Mapping Flood Exposure, Damage, and Population Needs Using Remote and Social Sensing: A Case Study of 2022 Pakistan Floods

Zainab Akhtar
Qatar Computing Research Institute, Hamad Bin Khalifa University, Doha
Qatar
zakhtar@hbku.edu.qa

Umair Qazi
Qatar Computing Research Institute, Hamad Bin Khalifa University, Doha
Qatar
uqazi@hbku.edu.qa

Rizwan Sadiq
Qatar Computing Research Institute, Hamad Bin Khalifa University, Doha
Qatar
rsadiq@hbku.edu.qa

Aya El Sakka
Qatar Computing Research Institute, Hamad Bin Khalifa University, Doha
Qatar
aelsaqa@hbku.edu.qa

Muhammad Sajjad
Hong Kong Baptist University, Hong Kong SAR
msajjad@hkbu.edu.hk

Ferda Ofli
Qatar Computing Research Institute, Hamad Bin Khalifa University, Doha
Qatar
fofli@hbku.edu.qa

Muhammad Imran
Qatar Computing Research Institute, Hamad Bin Khalifa University, Doha
Qatar
mimran@hbku.edu.qa

ABSTRACT

The devastating 2022 floods in Pakistan resulted in a catastrophe impacting millions of people and destroying thousands of homes. While disaster management efforts were taken, crisis responders struggled to understand the country-wide flood extent, population exposure, urgent needs of affected people, and various types of damage. To tackle this challenge, we leverage remote and social sensing with geospatial data using state-of-the-art machine learning techniques for text and image processing. Our satellite-based analysis over a one-month period (25 Aug–25 Sep) revealed that 11.48% of Pakistan was inundated. When combined with geospatial data, this meant 18.9 million people were at risk across 160 districts in Pakistan, with adults constituting 50% of the exposed population. Our social sensing data analysis surfaced 106.7k reports pertaining to deaths, injuries, and concerns of the affected people. To understand the urgent needs of the affected population, we analyzed tweet texts and found that South Karachi, Chitral and North Waziristan required the most basic necessities like food and shelter. Further analysis of tweet images revealed that Lasbela, Rajanpur, and Jhal Magsi had the highest damage reports normalized by their population. These damage reports were found to correlate strongly with affected people reports and need reports, achieving an R-Square of 0.96 and 0.94, respectively. Our extensive study shows that combining remote sensing, social sensing, and geospatial data can provide accurate and timely information during a disaster event, which is crucial in prioritizing areas for immediate and gradual response.

KEYWORDS

crisis response, remote sensing, social sensing, text processing, image processing

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1 INTRODUCTION

Pakistan, a country in South Asia, is among the top-10 most vulnerable countries to natural disasters according to the 2021 Global Climate Risk Index [6]. High exposure to flooding has contributed to great economic and human loss in Pakistan and beyond. This is because heavy seasonal rainfall is worsened by climate change and human actions, and triggered a catastrophe like the recent 2022 floods, which "have broken a century-long record" according to the United Nations. The situation was declared a national emergency on 25 August 2022 [27] where most parts of Pakistan saw more than two times the 30-year average of rainfall [12].

Under such calamitous circumstances, rapid assessment of inundated regions and near-real-time evaluation of the situation is imperative to estimate the impacts, effectively respond, and recover faster through informed resource allocation. In social sensing literature, researchers have focused on detection of flood-related text and images using social media [3, 4], including early detection of disasters [9] and flood severity assessment [16]. Likewise, within

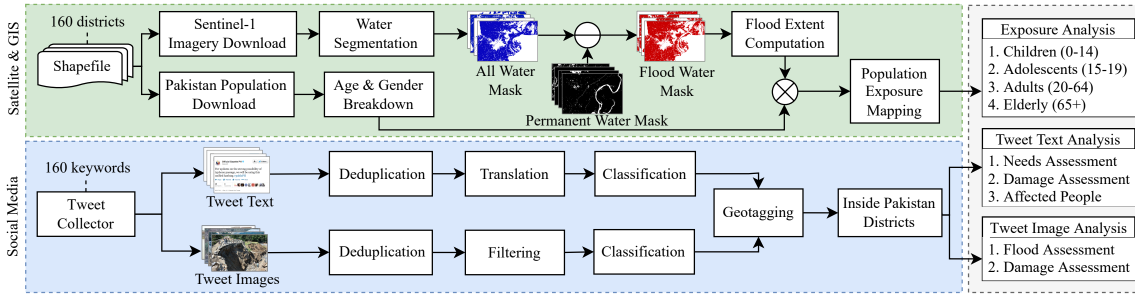


Figure 1: Overall methodology and data processing pipeline for social media, satellite imagery, and geospatial data

remote sensing, [5] and [2] have used satellite imagery for disaster detection and identification of severely affected areas. Some studies have investigated the fusion of both data sources where [22] identified three types of signals through qualitative analysis and [23] produced flood hazard maps through fusion techniques. Unlike previous studies, the goal of this paper is to assess the utility of combining three different data sources, i.e., satellite imagery, social media, and geospatial data, for immediate flood response. In particular, we investigate the added value of jointly analyzing these three disparate information sources to answer vital humanitarian questions such as:

(1) What is the extent of flooding?
(2) What proportion of the population is exposed to flooding?
(3) What are the urgent needs of the affected population?
(4) What types of damage can be identified due to flooding?
(5) How are the exposed population being affected?

To answer these questions altogether for a comprehensive understanding of the 2022 Pakistan floods, we analyzed the country-level flooding across a one-month period (25 August–25 September) to determine highly impacted districts and communities. Our satellite imagery-based assessment revealed that 11.48% of the entire country was inundated, which is consistent with the flood extent of 15% reported in [20] over a period of 45 days from 10 August to 23 September. While prior works only examined the flood extent of Pakistan floods [11, 20], we further utilized geospatial data to pinpoint highly exposed population groups due to flooding, making this our first contribution. We identified that ~18.9 million people were exposed to flooding, with adults making up ~9.6 million, followed by children (~6.8 million), adolescents (~1.7 million), and the elderly (~0.9 million). It is noted that the term 'exposed people' here reflects the number of people potentially at risk to 2022 floods.

Although remote sensing and geospatial methods can rapidly outline flooded locations and exposed populations at the national scale, they cannot help with fine-grained understanding of the flood impacts. Thus, as our second contribution, we performed an extensive analysis of social sensing data from Twitter to detect reports pertaining to the urgent needs of the affected population, the various types of damage impacts incurred, and the causes of people being affected. With the help of state-of-the-art deep learning techniques, we processed, filtered, and automatically geotagged 9.4 million tweets and 411k images to identify severely hit districts across the entire country. For instance, across all districts, 22 different types of urgent needs were analyzed where South Karachi,

Table 1: Number of satellite images downloaded for each province across four weeks

	AK	BA	GB	IS	KPK	PU	SI	Total
Week 1	25	93	27	2	105	104	85	441
Week 2	5	86	18	1	79	63	70	322
Week 3	20	105	13	3	105	103	70	419
Week 4	25	82	23	2	105	104	85	426
Total	75	366	81	8	394	374	310	1,608

* AK: Azad Kashmir, BA: Balochistan, GB: Gilgit Baltistan, IS: Islamabad, KPK: Khyber Pakhtunkhwa, PU: Punjab, SI: Sindh

Chitral, and North Waziristan were observed to have a high number of need requests for shelter, rescue, and donation. In terms of damage impact, Lasbela, Rajanpur, and Jhal Magsi were identified as having the highest numbers of damage reports normalized by their population. These districts also had a high number of need reports and affected people reports where a strong correlation of 94% and 96% was found, respectively. Lastly, a country-wide analysis of 106.7k affected people reports revealed interesting findings where districts like Chitral reported more infrastructure damage whereas Lasbela and Dera Ghazi Khan witnessed more human or livestock loss. This is vital information for different disaster management authorities to understand the root causes of people being affected.

Altogether, this study shows the applicability of remote sensing, social sensing, and geospatial data for disaster response efforts as accurate and timely information can be derived regarding the location, exposure and impacts (needs, damage, affected people) of an ongoing disaster. This will greatly assist emergency aid providers with prioritizing hard-hit districts with high population exposure.

2 DATA

2.1 Satellite and Geospatial Data

We opted to analyze the Synthetic Aperture Radar (SAR) imagery due to its ability to penetrate through clouds as compared with the optical imagery, which inherits heavy clouds, especially during intensive rainfall and flood events. The most common freely available SAR imagery is Sentinel-1 with a spatial resolution of 10 meters. To this end, we obtained the administrative boundaries of all 160 districts of Pakistan from the UN OCHA's Humanitarian Data Exchange [7]. Later, we utilized the Google Earth Engine (GEE)—a cloud computing-based platform—to download all Sentinel-1 imagery captured over the entire Pakistan within the one-month

Table 2: Performance evaluation of deep learning model vs OTSU for flood segmentation

	Jacobabad		Shikarpur		Sanghar	
	OTSU	U-Net	OTSU	U-Net	OTSU	U-Net
Recall	0.518	**0.926**	0.437	**0.728**	0.186	**0.347**
Precision	**0.717**	0.520	**0.981**	0.860	**0.982**	0.975
F1-score	0.602	**0.666**	0.605	**0.789**	0.313	**0.512**

period of 25 August to 25 September. This effort resulted in a total of 1,608 images. Table 1 shows a breakdown of the number of images downloaded per province and per week, where weeks 1 and 4 have slightly higher numbers of downloaded images compared with weeks 2 and 3. The variation in downloaded images across different provinces can be explained by the varying areas of each province, where Punjab and Balochistan are significantly larger than Gilgit Baltistan and the capital territory of Islamabad. All the downloaded images were then visualized to examine the coverage over entire Pakistan. The highest area coverage was found for weeks 1 and 4 with ~99.95% whereas for weeks 2 and 3, the coverage achieved was ~92% and ~94.7%, respectively. Figure 2 highlights the areas not analyzed due to lack of available imagery across four weeks of the studied period. In addition to the satellite imagery data, we collected district-level population data disaggregated based on age and sex using GEE to query WorldPop Global Population Data [28].

2.2 Social Sensing Data

We used the AIDR system [10] to collect social sensing data (i.e., tweets) about the impacts of floods in terms of damages, affected people, and their needs. Relevant tweets in Urdu and English languages were collected using 160 keywords for the specified one-month period (25 August–25 September), which resulted in 9.4 million tweets posted by more than one million users. Around 65% of the tweets are in Urdu and 32% in English. As opposed to retweets, which are exact duplicates of existing tweets, we consider replies and quoted tweets as original tweets, because they offer additional content. Overall, the data contains 1.15 million (12%) original (original+replies+quotes) tweets and 8.25 million (88%) retweets. We also downloaded images associated with the original tweets and obtained a total of 411k images for further analysis.

3 METHOD

Figure 1 shows the overall methodology and data processing steps for social media, satellite imagery, and geospatial data. Next, we describe our methods in detail.

3.1 Satellite and Geospatial Data Processing

We employ a state-of-the-art flood segmentation model[1], which is based on the U-Net architecture [19]. The model is trained on the Cloud to Street Microsoft Flood Dataset [25] along with elevation data from the NASA Digital Elevation Model. The European Commission's Joint Research Centre (JRC) global surface water data including change, transitions, seasonality, recurrence, occurrence, and extent, is used to improve water detection. We evaluate the performance of the model against three ground truth flood extent maps available from Copernicus EMSR629[2] for Jacobabad and Shikarpur districts, and from EMSR631[3] for Sanghar district. A threshold-based algorithm, OTSU [15], is used as a baseline. The deep learning model outperforms OTSU for all three districts with much higher F1-scores as reported in Table 2.

All 1,608 satellite images are processed through the model to get water prediction masks representing all types of water, including flood and permanent water bodies. To separate flood water from permanent water bodies, we employ the seasonality layer (3 to 12 months inclusive) from JRC's Global Surface Water Explorer.[4] Finally, we compute district-level flood extent. Next, to obtain the exposed population, we combine flood extent and district population at different spatial granularities (e.g., 1x1 or 5x5 km^2).

3.2 Social Media Data Processing

3.2.1 Tweet Text Processing. As depicted in Figure 1, tweet textual content is processed through a series of steps, including deduplication, translation, classification, and geotagging, before the final analysis. The deduplication step examines all original tweets (1.15 million) and removes exact duplicates. As our tweet classification model is trained on English data, we translate all unique Urdu tweets into English using Google Translate.[5]

For tweet classification, we employ BART (large) model [13] in a zero-shot setting. BART is a transformer model with a bidirectional encoder and an autoregressive decoder. For zero-shot classification, we design a large, hierarchical taxonomy consisting of 38 classes representing three types of flood impacts we intend to capture through social media reports: *(i) damage reports*, such as road, building, sewage, utility, livestock damages—5 classes, *(ii) affected people reports*, such as dead, injured, missing people, or complaints—11 classes, and *(iii) urgent needs of affected people*, such as food, water, shelter, medical needs— 22 classes. Next, each class is further extended with several prompts. We design prompts to capture various semantically similar ways a concept can be expressed. For example, the prompts for the "shelter request" class include *'requesting shelter', 'asking for shelter', 'need of shelter', 'accommodation required', 'need accommodation', 'need tent', 'appeal for shelter', 'seeking shelter'*, among others. The full list of classes ($\{c_i\}_{i=1}^{38}$) and prompts ($\{x_j\}_{j=1}^{377}$) can be found in the Table **??** of the supplementary material. We use the following message as our template: *"The message in this text is related to* {prompt}*"*, where prompts fill in the blank. The final textual string prompts make a forward pass through the model. Since each class contains multiple prompts, we compute the final class score (S_{c_i}) based on its prompt scores (S_{x_j}) using Equation 1.

$$S_{c_i} = \frac{1}{\sum_{x_j} T_{c_i,x_j}} \sum_{x_j} T_{c_i,x_j} S_{x_j} \forall c_i \tag{1}$$

where $T_{c_i,x_j} = \mathbb{1}\left[S_{x_j} \geq 0.95 \quad \wedge \quad x_j \rightarrow c_i\right]$ is an indicator function that checks whether the confidence score of a prompt x_j is greater than 0.95 and prompt x_j maps to class c_i.

[1] https://github.com/drivendataorg/stac-overflow/tree/main/2nd_Place

[2] https://emergency.copernicus.eu/mapping/list-of-components/EMSR629

[3] https://emergency.copernicus.eu/mapping/list-of-components/EMSR631

[4] https://global-surface-water.appspot.com/

[5] https://translate.google.com/

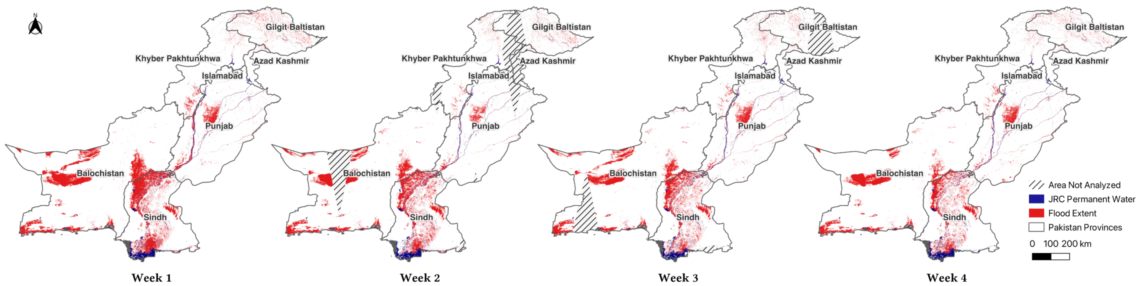


Figure 2: Pakistan maps showing flood extent (red) excluding unanalyzed areas (dashed) across four weeks

We evaluate the model's performance (F1-score at top 1—3 predictions) using the HumAID dataset [1]. Top-1 and top-2 predictions of the zero-shot model are comparable with the best performing model reported in [1], with weighted F1-score of 77.3% (ours) vs. 78.1% ([1]), whereas top-3 predictions achieve the best F1-score of 84.1% (ours).

3.2.2 Tweet Image Processing. Social media images typically contain a lot of noise. Therefore, the downloaded images go through a number of filtering steps including deduplication, denoising, and classification, as shown in Figure 1. The deduplication step removes near-or-exact duplicates by comparing the distance between the deep features of two images (threshold=7.1). We use a ResNet-50 model [8] pre-trained on the Places dataset [29] to extract image features.[6] Next, the images go through a denoising step, which eliminates the irrelevant content such as ads, cartoons, banners, etc. using a binary classification model (ResNet-50) pre-trained on ImageNet [21] and fine-tuned on a custom dataset [14]. Finally, the images are classified into two broad categories, i.e., *damage* and *flood*, using the Incidents model [26]. The Incidents model's labels that correspond to our *flood* category include 'flooded', 'heavy rainfall', 'tropical cyclone', 'mudslide mudflow' whereas the *damage* category labels include 'damaged', 'dirty contamined', 'earthquake', 'sinkhole', 'rockslide rockfall', 'landslide' and 'collapsed'.

3.2.3 Geotagging. To geotag tweets at the district level, we capitalize on location names (toponyms) mentioned in tweet text and tagged places. We use a state-of-the-art BERT-based model fine-tuned on disaster tweets for extracting toponyms from tweet text [24]. The identified location tokens are used to find georeferencing information (i.e., complete address with latitude and longitude) from OpenStreetMap (OSM). Similarly, tagged places (either bounding box or point) are used to make a reverse geo call to OSM to retrieve georeferencing information. Finally, all tweets within district boundaries are kept for future analysis. Tweets with multiple distinct location mentions are mapped to all mentioned locations.

4 RESULTS AND ANALYSIS

4.1 Satellite Imagery Analysis

4.1.1 Chronology of Pakistan Flooding. Figure 2 shows maps of the entire Pakistan with the area analyzed and flood extent for each of the four weeks separately. The dashed lines in the maps for weeks 2 and 3 show unanalyzed areas, which is due to the unavailability of satellite imagery. During the first week, where almost the entire country was analyzed, the floodwaters inundated Sindh and Balochistan severely compared with other provinces, with flood extents of 21.7% and 11%, respectively. This estimation is consistent with the UN OCHA statistics where Balochistan received 5.1 times more rain as of 27 August, while Sindh encountered 5.7 times more than their 30-year averages [17]. While the second week (with 92% analyzed area) shows a decrease in the flood extent for all the provinces, the highest reduction was seen in Balochistan, as reflected in Table 3. Notably, in week 3 (with 94.7% of the country), Punjab experienced an increase in flooding and reached a flood extent of 4.2%, close to the flooding witnessed in week 1, which was around 4.8%. Alongside Punjab, Balochistan, Khyber Pakhtunkhwa, and Azad Kashmir also witnessed increased flooding in the third week as compared with the previous week. While the floods in Sindh declined at the same rate in weeks 3 and 4, Gilgit Baltistan's flooding reduced in week 3 but later increased at the same rate in week 4. Overall, across all four weeks, the regions in southern and central Pakistan were hit the most, as most of the flooding occurred around the Indus River that runs north-south through the center of Pakistan. Given such circumstances, the districts located in the southern part of Pakistan are highly susceptible to flooding and its impacts as the floodwaters move downstream from high-elevation to low-elevation areas.

Table 3: Flood extent (km^2) and its weekly change (%) in each province

	Week 1	Week 2	Week 3	Week 4
BA	38,541	28,386 (-26%)	29,240 (+3%)	27,402 (-6%)
Sindh	30,634	26,249 (-14%)	23,342 (-11%)	21,178 (-9%)
Punjab	9,398	6,279 (-33%)	8,647 (+38%)	8,523 (-1%)
GB	4,523	2,526 (-44%)	1,383 (-45%)	2,733 (+98%)
KPK	2,533	1,656 (-35%)	2,299 (+39%)	1,755 (-24%)
AK	182	61 (-66%)	151 (+148%)	195 (+29%)

* BA: Balochistan, GB: Gilgit Baltistan, KPK: Khyber Pakhtunkhwa, AK: Azad Kashmir

4.1.2 Mapping Population Exposure to Flooding. According to our four weeks of satellite imagery-based flood extent assessment, approximately 18.9 million people are potentially exposed to flooding in the entire country. The most devastating period with high flood exposure was week 1 (Aug 25-31) affecting ~16 million people. More than 65% of the affected population over four weeks belong to the

[6] Available at http://places2.csail.mit.edu/models_places365/resnet50_places365.pth.tar

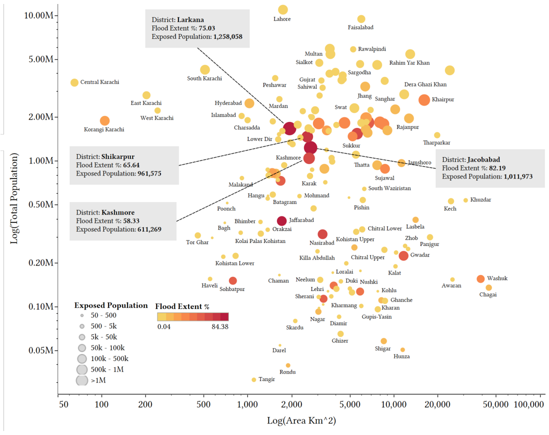


Figure 3: Exposed population estimates for all 160 districts

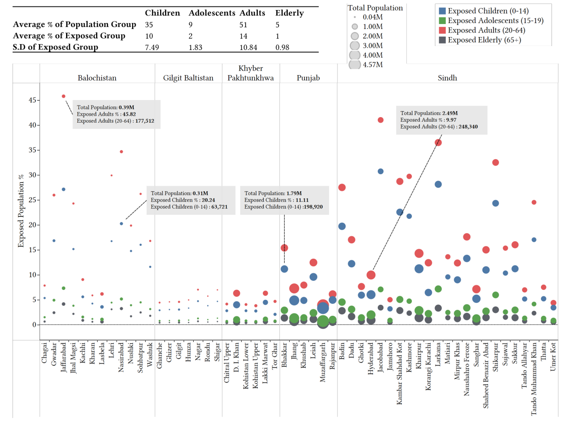


Figure 4: Exposed population by age groups for 54 districts

Sindh province (i.e., 12.4 million people). This situation highlights that almost a quarter of the population in Sindh is potentially living in the proximity of flood susceptible areas. Following Sindh, around 14% of the total population in Balochistan is exposed to flooding, where ∼1.1 out of ∼8.4 million people are estimated to be at risk in the face of 2022 alike flooding. This estimation is in line with the Government of Pakistan reports, where 66 districts were declared 'calamity hit', of which 31 districts belong to Balochistan and 23 to Sindh [18].

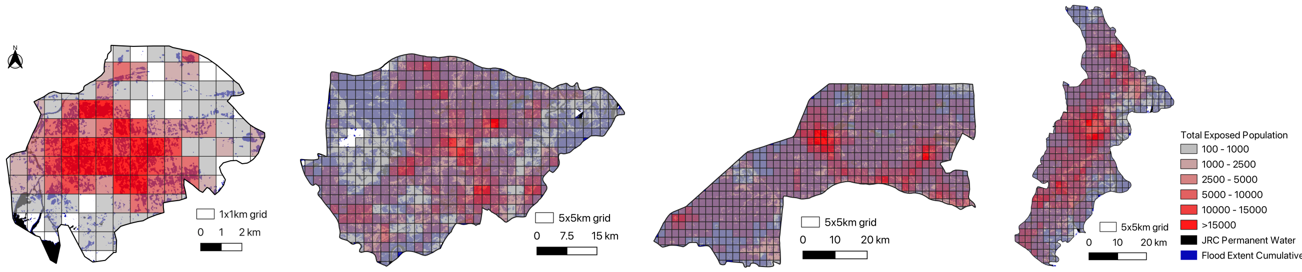
Figure 3 depicts the situation of all 160 districts in terms of flood extent intensity and affected population, along with the total district area and population. The circles' color represents the cumulative flood extent and the size reflects the estimated exposed population. It is observed that highly impacted districts of the Sindh province, including Larkana, Shikarpur, Jacobabad, and Kashmore, are similar in size (2-3 thousand km^2) with a total population of 1-1.5 million people. However, Korangi Karachi, an urban district in Sindh with a high population density (18,158 per km^2), was severely affected due to floods (22% flood extent). Similarly, highly affected districts in Balochistan include Jaffarabad, Nasirabad, Gwadar, and Sohbatpur.

Further segregation of the population into different age groups helps us understand most vulnerable population age groups across districts. For this analysis, districts with more than 7% accumulative flood extent are selected. Figure 4 shows the percentage of children, adolescents, adults, and elderly exposed to flooding in comparison to the total population for each district. With respect to the total population breakdown, adults make up almost half of the population, followed by children with ∼35%. Adolescents and the elderly are minorities making up the remaining 15%. Across all the districts, adults are exposed the most as compared to the remaining three groups, with the average being 14.35%. There are 12 districts that stand out as having an exposure greater than one standard deviation from the average, where Jaffarabad is observed to have the highest proportion of adults exposed (i.e., ∼46%). While the total population of Jaffarabad is just under 400k, the total number of people exposed is actually less compared with the districts with a relatively higher population, such as Hyderabad having ∼2.5 million people with ∼10% adults exposed. This situation reveals that ∼180k people are exposed in Jaffarabad as compared with ∼250k people in Hyderabad. Connectedly, children are the next highly exposed age group with an average of 9.85%. The districts in Punjab and Sindh have a similar percentage of children exposed due to the majority of these districts being highly populated. This is also the case for the adolescents and elderly group which have an overall lower exposure percentages as compared with adults and children across all districts.

To understand the geographic distribution of flood exposure within specific districts, we selected four districts from Sindh as our focus areas as presented in Figure 5. This includes Korangi Karachi, Larkana, Shikarpur, and Jacobabad. These districts are selected as they have the highest number of people exposed as well as flood extent percentage. To have an in-depth insight, we produced gridded flood exposure maps for each of these districts, where a 1x1km grid was used for Korangi Karachi due to its smaller area coverage. In total, 540,435 people are exposed in this highly urbanized district which has a population density of 18,158 people per km^2. High exposure can be seen in the central parts of the district, which is highlighted in red grids where more than 15,000 people are exposed per km^2. For the remaining three districts, a 5x5 km^2 grid was used due to the large area size. In Shikarpur, for example, which has a population density of 573 people per km^2, the total number of people exposed is similar to Korangi Karachi with a total exposure of 508,322 people. Even though the flood situation in Korangi Karachi is less compared with Shikarpur, the high population density in Korangi Karachi increases the likelihood of a larger proportion of people being exposed to flooding and associated impacts. In terms of the spatial distribution of exposed people in Shikarpur, more people are seen at risk in the central regions and towards the outskirts of the district where the flood impact is higher. Likewise, in Larkana and Jacobabad, which have a similar population density as Shikarpur with 545 and 456 people residing per km^2, respectively, the total number of people exposed in Larkana is higher with 670,303 people exposed as compared with Jacobabad with 494,191 people at risk. Similarly, the hot spots of highly exposed locations can be found in these districts where there are clusters of grids shaded in red.

4.2 Social Media Analysis

4.2.1 District-level Urgent Needs. Through the zero-shot text classification model, 42.9k tweets requesting 22 different types of urgent



(a) Korangi Karachi **(b) Shikarpur** **(c) Jacobabad** **(d) Larkana**

Figure 5: Gridded flood exposure maps of highly impacted districts in Sindh

Figure 6: Heatmap showing the percentage of need reports across all districts

needs across districts are identified, including basic necessities (e.g., blanket, mosquito net, hygiene items), food and water requests (e.g., milk, water, bread), medical-related requests (e.g., doctor/nurse, medical assistance, mask requests), and other important requests such as money, donation, shelter, and electricity. Figure 6 shows a heatmap of the percentage of unique need reports across all 160 districts. The analysis reveals that South Karachi has the highest overall percentage (darker red) of 'shelter', 'money', 'rescue', and 'donation' needs. Below we quote tweets from this district.

> "Brother there, please build my house in Sindh, steal the life of Karachi"

> "@User madam this is from district DG Khan husband divorced her everything was destroyed in flood now she is taking shelter with her uncle in Karachi ID card sent to, money not received she is entitled and flood affected please help her thank you"

The dire flood situation in South Karachi put lives in danger and forced people to send rescue requests on social media, giving out their addresses and contact details. In the following tweets, name, address, and contact details have been redacted.

> "No one has reached them, Help them as Soon Possible #HT. Name -. Address - Contact: URL"

> "This is the settlement of flood victims towards Sindh Karachi. There is nothing to eat, nothing to drink, nothing to eat. Head covering cloak. Pray for them, Allah, help every oppressed person Allah, they have none. URL"

A similar situation is observed in North Waziristan. Users are calling on politicians and high-profile celebrities to help them in this dire need.

> "@User @User Tank, DI Khan, North Waziristan & Swat r the most affected areas by the flood.. Need meticulous attention pl"

In Chitral Upper, users are requesting for food as observed in Figure 6 and the following tweet:

> "@User @User Normal life has been disrupted due to recent rains and floods in Yarkhun and Brughal valleys. Produced crops are completely destroyed. People are starving due to lack of food items. Ruined houses destroyed. People were shifted to cantonments, schools and tents. Road closed"

Figure 7: Images showing flood and damage impact in different scene contexts

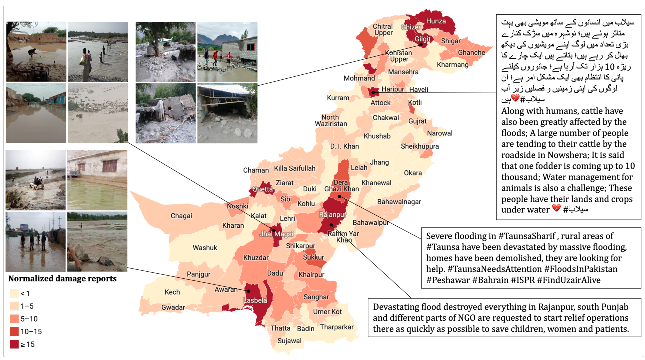


Figure 8: Damage reports (tweets & images) normalized by district population per 10k people

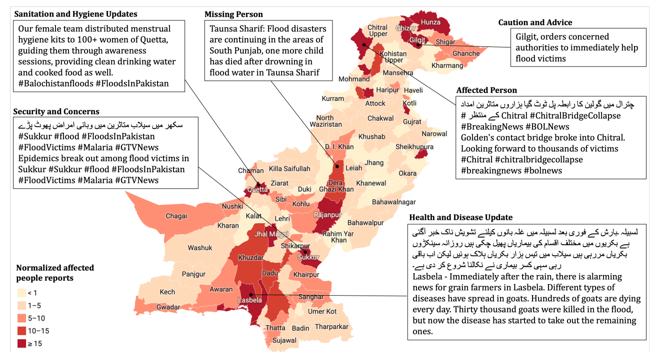


Figure 9: Affected people reports (tweets) normalized by district population per 10k people

In Killa Saifullah, users report about medical assistance as seen in the following tweet.

> "AF Medical Camp in Qila Saifullah, led by PAF doctors and paramedical staff, are also providing medical facilities to the flood affectees around the clock. #HT"

4.2.2 District-level Damage Reports. As described in the methods section, we identify tweets reporting damages (through tweet text analysis) and images showing floods and damage scenes. In total, 55.2k textual damage reports, 5.2k flood images, and 1.7k damage images are identified across all districts. A qualitative analysis of flood and damage images across districts reveals the devastation of floods in the country, as illustrated in Figure 7. The first two rows show the intensive flooding across various parts of the country, including densely populated areas and critical infrastructures such as flooded streets, communities, gas stations, railways, and bridges. The last two rows show images of different types of damage incurred during and post-flooding, which include ruptured roads, destroyed houses, and power failures.

Figure 8 visualizes the distribution of damage reports (both tweets and images) normalized by district population (per 10k people) for the entire country. The Lasbela district followed by Rajanpur, and Jhal Magsi show high damage reports (normalized) despite being mostly rural areas with less social media footprint. The map shows images (flooded roads/streets, destroyed houses) and tweets (reporting livestock and agriculture destruction) from these districts highlighting the devastating impacts of the floods. Overall, we remark that damage reports on social media carry important information useful for rapid damage assessment. Moreover, this real-time information can potentially inform several emergency response functions if processed timely and effectively.

4.2.3 District-level Affected People Reports. Our tweet text analysis surfaced 106.7k reports pertaining to affected people (including missing, injured, and death reports), complaints, and other concerns. Figure 9 shows the distribution of these reports across districts normalized by district population per 10k people. Although mostly rural, Gilgit, Lasbela, and Hunza districts show a high number of reports. These districts are located near the Indus river and thus are impacted severely. Reports across districts cover a variety of topics. In Quetta, reports about hygiene kit unavailability surfaced. Authorities in Gilgit were cautioned to take immediate action to help flood victims. In Sukkur, concerns about an epidemic breakout emerged due to flood water. Moreover, the analysis observed first-hand reports in Dera Ghazi Khan about child deaths. In Chitral, reports pertaining to transportation difficulties due to a collapsed

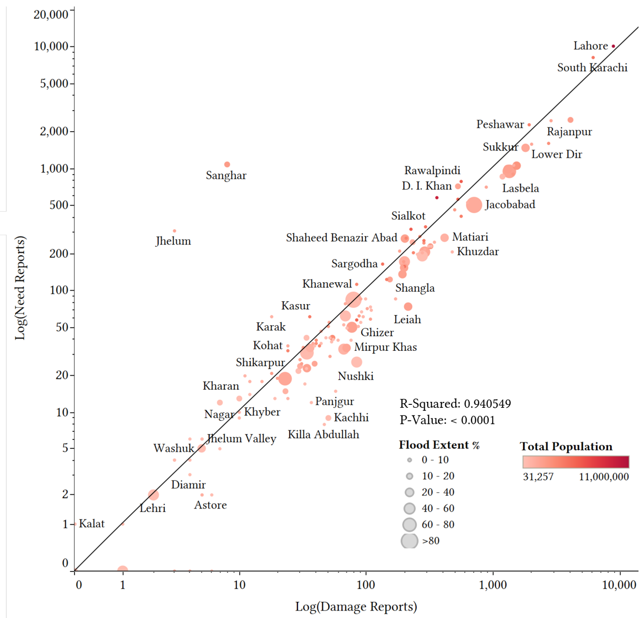


Figure 10: Need reports vs. damage reports

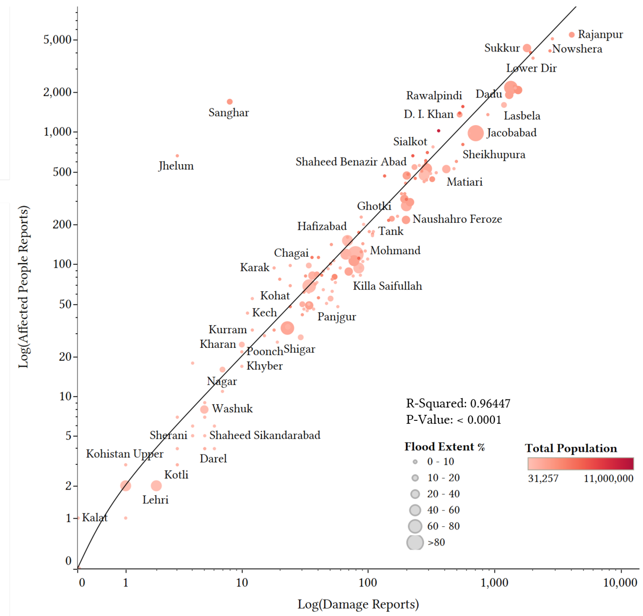


Figure 11: Affected people reports vs. damage reports

bridge were observed. Livestock destruction is reported in Lasbela alongside risks of disease spread. The first-hand reports coming in on social media show the magnitude and the extent of the effect of this flood. Furthermore, this near-real-time information is particularly important for local governments, and organizations working for aid and emergency assistance in different areas. However, the effective utilization of this information is only possible when such assessments are incorporated into the district disaster management action plans, which Pakistan currently lacks.

4.2.4 Relationship between Damage and Population Sufferings. Next, we sought to investigate if flood-induced infrastructure damage reports on social media have any relationship with people's reactions, concerns, and complaints as well as their needs that emerge on social media. Can social media-based damage indicators be used as a proxy to estimate population suffering and their needs or vice versa? To answer this question, we checked the correlation between needs vs. damage reports (Figure 10) and affected people vs. damage reports (Figure 11) on social media. The results from the linear relationship evaluation indicated a statistically significant correlation between both variables (99% confidence), with an R-Square of 0.94 for the needs vs. damage reports comparison and 0.96 for the affected people vs. damage reports comparison.

5 CONCLUSIONS

During the devastating 2022 floods in Pakistan, the governments at the national and provincial scales seek solutions to effectively respond and recover faster from such disasters. In this context, the present study leveraged remote and social sensing techniques integrated with geospatial data to provide an outlook on the 2022 floods. In particular, near-real-time situational awareness of flood extent mapping, estimation of population exposure, identification of urgent needs, types of damages incurred, and the reasons behind people being affected are all presented in this study. We employed state-of-the-art machine learning text and image processing models to perform extensive analysis and surfaced valuable insights.

Sentinel-1 earth observation data is employed to provide a comprehensive inundation extent at the district level, where flood maps are produced to provide geographical references. This allows crisis responders to get situational awareness of the disaster and deploy emergency assistance without having to wait for field surveys. For example, our comprehensive analysis suggests that crisis responders should prioritize Larakana, Shikarpur, Jacobabad, and Korangi Karachi, which are top districts with high population exposure and flood extent during the 2022 Pakistan floods. On the other hand, social sensing-based near-real-time information provides insights into the different needs of the affected population, the types of damages in different contexts, and an understanding of how people are affected. For instance, a high number of affected people and damage reports came from districts like Lasbela and Jhal Magsi, which showed intensive flooding in residential areas via images and relevant information via text (i.e., health and disease updates). Timely access to such information from non-traditional data sources provides a low-cost and rapid evaluation means to crisis responders in prioritizing highly impacted areas or population segments when ground-based methods are unavailable.

Whilst the insights from our study can assist crisis responders to an extent with prioritization, it should be noted that disaster information from social media data is inherited with uncertainty and biases. Uncertainty about the reliability of the data exists as tweets may contain misinformation, whereas biases exist with the accessibility and usage of Twitter across different regions in Pakistan. Given proper awareness of these limitations, seizing the opportunities social media brings can assist crisis responders with an improved ability to analyze and cope with flood disasters.

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