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Human-centric characterization of life activity flood exposure shifts focus from places to people

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A human-centric approach to assessing flood exposure moves beyond traditional spatial assessment by quantifying flood exposure based on life activity. This novel method characterizes flood exposure by measuring dwell time in flood-prone areas, using fine-resolution, anonymized smartphone data. Comparative analysis across 18 US cities reveals important disparities in life activity flood exposure (LAFE) and highlights the influence of urban forms and structures on LAFE. Furthermore, the research uncovers bimodal distributions in LAFE, indicating disparities even among cities with similar spatial flood risks. By focusing on the effect of daily human activities in flood-prone areas, this approach offers a more comprehensive understanding of flood impacts on daily activities and socioeconomic factors. The findings provide urban scientists and flood risk managers with a practical tool, underscoring the importance of human activity patterns in flood risk assessment, and offer valuable insights for enhanced analysis of flood exposure and risk.

As a consequence of climate change, the frequency of flooding has increased and its severity intensified[1–4]. Flooding can cause substantial loss of life, extensive property damage, as well as social and economic losses. Effective flood risk management and response relies on accurate evaluation of the extent of flood exposure. The predominantly place-based approach for assessing flood-hazard exposure involves comparing flood-hazard data with the residential population distribution[2,4–6]. This methodology effectively translates the flood exposure parameter into visual landscapes based on residential proximity to flood-prone areas. A study by Brouwer et al. from 2009[1] used this approach by measuring flood exposure based on the distance of residences from river banks, premising a linear correlation between flood probability and proximity to a water body, a methodology that, despite its practicality, may not be applicable universally due to variations in topographical features. Broadening the scope, Jongman and colleagues[2] integrated global flood databases with population and economic data, thereby constructing an exhaustive overview of economic and demographic exposures to flood hazards. This melding of data types reveals the multifaceted nature of flood exposure, extending beyond mere exposure of physical properties to include the socioeconomic implications of such disasters[7,8]. In the field of place-based flood exposure assessment, flood maps have been instrumental for estimating urban and population exposures to flood hazards, offering a quantitative interpretation of spatial flood risk distribution[9–11]. Furthermore, assessing flood exposure at the level of residential property provides valuable insights into potential flood damages, by considering the potential flood inundation depth and corresponding damage to residential properties as key components of the risk-assessment process[12,13]. Such approaches offer valuable insights, but they fundamentally perceive exposure as a spatial phenomenon, a perspective that fails to capture the full complexity of human interaction with flood hazards.

Notwithstanding the great strides made in understanding and assessing flood exposure, the current body of literature largely neglects the human-centric perspective—the extent to which daily life activities of individuals are prone to flood-induced disruptions. This human-centric perspective is critical for better characterizing the socioeconomic risks of floods at individual and household levels. Existing studies have predominantly focused on the static population distribution, mainly

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considering residential locations[9,14,15]. However, human activities are not confined to residential locations; they span a variety of locations described by daily visitation patterns, including workplaces, schools, recreation areas and shopping centers[16–18]. Consequently, a substantial portion of an individual's time is spent outside the residence, exposing people to flood hazards in diverse spatial contexts[19–21]. This raises several critical questions about our understanding of human exposure to flood hazards. How accurate is the place-based, residential-centered assessment of flood exposure in capturing the true human exposure to flood hazards? To what extent does the pattern of human activities influence an individual's exposure to flood hazards? To what extent do human activities exacerbate or alleviate exposure to flood hazards? These questions have been sparingly addressed by previous work, highlighting a need to shift the focus from a place-based approach to a human-centric approach that can better represent the dynamic nature of human exposure to flood hazards. To address this gap, this study proposes a novel, human-centric methodology and measure for the analysis of flood exposure. Leveraging privacy-preserving, fine-resolution, location-based data to quantify an individual's flood exposure based on dwell time in locations in flood-prone areas, this approach enables the characterization of life activity flood exposure (LAFE) at a scale never attempted before. Accordingly, the approach uncovers latent flood exposures where populations residing outside recognized flood-prone areas may still be at considerable risk due to their daily activities. Similarly, latent flood immunity is examined to identify flood-prone areas whose populations have a relatively lower LAFE. Figure 1 provides a conceptual illustration of these terms. Based on the characterization of LAFE in multiple US metropolitan areas, we examine spatial variations across the regions, and we also examine the characteristics of urban forms and structures that potentially shape population life activity exposure. We examine 18 US coastal cities (within 31 counties) as our study region, and compute LAFEs using millions of fully anonymized, fine-resolution, location-based data points. The results include intra-city characterization of LAFE, as well as the specification of areas with considerable latent flood exposure. The findings reveal that the combination of spatial clustering of flood hazards and the distance-decay law of human visitation patterns leads to the emergence of flood-exposure traps for people living in flood-prone areas.

The results also show that although the extent of LAFE is highly correlated with the spatial extent of flood hazards, variations exist in life activity exposure across cities with a similar extent of spatial flood hazard. This variation could be due to the effects of urban form and structure features, suggesting that cities with a similar extent of spatial flood hazard could have different levels of population LAFE depending on the patterns of facility distributions and levels of human mobility and population density. Also, a greater spatial extent of flood hazards would cause greater LAFE for people residing outside flood-prone areas. This finding reveals that exacerbating flood hazards in a county will increase the LAFE of all populations, not just those residing in flood-prone areas. The specification and quantification of latent flood exposure show that human mobility extends the spatial reach of flood hazards beyond flood-prone areas and influences the life activities of people living outside those areas. Also, the bimodal distribution of LAFE for individuals in different cities provides data-driven evidence of important disparities in individual-level LAFE.

In summary, the main contribution of this study is to provide a novel, data-driven and human-centric approach for evaluating population flood exposure at a high level of spatial detail. The approach and findings will be particularly valuable to academic disciplines and diverse stakeholder practitioners. First, the LAFE approach provides a human-centric method for urban scientists and flood researchers to quantify and evaluate the extent to which floods could disrupt the life activities of populations in different areas and across different cities. Second, the LAFE index provides a new measure with which public officials and urban economists can quantify the potential socioeconomic impacts of floods on individuals and households based on the extent of their disrupted life activities. Third, the specification of latent flood exposure enables public officials to evaluate how spatial flood hazards influence the entire population (people residing both inside and outside flood-prone areas) to better assess the flood exposure of the entire population. Fourth, discovering the ways in which urban forms and structures shape LAFE informs city planners and designers regarding how patterns of urban development and growth affect the LAFE of populations. These contributions could facilitate a paradigm shift in flood-exposure assessments towards achieving a more human-centric characterization and understanding.

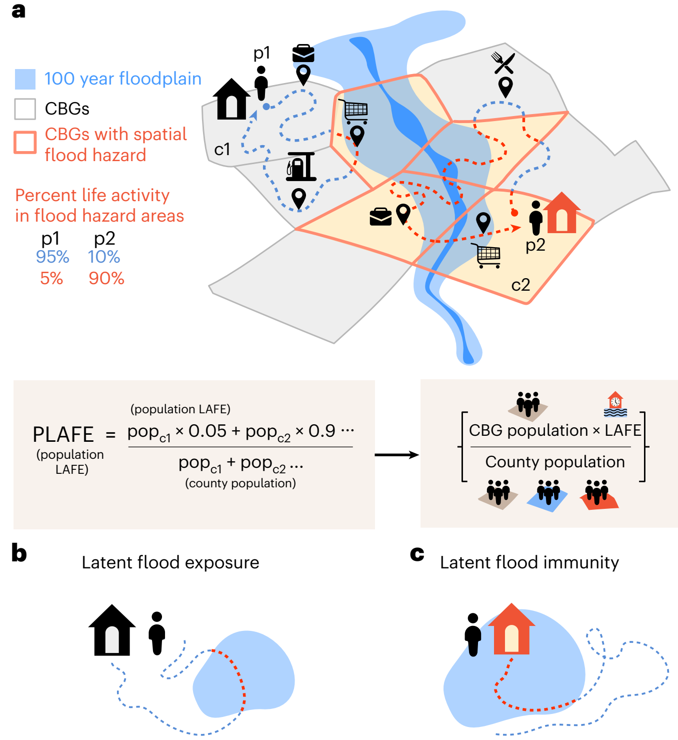

Fig. 1 | Conceptual representation of LAFE. a, Evaluation of LAFE. CBGs that intersect with the 100-year floodplain are denoted as areas with spatial flood hazard. LAFE is the total flood dwell time of all users residing in a CBG divided by the total dwell time. p1, person one; p2, person 2; c1, CBG1; c2, CBG2. **b**,**c**, Latent flood exposure (**b**) and immunity (**c**). Latent flood exposure occurs where CBGs outside of the designated flood-hazard zones exhibit high LAFE. Latent flood immunity comprises instances where CBGs within flood-hazard zones show surprisingly low LAFE due to dwell time in places outside flood-hazard areas.

Results

Intra-county characterization of LAFE

The distribution of census block group (CBG) LAFE within each county shows a bimodal distribution (Fig. 2). This bimodal distribution is distinct in each county, with the variation in the height of the peaks serving as indicators of distinct LAFE. A pronounced peak near 0 is observed in the LAFE distribution of counties characterized by a lesser spatial flood hazard. Conversely, counties with a greater spatial flood hazard display a less prominent peak near 0 and a much more substantial peak closer to 1.

Figure 2 depicts an increasing spatial flood hazard and corresponding LAFE for San Francisco, Orange, Santa Clara, Harris and Miami-Dade counties. The result is clearly represented in the variations in the two peaks near 0 and 1. As the extent of the spatial flood hazard increases, the overall distribution of LAFE tends to shift towards 1. This is because a larger number of CBGs fall within the spatial flood-hazard areas,

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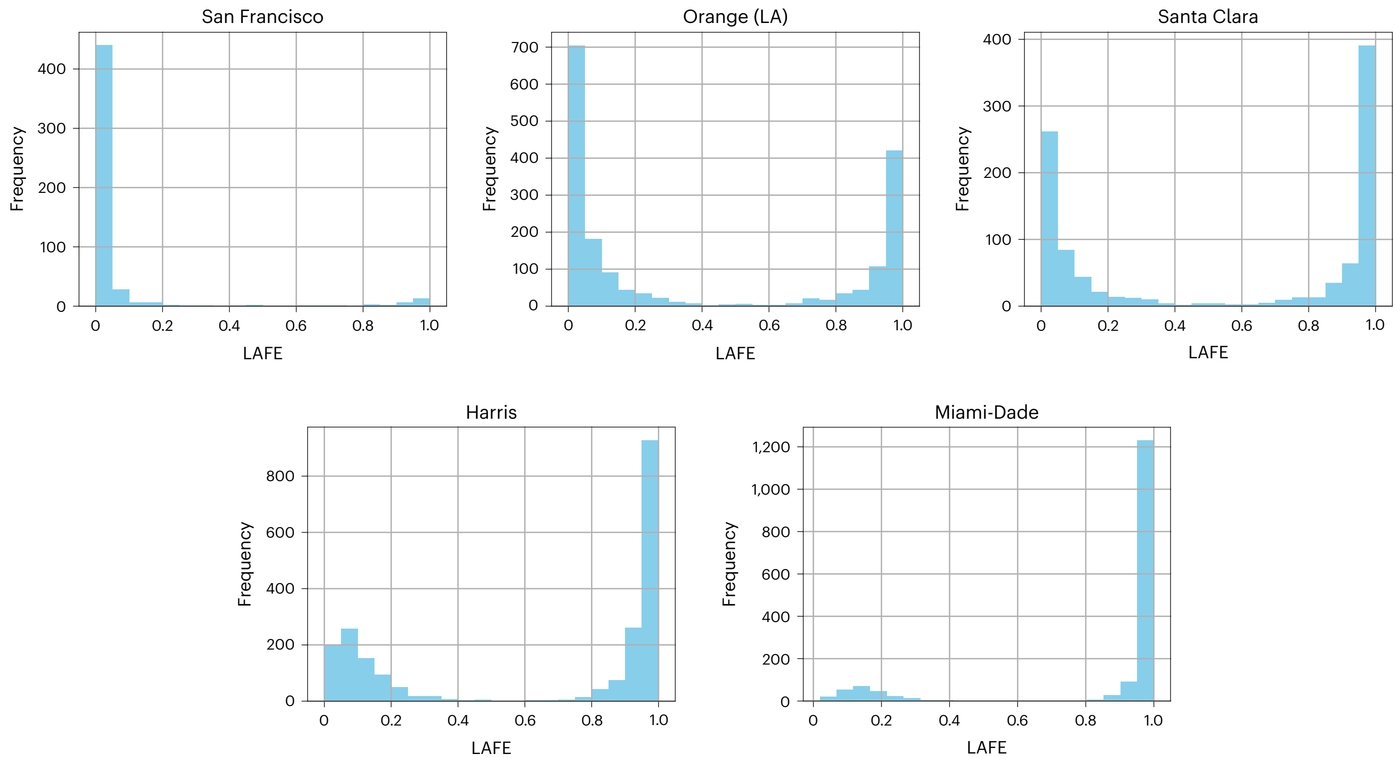

Fig. 2 | Bimodal LAFE distribution and spatial flood hazards across five example counties. Each county demonstrates distinct peaks near 0 and 1 on the LAFE scale. The shift in dominance of these peaks, from 0 towards 1, is evident with the intensification of spatial flood hazards extent. In areas with limited flood exposure, the peak at 1 is nearly imperceptible, but as flood hazards escalate, the prominence of the peak near 1 increases, dwarfing the peak at 0 in regions with substantial flood hazards. This progression indicates a rise in LAFE corresponding to an increase in spatial flood hazards extent. The presence of two distinct peaks indicates disparities in LAFE among the CBGs of a county.

so more CBGs have a higher LAFE value. For regions with less spatial flood-hazard extent, the peak near 1 is lower compared to the peak for values near 0. With the increase in spatial flood-hazard extent, however, a notable transition occurs where the peak near 1 becomes larger. In regions with the most substantial spatial flood-hazard extent, the peak near 0 is almost indiscernible, further reinforcing this phenomenon. The bimodal distribution of LAFE in each county suggests the extent of disparity in LAFE among residents within a county. For counties such as Miami-Dade and San Francisco, the extent of disparity is less, with only one dominant peak existing in the distribution of LAFE. For counties such as Orange County and Santa Clara, however, the extent of disparity is greater due to the presence of two peaks at the two extremes of the bimodal distribution of LAFE.

To further examine the characteristics of the LAFE values for CBGs within each county, we incorporated box plots with outliers representing the LAFE in areas both within a floodplain (Supplementary Fig. 1a) and outside a floodplain (Supplementary Fig. 1b). The sequence of counties, arranged from left to right, is consistent with the previous figures, with counties on the left having a lower percentage of CBGs in a floodplain, so they manifest lower spatial flood hazards, whereas those on the right exhibit a greater spatial flood-hazard extent.

Figure 3 shows the LAFE of Philadelphia County and Harris County in comparison to their respective CBGs within flood hazards, demonstrating the differences in the extent of LAFE for regions within-floodplain and outside-floodplain for counties having varied proportions of CBGs in the floodplain. In Philadelphia County, the LAFE distribution reveals that even those residing in CBGs outside flood-hazard areas are spending substantial time in flood-prone regions. This behavior may be attributed to life activities such as work or travel, resulting in ~3,000 h spent in flood-prone areas out of a total of ~17,000 h. Similarly, Harris County's LAFE distribution indicates that the average user within the same 5% of CBGs spends ~4,300 h out of a total of 16,000 h within-floodplain areas. This pattern underscores the intricate relationship between spatial flood-hazard areas and LAFE, regardless of the county's proportion of CBGs in the floodplain. The figure highlights the complexity of flood exposure, emphasizing that geographical boundaries do not solely define it. Instead, individual behavior and daily activities are vital in shaping the exposure to flood risk.

Across all counties, we observe that more than 75% of CBGs within spatial flood hazards present a LAFE exceeding 0.8. As the overall counties' spatial flooding extent increases, the variation in LAFE values decreases; most CBGs within flood-hazard areas have a LAFE close to 1. Similarly, for CBGs outside flood-hazard zones, more than 75% have a LAFE of less than 0.2, which remains the case even for counties subjected to very high spatial flood hazards. Here, the LAFE variation diminishes for counties with a lower overall spatial flooding hazard extent, with most CBGs in such scenarios exhibiting LAFE values closely approximating 0.

It is also important to note that the number of outliers in counties with less than 60% flood exposure are much higher as some CBGs experience very high LAFE, even though they are not in flood-hazard areas, and some have very low LAFE, even though they are in flood-hazard areas, hinting at the role of human mobility and visitation activities in shaping LAFE. We notice that a number of CBGs that are not positioned within flood-hazard zones are nonetheless experiencing exceedingly high LAFEs, suggesting that LAFE is not purely a product of the geographical location of an individual's residence, but is also influenced by patterns of population visitation activities and mobility[22,23]. For example, residents of these CBGs may need to commute regularly to areas within flood-hazard zones for work or to access services, thereby increasing their LAFE. In such cases, even though the CBGs themselves are geographically secure, the lifestyle of the inhabitants exposes

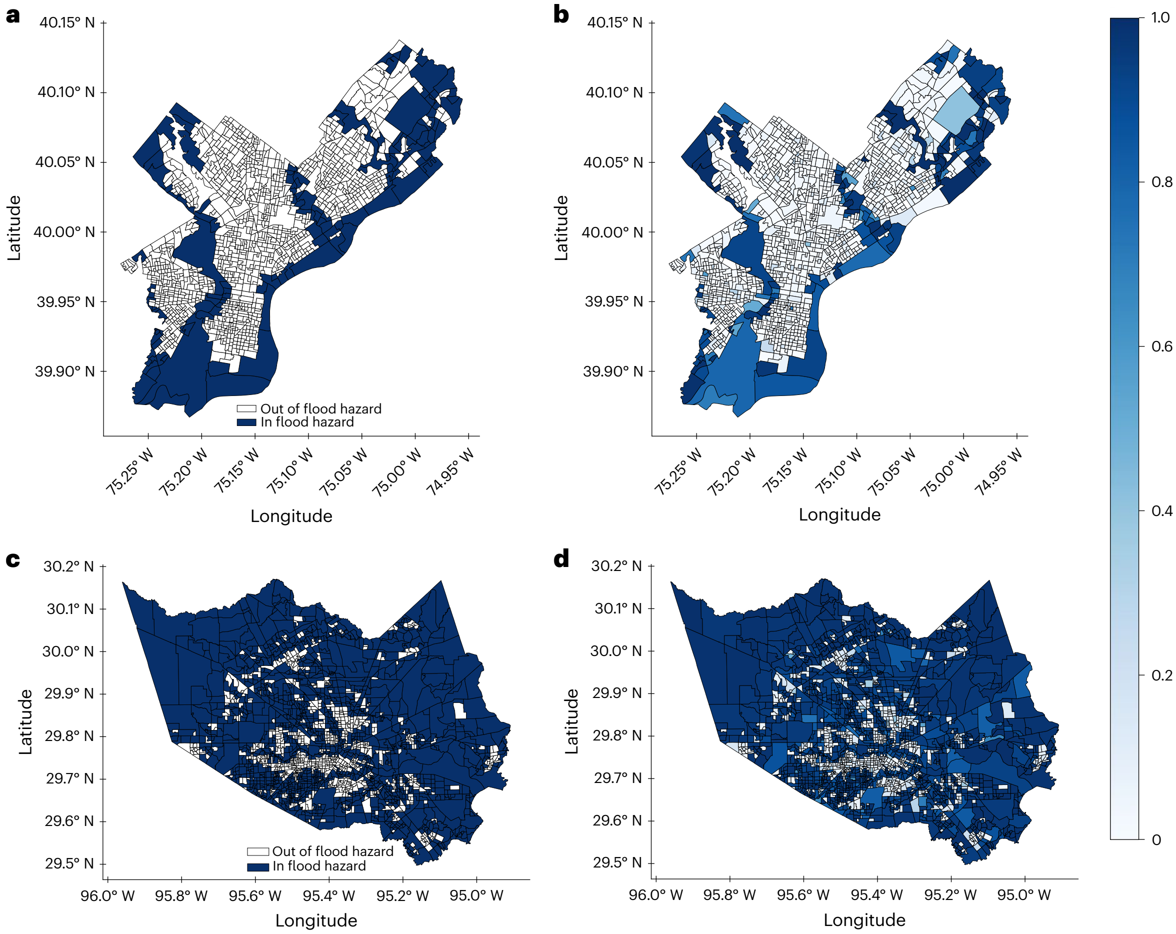

Fig. 3 | LAFE distribution in Philadelphia and Harris County. The figures capture the intricate relationship between spatial flood-hazard areas and LAFE in two distinct counties. **a**,**c**, Demarcation of CBGs based on their positioning either within or outside flood-hazard zones in Philadelphia (**a**) and Harris (**c**) counties. **b**,**d**, Distribution of LAFE across CBGs for Philadelphia (**b**) and Harris (**d**) counties, emphasizing the variance in flood exposure (shown by color intensity) among residents, based on their life activities. Color bar represents LAFE values for CBGs in **b** and **d**. In Philadelphia, users residing in 5% of the CBGs that fall outside flood-hazard areas still spend a substantial portion of their time (~3,000 h out of a total of ~17,000 h) in flood-prone areas. Similarly, in Harris County, the average user within the same 5% of CBGs spends ~4,300 h out of a total of 16,000 h within-floodplain areas.

them to high flood exposure. Conversely, we also observe a subset of CBGs situated within flood-hazard zones but with surprisingly low LAFE values. This shows that being within a flood-hazard zone does not automatically translate to a high LAFE. We examine these outliers of latent flood exposure and flood immunity in the next subsection.

Latent flood exposure and latent flood immunity

To deepen our understanding of the outlier patterns observed in the previous section, we introduce two novel concepts: 'latent flood exposure' and 'latent flood immunity'. Latent flood exposure characterizes situations where CBGs are not geographically situated within flood-hazard zones, yet exhibit high LAFE values. This seemingly paradoxical situation suggests that such CBGs possess an underlying, unapparent vulnerability to flood exposure, perhaps attributable to human mobility patterns or other socio-environmental dynamics. Latent flood immunity, on the other hand, captures instances where CBGs that lie within flood-hazard zones have surprisingly low LAFE values. These two concepts capture instances of human life activities and mobility that exacerbate or ameliorate their LAFE. Such instances emerge as a result of a lifestyle involving visitation to places in neighboring CBGs outside spatial flood hazards, reducing flood dwell time in flood-prone areas.

To visually demonstrate these concepts, we plotted cumulative LAFE curves for in-floodplain and out-of-floodplain CBGs for each county (Methods), as demonstrated in Fig. 4 and Supplementary Figs. 2–6. These figures collectively provide a combined snapshot of the overall county characteristics in terms of latent flood exposure and immunity. In these graphical representations, a larger area under the curve for out-of-flood hazard LAFE implies a lower degree of latent flood exposure. Conversely, a more extensive area under the in-flood-hazard LAFE curve suggests a greater level of latent flood immunity. However, it is important to note that the extent of latent flood exposure and immunity in a county are not always correlated; counties with high latent flood exposure do not necessarily demonstrate high latent flood immunity. For example, only a small number of counties (Los Angeles (C1), San Diego (C2) and Harris (C4)) exhibit both high latent flood exposure and high latent flood immunity based on their respective cumulative distribution function curves and associated areas. This county-level characterization of the combined latent flood exposure and immunity enables cross-county comparisons, as discussed in the following subsections.

Our findings also highlight a distinct trend: the propensity for latent flood exposure increases with an increase in the county's spatial flood hazard extent. As the proportion of CBGs within a county's flood-hazard zones increases, so do the chances of encountering higher LAFE values for the entire county. Conversely, latent flood immunity tends to decrease as the spatial flood-hazard extent grows, as fewer CBGs exist

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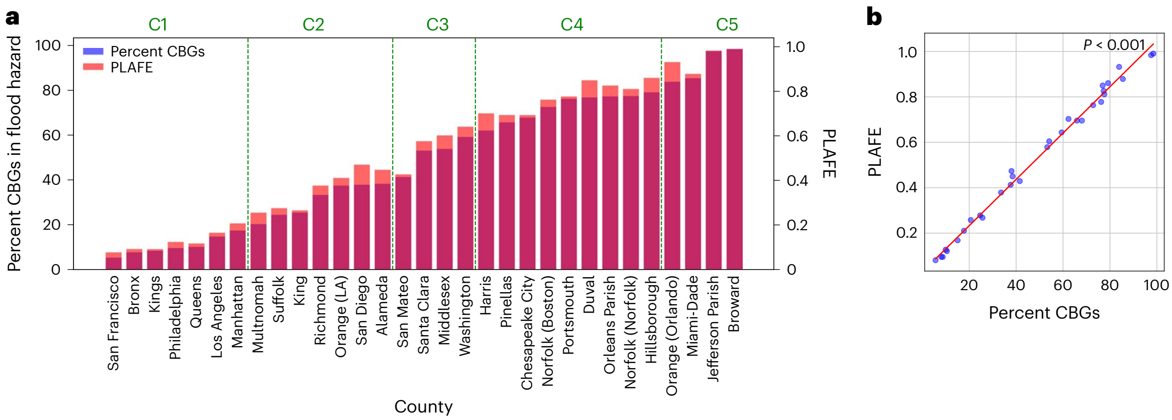

Fig. 4 | Evaluation of latent flood exposure and immunity. a, PLAFE across counties (right axis) compared to the percentage of CBGs in floodplains (left axis). **b**, Depiction of the linear correlation between these two variables using a two-sided test. Counties are categorized (C1 through C5) based on similar extents of spatial flood hazard, divided into increments of 20%. The linear relationship between spatial flood hazards and PLAFE implies that regions with greater spatial flood hazards have a greater PLAFE. Remarkably, certain counties with comparable spatial flood hazards show disparate levels of PLAFE, underscoring the possible role of urban form and structure features and mobility levels in shaping the extent of PLAFE.

outside flood-prone areas to alleviate flood exposure stemming from mobility patterns. The characterizations of latent flood exposure and immunity provide new insights regarding the way in which populations of a county are exposed to the potential impacts of floods in their daily life activities, irrespective of the location of their residence.

County-level population LAFE

PLAFE provides a novel measure for quantifying and evaluating county-level population LAFE. Unlike the traditional binary approach that categorizes regions mainly as either within or outside a floodplain, our method offers a more specific and quantitative measure of flood exposure for the populations of each city or county. PLAFE takes values between 0 and 1, providing a continuum that facilitates more objective comparisons across different cities and counties. Figure 5 illustrates the PLAFE values for counties across the United States, juxtaposed with the extent of spatial flood hazards. The extent of spatial flood hazards is assessed based on the proportion of CBGs that intersect with floodplains.

Our results show the direct relationship between PLAFE and spatial flood-hazard extent. Figure 5b highlights a clear linear relationship between spatial flood hazards and PLAFE, implying that regions with a greater spatial flood-hazard extent have a greater PLAFE. However, we also observed variations among the PLAFE values of counties with comparable spatial flood-hazard extents. The counties are categorized (from C1 to C5) according to their spatial flood-hazard extents, segmented into 20% increments (that is, 0–20%, 20–40% and so on). We found that certain categories exhibited a wide range of PLAFE values despite having a similar extent of spatial flood-hazard exposure. This result demonstrates the importance of considering the PLAFE metric when evaluating the population-level flood exposure for cities and counties. Furthermore, these results suggest that variations in the PLAFE of counties with similar spatial flood-hazard exposure might be due to differences in their mobility level as well as their urban form and structure features. In subsequent sections, we delve deeper into these factors, seeking to uncover the reasons behind the observed variations in PLAFE in areas with similar spatial flood exposure.

Spatial flood hazard and PLAFE disparity

To better understand the observed variability, we further analyzed PLAFE by computing and comparing the PLAFE for CBGs in-floodplain and outside-floodplain for each county. In this analysis, we examined the relationship between the spatial distribution of flood hazard (extent of CBGs in floodplains) and the PLAFE values of in-floodplain and out-of-floodplain CBGs in each county.

Figure 6a,b shows the spatial extents of flooding and PLAFE. Our observations from Fig. 6c,d clearly indicate that regions within spatial flood-hazard zones exhibit a higher PLAFE than regions outside such zones. More specifically, the PLAFE of CBGs situated within flood hazards typically ranges from 0.84 to 1, whereas in CBGs outside flood hazards the range is substantially lower, varying from 0.01 to 0.16. However, we noted some peculiar trends in regions with similar extents of spatial flood-hazard distribution. For example, Chesapeake City and Norfolk (Boston) counties, where ~70% of CBGs are within flood-hazard zones, show a similar out-of-floodplain PLAFE to regions with ~30% spatial flood exposure. Conversely, San Diego, Santa Clara, Harris and Duval exhibit higher PLAFE in areas outside flood-hazard zones than counties with similar spatial flood-hazard exposure. Remarkably, although these counties have higher out-of-floodplain PLAFE values, the corresponding in-floodplain PLAFE does not follow a similar or inversely proportional trend. This observation is consistent across all categories, indicating that PLAFE for areas within flood-hazard zones and those outside these zones seem to have distinct characteristics across different counties. The variation in the PLAFE values of counties with comparable spatial flood-hazard extent might stem from differences in urban form and structures. These differences, in turn, could lead to varying lifestyles and mobility patterns among the populace that subsequently shape the PLAFE of a county. In later sections of this Article, we present an early analysis of this aspect in favor of our hypothesis.

Role of urban form and structure

To examine the variation in the PLAFE of counties with comparable spatial flood-hazard extent, we examined the relationship of urban form and structure features with PLAFE, latent flood exposure and latent flood immunity. To understand this relationship, we used a Spearman correlation plot, observing the overall set of counties as well as specific county groupings based on spatial flood-hazard categories C1–C5. The results are illustrated in Supplementary Figs. 7, 8, 9, 10, 11 and 12, which respectively represent 'all counties' and C1, C2, C3, C4 and C5 counties. We considered urban form and structure features such as the human mobility index (HMI), the urban centrality index (UCI), points of interest (POI) density (based on area and per capita), road density and population per square kilometer. These features have been shown to shape human activities and mobility in cities[24]. When these features are examined across all counties, no important patterns emerge.

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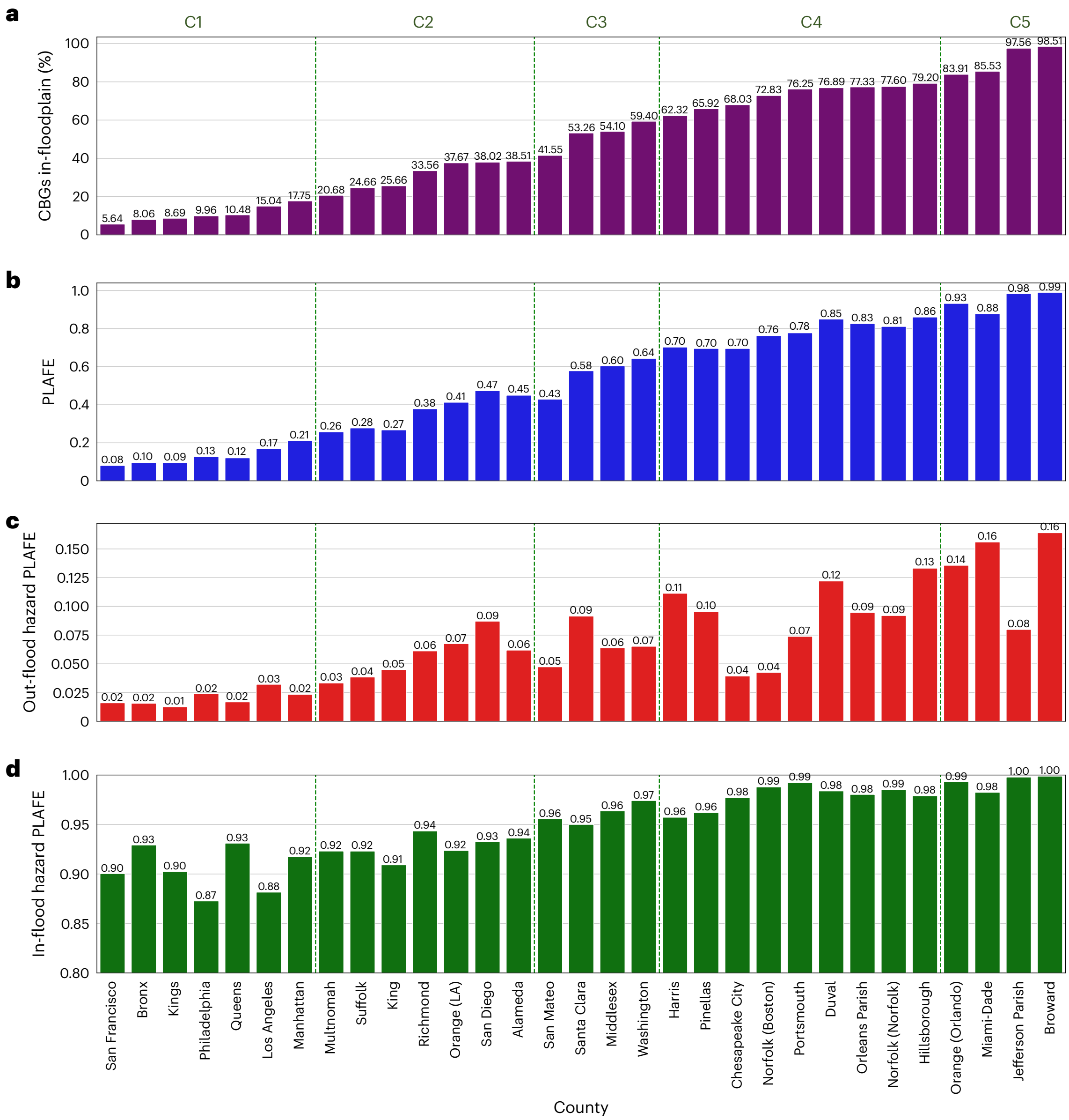

Fig. 5 | Relationship between PLAFE and spatial flood-hazard extent. **a**,**b**, Mapping of the spatial extent of flood hazards (**a**) alongside the corresponding PLAFE (**b**), providing a comparative view. **c**,**d**, A focus on PLAFE in regions outside (**c**) and within (**d**) the flood-hazard zones, highlighting the variations in population flood exposure based on their locations relative to flood-hazard zones.

This is due to the fact that the overall PLAFE values for each county are predominantly influenced by the extent of spatial flood hazard. When examining the relationship within each category of counties (with comparable spatial flood-hazard extent), however, interesting results start to emerge. For example, POI density (area-based) and road density explain the variation in PLAFE values in C1 counties, which have fewer than 20% of their CBGs within the floodplain. C1 counties with lower POI density and higher road density have a greater value of PLAFE. This result suggests that in counties with a relatively low extent of spatial flood hazard, dense development (measured by road network density) could exacerbate PLAFE. In the case of C3 counties, road density and urban centrality proved influential. This result suggests that in counties with moderate levels of spatial flood-hazard extent, decentralization of facilities and dense development lead to a greater PLAFE. Also, the HMI is strongly correlated with PLAFE in C5 counties. This result implies that, when counties have extensive spatial flood exposure, a greater level of human mobility amplifies PLAFE.

In these specific categories, a higher road density correlated with increased PLAFE. Notably, elevated POI density and a greater UCI resulted in lower PLAFE. This suggests that a polycentric city structure could potentially reduce PLAFE for counties with moderate levels of spatial flood-hazard extent. In addition, a greater POI density may indicate that essential POIs are concentrated outside flood-prone areas (land-use policy to encourage development outside flood-prone areas). These results underscore the critical role urban form and structure can play in the extent of PLAFE in cities and counties.

Discussion

The LAFE index, offering a data-driven, human-centric method to quantify flood exposure in cities, reveals the varying extents of population life activity exposure within and across different US counties. By categorizing counties from C1 to C5 based on spatial flood-hazard extents, we observed variations in the normalized PLAFE, even among counties with similar flood-hazard proportions. Our results show an

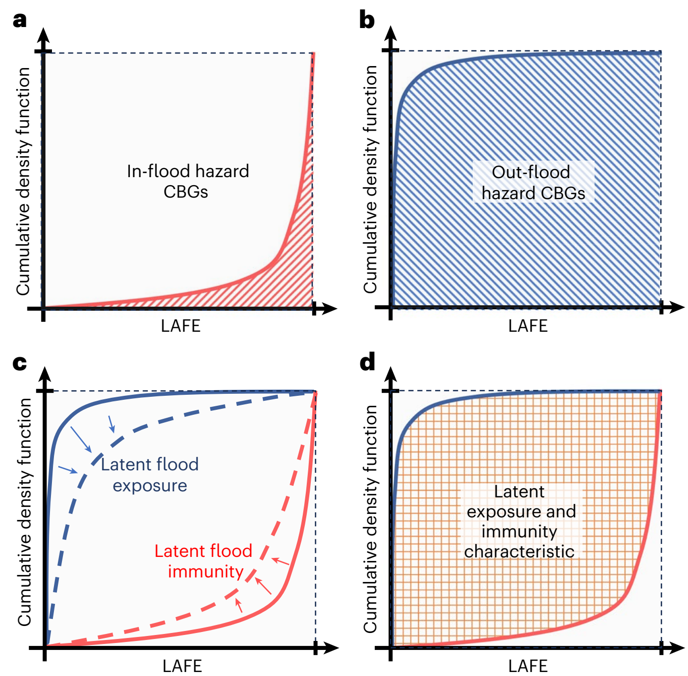

Fig. 6 | A comprehensive representation of PLAFE in various CBGs within the studied counties. a,b, The cumulative density function (CDF) of places within (**a**) and outside (**b**) spatial flood hazard, respectively. The area under the curves indicates the extent of LAFE for flood-prone (**a**) and non-flood-prone (**b**) CBGs in a county. **c**, The shape of the curves indicates the extent of latent flood exposure (blue) and immunity (red) in each county. **d**, The area between the two curves provides a combined metric that captures the extent of latent exposure and immunity for each county. This metric can be used for cross county–county comparison.

evident linear relationship between spatial flood-hazard extent and PLAFE across counties, with regions within flood-hazard zones exhibiting PLAFE values ranging from 0.84 to 1, and those outside ranging from 0.01 to 0.16. The large PLAFE value for CBGs in high flood-hazard areas is due to the combined effects of spatial clustering of hazards and the distance-decay law of human visitation, where people have greater visits and dwell times in locations in the proximity of their residence, which leads to a greater LAFE. Also, the concepts of latent flood exposure and latent flood immunity reveal hidden exposure and immunity due to human mobility that spatial flood risk maps cannot capture. Furthermore, the role of urban form and structure features, including road density, POI density and the UCI, is examined, showing their importance in explaining the variation in PLAFE for counties with similar spatial flood-hazard extent. The findings emphasize the multifaceted nature of population-level flood exposure assessment and the importance of considering spatial dynamics, human mobility and urban structure for a refined understanding of flood exposure. The results highlight the capability of the proposed approach to quantify populations' flood exposure.

Certain limitations stem from the representativeness of the data employed in this study. The location dataset utilized may not comprehensively encompass the diverse range of socio-demographic characteristics, potentially resulting in an underrepresentation of individuals who do not use smartphones and specific socioeconomic cohorts less inclined to engage with location-tracking services. Although it is acknowledged that the Spectus dataset possesses limitations in fully encapsulating the entire socio-demographic spectrum, it is important to note its substantial coverage, spanning ~20% of the US population. This extensive coverage facilitates a broad cross-sectional examination of the populace, thereby fortifying the generalizability of our research findings.

This study makes several noteworthy contributions to the field of flood exposure assessment and urban studies. The first is the creation of LAFE, a novel, human-centric measure of flood exposure allowing for a more quantitative and data-driven analysis of flood exposure at individual levels for inter- and intra-city analyses. Flood exposure studies have primarily focused on the exposure of physical properties and places of residence. By examining human activities, our study offers a deeper understanding of how flood hazards could affect the daily life activities of residents, irrespective of their place of residence. By providing a new human-centric way to quantify the extent of food exposure, the LAFE method extends beyond the existing binary approach (inside versus outside flood plain). The LAFE index, providing a continuum from 0–1, enables a more objective comparison of the extent to which people's life activities in certain areas are exposed to flood hazards. The index enables evaluation of the potential socioeconomic impacts of floods on individuals and households due to disruptions of daily life activities during flood events. These findings provide urban scientists and flood researchers with new measures for quantifying population flood exposure. LAFE and PLAFE can be analyzed every few years with updated data regarding spatial flood-hazard exposure and human life activity patterns to evaluate the extent to which flood mitigation measures and urban growth and development exacerbate or improve LAFE across different CBGs and at a city scale.

Our study also offers a detailed characterization of latent flood exposure. This aspect of flood exposure affects the life activities of populations residing outside traditional flood zones. The concept of latent flood exposure was introduced to describe instances where CBGs, although not directly located within flood-hazard zones, exhibit high LAFE, implying high susceptibility of their population activities to flood hazards. These insights are essential for urban planners and emergency managers to evaluate the flood exposure of the entire population, rather than just those residing in flood-prone areas. Third, an inter-city analysis of cities based on PLAFE revealed considerable variation in LAFE across cities with similar spatial flood-hazard extents. These variations could be explained based on urban form and structure features, such as POI density, road density and urban centrality, underscoring how these factors shape LAFE. We evaluated the extent to which features of urban form and structure explain the variability in PLAFE in cities with similar spatial flood-hazard extents. The results underscore the role of urban form and structure in shaping flood exposure, and the influence of development density, distribution of facilities, and level of human mobility in shaping the extent of PLAFE in counties with a similar spatial flood-hazard extent. These results can inform urban designers and city managers regarding ways to alleviate LAFE through urban growth and development strategies based on concentrating facilities in non-flood-prone areas and reducing the overall development density.

In summary, these contributions could facilitate a paradigm shift in flood exposure assessments towards a more data-driven and human-centric characterization and understanding. Future studies can build upon the LAFE method and approach presented in this study to further evaluate the characteristics of communities and cities that shape population LAFE. Also, longitudinal studies are needed to evaluate changes in LAFE as cities grow and develop and their spatial flood-hazard extents evolve due to flood mitigation strategies. Also, future empirical studies of flood events can examine the relationship between LAFE and the well-being and socioeconomic impacts of floods on individuals and households.

Methods

Approach for quantifying LAFE

Extracting stop-point data. Stop-point information is derived from high-resolution data from anonymous smartphone users who have voluntarily opted in to anonymized data collection for research purposes via mobile applications. The data are collected by Spectus[25], a location intelligence company that adheres to robust privacy policies, including The General Data Protection Regulation (GDPR) and The California Consumer Privacy Act (CCPA).

The stop-point table is a component of the Spectus main datasets that provides comprehensive information pertaining to each user stop, including user ID, date of occurrence, time of occurrence, duration of occurrence and the polygon representing the geographical location of each unique stop on a daily basis. This table serves as a valuable resource within the Spectus database, facilitating in-depth analysis and an understanding of stop-related patterns and behaviors. In accordance with its 'Sensitive Points of Interest' policy, visits to privacy-sensitive locations are omitted from the dataset by the data provider.

In addition to the stop-point table, the Spectus main database features a home CBG table. Data in this table capture each user's home CBG information. Alongside the user ID, the home CBG table contains geographic entity codes (GEOIDs), which provide a standardized identification system for geographical areas. Home location data are upleveled to the CBG by the data provider to preserve user privacy, serving as a means to identify the CBG where a user resides. The CBG shape table for each county is sourced from the US Census Bureau[26]. This table comprises GEOIDs corresponding to each CBG, alongside the geometry information that defines the boundaries and shape of each CBG.

To capture the life activity of users across different cities, we collected stop-point data spanning a duration of one month, from 1 March 2023 to 31 March 2023. Because the patterns of life activities do not change considerably, capturing activities over a month can provide a representative picture of population life activities. For our project, the focus was limited to stop-point data within each county. By merging the stop-point table with the home CBG table using the user ID as a common identifier, a home CBG GEOID could be assigned to each user. This enabled identifying and selecting individuals who reside within a particular CBG and treating them as the targeted population for analysis in each CBG. Accordingly, the stop-point table was filtered to extract information pertaining only to stops made by the targeted people. The data were extracted for 31 counties encompassing 18 major US metropolitan cities in proximity of the coast and having varied levels of flood susceptibility. A detailed list including county names, city names and GEIODs (unique spatial zone identifier) is provided in Table 1. The Spectus dataset, while extensive, may not capture the full diversity of socio-demographic characteristics, potentially underrepresenting non-smartphone users and certain socioeconomic groups that are less likely to opt into location-tracking services. Although the Spectus dataset may have limitations in capturing the full socio-demographic spectrum, its substantial coverage of ~20% of the US population through diverse mobile applications offers a broad cross-section of the populace, supporting the generalizability of our findings.

Identify spatial flood-hazard extent. To determine an area with spatial flood hazard, this study used 100-year floodplain data provided by the US Federal Emergency Management Agency (https://www.fema.gov/). The 100-year floodplain areas indicate areas with a 1% annual chance of flooding. The 100-year floodplain was overlaid with the CBG shape table, then the CBG was marked as flood-prone if it overlapped with any part of the floodplain. We considered these CBGs to be within spatial flood-hazard areas. Figure 1 provides a brief explanation of the core terminologies used in this study.

Total dwell time and flood-prone dwell time. The total dwell time (T_D) was calculated by aggregating the total dwell-time duration of people residing in a CBG. Flood-prone dwell time (F_D) was calculated by aggregating the dwell time related to visits to locations (POI) in flood-prone CBGs. The total and flood dwell times were first calculated for individual users then aggregated at the CBG level.

Table 1 | Cities and their respective counties used for this study

City	County	GEIOD
Boston	Middlesex	25017
	Norfolk	25021
	Suffolk	25025
New York	Richmond	36085
	Queens	36081
	Kings	36047
	New York (Manhattan)	36061
	Bronx	36005
Philadelphia	Philadelphia	42101
Jacksonville	Duval	12031
Orlando	Orange	12095
Miami	Broward	12011
	Miami-Dade	12086
Tampa	Pinellas	12103
	Hillsborough	12057
New Orleans	Jefferson Parish	22051
	Orleans Parish	22071
Houston	Harris	48201
San Diego	San Diego	06073
Los Angeles	Los Angeles	06037
	Orange	06059
San Jose	Santa Clara	06085
Fremont	Alameda	06001
San Mateo	San Mateo	06081
San Francisco	San Francisco	06075
Portland	Multnomah	41051
	Washington	41067
Seattle	King	53033
Norfolk	Norfolk	51710
	Portsmouth	51740
	Chesapeake City	51550

These include most of the coastal cities except for Washington, for which some data were unavailable.

LAFE and PLAFE. The LAFE, representing the level of flood exposure within a CBG, can be calculated using two variables, and is determined using the formula

$$\mathrm{LAFE} = \frac{F_D}{T_D} \tag{1}$$

Each county's PLAFE can be calculated by normalizing the LAFE by the total population in each CBG. This normalization allows for a comparison of LAFE levels across different counties as follows:

$$\mathrm{PLAFE} = \frac{\sum_i \mathrm{population}_i \times \mathrm{LAFE}_i}{\sum_i \mathrm{population}_i} \tag{2}$$

where i stands for the ith CBG in the county.

List of cities

We examined cities and their corresponding counties, with a primary focus on coastal cities. Washington was excluded due to there being unavailable data. See Table 1 for further details.

Urban form and structure parameters

To evaluate the extent to which variations in county-level LAFE are explained by urban form and structure features, we computed five different parameters that look at city structure, the distribution and density of POI, road density and population density as supporting data for our study. The UCI was computed at the county level, whereas other parameters were at the CBG level. For this study we used the median value across all CBGs as the representative value of the county for making cross-county comparisons.

Urban centrality index. The UCI quantifies the degree of centralization of facilities within a county. This metric was reproduced based on the methods provided in ref. 27. It was computed as the multiplication of two key factors: the local coefficient (LC) and the proximity index (PI). The LC is determined by the count of POI in each census tract, whereas the PI takes into account both the number of POI and a distance matrix, which encapsulates the distances between different census tracts. The UCI value can fall anywhere between 0 and 1. A value closer to 0 indicates a polycentric distribution of facilities, whereas a value closer to 1 denotes a monocentric distribution.

The LC is given by

$$\mathrm{LC} = \frac{1}{2}\sum_{i=1}^{N}\left(k_i - \frac{1}{N}\right) \tag{3}$$

The PI is expressed as

$$\mathrm{PI} = 1 - \frac{V}{V_{\max}} \tag{4}$$

The Venables index (V) is calculated as

$$V = K \times D \times K \tag{5}$$

where N denotes the total count of census tracts within a county, and K is a vector that encapsulates the number of POI for each census tract. The element k_i within vector K corresponds to the number of POI in the ith census tract. Matrix D represents the distances between the various census tracts, and $V_{\max}$ is derived by presuming that all POI are evenly distributed along the county's boundary. The LC is utilized to gauge the uneven distribution of POI, and the PI handles the normalization aspect[28,29].

These equations collectively define the UCI, providing a comprehensive measure of urban centralization:

$$\mathrm{UCI} = \mathrm{LC} \times \mathrm{PI} \tag{6}$$

Point of interest density. The calculation of POI density promotes an understanding of the distribution and concentration of various facilities within a given region. We computed the POI density in two forms for each CBG by normalizing the number of POI based on two distinct metrics: population and area. First, the number of POI is divided by the total population of the CBG, yielding a population-based POI density. This measure reflects the accessibility of POI per capita. Second, the POI count is also normalized by the total area of the CBG, providing an area-based POI density that illustrates the spatial concentration of facilities. The POI data utilized for these calculations were sourced from SafeGraph.

Road density. The road density metric quantifies the extent of the road network within a specific region, such as a CBG. Road data were obtained from the US Census TIGER dataset[30]. This metric was calculated by measuring the total length of all the roads (primary, secondary and local) and then normalizing this value by the total area of the CBG. This normalization by area provides a standardized measure that reflects the concentration of roads in the region, allowing for comparisons across different areas.

Population density. Population density was computed by taking the total population of the CBG and dividing it by its total area. This area-based normalization offers a uniform metric that illustrates the spatial distribution of the population. Population data were sourced from US Census data[31].

Human mobility index

To analyze the relationship between LAFE and mobility levels for each county, we used mobility data provided by Spectus. Spectus provides the HMI for each county. We selected data from a span of 28 days in April 2019, a period devoid of external anomalies that could disrupt normal human activities. The construction of the HMI involved attributing each visit point v_i to a specific CBG within a county. The HMI was then computed using the formula

$$\mathrm{HMI} = \frac{\Sigma v_i}{28n}$$

where n is the count of CBGs in the county. We then normalized the HMI values to a range of 0 to 1 by min–max scaling. This normalization allows the HMI to effectively indicate the level of human mobility within a county, with values nearer to 0 reflecting lower activity and those closer to 1 signifying higher activity. More details on this metric are available in ref. 32.

Latent population flood exposure and immunity calculation

The CBGs were categorized into two types: flood-prone CBGs (within spatial flood hazard) and non-flood-prone CBGs (outside spatial flood hazard). For flood-prone CBGs, the latent population flood immunity was determined based on the ratio of the dwell time in non-flood prone places (D(NF, user)) to the total dwell time at any place for each user (D(T, user)) living in the flood-prone CBG. This calculation can be represented as

$$\text{Latent population flood immunity} = \frac{D_{\mathrm{NF,\,user}}}{D_{\mathrm{T,\,user}}} \tag{7}$$

For the non-flood-prone CBGs, latent population flood exposure was determined as the ratio of the dwell time in any flood-prone places (D(F, user)) to the total dwell time at any location for each user (D(T, user)) living in the non-flood-prone CBG. This calculation can be expressed as

$$\text{Latent population flood exposure} = \frac{D_{\mathrm{F,\,user}}}{D_{\mathrm{T,\,user}}} \tag{8}$$

To evaluate the extent of latent flood exposure and latent flood immunity, we used the cumulative density function of LAFE to evaluate the combined extent of latent flood exposure and immunity at an aggregate level for each county, as shown in Fig. 4.

Cumulative distribution function for LAFE

We used a statistical approach to evaluate the variation of LAFE among CBGs for intra-county analysis. The measurement was accomplished using the discrete cumulative distribution function (CDF). The CDF $F(x)$ for a discrete random variable X is defined as the probability that X will take a value less than or equal to x. In the context of LAFE, the CDF was used to evaluate the proportion of CBGs in a county that have a LAFE index value less than or equal to a given threshold. Mathematically, the CDF of LAFE is defined as

$$F(x) = P(X \le x) = \sum_{x_i \le x} p(x_i) \tag{9}$$

where $p(x_i)$ represents the probability mass function at a given flood exposure level x_i.

By evaluating the CDF at various threshold levels, we can generate a detailed profile of LAFE across different CBGs within a county. These calculations also allow for the assessment of latent flood exposure and immunity across CBGs in each county.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this Article.

Data availability

The data used in this study are not publicly available under the legal restrictions of the data provider. Interested readers can request it from Spectus (https://spectus.ai/).

Code availability

The code that supports the findings of this study is available from the corresponding authors upon request.

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Author contributions

A.A.R., C.L., Z.L. and A.M. designed research. A.A.R., C.L. and Z.L. performed research. A.A.R. and C.L. contributed new analytic tools. A.A.R. and C.L. analyzed data. A.A.R., C.L., Z.L. and A.M. wrote the paper.

Competing interests

The authors declare no competing interests.

Additional information

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Policy information about availability of computer code

Data collection	The code used to aggregate data can be made available upon request. The data processing was done on Spectus (data provider) server and is not publicly available
Data analysis	Analysis for this paper was done using code written in Python 3.7. The code will be made available upon request.

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Study description	A human-centric perspective on flood exposure assessment of flood-hazard vulnerability transcends the conventional focus on spatial exposure by quantifying the effect of daily human activities in flood-prone areas. Using a novel index to quantify the time individuals spend in flood-prone areas, this method characterizes latent flood exposure. Calculations rely on millions of fine-resolution location-based data points collected anonymously from smartphones of opted-in users. A comparative analysis of multiple U.S. metropolitan cities based on latent flood exposure with similar extents of spatial flood risk reveals significant spatial disparities in LAFE.The collected data are quantitative. A bimodal distribution in life activity flood exposure index values in 18 coastal metropolitan areas reveals flood exposure disparities. The inter-city analysis results also uncovers the role of urban forms and structures in shaping LAFE, revealing how spatial clustering of flood hazards and distance-decay characteristic of human visitation can exacerbate flood exposure. Our findings provide a novel and more human-centric approach to characterizing and quantifying flood exposure by shifting focus from places to people. The life activity flood exposure captures the extent to which a population's daily life activities would be disrupted due to flooding and could capture the socio-economic aspects of flood exposure (such as loss of access to critical facilities and work) more objectively than the existing approaches. The findings provide interdisciplinary researchers and practitioners across urban sciences, flood risk management, emergency response with novel human-centric measure and insights to better examine flood exposure and risk.
Research sample	Users from Spectus. The detailed demographic of Spectus data are not accessible. However, the Spectus datasets have been widely used and verified for representativeness by multiple previous studies. The census data from U.S Census Bureau cover the total population of residents in U.S
Sampling strategy	Full sample
Data collection	For experiments, we collect human mobility datasets from Spectus, which is a location intelligence and measurement platform collecting mobility data of anonymized devices. The data is collected using the installed SDK on each phone users, and the collected data is accessed via granted account provided by Spectus. The researchers are blind to the experimental condition. Data from about 15 M active users are collected by Spectus in the United States. The previous studies have proven the high demographic representativeness of the Spectus dataset
Timing	The data were collected and processed in Jan - May, 2022
Data exclusions	No-data excluded
Non-participation	No participants involved in the study
Randomization	Participants were not allocated to control groups

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