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Advancing Human Displacement Modeling: A Case Study of the 2022 Summer Floods in Pakistan

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Key Points:

- Open-source data and impact modeling are used to estimate displacement during the 2022 Pakistan flooding
- The model links flood depth to displacement, finding that a 0.67 m depth threshold (CI 0.35 m–1.10 m) produces the best fit for the data
- Relative to the model estimates, we find that there is relatively less displacement in urban areas than in rural areas

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract The devastating 2022 summer flood in Pakistan displaced about 7 million people in the Sindh province alone. Up to one-third of the country's area, mostly the country's south, was flooded. Effective response to intensifying and compounding hazards requires a better understanding of these processes. We can gain insights if impact assessments include socio-economic components and uncertainties arising from the interactions between impacts. However, the quantitative evidence from impact assessments remains limited and fragmented, due to methodological challenges and data limitations. Using the open-source impact assessment platform CLIMADA, we study to what extent flood-related hazards can be used to quantify displacement outcomes in a data-limited region. Using flood depth, exposed population, and impact functions, we link flood vulnerability to displaced people. This allows us to estimate internal displacement resulting from the flood event, and to further assess how displacement varies across the region. We find that a flood depth threshold of 0.67 m, with a confidence interval (CI) from 0.35 to 1.10 m, provides a best fit to all data from Sindh province. We find a negative correlation between displacement and the degree of urbanization. By testing the performance of our model in explaining differing displacement estimates reported across Pakistan, we show the limitations of existing impact assessment frameworks. We emphasize the importance of estimating potential displacement alongside other impacts to better characterize, communicate, and ultimately mitigate the impacts of flooding hazards.

Plain Language Summary In the summer of 2022, Pakistan experienced severe flooding that displaced approximately 7 million people in the Sindh province alone. To better handle such disasters in the future, it's crucial to understand these events from a vulnerability perspective. However, current data and methods for assessing these impacts are limited. Using an open-source tool CLIMADA, we study how flood characteristics can help predict how many people might be displaced, even when data are scarce. By examining flood depth, the number of people exposed, and how vulnerable they are, our study estimated how many people were forced to move within the country due to the floods, with a focus on the Sindh region. Our study found that a flood depth of about 0.67 m, with a confidence range between 0.35 and 1.10 m, best matched the data from Sindh province. Interestingly, we also discovered that displacement was less likely in more urbanized areas. By applying the model to other displacement reports from across Pakistan, we highlighted the limitations of CLIMADA. We stress the importance of estimating potential displacement alongside other impacts to better understand, communicate, and ultimately reduce the consequences of flooding for vulnerable populations.

1. Introduction

Floods, heatwaves and other extreme weather events have major impacts on societies. Due to global warming, most of these are projected to become more intense, and weather patterns could change in unpredictable ways (IPCC, 2021; Tabari et al., 2021), making it harder for societies to prepare and adapt to impacts from climate change (Hirabayashi et al., 2013). Record-breaking flood events have already disproportionately affected vulnerable and poor populations in low- and middle-income countries in ways that are not well captured by traditional economic loss estimates (Kovats & Akhtar, 2008; Peduzzi et al., 2009). In 2022, Pakistan experienced two major extreme weather events, which were intensified by anthropogenic climate change: a heatwave in May 2022 (Zachariah et al., 2022) and extreme monsoon rainfall in August 2022 (Otto et al., 2023). The 2022 floods

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most severely hit the densely populated flood plain regions of Sindh and southern Baluchistan and caused approximately 1,700 deaths (CRED/UCLouvain, 2024) and large-scale humanitarian impacts (Bhutta et al., 2022; Nanditha et al., 2023). The impacts of the flood compounded the health and economic system that was already stretched by the COVID-19 pandemic, disproportionately affecting vulnerable population groups, including approximately 16 million children and 650,000 pregnant women (Moeen et al., 2020). As in all weather- and climate-related disasters, the climate component interacted with other factors to amplify flood hazard and its impacts. For example, poor maintenance of water delivery and flood control systems, combined with inadequate water management decisions led to exacerbated flooding in many areas during the 2022 Pakistan flood (Zia et al., 2023).

The loss and damage fund drafted at COP27 and agreed upon at COP28 (UNFCCC, 2022), allows additional funding resources to address the human costs associated with climate change (Wyns, 2023). By incorporating science-informed impact assessments, decision-makers can more effectively respond to disasters and allocate resources accordingly in preparation for future events (Coughlan de Perez et al., 2015). However, post-disaster displacement assessments depend on the quality and detail of available observations and data, the number of displaced people, their location and associated humanitarian impacts (Thalheimer & Oh, 2023). Improved understanding of historical events based on observations and model validation can support climate finance mechanisms for disaster response and anticipatory planning (P. M. Kam et al., 2024; Thalheimer et al., 2022).

One common approach to quantifying disaster impacts is to integrate the weather- and climate-related hazards, the exposure of people, or the economic and social assets, and the vulnerability of the people or assets to the hazards (IPCC, 2014) Previous studies focus on physical flood damages such as on buildings (e.g., Custer & Nishijima, 2015; Nadal et al., 2010; UNDRR, 2015); information on flood related displacement remains scarce. This is partly due to the fact that there has been much in-depth research on hazards and exposure. However, due to data limitations, our understanding of population vulnerability to flood-related displacement remains incomplete.

Quantitative modeling of human displacement remains an under-researched topic, mainly due to the complex nature of displacement and the lack of data. Yet displacement estimates, even with substantial uncertainty, nonetheless have the potential to be useful for governments, humanitarian organizations, and policymakers in drafting effective emergency response strategies and planning longer-term resilience for potential disasters. Quantitative modeling of displacement can help identify the areas most severely impacted, supporting a more focused and efficient allocation of emergency resources. It can help guide the distribution of aid, the prioritization of rescue efforts, and the establishment of temporary shelters in the most crucial locations. Moreover, by analyzing the patterns of displacement, these models can give insights into long-term planning and the development of more resilient communities and infrastructure in preparation for future disasters.

In this study we examine the 2022 Pakistan floods in order to advance modeling approaches to human displacement. These major floods displaced large parts of the population, with relatively detailed displacement data recorded (Nanditha et al., 2023; PDMA, 2022). We combine it with open-access data on flood extent, population distribution, and displacement. We then analyze the link between flooding and displacement using different impact function methodologies. We also explore contrasting displacement rates in rural versus urban areas by overlaying the degree of urbanization in our model prediction. This modeling approach entails many simplifications due to data limitations, hence we focus on describing modeling choices and assessing the extent to which such modeling approaches may be able to approximate reported displacement, and then highlight potential ways of improvement. Such an approach can complement reported displacements, which are themselves characterized by high uncertainty, over time supporting improved decision making around a highly impactful societal challenge.

2. Methodology and Data

We attempt to provide a quantitative estimate of the flood-related displacement from the 2022 floods. We carry out this analysis for districts in the Sindh province, Pakistan. Displacement is computed as a convolution of hazard, exposure, and vulnerability. We combine (a) the flood footprint with flood depth (hazard, Section 2.2), (b) gridded population data at a resolution of 3 arcseconds in Pakistan (exposure; Section 2.3), and (c) population vulnerability to displacement by floods at thresholds corresponding to specific flood depths (vulnerability; Section 2.4). We use the open-source, spatially explicit impact assessment platform CLIMADA (CLIMate ADAptation; Aznar-Siguan & Bresch, 2019; Bresch & Aznar-Siguan, 2021) to match the exposure data set to the hazard layer and incorporate the information on population vulnerability to estimate the number of people displaced by the flood. By spatially overlaying these layers, we estimate the number of displaced people at a resolution of 3 arc s (∼80 m).

2.1. Study Area and Displacement Data

We assess flood displacement in the Sindh province (administrative level 1) because it was substantially affected during the 2022 floods with roughly one third of the province's area inundated, and because the Provincial Disaster Management Authority (PDMA) in Sindh issued daily situation reports on the total number of people affected and the number of people displaced at the district level (administrative level 2) that covers the full 24 districts in Sindh province (PDMA, 2022). We use displacement totals reported for 17 September 2022, which is the date closest to the maximum flood extent based on available data (31 August 2022, see Section 2.2). We take this published number as reference for displaced persons and to calibrate our displacement model (Table S1 in Supporting Information S1). The district-level displacement data do not specify the place of origin of the displaced people counted, hence we are unable to assess to what degree people may have been displaced from one district to another. Therefore, for the district-level analysis, we assume that displacement totals reported per district are people who were internally displaced within that district, acknowledging that this would bias our analysis if cross-district displacement did take place.

We note that there are other estimates of total displacement from the 2022 Pakistan floods, but these are not broken down to cover the 24 districts of Sindh Province separately. Islamic Relief (2022) uses the number of people having lost their homes as a displacement proxy and reports 2.1 million displacements. Updated figures by UNHCR (2022) estimate 7.6 million people displaced and an additional 33 million people affected by the flood. Different estimates may be due in part to the lack of a general definition of displacement including timing, scale and scope. This can lead to methodological complications in displacement data analysis including inclusion and exclusion of displacement data points (Buhaug, 2023). The large range of estimates highlights that unfortunately no observations can be treated as a perfect representation of reality.

2.2. Calculating Flood Depth as Proxy for Hazard Intensity

We use spatially explicit flood depth maps at ∼30 m resolution (1 arcsecond) as input for the modeling framework, which we obtain by combining a cumulative flood extent map with a digital elevation model (DEM).

The cumulative flood extent map was obtained from UNITAR (2022) and is derived from daytime imagery of the VIIRS instrument onboard the NOAA-20 satellite from 1 July to 31 August 2022 over Pakistan. The spatial cumulative flood extent map was produced by combining all flooded areas identified during the period from 1 July to 31 August 2022. The spatial resolution of the map is 375 m. As DEM, we use the SRTM 1 arc s elevation data which is a void-filled DEM of global coverage with a spatial resolution of approximately 30 m obtained from NASA's Shuttle Radar Topography Mission (SRTM) (USGS, 2017) in September 2014. The cumulative flood depth maps were computed for each district individually by first extracting the flood extent in each district. The delineated cumulative flood extent polygons and the DEM raster were then fed into the Floodwater Depth Estimation Tool (FwDET v2.0; Cohen et al., 2019), implemented as a toolbox in the geographic information system software ArcGISPro. For each grid cell within a flooded domain, FwDET identifies the flood water height of that cell by extracting the elevation of its nearest flood-boundary grid cell, thus assuming a perfectly flat water surface between both cells. It then computes the flood depth of the flooded cell by subtracting the water height from the topographic elevation. Since the flood depth map is computed based on the cumulative satellite detected water between 1 July and 31 August 2022, the flood depth maps display the maximum flood depth. Finally, the maximum flood depth map is resampled to match the grid of the population exposure map (Section 2.3).

2.3. Population Exposure Data

To obtain the estimated population exposed to the floods, we use the constrained population data for the year 2020 from WorldPop (Bondarenko et al., 2020; Tatem, 2017). This data set uses admin-level population counts and various geospatial information to disaggregate population numbers to grid cells. The data set contains population per grid cell at a resolution of 3 arcseconds, that is, approximately 100 m at the equator. WorldPop has made further adjustments to match the United Nations national population estimates (UN, 2019). The constrained data

10.1029/2025EF006788

set uses only grid cells with built settlements, which appears pertinent for our analysis that assumes that people are displaced when floodwaters exceed a certain height in their settlements.

2.4. Modeling Population Displacement by Floods

We use two approaches to model displacement, both of which examine the relationship between flood depth and displacement. These are simplifications of a much more complex reality as we discuss further in the Results and Discussion. In a *prior knowledge* modeling approach, we assume that all people at a location are displaced by floods if the flood depth exceeds specific thresholds. We define these thresholds based on an empirical relationship between flood depth and displacement (detailed in Section 2.4.1). In a *calibration* modeling approach, we use the displacement numbers reported by PDMA (2022) to calibrate the flood depth thresholds for modeled displacement (detailed in Section 2.4.2). Through these two approaches, we evaluate how well the model captures displacement from flood events.

The thresholds are implemented as parameterized values in CLIMADA's impact function, taking the form of a step function (Aznar-Siguan & Bresch, 2019).

2.4.1. Prior Knowledge Modeling Approach

We first define flood depth thresholds based on *prior knowledge* from literature to model the number of displaced people. Previous work has shown that a reinforced concrete frame building can be substantially damaged by static water depths between 0.5 and 2.0 m (Nadal et al., 2010), while another study indicates that the damage rates of housing and assets in Japan reach nearly 100% when the water depth exceeds 2 m (Kazama et al., 2010). Housing damage is often used as a proxy to estimate the number of displaced people (e.g., IDMC, 2017). We therefore assume that people are displaced if they experience a flood depth exceeding predefined thresholds. We compute the number of displacements using flood depth thresholds of 0.5, 1.0, 1.5, and 2.0 m, providing a range of estimated displacements.

2.4.2. Calibration Modeling Approach

In the *calibration* modeling approach, we use reported displacement data for the 2022 Pakistan flood from PDMA (2022) to empirically estimate the flood depth thresholds. To do this, we minimize the average error between the model's predicted displacement and the reported displacement, utilizing a Python submodule in the CLIMADA platform developed by Riedel, Kropf, and Schmid (2024). This calibration method has previously been applied to calibrate impact functions for displacement in both flood impact-based forecasts (Riedel, Röösli, et al., 2024) and tropical cyclone impact-based forecasts (P. M. Kam et al., 2024). We calibrate the best-fit threshold parameter using reported displacement data from 24 districts (administrative level 2) in Sindh province (administrative level 1). Given that reported displacement numbers across districts range from hundreds to millions (see Table S1 in Supporting Information S1), we employ the root-mean-squared fraction (RMSF) as our error function, following Eberenz et al. (2021). This approach minimizes relative errors between modeled and reported displacement numbers. Unlike the more commonly used root-mean-squared error (RMSE), which weights more strongly locations with the highest displacement figures, RMSF weights all data points equally regardless of displacement magnitude. This method ensures a more accurate representation of displacement across all scales.

RMSF is expressed as follows:

$$\text{RMSF} = \exp\sqrt{\frac{1}{N}\sum_{i=0}^{N}\log\left(\frac{\hat{y}_i}{y_i}\right)^2} \tag{1}$$

Here, N is the number of districts where displacement is being reported, $\hat{y}_i$ is the model estimated displacement in district i and y_i is the reported number of displacements from the PDMA report (PDMA, 2022).

We use the calibration module within CLIMADA to minimize the RMSF (Riedel, Kropf, & Schmid, 2024). This module iteratively computes displacement as impact in CLIMADA to find the optimal thresholds for flood depth. In order to assess the confidence level of the calibration process, we calculate the displacement by considering a range of flood depth thresholds for which the RMSF falls within a 5% margin of the minimum RMSF.

10.1029/2025EF006788

2.5. Assessing District-Level Variation

We investigate whether the flood depth—human displacement relationship varies by district, using the fitting method described immediately above to estimate flood depth thresholds for each district separately. This enables us to examine questions such as whether displacement is more likely in urban versus rural districts.

We calibrate the best-fit thresholds for each district individually, with 5 m as the maximum allowed threshold. The thresholds obtained for each district can then be interpreted as a sensitivity index for that district—a larger flood depth threshold indicates that the population in the corresponding district is less likely to be displaced by floods of a given depth, while a smaller threshold indicates greater likelihood of displacement. Then, we overlay the Global Human Settlement (GHS) degree of urbanization stage (Schiavina et al., 2023) to identify the percentage of the flooded area which is classified as urban centers. We perform Pearson correlation analysis to investigate whether urbanization has an observable effect on flood displacement.

We note that many other variables can also influence displacement sensitivity. For example, the likelihood to be displaced also depends on the socio-economic vulnerability of the population and the sensitivity of their occupation or livelihood to flooding, as well as on physical properties of their housing. However, such considerations depend on a host of factors for which we do not have systematic data, and hence are beyond the scope of our proof-of-concept study.

3. Results

3.1. Flood Depth Estimation

Over the period from 1 July to 31 August 2022, we find that 32% of Sindh province was flooded at least once. Figure 1 shows the maximum flood depth map in Sindh, derived from the cumulative flood extent map over the same period; the methodologies are detailed in Section 2.2.

3.2. Estimates of Displacement for Sindh Province

We estimate the number of displaced people in Sindh during the 2022 summer floods by overlaying the flood depth map (Figure 1) with the population distribution, using flood depth thresholds based on prior knowledge (methodology in Section 2.4.1) and on calibration based on PDMA data (methodology in Section 2.4.2).

Figure 2a shows the estimated number of people displaced using the prior knowledge modeling approach. The range of estimates represents the number of people displaced if the flood depth exceeds thresholds ranging from 0.5 to 2.0 m. Overlaying the PDMA-reported number of displaced people shows that our initial estimation aligns well with the reported numbers in districts where the reported displacement falls roughly between 5,000 and 50,000 people. However, the model tends to underestimate displacement in districts with high reported numbers and to overestimate in districts with low reported numbers. Regarding the estimation of the total number of displacements in Sindh, our model predicts a range of 1.94–5.65 million people (under the 2 and 0.5 m depth thresholds respectively), compared to the total of 6.76 million displaced people reported by PDMA (2022).

We next use PDMA-reported displacement data to calibrate the optimal flood depth threshold that minimizes the RMSF across all 24 districts in Sindh province, yielding a best-fit depth threshold of 0.67 m. In addition to the single value of the threshold, we find a confidence range of thresholds from 0.35 to 1.10 m, for which the RMSF values fall within the 5% margin of the minimum RMSF.

Figure 2b shows the displacement numbers predicted by the model using this calibrated threshold, along with the numbers reported by PDMA. The blue lines represent the model estimates using the RMSF best-fitted threshold of 0.67 m and the threshold range from 0.35 to 1.10 m. We estimated a total displacement of 4.87 million people in Sindh using the best-fitted threshold, with a confidence range of 3.35–6.70 million. Despite the different methodological approaches in Figures 2a and 2b, the patterns are similar in the model estimates, confirming the general validity of the empirical assumptions about flood depth and displacement.

3.3. District-Level Variation in Displacement

Noting that populated cities such as Hyderabad, Larkana and Sukkur are situated within the heavily flooded area (Figure 1), we conduct an additional, exploratory analysis into connections between the degree of urbanization

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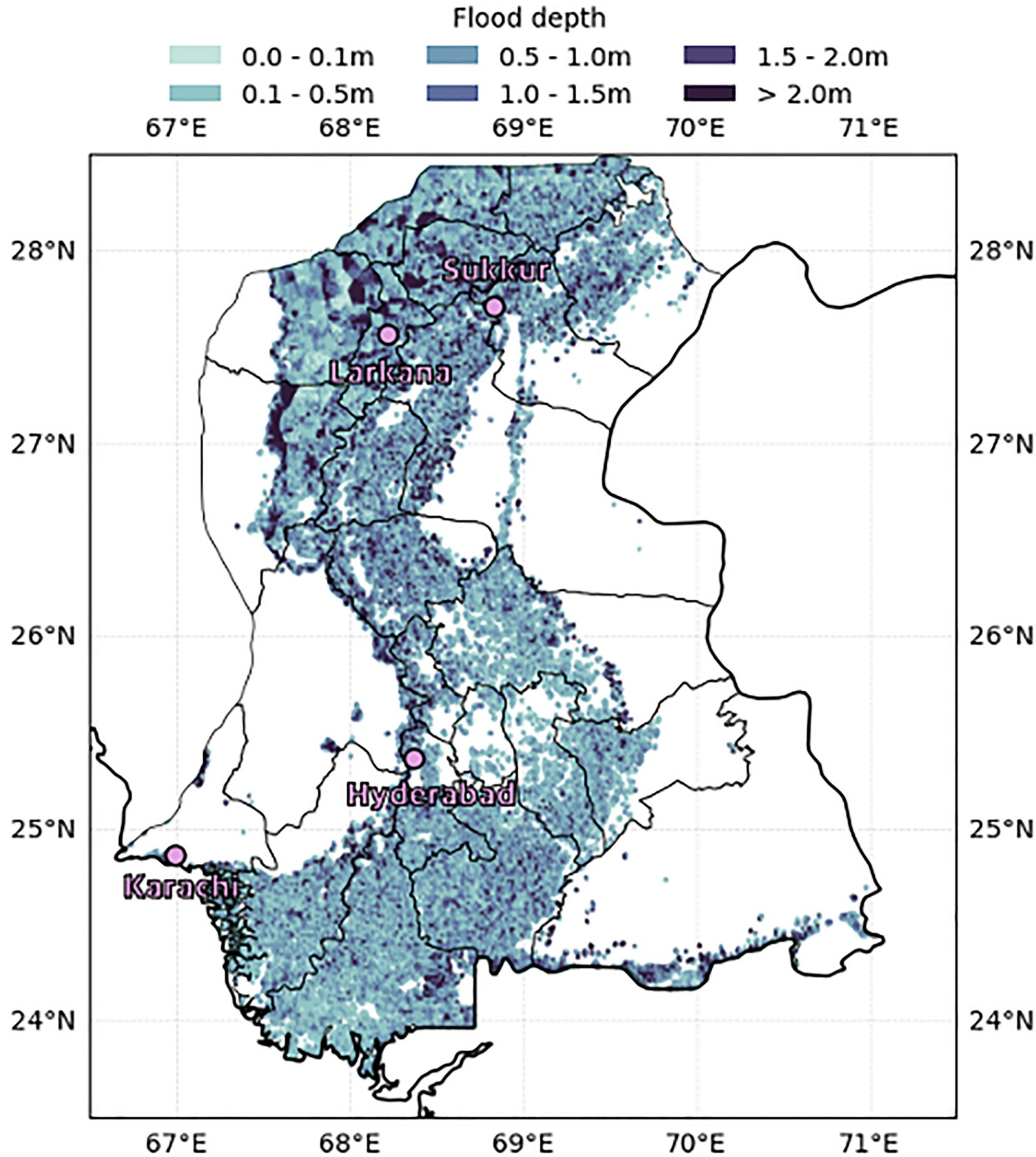

Figure 1. Calculated maximum flood depth between 1 July and 31 August 2022 showing 32% of the Sindh region (~45 thousand sq. kms.) was affected by the flood. Flood depth estimates are derived from NOAA-20 satellite cumulative flood extent maps and SRTM 1 arc-second elevation data. See Section 2.2 for detailed methodology.

and the displacement-flood depth relationship. We determine an optimal flood depth threshold for *each individual district* by minimizing the difference between model predictions and reported displacement data. This approach differs from the prior section, where a single flood depth threshold was optimized based on the *Sindh-total* based on equal weighting of each of the 24 districts' reported displacement. By fitting the flood depth threshold to each individual district, we can interpret the resulting values as proxy indicators of population vulnerability to displacement. A higher (lower) flood depth threshold value signifies less (more) likelihood of displacement to floods of a given depth.

Figure 3a shows flood depth thresholds fitted individually for each district in the Sindh region. We observe that districts with a larger percentage of flooded area that is urban (Sukkur, Hyderabad, and Karachi) tend to have higher calibrated flood depth thresholds, that is above 3 m. Correspondingly, the Pearson correlation between the percentage of flooded areas that are urban and the flood depth thresholds is substantively positive ($r = 0.73$, 95%

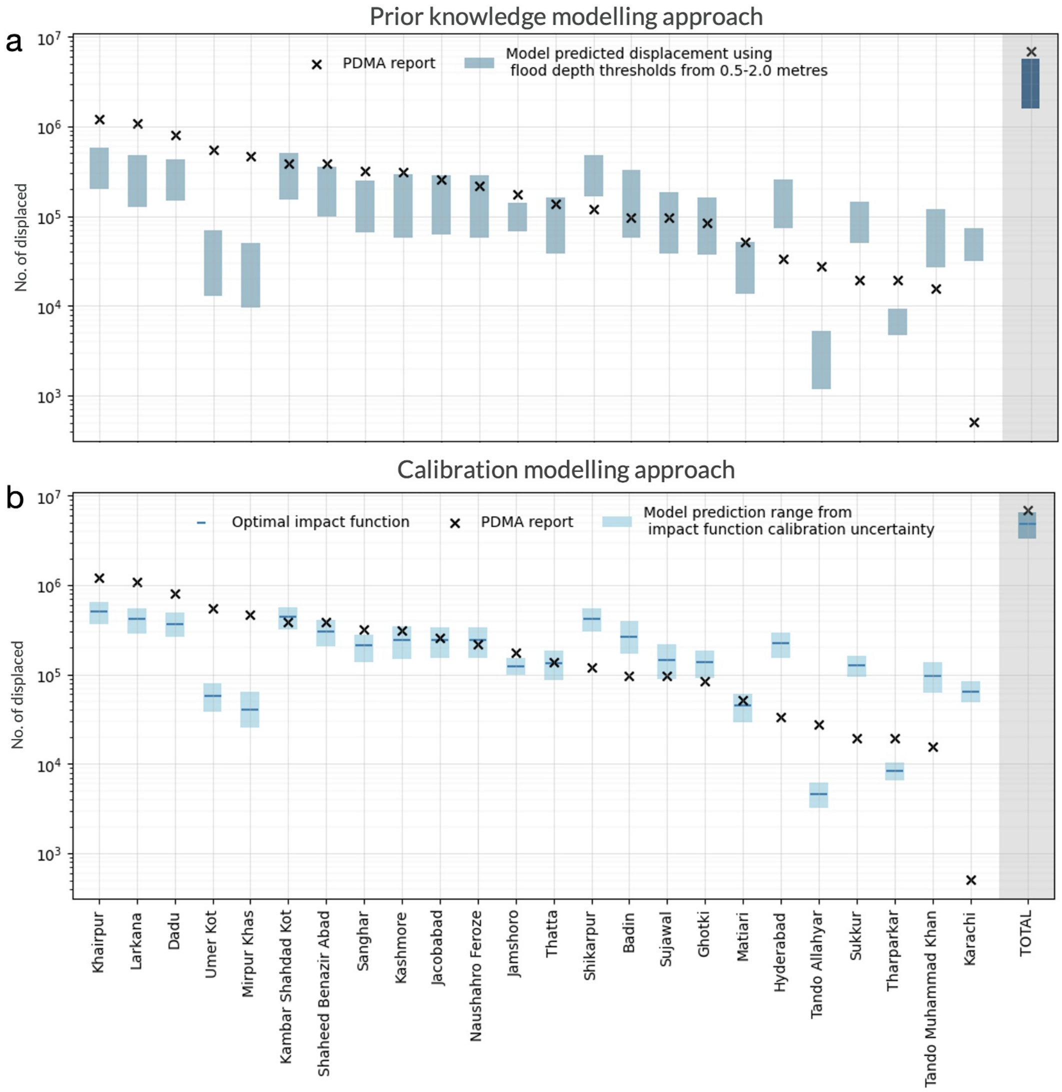

Figure 2. Number of displaced people estimated by CLIMADA. (a) Displacement estimated using the prior knowledge modeling approach with flood depth thresholds from 0.5 to 2 m flood depth (blue bars) for each of 24 districts in the Sindh province in Pakistan, and the 24-district total. The black crosses denote the PDMA reported number of displaced people. Note that the y-axis is in log scale. (b) Similar to (a), except the displacements are estimated using the calibration modeling approach (blue lines). The light blue boxes represent the model uncertainty range from the calibration.

confidence interval 0.47–0.88). In contrast, there are not strong correlations between flood depth thresholds and either the percentage of flooded areas that are suburban ($r = -0.14$) or the percentage of flooded areas that are rural ($r = -0.08$). It is not clear from these results what factors may lead to this apparent higher flood-depth threshold for displacement in urban areas; this is an important topic for future research.

Figure 3b presents the estimated displacement using the individually fitted depth thresholds as the CLIMADA model's impact step function. Ideally, the model should be able to accurately estimate the number of reported displacements from the PDMA data. However, in certain districts such as Larkana, Umer Kot, Mirpur Khas, Tando Allahyar, and Tharparkar, the model's estimates are still too low, even when using the lowest bound of the flood depth threshold at 0.05 m (Figure 3a). On the one hand, this suggests that there is additional displacement occurring in areas outside the satellite imagery derived flood footprints, which the model by definition cannot capture. On the other hand, our model overestimates displacement in Karachi despite using the maximum allowed

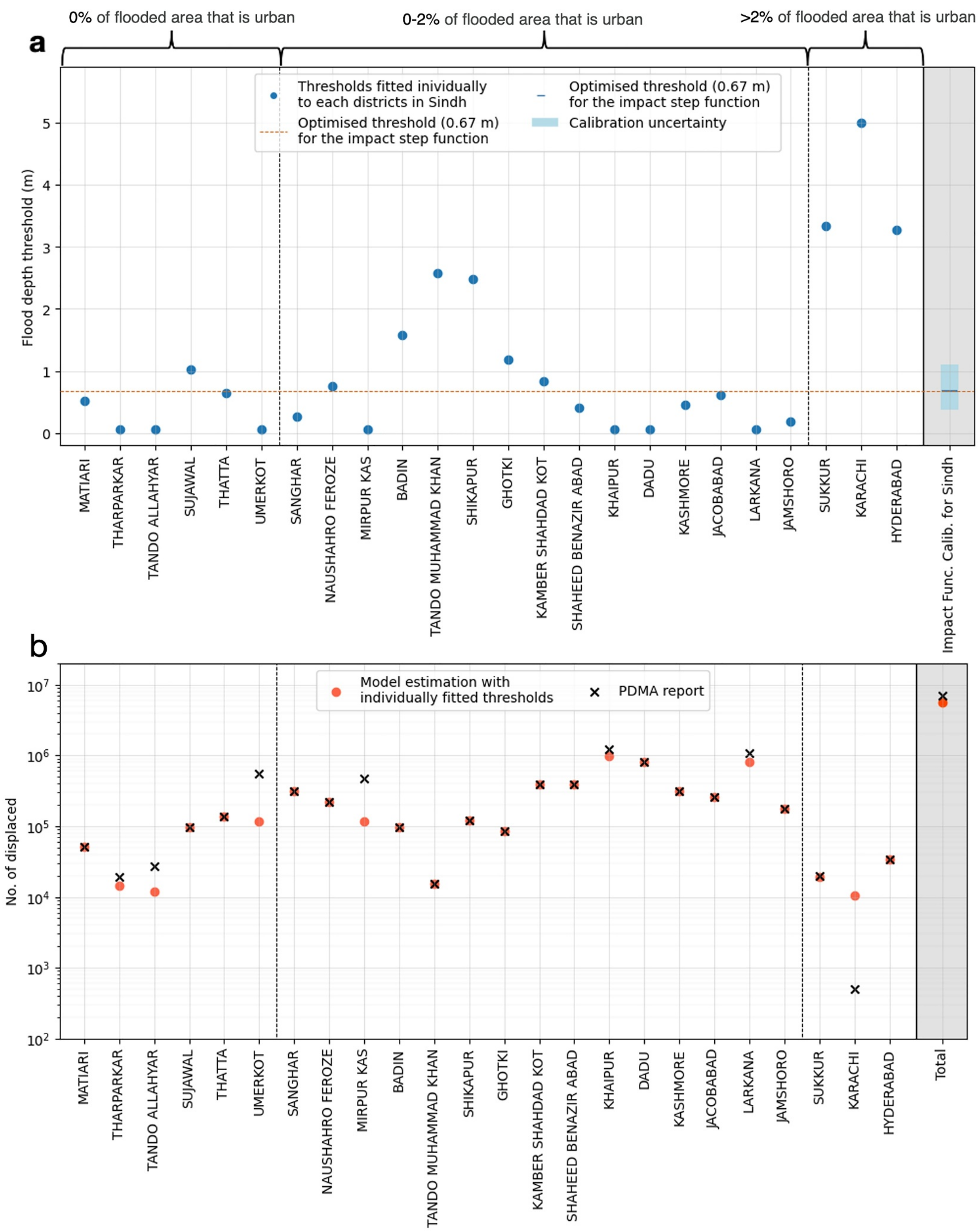

Figure 3. District-level variation in displacement. (a) Flood depth thresholds fitted individually to each district in Sindh, compared with the numerically calibrated threshold for the Sindh-wide impact step function which is based on displacement data aggregated across its 24 districts (blue line) and the associated uncertainty (light blue bar). (b) The model's estimated displacement using the individually fitted flood depth thresholds from (a) as a unique CLIMADA impact function for each district, and their sum (orange dots). The black crosses indicate displacement reported in the PDMA data. Note that the *y*–axis is in log scale.

flood depth threshold of 5 m. The underlying reasons for this overestimation in Karachi remain unknown, but they point to the inherent limitations in our basic model. Further insights into the implications of these findings will be discussed in the next section.

10.1029/2025EF006788

4. Summary and Discussion

This study presents a modeling approach that maps human displacement in the Sindh region, which was most affected by the Pakistan 2022 floods. We use the open-source impact assessment model CLIMADA, and open and publicly available data to conduct our analysis. The model estimates displacement based on: (a) the flood intensity expressed as water depth derived from satellite-based flood extent estimation (hazard), (b) population distribution (exposure), and (c) impact functions (vulnerability). In this section, we discuss the relevance of this case study (Section 4.1) and elaborate on the uncertainties and limitations of the model setup and displacement data (Section 4.2), while giving suggestions for advancing displacement modeling research.

4.1. Relevance of the Case Study

This study can be considered an initial effort to assess the extent to which simple modeling approaches can approximate reported flood-induced displacement. It is intended as a first step toward improved estimates in the future, based on model advances and improved data collection where possible. Concerning data, for example, defensible data are available for the flood hazard footprints (e.g., satellite-based flood extent estimation; UNITAR, 2022) and population exposure (e.g., WorldPop population count; Tatem, 2017). However, there is currently no established impact function to our knowledge that links displacement to flood depth, and reported displacements in the 2022 floods are characterized by high uncertainty.

We explore two approaches to formulate impact functions, using a simple step function form that assumes everyone is displaced if the flood water depth exceeds certain thresholds. One approach uses empirical knowledge from literature about the nature of flood depth impacts on displacement and other important criteria such as the base elevation of buildings to define a plausible range of water depth thresholds for displacement. The other approach starts from reported displacement, "working backwards" through numerical optimization to obtain a best-fit depth threshold for all districts in Sindh. The optimization process results in a threshold of 0.67 m (CI 0.35 m–1.10 m) of floodwater depth when a uniform threshold is applied to all Sindh's districts based on Sindh's total reported displacement. This threshold falls within the range spanned by empirical knowledge. This suggests that impact step functions with thresholds based on empirical knowledge can provide a reasonable initial estimate of displacement in data-scarce regions. However, as shown in Figure 3, while these impact functions can partially map flood-induced displacement, several districts exhibit out-of-range estimates, indicating district level variations in displacement sensitivity to flood depth.

We further investigate the local sensitivity of displacement in each individual district to flood depth by fitting the depth threshold to each district's individual reported displacement totals. While this inter-district difference in sensitivity could be due to many factors, one possible factor could be urban/rural differences. Even for urban/rural differences, there could be many potential explanations for differences. Still, one possibility relates to the inherent high population density of urban areas, which cannot align perfectly with the resolution of our population and flood data.

By overlaying the rural/urban classification layer on the flood footprint, we find that districts with a higher percentage of flooded area which is urban (>2%; cf. Figure 3a) tend to have a higher flood depth threshold (>3 m), possibly reflecting lower sensitivity of displacement to flood depth. While our model has limits in providing a comprehensive explanation of this phenomena. We propose possible explanations for our observation that urban areas have higher estimated flood depth thresholds for displacement: First, buildings and other critical infrastructure may be better protected from flood water damage in urban areas; relatedly, people might have a greater opportunity to move to upper storeys in urban areas (and hence themselves be less affected). Second, perhaps in urban areas a higher share of people can find refuge with a friend or relative in an unflooded location (or storey), and thus do not appear in official displacement statistics. A further important consideration for further research is whether urban and rural populations differ in their risk of being "trapped" in a location they do not want to be in, which could also lead to lower displacement numbers than expected.

At the same time, the model underestimates displacement in several districts with little flooded urban area, even when the minimum flood depth threshold is employed (Figure 3b). While more research is needed, displacement appears to be occurring outside the flooded areas, which could be explained by a myriad of factors, including but not limited to damage to infrastructure, loss of access to food and other sources of livelihood, and key services.

Our results suggest a potential relationship between the vulnerability to displacement caused by floods and the degree of urbanization. While the underlying reasons for this relationship remain unclear in the current research stage, it underscores the importance of incorporating ground research to complement displacement modeling. Additionally, while displacement modeling can provide initial estimates of displacement, effective decision-making for disaster response requires the inclusion of local knowledge when interpreting and communicating the modeling outputs.

4.2. Technical Choices and Limitations

4.2.1. Model Uncertainties and Limitations

Several limitations exist in our model setup. On the hazard side, we chose to restrict our analysis to the flood depth layer since that aspect of the flood footprint can most easily be obtained, from the satellite-based product combined with the DEM model. Due to data availability, we further restrict our analysis to the cumulative flood extent between July 1st and August 31st. The peak in spatial flood extent was reached by the end of August (Roth et al., 2023), justifying our selection. The FwDET model is computationally fast and cheap, relying solely on DEM and a flood extent layer. The computational efficiency depends upon the convenience of the model to compute a difference between two levels and the absence of calibration or validation of any parameters. Therefore, the model is widely used by the hydrological scientific community in order to estimate flood depths (e.g., Cohen et al., 2019; Schmitt et al., 2023; Taramelli et al., 2022). However, remaining uncertainties exist mainly due to the input data used to calculate the flood depth. Trigg et al. (2016) describe DEM as a major source of error in all flood models, mainly due to the absence of ground truth data for terrain elevation to validate the data set. The NOAA-20 satellite flood extent product has a spatial resolution of 375 m, restricting our analysis to the predetermined spatial scale. Regarding the overall spatial extent of the 2022 Pakistan flood (∼45 thousand sq. kms. in Sindh; cf. Figure 1), this predetermined spatial resolution can be seen as acceptable. Furthermore, satellites are prone to error from cloud cover. The absence or delayed availability of hydrological ground truth data does not allow a validation of this product (Schmitt et al., 2023).

On the impact side, the accuracy of displacement mapping relies on the precise alignment of the flood footprint and population distribution data sets. A slight deviation in the location information of these input data sets can result in significant variations in displacement estimates. Moreover, displacement can occur as indirect impacts either within or outside the flood footprints, which our model may not capture. Common factors contributing to such displacement include damage to critical infrastructure, roads, or people losing access to essential services (e.g., Mühlhofer et al., 2023). People may also be evacuated as a pre-emptive measure even if they haven't directly experienced flooding in their location (Buhaug, 2023). The compounding nature of hazards and vulnerability also contribute to displacement in complex ways that far exceed our modeling capacity; for example, the aforementioned preceding extreme heat event, along with the ongoing COVID-19 pandemic, very likely increased vulnerability to the July-August floods. Further research and development in displacement modeling can explore the causal relationships behind displacement, and work to unravel the complexity of displacement dynamics.

In light of these limitations, our calculated flood depth thresholds, impact functions, and numbers of people displaced should be considered a rough estimates. They are intended to improve general understanding and motivate future research advances. Future research could also examine further flood data sets that have been generated about this event, such as flood duration and refined water depth estimations. This could enable examining how other aspects of flooding, such as flood duration, may be related to displacement.

4.2.2. Displacement Data Uncertainties

High quality displacement data are essential for model evaluation and calibration, yet assessing the quality of these data is challenging due to displacement's complex nature, varying data collection methodologies, and potential political biases affecting reporting and data availability (Vestby et al., 2024). These factors often result in significant gaps and inconsistencies in displacement data (Buhaug, 2023; IDMC, 2019; Thalheimer & Oh, 2023). Displacement severity can range from short-term evacuations for risk reduction to long-term loss of homes and access to basic services necessitating immediate humanitarian aid (IDMC, 2019, 2020). Furthermore, data reported by different governmental and non-governmental organizations or agencies frequently present inconsistent information (Buhaug, 2023; Thalheimer & Oh, 2023), adding to the complexities of obtaining reliable and comprehensive data for displacement modeling.

For this case study, we relied on the daily situation reports of displacement at the district level published by PDMA. We chose PDMA data because of its comprehensive coverage of all 24 districts in Sindh and the consistency in methodology within the same institution. At the same time, the International Organization for Migration (IOM) also published in October 2022 a provincial assessment report on the flood impact in Sindh (IOM, 2022). They published temporary displacement estimation in five districts with the highest reported displacement numbers, which were included in Table S1 in Supporting Information S1 alongside the PDMA data. We observe that the numbers published by IOM are significantly lower compared to those published by PDMA. However, there is a lack of detailed information regarding the data collection methodologies used by these organizations, making it challenging to understand the reasons behind the discrepancies in the reported data.

Displacement data uncertainties and inconsistencies could propagate into the model uncertainty. In our study, we calibrated impact functions that link population exposure to flood hazards using published data (refer to Sections 2.4.2 and 3.2), a method that has also been used in other studies to derive impact functions for displacement modeling (e.g., Kam et al., 2021; Riedel, Röösli, et al., 2024). This data-driven approach is heavily reliant on the quality of the data used. For this reason, we stress the need for careful consideration when modeling and interpreting displacement model outputs, especially in the statistical analysis and interpretation of results, due to the potential impact of data quality on the model's accuracy and reliability.

Future displacement data collection would greatly benefit from detailed descriptions of data collection methodologies and categorizing the proximate drivers of displacement, such as housing damages, evacuations, or loss of livelihoods. The information gathered could provide deeper insights into the various displacement processes, thereby contributing to the refinement and development of the next generation of displacement models.

Data Availability Statement

The reported displacement numbers in Sindh Province were extracted from the Daily Situation Report on 17 September 2022 published by the Sindh Provincial Disaster Management Authority (PDMA, 2022). The flood extent map was obtained from (UNITAR, 2022), and the digital elevation model (DEM) from NASA's Shuttle Radar Topography Mission (SRTM) (USGS, 2017). Flood depth maps were calculated using the FwDET v2.0 (Cohen et al., 2019), available as a toolbox in ArcGISPro. The population exposure data set at a resolution of 3 arcseconds was obtained from WorldPop (Bondarenko et al., 2020; Tatem, 2017). All displacement calculations were processed using the open-source probabilistic risk assessment platform CLIMADA v4.0.1 written in python (Siguan et al., 2023).

All the codes used for producing the analysis in this manuscript can be accessed in the GitHub repository (https://github.com/manniepmkam/PaDiFlo) and permanently stored at https://doi.org/10.5281/zenodo.15716655 (Kam & Lohrey, 2025).

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