available literature on the impacts of natural disasters in general and wildfires in particular similarly indicates their uneven impact on people of different socioeconomic backgrounds and the subsequent increase in economic inequality [15, 18, 36, 38, 39]. Therefore, we expect similar behavioural patterns to occur in other natural disasters as well.

Other limitations include our choice of heuristics for identifying users' home locations and their socioeconomic status based on census zones. As in the previous limitation, the methods employed are consistent with current research using communication data [25, 34]. Furthermore, the alignment of our results with the findings of previous studies supports the validity and robustness of our methodology.

Future research should focus on differentiating the impact of various types of natural disasters on human mobility and displacement patterns. This is important because different disasters, such as wildfires, floods, and earthquakes, can trigger distinct displacement dynamics due to varying levels of severity, duration, and geographic scope. Understanding these nuances would provide deeper insight into how people respond to specific types of crises, allowing more targeted and effective disaster preparedness and response strategies. In addition, it would help policy makers and humanitarian organisations allocate resources more efficiently based on the nature of the disaster.

Establishing long-term relationships with industry partners is essential for continuous access to data, especially in the context of disaster management. When natural disasters or similar emergencies occur, timely access to data can facilitate the implementation of disaster response plans and enable researchers to develop strategies that ensure equitable access to necessary assistance and resources for those in greatest need.

Abbreviations
DiD, Difference-in-Differences; FBDM, Facebook Disaster Maps; GPS, Global Positioning System; RDiT, Regression Discontinuity in Time; XDR, eXtended Detail Record.

Supplementary information

Supplementary information accompanies this paper at https://doi.org/10.1140/epjds/s13688-025-00540-2.

Additional file 1. (PDF 6.3 MB)

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Author contributions
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Data Availability
The original datasets analysed in this study were provided by a mobile phone company and are not publicly available due to privacy concerns. However, the aggregated and further generated datasets (e.g., for plots), along with the analysis code, are available in the public repository https://github.com/nautim/valparaiso_wildfires.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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