PRE-PRINT / WORKING PAPER v3

EGU26 version 5 May 2026

Primary version and SI at [10.5281/zenodo.17386650](https://doi.org/10.5281/zenodo.17386650)

Future cost of climate change for humanitarian crises

J-P Jäpölä[1,2], A Berlin[3], C Fabri[2], A Hrast Essenfelder[4], S Marzi[5], K Poljanšek[4], M Ronco[4], S Van Passel[2], S Van Schoubroeck[2]

Abstract:

Humanitarian crises are the tip of the iceberg in climate change adaptation, yet their future is rarely quantified in human and economic terms. We use machine learning to simulate future estimates of people in need of humanitarian aid and required funding under the middle-of-the-road scenario (SSP2-RCP4.5) with 2,7°C warming by end of the century. Humanitarian needs rise to a baseline of 410±22 million people and USD_{2024} 64±8 billion annually by 2050 worldwide, increases of 127% and 130% respectively compared to 2024 (323 million people and USD 49 billion). A medium optimistic simulation holds needs near the current, while a medium pessimistic simulation leads to 614±68 million people and USD_{2024} 96±19 billion by 2050, increases of 190% and 196% respectively. Our results show empirical vulnerabilities and an opportunity cost, as resources for crisis response displace funding for adaptation and mitigation. Yet sustained investment could curb the impacts even with climate inertia.

Keywords:

climate change; economics; humanitarian aid; sustainability; people in need; machine learning

Declarations:

Acknowledgements: The information and views set out in this article are those of the authors and do not necessarily reflect the official opinion of the European Commission where applicable.

The authors thank discussants at the European Geosciences Union 2025 General Assembly (Vienna), the European Humanitarian Forum 2025 (Brussels), Towards the Future: International

[1] European Commission, DG for European Civil Protection and Humanitarian Aid Operations (ECHO)
[2] Faculty of Business and Economics, University of Antwerp
[3] Netcompany external service provider of European Commission
[4] European Commission, Joint Research Centre
[5] Fincons SpA external service provider of European Commission, Joint Research Centre

Forum and Symposium on Climate Change Adaptation and Environmental Governance (Taipei), and Systemic Risks and Climate Extremes Conference and Workshop (Hamburg), JPJ's doctoral jury, reviewers of the ISCRAM 2026 conference as well as colleagues for their support in critically assessing preliminary versions of the paper.

Funding: This research received no specific grant from public, commercial, or not-for-profit funding agencies. JPJ acknowledges conference attendance support from the Björkqvist Foundation (City of Kangasala, Finland).

Competing Interests: The authors have no competing interests to disclose.

Author Contributions: JPJ: Conceptualization, Methodology, Software, Data Curation, Formal Analysis, Investigation, Writing - Original Draft.

AB, CF, SM: Conceptualization, Methodology, Resources, Writing - Review & Editing.

AHE: Conceptualization, Methodology, Resources, Software, Writing - Review & Editing.

KP, MR: Conceptualization, Methodology, Writing - Review & Editing.

SVP, SVS: Conceptualization, Methodology, Supervision, Writing - Review & Editing.

Data and code Availability: Data and code used or created during the paper are in the replication package at https://doi.org/10.5281/zenodo.15336209. All raw data is available publicly and their link or reference listed in Methods.

Generative AI Statement: ChatGPT 4o-mini-high was used to support building the first versions of the Python 3.12 scripts to run the analysis. ChatGPT 5 and 5 Thinking were used for supporting the coding of the plotter scripts.

1. Introduction

Understanding the effects of extreme and compound events, such as disasters and crises, stemming from climate change have been a long-standing agenda (Dunz et al., 2023; Hallegatte et al., 2007; Noy, 2009; Zscheischler et al., 2018). Current economic assessment models have been instrumental in quantifying the economic and financial impacts of climate change. Traditionally, these models provide information on metrics like labour, productivity, and capital. Often relying on a data-rich environment, a critical gap remains in covering non-market climate-related impacts and cascading effects on humanitarian crises—especially when calibrating the model empirically to human cost (e.g., Lenton et al., 2023). Climate-related impact assessment models, including widely used integrated assessment models (IAMs) or macroeconomic models, often fall short in accounting for these dimensions (Auffhammer, 2018; Botzen et al., 2019; IPCC, 2023a; Rising et al., 2022; Stern et al., 2022).

The escalating number of people in need of humanitarian aid and its funding requirement, which are direct and indirect consequences of disaster and conflict risk, are central to this gap. They are essential to be accounted for when promoting successful climate change adaptation strategies, particularly in a context of extreme and compound events.

Every 25th person in the world needed humanitarian assistance in 2024 according to the United Nations Office for the Coordination of Humanitarian Affairs (UN OCHA) database[6]. The total was 323M people in need while the coordinated funding requirement, or appeal for support, to cover their needs was USD 49B. However, approximately only half of that appeal was funded in the end. This problem is compounded by growing volatility in global aid budgeting. In 2025, the US dismantled USAID (US Agency for International Development) and, among others, its humanitarian disbursement (OECD, 2025). The previous year, it accounted for 44% of global humanitarian aid funding towards the requirement[7] and its disappearance will weaken critical operations in several crisis-affected regions. In a world with scarce resources, the need to respond to active disasters and conflicts can (ceteris paribus) reduce the budget available for other climate change or welfare efforts.

Previous studies have come to varying conclusions of the humanitarian cost and possibly have underestimated the recent rise in people in need. For example, the amount of people in need due to climate-related disasters with a pessimistic scenario based on SSP4 was expected to be 200M by 2050 (IFRC, 2019) while the current global people in need, including

[6] https://humanitarianaction.info
[7] https://fts.unocha.org

from conflict, is 320M. McDougal and Patterson (2021) computed a near tripling (291%) of humanitarian spending by 2034 if there would be a 2,39°C increase in temperature over pre-industrial levels. An early report estimated a range of 16–800% increase in response costs between 2008 and 2028 without inflation (Webster et al., 2008). Historically, the funding requirement has risen 690% (from 7,1B to 49B) since 2008[7].

Besides gross domestic production (GDP), studies on human impact of hazards often resort to analytical variables, such as exposure to hazard or future risk of humanitarian crises, as their outcome (Marzi et al., 2021, 2025; Stalhandske et al., 2025)—that do not necessarily mirror the real human effect. We improve upon previous research by learning from past impact to estimate empirical vulnerability with a modified damage function (e.g., Hsiang et al., 2017). The improvement is based on a new proposed methodology that runs in three phases of estimation: 1) people exposed to risk of crises due to climatic-socioeconomic conditions; 2) people empirically in need of humanitarian aid due to crises; and 3) the funding requirement to support the people.

This methodology aims at covering the literature gap on an empirically calibrated quantification of the future human cost in extreme conditions. The methodology is based on people in need as it is an actionable and simple indicator of systemic climate and extreme event consequences that consolidates micro and macro levels, while remaining easy to understand (Jäpölä et al., 2024; Jäpölä, Van Schoubroeck, et al., 2025; Jäpölä & Van Passel, 2025). Its assessment is coordinated by UN OCHA annually and is a normal core indicator among others in humanitarian agencies' needs appraisals, but to our knowledge, this is the first time it is used as the main unit of climate change impacts.

The proposed approach leverages Gaussian Process Regression (GPR), a non-parametric Bayesian machine learning tool well suited for a complex, asymmetric, and data-sparse space (Rasmussen & Williams, 2005). We control for 18 climatic-socioeconomic variables in total, such as temperature, precipitation, GDP, population, extreme wet and dry days, net migration, and wind speed. The risk exposure variables include diseases, floods, storms, drought, and conflict among others. Our scope represents the most fragile areas of the world, such as the Democratic Republic of the Congo, Sudan and Afghanistan—the top three of 2024 in terms of absolute people in need according to UN OCHA's Global Humanitarian Overview[6].

Methods are applied to a middle-of-the-road SSP2-RCP4.5 (Shared Socioeconomic Pathway, Representative Concentration Pathway) scenario together with further simulations of crisis severity and climate inertia.

2. Methods

2.1. Conceptual rationale

To assess the economic magnitude of humanitarian crises, we create a modified climate damage function (e.g., Hsiang et al., 2017) where changes in climatic-socioeconomic variables are related to the impact of climate change. The paper's approach is based on the IPCC's latest Annual Report 6 (AR6) where the traditional model of risk—a function of hazard, exposure, and vulnerability (Blaikie et al., 2014)—was expanded to include response as a component (IPCC, 2023b, p. 147). See the Cross-Section Box.2, Figure 1 of IPCC AR6 synthesis report for a concise overview of our conceptual scope[8]. Furthermore, we incorporate a systemic multi-risk assessment approach. Although definitions vary, it essentially means considering interrelationships between multiple sources of hazard, exposure and vulnerability in a system (Higuera Roa et al., 2025; Hochrainer-Stigler et al., 2023)—in this case the system of humanitarian aid. The rationale comprises three distinct phases throughout the whole model and paper (Figure 1).

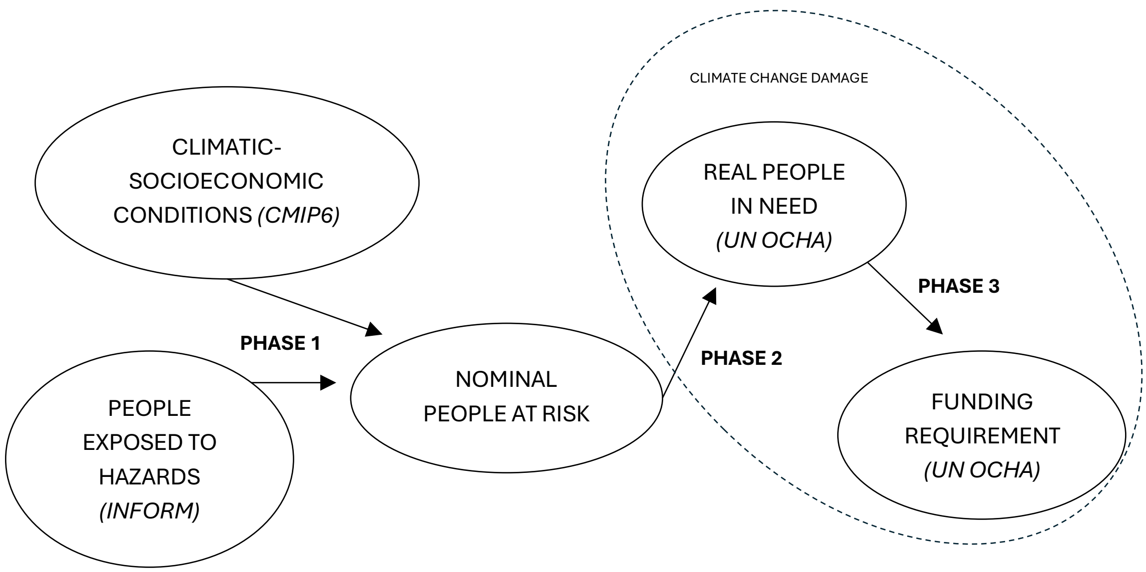

Figure 1. Assumed relationships in the paper's damage function.

In phase 1, we assume that aggregate people at risk are a relationship between people's aggregate exposure to multiple different ($\sum \mathrm{EX}$) hazards, such as flood, epidemics or conflict and their vulnerability stemming from global or country-level climatic-socioeconomic conditions, such as temperature, precipitation, or Human Development Index (HDI) under

[8] https://www.ipcc.ch/report/ar6/syr/figures/csb-2-figure-1

SSP2-RCP4.5. As this figure is mostly a computational one that cannot be verified, we denote it as nominal people at risk for sake of clarity. Writing, for example, that they are estimated would imply that we are able to disaggregate to how many hazards a single person is exposed, or which socioeconomic conditions are most related to certain exposures. Hence, there is for certain double or multiple counting in the aggregate, and we should treat it more as an intensity factor instead of real people. For example, one person can be at the same time exposed to flood, drought, and conflict yet counted three times in the aggregate and hence, this metric can go above population in the model.

Next, in **phase 2**, we assume that people in need (PIN) of humanitarian aid is a subset of people at risk. PIN is used by humanitarian agencies for analysing how much funding will be required for a given crisis and it serves as the multi-risk core of our framework. The rationale being that it is more actionable than large composite of proxies or an index—as motivated by our previous analyses (Jäpölä et al., 2024; Jäpölä, Van Schoubroeck, et al., 2025; Jäpölä & Van Passel, 2025). Contrary to nominal people at risk, we denote PIN as real people in need as the in-situ assessment of their existence and lack of double or multi counting is more verifiable because of the field process.

The assessment of PIN is comprehensive of different impacts as the needs cover 11 different sectors from food security to health and from logistics to education[9]. For example, how many tonnes of food or how many units of medication are required and the additional cost connected to providing them from storage to delivery. It does not directly cover material losses or reconstruction, but the destruction of infrastructure causes human needs of, for example, shelter, sanitation, logistical support, or coverage of water and food supply.

Finally, at the **phase 3**, the funding requirement of humanitarian need is used to indicate the economic climate change impact in the humanitarian system. This funding requirement is an assessment by UN OCHA on how much support would be needed to successfully cover all the people in need of a given crisis to save lives, alleviate suffering, and help in recovery. Different country offices and sectors contribute to the process of assessing and drafting humanitarian response plans (HRPs), that then together form the global estimate of people in need and the funding requirement. They are compiled on Humanitarian Action[6], a UN OCHA service.

This study is not intended to assess how mitigation of emissions affects the future of humanitarian aid. Therefore, no other scenario outside of SSP2-RCP4.5 is modelled. However, it is fair to ask if the geopolitical stance of today has more bearing towards SSP3 with regional rivalries instead of the middle-of-the-road SSP2 (Marzi et al., 2025).

[9] https://www.unocha.org/we-coordinate

2.2. Scope

Temporally, the model's scope is the years 2000–2100 for which most of the climatic and socioeconomic observations or projections exist. However, the analysis in the paper is provided for 2025–2050 as the most actionable range and due to model's sensitivity, that is discussed later. (Plots until 2100 are in Supplementary Figure 8.)

Geographically the panel dataset comprises all the 26 countries that had a UN OCHA-prepared HRP in 2023[7] (Figure 2). These countries either have protracted multi-year humanitarian crises are or prone to annual major disasters and thus, their empirical data exists primarily for 2018–2024—as detailed in the next sections. In essence, these countries are at the worse end of the spectrum of the Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index[10]. Their vulnerable status aligns with the Climate-Conflict Vulnerability Index[11] and Climate Finance Vulnerability Index[12].

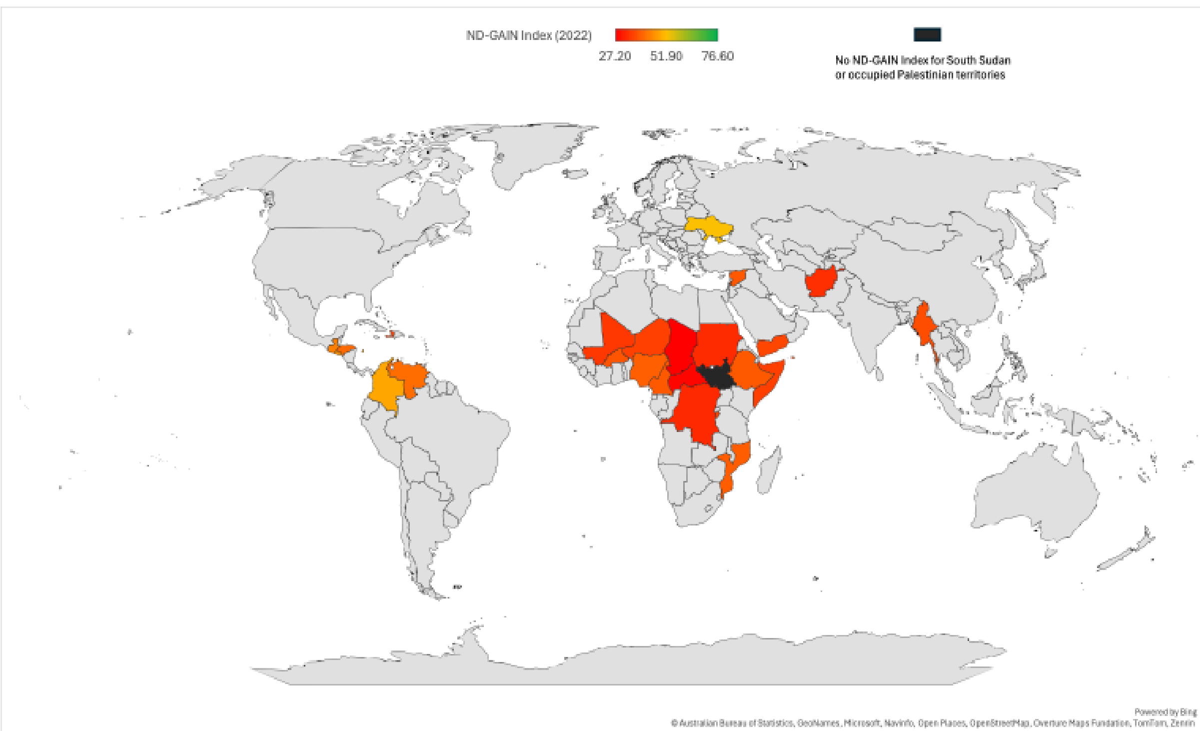

Figure 2. Geographical scope of the dataset.

The ND-GAIN Country Index (2022) scale and colouring resemble the original one so that Chad has the lowest score 27,2 and Norway would have the highest score 76,6[13]. Created by the authors with MS Excel. It uses Bing data for the map itself.

[10] https://gain.nd.edu/our-work/country-index/
[11] https://climate-conflict.org/www
[12] https://clifvi.org
[13] https://gain.nd.edu/our-work/country-index/

2.3. Estimating nominal people at risk from exposure and climatic-socioeconomic data

The full model is run in three concurrent phases, as explained previously, with estimation regressions. With these regressions we move from hazard exposure and SSP2-RCP4.5 climatic-socioeconomic observations and projections towards nominal people at risk ($\sum \mathrm{EX}$), then to people in need (PIN), and finally to the $\mathrm{funding\ requirement}$. The annual panel data and input for the model comprised the 26 countries (i) for years 2000-2100 (t) with varying amounts of data coverage. In total, 18 variables were included (see Supplementary Tables 1 and 2 for descriptive statistics). In essence, it is a modified damage function where variables of climate change are coupled to the humanitarian funding requirement via proxies (Figure 3).

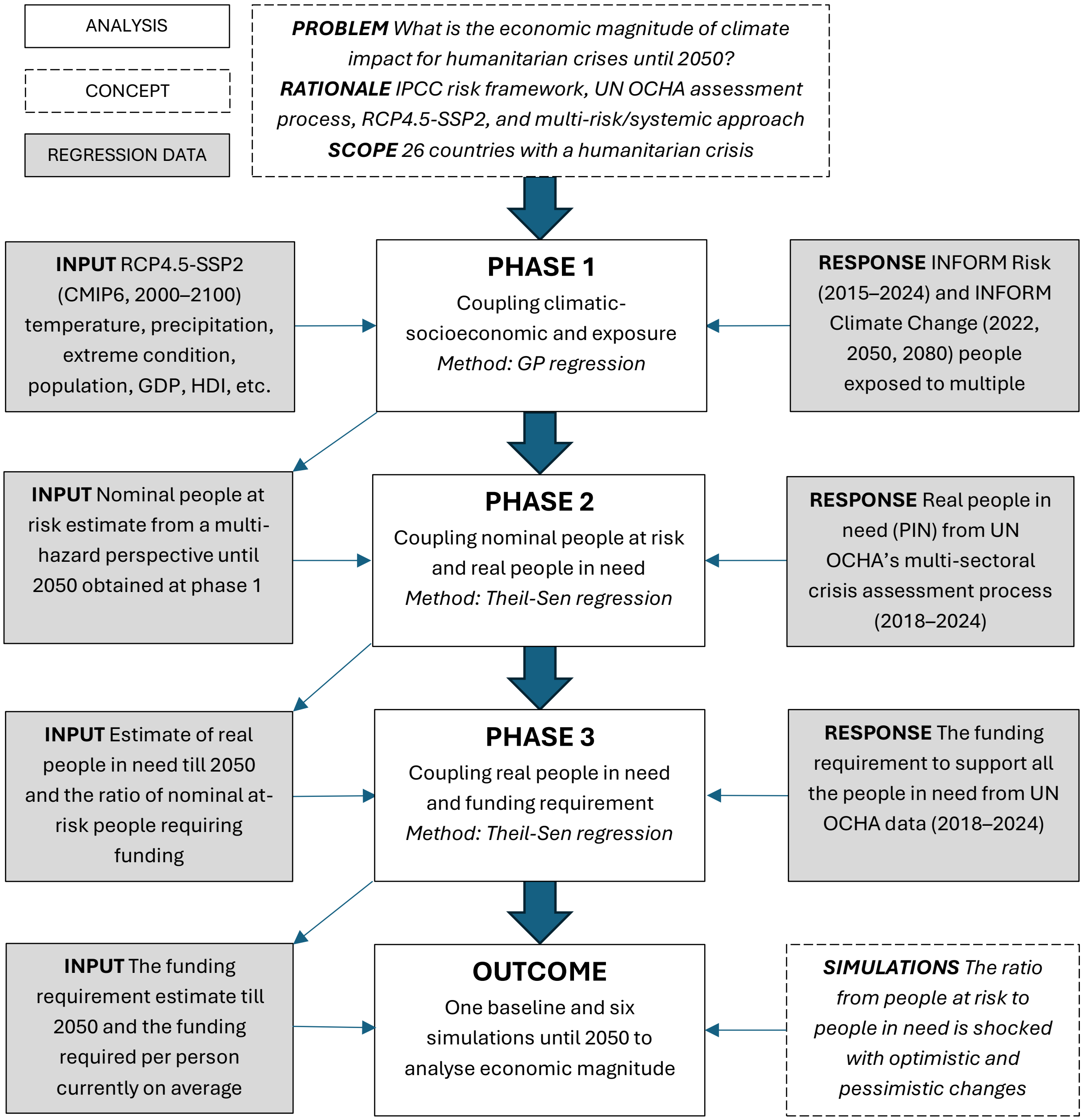

Figure 3. Estimation framework.

At the **phase 1**, we estimate nominal people at risk by regressing hazard exposure data from INFORM Risk and INFORM Climate Change against climatic and socioeconomic (representing vulnerability) variables from CMIP6 in Equation 1. (The hat notation for an estimate is omitted here and in the next two equations for easier readability.)

$$\sum EX_{i,t} = \ell_1 cdd_{i,t} + \ell_2 cdw_{i,t} + \ell_3 GDP_{i,t} + \ell_4 GSAT\Delta\_global_t + \ell_5 hd40_{i,t} + \ell_6 HDI_{i,t} + \ell_7 net\ migration_{i,t} + \ell_8 POP_{i,t} + \ell_9 pr_{i,t} + \ell_{10} PR\_global_t + \ell_{11} r20mm_{i,t} + \ell_{12} rx5day_{i,t} + \ell_{13} SFCWIND\_global_t + \ell_{14} SST\_global_t + \ell_{15} tas_{i,t} + \varepsilon \text{ (Equation 1)}$$

We use climatic-socioeconomic observation or projection data based around SSP2-RCP4.5. This is a combination of various factors that, according to the literature, would be determinants of climatic damage (e.g., Blaikie et al., 2014). Latest studies have explored using climatic data beyond averages as well as global data instead of only country-level variables with the main arguments being that averages do not represent extreme shifts well and that weather is a global system instead of a country-based one (Neal et al., 2025; van der Wijst et al., 2023; Waidelich et al., 2024).

Climatically, we use projections from CMIP6 multi-modal ensembles for the whole time series. These include global averages of sea surface temperature $\mathrm{SST\_global}$, precipitation $\mathrm{PR\_global}$, surface wind speed $\mathrm{SFCWIND\_global}$[14] (C3S/ECMWF, 2023), and the change in surface air temperature above pre-industrial levels $\mathrm{GSAT\Delta\_global}$[15] (Byers et al., 2022) in addition to country-level average surface air temperature tas and precipitation pr. To introduce more extreme climate indices, we added maximum number of consecutive dry (cdd) or wet days (cdw), number of days with daily maximum temperatures above 40°C $\mathrm{hd40}$, number of days with precipitation higher than 20mm $\mathrm{r20mm}$, and maximum 5-day cumulative precipitation $\mathrm{rx5day}$ for all country-level[16].

Inspired by (Marzi et al., 2021, 2025), the dataset includes the following socioeconomic variables that account for vulnerability in each country. For each we have observations for 2000–2024 from, for example the World Bank or UN Development Programme (UNDP), and projections based on SSP2-RCP4.5 for 2025–2100.

- Net migration[17],
- Population POP[18] (KC et al., 2024),
- Gross domestic product GDP adjusted for purchasing power parity (PPP)[19] (Crespo Cuaresma, 2017), and
- Human Development Index HDI[20] (Liu et al., 2024).

Although our initial variable analysis (Supplementary Section 4) suggested that certain variables had weak explanatory power for distinguishing people at risk and were highly collinear with other predictors, we kept them in the specification for control and to avoid any omitted variable bias. Different imputation and bias corrections were used. For example,

[14] https://cds.climate.copernicus.eu/
[15] https://data.ece.iiasa.ac.at/ar6
[16] https://climateknowledgeportal.worldbank.org
[17] https://databank.worldbank.org/ and http://www.wittgensteincentre.org/dataexplorer
[18] https://data.ece.iiasa.ac.at/ssp
[19] https://www.imf.org/external/datamapper/datasets/WEO and https://data.ece.iiasa.ac.at/ssp
[20] https://doi.org/10.1057/s41599-024-02941-6 and https://hdr.undp.org/data-center/human-development-index

missing values were imputed through interpolation or closest neighbour imputation. To ensure that INFORM Risk and INFORM Climate Change had coherent magnitudes for exposure, ratio-based delta shifts were applied.

The study leverages the INFORM Risk[21] and INFORM Climate Change[22] datasets as our source for people exposed to hazards (European Commission. Joint Research Centre., 2024). Shortly put, INFORM Risk covers structural baseline risk while INFORM Climate Change includes climate change projections. Both are collaborative efforts of INFORM partners, UN agencies, the European Commission, and various multilateral partners. They are increasingly used in different operational authorities, such as the World Food Programme (WFP) and the International Federation of Red Cross and Red Crescent Societies (IFRC), to support humanitarian decision-making. INFORM Risk has observations for 2015–2024 and INFORM Climate Change projections for 2022, 2050, and 2080 based on SSP2-RCP4.5. They aggregate analytical exposure data from multiple hazards per country by overlaying them with the Global Human Settlement Layer[23]. After data preprocessing, we used from INFORM Risk and INFORM Climate Change the following data (references are to the originals in the metadata):

- People exposed to dengue and malaria EX_DENMAL (Colón-González et al., 2021; Messina et al., 2019; WHO, 2023),
- People exposed to coastal and river floods EX_FL and EX_CFL (Dottori et al., 2016; Vousdoukas, Mentaschi, Voukouvalas, Bianchi, et al., 2018; Vousdoukas, Mentaschi, Voukouvalas, Verlaan, et al., 2018; Ward et al., 2020),
- People exposed to earthquakes with higher than 6 in Modified Mercalli Intensity EX_EQ_MM6 (Pagani et al., 2018),
- People exposed to tropical cyclone winds with higher than 1 in Saffir-Simpson category EX_TC_SS1 (Bloemendaal et al., 2020, 2023),
- People exposed to tsunamis EX_TS (UNISDR, 2015), and
- People exposed to drought based on 12-month standardized precipitation and evapotranspiration indices (SPI/SPEI) EX_DR (Marzi et al., 2021), and
- People exposed to conflict EX_CON (see below).

Finally, all the are summed up and then regressed against the climatic-socioeconomic data to estimate the nominal people at risk ($\sum \mathrm{EX}$) metric. The shares of each exposure driver can be found in Supplementary Figure 1. INFORM Climate Change and INFORM Risk slightly

[21] https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Risk
[22] https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Climate-Change
[23] https://human-settlement.emergency.copernicus.eu/

differ on many occasions due to different base data, and they were rescaled based on the overlapping year 2022 with the mentioned ratio-based delta shifts.

The authors prepared a new coherent variable for conflict exposure $\mathrm{EX\_CON}$. INFORM Risk only comprises organized violence fatalities from Uppsala Conflict Data Program[24] and intensities of conflict from Heidelberg Institute for International Conflict Research[25] while INFORM Climate Change only has a conflict probability metric for the SSP2 projections (Hegre et al., 2016). Thus, we used the new ACLED Conflict Exposure Calculator[26] as our main source for people exposed. It has observations for the number of people living within 1, 2, and 5 km of each conflict incident for 2020–2024.

We then used the INFORM Risk conflict data, that exists for 2015–2024, to impute 2015–2019 conflict exposure with a log-linear regression and 1 000 Monte Carlo iterations based on the ACLED Conflict Exposure Calculator. Finally, to come to an actionable future model, $\mathrm{EX\_CON}$ is projected to 2050 and 2080 based on INFORM Climate Change's 2022 ratio with the above imputed data. The assumption is that the conflict exposure follows the SSP2-RCP4.5 path (ceteris paribus) and returns to this equilibrium regardless of other exogenous factors. (More detailed steps are in Supplementary Section 1.) However, the causal connection between conflict and climate change has important literature behind it (e.g., Damette & Goutte, 2023; Hsiang & Burke, 2014) and is not fully resolved.

2.3.1. Gaussian Process Regression

The study's main computational model to estimate Equation 1 comprised a Gaussian Process Regression or GPR (Lyu et al., 2024; Rasmussen & Williams, 2005). GPR is a machine learning method suitable for complex non-linear analysis. It is non-parametric and based on Bayesian probability. It can handle small, noisy datasets whereas machine learning often prevails in very large datasets. It models the relationship between input and response variables by assuming that the function being learned follows a stochastic Gaussian process (see Supplementary Section 2 for full description). Thus, it is probabilistic and provides a measure of uncertainty for its predictions. This is particularly useful when dealing with limited and noisy data, as it allows for a more informed assessment in an uncertain environment, such as our dataset and context.

Initially, we had considered if traditional econometric analyses, such as vector autoregression (VAR) or the vector error correction method (VECM), would work for the research question. But our dataset was fundamentally data scarce with the noisy context of

[24] https://ucdp.uu.se/
[25] https://hiik.de/?lang=en
[26] https://acleddata.com/platform/conflict-exposure-calculator

humanitarian disasters and conflict, had short time series availability of hazard exposure (2015-2024, 2050, 2080) as well as non-stationarity, heteroskedasticity and multicollinearity (Supplementary Section 5). Exploring the use of a GPR to solve this gap was much more feasible. ChatGPT o4-mini-high was used to build and validate the code (as well as run the initial analyses in Supplementary Table 9).

GPR does not produce intercepts or coefficients in the traditional sense. However, GPR does optimize a length scale ℓ_d for each predictor that we interpret as signalling the variable's predictive power (Table 1). Similarly, ε means the white noise kernel that is further described together with the GPR itself after the variables.

Table 1. Indicators of nominal people at risk per length scale.

Variable in model phase 1 (shorthand in dataset)	Importance (length scale ℓ_d, 0,01–100) ↑
Country-level: Surface air temperature (tas)	most influential 1,2
Country-level: Precipitation (pr)	2,0
Country-level: Population (POP)	4,7
Global: Change in surface air temperature relative to the industrial period (GSATΔ_global)	6,4
Country-level: Average highest precipitation over a consecutive 5-day period during each month (rx5day)	10,8
Country-level: Human Development Index (HDI)	11,6
Global: ○ Sea surface temperature (SST_global) ○ Surface wind speed (SFCWIND_global) ○ Precipitation (PR_global) **Country-level:** ○ Gross Domestic Production (GDP) ○ Maximum of consecutive dry days (cdd) ○ Maximum of consecutive wet days (cdw) ○ Days over 40°C (hd40) ○ Heavy precipitation days (r20mm) ○ Net migration (net migration)	practically irrelevant 100

These come from Equation 1 in phase 1 of the model. We can interpret a shorter length scale to be a more impactful driver of nominal people at risk and vice versa. The Gaussian Process Regression (GPR) uses hyperparameter length scales ℓ_d to capture underlying patterns and complexity of the data as well as adapt to different scales in different dimensions. In the model, the GPR is allowed to optimize them within bounds of 0,01–100 to maximise the log-marginal likelihood, an indicator of model fit. A shorter length scale means that the values can change more rapidly, leading to a more agile function.

Conversely, a longer length scale results in a smoother function where the function values change more slowly. These are only applicable for the current model specification. Check against robustness tests in Supplementary Table 8 because the length scales change depending on the hyperparameters. Check against the marginal effect plots in Supplementary Figure 7 because, for example, HDI increases people at risk and is likely a proxy or a factor for population in the GPR core model.

The choice of covariance functions (or kernels) significantly influences the GPR model's performance and its ability to capture the underlying patterns in the data. We chose two commonly used components, the Radial Basis Function (RBF) kernel and the white noise model. RBF (or squared exponential kernel or Gaussian kernel) is universal and can approximate any continuous function. It expects the true function of the phenomenon to be smooth, which suited our assumption that climate change and humanitarian crises on country scales have an inertia to change incrementally on annual and decadal scales (instead of, for example, very rapid weather patterns).

The main hyperparameter in an RBF affecting how it learns the input data and constructs the model is length scale ℓ_{d}. It indicates the distance over which the input variables have a significant impact on the outcome variable. The RBF is specified here to be anisotropic so that each dimension of the input data has its own ℓ_{d}. This allows it to automatically determine the relevance of each input feature by learning different length scales for each dimension.

Thus, we let the model freely solve the optimisation problem, where it tries to maximise the probability of observing the data—or, more precisely, maximise the log marginal likelihood. Here, we set the RBF to learn freely between 0,01 and 100,0 for each variable (Supplementary Sections 2 and 3). These are standard and suitable bounds given the descriptive statistics of the dataset (Supplementary Table 2), but more robustness checks were done by altering the hyperparameters (Supplementary Table 8).

To account for the variability of climate change and humanitarian crises, a white noise model is added to the GPR alongside the RBF. This essentially includes a Gaussian noise term ε to the diagonal of the covariance matrix. The inclusion of ε makes the model more robust to outliers and measurement errors, as it accounts for the variability that is not explained by the input variables. The noise bounds were set similarly at 0,01 and 100. Note that this noise accounts for the credible interval (±1 σ) shown in the results. The GPR itself would use as low of a noise as possible (to a lower bound of 0,000619) to optimise the log marginal likelihood, but this is clearly not realistic.

We used scikit-learn[27], a standard and open-source machine learning library for Python 3.12 to execute the model (Pedregosa et al., 2011). To counter the black box tendency of machine learning, we followed guidance from explainable artificial intelligence (XAI) to

[27] https://scikit-learn.org/stable/

ensure interpretability, transparency, and expert supervision of the model (Dramsch et al., 2025; Hrast Essenfelder et al., 2025). Thus, we elected to have it as simple as needed to reduce the number of choices, layers, and hyperparameters. In effect, we want the model to be easy to understand rather than superfluously increasing model complexity.

For example, the covariance function comprises only two kernels added together although a more complicated structure could have yielded a more fitting model, yet less interpretable and explainable one. Although we tested and could have added regularization or parameter-reducing functions, such as Principal Component Analysis (PCA), this would have caused again extra layer to interpret and explain (see initial importance analyses in Supplementary Table 9). Therefore, setting the RBF as anisotropic and allowing the machine learning to learn and transparently show the importance of each variable itself via the length scales was an organic way to introduce the same.

Our main diagnostics of the GPR performance included the standard goodness-of-fit tests, such as root mean squared error (RMSE, 3,15), mean absolute error (MAE, 2,14), coefficient of determination (R^2, 0,997), and log marginal likelihood (LML, 207.66) as well as 5-fold cross-validation (CV) and nested CV. The relative RMSE, divided by the mean of the actual observations of $\sum \mathrm{EX}$, is 7.9% and in robustness checks it ranges between 2,7%–15% (Supplementary Table 8). Relative MAE is 5,4% and ranges between 1,9%–8,9% and LML ranges from -73,14 to 329,87. R^2 is close to 1 in all cases and indicates overfitting. However, with a domain expert visual analysis of the country graphs and considering the robustness tests, we found the model to be stable for our purposes of exploratory simulation. The CV results drop in accuracy in fold 5 for years 2050 and 2080 and goodness-of-fit is weak in all folds of the nested CV, indicating the model generalization is poor out of sample. (Supplementary Tables 5–7.) The robustness checks indicate that the results are firm until 2050 with a maximum difference of 12M for nominal people at risk when varying hyperparameters. In 2075 and 2100, the differences in nominal people at risk can be over 500 million to the paper's baseline (Supplementary Section 3.)

This was the expectation in a model spanning to the end of the century on very limited training data and is acceptable for simulation purposes, but we emphasise that it should not be taken as a predictive or inferential study. To account for the model's limitation, we used further simulations beyond the baseline to cover other plausible futures as detailed later.

2.4. Estimating real people in need and their funding requirement from nominal people at risk

Our target variables in the future are $\mathrm{funding\ requirement}$ and people in need PIN in **phases 2 and 3**. These are projected until 2100 in Equation 2 and 3 with the above nominal people at risk ($\sum \mathrm{EX}$), comprising hazard exposure and the SSP2-RCP4.5 climatic-socioeconomic conditions.

$$PIN_{i,t} = \alpha_i \sum EX_{i,t} \text{ (Equation 2)}$$

$$funding\ requirement_{i,t} = \beta_i\ PIN_{i,t} \text{ (Equation 3)}$$

The empirical observations are gathered annually per country from UN OCHA for years 2018–2024, the maximum that the Humanitarian Action database[6] offers. Contrary to nominal people at risk, we denote PIN as real people in need as their existence is more verifiable through teams on the ground in given humanitarian crises. This UN OCHA-coordinated process[9] involves country teams from other UN agencies, such as the WFP, UN High Commissioner for Refugees (UNHCR), and World Health Organization (WHO) as well as Save the Children and IFRC in addition to tens of non-governmental organizations (NGOs) in the field(called the cluster approach).

It is important to note that the funding requirement is more formally an appeal for support by UN OCHA. The actual funding provided by governments of the world, multilateral organizations (themselves funded by member states), NGOs and private organizations is less and, for example, in 2024 the global provided funding was 51% of the requirement (USD 25B out of USD 49B). Humanitarian funding can be monitored on the Financial Tracking Service[7] and it is a form of official development assistance (ODA) followed by OECD (Organisation for Economic Co-operation and Development). In 2024, humanitarian assistance was 11% of total ODA (USD 222B) that encompasses long-term development assistance[28]. All monetary information, such as GDP, was set to 2024 prices where possible.

Because it is a vast outlier, we have taken out those PIN and $\mathrm{funding\ requirement}$ data that specifically referred to COVID-19 response in the UN OCHA source. Likewise, joint or regional plans covering multiple countries have been attributed to the country where the crisis originated from—such as the Syrians displaced outside of Syria in Türkiye, Lebanon, Jordan, Iraq and Egypt (Syria 3RP, 2025). This can lead to the PIN being higher than nominal people at risk that is attributed to a single country (see example in results). In some cases, the 26 countries that had an HRP in 2023 did not have people in need or funding data for all years. Rationally, in some years they did not have a need for humanitarian assistance. This data was not imputed.

For both equations, we use a zero intercept Theil-Sen regressor. As we are only interested in the empirical ratio α_i of nominal people at risk $\sum \mathrm{EX}_{\mathrm{i,t}}$ turning into real people in need $\mathrm{PIN}_{\mathrm{i,t}}$, there is no need for an intercept term. Similarly, we are only interested in the empirical ratio

[28] https://www.oecd.org/en/data/dashboards/official-development-assistance-at-a-glance.html

β_i of how much the whole $\mathrm{PIN}_{i,t}$ creates as a $\text{funding requirement}_{i,t}$ (see results on country profiles).

The Theil-Sen is more robust than an ordinary least square (OLS) regression as it is insensitive to outliers and performs well in case of heteroskedasticity (Sen, 1968; Theil, 1950). Thus, in the noisy, data-scarce, and rapidly changing environment of humanitarian crises, we obtain a more conservative estimate of the true baseline by minimizing the effect of outliers and spikes. For example, when a country's situation escalated into a civil war or it encountered a once-in-100-years disaster during the observed period for PIN (2018–2024). The estimations of α_i and β_i utilise 10 000 bootstraps and Monte Carlo iterations to further account for the uncertainty.

No discounting or inflation-adjustment is added in the base model and thus, prices are at 2024 level continuously. We argue that this is the cleanest solution because the study is not a cost-benefit analysis, it is a simulation of how much humanitarian aid the global community would have to provide at any given time from today's context. Analytically, these adjustments can create arbitrarily large sensitivities that are prone to debate. Both positivist and ethicist approaches to discounting arrive at feasibility issues and it is more complicated when considering that this funding affects lives of people (Weisbach & Sunstein, 2009).

One could argue that the 15 regressors as well as the 3 response variables have simultaneous and multicollinear relationships. For example, that GDP and HDI would not only contribute to how many people are exposed, but how many people will be in need due to GDP and HDI affecting vulnerability. Likewise, there are possibilities of reverse causality. For example, that the funding provided to a country decreases the risk in it. However, as mentioned, our objective is not inference or prediction in the sense of showing what will occur, but simulations of possible alternatives. Therefore, we relax these assumptions to provide actionable insight based on a simple model. Similarly, as explained in the next section, we can transparently simulate different optimistic and pessimistic futures by keeping only one parameter in both Equation 2 and Equation 3 instead of a more inferential or predictive regression.

2.5. Simulations

We run six different simulations that are either pessimistic or optimistic relative to the baseline symmetrically. Their severities are labelled as most, medium or lightly pessimistic or optimistic. They were meant to represent exogenous factors both outside of the control of policy choice, but to signal what additional efforts and positive action could mean in contrast to declining funding.

The simulations modify the ratio α_i of nominal people at risk $\sum EX$ becoming real people in need PIN in Equation 2 with stochastic multiplications that are either short or long-term. Concurrently this spills over to $\mathrm{funding\ requirement}$ in Equation 3. All the simulations were built by the authors with ChatGPT o4-mini-high and executed in the same Python 3.12 script as the rest of the model.

Two types of specific modifications are introduced. First, temporary shocks that are momentary and transitory but intense (shock factor). They dissipate in a matter of a few years and mimic the non-linear and asymmetric nature of disaster and conflict. Two variations are used in each simulation with a smaller shock occurring more frequently and persisting only for a year or two and a larger, less frequent shock that decays in a few years.

The intensity of these shocks is grounded by historical data. In the dataset, the PIN of the 25th percentile rose by 142% and the 75th percentile by 295%. For example, significant rises are evident in Afghanistan (from 5,5M to 37M), Myanmar (from 2,1M to 20M) and Sudan (from 7,0M to 13M). Likewise, the number of disasters globally hovers around 400 per year since the year 2000 according to the disaster database EM-DAT[29] and conflict events have almost doubled in the last five years from over 100 000 to nearly 200 000 in the ACLED Conflict Index[30], see the Uppsala Conflict Data Program[24].

Table 2. Descriptions of the simulations.

	All shocks and breaks start occurring in 2025 simultaneously				
	TEMPORARY SHOCKS			**STRUCTURAL BREAK**	
Simulation	Probability of shock (event/year)	Shock factor to ratio α	Half-Life of shock effect (years)	Drift factor to ratio α	Coverage of drift among countries
Most pessimistic	1/8 1/20	1,30 (±0,25) 2,10 (±0,25)	2,0 (±0,25) 6,0 ±0,25)	0,02 (±0,0005)	75% (±9,4%)
Medium pessimistic	1/10 1/25	1,25 (“) 2,00 (“)	1,0 (“) 5,0 (“)	0,01 (”)	75% (”)
Lightly pessimistic	1/15 1/30	1,10 (“) 1,75 (“)	0,5 (“) 2,5 (“)	0,005 (“)	75% (”)
Baseline	-	-	-	-	-
Lightly optimistic	1/15 1/30	0,91 (“) 0,57 (“)	0,5 (“) 2,5 (“)	-0,005 (“)	75% (”)
Medium optimistic	1/10 1/25	0,80 (“) 0,50 (“)	1,0 (“) 5,0 (“)	-0,01 (“)	75% (”)

[29] https://www.emdat.be
[30] https://acleddata.com/conflict-index/

Most optimistic	1/8 1/20	0,77 (") 0,48 (")	2,0 (") 6,0 (")	-0,02 (")	75% (")

All temporary shocks and structural breaks start in 2025. They modify the ratio α that determines how many people at risk turn into people in need (Equation 2). All simulations are run 10 000 times with Monte Carlo iterations, and the shock factors are run additionally 10 000 times within this loop. The shock factors have chances of two different types occurring in each simulation. 1) More severe yet less probable; and 2) less severe but more probable. Author-chosen standard deviations around each Monte Carlo are in parentheses. The probability of a temporary shock comes annually from a Poisson distribution with Bernoulli trials and is specific for each country. All others are log-normal distributions except the drift factor (normal distribution) and the coverage (beta distribution). The drift factor is multiplicative and sampled again every year for each country affected. However, the country coverage is chosen one time at the start and thus, the drift remains consistently in an affected country.

However, we emphasise that these are choices by the authors that display a plausible way momentary shocks could progress. The shocks are modelled with standard statistical tools that fit the nature of disasters and conflict. For their probability of occurring, we follow Poisson functions with Bernoulli trials (e.g., Barro, 2006). For their severity and persistence, the simulations use fat tailed log-normal distributions (e.g., Weitzman, 2011).

Second, we added a structural break (e.g., Bai & Perron, 1998) where the steady-state of the baseline's ratio α_i exponentially starts to shift up or downward in 2025 (drift factor). This represents inertia in the level of investment and effort towards disaster prevention, climate change adaptation and conflict mediation as well as technological and innovative improvements (such as more effective relief delivery), and the uncertainty in our understanding of how much climate change will compound disasters and conflicts. A standard drift factor that multiplicatively modifies factor α_i every year for a random selection of the countries is used to model it.

The nominal people at risk and the projected population are used as upper boundaries of the simulations. The most pessimistic simulation of people in need surpasses nominal people at risk around 2090 and thus, it seems implausible to occur. However, it is an appropriate stress test to mimic so-called endgame or catastrophic simulations (Kemp et al., 2022; Wescombe et al., 2025).

2.6. Additional limitations

In addition to the main limitations in the discussion section, the GPR here does not exhaustively consider temporal and spatial correlation in the dataset. Each country has an annual series, so temporal structure is implicit in the panel. The autocorrelation analysis (Supplementary Figure 3) confirmed strong persistence in many variables, and GPR's anisotropic RBF kernel can capture smooth temporal changes. However, there is no explicit autoregressive structure in the steady-state baseline. The model learns from the predictors but does not use lagged values. These are accounted for in the post hoc simulations but are not organically included in the regression. Cross-validation includes folds over time, but the large drop in out-of-sample accuracy for far-future folds shows temporal extrapolation is still challenging. In essence, the core model is not generalizable. Then again, the literature indicates that many climate models are not (Morris et al., 2025; Myhre et al., 2025a; Newell et al., 2021; Tol, 2024).

The dataset had multicollinearity, autocorrelation, heteroskedasticity, and non-stationarity (see assessments in Supplementary Section 5). This was expected considering the complexity of the underlying phenomena and drove us to utilise GPR instead of, for example, VECM. The visual residual check (Supplementary Figure 1) shows that the GPR fits the mean trend well but has some remaining issues. The histogram and quantile–quantile (Q–Q) plot are close to normal in the middle but with clear fatter tails. The ±1 standard deviation (σ) bands will have over or underestimation in the tails and extreme misses are more frequent. The residual versus fitted figure shows a slight funnel shape where variance grows with level. Thus, there is heteroskedasticity consistent with the scale of PIN or $\Sigma\mathrm{EX}$ increasing over time and size. The white noise kernel doesn't fully capture all noise. The ACF (autocorrelation function) of residuals show small positive autocorrelation at short lags (e.g., lag 1–2). Thus, errors have temporal memory and the GPR's smooth mapping of covariates didn't completely remove the persistence. These are offset with the use of simulations rather than relying only on the steady-state baseline.

The INFORM Risk/Climate Change indicators combine disparate hazard exposure metrics some of which have different baselines, detection methods, and update frequencies (Marzi et al., 2021). For example, flood $\mathrm{EX\_FL}$ is probabilistic and calculated based on expected annual exposed population while drought $\mathrm{EX\_DR}$ and epidemics $\mathrm{EX\_DENMAL}$ are not probabilistic—partly explaining why in Supplementary Figure 1 their share is higher. Similarly, the different climate hazard measures, such as extreme heat days ($\mathrm{hd40}$), wind speed ($\mathrm{SFCWIND\_global}$), etc. have different modelling sources and resolutions, adding cross-variable noise. Conflict variables are especially volatile.

Finally, our dataset build-up relied on necessary harmonisation, rescaling, correction and imputation phases that can smooth variance and hide structural changes. Likewise, the INFORM Climate Change anchors are based on CMIP5 while the country-level and global climate drivers are from CMIP6 leaving the analysis open to cross-framework bias.

3. Results

3.1. Simulations of future needs and costs until 2050

The main outcome of the study is one baseline and six simulations of humanitarian need and its funding requirement until 2050 under the SSP2-RCP4 scenario—towards which we are now heading (Bevacqua et al., 2025; Cannon, 2025; Climate Action Tracker, 2025; IPCC, 2023a). The baseline provides a conservative estimate of the effects of climate change with the scenario's warming of 2,7 (range 2,1–3,5) °C warming by 2081–2100 above pre-industrial. The simulations are based on a historical context. They add either beneficial or detrimental temporary shocks and long-term structural changes to the baseline with stochastic elements in concurrent steps starting from 2025.

Examples of temporary shocks that we modelled are combinations of major disasters or wars that dissipate over a handful of years in most cases while the long-term structural change introduces a slow creep of climate change's amplifying effect on the crises—or subduing in case of sustained disaster prevention and adaptation. These six simulations are labelled from the most pessimistic to the most optimistic with light and medium versions of both in between. Each level increases or decreases the probabilities, magnitudes and persistence of the effects to the baseline; they cause the jaggedness of the paths instead of smooth lines. The pessimistic simulations in general follow these conditions although there are further conditions of randomness, persistence and coverage in the model (see Table 2):

- *Most pessimistic:* 5–13% annual chance of 130–210% more severe shocks; 2,0% annual creep of worsening disaster and conflict conditions due to climate inertia.
- *Medium pessimistic:* 4–10% annual chance of 125–200% more severe shocks; 1,0% annual creep.
- *Lightly pessimistic:* 3–7% annual chance of 110–175% more severe shocks; 0,5% annual creep.

Whereas the optimistic ones perform as follows:

- *Lightly optimistic:* 3–7% annual chance of 58–91% less severe shocks; 0,5% annual improvement of disaster and conflict conditions due to better risk reduction and adaptation.
- *Medium optimistic:* 4–10% annual chance of 50–80% less severe shocks; 1,0% annual improvement.
- *Most optimistic:* 5–13% annual chance of 48–77% less severe shocks; 2,0% annual improvement.

Figure 4 shows in summary how the future of humanitarian crises until 2050 in the 26 countries are simulated from the climatic-socioeconomic background data and calibrated with the risk datasets as well as empirical UN OCHA field analysis of humanitarian need.

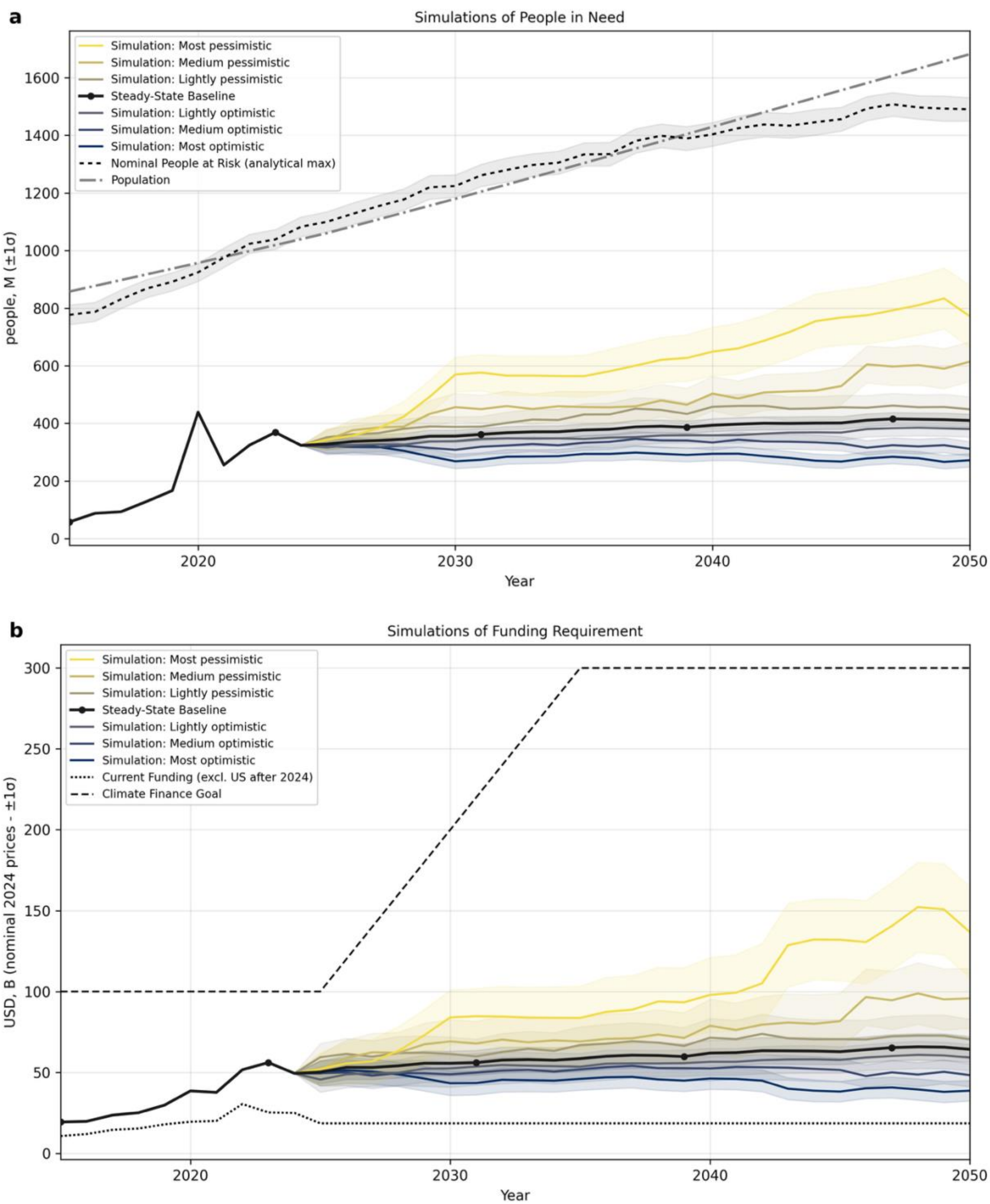

Figure 4. Simulations of people in need of humanitarian assistance and their funding requirement

a, b, The annual values (i.e., flow) here are an aggregate of all 26 countries in the dataset for the middle-of-the-road climate change scenario SSP2-RCP4.5 with optimistic and pessimistic simulations of the future. The simulations (with 10 000 Monte Carlo iterations each) start from 2025 while data before that is historical. The steady-state baseline is in the middle while beneficial and detrimental shocks in both short-term and in long-term structural breaks are added symmetrically around it. The spike of 2020 is COVID-19 and was removed from the training dataset as a huge outlier but shown here for transparency. Shaded areas represent ±1 global standard deviation (σ), a 68% credible interval.

a, Both population and nominal people at risk are shown as physical and analytical upper boundaries of the simulations. Nominal people at risk shoots higher than the population between 2020 and 2040, but this is due to it containing double counting and being treated more as an intensity factor here. Due to the multiplicative and aleatory nature of the simulations, standard deviations increase significantly in the pessimistic ones and decrease concurrently in the optimistic ones. This could imply that more severe and spiralling simulations are likewise more uncertain whereas optimistic simulations—where we reduce disaster risk and limit damage to the people in need early on—will be a more certain and controlled road.

b, The data is in 2024 prices to show how much would optimally need to be budgeted from today's viewpoint. No inflation or discount factor is added. The current humanitarian funding level excluding United States (US) funding after 2024 is shown as a reference (although the food security sector amount of USD 4.64B is kept and thus, USD 6.43B is removed from the current funding here after 2024). In addition, the past and future climate finance goal is shown as a upper boundary reference. This includes the New Collective Quantified Goal (NCQG) of USD 300 by 2035 as agreed at COP29.

The historical humanitarian funding level, excluding the contribution by the United States after 2024, is shown as a reference in addition to the past and future climate finance goal that should be provided to developing countries to curb climate damage. This includes the New Collective Quantified Goal (NCQG) of USD 300B annually by 2030 as agreed at COP29. There is no discounting in any of the results to keep them intergenerationally fair. Therefore, future funding is not altered to be less valuable for the current generation. Table 3 shows a snapshot of the data in 2050 from Figure *4*.

Table 3. Snapshot of humanitarian needs in 2050

	PEOPLE IN NEED		**FUNDING REQUIREMENT**	
Simulation	In 2050, ±1σ, million	Compared to 2024	In 2050, ±1σ, billion USD_{2024}	Compared to 2024
Most pessimistic	772±107	239%	137±28	280%
Medium pessimistic	614±68	190%	96±19	196%
Lightly pessimistic	449±44	139%	70±12	143%
Baseline	410±22	127%	64±8	130%
Lightly optimistic	380±28	118%	59±8	120%
Medium optimistic	311±25	96%	48±7	98%
Most optimistic	272±23	84%	39±6	80%

Same data as in Figure 4. See Table 3 for detailed descriptions of the simulations. 1 standard deviation (σ) represents a 68% credible interval.

Nominal people at risk shoots higher than the population between 2020 and 2040, but this is due to it containing double counting and being treated more as an intensity factor here. For example, one person can be at the same time exposed to multiple disasters at the same time yet counted multiple times in the aggregate here and thus, nominal people at risk is more an analytical metric than a real one (see below Syria example).

3.2. Severity profiles of the countries

To complement the forward-looking analysis, we examine the 26 countries' empirical vulnerability. This is measured as the average ratio from people at risk to people in need during 2018–2024 (Figure *5*).

Overall, more than half of the people at risk were people in need in six countries in average over 2018–2024 highlighting countries which are on the extreme edge of vulnerability. In addition to Syria, these were Afghanistan (61±28%), occupied Palestinian territory (79±13%), South Sudan (91±7%), Ukraine (62±28%), and Yemen (90±5%).

In 18 of the 26 countries, the funding requirement exceeds USD 100 per person and the average over all countries is 150 USD per person. In Mozambique (USD 206±13), Myanmar (USD 295±162), the occupied Palestinian territory (USD 227±96), Somalia (USD 254±31), South Sudan (USD 234±13), and Syria (USD 505±20), it is over USD 200 per person. The most severe crises here are human-driven conflict that will be amplified by human-created climate change (Supplementary Figure 1). This analysis corroborates 10 years of INFORM data (European Commission. Joint Research Centre., 2024).

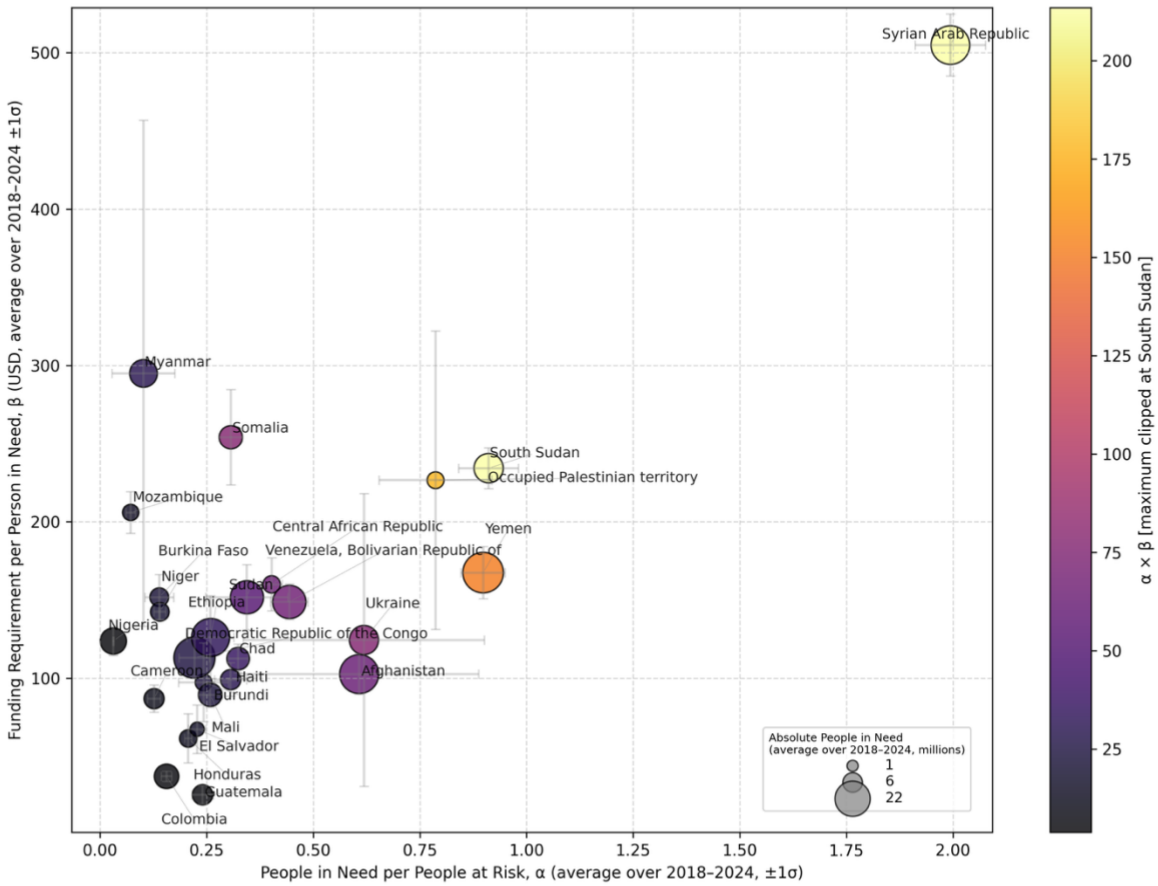

Figure 5. Heatmap of empirical vulnerability.

These are directly from Equations 2 and 3 of phases 2 and 3 in the model with ±1 standard deviation (σ) representing 68% credible interval. In essence, α on x-axis tells how many from nominal people at risk turn into real people in need based on empirical UN OCHA data (average over 2018–2024). Then, β on y-axis shows how much USD funding is required per person. The steady-state baseline assumes these ratios continue middle-of-the-road until 2050 while the simulations modify α to be either more or less severe. The heatmap is capped at South Sudan's level ($a \times b = 214$) while the Syrian Arab Republic's product is 1007. The script used a Theil-Sen regressor to estimate them and then ran 10 000 Monte Carlo iterations for both ratios and thus, the results here are their mean. The Theil-Sen estimator is robust to outliers and the results here conservative showing a core tendency of each country. Sizes of each country marker are based on their absolute people in need (average over 2018–2024).

The data and method indicate that in Syria there were two times (199±8%) more people in need than there were nominal people at risk—which seems faulty at first. However, the scope of both people in need and funding requirement included displaced population outside of the country that are caused by the crises. 6.4 million Syrians were in need in Türkiye, Lebanon, Jordan, Iraq and Egypt in 2024, 27% of the total people in need attributable to Syria itself (Syria 3RP, 2025). They are beyond the analytical exposure data that overlays hazard over population and thus not included in the nominal people at risk.

4. Discussion

4.1. Future and policy implications

The results show how much the humanitarian situation under climate change will potentially reduce funding available (ceteris paribus) for emission mitigation and adaptation. For example, any simulation between medium pessimistic and medium optimistic will mean that the humanitarian funding requirement constitutes 17–23% of the new climate finance goal of USD 300B annually to developing countries in 2035 when it is meant to be reached. In a sense, response funding to humanitarian crises would possibly crowd out other beneficial and sustainable investment.

This increases the potential that more countries spiral into a vicious loop whereby there are more crises due to less investment in mitigation and adaptation, such as disaster risk reduction. Hence, even less will be available to preventive and reductive efforts if every year humanitarian crises become worse with the creep and inertia of climate change as well as spill over and ripple to other countries and sectors in second-order effects. Then this feedback loop compounds. Hence, there would be more protracted crises in countries such as Democratic Republic of the Congo, Sudan and Afghanistan where there are extremely vulnerable conditions that persist, breakdowns in local governance, and unsustainable livelihood and food security systems (e.g., Kemp et al., 2022; Wescombe et al., 2025).

Nonetheless, the data indicates that the short-term fluctuation—such as transitory shocks from big or small disasters, wars, or momentary good conditions—will not be the most impactful factors for humanitarian crises in a future locked to the middle-of-the-road SSP2-RCP4.5 scenario. It will be the inertia of climate change because temperature and precipitation will continue to change even if all greenhouse gas emissions would stop immediately. In each simulation, the long-term creep will yield more cumulated damage than the short-term shocks (Supplementary Figure 9).

This requires determined and sustained investment in minimizing damage in advance of future impacts of climate change. Long-term alignment with the SSP2 or the even more sustainable SSP1 scenario would free opportunity costs to be used elsewhere. What simulation occurs depends on our policy and investment choices. We should not be constrained into the pessimistic ones (path dependency) and should strive to connect responses to immediate threats with achieving the Sustainable Development Goals (SDGs).

Tying decisions in the humanitarian-development-peace nexus obligatorily together could support in avoiding the ‘tyranny of the present’—a human tendency to focus on immediate effects—and in integrating long-term adaptation with short-term response and peace building. For example, that humanitarian funding decisions would be legally joined with a concurrent investment into adaptation of the cause of the humanitarian need, such as into an early warning system, nature-based solution or conflict mediation programme in the donor workflow and the project implementation. In some cases—such as when the crisis country has more self-resilience—anticipatory action or pre-arranged financing with a condition for the country to implement, for example, a climate resilience plan would have the same effect. Therefore, an integrated approach would become organic and alleviate siloed decision-making.

The deep uncertainty of the future simulations advocates to avoid unnecessarily gathering substantially more data, but to robustly act with what we have. This indicates that using low regret options—investments that we know will work regardless of the future scenario—could likewise be beneficial for decision-making and limit analysis paralysis.

4.2. Main limitations

The data available for humanitarian and hazard projection analysis itself is either sparse, noisy, or asymmetric—or all of them at the same time. To keep the simulation model—that is used for the first time in this kind of a task—explainable and interpretable, our specification was deliberately simple and has important limitations. To make the model inference or prediction-based, a more complex kernel structure with different covariance functions for space and time would be needed. Likewise, the residual analysis is consistent with our use case of simulation under deep uncertainty but might benefit from added components in future studies.

The future holds unknowable unknowns, and it is virtually impossible to eliminate the chance that the model might not reflect causal relationships, such as between climate change and conflict. Human-based or second order effects are not modelled. The dataset excludes adaptation and disaster risk reduction investment as a variable, changes in humanitarian efficiency, or socio-political shifts. They are all assumed constant or proportional in the baseline but are however mimicked in the simulations to a qualitative degree. For example, the change of regime in Syria during the turn of 2024–2025 could alter the country's future risk and humanitarian need tremendously. Likewise, knock-on effects from disasters and conflict to a country's industrial sector or trade would influence its GDP. While a quantification of humanitarian cost serves a purpose, it may obscure culturally specific needs or non-material dimensions. Likewise, emphasis on foreign aid, climatic variables and GDP growth may also overlook local agency, informal resilience or indigenous coping or underplay the political and historical drivers of vulnerability.

However, the results are mathematically robust—within its assumptions—until 2050 in all performed sensitivity checks with a maximum difference of 12M for nominal people at risk. (Supplementary Section 3.) Still, these results serve more as stress tests and we should be cautious with forward-looking analyses of climatic damage that can have widely varying and brittle outcomes (Morris et al., 2025; Newell et al., 2021; Tol, 2024).

5. References

Auffhammer, M. (2018). Quantifying Economic Damages from Climate Change. *Journal of Economic Perspectives*, *32*(4), 33–52. https://doi.org/10.1257/jep.32.4.33

Bai, J., & Perron, P. (1998). Estimating and Testing Linear Models with Multiple Structural Changes. *Econometrica*, *66*(1), 47–78. https://doi.org/10.2307/2998540

Barro, R. J. (2006). Rare Disasters and Asset Markets in the Twentieth Century. *The Quarterly Journal of Economics*, *121*(3), 823–866.

Bevacqua, E., Schleussner, C.-F., & Zscheischler, J. (2025). A year above 1.5 °C signals that Earth is most probably within the 20-year period that will reach the Paris Agreement limit. *Nature Climate Change*, 1–4. https://doi.org/10.1038/s41558-025-02246-9

Blaikie, P., Cannon, T., Davis, I., & Wisner, B. (2014). *At risk: Natural hazards, people's vulnerability, and disasters* (Second edition). Routledge.

Bloemendaal, N., de Moel, H. (Hans), Muis, S., Haigh, I. D. (Ivan), & Aerts, J. C. J. H. (Jeroen). (2023). *STORM tropical cyclone wind speed return periods* (Version 4) [Media types: application/vnd.google-earth.kml+xml, application/vnd.openxmlformats-officedocument.spreadsheetml.sheet, application/x-netcdf, application/zip, text/plain]. 4TU.Centre for Research Data. https://doi.org/10.4121/12705164.V4

Bloemendaal, N., Haigh, I. D., De Moel, H., Muis, S., Haarsma, R. J., & Aerts, J. C. J. H. (2020). Generation of a global synthetic tropical cyclone hazard dataset using STORM. *Scientific Data*, *7*(1), 40. https://doi.org/10.1038/s41597-020-0381-2

Botzen, W. J. W., Deschenes, O., & Sanders, M. (2019). The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies. *Review of Environmental Economics and Policy*, *13*(2), 167–188. https://doi.org/10.1093/reep/rez004

Byers, E., Krey, V., Kriegler, E., Riahi, K., Schaeffer, R., Kikstra, J., Lamboll, R., Nicholls, Z., Sandstad, M., Smith, C., van der Wijst, K., Al -Khourdajie, A., Lecocq, F., Portugal-Pereira, J., Saheb, Y., Stromman, A., Winkler, H., Auer, C., Brutschin, E., … van Vuuren, D. (2022). *AR6 Scenarios Database* (Version 1.1) [Data set]. Integrated Assessment Modeling Consortium & International Institute for Applied Systems Analysis. https://doi.org/10.5281/ZENODO.5886911

C3S/ECMWF. (2023). *Gridded monthly climate projection dataset underpinning the IPCC AR6 Interactive Atlas* [Data set]. ECMWF. https://doi.org/10.24381/CDS.5292A2B0

Cannon, A. J. (2025). Twelve months at 1.5 °C signals earlier than expected breach of Paris Agreement threshold. *Nature Climate Change*, 1–4. https://doi.org/10.1038/s41558-025-02247-8

Climate Action Tracker. (2025). *The CAT Thermometer. November 2025.* Climate Analytics and NewClimate Institute. https://climateactiontracker.org/global/cat-thermometer/

Colón-González, F. J., Sewe, M. O., Tompkins, A. M., Sjödin, H., Casallas, A., Rocklöv, J., Caminade, C., & Lowe, R. (2021). Projecting the risk of mosquito-borne diseases in a warmer and more populated world: A multi-model, multi-scenario intercomparison modelling study. *The Lancet Planetary Health*, *5*(7), e404–e414. https://doi.org/10.1016/S2542-5196(21)00132-7

Crespo Cuaresma, J. (2017). Income projections for climate change research: A framework based on human capital dynamics. *Global Environmental Change*, *42*, 226–236. https://doi.org/10.1016/j.gloenvcha.2015.02.012

Damette, O., & Goutte, S. (2023). Beyond climate and conflict relationships: New evidence from a Copula-based analysis on an historical perspective. *Journal of Comparative Economics*, *51*(1), 295–323. https://doi.org/10.1016/j.jce.2022.09.005

Dottori, F., Salamon, P., Bianchi, A., Alfieri, L., Hirpa, F. A., & Feyen, L. (2016). Development and evaluation of a framework for global flood hazard mapping. *Advances in Water Resources*, *94*, 87–102. https://doi.org/10.1016/j.advwatres.2016.05.002

Dramsch, J. S., Kuglitsch, M. M., Fernández-Torres, M.-Á., Toreti, A., Albayrak, R. A., Nava, L., Ghaffarian, S., Cheng, X., Ma, J., Samek, W., Venguswamy, R., Koul, A., Muthuregunathan, R., & Hrast Essenfelder, A. (2025). Explainability can foster trust in artificial intelligence in geoscience. *Nature Geoscience*, *18*(2), 112–114. https://doi.org/10.1038/s41561-025-01639-x

Dunz, N., Hrast Essenfelder, A., Mazzocchetti, A., Monasterolo, I., & Raberto, M. (2023). Compounding COVID-19 and climate risks: The interplay of banks' lending and government's policy in the shock recovery. *Journal of Banking & Finance*, *152*, 106306. https://doi.org/10.1016/j.jbankfin.2021.106306

European Commission. Joint Research Centre. (2024). *INFORM report 2024: 10 years of INFORM : shared evidence for managing crises and disasters.* Publications Office. https://data.europa.eu/doi/10.2760/555548

Hallegatte, S., Hourcade, J.-C., & Dumas, P. (2007). Why economic dynamics matter in assessing climate change damages: Illustration on extreme events. *Ecological Economics, Special Section: Ecological-Economic Modelling for Designing and Evaluating Biodiversity Conservation Policies*, *62*(2), 330–340. https://doi.org/10.1016/j.ecolecon.2006.06.006

Hegre, H., Buhaug, H., Calvin, K. V., Nordkvelle, J., Waldhoff, S. T., & Gilmore, E. (2016). Forecasting civil conflict along the shared socioeconomic pathways. *Environmental Research Letters*, *11*(5), 054002. https://doi.org/10.1088/1748-9326/11/5/054002

Higuera Roa, O., Bachmann, M., Mechler, R., Šakić Trogrlić, R., Reimann, L., Mazzoleni, M., Aerts, J. C. J. H., Buskop, F. E., Pirani, A., & Mysiak, J. (2025). Challenges and opportunities in climate risk assessment: Future directions for assessing complex climate risks. *Environmental Research Letters*, *20*(5), 053003. https://doi.org/10.1088/1748-9326/adc756

Hochrainer-Stigler, S., Trogrlić, R. Š., Reiter, K., Ward, P. J., Ruiter, M. C. de, Duncan, M. J., Torresan, S., Ciurean, R., Mysiak, J., Stuparu, D., & Gottardo, S. (2023). Toward a framework for systemic multi-hazard and multi-risk assessment and management. *iScience*, *26*(5). https://doi.org/10.1016/j.isci.2023.106736

Hrast Essenfelder, A., Toreti, A., & Seguini, L. (2025). Expert-driven explainable artificial intelligence models can detect multiple climate hazards relevant for agriculture. *Communications Earth & Environment*, *6*(1), 1–11. https://doi.org/10.1038/s43247-024-01987-3

Hsiang, S. M., & Burke, M. (2014). Climate, conflict, and social stability: What does the evidence say? *Climatic Change*, *123*(1), 39–55. https://doi.org/10.1007/s10584-013-0868-3

Hsiang, S. M., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., Rasmussen, D. J., Muir-Wood, R., Wilson, P., Oppenheimer, M., Larsen, K., & Houser, T. (2017). Estimating economic damage from climate change in the United States. *Science*, *356*(6345), 1362–1369. https://doi.org/10.1126/science.aal4369

IFRC. (2019). *The Cost of Doing Nothing*. International Federation of Red Cross and Red Crescent Societies.

IPCC. (2023a). *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]*. IPCC. https://doi.org/10.59327/ipcc/ar6-9789291691647

IPCC. (2023b). Point of Departure and Key Concepts. In *Climate Change 2022 – Impacts, Adaptation and Vulnerability* (1st edn, pp. 121–196). Cambridge University Press. https://doi.org/10.1017/9781009325844.003

Jäpölä, J.-P., Berlin, A., Fabri, C., Hrast Essenfelder, A., & Marzi, S. (2025). *Model to simulate the future cost of climate change for humanitarian aid (Replication Package)* [Data set]. Zenodo. https://doi.org/10.5281/zenodo.15336209

Jäpölä, J.-P., & Van Passel, S. (2025). The Usefulness of Climate Modelling for Humanitarian Aid Resource Allocation: An Exploratory Literature Review. *Economics of Disasters and Climate Change*, *9*(1), 189–207. https://doi.org/10.1007/s41885-024-00168-y

Jäpölä, J.-P., Van Schoubroeck, S., & Van Passel, S. (2024). Preferences on funding humanitarian aid and disaster management under climatic losses and damages: A multinational Delphi panel. *Climatic Change*, *177*(7), 113. https://doi.org/10.1007/s10584-024-03741-2

Jäpölä, J.-P., Van Schoubroeck, S., & Van Passel, S. (2025). Prioritising humanitarian and disaster aid funding in an era of climatic losses and damages. *International Journal of Disaster Risk Reduction*, *128*, 105751. https://doi.org/10.1016/j.ijdrr.2025.105751

KC, S., Moradhvaj, Potancokova, M., Adhikari, S., Yildiz, D., Mamolo, M., Sobotka, T., Zeman, K., Abel, G., Lutz, W., & Goujon, A. (2024). *Wittgenstein Center (WIC) Population and Human Capital Projections—2023* (Version V14) [Data set]. Zenodo. https://doi.org/10.5281/ZENODO.7767425

Kemp, L., Xu, C., Depledge, J., Ebi, K. L., Gibbins, G., Kohler, T. A., Rockström, J., Scheffer, M., Schellnhuber, H. J., Steffen, W., & Lenton, T. M. (2022). Climate Endgame: Exploring catastrophic climate change scenarios. *Proceedings of the National Academy of Sciences*, *119*(34). https://doi.org/10.1073/pnas.2108146119

Lenton, T. M., Xu, C., Abrams, J. F., Ghadiali, A., Loriani, S., Sakschewski, B., Zimm, C., Ebi, K. L., Dunn, R. R., Svenning, J.-C., & Scheffer, M. (2023). Quantifying the human cost of global warming. *Nature Sustainability*, *6*(10), 1237–1247. https://doi.org/10.1038/s41893-023-01132-6

Liu, K., Wang, R., Schrijver, I., & Hoekstra, R. (2024). Can we project well-being? Towards integral well-being projections in climate models and beyond. *Humanities and Social Sciences Communications*, *11*(1), 457. https://doi.org/10.1057/s41599-024-02941-6

Lyu, C., Liu, X., & Mihaylova, L. (2024). Review of Recent Advances in Gaussian Process Regression Methods. In G. Panoutsos, M. Mahfouf, & L. S. Mihaylova (Eds), *Advances in Computational Intelligence Systems* (pp. 226–237). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-55568-8_19

Marzi, S., Mysiak, J., Essenfelder, A. H., Pal, J. S., Vernaccini, L., Mistry, M. N., Alfieri, L., Poljansek, K., Marin-Ferrer, M., & Vousdoukas, M. (2021). Assessing future vulnerability and risk of humanitarian crises using climate change and population projections within the INFORM framework. *Global Environmental Change*, *71*, 102393. https://doi.org/10.1016/j.gloenvcha.2021.102393

Marzi, S., Poljanšek, K., Papadimitriou, E., Dalla Valle, D., Salvi, A., & Corbane, C. (2025). Assessing future risk of humanitarian crises using projections of climate-related hazards, population, conflict and other socioeconomic variables within the INFORM framework. *Big Earth Data*, *0*(0), 1–38. https://doi.org/10.1080/20964471.2025.2535852

McDougal, T. L., & Patterson, J. H. (2021). The global financial burden of humanitarian disasters: Leveraging GDP variation in the age of climate change. *International Journal of Disaster Risk Reduction*, *55*, 102073. https://doi.org/10.1016/j.ijdrr.2021.102073

Messina, J. P., Brady, O. J., Golding, N., Kraemer, M. U. G., Wint, G. R. W., Ray, S. E., Pigott, D. M., Shearer, F. M., Johnson, K., Earl, L., Marczak, L. B., Shirude, S., Davis Weaver, N., Gilbert, M., Velayudhan, R., Jones, P., Jaenisch, T., Scott, T. W., Reiner, R. C., & Hay, S. I. (2019). The current and future global distribution and population at risk of dengue. *Nature Microbiology*, *4*(9), 1508–1515. https://doi.org/10.1038/s41564-019-0476-8

Morris, J., Rose, S. K., Reilly, J., Gurgel, A., Paltsev, S., & Schlosser, C. A. (2025). Reconciling widely varying estimates of the global economic impacts from climate change. *Nature Climate Change*, *15*(2), 124–127. https://doi.org/10.1038/s41558-024-02232-7

Myhre, G., Hodnebrog, Ø., Loeb, N., & Forster, P. M. (2025a). Observed trend in Earth energy imbalance may provide a constraint for low climate sensitivity models. *Science*, *388*(6752), 1210–1213. https://doi.org/10.1126/science.adt0647

Myhre, G., Hodnebrog, Ø., Loeb, N., & Forster, P. M. (2025b). Observed trend in Earth energy imbalance may provide a constraint for low climate sensitivity models. *Science*, *388*(6752), 1210–1213. https://doi.org/10.1126/science.adt0647

Neal, T., Newell, B. R., & Pitman, A. (2025). Reconsidering the macroeconomic damage of severe warming. *Environmental Research Letters*, *20*(4), 044029. https://doi.org/10.1088/1748-9326/adbd58

Newell, R. G., Prest, B. C., & Sexton, S. E. (2021). The GDP-Temperature relationship: Implications for climate change damages. *Journal of Environmental Economics and Management*, *108*, 102445. https://doi.org/10.1016/j.jeem.2021.102445

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics*, *88*(2), 221–231. https://doi.org/10.1016/j.jdeveco.2008.02.005

OECD. (2025). *Cuts in official development assistance: OECD projections for 2025 and the near term* (26th edn, OECD Policy Briefs) [OECD Policy Briefs]. https://doi.org/10.1787/8c530629-en

Pagani, M., García-Pelaez, J., Gee, R., Johnson, K., Poggi, V., Simionato, M., Styron, R., Viganò, D., Danciu, L., Monelli, D., & Weatherill, G. (2018). *GEM Global Seismic Hazard Map v.2018.1*. Global Earthquake Model Foundation. https://doi.org/10.13117/GEM-GLOBAL-SEISMIC-HAZARD-MAP-2018.1

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, *12*(85), 2825–2830.

Rasmussen, C. E., & Williams, C. K. I. (2005). *Gaussian processes for machine learning*. MIT Press. https://doi.org/10.7551/mitpress/3206.001.0001

Rising, J. A., Taylor, C., Ives, M. C., & Ward, R. E. T. (2022). Challenges and innovations in the economic evaluation of the risks of climate change. *Ecological Economics*, *197*, 107437. https://doi.org/10.1016/j.ecolecon.2022.107437

Sen, P. K. (1968). Estimates of the Regression Coefficient Based on Kendall’s Tau. *Journal of the American Statistical Association*, *63*(324), 1379–1389. https://doi.org/10.1080/01621459.1968.10480934

Stalhandske, Z., de Ruiter, M. C., Chambers, J., Zimmermann, S., Colón-González, F. J., Sairam, N., Bresch, D. N., & Kropf, C. M. (2025). Global assessment of population exposure to multiple climate-related hazards from 2003 to 2021: A retrospective analysis. *The Lancet Planetary Health*, 101295. https://doi.org/10.1016/j.lanplh.2025.101295

Stern, N., Stiglitz Charlotte Taylor,Joseph, & and Taylor, C. (2022). The economics of immense risk, urgent action and radical change: Towards new approaches to the economics of climate change. *Journal of Economic Methodology*, *29*(3), 181–216. https://doi.org/10.1080/1350178X.2022.2040740

Syria 3RP. (2025). *Annual Report 2024—Syria Crisis Regional Refugee & Resilience Plan*. https://www.3rpsyriacrisis.org

Theil, H. (1950). Rank-Invariant Method of Linear and Polynomial Regression Analysis I, II, III. *Proceedings of the Royal Netherlands Academy of Sciences*, *53*, Part I: 386-392, Part II: 521-525, Part III: 1397-1412.

Tol, R. S. J. (2024). A meta-analysis of the total economic impact of climate change. *Energy Policy*, *185*, 113922. https://doi.org/10.1016/j.enpol.2023.113922

UNISDR (Ed.). (2015). *Making development sustainable: The future of disaster risk management*. https://www.undrr.org/publication/global-assessment-report-disaster-risk-reduction-2015

van der Wijst, K.-I., Bosello, F., Dasgupta, S., Drouet, L., Emmerling, J., Hof, A., Leimbach, M., Parrado, R., Piontek, F., Standardi, G., & van Vuuren, D. (2023). New damage curves and multimodel analysis suggest lower optimal temperature. *Nature Climate Change*, *13*(5), 434–441. https://doi.org/10.1038/s41558-023-01636-1

Vousdoukas, M. I., Mentaschi, L., Voukouvalas, E., Bianchi, A., Dottori, F., & Feyen, L. (2018). Climatic and socioeconomic controls of future coastal flood risk in Europe. *Nature Climate Change*, *8*(9), 776–780. https://doi.org/10.1038/s41558-018-0260-4

Vousdoukas, M. I., Mentaschi, L., Voukouvalas, E., Verlaan, M., Jevrejeva, S., Jackson, L. P., & Feyen, L. (2018). Global probabilistic projections of extreme sea levels show intensification of coastal flood hazard. *Nature Communications*, *9*(1), 2360. https://doi.org/10.1038/s41467-018-04692-w

Waidelich, P., Batibeniz, F., Rising, J., Kikstra, J. S., & Seneviratne, S. I. (2024). Climate damage projections beyond annual temperature. *Nature Climate Change*, *14*(6), 592–599. https://doi.org/10.1038/s41558-024-01990-8

Ward, P. J., Winsemius, H. C., Kuzma, S., Bierkens, M. F. P., Bouwman, A., Moel, H. D., Loaiza, A. D., Eilander, D., Englhardt, J., Erkens, G., Gebremedhin, E. T., Iceland, C., Kooi, H., Ligtvoet, W., Muis, S., Scussolini, P., Sutanudjaja, E. H., Beek, R. V., Bemmel, B. V., … Luo, T. (2020). *Aqueduct Floods Methodology*. https://www.wri.org/research/aqueduct-floods-methodology

Webster, M., Ginnetti, J., Walker, P., Coppard, D., & Kent, R. (2008). *The Humanitarian Costs Of Climate Change*. Feinstein International Center. https://fic.tufts.edu/wp-content/uploads/humanitarian-cost-of-climate-change-2008.pdf

Weisbach, D. A., & Sunstein, C. R. (2009). Climate Change and Discounting the Future: A Guide for the Perplexed. *Yale Law and Policy Review*, *433*. https://doi.org/10.2139/ssrn.1223448

Weitzman, M. L. (2011). Fat-Tailed Uncertainty in the Economics of Catastrophic Climate Change. *Review of Environmental Economics and Policy*, *5*(2), 275–292. https://doi.org/10.1093/reep/rer006

Wescombe, N. J., Martínez, J. G., Jehn, F. U., Wunderling, N., Tzachor, A., Sandström, V., Cassidy, M., Ainsworth, R., & Denkenberger, D. (2025). It's time to consider global catastrophic food failures. *Global Food Security*, *46*, 100880. https://doi.org/10.1016/j.gfs.2025.100880

WHO. (2023). *World Malaria Report 2023* (1st ed). World Health Organization. https://www.who.int/teams/global-malaria-programme/reports/world-malaria-report-2023

Zscheischler, J., Westra, S., van den Hurk, B. J. J. M., Seneviratne, S. I., Ward, P. J., Pitman, A., AghaKouchak, A., Bresch, D. N., Leonard, M., Wahl, T., & Zhang, X. (2018). Future climate risk from compound events. *Nature Climate Change*, *8*(6), 469–477. https://doi.org/10.1038/s41558-018-0156-3