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Evaluating prospects for subseasonal-to-seasonal forecast-based anticipatory action from a global perspective

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A B S T R A C T

Globally, the direct cost of natural disasters stands in the hundreds of billions of USD per year, at a time when water resources are under increasing stress and variability. Much of this burden rests on low- and middle-income countries that, despite their relative lack of wealth, exhibit considerable vulnerability such that losses measurably impact GDP. Within these countries, a growing middle class retains much of its wealth in property that may be increasingly exposed, while the few assets the poor may possess are often highly exposed. Vulnerability to extreme events is thus heterogeneous at both the global and subnational level. Moreover, the distribution and predictability of extreme events is also heterogeneous. Disaster managers and relief organizations are increasingly consulting operational climate information services as a way to mitigate the risks of extreme events, but appropriately targeting vulnerable communities remains a challenge. The advent of forecast-based anticipatory action has added to the suite of opportunities—and complexity—of operationalizing such services given varying prediction skill. Forecasts, including those at the subseasonal-to-seasonal (S2S) scale, may allow disaster managers to shift effort and therefore some risk from post-disaster response to pre-disaster preparedness; however, given the recent emergence of such programs, only a few, specific case studies have been evaluated. We therefore conduct a country-scale analysis pairing S2S forecast skill for monthly and seasonal lead times with flood and drought disaster risk to explore the potential for forecast-based anticipatory action programs broadly. To investigate subnational heterogeneity in risk and predictability, we also evaluate focused outcomes for the Greater Horn of Africa and Peru. Results suggest that forecast skill plays a large part in determining suitability for early action, and that skill itself varies considerably by disaster type, lead time, and location. Moreover, the physical and socioeconomic factors of risk can vary greatly between national and subnational levels, such that finer scale evaluations may considerably improve the effectiveness of early action protocols. By considering vulnerability at multiple spatial scales and forecast skill at multiple temporal scales, this analysis provides a first identification of promising locations for anticipatory action protocol development.

1. Introduction

Extreme climate and weather events are a major impediment to global development and are expected to become more frequent as climate changes (IPCC – The Intergovernmental Panel on Climate Change, 2014). These events are responsible for the majority of the US $165 billion per year in direct disaster-related losses, a figure which is steadily increasing with time (World Bank, 2014). Low- and middle-income countries are particularly vulnerable to natural disasters: a growing global middle class—numbering five billion by 2030—retains much of its wealth in property, and disaster losses in middle-income countries accounting for nearly 3% of GDP. Likewise, the minimal physical assets the poor have are often highly exposed, subjecting them to disaster-driven poverty traps (Borgomeo et al., 2017). There is increasing demand for management solutions to disaster risk, given the potential adverse effects of physical infrastructure and the relatively low capital costs (Di Baldassarre et al., 2018; Kelman, 2013). Early warning systems are one such solution, requiring minimal physical capital investments, and are increasingly popular in disaster-prone areas. More recently, there has been an increase in the coverage of index-based (or parametric) insurance, in which payouts are triggered by an index correlated to losses. These products offer a way for insurance to penetrate poor and middle-income markets by relying on transparent mechanisms based on a minimal number of observations, reducing administrative costs, moral hazard, and other challenges that often beset traditional insurance schemes (Skees, 2011). Coupling early warning systems and insurance concepts, aid organizations have developed anticipatory action frameworks in which forecast-based early warnings are used to trigger funds and allocate resources before a disaster occurs, allowing for timely preparatory actions.

Much of the impetus for the rise of early action protocols (EAPs) results from gains in the field of subseasonal-to-seasonal (S2S) forecasts,

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either alone or as complements to shorter-lead forecasts (Vitart and Robertson, 2018). Indeed, in-depth studies of EAPs have found that these medium-term forecasts, ranging from months to seasons in lead time, can have a major impact on project efficacy and cost as part of a "Ready-Set-Go!" approach (Bazo et al., 2019; Lala et al., 2021b). Forecast systems used for EAP development are independently developed by various agencies and organizations, such as the National Centers for Environmental Predictions (NCEP) Climate Forecast System version 2 (CFSv2; Saha et al., 2014) and the European Centre for Medium-Range Weather Forecasts (ECMWF) Seasonal Forecast System 5 (SEAS5; Johnson et al., 2019). In most cases, these systems provide a forecast ensemble based on various initial conditions and assumptions, allowing for probabilistic analysis that generally enhances user applications, particularly for longer lead times (Matte et al., 2017). The improvement in skill and spatial resolution of forecasts coupled with innovations in humanitarian aid has thus provided a clear roadmap for the development of EAPs and anticipatory action in general.

EAPs have been developed by the Red Cross and other aid organizations in Latin America, East and West Africa, and South and Southeast Asia (Coughlan de Perez et al., 2015; Lopez et al., 2017; Netherlands Red Cross, 2021). Despite the widening geographic scope of these projects, there remain outstanding questions on appropriately targeting high-risk populations. As the global community shifts from disaster management to disaster *risk* management (United Nations, 2015), there is an increasing need to identify risk as a distinct component of disaster response. The European Commission has launched the Index for Risk Management (INFORM) project to catalogue and share physical and socioeconomic factors that constitute disaster risk (Marin-Ferrer et al., 2017). Data is available for 191 countries at the national scale, and at the subnational scale for a few select locations, allowing for identification of risk based on a variety of hydro-meteorological hazards, including floods and droughts. Although this data is useful for identifying socio-economic and population risk, there is minimal integration with early warning systems to properly anticipate and mitigate disasters (OCHA, 2021). The identification of open, skillful, and global forecasts and standardized risk metrics is thus a major next step in the implementation of sustainable anticipatory action programs. Such global-scale analysis can highlight vulnerable regions which may therefore benefit from early action.

This study addresses outstanding challenges in disaster risk reduction by integrating global S2S precipitation forecasts with a standard, global definition of disaster risk. As many global disaster risk models are limited by granular data (Ward et al., 2015), we incorporate, where available, subnational data on risk, while also downscaling and bias correcting forecasts using gauge-corrected precipitation datasets to ensure a spatial scale fine enough for targeted relief efforts. At the country level, we conduct a global analysis, while at the subnational level, we focus on the Greater Horn of Africa, which is among the most drought-vulnerable regions in the world (Ahmadalipour and Moradkhani, 2018), as well as Peru, which is highly vulnerable to floods and extreme rainfall (Bazo et al., 2019).

2. Methodology

This study consists of three parts: (1) quantifying and evaluating risk scores for floods and droughts, (2) evaluating global S2S precipitation forecast skill through bias correction and spatial disaggregation, and (3) integrating the two into an anticipatory action "suitability score" in which areas with coincident high predictability skill and high risk scores are highlighted.

2.1. Evaluation of disaster risk

Risk data at the national level, as well as the regional level for the Greater Horn of Africa, comes from the Index for Risk Management (INFORM) project (Marin-Ferrer et al., 2017). INFORM defines risk as the product of three separate components: (1) hazard and exposure, including the existence of extreme events and populations exposed to them; (2) vulnerability, comprising of socioeconomic health factors that leave communities susceptible to a hazard; and (3) lack of coping capacity, indicating a lack of available resources to lessen the impact of a hazard. Each component is broken down into multiple subcomponents, collectively comprising 32 indicators, and normalized to a score of 0–10 (Fig. 1; full list of indicators in Appendix Table A1).

Given these components, INFORM then calculates a risk score, ranging from 0 to 10, as follows:

$$Risk = Hazard\ \&\ exposure^{\frac{1}{3}} \times Vulnerability^{\frac{1}{3}} \times Lack\ of\ coping\ capacity^{\frac{1}{3}} \quad (1)$$

with a score of 0–1.9 indicating very low risk, 2.0–3.4 low risk, 3.5–4.9 medium risk, 5.0–6.4 high risk, and 6.5–10 very high risk. Given that we investigate only precipitation hazards, the natural component of hazard and exposure is restricted to either flood or drought depending on the forecast; indicators relating to earthquakes, tsunamis, cyclones, or epidemics are disregarded in this analysis.

Although INFORM provides this data at the national level for 191 countries, disaster risk models are often limited by the coarse resolution of their input data (Ward et al., 2015). INFORM has addressed this by issuing subnational data for some regions, including parts of sub-Saharan Africa, Central America, and the eastern Mediterranean; however, subnational data in most of the world is sparse. We therefore consider two case studies for subnational data: the Greater Horn of Africa at the regional/provincial (Level 1) scale, using INFORM data, and Peru at the district (Level 2) scale, using data gathered from the Peruvian government and the Red Cross. The Greater Horn of Africa is highly drought-vulnerable, and risk of drought is only expected to increase in the region due to climate change (Ahmadalipour and Moradkhani, 2018). Contrastingly, Peru is a data-rich country that is highly susceptible to floods and extreme rainfall, particularly in the coastal north and Amazonia (Bazo et al., 2019).

Given the different sources of data for Peru, an exact one-to-one correspondence with INFORM indicators is difficult; however, we follow the same general approach of INFORM as the product of hazard and exposure, vulnerability, and lack of coping capacity. Lee et al. (2021) found that an equal weighting of socio-health vulnerability and coping capacity indicators was best correlated with forecast-informed estimates of flood impact; thus, we combine these socioeconomic indicators into a combined vulnerability and lack of coping capacity score with equal weighting of all indicators:

$$Risk = Hazard\ \&\ exposure^{\frac{1}{3}} \times Vulnerability\ \&\ Lack\ of\ coping\ capacity^{\frac{2}{3}} \quad (2)$$

To account for the potential differences in risk arising from a different set of metrics, the final risk score is normalized such that the average score over all districts equals the country-level score given by INFORM. All vulnerability and lack of coping capacity are derived from the Peruvian National Institute for Statistics and Informatics (INEI – Instituto Nacional de Estadística e Informática, 2017) and from the Netherlands Red Cross 510 Dashboard (Netherlands Red Cross, 2021). Hazard and exposure data for floods is the average of three normalized variables: number of damaged houses (INEI), number of affected people (INEI), and percent of area at risk of inundation from maximum daily precipitation (Aybar, 2018). For droughts, hazard and exposure data are derived from the water scarcity analysis of Veldkamp et al. (2016), aggregated to the regional scale via the ThinkHazard! database (GFDRR Labs, 2021). Indicators in all cases are normalized via min-max normalization; data that is not distributed normally is first transformed via a Box-Cox power transformation (Box and Cox, 1964). For a full list of indicators, refer to Table A2 in the appendix.

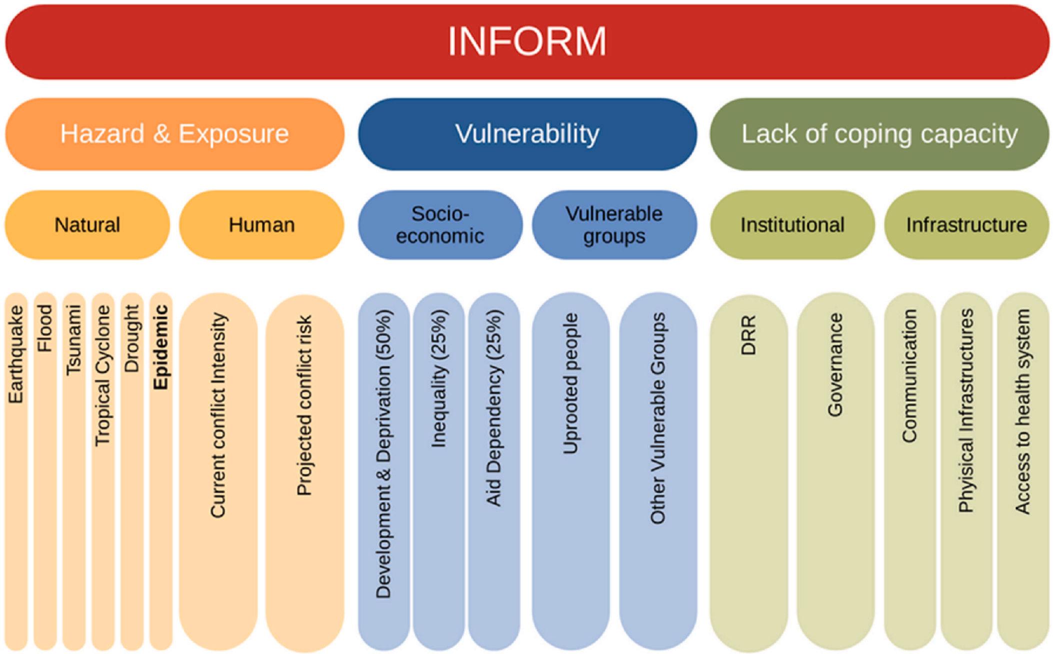

Fig. 1. Components of INFORM risk index (source: INFORM, 2020).

2.2. Evaluation of forecasts

Before evaluating forecast skill, a quasi-global timeseries of total precipitation for peak months and seasons are determined using CHIRPS, a satellite-based, gauge-corrected, quasi-global (50°S-50°N) precipitation dataset provided at 0.05° spatial resolution. Given that wet season totals tend to be particularly important for agriculture and runoff generation (Funk et al., 2019), precipitation and forecasts are only considered for the peak month—that is, the month in each grid cell with the highest mean climatological value—and peak season, which is defined as the peak month and one month to either side (e.g., if the highest mean precipitation in a location occurs in December, the peak season would be defined as November-December-January). Although the season with the highest mean precipitation may not necessarily correspond to the month with the highest mean, we nevertheless use this definition in order to conserve the "Ready-Set-Go!" approach of the Red Cross EAPs such that action at the seasonal and monthly scale can be activated concurrently. Fig. 2 depicts the peak month of each grid cell in the dataset (note that CHIRPS only extends from 50°S to 50°N, thus parts of North America, Europe, and Asia are not considered in this analysis).

Two seasonal-to-subseasonal forecast products are used for the global analysis: the National Centers for Environmental Predictions (NCEP) Climate Forecast System version 2 (CFSv2; Saha et al., 2014), and the European Centre for Medium-Range Weather Forecasts (ECMWF) Seasonal Forecast System 5 (SEAS5; Johnson et al., 2019). Both centers issue monthly forecasts with six (ECMWF) and nine (NCEP) months lead time and consist of 24 (NCEP) and 25 (ECMWF) ensemble members extending over their available records. Forecasts are evaluated for the peak month (1 month lead) or season (1–3 months lead) at each CHIRPS grid cell over the period 1982–2020 (NCEP) and 1993–2020 (ECMWF) and are spatially disaggregated and bias corrected approximately following the method of Lorenz et al. (2021). First, the individual ensemble members of the forecasts are downscaled to the 0.05° resolution of the precipitation dataset using bilinear interpolation, then, the disaggregated forecasts are bias corrected using quantile mapping of the empirical CDFs of the forecasts to the empirical CDFs of the precipitation (Cannon et al., 2015). Empirical CDFs are chosen as they tend to perform better in bias correction than do parametric CDFs (Gudmundsson et al., 2012). Although individual ensemble members are often pooled before performing bias correction, we find that bias correction of ensemble

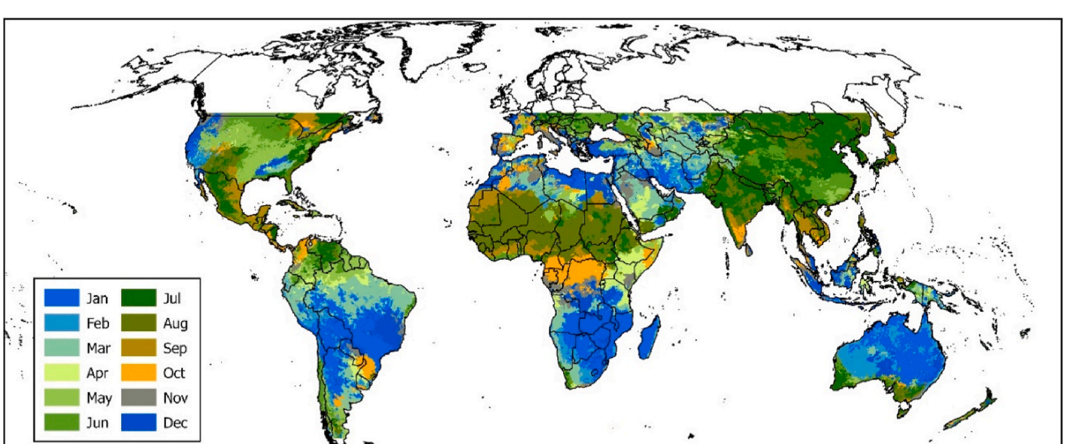

Fig. 2. Peak month of precipitation, based on highest mean, 1981–2020.

members individually generally results in better performance, and we elected to use the latter approach.

Defining floods and droughts is nontrivial; however, past EAP projects provide insight into coherent definitions. The Red Cross's current EAP trigger for extreme precipitation in Peru uses the 95th percentile of monthly or seasonal precipitation in its definition (Bazo et al., 2019; Lala et al., 2021b), while a project in England and Wales used a 1-in-30 year return period for rainfall intensity (~97th percentile; Coughlan de Perez et al., 2015). Yet another project for floods used the 2- to 20-year flood return period (50th-95th percentile; Bischiniotis et al., 2020). Given these studies, we select the 95th percentile of monthly or seasonal rainfall as the threshold for flood-based EAPs. Ideally, riverine flooding based on flow rates or river stage may be preferable, however we select precipitation based on limited riverine data observations and coarse resolution in global hydrologic models (Ward et al., 2020). Regarding droughts, past studies consider the bottom 15%–40% of crop yields (Guimarães Nobre et al., 2018); however, given our use of meteorological—rather than agricultural—drought, we elect to define drought as the 15th percentile of precipitation, based on the definition of "moderate drought" by the U.S. Drought Monitor as the 10th to 20th percentile of precipitation (NDMC, 2021).

Forecast skill is evaluated using the Brier skill score (Brier, 1950) according to the form:

$$BSS = 1 - \frac{BS_{fcst}}{BS_{clim}} \tag{3}$$

where *BS* is the Brier score of the forecast (*fcst*) or of a naïve climatology forecast (*clim*), defined as:

$$BS = \frac{1}{N}\sum_{t=1}^{N}(p_t - o_t)^2 \tag{4}$$

where N is the number of years in the study period, p is the forecast probability of exceedance (defined as the proportion of ensemble members predicting exceedance; i.e., 5% for floods and 15% for droughts), and o is the actual outcome (1 for exceedance, 0 otherwise). Forecasts thus have a BSS between -∞ and 1, with 1 representing a perfect forecast and values greater than 0 indicating an improvement over the naïve climatology forecast.

2.3. Identifying suitability scores

Finally, once a risk score (ranging from 0 to 10) and a Brier skill score (ranging from -∞ to 1) are determined for a given location, a *suitability* score is determined as the product of the two:

$$Suitability = Risk * BSS_{max} \tag{5}$$

where BSS_{max} is the maximum BSS value, between the NCEP or ECMWF model, at a given grid cell (Appendix Figure A1). Suitability can range from -∞ and 10, with 10 indicating a perfect score (i.e., maximum risk and perfect predictability), and any score above 0 indicating some degree of positive forecast skill and risk score. This score serves to provide a first step in guiding relief organizations on suitable locations for anticipatory action programs.

3. Results

3.1. Forecasts

Overall, forecast skill is generally modest, with most skill scores in the low positive ranges (Fig. 3). Skill is spatially heterogeneous, although some areas demonstrate relatively high skill. Moreover, when using the best of either the NCEP or ECMWF forecasts, very few locations have skill scores below zero. In general, we attribute the modest skill to the focus on extreme events within a relatively short study period (1982–2020 for NCEP, 1993–2020 for ECMWF); though not reported in this study, skill scores for more moderate percentiles (e.g., median precipitation) tend to be higher. For the drought (15th percentile) forecasts, parts of eastern Brazil, East Africa, Afghanistan, and Indonesia have skill scores near 0.5, while for floods (95th percentile), coastal Ecuador and Peru, the Horn of Africa, and parts of Ukraine, Mongolia, and China perform similarly well. Although skill scores are similar between the monthly and seasonal lead times, some areas differ considerably, notably Kenya (high monthly skill in the east but high seasonal skill in the west) for droughts and parts of China and Madagascar for floods.

3.2. Risk and suitability

Globally, risk for both droughts and floods is highest in Africa and

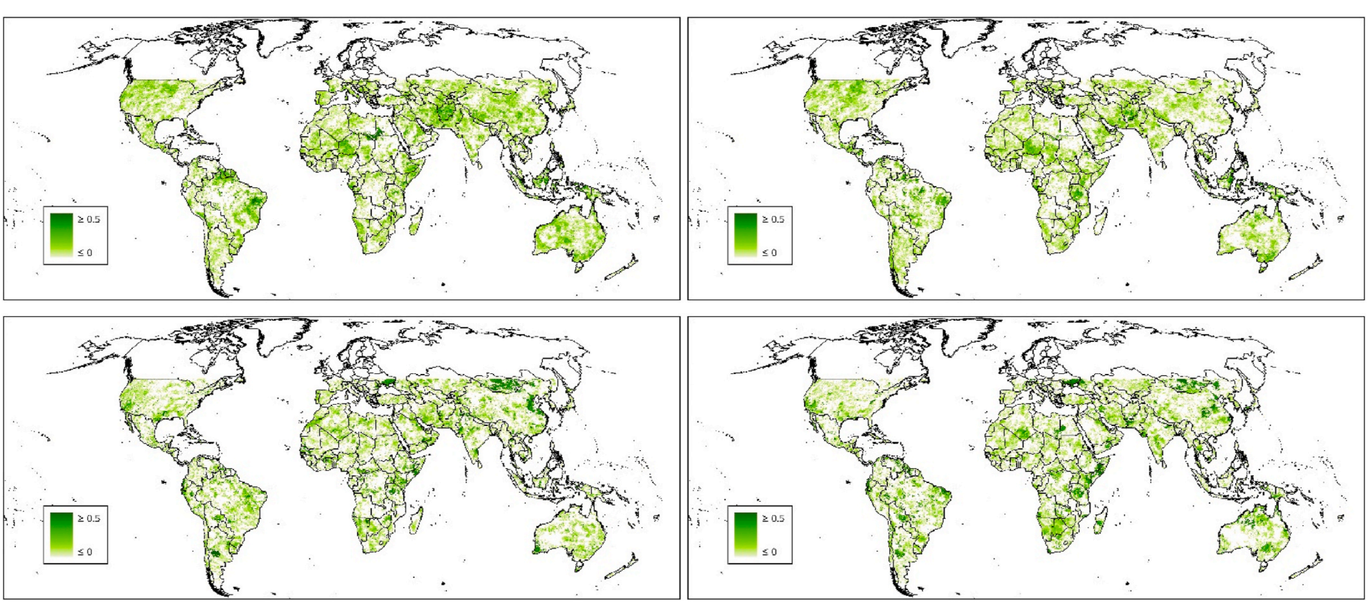

Fig. 3. Maximum Brier skill scores for NCEP and ECMWF forecasts (BSS_{max}), for peak month (left) and season (right), and for the 15th percentile (top; droughts) and 95th percentile (bottom; floods) of precipitation.

conflict-ridden countries of Asia (Fig. 4, top row). Correlation between drought and flood risk is high due to equivalent vulnerability and lack of coping capacity metrics; only hazard differs between the two. Suitability scores approximately mirror Brier skill scores but with an amplification effect in lower income countries—including much of Africa—and attenuation in wealthy countries (Fig. 4, middle and bottom rows).

Considerable variance in risk in the Greater Horn of Africa is evident at the region/province level, with southern Somalia, northeastern South Sudan, and Darfur exhibiting high risk and much of Burundi, Djibouti, Eritrea, and Rwanda exhibiting relatively low risk (Fig. 5). Suitability scores for droughts are particularly strong in eastern Ethiopia, Somalia, and southeastern Kenya at the monthly scale, although scores at the seasonal scale are notably lower in these regions, suggesting that potential anticipatory action programs in these areas may need to consider short-term water supply shocks as well as longer-term seasonal drought. Indeed, several previous studies highlight the strength of subseasonal forecasting in these regions, especially for the start of the rainy season (Lala et al., 2020; Endris et al., 2021). These same regions demonstrate strong suitability scores for floods, although the dominant timescale switches, with seasonal suitability exceeding monthly suitability. Although eastern Ethiopia and Somalia are generally arid, they are still prone to riverine flooding, including flash floods driven by local precipitation (OCHA, 2020), making them prime locations for the implementation of flood-based anticipatory action programs.

Finally, in Peru, risk is generally much higher for floods than for droughts, except in the far southeastern part of the country, due to the country's considerable geographic and climatic heterogeneity (Fig. 6). Flood risk is primarily focused on the Amazon basin in the north and east, although there exists some risk of coastal flooding in the northwest as well. Owing to the high levels of predictability in the northwest—primarily due to the effects of the El Niño-Southern Oscillation—suitability scores are generally higher than in the Amazon basin, where forecast skill is relatively poor (see Fig. 3). Indeed, the Red Cross already has an EAP for extreme rainfall in northwestern Peru (Bazo et al., 2019; Lala et al., 2021b). Regarding drought, suitability is focused primarily in the central Andes and the extreme southeast, owing mainly to high forecast skill in the former and high risk scores in the latter.

4. Discussion

This study serves to address a major gap in global disaster risk reduction, specifically the inclusion of anticipation in risk analysis. The primary source of this paper's risk data—the INFORM project—has recently called for the integration of early warning systems with hazard analysis in order to more effectively identify and mitigate future disaster risk (OCHA, 2021). Incorporating open-source and global forecasts into a globally standardized risk metric can improve the geographic determination and sustainability of future anticipatory action programs.

In general, the primary driver for suitability is forecast skill, with risk scores playing mainly an amplifying or attenuating role in the overall suitability scores. While risk scores are generally comparable between droughts and floods—owing to identical vulnerability and lack of coping capacity sub-scores—forecast skill and suitability scores are more generally distinct by disaster type. Peru is an exception; its considerable geographic diversity—consisting of both wet rainforests and extremely arid coasts and mountains—results in quite heterogeneous risk levels depending on disaster type. Indeed, the only major region in which suitability scores are high for both droughts and floods is East Africa, and the precise locations within this region still vary by timescale (monthly or seasonally). Given that anticipatory action programs are generally tailored to a single hazard type, however, there exists a wide

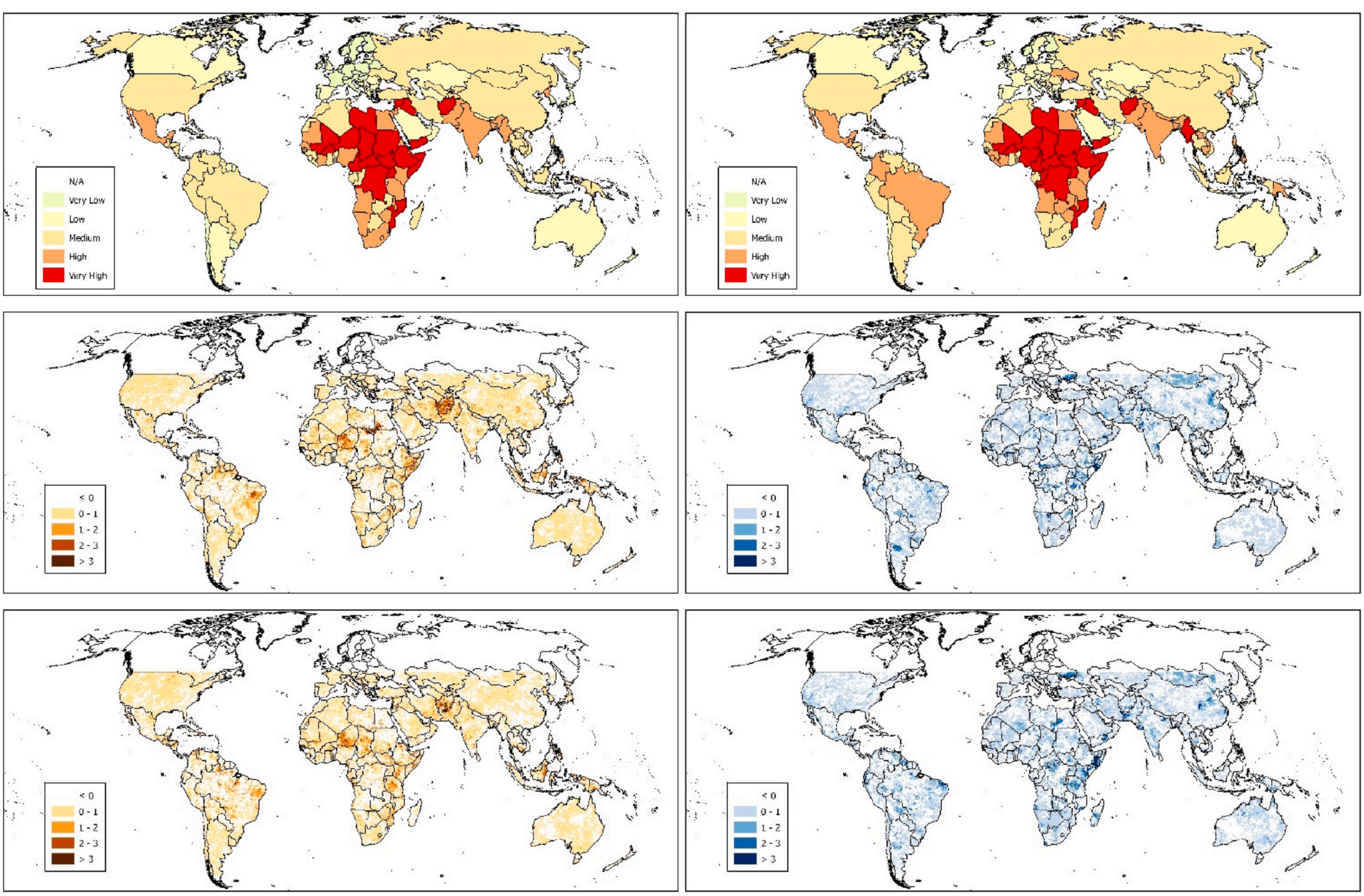

Fig. 4. Country-level risk score (INFORM, 2020; top), suitability score for peak month (middle) and peak season (bottom), for droughts (left) and floods (right).

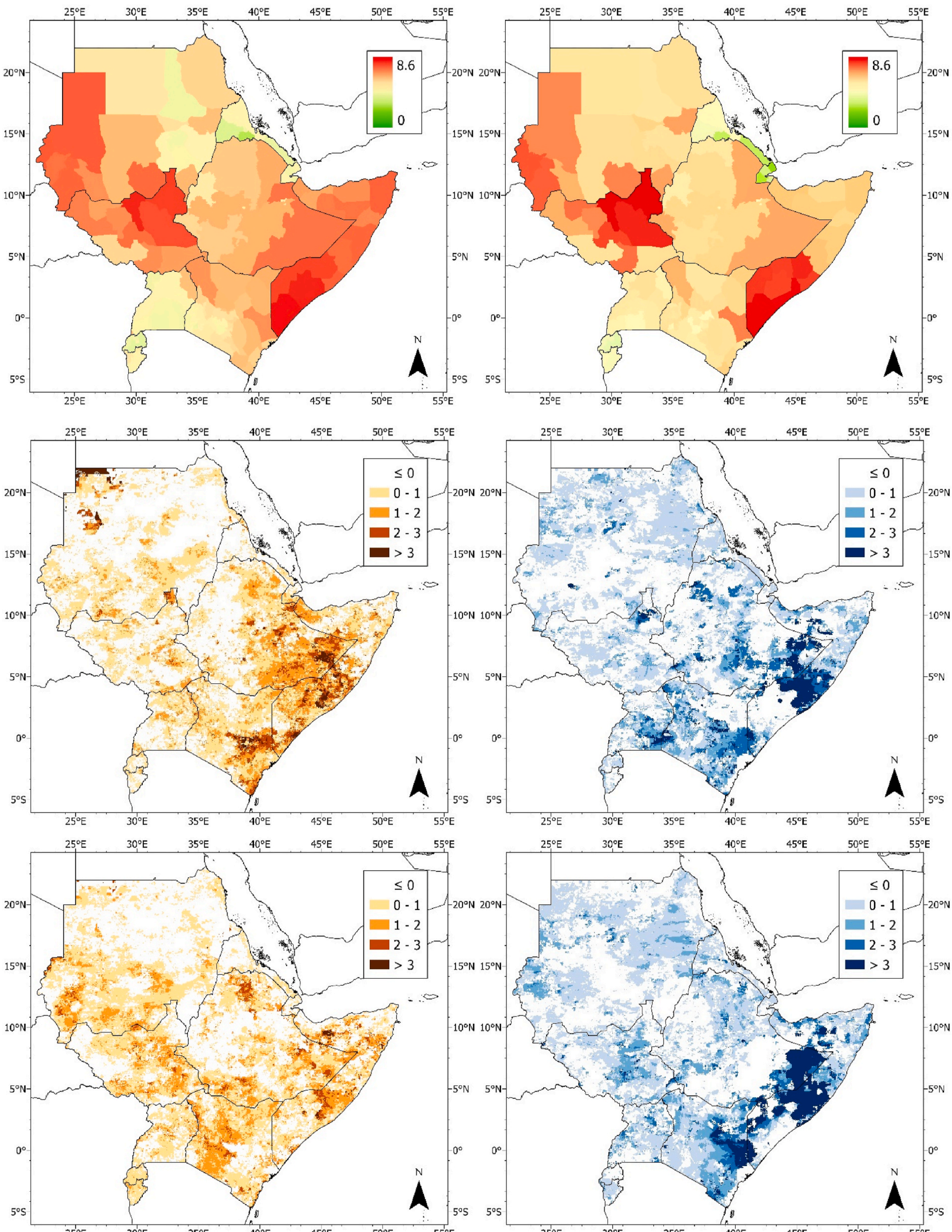

Fig. 5. Greater Horn of Africa: risk score (INFORM, 2020; top), suitability score for peak month (middle) and peak season (bottom), for droughts (left) and floods (right).

range of locations that may be suitable for these programs. For drought, much of the Sahel, Afghanistan, Indonesia, and eastern Brazil demonstrate high suitability scores, while for floods, coastal Ecuador and Peru, southern Ukraine, and some western regions of South Asia are suitable. We note that the results presented here are only valid for a single rainy season; secondary rainy seasons may also be of note in certain cases. East Africa, for example, is subject to both floods and droughts in its shorter secondary rainy season (Kolstad and MacLeod, 2022), despite the fact that the 97% of total crop production occurs during the long rains in Ethiopia (Taffesse et al., 2012). Given that this study only considers two

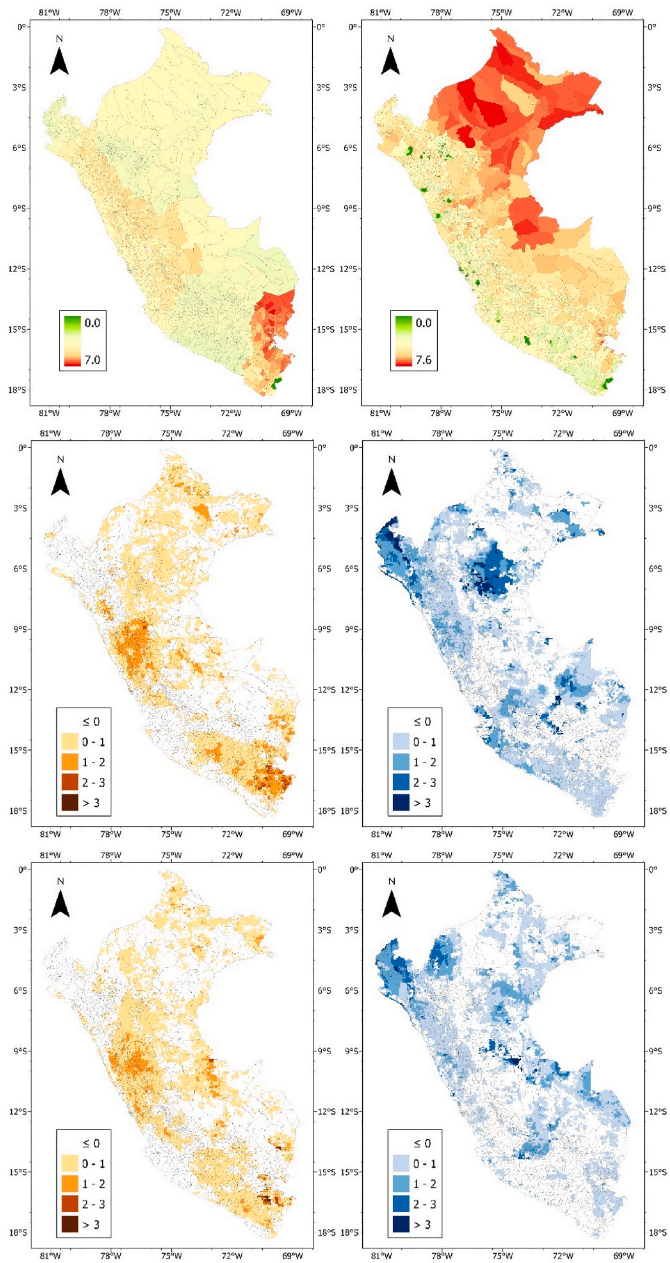

Fig. 6. Peru: risk score (top), suitability score for peak month (middle) and peak season (bottom), for droughts (left) and floods (right).

global forecasts, further studies may also benefit from regional or local forecasts, or the inclusion of other forecast models. It should be noted, however, that the dominance of forecast skill is partially the result of how the suitability score is defined (i.e., equal weighting of forecast skill and risk score); other formulations may yield different results.

The subnational analyses of the Greater Horn of Africa and of Peru also provide insights for disaster management. In the Greater Horn of Africa, suitability scores for droughts are generally higher at the monthly scale than at the seasonal scale, suggesting that projects may be suited for relatively short-term supply shocks. Despite the frequent focus on total seasonal precipitation in studying the agro-economic impacts of water shortages in East Africa, more recent studies have found that the start of the rainy season—a subseasonal process—has a strong influence on crop yields (Lala et al., 2021a) and market price at harvest (Davenport et al., 2021), and that even short-term water shortages can lead to conflict (Maystadt and Ecker, 2014). Regarding flooding in Peru, we reiterate the presence of the current EAP for coastal extreme rainfall (Bazo et al., 2019), while also suggesting options for improved forecasts in the high risk yet low predictability parts of the Amazon basin (Keating et al., 2021).

It should be noted that the results of this study are intended as a first step in identifying potentially suitable geographic regions for forecast-based anticipatory action projects, and by no means are definitive in highlighting all suitable locations. While we argue that an equal weighting of risk score and Brier skill score is a reasonable way to make an assessment, we caution that it is not the only way. For example, in countries or regions with lower capacity for taking action, the cost of acting in vain may factor more heavily, requiring communities to be more conservative in taking actions than communities with greater capacity for action. Indeed, financial considerations are not accounted for in this study, despite their importance in determining the success of a program (Lala et al., 2021b). Future studies or programs should therefore carefully consider financial implications, the capacity to act, or alternative forecast performance measures that have considerable influence on the efficacy of forecast-based anticipatory action programs. We do highlight, however, that our suitability results often correspond to current anticipatory action projects, including drought in Ethiopia and Somalia as well as flooding in northwestern Peru (see Bazo et al., 2019), for which there is an in-depth study of costs, benefits, and risk tolerance (Lala et al., 2021b).

Despite the use of case studies with subnational data to demonstrate more localized and tailored suitability, there are still data limits to conducting a global analysis. Although district-level data is available in a data-rich country like Peru, our case study in the Greater Horn of Africa is limited to the regional or provincial level which, although suitable for widespread disasters like droughts, may be too granular for in-depth flood analysis (Ward et al., 2015). The quality of precipitation data also presents a limitation to this analysis. The limited number of gauges used to correct the satellite-based observations in CHIRPS throughout most of the world may somewhat limit the reliability of observations. Indeed, the results on forecast skill—and by extension, the suitability scores—are rather noisy, which may partially be the result of random errors rather than genuine shifts in forecast quality. We highlight, however, that CHIRPS was specifically developed to support drought monitoring in East Africa (Funk et al., 2015), and it performs well when evaluated against precipitation gauge datasets in the tropical Andes and other topographically complex locations (López-Bermeo et al., 2022; Gao et al., 2018). We thus choose to maintain the CHIRPS native resolution of 0.05° to highlight localized characteristics—which are influential in disaster relief projects—in lieu of aggregating the results, which sacrifices detail and introduces other potential data artefacts. Nevertheless, we encourage future studies to incorporate higher resolution, skillful forecasts and datasets that may allow for more proper geographic targeting.

Finally, available historical forecast records (1982–2020 for NCEP CFSv2 and 1993–2020 for ECMWF SEAS5) also limit the applicability of extreme event analysis. For example, considering the 95th percentile of precipitation yields only ~2 instances of exceedance over the entire study period; the probability distributions inferred may thus misrepresent the extremes owing to this small sample size. This is especially apparent when mapping skill and suitability scores in the Greater Horn of Africa (Fig. 5); the stark gradient in suitability in parts of Ethiopia and Somalia is likely due to a discrete change in the peak month from April to October with a corresponding sudden increase in forecast skill. Such stark gradients, especially in dry areas and for extreme events, must therefore be taken with a degree of skepticism. The use of combined forecasts may partially mitigate this; however, insufficient forecast skill due to small sample sizes remains, and many regions of the world demonstrate relatively poor skill in our analysis. In general, anticipatory action programs use a large suite of forecasts (Bazo et al., 2019) but may still weigh a subset more heavily based on predictive skill (Lala et al., 2021b); the methodology in this paper thus presents a simplified version of a realistic operational protocol. Climate change is also a factor;

although the forecasts are bias corrected based on historic data, long-term changes in the climate may substantially change the distribution of precipitation in many regions (Cannon et al., 2015). The results of this work should therefore be limited to a short term first step and not be inferred in long-term climate projections.

5. Conclusion

This study advances the field of anticipatory action for humanitarian aid by integrating predictability of flood and drought hazards with a standardized risk metric to highlight geographic regions most suitable for program implementation. Results indicate that, even in the presence of limited forecast skill, some regions of the world demonstrate high levels of suitability, particularly in East Africa. Although data on risk is limited in spatial resolution, we find that forecast skill is a strong driver of suitability, suggesting that improvements in forecasts—via increases in skill and improvements in spatial resolution—may enhance the proper geographic targeting despite limits in risk data. On the other hand, higher resolution risk data—especially at the community scale—could be equally or more informative than forecast skill in certain contexts. Future studies may thus aim to improve forecasts, consider climate change, or investigate new regions with subnational data on risk, such that the emerging field of anticipatory action can become increasingly valuable for at-risk communities.

Author statement

Jonathan Lala: Conceptualization, Methodology, Software, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Visualization, Funding acquisition Donghoon Lee: Methodology, Investigation, Resources, Data curation, Juan Bazo: Methodology, Resources, Supervision, Project administration Paul Block: Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
List of INFORM indicators

Total affected by Drought
Frequency of Drought events
Agriculture Drought probability
Household size
Number of vets
IHR capacity score: Food safety
Population living in slums (% of urban population)
Children under 5 (% of population)
GCRI Violent Conflict probability
GCRI Highly Violent Conflict probability
Multidimensional Poverty Index
Humanitarian Aid (FTS)
Volume of remittances (in USD) as a proportion of total GDP (%)
U5 Under weight
Incidence of Tuberculosis
Estimated number of people living with HIV - Adult (>15) rate
Number of new HIV infections per 1000 uninfected population
Malaria incidence per 1000 population at risk
Number of people requiring interventions against neglected tropical diseases
Income Gini coefficient
People affected by Natural Disasters
Internally displaced persons (IDPs)
Refugees and asylum-seekers by country of asylum
Returned Refugees
Average Dietary Energy Supply Adequacy
Prevalence of Undernourishment
Access to electricity
Proportion of the target population with access to 3 doses of diphtheria-tetanus-pertussis (DTP3) (%)
Proportion of the target population with access to measles-containing-vaccine second-dose (MCV2) (%)
Proportion of the target population with access to pneumococcal conjugate 3rd dose (PCV3) (%)
Current health expenditure per capita
GDP per capita (current US$).

Table A2
List of indicators for Peru

Description	Normalization	Source
Percent weak population (age below 5 or above 65 years)	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percent females	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percent population with disability	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percent population with health insurance	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percent households without strong walls	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percent households without public water supply	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percent households without electricity	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percent households without sewage infrastructure	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percent population who cannot read and write	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percent population who dont complete primary education	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percent population who dont complete college degree	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percentage of rented houses	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Averaged Numer of people in family	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percent households with cell phone or landline	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Percent households with automobiles	MinMax	INEI – Instituto Nacional de Estadística e Informática (2017)
Number of educational facilities per 10,000 people	Power	510 Dashboards
Number of health facilities per 10,000 people	Power	510 Dashboards
Percent infant mortality	MinMax	510 Dashboards
Life expectancy	MinMax	510 Dashboards
Percent child malnutrition	MinMax	510 Dashboards
Poverty incidence	MinMax	510 Dashboards
Travel time to nearest city	Power	510 Dashboards
Vectorborne disease incidence per 10,000 people	Power	510 Dashboards
Waterborne disease incidence per 10,000 people	Power	510 Dashboards
Number of damaged houses	Power	510 Dashboards
Number of affected people	Power	510 Dashboards
Percent of area inundated	Power	Aybar (2018)
Water scarcity index	Power	Veldkamp et al. (2016) GFDRR Labs (2021)

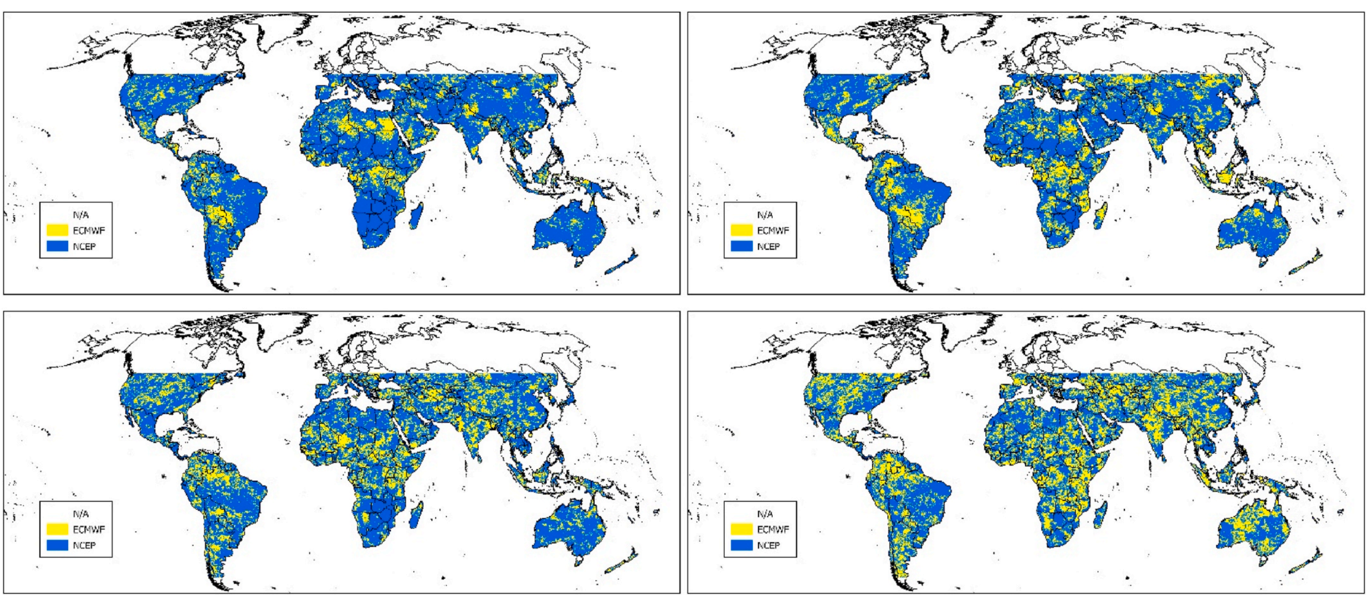

Fig. A1. Forecast source with higher Brier skill score for peak month (left) and season (right), and for the 15th percentile (top; droughts) and 95th percentile (bottom; floods) of precipitation

References

Ahmadalipour, A., Moradkhani, H., 2018. Multi-dimensional assessment of drought vulnerability in Africa: 1960-2100. Sci. Total Environ. 644, 520–535. https://doi.org/10.1016/j.scitotenv.2018.07.023.

Aybar, C., 2018. Flood SENAMHI. GitHub repository. https://github.com/csaybar/slides/tree/master/flood.

Bazo, J., Singh, R., Destrooper, M., Coughlan de Perez, E., 2019. Chapter 18 – Pilot Experiences in Using Seamless Forecasts for Early Action: the "Ready-Set-Go!" Approach in the Red Cross. Chapter in Sub-seasonal to Seasonal Prediction. A. W. Robertson and F. Vitart, pp. 387–398. https://doi.org/10.1016/B978-0-12-811714-9.00018-8.

Bischiniotis, K., de Moel, H., van den Homberg, M., Couasnon, A., Aerts, J., Guimarães Nobre, G., Zsoter, E., van den Hurk, B., 2020. A framework for comparing permanent and forecast-based flood risk-reduction strategies. Sci. Total Environ. 720. https://doi.org/10.1016/j.scitotenv.2020.137572.

Box, G.E.P., Cox, D.R., 1964. An analysis of transformations. J. Roy. Stat. Soc. B 26 (2), 211–252. JSTOR 2984418. MR 0192611.

Brier, G.W., 1950. Verification of Forecasts Expressed in Terms of Probability. Monthly Weather Review, pp. 1–3. https://doi.org/10.1175/1520-0493(1950)078<0001:VOFEIT>2.0.CO;2.

Cannon, A.J., Sobie, S.R., Murdock, T.Q., 2015. Bias correction of GCM precipitation by quantile mapping: how well do methods preserve changes in quantiles and extremes? J. Clim. 28 (17) https://doi.org/10.1175/JCLI-D-14-00754.1.

Coughlan de Perez, E., van den Hurk, B., van Aalst, M.K., Jongman, B., 2015. Forecast-based financing: an approach for catalyzing humanitarian action based on extreme weather and climate forecasts. Nat. Hazards Earth Syst. Sci. 15, 895–904. https://doi.org/10.5194/nhess-15-895-2015.

Davenport, F.M., Shukla, S., Turner, W., Funk, C., Krell, N., Harrison, L., Husak, G., Lee, D., Peterson, S., 2021. Sending out an SOS: using start of rainy season indicators for market price forecasting tro support famine early warning. Environ. Res. Lett. 16 https://doi.org/10.1088/1748-9326/ac15cc/.

Di Baldassarre, G., Wanders, N., AghaKouchak, A., Kuil, L., Rangecroft, S., Veldkamp, T.I. E., Garcia, M., van Oel, P.R., Breinl, K., Van Loon, A.F., 2018. Water shortages worsened by reservoir effects. Nat. Sustain. 1, 617–622. https://doi.org/10.1038/s41893-018-0159-0.

Endris, H.S., Hirons, L., Segele, Z.T., Gudoshava, M., Woolnough, S., Artan, G.A., 2021. Evaluation of the skill of monthly precipitation forecasts from global prediction systems over the Greater Horn of Africa. Weather Forecast. 36, 1275–1298. https://doi.org/10.1175/WAF-D-20-0177.1.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., Michaelsen, J.C., 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Sci. Data 2. https://doi.org/10.1088/1748-9326/ac15cc.

Funk, C., Harrison, L., Alexander, L., Peterson, P., Behrangi, A., Husak, G., 2019. Exploring trends in wet-season precipitation and drought indices in wet, humid and dry regions. Environ. Res. Lett. 14 https://doi.org/10.1088/1748-9326/ab4a6c.

Gao, F., Zhang, Y., Chen, Q., Wang, P., Yang, H., Yao, Y., Cai, W., 2018. Comparison of two long-term and high-resolution satellite precipitation datasets in Xinjiang, China. Atmos. Res. 212, 150–157. https://doi.org/10.1016/j.atmosres.2018.05.016.

GFDRR Labs, 2021. ThinkHazard! Database: Water Scarcity, Peru. https://thinkhazard.org/en/report/195-peru/DG.

Gudmundsson, L., Bremnes, J.B., Haugen, J.E., Engen-Skaugen, T., 2012. Technical note: downscaling RCM precipitation to the station scale using statistical transformations – a comparison of methods. HESS 16, 3383–3390. https://doi.org/10.5194/hess-16-3383-2012.

Guimarães Nobre, G., Davenport, F., Bischiniotis, K., Veldkamp, T., Jongman, B., Funk, C.C., Husak, G., Ward, P.J., Aerts, J., 2018. Financing agricultural drought risk through ex-ante cash transfers. Sci. Total Environ. 653, 523–535. https://doi.org/10.1016/j.scitotenv.2018.10.406.

INEI – Instituto Nacional de Estadística e Informática, 2017. Bases de datos. https://www.inei.gob.pe/.

INFORM, 2020. INFORM Risk Index 2021. Standing Committee Reference Group on Risk, Early Warning and Preparedness and the European Commission. The European Commission Joint Research Centre is the scientific lead of INFORM. https://drmkc.jrc.ec.europa.eu/inform-index. INFORM is a collaboration of the Inter-Agency.

IPCC – The Intergovernmental Panel on Climate Change, 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Working Group II Contribution to the Fifth Assessment Report of the IPCC. Cambridge University Press, © Intergovernmental Panel on Climate Change, New York, 2014.

Johnson, S.J., Stockdale, T.N., Ferranti, L., Balmaseda, M.A., Molteni, F., Magnusson, L., Tietsche, S., Decremer, D., Weisheimer, A., Balsamo, G., Keeley, S.P.E., Mogensen, K., Zuo, H., Monge-Sanz, B.M., 2019. SEAS5: the new ECMWF seasonal forecast system. Geosci. Model Dev. (GMD) 12, 1087–1117. https://doi.org/10.5194/gmd-12-1087-2019.

Keating, C., Lee, D., Bazo, J., Block, P., 2021. Leveraging multi-model season-ahead streamflow forecasts to trigger advanced flood preparedness. Nat. Hazards Earth Syst. Sci. 21, 2215–2231. https://doi.org/10.5194/nhess-21-2215-2021.

Kelman, Ilan, 2013. Disaster Mitigation Is Cost Effective. World Bank, Washington, DC. © World Bank. https://openknowledge.worldbank.org/handle/10986/16341 License: CC BY 3.0 IGO.

Kolstad, E.W., MacLeod, D., 2022. Lagged oceanic effects on the East African short rains. Clim. Dynam. 59, 1043–1056. https://doi.org/10.1007/s00382-022-06176-6.

Lala, J., Tilahun, S., Block, P., 2020. Predicting rainy season onset in the Ethiopian Highlands for agricultural planning. J. Hydrometeorol. 21 https://doi.org/10.1175/JHM-D-20-0058.1.

Lala, J., Yang, M., Wang, G., Block, P., 2021a. Utilizing rainy season onset predictions to enhance maize yields in Ethiopia. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/abf9c9.

Lala, J., Bazo, J., Anand, V., Block, P., 2021b. Optimizing forecast-based actions for extreme rainfall events. Climate Risk Management 34. https://doi.org/10.1016/j.crm.2021.100374.

Lee, D., Ahmadul, H., Patz, J., Block, P., 2021. Predicting social and health vulnerability to floods in Bangladesh. Nat. Hazards Earth Syst. Sci. 21, 1807–1823. https://doi.org/10.5194/nhess-21-1807-2021.

Lopez, A., Coughlan de Perez, E., Bazo, J., Suarez, P., van den Hurk, B., van Aalst, M., 2017. Bridging forecast verification and humanitarian decisions: A valuation approach for setting up action-oriented early warnings. Weather Clim. Extrem. 27 https://doi.org/10.1016/j.wace.2018.03.006.

López-Bermeo, C., Montoya, R.D., Caro-Lopera, F.J., Díaz-García, J.A., 2022. Validation of the accuracy of the CHIRPS precipitation dataset at representing climate variability in a tropical mountainous region of South America. Phys. Chem. Earth 127. https://doi.org/10.1016/j.pce.2022.103184. Parts A/B/C.

Lorenz, C., Portele, T.C., Laux, P., Kunstmann, H., 2021. Bias-corrected and spatially disaggregated seasonal forecasts: a long-term reference forecast product for the water sector in semi-arid regions. Earth Syst. Sci. Data 13, 2701–2722. https://doi.org/10.5194/essd-13-2701-2021.

Marin-Ferrer, M., Vernaccini, L., Poljansek, K., 2017. Index for Risk Management INFORM Concept and Methodology Report — Version 2017. https://doi.org/10.2760/094023. EUR 28655 EN.

Matte, S., Boucher, M.A., Boucher, V., Filion, T.C.F., 2017. Moving beyond the cost-loss ratio: economic assessment of streamflow forecasts for a risk-averse decision maker. HESS 21, 2967–2986. https://doi.org/10.5194/hess-21-2967-2017.

Maystadt, J.F., Ecker, O., 2014. Extreme weather and civil war: does drought fuel conflict in Somalia through livestock price shocks? Am. J. Agric. Econ. 96, 1157–1182. https://doi.org/10.1093/ajae/aau010.

Netherlands Red Cross, 2021. 510 Dashboard. https://dashboard.510.global.

NDMC – National Drought Mitigation Center, 2021. U.S. Drought Monitor, University of Nebraska-Lincoln. https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx.

OCHA – United Nations Office for the Coordination of Humanitarian Affairs, 2020. Somalia: Flash Floods – Oct 2020. OCHA Updates. https://reliefweb.int/disaster/ff-2020-000221-som.

OCHA – United Nations Office for the Coordination of Humanitarian Affairs, 2021. Proposal for INFORM Warning. June 2021. https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Warning.

Saha, S., Moorthi, S., Wu, X., Wang, J., Nadiga, S., Tripp, P., Behringer, D., Hou, Y., Chuang, H., Iredell, M., Ek, M., Meng, J., Yang, R., Peña Mendez, M., van den Dool, H., Zhang, Q., Wang, W., Chen, M., Becker, E., 2014. The NCEP climate forecast system version 2. J. Clim. https://doi.org/10.1175/JCLI-D-12-00823.1.

Skees, J., 2011. Innovations in Index Insurance for the Poor in Low-Income Countries. Chapter in Financial Inclusion, Innovation, and Investments: Biotechnology and Capital Markets Working for the Poor by R. D. Christy and V. L. Bogan. World Scientific Publishing Co. Pte. Ltd, Singapore.

Taffesse, A.S., Dorosh, P., Asrat, S., 2012. Crop production in Ethiopia: regional patterns and trends. IFPRI Discussion Paper ESSP2 16, 2012.

United Nations, 2015. Sendai Framework for Disaster Risk Reduction 2015-2030. UN World Conference on Disaster Risk Reduction, March 2015, Sendai, Japan. United Nations Office for Disaster Risk Reduction, Geneva.

Veldkamp, T.I.E., Wada, Y., Aerts, J.C.J.H., Ward, P., 2016. Towards a global water scarcity risk assessment framework: incorporation of probability distributions and hydro-climatic variability. Environ. Res. Lett. 11 https://doi.org/10.1088/1748-9326/11/2/024006.

Vitart, F., Robertson, A.W., 2018. The sub-seasonal to seasonal prediction project (S2S) and the prediction of extreme events. npj Climate and Atmospheric Science 1. https://doi.org/10.1038/s41612-018-0013-0.

Ward, P.J., Jongman, B., Salamon, P., Simpson, A., Bates, P., de Groeve, T., Muis, S., Coughlan de Perez, E., Rudari, R., Trigg, M.A., Winsemius, H.C., 2015. Usefulness and limitations of global flood risk models. Nat. Clim. Change 5, 712–715. https://doi.org/10.1038/nclimate2742.

Ward, P.J., Blauhut, V., Bloemendaal, N., Daniell, E.J., De Ruiter, C.M., Duncan, J.M., Emberson, R., Jenkins, F.S., Kirschbaum, D., Kunz, M., Mohr, S., Muis, S., Riddell, A. G., Schäfer, A., Stanley, T., Veldkamp, I.E., Hessel, W.C., 2020. Review article: natural hazard risk assessments at the global scale. Nat. Hazards Earth Syst. Sci. 20, 1069–1096. https://doi.org/10.5194/nhess-20-1069-2020.

World Bank, 2014. Financial protection against natural disasters: from products to comprehensive strategies." Washington, D.C.: the World Bank.yu, X., and Tang, Y. (2017). A critical review on the economics of disasters. J. Risk Analysis and Crisis Response 7 (1), 27–36. https://doi.org/10.2991/jrarc.2017.7.1.4.