



Beyond the flood map: an open-source framework for forecasting cascading impacts of natural hazards on people and essential services

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Abstract. Early warning and anticipatory action can help reduce negative consequences from weather and climate extremes. To inform preemptive decisions and anticipatory actions, actors in disaster risk reduction such as humanitarian organisations are increasingly relying on impact forecasts, as these can provide more concrete and actionable information in comparison to hazard-based forecasts. However, impact forecasts commonly focus on direct impacts, leaving indirect impacts such as service accessibility, which are relevant for emergency response planning, too often unaccounted for. To address this gap, we develop an impact forecasting framework to predict disruption in service access resulting from weather extremes. We illustrate the framework by predicting healthcare access disruptions for two high-impact flood events that impacted Somalia and Sudan in 2023 and 2024. Our model is able to provide actionable and spatially-explicit information such as forecast maps of where people may experience loss of service accessibility, and our results show that the pipeline is able to capture observed impacts up to a week in advance. Additionally, including indirect impacts such as healthcare access disruption significantly increases the estimated scale of a disaster. Comparison of modelling results with ground reports, satellite observations, and survey data reveals that observed post-disaster service accessibility disruption rates can be reproduced. Limitations remain in the precision of flood forecast input data and incompleteness of exposure data. An uncertainty and sensitivity analysis reveals large regional discrepancies in the sensitivity to the model parameters, and that uncertainty in exposure and accessibility thresholds can exceed the hazard forecast uncertainty. Our results illustrate how a model built on open-source data can provide decision-relevant and people-centric impact forecasts, that can be used to inform anticipatory action. We expect our findings to help improving impact forecast models and anticipatory action frameworks aimed at reducing human suffering.

1 Introduction

Weather and climate extremes are responsible for significant losses and suffering throughout the world, causing widespread and multi-faceted impacts to our societies. Damage from these events is expected to increase in the future, due to increasingly extreme weather and growth in built-up infrastructure. Early warning and anticipatory action are valuable ways to help mitigate the impacts of natural hazards and they can help manage residual risk that cannot be addressed by long term investments in



disaster risk reduction (Coughlan De Perez et al., 2015; International Federation of Red Cross and Red Crescent Societies IFRC, 2026). In humanitarian action, for instance, there has been a gradual shift from responding to acting in advance, where

25 hydro-meteorological forecasts are being leveraged to inform and trigger anticipatory action. This anticipatory perspective has been put into practice through forecast-based financing, and anticipatory action frameworks and early action protocols (Coughlan De Perez et al., 2015; International Federation of Red Cross and Red Crescent Societies IFRC, 2026). Most current early warning systems or anticipatory action frameworks rely on forecasts that only contain information on the physical intensity of the target hazards. However, such models have limitations, as they often do not provide actionable information to decision

30 makers (Potter et al., 2021; Geiger et al., 2024). To address this gap, impact forecasting models are being developed. Impact forecasts aim to provide information on the socioeconomic impacts of natural hazards by combining hydro-meteorological forecasts with impact models (World Meteorological Organization WMO, 2015; Merz et al., 2020). Providing such information is expected to improve decision making by providing more tailored and decision-relevant information (Harrowsmith et al., 2020). Consequently, impact forecasting is gaining traction and is starting to be implemented by a number of national weather

35 services or e.g. organisations such as the International Federation of the Red Cross and Red Crescent Societies (IFRC) in the humanitarian sector (Robbins et al., 2022; Harrowsmith et al., 2020; Anticipation Hub, 2026). However, the field is still at its infancy and several challenges remain at different steps of model development, implementation, calibration, and validation (Merz et al., 2020; Potter et al., 2025). For instance, the lack of impact and vulnerability data has been repeatedly reported as a limiting factor in the development of impact forecasts, while uncertainty communication is also seen as a challenge, due to

40 the increased complexity of the modelling chain (Potter et al., 2025). Another research gap in the field of impact modelling and impact forecasting relates to the quantification of indirect impacts. The majority of recent impact forecasting initiatives have focused on direct impacts (with the notable exception of Espejo et al., 2025). Most models forecast impacts in terms of "directly affected", tracking the number of people or assets directly located in regions where the target hazard is forecasted to reach a specific intensity (e.g. Godet et al., 2026; Alfieri et al., 2024; Kam et al., 2024; Sedhain et al., 2025; Moss et al.,

45 2026; Riedel et al., 2024; Kooshki Forooshani et al., 2024). However, such approaches fail to account for other indirect impact mechanisms, which may be relevant to the forecast or risk assessment. For instance, population may be indirectly impacted by disruptions in the provision of essential services such as healthcare, transportation, education, or food.

To address the missing representation of indirect impacts in impact forecasts, we develop and test a framework that models direct and indirect impacts of natural hazards on critical infrastructures to predict the consequences on people's access to es-

50 sential services. The framework helps going beyond the simplistic notion of direct impacts by including inter-dependencies between critical infrastructures and their end-users. The pipeline is based on open-source data and methods, and its modularity allows the user to incorporate their own data on hazard, exposure, and vulnerability. We demonstrate the use of the modelling pipeline by applying it to predict disruptions to healthcare access during river flooding in Eastern Africa. We select two case studies of recent high-impact flood events, based on their relevance for the field of humanitarian action, and the availability of

55 flood forecasts and impact data. First, we demonstrate how the framework can be applied to predict healthcare service access disruption during the 2024 floods in Sudan (International Federation of Red Cross and Red Crescent Societies IFRC, 2025). We show how including indirect impacts modifies the estimated scale of the event, and discuss the implications for the triggering



of anticipatory actions. We illustrate the capacity of the model to provide people-centric, actionable information, in the form of time series and forecasted service-access maps. We evaluate the temporal and spatial accuracy of the model by comparing the forecasts with observed impacts from written sources and satellite observations. Next, we extend our findings with a second case study, the 2023 Deyr floods in Somalia (Federal Government of Somalia et al., 2024; ReliefWeb, 2026). We illustrate the transferability of our modelling framework and conduct a direct evaluation of our modelling results using available survey data on disruption to healthcare service accessibility. We conclude with an uncertainty and sensitivity analysis to show how the uncertainty brought by the additional components of an impact forecast, such as exposures and vulnerability, adds up to the forecasting uncertainty of the hazard component.

Our findings demonstrate how incorporating indirect impacts such as service access disruption significantly reshapes the modelling and forecasting of disaster impacts. Our framework illustrates how open-source and open-access data and models can be combined to provide action-relevant and people-centric impact forecasts in a spatially-explicit and probabilistic manner. We showcase how such a framework can be applied to flood impact forecasting, and discuss the implications in terms of model and forecast uncertainty, and data limitations. We expect this model and results to help in the management and mitigation of disaster risks, and in the planning of humanitarian anticipatory action.

2 Data & Methods

This section introduces the impact modelling framework and describes the hazard, exposures, and vulnerability data, the infrastructure network and service-access module, and the uncertainty and sensitivity analysis framework. The section concludes with an introduction of the different case studies used to illustrate the model.

2.1 Impact modelling framework

We use CLIMADA (CLIMate ADaptation; Aznar-Siguan and Bresch, 2019) to model the impacts of floods on population and infrastructure. CLIMADA is an open-source and open-access weather and climate risk assessment platform coded in Python which allows to probabilistically and spatially-explicitly model the risks and impacts of weather and climate hazards. For this study we use CLIMADA version 6.1.0 (CLI, 2026b). CLIMADA uses the risk framework as described by the IPCC (Field and Barros, 2014) and hence requires input data describing hazard, exposures, and vulnerability. The flood hazard data is described in section 2.2, and the population and infrastructure exposures data is described in section 2.3. CLIMADA models vulnerability using simple functional relationships called impact functions that link hazard intensity to a mean damage degree on the exposures. These functions are described in section 2.4.

2.2 Flood forecast

We use the model of Riedel et al. (2024) to obtain re-forecasts and reanalysis of past flood events. This model combines daily stream-flow data from the global hydrological model Global Flood Awareness System (GLOFAS; Alfieri et al., 2013) with



flood hazard maps from Dottori et al. (2016). The model estimates the return period of each daily stream-flow value at each grid-cell of the GloFAS domain using extreme value distribution fitted on the reanalysis. Event-based inundation maps are derived from the estimated return periods by interpolating the nearest pre-computed flood hazard maps. For this analysis, we use operational stream-flow forecasts from GloFAS model version v4.1 (Copernicus Emergency Management Service CEMS and European Centre for Medium-Range Weather Forecasts ECMWF, 2025), and the updated version of the flood hazard maps released on 14 March 2024 (Baugh et al., 2024). This results in a daily reanalysis, and a daily probabilistic ensemble of 50 forecasts of flood extents and flood depths with a resolution of 20 arc-seconds.

2.3 Population and critical infrastructure exposures

We rely on open data from OpenStreetMap to model infrastructures exposures (OpenStreetMap contributors, 2017). We use the python package OSMNx to download and process data from the OpenStreetMap Overpass API (Boeing, 2025). The obtained geo-located lines or polygons are then disaggregated within CLIMADA for the impact calculation and later re-aggregated at their original shape (Mühlhofer et al., 2024). For road data, we filter-out roads at the residential level. For the exposures of healthcare facilities, we use the database from Maina et al. (2019) which was specifically derived for Sub-Saharan Africa and is more complete than OpenStreetMap for our regions of interest. To estimate the number of people affected by critical infrastructure failure, we use WorldPop data (Tatem, 2017). To reduce the computational burden, we up-scale the population data to a resolution of 2 km for regional analyses and 4 km for country-wide analyses. To align the road network and the population data for the service access model, we split road edges to ensure that they have a maximum length of 2 km.

2.4 Impact functions

We use simple threshold impact functions to estimate the vulnerability of our exposures to flooding. We select a threshold of 50 cm, in line with literature (Kam et al., 2021; Riedel et al., 2024). For simplicity, we use the same flood depth thresholds for population, healthcare and road exposures. We test the sensitivity of the model to these thresholds using an uncertainty and sensitivity analysis (see sections 2.6 and 3.2.1).

2.5 Infrastructure network and service access model

We use an infrastructure network model developed by Mühlhofer et al. (2023) to model direct impacts of weather extremes on critical infrastructures as well as indirect impacts resulting from infrastructure failure cascades. The model features a routing algorithm which allows to link population to the nearest critical infrastructures and hence to assess disruptions in service access. The model is open-source and integrated as a module in CLIMADA (CLI, 2026a), thus allowing a full coupling with the risk calculation capacities and additional features of the platform. In the infrastructure network module, inter-dependencies between the different components are modelled with a graph-based approach linking the different inter-dependent components together. For this study, we consider three different inter-dependent components; healthcare facilities, roads, population, and the following three inter-dependencies; the dependency of the healthcare facilities on the road network, the dependency of the



120 population on the road network, and the dependency of the population on the healthcare facilities. To set-up the dependencies, we require a set of two parameters per type of dependency. The first parameter specifies the dependency condition, e.g. the distance up to which two components can be linked, and the second the number of dependency links to be made between the different components. For simplicity, we only consider dependency condition based on distance, and do not consider other conditions such as travel duration or the population's displacement capacity. First, we link each healthcare facility to its nearest
 125 two road nodes (Healthcare-road links in Tab. 1), regardless of the distance (Healthcare-road distance in Tab. 1). Next, each population node is linked to its nearest road node (Population-road in Tab. 1), until a distance of 2 km (Population-road distance in Tab. 1). If the distance is larger than this threshold, the population node is considered as being deprived from road access. Finally, each population node having access to the road network is linked to the nearest hospital (Population-healthcare links in Tab. 1), up to a distance of 50 km (Population-healthcare distance in Tab. 1). Nearest hospitals are found using a shortest
 130 path algorithm, and the distances calculated along the path. Table 1 summarizes the different dependency parameters. For the uncertainty and sensitivity analysis, we vary the population-road and population-healthcare distance thresholds (Sect. 2.6, 3.2.1 and 3.2.2).

The impacts of floods on infrastructure and service accessibility are modelled in a three-step approach (Fig. 1). First, the baseline accessibility state is computed, where all infrastructures are considered as fully functioning. Secondly, the direct
 135 impacts of floods are modelled using CLIMADA, by combining the flood hazard forecast, with the infrastructure exposures and infrastructure vulnerability. These impact forecasts are then re-aggregated and used to update the infrastructure network, to account for infrastructure failures. Finally, the new, disrupted accessibility state is re-computed using the service-access model. Previous population-healthcare dependencies are re-calculated from scratch, thus allowing population nodes to adapt to possible service-access losses. In this set-up, population nodes can lose access to healthcare through three distinct mechanisms;
 140 the population node loses access to the road network, the population node cannot access a functioning healthcare in less than 50 km due to blocked roads, or the population cannot access a functioning healthcare in less than 50 km due to impacts to the healthcare facilities.

2.6 Uncertainty and sensitivity analysis

We use the uncertainty and sensitivity quantification module implemented in CLIMADA to study how the uncertainty sources
 145 from the modelling pipeline contribute to the output uncertainty of the impact forecast (Kropf et al., 2022). The uncertainty quantification consists in analysing the spread of a large ensemble of simulations, obtained by repeating model runs with varying configurations. The different configurations are selected to reflect uncertainty in the input data and parameters. Here, we quantify input data uncertainty associated with hazard, exposures and vulnerability, and parameter uncertainty associated with the service-access module. We model uncertainty in the hazard data by considering different quantiles of the ensemble
 150 forecast, and the inclusion or non-inclusion of flood-protection measures. We select the 10th, 50th and 90th quantiles of the probabilistic flood ensemble to approximate the stochastic uncertainty stemming from the 50 ensemble members. Uncertainty associated with flood adaptation is approximated using the FLOPROS dataset included in the GloFAS framework (Riedel et al., 2024; Scussolini et al., 2016). We keep the lead-time fixed to five days, corresponding to a medium-range forecast lead-time



Table 1. Names, descriptions, and default values of the parameters of the infrastructure network and service access model used for this study.

Parameter name	Description	Default value
Healthcare-road distance	Distance threshold for the dependency of healthcare infrastructure on road infrastructure. A healthcare infrastructure can be connected to a road node if their geographical distance is below this threshold.	∞
Population-road distance	Distance threshold for the dependency of population on road infrastructure. A population node can be connected to a road node if their geographical distance is below this threshold.	2 km
Population-healthcare distance	Distance threshold for the dependency of population on healthcare infrastructure. A population node can be connected to a healthcare infrastructure if their geographical distance is below this threshold.	50 km
Healthcare-road links	Number of dependencies of healthcare infrastructure on road infrastructure. Healthcare-road = 2 means that each healthcare infrastructure is linked to two nodes of the road network. Dependencies are constrained by the specific distance parameters.	2
Population-road links	Number of dependencies of population on road infrastructure. Dependencies are constrained by the specific distance parameters.	1
Population-healthcare links	Number of dependencies of population on healthcare infrastructure. Dependencies are constrained by the specific distance parameters.	1

large enough to implement anticipatory actions. For exposure uncertainty, we consider one additional population exposure
 155 dataset from the Global Human Settlement Layer (Kemper et al., 2021), one additional healthcare exposure dataset from
 OpenStreetMap (OpenStreetMap contributors, 2017), and one additional road exposure dataset from the GRIP dataset (Meijer
 et al., 2018). Uncertainty from the vulnerability component is modelled by using three different thresholds for the step functions
 used as impact functions; 0.1, 0.5, and 1.0 m. Finally, parameter uncertainty from the service-access module is estimated by
 varying two parameters, the population-healthcare distance access threshold (cf. Population-healthcare distance in Tab. 1), and
 160 the population-road distance access threshold (cf. Population-road distance in Tab. 1). For the population-healthcare distance
 access threshold, we consider values of 25, 50, and 75 km, and values of 1, 2, and 3 km for the population-road distance
 access threshold. For each study region, we generate an ensemble of 5632 simulations sampling the parameter space with the
 sampling sequence from Saltelli et al. (2010). We use uniform distributions to draw samples for each parameter as we estimate
 each parameter's values as equiprobable. Next, we assess the sensitivity of the model to the different uncertainty parameters
 165 by computing Sobol sensitivity indices (Sobol', 2001). The Sobol sensitivity indices are variance-based indices, allowing the
 attribution of the variance in the modelling output, to the variance in the input data and parameters varied across the simulations.
 We compute first- and total-order sensitivity indices, which quantify the contribution of a single input parameter to the output

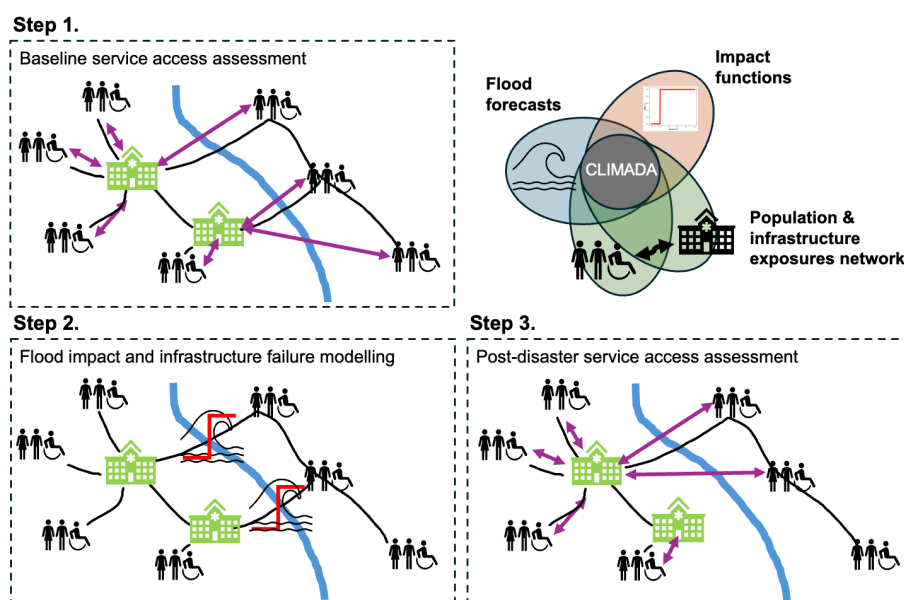


Figure 1. Scheme of the modelling framework. The pipeline consists in three steps; step 1. leverages the infrastructure network and service access model to compute baseline service accessibility, step 2. uses the CLIMADA platform to compute impacts from riverine floods on the infrastructure network and finally, step 3. assesses the post-disaster service accessibility using the disrupted infrastructure network. The entire framework is incorporated in the CLIMADA platform (Aznar-Siguan and Bresch, 2019).

variance and the total contribution of an input parameter to the output variance, including the parameters' direct contributions and all the higher-order contributions resulting from interactions with the other parameters.

170 2.7 Case studies & evaluation design

We showcase the use of our model in two countries, Sudan and Somalia. These two countries are frequently exposed to damaging floods that severely impact the countries' population and critical infrastructure. To address these challenges and reduce the flood damage, government authorities and humanitarian organisations are developing early warning systems and flood early action protocols (Anticipation Hub, 2023; MacLeod et al., 2026; Somalia Disaster Management Agency, 2026). In Somalia, the Somali Disaster Management Agency (SoDMA) recently published its Anticipatory Action Road-map, advocating for a multi-hazard (focusing on floods and droughts), multi-sectoral and people-centric approach to address natural hazards impacts through anticipatory action (Somalia Disaster Management Agency, 2026). In Sudan, there has been efforts to implement an anticipatory action framework for river flooding in the recent years, but the project has been halted due to the on-going conflict, which started in 2023 (Anticipation Hub, 2023).

180 For these reasons, we consider the application of our flood impact forecasting pipeline to these two countries relevant. We



test our modelling framework through two specific case studies of recent high-impact flood events, the 2024 floods in Sudan and the 2023 "Deyr" floods in Somalia. For both flood events, the availability of specific data documenting impacts on the population and critical infrastructure across different sectors allows us to validate our modelling approach. We select several of these documents to assess the accuracy of our model in time, spatial, and magnitude dimensions. For the 2024 Sudan floods, we use reports of the International Federation of the Red Cross and Red Crescent Societies (IFRC) for the Disaster Response Emergency Fund (DREF MDRSD034; International Federation of Red Cross and Red Crescent Societies IFRC, 2025), reports from the International Organisation for Migration (IOM) International Organization for Migration IOM (2024), and news reports (Hussein, 2024; Dabanga Radio TV Online, 2024a, b). The reports contain detailed information on the impacts of the floods on the ground, including the number of people and infrastructure affected with approximate timelines, thus allowing us to evaluate the accuracy of our forecast in the time dimension. In addition, a UNOSAT' disaster charter mission produced maps of impacted healthcare infrastructures for the city of Abu Hamad, in Sudan's River Nile state and the city of Tokar, in Sudan's Red Sea state (UNOSAT, 2024c, b), which we use to estimate the spatial accuracy of our forecast. For the Somalia 2023 Deyr floods, we use reports from the United Nations Office for the Coordination of Humanitarian Affairs (UN OCHA; ReliefWeb, 2026) and a detailed post-disaster needs assessment report produced by the SoDMA and the Worldbank (Federal Government of Somalia et al., 2024). The post-disaster needs assessment report includes surveys on the impacts of the floods to healthcare service access, allowing us to evaluate our baseline and post-disaster service accessibility forecasts against ground-truth observations. For regional analyses, we use administrative boundaries from UN OCHA downloaded on the Humanitarian data exchange platform (Information Management Working Group IMWG, OCHA, 2025; OCHA Somalia, 2025).

3 Results

The results section is organised as follows: First, we demonstrate the framework by applying it to the 2024 Sudan floods (3.1). We show how considering indirect impacts on the population amplifies the estimated magnitude of the crisis by analysing time series of the accumulated impacts for the entire country (3.1.1), we illustrate the capacity of the model to provide spatially-explicit and decision-relevant information by displaying maps of forecasted impacts on infrastructures and resulting service access loss for the population (3.1.2), we analyse how the inclusion of indirect impacts changes the probability of detecting impacts of different magnitudes (3.1.3), and conclude by evaluating the accuracy of the impact forecast in the spatial dimension using satellite data (3.1.4). Next, we complement our analysis with a case study illustrating the model transferability to the 2023 Somalia Deyr floods (3.2). We compare modelling results with survey data on healthcare accessibility and run an uncertainty analysis (3.2.1), and conclude with a sensitivity analysis (3.2.2).

3.1 Illustrative case study: Sudan floods 2024

Between June and October 2024, heavy rains in Sudan caused large-scale flooding, with flash and river floods causing devastating impacts in several regions, resulting in dozens of fatalities and thousands of injuries. The number of people displaced and affected by the floods were 170 thousand and 460 thousand, respectively, by the end of August 2024 (International Federation

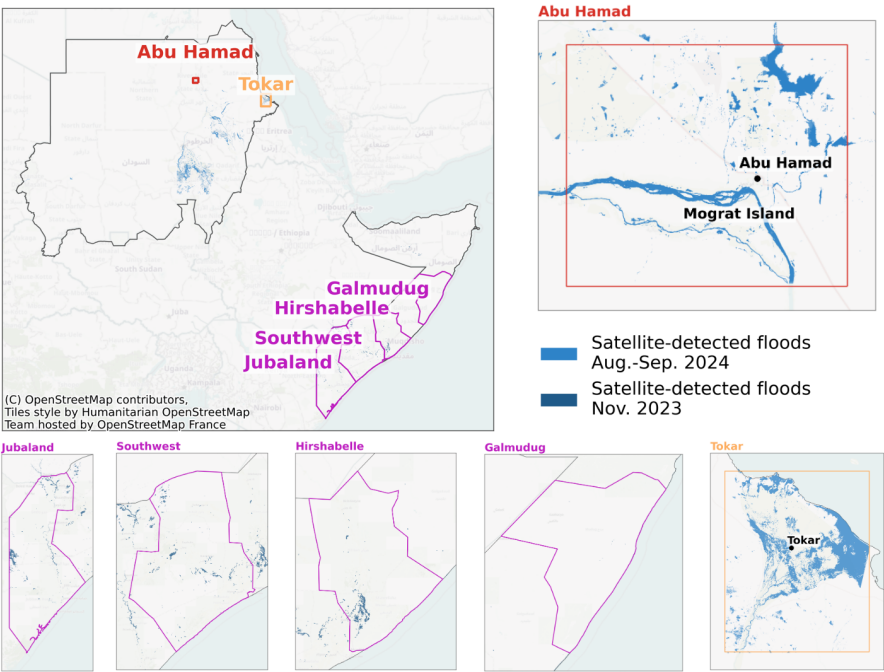


Figure 2. Maps of the case study regions considered.

of Red Cross and Red Crescent Societies IFRC, 2025). Houses and critical infrastructure such as roads, health facilities, Water Sanitation and Hygiene (WASH) infrastructure, and water resources were also severely affected. These impacts on critical infrastructure resulted in severe effects on the populations’ health and well-being. On 25 August 2024, the Sudanese Red Cross Society requested the release of emergency funds from the IFRC’s DREF mechanism and started a diversity of disaster relief actions, including damage and needs assessments, distribution of water and provision of health and hygiene kits.

3.1.1 Indirect impacts increase event magnitude

Figure 3 shows the cumulative count of direct and indirect impacts over time for the entire country of Sudan. The impacts are modelled using GloFAS reanalysis, thus representing the model’s estimation of flood impacts stripped from the forecasting uncertainty. We compare the number of directly affected people, corresponding to population directly affected by a flood depth of 50 cm, and the total number of people affected. The total number of people affected represents people either directly affected, or affected indirectly by disrupted accessibility to the road network or nearby healthcare facilities. The time series show that the first impacts of the floods on the population start to emerge towards the end of July, with a sharp increase in the impacts on 1 August. The IFRC reports 460,743 people affected by 25 August, which is in line with the number of people directly affected in our modelling framework. The total number of people affected at the end of the event (reported on December 2024)

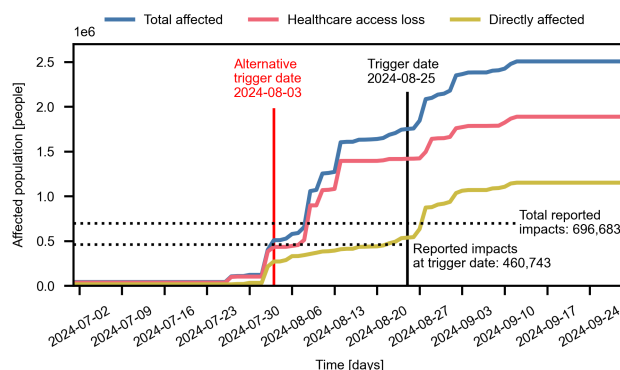


Figure 3. Cumulative counts of directly affected, indirectly affected by healthcare access loss, and total affected people for Sudan over the 2024 flood events (10 July - 30 October 2024).

amounts to 696,000 people according to UN OCHA (OCHA, 2024). This is slightly below our cumulative number of directly affected people by the end of the event, which amounts to about a million. When accounting for indirect impacts of the floods, the number of affected people increases drastically, with a total number of people directly and indirectly affected at the end of the event of about 2.5 million and a number of people facing disrupted healthcare access close to 2 million. Therefore, the inclusion of indirect impacts such as service access can significantly increase the scale of a humanitarian disaster and can help obtain a more complete overview of the impacts on the population. Adopting such an approach for rapid post-disaster damage assessments could lead response funds payout based on predefined triggers to be released earlier. This is illustrated in this example as the number of people affected at the trigger date on 25 August is already reached more than 20 days before when including indirect impacts on the population.

3.1.2 Forecasts predict spatial patterns of infrastructure impacts and service access loss

We illustrate how the forecasting pipeline can provide spatially-detailed information by examining maps of the forecasted impacts. We focus on the city of Abu Hamad, in the River Nile state, and the city of Tokar, in the Red Sea state, two locations that have been heavily impacted by the floods, and for which impacts on roads and healthcare infrastructure have been reported. Figure 4 shows a map of the forecasted impacts for the town of Abu Hamad. According to the IFRC, the city of Abu Hamad suffered heavily from the floods of 2024, with 34 deaths, 588 injuries, more than 30 thousand homes destroyed or damaged, and damages to critical infrastructure such as latrines, roads or health facilities (International Federation of Red Cross and Red Crescent Societies IFRC, 2025). The report states that roads in the region of Abu Hamad have been closed as of 28 August 2024. In addition, IOM reported that heavy rains and floods destroyed houses and displaced families in Abu Hamad on 6 August (International Organization for Migration IOM, 2024). Hussein (2024) also reports two separate flood waves and several road closures in the region of Abu Hamad, and mentions that the Sudanese Meteorological Authority emitted a warning against thunderstorms of extreme severity and torrential floods on 7 August (Sudan Meteorological Authority, 2024). We examine



spatial maps of the impacts forecasted on 1 August, computed using the maximum flood extent forecasted over the next 10
 250 days. We select the ensemble member whose forecasted impacts correspond to the 90th percentile of the forecast ensemble.
 Hence, the map represents a high-impact, low-probability forecast of flood impacts expected to occur between 1 August and
 11 August. The map displays roads, healthcare infrastructures, and population nodes directly affected by a flood height of 50
 cm, and population nodes indirectly affected by a loss of access to the nearest health facility. The forecast shows flooding
 along the Nile river and around the island of Mogerat (cf. Fig. 2), resulting in flood impacts affecting the population and critical
 255 infrastructures. About 10 thousand people are forecasted to be directly impacted by the flood, mainly near the main river
 channels and on the Mogerat island. Meanwhile, the forecast predicts indirect impacts due to flooding to a road on the northern
 river bank west of the city, and to a hospital south of the island. The number of people affected by healthcare accessibility loss
 or mobility disruption significantly increases the forecasted scale of the event, affecting an additional six thousand people.
 Figure 5 reproduces Fig. 4 but for the city of Tokar and for a forecast ensemble initiated on 20 August. In Tokar, sources
 260 reported flood impacts on 25 August, with dozens of fatalities and hundreds of displaced, and severe damage to the roads
 and the city's main hospital. The impacts to the road and healthcare infrastructure left parts of the population stranded and
 unable to access health services (International Federation of Red Cross and Red Crescent Societies IFRC, 2025; Dabanga
 Radio TV Online, 2024a, b). The map shows large parts of the delta of the Khor Baraka river to be expected to flood, resulting
 in significant impacts for the city of Tokar situated in the river's delta, and for other population nodes situated near the river's
 265 banks. The model predicts mobility and healthcare service disruption in Tokar and for all population nodes located on the
 western bank of the river due to direct impacts to the city's hospital and road blockages, in line with the impacts reported in
 Dabanga Radio TV Online (2024a) and Dabanga Radio TV Online (2024b). Overall, the model forecasts a total of 16 thousand
 people to be affected directly and indirectly within the 10 days following the forecast issue date.

3.1.3 Indirect impacts enhance forecast-based trigger decisions

270 Next, we assess the suitability of the forecast pipeline to trigger anticipatory actions prior to flood events. To do so, we exam-
 ine time series of exceedance probabilities for different thresholds relevant to humanitarian anticipatory action. We select two
 thresholds based on the number of affected people, which we compare with thresholds based on the return periods of certain
 river discharge levels. The discharge thresholds are based on established early action protocols and represent common practice
 in the field of humanitarian anticipatory action, where early action triggers are usually based on hazard forecasts (International
 275 Federation of Red Cross and Red Crescent Societies IFRC, 2021a, b, c). Early action protocols based on impact triggers are
 still rare and examples of impact-based triggers for anticipatory action against river flooding were lacking at the time of this
 study. Hence, we select two triggers based on population impacts that we estimate to be operationally relevant for anticipatory
 action. The first threshold represents the occurrence of a flood event affecting at least one person in the area of interest (i.e.
 more than 0% of the total population affected). The second threshold represents the occurrence of a high-impact flood event
 280 affecting more than 10% of the population in the area of interest. A value of 10% has already been used in a pilot early action
 protocol for tropical cyclones in the Philippines and is therefore relevant for anticipatory action (International Federation of
 Red Cross and Red Crescent Societies IFRC, 2019). Impacts are computed for each member of the 50-members ensemble by

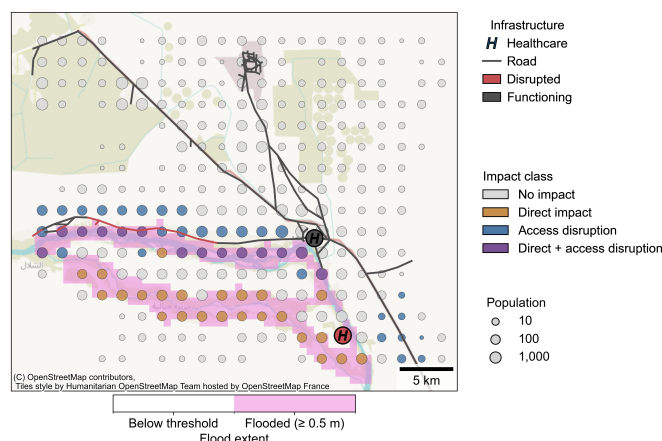


Figure 4. Forecast maps of directly impacted roads and healthcare facilities and population nodes losing access to healthcare services for the town of Abu Hamad. The forecast shows the impacts for the maximum flood extent over a lead-time of 10 days for the ensemble member showing the 90th most extreme event from the forecast ensemble initiated on 1 August 2024. Pink shading show location for which a flood depth higher than 50 cm is forecast. Disrupted infrastructures are colored in red. Population nodes are represented as dots with sizes proportional to the population counts and are colored according to the forecasted impacts; grey no impact, orange direct impacts, blue disrupted access to healthcare, and purple direct impacts and healthcare access disruption.

using the maximum forecasted flood extent over a lead-time of 10 days. Similarly, discharge return periods are calculated for each member over a lead-time of 10 days for locations in the river directly upstream of the areas of interest (see supplementary
 285 Sect. E1). The probabilities of exceedance are computed by counting the number of ensemble members whose forecasts exceed the specific thresholds.

Figure 6 shows the temporal evolution of the probabilities of exceeding the different thresholds calculated from the forecast ensemble. The top row (a, b) shows the probabilities for an event affecting more than 0% of the total population and the second row (c, d), the probabilities for an event affecting more than 10% of the population. Probabilities of the forecasted river
 290 discharge to exceed certain return periods are shown on the last row (e, f). Left column (a, c, e) shows results for the city of Abu Hamad in the River Nile state and right column (b, d, f) for the city of Tokar in the Red Sea state. Reported timings of flood impacts are also shown for comparison. In Abu Hamad, IOM reported heavy rains that led to flooding and displacement on 6 August, and IFRC reported road closures due to floods on 28 August. In Tokar, several sources reported that heavy floods
 295 occurred around 25 August, damaging the city's hospital, destroying roads and bridges, and displacing populations. Top row of Fig. 6 reveals that the forecasting pipeline is able to capture the timing of the flood impacts, with high impact probabilities being reached in both locations before the actual timing of the impacts estimated from the ground reports. In Abu Hamad, a probability of 75% is reached once on 29 July, and a second time on 25 August. Considering the impact reports from 6 August

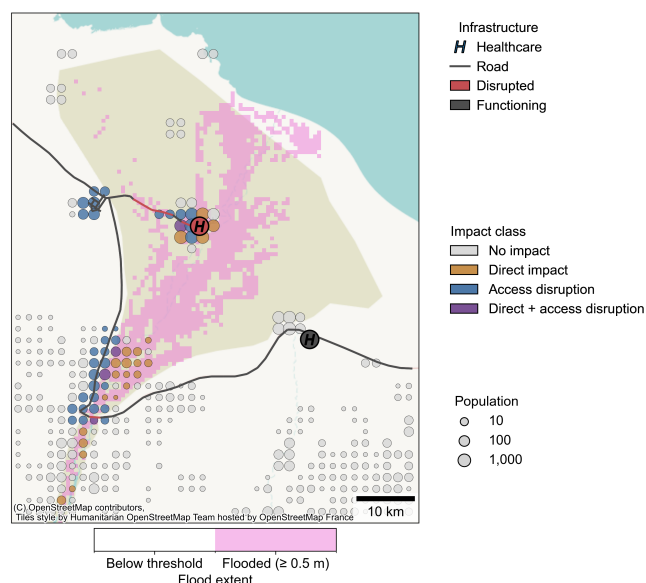


Figure 5. Forecast maps of directly impacted roads and healthcare facilities and population nodes losing access to healthcare services for the town of Tokar. The forecast shows the impacts for the maximum flood extent over a lead-time of 10 days for the ensemble member showing the 90th most extreme event from the forecast ensemble initiated on 20 August 2024. Pink shading show location for which a flood depth higher than 50 cm is forecast. Disrupted infrastructures are colored in red. Population nodes are represented as dots with sizes proportional to the population counts and are colored according to the forecasted impacts; grey no impact, orange direct impacts, blue disrupted access to healthcare, and purple direct impacts and healthcare access disruption.

and 28 August, this corresponds to a lead-time of eight and two days, respectively. In Tokar, the flood impacts are predicted with a 75% probability with a lead-time of seven days. In both cases, this leaves a window of about a week to undertake anticipatory action. Impacts are also predicted with lower probabilities longer ahead the reported impacts. While these anticipated threshold exceedances can be considered as false alarms, they could also be leveraged to undertake low-regret actions. Figure 6 (a) and (b) also suggest that including indirect impacts does not influence the probability of detecting an event, as the exceedance probabilities are the same for direct and indirect impact forecasts. However, Fig. 6 (c) and (d) show that including indirect impact changes the magnitude of the forecasted impacts, thus leading to higher probabilities of occurrence when considering a higher impact-based trigger of 10%. In Abu Hamad, the indirect impact forecast that includes mobility and healthcare accessibility disruption still predicts an event with a probability of 75% one week ahead of the reported impacts, when considering a threshold of 10%. In contrast, the direct impact forecast only reaches high exceedance probabilities a couple days before 28 August. In Tokar, there is no significant differences between the direct and indirect impact forecasts, and the probabilities of occurrence of an event affecting 10% or more of the population remain low throughout the period investigated.



Next, we illustrate the added value of our impact forecast with respect to a hazard forecast by comparing the probabilities of exceedance of the thresholds based on population impacts against the threshold based on discharge levels. The comparison reveals that including impacts significantly helps in detecting the occurrence of a flood and its impacts. In Abu Hamad, probabilities of exceeding operational discharge-based thresholds of five and 10 years remain low throughout the event (below 10%). Return period levels of two years are reached with a probability of 40% about a week before the second flood peak, but the signal is likely too weak to trigger anticipatory action. In Tokar, the probabilities of exceeding the predefined levels of discharge remain relatively high the month preceding the flood event, even though very high exceedance probabilities are never reached. In contrary, the probabilities of impacts on the population reach 80% the week before the reported event, showing that including impacts better correlates with the actual occurrence of flood impacts in this location. We repeat the discharge forecast analysis using different station locations in supplementary Sect. E1. The additional analysis does not reveal that the results are sensitive to details in the station's location.

3.1.4 Model evaluation against satellite observations

We examine how the produced forecasts compare with observations by using satellite data. Figure 7 (a) shows satellite-detected flood extents and possible damage to healthcare structures, acquired on 29 August 2024 by a UNOSAT mission for the region of Abu Hamad (UNOSAT, 2024c). For comparison, the satellite-detected flood extents are down-scaled to the model resolution of 20 arc-seconds and plotted alongside the maximum flood extent from the reanalysis and from the forecast ensemble with a lead-time of 10 days. The satellite data reveals the significant contribution of flash and pluvial floods for this specific event, as shown by the numerous and scattered patches of water which are found away from the main channels of the Nile river. In comparison, the flood model only predicts flooding near the main channels of the Nile. This highlights the limitation of the flood forecast model, which is only able to model riverine floods and hence misses floods which are not in the direct vicinity of the main river channels. Regarding accuracy, the flood model also shows moderate precision and recall, with a precision of 0.19 and a recall of 0.43 for a F1-score of 0.26 for the forecast and a precision of 0.53 and a recall of 0.09, for a F1-score of 0.16 for the reanalysis.

Figure 7 (b) reproduces Fig. 7 (a) for the city of Tokar using UNOSAT data acquired on 2 September (UNOSAT, 2024b). Satellite imagery reveals that most of the observed and forecasted flooding occurs in the flood plain of the delta of the Khor Baraka river, and the contribution of flash and pluvial flooding seems to be relatively less, in comparison to Abu Hamad. This type of flooding can be better captured by the riverine flood model, as the larger overlap between forecast and observed floods suggests. In this location, the accuracy of the forecast is higher, with a precision and recall reaching respectively 0.36 and 0.58, for a F1-score of 0.45. However, the accuracy of the reanalysis is significantly lower, with a precision of 0.13 and a recall and F1-score below 0.01, indicating that the model still suffers from significant performance issues.

Satellite-detected damages to healthcare infrastructures on Fig. 7 also reveals possible limitations on the completeness of the exposures data, where the satellite product assesses damage to five and 10 healthcare facilities in the city of Abu Hamad and Tokar, respectively, where our exposure data only contains one facility in each of these two locations. In terms of impacts, the satellite indicates possible damages to three and seven healthcare facilities in Abu Hamad and Tokar, respectively, where our

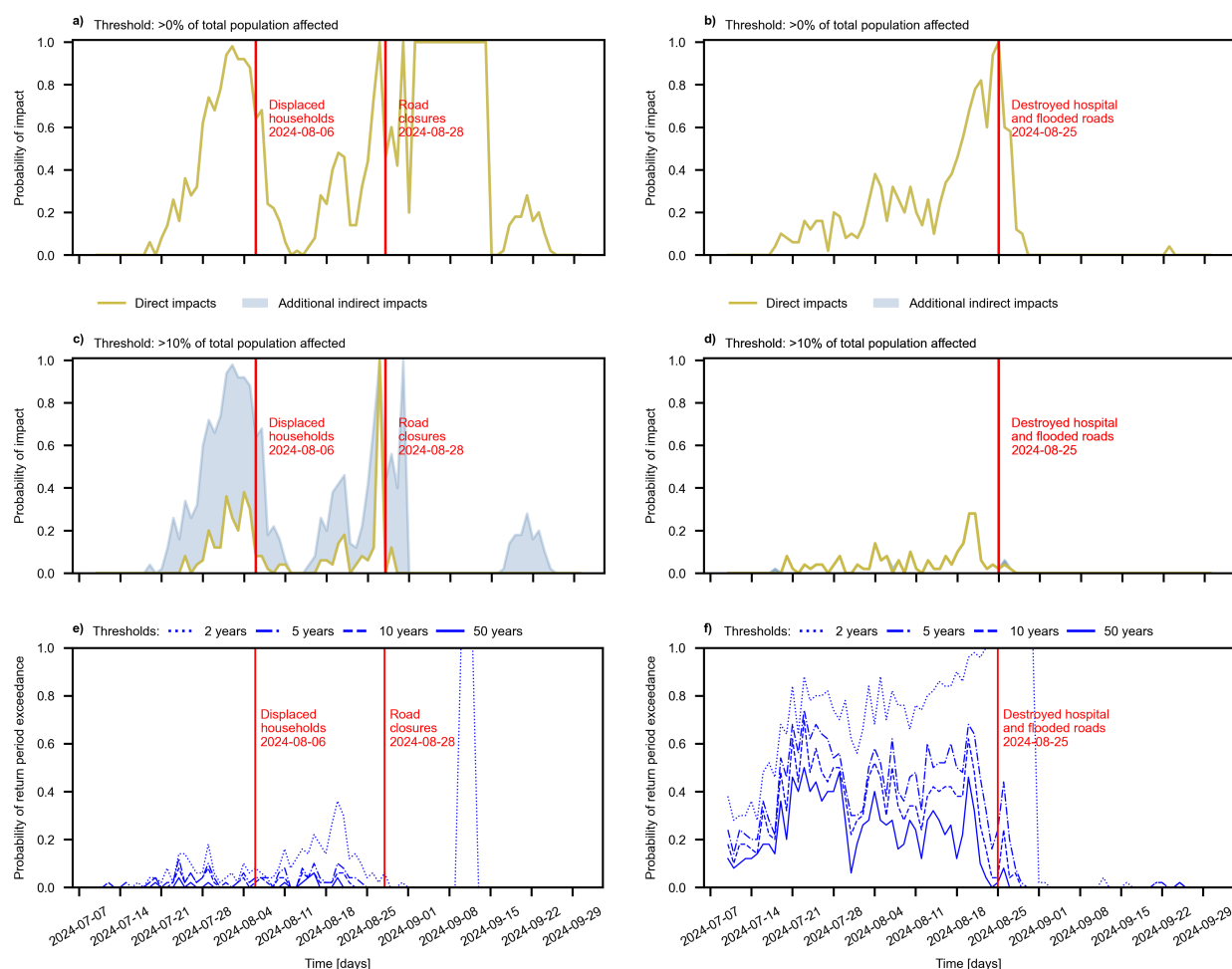


Figure 6. Times series of probabilities of the daily forecasts exceeding certain thresholds. First, second and third rows show exceedance probabilities for the impact forecast to exceed 0, 5, and 10% of the total population to be directly affected by a flood depth of 50 cm. The blue envelopes show the additional exceedance probabilities from including the number of people losing access to roads or healthcare to reach the thresholds. Fourth row shows the exceedance probabilities of the discharge forecast to exceed return periods of two (dotted line), five (dashed-dotted), 10 (dashed) and 50 years (solid). Left column shows results for the city of Abu Hamad in the River Nile state and right column for the city of Tokar in the Red Sea state. Red vertical lines show estimated timings of the flood impacts from International Federation of Red Cross and Red Crescent Societies IFRC (2025) and International Organization for Migration IOM (2024).

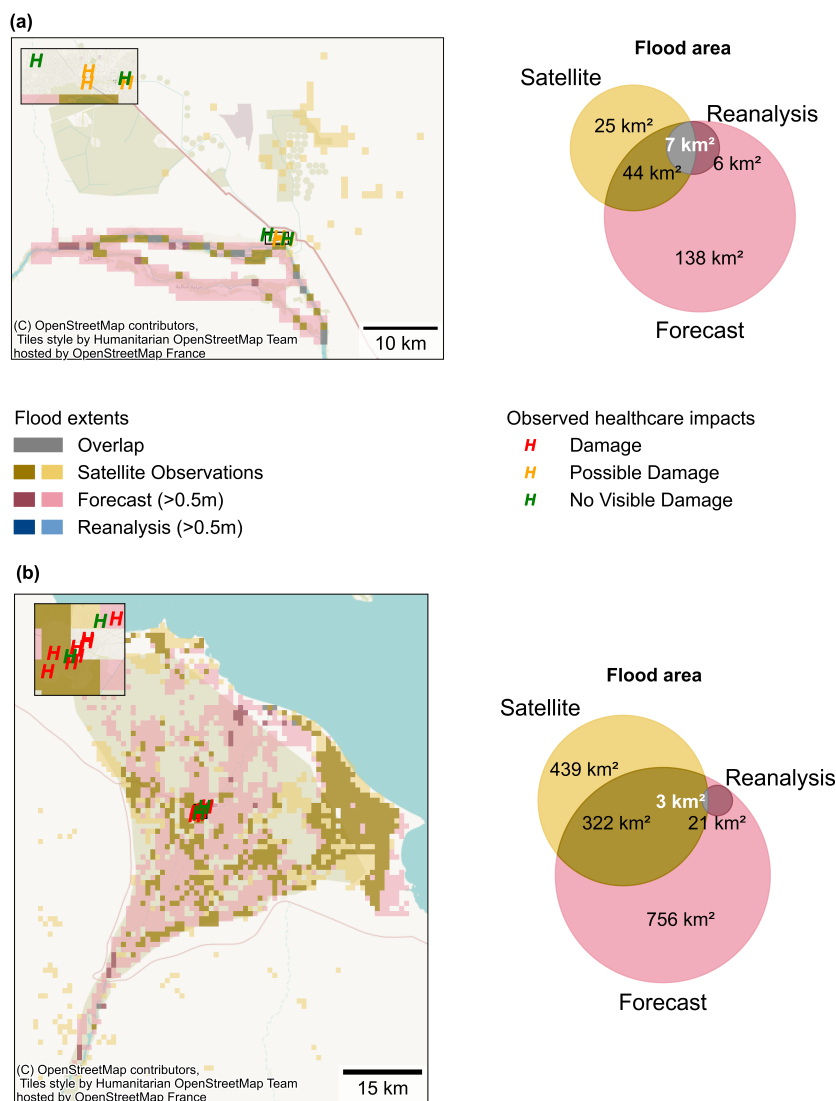


Figure 7. Comparison between modelled and satellite-detected flood extents for the city of Abu Hamad (a), and the city of Tokar (b). Yellow shading indicates satellite-detected flood extent acquired by UNOSAT on 29 August 2024 for Abu Hamad and 2 September 2024 for Tokar, and blue and red shading the maximum flood extent computed for 10 July to 30 October for the GloFAS reanalysis and forecast with a lead-time of 10 days, respectively. Colored H symbols represent possible damages to health facilities detected from the satellite.

345 model does not forecast any in Abu Hamad, and one in Tokar. Additionally, our model forecasts impacts on a facility located south of Mograt island near Abu Hamad, whereas the satellite does not provide any information on this facility.

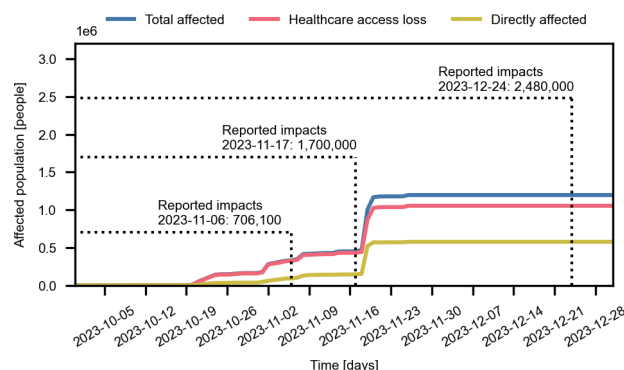


Figure 8. Cumulative counts of directly affected, indirectly affected by healthcare access loss, and total affected people for Somalia over the 2023 flood events (20 September - 31 December 2023).

3.2 Complementary case study: Somalia Deyr floods 2023

We illustrate the transferability of the model by applying it to a second case study, the Somalia Deyr floods of 2023. Somalia is regularly subjected to floods during the Deyr rainy season which occurs from October to December. In 2023, strong El-Nino conditions brought above-normal precipitation which lead to widespread flooding, affecting close to 2.5 million people and leaving the regions of Galmudug, Hirshabelle, Jubaland, and Southwest particularly impacted (Federal Government of Somalia et al., 2024). Figure 8 shows the cumulative count of the number of people affected over the entire event using GloFAS reanalysis, similarly as in Fig. 3. The time series shows the first impacts from this flood events to emerge on 20 October 2023, followed by a gradual increase in the impacts until 18 November. After this date, the modelled impacts more than double over a period of four days, and finally stabilize on 21 November, with 500 thousand and one million people directly and indirectly affected, respectively. Including indirect impacts from disrupted accessibility to healthcare doubles the estimated magnitude of the event, in agreement with the numbers found for the flood event of 2024 in Sudan. A comparison of the modelling results with data from UN OCHA (ReliefWeb, 2026) reveals that our model significantly underestimates the scale of the event even when including indirect impacts, with differences between observed and modelled values in the order of 50 % at the three different report snapshots of 6 November, 17 November, and 12 December 2023.

3.2.1 Model evaluation against survey data and uncertainty analysis

Next, we compare our model with surveyed baseline healthcare accessibility and healthcare accessibility disruption obtained from a post-disaster needs assessment report for the regions of Galmudug, Hirshabelle, Jubaland, and Southwest (Federal Government of Somalia et al., 2024). We construct an ensemble of 5632 impact forecast simulations in each of the four regions, varying uncertain input parameters, as explained in Sect. 2.6. This allows us to account for uncertainties originating from the hazard forecast, exposure, vulnerability, and accessibility models.

The box-plots in Fig. 9 shows the distributions of the modelled healthcare access statistics for each region, compared with

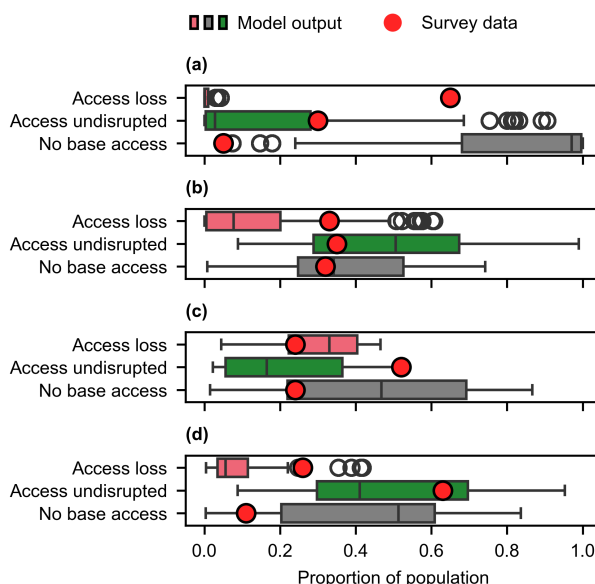


Figure 9. Comparison of modelled versus surveyed flood-induced healthcare access loss for the 2023 Deyr floods in Somalia. Model spread is quantified following the uncertainty analysis described in Sect. 2.6. Panel (a) shows results for the region of Galmudug, (b) Hirshabelle, (c) Jubaland, and (d) Southwest. Survey data is obtained from Federal Government of Somalia et al. (2024).

the statistics obtained from the surveys. The grey box-plots indicate that the model is able to reproduce the observed baseline
 370 healthcare access rates, as the surveyed statistics are within the bounds of the modelling spread in all regions except Galmudug. On average, the model tends to underestimate the baseline healthcare access, with a median difference between modelled and surveyed baseline healthcare access (expressed as a fraction of the population) of -0.92 in Galmudug, -0.02 in Hirshabelle, -0.23 in Jubaland, and -0.4 in Southwest.

The proportions of population being affected or not affected by healthcare accessibility disruptions are shown with the red
 375 and green box-plots, respectively. The model tends to underestimate healthcare accessibility losses, with median differences between modelled and surveyed healthcare accessibility loss of -0.65 in Galmudug, -0.25 in Hirshabelle, 0.09 in Jubaland, and -0.20 in Southwest. This is in line with the negative bias found for the baseline healthcare accessibility. However, the results for Jubaland show an overestimation of the post-disaster healthcare accessibility which is in contradiction with the underestimation of the pre-disaster accessibility. This suggests that the flood forecast might overestimate the flood exposure
 380 for this region, revealing that flood forecast and accessibility model contribute to the modelling errors.

3.2.2 Sensitivity analysis

We investigate which of the modelling components contribute the most to modelling uncertainty highlighted in the previous section by conducting a sensitivity analysis. The sensitivity analysis attributes the variance in the modelling output to the vari-



ance in the input data and parameters, allowing to measure the contribution of the different inputs to the output uncertainty.

385 Figure 10 shows the first-order sensitivity indices for the modelled statistics of access loss, access undisrupted and no base access in each of the four regions. The baseline healthcare access shows different sensitivities between the regions, with higher sensitivities to the population exposure data source (Population source) in Galmudug and Southwest. In contrast, sensitivity is highest to the distance accessibility threshold between population nodes and healthcare facilities (Population-healthcare distance) in Hirshabelle, and to the healthcare facilities exposures data source (Healthcare source) in Jubaland. These results

390 suggest that the accuracy of the exposure datasets can vary per region, and that the sensitivity of the accessibility model to the different parameters can vary spatially. Regarding the healthcare accessibility loss, the sensitivity results show different behaviors. In Galmudug (panel a) and Jubaland (panel c) the strongest sensitivity is shared between the parameters that dictate the Healthcare source and the Population-healthcare distance. Interestingly, baseline and post-disaster healthcare accessibility estimates show similar sensitivities in Jubaland, but not in Galmudug. In Hirshabelle (panel b) and Southwest (panel d) the

395 modelled healthcare access loss is most sensitive to the quantile of the forecast ensemble (Forecast quantile), but shows negligible sensitivity to this parameter in Galmudug (panel a) and Jubaland (panel c). These results shows that the uncertainty in the impact forecasts is not only dominated by the hazard forecast uncertainty, and that contribution of the different modelling components to the output uncertainty can vary regionally. We control for parameter interaction using total-order sensitivity indices in supplementary Fig. K1. While the results between first- and total-order sensitivities show similar outcomes in most cases,

400 we note significant parameter interaction in Galmudug. This suggests that modelling results in this region are not stable, and warrants further detailed analysis to understand the large parameter interaction. We also note that our modelling results do not show a significant sensitivity to vulnerability thresholds. This may be because the forecasted flood depths are systematically higher or smaller than the vulnerability thresholds.

4 Discussion

405 4.1 Application to anticipatory action

We combine an infrastructure impact and service accessibility model with GloFAS-based flood inundation forecasts to illustrate the potential of forecasting indirect impacts of floods on the population. We show that our approach can enrich flood forecasts with specific people-centric information, which may be able to better inform preemptive decisions or anticipatory actions. Our model is able to provide information on both the location, and number of people which may be at risk of losing access

410 to healthcare, or at risk of reduced mobility. This kind of information may be used to inform anticipatory actions such as the deployment of mobile healthcare units, the distribution of medical supplies, or the preemptive evacuation of hospitals or residents. Setting up this kind of anticipatory action is particularly relevant for a country like Sudan, where citizens have reported difficulties in accessing healthcare facilities to obtain medical necessities such as anti-venom kits after the floods of 2024 (Hussein, 2024). Our results also suggest that including indirect impacts such as disruption in access to essential services

415 can more than double the estimated magnitude of impacts of a flood. This is consistent with the literature, as, for example, Mühlhofer et al. (2023) found that the number of people affected by service disruption in poor and sparsely-built areas could

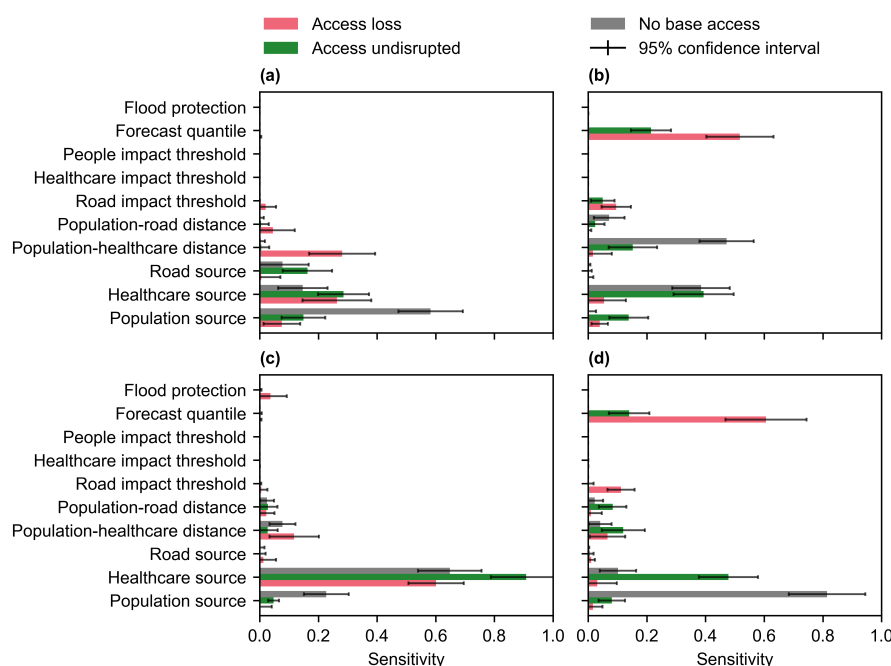


Figure 10. First-order sensitivity indices for the modelled baseline healthcare access and the flood-induced healthcare access loss for the 2023 Deyr floods in Somalia. Sensitivity is quantified following the sensitivity analysis described in Sect. 2.6. Panel (a) shows results for the region of Galmudug, (b) Hirshabelle, (c) Jubaland, and (d) Southwest.

be up to 10 times the number of people directly impacted. This increase in the estimated number of people affected can significantly amplify the scale of a disaster, and be used to better estimate the required funds for disaster response. Moreover, the inclusion of indirect impacts in predefined triggers for disaster fund can lead to a release several days earlier than when accounting for direct impacts on the population only, as highlighted in Sect. 3.1.1. We assess the suitability of the framework to be used to trigger anticipatory action (Sect. 3.1.3). The analysis suggests that the model is able to predict flood impacts with a probability of 75% five to eight days in advance, showing its potential to be used to trigger anticipatory action. Moreover, a comparison with discharge forecasts, the standard to trigger anticipatory action against river floods, reveals that impact forecasts are able to provide a clearer predictive signal and correlate better with the reported timing of flood impacts. This suggests that impact forecasts might be able to improve current anticipatory action triggers for river flooding that rely on discharge forecasts only. Including service access disruption to the forecast increases the magnitude of the predicted impacts, thus leading to a stronger signal in reaching or exceeding some predefined impact-based thresholds. However, our analysis did not show that including indirect impact does change the predicted timing of the flood impacts when compared to a model forecasting direct impacts.



430 4.2 Model performance, uncertainty and sources of error

We assess the influence of considering healthcare access disruption in estimating the scale of a humanitarian disaster at the level of two countries, Sudan and Somalia, for two distinct flood events. Comparison with reported impact figures reveals that our model overestimates the direct impacts on population in Sudan by an order of magnitude of 40%, but underestimates the impacts in Somalia by an order of 50%. These results are computed using reanalysis. Thus, they are independent of the
 435 forecast uncertainty and only reflect potential errors from the flood or impact model. While these differences may appear large, we note that the model uses globally-available data, which have not been specifically calibrated for the regions investigated. Furthermore, the focus of the study is not to reproduce observed flood impacts, but rather to highlight the benefits and limitations of including additional impact metrics in the assessment. Additionally, the reported impact numbers are taken from different sources, and are subject to reporting biases, specifically as the different organisations such as IFRC or UN OCHA
 440 might report impacts differently. Our estimated counts of population indirectly impacted by healthcare access loss could also not be evaluated on the country scale as these statistics are difficult to estimate and thus not standardly reported by disaster management agencies or humanitarian organisations.

The comparison against impact reports highlights the potential for the model to be able to detect flood impacts with several days of lead-time. For instance, our framework forecasts flood impacts with a probability of 75% eight days before the first
 445 flood occurrence reported by International Organization for Migration IOM (2024) and Hussein (2024) for the region of Abu Hamad. Similarly, our framework forecasts impacts with a probability of 75% seven days before the reported flood impacts of 25 August in the region of Tokar (International Federation of Red Cross and Red Crescent Societies IFRC, 2025). However, this analysis rests on only two case studies from one single flood event. Thus, these results should be interpreted as a proof of concept and the robustness of these findings should not be overstated. Furthermore, the analysis relies on impact data that is
 450 subject to significant biases. Specifically, the ground reports used for this assessment rely on human testimonies, and describe complex and rapidly-evolving situations. Hence, it is possible that the timings of the flood impacts estimated from these reports are incorrect and occurred earlier than what our assessment suggests. This would lead to an overestimation of the predictive capacity of the model, and thus reduce the temporal window to undertake anticipatory actions.

We assess the spatial accuracy of our framework using satellite data. The examined satellite products provide information on
 455 the observed flood extents, with possible damages on the nearby health facilities. The comparison with the satellite-detected flood extents highlights the limitation of the flood forecast model, with floods in the regions investigated being modelled with a low accuracy. One reason for the limited performance resides in the inability of the riverine flood model to capture the pluvial flooding. For instance, the satellite-detected flood extent in the region of Abu Hamad shows significant patches of flood water scattered away from the main channels of the Nile rivers, suggesting that pluvial flooding also contributed to this flood event
 460 (Fig. 7). While this can explain the low recall of the model, the comparison also reveals that riverine flood may be overestimated by the forecast, thus leading to a low precision. The situation is similar in the region of Tokar, although the contribution of pluvial flooding seems to be slightly less important than for Abu Hamad. The model showed similarly low performance in Somalia (cf. Fig. H1 in Supplementary). In particular, flood extents obtained with the model's reanalysis show very little over-



lap with the satellite-detected flood extents. These discrepancies suggest a low model performance for the region, in-line with
 465 previous analyses highlighting low skill for GloFAS in the Greater Horn of Africa (Taye et al., 2025; Harrigan et al., 2020).
 However, satellite data might themselves be subject to bias and errors, and should thus not be considered as ground truth. For
 instance, the satellite-estimated flood extent for the 2023 flood event for the region of Galmudug in Somalia shows only very
 little flooded area, scattered along the coast (Fig. H1 a). This is inconsistent with the results of the post-disaster needs assess-
 ment survey that reported heavy flood impact in this region (Federal Government of Somalia et al., 2024). The satellite product
 470 also provides indications of healthcare facilities potentially impacted by the floods, thus allowing us to validate the spatial ac-
 curacy of the direct impacts forecasted on the health facilities. The satellite-detected damages reveals significant discrepancies
 in the exposures data, where our exposures model only contains a small subset of the actual health facilities exposures. For
 instance, the satellite product indicates five and 10 healthcare facilities in the city of Abu Hamad and Tokar, respectively, while
 our exposures model only contains one facility in each of these locations. A possible explanation for these discrepancies is
 475 that the different sources include different types of healthcare facilities in their assessment. For instance, it might be that the
 assessments conducted by UNOSAT, which relies on data provided by the World Health Organisation, includes more specific
 health facilities than the ones included in Maina et al. (2019). Considering different healthcare facility exposure data such as
 from OpenStreetMap did not help close this gap, as OpenStreetMap data features even less healthcare facilities than Maina
 et al. (2019) in the two regions of interest (cf. supplementary Fig. C1 and D1). These differences in the exposure data make
 480 the comparison of the observed and modelled impacts difficult, and highlight that impact forecast models are also impacted by
 inaccuracies in exposures data.

We validate the magnitude of the forecasted and baseline healthcare accessibility using pre- and post-disaster accessibility
 surveys for the 2023 Deyr floods in Somalia. We generate a simulation ensemble to account for uncertainty in the input data
 and parameters and compare the survey data against the obtained model distribution. The comparison reveals that the sur-
 485 veyed accessibility statistics are contained in the uncertainty bounds of the modelled statistics for all four regions except in
 one, suggesting that the model can reproduce observed accessibility rates. However, the model exhibits a significant spread,
 indicating a significant modelling uncertainty. Furthermore, the model tends to underestimate the baseline and post-disaster
 healthcare accessibility, with an average error of -0.39 for the baseline access and -0.25 for the forecast post-flood access. We
 expect this underestimation to originate primarily from incomplete exposure data, which is an issue that the comparison with
 490 satellite products already highlighted. Additionally, miscalibrated accessibility thresholds can also lead to an underestimation
 of the accessibility rates, but this limitation can be reduced through parameter calibration. While the survey data is the best
 estimation of the pre- and post-disaster healthcare accessibility available for this event, this data is also likely to be biased. In
 particular, sampling uncertainty and representativeness biases are likely to affect the accessibility statistics. However, the lack
 of information on the sample sizes and methodology used for the surveys prevents us from estimating these biases further. We
 495 use a sensitivity analysis to attribute the output uncertainty to the different model input and parameters. The analysis reveals
 regional differences in the sensitivities. Specifically, baseline healthcare accessibility is most sensitive to population data source
 in two of the four regions assessed, whereas it is more sensitive to healthcare exposure data or road accessibility threshold in
 the remaining two regions. In comparison, forecasted healthcare accessibility is most sensitive to the forecast uncertainty in



two regions, but exposures data and accessibility parameters remain the largest contributors to the uncertainty in the other two regions. These results confirm that impact modelling comes with significant uncertainties, where the uncertainty in the input data and parameters and the complex interactions between the different modelling components add up to the uncertainty in the hazard forecast. Furthermore, the regional differences in the sensitivities suggest that the accuracy of the different exposures or hazard models or the interactions between them can vary spatially, potentially leading the modelling errors to differ regionally.

4.3 Limitations, improvements and future research

The complexity of the modelling chain and data scarcity challenged the assessment of the true skill of the model. In particular, the lack of impact data on post-disaster healthcare accessibility and infrastructure damage restricted our analysis to a couple case studies. We expect an analysis based on a more extensive number of case studies, spanning longer time frames and expanding over different regions to provide more robust results, yielding a clearer picture of the actual benefits of impact forecasting and the inclusion of indirect impacts. Such an extended analysis requires structured data documenting impacts on service accessibility, at specific levels of spatial and temporal disaggregation. While an established impact database with the desired qualities is currently lacking, recent initiatives for systematic and structured collection of detailed impact data such as the SENDAI's monitoring framework (former DesInventar), and data mining projects leveraging artificial intelligence such as Li et al. (2026) or Hasbini et al. (2026) can help address these data limitations. Similarly, our results suggesting that impact forecasts can better predict the timing of flood impacts when compared to hazard forecasts warrant further investigation. While we tested the sensitivity of our results to the choice of the location used for the discharge forecast (see supplementary Sect. E1), an analysis based on a larger number of events, ideally spanning multiple countries, would increase the robustness of this finding.

We demonstrated the modelling framework using global and open-access flood and exposures models, thus allowing us to illustrate the transferability and generalisability of our approach. Some of these models such as the hydrological forecasting model GloFAS, are already being used operationally for flood anticipatory action in Eastern Africa (e.g. International Federation of Red Cross and Red Crescent Societies IFRC, 2021c, b, a), thus making the results of this study relevant to real-world applications. However, our analysis based on the couple case studies revealed limitations in the quality of the flood and exposures models, potentially limiting their operational use. This can be expected as global models might under-perform in regions where data required for model calibration is scarce (Winsemius et al., 2009; Tu et al., 2024). However, the demonstrated pipeline is modular and allows for the incorporation of local and regional hazard or exposures data. We expect that an impact forecast model built on regional or local flood and exposures data can provide more accurate and reliable results. Regarding uncertainty and sensitivity quantification, our analysis only represents the uncertainties that we were able to incorporate into the framework. For instance, no alternative spatially-explicit flood forecast data were available in open-access at the time of this study. Hence, our analysis likely underestimates the contribution of uncertainties in the flood modelling. This is particularly relevant in the Greater Horn of Africa due to the known limitation of the global hydrological model GloFAS in this region (Taye et al., 2025; Harrigan et al., 2020). We recommend repeating the analysis assessing other flood forecast sources to better understand the



uncertainties associated with this modelling component. Similarly, the uncertainty associated with other modelling components such as the vulnerability might have been underestimated due to their simplistic representation in our modelling framework.

5 Conclusions

- 535 Our research highlights the benefits and limitations of including service accessibility in impact forecasts. Although such people-centric forecasts can be helpful in the management and scaling of anticipatory actions, future work should aim at improving hazard and exposures models, so that they can efficiently support impact forecasting for disaster risk management. In addition, efforts aimed at collecting and structuring people-centric and decision-relevant impact data such as infrastructure damage and service accessibility disruption should help obtain the data required for the development and calibration of these impact models.
- 540 We provide and demonstrate a pipeline that is modular and open-source, thus encouraging future developments on the research and application of impact forecasting to disaster management.

Code availability. CLIMADA is available open-source and open-access at <https://github.com/CLIMADA-project>. For this study, a specific version of CLIMADA was used: https://github.com/CLIMADA-project/climada_petals/tree/nw_update-glofasv4. The code to reproduce the results is available for the reviewers at <https://figshare.com/s/2d0b058ab569ec5036f1>, and will be made available openly after publication.

545 Appendix A: Supplementary figures

This section contains supplementary figures to the publication.

A1 Forecast maps of healthcare access

- Figure A1 reproduces Fig. 4 in the manuscript but shows results for the ensemble member corresponding to the median impact for the region of Abu Hamad. The ensemble member corresponding to the 10th percentile produced a similar result (not shown).
- 550 Figure B1 shows the results for the ensemble member corresponding to the 10th percentile (left) and median impact (right) in Tokar.
- Figure C1 reproduces Fig. 4 but for different model parameterizations. Left panel shows results using the Global Human Settlement Layer at 30 arc-seconds resolution for population data (Kemper et al., 2021), healthcare data from OpenStreetMap, and road data from the Global Roads Inventory Project (Meijer et al., 2018). Right panel shows results using WordlPop at 1
- 555 km resolution, healthcare, healthcare data from Maina et al. (2019), and road data from OpenStreetMap but without applying a filter on the road type. Figure D1 reproduces the same but for the region of Tokar.

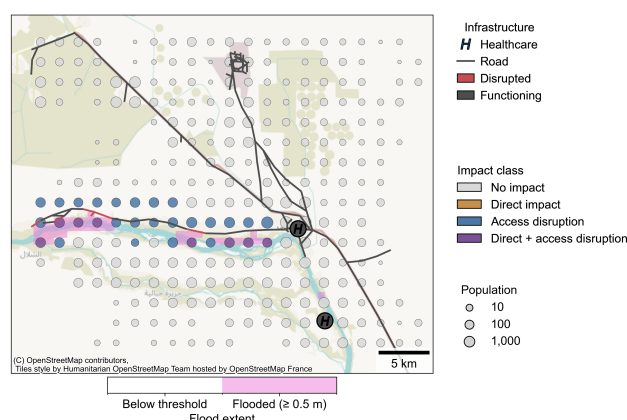


Figure A1. Forecast maps of directly impacted roads and healthcare facilities and population nodes losing access to healthcare services for the town of Abu Hamad. The forecast shows the impacts for the maximum flood extent over a lead-time of 10 days for the ensemble member showing the median from the forecast ensemble initiated on 1 August 2024. Pink shading show location for which a flood depth higher than 50 cm is forecast. Disrupted infrastructures are colored in red. Population nodes are represented as dots with sizes proportional to the population counts and are colored according to the forecasted impacts; grey no impact, orange direct impacts, blue disrupted access to healthcare, and purple direct impacts and healthcare access disruption.

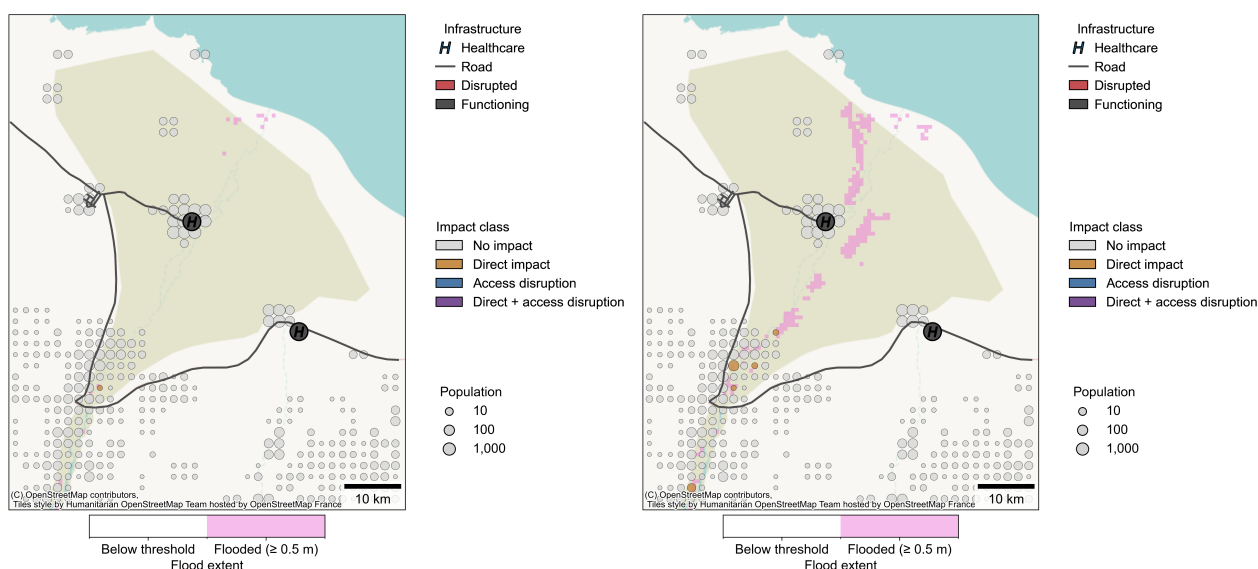


Figure B1. Forecast maps of directly impacted roads and healthcare facilities and population nodes losing access to healthcare services for the town of Tokar. The forecast shows the impacts for the maximum flood extent over a lead-time of 10 days for the ensemble member showing the 10th percentile (left) and median (right) from forecast ensemble initiated on 20 August 2024. Pink shading show location for which a flood depth higher than 50 cm is forecast. Disrupted infrastructures are colored in red. Population nodes are represented as dots with sizes proportional to the population counts and are colored according to the forecasted impacts; grey no impact, orange direct impacts, blue disrupted access to healthcare, and purple direct impacts and healthcare access disruption.

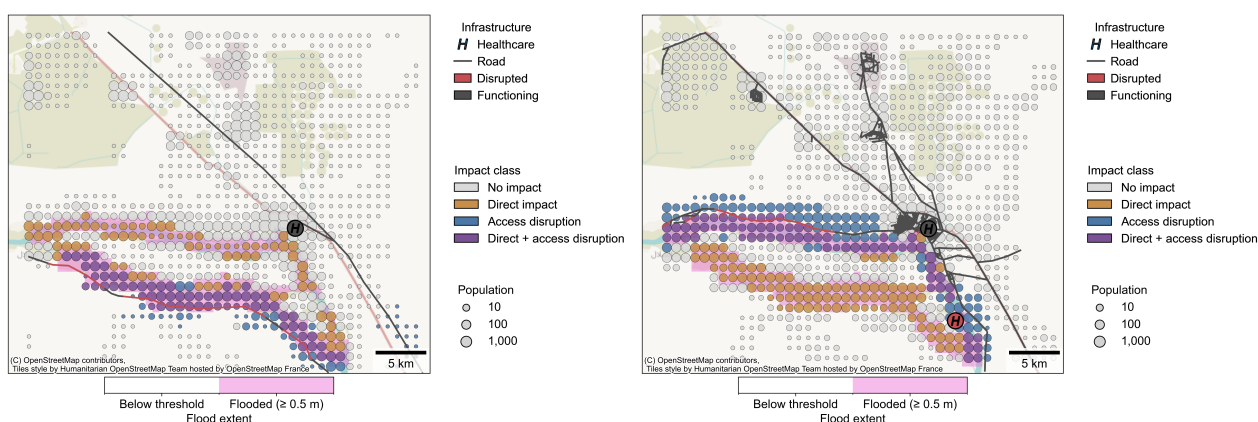


Figure C1. Forecast maps of directly impacted roads and healthcare facilities and population nodes losing access to healthcare services for the town of Abu Hamad. The forecast shows the impacts for the maximum flood extent over a lead-time of 10 days for the ensemble member showing the 90th most extreme from the forecast ensemble initiated on 1 August 2024. Pink shading show location for which a flood depth higher than 50 cm is forecast. Disrupted infrastructures are colored in red. Population nodes are represented as dots with sizes proportional to the population counts and are colored according to the forecasted impacts; grey no impact, orange direct impacts, blue disrupted access to healthcare, and purple direct impacts and healthcare access disruption. Left panel shows results using the Global Human Settlement Layer at 30 arc-seconds resolution for population data (Kemper et al., 2021), healthcare data from OpenStreetMap, and road data from the Global Roads Inventory Project (Meijer et al., 2018). Right panel shows results using WordIPop at 1 km resolution, healthcare, healthcare data from Maina et al. (2019), and road data from OpenStreetMap but without applying a filter on the road type.

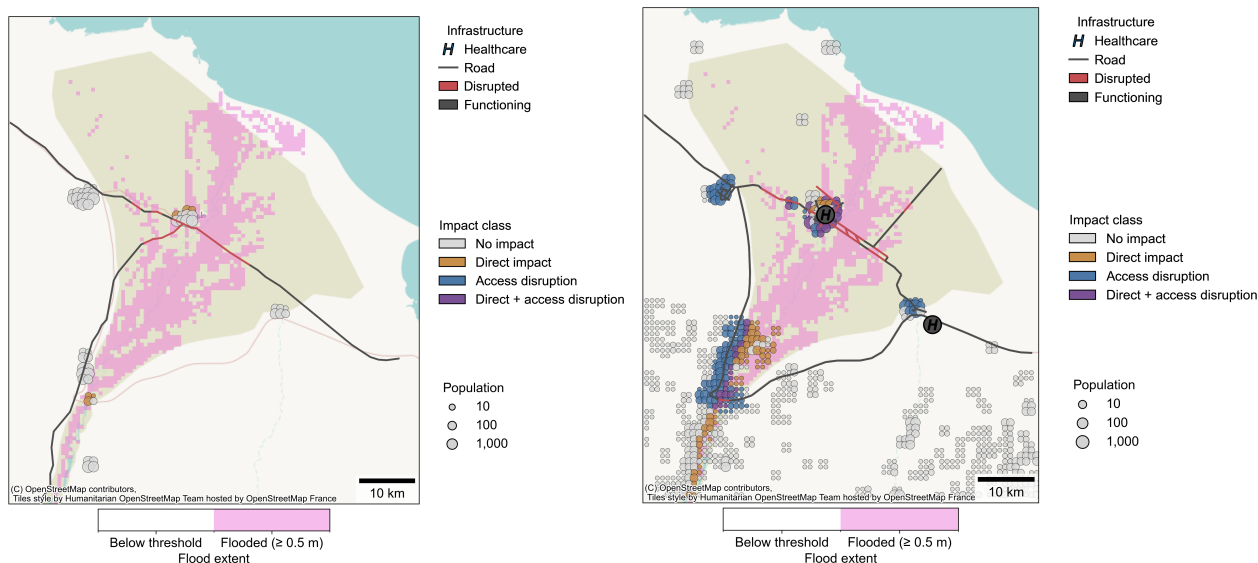


Figure D1. Forecast maps of directly impacted roads and healthcare facilities and population nodes losing access to healthcare services for the town of Tokar. The forecast shows the impacts for the maximum flood extent over a lead-time of 10 days for the ensemble member showing the 90th most extreme from the forecast ensemble initiated on 20 August 2024. Pink shading show location for which a flood depth higher than 50 cm is forecast. Disrupted infrastructures are colored in red. Population nodes are represented as dots with sizes proportional to the population counts and are colored according to the forecasted impacts; grey no impact, orange direct impacts, blue disrupted access to healthcare, and purple direct impacts and healthcare access disruption. Left panel shows results using the Global Human Settlement Layer at 30 arc-seconds resolution for population data (Kemper et al., 2021), healthcare data from OpenStreetMap, and road data from the Global Roads Inventory Project (Meijer et al., 2018). Right panel shows results using WordIPop at 1 km resolution, healthcare, healthcare data from Maina et al. (2019), and road data from OpenStreetMap but without applying a filter on the road type.

D1 Impact forecasts time series

Figure E1 shows the impact forecast time series that were used to generate the forecasted impact exceedance probabilities in Sect. 3.1.3.

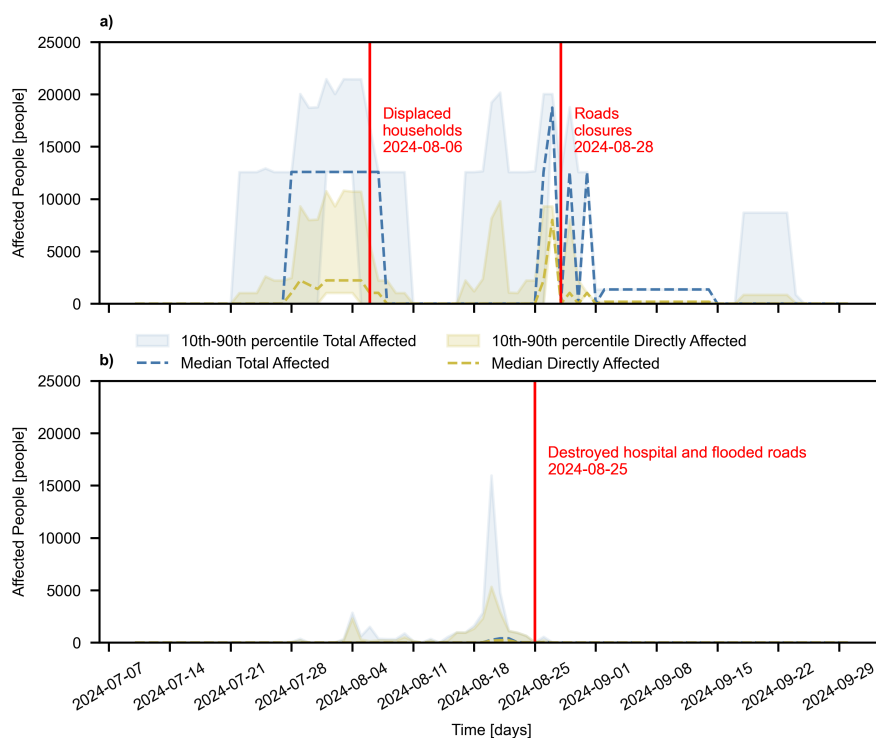


Figure E1. Time series of daily forecasts of the number of people affected with a lead-time of 10 days for the city of Abu Hamad (a) in the River Nile state and for the city of Tokar (b) in the Red Sea state. Blue colour shows the forecast of the total number of people affected both directly by a 50 cm flood depth and indirectly by a loss of access to roads or healthcare; yellow color shows the forecast of the number of people directly affected by a 50 cm flood. Dashed lines represent the median of the forecast ensemble and coloured envelopes the 10th to 90th percentile spread. Red vertical lines represent observed flood impacts obtained from International Organization for Migration IOM (2024); International Federation of Red Cross and Red Crescent Societies IFRC (2025).

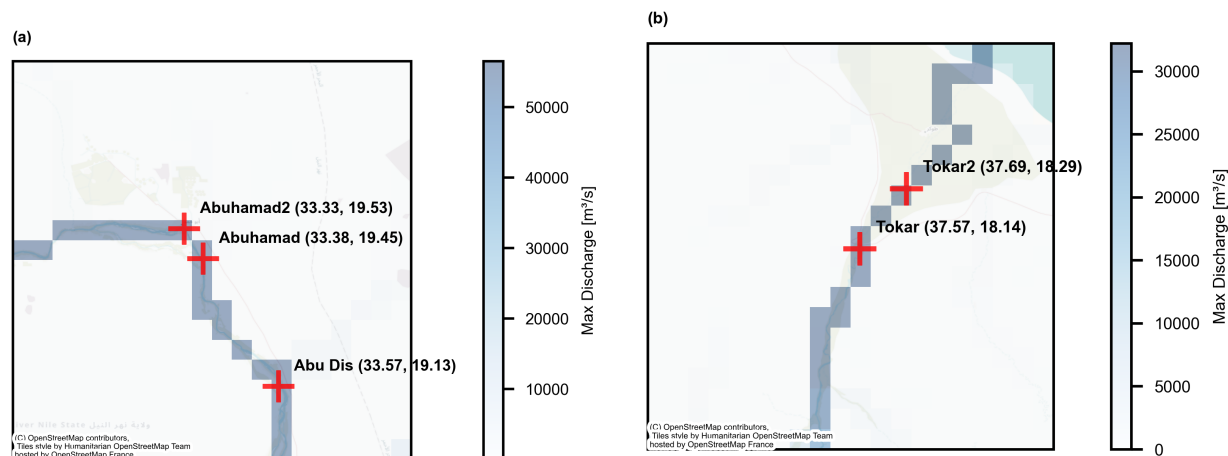


Figure F1. Station locations used for the discharge forecast analysis. Red crosses represent the station location and colour map the maximum forecasted discharge in GloFAS computed over the period 10 July to 30 October 2024 in Sudan.

560 E1 Discharge forecast analysis

Figure F1 shows the locations of the station used for the discharge forecast analysis in Sect. 3.1.3. Figure G1 shows the forecasted discharge exceedance probabilities at these stations.

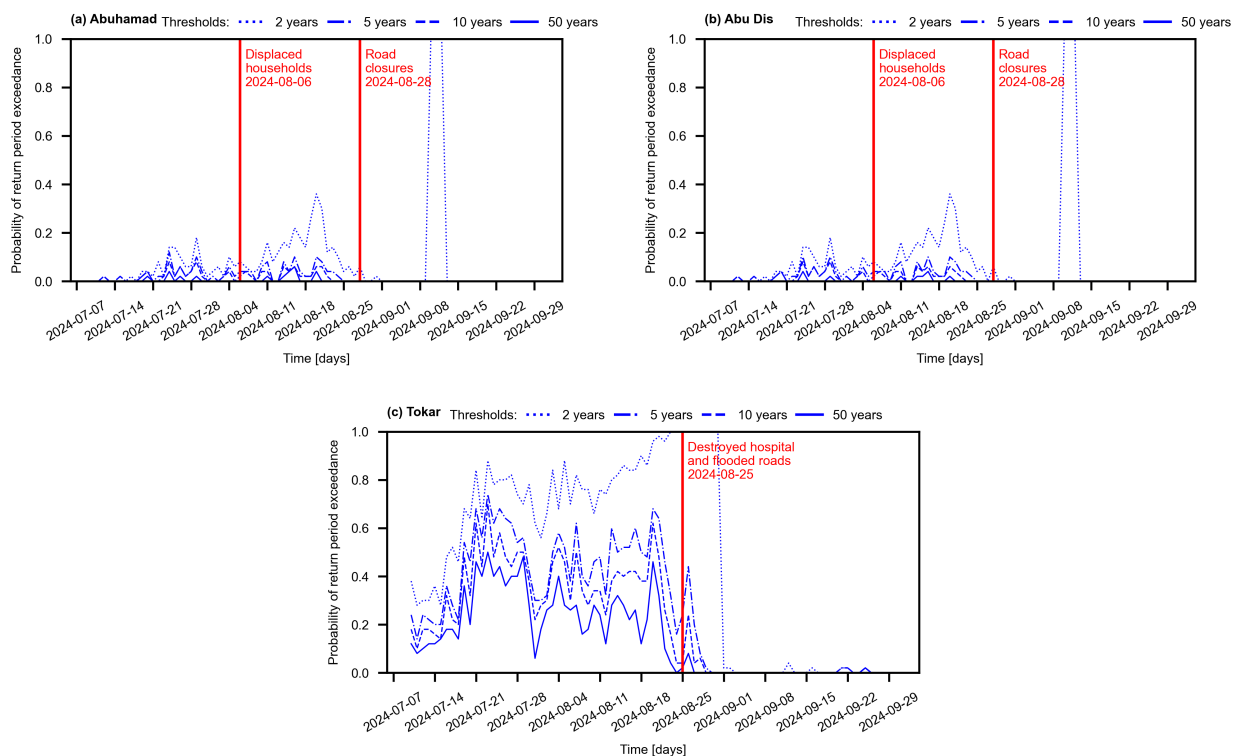


Figure G1. Times series of the exceedance probabilities of the discharge forecast to exceed return periods of two (dotted line), five (dashed-dotted), 10 (dashed) and 50 years (solid) for the stations in Fig. F1. Red vertical lines show estimated timings of the flood impacts from International Federation of Red Cross and Red Crescent Societies IFRC (2025) and International Organization for Migration IOM (2024).



G1 Model evaluation against satellite observations

Figure H1 compares modelled and satellite-detected flood extents for the four investigation regions that were hit by the 2023
565 Deyr floods in Somalia; Galmudug, Hirshabelle, Jubaland, and Southwest. Figures I1 and J1 show this comparison at the
country level, for the 2023 Somalia Deyr floods and the 2024 Sudan floods, respectively.

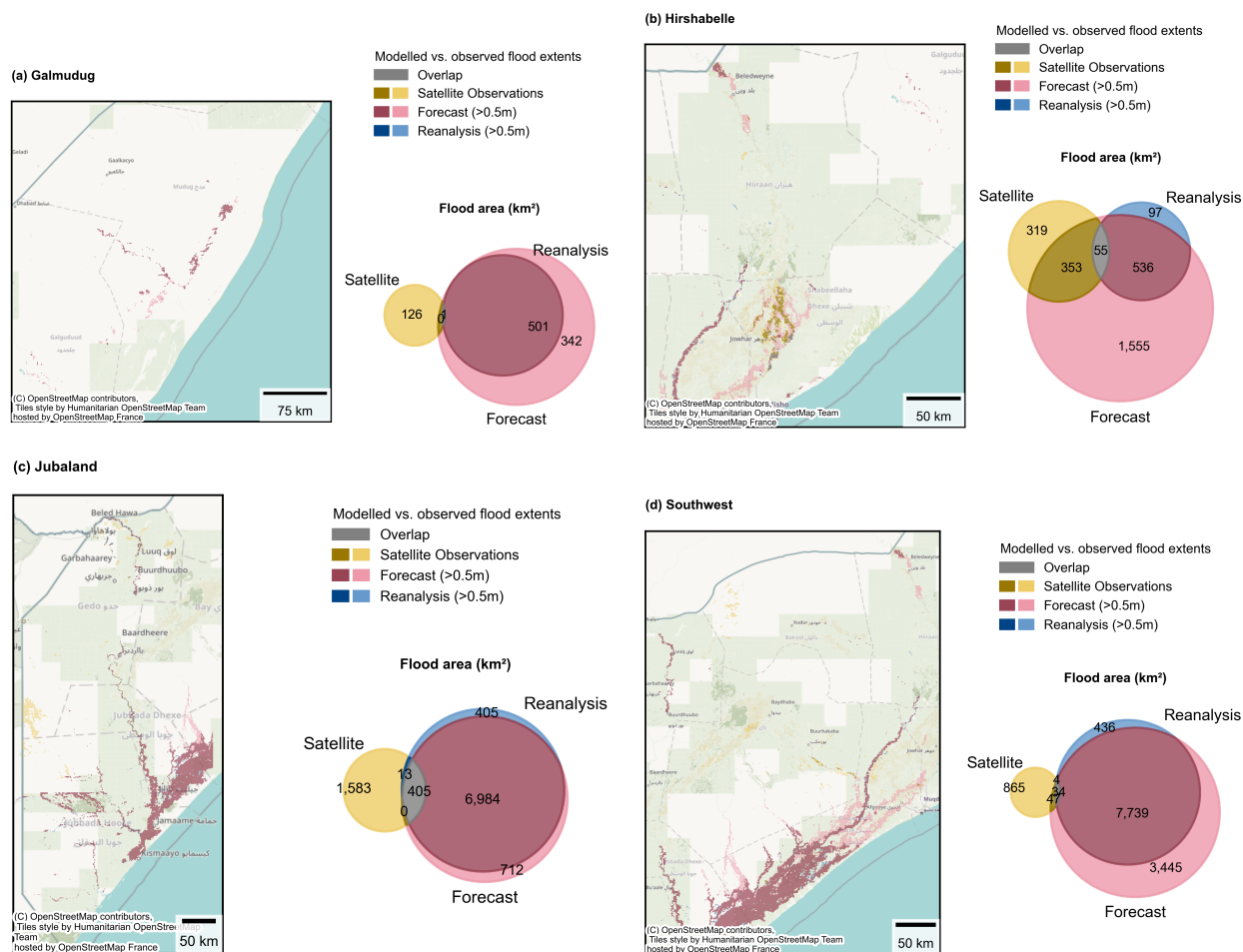


Figure H1. Comparison between modelled and satellite-detected flood extents for the 2023 Deyr floods in the region of Galmudug, Hirshabelle, Jubaland, and Southwest in Somalia. Yellow shading indicates satellite-detected flood extent acquired by UNOSAT on 5 and 7 November 2023, blue and red shading the maximum flood extent computed between 20 September and 31 December 2023 for the GloFAS reanalysis and forecast with a lead-time of 10 days, respectively.



(e) Somalia

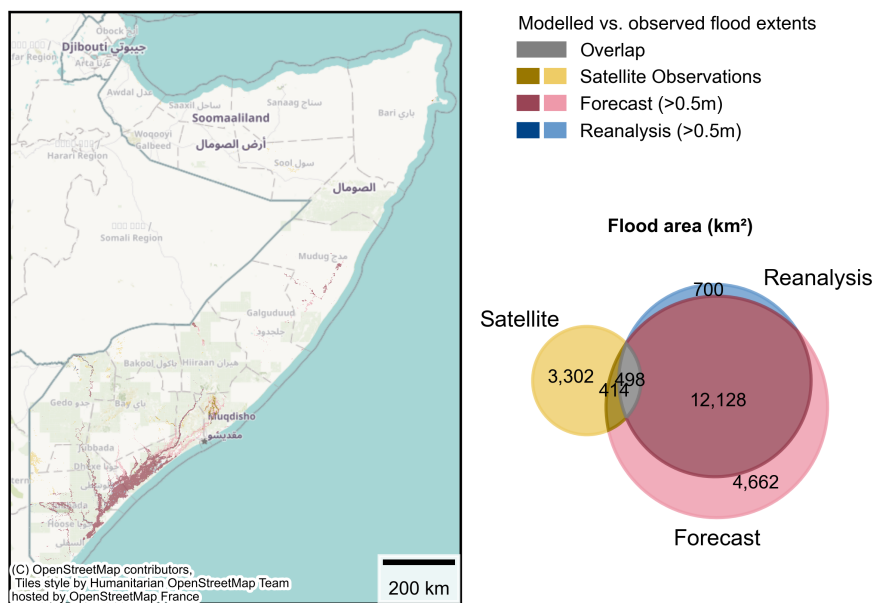


Figure 11. Comparison between modelled and satellite-detected flood extents for the 2023 Deyr floods in Somalia. Yellow shading indicates satellite-detected flood extent acquired by UNOSAT on 5 and 7 November 2023, blue and red shading the maximum flood extent computed between 20 September and 31 December 2023 for the GloFAS reanalysis and forecast with a lead-time of 10 days, respectively.



(f) Sudan

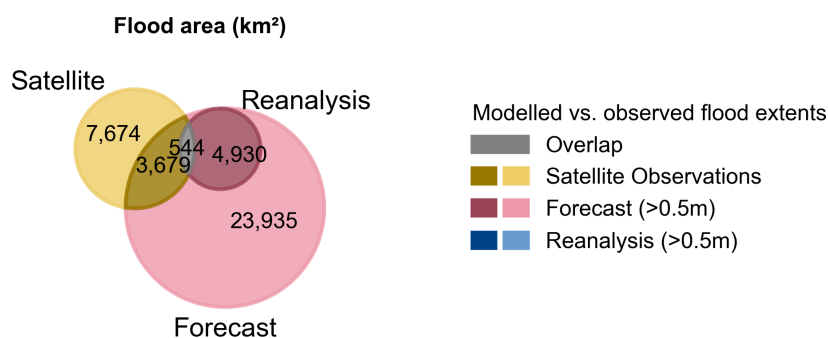
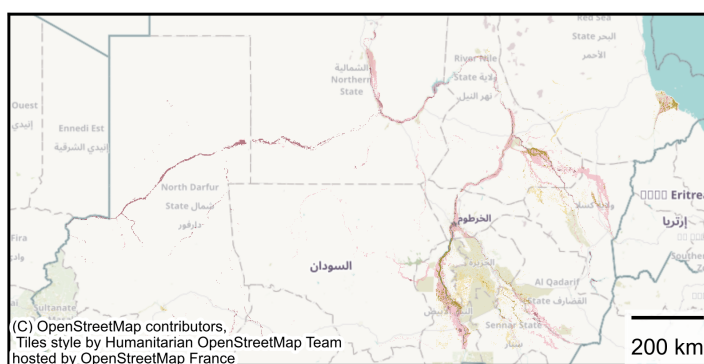


Figure J1. Comparison between modelled and satellite-detected flood extents for the 2024 Sudan flood event. Yellow shading indicates satellite-detected flood extent acquired by UNOSAT between 28 August 2024 and 10 September 2024 (UNOSAT, 2024a), and blue and red shading the maximum flood extent computed for 10 July to 30 October for the GloFAS reanalysis and forecast with a lead-time of 10 days, respectively.

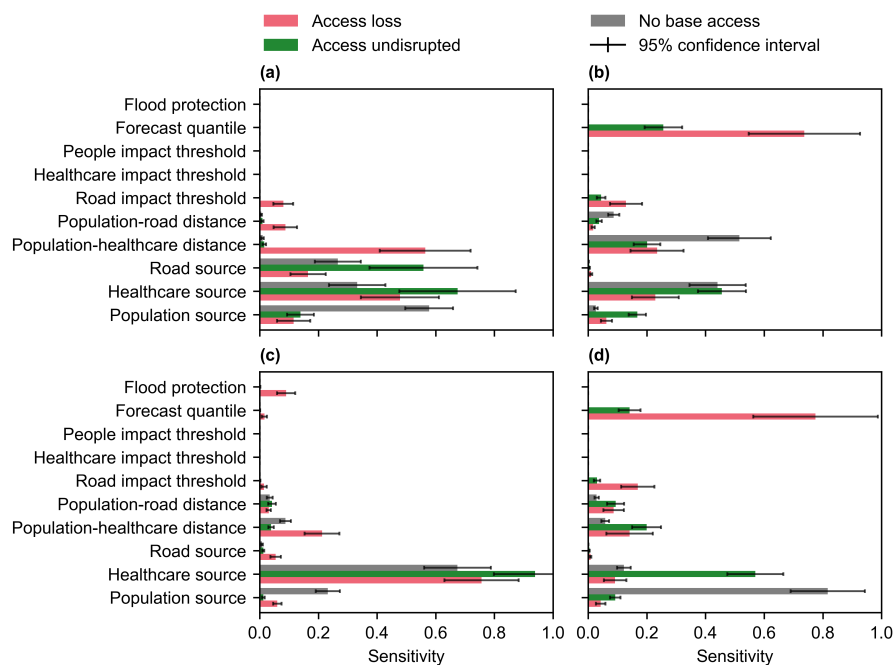


Figure K1. Total-order sensitivity indices for the modelled baseline healthcare access and the flood-induced healthcare access loss for the 2023 Deyr floods in Somalia. Panel a) shows results for the region of Galmudug, b) Hirshabelle, c) Jubaland, and d) Southwest.

J1 Sensitivity analysis

Figure K1 reproduces 10 but for the first-order sensitivity indices.



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References

- CLIMADA-project/climada_petals, https://github.com/CLIMADA-project/climada_petals, original-date: 2021-07-20T08:26:42Z, 2026a.
- CLIMADA-project/climada_python, https://github.com/CLIMADA-project/climada_python, original-date: 2017-12-01T10:47:53Z, 2026b.
- Alfieri, L., Burek, P., Dutra, E., Krzeminski, B., Muraro, D., Thielen, J., and Pappenberger, F.: GloFAS - global ensemble streamflow
 580 forecasting and flood early warning, *Hydrology and Earth System Sciences*, 17, 1161–1175, <https://doi.org/10.5194/hess-17-1161-2013>, 2013.
- Alfieri, L., Libertino, A., Campo, L., Dottori, F., Gabellani, S., Ghizzoni, T., Masoero, A., Rossi, L., Rudari, R., Testa, N., Trasforini, E., Amdihun, A., Ouma, J., Rossi, L., Trambly, Y., Wu, H., and Massabò, M.: Impact-based flood forecasting in the Greater Horn of Africa, *Natural Hazards and Earth System Sciences*, 24, 199–224, <https://doi.org/10.5194/nhess-24-199-2024>, 2024.
- 585 Anticipation Hub: Forecast-based Financing in Sudan - Anticipation instead of reaction, <https://www.anticipation-hub.org/global-overview/countries/sudan/forecast-based-financing-in-sudan-anticipation-instead-of-reaction>, 2023.
- Anticipation Hub: Anticipatory Action in 2025: A Global Overview, Tech. rep., <https://www.anticipation-hub.org/download/file-6109>, 2026.
- Aznar-Siguan, G. and Bresch, D. N.: CLIMADA v1: a global weather and climate risk assessment platform, *Geoscientific Model Develop-*
 590 *ment*, 12, 3085–3097, <https://doi.org/https://doi.org/10.5194/gmd-12-3085-2019>, 00003 tex.ids= Aznar-Siguan2019b, 2019.
- Baugh, C., Prudhomme, C., D'Angelo, C., Dottori, F., Neal, J., Colanese, J., and Salamon, P.: Global river flood hazard maps, <https://doi.org/10.2905/JRC.VD32YWG>, 2024.
- Boeing, G.: Modeling and Analyzing Urban Networks and Amenities With OSMnx, *Geographical Analysis*, 57, 567–577, <https://doi.org/10.1111/gean.70009>, eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/gean.70009>, 2025.
- 595 Copernicus Emergency Management Service CEMS and European Centre for Medium-Range Weather Forecasts ECMWF: GloFAS v4.1, <https://confluence.ecmwf.int/spaces/CEMS/pages/473828729/GloFAS+v4.1>, 2025.
- Coughlan De Perez, E., Van Den Hurk, B., Van Aalst, M. K., Jongman, B., Klose, T., and Suarez, P.: Forecast-based financing: an approach for catalyzing humanitarian action based on extreme weather and climate forecasts, *Natural Hazards and Earth System Sciences*, 15, 895–904, <https://doi.org/10.5194/nhess-15-895-2015>, 2015.
- 600 Dabanga Radio TV Online: Sudan flooding: Death toll rises amid rescue efforts, <https://www.dabangasudan.org/en/all-news/article/sudan-flooding-death-toll-rises-amid-rescue-efforts>, 2024a.
- Dabanga Radio TV Online: Sudan Media Forum: Toker and Agig, forgotten areas torn apart by hunger and floods, <https://www.dabangasudan.org/en/all-news/article/sudan-media-forum-toker-and-agig-forgotten-areas-torn-apart-by-hunger-and-floods>, 2024b.
- Dottori, F., Salamon, P., Bianchi, A., Alfieri, L., Hirpa, F. A., and Feyen, L.: Development and evaluation of a framework for global flood
 605 hazard mapping, *Advances in Water Resources*, 94, 87–102, <https://doi.org/10.1016/j.advwatres.2016.05.002>, 2016.
- Espejo, G. G., Stalhandske, Z., Mühlhofer, E., Rösli, T., Brönnimann, S., Bresch, D. N., and Zischg, A. P.: From hazard to disruption: forecasting direct and indirect tropical cyclone impacts on infrastructure in Mozambique, *Frontiers in Climate*, 7, <https://doi.org/10.3389/fclim.2025.1666586>, 2025.
- Federal Government of Somalia, United Nations, World Bank, and European Union: Somalia 2023 Deyr Floods Rapid-Post Disaster Needs
 610 Assessment, Tech. rep., Mogadishu, Somalia, 2024.



- Field, C. B. and Barros, V. R.: Climate change 2014: impacts, adaptation, and vulnerability Working Group II contribution to the fifth assessment report of the Intergovernmental panel on climate change, Cambridge university press, New York, ISBN 978-1-107-64165-5 978-1-107-68386-0 978-1-107-05807-1 978-1-107-05816-3, 2014.
- Geiger, T., Rösli, T., Bresch, D. N., Erhardt, B., Fischer, A. M., Imgrüth, D., Kienberger, S., Mainetti, L., Mühlbacher, G., and Spiekermann, R.: How to provide actionable information on weather and climate impacts?—A summary of strategic, methodological, and technical perspectives, *Frontiers in Climate*, 6, <https://doi.org/10.3389/fclim.2024.1343993>, 2024.
- Godet, J., Gaume, E., Javelle, P., Dias, T., Nicolle, P., and Payrastre, O.: Quantifying the added value of impact-based warnings for flash flood monitoring using innovative multi-source impact data, *International Journal of Disaster Risk Reduction*, 136, 106058, <https://doi.org/10.1016/j.ijdr.2026.106058>, 2026.
- Harrigan, S., Zsoter, E., Alfieri, L., Prudhomme, C., Salamon, P., Wetterhall, F., Barnard, C., Cloke, H., and Pappenberger, F.: Evaluation of GloFAS river discharge reanalysis and forecast skill, 2020.
- Harrowsmith, M., Nielsen, M., Jaime, C., Coughlan de Perez, E., Uprety, M., van den Homberg, M., Tijssen, A., Page, E., Lux, S., and Comment, T.: IMPACT-BASED FORECASTING FOR EARLY ACTION THE FUTURE OF FORECASTS, <https://doi.org/10.13140/RG.2.2.12366.89920>, 2020.
- Hasbini, L., Severino, L. G., Brito, M. M. d., Gesualdo, G. C., Rotaru, A. M., Bresch, D. N., Mühlhofer, E., Wang, J., and Carvalho, T. M. N.: ROUGE : A database of disaster impacts in the Global South using Red Cross reports and Large Language Models, <https://doi.org/10.21203/rs.3.rs-8778674/v2>, iSSN: 2693-5015, 2026.
- Hussein, M.: Rain Adds Salt to War Injury in as People in Eastern and Northern States as Autumn Checks in, <https://atarnetwork.com/?p=5734>, 2024.
- Information Management Working Group IMWG, OCHA: Sudan - Subnational Administrative Boundaries, <https://data.humdata.org/dataset/cod-ab-sdn>, 2025.
- International Federation of Red Cross and Red Crescent Societies IFRC: Philippines: Typhoon Early Action Protocol summary, <https://adore.ifrc.org/Download.aspx?FileId=381877>, 2019.
- International Federation of Red Cross and Red Crescent Societies IFRC: Ethiopia: Flood Early Action Protocol summary, <https://www.anticipation-hub.org/download/file-1365>, 2021a.
- International Federation of Red Cross and Red Crescent Societies IFRC: Kenya: Riverine Floods Early Action Protocol summary, <https://www.anticipation-hub.org/download/file-3666>, 2021b.
- International Federation of Red Cross and Red Crescent Societies IFRC: Uganda: Floods Early Action Protocol summary, <https://www.anticipation-hub.org/download/file-3684>, 2021c.
- International Federation of Red Cross and Red Crescent Societies IFRC: Sudan Floods 2024: DREF Operational Update, Tech. rep., <https://reliefweb.int/report/sudan/sudan-floods-2024-dref-operational-update-appeal-mdrsd034-17032025>, 2025.
- International Federation of Red Cross and Red Crescent Societies IFRC: FbF Practitioners Manual, 2026.
- International Organization for Migration IOM: DTM Sudan Flash Alert: Heavy Rains and Flooding in Abu Hamad locality, River Nile, Update 002 (6 August 2024), <https://reliefweb.int/report/sudan/dtm-sudan-flash-alert-heavy-rains-and-flooding-abu-hamad-locality-river-nile-update-002-6-august-2024>, 2024.
- Kam, P. M., Aznar-Siguan, G., Schewe, J., Milano, L., Ginnetti, J., Willner, S., McCaughey, J. W., and Bresch, D. N.: Global warming and population change both heighten future risk of human displacement due to river floods, *Environmental Research Letters*, 16, 044026, <https://doi.org/10.1088/1748-9326/abd26c>, 2021.



- Kam, P. M., Ciccone, F., Kropf, C. M., Riedel, L., Fairless, C., and Bresch, D. N.: Impact-based forecasting of tropical cyclone-related human displacement to support anticipatory action, *Nature Communications*, 15, 8795, <https://doi.org/10.1038/s41467-024-53200-w>, 2024.
- Kemper, T., Melchiorri, M., and Ehrlich, D.: *Global Human Settlement Layer*, <https://doi.org/10.2760/456883>, iISBN: 9789276420613 9789276420620, 2021.
- Kooshki Forooshani, M., Van Den Homberg, M., Kalimeri, K., Kaltenbrunner, A., Mejova, Y., Milano, L., Ndirangu, P., Paolotti, D., Teklesadik, A., and Turner, M. L.: Towards a global impact-based forecasting model for tropical cyclones, *Natural Hazards and Earth System Sciences*, 24, 309–329, <https://doi.org/10.5194/nhess-24-309-2024>, 2024.
- Kropf, C. M., Ciullo, A., Otth, L., Meiler, S., Rana, A., Schmid, E., McCaughey, J. W., and Bresch, D. N.: Uncertainty and sensitivity analysis for probabilistic weather and climate-risk modelling: an implementation in CLIMADA v.3.1.0, *Geoscientific Model Development*, 15, 7177–7201, <https://doi.org/10.5194/gmd-15-7177-2022>, 2022.
- Li, N., Thiery, W., Zahra, S., Madruga de Brito, M., Worou, K., Kurfali, M., Lampe, S., Muñoz, P., Flynn, C., Trigos, C., Nivre, J., Zscheischler, J., and Messori, G.: Wikimpacts 1.0: a new global climate impact database based on automated information extraction from Wikipedia, *Natural Hazards and Earth System Sciences*, 26, 2609–2636, <https://doi.org/10.5194/nhess-26-2609-2026>, 2026.
- MacLeod, D., Ambani, M., Graham, R., Hassan, S., Heinrich, D., Jaime, C., Jack, C., Kazouini, A., Morris, L., Murray, M., Paron, P., Swift, L., Stephens, E., and Wheatley, A.: Dress Rehearsal: 2023 El Niño Anticipatory Action Somalia, in the Shadow of 1997, <https://eartharxiv.org/repository/view/13443/>, 2026.
- Maina, J., Ouma, P. O., Macharia, P. M., Alegana, V. A., Mitto, B., Fall, I. S., Noor, A. M., Snow, R. W., and Okiro, E. A.: A spatial database of health facilities managed by the public health sector in sub Saharan Africa, *Scientific Data*, 6, 134, <https://doi.org/10.1038/s41597-019-0142-2>, 2019.
- Meijer, J. R., Huijbregts, M. A. J., Schotten, K. C. G. J., and Schipper, A. M.: Global patterns of current and future road infrastructure, *Environmental Research Letters*, 13, 064 006, <https://doi.org/10.1088/1748-9326/aabd42>, 2018.
- Merz, B., Kuhlicke, C., Kunz, M., Pittore, M., Babeyko, A., Bresch, D. N., Domeisen, D. I. V., Feser, F., Koszalka, I., Kreibich, H., Pantillon, F., Parolai, S., Pinto, J. G., Punge, H. J., Rivalta, E., Schröter, K., Strehlow, K., Weisse, R., and Wurpts, A.: Impact Forecasting to Support Emergency Management of Natural Hazards, *Reviews of Geophysics*, 58, e2020RG000 704, <https://doi.org/10.1029/2020RG000704>, eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2020RG000704>, 2020.
- Moss, F., Mejova, Y., Kaltenbrunner, A., Downing, T., Van Den Homberg, M., Ndirangu, P., Milano, L., and Kalimeri, K.: Global Sub-national Impact-based Forecasting for Tropical Cyclones Using Open Data: Combining Machine Learning and Exposure-based Approaches, <https://doi.org/10.5194/egusphere-2026-1996>, 2026.
- Mühlhofer, E., Koks, E. E., Kropf, C. M., Sansavini, G., and Bresch, D. N.: A generalized natural hazard risk modelling framework for infrastructure failure cascades, *Reliability Engineering & System Safety*, 234, 109 194, <https://doi.org/10.1016/j.ress.2023.109194>, 2023.
- Mühlhofer, E., Kropf, C. M., Riedel, L., Bresch, D. N., and Koks, E. E.: OpenStreetMap for multi-faceted climate risk assessments, *Environmental Research Communications*, 6, 015 005, <https://doi.org/10.1088/2515-7620/ad15ab>, 2024.
- OCHA: Sudan Floods: People and Areas Affected, <https://app.powerbi.com/view?r=eyJrIjoiaMDIhOTg2M2YtYWYWM3OC00MzVILWJmYjQtZmU5NTkwY2Q3ODcxIiwidCI6IjBmOWUzNWRLTU0NGYtNGY2MC1iZGNjLTVIYTYxNmU2ZGM3MCIslmMiOjh9>, 2024.
- OCHA Somalia: Somalia - Subnational Administrative Boundaries, <https://data.humdata.org/dataset/cod-ab-som>, 2025.
- OpenStreetMap contributors: OpenStreetMap, <https://www.openstreetmap.org/>, 2017.



- 685 Potter, S., Harrison, S., and Kreft, P.: The Benefits and Challenges of Implementing Impact-Based Severe Weather Warning Systems: Perspectives of Weather, Flood, and Emergency Management Personnel, *Weather, Climate, and Society*, 13, 303–314, <https://doi.org/10.1175/WCAS-D-20-0110.1>, 2021.
- Potter, S. H., Kox, T., Mills, B., Taylor, A., Robbins, J., Cerrudo, C., Wyatt, F., Harrison, S., Golding, B., Lang, W., Harris, A. J. L., Kaltenberger, R., Kienberger, S., Brooks, H., and Tupper, A.: Research gaps and challenges for impact-based forecasts and warnings: Results of international workshops for High Impact Weather in 2022, *International Journal of Disaster Risk Reduction*, 118, 105 234, <https://doi.org/10.1016/j.ijdr.2025.105234>, 2025.
- 690 ReliefWeb: Somalia: Floods - Oct 2023, <https://reliefweb.int/disaster/fl-2023-000190-som>, 2026.
- Riedel, L., Rössli, T., Vogt, T., and Bresch, D. N.: Fluvial flood inundation and socio-economic impact model based on open data, *Geoscientific Model Development*, 17, 5291–5308, <https://doi.org/10.5194/gmd-17-5291-2024>, 2024.
- 695 Robbins, J., Ruin, I., Golding, B., Dankers, R., Nairn, J., and Millington, S.: Connecting Hazard and Impact: A Partnership between Physical and Human Science, in: *Towards the “Perfect” Weather Warning: Bridging Disciplinary Gaps through Partnership and Communication*, edited by Golding, B., pp. 115–147, Springer International Publishing, Cham, ISBN 978-3-030-98989-7, https://doi.org/10.1007/978-3-030-98989-7_5, 2022.
- Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., and Tarantola, S.: Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index, *Computer Physics Communications*, 181, 259–270, <https://doi.org/10.1016/j.cpc.2009.09.018>, 2010.
- 700 Scussolini, P., Aerts, J. C. J. H., Jongman, B., Bouwer, L. M., Winsemius, H. C., de Moel, H., and Ward, P. J.: FLOPROS: an evolving global database of flood protection standards, *Natural Hazards and Earth System Sciences*, 16, 1049–1061, <https://doi.org/10.5194/nhess-16-1049-2016>, 2016.
- 705 Sedhain, S., van den Homberg, M., Teklesadik, A., van Aalst, M., and Kerle, N.: Evaluating impact-based forecasting models for tropical cyclone anticipatory action, *International Journal of Disaster Risk Reduction*, 129, 105 782, <https://doi.org/10.1016/j.ijdr.2025.105782>, 2025.
- Sobol’, I.: Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates, *Mathematics and Computers in Simulation*, 55, 271–280, [https://doi.org/10.1016/S0378-4754\(00\)00270-6](https://doi.org/10.1016/S0378-4754(00)00270-6), 2001.
- 710 Somalia Disaster Management Agency: Somalia National Anticipatory Action Roadmap, <https://reliefweb.int/report/somalia/somalia-national-anticipatory-action-roadmap>, 2026.
- Sudan Meteorological Authority: Heavy Rainfall and Flood Warning 08/07/2024, <https://meteosudan.sd/alerts/heavy-rainfall-and-flood-warning-08072024/>, 2024.
- Tatem, A. J.: WorldPop, open data for spatial demography, *Scientific Data*, 4, 170 004, <https://doi.org/10.1038/sdata.2017.4>, 2017.
- 715 Taye, M. T., Ebrahim, G. Y., Birhanu, D., Seid, A. H., and Ruckstuhl, S.: Recommendations for Improved Flood Forecasts and Early Action Plans in Dolo Ado and Bokolmayo, Somali Region, Ethiopia, 2025.
- Tu, T., Wang, J., Zhao, G., Zhao, T., and Dong, X.: Scaling from global to regional river flow with global hydrological models: Choice matters, *Journal of Hydrology*, 633, 130 960, <https://doi.org/10.1016/j.jhydrol.2024.130960>, 2024.
- UNOSAT: Flood in Sudan - Charter Activations, <https://disasterscharter.org/activations/flood-in-sudan-activation-906->, 2024a.
- 720 UNOSAT: Preliminary satellite-derived impact assessment on health facilities - Tawkar Locality, Red Sea State, Sudan (29 August 2024) - Sudan, <https://unosat.org/products/3935>, 2024b.



UNOSAT: Preliminary satellite-derived impact assessment on health facilities - Abu Hamad City, Abu Hamad Locality, River Nile State, (2 September 2024), <https://unosat.org/products/3942>, 2024c.

725 Winsemius, H. C., Schaefli, B., Montanari, A., and Savenije, H. H. G.: On the calibration of hydrological models in ungauged basins: A framework for integrating hard and soft hydrological information, *Water Resources Research*, 45, <https://doi.org/10.1029/2009WR007706>, 2009.

World Meteorological Organization WMO: WMO Guidelines on Multi-hazard Impact-based Forecast and Warning Services, Tech. rep., WMO, Geneva, https://etrp.wmo.int/pluginfile.php/16270/mod_resource/content/0/wmo_1150_en.pdf, 2015.