

# **Understanding Human Displacement and Mobility Dynamics from Cell Phone Data: The Case of 2024 Floods in Rio Grande do Sul, Brazil**

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**Keywords:** Flooding, Human Mobility, Displacement Patterns, Geospatial Big Data, Disaster Resilience, Evacuation Behavior

## **Introduction**

Climate change has intensified extreme weather events, leading to unprecedented floods that expose growing populations to risk (Tellman et al., 2021). Low- and middle-income countries, home to 89% of the world's flood-exposed population, bear disproportionate consequences due to higher vulnerability and limited coping capacity (Rentschler et al., 2022). Latin America is particularly susceptible, where climate variability, rapid urbanization, and informal settlements in flood-prone areas create compounding risk (Pinos & Quesada-Román, 2022). A stark illustration occurred in late April 2024, when Rio Grande do Sul in southern Brazil experienced its worst flooding in over 80 years, claiming 183 lives, affecting nearly 2.4 million people across 478 municipalities, displacing roughly 600,000 residents, and forcing the closure of Porto Alegre's international airport for over five months (Mantovani et al., 2025; UNOCHA, 2025). Such events underscore the importance of examining human behaviors during disasters, particularly evacuation decisions, to enhance future resilience.

Yet obtaining accurate data on human responses during floods has historically been challenging due to infrastructure damage, time-intensive field surveys, and biases inherent in traditional methods (Cai et al., 2018; Khazai et al., 2018), often failing to represent marginalized groups. Moreover, the literature predominantly examines flood-related behaviors in South and Southeast Asia, Europe, and North America (Becker et al., 2024; Duijndam et al., 2023; Li et al., 2024; Wang et al., 2025), leaving Latin America underrepresented despite its high vulnerability (Pinos & Quesada-Román, 2022).

This study addresses this gap using location-based service (LBS) data from Quadrant to analyze human mobility during the 2024 Rio Grande do Sul flood. We examine how flooding affects displacement patterns and their socio-economic and spatial determinants, focusing on evacuation trends and the temporal characteristics of displacement decisions.

This study employs a data-driven approach using location-based service (LBS) data from Quadrant ([Quadrant.io](https://www.quadrant.io)) to analyze human activity during the 2024 flood in Rio Grande

do Sul, Brazil. We examine how flooding affects displacement patterns and their socioeconomic and spatial determinants, focusing on evacuation trends and the temporal characteristics of displacement decisions.

Specifically, this study addresses the following three research questions:

**RQ1.** How did the 2024 flood alter daily mobility patterns in Rio Grande do Sul?

**RQ2.** How did flood-induced displacement evolve temporally and spatially across Rio Grande do Sul?

**RQ3.** What socioeconomic and demographic characteristics are associated with higher displacement rates at the census tract level?

We propose three hypotheses accordingly. First, daily mobility in Rio Grande do Sul declines sharply following the flood onset before gradually recovering. Second, flood-induced displacement varies spatially across regions in Rio Grande do Sul and intensifies rapidly following the flood onset before gradually subsiding. Third, areas with higher income levels, larger proportions of children ( $< 10$  yrs), and higher adult literacy rates exhibit greater displacement likelihood, whereas areas with larger elderly ( $> 60$  yrs) populations demonstrate lower relocation rates.

## **Methods**

### ***Data Acquisition and Pre-processing***

This study utilizes anonymized GPS-based mobile device location data provided by Quadrant (<https://www.quadrant.io/>), spanning March 1 to May 31, 2024, for the state of Rio Grande do Sul, Brazil. The raw dataset comprises 980.4 million location pings, each containing a unique anonymized device identifier, latitude, longitude, timestamp, and horizontal accuracy estimate.

To derive meaningful mobility events, we identified stationary episodes, or "stops," defined as sequences of consecutive pings within 20 meters of one another, sustained for at least 5 minutes, with no temporal gap exceeding one hour. We then applied the DBSCAN algorithm ( $\epsilon = 20$  m,  $\text{MinPts} = 2$ ) to consolidate spatially proximate stops and filter residual GPS noise, reducing the raw data to 215.6 million validated stops.

From these stops, we inferred home locations using temporal and frequency-based heuristics. A stop cluster was designated as a device's home if it occurred predominantly during nighttime hours (7:00 PM-8:00 AM on weekdays, all hours on weekends) and was visited on at least 14 distinct days with the highest frequency among candidate clusters. This process yielded 2.1 million inferred home locations in Rio Grande do Sul, from which we extracted a final sample of 138,100 active users (devices recording at least one daily ping with a valid home location), contributing 59.4 million stops to the analysis.

### ***Mobility Measures***

We employed two complementary metrics to quantify changes in mobility patterns during the flood event, i.e., anomaly scores and radius of gyration, each capturing a distinct

dimension of mobility pattern. Anomaly scores are built from stop frequency. Stop frequency measures the total number of stops recorded within a given spatial unit per day. We adopted the Uber H3 hexagonal grid system at resolution 8 (approximately 0.74 km<sup>2</sup>) as our spatial unit to ensure uniform area coverage and avoid edge effects associated with administrative boundaries.

*Anomaly score* (Z-score) quantifies the magnitude of deviation in stop frequency relative to a pre-flood baseline period (March 4–April 14, 2024, 6 weeks in total). For each H3 hexagonal unit and day, the anomaly score is computed as:

$$Z = \frac{X_i - \mu}{\sigma}$$

where  $X_i$  is the observed stop count on a given day, and  $\mu$  and  $\sigma$  are the mean and standard deviation of stop counts for the same weekday during the baseline period, accounting for regular weekly variation. Negative Z-scores indicate suppressed activity; positive scores indicate elevated activity.

*Radius of gyration* ( $R_g$ ) captures the spatial extent of an individual device's daily movement. It is calculated as:

$$R_g = \sqrt{\frac{1}{N} \sum_{i=1}^N d_i^2}$$

where  $N$  is the number of daily pings per device, and  $d_i$  is the distance from each ping ( $i$ ) to the centroid of all pings that day. Higher  $R_g$  values indicate wider daily travel patterns.

### ***Displacement Inference and Statistical Analysis***

A device was classified as displaced if no pings were recorded within 0.5 km of its home location for four or more consecutive days after the flood onset (April 29, 2024), distinguishing sustained displacement from routine short-term absences.

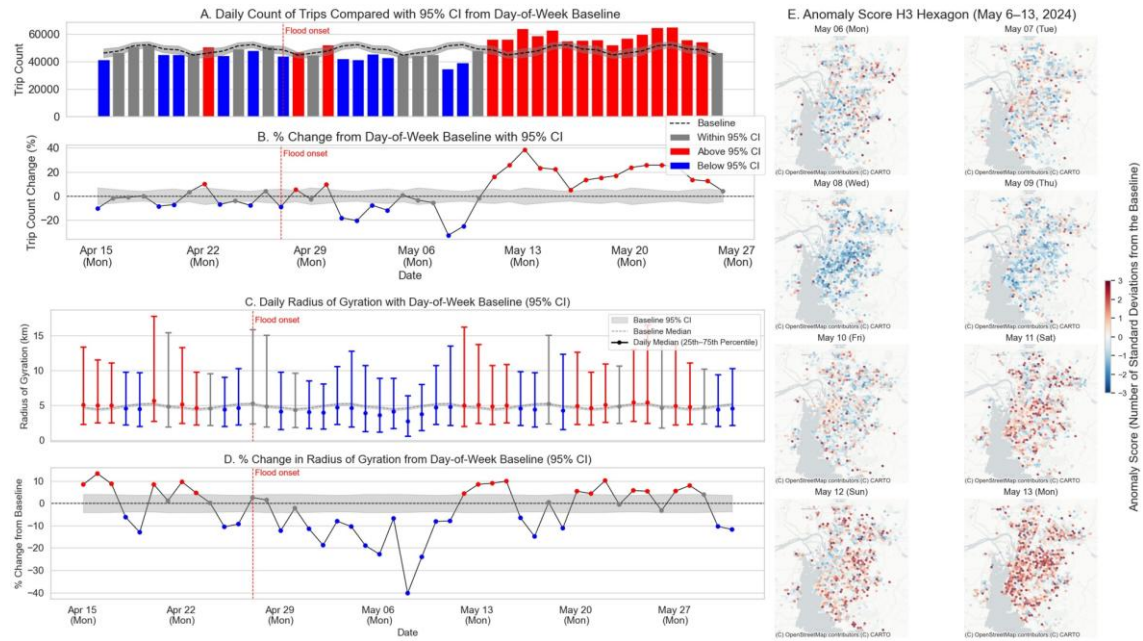
We then aggregated displacement classifications to the census tract level and computed displacement ratios (proportion of active users displaced per tract). These were correlated with 2022 Brazilian Census variables, including median household income, adult literacy rates ( $\geq 30$  yrs), and proportions of children ( $< 5$  yrs) and elderly ( $> 60$  yrs), using Spearman ( $\rho$ ) correlation coefficients to account for non-linear relationships.

## **Results**

Using March 4–April 14 as the baseline, the average trip count was 3.52 trips per device per day, compared to 3.60 during the analysis period. Weekend trips were slightly lower than weekday trips in both periods (baseline: 3.37 vs. 3.57; assessment: 3.54 vs. 3.63). Following the flood onset, trip counts dropped below the baseline until May 11, indicating substantial mobility disruption, before rebounding above baseline levels through the end of the monitoring window (Figure 1A & 1B).

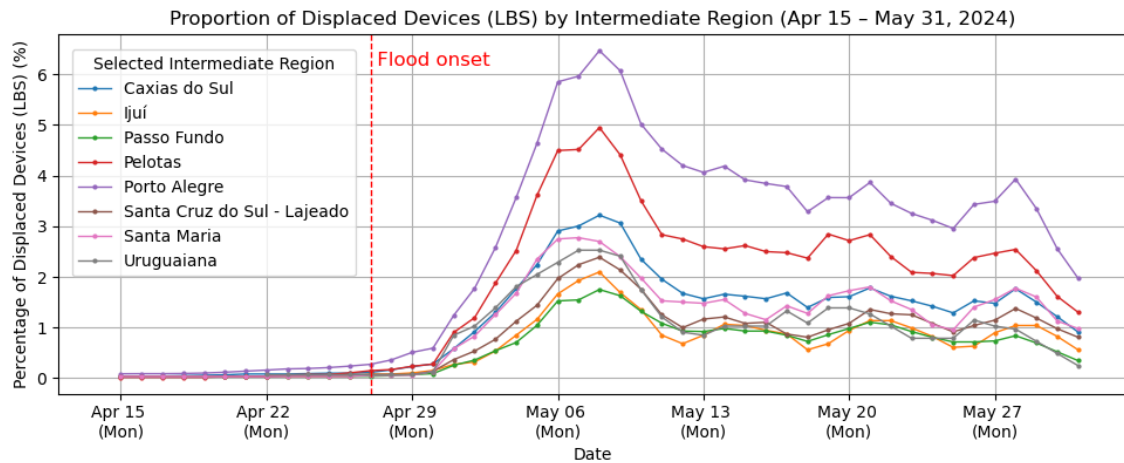
Radius of gyration showed a similar pattern. The median declined from 4.81 km during the baseline to 4.65 km during the assessment period, with weekend travel consistently exceeding weekday travel in both periods (baseline: 5.02 vs. 4.75 km; assessment: 4.92 vs. 4.56 km). During the peak impact, radius of gyration decreased by up to 40%, reflecting severely constrained daily activity spaces (Figure 1C & 1D).

Figure 1E maps the spatial distribution of anomaly scores in Porto Alegre. May 8 exhibited the most pronounced decline, consistent with the trip count and radius of gyration results, while elevated values persisted in the post-peak phase.



**Figure 1.** Mobility disruption in Rio Grande do Sul during the 2024 flood. (A) Daily trip counts with 95% confidence intervals from the day-of-week baseline. (B) Percentage change in daily trip counts relative to the day-of-week baseline, with 95% confidence intervals. (C) Daily radius of gyration with 95% confidence intervals from the day-of-week baseline. (D) Percentage change in radius of gyration relative to the day-of-week baseline. (E) Anomaly scores at the H3 hexagonal grid (resolution 8) in Porto Alegre from May 6 to May 13, 2024.

We assessed displacement patterns within Rio Grande do Sul by calculating the percentage of displaced devices per intermediate region from April 15 – May 31, 2024 (Figure 2). Of the 138.1K active users, 13,932 (10.09%) were classified as displaced. Porto Alegre accounted for the vast majority (11,284 devices), followed by Pelotas (833), Caxias do Sul (776), Passo Fundo (346), Santa Maria (243), Santa Cruz do Sul–Lajeado (219), Ijuí (149), and Uruguaiana (82). Displacement peaked on May 8 with 7,347 displaced devices, then gradually declined through the end of the monitoring window.



**Figure 2.** Percentage of displaced devices by intermediate region in Rio Grande do Sul, Brazil (April 15 – May 31, 2024). The vertical dashed line marks the flood onset (April 27).

Finally, we examined the relationship between displacement ratio and sociodemographic characteristics at the census-tract level (Table 1). Adult literacy showed the strongest negative association with displacement (Spearman's  $\rho = -0.163$ ,  $p < 0.001$ ), followed by average monthly income ( $\rho = -0.125$ ,  $p < 0.001$ ) and the share of residents over 60 ( $\rho = -0.099$ ,  $p < 0.001$ ). In contrast, the share of children under 5 was positively associated with displacement ( $\rho = 0.058$ ,  $p = 0.001$ ). Although the magnitudes are modest, these patterns consistently suggest that socioeconomically advantaged census tracts, those with higher literacy, higher income, and more elderly residents, experienced less displacement, while tracts with more young children were more affected, raising concerns about equity in disaster impact.

**Table 1.** Spearman correlations between census-tract-level socioeconomic characteristics and displacement ratio in Rio Grande do Sul, Brazil (April 15 – May 31, 2024).

| Socioeconomic variable                         | Spearman's $\rho$ (p-value) |
|------------------------------------------------|-----------------------------|
| % population > 30 years old can read and write | -0.163 ( $p < 0.001$ )      |
| % population > 60 years old                    | -0.099 ( $p < 0.001$ )      |
| % population < 5 years old                     | 0.058 ( $p = 0.001$ )       |
| Average monthly income (in Brazilian Reals)    | -0.125 ( $p < 0.001$ )      |

## Discussion and Conclusion

Our results partially support the initial hypotheses. Consistent with Hypothesis 1, mobility declined sharply after the flood onset, with trip counts falling below baseline and radius of gyration dropping by up to 40%, before gradually recovering. Hypothesis 2 was also supported: displacement varied across regions, concentrated in Porto Alegre, and peaked on May 8 before subsiding. Hypothesis 3 was only partially supported. As expected, census tracts with more young children showed higher displacement and those with more elderly residents showed lower displacement. However, contrary to our hypothesis, higher income and literacy were associated with lower displacement. The underlying reasons are likely complex, including uneven hazard exposure across socioeconomic groups, and need further investigation.

Future work should validate these findings through sensitivity analyses and cross-referencing with external data sources, such as household travel surveys, disaster damage reports, and meteorological records. Natural and built environment factors, including elevation, proximity to floodplains, and drainage infrastructure, should also be incorporated, as they could potentially shape exposure. More broadly, cell phone data offers promise for assessing real time disaster impacts, modeling longer term recovery, and quantitatively measuring community resilience to support sustainable development.

In conclusion, we detected clear mobility disturbances in cell phone data following the 2024 Rio Grande do Sul floods, with people traveling less immediately after the flood and exceeding baseline mobility after the peak impact passed. Impacts were most pronounced in flooded areas and in Porto Alegre, where downtown emerged as a popular destination. Using a newly developed method, we identified 10.1% of active users as displaced, a figure consistent with reported state level estimates. Displacement patterns varied across population subgroups, raising potential social justice concerns and underscoring the need to integrate environmental exposure with social vulnerability to ensure disaster response reaches the populations least equipped to recover.

### **Acknowledgements:**

Funding sources and assistance from individuals. This project did not receive external funding. We gratefully acknowledge the support and data exploration contributions of UC Berkeley MaCSS students Eloise Wenxi Qin, Chelsea Javier, and Postdoc Ollin Langle-Chimal.

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