Evaluating the spatial-temporal impact of urban flooding on mobility patterns and point of interest

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***Abstract*—Urban flooding poses significant challenges to densely populated areas, increasing vulnerability to environmental changes. This study assesses the spatial and temporal mobility patterns in response to flood events in Lagos State, Nigeria, a region prone to severe flooding due to its low-lying topography and rapid urbanization. By integrating human mobility and geospatial data, the study analyzes the correlation between flooding and POI visits using the Maximum Information Coefficient (MIC) and Difference-in-Differences (DiD) models. Results indicate significant variations across POI categories, with increased visits to Healthcare & Medical services reflecting emergency needs, while Transportation and Outdoor Recreation experience declines, highlighting the negative impact on general mobility and economic activities. The findings underscore the importance of targeted urban planning and policy interventions to mitigate the effects of urban flooding on communities.**

Keywords— Urban flood; Human mobility, Point of interest, Maximum Information Coefficient, Difference in Difference

I. INTRODUCTION

The interplay between global climate change, rising sea levels, and urbanization has increased the frequency and severity of hydro-meteorological disasters, particularly urban flooding. Such events pose profound challenges to the structural integrity of cities and the well-being of their populations. The compounded effects of environmental changes are increasingly evident, as urban areas become hotspots for severe flooding incidents that result in significant socio-economic disruptions. Statistically, floods account for over 30% of all economic losses from natural disasters, underscoring their devastating impact on global scales[1-3]. Flooding directly impacts human lives, leading to extensive property damage, physical injuries, and fatalities. The rapid inundation can demolish homes, hinder transportation systems, and impair critical infrastructure, resulting in significant financial strains for individuals and communities[4-6]. Additionally, the aftermath of flooding frequently aggravates public health challenges. A robust and well-coordinated emergency response is crucial in mitigating these effects, it helps prevent the spread of waterborne diseases and ensures the provision of necessary aid and resources. While an inadequate response can worsen these conditions, prolonging recovery periods, increasing vulnerability to diseases, and exacerbating economic and social difficulties[7, 8]. However, flood models, particularly in densely urban areas are highly uncertain due to the complex urban environment, hindering emergency planning. Therefore, it is crucial to investigate public response patterns of city residents during disastrous flooding events, particularly concerting changes in their mobility. Understanding these patterns and providing insights into causal dynamic before and after flooding events is vital for governments to initiate timely and effective responses to imminent flooding, formulate policies, and implement measures aimed at safeguarding lives and properties. This proactive approach can significantly enhance disaster planning, preparedness, and resilience.

Research has been conducted on the impact of flooding on mobility patterns[9-12] with recent advancements in utilizing Point of interest (POI) data significantly enhancing flood risk assessments[13]. Despite these improvements, several deficiencies remain, particularly concerning the differential impacts of floods on various categories of POI visits. While studies have effectively mapped urban functions and population vulnerabilities, there is a knowledge gap in understanding how different types of POIs—such as residential, commercial, or educational—vary in terms of flood susceptibility and recovery needs[14]. Additionally, the integration of POI data often does not directly account for causal variations in POI visits, which can vary significantly across different categories. Some categories, such as healthcare facilities, transportation facilities, and commercial areas are expected to be more sensitive to flooding events, while others may not be affected. There has study that incorporated commuter data to assess road inundation impacts[15], yet the broader implications for sudden disruptions, unavailability, and economic losses across various

POI categories were not extensively explored[16] in existing literatures. These gaps delineate the need for evaluating the causal impacts of a specific climate event by comparing the changes in POI visits over time. The statistical model provides a differentiated understanding of how floods affect diverse urban functions, which could enhance targeted response strategies and resource allocation during flood events.

In this study, we aim to explore the impacts of flooding events on POI visits in Lagos State, Nigeria, from June to July 2020. Flooding has been a persistent challenge in Nigeria since the 1950s, attributable to three primary factors: (i) The geographical vulnerability due to low-lying topography;[17] (ii) rapid urban expansion in Lagos, which has resulted in inadequate and often overwhelmed drainage systems[18, 19]; and (iii) the increased intensity and frequency of rainfall events during the rainy season, leading to immediate and severe flooding incidents. Lagos State, located in southwestern Nigeria encompasses 22% of its 3,577 square kilometers in water resource and has a coastline of approximately 180 kilometers along the Gulf of Guinea. It experiences a tropical savanna climate, characterized by distinct wet and dry seasons. The annual rainfall typically ranges from 1,500 to 2,000 millimeters. The wet season in Lagos State spans from April to October with the rainy season peaking between June and July experiencing significant precipitation which often results in flooding. Additionally, it is the second most populous state in Nigeria and contains the city of Lagos, which is not only the most populous city in Lagos State but also in the entire continent of Africa and the foremost seaport in West Africa, with its population increasing from approximately 7.9 million in 2006 to over 14 million in 2020. Despite the rapid economic development and prosperity in Lagos, many management challenges, such as poor drainage systems and inadequate waste disposal, which lead to garbage clogging drainage channels, exacerbate the impacts of flooding during the rainy season. Maplecroft's Climate Change Vulnerability Index (CCVI) has ranked Lagos among the ten global cities at "high risk" from climate change[18], as evidenced by the increased frequency and severity of both inland and coastal flooding.

II. Methodology

A. Data collection and processing

Precipitation data and satellite images of floods

All data related to precipitation and flooding were sourced from publicly available datasets. Precipitation data were obtained from the EURA5 dataset. The SAR image data used for testing the proposed method were acquired during the flood period in Lagos state, Nigeria, in June to September 2020. The assessment of flooding areas involved a systematic workflow utilizing satellite imagery processed through Google Earth Engine. This process included: (i) Filtering noise and detecting changes in Sentinel-1 satellite imagery and create before-and-after flood mosaics by applying the Otsu thresholding method. (ii) Enhancing accuracy by excluding areas with slopes over 3% and permanent water bodies, as these areas do not typically retain floodwater. Pixels with slopes higher than 3% are likely to drain water to lower elevation areas. Additionally, areas that contained water for more than five months were considered permanent or semi-permanent water areas. The JRC Global Surface Water dataset, which provides the temporal distribution of global surface water from 1984 to 2018, was used to refine these exclusions. (iii) Improving the delineation of flood extents by removing isolated pixels. Areas with fewer than 39 connected pixels classified as flooded were eliminated, as extremely small regions are not considered significant flooded zones in this study.

Table I. Proposed POI categories and labels of POI in OSM or Google Map

POI Categories	POI labels
Accommodation	Hotel, lodging
Education	University, secondary school, primary school, school, college, childcare, library
Healthcare& Medical	Hospital, dentist, doctor, veterinary care, physiotherapist, pharmacy, drugstore, clinic
Financial& Professional	Accounting, lawyer, electrician, plumber, roofing contractor, moving company, car dealer, car repair, locksmith, carwash laundry, construction, industrial, manufacture, farm, farm auxiliary studio, office, bank, atm, insurance agency, real estate agency
Residential	Apartments, detached
Religious	Mosque, church, Hindu temple, place of worship
Transportation	Airport, bus station, taxi stand, train station, transit station, hangar, parking, ferry terminal, car rental, travel agency, bicycle store, transportation
Energy& Storage	Gas station, storage, warehouse, fuel
Outdoor recreation	Nature reserve, track, pitch, amusement park, campground golf course, playground, stadium, park
Public agencies	City hall, fire station, police, local government office, courthouse, embassy, civic, community center, post office, service
Retail& Shopping	Bookstore, clothing store, convenience store, department store, electronics store, furniture store, hardware store, home goods store, jewelry store, liquor store, supermarket, commercial, common, marketplace, pet store, shoe store, shopping mall, store
Entertainment	Art gallery, movie theater, nightclub, casino, bowling alley, Sports center, museum, cinema, arts center, events venue, movie rental, nightclub, fitness center, tourist attraction, spa, beauty salon, hair care, gym, swimming pool, painter, horse-riding

POI extraction and classification

A location with coordinates and category information is usually referred to as a POI. All POI data were extracted from the OpenStreetMap and Google Earth Engine APIs. The 118 labels of POI are categorized into 12 major categories including Accommodation, Education, Healthcare & Medical, Financial & Professor, Religious, Residential, Transportation, Energy & Storage, Outdoor Recreation, Public Institutions, Retail & Shopping, Entertainment. Specific POI labels included in each major category can be found in Table I.

Smartphone geolocation data and preprocessing

The primary data source for measuring human mobility was anonymized smartphone geolocation data from third-party data providers. This data included anonymized advertisement IDs, application IDs, IP addresses (if applicable), timestamps in UNIX format, device details, geographic coordinates, and geolocation accuracy. For this analysis, we extracted a subset of data spanning four months (2020-06-01 to 2020-09-30) in Lagos state, localizing timestamps to UTC+1. We matched each unique device to the corresponding POI polygon based on latitude and longitude coordinates. The resultant dataset consists of nearly 2,364,139 unique devices each month. The provided data is able to link application movement and activity of the device in both time and space.

B. Preliminary impact analysis of seasonal flooding

A preliminary analysis is implemented to explore the general relationship between flooding and trends of mobilities. To view the flooding-induced shifts in each type of POI visits during the rainy season over time, the following three steps was implemented: (i) Activity POINT were mapped onto the geometric areas of the POI (POI polygons) to accurately attribute visits to the correct locations. (ii) The number of visits to each POI per day was calculated to track daily mobility patterns. (iii) Visits to individual POI were aggregated into broader categories to analyze trends at a more generalized level.

To view the flooding-induced shifts in each type of POI visits during the rainy season over time, the following three steps was given potential discrepancies in sample sizes among different POI types, it was necessary to normalize the visit numbers. The normalization method used is outlined below. Let the visit number of POI category p at time t be Npt. The absolute difference of POI category p at time t is defined as Δ_{pt} and the relative percentage difference is expressed as $\Delta_{pt}\%$, as the equations:

$$\Delta_{pt} = \frac{\sum_p N_{pt}}{\sum_{p,t} N_{pt}} - \frac{N_{pt}}{\sum_t N_{pt}} \quad (1)$$

$$\Delta_{pt}\% = \frac{\Delta_p \sum_{p,t} N_{pt}}{\sum_p N_{pt}}\ \% \quad (2)$$

C. Analysis of correlation between POI visits and precipitation

The correlation of changes in the visit frequency of different categories of POINT of interest and day-by-day precipitation data specifically from June 11 to July 13, 2020, was investigate using MIC method. Assume that there are n_EPOI visit number and $n_m$precipitation to be investigated in the data association analysis. The training samples of the $q-th$ $(q=1,2,\cdots,n_E)$ POI visit number are denoted by x_i, while the samples $m-th$ $(m=1,2,\cdots,n_m)$of the precipitation are denoted by $y_i$with $i=1,\cdots,n_{train}$ and n_{train} denote the total number of pairs. Given a finite set $\mathcal{D}=\{x_i,y_i|i=1,\cdots,n_{train}\}$ of ordered pairs[20], a grid partitionG, called an a-by-b grid, partitions the x_i values and y_i values into a-bins and b-bins, respectively. D_Gdenotes the distribution induced by the cells of G on the POINT in $\mathcal{D}_G$. Since various grids can be obtained with a columns and b rows, the maximum mutual information of these grids on D_G is defined as:

$$\hat{I}(x,y) = maxMI(\mathcal{D}_G) \quad (3)$$

where the maximum is over all grids G with a columns and b rows, and MI is the mutual information of $\mathcal{D}_G$. For the POI visit number and precipitation denoted by $X=\{x_1,x_2,\cdots,x_{n_{train}}\}$ and $Y=\{y_1,y_2,\cdots,y_{n_{train}}\}$, the mutual information between X and Y is given by:

$$MI(x,y) \sum_{x\in X}\sum_{y\in Y} p(x,y) log \frac{p(x,y)}{p(x)p(y)} \quad (4)$$

where $p(x,y)$ is the joint data of random variables X and Y, and $p(x)$ and $p(y)$ are the marginal random variables X and Y, respectively. The probability mass in each cell of G is the fraction of POINT in $\mathcal{D}$ falling in that cell. A simple approach is to superimpose a rectangular grid on the scatterplot of these two variables, and then counting the data POINT falling into each bin created by the partition of values[21].

Normalizing by $\log_2(min\,(a,b))$ to make the values from different grids comparable, the entry of the characteristic matrix of various possible grids is given as follows:

$$M(\mathcal{D})_{a,b} = \frac{\hat{I}(x,y)}{\log_2(min\,(a,b))} \quad (5)$$

As a result, the MIC is defined as the maximum value of normalized mutual information:

$$MIC(x,y) = \max_{a,b<B} M(\mathcal{D})_{a,b} \quad (6)$$

where B is the upper bound of the grid size. According to, the MIC works well in practice when setting $B = n_{train}^{0.6}$.

D. Difference-in-Differences (DiD) analysis

DiD estimation is employed to elucidate the causal relationship between the flooding event and the variations in visits to POI by comparing the differences between the treatment and control groups[22, 23]. The fundamental premise of the DiD approach is that in the absence of the event, the differences between the treatment and control groups would remain constant over time. However, if flooding significantly influences POI visit trends, greater disparities should be observed before and after the flooding events, which serve as the intervention in this study.

The DiD model is formally expressed in Equation (7), depicted graphically in Fig. 2, and supported by Table II

$$Y_{i,t} = \beta 0 + \beta 1 \mathrm{Treated}_i + \beta 2\ \mathrm{Post}_t + \beta 3\ (\ \mathrm{Treated}_i \times \mathrm{Post}_t\ ) + \varepsilon_{it} \tag{7}$$

In Eq. (7), where $Y_{i,t}$ is the response for entity i at time t, β0 is the intercept of regression.$\mathrm{Treated}_i$ is 0 or 1, denoting control or treatment group. Post_t is 0 or 1, indicating pre- or post-treatment.$\mathrm{Treated}_i \times \mathrm{Post}_t$ reflects the combined effect at time t, and ε_{it} is an error term.

Table II. The response matrix for control and treatment groups.

	Control group ($\mathrm{Treated}_i = 0$)	Treatment group ($\mathrm{Treated}_i$=1)	
Before (Post_t=0)	β0	β0 + β1	
After (Post_t=1)	β0 + β2	β0 + β1 + β2 + β3	
Difference	β2	β2 + β3	β3(DiD)

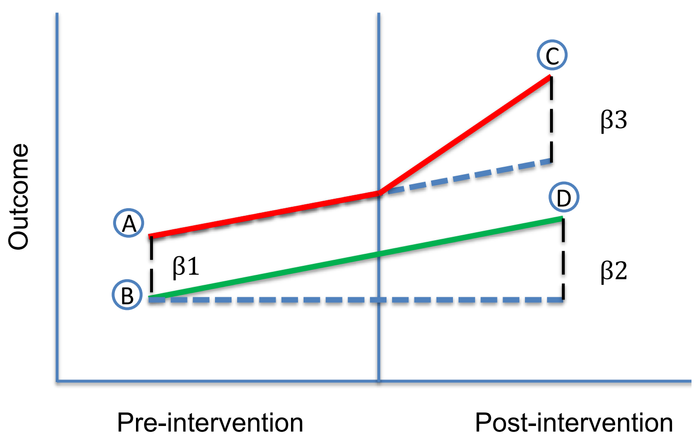

Fig. 1. The illustration of parameters of the applied DiD model.

III. RESULTS

A. Flooding area assessment in Lagos state

The precipitation and temperature data for Lagos State based on period 1991-2020 are presented in Fig. 2a. A clear cyclical pattern, driven by seasonal temperature fluctuations, is evident. High temperatures typically correspond to significantly dry conditions during the dry season, which is characteristic of a tropical savanna climate. It is also noteworthy that Lagos State, being one of the most flood-prone regions in Nigeria, generally experiences its most severe flooding during the rainy season, particularly in June. Consequently, this study on the impact of flooding on human mobility concentrates on the rainy season months of June and September.

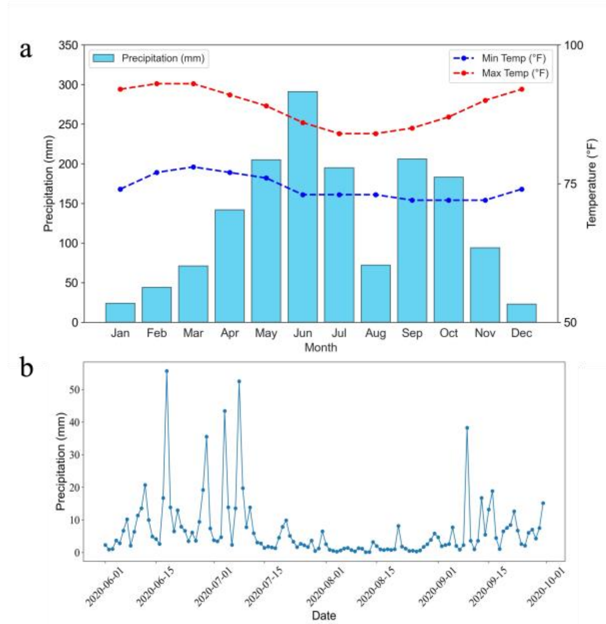

Fig. 2. Lagos state precipitation. (a) the precipitation and temperature in 2020. (b) the day-by-day precipitation from June to September.

The Sentinel-1 satellites, Sentinel-1A and Sentinel-1B, collaboratively provide images of the Earth every six days at the equator. As illustrated in Fig. 3, during the rainy season months of June, flood events were detected on June 23,. The areas affected by flooding are predominantly concentrated on the west side of Lagos Lagoon, which is also a region characterized by higher population density and urban development (as shown in Fig. 3d).

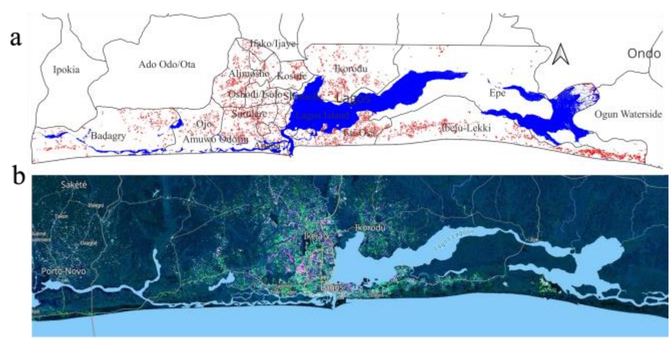

Fig. 3. Detected of flood events (indicated by red POINT) and permanent water areas (highlighted in blue) during the rainy season on different dates: (a) Flooding on June 23, (b) Urban mapping for Lagos State.

B. POI recognition and analysis

When mobility data intersects with the geometric area of POI, a POI polygon, a visit to that specific POI at that time is recorded. We demonstrate the distribution of mobility data POINT for a single day on Lagos Island, alongside the POI of Lagos Island, as depicted in Fig. 4.

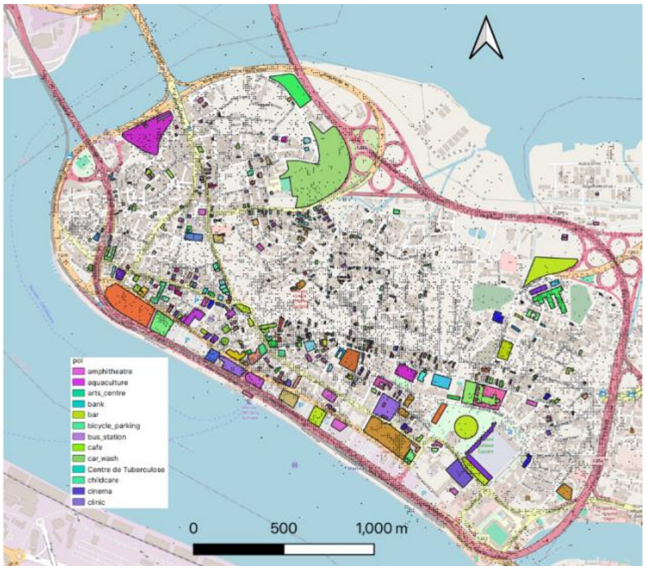

Fig. 4. Spatial distribution of mobility data (black point) in Lagos Island and POINT of interests (polygons) located in Lagos Island on June 25.

C. Flooding impact on human mobility

We applied a preliminary analysis here to calculate the relative percentage difference for each category of POI during rainy season period as shown in Table III. Notably, the flooding period significantly impacts POI visits, with Health & Medical and Public Services categories experiencing substantial increases (26.9% and 17.8%, respectively), likely due to flood-related emergencies and increased need for public support. Monthly trends reveal distinct visitation patterns across categories, can be influenced by many factors such as seasonal changes, weather conditions, and social events. For instance, Religious Buildings saw a sharp increase in June, followed by declines, possibly reflecting seasonal religious activities. Similarly, Entertainment and Retail Shopping categories demonstrate recovery in September, suggesting improved consumer confidence as weather conditions ameliorate. The Transportation category exhibited a sharp decline during flooding but rebounded significantly in September as services were restored. In contrast, Professional Services and Outdoor categories continued to experience declines during the flooding, indicating sustained disruptions. The results highlight the critical impact of flooding on urban mobility and sector-specific activities, emphasizing the need for targeted disaster preparedness and adaptive responses to mitigate such effects and support recovery efforts more effectively.

Table III. Relative percentage difference in POI visits monthly during rainy season period (June to September) and during the flooding period (June 23 to July 08).

	June	July	August	September	Flooding
Health & Medical	14.3%	20.5%	-14.9%	-20.8%	26.9%
Public Services	4.3%	3.1%	-14.6%	-6.3%	17.8%
Religious Buildings	36.5%	-19.4%	-13.0%	5.1%	14.6%
Utilities Storage	7.7%	-2.9%	-3.4%	-4.5%	4.6%
Entertainment	1.9%	-6.8%	1.3%	9.4%	4.4%
Retail Shopping	1.0%	4.9%	-2.9%	-6.3%	1.1%
Residential	0.2%	-3.8%	10.0%	0.7%	1.1%
Education	-9.5%	4.0%	2.5%	4.1%	-7.1%
Accommodation	3.7%	9.4%	-7.1%	-2.4%	-11.1%
Transportation	-18.4%	-12.1%	8.2%	26.4%	-16.2%
Professional Services	-3.2%	-17.3%	8.9%	1.7%	-18.6%
Outdoor	4.2%	-8.3%	13.8%	-5.7%	-20.8%

The Fig. 5. presents the temporal changes in mobility patterns and health service visits in response to flooding events and heavy rainfall in Lagos State, Nigeria. From the onset of the first flooding event, there is a noticeable increase in visits to hospitals and clinics. This trend persists until the second flooding event and continues into the following week, indicating a heightened demand for medical services likely due to flood-related health issues such as waterborne diseases and injuries. Concurrently, the number of visits to outdoor locations drops significantly, reflecting the population's reduced mobility due to the hazardous conditions caused by the flooding. The sharp decline in outdoor activities suggests that the floodwaters may have rendered many areas impassable, thereby limiting people's ability to engage in routine outdoor activities. This disruption in normal mobility patterns underscores the immediate impact of severe weather events on transportation infrastructure and public behavior. The correlation between these trends highlights the need for robust flood management and emergency response strategies to mitigate the adverse effects on health and mobility in urban settings. This normalized research result focuses more on the relative changes of different types of POI compared to other types of POI during the flood periods of high-intensity rainy seasons.

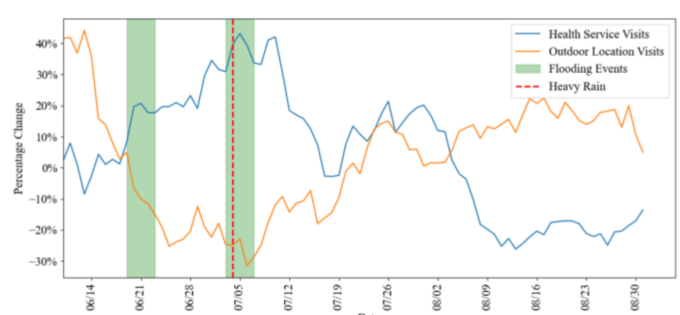

Fig. 5. Impact of flooding events on health service and outdoor visits

The Fig. 5. presents the temporal changes in mobility patterns and health service visits in response to flooding events and heavy rainfall in Lagos State, Nigeria. From the onset of the first flooding event, there is a noticeable increase in visits to hospitals and clinics. This trend persists until the second flooding event and continues into the following week, indicating a heightened demand for medical services likely due to flood-related health issues such as waterborne diseases and injuries. Concurrently, the number of visits to outdoor locations drops significantly, reflecting the population's reduced mobility due to the hazardous conditions caused by the flooding. The sharp decline in outdoor activities suggests that the floodwaters may have rendered many areas impassable, thereby limiting people's ability to engage in routine outdoor activities. This disruption in normal mobility patterns underscores the immediate impact of severe weather events on transportation infrastructure and public behavior. The correlation between these trends highlights the need for robust flood management and emergency response strategies to mitigate the adverse effects on health and mobility in urban settings. This normalized research result focuses more on the relative changes of different types of POI compared to other types of POI during the flood periods of high-intensity rainy seasons.

D. Data association analysis for heavy rainfall and POI visits

The above part explores the normalized research result focuses more on the relative changes of a certain category of POI compared to other types of POI during the flood periods of high-intensity rainy seasons. For further detected the characteristics of the raw data, we will next examine the relationship between the original number of visits and the precipitation. The DiD analysis method, a statistical technique designed to infer causal relationships by comparing temporal changes between a treatment group and a control group.

In addition to this, we utilized the MIC method to rank correlations between visits to different POI and precipitation data collected from June 11, 2020, to July 13, 2020. This approach allowed us to quantify the strength of the relationships between these variables, acknowledging that precipitation is often a direct or indirect precursor to flooding.The findings from the MIC analysis are detailed in Fig.6.

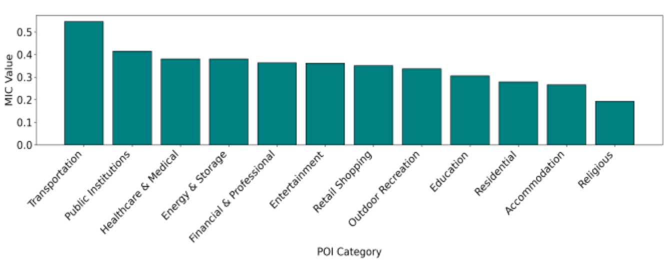

Fig. 6. MIC values for different POI categories.

For this figure, Transportation and Public Institutions show the highest correlations, indicating significant responsiveness to rainfall, likely due to the direct impact on transportation and increased reliance on public services during adverse weather. Healthcare & Medical, Energy & Storage, and Entertainment also display substantial correlations, reflecting the necessity of healthcare during poor weather, the sensitivity of energy infrastructure to environmental conditions, and the impact on predominantly indoor entertainment activities. Financial & Professional, Outdoor recreation, and Retail & Shopping show moderate correlations, pointing to a noticeable impact of rainfall on these activities. Education and Residential sectors, while affected, exhibit lower sensitivity due to their structured and predominantly indoor nature. Accommodation shows resilience, potentially due to the transient nature of its clientele and internal management of facilities. Significantly, Religious Buildings demonstrate the lowest correlation, making them an excellent control group for DiD analysis.

E. DiD analysis of how flooding effect on human mobility

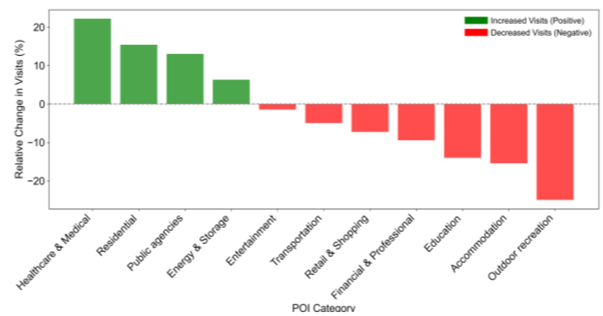

Fig.7. DiD Estimate percentage value for different POI categories. The Religious is chosen to be the control group.

The visits frequency of Religious Buildings stable visitation patterns, minimally influenced by rainfall, provide a reliable baseline for comparing more variable responses in other sectors, thereby allowing for a more accurate assessment of the direct and indirect impacts of weather on human mobility and activities across different sectors. On observing significant flooding on June 23rd, as depicted in Fig. 4a, we designated the seven days prior as the pre-treatment period and the seven days following as the post-treatment period. The results show in Fig. 7, the DiD estimation provides a detailed perspective on the impact of that flooding on various POI, employing Religious Buildings as the baseline for comparison. Healthcare & Medical POI experienced a significant increase in visits, shows a response to flood-related health emergencies, while Residential areas also displayed a statistically significant rise in visits, suggesting an increased tendency for individuals to remain at home during the flood. Categories such as Transportation, Financial & Professional Services, and Retail & Shopping experienced downturns in visitation, reflecting a reduction in economic activity; however, these changes were not statistically significant. Conversely, Energy & Storage and Public Agencies saw increases in visits, indicating a surge in demand for energy and public services, though these results also lacked statistical significance. The most profound decrease occurred in Outdoor Recreation, which plummeted by 24.95%, severely affected by the inclement weather conditions that rendered outdoor activities impractical.

IV. Conclusion

This study examines the impact of flooding on urban mobility in Lagos State, Nigeria, a region highly susceptible to severe flooding. Through a robust methodology that includes flood detection, mobility data analysis, DiD estimations, and MIC correlations, we have uncovered key behavioral patterns in response to flooding events.The findings have significant implications for urban planning and disaster management: (i) Identifying the most affected POI categories allows for strategic resource allocation during emergencies, such as enhancing healthcare services in flood-prone areas. (ii) Infrastructure improvements can be more effectively targeted, like upgrading drainage systems in commercially active regions to mitigate economic losses. (iii) Promoting flood risk awareness in areas with high public presence during floods, such as residential neighborhoods, can improve preparedness.

Despite its contributions, this study has limitations that warrant further research. Longitudinal studies could provide deeper insights into the long-term impacts of flooding on urban mobility and reveal recovery patterns over time. Expanding the scope to include cities with diverse geographical and socio-economic conditions would enhance the generalizability of the findings. Additionally, integrating socio-economic data with mobility data could offer a more nuanced understanding of how different population segments are affected by and respond to flooding.

In conclusion, this research highlights the urgent need for cities like Lagos to bolster their urban resilience. Understanding the interplay between flooding and human mobility enables policymakers to devise strategies that not only address immediate disaster impacts but also build long-term capacity to withstand future events. As climate change intensifies, the importance of informed, data-driven approaches in urban planning and disaster management becomes increasingly critical. This study contributes valuable insights to these efforts and underscores the need for ongoing research in public safety and urban sustainability.

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