Sampling Uncertainty is Critical for Setting Forecast-Based Anticipatory Action Triggers

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ABSTRACT: As of 2022, nearly 5 million smallholder farmers across more than a dozen countries are covered by Anticipatory Action (AA) programs. AA programs are aid schemes triggered when seasonal forecasts of precipitation fall below a locally-determined drought threshold. These thresholds are generally calculated to meet a donor- or government-specified expected trigger frequency. However, the observational precipitation record in many regions with AA programs is limited, and interannual and interdecadal autocorrelation in the climate patterns driving seasonal precipitation further reduce the effective sample size used to calculate these thresholds. AA trigger thresholds are highly sensitive to this limited observational record, increasing the risk that action is not triggered when it is needed or that programs become financially unsustainable due to excessive triggers. In practice, forecasters are aware of this uncertainty and ad hoc decisions on whether to trigger action are often made if seasonal forecasts are close to the threshold. Seeking a more formalized, statistically sound alternative to these ad hoc approaches, governments and humanitarian agencies have asked for transparent and intuitive metrics of trigger uncertainty. To address this demand, we illustrate how a simple statistical method (bootstrap resampling) can quantify the practical uncertainty in drought thresholds due to a limited observational record. Examining United Nations-supported operational AA forecasts in sub-Saharan Africa, we demonstrate how this method quantifies critical underlying uncertainty, enabling these AA systems to meet the state-of-the-art demanded by donors and the WMO.

SIGNIFICANCE STATEMENT: Millions of smallholder farmers across the world are covered by Anticipatory Action (AA) programs, aid schemes designed to trigger when seasonal forecasts of precipitation fall below a locally-determined drought threshold. For aid allocation to remain transparent and financially sustainable, AA drought trigger thresholds are generally calculated to meet an expected frequency of action. However, these thresholds are estimated with a high degree of uncertainty due to the limited historical record of precipitation. To address this issue, we show how a simple statistical method, bootstrap resampling, can establish practical bounds on this sampling uncertainty. This method allows practitioners to estimate clear, interpretable confidence intervals on drought thresholds. Using a real-world case study based on United Nations-supported operational AA forecasts, we illustrate how this method quantifies critical underlying uncertainty, enabling these AA systems to meet the state-of-the-art demanded by donors and the WMO.

1. Introduction

Increasingly, the international community is turning to forecast-based anticipatory action (AA) to mitigate the humanitarian impacts of disastrous weather events (World Food Programme 2024). This shift from a reactive to a proactive model of humanitarian assistance is made possible through scientific advances in medium-term forecasting, which allow skillful forecasts of seasonal total precipitation to be made as early as 3-6 months in advance. Seasonal forecasting is a comparatively young science when compared to weather forecasting, and the policy application of seasonal forecasting is even younger – the UN World Food Programme (WFP) has only been supporting governments on the use seasonal forecasts for humanitarian action since the mid-2010s. In these programs, usually focused on drought, funding is released if the forecast reaches some agreed-upon threshold of severity (the AA ”trigger”).

This emerging field of practice demands new standards of consistency, robustness, and transparency, particularly when the human costs of inaction are high. Accordingly, the WFP has adopted the World Meteorological Organization (WMO) Guidelines for Seasonal Forecasting (World Meteorological Organization 2020), which mandate that forecasts be rooted in process-based modeling of hydrological conditions and use statistical methods that can accurately represent both observation- and model-based uncertainty in a probabilistic prediction. A key aspect of these guidelines is that a forecast can be compared against a historical record of what the forecast model would have

predicted in past years (the "hindcasts") in order to establish an internally consistent threshold for extreme events. This is important because typically, forecast-based AA decision rules are based on some historically derived drought threshold. For example, drought-related humanitarian actions may be triggered only during the driest 20% of years as defined using the historical record.

However, the WMO guidelines do not specify how to account for one very practical source of uncertainty: the uncertainty in the threshold for a drought event due to the limited historical record. In practice, these thresholds are thus often estimated using samples of only several dozen observations, representing the number of years in a local observational record or over which seasonal forecast models have been run, and the true effective sample size is further reduced by the presence of low-frequency variability in the climate system and the resultant autocorrelation in precipitation signals. This type of uncertainty, hereafter called sampling uncertainty, matters because in practice, forecasts often fall very close to the trigger threshold. Because decision makers have an intuitive understanding that these thresholds are uncertain, they must exercise discretion in determining whether or not to act in these situations. At the same time, they must ensure that the frequency of action is predictable enough that donors and governments can budget based on estimates of long-term expected program cost.

While the sampling uncertainty in trigger threshold is currently handled in practice qualitatively, it can be quantified through the resampling of historical records. Accordingly, we show how a simple bootstrap resampling-based method can be applied to quantify the uncertainty in forecast triggers due to limited observational records. This method was chosen to meet a practical need expressed by WFP and its government partners. We demonstrate the application of this method to operational seasonal forecasts used in WFP's drought anticipatory action projects and discuss how the incorporation of our threshold uncertainty methodology addresses crucial aspects of practical decision-making that conventional metrics of predictive skill alone cannot. We conclude with a discussion on how this methodology could be applied more broadly.

2. Forecast-based anticipatory action

a. Institutional background of AA

According to WFP's 2024 Anticipatory Action - A Decade in Review report, "WFP expanded its Anticipatory Action operations from covering 4.1 million people in 36 countries in 2023 to

over 6.2 million people in 44 countries in 2024" (World Food Programme 2024). More broadly, Anticipation Hub lists 154 active or planned forecast-based donor frameworks globally as of August 2026 (Anticipation Hub 2026). In 2024 alone, WFP's AA programs triggered over $27 million USD in early action programming, reaching nearly 9 million people. WFP's AA programming includes forecasts of drought, flood and cyclones; this paper focuses on seasonal drought forecasting as a case study, but the practical problems of forecast interpretation described herein are applicable across a variety of timescales and hazards.

As a member of the United Nations inter-agency Central Emergency Response Fund (CERF), WFP is subject to common standards for transparency, accuracy and reliability of its forecast-based AA programs. These standards are particularly crucial when negotiating the conditions under which AA donor funds will be disbursed - the so-called "anticipatory action plan" (AAP) - and determining the long-term expected cost of these programs. For seasonal forecasts of drought, the technical standards are primarily determined by the WMO Seasonal Forecasting Guidelines (World Meteorological Organization 2020).

The primary concern of the WMO guidelines is ensuring the seasonal forecasts are physically plausible, not overfit to limited data, and accurately represent the various sources of uncertainty in their probabilistic predictions. For drought forecasts, WFP and its meteorological service partners predominately rely on the Climate Predictability Tool (CPT) forecasting system (Acharya et al. 2021), which was developed with the WMO guidelines in mind. This system allows meteorological services to generate locally calibrated multi-model ensemble forecasts that account for model uncertainty, resulting in a probabilistic prediction of whether seasonal total rainfall will exceed some user-defined drought threshold.

However, while forecasting systems like CPT adhere to WMO's scientific best practices for accuracy, transparency and reproducibility, forecasts alone cannot determine the criteria for triggering anticipatory action, a crucial part of the AAP. To do so, stakeholders must exercise some judgment in assessing the historical record to determine a quantitative threshold of predicted drought severity for triggering action; the following section describes the typical procedure employed for that task.

b. Triggering humanitarian action using seasonal forecasts

A core component of the Anticipatory Action Plan is the forecast trigger, i.e., the quantitative threshold of predicted rainfall below which a certain anticipatory action will be taken. The basic rationale behind the choice of triggers is that they should be transparent, consistently applied and easily related to the expected frequency with which action will be taken. A humanitarian agency planning budgets for AA programs should be able to look at the trigger rule associated with a specific action and know its long-term expected value based on historical analysis.

Accordingly, the trigger rule used for WFP's AA programs is based on a intended frequency of action for a given type of programming, across locations and times of year. For instance, in the Somali Region of Ethiopia, WFP's Severe level actions are associated with an intended 20% frequency of action. This means that for a given location, for the forecast issued in a given month, one should expect "Severe" actions to trigger during the strongest 20% of drought forecasts. To determine the numeric threshold associated with acting 20% of the time, the decision-maker ranks all of the historical forecasts (hindcasts) available from the least likely prediction of drought to the most likely and computes the 20th percentile of this distribution.

This method is highly sensitive to the estimated percentile value used to set the trigger threshold. Even though forecast downscaling methods like CPT calibrate for model uncertainty, the drought threshold itself is subject to the inherent limitations of he comparatively short satellite observational record, which begins in the 1980s for commonly used gridded precipitation products like CHIRPS (Funk et al. 2015) and GPCP (Huffman et al. 2009). Consequently, decision-makers must exercise some judgment when a seasonal forecast is just above or just below the agreed-upon trigger threshold, as often happens. This is typically done through heuristic means such as adjusting the trigger threshold down by a few percentage points when observational indicators of a potential humanitarian crisis are present. Examples of such observational indicators include vegetation conditions leading up to the season and assessments of food insecurity from the Integrated Phase Classification (Funk et al. 2019). However, such heuristic approaches for determining when to trigger aid are inherently subjective, and risk becoming financially unsustainable if the choice to trigger is exercised too frequently. A more systematic way of assessing threshold sampling uncertainty is needed to meet the WFP's call for a robust, transparent decision support system.

c. Uncertainty due to the limited historical record

The observational precipitation record is limited to fewer than 50 years in many regions with AA programs. Interannual and interdecadal autocorrelation in the climate patterns driving seasonal precipitation further reduce the effective sample size used to calculate percentile-based thresholds (Martinez et al. 2022). For example, El Nio and La Nia (ENSO) conditions - which drive seasonal precipitation extremes in many parts of the world - tend to last for several years, meaning that the number of unique above- or below-normal events in the historical record is less than the number of unique years, and can in practice be quite small. This sampling uncertainty in AA thresholds increases the risk that action is not triggered when it is needed or that programs become financially unsustainable due to excessive triggers.

To address this problem, decision makers need a statistical method to estimate the true **distribution** of the threshold value given this limited information, instead of relying on a single point estimate from the historical record. Estimating a distribution of plausible threshold values will allow the decision-maker to better interpret the next, out-of-sample forecast. To this end, we aim to construct confidence intervals for trigger thresholds such that forecasts falling within these intervals are statistically indistinguishable. Then, decision-makers can determine whether or not to exercise discretion in the decision to trigger action by assessing whether a given forecast value is above/below the threshold due to sampling uncertainty alone.

Here, we present a flexible, resampling-based method for quantifying this uncertainty that can be easily adapted to existing operational AA frameworks. We illustrate the application of this method using commonly employed observational (GCPC) and forecast (CFSv2) rainfall datasets, but it could be applied to any AA dataset with a historical record, and is orthogonal to other kinds of uncertainty quantification (like those employed by the CPT system mentioned above).

3. Bootstrapping to Quantify Sampling Uncertainty of Trigger Thresholds

This section presents an uncertainty analysis to determine the sensitivity of a forecast-based anticipatory action protocol to the chosen trigger threshold. To do so, we repeatedly re-estimate the trigger threshold with resampled draws of the historical record. Repeating this procedure many times gives us an estimated distribution of how much the threshold might be expected to vary due to sampling error of a limited historical record. To account for correlation in time series due to modes

of interannual climate variability such as ENSO, we implement block-boostrapping. As such, we run 1,000 iterations of the re-sampling process in which we draw a sample with replacement from the original data comprised of randomly sampled blocks of 5 consecutive years. We chose a block length of 5 years to approximate the typical duration of ENSO events, but our key findings are robust to block lengths of as little as 2 years or as many as 7 (**Figures S1-S5**).

We note that this block-bootstrapping method makes the assumption that the historical precipitation record is stationary. That is, free from trends over time. This is a reasonable assumption for much of the world, particularly due to the high internal variability of seasonal precipitation. However, this method will provide biased estimates in the presence of substantial historical or projected trends. If a user is employing this method in regions with known trends, a non-stationary method that accounts for this underlying trend should be used.

To illustrate this method, we first apply it to the observational record of precipitation from the Global Precipitation Climatology Project (GCPC) dataset (Huffman et al. 2009) over the period 1981-2025. **Figure 1** depicts, for each season, the variability in the 20th percentile threshold for seasonal total precipitation (a common choice for the anticipatory action trigger, as described above). We see that the degree of sampling uncertainty is proportionally large in much of the world, and varies across regions. Areas of greater uncertainty tend to be in regions that exhibit greater decadal variability in precipitation (**Figure S7**), per the discussion in **Section 2c**, although the degree of uncertainty may also be influenced by factors like missing data in the historical record.

Figure 2 illustrates the same method applied to hindcast data from CFSv2 (Saha et al. 2014), initialized with a half-month lead time, instead of observed precipitation. The CFSv2 model is among those commonly used by WFP as the basis for downscaled seasonal forecasting. We see similar patterns of spatial variability in trigger uncertainty in both the forecast and observational datasets, although the absolute amount of uncertainty tends to be lower in the forecast dataset. In places where the degree of sampling uncertainty is comparatively high, the true trigger frequency is more likely to be above or below the intended 20% of the time; **Figure S6** illustrates this by mapping the proportion of years that fall into the 95% trigger confidence interval.

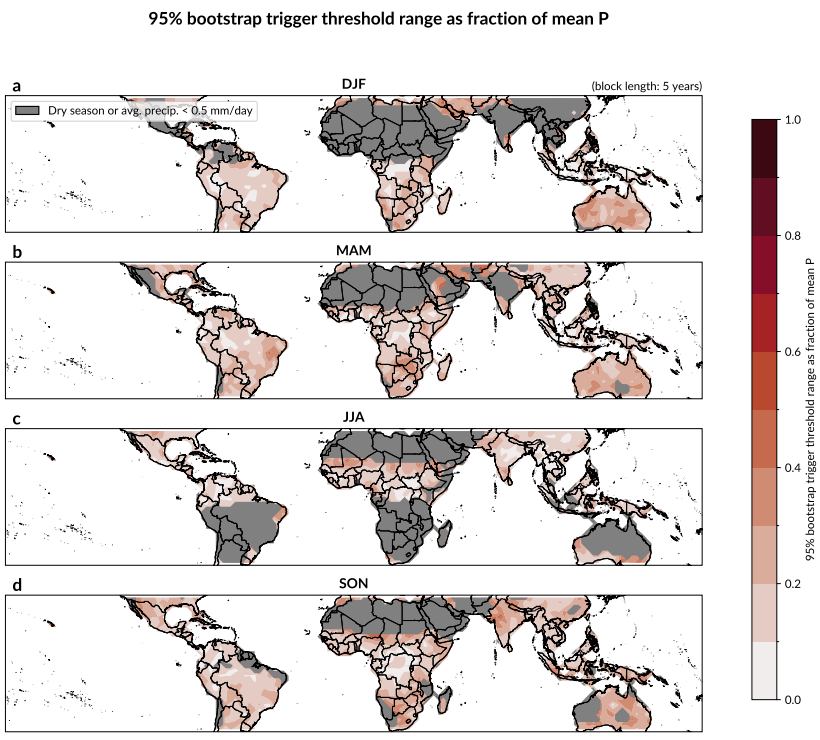


FIG. 1. Summary of bootstrapped variability in GPCP seasonal precipitation trigger thresholds, expressed as the 95% range of bootstrapped 20th percentile estimates of three-month seasonal mean rainfall, divided by the seasonal mean precipitation in that pixel. Figure shows results for a block size of 5 years; versions with other block sizes are shown in Figs. S1-2. Areas experiencing a dry season (computed according to Dunning et al. (2017)) during more than 80% of the season and areas for which the seasonal mean precipitation is less than 0.5 mm/day on average are shaded in grey.

4. Application to WFP assistance programs

Finally, we illustrate how the results of our bootstrapping method could be applied to common problems in forecast-based humanitarian decision-making. We look at a setting similar to WFP's actual seasonal forecast decision-making, in which anticipatory action against drought is triggered if seasonal total rainfall is forecast to fall below the 20th percentile of historical in rainfall in that locality, based on the hindcast record from 1981-present. Since this historical record is comparatively short, this decision criteria often leads to situations in which local decision-makers

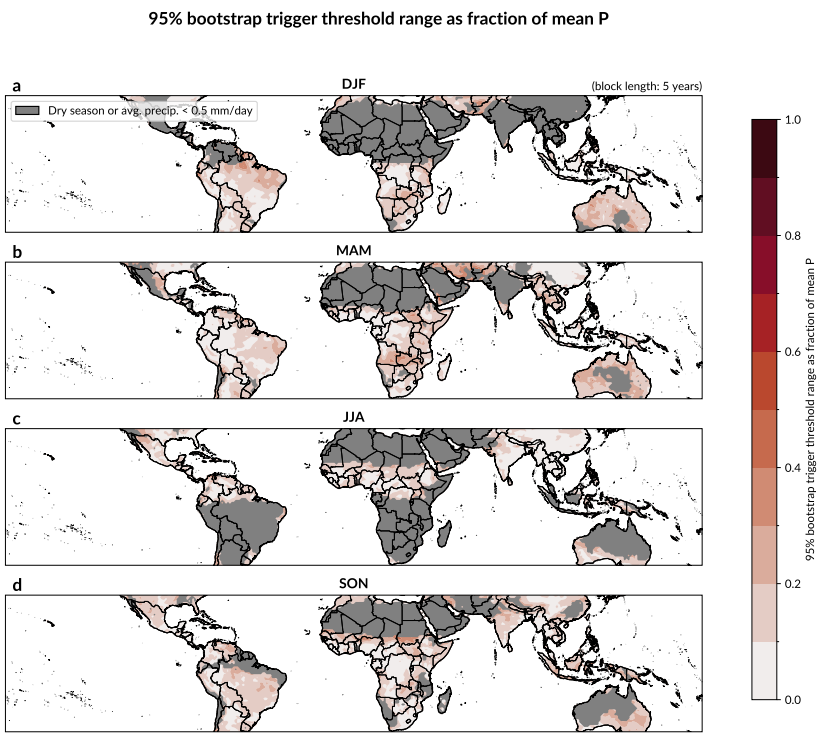


FIG. 2. Summary of bootstrapped variability in trigger thresholds for the ensemble mean of CFSv2 half-month-lead-time forecasts, expressed as the 95% range of bootstrapped 20th percentile estimates of three-month seasonal mean rainfall, divided by the seasonal mean precipitation in that pixel. Figure shows results for a block size of 5 years; versions with other block sizes are shown in Figs. S3-4. Areas experiencing a dry season (computed according to Dunning et al. (2017)) during more than 80% of the season and areas for which the seasonal mean precipitation is less than 0.5 mm/day on average are shaded in grey.

must exercise discretion in whether or not to trigger action on the basis of a borderline drought forecast, as detailed in **Section 2b**.

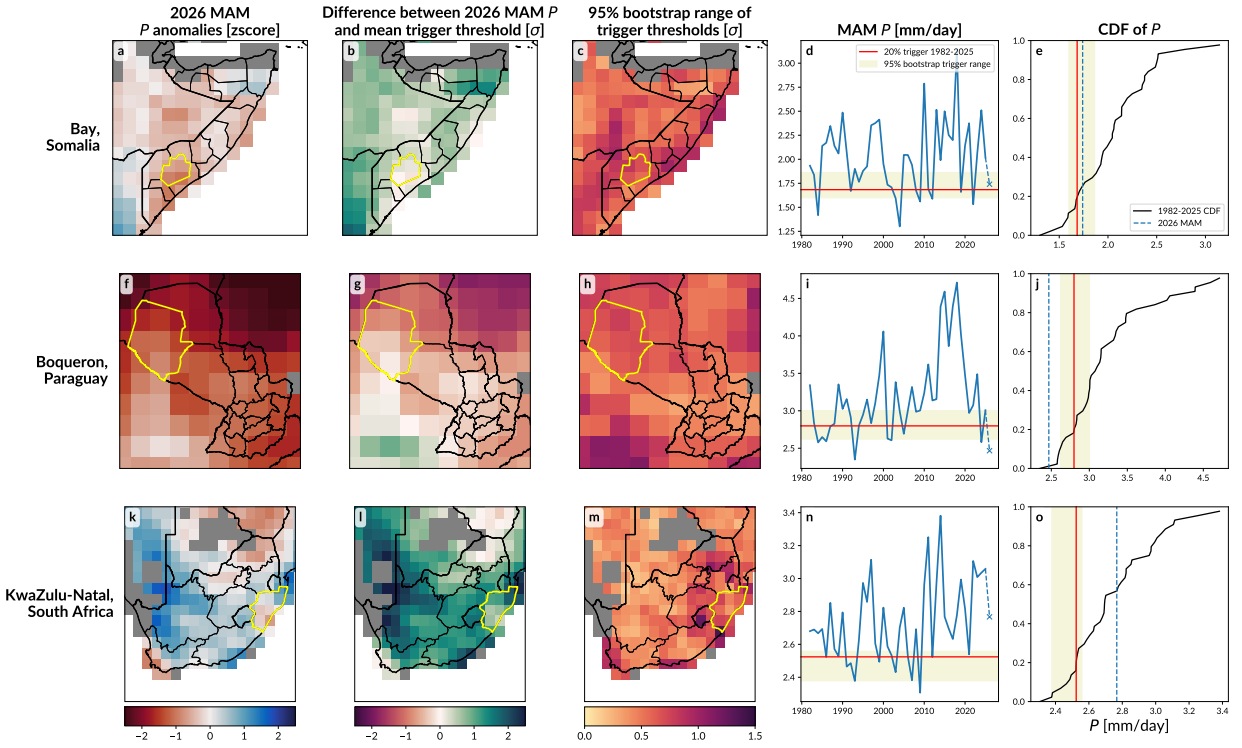
As an illustration, **Figure 3** shows the forecast March-April-May 2026 rainfall, based on the CFSv2 global climate model initialized in February 2026, in three drought-prone regions of the world. The point estimate for the 20th percentile trigger threshold, based on the 1982-2025 historical record, is shown as the red line in the rightmost two columns, while our bootstrapped 95% confidence interval for the trigger threshold is shown as the yellow shaded range.

We select three cases for this illustration: One in which the forecast rainfall is clearly below the trigger threshold (Paraguay, second row), one in which it is clearly above (South Africa, third row), and one in which it is just barely above (Somalia, first row). The case of Somalia illustrates how our bootstrapping method can provide crucial information for AA decision support. In this case, forecast rainfall falls within the bootstrapped confidence interval, meaning that decision-makers would be justified in exercising discretion in whether or not to trigger action here. Distinguishing this case from the others requires a principled way of quantifying the amount of trigger uncertainty due to the historical record, which our method offers.

This method addresses a practical problem with AA raised by WFP and its government partners: While in hindsight, there are many cases in which the use of local expert discretion could have adverted a costly failure to trigger, discretion cannot be exercised on a completely ad hoc basis if anticipatory action is to remain predictable, transparent and financially sustainable.

We can further visualize the utility of this method through application to a known major drought: the 2000 MAM season in southern Ethiopia, shown in **Figure 4**. Here, a decision rule based on the forecast alone would have led to costly inaction, since forecast rainfall was (barely) above the trigger threshold. However, the forecast fell within the bootstrapped confidence interval. Furthermore, several antecedent factors associated with heightened risk of drought impact were present in February 2000, such as below-average vegetation conditions and below-average rainfall in the previous OND season (Mauerman et al. 2023). Accounting for these factors explicitly in the trigger rule - by allowing for action to trigger if antecedent conditions indicate high humanitarian risk and the forecast falls within the trigger uncertainty bounds - is one way our bootstrapping analysis can be operationalized.

WFP and the Ethiopian Meteorological Institute have adopted such a rule for official Anticipatory Action in southern Ethiopia, allowing for triggering in instances where preceding seasonal conditions are below average and the forecast falls within the bootstrapped uncertainty range, even if it does not fall below the threshold (ReliefWeb 2025). This is one of several real-world cases of how our boostrapping method is being applied. Other ex ante risk criteria employed by WFP and its government partners in this fashion include food insecurity scores from FEWSNet and Cadre Harmonise, depending on the country. In some cases, like in Ethiopia, the accounting for ex ante risk factors is mechanistic; in other cases, like in Madagascar, the final decision of whether



237 FIG. 3. Sample use of bootstrapped confidence intervals to diagnose seasonal forecasts with a 20th percentile
238 trigger target, using the 2026 March-April-May (MAM) season as an out-of-sample case study. In all cases,
239 the confidence interval in the 20th percentile trigger was calculated using 5-year blocks and 1982-2025 CFSv2
240 half-month-lead-time hindcasts. The figure shows a case where the 2026 MAM regionally-averaged forecast
241 falls into the bootstrapped confidence interval of trigger thresholds (Bay Gobol in Somalia, top row), where it is
242 clearly below the trigger threshold (Boquern Department in Paraguay, middle row), and where it is clearly above
243 the trigger threshold (KwaZulu-Natal Province, South Africa). See Figure S8 for a map of regions corresponding
244 to each case for 2026 MAM forecasts. Columns show, from left to right, the 2026 MAM CFSv2 ensemble mean
245 forecast as z-scores vs. the 1982-2025 mean and standard deviation, the difference between that forecast and the
246 mean 20th percentile trigger calculated over 1982-2025 as standard deviations of hindcast precipitation, the 95%
247 range of bootstrapped trigger thresholds as standard deviations of hindcast precipitation, hindcast regional mean
248 MAM precipitation, and the empirical CDF of 1982-2025 rainfall. In the two rightmost columns, the 95% range
249 of bootstrapped trigger thresholds is shown in beige, the trigger threshold calculated over the whole 1982-2025
250 sample in red, and the 2026 forecast in a blue cross (4th column) or a blue dashed line (5th column). Grey areas
251 in maps do not have a wet season in MAM or experience less than 0.5 mm/day of rain over MAM.

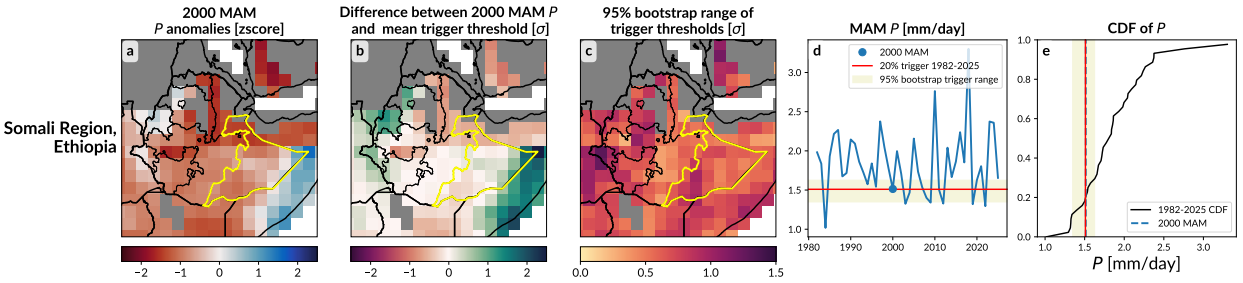


FIG. 4. Figure as in **Figure 3** , but for the ensemble mean CFSv2 hindcast of MAM 2000 in the Somali Region of Ethiopia.

or not to trigger is decided by a panel of government stakeholders if the forecast falls within the uncertainty bounds. In all of these cases, the bootstrapping method is applied **after** accounting for other sources of scientific uncertainty, such as predictive inaccuracy or between-model variability, using the CPT probabilistic forecast calibration system.

Importantly, this bootstrapping method can only capture the uncertainty from variability on a temporal scale of similar or lower order than the length of the record used. If, for example, a major flood (such as MAM 1981 in southern Ethiopia, shown in **Figure S9**) occurs roughly every 50 years, but we only have 30 years of data with which to measure precipitation, our bootstrapping method will be unable to capture uncertainty in the threshold for events of that return period. However, since humanitarian anticipatory action tends to be based on relatively frequent return periods (e.g. the 1 out of 5-year drought), this limitation is less of a concern in our practical setting.

5. Conclusions and best practices

Uncertainty due to the limited historical record of drought events is a significant issue for forecast-based anticipatory action, but is rarely accounted for when deciding whether to trigger AA efforts in a particular season. This uncertainty comes both from the limited length of the historical record (or the years for which hindcasts from seasonal forecast models are available) and from autocorrelation caused by variability in the climate system at different timescales, both of which limit the effective sample size over which AA thresholds are calculated. In this paper, we propose a methodology based on block-bootstrap resampling of this limited record to estimate the sampling uncertainty in AA thresholds. This methodology can be implemented easily, requires minimal assumptions, can be flexibly applied to any threshold, and accounts for interannual and decadal correlation in the

historical record. The method is agnostic to the type of data used, and could accommodate more elaborate forecast-based decision rules so long as the historical data necessary to evaluate those rules is available. Through a case study illustrative of United Nations operational AA forecast procedures, we demonstrate how our method provides a more comprehensive quantification of critical underlying uncertainty, enabling these AA systems to meet the state-of-the-art demanded by donors and the WMO.

Balancing the need to provide effective humanitarian responses with the need to ensure the long-term financial solvency of a given AA program, which is based on an accurate calculation of the triggering rate, is a challenge when observational or modeling records are short. In practice, forecasts close to the trigger threshold invite judgment calls on whether to trigger AA responses, often informed by the presence of non-climate risk factors, such as existing levels of food insecurity. A more comprehensive quantification of uncertainties in the trigger threshold, as proposed here, will allow for a more systemic treatment of these edge cases, by arming an operational forecaster with a way of judging whether the same forecast, when compared to an observational record of a different length or a sequence of years that were slightly different within plausible internal variability, would have instead triggered. In future work, this method could be applied to frameworks for quantifying the tradeoff between worthy action and false alarms to allow for a more thorough treatment of sampling uncertainty in a decision-analytic setting (Jaime et al. 2026).

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Data availability statement. The authors are currently cleaning up their code for public release. Full replication files for the analysis and figures shown in this paper will be provided upon journal acceptance. All of the observational (Huffman et al. 2009) and forecast (Saha et al. 2014) precipitation data used for this paper is freely available from the respective data providers.

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Supplemental Material

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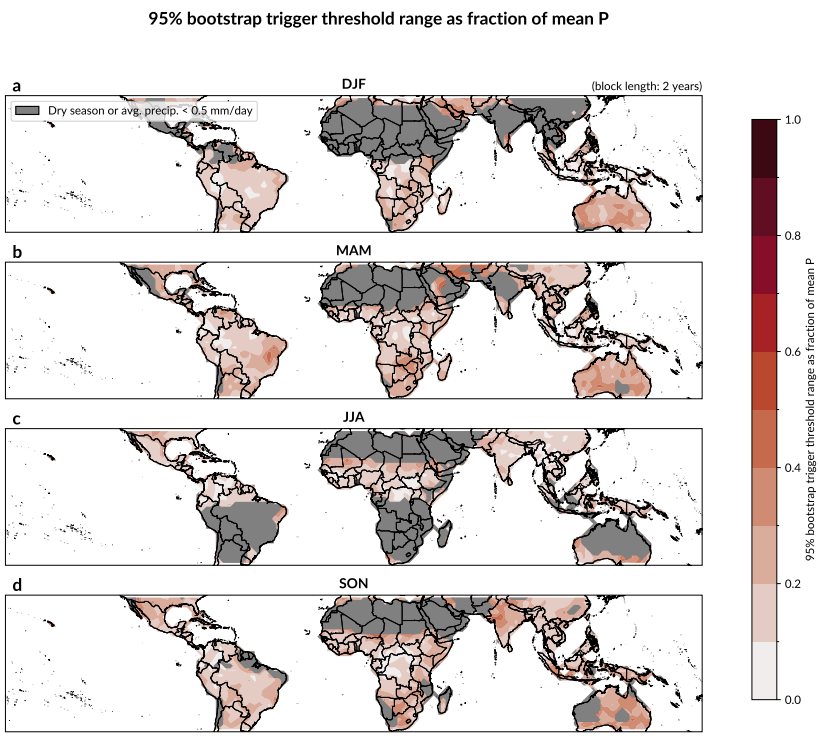
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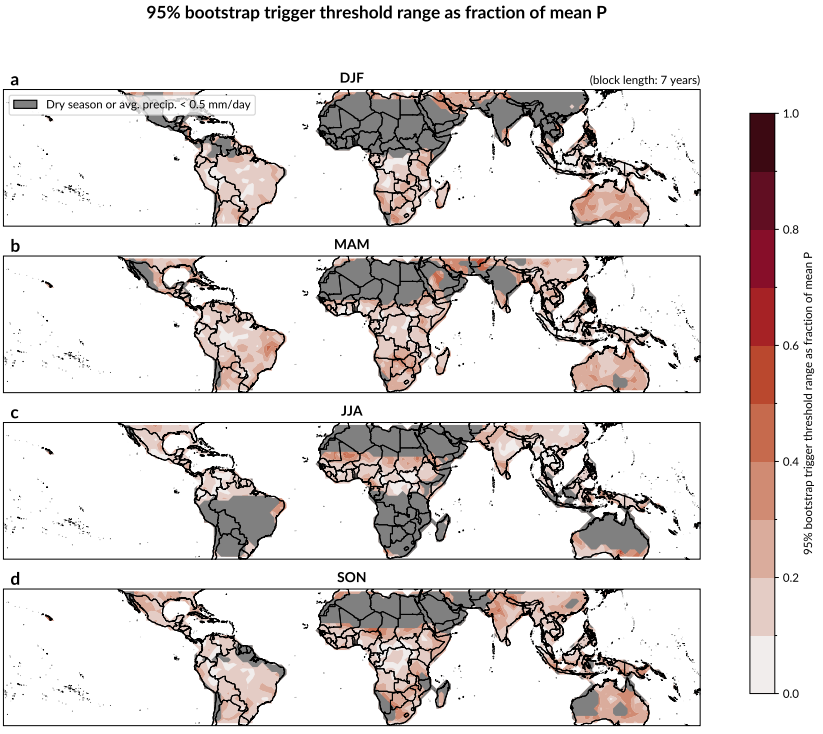
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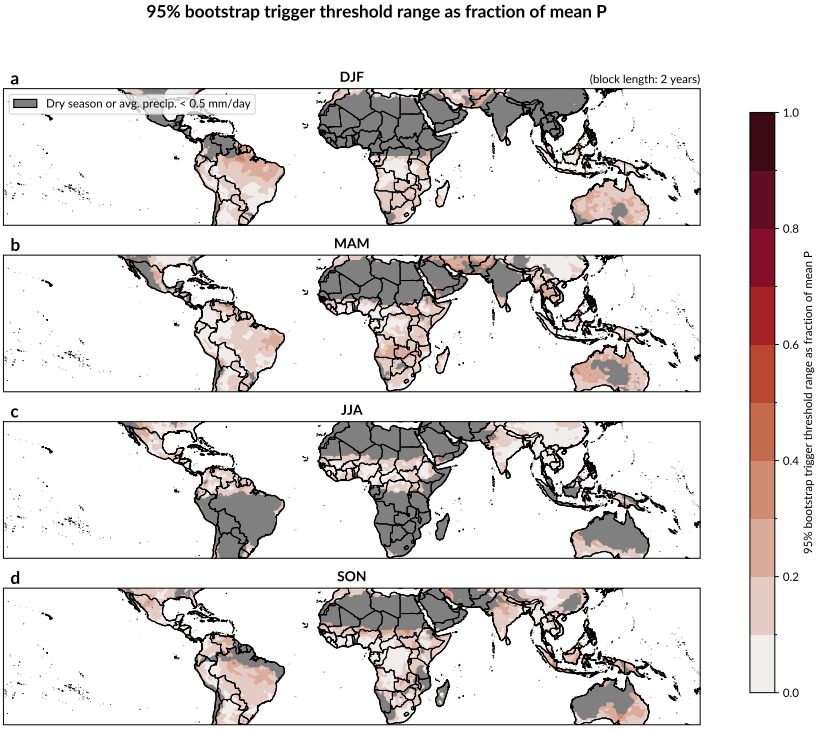


S1. Figure showing 95% bootstrap trigger threshold ranges as a fraction of mean precipitation at each location for GPCP, as in main text Figure 1, but calculated with 2-year bootstrap blocks.

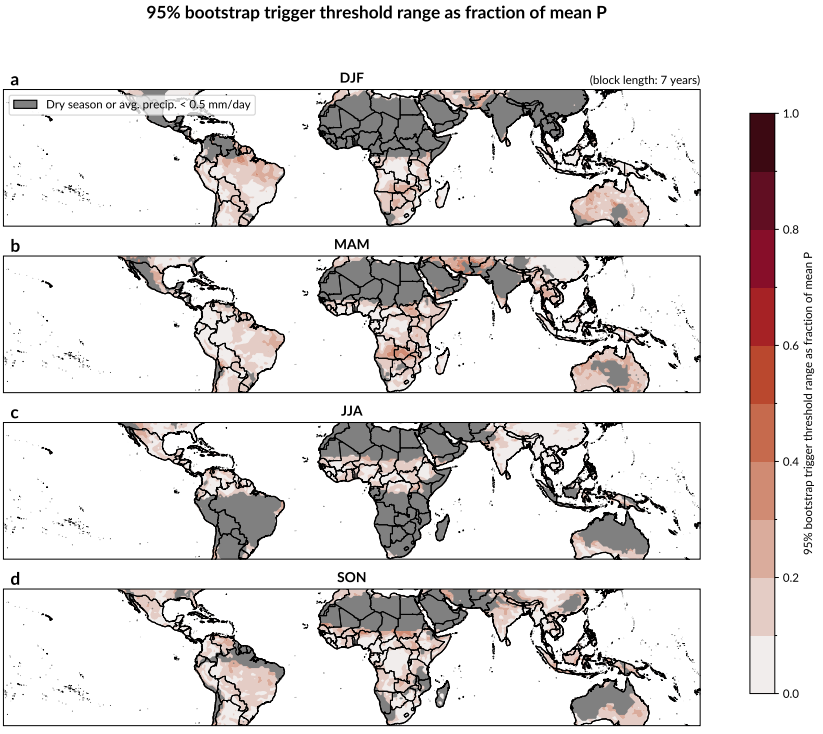
APPENDIX



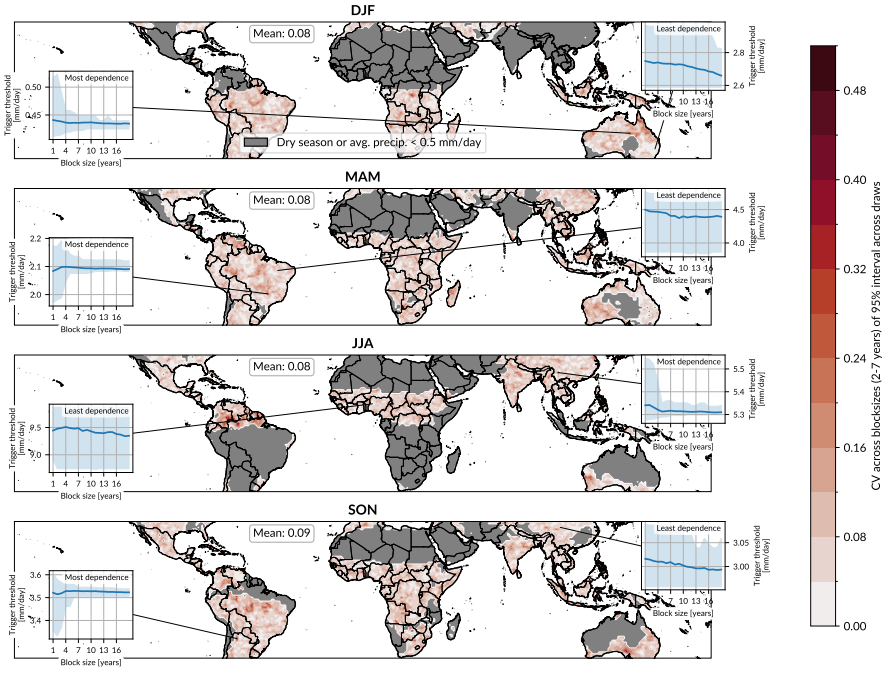
S2.Figure as in Figure S1, but with ranges calculated using 7-year bootstrap blocks.



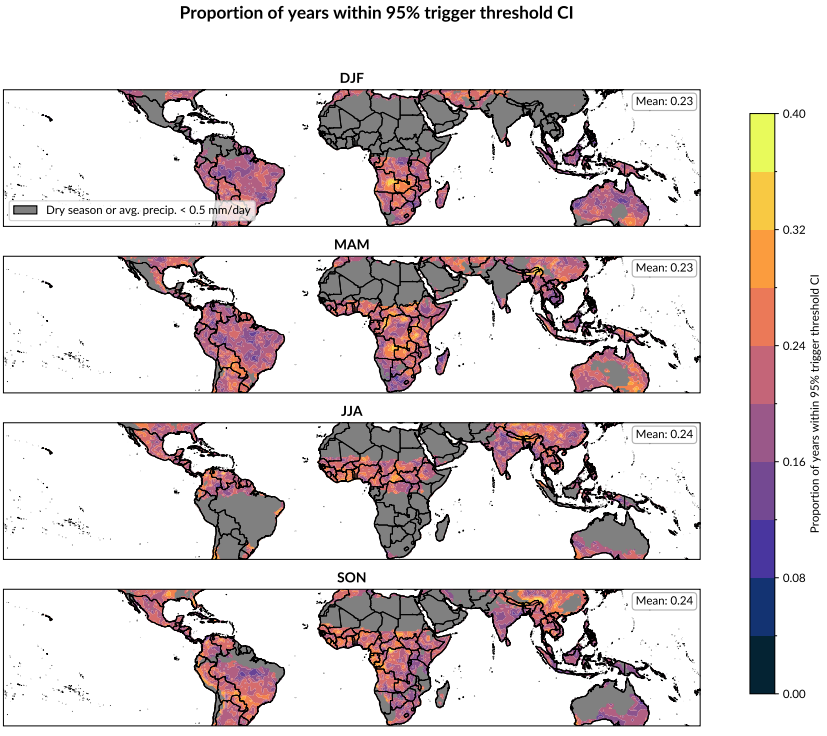
S3.Figure showing 95% bootstrap trigger threshold ranges as a fraction of mean precipitation at each location for CFSv2 half-month-lead-time hindcasts, as in main text Figure 2, but calculated with 2-year bootstrap blocks.



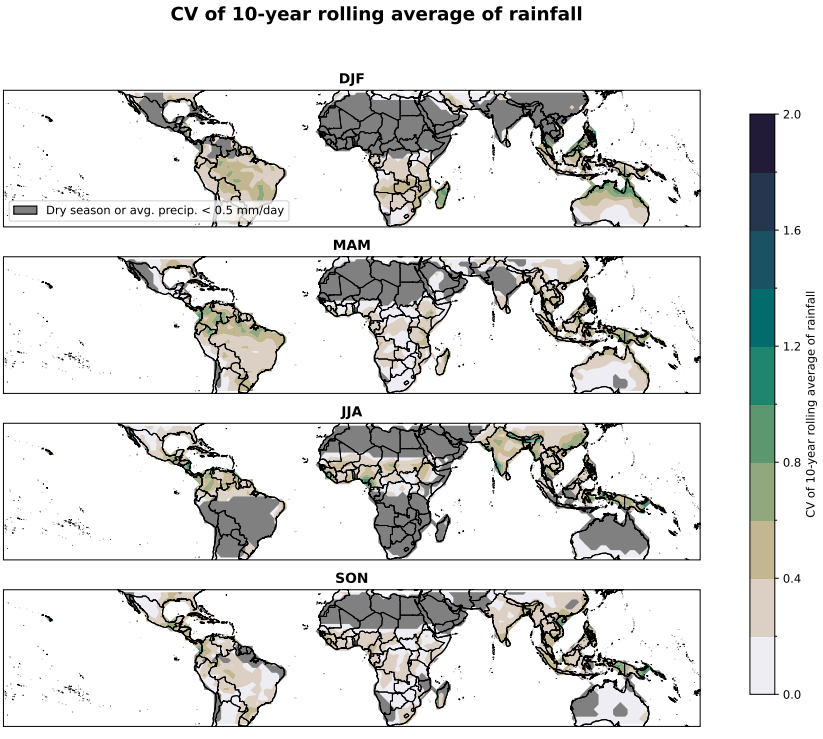
S4.Figure as in Figure S3, but with ranges calculated using 7-year bootstrap blocks.



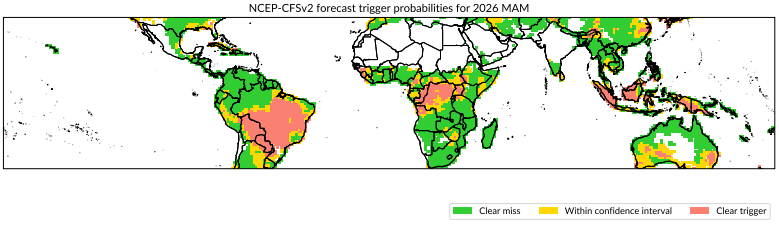
S5.Dependence on length of block size of 95% range across bootstrapped trigger thresholds for 1982-2025 CFSv2 half-month-lead-time hindcasts of seasonal (3-month) average precipitation. Map shows the coefficient of variation (CV; standard deviation over mean) of the 95% range over block sizes from 2 to 7 years. The area-weighted average CV of land areas 35 S to 35 N is shown in the box in each map panel. Inset axes show the evolution of the mean trigger threshold (thick blue line) and the 95% range (light blue shading) in the grid cell in which the 95% range has the most or least dependence on the block size, i.e., in which the CV is highest or lowest of the shown portion of the world. Locations in grey experience a dry season or rainfall less than 0.5 mm / day on average during the relevant season.



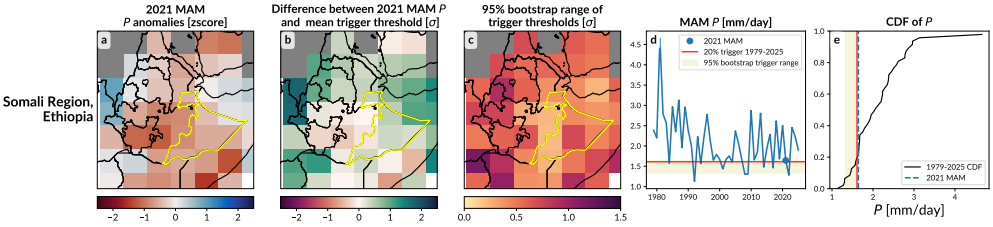
S6.Proportion of years 1982-2025 that are within the 1982-2025 bootstrapped 95% range of trigger thresholds for CFSv2 half-month-lead-time hindcasts of seasonal (3-month) average precipitation. The area-weighted average of land areas 35 S to 35 N of this proportion is shown in the box in each map panel. Locations in grey experience a dry season or rainfall less than 0.5 mm / day on average during the relevant season.



S7.Typical decadal variability of precipitation as the coefficient of variation (CV; standard deviation over mean) of the 10-year rolling average of 1982-2025 GPCP precipitation at each location. Locations in grey experience a dry season or rainfall less than 0.5 mm / day on average during the relevant season.



S8.Map of classification of half-month-lead-time CFSv2 ensemble mean 2026 MAM forecasts of precipitation vs. bootstrap trigger range. In green areas, the forecast is above the 95% bootstrap trigger range (using 5-year blocks), in yellow regions, the forecast is within that range, and in red regions the forecast is below that range. In other words, in green areas, the drought trigger is clearly missed, in red areas the drought trigger is clearly met, and in yellow areas, it is uncertain whether the forecast is above or below the true trigger threshold, given the limited data record it was calculated with.



S9.Case study as in main text Figure 4, but for the 2021 MAM season, and showing GPCP precipitation instead of CFSv2 hindcasts.