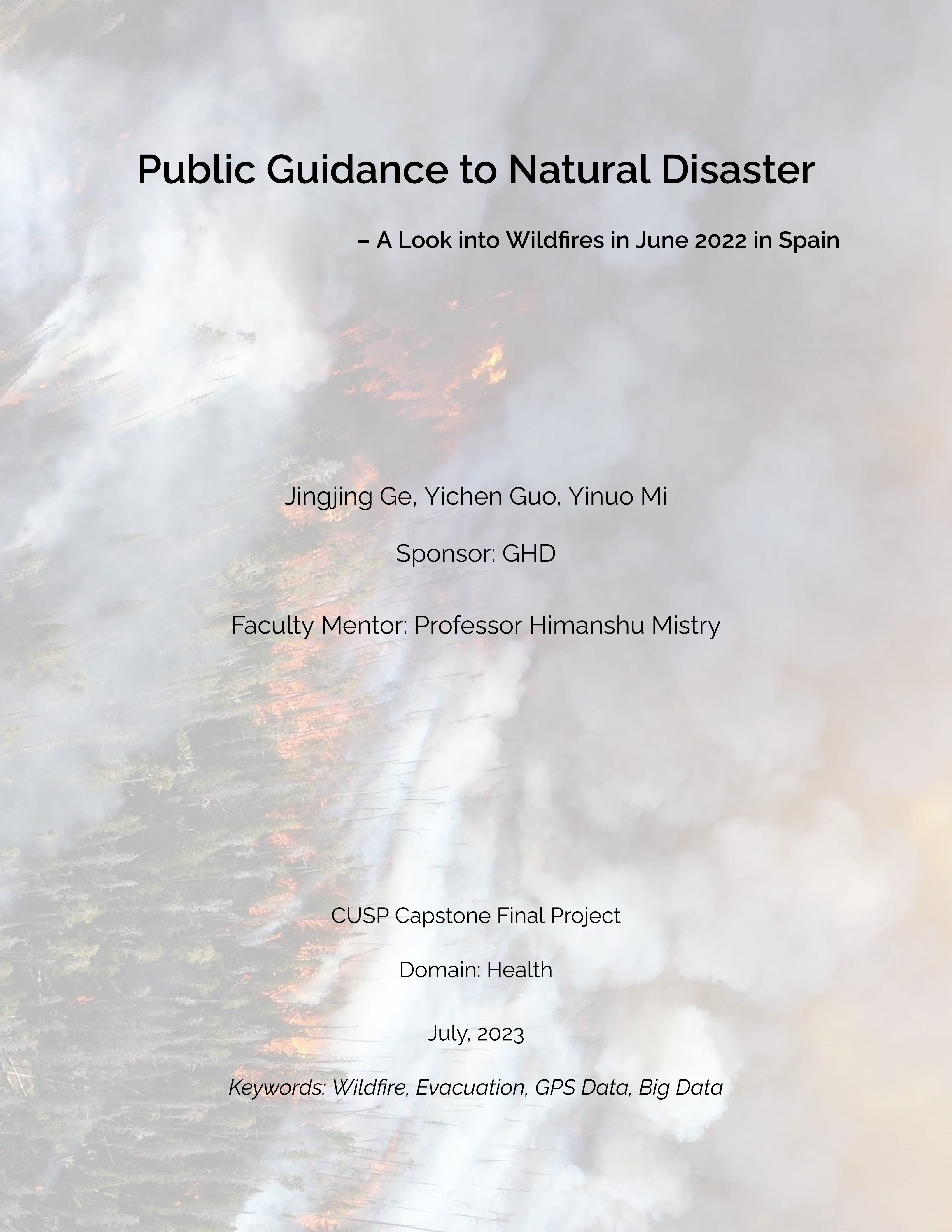

Public Guidance to Natural Disaster

– A Look into Wildfires in June 2022 in Spain

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Domain: Health

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Abstract

Wildfires have gradually become a growing threat to communities worldwide due to climate change, leading to severe environmental and social harms. The rapid urban growth has further led to the expansion of wildland-urban interface (WUI), which resulted in a rise in the number of communities at risk from wildfires. To mitigate the risks associated with wildfires and enhance the safety of communities in the WUI, this project aims to use large scale GPS dataset to analyze wildfire evacuation patterns during wildfire in Spain in June 2022 by adapting proxy-home-location inference algorithm and the evacuation-behavior inference algorithm. The study found that more than half of the residents and nearly 80% of non-residents did not evacuate during the wildfire. Still, shadow evacuees were identified, and residents displayed changes in their movement patterns. The presence of highways across the fire area resulted in a decrease in the number of individuals passing through, suggesting route diversion to avoid the impacted region. The study's findings can guide emergency managers and transportation planners in preparing WUI households for future wildfire events or other natural disasters.

1. Introduction

1.1 Project Overview

Natural disasters such as earthquakes, hurricanes, floods, and wildfires can strike at any time and have devastating consequences. In order to mitigate the impact of these disasters, it is important for individuals, families, and communities to be prepared and informed. Public guidance to natural disasters aims to provide this necessary information and guidance to help people prepare, respond, and recover from natural disasters. As the frequency and intensity of wildfires continue to escalate globally in recent years, it is crucial to improve public guidance on wildfire preparedness and safety. Spain, with its diverse landscapes and varying climate conditions, has experienced a surge in the occurrence and severity of wildfires in 2022. Starting from early June to the end of October, approximately 493 fires were reported and more than 306,000 hectares of area were burnt, hitting the highest record in the last 15 years (EFFIS, 2023).

1.2 Fire information and impact

Our study focuses on the unprecedented wildfires in Spain during 2022, which marked the most severe fire season in the nation's history. The Lleida fire (EMSR 578) affected 3,008 hectares and led to the evacuation of about 800 people. The Navarra fire (EMSR 579) damaged 16,202 hectares and necessitated the evacuation of residents from 15 villages. The Zamora fire (EMSR 580), the most severe, scorched 25,217 hectares and displaced 205 people. The Zaragoza fire (EMSR 581) and Teruel fire (EMSR 583) also caused significant upheaval, resulting in the evacuation of around 1,500 and 550 individuals respectively. This historical fire season highlights the critical need for studying and understanding wildfire patterns and their human impact as shown in Appendix A (Copernicus, 2022; León, 2022; Wilson, 2022; Welle, 2022).

1.3 Problem definition

To enhance community safety in wildfire-prone areas, understanding how people behave and move during the fire season is crucial. Traditional methods like surveys and simulation models have been used to study evacuation patterns, but there is limited exploration of GPS data for this purpose. Our project fills this gap by utilizing large GPS datasets to uncover valuable insights into evacuation routes, timing, and behavior during wildfire events in Spain. By applying spatial analysis and data science techniques, we identified residents' locations and tracked their movements during and after the fires. Our study adapts a methodology proposed by Zhao et al. that was previously tested in California, USA, to assess its applicability and provide regionally relevant insights for enhancing evacuation strategies in Spain.

1.4 Research Question

The goal is to gain insights of evacuation patterns regarding natural disasters, therefore this project is more based on inference and exploration than prediction, hoping to address following research questions:

1. What are the evacuation patterns during the wildfire in Spain? More specifically, how did people make evacuation decisions (i.e., evacuate or stay) with respect to the whole wildfire timeline (i.e., departure time)?
2. Based on different evacuee groups categorized in previous studies (i.e., self-evacuee, shadow evacuee), which group consists the most in this wildfire event? How does the result correlate with the geographical and social demographic factors in the area?
3. What is the sampling rate of the GPS data? Could it be an appropriate sampling of the whole population and whether this method could be applied to other evacuation models for disaster management?

2. Literature review

2.1 Evacuation Pattern Analysis

As mentioned in the previous section, the paper written by Zhao et.al serves as a guideline for this project's research flow. This paper addresses the challenge of accurately estimating evacuation decision-making and departure timing during wildfires. The authors used large-scale GPS data collected from a ride-hailing platform in California during the 2017 wildfire season to identify patterns in evacuee behavior. The author's use of clustering techniques to systematically categorize different types of evacuee based on their home location is innovative and could be possibly applied to other types of disasters or emergencies (e.g people who choose to stay/evacuate living inside/outside the fire area). Zhao's paper provided a comprehensive structure for the research; however, we want to see if similar methods could be applied to Spain's context as well with different data collection and much less population compared to the USA (Zhao et al, 2023).

2.2 GPS Data Processing

GPS data analysis is a critical component in various fields, such as transportation and disaster management. Researchers have focused on trajectory analysis to extract meaningful insights from GPS data, including identifying stop locations, detecting movement patterns, and understanding activity behavior. Integration with geographic information systems (GIS) has enabled the visualization and spatial analysis of GPS data, enhancing our understanding of urban mobility and emergency response planning. Thesis paper written by Siyao Li, provided by our client, studied the arrival profile of 23 large events from 4 sports types utilizing 4.7 million data from 14101 individuals around the venue area. The paper explained in detail about mobility analysis using python and GIS. Although our project focuses on the wildfire evacuation pattern, this paper serves as an excellent source for GPS data processing, interpretation and cross-location comparison analysis (Li, 2022). Our project mainly referred to its data cleaning method by setting a benchmark on the vertical and horizontal accuracy of data points to filter out inaccurate GPS location data.

3. Data

3.1 Data Sources

3.1.1 GPS Locational Data

High-volume mobile phone GPS data from Spain was provided by our clients, which included 30-day GPS location collected from residents in Spain during wildfires from June 1st, 2022 to June 30th, 2022. Each day had approximately 1.5 million rows and each row represented a GPS signal from an individual's electronic device that utilized the GPS service. The data was granted within company and research usage and is closely related to personal information and location, thus should not be made available for public access. The whole dataset had 28 features, and the following columns were utilized:

- Advertiser_id: identifies individual devices.
- Location_at: the date and time when the location of the device was recorded.
- Latitude and longitude: the coordinates of the GPS location of the device.
- Horizontal_accuracy: the value that represents the horizontal dimension’s error range of the GPS in meters, which was used for data cleaning.
- Vertical_accuracy: the value that represents the vertical dimension’s error range of the GPS in meters (altitude), which was used for data cleaning.

3.1.2 Geographical Data

In our data analysis, we integrated GPS locational data with the wildfire area map sourced from the European Forest Fire Information System (EFFIS). EFFIS offers comprehensive, timely information on European wildfires, including those in Spain. Each

Spanish wildfire is assigned a unique EMSR ID, and an associated polygon called Area of Interest (AOI) illustrates the wildfire's extent, encompassing the observed burnt area and estimated surrounding impact zone. This shapefile map includes details of the region’s natural terrain, infrastructure, hydrography, and major transport routes, and is easily incorporated into GIS for analysis. Moreover, we utilized the Copernicus Emergency Management Services (EMS) for near-real-time wildfire monitoring and impact assessment, which further augmented our understanding of the evolving wildfire situations and supported our investigation of evacuation patterns.

3.1.3 Demographic Data

To gain insights into the population distribution of each region in Spain, we incorporated demographic data from the National Institute of Statistics in Spain (Instituto Nacional de Estadística, INE). This data provides information about the population, age distribution, and socioeconomic characteristics across different regions of Spain. The demographic data was downloaded directly from the website by selected provinces that were affected by wildfire, with specific data for each municipality. By comparing the demographic data with our GPS data, we can evaluate if our GPS sampling adequately represents the population distribution and identify any potential biases or limitations in our dataset.

3.2 Data Cleaning, Processing and Aggregation

Our analysis began with thorough cleaning of the obtained GPS data. With no missing values in the dataset, data integrity was preserved. We evaluated data accuracy both horizontally and vertically, setting thresholds at 83 meters and 17 meters respectively to include 95% of the data, while maintaining high accuracy standards. Any data points outside these thresholds were discarded.

We divided the GPS data into pre-fire and post-fire periods, allowing a comparison of residents' movements before and after fire incidents. The cleaned and segmented data were stored as separate CSV files, ensuring data preservation and ease of access for subsequent analysis.

Lastly, we extracted individual-level data from the cleaned GPS set to identify unique behaviors or deviations that may be lost in aggregated data. This data was also stored in a CSV format for future analysis.

3.3 Exploratory Analysis

In the early phase of our research, we carried out an exploratory data analysis focusing on demographic distribution within the fire-stricken province and the sampling rate of our GPS data. The demographic study helped understand the age composition of the area, potential bias in GPS usage by age, and identification of subgroups that might need specific attention. We calculated our GPS data's sampling rate within each province to ensure data comprehensiveness and representation. Additionally, we estimated the active user count per hour, aiding in the inference of night time home locations.

3.4 Data Limitations

One of the main limitations pertains to the lack of additional user information associated with the GPS data. The dataset did not contain any further user demographic information, such as age, gender, or socioeconomic status. Consequently, our ability to draw nuanced conclusions about specific subgroups within the population was limited. We could not ascertain whether certain patterns of movement or reactions to the fire incidents were specific to certain demographic groups. This limitation also restricted our ability to adjust for potential confounding factors in our analysis, or to identify any demographic-specific patterns or correlations.

Additionally, the area under study was characterized by a low population density, with a significant portion of the territory being forested. This led to two notable challenges: First, the small population size could have limited the number of GPS data points collected, potentially making it harder to identify robust patterns or trends. Second, the predominance of forested areas may have influenced residents' movements in ways that are not typical in more urban or densely populated areas, making it harder to generalize our findings to other contexts.

4. Methodology

4.1 Demographic attribute and sampling rate

A significant limitation of our study was the lack of demographic information in the GPS dataset, such as age, gender, or socioeconomic status. This absence limited our ability to examine specific subgroups or adjust for potential confounding factors.

Furthermore, the low population density of the area, particularly given its forested nature, presented challenges. The small population size could have led to a fewer number of GPS data points collected, making pattern identification difficult, while the predominance of forested areas might have affected residents' movements in ways not typical in more urban areas, limiting the generalizability of our findings.

4.2 Home Location Inference

Our study involved inferring home locations of local residents using pre-fire GPS data between 10 pm and 6 am, based on both our analysis and prior research. We used the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm to detect clusters of location points signifying potential home locations. The clustered data were then overlaid on a satellite map via QGIS for visual confirmation that they represented residential areas. We further validated our inference by considering a location as a probable home only if a resident spent at least three nights there, helping ensure that the identified locations weren't merely frequently visited spots, but likely home locations.

4.3 Evacuation pattern definition and analysis

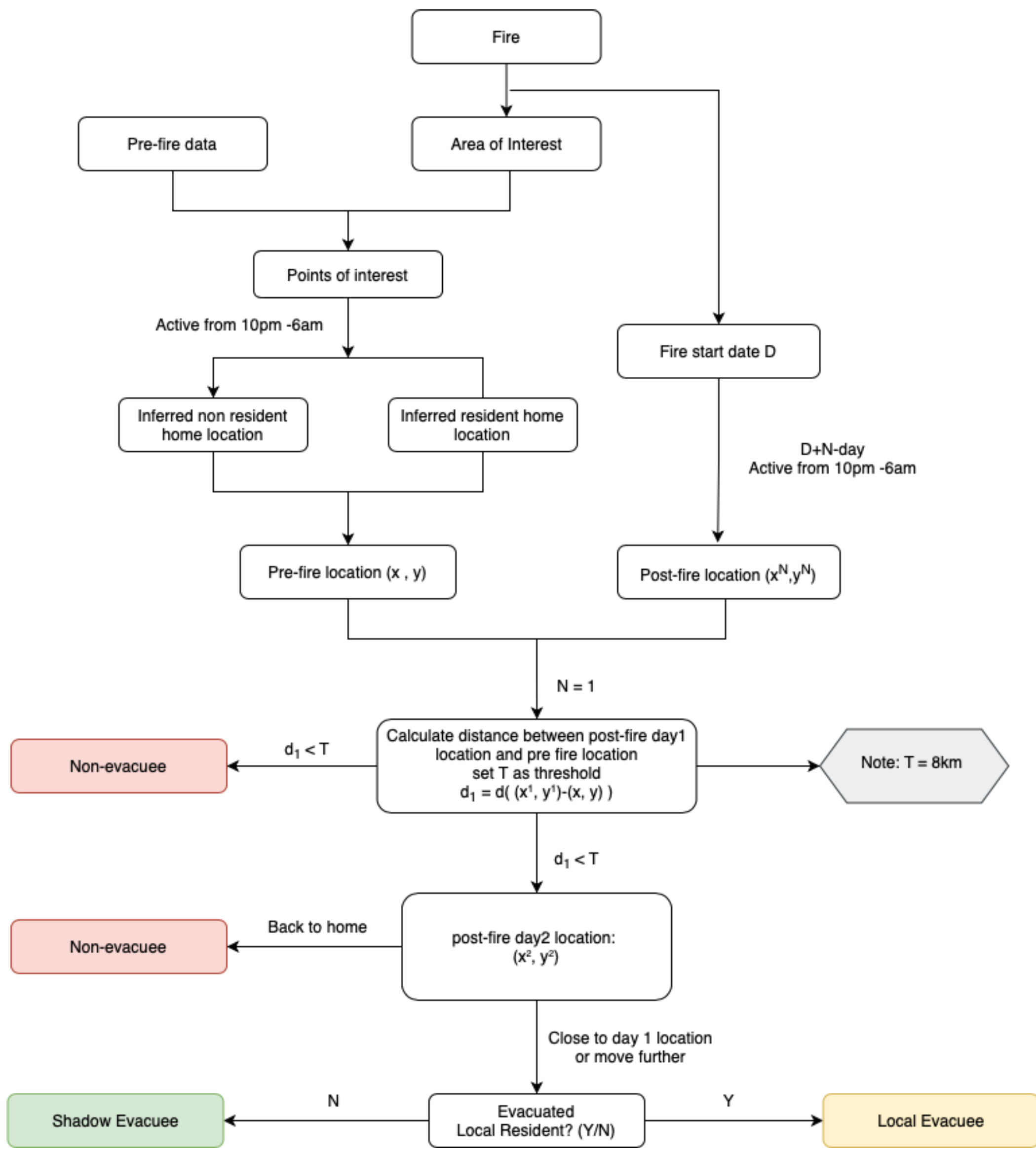


Figure 1: Evacuation-behavior inference algorithm

In analyzing the effects of the fire, we classified individuals within the area of interest (AOI) into distinct categories: resident evacuees, resident non-evacuees, shadow evacuees, travelers altering their routes, and an uncategorized group.

Resident evacuees were defined as those who, post-fire, moved at least 8 km away from their homes for at least two consecutive days. Those who didn't meet these criteria were classified as resident non-evacuees. Shadow evacuees included non-residents who, despite residing outside the AOI, chose to leave the area for two consecutive days post-fire. A distinct category was also created for non-resident travelers who used to pass through the AOI before the fire but modified their routes to avoid the AOI post-fire, which was defined as fire avoidant. Individuals with insufficient data were placed in an uncategorized group.

4.4 Passenger Pattern Analysis

We also investigated the behaviors of "passengers," individuals who were in the Area of Interest (AOI) before the fire but stayed less than three days. The passenger data offered insights into transient population interactions with the AOI and their reactions to the fire. We compared pre-fire and post-fire passenger counts in the AOI to quantify the fire's influence on temporary visitation and potential shifts in short-term mobility patterns. By assessing changes in passenger volume, we expanded our understanding of the fire's impact beyond residents, incorporating those briefly in the area, enhancing our overall knowledge of human mobility in response to fire incidents.

5. Results

5.1 Demographic Analysis and Sampling Rate

To understand the demographics of the wildfire region, we created maps and bar plots. Our map (Figure 2) shows population density distribution across Spanish provinces, with lighter colors indicating lower population density. Wildfire-affected provinces have notably low densities.

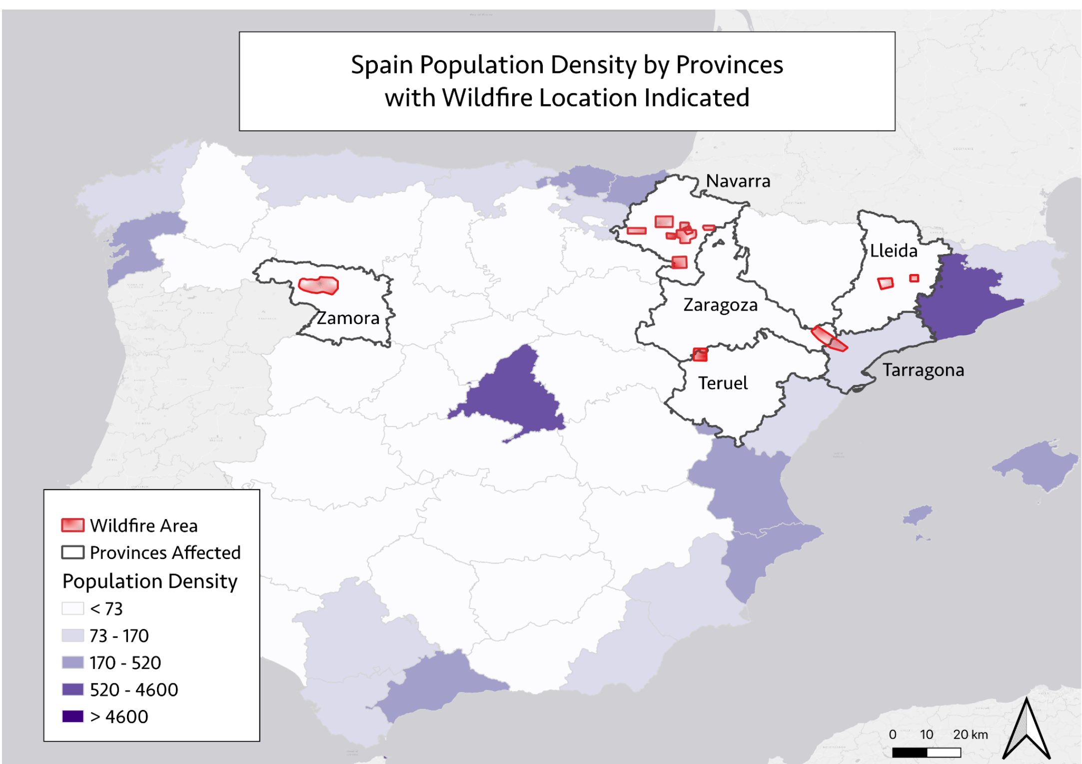
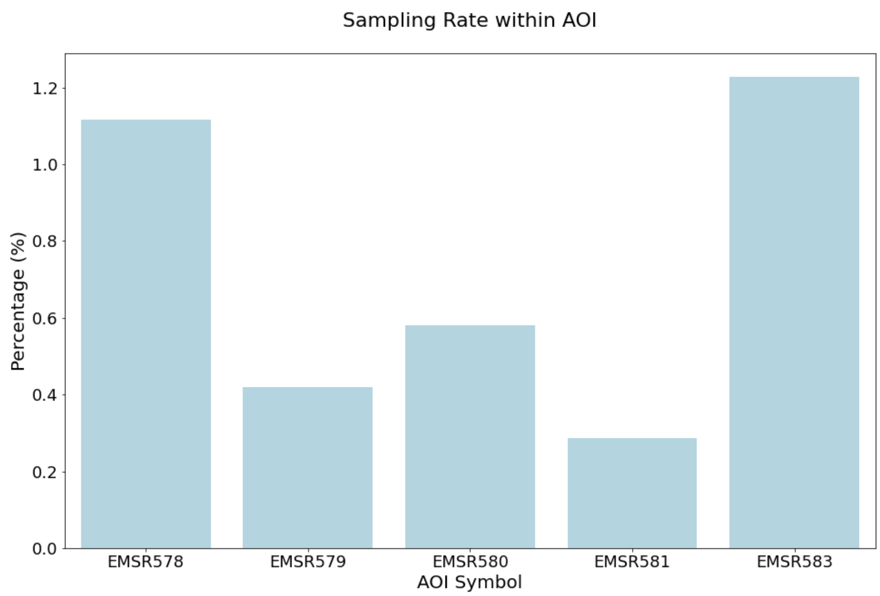


Figure 2: Population Density Distribution By Provinces in Spain

Demographic distribution analysis (Figure B.1) across five provinces revealed that the largest age group in each was 18-44, making up about a third of the population. The 45-64 age group was second largest, making up 29-31% of the population, with the under-18 and over-65 groups being smaller. These figures provide valuable context for understanding potential impacts of wildfires on various population segments. When we looked at the sampling rate among these provinces (Figure B.2), the lowest was Amora with less than 0.02% sampling rate, while the highest is Lleida with almost 0.3% sampling rate. However, no direct relationship between sampling rate and age group population distribution were noticed.



Fire ID	# of Sample	Population in AOI
EMSR 578	21	1881
EMSR 579	159	37808
EMSR 580	24	4137
EMSR 581	16	5600
EMSR 583	25	2308

Figure 3: Sampling rate and population within AOI

We also examined sampling rates within the fire-impacted Area of Interest (AOI), coded by the European Union's Emergency Response Coordination Centre (ERCC). Sampling rates ranged from 0.29% to 1.23% across different regions.This analysis provided an understanding of the representativeness of our sample within the impacted areas.

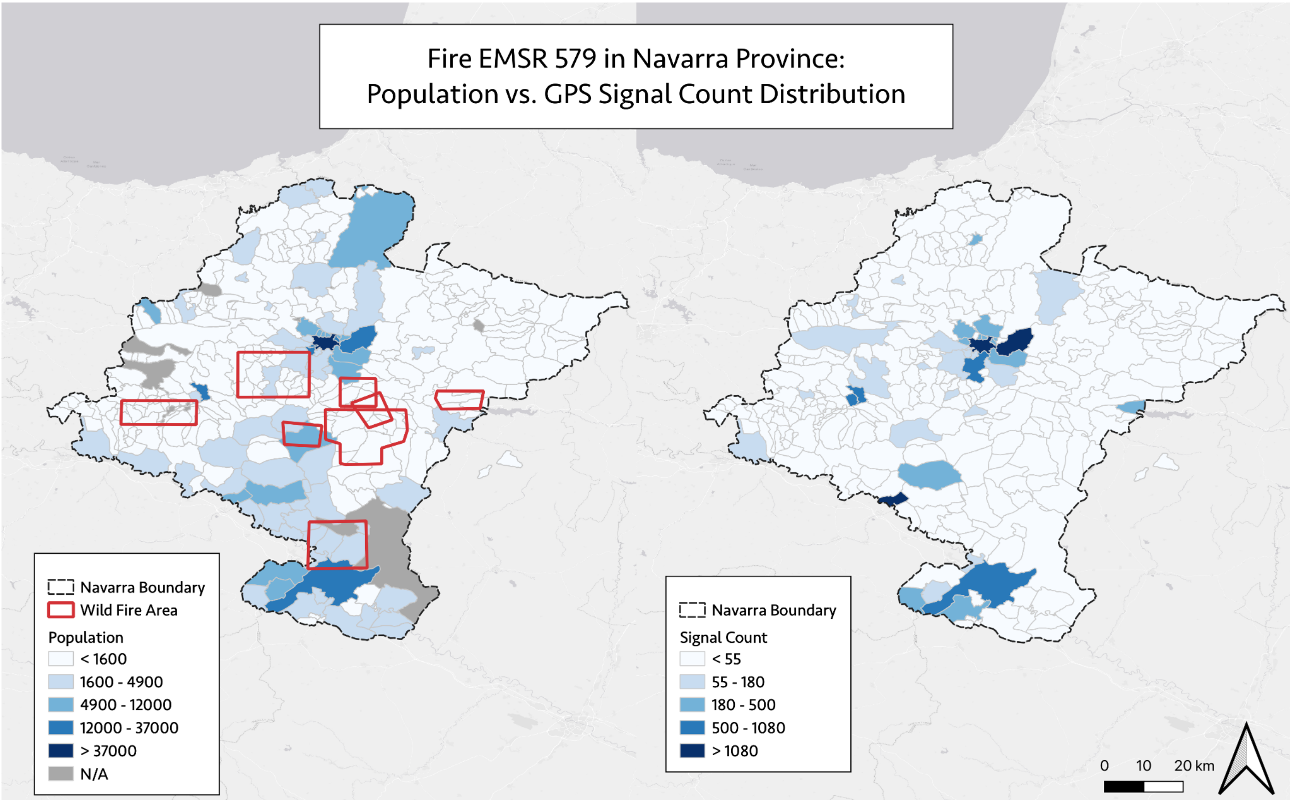


Figure 4: Comparison of Actual Population and GPS Signal Count Distribution

Despite the low sampling rate, the GPS data mirrors the region's population distribution, suggesting it's representative. The map (Figure 4) of the EMSR 579 wildfire event in Navarra province confirms this, showing similar distribution patterns in actual population and GPS signals. Most wildfires occurred in less populated or suburban areas, indicating the impact on the population was likely minimal.

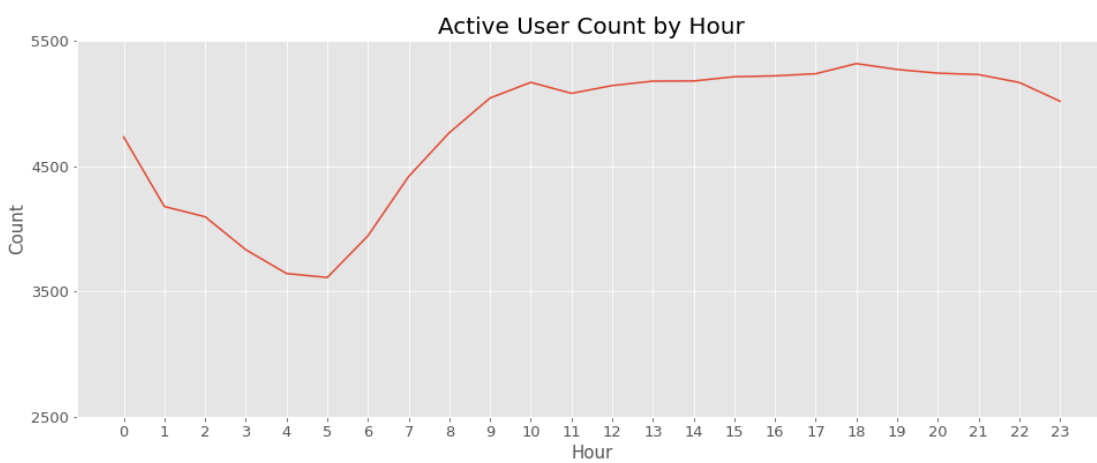


Figure 5: Active user count by hour

Our analysis of the user count by hour, represented in figure 5, reveals a daily cyclical pattern, with counts lowest around 5 AM and peaking around 6 PM and starting to decrease around 10pm. Given this trend, we inferred the nighttime hour was between 10 PM and 6 AM. This period was then used for home location inference, under the assumption that users are most likely at home during these hours.

5.2 Proxy-home location inference

Our analysis identified 245 individual signals prior to the fire event. However, during the post-fire period, only 60 out of the 245 remained in the AOI. We implemented a specific criterion to identify potential residents, focusing on active users from 10pm to 6am, leading us to pinpoint 55 individuals. Further investigation was conducted by overlaying these data points onto a satellite map, which assisted us in confirming that 16 out of these individuals were genuine residents. The remaining individuals were classified as workers, passengers, or those whose residential status could not be confirmed due to insufficient data.

5.3 Evacuation Estimation

Our evacuation estimation took a look at the inferred residents and non residents evacuation pattern.

5.3.1 Residents

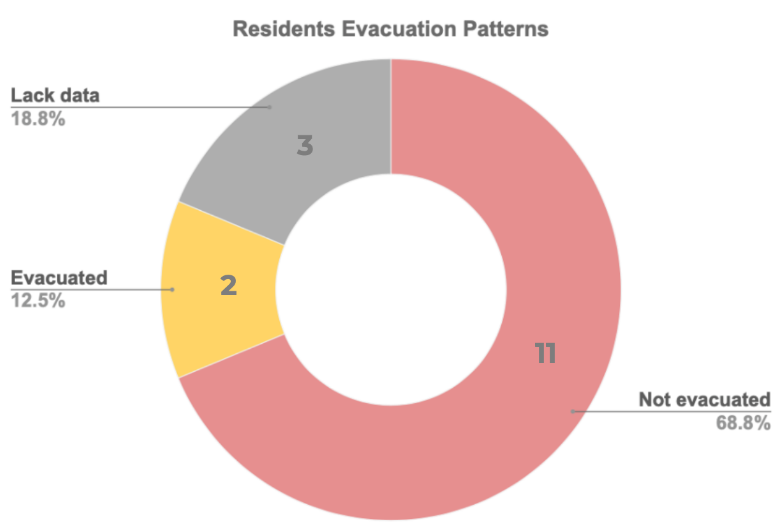


Figure 6: Residents evacuee pattern inference

Out of the 16 inferred residents, we had 2 confirmed evacuees, 11 residents that live at the edge of the AOI didn't evacuate, and the other 3 lacked data for analysis (Figure 6).

5.3.2 Non-residents

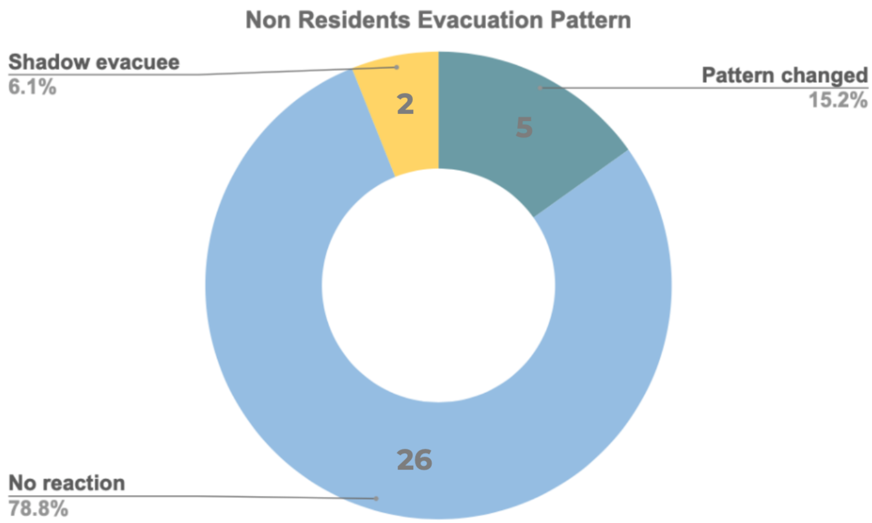


Figure 7: Non-residents evacuee pattern inference

For the non-residents, we inferred 2 shadow evacuees, 5 fire avoidants (Appendix), and 26 non-residents with no reactions (Figure 7).

5.3.3 Transient Population Analysis

Due to the relatively low population in the wildfire-affected areas, the available data is limited for inferring residents and their home locations. Therefore, our analysis focuses on examining the number of transient populations, including individuals who do not normally reside in these areas and appear in the region for less than 3 days. We aim to observe whether the count of these transient individuals changes during and after the wildfire events. The line charts below present the number of unique passengers throughout the entire month of June in each AOI region. Additionally, the map (figure 8) displays the major highways in each AOI, allowing for reference and analysis of variations in passenger movement patterns.

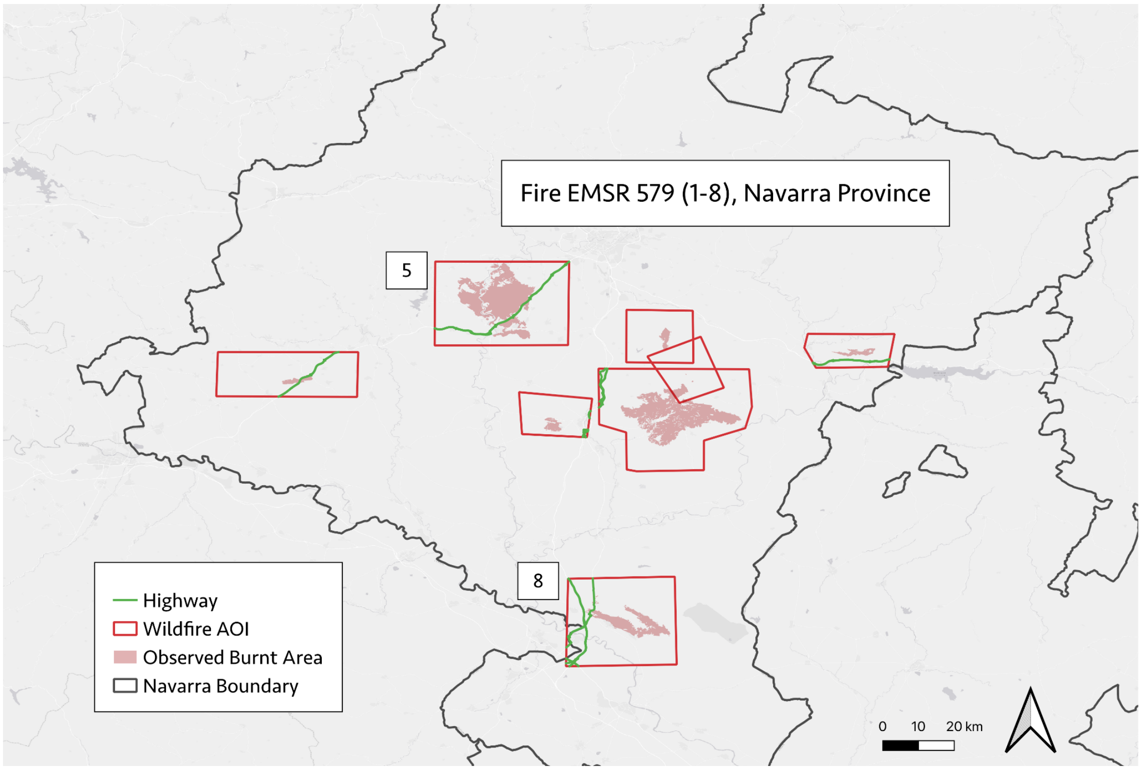


Figure 8: Major Road of EMSR 579 Wildfire Area of Interest in Navarra Province

We inferred 458 passengers, Appendix C.1, C.2 and C.3 show their activity patterns within each AOI. The red line shows the original number of individuals, and the blue line shows the smoothed line by creating a moving average of 5 days. We cross referenced the major highway location within the AOI, and noticed that for regions with highways across the burnt areas such as in AOI 5 (figure 9), there were less active passengers during the first few days after the fire outbreak. However, for regions with highways outside the burnt areas such as in AOI 8 (figure 10), there was increased passenger traffic. For regions with less transient population, no obvious patterns were found. Still, during evacuations, it is expected that there will be an increase in the number of passengers passing through the wildfire-affected areas. This is because some individuals may need to traverse these burnt areas to reach their intended destinations. As a result, the count of transient populations, including evacuees and those traveling through the region, is likely to rise.

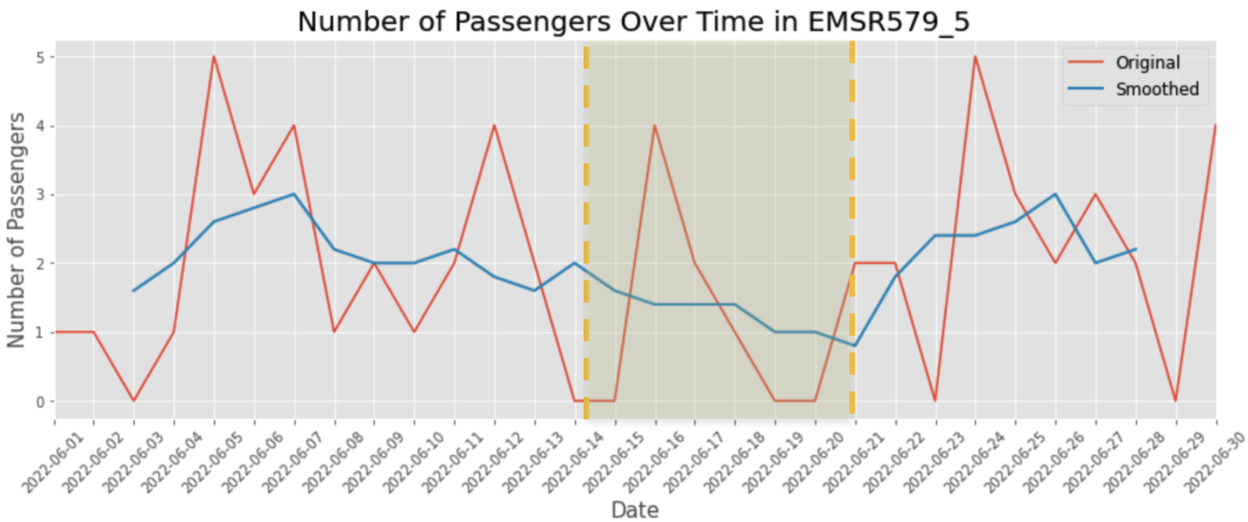


Figure 9: Passenger count over time in EMSR579_5

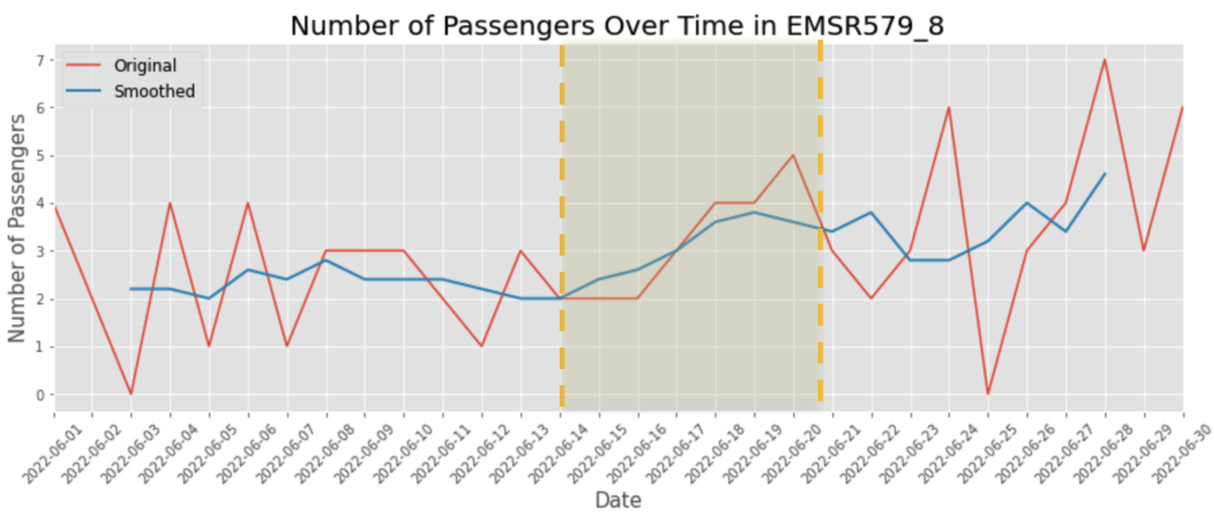


Figure 10: Passenger count over time in EMSR579_8

6. Conclusions

In conclusion, our data-driven study shed light on resident, non-resident, and transient behavior during a fire event, revealing distinctive evacuation patterns. Despite limitations such as a lack of additional user information and a largely forested study area, we gleaned useful insights. Our findings indicate varying evacuation behaviors between groups, aiding in identifying specific movement patterns. 'Nighttime' hours, inferred from daily user activity cycles, facilitated home location inference. Furthermore, the transient population, defined as 'passengers,' contributed additional context to pre-fire activity in the area.

6.1 Major findings

We notice that most of the local residents within the AOI didn’t choose to evacuate, and all of these non-evacuee resided outside the burnt areas. Although there were very few shadow evacuees, this still indicates some citizens have higher risk perception. The reasons for people evacuating differ by individual, some may have higher risk perception, accessibility to up-to-date fire information, or even due to past experiences.

For transient population analysis, an increase in passenger count post-fire might suggest that people were drawn to the area, perhaps due to curiosity, rescue efforts, or other reasons. Conversely, a decrease might suggest that people avoided the area due to safety concerns, road closures, or other disruptions caused by the fire.

6.2 Feedback and evaluation

This study provides insights into resident and transient behavior during wildfires, using a unique approach to discern evacuation patterns. However, cultural factors, limited additional user data, and low population density in the examined forested areas restrict the generalizability and richness of our findings. Our results should be interpreted cautiously given these constraints. Future studies should include a broader, diverse range of data to increase understanding and applicability of findings. While data-driven approaches offer valuable insights, the necessity of context-specific understanding in disaster management remains critical.

6.3 Policy Implications and Recommendations

Our wildfire evacuation pattern analysis in Spain has led to significant insights into the behavior of residents and transient populations during fire events, and highlighted key data limitations. Based on these findings, we put forth the following recommendations to improve wildfire management and response strategies. It is crucial to note that these recommendations are general and should be tailored to align with Spain's unique cultural and communication customs.

1. **Improve Information Sharing and Data Quality:** Given the data limitations faced in our study, we recommend the establishment of a centralized data platform. This would enhance access to high-quality wildfire data, enabling a more nuanced understanding of wildfire behavior, and aiding in crafting effective management strategies.
2. **Effective Use of Data:** Our data-driven insights emphasize the importance of leveraging data to comprehend and predict evacuation behaviors. Collaborations with researchers and data analysts should be fostered to develop comprehensive risk assessment models. These models, informed by both historical and current data, can provide invaluable insights into wildfire dynamics and assist in designing targeted mitigation plans.
3. **Raise Public Awareness:** The variety of evacuation decisions among residents and the existence of shadow evacuees in our findings underscore the need to heighten public awareness about wildfires. Utilizing Spain's prevalent communication channels, such as

television and radio, can effectively disseminate educational programs and public service announcements, thus ensuring residents are well-informed about wildfire risks and suitable responses.

4. **Centralize Risk Management:** Our study noted that essential updates were often posted on Twitter, suggesting a decentralized and potentially unreliable mode of information dissemination. A dedicated authority for centralized risk management can streamline the communication process, ensuring efficient and timely sharing of crucial information during emergencies.

6.4 Future steps

While this project has yielded important insights, there are several areas for improvement and further investigation.

1. **More Data:** Gathering additional data would be advantageous. A more extensive dataset would facilitate a more in-depth analysis and could potentially lead to a higher sampling rate, thereby improving the representativeness and robustness of our results.
2. **Demographic Information:** Including demographic information for each user in our dataset would enrich our analysis considerably. This would allow us to conduct more detailed subgroup analyses, enabling a better understanding of how different demographic groups respond to fire events
3. **Local Surveys:** Conducting local surveys to capture residents' attitudes and perceptions towards the fire could offer additional context to our findings. These surveys could provide a more nuanced understanding of why certain individuals choose to evacuate while others do not.
4. **Health Data Integration:** Incorporating health data could potentially yield important insights. By comparing evacuation rates and health problems, we might be able to discern whether there are correlations between these factors. For example, regions with higher evacuation rates might be experiencing higher rates of health problems due to the fire, or individuals who evacuate might have different health profiles than those who don't.
5. **Travel Speed Analysis:** By analyzing the travel speed of both passengers and residents, we could potentially gain additional insights into movement patterns and behaviors. Faster travel speeds might indicate urgency or panic, while slower speeds might suggest a more measured response to the fire event.
6. **Fire Data Integration:** Incorporating more detailed information about the fire, such as its spreading speed and direction, could enable a more comprehensive analysis. Understanding how the fire's characteristics influence evacuation behaviors could be crucial for predictive modeling and planning.

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Appendix

Appendix A: Wildfire Information

Table A.1: Wildfire Location and Timeline

Fire ID	Location (Province)	Burnt Areas (Hectares)	Start Date	Approx. Evacuation	Fire Contained Date	Approx. # of Evacuated people
EMSR 578	Lleida	3,008	6/16	6/16	6/18	Around 800 people
EMSR 579	Navarra	16,202	6/16	6/19	6/20	15 villages (precaution)
EMSR 580	Zamora	25,217	6/17	6/17	6/25	205 people
EMSR 581	Zaragoza	2,211	6/17	6/18	6/22	1500 people (8 villages)
EMSR 583	Teruel	1,790	6/21	6/22	6/28	550 people

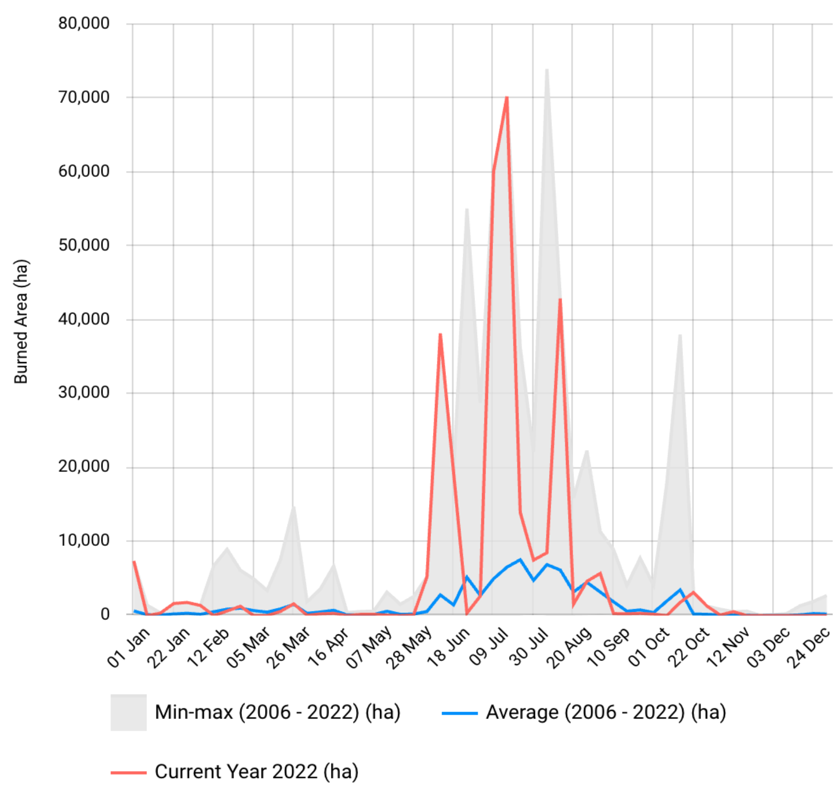

Figure A.2 Weekly burnt area in Spain 2022 (EFFIS, 2023)

Appendix B Demographics Distribution and Sampling Rate

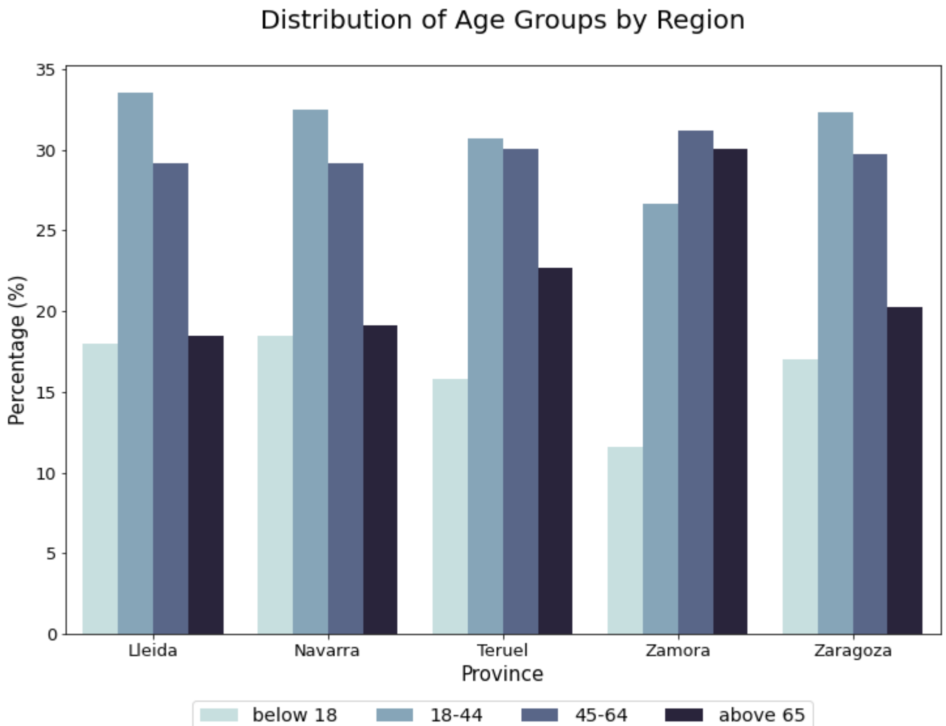

Figure B.1: Distribution of age groups by region

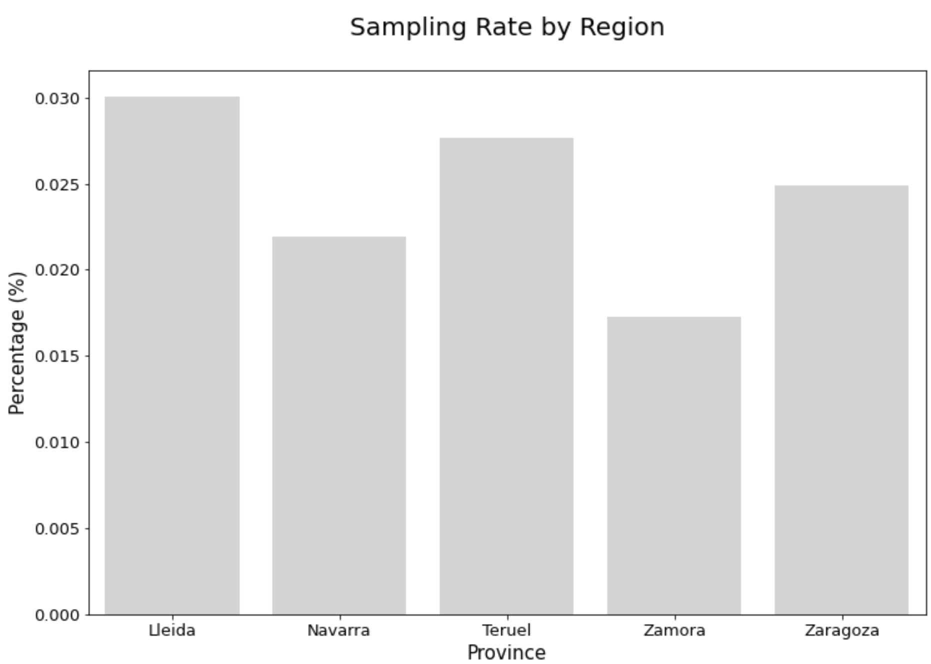

Figure B.2: Sampling rate by region

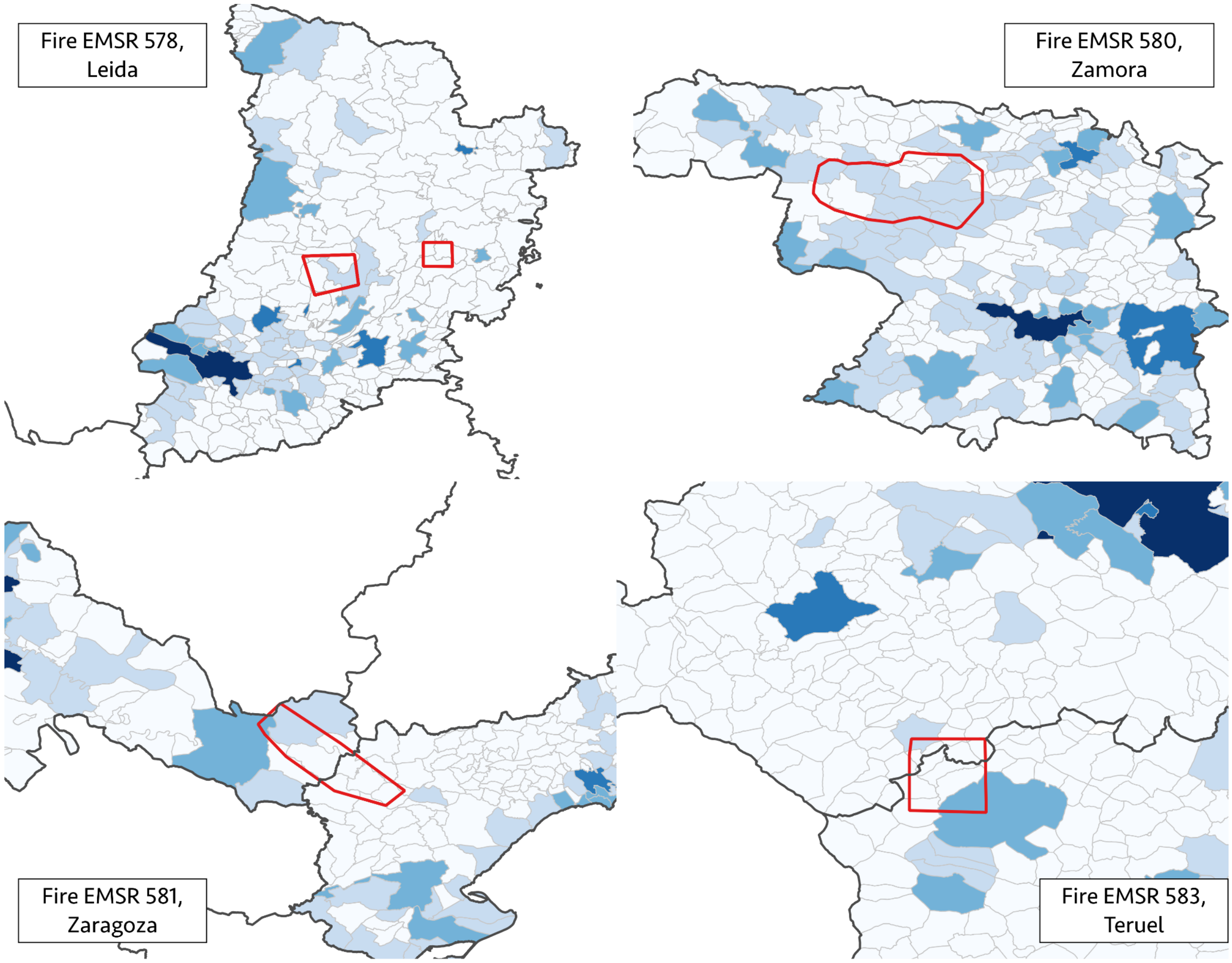

Figure B.3: EMSR 578, 590, 581, 583 Fire Location and Population Distribution

Appendix C: Transient Population Analysis

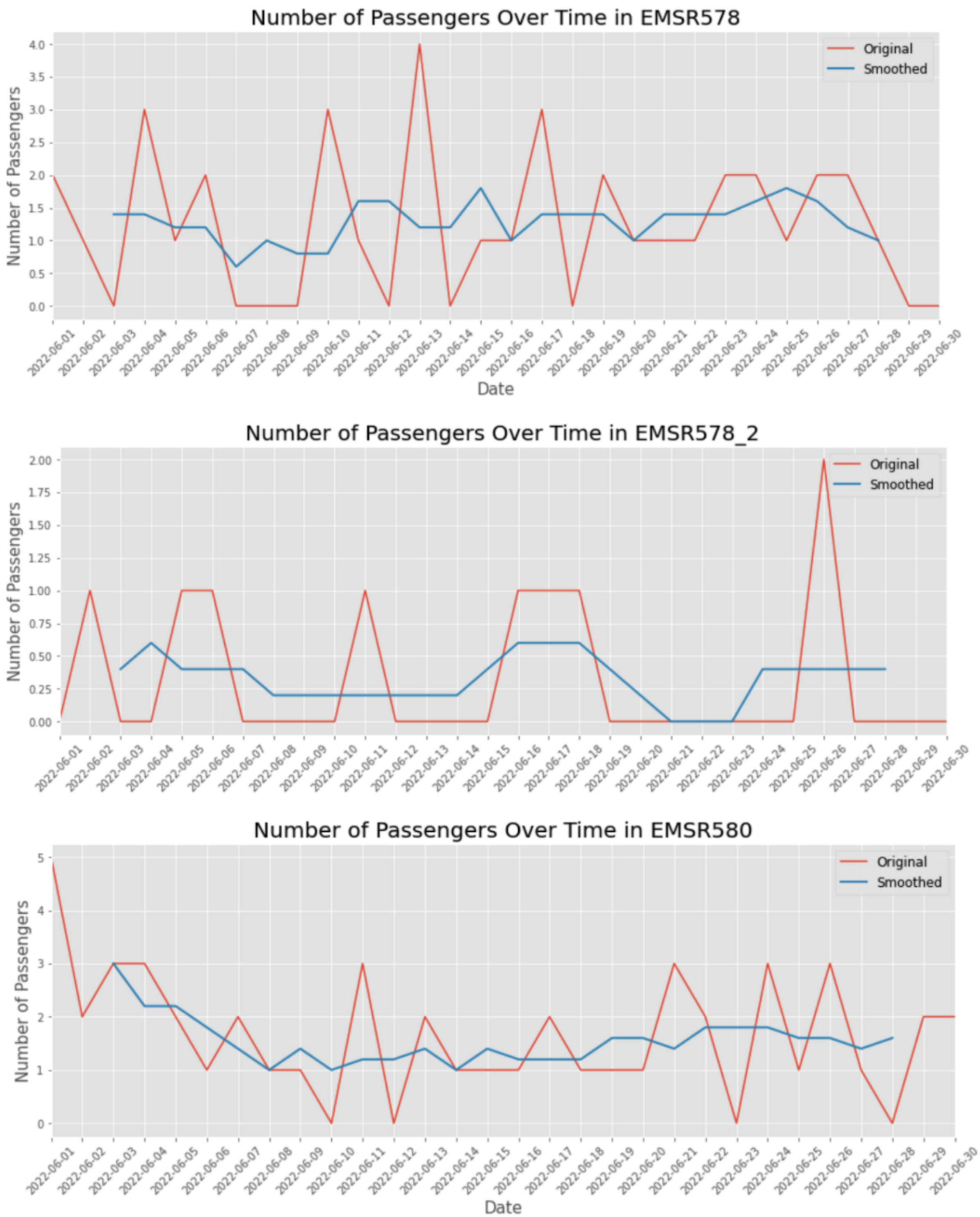

Figure C.1: Passenger count by day (EMSR578, E SR578_2, EMSR580)

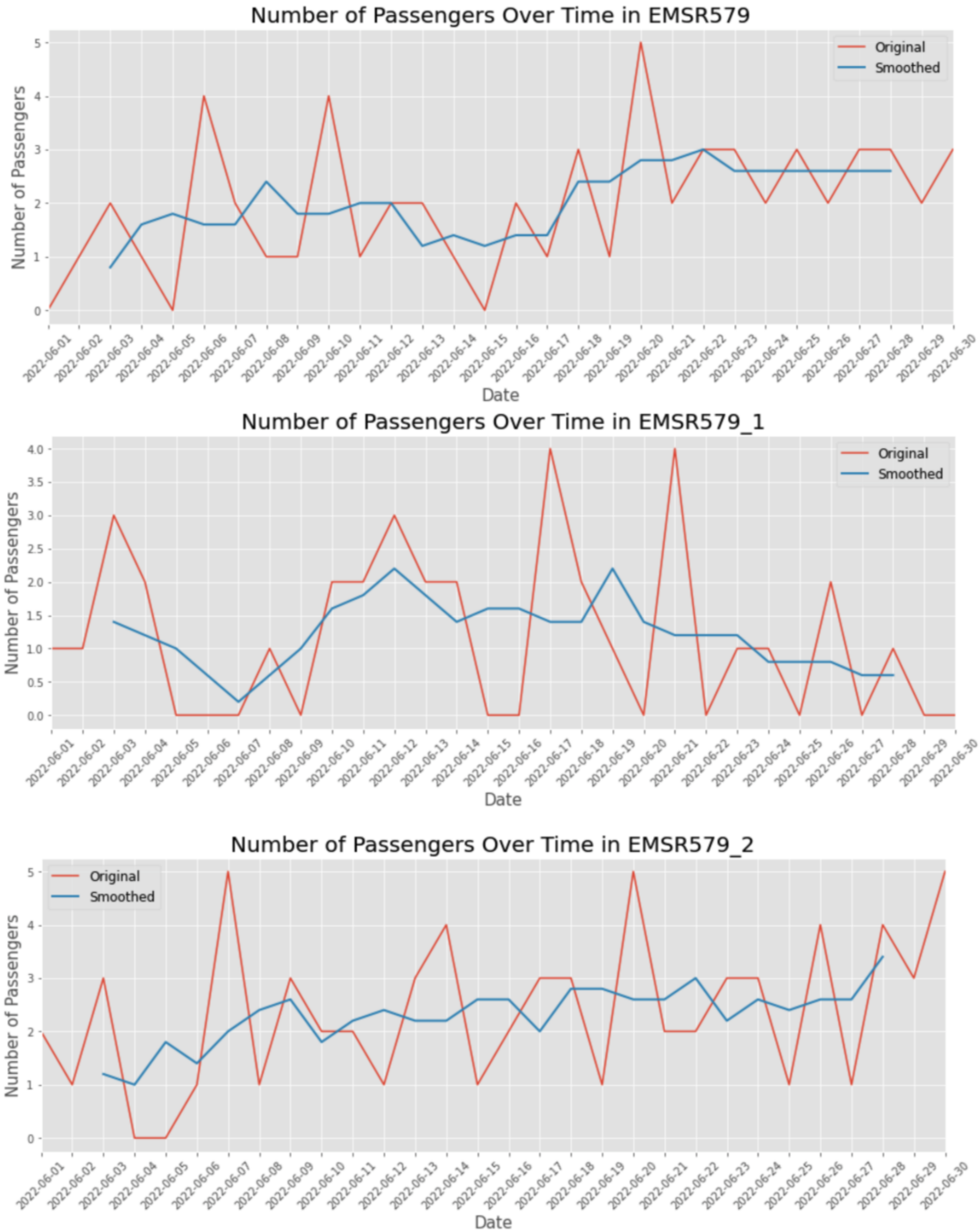

Figure C.2: Passenger count by day (EMSR579, E SR579_1, EMSR579_2)

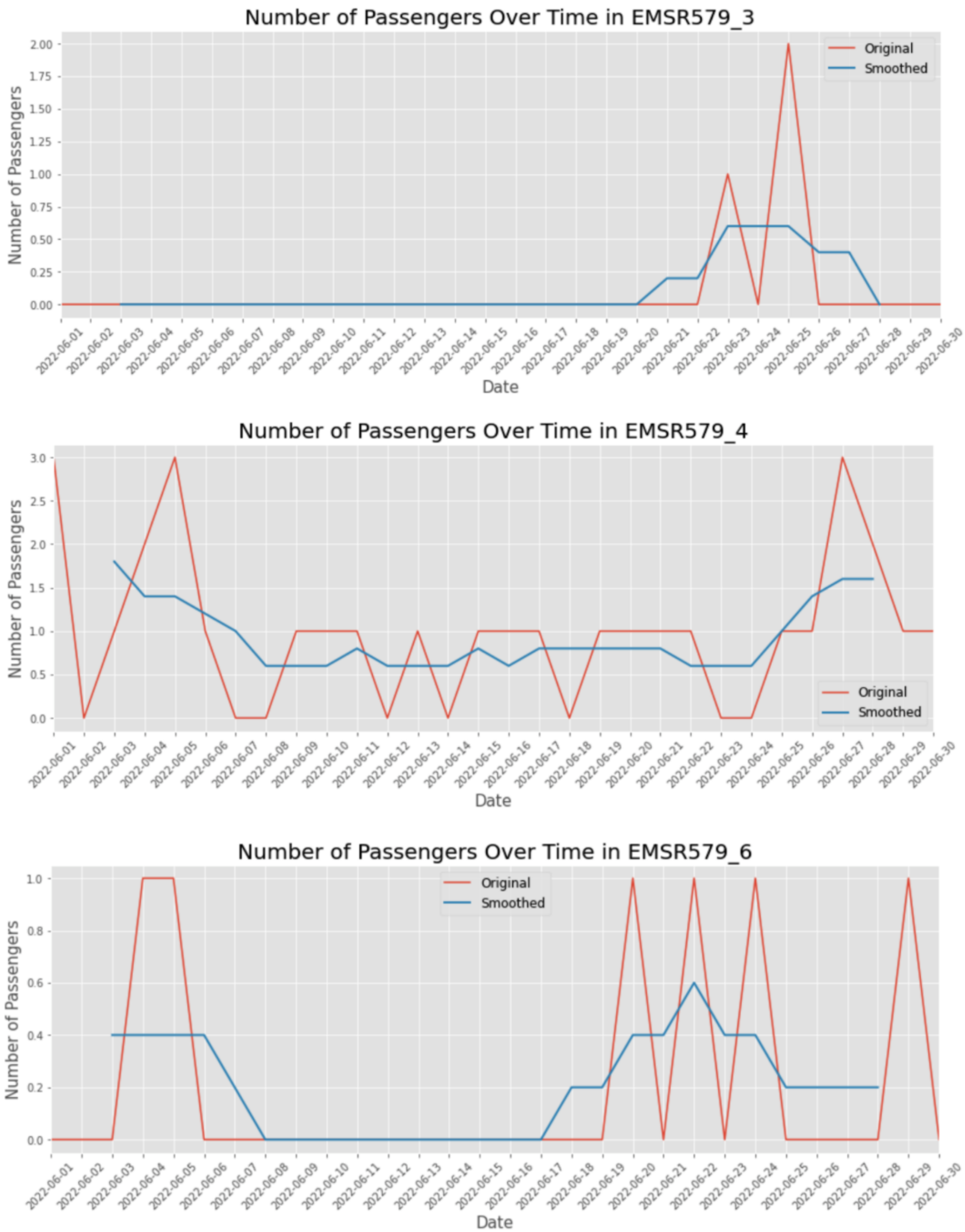

Figure C.3: Passenger count by day (EMSR579_3, E SR579_4, EMSR579_6)