Methodology: Projecting humanitarian need resulting from climate impacts to the year 2100

Contact

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Introduction

The increasing impacts of climate change are leading to multifaceted humanitarian needs, contributing to, and exacerbating, crises such as those related to conflict, displacement and food security. In 2022, three-quarters of the 406.6 million people in need of humanitarian assistance were simultaneously experiencing two intersecting dimensions of risk: high-intensity conflict, high levels of socioeconomic fragility and high levels of vulnerability to climate change.[1] Yet, over the last decade, humanitarian appeals have been funded an average of only 59% and humanitarian funding saw a record shortfall of more than US$20 billion.[2]

There is an increasing emphasis on the need for humanitarian programmes to act before a crisis and lessen impacts. Collaboration between climate and humanitarian finance to expand the reach and scale of this anticipatory action could offer significant benefits.[3] Currently, however, it remains an uncommon approach, with most projects being small-scale pilots with limited funding. Data from Start Network indicates that approximately 55% of humanitarian funding is allocated to somewhat predictable crises, yet merely 1% of funding is pre-arranged, making it an increasingly pivotal area for humanitarian–development–peace nexus cooperation.[4] Projections modelling future humanitarian need as the result of accelerated climate impacts could support more enhanced anticipatory action, preparing communities for climate impacts and mitigating humanitarian crisis.

While climate change impacts are increasingly predictable,[5] understanding the extent to which they will impact humanitarian need by the end of the century is a complex endeavour, requiring not only the forecasting of direct climate impacts and socioeconomic conditions, but a consideration of changing geopolitics and policy, and of innovations in humanitarian response. Creating a machine learning model using the combined narrative frameworks of the Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs) (see below) can be used to project conflict and displacement needs to 2100. This modelling can offer some insight into how these drivers of risk may intersect with climate change impacts and socioeconomic factors in the future. However, projecting humanitarian need is not without challenges, and existing scenarios and resulting models could be improved. Underlying data derived from narrative frameworks lacks precision and certainty and is limited to selected variables. Existing projections also fail to account for the interrelationships between the drivers of crisis, and the feedback loops they create, for example, when displacement due to conflict creates additional pressure on climate, which, in turn, exacerbates climate-related crises.

How can we anticipate need?

Anticipating humanitarian needs is challenging, even in the short-term: the drivers of need can arise quickly and unexpectedly (for example, the Covid-19 pandemic placed 200 million people in need of humanitarian assistance in 2020).[6] Longer-term projections rely on imperfect historical knowledge and future expectations of risks and resilience. As such, longer-term projections cannot precisely forecast crises that will drive humanitarian need, but instead provide a trajectory of the scale of need at a global level based on the likelihood of crises occurring.

The primary challenge in estimating the drivers of humanitarian need is that they each constitute relatively rare events on a global basis: most countries in most years do not experience any of these drivers. This data sparseness poses a problem for traditional estimation methods such as linear regressions, as they optimise across the entire dataset equally, leading to significant under- or overestimations of rare events.

A machine learning (ML) model can be used to separately estimate the incidence of conflict and displacement under the combined baseline scenarios (see Methodology), with consideration of the effects specific to individual countries- for example, the extent to which precipitation is an adverse impact largely depends on location and amount. Although the individual nature of each location is not directly input to the machine learning model, the model is able to 'learn' these differences through fixed country effects and apply them to the projection outputs. In this way, machine learning assists in making more accurate predictions of humanitarian need. It is able to detect and learn from the small deviations in the sparse data and learn to recognise more complicated patterns than traditional estimation methods.

Using Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs)

Projecting the impact of climate change on humanitarian need relies on forecasting both direct climate effects and the associated socioeconomic situation.

The Intergovernmental Panel on Climate Change (IPCC) has crafted narrative pathways outlining potential future climate change scenarios, considering both socioeconomic and climatic outcomes. Shared Socioeconomic Pathways (SSPs) address potential challenges for climate adaptation and mitigation. Representative Concentration Pathways (RCPs) focus on the climatic effects of varying greenhouse gas emissions from now until 2100.[7]

SSPs

Five scenarios describe possible societal trajectories[8] to the year 2100.

- SSP1 (‘sustainable/green’) envisions low barriers to climate change adaptation and mitigation.
- SSP2 (‘middle of the road’) depicts a middle-ground scenario with moderate challenges for both.
- SSP3 (‘regional rivalry’) anticipates high challenges in both areas.
- SSP4 (‘inequality’) presents high challenges to adaptation, but low to mitigation.
- SSP5 (‘fossil-fuelled development’) balances high socioeconomic challenges to climate mitigation (emissions reduction) with low challenges to climate adaptation.[9]

RCPs

The RCPs are centred around a metric known as ‘radiative forcing’, a measure of how much energy is retained in the atmosphere due to the greenhouse effect. Different RCP scenarios point to different climatic outcomes, such as precipitation and temperature. There are currently seven distinct scenarios, which are labelled according to the level of radiative forcing in 2100, ranging from the lowest and most optimistic scenario (RCP1.9) up to a higher, pessimistic scenario (RCP8.5).

Combined scenarios

The five SSPs and seven RCPs are used together to create a range of combined scenarios that match the socioeconomic situations with greenhouse gas emissions.[10] From these, four combined scenarios that serve as the most practical and comprehensive baselines are derived, encompassing a range of what is deemed plausible.[11]

Machine learning projections do not attribute causality to individual variables; instead, they mirror the unique circumstances of the combined scenario; when these conditions (including both single variables and their interactions) change, the projections also change accordingly. The scenarios themselves are not variables that directly correspond to specific outcomes but rather define the contextual conditions within which a projection becomes viable.

Table 1: SSP–RCP baseline combined scenarios[12]

Scenario	A	B	C	D
SSP socioeconomic	SSP1 ‘sustainable/green’	SSP2 ‘middle of the road’	SSP3 ‘regional rivalry’	SSP5 ‘fossil-fuelled development”
RCP climate	RCP2.6 ‘very stringent’	RCP4.5 ‘intermediate’	RCP7.0 ‘baseline outcome’	RCP8.5 ‘worst case scenario’
Economic growth				
Population growth				
Precipitation increase				
Temperature increase				

Source: Development Initiatives based on WorldClim and IIASA.
Notes: Qualitative categorisation based on cumulative outcome over 2020 –2100.

Methodology

In order to show the possible projected impact of climate change on humanitarian need, we selected four ‘baseline’ scenarios combining Shared Socioeconomic Pathways and Representative Concentration Pathways to illustrate the range of feasible outcomes described by the frameworks. These combined scenarios present potential variations of the world in 2100. From these, we identified four key descriptive statistics – two socioeconomic variables: economic (GDP) growth and population growth; and two climatic variables: mean temperature and mean precipitation (see Figures A1-A4) – to form the basis of our model of estimating the drivers of humanitarian need.

The primary challenge in estimating changes in the drivers of humanitarian need is that they each constitute relatively rare events on a global basis: most countries in most years do not experience any of these drivers. This data sparseness poses a problem for traditional estimation methods such as linear regressions, as they optimise across the entire dataset equally, leading to gross under- or overestimations of rare events.

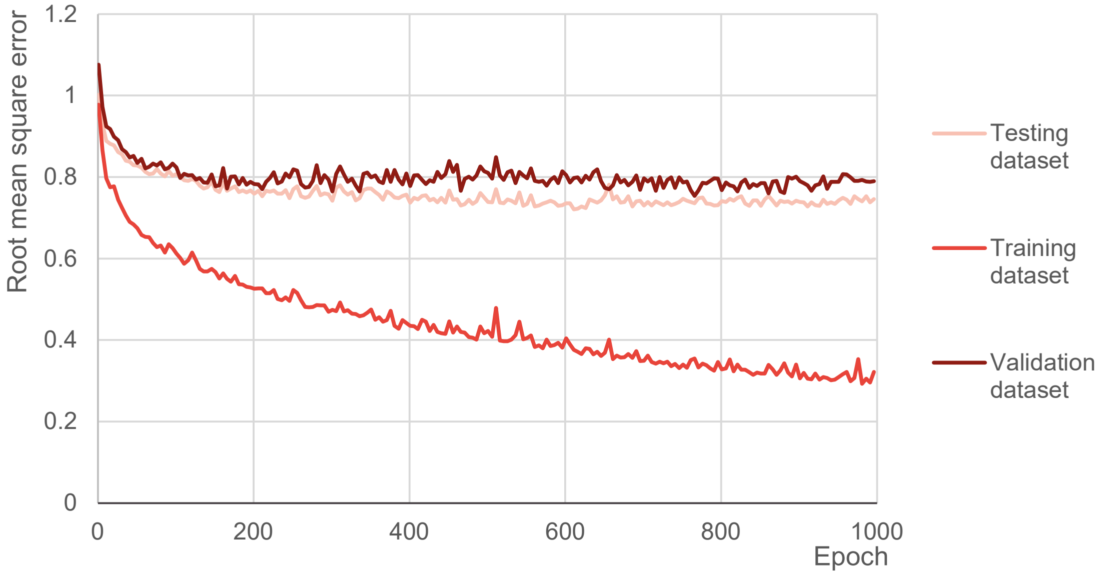
Conflict can directly influence displacement, and displacement can directly influence conflict; this relationship is called endogeneity, and it is the reason why these two variables need to be estimated separately first. By adding in country fixed-effects variables, we also allow the ML model to learn the implicit and constant differences between each recipient country. For example, precipitation may be a good variable for primarily agricultural economies but may hurt economies that depend on tourism; although we do not directly tell the model the nature of each country’s economies, it is able to learn these differences through the fixed-effects.

We source historical dependent variables for conflict and displacement from authoritative global datasets with a country–annual granularity. For climatic independent variables, we use WorldClim datasets;[13] for socioeconomic independent variables we use the SSP Database from the IIASA.[14]

While an ML model improves accuracy for estimating rare events, it poses an additional challenge in the form of requiring more data for training. In all our models, data was split into training, validation and testing sets, and the best model within the epoch limit was determined by accuracy against the unseen validation set. An example of how the ML model training progresses is show in Figure A1.

We also made use of a geospatial network graph inspired by a methodology developed by Uppsala[15] to construct two-country 'mini-regions' and supplement our model data. We theorise that these artificial mini-regions would also assist the model in forecasting future values, as they can train the model on greater independent variable values that would not otherwise appear in the historical data.

Figure A1: Historical displacement error for model datasets



Source: Development Initiatives based on UNHCR, WorldClim, and IIASA.

Conflict

For training the conflict ML model, we sourced the historical conflict dependent variable (DV) from Uppsala.[16] Conflict was modelled based on temperature, precipitation, GDP growth, population and country-level fixed-effects at a country–annual level.

The ML model achieved a recall of 76%, precision of 78% and accuracy of 87%. This outperformed a traditional logit estimator on precision and overall accuracy, which achieved a recall of 96%, precision of 13%, and accuracy of 62%. Although a logit estimator recalled more positive events, it did so by vastly overestimating the probability of conflict. According to the coefficients from the logit model, the chance of conflict was negatively correlated with GDP growth, and positively correlated with both precipitation and temperature.

Displacement

For training the displacement ML model, we sourced the historical displacement DV from United Nations High Commissioner for Refugees (UNHCR).[17] Displacement was modelled based on temperature, precipitation, GDP growth, population and country-level fixed-effects at a country–annual level.

As observed in the testing data, the ML model underestimated the total displacement by 3% and explained 48% of the variation in country–year displacement. This can be compared to linear regression, which underestimated total displacement by 28%, and explained 43% of the variation. According to the coefficients from the linear regression, no significant relationship with GDP growth was found, but displacement was negatively correlated with precipitation and positively correlated with temperature.

Climate-related disasters

We examined the possibility of projecting the incidence of climate-related disasters based on data from the Centre for Research on the Epidemiology of Disasters's Emergency event database.[18] However, the quality and consistency of data on climate-related disasters is historically poor – reporting is biased to high-income countries, and is particularly poor for slow-onset disasters such as droughts.[19]

Upon estimating climate-related disasters based on temperature, precipitation and country-level fixed-effects at a country–annual level, the model did not perform significantly better than linear regression, overestimating disasters by 3% and explaining 48% of the variation. Ultimately, we opted to not separately project climate-related disasters as a separate driver and instead directly included climatic variables in final humanitarian needs model.

Humanitarian need

For ease of interpretation, we made use of a linear regression to estimate and forecast the number of people in need based on the individual drivers estimated above, and the climatic variables of mean maximum temperature and annual precipitation. All variables were found to have a statistically significant relationship with people in need. The resulting projections by SSP-RCP scenario are indicative trajectories, rather than precise annual estimates, with the observed level of humanitarian need varying around these trajectories.

Figure A1: Global GDP by SSP-RCP scenario[20]

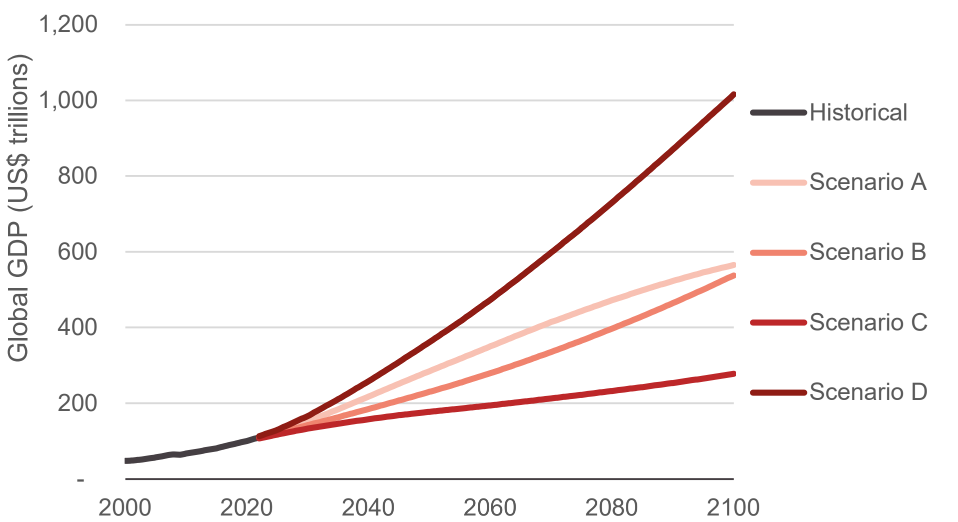


Figure A2: Global population by SSP-RCP scenario[21]

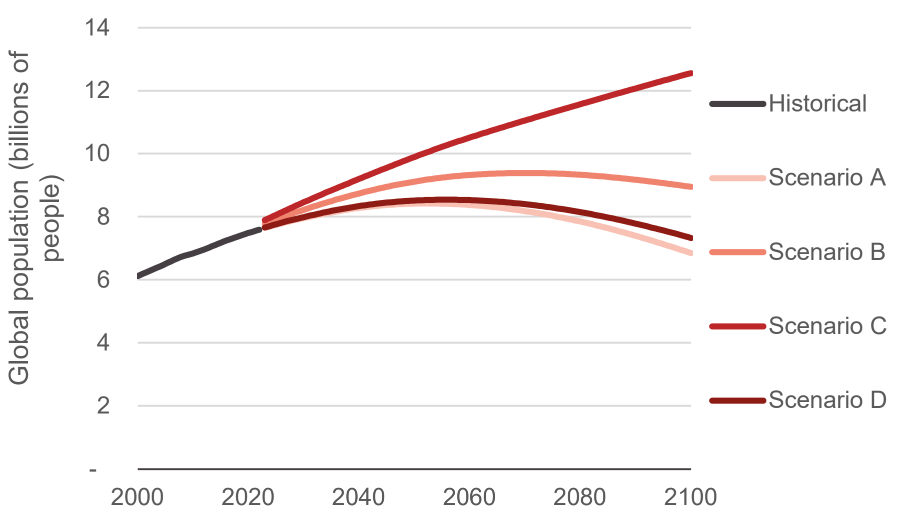


Figure A3: Mean maximum temperature increase by SSP-RCP scenario[22]

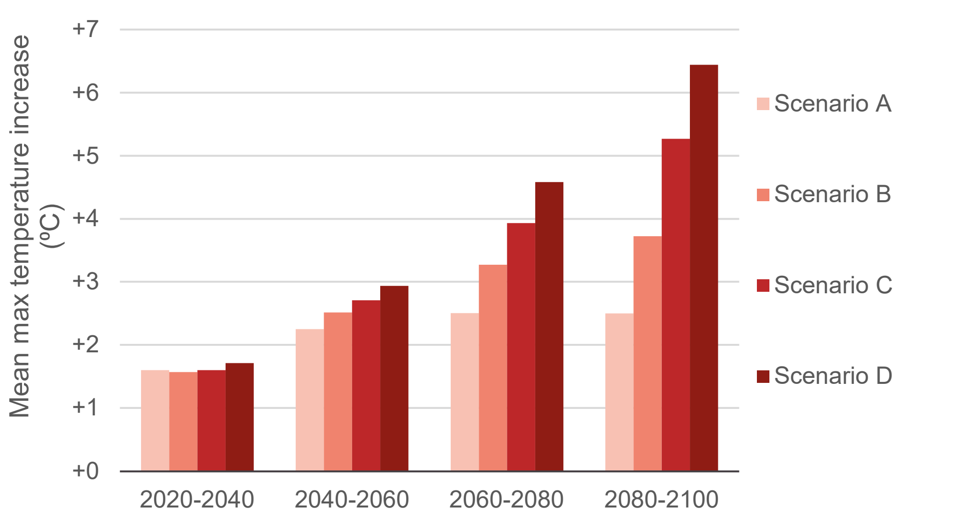
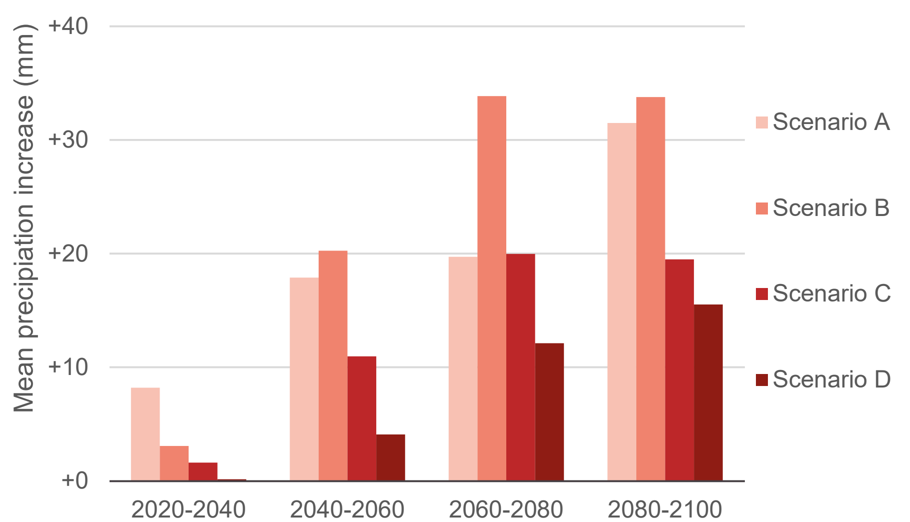


Figure A4: Mean annual precipitation increase by SSP-RCP scenario[23]



About Development Initiatives

Development Initiatives (DI) DI unlocks the power of data to enable policies and investments that improve the lives of people experiencing poverty, inequality and crisis.

Our mission is to work closely with partners to ensure data-driven evidence and analysis are used effectively in policy and practice to end poverty, reduce inequality and increase resilience.

While data alone cannot bring about a better world, it is a vital part of achieving it. Data has the power to unlock insight, shine a light on progress and empower people to increase accountability.

To find out more about our work visit:
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Endnotes

1 Development Initiatives, 2023. The Global Humanitarian Assistance Report 2023, https://devinit.org/resources/global-humanitarian-assistance-report-2023/ (accessed 5 September 2023).

2 Development Initiatives, 2023. The Global Humanitarian Assistance Report 2023. https://devinit.org/resources/global-humanitarian-assistance-report-2023/ (accessed 5 September 2023).

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4 Oxfam, forthcoming 2023. Climate and Humanitarian Finance; Collaboration not Competition

5 Erin Coughlan de Perez, Laura Harrison, Kristoffer Berse, Evan Easton-Calabria, Joalane Marunye, Makoala Marake, Sonia Binte Murshed, Shampa, Erlich-Honest Zauisomue. 2022. Adapting to climate change through anticipatory action: The potential use of weather-based early warnings, Weather and Climate Extremes. Volume 38. 100508. https://doi.org/10.1016/j.wace.2022.100508

6 Development Initiatives, 2023. The Global Humanitarian Assistance Report 2023, https://devinit.org/resources/global-humanitarian-assistance-report-2023/ (accessed 5 September 2023).

7 Brian C. O'Neill, Elmar Kriegler, Kristie L. Ebi, Eric Kemp-Benedict, Keywan Riahi, Dale S. Rothman, Bas J. van Ruijven, Detlef P. van Vuuren, Joern Birkmann, Kasper Kok, Marc Levy, William Solecki. 2017. The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century, Global Environmental Change. Volume 42, Pages 169–80. https://doi.org/10.1016/j.gloenvcha.2015.01.004 (accessed 5 September 2023).

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9 'Mitigation' and 'adaptation' are classifications of activities under the United Nations Framework Convention on Climate Change. 'Mitigation' refers specifically to activities that stabilise greenhouse gas concentrations in the atmosphere and reduce emissions. 'Adaptation' projects seek to reduce climate impacts on vulnerable populations, usually through large infrastructure projects such as river realignment or climate-smart housing.

[10] Not all combinations of SSPs and RCPs are considered likely or possible; for example, a combination of SSP3 (describing a world with high barriers to climate mitigation and adaptation), and RCP2.6 (moderately low emissions of greenhouse gases) is deemed almost impossible based on current modelling.

[11] A combined scenario with SSP4 is not derived here.

[12] Conditions of the scenarios include:

- Scenario A (SSP1 – RCP2.6): Moderate economic growth, low population growth, and lower radiative forcing, which will have resulted in low temperature increases and a moderate level of precipitation increase.
- Scenario B (SSP2 – RCP4.5): Moderate changes in socioeconomic and population growth, as well as moderative radiative forcing, which will have resulted in high levels of precipitation increase and moderate temperature increases.
- Scenario C (SSP3 – RCP7.0): Low economic growth, high population growth, and high radiative forcing, which will have resulted in in low precipitation increases, and high temperature increases.
- Scenario D (SSP5 – RCP8.5): High economic growth, low population growth, and very high radiative forcing, which will have resulted in low precipitation increases, and high temperature increases.

[13] WorldClim: Future Climate Data, https://www.worldclim.org/data/cmip6/cmip6climate.html (accessed 5 September 2023).

[14] SSP Database (Shared Socioeconomic Pathways) - Version 2.0, https://tntcat.iiasa.ac.at/SspDb/dsd (accessed 5 September 2023).

[15] Heard Hegre et al., 2016. Environ. Res. Lett. 11 054002, Forecasting civil conflict along the shared socioeconomic pathways, https://iopscience.iop.org/article/10.1088/1748-9326/11/5/054002 (accessed 5 September 2023).

[16] Ibid.

[17] UNHCR: Refugee Data Finder, https://www.unhcr.org/refugee-statistics/download/?url=KWaX3w (accessed 5 September 2023).

[18] Center for Research on Epidemiology of Disasters, EM-DAT: The International Disaster Database https://emdat.be/ (accessed 5 September 2023).

[19] Debarati Guha-Sapir and Regina Below, 2000. The Quality and Accuracy of Disaster Data: A Comparative Analyses of Three Global Data Sets. https://www.unisdr.org/2005/task-force/working%20groups/wg3/Comparative_Analysis_of_3_Global_Data_Sets.pdf (accessed 5 September 2023).

[20] Source: Development Initiatives based on IIASA.

[21] Source: Development Initiatives based on IIASA.

[22] Source: Development Initiatives based on WorldClim. Notes: Increase averaged globally across 20-year increments.

[23] Source: Development Initiatives based on WorldClim. Notes: Increase averaged globally across 20-year increments.