Flooding in Chad: Analyzing incidence and impacts

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Executive Summary

Chad is consistently rated among the most vulnerable countries in the world to climate change. Increasing temperatures and precipitation are raising the threat of drought, flood, heatwaves, and vector-borne diseases. Infrastructure challenges and Chad's young, poor, and growing population make it especially vulnerable to these threats. The threat from floods in particular is becoming increasingly salient in Chad due to a series of devastating floods in recent years, notably in 2012, 2022, and 2024. This report analyzes information on flood risk in Chad together with multiple sources of data on flooding incidence over the past 10-15 years to evaluate current and projected exposure to flooding and identify areas at particular risk, in order to inform planning around the World Bank's social protection programs in the country.

Flood hazard and exposure in Chad

Large parts of Chad face high and increasing risk from floods, caused by periods of heavy concentrated rainfall and exacerbated by population growth in flood-prone zones, land degradation, and poor drainage and water management infrastructure. We analyze *flood hazard*—estimated depths of floods with a probability of occurring once every 100 years—and *flood exposure*—a measure of land area or population at risk from a certain level of flood hazard—using data from the Fathom flood risk database, a recent study by Rogers et al. (2025), and selected additional sources.

The main driver of flooding hazard in Chad is *fluvial (or riverine) flooding* as heavy precipitation flows into river networks and lakes, increasing water levels and inundating nearby areas. Extreme rainfall may also cause *pluvial flooding* if water cannot be absorbed or drain towards rivers fast enough, as well as direct damage not associated with inundation. According to data from Fathom, a global leader in flood hazard mapping, just 4% of Chad's land area is estimated to be at risk from fluvial floods compared to 18% for pluvial floods. However, the median inundation depth of a pluvial flood with a *100-year return period* (expected to occur once every 100 years on average) is less than 10 cm compared to 45 cm for a fluvial flood. A map of the hazard from 100-year floods shows how the greatest inundation depths are concentrated in the areas near to Chad's rivers, including seasonal wadis.

Rural communities are vulnerable to flood damages due to their reliance on rain-fed agriculture and often less durable dwelling materials, but the greatest population exposure to flood risk is in urban areas which are typically in proximity to lakes and rivers. The higher flooding hazard in these areas is compounded by the the spread of informal settlements—especially in N'Djamena—which have often expanded into low-lying, flood-prone zones. Poorly maintained or non-existent drainage systems are often unable to deal with heavy precipitation or rising river flows, leading to chronic flooding, housing destruction, and widespread water stagnation. The area around and between the Logone and Chari rivers stands out as combining both high flood hazard and high population exposure. Maps of population density in areas with 100-year flood depths of at least 10 or 100 cm show clearly that although flood hazard is widespread in Chad, population exposure is concentrated primarily in particular departements, mainly in the west and south of Chad.

Climate change is projected to increase flood hazard, making floods of a given severity or inundation depth more common across much of the country, but in general the estimated increases in 100-year flood depths are not large. According to Fathom projections for conditions in 2050 under the SSP1-2.6 climate change scenario, the share of pixels exposed to fluvial floods will increase from 4.1% to 4.4%, and the median depth of 100-year floods will increase from slightly under to slightly over 45 cm. Results are similar under the less optimistic SSP2-4.5 scenario. Increasing fluvial flood hazard in recent decades is reflected in data from the Chad Direction des Ressources en Eau (DRE) on river flows through hydrological stations. Average river levels have been increasing over time and particularly in the flooding season from July through November, despite flat or slightly decreasing trends in total precipitation since the 1950s.

Despite limited increases in flood hazard, flood exposure in Chad will increase because Chad's population is expected to at least double between 2017 and 2050. Rogers et al. (2025) analyze the relative contribution of changes in flood hazard and population to determining future flood exposure, and find that 77% of predicted changes in exposure by 2100 globally are due to population growth, compared to 21% due to climate change (and 2% to a combination of the two). The study finds that the area exposed to combined fluvial and pluvial 100-year floods of at least 10 cm will only increases from 17.9% to 18.9% of Chad's land area by 2050 under the SSP2-4.5 scenario, but that the population exposed to such a flood risk is projected to increase from 4.2 to 9.9 million people. Most of the increased exposure will occur in the same departements with the highest current levels of population exposure.

Incidence of flooding since 2012

Major flood disasters in Chad were infrequent historically but have occurred in a majority of recent years, in line with concerns about increasing flood hazard due to climate change and rising populations in high-risk areas. The increasing concentration of precipitation is reflected in data on river flows through hydrological stations, which have been increasing over time, particularly during the flooding season from July through November. Floods are also increasing in duration and are occurring earlier in the year, a consequence of more erratic and concentrated precipitation. Millions of people were affected by the worst floods in Chad's history in 2012, 2022, and 2024 which affected most provinces of Chad, with more spatially concentrated floods occurring in many other years since 2010.

An analysis of survey and satellite data allows greater insight on the specific areas affected by floods than media or government reports which often aggregate information to the province or country level or focus on a subset of specific locations. All sources agree on the years with the most severe flood disasters. For example, 47% of households covering 86% of rural communities in the

2024 ENSA survey reported experiencing a flood shock over the previous six months, compared to just 5% of households the previous year. Data from the NOAA/George Mason University VIIRS Flood Mapping (VFM) archive, which uses VIIRS daily satellite imagery to identify changes in the presence of surface water, detects flooding in 6.3% of Chad's land area in 2024, by far the highest level since tracking began in 2012. The mean count of days with flooding detected for flooded pixels in 2024 was 33 days, compared to less than 20 days in most years, and the 75th percentile was 43 days compared to less than 30 in all other years.

Both data sources also show that flooding is quite common even outside years of major floods that have been the subject of major media attention. The VFM archive shows that at least 2% of land pixels have some flooding detected in every year, though some portion of this may represent seasonal water fluctuations not fully captured in the VFM algorithm. Three percent of households in the ENSA surveys from 2016-2018 reported experiencing a flood shock each year on average and 10% of households in the 2018-19 ECOSIT surveys reported at least one flood shock from 2015-2018, though no major flood events occurred in this period. These events are generally concentrated in areas with high flooding hazard, implying a potential need for more flood monitoring in these areas to respond to isolated flood shocks.

There is substantial variation in flood exposure across households within communities. The majority of households in communities with at least one household flood report in a given period do not report experiencing any flooding shock. Households engaged in agricultural production or having dwellings made of less durable materials are more likely to report a flood shock, highlighting how differences in vulnerability can determine who is affected by flooding as opposed to simply exposed.

Household surveys are useful for understanding who is being affected by floods, but they are limited in their spatial and temporal coverage and may also conflate inundation shocks with shocks related to heavy precipitation that does not lead to inundation. For the same reason, deviations in local precipitation from historical averages can only roughly proxy for flood incidence. River flow data serve as validated indicators of fluvial flood hazard but cannot measure inundation beyond the river and are only available at a small number of locations. Remote sensing, and particularly satellite imagery, radar, and microwave data, now enables flood detection at a granular temporal and spatial level. Satellite-based measures remain constrained by measurement issues (cloud cover for optical imagery, long revisit periods for radar, challenges with water detected in urban, forest, and arid areas) and are subject to flood detection algorithm decisions, such as how to account for seasonal water fluctuations. For these reasons, satellite-based sources should not be considered definitive measures of flood incidence, particularly at very specific points in time and space. At a more aggregate level, however, they are very useful in identifying and monitoring areas where floods are likely occurring.

Several publicly-available databases monitor near-real time (NRT) flooding worldwide using different data inputs and algorithms. The results from these databases could be combined for real-time monitoring of flooding in Chad to inform disaster response. For example, the World Food Programme in Chad has used data from the Automated Disaster Analysis and Mapping (ADAM) floods database, which uses an algorithm combining satellite imagery from VIIRS and MODIS, satellite synthetic aperture radar from Sentinel-1, and FloodScan data, to map out flooding incidence during the major floods in 2022 and 2024.

We analyze historical remotely-sensed flooding incidence using data from the NOAA/George Mason University VIIRS Flood Mapping (VFM) product, based on daily VIIRS satellite imagery from 2012-2024. Flooding is detected in the VFM archive in at least one year from 2012-2024 for 10% of all land pixels in Chad. The highest levels of mean annual flood exposure—measured as the number of days flooding is detected in each pixel—are in the areas identified in the Fathom data as having greater fluvial flood hazard. Around Lakes Chad, Fitri, and Iro, between the Chari and Logone rivers near northern Cameroon, and further south along the Logone river, many pixels experience an average of over 100 days of detected floods annually from 2012-2024. Outside of these areas it is rare for the mean annual days of detected flooding to exceed 40. This is consistent with a greater threat from fluvial floods but could also reflect the fact that VIIRS satellite imagery cannot see through clouds and is therefore constrained in detecting pluvial floods, though it does detect floods in the northern half of Chad that may reflect pluvial floods. The Sentinel-1 satellite captures synthetic aperture radar data which can see through clouds, but visits each point on earth much less frequently than the VIIRS satellite and so will miss many short duration floods.

We combine the mean annual days of flooding data from the VFM archive with data on population density from WorldPop to highlight the populated areas with the highest recurring flood incidence. These areas closely mirror the populated areas exposed to 100-year flood depths of at least 10 cm according to Fathom. In particular, the highest levels of population exposure to detected flooding in Chad are primarily concentrated in the area around the Logone River, though many other populated areas also have high recurring flood incidence.

Comparing estimated national annual population flood exposure to reports of affected populations, we find that in years where affected populations are reported this represents 29% of the estimated exposed population. In years of major flood disasters such as 2012, 2020, and 2024, this share increases to 48%. This comparison shows that floods do not affect everyone equally, in line with the survey analysis of correlates of flood shock reports. The larger share of the population affected by more severe floods may represent broader indirect effects of these floods, in addition to direct effects of flooding.

An important question is how well the remotely-sensed flood detection reflects flooding experiences on the ground. At the community level, there is a strong relationship between the amount of flooding detected in pixels around a community's location in the VFM archive data and the probability that any survey household in the community reports a flood shock in the same time period in both the ECOSIT and ENSA surveys. The ECOSIT surveys show evidence of recency bias in household survey recall, with more recent detected floods more predictive of flood reports over the 3 year recall periods. Floods detected within 1 km radius of a community are also more strongly predictive of survey reports than floods within a 5 km radius. In the ENSA surveys recency bias is less of a concern because of the 6 month recall period, but flood reports are indeed predicted by flooding detected in the same period and not prior years. The association between detected flooding and the probability of any flood report is similar when considering both a 1 and 5 km radius.

Although both survey flood reports and satellite-based flood detection using the VFM archive are concentrated relatively more in areas with higher flood hazard and in years of major flooding disasters and the two measures are correlated at the community level, the sources also can identify different sets of communities as exposed to flooding. In both the ECOSIT and ENSA surveys, many communities with a large share of pixels flooded within 1 km do not have any household flood reports, while many communities with a household flood report do not have any flooded pixels detected even within 5 km. These differences can be attributed to both limitations of remotely-sensed measures—challenges in capturing pluvial, short duration, and urban floods in particular—and heavy precipitation shocks that do not result in inundation but cause damages reported in surveys as floods due to a lack of more specific shock categories. Part of the former challenge could potentially be addressed with more sophisticated remotely-sensed flood detection techniques, but the latter challenge suggests there will always be disagreement between survey and satellite flood measures.

Despite these differences, the results suggest that satellite-based flood detection can identify a subset of flooded communities with quite high accuracy. Indeed, 84% of ENSA communities and 64% of ECOSIT 4 communities with at least 10% of pixels within 1 km detected as flooded have at least one survey flood report. The accuracy reaches 89% in the ENSA data when using a 20% threshold for flooded pixels and a 5 km radius around the community. Further analysis could seek to identify a threshold and distance to maximize predictive accuracy.

Household-level impacts of flooding

Flood exposure causes a variety of direct damages to agriculture, property, health, and life, but also has broader indirect effects through sanitation, disease, land degradation, and infrastructure damages. A large economics literature finds adverse impacts of flood exposure on many household outcomes including food security, health, agricultural production, poverty, well-being, as well as increases in displacement and temporary migration. We use panel data from the Enquête sur les Conditions de vie des Ménages et la Pauvreté au Tchad (ECOSIT) survey rounds from 2018-2019, 2020-2021, and 2022 to identify causal effects of flooding in Chad. Community-level flood exposure is identified by matching community coordinates to observations of flooding incidence in the surrounding area in 2019-2020 after the baseline round using data from the VFM archive (VFM data for 2021 and 2022 are not available). In addition, we also consider household reports of flood exposure over the 2019-2022 period from the last survey round. We account for the non-random components of flood exposure by estimating the probability of experiencing flooding during these time periods as a function of location characteristics and prior flooding history. Households in exposed and non-exposed communities are well-balanced in terms of baseline characteristics after controlling for this probability.

The identification strategy compares changes in outcomes over time for households in communities exposed to flooding against households in non-exposed communities in the same provinces with the same estimated probability of exposure. The estimated impacts of flood exposure depend on how exposure is defined. Exposure to pixels detected as flooded in the VFM data increases the probability that households engage in non-farm enterprise activities in subsequent periods, particularly in urban areas and in the periods immediately following the flood exposure. Being in a community where at least one household reported a flood shock increases engagement in agricultural production in the following periods, particularly for households with female heads and engaged in non-farm enterprise at baseline. The estimated effect on non-farm enterprise engagement is also positive and close to being statistically significant. These effects may represent household efforts to diversify their livelihood strategies following a shock to their main source of income.

There are no average effects among the sample households of flood exposure on measures of household well-being such as food insecurity or perceived absolute or relative well-being, although survey-based flood exposure increases the likelihood that households report exposure to other kinds of shock. The average intent to treat effects based on community-level flood exposure likely mask important heterogeneity across households by household-level exposure because only around 20% of households in exposed communities typically report being directly affected by a flood shock themselves. The low levels of direct exposure in most communities may drive estimated impacts of flooding toward zero if other households in the community do not face adverse indirect effects. Though not statistically significant, the positive and large coefficient for the effect of flood exposure on an index of household food insecurity may suggest that directly affected households are persistently more food insecure, but not sufficiently so to overcome null effects on other community households.

Further research using the same data and identification strategy could explore this by using community flood exposure to instrument for households reporting a flood shock. This approach would identify local average effects of direct flood exposure under the assumption that community-level exposure only affects households through the probability that a household experiences direct flood-related damages. This assumption would fail if indirect effects—for example through effects of floods on prices or transportation—are important, so additional work could also try to separate out direct and indirect effects of flood exposure. Data from the ENSA surveys could also be particularly valuable for testing effects on food insecurity, though the identification strategy would be different because the ENSA data are not a panel. One approach would be to conduct a stacked cross-sectional event study relying on different timing of when communities surveyed at different points in time are first exposed to satellite-detected flooding.

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1 Introduction

The Republic of Chad is one of the largest countries in Africa, covering nearly 1.3 million km^2, much of this in the Sahara Desert in the north and arid Sahel in the center. Chad's population of over 17 million is among the fastest growing in the world and is primarily rural and concentrated in the more agricultural south of the country (Figure A1). In line with this, the main household activity is subsistence agriculture focused on staples such as millet, sorghum, and maize, and around 40% of the population lives below the poverty line. Chad's government revenues come largely from exploiting its considerable oil reserves, whose exports account for 40% of GDP compared to 30% for agriculture.

Chad is among the countries most threatened by climate change. It ranks last among 187 countries in the 2023 Notre Dame Global Adaptation country index ratings (ND-GAIN; C. Chen et al., 2015), based on a country's vulnerability to climate change and its ability to improve resilience, and fifth out of 190 on an index of vulnerability to humanitarian crises and disasters (Thow et al., 2023). Though it rates better (148th of 188) on the Columbia Climate School's recently released 2025 climate finance vulnerability index (Columbia Climate School, 2025, these assessments highlight the extent to which climate change represents a threat to Chad.

This vulnerability is due to a combination of multiple factors. First, climate change is directly threatening livelihoods and well-being. Increasing temperatures and more erratic rainfall create major concerns about projected changes in cereal yields and in vector-borne diseases (such as cholera and malaria) while also contributing to spreading desertification (shown most clearly by the drying up of Lake Chad) and growing flood hazard (Abdi, 2017; ND-GAIN, 2025). More frequent and intense droughts, floods, and heatwaves will affect human health, food security, and nutrition, decrease crop and livestock productivity, reduce water availability, increase risk from agricultural pests and diseases, force greater population displacement, and generally disrupt livelihoods (RCCC, 2024).

Chad's infrastructure and socioeconomic characteristics make it more vulnerable to these threats. The calculations in the ND-GAIN give Chad the worst score among all countries on access to reliable drinking water, medical staff, and access to paved roads, along with low scores on access to sanitation, electricity access, slum population, and rural population (ND-GAIN, 2025). These characteristics suggest major infrastructure and institutional constraints to protecting households from the risk of floods and other climate shocks and to mitigating adverse effects of these shocks. In addition, chronic regional and national insecurity, very high poverty rates, subsistence livelihoods for a large share of the population, and a young and rapidly growing population all make Chad highly vulnerable to the changing climate by limiting assets and other resources that could help populations to adapt to or mitigate its effects (Abdi, 2017; ND-GAIN, 2025). Climate change is likely to increase the risk of conflict and worsen current youth unemployment problems (RCCC, 2024), creating further vulnerability.

A particularly salient way that the threat from climate change is being realized in Chad is through devastating flood disasters. Nearly three-quarters of floods reported in Chad since 1980 have occurred in the last 20 years, and three of the worst floods in Chad's recent history (going back to 1961) have occurred in the last decade and a half (ACAPS, 2024; Government of Chad, 2023a; OCHA, 2012). In 2012, 2022, and 2024, torrential downpours across much of the country caused widespread flooding causing death, displacement, and major damages to cropland, homes, and infrastructure, in addition to secondary effects from deteriorating sanitation conditions, spread of disease, and disrupted livelihoods. The floods in 2022 and 2024 were particularly devastating, directly affecting millions of people and causing displacement, infrastructure damage, destruction of homes and agricultural production, and hundreds of deaths. Economic losses from the 2022 floods are estimated at over USD 400 million (World Bank, 2023), and the 2024 were even more destructive.

In this report, we analyze the risk, incidence, and impacts of flooding in Chad. In Subsection 2.1 we review data on the geographic distribution of current fluvial and pluvial flood hazard and exposure in Chad, where hazard is measured in terms of the depth of floods with a 1 in 100 annual probability of occurring and exposure combines data on population distribution over space with flood hazard data. In Subsection 2.2 we present projections of expected changes in flood hazard and exposure under climate and population change projections for 2050 and discuss the implications for flood vulnerability in Chad. Section 3 evaluates the annual incidence of flooding in Chad with a focus on the period after 2010. We first discuss reports on aggregated flooding damages drawing on government, multilateral, non-profit, and media reports, and present trends in river flows over time from selected hydrological stations in Chad. In Subsection 3.1 we analyze reports of flood shocks in multiple sources of household survey data over time. Subsection 3.2 provides an overview of publicly-available databases using remote sensing methods to identify flood events in Chad. We discuss how these could be used for near-real time flood monitoring, and then evaluate historical incidence of flooding from 2012-2024 using data from the NOAA/George Mason University VIIRS Flood Mapping product. Subsection 3.3 analyzes the level of agreement between survey reports and remotely-sensed flood detection. Finally, in Section 4 we use data from the ECOSIT household surveys to estimate impacts of community flood exposure on measures of household well-being, adding to a growing literature on the short-term impacts of flooding on households with results specific to the Chadian context.

The results of this report may be useful for policymakers and stakeholders working on climate change resilience, disaster response, and social protection in Chad. Understanding the geographic distribution of flood hazard and realizations may help to target resources and efforts to support adaptation and resilience to increasing flood risk. Results emphasizing the recent and projected increases in flood exposure and presenting causal household-level impacts of floods in Chad may motivate greater attention and financing to such activities. This analysis also demonstrates that many floods may occur in remote areas and go unreported by media or government sources, suggesting a need for additional monitoring resources in remote but high-risk areas with vulnerable populations.

2 Flood risk in Chad

Flooding is a recurring risk in many parts of Chad, with most floods occurring in the rainy season from around May to October when heavy rains lead to a rapid rise in the levels of water courses and bodies (Centre Régional AGRHYMET, 2024). The diverse geography of Chad results in significant spatial variation in climate and precipitation (Red Cross Climate Centre, 2023). While the northern regions receive less than 300 mm of rainfall annually, the southern provinces often exceed 1,000 mm, creating distinct flood dynamics across the country (ACAPS, 2024; Government of Chad, 2014, 2024). These difference dynamics contribute to the occurrence of various types of floods, ranging from river overflows in the south to pluvial floods caused by intense rainfall. The increasing frequency and severity of these events, driven by climate change and environmental degradation, have turned flooding into a recurrent challenge for both rural and urban communities (United Nations OCHA, 2024a).

Populations across Chad have different forms of flood vulnerability. Rural communities are particularly vulnerable due to their reliance on rain-fed agriculture, which is highly exposed to seasonal floods, and their dwellings often built with non-durable materials (ACAPS, 2024; FAO, 2023b; IFRC, 2024). In urban areas, informal settlements—especially in N'Djamena—have expanded into low-lying, flood-prone zones. Poorly maintained or non-existent drainage systems exacerbate the effects of heavy rainfall, leading to chronic flooding, housing destruction, and widespread water stagnation. This, in turn, increases the risk of waterborne diseases, particularly in neighborhoods where floodwaters mix with sewage (ACAPS, 2024; Government of Chad, 2014). Displaced populations are among the most at risk, as they often shelter in temporary flood-exposed areas. Recurrent floods have led to large-scale destruction and further displacement and dependency on humanitarian aid (ACAPS, 2024; IFRC, 2024).

In this section we evaluate modeled estimates of current flood hazard and exposure in Chad as well as predictions of how flooding risk is forecast to evolve over time. We present evidence on realized flooding and exposure in Section 3.

Definitions
Fluvial/riverine flood: Inundation due to overflowing rivers or other water bodies.
Pluvial flood: Inundation due to precipitation exceeding soil absorption or drainage capacities.
Return period: The number of years within which a flood of a particular depth of inundation would be expected to occur once. For example, inundation depths for floods with a 100-year return period have a 1% chance of occurring in a given year (occur once in a 100 years in expectation).
Flood hazard: Estimated inundation depths of floods with a given return period.
Flood exposure: Land area, population, or economic activity at risk from a given level of flooding hazard.
SSP climate scenarios: Shared Socioeconomic Pathways projecting global changes up to 2100 as defined in the IPCC Sixth Assessment Report on climate change in 2021. SSP1-2.6 represents an optimistic 'sustainable development' scenario, and SSP2-4.5 a 'middle of the road/business as usual' scenario.

2.1 Present-day flood risk

Two main factors contribute to flood risk in Chad: vulnerability to extreme precipitation events distributed through the river network and growing populations, particularly informal urban settlements, in high-flood risk areas. The former factor affects flood hazard and the latter affects flood exposure, and these are the two key elements of flood risk analysis.

2.1.1 Mapping flood hazard in Chad

Flood *hazard* relates to the estimated frequency and intensity of flood events. Estimates of flood hazard draw on a large variety of models (Table A1 presents a summary of selected flood hazard databases). The models incorporate high-resolution digital elevation, hydrological, and hydraulic data and models primarily derived from remote sensing along with geospatial data on infrastructure which may affect water flows to simulate water flows over space under different potential realizations of precipitation over broad geographic areas. To accurately model flood hazard, the distribution of precipitation in these simulations is designed to match historical patterns, but it may also be modified based on predicted changes in precipitation, for example under various climate change scenarios. Global flood hazard modeling has improved significantly in recent years, but still faces limitations due to issues like data resolution, limited ground truth data in certain areas, and lack of local calibration/validation (see Devitt et al. (2021, 2023) and Smith et al. (2018) for detailed discussions). A discussion of these limitations is beyond the scope of this report. We present flood hazard data from multiple sources, and these should be interpreted as strongly suggesting where flood hazard is most concentrated.

To capture both the frequency and intensity dimensions of flood hazard, assessments typically present results under different *return periods*. A return period is the estimated interval of time between flood events of a given magnitude, where magnitude is typically estimated as depth of inundation—the height of the water covering the ground. For example, a 100-year flood in a given location is defined as a flood of a particular depth such that it has a 1% probability of occurring in any given year. This means that in expectation we would have one such flood every 100 years, but in reality there may be multiple or no such floods in any given 100-year period.

To quantify and map estimated flood hazard in Chad, we first present data the Fathom Global Flood Map 3. These data are not public but were obtained with support from the World Bank Social Protection team. The Fathom data have many advantages, including incorporating the world's most accurate published terrain model for flood modelling (FABDEM), presenting data at a very high (30 m) resolution, and breaking out flood hazard from multiple different scenarios (Fathom, 2022).[1] We present data on the depth of 100-year return period floods under 2020 climate conditions and estimated flood defenses for two main types of floods. The database also includes data on coastal flooding which is not relevant for Chad. *Pluvial* flooding results from intense precipitation exceeding the absorption or drainage capacity of soils and infrastructure in locations

[1] Similar flooding hazard data is provided by the JBA Group, which is also not freely available but may be accessed by partners such as the World Bank through their Development Data Partnership.

where the water is not able to drain or flow toward river networks sufficiently quickly to prevent inundation. *Fluvial* or riverine flooding results when rivers or other water bodies exceed their capacity and inundate surrounding areas as excess water flows into these bodies from throughout the associated water catchment area. For both cases, we present estimated depth of defended floods, which accounts for infrastructure that is designed to protect against floods of a given return period.[2] Estimated depths of undefended fluvial floods are consistently greater but the results are qualitatively very similar.

We focus on 100-year floods to represent the hazard from more extreme and damaging flood events, and noting that hazard from more frequent and less severe floods is highly correlated with hazard from 100-year floods. Studies analyzing global or national exposure to flood hazards tend to focus on 100-year return periods (Arnell and Gosling, 2016; Boulange et al., 2021; Jongman et al., 2012) and often use thresholds such as 10 or 15 cm depth under these flood events to identify areas at medium risk from floods (Rentschler et al., 2022; Rogers et al., 2025). This depth might seem low but 10 cm of average flood depth over a large area can cause a great deal of damage, particularly taking into consideration how the water accumulates and flows. High-hazard areas with more frequent floods of this depth or with 100-year floods of greater depth are a subset of these medium hazard areas.

Figure 1 presents maps and histograms of the estimated depth of 100-year return period floods in Chad under 2020 conditions.[3] The hazard from pluvial flooding is more widespread across Chad, as 18.2% of Chad's non-permanent water area has predicted 100-year pluvial flood depth above 0 cm compared to 4.1% for fluvial floods. But the estimated depths are much lower for pluvial floods, with 60.2% of pixels at risk estimated to experience less than 15 cm of inundation from 100-year pluvial floods, compared to 15.4% of pixels at risk of fluvial floods. The median inundation depth for 100-year fluvial floods in at-risk pixels is just under 45 cm, compared to less than 10 cm for a 100-year pluvial flood.

These results indicate that although pluvial flooding is a hazard for many parts of Chad, fluvial flooding is by far the main driver of overall flooding hazard as measured by inundation depth.

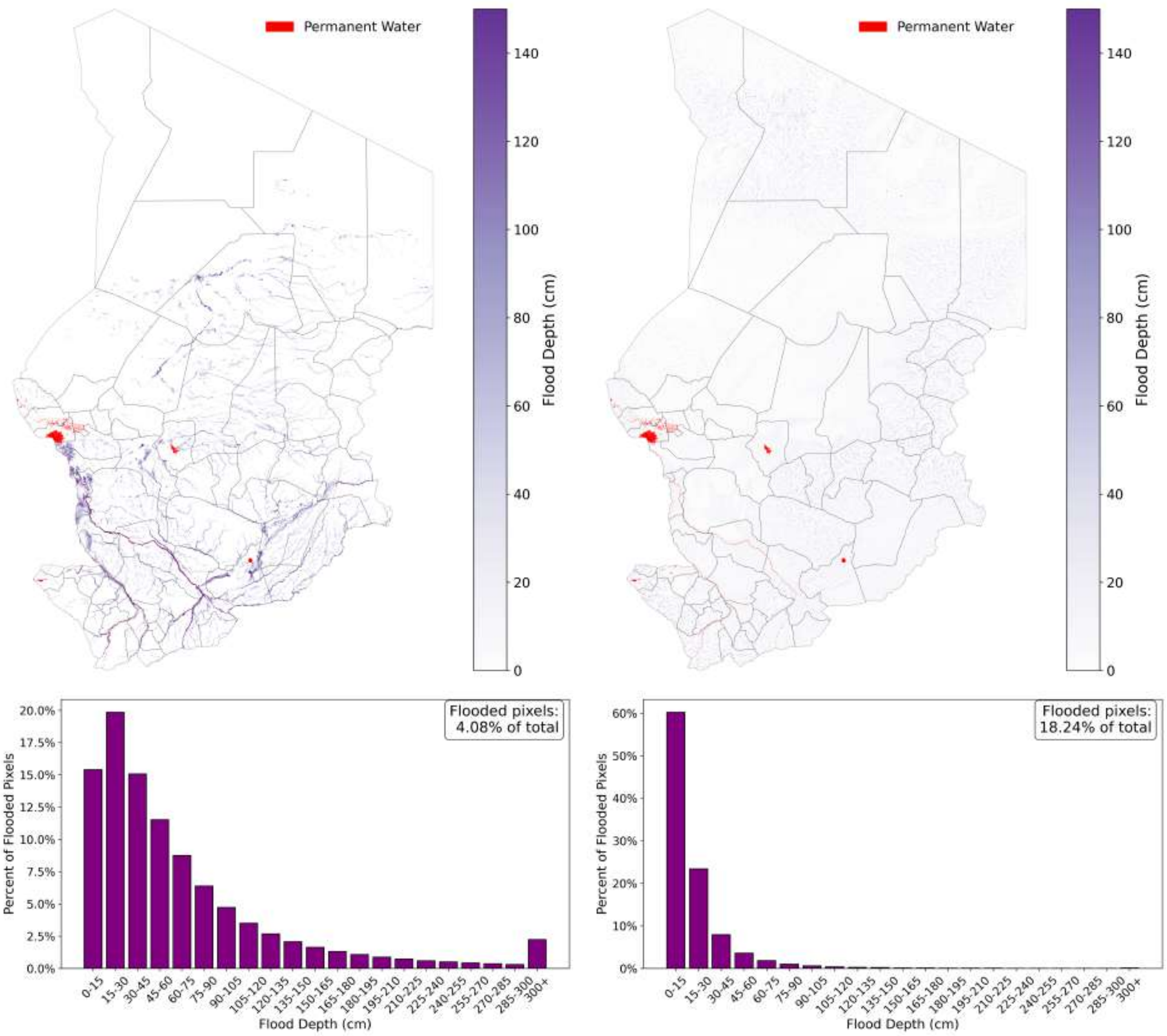
[2]We focus on estimates for defended floods because these likely better represent what would truly be realized on the ground. According to the Fathom Global Flood Map 3.0 methods document, "Known and estimated defence standards are also applied at the same spatial scale as climate change factors, removing floods more frequent than the given design standard. Known defences are generally available in North America and Europe, and so in their absence elsewhere we estimate design standards based on a global flood protection dataset (Scussolini et al., 2016) and degree of urbanisation. Where floods exceed the design standard of a defence, overtopping is represented by calculating the return period of the marginal overtopping discharge" (Fathom, 2022, p. 7).

[3]Administrative boundaries in these maps are from the geoBoundaries database (Runfola et al., 2020). These are the boundaries used in Rogers et al. (2025) to assess changes in flood hazard and impact, and for consistency we therefore use these same boundaries in all maps of flood hazard in this section. For maps showing survey-reported flood incidence at the administrative level 2 (ADM2), we use the 2023 boundaries provided by the Institut National de la Statistique, des Etudes Economiques et Démographiques du Tchad (INSEED, 2025) and hosted on the HDX data portal. These boundary files, which include 70 departments, offer the most recent and comprehensive description of Chad's subnational units currently available, thus ensuring better alignment with recent survey data and current administrative structures. At administrative level 3 (ADM3), the only available and sufficiently detailed shapefile was sourced from the GADM database (version 2.5, July 2015). This dataset was used for finer-scale analysis where ADM3 resolution was necessary.

Though heavy precipitation may also cause damages without resulting in inundation, this type of extreme weather event is considered as distinct from flooding even if it may have the same proximate causes. In this report we focus exclusively on the threat from excess water that results in inundation of dry land, though household reports of 'flood' shocks may conflate inundation and more general water-related damages.

Figure 1: 100-year flood depths in Chad under 2020 conditions (Fathom)

A) Fluvial floods B) Pluvial floods



Note: Authors' calculations based on data from Fathom (2022). Both panels present data on the depth of inundation under 100 year floods in cm, with hazard from fluvial floods on the left in Panel A and hazard from pluvial floods on the right in Panel B (left). On the top of each panel we map out flood depth over space. We cap values at 150 cm to better show the distribution of depths below this level, and represent areas with permanent water in red. On the bottom we present histograms of the distribution of flood depths among pixels with non-0 flood depth.

The map of 100-year fluvial flood depths in Panel A clearly shows how the level of hazard is linked to the locations of lakes and rivers in Chad.[4] Consequently, the highest inundation levels are

[4] Figure A2 shows a map of major rivers in Chad using data from HydroSHEDs (Grill et al., 2019).

found along the Western border below lake Chad at the confluence of the Chari and Logone rivers as well as along those two rivers, their tributaries, and the Salamat river. The 18.3% of pixels at risk of fluvial floods with estimated 100-year depth greater than 105 cm are nearly all concentrated in these areas, with the exception of some areas around wadis in and near the Djourab Depression in Borkou. This hazard analysis is consistent with frequent reports of riverine flooding in these regions during recent flood seasons (FAO, 2023b; IFRC, 2022, 2023; United Nations OCHA, 2022a).

We also consider data on fluvial flood hazard from two databases publicly available through the Google Earth Engine portal. The World Resources Institute (WRI) Aqueduct v2 database provides global estimated water depths for floods under various return periods and climate scenarios at a 1km resolution for large-scale river flows (World Resources Institute, 2025), and are widely used for country hazard analysis. The EU Joint Research Center (JRC) Global River Flood Hazard Maps v1 database provides estimates of flood hazard globally for river systems with basins larger than 500 km^2 for return periods from 10 to 500 years (Baugh et al., 2024), also at a 1km resolution. Both databases exclude purely pluvial floods, and we also observe that they do not identify flooding hazard around small rivers and tributaries identified in shown in Figure 1, justifying our focus on the Fathom data.[5]

Maps of estimated depth of 100 and 10 year floods using the WRI and JRC data are shown in Figure A3 and Figure A4, respectively. The results for 10-year flooding hazard correspond quite closely with maps of 100-year flooding hazard, with uniformly lower inundations depths but the same areas with the highest estimated depths in both scenarios. The 100-year flood depths help to better highlight the full spatial distribution in flooding hazard, supporting our decision to focus on this hazard level. Results using the WRI database align fairly well with those from the Fathom database with similar levels of estimated 100-year flood depth and locations of the most at-risk areas, but identifying hazard along around major rivers. The JRC database has much higher estimated flood depths across the whole country with high flood hazard extending at much greater distances from rivers and lakes, with very high estimated depths across entire departements at the confluence of the Logone and Chari rivers. This suggests that the JRC global flood model may not be as well-calibrated to conditions in Chad.

To further analyze the relative hazard from fluvial and pluvial floods, we use data from Rogers et al. (2025), a recent publication analyzing the roles of climate change and population growth in determining predicted population flood exposure through the rest of the the 21st century. The authors analyze flood hazard using a variety of models at a 90m resolution to capture hazard from fluvial, pluvial, and coastal (from lakes and oceans) flooding.[6] The publicly-available data provided

[5]For reasons we do not understand, the JRC data do not cover the northernmost part of Chad.

[6]The fluvial model uses "a cascading sequence of hydrologic and hydraulic simulators that derive depths within a river network by routing daily runoff from a suite of 27 simulations of the CMIP6 suite of GCMs" (p.8). The pluvial model "was forced by global extreme precipitation projections derived from CMIP6 GCM results" and "combined an efficient fill-spill-merge (FSM) algorithm that infills low areas with a modified rational method model used in combination with Manning's equation to approximate overland flow depth" (p.8). The coastal/lake model "used multiple climate projection datasets to estimate the effects of sea-level rise and storm surge, tides, and waves on coastal inundation, as well as storm surge and lake levels on lake shoreline inundation" (p.7). The For both the fluvial and coastal flood models, the floodplain inundation model "was based on the Height Above Nearest Drainage

by the authors is aggregated to the admin-2 level globally and focuses exclusively on hazard and exposure from floods with 100-year inundation depth of at least 10 cm, but nevertheless allows us to map spatial variation in flood hazard by flooding type across Chad.

The first row of Figure 2 presents the total area by departement estimated to suffer at least 10 cm of inundation depth during 100-year floods in Chad under 2020 conditions across all flood types (Panel A) and separately for fluvial (Panel B) and pluvial (Panel C) floods.[7] The results should therefore be interpreted as representing land exposure to moderate flooding, though in the case of Chad a large portion of this exposure will include areas at more regular hazard of more severe floods. As with the results from the Fathom database, the figure shows that the greatest flood hazard is in the southern half of Chad. This is particularly striking when presented in terms of the percentage of departement area exposed to floods (second row), with over 40% of land area exposed in a large number of departements, notably in Lac, Hadjer-Lamis, N'Djamena, Chai-Baguirmi, Mayo-Kebbi Est, Tandjile, Moyen-Chari, and Salamat provinces.

The figure further emphasizes that while pluvial flooding does contribute to overall flood hazard in Chad, and is a relatively more important hazard in the arid north, the main driver of flood hazard is fluvial flooding, indicating that a focus on riverine floods should reveal the locations with the greatest estimated flood hazard. While large land areas are exposed to pluvial floods, at the departement level the shares of area exposed are uniformly small. As shown in the Fathom data, these exposed areas also largely represent locations with inundations depths not much greater than 10 cm from 100-year return period pluvial floods, whereas the inundation depths for many of the areas exposed to fluvial floods are much greater.

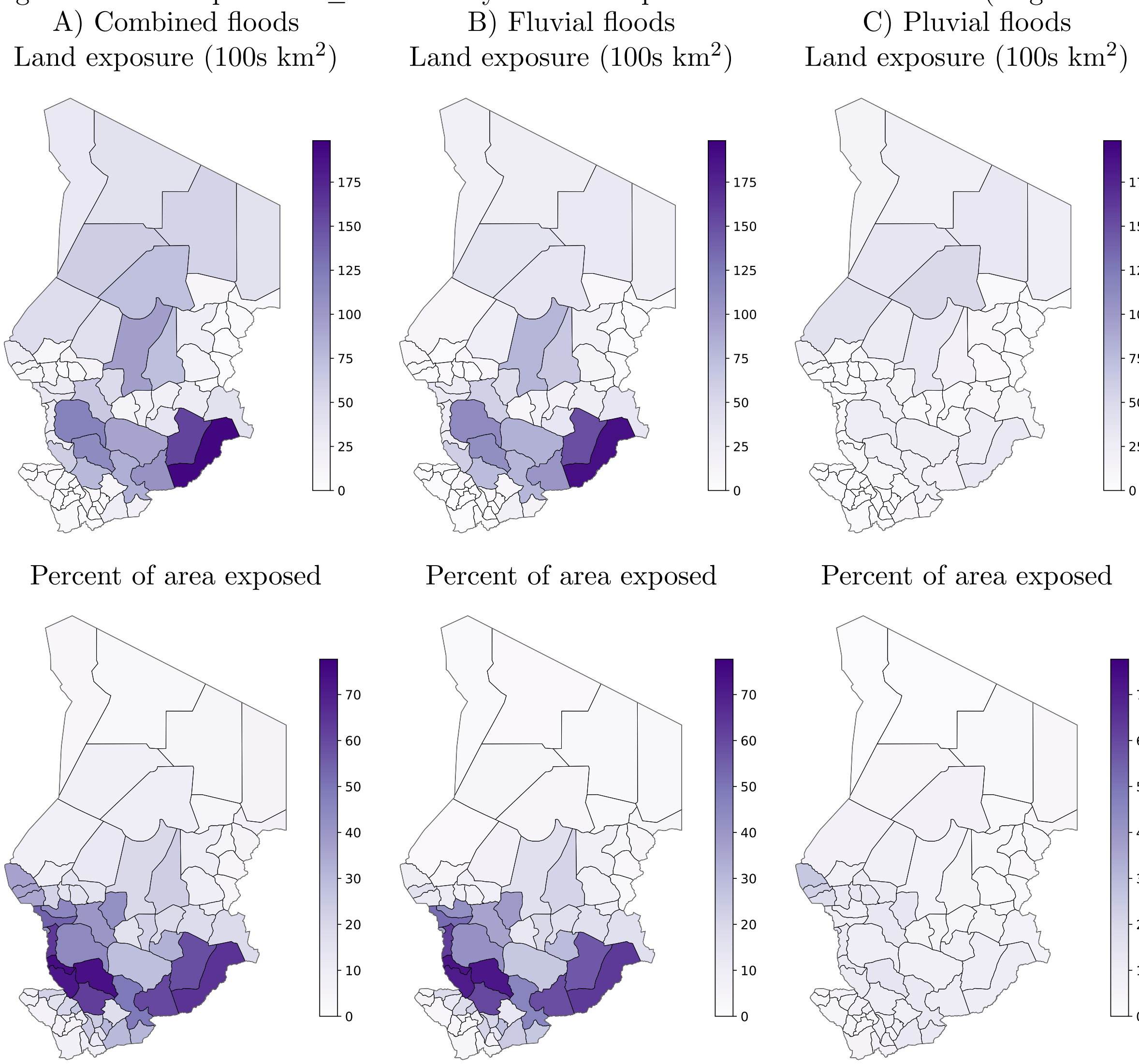
2.1.2 Mapping flood exposure in Chad

Flood hazard alone is not sufficient to determine appropriate policy responses, so flood risk assessments also consider human and natural consequences in terms of both exposure and vulnerability. *Exposure* relates to the human elements—population, infrastructure, economic activity—affected by a given level of flood hazard. *Vulnerability* measures susceptibility to damage under a given flood event, which is a function of both exposure and any measures used to mitigate or recover from flood damages. While data on vulnerability to flooding is scarce in the context of Chad, data on the distribution of population allows estimates of flood exposure. Exposure can also be analyzed in terms of economic activity, agricultural land, and more, but in this report we focus on population exposure which broadly captures where people are at higher risk from floods regardless of their economic activities. An understanding of flooding population exposure is critical for identifying priority areas for flood risk prevention, mitigation, and response particularly in the context of social protection programs, whereas economic development programs might be more concerned with economic exposure.

(HAND) algorithm, which applies flood levels of constant elevation along flow paths" (p.8). Additional detail on the methods are included in the paper (Rogers et al., 2025).

[7] Coastal/lake flooding contributes minimally to flood hazard in Chad except in very specific areas, so we do not show it separately.

Figure 2: Land exposed to ≥10 cm 100-year flood depths under 2020 conditions (Rogers et al)



Note: Authors' calculations based on data from Rogers et al. (2025) provided at the admin-2 level. Flood exposure is defined as estimated depth of 100-year floods of at least 10 cm.

Rural communities are vulnerable to flood damages due to their reliance on rain-fed agriculture and often less durable dwelling materials, but the greatest population exposure to flood risk is in urban areas. Chad's urban population more than doubled between 1995 and 2015 (UNDESA, 2018). A large share of the population remains rural but there is increasing migration to urban areas, most of which are in close proximity to rivers and lakes and therefore face greater flooding hazards. For example, N'Djamena is located at the confluence of the Chari and Logone rivers. But also, many of the areas settled by recent arrivals in urban areas are in low-lying, flood-prone zones. Population growth in such areas contributes to high flood exposure.

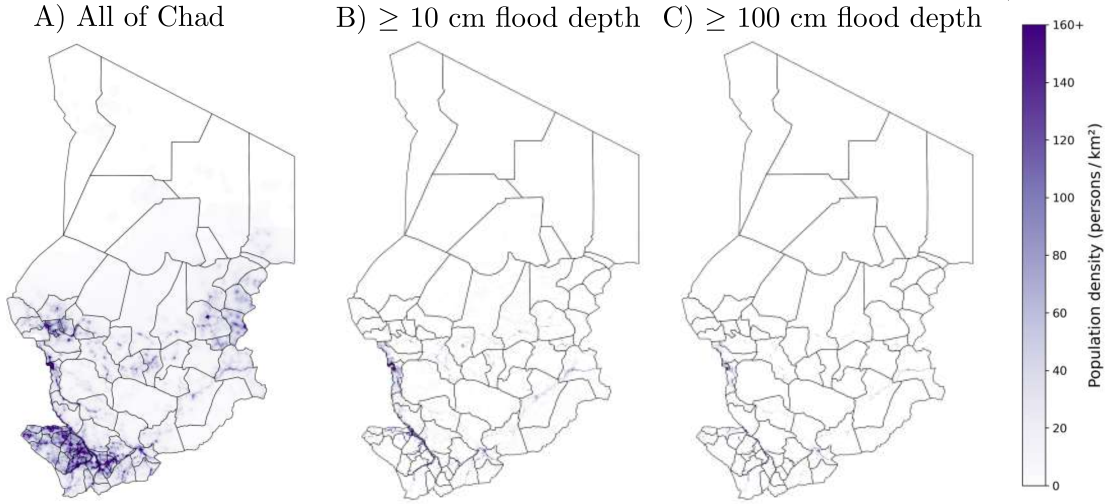
In addition to having higher populations in areas of higher flood hazard, other factors are also contributing to high vulnerability of populations in urban areas: unregulated build-up in high flood hazard zones, inadequate infrastructure, and land degradation (World Bank, 2023). Urban infrastructure, in particular for water drainage and flood management, is inadequate to meet the growing flooding hazards due to climate change and the growing needs from increasing populations, many of which reside in informal structures more vulnerable to flooding. Finally, deforestation and land degradation around settled communities is reducing natural sources of flood protection, compounding the increasing risk from urbanization. These characteristics contribute to making Chad the country rated as most vulnerable to climate change in the world (ND-GAIN, 2025).

To highlight the areas with the highest populations exposed to flood risk, we combine data from Fathom with data from WorldPop (2025). WorldPop provides 1 km gridded population density estimates for the year 2020 based on data on administative unit-based census counts together with detailed geospatial datasets used to disaggregate the data to a grid level. Population density is computed by dividing the estimated population by cell area. Chad last completed a census in 2009, meaning subnational variation in migration, fertility, or mortality could create uncertainty in the 2020 population projections, but the WorldPop data are considered to be among the most accurate available disaggregated sources of population data (Bai et al., 2018; Thomson et al., 2022).

Figure 3 maps population density data from WorldPop in areas with a particular level of flood hazard, showing all land area and then only areas with 100-year fluvial flood depths of at least 10 and 100 cm. The maps show clearly that although flood hazard is widespread in Chad, population exposure is concentrated primarily in particular departements. The area around and between the Logone and Chari rivers stands out as combining both high flood hazard and high population exposure.

Figure 3: Population density exposed to different 100-year fluvial flooding hazards (Fathom)

A) All of Chad B) $\geq$ 10 cm flood depth C) $\geq$ 100 cm flood depth



Source: Authors' calculations based on data from Fathom (2022) and WorldPop (2025). Flood hazard is based on the estimated depth of 100-year fluvial floods under current conditions.

Rogers et al. (2025) combine their flood hazard model results with population data from the Gridded Population of the World project (Center for International Earth Science Information Network - CIESIN - Columbia University, 2018) and projections from the United Nations World Population Prospects medium variant projection to estimate population exposure to moderate flood risk (100-year floods of at least 10 cm) globally at the admin-2 level. Figure 4 shows that the results are quite similar to those in Figure 3, highlighting the same departements as being the areas with the greatest population exposure. The figure reveals that hundreds of thousands of people are exposed to 100-year floods over 10 cm in depth in many departements in Chad, and particularly in the southern part of the country. In total, over 25% of the population—4.2 million people—are at risk of such floods across all of Chad (Table 1). These populations are largely concentrated in densely populated towns in the south and west; N'Djamena alone includes 538,000 people exposed to this level of flood risk, partly due to rapid urban growth in flood-prone zones (Croix-Rouge du Tchad (CRT), 2024a, 2024b).

Exposure in the more arid north is limited due to both lower flood hazard and limited population in these areas. Of these 4.2 million people at risk of at least 10 cm of inundation under 100-year floods according to Rogers et al. (2025), 3.6 million are exposed to this risk from fluvial floods and 1.3 million are exposed to this risk from pluvial floods, indicating that 0.7 million are exposed to at least moderate risk from both types of flooding. The population exposure to pluvial floods is thinly spread across the country and hard to detect visually (Panel C, top row) while exposure to fluvial floods is by definition concentrated in areas with rivers and therefore easier to identify in the Figure.

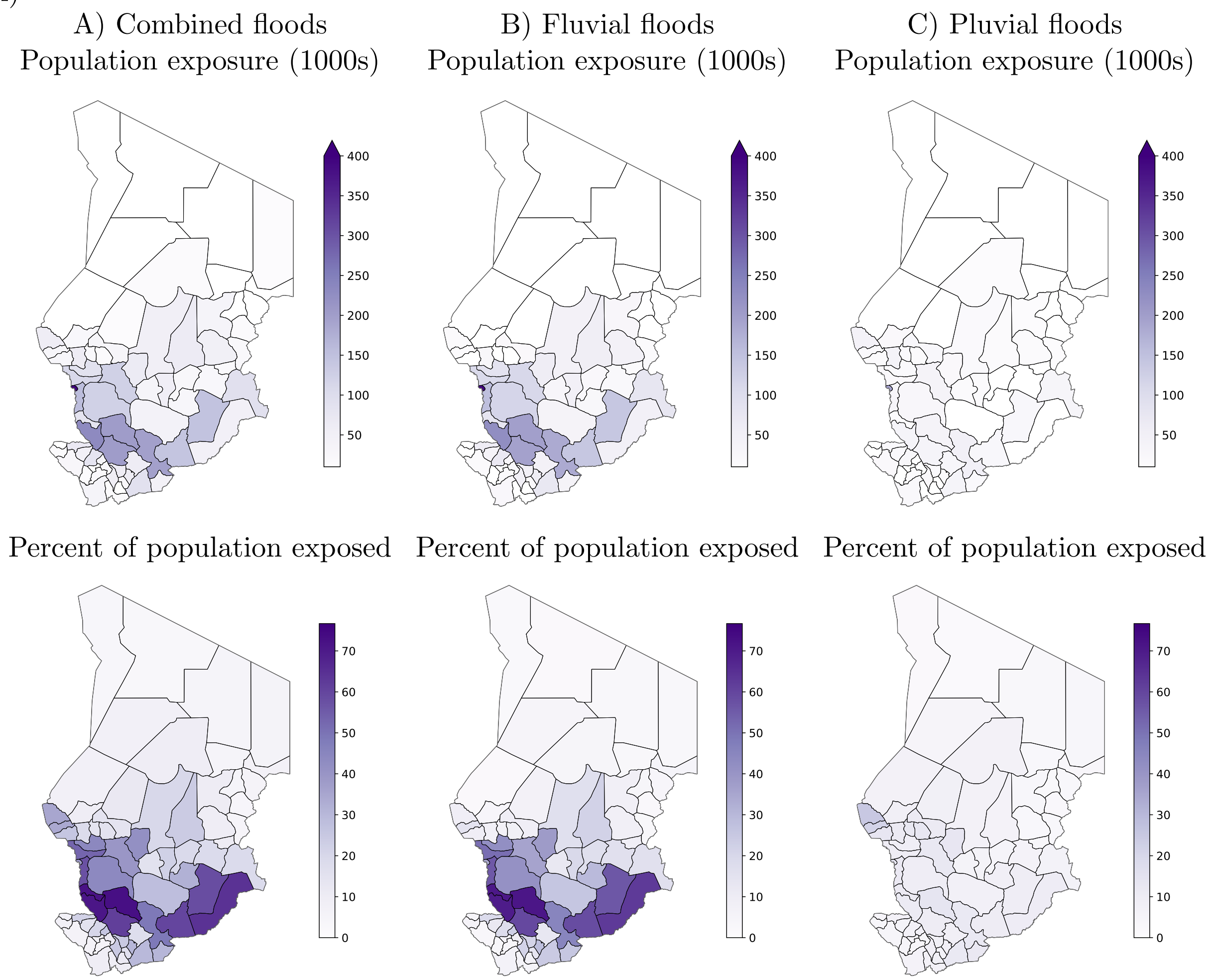
The second row of Figure 4 shows the shares of total departement population exposed to 10 cm 100-year floods. These figures emphasize the high levels of exposure in certain southern departements. Although the absolute populations exposed are much smaller than the exposed population in N'Djamena, nine departements have over 50% of their population exposed to this level of flood risk: Loug Chari, Mayo Lemye, Mayo Boneye, Haraze Manguiegne, Tandjile Est, Lac Iro, Bahr Azoum, Chari, and Haraze Al Biar. The median departement has 18% population exposure. This aligns with research from Rentschler et al. (2022), which shows that the share of the population in Chad exposed to 100-year floods of at least 15 cm is among the highest in the world, with the highest exposure in the southern provinces (Figure A5).

We calculate additional departement-level measures of population flood exposure using the data from the WRI, combining these with administrative boundary data from Runfola et al. (2020) and use 1 km resolution population data from Center for International Earth Science Information Network - CIESIN - Columbia University (2018) to identify the population exposed to 100-year floods of at least 10 cm (Figure A6). We note that exposure measures are likely to be sensitive to the choice of population data, but we use the same population data as Rogers et al. (2025) for comparability.[8] The WRI database suggests population exposure is greatest around Lake Chad, Lake Fitri and N'Djamena. In general, it yields lower exposure estimates than the Rogers et al. (2025) estimates. This is likely because the WRI flooding model only includes fluvial risk along major rivers while the Rogers et al. (2025) model considers all fluvial and pluvial flooding risk.

Despite these differences, all three sources—Fathom, Rogers et al. (2025), and WRI—point to the same conclusions: the Lake Chad basin, the capital N'Djamena, the Logone basin (Mayo

[8]We use data from WorldPop (2025) when mapping population exposure to satellite-detected floods as some research suggests these data may be more accurate than the GPW population data.

Figure 4: Population exposed to ≥10 cm 100-year flood depths under 2020 conditions (Rogers et al)



Note: Authors' calculations based on data from Rogers et al. (2025) provided at the Admin-2 level. Flood exposure is defined as estimated depth of 100-year floods of at least 10 cm.

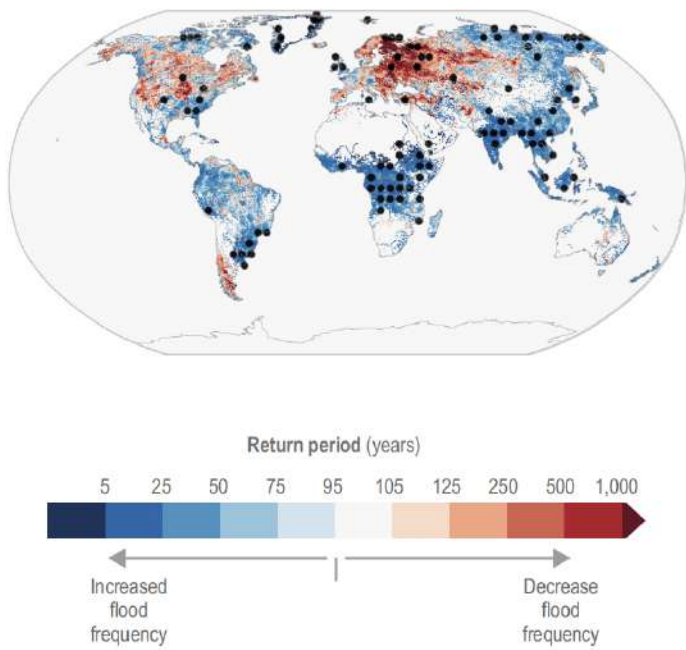
Kebbi, Tandjilé), and the Chari basin (Moyen-Chari, Mandoul) stand out as areas combining high inundation depths under 100-year floods and high populations, leading to greater population exposure.

2.2 Looking forward: increasing flood risk

Globally, climate change is expected to increase flood hazard by increasing the variability of rainfall and the frequency of extreme rainfall events, while population growth in floodplains increases the number of people potentially exposed to flooding (Pörtner et al., 2022; Rogers et al., 2025). Changes in infrastructure and flooding defenses will affect vulnerability to flooding but are difficult to model. On the other hand, climate change and population growth projections can be incorporated into flood risk models to estimate changes in flood risk over the coming decades.

Considering first how climate change is affecting flood hazard, Figure 5 illustrates that floods causing a depth of inundation that we would expect once every 100 years under current conditions are expected to become more frequent across most of the world by the year 2100. The increases in flood hazard are greatest in developing countries, including notably in sub-Saharan Africa.

Figure 5: Projected changes in flood hazard from 2017 to 2100



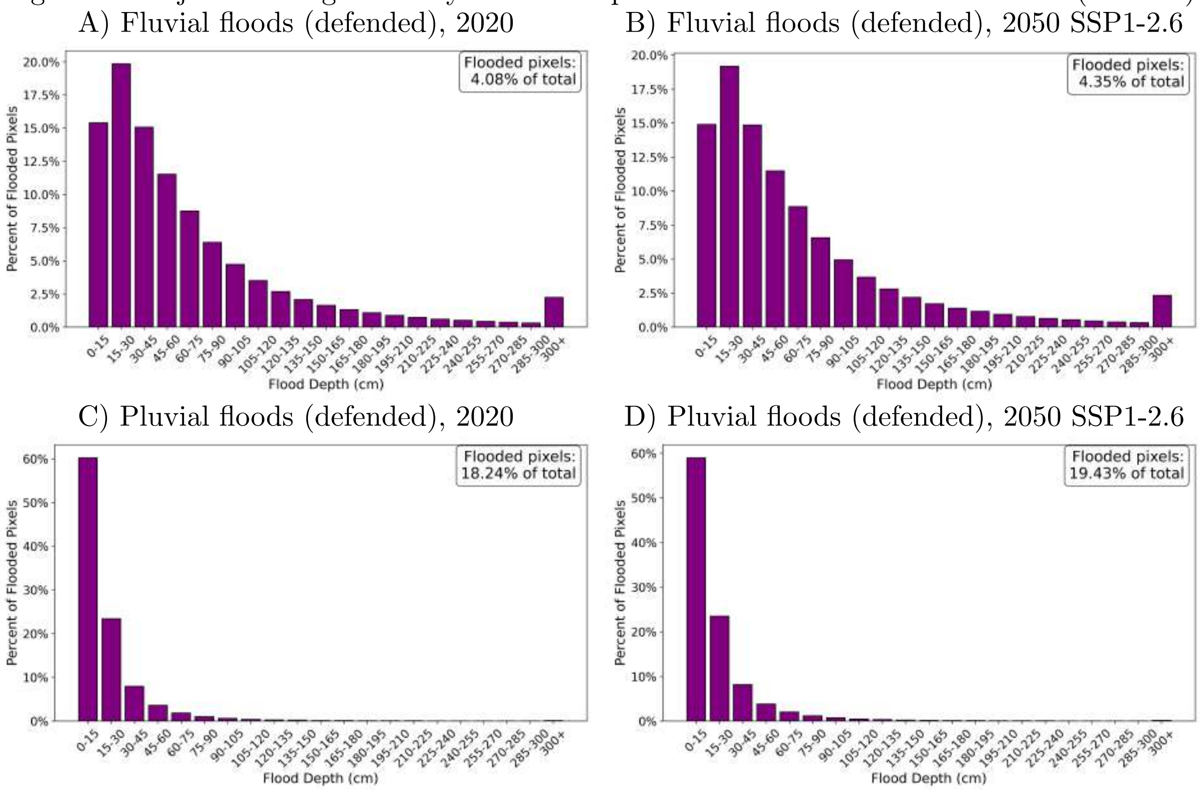
Note: Figure from Pörtner et al. (2022). The figure illustrates the change in the return period for a flood with the inundation depth of a 100-year flood in 2017.

To evaluate predicted changes in flood hazard for Chad specifically, we use data on 100-year floods under 2050 conditions from Fathom, Rogers et al. (2025), and the WRI database. For each database we consider predictions based on climate change and population growth scenario from the IPCC Sixth Assessment Report on climate change. In particular we consider the 'sustainable development scenario' SSP1-2.6, in which global CO_2 emissions decrease strongly, economies shift toward sustainable development practices, and the temperature increase stabilizes at around 1.8° by 2100, as well as the 'middle of the road/business as usual' scenario SSP2-4.5, in which CO_2 emissions remain stable before beginning to decrease around 2050, socioeconomic factors do not change significantly, and temperatures increase by 2.7° by 2100. While patterns of climate change and population growth may deviate from these scenarios, they is illustrative of potential future flood risk conditions.

Figure 6 shows that calculations based on the Fathom models and projected climate change and population growth predict limited increases in flood hazard between 2020 and 2050. We consider the SSP1-2.6 scenario as data on defended fluvial and pluvial flood hazard under the SSP2-4..5 scenario in Chad was not provided by Fathom. The share of pixels exposed to fluvial floods will increase from 4.1% to 4.4%, and median depth of 100-year floods increases from slightly under to slightly over 45 cm consistent with a slight rightward shift of the distribution of inundation depths. For fluvial floods, the share of pixels exposed to any flooding will increase from 18.2% to

19.4%—a larger absolute increase but a slightly smaller relative increase—and the median 100-year flood depth remains between 10-15 cm. Looking at data for undefended fluvial floods as data on SSP2-4.5 scenario were not provided for defended fluvial floods, we find that the increased hazard is similar under climate change scenarios SSP1-2.6 and SSP2-4.5 (Figure A7). The share of exposed cells increases from 4.1% to 4.4% and 4.5% respectively and median flood depth is only slightly greater under SSP2-4.5 despite this being a less optimistic climate change scenario.

Figure 6: Projected change in 100-year flood depths in Chad under 2050 conditions (Fathom)

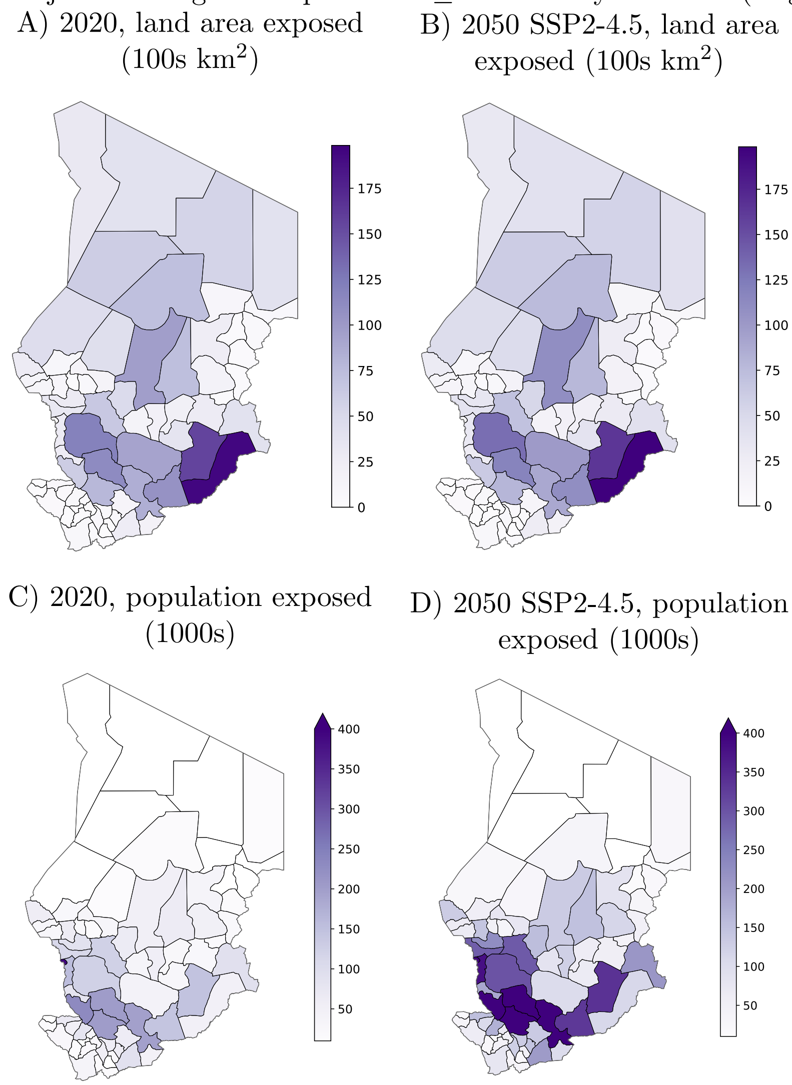


Note: Authors' calculations based on data from Fathom (2022). Each panel presents data on the depth of inundation under 100 year floods in cm for fluvial and pluvial floods separately. The data in panels B and D are projections of changes in flood hazard under climate change and population growth scenario SSP1-2.6 from the IPCC Sixth Assessment Report on climate change.

Data from World Resources Institute (2025) which primarily captures fluvial flooding, shows larger predicted increases in depths of 100 year floods than the Fathom data (Figure A8). The largest predicted increases are in Bahr el Gazel, Borkou, and Kanem provinces. We place greater confidence in the Fathom data and predictions but these differences, related to different modeling choices and input data, show there is some uncertainty in how flooding risk will evolve in Chad and that increases in flood hazard may be large in certain areas.

Figure 7 presents results from Rogers et al. (2025) considering both fluvial and pluvial flooding together showing projected changes in the area and population exposed to 100-year floods of at least 10 cm between 2020 and 2050 SSP2-4.5 conditions. In total, the area exposed to floods of such a depth is predicted to increase from 226,000 km^2 to 238,000 km^2. This represents an increase from 17.9% to 18.9% of Chad's land area, similar to the changes in exposure to pluvial flood risk in Figure 6. The largest increases in exposure under this model are predicted around Lake Chad and the Chari river basin, though in general these increases are small and spread across many departements so are hard to detect visually (first row of Figure 7). The Fathom data suggests that much of this change is due to small increases in inundation depths in areas with currently small risk of flooding, with a smaller share due to areas newly at risk of inundation.

Figure 7: Projected changes in exposure to ≥10 cm 100-year floods (Rogers et al)



Note: Authors' calculations based on data from Rogers et al. (2025). The figure compares population flood exposure from all flood types under 2020 conditions (Panel A) compared to 2050 climate and population conditions projected under SSP2-4.5 (Panel B). Flood exposure is based on 100-year floods causing at least 10 cm of inundation depth.

In addition to increases in flood hazard, population growth will affect exposure to floods in coming decades. Most of projected population growth between now and 2050 is expected to come from developing countries, with 26 African countries—including Chad—expected to at least double in population between 2017 and 2050 (UNDESA, 2017). Current population exposure to floods is greatest in South, East, and Southeast Asia but the largest increases in coming decades are predicted to occur in South Asia and sub-Saharan Africa, with certain parts of the world experiencing decreases in exposure (Figure A9).

Rogers et al. (2025) analyze the relative contribution of changes in flood hazard and population to determining future flood exposure, and find that 77% of changes in exposure by 2100 globally are due to population growth, compared to 21% due to climate change (and 2% to a combination of the two). This results can be seen directly from Figure 7, where we observe limited changes in area at risk of 10 cm 100-year flood depths in the top row while the bottom row shows large increases in population exposure across most of Chad, with the greatest increases along the Chari river basin. The authors' calculations indicate that the population exposed to this level of flood risk will more than double from 4.2 to 9.9 million people, compared to just a 5% increase in the area exposed.

Table 1 shows the ten departements with the highest levels of population exposure to floods in Chad. As most of the forecast population growth is expected to take place in urban areas that already have the largest population flooding exposure, these departements are the same when considering exposure under 2020 and 2050 conditions. The fraction of the population exposed in each departement is also only forecast to increase slightly (Figure A10), indicating that the predictions are based on similar rates of population growth inside and outside of high flood hazard areas. These results indicate that flood protection interventions targeting areas with the highest current levels of flood exposure will also be useful in protecting against projected increases in flood risk over time.

Table 1: Departements with greatest exposure to ≥10 cm 100-year floods

	2020 conditions				2050 SSP2-4.5 conditions			
Departement	Pop. (1000s)	Pop. (%)	Area (1000s km^2)	Area (%)	Pop. (1000s)	Pop. (%)	Area (1000s km^2)	Area (%)
Baguirmi	123.72	43.85	11.98	44.26	299.93	48.24	13.18	48.70
Bahr-Azoum	145.93	58.34	15.62	58.64	338.66	61.45	16.45	61.76
Bahr-Köh	195.88	48.82	8.49	49.45	453.93	51.35	8.93	52.01
Chari	156.54	57.28	2.77	63.86	380.70	63.22	3.04	70.24
Dababa	122.83	39.70	6.48	40.11	293.06	42.99	7.02	43.44
Lac Iro	143.95	59.91	10.57	60.43	330.11	62.36	11.00	62.90
Loug-Chari	202.36	72.81	11.21	73.74	469.47	76.67	11.81	77.69
Mayo-Boneye	231.11	71.02	6.09	72.04	527.20	73.53	6.30	74.59
N'Djaména	538.09	38.41	0.17	42.26	1412.12	45.75	0.21	50.95
Tandjilé Est	202.50	61.50	7.77	62.57	456.78	62.97	7.96	64.07
Total	**4176.85**	**25.50**	**225.93**	**17.95**	**9852.03**	**27.30**	**238.24**	**18.93**

Note: Authors' calculations based on data from Rogers et al. (2025). Flood exposure is based on 100-year floods with at least 10 cm of inundation depth combined across all flood types.

The large increases in population exposure despite limited increases in flood hazard emphasize that population growth is the main driver of predicted exposure to flooding going forward in Chad.

Predicted increases in flood risk may not be realized if efforts are made to prevent or mitigate flood exposure. Improved communications, investment in flood defenses, water management infrastructure, and improved housing, and support for relocation or protection of informal settlements in areas with high flooding hazard could reduce vulnerability to flooding even as flood hazards and the exposed population increase. A review of efforts that are being undertaken to attempt to respond to floods and reduce flood vulnerability in Chad is outside of the scope of this report, but we present a general overview of selected key stakeholders in flood management in Chad in Appendix C.

3 Incidence of flooding

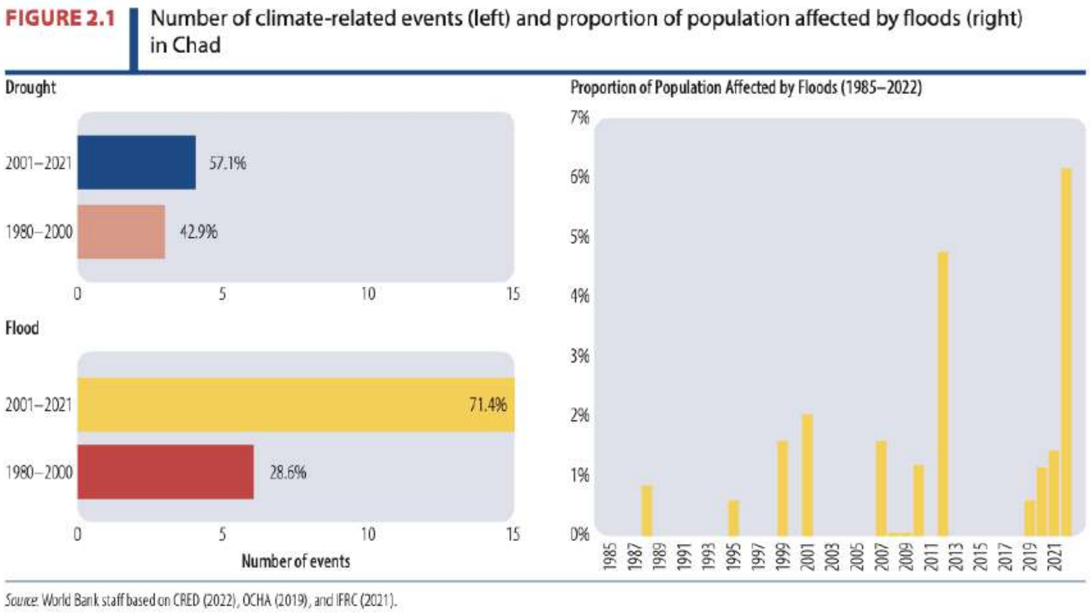
The analysis of predicted flooding hazard and exposure is useful for identifying the areas at greatest risk of future floods under different climate change scenarios. Another approach to analyzing flooding risk is to consider historical incidence of flooding. Areas that have experienced more frequent or more severe flooding may also be at higher risk of future floods, particularly for areas exposed to multiple or recurring floods. Considering flooding incidence also provides an opportunity to validate flood risk predictions by considering whether flood realizations are indeed more concentrated in areas with higher flood hazard.

Historically, flooding in Chad was an infrequent event but it has now become an almost annual occurrence, due to both climate change and shifting precipitation patterns as well as population growth in flood-prone areas (Government of Chad, 2023c; IRD, 2024; United Nations OCHA, 2024a). Over the past three decades, Chad has experienced several major floods, with the 2022 and 2024 floods considered the most severe since 1961 (Government of Chad, 2014, 2023b, 2023c). Figure 8 illustrates how major reported flood events have been increasing over time from 1980-2021, with 71% in the last 20 years in contrast to major drought events which have been more stable in frequency over this period. Data on flood events from the International Disaster Database EM-DAT (Guha-Sapir et al., 2023), based on official and media reports, shows similar patterns of increasing population exposure over the last 25 years (Figure A11).

In addition to increasing annual frequency, the extent of flooding has expanded, with some areas experiencing more than 120 days of annual flooding in recent years, a significant increase from previous decades (FAO, 2023b, 2023d). Moreover, flooding seasons have begun earlier in recent years, with major river overflows now occurring before historical peak rainfall periods (FAO, 2023c, 2024a). In 2024, for example, heavy rains had already started causing flooding in early July, whereas the flooding season typically begins in August.

Data from the Chad Direction des Ressources en Eau (DRE) on river flows through selected hydrological stations going back to 1985 illustrates how river flows have changed over time. Figure 9 presents monthly water flows averaged across stations over five year periods. We observe that average water levels have increased significantly for all months relative to the period from 1985-1994. The largest absolute increases are seen in the months of greatest flooding risk in Chad and

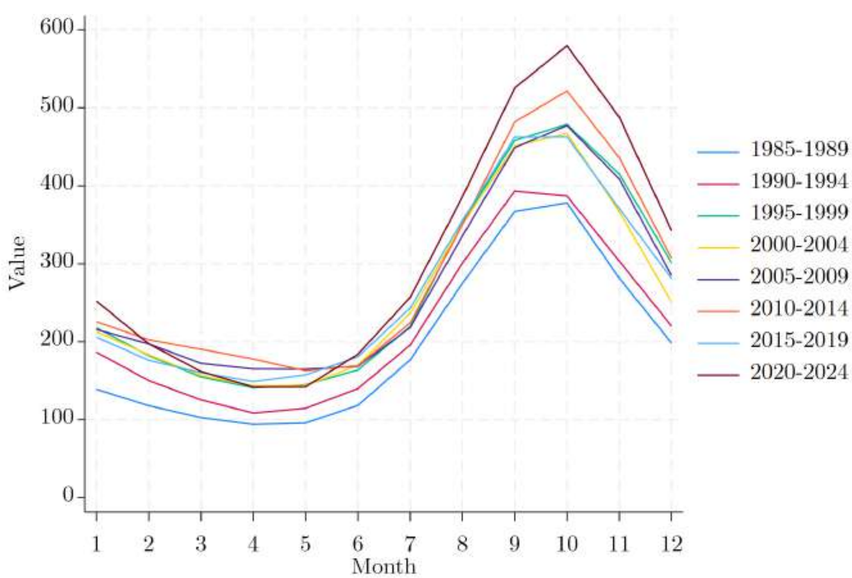
Figure 8: Historical exposure to flooding in Chad



Note: Figure from World Bank (2023).

particularly from September to November. The most recent period from 2020-2024 stands out as having the highest average water flows during the flooding season, consistent with these being a period with multiple years of widespread flooding in Chad.

Figure 9: Average water flows across stations by month, over time



Note: Authors' analysis based on data obtained from the Chad Direction des Ressources en Eau (DRE). The original data are station-level monthly average water flows by year. We take the average by month across all stations in each year, and then the average of these values for each five-year period to better illustrate changes over time. Annual averages are shown in Figure A12.

Higher average water levels across all periods of the year over time are consistent with increasing fluvial flood hazard in Chad. This pattern would appear to be inconsistent with research that has found stagnant or decreasing trends for total precipitation levels in Chad since at least the 1950s (Mahmood et al., 2019; Pattnayak et al., 2019). But changes in land use, land cover, and water management can lead to more precipitation making its way into rivers even as precipitation falls, and this could be an important reason for fluvial flooding being a much greater hazard in Chad than pluvial flooding. Farmland expansion, urbanization, deforestation, and soil degradation have all been documented in Chad in recent decades (CIAT et al., 2021) and could all lead to increased surface water runoff.

The increase in flooding hazard over time has resulted in larger areas and populations being reported as affected by flooding. Some of this increase may be due to better monitoring and reporting of floods over time, but available sources agree that more recent floods have been more damaging. Table 2 summarizes evidence on the aggregate effects of flooding for selected recent major flood events. We note that the numbers presented in this table are just estimates of flooding damages, and that there is disagreement across sources. The 2024 floods in Chad have the highest reported population affected, area flooded, and number of houses destroyed, followed by the 2022 floods.

The 2022 floods impacted 19 of Chad's 23 provinces, with the most affected areas including Mayo-Kebbi Est, Logone Occidental, Tandjilé, Mandoul, and N'Djamena. Multiple sources report that Mayo-Kebbi Est and Tandjilé were among the hardest hit in terms of population affected, with the Lac province also experiencing a high number of displaced people (FAO, 2023b; Government of Chad, 2023b; IFRC, 2022, 2023; United Nations OCHA, 2022a). In total 1.4 million people were affected, 465,030 hectares of farmland flooded, 80,000 houses destroyed, and 20,000 cattle lost (Government of Chad, 2023b, 2023c; United Nations OCHA, 2022a).

Table 2: Summary of reported effects of recent major flood events

Year	Affected population	Flooded land (ha)	Houses destroyed
2012	466,000[a] - 613,631[f]	255,000[a]	96,000[a]
2014	8,000[a]	–	–
2019	171,000[a]	18,000[a]	2,700[a]
2020	36,934[d] - 388,000[a]	150,000[a]	–
2021	255,000[a] - 269,180[d]	–	–
2022	1,100,229[d] - 1,426,948[b]	465,030[b]	80,000[b]
2023	–	18,130[a]	2,700[a]
2024	1,945,674[d] - 2,000,000[c]	1,862,800[e]	218,000[c]

[a] OCHA, 2012, 2014, 2019, 2020, 2022, 2023.
[b] Government of Chad, 2023c. [c] ACAPS, 2024. [d] Guha-Sapir et al., 2023 (EM-DAT). [e] FAO, 2024b.

In 2024, water levels along the Chari-Logone system reached or surpassed the peaks recorded during the devastating 2022 floods (IFRC, 2024; IRD, 2024; UNICEF, 2024). Flooding intensified in this region compared to 2022 but was also more widespread, affecting nearly all departements in Chad. As of October 1, 2024, around 2 million people were affected, 576 fatalities recorded, 432,203 hectares of cropland were destroyed, and over 72,170 heads of livestock lost. In addition, 217,779 homes were demolished resulting in the displacement of 342,471 households (IFRC, 2024; MASSAH, 2025; United Nations OCHA, 2024b, 2025).

While this aggregate view of flood realizations and damages from government and media reports is useful to establish a broad perspective of the evolution in flooding incidence in Chad, it is less helpful for understanding geographic variation in flooding incidence and therefore to identify the most at-risk areas. Moreover, these sources often have better coverage of flood exposure in more populated areas and worse in remote areas. Flood event databases focusing on major reported floods include the International Disaster Database (EM-DAT), the Global Flood Monitor, DesInventar Sendai, the Dartmouth Flood Observatory (DFO) Archive, and the Global Flood Database (Table A2). These vary in the level of geographic detail they provide on flood events but most do not go below the admin2 level. They are also not updated frequently and include only a subset of total flood events. Patel (2025) for example finds that the DFO reports over 800 more country-years with flood events than does EM-DAT while EM-DAT lists nearly 800 floods not included in the DFO, and that the databases are more likely to miss smaller floods and floods in lower-income areas. We find that the EM-DAT archive lists no flood events in Chad in 2019 or 2023 (Figure A11) although other sources document important localized flooding in both of these years.

A variety of other data sources may be used to detect flooding incidence, as summarized in Table 3. Survey reports can provide a local and direct measure of flooding experiences, similar to the type of information that may feed into government and media reports. An advantage of using survey data is that it directly measures flood exposure, whereas the other measures described above only proxy for flooding, though what is measured depends on how questions about flooding are asked and reports are subject to human error. In addition, while surveys can ask retrospectively about flooding over a given time period, survey data are restricted to a limited number of points in space and time. Extreme precipitation is associated with increased risk of flooding, but challenges in accurate measurement of local precipitation over space together with the fact that rainfall may increase flood risk downstream rather than where the rainfall is realized make it an imperfect proxy of flooding. River flow data such as the DRE data presented in Figure 9 can show when river levels are unusually high, a potential indicator of elevated flooding risk, but are restricted to only a few locations in space.[9] Finally, remotely-sensed data—in particular data collected by satellites—is increasingly being used in flood detection thanks to algorithms that allow the detection of surface water. These data are now available at high spatial and temporal frequency, but are limited in terms of the types of flooding events they can detect and in their accuracy.

Numerous sources have begun tracking and reporting on flooding in Chad in recent years,

[9] Figure A13 maps station-level average water flows for the August-November period over time.

Table 3: Comparison of general flooding incidence data sources

Data source	**Advantages**	**Disadvantages**
Media/ government/ other published reports	Usually validated on the ground; often include data on human and economic impacts	Usually limited geographic detail; many flood events not documented; limited historical coverage
Survey reports	Validated measure of exposure; high geographic detail; often include data on human and economic impacts	Measurement differences across surveys, confounding of precipitation and inundation shocks; typically identifies only affected households and not general exposure; only available at selected points in space and time
Precipitation	Key driver of flood incidence, may also cause direct damage; estimates available at high resolution over many decades	Does not measure inundation; challenges in accurate measurement of local precipitation, especially in remote areas
River flows	Validated indicator of fluvial flood hazard; ability to compare over time	Not a direct measure of inundation outside a river; only available at a small number of points in space
Remote sensing (satellites)	High-frequency and high-resolution detection of surface inundation	May miss certain floods (short duration; in urban or forested areas) or misidentify inundation (seasonal/anticipated water fluctuations, bare earth)

Note: Authors' summary based on information provided by each source.

often combining data from government sources with other measures of flood incidence, notably remotely-sensed measures. The World Food Programme now publishes regular flooding bulletins using information from the Advanced Disaster Analysis & Mapping (ADAM) database, overlaid with spatial population and land cover data to estimate exposure and impacts (see Figure A14 for example). The ADAM database uses publicly-available VIIRS and MODIS satellite imagery and Sentinel-1 satellite radar together with paid Floodscan near real-time remotely-sensed incidence maps. The United Nations Food and Agriculture Organization (FAO) Data in Emergencies Monitoring (DIEM) conducts household surveys in emergency settings and also publishes reports which combine data from the ADAM database with other sources. The United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA) produces reports that aggregate data from government sources and local NGOs (see Figure A15 for example). Other sources, including government agencies and the Chadian Red Cross, also publish reports on flooding in Chad, but none of these sources provide public access to the underlying data to support analysis.

In the following sub-sections, we present data on incidence of flooding as reported in various household surveys in Chad and as detected using satellite data, test the correlations in flood detection across survey and satellite sources, and use satellite data to identify 'hot spots' for recent

Key flood incidence data sources
ENSA surveys (Enquête Nationale sur la Sécurité Alimentaire): nationally-representative for rural communities, conducted annually; data from 2016-2024 obtained from SISAAP
ECOSIT surveys (Enquête sur les Conditions de vie des Ménages et la Pauvreté au Tchad): nationally-representative; data from 2018-19 and 2022 obtained from INSEED
VFM Archive (NOAA/George Mason University VIIRS Flood Mapping archive): global database of daily flood detection at a 375m resolution based on an algorithm using VIIRS satellite imagery to identify changes in the presence of surface water

flood exposure.

3.1 Survey-reported flood incidence

We identified four sources of household surveys conducted in Chad at different points in time which ask respondents about recent flood experiences and for which we were able to obtain data. The available data are summarized in Table 4. While each survey differs in geographic scope, methodology, and timing, together they provide an on-the-ground perspective on where floods have affected populations across the country in recent years.

Table 4: Summary of available survey reports of flood incidence

Survey	Round (period)	Total respondents	Count reporting any flood	% Survey communities w/ any flood reported	Time period covered	Geographic identifier	Coverage
RIMA	Oct 2014	8516	–	3.57	Apr – Oct 2014	ADM2	Rural
ENSA	Oct 2016	9544	209	8.85	May – Oct 2016	ADM3	Rural
	Oct 2017	9165	413	15.80	May – Oct 2017	ADM3	Rural
	Oct 2018	8924	181	10.23	May – Oct 2018	ADM3	Rural
	Oct–Nov 2019	6920	542	25.41	May – Nov 2019	ADM3	Rural
	Oct–Nov 2020	13208	2627	45.20	May – Nov 2020	Community	Rural
	Oct–Nov 2021	14761	893	25.39	May – Nov 2021	Community	Rural
	Oct–Nov 2022	13691	4291	60.52	May – Nov 2022	Community	Rural
	Oct–Nov 2023	14776	803	21.92	May – Nov 2023	Community	Rural
	Oct–Nov 2024	19672	9151	85.94	May – Nov 2024	Community	Rural
ECOSIT 4	Jun–Sept 2018 (R1)	3744	387	51.25	Jun 2015 – Sep 2018	Community	National
	Jan–Apr 2019 (R2)	3756	368	48.74	Jan 2016 – Apr 2019	Community	National
ECOSIT 5	Jan-Apr 2022 (R1)	3809	438	52.20	Jan 2019 – Apr 2022	Community	National
	Sep-Dec 2022 (R2)	3723	284	42.12	Sep 2019 – Dec 2022	Community	National
DIEM	Nov–Dec 2021(R2)	1692	173	4.49	Aug – Dec 2021	ADM2	Limited
	Aug–Sep 2022 (R3)	3704	194	5.04	May – Sept 2022	ADM2	Limited
	Dec 2022–Jan 2023 (R4)	5310	1425	37.05	Sept 2022– Jan 2023	ADM2	Limited
	Aug–Oct 2023 (R5)	5821	122	3.17	May – Oct 2023	ADM2	Limited
	Dec 2023–Jan 2024 (R6)	5683	409	10.63	Sept 2023– Jan 2024	ADM2	Limited
	Aug–Sep 2024 (R7)	4853	825	21.45	May – Sept 2024	ADM2	Limited
	Jan–Feb 2025 (R8)	5624	698	18.14	Oct 2024 – Feb 2025	ADM2	Limited

Note: Authors' analysis based on separate household surveys. This table summarizes the number and share of households reporting flood-related shocks across four household surveys (RIMA, ENSA, ECOSIT, and DIEM). In RIMA and ENSA, floods are reported over the past 6 months, in ECOSIT, over the past 3 years, and in DIEM, over the past 3 months. Covered time periods are based on survey timing and recall periods. The geographic identifier is the most precise location we are able to identify in the data. Coverage indicates the degree to which the survey samples are representative of the population of Chad.

In all surveys, we use questions related to households' recent flooding experience to categorize households and communities as having had any flood exposure. Because the time periods and specific questions used to ask about household flooding experiences differ across surveys, the frequency of flood reporting over time across surveys cannot be directly compared. However, differences across communities within surveys help to highlight geographic differences in flooding incidence over time.

The periods with the highest shares of communities with any flooding reported are in 2022 and 2024, consistent with these being the periods with the worst reported floods over this timeframe (Table 2). A stunning 86% of communities in the ENSA survey have at least one households reporting a flood shock in 2024, much higher than the previous high of 61% of communities in 2022. Nearly half (46.5%) of all ENSA households surveyed reported a flood shock in 2024, compared to less than a third (31.3%) in 2022 and just 5% in 2023. Consistent with government and media reports that flooding began earlier than usual in 2024, the DIEM surveys show that 21% of communities experienced floods from May to September of 2024 compared to 18% from October 2024 to February of 2025. In contrast, in 2022 just 5% of communities were exposed to flooding from May to September compared to 37% from September 2022 to January of 2023.

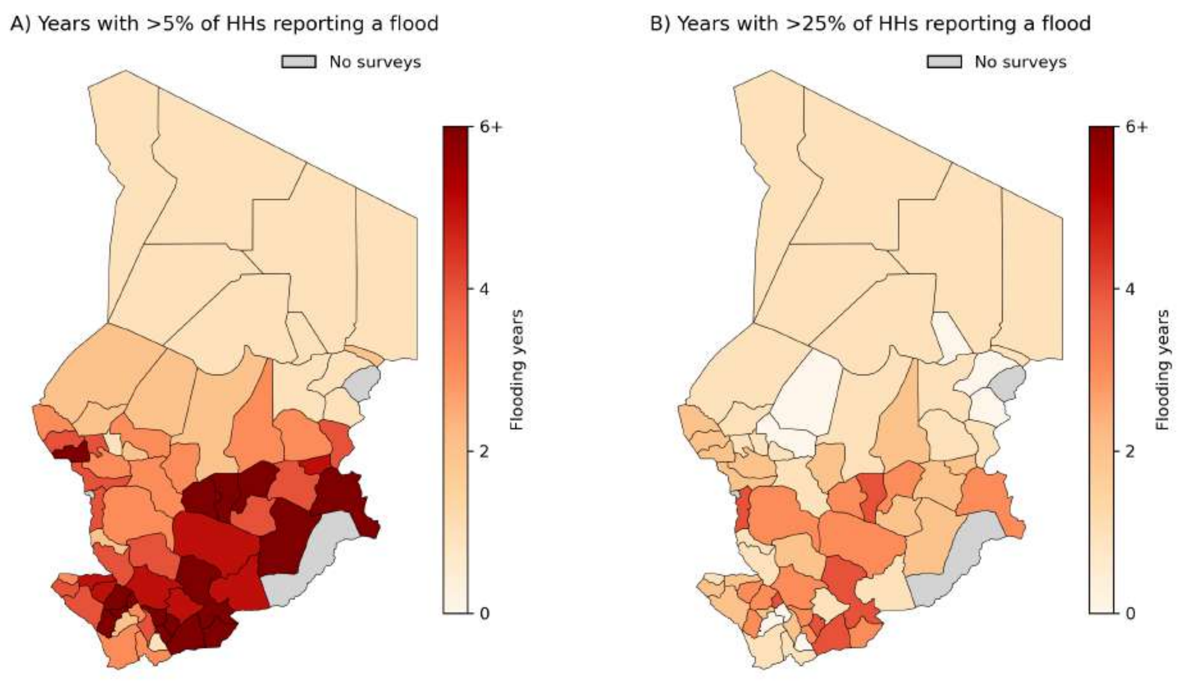
An important takeaway of the household flooding reports is that the share of communities where any flooding is reported greatly exceeds the share of households reporting a flood shock. One reason for this is that survey questions about floods are generally included in a module about adverse shocks experienced by the households, and ask households whether they were harmed by floods and not simply whether any flooding occurred. Not all households are adversely affected when a flood occurs in their community, either because they live in a different part of the community from where floods occurred or because they were otherwise less exposed to or better protected from flood damages. Another possibility is survey measurement issues. For example, in some cases (such as the ENSA surveys) households can only report one primary shock experienced over the past 6 months, and in some cases floods may not be the most important shock a household has experienced. Regardless of the reason, we find more widespread flooding across communities than across households. Community-level flood exposure therefore will have different effects on households depending on their own specific exposure.

A particularly useful source of survey flood reports is the Enquête Nationale sur la Sécurité Alimentaire (ENSA). This survey is conducted annually in Chad by the Ministry of Agriculture and Irrigation and Système d'Information sur la Sécurité Alimentaire et l'Alerte Précoce (SISAAP), in collaboration with FEWSNET, the FAO, and the World Food Programme. The data for these surveys is not publicly available but we obtained data for 2016-2024 from SISAAP, including community coordinates for the years 2020-2024. The survey sample is an annual cross-section that is representative of rural populations in each region. It therefore does not include the urban areas with the highest population exposure and vulnerability to flooding but provides a valuable source of data on annual flooding experiences across the country. The objective of the survey is to track measures of food security across the country but the questionnaires cover a wide variety of topics including household shocks. Respondents are asked whether they experienced any adverse shocks in the past 6 months and, if yes, to name the primary shock they experienced, which may be a flood.

In most years data can only be consistently mapped at the departement level, so we start by calculating the share of households reporting a flood shock by departement each year. Figure 10 summarizes this information by mapping the count of years in which this share exceeded 5% (Panel A) and 25% (Panel B), by departement. We also show annual maps of the share of households reporting any flooding at the departement level in Figure A16 and at the community level for 2020-2024 Figure A17.

Panel A of Figure 10 shows that every departement has at least 5% of households reporting flooding in at least one year during this period, largely because of the very widespread exposure—even in the northern departements which otherwise typically report no or very low flooding—in 2024 (Figure A16). But it is clear that flood exposure is a more regular occurrence in southern Chad and in particular departements. Of the nine years from 2016-2024, eleven departements have at least 5% of households reporting a flood shock in six separate years (Abtouyour, Bahr Azoum, Bahr Sara, Djode, Guera, Kimiti, Kouh Est, La Pende, Mangalme, Tandjile Centre, and Tandjile Ouest), four have this level of exposure in seven years (Grande Sido, Gueni, Mamdi, and Mandoul Occidental), and one has this level of exposure in eight of the nine years (Bahr Koh). Low levels of flood exposure are therefore very common in many parts of Chad in the past decade.

Figure 10: Summary of flood exposure in ENSA surveys, 2016-2024



Note: Authors' calculations based on data from the ENSA surveys. The data are from a nationally-representative sample of rural households about flooding experienced in the 6 months prior to the survey date. Geographic identification is not available below the admin2 level for all years, so we show the share of households reporting any flooding by departement. In each year, we determine whether this share exceeded 5% (panel A) and 25% (panel B), and then visualize the number of years with this level of flood exposure in the departement.

Panel B shows that higher flood exposure events are less common, but 60 of 70 departements have at least one year with more than 25% of survey households reporting a flood shock. Again, much of this is driven by 2024, when high exposure to floods was widespread across a much larger part of the country than even in 2022 or 2020 as shown in Table 4. Thirty-five of seventy departements have more than one year with this high level of flood exposure, which is primarily due to the major flood events in 2020, 2022, and 2024. Six departements have experienced four separate years with more than 25% of survey households reporting a flood shock: Bahr Koh, Bahr Sara, Chari, Guera, Mandoul Occidental, and Tandjile Centre.

It is important to highlight here that the household sample for the ENSA only includes *rural* populations, so these results should not be taken as a definitive indicator of the areas with the highest risk of flood exposure in Chad. The urban areas with high exposure might be in other departements which could change conclusions about what areas are most exposed. The Resilience Index Measurement and Analysis (RIMA) survey was conducted in 2014 and also targets rural populations, and reveals little flood exposure in this year (Figure A19 Panel A).[10] The DIEM and ECOSIT surveys include urban as well as rural populations, allowing some comparison with the ENSA survey reports, although their coverage and flood-related questions differ from the ENSA surveys.

The Data in Emergencies Monitoring (DIEM) surveys have been conducted repeatedly from 2021-2025 but only in selected departements in each round.[11] With the exception of high levels of survey flood reporting in Kanem in 2024, the provinces with higher levels of DIEM survey flood reports generally align with the areas identified by government and media reports as having larger affected populations in 2022 and 2024 (Figure A15) We do not observe any consistent pattern in comparing the share of households reporting floods at the departement level by year between the DIEM surveys (Figure A18) and the ENSA surveys (Figure A16). At a high level reported flooding incidence is similar but across years, we observe some departements with similar shares of households reporting floods, some with higher shares in DIEM, and some with higher shares in ENSA. Based on this, it is unclear whether flood exposure is typically higher or lower among urban households.

The Enquête sur les Conditions de vie des Ménages et la Pauvreté au Tchad (ECOSIT) surveys are nationally-representative surveys and are conducted by the National Institute for Statistics, Economic and Demographic Studies of Chad (INSEED) with support from the World Bank, with the aim of generating updated indicators on poverty and living conditions. We received community coordinates from the INSEED team to allow precise geographic mapping of flooding incidence

[10] The RIMA survey was conducted in 2014 by the FAO together with Chad's Ministry of Agriculture and Irrigation using the same sampling and similar methods as the ENSA. The relevant period for recalling flood shocks covers April-October 2014, which was not a period of major flooding in Chad.

[11] The DIEM survey, led by the FAO, has been conducted around twice per year since November 2021, with seven rounds of data available as of May 2025 (round 1 is not publicly available). Designed as a rapid-response monitoring system, each round of the DIEM targets specific departements based on recent exposure to shocks and collects data on livelihoods, food security, and vulnerability to shocks for a representative sample of households. Although its geographic coverage is limited and locations can only be identified at the departement level, the survey allows for high-frequency monitoring of household conditions in vulnerable areas. In the survey shocks module, households are asked whether they or the community experienced flood or riverbank erosion that affected their ability to raise an income or produce food in the past three months. The timing of the surveys is designed so that one round each year takes place around the beginning of the high flood risk season and the second round takes place shortly after this season.

during ECOSIT rounds 4 and 5, conducted in 2018-19 and 2021-22, respectively. In the survey, respondents are asked whether they were adversely affected by a variety of shocks over the past three years, including flooding. Reports of flood exposure therefore cover a long time period.

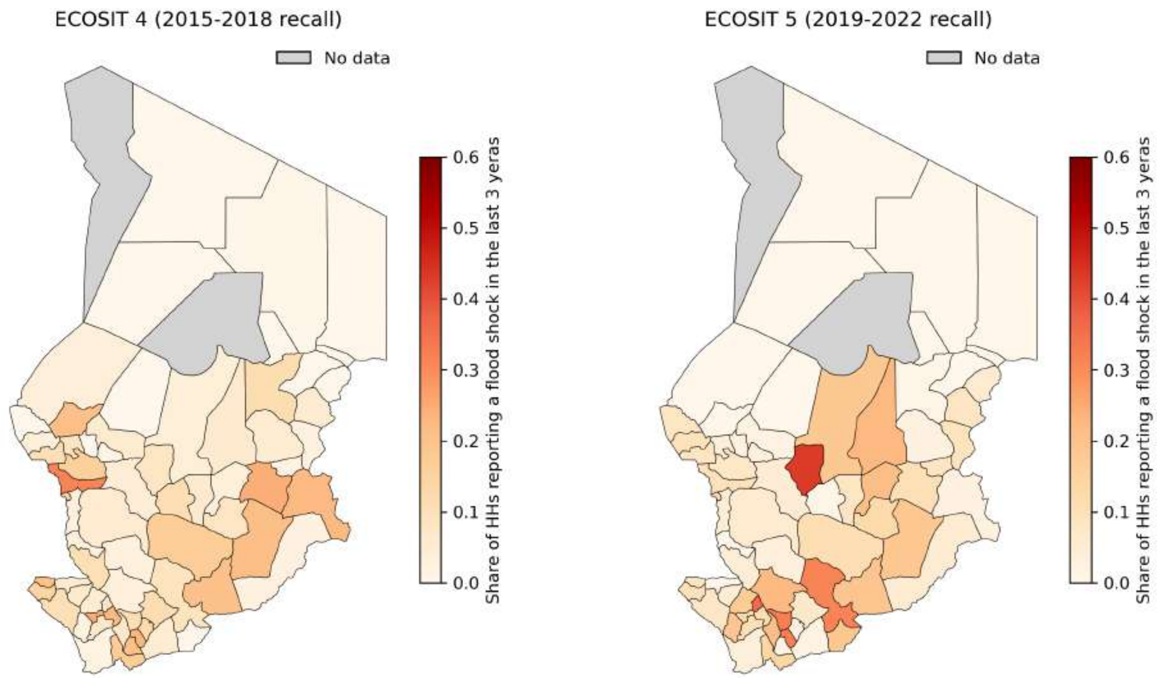
The recall period for ECOSIT 4—June 2015-April 2019—does not overlap with any major flooding events in Chad but 10% of households report experiencing a flood over this time period. These are spread across a large number of communities such that around half of communities include at least one household reporting any flood shock. The recall period for ECOSIT 5—January 2019-December 2022—overlaps with several years of severe flooding across Chad, yet we still observe around 10% of households reporting a flood shock in this period, and a similar share of communities as in ECOSIT 4. Most surprising is that the share of communities with any reported flooding is actually lower in the second wave of ECOSIT 5 than the first, even though the major flood disaster of 2022 happened in between these waves. These results suggest household recall errors which may be related to the long recall periods in the ECOSIT shock modules.

Figure 11 maps the share of households reporting any flood exposure by departement in each round. Forty departements have at least 5% of households reporting a flood over the 4 year period from 2015-2018, compared to just 24 in the ENSA surveys for the same period. Two departements have more than 25% of ECOSIT households reporting flooding over this period, Haraze Al Biar and Gueni, but these are not the same as the three departments with similarly high shares of ENSA flood reports: Bahr Sara, Kouh Est, and Mandoul Occidental. Forty departements also have more than 5% of households reporting any flooding during the 4 year period from 2019-2022, though these are not the same departements as for the 2015-2018 period. This compares to 57 departements according to the ENSA data. Five departements have more than 25% of ECOSIT households reporting flooding over this period, Fitri, Tandjile Centre, La Pende, Kouh Est, and Bahr Koh. In contrast, there are 40 departements with at least this level of flood reports in the ENSA surveys over this period, though these include all five of those highlighted by the ECOSIT data.

Overall, the ECOSIT survey flood reports do not align well with the timing of major flood events over the same time period or with the ENSA survey data. Part of the difference between ECOSIT and ENSA may reflect the inclusion of urban households in the ECOSIT data, but higher flood reports over a low-flooding period and lower flood reports over a high-flooding period are difficult to explain by sampling differences. Instead, this suggest differences due to how the flooding questions were asked, and potentially to challenges with accurately recalling exposure over such a long period (three years). These conclusions motivate a decision to consider remotely-sensed flooding incidence alongside than survey-reported incidence for the analysis of impacts of flood exposure in the ECOSIT data in the next section of this report.

In summary, the survey reports of household-level flood experiences offer three important insights. First, households are more likely to report being affected by a flood in regions with higher flooding hazard and exposure risk according to data from Fathom (2022) and Rogers et al. (2025). This indicates that the models used in these sources are indeed reflecting true variation in flood risk.

Figure 11: Flood exposure in ECOSIT surveys, 2015-2022



Note: Authors' calculations based on data from the ECOSIT surveys. The data are from a nationally-representative sample of households about flooding experienced in the 6 months prior to the survey date. Geographic identification is not available below the admin2 level for all years, so we show the share of households reporting any flooding by departement. In each year, we determine whether this share exceeded 5% (panel A) and 25% (panel B), and then visualize the number of years with this level of flood exposure in the departement.

Second, a low but non-trivial share of households report experiencing flood shocks outside years of major flood events in Chad. These events are primarily concentrated in the same areas at higher risk of severe floods. This recurring flood risk implies that flood monitoring and response efforts focused on major floods may miss many important more local or less severe floods that nevertheless adversely affect households. Third, there is substantial variation in household flooding exposure within communities, with many households in communities exposed to floods not reporting any damages or losses.

We explore the correlates of this within-community variation using data from the ECOSIT and ENSA surveys. In ECOSIT 4, just over 10% of households reported being affected by a flood from 2015-2018. Households engaged in any agricultural activity are 3 percentage points (pp) more likely to report a flood shock, while households with a cement or metal roof (as opposed to straw, leaves, fabric, or other materials) and with a cement or tile floor (primarily as opposed to earth) are 2 and 5 pp less likely to report a flood shock, respectively (Table 5). Households with more members are also more likely to report a flood shock, potentially because this increases the number of ways in which a household could be affected by flooding. Characteristics of the household head (age, religion, and literacy) and dwelling ownership are not correlated with flood reports.

In the ENSA surveys of rural households from 2016-2024, 17% of households report being affected by a flood over the past 6 months on average. As in the ECOSIT sample, being engaged in agriculture increases the probability of reporting a flood shock (by 8 pp) and having a cement

Table 5: Correlates of ECOSIT 4 household flood reports

	(1)	(2)	(3)
Rural location	-0.017***		
	(0.006)		
Any HH crop or livestock activity	0.012	0.032***	0.071***
	(0.009)	(0.011)	(0.023)
Household size	0.003**	0.002*	0.005*
	(0.001)	(0.001)	(0.002)
Household head is female	-0.003	-0.003	-0.006
	(0.008)	(0.009)	(0.018)
Household head is Muslim	0.001	0.020	0.043
	(0.006)	(0.015)	(0.031)
Household head is literate	0.003	0.002	0.003
	(0.009)	(0.010)	(0.019)
Household head completed primary school	0.004	0.005	0.007
	(0.010)	(0.011)	(0.021)
Household owns its dwelling	-0.015	-0.005	-0.008
	(0.009)	(0.011)	(0.020)
Roof is cement or metal	-0.006	-0.024**	-0.054**
	(0.009)	(0.011)	(0.023)
Floor is tile or cement	-0.045***	-0.055***	-0.089***
	(0.011)	(0.013)	(0.022)
Main source of light is electricity	0.005	-0.004	-0.011
	(0.012)	(0.015)	(0.026)
Household has toilet or latrine	-0.004	-0.020	-0.036
	(0.010)	(0.013)	(0.024)
Count of other HHs in comm. reporting flood	0.064***		
	(0.003)		
Observations	7493	7493	3718
Mean, HH reported flood	0.101	0.101	0.203
Community FE	No	Yes	Yes
Wave FE	Yes	Yes	Yes
Sample	All	All	Any comm. flood rept.

Note: Authors' calculations based on data from the ECOSIT 4 surveys. The table shows the results of separate regressions where the outcome variable is a dummy for whether the household reported experiencing a flood shock from 2015-2018. Communities typically include around 12 households in the survey sample. The count of other households reporting a flood is calculating by taking the sum of household flood reports and subtracting the household's own report. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

or metal roof—floor material is not recorded in the surveys—decreases it (by 1 pp). Household size is again positively associated with flood reports, and we also find small significant positive relationships between having a female and literate household head and the probability of reporting a flood (Table 6).

In both samples, the magnitudes of the relationships are larger within communities where any flood shock is reported, indicating that household characteristics can explain much of the variation in within-community flood exposure we observe in Table 4. Together, results show that, as would be expected, households more vulnerable to damages from flooding—those engaged in agricultural production and those with less durable dwellings—are more likely to report a flood shock.

Table 6: Correlates of ENSA household flood reports

	(1)	(2)	(3)
Any HH crop or livestock activity	0.071***	0.079***	0.173***
	(0.004)	(0.006)	(0.011)
Household size	0.002***	0.001***	0.003***
	(0.000)	(0.000)	(0.001)
Household head is female	0.008***	0.009***	0.020***
	(0.003)	(0.003)	(0.006)
Household head is literate	0.014***	0.012***	0.029***
	(0.002)	(0.002)	(0.006)
Roof is cement or metal	-0.002	-0.012***	-0.023***
	(0.003)	(0.004)	(0.007)
Household has toilet or latrine	-0.000	-0.002	-0.004
	(0.003)	(0.003)	(0.007)
Count of other HHs in comm. reporting flood	0.060***		
	(0.001)		
Observations	107010	106273	43095
Mean, HH reported flood	0.171	0.171	0.423
Community FE	No	Yes	Yes
Year FE	Yes	Yes	Yes
Sample	All	All	Any comm. flood rept.

Note: Authors' calculations based on data from the ENSA surveys from 2016-2024. The table shows the results of separate regressions where the outcome variable is a dummy for whether the household reported experiencing a flood shock in the past 6 months. Communities typically include around 12 households in the survey sample. The count of other households reporting a flood is calculating by taking the sum of household flood reports and subtracting the household's own report. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.2 Remotely-sensed flood incidence

The most promising data source for identifying flood incidence at a high temporal and geographic resolution in recent years is remotely-sensed data, and in particular satellite imagery and radar. In this section we briefly discuss how flooding is detected by satellite sources, present and compare different remotely-sensed flood monitoring databases, provide guidance for near real-time flood monitoring, and present data on annual flooding in Chad from 2012-2024 using data from the NOAA/GMU VIIRS Flood Mapping archive.

Satellites carry sensors that measure signals emitted from Earth, which can be used to detect the presence and characteristics of surface water. Satellite imagery, as collected by the MODIS and VIIRS optical sensors for example, can identify water based on differences in what wavelengths are reflected or absorbed by water. Satellite synthetic aperture radar (SAR), as collected by Sentinel-1 for example, can identify water based on differences in radar backscatter patterns. After detecting water and accounting for errors due to cloud cover, terrain shadow, and elevation, different algorithms are used to determine whether water observed in a particular place and time represents flooding. These typically involve comparing detected water to data on locations of permanent water. Appendix D provides more data on how satellite data may be used for flood detection.

Flood detection by satellite is based on specific algorithms meaning it is not subject to reporting errors and can be particularly valuable in contexts where no survey reports are available. But there are also several important limitations to satellite-based flood detection. First, satellite optical imagery generally has shorter revisit periods on average but is constrained by cloud cover, while satellite radar is not affected by clouds but has longer intervals of days between data collection. These limitations mean satellites may miss fast-moving or short-duration floods as well as floods occurring under clouds, implying a reduced likelihood of capturing pluvial foods in particular. Second, flood detection algorithms may be biased based on how the algorithm is developed, for example by not accounting for seasonal fluctuations in water cover or from inaccurate elevation data. Differences in data availability and algorithms mean that maps of flooding incidence for a given time and place can vary substantially across different flood monitoring databases. Third, satellite-based measures can have difficulty identifying floods in urban areas, under tree canopies, and in arid areas leading to potential false positive detections as well as flooding that is not detected.

For these reasons, satellite-based sources should not be considered as definitive measures of flooding incidence, particularly at very specific points in time and space. At a more aggregate level, however, they are very useful in identifying and monitoring areas where floods are determined to be very likely to be occurring.

3.2.1 Near real-time flood monitoring

While it is possible to estimate flooding incidence directly from raw satellite data,[12] many publicly-accessible databases now provide near real-time (NRT) monitoring of flood incidence globally, relying on different satellites and algorithms.[13] We reviewed these databases in order to identify one that we could access and use to analyze recent historical trends in flooding incidence across Chad. Table 7 provides a summary of a selection of flood databases that allow online viewing of NRT flood detection. Table A2 provides additional detail on these datases along with other public flood event databases that record a subset of past major global flood events typically with very limited spatial resolution. We do not include flood forecasting services such as GloFAS, which can provide early warning of locations at heightened risk of flooding (see Kar et al. (2024) for a review of selected flood forecasting and detecting data sources and how they can be combined for flood monitoring).

These NRT databases could each potentially be useful for monitoring and responding to *real-time* flooding events in Chad, but we would recommend using databases that allow users to download data from recent days and that represent different approaches to flood mapping and sources of

[12] For example, we followed the methods described in Tripathy and Malladi (2022)'s Global Flood Mapper interface to attempt to detect flooding in Chad in recent years using Sentinel-1 SAR data in Google Earth Engine, but the algorithm is tailored to identifying specific floods at specific points in space and time. As such it is not well-suited to the task of identifying all floods over a large geographic area over a large timeframe, which is the objective in estimating annual flood incidence in Chad. This limitation holds for many other methods for directly estimating flooding incidence as well, and while it is possible to revise these methods for our task it is very computationally-intensive and requires many subjective decisions in refining the algorithm. We therefore prefer to rely on flood detection methods used in existing flooding databases. These methods also typically bring incorporate various error correction steps that are difficult to replicate.

[13] Schumann et al. (2018) reviews databases available as of 2018 and provides additional information on many of the same databases we identify though the information in their review is no longer up to date. A number of public and private organizations also provide flood detection and monitoring services for a fee, or otherwise have flood monitoring data that they do not make publicly available.

Table 7: Overview of NRT Flood Databases

Database	Data	Years of coverage	Spatial resolution	Temporal resolution	Accessibility
VIIRS Flood Mapping (VFM)	VIIRS imagery	2012-present	375 m	1/5 day composites	Publicly available archive
GloFAS Global Flood Monitoring (GFM)	Sentinel-1 SAR	2021-present	20 m	6-12 days	Web portal/API with download restrictions
Global Flood Monitoring System (GFMS)	TRMM/ GPM precipitation	2013-present	12 km	Daily	Publicly available archive
Near Real-Time (NRT) Global Flood Product	MODIS imagery	2011-2022 (legacy); 2021-present (current)	250 m	1/2/3 day composites	Web portal for last 8 days
African Flood and Drought Monitor	Precipitation gauges + satellite-derived precipitation	2008-present	5 km	Daily	Web portal viewing but not downloading
Automated Disaster Analysis and Mapping (ADAM) Floods	VIIRS, MODIS, and Sentinel-1 satellites, Floodscan	post 2018-present	At least 375 m	Unclear	Web portal viewing but not downloading
FloodScan	Satellite microwaves and imagery	1998-present	90 m	Daily	Web portal viewing but not downloading

Note: Authors' summary based on information provided by each source. Table A2 provides additional detail.

data. In particular, the NASA NRT product, the NOAA/George Mason University VIIRS Flood Mapping (VFM) product, and the Copernicus Emergency Management Service Global Flood Monitoring (GFM) product provide data at a relatively high spatial resolution and use different satellites (MODIS imagery, VIIRS imagery, and Sentinel-1 SAR respectively) for a multi-faceted detection of flooding. We note that the longer flyover periods for Sentinel-1 imply that data for the GFM product at a given point in space will not be updated as frequently as data for the databases using optical satellites, but this data source will not be constrained by cloud cover.

An approach that considers these three NRT flood databases would likely be most robust. Combining and comparing results would reduce the number of flood events that are not detected as well as potentially reduce the number of incorrectly identified flood events. The NASA/University of Maryland Global Flood Monitoring System (GFMS) could additionally complement these data sources to identify potential pluvial flooding as its algorithm uses satellite-detected rainfall with a hydrological model. We would not recommend this data as a primary source for identifying flooding as the resolution of the data is coarse (12km) and this method may be more likely to incorrectly detect flood events due to issues detecting extreme precipitation events using satellite-derived data.

The World Food Programme's Advanced Disaster Analysis and Mapping (ADAM) tool follows a similar approach for NRT monitoring of floods that has been applied to tracking the incidence of the 2022 and 2024 floods in Chad. The ADAM tool combines raw data from the VIIRS, MODIS, and Sentinel-1 satellites together with estimates from Floodscan to estimate flooding extent. An approach that scrapes data from the NASA NRT product, VFM product, and GFM product would incorporate data from the same satellites but with the advantage of leveraging the rigorous error detection and correction methods of each product's algorithms. A conservative method would be to identify flooding based on the maximum of flood detection across all three sources. Overlaying these data on maps of cropland and population density—as done in WFP flood bulletins for Chad using ADAM data (for example, WFP, 2024b)—could help targeting flood response.

3.2.2 Mapping historical flood incidence

The key considerations in choosing a database for mapping *historical* flood incidence in Chad are data accessibility and consistency, temporal coverage (the ability to retrieve data from as many years as possible), spatial resolution, and algorithm quality. The first two criteria are the most binding when moving from real-time monitoring to historical analysis.

We eliminated the NASA NRT Global Flood Mapping product, African Flood and Drought Monitor, Advanced Disaster Analysis and Mapping (ADAM) tool, and FloodScan from consideration because of restrictions in accessing historical flooding data.[14] We identify three databases with archived flood mapping data available to download. The NASA/University of Maryland GFMS has public archived daily data going back to 2013,[15] but as discussed above the data are at a relatively coarse resolution (around 12 km) and are based on satellite precipitation data which has been shown to be less accurate for identifying inundation. The Copernicus Emergency Management Service GFM tool has the joint advantages of being very high resolution (20 m) and based on radar data which can detect floods at night and in cloudy conditions. The main drawbacks are that the return period is 6-12 days, meaning this source will fail to detect floods of short duration unless they coincide with the satellite overpass. Data access also begins only in 2021 and we faced challenges accessing and processing historical data through the API, though this constraint should be reduced for real-time monitoring.[16]

We determined that the NOAA/George Mason University VFM product archive (Li et al., 2018; NOAA and George Mason University, 2025) is the best option for conducting an analysis of historical flooding in Chad. It is moderately high resolution (375 m) and available at daily intervals starting in 2012, though for reasons we do not understand there are no data available for 2021 and 2022. This database uses VIIRS satellite imagery, so the main drawback is that the floods that can be detected are constrained by cloud cover. We use the 5-day product which interpolates data from nearby cloud-free observations to help address this limitation, but this source will still miss

[14] The NASA NRT Global Flood Mapping product has been commonly used in empirical research but no longer provides public access to its archive. While historical flood maps can be viewed on the online portal, only data for the last 8 days can be downloaded for analysis. We requested additional data but received only three months of archived maps, which is insufficient for historical mapping. The African Flood and Drought Monitor only allows viewing but not downloading of data for the current date and the past one month. The World Food Programme's ADAM tool has been used for flood monitoring in Chad by the WFP and other organizations, but while live data can be viewed in the online portal there is no public way to access historical records. FloodScan similarly allows viewing of the live map but historical records are only accessible for a fee which depends on the amount of data requested.

[15] The archive includes links to data going back to 2001 but access is restricted so it is unclear how these data may be obtained.

[16] The very high resolution of the data made extracting and compiling a database of GFM records even for N'Djamena alone computationally challenging.

inundation caused by heavy rainfall that does not persist until the next cloud-free flyover. It is also lower resolution than the radar-based Copernicus GFM, but it has a much more frequent flyover period which is an advantage for capturing short-duration floods. Tests of the VFM method show that under clear-sky coverage its maps are consistent with radar flood products overall, and that it is better at detecting floods on land with vegetation cover and less likely to falsely detect floods on barren land than radar-based methods (Li and Sun, 2021).

Data from the VFM archive identify each pixel as either land, permanent water, or flooded to an extent defined as the share of the 375 m pixel where flooding is detected each day.[17] To analyze historical flooding incidence in Chad, we aggregate these data to the annual level by taking the sum of days with any flooding to create a continuous measure of flooding incidence. Annual days of flooding can serve as a simple measure of flood duration and intensity that is useful for identifying areas potentially most affected.

We consider pixels with over 150 days of detected flooding in a majority of years to be pixels with seasonal "recurring water," a situation which is not accounted for in the VFM flood detection algorithm but which is distinct from floods as there expected seasonal fluctuations. These areas are primarily located around Lake Chad and to a lesser extent Lake Fitri, and separate out these pixels from the representation of flooding incidence in the following analyses. Across all of Chad's approximately 15 million 375 m pixels, 0.23% are classified as permanent water and 0.12% are classified as recurring water; the remaining 99.65% are land.

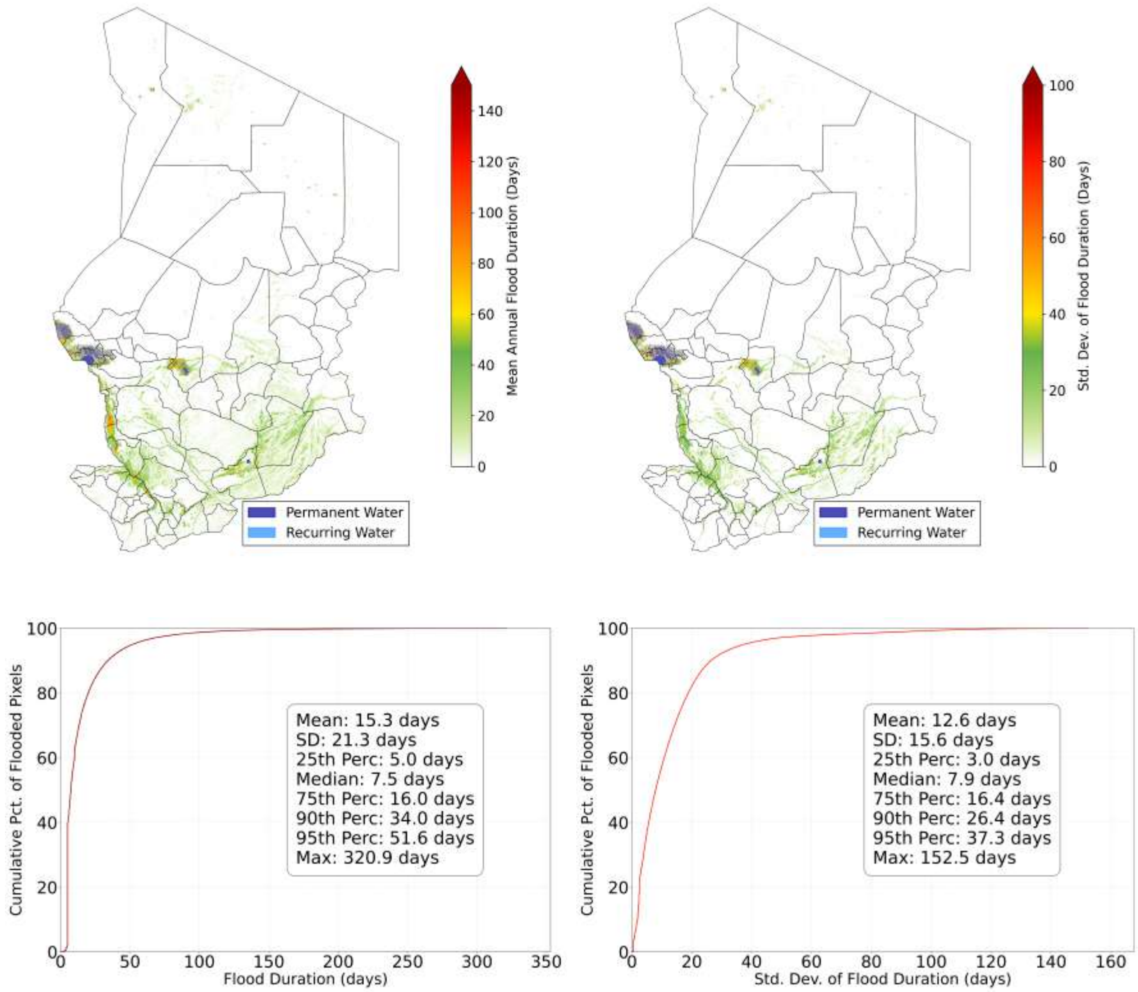
We first present data on the mean and standard deviation of the annual days of flooding at the pixel level across Chad for the 2012-2024 period. Figure 12 maps out the spatial distribution of these values across Chad (top row) and shows the cumulative distribution of values across all pixels (bottom row). The top row shows that flooding is largely concentrated in the south of the country around lakes and rivers (Figure A2), reflecting the high risk from fluvial floods. The areas with the highest mean days of flood exposure are located in close proximity to these water bodies, particularly around Lakes Chad, Fitri, and Iro, between the Chari and Logone rivers near northern Cameroon, and further south along the Logone river. Outside of these areas it is rare for the mean annual days of detected flooding to exceed 40, but in these areas it can reach over 100. Flooding is also detected in the more arid north of the country, around seasonal wadis, and in many scattered pixels. This could reflect detection of pluvial floods but may also indicate false positives, such as small oases not included in permanent water maps or inaccurately classified bare earth.

The areas in Figure 12 with regular flooding detected align well with the areas indicated in Figure 1 and Figure 2 as having higher flooding hazard. Across all land pixels in Chad, almost exactly 10% have at least one day of detected flooding from 2012-2014. This implies that the large majority of Chad's area faced limited flooding hazard. This result also supports the conclusion from Fathom (2022) and Rogers et al. (2025) showing that fluvial flooding is a relatively much more important driver of flood hazard in Chad than pluvial flooding, though one potential reason

[17] The share of the pixel that is flooded is measured by comparing reflectance of different bands of light in mixed land/water pixels compared to otherwise similar pure land or pure water pixels. We consider a pixel to be flooded if there is any flooding detected in the pixel.

Figure 12: Estimated annual days of pixel flood exposure, 2012-2024

A) Mean of annual flood duration (days) | B) Standard deviation of annual flood duration (days)



Note: Authors' calculations based on data from the VFM archive NOAA and George Mason University (2025). We aggregate daily flood detection maps across the year, taking the sum of days in the year with any flooding detected for each pixel. We then calculate means and standard deviations of this value across years at the pixel level. Cumulative distribution functions shown in the bottom row are for pixels with at least one day of flooding over the 2012-2024 period.

for this is that short-duration pluvial floods masked by clouds cannot be detected by VIIRS imagery used in the VFM archive meaning fluvial floods are more likely to be detected.

Among the 10% of land pixels with flooding detected in at least one year from 2012-2024, the median number of days of annual mean flooding is 7.5, and the mean is 15.3. Close to 40% of these cells are flooded an average of 5 days annually. In some cases this reflects a single satellite image with flooding detected, as we use the 5-day VFM product which smooths detection across five day periods to account for missing data due to cloud cover. The 75th percentile for mean annual flooding days is 16 days, the 90th percentile is 34 days, and the 95th percentile is 51.6 days. The pixels with values above the 90th percentile are almost exclusively in the areas near lakes and rivers identified above.

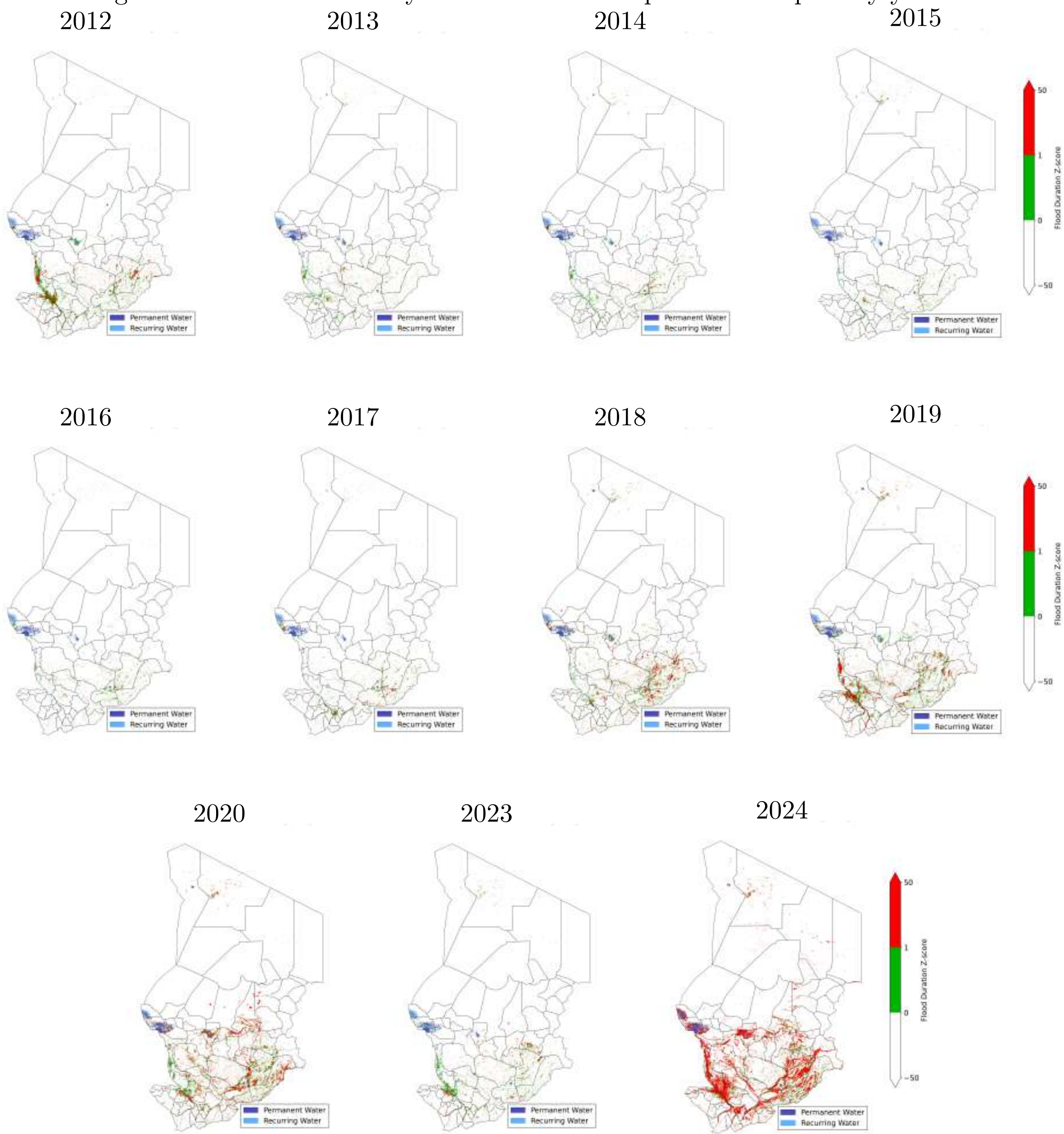
The map of the standard deviation of annual flooding days shows that higher deviations are typically in the same areas where we observe higher means. A higher standard deviation implies more variation from year to year, and therefore a greater likelihood that the VFM-detected flooding represents a true inundation shock in a local area. Higher standard deviations in areas with higher means imply that the high means are driven by some years with very many flooding days and some years with few. Among pixels with any detected flooding, the 25th percentile is 3.0 days, driven largely by limited variation in many of the cells with low mean annual flooding days. But the mean standard deviation is 12.6 and the 75th percentile is 16.4 days, however, indicating that a large number of pixels experience important fluctuation in flooding incidence as detected by the VFM.

To clearly identify the variation in flooding days detected over time, we calculate normalized deviations in each year by subtracting mean days of flooding over all other years from 2012-2024 and then dividing by the standard deviation of days of flooding over that period. The resulting units are standard deviations of days of flooding away from the mean for each pixel, where large positive values indicating unusually high days of flooding in the current year relative to the average across other years, and large negative values indicating unusually low days of flooding. Pixels with a standard deviation of 0 days of flooding outside the current year are assigned a value of 0 unless they have more than 5 days of flooding in the current year, in which case they are assigned a value of 10 in recognition that this is a highly unusual location to detect flooding.

Figure A20 presents maps of annual normalized deviations in flooding days each year from 2012-2024, except for 2021 and 2022 where no data are available. To focus attention on higher than usual flooding incidence, we mask all pixels with fewer flooding days in the given year than usual. We present all pixels with small positive deviations in flooding days—between 0 and 1 standard deviations more than the average in other years—in green and pixels with larger deviations, representing really unusually high levels of detected flooding, in red. The patterns clearly line up with expectations based on the timing of the most severe reported floods in Chad over this time period. By far the largest concentration of red pixels, with much higher days of flood detection than in other years, is in 2024, the year of the worst recorded floods in Chad's history. The next largest concentrations is in 2020, followed by 2019, 2018, and 2012, all years of widespread reported flooding. These are also the years with the highest peak average monthly water flows through DRE hydrological stations among all years with VFM data available (Figure A12). All other years include small numbers of scattered pixels with higher than average numbers of detected flood days, with relatively more green than red. These may represent either isolated flooding events or incorrectly identified floods. The results for 2024 would likely be less striking if data for 2021 and 2022 were available, as the deviations in 2024 would be less extreme when comparing against those other two years of severe widespread flooding, but in general this method of identifying severe floods aligns with expectations.

We show maps of the raw days of annual flood exposure over space by year in Figure A20. The pattern of the maps is similar to what we show in Figure 13 but the differences across years are

Figure 13: Deviations in days of annual flood exposure over space by year



Note: Authors' calculations based on data from the VFM archive, NOAA and George Mason University (2025). We aggregate daily flood detection maps across the year, taking the sum of days in the year with any flooding detected for each pixel. The figure shows Z-scores for the difference in these pixel-level annual days of detected flooding detected in a given year compared to the mean for all other years from 2012-2024, normalized by the standard deviation in flooding days over the same period. Larger Z-scores indicate significantly more flooding days in a given pixel in a given year relative to previous years. Negative values indicate significantly less detected flooding. Data for 2021 and 2022 are not available.

less stark as most years include large numbers of pixels with 10 or fewer days of detected flooding. These areas are largely concentrated in Tandjilé and Salamat provinces, which are also some of the areas with the lowest mean and standard deviation of annual flooded days in Figure 12. We observe that some flooding is detected across the northern half of Chad in every year, typically occurring in the same areas of Tibesti province. The affected pixels typically have 10 or fewer days of detected floods and are far from rivers, suggesting these are pluvial floods. A few pixels with high days of detected water across years likely reflect some of the scattered oases in this desert area, many of which we identify as areas with recurring water coverage. Figure A22 presents the share of each departement where any flooding is detected in each year.

At least 2.0% of land pixels have some flooding detected in every year. This share does not exceed 2.5% from 2013 to 2017, where the only areas with more than 10 days of flooding detected are around Lake Chad, south of N'Djamena between the Chari and Logone rivers, and southwest of Lake Iro. In 2023, 2.9% of pixels are identified as flooded while in 2012, 2018, and 2019 the share is between 3.3 and 3.9%. The highest shares of flooded pixels are in 2020 and 2024, with 4.8% and 6.3% of land cells identified as flooded respectively. The areas with higher days of flooding on these maps correspond to the green and red areas in Figure 13, though it is notable that in 2024 there are simply more pixels experiencing flooding than ever before. Even though many of these pixels are only flooded for 5 or 10 days, these represent very large deviations because no flooding is detected in these pixels in other years.

The distribution of the number of days of flooding among flooded cells is fairly similar across years, with medians around 10 days and means around 20 days (Figure A21). The 25th percentile in all years is 5 days and the median only exceeds 10 days in 2020 (11 days) and 2024 (16 days). The mean only reaches or exceeds 25 days in 2012 (25.3), 2019 (25.0), 2020 (25.4), and 2024 (33.4). More differences are observed at the higher end of the distribution, as in 2013-2018 and in 2023 the 75th percentile is below 26 days of flooding detected and the 90th percentile is below 60 days. These thresholds are slightly exceeded in 2012, 2019, and 2020, but in 2024 the 75th percentile is 43 days and the 90th percentile is 79 days. These results highlight how the floods in 2024 were extreme in terms of both the size of the area affected and in the duration of the floods.

3.2.3 Population exposure to detected flooding

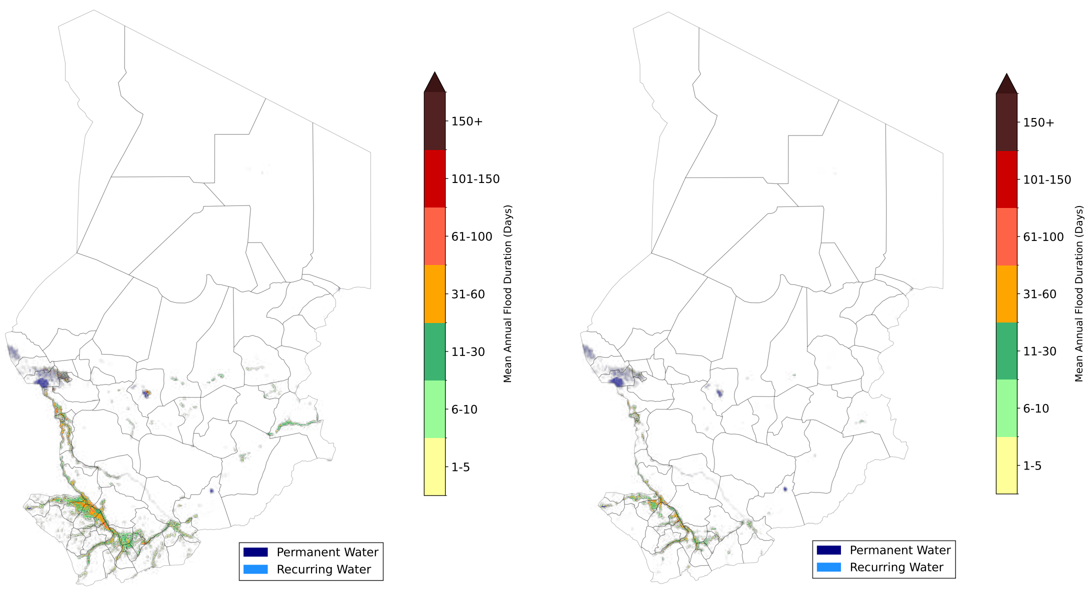
We combine the VFM data with population data from WorldPop (2025) to analyze population exposure to detected flooding. Large portions of Chad are unpopulated, and the median population density even among populated cells is just 2.66 people per km^2. Much of the flooding detected in the VFM data may therefore have limited human effects. To identify areas with the greatest average population exposure to floods, we identify all pixels where the population density exceeds 50 and 100 people per km^2, or roughly the 94th and 98th percentiles of the distribution. There areas are almost exclusively in the southern half of Chad, and primarily in the western and southwestern provinces.

Figure 14 presents maps of mean annual days of detected flooding at the pixel level from 2012-2024, as shown in Figure 12, but restricted to these more populated areas. The results show that the main areas with high population density (for Chad) and high average exposure to detected flooding are along the Logone river in western parts of Hadjer-Lamis and Chari-Baguirimi provinces and in N'Djamena, Mayo-Kebbi Est, Tandjile, and Logone Oriental. Lowering the population threshold to 50 people per km^2, we identify additional areas of high exposure to the east of Lakes Chad and Fitri, along the river Chari in Chari-Baguirmi, and in Mandoul, Moyen-Chari, and Sila, with more scattered exposure in other southern provinces. The areas combining the highest mean days of annual flooding detected (in orange and red) together with higher population densities are largely all concentrated in the areas around the Logone River.

Figure 14: Areas of high population exposure to VFM-detected flooding

A) Mean annual flooding days, >= 50 people per km^2

B) Mean annual flooding days, >= 100 people per km^2



Note: Authors' calculations based on data from the VFM archive NOAA and George Mason University (2025) and WorldPop (2025). The figure presents the mean annual days of flooding data presented in Figure 12, but restricted to areas with at least 50 (Panel A) or 100 (Panel B) people per km^2 in 2020 according to WorldPop gridded data.

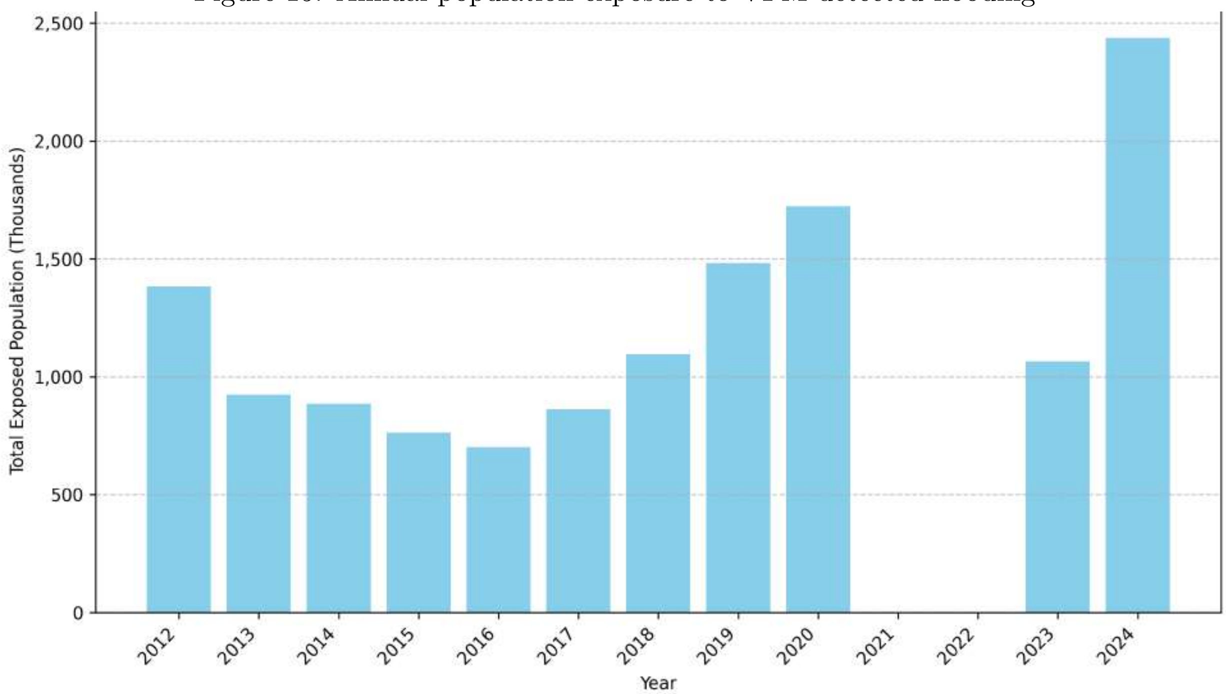
Next, we combine WorldPop population data with annual flood detection data to estimate the population exposed to satellite-detected flooding each year, without no filtering by population density.[18] We define every 1 km pixel in the WorldPop data as exposed to flooding in a given year if there is any flooding detected in any overlapping 375 m pixel in the VFM data, and take the sum of population exposure at the departement and national levels.

Figure 15 shows the estimated total population exposed to floods in each year from 2012-2024. The results align fairly well with reported numbers of affected persons during major flood disasters (Table 2), with 2.4 million people classified as exposed in 2024, 1.7 million in 2020, 1.5 million in 2019, and 1.4 million in 2012. The numbers are not directly comparable, however, as many people may be exposed to flooding without being affected and indeed we find higher levels of exposed persons than are reported as affected in every year. The gap between the number exposed and reported as affected is smallest in 2024. This could reflect the fact that the floods that year were

[18]We adjust WorldPop population data upward by scaling population in all pixels equally so that the total for all of Chad matches the reported total population in 2020.

much more severe than in other years, meaning flood exposure was more likely to adversely affect households.

Figure 15: Annual population exposure to VFM-detected flooding



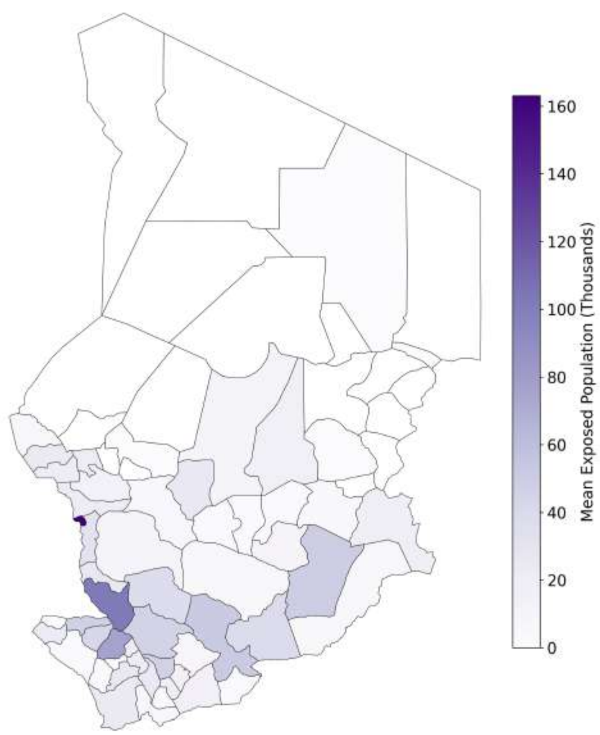
Note: Authors' calculations based on data from the VFM archive NOAA and George Mason University (2025) and WorldPop (2025). The figure presents the total annual population exposed to floods detected in the VFM data. Note that data for 2021 and 2022 are not available in the VFM archive.

A relatively large population is classified as exposed to floods even outside of major flood disasters: at least 600,000 households are identified as exposed in every year. The fact that there is little media discussion of flood events in Chad from 2013-2018 despite such levels of exposure could have several explanations. First, the flooding in these years was less severe in both extent and duration, as shown in Figure 13, so the detected floods may not have been very harmful for nearby populations. Second, some of the detected floods may have been anticipated, particularly given the recurring nature of flooding in Chad. Floods are more likely to cause damages if the severity is greater than is expected, as was the case in 2022 and 2024 for example. Third, it may be that many of the people identified as exposed to floods from 2013-2018 were indeed harmed but that these impacts were sufficiently spread out to not have attracted media attention.

We compare the estimated national annual population exposed to VFM-detected floods to the reported of national population affected by floods, as summarized in Table 2. On average, 16% of the estimated exposed population is reported as affected by flooding, though this includes years where there are no reports of flood effects in Chad. In years where affected populations are reported, they represent 29% of the estimated exposed population. In years of major flood disasters such as 2012, 2020, and 2024 (as no VFM data are available for 2022), this share increases to 48%. This comparison shows that floods do not affect everyone equally, in line with the survey analysis of correlates of flood shock reports. The larger share of the population affected by more severe floods may represent broader indirect effects of these floods, in addition to direct effects of flooding.

Figure 16 presents the mean total annual population exposed to VFM-detected flooding across 2012-2024 by departement in Chad. The highest levels of average exposure are in N'Djamena and Mayo-Kebbi Est. In terms of the share of population exposed to detected floods, 21 departements have more than 10% of the population exposed annually on average, and 5 have more than 20% population exposure: Mamdi, Mayo Boneye, Mayo Lemyé, Bahr Azoum, and Tandjilé Centre. Table A4 presents the data on population exposure totals and shares by departement in a table.

Figure 16: Mean annual population exposure by departement



Note: Authors' calculations based on data from the VFM archive NOAA and George Mason University (2025) and WorldPop (2025). The figure presents the mean total annual population (in 1000s) exposed to floods detected in the VFM data across 2012-2024 by departement. Note that data for 2021 and 2022 are not available in the VFM archive.

In general, patterns in average annual population exposure to VFM-detected floods across departements are very similar to patterns in estimated population exposure using the Fathom and Rogers et al. (2025) data (Figure 3, Figure 4). Another observation is that the estimated exposed population in N'Djamena (163 thousand people, or 11% of the population, on average) may seem somewhat low given its location in a high flood hazard zone and high population. This may reflect challenges for satellite imagery in identifying floods in built-up urban areas, due to obstruction by buildings, more heterogeneous surfaces, and difficulties distinguishing flooding from other dark surfaces such as asphalt or shadows.

3.3 Comparing flooding incidence between surveys and satellites

We compare flooding incidence as reported in household surveys to the results from the VFM archive. In all cases, we consider all years of VFM data which overlap with the survey recall periods. The periods considered in the VFM data can therefore be longer than those considered by the survey respondents. For example, the ENSA surveys ask about the past 6 months, covering the main flooding season, and we compare this to VFM data over the whole year including this 6 month period.

A visual comparison the two sources appear to be quite correlated but not perfectly aligned. The ENSA community-level flood report maps in Figure A17 show much higher concentrations of households reporting flood shocks in 2020 and 2024 and in much the same areas with high deviations in annual flooding days as in Figure 13, including in many of the same parts of Northern Chad. But it is also the case that the ENSA survey reports indicate widespread flooding in areas and years where little flooding is identified in the VFM data, such as in Wadi Fira, Ouaddai, and Mayo-Kebbi Ouest in 2024.

As another example of a visual discrepancy between survey flood reports and the satellite-based flood detection, there are repeated instances of survey reports of flooding Kanem where no flooding is typically ever detected in the VFM data. The RIMA survey shows some flooding in Kanem in 2014 and the ECOSIT 4 survey shows some from 2015-2018 (Figure A19), while the DIEM surveys show high levels of flood reports there in 2024 (Figure A18). The ENSA surveys show almost no flood reports in Kanem from 2016 to 2021, but some reports in 2022 and higher levels in 2024 consistent with generally higher flood reports that year (Figure A16). The differences could indicate pluvial flooding that is not detected by the VFM, or damages caused by heavy rainfall that did not lead to inundation. The floods in July-September 2024 were caused by torrential rains and in Kanem there is no river so it is less likely the floods would have remained detectable by the VIIRS optical satellite sensor after the clouds dispersed. However, we also find no detected floods in Kanem in 2024 when extracting data from the Copernicus Emergency Management Service GFM tool, which is based on Sentinel-1 radar data that is not affected by cloud cover (Figure A23). WFP bulletins on flooding Chad using ADAM also show no flooding detected in Kanem province (Figure A14). Both of these tools could also miss short-duration pluvial floods, but government and media reports further indicate limited population exposure to flooding in Kanem (Figure A15).

The discrepancies between survey data and satellite imagery in Kanem therefore do not necessarily imply a limitation of the VFM database in particular, but rather a combination of limitations of remotely-sensed flood detection and differences in what households may define as flooding as opposed to what is defined in the algorithms using satellite data. In particular, survey households may report precipitation-related shocks that did not result in inundation as flood shocks, or report adverse effects of disruption from more distant flooding. The surveys do not allow respondents to distinguish between these types of shocks.

We now analyze more systematically the relationship between survey flood reports and VFM flood detection. For both the ECOSIT and ENSA surveys where community coordinates were provided by INSEED and SISAAP, respectively, we use these coordinates to measure VFM-detected flooding in the area around the communities. In particular, we aggregate data on flood detection for each 375 m pixel within 1 km, 2 km, and 5 km of the community centroids in each year that the VFM data are available, to create a time series of community-level satellite-based flood detection. We then test the correlations between an indicator for any survey flood report in the community and both community characteristics and measures of VFM flood detection at these different radiuses around the community, controlling for fixed departement characteristics. Effectively, we identify what community characteristics and measures of VFM flood detection explain differences between community flood survey reports within departements.

Looking first at results in the ECOSIT 4 survey on flood reports for the period from 2015-2018, the first row of Table 8 shows that rural communities are around 14 percentage points less likely to have any flood shock report. This may reflect that urban communities are often closer to rivers than rural communities and therefore more exposed to fluvial floods. The next three rows show that characteristics of community households—the share of households engaged in agriculture, with cement/metal roofs, and with cement/tile floors—are not consistently associated with the probability of any household flood report, though there is some evidence that in communities where more households have cement or tile floors this probability is smaller. These results indicate that although indicators of flood vulnerability explain *household*-level flood reports (Table 5), it is not the case that the most vulnerable *communities* are more likely to have households report a flood shock.

Columns 2-7 of the table bring in flood detection information from the VFM archive, focusing on the total number of pixels in a given radius around the community with any flooding detected in each year from 2015-2018, the recall period of the surveys. The pattern of results is similar if we instead consider the total number of days that pixels are flooded in each year. Looking first at a continuous measure of flooded pixels (column 2-4), we find that correlations with community flood reports are generally larger in magnitude when considering a 1 km radius compared to a 2 or 5 km radius and that the relationship varies a lot across years. Surprisingly, point estimates are negative for VFM flood detection in 2015 and 2016, suggesting this made survey flood reports *less* likely although the effects are only statistically significant for detection within a 1 km radius. The point estimates are positive but generally not significant for floods detected in 2017. Only for 2018 and detection within 1 and 2 km is the correlation between the number of flood pixels and community survey reports positive, large, and strongly statistically significant. A 100% percent increase in the number of days of flooding within 1 km of the community in 2018—quite plausible given the mean number of flooded pixels is less than 2 out of 22—is associated with a 14 percentage point increase in the probability of any survey flood report. This represents a 28% percent increase compared to the mean probability of any survey flood report.

We also consider effects of being above a certain number of flooded pixels around a community

Table 8: Correlates of ECOSIT 4 community flood reports

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rural location	-0.133**	-0.142**	-0.147**	-0.157**	-0.138**	-0.147**	-0.148**
	(0.063)	(0.062)	(0.062)	(0.063)	(0.062)	(0.062)	(0.063)
Share of HHs engaged in agriculture	0.033	0.015	0.004	0.012	0.034	0.025	0.008
	(0.132)	(0.130)	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)
Share of HHs with cement/metal roof	-0.061	-0.088	-0.098	-0.105	-0.097	-0.071	-0.097
	(0.115)	(0.113)	(0.115)	(0.115)	(0.114)	(0.114)	(0.114)
Share of HHs with cement/tile floor	-0.234	-0.209	-0.244	-0.280*	-0.232	-0.282*	-0.290*
	(0.154)	(0.153)	(0.153)	(0.153)	(0.153)	(0.154)	(0.154)
Log total flooded pixels in 2015		-0.071*	-0.036	0.006			
		(0.037)	(0.029)	(0.029)			
Log total flooded pixels in 2016		-0.105**	-0.026	-0.013			
		(0.044)	(0.033)	(0.030)			
Log total flooded pixels in 2017		0.068	0.037	0.059**			
		(0.048)	(0.032)	(0.028)			
Log total flooded pixels in 2018		0.137***	0.070***	-0.002			
		(0.036)	(0.027)	(0.026)			
>=10% of surrounding pixels flooded in 2015					-0.123*	-0.109	-0.163*
					(0.074)	(0.072)	(0.090)
>=10% of surrounding pixels flooded in 2016					-0.156**	-0.107	-0.010
					(0.078)	(0.074)	(0.104)
>=10% of surrounding pixels flooded in 2017					0.128	0.114	0.216**
					(0.085)	(0.087)	(0.098)
>=10% of surrounding pixels flooded in 2018					0.228***	0.190***	0.095
					(0.070)	(0.065)	(0.084)
Observations	625	625	625	625	625	625	625
Mean, Any reported flood	0.496	0.496	0.496	0.496	0.496	0.496	0.496
Mean, Flooded pixels 2015		1.382	1.382	1.382	1.382	1.382	1.382
Mean, Flooded pixels 2016		1.296	1.296	1.296	1.296	1.296	1.296
Mean, Flooded pixels 2017		1.376	1.376	1.376	1.376	1.376	1.376
Mean, Flooded pixels 2018		1.939	1.939	1.939	1.939	1.939	1.939
Departement FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flood detection buffer	–	1 km	2 km	5 km	1 km	2 km	5 km

Note: Authors' calculations based on data from the ECOSIT 4 surveys and the VFM archive. The table shows the results of separate regressions where the outcome variable is a dummy for whether any household in the community reported experiencing a flood shock from 2015-2018. Flood incidence data from the VFM archive are linked to the ECOSIT data based on community centroids, and we present results linking data from pixels at various distances from these centroids. On average there are 22 land pixels within 1 km, 89 pixels within 2 km, and 553 pixels within 5 km. Wave FE are controls for whether the sample households were surveyed in the first ECOSIT 4 wave (July-September 2018) or the second (January-April 2019). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

in a given year, using 10% of pixels as a threshold to focus on situations with more widespread flooding and reduce potential measurement error from situations where a single pixel may be incorrectly categorized as flooded in the VFM archive. Columns 5-7 of Table 8 show a similar pattern of results as with the continuous measure of flood exposure, which is expected as both sets of variables are based on the count of flooded pixels. Within 1 km we find that having more than

10% of surrounding pixels flooded—on average, at least 3 out of 22—in 2015 or 2016 is associated with a *decrease* in the probability of any survey flood report, while being above this threshold in 2017 or 2018 is associated with an *increased* probability. In 2018, having more than 10% of pixels within 1 km flooded is associated with a 23 percentage point increase in the likelihood of a flood report.

Table 9 shows the results from aggregating VFM flood detection across years for the period 2015-2018, either by taking the maximum number of pixels with detected flooding or by taking the sum. The table shows a clearer positive relationship between flood detection and the probability of any household flood report in a community. The estimated magnitudes are larger when considering the maximum detected flood extent over 2015-2018 (columns 1-3) than when considering the total flood extent (columns 4-6). This indicates that extremes of flood exposure are more predictive of flood shock reports than accumulated flood exposure. The coefficients are similar when considering different bandwidths of flood detection around the community centroid. We also find similar results when focusing only on predicting communities where at least one third of respondents report a flood shock.

Table 9: Correlates of ECOSIT 4 community flood reports, aggregated detection over years

	(1)	(2)	(3)	(4)	(5)	(6)
Log max flooded pixels 2015-2018	0.054^{**} (0.024)	0.047^{**} (0.018)	0.041^{***} (0.015)			
Log total flooded pixels 2015-2018				0.037^{**} (0.018)	0.038^{**} (0.015)	0.036^{***} (0.013)
Observations	625	625	625	625	625	625
Mean, Any reported flood	0.496	0.496	0.496	0.496	0.496	0.496
Departement FE	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Flood detection buffer	1 km	2 km	5 km	1 km	2 km	5 km

Note: Authors' calculations based on data from the ECOSIT 4 surveys and the VFM archive. The table shows the results of separate regressions where the outcome variable is a dummy for whether any household in the community reported experiencing a flood shock from 2015-2018. Flood incidence data from the VFM archive are linked to the ECOSIT data based on community centroids, and we present results linking data from pixels at various distances from these centroids. On average there are 22 land pixels within 1 km, 89 pixels within 2 km, and 553 pixels within 5 km. In this table we aggregate flood detection records for 2015-2018 by either taking the max (columns 1-3) or the sum (columns 4-6). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In summary, the results from the ECOSIT 4 survey show that more proximate and more recent satellite-detected flooding is a strong and significant predictor of survey flood reports. There are limited differences by distance of detected floods from the community centroid, potentially because similar increases in the proportion of pixels with detected flooding at different bandwidths imply larger increases in the absolute number of flooded pixels at larger bandwidths. The negative coefficients for flooded pixels in 2015 and 2016 can be explained by correlations in flooded pixels over time. When estimating relationships between survey reports and flood detection in each year separately, the coefficients on 2015 and 2016 are much closer to zero and no longer statistically significant, while the coefficient on 2018 remains large, positive, and significant, and the coefficient on 2017 is marginally significant (Table A3). So it is not the case that more flood detection in 2015 or 2016 actually *decreases* the likelihood of a flood report, but rather that locations with flooding identified in both these years and 2018 are less likely to report a flood. This might imply some level of adaptation to flood risk among communities repeatedly exposed to flooding. The differences by year also indicate recency bias in household survey recall, with much greater weight being placed on flood realizations in the most recent years. This is a commonly documented phenomenon in household survey collection and a function of the long recall period used in the flood shock survey questions.

Table 10 presents results from the same analyses using data from the ENSA surveys. We include data from the 2020, 2023, and 2024 surveys as these are the only rounds where both community coordinates and VFM archive data are available. All sample communities are rural so we cannot test if this is associated with flood reports, but we find no association with the share of households engaged in agriculture. Unlike in the ECOSIT sample, more households with durable housing materials (in this case, a cement or metal roof) is associated with a greater likelihood of any flood report in a community, despite a negative association between durable roofs and household-level flood reports (Table 6). This could potentially reflect a greater share of durable roofs being a proxy for relatively more economically developed rural communities, which could be correlated with other factors affecting flood risk.

Table 10: Correlates of ENSA community flood reports

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of HHs engaged in agriculture	-0.061	-0.028	-0.009	0.000	-0.038	-0.018	-0.003
	(0.051)	(0.050)	(0.049)	(0.048)	(0.050)	(0.049)	(0.049)
Share of HHs with cement/metal roof	0.130^{***}	0.119^{***}	0.122^{***}	0.131^{***}	0.116^{***}	0.126^{***}	0.141^{***}
	(0.043)	(0.042)	(0.041)	(0.040)	(0.042)	(0.042)	(0.041)
Log total flooded pixels in same year		0.154^{***}	0.126^{***}	0.103^{***}			
		(0.013)	(0.008)	(0.005)			
>=10% of surrounding pixels flooded in same year					0.275^{***}	0.330^{***}	0.371^{***}
					(0.025)	(0.024)	(0.025)
Observations	3466	3466	3466	3466	3466	3466	3466
Mean, Any reported flood	0.543	0.543	0.543	0.543	0.543	0.543	0.543
Mean, Count of flooded pixels		0.901	3.611	22.166	3.611	3.611	3.611
Departement FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flood detection buffer	–	1 km	2 km	5 km	1 km	2 km	5 km

Note: Authors' calculations based on data from the ENSA surveys and the VFM archive. The table shows the results of separate regressions where the outcome variable is a dummy for whether any household in the community reported experiencing a flood shock in the past 6 months during the 2020, 2023, and 2024 survey rounds. Flood incidence data from the VFM archive are linked to the ENSA data based on community centroids, and we present results linking data from pixels at various distances from these centroids. On average there are 23 land pixels within 1 km, 90 pixels within 2 km, and 565 pixels within 5 km. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Columns 2-7 of the table again bring in measures of the number of flooded pixels within a given radius of the community using data from the VFM archive. We use data for the same year as each survey, as the surveys are conducted in October-November, around the end of the flood season, and ask about flood shocks in the prior six months. The numbers of flooded pixels within a 1, 2, and 5 km radius are all significantly and positively associated with the probability of any flood report (column 2-4). The magnitudes are larger than those for 2018 flooded pixels in the ECOSIT sample and there is also less of a difference across distance bandwidths, though the point estimate for the 1 km bandwidth remains the largest. A 100% increase in the number of flooded pixels within 1 km—again quite plausible given the mean is 0.9 pixels flooded out of 22—is associated with a 15 percentage point (28%) increase in the probability of a survey flood report, compared to a 10 percentage point increase for a 100% increase in the number of flooded pixels within 5 km.

Using the threshold of 10% of pixels within a given bandwidth with flooding detected (columns 5-7), we find that being above this threshold is associated with a 28 percentage point increase for a 1 km bandwidth, compared to 33 for a 2 km bandwidth and 37 for a 5 km bandwidth. Therefore, as in the ECOSIT sample, flood shock reports are not more associated with more proximate flood detection. Even if more proximate floods may be more likely to cause direct damages, an equivalent proportional increase in detected flooding over a 5 km radius implies a much larger number of flooded pixels and therefore more potential for both direct and indirect effects of flooding.

While Table 8 and Table 10 show that there is a strong and significant correlation between survey flood reports and remotely-sensed flood detection there are still disagreements on flood exposure between the two sources. In the three ENSA surveys matched to VFM data, 72 of 442 (16%) of communities with more than 10% of pixels within 1 km detected as flooded do not have any floods reported in the household surveys, but 72% of communities with a flood report do not have any flooded pixel within 1 km and 45% do not have any within 5 km. In the ECOSIT 4 sample, 36% of communities with more than 10% of pixels within 1 km detected as flooded in the VFM archive in 2018 do not have any floods reported in the household surveys. Further, 42% of communities with a household flood shock report do not have any pixels within 1 km with any flooding detected from 2015-2018. Even within 5 km, 17% of communities with a flood report have no pixels with any flooding detected over this period. This mismatch is not due to communities with isolated flood reports that might be hard to detect. In fact coefficients on the counts of pixels detected as flooded in the VFM data in different years are smaller when predicting whether communities have at least 4 of 12 households report experiencing a flood shock, as a proxy for high confidence in survey flood reporting. Of these 68 communities, 34% had no flooded pixels within 1 km from 2015-2018 and 13% had none within 5 km.

These disagreements emphasize challenges in predicting survey flood reports using satellite data, but suggest that using satellite-based flood detection to identify flooded communities may hold promise. This approach will not capture all flooded communities, but the results suggest a satellite-based flood detection threshold could be quite accurate in identifying a subset of flooded communities. The results show that 84% of ENSA communities and 64% of ECOSIT 4 communities with at least 10% of pixels within 1 km detected as flooded have at least one flood report. The accuracy does not improve if considering a 20% threshold or a wider radius in the ECOSIT 4 data but improves slightly in the ENSA data, reaching 89% for a 20% threshold and a 5 km radius.

Further analysis could seek to identify a threshold and distance to maximize predictive accuracy.

We test whether certain community characteristics affect the ability of the VFM flood detection to predict survey flood reports using the ECOSIT data. Table 11 shows that there is considerable heterogeneity. On average, doubling the count of flooded pixels detected within 1 km in 2018 (a 100%) is associated with an 8.0 percentage point increase in the probability that any household reported a flood shock from 2015-2018 (Column 1). But this correlation is driven entirely by communities in rural areas, with many households engaged in agriculture, and with no nearby water. In rural areas, doubling the count of flooded pixels detected within 1 km in 2018 (a 100%) is associated with an 13.5 percentage point increase in the probability that any household reported a flood shock, but there is no correlation between this satellite measure and survey reports in urban areas (Column 2). Agricultural engagement is highly correlated with rural location, so the heterogeneity by this measure is similar to the difference by rural location (Column 3). We find no difference in predictive power by whether more households have solid floors (Column 4). Importantly, the correlation is not significantly larger in communities with no permanent water pixel within 1 km (Column 5), but there is no significant correlation in communities closer to water.

Table 11: Heterogeneity in ECOSIT 4 reported flooding prediction

	(1)	(2)	(3)	(4)	(5)
Log total flooded pixels in 2018 2018	0.080*** (0.024)	0.028 (0.038)	0.007 (0.044)	0.086*** (0.029)	0.138** (0.067)
Log total flooded pixels in 2018 × Rural location		0.107** (0.053)			
Log total flooded pixels in 2018 × >50% of HHs engaged in agriculture			0.109** (0.053)		
Log total flooded pixels in 2018 × >1/3 of HHs have a cement/tile floor				-0.027 (0.061)	
Log total flooded pixels in 2018 × Any permanent water pixel within 1 km					-0.075 (0.073)
Observations	625	601	608	614	594

Note: Authors' calculations based on data from the ECOSIT 4 surveys and the VFM archive. The table shows the results of separate regressions where the outcome variable is a dummy for whether any household in the community reported experiencing a flood shock from 2015-2018. Flood incidence data from the VFM archive are linked to the ECOSIT data based on community centroids. We focus on flooding within 1 km in 2018 as the magnitude of the correlations in Table 8 are strongest for this measure. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Stronger correlations between satellite-detected floods and survey reports of flood shocks in rural and agricultural areas may suggest that flooding is more likely to cause damages or affect livelihoods and therefore be reported as a shock in rural and agricultural areas. It may also reflect difficulties in detecting water in more built-up urban areas, or differences in how long inundation persists in urban compared to rural settings. Despite the stronger correlation, overlap between satellite and survey reports remains limited even in rural communities. Just under one-third of rural communities where more than 10% of surrounding pixels were detected as flooded in 2018 have no survey flood reports, and 53% of rural communities with any flood report have no pixels detected as flooded within 1 km from 2015-2018.

The larger magnitude of the correlation between pixels detected as flooded and survey flood reports in communities farther from water, though not significantly different from the magnitude in areas closer to water, could have two potential explanations. First, communities closer to water may be more adapted to flooding risk and therefore less likely to report a shock following some local inundation. Second, some seasonal fluctuations in the extent of water near rivers may be anticipated by households but detected as flooding by the VFM algorithm. A large number of flooded pixels in an area farther from water is a strong predictor of flood reports: 86% of communities with at least 10% of pixels within 1 km flooded in 2018 have a survey-reported flood shock. But even in these areas, 26% of communities with a flood report have no flooded pixels detected within 5 km from 2015-2018.

These results show that using flood detection in the area around a community can identify areas where household flood shocks are very likely, but will also identify areas where households are not affected and can miss many communities reporting flood shocks. The former type of classification error—identifying flooding in a community with no flood report—could have three main explanations. First, the VFM algorithm may inaccurately identify some pixels as flooded but to either measurement issues or inaccurate water masking. Second, households affected by nearby detected floods may not be included in the survey samples either due to random sampling or to differential sampling probability: they may be displaced or unavailable to complete an interview. Third, nearby flooding may not cause damages to households that result in a flood report, either because of where the flooding occurred relative to the locations of homes, farms, or infrastructure, or because households have taken measures to protect against flood damages. Households may also fail to recall and report some nearby flooding. We identify high levels of population flood exposure in many years with no major media reports of flood disasters in Chad and note that in most of these years flooding was limited in both extent and duration. These less severe floods may therefore be less likely to result in household flood shock reports. Overall, however, the results suggests that flood detection is strongly predictive of flood shock reports.

Cases where the VFM data does not identify flooding in communities where flood shocks are reported are an important challenge from the perspective of identifying a trigger for flood responses, suggesting potentially high levels of basis risk. As we show that accuracy of flood detection in predicting flood reports is not lower when considering a 5 km as opposed to a 1 km around a community, larger radiuses may be preferred for determining flood response to help reduce the risk of not identifying some flooded communities. Indeed, the share of ENSA communities with flood reports but no detected flooding fall from 72% when using a 1 km radius to 45% with a 5 km radius. The corresponding numbers for ECOSIT 4 communities are 42% and 17%. Sous-prefecture or departement level flood detection may also be useful as a first pass for identifying areas where communities are at greater risk of flood exposure.

Two main factors could explain the cases with survey flood reports but no VFM flood detection. The first is again measurement issues with the VFM data, as the VIIRS satellite imagery cannot capture floods that occur under cloud cover or that occur but do not persist long enough to be captured at the time the satellite passes overhead. Satellites also have difficulty identifying urban flooding, as obstruction by buildings, more heterogeneous surfaces, and many flat dark surfaces such as asphalt and building shadows make it challenging to identify flood waters. Similar challenges constrain flood detection in areas with steep slopes and in flat barren arid areas. The second is measurement issues with the survey data, particularly the fact that households may report as flood shocks events that involve water-related damages but did not involve any inundation of dry land. The estimated relationships are similar when focusing on predicting communities where at least a third of households report flooding, indicating the mismatches are not due solely to household misreporting.

Issues related to flood identification in the VFM algorithm could potentially be reduced with a more sophisticated approach to flood detection. Considering deviations in detected surface water at the same location and time of year across years could help separate flooding from seasonal water fluctuations and reduce false flood identifications. Incorporating satellite radar data and using machine learning tools to fill in missing data from periods and areas covered by clouds could reduce the number of flood events that are missed. Machine learning tools could also be used to identify what characteristics of detected flooding under what conditions can best predict flood reports. Patel (2025)'s study of the impact of floods in Bangladesh describes an approach to remotely-sensed flood measurement that incorporates all of these partial solutions, offering one path toward better predicting where household flood shocks have occurred.

4 Estimating economic impacts of flooding in Chad

Recent floods in Chad have had devastating human and economic impacts, as summarized in Table 2. Millions of people have been displaced as hundreds of thousands of homes and hectares of cropland have been destroyed. Hundreds of individuals have been killed and more have suffered from disease and hunger following flooding.

Exposure to flooding can affect households through multiple different channels, summarized in Table 12. Floods cause direct damages to health, agriculture, and property, as well as causing displacement. These direct impacts can then lead to adverse effects on health, productivity, income, and food security. At the same time, broader community and environmental effects of floods such as water pollution, land degradation, infrastructure damages, and disrupted trade can compound negative effects on households.

A large economics literature has studied the household-level impacts of flood exposure using survey data in developing countries, part of a much larger literature estimating aggregate impacts of flooding on economic outcomes. Studies find that flooding decreases household food security (Devereux, 2007; Reed et al., 2022), worsens health outcomes (Carias et al., 2022; Djoumessi Tiague,

Table 12: Channels of household flood impacts

Direct damages	Indirect effects	Environmental effects
Health (drowning, injury)	Decreased health (i.e., water-borne illnesses)	Unsanitary water
Agricultural damages	Decreased agricultural productivity	Land degradation
Property damages	Decreased productivity and income	Infrastructure damages
Displacement	Increased debt, food insecurity	Higher prices, disrupted trade

2023; Sajid & Bevis, 2021), and generally increases poverty and decreases well-being (Baez et al., 2020; Freudenreich & Kebede, 2022; Stein & Weisser, 2022). In agricultural areas, flooding has been shown to reduce crop production (Banerjee, 2010; Bangalore & McDermott, 2023; Djoumessi Tiague, 2023). Efforts to cope with flood shocks often include temporary migration and short-term wage labor (Akter, 2021; J. J. Chen et al., 2017; Gray & Mueller, 2012; Maystadt et al., 2016; Mueller & Quisumbing, 2011; Vitellozzi & Giannelli, 2023). Much of this literature has focused on floods in Asian countries, and there have been no studies of the impacts of floods in Chad.

Most studies using household survey data focus on short-term effects in the period immediately after the flood, though recent work has started exploring long-term effects. Patel (2025) finds that past exposure to floods in Bangladesh decreases economic activity, but increases out-migration, agricultural exit, and school enrollment, which he interprets as strategies to diversify livelihoods. Sajid (2023) finds that flooding in a past decade in India decreases rural wealth, inhibits migration to urban areas, and increases engagement in household agriculture, which together suggest households are constrained to lower-productivity livelihood strategies Biscaye and Isah (2025) find that extreme flooding in Nigeria decreases food security and farm income and increases wage employment and rice cultivation in following years, which indicates both livelihood diversification and farm adaptation strategies.

These studies generally apply difference-in-difference methods to identify impacts of flooding using panel survey data, comparing changes after flood exposure in exposed areas to changes in unexposed areas. The advantage of such an approach is that it controls for time-invariant characteristics that might be associated with the risk of flood exposure. Flooding is measured in a variety of ways including survey reports, administrative reports, flooding databases, and direct detection from satellite data, and is typically defined at the community level.

In this section we use similar methods estimate household impacts of flood exposure using ECOSIT panel survey data from Chad and measuring flood exposure at the community level using data from the VFM archive and survey reports.

4.1 Data

The key to identifying causal impacts of flood exposure is to be able to identify areas to serve as counterfactuals for areas exposed to a given flood event. With cross-sectional data this could be accomplished using propensity score matching techniques based on characteristics associated with the probability of flood exposure. But the assumption that exposure to floods in a given time period is the only difference between two sets of communities is a strong one even after matching and controlling for observed factors correlated with flood risk, particularly since outcomes are only observed once, post-flooding.

Panel data allows for a weaker assumption: communities exposed to a flood and comparison communities may differ in their characteristics but would have been expected to change similarly over time in the absence of flooding, conditional on some control variables. With panel data we can control for time-invariant location characteristics that might be associated with both flood risk and the outcomes of interest, and can also test for balance in key characteristics and outcomes *prior* to the period of flood exposure.

While the Disaster in Emergencies Monitoring (DIEM) survey has been implemented twice yearly in Chad since 2021, it is not a panel at the household level and also includes different samples of departements in each year. The Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS) have been conducted multiple times in Chad but are also not a panel at the household level and although they are nationally-representative the publicly-available data do not include location identifiers below the province level, meaning we cannot construct a geographic panel with sufficient sample size. We have obtained access to data with community coordinates for the Enquête Nationale de Sécurité Alimentaire (ENSA), surveys from 2020-2024 from SISAAP in Chad, but this survey is cross-sectional and different communities are sampled in each year meaning we cannot construct a household- or even community-level panel.[19]

To the best of our knowledge, there is only one source of panel household survey data in Chad: the Enquête sur les Conditions de vie des Ménages et la Pauvreté au Tchad (ECOSIT). ECOSIT 4 was conducted between 2018 and 2019 with a sample of 7,493 households is representative at the national, province, and urban/rural levels. Then, the COVID-19 High Frequency Phone Surveys (HFPS) were conducted in four rounds from 2020-2021 with a sample drawn from the ECOSIT 4 intended to be representative at the national and N'Djamena/other urban/rural levels. Among 2,833 households sampled for the survey, 1,748 were surveyed successfully and were contacted for each rounds of the HFPS.[20] Finally, ECOSIT 5 was conducted in 2022 with a sample of 7,532 households of which 5,761 were also surveyed in ECOSIT 4. Across all survey rounds, 6,223 households from ECOSIT 4 are surveyed at least twice.[21] Of these, 4,475 are observed only in ECOSIT 4 and ECOSIT 5 while 1,748 are also observed at least once in the HFPS.

The ECOSIT surveys include data on household and community characteristics which we can use to test for baseline balance between flooded and non-flooded communities. The data also include modules on outcomes such as livelihood activities, assets, food insecurity, and subjective well-being which could be affected by flood exposure. Importantly, the survey also asks about household shocks, including the flood reports presented in Figure 11.

[19] The ENSA data could instead be used to implement a stacked cross-sectional event study research design.

[20] Although just 23% of ECOSIT 4 households are included in the HFPS, 519 out of 625 communities are represented, which is in line with the HFPS sampling approach at the household rather than community level. Figure A24 shows no clear patterns in which communities are represented, though the share of ECOSIT 4 households included in the HFPS appears to be larger in more urban communities.

[21] Households in communities exposed to flooding after ECOSIT 4 are not significantly less likely to be surveyed in a later round.

Table A5 presents baseline characteristics of households in the ECOSIT panel. Sample households are split between urban (45%) and rural (55%) communities and have 5.6 members on average. Three-quarters live in a dwelling that they own, mostly with non-durable roof materials (56%) and earthen floors (88%). Access to electricity (16%) and toilets or latrines (29%) is limited, and 29% of households have annual per capita consumption below the national poverty line. Household heads are primarily male (77%) and Muslim (64%). Less than half are literate (47%) and just 33% have completed at least primary schooling. Households report having experienced a variety of shocks over the previous three years. Shocks to household members including severe illness, death, and divorce are most common (51%), followed by shocks to income sources of work outside of agricultural shocks (22%). Environmental and agricultural shocks are less common; 10% of households report any flood, 19% report any drought, and 21% report any other agricultural shocks. Over two-thirds of households are engaged in any agricultural activity including raising livestock (71%), more than are engaged in any non-farm household enterprise (45%). The survey respondent was working in some activity in the last seven days in 72% of households. Households commonly receive transfers from family or friends (24%) and many report experiencing some forms of food insecurity. In terms of how they perceive their own well-being, 30% of households see themselves as worse off than their neighbors (as opposed to equal or better off) and 79% consider themselves poor or very poor.

4.1.1 Flood exposure definitions

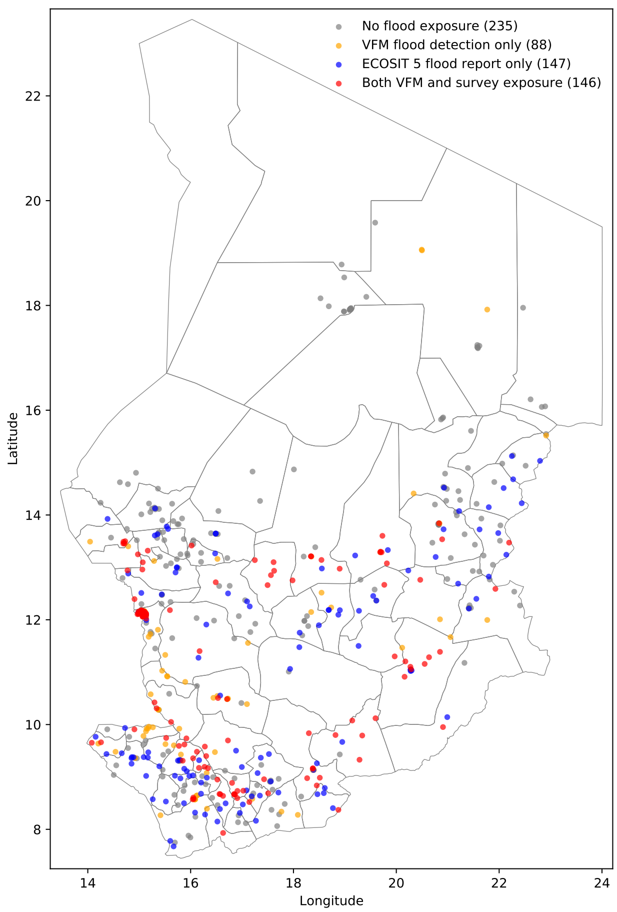
To conduct our analysis of the impacts of flood exposure on household outcomes, we match community locations with flooding incidence data from the VFM archive as described in Subsection 3.3. We focus on flood realizations in 2019 and 2020, while controlling for flooding exposure in previous years as reported in the survey and detected in the VFM archive. ECOSIT 4 was completed in April 2019, while the four rounds of the HFPS were conducted in June 2020, late July-August 2020, January-February 2021, and March-April 2021, and ECOSIT 5 was conducted in 2022. The main flooding season in Chad is typically July-October (coinciding with the rainy season from June-September), so any floods identified in 2019 would be after the ECOSIT 4 baseline and before the HFPS, while floods in 2020 would be in between rounds of the HFPS. Based on the results in Table 8 showing a greater correlation between ECOSIT flood reports and flood detection within 1 km, we define communities as exposed to flooding in 2019-2020 if at least 1 pixel within 1 km of the community centroid was flooded during this period. We then define treatment timing based on the first year a community was exposed between 2019-2020. The results are similar with a more restrictive treatment definition of at least 20% of pixels within 1 km identified as flooded during one of these years.

As an alternative flood treatment variable, we also consider household flooding reports for the 2019-2022 period collected during ECOSIT 5. Figure A19 maps the share of households by community reporting a flood shock in both ECOSIT 4 and 5. Since the recall period covers three years, we cannot know when exactly the flooding took place. For analyses using this flooding definition we therefore drop the HFPS sample and retain only the ECOSIT 4 (pre-flooding) and

ECOSIT 5 (post-flooding) samples.

Figure 17 maps panel community locations colored by their exposure to flooding under each treatment definition. In line with evidence of widespread flooding in both 2019 and 2020 from the ENSA surveys and VFM data, the VFM-based flood definition results in 38% of communities (234 of 616) categorized as exposed to flooding in 2019-2020, widely spread across the country. Most of these communities were first exposed in 2019, with just 41 exposed in 2020 but not 2019. Major floods also occurred across much of the country in 2021 and especially in 2022. As a result, the share of communities categorized as exposed to flooding using survey reports for the period 2019-2022 is larger, at 48%, also widely spread across the country including in several departements with no flooding identified in the VFM 2019-2020 data.

Figure 17: ECOSIT panel community flood exposure by definition



Note: Authors' calculations based on data from ECOSIT 4 and 5 and the VFM archive. Community flood exposure is based being within at least 1 km of a pixel detected as flooded at any point in the 2019 or 2020 for the VFM definition, and based on any household reporting a flood shock over the period 2019-2022 for the flood report definition.

The figure highlights that different communities are identified as exposed to flooding under the two definitions, consistent with significant but limited correlations between VFM flood detection and ECOSIT 4 flood reports discussed in Subsection 3.3, but also with differences in the periods considered. Out of 616 communities, 235 are not identified as flooded by either definition and 146 are identified as flooded by both, but of the remaining 235 (38%), 147 are identified as flooded only according to ECOSIT 5 reports and 88 only according to VFM flood detection. The communities identified only according to ECOSIT 5 reports likely represented exposure in 2021 and 2022, major years of flooding in Chad not captured in the VFM archive. The communities identified only according to the VFM archive are not surprising given the results in Table 8 showing recency bias in survey flood reports, as households may not accurately have recalled their exposure in 2019 and 2020 when surveyed in 2022, especially given the widespread flooding in 2022. An important implication is that the analysis of the impact of flood exposure on household outcomes is therefore identified off of different sets of communities according to each definition, and represents the impacts of different flood events.

4.2 Empirical approach

We conduct a difference-in-differences analysis to identify the impact of community flood exposure on household outcomes. Regressions take the form:

$$Y_{icrt} == \alpha + \beta Flood_c \times Post_t + \mu_i + \gamma_{rt} + \lambda X_{icrt} + \epsilon_{icrt} \tag{1}$$

where outcome Y varies across households i, communities c, provinces r, and rounds t. *Post* is an indicator for being observed after the first flood event. For the VFM definition, this is 2019 or 2020, and for the flood report definition, this is ECOSIT 5 only. *Flood* is an indicator for the flood exposure treatment: having ever been exposed during the relevant period. This is an intent to treat analysis as flood exposure is defined at the community level based on proximity to detected flooding events and therefore not all households in the treatment group will have been directly affected by flooding. This may bias estimated effects downward but avoids concern about selection in which households are exposed and will capture both direct effects of household flood damages as well as any indirect impacts from proximity to flooding. We cluster standard errors at the level of the community of residence in ECOSIT 4 since this is the level at which the flooding treatment is assigned.

As the HFPS was implemented as a short phone survey with few modules each round, we are restricted in the set of panel outcomes we can study. We focus on a subset of outcomes tracked across all survey rounds. These include whether the household is engaged in agriculture and non-farm household enterprise, whether the survey respondent did any form of work activity in the 7 days before the survey, a normalized food insecurity index composed of self-reports of different forms of food insecurity, household perceptions of absolute and relative well-being, and an indicator for whether the household reported experiencing any non-flood shock. We note that the timeframe for some of these questions differs between ECOSIT 4/5 and the HFPS, with the food security questions in particular asking about the past 12 months in ECOSIT 4 and 5 compared to the last 30 days in the HFPS, as those surveys were more frequent. As these differences are common across all households they should be captured by the round fixed effects.

The main results we present estimate Equation 1 using two-way fixed effects (TWFE). We include household fixed effects (μ) to control for time-invariant household characteristics which might affect outcomes and flood exposure, and province-by-year fixed effects (γ) to control for common changes over time across broad geographic areas. Notably, this will account for local differences in the effects of the COVID-19 crisis which began after ECOSIT 4 and before the HFPS survey rounds. X_{icrt} are time-varying controls at the community level which might be correlated with both flood exposure and the outcomes.

Because there are multiple flood exposure events in the VFM definition, we also estimate Equation 1 using methods from the modern difference-in-differences literature that account for staggered treatment timing (De Chaisemartin and d'Haultfoeuille, 2023). In particular, we apply the Borusyak et al. (2024) and Callaway and Sant'Anna (2021) and estimators. These methods apply a weighted approach to handle staggered timing and treatment effect heterogeneity which may lead to more accurate pre-trend estimates, though each method calculates pre-trends differently. We include the same fixed effects, controls, and clustering as in the TWFE estimators when using these alternative estimators, and use them to compare both average treatment effects and changes in treatment effects over time. In general, average estimated treatment effects are similar across methods. We apply only the TWFE estimator when defining flood exposure based on survey reports as with this definition we cannot identify specific treatment timing and for all exposed households the treatment occurred between when they were surveyed in ECOSIT rounds 4 and 5.

4.2.1 Identifying causal impacts of flood exposure

The effects of experiencing flooding for all estimators are identified using variation within households over time across communities with similar observable characteristics that were and were not exposed to flooding within regions and survey rounds. The key assumption for this empirical strategy to identify causal effects of flood exposure is that, conditional on control variables, outcomes in communities exposed to flooding would have evolved in the same way as unexposed communities had it not been for the flood shock. This would be the case in expectation if flood exposure were randomly assigned to communities, but while flooding realizations have an exogenous or quasi-random component linked to variation in weather patterns, flood risk is not distributed randomly over space as discussed in Subsection 2.1. In other words, flood realizations have an endogenous component which must be accounted for in the analysis.

To do this, we follow Borusyak and Hull (2023)'s method for dealing with non-random exposure to exogenous shocks. In short, we separate out the endogenous component of flood exposure by estimating the probability that a community was exposed to a flood during the relevant time period under each definition, and controlling for differences in outcomes by flood exposure probability in each round. This approach is similar conceptually to combining difference-in-differences with matching on covariates (Ham and Miratrix, 2024; Stuart et al., 2014). Including these exposure probability by round controls in the regression models means that effects of flood exposure are identified by comparing communities in the same province with the *same* exposure probability but *different* exposure realizations, therefore isolating impacts of the weather-driven exogenous flood shock component. Exposure probabilities are estimated in a machine learning framework using lasso regression to identify relevant predictors from among annual VFM flood detection measures in each community together with ECOSIT 4 flood reports and the community characteristics included in Table 8, and then including these in a logit model to predict flood exposure probability according to both the VFM and ECOSIT 5 reports. We then only retain communities within the range of common support of estimated probabilities among exposed and non-exposed communities. We find that controlling for the estimated probability of flood exposure fully accounts for the relationship between exposure status and historical VFM-detected annual exposure from 2012-2018: we cannot reject that there is not relationship between past flood detection and either flood exposure treatment definition we use after controlling for exposure probability (Table A6, Table A7).

While controlling for flood exposure probability increases the plausibility that communities would have evolved similarly in the absence of any flooding, this assumption is not empirically testable. Still, one suggestive test is to analyze balance in baseline characteristics of households during ECOSIT 4 by community flood exposure status. We test for balance on a variety of household and household head characteristics, on reports of shock exposure, and on measures of livelihood activities and household well-being. We find significant differences in baseline characteristics of households in communities exposed to either VFM-detected floods in 2019-2020 or household-reported floods in 2019-2022 (Table A8, Table A9), consistent with Table 8 and Table 5 showing that a variety of community and household characteristics are associated with ECOSIT flood reports. However, these differences disappear after controlling for the estimated probability of flooding, and we cannot reject the null that all of the characteristics we consider together explain no significant variation in flood exposure conditional on this probability.[22] Balance in baseline characteristics is not necessary to identify causal impacts of flooding in a difference-in-differences framework but showing strong baseline balance suggests that the assumption of parallel trends in outcomes in the absence of flooding seems plausible.

4.3 Results

Table 13 presents the results of two-way fixed effects analyses of the impacts of flooding defined based on VFM detection of flooded pixels within 1 km (column 1) and reported recall of flood shocks at the time of the ECOSIT 5 surveys (column 2). We note again that in addition to reflecting different measures of flood exposure, the two measures also capture different flood events. The flooded pixel measure only considers flood exposure in 2019 or 2020, while the flood report measure considers any exposure from 2019-2022.

Under both definitions there is no average effect of community flood exposure after the ECOSIT 4 round on whether the survey respondent is engaged in any work activity at the time of later surveys, respondent perceptions of household well-being, or household food insecurity. We emphasize that these are *intent to treat* estimates averaging over all households in affected communities, which

[22] The F-test p values are $p = 0.250$ for the VFM-based definition and $p = 0.156$ for the report-based definition.

are likely to be attenuated toward zero if households not directly harmed by local flooding do not experience any adverse effects. This is important in a context where just 21% of households in communities with any report of a flood shock during ECOSIT 5 reported such a shock, on average. Impacts on households directly experiencing the flood shock may be larger than the average effects at the community level that we estimate. For example, the point estimates for the food insecurity index are large but not statistically significant, and may reflect large insecurity effects for directly affected households and null effects for others in the same community. We do not estimate these direct "treatment on the treated" effects, first because we do not know which households were specifically affected by the 2019-2020 floods under the VFM definition, and second because direct flooding exposure is correlated with many household characteristics likely to affect levels and trends in the outcomes of interest (Table 5).

Table 13: Average impacts of community flood exposure

	(1) Any flooded pixel (SE)	(2) Any flood report (SE)
Respondent did any work in last 7 days	-0.05	-0.01
	(0.03)	(0.03)
Any HH non-farm enterprise	0.07*	0.04
	(0.04)	(0.03)
Any HH crop or livestock activity	-0.00	0.04***
	(0.02)	(0.01)
HH believes is is worse off than neighbors	-0.03	-0.03
	(0.03)	(0.02)
HH believes it is poor or very poor	0.02	0.01
	(0.02)	(0.02)
Normalized HH food insecurity index	0.09	0.03
	(0.07)	(0.05)
Household reported a non-flood shock	-0.06	0.10***
	(0.04)	(0.03)

Note: Authors' calculations based on data from the ECOSIT surveys and VFM archive. The table shows the results of separate regressions of a particular variable (shown in the rows) on the interaction of flood exposure and a post-exposure dummy, following Equation 1. Flood exposure in column (1) is based on VFM detection of any flooded pixel within 1 km of the community centroid in 2019 or 2020. In column (2) it is based on any household in a community reporting a flood shock over the 2019-2022 recall period. All specifications include household, region by round, and flood exposure probability by round fixed effects. Respondent work in the last 7 days can include any household farm or non-farm work as well as wage employment or unpaid labor, but not domestic work. Participation in crop or livestock activity is defined over the past agricultural season. Participation in non-farm enterprise is defined based on any active enterprises at the time of the survey. The food insecurity index is constructed as the sum of eight normalized variables capturing different aspects of self-reported food insecurity. Household well-being is based on the respondent's own perceptions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Despite considering only average effects of community flood exposure, we do find evidence of significant impacts on certain outcomes, though the results differ by flooding definition. Households in communities with nearby flooded pixels in 2019 or 2020 are 7 percentage points more likely to be engaged in non-farm enterprise in the post-flood surveys, or a 16% increase over the mean of 43% of households in unexposed communities. The point estimate is also positive but not statistically significant using the reported flood definition. Households in communities with any reported flood from 2019-2022 are 4 percentage points more likely to be engaged in household agriculture in the post-flood surveys, which is a 6% increase over the control mean. Reported community flood exposure also increases the probability the household reports any non-flood shock in the period after the flooding by 10 percentage points (14%). This indicates that flooding may increase vulnerability to later shocks, though there is no significant effect and the point estimate is negative under the VFM flooding definition.

Table 14 presents estimates of impacts of flood exposure over time as well as average impacts using the Borusyak et al. (2024) estimator for the VFM-based flood definition only, as the estimates using the survey-based definition are based on only two time periods, ECOSIT 4 and 5. Consistent with balance in baseline characteristics, there are no significant differences by flooding status in the period before exposure. Average effects over all post-exposure periods (at the bottom of the table) are similar to those in Table 13; only the effect on household engagement in non-farm enterprise is statistically significant. This effect is driven partly by large and significant increases in the period during and immediately following flood exposure: in this case, the first two rounds of the HFPS. Estimated effects remain positive but are not statistically significant in subsequent rounds. This pattern indicates that engaging in non-farm enterprise work may represent a coping mechanism for households whose livelihoods are disrupted by flooding, and that this engagement does not persist for all affected households.

Table 14: Impacts of community flood exposure over time

	(1) Respondent working	(2) Any non-farm enterprise	(3) Any HH agriculture	(4) Well-being worse than neighbors	(5) Considers HH poor	(6) Food insecurity index
t-1	-0.07	0.06	-0.02	0.03	0.01	0.08
	(0.07)	(0.08)	(0.03)	(0.08)	(0.04)	(0.21)
Treatment period	0.04	0.11**	0.00	-0.07*	0.04	0.08
	(0.04)	(0.05)	(0.02)	(0.04)	(0.03)	(0.10)
t+1	0.02	0.11**	0.00	-0.03	-0.01	0.02
	(0.04)	(0.05)	(0.03)	(0.04)	(0.03)	(0.11)
t+2	0.02	0.08	0.00	-0.04	0.00	-0.02
	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)	(0.11)
t+3	-0.04	0.08	0.01	-0.07**	0.02	0.02
	(0.04)	(0.05)	(0.02)	(0.04)	(0.03)	(0.08)
t+4	-0.04	0.06	0.00	-0.03	0.03	0.06
	(0.05)	(0.06)	(0.03)	(0.04)	(0.03)	(0.09)
Observations	14267	14267	14267	13478	14171	14267
Average effect	-0.01	0.08	0.00	-0.05	0.02	0.03
(Standard error)	0.03	0.04	0.02	0.03	0.02	0.07

Note: Authors' calculations based on data from the ECOSIT surveys and VFM archive. The table shows the results of separate regressions of a particular variable (shown in the columns) on flood exposure over time, using the Borusyak et al. (2024) staggered difference-in-differences estimator accounting for the timing of first exposure across communities. Flood exposure in column is based on VFM detection of any flooded pixel within 1 km of the community centroid in 2019 or 2020. All specifications include household, region by round, and flood exposure probability by round fixed effects. See Table 13 for outcome variable descriptions * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The only other significant average estimated effects of flood exposure in Table 14 are decreases in the likelihood that the respondent perceives the household as being less well-off than its neighbors. Both immediately during the period of flood exposure and a few rounds later, respondents are 7 percentage points (26%) less likely to perceive themselves as being worse off than other households in the same community. We also find a negative point estimate for the effect of the reported flood treatment on this outcome (Table 13 column 2), which is close to being marginally statistically significant ($p = 0.120$). One explanation is that the majority of households in flooded communities are not directly affected (as shown in the flood shock reports), and therefore perceive themselves as better off in subsequent periods than the minority of households that directly experience a shock.

4.3.1 Heterogeneity

The differences in effects by flooding definition Table 13 suggest that impacts of flood exposure may depend on community characteristics, as the two flooding definitions identify different sets of treated communities. The VFM definition is more likely to identify flooding in urban communities than the survey-based definition, for example. Table 15 presents tests of differences in flood impacts by rural/urban location. Although differences in effects by location are not statistically significant under either treatment definition for almost all outcomes, we do observe several interesting results. First, both definitions show large and significant increases in non-farm enterprise participation after flood exposure in urban areas. This implies that opportunities to earn income from such activities may be more restricted in rural areas making it a less attractive flood coping strategy.

Table 15: Impacts of community flood exposure by rural/urban location

	(1) Any flooded pixel, rural= 0 (SE)	(2) Any flooded pixel × rural= 1 (SE)	(3) Any flood report, rural= 0 (SE)	(4) Any flood report × rural= 1 (SE)
Respondent did any work in last 7 days	0.00	-0.08	-0.07*	0.11*
	(0.04)	(0.06)	(0.04)	(0.06)
Any HH non-farm enterprise	0.08**	0.03	0.08*	-0.06
	(0.04)	(0.08)	(0.04)	(0.06)
Any HH crop or livestock activity	-0.00	-0.00	0.03	0.03
	(0.02)	(0.03)	(0.02)	(0.03)
HH believes is is worse off than neighbors	-0.03	0.03	0.00	-0.06
	(0.04)	(0.06)	(0.03)	(0.04)
HH believes it is poor or very poor	0.04	-0.04	0.00	0.01
	(0.03)	(0.04)	(0.03)	(0.04)
Normalized HH food insecurity index	0.00	0.15	0.07	-0.12
	(0.10)	(0.13)	(0.08)	(0.10)
Household reported a non-flood shock	-0.07	0.04	0.11***	-0.03
	(0.06)	(0.08)	(0.04)	(0.06)

Note: Authors' calculations based on data from the ECOSIT surveys and VFM archive. The table shows the results of separate regressions of a particular variable on the interaction of flood exposure and the community being rural. Flood exposure in columns 1 and 2 is based on VFM detection of any flooded pixel within 1 km of the community centroid in 2019 or 2020. In columns 3 and 4 it is based on any household in a community reporting a flood shock over the 2019-2022 recall period. In each set of 2 columns, the first column represents the estimated effect in urban areas, and the second column represents the differential effect in rural areas compared to urban areas. All specifications include household, region by round, and flood exposure probability by round fixed effects, fully interacted with rural location. See Table 13 for outcome variable descriptions
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

For the other outcomes, there is more disagreement between the two flood exposure definitions. According to the survey-based definition, flood exposure tends to decrease respondent work engagement in urban areas only, with significantly more positive effects in rural areas. The VFM definition on the other hand shows reductions in work engagement in rural areas. The VFM definition suggests food insecurity is more likely to increase after rural flooding with little effects in urban areas, which would be consistent with better market access in urban areas, but the survey-based definition suggests the opposite. Finally, households in communities with any flood report are significantly more likely to report experiencing another type of shock in urban areas only, while there is not effect on shock reports in any area according to the VFM definition of exposure. These differences imply that it is not just the locations where flood exposure is identified according to the two definitions that drives the difference in results, but potential differences in the nature of the flooding events that are less straightforward to understand.

We also test for heterogeneity in impacts according to several household characteristics defined at baseline during ECOSIT 4: whether the household head is female, has a household wealth index is above the median, reported any flood from 2015-2018, is engaged in agriculture, and is engaged in non-farm enterprise. The results are shown in Figure A25, and in general we find limited evidence of consistent significant differences in impacts of flood exposure by these characteristics. Both flood exposure measures decrease the likelihood that the respondent has worked in the last 7 days among households that reported a flood shock at baseline, during the period from 2015-2018. The difference in effects by prior flood exposure is statistically significant when considering the survey-based flood definition.

Outside of this, the differences are either not significant or depend on the flood exposure definition. The decrease in respondent work is concentrated among less wealthy households according to the VFM-based definition but among more wealthy households according to the survey-based definition. Increases in engagement in agricultural activity identified using the survey-based definition are significantly larger among households with a female head and that were engaged in non-farm enterprise at baseline, and become negative and non-significant among households that reported any flood exposure in the period before the baseline survey. Decreases in the likelihood that the household perceives itself as worse off than its neighbors are driven by households that reported a flood shock before the baseline, according to the VFM-based exposure definition, and by households that are engaged in agriculture, according to the survey-based exposure definition. Households with a baseline flood report have significantly smaller effects of flood exposure on the probability that they believe they are poor or very poor according to the VFM-based definition, but significantly larger effects according to the survey-based definition. Effects of VFM-based flood exposure on the household food insecurity index are significantly larger and only statistically significant among households that reported a baseline flood.

4.4 Discussion

We estimate average effects of being in a community exposed to flooding on household outcomes in subsequent periods. Results from defining flood exposure based on VFM detection of flooded pixels in proximity to the community in 2019-2020 show that households exposed to flooding respond by increasing participation in non-farm enterprise activities, particularly in urban areas. These households are not significantly worse off over time than households in unexposed communities that had a similar estimated probability of exposure. The largest effects of flood exposure occur in the period when the exposure is realized and effects do not persist over the full sample period, suggesting households are generally able to recover form the shock on average.

Results from defining flood exposure based on having any household report a flood over the period between ECOSIT 4 and 5 show that households in exposed communities increase engagement in agricultural production, particularly if they have a female head or were engaged in non-farm enterprise at baseline. Community flood exposure also increases the likelihood that households report another type of shock, suggesting decreased resilience or greater vulnerability to repeated shocks.

Increased engagement in non-farm enterprise and household agriculture following flood exposure may represent household efforts to diversify their livelihood strategies following a shock to their main source of income. We do not have data on individual migration as a response to flood exposure, but find that attrition from the ECOSIT panel is not correlated with flood exposure suggesting limited effects on the likelihood that an entire household is persistently displaced or moves away.

An important consideration is that the results all represent intent to treat effects of community-level flood exposure, averaging effects across households that are directly affected by damages to their livelihood activities or possessions or harm to household members and households that are not directly affected. If indirect impacts of community flood exposure are limited, the low share of households reporting flood shocks in communities where at least one other household reports such a shock means that estimated average effects will be attenuated toward zero relative to effects of flooding on directly affected households. In this situation, positive point estimates on a food insecurity index may suggest that directly affected households are persistently more food insecure, but not sufficiently to overcome null effects on other community households.

Further research using the same data and identification strategy could explore this by using community flood exposure to instrument for households reporting a flood shock. This approach would identify local average effects of direct flood exposure, but requires the potentially strong assumption that community-level exposure only affects households through the probability that a household experiences direct flood-related damages. Estimated effects under this strategy would likely be larger than those reported here.

Another extension to this work would be to consider impacts of flood exposure additional outcome variables available only in the main ECOSIT 4 and 5 rounds but not in the HFPS such as measures of agricultural production, incomes from different sources, and household health, as well as individual-level labor supply data. Data from the ENSA surveys could also be particularly valuable for testing effects on food insecurity, though the identification strategy would be different because the ENSA data are not a panel. One approach would be to conduct a stacked cross-sectional event study, using the Callaway and Sant'Anna (2021) estimator for example, relying on different timing of when communities surveyed at different points in time are first exposed to flooding. This approach would require relying on remotely-sensed flooding treatment measures, as the surveys themselves only measure flooding in the 6 months prior to the survey.

5 Conclusions

The results of this report may be useful for policymakers and stakeholders working on climate change resilience, disaster response, and social protection in Chad. Understanding the geographic distribution of flood risk and occurrences may help to target resources and efforts to support adaptation and resilience to increasing flood risk. Both flood hazard and population exposure are concentrated primarily along bodies of water in Chad. Pluvial flooding also poses an important risk but it is more challenging to measure and monitor than fluvial floods, and affects a smaller share of Chad's population. The areas combining the highest mean days of annual flooding detected in the VFM archive together with higher population densities are largely all concentrated in the areas around the Logone River. These are also the areas with the highest levels of flood hazard according to Fathom. Given limited resources, investments in flood mitigation and response may therefore be most impactful in these areas.

Results emphasizing the recent and projected increases in flood exposure in Chad may motivate greater attention and investment in these areas. Flood hazard is projected to increase in the coming decades, with some areas becoming newly exposed to flood risk and others experiencing floods of greater severity. However, population growth is the main driver of projected increases in population flood exposure. These projected increases could potentially be reduced somewhat if efforts are made to prevent or mitigate flood exposure. Improved flood risk communications, investment in flood defenses, water management infrastructure, and more durable housing, and support for relocation or protection of informal settlements in areas with high flood hazard could reduce vulnerability to flooding even as flood hazard and the exposed population increase. Such policies would be most important in fast-growing parts of urban areas in proximity to rivers. Although this analysis finds limited household-level effects of recent community flood exposure using the ECOSIT surveys, the millions of displaced persons, hundreds of deaths, and hundreds of thousands of homes destroyed and cropland flooded in recent years suggest large potential economic and human benefits of flood protection policies.

This study also demonstrates that many floods may occur in remote areas and go unreported by media or government sources. Hundreds of thousands of people live in areas with floods detected by satellite each year, and a low but non-trivial share of households report experiencing flood shocks outside the years of major flood events in Chad. These populations are primarily concentrated in areas with high flood hazard, suggesting a need for additional monitoring resources in remote but high-risk areas with vulnerable populations. Vulnerability also varies within communities suggesting a need for targeted allocation of resources. The probability that a household reports a flood shock is correlated with factors making direct flood damages more likely: engagement in agriculture and less durable dwelling materials. Adding considerations of flood vulnerability to measures of exposure may help make investments more efficient and effective.

Finally, differences in community flood detection using satellite and survey data highlight challenges in using remote sensing alone to identify flood incidence. Flood detection in the area around a community can identify areas where household flood shocks are very likely, but will also identify areas where households are not affected and can miss many communities reporting flood shocks. This makes rapidly responding to flood events challenging and may result in an inefficient allocation of resources. Flood detection algorithms can mistakenly identify 'floods' in communities with no flood report, but may also correctly identify flooding that does not harm households if the flooding is anticipated or not severe or if households are otherwise protected. More specific measures of deviation in the presence of surface water relative to the same place at the same time of year can reduce potential false positives for flood detection.

We show that communities with flooding detected in close proximity are very likely to have households reporting flood shocks. Additional work could consider whether particular thresholds for levels of detected flooding, as well as particular distances around communities, lead to more accurate identification of communities with reported floods. A machine learning approach could consider this prediction problem systematically and allow for different thresholds and distances based on community characteristics such as rural location, distance from a river, and so on.

Failing to detect flooding in communities where households report flood shocks may be more concerning, as this would imply that these areas are less likely to receive relief. This situation also creates greater basis risk from the perspective of a threshold-based flood response policy using remotely-detected flooding. We find that the share of communities with a flood report but no detected flooding in proximity falls as we increase the area around a community in which flood detection is considered. Further work could analyze how basis risk changes with the scale of the geography considered. The tradeoff of increasing the geographic scale of flood detection is that the share of communities identified as potentially exposed with actual flood reports will fall.

Constraints in what types of flood events different types of satellite data can capture mean that some flooding will always be missed, though this can potentially be reduced by combining results from multiple satellites and algorithms. A machine learning model using multiple flood detection inputs and trained on 'ground truth' data (likely survey reports) may be most effective in improving the accuracy of flood detection. Another consideration is that inundation is not the only way that households can be harmed by heavy precipitation, which can cause direct damage as well. Such shocks require their own set of interventions.

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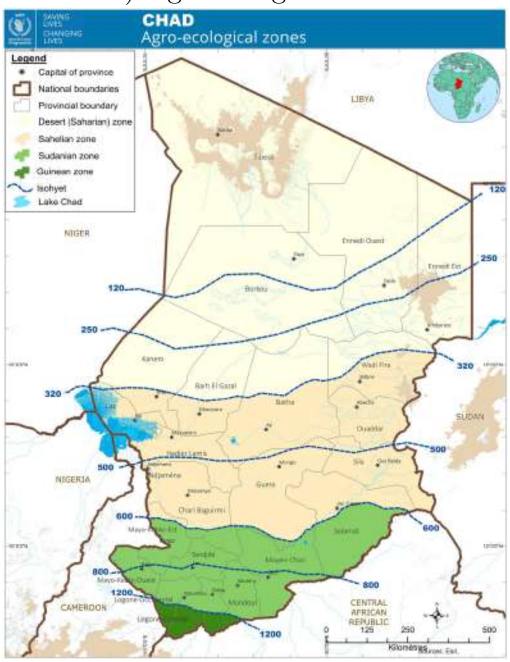
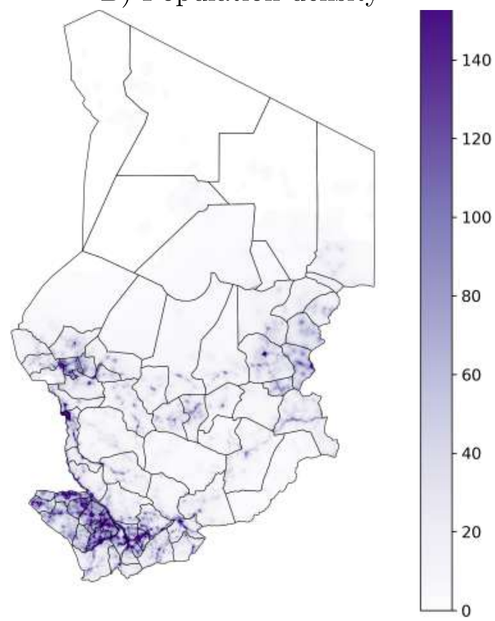
A Additional figures

Figure A1: Chad agroecological zones and population density

A) Agroecological zones

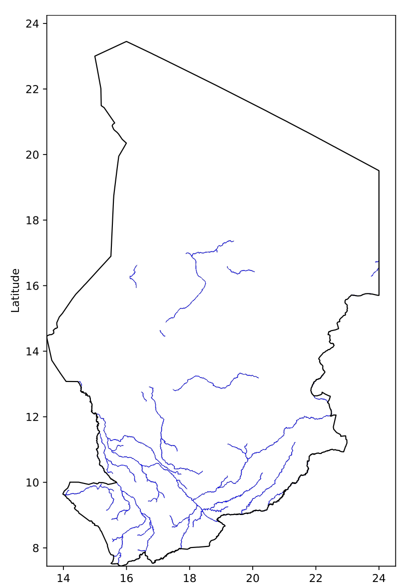


B) Population density



Note: Panel A is from the World Food Programme. Panel B is from authors' calculations based on data from WorldPop (2025). We cap values at 160 people per km^2 to better show the distribution of population density.

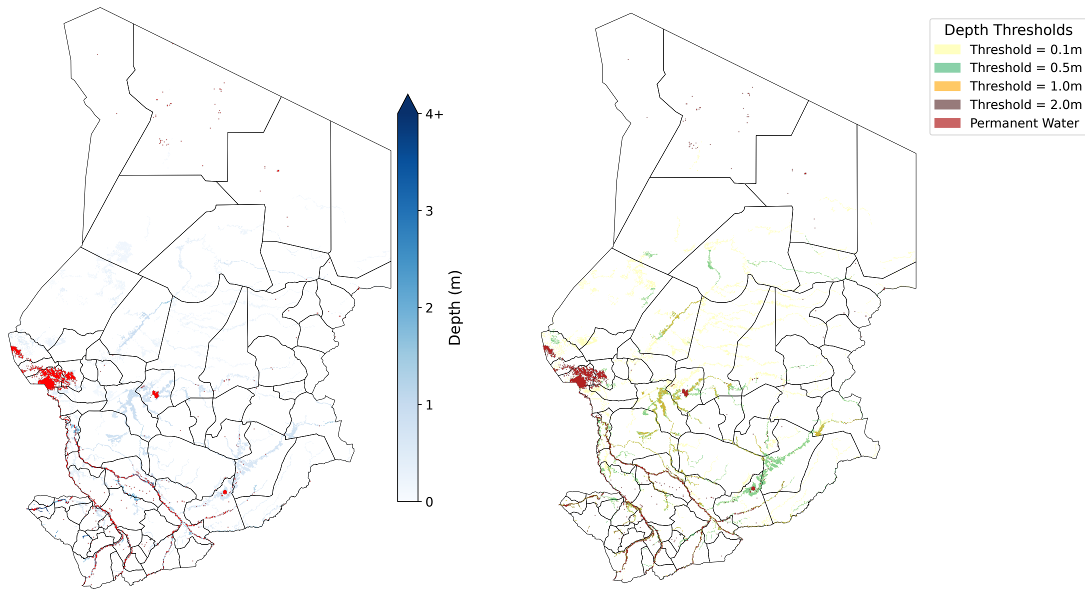
Figure A2: Major rivers in Chad



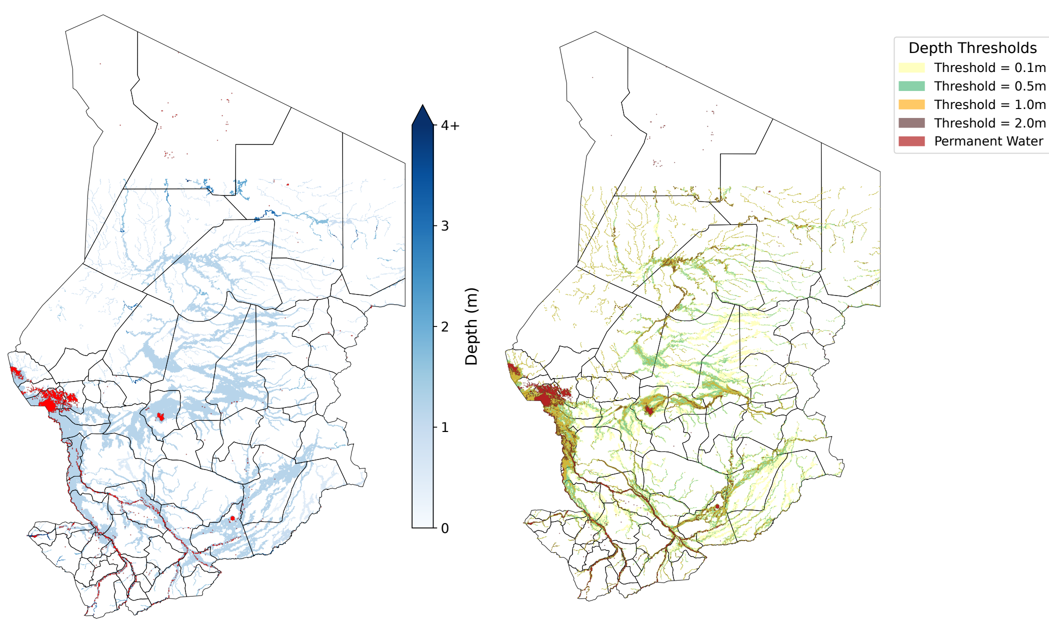
Note: Figure based on 30 m resolution data from HydroSHEDS Free Flowing Rivers Network v1 (Grill et al., 2019), showing major river networks.

Figure A3: 100-year flood depths in Chad under 2020 conditions (WRI and JRC)

A) WRI Aqueduct v2



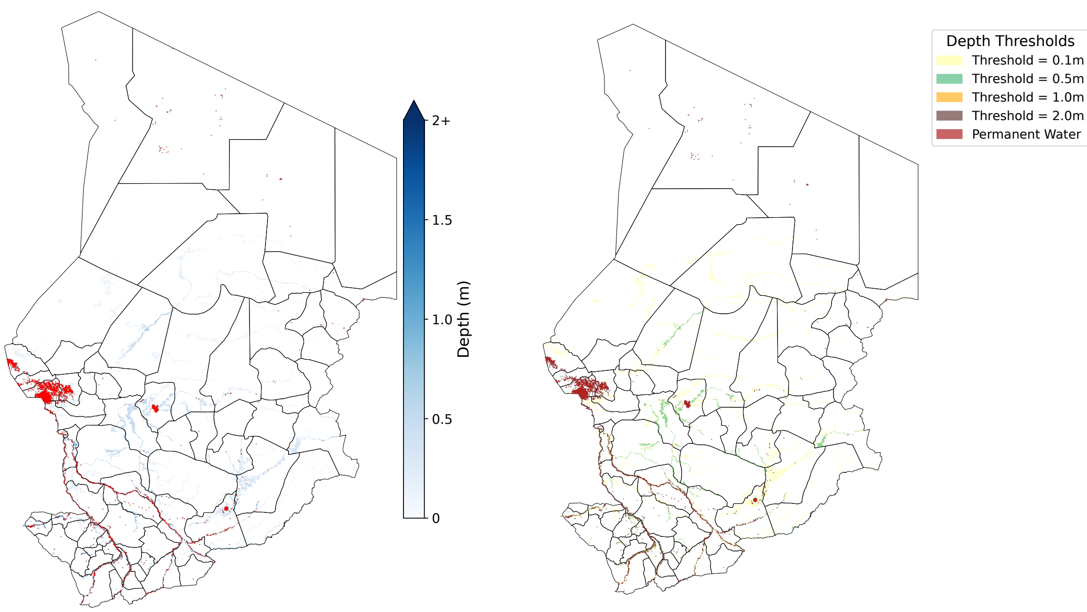
B) JRC Global River Flood Hazards Maps v1



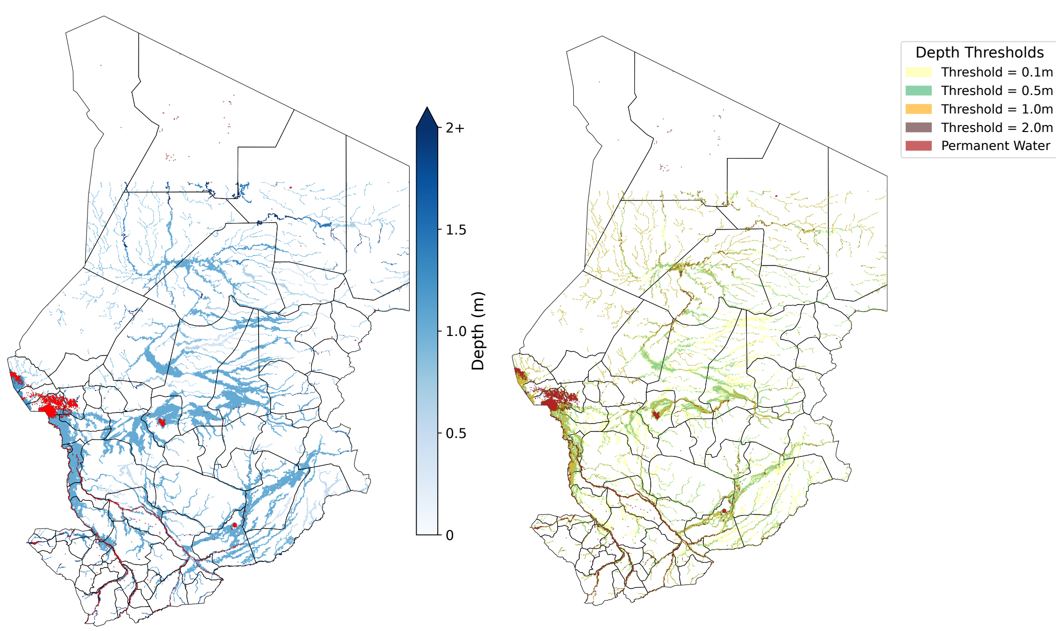
Note: Authors' calculations based on data from the WRI (World Resources Institute, 2025) and JRC (Baugh et al., 2024) flood hazard models. Both panels show the depth of inundation under 100 year floods in meters (left) and highlight areas at risk of floods of particular depths (right).

Figure A4: 10-year flood depths in Chad under 2020 conditions (WRI and JRC)

A) WRI Aqueduct v2

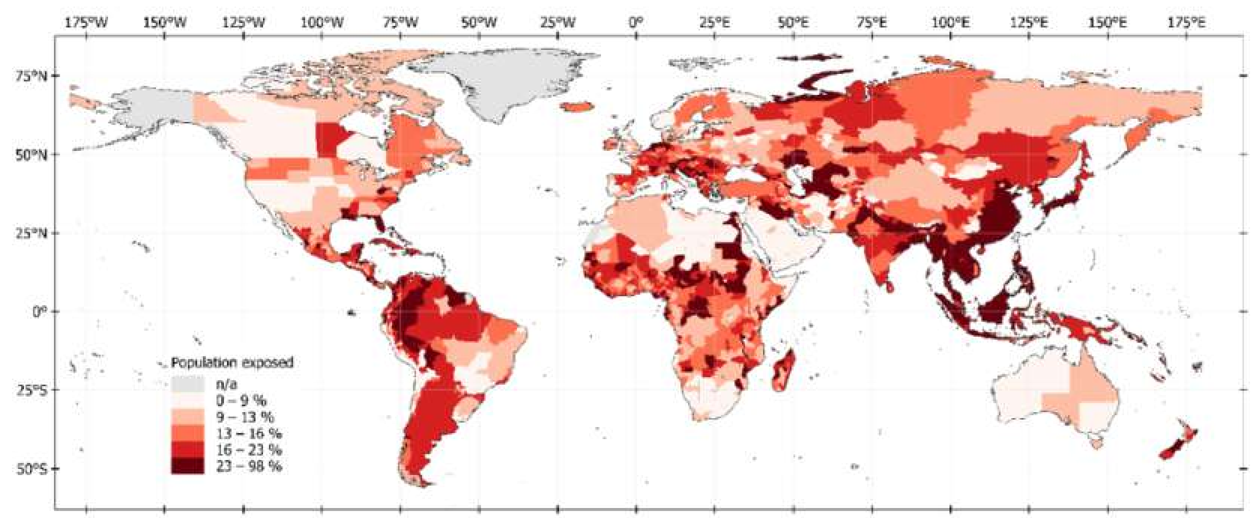


B) JRC Global River Flood Hazards Maps v1



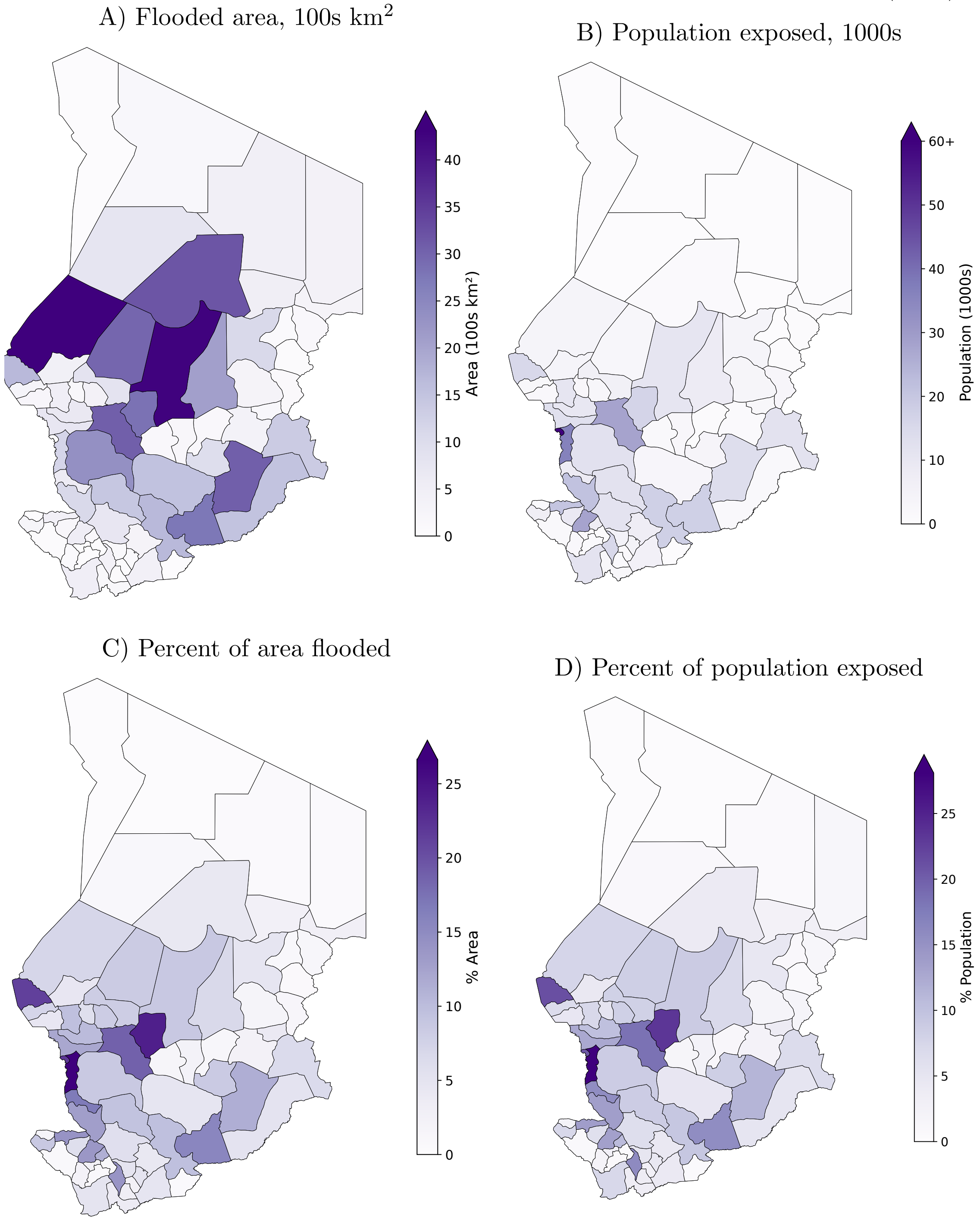
Note: Authors' calculations based on data from the WRI (World Resources Institute, 2025) and JRC (Baugh et al., 2024) flood hazard models. Both panels show the depth of inundation under 10 year floods in meters (left) and highlight areas at risk of floods of particular depths (right).

Figure A5: Global population exposure to medium flood risk



Note: Figure from Rentschler et al. (2022). The map shows the share of the population by administrative division exposed to 100-year floods with a depth of at least 15 cm. In aggregate, 23% of the world's population is exposed to such floods, and 44% of the world's poor population exposed to such floods is located in Africa.

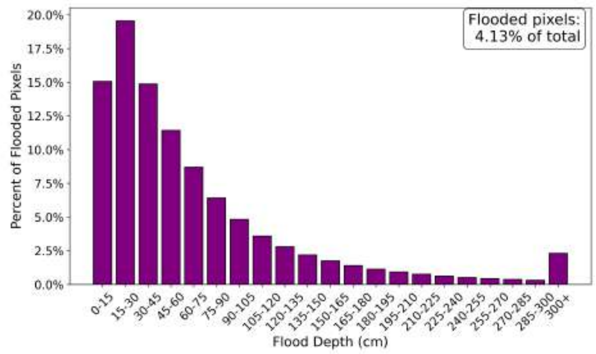
Figure A6: Exposure to ≥10 cm 100-year flood depths under 2020 conditions (WRI)



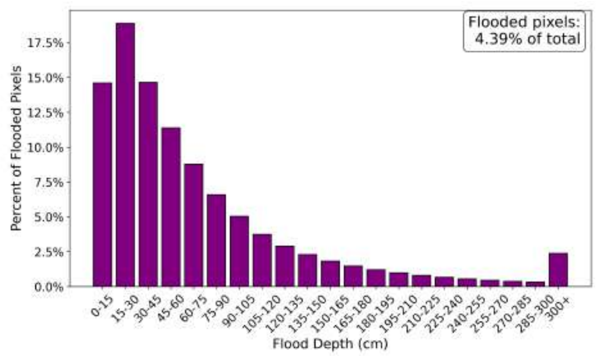
Note: Authors' calculations based on data from World Resources Institute (2025). Flood exposure is defined as estimated depth of 100-year floods of at least 10 cm. Gridded population data are from Center for International Earth Science Information Network - CIESIN - Columbia University (2018).

Figure A7: Projected change in 100-year undefended flood depths in Chad under 2050 conditions (Fathom)

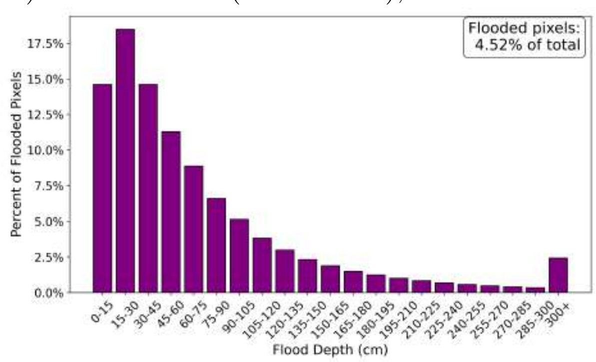
A) Fluvial floods, 2020



B) Fluvial floods, 2050 SSP1-2.6

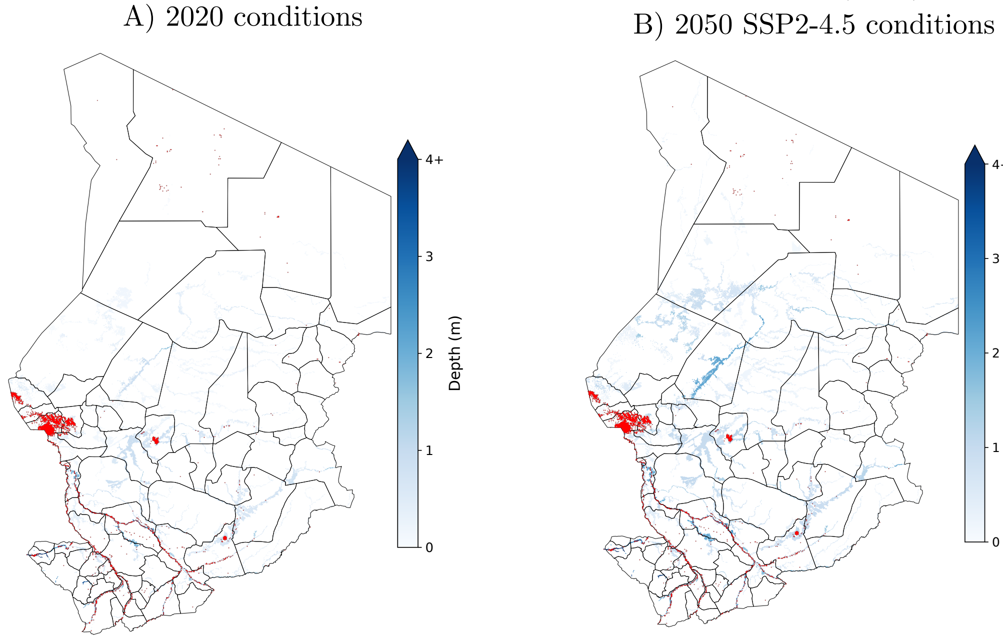


C) Fluvial floods (undefended), 2050 SSP2-4.5



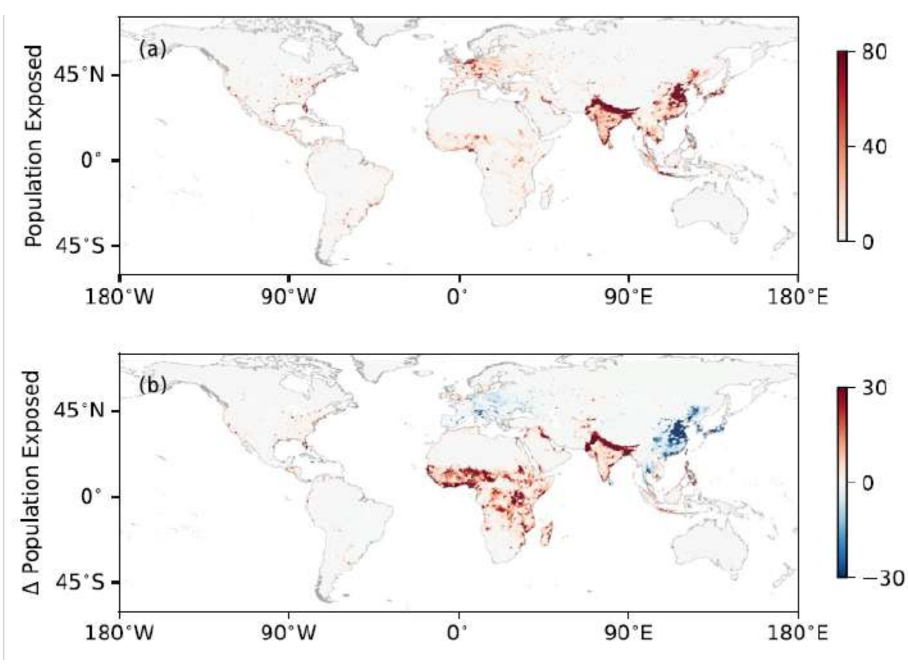
Note: Authors' calculations based on data from Fathom (2022). Each panel presents data on the depth of inundation under 100 year floods in cm. The data in panels B and C are projections of changes in flood hazard under different climate change and population growth scenarios from the IPCC Sixth Assessment Report on climate change.

Figure A8: Projected changes in 100-year flood depths (WRI)



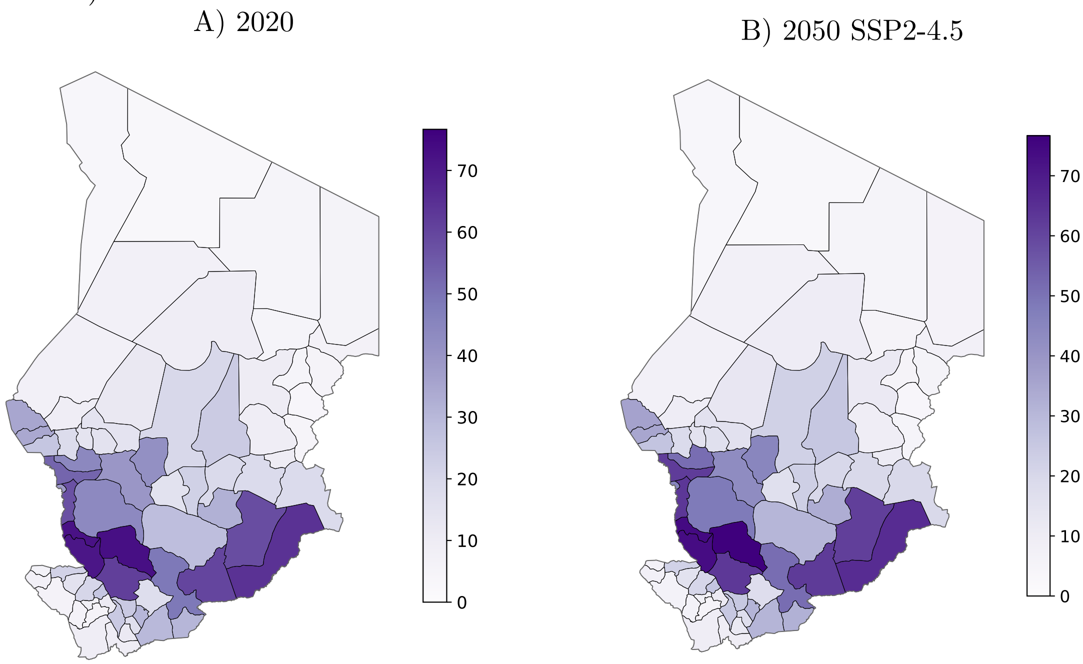
Note: Authors' calculations based on data from World Resources Institute (2025). We compare flood hazard under 2020 (left) compared to 2050 climate conditions projected under SSP2-4.5 in 2050 (right).

Figure A9: Population exposure to floods in 2020 v. 2100



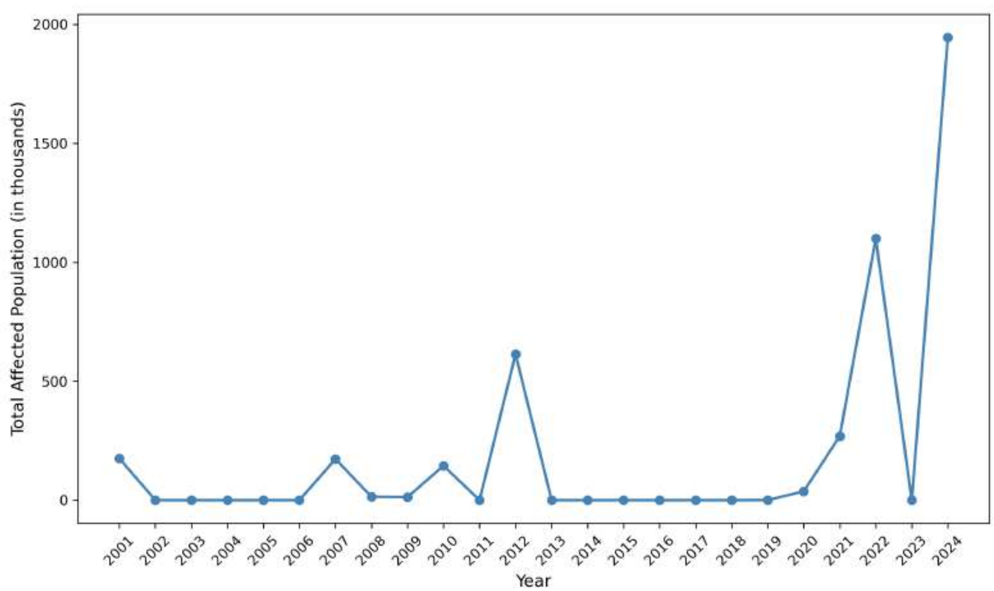
Note: Figure from Rogers et al. (2025). Population is per km^2, and flood exposure is based on at least 10 cm of inundation for a 100-year flood.

Figure A10: Projected changes in population exposure percentage for ≥10 cm 100-year floods (Rogers et al)



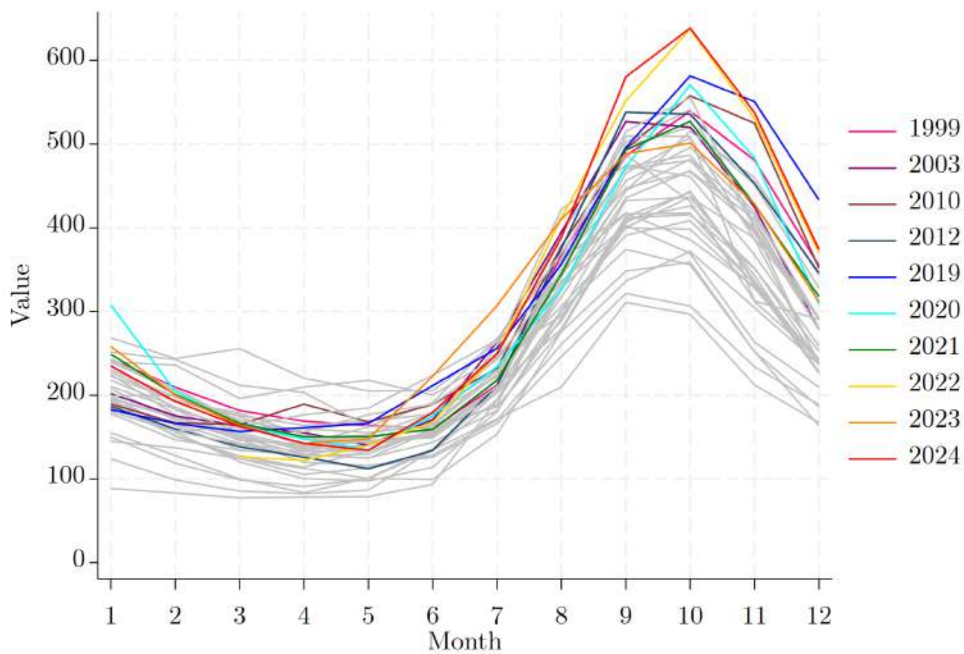
Note: Authors' calculations based on data from Rogers et al. (2025). The figure compares population flood exposure percentage (relative to the total departement population) from all flood types under 2020 conditions (Panel A) compared to 2050 climate and population conditions projected under SSP2-4.5 (Panel B). Flood exposure is based on the share of the population exposed to 100-year floods causing at least 10 cm of inundation depth.

Figure A11: Reported population affected by major flood events since 2001



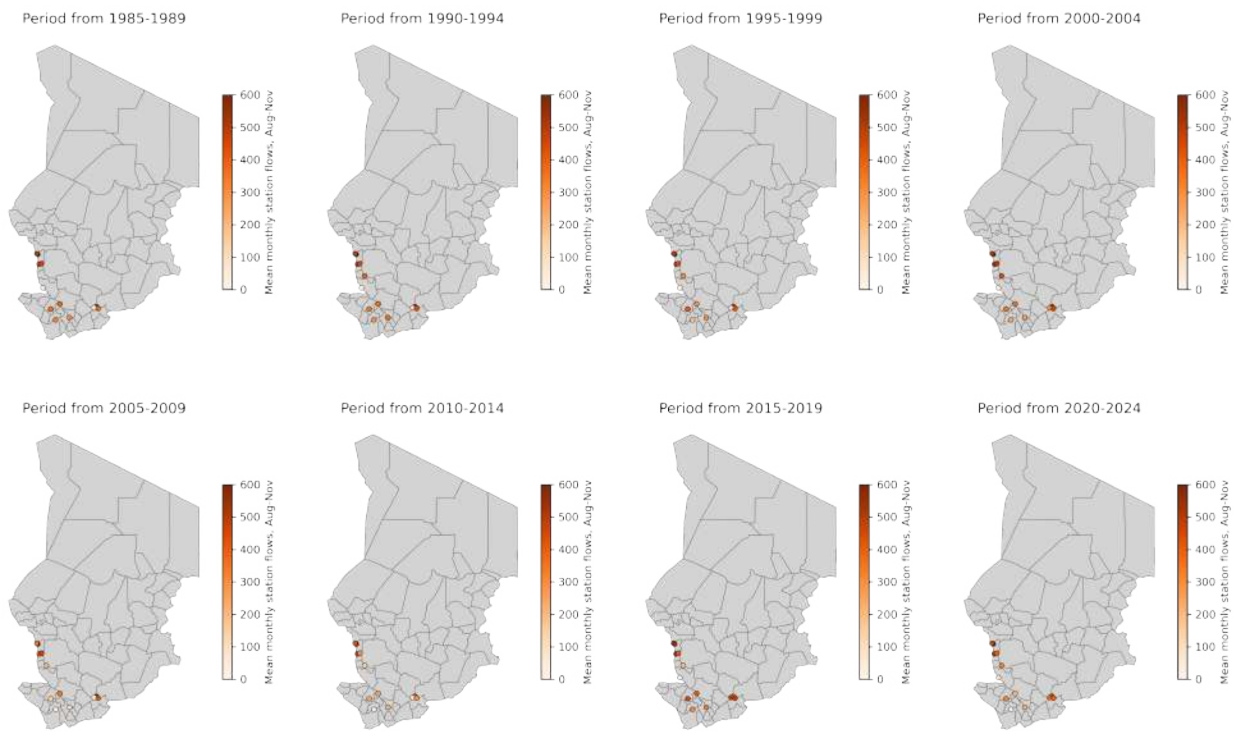
Note: Authors' calculations based on data from EM-DAT (Guha-Sapir et al., 2023). The dataset includes information on disaster type, location, timing and the total number of people affected. For years with multiple flood events recorded (2006, 2007, 2008, 2009, 2010, 2020, 2021, and 2024), we take the sum of populations exposed across different events in the year. The EM-DAT database does not record all flood events, and other sources indicate larger populations exposed to floods in certain years.

Figure A12: Yearly average water flows across stations by month



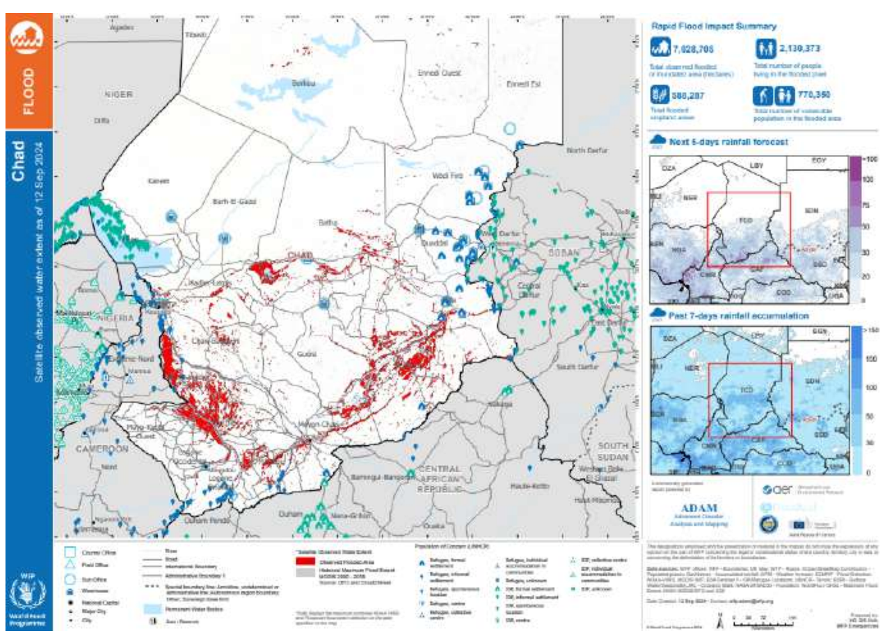
Note: Authors' analysis based on data obtained from the Chad Direction des Ressources en Eau (DRE). The original data are station-level monthly average water flows by year. We take the average by month across all stations in each year. Figure 9 shows averages of these values across five-year periods to better illustrate changes over time.

Figure A13: Annual station-level average water flows for peak August-November period



Note: Authors' analysis based on data obtained from the Chad Direction des Ressources en Eau (DRE). The original data are station-level monthly average water flows by year. We take the average by station for the period from August-November with the highest typical water flows, and then average these values across five-year period to better illustrate changes over time.

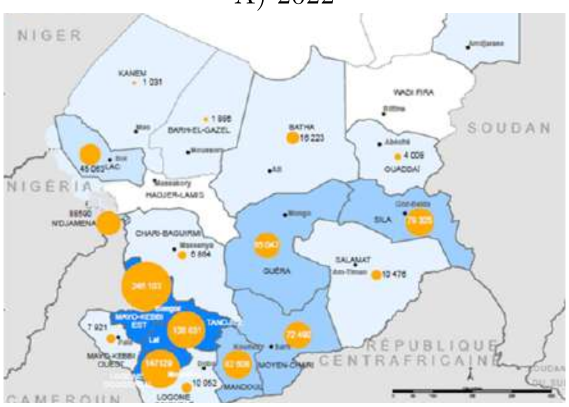
Figure A14: WFP bulletin on flooding incidence in Chad as of 12 Sep 2024



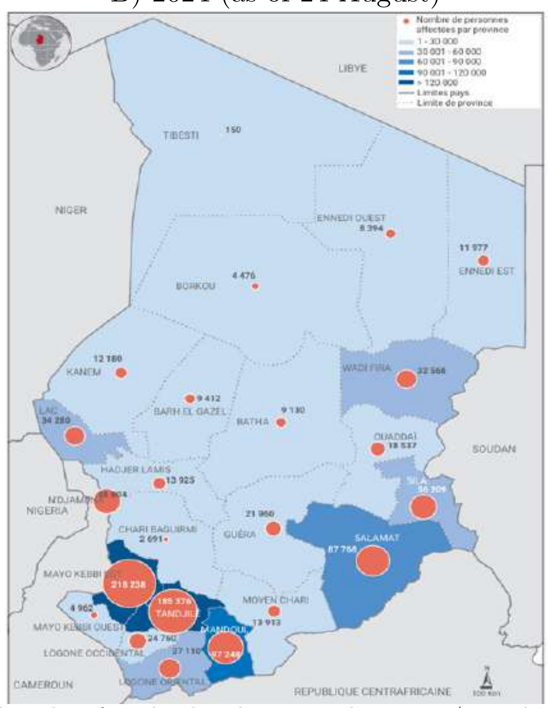
Note: Figure from WFP (2024c). Flood extent is based on satellite imagery from NOAA VIIRS and Floodscan.

Figure A15: Estimated population affected by flooding by province, 2022 and 2024

A) 2022

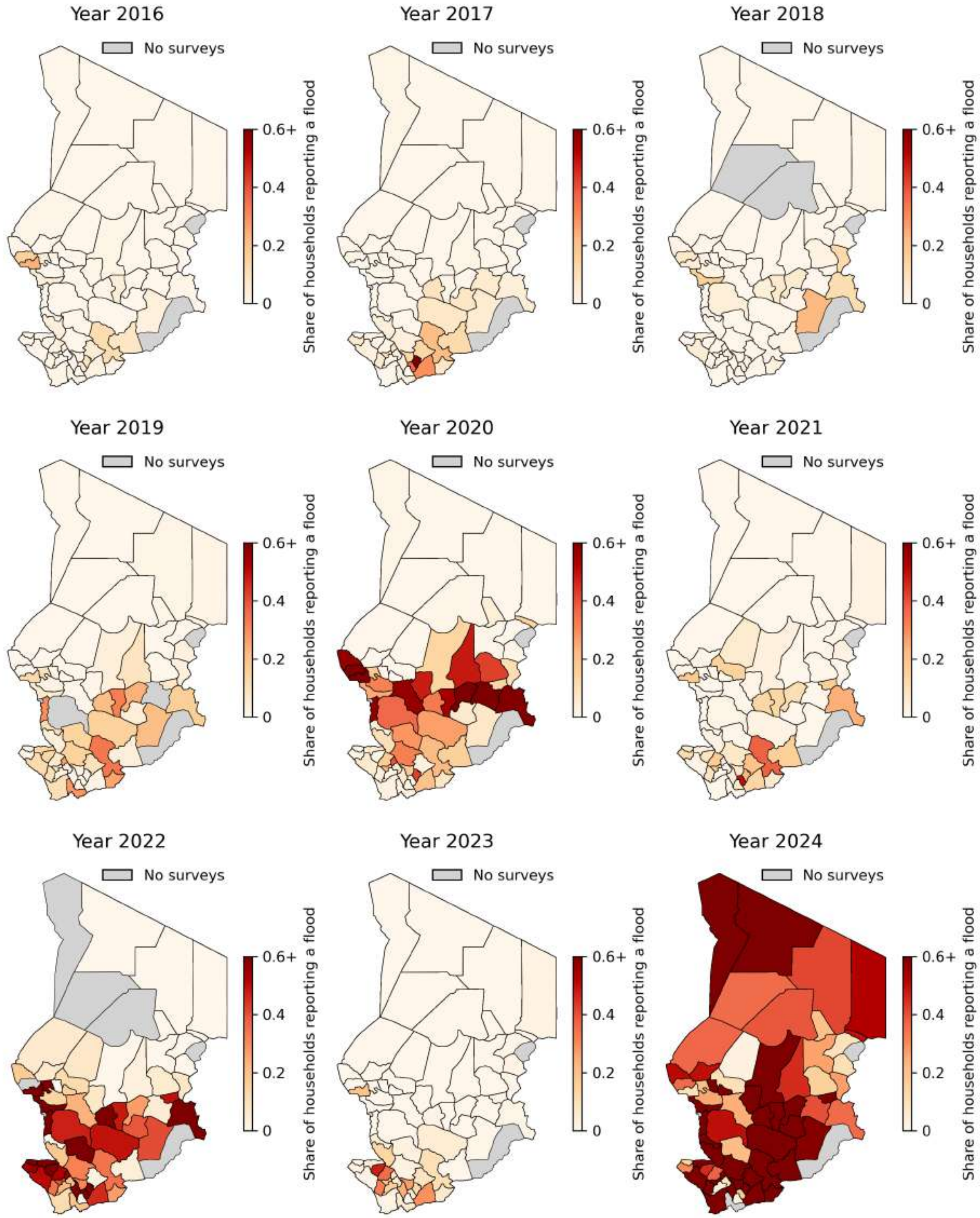


B) 2024 (as of 24 August)



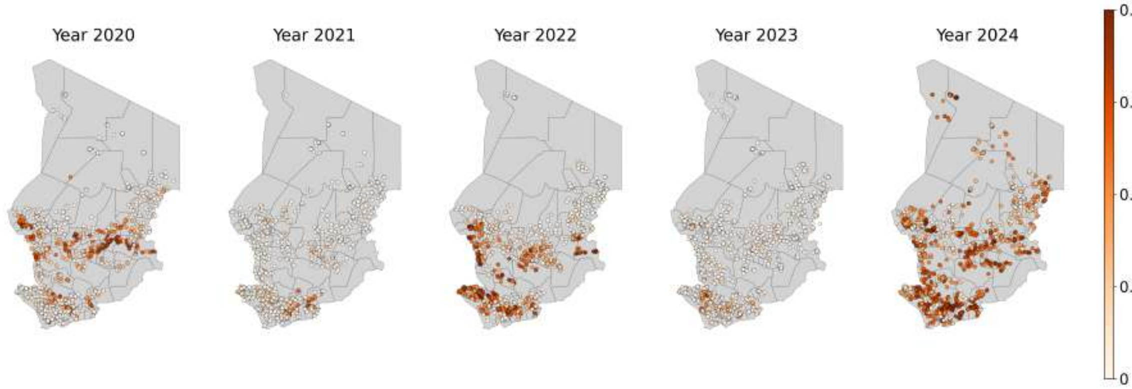
Note: Produced by OCHA and the Government of Chad, based on data from local authorities and partners (United Nations OCHA, 2022a, 2024a). The maps show the estimated number of people affected by flooding by province.

Figure A16: ENSA survey reports of flood incidence, 2016-2024



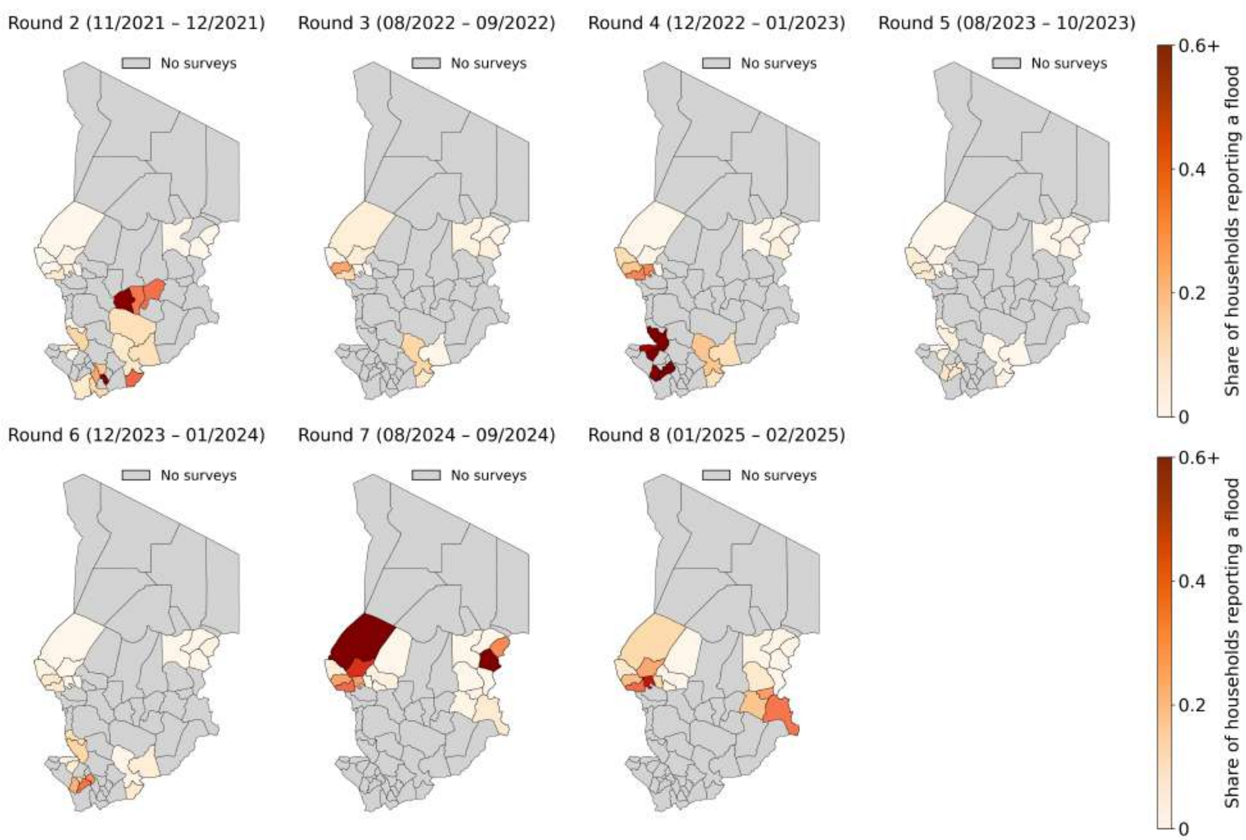
Note: Authors' calculations based on data from the ENSA surveys. The data are from a nationally-representative sample of rural households about flooding experienced in the 6 months prior to the survey date. Geographic identification is not available below the admin2 level for all years, so we show the share of households reporting any flooding by departement.

Figure A17: ENSA community shares of household flood reports, 2020-2024



Note: Authors' calculations based on data from the ENSA surveys. The data are from a nationally-representative sample of rural households about flooding experienced in the 6 months prior to the survey date. Community coordinates are available starting in 2020, so we show the share of households reporting any flooding by community.

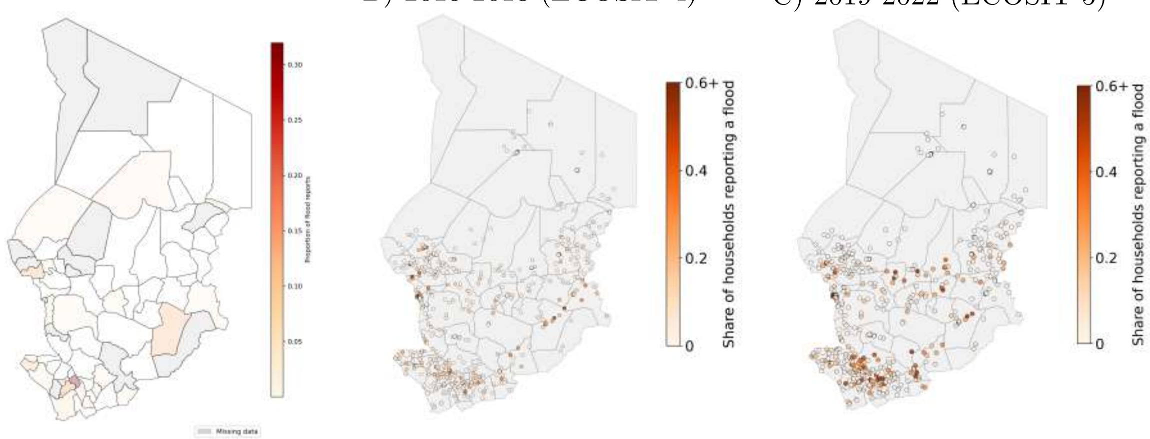
Figure A18: DIEM survey reports of flood incidence, 2021-2024



Note: Authors' calculations based on data from the DIEM surveys. The surveys are representative at the level of the departements selected for each survey round. Households are asked about flood experiences over the previous three months. Geographic identification is not available below the admin2 level, so we show the share of households reporting any flooding by departement. On all maps, 0.6+ indicates at least 60% of households surveyed in the departement reporting a flood shock.

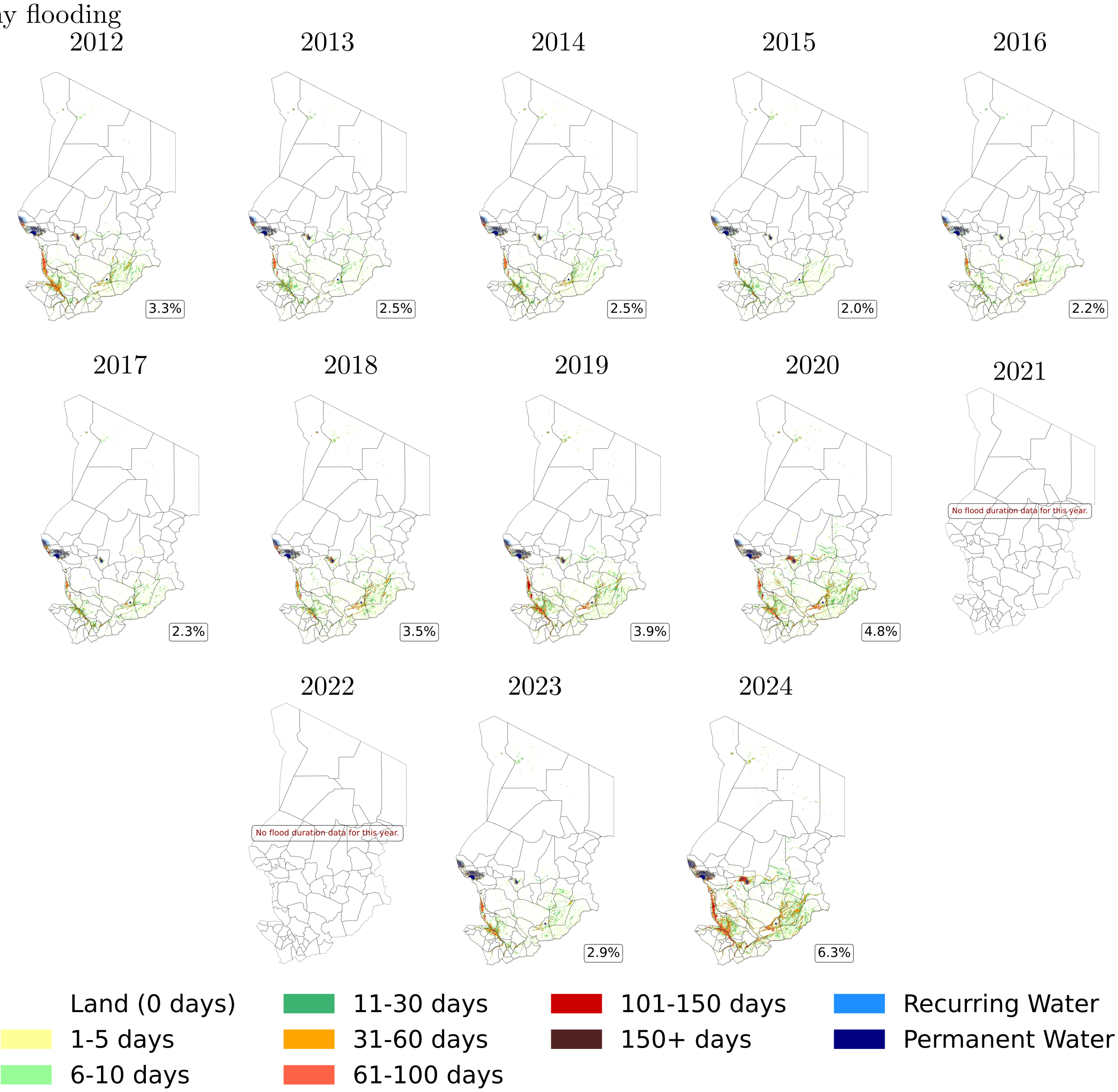
Figure A19: RIMA and ECOSIT survey reports of flood incidence, 2014-2022

A) 2014 (RIMA) B) 2015-2018 (ECOSIT 4) C) 2019-2022 (ECOSIT 5)



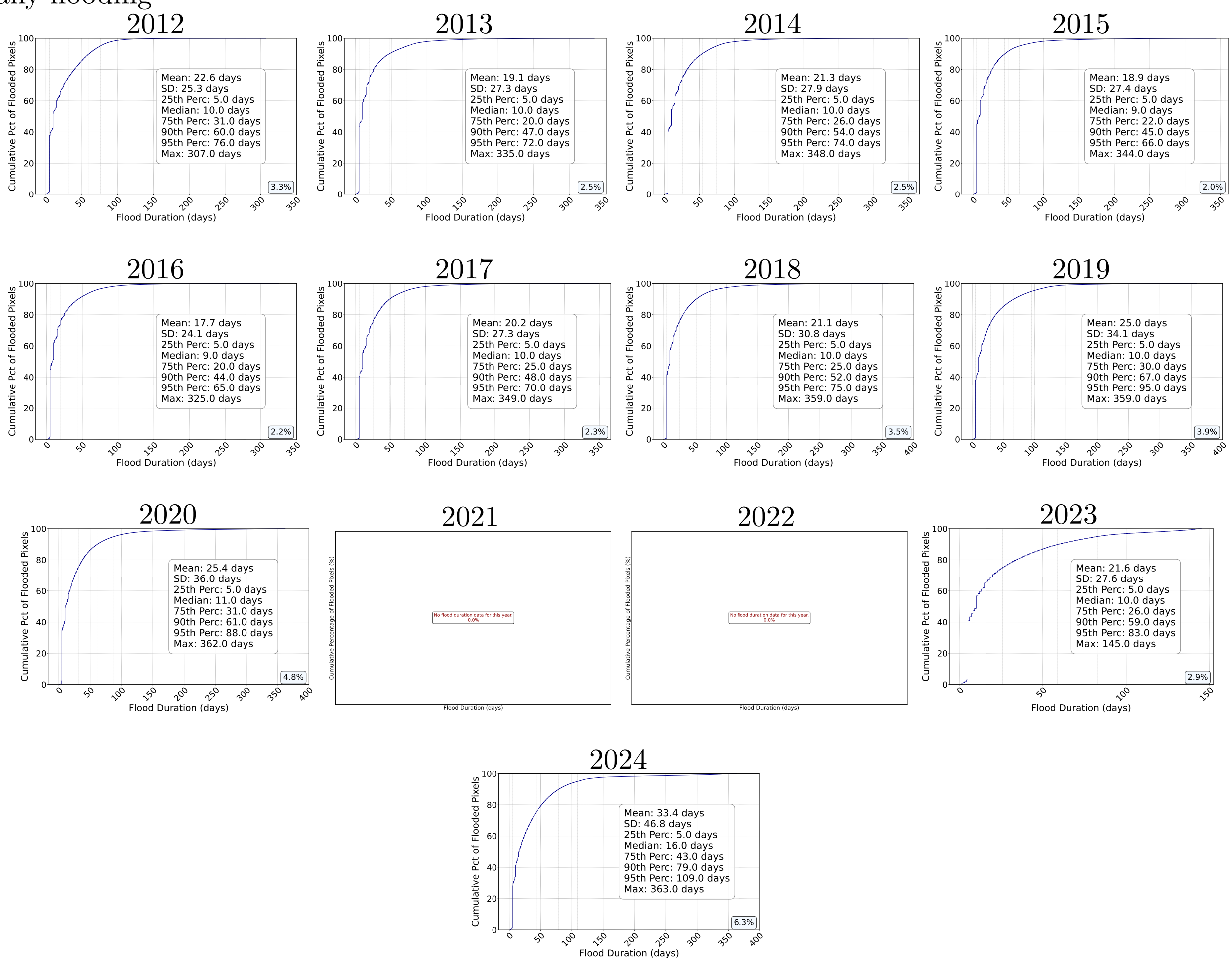
Note: Authors' calculations based on data from the RIMA and ECOSIT 4 surveys. Panel A shows data from RIMA based on a nationally-representative sample of rural households about flooding experienced in the 6 months prior to the survey date in 2014. Geographic identification is not available below the admin2 level, so we show the share of households reporting any flooding by departement. Panels B and C shows data from ECOSIT based on a nationally-representative sample of all households about flooding experienced in the 3 years prior to the survey date. For each community in the survey, we map the share of households reporting any flooding, where 0.5 indicates at least 50% of households reporting a flood.

Figure A20: Days of annual flood exposure over space by year and percentage of land area with any flooding



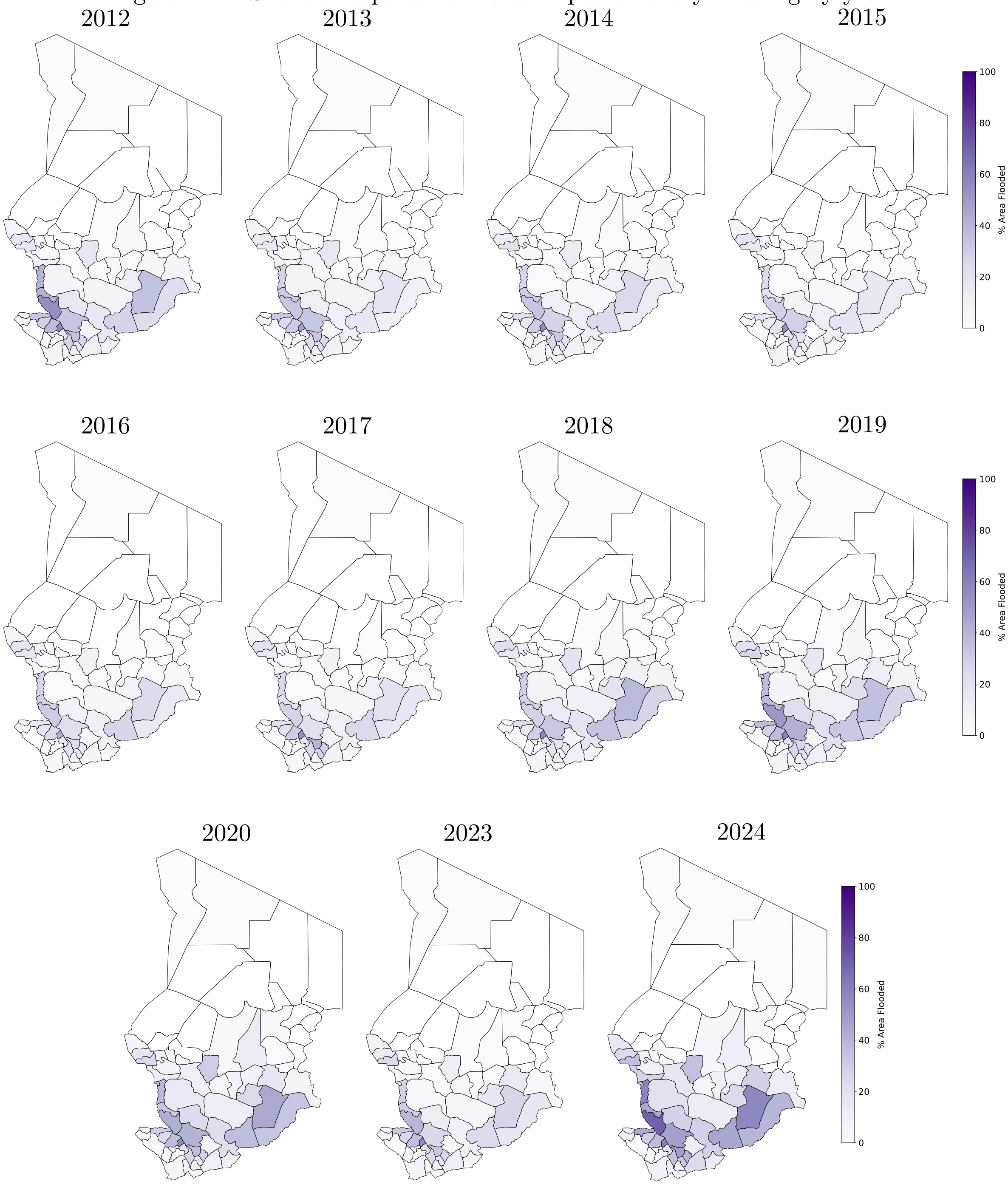
Note: Authors' calculations based on data from the VFM archive NOAA and George Mason University (2025). We aggregate daily flood detection maps across the year, taking the sum of days in the year with any flooding detected for each pixel. Data for 2021 and 2022 are not available.

Figure A21: Distribution of days of annual flood exposure over space by year among pixels with any flooding



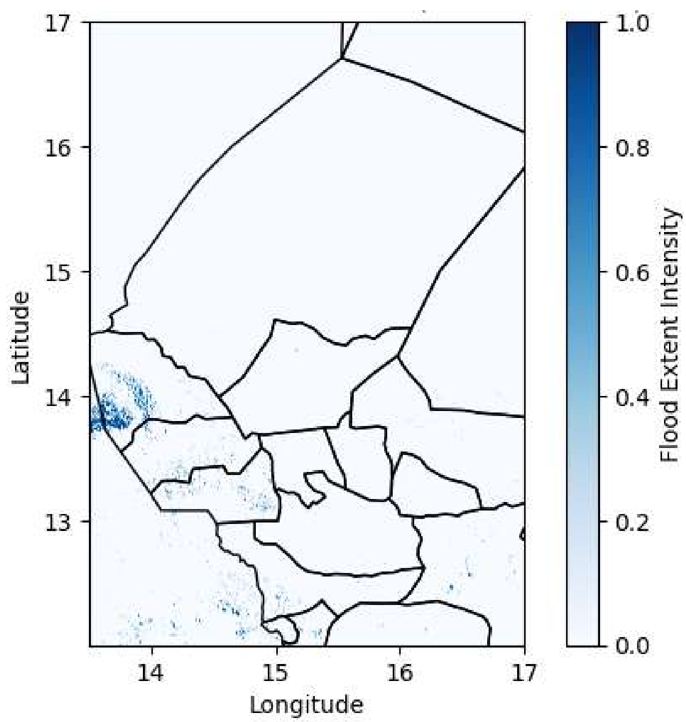
Note: Authors' calculations based on data from the VFM archive NOAA and George Mason University (2025). We aggregate daily flood detection maps across the year, taking the sum of days in the year with any flooding detected for each pixel. Data for 2021 and 2022 are not available.

Figure A22: Share of departement area exposed to any flooding by year



Note: Authors' calculations based on data from the VFM archive, NOAA and George Mason University (2025). We define a pixel as flooded if any flooding is detected during the year, and calculate the share of pixels that are flooded in each departement by year. Data for 2021 and 2022 are not available.

Figure A23: GFM (Sentinel-1) detection of flooding around Kanem province in 2024

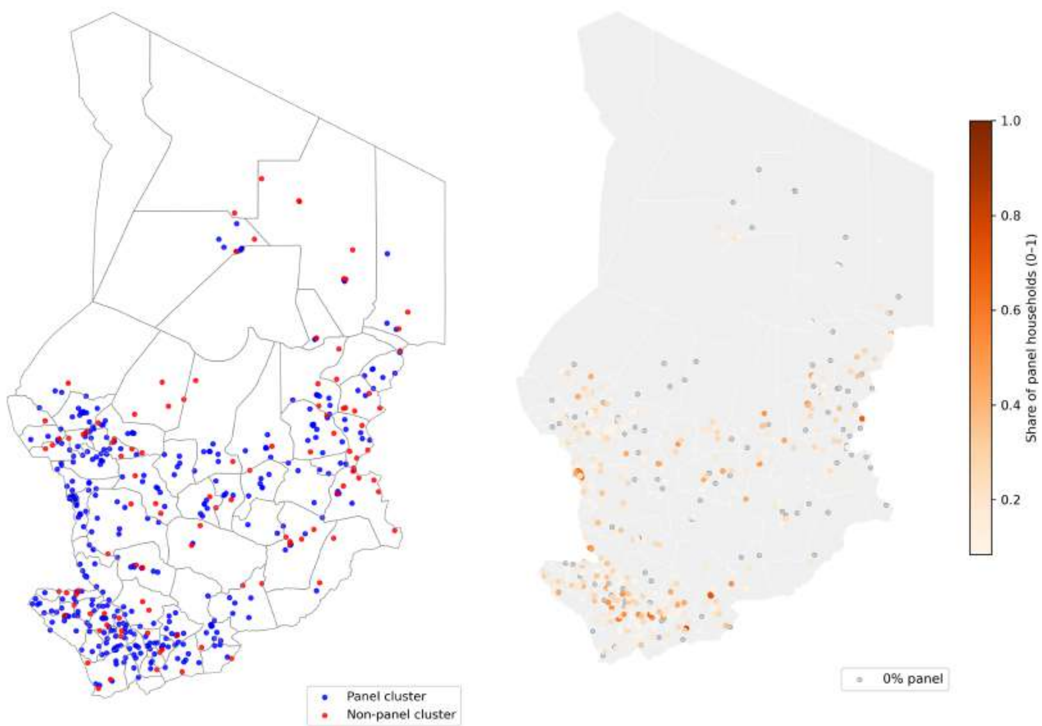


Note: Authors' calculations based on data the Copernicus Emergency Management Service Global Flood Monitoring tool. The database detects flooding using Sentinel-1 SAR data which is not affected by cloud cover but has a relatively long lag between flyovers. Data at at 90m resolution for the area around Kanem province were extracted for the period from July 17-September 17 2024, the peak of the flooding season. Maximum flood extent indicates the highest pixel-level flood intensity value over this period, where flood intensity is a binary value.

Figure A24: ECOSIT 4 communities and households included in the HFPS

A) Communities represented in the panel

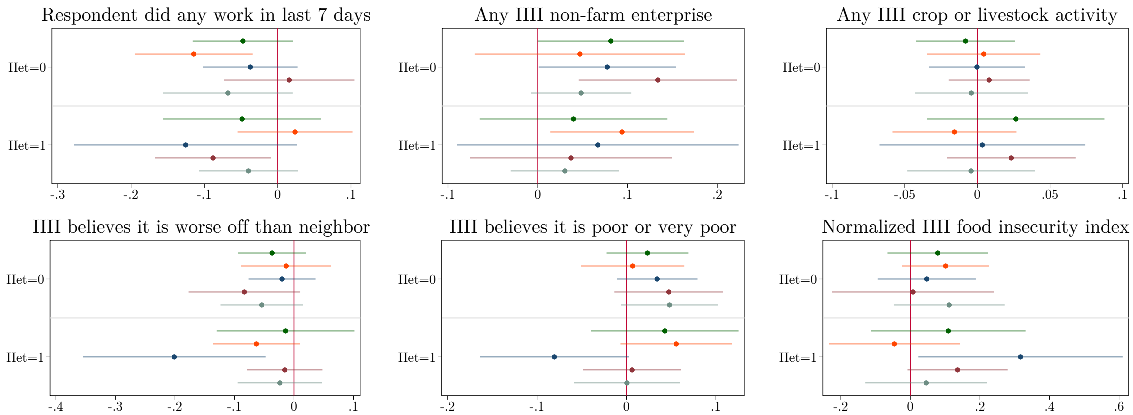
B) Households represented in the panel



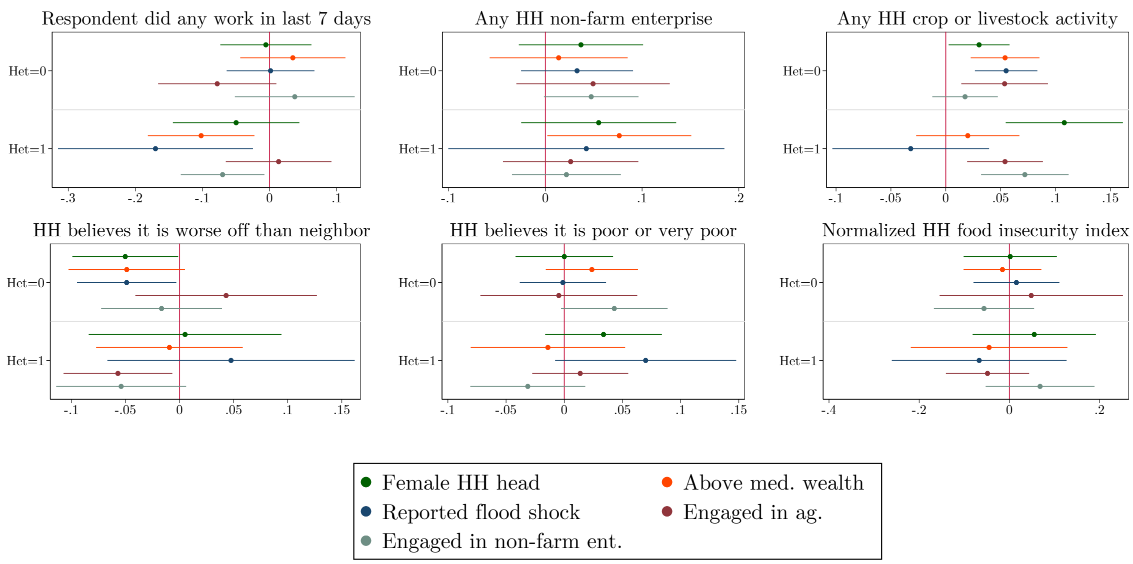
Note: Authors' calculations based on data from the ECOSIT 4 and HFPS surveys. A community is considered included in the panel if at least one household was surveyed in the HFPS.

Figure A25: ECOSIT heterogeneity in flood exposure impacts

A) VFM-based definition



B) Survey-based definition



Note: Authors' calculations based on data from the ECOSIT surveys and VFM archive. The figures show the results of separate regressions of a particular variable on the interaction of flood exposure and various household characteristics indicated in the legend. Each panel uses a different flood exposure definition. Each household characteristic is a binary variable and we show the estimated impact in households where the value is 0 and where the value is 1, where the latter is the sum of the effect where the value is 0 and the differential effect when the value is 1. All specifications include household, region by round, and flood exposure probability by round fixed effects, fully interacted with the particular household characteristics. See Table 13 for outcome variable descriptions

B Additional tables

Table A1: Comparison of selected flood hazard databases

Database	Flooding types	Data resolution	Model	Notes
Rogers et al (2025)	Coastal/Lake, Fluvial, Pluvial	90m	Separate models by flood type	Public data aggregated to ADM2 level, DEM based on many public sources
World Resources Institute Aqueduct v2	Coastal/Lake, Fluvial	1km	GLOFRIS	Open source available in GEE, focuses on large rivers
JRC Global River Flood Hazard Maps v1	Fluvial	1km	LISFLOOD	Open source available in GEE, focuses on large rivers
Fathom	Coastal/Lake, Fluvial, Pluvial	30m	Bates et al 2010, Neal et al 2021	Private/paywalled, improved DEM (FABDEM+)
JBA Global Resilience	Coastal/Lake, Fluvial, Pluvial	30m	Unclear	Private/paywalled, bare-earth Digital Terrain Model

Note: DEM means Digital Elevation Model. A review or more detailed considerations of specific flood hazard models used in these databases is beyond the scope of this report. Baugh et al. (2024), Fathom (2022), Rogers et al. (2025), and World Resources Institute (2025), provide more detail. There is limited public information on the methods used in the JBA Group models.

Table A2: Summary of main historical flooding databases

Database	Source	Flood detection inputs	Years of coverage	Spatial resolution	Temporal resolution	Accessibility	Update frequency
VIIRS Flood Mapping (VFM), https://noaa-jpss.s3.amazonaws.com/index.html#JPSS_Blended_Products/	NOAA, George Mason University, University of Wisconsin	VIIRS satellite imagery	2012-present	375 m	1/5 day composites	Publicly available archive	Near-real time (daily)
GloFAS Global Flood Monitoring (GFM), https://global-flood.emergency.copernicus.eu/technical-information/glofas-gfm/	Copernicus Emergency Management Service	Sentinel-1 satellite Synthetic Aperture Radar	2021 - present	20 m	6-12 days (each Sentinel-1 pass, varies by location)	Publicly available after registering in web portal; data may be accessed in portal or through API but there are restrictions on the duration and geographic extent of data that can be accessed at once	Near-real time (daily)
Global Flood Monitoring System (GFMS), https://flood.umd.edu/	NASA, University of Maryland	Satellite-based precipitation (TRMM/GPM) and hydrological	2013 - present	12 km	Daily	Publicly available archive	Near-real time (daily)

Table A2 (continued)

Database	Source	Flood detection inputs	Years of coverage	Spatial resolution	Temporal resolution	Accessibility	Update frequency
Near Real-Time (NRT) Global Flood Product, https://www.earthdata.nasa.gov/data/instruments/viirs/near-real-time-data/nrt-global-flood-products	NASA Earth-Data	MODIS imagery (Terra/Aqua satellites); moving toward VIIRS satellite imagery	2011 - 2022 (legacy product); 2021 - present (current)	250 m	1/2/3 day composites	Only data from the last 8 days are available for download through the online database. Archives are no longer available online but specific data may be requested.	Near-real time (daily)
African Flood and Drought Monitor, https://hydrology.soton.ac.uk/apps/afdm/	Princeton Climate Institute and University of Southampton	Combination of ground water gauges, satellite rainfall estimates, and hydrological models	2008-present	5 km across Africa	Daily	Data for the past month viewable in online interface but not downloadable.	Near-real time (daily)
Automated Disaster Analysis and Mapping (ADAM) Floods, https://gis.wfp.org/adam/	World Food Programme	VIIRS, MODIS, and Sentinel-1 satellites, Floodscan (SFED and MFED 90m)	Unclear; post 2018 - present	Unclear, likely at least 375 m	Unclear	Current flood data viewable in online portable but archives not accessible	Near-real time (daily)
FloodScan, https://aer.powerserve.net/weather-risk-management/floodscan-near-real-time-and-historical-flood-mapping/index.html	Atmospheric and Environmental Research (AER)	Multiple passive satellite microwave scanners and imagers	1998 - present	90 m	Daily	Interactive web interface is publicly available for viewing but downloads only available for a fee	Near-real time (daily)

Table A2 (continued)

Database	Source	Flood detection inputs	Years of coverage	Spatial resolution	Temporal resolution	Accessibility	Update frequency
EM-DAT International Disaster Database, https://www.emdat.be/	Centre for Research on the Epidemiology of Disasters (CRED)	Government reports, UN agencies, NGOs, insurance agencies, research institutes, news reports	1900 - present	Country-level reporting (uses national administrative unit for location)	Event-based; provides start/end dates for individual events	Publicly available spreadsheet download	Varies by event (post-event compilation); often days to weeks post-event
Twitter Global Flood Monitor, https://www.globalfloodmonitor.org/	de Bruijn et al. (2019)	Twitter text mining in 11 languages to geolocate flood mentions	2014 - 2023	Country and admin-1 level based on tweet location aggregation	Event based; identifies dates of tweets for a given event	Publicly available spreadsheet download	No longer updated
DesInventar Sendai Hazardous Events Database, https://www.desinventar.net/	United Nations Office for Disaster Risk Reduction (UNDRR)	Official government and local reports, disaster agency records, news reports	1970s - present but varies by country	Subnational; granular administrative units within each country for selected countries (not global)	Event-based; provides start/end dates for individual events	Publicly available country-level event databases	Typically weeks to months after events (entered by local authorities)

Table A2 (continued)

Database	Source	Flood detection inputs	Years of coverage	Spatial resolution	Temporal resolution	Accessibility	Update frequency
Dartmouth Flood Observatory (DFO), https://floodobservatory.colorado.edu/	University of Colorado, INSTAAR, CSDMS	News and government reports supplemented by remote sensing-based detection (e.g., MODIS)	1985 - 2022	Event polygons covering affected areas (often whole river basins or admin regions)	Event-based; provides start/end dates for individual events	Publicly available spreadsheet and shapefile downloads	Days to weeks after flood (dependent on detection & reports); appears to no longer be updated
Global Flood Database, https://global-flood-database.cloudtostreet.ai/	Floodbase, Dartmouth Flood Observatory (DFO)	MODIS imagery (Terra/Aqua satellites) and DFO Archive	2000 - 2018	250 m for flood events in DFO Archive	Event-based; provides start date and duration of flood in days for individual events	Publicly available on Google Earth Engine (GEE)	No longer updated

Table A3: Correlates of ECOSIT 4 community flood reports, by year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rural location	-0.132**	-0.133**	-0.130**	-0.131**	-0.133**	-0.133**	-0.130**	-0.132**
	(0.063)	(0.063)	(0.063)	(0.062)	(0.063)	(0.063)	(0.063)	(0.062)
Share of HHs engaged in agriculture	0.029	0.031	0.018	0.003	0.034	0.033	0.016	0.009
	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.133)	(0.132)	(0.131)
Share of HHs with cement/metal roof	-0.065	-0.063	-0.073	-0.091	-0.061	-0.061	-0.073	-0.097
	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)
Share of HHs with cement/tile floor	-0.237	-0.234	-0.225	-0.235	-0.233	-0.234	-0.229	-0.244
	(0.154)	(0.154)	(0.154)	(0.153)	(0.154)	(0.154)	(0.154)	(0.153)
Log total flooded pixels in year	0.007	0.002	0.019	0.031***				
	(0.013)	(0.013)	(0.012)	(0.011)				
>=10% of surrounding pixels flooded in year					-0.006	-0.002	0.100*	0.156***
					(0.057)	(0.055)	(0.057)	(0.052)
Observations	625	625	625	625	625	625	625	625
Year of flood detection	2015	2016	2017	2018	2015	2016	2017	2018

Note: Authors' calculations based on data from the ECOSIT 4 surveys and the VFM archive. The table shows the results of separate regressions where the outcome variable is a dummy for whether any household in the community reported experiencing a flood shock from 2015-2018. Flood incidence data from the VFM archive are linked to the ECOSIT data based on community centroids. On average there are 22 pixels within 1 km. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Average estimated flood exposure 2012-2024 by department

Departement	Avg total pop. exposed (1000s)	Avg. share of pop. exposed
Abdi	0.55	0.003
Aboudeia	9.98	0.121
Abtouyour	2.88	0.012
Amdjarass	0.22	0.001
Assoungha	0.48	0.001
Baguirmi	11.12	0.040
Bahar Signaka	6.51	0.046
Bahr Azoum	49.75	0.201
Bahr Koh	51.75	0.122
Barh El Gazel Nord	0.00	0.000
Barh El Gazel Ouest	0.27	0.005
Barh El Gazel Sud	0.82	0.003
Barh Sara	15.22	0.051
Batha Est	16.05	0.064
Batha Ouest	10.79	0.040
Biltine	0.45	0.001
Borkou	0.00	0.000
Borkou Yala	0.00	0.000
Chari	31.64	0.191
Dababa	5.94	0.019
Dagana	13.82	0.054
Dar Tama	0.01	0.000
Djode	2.67	0.016
Djourf Al Ahmar	4.55	0.037
Fada	0.97	0.012
Fitri	25.88	0.168
Fouli	5.55	0.057
Grande Sido	3.78	0.026
Gueni	1.50	0.014
Guéra	3.35	0.013
Haraze Al Biar	22.10	0.114
Haraze Mangueigne	6.71	0.087
Kanem	0.00	0.000
Kaya	23.62	0.146
Kimiti	17.69	0.038
Kobé	0.24	0.001
Kouh Est	15.79	0.106
Kouh Ouest	2.92	0.034
La Nya Pendé	5.17	0.033
La Kabbia	42.44	0.136
La Nya	24.58	0.115
La Pendé	46.41	0.198
Lac Iro	38.98	0.159
Lac Léré	22.92	0.094
Lac Wey	26.02	0.069
Loug Chari	37.32	0.147
Mamdi	22.13	0.251
Mandoul Occidental	15.01	0.072
Mandoul Oriental	7.62	0.022
Mangalmé	2.66	0.020
Mayo Binder	0.73	0.011
Mayo Boneye	102.01	0.308
Mayo Dallah	3.33	0.007
Mayo Lemyé	24.90	0.232
Megri	0.03	0.000
Mont Illi	47.47	0.152
Monts de Lam	24.00	0.063
Mourtcha	0.00	0.000
N'Djamena	163.07	0.112
Ngourkosso	20.14	0.088
Nord Kanem	0.01	0.000
Ouara	1.29	0.002
Tandjilé Centre	21.02	0.273
Tandjilé Est	45.56	0.140
Tandjilé Ouest	76.61	0.175
Tibesti Est	0.51	0.016
Tibesti Ouest	0.04	0.001
Wadi Bissam	0.04	0.000
Wadi Hawar	1.23	0.015
Wayi	21.93	0.081

Note: Authors' calculations based on data from the VFM archive NOAA and George Mason University (2025) and WorldPop (2025). The table shows the mean total annual population (in 1000s) exposed to floods detected in the VFM data across 2012-2024 by departement, along with the mean share of departement population exposed. Note that data for 2021 and 2022 are not available in the VFM archive.

Table A5: Baseline characteristics of ECOSIT panel households

	Mean	SD	Min	25^{th}	50^{th}	75^{th}	Max	N
Household characteristics								
Rural location	0.55	0.50	0.0	0.0	1.0	1.0	1.0	6223
Household size	5.63	3.05	1.0	4.0	5.0	7.0	40.0	6223
Household owns its dwelling	0.78	0.41	0.0	1.0	1.0	1.0	1.0	6223
Roof is cement or metal	0.44	0.50	0.0	0.0	0.0	1.0	1.0	6223
Floor is tile or cement	0.12	0.32	0.0	0.0	0.0	0.0	1.0	6223
Main source of light is electricity	0.16	0.37	0.0	0.0	0.0	0.0	1.0	6223
Household has toilet or latrine	0.29	0.45	0.0	0.0	0.0	1.0	1.0	6223
Normalized HH wealth index	-0.03	0.99	-0.9	-0.6	-0.3	0.2	5.7	6223
Household is below national poverty line	0.29	0.46	0.0	0.0	0.0	1.0	1.0	6223
Household head characteristics								
Household head age	43.62	14.60	15.0	32.0	41.0	54.0	106.0	6223
Household head is female	0.23	0.42	0.0	0.0	0.0	0.0	1.0	6223
Household head is Muslim	0.64	0.48	0.0	0.0	1.0	1.0	1.0	6223
Household head is literate	0.47	0.50	0.0	0.0	0.0	1.0	1.0	6223
Household head completed primary school	0.33	0.47	0.0	0.0	0.0	1.0	1.0	6223
Any 2019-2020 flooded pixel within 1 km	0.37	0.48	0.0	0.0	0.0	1.0	1.0	6223
Baseline household shock exposure								
Any flood shock in 3 years before baseline	0.10	0.30	0.0	0.0	0.0	0.0	1.0	6223
Any drought shock in 3 years before baseline	0.19	0.39	0.0	0.0	0.0	0.0	1.0	6223
Any other agricultural shock in 3 years before baseline	0.21	0.41	0.0	0.0	0.0	0.0	1.0	6223
Any income/job shock in 3 years before baseline	0.22	0.41	0.0	0.0	0.0	0.0	1.0	6223
Any conflict shock in 3 years before baseline	0.09	0.29	0.0	0.0	0.0	0.0	1.0	6223
Any shock to HH member in 3 years before baseline	0.51	0.50	0.0	0.0	1.0	1.0	1.0	6223
Household activity and well-being outcomes								
Any HH crop or livestock activity	0.71	0.45	0.0	0.0	1.0	1.0	1.0	6223
Any HH non-farm enterprise	0.45	0.50	0.0	0.0	0.0	1.0	1.0	6223
Respondent did any work in last 7 days	0.72	0.40	0.0	0.5	1.0	1.0	1.0	6223
Received any transfer or assistance	0.24	0.43	0.0	0.0	0.0	0.0	1.0	6223
Normalized HH food insecurity index	0.00	0.97	-2.2	-0.5	-0.1	0.4	5.9	6223
HH believes is is worse off than neighbors	0.30	0.46	0.0	0.0	0.0	1.0	1.0	6043
HH believes it is poor or very poor	0.79	0.41	0.0	1.0	1.0	1.0	1.0	6190

Note: Authors' calculations based on data from the ECOSIT 4 surveys. Panel households are those that were successfully surveyed again in either the HFPS or in ECOSIT 5. The wealth index is constructed as the sum of normalized variables related to housing quality and household assets. The food insecurity index is constructed as the sum of eight normalized variables capturing different aspects of self-reported food insecurity. Household poverty is based on estimated annual per capita consumption. Household well-being is based on the respondent's own perceptions.

Table A6: Balance in historical VFM-detected community flooding by 2019-2020 VFM-based exposure

	No flood propensity control		With flood propensity control	
	Non-flooded HH Mean (SD)	Flooded difference (SE)	Non-flooded HH Mean (SD)	Flooded difference (SE)
Count of flooded pixels in 2012,	0.10	4.52***	0.23	0.39*
1km buffer	(0.82)	(0.41)	(1.45)	(0.23)
Count of flooded pixels in 2013,	0.04	3.61***	0.08	-0.02
1km buffer	(0.32)	(0.32)	(0.39)	(0.07)
Count of flooded pixels in 2014,	0.01	3.61***	0.02	-0.01
1km buffer	(0.10)	(0.33)	(0.14)	(0.02)
Count of flooded pixels in 2015,	0.34	2.79***	0.33	-0.34
1km buffer	(1.76)	(0.34)	(1.62)	(0.25)
Count of flooded pixels in 2016,	0.17	3.01***	0.23	-0.03
1km buffer	(1.03)	(0.29)	(1.10)	(0.19)
Count of flooded pixels in 2017,	0.08	3.45***	0.16	0.24*
1km buffer	(0.54)	(0.33)	(0.79)	(0.15)
Count of flooded pixels in 2018,	0.25	4.51***	0.37	-0.05
1km buffer	(1.18)	(0.37)	(1.27)	(0.20)
Observations		616		479
Test of joint significance		$F = 29.18$		$F = 1.70$
		$p < 0.001$		$p = 0.107$

Note: Authors' calculations based on data from the ECOSIT surveys and VFM archive. The table shows the results of separate regressions of a particular variable on flood exposure. Flood exposure is based on VFM detection of any flooded pixel within 1 km of the community centroid in 2019 or 2020. We include results for the joint test of significance of all the variables in explaining flood exposure. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Balance in historical VFM-detected community flooding by 2019-2022 report-based exposure

	No flood propensity control		With flood propensity control	
	Non-flooded HH Mean (SD)	Flooded difference (SE)	Non-flooded HH Mean (SD)	Flooded difference (SE)
Count of flooded pixels in 2012,	1.13	1.43***	1.56	-0.43
1km buffer	(3.26)	(0.37)	(3.99)	(0.32)
Count of flooded pixels in 2013,	0.81	1.27***	1.20	-0.18
1km buffer	(2.32)	(0.29)	(2.95)	(0.24)
Count of flooded pixels in 2014,	0.72	1.38***	1.15	-0.14
1km buffer	(2.24)	(0.29)	(2.99)	(0.25)
Count of flooded pixels in 2015,	0.89	1.08***	1.20	-0.29
1km buffer	(2.70)	(0.30)	(3.19)	(0.27)
Count of flooded pixels in 2016,	0.81	1.05***	1.11	-0.15
1km buffer	(2.26)	(0.26)	(2.61)	(0.21)
Count of flooded pixels in 2017,	0.70	1.45***	1.18	-0.04
1km buffer	(2.13)	(0.29)	(2.96)	(0.23)
Count of flooded pixels in 2018,	1.05	1.91***	1.72	-0.04
1km buffer	(2.65)	(0.34)	(3.70)	(0.28)
Observations		616		607
Test of joint significance		$F = 8.71$		$F = 0.89$
		$p < 0.001$		$p = 0.513$

Note: Authors' calculations based on data from the ECOSIT surveys and VFM archive. The table shows the results of separate regressions of a particular variable on flood exposure. Flood exposure is based on any household in a community reporting a flood shock over the 2019-2022 recall period. We include results for the joint test of significance of all the variables in explaining flood exposure. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Baseline balance by VFM-detected community flood exposure

	No flood propensity control		With flood propensity control	
	Non-flooded HH Mean (SD)	Flooded difference (SE)	Non-flooded HH Mean (SD)	Flooded difference (SE)
Household characteristics				
Rural location	0.61	-0.15***	0.58	0.05
	(0.49)	(0.04)	(0.49)	(0.06)
Household size	5.54	0.22**	5.64	0.14
	(2.97)	(0.10)	(3.07)	(0.16)
Household owns its dwelling	0.82	-0.12***	0.80	0.01
	(0.38)	(0.02)	(0.40)	(0.04)
Roof is cement or metal	0.36	0.19***	0.40	-0.03
	(0.48)	(0.03)	(0.49)	(0.05)
Floor is tile or cement	0.08	0.10***	0.10	-0.01
	(0.28)	(0.02)	(0.30)	(0.03)
Main source of light is electricity	0.14	0.05**	0.16	-0.04
	(0.35)	(0.02)	(0.36)	(0.04)
Household has toilet or latrine	0.26	0.09***	0.28	-0.06
	(0.44)	(0.03)	(0.45)	(0.05)
Normalized HH wealth index	-0.13	0.27***	-0.06	-0.06
	(0.91)	(0.06)	(0.97)	(0.12)
Household is below national poverty	0.31	-0.04*	0.30	0.02
line	(0.46)	(0.02)	(0.46)	(0.03)
Household head characteristics				
Household head age	43.76	-0.37	43.86	0.22
	(14.80)	(0.43)	(14.74)	(0.60)
Household head is female	0.23	-0.01	0.23	-0.03
	(0.42)	(0.01)	(0.42)	(0.02)
Household head is Muslim	0.70	-0.15***	0.69	0.02
	(0.46)	(0.04)	(0.46)	(0.06)
Household head is literate	0.44	0.09***	0.46	-0.02
	(0.50)	(0.02)	(0.50)	(0.04)
Household head completed primary	0.27	0.14***	0.29	0.01
school	(0.44)	(0.02)	(0.46)	(0.04)
Baseline household shock exposure				
Any flood shock in 3 years before	0.08	0.07***	0.09	-0.00
baseline	(0.27)	(0.01)	(0.28)	(0.02)
Any drought shock in 3 years before	0.20	-0.03	0.19	0.02
baseline	(0.40)	(0.02)	(0.39)	(0.03)
Any other agricultural shock in 3	0.23	-0.04**	0.21	-0.02
years before baseline	(0.42)	(0.02)	(0.41)	(0.02)
Any income/job shock in 3 years	0.20	0.04***	0.22	0.01
before baseline	(0.40)	(0.02)	(0.41)	(0.03)
Any conflict shock in 3 years	0.10	-0.02	0.10	0.02
before baseline	(0.29)	(0.01)	(0.30)	(0.03)
Any shock to HH member in 3 years	0.49	0.04**	0.50	-0.01
before baseline	(0.50)	(0.02)	(0.50)	(0.03)
HH activity and well-being outcomes				
Any HH crop or livestock activity	0.75	-0.11***	0.73	0.03
	(0.43)	(0.03)	(0.45)	(0.05)
Any HH non-farm enterprise	0.44	0.02	0.44	-0.06
	(0.50)	(0.02)	(0.50)	(0.04)
Respondent did any work in last 7	0.72	0.01	0.72	0.02
days	(0.41)	(0.02)	(0.41)	(0.03)
Received any transfer or assistance	0.25	-0.03*	0.25	-0.03
	(0.44)	(0.02)	(0.43)	(0.02)
Normalized HH food insecurity index	-0.11	0.31***	-0.04	-0.05
	(0.93)	(0.06)	(0.97)	(0.10)
HH believes is is worse off than	0.28	0.06***	0.29	0.02
neighbors	(0.45)	(0.02)	(0.45)	(0.03)
HH believes it is poor or very poor	0.80	-0.03**	0.80	0.02
	(0.40)	(0.02)	(0.40)	(0.02)
Observations		6018		4704
Test of joint significance		$F = 6.69$		$F = 1.18$
		$p < 0.001$		$p = 0.250$

Note: Authors' calculations based on data from the ECOSIT surveys and VFM archive. The table shows the results of separate regressions of a particular variable on flood exposure. Flood exposure is based on VFM detection of any flooded pixel within 1 km of the community centroid in 2019 or 2020. See Table A5 for additional outcome variable descriptions. We include results for the joint test of significance of all the variables in explaining flood exposure. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Baseline balance by household-reported community flood exposure

	No flood propensity control		With flood propensity control	
	Non-flooded HH Mean (SD)	Flooded difference (SE)	Non-flooded HH Mean (SD)	Flooded difference (SE)
Household characteristics				
Rural location	0.58	-0.06	0.55	0.03
	(0.49)	(0.04)	(0.50)	(0.04)
Household size	5.57	0.12	5.62	0.01
	(2.88)	(0.10)	(3.05)	(0.11)
Household owns its dwelling	0.82	-0.08***	0.78	-0.02
	(0.38)	(0.02)	(0.41)	(0.02)
Roof is cement or metal	0.39	0.11***	0.44	-0.02
	(0.49)	(0.03)	(0.50)	(0.03)
Floor is tile or cement	0.10	0.04**	0.12	-0.01
	(0.30)	(0.02)	(0.33)	(0.02)
Main source of light is electricity	0.13	0.05**	0.16	0.01
	(0.34)	(0.02)	(0.37)	(0.02)
Household has toilet or latrine	0.26	0.07**	0.30	-0.01
	(0.44)	(0.03)	(0.46)	(0.03)
Normalized HH wealth index	-0.11	0.19***	-0.02	-0.00
	(0.90)	(0.06)	(0.99)	(0.06)
Household is below national poverty line	0.30	-0.01	0.29	0.02
	(0.46)	(0.02)	(0.45)	(0.02)
Household head characteristics				
Household head age	43.95	-0.68	43.65	-0.50
	(15.01)	(0.42)	(14.62)	(0.46)
Household head is female	0.23	0.00	0.23	0.00
	(0.42)	(0.01)	(0.42)	(0.01)
Household head is Muslim	0.70	-0.12***	0.65	-0.06
	(0.46)	(0.04)	(0.48)	(0.04)
Household head is literate	0.44	0.07***	0.47	0.01
	(0.50)	(0.02)	(0.50)	(0.02)
Household head completed primary school	0.27	0.11***	0.32	0.05*
	(0.44)	(0.02)	(0.47)	(0.03)
Baseline household shock exposure				
Any flood shock in 3 years before baseline	0.08	0.05***	0.10	-0.01
	(0.27)	(0.01)	(0.30)	(0.01)
Any drought shock in 3 years before baseline	0.21	-0.05**	0.19	-0.03
	(0.41)	(0.02)	(0.39)	(0.02)
Any other agricultural shock in 3 years before baseline	0.23	-0.04**	0.21	-0.02
	(0.42)	(0.02)	(0.41)	(0.02)
Any income/job shock in 3 years before baseline	0.20	0.04**	0.22	0.01
	(0.40)	(0.01)	(0.41)	(0.02)
Any conflict shock in 3 years before baseline	0.08	0.02	0.09	0.03**
	(0.27)	(0.01)	(0.28)	(0.02)
Any shock to HH member in 3 years before baseline	0.48	0.06***	0.51	0.04**
	(0.50)	(0.02)	(0.50)	(0.02)
HH activity and well-being outcomes				
Any HH crop or livestock activity	0.74	-0.06**	0.71	0.01
	(0.44)	(0.03)	(0.45)	(0.03)
Any HH non-farm enterprise	0.42	0.05**	0.45	0.01
	(0.49)	(0.02)	(0.50)	(0.02)
Respondent did any work in last 7 days	0.73	-0.01	0.72	0.00
	(0.40)	(0.02)	(0.41)	(0.02)
Received any transfer or assistance	0.27	-0.04***	0.25	-0.04***
	(0.44)	(0.02)	(0.43)	(0.02)
Normalized HH food insecurity index	-0.10	0.23***	0.01	0.04
	(0.96)	(0.05)	(0.98)	(0.06)
HH believes is is worse off than neighbors	0.27	0.06***	0.30	0.04**
	(0.44)	(0.02)	(0.46)	(0.02)
HH believes it is poor or very poor	0.80	-0.02	0.79	-0.00
	(0.40)	(0.01)	(0.41)	(0.02)
Observations		6018		5931
Test of joint significance		$F = 3.05$		$F = 1.28$
		$p < 0.001$		$p = 0.156$

Note: Authors' calculations based on data from the ECOSIT surveys and VFM archive. The table shows the results of separate regressions of a particular variable on flood exposure. Flood exposure is based on any household in a community reporting a flood shock over the 2019-2022 recall period. See Table A5 for additional outcome variable descriptions. We include results for the joint test of significance of all the variables in explaining flood exposure. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C Flood management stakeholders in Chad

High levels of flood risk and population exposure across the vast country of Chad present a major challenge for flood monitoring, prevention, management, and response. Flood management in Chad involves a diverse range of stakeholders, including governmental agencies, non-governmental organizations (NGOs), and international actors playing different roles (Government of Chad, 2014, 2023b, 2024). We present information on a selection of key stakeholders in Chad in Table A10, summarizing their roles and primary activities.

Governmental agencies primarily focus on policy development, disaster preparedness, infrastructure planning, and emergency response coordination (ACAPS, 2024; Government of Chad, 2022, 2023a, 2024). Flood prevention activities undertaken by government ministries in collaboration with local authorities include the reinforcement of dikes and riverbanks along the Chari and Logone rivers, the deployment of heavy machinery for flood control infrastructure in N'Djamena, and the strengthening of pumping stations to prevent urban flooding (Government of Chad, 2023a). These investments and activities are helpful but will likely provide little protection against the threat of increasingly severe 100-year floods.

Among key government stakeholders, the Ministry of Social Action, National Solidarity and Humanitarian Affairs (MASAH)'s Direction de la Solidarité Nationale coordinates humanitarian aid and emergency flood relief, and is the primary actor responsible for responding to most flood events. The National Meteorology Agency (ANAM) is responsible for weather forecasting to anticipate flooding risk and support early warning systems. In response to increasing flood risk, in 2022 the Strategic Committee for Flood Management and Prevention was formed by government decree. This committee is responsible for integrating various ministerial departments, United Nations agencies, international NGOs, and local disaster management actors. Its work is structured around three specialized sub-committees focusing on flood prevention and management, humanitarian response and post-flood recovery, and health and sanitation for affected populations (Government of Chad, 2024). However, this committee is primarily active only in case of major flood disasters, and does not coordinate responses to most flood events.

To strengthen institutional response capacity, the government has expanded the roles of key ministries such as MASAH, the Ministry of Land Management, Housing, and Urban Planning (MATHU), the Ministry of Public Health, and the Ministry of Water and Energy. These ministries, in collaboration with local authorities and the Office of Military Engineering and Production (OGEMIP), have undertaken various flood prevention activities, including the reinforcement of dikes and riverbanks along the Chari and Logone rivers, the deployment of heavy machinery for flood control infrastructure in N'Djamena, and the strengthening of pumping stations to prevent urban flooding (Government of Chad, 2023a). MASAH remains the central government actor in flood response.

Non-governmental organizations (NGOs) and international organizations are essential in both immediate disaster response and long-term resilience-building (ACAPS, 2024; Government of Chad, 2023a; United Nations OCHA, 2022a, 2024a). NGOs often fill gaps where government resources are limited, particularly in remote or highly vulnerable areas. Their work is crucial not only in emergency interventions but also in risk reduction strategies, capacity-building programs, and advocating for sustainable flood management policies (IFRC, 2022, 2023, 2024). For example, the Food and Agriculture Organization (FAO) of the United Nations has conducted post-flood agricultural damage assessments in the most affected provinces, namely Logone Occidental, Logone Oriental, Mandoul, Mayo-Kebbi Est, Moyen Chari, and Tandjilé, to evaluate the long-term impact on food security and recommend appropriate interventions since 2022s floods (FAO, 2023a, 2023b, 2023d, 2024a). The Chadian Red Cross, supported by the IFRC, plays a key role in supporting flood response efforts across all 23 provinces (IFRC, 2022, 2023, 2024).

International and national organizations have strengthened their coordination mechanisms to enhance disaster preparedness, emergency response, and long-term resilience-building. The United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA), the FAO, the World Food Programme (WFP), the United Nations Children's Fund (UNICEF), the United Nations High Commissioner for Refugees (UNHCR), and the World Health Organization (WHO) have played an important role in mobilizing humanitarian aid, coordinating flood response logistics, and ensuring food security, health services, and water sanitation for affected populations (UNICEF, 2024; United Nations OCHA, 2022a, 2022b, 2024a, 2025; WFP, 2024a; WHO, 2022). In particular, UNOCHA has enhanced data-sharing and response coordination between humanitarian actors and government agencies (United Nations OCHA, 2022a, 2024a, 2025).

Local community organizations and civil society groups play an essential role in engaging affected populations, disseminating information, and supporting response efforts at the grassroots level. These groups often act as intermediaries between large organizations and local communities, ensuring that aid and flood mitigation efforts are appropriately targeted.

Despite increased attention and funding and efforts to organize around flood preparedness and response, critical vulnerabilities persist, limiting the effectiveness of flood response efforts. The absence of a legally binding multi-sectoral contingency plan, over-reliance on external humanitarian aid, and weak enforcement of urban planning policies continue to hinder long-term disaster resilience in Chad (Government of Chad, 2024; MASSAH, 2025). Communication and technological challenges are another constraint. For example, the April-May 2024 seasonal forecast bulletins from ANAM had predicted above-average rainfall and rising water levels in the Chari and Logone river basins, which ultimately resulted in widespread flooding (IRD, 2024), but there was limited capacity to disseminate and act on these forecasts to mitigate flood risk and exposure. The General Directorate of Water Resources (DRE) has expanded hydrological observation networks, but many water-level monitoring stations remain non-functional, highlighting the urgent need for technological upgrades, including automated water level sensors (Government of Chad, 2023b, 2024). There are also challenges in identifying flood incidence locally to help target relief efforts.

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Infrastructure limitations compound Chad's vulnerability to flooding (ND-GAIN, 2025). Planning and funding for flood defenses, urban water management infrastructure, river flow management, erosion control and prevention, and durable and resilient housing across many parts of the country are a significant challenge.

Table A10: Main stakeholders involved in flood management

Organization	**Roles / Missions**	**Activities / Responsibilities**	**Outputs**
Chad Strategic Committee for Flood Management and Prevention	Oversees the planning, coordination, and implementation of flood-related prevention and response efforts in Chad.	Coordinates humanitarian interventions, maps flood-prone areas, evaluates relevant legislation, drafts contingency plans, mobilizes resources, and develops communication strategies to enhance preparedness and response.	The committee generates flood risk maps, contingency plans, emergency response reports, and updates on funding mobilization.
Chad Ministry of Social Action, National Solidarity and Humanitarian Affairs (MASAH)	Coordination of flood response and relief (Direction de la Solidarité Nationale).	Deployment of emergency shelters, food aid, and medical assistance for flood victims.	Continuous relief activities, especially during flood crises.
Chad Ministry of Spatial Planning, Housing and Urban Planning (MATHU)	Urban planning and development of flood mitigation infrastructures.	Construction of flood control barriers, risk mapping, and urban drainage improvements.	Urban development plans, risk mapping reports (annually or as needed).
Chad Ministry of Public Health	Manages health-related crises and responses during floods.	Strengthens health facilities, deploys emergency medical teams, monitors epidemiological risks, provides psychosocial support.	Epidemiological reports, emergency health response updates (regularly and post-flood events).
Chad Ministry of Water and Energy (MEE)	Oversees water resource management and flood-related hydrological monitoring.	Collects and analyzes hydrological data, manages flood forecasting models, oversees emergency water resource distribution.	Issues hydrological reports (regular updates during flood seasons)
Chad ANAM (National Meteorology Agency)	Responsible for monitoring, analyzing, and forecasting weather and hydrological conditions to anticipate flood risks in Chad.	Collects and analyzes meteorological data, publishes climate and hydrological forecasts, and alerts authorities and the public about risks related to rainfall and flooding.	Regularly publishes meteorological and hydrological bulletins, including seasonal forecasts (such as the April-May 2022 forecasts for that year's floods) and post-season analyses to assess the impact of rainfall and water flow.

Table A10 (continued)

Organization	Roles / Missions	Activities / Responsibilities	Outputs
Chad General Directorate of Water Resources (DRE)	Coordinates the hydrological monitoring network and water data management.	Aggregates flood-related data, provides forecasts, works with hydrological models.	Issues periodic reports on river levels and water management.
Chad Provincial and Local Authorities (Governors, Prefects, Mayors)	Oversee and implement flood response measures at the local level.	Coordinate emergency response within provinces, support crisis committees, facilitate logistics for evacuations, mobilize local resources, and oversee disaster risk reduction actions.	Local emergency reports, coordination meetings, and crisis updates (as needed during flood events)
Chad Office of Military Engineering and Production (OGEMIP)	Coordinates and implements technical and infrastructural interventions for flood prevention and management in Chad.	Development of resettlement sites, construction of drainage and flood protection structures, installation of shut-off valves, maintenance of canals, provision of temporary shelters, solar electrification, and water supply infrastructure.	Reports on infrastructure progress (as needed), monitoring of maintenance and operational activities (regularly), post-flood intervention assessments (after flood events).
OCHA (United Nations Office for the Coordination of Humanitarian Affairs)	Facilitates coordination between governmental bodies and humanitarian organizations.	Mobilizes international funding, coordinates humanitarian interventions, supports needs assessments.	Humanitarian updates, funding reports, disaster response bulletins (frequent)
FAO (Food and Agriculture Organization)	Monitors flood impact on agriculture and food security, provides technical assistance, and supports resilience-building efforts.	Uses satellite imagery for flood assessments, supports early warning systems, provides emergency aid to farmers, implements food security measures.	Produces flood monitoring reports (during the rainy season), agricultural impact assessments (post-flood events), early warning bulletins (periodic based on forecasts), and livelihood/food security reports (as needed in response to crises).

Table A10 (continued)

Organization	Roles / Missions	Activities / Responsibilities	Outputs
WFP (World Food Programme)	Provision of emergency food assistance, logistics, and nutritional support.	Rapid deployment of emergency food supplies and logistical support to affected populations.	Food security assessments, distribution reports (monthly and post-floods)
UNICEF, WHO, UNHCR	Medical assistance, child protection, and refugee response coordination.	Health interventions, vaccination campaigns, and emergency response for vulnerable groups.	Regular, particularly for health and child protection during crises
Chadian Red Cross	Emergency response, first aid, and humanitarian relief for disaster-affected populations.	Emergency evacuation, first aid and psychosocial support, distribution of emergency shelter and essential household items, cash assistance for affected households, water purification and hygiene promotion, community health interventions, disaster risk reduction training.	Needs assessments, disaster response reports (regularly during crises), post-flood evaluations, and operational updates (periodic)
Institute of Research for Development (IRD) & University of N'Djamena (Laboratory of Hydro-Geosciences and Reservoirs)	Institute of Research for Development (IRD) & University of N'Djamena (Laboratory of Hydro-Geosciences and Reservoirs).	Develops predictive flood models, monitors river levels, analyzes hydrological data, collaborates on early warning systems.	Publishes technical and operational reports (weekly and during flood crises).

D Measuring flooding by satellite

Earth observation satellites have been consistently collecting data on the Earth's surface since the 1960s and hundreds of satellites are currently in orbit. Satellites with publicly-available data that have commonly been used to detect flooding include Landsat-8, MODIS (Aqua and Terra), VIIRS, and Sentinel-1 and -2 (see Schumann et al. (2018) for a recent review). Table A11 summarizes information on the data collected by these satellites, along with two others less commonly used, ALSO PALSAR and SMAP.[23]

Each satellite carries sensors that measure signals emitted from Earth. Optical/multispectral or microwave sensors passively record signals. Optical sensors all high spatial and spectral detail but are limited by clouds and sunlight. Microwave sensors penetrate clouds but have a much coarser resolution. Active sensors, notably synthetic aperture radar (SAR), collect data by emitting energy and measuring the backscatter. SAR works in all weather and in both day and night, but is typically collected at lower frequency. All of the satellites listed above carry optical/MS sensors except for Sentinel-1 which carries SAR sensors.

Both optical and radar can be used to detect the presence of water. For example, the Normalized Difference Water Index (NDWI) based on optical data leverages differences in how surface water reflects and absorbs different portions of the electromagnetic spectrum. This index is commonly used as an indicator of water or moist surfaces. Algorithms for radar data leverage differences in the backscatter for radar signals bouncing off of water relative to other features of the Earth's surface. Special attention must be paid in this algorithm to account for other features which could have similar signals as water, such as cloud or terrain shadow.

The identification of surface water is key for the detection of floods using satellite data. If water is identified in pixels where there is not typically any surface water (on average or in a given time period), this is an indication of a potential flood event. Different flood detection algorithms take different approaches to determining whether water detected at a particular place and time constitutes a flood. One common method is applying a 'permanent water mask' which identifies all pixels where surface water is expected, based either on geospatial representations of water bodies or on historical patterns in satellite data. All areas with surface water outside of the permanent water mask could be considered flooded. An alternative or additional method involves comparisons of water cover in the same location at different points in time, with a larger variation indicating a greater likelihood of flooding. Flood detection algorithms also make a variety of adjustments to account for measurement issues such as dropping areas with steep slopes (based on a digital elevation map), interpolating over time to overcome issues related to cloud cover or gaps between satellite flyovers, and more.

Some remote sensing approaches rely on precipitation data rather than the detection of surface water. Microwave and radar sensors can be used to estimate precipitation patterns, which can be

[23] A number of other satellites are also used in flood mapping but these are the most common. Commercial satellites such as Planetscope (Planet), WorldView (Maxar), and ICEYE offer very high resolution and high frequency data but these data must be purchased.

combined with hydrological models to predict flooding. The accuracy of these methods depends on the local reliability of hydrological model inputs, which can be limited in many lower-income countries.

Sentinel-1 SAR data is increasingly being preferred for flood mapping due to the advantages of SAR over optical data, but the longer revisit period (6-12 days) is an important limitation. MODIS and VIIRS satellite imagery are well-suited for large-area flood mapping due to their frequent (near daily) revisit periods, but are constrained by their inability to see through clouds. Sentinel-2 has the same constraint but offers higher resolution imagery, though with a longer revisit period. The most advanced current methods for identifying flooding combine Sentinel-1 SAR data with imagery from another satellite, often incorporating machine learning methods to leverage the different advantages of each source, but no publicly-available flooding database uses such methods, which are very computationally demanding.[24]

Flood detection by satellite has two main advantages. First, satellite data allows for high-frequency data collection across the world at a high spatial resolution. Second, satellite-based measures are objective and based on a specific algorithm, meaning they are not subject to reporting errors. But there are also several important limitations to satellite-based flood detection.

For one, the frequency of satellite data collection, covering each point on Earth every 1-16 days for the main satellites in Table A11, still implies that fast-moving floods are likely to be missed. This has particularly important implications for non-fluvial floods, as pluvial floodwaters flow towards low ground and are unlikely to stay stagnant for very long except on very flat ground with very limited soil absorption capacity and large amounts of water. Another limitation is that cloud cover prevents optical sensors from capturing floods caused by heavy precipitation; detection of these floods requires that inundation remains detectable until the next cloud-free data the satellite passes overhead. Microwave and radar satellite data resolve this issues but are not available at high temporal frequency. Finally, although the identification of floods based on algorithms using data may be objective, it may still be biased based on how the algorithm is developed. For example, algorithms that do not account for seasonal fluctuations in water cover may misclassify some such fluctuations as floods and in general flood detection algorithms are very sensitive to the choice of reference periods for 'non-flooding' conditions. Indeed, maps of flooding incidence for a given time and place can vary substantially across different flood monitoring databases.

For these reasons, satellite-based sources should not be considered as definitive measures of flooding incidence, particularly at very specific points in time and space. At a more aggregate level, however, they are very useful in identifying and monitoring areas where floods are determined to be very likely to be occurring.

[24] Patel (2025) develops such a method which also incorporates survey data from Bangladesh as a ground-truth flood measure for tuning the flood detection algorithm.

Table A11: Summary of main satellites used in flood detection

Satellite	**Source**	**Sensor Type**	**Spatial Resolution**	**Revisit Period**	**Spectral Bands**	**Swath Width**	**Years of availability**
Landsat 7	NASA/ USGS	Optical + Infrared	15 m (panchromatic), 30 m (MS), 60 m (thermal)	16 days	8 bands	185 km	1999-2022
Landsat 8	NASA/ USGS	Optical + Infrared	15 m (panchromatic), 30 m (MS), 100 m (thermal)	16 days	11 bands + 1 panchromatic	185 km	2013-
MODIS (Aqua and Terra)	NASA	Optical + Infrared	250 m (Red/NIR), 500 m, 1000 m	1-2 days	36 bands	2330 km	1999- (Terra), 2002- (Aqua)
Sentinel-1	ESA	Synthetic Aperture Radar (SAR)	10 m	6-12 days (region-dependent)	C-band SAR	250 km (varies by mode)	2014- (S1A), 2016-2021 (S1B)
Sentinel-2	ESA	Optical + Infrared	10 m (visible/NIR), 20m, 60m	5 days	13 bands	290 km	2015-
VIIRS	NASA/ NOAA	Optical + Infrared	375 m (I bands), 750 m (M bands)	1 day	22 bands	3000 km	2011- (Suomi NPP), 2017- (NOAA-20)
ALOS PALSAR	JAXA	Synthetic Aperture Radar (SAR)	10–100 m (depends on mode)	∼46 days (ALOS-1); 14 days (ALOS-2, partial access)	L-band SAR	70–350 km	2006–2011 (ALOS-1), 2014– (ALOS-2)
SMAP	NASA	Passive Microwave Sensor	9–36 km (passive); 3 km (active, until 2015)	2–3 days	L-band radiometer	1000 km	2015–present