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Article

Anomalous Surge in the Mobility Scaling Exponent Reveals Unique Collective Behavior during the 2024 Noto Peninsula Earthquake

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Abstract: A scaling law, $S \propto L^{\alpha}$, governs the relationship between the area S enclosed by a human mobility loop and its trajectory length L. Previous studies have established that for short-range movements ($L < 5$ km), the scaling exponent is typically $\alpha \sim 2.0$, indicative of two-dimensional efficient exploratory behavior that efficiently covers the surrounding area. For long-range movements ($L \geq 5$km), it is typically $\alpha \sim 1.5$–1.6, corresponding to one-dimensional destination-oriented behavior characterized by a nearly straight-line trajectory toward the destination. In this study, we analyze high-resolution (1-min interval) GPS data from Agoop, comprising approximately 20,000 daily records, to examine human mobility traces in Ishikawa Prefecture before and after the Noto Peninsula Earthquake on 1 January 2024. We focus on the changes in the scaling exponent α. This major earthquake provides a valuable "natural experiment" to investigate collective human behavior under established social norms. Our analysis revealed a highly anomalous phenomenon immediately following the earthquake. Contrary to normal conditions, the long-range scaling exponent, α_{Long}, surged to $\alpha \sim 1.8$ across the entire prefecture, a value comparable to the short-range exponent, α_{Short}. This phenomenon was observed even in areas with relatively minor physical damage and returned to its baseline value by the next day. This anomalous change in the scaling exponent strongly suggests that the shift in mobility patterns was not a direct result of the earthquake's physical damage. Rather, it indicates that individuals who were outdoors temporarily altered their movement from one-dimensional, destination-oriented travel to two-dimensional, exploratory behavior while evacuating to safer locations, such as higher ground, in response to tsunami alerts. This study is the first to demonstrate that the mobility scaling exponent can function as a real-time quantitative indicator for characterizing collective psychological states, such as widespread precautionary evacuation, even in the absence of direct physical damage.

Keywords: sociophysics; computational social science; human mobility; scaling law; big data; disaster science; mobility during disasters; evacuation behavior

1. Introduction

Sociophysics, a field that seeks to understand social phenomena using concepts and methods from physics, is entering a new golden age with the advent of large-scale digital data. In particular, high-resolution location data obtained from sources such as smartphones and GPS devices have enabled the analysis of human mobility patterns at a high spatiotemporal resolution, capturing dynamics that were previously unobservable. Research has demonstrated that human mobility, despite its diversity, is governed by remarkably universal statistical laws. For instance, Noulas et al. showed that a model based on the "rank distance" of intervening locations between an origin and destination is universally applicable across different cities [1]. Additionally, Zhao et al. analyzed travel distance distributions by transportation mode, revealing how a power law emerges from the superposition of different modes [2]. Furthermore, using large-scale data, Yan et al. identified statistical features of mobility patterns common to both individuals and populations and proposed a universal model [3]. Schläpfer et al. proposed a "universal visitation law", where a power-law relationship exists between visitation distance and frequency, which they successfully validated in multiple cities [4]. Moreover, Zhao et al. offered an explanation for the power laws often found in travel distance distributions, considering factors such as transportation modes and the environment [5]. Collectively, these studies strongly indicate that human mobility is not a random process but one that adheres to universal statistical laws. Seminal works by Brockmann et al. [6], using banknote dispersal, and González et al. [7], using mobile phone data, established that human travel is governed by robust scaling laws and possesses a high degree of predictability. Subsequent models, such as the "exploration and preferential return" framework by Song et al. [8], provided microscopic mechanisms to explain these observed regularities.

The scaling law of mobility traces, which is the focus of the present study, is one such example of these universalities. In our previous research, we reported that the area S and perimeter L of a loop formed by a mobility trace follow a power law, $S \propto L^{\alpha}$ [9]. This exponent, α, characterizes the dimensionality of the movement: $\alpha = 2$ corresponds to two-dimensional motion that efficiently explores a space (such as Brownian motion), while $\alpha = 1$ corresponds to one-dimensional movement, like a round trip to a destination. Previous studies have shown that for human mobility, $\alpha \sim 2.0$ for short distances ($L < 5$km) and $\alpha \sim 1.5-1.6$ for long distances ($L \geq 5$km). This aligns with our intuition that people engage in efficient exploratory behavior over short distances and destination-oriented behavior over long distances.

This scaling exponent also serves as a sensitive indicator of collective behavior patterns and their underlying socio-geographical contexts. For example, it has been reported that on the same public holiday, the long-distance exponent α_{Long} in Urayasu City, home to Tokyo Disney Resort, one of Japan's largest theme parks, becomes lower than on weekdays (i.e., more one-dimensional). In contrast, the exponent in the historic city of Kyoto becomes higher (more two-dimensional). The former is thought to reflect an increase in round trips to a specific destination, while the latter likely reflects an increase in touring behavior, with people visiting various points of interest within the city. Thus, the scaling law is an effective tool for quantifying mobility patterns that reflect regional characteristics under normal conditions.

Previous studies leveraging large-scale mobility data have made significant strides in quantifying evacuation rates, resilience, and recovery patterns in response to disaster intensity [10–14]. For instance, Yabe et al. revealed that evacuation probability is strongly correlated with the experienced seismic intensity [15]. However, these studies have primarily focused on macroscopic changes in flow volume, direction, or the discrete outcomes of decision-making processes. It remains largely unknown how massive shocks, such as earthquakes, affect the fundamental statistical laws and geometric properties that govern mobility itself. This study aims to fill this critical gap by examining the impact of a disaster on the universal scaling laws of human movement.

This study, therefore, aims to fill this research gap from a sociophysical perspective. We treat the large-scale Noto Peninsula Earthquake, which occurred in Japan on 1 January 2024, as a form of "natural experiment". While the choice of January 1 as the analysis date may initially seem to be a special case, it is this very uniqueness that provides a powerful backdrop for our analysis. In Japan, mobility on the afternoon of New Year's Day is dominated by highly destination-oriented behavior, typified by Hatsumōde, the first shrine or temple visit of the year. Analyses of past GPS data show that the peak time for these visits is between 14:00 and 15:00 [16]. Such movements are intrinsically one-dimensional and are expected to yield a low scaling exponent. Indeed, our data confirms that the exponent before the earthquake was low, consistent with normal conditions. It is therefore reasonable to assume that this one-dimensional mobility pattern would have continued had the earthquake not struck at 16:10. What we observed, however, was a significant increase in the exponent to a value indicative of two-dimensional movement, in contrasts with this expectation. This suggests that the established social norms for holiday behavior collapsed instantaneously under the massive external shock of the earthquake, giving way to a collective behavior of a completely different nature. Thus, the context of New Year's Day serves as a robust baseline that highlights emphasizes the anomalous nature of the observed change in the exponent was.

Specifically, we hypothesize that the earthquake induced a fundamental shift from one-dimensional destination-oriented movement to two-dimensional exploratory movement. We posit that the long-range scaling exponent, α_{Long}, serves as a quantifiable metric that captures the collective state of the system. Based on this hypothesis, this study addresses the following research questions:

1. How does the occurrence of a large-scale earthquake alter the scaling exponent α of human mobility traces, particularly the long-range exponent α_{Long}?

2. Is this change correlated with the magnitude of physical damage caused by the earthquake, or is it driven by other factors?
3. Is it possible to characterize collective human behavior during a disaster, such as evacuation, through the analysis of this scaling law?

By answering these questions, this paper aims to show the potential of sociophysical indicators to contribute to understanding human behavior in real-time and devising more effective response measures in the context of disaster prevention and crisis management.

The remainder of this paper is organized as follows. Section 2 describes the data and our analytical methods. Section 3 presents the results, Section 4 discusses these findings, and finally, Section 5 provides the conclusion.

2. Data and Methods

2.1. Data

In this study, we utilize location data provided by Agoop, Inc. [17], which is collected from smartphone applications. The data is fully anonymized to protect individual privacy. The dataset consists of latitude and longitude information at a minimum interval of one minute. The geographical area for analysis is the entire Ishikawa Prefecture (see Figure 1), and the primary period of analysis is January 2024. For comparison, data from August and September 2023 are also referenced. The dataset comprises approximately 20,000 unique trajectory records per day.

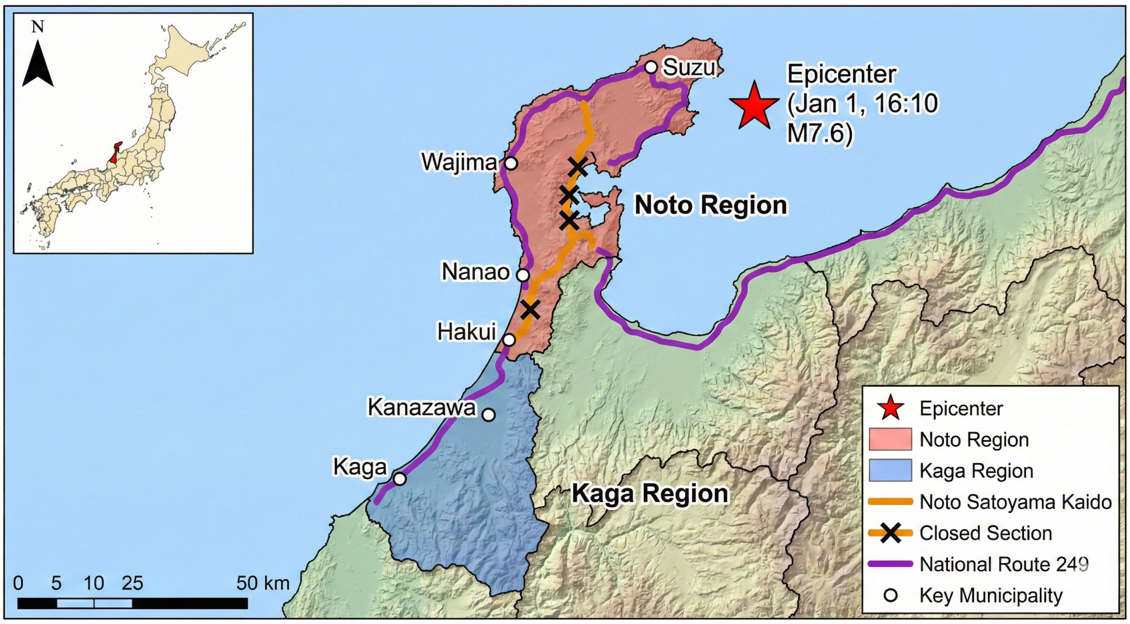


Figure 1. Map of Ishikawa Prefecture and the spatial context of the 2024 Noto Peninsula Earthquake. The Red Star indicates the epicenter (37.498° N, 137.242° E). The prefecture is analytically divided into the Noto Region (severe damage zone, shaded red) and the Kaga Region (minor damage zone, shaded blue), corresponding to the municipal classifications listed in the text. Key municipalities and severed infrastructure networks (Noto Satoyama Kaido and National Route 249) are highlighted against the topographic relief to illustrate the physical constraints on mobility.

2.2. Trajectory Extraction and Definition

The mobility trajectories selected for this analysis were required to meet the following conditions: (1) The trajectory must consist of a time series of five or more location data points. (2) The linear distance between the start and end points of the trajectory must be less than 50 m. This is a necessary condition for forming a closed-loop trajectory by connecting the start and end points. The 50-m threshold was determined based on the positional accuracy of the GPS data (on the order of tens of meters, according to the provider, Agoop) and a conservative estimate of the walking distance for an average adult in one minute. (3) Due to the data specifications, trajectories do not (and cannot) span across multiple days.

For each trajectory, we defined a polygon by closing the loop between its start and end points and calculated the following two quantities: (a) Trajectory Length (L): The total travel distance, calculated by summing the distances between consecutive points along the trace. (b) Enclosed Area (S): The area of the polygon formed by the trajectory and the line segment connecting its start and end points.

2.3. Calculation of the Scaling Exponent

The core analytical method of this study is based on the scaling law between the area S and the length L of a mobility trace, given by $S \propto L^{\alpha}$. This relationship can be expressed as a linear equation on a log-log plot: $\log_{10}(S) = \alpha \log_{10}(L) + C$. Therefore, by plotting the (L, S) pairs from numerous trajectories within a given period and region, the scaling exponent α can be estimated as the slope of a linear regression (see Figures 2 and 3 below for illustration).

Following previous research, we classified movements into two categories and calculated a separate exponent for each:

- Short-range mobility: $L < 5$ km, with its corresponding exponent denoted as α_{Short}.
- Long-range mobility: $L \geq 5$ km, with its corresponding exponent denoted as α_{Long}.

The 5 km threshold was chosen as it approximates the distance an adult can walk in about one hour. The scaling exponent α was estimated as the slope of the linear regression model using the Ordinary Least Squares (OLS) method. All reported error margins represent the standard error of the estimated slope.

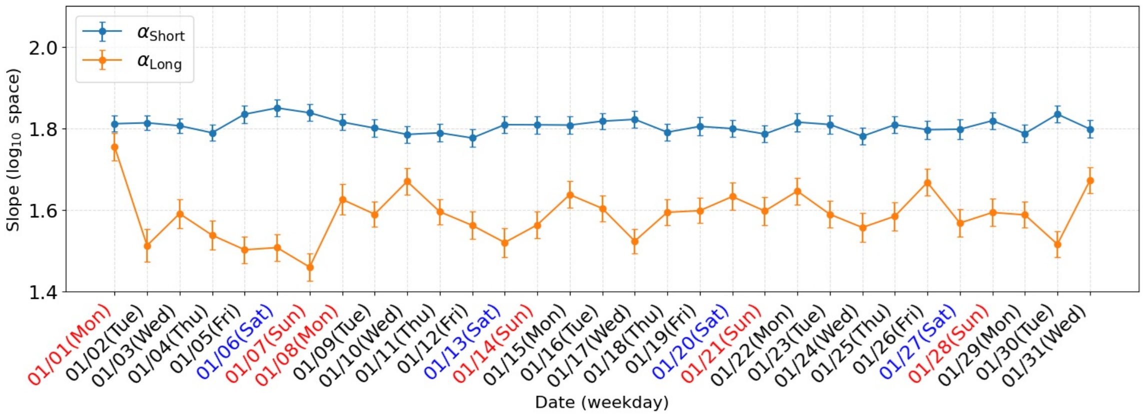
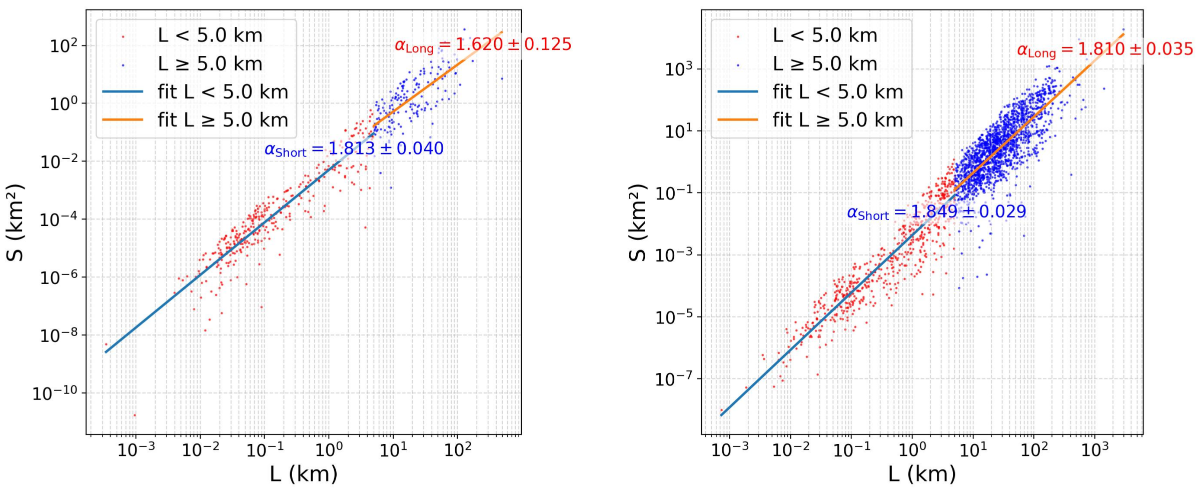


Figure 2. On 1 January, α_{Long} exhibited an anomalous increase, approaching the value of α_{Short}, before returning to its normal level on the following day. The colors of the dates on the x-axis correspond to the day type: Black indicates weekdays, Blue indicates Saturdays, and Red indicates Sundays and public holidays.



(a) **(b)**

Figure 3. Hourly scatter plots for 1 January 2024: (**a**) trajectories completed before the earthquake and (**b**) trajectories completed after the earthquake.

2.4. Analysis of the Earthquake's Impact

To analyze the effects of the Noto Peninsula Earthquake, which occurred at 16:10 on 1 January 2024, we conducted the following comparative analyses on the data from Ishikawa Prefecture.

1. Pre- vs. Post-Earthquake Comparison: We divided the trajectory data from 1 January 2024, into two groups based on the earthquake's timing: "trajectories completed before the event" and "trajectories completed after

the event". We then compared the respective α values for each group.

2. Inter-Regional Comparison: We segmented the data into two regions with differing levels of physical damage: the severely damaged "Noto region" and the relatively lightly damaged "Kaga region". We then compared how the α value changed in each region. The Noto region comprises Nanao City, Wajima City, Suzu City, Hakui City, Kahoku City, Tsubata Town, Uchinada Town, Shika Town, Hodatsushimizu Town, Nakanoto Town, Anamizu Town, and Noto Town. The Kaga region consists of Kanazawa City, Hakusan City, Nonoichi City, Nomi City, Kawakita Town, Komatsu City, and Kaga City. This classification follows that used in official survey reports on the 2024 Noto Peninsula Earthquake.

The geographical configuration of these regions is visualized in Figure 1. The map illustrates the proximity of the Noto region (severe damage zone) to the epicenter and highlights the physical severance of major arteries, such as the Noto Satoyama Kaido, in contrast to the distant Kaga region (control group).

3. Verification of Evacuation Behavior: To investigate the possibility that post-earthquake movements were related to tsunami evacuation, we appended elevation data to the trajectories and analyzed changes in altitude for movements that occurred after the earthquake.

3. Results

3.1. Anomalies in the Scaling Exponent on the Day of the Noto Peninsula Earthquake

The primary finding of this study is the drastic change in the scaling exponent observed at the time of the Noto Peninsula earthquake on 1 January 2024. Figure 1 shows the time-series variation of α_{Short} and α_{Long} in Ishikawa Prefecture during January 2024. The error bars in the figure, and for α hereafter, represent the standard error of the regression coefficient.

As shown in Figure 2, on 1 January, the day of the earthquake, the long-range mobility index, α_{Long}, was observed to surge from its normal range of 1.5–1.6 to approximately 1.8, a level comparable to the short-range mobility index, α_{Short}. This anomalous increase was also observed when the threshold separating short and long ranges was varied to 3, 4, 6, and 7 km. Furthermore, to verify the robustness of our results against the choice of the loop-closure threshold (baseline: 50 m), we conducted a sensitivity analysis using thresholds of 25 m, 100 m, and 200 m. The analysis confirmed that the surge in α_{Long} on 1 January is consistently observed across all thresholds (see Appendix Figure A1 for a side-by-side comparison). This change is highly unusual; given that α_{Long} returned to its normal value on the following day, 2 January (see Table 1). A Z-test confirmed that the difference between α_{Long} on 1 January (post-quake) and 2 January is statistically significant ($Z = 5.25, p < 0.001$). This suggests a transient phenomenon strongly associated with the sudden event of the earthquake. Such a change was not observed in the analysis for Ishikawa Prefecture in August and September 2023 [9].

Table 1. Summary of scaling exponents (α) and number of trajectories (N) under different conditions. The "Post-quake" data consists of trajectories that began before 16:10 and completed after 16:10. Trajectories initiating after the earthquake were excluded to ensure the analysis captures the behavioral shift of individuals affected during their journey. Data from January 2 is included as a reference for normal conditions.

Condition	Region	α_{Short}	N_{Short}	α_{Long}	N_{Long}	$\Delta\alpha_{\mathrm{Long}}$
Baseline Pre-quake	Ishikawa	1.81 ± 0.04	339	1.62 ± 0.13	165	–
Post-quake	Ishikawa	1.85 ± 0.03	615	1.81 ± 0.04	1683	+0.19
Severe Damage	Noto	1.82 ± 0.06	161	1.92 ± 0.16	159	+0.30
Minor Damage	Kaga	1.81 ± 0.02	1018	1.75 ± 0.04	1646	+0.13
Reference (2 January)	Ishikawa	1.81 ± 0.02	1362	1.51 ± 0.04	1,677	–

3.2. Detailed Analysis of Earthquake Impacts

To further investigate the cause of the anomalous changes observed on 1 January 2024, we analyzed the data from that day by dividing it into pre-earthquake and post-earthquake periods. In Japan, 1 January, known as Ganjitsu, is a special public holiday characterized by unique social customs. These include the tradition of visiting shrines and temples to pray for health, safety, and fortune for the year (Hatsumōde), gathering with relatives, and adult children returning to their hometowns. Another custom is viewing the first sunrise of the year, called goraikō. These activities could potentially cause the unique mobility fluctuations observed, meaning they might be inherent to New Year's Day itself.

To distinguish these holiday-specific effects from the impact of the earthquake, we segmented the mobility trajectories based on the earthquake's occurrence time (16:10 JST). The analysis yielded the following results:

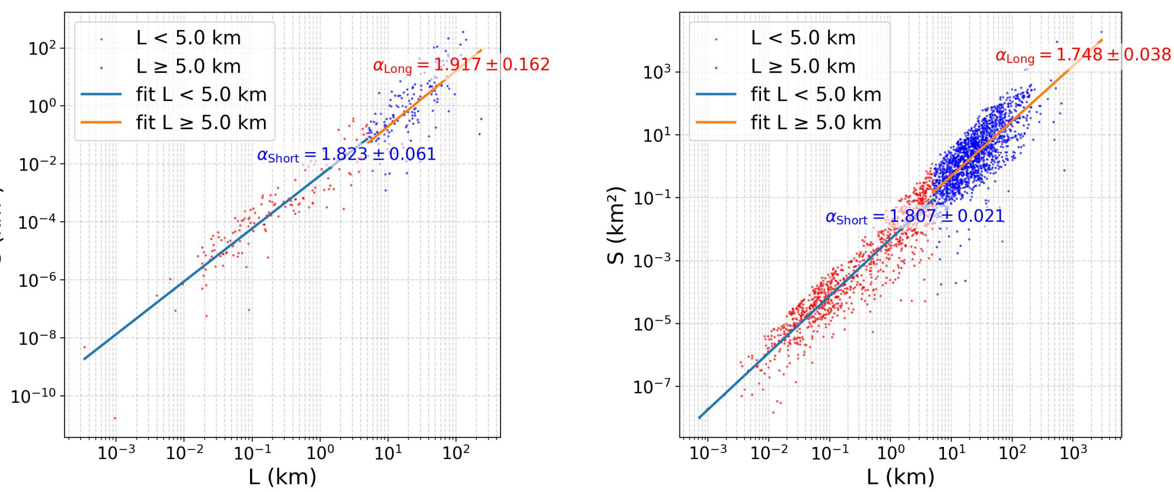
- For trajectories that closed before the earthquake, we estimated the scaling exponents using Ordinary Least Squares (OLS) regression. The results were: $\alpha_{\mathrm{Short}} = 1.81 \pm 0.04$, $\alpha_{\mathrm{Long}} = 1.62 \pm 0.13$
- For trajectories that closed after the earthquake: $\alpha_{\mathrm{Short}} = 1.85 \pm 0.03$, $\alpha_{\mathrm{Long}} = 1.81 \pm 0.04$

As these analysis results indicate, the trajectories that closed before the earthquake on 1 January show a clear, conventional difference between α_{Short} and α_{Long}, consistent with any other day. It was only in the long-range trajectories completed after the earthquake that α_{Long} rose significantly, approaching the value of α_{Short}. Therefore, we conclude that the fluctuation on 1 January can be attributed to the impact of the earthquake. To further rule out the hypothesis that the surge was simply due to irregular return trips typical of New Year's Day, we referenced data from Shimogyo Ward, Kyoto City, on 1 January 2022. Despite similar social customs involving shrine visits and evening returns, no such increase in the scaling exponent was observed in this control case. This supports the conclusion that the anomaly in Ishikawa was a direct consequence of the earthquake. Comparing this post-earthquake value with the pre-earthquake baseline (1.62 ± 0.13) yields a p-value of 0.16, which is not statistically significant due to the large standard error associated with the small pre-quake sample size. However, the difference from the robust baseline of 2 January (1.51 ± 0.04) is highly significant ($p < 0.001$), confirming the anomalous nature of the mobility shift.

Next, to examine whether the severity of physical damage influenced the increase in α_{Long}, we conducted a separate analysis for the Noto and Kaga regions. The Noto region suffered extensive road damage. Numerous roads were severed. In particular, the Noto Satoyama Kaido, an expressway running through the peninsula, experienced widespread sinkholes and ruptures, leading to the long-term closure of the section from the Yanagida IC in Hakui City to the northern tip. Furthermore, National Route 249, a major coastal trunk road, became impassable in many sections due to slope failures, landslide debris, and severe cracks on the road surface. As a result, widespread traffic disruptions, including closures and congestion, were reported. In contrast, the Kaga region sustained much less damage. Although a section of the Hokuriku Expressway was temporarily closed for safety inspections, it was subsequently reopened. Road closures were limited to one municipal road in Kaga City and two in Komatsu City. Consequently, no significant traffic disruptions were reported in this area. Under these differing conditions, the analysis for each region (see Figure 4) yielded the following results:

- Noto region only: $\alpha_{\mathrm{Short}} = 1.82 \pm 0.06$, $\alpha_{\mathrm{Long}} = 1.92 \pm 0.16$
- Kaga region only: $\alpha_{\mathrm{Short}} = 1.81 \pm 0.02$, $\alpha_{\mathrm{Long}} = 1.75 \pm 0.04$

Notably, the significant increase in α_{Long} was observed not only in the Noto region, which suffered severe physical damage, but also in the Kaga region, where the damage was relatively minor. This result suggests that the observed change in mobility patterns cannot be explained solely by direct physical damage, such as road severances and the resulting traffic disruptions, but was instead caused by more widespread factors. Statistical testing showed no significant difference between the exponents of the Noto and Kaga regions ($Z \approx 1.03, p \approx 0.30$), further supporting the interpretation that the behavioral shift occurred uniformly across the prefecture.



(a) **(b)**

Figure 4. Regional scatter plots for 1 January 2024: (**a**) Noto region only, and (**b**) Kaga region only.

The measurement results presented thus far are summarized in Table 1. The small number of data points for the period before 16:10 on 1 January is because this count represents only the trajectories that closed before this time. In contrast, the data count for the period after 16:10 is strictly limited to trajectories that began before the earthquake and completed after it (i.e., “Crossing” trajectories). We attempted to analyze trajectories that began after 16:10 (“Pure Post-quake”), but they were excluded from the final results. This is because the number of such trajectories forming a long-range closed loop ($L \geq 5$ km) was extremely small ($N = 77$), likely due to the insufficient remaining time in the day, which rendered the statistical analysis unreliable. Thus, our results primarily capture the behavioral changes of individuals who were already away from home at the time of the shock.

3.3. Association with Evacuation Behavior

As an interpretation of the increase in α_{Long} which signifies the “two-dimensionalization of long-range movement”, we hypothesized that it is primarily driven by widespread “evacuation behavior”. Immediately following the earthquake, major tsunami warnings were issued via television and radio. It is therefore presumed that not only people in coastal areas but also those considering the possibility of a tsunami evacuated to safer locations, such as higher ground. Indeed, such evacuation behavior has been widely reported. A resident survey in Suzu City found that over 80% of respondents evacuated, with 60% taking action within five minutes of the quake, using vehicles and walking in nearly equal measure [18]. A study in the neighboring Toyama Prefecture also confirmed that many coastal residents evacuated following the tsunami warning [19]. Further academic analyses have clarified the relationship between tsunami behavior and evacuation actions along Toyama Bay [20], compiled case studies on the decision-making processes of non-residents such as tourists [21], and conducted field surveys on the realities of tsunami evacuation in multiple areas of Ishikawa and Toyama [22]. In addition, publicly available field survey datasets from the Noto Peninsula [23] and field reports detailing challenges in shelter management [24] provide further evidence of widespread evacuation.

Such evacuation behavior, unlike linear travel toward a specific destination, is more likely to trace exploratory, two-dimensional trajectories as individuals move from their current location in search of safety. To test this hypothesis, we analyzed the elevation of post-earthquake trajectories. Figure 5 shows the distribution of trajectory elevations by time period on 1 January.

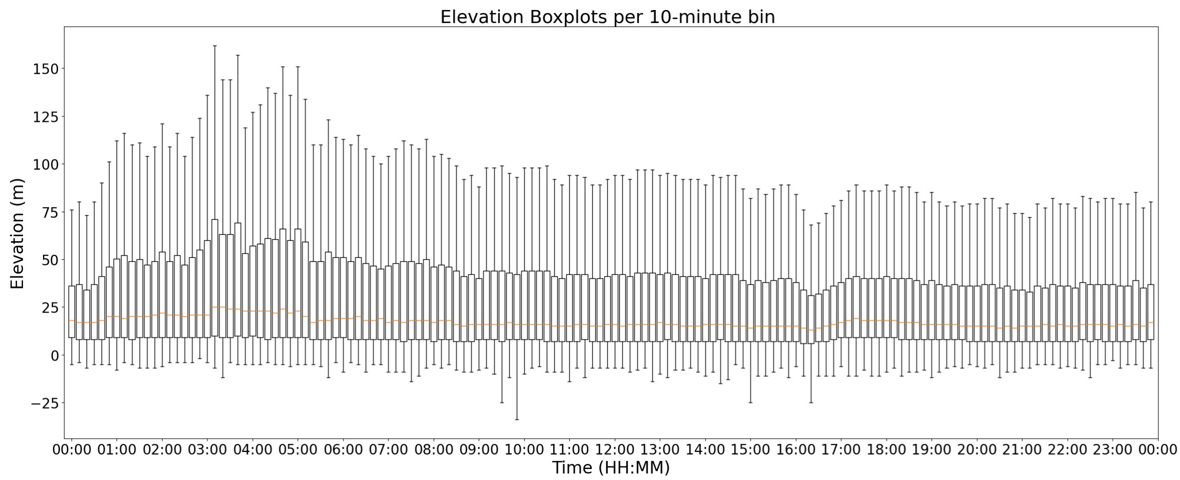


Figure 5. Box-and-whisker plot of trajectory elevations by time period (Time of day, JST) on 1 January 2024. The bottom and top of the box represent the first (Q1) and third (Q3) quartiles, respectively, with the center line indicating the median. The whiskers extend to the minimum and maximum elevations, excluding outliers. After the earthquake, the maximum value, Q3, and median all show an increasing trend from 16:10 to approximately 17:40.

As illustrated in the figure, an increase in the maximum value, third quartile (Q3), and median of trajectory elevation was observed between 16:10 and approximately 17:40 following the earthquake. This indicates that people moved to locations of higher elevation, a finding that strongly supports the hypothesis of evacuation behavior in response to the tsunami. Note that elevation values were derived from the topographic data corresponding to the GPS coordinates, ensuring stability against vertical GPS errors. Quantitatively, we analyzed the trajectories of 3397 individuals tracked both at the time of the earthquake and afterwards. We found that 64.9% (2203 individuals) recorded a maximum elevation increase of more than 10 meters relative to their initial position. This widespread vertical movement strongly corroborates the occurrence of mass evacuation to higher ground.

4. Discussion

The results of this study quantitatively demonstrate for the first time that the scaling laws inherent in human mobility trajectories can be dramatically altered by an extraordinary event like a large-scale disaster. In particular, the anomalous rise in the long-range mobility index, α_{Long}, observed immediately after the Noto Peninsula earthquake offers significant insights into understanding human collective behavior during a disaster. Our findings indicate a structural change in collective mobility patterns. The scaling exponent α_{Long} functions as a metric describing the collective state of mobility. The pre-earthquake state ($\alpha_{Long} \sim$ 1.5–1.6) corresponds to predictable, destination-oriented movement governed by established social norms. The earthquake and subsequent tsunami warning acted as a critical perturbation, triggering a rapid shift to a state ($\alpha_{Long} \sim 1.8$) characterized by exploratory safety-seeking behavior. The observation of this shift even in the Kaga region, where physical damage was minimal, indicates that the driving force was primarily informational. This interpretation is also consistent with established findings in disaster sociology, which indicate that collective responses to disasters are not characterized by irrational panic, but rather by adaptive and pro-social behaviors as individuals attempt to navigate an uncertain environment. The observed two-dimensional movement can be seen as a physical manifestation of "milling", a process where people in an ambiguous situation engage in search behaviors to define the situation and determine an appropriate course of action.

Our analysis reveals that the surge in α_{Long} cannot be explained solely by the physical destruction of infrastructure. This is because a similar phenomenon was widely observed in the Kaga region, which sustained little physical damage. Furthermore, the transient nature of this change corroborates that it was not caused by permanent physical constraints. We also considered the alternative explanation that minor traffic disruptions forced drivers to take circuitous detours, thereby artificially increasing the scaling exponent. However, this is unlikely to explain the high values observed in the Kaga region. In this area, the primary disruption was the closure of the Hokuriku Expressway, for which the standard detour is National Route 8—a wide, straight trunk road running parallel to the expressway. A simple diversion to a parallel route would not increase the trajectory complexity to $\alpha \sim 1.75$, a value indicative of random-walk-like exploratory behavior. Thus, the surge implies active "searching" or "wandering" (e.g., seeking safety or information) rather than a determined drive to a destination via a detour. The most plausible mechanism we propose is the "two-dimensionalization of movement patterns due to widespread evacuation behavior". Under normal conditions, long-range travel is predominantly one-dimensional (linear), connecting specific points such as home and work, school, or commercial facilities. However, when individuals encounter a large-scale earthquake and subsequent tsunami warnings while away from home, their primary motivation shifts from "reaching a destination" to "ensuring personal safety". Consequently, two-dimensional (areal) movement, such as searching the vicinity for the nearest high ground or shelter, becomes dominant. The observed convergence of α_{Long} towards α_{Short} can be interpreted as capturing this very qualitative change in long-range travel—a fundamental shift from one-dimensional, goal-oriented movement to two-dimensional, exploratory movement, as hypothesized in the introduction. The results of our elevation data analysis are also consistent with this interpretation. Our findings offer a complementary perspective to studies that directly link evacuation behavior with physical intensity. For example, a comparative analysis of four major earthquakes in Japan by Yabe et al. [15] showed that evacuation probability is strongly correlated with the experienced seismic intensity, with a critical threshold around a seismic intensity of 5.5. In contrast, our results show that the change in the nature of mobility, as captured by α_{Long}, is largely independent of the local intensity of physical damage. This suggests that while the decision of whether to evacuate may be a function of physical shock, the collective mode of behavior post-shock is governed by more global factors, such as the widespread dissemination of the tsunami warning and the associated collective uncertainty.

4.1. Contributions

This study makes several important contributions to the field of sociophysics. First, it demonstrates, based on empirical data, how the scaling exponent of human mobility changes under extraordinary circumstances. This provides fundamental insights for evaluating the robustness and resilience of social systems using physical indicators. Second, our work shows that large-scale location data can be a powerful tool for understanding collective human behavior during disasters in near real-time. By continuously monitoring aggregate indices like the scaling exponent α, it may be possible to rapidly detect where and on what scale evacuations have begun. This offers an immediacy and comprehensiveness not available from traditional surveys or interviews and could support disaster response agencies in making more data-driven decisions. Furthermore, this study suggests that the scaling exponent of collective mobility can serve as a novel, real-time "sociometer" for collective psychological states. Unlike metrics tied to physical damage, the α exponent quantifies the emergence of widespread precautionary behaviors in response to alerts. For disaster response agencies, continuous monitoring of this index could offer an unprecedented means to quantitatively gauge public anxiety, identify regions where risk communication is most needed, and anticipate population movements before large-scale evacuations fully materialize.

4.2. Limitations

This study also has several limitations. First, our analysis does not classify individuals by demographic attributes (e.g., resident or tourist, age, gender), and thus does not analyze in detail who took evacuation actions. Second, due to data specifications, it is difficult to track movements that span multiple days or to follow long-term evacuation patterns. Third, and most critically, our analysis is subject to a selection bias inherent in the loop-based methodology. As the calculation of the enclosed area S requires a mobility trace to form a closed loop (start-to-end distance ¡ 50 m), our dataset inevitably excludes the trajectories of “one-way” evacuees. Quantitatively, the proportion of trajectories forming closed loops was 13.61% on 2 January (a normal day) and 12.64% on 1 January (the earthquake day). The slight decrease on the day of the earthquake likely reflects individuals who evacuated and did not return. We acknowledge that excluding these one-way trajectories—which typically involve linear movements ($\alpha \approx 1$)—may cause our calculated α to underestimate the linear component of the total population’s mobility. However, the observation that α surged to ≈ 1.8 even within the “returning” population (the approx. 12.6% subset) is significant. It indicates that the behavioral shift to a disordered, exploratory state was not limited to one-way evacuees but was a widespread phenomenon that affected even those who managed to return. This suggests that post-quake mobility was characterized by complex behaviors—such as wandering in search of safety, information, or passable routes—rather than simple linear travel.

4.3. Future Outlook

Future work includes advancing the analysis with demographic attributes and, concurrently, conducting similar analyses on other types of disasters (e.g., floods from heavy rain, volcanic eruptions) to compare how mobility patterns change depending on the disaster type. Furthermore, combining this data with other forms of big data, such as telecommunication data, to clarify the relationship between information propagation and evacuation behavior will be an important research avenue.

5. Conclusions

Using large-scale GPS data, this study analyzes the scaling laws present in human mobility trajectories, with a detailed investigation into the impact of the Noto Peninsula earthquake of 1 January 2024, on movement patterns. We discovered a highly anomalous phenomenon: immediately following the earthquake, the scaling exponent for long-range travel ($L \geq 5$km), α_{Long}, surged from its typical range of 1.5–1.6 to 1.8, a level comparable to the index for short-range travel. This change was observed throughout Ishikawa Prefecture, regardless of the severity of physical damage, and disappeared by the next day. We conclude that this sharp increase in α_{Long} reflects widespread evacuation behavior among people who were away from home, particularly movement toward higher ground in response to tsunami warnings. This suggests that under the extraordinary circumstances of a disaster, the nature of long-range human mobility undergoes a fundamental shift from one-dimensional goal-oriented travel to two-dimensional exploratory searching for safety. The findings of this study demonstrate that a sociophysical approach provides an effective lens for quantitatively understanding complex and unpredictable human behavior during disasters. This study has demonstrated that a collective index like the scaling law of mobility trajectories can function as a novel, quantitative, real-time proxy for detecting the occurrence and geographical extent of large-scale evacuation. In the future, integrating such sociophysical indicators into disaster management systems could provide authorities and response agencies with a new layer of situational awareness that complements traditional information sources, thereby facilitating a more rapid, data-driven crisis response.

Author Contributions

A.I.: Data curation, Methodology, Formal Analysis, Software, Supervision, Writing—original draft, Funding acquisition, Investigation, Visualization, Conceptualization, Validation, Resources, Writing—review and editing, Project administration. S.F.: Software, Writing—review and editing. T.M.: Writing—review and editing, Validation, Conceptualization, Supervision. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Ethical approval was not required for the study involving humans in accordance with the local legislation and institutional requirements.

Informed Consent Statement

Written informed consent to participate in this study was not required from the participants or the participants' legal guardians/next of kin in accordance with the national legislation and the institutional requirements.

Data Availability Statement

Publicly available datasets were analyzed in this study. This data can be found here: https://agoop.co.jp/service/dynamic-population-data/.

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Conflicts of Interest

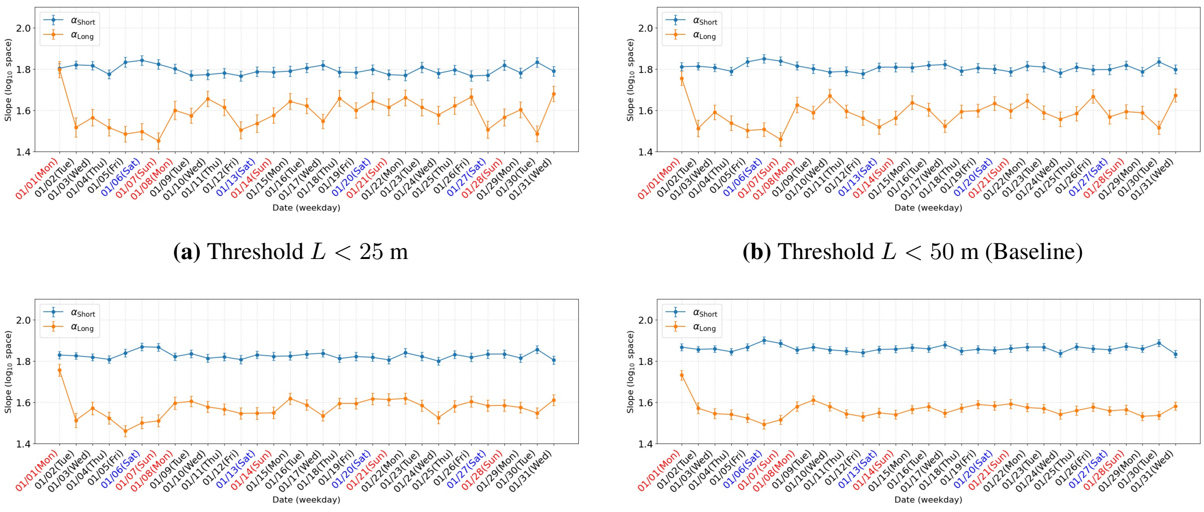
The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used AI-assisted writing tools to check for grammatical errors and improve the English language style. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Appendix A. Sensitivity Analysis of Loop-Closure Thresholds

This appendix presents the sensitivity analysis of the loop-closure threshold used in trajectory extraction. Figure A1 compares the time-series variations of the scaling exponents (α_{Short} and α_{Long}) calculated with four different thresholds: 25 m, 50 m, 100 m, and 200 m.



(**a**) Threshold $L < 25$ m

(**b**) Threshold $L < 50$ m (Baseline)

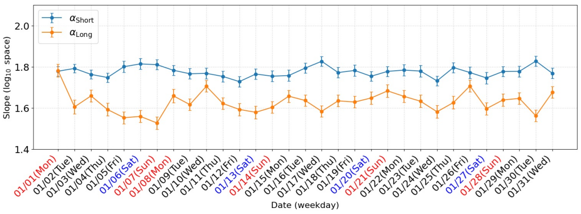
(**c**) Threshold $L < 100$ m

(**d**) Threshold $L < 200$ m

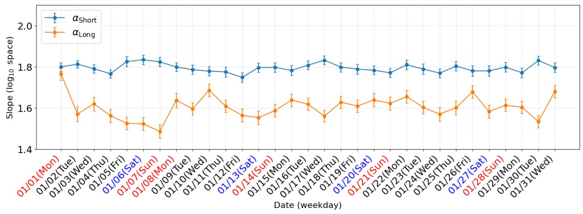
Figure A1. Sensitivity analysis of the scaling exponents with different loop-closure thresholds: (**a**) 25 m, (**b**) 50 m (baseline used in the main text), (**c**) 100 m, and (**d**) 200 m. The anomalous increase in α_{Long} on January 1 is consistently observed across all thresholds, confirming that the main finding is robust to the choice of the threshold parameter.

Appendix B. Sensitivity Analysis of Distance Thresholds

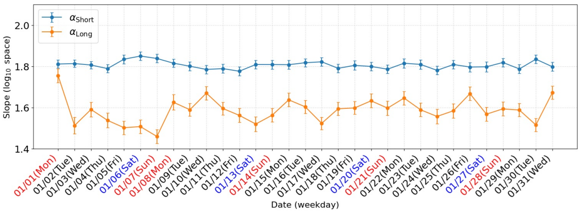
This appendix presents the sensitivity analysis regarding the distance threshold used to distinguish between short-range and long-range mobility. While the main text utilizes a 5 km threshold, Figure A2 demonstrates the temporal variation of scaling exponents when this threshold is adjusted to 3 km, 4 km, 6 km, and 7 km, alongside the baseline 5 km result.



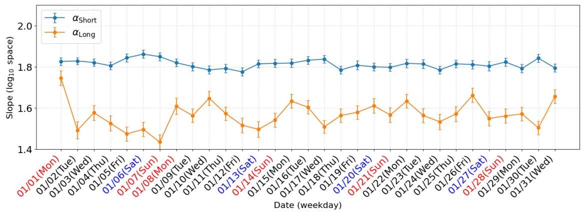
(**a**) Threshold: 3 km



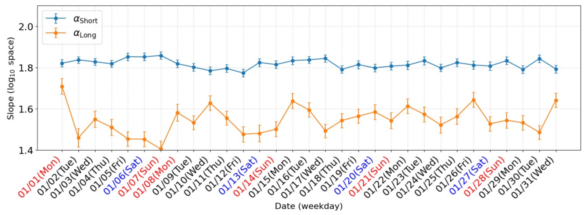
(**b**) Threshold: 4 km



(**c**) Threshold: 5 km (Baseline)



(**d**) Threshold: 6 km



(**e**) Threshold: 7 km

Figure A2. Sensitivity analysis of scaling exponents with varying distance thresholds. The plots show the results for thresholds of (**a**) 3 km, (**b**) 4 km, (**c**) 5 km (baseline), (**d**) 6 km, and (**e**) 7 km. In all scenarios, the long-range exponent α_{Long} exhibits a distinct surge on 1 January, confirming that the observed behavioral shift is robust regardless of the specific threshold chosen.

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