



Poverty Impacts of the Pakistan Flood 2022

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Abstract

In the summer of 2022, devastating floods hit Pakistan with a profound negative impact on lives and livelihoods. Apart from the irreconcilable loss of life, household welfare was negatively impacted through the loss of household income, loss of assets, and rising food prices. Yet, in the absence of just-in-time household survey data, evaluating the welfare impact is challenging, particularly in terms of estimating monetary poverty. This paper demonstrates how real-time satellite data, in combination with administrative data and historical household survey data, can be used to model the impact of floods on Pakistani households. In the context of data and time constraints, we present a practical methodology to simulate the expected impact of a natural disaster on monetary poverty from an ex-ante perspective. Estimates show that, as a direct consequence of the floods, the national poverty rate would increase by 4.0 to 4.3 percentage points, pushing around 9 million people below the national poverty line. Moreover, a spatially disaggregated analysis showed that the magnitude of shocks varied across locations and households depending on the intensity of the flooding and household characteristics. These estimates, which informed the Post Disaster Needs Assessment and were later used to frame the Donor Conference for Pakistan, provide an example of rapid modeling in the absence of real-time household survey data.

Keywords Poverty and inequality · Natural disasters · Climate change · South asia

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Introduction

With natural disasters increasingly frequent and severe, the poorest households are both more exposed and more vulnerable to climate change. At the 2022 United Nations Climate Change Conference (COP 27), the international community recognized the importance of quantifying ‘loss and damages’ from climate change. After a natural disaster, the immediate focus is on lives lost and material damage to infrastructure and capital stock. Yet, often, the most lasting effects are on household livelihoods. By wiping away assets and forcing households to revert to adverse coping mechanisms, these shocks reduce household incomes and push households into poverty.

The challenge in a natural disaster’s immediate aftermath is quantifying these adverse effects, often in the absence of new household survey data. Rapid response surveys are the best option, but these take time to develop and deploy and are constrained in scope and scale by the constraints inherent in an emergency. In this paper, we propose an approach that combines existing household data with real-time satellite data and administrative data to simulate the expected welfare impacts of natural disasters from an ex-post perspective (i.e. after the disaster occurs). Findings from this approach inform the post-disaster needs assessment when post-disaster household survey data is not available. These results can then be cross-validated with administrative data as they become available. We showcase this method in the context of the 2022 floods in Pakistan.

Event Summary: The Pakistan Floods 2022

Record-setting monsoon floods hit Pakistan between July and September 2022, severely affecting millions of households, mainly in Sindh and Balochistan. As of October 11th, 2022, the Government declared 94 districts ‘calamity-hit’; around 33 million people were affected, and more than 8 million people were displaced.¹ According to the Post Disaster Needs Assessment published in October 2022, “approximately 8,330 kilometers of roads and 3,127 kilometers of railway track have been damaged to various extents due to the floods. 780,000 houses were destroyed, and more than 1.27 million houses were partially damaged. Around 4,410 million acres of agricultural land were damaged, and 0.8 million livestock are estimated to have perished, adversely affecting rural livelihoods.” In the aftermath of the floods, limited access to input and output markets and temporary disruptions to supply chains drove up (food) prices for all households in the country and added to existing price pressures arising from reduced agricultural yields and the global rise of food and energy prices.

The flood-affected districts were already affected by higher monetary and non-monetary deprivations, especially among households in rural areas^{2,3}. The latest available figures from the national household survey HIES 2018/19 suggested that 21.9% of the popula-

¹ See the official damage reports from the Post Disaster Needs Assessment, published October 2022.

² Estimates are based on the national household surveys PSLM, HIES and MICS, and relate to the four provinces Punjab, Sindh, Balochistan, and KP. Due to data access limitations, numbers are not available for GB and AJK.

³ The definition of calamity affected districts follows the communication by the National Flood Response Coordination Center’s (NFRCC) and the National Disaster Management Authority (NDMA).

Table 1 Monetary poverty in Pakistan, province and district level estimates

Province	Poverty rates among all districts	Minimum and Maximum poverty rates among all districts	Provincial poverty rates among calamity-affected districts	Minimum and Maximum poverty rates among calamity-affected districts
Balochistan	42.7	[22.7, 69.4]	39.3	[22.7, 69.4]
KP	29.5	[7.0, 65.6]	29.2	[19.0, 45.1]
Punjab	16.2	[3.8, 45.9]	34.8	[11.2, 45.9]
Sindh	24.1	[6.0, 76.9]	30.0	[14.3, 52.8]
National	21.9	[3.5, 76.9]	31.8	[11.2, 69.4]

Source HIES 2018-19. District-level poverty estimates are based on small-area estimates of Poverty using HIES and PSLM surveys. Note: Poverty rates are reported as percentages of the respective population

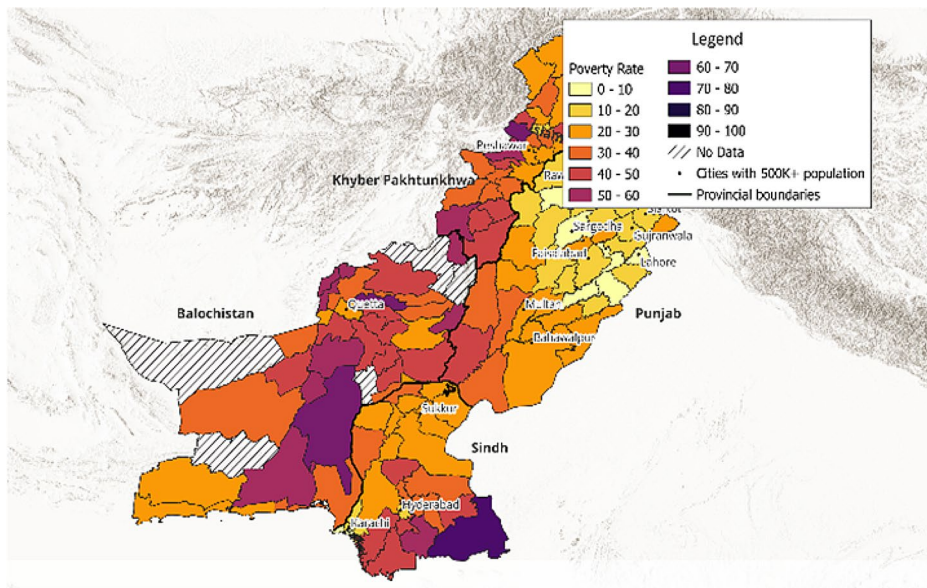


Fig. 1 Population below the national poverty line. Source: Author Calculations

tion (around 50 million people) lived below the national poverty line⁴. Beyond the national average, rural poverty was more than twice as high as urban poverty (28.2% compared to 10.9%), and four out of five poor households lived in rural areas. 19 out of 25 of Pakistan’s poorest districts were calamity-hit. Households in calamity-hit districts were more impoverished than the national average (31.8% compared to 21.9%), and poverty rates for many calamity-affected districts ranged between 11.2% and 69.4%⁵ calamity (see Table 1 and Fig. 1). Satellite data combined with survey data suggested that even within tehsils (geographic

⁴ Poverty is measured using data from the national household survey HIES 2018/19, and based on the national poverty measurement methodology, with a poverty line of Rs. 3,741 and Rs. 3,769 in 2018-19 urban and rural prices, respectively.

⁵ While poverty estimates from the national household survey HIES 2018/19 are only available on the national and provincial level (urban/rural), small area estimates of poverty can be calculated on the district level by combining information from the HIES 2018/19 and the PSLM 2019/10.

units below the district level), poorer areas were more likely to be affected by the flood.⁶ In two-thirds of flood-affected tehsils, flooded areas had lower levels of relative wealth compared to unaffected locations.

Higher poverty rates in calamity-hit districts reflect lower productivity and limited resilience arising from the socio-demographic and socio-economic characteristics of households and individuals. Before the 2022 floods hit, households in these areas were already more vulnerable to natural disasters due to overlapping deprivations. Ex-post, these development gaps have exposed them to further risks, with many falling deeper into poverty. For instance, the Human Capital Index (HCI) for Pakistan suggests that a child born today will be 41% as productive when s/he grows up as s/he could be if she enjoyed complete education and full health. This is lower than the average for the South Asia region and lower-middle-income countries. Due to lower school attendance rates in Balochistan and Sindh and worse health outcomes, the HCI is likely to be lower in calamity-hit districts than in the rest of the country.

Non-monetary poverty measures highlight that households in calamity-affected districts also experienced gaps in access to public utilities and worse living standards during the pre-flood period. Households were likelier to live in mud-brick homes, which heightened their vulnerability to natural disasters like flooding. These homes are particularly vulnerable to washing away in the floods, leaving them homeless. 15.7% of people in calamity-hit districts lacked access to electricity, compared to 9.3% nationally. Households were also more likely to lack access to a sanitation facility and clean water. About 11% didn't have access to water near their homes, almost twice the national average of 6.5%.

Within this context, and in the absence of a post-disaster household survey, the challenge was to estimate the impact of the floods at the household level. This paper proposes an approach that combines real-time satellite data, administrative data, and existing household survey data to model the impact of such a natural disaster on households, producing just-in-time estimates that can inform decision making. The results suggest that the national poverty rate would increase by 4.0 to 4.3 percentage points, pushing over 9 million people into poverty. In addition to its implications for Pakistan's post-disaster recovery trajectory, the paper offers methodological innovations for evaluating welfare in a post-disaster context.

Literature Review

The existing literature on the impact of natural disasters, especially floods, on household welfare outcomes underscores their multifaceted and enduring consequences on income, poverty, human capital, and well-being. Studies across different countries and within Pakistan consistently highlight households' severe challenges in the aftermath of such disasters, calling for targeted policies and interventions to mitigate these adverse effects and enhance resilience among vulnerable communities.

⁶ Variation in living standards within districts and tehsils is estimated using the relative wealth index produced by Chi, G., Fang, H., Chatterjee, S., & Blumenstock, J. E. (2022). The relative wealth index predicts the relative standard of living within countries using a combination of high-resolution remote sensing data trained on household data; the index predicts the living standards using de-identified connectivity data, satellite imagery and other nontraditional data sources. The data is provided for 93 low and middle-income countries at 2.4 km resolution.

As defined by the Intergovernmental Panel on Climate Change (IPCC) and outlined in Doan et al. (2023), three components determine the impact or risk of an extreme weather event on people: hazard, exposure, and vulnerability (Fig. 2). *Hazard* is the potential occurrence of an extreme weather event ex-ante. *Exposure* refers to what or who could be affected by the weather event in that location. *Vulnerability* describes the extent to which those exposed are adversely affected depending on their characteristics, including assets, livelihoods, and socioeconomic and sociodemographic profile.

Hallegatte et al. (2013) conducted a comprehensive analysis of the global impact of natural disasters on poverty, emphasizing the long-term economic consequences on households, particularly in low-income countries. Their findings describe a persistent cycle of poverty exacerbated by these calamities as households struggle to recover lost assets and income sources.

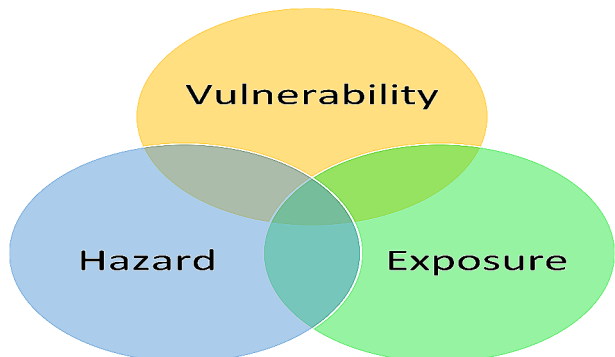
Across different shock types, flooding is the most frequent natural hazard, with particularly disastrous impacts in low-income countries. Rentschler et al. (2022) find that an estimated 23% of the world's population is directly exposed to one-in-100-year floods. Low—and middle-income countries are home to 89% of the world's flood-exposed people. At the household level, over 780 million people under the poverty line of \$5.50 per day face high flood risk.

Regarding welfare dynamics, Dercon (2004) discussed the concept of poverty traps in the aftermath of natural disasters, emphasizing how floods push vulnerable households deeper into poverty, trapping them in a cycle of deprivations. His research underscores how shocks like floods erode assets and income and hinder households' ability to recover and rebuild. This likelihood of backsliding into poverty is defined as socio-economic vulnerability (Dercon 2006).

In a study focusing on the impact of flooding on agricultural productivity, Chen et al. (2017) employ integrated remote sensing imagery and hydraulic modeling to evaluate the effects on crop yields. Their findings suggest that flooding can lead to substantial reductions in agricultural output, thereby threatening food security and exacerbating rural poverty. This integrated approach outlines how floods can perpetuate poverty traps by undermining agricultural livelihoods.

Salvucci and Santos (2020) examine the short-term impacts of flooding on consumption and poverty in Mozambique, providing a framework for assessing vulnerability to natural shocks. Having access to panel data from a household consumption survey which was in the field at the time of the floods, they conduct a pre- and post-incidence comparison of

Fig. 2 Threefold definition of risk, according to the Intergovernmental Panel on Climate Change (IPCC). Source: IPCC 2022



consumption patterns using difference-in-difference. Their study underscores the immediate economic consequences of floods, highlighting disruptions to livelihoods and income sources that exacerbate poverty levels in affected communities.

In Pakistan, Kurosaki (2015) investigated the effect of drought, floods, and health shocks on household consumption, highlighting their detrimental effects on household incomes and poverty. The 2010 flood was particularly destructive, with long-term adverse effects on education outcomes (Khan and Ali 2014) and household welfare (Shah et al. 2018). Due to the cumulative effect of such shocks, vulnerability increased, though local disaster management authorities can play a vital role in building resilience.

From a methodological perspective, the gold standard for quantifying post-disaster welfare changes is to have systematic monitoring systems in place, collecting consumption data for the same households over time. Headey and Barrett (2015) called for a series of sentinel sites to be established in areas prone to natural disasters to continuously monitor household welfare trends and quickly establish the effect of the shock. Examples of these sentinel sites have been piloted, notably in Malawi (see Knippenberg et al. 2019), and are gradually being scaled up. An alternative is rapid-response surveys post shocks, which are necessarily short, difficult to administer to a representative sample, and logistically complicated.

As an alternative to post-shock data collection, Hill and Porter (2017) outline an approach that simulates probability distributions for consumption based on historical weather trends. This allows them to run counterfactual shock scenarios and construct estimates of vulnerability conditional on location and household characteristics.

In this context, the paper seeks innovation by proposing a methodology for rapidly evaluating the short-term poverty impacts of natural disasters in the absence of post-disaster household data. It provides a relevant case study in Pakistan, a country particularly exposed to flood risk.

Model

The impact of the floods is modeled accounting for different shocks that impact household welfare through three distinct channels: (i) the loss of household income due to destroyed harvest, killed livestock, or inactivity of businesses; (ii) the loss of assets, including homes, livestock, productive equipment, and household durables; (iii) the shortages of food due to lost food stocks, poor harvests, and rising food prices. Since the intent is to evaluate the short term effects, the model does not factor in potential government response in the form of direct cash-transfers or humanitarian assistance. Rather, the output of the model can go towards informing these discussions by quantifying the extent of welfare loss.

The model draws from the canonical agricultural household model (Singh, Squire and Strauss 1986), which posits a representative household working in agriculture. This household is both a profit-maximizing firm, in that it optimizes its allocation of labor and capital to generate income, and optimizes its consumption subject to income. The household's consumption is therefore subject to

$$p_m^* X_m = p_a (Q - X_a) - p_l (L - F) - V - E$$

Where p is price, X consumption, Q own production, L is labor input, V the (often implicit) cost of rent for their home. F own family labor, and E outside income, and m and a denote market product and the staple, respectively. Production Q is a function of labor input and capital $Q(L, K)$. Here we assume that the flood reduces the capacity for own production, washes away their home, that in the short-term households cannot re-allocate labor to non-farm activities, and that they are price takers.

Empirically, household welfare is proxied by Y_{it} , which is the total consumption of household i for period t (0 is the baseline, and 1 flood scenario), such that:

$$\widehat{Y}_{i,1} = Y_{i,0} \times \prod_s (1 - z_{i,s}) \text{ with } z_{i,s} = (\beta_s | X_{i,s}, \delta_{s,d})$$

Here, the household i 's welfare is a function of multiple shocks that the household experiences between periods 0 and 1, where $z_{i,s}$ is the percent decrease in household consumption of household i due to a shock channel s . The subscript “ s ” stands for the potential channels through which households may be affected: livelihoods, buildings, livestock, inflation.

Specifically, $z_{i,s}$ is a function of β_s that captures the percent decrease in household consumption due to a shock s . Note, however, that a household only experiences this shock if they have specific household characteristics $X_{i,s}$, and conditional on exposure $\delta_{s,d}$ to the shock s within their district d , such that:

- $X_{i,s}$ characteristics of household i ; $X_{i,s} = 1$ if household i has characteristics which make them vulnerable to shock s (directly observed from household survey, see below); and
- $\delta_{s,d}$ exposure to shock s in district d , defined as a probability affecting proportional subset of households in district based on share of district affected.

The model assumes that the population increased from 207 million to 228 million between 2018 and 2022, and accordingly, population weights are updated using historical provincial population growth rates from the Pakistan Bureau of Statistics.

Household Data

The Pakistan Household Income and Expenditure Survey (HIES) for 2018–19, collected by the Pakistan Bureau of Statistics (PBS), collects detailed information on living standards, income, and expenditures of households. The survey had a sample size of 24,809 households sample so as to be representative of the entire population, stratified by rural/urban and by province. The questionnaire covered household demographics, education, health, employment, income sources, consumption patterns, and expenditures on a variety of goods and services. Based on data from the HIES, the PBS estimates household expenditure, which when benchmarked against the poverty line, yields the national and international poverty rates.

The National Household Survey HIES 2018–19 provides detailed information on household consumption Y (in period 0) and household characteristics X (in period 0) for a rep-

representative subset of households.⁷ The following household characteristics $X_{i,s}$ are used to determine whether a particular household i would be affected by a shock through the channel s :

- **Livelihoods:** the extent to which households relied on agricultural income;
- **Assets:** whether a household lived in a mudbrick home; and
- **Food Consumption:** the proportion of consumption dedicated to food to determine the welfare implications of rising food inflation.

The damage to the households β_s relates to the consumption loss attributable to shock s . These parameters were calibrated based on reported income and expenditure in the household data.

- Since the principal loss of livelihoods is assumed to be through lost agricultural productivity, damage was benchmarked to the ratio of agricultural income to total income. This varied significantly by livelihood type. For example, on average livestock owners would experience a welfare loss of 40% (see Table 2).
- Damage to buildings was based on the share of household consumption dedicated to housing costs, which was estimated to be 20%.⁸
- Finally, the effect of inflation was benchmarked to the CPI published by the Pakistan Bureau of Statistics, calculating cumulative food inflation for July, August, and September 2022. The effects of inflation were distributed to households in accordance with the share of food consumption per decile, reflecting that poorer households spend proportionally more on food.⁹

Once the potential damage is calibrated, the household's exposure, $\delta_{s,d}$ defines the probability of shock channel s affecting a household in district d . Exposure to each shock channel is

Table 2 Damage to livelihood parameters, by occupation

	Livelihoods	Distribution (HIES, rural)	Damages
	Self-employed	16%	3%
	Paid employee: Construction	13%	4%
	Paid employee: Manufacturing	7%	2%
	Paid employee: Services	19%	2.7%
	Paid employee: Agriculture	10%	76%
	Own cultivator	22%	63%
	Sharecropper	7%	72%
	Contract cultivator	3%	66%
	Livestock owners	4%	40%

based on ratio of income from agriculture to total income; this explicitly captures diversified households which rely on a combination of agricultural and non-agricultural income

⁷ The HIES is the official national household survey to measure monetary poverty using the national poverty measurement methodology.

⁸ These are based on the average household expenditure on rent or rent-equivalent corresponding to the value of their home using a hedonic model imputation.

⁹ We assumed no substitution and that 50% of inflation could be attributed to the floods. (see Table 2)

modeled as a uniform distribution independent of other channels. Damages across channels are cumulative.

The following section discusses the real-time satellite data used to calibrate the probability $\delta_{s,d}$ which describes the exposure to shock s in district d .

Real-time Satellite Data

To determine the exposure of a household to a shock, we use the location of households according to the national household survey HIES and then combine this with information on the estimated probability of a shock for a specific location. By design, the HIES is only statistically representative on the province level (urban/rural), but all households can be mapped into districts (geo-coordinates of households are not available from the survey). For the baseline scenario, $\delta_{s,d}$ describes the exposure based on real-time satellite data. As a robustness check, this paper also presents findings where $\delta_{s,d}$ is the exposure based on incoming administrative data.

For each observation in the household survey data, we determine the probability that a given household was exposed to the shock by merging shock exposure from satellite data (aggregated at the district level) with the respective district of residence for households in the HIES data. Since exposure $\delta_{s,d}$ is a probability, we iterate the model 500 times using a uniform distribution to allow for variation in which households are affected by the shock in each district. When aggregated, this produces a range of plausible welfare outcomes, allowing us to construct confidence intervals.

Exposure Data and Administrative Boundaries

For the baseline, real-time satellite data are used to estimate the extent of the exposed population, built-up and agricultural land, and production (crops and livestock) by district and construct $\delta_{s,d}$.¹⁰ These included the following information:

- **Population:** reported percentage of the population affected per province;
- **Agricultural land:** estimated value of crops lost as a percent of the total (not available for KP at time of analysis); and
- **Built-up area:** area of *katcha* houses reported destroyed or damaged as a percent of the estimated number in baseline, per province.

Flood Event Observations

Remote-sensing data from multiple sources were applied to identify the flood extent, including Visible Infrared Imaging Radiometer Suit (VIIRS), Sentinel 1 and Sentinel 2 data. VIIRS offers a 300 m resolution layer; Sentinel 1 synthetic aperture radar (SAR) offers data at 10 m spatial resolution day and night for all weather conditions, being able to penetrate clouds (Torres et al., 2012). Sentinel 2 offers multi-spectral imagery at 30-meter resolution.

¹⁰ Damages from the flood are reported on the NDMA website and were collated with administrative data to establish baseline values.

For our analysis, we considered households flood-affected if they were adjacent to or surrounded by standing water. The flood extent information detected using Sentinel 1, Sentinel 2, and VIIRS satellite data was combined over the period July 12–August 29 to obtain a description of the cumulative floodwater extent.

However, the representativeness of high-resolution sentinel data suffers from limited water detection in urban areas. For the analysis, we considered two different versions of the Sentinel data: first from the United Nations Institute for Training and Research (UNITAR); and second from Ipsos Group (IPSOS), which is a multinational market research and consulting firm. The data layer provided by UNITAR is upscaled and simplified, and urban gaps were filled (see Figs. 1, 3 and 4 below). As a result, estimates from the UNITAR layer show that 17.4 million people were impacted, which is close to the official estimates provided by the NDMA. In contrast, the analysis conducted by overlaying the IPSOS layers against population density undercounts the number of people directly affected, estimating a much smaller total of 2.4 million for the whole country.

Ultimately, the UNITAR flood extent was selected to measure exposure. The numbers, therefore, refer to the total amount of value located within the flood extent for each exposed category. While a better characterization of flood intensity parameters would likely improve the exposure estimate and allow for a calculation of direct physical impacts, the purpose of this exercise is to evaluate data that are close to real-time availability after a disaster strikes; the modeling of water hazard intensity parameters (e.g., water depth, velocity, duration of submersion, sediment load) is not usually available right after an event. Sources for the real-time satellite estimates are summarized in Table 3 below. Additional details are provided in the Annex.

Results

The 2022 floods had a profound impact on lives and livelihoods. The assessment focused on the direct impact on monetary poverty and accounts for changes in household welfare arising from damages and losses in the aftermath of the floods. The impact on household welfare came through at least three channels: (i) loss of household income and employment/

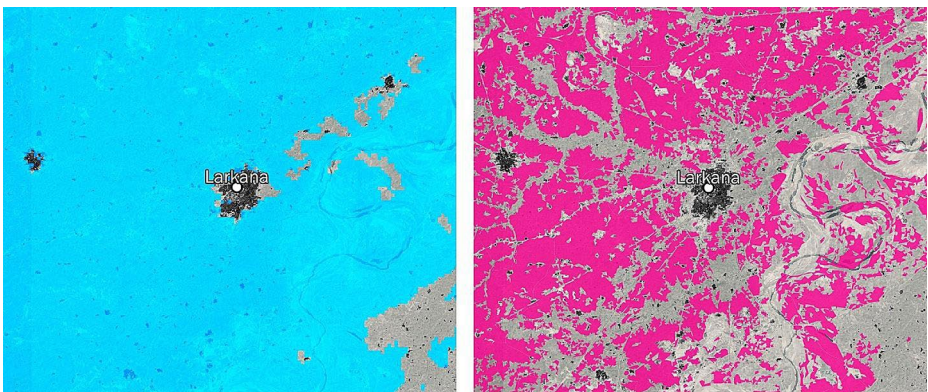


Fig. 3 Difference in flood extent between UNITAR and IPSOS layers. Source: Author Calculations based on cumulated flood extent (UNITAR and IPSOS)

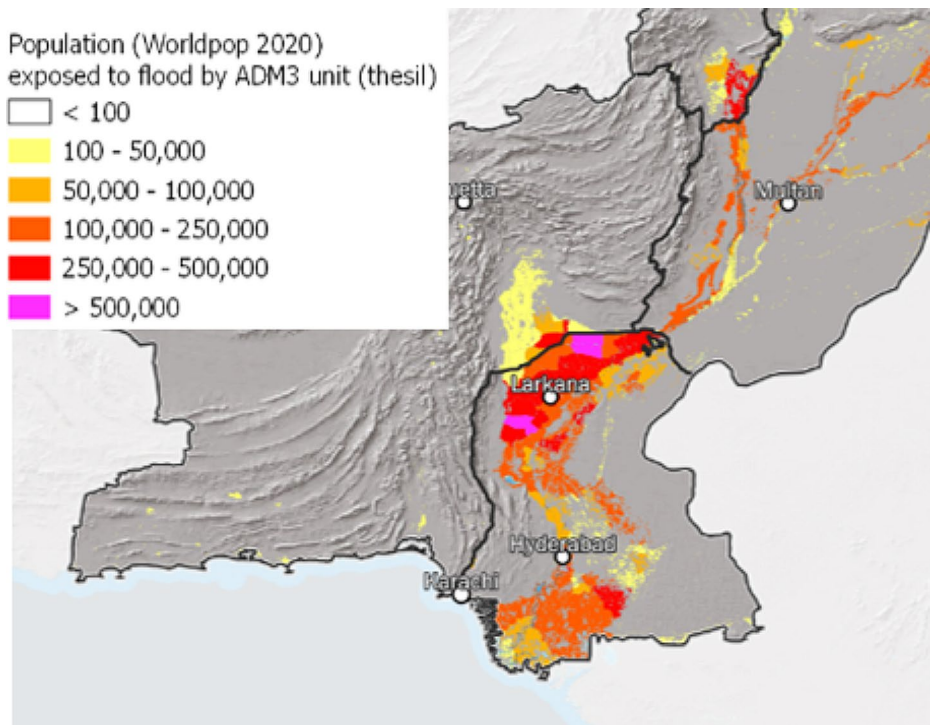


Fig. 4 Population exposed to flood in absolute numbers. Source: Author Calculations based on cumulated flood extent (UNITAR) and population layer (WorldPop 2020)

livelihood due to destroyed harvest, killed livestock, or inactivity of businesses; (ii) loss of assets, including productive assets and homes; and (iii) rising food prices due to shortages of food arising from lost food stocks, and poor harvests.

In addition, households are likely to experience a loss of human capital, given the significant threat of disease outbreaks, food shortages, and prolonged school closures, with attendant learning losses. Since these are long-term effects, the ex-ante simulation results do not model the loss of human capital.

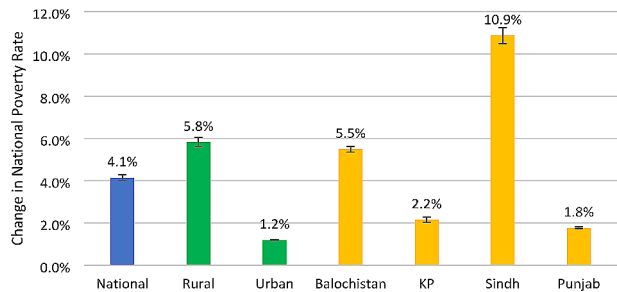
Estimates suggested that as a direct consequence of the 2022 floods, the national poverty rate increased by 4.0 to 4.3 percentage points, pushing around 9 million people into poverty (see Figs. 5 and 6). Beyond the national average, poverty in Sindh increased by between 8.2 and 9.0 percentage points, and in Balochistan by 5.2 and 5.4 percentage points.

Moreover, households that had been poor before the floods have fallen further behind, increasing the depth and severity of poverty (Fig. 7). The poverty gap increased substantially, with the number of extremely poor people living more than 20% below the poverty line rising from 18 to almost 28 million. Households with dependents were among the most affected, with a 5.4% increase in poverty, highlighting higher levels of precarity (see Fig. 8). In addition to those falling below the poverty line, an estimated 6.1 million people were newly vulnerable, living just above the poverty line.¹¹

¹¹ Vulnerable households are defined as households whose consumption lies between 100% and 125% of the poverty line.

Table 3 Input data used to produce geospatial exposure estimates

Item	Description
Flood extent from 12/07 to 29/08 (MAX)	The sum of individual extent layers obtained from UNITAR includes the extent of individual events in the period as detected from S1, S2, and VIIRS. It is used to identify the total flood extent.
Population layer	Global Human Settlement Layer (GHSL) 2020. The distribution of the residential population is expressed as the number of people per 100 m square cell. Residential population estimates derived from CIESIN GPWv4.11 are disaggregated from census or administrative units to grid cells, informed by the distribution, volume, and classification of built-up as mapped in the Global Human Settlement Layer (GHSL) global layer per corresponding epoch.
Built-up	World Settlement Footprint (WSF) 2019. The ratio of built-up (buildings) presence in a cell is used to estimate the built-up area within the flood extent.
Agricultural land	European Space Agency (ESA), 2020 global land cover filtered for agricultural classes. Used to estimate the area of agricultural land located within the flood extent.
Crop production	Food and Agriculture Organization (FAO) Global Agro-Ecological Zoning (GAEZ), v4, 2015. Total annual production (1,000 tons) for 26 crop types. Year 2015 (2014–2016 average). Used to estimate agricultural production exposed to the flood.
Administrative boundaries	ADM0 (country), ADM1 (provinces), ADM2 (districts), and ADM3 (tehsils) from UN-OCHA 2022 aggregate exposure and impact estimates.

Fig. 5 Simulated changes in the national poverty rate due to the floods (percentage points, point estimates). Source: Author calculations

By looking at the distributional impact, we calculate the total welfare loss for households, which if taken over a 3 month period amounts to 223 billion rupees in 2018, or about a billion USD.¹² This estimate helped quantify the amount of immediate relief households would need to maintain their consumption. This estimate helped to inform the design and magnitude of shock responsive cash transfers.¹³ This of course does not factor in the cost of replenishing lost assets and the long-term damages to human capital.

¹² At an exchange rate in October 2022 of 0.0046 Pakistan rupees per USD.

¹³ During the 2022 flooding in Pakistan, the World Bank was able to mobilize \$150 million to provide a one-off cash transfer (\$88 per recipient) to 1.3 million households from September to November.

Fig. 6 Estimated number of additional poor due to the floods. Source: Author calculations. Note: Population count based on 2022 projected population

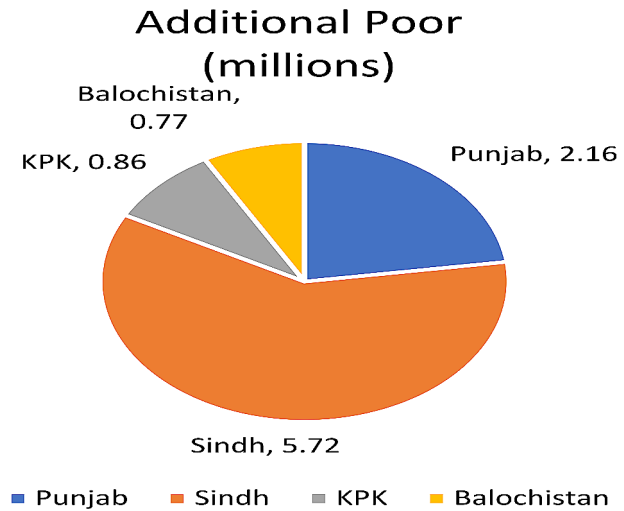


Fig. 7 Estimated increase in the depth of poverty. Source: Author calculations. Note: Poverty gap calculated as the difference between own consumption and the national poverty line

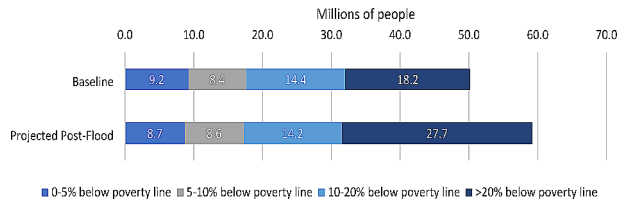
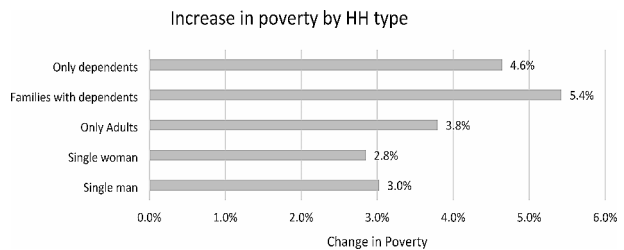


Fig. 8 Estimated increase in the national poverty rate, by household types. Source: Author calculations



In addition to the increase in monetary poverty, the 2022 floods had a detrimental impact on human development outcomes. The floods triggered substantial losses to human capital (education and health) with an increased incidence of stunting and learning losses, which are expected to have a long-lasting impact on productivity and resilience unless addressed during rehabilitation. Moreover, some population groups experienced disproportional losses. These poverty estimates do not account for impacts on specific vulnerable groups, including refugees and displaced persons from Afghanistan, since they are inadequately covered in national household surveys. Finally, the loss of the current harvest will likely prevent poor farmers, especially, from repaying their loans. This will impact their creditworthiness and their ability to take on new loans to finance the purchase of needed productive assets or farm inputs, which is likely to put smallholder farmers under further livelihood stress.

Robustness Checks

Cross-Validation Using Administrative data

One of the critical inputs for the model presented in this paper is the exposure of population, agriculture, built-up area, and livestock to the floods. The main specification used real-time satellite data to calibrate the exposure parameters $\delta_{s,d}$, since this was the exposure data available immediately after the flood. As a robustness check, we ran the same calculations using an alternative exposure metric $\delta'_{s,d}$, as reported by the National Disaster Management Authority (NDMA). This administrative data became gradually available in the months after the disaster and required extensive cleaning. By comparing exposure estimates across the two models, it provides a cross-validation of the initial rapid geo-spatial estimates.

Table 4 summarizes the inputs used to calculate the results, which are based on real-time satellite data, and which are based on NDMA reports. These sometimes differ substantially. Geospatial population exposure estimates are lower for KP and Balochistan because the satellite data are based on standing water and do not account for damages from flash floods. The lower livestock estimates from NDMA suggest either incomplete data or that many owners could relocate their livestock to higher grounds. This highlights how the two data sources offer potentially complementary insights into the effect of flood exposure. While real-time satellite data offer a rapid post-shock estimate, administrative data offer a more nuanced, ground-truthed snapshot of the reality.

This difference in exposure estimates translates into a 0.6% point higher estimate of the impact of poverty, particularly in Sindh and Balochistan. In both models, the effects are concentrated in calamity-hit districts and affected households, with characteristics rendering them vulnerable to overlapping losses through various shocks. There are several potential drivers of these differences. The first is that the satellite-based estimates of population are extrapolated from the 2017 census data, which may be slightly out-of date in the context of a rapidly growing population with significant internal migration. A second consideration is that administrative data tend towards higher end of exposure estimates in to minimize the risk or areas of individuals being improperly excluded. Therefore, we should consider the satellite-based estimates a lower-bound and the administrative estimates an upper bound of the impact of welfare. (see Fig. 9)

Varying Damage Parameters

As noted, the model combined the exposure estimates with damage parameters calibrated to the household survey data. While these are rooted in empirical data, as a robustness test, we vary these parameters by +/- 5 and 10 percentage points. Unsurprisingly, the impact on

Table 4 Reported exposure, geospatial vs. NDMA reports

	Population		Agriculture		Built-up area	
	Satellite	NDMA	Satellite	NDMA	Satellite	NDMA
Punjab	4%	5%	17%	2%	6%	1%
Sindh	25%	28%	39%	55%	30%	25%
KPK	2%	11%	6%	N/A	2%	2%
Balochistan	7%	60%	14%	22%	9%	13%
National	9%	15%	20%	15%	11%	7%

Fig. 9 Comparison of simulated changes in the national poverty rate using administrative and geospatial exposure. Source: Author calculations

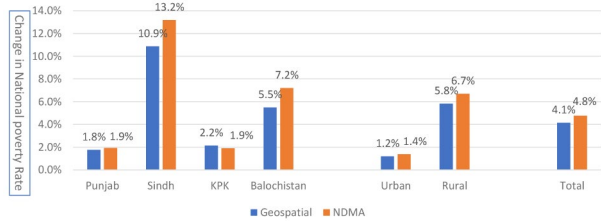


Table 5 Change in poverty estimates by varying shock parameters

	-10%	-5%	Base-line: Original parameters	+5%	+10%
Punjab	1.7%	1.8%	1.8%	1.8%	1.9%
Sindh	10.1%	10.4%	10.9%	11.7%	12.4%
KPK	2.0%	2.1%	2.2%	2.2%	2.3%
Balochistan	5.1%	5.4%	5.5%	5.8%	5.8%
Urban	1.2%	1.2%	1.2%	1.2%	1.2%
Rural	5.5%	5.6%	5.8%	6.2%	6.5%
Total	3.9%	4.0%	4.1%	4.4%	4.6%

Source Author calculations

Table 6 Allowing households to frontload income from assets

	Baseline	Cashing in assets
Punjab	1.7%	1.6%
Sindh	10.9%	9.7%
KPK	2.2%	1.9%
Balochistan	5.5%	5.2%
Urban	1.2%	1.1%
Rural	5.8%	5.3%
Total	4.1%	3.8%

Source Author calculations

poverty varies monotonically with the magnitude of the parameter estimates, yet the model remains quite robust, with a lower bound of 3.9 percentage point increase in poverty and an upper bound of 4.6 percentage point increase (see Table 5 below).

Behavioral Response of Households

Assets can help a household buffer the effects of shocks. We model this explicitly by looking at damages to housing, often a rural household’s biggest asset. In addition, about 10% of household income is drawn from agricultural and non-agricultural assets. If we assume that they can draw on at least as much by borrowing or drawing down their liquid assets, we can add this back in as a buffer to the consumption loss. The results suggest that cashing-in income from assets would only have a small buffering effect, reducing the change in poverty by 0.3% points (see Table 6). In addition, many of these assets, such as land and livestock, are likely illiquid and may have lost their value due to the floods. Households with financial assets may also have to pay steep fees in the form of interest rates or penalties in order to access them. Privately held assets are therefore not sufficient to act as a buffer.

Limitations

This paper focuses on the immediate impact of the 2022 floods on household welfare. As such, the model, the calibration, and the findings should be considered within the objective of this exercise, which comes with certain limitations. First, estimates focus on the direct consequences of the flood on poverty and do not account for second-order effects, including implications for household growth and productive capacity. As noted previously, they also do not account for the potential response in the form of humanitarian assistance, shock-responsive cash-transfers or insurance payouts. Instead, these first order estimates are intended to inform the design of the response.

Second, estimates focus on the short-term impact. The impact might vary depending on the location and design of relief and reconstruction. Even in the best case, reversing these adverse shocks to household welfare would take considerable time, and some losses, such as losses to human capital and loss of land productivity, could set in motion more durable declines in welfare and will need specific attention. The impact of the natural disaster is also a function of the duration of the flooding. Since this analysis used an ex-ante simulation approach, findings did not delve into the duration of the inundation or, related to this, the duration of limited access to services and markets.

Third, the model outcomes depend on the validity of pre-disaster household survey data. Due to natural disasters, household characteristics may change, which could undermine the reliability of pre-existing household surveys. Moreover, results from the simulation could be biased if the model relies on information from an outdated household survey. In the case of Pakistan, the data collection for the HIES happened in 2018/19, before COVID-19 hit the country.

Finally, findings from the ex-ante impact simulations are partially a function of the calibrated damages to livelihood parameters. To the extent possible, these parameters should be validated against empirical data to ensure they align with the actual loss of livelihoods a household experiences due to a shock.

Conclusion

This paper demonstrates how real-time satellite data, in combination with administrative data and historical household survey data, can be used to model the impact of floods on household welfare. It provides an example of rapid modeling in the absence of real-time household survey data.

Estimates showed that, as a direct consequence of the floods, the national poverty rate would increase by 4.0 to 4.3 percentage points, pushing more than 9 million people into poverty. Moreover, a spatially disaggregated analysis showed that the magnitude of shocks varied across locations and households depending on the intensity of the flooding and household characteristics. These estimates informed the Post Disaster Needs Assessment and were later used to inform the Donor Conference for Pakistan as-well as make the case for loss-and-damages financing.

The model does not account for response by design, to quantify the full magnitude of the potential impact to welfare. In addition to the shock-responsive cash transfers, further iterations of the model could explore the benefits of subsidized insurance. For example, Sur-

minski and Oramas-Dorta (2014), examines flood insurance schemes as a means of climate adaptation in developing countries. Their study shows that insurance can be a critical tool in mitigating the financial impact of floods on the poor by providing a safety net that supports recovery and resilience. This is particularly relevant for Pakistan, where such financial protection mechanisms are underdeveloped, yet the need is significant due to the high risk of flooding and widespread poverty.

A survey will always be the first-best solution in evaluating the welfare effects post-disaster. Ideally, monitoring system combining satellite, administrative and survey data is set up in anticipation so as to monitor changes in welfare before and after the shock. However, in a post-disaster humanitarian emergency, logistical constraints may make this infeasible in the short timeframe when a disaster response is being crafted. These same constraints also make data quality particularly challenging. Accordingly, the above proposes an approach allowing calibrated estimates to be constructed, fine-tuned, and subsequently validated. It also hints at potential limitations; notably, satellite data can only ever capture certain types of exposure, and it is much better at observing standing water than damages due to flash floods.

Looking forward, this model offers a ready-made approach to quantifying welfare impacts in a post-disaster setting, given limited data availability and time constraints. However, this rapid turnaround was only possible because many elements were already in place, most notably, pre-existing household survey data and the in-house expertise to access and process geospatial data. These basic investments in foundational data and capacity can pay dividends when disaster strikes.

Annex- GeoSpatial Data Sources

Population.

Name	<i>Global Human Settlement Layer [GHS-POP]</i>
Source	EU Joint Research Centre
Format	Raster grid
Resolution	100 m
Time reference	2020
Metric	Population count
License	Open
Notes	Constrained by built-up (2020)

Land cover, land use, and built-up.

Name	<i>ESA WorldCover</i>	<i>World Settlement Footprints</i>	<i>Global Human Settlement Layer [GHS-BUILT-S]</i>
Developer	VITO and consortium for ESA	ESA	EU Joint Research Centre
Format	Raster	Raster grid	Raster grid
Resolution	10 m	10 m	100 m
Time reference	2020	2019	2020
Metric	Land cover classes	Presence of built-up (binary)	Built-up area

Name	<i>ESA WorldCover</i>	<i>World Settlement Footprints</i>	<i>Global Human Settlement Layer [GHS-BUILT-S]</i>
License	Open	Open	Open

Crops and livestock.

Name	<i>Gridded Livestock of the World (GLW)</i>	Global Agro-Ecological Zones (GAEZ+)
Developer	FAO	FAO
Format	Raster	Raster grid
Resolution	10 km	10 km
Time reference	2015	2015
Metric	The layers contain the density of animals per pixel, with weight estimated by the Random Forest model. The livestock species modeled include buffaloes, cattle, chickens, ducks, goats, horses, pigs, and sheep.	Crop harvest area, crop production, and crop yield maps (Fischer et al., 2012), using national-scale data on the fractional change in crop harvested area and production from 2010 to 2015, based on statistics for 160 crops from FAOSTAT.
License	Open	Open

Administrative boundaries.

Name	<i>Pakistan Administrative Boundaries</i>
Source	National Agency
Format	UN-OCHA
Time reference	2022
License	Open

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Data Availability Geospatial datasets are publicly available (see annex). The household survey data analyzed for this study are not publicly available but can be requested from the Pakistan Bureau of Statistics.

Declarations

Competing Interests The authors declare no competing interests.

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