The tip of the iceberg : Future of humanitarian crises under climate change and a funding model to support them

Juha-Pekka Jäpölä

Supervisors **Prof. Dr. Steven Van Passel | Dr. Sophie Van Schoubroeck**

Thesis submitted for the degree of Doctor of Applied Economics
Faculty of Business and Economics | Antwerp, 2026

University of Antwerp

EQUIS ACCREDITED AACSB ACCREDITED NVAO

The PhD researcher and supervisors declare that the PhD research was conducted according to the principles of scientific integrity, as mentioned in the general PhD regulations and charter for PhD researchers of UAntwerp and the integrity charter for PhD researchers and supervisors affiliated with the University of Antwerp.

The information and views set out in this thesis are those of the author (who works simultaneously at the European Union) and do not necessarily reflect the official opinion of the Union.

Cover Photo: Christopher Scott / Alamy (IY06372244)

Members of the Jury

Chair **Prof. Dr. Tine COMPERNOLLE**	Faculty of Business and Economics, University of Antwerp
Supervisor **Prof. Dr. Steven VAN PASSEL**	Faculty of Business and Economics, University of Antwerp
Supervisor **Dr. Sophie VAN SCHOUBROECK**	Faculty of Business and Economics, University of Antwerp
Prof. Dr. Hans BRUYNINCKX	Faculty of Social Sciences, University of Antwerp
Dr. Jan HOOGMARTENS	Head of Cabinet, European Commissioner for Equality, Preparedness and Crisis Management Hadja Lahbib, Brussels
Dr. Artur MALANTOWICZ	Policy Assistant to the Director-General for European Civil Protection and Humanitarian Aid Operations (ECHO), European Commission, Brussels
Dr. Loic De WEERDT	Economist, World Bank, Washington, D.C.

Summary

In a world where climate change is accelerating humanitarian crises, understanding the future economic magnitude of these crises is critical. Every 26th person in the world needed humanitarian assistance in 2025. The total was 307 million people in need—almost the size of the United States—while the coordinated funding requirement, or appeal for support, to cover their needs was USD 45 billion—comparatively almost the GDP of Jordan. Yet, despite the growing need, only 35% of the appeal was met in 2025, leaving millions without critical support. Simultaneously, traditional economic models, which often focus on market-based impacts, fail to capture the compounding, non-market risks of climate-humanitarian crises. This gap leaves policymakers and humanitarian actors without the tools they need to allocate resources effectively in a rapidly changing world marked with cuts to multilateral development budgets, and increased state-level hostilities. In short, our knowledge of the future trade-off between adaptation and humanitarian response is limited.

The thesis addresses this shortcoming by developing a climate-informed humanitarian funding model that bridges scientific projections with actionable policy insights. It began by examining the current state of climate modelling in humanitarian contexts, indicating that more than half of the studies in the sample lacked actionable utility for funding decisions. Then, a Delphi panel of 36 international experts, such as the World Bank, identified stated preferences in funding priorities, emphasizing people-centric and disaster risk criteria over more institutional metrics like governance or rule of law.

Next, for the first time, this dissertation uses a stochastic multi-attribute analysis (SMAA) model against real-world data from the United Nations Office for the Coordination of Humanitarian Affairs (UN OCHA), showing strong alignment. Finally, the research culminates in machine learning-based simulations of future humanitarian needs under the business-as-usual SSP2-RCP4.5 climate scenario with warming limited to 3°C by 2100—likewise a first time to be performed at this level and scale. Humanitarian needs rise to a baseline of 410±22 million people and USD_{2024} 64±8 billion annually by 2050 worldwide, increases of 28% and 30% respectively compared to 2024 (320 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 92% and 96% respectively. The results show an opportunity cost, as resources for crisis response displace funding for adaptation and mitigation. This poses a plausible future where saving immediate lives can become more imperative than reserving funds for future generations, creating a feedback loop. Yet sustained investment could curb the impacts even with climate inertia and pressure to cut development cooperation and humanitarian assistance.

This thesis introduces three key innovations: (1) Actionable and policy-proof metrics that use people in need and funding requirements as proxies for climate damage; (2) use of machine learning—namely Gaussian Process Regression (GPR)—and stochastic methods as an econometric tool in a data sparse and asymmetric environment, and (3) behavioural insights from the Delphi panel that ground the modelling parameters and choices. Its main contribution is to propose a new way to build a sectoral damage function to inform climate policy and close gaps in traditional economic modelling that struggles with non-market and extreme event data as well as human cost. The findings underscore the urgency of investing in adaptation to prevent a future where reactive spending crowds out preventive measures and creates vicious loops or gravity wells for vulnerable countries.

The results of the thesis could be useful for the on-going negotiation around the European Union's next multiannual financial framework for 2028–2034 or for discussions around an integrated approach for fragility. By quantifying the human cost of inaction, the research in it provides policymakers with a framework and evidence to reallocate resources from reactive aid to proactive resilience—before the inertia of climate change locks us into irreversible damage. It argues that humanitarian crises are the tip of iceberg for climate change adaptation, first indicators of possibly irreversible societal damage in fragile countries before the larger mass.

Its policy recommendations include more bundled and legally coupled funding instruments in the humanitarian-development-peace nexus (e.g., climate resilience investment following humanitarian response) to achieve an integrated approach. Similarly, practical technical suggestions to introduce simplified consensus-based indicator frameworks across nexus funding and addition of probabilistic funding solutions.

Samenvatting (Dutch Summary)

Proefschrift ingediend voor het behalen van de graad doctor in de toegepaste economische wetenschappen:

Het topje van de ijsberg

De toekomst van humanitaire crisissen onder klimaatverandering en een financieringsmodel om deze te ondersteunen

In een wereld waarin klimaatverandering humanitaire crisissen in de hand werkt, is het van cruciaal belang om inzicht te krijgen in de toekomstige economische omvang van deze crisissen. In 2025 had één op de 26 mensen wereldwijd humanitaire hulp nodig. In totaal waren er 307 miljoen mensen in nood – bijna evenveel als de bevolking van de Verenigde Staten – terwijl de gecoördineerde financieringsbehoefte, of oproep tot steun, om in hun behoeften te voorzien 45 miljard dollar bedroeg – vergeleken met bijna het bbp van Jordanië. Maar ondanks de groeiende behoefte werd in 2025 slechts 35% van de oproep gehonoreerd, waardoor miljoenen mensen zonder cruciale steun kwamen te zitten. Tegelijkertijd slagen traditionele economische modellen, die vaak gericht zijn op marktgerichte effecten, er niet in om de samengestelde, niet-marktgerelateerde risico's van klimaat-humanitaire crisissen in kaart te brengen. Door deze kloof beschikken beleidsmakers en humanitaire actoren niet over de instrumenten die zij nodig hebben om middelen effectief toe te wijzen in een snel veranderende wereld die wordt gekenmerkt door bezuinigingen op multilaterale ontwikkelingsbudgetten en toegenomen vijandigheden op staatsniveau. Kortom, onze kennis van de toekomstige afweging tussen aanpassing en humanitaire respons is beperkt.

Dit proefschrift pakt deze tekortkoming aan door een op klimaatgegevens gebaseerd financieringsmodel voor humanitaire hulp te ontwikkelen dat een brug slaat tussen wetenschappelijke prognoses en bruikbare beleidsinzichten. Het onderzoek begon met een analyse van de huidige stand van zaken op het gebied van klimaatmodellering in humanitaire contexten, waaruit bleek dat meer dan de helft van de onderzochte studies onvoldoende bruikbaar was voor financieringsbeslissingen. Vervolgens heeft een Delphi-panel van 36 internationale deskundigen, waaronder de Wereldbank, de aangegeven voorkeuren voor financieringsprioriteiten in kaart gebracht, waarbij de nadruk lag op mensgerichte criteria en criteria voor rampenrisico's boven meer institutionele maatstaven zoals bestuur of de rechtsstaat.

Vervolgens wordt in dit proefschrift voor het eerst een stochastisch multi-attribuutanalysemodel (SMAA) toegepast op praktijkgegevens van het Bureau voor de coördinatie van humanitaire zaken van de Verenigde Naties (UN OCHA), waarbij een sterke overeenstemming blijkt. Ten slotte culmineert het onderzoek in op machine learning gebaseerde simulaties van toekomstige humanitaire behoeften onder het ‘business-as-usual’ SSP2-RCP4.5-klimaatscenario, waarbij de opwarming tot 2100 beperkt blijft tot 3 °C – eveneens een primeur op dit niveau en deze schaal. De humanitaire behoeften stijgen wereldwijd tot een basisniveau van 410±22 miljoen mensen en 64±8 miljard USD_{2024} per jaar tegen 2050, een stijging van respectievelijk 28% en 30% ten opzichte van 2024 (320 miljoen mensen en 49 miljard USD). In een gematigd simulatie houdt de behoeften dicht bij het huidige niveau, terwijl een gemiddeld pessimistische simulatie leidt tot 614±68 miljoen mensen en 96±19 miljard USD_{2024} tegen 2050, een stijging van respectievelijk 92% en 96%. De resultaten laten opportuniteitskosten zien, aangezien middelen voor crisissenrespons ten koste gaan van financiering voor aanpassing en mitigatie. Dit schetst een aannemelijk toekomstscenario waarin het redden van levens op dit moment dringender kan worden dan het reserveren van middelen voor toekomstige generaties, waardoor een vicieuze cirkel ontstaat. Toch zouden aanhoudende investeringen de gevolgen kunnen beperken, zelfs bij klimaatinertie en druk om te bezuinigen op ontwikkelingssamenwerking en humanitaire hulp.

Dit proefschrift introduceert drie belangrijke innovaties: (1) Bruikbare en beleidsbestendige maatstaven die mensen in nood en financieringsbehoeften gebruiken als indicatoren voor klimaatschade; (2) het gebruik van machine learning—namelijk Gaussiaanse procesregressie (GPR) —en stochastische methoden als econometrisch instrument in een omgeving met schaarse en asymmetrische gegevens, en (3) gedragsinzichten uit het Delphi-panel die de basis vormen voor de modelleringsparameters en -keuzes. De belangrijkste bijdrage van dit

proefschrift is het voorstellen van een nieuwe manier om een sectorale schadefunctie op te stellen ter ondersteuning van het klimaatbeleid en om hiaten te dichten in traditionele economische modellen die worstelen met gegevens over niet-marktgerelateerde en extreme gebeurtenissen, evenals met menselijke kosten. De bevindingen benadrukken de urgentie van investeringen in aanpassing om een toekomst te voorkomen waarin reactieve uitgaven preventieve maatregelen verdringen en vicieuze cirkels of zwaartekracht voor kwetsbare landen.

De resultaten van het proefschrift kunnen van nut zijn voor de lopende onderhandelingen over het volgende meerjarig financieel kader van de Europese Unie voor 2028–2034 of voor discussies over een geïntegreerde aanpak van kwetsbaarheid. Door de menselijke kosten van nietsdoen te kwantificeren, biedt het onderzoek beleidsmakers een kader en bewijs om middelen te herverdelen van reactieve hulp naar proactieve veerkracht – voordat de inertie van klimaatverandering ons opzadelt met onomkeerbare schade. Het stelt dat humanitaire crises het topje van de ijsberg zijn voor aanpassing aan klimaatverandering, de eerste indicatoren van mogelijk onomkeerbare maatschappelijke schade in kwetsbare landen, nog voordat de grotere massa zich aandient.

De beleidsaanbevelingen omvatten onder meer meer gebundelde en juridisch gekoppelde financieringsinstrumenten binnen het raakvlak tussen humanitaire hulp, ontwikkeling en vrede (bijvoorbeeld aanpassingsmaatregelen in het verlengde van humanitaire hulp) om tot een geïntegreerde aanpak te komen. Daarnaast worden er praktische technische suggesties gedaan om vereenvoudigde, op consensus gebaseerde indicatorenkaders in te voeren voor de financiering van dit raakvlak, en om probabilistische financieringsoplossingen toe te voegen.

Table of Contents

INTRODUCTION

I Background

2025 ranks as the third warmest year on record, following the unprecedented temperatures observed in 2023 and 2024 (Figure 1). The average annual temperatures exceeded 1,5°C above pre-industrial levels (C3S/ECMWF, 2026) and at least momentarily above the Paris Agreement limit—although the effects of, for example, El Niño can contribute (Bevacqua et al., 2025; Cannon, 2025). This unprecedented heat, coupled with extreme weather attributed to climate change (World Weather Attribution, n.d.) signals a new era that the humanitarian system will have to cope with. In 2022, the Glasgow Climate Pact of the UN Climate Change Conference (COP26) acknowledged that "impacts from climate and weather extremes, as well as slow onset events, will pose an ever-greater social, economic and environmental threat." (United Nations, 2021). In 2025, three years later, the Fund for Responding to Loss and Damage (FRLD) was created in COP29 in Baku with an aim to assist developing countries that are particularly vulnerable to the adverse effects of climate change. It received over USD 750 million in pledges. COP29 also saw agreement on the New Collective Quantified Goal on Climate Finance (NCQG) to triple climate finance to USD 300 billion annually by 2035. At COP30 in Belém, the parties agreed to triple the share of financing going to adaptation also by 2035 within the larger climate finance umbrella—although the baseline was left undetermined.

A humanitarian crisis occurs when people's needs far exceed local capacities to support them. This is often due to a combination of natural and human-induced hazards, requiring significant external aid.[1] Afghanistan, the occupied Palestinian territory, Sudan, and Ukraine are likely the most known crises with significant humanitarian needs in 2025. Climate change is contributing to humanitarian crises increasingly, especially in the most vulnerable regions (IPCC, 2023a, p. 16). For example, in September 2023, Storm Daniel killed at least 4 300 in the Mediterranean. It created an aid appeal of USD 71 million to support the 250 000 affected people in Libya alone (UN OCHA, 2023). World Weather Attribution assessed that a similar extreme storm was 50 times more likely and 50% more intense compared to a climate that had not warmed up due to anthropogenic activity (Zachariah et al., 2023, p. 2).

This aid, also often called humanitarian relief or emergency assistance, is the provision of lifesaving, material, and logistic assistance to the people affected to alleviate their suffering and maintain human dignity. It is based on the principles of humanity, impartiality, neutrality, and independence. Assistance can comprise the delivery of essential supplies like food, water, shelter, and medical care, often as a short-term response to acute emergencies—but equally well to protracted long-term crises that are locked in a vicious cycle, such as in Yemen or in the Democratic Republic of the Congo[2]. Rationally and in the humanitarian-development nexus, both disaster risk reduction and climate change adaptation, as long-term preparedness instruments, as well as conflict mediation, coalesce into humanitarian envelopes. Humanitarian funding is globally coordinated by the United Nations (UN) Office for the Coordination of Humanitarian Affairs (OCHA)[3] often provided from state budgets or the European Commission's Directorate-General for European Civil Protection and Humanitarian Aid Operations (DG ECHO) to international organisations, such as the World Food Programme (WFP), the UN Refugee Agency (UNHCR), or the UN Children's Fund (UNICEF)—as well as non-governmental organisations like Red Cross, Oxfam, Save the Children, or Médecins Sans Frontières—who then manage the project or programme to bring the aid in cooperation with local partners (Picture 1).

---

[1] See e.g., UN General Assembly Resolution 46/182, UN General Assembly Resolution 58/114, and the European Consensus on Humanitarian Aid.
[2] https://www.consilium.europa.eu/en/policies/humanitarian-aid/
[3] https://www.unocha.org/we-coordinate

Picture 1. Different forms of humanitarian aid.

In clockwise order from top right. (1) Garineh, displaced from Nagorno-Karabakh to Armenia, received a food card. (2) Along a narrow path lined with temporary shelters, trucks offload relief items after Pakistan's devastating floods. (3) Delivery of rice in Nyampoka, a community cut off in Mozambique by the floodwaters following cyclone Idai. (4) Distribution of essential hygiene items to the displaced amid COVID-19 and illegal armed groups in Colombia. (5) Assessing drought damage from El Niño in Ethiopia. (6) A group of children, displaced by fighting in Yemen, participate in catch-up classes. (7) One year after the earthquake, the women in temporary camps in Türkiye are learning new skills like giving haircuts. (8) Clear drinking water and sanitation facilities provided to Rohingya refugees in Bangladesh's Cox Bazar district.

Notwithstanding the COP process, the scarce resources available for humanitarian or development funding were and are not expected to improve significantly de facto. Different annual levels of humanitarian need and funding are introduced throughout this dissertation. In 2022, 274 million people—or every 29th person in the world—were estimated to need humanitarian aid in 2022. A noteworthy increase from the 2021 number, 235 million, which was already the highest figure in decades. In 2025, **one in every 26 people worldwide needed humanitarian assistance**, totalling 307 million with a funding requirement of USD 45 billion (UN OCHA, 2025). In the early 2010s, the funding appeals were around USD 6–10 billion. We can provide these amounts, while the estimated need has been 1,5–2,0 times higher. In 2022, the EUR 19,2 billion gap back then between requirements and funding was the highest ever (UN OCHA, 2021, p. 9, 23). The funded envelope comprised 10% of the total USD 213 billion in Official Development Assistance (ODA) at the same time. (OECD ODA, 2023; UN FTS, n.d.).

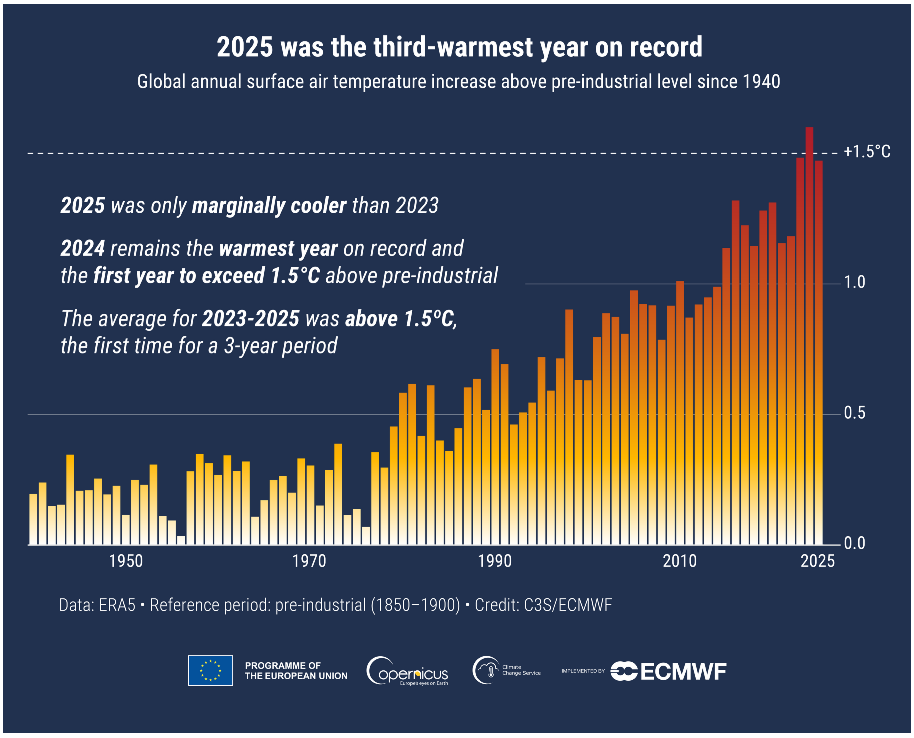


Figure 1. Global surface air temperature increase

The figure comprises °C above the average for the 1850–1900 designated pre-industrial reference period based on the ERA5 dataset, shown as annual averages since 1940 (C3S/ECMWF, 2026).

Past examinations have come to different estimates of the humanitarian cost of climate change and *are trailing behind 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 200 million by 2050 (IFRC, 2019) while the global people in need in 2025, including from conflict, is 320 million. McDougal and Patterson (2021) computed an almost 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 calculated a range from 16% to 800% in increase of response costs between 2008 and 2028 without inflation (Webster et al., 2008). However, historically, the funding requirement has risen 690% (from 7,1B to 49B) since 2008[4].

Next, the dissertation identifies the problem more concretely and examines its policy context.

[4] https://fts.unocha.org

II Problem identification and policy context

Status in the literature and real-world problem

Economic assessments of climate change damage often leverage ample amounts of data to assess labour and production. They receive criticism or have gaps in, among others, empirical calibration, in utilising non-monetary insight, and in accounting for extreme events or fragile countries (Auffhammer, 2018; Botzen et al., 2019; Stern et al., 2022). Humanitarian aid is a legal and moral obligation while also altruistic and meant to save human life. Thus, it does not have a market that directly corresponds to its cost and monetary valuation of a human life is in any case a complex procedure with a moral implication. Common methods to elicit it include revealed or stated preferences, such as contingent valuation or discrete choice where participants have to make trade-offs between scenarios and place a monetary value on the non-market item (e.g., Keller et al., 2021; Lenton et al., 2023).

Likewise, discerning climate change's effects on extreme cascading events, such as humanitarian crises, is a long-term research agenda (Dunz et al., 2023; Hallegatte et al., 2007; Noy, 2009; Zscheischler et al., 2018). Beyond studies on production and labour, analyses on human impact of hazards often stay at the level of risk or exposure (Marzi et al., 2021, 2025; Stalhandske et al., 2025) that do not necessarily translate to actionability.

While decision-making on allocating resources in humanitarian and disaster aid has become more informed by evidence, the requirement to have robust analysis behind it has increased considerably. For example, the INFORM composite indices[5] are good base datasets on comparability of severity and risk of crises (Poljansek et al., 2020, 2022). The indices, leveraging global data on hazard and vulnerability, 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 WFP and the International Federation of Red Cross and Red Crescent Societies (IFRC), to support humanitarian and disaster risk reduction decision-making (European Commission. Joint Research Centre., 2024).

Fundamentally, there is no significant difference for humanitarian aid in responding to emergencies that are more climate-driven (e.g., floods) versus more human-induced (e.g., war) excluding the conditions and the type of assistance needed—an impact is an impact and often they are present together while cascading and compounding. However, attributing effects of climate change and allocating funds effectively is a challenge because the current ensemble of economic models, such as integrated assessment models (IAMs), were not built to obtain analyses with the range of extreme events—especially if it includes non-market data (Auffhammer, 2018; Botzen et al., 2019; IPCC WG3, 2022, p. 88; Newman & Noy, 2023; Rising et al., 2022; Stern et al., 2022). This is particularly valid in response to crises in chaotic states with minimal amount of data. Here, delineating the possible influence of climate change on a disaster or an event could be near impossible in a reasonable timespan. For instance, in South Sudan, record floods have worsened food and livelihood insecurity. This pushes pastoralists south, where their presence increases violent tensions with resident farmers (International Crisis Group, 2022). In total, 9 million people required humanitarian assistance in 2024, including 7 million facing famine-like conditions during the lean period (European Commission, 2024). Here, even with years of careful analyses, we might not be able to know what the ratio of climate change impact was compared to human factors.

Besides gross domestic production (GDP), studies on human impact of (climate) hazards often resort to analytical layers, such as exposure to hazard or future risk of humanitarian crises, as their result (Marzi et al., 2021, 2025; Stalhandske et al., 2025). The work of the thesis seeks to improve them by estimating empirical vulnerability – based on historical data – with a modified damage function (e.g., Hsiang et al., 2017). The improvement is based on a new methodological framework that is empirically calibrated with UN OCHA assessments of people in need and required funding. The scope of the dissertation represents the most vulnerable 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].

Allocating limited public resources—both now and in the long term—to diverse groups with varying needs presents an immense challenge. Beyond the urgency of time constraints, the process of prioritization is shaped by factors such as political dynamics, scientific ambiguity, public opinion, and a multitude of geographic and temporal considerations (Neumayer et al., 2014; Polasky et al., 2019). Within humanitarian and disaster response

[5] https://drmkc.jrc.ec.europa.eu/inform-index/

organizations, decisions about the criteria and predictive models used to distribute funding are made regularly, though the underlying justifications are often implicit or informal (IPCC WG2, 2022, p. 2575). Strengthening the human expertise required for these assessments is critical, particularly in operational agencies tasked with evaluating complex, high-dimensional forecast models or the long-term behaviour of intricate systems (UNDRR, 2021; World Bank, 2021; Millner & Heyen, 2021; Puy et al., 2022).

The humanitarian sector is a crucial lens to climate change. **They are the tip of the iceberg for climate change damage and are most vulnerable to it.** As any funding provided to solve humanitarian crises does not effectively have a net economic benefit, it is an effective broken window. In other words, all funding to it, while important on its own for lifesaving and safeguarding efforts, is an opportunity cost to other sectors, such as disaster risk reduction or climate change adaptation. *In a world with scarce resources, the need to manage humanitarian crises will (ceteris paribus), reduce the funding available for other climate change or welfare-related initiatives*. Adaptation financing reaches the most fragile and conflict-ridden countries less than others (Läderach et al., 2021), there are recommendations to increase the preventive and longer term temporal scope of humanitarian assistance (de Geoffroy, 2021; Steinke, 2023) while the humanitarian-development nexus, where effective synergies from short term response to long term adaptation should form, is a contested topic (Lie, 2020). **In short, our knowledge of the future trade-off between adaptation and short-term humanitarian response is limited.** Especially in a plausible scenario saving more lives imminently or controlling the live spiralling feedback effects of climate change, such as spillovers of large-scale cascading disasters and crises, can become more imperative for the policy apparatus than reserving funds for future generations.

Economic theory and concept

The real-world situation brings us to the economic concepts wherein I examine the problem. Apart from belonging to the domain of environmental economics, the general approach of the study is a **neoclassica**l take so that the impact of climate change is a market failure that can and should be corrected by a public intervention. Here primarily that more disasters and conflict will result in humanitarian need that is predominantly corrected with the non-excludable and non-rivalrous public good of humanitarian aid. That is, it is provided by a government and paid through taxation. The good of humanitarian aid can be thus juxtaposed with the goods of climate adaptation, disaster risk reduction, and preparedness that attempt to correct the market failure in the future. Key builders of neoclassical economics include, for example, Marshall (1890), (1936), and Samuelson (1947). Formally, I take a mainly marginalist stance that both have binding trade-offs and utility of their own, but with fixed resources they can eat each other's shares from the common cake that is available from public funding—also called the cake cutting problem in a resource allocation. Or the other way around, that policy will always have to choose between the two.

However, this can be too simplistic of an assumption. For example, instead of a stark division between two utilities, the process of adapting to climate change and reducing the need for humanitarian aid can be **evolutionary or institutional** whereby investments address both at the same time, institutions locally become more effective in governing a sustainable path, and that innovation creates efficiency gains in response and adaptation technologies through creative destruction (e.g., North, 1990; Ostrom; 1990; Schumpeter, 1934). This school of thought can have more validity and prevail in the thesis' setting because climate change's humanitarian effects can follow a cascading and compounding path whereby decisions or conditions far away from the initial marginalist goods of humanitarian support and adaptation are the root cause for it. For example, that the primarily cause for a humanitarian crisis could be pure human conflict which climate amplifies or that legal land management issues were the reason why a community is now vulnerable to extreme events. In the end, the thesis has been constructed mathematically as a marginalist one but discusses its results in the context of the messy real world with wicked problems where more nuanced transformation is needed. In line with the humanitarian principle of impartiality, the most applicable maximisation strategy throughout the thesis is a Rawlsian or egalitarian distribution where the least advantaged or vulnerable would have the greatest benefit of humanitarian aid (Rawls, 1971).

Likewise, on decision-making, this thesis delves into the tension between expected utility theory (EUT) and observed empirical behaviour. At its core, EUT assumes that decision-makers or social planners, when faced with uncertainty, will select the option that maximizes expected utility. In contrast, **behavioural** economics posits that decision-makers and their processes are inherently constrained by cognitive limitations, incomplete information, and tight timelines, which often prevent the identification of an optimal solution—a concept known as bounded rationality. The pursuit of optimal resource allocation, alongside the capacity of economic actors to make rational choices and accurately forecast future outcomes, has been a central theme in economic theory. Scholars like Thaler (1980) expanded on the foundational work of Simon, Tversky, and Kahneman (Kahneman, 2003), exploring these challenges within behavioural economics. Notably, the IPCC (Intergovernmental Panel on Climate Change) Working Group 2 has seen limited engagement from economists (Noy, 2023), and its Sixth Assessment Report's chapter on 'Decision-making options for managing risk' only briefly addresses these considerations (IPCC WG2, 2022, Chapter 17).

Policy trend

During the last year of preparing this dissertation, the "cruel math of aid cuts" (as UN OCHA called it) became reality[6]. For example, more than 83% of USAID's (United States Agency for International Development) programmes (except for emergency food assistance and military aid) were terminated. USAID accounted for 41% of the USD 35 billions of global humanitarian aid funding (including to the UN OCHA coordinated plan) the previous year[7]. See Figure 2 for context. Similarly, the Organisation for Economic Co-operation and Development (OECD) reported that official development assistance in 2027 is due to fall to the 2022 levels due to cuts (OECD, 2025).

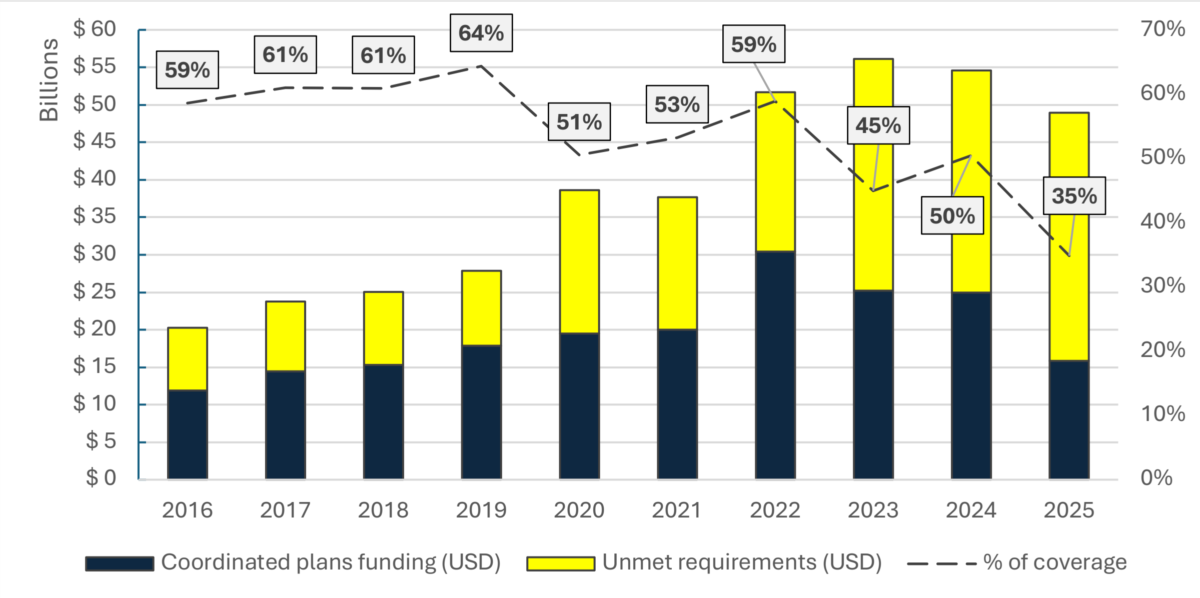


Figure 2. Total humanitarian funding needs and their coverage of funding.

By author based on UN OCHA[7].

Internally, this project originates in 2021 within the European Commission's DG ECHO, specifically in its humanitarian aid analysis team. Humanitarian aid funds assistance to people affected by human-induced or natural disasters. These disasters include not only conflict, but also floods, droughts, etc.—all of which are assumed to have a link with climate change. The team coordinates the annual humanitarian needs assessment of the European Union's (EU) aid budget[8]. The motivation came from a policy interest to introduce climate change-based factors into the assessment process as well as from lessons learned to further formalise what value-based indicators are the most critical in assessing the need. Likewise, it continues rationally from my previous thesis on development cooperation (Jäpölä, 2015).

The European Union's (EU) next long-term budget for 2028–2034 entered negotiation after the European Commission published its proposal in July 2025. Among others, the proposal included USD 230 billion—a nominal 75% increase compared to the previous budget—for global investments including support to humanitarian aid,

[6] https://humanitarianaction.info
[7] https://fts.unocha.org
[8] https://civil-protection-humanitarian-aid.ec.europa.eu/what/humanitarian-aid/needs-assessment_en

climate change, sustainable development, and peace[9]. The research within this thesis, especially the final working chapter, could be beneficial to the negotiation process as evidence as well as to support the EU's Integrated Approach to Fragility.

In the next section, I explain how the research framework to examine the problem is set up.

III Research questions and thesis structure

Hence, the overall research topic of the thesis was set to explore **a model for inserting climate change adaptation criteria into forecast-based funding for humanitarian aid**. Effectively, to (1) ascertain the status of taking climate change into account in humanitarian funding, (2) define what criteria and indicators are most relevant for forecast-based (i.e., planning funding for the future years based on projection) assessments, (3) how would the model compare against real world funding allocations, and (4) what humanitarian needs would it simulate for the International Panel on Climate Change (IPCC) scenario we are currently heading towards, a warming of 2,1–2,4°C above pre-industrial levels by 2100 (IPCC, 2023a). It aims to contribute to quantifying the human cost of climate change (e.g., Lenton et al., 2023) and in operationalizing climate modelling (Jakob et al., 2023). The dissertation presents several novelties, such as for the first time using both stochastic multi-criteria modelling in prioritisation of humanitarian crises and machine learning regression in covering the data scarcity of crisis zones for a future simulation. Their use is further explained below.

The method intended was, in all simplicity, to produce a quantitative model that fulfils the research topic's requirements including secondary questions, such as investigating equal and effective distribution according to the humanitarian principle of impartiality and correlation with the situation on the ground according to policy and expert views. The method was therefore mixed—although the end goal was a quantified outcome. This is reflected in the dissertation structure; whereby social and behavioural methods (Delphi panel and stated preference) are used for expert elicitation to complement and calibrate the operative (stochastic multi-attribute analysis [SMAA]) and econometric models (Gaussian Process Regression [GPR]).

The dissertation's concept 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 extended to include response as an additional component (IPCC, 2023b, p. 147). See the Cross-Section Box.2, Figure 1 of IPCC AR6 synthesis report for a concise overview of my conceptual scope[10]. In addition, the research uses a systemic multi-risk assessment approach. Although definitions vary, it essentially means taking into account multiple sources of hazard, exposure and vulnerability as well as their interconnections in a system (Higuera Roa et al., 2025; Hochrainer-Stigler et al., 2023)—in this case within the system of humanitarian assistance.

Therefore, this dissertation has four sub research questions (RQ) that move towards the model that could support in allocating funding for preparedness and adaptation as well as in estimating future costs (Figure 3).

---

[9] https://commission.europa.eu/strategy-and-policy/eu-budget/long-term-eu-budget/eu-budget-2028-2034_en
[10] https://www.ipcc.ch/report/ar6/syr/figures/csb-2-figure-1

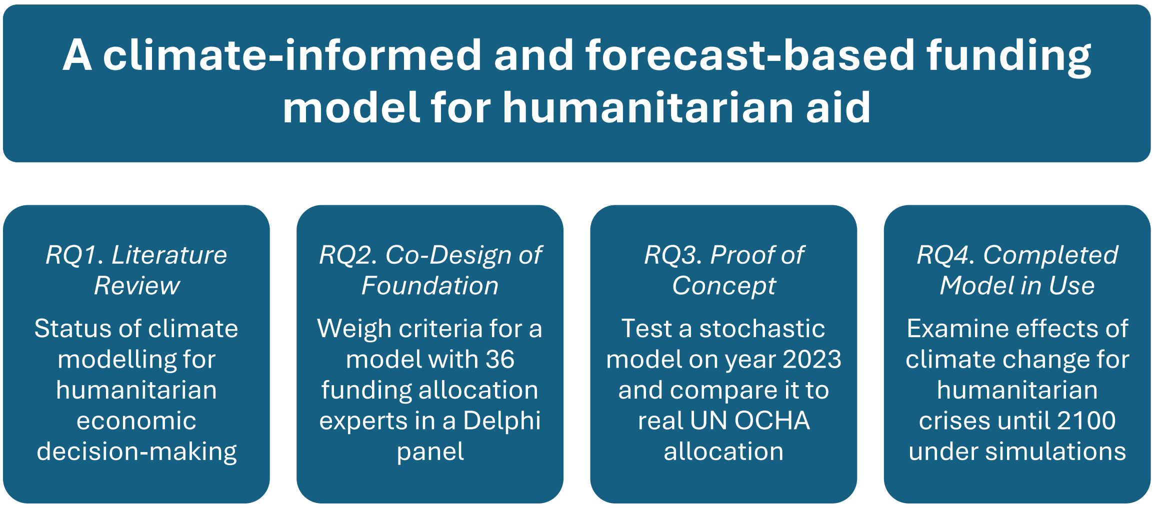


Figure 3. Research framework of the thesis.

Each numbered chapter of the thesis from now on corresponds to the respective RQ for ease of navigation. The first working chapter on RQ1, Chapter 1, is a literature review, while the next two build the concept of the model. In the final working chapter of RQ4, the model is used to simulate pathways of costs. Here, I further elaborate on the function of each RQ and chapter.

RQ1 / Chapter 1. How applicable is climate change-related modelling for economic decision-making in humanitarian aid resource allocation?

This question examines the state of the art and the general need for enhancing modelling in the sector as a basis for the dissertation. The hypothesis was that while the modelling of climate change as a physical mechanism is sound and valid, it is not transformed fluidly for economic decision-making needs in the humanitarian sector. For example, that economists are not engaged enough with the IPCC (Noy, 2023) or that the categories in anticipatory humanitarian financing are too blurred to be actionable (de Wit, 2019).

RQ2 / Chapter 2. What are the priority criteria in allocating humanitarian or disaster aid funding per future forecasts in view of climate change response or adaptation?

For the model to be explainable to the target audience of policymaking and funding decision-making, it should be co-designed with their viewpoint in mind. A key research area in this domain was to understand methodological strengths and weaknesses in damage estimation and reconcile the comparability differences (e.g., IPCC WG2 2022). Most importantly, what weight should be given to different types of data coming from the field and from other sources in the funding model?

This part of the thesis intends to find a scientifically transparent and stable consensus among a humanitarian and disaster aid expert panel who would prioritise criteria in computing funding. Should it be more structural criteria, such as rule of law, or more response-oriented ones, such as the estimated amount of people in the affected area? The widely applied Delphi method is used to come to terms on the weighting scheme for the next phase. Using a Delphi panel resolves expert disagreement on criteria and provides the model with a more realistic basis, contrasting with assumptive models.

In response to calls from Lentz and Maxwell (2022), Rising et al. (2022), and Stern et al. (2022), this part seeks to better inform decision-makers in humanitarian and disaster response, as well as climate change adaptation, by uncovering their inherent preferences. As highlighted in the IPCC AR6 WG2 report, the existing literature often overlooks the growing difficulty of adapting to future climate extremes and increased variability (IPCC, 2022, p. 2489).

RQ3 / Chapter 3. How would stochastic multi-attribute analysis (SMAA) and Delphi panel weighting prioritise resources in humanitarian crises with multiple disasters affecting them? How does the model compare versus official funding requirements?

Next, a model is tested. With the stated preferences from RQ2, we see how a standard humanitarian assessment dataset, such as INFORM Severity (Poljansek et al., 2020), would perform. For the first time, SMAA is used to compare and prioritise funding for 26 fragile countries that were encountering a humanitarian crisis in 2023.

SMAA is a subvariant of MCDA (multi-criteria decision analysis) that had been proposed as one solution to the wicked problems of climate change's deep uncertainty (IPCC WG2, 2022). The model test is compared against actual UN OCHA funding requirement data as a proof-of-concept. In addition, we conceptually investigate the use of the multi-risk concept (Hochrainer-Stigler et al. 2023; Lee et al., 2024) to overcome the difficulty in rapidly attributing a crisis to a specific natural or human-induced hazard—or a climatic or non-climatic driver (Otto et al., 2024).

According to IPCC AR6, MCDA is mainly used to explore conflicting objectives in climate risk management. MCDA's strengths include incorporating elements from other decision-analytic tools, such as Bayesian methods and decision-making under deep uncertainty (DMDU). However, it lacks in addressing stochastic and epistemic uncertainties (IPCC WG2, 2022, pp. 2569–2575). The chapter's method is novel, marking the first use of MCDA in a humanitarian context. Previously, MCDA has been used for sub-national or national recommendations or theoretical studies (Nain et al., 2023). The probabilistic nature of SMAA better reflects the chaotic nature of climate change and humanitarian crises. Likewise, it handles uncertainty in multi-criteria allocation.

RQ4 / Chapter 4. What is the economic magnitude of climate impact for humanitarian crises till 2100?

Finally, this chapter uses the findings, datasets, and insight of the previous steps to build a self-standing model. It creates simulations of economic pathways of humanitarian crises until 2050 under the SSP2-RCP4.5 climate scenario that we are now heading towards. It leverages people in need and funding requirement of aid as actionable metrics, calibrated by historical UN OCHA field assessments and computed with Gaussian Process Regression (GPR), a non-parametric Bayesian machine learning technique. GPR is especially designed for non-linear, sparse and noisy data where traditional regression methods would fail.

The chapter aims to cover gaps in the agenda on understanding the economic effects of extreme and compound events (Hallegatte et al., 2007; Noy, 2009; Zscheischler et al., 2018) and using recent knowledge from assessments of climatic damage, such as incorporating both global and country-level temperature (Neal et al., 2025; van der Wijst et al., 2023; Waidelich et al., 2024). The main intent of the analysis is to show what resources one would need to respond to the damage of climate change in a simulated future point.

The proposed methodological framework responds to the literature gap on the quantification of future projections of people in need of humanitarian aid. 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 primary unit of climate change impacts.

Each chapter from now on works towards answering these RQs in the same order. The first three working chapters have been published as separate articles in journals, while the last one, Chapter 4, has been submitted for publication. A final chapter concludes this dissertation with a short discussion on the main contributions, policy, as well as limitations and future research needs. The appendices of each chapter are available as online supplementary material on p. 90.

CHAPTER 1 The usefulness of climate modelling for humanitarian aid resource allocation: An exploratory literature review

ABSTRACT

The threats of climate change have become fundamental for the humanitarian sector. 305 million people—or every 26th person worldwide—will need humanitarian aid in 2025 comprising a funding requirement of USD 47,4 billion. Inserting climate change-related forecast information to compute sound economic decisions is a cutting-edge consideration for global humanitarian financing institutions, such as the United Nations and the European Union, to cope with the era of climate losses and damages.

Thus, we asked an interdisciplinary question: How useful is climate change-related modelling for economic decision-making in humanitarian aid resource allocation? We ran an exploratory literature review on this specific question by taking a snapshot of 41 studies on the Web of Science, assessed to which extent the utility of the modelling for economic decision-making was examined, and ranked them based on their usefulness.

The review indicates that there should be more efforts to improve the forecasting ability and the transformation of information from climate modelling fluidly to economic decision-making in the humanitarian sector to be actionable for effective resource allocation. We assessed that more than half (23/41) of our dataset had limited discussion on the utility or mostly challenges of further use for utility documented, the two least valuable ranks. By extension, similar allocation issues will exist in development and climate policy, where we adapt and build resilience before assistance is needed. To curb the problem, research on integrating the different communities is proposed.[11]

1.1 Introduction

With the era of climatic losses and damages starting, using climate change-related information to compute forecast-based economic decisions as equitably as possible is a cutting-edge problem for distributing global humanitarian aid. Several relevant institutions have only begun to produce the first set of guidance on it (European Commission, 2022; IFRC and Red Cross Red Crescent Climate Centre, 2023; UNDRR, 2023) – indicating the need to operationalise climate modelling (Jakob et al., 2023).

305 million people—or every 26th person worldwide—will need humanitarian aid in 2025 in 72 countries. This comprises an estimated funding requirement of USD 47,4 billion (UN OCHA, 2024). Humanitarian aid and disaster management funds assistance to people affected by disasters. These include conflict and floods, droughts, and forest fires—all assumed to be linked to climate change. They can be classified as market failures complicated by information asymmetry and requiring government intervention from root causes to post-shock recovery. (Carbonnier, 2016; Enríquez-de-Salamanca et al., 2017; Helm, 2010) Here, the research of distributing scarce

[11] This chapter has been published in 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.

public resources is at the heart of economics and the intersection of science and decision-making—influenced by various spatial and temporal variables and, e.g., political context, publicity, or scientific uncertainty. (Neumayer et al., 2014; Polasky et al., 2019)

The connection between humanitarian work and climate change is all but certain: The Working Group II (WG2) contribution to the IPCC (Intergovernmental Panel on Climate Change) Sixth Assessment Report (AR6) on "Impacts, Adaptation and Vulnerability" summarises with high confidence that "[c]limate change is contributing to humanitarian crises where climate hazards interact with high vulnerability" (IPCC WG2, 2022, p. 11) Concurrently, the scarce resources available are not expected to improve significantly. Equity and distributive justice will become a significant challenge with less funding for more people facing climate pressure. At the United Nations (UN) Climate Change Conference COP29, the Loss and Damage Fund was operationalized with more than USD 730 million in pledged support.

Thus, we ask an interdisciplinary question on the link between the forecasted outcome by modellers and its valorisation by decision-makers: **How useful is climate change-related modelling for economic decision-making in humanitarian aid resource allocation? Thus, we conduct a literature review on this specific question in an exploratory manner.** We will use what the author(s) of the studies express and identify relevant information (e.g., time and geographic scale) that could be informative for allocation purposes. The hypothesis is that while the modelling is sound and valid, it is not transformed fluidly for economic decision-making needs. For example, Noy (2023) has found vice versa that economists are not engaged enough with the IPCC.

For example, imagine a thought experiment where a governmental decision-maker is drafting the next multi-year budget for humanitarian aid between a set of countries. They are handed over a scientifically produced map based on country indices depending on their vulnerability to extreme threats of climate change in the next ten years. On the map, country A is heat mapped red or severe (e.g., index score of 65/100) and country B is mapped green and less severe (e.g., index score of 23/100). The first question from the drafter would be, "So how much more funding should we allocate in expected multi-year humanitarian aid for country A than country B according to the index? Half more? Approximately 3 times more as is the proportional index difference? Something else?" A climate model not tuned to equitable parameters (e.g., providing the magnitude of people involved) will likely not be able to give a credible enough answer—although it can serve informative purposes in justifying the budget decision or policy.

This hypothetical example already brings up a key point of our study: The relevant information must be combined in the hands of two communities, climate modellers and humanitarian aid professionals. Therefore, effective communication between these communities is critical. Here, we assess the problem from the policy side, or in other words, with the lens of a benevolent social planner in humanitarian aid. Lentz & Maxwell (2022, p. 11), being especially mindful of how decision-making is overloaded by the sheer amount of information to digest – recently proposed to reverse engineer the process and ask, "what information do we need for anticipatory (and other) action" instead of asking "what we can do with the information ([early warning] and otherwise) to inform action.

While one could assume that the longer-term perspective of climate change adaptation per se would not necessitate humanitarian aid involvement, the UN Office for the Coordination of Humanitarian Affairs (OCHA) holds that the growing humanitarian climate emergency requires more adaptation investments diverted to fragile and conflict-ridden countries, such as into disaster risk reduction (DRR) and early warning systems to enable anticipatory action (UN OCHA, 2024). Even more so, research on the INFORM Climate Change Risk tool has gone as far as to assess future vulnerability and risk of humanitarian crises per the IPCC's scenarios up to 2050 and 2080 (Marzi et al., 2021). The balance in allocation between different temporal phases is and will be a vital issue in climate change adaptation. Thus, forecast quality is relevant, as are time and geographic scales. This balance could be informed by the more articulated relationships between long-term, medium-term and short-term forecasts with their uses for humanitarian prevention, preparedness, and response.

Therefore, there is a discussion on where short-term/micro emergency response ends or long-term/macro development investment starts (e.g., the humanitarian-development nexus). Similarly, what is the scope of each naming convention, hazard focus or policy field (e.g., DRR versus emergency relief) (Knox Clarke, 2022; UNDRR & ISC, 2020)? The thesaurus of anticipatory humanitarian action notes that "there are many grey areas in terms of terminology" and that the "blurred categories hold true for both longer and shorter-term approaches and immediate timescales" (de Wit, 2019, p. 32). While weather prediction (short-term) and climate forecasting (long-term) are carefully specified regarding their timescale and associated uncertainty, the end use in resource allocation might not be.

For example, Taylor writes on disaster risk financing that while there is a complex terminology debate trying to lead to a consensus surrounding each instrument, they are usually distinguished by 1) temporality, whether it is ex-ante or ex-post of a disaster, and 2) by the implementing or funding agency, whether they have a humanitarian mandate or not (Taylor, 2023, pp. 750–751). We are prone to agree with Taylor. The qualitative temporal distinctions (e.g., risk mitigation versus preparedness) are not likely very useful as they do not coalesce so neatly in actual practice as in a conceptual view of DRM. Economists would be more comfortable defining the expected disaster situation and the required financing window to intervene via a continuous-time path or a time derivative instead of a muddy policy interval.

As to how far we could hope to proceed in finding optimal utility, the ability of economic decision-makers to make a rational decision and form a coherent forecast of the future is a long-standing examination in economic theory, for example, by Thaler (1980) building up on the work of Simon, Tversky and Kahneman (Kahneman, 2003) in behavioural economics. Rather than go into a lengthy discussion around the theoretical approach, we will contend for this article that economic decision-making is often imperfect and has limited cognition, information, and lead time to make an optimal solution (coined as bounded rationality).

Next, the method section explains the approach, while in section 3, the results are presented and discussed. The final section concludes this review with the key findings as well as the limitations of the work.

1.2 Literature review method

Our review used Noguchi's classification of briefly summarising the current research situation in the field (2006, p. 120). To find a heterogenous sample of peer-reviewed literature, we used a search with Boolean operators on Web of Science (WoS) considering articles published up to and including April 2022 (Figure 4). These were centred around a humanitarian crisis that requires aid and additional terms to focus our search on climate change and economic resource allocation.

The 1st basic query of "(*humanitarian aid* OR *humanitarian crisis*) AND *climate change*" supplied 195 results. A 2nd additional query aimed more at the economic aspect with the terms "(*humanitarian aid* OR *humanitarian crisis*) AND (*funding* OR *forecast* OR *needs assessment* OR *prioritisation*)" resulted in 853 articles. We detected 48 and 63 suitable papers based on title and abstract, with overlapping titles already excluded from the 2nd query. Studies to include in the review were based on two criteria that would support us in capturing material relevant to the problem description but be broad enough that they are not dominated by the work of a single field:

- **Criterion I:** Studies that were intended for predicting or modelling threats of climate change in a humanitarian aid or crisis context for adaptation (i.e., emergency response, disaster preparedness, DRR) in fragile settings; AND
- **Criterion II:** Studies that were intended for forecast-based economic decision-making (i.e., funding, needs assessment, or resource prioritisation) of humanitarian aid.

The chosen keywords will likely reflect a concentrated snapshot of the whole scope of research on the issue. Articles on de facto a similar rationale as *humanitarian aid* could be labelled, for example, *humanitarian action, humanitarian planning, emergency response,* or *emergency relief,* and not found by the search parameters. This significant limitation is discussed more in the conclusion.

After examining the papers and references within them for potential additional sources, 25 and 14 remained from the two queries; therefore, N_s = 39 studies were determined to meet the criteria appropriately (Appendix A).

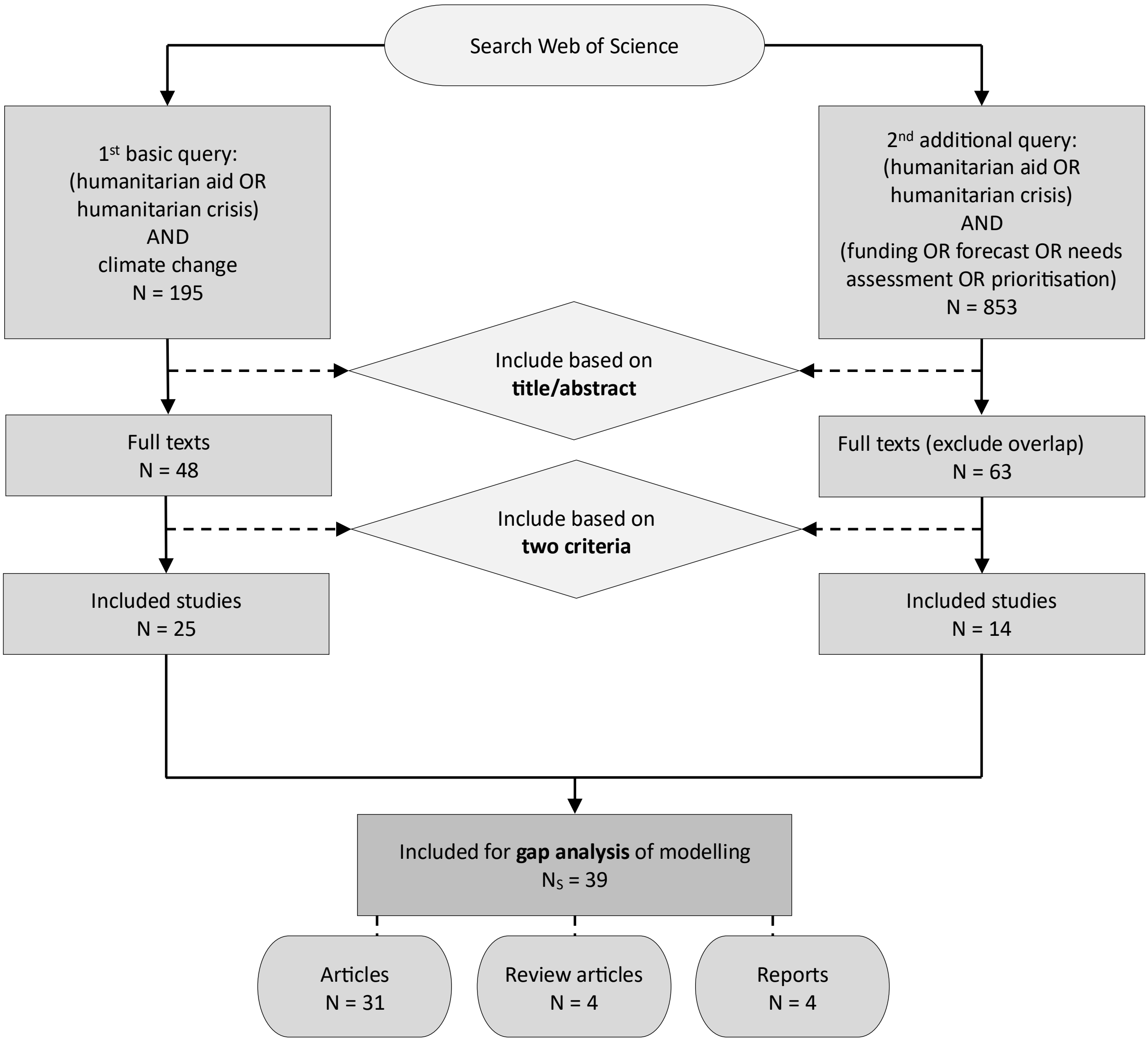


Figure 4. Flowchart of article search and selection pattern.

Within the selected studies, the critical characteristics of modelling were summarised (Appendix B). Finally, a four-step analysis was devised to seek out root causes and gaps in the dataset that could give us added information related to the problem description. They comprise the following sub-sections in section 3. Results and discussion:

- 3.1 Assess to which extent the usability of the climate change-related modelling for forecast-based economic decision-making purposes was examined and discussed in the studies;
- 3.2 Map the main climate change-related threats modelled;
- 3.3 Disaggregate the temporal distribution of the forecast; and
- 3.4 Disaggregate the geographic scope of the modelling.

1.3 Results and discussion

The dataset included 31 articles, 4 review articles, and 4 reports published from 2005 up to and including April 2022 (Figure 5). Initially, we notice that there are increasingly more papers published closer to the 2020s than at the beginning of the series: Of the included studies, 17 were published during 2020–2022 alone and 22 before that period.

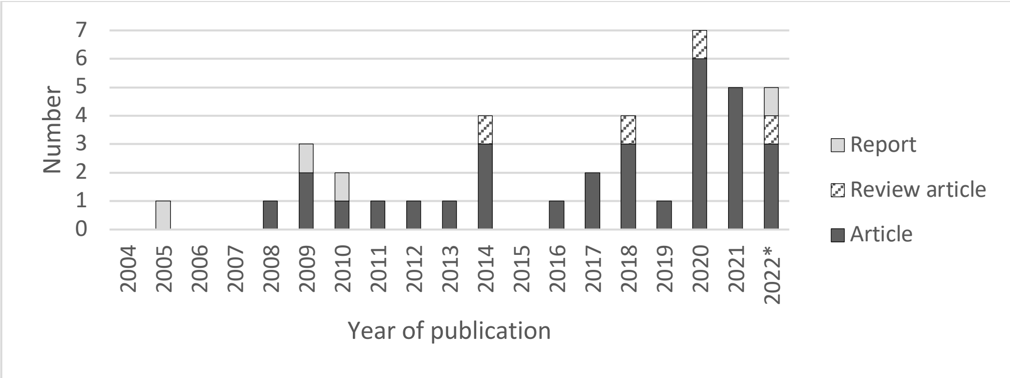


*Figure 5. Number of included publications 2004–2022 (N_S = 39, * = up to and including April).*

The N_S = 39 studies held N_M = 41 versions of various modelling (i.e., the generation of a physical, conceptual, or mathematical representation of a phenomenon) examined in more detail. Some studies complement or overlap by combining the same IPCC scenarios with different inputs or assumptions based on the study's research question (Döll, 2009; Parish et al., 2012; Piontek et al., 2014). Alternatively, their angle was different altogether, such as by reverse studying past humanitarian aid funding decision logic or development progress versus a model (Dellmuth et al., 2021; Martin et al., 2016; Robinson et al., 2017), by understanding sensitivity and accuracy in earlier modelling (Krishnamurthy et al., 2020), or by exploring reasonable interlinkages between complex climate change-related sequences (Brzoska, 2018; Warner et al., 2009).

As expected, models using quantitative methods were more abundant in the dataset (34/41), with the rest employing qualitative or mixed techniques, e.g. household surveys on coping capacity (Maxwell et al., 2008) or social science methods for finding local knowledge (Bucherie et al., 2022). On the type of data, 12/41 of the models used purely physical parameters alone, such as rainfall (Mude et al., 2009), land surface temperature (Enenkel et al., 2016), windspeed (Nusrat et al., 2022) or hydrology (de Stefano et al., 2012; Parish et al., 2012), and all of them with a quantitative method. 26/41 mixed both physical and socio-economic metrics to produce their outcome (i.e., they were integrated assessment models). Socio-economic indicators included, for example, population density (Samson et al., 2011), dependence on water (Döll, 2009), conflict incidence (Altare & Guha-Sapir, 2014), and vulnerability of governance (Busby et al., 2018).

1.3.1 Assess to which extent the usability of the climate change-related modelling for forecast-based economic decision-making purposes was examined and discussed in the studies.

The models were assessed to which extent their utility for forecast-based economic decision-making purposes was discussed and examined in the papers (see column 'Discussion on economic decision-making utility' in Appendix B). The five distinct types of assessment categories were derived from the text used by the article itself and not from a generally agreed typology. For example, if the authors themselves noted that their findings were meant as “preliminary focal points for discussion” (Busby et al., 2018, p. 102) or if the authors proposed that the results will first have to be evaluated “to identify which degree of uncertainty is acceptable to decision-makers” (Enenkel et al., 2016, p. 19), then they were labelled as *3. Exploratory results that need further refinement before useful*.

The strongest argument for utility we noticed in the material was when a tested way for integrating the model into decision-making and underlying challenges were already considered; thus, these were labelled as *1. Use case for forecast-based economic decision-making described*. For example, the two papers by Dellmuth et al. (2021) and Robinson et al. (2017) showed by reverse modelling that UN OCHA’s funding, such as the Central Emergency Response Fund (CERF), responded to disasters based on the chosen criteria—and this effectively proves the model to work at least on past funding decision-making.

We categorised models as *5. Limited discussion on economic decision-making utility* if the paper’s results were not assessed from an economic suitability and financing point of view. This is expected in cases with proper scoping, e.g., it is not usually the “job” of climate modellers to acquaint their results with an economic-ready perspective. The results were often left as is, and the following user was responsible for interpreting and utilising them. To reflect the problem description of each category's usefulness for forecast-based economic decision-making in humanitarian aid, we implemented a ranking on the categorisations based on the above reasoning (Table 1).

Table 1. The authors' rankings of utility.

RANKING DIRECTION	RANK POSITION	ASSESSMENT CATEGORY
More useful	1.	Use case for forecast-based economic decision-making described
↑	2.	Suggestions for improving current model's utility for economic decision-making
	3.	Exploratory results that need further refinement before useful
	4.	Mostly challenges of further use documented
Less useful	5.	Limited discussion on economic decision-making utility

For forecast-based economic decision-making in the reviewed modelling.

This qualitative categorisation and ranking can hold biases of the authors, such as confirmation bias, in the present review. Notwithstanding, the summary descriptions in Appendix B provide justification and reproducibility of our analysis. In Figure 6, the results of our assessment of the dataset and the ranking are shown. The rest of the review will use the same ranks, shading and order.

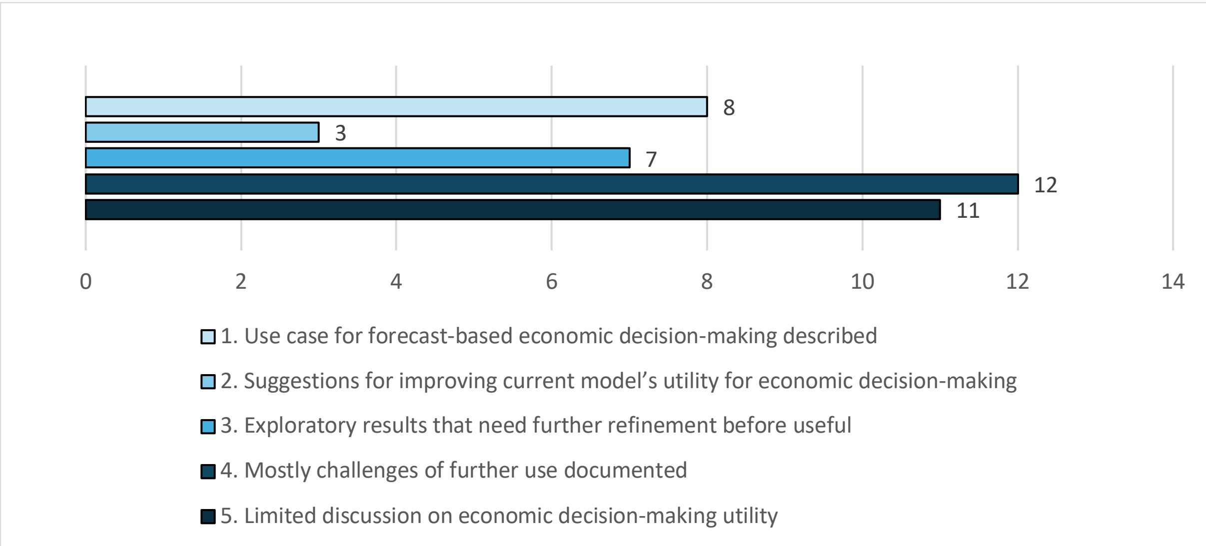


Figure 6. Number of derived categories.

From authors' assessment of the studies' discussion on utility for forecast-based economic decision-making (N_M = 41).

We assessed over half (23/41) of the models to have the two lowest rankings of *5. Limited discussion on economic decision-making utility* or *4. Mostly challenges of further use documented*—while the rest (18/41) showed more discussion on possible or realised utility in the top three rankings. This seems valid if we compare it to the knowledge that 46% of WMO's (World Meteorological Organization) Members reported the existence of impact-based forecast and warning services and 95 countries (out of the hypothetical maximum of 193 UN member states) reported to UNDRR (UN Office for Disaster Risk Reduction) the presence of multi-hazard early warning systems (WMO & UNDRR, 2022, pp. 19, 23).

The difficulty of utility becomes more apparent from the range of documented challenges: For example, 1) integrability issues, such as tailoring the information workflow sustainably to an operational organisation (Lang et al., 2019); 2) difficulty in communicating results or inherent limitations to the audience (Aylett-Bullock et al., 2022; Mwangi et al., 2021; Sandström et al., 2020); and 3) difficulties in transforming scientific analyses to relevant context and in an understandable format for the end user (Bucherie et al., 2022; Ganguly et al., 2014).

1.3.2 Map the main climate change-related threats modelled

Second, the 41 models were classified according to the broader climate change-related threat they intended to study or counter (see columns 'Threat modelled' and 'Intended application and timeframe' in Appendix B). As in the previous sub-section, the different categories were derived from the text used by the article and not from a standard taxonomy. For example, an index simulating river discharge (Mokkenstorm et al., 2021) and a tropical cyclone early warning system (Kuleshov et al., 2020) were classified within *storms and floods*. Finally, we cross-analyse these with the economic decision-making utility to see whether some thematic scopes would have discernible patterns with the assessment. (Figure 7.)

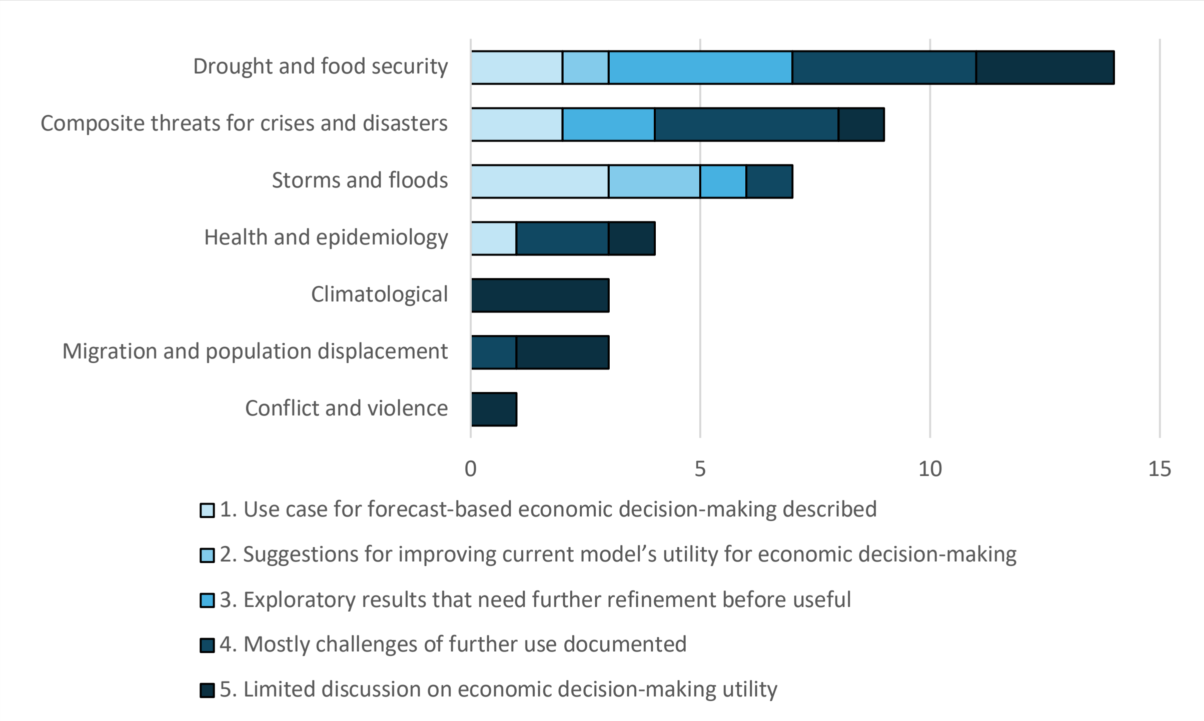


Figure 7. Number of derived main threats the models studied.

Cross-referenced with the authors' assessments on forecast-based economic decision-making utility from Figure 6 (N_M = 41). There is overlap and ambiguity between multiple threats. There is no single consensual way to define them; our categorisation has been to show a meaningful overview. For example, where drought ends, and food insecurity starts in their causal continuum, Coughlan de Perez et al. intended to quantify rainfall as a driver for drought and food insecurity (2019). In contrast, Mwangi et al. added social factors, such as crop yield and water price, to indicate the end outcome of a food-insecure population (Mwangi et al., 2021).

The category composites of threats for crises and disasters is an umbrella for composite indicators that were intended to assess most other categories together comprehensively (Ehrhart et al., 2008; UNDRR, 2022), such as by combining the INFORM Risk Index with IPCC scenarios to assess population under vulnerability (Marzi et al., 2021) or assessing historical exposure to all disasters (Dilley et al., 2005). Climatological includes long-term precipitation or temperature changes, such as when temperature changes cross multisectoral thresholds (Piontek et al., 2014).

The top three categories of *drought and food security, composite threats for disasters and crises,* and *storms and floods* form a supermajority (30/41) of the assessed models. When compared with, for example, the 2021 report of the Emergency Event Database (EM-DAT), corresponding categories were by far the largest three when measured by the annual average number of affected people by disaster type during 2001–2020: Flood stood at 82,7 million affected people annually on average, drought at 67,5 million, and storm at 37,4 million while the fourth one, earthquake, is considerably lower with 6,2 million (CRED, 2022, p. 6).

The top studied main threats have higher amounts of assessments with utility or benefit (ranks 1–3), but this could suggest that the most used models have the most experience and literature behind them. For example, *storms and floods* have the highest proportion of its models in the *1. Use case for forecast-based economic decision-making described* category (3/7). Still, they are highly studied phenomena in our dataset – and unlike *drought and food security*, it does not necessarily have to account for complex social factors (e.g., food price)—the lowest rank of *5. Limited discussion on economic decision-making utility* is non-existent in *storms and floods* and evenly spread out in the rest of the derived threats.

The derived threats and their underlying primary data closely resemble all eight of the IPCC key representative risks from the contribution of WG2 to AR6 that intuitively would be connected to humanitarian aid, such as risks to water security or human health (IPCC WG2, 2022, p. 113) and the results seem valid in this sense. While the main threats that were studied did not constitute risks to living standards or risks to terrestrial and ocean ecosystems from the key representative risks, their underlying parameters—such as the projection of maise production (Fraser et al., 2013) as an indicator for transformation of terrestrial ecosystems or gross domestic product (GDP) per capita (Robinson et al., 2017) for economic impact—take them into account.

The overlap between the categories creates difficulty in defining their exact borders. Still, one could expect that to be the norm in a global conglomerate of systems as complex as climate-related crises. Consider, for example, the division between models assessing parts of the interlinked threats from climatology (de Sherbinin, 2013) to drought and food security (Krishnamurthy et al., 2020) and continuing to more distant consequences of migration (Warner et al., 2009) or health during conflict (Garber et al., 2020)—where the distinct lines of separation between causes-and-effects, exogenous factors and feedback loops blur very quickly (Figure 8).

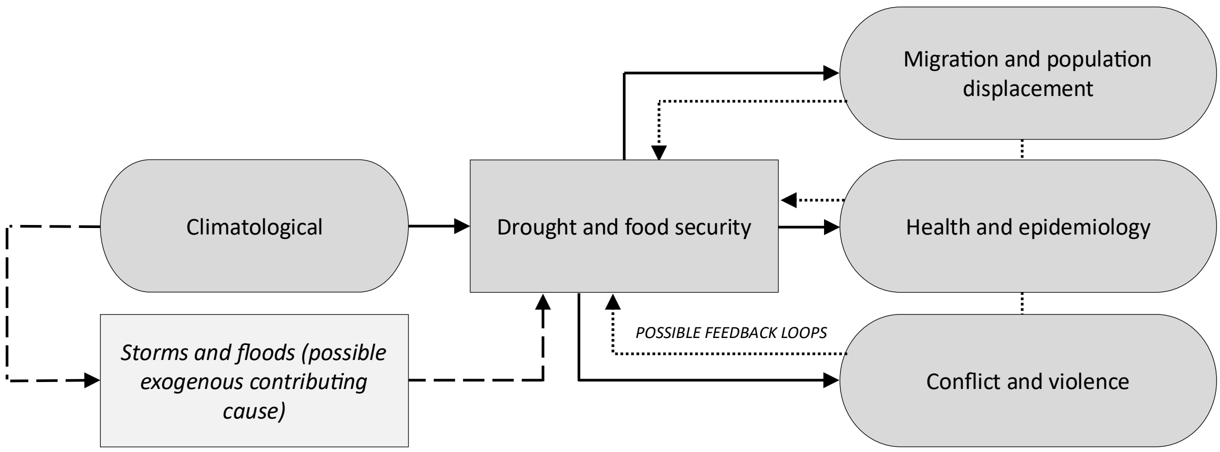


Figure 8. Simplistic example of cause-and-effect.

Between derived main threats that the models assess (including an exogenous contributing cause [dashed lines] and feedback loops [dotted lines]) by authors based on synthesis of review material

The low amount of studies on *conflict and violence* aligns with the IPCC AR6 WG2 consensus that "[w]hile non-climatic factors are the dominant drivers of existing intrastate violent conflicts, in some assessed regions extreme weather and climate events have had a small, adverse impact on their length, severity or frequency, but the statistical association is weak" (2022, p. 11) as well as with Brzoska's review stating, among others, that there is an increasing majority of large-N studies whereby extreme events and disasters weakly increase likelihood of violence (2018, pp. 322–323). On the other hand, while seemingly plausible – our finding could be an artefact of the search parameter or that they are more prominently included in the composite modelling category. Perhaps it is rational that a climate change-related forecast on conflict – a very chaotic process in itself – is the most difficult to quantify for an economic outcome out of all the categories our review assessed.

1.3.3 Disaggregate the temporal distribution of the forecast

The timeframe of the models' forecast affects the intrinsic uncertainty and actionability of the resulting information to a large degree. Generally, the further from the current time t_0 we are projecting to, the less reliable the projection will likely be. Likewise, the further the projection is from t_0, the less likely it would be directly helpful for a financing decision—although more distant scenarios (e.g., t_0 + 25 years) can and do influence investing and policy, as is evident from IPCC assessment cycles.

As discussed, this study holds that short-term emergency response forms a continuum with long-term disaster preparedness (DP) and DRR. In contrast, both can be climate change adaptation within the IPCC Glossary's definition of adjusting to actual or expected climate. Long-term investment, DP, DRR, and adaptation typically consider longer-term risk modelling. Then forecast-based financing (FbF) or anticipatory action (AA) focuses more on the seasonal, such as El Niño-Southern Oscillation (ENSO) weeks-to-months lead time forecasts and shorter timescales, such as days-to-weeks in riverine flooding to provide early warning for pre-emptive financing.

However, scenarios of how the world with more disasters will look decades from now likely influence the multiannual budgeting of pure humanitarian response and its strategic foresight for institutional change. With scarce resources, "short-term/micro" and "long-term/macro" eat money from each other. Thus, we assess it pertinent not to have a set focus on any policy theme or a distinct time interval in this study.

The studies' disaggregation into temporal distributions of the forecast is in Figure 9. If the model was targeted to predict multiple subclasses, such as with floods or droughts from immediate warnings (e.g., hours or days forward) (Jitt-Aer et al., 2022; Nauman et al., 2021) to seasonal forecasts (i.e., a year ahead) (Mwangi et al., 2021; Sandström et al., 2020), they were disaggregated into the suitable subclasses based on their scope; thus, raising the total to N_T = 64. The derived results were arranged in ascending order according to the forecast lead time. As previously, we combined them with the economic utility assessment from Figure 6.

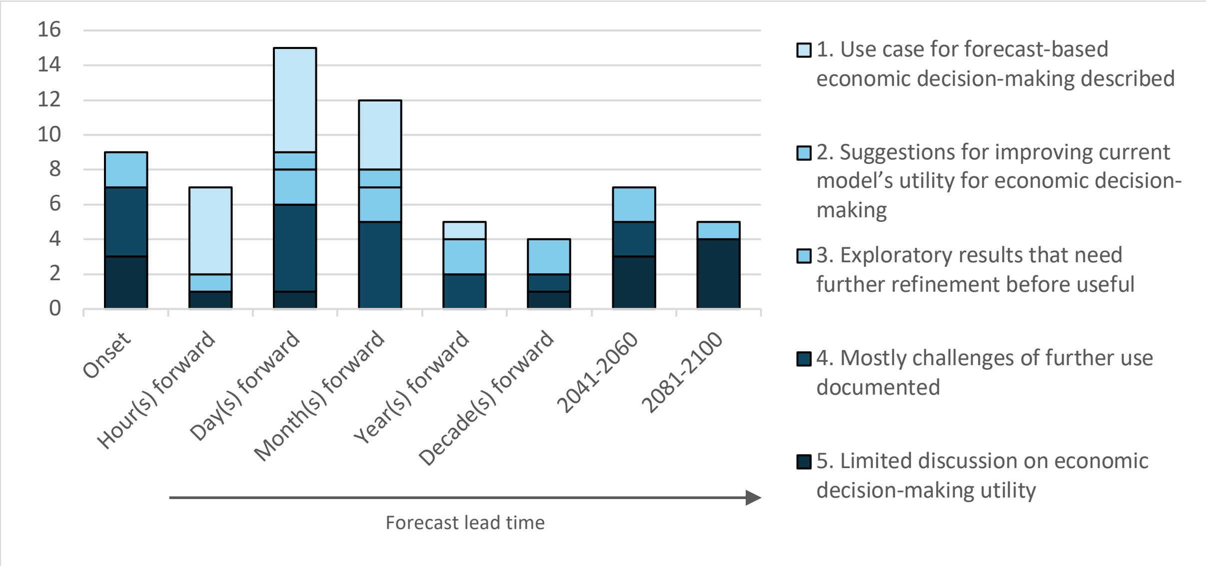


Figure 9. Number of disaggregated timeframes that the models predict to.

Cross-referenced with the authors' assessments on forecast-based economic decision-making utility from Figure 6 (N_T = 64). The timeframes that the papers reported to be aiming for were derived and disaggregated into three general classes and their relevant sub-classes: 1) Onset as in models that analysed the most recently observed risk (i.e., probability or variability) of climate change-related threats without a locked timing; 2) those forecasting hour(s), day(s), month(s), year(s), or decade(s) forward from a current point in time t_0; and 3) further reaching projections up to the IPCC-based periods 2041–2060 or 2081–2100. (See column 'Intended application and timeframe' in Appendix B.)

While *onset* seems like a misnomer as a forecasting category, it can be valid until time goes forward from t_0 enough. For example, Busby et al. developed a climate security vulnerability mapping from historical data. They assumed it to stay sufficiently informative for the next decade or two after creation, justifying that "in the short-run, perhaps the best guide to future exposure is past exposure" (2018, p. 92).

By far, the most prevalent timeframe in our dataset is the immediate future. For example, if we insert every derived timeframe within the IPCC-agreed periods and terminology, then the near term of *2021–2040* would form 52/64 in contrast to 7/64 for the mid-term of *2041–2060* and 5/64 for the long-term *2081–2100*. Models focusing on forecasting *hour(s), day(s)* and *month(s)* forward from t_0 constitute just over half of the total (34/64), while IPCC-based projections up to the years 2041–2100 include a much lower proportion (12/64).

These are likely more actionable lead times (versus informative alone) for the standard operating timeframe of a humanitarian or disaster aid supplying organisation—which would usually be the budgeting year and possibly a few years forward as horizon scanning. For example, the EU's multiannual financial frameworks are established for at least five years and thus, climate forecasting to support it would not necessarily expand even to the *decade(s) forward* range.

Similarly, funding utility is proportionally more assessed and mature in the closer forecasts than in the further estimates. The time ranges of *hour(s), day(s)* or *month(s) forward* from t_0 hold only 2/13 of the lowest rank, *5. Limited discussion on economic decision-making utility*. Likewise, it contains 15/16 with the *1. Use case for forecast-based economic decision-making was described* category—which we determined to be the highest utility rank—predicted to this time range. In contrast, the timeframe 2041–2100 sums up to a higher 7/13 of *5. Limited discussion on economic decision-making utility* even though it has a lower proportion (12/64) of models in total.

Out of widely accepted future scenarios, the IPCC is mentioned in 8/41 frameworks. Both SRES (Special Report on Emissions Scenarios) from AR3 and AR4 eras (de Sherbinin, 2013; Döll, 2009; Parish et al., 2012), as well as RCPs (Representative Concentration Pathways) from AR5 onwards, were used (Gizaw & Gan, 2016; Piontek et al., 2014). One study by Marzi et al. used SSPs (Shared Socioeconomic Pathways) from AR6 in conjunction with RCPs (2021).

1.3.4 Disaggregate the geographic scope of the modelling

Finally, the geographic scope of the models was catalogued (see column 'Scope' in Appendix B) and combined with the assessments on forecast-based economic decision-making utility (Figure 10).

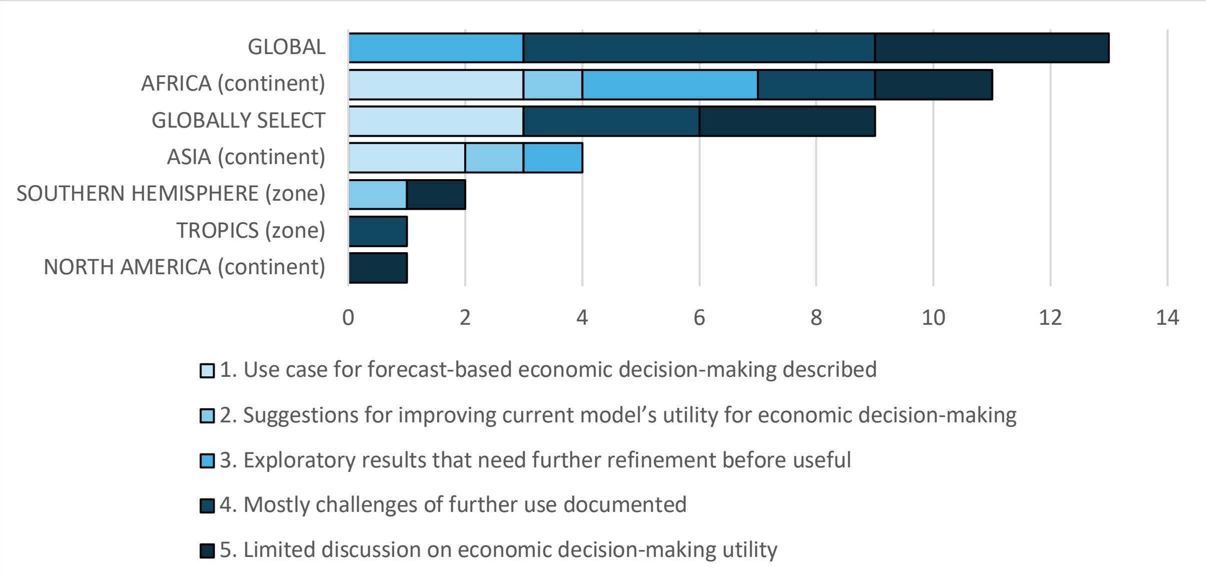


Figure 10. Number of geographic scopes in the models.

Cross-referenced with the authors' assessments on forecast-based economic decision-making utility from Figure 6 (N_M = 41). Four overall and non-exhaustive scope groups were found: Global, globally select, continental, and zonal. Models were classified into continents if their target area was explicitly only on one continent. Globally select includes models with a global distribution but without full coverage.

For example, case studies where countries were selected in multiple international locations (e.g., Egypt, Vietnam, and Mozambique (Warner et al., 2009) or conflict-affected countries (Altare & Guha-Sapir, 2014; Garber et al., 2020). In contrast, zonal refers to studies restricted to a latitudinal area of the globe, such as a climate zone or a hemisphere.

The highest amount in the review were globally comprehensive models, such as utilising pixels that cover the Earth fully, with 13 of the total 41. The highest proportion of the *global* category is explained via the number of climate-related models that combine datasets—e.g., temperature (de Sherbinin, 2013; Piontek et al., 2014), soil moisture availability (Fraser et al., 2013) or population (Marzi et al., 2021; Samson et al., 2011) by matching gridding over the Earth for analysis.

The continent of Africa was second highest with 11. The models on Africa concentrated totally on Sub-Saharan Africa with 7 models specifically in the drought-frequent and conflict-torn Greater Horn of Africa, such as Coughlan de Perez et al., Martin et al., or Mpelasoka et al. (2019; 2016; 2018), and 2 on flooding in Malawi (Bucherie et al., 2022; Mokkenstorm et al., 2021).

If we compare the continent distribution again to the international disasters report of EM-DAT, the situation for the top 2 continents is inverse: On average, Africa has 8,0 million people affected annually during 2001–2020, while Asia has a 10x higher of 84,5 million. The position of the Americas and the lack of Europe are more corresponding as their equivalent numbers are 7,0 and 0,3 million (CRED, 2022, p. 6). If we compare to the crisis-measuring INFORM Severity Index, the results are concurring: According to the December 2020 release of the index, the severity score (on a scale of 1-5) was 3,5 in Asia, 3,3 in Africa, 2,8 in the Americas, and 2,2 in Europe—the majority of which we can assume to be protracted (European Commission, n.d.).

The earlier sets are not fully comparable due to differing timing and definition, but they give some guiding comparative view. Likewise, our review and the examined data could include selection bias, e.g., accounting for the European political interest in Africa while not accounting for data in Asia or South America due to language differences in publication.

The lowest rank *5. Limited discussion on economic decision-making utility* is evenly distributed in the corresponding scope, as in sub-section 1.3.2. All the instances of *1. Use case for forecast-based economic decision-making described* are within *continental* or *globally select* studies—possibly reflecting that an actual use case is more accessible to construct to a well-defined scope. At the same time, with global studies, the generalised result can become too abstract or grandeur for an evident utilisation. Regardless, the representativeness of our survey seems valid because most continentally or zonally attributed studies are in the global south—where humanitarian aid is predominantly provided instead of developed countries.

1.4 Conclusions

1.4.1 Limitations and strengths

Our study has significant limitations and should be read with caution. The exploratory and interdisciplinary research question combines ambiguous fields and terminological differences of forecast-based economic decision-making in humanitarian aid (de Wit, 2019; Knox Clarke, 2022; Taylor, 2023; UNDRR & ISC, 2020). Our article selection and strategy of a status quo review inherently only consider a part of the work done in this arena. For example, we are especially aware of many operational or governmental tools in active use worldwide that are not necessarily represented in the literature. Articles on de facto a similar rationale as *humanitarian aid* could be labelled *humanitarian action, disaster aid or emergency relief* and not found by the search parameters. See the discussion around Figure 8 on the blurred borders of different climate change-related threats or around Figure 10 whereby our sample could be predominantly Europe-lensed.

The narrowness of the query means that it is possible, if not probable, that the entire analysis would look structurally different with more inclusive query criteria. In defence, Altay & Narayanan (2022) and Yan (2023) ran reviews with a like-minded focus and concluded with a similar finding. Nevertheless, our review and its ranking assessment carry risks of confirmation, selection, and sampling bias by the authors and the method. This is a tolerable scope as the experiment was intended as an exploratory review to inform the next research step. In future studies, these limitations could be avoided with a more ambitiously systematic review combining statistically more stringent procedures, a greater scope of underlying terminology, and article evaluation based on standardised criteria.

The benefit of the methodology was that it provided a concise snapshot of information to grasp and assess. The results of the dataset are in rational alignment with other sources, such as IPCC consensus, global databases (EM-DAT and INFORM Severity), and WMO & UNDRR reporting, as well as what one would intuitively expect from a humanitarian aid-focused review (e.g., geographic scope mainly in the global south).

1.4.2 The paucity of literature on integrating climate forecasting with humanitarian aid resource allocation

Our most important finding is simply the paucity of research literature that correctly addresses, let alone successfully integrates, climate forecasting with humanitarian aid resource allocation – concurring with two other similar reviews (Altay & Narayanan, 2022; Yan, 2023). We assessed that more than half (23/41) of our dataset had the lowest rank *5. Limited discussion on utility for economic decision-making,* or rank *4. Mostly challenges of further use for utility documented*. This can be a grave condition because modelling might go to waste merely because it is not easily engineerable for decision-making, and climate policy could benefit from reflecting this to lower opportunity costs.

Humanitarian efforts should follow the principle of impartiality (i.e., that aid is provided solely based on need) and be independent of political objectives. If the modelling cannot be transformed into a quantifiable demand, such as the number of people likely needing assistance in the future, then its valorisation in policy can diminish. Climate forecasting should be integral to the process because humanitarian planning, reducing the risk of disasters, and climate change adaptation depend on international and national baskets of budgeting stretching multiple years into the future.

More accurately, we found that predicting *hour(s), day(s)* or *month(s) forward* from current time t_0 seems the most prevalent period for operationalising the result of the models into funding—in contrast to *year(s)* or *decade(s)*, or the timeframe of *2041–2100* in longer-term IPCC scenarios. Likewise, the most integrated models tend to be about weather prediction rather than longer-term climate change. **While this is a discouraging finding from one perspective, it indicates opportunities for improvement. To make longer-term models benefit resource allocation, climate policy and humanitarian-development nexus communities could determine what information would be useful.** Then, communicate this requirement to the modellers to learn whether there are capabilities to provide input. Modellers will want their results to benefit policymaking but will not identify the most relevant needs.

The degree how well climate modelling accurately forecasts the future inhibits its usefulness. For example, (Scafetta, 2024) finds that the most dominant climate models run too hot and that the extreme SSP3-RCP7.0 and SSP5-RCP8.5 scenarios are unlikely. A prerequisite for economic integration is that the modelling produces reasonably accurate forecasts, such as the short-term mentioned above.

Thus, our study indicates that more research and attention should be paid to improving forecasting ability and transforming climate change-related modelling results into economic decision-making in humanitarian aid and DRR. Especially with climate change becoming fundamental for humanitarian crises, there is a need and an avenue to progress on the matter (European Commission, 2024; IPCC WG2, 2022; Jakob et al., 2023; Noy, 2023). Putting it simply, "[w]e need smart, forecast-based decisions as well as simple, decision-based forecasts" (Suarez, 2009, p. 29).

Consequently, if one is to examine the problem of further transforming climate change-related forecasts into actionable economic decision-making in the humanitarian or DRR field, we recommend assessing expert preferences on what sort of information is needed i.e., like what Lentz & Maxwell (2022) proposed. Thus, modelling results could be more tuned to policy-practitioner requirements instead of possibly creating and processing superfluous material. In a recent study with stakeholder consultation, we took one step forward in the mentioned space (Jäpölä et al., 2024). The preference data was then inserted into a multi-criteria decision analysis to find an optimal way to use climate-related information in allocating funding equitably (Jäpölä et al., 2025).

CHAPTER 2 Preferences on funding humanitarian aid and disaster management under climatic losses and damages: A multinational Delphi panel

ABSTRACT

Losses and damages (l&d) from climate change and the frequency of extreme events will burden our global budgetary constraints and adaptive capacities. Scientific and analytical support for allocating public funding in humanitarian aid and disaster management to counter them involves determining the most pertinent criteria to use or where to design forecasting. Their priorities are often assumed, and assumptions can be ill-fitting. Thus, we asked the key users of such information for their preferences.

A two-round anonymous Delphi method utilising global frameworks for a funding allocation simulation was employed to survey the stated preferences of a stratified panel of l&d experts (N=36). They were experts from 19 countries of origin representing international organisations (e.g., United Nations, European Union, World Bank), the research sector, the public sector, and civil society (e.g., Save the Children, World Vision). The consensus and stability were analysed with parametric measures.

We find that the near-future preference for magnitude-indicating criteria, such as people-centric and disaster risk-based, outweighs the importance of indicators related to governance, the rule of law, or a socio-economic aspect. Likewise, financing adaptation options to climate change-related risks to food security, human health, and water security are a high near-future priority for minimising l&d compared to, for example, risks to living standards or risks to terrestrial and ocean ecosystems. The covariance suggests that these priorities are an emergent preference in the l&d sector. Thus, it raises further questions on what we can and should prioritise with scarce resources.[12]

2.1 Introduction

In September 2023, Storm Daniel wreaked havoc across the Mediterranean – killing at least 4 300 and creating an aid requirement of USD 71 million to support the 250 000 affected people in Libya alone (UN OCHA, 2023). World Weather Attribution assessed that an extreme event comparable to what the Storm caused in Libya “has become up to 50 times more likely and up to 50% more intense compared to a 1,2C cooler climate“ (Zachariah et al., 2023, p. 2).

As climate change and the frequency of extreme events will further burden our global budgetary constraints and adaptive capacities via losses and damages (Coronese et al., 2019; Juhola et al., 2022; van der Wijst et al., 2023),

---

[12] This chapter has been published in 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.

two classic questions of the 'fair cake-cutting problem' are prevalent for the humanitarian aid and disaster management mechanism: Where to disperse the limited amount of public funding in the future and based on what objective criteria? This study explores priority preferences for these questions with a Delphi panel gathered from international expertise and using global frameworks from the IPCC Assessment Report 6 (AR6) and the INFORM decision-making indices as our baseline. Both frameworks are transparent and freely accessible, cover multiple types of hazards scientifically robustly, and provide a common language for comparability. Our motivation was a simple premise: It is better to ask than to assume what is essential (Rising et al., 2022; Yan, 2023).

The status of humanitarian and disaster response to losses and damages, such as shelter support or food security early warning, around the globe shows the importance of the study for climate policy: Around USD 18-30 billion has been allocated annually between 2020-2022 to humanitarian and disaster aid globally; compared to the USD 6-10 billion in the early 2010s and a steady rise ever since. We can provide these amounts, while the estimated need has been 1,5-2,0 times higher. The funded envelope comprised 10% of the total USD 213 billion in Official Development Assistance (ODA) in 2022. (OECD ODA, 2023; UN FTS, n.d.) Regarding the need for aid, climate-related disasters almost tripled in the current decade compared to the 1980s per EM-DAT data in the Global Humanitarian Overview 2023 report (UN OCHA, 2022). The IPCC AR6 synthesis states that "[c]limate change [--] is contributing to humanitarian crises where climate hazards interact with high vulnerability (high confidence)" (IPCC, 2023a, p. 16).

Forecast research with the INFORM Climate Change Risk tool has assessed future vulnerability and risk of humanitarian crises per the IPCC's scenarios up to 2050 and 2080 (Marzi et al., 2021). A report based on that research by Thow et al. estimates that by 2050, the number of people living in 'very high' crisis risk countries will roughly double from 580 million to 1 billion within the optimistic scenarios for greenhouse gas emissions and socio-economic development (2022, p. 11). In December 2023, the UN climate change conference COP28 agreed on operationalising the "Loss and Damage" fund and funding arrangement for vulnerable countries.

Distributing scarce public resources now and in the future equitably to people in need facing vastly different circumstances is a monumental task. In addition to working under time pressure, prioritisation is influenced, e.g. by political economy, scientific uncertainty, public pressure, and numerous spatial and temporal variables. (Neumayer et al., 2014; Polasky et al., 2019) Decision-making on which criteria and according to which forecasts funding allotments should be distributed to counter these effects is naturally done routinely in different humanitarian and disaster aid offices, often with discreet or informal rationales. (IPCC WG2, 2022, p. 2575) The human capacity required is significant and needs to be improved in operational agencies (UNDRR, 2021; World Bank, 2021), especially when assessing forecast models with higher effective dimensions or long-run behaviour of complex systems. (Millner & Heyen, 2021; Puy et al., 2022)

At the European Humanitarian Forum of 2023, policymakers emphasised the importance of "principled prioritisation of scarce resources" in addition to proceeding further with comparability of need severity analyses as well as mitigation of climate-driven disasters and anticipatory action to them (EHF, 2023, paras 11–14). Our previous investigation indicated a research gap in transforming climate change-related modelling into forecast-based economic decision-making (Jäpölä & Van Passel, 2025). Financial modelling of climate change is not suitable for analysis of deep uncertainty, extreme risk, or endogenous preferences connected to it (Stern et al., 2022), research on humanitarian forecasting itself is sparse (Altay & Narayanan, 2022), and the amount of climate information available for crisis resource allocation is overabundant (Lentz & Maxwell, 2022). Blankespoor et al. argue that researchers have low incentive to translate results to decision-maker formats – even though a study would be more legitimate if it is tasked and acceptable to the end user (2023).

To highlight what can make policymakers cautious of utilising results of global risk indicators for de facto funding allocation, Visser et al. concluded that "the coherence between indicators from different organisations but with identical definitions varies enormously" (2020, p. 1). Thus, Working Group II (WG2) of IPCC AR6 states that "[--] a key research priority is to understand and evaluate methodological strengths and weaknesses in damage estimation and reconcile the differences affecting comparability [--]" (2022, p. 2496) and is echoed by IPCC WG3 (2022, p. 88).

Based on the above problem setting, our study intended to find a scientifically transparent and stable consensus among a humanitarian and disaster aid expert panel. Their focus was the priority criteria in computing funding and the priority key risks of climate change that are the most critical to finance. We used the widely applied Delphi method for this examination with a relaxed basis of stated preference during a funding allocation simulation. Instead of monetary valuation or discrete choices, our panel assigned priorities on funding criteria from the INFORM decision-making indices and risk options to fund from IPCC AR6 along with their preferred timescale, thus mimicking a real-life economic decision-making mechanism. We hypothesised that the expert panel would predominantly select people-centred indicators of need or risk as the most emergent factor for funding allocation. Because these could simultaneously be the most umbrella-type criteria and be inequity-averse (Dellmuth et al., 2021; Robinson et al., 2017).

From an economic point of view, the paper investigates the tension between the expected utility theory (EUT) and empirical behaviour. EUT would hold, in the most simplistic sense, that a decision maker or social planner naturally chooses from risky or uncertain futures the one with the most valuable expected utility. On the other hand, a behaviouralist approach determines that she can be a flawed human with limited cognitive capacity or self-interest that is a partial driver of their choice - known as bounded rationality. (Friedman & Savage, 1952; Kahneman, 2003; Thaler, 1980) For example, Taberna et al. found that a rational household agent significantly overestimates adaptation and underestimates damages in flood hazards compared to boundedly rational behaviour (2023). In contrast, the IPCC WG2 generally has low engagement from economics (Noy, 2023), and its AR6 chapter on 'Decision-making options for managing risk' discusses these considerations to a limited extent (2022, Chapter 17).

Next, the paper determines the material and methods used. Section 3 displays the quantitative and qualitative results of the preferences and the applicable forecast timeframe. Section 4 discusses the study's strengths and limitations, the importance of the results to the science-policymaking interface, and pertinent conclusions.

2.2 Material and methods

2.2.1 Research design

The Delphi method has been successfully and widely used in the past decades to form a unified group opinion on a problem or a forecast. It does not use a representative statistical sample but a human panel of sectoral expertise iteratively until a consensus forms. It is especially suited to resolve decision-making in highly complex and uncertain settings. Anonymity between the panellists during the survey rounds removes usual biases – such as anchoring or halo effect – that could be in a live debate. (Akins et al., 2005; Van Schoubroeck et al., 2022; von der Gracht, 2012) Okoli & Pawlowski (2004) have determined that the small panel, with literature recommending at least ten experts, does not depend on statistical power. They likewise note that in the setting mentioned above, the average of individual responses is inferior to the averages produced by expert group judgment – where the Delphi method excels. The technique has been suggested in the climate field to help practitioners project the future (Calleo & Pilla, 2023).

We used the EUSurvey (European Commission) platform to manage the study via email-invited online surveys). We estimated that two Delphi rounds (R1 and R2) would be sufficient in gathering enough evidence versus exhausting the panellists' time capital and increasing motivation to participate (Beiderbeck et al., 2021). Our main questions (Q1 and Q2) to the panel were according to two factors prevalent in a social planner's resource allocation decision-making: The *criteria* she uses to allocate and the *options* to assign the funding to. Within these two, the objective of our study was to find the most prioritised stated preferences relating to funding humanitarian or disaster aid in a future world under climate change, according to the expert group (Table 2).

Table 2. Main questions subjected to the Delphi panel.

Q1	What are the priority *criteria* in allocating humanitarian or disaster aid funding per future forecasts in view of climate change response or adaptation?
Q2	What are the priority *options* for which to allocate humanitarian or disaster aid funding regarding adaptation to representative key risks of climate change?

In each question, Q1 and Q2, the panellists were introduced to a simulation where to allocate funding for future humanitarian or disaster aid under climate change. Although the Delphi method is a simple questionnaire, we assessed that the mental accounting required to assess the complex relationships between the multitude of criteria or options as professionally as possible would be heavy. They had to choose the most prioritised criteria and options suitable for completing the task from their expert viewpoint (i.e., mimicking a real-life economic decision-making process as much as possible). The panellists received guidance to answer according to their role and that effective prioritisation was the expectation. Below is the situation described in R1 of Q1 as an example:

> *SITUATION: Imagine that you have been tasked to allocate humanitarian or disaster aid funding for climate change adaptation between different possible crises and countries according to the forecast timeframe(s) you chose above in T with the below indicators as your criteria. Your tasking authority has noted that they are expecting an effective prioritisation of the most important criteria (i.e., all can't be a high priority).*
>
> *In the given situation, how would you assess the priorities of the criteria in allocating the funding? (i.e., higher priority = higher importance in allocating funding, lower priority = lower importance in allocating funding)*

There was no forced ranking and panellists could e.g., choose multiples of the same level. We used a 4-point scale for the survey, but only verbal descriptions were provided to the panellists in lieu of numerical. Instead of the typical Likert questions of agree or disagree, we chose to use terms indicating priority more explicitly (i.e., from 'low priority' to 'high priority') to mimic a de facto task of resource allocation as well as to introduce equidistance. The survey and its question formulation were pre-tested with three experts in advance for conformity.

To utilise the time capital of the (presumably) busy panellists better and jump more straightforwardly into actual prioritisation, we used the best possible global consensuses as a baseline from the INFORM suite and IPCC AR6 to create both the criteria and option items. Our reasons for using them were that they cover multiple types of hazards globally and scientifically robustly, they are transparent and freely accessible, and they provide a common ground for comparability. Choosing a priority was mandatory in all criterion and option items, as in actual resource allocation. The questionnaires are in Appendices A and B.

For Q1's initial criteria, we amalgamated at first ten different types of criteria groups from the methodologies of the operational INFORM Severity (Lopez et al., 2023; Poljansek et al., 2020, pp. 26–34) and INFORM Climate Change Risk (Marzi et al., 2021; Poljansek et al., 2022, pp. 28–47) indices. As the INFORM suite is developed under the Inter-Agency Standing Committee (IASC) and used by IPCC WG2 (2022, pp. 76, 78), we chose it as a representation of the best possible baseline on which indicators an entity should consider when allocating resources either in observable short-term or in a projected future. Between R1 and R2, we collated the ten initial items into eight according to the panel responses. (Table 3.)

Table 3. The eight Q1 criterion items.

CAPACITY OF LOCAL ACTORS AND ON-GOING PROGRAMMING TO RESPOND/ADAPT For example, analyses and projections of the local actors' (e.g., government, NGO presence, on-going programming) capacity to respond and adapt, such as 1) capability to take anticipatory or early action vis-à-vis forecasted hazard or 2) efficiency of preparedness to reduce/prevent humanitarian impact and risk in the future
HUMANITARIAN ACCESS INDICATORS For example, indicators of impediments to entry into country, restriction of movement, interference into the implementation of humanitarian activities, on-going insecurity/hostilities affecting humanitarian assistance, presence of mines and improvised explosive devices, etc. and their possible extrapolation into the future
INDICATORS ON VULNERABLE GROUPS OR DIVERSITY OF GROUPS AFFECTED For example, indicating the following either pre-existing or forecasted vulnerability: uprooted people, estimated number of people living with HIV, child mortality or children underweight, prevalence of undernourishment, Domestic Food Price Index, count of different types of affected population groups from IASC humanitarian profile common operational dataset
LACK OF INFRASTRUCTURAL COPING CAPACITY For example, indicators on communication capacity measured via access to electricity (World Bank) or adult literacy rate (UNESCO), physical infrastructure quality via roads density (OpenStreetMap) or access to improved water source (WHO /UNICEF), or access to health systems via physician density, health expenditure per capita or proportion of population with access to vaccines (WHO)
PEOPLE IN NEED (PIN) PER SEVERITY LEVEL OF THEIR HUMANITARIAN CONDITIONS (INCL. AFFECTED AND DISPLACED) The estimated distribution of affected people in severity categories according to their conditions and humanitarian needs, such as from level 1 (minimal needs) to level 5 (extreme needs), based on e.g., projections from Humanitarian Data Exchange (HDX), local disaster relief or civil protection authorities, UN OCHA Humanitarian Needs Overviews (HNOs), or Integrated Phase Classification (IPC, incl. Acute Food Insecurity AFI classification)/FEWS NET for food security - including displaced people generated by the crisis and their forecast, such as refugees or internally displaced persons (IDPs), from UNHCR, IOM, national statistics or similar
RISK OF HAZARD AND EXPOSURE TO DISASTERS Regarding *human disasters*, for example: conflict intensity via the HIIK conflict barometer or Global Conflict Risk Index (GCRI), total people killed from Armed Conflict Location & Event Data Project (ACLED), or other suitable source for future projection Regarding *natural disasters*, for example: future risks of earthquake, tsunami, river flood, coastal flood, cyclone, drought, epidemics, etc. from e.g., Aqueduct Global Flood Maps, Standardised Precipitation Evapotranspiration Index (SPEI), European Drought Observatory (EDO), models of vector-borne diseases, Global Earthquake Model (GEM), or cyclone wind intensity maps with Saffir-Simpson Hurricane Scale
RULE OF LAW INDICATORS AND LACK OF INSTITUTIONAL COPING CAPACITY For example, country self-assessments in disaster risk reduction from the Sendai Framework, government effectiveness index from the World Bank, Corruption Perception Index (CPI), rule of law from Bertelsmann Stiftung's Transformation Index (BTI) or World Governance Indicators (WGI) via the World Bank, Freedom in the World report from Freedom House, etc. or similar sources for projection
SOCIAL COHESION INDICATORS AND SOCIO-ECONOMIC VULNERABILITY For example, indicators on development and deprivation via HDI or MPI, inequality via GINI, aid dependence via public aid per capita or net ODA received, empowerment from the CIRI Human Rights Dataset, BTI – democracy status, ethnic fractionalisation from the Ethnic Power Relations (EPR) dataset, size of excluded ethnic groups, Gender Inequality Index (GII), etc. and their possible extrapolation

Their descriptions based on the INFORM Climate Change Risk and INFORM Severity suite for the panel to prioritise from low to high priority (4-point scale) in R2 after amending them based on panel responses in R1. Here, they are alphabetically but randomised during the survey.

For the initial options in Q2, we took the eight representative key risks (RKR) from IPCC's WG2 contribution to AR6 as a thematic baseline. The logic of choosing RKRs as the options to fund was that humanitarian aid and disaster management would likely focus their resource allocation on risk-based themes. IPCC defines the RKRs as a clustered synthesis of 127 regional and sectoral key risks that could enter a severe phase by the end of the century under a distinct set of climate hazard, exposure, and vulnerability. (IPCC WG2, 2022, p. 113)

Table 4. The eight Q2 option items.

RISK TO FOOD SECURITY Food insecurity and the breakdown of food systems due to climate change effects on land or ocean resources
RISK TO HUMAN HEALTH Human mortality and morbidity, including heat-related impacts and vector-borne and water-borne diseases
RISK TO LIVING STANDARDS Economic impacts across scales, including impacts on GDP, poverty and livelihoods, as well as the exacerbating effects of impacts on socio-economic inequality between and within countries
RISK TO LOW-LYING COASTAL SOCIOECOLOGICAL SYSTEMS Risks to ecosystem services, people, livelihoods, and key infrastructure in low-lying coastal areas and associated with a wide range of hazards, including sea level change, ocean warming and acidification, weather extremes (storms, cyclones) and sea ice loss, for example
RISK TO TERRESTRIAL AND OCEAN ECOSYSTEMS Transformation of terrestrial and ocean/coastal ecosystems, including change in structure and/or functioning and/or loss of biodiversity
RISK TO WATER SECURITY Risk from water-related hazards (floods and droughts) and water quality deterioration; focus on water scarcity, water-related disasters and risk to Indigenous and traditional cultures and ways of life
RISKS ASSOCIATED WITH CRITICAL PHYSICAL INFRASTRUCTURE, NETWORKS AND SERVICES Systemic risks due to extreme events leading to the breakdown of physical infrastructure and networks providing critical goods and services
RISKS TO PEACE AND TO HUMAN MOBILITY Risks to peace within and among societies from armed conflict as well as risks to low-agency human mobility within and across state borders, including the potential for involuntarily immobile populations

Their descriptions based on IPCC WG2 AR6 key representative risks for the panel to prioritise from low to high priority (4-point scale) in R1 and R2. Here, they are alphabetically but randomised during the survey.

Our motivation in combining indicators from the short-term/micro INFORM Severity index with the long-term/macro INFORM Climate Change Risk as well as the high-level and century-encompassing RKRs of IPCC AR6 was to explore the forward-looking criteria and options that are priorities in humanitarian or disaster aid funding in general and regardless of organisation, policy background/job function, region of focus, discrete time horizon, or similar factors (i.e., an attempt to find covariant variables in continuous time).

2.2.2 Data collection and processing

Recruitment for R1 was opened on 7 March 2023 by email to the initial pool and closed on 5 May (Figure 11.) The authors prepared an analysis of R1 (Appendix C) for the panellists to fuel their further deliberation as well as to document the R1 results. There are studies indicating that this could lead to the minority moving towards the assessment of the majority (Makkonen et al., 2016; Meijering & Tobi, 2018), but we favoured transparency in a complex problem as well as to appreciate the time and effort that the panel put into the research (Beiderbeck et al., 2021). Based on the panellists' comments or suggestions and the intermediate analysis, we made minor amendments to question titles and descriptions, merged equivalent question items, and formed one new criterion (Appendix C, pp. 11-12).

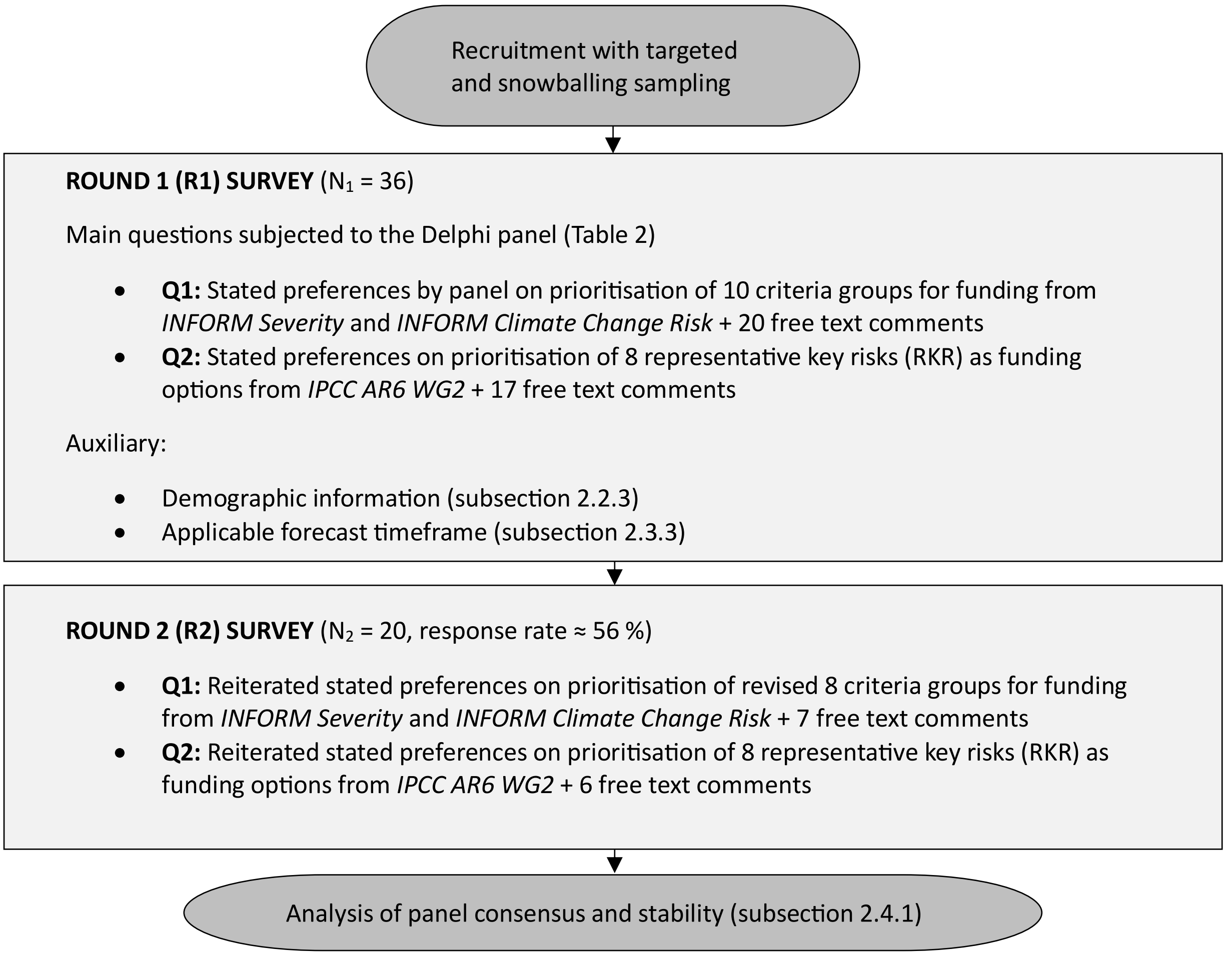


Figure 11. Flowchart of Delphi data collection and processing.

R2 was opened to the panel of R1 on 12 June 2023 and closed on 31 July. During the opening, the panellists received the intermediate analysis via email and as an attachment within the new survey form. The panel's responses to the substantive questions Q1 and Q2 are in the respective subsections on results.

2.2.3 Panel recruitment and composition

We started formal recruitment of the Delphi panel when R1 opened—our initial pool of invitations comprised over two hundred email addresses. The pool included government units or officials, international experts, or civil society employees working on, among others, combinations of humanitarian aid operations, forecast-based financing (or early action, FbF or FbA), anticipatory action (AA), disaster risk management, risk reduction or preparedness (DRM, DRR, or DP), climate resilience, or climate change adaptation (CCA) as well as academics who had published in the mentioned fields or private sector entities working on them (e.g., disaster risk insurance firms). Our purposive sampling of professions related to climatic losses and damages was designed to eliminate unintended bias as much as possible. (Beiderbeck et al., 2021; Okoli & Pawlowski, 2004)

During R1, we requested basic demographic information from the panel members (Table 5). Panellists could select "Prefer not to say" at any question, but none used it. The panel comprised, in general, the following target groups: 1) UN system (incl. OCHA, UNICEF, WFP, WMO), European Commission (DG ECHO), Red Cross Red Crescent, and World Bank staff; 2) universities & research institutions; 3) government and public sector officials; and 4) civil society/INGOs/NGOs (e.g., ACAPS, Action Against Hunger, CARE, GEM, REACH, OXFAM, Save the Children, World Vision). It included personnel serving both in headquarters and in field operations. In the primary field, some panellists elaborated further on their functional backgrounds by selecting "Other", such as a technical advisor on programming, two nutrition experts, a technical assistant, and humanitarian financing. (Appendix C, pp. 9-10.)

Table 5. Demographics of the panel (N_1=36).

Gender	n	Country of Origin	n
Female	18	Australia	1
Male	18	Belgium	3
Other	0	Czechia	1
		Finland	1
Primary Sector of Employment	**n**	France	4
Academic/Research Institute	4	Germany	6
Civil Society/NGO/INGO	13	Iraq	1
International Organisation/Intergovernmental Organisation	13	Italy	4
National Government/Public Sector	6	Mozambique	1
Private	0	Netherlands	2
		Nicaragua	1
Primary Field	**n**	Philippines	1
Analysis/Research	10	Spain	1
Coordination/Stakeholder Relations	4	Sweden	2
Desk/Policy/Project Officer	7	Switzerland	1
Financing/Budgeting	1	Türkiye	1
Leadership	3	United Kingdom	2
Legal	0	United States of America	2
Information Management	0	Viet Nam	1
Operations/Logistics	4		
Other	7		

In general, we concluded that the panel had a good level of heterogeneity for this expert Delphi research and corresponding to the amount of personnel available with expertise in the three distinct sectors of climate change, funding, and humanitarian or disaster aid. For example, ReliefWeb had 186 vacancies open on 29 February 2024 for the theme 'Climate Change and Environment.' There were no panel members from the private sector and the countries of origin are more oriented toward the Global North (mainly Europe). Still, these were both expected, considering the nature of the topic and the direction of the flow of funding.

2.3 Results

To compare the Delphi panel's stated preferences for each sub-question, we transformed their choices per category into numerical values for quantitative analysis (4-point linear scale, 1 = low priority and 4 = high priority). Mean and standard deviation (SD) were used as the primary parametric methods to determine the rank and consensus of each item. They are intuitive, straightforward, and naturally readable; similarly, SD and mean show a negligible risk of a false position or consensus in a corresponding field of disaster medicine. (Franc et al., 2023) In Appendix D, the disaggregated results and more descriptive statistics are available.

2.3.1 Q1 - Priority criteria in allocating humanitarian or disaster aid funding per future forecasts in view of climate change response or adaptation

The quantitative results of R1 and R2 for Q1 are displayed in descending order of priority (Table 6, Table 7). Between the rounds, we merged categories Q1.1-3 on people-centred criteria and Q1.4-5 on disaster risk-based criteria into single items due to their similarity and proximity in both quantitative and qualitative results as well as adding a new criterion Q1.X per panel suggestions (Appendix C, pp. 11-12).

We asked the panel to justify their assessments, measure their confidence, and suggest amendments to the survey. R1 had 20 free-text comments and R2 had 7. A synthesis of common topics that the panellists discussed follows. **First, people-centred criteria were predominantly the top criteria.** While it is true that many criteria items overlap and have a complex interplay between them, most focus on people-centred criteria, especially emphasising the magnitude and severity of the need (e.g., the number of people affected by the disaster). Other key human-related terms mentioned were a lifesaving, humanitarian mandate, or saving livelihoods (ID12, ID2, ID6, ID9, ID33, ID14, ID11, ID16.) One panellist stated fittingly that "experience tells me that at the end of the day, the most relevant are people-centred criteria reflecting those in need of humanitarian assistance" while emphasising that other elements (e.g., resilience, coping capacity) are also essential (ID6).

Table 6. Stated preferences on Q1 for R1 by panel.

Priority ↓	Item	Mean ↓	SD	Median	Range	Mode
HIGH PRIORITY (4)	Q1.1 PEOPLE IN NEED (PIN) PER SEVERITY LEVEL OF THEIR HUMANITARIAN CONDITIONS	3,64	0,67	4,00	3,00	4,00
SOMEWHAT HIGH PRIORITY (3)	Q1.2 PEOPLE AFFECTED BY THE CRISIS	3,42	0,72	4,00	2,00	4,00
	Q1.3 PEOPLE DISPLACED BY THE CRISIS	3,33	0,82	4,00	3,00	4,00
	Q1.4 RISK OF HAZARD AND EXPOSURE TO NATURAL DISASTERS	3,31	0,78	3,50	2,00	4,00
	Q1.5 RISK OF HAZARD AND EXPOSURE TO HUMAN DISASTERS	3,28	0,73	3,00	3,00	3,00
	Q1.6 INDICATORS ON VULNERABLE GROUPS OR DIVERSITY OF GROUPS AFFECTED	3,17	0,93	3,00	3,00	4,00
	Q1.7 HUMANITARIAN ACCESS INDICATORS	2,53	0,76	3,00	3,00	3,00
SOMEWHAT LOW PRIORITY (2)	Q1.8 SOCIAL COHESION INDICATORS AND SOCIO-ECONOMIC VULNERABILITY	2,44	0,96	2,00	3,00	2,00
	Q1.9 LACK OF INFRASTRUCTURAL COPING CAPACITY	2,28	0,90	2,00	3,00	2,00
	Q1.10 RULE OF LAW INDICATORS AND LACK OF INSTITUTIONAL COPING CAPACITY	2,14	0,95	2,00	3,00	2,00
LOW PRIORITY (1)	-	-	-	-	-	-

(N_1=36) on priority criteria in allocating humanitarian or disaster aid funding per future forecasts in view of climate change response or adaptation (Q1). Scale and colouring for median and mean: 1 = low priority (white), 4 = high priority (green); the closest point assigns priority. Colouring for standard deviation (SD): 0 = blue, 1 ≤ white. Order was randomised for each panel member but is now in descending order per mean. Item coding is with this order.

Table 7. Same as above on Q1 but for R2.

Priority ↓	Item	Mean ↓	SD	Median	Range	Mode
HIGH PRIORITY (4)	Q1.1-3 PEOPLE IN NEED (PIN) PER SEVERITY LEVEL OF THEIR HUMANITARIAN CONDITIONS (INCL. AFFECTED AND DISPLACED)	3,80	0,51	4,00	2,00	4,00
	Q1.4-5 RISK OF HAZARD AND EXPOSURE TO DISASTERS	3,55	0,59	4,00	2,00	4,00
SOMEWHAT HIGH PRIORITY (3)	Q1.6 INDICATORS ON VULNERABLE GROUPS OR DIVERSITY OF GROUPS AFFECTED	3,20	0,93	3,00	3,00	4,00
	Q1.9 LACK OF INFRASTRUCTURAL COPING CAPACITY	2,65	1,06	2,50	3,00	2,00
	Q1.X CAPACITY OF LOCAL ACTORS AND ON-GOING PROGRAMMING TO RESPOND/ADAPT	2,60	0,86	3,00	3,00	3,00
SOMEWHAT LOW PRIORITY (2)	Q1.8 SOCIAL COHESION INDICATORS AND SOCIO-ECONOMIC VULNERABILITY	2,35	0,79	2,00	3,00	3,00
	Q1.7 HUMANITARIAN ACCESS INDICATORS	2,21	0,69	2,00	3,00	2,00
	Q1.10 RULE OF LAW INDICATORS AND LACK OF INSTITUTIONAL COPING CAPACITY	2,10	0,83	2,00	3,00	2,00
LOW PRIORITY (1)	-	-	-	-	-	-

(N_2=20). Item coding, scale, colouring, and order logic are from Table 6, excluding merging of equivalent items Q1.1-3 and Q1.4-5 to single items and creating new item Q1.X.

Second, the nuanced interplay between people-centred criteria, risk, and vulnerability is crucial. For example, people-centred needs often interconnect with other elements, such as pre-existing vulnerability (ID9), assessing how some of the indicators are more directly or indirectly linked to saving lives and livelihoods (e.g., humanitarian access and pre-existing assets) (ID33), or conducting an analysis of current severity and magnitude of the need for pre-existing vulnerability before layering risk of shocks (ID14). ID12 condensed the assessment on this interplay by noting that while risks are crucial to know about, it is more important to be aware of the population at risk and their capacity to cope: “A disaster does not trigger humanitarian need if there is no one living in its area of impact.”

During R2, the focus on interplay continued. For example, the risk-based criteria should capture all the vulnerabilities mentioned as is commonly defined (ID41). Similarly, ID52 set the risk-based criteria in ‘somewhat low priority’ as more well-off countries will likely be able to cope with a high risk.

Third, the most essential criteria could depend on the expected timewise sequence of interventions and disasters. The further the panellists looked to the future, the more emphasis there was on elements of risk – which we noticed in the timeframe analysis (subsection 2.3.3). For example, ID1 stated that “high priority on risk assessments to determine physical and socio-economic impacts of disasters (including both rapid and slow onset hazard)”, which we can then invest today to build resilience and coping capacity to reduce risk in the future. This interplay between magnitudes of people in need, existing vulnerabilities/coping capacities, and risk of future hazard and exposure depends on the forecast timeframe and the expected intervention time. Risk is naturally irrelevant if the disaster has already happened (excluding residual risk) or the impact projection is reliable (ID8, ID9). The answers reflected the timewise sequence of policy-wise terminology and overlaps of different nexuses (ID7, ID8, ID1, ID14, ID35), such as forecast-based funding or anticipatory action, early action funding or post-hazard humanitarian response, build back better and mitigating residual risk, and humanitarian-development nexus programming (building resilience, climate change adaptation, disaster risk reduction).

Fourth, there were differences in confidence in answering, but it improved in R2. Two panellists reflected that they were confident or quite confident in their answers or assessments - particularly pointing to the use of humanitarian or people-based needs and the magnitude and extent of the need (ID28, ID10). Two noted that the priority of criteria would also depend on context, such as whether it is a particular forecast or in general, as well as dependent on whether data sources allow for a sufficiently local visual of potential humanitarian impact (ID4, ID15). Two found disentangling and separating the criteria for prioritisation challenging. Regardless, even in these cases, there was a verge of leaning on the people-centred criteria or more all-encompassing categories, i.e., where multiple characteristics come together (ID11, ID16). During R2, three panellists reflected that they were more confident or somewhat more confident because of the intermediate analysis and the refining of the categories (ID42, ID46, ID50).

Fifth, during R2, panellists also reflected that we should consider the practicality of funding in the end. For example, despite the focus on people-centred and humanitarian indicators being the most pertinent, we must recognise the level of humanitarian access, institutional coping capacity, and capacity of local actors to either act, absorb, or utilise funding. (ID42, ID43.) One member chose the priorities based on what is likely the most effective or meaningful use of resource supply, e.g., where needs are highest and the capability to respond is at a good level versus a complex situation where successful aid programming is difficult (ID45).

2.3.2 Q2 - Priority options for which to allocate humanitarian or disaster aid funding regarding adaptation to representative key risks of climate change

The panel’s quantitative stated preferences in Q2 are below (Table 8, Table 9) in the same layout as in Q1.

As in Q1, we provide a qualitative synthesis per topic of the optional free-text comments (17 for R1, 6 for R2) the panellists wrote. **First, risks to water security, food security, and human health are the most essential options for allocating funding.** The free-text answers reflect the quantitative results to a large degree. Like in Q1, IPCC's key representative risks of climate change are interlinked and not separable (e.g., ecosystem risks can cascade into food security risks), but even then, the highest priorities were already stable in R1 among the panel.

Like in Q1, the panel indicated that a focus on the human and lifesaving elements is the most critical (ID6, ID2, ID9, ID10, ID12, ID14, ID33). While other options are relevant as well, they likely are secondary when people’s lives are at risk (ID6), and the funding should prioritise the worst outcomes (loss of human life and rising mortality) versus other risk trends (ID14). ID12 wrote that even with climate change effects, the primary driver of humanitarian aid is probable caseload within the short term (the successive funding cycles, typically a year) – deriving back to the people-centred criteria. During R2, ID45 summarised that “water and food are essential resources that will destabilise the society at large and, thus, deserve the highest priority”.

Table 8. Stated preference on Q2 for R1 by panel.

Priority ↓	Item	Mean ↓	SD	Median	Range	Mode
HIGH PRIORITY (4)	Q2.1 RISK TO FOOD SECURITY	3,75	0,43	4,00	1,00	4,00
	Q2.2 RISK TO HUMAN HEALTH	3,69	0,62	4,00	2,00	4,00
	Q2.3 RISK TO WATER SECURITY	3,67	0,67	4,00	3,00	4,00
SOMEWHAT HIGH PRIORITY (3)	Q2.4 RISKS TO PEACE AND TO HUMAN MOBILITY	2,94	0,88	3,00	3,00	3,00
	Q2.5 RISKS ASSOCIATED WITH CRITICAL PHYSICAL INFRASTRUCTURE, NETWORKS AND SERVICES	2,61	0,92	3,00	3,00	3,00
	Q2.6 RISK TO LIVING STANDARDS	2,50	0,93	2,00	3,00	2,00
SOMEWHAT LOW PRIORITY (2)	Q2.7 RISK TO LOW-LYING COASTAL SOCIOECOLOGICAL SYSTEMS	2,42	0,95	2,00	3,00	3,00
	Q2.8 RISK TO TERRESTRIAL AND OCEAN ECOSYSTEMS	2,14	0,95	2,00	3,00	2,00
LOW PRIORITY (1)	-	-	-	-	-	-

(N_1=36) on priority options for which to allocate humanitarian or disaster aid funding regarding adaptation to representative key risks of climate change (Q2). Scale and colouring for median and mean: 1 = low priority (white), 4 = high priority (green); the closest point assigns priority. Colouring for standard deviation (SD): 0 = blue, 1 ≤ white. Order was randomised for each panel member but is now in descending order per mean. Item coding is on this order.

Table 9. Same as above on Q2 but for R2.

Priority ↓	Item	Mean ↓	SD	Median	Range	Mode
HIGH PRIORITY (4)	Q2.3 RISK TO WATER SECURITY	3,95	0,22	4,00	1,00	4,00
	Q2.1 RISK TO FOOD SECURITY	3,85	0,36	4,00	1,00	4,00
	Q2.2 RISK TO HUMAN HEALTH	3,80	0,68	4,00	3,00	4,00
SOMEWHAT HIGH PRIORITY (3)	Q2.4 RISKS TO PEACE AND TO HUMAN MOBILITY	2,95	0,86	3,00	3,00	3,00
SOMEWHAT LOW PRIORITY (2)	Q2.6 RISK TO LIVING STANDARDS	2,45	0,74	2,50	3,00	3,00
	Q2.5 RISKS ASSOCIATED WITH CRITICAL PHYSICAL INFRASTRUCTURE, NETWORKS AND SERVICES	2,45	0,80	2,00	3,00	2,00
	Q2.7 RISK TO LOW-LYING COASTAL SOCIOECOLOGICAL SYSTEMS	2,30	0,84	2,00	3,00	3,00
	Q2.8 RISK TO TERRESTRIAL AND OCEAN ECOSYSTEMS	2,20	0,93	2,00	3,00	2,00
LOW PRIORITY (1)	-	-	-	-	-	-

(N_2=20). Item coding, scale, colouring, and order logic are from Table 8.

Second, the panel members prioritised imminent versus underlying and cascading risks (e.g., risks to ecological systems). Three panellists noted that even though the top options are the most critical imminently, the underlying risks, such as protecting ecological systems and minimising risks to peace and human mobility, will inevitably come after the initial priority (ID6, ID33, ID7). R2 echoed similar sentiments that the lower priorities could cascade into the higher stresses, e.g., lack of essential water and food destabilising a society (ID52). Those forecasting furthest into the future determine that "the environment and clean water are the most important to assure the viability of life, health, and livelihood" (ID1). ID25 commented that "ecosystems are directly linked to the top priorities; thus, protecting them is instrumental."

As in Q1, the intervention time matters. Four panellists selected the priorities based on what is viable to be amended or could realistically make a difference in the short or medium term (ID15, ID11, ID36, ID12). For example, water and food security are more prominent on seasonal timescales than ecosystem quality or conflict. Still, on a longer timescale, these could switch places (ID11), or the priority should be on imminent suffering as there might not be enough time for longer-term type intervention – although we should implement this in parallel to resilience building and coherent with humanitarian anticipation and development intervention in the face of the subsequent disasters (ID36).

Third, prioritising which climate change risks to focus on is naturally challenging. For example, ID7 remarked, “would want to put everything in high priority”, or ID19 noted, "I find all categories as a high priority, while few are outcomes of the others and hence a higher priority". At the same time, ID28 stated being "rather confident" by assessing them out of long-term sustainable adaptation design. Quantitatively, the panel seemed confident and like-minded in the prioritisation. Thus, it is more likely that a seasoned expert will admit the difficulty but can perform it, nonetheless. During R2, panel members were more confident (ID50) or equally sure – although unpacking each risk category further would be beneficial (ID42). One would favour everything in high priority but chose to deprioritise those that are more underlying or potentially cascading (ID52), and another still had difficulty due to all the themes deserving priority but focused on the actions that are most viable in building resilience to climatic pressure (ID45).

2.3.3 Applicable forecast timeframe

The future timeframe that the social planner or expert is most likely to allocate funding for and to use for forecast plays a significant part in the priority preference for Q1 and Q2. Thus, we requested the panellists to determine during R1 the forecast timeframe(s) most suitable for their role and to use this as their anchor when responding to Q1 and Q2. The choices available ranged from a lead time of hour(s) or year(s) forward until the IPCC long-term scenarios and panel members could choose multiple (Figure 12).

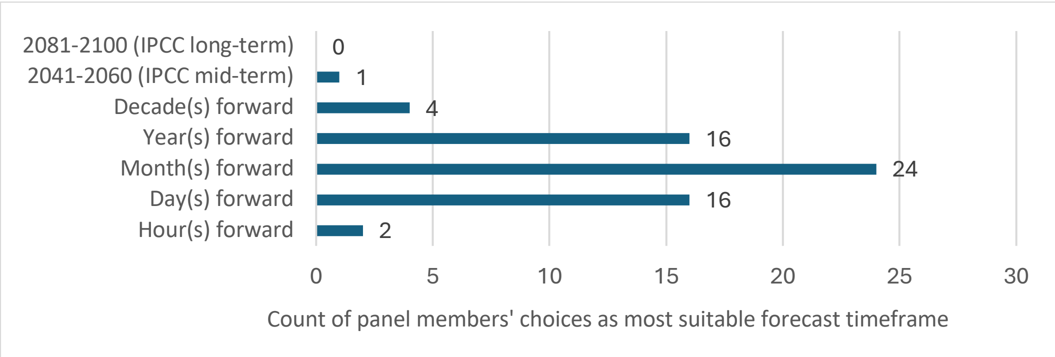


Figure 12. Count of panel members' choice for the timeframe(s).

Most suitable for their role (N_T=63) from R1 arranged in descending order from farthest to earliest. The panel members (N_1=36) could choose multiple with the caveat, "Try to stay consistent, i.e., that you choose timeframes close to each other and not, for example, that you only choose hour(s) forward and 2041-2060."

The distribution of the preferred timeframes resembles a bell curve-type shape with 'month(s) forward' as the most preferred - followed by both 'year(s) forward' and 'day(s) forward' in second place. Most timeframe groups had positive Pearson correlation coefficients of either moderate or strong between them when compared within question sets Q1 and Q2. Still, there was a weak correlation between the earliest and farthest timeframes on the priority criteria in Q1 - whereby, in essence, the most distant-looking panel members favoured risk-based indicators over people-centred criteria. (Appendix C, p. 8.) This interplay can be noticed in qualitative answers to Q1 as well. On priority options in Q2, all cohorts answered similarly with strong positive correlations.

We do not draw a quantitative conclusion because the sample sizes of the earliest and farthest timeframe groups are small. We could, for example, posit that at some point around 'year(s) forward' the projection uncertainty could start turning intolerable to decision-making and risk-based indicators would become a more dominant preference. This could also reflect the feasibility boundary between a forecast, that is an estimate of the actual evolution of a system (i.e., as defined in the IPCC Glossary), and foresight, where different representations or scenarios of the future are discussed. (Calleo & Pilla, 2023).

2.4 Discussion

2.4.1 Strengths and limitations

A Delphi panel can give evidence of the most likely result embedded among global expertise and the best way forward for a complex problem – especially with a heterogeneous panel (subsection 2.2.3) and by measuring its consensus and stability. If the panellists have a similar expert understanding and knowledge of the field, even a small sample of 10 can provide a reliable outcome, e.g. compared to augmented sampling. (Akins et al., 2005;

Beiderbeck et al., 2021; Diamond et al., 2014; Okoli & Pawlowski, 2004) Our study was designed to halt after two rounds regardless of the answers achieved.

We used standard deviation (SD) as our leading consensus indicator among the panel members, where SD ≤ 1,00 is a standard cut-off for good consensus. At the same time, SD ≤ 0,50 could be considered a high consensus (Franc et al., 2023). In the whole dataset, the only item that had SD > 1,00 was Q1.9 during R2 with 1,09. Average SD also improved (i.e., decreased) by 0,10 and 0,11 in both item sets from R1 to R2. In general, the high priorities were more consensual and reached SDs ranging between 0,22–0,62 during R2, while items in somewhat high or somewhat low priority were more contested with SDs of 0.74–1.09. (Tables 5–8.) Interquartile ranges, coefficients of variation (CoV) and other measures in Appendix D provide similar support to the validity of the results (Beiderbeck et al., 2021; Dajani et al., 1979; Diamond et al., 2014; von der Gracht, 2012). For example, the average CoV for both Q1 and Q2 in R2 was 0,25; where CoV ≤ 0,50 is considered a good consensus.

In the qualitative parts, many whole sentences indicate good engagement by the panellists (Beiderbeck et al., 2021). All 50 free-text comments (total for Q1 and Q2 in R1 and R2) were complete sentences (ranging from 1219 words and 62 sentences in Q1 of R1 to 207 words and 13 sentences in Q2 of R2). Correlations and tests of variation can also provide information on how stable or similar the panel's answers were between rounds (Dajani et al., 1979; von der Gracht, 2012). Pearson correlation coefficient (Pearson's r) between the means of the items indicated a strong positive correlation for Q1 (0,95) and Q2 (0,99) between the panel's answers in R1 and R2. Similarly, the average differences in CoV were minimal between the rounds for both Q1 (-0,04) and Q2 (-0,04), as well as the averages of F-ratios in Q1 (0,76) and Q2 (0,76); close to 1,00 is considered stable.

Thus, based on these parametric measures, this exact panel had strong consensus and stability on the ranking of the priorities. Nevertheless, our research has significant limitations. The Delphi method does not necessarily represent the actual global consensus or the true answer to the research question. The small sample size can limit its generalisation even though the central limit theorem and statistical rigour should hold above a size of 30. Furthermore, it cannot naturally speak of other sectors' priorities, such as environmental or ecosystem protection. To alleviate this, we intend to make our results more robust and test their sensitivity vis-à-vis real-world data and budgeting in the next phase with, e.g., Monte Carlo and multi-criteria decision-making (MCDA) analyses.

2.4.2 Relevancy for climate change adaptation

We did what many (Lentz & Maxwell, 2022; Rising et al., 2022; Stern et al., 2022) call for in better informing decision-makers of humanitarian and disaster response as well as climate change adaptation and deciphering their endogenous preferences: Ask the key users what criteria and options they consider priorities when allocating scarce public resources to adapt and to counter losses and damages. The problem of cutting the global budgetary cake fairly and equitably is not trivial – especially when more operational discussions on the COP28-agreed "Loss and Damage" funding are ongoing, and climate change exacerbates crises.

Here, we contribute to behavioural climate economics by providing prioritised expert preferences on the above questions. As IPCC AR6 WG2 states, the current literature "largely does not consider the increased difficulty of adapting to climate extremes and general higher variability in climate that is projected to occur in the future" (2022, p. 2489).

The forecast time preference that the panel members work primarily on is the near future: Thus, predominantly days(s), month(s) or year(s) forward (subsection 2.3.3). The results could be different if we aimed the Delphi method at purely developmental or investment actors looking strictly at decades ahead. Notwithstanding that, for example, the World Bank's corporate scorecard or the Asian Development Bank's results framework heavily depend on people-centric indicators, such as 'people with strengthened climate and disaster resilience'. This would indicate that the panel's results are covariant, at least on the criteria, for those looking at a longer investment horizon. An explanation could be that public institutions are bound via constitutions to be equity-driven in resource allocation. Nevertheless, further preference studies aimed at different groups or with a larger sample could build valuable additional evidence on the current paper's gaps.

For the timeframe, this paper raises at least one issue to examine further on the 'tyranny of the present' or 'myopic behaviour' problems of losses and damages: How much will our adaptive capacity and its funding envelope in the future pathway contain simply responding more and more effectively to crises and disasters (e.g., using diverse financial instruments or insurance mechanisms, involving private actors) instead of preventing them decades ahead? Especially with scarce resources to distribute timewise between response and prevention among already rising amounts of climate change-attributable extreme events. In other words, in an era of losses and damages.

Our objective was to explore the forward-looking criteria and options that would be prioritised in humanitarian aid and disaster risk management funding allocations regardless of organisation, policy background or job function, region of focus, definitive terminology, exact time horizon, or similar factors. In other words, it attempts to find covariant variables in continuous time for general use. Thus, it seems remarkable how similarly the very diverse panel answered when put in front of an ensemble of composite criteria or complexly interlinked risks – where, in both cases, they often overlap. This consensus suggests that the results of this paper show an emergent preference for the loss and damage sector.

Thus, it raises further questions on what we can and should prioritise with scarce resources. In other words, what is the time value of a human life according to behavioural preference? Should we first extinguish the imminent "house is on fire" issues or focus on adapting and reducing the residual risk of the cascading collapses possible in the longer timeframe? Both can be rational or irrational depending on the expected utility, but our paper examined what a behavioural 'damage and losses' agent would prefer. Future research could expand on these scopes and discuss our societal preferences.

2.4.3 Conclusions

In Table 10, we have summarised the results of the 2nd Delphi round (subsections 3.1 and 3.2). Instead of the numerical values assigned for analysis, focusing on the qualitative importance of the priority choices available to the panel during the funding simulations is likely better. Effectively, a criterion or option labelled as "somewhat low priority" would probably not be considered important enough in an actual prioritisation exercise to be included in the final cut, whereas a "high priority" would be examined much more carefully.

This panel's preference for people in need-centric and disaster risk-based criteria outweighs the importance of indicators related to governance, the rule of law, or a socio-economic aspect in humanitarian aid and disaster management (Table 10, col. Q1). The experts on the issue prefer those criteria that are inherently equity-driven and likely forecast the severity and magnitude of disasters and humanitarian crises most effectively and in an all-encompassing umbrella manner. Logically, these would estimate the final required funding per capita in need of aid – as likewise discussed in the qualitative comments. The notion corresponds with humanitarian principles and operational needs assessments of, for example, UN OCHA and the Integrated Food Security Phase Classification (IPC). In other words, that action should be based on need alone, prioritising the most urgent cases of distress.

The other indicators are by no means unimportant. Although focusing on people is often labelled as most relevant, there is a complex and crucial interplay between the magnitude and severity of the people-centred criteria vis-à-vis risk assessments and vulnerability, especially when moving farther in the forecast and intervention time. Principally, when closing in on the conceptual borders between responding and adapting to climate change or nexuses between humanitarian and development work. As discussed, hazard and exposure do not create people in need without vulnerability. The various versions of what encompasses 'risk' across different frameworks likely also contribute to the divergence (Visser et al., 2020). Similarly, the other criteria could have, for example, practical effects (e.g., logistical issues in delivering aid due to low humanitarian access) or development effects (an unstable rule of law causing permacrisis in conjunction with frequent disasters). They might not necessarily act as criteria per se, but as a stopper whereby funding might not be altogether feasible due to its low possibility for impact (e.g., aid flowing to corrupt institutions instead of people in need).

Likewise, focusing funding on adapting to climate change-related risks to food security, human health, and water security is a high near-future priority compared to, for example, risk to living standards or risk to terrestrial and ocean ecosystems (Table 10 ,col. Q2). As with the priority criteria, the results propose a clear prioritisation of where our counter-risk funding should go in the basket of options, but we should consider nuances. The panel noted in the qualitative comments that their choices reflected a timewise priority of the most urgent and life-threatening risks versus fundamental risks that can cascade in the long run – and that the choices were far from easy. For example, risks to ecosystems and socioecological systems can become threat multipliers for the more imminent risks. Then again, the long-term risks might be less irrelevant if a society collapses beforehand due to lack of food. Indeed, the IPCC defines that the representative key risks are not separable and that some are already occurring while others will occur before mid-century or before the end of the century (IPCC WG2, 2022, pp. 114, 117).

Table 10. Summary of panel preferences.

Priority ↓	Q1: *Criteria* in allocating humanitarian or disaster aid funding per future forecasts in view of climate change response or adaptation	Q2: *Options* for which to allocate humanitarian or disaster aid funding regarding adaptation to representative key risks of climate change
HIGH PRIORITY	• PEOPLE IN NEED (PIN) PER SEVERITY LEVEL OF THEIR HUMANITARIAN CONDITIONS (INCL. AFFECTED AND DISPLACED) • RISK OF HAZARD AND EXPOSURE TO DISASTERS	• RISK TO FOOD SECURITY • RISK TO HUMAN HEALTH • RISK TO WATER SECURITY
SOMEWHAT HIGH PRIORITY	• CAPACITY OF LOCAL ACTORS AND ON-GOING PROGRAMMING TO RESPOND/ADAPT • INDICATORS ON VULNERABLE GROUPS OR DIVERSITY OF GROUPS AFFECTED • LACK OF INFRASTRUCTURAL COPING CAPACITY	• RISKS TO PEACE AND TO HUMAN MOBILITY
SOMEWHAT LOW PRIORITY	• HUMANITARIAN ACCESS INDICATORS • RULE OF LAW INDICATORS AND LACK OF INSTITUTIONAL COPING CAPACITY • SOCIAL COHESION INDICATORS AND SOCIO-ECONOMIC VULNERABILITY	• RISK TO LIVING STANDARDS • RISK TO LOW-LYING COASTAL SOCIOECOLOGICAL SYSTEMS • RISK TO TERRESTRIAL AND OCEAN ECOSYSTEMS • RISKS ASSOCIATED WITH CRITICAL PHYSICAL INFRASTRUCTURE, NETWORKS AND SERVICES
LOW PRIORITY	-	-

Based on the 2nd round results from Table 7 and Table 9. Colouring matches the mentioned tables so that high priority = green, low priority = white. Within priority boxes, the categories are alphabetically. See Tables 2–3 for descriptions of each item's metrics and scopes during the Delphi panel.

CHAPTER 3 Prioritising humanitarian aid funding for multi-risk disasters in an era of climatic damage

ABSTRACT

The intersection of multi-risk disasters is a wicked problem for resource prioritisation. How do we effectively allocate funding to humanitarian aid when disasters compound and cascade with natural and human-made hazards – especially with climatic and non-climatic factors? Our research builds on the Intergovernmental Panel on Climate Change (IPCC) recommendation to use multi-criteria decision analysis (MCDA) to examine this.

For the first time, stochastic multi-attribute analysis (SMAA), a subtype of MCDA, is used to compare and prioritise funding for 26 fragile countries that were encountering a humanitarian crisis in 2023. The model integrates field data from the INFORM Severity dataset and expert weighting preferences from the United Nations, European Union, World Bank, research and public sectors, and civil society. Finally, we compared the prioritisation with the official funding requirements of the United Nations Office for the Coordination of Humanitarian Affairs (UN OCHA).

Our descriptive analysis broadly aligns with the current humanitarian funding requirements, except for countries like the Democratic Republic of Congo and Myanmar, which should receive a higher allotment, and Ukraine and Syria, which seem to be provided with undue support. The results confirm that a probabilistic multi-risk assessment combined with expert weighting produces a tangible and explainable funding allocation for policymaking and operational activities. These findings provide important insights in distributing scarce resources transparently yet effectively - particularly considering the funding freeze of the United States Agency for International Development (USAID).[13]

3.1 Introduction

In 2024, the world experienced its second consecutive year of record-breaking warmth, with average temperatures exceeding 1.5°C above pre-industrial levels (C3S/ECMWF, 2025). This unprecedented heat, coupled with multiple extreme weather disasters (World Weather Attribution, n.d.) signals a new era of impacts from climate change. The Fund for Responding to Loss and Damage (FRLD), created at the UN Climate Change Conference COP29 in Baku, aims to assist developing countries that are particularly vulnerable to the adverse effects of climate change and has received over USD 750 million in pledges. COP29 also saw agreement on the New Collective Quantified Goal on Climate Finance (NCQG) to triple climate finance to USD 300 billion annually by 2035.

A humanitarian crisis occurs when people's needs exceed local capacities, often due to a combination of natural and human-made hazards, requiring significant external aid. Climate change is increasingly contributing to these crises, especially in vulnerable regions (IPCC, 2023, p. 16). In 2025, one in every 26 people worldwide will need

---

[13] This chapter has been published in 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.

humanitarian assistance, totalling 305 million individuals with a funding requirement of USD 47,4 billion (UN OCHA, 2024).

However, evaluating costs and allocating funds effectively remains challenging, as traditional economic models struggle to capture the full range of disasters and climate damage, particularly the non-monetary ones (IPCC WG3, 2022, p. 88; Jäpölä & Van Passel, 2025; Rising et al., 2022). This is especially true in response to urgent crises in chaotic states with scarce data where delineating between whether a disaster or event was or was not influenced by climate change could be near impossible in sufficient time. At the same time, the concept of multi-risk has gained traction as a pragmatic approach to handle this sort of intangibility (Hochrainer-Stigler et al., 2023; Lee et al., 2024). In short, all risks should be assessed simultaneously to capture the full picture.

For instance, in South Sudan, unprecedented floods have worsened food and livelihood insecurity. This pushes pastoralists south, where their presence increases violent tensions with resident farmers (International Crisis Group, 2022). Currently, in total, 9 million people require humanitarian assistance, including 7 million facing famine-like conditions during the lean period and almost 4 million who are displaced (European Commission, 2024). However, it will be difficult to attribute the resulting people in need and their humanitarian funding requirements to a specific natural and human-made hazard—or a climatic or non-climatic driver. Even with the incredible progress in rapidly disentangling the drivers of extreme weather disasters in the last 10 years, for example quantifying the effect of climate change as a driver of the three deadliest cyclones this century remains highly uncertain (Otto et al., 2024).

While precise attribution of climate change impacts remains challenging (Newman & Noy, 2023), the urgency to act is clear—even more so with the United States Agency for International Development (USAID) funding freeze. The International Panel on Climate Change (IPCC) has proposed the multi-criteria decision analysis (MCDA) as a solution to manage the complex problem of allocating resources. (IPCC WG2, 2022, Chapter 17). Inspired by this, we tested a sub-variant of MCDA, stochastic multi-attribute analysis (SMAA), to handle the complexities and uncertainties involved in these decisions (Rising et al., 2022, p. 8; Stern et al., 2022, pp. 205–207).

To address the gap, we used INFORM Severity, a composite indicator measuring crisis-related data, to provide input to the empirical model. It is increasingly used to support crisis prioritisation decision-making in the European Union (EU), World Food Programme (WFP), and UN OCHA (IASC & European Commission, 2024). With INFORM Severity, our approach considered humanitarian needs arising from both natural and human-made hazard, including conflict and population displacement, as well as climate and non-climate factors. In addition, the SMAA requires weighting of the indicator data. Thus, we based them on preference information gathered with a Delphi panel involving crisis funding experts from the United Nations, the European Union, the World Bank, research and public sectors, and civil society (Jäpölä et al., 2024).

This line of investigation comprises our initial research question: RQ1 How would the SMAA and Delphi panel weighting prioritise resources in humanitarian crises with multiple disasters affecting them? We also wanted to see how realistic this model would be for policy or funding-oriented readers who work in the sector. Therefore, we compared it with different methods against the UN OCHA-coordinated funding assessments and the Notre Dame Global Adaptation Initiative (ND-GAIN) index. Our second phase was: RQ2 How does the model compare versus official funding requirements?

The descriptive results contribute to the discussion on crisis funding allocations and how to make them more fit for purpose. It is a proof of concept for a probabilistic multi-risk assessment supplemented by expert insight to support economic resource allocation. Judging from the results, attempting to clearly attribute natural or human-made hazards can become redundant, at least in this sector, as people in need will be people in need regardless of the exact causation. Thus, to avoid Pandora's boxes and focus straightforwardly on building resilience, we propose examining low-regret options to address the deep uncertainties of climate change—decisions that are justifiable under any plausible future scenario (IPCC WG2, 2022, pp. 2543, 2579; World Bank, 2024). For example, building early warning systems or nature-based solutions in areas that are prone to disasters with or without climate change impact.

The following sections will detail our methods, present our findings in section 3.1 for RQ1 and in section 3.2 for RQ2, and discuss their implications for global humanitarian funding. Both the dataset (Jäpölä, 2024) and the code (Van Schoubroeck & Jäpölä, 2025) are stored openly. Supplementary material allows readers to scrutinize our work in more detail.

3.2 Methods

3.2.1 Scope

The scope of our dataset was 26 countries with a humanitarian response plan (HRP) assigned by UN OCHA in 2023 (Table 11). These represent the areas with the highest current and near-future humanitarian needs for large-scale resource mobilisation and often an increased political risk in contrast to higher-income economies. The HRPs signal what the collective humanitarian and disaster response community has assessed as the most viable funding levels in response to the situation in 2023.

Table 11. The 26 analysed countries.

ISO3	Name in UN system	ND-GAIN	ISO3	Name in UN system	ND-GAIN
AFG	Afghanistan	32,8	MOZ	Mozambique	38,5
BDI	Burundi	35,5	NER	Niger	35,5
BFA	Burkina Faso	37,6	NGA	Nigeria	38,5
CAF	Central African Republic	27,7	PSE	occupied Palestinian territory	-
CMR	Cameroon	40,0	SDN	Sudan	32,8
COD	Democratic Republic of the Congo	32,4	SLV	El Salvador	45,9
COL	Colombia	47,8	SOM	Somalia	32,8
ETH	Ethiopia	37,5	SSD	South Sudan	-
GTM	Guatemala	43,9	SYR	Syrian Arab Republic	38,3
HND	Honduras	40,3	TCD	Chad	27,7
HTI	Haiti	35,5	UKR	Ukraine	53,3
MLI	Mali	34,6	VEN	Venezuela, Bolivarian Republic of	40,2
MMR	Myanmar	37,7	YEM	Yemen	35,0

These countries (including occupied Palestinian territory) had a UN Humanitarian Response Plan (HRP) in (UN OCHA, n.d.). The ND-GAIN index score is a comparative figure for their vulnerability to climate change. For scale understanding, Norway has a score of 75,0 at rank 1, and Chad has the lowest score of 27,7 at rank 185. (University of Notre Dame, 2021).

We excluded countries with different UN OCHA plans, such as flash appeals or regional response plans, to keep the dataset focused for the whole year of 2023 and to keep as close as possible symmetry between UN OCHA and INFORM Severity for comparative analysis. The year is appropriate for our investigation as the second hottest on record.

This sample is fitting to assess future effects of climate change adaptation as seven from the dataset are in the bottom 10 of the ND-GAIN index. All of them except Ukraine (and those without a score) are in the lower half of the index; thus, generally, they are climate-vulnerable and unready to improve resilience (University of Notre Dame, 2021). The drivers of the crises in the countries vary from conflict, violence, and displacement to earthquakes and directly climate-linked ones, such as drought, floods, cyclones, and other seasonal events. The majority have a combination of them and are thus complex crises (ACAPS, n.d.). 13 out of 26 have a climatic driver in addition to a conflict or socio-political driver (Table 15).

3.2.2 Research design

For RQ1, MCDA is one proposed solution to support comprehensive decision-making with objective intelligence in a conflicted and highly uncertain climate change setting. Predicting its impacts involves multiple systems, from atmospheric to economic – thus creating uncertainties and disagreements on magnitudes and distributions onto the decision-making apparatus. (Bell et al., 2001) The need for real-world utility using decision-analytic methods, such as MCDAs, is a crucial gap (IPCC WG2, 2022, p. 2568; Stanton & Roelich, 2021).

Deterministic decision analysis does not allow for data uncertainties, particularly relevant for the hectic and asymmetric information around disasters and humanitarian issues. Because of the high uncertainty of the situation on the ground when mixing climatic and non-climatic drivers, we chose SMAA to build an appropriate MCDA method and complement its weaknesses in inducing more uncertainty into the assessment phase. In addition to inducing stochasticity to the observed values via Monte Carlo simulations (Metropolis & Ulam, 1949), the indicators' weighing is varied.

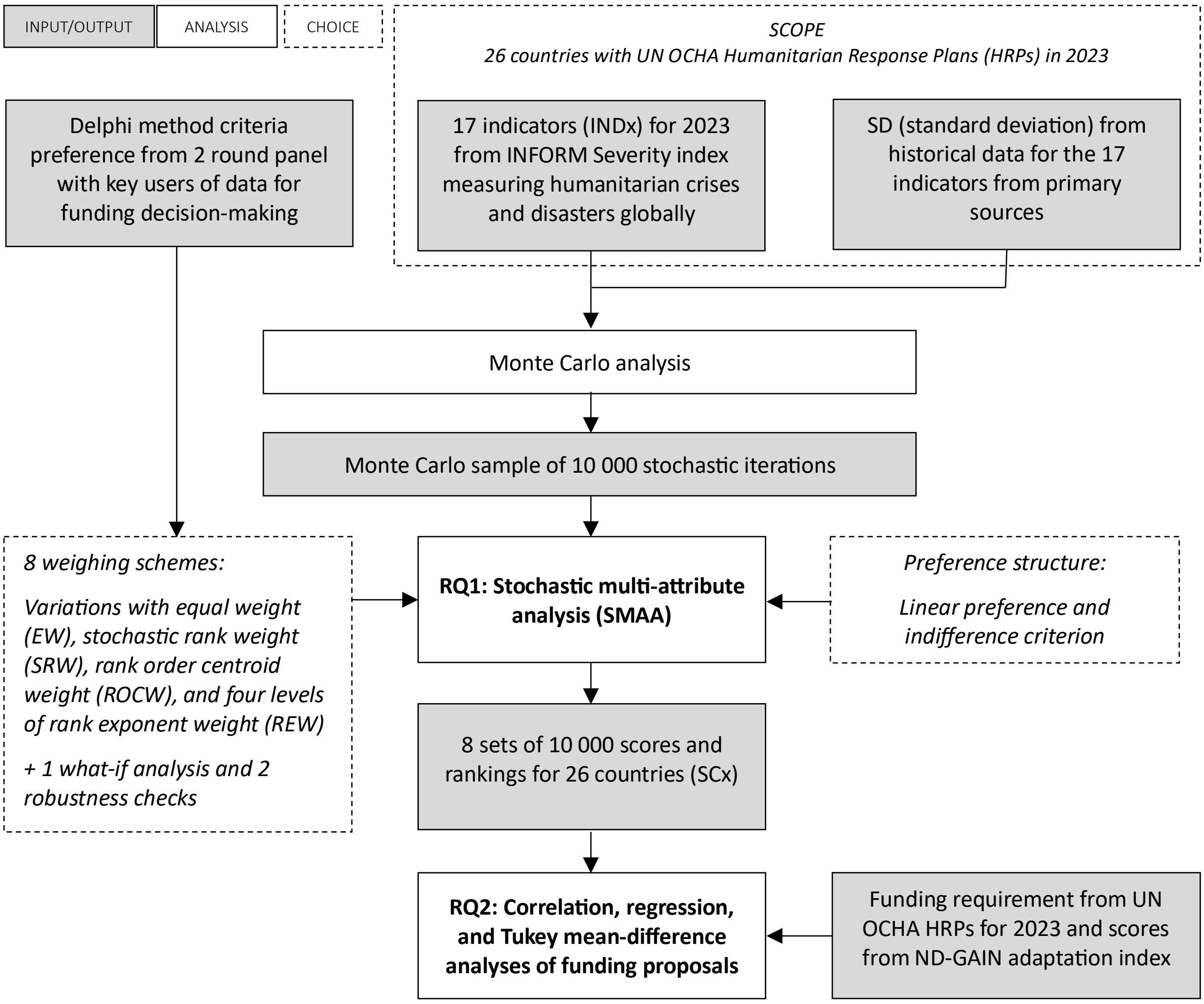


Figure 13. Workflow of the MCDA and comparability tests applied in the study.

Adapted from Van Schoubroeck et al. (2021).

The study on sustainability by Van Schoubroeck et al. (2021) was used as a foundation to construct our research design and the eventual algorithm (Figure 13). It was, in turn, based on the environmental SMAA work of Prado & Heijungs (2018). The Python script is available openly (Code S1) and S3 of SI includes more details on the formula and structure of the model. The input data from INFORM Severity as well as the ranking and weighing logic coming from the Delphi study are introduced below in sections 3.2.3 and 2.4.

After the SMAA had produced its results and to answer RQ2, we compared its funding allocation proposals against the UN OCHA funding requirements from the same year (Section S2, SI) using three different standard methods and examined controlled correlation with the ND-GAIN index. Finally, sensitivity and what-if analyses were used to test the robustness of the variations and the underlying uncertainty of both the input data and the ranking preference (Section S6).

3.2.3 INFORM Severity indicator data as input for SMAA

As input data for the SMAA, we used observations recorded in the INFORM Severity framework (ACAPS, n.d.). It was developed under the umbrella of the INFORM multi-stakeholder forum, including the Inter-Agency Standing Committee (IASC) Reference Group on Risk, Early Warning and Preparedness, and partners from the humanitarian and development sector, donors, and technical parties to compare the severity of humanitarian crises and disasters objectively.

In our multi-risk approach, the INFORM Severity dataset is a good choice because it considers all hazardous events that might compound and cascade among each other to create a complex crisis—where their impacts are impossible to isolate. These events can be natural, anthropogenic or socionatural (Poljansek et al., 2020, pp. 24, 72–73). Thus, for example, the indicators on people in need would provide the full amount of people severely impacted by a combination of climatic and non-climatic drivers – reflecting the reality better in the empirical model. We assume the comprehensiveness of the indicators (e.g., rule of law, democracy status) to cover countries with a high political risk. Thus, areas of fragile governments where traditional development or investment allocations would not necessarily operate or where assigning funding is less appealing to donors due to constraints.

In practice, we collated historical data from INFORM Severity (Table 12). In contrast to risk-based analytical frameworks, the observation-based INFORM Severity is a pragmatic solution for our proof-of-concept paper as it can be rigorously compared with the UN HRPs temporally – in essence, they should be non-orthogonal. We took 17 indicators from INFORM Severity as input, reflecting the interacting multi-risk relationship between climate change and disasters. Section S11 of SI has further information on the framework and data processing.

Table 12. Descriptive statistics of the indicator data and used as input for the SMAA.

	EXTRACTED FROM INFORM SEVERITY (2023)							AUXILIARY INFORMATION		
INDx	A. Indicator	B. Data type	C. Mean	D. Median	E. Min (true)	F. Max (true)	G. Timestamp	H. Mean SD (period)	I. Rank	J. Data source(s) (Table S8)
3	# of people living in the crises-affected area(s)	Continuous, ratio	38 600 000	21 000 000	5 400 000 (0)	217 600 000 (∞)	2023 (mean of every 2nd mo)	2 300 000 (every 2nd mo of 2023)	1	Derived by ACAPS from UN OCHA, GDACS, USGS, UNOSAT; ACLED, INSO, HIIK, GHSL, JRC
5	# of people affected by the crises	"	19 600 000	12 500 000	2 200 000 (0)	86 100 000 (∞)	"	3 600 000 (")	1	Derived by ACAPS from government, UN OCHA, humanitarian clusters
7	# of crises-related displaced people	"	4 900 000	2 900 000	100 000 (0)	22 500 000 (∞)	"	800 000 (")	1	Derived by ACAPS from government, humanitarian clusters, UN OCHA, IOM, UNHCR, IDMC
11–13	# of people in need (in levels 3–5 of moderate, severe, or extreme humanitarian conditions)	"	10 800 000	7 900 000	1 200 000 (0)	29 500 000 (∞)	"	1 300 000 (")	1	Derived by ACAPS from government, humanitarian clusters, UN OCHA, HNOs, UN and NGOs, IPC
21	Empowerment Rights Index	Discrete, interval	6,7	7,0	0,0 (0,0)	12 (14)	2011	2,0 (1981–2011)	6	EPR Core dataset from ETHZ
22	Democracy Status	"	4,1	3,9	1,5 (1,0)	7,2 (10)	2020	0,28 (2018–2022)	6	BTI
23	Ethnic Fractionalisation Index	"	0,5	0,55	0,0 (0,0)	0,9 (1,0)	2017	0,1 (1946–2021)	6	HHI by ACAPS from CIRI Human Rights Data Project
25	Gender Inequality Index (GII)	"	0,6	0,6	0,3 (0,0)	0,8 (1,0)	2018	0,0 (1990–2021)	6	UNDP
26	Income Gini coefficient	"	40	39	27 (0,0)	56 (100)	2006–2018 (latest)	3,7 (1981–2022)	6	The World Bank
27	Conflict Intensity	"	4,3	5,0	2,0 (1,0)	5,0 (5,0)	2019	0,5 (2019–2022)	2	HIIK
28	# people killed in crises	Continuous, ratio	3 600	1 600	100 (0,0)	40 000 (∞)	2023 (mean of every 2nd mo)	1 800 (every 2nd mo of 2023)	2	Derived by ACAPS from ACLED, KII, INSO, government
29	Corruption Perceptions Index (CPI)	Discrete, interval	24	25	9,0 (0,0)	40 (100)	2019	1,8 (2017–2022)	8	Transparency International
30	Rule of Law	"	-1,2	-1,1	-2,3 (-2,5)	-0,4 (2,5)	"	0,3 (1996–2022)	8	The World Bank's WGI
31	Rule of Law	"	3,3	3,1	1,0 (1,0)	6,3 (10)	2020	0,4 (2018–2022)	8	BTI
32	Freedom in the World Index	"	30	26	-2,0 (0,0)	66 (100)	"	5,2 (2013–2022)	8	Freedom House
33	# of different types of population groups affected by crises	Continuous, ratio	4,3	4,8	2,0 (0,0)	5,7 (∞)	2023 (mean of every 2nd mo)	0,5 (every 2nd mo of 2023)	3	Derived by ACAPS from UN OCHA, IOM, CCCM cluster, UNHCR
34–42	Sum of Humanitarian Access scores	Discrete, interval	17	19	4,3 (0,0)	23 (27)	"	1,3 (")	7	Scores calculated by ACAPS and summed up by authors

Note for Table 12. INDx refers to coding in INFORM Severity (Poljansek et al., 2020, p. 54). SD (standard deviation, column H) is calculated from the primary data source and used for the Monte Carlo simulation. The rank of column I (1-8, higher is more impactful) follows a previous Delphi study (Jäpölä et al., 2024); see ranking logic in Supplementary Tables S3-S5. Missing ranks (4 and 5) are not applicable for INFORM Severity because they refer to the lack of infrastructural coping capacity in the INFORM Climate Change framework instead of the status of humanitarian crises and disasters. See Dataset S1 for all details. Acronyms not opened elsewhere: ACLED = Armed Conflict Location & Event Data Project, BTI = Bertelsmann Transformation Index, CCCM = Camp Coordination and Camp Management, CIRI = Cingranelli-Richards, EPR = Ethnic Power Relations, ETHZ = Eidgenössische Technische Hochschule Zürich, GDACS = Global Disaster Alert and Coordination System, GHSL = Global Human Settlement Layer, HHI = Herfindahl–Hirschman Index, HIIK = Heidelberg Institute for International Conflict Research, HNO = Humanitarian Needs Overview, INSO = International NGO Safety Organisation, IDMC = Internal Displacement Monitoring Centre, IOM = International Organization for Migration, IPC = Integrated Food Security Phase Classification, JRC = European Commission Joint Research Centre, KII = Key Informant Interview, UNDP = UN Development Programme, UNHCR = UN High Commissioner for Refugees, UNOSAT = UN Satellite Centre, USGS = United States Geological Survey, WGI = Worldwide Governance Indicators

3.2.4 Ranking indicators with Delphi panel preference and weighing them

The subjectivity of ranking the different indicators in Table 12 is a common question regarding the rigour of such composite indicators because they, in essence, could be arbitrary or not reflective of a consensus (Visser et al., 2020). To ascertain specific rank preference on the indicators of INFORM Severity, we used findings from a two-round Delphi study with a panel (N=36) of crucial experts from 19 countries representing, e.g., international organisations (such as the UN, EU, World Bank, and Red Cross Red Crescent), the research and public sectors, and civil society (Jäpölä et al., 2024). The panel was asked to prioritise the indicators of both INFORM Severity and INFORM Climate Change Risk regarding their importance as criteria in allocating humanitarian or disaster aid funding per future forecasts, given climate change response or adaptation. Their consensus was used as the rank data for the current paper. The ranks (1–8, higher is more impactful) are shown in column I. Ranks not used here, such as 4 or 5, only relate to INFORM Climate Change Risk's indicators. Section S4 contains details of the process.

Exposing weights to the indicator ranks is a complex and subjective process. The Delphi preference data does not explicitly indicate the relative distance (weight) between the ranks. For example, people in need criteria are a high priority, and the rule of law indicators are somewhat low, but the numerical distance is unclear. Various weighing schemes are available within the developed SMAA models to satisfy the gap and are compared for robustness checks of the results.

Effectively, five different weighing systems with one of them in four ranges were chosen according to the literature: stochastic random weights (SRW), equal weights (EW), rank-order centroid weights (ROCW), and rank exponent weights (REW). (Prado & Heijungs, 2018; Roszkowska, 2013). REW can be varied from 0 to infinity according to its exponent (ε) where low is a shallow difference between the impact of weights and high produces a steep difference. For example, in REW ε = 1, rank 1 is eight times more impactful than rank 8, and in REW ε = 5, it is 33 000 times. However, the actual SMAA utilised uniform distributions in four different ε ranges from $0 \leq \varepsilon \leq 1$ to $4 \leq \varepsilon \leq 5$. Section S5 of SI contains a more detailed background on the logic, see especially Figure S2 for an illustration of the weights' importance.

3.3 Results

3.3.1 SMAA and Delphi panel weighting to prioritise resources

Our first phase was to see how the SMAA arrays and Delphi panel weighting would prioritise resources in humanitarian crises with both climatic and non-climatic influences. The SMAA computation runs 10 000 iterations of the real-world observation inputs from the indicators of the INFORM Severity index varied under historical standard deviation. This results in two different components: Scores and ranks relative to one another (Behzadian et al., 2010; Brans et al., 1986; Prado & Heijungs, 2018) for each country. The scores and ranks are based on how dire the situation is in line with INFORM Severity's indicators under stochastic settings and the panel's preference. It judges the indicators according to the Delphi panel's preferences and proposes, in essence, probabilistic solutions to the funding prioritisation of RQ1 with the uncertainty of the underlying data from Table 12.

Out of the eight various weighing schemes (Roszkowska, 2013; Xu, 2001), we display below one example of the results: The rank probabilities for each country (Table 13) with a rank exponent weight (REW) uniformly distributed at $2 \leq \varepsilon \leq 3$ where ε is the exponential factor. Effectively, the results in the table assess the probability of where each country would be placed during a resource allocation process under the panel-based weighing and the stochastic standard deviation-based Monte Carlo simulation (Metropolis & Ulam, 1949) input from historical data. A higher rank means that the country is in a worse situation and would require more funding – and vice versa.

The primary explaining factor of the probabilistic rank position is people-based indicators. For example, in December 2023 the Democratic Republic of the Congo had 26 million people in need at levels from moderate to extreme while Ukraine had 18 million (ACAPS, n.d.). But the more structural indicators, such as rule of law or Gini coefficient, can become a crux as well: Mali is higher in probabilistic rank than Ukraine while having less people in need in December 2023 (9 million). The what-if analysis, where structural indicators are the topmost rank, indicates this best when Mali would be of a considerably higher rank than Ukraine (Table S7).

Note for Table 13. From the 10 000 permutations of SMAA in weight scheme 6) REW (rank exponent weight) with $2 \leq \varepsilon \leq 3$. A higher rank effectively means more funding is required. Colour code: white = 0%, orange ≥ 50%. Those rounding to 0% have been removed for clarity. The rows indicate how often the country reached each rank out of 10 000; thus, they effectively represent probabilities of the country's actual rank under the stochastic variations. For example, the Democratic Republic of the Congo was at 1st rank 3 434 times, 2nd rank 2 355 times and 3rd rank 1 549 times, while El Salvador was 26th rank every time. Descending order is determined by the highest rank probability per country (in bold). The same data is plotted graphically in Figure S3. This weighing scheme (REW $2 \leq \varepsilon \leq 3$) is shown because it had the highest Spearman mean rank correlation coefficient (r_s=0,851) with the real-world funding. Later we compare with the scenario scores rather ranks and another scheme shows slightly higher similarity. Results of the other variations with mean scores (Table S6), mean ranks (Table S7), and probability density functions (Figure S4) are available in the SI and Dataset S2 for the reader.

Table 13. Probabilities of the 26 HRP (humanitarian response plan) countries' rank positions.

	Rank (and probabilities of rank positions)																									
Country ↓	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
Democratic Republic of the Congo	**34%**	24%	15%	10%	7%	5%	3%	1%																		
Afghanistan	**27%**	21%	16%	12%	8%	7%	5%	3%	1%																	
Syrian Arab Republic	18%	**24%**	21%	13%	8%	5%	4%	3%	2%																	
Sudan	15%	**16%**	15%	13%	10%	9%	9%	8%	4%	1%																
Yemen	3%	7%	12%	16%	**17%**	15%	14%	10%	5%	1%																
Somalia	1%	4%	9%	16%	20%	**21%**	16%	9%	3%	1%																
Myanmar	1%	3%	8%	13%	17%	20%	**21%**	13%	4%																	
Nigeria		1%	3%	6%	8%	12%	17%	**26%**	18%	7%	3%															
Ethiopia			1%	2%	3%	6%	10%	20%	**36%**	17%	6%															
South Sudan							1%	5%	20%	**52%**	21%	1%														
Venezuela, Bolivarian Republic of								2%	7%	21%	**51%**	11%	6%	2%	1%											
Mali											12%	**50%**	29%	6%	1%											
Ukraine											6%	31%	**36%**	13%	6%	3%	2%	1%	1%							
Chad											1%	5%	18%	**42%**	20%	9%	3%	1%								
Cameroon												1%	4%	13%	**23%**	23%	16%	11%	6%	2%	1%					
Central African Republic												1%	4%	13%	**18%**	17%	15%	13%	10%	6%	3%	1%				
Colombia													1%	6%	15%	20%	**21%**	18%	12%	6%	1%					
Haiti													1%	3%	9%	15%	20%	**22%**	17%	9%	4%	1%				
Mozambique														2%	5%	9%	13%	17%	**22%**	17%	9%	4%	1%			
occupied Palestinian Territory															1%	3%	6%	10%	15%	**19%**	15%	14%	14%	5%		
Burundi																		1%	5%	16%	**29%**	28%	17%	4%		
Burkina Faso															1%	2%	4%	6%	11%	20%	**23%**	17%	13%	4%		
Guatemala																			1%	5%	14%	30%	**40%**	10%		
Niger																				1%	2%	6%	14%	**58%**	18%	
Honduras																							1%	18%	**81%**	
El Salvador																										**100%**

3.3.2 Comparison versus official funding requirements and ND-GAIN index

For a policy or funding expert who works in the field, the next question is how realistic the results are. For example, does it offer vastly different prioritisation than what is used now? Thus, this section determines how does the model compare versus official funding requirements from UN OCHA's humanitarian response plans (HRPs, available in Section S2, SI) and the ND-GAIN index.

From this point on, we use the arithmetic means of the scores and ranks proposed by SMAA to simplify the analysis to a meaningful level, reducing the study's probabilistic nature of the first section[14]. In addition to correlation analyses, we ran an exponential regression analysis to fit the SMAA's proposed solutions to the requirement level of the HRPs (Chen & Qi, 2023; Mayer, 1975). Our main choice was a logarithmic transformation of the HRPs' funding requirements for a better model fit.

The results show moderate to strong positive correlations (r or r_s of 66,1–85,1%) between what the SMAA proposes as a resource allocation solution for the 26 countries and what UN OCHA deemed required in the same year. With adjusted coefficients of determination (R^2 adj.) rising to 71,9% for scheme 3, there was a high goodness-of-fit between the SMAA results and the official requirements. (Table 14.)

Table 14. Descriptive statistics between the SMAA arrays.

		CORRELATION		**EXPONENTIAL REGRESSION (with scores)**						
Weight scheme	**Explanatory setting**	**Pearson's r**	**Spearman's r_s**	**Estimate β_1 (antilog)**	**SE**	**F**	**dF**	***P*-value**	**R^2**	**R^2 adj.**
1	EW	0,661	0,765	1,123	0,710	37,80	1, 25	< 0,001	0,612	0,595
2	SRW	0,661	0,767	1,123	0,709	37,90	"	"	0,612	0,596
3	ROCW	0,731	0,850	1,065	0,592	64,84	"	"	0,730	0,719
4	REW 0 ≤ ε ≤ 1	0,681	0,850	1,100	0,675	44,32	"	"	0,649	0,634
5	REW 1 ≤ ε ≤ 2	0,707	0,834	1,077	0,626	55,41	"	"	0,698	0,685
6	REW 2 ≤ ε ≤ 3	0,720	0,851	1,065	0,602	62,10	"	"	0,721	0,710
7	REW 3 ≤ ε ≤ 4	0,725	0,846	1,058	0,597	63,39	"	"	0,725	0,714
8	REW 4 ≤ ε ≤ 5	0,724	0,840	1,050	0,603	61,73	"	"	0,720	0,708
-	What-if	0,549	0,615	1,047	0,868	17,40	"	"	0,420	0,396
-	INFORM Severity	0,678	0,877	8,332	0,614	58,72	"	"	0,710	0,698
-	INFORM Risk	0,464	0,680	0,906	0,826	21,59	"	"	0,474	0,452

Mean scores or mean ranks (Tables S6 and S7) and the UN OCHA HRPs' funding requirements (natural logarithm, Table S1). The higher the R^2 adj. is the less error there is. An R^2 adj. of +1 perfectly fits predicted and observed values. (Mayer, 1975) *Spearman's r_s is used for rank data while everything else is used with the interval data of scores (de Winter et al., 2016; Schober et al., 2018).*

[14] Note added for thesis only: Because official UN OCHA figures are deterministic, the probabilistic solutions from section 3.1.1 must be reduced to point data for a proper comparison. As the distributions are now lost, this undermines the inferential interpretation of, for example, the regression tests. For example, due to heteroskedastic error, the results of the regressions could be different with robust approaches. The tests here were meant as purely comparative - and not inferential - with adjusted R^2 as the main indicator of agreement between the stochastic model and UN OCHA figures. They, including the correlations and the Tukey mean difference plot, show that a probabilistic model works equally well, but would in the end give more real information of the situation to decision-making with the probability distribution as well as flexibility outside of a deterministic, rigid approach.

See Dataset S2 for complete analysis and with residuals. Pearson's r = Pearson product correlation coefficient, SE = standard error of regression, F = F-test of significance, dF = degrees of freedom. R^2 adj. = adjusted coefficient of determination. 1) EW (equal weight); 2) SRW (stochastic random weight); 3) ROCW (rank order centroid weight); 4) REW (rank exponent weight) with $0 \leq \varepsilon \leq 1$; 5) REW with $1 \leq \varepsilon \leq 2$; 6) REW with $2 \leq \varepsilon \leq 3$; 7) REW with $3 \leq \varepsilon \leq 4$; and 8) REW with $4 \leq \varepsilon \leq 5$. Increases of ε effectively increase the weights of the top ranks exponentially (Figure S2). What-if is scheme 6 with ranks inversed and INFORM Severity is its June 2023 scores and INFORM Risk with its 2023 scores, all included for robustness check.

In the what-if analysis, all the ranks are inverse so that people and risk-based indicators have a lower weight than more governance and structure-related indicators; closer to INFORM Risk. Both obtained lower levels of goodness-of-fit than the rest of the ensemble. INFORM Severity had the highest Spearman rank correlation and almost as high Pearson product correlation and R^2 adj. as the SMAA model's top schemes. This indicates that INFORM Severity is very well specified already especially for simple ranking, but its framework contain some noisy indicators or less range in its scale that prevents it from explaining the order of magnitude differences in funding levels. Full heat maps for sensitivity analysis are available in Section S6, SI.

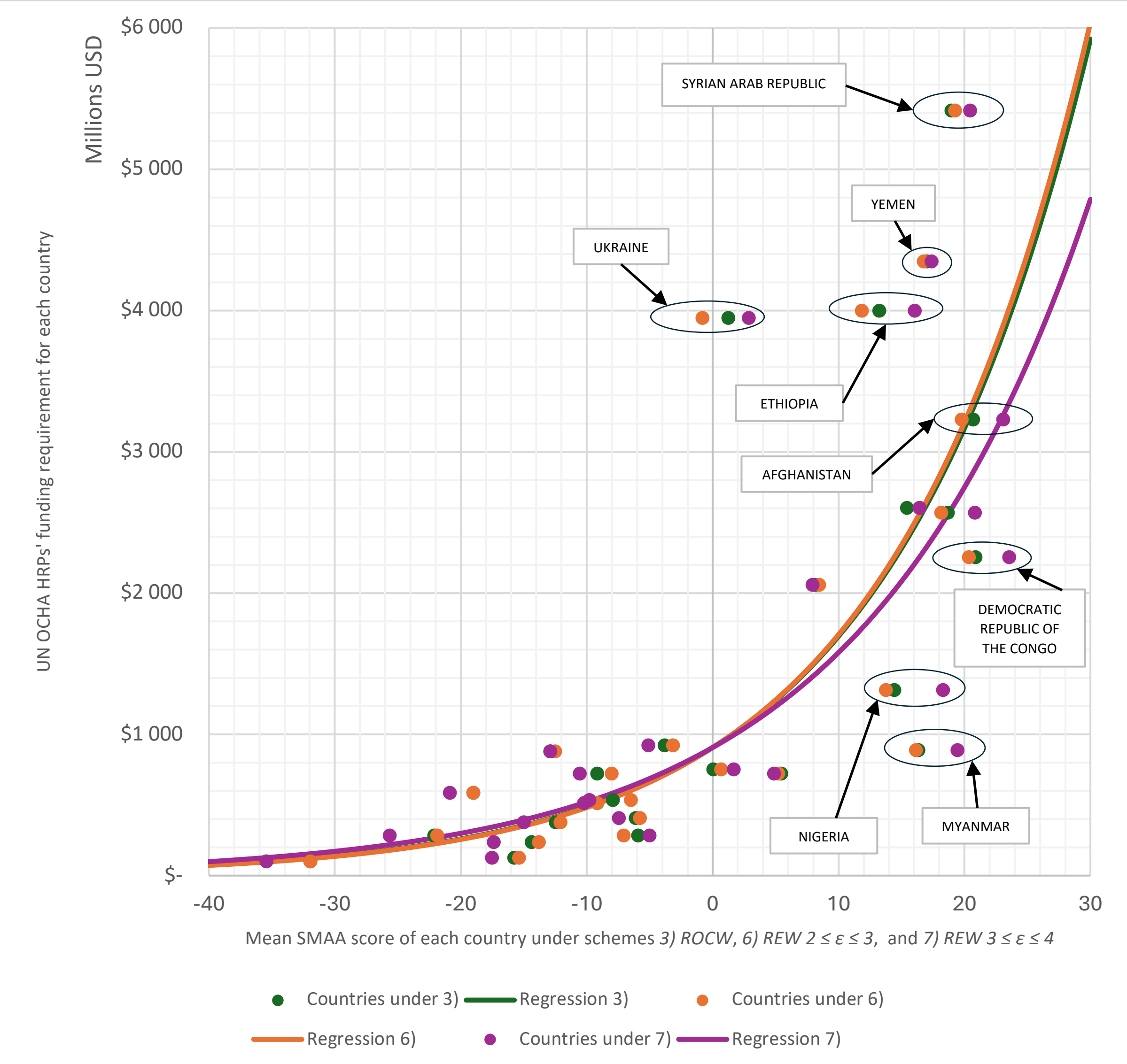


Figure 14. Scatterplots and exponential regressions of each country's mean scores.

From INFORM Severity SMAA (x-axis, Table S6) against UN OCHA HRP's funding requirements (y-axis, Table S1) under schemes 3, 6 and 7. These three schemes had the highest adjusted coefficients of determination R^2 adj. (71,0–71,9%). The curves represent allocations proposed by SMAA for the same amount as the total funding requirement and when fitted to the same exponential rise as the HRPs show. The further the dots are from the curve; the further the respective country's UN OCHA-determined funding requirement is from the SMAA proposal. Schemes 3 and 6 are practically the same curve.

Visually, the fit is far better in less severe countries with lesser magnitudes of crises and disasters, where scores range from -40 to 0. Between scores from 0 to 30, there are more widespread outliers on both sides of the proposed funding solutions' curves to the most severe crises, such as Ukraine, Yemen, the Syrian Arab Republic, and Myanmar. These countries have a complex ongoing conflict (IASC & European Commission, 2024). The estimated slope β_1 of the curves for weight schemes 3 and 7 is approximately 1,065. This indicates that funding requirements rise steeply with marginal increments in the magnitude of the crises and disasters, 6,5% per every score unit increase. We examined a power law regression as a possibility with scheme 3 (the one with the highest R^2 adj. in exponential). Still, it resulted in R^2 adj. of 53,9% and, thus, a lower goodness-of-fit than any of the exponential curves. All correlation and regression information are provided in the Dataset S2.

These alone are not an appropriate test between two methods assessing similar underlying phenomena, and do not necessarily imply agreement (Ranganathan et al., 2017). Thus, we graphically evaluated the fit of three schemes with the highest R^2 adj. with scatterplots and their exponential trendlines (Figure 14).

According to the literature, a Tukey mean-difference (or Bland–Altman) plot is the most suitable test for agreement when both measurements analyse the same core phenomenon (funding needed due to real-world situations). (Giavarina, 2015; Ranganathan et al., 2017) Thus, this was our third and most rigorous test for the INFORM Severity-based SMAA.

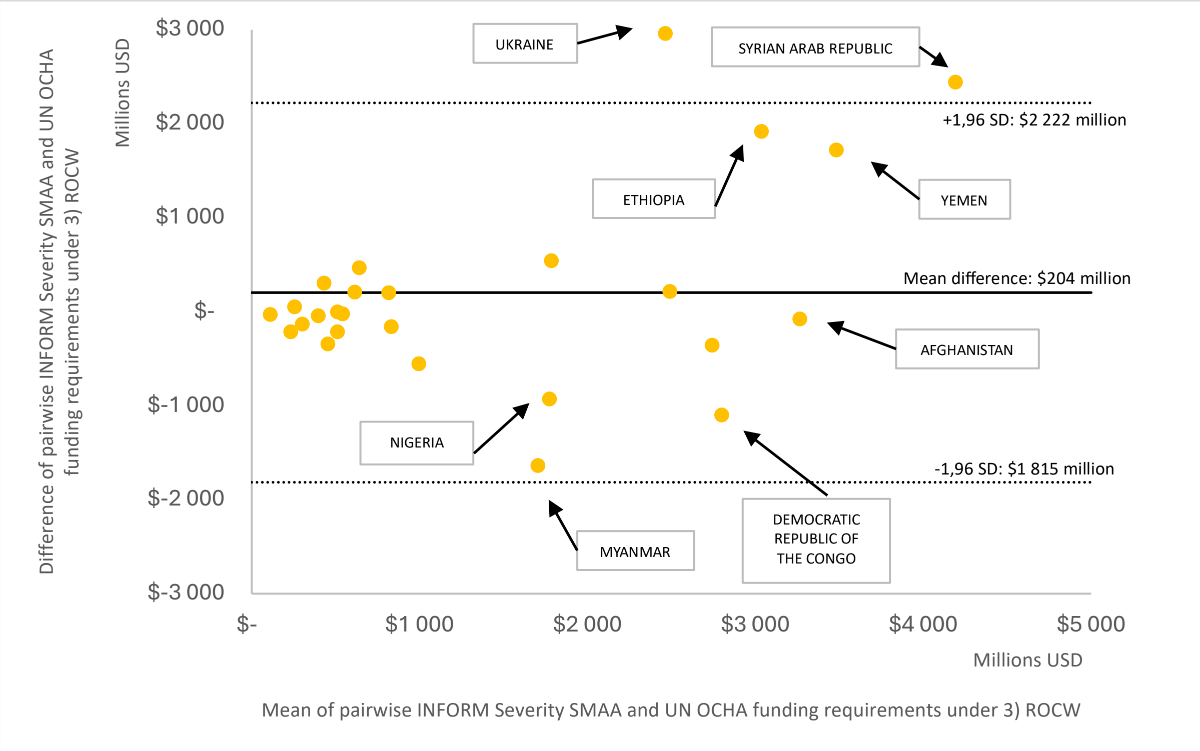


Figure 15. Tukey mean-difference plot.

To test agreement between funding requirement results of INFORM Severity SMAA and UN OCHA HRPs under weighing scheme 3) ROCW. This represents more accurately the difference between how SMAA would allocate the same amount as UN OCHA-determined total funding requirements (intersections of the curves and y-axis in Figure 14). The further the dots are away from the mean difference, the greater the disagreement. Scheme 3 had the ensemble's highest adjusted coefficient of determination (R^2 adj. = 71,9%) in the mean scores. In contrast to Table 13, where scheme 6 had the highest mean rank correlation.

24/26 of the funding target differences (yellow) are within the ±1,96 standard deviations (SD) limit of agreement (LoA, dotted lines) from their mean difference (solid line). This indicates a 95% confidence interval, commonly used in the literature (Giavarina, 2015). *Still, it can vary as extreme as from USD -1,8 billion to USD +2,2 billion, especially in countries with higher magnitudes of impact and severity (more on the right side starting at approximately USD 1,5 billion on the X-axis)—data at Table S9. If the LoA would be ±1,00 SD (i.e., from USD -0,8 billion to USD 1,2 billion), then Ukraine, the Syrian Arab Republic, Ethiopia, Yemen, Nigeria, the Democratic Republic of the Congo, and Myanmar would be outside. The plot's data is available in Table S9.*

It is a method to quantify the difference between two quantitative measurements by constructing limits of agreement. Here, it compares the differences between scheme 3's proposed allocations and the UN HRPs' data (Figure 15) and provides the most suitable evidence of similarity between the two measurement mechanisms. Excluding the outliers of Ukraine and the Syrian Arab Republic, all countries fit within the limits. In addition, the mean absolute percentage error (MAPE) of the SMAA funding requirements predictions in contrast to the UN OCHA requirements was 49% whereas weighted MAPE (WMAPE) was 2%. The weighted version provides a better interpretation as it relates the error to its magnitude. For example, a large percentage error in the smaller budget allocated for Guatemala does not outweigh a small percentage error in the very large allocation for Syria.

As a final step, we assessed the correlation between the results Table 11's ND-GAIN index (Table 15). The correlation between scheme 3 and ND-GAIN with all the countries is weak (r or r_s of 31,1–39,1%). However, when we only assess those 13 countries that are climatically driven in addition to other drivers (e.g., conflict), the correlations are moderate to strong (67,1–71,1%).

Table 15. Drivers of the crises in the analysed 26 countries.

Country	ISO3 ↑	Drivers	ND-GAIN score	SMAA score	ND-GAIN rank**	SMAA rank
Afghanistan	*AFG*	Conflict, Violence, Displacement, Drought*, Earthquake, Socio-political	32,8	20,7	4	2
Burundi	*BDI*	Violence, Displacement, Floods*	35,5	-14,4	9	22
Burkina Faso	*BFA*	Conflict, Displacement, Violence	37,6	-12,9	13	21
Central African Republic	*CAF*	Conflict, Displacement	27,7	-7,9	1	17
Cameroon	*CMR*	Conflict, Displacement	40,0	-6,1	18	16
Democratic Republic of the Congo	*COD*	Conflict, Displacement, Socio-political	32,4	20,9	3	1
Colombia	*COL*	Socio-political, Conflict, Violence, Floods*, Displacement	47,8	-5,9	23	15
Ethiopia	*ETH*	Displacement, Floods*, Conflict	37,5	13,2	12	9
Guatemala	*GTM*	Violence, Socio-political, Other seasonal event*	43,9	-15,8	21	23
Honduras	*HND*	Violence, Socio-political, Other seasonal event*	40,3	-22,1	20	25
Haiti	*HTI*	Earthquake, Violence, Socio-political, Other seasonal event*	35,5	-9,2	9	18
Mali	*MLI*	Conflict	34,6	0,1	7	13
Myanmar	*MMR*	Socio-political, Conflict, Violence	37,7	16,4	14	6
Mozambique	*MOZ*	Conflict, Displacement, Cyclone*	38,5	-9,2	16	19
Niger	*NER*	Conflict, Displacement	35,5	-19,0	9	24
Nigeria	*NGA*	Conflict, Displacement, Violence	38,5	14,4	16	8
occupied Palestinian territory	*PSE*	Conflict, Socio-political, Violence	-	-12,4	-	20
Sudan	*SDN*	Displacement, Violence, Floods*	32,8	18,7	4	4
El Salvador	*SLV*	Displacement, Violence, Floods*, Drought*	45,9	-31,9	22	26
Somalia	*SOM*	Conflict, Displacement, Floods, Drought*	32,8	15,4	4	7
South Sudan	*SSD*	Conflict, Floods*, Displacement	-	8,2	-	10
Syrian Arab Republic	*SYR*	Conflict, Displacement, Violence	38,3	19,0	15	3
Chad	*TCD*	Conflict, Displacement	27,7	-3,8	1	14
Ukraine	*UKR*	Conflict, Displacement	53,3	1,2	24	12
Venezuela, Bolivarian Republic of	*VEN*	Socio-political, Violence, Floods*	40,2	5,4	19	11
Yemen	*YEM*	Conflict	35,0	17,0	8	5
Pearson's r with scores (N=26)				**-0,311**		
Spearman's r_s with ranks (N=26)						**0,391**
Pearson's r with scores assessing only those with a climatic driver* (N_C=13)				**-0,671**		
Spearman's r_s with ranks assessing only those with a climatic driver* (N_C=13)						**0,711**

According to INFORM Severity of December 2023 and correlations of the whole population (N=26) and those with climatic drivers (N=13c) to the ND-GAIN Index (2021) an SMAA scores/ranks (University of Notre Dame, 2021). Respective ND-GAIN (2021) scores and ranks as well as SMAA scores and ranks under weighing scheme 3) ROCW are included. Correlation tests are then done with all countries (N = 26) and only between those with a climatic driver * (NC = 13). South Sudan and occupied Palestinian territory do not have an ND-GAIN score. Note that ND-GAIN score and the SMAA proposed score have different directions, so a low ND-GAIN score means higher climate vulnerability whereas a high SMAA score means more funding is needed to cope. Hence, the score correlations are negative. ** = rank in this cohort, not in the whole ND-GAIN index.*

3.4 Discussion

3.4.1 Implications for effective funding strategies to counter natural and human-made disasters

First, to discuss the results' compatibility, they showed high agreement and strong correlations between the SMAA-based dataset and real-world UN OCHA funding requirements (Table 14, Figure 15) aligning with, for example, Dellmuth et al. (2021). However, there is room to improve indicator alignment with funding neutrality and impartiality. For example, the Democratic Republic of the Congo should probabilistically be on par with Afghanistan regarding needs and the chronic vulnerable situation (Table 13), but is considerably lower in the UN OCHA-indicated funding requirement (Figure 14). Ukraine and Syria were clear outliers in our SMAA-proposed funding solutions and both more than two standard deviations (approximately USD ±2 billion) away from the UN OCHA proposal.

Funding needs for humanitarian crises increase exponentially with the severity of the situation (Figure 14). The rigour of transparent and impartial funding methodologies decreases as context complexity and required funding increase. In addition to Ukraine and the Syrian Arab Republic as clear outliers, the countries of Ethiopia, Yemen, Nigeria, the Democratic Republic of the Congo, and Myanmar are beyond one standard deviation (approximately USD ±1 billion) from the SMAA-proposed solutions (Figure 15). One future research aim is to assay from donors what level of divergence would prompt a change in funding decisions. Errors in the assessments, the qualitative severity or intensity of human needs (e.g., famine versus stressed food insecurity), and discretion are always factors during resource allocation, but differences of USD 1–2 billion seem very distant.

Conflict-ridden countries, such as Ethiopia and Yemen, have the highest funding needs, aligning with INFORM data analysis (IASC & European Commission, 2024). Climate change often amplifies these needs. The model had high correlations with the SMAA's results against the ND-GAIN index, when controlling for climatic drivers (Table 15).

All in all, the above findings indicate that a model which considers all vulnerability and severity affecting determinants, including natural and human-made hazard as well as climatic and non-climatic, will work in prioritising need regardless of causation. In addition, decision-makers are often overwhelmed by information, (Lentz & Maxwell, 2022) leading to analysis paralysis. Even when compounded, the number of indicators included in analysis frameworks seems superfluous. Our optimal weighing conditions (Table 14) showed that people-based indicators are between 1-2 orders of magnitude more important than societal or institutional indicators (Table S5, Section S5). Too much data to curate is not necessarily feasible for robust decision-making, and without sufficient upkeep, indices can quickly become old and less agile.

Our results agree, for example, with Lopez et al. (2023), Puy et al. (2022) and Slim (2023) that prioritisation should focus on parsimonious models reflecting the severity of the situation and the core necessary needs of a population as climatic loss and damage increase. The INFORM Severity's goodness-of-fit was on par with the SMAA model (Table 14). Because their performance was similar, the comparative tests indicate that INFORM Severity has unnecessary indicators in its framework that do not provide more predictive[15] power. Its additional layer of scoring countries by the severity of the affected people's condition (from minimal to extreme needs like in the Integrated Food Security Phase Classification [IPC]) could provide the pertinent accuracy instead of many indicators. However, this paper also shows its current robustness.

Similarly, we argue for low-regret options to be used (World Bank, 2024). These options, such as investing in early warning systems or nature-based solutions, are beneficial regardless of climate change and avoid contentious attribution debates. They seem the most feasible route to accentuate robust decision-making in the uncertain climatic future. Especially because comprehensively disaggregating climatic drivers from non-climatic ones at the pace needed for response and adaptation can stay impractical for a long time (Newman & Noy, 2023; Otto et al., 2024)—even more so if we wish to move to anticipatory or early warning-based action.

[15] Note added for thesis only: Here, *predictive* means predicting funding needs from crisis severity. INFORM Severity is otherwise mainly tuned for the current crisis status and not necessarily as a projection of the future although, for example, it contains information from the Integrated Food Security Phase Classification (IPC) where analyses usually cover an estimate for months ahead.

Our paper contributes to developing a sectoral climate damage model that estimates the human cost of climate change in humanitarian aid and disaster risk. It provides rigorous estimates and better accounts for externalities and non-market effects (Rising et al., 2022; Stern et al., 2022) and accounts for the bounded rationality – or limited capacity to process data – of public decision-making on funding prioritisation (Kahneman & Tversky, 1979).

3.4.2 Limitations and strengths

According to IPCC AR6, MCDA is primarily used to model, explore, and rank conflicting objectives in climate risk management. We applied it to prioritize funding for humanitarian crises. MCDA's strengths include incorporating elements from other decision-analytic tools, such as Bayesian methods and decision-making under deep uncertainty (DMDU). However, it lacks in addressing stochastic and epistemic uncertainties (IPCC WG2, 2022, pp. 2569–2575). Section S6 in SI contains our sensitivity and what-if analyses.

Our method is novel, marking the first use of MCDA in a humanitarian context. Previously, MCDA has been used for sub-national or national recommendations or theoretical studies (Nain et al., 2023). The probabilistic nature of SMAA better reflects the chaotic nature of climate change and humanitarian crises. Using a Delphi panel grounds the model, contrasting with assumptive models.

The study has significant limitations, including the use of 2023 data, which aids comparison with UN OCHA assessments but reduces generalizability. Likewise, using only INFORM Severity limits our scope as it, for example, does not include indicators on infrastructural capacities (e.g., building damage) or forward-looking risk assessments suitable more for intertemporal choices in climate change adaptation (i.e., as in the INFORM Climate Change Risk index). A multi-risk approach reduces the direct attributability of the crises to natural or human-made disasters. Still, it is a far more realistic tactic because relevant variables will interact in highly complex, cascading, and compounding manners (IPCC WG2, 2022, pp. 18–19; Knox Clarke & Hillier, 2023; Red Cross Red Crescent Climate Centre, 2023) and could remain a Pandora's box for effective decision-making.

While our research did not cover exogenous political interests, acknowledging them as potential variables is valid. Media coverage significantly influences donors' allocation decisions, possibly explaining our outliers. In general, three factors play a role: Humanitarian needs, strategic interests, and agenda-setting (Rost & Clarke, 2025). Our results, based on the Delphi panel's input, primarily reflect reactive humanitarian needs rather than structural factors like rule of law or democratization scores (Table 12). A what-if analysis, inverting these factors, as well as comparatively using INFORM Risk yielded less accurate modelling. Exogenous human factors not captured in our dataset, such as resource misallocation, political interests, or operational gaps, could explain differences in funding proposals

As a proof-of-concept paper, these are tolerable trade-offs to comparative rigour but should be investigated more in future studies, such as methods for integrating exogenous drivers more. Avenues include by regressing against media coverage or forgetfulness of the crisis (Scott et al., 2022) or with quantified large language model (LLM) analysis of donors' self-stated foreign policies and strategies.

The method only used the humanitarian response plans as a real-world comparison to our results. We omitted other data, such as flash appeals or regional response plans, as attributing these correctly to each country and period would induce more arbitrary human judgment in our analysis. A critical gap in the MCDA and SMAA techniques is their inability to consider the epistemic uncertainty of climate change (IPCC WG2, 2022), such as endgame scenarios (Kemp et al., 2022). A potential next step is to expand and extrapolate this SMAA proof-of-concept to the IPCC scenarios up till 2100. Hence, we could assess how much our multi-risk human costs will be via disasters, extreme events, and crises in the coming decades with every projected increment of global warming. Temporally, there is no rational barrier to using the same model and expert insight with input data from different time series.

3.4.3 Conclusions

Following IPCC recommendations, our paper used MCDA to address the complexities in prioritizing humanitarian crises stemming from both natural and human-made hazards as well as climatic and non-climatic divers. We compared our results with the official UN funding requirements and the ND-GAIN index.

Our results demonstrate the feasibility of using SMAA and the INFORM Severity index in an operational setting, supplemented by a Delphi expert panel. They confirm that a probabilistic multi-risk assessment combined with expert weighting produces a tangible and explainable funding allocation. The model reduces complex situations to a more digestible level for policymaking and operational activities while yet appreciating the various factors affecting the magnitude of a humanitarian crisis.

Function-before-form is required for robust progress ahead of climate change on disaster risk reduction and adaptation. The actual need for loss and damage, including the people in need in the humanitarian window, could range from USD 150 to USD 580 billion by 2030, (Markandya & González-Eguino, 2019; Songwe et al., 2022) with the COP29-agreed NCQG at USD 300 billion annually by 2035. Therefore, the comparative size of the humanitarian and disaster aid funding requirement of USD 50 billion is significant. Especially if it keeps rising.

CHAPTER 4 Future cost of climate change for humanitarian crises

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 USD2024 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 USD2024 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.[16]

4.1 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[17]. 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[18] and its disappearance will weaken critical operations in

[16] This chapter has been submitted for publication as Jäpölä, J.-P., Berlin, A., Fabri, C., Hrast Essenfelder, A., Marzi, S., Poljanšek, K., Ronco, M., Van Passel, S. & Van Schoubroeck, S. (2025). Future cost of climate change for humanitarian crises. Working Paper available at https://doi.org/10.5281/zenodo.17386650.
[17] https://humanitarianaction.info
[18] https://fts.unocha.org

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 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[18].

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[17].

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.

4.2 Methods

4.2.1 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[19]. 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 16).

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

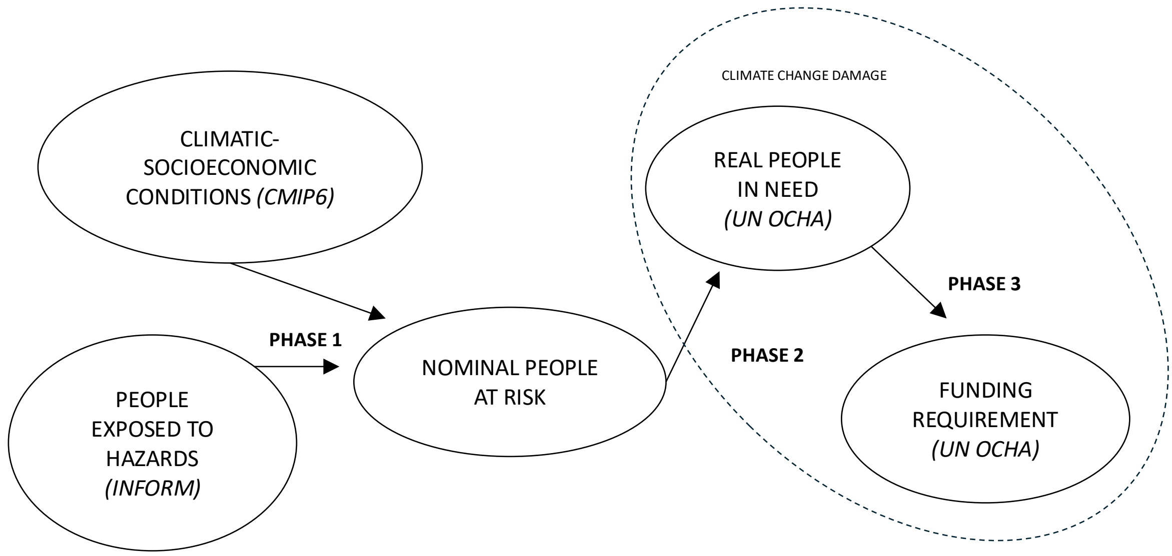


Figure 16. Assumed relationships in the paper's damage function.

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 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[20]. 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[17], a UN OCHA service.

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

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).

4.2.2 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[18] (Figure 17). 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[21]. Their vulnerable status aligns with the Climate-Conflict Vulnerability Index[22] and Climate Finance Vulnerability Index[23].

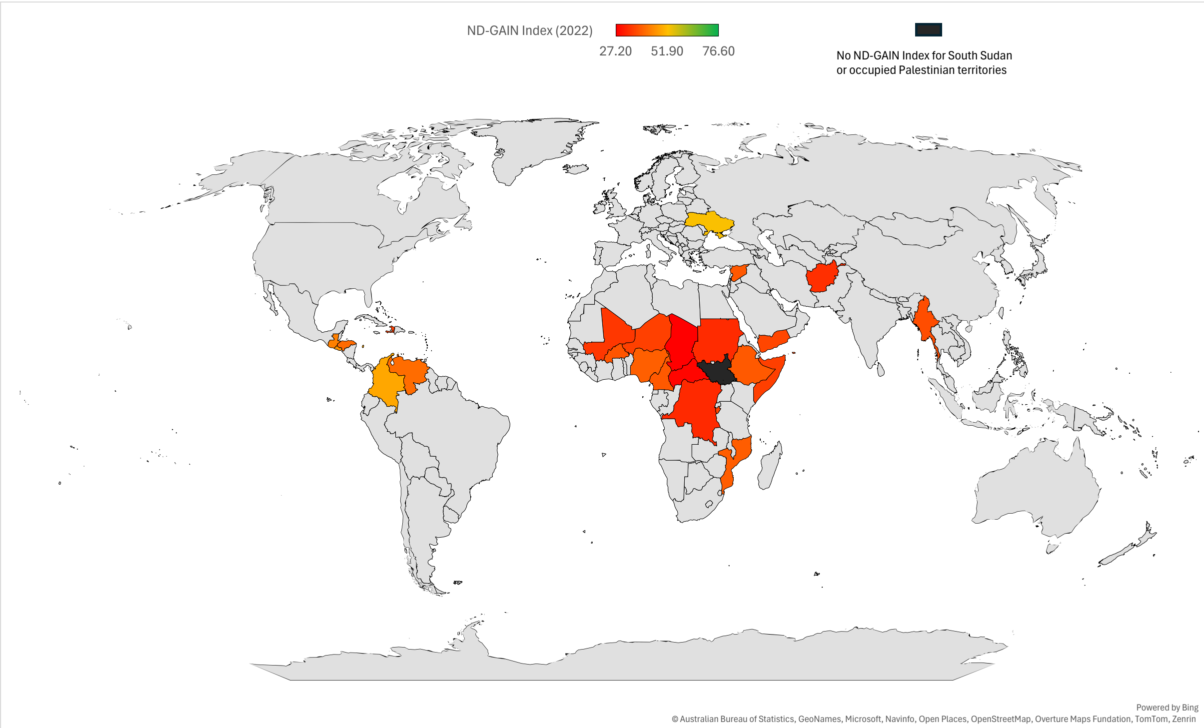


Figure 17. Geographical scope of the dataset.

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[24]. Created by the authors with MS Excel. It uses Bing data for the map itself.

4.2.3 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 ($\sum EX$), then to people in need (PIN), and finally to the funding requirement. The annual panel data and input for the model comprised the 26 countries (i) for years 2000-2100

[21] https://gain.nd.edu/our-work/country-index/
[22] https://climate-conflict.org/www
[23] https://clifvi.org
[24] https://gain.nd.edu/our-work/country-index/

(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 18).

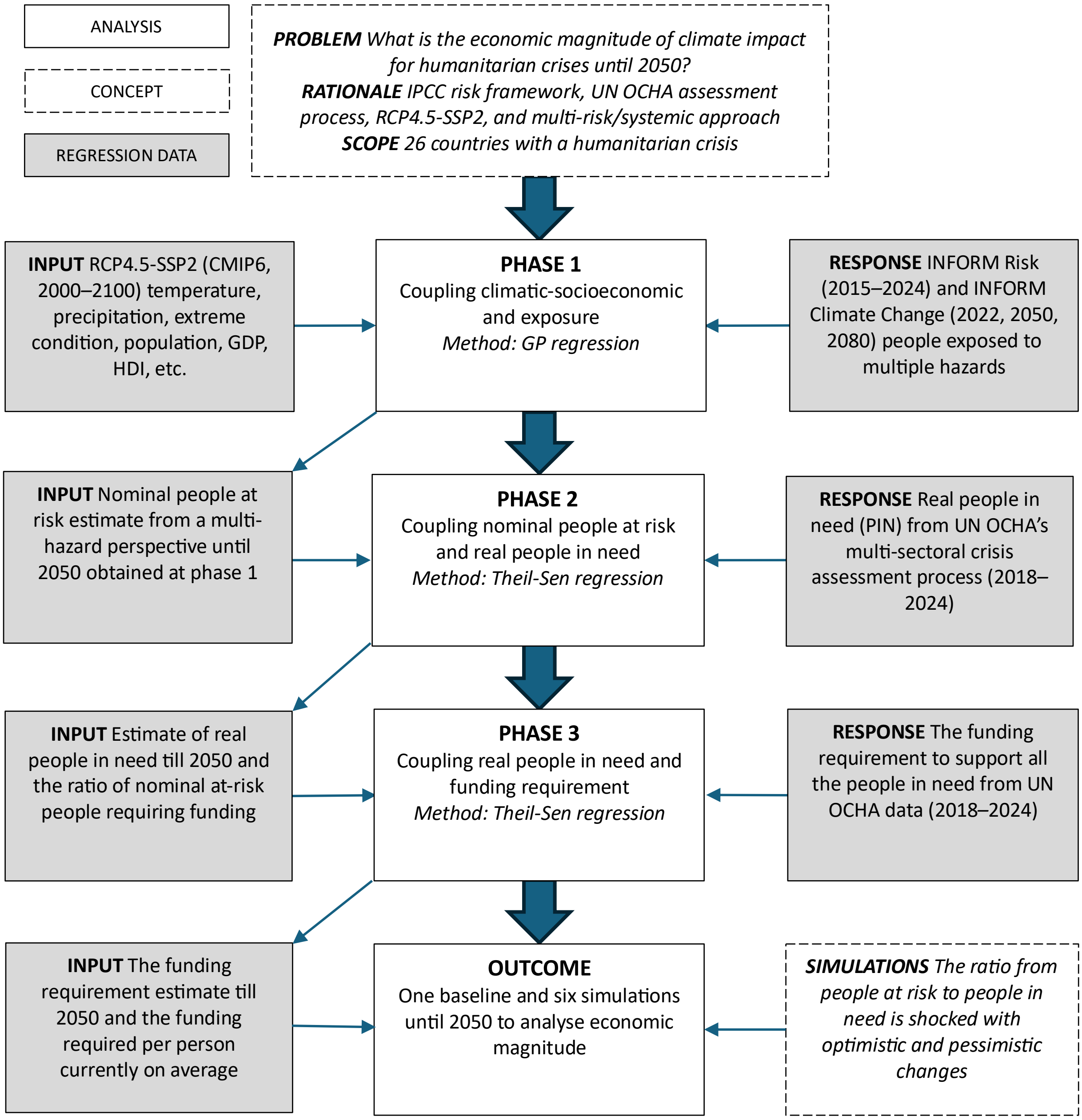


Figure 18. Estimation framework.

At **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.)

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

(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 $\mathrm{SFCWIND\_global}$[25] (C3S/ECMWF, 2023), and the change in surface air temperature above pre-industrial levels $\mathrm{GSAT\Delta\_global}$[26] (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[27].

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[28],
- Population POP[29] (KC et al., 2024),
- Gross domestic product GDP adjusted for purchasing power parity (PPP)[30] (Crespo Cuaresma, 2017), and
- Human Development Index HDI[31] (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, 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[32] and INFORM Climate Change[33] 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[34]. 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),

---

[25] https://cds.climate.copernicus.eu/
[26] https://data.ece.iiasa.ac.at/ar6
[27] https://climateknowledgeportal.worldbank.org
[28] https://databank.worldbank.org/ and http://www.wittgensteincentre.org/dataexplorer
[29] https://data.ece.iiasa.ac.at/ssp
[30] https://www.imf.org/external/datamapper/datasets/WEO and https://data.ece.iiasa.ac.at/ssp
[31] https://doi.org/10.1057/s41599-024-02941-6 and https://hdr.undp.org/data-center/human-development-index
[32] https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Risk
[33] https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Climate-Change
[34] https://human-settlement.emergency.copernicus.eu/

- 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 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[35] and intensities of conflict from Heidelberg Institute for International Conflict Research[36] 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[37] 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.

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 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).

[35] https://ucdp.uu.se/
[36] https://hiik.de/?lang=en
[37] https://acleddata.com/platform/conflict-exposure-calculator

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 16). Similarly, ε means the white noise kernel that is further described together with the GPR itself after the variables.

Table 16. 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: o Sea surface temperature (SST_global) o Surface wind speed (SFCWIND_global) o Precipitation (PR_global) **Country-level:** o Gross Domestic Production (GDP) o Maximum of consecutive dry days (cdd) o Maximum of consecutive wet days (cdw) o Days over 40°C (hd40) o Heavy precipitation days (r20mm) o 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[38], 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 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.

4.2.4 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.

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

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

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

The empirical observations are gathered annually per country from UN OCHA for years 2018–2024, the maximum that the Humanitarian Action database[17] 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[20] 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[18] 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[39]. 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 $\text{funding requirement}$ 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 $\sum \mathrm{EX}_{i,t}$ turning into real people in need $\mathrm{PIN}_{i,t}$, there is no need for an intercept term. Similarly, we are only interested in the empirical ratio 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.

4.2.5 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

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

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 $\sum \mathrm{EX}$ 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[40] and conflict events have almost doubled in the last five years from over 100 000 to nearly 200 000 in the ACLED Conflict Index[41], see the Uppsala Conflict Data Program[35].

Table 17. 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% (”)
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.

[40] https://www.emdat.be

[41] https://acleddata.com/conflict-index/

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).

4.2.6 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.

4.3 Results

4.3.1 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.

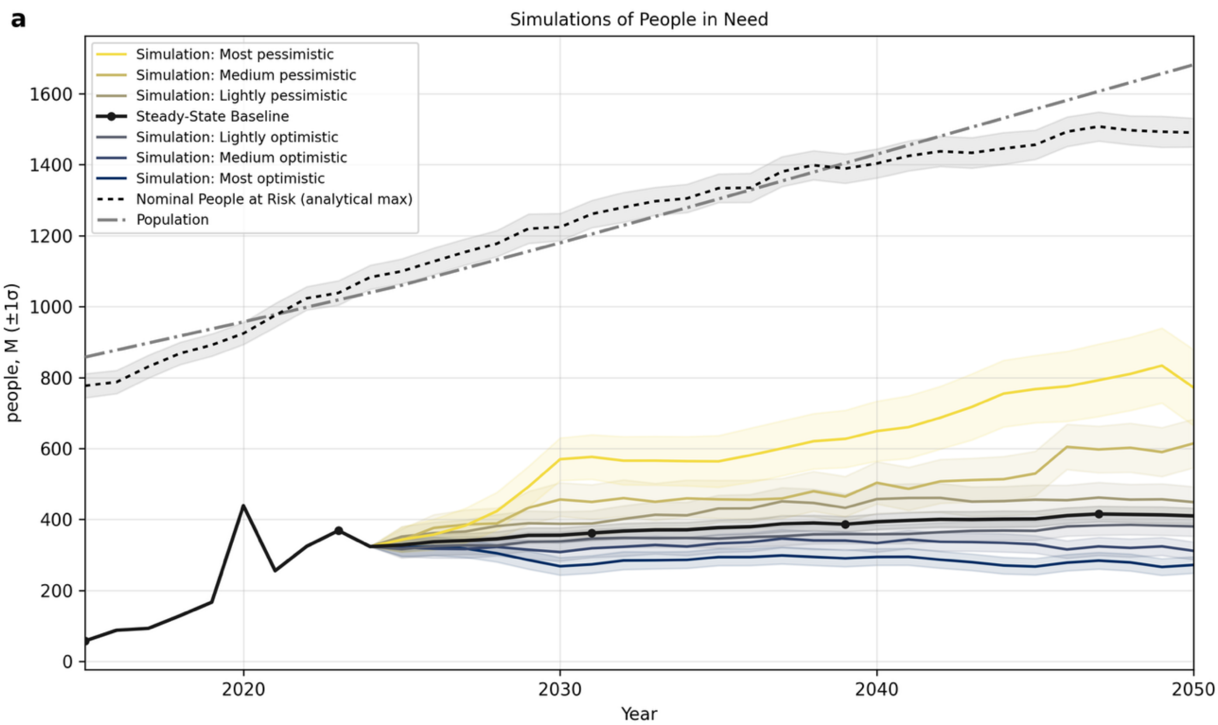
Examples of temporary shocks that we modelled are combinations of major disasters or wars that dissipate over a handful of years in most cases while the long-term structural change introduces a slow creep of climate change's amplifying effect on the crises—or subduing in case of sustained disaster prevention 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 17):

- *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 19 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.



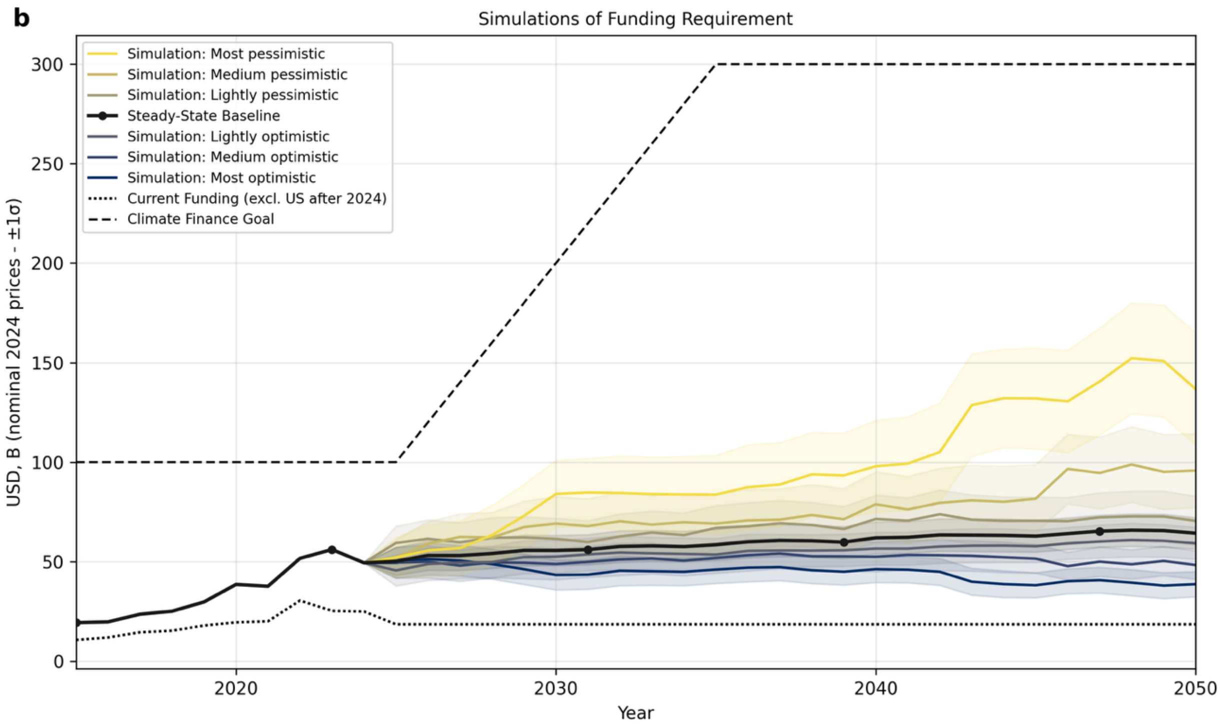


Figure 19. Simulations of people in need of humanitarian assistance and their funding requirement.

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 18 shows a snapshot of the data in 2050 from Figure 19.

Table 18. 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 19. See Table 18 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).

4.3.2 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 *20*).

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).

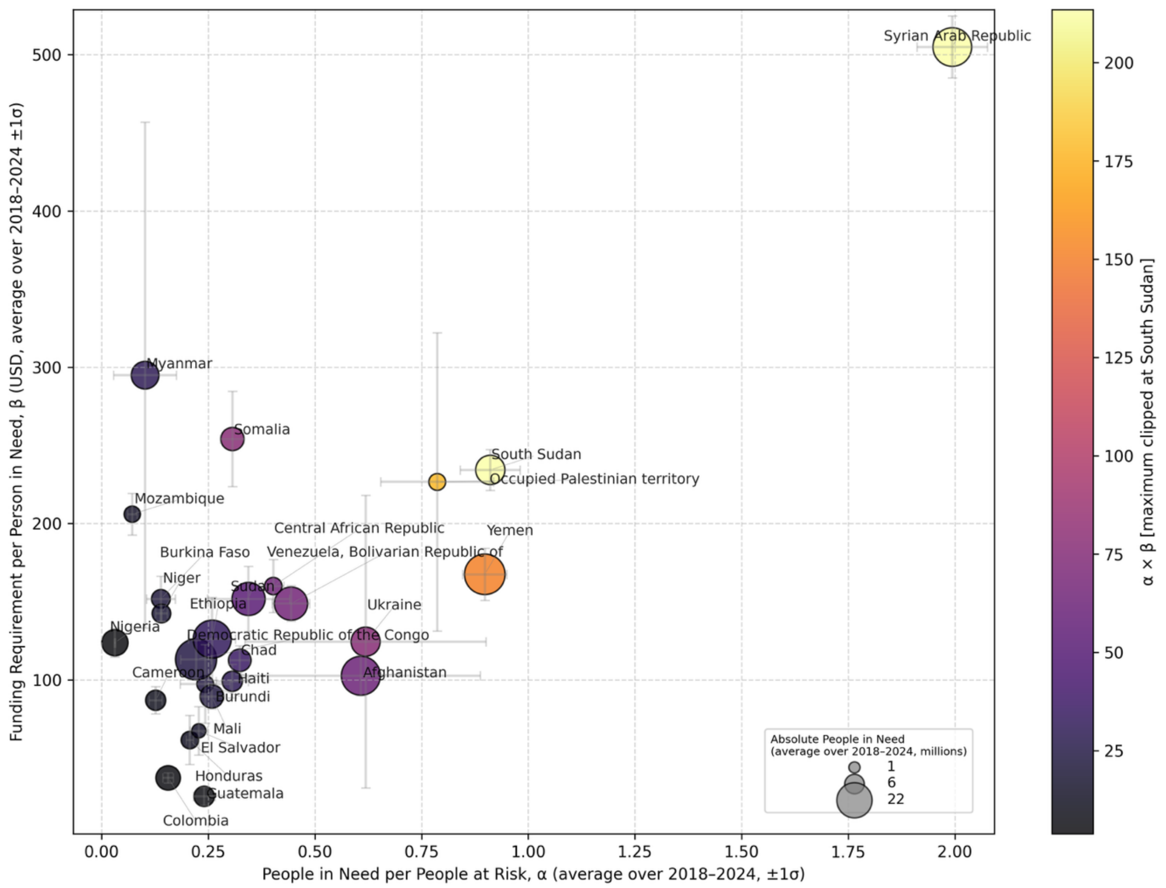


Figure 20. Heatmap of empirical vulnerability.

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.

4.4 Discussion

4.4.1 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.

4.4.2 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).

CONCLUSION

I Contributions, key findings and policy recommendations

The objective of this dissertation was to build a climate-informed and forecast-based funding model for humanitarian aid (Figure 3, p. 8). The four sub research questions (RQ), explored respectively in the previous working chapters, were as follows:

> RQ1. How applicable is climate change-related modelling for economic decision-making in humanitarian aid resource allocation?
>
> RQ2. What are the priority criteria in allocating humanitarian or disaster aid funding per future forecasts in view of climate change response or adaptation?
>
> RQ3. How would stochastic multi-attribute analysis (SMAA) and Delphi panel weighting prioritise resources in humanitarian crises with multiple disasters affecting them? How does the model compare versus official funding requirements?
>
> RQ4. What is the economic magnitude of climate impact for humanitarian crises till 2100?

Regarding its contributions, the thesis introduces three major innovations: (1) Actionable and policy-proof metrics that use people in need and funding requirements as proxies for climate damage, (2) use of machine learning and stochastic methods as an econometric tool in a data sparse and asymmetric environment, and (3) behavioural insights from the Delphi panel that ground the modelling parameters and choices. The findings underscore the urgency of investing in adaptation to prevent a future where reactive spending crowds out preventive measures or creates vicious loops for vulnerable countries.

The European Union's (EU) next long-term budget for 2028–2034 entered negotiation after the European Commission published its proposal in July 2025[42]. The negotiation will last until 2027 when all the bodies, the Council of the European Union and the European Parliament as well as the Commission, agree. The findings of the thesis, especially the final chapter, could prove useful as evidence to the expected levels of funding needs and to strategies on integrated approaches[43]. I will now elaborate further in two parts on the contributions and key findings of the dissertation as well as policy recommendations stemming from them in a backwards order from the research questions. The recommendations are labelled with grey boxes for further clarity and actionability.

The future of humanitarian crises under climate change if there is no integrated approach across the humanitarian-development-peace nexus

First, to answer RQ4, the main contribution of this thesis is the machine learning-based economic simulation model where climate change projections are coupled with humanitarian crisis factors—such as people in need and the funding they would require—for the first time to our knowledge (Chapter 4). The model was built upon an exploratory literature review that examined its needs and barriers (Chapter 1) by ascertaining the preferences of experts on its most pertinent criteria and weighting (Chapter 2), and finally by testing its core with real world humanitarian data (Chapter 3). It especially supports understanding the effects of extreme and compound events, such as disasters and crises, stemming from climate change—which has been a long-standing agenda

[42] https://commission.europa.eu/strategy-and-policy/eu-budget/long-term-eu-budget/eu-budget-2028-2034_en

[43] https://ec.europa.eu/commission/presscorner/detail/en/SPEECH_25_347

(Dunz et al., 2023; Hallegatte et al., 2007; Noy, 2009; Zscheischler et al., 2018). Current economic assessment models have been instrumental in quantifying the financial impacts of climate change. Yet, these models provide information on traditional metrics like labour, productivity, and capital and often based on a data-rich environment (Auffhammer, 2018; Botzen et al., 2019; Rising et al., 2022; Stern et al., 2022). Knowledge on the future trade-off between adaptation and humanitarian response is limited. With the expanded damage function, we covered a wider and deeper spectrum of losses and damages, especially for the non-market climate-related impacts and the cascading effects on humanitarian crises. It is a promising direction in bridging, for example, integrated assessment models (IAMs) with more real world validated data and gaining a better understanding of the effects of climate change in the extreme vulnerable ends. Instead of a more analytical concept on vulnerability, the model was calibrated to show empirical vulnerabilities—that is, how many people suffer per risk point (p. 68).

Humanitarian crises are the tip of the iceberg of climate damage wherein they indicate the most vulnerable and fragile contexts of the world that will bear the brunt first. The model's findings illustrate how climate change could significantly divert funding away from emission mitigation and adaptation efforts in the SSP2-RCP4.5 scenario or an approximately 2,7°C warming by end of the century—towards which we are now heading. For instance, simulations ranging from medium pessimistic to medium optimistic suggest that humanitarian funding needs could consume 17–23% of the new annual climate finance target of USD 300 billion for developing countries by 2035—assuming the goal is met and inflation remains constant (p. 66.). This shift risks siphoning resources from sustainable investments, potentially undermining long-term climate action.

The lightly optimistic simulation leads to 380±28M people in need with a USD_{2024} 59±8B funding appeal by 2050 (increases of 118–120% compared to 2024) while the lightly pessimistic one accounts for 449±44M and USD_{2024} 70±12B respectively (increases of 139–143%). The medium pessimistic simulation would reach 2/3 higher levels of the lightly optimistic one in the same timeline—614±68M people in need and 96±19B funding requirement. The people comprised in it would be almost half of China's current population and the funding requirement more than the current GDP of Luxembourg. Out of all the simulations, only the medium optimistic and most optimistic lead to either stabilisation or a reduction of the needs (p. 67). However, these numbers should be interpreted as scenario-based stress tests rather than precise forecasts.

Such financial strain heightens the risk of countries falling into a destructive cycle: reduced investment in mitigation and adaptation—such as disaster risk reduction—could exacerbate crises. Over time, worsening humanitarian emergencies, driven by the progression of climate change and its cascading effects across borders and sectors, would further deplete resources available for preventive measures. *This feedback loop could intensify*, leading to prolonged crises in highly vulnerable nations like the Democratic Republic of the Congo, Sudan, and Afghanistan, where fragile governance, unsustainable livelihoods, and food insecurity already prevail (Kemp et al., 2022; Wescombe et al., 2025). The data of the dissertation indicates that the inertia and creep of climate change will be the most damaging element for humanitarian aid in a future locked to the middle-of-the-road SSP2-RCP4.5 scenario because slow onset of the changes, such as temperature and precipitation will continue even if all greenhouse gas emissions would stop immediately.

The dissertation argues that preparing and curbing the effect of climate change for humanitarian aid and the wider peace-development nexus requires determined and sustained investment in minimizing damage in advance of climate change. Otherwise, we risk that the most vulnerable countries will be even more prone to vicious loops of protracted crises and our crisis response funding will displace much needed resources for adaptation and mitigation. This is like the dismal theorem of Weitzman (2011) whereby the fat-tail distribution of unlikely but highly damaging sequences is not necessarily accounted in our frameworks that regress towards the mean but should be duly included according to a precautionary principle. In summary, the thesis serves as an early warning of the systemic risks in humanitarian crises and of a situation where we do not put enough long-term effort in resolving them before climate change.

Recommendation: **Account for the risk that insufficient funding into adaptation and disaster risk reduction could lead to vicious loops in vulnerable countries and a near doubling of people in need to 600M by 2050 because of the creep of climate change.** In a world of scarce resources, the humanitarian response directed towards these cases would displace funding for other beneficial development, climate resilience or welfare investments. Current economic models might not account enough for risks of extreme or cascading events brought by a warming climate.

A key policy implication of the work is that humanitarian aid alone is not sufficient to address the humanitarian impacts of climate change. In short, we need systemic and coordinated solutions to address the root causes of climate-related vulnerabilities. The thesis provides quantitative and narrative arguments that humanitarian funding, climate adaptation, and development cooperation cannot be treated in isolation, and offers figures that can be mobilised to justify robust humanitarian envelopes while strengthening long-term climate resilience, prevention and preparedness, and adaptation investments in fragile contexts in an integrated approach. They are necessary to avoid a future where the demands of humanitarian response crowd out resources for adaptation and mitigation.

But how to do this in practice? Administration of funding will most likely always be divided between different departments and directions to keep it governable—which can lead to misalignment and gaps. One pragmatic suggestion that stems from the thesis is to legally tie different funding streams together to make them more coherent yet flexible.

Recommendation: **Move into more blended and flexible funding between humanitarian-development-peace nexus instruments to reform them into an integrated approach.** For example, legally tie different humanitarian-development-peace nexus funding streams or instruments together into packages so that they act in cohesion organically and follow each other rationally—such as climate resilience investment tied to a humanitarian response's root cause.

For example, that a humanitarian intervention would mandatorily trigger a long-term loss & damage investment into the root causes of the crisis (such as massive drought or destructive flood). Similarly, that anticipatory action responses or pre-arranged financing would be blended or bundled with concurrent climate resilience investments. As programming of investing can take multiple years, the instruments need the flexibility so they can be integrated coherently with each other. However, *the feasibility of conducting these kinds of reforms is not without challenges*, such as institutional complexities or different mandates locked in higher level agreements. Thus, pilots between smaller programmes could be more digestible.

Picture 2. A hopeful future.

10 years after Zaatari camp opened in July 2012, it has become a vibrant place with more than 1,800 shops on its 'Sham Elysées' – a play on ash-Sham, a word Syrians use for Damascus, and the famous Parisian boulevard, Champs-Élysées.

The trajectory of the model's simulations hinges on decisions made within the humanitarian-development-peace nexus. Prioritizing investments in disaster prevention, climate change adaptation, conflict mediation, and advancements in technology and innovation will shape future outcomes (European Commission, Joint Research Centre, 2024; IPCC, 2023a). Aligning long-term strategies with the SSP2 scenario—or the even more sustainable SSP1—could unlock opportunity costs, redirecting resources toward mitigation efforts and poverty alleviation. (Picture 2.)

The model was built, for calculative reasons, to have a neoclassical and marginalist approach with fixed resources in examining trade-offs between escalating crises requiring response and the future adaptation to them. However, the future does not need to be so strict, and we should not create a path dependency towards it. A more favoured path is a Schumpeterian transformation where society will dynamically find financing solutions that provide to utility to both problems at the same time as well as innovate and reform the processes, technologies, and institutions behind them.

Models with machine learning are an emerging area. As with the below recommendation on parsimony and co-creation in general on modelling, it is even more important with artificial intelligence. During the thesis, to counter the black box tendency of machine learning, we followed guidance from explainable artificial intelligence (XAI) to ensure interpretability, transparency, and expert supervision of the model (Dramsch et al., 2025; Hrast Essenfelder et al., 2025). Thus, it as simple as needed to reduce the number of choices, layers, and hyperparameters. In effect, the aim was for the model to be easy to understand rather than superfluously increasing model complexity. Similar approaches should be followed in all future studies in complex fields. Specifying modelling with the input and needs of the policy-operation side as well as keeping actionability as a main characteristic will support in making the results useful.

Putting the insights on funding models into practical use in policy cycles

The findings on a funding model put forward in the thesis have several elements that could be integrated into policy or operational cycles step-by-step, for example, at the EU level. However, any such recommendations should be based on amending or adapting existing frameworks or instruments instead of creating new ones.

In RQ3, the thesis tested how stochastic multi-attribute analysis (SMAA) would prioritise resources to active humanitarian crises when weighted with expert preferences from a Delphi panel—a first as well. It especially advocated for a more probabilistic funding solution to humanitarian crises in contrast to a deterministic one (p. 45). The data, even the most quality data, is highly uncertain in humanitarian crises. Techniques such as SMAA, which in this case ranks the to-be-funded countries over 10 000 times with different ranges of error in the underlying indicators, could be helpful in turning funding calculations to be more digestible. (Chapter 3.)

> *Recommendation:* **Use more probabilistic solutions in funding models to capture the real uncertainty of the underlying data and allow for more flexibility in decision-making.** Adding natural stochasticity or error terms (such as the historical range of deviations in people in need) into the calculations increases its robustness and a probabilistic method also allows the decision-making chain to qualitatively account for contextual factors that cannot be included in a quantified way. A machine learning method, such as the Gaussian Process Regression, could be an option as it would learn the funding needs from previous iterations and prioritise indicators based on the observed relationships without being arbitrary.

This was a proof-of-concept for the simulation modelling of Chapter 4 and introduced, for example, the requirement of explainability and actionability to the core model. The results of showed high agreement and strong correlations between the SMAA-based INFORM Severity and real-world UN OCHA funding requirements aligning with, for example, Dellmuth et al. (2021). However, there is room to improve indicator alignment with funding neutrality and impartiality.

Humanitarian funding requirements escalate exponentially as crises deepen, while the rigor of transparent and unbiased allocation methods tends to weaken in the face of growing complexity and financial demands. Beyond the clear outliers of Ukraine and the Syrian Arab Republic, countries like Ethiopia, Yemen, Nigeria, the Democratic Republic of the Congo, and Myanmar deviate by more than one standard deviation—approximately USD ±1 billion—from the solutions proposed by the SMAA-based INFORM Severity (p. 48). However, this analysis should only be assessed within its own scope and context along with very important limitations, such as missing variables on political or other similar exogenous factors.

The results suggest that a model incorporating all determinants of vulnerability and severity—whether natural, human-induced, climatic, or non-climatic—can effectively prioritize needs regardless of their root causes. This is important in the sense that attributing complex humanitarian crises and the individual people suffering from it with cascading effects between different factors to climatic or non-climatic drivers can be a complex endeavour. The findings formally validate operational practices of humanitarian agencies focusing on humanitarian need as the primary set of indicators, such as the Joint and Intersectoral Analysis Framework (JIAF), and show that INFORM Severity is a good basis for determining the funding needs of a crisis.

However, decision-makers often face information overload (Lentz & Maxwell, 2022), which can lead to indecision and analysis paralysis. The volume of indicators in analytical frameworks can become unwieldy or unexplainable in contrast to the maxim of finding a handful of the most influential factors via, for example, regression studies. Without regular updates, these indices risk losing relevance and adaptability. The SMAA was also used to test different weights between the expert-proposed ranks of the indicators in the INFORM Severity framework (p. 42). **Our findings on optimal weighting reveal that human-centred indicators, such as people in need, carry between one to two orders of magnitude more significance than societal or institutional metric**. In short, more simple weighting schemes with just a handful of primary indicators were as good in indicating the required funding as a composite indicator with tens of variables and internal transformations (p. 46). The most likely reason is that the umbrella indicators already contain the underlying information within them, and it does not need to be added again. For example, a high number of people in need and high risk of crises are already partly a result of low rule of law and low political rights.

This underscores the value of *simplicity:* less can be more. These results agree, for example, with Lopez et al. (2023), Puy et al. (2022) and Slim (2023) that prioritisation should focus on parsimonious models reflecting the severity of the situation and the core necessary needs of a population. In Chapter 4, the machine learning proposed relatively simple set of factors that drive climate change risk in humanitarian crises, such as temperature, both general and heavy precipitation, population, and the HDI, the Human Development Index (p. 60).

Recommendation: **Take note of the finding that funding models do not necessarily need many indicators, only the handful of primary ones that are most comprehensive on their own.** This could increase both explainability and actionability, reduce the administrative work needed to update less important indicators, and support in focusing on the data that has the best quality. This can also apply to operational early warning or anticipatory action frameworks.

Likewise, the future is so deeply uncertain that having proper forecasts or cost-benefit analyses is an equally intensive process, yet the effects of climate change are already here, and our models might be underestimating its magnitude. This dilemma advocates the use of low-regret options throughout the humanitarian-development-peace nexus—essentially, the investments that we know will have a net benefit regardless of how climate change or the future develops. Rising needs, increasing cuts, and the complexity of the field data in the humanitarian sector will make it difficult to have sufficient administrative and analytical capabilities to deliver on the actual impact. Especially when attribution of climate effects will remain an intensive process and there is a requirement to coordinate between multiple actors with different mandates and incentives.

Recommendation: **Due to deep uncertainty, prefer low-regret options that will be beneficial investments regardless of the exact future of climate change and that are robust without unnecessary delay.** For example, early warning systems or nature-based disaster preparedness solutions. The use of low-regret options is not without critique, and they can lead to maladaptation, but lack of action seems the least favourable route in the urgency of climate change.

Therefore, the thesis shows that relatively simple methodologies focusing on primary indicators, such as people in need per severity level of their humanitarian conditions as well as of risk of hazard and exposure to disasters, produce a robust and governable allocation of funding. **How then to reach a consensus on a more simplified funding framework that could support the humanitarian-development-peace nexus with the institutional challenges of multiple actors operating under different mandates that can be rigid?** For RQ3**,** to feed the economic model, we did what many ask for in better informing decision-makers of humanitarian and disaster response as well as climate change adaptation: Ask the key users what criteria and options they consider priorities when allocating scarce public resources to adapt and to counter losses and damages. This work was the basis for the proof-of-concept model test. By aligning modelling outputs more closely with the needs of policymakers and practitioners, different communities can avoid generating unnecessary data and instead focus on what truly drives effective decision-making. Chapters 2 and 3 especially, focusing on the preferences of experts, followed a Rawlsian approach of maximisation (Rawls, 1971) whereby the distribution of resources aims to be fair and egalitarian so that the welfare of the worst-off individual would be maximised (and concurring with the humanitarian principle of impartiality).

The exact method was the Delphi panel where 36 experts from 19 countries of origin representing international organisations (e.g., United Nations, European Union, World Bank), the research sector, the public sector, and civil society (e.g., Save the Children, World Vision) ranked the INFORM Severity indicators as well as key risks of climate change. In contrast to one-off surveys or open consultation meetings, the Delphi panel is fully anonymous and is run iteratively as many times before stability is reached (p. 28). In this case, the panel's consensus on the complex prioritisation was stable already during round 2 which indicates a high level of agreement even with a heterogenous group.

The panel's preference for people in need-centric and disaster risk-based criteria outweighs the importance of indicators related to governance, the rule of law, or a socio-economic aspect in humanitarian aid and disaster management (p. 30). **The experts on the issue prefer those criteria that are inherently equity-driven and likely forecast the severity and magnitude of disasters and humanitarian crises most effectively and in an all-encompassing umbrella manner.** Logically, these would estimate the final required funding per capita in need of aid. The notion corresponds with humanitarian principles and operational needs assessments of, for example, UN OCHA and the Integrated Food Security Phase Classification (IPC). In other words, that action should be based on need alone, prioritising the most urgent cases of distress. The results could be different if we aimed the Delphi method at purely developmental or investment actors looking strictly at decades ahead. Notwithstanding that, for example, the World Bank's corporate scorecard heavily depends on people-centric indicators, such as 'people with improved food security' or 'beneficiaries of better climate risk resilience'.

Recommendation: **Find a consensus between key humanitarian-development-peace nexus actors on a more simplified and harmonised funding framework with primary indicators, such as people in need and people with strengthened climate resilience.** They should be equity-based and cover all the sectors in an umbrella-type manner, such as health, climate change, protection, displacement, and food security. It could bridge gaps to support the first recommendations, reduce administrative burden, and enable more integrated funding strategies. While inter and intra-institutional challenges are complex, using the anonymous Delphi panel method to come to an objective and transparent prioritisation of indicators could support in seeing eye to eye. For example, The INFORM[44] assessment framework, the Joint and Intersectoral Analysis Framework (JIAF)[45] or the World Bank corporate scoreboard[46] could be a good basis for mapping purposes. The same recommendations work for operational systems, such as early warning early action.

According to the panel, focusing funding on adapting to climate change-related risks to food security, human health, and water security is a high near-future priority compared to, for example, risk to living standards or risk to terrestrial and ocean ecosystems (p. 32). As with the priority criteria, the results propose a clear prioritisation of where our counter-risk funding should go in the basket of options, but we should consider nuances. The panel noted in the qualitative comments that their choices reflected a timewise priority of the most urgent and life-threatening risks versus fundamental risks that can cascade in the long run – and that the choices were far from easy. For example, risks to ecosystems and socioecological systems can become threat multipliers for the more imminent risks. Then again, the long-term risks might be less irrelevant if a society collapses beforehand due to lack of food.

During the literature review of the thesis concerning RQ1, the most important finding was simply the paucity of research literature that successfully integrates climate forecasting with humanitarian aid resource allocation—concurring with two other similar reviews (Altay & Narayanan, 2022; Yan, 2023). The study assessed that more

[44] https://drmkc.jrc.ec.europa.eu/inform-index
[45] https://interagencystandingcommittee.org/operational-policy-and-advocacy-group/iasc-technical-manual-joint-and-intersectoral-analysis-framework-jiaf-20
[46] https://scorecard.worldbank.org/en/home

than half of the dataset had the two lowest ranks, indicating limited usability for forecast-based economic decision making (p. 15).

More precisely, the thesis found that predicting *hour(s), day(s)* or *month(s) forward* from current time seems the most primary period for operationalising the result of the models into funding—in contrast to *year(s)* or *decade(s)*, or the timeframe of *2041–2100* in longer-term IPCC scenarios (p. 18). Likewise, the most integrated models tend to be about weather prediction rather than longer-term climate change. While this was a discouraging finding from one perspective, it indicated opportunities for improvement and set the tone for the rest of the thesis. To make longer-term models benefit resource allocation, climate policy and humanitarian-development nexus communities could determine what information would be useful. Then, communicate this requirement to the modellers to learn whether there are capabilities to provide input. Modellers will want their results to benefit policymaking but will not identify the most relevant needs—paving the way for the Delphi panel. These literature review findings are in support of the earlier, more actionable findings.

Finally, I will discuss what other gaps remain in the thesis and relevant research.

II Main limitations and future research needs

The dissertation has multiple important limitations, and each chapter comprises its own section discussing these in detail. The future is inherently uncertain, and it remains nearly impossible to guarantee that the thesis' modelling framework—and the assumptions underpinning it—fully captures true causal relationships. Second-order or human-driven effects often lie beyond the scope of such models. For instance, the ripple effects of disasters or conflicts on a nation's industrial output or trade networks can significantly alter GDP trajectories, yet these dynamics are rarely accounted for in existing datasets. The **data available for humanitarian and hazard projections tends to be sparse, noisy, or asymmetric, if not all three simultaneously.**

To ensure clarity and interpretability, the simulation model—applied here for the first time in this context—was intentionally simplified. While a multi-risk approach may dilute the direct attribution of crises to specific natural or human-induced causes, it offers a more realistic perspective by acknowledging the complex, cascading, and compounding interactions among variables. The modelling focuses illustratively on 26 countries with a Humanitarian Response Plan (HRP) in 2023 which are the most vulnerable and protracted contexts, but do not cover the full range of possible humanitarian risk. The funding data (UN OCHA's Financial Tracking System) has its limitations in representing humanitarian and development resources as it only captures funding reported to UN OCHA (e.g., in contrast to OECD's Official Development Assistance figures). For example, it might not represent non-traditional donors (such as philanthropic organisations) outside of the HRPs and has challenges in capturing multi-year contributions or resilience funding that could be classified as "semi-humanitarian". However, FTS was the best option in terms of having coherence with HRP needs assessments.

The research **did not explicitly address exogenous political interests**, though their potential influence as latent variables is undeniable. Media coverage, for example, plays a pivotal role in shaping donor allocation decisions, which may explain some of the observed outliers. For example, regime change in the Syrian Arab Republic fundamentally altered humanitarian dynamics and illustrated that abrupt political shifts can dominate over climatic drivers. The current situation in the Strait of Hormuz is another example with possible cascading impacts via energy prices to humanitarian supply chains and availability of public funding to adaptation investing. These necessitate a qualitative overlay that would incorporate further elements from political economy and donor geopolitics. Generally, three key factors drive funding decisions: humanitarian needs, strategic interests, and agenda-setting dynamics (Rost & Clarke, 2025).

Epistemologically, this exploratory and interdisciplinary study navigates ambiguous fields and terminological disparities in forecast-based economic decision-making within humanitarian contexts (de Wit, 2019; Knox Clarke, 2022; Taylor, 2023; UNDRR & ISC, 2020). As a proof-of-concept, certain trade-offs are inevitable, but future research should delve deeper into integrating exogenous drivers—whether through regression analyses of media coverage, crisis "forgetfulness" (Scott et al., 2022), or quantitative assessments of stated foreign policies of donors using large language models (LLMs). Temporally, the model and expert insights could be adapted to alternative datasets, such as those derived from different SSP and RCP climate scenarios, without conceptual limitations

Our model, informed by Delphi panel inputs, primarily reflects reactive humanitarian priorities rather than structural indicators like governance quality or democratization levels. Unaccounted human factors—such as resource misallocation, political motivations, or operational inefficiencies—could further explain variations in funding patterns. However, it's important to note that a Delphi panel, while methodologically rigorous, may not fully represent global consensus or definitively answer our second research question. The limited sample size, though statistically robust above 30 observations, may constrain generalizability and does not inherently address priorities in other sectors, such as environmental or ecosystem conservation. Likewise, it represents primarily the Global North, and future studies could **complement expert panels with more bottom-up perspectives** and align with localisation efforts. It is worth reflecting how well the panel captures systemic and cascading risks or **how would pure development actors in the panel change the results**. The ranking process and expert selection might inherently favour more immediate and observable risks although the panellists clearly reflected the difficulty in choosing among the priorities due to these very factors.

Determining the threshold of divergence that would prompt donors to reconsider funding allocations is a future inquiry. This study also raises broader ethical and practical dilemmas: *With finite resources, what should—and what can—we prioritize?* The concept of the time value of human life in decision-making raises a critical question: Should priority be given to addressing immediate, urgent crises—those metaphorical "house on fire" scenarios—or should efforts focus on mitigating the long-term risks of systemic, cascading failures? The rationality of either approach ultimately hinges on the expected utility derived from each course of action.

This **tension between short-term urgency and long-term resilience** reflects broader societal values and priorities. Exploring these dynamics further could offer valuable insights into how we, as a society, weigh and allocate resources across different temporal horizons. Future studies might delve deeper into these trade-offs, examining the underlying preferences that shape our collective responses to risk and uncertainty. Behaviourally, humans tend to be locked into tyranny of the present-type path (or myopic behaviour) whereby the most immediate and obvious issues become a priority. Likewise, more conceptual bridging on how the findings of the thesis could support in reconciling differences in earth system models and economic models as well as its linkage to the Sustainable Development Goals (SDGs) would be advantageous. For example, how do these findings relate to the new paper by Bilal & Känzig (2026) where they estimate that the macroeconomic damages from climate change are an order of magnitude larger than previously thought? As an applied and pragmatic study, it strived to bring clarity to the humanitarian sector and its immediate links as well as contribute to the integration of extreme events and complex systems into economic modelling, but a more all-encompassing approach would also be beneficial in future work.

In the realm of economic modelling, there is potential in refining Gaussian Process Regression by adopting a more intricate kernel framework—one that incorporates distinct covariance functions for spatial and temporal dimensions. Further enhancements could arise from integrating additional elements, such as spatial dependencies, lagged variables, or a comprehensive reanalysis using the full CMIP6 ensemble. Moving forward, a compelling research direction involves rigorously evaluating and deploying machine learning and AI-driven methodologies for economic impact assessments, particularly in contexts characterized by sparse, asymmetric data where conventional models fall short. Given the inherent challenges of conflict and fragility, **it is unlikely that the availability or quality of data in crisis management will improve significantly soon**. This reality underscores the importance of advancing alternative analytical approaches.

These advancements alone might not be enough to address the problems covered during the thesis. Therefore, one important research direction would be to ascertain **at what macroeconomic level would the affected countries be self-resilient against future disasters and crises.** For example, if there is a ratio of humanitarian funding need and national GDP that we should aim towards in state-building? The preliminary data of Chapter 4 indicated that a supermajority of the countries would have a lower than 1% of humanitarian funding need with relation to their GDP under growth projections of SSP2-RCP4.5 by 2050, but this would warrant more thorough investigation—for example by utilising the World Bank's databases on revenue from taxes and non-taxes. Although increases of effectiveness or more successful disaster risk reduction were implicitly included in the optimistic simulations of the thesis, a more quantitative approach to determining how learning, innovation or state-building could affect the future is an actionable research gap.

References

ACAPS. (n.d.). INFORM Severity Index. https://data.humdata.org/dataset/inform-global-crisis-severity-index

Akins, R. B., Tolson, H., & Cole, B. R. (2005). Stability of response characteristics of a Delphi panel: application of bootstrap data expansion. BMC Medical Research Methodology, 5(1), 37. https://doi.org/10.1186/1471-2288-5-37

Altare, C., & Guha-Sapir, D. (2014). The Complex Emergency Database: a global repository of small-scale surveys on nutrition, health and mortality. PLOS One, 9(10), e109022–e109022. https://doi.org/10.1371/journal.pone.0109022

Altay, N., & Narayanan, A. (2022). Forecasting in humanitarian operations: Literature review and research needs. International Journal of Forecasting, 38(3), 1234–1244. https://doi.org/10.1016/j.ijforecast.2020.08.001

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

Aylett-Bullock, J., Gilman, R. T., Hall, I., Kennedy, D., Evers, E. S., Katta, A., Ahmed, H., Fong, K., Adib, K., al Ariqi, L., Ardalan, A., Nabeth, P., von Harbou, K., Hoffmann Pham, K., Cuesta-Lazaro, C., Quera-Bofarull, A., Gidraf Kahindo Maina, A., Valentijn, T., Harlass, S., … Luengo-Oroz, M. (2022). Epidemiological modelling in refugee and internally displaced people settlements: challenges and ways forward. BMJ Global Health, 7(3), e007822. https://doi.org/10.1136/bmjgh-2021-007822

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.

Beiderbeck, D., Frevel, N., von der Gracht, H. A., Schmidt, S. L., & Schweitzer, V. M. (2021). Preparing, conducting, and analyzing Delphi surveys: Cross-disciplinary practices, new directions, and advancements. MethodsX, 8, 101401. https://doi.org/10.1016/j.mex.2021.101401

Bell, M. L., Hobbs, B. F., Elliott, E. M., Ellis, H., & Robinson, Z. (2001). An evaluation of multi-criteria methods in integrated assessment of climate policy. Journal of Multi-Criteria Decision Analysis, 10(5), 229–256. https://doi.org/10.1002/mcda.305

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

Bilal, A. & Känzig, D.R. (2026). The Macroeconomic Impact of Climate Change: Global Versus Local Temperature The Quarterly Journal of Economics, qjag011. https://doi.org/10.1093/qje/qjag011

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

Blankespoor, B., Dasgupta, S., Wheeler, D., Jeuken, A., van Ginkel, K., Hill, K., & Hirschfeld, D. (2023). Linking sea-level research with local planning and adaptation needs. Nature Climate Change, 13(8), 760–763. https://doi.org/10.1038/s41558-023-01749-7

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

Brans, J. P., Vincke, Ph., & Mareschal, B. (1986). How to select and how to rank projects: The Promethee method. European Journal of Operational Research, 24(2), 228–238. https://doi.org/10.1016/0377-2217(86)90044-5

Brzoska, M. (2018). Weather Extremes, Disasters, and Collective Violence: Conditions, Mechanisms, and Disaster-Related Policies in Recent Research. Current Climate Change Reports, 4(4), 320–329. https://doi.org/10.1007/s40641-018-0117-y

Bucherie, A., Werner, M., van den Homberg, M., & Tembo, S. (2022). Flash flood warnings in context: combining local knowledge and large-scale hydro-meteorological patterns. Natural Hazards and Earth System Sciences, 22(2), 461–480. https://doi.org/10.5194/nhess-22-461-2022

Busby, J., Smith, T. G., Krishnan, N., Wight, C., & Vallejo-Gutierrez, S. (2018). In harm's way: Climate security vulnerability in Asia. World Development, 112, 88–118. https://doi.org/10.1016/j.worlddev.2018.07.007

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

C3S/ECMWF. (2026). Global Climate Highlights 2025. Copernicus Climate Change Service / European Centre for Medium-Range Weather Forecasts. Bonn, Germany. https://doi.org/10.24381/b3nm-p354

Calleo, Y., & Pilla, F. (2023). Delphi-based future scenarios: A bibliometric analysis of climate change case studies. Futures, 149, 103143. https://doi.org/10.1016/j.futures.2023.103143

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

Carbonnier, G. (2016). Humanitarian Economics. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780190491543.001.0001

Chen, Q., & Qi, J. (2023). How much should we trust R2 and adjusted R2 : evidence from regressions in top economics journals and Monte Carlo simulations. Journal of Applied Economics, 26(1). https://doi.org/10.1080/15140326.2023.2207326

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

Coronese, M., Lamperti, F., Keller, K., Chiaromonte, F., & Roventini, A. (2019). Evidence for sharp increase in the economic damages of extreme natural disasters. Proceedings of the National Academy of Sciences, 116(43), 21450–21455. https://doi.org/10.1073/pnas.1907826116

Coughlan de Perez, E., van Aalst, M., Choularton, R., van den Hurk, B., Mason, S., Nissan, H., & Schwager, S. (2019). From rain to famine: assessing the utility of rainfall observations and seasonal forecasts to anticipate food insecurity in East Africa. Food Security, 11(1), 57–68. https://doi.org/10.1007/s12571-018-00885-9

CRED. (2022). 2021 Disasters in numbers. https://cred.be/sites/default/files/2021_EMDAT_report.pdf

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

Dajani, J. S., Sincoff, M. Z., & Talley, W. K. (1979). Stability and agreement criteria for the termination of Delphi studies. Technological Forecasting and Social Change, 13(1), 83–90. https://doi.org/10.1016/0040-1625(79)90007-6

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

de Geoffroy, V., Knox Clarke, P., Bhatt, M. and Grunewald, F. (2021). Adapting humanitarian action to the effects of climate change. London: ALNAP (Active Learning Network for Accountability and Performance). https://alnap.org/documents/20438/ALNAP-Climate-Paper-FINAL.pdf

de Sherbinin, A. (2013). Climate change hotspots mapping: what have we learned? Climatic Change, 123(1), 23–37. https://doi.org/10.1007/s10584-013-0900-7 de Stefano, L., Duncan, J., Dinar, S., Stahl, K., Strzepek, K. M., & Wolf, A. T. (2012). Climate change and the institutional resilience of international river basins. Journal of Peace Research, 49(1), 193–209. https://doi.org/10.1177/0022343311427416

de Winter, J. C. F., Gosling, S. D., & Potter, J. (2016). Comparing the Pearson and Spearman correlation coefficients across distributions and sample sizes: A tutorial using simulations and empirical data. Psychological Methods, 21(3), 273–290. https://doi.org/10.1037/met0000079

de Wit, S. (2019). Getting ahead of crises: A thesaurus for anticipatory humanitarian action. https://cerf.un.org/sites/default/files/resources/Thesaurus_single%20column_WORKING_DRAFT.pdf

Dellmuth, L. M., Bender, F. A.-M., Jönsson, A. R., Rosvold, E. L., & von Uexkull, N. (2021). Humanitarian need drives multilateral disaster aid. Proceedings of the National Academy of Sciences of the United States of America, 118(4), e2018293118. https://doi.org/10.1073/pnas.2018293118

Diamond, I. R., Grant, R. C., Feldman, B. M., Pencharz, P. B., Ling, S. C., Moore, A. M., & Wales, P. W. (2014). Defining consensus: A systematic review recommends methodologic criteria for reporting of Delphi studies. Journal of Clinical Epidemiology, 67(4), 401–409. https://doi.org/10.1016/j.jclinepi.2013.12.002

Dilley, M., Chen, R. S., Deichmann, U., Lerner-Lam, A. L., & Arnold, M. (2005). Natural Disaster Hotspots. The World Bank. https://doi.org/10.1596/0-8213-5930-4

Döll, P. (2009). Vulnerability to the impact of climate change on renewable groundwater resources: a global-scale assessment. Environmental Research Letters, 4(3), 035006. https://doi.org/10.1088/1748-9326/4/3/035006

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

EHF. (2023, March). New global realities – Shaping humanitarian action together. Co-Hosts Summary by the European Commission and the Swedish Presidency of the Council of the EU. https://civil-protection-humanitarian-aid.ec.europa.eu/system/files/2023-03/EHF%20-%20Co-Hosts%20Summary%20by%20the%20European%20Commission%20and%20the%20Swedish%20Presidency%20of%20the%20Council%20of%20the%20EU%20-%20March%202023.pdf

Ehrhart, C., Thow, A., de Blois, M., & Warhurst, A. (2008). Humanitarian Implications of Climate Change: Mapping emerging trends and risk hotspots. https://www.preventionweb.net/files/8328_ochaaug20081.pdf

Enenkel, M., Steiner, C., Mistelbauer, T., Dorigo, W., Wagner, W., See, L., Atzberger, C., Schneider, S., & Rogenhofer, E. (2016). A Combined Satellite-Derived Drought Indicator to Support Humanitarian Aid Organizations. Remote Sensing, 8(4), 340. https://doi.org/10.3390/rs8040340

Enríquez-de-Salamanca, Á., Díaz-Sierra, R., Martín-Aranda, R. M., & Santos, M. J. (2017). Environmental impacts of climate change adaptation. Environmental Impact Assessment Review, 64, 87–96. https://doi.org/10.1016/j.eiar.2017.03.005

European Commission. (2022). Humanitarian Aid Funding Allocation - flyer. https://civil-protection-humanitarian-aid.ec.europa.eu/system/files/2023-03/Humanitarian%20Aid%20Funding%20Allocation%20flyer.pdf

European Commission. (2024, November 18). South Sudan. https://civil-protection-humanitarian-aid.ec.europa.eu/where/africa/south-sudan_en

European Commission. (2024). The next frontier for climate change science : Insights from the authors of the IPCC 6th assessment report on knowledge gaps and priorities for research. https://doi.org/10.2777/34601

European Commission. (n.d.). INFORM Severity Index. Retrieved October 22, 2022, from https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Severity

European Commission. Joint Research Centre. (2022). INFORM Climate Change: Quantifying the impacts of climate and socio economic trends on the risk of future humanitarian crises and disasters. Publications Office. https://data.europa.eu/doi/10.2760/383939

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

Franc, J. M., Hung, K. K. C., Pirisi, A., & Weinstein, E. S. (2023). Analysis of Delphi study 7-point linear scale data by parametric methods: Use of the mean and standard deviation. Methodological Innovations, 16(2), 226–233. https://doi.org/10.1177/20597991231179393

Fraser, E. D. G., Simelton, E., Termansen, M., Gosling, S. N., & South, A. (2013). "Vulnerability hotspots": Integrating socio-economic and hydrological models to identify where cereal production may decline in the future due to climate change induced drought. Agricultural and Forest Meteorology, 170, 195–205. https://doi.org/10.1016/j.agrformet.2012.04.008

Friedman, M., & Savage, L. J. (1952). The Expected-Utility Hypothesis and the Measurability of Utility. Journal of Political Economy, 60(6), 463–474. http://www.jstor.org/stable/1825271.

Ganguly, A. R., Kodra, E. A., Agrawal, A., Banerjee, A., Boriah, S., Chatterjee, Sn., Chatterjee, So., Choudhary, A., Das, D., Faghmous, J., Ganguli, P., Ghosh, S., Hayhoe, K., Hays, C., Hendrix, W., Fu, Q., Kawale, J., Kumar, D., Kumar, V., … Wuebbles, D. (2014). Toward enhanced understanding and projections of climate extremes using physics-guided data mining techniques. Nonlinear Processes in Geophysics, 21(4), 777–795. https://doi.org/10.5194/npg-21-777-2014

Garber, K., Fox, C., Abdalla, M., Tatem, A., Qirbi, N., Lloyd-Braff, L., Al-Shabi, K., Ongwae, K., Dyson, M., & Hassen, K. (2020). Estimating access to health care in Yemen, a complex humanitarian emergency setting: a descriptive applied geospatial analysis. The Lancet, 8(11), e1435–e1443. https://doi.org/10.1016/S2214-109X(20)30359-4

Giavarina, D. (2015). Understanding Bland Altman analysis. Biochemia Medica, 25(2), 141–151. https://doi.org/10.11613/BM.2015.015

Gizaw, M. S., & Gan, T. Y. (2016). Impact of climate change and El Niño episodes on droughts in sub-Saharan Africa. Climate Dynamics, 49(1–2), 665–682. https://doi.org/10.1007/s00382-016-3366-2

Hallegatte, S., Hourcade, J.-C., & Dumas, P. (2007). Why economic dynamics matter in assessing climate change damages: Illustration on extreme events. Ecological Economics, 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

Helm, D. (2010). Government failure, rent-seeking, and capture: the design of climate change policy. Oxford Review of Economic Policy, 26(2), 182–196. https://doi.org/10.1093/oxrep/grq006

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., Šakić Trogrlić, R., Reiter, K., Ward, P. J., de Ruiter, M. C., 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), 106736. 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

IASC & European Commission. (2024). INFORM REPORT 2024: 10 years of INFORM. https://doi.org/10.2760/555548

IFRC and Red Cross Red Crescent Climate Centre. (2023). A guide to climate-smart programmes and humanitarian operations. https://www.ifrc.org/document/guide-climate-smart-programmes-and-operations

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

International Crisis Group. (2022). Floods, Displacement and Violence in South Sudan. https://southsudan.crisisgroup.org

IPCC WG2. (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability : Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (H.-O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, & B. Rama, Eds.). Cambridge University Press. https://doi.org/10.1017/9781009325844

IPCC WG3. (2022). Climate Change 2022: Mitigation of Climate Change Working Group III Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (P. R. Shukla, J. Skea, R. Slade, R. Fradera, M. Pathak, A. Al Khourdajie, M. Belkacemi, R. van Diemen, A. Hasija, G. Lisboa, S. Luz, J. Malley, D. McCollum, S. Some, & P. Vyas, Eds.). Cambridge University Press. https://doi.org/10.1017/9781009157926

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

Jakob, C., Gettelman, A., & Pitman, A. (2023). The need to operationalize climate modelling. Nature Climate Change, 13(11), 1158–1160. https://doi.org/10.1038/s41558-023-01849-4

Jäpölä, J.-P. (2015). Legal View of Controlling Development Cooperation Appropriations in Finland. University of Tampere. https://urn.fi/URN:NBN:fi:uta-201512072502

Jäpölä, J.-P. (2024). Datasets for input and output of INFORM Severity-based SMAA study of resource allocation in humanitarian aid and disaster management under climatic losses and damages. Zenodo. https://doi.org/10.5281/zenodo.11001799

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). 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. EconDisCliCha 9, 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

Jitt-Aer, K., Wall, G., Jones, D., & Teeuw, R. (2022). Use of GIS and dasymetric mapping for estimating tsunami-affected population to facilitate humanitarian relief logistics: a case study from Phuket, Thailand. Natural Hazards, 113(1), 185–211. https://doi.org/10.1007/s11069-022-05295-x

Juhola, S., Filatova, T., Hochrainer-Stigler, S., Mechler, R., Scheffran, J., & Schweizer, P.-J. (2022). Social tipping points and adaptation limits in the context of systemic risk: Concepts, models and governance. Frontiers in Climate, 4. https://doi.org/10.3389/fclim.2022.1009234

Kahneman, D. (2003). Maps of Bounded Rationality: Psychology for Behavioral Economics. American Economic Review, 93(5), 1449–1475. https://doi.org/10.1257/000282803322655392

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. Econometrica, 47(2), 263. https://doi.org/10.2307/1914185

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

Keller, E., Newman J.E., Ortmann, A., Jorm, L.R. & Chambers, G.M. (2021). How Much Is a Human Life Worth? A Systematic Review. Value in Health, 24(10), 1531–1541, https://doi.org/10.1016/j.jval.2021.04.003

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

Keynes, J.M. (1936). The General Theory of Employment, Interest and Money. London, UK. Macmillan & Co.

Knox Clarke, P. (2022). Glossary of Early Action Terms. https://www.early-action-reap.org/sites/default/files/2022-10/REAP_Glossary%20of%20Early%20Action%20terms_2022%20edition_FINAL.pdf

Knox Clarke, P., & Hillier, D. (2023). Addressing loss and damage: Insights from the humanitarian sector. https://www.mercycorps.org/sites/default/files/2023-05/ZFRA-Addressing-loss-and-damage-working-paper-May-2023_0.pdf

Krishnamurthy, P. K., Choularton, R. J., & Kareiva, P. (2020). Dealing with uncertainty in famine predictions: How complex events affect food security early warning skill in the Greater Horn of Africa. Global Food Security, 26, 100374. https://doi.org/10.1016/j.gfs.2020.100374

Kuleshov, Y., Gregory, P., Watkins, A. B., & Fawcett, R. J. B. (2020). Tropical cyclone early warnings for the regions of the Southern Hemisphere: strengthening resilience to tropical cyclones in small island developing states and least developed countries. Natural Hazards, 104(2), 1295–1313. https://doi.org/10.1007/s11069-020-04214-2

Lang, S., Füreder, P., Riedler, B., Wendt, L., Braun, A., Tiede, D., Schoepfer, E., Zeil, P., Spröhnle, K., Kulessa, K., Rogenhofer, E., Bäuerl, M., Öze, A., Schwendemann, G., & Hochschild, V. (2019). Earth observation tools and services to increase the effectiveness of humanitarian assistance. European Journal of Remote Sensing, 53(sup2), 67–85. https://doi.org/10.1080/22797254.2019.1684208

Lee, R., White, C. J., Adnan, M. S. G., Douglas, J., Mahecha, M. D., O'Loughlin, F. E., Patelli, E., Ramos, A. M., Roberts, M. J., Martius, O., Tubaldi, E., van den Hurk, B., Ward, P. J., & Zscheischler, J. (2024). Reclassifying historical disasters: From single to multi-hazards. Science of The Total Environment, 912, 169120. https://doi.org/10.1016/j.scitotenv.2023.169120

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

Lentz, E. C., & Maxwell, D. (2022). How do information problems constrain anticipating, mitigating, and responding to crises? International Journal of Disaster Risk Reduction, 81, 103242. https://doi.org/10.1016/j.ijdrr.2022.103242

Lie, J.H.S. The humanitarian-development nexus: humanitarian principles, practice, and pragmatics. Int J Humanitarian Action 5, 18 (2020). https://doi.org/10.1186/s41018-020-00086-0

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

Lopez, V. K., Nika, A., Blanton, C., Talley, L., & Garfield, R. (2023). Can severity of a humanitarian crisis be quantified? Assessment of the INFORM severity index. Globalization and Health, 19(1), 7. https://doi.org/10.1186/s12992-023-00907-y

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

Läderach, P., Ramirez-Villegas, J.,Caroli, G., Sadoff, C., Pacillo, G., (2021). Climate finance and peace—tackling the climate and humanitarian crisis. The Lancet Planetary Health, 12(5), e856-e858, https://doi.org/10.1016/S2542-5196(21)00295-3

Makkonen, M., Hujala, T., & Uusivuori, J. (2016). Policy experts' propensity to change their opinion along Delphi rounds. Technological Forecasting and Social Change, 109, 61–68. https://doi.org/10.1016/j.techfore.2016.05.020

Markandya, A., & González-Eguino, M. (2019). Integrated assessment for identifying climate finance needs for loss and damage: A critical review. In R. Mechler, L. Bouwer, T. Schinko, S. Surminski, & J. Linnerooth-Bayer (Eds.), Loss and Damage from Climate Change - Concepts, Methods and Policy Options (pp. 343–362). Springer, Cham. https://doi.org/10.1007/978-3-319-72026-5_14

Marshall, A. (1890). Principles of Economics. London, UK and New York, US. Macmillan & Co.

Martin, J. A. R., de Dios Jiménez Aguilera, J., Martín, J. M. M., & Fernández, J. A. S. (2016). Crisis in the Horn of Africa: Measurement of Progress Towards Millennium Development Goals. Social Indicators Research, 135(2), 499–514. https://doi.org/10.1007/s11205-016-1491-2

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

Maxwell, D., Caldwell, R., & Langworthy, M. (2008). Measuring food insecurity: Can an indicator based on localized coping behaviors be used to compare across contexts? Food Policy, 33(6), 533–540. https://doi.org/10.1016/j.foodpol.2008.02.004

Mayer, T. (1975). Selecting Economic Hypotheses by Goodness of Fit. The Economic Journal, 85(340), 877. https://doi.org/10.2307/2230630

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

Meijering, J. V., & Tobi, H. (2018). The effects of feeding back experts' own initial ratings in Delphi studies: A randomized trial. International Journal of Forecasting, 34(2), 216–224. https://doi.org/10.1016/J.IJFORECAST.2017.11.010

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

Metropolis, N., & Ulam, S. (1949). The Monte Carlo Method. Journal of the American Statistical Association, 44(247), 335. https://doi.org/10.2307/2280232

Millner, A., & Heyen, D. (2021). Prediction: The Long and the Short of It. American Economic Journal: Microeconomics, 13(1), 374–398. https://doi.org/10.1257/mic.20180240

Mokkenstorm, L. C., van den Homberg, M. J. C., Winsemius, H., & Persson, A. (2021). River Flood Detection Using Passive Microwave Remote Sensing in a Data-Scarce Environment: A Case Study for Two River Basins in Malawi. Frontiers in Earth Science, 9. https://doi.org/10.3389/feart.2021.670997

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

Mpelasoka, F., Awange, J. L., & Zerihun, A. (2018). Influence of coupled ocean-atmosphere phenomena on the Greater Horn of Africa droughts and their implications. Science of The Total Environment, 610–611, 691–702. https://doi.org/10.1016/j.scitotenv.2017.08.109

Mude, A. G., Barrett, C. B., McPeak, J. G., Kaitho, R., & Kristjanson, P. (2009). Empirical forecasting of slow-onset disasters for improved emergency response: An application to Kenya's arid north. Food Policy, 34(4), 329–339. https://doi.org/10.1016/j.foodpol.2009.05.003

Mwangi, E., Taylor, O., Todd, M. C., Visman, E., Kniveton, D., Kilavi, M., Ndegwa, W., Otieno, G., Waruru, S., Mwangi, J., Ambani, M., Abdillahi, H., MacLeod, D., Rowhani, P., Graham, R., & Colman, A. (2021). Mainstreaming forecast based action into national disaster risk management systems: experience from drought risk management in Kenya. Climate and Development, 14(8), 741–756. https://doi.org/10.1080/17565529.2021.1984194

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

Nain, A., Jain, D., & Trivedi, A. (2023). Multi-criteria decision-making methods: application in humanitarian operations. Benchmarking: An International Journal. https://doi.org/10.1108/BIJ-11-2022-0673

Nauman, C., Anderson, E., Coughlan de Perez, E., Kruczkiewicz, A., McClain, S., Markert, A., Griffin, R., & Suarez, P. (2021). Perspectives on flood forecast-based early action and opportunities for Earth observations. Journal of Applied Remote Sensing, 15(03). https://doi.org/10.1117/1.jrs.15.032002

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

Neumayer, E., Plümper, T., & Barthel, F. (2014). The political economy of natural disaster damage. Global Environmental Change, 24, 8–19. https://doi.org/10.1016/j.gloenvcha.2013.03.011

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

Newman, R., & Noy, I. (2023). The global costs of extreme weather that are attributable to climate change. Nature Communications, 14(1), 6103. https://doi.org/10.1038/s41467-023-41888-1

Noguchi, J. (2006). The Science Review Article: An Opportune Genre in the Construction of Science. Peter Lang.

North, D. (1990). Institutions, Institutional Change and Economic Performance. Cambridge University Press. 10.1017/CBO9780511808678

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

Noy, I. (2023). Economists are not engaged enough with the IPCC. Npj Climate Action, 2(1), 33. https://doi.org/10.1038/s44168-023-00064-3

Nusrat, F., Haque, M., Rollend, D., Christie, G., & Akanda, A. S. (2022). A High-Resolution Earth Observations and Machine Learning-Based Approach to Forecast Waterborne Disease Risk in Post-Disaster Settings. Climate, 10(4), 48. https://doi.org/10.3390/cli10040048

OECD ODA. (2023, June 22). April 2023 - preliminary figures. https://public.flourish.studio/story/1882344/

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

Okoli, C., & Pawlowski, S. D. (2004). The Delphi method as a research tool: an example, design considerations and applications. Information & Management, 42(1), 15–29. https://doi.org/10.1016/j.im.2003.11.002

Ostrom, E. (1990). Governing the Commons: The Evolution of Institutions for Collective Action. Cambridge University Press.

https://doi.org/10.1017/CBO9780511807763

Otto, F., Clarke, B., Barnes, C., Kimutai, J., Zachariah, M., Merz, N., Vrkic, D., Philip, S., Kew, S., Pinto, I., Vahlberg, M., Singh, R., Horne, Z., Arrighi, J., Sparks, N., Giguere, J., & Gilford, D. (2024). 10 years of rapidly disentangling drivers of extreme weather disasters. https://doi.org/10.25561/115431

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

Parish, E. S., Kodra, E., Steinhaeuser, K., & Ganguly, A. R. (2012). Estimating future global per capita water availability based on changes in climate and population. Computers & Geosciences, 42, 79–86. https://doi.org/10.1016/j.cageo.2012.01.019

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.

Piontek, F., Müller, C., Pugh, T. A. M., Clark, D. B., Deryng, D., Elliott, J., Colón González, F. de J., Flörke, M., Folberth, C., Franssen, W., Frieler, K., Friend, A. D., Gosling, S. N., Hemming, D., Khabarov, N., Kim, H., Lomas, M. R., Masaki, Y., Mengel, M., … Schellnhuber, H. J. (2014). Multisectoral climate impact hotspots in a warming world. Proceedings of the National Academy of Sciences of the United States of America, 111(9), 3233–3238. https://doi.org/10.1073/pnas.1222471110

Polasky, S., Kling, C. L., Levin, S. A., Carpenter, S. R., Daily, G. C., Ehrlich, P. R., Heal, G. M., & Lubchenco, J. (2019). Role of economics in analyzing the environment and sustainable development. Proceedings of the National Academy of Sciences of the United States of America, 116(12), 5233–5238. https://doi.org/10.1073/pnas.1901616116

Poljansek, K., Disperati, P., Vernaccini, L., Nika, A., Marzi, S., & Essenfelder, A. H. (2020). INFORM Severity Index - Concept and methodology. https://doi.org/10.2760/94802

Poljansek, K., Marzi, S., Galimberti, L., Dalla Valle, D., Pal, J., Essenfelder, A. H., Mysiak, J., & Corbane, C. (2022). INFORM Climate Change Risk Index - Concept and methodology. https://doi.org/10.2760/822072

Prado, V., & Heijungs, R. (2018). Implementation of stochastic multi attribute analysis (SMAA) in comparative environmental assessments. Environmental Modelling & Software, 109, 223–231. https://doi.org/10.1016/j.envsoft.2018.08.021

Puy, A., Beneventano, P., Levin, S. A., Lo Piano, S., Portaluri, T., & Saltelli, A. (2022). Models with higher effective dimensions tend to produce more uncertain estimates. Science Advances, 8(42). https://doi.org/10.1126/sciadv.abn9450

Ranganathan, P., Pramesh, C., & Aggarwal, R. (2017). Common pitfalls in statistical analysis: Measures of agreement. Perspectives in Clinical Research, 8(4), 187. https://doi.org/10.4103/picr.PICR_123_17

Rasmussen, C. E., & Williams, C. K. I. (2006). Gaussian processes for machine learning. MIT Press.

Rawls, J. B. (1971). A Theory of Justice. Cambridge, US. Belknap Press.

Red Cross Red Crescent Climate Centre. (2023). Key findings related to loss and damage from the Working Group II report of the sixth IPCC assessment of the global climate. https://www.climatecentre.org/publications/13046/key-findings-related-to-loss-and-damage-from-the-working-group-ii-report-of-the-sixth-ipcc-assessment-of-the-global-climate/

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

Robinson, T. D., Oliveira, T. M., & Kayden, S. (2017). Factors affecting the United Nations' response to natural disasters: what determines the allocation of the Central Emergency Response Fund? Disasters, 41(4), 631–648. https://doi.org/10.1111/disa.12226

Rost, N., & Clarke, J. N. (2025). Why do governments fund some humanitarian appeals but not others? Development Policy Review, 43(1). https://doi.org/10.1111/dpr.12819

Roszkowska, E. (2013). Rank Ordering Criteria Weighting Methods – a Comparative Overview. Optimum. Studia Ekonomiczne, 5(65), 14–33. https://doi.org/10.15290/ose.2013.05.65.02

Samson, J., Berteaux, D., McGill, B. J., & Humphries, M. M. (2011). Geographic disparities and moral hazards in the predicted impacts of climate change on human populations. Global Ecology and Biogeography, 20(4), 532–544. https://doi.org/10.1111/j.1466-8238.2010.00632.x

Samuelson, P. A. (1947). Foundations of Economic Analysis. Cambridge, US. Harvard University Press.

Sandström, S., Juhola, S., & Räsänen, A. (2020). Fluctuating Rainfall, Persistent Food Crisis—Use of Rainfall Data in the Kenyan Drought Early Warning System. Atmosphere, 11(12), 1328. https://doi.org/10.3390/atmos11121328

Scafetta, N. (2024). Impacts and risks of "realistic" global warming projections for the 21st century. Geoscience Frontiers, 15(2), 101774. https://doi.org/10.1016/j.gsf.2023.101774

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation Coefficients: Appropriate Use and Interpretation. Anesthesia & Analgesia, 126(5), 1763–1768. https://doi.org/10.1213/ANE.0000000000002864

Schumpeter, J.A. (1934). The Theory of Economic Development. Cambridge, US. Harvard University Press.

Scott, M., Bunce, M., & Wright, K. (2022). The Influence of News Coverage on Humanitarian Aid: The Bureaucrats' Perspective. Journalism Studies, 23(2), 167–186. https://doi.org/10.1080/1461670X.2021.2013129

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

Slim, H. (2023). How should we define and prioritise humanitarian need? An ethics-based perspective for IMPACT Initiatives. https://www.humanitarianstudies.no/wp-content/uploads/NCHS-paper-15-November-2023-How-should-we-define-and-prioritise-humanitarian-need.pdf

Songwe, V., Stern, N., & Bhattacharya, A. (2022). Finance for climate action: Scaling up investment for climate and development. https://www.lse.ac.uk/granthaminstitute/wp-content/uploads/2022/11/IHLEG-Finance-for-Climate-Action-1.pdf

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

Stanton, M. C. B., & Roelich, K. (2021). Decision making under deep uncertainties: A review of the applicability of methods in practice. Technological Forecasting and Social Change, 171, 120939. https://doi.org/10.1016/j.techfore.2021.120939

Steinke, A. (2023). Climate change and humanitarian change. Challenging norms, mandates and practices. Berlin: Centre for Humanitarian Action. https://www.chaberlin.org/wp-content/uploads/dlm_uploads/2023/11/climate-change-en-web.pdf

Stern, N., Stiglitz, J., & 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

Suarez, P. (2009). Linking Climate Knowledge and Decisions: Humanitarian Challenges. https://www.bu.edu/pardee/files/2010/01/Pardee_Paper__7_Linking_Climate_Knowledge.pdf?PDF=pardee-paper-007-climate

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

Taberna, A., Filatova, T., Hadjimichael, A., & Noll, B. (2023). Uncertainty in boundedly rational household adaptation to environmental shocks. Proceedings of the National Academy of Sciences, 120(44). https://doi.org/10.1073/pnas.2215675120

Taylor, O. G. (2023). The policy landscape and challenges of disaster risk financing: navigating risk and uncertainty. Disasters, 47(3), 745–765. https://doi.org/10.1111/disa.12560

Thaler, R. (1980). Toward a positive theory of consumer choice. Journal of Economic Behavior & Organization, 1(1), 39–60. https://doi.org/10.1016/0167-2681(80)90051-7

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.

Thow, A., Poljansek, K., Marzi, S., Galimberti, L., & Dalla Valle, D. (2022). INFORM Climate Change Quantifying the impacts of climate and socio-economic trends on the risk of future humanitarian crises and disasters. https://drmkc.jrc.ec.europa.eu/inform-index/Portals/0/InfoRM/2022/INFORM%20Climate%20Change%20Brochure.pdf

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

UN FTS. (n.d.). Coordinated plans 2022. Retrieved 17 September 2023, from https://fts.unocha.org/plans/overview/2022

UN OCHA. (2021) Global Humanitarian Overview 2022. https://reliefweb.int/report/world/global-humanitarian-overview-2022

UN OCHA. (2022). SECTION 1 : GLOBAL TRENDS - The climate crisis is a humanitarian crisis. In Global Humanitarian Overview 2023. https://humanitarianaction.info/article/climate-crisis-humanitarian-crisis

UN OCHA. (2023, October 4). Libya - Situation Report. https://reports.unocha.org/en/country/libya/

UN OCHA. (2024, December 4). Global Humanitarian Overview 2025. https://humanitarianaction.info/document/global-humanitarian-overview-2025

UN OCHA. (n.d.). Humanitarian Action : inter-agency plans for 2023. Retrieved January 15, 2024, from https://humanitarianaction.info/overview/2023

UN OCHA. (2024, December 4). Global Humanitarian Overview 2025. https://humanitarianaction.info/document/global-humanitarian-overview-2025

UN OCHA. (2025, December 8). Global Humanitarian Overview 2026. https://humanitarianaction.info/document/global-humanitarian-overview-2026

UNDRR & ISC. (2020). Hazard definition and classification review (Technical Report). https://www.undrr.org/media/47681/download?startDownload=true

UNDRR. (2021). Scaling up Disaster Risk Reduction in Humanitarian Action 2.0 - Recommendations for the Humanitarian Programme Cycle. https://www.undrr.org/quick/13010

UNDRR. (2022). Global Assessment Report on Disaster Risk Reduction 2022 - Our World at Risk: Transforming Governance for a Resilient Future. www.undrr.org/GAR2022

UNDRR. (2023). Strengthening Risk Analysis for Humanitarian Planning: Integrating disaster and climate risk in the Humanitarian Programme Cycle. https://www.undrr.org/publication/strengthening-risk-analysis-humanitarian-planning

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

United Nations. (2021). Glasgow Climate Pact, article 15. FCCC/PA/CMA/2021/L.16. https://unfccc.int/sites/default/files/resource/cma2021_L16_adv.pdf

University of Notre Dame. (2021). Notre Dame Global Adaptation Initiative (ND-GAIN). https://gain.nd.edu/our-work/country-index/

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. https://doi.org/10.1038/s41558-023-01636-1

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

Van Schoubroeck, S., & Jäpölä, J.-P. (2025). SMAA model in paper Prioritising humanitarian aid funding for multi-risk disasters in an era of climatic damage. Zenodo. https://doi.org/10.5281/zenodo.16413903

Van Schoubroeck, S., Thomassen, G., Van Passel, S., Malina, R., Springael, J., Lizin, S., Venditti, R. A., Yao, Y., & Van Dael, M. (2021). An integrated techno-sustainability assessment (TSA) framework for emerging technologies. Green Chemistry, 23(4), 1700–1715. https://doi.org/10.1039/D1GC00036E

Van Schoubroeck, S., Vermeyen, V., Alaerts, L., Van Acker, K., & Van Passel, S. (2022). How to monitor the progress towards a circular food economy: A Delphi study. Sustainable Production and Consumption, 32, 457–467. https://doi.org/10.1016/j.spc.2022.05.006

Visser, H., de Bruin, S., Martens, A., Knoop, J., & Ligtvoet, W. (2020). What users of global risk indicators should know. Global Environmental Change, 62, 102068. https://doi.org/10.1016/j.gloenvcha.2020.102068 von der Gracht, H. A. (2012). Consensus measurement in Delphi studies. Technological Forecasting and Social Change, 79(8), 1525–1536. https://doi.org/10.1016/j.techfore.2012.04.013

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

Warner, K., Hamza, M., Oliver-Smith, A., Renaud, F., & Julca, A. (2009). Climate change, environmental degradation and migration. Natural Hazards, 55(3), 689–715. https://doi.org/10.1007/s11069-009-9419-7

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

WMO & UNDRR. (2022). Global status of multi-hazard early warning systems: Target G. https://www.undrr.org/publication/global-status-multi-hazard-early-warning-systems-target-g

World Bank. (2021). Investment in Disaster Risk Management in Europe Makes Economic Sense - SUMMARY REPORT. https://openknowledge.worldbank.org/entities/publication/cfcfb027-1ce7-599f-9d36-8f1449a43f05

World Bank. (2024). Climate Adaptation Costing in a Changing World : Valuing Climate Adaptation Helps Us Orient Our Compass Toward Effective and Resilient Pathways. https://doi.org/10.1596/41594

World Weather Attribution. (n.d.). WWA analyses of extreme weather events. https://www.worldweatherattribution.org/analyses/

Xu, X. (2001). The SIR method: A superiority and inferiority ranking method for multiple criteria decision making. European Journal of Operational Research, 131(3), 587–602. https://doi.org/10.1016/S0377-2217(00)00101-6

Yan, Q. (2023). The use of climate information in humanitarian relief efforts: a literature review. Journal of Humanitarian Logistics and Supply Chain Management, 13(3), 331–343. https://doi.org/10.1108/JHLSCM-01-2022-0003

Zachariah, M., Kotroni, V., Kostas, L., Barnes, C., Kimutai, J., Kew, S., Pinto, I., Yang, W., Vahlberg, M., Singh, R., Thalheimer, D., Marghidan Pereira, C., Otto, F., Philip, S., El Hajj, R., El Khoury, C., Walsh, S., Spyratou, D., Tezapsidou, E., … Bloemendaal, N. (2023). Interplay of climate change-exacerbated rainfall, exposure and vulnerability led to widespread impacts in the Mediterranean region. https://doi.org/10.25561/106501

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

Online Supplementary Material (Appendices)

Chapter 1	Appendices A and B. https://static-content.springer.com/esm/art%3A10.1007%2Fs41885-024-00168-y/MediaObjects/41885_2024_168_MOESM1_ESM.pdf
Chapter 2	Appendix A. https://static-content.springer.com/esm/art%3A10.1007%2Fs10584-024-03741-2/MediaObjects/10584_2024_3741_MOESM1_ESM.pdf
	Appendix B. https://static-content.springer.com/esm/art%3A10.1007%2Fs10584-024-03741-2/MediaObjects/10584_2024_3741_MOESM2_ESM.pdf
	Appendix C. https://static-content.springer.com/esm/art%3A10.1007%2Fs10584-024-03741-2/MediaObjects/10584_2024_3741_MOESM3_ESM.pdf
	Appendix D. https://static-content.springer.com/esm/art%3A10.1007%2Fs10584-024-03741-2/MediaObjects/10584_2024_3741_MOESM4_ESM.xlsx
Chapter 3	Supplementary Information (SI). https://ars.els-cdn.com/content/image/1-s2.0-S2212420925005758-mmc1.pdf
	Code. https://doi.org/10.5281/zenodo.16413903
	Data. https://doi.org/10.5281/zenodo.11001798
Chapter 4	Supplementary Information (SI). https://doi.org/10.5281/zenodo.17386650
	Replication Package. https://doi.org/10.5281/zenodo.15336209

List of Figures

List of Tables