A POIs Average Temporal Degree Distribution

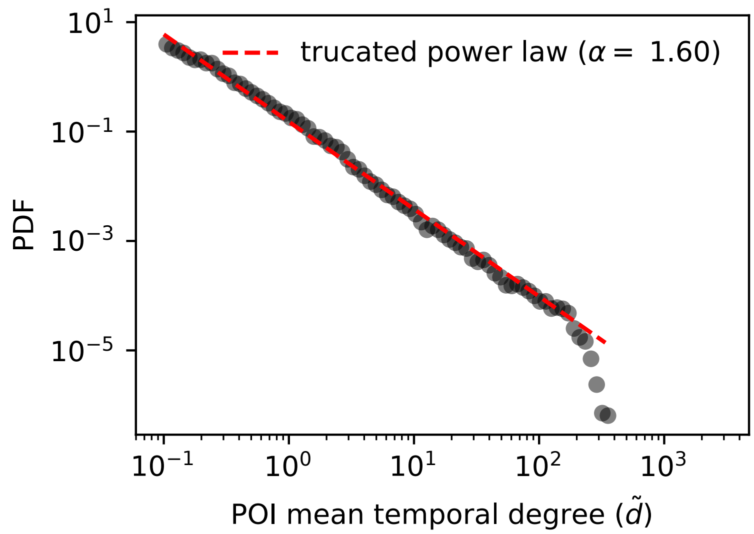

Figure 12. POIs average temporal degree

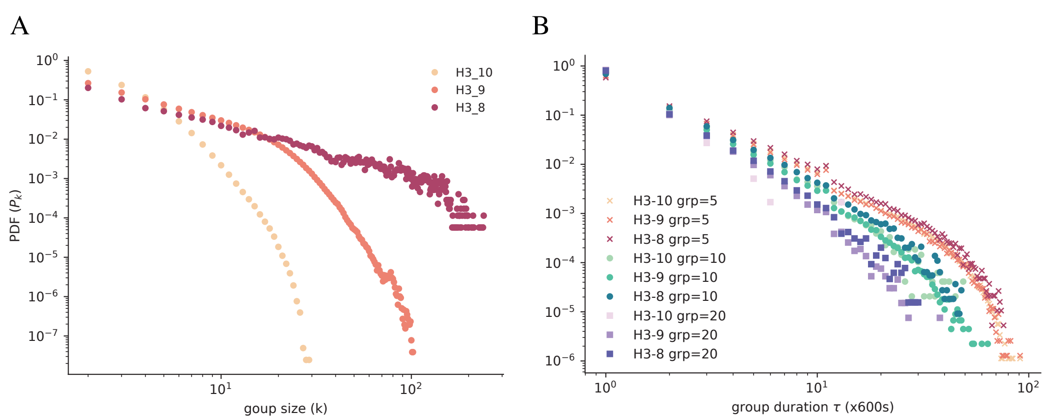

Figure 13. A) Group size distribution for different spatial aggregation level H3 (8,9,10), B) group duration distributions for different group size

B Household Detection Algorithm

Identifying the home location of individuals within the TrajDataFrame is crucial for our study as it allows us to establish a baseline for normal mobility patterns.With the result of the previous algorithm, we get real stay location of user's trajectories dataset, after that, the home location $h(u)$ for an individual u is deduced by determining the most frequently visited location during the designated nighttime period as per the studies[51,52]:

$$h(u) = \underset{r_i}{\operatorname{argmax}} \left| \{ t(r_i) \mid t(r_i) \in [t_{\text{startnight}}, t_{\text{endnight}}] \} \right| \tag{8}$$

where r_i is a location visited by u, $t(r_i)$ denotes the timestamp of u's visit to r_i, and $[t_{\text{startnight}}, t_{\text{endnight}}]$ is the interval defining nighttime. Here, the start night time is defined as 22h, end night time as 7h.

C Radius of Gyration Algorithm

The radius of gyration (r_g) measures the spatial extent of mobility by evaluating the dispersion of visited locations around their center of mass[33]. It can be analyzed in two forms, Non-Temporal Radius of Gyration and Temporal Radius of Gyration. The non-temporal radius of gyration quantifies the overall dispersion of a user's visited locations over a period, irrespective of time:

$$r_g^u = \sqrt{\frac{1}{n_u}\sum_{i=1}^{n_u}\left(dist\left(r_i(u), r_{cm}(u)\right)\right)^2} \tag{9}$$

where n_u is the total number of locations, $r_i(u)$ is the i-th visited location, and $r_{cm}(u)$ is the center of mass of all locations.

The temporal radius of gyration incorporates time, capturing mobility dispersion during specific time intervals:

$$r_g^u(t) = \sqrt{\frac{1}{n_u(t)}\sum_{i=1}^{n_u}\left(dist(r_i(u) - r_{cm}(u))\right)^2} \tag{10}$$

Here, $n_u(t)$ and $r_{cm}(u)$ are restricted to the time interval t, enabling the analysis of dynamic mobility patterns.

D Spatial Directionality of Human Mobility

The spatial directionality of urban mobility is a key indicator of how inhabitants navigate urban environments, reflecting both concentrated and dispersed patterns of movement. Building on the work of Zhao et al.[37], which introduced metrics of anisotropy Λ (directional imbalance) and centripetality Γ (movement orientation toward city centers) using data from 90 million of mobile users across 60 Chinese cities. The present study adopts a similar analytical framework to examine mobility patterns in Lima. Stop locations, identified using the H3 spatial indexing system at resolution level 6, were aggregated from a comprehensive mobility dataset covering the period from May 1 to June 1, 2020. This approach facilitated the construction of Origin-Destination (OD) flow matrices, enabling the quantification of mobility flows and their force vectors. These vectors were used to evaluate, **Centripetality** Γ: The degree to which mobility flows converge towards the city center.**Anisotropy** Λ : The directional bias or imbalance of these flows.

The analysis revealed that centripetality peaks during the morning rush hour (9:00–10:00 AM), underscoring the city center's role as a socio-economic hub. This convergence reflects the concentrated nature of urban flows during the start of the workday. In contrast, anisotropy remained consistently low throughout the day, indicating an evenly distributed accessibility to the city center from all urban directions. This uniformity highlights the center's function as a central node with equitable connectivity. These findings provide actionable insights for urban planning, Optimizing Connectivity, enhanced infrastructure in central areas to manage peak-hour flows. Congestion mitigation, strategies to balance mobility demands across peripheral zones. Support for Polycentric Development, encouraging secondary hubs to reduce commuting distances, as observed in polycentric cities studied in[37].

By combining advanced spatial indexing, OD flow analysis, and directionality metrics, this study offers a robust framework for understanding urban mobility dynamics. The methodology not only captures spatial patterns but also integrates temporal dimensions, making it a powerful tool for designing resilient and efficient urban environments.

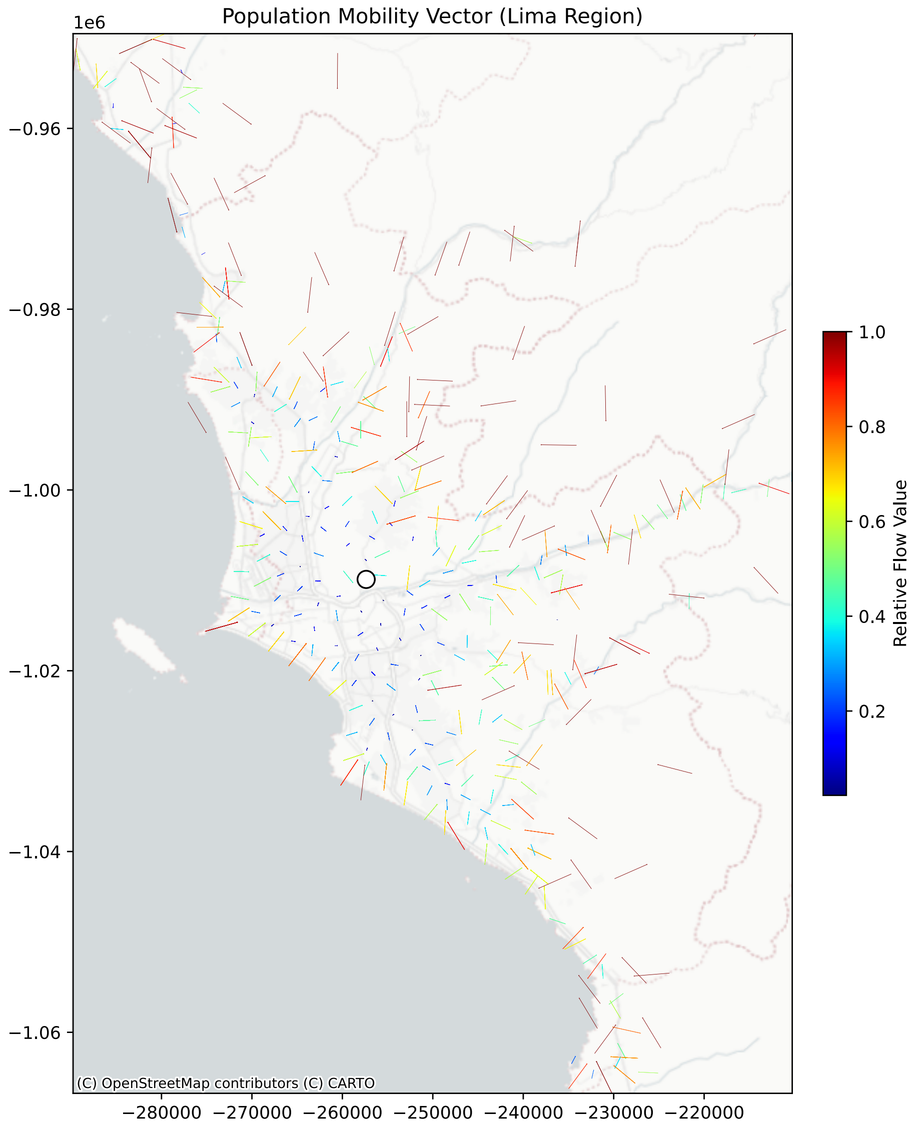

Figure 14. Population Mobility Vector (PMV) field for the Lima Region between 6:00 AM and 10:00 AM, derived from H3 resolution 7 spatial bins and 15-minute interval data. Each vector represents the aggregated direction and relative magnitude of population flows during the morning period. Warmer colors (red) indicate stronger relative flow intensity, while cooler colors (blue) reflect weaker flows. The pattern reveals a marked centripetal trend, with many vectors oriented toward central Lima, highlighting the morning influx toward the urban core.

E Fine-grained Mobility Variables

Table 2 presents the definitions of variables used in fine-grained mobility analysis.

Variable	Definition
Within flow	Total number of devices' Stop patterns within a single cell(h3).
In flow	Total number of individuals entering a specific cell from others cell.
Average contacts	Average number of social interactions an individual has within a cell.
N home	Number of home locations (individuals' primary residences) in a cell.
Radius of gyration	Average distance traveled by individuals from their home cell.
Social strata	Metric capturing the socioeconomic level.
Presence	Total number of individuals spending time in a specific cell.
Out flow	Total number of individuals living a specific cell for other cell.
Shannon entropy	Metric quantifying the spatial diversity of user locations, indicating how uniformly time or visits are distributed across different cells.
Stay at home	Proportion of time individuals spent at their inferred home location.

Table 2. Definitions of variables used in fine-grained mobility analysis.

F Redistributing County-Level Socioeconomic and Population Data

To enable the analyses of the social strata with the mobility variables, the Census unit level, which is about 0.004 km^2, is aggregated to the POIs represented by H3 cells at resolution 6. In cases where an H3 cell overlaps multiple Census units, the population data are weighted by the relative intersection area, ensuring accurate and consistent allocations as shown in Equation 11.

$$P_n = \sum_{x \in X} \left(\frac{r_{n,x}}{\mathrm{A}_x} \cdot P_x \right), \tag{11}$$

Where P_n is the total population corresponding to a POI, X represents the set of Census units intersecting a POI, P_x is the population of the Census unit x, $r_{n,x}$ is the area of the intersection between the POI n and Census unit's polygon x, and A_x is the total area of a Census units population x.

Socioeconomic values are similarly computed as weighted averages of intersecting Census unit as illustrated in Equation 12.

$$S_n = \sum_{x \in X} r_{n,x} \cdot S_x, \quad \text{with} \sum_{x} r_{n,x} = 1. \tag{12}$$

where X denotes the set of Census units that intersect POI n, and S_x is the socioeconomic value of Census unit x. The coefficient $r_{n,x}$ serves as the area-based weight representing the fraction of POI n covered by Census unit x, normalized so that the total weight of all intersecting units sums to 1. Hence, S_n is a true weighted average that accounts for the proportional overlap of different Census units, ensuring fine-grained spatial variations in socioeconomic measures are accurately preserved at the POI level.

G Influence of Sociodemographic Variables over Mobility

Figure 15 shows a correlation coefficient of 0.88 between the number of Covid-19 related deaths reported by Death Information System[53] and the unemployment rate provided by the National Institute of Statistics and Informatics in the National Household Survey[54] for each district. The 43 districts of Metropolitan Lima and the seven districts of Callao province were considered together, as Lima and Callao are geographically adjacent, with people commuting between the two areas as though they form a single city.

To account for population differences and allow for a comparison between the most populous district of Lima, San Juan de Lurigancho, with approximately one million inhabitants, and smaller districts such as Rimac, with 150,000 inhabitants, the variable was re-scaled per 1000 inhabitants. This was achieved using Equation 13, where the ratio between the variable and the district population is multiplied by the number of inhabitants targeted for the indicator.

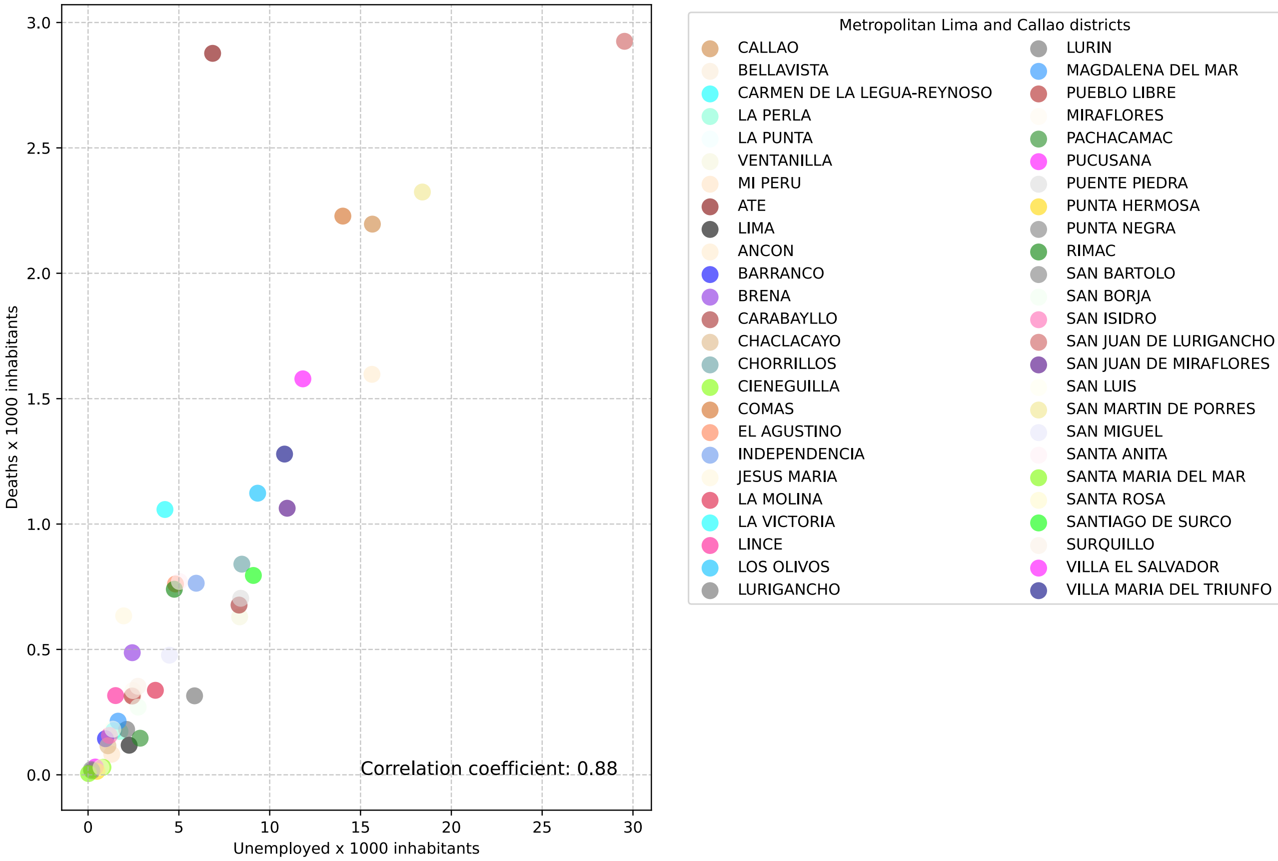

Figure 15. Correlation between deaths caused by COVID and the unemployment rate per district in Metropolitan Lima and Callao.

$$\text{Variable per 1000 inhabitants} = \left(\frac{\text{Total Variable}}{\text{Total Population}} \right) \times 1000 \tag{13}$$