MEASURING THE CRISIS PROTECTION GAP

A SUMMARY OF RESEARCH EXPLORING TECHNICAL APPROACHES FOR ESTIMATING GLOBAL CRISIS PROTECTION COSTS

CENTRE FOR DISASTER PROTECTION

UKaid from the British people

SYNTHESIS REPORT

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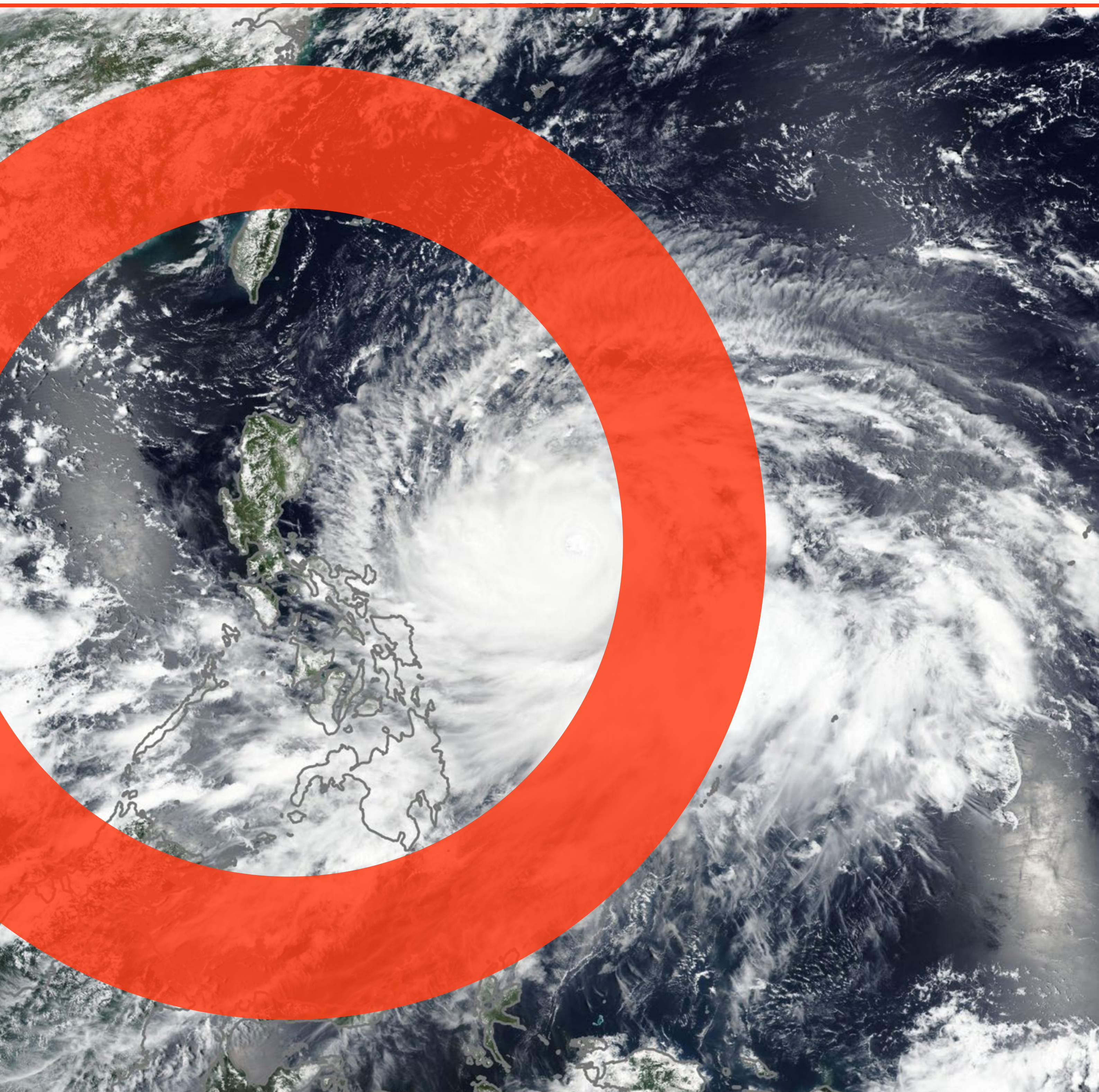

About the Centre for Disaster Protection

The Centre for Disaster Protection works to prevent disasters devastating lives, by helping people, countries, and organisations change how they plan and pay for disasters. The Centre is funded with UK aid through the UK government.

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EXECUTIVE SUMMARY

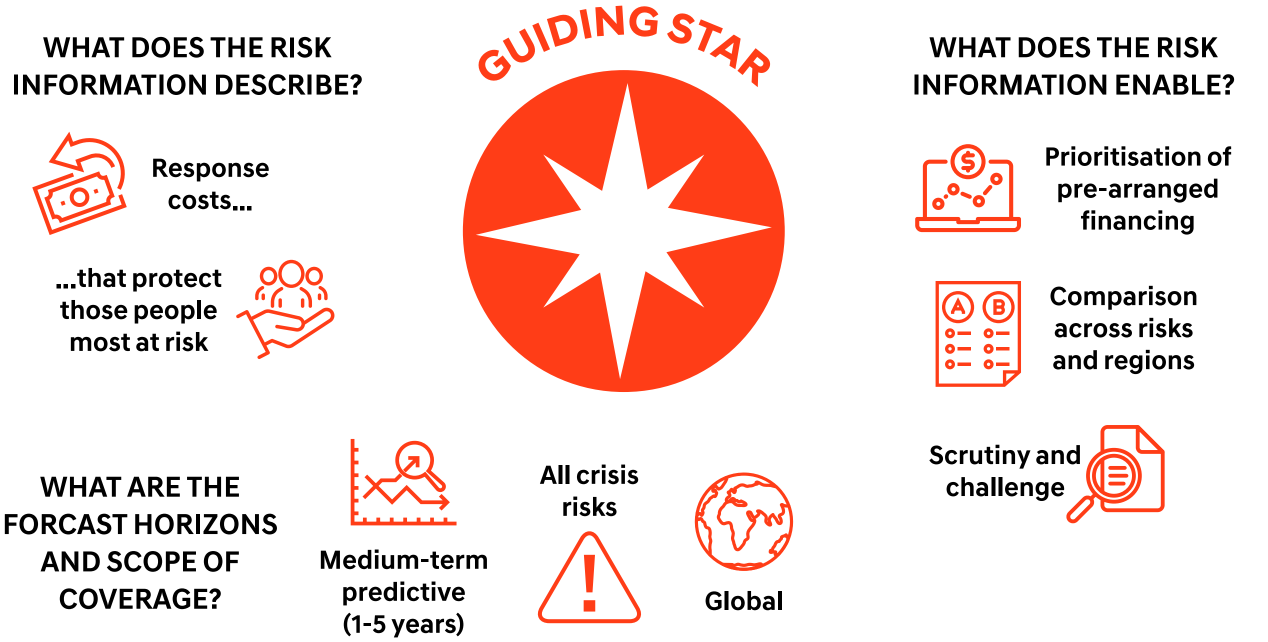
The number of people whose lives are threatened by crises is increasing. In 2022, 274 million people (more than 1 in 30 of the world's population) needed humanitarian assistance and protection. These trends are worsening: between 2021 and 2022, the number of people in need of humanitarian assistance increased by 16%; the 2021 figure was already the highest number in decades. Climate change threatens to exacerbate these challenges. It is already causing more frequent and more severe extreme events, revealing the fundamental fragility of many people's lives and livelihoods, and the systems on which they depend. The number of climate-related crises has tripled in the past 40 years.

Current responses to crises are inadequate and inefficient. There is chronic underinvestment in risk reduction; humanitarian response appeals are underfunded and often only provide resources months after a crisis has occurred. Evidence from the covid-19 pandemic suggests that the countries that find it easiest to borrow money are the ones that are able to mobilise the most resources to respond to crises, rather than the countries that are most affected.

Pre-arranged financing (PAF) is a critical component in improving crisis response. Risk reduction activities are often highly cost effective and should be supported to go to scale. However, it is inevitable that crises will continue to affect many people. PAF refers to 'financing that has been approved in advance of a crisis and that is guaranteed to be released to a specific implementer when a specific pre-identified trigger condition is met' (Centre for Disaster Protection 2023). There is emerging evidence that use of PAF reduces the short- and long-term humanitarian impact of crises.

Understanding the gap between how much crisis financing would be needed, and how much is pre-arranged, could have a wide range of benefits. First, the design and use of PAF mechanisms requires an understanding of what crises are likely to occur and what costs they will entail, to ensure that PAF mechanisms provide the right amount of funding in the right place at the right time. However, information on crisis protection costs and gaps could also be used as an information tool to better enable monitoring, education and advocacy around PAF; to inform resource allocation decisions by funding organisations making PAF decisions; or to enhance strategic decision-making in those organisations engaged in, and responsible or accountable for, responding to crises.

This report presents the results of research that explores the feasibility of producing quantitative estimates of the costs of crisis protection across a variety of geographies and crisis types. The research focuses on whether it is possible to produce medium-term (1–5-year) estimates of the costs of providing immediate crisis protection (responses provided in the first 100 days of a crisis) for the crises the world's poorest and most crisis-vulnerable people face.



Source: Centre for Disaster Protection

The report presents a conceptual framework for estimating crisis protection costs and provides demonstration analyses that illustrate key elements of this framework in relation to tropical cyclone and drought risk. This work defines the crisis protection gap as the difference between the total expected contingent liabilities of national or international responders (i.e. the costs they can expect to incur in responding to crises) and the amount of funding available to meet these costs through PAF mechanisms (including, but not limited to, insurance).

The framework has three modules:

1. **An exposure module** identifies which people are most at risk from crises and some of the key characteristics that will determine their vulnerability. This module can benefit from recent rapid advances in remote sensing and machine learning, which provide insights into the location of poor and crisis-vulnerable people, their socio-demographic characteristics and income estimates, and the extent to which they are currently served (or not) by critical infrastructure.
2. **A crisis event module** provides forward-looking information on the likely footprint of different types of crisis events, and what the likelihood of events of different severity might be. Combined with the exposure module, it provides an understanding of how many people crises of differing severities could affect. The most readily available (and sophisticated) information of this type exists for climatological hazards such as tropical cyclones and floods. The ability to make

probabilistic predictions about drought and disease outbreaks has also improved considerably in recent years. It is currently more difficult to generate predictive information for some other types of crises, such as conflict-related displacement, although estimates are improving yearly.

3. **A cost module** takes estimates of the number of people who may be affected by a crisis and assesses the cost of meeting their needs. The report presents new 'top-down' evidence that uses proxies for these costs by looking at the amount that international humanitarian actors have appealed for in response to a new crisis. It examines how these appeal amounts vary according to crisis type, the number of people the response targets and the location of the crisis. It illustrates how this information could be combined with the other modules to produce forward-looking cost estimates. In principle, this top-down approach could be complemented by a bottom-up approach that looks at the activities carried out in humanitarian response and uses this analysis of activities as a basis for estimating costs. This latter approach could incorporate information on costs that national responders incur, which is difficult to include in a top-down analysis due to data constraints.

KEY CONCLUSIONS

The combination of conceptual and demonstration analysis yields five key conclusions:

1. **It is increasingly possible to generate forward looking estimates of crisis protection costs and, hence, crisis protection gaps.** Rapid advances in data use to populate the exposure module; increasing sophistication of tools to make predictions about crises; and continued interest in and availability of data for costing crisis responses provide confidence in the ability to generate robust estimates of crisis protection costs. This conclusion is further strengthened by demonstration analysis, particularly in relation to tropical cyclones.

2. **Measuring crisis protection costs and gaps requires design choices that should be made explicit.** This report focuses on the immediate response costs associated with meeting the needs of the most vulnerable people. This focus reflects the expectation that it is in relation to these costs and needs that additional PAF is likely to be most valuable. Others may have legitimate reasons for defining crisis preparedness costs and gaps differently. However, the demonstration analysis suggests that the results of any assessment of crisis protection costs are likely to be sensitive to the definition used. It is therefore crucial that those making estimates of crisis protection costs are explicit about the approach they have taken and their reasons for taking it. In addition, the greatest value will come from maintaining the same methodological approach over time and across locations, providing a consistency that allows stakeholders to understand trends.

3. **A common approach to defining and measuring exposure is critical when making comparative assessments of different crisis types.** While making comparisons between different crisis types is inherently challenging, it can be made much easier by using the same exposure data. This allows users of crisis protection gap information to be confident that they are comparing the impacts of different crisis types, and the protection needs and costs they generate, with a common understanding of what and whose needs they are trying to understand. The exposure module thus

provides the 'glue' that facilitates comparisons between crises that may have very different impacts. Recent advances in disaggregated population data mean that it is much easier for common exposure data to provide this function than would have been the case just a few years ago.

4. **There are important conceptual and modelling challenges that this work has only begun to address.** Of critical importance is the need for further work on defining 'affectedness'. As the demonstration analysis for drought risk shows, even when relevant data exists for a particular type of crisis (such as Integrated Food Security Phase Classification data for droughts), it can be difficult to define who is affected by a crisis, or to account for the fact that a crisis may affect people to varying degrees, depending on both the characteristics of the crisis event and the vulnerability of those exposed to that event. This complicates the task of estimating response costs. The challenge of defining affectedness becomes more difficult, but also more critical, when trying to make comparisons across crisis types, as definitions of affectedness are not standardised. Other areas that would contribute to more reliable and robust estimates of crisis protection costs include: better understanding of the numbers and locations of people affected by crises (especially displaced people and refugees, where they are not captured in census or survey data); allowing for the possibility that people's vulnerability to crises may change over time; and further improving forecasting capabilities for certain types of crises, especially those such as displacement, which are largely determined by short-term human action.

5. **Much better information on the costs of crisis response would be of considerable value.** Securing access to cost data and using it wisely to produce robust and credible costing analysis appears to be the main challenge that needs to be overcome if the international community is to further develop an understanding of the costs of crisis protection. While this report presents an illustrative costing analysis, this type of top down analysis could be improved in various ways and additional issues need to be considered. These include, critically, accounting for the quality and completeness of any crisis response effort. In principle, complementary bottom-up costing analysis could help address weaknesses in a top-down costing approach. However, questions remain about public access to the activity-based data needed to support such analysis, which would also need to be carefully conducted to ensure results could be applied across a range of geographic contexts.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DATA SOURCES

This research relies on a range of publicly available data and information. These data sets are used to test suitable approaches for developing response cost functions, and to develop a demonstration analyses for tropical cyclone and drought risks. The analyses presented here are therefore not intended to provide actual crisis protection gap estimates, but rather to test whether technical certain approaches are feasible, and to identify key challenges.

Source data has been adapted for the purposes of these analyses - readers should refer to original sources for unmodified versions of the data.

Some data is available under the Creative Commons Attribution 4.0 International License http://creativecommons.org/licenses/by/4.0/.

See Annex A3 for detailed descriptions of data sources.

ACRONYMS

AEP	Aggregate exceedance probability
DREF	Disaster Response Emergency Fund
FEWS NET	Famine Early Warning Systems Network
FTS	Financial Tracking Service
IDA	International Development Association
IFRC	International Federation of Red Cross and Red Crescent Societies
IPC	Integrated Food Security Phase Classification
OCHA	United Nations Office for the Coordination of Humanitarian Affairs
ODA	Official Development Assistance
OEP	Occurrence exceedance probability
PAF	Pre-arranged financing
SWI	Soil Water Index
YELT	Year-event loss table

GLOSSARY

Definitions are those of the Centre for Disaster Protection except where stated.

Affected

People who are affected, either directly or indirectly, by a hazardous event. Directly affected people are those who have suffered injury, illness or other health effects; who were evacuated, displaced, relocated or have suffered direct damage to their livelihoods, and economic, physical, social, cultural and environmental assets. Indirectly affected people are those who have suffered consequences, other than or in addition to direct effects, over time, due to disruption or changes in economy, critical infrastructure, basic services, commerce or work, or social, health and psychological consequences (UNGA 2016).

Contingent liabilities

Obligations to pay costs associated with a possible, but uncertain, future event. Given there is no obligation to pay unless the event occurs, contingent liabilities might not be formally listed as a liability on an organisation's balance sheet. Contingent liabilities might be explicit or implicit:

- Explicit contingent liabilities are contractual commitments to make certain payments if a particular event occurs - the basis of these commitments can be contracts, laws or clear policy statements.
- Implicit contingent liabilities are political or moral obligations to make payments; for example, in the event of a crisis - governments do not recognise these liabilities until a particular event occurs; implicit contingent liabilities are difficult to assess, let alone manage in a consistent manner, precisely because of their implicit nature.

Crisis

A situation creating severe and widespread needs that exceed existing local and national capacities to prevent, mitigate or respond to them. This includes crises arising from a range and combination of hazards including conflict, weather- and climate-related events and stresses, and disease.

Crisis financing

Funding and financing that promotes and specifically targets prevention, preparedness, and response to crises. It could take the form of: (1) cash flow to recipients (e.g. grants) that could be arranged in advance or agreed in real time; or (2) cash flow to and from recipients via a financial intermediary (e.g. loan or insurance).

Crisis financing instruments

The combination of a crisis objective, payment plan, disbursement plan and accountability mechanism, which together contribute to crisis prevention, preparedness and response.

Crisis protection gap

The 'protection gap' is traditionally the difference between total losses associated with an event (or events) and the funds available to recover these losses through insurance.

Protection gap metrics can refer to the shortfall for a single event (e.g. for a historical event), or to an expected shortfall based on the difference between expected losses in relation to possible future events and the financial protection provided by insurance.

In the context of this work, the term 'crisis (financing) protection gap' is used to describe the difference between the total expected contingent liabilities of national or international responders (i.e. the costs they incur in responding to crises, and the amount of funding available to meet these costs through pre-arranged financing (insurance or otherwise)).

Crisis risk

The potential suffering and loss of life that could occur in a specific time period due to a crisis, determined probabilistically as a function of hazard, exposure, vulnerability and capacity.

Displacement

The movement of people who have been forced or obliged to flee or to leave their homes or places of habitual residence (whether within their own country or across an international border), in particular as a result of or in order to avoid the effects of armed conflict, situations of generalised violence, violations of human rights or disasters (UNHCR 2020).

Exposure

The situation of people, infrastructure, housing, production capacities and other tangible human assets located in hazard-prone areas (UNGA 2016).

Hazard

A process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption, or environmental degradation (Ibid.).

Migrant

While there is no formal legal definition of an international migrant, most experts agree that an international migrant is someone who changes their country of usual residence, irrespective of their reason for migration or legal status. Generally, a distinction is made between short-term or temporary migration, covering movements with a duration of 3-12 months; and long-term or permanent migration, referring to a change of country of residence for a duration of one year or more (UNDESA 2016).

Pre-arranged financing

Financing that has been approved in advance of a crisis and that is guaranteed to be released to a specific implementer when a specific pre-identified trigger condition is met.

The trigger may be based on data or models related to impact, forecasts or projections of need, or a declaration of emergency (or similar) by the specified respondent. The funding may be used for anticipatory action or in response to a crisis, either linked to a clear plan for a very specific purpose or general budget support.

Preparedness

The knowledge and capacities governments, response and recovery organisations, communities and individuals develop to effectively anticipate, respond to and recover from the impacts of likely, imminent or current crises. Preparedness distinguishes between financial preparedness (e.g. the creation of budgetary or financial mechanisms to respond to a particular type of crisis) and delivery system preparedness (e.g. investments in enabling social protection systems to scale up rapidly following a disaster).

Refugee

People who are outside their country of origin for reasons of feared persecution, conflict, generalised violence or other circumstances that have seriously disturbed public order, and who require international protection as a result (UNHCR 1950).

Resilience

Actions taken directly before, during or immediately after a disaster to save lives, reduce health impacts, ensure public safety and meet basic subsistence needs of the people affected (UNGA 2016).

Risk

The probability of an outcome having a negative effect on people, systems or assets. Risk is typically depicted as being a function of the combined effects of elements that together contribute to these negative effects: hazards, the assets or people exposed to hazard and the vulnerability of those exposed elements (Knox Clarke and REAP Secretariat 2022).

Vulnerability

The conditions determined by physical, social, economic and environmental factors or processes that increase the susceptibility of a community to the impact of hazards (UNGA 2016).

1

INTRODUCTION

This report provides an overview of the approach and findings from a research exercise undertaken by the Centre for Disaster Protection (hereafter, 'the Centre'), with the inputs of many partner organisations, to better understand the feasibility and challenges of generating estimates of the 'crisis protection gap'. As set out below, the crisis protection gap is defined as the difference between the total expected contingent liabilities of national or international responders (i.e. the costs they can expect to incur in responding to crises) and the amount of funding available to meet these costs through pre-arranged financing (PAF).

Estimating the crisis protection gap relies on a number of fundamental building blocks, including definitions of crisis protection needs and costs. This research explores definitional and technical options, alongside a corresponding range of potential applications for this information. The discussion also describes the rationale for – and decisions taken to manage – the scope and focus of the research exercise.

The report is structured as below.

SECTION 2: OVERVIEW

This section introduces the research exercise, including a discussion of the context and rationale, the guiding research objective, a review of the approach taken and a summary of key findings.

SECTION 3: TECHNICAL FEASIBILITY

This section presents an underlying conceptual model for estimating crisis protection needs and costs, from which an assessment of crisis protection gaps can be estimated, and assesses what data and information relating to the conceptual model are currently available.

SECTION 4: DEMONSTRATION ANALYSIS

This section provides a practical demonstration of feasibility and challenges in estimating crisis protection costs (and, implicitly, crisis protection gaps). It focuses on tropical cyclone and drought risk, illustrating some of the practical options and challenges that can arise when moving from a conceptual model to specific calculations.

SECTION 5: USE CASES

This section provides an initial overview of a range of potential users and use cases, alongside a discussion of technical implications for different preferred applications.

SECTION 6: SUMMARY OF RESEARCH FINDINGS

This section summarises the key findings from this initial technical research.

A series of technical annexes provide detailed further information on the costing and demonstration analyses.

2

OVERVIEW

The current landscape of financing crisis response is flawed. Insufficient resources are available to adequately prepare for crises and reduce risks. When crises occur, the funds available to meet immediate needs are often inadequate and delayed. The poorest and most vulnerable people bear the brunt of these problems.

Increased flows of PAF - financing that has been approved in advance of a crisis and that is guaranteed to be released to a specific implementer when a specific pre-identified trigger condition is met - could help address these weaknesses.

The crisis protection gap measures the difference between the total expected contingent liabilities of national or international responders (i.e. the costs they expect to incur in responding to crises) and the amount of funding available to meet these costs through PAF. Understanding the size and distribution of this gap is critical information when designing the scale-up of PAF.

To operationalise this definition requires answers to two critical questions. This work starts with a set of 'preferred' answers to these questions and explores whether it is possible to measure the crisis protection gap in a way that is consistent with these answers:

- **What types of crises?** The study explores whether it is possible to examine all crisis types to understand their comparative importance in the crisis protection gap.
- **What funding needs?** The work looks at the immediate crisis response costs for protecting the most vulnerable people. This is taken as those costs associated with meeting needs in the first 100 days of a crisis. The aim is to understand the extent to which it is possible to predict the size and distribution of these costs over a 1-5-year window into the future.

This is an ambitious research agenda. A number of potential weaknesses should be acknowledged at the outset. These include the various simplifications that modelling tools make when confronted with the complexity of the real world, and the difficulty of using historical information to predict the future.

Nonetheless, a wide range of researchers and practitioners have made important advances in recent years. This makes the task more feasible than ever before. This research project has engaged extensively with these stakeholders - who come from a wide range of disciplines and backgrounds - using a combination of structured interviews and workshops. This has been complemented by a range of quantitative and qualitative analyses.

2.1. WHAT IS THE CRISIS PROTECTION GAP AND WHY MEASURE IT?

At present, the approaches policymakers and practitioners use to predict and prepare for crises are inadequate. A range of biases and political economy incentives often lead decision makers in crisis-affected countries and those involved in crisis response to focus on responding to events that have happened, rather than trying to understand and prepare for what might happen, even when there are clear forecasts or the risks of crises occurring are high.

An approach that considers crisis response only after a crisis has occurred is likely to be inadequate and unfair. For example, work reviewing the multilateral system's immediate response to the covid-19 pandemic found that the level of support low- and middle-income countries received depended heavily on their ability to borrow at the time of the crisis. This meant that the countries with the largest expected increases in extreme poverty received only USD41 per capita, compared with USD108 per capita in countries with minimal increases in extreme poverty. Moreover, virtually none of this funding arrived before households started losing income and reducing consumption (Yang et al. 2021).

PAF is a critical component in improving crisis response. Risk reduction activities are often highly cost effective and should be supported to go to scale. However, it is inevitable that crises will continue to affect many people. PAF refers to 'financing that has been approved in advance of a crisis and that is guaranteed to be released to a specific implementer when a specific pre-identified trigger condition is met' (Centre for Disaster Protection 2023 – also see Glossary for full definition). There is emerging evidence that the potential for PAF to be allocated more quickly than traditional humanitarian support helps to reduce both short- and long-term humanitarian impacts of crises (Pople et al. 2021).

Understanding the gap between how much crisis financing would be needed, and how much is pre-arranged, could have a wide range of benefits. First, the design and use of PAF mechanisms requires an understanding of what crises are likely to occur and what costs they will entail, to ensure that PAF mechanisms provide the right amount of funding in the right place at the right time. However, information on crisis protection costs and gaps could also be used as an information tool to better enable monitoring, education and advocacy around PAF; to inform resource allocation decisions by funding organisations making PAF decisions; or to enhance the strategic decision making of those organisations engaged in, and responsible or accountable for, responding to crises.

The value and importance of PAF is reflected in growing calls to quantify the 'crisis protection gap'. The Centre's flagship report 'The Future of Crisis Financing: A Call to Action' (Poole et al. 2020) set out a new vision for crisis response. Following this, the Centre convened the Crisis Lookout Coalition. Coalition members made three requests to G7 leaders – the first being to 'Predict crises better by creating a new "Crisis Lookout" function to increase engagement with risk information and support the prioritisation of crises globally, regionally, and nationally' (Scott and Clarke 2021). More recently, the launch of the Global Shield Against Climate Risks marks an important step forward in the PAF agenda. Measuring and then addressing the crisis protection gap is a common theme in publications related to this launch, as well as in other materials from the V20 group[1] and other stakeholders

1 The Vulnerable Twenty (V20) Group of Ministers of Finance of the Climate Vulnerable Forum is a dedicated cooperation initiative of economies systemically vulnerable to climate change.

(Federal Ministry for Economic Cooperation and Development 2022).

A major obstacle to accelerated reform is the question of whether it is possible to make forward looking predictions about the costs of crisis response to inform the assessments and monitoring of the crisis protection gap.

A critical first step to assessing the crisis protection gap is agreeing what exactly we mean by this. As Box 1 explains, the term protection gap originated in the (re)insurance sector, where it is used as a measure of the difference between insured losses and total losses (or the proportion of total losses that are insured); in other words, the original formulation of meeting financial needs after a crisis event using PAF, but with a specific focus on insurance as the instrument that provides this PAF.

Box 1: Defining the 'protection gap' in the (re)insurance sector

In the (re)insurance sector, the protection gap is used to describe the portion of total disaster-related losses that are not protected by insurance. It is often used to highlight risk types and regions where there is potentially a greater role for insurance.

The protection gap is calculated in one of two ways, depending on the circumstances:

- Historically, looking at the losses caused by events in the past and assessing what proportion of these were covered by insurance.
- On a forward-looking basis, using modelling tools to generate (probabilistic) estimates of the losses that might be expected, with different probabilities, and assessing what proportion of these losses will be covered by existing insurance policies.

In either case, losses are typically defined in terms of the damage that is caused to buildings, infrastructure and other fixed assets. On some occasions, the loss in value of crops and/or livestock is used as well or instead.

Building on this, this work defines the term 'crisis protection gap' as the difference between total expected contingent liabilities of national or international responders (i.e. the costs they can expect to incur in responding to crises) and the amount of funding available to meet these costs through PAF mechanisms (including, but not limited to, insurance).[2]

To operationalise this definition, two critical questions need to be answered:

1. **Which crises are of interest?** In some cases, there may be an interest in understanding the crisis protection gap associated with only one type of crisis, such as, for example, floods or earthquakes. In other cases, a more comprehensive assessment may be

2 It should be noted that while it is generally recognised that there would be value in scaling up the use of PAF mechanisms, the optimal crisis protection gap may not always be zero. In other words, there may be some cases in which it is not desirable for all of the contingent liabilities of national and international responders to be met by PAF. Some role for ex-post financing mechanisms is also likely to be valuable. This report does not explore the optimal size of the crisis protection gap, although the concluding section offers preliminary thoughts on this topic.

appropriate; for example, covering all crises relating to natural hazards or, indeed, resulting from any cause. **This work has been developed on the basis that, in principle, there is value in understanding crisis protection needs at global level and for all risks.**

2. **What financial needs should be considered?** There are many ways of looking at and disaggregating the expected financial needs arising from a crisis. They include identifying which phases(s) of a response are being costed. Some costs (response costs) are incurred in the immediate aftermath of a crisis; other costs are associated with compensating for or rebuilding property damage associated with a crisis event; whereas others might be incurred before the impact of a crisis is felt. Increasingly, humanitarian organisations are also allocating funds for anticipation, prevention and preparedness activities prior to a crisis event. Identifying who within a population will be prioritised, what response is needed and who will deliver it can all influence the timing and scale of response costs. **This work focuses on the immediate crisis response costs incurred in protecting the people most at risk when crises occur.**

2.2. RESEARCH OBJECTIVE

The overall objective of this research is to understand the technical challenges and options associated with making forward-looking predictions of the crisis protection/PAF gap. It uses the definition of the crisis protection gap set out above. Box 2 explains how it approaches the issues of prediction and forecasting.

Box 2: Prediction and forecasting

In the context of this work, 'prediction' and 'forecasting' refer to a forward-looking assessment of the crisis events and associated PAF needs that could occur in a defined region within a defined time horizon.

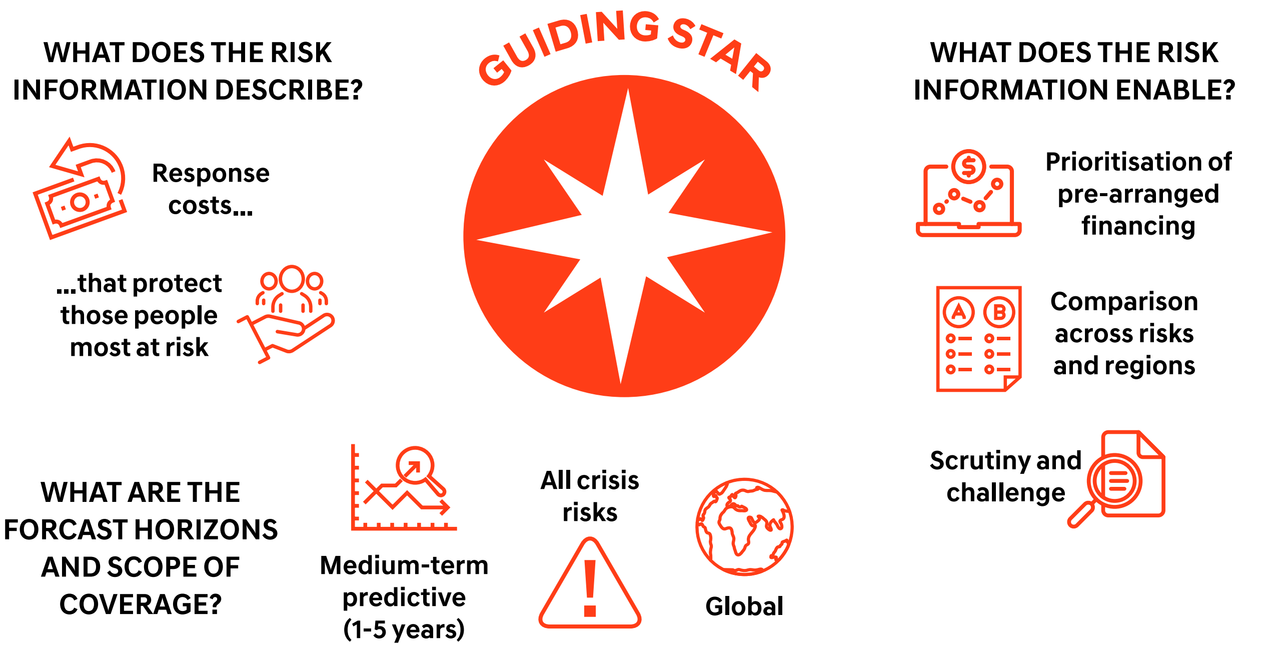
These forecasts may be probabilistic or scenario-based (deterministic) assessments. A probabilistic forecast provides a view of the potential scale of financing needs, along with an assessment of the likelihood of a particular event occurring. Scenario-based, or deterministic, assessments provide a view of potential scale or trajectory, but without an assigned likelihood.

Within this overall approach, the analysis focuses on the feasibility of predicting crisis protection costs. It has not considered the extent to which PAF may already be in place to meet these costs, or what the optimal amount of PAF may be, for two reasons:

1. The conceptual and technical challenges associated with estimating crisis protection costs are significantly greater than those associated with measuring existing PAF availability.
2. There is widespread recognition that the existing use of PAF is modest and fragmented (Crossley et al. 2021). For example, previous research suggests that only 2% of the financing provided in response to the covid-19 crisis was pre-arranged (Yang et al. 2021).

This approach has been further elaborated in a 'guiding star' framework in Figure 1, which orients the research and further defines its parameters. This provides a concise summary of the key dimensions of the research and its potential applications (as discussed further in section 2). The guiding star is deliberately ambitious: an ambitious approach allows existing data and models to be 'stress-tested' to gain a more robust understanding of both what is and is not possible at present, and how this might change in the future.

FIGURE 1: CRISIS PROTECTION GAP RESEARCH 'GUIDING STAR'



Source: Centre for Disaster Protection

The guiding star is divided into three main elements:

1. **What are the funding needs?** As noted above, the focus is on whether it is possible to understand the immediate crisis response costs incurred in protecting the most vulnerable people when crises occur:

- The intended focus is on the first 100 days of crisis response costs. Ideally, this definition would also include costs incurred after a crisis becomes likely, but before it occurs. However, systemic data on these costs are difficult to obtain.
- The research assumes that vulnerability is determined by both economic characteristics, such as income, and demographic factors, such as age and gender.
- The research is intended to be comprehensive, covering the financial needs of international and national responders. However, this may not always be easy, as discussed below.

2. **What time horizon and geographic scope?** The focus is on understanding whether it is possible to predict the size and distribution of these costs over a 1–5-year window into the future. Importantly, the research does not focus on whether it is possible to predict the crisis protection costs of a specific event. Rather, the focus is on what costs might be expected on average, and how they might be distributed.
3. **To support what action?** The above two elements of the guiding star reflect expectations about how this information could (or should) be used to support the allocation of PAF. For example, the focus on immediate crisis response costs reflects the fact these are the costs where the ability to quickly access PAF can make the biggest difference to the overall impact of a crisis (Lung 2020). Similarly, the focus on all risks could allow PAF to be targeted at the risks with the greatest response needs – rather than, for example, where political attention is greatest. Finally, the research also focuses on understanding whether crisis protection information that meets this specification can be made available in a way that allows for scrutiny and challenge. This is likely to mean that users of crisis protection gap information will have greater confidence in the data and that it will be easier to improve over time.

At times, however, the research takes a narrower perspective to explore specific aspects in more detail. For example, to analyse data on the costs and drivers of crisis response, the research explicitly focuses on international humanitarian actors as there is significantly more publicly available information on the responses these agencies provide, and proxies for the costs they incur, than there is for national responders.

In pursuing this objective, the research has three analytical starting points:

1. First, it seeks to build on the tools and modelling approaches of the (re)insurance and risk modelling community for predicting and managing crisis-related risks, and to apply these to understanding the crisis protection needs of the world's most vulnerable people. This reflects the fact that these tools have a long track record of helping stakeholders understand and manage crisis risk, although they have rarely been used for purposes similar to those envisaged in this research effort. It is also consistent with the origins of the interest in measuring the crisis protection (PAF) gap as outlined above.

2. Second, many of the data challenges that may have hampered this research in the past are in the process of being addressed. For example, in the past, accurate estimates of the location and likely vulnerability of at risk groups (as indicated, for instance, by income levels) would have been undermined by outdated and potentially inaccurate census data. Although still imperfect, a range of techniques – including remote sensing, machine learning and big data analytics – have significantly reduced data gaps in lower-income, and fragile and conflict-affected situations in recent years.
3. Third, even if there are technical challenges that make it difficult to achieve the ultimate goal, the exercise of attempting to predict future crisis protection needs and costs to measure the crisis protection gap can provide important and useful insights. Individual components of a predictive model of the crisis protection gap, such as information on the location and characteristics of crisis-exposed households, can provide important insights even when used in isolation. In addition, even relatively simple models can establish a comparative framework that provides important insights into expected future costs, even if the accuracy of the metrics or the ability of the model to predict individual response costs is limited.

2.3. KNOWN LIMITATIONS

The work recognises a number of challenges and limitations. Four of the most important of these are outlined below:

- **Real-world complexity** – Many factors influence the impact and costs of responding to crises in lower-income and fragile settings. This is particularly true in settings where the costs of crises can be compounded by other factors, such as the emergence of conflict or international supply chain issues. This real-world complexity makes forward-looking, predictive modelling challenging. While simple models are a useful tool for understanding these complex systems, there are limits to how accurate a model can be. However, complexity is a well-known challenge in any modelling exercise, and technical approaches can help measure and manage the uncertainty introduced by factors not explicitly included in the model.
- **Historical bias** – To model future financial needs, it is necessary to rely on information about past events. However, historical records also reflect the context at that time, whereas in reality, risk is dynamic. Historical information can therefore provide a biased view of future financial needs. For example, exposed populations, their vulnerability, government and humanitarian response systems, costs, and the likelihood and severity of hazards all change. These dynamic factors must all be considered in any analysis of future risk that relies on historical data. It is possible to manage historical bias, but challenges remain in terms of the availability and reliability of historical data. Some of the challenges associated with using historical information are explored in sections 3.3 and 3.4.

- **Alignment between modelling approaches and financial planning decisions** – The technical approach to measuring the crisis protection gap should reflect the questions decision makers are asking, especially those about response costs. Model development exercises typically involve compromises; for example, between local-level accuracy and global-level comparability. The range of potential use cases for this information and associated implications for the modelling approach are discussed in section 5.
- **Technical skills** – Risk modelling involves specialised tools. A certain level of technical experience is required to understand and use those tools and results for decision-making. There are ways of communicating the technical information models produce in ways that are accessible to non specialists. However, it is expected that if use of crisis protection gap information is to increase, there will need to be a parallel effort to develop the necessary technical skills within the organisations that will use this information.

2.4. RESEARCH APPROACH

The work involved a comprehensive review of relevant modelling approaches and related literature. The scope of the research agenda required an understanding of the current debates and state of knowledge in a wide range of different topic areas including: geospatial identification of people and their socioeconomic characteristics; predictive risk modelling of a wide range of different crisis types (and how climate change may change these in future); and costing methodologies. It also included an assessment of current tools that are used to provide information about future crises and crisis protection costs, and an evaluation of how these analyses compare with the guiding star.

This literature was complemented by consultations and research interviews with more than 35 experts from over 20 organisations. These experts represented a wide range of different institutions including:

- academia
- data providers
- humanitarian agencies
- the (re)insurance sector
- international financial institutions
- NGOs
- policymakers.

These interviews helped to test and refine initial ideas, provide avenues for research, and identify initiatives and stakeholders relevant to the research focus.

Based on the insights gained from the preliminary research and interviews, the work formulated a conceptual model for how to predict crisis protection costs. This conceptual model is inspired by the approach taken to risk modelling in the (re)insurance sector, where the application of probabilistic risk information has become a core part of strategic decision-making and financial planning. However, both the research objectives, as reflected in the guiding star, and the availability of data required important adaptations to the (re)insurance sector approach. Section 2 describes the conceptual model in more detail, including the results of new 'top-down' costing analysis undertaken to generate data that could be fed into this conceptual model.

Demonstration analyses complement the conceptual model. These provide insights into how easy or difficult it would be to implement a more comprehensive model by providing a deeper understanding of how much data would be required, and the modelling challenges associated with manipulating and combining different data sets. Section 3 describes these demonstration analyses in more detail.

An advisory group helped to refine and improve the research. This small group of 10 experts was drawn from the same background as those described above. Among other things, the scrutiny this group provided helped to think through where and when crisis protection gap information might be most valuable (and also where it might be less useful). The group also helped identify challenges that might arise in developing a comprehensive predictive model and how to overcome them.

Finally, the results of the research were presented and discussed in a one-day hybrid workshop. This workshop brought together 50 people, drawing on the same backgrounds and institutions as above, to provide feedback and reflection on the work. This research report captures the workshop participants' contributions.

3

TECHNICAL FEASIBILITY

This section presents an analytical framework to assess crisis protection costs. It consists of three elements: an exposure module, which considers who or what may be at risk; a crisis event module, which considers the timing, scale and likelihood of crises; and a cost module, which considers the costs of responding to those people exposed to a particular crisis. This builds on the risk-modelling approach used in the (re)insurance sector.

The exposure module focuses on the location and characteristics of the world's poorest and most vulnerable people. Relevant data sets have proliferated in recent years. These combine traditional survey-based analysis with geospatial data and machine-learning algorithms. These data sets can still be improved on, but in terms of comprehensiveness they provide a significant improvement on data collected using traditional methods.

The purpose of the crisis event module is to define the likely timing and severity of expected future events in a way that can be translated into financing need. A range of tools and analytical approaches are available. These vary according to the type of crisis - some types of crisis are inherently easier to model than others. For example:

- Droughts are typically defined and modelled relative to normal conditions, using a range of indices.
- Probabilistic models can generate information on the severity of future tropical cyclones.
- It is more difficult to generate forward-looking expectations of conflict-induced displacement, but modelling approaches are emerging that can be complemented by scenario analysis.

For the cost module, two approaches can be used:

- **Top-down** - This examines the costs international humanitarian actors incurred in responding to previous crises and uses econometrics to understand their drivers. An indicative example of this approach suggests that costs increase as the number of people targeted grows, but at a decreasing rate; that costs may be higher in more fragile settings; and that epidemics and floods have lower response costs than other types.
- **Bottom-up** - This identifies the specific activities that need to be carried out following different types of crisis, identifies the resources required for them, and then calculates their costs. This could provide a more detailed understanding of costs than a top-down approach and should be better able to include information from national responders.

Securing access to cost data, then using this data to develop a robust and credible costing module, is the main challenge in developing robust predictions of crisis protection costs.

3.1. OVERVIEW OF CONCEPTUAL MODEL

The basic framework of the conceptual model consists of three elements (or modules):

- identifying people **exposed** to risk
- assessing the likelihood they will experience different types of **crises** (with varying degrees of severity)
- estimating the **costs** associated with meeting the needs of these people when they experience different crises (of differing severity).

Figure 2 illustrates this framework.

FIGURE 2: OVERVIEW OF THE CONCEPTUAL MODEL.

Exposure		Crisis event		Costs
Identifying the people in harm's way	X	Assessing the pobability that they suffer crises (of differing severities)	X	Estimating the cost of meeting the needs of those who suffer harm

Source: Centre for Disaster Protection

Risk modelling in the (re)insurance sector shares a similar conceptual framework. Indeed, the approach used by this sector to estimate the probability and severity of different crisis events can be adopted in its entirety, at least for the types of crisis events analysed in the sector, such as tropical cyclones, floods, earthquakes and disease outbreaks.[3] There are bigger differences in the exposure and cost modules:

- In the (re)insurance sector, the exposure module focuses on identifying the location of the insured interest, such as buildings or crops. In contrast, the focus of this analysis is on the location of vulnerable people. As discussed below, this difference in the exposure module poses specific challenges.
- With respect to the cost module, the focus of the (re)insurance sector is typically on estimating the loss in value of the insured interest, rather than the cost of meeting the needs of the people affected by crises. This justifies a different methodological approach.

3.2. EXPOSURE: WHO IS AT RISK?

Following the guiding star, the critical exposure module issue is whether it is possible to understand the location and characteristics of the world's poorest and most vulnerable people. These are the people for whom the need to close the crisis protection gap is most urgent. In addition, by making these people the focus of the exposure module, and by using the same information when considering different hazards that may entail different crisis protection needs and costs, it should be possible to understand the comparative importance of different risks to this group of people.

3 The (re)insurance sector has less experience in understanding the probability and severity of other types of crises that are of interest in this analysis such as, for example, conflict-induced displacement.

In recent years, there has been a significant growth in data sets providing granular demographic information. These combine traditional approaches to collecting population data – such as censuses or surveys (e.g. USAID's Demographic and Health Surveys Program or the World Bank's Living Standards Measurement Study) – with geospatial data that provides information on, for example, building density and land elevation. Statistical analysis can help to understand the relationship between these different types of data. This allows, for example, for population data at a high level of aggregation to be allocated in a more granular way, or for information about populations in one place to be used to infer population numbers and demographic characteristics in another. These techniques allow researchers to gain much more granular information about populations than has been available in the past, with data available at resolutions of 100 m by 100 m or lower.

These approaches also provide information about the sex and age characteristics of the population. This may be important because the costs associated with responding to crisis events can vary according to these characteristics. This may either be because certain population groups are relatively more vulnerable to crises than others, or because the activities and associated costs of responding to crises are different depending on who a crisis response reaches. The inclusion of these characteristics within the exposure module opens up the possibility that these effects can be captured. It also allows identification of costs associated with meeting the needs of particular demographic groups.

Examples of this type of modelling are available from both open source and commercial providers. In terms of the former, the University of Southampton's World Pop initiative makes much of its core data available free of charge to all users.[4] World Data Lab is a commercial provider whose offering includes forward-looking projections of this demographic data, allowing incorporation of expected trends.[5]

One aspect of demographic data where research efforts need to continue concerns the inclusion of displaced populations. As described above, these techniques are based on census or survey data, and either allocate this population in a more detailed way than the original data allows or extrapolate observed trends to other areas where the sample was not or cannot be collected. In both cases, however, the starting point remains the census or survey. This may mean that if displaced people are under-represented in the original data set, subsequent analysis will reflect this.

There are increasing efforts to supplement demographic data with socioeconomic information, which is of great value to this type of analysis. As with the demographic breakdowns discussed above, understanding the socioeconomic characteristics of the people who may be affected by crises is important both because these characteristics may influence response costs and/or because there is a desire to identify the costs of meeting the needs of those people in specific socioeconomic circumstances.

4 https://www.southampton.ac.uk/research/groups/world-pop

5 https://worlddata.io/

However, combining demographic data with socioeconomic information presents further technical challenges. The basic process involves using statistical analysis, including the use of machine learning algorithms, in certain 'within-sample' locations to understand the relationship between measures of prosperity in census and survey data, and geospatial information. For example, it could explore the relationship between household income and geospatial data, such as night light data, building density or anonymised information on mobile phone use etc. The relationships this statistical analysis uncovers can then be applied to geospatial data across larger areas to generate spatially explicit 'out-of-sample' predictions. These can be generated at whatever level of granularity the satellite data allows (Chi et al. 2022; McCallum et al. 2022). Often, these out-of-sample wealth predictions are relative (e.g. they allow researchers to develop spatially explicit granular predictions of which 1 km by 1 km grid cells are more or less prosperous). However, this can then be combined with information on income levels and their distribution to allow researchers to make absolute income predictions.

This socioeconomic data can either be generated using open source data or it can be bought from commercial data providers. The demonstration analyses described in section 4 use open source data published as part of a recent academic analysis. Commercial providers, such as Atlas AI,[6] offer this type of data on a commercial basis. Part of the rationale for commercial provision is to give users confidence that the data will continue to be updated on a regular and frequent basis.

Approaches to generating granular socioeconomic information are imperfect. There are at least three major concerns:

- The within-sample relationship between geospatial data and measures of socioeconomic wellbeing will be imperfect. In most cases, geospatial data can only account for 50–80% of the variation in survey-based measures of income or wealth. This means that, even in the best case, the approach will not provide a perfect understanding of the within-sample distribution of wealth. It has also been suggested that, if not analysed carefully, the relationship between spatial data and socioeconomic wellbeing can easily be mis-specified, leading to inaccuracies. This problem may be more acute when conducting analysis at fine spatial resolutions, as there is much more scope for error in these cases. For example, more than one household may have access to a particular field, or the household closest to a field may not be the one that has exclusive access to it (Watmough et al. 2019).
- It may be inappropriate to assume that the within-sample relationship between socioeconomic data and geospatial information is representative out of sample. For example, cultural factors – such as the importance of certain types of livestock – may mediate the relationship between wealth and geospatial data in one location in a way that would not apply in another. This challenge becomes more significant the greater the difference between the within sample data used to generate the relationships, and the out-of-sample analysis to which these relationships are applied. However, if this form of extrapolation is required, looking at a wide range of geospatial information to reduce reliance on any one indicator can reduce risks.

6 https://www.atlasai.co/

- Further inaccuracies can arise from converting relative measures of prosperity to absolute measures. This conversion requires information on the distribution of income, represented using measures such as Gini coefficients[7], which may be several years out of date. Alternatively, this supplementary data may have been calculated by looking at the distribution of a different measure of prosperity to that which is of interest. For example, the Gini coefficient may have been calculated by looking at the distribution of consumption, whereas the researcher is interested in the (spatial) variation of income levels. More fundamentally, the conversion from relative to absolute measures implicitly requires an assumption that all households within a certain geographic area (such as a grid cell) have the same level of prosperity; for example, the same average income. This allows the researcher to assume that all of the variation in income or wealth seen within a country can be explained by variation between different grid cells. While this may be a reasonable simplification in rural areas, where most households in grid cells may have roughly similar levels of income, it may introduce significant error in urban areas where pockets of poverty or comparative affluence may be extremely localised.

Nonetheless, these approaches to gaining a detailed understanding of people's income at a granular level are improving all the time and represent an improvement on the alternative. Traditionally, this type of socioeconomic information has been obtained through survey-based analyses carried out every three years or so. In contrast, use of satellite data allows analysis to be carried out annually, or even more frequently. It is also less costly: studies suggest that, for an indicative 100 km^2 rural site in western Kenya with 330 households, survey-based approaches would result in costs that are 20–60 times higher than the acquisition of high-resolution satellite imagery of the same area (Watmough et al. 2019). Thus, while efforts to infer socioeconomic information using these types of technique will continue to evolve and improve, they represent the most attractive approach to generating key exposure information for developing estimates of the crisis protection gap.

It is also possible to access and incorporate a range of other information into the exposure module. Much of this information provides additional insight that may influence the cost of meeting the needs of people affected by crises. For example:

- **Agro-ecological zone** – Some hazard types, such as drought, affect people with specific livelihoods living in specific climatic or environmental zones. Spatial agro-ecological zone information may be relevant when determining the degree to which people living in an area may be affected by a defined hazard (FAO 2023).
- **Land-use land-cover** – Land use data provides information about the environments where people live; for example, whether there are higher densities of crops, buildings or pasture. These characteristics may in some cases be necessary to differentiate where and how badly people might experience hazard impacts (Copernicus n. d. a.).
- **Accessibility** – The accessibility of an affected location, in terms of distance to international airports or sea ports, distance to cities or road access, may influence how costly a response is in that location (OpenStreetMap n.d.).

7 See Annex A3 for details of Gini coefficients.

- **National context** – Higher-level information about the current status of a country may be relevant to determining the response cost in different settings; for example, whether a country is in a state of conflict may increase cost loads, as might other characteristics, such as whether a country is a small island state.

In summary, it is possible to obtain demographic and socioeconomic information, as well as complementary information, which allows the exposure module of a crisis protection gap model to focus on the risks the world's poorest and most vulnerable people face. This is in line with the thinking set out in the guiding star. While there are important ways in which this data can be refined and improved over time, most notably through explicit consideration of displaced people, this component of a crisis protection gap assessment model is increasingly within reach.

3.3. CRISIS EVENTS: HOW ARE THE TIMING, SCALE AND LIKELIHOOD OF CRISIS EVENTS DEFINED?

A broad range of crisis event types generate national or international funding needs. The United Nations Office for Disaster Risk Reduction Hazard Definition and Classification Review (UNDRR and ISC 2020) highlights the breadth of risks that people face globally, and points to some of the definitional challenges in classifying events. This classification provides a taxonomy for all the crisis events that would ultimately need to be reflected in a global, all-risks view of the crisis protection gap.

A typical approach in physical modelling is to define an event in terms of its 'footprint'. For event types that cause physical damage, such as earthquakes or tropical cyclones, the event footprint typically describes the maximum hazard intensity in all affected locations. However, crises affect people in different ways; as well as any direct damage to buildings or infrastructure they cause, there may well be impacts on health and wellbeing, and loss of life. Events can also cause 'downstream' or disruptive impacts; for example, disruption of essential and critical services, effects on livelihoods, or displacement of people from where they live.

In modelling exercises, it is necessary to define the timing, spatial extent, and severity of an event in a way that translates to funding need. Once an event can be defined in this way, event sets can be built that allow for a probabilistic estimation of the funding needs that could be generated over the next 1–5-year time horizon. The crisis event module is a data set that contains either historical or simulated event hazard footprints. These event footprints contain a realistic range of possible future outcomes; collectively, they describe the severity and likelihood distribution for a given crisis type at a given location.

The crisis types that have the greatest impact in lower-income and fragile settings are often complex and difficult to define consistently. The physical modelling tools used most often in the (re)insurance sector do not address certain event types well (e.g drought and conflict-induced displacements).

For events that impact people or services in an indirect manner, event definitions are more challenging due to the less tangible nature of the events. Indirect or disruptive events (e.g. household-level livelihood or welfare impacts due to drought) can cause significant impacts on vulnerable people in lower-income and fragile settings, so must be addressed as a priority according to the approach outlined in the guiding star.

The analytical approach therefore needs to identify opportunities for these different event types to be characterised in a way that promotes and enables comparability across risk types. If event definitions do not allow comparison, then the global all-risks framework will be a collection of individual risk analysis rather than a comparative framework.

While the approach to defining event footprints varies according to different crisis types, the 'number of people affected' metric is intended to provide a degree of consistency and comparability, even across crisis event types that manifest very differently. This common severity metric must be calibrated for each risk type separately. We have reviewed a range of hazard types to explore how event footprints might be defined and test some of the challenges of estimating the 'number of people affected' metric.

In this initial research, we focus on a subset of crisis types. These have been chosen to reflect a range of crisis types with varying definitional and modelling challenges, including complex risks such as drought and displacement, which are critically important in lower-income and fragile settings. This small subset also explores events that affect people differently and have different associated types of response costs. The following sections outline some of the specific options and challenges faced when defining different types of crisis events.

3.3.1. DROUGHT

Drought is a key driver of food insecurity in lower-income and fragile settings. At the time of writing, countries in East Africa are experiencing high levels of acute food insecurity (FEWS NET 2023), driven by multiple consecutive below-average rainy seasons, and compounded by conflict related, price inflation and global supply chain-related factors.

Climate change is exacerbating these challenges. Some assessments find that the severity of the drought conditions in areas of the Horn of Africa, measured in terms of moisture available for plant growth ('agricultural drought'), are only now climatologically possible due to the present-day effects of global heating (Kimutai et al. 2023).

Drought is generally characterised as a slow-onset event, which is the result of prolonged periods of drier conditions than average. It is often described as a multi-dimensional risk type, since climatological factors such as rainfall and temperature interact in complex ways with local geographic and contextual factors, including livelihood practices and access to markets.

Drought events are difficult to define consistently across contexts since local communities are adapted to different climate conditions. For example, 100 mm of rainfall might represent drought conditions in one location but reflect better conditions than average in another.

For this reason, droughts are often defined in relative terms (i.e. the severity of a drought at a given time and location is defined by the differences from average conditions at the same time and location in previous years). There are various ways to characterise the timing and severity of drought, typically using drought indices, which measure drought using different means. For example:

- **Dry spell-based indices** measure the difference in total rainfall during defined periods in relation to historical measurements.
- **Precipitation-evapotranspiration indices** (e.g. Standardised Precipitation Evapotranspiration Index) combine rainfall- and temperature-based measurements.

- **Soil-moisture indices** (e.g. Soil Water Index) incorporate soil information and use models to estimate soil moisture given historical rainfall and temperature conditions at that location.
- **Vegetation greenness indices** (e.g. Normalised Difference Vegetation Index) typically use satellite observation data to measure the reflectivity of crops as a proxy for drought stress on biomass.
- **Crop water stress indices** (e.g. Water Requirement Satisfaction Index) measure rainfall conditions in relation to specific crop water requirements, and planting and harvest cycles.
- **Crop yield information** can also provide secondary information about conditions for crop health. However, yields can relate to factors other than drought conditions, so might provide an imperfect index for drought.

Each of these indices can be customised differently. Timing of onset and duration of measurement window are important parameters, as is the spatial scale of measurement; these factors can strongly affect whether an index signals that a drought event is occurring. Also, given that the indices are continuous, it is necessary to define thresholds at which conditions are severe enough to indicate that populations are affected to a degree that warrants an associated funding response.

Another challenge with estimating drought impacts, is that drought conditions in one location can affect people at a separate location if, for example, their food supply or livelihood is linked to the drought-affected area. Another associated factor is the integration of local and external markets. These contextual factors further complicate the exercise of defining drought footprints and estimating associated response costs.

There are useful examples of using drought indices to estimate associated impacts and response costs. The Africa RiskView model,[8] which Africa Risk Capacity uses to monitor and trigger insurance payments to support drought response costs, is an example of the type of model that can be developed to estimate drought-related response costs (ARC Secretariat Technical Team 2016). Experience using this model to trigger drought payments has highlighted some of the challenges in accurately characterising drought events and costs, and shows how customising such models can substantially change the results (Bavandi 2017).

Recent initiatives aim to advance the technical approaches available for measuring and predicting drought impacts (e.g. Next Generation Drought Index) (Bavandi 2021). However, many of the indices available do not explicitly consider impacts on affected people or the associated response costs. These advances in the development of indices that more accurately reflect conditions on the ground do, however, provide a good foundation for customising models that use drought hazard indices to estimate associated protection needs.

3.3.2. TROPICAL CYCLONES

Tropical cyclone events are typically characterised as fast-onset shocks, which can cause direct damage to the built environment and associated disruptions to affected people. Tropical cyclones are associated with various sub-hazards, including wind, but also storm surge and inland flooding from excess rainfall. Tropical cyclone event footprints can therefore be characterised in a number of ways, depending on which hazard impacts and associated costs are being modelled. For example, the spatial footprint of maximum sustained wind speed or maximum peak gust can be used to describe the wind experienced at a given location. It is also possible

8 https://arc.int/africa-riskview

to describe storm surge and flooding hazard footprints (i.e. flood depth at a location), although these water-based hazards are much more challenging to model.

The overall intensity of a tropical cyclone can be approximated using macro-level event characteristics, including track location, maximum sustained wind speed (or storm category), and radius to maximum winds. This macro-level event information is available for historical storms through the International Best Track Archive for Climate Stewardship (NCEI 2021). This macro-level event information is useful to characterise the scale of an event at a high level, although it does not fully reflect the wind speed experienced at a given location, and it also may not reflect the severity of local impacts from storm surge and inland flooding, which can have a significant impact even at lower storm severities, depending on factors such as local bathymetry, terrain roughness and antecedent soil conditions. For example, the storm surge from Cyclone Nargis in 2008 caused catastrophic loss of life and damage to infrastructure in Myanmar (UNEP 2009). While macro-level event characteristics such as track location and storm category might serve as proxies for the effects of specific sub-hazards, a 'full' model of tropical cyclone impacts would have to consider these separately.

Given that tropical cyclones are a priority risk type in North America, where insurance markets are developed, the private sector has decades of experience with modelling tropical cyclone events and their associated impacts in terms of property damage and associated insurance claims. Historically, tropical cyclone model coverage has focused on areas with high levels of insurance coverage; however, global model coverage is now available. Existing model coverage is more globally comprehensive for wind hazard than for the inland and coastal flooding associated with tropical cyclones.

These models provide a useful template for estimating emergency response costs in lower-income and fragile settings. However, it is important to note that existing models might not explicitly relate to the contingent liabilities of governments or international responders. These models would need to be customised so they could be used to reliably estimate the crisis funding needs that relate to protecting the most vulnerable people in these settings.

3.3.3. CONFLICT-INDUCED DISPLACEMENT

Conflict-related humanitarian responses drive a significant portion of total global humanitarian responses and associated funding needs. At the end of 2021, the total number of internally displaced people had reached a record 59.1 million people, with 53.2 million displaced by conflict and violence, and 5.9 million displaced by other crisis events (IDMC 2022b; OCHA Services 2022).

Internationally agreed footprint definitions relate to the size and location of displacement events. According to the Guiding Principles on Internal Displacement (Deng 1998), internally displaced people are: 'persons or groups of persons who have been forced or obliged to flee or to leave their homes or places of habitual residence, in particular as a result of or in order to avoid the effects of armed conflict, situations of generalized violence, violations of human rights or natural or human-made crises, and who have not crossed an internationally recognized border.'

The footprint of conflict-induced displacement can, then, be defined directly in terms of the total number of people who have been displaced from their homes in a defined time period (e.g. number of newly displaced people

in a particular country each year). This metric might be difficult to accurately monitor or predict, but the severity metric (number of people affected) is conceptually very well defined, at least when compared to other risk types. Indeed, the Internal Displacement Monitoring Centre monitors numbers of displaced people (IDMC 2022c).

While PAF tends to focus on natural hazards, in principle, in some circumstances funding can also be arranged in advance of other events that cause displacement of people, so that funds can flow quickly to support immediate humanitarian responses. Conflict is a key driver of internally and internationally displaced people; while it is difficult to anticipate individual episodes of conflict and the associated displacement of people, there are ways to both monitor and estimate future numbers of displaced people.

Organisations that have developed or are currently developing methods for estimating future numbers of displaced people, including models that estimate origin-destination specific population movements, were consulted (e.g. the Danish Refugee Council's Foresight model (DRC n.d.)). Displacement monitoring organisations, such as the Internal Displacement Monitoring Centre, have also developed processes and tools for identifying and reporting on numbers of displaced people (IDMC 2022a). These methods use data about historical population movements to estimate future flows. Such approaches produce reasonable estimates for future displacement in settings that have experienced high levels of historical displacement, but they are not good at predicting new episodes of conflict induced displacement such as the large-scale displacement of people in Ukraine in 2022 (DRC 2023).

For crisis types where the future probability is challenging to define, it can be useful to use a range of other tools such as 'scenario-analysis' or 'stress testing'. These scenario-based approaches do not aim to provide a full probabilistic view of future outcomes, but rather describe a representative scenario that can help to inform and test options, including in relation to financial planning (TCFD n.d.).

For conflict-induced displacement, given that the trends in future displacement in the coming years can be estimated to provide a base envelope of costs, additional sensitivity analyses could be combined with this to estimate additional funding needs related to new spikes in displacement due to conflict in regions that are not currently experiencing large-scale population movement.

3.3.4. OTHER CRISIS TYPES

The crisis types reviewed in this exercise reflect a subset of event types that contribute to the global crisis protection gap. Ultimately, all event types and hazards would need to be addressed in turn to develop a full, global all-risks view of the crisis protection gap. However, the selected crisis types provide some insights into other event types, which might face similar definitional challenges or relevant modelling approaches.

For example:

- **Drought is a complex slower-onset event** – Some of the definitional challenges relating to drought may also be relevant to other weather-related hazards, such as extreme temperature. For these risk types, which can be described in terms of deviation from average conditions, the challenges in terms of describing the timing of the onset and duration of an 'event' may be similar, and the tools used to describe drought severity might be useful.

- Tropical cyclone events are damaging fast-onset events, whose associated costs might be similar to other damaging events such as earthquakes or floods. While the timing and definitions of discrete events such as this can be defined, there are still calibration challenges in terms of identifying the hazard thresholds at which people are considered to be affected to a level where they require additional support.
- The footprint of conflict-induced displacement can be characterised directly in terms of the numbers of displaced people. This sort of approach, where 'affectedness' is binary, might also apply to disease-related events such as epidemics and pandemics, where the severity of an event might be defined in terms of numbers of infected people in a given location.

Future work could consider a more comprehensive range of event types. It is anticipated that if the modelling approach aimed to understand protection gaps at the level of individual event classes, then each event type would need to be defined and customised separately.

3.4. RESPONSE COST FUNCTIONS: HOW DO RESPONSE COSTS SCALE WITH EVENT SEVERITY?

The final module considers the costs associated with responding to crises. The combination of the previous modules provides insight into how many poor and vulnerable people may be exposed to different hazards with different probabilities. The module considers the costs associated with meeting the needs of these people when they experience crises, developing estimates for crisis protection.

In other use-cases, information other than costs could be combined with information from the exposure and hazard module. For example, economic researchers might want to generate estimates of the welfare losses that poor and vulnerable people suffer as a result of different types of crises.[9] An estimate of these welfare losses might inform an assessment of the compensation that it may be appropriate to provide. However, for many of the use cases identified in section 2, there is value in understanding the financial resource implications of meeting crisis protection needs.

Following the guiding star, the analysis seeks to understand whether it is possible to identify response costs associated with crisis protection needs in the first 100 days of a crisis.[10] It is in relation to these costs that the timeliness of PAF is most advantageous – studies show that quick access to resources in the immediate aftermath of a crisis event is a critical determinant of its overall impact (Pople et al. 2021).

The research focuses on whether this cost information can be obtained for international humanitarian response. This constitutes only a subset of the response costs that need to be supported after a crisis, with critical roles for national governments and other national responders such as civil society organisations. Indeed, the significance of these other actors is increasingly recognised as being vital in supporting effective crisis response.[11] However, the focus on international humanitarian response reflects that there is centralised, internationally comparable data available for these actors,

9 For an example of this sort of work, see Verschuur et al. (2023).

10 Recognising, as discussed in section 3.3, that for some crisis types, the definition of when a crisis begins is itself challenging.

11 See, for example, the list of actions identified for national and local actors in Priority 4 ('Enhancing disaster preparedness for effective response and to "Build Back Better" in recovery, rehabilitation and reconstruction') in the Sendai Framework for Disaster Risk Reduction.

alongside their continuing importance in supporting crisis response. This is a recognised departure from the guiding star, undertaken for pragmatic reasons. The implications of this for future efforts to estimate crisis protection needs and gaps is discussed in section 3.4.3.

Two broad methodological approaches might yield useful information on response costs:

1. A top-down analysis, which looks at the range of different costs international humanitarian actors incur in response to previous crises, using econometric analysis to understand the drivers that explain the variation in the costs of these responses.
2. A bottom-up analysis, which attempts to understand the costs associated with crisis response by identifying the activities that responders need to undertake, then analysing the costs associated with these activities.

The research explored the first option in more detail and undertook new analysis in line with this approach. By contrast, it was only possible to set out in broad terms how a bottom-up costing analysis might be undertaken.

In both cases, the focus is on whether these methodologies are useful ways to explore 'macro level' analysis of the costs of crisis response, and reasons why these costs may vary. In other words, the intention is not to try and use either methodological approach to generate estimates of the costs of responding to any specific crisis, where a range of idiosyncratic factors – such as what time in the year the crisis arises – will influence response costs. This provides a parallel with the hazard modelling, which does not seek to predict when specific crises will arise, but instead informs an understanding of how likely it is that events of different severities will arise.

The exploration is only indicative. As with the other modules, the intention is to explore what could be possible and what barriers might be faced, rather than to fully develop and operationalise a cost module.

3.4.1. TOP-DOWN ANALYSIS

The analysis developed new top-down estimates of the costs of crisis response using two different data sets:

1. One publicly available data set from the International Federation of Red Cross and Red Crescent Societies (IFRC) provides information on the amount requested for emergency appeals. These appeals are launched 'for big and complex disasters affecting lots of people who will need long-term support to recover'.[12] The analysis assumes that the 'amount requested' provides a proxy for the costs IFRC expected to incur to meet immediate crisis protection needs (although this assumption is discussed further below). This data set contains 479 data points, covering a range of crisis types, the most common of which were floods, epidemics, tropical cyclones and population movements. Most of the amounts requested fell within the range of CHF1.2m–8.8m (USD1.3m–9.3m).[13]
2. A second analysis focuses on a data set labelled the 'FTS+ data'. This analysis uses information on the amount requested for 'flash appeals' as documented by the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) Financial Tracking Service (FTS). A flash appeal is defined as: 'an inter-agency humanitarian response strategy to a major disaster that requires a coordinated response beyond the capacity of the government plus any single agency. The appeal addresses acute needs for a common planning horizon,

12 https://www.ifrc.org/appeals

13 Using average exchange rates in November 2022.

normally up to six months' (IASC 2009).[14] This data set is augmented with data on amounts requested from the UN's Central Emergency Relief Fund in response to a crisis, for those crises not already included in the FTS database. In total, this data set consists of 250 data points (96 FTS emergency appeals and 154 additional data points), with the most common crises being flood, conflict or displacement, drought, tropical cyclone and epidemic. Most of the amounts requested fell within the range of USD9m–USD65m.

In both cases, the analyses explored a number of factors that it was anticipated may help to explain the variation in response costs, including:

- number of people targeted[15]
- type of crisis
- country fragility (as measured by the Fragile States Index)[16]
- poverty levels in the country (as measured by the proportion of people above various poverty line benchmarks identified by the World Bank)
- year in which the crisis arose.

The analysis proceeded separately for each data set, as the funding mechanisms take decisions on how to fund crises in different ways.

In both cases, the analysis proceeded using a generalised linear model. This involved regressing the natural logarithm of the amount of funding requested (as a proxy for response costs) against the natural logarithm of the number of people targeted; the number of years between successive crises of the same type; the poverty gap in the country; a measure of country fragility in the year of the crisis; and a series of dummy variables to account for the region in which the crisis took place and the crisis type. A general-to-specific approach was then used to eliminate those variables that the analysis suggested were not significant in explaining the variation in the amount of funding requested.

For both data sets, a broadly similar model best explains the pattern in response costs:

- **Costs increase as the number of people targeted increases, but at a declining rate.** In the IFRC data set, a 10% increase in the number of people targeted results in a ~6% increase in the amount requested, a result that is statistically significant. In the FTS+ data set, a 10% increase in the number of people targeted results in a ~3.8% statistically significant increase in the amount requested.
- **The FTS+ data also suggested that the greater the fragility of the country, the greater the crisis response costs,** and that this result is statistically significant. This result controls for the crisis type and number of people targeted. However, a similar finding was not suggested by the IFRC data set.

14 It is acknowledged that flash appeals have a six-month planning horizon, compared with the three-month horizon identified as the focus in the guiding star. However, given that the data set otherwise aligned with the focus of the analysis, it was considered suitable for this initial analysis.

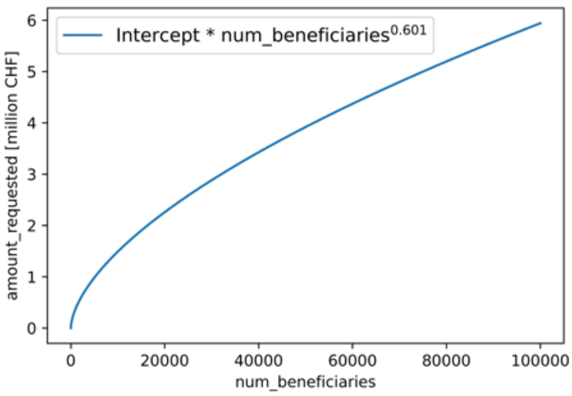
15 In the IFRC database, the analysis uses the column titled 'num_beneficiaries'.

16 https://fragilestatesindex.org/

- The responses to floods and epidemics tend to have lower costs than responses to other crisis types. In both the IFRC and FTS+ data sets, for an 'average' crisis[17], the response costs for floods are around 45–50% lower than the response costs for the average of other crisis types; and the response costs for epidemics are around 90% lower.

Figures 3 and 4 illustrate some of the key results from both analyses. Specifically, Figure 3 illustrates what analysis of the IFRC data shows to be the relationship between the number of people targeted and the amount requested, holding all other variables constant.

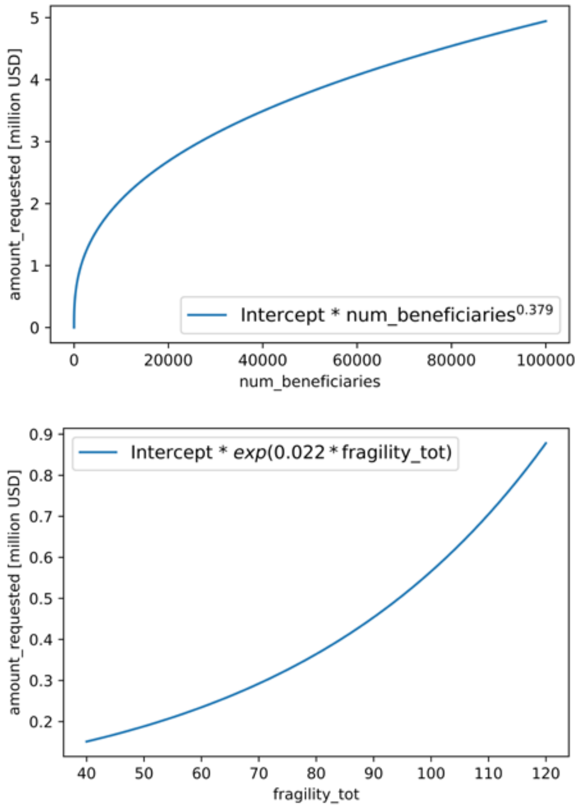
FIGURE 3: KEY RESULTS FROM TOP-DOWN ANALYSIS OF IFRC DATA SET



Source: Centre for Disaster Protection, based on data from IFRC (n. d.).

Figure 4a shows this relationship for the FTS+ data, while Figure 4b shows the estimated relationship between the index of country fragility and the amount requested, again holding other variables constant.

FIGURE 4: KEY RESULTS FROM TOP-DOWN ANALYSIS OF FTS+ DATA SET



Source: Centre for Disaster Protection, based on data from FTS (2023) and Fund for Peace (n. d.).

17 A crisis where the significant dependent variables in each model are set at their mean value.

Further details about the choice of model and the results are provided in Annex 1. This shows that the models are able to explain between 43% (FTS+) and 50% (IFRC) of the variation in response costs and that the models satisfy various statistical robustness tests (i.e. the residuals in both models are normally distributed and homoscedastic – equally spread; there is no collinearity between predictor variables).

These results suggest that the number of people targeted, in conjunction with other factors, can be useful in understanding the amount of funding requested for humanitarian response (as a proxy for response costs). Crucially, however, the number of people targeted is not the same as the number of people who may be affected by a crisis. Typically, humanitarian response agencies may target only a fraction of those who have been affected. Therefore, care needs to be taken when combining these results with results from the hazard and exposure module on the number of people who may be expected to be affected by a crisis. This, and other similar challenges, are discussed further in section 5.1 in the context of the next steps for this analysis.

Nonetheless, this preliminary analysis provides cautious optimism that it should be possible to use top-down analysis to generate estimates of response costs in a way that can be combined with the exposure and hazard modules.

3.4.2. BOTTOM-UP ANALYSIS

The bottom-up costing approach aims to address one of the biggest weaknesses with the top down costing approach: that it fails to provide an understanding of the underlying activities that need to be undertaken. Using top-down analysis only, it is not possible to understand the nature of the underlying activities driving the observed costs. This leads to the possibility that the results may give erroneous conclusions. For instance, in responding to an epidemic, a key cost driver might be the number of different locations in which an outbreak is reported and people require treatment. In each new location, facilities would need to be put in place to support treatment and to enforce social distancing and other interventions to reduce the spread of the disease.

However, in any given location, the number of people affected or treated may only have a very modest impact on costs. This would be easy to identify if there was a clear understanding of the underlying activities that comprise the response. By contrast, it could be missed in a top down analysis where an analyst could 'mistake' the number of people affected or treated for the number of locations in which there is an outbreak.[18] A further advantage of the bottom-up costing approach is that it should be easier to integrate the costs of national responders with those of international responders, providing a more complete understanding of costs.

A bottom-up analysis might follow a five-step process:

1. For any particular crisis type, determine in which humanitarian sectors the bulk of the response is likely to be provided.
2. For each cluster, generate a calendar of projects or activities that would need to be undertaken for the period of interest after the crisis starts (~100 days, following the guiding star). This could be informed by the work undertaken by OCHA and others on anticipatory action (OCHA 2021).

18 The mistake would be made because, on average, as the number of locations where there is an outbreak increases, so the number of people affected or treated would generally increase. However, relying on this relationship for estimating the possible response costs for future disease outbreaks could give very misleading results.

3. Break down those projects or activities into a series of sub-tasks.
4. Create a list of the resources needed for each sub-task (e.g. personnel, equipment, supplies and materials).
5. Gather costs according to this breakdown of sub-tasks and resources from several implementing entities to generate estimates.

A number of resources and ongoing conversations should provide a foundation on which to try to generate such estimates. In recent years, interest has grown in better understanding the costs of humanitarian response. While a lot of this discussion has focused on understanding the costs of humanitarian response in protracted crises rather than immediate response activities – in particular, as part of humanitarian response plans – this work and insight could be leveraged towards costing immediate response activities as well. Examples of the sort of work and discussion include:

- the insights gained from ongoing discussions on project- versus unit-based versus mixed approaches to costing humanitarian response plans (IASC 2017; SALT Analytics 2022)
- the work that has been undertaken to understand how to calculate minimum expenditure baskets to calculate cash transfer amounts (Klein and Gil Baizan 2020)
- the growth of cost benchmarking tools, such as the Dioptra tool developed by the International Rescue Committee (Dioptra n.d.).

Consistent with this, discussions with stakeholders suggest that a number of international humanitarian actors use other types of bottom-up costing models to support their own internal planning of response activities, although it has not been possible to verify this or scrutinise these models.

3.4.3. CHALLENGES AND DISCUSSION

While the analysis above illustrates that it should be possible to develop a costing module to understand crisis protection costs, data constraints are a critical challenge. These relate to, for example, the extent to which it is possible to access the information needed to generate bottom-up costing estimates or how to obtain the costs associated with national response efforts. Indeed, ensuring access to data and then using this data to develop a robust and credible costing module seems to be the biggest challenge to overcome if the international community wants to further enhance its understanding of crisis protection costs and gaps.

There are specific opportunities to extend and improve the top-down analysis in the short run:

- There is scope for more sophisticated data science analysis, with more predictor variables and the use of more advanced techniques to validate and enhance the reported relationships. For example, this work has not been able to consider whether event severity, independent of the number of people targeted, might help explain the variation in response costs. The use of machine learning techniques to explore the possibility of more complicated relationships between funding requested and predictor variables could also be explored.
- The disconnect between the focus of the costing analysis on the number of people targeted, and the focus of the exposure and hazard modules on the number of people affected, needs to be addressed. This could be looked at through more detailed analysis of the relationship between reported measures of the number of people affected and the number of people targeted, and/or by exploring the combined impact of the number of people targeted and the number of people affected on estimates of response costs. Data on the number of people affected by crises is available in the documentation associated with more recent flash appeals.

There is also a range of more general challenges that would need to be considered as part of a longer term research effort on costing humanitarian response:

- Any historic data may not provide a full measure of crisis protection needs. This is a challenge in relation to the top-down methodology, where the funding amount requested could reflect a variety of political economy factors unrelated to the underlying needs of those people affected by the crisis. In particular, if those making funding requests adjust their request according to how they think funders will respond, then the resulting analysis will provide an inaccurate assessment of crisis protection needs and costs.
- Linked to this, it is important to ensure that what is being costed represents a high-quality and effective response. There is a risk that a narrow focus on measuring the costs of response could lead to a preference for selecting and reporting on measures that can easily reach a large number of people affected by a crisis, even if they only make a marginal contribution to meeting their needs.
- Both the top-down analysis presented above, and the simplest applications of a bottom-up costing analysis, would implicitly treat all those people affected by a crisis as having equal needs. In practice, people affected by a crisis will be affected differently and therefore have quite different needs and associated costs. For example, the most vulnerable people, such as people with disabilities or older people, may have complex needs that demand additional resources. Future analysis may need to explore whether there is evidence that crises that disproportionately affect these groups of people have higher costs, and whether and how to integrate this into forward-looking cost estimates.
- It is generally recognised that historic crisis funding has focused too much on crisis response and insufficiently on crisis preparedness. This may lead to reported response costs (funding requests) being an inaccurate – inflated – estimate of what response costs could be if more funding were allocated to preparedness. Moreover, there is a risk that using historic analysis of crisis response costs to estimate what finance should be pre-positioned for these costs in the future could perpetuate this inappropriate focus. This issue, in principle, could be addressed in a sophisticated bottom-up analysis.
- The costing analysis presented above at least partially misses the impacts of compounding factors. In particular, in some cases new crisis events will aggravate what is already a challenging humanitarian context, potentially increasing crisis protection needs by more than would otherwise be expected. Alternatively, or additionally, the costs of providing response will be higher than they would be otherwise. For example, the current food security crisis in the Horn of Africa, caused by one of the worst droughts in recent decades, has been compounded by the impact of covid-19 and rising food prices caused, in part, by the war in Ukraine (WHO 2023). In principle, these sorts of events can be accommodated within analysis through cost multipliers, though calibrating their size is likely to be challenging.

4

DEMONSTRATION ANALYSIS

This section uses specific demonstration analyses to illustrate how the analytical framework could be used and what kinds of results can be expected. They also help to illustrate the challenges that can be expected in any full-scale assessment of crisis protection costs.

The tropical cyclone demonstration analysis illustrates how all three modules of the framework can be combined. The indicative results provide a preliminary understanding of crisis protection costs in different countries.

The results show that it is crucial to be explicit about what and whose needs are of interest. A focus on understanding the overall number of people affected, and associated costs and PAF needs, identifies China and the Philippines as hotspots. By contrast, a focus on the crisis protection costs associated with those living on less than USD2.15/day pinpoints Madagascar and Haiti as key countries.

A drought demonstration analysis shows how the protracted and spatially dispersed nature of droughts creates the specific challenges that arise when trying to assess crisis protection costs for this crisis type.

In some countries, such as Kenya, it appears possible to generate forward-looking estimates of food insecurity (as measured by the Integrated Food Security Phase Classification (IPC) classification system) by looking at previous changes in the Soil Water Index (SWI). This suggests that future analyses could use modelled SWI values to create a drought hazard event set. In turn, this hazard event set could be used to understand the modelled number of people affected by food insecurity and expected crisis protection costs.

However, in other countries, such as South Sudan, there is little evidence of a discernible relationship between SWI and the IPC measure of food insecurity. This reflects that drought conditions are only one of many potential drivers of food insecurity. Further analysis is needed to better understand whether it is possible to make forward-looking predictions of food insecurity based on these other factors.

4.1. OVERVIEW OF MODELLING APPROACH IN DEMONSTRATION ANALYSIS

4.1.2 EXPOSURE

The first step in estimating the number of people affected by a crisis involves identifying where people are located. As discussed above, in recent years there has been significant growth in the availability of data sets that provide granular demographic information by combining traditional census data with geospatial data and statistical techniques. The demonstration analysis uses openly available population estimate data at 1 km resolution produced by the WorldPop applied research group, which can be disaggregated by age and sex. To reduce the computational resources to store and manipulate this data in later steps, this was aggregated to a global grid resolution of 0.05 degrees (roughly 5 km). Each grid cell was given a unique identifier; all later steps and calculations use this same global grid.

The exposure layer was augmented by estimating the average income and number of people living below the poverty line (USD2.15/day, 2017 PPP) in each grid cell. This was estimated using the Relative Wealth Index data set produced by Data for Good at Meta to estimate the relative position within each country's income distribution of each grid cell (Meta 2023) and combining these estimates with theoretical income distributions constrained using World Bank poverty headcount ratio estimates (use of novel data sets to estimate socioeconomic information is discussed in section 3.2). This population-at-risk exposure layer comprising demographic and income estimates across a global grid was used as the first step in the modelling for both tropical cyclone and drought in the demonstration, allowing comparability and a common approach between hazard types.

Box 3: Disaggregated data: estimating financing needs according to the sex, age, and income level of people affected by crises

The discussion above illustrates how the demonstration analysis generated estimates of population by age, sex and income. This is important for at least three reasons:

- These factors may determine how vulnerable people are to a crisis.
- The activities and associated costs of crisis response might vary according to these characteristics.
- Policymakers may want to identify crisis protection costs for specific groups.

In principle, if there is information about other population characteristics that are important for any one (or all three) of these factors, then this could also be reflected in future analyses to refine the results.

4.1.3 HAZARD

The next step involves characterising a hazard event footprint to estimate the number of people affected by a crisis. As outlined in section 3.3, defining what it means to be 'affected' by an event is a significant challenge; for more protracted or compound crises, even defining what the event is presents difficulties. In the demonstration analysis, physical characteristics (e.g. tropical cyclone wind speed) are used to define individual grid cells as 'affected' or 'unaffected'. This allows the identification and aggregation of the number of people affected to be aggregated for any one event. This can be repeated many times, using either historical or synthetic data about hazard characteristics.

4.1.4 RESPONSE COST FUNCTION

A response cost function allows an estimation of the response cost associated with meeting crisis protection needs arising from an event, based on the number of people estimated to be 'affected' as well as other factors. These other factors might include country fragility, physical hazard characteristics or demographics of affected people. The exact form of the response cost function will influence exactly how it is implemented in the model. Due to the data limitations and challenges in characterising a response cost function outlined in section 3.4, the demonstration analysis did not aim to calculate reliable response costs, although illustrative figures have been calculated for tropical cyclone risk using the methodology described in section 4.2.

4.1.5 OUTPUTS

The process of calculating the number of people affected by a crisis and associated emergency response costs is repeated many times for a collection of simulated events known as an event set. The raw output of these results can then take the form of a year-event loss table (YELT), consisting of the response costs for each of the events in the event set (and their associated year) at the desired geographic level, from global to subnational. The calculation of a range of probabilistic summary statistics from the YELT is possible, including average expected response costs in a given country per year or the total annual response costs expected to be exceeded across a range of return periods.

4.2. GLOBAL TROPICAL CYCLONE RISK ANALYSIS

4.2.1 DETERMINING PEOPLE AFFECTED (EXPOSURE AND HAZARD)

As outlined in section 4.1, the first stage in the modelling approach for all hazards is to produce the population-at-risk exposure layer. In the demonstration analysis, this involved mapping World Pop demographic data (World Pop 2023) to the global 0.05-degree grid and augmenting this data set by estimating the average income in each grid. Average income (PPP adjusted) was estimated using World Bank poverty data to constrain country-level income distributions and the Relative Wealth Index to understand the spatial distribution of income across each country.

The next stage in the modelling approach for tropical cyclones involves defining what it means to be 'affected' by an event. Compared to other hazard types, tropical cyclones present one of the more tractable event definition challenges. Tropical cyclones are discrete named events with impacts that are directly attributable to the physical characteristics of the tropical cyclone. For this reason, the event definition problem becomes an issue of selecting thresholds (in this case, windspeed and distance from centre of storm) within which people are considered 'affected'.

Although perils such as storm-surge and flooding can be significant or, in some cases, the primary driver of impacts from tropical cyclones (see section 3.3.2), in the demonstration analysis the selected physical characteristic defining 'affectedness' is windspeed. Tropical cyclone modelling is a mature area of catastrophe modelling and a range of options exist for generating an event set. The demonstration analysis uses a data set consisting of 10,000 years of synthetic tropical cyclone tracks generated using the STORM (Synthetic Tropical cyclOne geneRation Model) modelling process (Bloemendaal et al. 2020). This global synthetic tropical cyclone track data set is based on the historical data available from the International Best Track Archive for Climate Stewardship (IBTrACS) (NCEI 2021).

For demonstration purposes, 'affectedness' is defined as being situated within a 100 km radius of a track of a tropical cyclone with winds of at least category 2 on the Saffir-Simpson hurricane wind scale, equivalent to 1-minute sustained winds of 43 m/s or above. Given the radius of maximum wind of a tropical cyclone is around 50 km on average, using a 100 km radius is sufficiently conservative to encompass the strongest winds of a tropical cyclone in most cases. To calculate the total-population-affected metric for every synthetic event in the STORM event set, the demonstration analysis aggregated the population in each grid cell within 100 km of the centre of the storm at times when maximum winds were above this threshold.

Figure 5 illustrates how the population-at-risk exposure layer can be overlaid with an individual cyclone track in the event set to aggregate the number of people within 100 km of category 2 winds. In this case, combining the simulated tropical cyclone track with the exposure layer allows us to calculate that around 10m people would be affected by a tropical cyclone with this footprint.

FIGURE 5: POPULATION-EXPOSED TO TROPICAL CYCLONE IMPACTS

FIGURE 5A

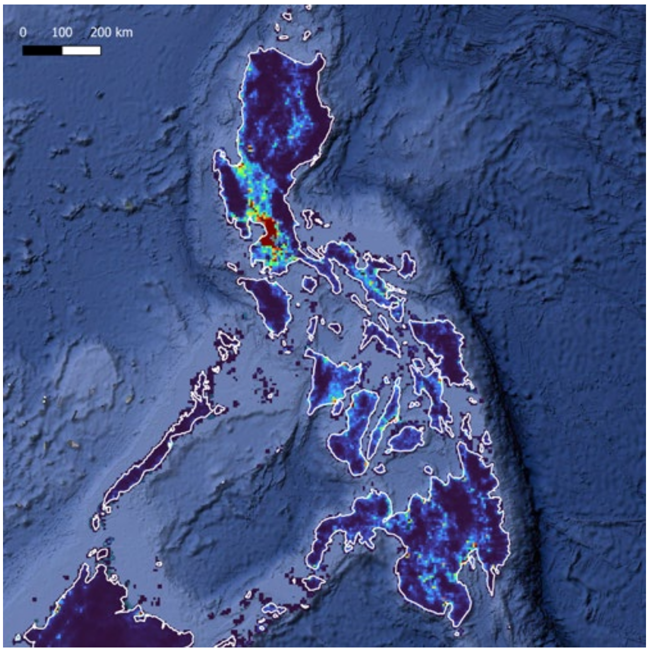
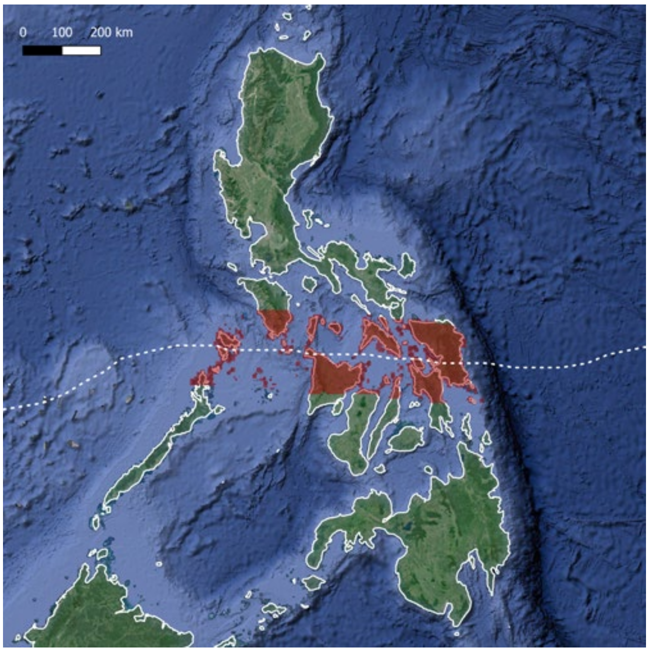


FIGURE 5B



Source: Centre for Disaster Protection, based on data from WorldPop (n.d.) and Bloemendaal et al. (2020).

Note: Figure 5a shows the spatial population density across the Philippines, with each pixel representing the number of people within an individual grid cell. Figure 5b shows an individual simulated tropical cyclone track within the event set, with the red shaded area representing pixels within 100 km of winds in excess of category 2.

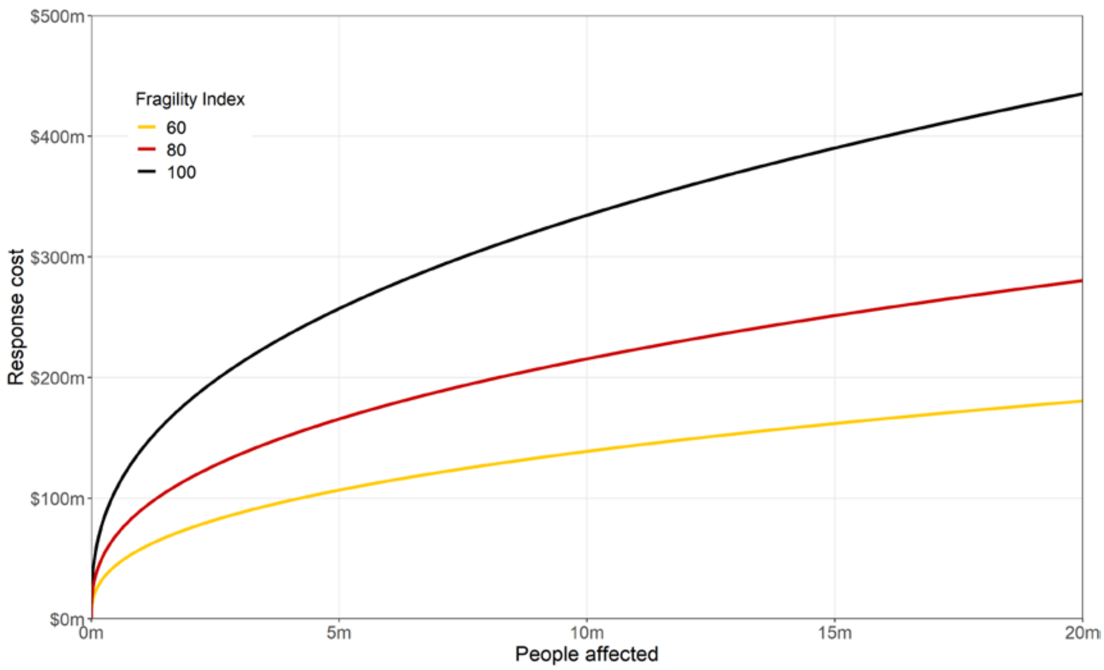
There are several limitations to this definition of affectedness. A binary metric such as this does not account for variations in storm radius or the increase in impacts as wind speeds rise above the threshold set. Also, it does not account for a range of additional factors that may influence the extent of impacts, such as passing speed and precipitation. In the future development of modelling emergency response costs for crises, more sophisticated modelling could be used to define affectedness, including using windfield data to ascertain the modelled windspeed more accurately at each location.

Event monitoring tools, such as the Global Disaster Alert and Coordination System and World Food Programme Advanced Disaster Analysis and Mapping (WFP 2023) tools, already provide some estimates of populations and infrastructure 'affected' by wind and other tropical cyclone related hazards for live events. A calibration exercise would be necessary to understand the correct windspeed threshold(s) to choose and how these may relate to expected costs. For the purposes of a demonstration analysis, this simple index helps illustrate how an event footprint can be produced.

4.2.2 DETERMINING EVENT RESPONSE COSTS

The response cost to a tropical cyclone event is estimated using the number of people 'affected' by the storm. To estimate the emergency response costs that would be incurred for a tropical cyclone event with an estimated number of people affected, the demonstration model applies the cost function estimated in section 3.4.1. The inputs into this function are the hazard type (in this case, tropical cyclone), Fragile States Index value for the country affected, and number of people targeted by an emergency response. Figure 6 depicts this cost function.

FIGURE 6: RESPONSE COST FUNCTION



Source: Centre for Disaster protection, based on data from IFRC (n. d.), FTS (2023), Fund for Peace (n. d.), WorldPop (n. d.) and Bloemendaal et al. (2020).

Note: the graph shows how the relationship between people affected and estimated response costs is assumed to vary based on the Fragile States Index score of the country affected, using the illustrative cost function applied in the demonstration analysis.

The use of this response cost function is purely for illustrative purposes. As discussed in section 3.4, while this cost function provides useful insight on the drivers of protection costs, there are a number of challenges in its application. One of the most important is that, for the purposes of the demonstration analysis, the number of people targeted is assumed to be the entire population 'affected' by each event.

Table 1 shows in practice the estimated response costs for a selection of events in the event set across a subset of three countries. These three countries have Fragile States Index values roughly corresponding to those in Figure 6. Although these numbers are intended to be illustrative, due to the limitations already outlined, they provide insight into the comparative estimated response costs between countries and how the shape of the distribution of annual response costs varies across geographies.

The risk analysis results are provided in terms of numbers of people affected across a range of return period thresholds. The return period describes the probability of at least this number of people being affected in a given year; for example, if the return period for 10,000 people is 1-in-10 years, the likelihood of at least 10,000 people being affected by tropical cyclone in a year is 10%.

TABLE 1: ESTIMATED RESPONSE COSTS FOR THREE COUNTRIES

Country	Fragility index*	Return period [19]	People affected	Total population (%)	Estimated response cost (million USD)
Haiti	99.7	1-in-5	-	0	-
		1-in-10	1,498,938	10	162
		1-in-50	11,414,269	77	349
		1-in-100	12,545,083	85	362
Philippines	80.5	1-in-5	13,221,413	12	242
		1-in-10	33,386,317	30	344
		1-in-50	44,852,943	41	385
		1-in-100	47,619,778	43	394
Cuba	60.1	1-in-5	47,588	0	18
		1-in-10	1,492,147	13	68
		1-in-50	4,129,294	37	99
		1-in-100	5,067,557	45	107

Source: Centre for Disaster Protection, based on data from WorldPop (n. d.) and Bloemendaal et al. (2020).

Notes: * 0 = least fragile, 100 = most fragile; estimated response costs for four individual events in the event set for each of Haiti, Cuba and the Philippines corresponding to occurrence exceedance probability return periods of 1-in-5, 1-in-10, 1-in-50 and 1-in-100.

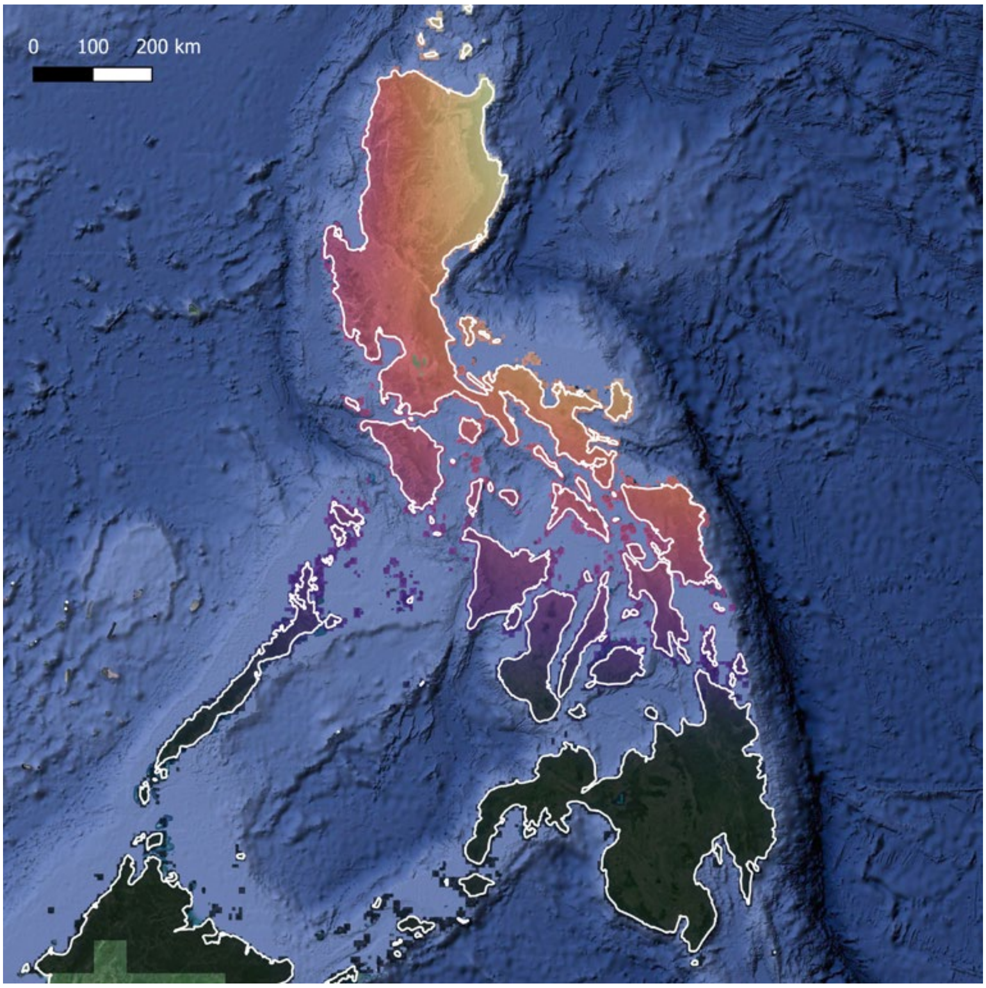
19 https://www.gfdrr.org/en/100-year-flood

4.2.3 KEY OUTPUTS

The demonstration analysis aggregates each event in the event set to produce YELTs of both costs and people affected at the desired granularity. Each YELT consists of the full list of events that affect the geography being considered and the simulation years they occur in, along with the estimated people affected and response costs for each. An example of this output is shown in section A.6.4 in the annex.

Figure 7 shows how several individual tropical cyclone tracks in the event set can be combined to produce probabilistic metrics. In this case, the heatmap shows the annual probability of each individual grid cell being affected by category 2+ windspeeds in the Philippines, with the highest probabilities being found in the north.

FIGURE 7: HEATMAP SHOWING LIKELIHOOD OF THAT LOCATION FALLING WITHIN THE 'AFFECTEDNESS' INDEX.



Source: Centre for Disaster Protection, based on data from Bloemendaal et al. (2020).

Note: the heatmap shows the annual probability of each individual grid cell being affected by category 2+ windspeeds in the Philippines, with yellow representing areas with the highest probability of being affected.

The YELTs can be interrogated to generate a wide range of outputs, depending on the use case (outlined in section 4). Table 2 shows the expected annual tropical cyclone response costs for the top 10 countries eligible to receive official development assistance (ODA). These results illustrate that the ranking of countries may differ depending on whether the annual average response costs or response costs at higher return periods (i.e. higher-severity, lower-frequency events) are being considered. For example, Bangladesh may experience many years where no tropical cyclone response is needed, but more infrequently will be susceptible to high-severity, costly events. In other words, the relative contribution to the estimated annual average costs is skewed towards low-frequency, high severity events. By contrast, Papua New Guinea is expected to experience tropical cyclones, with associated crisis protection needs and costs, on a very frequent basis, but not as many high-severity events, which would have very high crisis protection costs.

TABLE 2: ILLUSTRATIVE ANNUAL TROPICAL CYCLONE RESPONSE COSTS (MILLION USD)

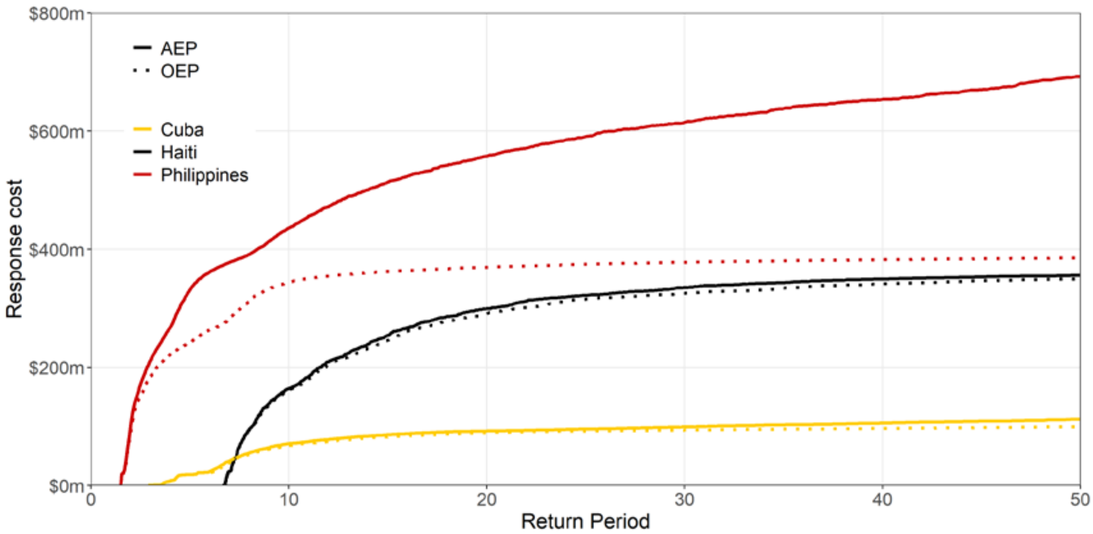
Country	Annual average	Return period					
		1-in-5	1-in-10	1-in-25	1-in-50	1-in-100	1-in-200
Philippines	165	331	436	591	693	789	886
China	97	214	302	425	521	604	690
India	42	-	207	291	362	431	512
Haiti	34	-	164	322	356	367	440
Mexico	26	68	91	128	167	196	225
Dominican Republic	19	2	96	145	153	187	250
Madagascar	16	-	92	123	142	185	221
Cuba	15	19	71	95	112	135	169
Bangladesh	14	-	-	150	325	420	490
Papua New Guinea	13	27	45	62	73	90	97
Global	**536**	**820**	**1,031**	**1,272**	**1,446**	**1,592**	**1,732**

Source: Centre for Disaster Protection, based on data from WorldPop (n. d.), World Bank (2023) and Bloemendaal et al. (2020).

Note: expected annual tropical cyclone response costs for the top 10 ODA-eligible countries on an annual average basis, calculated from the YELTs produced in the analysis, along with estimated costs across a range of return periods.

The estimated distribution of costs can be visually depicted using aggregate exceedance probability (AEP) curves. These show the total annual response cost from all events within a year that is expected to be met or exceeded across a range of return periods, as shown for Cuba, Haiti and the Philippines in Figure 8. The shape of the curve is affected both by the relationship between people affected and response costs (which depends on the Fragile States Index score of the country affected), and on the number of people affected by each event in the YELT for each country. The figure also shows the occurrence exceedance probability (OEP) curves, which can also be derived from the YELT, and which illustrate the probability of a certain level of required response costs being exceeded by any given tropical cyclone event. The AEP is higher than the OEP as it relates to total annual impacts as opposed to maximum impacts per simulated year. The AEP and OEP differ most in situations where, for example, the country is large and experiences multiple large storms per year. They are most similar in situations where, for example, the country is less likely to experience multiple large impacts (e.g. in small island states where people are spatially more concentrated).

FIGURE 8: ESTIMATED DISTRIBUTION OF RESPONSE COST

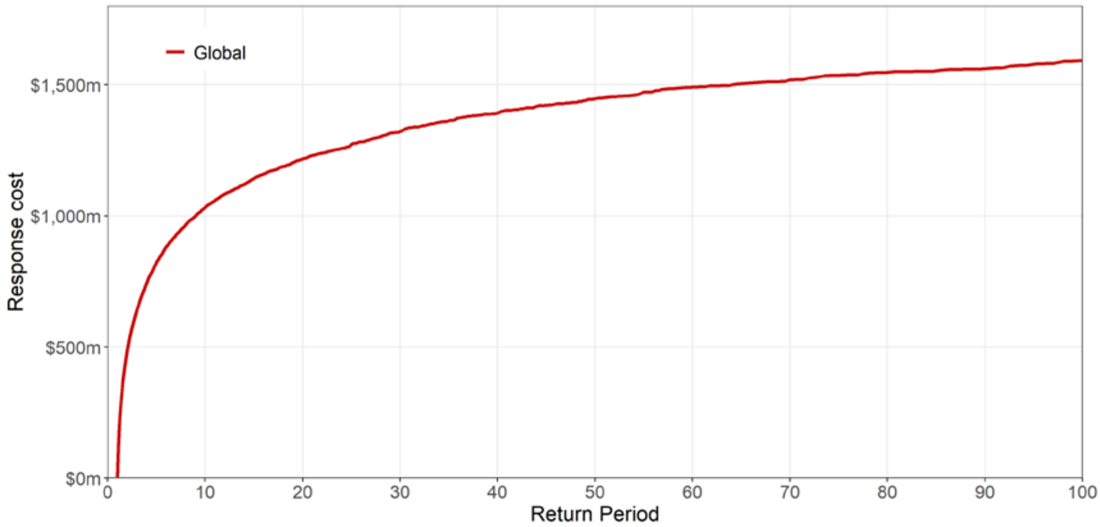


Source: Centre for Disaster Protection, based on data from WorldPop (n. d.), World Bank (2023) and Bloemendaal et al. (2020).

Note: AEP response cost curves for Cuba, the Philippines and Haiti.

AEP curves can also be produced at the global or regional levels by aggregating response cost YELTs. Taking the 1-in-50 return period as an example, the global response cost expected for the return period will be lower than the sum of the country level 1-in-50 response cost due to the effects of diversification. That is, you would not expect each country to experience a 1-in-50 tropical cyclone event in the same year, so the events comprising the global 1-in-50 return period response cost will be a different set of events to those in the country level 1-in-50 response cost losses.

FIGURE 9: GLOBAL TROPICAL CYCLONE RESPONSE COST EXCEEDANCE PROBABILITY CURVE



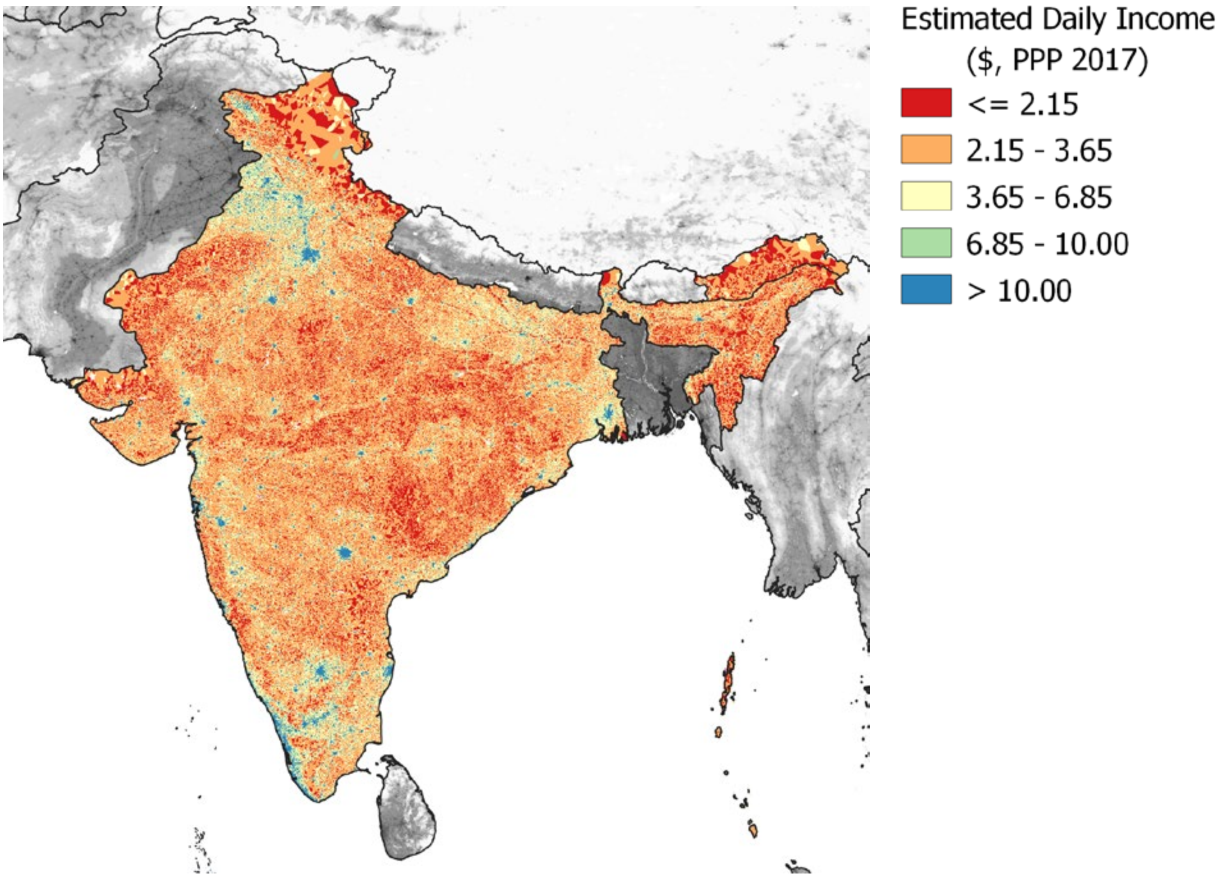
Source: Centre for Disaster Protection, based on data from WorldPop (n. d.), World Bank (n. d.) and Bloemendaal et al. (2020).

Future development of crisis protection modelling could include a cost function that allows costs to be estimated at a more granular level.

The costs of responding to crises are likely to vary according to characteristics of the affected population such as income level, age, sex, and other household-level and contextual factors. If response cost functions can provide estimates of how response costs vary according to these characteristics, then this granular information could be incorporated in future crisis protection gap analyses.

An additional advantage of considering more granular population characteristics is that risk metrics can be further disaggregated to identify protection gaps for specific groups of people. This type of disaggregated view of risk may be relevant when decisions are tailored to respond to specific groups of people.

FIGURE 10: SAMPLE POPULATION DATA FOR INDIA DISAGGREGATED BY ESTIMATED DAILY INCOME



Source: Centre for Disaster Protection, based on data from WorldPop (n .d.), World Bank (n. d.), and Chi et al. (2022).

The exposure dataset developed for the demonstration analysis contains local level estimates of daily income – an example of high-resolution estimates of daily income is shown for India in Figure 10. An analysis based on this high-resolution exposure data is used to show how the tropical cyclone risk metrics can be disaggregated by income-level of affected populations. The annual expected numbers of people affected have been disaggregated according to estimated daily income of affected populations in Table 3. This analysis highlights how risk metrics vary depending on the characteristics of populations that are considered in the analysis. Similar analysis could be conducted based on demographic characteristics, such as age and sex.

TABLE 3: THE PERCENTAGE CONTRIBUTION TO THE EXPECTED ANNUAL NUMBER OF PEOPLE AFFECTED BY CATEGORY 2+ WINDS FOR A RANGE OF COUNTRIES WHERE INCOME ESTIMATES HAVE BEEN CALCULATED.

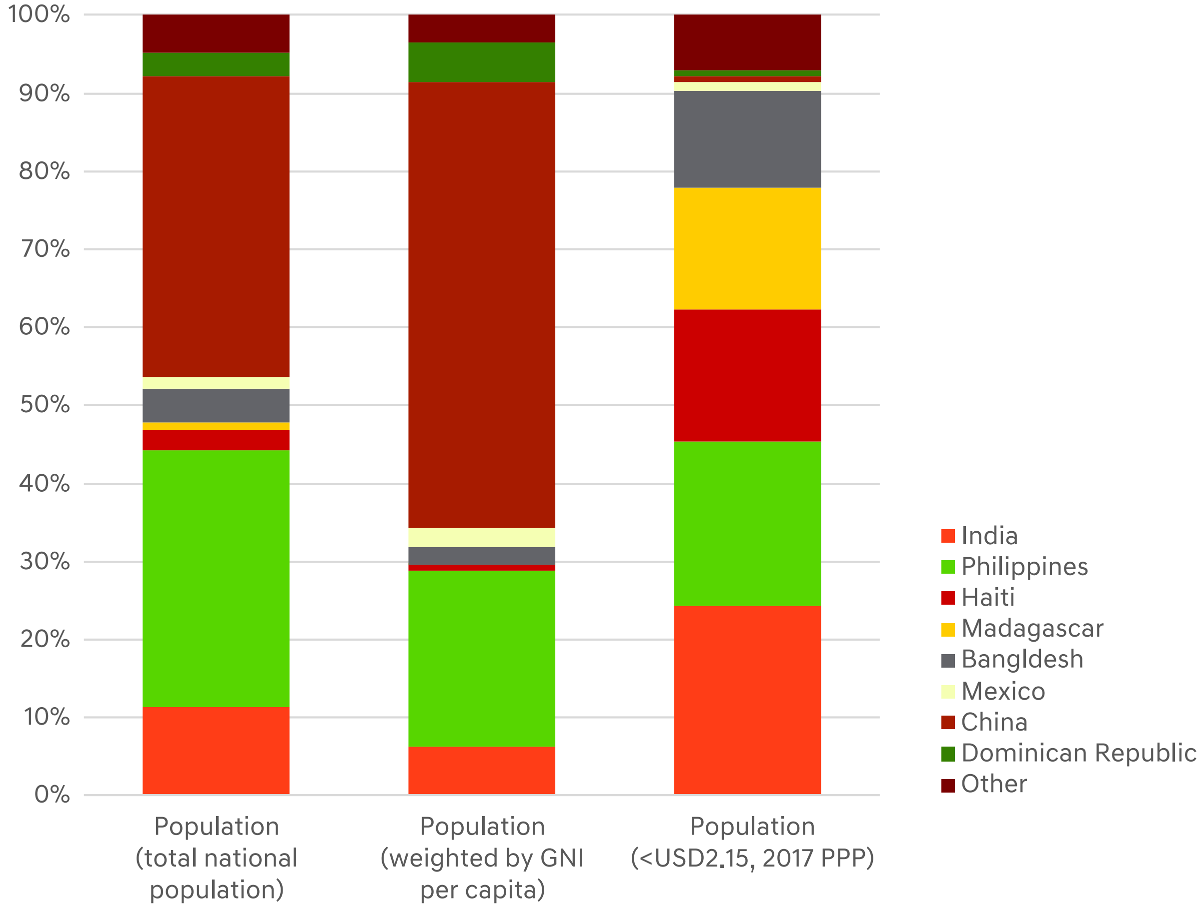
Country	Total Population (million people)	Poverty Headcount Ratio (USD2.15, 2017 PPP)	Expected annual number of people affected ('000s)	Contribution to total expected annual impact by income band of affected populations			
				<= 2.15 USD/day	2.15 - 3.65 USD/day	3.65 - 6.85 USD/day	> 6.85 USD/day
Philippines	116	3.0%	9,824	2%	19%	25%	54%
Madagascar	30	80.7%	269	84%	8%	5%	4%
Bangladesh	171	13.5%	1,258	13%	41%	24%	23%
India	1417	10.0%	3,248	4%	29%	27%	39%
Haiti	12	29.2%	502	27%	26%	22%	26%

4.2.4 FOCUS ON MODEL CHOICES – WHY THEY MATTER

Choices about which populations to include in the model significantly determine the results. Information around where people are most likely to be affected by cyclones and associated responses costs could be used to inform better decision making, for example in selecting countries to prioritise allocation of funding. However, simply looking at aggregated expected numbers of people affected or expected costs may not be sufficient if the priority is targeting those most vulnerable to crises. To illustrate this, figure 11 shows the contribution of a range of countries to the overall annual expected number of cyclone-affected people.

The analysis contains 3 views: (1) contribution to total global expected number of people affected among ODA eligible countries, considering total national populations; (2) population weighted by GNI per capita, this view reflects an analysis where response costs are assumed to scale with economic productivity; (3) populations screened for households whose estimated daily income is less than the international poverty line of USD2.15 per day.

FIGURE 11: ILLUSTRATIVE CONTRIBUTION TO GLOBAL CYCLONE RISK.



Source: Centre for Disaster Protection, based on data from WorldPop (n .d.), World Bank (n. d.), Chi et al. (2022) and Bloemendaal et al. (2020).

Note: The percentage contribution by country overall expected number of people affected by Category 2+ winds per year for: (a) ODA eligible countries, total national populations (b) ODA eligible countries, weighting the expected numbers of people by the country, (c) ODA eligible countries, screened on population with estimated daily income <USD2.15 per day.

The contribution to the global view of tropical cyclone risk changes significantly when considering different views of exposed populations. Some key insights are shared below:

- When total national populations are considered, the cyclone risk in China and the Philippines dominate the view of cyclone risk among ODA eligible countries, largely due to their high national populations combined with high frequency of tropical cyclone impacts. Note that this view does not reflect different vulnerabilities across different countries.
- When exposed population is weighted by GNI per capita, the view of tropical cyclone risk among ODA eligible countries changes, and the relative contributions of higher income countries increases. In this view, China contributes the majority of cyclone risk at a global level, and relative contributions of countries with lower GNI per capita such as the Philippines decrease. This GNI per capita weighted view is a coarse approximation of what the results may look like if they considered the value of the built environment, since replacement value of affected assets generally scales with GNI in affected countries. This view may be relevant when considering damage to infrastructure, but noting that this assumption will bias the view of risk towards areas with higher economic productivity, which may be less relevant when considering response costs relating to the most vulnerable populations.
- When the analysis only considers people whose estimated daily income is <USD2.15 per day (the international poverty line), the view of relative global cyclone risk changes substantially. Countries with higher poverty headcounts are relatively much higher among ODA eligible countries, with countries such as Madagascar, Haiti, and Bangladesh contributing much more to the relative global total than when the analysis is not screened for household level income. The contribution from China decreases from 38% (when total population is considered) to 1% when population is screened based on income <USD2.15 per day.

These various views of risk highlight that if income level is used to screen populations, then there is a very different view of 'priority', than if exposure is weighted according to economic productivity, or if all populations are included in the analysis.

The magnitude of a crisis impact relative to the size of the affected country can impact the severity of any shock. Small countries may appear to have relatively small numbers of expected affected people or costs, but relative to the size of the country's population or GDP respectively these figures may indicate far more severe impacts when compared to other, larger countries with higher populations.

TABLE 4: ANNUAL EXPECTED NUMBER OF TROPICAL CYCLONE PEOPLE AFFECTED AS RATIO OF NATIONAL POPULATION.

Country	Annual expected number of people affected (thousand people)	Contribution to global total among ODA eligible countries	Annual Expected Number of People Affected (% of total national population)
Dominica	7	0.02%	9.65%
Philippines	9,471	32.27%	8.59%
St. Lucia	14	0.05%	7.95%
Dominican Republic	905	3.08%	7.47%
St. Vincent & the Grenadines	7	0.03%	6.70%
Jamaica	155	0.53%	5.58%
Haiti	768	2.62%	5.18%
Grenada	5	0.02%	4.70%
Mauritius	52	0.18%	4.02%
Fiji	36	0.12%	3.95%
Cuba	396	1.35%	3.52%
Vanuatu	11	0.04%	3.46%
Belize	9	0.03%	2.14%
Madagascar	259	0.88%	0.93%
China	11,034	37.60%	0.78%
Bangladesh	1,231	4.19%	0.74%
Other	4,986	16.99%	-
Total	29,346	100.00%	-

Source: Centre for Disaster Protection, based on data from WorldPop (n .d.), World Bank (n. d.), Chi et al. (2022) and Bloemendaal et al. (2020).

For example, while 11m people are expected to be 'affected' by Category 2 winds in any given year in China according to the analysis, this represents less than 1% of the total country population, whereas the roughly 7 thousand people expected to be 'affected' annually in Dominica represents 9.65% of the country's population.

This additional view of risk shows that while at a global level, the tropical cyclone risk in smaller counties may be negligible, at a county level, even small total estimates may be large relative to the size of a country's population. This view is especially important in small island states, who experience frequent and severe tropical cyclone impacts, but whose relatively low populations and exposed economies are small when compared at a global level.

4.3. DROUGHT RISK ANALYSIS

4.3.1 OVERVIEW OF ANALYSIS

Drought is one of the crises that has the greatest impact on people's lives and livelihoods globally, particularly in the world's poorest countries. Drought accounted for 44% of non disease-related deaths in the 1960s–2010s according to data from the US Office of Foreign Disaster Assistance/Centre for Research on the Epidemiology of Disasters International Disaster Database (CRED 2009). The geographic scale of drought events can cover whole countries, and impacts can often be felt on a timescale of years, meaning adverse effects on a country's development can be particularly acute, as discussed in section 3.3.1.

There are particular issues in characterising a drought event and modelling response costs that are not present when considering other hazards such as tropical cyclones. Unlike the demonstration analysis of tropical cyclones outlined in section 4.2, the demonstration analysis of drought is not intended to illustrate an end-to-end solution of the conceptual modelling approach, but rather to focus on the challenges that are specific to drought, and potentially other crisis types that can be of a protracted and spatially dispersed nature.

4.3.2 BUILDING AN EVENT FOOTPRINT

Compared with building an event footprint for a tropical cyclone, building one for a drought is challenging since there is no single definition of what constitutes a drought event. The severity of food insecurity a drought causes depends not only on the spatial and temporal distribution of precipitation but also a range of other factors that can influence the vulnerability of a region, including land use or time of year. Moreover, impacts can be spatially decoupled from those areas experiencing the most severe physical conditions. An additional challenge is that the impacts of drought can build slowly over many years of below-average rainfall, making it difficult to define the point in time at which a drought can be said to have begun.

For example, at the end of 2022 the Horn of Africa was experiencing its fifth consecutive dry rainy season, creating a food insecurity situation that compounded with each further season with insufficient rain. Ideally, a modelling approach would take compounding factors into account rather than focusing on each rainy season in isolation. In addition to drought-specific factors that make characterising a drought footprint challenging, as with other hazards, defining what it means to be 'affected' is challenging.

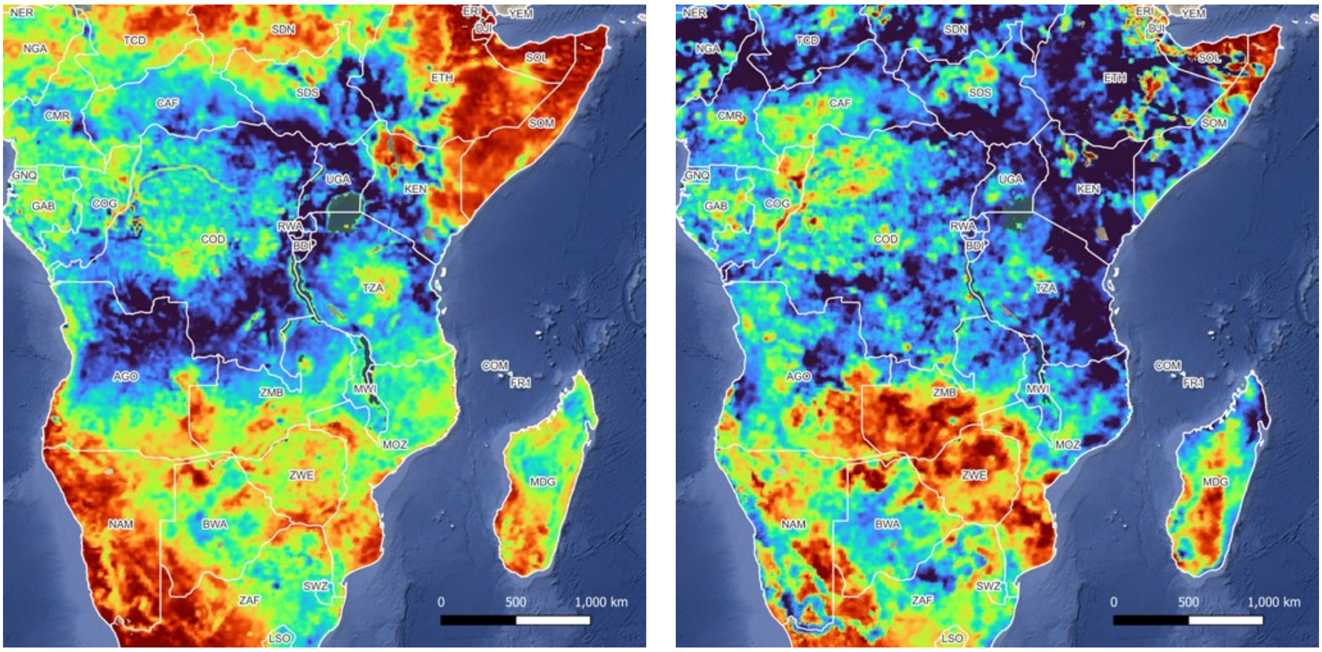
The demonstration analysis uses the Soil Water Index (SWI) as the basis for modelling drought. Leaving aside the many other factors that could create food insecurity to focus on the physical conditions that define a drought, on a basic level an area is considered in drought when soil moisture is below a defined threshold over a defined period. For historical drought events, the moisture condition at various depths in the soil can be measured using the SWI, with 10-daily estimates available at a 0.1 degree resolution (Copernicus n. d. a.). This index is used as the basis for producing drought event footprints in the demonstration analysis, as it meets the criteria for being able to estimate soil dryness at a fine enough spatial and temporal resolution, while also being amenable to stochastic modelling to extend the historical timeseries and produce a synthetic event set over many simulated years.[20] The historical timeseries was mapped to the 0.05-degree resolution global grid to enable the data to be easily overlaid onto the population-at-risk exposure layer at the same resolution.

The expected level of soil moisture varies by location and time of year, so the demonstration analysis converts the SWI values to standard scores to define when an area has experienced drier conditions than normal. The calculation of standard scores per grid cell and 10-day period within the year allow identification of deviations from the average. The output of this data transformation comprised historical timeseries of SWI deviations between 2008 and 2022 at grid cell level for each country in Africa, as Figure 12 shows.

FIGURE 12: SWI DEVIATIONS FROM AVERAGE SOIL MOISTURE CONDITIONS

FIGURE 12A

FIGURE 12B



Source: Centre for Disaster Protection, based on data from Copernicus (n. d. b.).

Note: Figure 12a shows the raw SWI values for October 2020, with blue representing high (wet) values and red representing low (dry) values. Figure 12b (right) shows these same SWI values converted into standard scores relative to the mean at the time of year for each pixel.

20 Section 3.3.1 discusses a range of other indices that might be used to produce drought event footprints.

To capture the temporal component of drought, over a rolling three-month period the demonstration analysis calculated the number of days that each grid cell spent below a series of SWI thresholds. This allowed the production of three indices that use different thresholds to define drought conditions:

- **Below average** – the number or percentage of days over three months that the SWI was below the average for that time of year.
- **Moderate** – the number or percentage of days over three months that the SWI was more than one standard deviation below the average for that time of year.
- **Extreme** – the number or percentage of days over three months that the SWI was more than two standard deviations below the average for that time of year.

Figure 13 shows heatmaps of these three indices, representing the same point in time as Figure 12. Figure 13a represents the percentage of days over the preceding three months with below average dryness, with Figures 13b and 13c representing the percentage based on the moderate and extreme thresholds, respectively.

FIGURE 13: HEATMAPS OF THREE INDICES USING DIFFERENT THRESHOLDS FOR DEFINING DROUGHT CONDITIONS

FIGURE 13A

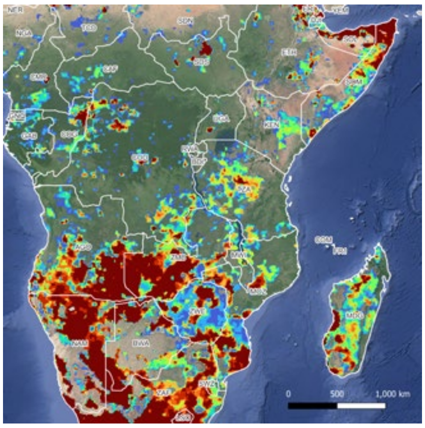


FIGURE 13B

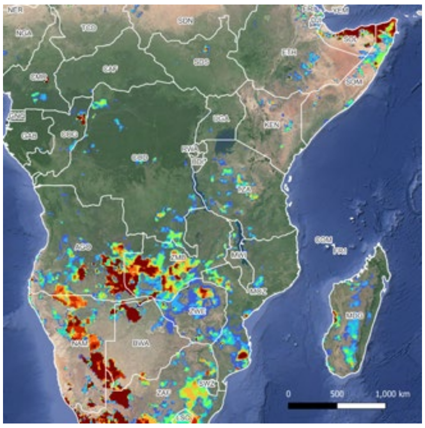


FIGURE 13C

Source: Centre for Disaster Protection, based on data from Copernicus (n. d. b.).

Note: Figure 13a shows the percentage of days each cell recorded below-average standard scores (< 0) over the three-month period up to October 2020, with dark red representing 100% of days and no fill representing 0% of days. Figure 13b shows the same data using the moderate (standard score < -1) threshold and Figure 13c shows the same data using the extreme (standard score < -2) threshold.

Different regions have varying levels of susceptibility to drought; therefore, it is possible that more extreme deviations from normal moisture conditions may be required to trigger a drought 'event' in some locations than others. The model should therefore be calibrated to choose the correct SWI standard score thresholds that best predict when a drought event could be said to be occurring. It could be the case that in more resilient regions, the extreme SWI index may be the best predictor of drought-induced food insecurity, whereas in regions more susceptible to drought the below-average SWI index would be the best predictor. In recognition of differences in susceptibility, the demonstration analysis used all three indices described above.

4.3.3 CALIBRATION CHALLENGE

There is a complex relationship between the drought event footprint and that of any associated food insecurity event. This is due to both the uncertainty in the relationship between dryness and drought-related impacts (which will vary according to the vulnerability of different populations) and because impacts may extend to areas outside of the physical drought footprint. The steps outlined in the previous section allow a footprint of the physical impacts of drought (i.e. the extent of dry conditions over a period of time) to be produced, but the relationship between this footprint and resultant food insecurity must then be understood.

To assist with understanding this relationship, and therefore allow the number of people affected by drought-related food insecurity to be estimated from SWI footprints, the demonstration analysis compared historical estimates of the number of people experiencing food insecurity with the historical SWI timeseries. The only multi-source, standardised classification of food insecurity comes from the IPC Acute Food Insecurity classification, with historical shapefiles (a file format storing the location, shape and attributes of geographic features) available via the Famine Early Warning Systems Network (FEWS NET) platform (FEWS NET n.d.). The IPC classification system does not distinguish between drought-caused food insecurity and food insecurity due to other causes, making it an imperfect data source to use for calibration; however, it was considered to be the most appropriate system to use due to its wide acceptance and comparability between countries.

The analysis assumed that areas in IPC classification level 3 (IPC3, severe food insecurity) or above are representative of areas being 'affected' by food insecurity. The analysis then sought to understand the relationship between the drought footprint and this measure of the spatial extent of food insecurity. The analysis first mapped historical FEWS NET IPC classification data to the global 0.05-degree grid to produce historical timeseries of the classification status (between 1 and 5) of each grid cell. This allowed the aggregation of the number of people under IPC3 at national level for countries in Africa covered by FEWS NET at different points in time. Figure 14a shows an example of the raw FEWS NET IPC classification shapefile data (as at February 2020), with the heatmap representing the level of food insecurity in each location. Figure 14b shows the average percentage of days in a year that each location has been categorised as being in IPC2+ in the historical data set.

FIGURE 14: HEATMAP OF FEWS NET IPC CLASSIFICATION DATA

FIGURE 14A

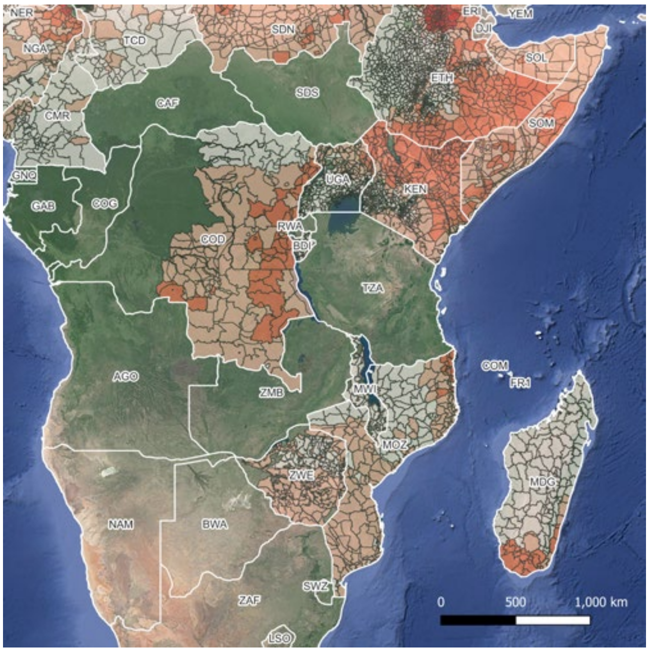
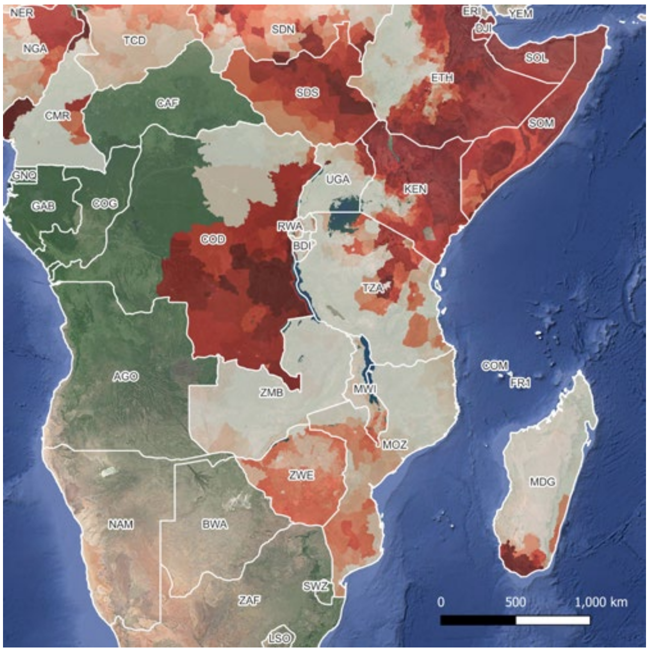


FIGURE 14B

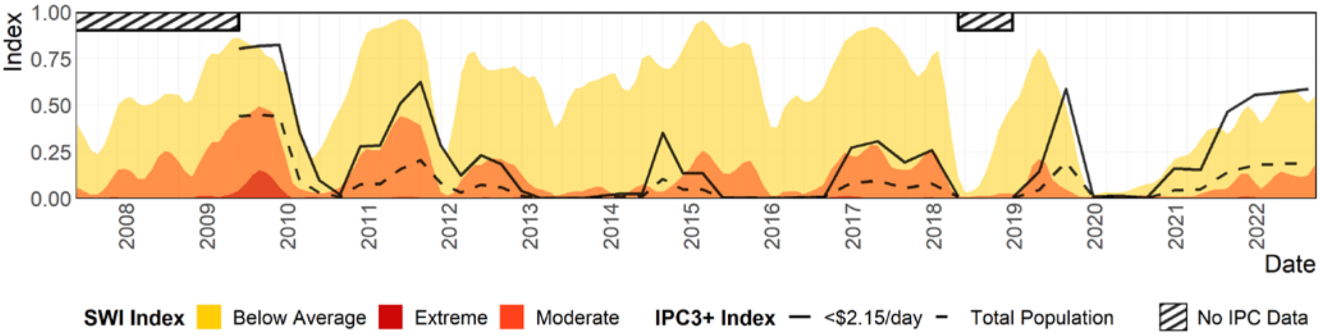


Source: Centre for Disaster Protection, based on IPC data from FEWS NET (n. d. a.).

Note: Figure 14a shows an example of the FEWS NET IPC classification shapefile data as at February 2020, with the shading representing the classification number from 1 to 5. Figure 14b shows the average percentage of days in the year each pixel has been classified as being in IPC2+ in the historical data set.

The analysis found that, in some countries, there is a clear relationship between the number of people experiencing severe food insecurity and the different indices for measuring SWI. For example, Figure 15 shows how both these indices have varied over time in Kenya, showing that, in most cases, the greater the percentage of people who experienced drought conditions (as captured by the different SWI thresholds that were arbitrarily defined for ease of communication), the greater the proportion of people in IPC3 or above. There is sometimes a short lag between the percentage of people experiencing drought conditions and the number of people facing food insecurity (as would be expected). Using the moderate SWI index and total population above IPC3 index, over the period covered there is a Spearman correlation coefficient of 0.579, indicating a strong relationship between SWI measurements and the number of people suffering from food insecurity.

FIGURE 15: VARIATIONS IN SWI AND IPC INDICES OVER TIME, KENYA



Source: Centre for Disaster Protection, based on data from Copernicus (n. d. b.), FEWS NET (n. d. a.), WorldPop (n. d.), World Bank (n. d.) and Chi et al. (2022).

Note: the graph shows the historical IPC and SWI indices over time in Kenya. The IPC index timeseries represents the percentage of individual grid cells in the country classified as being in IPC3 or above, both in total and filtering to only include cells with an estimated average income below USD2.15/day. The three SWI indices represent the average percentage of days that each grid cell in the country has recorded SWI measurements below the three thresholds described above over a rolling three-month period.

Although further analysis is required to understand this relationship, the data suggests that the calibration challenge is tractable in some areas. In future development of modelling of crisis protection needs and costs, several avenues of analysis could be explored to better use modelled SWI values to create a drought hazard event set from which modelled numbers of people affected by food insecurity (and therefore response costs) could be calculated:

- **Exploring the correlation between dry conditions and food insecurity at a more granular, grid cell level** – The demonstration analysis focused on examining the relationship between SWI values and food insecurity at the national level; however, it may be possible to analyse the relationship at a more granular level. Due to differences in vulnerability between regions, different standard score thresholds may be more appropriate to define 'affectedness' in different settings.
- **Focusing on poverty as a key element of vulnerability to drought** – The population-at-risk exposure layer in the demonstration analysis allows populations to be filtered on estimated household income, meaning the number of people living below or close to the poverty line can be obtained. The results of filtering the IPC index to only include people living below USD2.15/day (2017 PPP) is shown in Figure 15. Any calibration exercise could focus on those people who may be most vulnerable to food insecurity, and explore whether poverty screened data provides a more robust relationship between SWI data and the number of people experiencing food insecurity.
- **Using other data sources in addition to SWI as inputs for a predictive modelling approach** – Factors that may influence the vulnerability of certain regions to drought could be implicitly captured in any model by selecting different standard score thresholds to use in different areas, but other data sources (such as those described in section 3.3.1) could also be considered to explicitly capture this; for example, information on land use or distance to market.

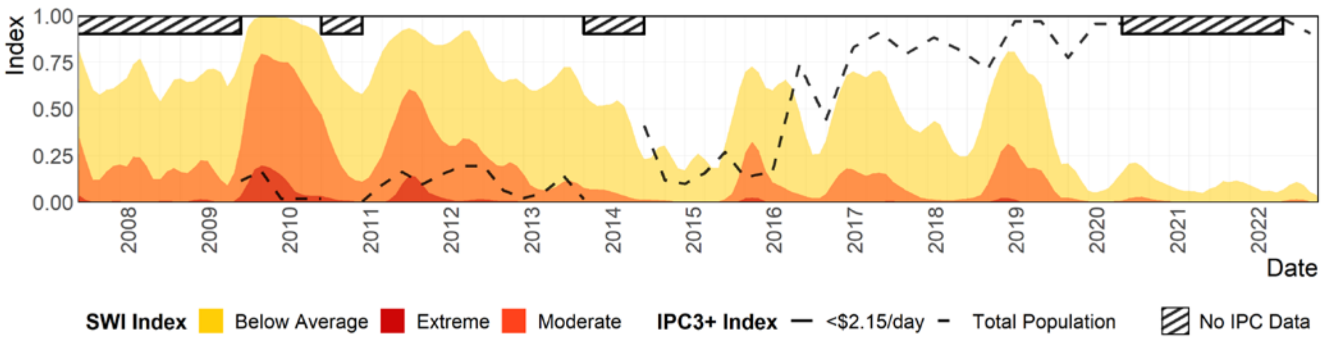
- **Identifying any potential issues in using SWI (or other indices) to predict food insecurity** – Given that limited data is available to inform classification of food insecurity, it is expected that data such as SWI might partially inform IPC classifications. However, effects such as this may not ultimately be an issue if the objective is to model food insecurity as monitored by the IPC. However, deeper analysis would be needed to ensure that we understood the causal influence of drought on food insecurity well in each geographic context.

4.3.4 COMPOUNDING FACTORS IN PRACTICE

Although SWI data appears to be a promising predictive variable for food insecurity in some settings, in others this relationship partially or completely breaks down. This is unsurprising, given that the IPC classification system captures food insecurity from all causes, and many countries at risk of drought are also susceptible to other complex crises such as war or high inflation. In South Sudan, large areas of the country were assessed as being in IPC3+ in the period between 2016 and 2022; at times, more than 75% of the country was experiencing food security categorised as 'severe' or worse. Although parts of the country experienced drought conditions in 2015–16, a significant driver of widespread food insecurity at the time was a result of several years of war impacting the country's food supply.

Figure 16 shows the number of people in South Sudan identified as being in at least the 'severe' food insecurity classification increased rapidly from around 2016 and has remained at extremely elevated levels since, with the rise decoupled from the percentage of areas experiencing unusually dry conditions. In fact, since 2019 South Sudan has experienced unusually high levels of rainfall, which have led to flooding across the country, further exacerbating the food insecurity situation.

FIGURE 16: VARIATIONS IN SWI AND IPC INDICES OVER TIME, SOUTH SUDAN



Source: Centre for Disaster Protection, based on data from Copernicus (n. d. b), FEWS NET (n. d. a.), WorldPop (n. d.), World Bank (n. d.) and Chi et al. (2022).

Note: the graph shows the historical IPC and SWI indices over time in South Sudan. The IPC index timeseries represents the percentage of individual grid cells in the country classified as being in IPC3+. The three SWI indices represent the average percentage of days that each grid cell in the country has recorded SWI measurements below the three thresholds described above over a rolling three-month period. In South Sudan, the poverty headcount ratio is very high, therefore, and the index of total population is expected to follow a similar trend to the < USD2.15/day-based index.

The example of South Sudan highlights the limitation of isolating drought-induced food insecurity from other causes of food insecurity. The timeseries of SWI and IPC indices for a range of African countries in Annex 2 provide additional examples showing the complexity of the relationship between the two indices. The data for some countries (e.g. Ethiopia and Somalia) suggests a relationship between SWI measurements and food insecurity, but a minimal relationship is visible in other countries such as Madagascar. Further analysis (potentially including other drought indicators) would be required to better understand the relationship between drought events and food insecurity in more fragile, complex settings such as South Sudan.

This analysis highlights that even in complex settings where there are multiple concurrent and compounding issues that affect levels of food insecurity, there can be value in understanding what contribution drought stress may be causing. In the context of this crisis protection gap research, if the data supports the view that, at least in some cases, the effects of drought can be isolated and used to define drought-related costs, then this might add value even in more complex settings.

5

USE CASES

There are at least four main use cases where information on crisis protection costs could be helpful:

1. **As the core element of a 'crisis protection monitor' function**, helping civil society and other stakeholders to advocate for more and/or a different allocation of PAF.
2. **As an allocation tool**, informing development partners' decisions on whether and how much to support PAF mechanisms that cover different countries or crisis types.
3. **As a strategic planning tool**, to facilitate responding agencies' financial planning.
4. **As a design tool**, to support the design of specific PAF instruments.

While these need not be mutually exclusive, supporting a crisis protection monitor function is the area where information on crisis protection costs could have the greatest value. However, developing the information to the extent that it could support this function will require both significant resources and a dedicated institutional home.

5.1. OVERVIEW OF POTENTIAL USE CASES

Crisis protection costs and an assessment of the crisis protection gap can be useful in a wide range of applications. For example, a range of actors might use the information to determine how much money should be allocated to PAF (for different hazards or in different geographies), to inform assessments of whether PAF instruments are fit for purpose, or to help organisations plan for crises to which they may need to respond.

However, the specific role of crisis protection gap information will vary across users, with important implications for how the information should be generated. For instance, different users may make different trade-offs when it comes to accuracy versus comprehensiveness; some users will place greater emphasis on open access and being able to replicate results than others.

Table 5 illustrates a range of specific users of, and roles for, crisis protection gap information. It summarises the implications of these use cases for the way in which crisis protection gap information might be generated. The subsequent subsections explain these use cases and the implications for information generation (modelling) in more detail. The section concludes with a discussion of where the role for new crisis protection needs, cost and gap information might be greatest.

TABLE 5: COMPARISON OF CRISIS PROTECTION GAP POTENTIAL 'USE CASES'

Application	Description	Illustrative user profile	Illustrative example	Model implications
Crisis protection monitor	Publicly available information about global crisis protection gaps is used as a tool to advocate for more PAF and/or a different allocation.	Communities and organisations that are affected by decisions about PAF, which are not currently involved in the decision making process. This could include the public, either in crisis affected or donor countries; advocacy or campaign organisations; or national or international recipients of donor support for PAF.	A civil society organisation in a fragile and conflict affected setting uses crisis protection gap information to identify that other countries with similar contexts and risk profiles have received higher levels of donor support for PAF, relative to their estimated protection gaps. The organisation uses this information to highlight the need for greater levels of PAF in its country and campaigns accordingly.	The data must be publicly available and trusted, which implies it must be both open to scrutiny and accessible for non experts. The developer of the information should be - and should be perceived to be - impartial.
Allocation framework	A transparent assessment of existing crisis protection gaps is used as the basis for making resource allocations for PAF and premium subsidies, and/or investments to help reduce risks.	Donors and other development partners making resource allocation decisions.	A global risk-financing facility has been established with a mandate to allocate donor funds towards investments in risk reduction and PAF, with a priority on PAF that supports the poorest and most at-risk people globally. The crisis protection gap analysis is used to quantify how much funding should be allocated across different geographies and/or risk types.	Modelling needs to generate outputs that are as comprehensive as the mandate of the organisation(s) making the allocation decision. Modelling needs to be aligned to an agreed definition of a crisis protection gap, or have the functionality for customisation to different definitions. The absolute value of crisis protection gap information is less important than avoiding bias across crisis type or geography. Modelling needs to be transparent and derived from sources that users trust (but full open access may be less important to immediate users).

TABLE 5 CONTINUED

Application	Description	Illustrative user profile	Illustrative example	Model implications
Strategic planning tool	Analysis of crisis protection needs and existing levels of protection is used to enhance strategic decision-making in organisations with a responsibility to respond to crises.	Operational and/or financial planners in national or international response organisations making decisions about which types of crisis response needs should be prioritised (i.e. what type of staff to employ, where fundraising efforts should be prioritised).	An international humanitarian organisation identifies expected flood response costs to be 10 times higher than the expected wildfire response costs in the countries where the organisation has a responding role. It makes additional efforts to build anticipatory actions for floods, and to invest in the equipment and staff needed to support flood response efforts.	Similar to allocation framework, although with less emphasis on the need for transparency.
Design tool	Accurate models of crisis protection needs can be used to support trigger and instrument design.	Teams involved in designing and implementing risk financing instruments (e.g. in parametric trigger design, or pricing of risk transfer instruments designed to cover specific protection needs).	A technical advisory team in a regional bank is working with a small island state to design and purchase a parametric insurance policy from a private markets (re)insurer. A crisis protection gap analysis of earthquake risk is used to calculate the amount of insurance cover to purchase.	Modelling analysis needs to generate reliable USD estimates of the crisis protection gap for that risk in that geography. Comparability to other risks and geographies is less important. In this context, it is important that all parties to the transaction understand and trust the results of the risk analysis.

Source: Centre for Disaster Protection.

5.2. CRISIS PROTECTION MONITOR

Crisis protection gap information could be used to help advocate for more and/or a different allocation of PAF. This might be used at different scales:

- At the global level, an all-risks analysis of expected crisis response needs and costs, combined with information about existing levels of PAF, could be used to track progress against targets for increased levels of financial protection and highlight risks and regions that are under-protected. It could help donor organisations in developing and monitoring targets, or national or international responders in responding to crises. Similar stock taking analyses are already undertaken, for example, in relation to the amount of finance developed countries provide to developing countries to help reduce greenhouse gas emissions and adapt to climate impacts (OECD 2022).
- At a more specific level, information on crisis protection needs, costs and gaps might enhance the accountability of particular decisions to provide PAF, including, most notably, accountability to people affected by crises. At both the national and international levels, many factors influence decisions about developing and purchasing PAF mechanisms. In principle, a trusted public source information about crisis protection needs, costs and gaps could highlight the extent to which existing PAF schemes target the needs of the most vulnerable people.

In both cases, crisis protection gap information would act as an independent benchmark, allowing individuals or organisations to advocate for greater or different investments in PAF.

Over time, crisis protection gap information designed and provided for this purpose could support assessments of financial resilience. Credit rating agencies and financial regulators are increasingly cognisant of how different types of crises pose a threat to financial stability (Fitch Ratings 2021; IDA and IMF 2021). An understanding of crisis protection needs, and the extent to which they are currently being met, would help inform these decisions.

Crisis protection gap information prepared for these purposes would need to be derived from a modelling approach with a number of characteristics:

- **Focused on comparability of risk** – If crisis protection information is to be used to support assessments of the extent to which efforts to close the protection gap are well targeted, then different risks and geographies need to be analysed consistently.
- **Open to public scrutiny** – A wider range of different users must trust a public monitoring function. One way to promote trust is to ensure that methods and data are open to public scrutiny. This would imply that the modelling approach, including key limitations and assumptions, should be openly available and transparent.
- **Understandable to a range of users** – Information that describes probabilities can be challenging to communicate clearly to non-technical specialists. If a range of stakeholders, including non-specialists, are to use the information, it is important that key metrics are communicated clearly.

There are some precedents, although from slightly different contexts, which illustrate this function. For example, First Street Foundation (see Box 4) provides location-level risk scores for flood and other hazards in the US. This information is designed to be accessible and understandable by anyone, so they can use it to campaign for or challenge risk management decisions that affect them.

Box 4: First Street Foundation[21]

First Street Foundation is a non-profit research and technology group, whose mission is to make climate risk accessible, easy to understand and actionable for individuals, governments, and industry.

First Street uses transparent methodologies to model physical climate risks to individual properties across the US. Through the RiskFactor platform (riskfactor.com), it makes data on flood, fire, heat and wind accessible to the public for free.

Recently, commentators have criticised First Street's work over concerns that the underlying modelling on which it bases its analysis has not been subject to as rigorous a peer review process as it could have been, and for not giving users sufficient understanding of the uncertainty that surrounds some of its analysis (Harris 2023). First Street disputes these claims. Regardless of the merits of these criticisms, they illustrate the importance of making analysis used for this purpose openly available to public scrutiny, and the challenges that accompany communicating risk information.

5.3. ALLOCATION FRAMEWORK

Information on crisis protection needs, costs and gaps can help development partners make objectively verifiable decisions about how to allocate scarce financial resources between competing priorities. As the development of the Global Shield Against Climate Risks illustrates, development partners are increasingly allocating resources to PAF schemes and broader disaster risk management activities in light of the growing evidence base on their importance and effectiveness. However, they often face challenges in deciding how to prioritise resources; for example, whether they should focus resources on specific crisis types or in particular countries.

A very specific example of this challenge is the InsuResilience Global Partnership. Members of the partnership are looking to scale up climate and disaster risk and finance insurance; and, as part of this, to develop an objective methodology to allocate donor support that should be provided to developing countries to reduce insurance premiums (Panwar et al. 2022). While a range of development finance and multilateral organisations already use allocation formulae to help inform the distribution of resources (see Box 5), there is no equivalent tool to support allocation decisions for PAF.

Crisis protection cost and gap information could be used as a measure of the 'need' for financial support within any allocation formula. One approach development partners use to allocate resources combines assessment of the *need* for these resources with an assessment of *country performance* (which guides development partners in understanding how effectively funding might be used, as well as providing an incentive to

21 https://firststreet.org/mission/

enhance performance over time). A measure of the crisis protection costs and gap in each country would provide a transparent assessment of needs to plug into this sort of allocation framework.

Crisis protection cost and gap information generated for this purpose would need to have a number of characteristics:

- It should provide geographic and risk coverage consistent with the funding mandate. Information on the protection gap could only help inform allocation decisions if it covered the same risks and the same countries or geographies that funders were targeting.
- As discussed in section 1.3, the crisis protection gap can be defined in different ways. Development partners will want to see their funding for crisis protection allocated in a way that is consistent with their definition. Any modelling would need to reflect this. A more flexible approach would involve crisis protection gap modelling being able to accommodate multiple definitions, with particular users choosing the modelling analysis that aligns with their definition.
- In this application, the absolute value of the protection gap calculated will be less important than ensuring that different geographies and risks are treated in a comparable and consistent manner. It is likely that in most cases where protection gap costs and gap assessments are being used for this purpose, the overall budget allocated to closing the crisis protection gap will already have been set. The decision development partners face is how to allocate this fixed budget across countries and risks with different demands. In this setting, the most important requirement is ensuring that different countries, and those exposed and responding to different crises, are satisfied that the treatment of different risks and countries has been analysed in a manner that is fair and consistent.

Both users of the risk information, and people affected by decisions made using that information, need to be able to trust the approach to modelling crisis protection costs and gaps. This characteristic is most immediately important for the organisation that is using the information to make allocation decisions. However, those who receive (or do not receive) allocations because of the quantification of the crisis protection costs and gaps also need to be satisfied that the information has been generated in an impartial way that engenders trust. The most obvious way to secure this will be if the analysis and results are fully open to scrutiny and replicable, although it may also be possible to build trust in the results using other methods (such as demonstrating how the analysis aligns with historic records and experience).

Box 5: International Development Association Resource Allocation Index[22]

The International Development Association (IDA) uses the Resource Allocation Index to evaluate the allocation of its resources to its member countries. IDA is a part of the World Bank that supports the world's poorest countries. The Resource Allocation Index is a composite index that reflects a country's resource needs, taking into account poverty levels, economic performance, and other factors. This index helps IDA determine the level of support it should provide to a country in the form of grants and concessional loans. Specifically, the formula used is:

$$\begin{aligned} &Allocation\ share \\ &= Population * \left(\frac{GNI}{population}\right)^{-0.125} \\ &* (0.24CPIA_{A-C} + 0.68CPIA_{D} + 008Portfolio)^{3} \end{aligned}$$

where GNI is gross national income; CPIA is country policy and institutional assessment, which is an assessment of a country's policies and institutions consisting of a series of pillars (A-D); and Portfolio refers to the country's portfolio rating in the World Bank's Annual Report on Portfolio Performance.

5.4. STRATEGIC PLANNING TOOL

Crisis protection gap information can help support responding organisations to plan and position resources in advance of crises. Information about the relative size and likelihood of response needs and costs could help organisations to manage limited resources. Given the medium term time horizon of this work (as discussed in section 2.2), organisations could use crisis protection information to undertake financial planning on the likely future scale of their activity, and how it may be distributed around the world and in responding to different crisis types. It could also help inform fundraising strategies.

There are tools that provide some of these insights, but not the full range that crisis protection gap information would provide. For example, the INFORM risk index helps highlight relevant risk types at national and subnational levels. However, these risk indices do not provide estimates of the expected levels of funding that will be needed. Similarly, predictive information on food security from FEWS NET is updated regularly (see Box 6) – this type of risk information is useful for real-time operational planning. However, while this information could in theory be modified to estimate impacts and costs, it does not currently provide a fully probabilistic estimate of expected annual response costs. The horizon of forecasts is also near-term seasonal, whereas the objective of this research is to understand methods that can form predictions of outcomes over a 1–5-year timescale.

22 https://ida.worldbank.org/en/financing/resource-management/ida-resource-allocation-index

Box 6: Famine Early Warning Systems Network[23]

FEWS NET, the Famine Early Warning Systems Network, is a leading provider of early warnings and analysis on acute food insecurity around the world.

Created in 1985 by USAID in response to devastating famines in East and West Africa, FEWS NET provides unbiased, evidence-based analysis to governments and relief agencies that plan for and respond to humanitarian crises. The network also analyses support resilience and development programming. FEWS NET analysts and specialists work with scientists, government ministries, international agencies and NGOs to track and publicly report on conditions in the world's most food-insecure countries.

For strategic planning applications, the characteristics of the underlying modelling would be similar to the allocation framework. In particular, it would need to have a geographic and risk coverage that was broadly consistent with the organisation's mandate and operating model.[24] Users would need to be confident that the analysis provided an accurate relative assessment of crisis protection needs across different risks and countries; given resource-constrained budgets of responder organisations, the absolute value of crisis protection needs may be less important. The greatest difference may be in relation to the extent to which modelling analysis could be easily scrutinised. As the tool would be used for decision-making, the key requirement is that organisations using it were confident that it provided reliable, unbiased and decision-relevant information. This could be satisfied in a number of ways – for instance, through some sort of quality assurance process. The ability to scrutinise the specific workings and data inputs into the modelling may be less important, especially as the tool may incorporate proprietary information to enable planning.

5.5. DESIGN TOOL

Information on crisis protection needs, costs and gaps could be used to help design specific instruments that aim to close the crisis protection gap. As described below, the approach that has been explored to estimate the crisis protection gap draws heavily on risk-modelling techniques that are common in the (re)insurance sector. This implies that crisis protection gap information could therefore be relevant when these insurance tools are being developed.

Indeed, crisis protection needs and gap information have been used in this way in several instances. Box 7 explores how Africa RiskView has been used to inform the development and purchase of risk transfer policies that are intended to help African countries respond to crisis protection needs caused by droughts.

23 https://fews.net/about-us

24 For example, some responder organisations may place greater attention on reconstruction rather than recovery activities.

Box 7: Africa RiskView[25]

The objective of Africa RiskView (ARV) is to estimate the number of people affected by a drought event during a rainfall season and then the dollar amount necessary to respond to these affected people in a timely manner. To do this, ARV translates satellite-based rainfall information into near real-time impacts of drought on agricultural production and grazing using existing operational early warning models; by then overlaying these data with vulnerability information, the software produces a first-order estimate of the drought-affected population, and in turn response cost estimates. This analysis is made available to policyholders and other interested stakeholders.

The requirements of the modelling underpinning the assessment of crisis protection needs in this instance are quite specific:

- In this use case, the design feature of greatest importance is that any analysis captures crisis protection needs and costs in the particular geography and in relation to a particular risk as accurately as possible. This is the information that will allow parties in a potential transaction to understand its potential implications and whether it represents good value for money. By contrast, there is little need for information that might facilitate a comparison of different risks and/or a comparison of the same risk across many different geographies.
- In a similar way to the strategic planning use case, while it is important that all parties involved in the design and sale of the instrument consider the analysis of crisis protection needs to be reliable and trustworthy, this can be achieved in various ways. It is unlikely to be necessary for all parties involved in the transaction to be able to scrutinise all aspects of the modelling (although some functionality to be able to test critical assumptions is likely to be important).

5.6. DISCUSSION

An assessment of crisis protection costs or the crisis protection gap could be helpful in a broad range of potential applications. These range from highly specific design tools, similar to those used by the (re)insurance sector to measure and manage risk, to global-level tools that seek to provide metrics that can be used to compare and monitor PAF levels against defined targets.

A host of technical tools have been developed to support PAF-related activities. Tools that have been developed to support operational planning or guide decisions could likely be adapted to estimate crisis response costs. Similarly, (re) insurance sector catastrophe models that are designed to price and manage insurance policies could be customised to measure the types of crisis response costs that are a priority in lower-income and fragile settings.

25 https://africariskview.org/Content/Technical-Note_en.pdf

However, none of these existing tools provide insights that closely match the specification set out in the guiding star. For example, catastrophe models typically focus more on estimating physical damage and repair costs, since this is relevant to property claims, whereas existing catastrophe models with a focus on response costs have a narrower geographic and sectoral focus than suggested in the guiding star. Likewise, the existing tools to support planning provide near-term and seasonal insights, rather than insights that would directly inform a 1–5-year strategic planning horizon.

Arguably, of the various use cases, the crisis protection monitor is the application where additional crisis protection gap information, of the type elaborated in the guiding star, could be most valuable. In contrast:

- Allocation frameworks typically involve making decisions over how to allocate a fixed budget between competing priorities. In these contexts, as the absolute budget is fixed (at least in the short term), it will often be sufficient for measures of relative risk (e.g. information about the number of people who might be exposed to various types of crisis) to inform decisions, with less need for absolute estimates of protection costs or gaps.
- Existing tools can already inform strategic planning tools, while organisations' mission and the judgement of leadership teams will determine organisations' overall strategic direction.
- Design tools may be able to make use of existing (re)insurance sector tools[26] and, as noted above, the comparative information on different crisis types and geographies envisaged in the guiding star will often be less relevant in this use case.

However, to develop a crisis protection monitor that covers all risks globally requires both resources and an institutional home. Both the technical feasibility assessment (section 3) and, in particular, the demonstration analysis (section 4) illustrate that while it should be feasible to develop such a monitoring tool, there are significant additional decisions to make and analysis to undertake; for example, in relation to refining cost estimates and linking costs to measures of people affected by crises. These conceptual issues, alongside operational issues such as how to develop and maintain the monitor, would all be managed by whichever entity takes responsibility for producing the information.

26 It should be noted that many of the existing (re)insurance sector tools that consider response costs assume that these will be a function of asset damage caused by a crisis. However, for many crisis types, such as drought, this is an inappropriate assumption. In other cases, it will very likely lead to a focus that gives little weight to the poorest and most vulnerable people.

6

SUMMARY OF RESEARCH FINDINGS

The research - both the conceptual analysis in section 3 and the demonstration analysis in section 4 - suggests five main conclusions:

- It is increasingly possible to generate forward-looking estimates of crisis protection costs and therefore gaps.
- Measuring crisis protection costs associated gaps requires design choices that should be made explicit.
- Use cases relating to drawing comparisons across different crisis types and across geographies are particularly salient – a common approach to defining and measuring exposure is critical when undertaking comparative assessments of different crisis types.
- Important conceptual and modelling challenges remain.
- Much better information on the costs of humanitarian action would be of considerable value.

Each of these are discussed in more detail below.

6.1 FORWARD-LOOKING ESTIMATES OF CRISIS PROTECTION COSTS

It is increasingly possible to generate forward-looking estimates of crisis protection costs and therefore gaps.

This report shows how crisis protection costs can be estimated by combining information on exposure, crisis events and response costs. This is a methodology that harnesses the techniques, knowledge and experience of the (re)insurance sector and applies it to the protection needs of the most vulnerable people. In this context, section 3 of the report demonstrates that:

- There has been significant growth in data sets that provide granular demographic information; and remote sensing and other geospatial tools that provide methods for estimating people's socioeconomic conditions and many of the factors that determine their vulnerability to crises.
- Forward-looking information on the likelihood of crisis events of different severities affecting particular communities is available, although methodologies and robustness vary significantly by crisis type. Information is most robust for certain climatological and geophysical crisis events, over which anthropological factors play very little or no role in determining whether specific events arise and their physical characteristics (e.g. tropical cyclones and earthquakes). In other cases, such as droughts or internal displacement, analytical approaches are advancing, but have to contend with various challenges that can be harder to capture within modelling frameworks.

- Information on the cost of crisis response, and the factors that affect this, can be obtained from a combination of top-down and/or bottom-up analyses. While important gaps and conceptual challenges are associated with both methodologies (as discussed below), there is a clear direction of travel for generating more robust cost analysis over time.

The demonstration analysis reinforces this finding. Tropical cyclone analysis, in particular, showed how the different modules of the conceptual model can be combined to provide estimates of crisis protection costs for responding to tropical cyclones and how these costs may vary across countries (see Table 3 and Figure 11) or the range and probability of possible crisis response costs that might be expected across all developing countries in any one year (Figure 11).

The combination of individual elements within the conceptual model also provides useful insights. Most notably, combining the exposure and hazard modules – but excluding the cost module – will provide forward-looking estimates of the number of people who might be affected by different crises (of varying severities). This in itself could be valuable in, for example, making decisions about how to allocate a fixed budget between different countries or risks (see section 5.1).

This analysis has focused on how to estimate total crisis protection costs - estimating the gap requires incorporating information about current amounts of PAF. The Centre is currently undertaking analysis on developing a methodological approach to this task and applying it to the current landscape of crisis financing. However, the relatively small amount of finance that has been pre-positioned to support crisis response and recovery means that estimates of crisis protection costs are easily the most important driver of the crisis protection gap.

6.2 MEASURING CRISIS PROTECTION COSTS AND GAPS

Measuring crisis protection costs and gaps requires design choices that should be made explicit.

Research shows that the appropriate way to measure the crisis protection costs and gaps depends on both:

- users' interests and values and, in particular, what and whose needs following a crisis event users want to understand
- the decisions that the crisis protection information will inform.

In terms of users' interests and values, the focus of the report has been on the needs and associated costs of the most vulnerable people in the immediate aftermath of a crisis event. This reflects how crises disproportionately affect the lives and livelihoods of the most vulnerable people, and that PAF is most valuable in meeting immediate post-crisis response needs. Depending on one's interests, other definitions may legitimately be used. Given this multiplicity of possible methodological approaches, it is crucial for estimates of crisis protection costs to be explicit in the approach they have taken. Moreover, the greatest value will come from maintaining the same methodological approach over time and locations, providing a consistency that allows stakeholders to understand trends.

The demonstration analysis on tropical cyclones illustrates the importance of being explicit about these decisions. Figure 11 shows the crisis protection needs of different countries exposed to tropical cyclone risk. If crisis protection is defined in terms of the overall number of people affected, China and the Philippines are the two countries with the greatest needs, each accounting for around 25% of the total. To measure crisis protection needs in terms of the economic activity that could be affected, if the number of people is weighted by average GDP per capita, then China is easily the most important at risk country, accounting for over 50% of the aggregate protection gap needs under this metric. However, if the focus is instead only on the crisis protection needs of people living on less than USD2.15/day, then Madagascar and Haiti move from countries that barely register when using the other two metrics to being the countries with the highest crisis protection needs. Alternative definitions lead to fundamental differences in the understanding of where crisis protection needs are greatest.

Even when a consistent definition has been agreed on, different techniques for generating crisis protection costs and gaps may be more or less appropriate, depending on how information will be used. The examples in Table 5 illustrate how different applications warrant different technical approaches. In one use case, crisis protection costs might be used to help inform the design of a specific PAF instrument. In this case, accuracy in estimating protection costs is of primary importance. Ensuring comparability with analyses in other geographies or for risks not covered by the instrument will be of little importance. In another use case, crisis protection costs might be used to support a crisis protection monitor (i.e. as an input into a tool to advocate for more PAF and/or a different allocation). In this case, a modelling approach that emphasises comparability across risks and geographies will be a primary consideration, even if this sacrifices accuracy in specific applications, as will the ability to easily understand, scrutinise and update analysis of crisis protection costs with alternative assumptions.

6.3 COMMON APPROACH TO DEFINING AND MEASURING EXPOSURE

A common approach to defining and measuring exposure is critical when undertaking comparative assessments of different crisis types.

Many use cases for crisis protection costs and gaps will require information that allows comparisons between different crisis types. For example, the crisis protection monitor use case discussed above would allow users to explore differences in crisis protection costs or gaps so they could draw conclusions regarding whether current allocations of PAF are optimal. Likewise, crisis protection information used within an allocation framework or to support operational decision-making will often inform funding allocations or support organisations to change their internal resource allocations between crisis types.

Comparative crisis-type assessments require use of a common exposure module. While comparisons between different crisis types are inherently challenging,[27] it can be made much simpler if analyses apply the same exposure data. This allows users to be confident that they are comparing the impacts of different crisis types, and the protection needs and costs that they create, with a common understanding of what and whose needs following a crisis event users want to understand. The exposure module therefore provides the 'glue' that facilitates comparison across crisis types that can have very different impacts.

27 As noted below, a key remaining challenge relates to calibrating what it means to be 'affected' by a crisis.

6.4 CONCEPTUAL AND MODELLING CHALLENGES

Important conceptual and modelling challenges remain.

Although the work demonstrates that estimating crisis protection costs and gaps is increasingly feasible, a large number of challenges remain where continued work will be required. The discussion below focuses on four key areas where more work is required (excluding issues related to cost estimation, which are detailed separately in section 5.1).

First, for each specific crisis type, there can be challenges in calibrating what it means for people to be 'affected' by a crisis. The two hazards considered in the demonstration analysis illustrate how these challenges differ across crisis type. In the case of tropical cyclones, it is generally clear how to define an event as each storm has a clear start and end point in time and geographic location. In this case, a key challenge in defining 'affectedness' centres on picking thresholds (e.g. windspeed) above which people are considered to be affected. At the other end of the spectrum, defining a drought event is much more challenging. A wide range of data may be required to enhance the types of modelling used in the demonstration analysis, including considering whether the threshold(s) of what it means to be 'affected' by drought might vary by location or at different points in the year. For all crisis types, there will be value in exploring whether affectedness is better captured as a binary indicator or if it would be better to consider degrees of affectedness, which both the physical characteristics of the event and the vulnerability of the people exposed to that event might affect.

The challenge of determining affectedness becomes even more difficult when undertaking comparative assessments of crisis protection costs and gaps. There is a risk that the modeller might determine that a particular crisis type is a much bigger driver of crisis protection costs than another crisis type in a particular location; when, in fact, this result is driven by using a much lower threshold for determining what it means to be affected by the first crisis type than the second. As discussed in section 2.3 there should be ways to make use of the information in historical emergency appeals to infer estimates of what these appeals have implicitly determined as a threshold for affectedness that necessitates a crisis protection response. However, the wide range of factors that help to shape emergency appeal requests may make this analysis challenging, as the implicit thresholds for what determines affectedness may vary widely across crises in different locations and over time.

A second key area requiring more work concerns the need to improve understanding of the numbers and locations of vulnerable people. As discussed in section 3.2, these data sets can be improved in important ways. This includes ensuring that data sets fully account for displaced people and refugees if they are not reflected in underlying census or survey data. It also includes improvements in techniques used to understand the socioeconomic characteristics of people in different locations.

A third area relates to capturing (time-varying) drivers of vulnerability currently excluded from the analytical approach. The conceptual discussion and related demonstration analysis focused on understanding key demographic characteristics of the people affected (e.g. age, gender) and estimates of their socioeconomic condition, using their estimated income levels as a proxy. However, a wide range of other factors that are not reflected in these dimensions also determine vulnerability. They include other demographic variables (e.g. health and disability) and wider socioeconomic factors partly or wholly excluded from income statistics (e.g. food prices or the extent to which people can sustainably rely on natural ecosystems for food and other provisioning services). A further modelling challenge relates to capturing the impacts of compounding events; people suffering from a crisis event that has happened in the recent past will be more vulnerable if there is a subsequent event in the near future. Compounding events may also increase response costs. Better analysis of all these factors will provide a more holistic understanding of crisis protection costs.

A final area where it will be particularly valuable to continue to develop analytical approaches to improve understanding of crisis protection costs and gaps concerns improving forward looking estimates of some hazards. For example, as discussed above, it can be difficult to generate forward-looking estimates of droughts and their impacts due to challenges in event definition, and because people may be affected by the consequences of droughts even if they are not located in the area that has directly suffered droughts. The frequency and intensity of a wide range of hazards will also be heavily influenced by climate change. The integration of climate science with conventional approaches for modelling the probability and severity of hazards is only in its infancy (Bertogg 2021).

Particular challenges are associated with those hazards where human factors determine intensity of impact. This applies, for instance, to the interrelated challenges of food insecurity driven by non climatological factors and conflict-related displacement. In relation to both these hazards, path dependency[28] means that the approaches used for modelling most natural hazards – where it can be assumed that the probability of a hazard event happening in the future is independent of whether there has been an event in the recent past – is less relevant.

In relation to both, there have been impressive developments in recent years. For example, the World Bank has undertaken important work using different methodological approaches to generate predictions of future food insecurity (Wang et al. 2020). Likewise, the Danish Refugee Council (DRC n.d.) has developed models to predict population movements, an area that UNHCR and the Violence Early Warning System (based at the Department of Peace and Conflict Research at Uppsala University) are also actively exploring.

These approaches and others have significantly advanced the ability to predict future crisis events. But generating accurate predictions of significant changes from or jumps in trends seen in the recent past is particularly challenging. In these cases, it is plausible that traditional humanitarian support will be relatively more important than PAF, which will meet a smaller proportion of crisis protection needs. Conversely, PAF is likely to be particularly valuable for those crises and crisis types that are inherently more predictable.

28 The fact that a critical determinant of whether the hazard will be observed in the future is whether the hazard existed (and how intense it was) in the past.

6.5 INFORMATION ON THE COSTS OF HUMANITARIAN ACTION

Much better information on the costs of humanitarian action would be of considerable value.

Ensuring access to cost data, then using this data wisely to undertake robust and credible costing analysis, appears to be the biggest challenge that the international community will need to overcome if it means to develop its understanding of crisis protection costs. The analysis presented in section 3, then used in the tropical cyclone component of the demonstration analysis in section 4, demonstrates that, even today, top-down costing analysis can provide useful insights on the costs and cost drivers associated with international humanitarian response efforts to meet crisis protection needs.

This work, and similar analysis other organisations have undertaken, provides a platform on which more sophisticated efforts can build. As discussed above, a short-term priority for this work is to address the methodological disjoint between the number of people who may be affected by a crisis and the number of people targeted in a humanitarian response to that crisis.

Over time, further development of top-down methods needs to contend with a range of challenges. These include considering:

- whether existing international humanitarian response efforts can be considered to offer a sufficiently high-quality response for the purposes of assessing protection needs, costs and gaps
- whether political economy factors may shape appeal requests in a way that makes them an unreliable measure of appropriate response costs
- whether humanitarian efforts have focused too much on crisis response and insufficiently on crisis preparedness, with the risk that estimating crisis protection needs and costs on this basis may lead to flawed cost predictions
- whether there is a need to account for the extent to which different crises differentially affect those with complex needs in a way that materially drives response cost differences
- whether to include the impacts of compounding events and the best methodological approach for this.

It would be valuable to complement top-down costing efforts with bottom-up costing analyses. In principle, this type of approach may make it easier to capture the costs of national responders and understand whether and in which circumstances they offer a more cost-effective approach for meeting crisis protection needs. In principle, a bottom-up approach could also help address some of the challenges described above, especially on issues around quality, political economy biases, and the appropriate balance between preparation and response costs. However, questions remain over accessing the data that could support such analysis, which would also need to be conducted carefully to ensure that any results could be applied across a range of different geographic contexts.

ANNEX 1: FURTHER DETAILS ON TOP-DOWN COSTING ANALYSIS

A.1.1 MODEL SELECTION

The costing analysis had three main objectives: (1) to identify the variables that contribute to the variation in the costs of responding to humanitarian crises; (2) to quantify the relationships between the identified variables and response costs; and (3) to predict future costs using the quantified relationships.

To achieve this goal, a predictive model was developed to identify the relationship between predictor variables and costs. It was decided to use a simple regression model rather than more advanced machine learning models – the former being inherently interpretable and easier to implement, although the latter may provide greater predictive accuracy. However, subsequent work could use machine learning models to validate the results.

Among the various regression models, the statistical characteristics of the data[29] led to the use of a *generalised linear model*, which is equivalent to applying an ordinary linear regression model to a transformed (i.e. logarithmic) version of the data, as explained in section A.1.2. A *backward stepwise strategy* was used to select the significant predictor variables. First, a comprehensive model – inclusive of all predictor variables in Table A.1 – was fitted to the data and then non-significant predictors were successively eliminated until all the remaining predictors were significant (p-value < 0.05).[30]

Once the significant predictors were identified, *interaction terms* between numerical predictors were also tested and included in the model if significant. An interaction between two predictors occurs when the effect of one predictor on the response variable depends on the value of another predictor. For example, testing whether there is an interaction between the level of poverty (or fragility) and the amount requested per person targeted would provide an understanding of whether the relationship between the amount requested per person targeted changes in countries with higher or lower levels of poverty (or fragility).

29 The response variables' distribution belongs to the family of exponential dispersion models. In this study, the amount requested follows an exponential distribution.

30 When the dummy variables corresponding to the different levels of a categorical variable were associated with p-values > 0.05, an F-test for the overall significance of the categorical variable was conducted by comparing the model with and without its inclusion.

A.1.2 DATA SETS

The model was fitted to the data estimated from two different data sets as explained in the main report: the IFRC data set (514 crises in the period 1995–2022)[31] and the FTS+ data set (250 data points: 96 from the Central Emergency Relief Fund database and 154 from the FTS database, in the period 2005–2022).

A.1.2.1 PREDICTOR AND RESPONSE VARIABLES

The variables considered relevant for predicting the cost of humanitarian crises are summarised in Table A.1. Both data sets were augmented with additional variables representing levels of poverty and fragility in relation to the country and year in which a humanitarian crisis occurred. Specifically, poverty levels were represented by the poverty gap at USD1.90/day (2011 PPP) reported by the World Bank, which is defined as the average (mean) shortfall in income or consumption from the poverty line USD1.90/day, expressed as a percentage of the poverty line.[32] Due to the presence of multiple missing values in the poverty gap data set, the poverty gap data sets were compiled using fuzzy logic, where the last available poverty gap value for a country was used to fill missing values for successive years. The level of fragility was represented by the sum of the Fragile State Indices for different sectors, based on the Conflict Assessment Framework.[33]

TABLE A.1: PREDICTOR VARIABLES

Predictor variable	Definition
Num_people_targeted	Number of people targeted to received support to mitigate a crisis
Disaster_type_name	Type of disaster (crisis) that triggered a crisis
Region_label	World region in which the crisis occurred (i.e. Africa, Americas, Asia Pacific, Europe, Middle East and North Africa)
Interarrival_time	Years between successive crises triggered by the same crisis type and in the same region
Poverty_gap	Poverty gap at USD1.90/day (2011 PPP)
Fragility_tot	Sum of sector-related Fragile State Indices

Note: numerical variables in bold italics. In the data analysis, the term 'disaster' is used in relation to the labelling of some of the variables; elsewhere, the report uses the term 'crisis'. These terms should be considered interchangeable. Also, in the IFRC data extract, the analysis uses the field 'num_beneficiaries'.

31 https://go.ifrc.org/appeals/all; the complete data set contained 3,549 data points in the period 1919-2022. However, data points recorded before 1995 were discarded. The remaining 1,458 data points in the period 1995-2022 were considered for the analysis. Of these, 514 were emergency appeals, 942 were Disaster Response Emergency Fund (DREF) appeals and two were international appeals. DREF and international appeals were discarded from the data set: DREF appeals have an upper ceiling on the amount disbursed and would lead to bias in the results; international appeals are only represented by two data points.

32 https://databank.worldbank.org/metadataglossary/world-development-indicators/series/SI.POV.GAPS.D

33 https://fragilestatesindex.org/indicators

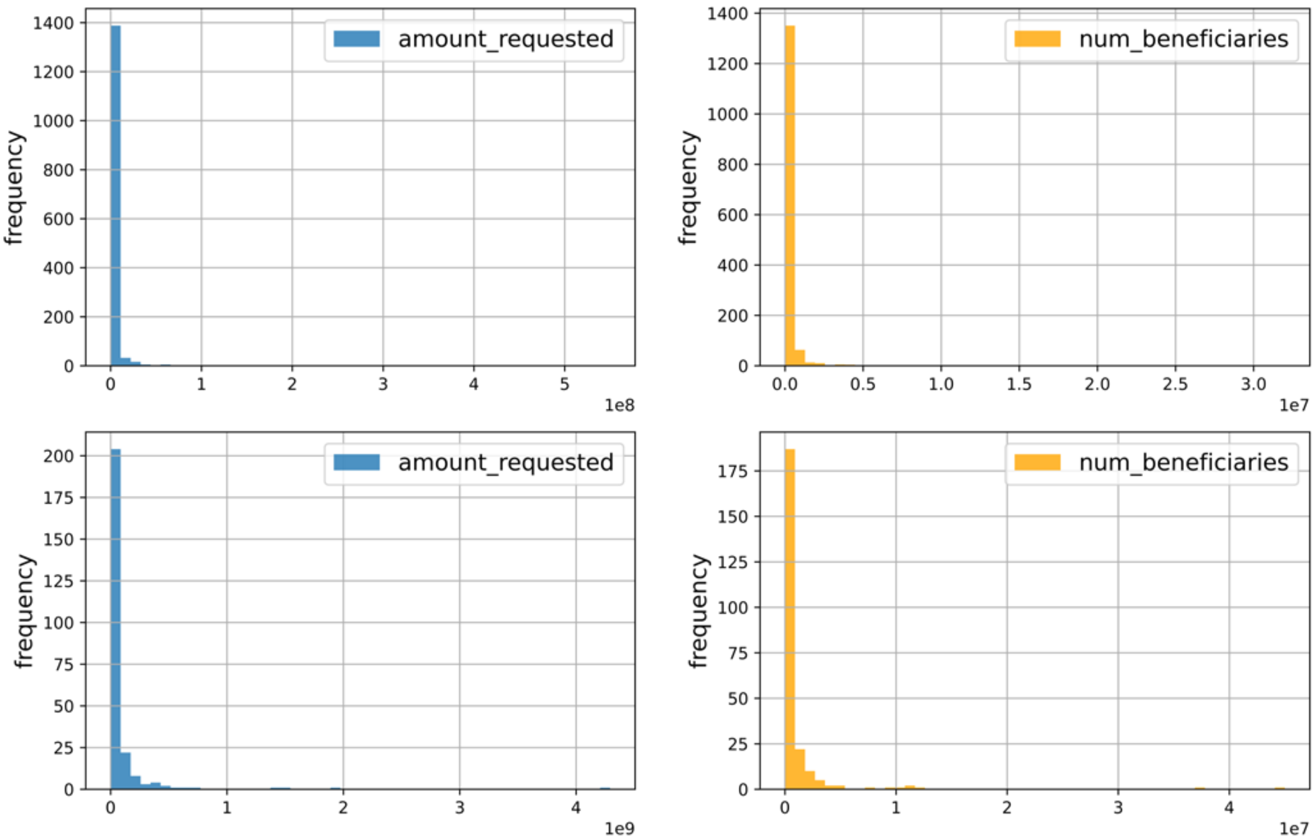
In both data sets, the cost of humanitarian crises could be associated with two variables; namely, the amount requested and the amount funded (measured in CHF in the IFRC data set and in USD in the FTS+ data set). The analysis used the amount requested as the response (dependent) variable, recognising that a wider range of other factors, which were not included in the data sets, may affect the amount funded.

A.1.2.2 DATA PREPARATION

Variable normalisation

In both data sets, num_people_targeted and amount_requested had a highly skewed distribution, with a relatively low mode and a heavy right tail (Figure A.1). To normalise the data, the natural logarithm of these variables was used in the regression model (i.e. num_people_targeted_log and amount_requested_log) (Figure A.2).

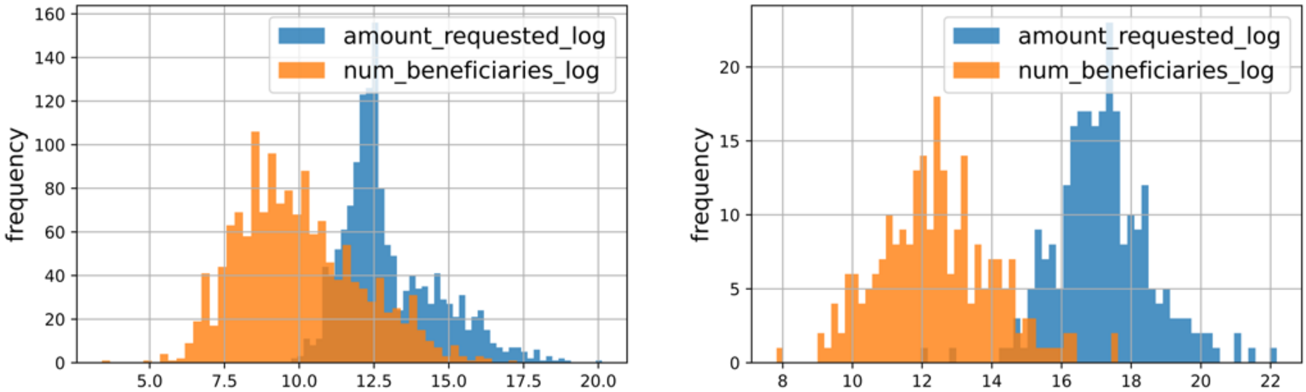
FIGURE A.1: SKEWED DISTRIBUTIONS OF VARIABLES



Source: Centre for Disaster Protection, based on data from IFRC (n. d.) and FTS (2023).

Note: skewed distributions of the variables in the IFRC data set (top row) and FTS+ data set (bottom row).

FIGURE A.2: NORMALISED DISTRIBUTIONS OF LOG-TRANSFORMED VARIABLES



Source: Centre for Disaster Protection, based on data from IFRC (n. d.), FTS (2023) and Fund for Peace (n. d.).

Note: normalised distributions of the log-transformed variables in the IFRC data set (left) and FTS+ data set (right).

Data numerosity check

To ensure the robustness of the model against outliers, the number of data points for each crisis type was checked, and crisis types with insufficient data points (i.e. fewer than 25 data points for the IFRC data set and fewer than four data points for the FTS+ data set) were included in the 'other' crisis type. The thresholds of 25 and four data points were chosen to obtain consistent sample sizes across crisis types.

Time series analysis

A timeseries analysis was performed on the numerical variables num_people_targeted_log and amount_requested_log. The statistical analysis showed the presence of a positive trend in both variables and co-integration of the two variables (i.e. they showed a similar trend). This suggested that the predictor variable was already correcting for any trend in the response variable, without the need for further de-trending of the timeseries.

Outlier detection

Outliers were identified in both data sets after fitting the regression model using Cook's distance criterion.[34] The results of this analysis revealed the presence of one outlier in the IFRC data set and two outliers in the FTS+ data set. Due to the relatively small sample in the FTS+ data set, the presence of outliers had a significant effect on the model coefficients; therefore, the outliers were removed from this data set.

Missing values treatment

Both data sets had values missing, resulting in 35 incomplete data points in the IFRC data set and 46 in the FTS+ data set, which were discarded for the analysis. A total of 479 data points in the IFRC data set and 204 data points in the FTS+ data set were used to fit the model.

34 The Cook's distance criterion measures the effect of excluding a given observation from the fitted model. Observations with a high Cook's distance have a high influence in determining the model.

A.1.3 RESULTS AND INTERPRETATION

The generalised linear model was fitted to the two data sets separately using ordinary least squares.

A.1.3.1 IFRC DATA SET-FITTED MODEL

The model fitted to the IFRC data set-fitted model (Table A.2) was able to explain 52.8% of model variability, as indicated by the R-squared statistics, based on 479 observations. The analysis revealed that the three statistically significant variables were: disaster_type_name (in some cases), num_people_targeted_log and poverty_gap. The interaction terms were not significant.

TABLE A.2: IFRC DATA SET-FITTED MODEL

Predictor variable	Coefficient	Standard error	p-value	Confidence interval	
				[0.025	0.975]
Intercept***	8.680	0.407	0.000	7.882	9.480
Disaster_type_name [cold wave]	-0.247	0.411	0.548	-1.054	0.560
Disaster_type_name [cyclone]	-0.295	0.273	0.281	-0.832	0.242
Disaster_type_name [drought]	-0.675	0.301	0.025	-1.267	-0.085
Disaster_type_name [earthquake]	0.379	0.293	0.197	-0.197	0.955
Disaster_type_name [epidemic]***	-2.281	0.311	0.000	-2.892	-1.670
Disaster_type_name [flood]*	-0.631	0.259	0.015	-1.139	-0.122
Disaster_type_name [food insecurity]	-0.403	0.296	0.175	-0.985	0.179
Disaster_type_name [other]*	-0.646	0.297	0.030	-1.230	-0.062
Disaster_type_name [pluvial/flash flood]	0.438	0.702	0.533	-0.941	1.816
Disaster_type_name [population movement]	-0.371	0.277	0.181	-0.916	0.174
Disaster_type_name [volcanic eruption]	-0.401	0.591	0.498	-1.562	0.760
Num_people_targeted_log***	0.601	0.029	0.000	0.544	0.657
Poverty_gap*	-0.009	0.004	0.028	-0.016	-0.001

Model statistics	
R-squared	0.528
Adj. R-squared	0.515
F-statistic	39.980
Prob (F-statistic)	0.000
Log-likelihood	-636
AIC	1300
BIC	1359
No. observations	479
Df residuals	465

Note: number of stars denotes the significance level of the variable; p-values: * = < 0.05, ** = < 0.01, *** = < 0.001.

A.1.3.2 FTS+ DATA SET-FITTED MODEL

The model fitted to the FTS+ data set-fitted model (Table A.3) explained 43.3% of the model variability, as indicated by the R-squared statistics, based on 204 observations. Analysis showed that three significant variables were: disaster_type_name (in some cases), num_people_targeted_log and fragility_tot. The interaction terms were not significant.

TABLE A.3: FTS+ DATA SET-FITTED MODEL

Predictor variable	Coefficient	Standard error	p-value	Confidence interval	
				[0.025	0.975]
Intercept***	11.046	0.677	0.000	9.710	12.381
Disaster_type_name [cyclone]	-0.267	0.230	0.246	-0.721	0.196
Disaster_type_name [drought]	-0.095	0.222	0.671	-0.532	0.343
Disaster_type_name [earthquake]	0.252	0.300	0.403	-0.341	0.844
Disaster_type_name [epidemic]***	-1.689	0.259	0.000	-2.799	-1.179
Disaster_type_name [flood]***	-0.712	0.198	0.000	-1.102	-0.321
Disaster_type_name [other]**	-0.753	0.288	0.010	-1.320	-0.186
Num_people_targeted_log***	0.379	0.043	0.000	0.295	0.464
Fragility_tot***	0.022	0.006	0.000	0.011	0.033
Model statistics					
R-squared	0.433				
Adj. R-squared	0.411				
F-statistic	19.460				
Prob (F-statistic)	0.000				
Log-likelihood	-279				
AIC	576				
BIC	607				
No. observations	204				
Df residuals	8				

Note: number of stars denotes the significance level of the variable; p-values: * = < 0.05, ** = < 0.01, *** = < 0.001.

A.1.3.3 COEFFICIENT INTERPRETATION

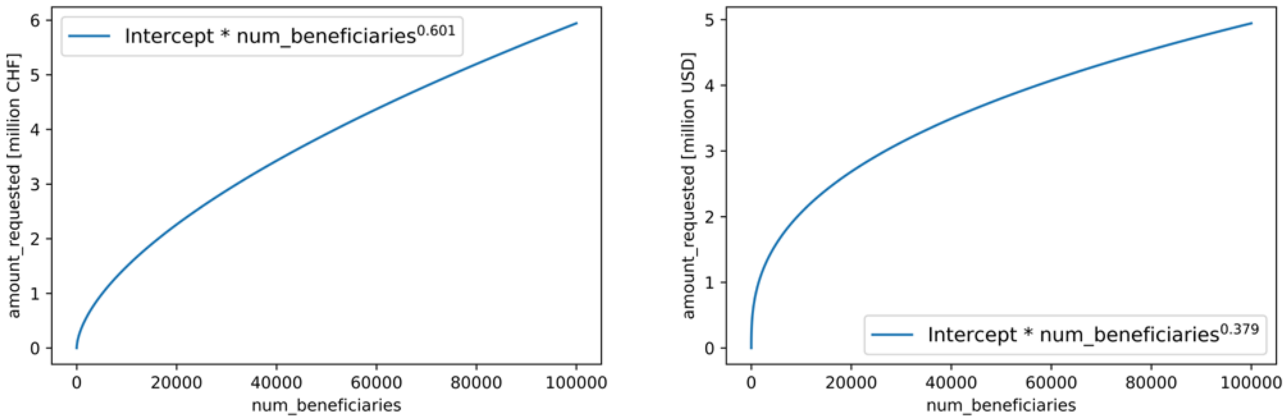
The regression models provide coefficient estimates related to the logarithm of amount_requested and num_people_targeted. To provide a real-world interpretation, it is necessary to apply an exponential transformation. Applying the transformation results in a multiplicative (exponential) model with the equation:

amount_requested = exp[intercept + a] num_people_targetedb exp[c poverty_gap (or fragility_tot)]

Where a, b, and c are the coefficients of the predictors disaster_type_name, num_people_targeted and poverty_gap (or fragility_tot).

In both data sets, amount_requested increased with num_people_targeted, as shown in Figure A.3, but at a decreasing rate due to the exponent being below one. Specifically, a 10% increase in num_people_targeted resulted in a 6% increase and 3.8% increase in amount_requested for the IFRC and the FTS+ data sets, respectively.

FIGURE A.3: EFFECT OF NUMBER OF PEOPLE TARGETED ON AMOUNT REQUESTED

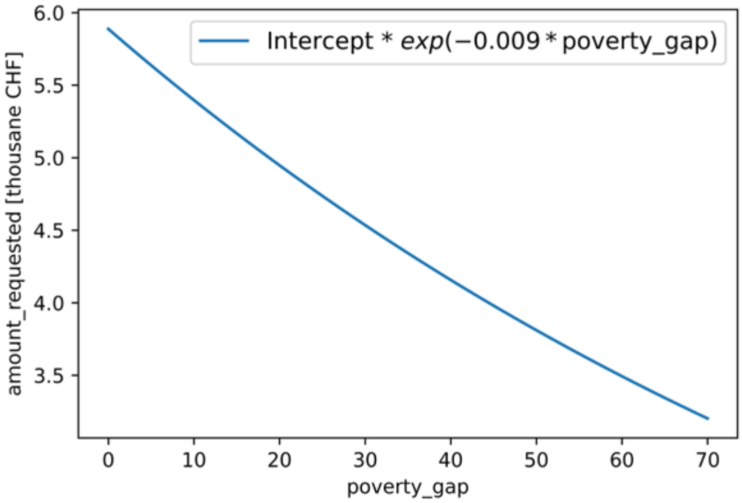


Source: Centre for Disaster Protection, based on data from IFRC (n. d.) and FTS (2023).

Note: effect of the number of people targeted on the amount requested according to the IFRC data set-fitted model (left) and the FTS+ data set-fitted model (right).

For the model fitted with the IFRC data set, amount_requested decreased with poverty_gap, as shown in Figure A.4. Specifically, a one-unit increase in poverty_gap resulted in a 1% decrease in amount_requested, while a 20-unit increase in poverty_gap resulted in a 16% decrease in amount_requested. This counter-intuitive result could be due to the imbalance of the data sample, in which data points with high poverty_gap values were under-represented. It is worth noting that there is a relatively low significance level for this variable.

FIGURE A.4: EFFECT OF POVERTY GAP ON AMOUNT REQUESTED

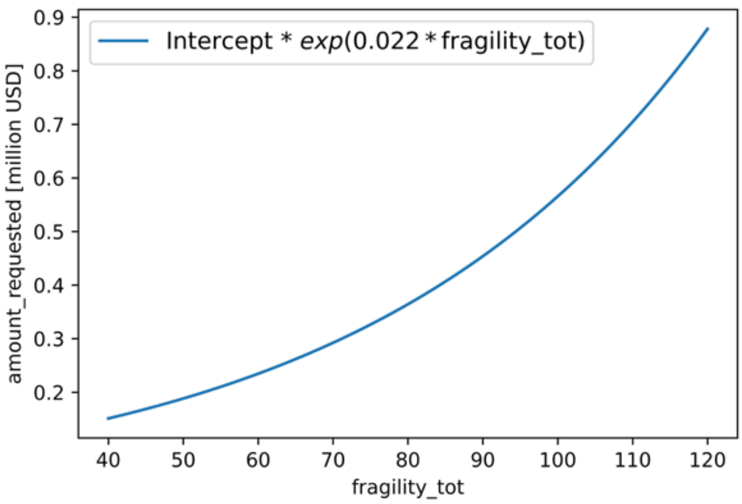


Source: Centre for Disaster Protection, based on data from IFRC (n. d.) and World Bank (2023).

Note: effect of the poverty gap on the amount requested (assuming one person targeted) according to the IFRC data set-fitted model.

For the model fitted with the FTS+ data set, amount_requested increased with fragility_tot, as shown in Figure A.5. Specifically, a one-unit increase in fragility_tot resulted in a 2% increase in amount_requested, while a 20-unit increase in fragility_tot resulted in a 55% increase in amount_requested.

FIGURE A.5: EFFECT OF FRAGILITY ON AMOUNT REQUESTED



Source: Centre for Disaster Protection, based on data from FTS (2023) and Fund for Peace (n. d.).

Note: effect of fragility on the amount requested (assuming one person targeted) according to the FTS+ data set-fitted model.

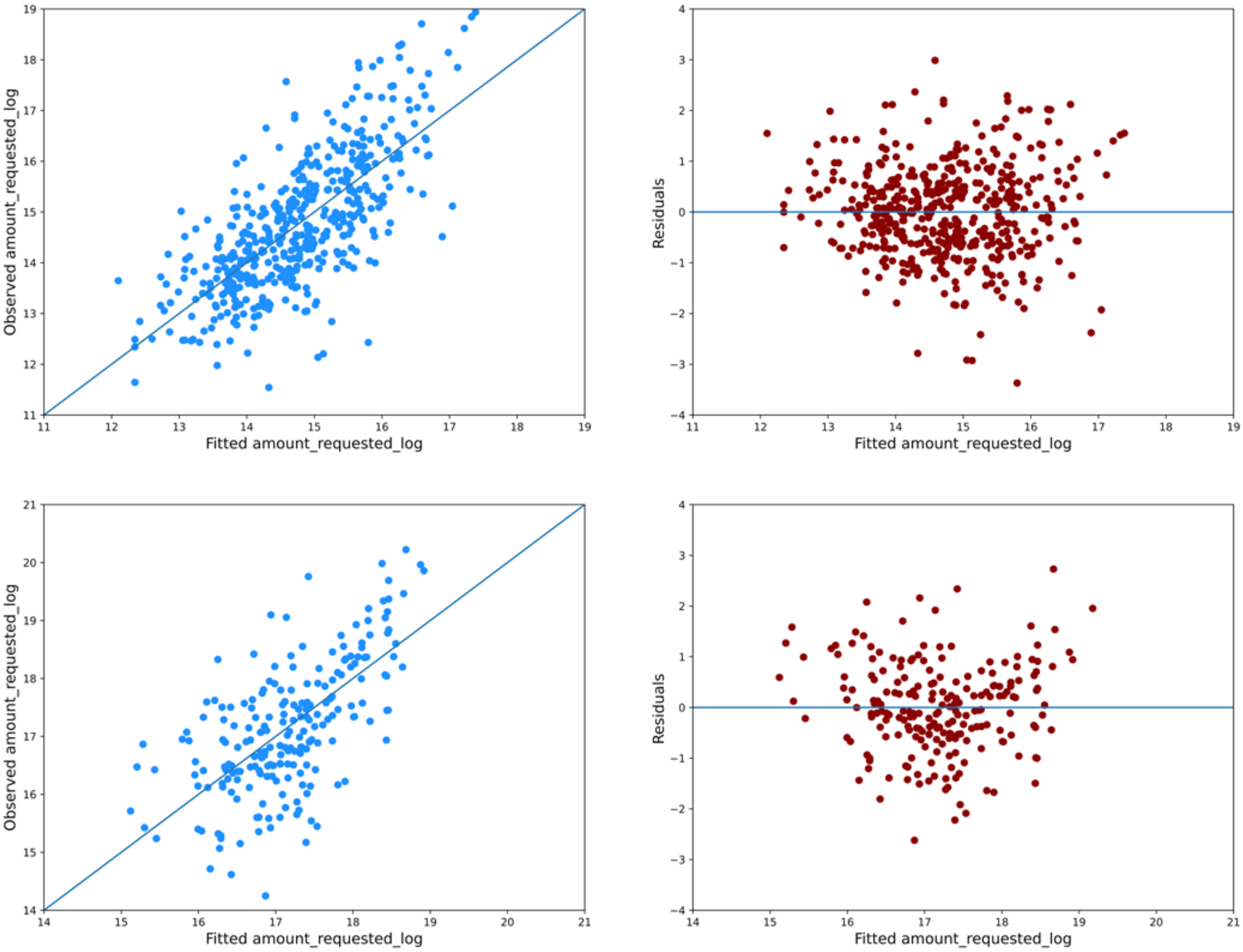
A.1.4 ROBUSTNESS TESTS

To test the robustness of the fitted models, visual and statistical analyses were performed to check for (1) anomalous behaviour of the residuals; (2) non-collinearity of the predictor variables; (3) normality of the residuals; and (4) homoscedasticity of the residuals.

A.1.4.1 ANOMALOUS BEHAVIOUR OF THE RESIDUALS

The residuals should be independent and identically distributed random error terms. This means that the residuals do not have any explanatory power over the response variables. In our analysis, the residuals did not show any correlation (i.e. explanatory power) with the response variables (Figure A6).

FIGURE A.6: DISTRIBUTION OF RESIDUALS



Source: Centre for Disaster Protection, based on data from IFRC (n. d.) and FTS (2023).

Note: distribution of the residuals over the response variable for the IFRC data set-fitted model (top) and the FTS+ data set-fitted model (bottom).

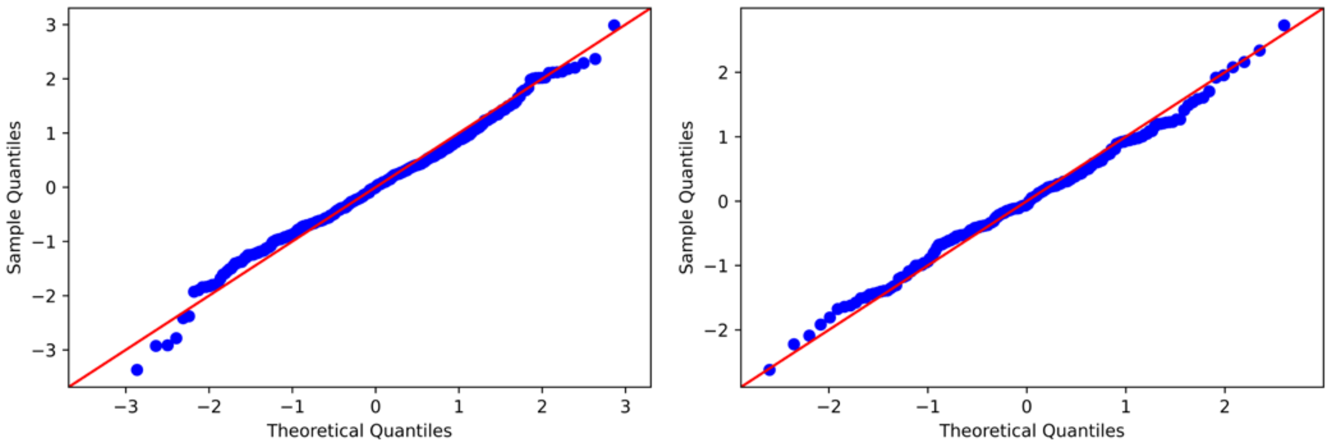
A.1.4.2 NON-COLLINEARITY OF PREDICTOR VARIABLES

Non-collinear predictor variables ensure that each variable adds new information to explain the response variable without adding noise to the model. Statistical analysis showed there was no collinearity between the predictor variables (the Pearson correlation coefficient was 0.08 between num_people_targeted_log and poverty_gap for the model fitted with the IFRC data set and 0.19 between num_people_targeted_log and fragility_tot for the model fitted with the FTS+ data set).

A.1.4.3 NORMALITY OF THE RESIDUALS

Normally distributed residuals ensure that the errors cancel each other out. In addition, standard normally distributed residuals (i.e. mean = 0; standard deviation = 1) ensure that the estimated model output is close to the actual response. In our analysis, the residuals were normally distributed as shown by the QQ-plots (Figure A.7) and the statistical analysis (Jarque-Bera test and Omni test for normality returned p-values > 0.05).

FIGURE A.7: QQ-PLOTS OF RESIDUALS



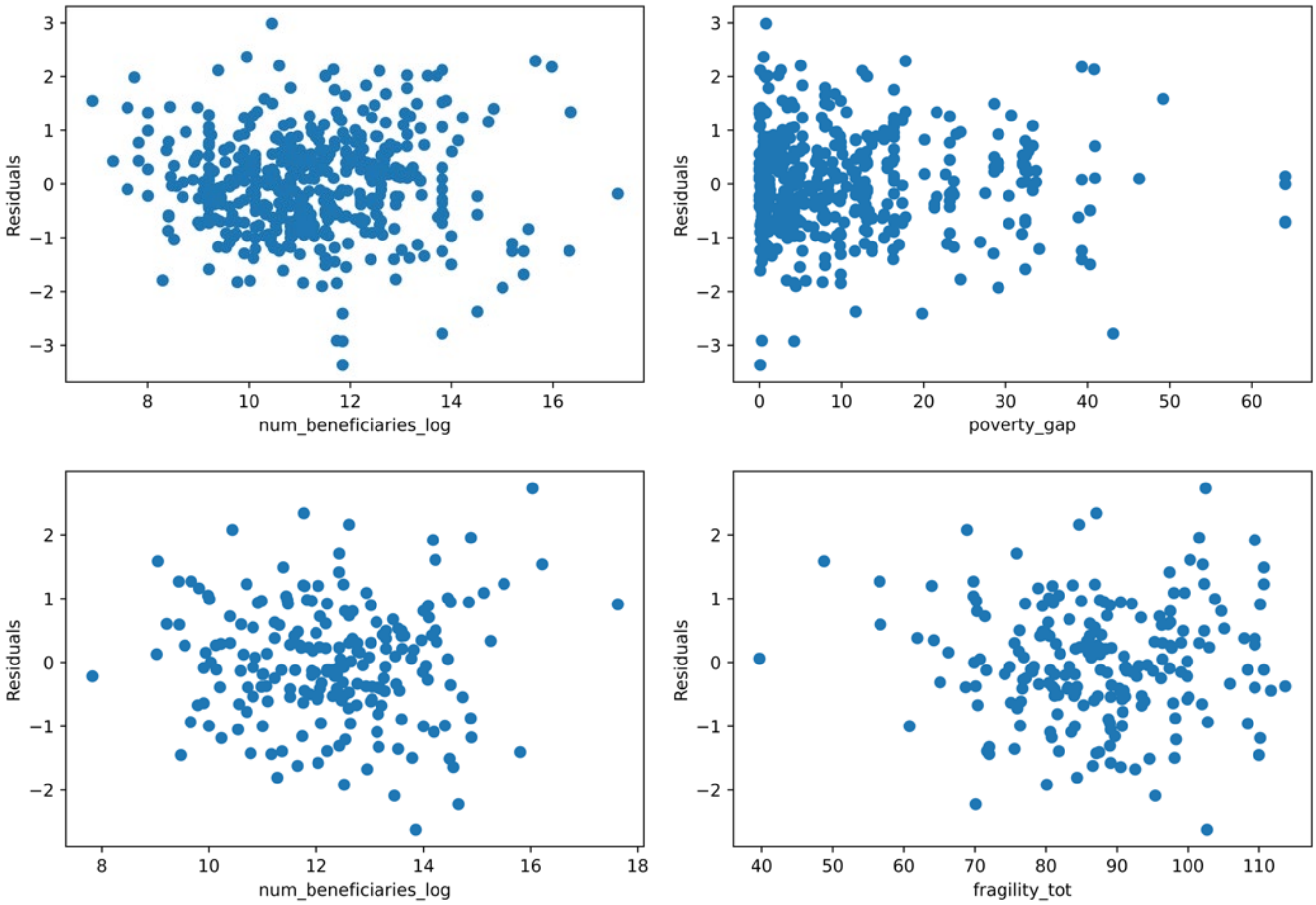
Source: Centre for Disaster Protection, based on data from IFRC (n. d.) and FTS (2023).

Note: QQ-plots of the residuals for the IFRC data set-fitted model (left) and the FTS+ data set-fitted model (right).

A.1.4.4 HOMOSCEDASTICITY OF RESIDUALS

Homoscedasticity (equal spread) of the residuals ensures that the model is equally accurate across the range of the predictor variables and that predictions do not deteriorate as the values of the predictors increase or decrease. In our analysis, the residuals were homoscedastic as shown by the plots in Figure A.8 and the statistical analysis (Goldfeld-Quandt test returned a p-value > 0.05).

FIGURE A.8: DISTRIBUTION OF RESIDUALS OVER PREDICTOR VARIABLES



Source: Centre for Disaster Protection, based on data from IFRC (n. d.), FTS (2023), and Fund for Peace (n. d.).

Note: distribution of the residuals over the predictor variables for the IFRC data set-fitted model (top) and the FTS+ data set-fitted model (bottom).

ANNEX 2: FURTHER DETAILS ON DROUGHT DEMONSTRATION ANALYSIS

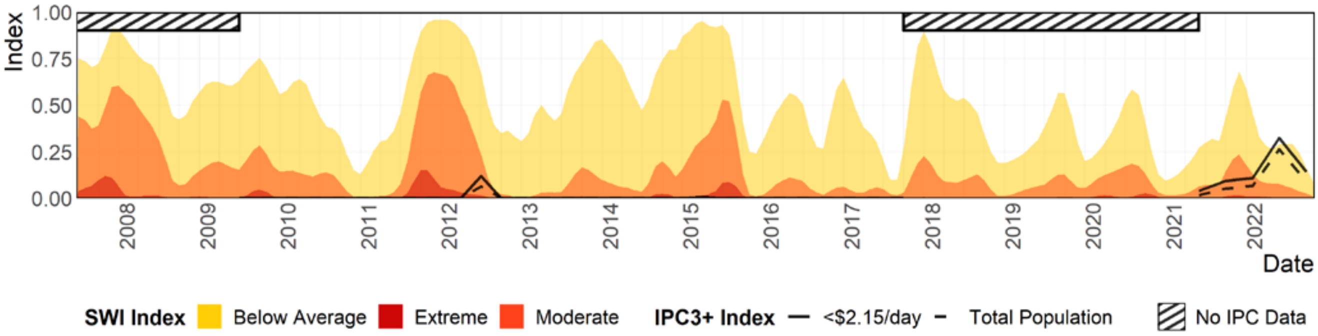
A.2.1 CALCULATION OF SOIL WATER INDEX INDICES

1. Raw measurements of the SWI globally between 2007 and 2022 were obtained from the Copernicus Global Land Service. This data set comprises satellite-derived SWI measurements at a resolution of 0.1 degrees at 10 daily intervals across a range of characteristic time periods. The demonstration analysis used the data corresponding to a characteristic time length of 40 days.
2. The raw SWI data was mapped to the global 0.05-degree grid used in the demonstration analysis.
3. For each grid, the average and standard deviation of SWI values was calculated for each 10 day period (dekad) within the year.
4. Using the mean and standard deviation at each location, the SWI value timeseries were converted into standard scores.
5. The number of days between each dekad were calculated, with the final dekad of each month varying based on the length of the month.
6. For each grid across all the countries considered, the number of days over a rolling three month period for which the standard scores were at or below 0, –1 and –2 was calculated.
7. The number of days below each threshold was converted into an index by taking a percentage of the total days over each rolling three-month period. The percentage of days below standard scores of 0, –1 and –2 represent the below average, moderate and extreme SWI index, respectively, for each grid.
8. To calculate the index at the country level, the total number of days below each threshold was summed across all grids and divided by the total number of days in the three-month period multiplied by the overall number of grid cells in the country.

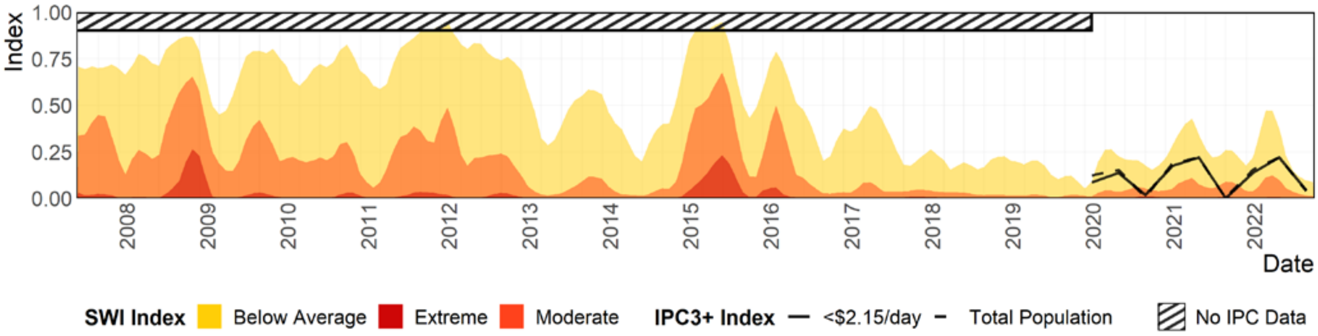
A.2.2 TIMESERIES OF SOIL WATER INDEX INDICES AND INTEGRATED FOOD SECURITY PHASE CLASSIFICATION 3+ INDEX

The following timeseries show the three SWI indices produced (using the methodology described in A.2.1 in the annex) against the percentage of population in each country categorised as being in IPC3+. Time periods for which no IPC data is available are indicated on each graph.

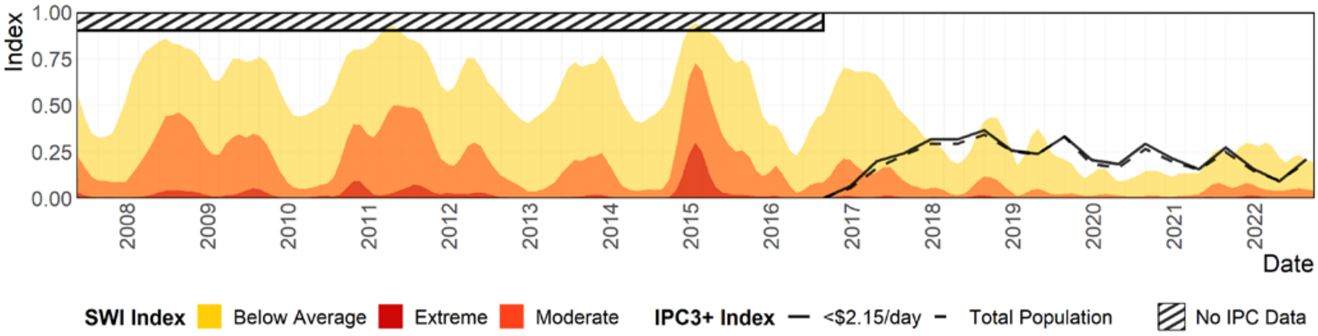
SWI and IPC indices - Burkina Faso



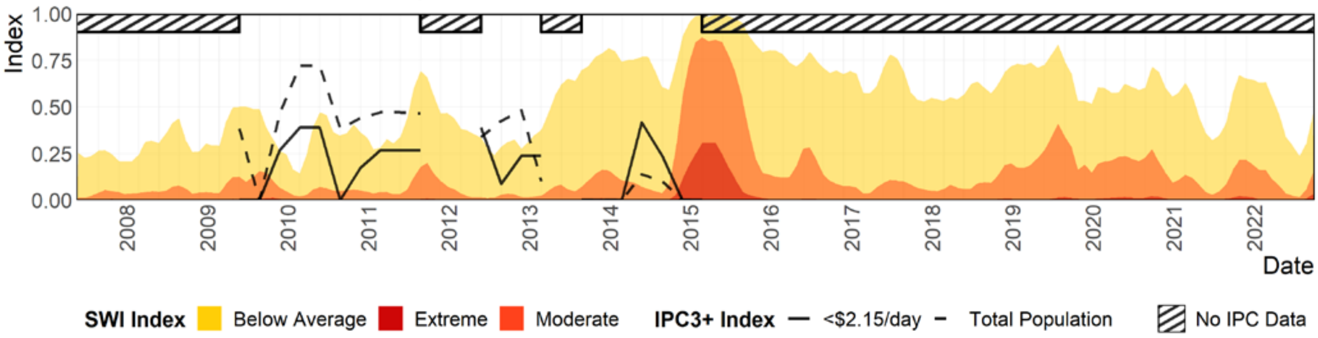
SWI and IPC indices - Cameroon



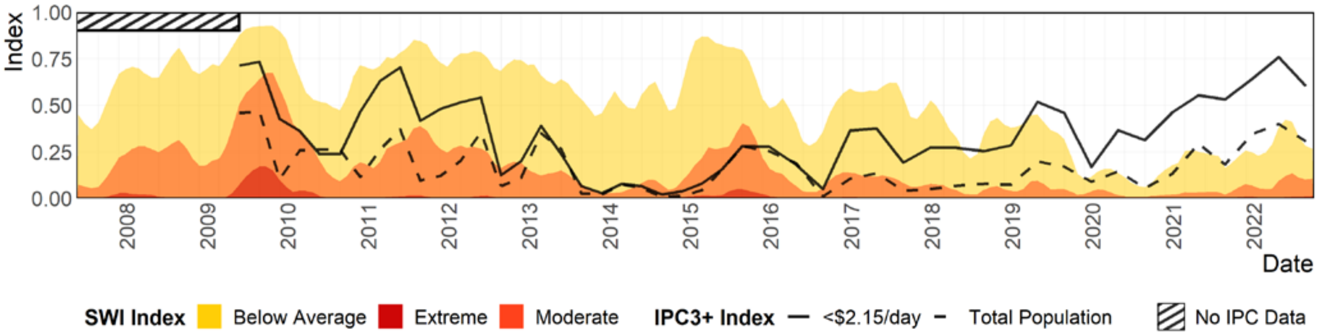
SWI and IPC indices - Congo - Kinshasa



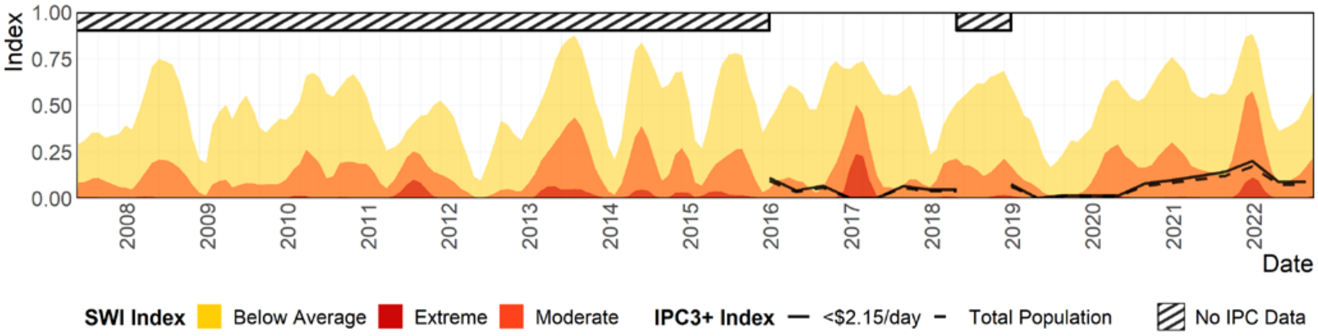
SWI and IPC indices - Djibouti



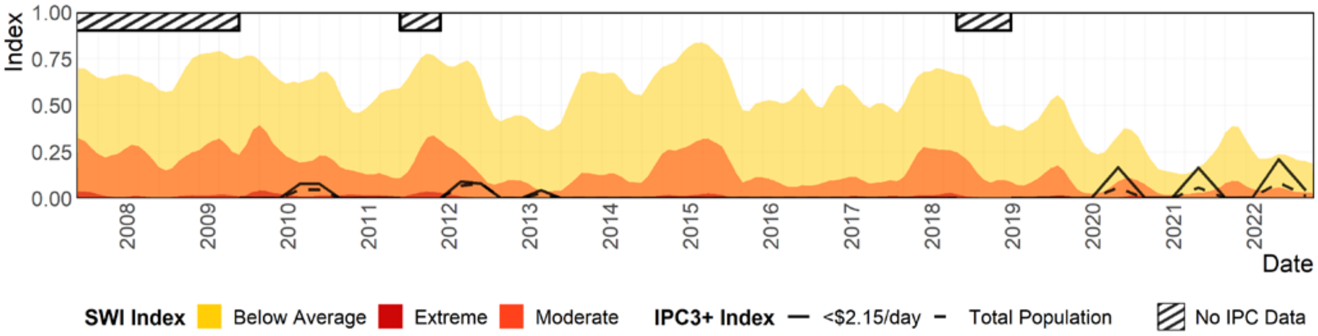
SWI and IPC indices - Ethiopia



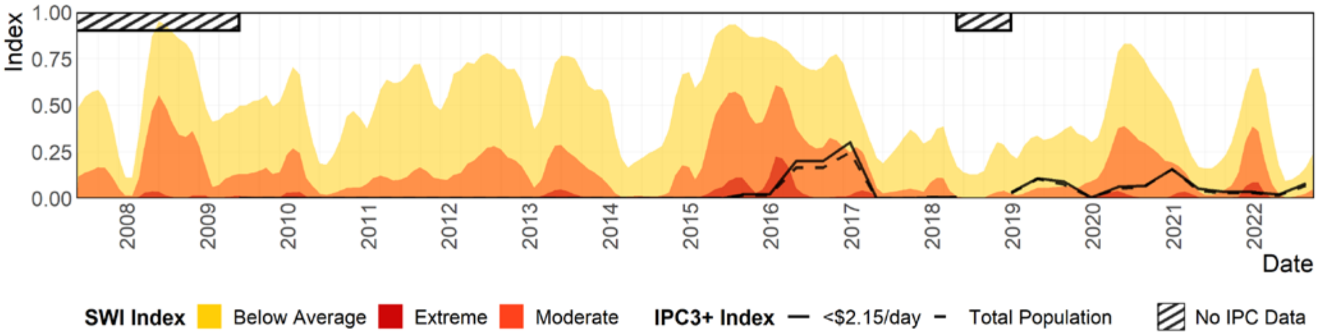
SWI and IPC indices - Madagascar



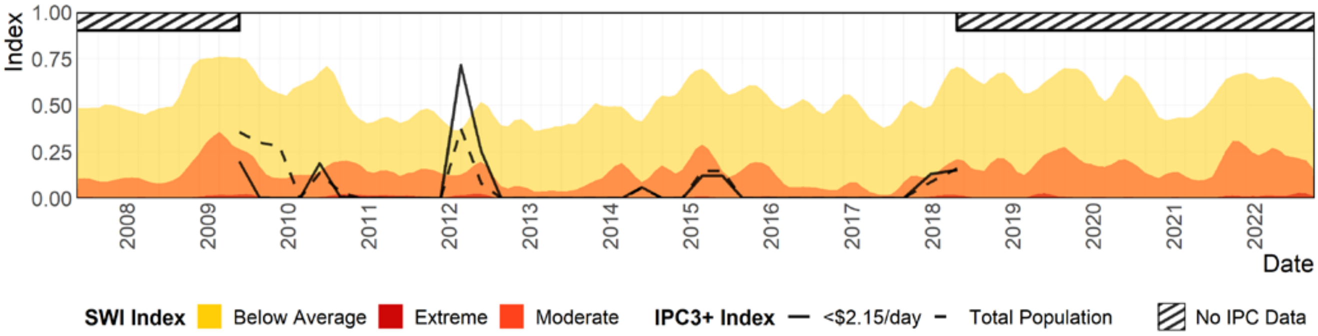
SWI and IPC indices - Mali



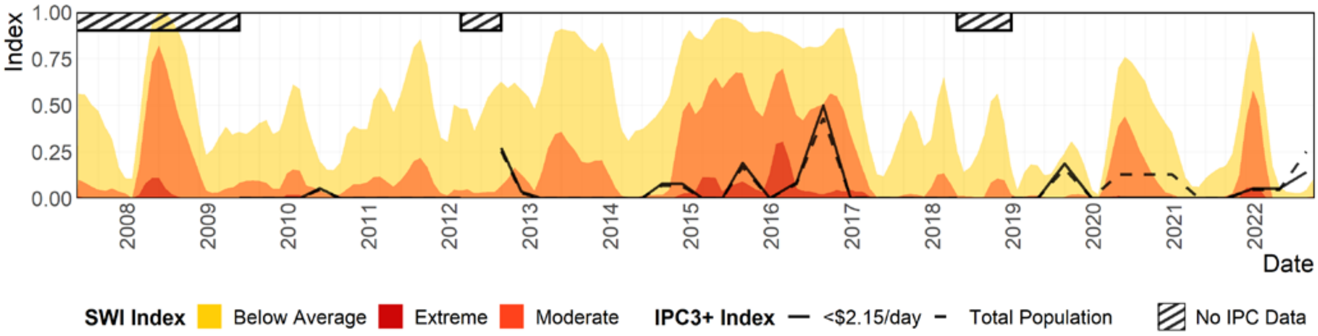
SWI and IPC indices - Mozambique



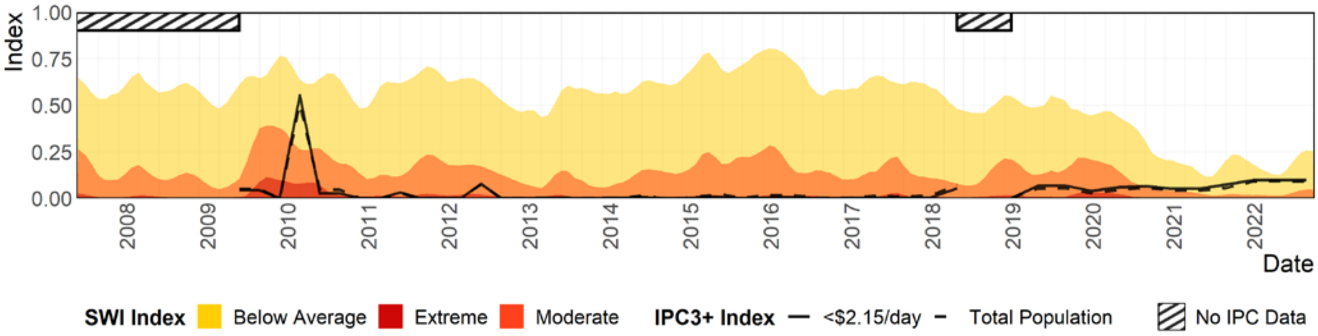
SWI and IPC indices - Mauritania



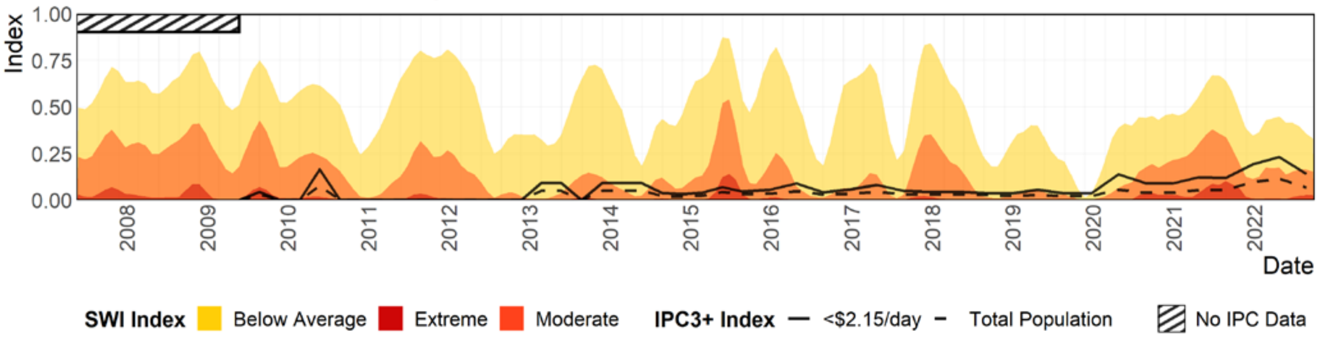
SWI and IPC indices - Malawi

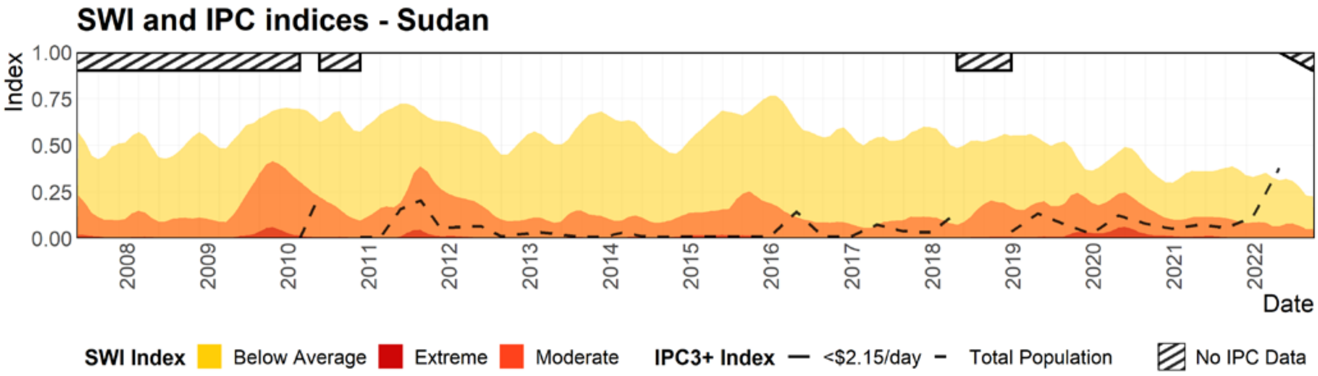


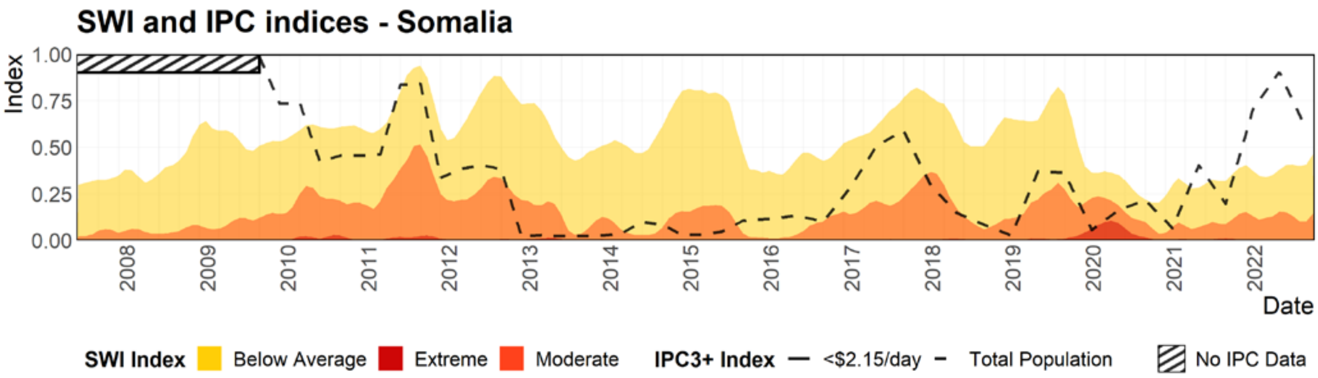
SWI and IPC indices - Niger

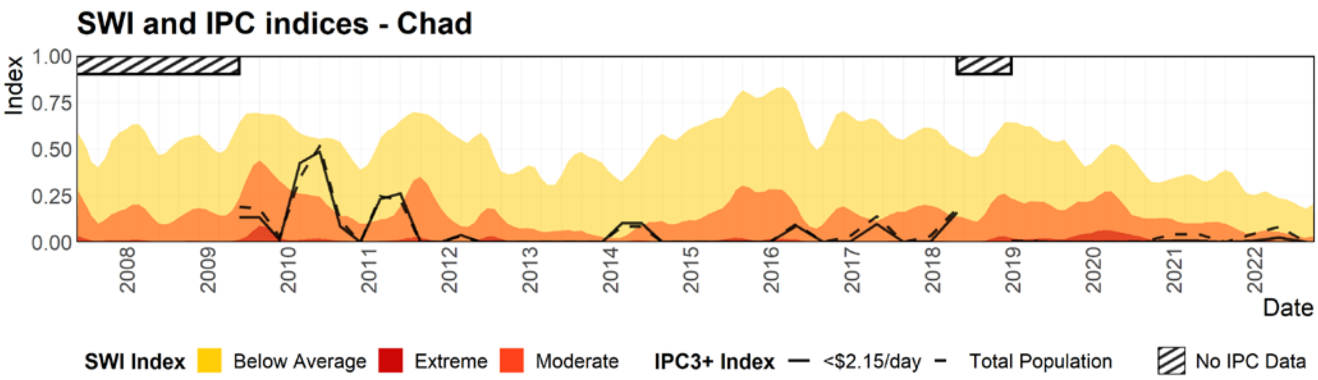


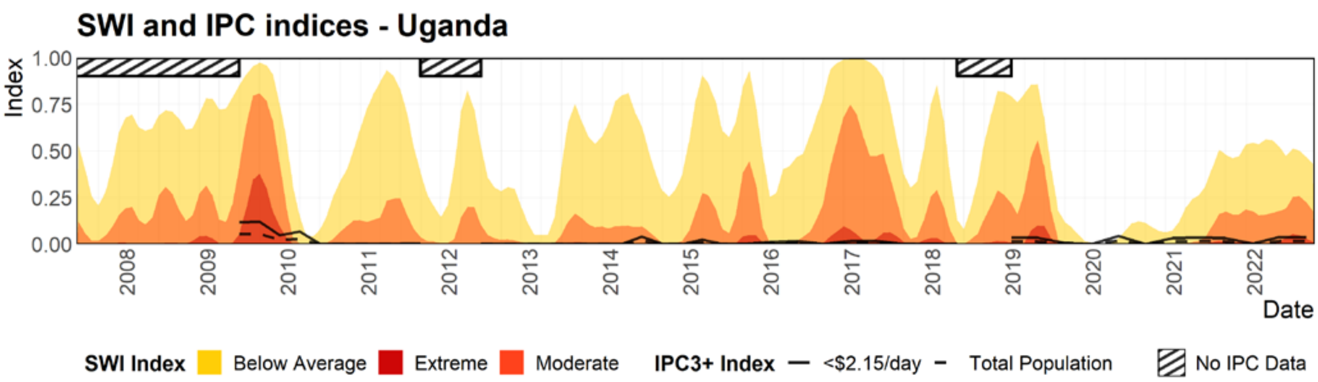
SWI and IPC indices - Nigeria

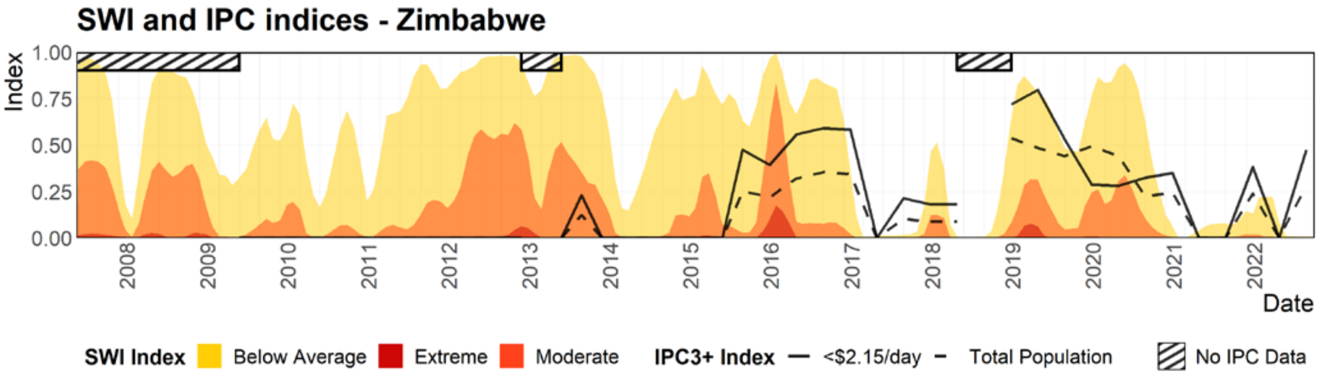



SWI and IPC indices - Sudan
Index
1.00
0.75
0.50
0.25
0.00
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
Date
SWI Index
Below Average
Extreme
Moderate
IPC3+ Index
<$2.15/day
Total Population
No IPC Data


SWI and IPC indices - Somalia
Index
1.00
0.75
0.50
0.25
0.00
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
Date
SWI Index
Below Average
Extreme
Moderate
IPC3+ Index
<$2.15/day
Total Population
No IPC Data


SWI and IPC indices - Chad
Index
1.00
0.75
0.50
0.25
0.00
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
Date
SWI Index
Below Average
Extreme
Moderate
IPC3+ Index
<$2.15/day
Total Population
No IPC Data

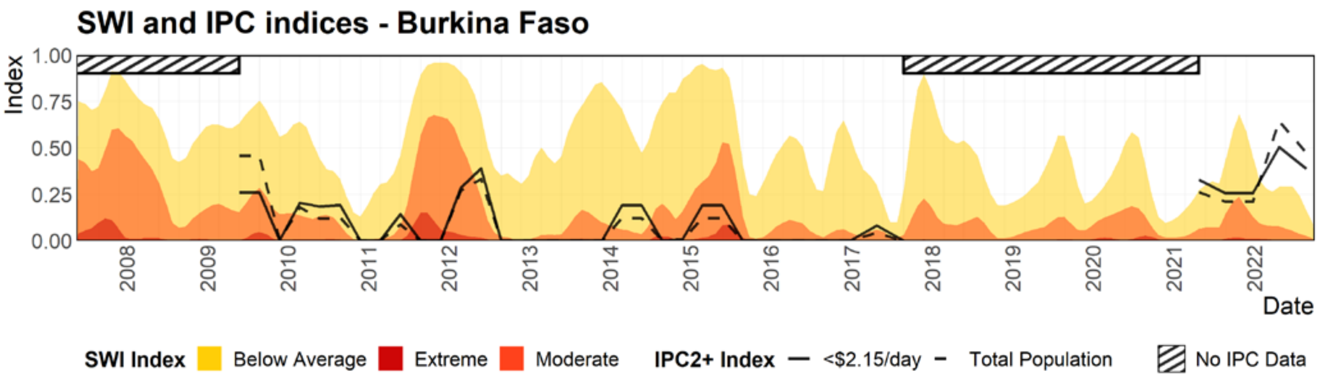

SWI and IPC indices - Uganda
Index
1.00
0.75
0.50
0.25
0.00
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
Date
SWI Index
Below Average
Extreme
Moderate
IPC3+ Index
<$2.15/day
Total Population
No IPC Data

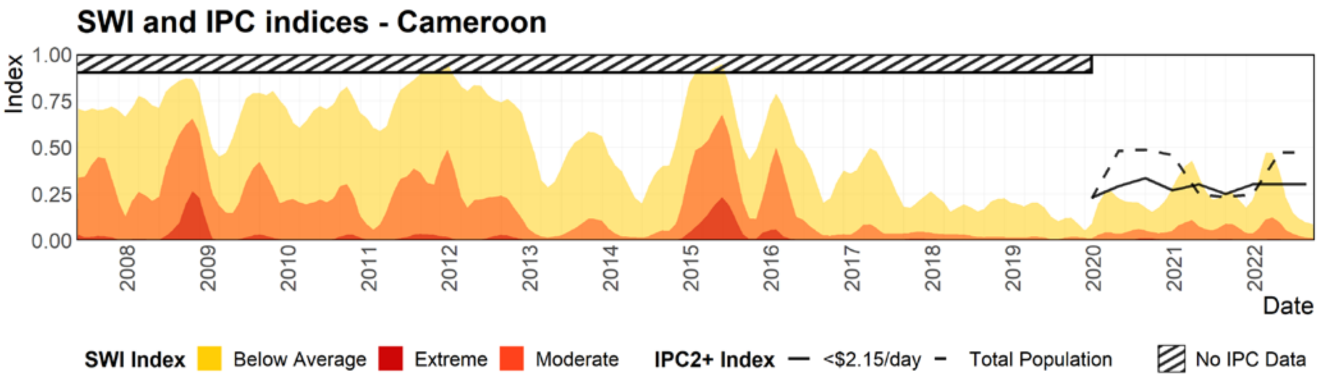


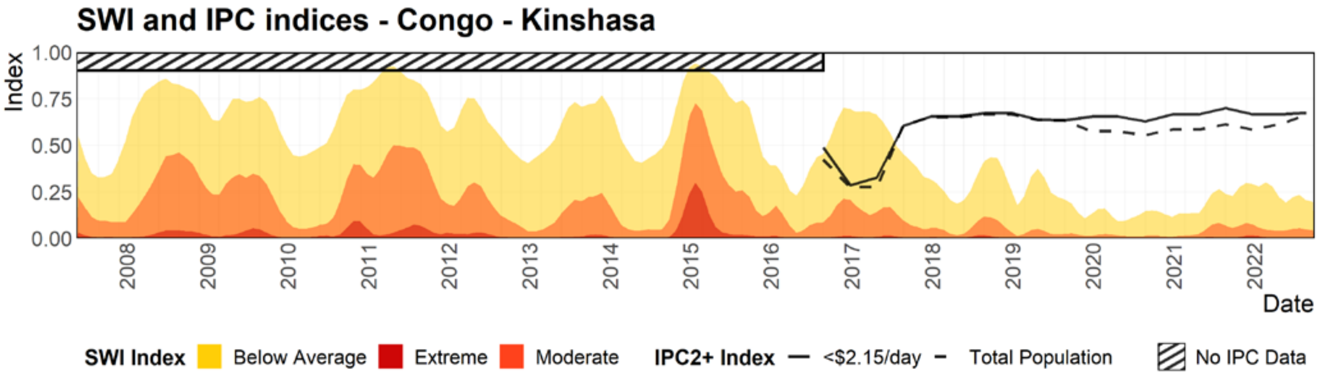
Source: Centre for Disaster Protection, based on SWI data from Copernicus (n. d. b), IPC data from FEWS NET (n. d. a.), and exposure data from WorldPop (n. d.), World Bank (n. d.) and Chi et al. (2022).

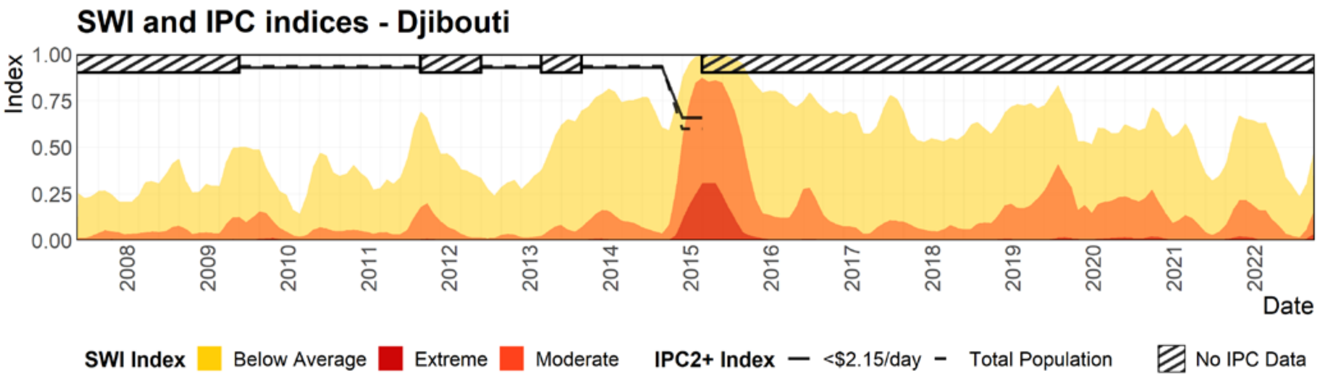
A.2.3 TIMESERIES OF SOIL WATER INDEX AND INTEGRATED FOOD SECURITY PHASE CLASSIFICATION 2+ INDEX

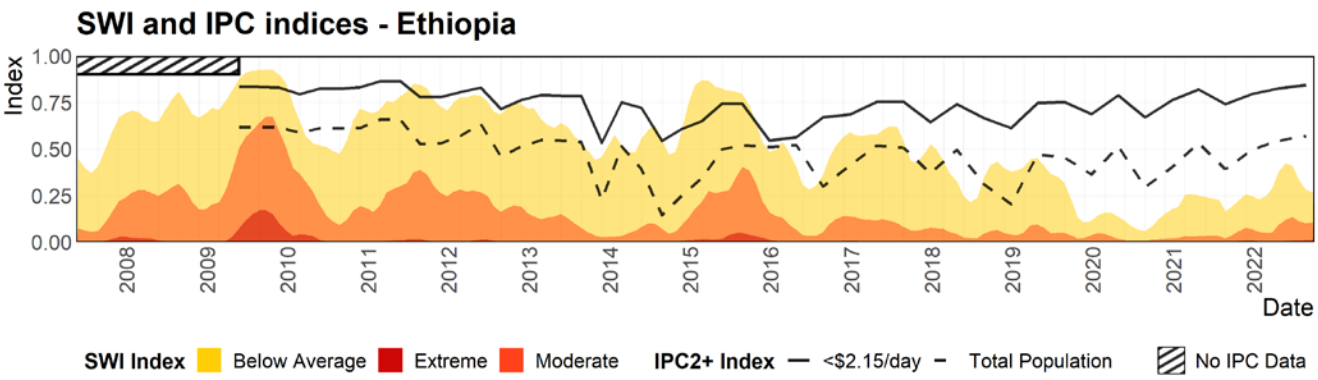
The following timeseries show the three SWI indices produced (using the methodology described in A.2.1) against the percentage of population in each country categorised as being in IPC2+. Time periods for which no IPC data is available are indicated on each graph.

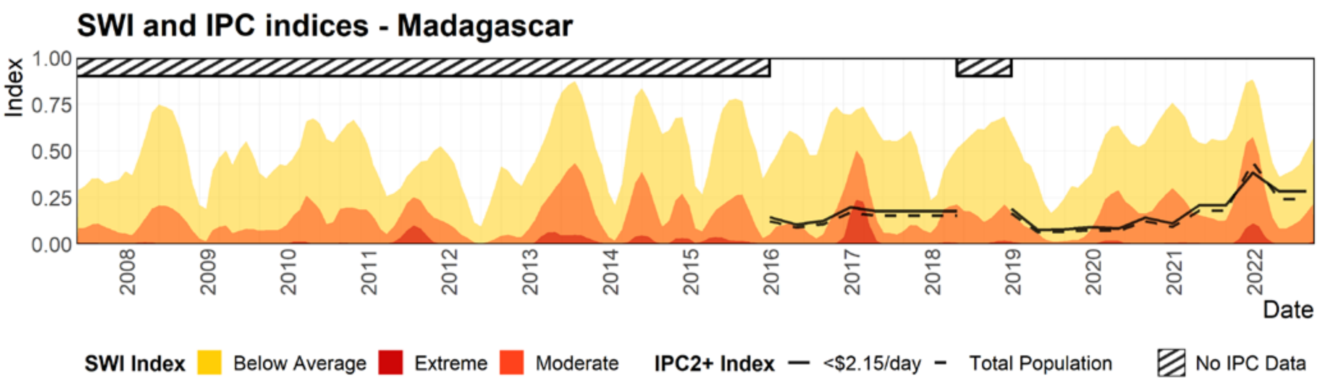


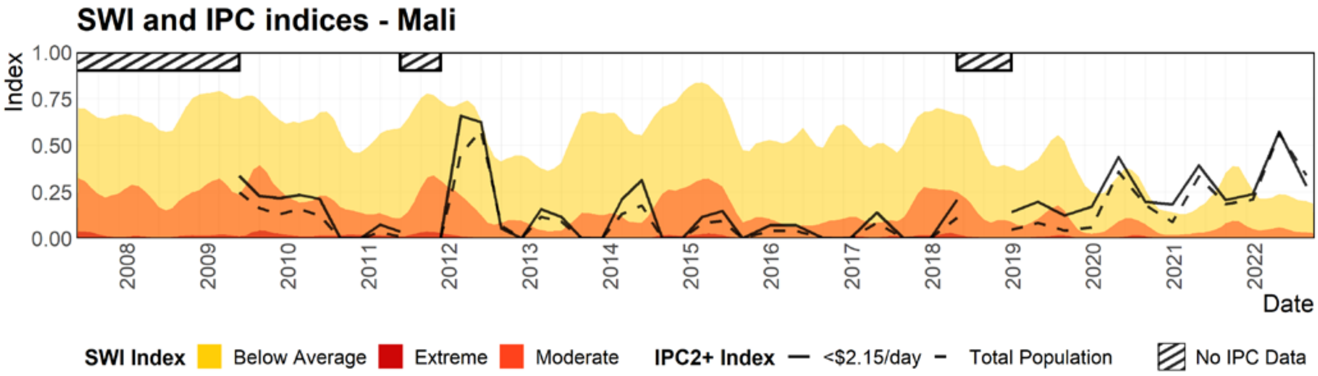


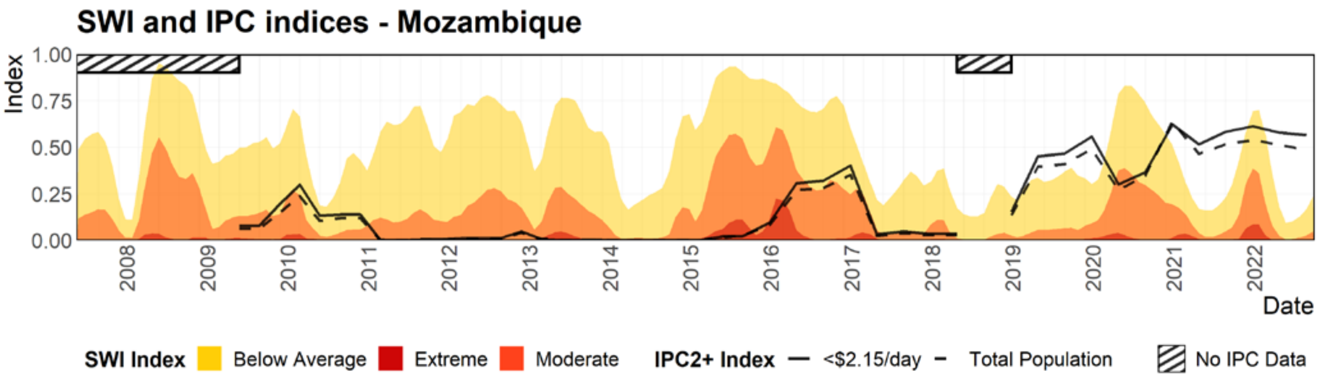

SWI and IPC indices - Congo - Kinshasa
Index
1.00
0.75
0.50
0.25
0.00
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
Date
SWI Index
Below Average
Extreme
Moderate
IPC2+ Index
<$2.15/day
Total Population
No IPC Data

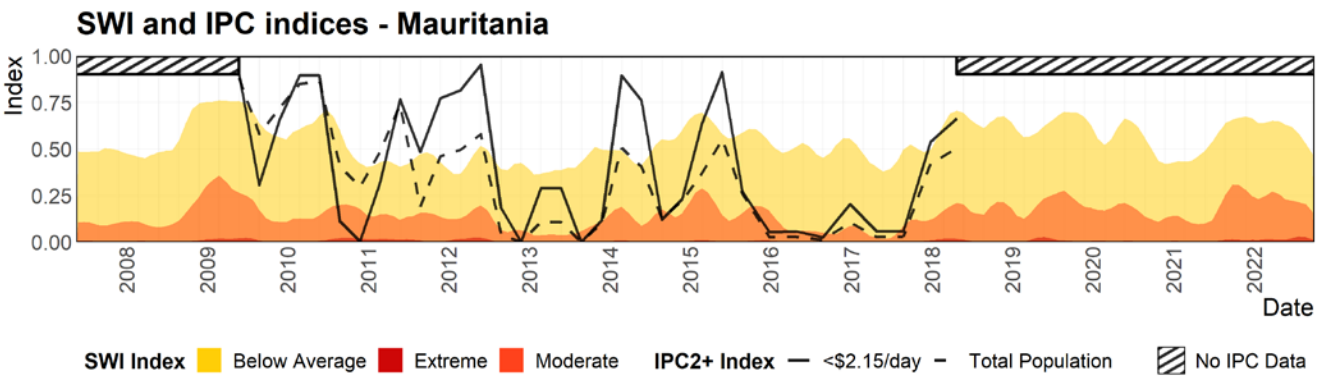

SWI and IPC indices - Djibouti
Index
1.00
0.75
0.50
0.25
0.00
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
Date
SWI Index
Below Average
Extreme
Moderate
IPC2+ Index
<$2.15/day
Total Population
No IPC Data

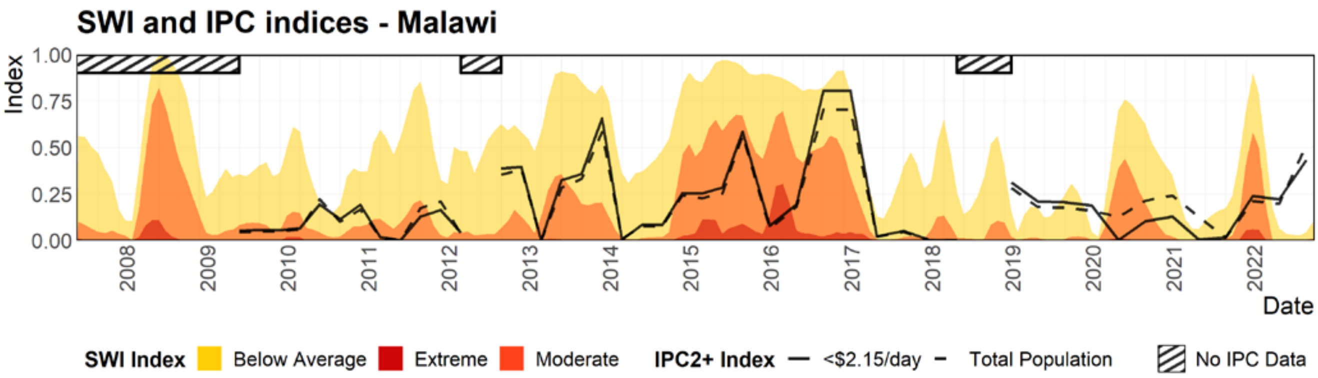

SWI and IPC indices - Ethiopia
Index
1.00
0.75
0.50
0.25
0.00
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
Date
SWI Index
Below Average
Extreme
Moderate
IPC2+ Index
<$2.15/day
Total Population
No IPC Data

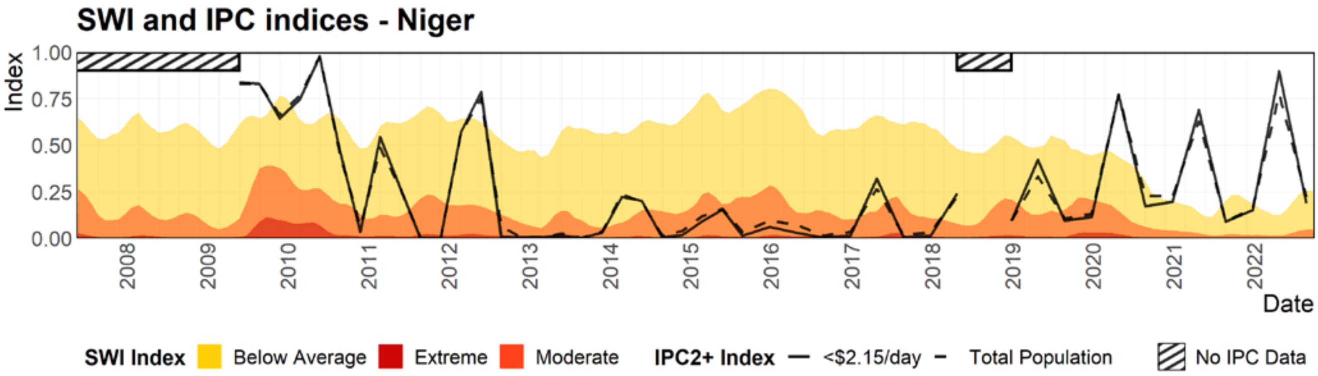

SWI and IPC indices - Madagascar
Index
1.00
0.75
0.50
0.25
0.00
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
Date
SWI Index
Below Average
Extreme
Moderate
IPC2+ Index
<$2.15/day
Total Population
No IPC Data


SWI and IPC indices - Mali
Index
1.00
0.75
0.50
0.25
0.00
2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022
Date
SWI Index Below Average Extreme Moderate
IPC2+ Index <$2.15/day Total Population
No IPC Data


SWI and IPC indices - Mozambique
Index
1.00
0.75
0.50
0.25
0.00
2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022
Date
SWI Index Below Average Extreme Moderate
IPC2+ Index <$2.15/day Total Population
No IPC Data


SWI and IPC indices - Mauritania
Index
1.00
0.75
0.50
0.25
0.00
2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022
Date
SWI Index Below Average Extreme Moderate
IPC2+ Index <$2.15/day Total Population
No IPC Data


SWI and IPC indices - Malawi
Index
1.00
0.75
0.50
0.25
0.00
2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022
Date
SWI Index Below Average Extreme Moderate
IPC2+ Index <$2.15/day Total Population
No IPC Data


SWI and IPC indices - Niger
Index
1.00
0.75
0.50
0.25
0.00
2008
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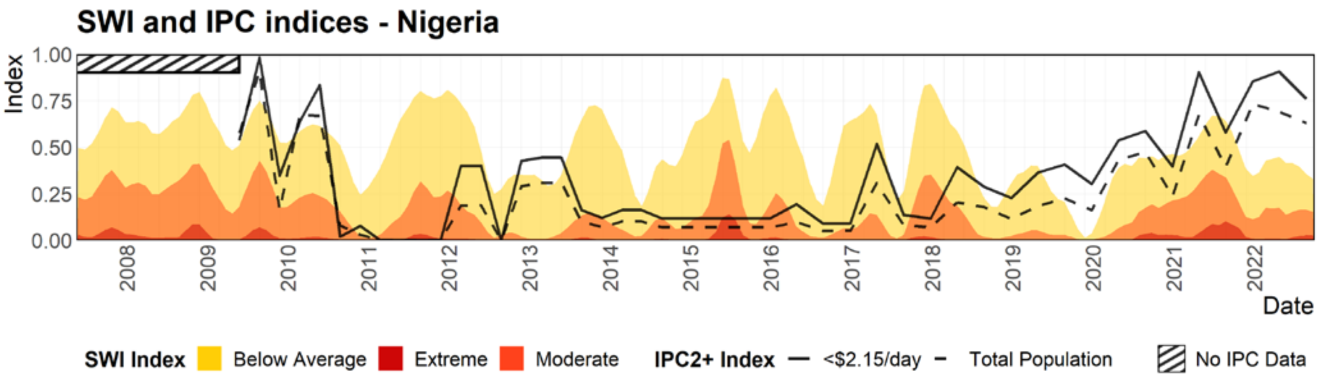
2022
Date
SWI Index
Below Average
Extreme
Moderate
IPC2+ Index
<$2.15/day
Total Population
No IPC Data


SWI and IPC indices - Nigeria
Index
1.00
0.75
0.50
0.25
0.00
2008
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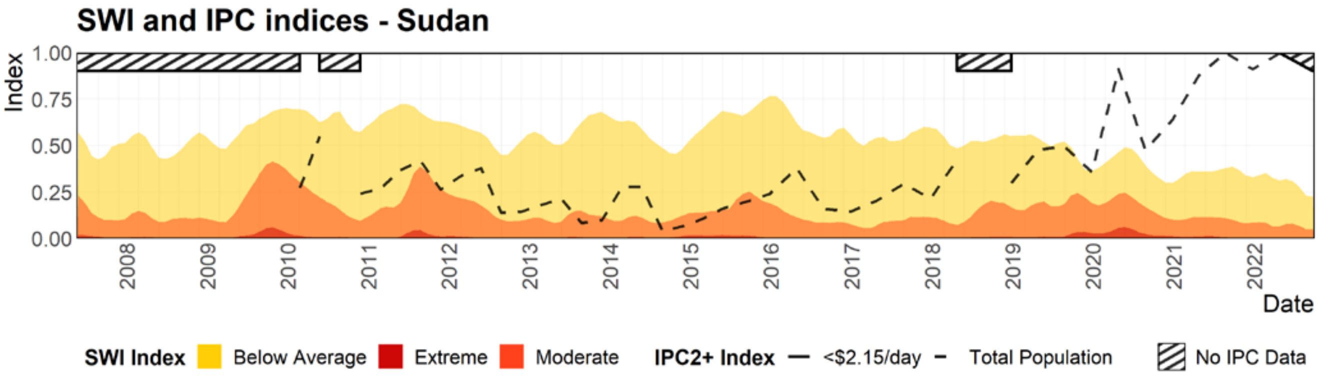
2021
2022
Date
SWI Index
Below Average
Extreme
Moderate
IPC2+ Index
<$2.15/day
Total Population
No IPC Data


SWI and IPC indices - Sudan
Index
1.00
0.75
0.50
0.25
0.00
2008
2009
2010
2011
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2016
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2018
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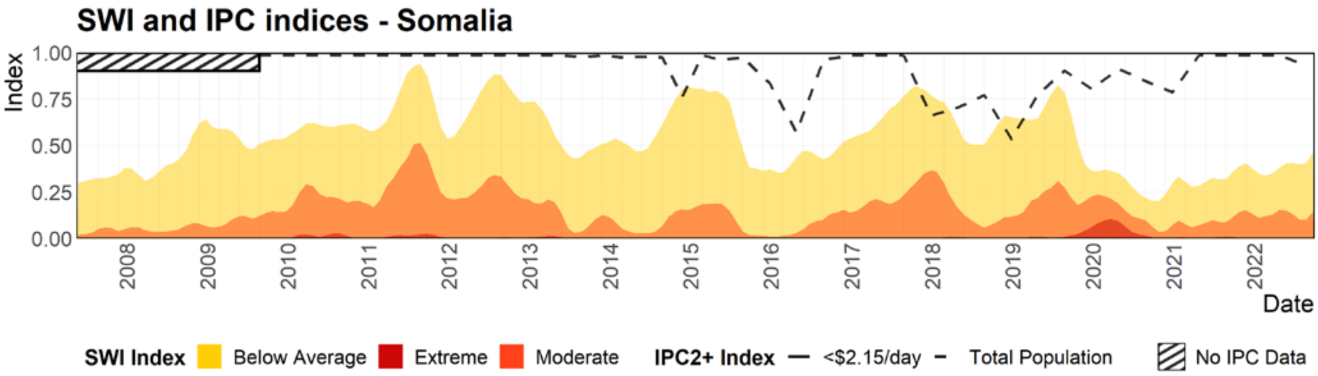
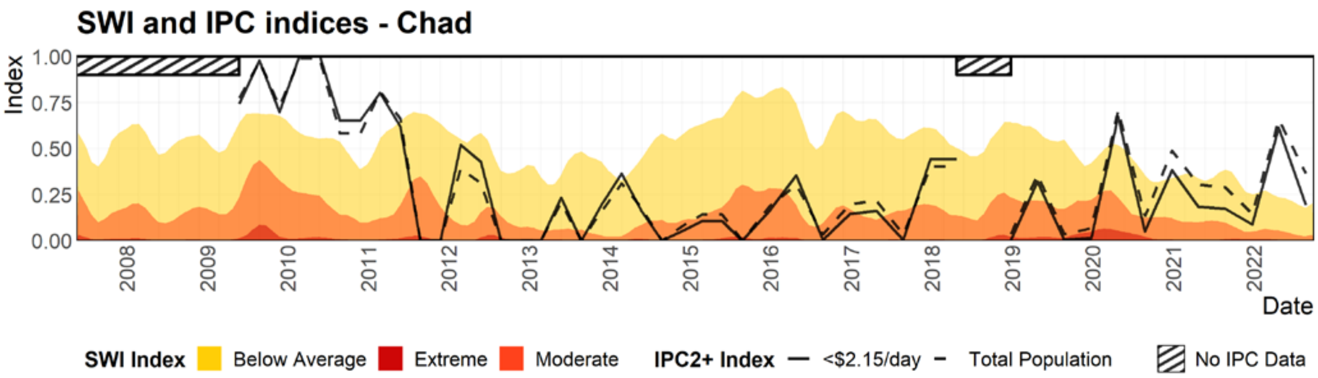
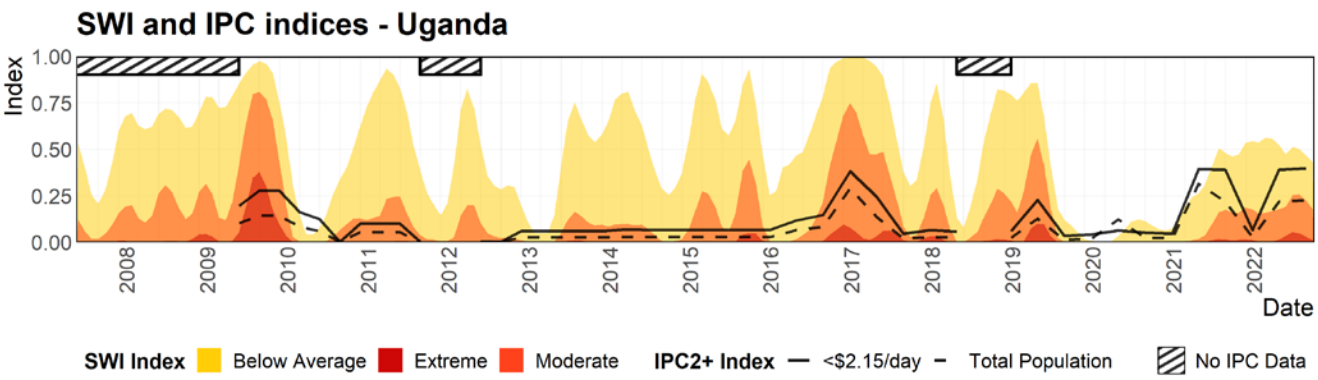
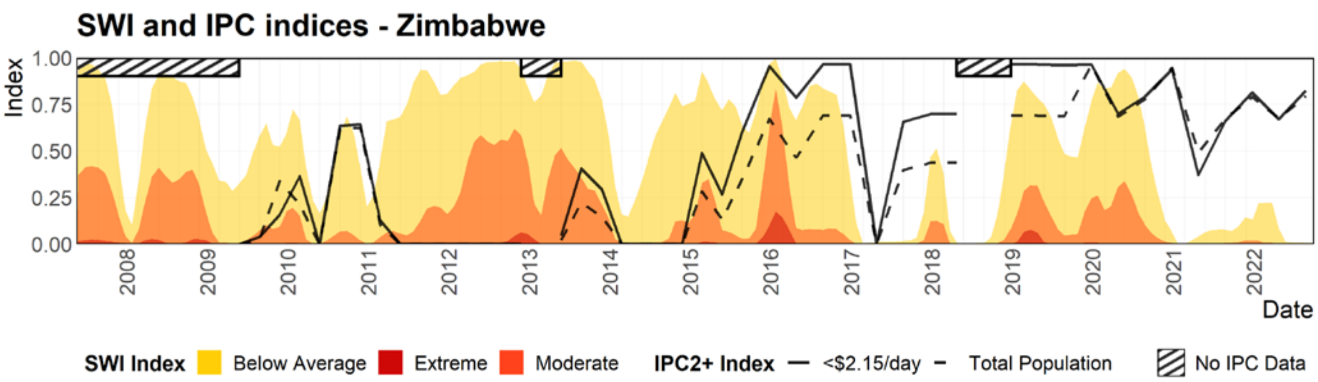
2020
2021
2022
Date
SWI Index
Below Average
Extreme
Moderate
IPC2+ Index
<$2.15/day
Total Population
No IPC Data


SWI and IPC indices - Somalia
Index
1.00
0.75
0.50
0.25
0.00
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
Date
SWI Index
Below Average
Extreme
Moderate
IPC2+ Index
<$2.15/day
Total Population
No IPC Data







Source: Centre for Disaster Protection, based on data from Copernicus (n. d. b), FEWS NET (n. d. a.), WorldPop (n. d.), World Bank (n. d.) and Chi et al. (2022).

A.2.4 YEAR-EVENT LOSS TABLE SAMPLE

The table shows a sample of the structure of a YELT output table for Madagascar in the tropical cyclone analysis.

ISO	YearID	EventID	EstimatedPeopleAffected	EstimatedResponseCost
MDG	1	0_0_12_SI	1,169,211	96,293,933
MDG	14	0_13_6_SI	4,393,660	159,121,460
MDG	16	0_15_3_SI	296,252	57,199,055
MDG	16	0_15_6_SI	1,093,406	93,875,899
MDG	35	0_34_0_SI	2,480,188	128,087,840
MDG	63	0_62_1_SI	854,967	85,510,989
MDG	66	0_65_9_SI	783,673	82,732,320
MDG	73	0_72_7_SI	329,115	59,528,087
MDG	80	0_79_8_SI	854,268	85,484,458
MDG	88	0_87_3_SI	1,149,166	95,664,239
MDG	88	0_87_4_SI	4,689,382	163,102,891
MDG	91	0_90_5_SI	1,940,782	116,707,511
MDG	96	0_95_3_SI	18,805	20,095,484
MDG	102	0_101_4_SI	1,622,510	109,039,923
MDG	115	0_114_6_SI	2,313,643	124,753,987

A.2.5 POPULATION AND INCOME DATA SAMPLE

The table shows a sample of the structure of the population-at-risk exposure layer data used in the demonstration analysis.

Long	Lat	CountryISO	TotalPopulation	EstimatedDailyIncome	PctUnder25
19.225	13.125	TCD	339	3.50	67%
14.825	5.425	CAF	62	1.22	64%
-40.925	-4.175	BRA	10639	9.45	42%
23.925	-33.825	ZAF	203	1.86	43%
1.325	11.925	BFA	938	2.54	67%
70.625	53.525	KAZ	17	13.28	36%
73.175	36.175	PAK	372	2.40	53%
73.125	31.075	PAK	25871	3.11	50%
77.525	23.775	IND	6162	3.10	48%
35.175	-4.175	TZA	4815	1.80	66%
-58.725	-11.325	BRA	23	4.76	40%
-43.225	-11.075	BRA	71	4.26	44%
66.125	29.825	PAK	29	2.38	58%
-15.275	12.425	GNB	1872	3.24	61%
82.725	26.175	IND	28004	3.24	51%

ANNEX 3: DATA SOURCES

Data source	Description
Drought Index	The Drought Index was developed from Copernicus Soil Water Index (10-day aggregate version - SWI10) data for the period 2007-23: https://land.copernicus.eu/global/products/swi SWI10 products were generated by the Copernicus Global Land Service, the Earth Observation programme of the European Commission. The research leading to the current version of the product has received funding from various European Commission Research and Technical Development programmes. The product is based on MetOp/ASCAT surface soil moisture data distributed by EUMETSAT.
Fragile States Index	The Fragile States Index compiled by the Fund for Peace was used as a national-level indicator for fragility: https://fragilestatesindex.org/ Emergency response cost functions were developed from Flash Appeal data from the United Nations Office for the Coordination of Humanitarian Affairs Financial Tracking Service (https://fts.unocha.org/), and allocation data from the Central Emergency Response Fund (https://fts.unocha.org/pooled-funds/cerf/summary/2022).
IFRC Emergency Appeals	Emergency response cost functions were developed from the Emergency Appeals data from International Federation of Red Cross and Red Crescent Societies: https://go.ifrc.org/appeals/all
International Phase Classification	International Phase Classification data was downloaded from the Famine Early Warning Systems Network: https://fews.net/data/acute-food-insecurity-data
Relative Wealth Index	The spatial population data was adapted using the Relative Wealth Index to estimate spatial variation in income. The Relative Wealth Index predicts the relative standard of living within countries using deidentified connectivity data, satellite imagery and other non-traditional data sources. The data is provided for 93 low- and middle-income countries at 2.4-km resolution: Chi et al. 2022. https://dataforgood.facebook.com/dfg/tools/relative-wealth-index
Synthetic Tropical Cyclone Track	A 'tropical cyclone-affected' index was developed from a global synthetic tropical cyclone track data set produced by Bloemendaal et al. (2020).

Data source	Description
World Bank	The Relative Wealth Index was calibrated to income distributions and poverty headcount estimates reported by the Work Bank: Gini Index and Poverty Headcount Ratio at USD2.15/day (2017 PPP) from the World Bank Group Archives. World Bank (n.d.). The Gini Index measures the extent to which the distribution of income or consumption among individuals or households within an economy deviates from a perfectly equal distribution. A Gini Index of 0 represents perfect equality, while an index of 100 implies perfect inequality: https://data.worldbank.org/indicator/SI.POV.GINI The Poverty Headcount Ratio at USD2.15/day (2017 PPP) is the percentage of the population living on less than USD2.15/day at 2017 purchasing power-adjusted prices. As a result of revisions in PPP exchange rates, poverty rates for individual countries cannot be compared with poverty rates reported in earlier editions: https://data.worldbank.org/indicator/SI.POV.DDAY
WorldPop	A population-based exposure data set was developed from spatial population and demographic data from WorldPop (www.worldpop.org) - School of Geography and Environmental Science, University of Southampton. WorldPop (n.d.). Global High Resolution Population Denominators Project - Funded by The Bill and Melinda Gates Foundation (OPP1134076). https://dx.doi.org/10.5258/SOTON/WP00647

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Cover image: Super Typhoon Mangkhut (known locally as Ompong) Bearing Down on The Philippines. Source: NASA, Shutterstock.