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# Catastrophe risk models as quantitative tools for climate change 5 loss and damage: A demonstration for flood in Malawi, Vietnam, and the Philippines

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## Abstract

We show how catastrophe models, as commonly used in the insurance and reinsurance industries, can  
20 be used to quantify climate change loss(es) and damage(s), fulfilling a key need to make urgent  
progress in this arena of international climate policy. We explore the impact of climate change on  
inland flood risk in three Global South regions (Chikwawa in Malawi, Hanoi in Vietnam, and  
Cagayan in the Philippines) and three exposure types (residential buildings, agricultural crops, and  
population) to demonstrate the ability and potential flexibility of catastrophe models to quantify  
25 impacts for both economic and non-economic loss and damage. We show that standard metrics can be  
used to quantify loss and damage, as well as guide and evaluate adaptation and disaster risk resilience  
measures. We also discuss and summarise the challenges that remain to be overcome, including  
sourcing high-quality exposure and vulnerability data and confronting the deeply uncertain climate  
change information at the scales of interest for loss and damage. For the latter, we propose a  
30 “storylines” framework to tractably sample the uncertainty space. Finally, we emphasise that progress  
in this area will need meaningful collaboration between stakeholders, developers, local experts, and  
vulnerable communities, to increase the quality of the data and ensure that the economic and non-  
economic losses are appropriately, legitimately, and justly chosen and quantified. Overall, we hope to  
encourage new activity, improvements to our work, and extensive collaboration in this important  
35 space.

## Key points

- Catastrophe models are excellent candidate tools to contribute to the challenge of climate change loss and damage quantification.

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- Standard frameworks used in (re)insurance can be adapted to account for many different loss types, including non-economic losses.
  - Their use in this manner will require collaboration and engagement with a wide range of stakeholders, including vulnerable communities.

45 **1. Introduction**

Article 8 of the Paris Agreement, arising from the 2015 United Nations (UN) Framework Convention on Climate Change (UNFCCC) 21<sup>st</sup> Conference of the Parties (COP21), formally recognised “averting, minimising, and addressing loss and damage associated with the adverse effects of climate change” (UNFCCC, 2016) particularly in vulnerable and developing countries. Seen as an important  
50 step towards climate justice, this prompted increased debate and discussion as to the scope and definition of loss and damage,<sup>1</sup> particularly whether it should also include adaptation measures to climate change (e.g., Boyd et al., 2017; Mechler et al., 2019), as well as how it should embrace economic, non-economic, and indirect losses and damages (Serdeczny, 2019; Richards, 2022). At the same time, a lack of standards and frameworks to quantify harm, review evidence of impacts, and  
55 inform eligibility for support has meant that real-world progress towards addressing loss and damage has been slow (e.g., Otto and Fabian, 2023). Yet, with the agreement to establish loss and damage financing to support climate-vulnerable countries at COP27 (e.g., McDonnell, 2023 and refs. therein) (with continuing discussions at later COPs), progress is more urgent. Here, building on other work (CISL, 2023), we argue that catastrophe (cat) models, widely used in the insurance and reinsurance  
60 industries, can be used to address some core challenges for loss and damage, chiefly by providing quantitative information at meaningful spatial scales. We demonstrate this by exploring climate change-driven shifts in flood risk in three distinct Global South case study regions.

Floods are among the most destructive natural disasters worldwide, affecting 1.6 billion people and  
65 causing \$651 billion (USD) of economic damage between 2000 and 2019 (CRED-UNDRR, 2020). By combining flood models and climate projections, numerous studies have explored changes in future flood risk, which may increase or decrease in different regions, as well as its impacts and potential adaptation strategies (Ward et al., 2017; Dottori et al., 2018, 2023; Willner et al., 2018; Yamamoto et al., 2021; Bates, 2022). While a diverse range of flood adaptation methods exist to  
70 reduce losses (Kreibich et al., 2015; Hill et al., 2023), flood protection standards are often lower in more vulnerable regions (Scussolini et al., 2016; Rozenberg and Fay, 2019). Moreover, as 89% of the world’s flood-exposed population live in low and middle-income countries, a focus on exposure of monetary assets – as per a standard cost-benefit analysis – would drive flood protection measures

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<sup>1</sup> We follow the IPCC Special Report on 1.5°C (IPCC, 2018) and use “loss(es) and damage(s)” (lower case) to refer broadly to the harm from climate change, as opposed to “Loss and Damage” (capital letters), which refers to the wider political debate under the UNFCCC.

75 away from these vulnerable regions (Rentschler et al., 2022). Therefore, a broad understanding of future flood risk is vital from a loss and damage perspective, to guide building resilience in vulnerable communities and highlight priority areas where vulnerability can be reduced (McDermott, 2022; Rentschler et al., 2022).

80 Cat model developers have begun to focus more on flooding resulting from climate change in recent years as global flood risk and losses have increased (e.g., Franco et al., 2020). Working from a conceptually simple risk framework of hazard, exposure, and vulnerability components, cat models offer several important benefits for quantifying flood risk: long, high resolution, synthetic time series of flood event footprints (“event sets”), whose distribution can be adjusted to account for climate change; corresponding flood hazard maps for the events; the ability to quantify flood risk  
85 probabilistically at a portfolio of locations; and the ability to explore different flood-vulnerability relationships, which means a range of “exposures” can be considered flexibly (i.e., not just buildings).

The standard output metrics of cat models are well-suited to usefully quantify impact for climate change loss and damage. For example, the expected impact (or loss) in a given year from a natural  
90 hazard is captured by the average annual loss (AAL), which we focus on in this study. The change in AAL between simulations representative of two different climates (or other chosen metric) is a robust quantitative measure of the change in risk, which could be used in a loss and damage framework. Moreover, high-resolution spatially disaggregated versions of such metrics can not only be used to identify hotspots of risk to climate change but can also be combined with indicators of social  
95 vulnerability. This adds a social dimension to quantitative loss estimates, helping to guide decision making around loss and damage to priority locations, including identifying the adaptation required to combat future risks (Mechler et al., 2019). In this study, we demonstrate this process by first producing high-resolution spatial estimates of flood losses under climate change and integrating our results with high-resolution vulnerability estimates to identify hotspots of both high flood risk and  
100 high social vulnerability.

Quantifying non-economic loss and damage due to climate change is challenging precisely because they cannot easily be monetised or assigned value through the market (e.g., Barnett et al., 2016; Serdeczny, 2019). Non-economic loss and damage broadly captures impacts on individuals, society,  
105 or the environment, and is particularly important in relation to those vulnerable communities at risk of being overlooked in traditional economic risk assessments (Cao et al., 2023). Yet it is seldom considered in planning and policy (Pill, 2022), including for decisions such as prioritising adaption measures in response to potential future climate change threats (Serdeczny et al., 2016). While cat models are typically used to quantify economic losses to assets (such as buildings) in the  
110 (re)insurance industry, we will argue here that their flexible framework allows the exposure of a

portfolio of any type of asset to be assessed, provided the relationship between hazard and loss can be quantified.

115 The aim of this study is to show how cat models can be leveraged to provide a quantitative tool for climate change loss and damage. We demonstrate this through three sub-national flood risk case studies in Global South countries that are also part of the Vulnerable Twenty economies who are “systematically vulnerable to climate change” (<https://www.v-20.org>): Chikwawa, a highly rural district of Malawi; Hanoi, a province-level municipality in Vietnam consisting of a highly urbanised area with surrounding rural regions; and Cagayan, a province in the Philippines with both rural and  
120 urban elements. Using simulations for both a present day and 2°C global warming scenario, we demonstrate the utility of a cat model framework in accommodating various dimensions of loss and damage by quantifying economic losses from residential damage and crop yield reduction, as well as non-economic loss in terms of population affected. To this end, we extend a recent study that used cat models to inform a process for financing (CISL, 2023).

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The rest of this study is organised as follows. Section 2 presents more information on the case study regions. Section 3 briefly describes the JBA cat model and its configuration and inputs for this study. Section 4 presents an overview of the results for each case study region, followed by a more detailed spatial analysis of losses at high resolution both directly and in conjunction with high-resolution  
130 socioeconomic indicators. Section 5 considers the broader issues and open questions that remain. Finally, Section 6 presents our conclusions.

## **2. Case study regions**

The following sub-sections describe our three case study regions. Maps identifying each case study  
135 location within their respective countries are shown in Figure 1.

### **2.1 Chikwawa District, Malawi**

Malawi is classed as one of the world’s 45 Least Developed Countries (LDCs), with around 70% of the population falling below the poverty line and 80% relying on agriculture for their income (World  
140 Bank, 2024). The Shire River valley in southern Malawi has a high risk of flooding due to both its rainfall, characterised by dry and rainy seasons (Jury, 2014), and drainage system, particularly in the south of the country, with an estimated 100,000 people affected every year (World Bank, 2019). At the same time, its citizens’ dependence on agriculture, attachment to the land, and lack of mobility means relocation is rarely an attractive option (Mixed Migration Centre, 2023). Chikwawa is a rural district  
145 in southern Malawi. It is among the most exposed and vulnerable regions to flooding in the country (Mwale et al., 2015; Šakić Trogrlić et al., 2018), and was heavily impacted by Tropical Storm Ana in January 2022, which saw 190,000 internally displaced people across southern Malawi (iDMC, 2023).

## 2.2 Hanoi, Vietnam

150 Hanoi, both a capital city and province-level municipality, is in the Red River Delta region of northern Vietnam and has a high population density and population of ~8.5 million people as of 2022 (General Statistics Office of Vietnam, 2023). Large parts of the urbanised areas of Hanoi are protected by dikes; however, recent urbanisation and economic development (Luo et al., 2018), a low-lying geography, and the fact that some residential areas remain outside of the dike's protection, makes it  
155 vulnerable to flooding and flood losses (World Bank, 2016; Sai et al., 2020; Anh et al., 2021). Flooding causes considerable impacts each year in Vietnam (Nguyen et al., 2021), including economic loss as well as health and wellbeing impacts (Bich et al., 2011; Hudson et al., 2019).

## 2.3 Cagayan, the Philippines

160 Cagayan, a forested province in the north of the Philippines on the island of Luzon, is a major agricultural supplier and has a population of ~1.3 million (Philippine Statistics Authority, 2022). The Philippines is one of the most impacted countries in terms of disaster displacement, exposed to multiple geological and hydrometeorological hazards (iDMC, 2023 and refs. therein). Flooding is frequent and is exacerbated by factors such as deforestation in many locations (Calang, 2017). In  
165 2020, Typhoon Vamco caused widespread flooding across the broader Cagayan Valley region, with especially large impacts in the Cagayan province (OCHA, 2020).

## 3. Catastrophe model framework and simulations

We use JBA Risk Management's flood cat model, a proprietary model used extensively in the  
170 (re)insurance, financial, development, and disaster risk reduction sectors that is designed to quantify flood risk by integrating hazard, exposure, and vulnerability components. This section briefly summarises the framework and the input datasets we used. The focus is not on the precise details of the model itself but rather the utility of any suitably flexible cat modelling framework to address the challenge of quantifying climate change losses and damages.

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### 3.1 Hazard data

Globally, the hazard component consists of over 15 million plausible fluvial (river) and pluvial (surface water) flood events (the "event set"), which occur with a range of probabilities (return periods) under the climate of interest. The present day (baseline) event set is built with a synthetic precipitation time series (Keef et al., 2013) and rainfall-runoff models (Jakeman et al., 1990; Andrews and Guillaume, 2014), calibrated with historical rainfall (Saha et al., 2010), climate (Kottek et al., 2006), and land cover (Zobler, 1999; Arino et al., 2012) data. Flood depths and extents are determined by reference to JBA's high-resolution (30 m) global flood hazard maps, incorporating both fluvial and pluvial flooding (Lamb et al., 2009; D'Ayala et al., 2020; Massam et al., 2023).

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Events under future climates are generated by scaling the baseline event set with return period change factors, which estimate the magnitude and spatial pattern of the climate change signal. In extreme value space, the overall impact of the return period change factors is to shift the “location” parameter of a generalised extreme value model (e.g., a change factor of 2 means that a future 100-year event has the same intensity as a present-day 200-year event) rather than also adjust the “shape” and “scale” parameters (e.g., allowing for different change factors at different return periods).

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These change factors are determined using output from global climate models (GCMs). In our case, we used output from one of the UK Met Office GCMs (UKESM1-0-LL) (Sellar et al., 2019) that contributed to the sixth Coupled Model Intercomparison Project (CMIP6) (Eyring et al., 2016), generating an event set for a 2°C global warming scenario (2°C above pre-industrial temperatures), a level of warming that is broadly consistent with mid-century projections for a range of GCMs and scenarios (IPCC, 2021). While the change factor approach is simplified, this methodological choice respects the large uncertainty in GCM output and in determining spatially resolved future climate projections (e.g., Shepherd, 2014).

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### 3.2 Vulnerability functions

The vulnerability component quantifies the expected damage for a given hazard intensity using depth-damage curves, which are critical for quantifying loss (Kreibich et al., 2009; Merz et al., 2013; Lazzarin et al., 2022). In this study, we are concerned with agricultural crops and residential buildings (we also calculate a population-weighted impact; see below) and we use flood depth-damage curves from the Joint Research Commission (Huizinga et al., 2017). These are derived primarily from data in the literature, covering multiple continents and exposure types as well as providing continent-level normalised damage functions and country-level maximum damage values, which we use to translate the curves into quantitative losses. We linearly interpolated the curves to give damage estimates at flood depth intervals of 0.1m, which increases the sensitivity of loss estimation to flooding and more closely imitates the continuous functions often used to quantify flood damages (e.g., Merz and Thielen, 2009).

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### 215 3.3 Exposure data

Locations of exposed assets were compiled from various open data sources, allowing us to demonstrate the flexibility of cat models for different exposure types. Details of the data sources, justification for their use, and any modification are provided below. Analysis was carried out at the resolution of the exposure for each exposure type. Maps showing the final exposure datasets are shown in Figure 1. While we can expect exposures – and their vulnerabilities – to evolve through

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time, we kept this aspect constant in all our simulations, which simplifies the analysis and isolates the hazard component of any future change in risk.

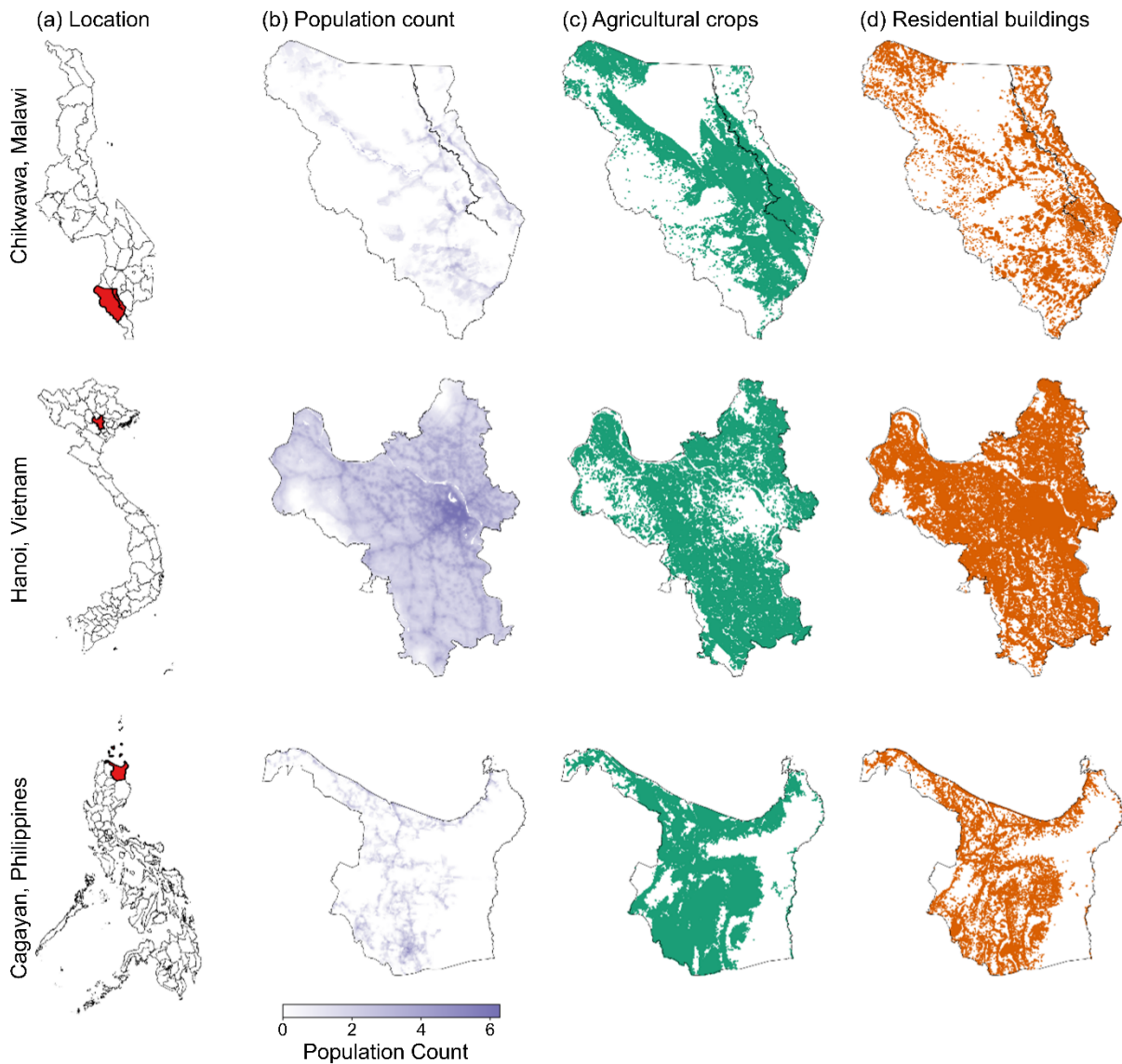
225 **Population.** Population data were sourced from WorldPop (Tatem, 2017) and consist of population counts for 2020 at 100 m resolution. In our analysis, we define the “exposed population” as that encountering flooding of any depth. The AAL for this exposure represents the average number of people affected per year per grid point.

230 **Agricultural Crops.** Agricultural crop exposure data were sourced from the Global Land Analysis & Discovery Lab Global Land Cover and Land Use Change dataset (Potapov et al., 2022), extracting the 30m pixels classified as cropland for 2020. The value of exposed crop at each point was calculated following Huizinga et al. (2017), estimating the value added by 30 m<sup>2</sup> of cropland for each country in 2020 by dividing the gross domestic product contributed through agriculture in each country (FAO agriculture, forestry, and fishing data via FAOSTAT; <https://www.fao.org/faostat/en/>) by the total  
235 agricultural area in each country (World Bank data; <https://data.worldbank.org>). The AAL for this exposure represents the average value lost per year per grid point.

**Residential Buildings.** Residential building exposure data were sourced from the Global Human Settlement Layer (Pesaresi and Politis, 2023). Data representing residential buildings was extracted  
240 and the resolution was resampled from 10m to 30m to reduce the computational burden. The value exposed at each grid point was taken from the Joint Research Commission estimates for land-use based maximum damages for residential buildings (Huizinga et al., 2017), adjusted to the exposure data’s resolution. The AAL for this exposure represents the average value damaged per year per grid  
point.

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**Figure 1.** Case study regions and the distribution of exposure types, showing (a) the location of each sub-national region within the larger country and the exposure locations for (b) population count (additionally coloured by density), (c) agricultural crops, and (d) residential buildings.

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### 3.4 Socioeconomic vulnerability data

To meet our aim of demonstrating how cat model outputs can provide a social dimension, we also use the relative wealth index (RWI) (Chi et al., 2022). This is constructed by estimating the spatial distribution of wealth for all low- and middle-income countries at a resolution of 2.4 km using machine learning methods, providing a dataset that can be suitably combined with the high-resolution cat model output. We note that wealth alone is just one proxy for socioeconomic vulnerability and more complex, multi-indicator versions have been created (e.g., Edmonds et al., 2020), and would be a natural extension to this work.

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## 4. Results

The analysis presented below demonstrates a quantification of the impact of climate change on flood risk for our three case study regions and three exposure types. However, the “demonstration” aspect is important: we are not seeking to generate precise values (which, not least, would require a deeper exploration of uncertainty) but instead show the utility of cat models in generating the quantities and insights that would be useful for climate change losses and damages. Moreover, as noted above, our simulations only explore the impact of hazard change rather than exposure and vulnerability. To this end, we do not present monetary values in this analysis, expressing losses as relative changes. We return to these broader points in Section 5.

### 4.1 Total expected annual loss

The overall change in AAL between the present day (hereafter “baseline”) and 2°C warming scenario provides an indication of risk to climate change-related flood losses (Table 1). In our demonstration, Hanoi exhibits the highest risk overall when using change in AAL as the indicator of risk, showing the greatest percentage increases in AAL. For all exposure types in Hanoi, increases in AAL under the 2°C warming scenario exceed 60% compared to baseline, exceeding 70% for residential buildings. Cagayan also shows increases in losses under the 2°C warming scenario, although at close to 35% across all exposure types, the relative change is approximately 1/2 to 2/3 that for Hanoi. Chikwawa has the lowest overall risk to increasing flood damage, with negligible changes AAL for all exposure types (1% decrease to ~2% increase).

**Table 1.** Total percentage change in annual expected loss aggregated over each case study area between baseline and climate change scenarios. Blue cells indicate decreases in loss whilst orange cells indicate increases in loss. See section 3 for details on exposure datasets and calculating exposed value and loss.

Exposure Type	% Change in AAL		
	Chikwawa	Hanoi	Cagayan
Population	-0.6	63.2	37.6
Agriculture	-0.7	68.9	37.5
Residential Buildings	1.8	71.3	34.2

### 4.2 Spatial distribution of losses

To demonstrate the ability of cat models to estimate losses at high spatial resolutions whilst maintaining realistic results, we consider the spatial distribution of the AAL and its change between baseline and the 2°C warming scenario within each region, aggregating the metric to 0.01° resolution, which is ~1 km at the equator. We present our analysis by region in sub-sections below.

Throughout this section, we report losses using a ‘relative AAL’ metric (Figures 2–4, panels (a) and  
295 (b)). For population, the relative AAL is calculated using the average annual number of people  
exposed to flooding as a percentage of the total population count for each point; for residential  
buildings and agricultural crops, the relative AAL is calculated using the average annual economic  
loss as a percentage of the total value exposed at each point. Particularly for the latter two exposure  
types, reporting the results in this way avoids placing unnecessary emphasis on the value of assets,  
300 which is important given the assumptions involved in their calculation, and brings focus to the general  
trends both spatially and between scenarios. The openly available vulnerability functions allow for  
consistency between countries; however, the assumptions made during their calculation (Huizinga et  
al., 2017) also means the outputs presented here are more suited to estimating general trends across  
regions and through time. The change in the relative AAL is used to quantify the impact of climate  
305 change (Figures 2–4, panel (c)).

To introduce a vulnerability dimension, our analysis also includes an RWI-weighting of the relative  
AAL. This provides an insight into the relationship between flood risk and relative vulnerability  
across the case study regions, which, for example, can emphasise areas where high flood risk and high  
310 vulnerability coincide. RWI values for each region are first converted to deciles (i.e., put into 10  
equally distributed groups and given a value of 1 (low) to 10 (high)), which are then assigned to the  
aggregated cat model output using a nearest neighbour approach. Where there are gaps in the RWI  
data (e.g., in areas of low population), we do not present RWI-weighted results; overall, no analysed  
exposure point is further than twice the RWI data resolution from an RWI data point, meaning that we  
315 do not assume distant locations have similar vulnerabilities. The weighted AAL is calculated by  
dividing the relative AAL by the RWI decile. This means that, compared to the unweighted relative  
AALs, expected losses in areas with the highest RWIs (indicating highest wealth) are down-weighted  
the most whereas expected losses in areas with the lowest RWIs (indicating lowest wealth) expected  
losses remain more similar (Figures 2–4, panel (d)). The locations with high weighted relative AAL  
320 values therefore represent high flood risk coinciding with high socioeconomic vulnerability.

#### **4.2.1 Chikwawa, Malawi**

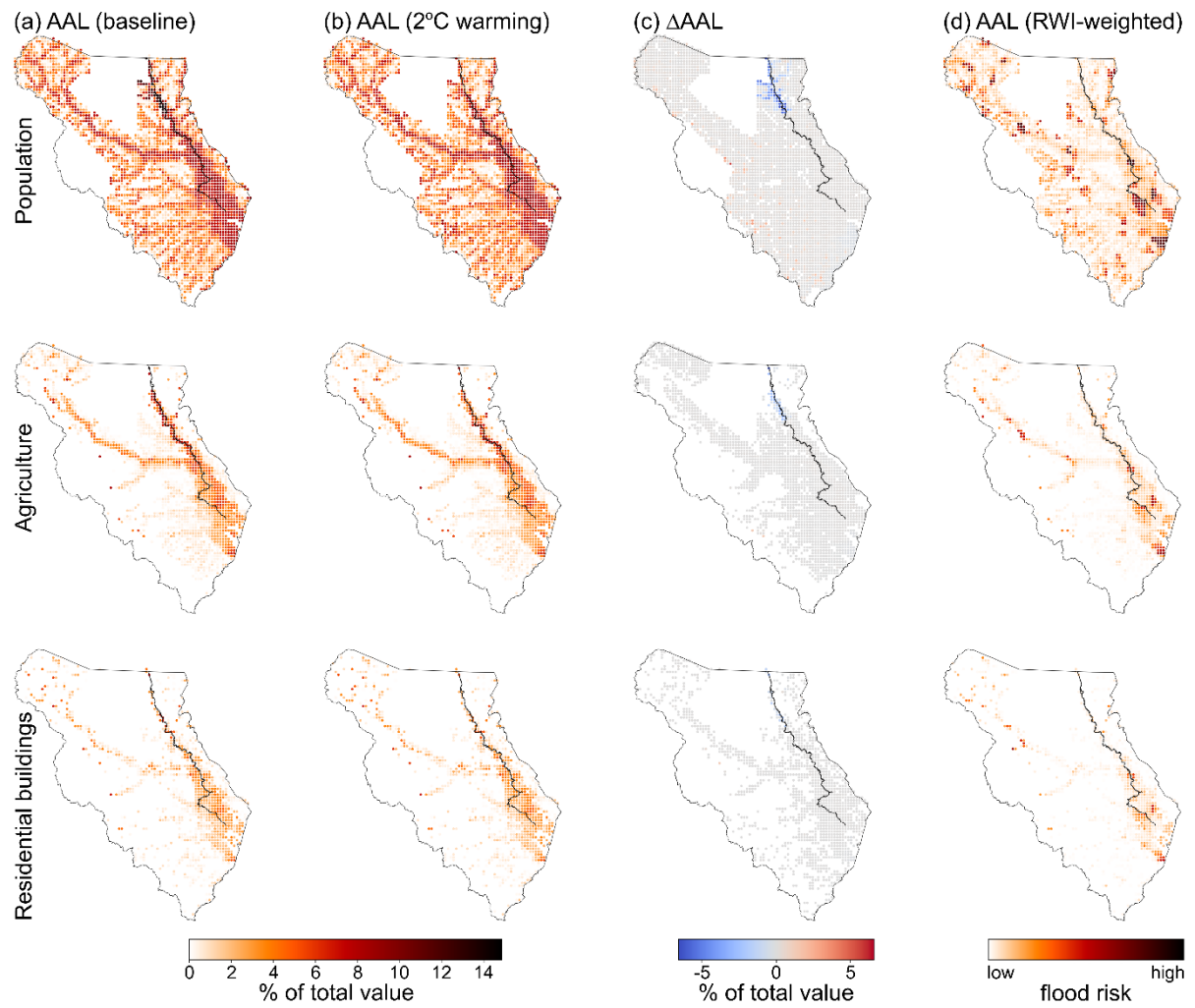
For baseline, flood risk impacts ~14% of the population, ~14% of agricultural crop value, and ~8% of  
residential building value when aggregating the relative AAL across the whole region. The change in  
325 relative AALs between the baseline and the 2°C warming scenario is generally negligible, with a few  
points of increasing AAL mainly seen for population affected. This latter result is due to the choice of  
custom vulnerability function where population is ‘affected’ by *any* flood depth, meaning that this  
exposure type is more sensitive compared to the others. An area of decreasing relative AALs  
surrounding the river is seen in the northeast of the region, consistent across the exposure types

330 (Figure 2c), suggesting decreased risk to flooding in this area under the 2°C warming scenario. However, there is large uncertainty as to the magnitude and direction of precipitation change under global warming over Malawi (Warnatzsch and Reay, 2019).

The RWI-weighted relative AALs in Chikwawa reveal a patchy pattern of flood risk and vulnerability  
335 co-location, with a particularly dense area of high RWI-weighted AALs in the southeast of the district, suggesting this is an area of high relative vulnerability within Chikwawa province as well as high flood risk under the 2°C warming scenario (Figure 2d). These patterns are consistent with areas of higher and lower vulnerability in a previous assessment of flood vulnerability (Mwale et al., 2015). That assessment pointed to its use of coarse spatial resolution data as a limitation in identifying some  
340 of the finer-scale patterns in vulnerability. With our higher-resolution approach, we can see both the general patterns of large areas of higher and lower vulnerability, alongside the finer details within these areas where the AAL and RWI-weighted relative AAL change significantly over short distances (Figure 2d). However, establishing the veracity of our results would require further validation.

#### 345 **4.2.2 Hanoi, Vietnam**

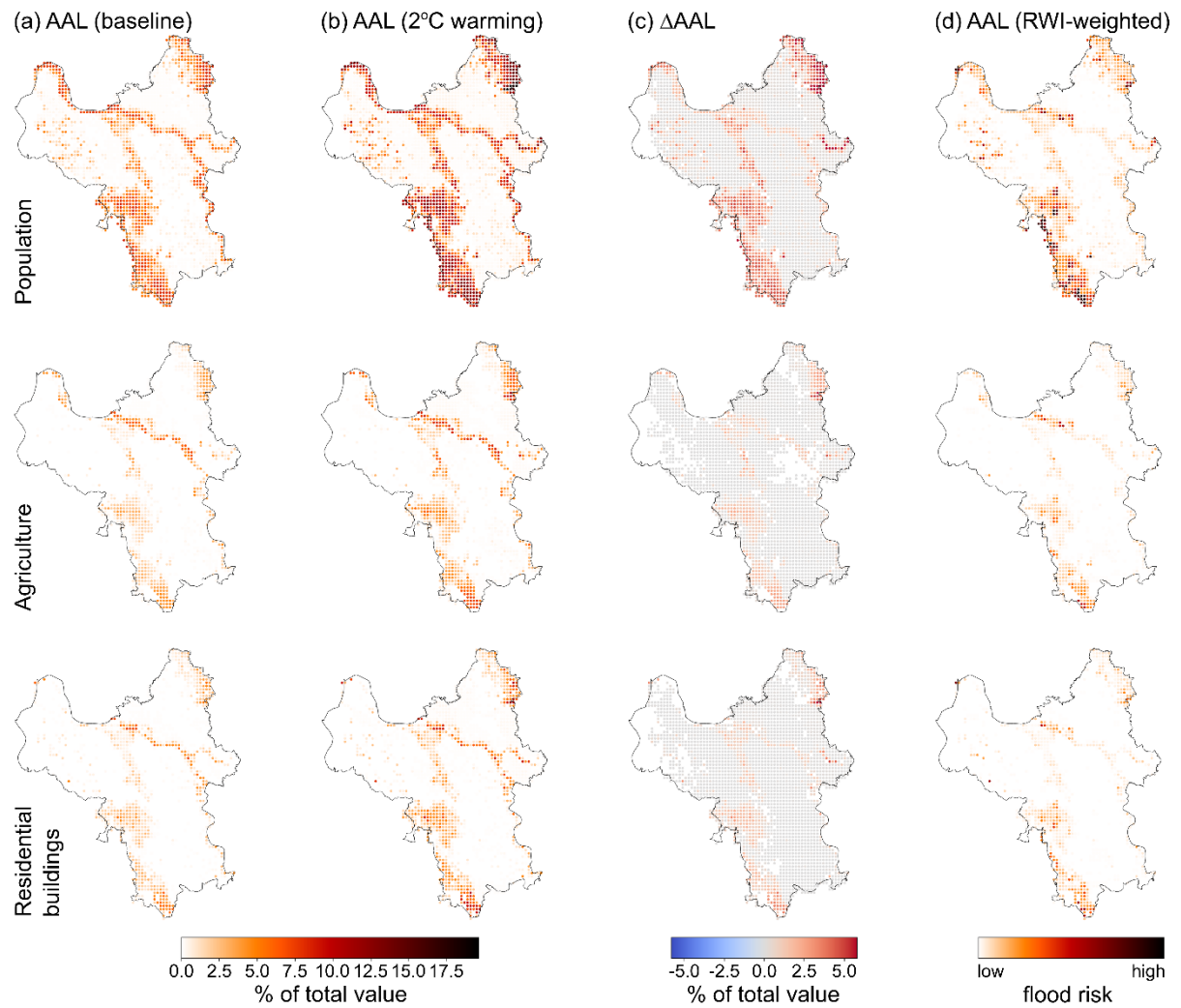
For Hanoi, flood risk impacts ~9% for population in the baseline, which more than doubles to ~20% in the 2°C warming scenario when aggregating relative AALs across the whole region. For agricultural crops, the aggregate relative AAL increases from ~7% in baseline to ~11% in the 2°C warming scenario, with a similar increase from ~7% to ~12% for residential buildings. The spatial  
350 distribution of changes in relative AALs between baseline and climate change scenarios shows a mix of areas of negligible changes and areas of positive changes, with no locations showing decreasing flood risk (Figure 3c). Areas of particularly high increases in relative AALs are seen in the northeast and southwest edges of the province, away from the highly urbanised central region, coinciding more with rural areas. These also coincide with some of the greatest RWI-weighted AALs, with the highest  
355 of these clustered towards the southwest edge of the region (Figure 3d). This suggests that, for Hanoi, the highest RWI-weighted AALs are driven both by high flood risk and high socioeconomic vulnerability.



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**Figure 2.** Cat model results for Chikwawa showing AAL relative to total exposed value aggregated to 0.01° for (a) the baseline scenario, (b) the 2°C warming scenario, (c) the change in relative AAL between these, and (d) the 2°C warming AAL weighted by the relative wealth index (RWI). Results are shown for (top) population, (middle) agricultural crops, and (bottom) residential buildings. In all panels, areas shown in white indicate either no exposure or a relative AAL of zero.

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**Figure 3.** Cat model results for Hanoi showing AAL relative to total exposed value aggregated to  $0.01^\circ$  for (a) the baseline scenario, (b)  $2^\circ\text{C}$  warming scenario, (c) the change in relative AAL between these, and (d) the  $2^\circ\text{C}$  warming AAL weighted by the RWI. Results are shown for (top) population, (middle) agricultural crops, and (bottom) residential buildings. In all panels, areas shown in white indicate either no exposure or a relative AAL of zero.

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#### 4.2.3 Cagayan, Philippines

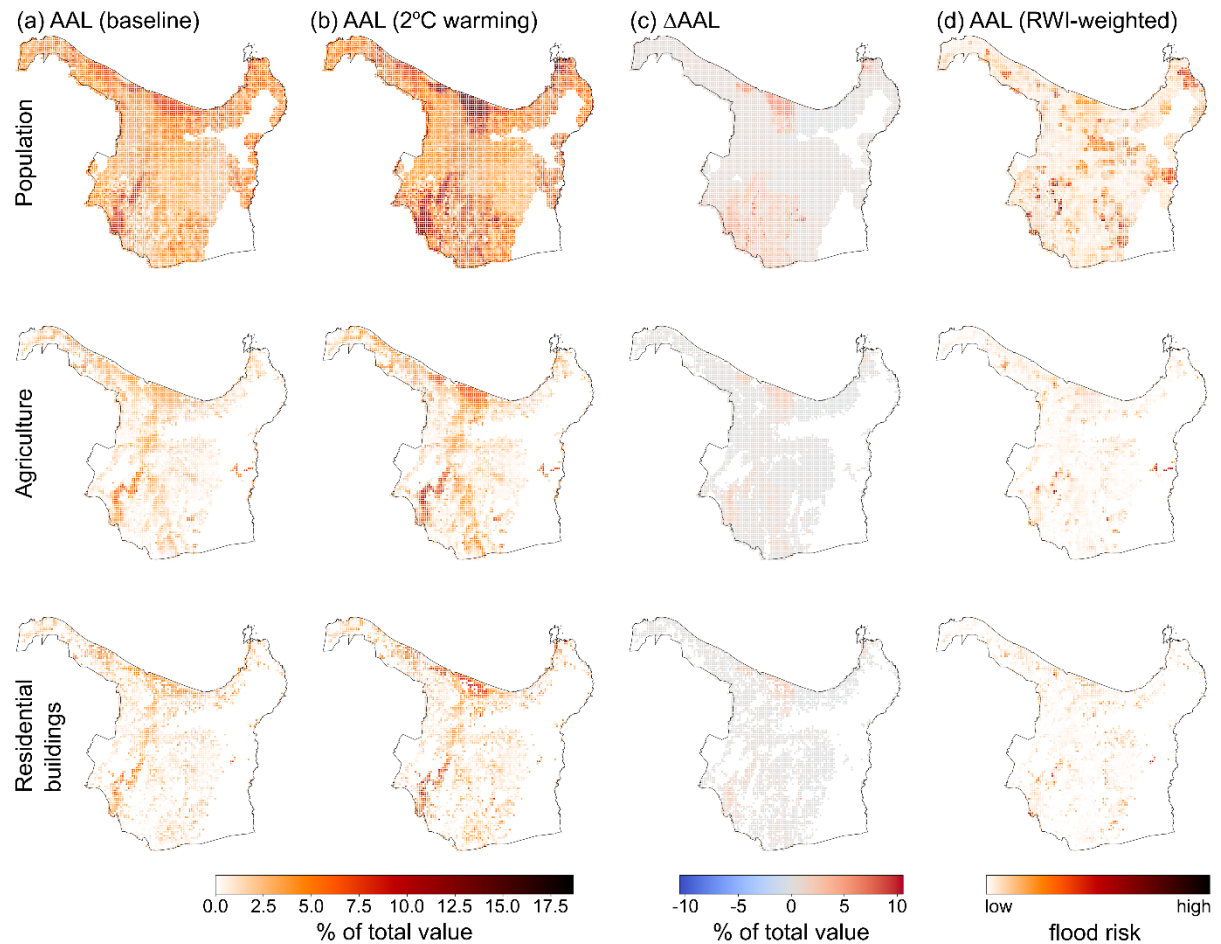
Model results for Cagayan show similar magnitudes of increases in relative AALs to Hanoi. For the baseline,  $\sim 9\%$  of the population is affected by flooding in any one year, increasing to  $\sim 19\%$  in the  $2^\circ\text{C}$  warming scenario, when aggregating relative AALs across the whole region. For agricultural crops, the aggregate loss increases from  $\sim 8\%$  of the overall value in baseline to  $\sim 12\%$  under the  $2^\circ\text{C}$  warming scenario, with a similar increase of  $\sim 7\%$  to  $\sim 12\%$  for residential buildings (Figures 4a and 4b). In terms of spatial distribution, the changes in relative AAL are dominated by hotspots of positive changes in the northeast and southwest, in among large areas of low or zero changes, and a few locations with small decreases (Figure 4c). Whilst some of the locations of large AAL increases coincide with the largest RWI-weighted AALs, areas of high RWI-weighted risk are seen across the

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province and are less confined to areas of high flood risk (Figure 4d). This suggests that for some locations in Cagayan, the RWI-weighted AAL is more strongly driven by high vulnerability than high flood risk.

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**Figure 4.** Cat model results for Cagayan showing AAL relative to total exposed value aggregated to 0.01° for (a) the baseline scenario, (b) the 2°C warming scenario (b), (c) the change in relative AAL between these, and (d) the 2°C warming AAL weighted by the RWI. Results are shown for (top) population, (middle) agricultural crops, and (bottom) residential buildings. Areas shown in white represent either no exposure or a relative AAL of zero.

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### 5. Cat models as tools for loss and damage: reflections and open questions

With the example of flood risk in three Global South countries, we have demonstrated the utility of a cat model framework, augmented with high-resolution geospatial datasets, to quantify loss and damage under climate change. We used the average annual loss (AAL), a standard (re)insurance metric, to quantify flood risk under present-day (baseline) conditions and a 2°C warming scenario. Overall, with these simulations, we found that our three chosen regions would face different degrees of change in flood risk under this measure: a ~70% increase for Hanoi, Vietnam; a 35% increase for Cagayan, the Philippines; and a negligible change for Chikwawa, Malawi. These changes hold true

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for the three exposure types that we investigated: population, residential buildings, and agricultural crops. With the diverse regions and exposure types, our study has provided a glimpse of the flexibility – and underexplored potential – of cat models in a loss and damage framework, which can provide the customisable and context-specific quantitative estimates central to the loss and damage financing process (Otto and Fabian, 2023).

The change in AAL represents the probability-weighted impact of climate change on flood risk and is one candidate metric that could be used to quantify loss(es) and damage(s). By integrating over all possible severities in the cat model event set, this metric has advantages over comparing different scenarios and time periods from direct climate model output, since the latter will not capture such a broad range of possibilities. Similar advantages are also present in other cat model metrics, which may be selected as a stronger evidence base to inform a particular action. For example, one could focus on the change in loss from an event of a given return period, seek to determine a “probable maximum loss”, or explore whether impact is coming from changes in frequent, low-impact events vs infrequent, high-impact events.

While offering advantages over direct use of climate model outputs, cat models are still dependent on the output of climate models to project the change in hazard. Such projections are fraught with deep uncertainties at the spatial scales of interest, with different climate models often projecting opposite signs of change in variables like precipitation (Seneviratne et al., 2021). As well as model deficiencies (e.g., Wehner et al., 2021), this pertains to uncertainties in how large-scale weather patterns might be altered under climate change, in turn driven by the highly uncertain response of atmospheric dynamics to greenhouse gas forcing (e.g., Shepherd, 2014). In practice, this means that any use of a cat model framework to quantify losses and damages should go beyond our demonstration and explore a range of possibilities for how climate change could impact natural hazards in the region(s) of interest, such as by using a storylines framework (Shepherd et al., 2018).

In a storylines framework, cat models could be used to explore a range of plausible regional climate changes and the required adaptation measures to mitigate any increase in loss and damage that would otherwise result. This could include integrating data on flood defences and other mitigation strategies, including projections of urbanisation and population changes, and quantifying the cost of inaction (it is generally understood that the cost of disaster risk reduction measures is less than the cost of recovery (Mechler, 2016). Indeed, the JBA cat model has already been used to explore these kinds of questions recently (Sarailidis et al., 2023).

Moreover, mediated by their high resolution, flood cat models can help stakeholders target vulnerable localities with practical adaptation measures. For example, in Hanoi province, our results suggest that



the largely agricultural south-west of Hanoi province faces the highest flood risk, both under baseline conditions and a 2°C warming scenario. Flooding has a significant impact on agricultural productivity  
445 in Hanoi, leading to compounding impacts such as risk to food supplies (Ha, 2024). Therefore, a spatial analysis of flood risk is crucial for effectively directing loss and damage finance, ensuring resources are allocated to the most vulnerable regions to mitigate future impacts.

At the same time, we must recognise that uncertainty extends beyond the hazard component of the cat  
450 model to include the exposure and vulnerability components necessary for investigating storylines of adaptation. In conducting this study, a lack of data meant pragmatic choices had to be made concerning exposures and their vulnerabilities, including a uniform distribution of value across exposure points and the use of generalised vulnerability functions to translate flood depth into damage, whereas we would expect both to be spatially heterogenous. Moreover, sourcing information  
455 of sufficient quality at a regional level was a key challenge in this study and generating exposure portfolios from available, high-resolution data sources introduces uncertainty arising from data accuracy. Recognising, quantifying, and reducing these and other uncertainties is needed, working across academia, industry, and with local actors (Balzter et al., 2023; Déroche, 2023). Given the complexities and non-linearities that are pervasive in cat models, the importance of the different  
460 uncertainty sources on the final output uncertainty is generally not immediately obvious (Sarailidis, 2023). Strategies such as global sensitivity analysis can help identify the dominant drivers of uncertainty and help developers focus efforts for model improvement (Sarrazin et al., 2016).

Beyond the technical considerations for designing and implementing simulations, engagement in the  
465 loss and damage space requires cat model developers and users to engage with fields, concepts, and collaborators beyond the domains usually explored in (re)insurance. With many seemingly well-established concepts occupying a highly contested space – poverty metrics (e.g., Alkire and Santos, 2014; Ravallion, 2020), climate adaptation governance (e.g., Persson, 2019), climate resilience (e.g., Mikulewicz, 2019), human rights (McNamara et al., 2023) to name but a few – one might question  
470 the tractability of the endeavour. Ways forward include recognising that a perfect technical solution will not emerge without challenges and that approaches need to be transdisciplinary, enveloping a range of skills and perspectives and being codesigned and coproduced with stakeholders (e.g., Balzter et al., 2023). This is particularly relevant for non-economic losses, which are not always quantifiable in a traditional economic sense (Tschakert et al., 2019). For instance, one might begin (as we did) by  
475 quantifying the affected population: although a residence may not be damaged, damage to surrounding businesses, infrastructure, food production or cultural sites and sacred places could indirectly “damage” wellbeing or livelihood (e.g., Walker-Springett et al., 2017; Steadman et al., 2022). However, making legitimate assessments and quantifications needs representatives of the region(s) under question: “nothing about us without us”.

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In addition to ethical considerations, these questions have a political dimension too, as they are likely to have a profound impact on how a loss and damage fund will be operationalised. For instance, given the prevailing economic paradigm that focuses on *quantifiable* losses, it is not only crucial to include non-economic losses into loss and damage models and finance but also include vulnerable  
485 communities into the very process of assessing and valuing those losses (McShane, 2017). This would be a more just approach while also going some way to closing the “adaptation gap” (UNEP, 2023) and to better direct the loss and damage finance that currently does not reach the most vulnerable communities (IFRC, 2022; Oxfam, 2023; Wilkinson et al., 2023).

## 490 **6. Summary and conclusions**

In this study, we have demonstrated how catastrophe (cat) models, as commonly used in the insurance and reinsurance industries, can be used to quantify climate change loss(es) and damage(s), fulfilling a key need to make urgent progress in this arena of international climate policy. With a focus on the impact of climate change on inland flood risk in three Global South regions – Chikwawa in Malawi,  
495 Hanoi in Vietnam, and Cagayan in the Philippines – and three exposure types – residential buildings, agricultural crops, and population – we have shown the ability and potential flexibility of cat models to quantify impacts for economic and non-economic loss and damage. Their utility is chiefly in their ready-made risk framework, which incorporates hazard, exposure, and vulnerability and generates a range of metrics to explore the impacts of extreme events. Unlike direct use of climate model output,  
500 cat models create a multi-thousand-year representation of the climate of interest, meaning that their metrics can reflect the weighted impact of a spectrum of extreme events or focus in on different ends of the extreme event distributions. The change in these metrics between simulations of different climates can be used to quantify loss and damage, as well as guide and evaluate adaptation and disaster risk resilience measures.

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Nevertheless, one must consider the quality of the hazard, exposure, and vulnerability data used in the model framework. Here, while we were able to demonstrate the utility of a cat model framework for a range of exposure types, sourcing high-quality exposure and vulnerability data was challenging (the Global South is less well served with this information (e.g., Glas et al., 2019), resulting in the need to  
510 make assumptions and pragmatic choices. Moreover, climate change information is deeply uncertain at the scales of interest for loss and damage (Shepherd, 2014). Recognising this, we proposed using a storylines framework (Shepherd et al., 2018) to tractably sample the uncertainty space for future projections, as well as global sensitivity analysis to better understand and quantify inherent cat model uncertainties (Sarrazin et al., 2016).

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Finally, and most importantly, building on this proof-of-concept will need meaningful collaboration between stakeholders, developers, local experts and vulnerable communities, to increase the quality of the data and ensure that the economic and non-economic losses are appropriately, legitimately, and justly chosen and quantified (Balzter et al., 2023).

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Overall, we hope that demonstrating the application of cat models in the loss and damage domain and highlighting the key challenges encourages future activity, improvements, and collaboration in this crucial space.

## 525 **Code and data availability**

Those interested in licensing the catastrophe model used in this study should contact [hello@jbarisk.com](mailto:hello@jbarisk.com). Details on the other datasets (exposures, vulnerabilities etc.) are available from the citations provided.

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