Ready, set, go! An anticipatory action system against droughts

Gabriela Guimarães Nobre[1,*], Jamie Towner[1,] Bernardino Nhantumbo[2], Célio João da Conceição Marcos Matuele[2], Isaias Raiva[2], Massimiliano Pasqui[3], Sara Quaresima[3], Rogério Bonifácio[1]

[1] World Food Programme (WFP), Rome, Italy
[2] Mozambique National Meteorology Institute (INAM)
[3] National Research Council, Institute for Bioeconomy, Rome, Italy

*Corresponding author: gabriela.nobre@wfp.org

ABSTRACT

The World Food Programme, in collaboration with the Mozambique National Meteorology Institute, is partnering with several governmental and non-governmental organizations to establish an advanced early warning system for droughts in pilot districts across Mozambique. ~~This warning system, named~~The "Ready, Set & Go!" system is operational in Mozambique for activating anticipatory action (AA) against ~~, aims to proactively address impending~~ droughts ~~by setting~~based on predefined thresholds, triggers, and ~~funding mechanisms~~pre-allocated financing. ~~for anticipatory actions.~~ The system uses bias corrected and downscaled seasonal forecasts from the European Center for Medium-Range Weather Forecast (ECMWF) as core information to anticipate severe reductions in rainfall during the rainy season. This information guides the implementation of actions to reduce the impacts of rainfall deficits in the critical window between a forecast and the onset of the drought event. Within this window of opportunity, the system releases an alert for readiness (Ready) and activation (Set) preceding the mobilization of anticipatory action on the ground (Go). With the recent adoption of the Southern African Development Community Maputo Declaration *on Bridging the Gap between Early Warning and Early Action*, member states have committed to enhancing the reach of early warning system by leaving no one behind. Therefore, there is a need to assess the opportunities and limitations of the Ready, Set & Go! system to scale up drought AA information to all districts in Mozambique. This study describes the Ready, Set & Go! system which uses ensemble forecasts of the Standardized Precipitation Index to trigger anticipatory action against droughts on a seasonal timescale. The Ready, Set & Go! optimizes the use of seasonal forecast information by choosing triggers for anticipatory action based on verification statistics and on a double confirmatory process, which combines longer lead times with shorter lead time forecasts for issuing drought alerts. In this study, we show the strengths of the system by benchmarking it against three simpler triggering approaches. Our findings indicate that the Ready, Set & Go! system has significant potential to scale up AA activities against severe droughts throughout the entire rainy season, covering on average 76% of the Mozambican districts. This approach outperforms the three benchmarked methods, demonstrating higher hit rates, extended lead times, and a lower false alarm. If efforts are concentrated on the first part of the rainy season, national coverage against severe droughts could be expanded to 87% of all districts. ~~We found that the Ready, Set & Go! system has the potential for scaling up AA activities against severe droughts to 76% of the Mozambican districts with increased hit rate and lead time, and decreased false alarm ratio compared to the other three benchmarked approaches. National coverage against severe~~

Formatted: Not Highlight

~~droughts could be reached to 87% of all districts if targeting only the first part of the rainy season.~~ By aligning with the objectives outlined in the Maputo Declaration and the Early Warning for All initiative, this research contributes to safeguarding communities against the adverse impacts of climate-related events, aligning with the ambitious goal of universal protection by 2027.

1. INTRODUCTION

Mozambique experienced in 2015/16 one of its worst drought events in decades, which affected the food security of approximately 2.3 million people leading to its government to declare a state of national emergency (OCHA, 2017). This El Niño induced drought caused an exceptional lack of precipitation in two consecutive rainy seasons, which resulted in significant losses in rain-fed yields, below-average irrigated crops, poor pasture conditions and high cattle mortalities (WFP, 2016). The dryness propagated into water reservoirs in southern Mozambique, where the impact on water levels remained for five years (ECHO, 2021).

Mozambique is a country exposed and vulnerable to multiple hazards due to its geographical location and ~~long~~ latitudinal extent. Its climate is affected by several modes of climate variability such as the El Niño-Southern Oscillation (ENSO; Rapolaki et al., 2019; Blamey et al., 2018), Indian Ocean Dipole (IOD; Ashok et al., 2001; Manatsa et al., 2011; Saji et al., 1999) and the Subtropical Indian Ocean Dipole (SIOD; (Behera & Yamagata, 2001). These climate modes of variability modulate the frequency and intensity of the various weather systems that are directly associated to multiple natural hazards happening as a single or consecutive risk (e.g., Hart et al., 2010; A. J. Manhique et al., 2015; Atanásio João Manhique et al., 2021; Mawren et al., 2020; Rapolaki et al., 2019; Reason & Keibel, 2004). Impacts of ~~multi~~ single and consecutive hazards including flooding, cyclones and droughts are exacerbated by poverty and weak institutional development, where climate related disasters are one of the main driving forces of inequalities and food insecurity in the country (Baez et al., 2019). In Mozambique, nearly 25% of its population live in areas with a high probability of experiencing a climate shock (World Bank, 2018). Therefore, the adoption of protective mechanisms and systems to anticipate and prepare the government and communities to climate shocks is crucial for building resilience and sustainable development. Recently, the national government has made climate risk management a priority strategy following the adoption of the Maputo Declaration *on Bridging the Gap between Early Warning and Early Action*, in which member states of the Southern African Development Community (SADC) have committed to take an active people-centered role to ensure all citizens access to effective Early Warning and Early Action systems (SADC, 2022).

Since 2019, a multi-sector government-led anticipatory action (AA) trigger system against drought (WFP, 2023) has been under development in Mozambique coordinated by the Mozambique National Institute of Disaster Management (INGD) with the technical support of relevant actors, including the National Meteorological Institute (INAM) and the World Food Programme (WFP). Droughts are a slow, recurrent, and predictable phenomena (Guimarães Nobre et al., 2023) and yet, they cause an estimated yearly loss of US$20 million (Baez et al., 2019) to Mozambique. Drought early warning system (EWS) have a great potential to reduce some of these losses when anticipatory action (AA) is implemented ahead of a shock based on forecast information. Previous studies have assessed the skill of seasonal forecasts to predict the onset of droughts (Gebrechorkos et al., 2022; Guimarães Nobre et al., 2023; Trambauer et al., 2015; Winsemius et al., 2014) whereas only few have focused on an in depth interpretability of the forecast quality through the lenses of decision-making and practical implications. For instance, a reflection on the adequateness of lead time of information for action, and/or definition of probabilistic trigger values for releasing drought alerts and advisories for AA are aspects largely missing in the scientific literature.

AA approaches are gaining more traction with an increased number of institutions dedicating funding and pilot studies in Mozambique. However, the evidence on the benefits of acting earlier is still fairly new and limited. Overall, existing evidence based on pilot experiences in other parts of the world have mainly suggested a positive impact of AA at household level, with beneficiaries reporting higher crop productivity and less food insecurity during prolonged periods of drought (Weingärtner et al., 2020). In Mozambique, AA drought pilots are limited - to date - to eleven districts and further scale up of activities to the national level is desired. However, an assessment of the opportunities and limitations of the current drought AA trigger system is currently missing, especially given the 2023 El Ninõ scenario, which is expected to negatively affect the 2023-24 rainy season. In response to the need of assessing the potential to bring AA to scale, this study describes the operational triggering system for drought AA being piloted in Mozambique during the southern Africa rainy season 2023-24. This article presents the analytical routines involved in the definition and monitoring of triggers for AA as describes the technical methodologies of the system by outlining data processes, forecast application, decision-making and operational activities linked to the release of AA advisories to pilot areas.

2. CASE STUDY & METHODS

2.1 Case Study

We developed a methodology that is being piloted and scalable for triggering AA against droughts for all districts in Zimbabwe and Mozambique, although this study has a special focus on the latter. Currently in Mozambique, a government-led AA plan is in place for 11 pilot districts (see Figure 1). However, an ~~operational triggering system~~ anticipatory action system is desired for the whole country requiring the upscaling of the current set up. Concerning climatology, the rainy season in Mozambique lasts from October to May, although the largest amounts are experienced between November and April. The wettest months are December and January, however January alone is the wettest month across the country (WFP, 2018). Rainfall amounts increase from south to north. For instance, areas of low annual rainfall (less than 500 mm) include the southern provinces of Maputo, Gaza, Inhambane and the southern half of Tete, whereas areas of high total rainfall (over 2000 mm) include the provinces of Cabo Delgado, Niassa, Nampula and Zambezia. Rainfall interannual variability is stronger in areas of lower rainfall totals and is a major limiting factor to livelihoods and small-scale rain-fed agriculture (Guimarães Nobre et al., 2023). In addition, the province of Gaza has a remarkably variable and short growing season length (mostly below 3 months). Interannual climate variability in the southern Africa region is particularly linked to the El Niño-Southern Oscillation (ENSO) (Richard et al., 2001). During the months of October to December, the El Niño phase often drives rainfall increases (decreases) in Cabo Delgado and Niassa in northern Mozambique (southern provinces of Maputo, Gaza and Inhambane). During these months, when a La Niña state is observed, rainfall increases are observed in parts of the central provinces of Manica, Sofala and northern Inhambane. In addition, during the months of January to March, El Niño leads to drier conditions across most of the country, whereas in the south and centre of the country a moderate increase in rainfall is observed during La Niña phases (WFP, 2018). Mozambique is highly climate vulnerable country where livelihoods rely on local natural resources (e.g., agriculture and fisheries) as their primary economic activity. Drought events affect the ability of farmers and fishermen to sustain crops and fish, often cascading into situations of food insecurity, malnutrition, and unsustainable incomes.

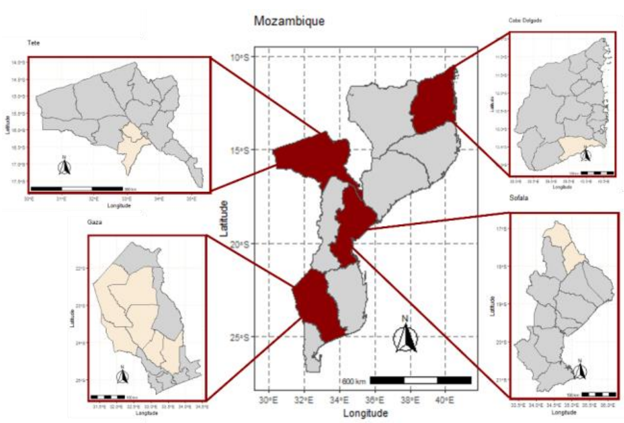


Figure 1: Districts in Mozambique with government-approved anticipatory action plans.

2.2 Methodological Framework

The operational triggering system for drought AA is developed and tested in three stages (Figure 2): (1) data pre-processing, (2) forecast application and decision-making, and (3) sensitivity analysis. A detailed explanation of each stage is provided in sections 2.2.1 to 2.2.3.

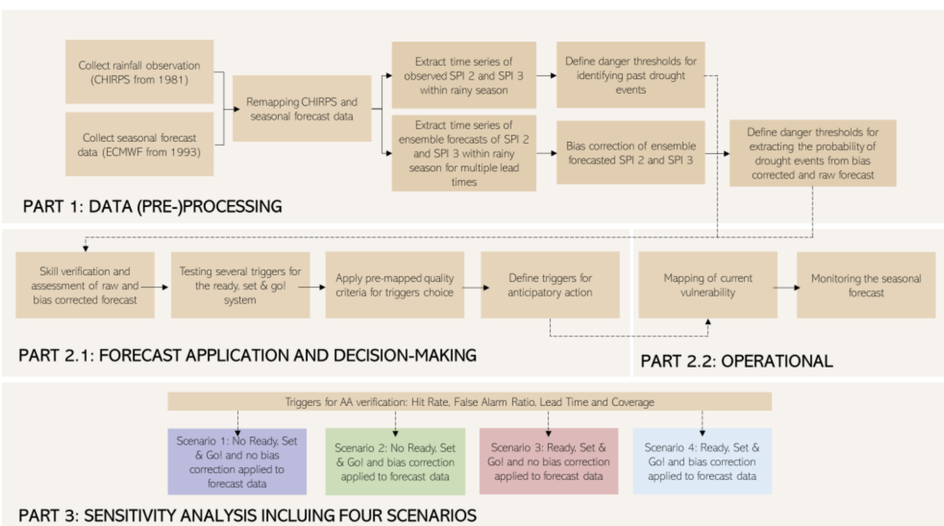


Figure 2*:* Flowchart of the methodological framework applied in this study, handled in three stages: (1) data pre-processing; (2) forecast application and decision-making; and (3) sensitivity analysis.

2.2.1 Part 1: Data pre-processing

Collect~~ion of datasets and rescaling~~rainfall observation (from 1981)

As source of rainfall ~~observations~~estimates, we use daily blended precipitation records from the Climate Hazards group Infrared Precipitation with Stations version 2 (CHIRPS) for the period of January 1981 to near present~~date~~. CHIRPS is a high resolution (0.05°) precipitation dataset, which is used for drought early warning purposes by the Famine Early Warning Systems Network ~~(Funk et al., 2015).~~This dataset integrates data from real-time meteorological stations with infrared satellite data (therefore called blended precipitation product), covering from 50°N to 50°S via a blending procedure further described in Funk et al. (2015).

Collect seasonal forecast data (ECMWF from 1993)

As source of forecast data, we use seasonal precipitation forecasts from the ECMWF's seasonal forecasting system (SEAS5) for the period 1993–2022. In its native resolution, the forecast is available at 1 arc-degree and new forecasts are released monthly on the fifth day covering the coming 7 months. SEAS5 is composed of a set of 25 ensemble members until 2016 (hindcast period), and 51 ensemble members from 2017 onwards as part of the operational system (Ratri et al., 2019). It is important to highlight that ECMWF SEAS5 has a new version (SEAS5.1) since November 2022 with extended hindcast until 1981 which full time series of hindcast and operation forecast can be freely downloaded from the Copernicus Climate Data Store.

Remapping CHIRPS and seasonal forecast data

Since the datasets of rainfall estimates and forecasts are available in different spatial resolutions, we remapped them into an intermediate resolution of 0.25°. This moderate resolution was chosen taking into consideration the size of pilot districts in which the system will be implemented, computational capacity as well as to reduce the impact of rainfall small-scale variability. For this process, we used bilinear interpolation one of the most commonly used methods of climate grid interpolation (National Center for Atmospheric Research Staff, 2014). Bilinear interpolation resizes the data by estimating values at a point by averaging the values of the surrounding points.

~~We downscale the forecasting data to a 0.25° regular mesh by applying bilinear interpolation using the above mentioned upscaled CHIRPS gridded data.~~

Extract time series of observed SPI 2 and SPI 3 within rainy season

From the daily CHIRPS rainfall estimates, we extract the Standard Precipitation Index (SPI), a widely used indicator for measuring rainfall variability over a long-term climatological period (Svoboda et al., 2012). The SPI is centered around the mean rainfall for a given time and location, with values ranging from -4 to +4. Negative SPI values indicate various levels of rainfall deficits, which are particularly relevant to the designed trigger system. The SPI can also highlight drought situations when a "danger threshold" is identified signaling rainfall deficits severe enough to prompt anticipatory to mitigate the impacts on livelihoods.

In this study, SPI values are calculated using two- and three-month accumulation periods (SPI 2 and SPI 3, respectively). These accumulation windows are particularly suitable for detecting risks to agricultural systems during the crop development cycle. It is crucial to note that the AA framework aims to protect food security by reducing the risk of crop failures in rain-fed systems. Therefore, only SPI values extracted during the rainy season are relevant to the trigger system (see the section below for a detailed explanation of windows of opportunity for anticipatory action).

To derive the SPI estimates, the CHIRPS rainfall dataset, accumulated over two and three months, is fitted to a gamma distribution and subsequently transformed to a normal distribution with z-values (Lloyd-Hughes & Saunders, 2002). The period from 1981 to 2018 serves as the reference climatology for calculating the gamma distribution parameters. This period was selected due to the availability of a complete series of rainfall observations at the start of the project in 2019. Periods with zero precipitation are handled by assigning SPI values based on the historical occurrence of such periods from 1981 to 2018. However, since we use precipitation data accumulated over two and three months, zero values are rare, especially as SPI is only extracted during the rainy season. For extracting SPI during the dry season or in arid regions, more sophisticated techniques, such as those described by Stagge et al., (2015), are available and should be preferred.

Extract time series of ensemble SPI 2 and SPI 3 within rainy season for multiple lead times

For the forecasting series, the parameters of the gamma distribution are determined using data from all ensemble members for the years 1993 to 2018, as data prior to 1993 is not available in the Copernicus Climate Data Store (SEAS5). The routine adopted for handling zero values is similar to the one described for deriving SPI estimates (see above). In Figure 3, we illustrate the extraction of SPIs for various lead times of the forecast system with a seven-month lead time. For example, the seasonal forecast released at the beginning of May covers the subsequent months (May to November). Therefore, the only indicator extracted from this forecast is SPI 2 ON, as October marks the first month of the rainy season in the country.

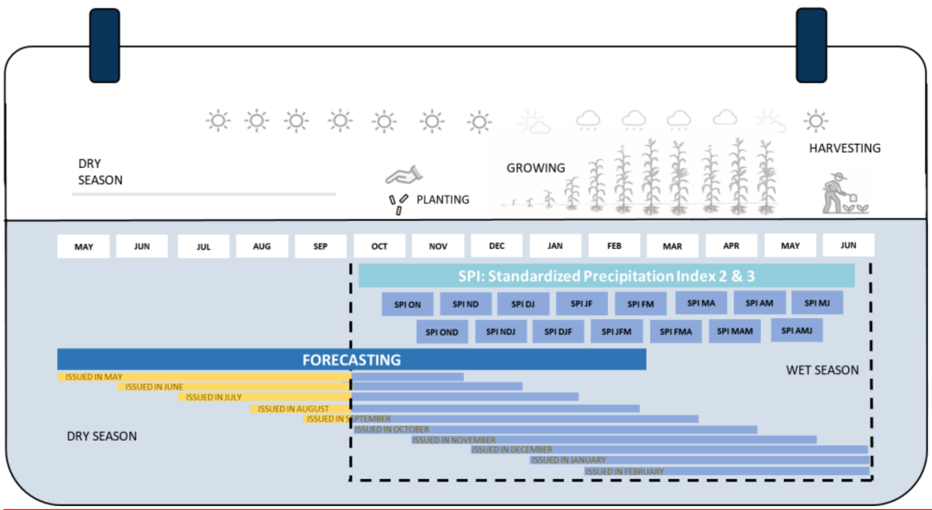


Figure 3 Illustration of the SPIs representing rainfall anomalies during Mozambique's rainy season, along with the corresponding forecast months used for their extraction.

Define danger threshold for identifying past drought events

Given that the Standardized Precipitation Index (SPI) is linked to the probability of certain rainfall amounts, we convert a specific z-value into an expected frequency by calculating the area under the normal distribution curve up to that z-value. This proportion, or probability (p), is then converted into a return period (T) by taking the inverse of the probability ($p = 1/T$). In the operational AA trigger system, three z-value thresholds are used, as highlighted by Guimarães Nobre et al (2023), corresponding to different severity levels. This article focuses on the most severe category in the AA trigger system, which is SPI ≤ -1 as this negative anomaly is expected to cause the most significant damage among those adopted by the system.

However, it is important to highlight that the impact of a drought threshold should ideally be estimated using historical observations combined with information on who and what is exposed to a hazard (exposure and vulnerability). Due to the lack of extensive drought impact data at the district level, the choice of a threshold level is based on frequencies suitable for AA operations in the region. Typically, AA programs target hazards that occur at least once every three years on average. Implementing AA pilots periodically is crucial for enhancing program activities. Consequently, thresholds for AA operations should not be set too low, given that the occurrence of drought events of such intense magnitude is rare. A SPI ≤

-1 (named severe category in the AA trigger system) corresponds to an event occurring approximately once every 6 to 7 years (or p = 15.87%). By applying the SPI ≤ -1 threshold to the SPI2 and SPI3 estimated series, we obtain a time series since 1981 of past drought events for the respective two- and three-month periods in the pilot districts.

Bias correction of ensemble forecasted SPI 2 and SPI 3

We employ a quantile-quantile mapping technique, conditioned on the state of ENSO, to adjust SPI forecast values. This is achieved by aligning the cumulative density function of SPI forecasts at each grid cell with the reference SPI data extracted from CHIRPS at the corresponding grid cell and its k nearest neighbors. The SPI forecast and reference distributions are matched by establishing an ENSO-informed, quantile-dependent correction function. This function adjusts the forecast quantiles based on their observed SPI counterparts, translating the SPI forecast time series into bias-adjusted values that accurately represent the observed SPI data distribution.

The transfer functions for bias correction are developed based on the SPI reference and SPI forecast time series, specifically targeting the AA drought indicator rather than daily or monthly rainfall. By incorporating ENSO information, we aim to ensure that rainfall variability is more accurately represented in the corrected forecast data, especially in regions and timescales where ENSO has a significant impact (Manzanas & Gutiérrez, 2019). This approach combines statistical quantile mapping bias correction with ENSO state knowledge during rainy seasons. Furthermore, information from the nearest neighbors from the reference pixel is used to account for the spatial dependence inherent in climate data (k=9) (Cannon, 2018) and to extend the SPI time series used to create the transfer function. By targeting the SPI indicator directly with the transfer function, we aim at increasing the accuracy of drought detection by bringing SPI forecasts closer to the observed SPI climatology, ensuring that the SPI derived from forecasts are more consistent with historical patterns and trends. This is critical for the Ready, Set and Go! System that releases alerts based on negative anomalies through the SPI indicator rather than on rainfall amounts.

In practical terms, incorporating ENSO information into quantile mapping involves: (i) categorizing data by ENSO phases; (ii) generate empirical cumulative distribution functions for each ENSO phase separately for both SPI observed and SPI forecast; (iii) perform quantile mapping by applying the transfer function to the test year (year left out during cross validation) of the analysis according to the ENSO phase of the year being bias corrected; iv) combine corrected forecast outputs if bias correction is found to improve skill in detecting droughts.

In summary, the quantile mapping transfer function corrects the SPI forecast based on the SPI reference value of the pixel under investigation and its nine neighboring pixels conditioned on the state of ENSO. To prevent inflating the skill of the bias correction, a leave-one-year-out cross-validation (LOCV) scheme is used. The bias correction transfer function is constructed by pooling all ensemble members of the forecast and then applied to all members of the left-out test year.

An overview of this scheme is available in Figure 3. For a list of ENSO years, see Supplementary Material S1.

Define danger threshold for extracting the probability of drought events from bias corrected and raw forecasts

From both raw and bias-corrected forecasts, we apply the danger threshold (SPI ≤ -1, classified as severe in the AA trigger system) to determine the probability of a severe drought. This is done by calculating the proportion of ensemble members that meet or fall below the threshold. We repeat this process for each forecast issue month from 1993 to 2022, creating a time series of drought probabilities at different lead times for both the raw and bias-corrected forecasts.

In practice, the bias-corrected drought probabilities replace those from the raw forecast only when there is a demonstrable gain in skill for forecasting severe drought. This gain in skill is evaluated by comparing the area under the Receiver Operating Characteristic (AUROC) curve scores of the raw and bias-corrected forecasts (further detailed in the section below). Consequently, the bias-corrected drought probability information is used only if it shows an improved ability to predict severe droughts in the pilot districts, considering specific cases (such as a particular forecast lead time and SPI 2 and SPI 3 aggregation).

~~It is important to highlight two features of the bias correction methodology: (i) the bias correction targets the SPI indators directly instead of the daily or (multi-)monthly rainfall totals and (ii) in practice, the bias corrected forecast only replaces the raw SPIs forecast when actual skill is gained when forecasting severe drought. The gain in skill is assessed by calculating and comparing the area under the Receiver operating characteristic curve (AUROC) score (further explained in section 2.2.2) of the raw and bias corrected forecasts. Therefore, the SPI bias corrected series is only used if demonstrated gain in skill for predicting severe droughts at the pilot districts and per specific cases (for a particular forecast lead time and SPI 2 and SPI 3 aggregation).~~

~~As source of rainfall observations, we use daily blended precipitation records from the Climate Hazards group Infrared Precipitation with Stations version 2 (CHIRPS) for the period of January 1981 to date. CHIRPS is a high resolution (0.05°) precipitation dataset, which is used for drought early warning purposes by the Famine Early Warning Systems Network (Funk et al., 2015). For the trigger system, we upscale the CHIRPS dataset to a 0.25° grid using a bilinear remapping. This moderate resolution was chosen based on the size of pilot districts and to reduce the impact of rainfall small-scale variability. Furthermore, it allows for the downscaling (see section below) of the forecasting data and its computational handling~~. ~~As source of forecast data, we use seasonal precipitation forecasts from the ECMWF's seasonal forecasting system (SEAS5) for the period 1993–2022. In its native resolution, the forecast is available at 1 arc-degree and new forecasts are released monthly on the fifth day covering the coming 7 months. SEAS5 is composed of a set of 25 ensemble members until 2016 (hindcast period), and 51 ensemble members from 2017 onwards as part of the operational system (Ratri et al., 2019). We downscale the forecasting data to a~~

~~0.25° regular mesh by applying bilinear interpolation using the above mentioned upscaled CHIRPS gridded data.~~

~~Extracting the Standard Precipitation Index from datasets~~

~~From both sources of rainfall data (observation and forecast), we extract the Standard Precipitation Index (SPI). The SPI is a widely used indicator to measure rainfall variability from the long-term climatological period (Svoboda et al., 2012). In this study, the SPI indicator is centered around the mean of the rainfall, for a given time and location, and values can range from -4 to +4. Negative SPI values represent different levels of rainfall deficits, which is of special relevance to the designed trigger system. In addition, the SPI can be used to monitor droughts when a “danger threshold” is identified. This threshold aims at depicting rainfall deficits of alarming levels, in which anticipatory actions would be triggered by the seasonal forecast to reduce the impacts of an upcoming shock to livelihoods. Furthermore, the SPI values are calculated with reference to a time window of accumulation, which in this study, two- and three-month aggregations are adopted (SPI-2 and SPI-3, respectively). SPI indicators at these accumulation windows are more suitable for detecting risks to agricultural systems within the crop development cycle. It is important to highlight that the AA seeks to create windows of opportunity to protect people’s food security by reducing the risk of crop failures of rain fed systems, and therefore, only SPI within the rainy season is of relevance to the trigger system (see explanation for windows of opportunity for anticipatory action in section below). To derive the SPI observation and forecast series, the dataset is fitted to a gamma distribution and subsequently transformed to a normal distribution with~~ ~~*z*~~ ~~values (Lloyd-Hughes & Saunders, 2002). The period of 1981 to 2018 is used for the observation series as a reference climatology to calculate the parameters of the gamma distribution. This period is chosen given the availability of complete series of rainfall observation at the start year of the project (in 2019). For the forecasting series, the parameters of the gamma distribution are obtained by pulling values all ensemble members during the years 1993 to 2018 (given the lack of data previous to 1993 in the climate data store).~~

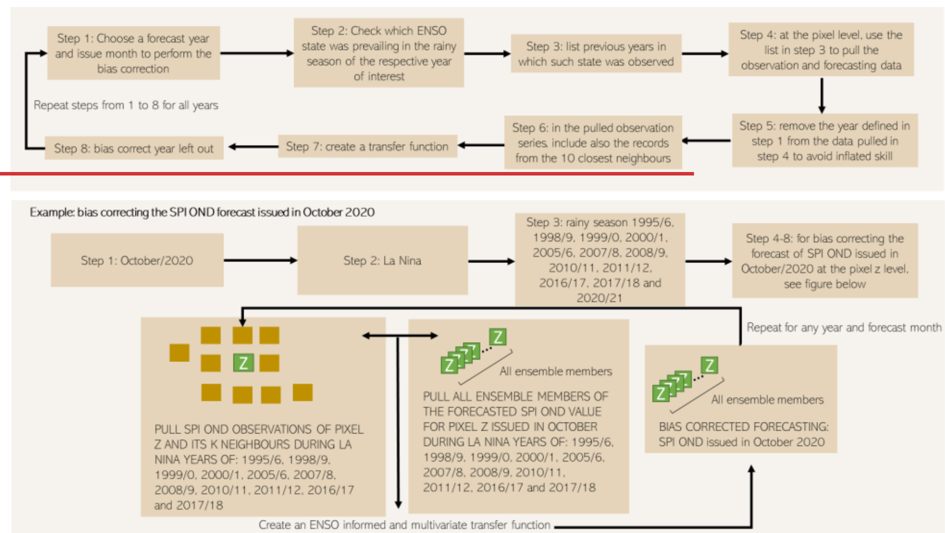
~~Defining and applying a “danger threshold” for identifying drought events~~

~~Given that SPI is a standardized index linked to the probability of occurrence of rainfall amounts, we convert a certain~~ ~~*z*~~ ~~into an expected frequency by calculating the area below the normal distribution curve using some~~ ~~*z*~~ ~~threshold as reference. Subsequently, the proportion (or probability~~ ~~*p*) is converted into a return period (*T*) by inverting the obtained probability value (*p* = 1/*T*). In the operational AA trigger system, three thresholds are adopted (as highlighted in Guimarães Nobre et al., 2023) corresponding to different severity levels. For simplicity, this article focuses on the most severe one (SPI ≤ -1) as such a negative anomaly is expected to cause increased damage among the ones adopted by the system. However, it is important to highlight that the impact of a specific threshold should ideally be estimated using historical observations, in combination with information of who and what is exposed to a hazard (exposure and vulnerability). However, due to lack of extensive drought impact data at the district level, the adopted threshold levels are primarily based on frequencies that are suitable for AA operations in the region. A severe category corresponds to an event happening approximately 1 in 6/7 years (or~~ ~~*p*~~ ~~= 15.87%). Following the identification of a threshold of interest, we applied this value to the observation series to obtain a time series of past drought events. However, prior to applying this threshold in the forecasted~~

~~SPIs to obtain drought probabilities (from the ensemble model), we attempt at adjusting the SPI 2 and SPI 3 series forecasts by carrying out a bias correction methodology, which is described below.~~

~~Bias correction of the SPI 2 and SPI 3 ensemble series~~

~~We use Quantile Mapping to adjust the forecast values to the reference data (CHIRPS) by matching the cumulative density function of the SPI simulations at each grid cell. SPI forecast and observation distributions are matched by establishing a multivariate and ENSO process-informed quantile-dependent correction function, which adjusts the quantiles of the forecast values based on the ones from their observed counterparts. This function is then used to translate the SPI forecast time series into bias-adjusted values with a distribution representative of the observed data, which is the SPI derived from CHIRPS. In more detail, the transfer functions for bias correction are built based on the SPI 2 and SPI 3 time series, and therefore directly towards the target variable. In order to overcome an arbitrary temporal change which can deteriorate the inter-annual variability of the raw predictions, we use a process-informed bias correction method (Manzanas & Gutiérrez, 2019). This is done by combining the statistical bias correction with the knowledge about the ENSO states within the rainy seasons of previous years and latest ENSO forecast. Furthermore, to take into consideration the spatial dependence inherent to climate data, we build transfer functions based on the reference value of the pixel under investigation and its ten neighbors (k=10)(Cannon, 2018). Lastly, we adopt a scheme of leave-one-year-out cross-validation in order to avoid inflating the skill of bias correction. The bias correction transfer function is built by pulling all ensemble members of the forecast and applied to all members left out. An overview of the scheme is available in Figure 3. For a list of ENSO years, see Supplementary Material S1.~~



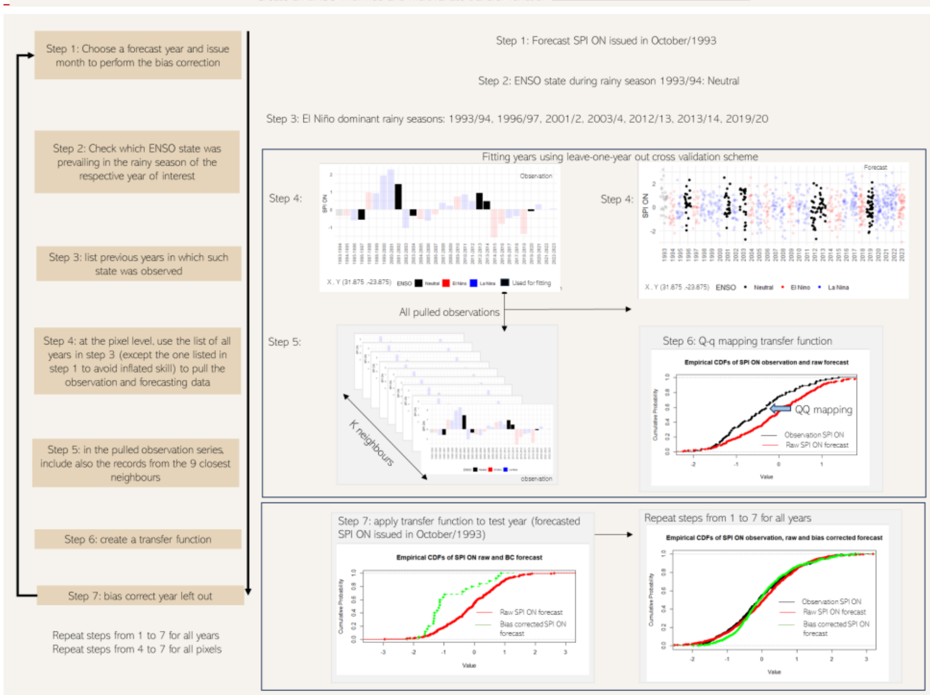


Figure ~~4~~3: Bias correction methodology in seven steps next to ~~and~~an illustrative example.

~~It is important to highlight two features of the bias correction methodology: (i) the bias correction targets the SPI indators directly instead of the daily or (multi-)monthly rainfall totals and (ii) in practice, the bias corrected forecast only replaces the raw SPIs forecast when actual skill is gained when forecasting severe drought. The gain in skill is assessed by calculating and comparing the area under the Receiver operating characteristic curve (AUROC) score (further explained in section 2.2.2) of the raw and bias corrected forecasts. Therefore, the SPI bias corrected series is only used if demonstrated gain in skill for predicting severe droughts at the pilot districts and per specific cases (for a particular forecast lead time and SPI 2 and SPI 3 aggregation).~~

2.2.2 Part 2.1: Forecast application and decision-making

Skill verification and assessment of raw and bias corrected data

As described in the previous section, we obtain drought probabilities from both the raw and bias-corrected forecasts. For each specific district, lead time, and SPI indicator, we use the forecast with the higher skill in predicting severe drought to develop triggers for the AA. The forecast with lower skill is discarded from the AA system. Skill is assessed by extracting and comparing the AUROC scores of the forecasts.

The AUROC score (e.g., Fawcett, 2006) is a widely applied indicator that measures the ability of a probabilistic forecast to discriminate between a binary outcome (e.g., severe drought or no drought). The AUROC score calculation requires setting a range of trigger values to convert a probability forecast into categorical, and therefore is related to decision-making in response to whether the forecast should release an alert. For the releasing of a “drought alert”, several triggers are tested, and a graph (known as a ROC curve) is produced to summarize the hit rate and false alarm rate that can be expected from different probability trigger values. The area under the ROC provides a summary statistic for the performance of probability forecasts, ranging from 0 to 1 (worst to best). Forecasts with little or no skill have a ROC score of approximately 0.5. Forecast is perfectly incorrect when the ROC is zero. In summary, for a specific district, lead time and SPI indicator, we choose which source of forecast to use for the Ready, Set & Go! triggers (raw or bias corrected) based on the forecast skill assessment informed by the AUROC score at the district level.

~~**Forecast skill verification and assessment**~~

~~Subsequent to the bias correction of the several SPI 2 and SPI 3 ensemble forecast series, we apply the severe drought threshold to extract drought probabilities. We do this by counting the number of ensemble members with a forecast of SPI value ≤ -1 and divide it by the total number of ensembles. We perform this step from both sources of SPIs ensemble forecasts (bias corrected and raw forecasts). We use these two different outcomes of drought probability to inform the AA system depending on which approach leads to the higher skill at the district level, as measured by the AUROC score.~~

~~The AUROC score (e.g., Fawcett, 2006) is a widely applied indicator that measures the ability of a probabilistic forecast to discriminate between a binary outcome (e.g., severe drought or no drought). The AUROC score calculation requires setting a range of trigger values to convert a probability forecast into categorical, and therefore is related to decision-making in response to whether the forecast should release an alert. For the releasing of a “drought alert”, several triggers are tested, and a graph (known as a ROC curve) is produced to summarize the hit rate and false alarm rate that can be expected from different probability trigger values. The area under the ROC provides a summary statistic for the performance of probability forecasts, ranging from 0 to 1 (worst to best). Forecasts with little or no skill have a ROC score of approximately 0.5. For a specific district, lead time and SPI indicator, we choose which source of forecast to use for the Ready, Set & Go! triggers (raw or bias corrected) based on the forecast skill assessment informed by the AUROC score at the district level.~~

Testing several triggers for the for the Ready, Set & Go! system

~~**Testing triggers for the Ready, Set & Go! drought alert**~~Triggers for anticipatory action indicate the forecasted severity of drought that would prompt a response. If the forecast exceeds the trigger, funds are automatically allocated, and anticipatory actions are initiated. A trigger is essentially a value that converts a probability forecast into a decision on whether to take action, effectively determining whether a drought alert should be issued. Defining a trigger involves understanding when forecasting information can be trusted to successfully mobilize anticipatory actions, despite inherent uncertainties. Therefore, triggers are based on the skill levels of the forecasts, requiring an investigation of past forecast accuracy and an acknowledgment of forecast uncertainty.

Forecasts at any lead time can be tested to derive triggers for anticipatory action. It is common practice for organizations to define two types of triggers for anticipatory action: (i) a preparedness trigger with a longer lead time and (ii) a confirmatory trigger for the activation of activities with a shorter lead time before the drought onset. These triggers are defined based on the skill levels of the forecasts for each lead time. However, testing lead times independently may result in an unrealistic performance of the anticipatory action program, as the system relies on both triggers being exceeded, even though they are set based on their individual performance. Additionally, organizations may assign preparedness and activation activities based on a single trigger from a specific lead time. This approach can vary depending on the organization's specific capacity to respond to the forecasted information.

The Ready, Set, & Go! system employs a double confirmatory approach for drought alerts. This means that the trigger value, tailored for each forecast month, district, and SPI indicator, must be exceeded for two consecutive months to prompt action. The performance of these triggers for anticipatory action is evaluated in combination rather than individually. For example, if the trigger based on the August forecast for Chibuto district, which predicts potential severe droughts in October-November, is exceeded, the "ready" phase is activated. If the trigger based on the September forecast for the same district is also exceeded, the "set" phase is activated, and activities are immediately mobilized on the ground, initiating the "Go!" phase. Testing triggers in combination with a double confirmation process aims to create a more accurate trigger system and provide a longer window for readiness and preparedness activities before AA implementation. This approach is validated using a sensitivity analysis explained in section 2.2.4.

For instance, readiness activities might involve preparing internal documents, which can then lead to initiating a procurement process if an AA advisory is issued. Practically, for each forecast month that can produce a "ready" and "set" trigger, we jointly test several candidate pairs of triggers. This testing is conducted in steps of 1% ranging from 0% to 100%, resulting in 10,201 combinations of candidate triggers. This is done for each district, pair of forecast months, and SPI 2/SPI 3 indicator. For a complete overview of the triggers for SPI ON for a given district, we test all candidate pairs of triggers for the following forecast month combinations: May (ready) and June (set), June (ready) and July (set), July (ready) and August (set), August (ready) and September (set), and September (ready) and October (set). For each pair of triggers, we calculate key performance metrics (e.g., hit rate and false alarm ratio) to evaluate how the drought alerts would have performed in the past. The relevance of these metrics was identified during a workshop held in 2022 with governmental partners.

~~In a nutshell, the Ready, Set & Go! system uses a double confirmatory approach for the drought alert. In other words, the trigger value (tailored for each month of the forecast, district, and SPI indicator) should be exceeded for two consecutive months prior to issuing an advisory for Aa. For instance, if the trigger based in the forecast of August is exceeded for the district of Chibuto, which alerts for potential severe droughts in October-November, the "ready" phase is activated. Under the circumstances that the trigger established (for Chibuto district for potential droughts in October-November) based on forecast issued in September is exceeded (the consecutive month), the "set" phase is activated, and an advisory for AA is issued. If AA is mobilized on the ground, the Go! phase starts. It is important to highlight that the Go! phase relies on programmatic decisions to be initialized, such as funding request, timely beneficiaries identification among others rather than on additional forecasts. This double confirmation seeks to create a more robust trigger system and a longer window of opportunity for readiness and preparedness activities that proceeds the implementation of AA on the ground. This assumption is tested using sensitivity analysis explained in section 2.2.4. Example of readiness activity may involve the preparation of internal documents which can be followed by the signing off of a procurement process if an advisory for AA is released.~~

~~In practical terms, for each forecast month that can produce a "ready" trigger and "set" trigger we jointly test several candidates' pairs of triggers. This testing is done in steps of 1% ranging from 0% to 100%, which results on 10201 combinations of candidates' triggers. This testing is done for each district, pair of forecast months and SPI 2/SPI 3 indicator. For instance, for a complete overview of the triggers for the SPI ON for a given district, we test all candidate' pairs of triggers for the forecast of May (ready trigger) and June (set trigger), June (ready trigger) and July (set trigger), July (ready trigger) and August (set trigger), August (ready trigger) and September (set trigger), and September (ready trigger) and October (set trigger). For each pair of triggers, we calculate key performance metrics (e.g., hit rate and false alarm ratio) of how the drought alerts would have performed on the past. The relevance of the extracted metrics has been identified during workshop carried out in 2022 with governmental partners.~~

Apply pre-mapped quality criteria for the triggers' choice

~~Pre-mapped quality criteria for the choice of triggers~~

The definition of a trigger value for drought AA is intrinsically linked to the skill of the forecast and the identification of a certain degree of risk tolerance levels by users of the forecast (Lopez et al., 2018). In practice, when a low probability trigger value is chosen, one can expect to forecast droughts frequently, whereas if a very high value is chosen, the opposite is expected to happen. The optimum trigger value should reflect appropriateness through the lenses of the decision-maker and the relative importance given to drought false alarms versus missed drought events.

Users who are averse to missing a drought, will choose a lower trigger value and deal with an increase in false alarms. For instance, a low trigger value can be a suitable option for actors that seek to assist very fragile populations and/or when the portfolio of AA is considered “non-regret” (Chaves-Gonzalez et al., 2022). Anticipatory actions are classified as “non-regret” when they are worth investing in even if a crisis does not materialize and would not be regretted with hindsight. Following this approach, we have created a menu of “emergency triggers”, to be used when pilot districts are experiencing high levels of vulnerability. On the other hand, users who are averse to false alarms will choose a higher trigger and manage occasional missed events. For instance, a high trigger value can be a suitable option for actors that have limited funds and/or when the portfolio of AA contains actions that affect livelihoods, such as evacuations, which are considered highly regrettable if a false alarm occurs. This approach can be of high relevance for scaling up AA to all districts in Mozambique as the largest geographical coverage is desired and funding distribution/sharing across a wide area is expected. Following this approach, we have created a menu of "general triggers”, to be used when pilot areas are experiencing normal to low levels of vulnerability. As displayed in Table 1, the expected performance of both menus is different, especially concerning the tolerance to false alarms and the probability of drought detection. Operationally, the assessment of vulnerability information is done prior to the start of AA season in Mozambique (more explanation in section 2.2.3).

Table 1: List of quality criteria for assigning forecast-based triggers for severe drought events. It is important to highlight that criterion 5 plays a role in the calculation of criteria 2, 3 and 4.

Number	Criteria for determining triggers	General menu	Emergency Menu
1	The selected trigger must have predicted at least (x%) of the past droughts	55	70
2	The chance of successfully implementing AA following a ready & set alert must be greater than (x%)	65	55
3	The chance of unsuccessfully implementing AA following a ready & set alert must be less than (x%)	35	45
4	Return period (years) for the implementation of AA against droughts	7	6
5	Actions will only be counted as “in vain” if the ready & set alert for severe drought is followed by an SPI of:	SPI > -0.68	
6	Minimum number of full months for the Go! Phase (implementation)	1	

Formatted: Font: +Headings (Calibri)

Formatted Table

Formatted: Font: +Headings (Calibri)

Formatted: Font: +Headings (Calibri)

Formatted: Font: +Headings (Calibri)

Formatted: Font: +Headings (Calibri)

Formatted: Font: +Headings (Calibri)

Formatted: Font: +Headings (Calibri)

~~Defining~~ Define triggers for anticipatory action

After testing all combinations of trigger pairs for the "ready" and "set" phases and recording the statistics listed in Table 1, we began a selection process based on the quality criteria outlined in the same table. The suitable pairs were ranked according to their hit rate and false alarm ratio, considering both district-specific performance and the stage of the rainy season: (i) start to mid-season (referred to as Window 1) and (ii) mid- to end of season (referred to as Window 2). Only the best-performing trigger pairs were selected for further analysis, which is presented in the results section 3.4.

It is important to clarify that anticipatory action (AA) targets these two windows of the rainy season because the activities implemented before the onset of drought within these periods serve different purposes. The forecast of drought risks within these windows informs the refinement of the AA portfolio, as rainfall deficits during the start to mid-season and mid- to end-season are expected to impact crops differently. For example, AA implemented before potential droughts in Window 1 aims to support planting and sowing activities, such as distributing drought-tolerant seeds, while AA implemented in Window 2 focuses on supporting livelihoods, such as providing cash transfers.

Furthermore, due to the variation in climatology across the country, the periods covered by Windows 1 and 2 differ by zone, shifting by approximately one month from south to north. Table 2 provides an overview of the timing of these windows, the indicators used to assess drought risks within them, and the provinces associated with each zone. The division of the rainy season into these windows was defined by the Technical Working Group (TWG) for drought early warning systems (EWS) and AA, which includes several governmental and non-governmental institutions (WFP, 2023). Further details can be found in the discussion section.

~~After testing all combinations of triggers' pair for the ready and set phases and recording for each of them the statistics listed in Table 1, we start a selection process by applying the quality criteria mentioned in Table 1. Then, the suitable pairs are ranked according to the hit rate and false alarm ratio per district and window of AA implementation. Only the best performing pair of triggers are selected for further analysis displayed in the results section below. It is important to clarify that there are two windows of AA implementation in Mozambique: (1) Window 1 covers the period from start to mid of the rainy season, and (2) Window 2 covers the period of mid to end of the rainy season.The forecast of drought risks within the above-mentioned windows supports the further refinement of the portfolio of anticipatory action as rainfall deficits at the start to mid and mid to end of the season are expected to impact crops in different ways. As climatology varies within the country, windows 1 and 2 differ per zone. The forecast of drought risks within the above-mentioned windows supports the further refinement of the portfolio of anticipatory action as rainfall deficits at the start to mid and mid to end of the season are expected to impact crops in different ways. Table 2 provides an overview of the timing of the windows, the indicators used to inform drought risks within them and the provinces belonging to each zone. The division of the rainy season within windows have been defined by the Technical Working Group (TWG, read discussion~~

~~section for more details) for drought EWS and AA, which is composed of several governmental and non-governmental institutions (WFP, 2023).~~

Table 2: Description of anticipatory action windows per zone and province ~~and~~ with an illustration of SPI indicators informing drought events

Zone	Provinces	Months within window 1	SPI 2 and SPI 3 informing window 1	Months within window 2	SPI 2 and SPI 3 informing window 2
North	Nampula, Cabo Delgado and Niassa	December to March	SPI DJ, SPI DJF, SPI JF, SPI JFM, SPI FM	March to June	SPI FMA, SPI MA, SPI MAM, SPI AM, SPI AMJ, SPI MJ
Central	Manica, Sofala, Tete and Zambezia	November to February	SPI ND, SPI NDJ, SPI DJ, SPI DJF, SPI JF	February to May	SPI JFM, SPI FM, SPI FMA, SPI MA, SPI MAM, SPI AM
South	Gaza, Inhambane, Maputo City and Maputo	October to January	SPI ON, SPI OND, SPI ND, SPI NDJ, SPI DJ	January to April	SPI DJF, SPI JF, SPI JFM, SPI FM, SPI FMA, SPI MA

2.2.3 Operational

Once the repository of triggers for AA has been finalized, several operational activities follow. Although these activities do not impact the overall system performance (as presented in the results section), they provide valuable insight into the operationalization of the methodology showcased in this study. The first key activity following the initiation of forecast and trigger monitoring for AA is a vulnerability analysis. This analysis is conducted annually, typically around April and May as the rainy season concludes. Its purpose is to assess the levels of vulnerability in the AA pilot districts by examining recent climate shocks and projected food security outcomes. The results of this analysis inform decisions about which set of triggers—general or emergency—each pilot district should employ for the upcoming AA season. For example, if a district experienced drought during the most recent rainy season, with anticipated negative impacts on food security, the emergency triggers are selected for the next AA season due to the heightened vulnerability in that area. Once this decision is made, forecasts from May to February of the following year are processed, and the AA triggers are monitored on a monthly basis. The monitoring of the Ready, Set, & Go! system triggers is conducted by INAM and WFP, with updates communicated to the Technical Working Group (TWG) for drought early warning systems (EWS) and AA through a dashboard and regular bulletins.

~~Once the repository of triggers for AA has been finalized, there are a number of operational activities that follow. Even though these operational angles will not affect the overall performance of the system (which we present in the results section), it may provide a view to the reader of the operationalization of the methodology showcased in this study. The first key activity that proceeds the starting of the monitoring of forecasts and triggers for AA is a vulnerability analysis, which is performed yearly around the months of April and May as the rainy season is coming to an end. Such vulnerability analysis seeks to understand~~

Formatted: Font: +Headings (Calibri), English (United States)

Formatted Table

Formatted: Font: +Headings (Calibri)

Formatted: Font: +Headings (Calibri)

Formatted: Font: +Headings (Calibri), English (United States)

Formatted: Font: +Headings (Calibri), English (United States)

Formatted: Font: +Headings (Calibri), English (United States)

Formatted: Font: +Headings (Calibri), English (United States)

~~the levels of vulnerability in the AA pilot districts by looking at recent climate shocks and projected food security outcomes. This analysis informs the decision of which menu of trigger (general or emergency) each pilot district should use for the coming AA season. For instance, if a district has experienced a drought in the most recent rainy season, with projected negative consequences to food security, the menu of emergency triggers is used in the upcoming AA season given the increased level of vulnerability being experienced in that location. Once this decision is made, the forecasts of May to February (next year) are processed and triggers for AA are monitored. The monitoring of triggers of the Ready, Set & Go! System is done by INAM and WFP and communicated through a dashboard and bulletins to the TWG for drought EWS and AA.~~

2.2.4 Sensitivity analysis including four scenarios

We ~~test the strength~~evaluate the robustness of our methods through a ~~by performing a~~ sensitivity analysis, considering four distinct scenarios. For each scenario, we extract four key metrics ~~are extracted~~:

1. **Hit Rate:** percentage of past severe droughts accurately captured by the AA trigger(s).
2. **Tolerant False Alarm Ratio:** This metric accounts for false alarms when the AA trigger is exceeded, but the drought threshold is narrowly missed.~~false alarms can occur when the trigger for AA is exceeded but the exact threshold of the drought is not met~~. For ~~instance~~example, a false alarm occurs if a severe drought trigger (SPI ≤ -1) is followed by an SPI value just below the threshold (e.g., -0.99). ~~when a trigger for a severe drought is exceeded (SPI <= -1), a false alarm would have occurred if a drought alert is followed by an SPI equal to e.g. -0.99~~, ~~which is very close to the established threshold~~. ~~For a~~To better contextualiz~~eation of~~ false alarms, we calculate "tolerant" false alarm ratio , which considers the number of severe drought alarms followed by an SPI greater than -0.68 (see Table 1). ~~a metric of false alarm with tolerance, which informs the amount of severe drought alarm that were followed by a SPI > -0.68 (see Table 1)~~. introduces extra tolerance when analyzing forecasting errors, as severe drought alerts followed by SPI values between -0.68 and -0.99 are not counted as non-drought situations. This approach is based on the practical assumption that AA interventions will still benefit the population, even if implemented during a slightly less severe dryness.~~This metric provides extra tolerance when analyzing forecasting error in comparison to a classical false alarm ratio as severe droughts alerts followed by SPIs ranging from -0.68 to -0.99 are not counted as a non-drought situation. This follows a practical assumption that drought AA will be beneficial to the population even if implemented at a milder level of dryness.~~
3. **Lead time of implementation**: the time difference between the starting month of the SPI indicator and the month in which the forecast was issued. For instance, ~~the~~ a forecast issued in May is considered to have a lead time of 4 months when providing outlooks of SPI ON.
4. **AA percentage coverage:** percentage of Mozambican districts ~~with~~ where an~~a found~~ AA trigger was identified, meeting the criteria outlined in Table 1.~~, which satisfies criteria highlighted in Table 1.~~

It is important to clarify that these metrics were derived from the skill assessment of the forecasts from 1993 to 2021. Specifically, the number of hits and false alarms during this period is used to calculate a key

Formatted: Not Highlight

metric from the quality criteria list: the "Return Period (Years) for the Implementation of AA Against Droughts." This metric helps determine whether the empirical frequency of AA interventions aligns with the frequency of the threshold for severe droughts. Furthermore, the scenarios for the sensitivity analysis are defined as follows:

1. Scenario 1: An AA advisory based solely on a single alert, using only one lead time from the raw SPI forecasts.
2. Scenario 2: An AA advisory based solely on a single alert, using either raw or bias-corrected SPI forecasts, depending on which has the highest skill.
3. Scenario 3: An AA advisory requiring double confirmation but using only raw SPI forecasts.
4. Scenario 4: An AA advisory based on the Ready, Set, & Go! system, requiring double confirmation and using a combination of bias-corrected and raw SPI forecasts.

~~1.~~

~~The scenarios for the sensitivity analysis are defined as following: (1) an advisory for AA solely based in a single alert and therefore using only one of the lead times of the raw forecasts of the SPIs, (2) an advisory for AA solely based in a single alert and therefore using only one of the lead times of the raw or bias corrected forecasts of the SPIs (depending which one has highest skill), (3) an advisory for AA based on Ready, Set & Go! double confirmation only using the raw SPIs forecasts, and (4) an advisory for AA based on Ready, Set & Go! double confirmation using a mix of bias corrected and raw SPIs forecasts.~~

3. ~~-~~RESULTS

3.1 Zonal based overview of the years with ~~S~~severe drought ~~years according to adopted threshold~~conditions within the rainy season

In Figure 4, we illustrate the frequency of severe drought occurrences during the rainy season from 1981 to the present. We began by extracting SPI 2 and SPI 3 indicators for each district, focusing on the rainy windows relevant to each district (see Table 2 for SPI indicators and their associated windows). We then counted how often the severe drought threshold was met or exceeded. The top 5 years with the highest number of 2- and 3-month periods experiencing severe drought conditions are highlighted. Bars in the figure are colored to indicate the ENSO phase during the respective rainy seasons in Mozambique (see Supplementary Material S1 for classification). To simplify the data presentation, districts are grouped by zones (refer to Table 2 for zone-to-province list). A similar overview of severe drought years at the province and district levels is provided in Supplementary Material S2.

Overall, severe drought conditions can occur during any of the three ENSO phases across all zones. This underscores the need for an AA system that is effective regardless of the ENSO phase. However, we found that severe droughts are significantly more frequent during El Niño phases (mean frequency = 66) compared to Neutral (mean frequency = 41) and La Niña phases (mean frequency = 31), as confirmed by a t-test ($p < .01$). Previous studies also support this finding (Araneda-Cabrera et al., 2021; Lyon & Mason, 2007). Additionally, the top 5 drought years for different windows vary considerably. In the North zone, only the rainy season of 2004-05 appears in the top 5 for both windows. In the Central zone, only the

1991-92 rainy season ranks in the top 5 for both windows. In the South zone, the rainy seasons of 1991-92 and 2015-16 are among the top 5 for both windows. This variation highlights the importance of developing an early warning system that accounts for different intra-seasonal rainfall patterns and adjusts operations according to the stages of the rainy cycle.

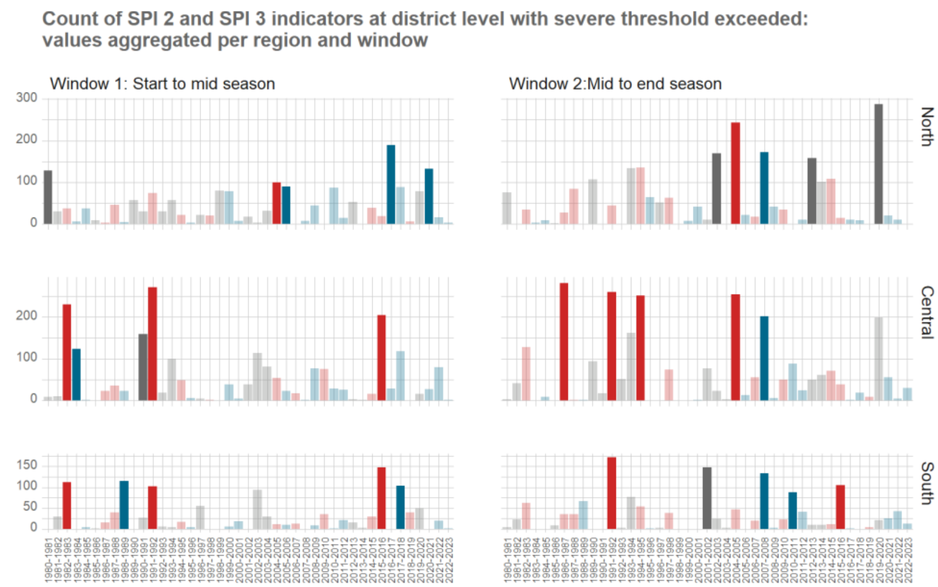


Figure 54: The frequency with which the SPI 2 and SPI 3 indicators exceeded or equaled the severe drought threshold since 1981 is shown for each zone and window. The counts are first calculated at the district level and then aggregated by zone for window 1 (left) and window 2 (right). For details on which SPI 2 and SPI 3 indicators correspond to each window, refer to Table 2. The zones are defined as follows: i) Central zone includes districts from the provinces of Manica, Sofala, Tete, and Zambezia, ii) North zone includes

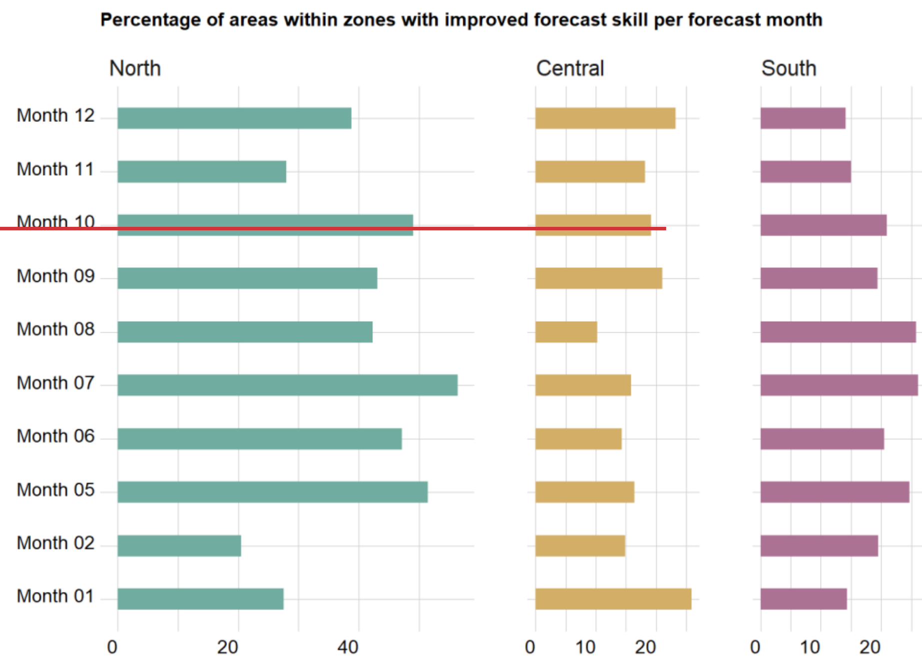
districts from Nampula, Cabo Delgado, and Niassa, and iii) South zone includes districts from Gaza, Inhambane, Maputo City, and Maputo Province. Bars are color-coded according to the dominant ENSO phase during the rainy season in Mozambique (red = El Niño, blue = La Niña, and grey = Neutral). The top 5 years for each window and zone are highlighted.~~Frequency in which the extracted SPI 2 and SPI 3 indicators were per zone and window exceeded or equaled the severe threshold since 1981. First, the counting is done per district and subsequently aggregated at the zonal level within window 1 (left) and window 2 (right). For an overview of the SPI 2 and SPI 3 belonging to windows 1 or 2, see Table 2. Zones are compiled as follow: i) Central districts by the provinces of Manica, Sofala, Tete and Zambezia, ii) North districts by the provinces of Nampula, Cabo Delgado and Niassa, and iii) South districts by the provinces of Gaza, Inhambane, Maputo City and Maputo. Bars are colored according to the ENSO dominant phase during the rainy cycle in Mozambique (red = El Niño, blue = La Niña and grey=Neutral). Top 5 years are highlighted per window and zone.~~

3.2 Zonal based overview of bias correction

Figure 6 presents the percentage of areas per zone, SPI indicator, and forecast month that showed an improved AUROC score after applying bias correction. The primary focus of our evaluation is the AUROC score, as it offers a practical measure of whether bias correction enhances the accuracy of severe drought forecasts, which is crucial for users. The goal of this approach is to identify opportunities for improving forecast accuracy, thereby reducing the risk of misallocated anticipatory action resources due to inaccurate predictions. For a spatial representation, similar results are displayed in a series of maps in Supplementary Material S3.

Overall, the North zone showed the highest mean percentage of improved forecast areas (38%), followed by the Central and South zones (both at 19%). In the North zone, the forecast month with the highest mean improvement was July (56%), while February had the lowest (20%). For the Central zone, January showed the greatest improvement (26%), while August showed the least (10%). In the South zone, July and August had the highest mean improvement (26%), whereas December and January had the lowest (14%). Across all forecast months, the SPI indicators that demonstrated the greatest skill improvement were SPI ON, SPI DJ, and SPI NDJ for the North zone, SPI JFM for the Central zone, and SPI ON for the South zone. Most of these indicators pertain to the first window of the rainy season in the country.

Additionally, for all districts and all SPI 2 and SPI 3 indicators across all lead times, 24% demonstrated improved skill (measured by AUROC score) after bias correction compared to the raw forecast. A more detailed overview of the AUROC scores can be found in section 3.3.


Percentage of areas within zones with improved forecast skill per forecast month
North
Central
South
Month 12
Month 11
Month 10
Month 09
Month 08
Month 07
Month 06
Month 05
Month 02
Month 01
0
20
40
0
10
20
0
10
20

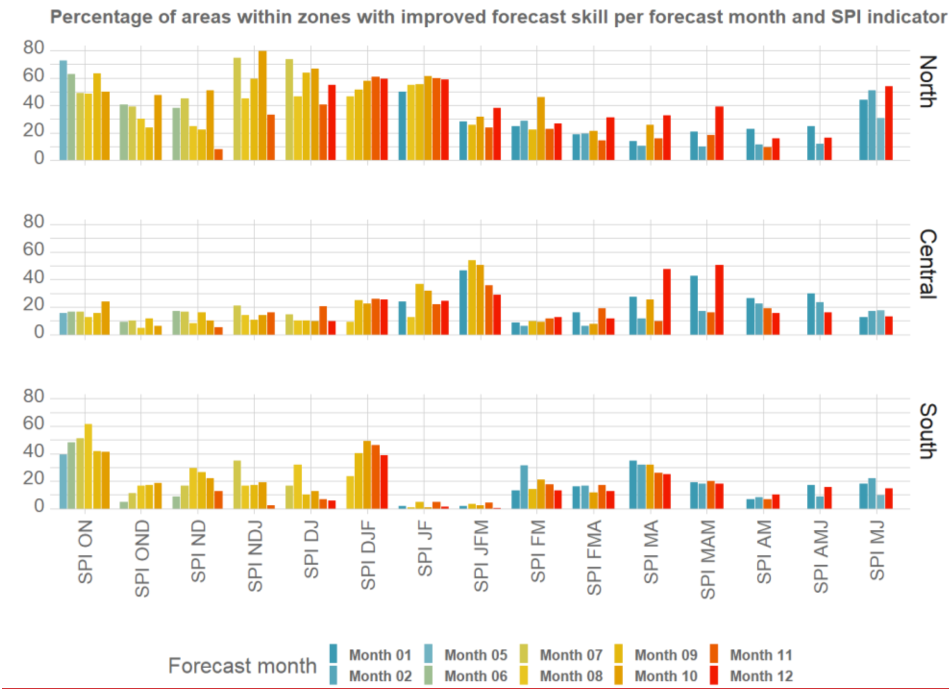


Figure 6~~5~~: Percentage of zonal areas in which skill has gained using bias correction for different lead times of the forecast used to extract the SPI 2 and SPI 3 indicators.

3.3 Overview of the maximum AUROC score

Figure 7 shows the mean AUROC index per district for predicting severe droughts, combining outcomes from both raw and bias-corrected forecasts across all extracted SPI 2 and SPI 3 periods and lead times. On average, the SPI DJ indicator had the highest AUROC score (0.79), while SPI AM had the lowest (0.63). Severe drought events are generally more predictable during the early to mid-rainy season (average AUROC score of 0.76 for window 1; see Table 2 for indicator details) compared to the mid to late rainy season (average AUROC score of 0.69 for window 2). In particular, the predictability of severe droughts in districts located in the South zone is notably high during window 1 (average AUROC = 0.77), primarily driven by high forecast accuracy in December and January (SPI 2 DJ). In the Central and North zones, severe droughts are most predictable during December to February (average AUROC of 0.78) and November to January (average AUROC of 0.80), respectively.

In Supplementary Material S4, we highlight the lead times that yield the highest forecast skill for severe drought prediction. In the South zone, about 44% of districts achieve the highest AUROC score using the December forecast for SPI DJ. In the Central zone, 55% of districts achieve their best performance using the August forecast for SPI DJF. In the North zone, around 66% of districts see their highest AUROC scores based on the November forecast for SPI NDJ.

However, it is crucial to note that the implementation of AA requires at least one full month for the "Go!" phase (see Table 1 for criteria). As a result, forecasts released in November, which predict severe droughts between November and January, are not used in operational mode. This means that the "Ready, Set, Go!" trigger system often cannot rely on the most accurate lead times, as they do not allow enough time for action mobilization.

~~In Figure 6, we display the mean AUROC index per district for predicting severe droughts across all extracted SPI 2 and SPI 3 periods and lead times combining outcomes of both raw and bias corrected forecasts. On average, the single SPI indicator with highest and lowest AUROC score is SPI DJ (0.79) and SPI AM (0.63). Across all zones, severe drought events are more predictable at the start to mid-period of the rainy season (average AUROC score 0.76 for window 1, see Table 2 for indicators) than in comparison to mid to end-season (average AUROC score 0.69 for window 2). The predictability of severe droughts within window 1 for districts located in the South zone is remarkably good (average AUROC = 0.77). This is mostly driven by the high predictability of severe droughts in December and January (SPI 2 DJ). For the Central and North zones, severe droughts are most predictable within December and February (average AUROC of 0.78) and November to January (average AUROC of 0.80, respectively).~~

~~In Supplementary Material S4, we display the lead time of the forecast that produces the highest skill to predict severe droughts. For the south zone and SPI DJ, about 44% of the districts show the highest AUROC score based on the forecast of December. For the central zone and SPI DJF, 55% of the districts show the highest AUROC score based on the forecast of August. For the north zone and SPI NDJ, about 66% of the districts show the highest AUROC score based on the forecast of November. It is important to highlight that, the implementation of AA requires at least 1 full month for the Go! Phase (see criteria Table 1). Therefore, the forecast released in November for predicting severe droughts within the months of November and January is not used in operational mode. Thus, the Ready, Set & Go! trigger system is often not informed by the most skillful lead times of the forecast since these do not enable timeliness for the mobilization of actions.~~

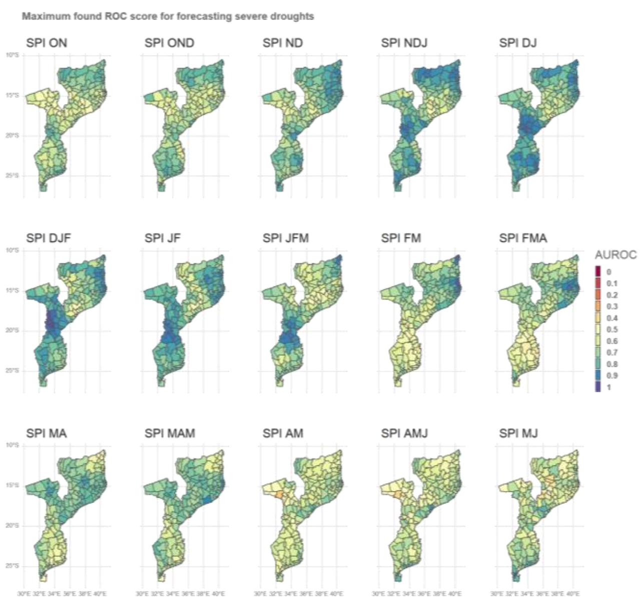


Figure 7~~6~~: Overview of the maximum AUROC score across lead times combining outcomes of both raw and bias corrected forecast.

After determining whether to use the raw or bias-corrected forecast for a specific lead time, SPI indicator, and district, we move to the most computationally intensive phase of the "Ready, Set, Go!" trigger system. This phase involves testing pairs of triggers for anticipatory action (AA), as described in the section "Testing Several Triggers for the Ready, Set, Go! System." The testing is conducted in 1% increments, ranging from 0% to 100%, resulting in 10,201 combinations of candidate triggers per district, forecast month pair, and SPI 2/SPI 3 indicator. After testing all combinations and recording their statistical performance, only the best-performing trigger pair for each window is selected for presentation in the next section. The statistical performance of triggers, for the different scenarios, is based on the overall performance using hindcasts from 1993 and 2021 against observed SPI 2 and SPI 3 values within this period.

All selected trigger pairs must meet the quality criteria outlined in Table 1. To evaluate the value of using mixed forecast information (raw and bias-corrected) with a double-confirmation approach, we expanded the analysis to include additional testing. This extended analysis examines the performance of single versus double triggers and the impact of including or excluding bias correction in the methodology.

3.4 ~~3.4~~ Sensitivity Analysis

Table 3 presents the average performance of the best triggers for AA during both window 1 and window 2, comparing different activation mechanisms. To recap:

- Scenario 1: Issues an AA advisory based on a single alert using only the raw SPI forecasts from a specific lead time. If the forecast for a specific month, district, and indicator exceeds the assigned probabilistic trigger, an AA advisory is issued and implemented.
- Scenario 2: Issues an AA advisory based on a single alert, using either raw or bias corrected SPI forecasts, depending on which has higher predictive skill.
- Scenario 3: Requires double confirmation of drought conditions but uses only raw SPI forecasts.
- Scenario 4: Represents the operational Ready, Set, & Go! system, which issues an AA advisory based on double confirmation, using a combination of both bias corrected and raw SPI forecasts.

Overall, scenarios using a double-confirmation approach perform better than those relying on a single drought alert for AA activation.

Specifically, in the simplest scenario (Scenario 1), 59% of districts in Mozambique would be covered by a General AA trigger, while 42% would be covered by an Emergency trigger (see the section “Apply pre-mapped quality criteria for the triggers’ choice” for definitions of these trigger types). This indicates that raw forecasts alone provide reasonably accurate severe drought predictions for many districts. Incorporating bias correction (Scenario 2) only marginally increases coverage to 61% (General trigger) and 43% (Emergency trigger).

However, applying a double-confirmation approach significantly increases the proportion of districts covered by an AA trigger. In Scenario 3, coverage increases to 73% (General trigger) and 59% (Emergency trigger). Scenario 4, which is the operational system in Mozambique, achieves the highest national AA coverage across all approaches. Additionally, the Ready, Set, & Go! system improves both the hit rate and reduces the false alarm ratio compared to single-alert systems (Scenarios 1 & 2).

Furthermore, the Ready, Set, & Go! approach extends the lead time for preparedness activities. While single-alert scenarios provide, on average, 2 months of lead time for AA implementation once the trigger is exceeded, the Ready, Set, & Go! system increases this lead time to nearly 3 months.

~~In Table 3, we display the average performance of the best-found trigger(s) for AA within window 1 and window 2 using different approaches as mechanism of activation.~~ ~~Overall, the scenarios adopting a Ready, Set & Go! approach (scenarios 3 & 4) achieve better performance than the ones using one single drought alert for AA.~~~~In scenario 1, AA is triggered based solely on the raw forecasts and in one alert. In other words, if the raw forecast released on a specific month exceeds the assigned probabilistic trigger (for a specific month, district, and indicator), an AA advisory would be issued, and AA theoretically implemented. In scenario 2, AA is triggered based on the raw and bias corrected forecast (depending on which output produces the highest skill) and using one alert only. In scenario 3, AA is triggered based on the raw forecast and using a double confirmatory approach for the drought alert (see methods section explaining the Ready, Set & Go! system). Finally, in scenario 4, AA is triggered based on the raw and bias corrected forecast (depending on which output produces the highest skill) and using a double confirmatory approach for the drought alert.~~ ~~The statistical performance of triggers, for the different~~

~~scenarios, is based on the overall performance using hindcasts from 1993 and 2021 against observed SPI 2 and SPI 3 values within this period.~~ ~~It is important to highlight that as variety of SPI 2 and SPI 3 indicator is extracted per window, often more than one indicator and trigger for AA can be found for each district. For displaying Table 3, we rank all candidate triggers according to the Hit rate, false alarm ratio and lead time and display the average performance of the top one indicator across all districts (those with a found trigger only).~~ ~~Overall, the scenarios adopting a Ready, Set & Go! approach (scenarios 3 & 4) achieve better performance than the ones using one single drought alert for AA.~~

~~In detail, using the simplest triggering approach (scenario 1), 59% and 42% of the districts in Mozambique would be covered by an AA General and Emergency trigger against severe droughts, respectively (see definition of these two types of triggers in section 2.2.3). This means that the raw forecast produces sufficiently good outlooks of severe drought, as per criteria defined in Table 1, for a large proportion of districts. The proportion of districts covered by an AA trigger shows only a marginal increase when incorporating the bias correction methodology (scenario 2). Bias correction increases AA coverage from 59% to 61% (General trigger) and 42% to 43% (Emergency trigger). However, we observe that when the Ready, Set & Go! approach is applied, the proportion of districts covered by an AA trigger increases considerably. This means that the approach of a double confirmatory drought alert creates prior to implementing AA leads to sufficiently good performance for more than 60% of the districts in Mozambique. Scenario 4, which is currently in operational use in Mozambique results in the highest national AA coverage across all tested approaches. Furthermore, the Ready, Set & Go! approach (scenarios 3 & 4) increases the hit rate and decreases the false alarm ratio of AA triggers in comparison to a single drought alert (scenarios 1 & 2). Finally, the lead time for preparedness AA activities is also longer when using the Ready, Set & Go! approach. While the scenarios with a single drought alert allows for, on average, 2 months for AA implementation once the trigger is exceeded, the Ready, Set & Go! system increases the AA lead time to nearly 3 months.~~

Table 3: Sensitivity analysis of different approaches for establishing an AA drought trigger system for the two menu of triggers. Statistics of the different scenarios are based on the average of the best performing SPI 2 or SPI 3 indicator for AA within windows 1 and 2.

		Scenario 1: single drought alert and ~~no bias correction applied to forecast data~~raw forecast only	**Scenario 2: single drought alert** ~~and bias correction applied to forecast data~~including bias corrected forecast	**Scenario 3:** ~~Ready, Set & Go!~~double confirmation **and** ~~no bias correction applied to forecast data~~raw forecast only	**Scenario 4: Ready, Set & Go! and** ~~bias correction applied to forecast data~~including bias corrected forecast
General triggers	Hit Rate	62%	62%	64%	64%
	False Alarm Ratio	21%	21%	17%	16%
	Lead Time for preparedness	2,10	2,00	2,90	2,90
	AA coverage	59%	61%	73%	76%
Emergency triggers	Hit Rate	72%	72%	73%	73%
	False Alarm Ratio	29%	30%	26%	26%

Formatted: Font: (Default) +Headings (Calibri), Bold, Font color: Auto,

Formatted Table

Formatted: Font: (Default) +Headings (Calibri),

Formatted: Font: (Default) +Headings (Calibri), Font color: Auto,

Formatted: Font: (Default) +Headings (Calibri), Font color: Auto,

Formatted: Font: (Default) +Headings (Calibri), Font color: Auto,

Lead Time for preparedness	2,10	2,10	3	2,90
AA coverage	42%	43%	59%	63%

3.5 Spatial Overview of Ready, Set & Go! System

Figure 8 provides a detailed spatial statistical overview of the performance of the Ready, Set, & Go! triggers, complementing the results for Scenario 4 presented in section 3.4. As noted earlier, severe droughts are predicted with greater skill in window 1 compared to window 2, allowing for AA triggers to be assigned to more districts in window 1. The percentage of districts with a valid AA trigger is as follows: i) 66% for the emergency trigger menu in window 1 and 59% in window 2, and ii) 87% for the general trigger menu in window 1 and 64% in window 2. Notably, every district with an emergency AA trigger also has a general AA trigger, indicating that for most districts, AA triggers can be adjusted annually based on current vulnerability levels. However, in some cases, the general trigger is the only applicable option.

In terms of trigger performance across windows, the Central zone showed the highest and lowest mean hit rates, with window 1 achieving 74% and window 2 achieving 61%. Across all menus and windows, the emergency menu in window 1 had the highest mean hit rate (77%), while the general menu in window 2 had the lowest (61%). This result is expected, as the emergency menu is designed for higher hit rates, particularly given the greater predictability of severe droughts in window 1.

In addition to the highest drought predictability, the South zone of Mozambique also exhibited the highest total AA coverage, with an average of 86% of districts having an AA trigger. The highest single window and trigger menu coverage was in the South zone under the general menu, with 97% of districts having a trigger. Spatial differences in trigger performance were also observed between neighboring provinces, such as Manica and Tete in window 1 under the general menu. These differences could be driven by varying forecast skill levels. For instance, the AUROC scores for the general trigger in window 1 are 0.82 for Manica and 0.68 for Tete. Factors contributing to these differences could include under- or over-estimation of rainfall events used to verify forecasts in Mozambique (as noted in a previous study by Toté et al., 2015), numerical effects from data rescaling, and the resolution of district-level assessments using CHIRPS and ECMWF forecasts.

~~In Figure 7, we provide the detailed spatial statistics overview of the performance of Ready, Set & Go! triggers in complement to results shown for scenario 4 in section 3.4. As previously mentioned, severe droughts are predicted with higher skill within window 1 than window 2. This enables triggers for AA to be assigned for a higher number of districts within window 1 (following minimum standards pre-defined in Table 1). As several SPI 2 and SPI 3 indicators are extracted per window, often more than one indicator and trigger for AA can be found for each district. For displaying Figure 7, we rank all candidate triggers according to their hit rate, false alarm ratio and lead time, and display the performance of the top one indicator for each district. The percentage of districts with a found AA trigger are: i) 66% and 59% for the~~

Formatted: Font: (Default) +Headings (Calibri), Font color: Auto,

Formatted: Font: (Default) +Headings (Calibri), Font color: Auto,

~~emergency trigger menu and window 1 and window 2, respectively ii) 87% and 64% for the general trigger menu and window 1 and window 2, respectively. Overall, all districts with a found AA trigger for the emergency menu has also an AA trigger for the general menu. Therefore, we show that for the majority of the Mozambican districts, AA triggers can be yearly modulated by an assessment of current vulnerability levels while in others, the general trigger is the only option applicable.~~

~~Regarding the performance of the triggers across the different windows (Figure 7), triggers for AA reach, on average, the highest and lowest hit rates both for the Central Zone window 1 (74%) and window 2 (61%), respectively. Across the different menus and windows, the highest and lowest hit rate are found for the emergency menu and window 1 (77%) and general menu for window 2 (61%), respectively. This is expected as triggers for AA under the emergency menu are chosen to have a higher hit rate than in comparison to the general ones, which is also leveraged by the higher predictability of severe droughts within window 1. Furthermore, on top of showing the mean highest drought predictability for severe droughts in window 1, the south zone of Mozambique also shows the highest total AA coverage (average of 86% of districts with a found AA trigger). The single window and trigger menu with highest AA coverage is found for the south zone and general menu (97%). Furthermore, when comparing the spatial differences in the performance of the triggers, we observe some dissimilarities between neighbor provinces (e.g., general trigger window 1: Manica and Tete). Whereas it is challenging to depict a single driver of such differences, a potential one may be emerging from the differences in skill of the forecast information used as trigger. For instance, the triggers used for informing AA in Manica and in Tete (window 1 and general menu), have a mean AUROC scores of 0.82 and 0.68, respectively. Furthermore, differences in skill may be due to a number of reasons including the under and/or over estimation of rainfall events used to verify the forecast in Mozambique (CHIRPS) as mentioned in previous study (Toté et al., 2015); a numerical effect due data rescaling and assessment at the district level (from both CHIRPS and ECMWF forecast) among others.~~

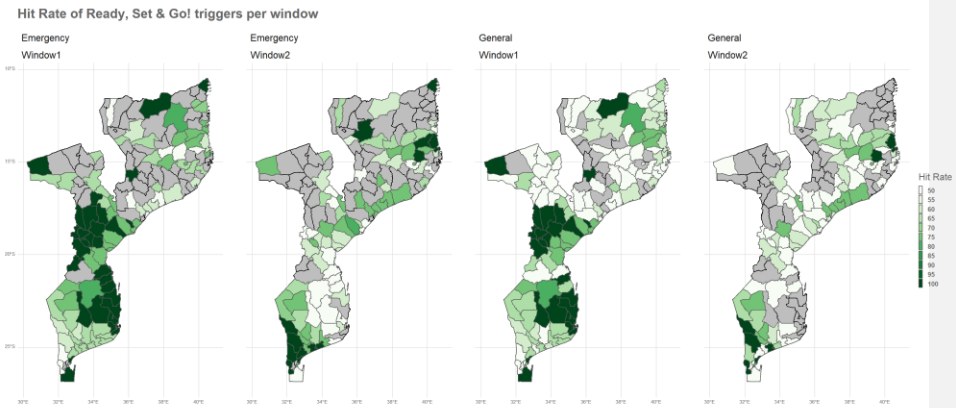


Figure 8~~7~~: Hit rate of the Ready, Set & Go! Trigger system for severe droughts for two trigger menu (emergency and general) and two windows of intervention (window 1 and window 2). No trigger for the Ready, Set & Go! for severe droughts were found for the districts in grey.

Regarding the average false alarm ratio of the triggers across different windows (Figure 9), the highest and lowest ratios are observed in the South zone for window 2 (20%) and the Central zone for window 1 (10%), respectively. Across various menus and windows, the emergency menu and window 2 exhibit the highest false alarm ratio (16%), while the general menu and window 1 have the lowest (10%). This pattern is expected, as the emergency menu is designed to tolerate a higher false alarm ratio to ensure a higher hit rate, making it less prone to missing a drought forecast.

Supplementary Material S5 details the specific SPI indicators used for AA triggers. For window 1, SPI DJ is the most commonly selected indicator across all zones. In window 2, different SPIs are chosen per zone: i) SPI FMA for the North zone, ii) SPI JFM for the Central zone, and iii) SPI DJF for the South zone.

Regarding lead times, the earliest “ready” alert for preparedness in window 1 can be issued for a few districts in the South zone based on the May forecast. However, for most districts in the South zone, the July forecast is used for preparedness, whereas in the North and Central zones, the September forecast is most commonly used for the “ready” alert. In window 2, most districts in the South zone use the August forecast for preparedness, while the North and Central zones typically use the October forecast.

It is important to note that regional rainfall climatology significantly influences the choice of intervention windows and indicators. As a result, districts in the South zone may receive readiness alerts earlier in the season compared to other areas. This factor is crucial for planning AA activities and allocating geographical funding.

~~Regarding the average false alarm ratio of the triggers across the different windows (Figure 7), triggers for AA reach the highest and lowest scores for the south zone window 2 (20%) and central zone window 1 (10%), respectively. Across the different menus and windows, the highest and lowest false alarm ratio are found for the emergency menu and window 2 (16%) and general menu for window 1 (10%), respectively. This outcome is expected as triggers for AA under the emergency menu are accept a higher hit rate and false alarm ratio than in comparison to the general ones and therefore more averse to missing to forecast a drought. In the Supplementary Material S5, we display which specific SPI indicator informs the AA triggers. Across all zones, SPI DJ is the indicator most chosen to inform AA within window 1, whereas in window 2 different SPIs are chosen per zone as following: i) SPI FMA for the north zone, ii) SPI JFM for the central zone and iii) SPI DJF for the south zone. In regard to lead time, the earliest "ready" alert for preparedness within window 1 can be issued for few districts in the south zone based on the forecast of May. However, for window 1, most districts in the south zone uses the forecast of July for preparedness, whereas in the north and central zones, the forecast of September is the most used for the "ready" alert. Furthermore, for window 2, most districts in the south zone use the forecast of August for preparedness, whereas in the north and central zones, the forecast of October is the most used for the "ready" alert. It is important to highlight that the climatology of rainfall is decisive for defining windows of intervention and therefore some indicators are of relevance or not to the three zones. Therefore, it is expected that districts in the south zone may show readiness alert earlier in the season than the remaining areas. This is an important factor when planning for AA activities and geographical funding distribution~~.

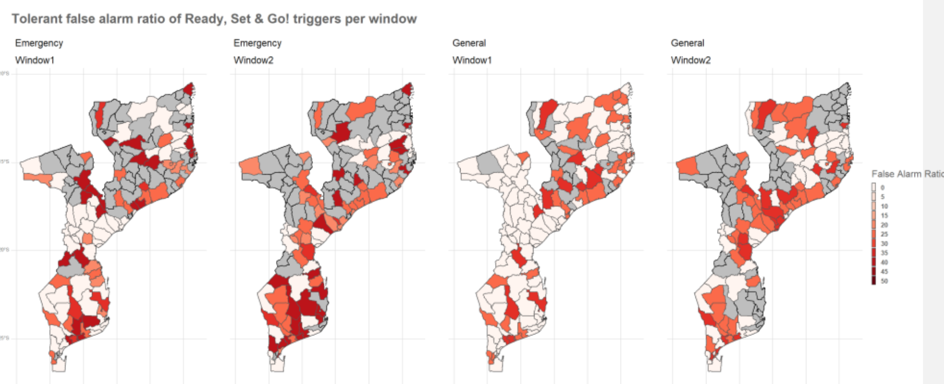


Figure 9~~8~~: False Alarm ratio of the Ready, Set & Go! Trigger system for severe droughts for two trigger menu (emergency and general) and two windows of intervention (window 1 and window 2). No trigger for the Ready, Set & Go! for severe droughts were found for the districts in grey.

4. DISCUSSION, LIMITATIONS AND NEXT STEPS

In this study, we present the ~~technical approach~~methodology ~~adopted~~ behind ~~by~~ the operational Ready, Set & Go! trigger system ~~which is~~ used by Mozambican governmental institutions and their ~~implementing~~ partners ~~for~~ to ~~supporting~~ guide AA activities against droughts. ~~We show that t~~The ~~Ready, Set & Go!~~system optimizes the use of seasonal forecast information by ~~finding~~ identifying triggers for AA through a ~~based on a~~ double confirmation process.~~,~~ This ~~which~~ approach combines longer and shorter lead time ~~with shorter lead time~~ forecasts ~~information for issuing~~to issue more reliable drought alerts. ~~We~~ Our findings indicate ~~observe~~ that by ~~using~~utilizing both ~~ensemble~~ bias corrected and raw ensemble rainfall forecasts, AA ~~activities~~ efforts could potentially be scaled up to cover the entire rainy season in, ~~against droughts could be scaled up, on average, to~~ 76% of ~~Mozambican~~ Mozambique's district.~~s~~. If focused solely on the first part of the rainy season, where drought predictability is higher, AA activities ~~National coverage against severe droughts~~ could expand to ~~be~~ ~~reached to~~ 87% of all districts. ~~if targeting only the first window of the rainy season (general triggers).~~ This ~~means~~ demonstrates that seasonal forecasts ~~are~~ can ~~able to~~ reliably inform AA months before the onset of severe droughts, meeting the quality criteria established by ~~as per multi-~~ multiple institutions. ~~al criteria, several months ahead of the onset of severe droughts.~~ Such scalability ~~This shows~~indicates strong ~~a~~ potential for ~~a~~ expanding ~~major national scale up of~~ current AA pilots nationwide, ~~contributing~~ supporting ~~to~~ the ambitious goals of the Maputo Declaration ~~in which~~where Southern Africa governments committed to ~~expand~~ extending early warning systems across the ~~in~~ ~~Southern Africa~~ region (SADC, 2022). ~~At the global level~~Globally, ~~our~~ the Ready, Set & Go! s~~S~~ystem also ~~partially contributes~~aligns with ~~to~~ the *Early Warning for All* initiative, which aims ~~that seeks~~ to ensure that ~~everyone~~ every individual worldwide ~~in the globe~~ is protected from climate events through ~~life-saving~~ early warning systems by ~~the end of~~ 2027 (WMO, 2022). This ~~may imply an~~initiative underscores the need for expanding the ~~increased~~ climate information portfolio ~~for~~ of the ~~N~~national m~~M~~eteorological and h~~H~~ydrological s~~S~~ervices ~~with a~~for direct application ~~downstream~~in disaster risk management. However, there are still limitations and opportunities for ~~further~~ improvements ~~of the system~~, which we discuss in the ~~paragraphs below~~following sections.

This study demonstrates that the Ready, Set & Go! Trigger system can effectively issue severe drought alerts using SPI 2 and SPI 3 indicators, which the Technical Working Group in Mozambique has deemed suitable for monitoring and anticipating drought risks in agricultural systems. However, these indicators and thresholds are not flawless in detecting drought damage, as the relationship between drought risk and impact is often location-specific, non-linear, and influenced by non-climatic factors such as vulnerability (Brida et al., 2013; Silva & Matyas, 2014). The ideal method for establishing AA thresholds that reliably detect drought-related losses would involve an historical analysis examining the connection between drought events and socio-economic impacts, such as crop yields, income losses, health outcomes, and food security. Past studies on index-based insurance for the agricultural sector have extensively explored the gap between rainfall measurements and actual agricultural losses, highlighting challenges in accurately capturing real world farmer impacts (Clarke & Dercon, 2009; Clement et al., 2018; Greatrex et al., 2015). Unfortunately, comprehensive, downscaled impact data is largely unavailable, particularly across African countries, limiting further refinement of thresholds and indicators within the system and hindering the ability to solidify links between drought conditions and past impacts. Future efforts should focus on refining these thresholds to strengthen the relationship between physical drought hazards and expected impacts. This could be achieved by utilizing spatially explicit socio-economic

Formatted: Not Highlight

Formatted: Not Highlight

Formatted: Not Highlight

datasets, such as the Integrated Food Security Phase Classification indicator from the Famine Early Warning Systems Network, along with data recovery exercises. This would allow users to better understand food security outcomes tied to drought events.

Additionally, the Ready, Set & Go! system issues drought alerts based on a multi-month SPI indicator, which can overlook the effects of short but impactful dry spells, poorly distributed rainfall, intense rainfall episodes, or delayed/early cessation of rains. Incorporating additional drought indicators could help better capture these risks, ideally through an exploratory analysis that links specific drought indicators to negative impacts and evaluates their predictability.

Two technical aspects related to the extraction of the SPI indicator also requires further improvement. First, more sensitive statistical tests could be used to identify candidate probability distributions for normalizing drought indices. Although this study applies the two-parameter gamma distribution, as recommended by Stagge et al. (2015), a more rigorous assessment of the assumed SPI distributions could be beneficial. Second, the handling of zero precipitation poses challenges, particularly in regions with very low seasonal rainfall. In this system, zero precipitation events are accounted for by assigning SPI values based on their historical occurrence. However, this approach can be problematic when many zero values are present, as SPI requires a mean value of 0 to reflect typical conditions, where half of the years is wetter, and half is drier. While the presence of zero precipitation was rare in this study, further refinement is needed to handle these cases more effectively. Using a method such as the center of probability mass, as suggested by Stagge et al. (2015), could offer a more robust approach to calculating SPI in extremely dry regions.

~~As it is shown in this study, the Ready, Set & Go! Trigger system can produce alerts of severe droughts through the lenses of the SPI 2 and SPI 3 indicators. These indicators and thresholds are considered by the TWG in Mozmabique as a suitable option for monitoring and anticipating severe risks to agricultural systems. However, such indicators and thresholds are not perfect at detecting drought damages, especially given that the relationship between drought risk and impact can often be location-specific, non-linear and modulated by non-climatic factors such as vulnerability (Brida et al., 2013; Silva & Matyas, 2014). Given that a historical and comprehensive drought losses or impact data is unavailable, especially at district level, no further tuning of thresholds and indicators could be done to enrich the system. Therefore, instead of using a single severity level, the operational Ready, Set & Go! system can release alerts for two other addition thresholds: mild and moderate droughts (see explanation in Guimarães Nobre et al., 2023). Future efforts could focus on refining such thresholds in order to build a stronger link between the physical hazard and expected impacts through the support of spatial explicit socio-economic datasets such as the Integrated Food Security Phase Classification indicator produced by the Famine Early Warning Systems Network. This way, users can be aware of the food security outcomes linked to drought events. Furthermore, the Ready, Set & Go! Could benefit from incorporating other drought indicators to better capture drought risks within the two windows of intervention. In practice, the Ready, Set & Go! System already releases alerts based on dry spells, but other metrics such as the onset of rains, rainfall cessation and Standardized Precipitation Evapotranspiration Index could also be explored.~~

T~~With t~~he Ready, Set & Go! Trigger system~~, we ultimately seek~~ aims to ~~bring~~ extend AA and reliable early warning information ~~for~~ to all districts in Mozambique. Although we ~~a~~have~~re~~ not yet fully ~~able to~~ achieved this goal ~~with the~~using our current technique~~s~~ ~~adopted~~, we believe that refining the bias correction methodology ~~may further leverage the~~will enhance the system's effectiveness. Bias correction is ~~considered~~ a critical element ~~a key component of~~in precipitation forecasts, with ~~and~~ QM ~~is~~ being one of the most commonly ~~technique~~ applied techniques. ~~For setting up the~~In developing AA trigger~~'~~ system, we ~~developed~~ designed and ~~assessed~~ evaluated a bias correction methodology ~~in order~~ to ~~identify~~ improve ~~opportunities for increasing~~ the accuracy of ~~skill of the~~ seasonal forecast in predicting severe droughts. While our methodology has increased forecast ~~Despite increasing skill~~ for 24% of ~~all~~ the predicted ~~forecasted~~ SPI ~~(~~at the district level~~)~~ and ~~increasing~~ expanded AA coverage by 4% (as shown in Table 3, comparing scenario 3 to 4~~Table 3, scenario 3 compared to 4~~), there ~~are~~ is still potential ~~currently improvements that can be taken to advance the~~to further enhance the bias correction approach. Below, we outline the improvements that can be made.~~, which we describe below.~~

Firstly, our method uses an ENSO-informed quantile mapping transfer function to correct the SPI forecast based on the SPI reference value of the pixel under investigation and its nine neighboring pixels conditioned on the state of ENSO.~~ process for selecting samples to build the bias correction transfer function.~~ This ~~seeks~~ process ~~to~~ ensures that the bias correction accounts ~~adjusts~~ for variations in the SPI~~rainfall~~ quantities according to the climatology of ~~rains during~~ different ENSO phases, effectively capturing ~~and therefore capturing~~ relevant global processes (Manzanas & Gutiérrez, 2019; Maraun et al., 2017). In practice, this ~~means~~ involves splitting ~~that the~~SPI time series~~ of SPIs~~, ~~extracted~~ derived from both CHIRPS and ECMWF ensemble forecasts, ~~are split~~ into Neutral, La Niña and El Niño years depending on the~~the actual and retrospective prevalent~~ ENSO phase ~~of ENSO~~ (~~overview~~ detailed in Supplementary Material S1). However, ~~for~~ in some regions ~~in~~ of Mozambique, such as part of Tete, the ENSO-rainfall signal is ~~less present~~weak, ~~such as the rainfall from~~particularly during October to December ~~in parts of Tete~~ (WFP, 2018). Therefore, ~~using~~ relying ~~only~~ solely on an ENSO-based approach ~~informed process~~ may not be the ideal in these areas~~approach given the weak ENSO-rainfall link~~. ~~In addition, there are other~~Other ~~modes of~~ climate variability modes, such as the Indian Ocean Dipole, ~~which is well~~are also known to ~~drive~~ influence ~~year to year~~annual rainfall variability in the ~~country~~ Mozambique (B. A. et al., 2021; Ficchì et al., 2021; Harp et al., 2021). This ~~creates~~ suggests ~~the~~a need to ~~for further~~ investigate~~ing~~ the suitability of ~~other~~ incorporating additional ~~modes of~~ teleconnections modes ~~to the Mozambican~~into ~~climate in~~ the bias correction ~~approach~~process.

Second, since extreme droughts generally affect broad areas rather than single locations (Eskridge et al., 1997; Liu et al., 2021), our bias correction methodology accounts for the spatial dependence of SPI. To bias correct a single grid point of the SPI ensemble forecast, we incorporate data from multiple grid points (the target grid point and its nine neighbors) from the reference SPI dataset to build the transfer function. Previous research has shown that addressing spatial dependence reduces bias in climate model outputs (Cannon, 2018; Nahar et al., 2018). To avoid overfitting, we use a leave-one-year-out cross-validation scheme, excluding the year being bias corrected from the transfer function. For the spatial dependence setup, we tested two k values (4 and 9), ultimately selecting 9 based on improved spatial homogeneity of

AUROC scores. However, this approach could benefit from further optimization by assessing the k value that yields the highest AUROC scores for specific locations.

Third, improvements in bias correction may be achieved by exploring emerging methodologies such as Machine Learning (ML). Recent studies indicate that ML has the potential to outperform traditional techniques like QM (e.g., Yoshikane & Yoshimura, 2023; Zarei et al., 2021). Lastly, our initial internal tests showed significant improvements in drought predictability by creating a transfer function that directly links SPI forecasts to SPI observations, rather than taking the traditional approach of bias correcting daily or monthly raw rainfall forecasts before converting them into SPI values. This direct approach has led to both statistical and practical gains, as it allows the system to focus directly on drought detection. If the system evolves to include additional rainfall-based indicators, such as dry spells or the start/cessation of rains, a method that directly bias corrects raw forecasts could offer operational advantages, as it can be widely applied to generate additional indicators.

~~However, it is important to mention that, in an operational manner and in alignment with the methodology, at least the dominant phase of the indicator of climate variability should be forecastable with a long lead time, such as ENSO phases that are predicted months in advance (IRI, 2023). The long lead time of such forecasts help us to determine which of the three phases of ENSO to select for building the transfer function to be applied in the newly received forecast information (received each year from May onwards). Secondly, since extreme droughts generally do not occur at a single location, but in a broader spatial extent (Eskridge et al., 1997; Liu et al., 2021), our bias correction methodology takes a multivariate approach. This means that for bias correcting a grid point of the ensemble forecast, multiple grid points (specific grid point and its *k* neighbors) of the reference rainfall dataset are pulled together for building the transfer function. As shown by previous research, correcting for the spatial dependence of rainfall leads to reduced bias in climate model outputs (Cannon, 2018; Nahar et al., 2018). In addition, to help avoid overfitting, the year being bias corrected is left out from the transfer function, applying a scheme of leave-one-year-out cross-validation. For the setup of the spatial dependence, only two *k* values were tested (5 and 10) and the latter one used as we found a more (eyeballed) spatial homogeneity of AUROC scores. However, this multivariate approach could benefit from a process that optimizes the number of *k* neighbors by assessing the value that results in the highest AUROC scores for a particular location. Thirdly, bias reduction in the forecasting data may be achieved by exploring emerging methodologies such as Machine Learning (ML) given that recent studies have shown that ML has the potential to outperform traditional techniques such as QM (e.g., Yoshikane & Yoshimura, 2023; Zarei et al., 2021).~~

~~Furthermore,~~ W~~w~~e also highlight ~~show~~ the potential ~~for~~ to scale up~~scaling up~~ AA ~~using~~ by utilizing rainfall seasonal forecasts from the ECWMF. In our ~~setup~~approach, the seasonal forecast is downscaled from 1 degree to 0.25 degrees ~~via~~ using bilinear interpolation, which ~~enables~~ allows us to assess forecasting skill ~~to be assessed~~ at the district level. ~~Being able to extract~~Extracting drought alerts at the district level is ~~key~~ crucial ~~in order~~ to align ~~match~~ with the geographical targeting of AA interventions. However, further investigation ~~could~~ into ~~be done to evaluate~~ other ~~suitable~~ downscaling techniques, such as ML, ~~which~~

could be beneficial, as ML has been shown ~~was shown~~ to ~~increase~~enhance ~~the~~forecast skill ~~of forecasts~~ (Jin et al., 2023). ~~Furthermore,~~ ECMWF was initially ~~chosen~~ selected as ~~the~~ our ~~main~~ primary source of forecasting information ~~mainly~~ due to its ~~motivated by the known~~ superior ~~higher~~ skill in predicting precipitation over the African continent ~~in comparison~~compared to other centers (Gebrechorkos et al., 2022). ~~However~~Nevertheless, future studies ~~could~~ may benefit from ~~moving~~ shifting from a single-model approach ~~center~~ to a Multi-Model Ensemble (MME) ~~approach~~strategy. MME ~~links~~ integrates independent models ~~emerging~~ from ~~different~~ various ~~producing~~ forecasting centers of ~~forecasting~~ information, ~~and its~~which ~~key at reducing the effect of~~helps mitigate ~~individual~~ model errors ~~which in turn can improve~~and can enhance the reliability of seasonal outlooks (Doblas-Reyes et al., 2010; Gebrechorkos et al., 2022; Rozante et al., 2014)~~.~~

~~As it is shown in this study, the Ready, Set & Go! Trigger system can produce alerts of severe droughts through the lenses of the SPI 2 and SPI 3 indicators. These indicators and thresholds are considered by the TWG in Mozmabique as a suitable option for monitoring and anticipating severe risks to agricultural systems. However, such indicators and thresholds are not perfect at detecting drought damages, especially given that the relationship between drought risk and impact can often be location-specific, non-linear and modulated by non-climatic factors such as vulnerability (Brida et al., 2013; Silva & Matyas, 2014). Given that a historical and comprehensive drought losses or impact data is unavailable, especially at district level, no further tuning of thresholds and indicators could be done to enrich the system. Therefore, instead of using a single severity level, the operational Ready, Set & Go! system can release alerts for two other addition thresholds: mild and moderate droughts (see explanation in Guimarães Nobre et al., 2023). Future efforts could focus on refining such thresholds in order to build a stronger link between the physical hazard and expected impacts through the support of spatial explicit socio-economic datasets such as the Integrated Food Security Phase Classification indicator produced by the Famine Early Warning Systems Network. This way, users can be aware of the food security outcomes linked to drought events. Furthermore, the Ready, Set & Go! Could benefit from incorporating other drought indicators to better capture drought risks within the two windows of intervention. In practice, the Ready, Set & Go! System already releases alerts based on dry spells, but other metrics such as the onset of rains, rainfall cessation and Standardized Precipitation Evapotranspiration Index could also be explored.~~

~~We show that the Ready, Set & Go! System leads to AA advisories with an increased hit rate and decreased false alarm ratio in comparison with a system using only a single alert for AA advisories. Furthermore, we observe that the Ready, Set & Go! System increases the timing for preparedness activities and would enable the scale up of AA against severe droughts in the first window of the rainy season to 87% of the districts in Mozambique. However, given that triggers for AA are identified and optimized at the district scale, the system is prone to issuing AA advisories for individual districts whereas past severe droughts are often observed at a broader scale, including large-scale socio-economic consequences (Baez et al., 2020). This may happen given that the system uses different lead times of the forecasting information for districts within a given province and/or if the trigger for the different windows of implementation within a province is informed by different SPI indicators. For instance, this situation can be observed in the southern regions in Mozambique (shown in the Supplementary Material S5). Despite having statistical gains, the decision of optimizing the triggers at the district scale needs to be further contextualized for~~

Formatted: Portuguese (Brazil)

Formatted: Portuguese (Brazil)

Field Code Changed

Formatted: Portuguese (Brazil)

Formatted: Portuguese (Brazil)

Field Code Changed

Formatted: Portuguese (Brazil)

Field Code Changed

~~practical decisions, which can include large-scale operations and funding distribution/management. Thus, this optimization process may not be perceived as the most appropriated approach for AA planning, especially given the plans to scale up AA to the country level. However, one way to avoid the asynchrony of AA triggers may lie in refining the final triggers' selection of indicators and lead times based on their performance across the majority of the districts within a province.~~

We demonstrate that the Ready, Set & Go! system improves the accuracy of AA advisories, resulting in a higher hit rate and a lower false alarm ratio compared to a system that relies on a single alert for AA advisories. Additionally, we observe that this system extends the lead time for preparedness activities, allowing for the scaling up of AA efforts against severe droughts during the first window of the rainy season, covering 87% of districts in Mozambique. However, since AA triggers are identified and optimized at the district level, the system is prone to issuing advisories for individual districts, even though past severe droughts have often had broader impacts, including widespread socio-economic consequences (Baez et al., 2020). This discrepancy may occur because the system uses different lead times for forecasting information across districts within the same province or because triggers for different implementation windows within a province are based on varying SPI indicators. An example of this can be seen in southern Mozambique (refer to Supplementary Material S5). Despite these statistical gains, optimizing AA triggers at the district level needs to be contextualized for practical decision-making, particularly for large-scale operations and the distribution and management of funding. Therefore, while district-level optimization may be effective statistically, it may not always be the most appropriate approach for AA planning, especially when scaling up AA across the entire country. One potential solution to avoid asynchrony in AA triggers is to refine the selection of indicators and lead times by evaluating their performance across the majority of districts within a province, ensuring more synchronized and coordinated AA efforts.

We also demonstrate that the triggers for the Ready, Set & Go! system can be adjusted based on vulnerability information, adding an important nuance to AA operations (Baez et al., 2020). However, measuring vulnerability is a complex task that often requires frequent updates, location-specific data, and further disaggregation by age and gender (Chaves-Gonzalez et al., 2022). In Mozambique, the Technical Secretariat for Food Security and Nutrition (SETSAN) is responsible for providing such information. AA operations would greatly benefit if this data were made available in a timely manner, ideally before the start of the AA season. Unfortunately, this is not always the case. More research is needed to understand vulnerability trends and their relationship to climate hazards (Baez et al., 2020; Hallegatte et al., 2016). As the system expands, collecting timely vulnerability data may become increasingly challenging. Therefore, a systematic, rapid, yet robust methodology for vulnerability analysis is essential. We have also observed a lower percentage of districts covered by AA when emergency triggers—modulated by vulnerability—are used. These emergency triggers inherently allow for a higher rate of false alarms and focus on "no-regret" actions (Chaves-Gonzalez et al., 2022) while increasing the probability of detection. This approach aims to maximize the number of extreme droughts anticipated by AA interventions and provide a safety net for areas with high vulnerability. However, the current criteria for identifying emergency triggers are not achieving higher coverage compared to general triggers. Revisiting these criteria (see Table 1) through a statistical optimization process may help enhance the system's effectiveness.

~~Furthermore, we show that the triggers for the Ready, Set & Go! System can be modulated based on vulnerability information, which is an important nuance to be added to AA operations (Baez et al., 2020). However, it is key to highlight that measuring vulnerability can be a difficult task, often requiring regular updates, location-specific information, which can also be further disaggregated by age and gender (Chaves-Gonzalez et al., 2022). The Mozambique Technical Secretariat for Food Security and Nutrition (SETSAN) has the mandate to provide such information. The AA operations will benefit if the information is made available timely and prior to the start of the AA season, which is often not the case. More studies are needed to understand trends in vulnerability and its relationship with climate hazards (Baez et al., 2020; Hallegatte et al., 2016). As the system scales up, collecting timely vulnerability information may become a challenge. Therefore, a systematic, fast, and yet robust methodology for extracting such vulnerability analysis is required. Furthermore, we have shown a lower percentage of districts with AA coverage when adopting emergency triggers, which is modulated by vulnerability. Intuitively, this menu accepts a higher degree of false alarms, and actions considered as "non-regret" (Chaves-Gonzalez et al., 2022), with an increased probability of detection. This menu of triggers is expected to maximize the possible number of extreme droughts that are preceded by the AA, and in turn to offer a safety net to areas facing high levels of vulnerability. However, the currently adopted criteria for finding emergency triggers are not enabling a higher coverage in comparison to the general triggers. Therefore, it may be useful to revise the established criteria (Table 1) by applying a statistical optimization process.~~

As previously mentioned, the Ready, Set & Go! system is currently being piloted in 11 districts across Mozambique, with plans to scale up AA operations in 2024. Due the 2023-24 El Niño, several AA advisories have already been issued to districts in the Gaza, Sofala, and Tete provinces, marking the system's first operational deployment during the 2023-24 rainy season. While humanitarian and governmental organizations have substantial experience in responding to hazards after they occur, most monitoring and evaluation (M&E) efforts have focused on the effects of emergency responses post-crisis. There is limited evidence on the benefits of AA, particularly regarding drought interventions partially given the small number of pilot interventions to date as well as with challenges faced by studies on benefit estimations/modelling. As the evidence base for value for money begins to form, WFP's AA programs are showing potential as a sustainable way to support climate-vulnerable governments with limited resources (WFP, 2023a). In Kenya, drought-related AA could save up to US$20 billion over 20 years, even with false alarms costing significantly less than a late response. In Ethiopia, Kenya, and Somalia, AA could save US$1.6 billion over 15 years by mitigating drought impacts before price spikes and negative coping strategies. In Nepal, AA reduced damage to vulnerable populations by 75% and cuts asset losses by 50%, saving US$34 for every dollar invested and reducing long-term recovery costs. In Zimbabwe, AA reached 32,500 people before drought impacts, with 97% of farmers benefiting from climate information and 80% adapting their practices, leading to higher resilience compared to a control group.

Given that AA represents an innovative approach and a relatively new concept in risk management, it is crucial to establish a robust M&E system to evaluate the effectiveness of AA interventions. This system will provide valuable insights into what has worked well in practice and highlight areas for improvement in future operations. Ultimately, a well-designed M&E process will help determine whether AA

Formatted: Not Highlight

Formatted: Not Highlight

Formatted: Not Highlight

interventions are effectively reducing or mitigating the impacts of droughts on affected populations (Gros et al., 2021)

~~As previously mentioned, the Ready, Set & Go! system is being piloted in Mozambique in 11 districts and the scale-up of AA operations planned for 2024. Given the on-going El Niño, a number of AA advisories have been already issued to districts located in the Gaza, Sofala and Tete provinces and therefore, for the first time, the system is being operationalized in the rainy season 2023-24. As humanitarian and (non-) governmental organizations have extensive experience responding to the impacts of hazards after a shock, most of the body of monitoring and evaluation (M&E) findings focus on the effects of emergency response on the lives and livelihoods post-crises. However, less evidence exists on the benefits of AA, especially in relation to drought interventions. As AA is considered an innovative approach and a fairly new concept within the scope of risk management, it is necessary to have in place a proper M&E system to identify the effectiveness of AA interventions. This will create learning opportunities for a deeper understanding of what has, in practical terms, worked well but also how to do better in future operations. Ultimately, this process shall be able to identify whether AA interventions are making a difference in reducing or mitigating the impacts of droughts on affected populations (Gros et al., 2021).~~

5. CONCLUSIONS AND RECOMMENDATIONS

In this article, we introduced and benchmarked the “Ready, Set & Go!” system, which is being piloted in Mozambique to trigger anticipatory action against severe droughts. This system is designed to implement measures that mitigate the impacts of rainfall deficits during the critical period between forecasting and the onset of drought. Following the recent adoption of the SADC Maputo Declaration by its member states, there is a need to evaluate the system's opportunities and limitations for expanding drought AA coverage to all districts in Mozambique. Our study findings include:

- Potential for Expansion: The Ready, Set & Go! system could potentially scale AA activities to 76% of Mozambican districts. Additionally, 63% of these districts could adopt an alternative trigger system tailored to vulnerability levels. This feature allows the system to proactively address potential vulnerabilities for the upcoming season. If only the first window of the rainy season is targeted, coverage could increase to 87%.
- Impact of Bias Correction: The bias correction methodology used in the Ready, Set & Go! system enhances forecasting skill for 24% of all forecasted SPI indicators at the district level. This improvement raises AA coverage from 73% to 76% for the general menu, and from 59% to 63% for the emergency menu. This means bias correction can extend operational AA coverage to about six additional districts, representing a slight improvement but also enhancing the potential for life-saving AA.
- Increased Hit Rate and Lead Time: The Ready, Set & Go! system improves both the hit rate and lead time for AA compared to three alternative triggering approaches. The highest mean hit rate across different windows was observed in the Central Zone within window 1 (74%). SPI DJ is the

most commonly used indicator for AA in window 1. The earliest "ready" alert for preparedness can be issued for a few districts in the South zone based on the May forecast.

- Reduced False Alarm Ratio: The Ready, Set & Go! system achieves a lower false alarm ratio compared to the three alternative approaches. The mean lowest average false alarm ratio is found in the Central Zone for window 1 (10%). Among different menus and windows, the mean highest false alarm ratio is 21% for the emergency menu in window 2, while the mean lowest is 10% for the general menu in window 1.

~~In this article, we introduced and benchmarked the "Ready, Set & Go!" system, which is being piloted in Mozambique for triggering AA against severe droughts. This system is used to implement actions to reduce impacts of rainfall deficits in the critical window between a forecast and the onset of the drought event. With the recent adoption of the SADC Maputo Declaration by its member states, there is currently the need for assessing the opportunities and limitations of the system to scale up drought AA information to all districts in Mozambique. Our study has shown that:~~

- ~~The Ready, Set & Go! system has the potential for scaling up AA activities against severe droughts, on average, to 76% of the Mozambican districts, and in 63% of them, an alternative trigger system modulated by vulnerability levels can be adopted. This is an important feature of the system as it can identify potential vulnerabilities for the upcoming season that can be addressed proactively and protectively by the AA triggers. AA system's coverage could be increased to 87%, if only the first window of the rainy season is targeted.~~
- ~~The used bias correction methodology in the Ready, Set & Go! system produces increased skill in forecasting severe droughts for 24% of all forecasted SPI at the district level. This results on an AA coverage increase from 73% to 76% (general menu), and from 59% to 63% (emergency menu). This means that bias corrections enable AA to become operational to about six extra districts (compared to a system without bias correction), which can be interpreted as a slight improvement in the system coverage but also as an enabling mechanism for life-saving AA to thousands of citizens.~~
- ~~The Ready, Set & Go! system increases the hit rate and lead time for AA in comparison to three alternative triggering approaches benchmarked. We showed that across the different windows of implementation, triggers for AA reached the highest hit rate for the Central Zone of Mozambique within window 1 (74%). Across all zones, SPI DJ is the indicator most chosen to inform AA within window 1. In regard to lead time, the earliest "ready" alert for preparedness can be issued for few districts in the south zone based on the forecast of May.~~
- ~~The Ready, Set & Go! system decreased the false alarm ratio for AA in comparison to three alternative triggering approaches benchmarked. The average lowest false alarm ratio of AA triggers is found for the Central zone window 1 (10%). Across the different menus of AA and windows, the highest and lowest false alarm ratio are found for the emergency menu - modulated by vulnerability - and window 2 (21%) and general menu for window 1 (10%), respectively.~~

We observed that the piloted drought EWS has significant potential for scaling up AA across Mozambique, aligning with the goals of the Maputo Declaration and the Early Warning for All initiative to provide climate event coverage and protection to all citizens by 2027. However, several next steps could further enhance the effectiveness of the EWS:

1. Enhance Bias Correction Methodology

- Explore Additional Climate Indices: Incorporate more indices related to climate variability to refine the transfer function.
- Optimize Nearest Neighbors: Fine-tune the number of nearest neighbors used in bias correction.
- Investigate Emerging Techniques: Explore advanced methods such as Machine Learning to improve accuracy.

2. Improve Forecast Resolution

- Explore Downscaling Techniques: Investigate alternative downscaling methods to enhance the resolution of seasonal forecasts.
- Consider Multi-Model Ensemble Approaches: Evaluate whether combining multiple models could improve the reliability of seasonal outlooks.

3. Strengthen Impact Links

- Connect Thresholds to Socio-Economic Impacts: Enhance understanding of the socio-economic consequences of droughts to better plan and target AA activities.
- Incorporate Additional Indicators: Include other relevant drought indicators, such as the onset of rains and rainfall cessation, to provide a more comprehensive assessment.

4. Contextualize Trigger Optimization

- Refine Triggers for Practical Decision-Making: Consider the impact of optimizing triggers at the district level, which may lead to asynchrony in AA activations among neighboring districts. Select SPI 2 or SPI 3 indicators and lead times based on their performance across most districts within a province.

5. Invest in Monitoring and Evaluation

- Support Ongoing Pilots: Invest in monitoring, evaluation, and learning to inform future expansion of the anticipatory approach and maximize the impact of AA activities.

These steps may help to maximize the effectiveness and coverage of the EWS, ensuring that AA efforts are timely, more accurate and well-targeted.

~~We observed that the piloted drought EWS can enable a major scale up of AA activities in the country, which contributes to the ambitious goals of the Maputo Declaration and the Early Warning for All initiative in ensuring coverage and protection from climate events by 2027 to all citizens. However, there are number of next steps that can further leverage the potential of the presented EWS such as:~~

- ~~Improving the adopted bias correction methodology of the system by i) exploring additional indices of the modes of climate variability that informs the transfer function, ii) optimizing the~~

~~number of nearest neighbors, and iii) exploring emerging methodologies such as Machine Learning.~~

- ~~Investigating other suitable downscaling techniques to improve the resolution of the seasonal forecast, as well as exploring whether a Multi-Model Ensemble approach could improve the reliability of seasonal outlooks.~~
- ~~Strengthening the links between threshold (the physical hazard) and impact to promote awareness around socio-economic consequences of droughts as well as to improve the planning and targeting of anticipatory action activities. Furthermore, the Ready, Set & Go! could benefit from incorporating other drought indicators such as the onset of rains and rainfall cessation.~~
- ~~Despite having statistical gains, the decision of optimizing the triggers at the district scale need to be further contextualized for practical decision-making as it may cause asynchrony of AA activations, even at neighbors' districts. Thus, AA triggers' choice can be refined by selecting a SPI 2 or 3 indicator and lead times of the forecast information based on their performance across the majority of the districts within a province.~~
- ~~Investing in monitoring, evaluation and learning of activities of on-going pilots in order to inform future expansion of the anticipatory approach in the country and ensure maximum impact of activities.~~

COMPETING INTERESTS

The contact author has declared that none of the authors has any competing interests.

REFERENCES

Araneda-Cabrera, R. J., Bermudez, M., & Puertas, J. (2021). Revealing the spatio-temporal characteristics of drought in Mozambique and their relationship with large-scale climate variability. *Journal of Hydrology: Regional Studies*, *38*, 100938. https://doi.org/10.1016/j.ejrh.2021.100938

Ashok, K., Guan, Z., & Yamagata, T. (2001). Impact of the Indian Ocean dipole on the relationship between the Indian monsoon rainfall and ENSO. *Geophysical Research Letters*, *28*(23), 4499–4502. https://doi.org/10.1029/2001GL013294

B. A., O., V., O., Z. W., S., T. S., R., M., L., & J. N., N. (2021). Influence of Indian Ocean dipole on rainfall variability and extremes over southern Africa. *MAUSAM*, *71*(4), 637–648. https://doi.org/10.54302/mausam.v71i4.50

Baez, J. E., Caruso, G., & Niu, C. (2019). Extreme Weather and Poverty Risk: Evidence from Multiple Shocks in Mozambique. *Economics of Disasters and Climate Change 2019 4:1*, *4*(1), 103–127. https://doi.org/10.1007/S41885-019-00049-9

Baez, J. E., Caruso, G., & Niu, C. (2020). Extreme Weather and Poverty Risk: Evidence from Multiple Shocks in Mozambique. *Economics of Disasters and Climate Change*, *4*(1), 103–127. https://doi.org/10.1007/s41885-019-00049-9

Behera, S. K., & Yamagata, T. (2001). Subtropical SST dipole events in the southern Indian Ocean. *Geophysical Research Letters*, *28*(2), 327–330. https://doi.org/10.1029/2000GL011451

Blamey, R. C., Kolusu, S. R., Mahlalela, P., Todd, M. C., & Reason, C. J. C. (2018). The role of regional circulation features in regulating El Niño climate impacts over southern Africa: A comparison of the 2015/2016 drought with previous events. *International Journal of Climatology*, *38*(11), 4276–4295. https://doi.org/10.1002/joc.5668

Brida, A. B., Owiyo, T., & Sokona, Y. (2013). Loss and damage from the double blow of flood and drought in Mozambique. *International Journal of Global Warming*, *5*(4), 514. https://doi.org/10.1504/IJGW.2013.057291

Cannon, A. J. (2018). Multivariate quantile mapping bias correction: an N-dimensional probability density function transform for climate model simulations of multiple variables. *Climate Dynamics*, *50*(1–2), 31–49. https://doi.org/10.1007/s00382-017-3580-6

Chaves-Gonzalez, J., Milano, L., Omtzigt, D.-J., Pfister, D., Poirier, J., Pople, A., Wittig, J., & Zommers, Z. (2022). Anticipatory action: Lessons for the future. *Frontiers in Climate*, *4*. https://doi.org/10.3389/fclim.2022.932336

Doblas-Reyes, F. J., Déqué, M., & Piedelievre, J.-P. (2010). Multi-model spread and probabilistic seasonal forecasts in PROVOST. *Quarterly Journal of the Royal Meteorological Society*, *126*(567), 2069–2087. https://doi.org/10.1002/qj.49712656705

ECHO. (2021). *Echo Flash*. https://erccportal.jrc.ec.europa.eu/ECHO-Products/Echo-Flash#/daily-flash-archive/4117

Eskridge, R. E., Ku, J. Y., Rao, S. T., Porter, P. S., & Zurbenko, I. G. (1997). Separating Different Scales of Motion in Time Series of Meteorological Variables. *Bulletin of the American Meteorological Society*, *78*(7), 1473–1483. https://doi.org/10.1175/1520-0477(1997)078<1473:SDSOMI>2.0.CO;2

Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recognition Letters*, *27*(8), 861–874. https://doi.org/10.1016/j.patrec.2005.10.010

Ficchì, A., Cloke, H., Neves, C., Woolnough, S., Coughlan de Perez, E., Zsoter, E., Pinto, I., Meque, A., & Stephens, E. (2021). Beyond El Niño: Unsung climate modes drive African floods. *Weather and Climate Extremes*, *33*, 100345. https://doi.org/10.1016/j.wace.2021.100345

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes. *Scientific Data*.

https://doi.org/10.1038/sdata.2015.66

Gebrechorkos, S. H., Pan, M., Beck, H. E., & Sheffield, J. (2022). Performance of State-of-the-Art C3S European Seasonal Climate Forecast Models for Mean and Extreme Precipitation Over Africa. *Water Resources Research*, *58*(3). https://doi.org/10.1029/2021WR031480

Gros, C., Heinrich, D., Kazis, P., Merola, S., & others. (2021). *Monitoring and evaluation of anticipatory actions for fast and slow-onset hazards: Guidance and tools for Forecast-based Financing*.

Guimarães Nobre, G., Pasqui, M., Quaresima, S., Pieretto, S., & Lemos Pereira Bonifácio, R. M. (2023). Forecasting, thresholds, and triggers: Towards developing a Forecast-based Financing system for droughts in Mozambique. *Climate Services*, *30*, 100344. https://doi.org/10.1016/j.cliser.2023.100344

Hallegatte, S., Bangalore, M., Bonzanigo, L., Fay, M., Kane, T., Narloch, U., Rozenberg, J., Treguer, D., & Vogt-Schilb, A. (2016). *Shock Waves: Managing the Impacts of Climate Change on Poverty*. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-0673-5

Harp, R. D., Colborn, J. M., Candrinho, B., Colborn, K. L., Zhang, L., & Karnauskas, K. B. (2021). Interannual Climate Variability and Malaria in Mozambique. *GeoHealth*, *5*(2). https://doi.org/10.1029/2020GH000322

Hart, N. C. G., Reason, C. J. C., & Fauchereau, N. (2010). Tropical–Extratropical Interactions over Southern Africa: Three Cases of Heavy Summer Season Rainfall. *Monthly Weather Review*, *138*(7), 2608–2623. https://doi.org/10.1175/2010MWR3070.1

IRI. (2023). *ENSO Forecast*. https://iri.columbia.edu/our-expertise/climate/forecasts/enso/current/

Jin, H., Jiang, W., Chen, M., Li, M., Bakar, K. S., & Shao, Q. (2023). Downscaling long lead time daily rainfall ensemble forecasts through deep learning. *Stochastic Environmental Research and Risk Assessment*, *37*(8), 3185–3203. https://doi.org/10.1007/s00477-023-02444-x

Liu, Z., Xie, Y., Cheng, L., Lin, K., Tu, X., & Chen, X. (2021). Stability of spatial dependence structure of extreme precipitation and the concurrent risk over a nested basin. *Journal of Hydrology*, *602*, 126766. https://doi.org/10.1016/j.jhydrol.2021.126766

Lloyd-Hughes, B., & Saunders, M. A. (2002). A drought climatology for Europe. *International Journal of Climatology*, *22*(13), 1571–1592. https://doi.org/10.1002/JOC.846

Lopez, A., Coughlan de Perez, E., Bazo, J., Suarez, P., van den Hurk, B., & van Aalst, M. (2018). Bridging forecast verification and humanitarian decisions: A valuation approach for setting up action-oriented early warnings. *Weather and Climate Extremes*, *April 2016*, 1–8. https://doi.org/10.1016/j.wace.2018.03.006

Lyon, B., & Mason, S. J. (2007). The 1997–98 Summer Rainfall Season in Southern Africa. Part I: Observations. *Journal of Climate*, *20*(20), 5134–5148. https://doi.org/10.1175/JCLI4225.1

Manatsa, D., Matarira, C. H., & Mukwada, G. (2011). Relative impacts of ENSO and Indian Ocean dipole/zonal mode on east SADC rainfall. *International Journal of Climatology*, *31*(4), 558–577. https://doi.org/10.1002/joc.2086

Manhique, A. J, Reason, C. J. C., Silinto, B., Zucula, J., Raiva, I., Congolo, F., & Mavume, A. F. (2015). Extreme rainfall and floods in southern Africa in January 2013 and associated circulation patterns. *Natural Hazards*, *77*(2), 679–691. https://doi.org/10.1007/s11069-015-1616-y

Manhique, Atanásio João, Guirrugo, I. A., Nhantumbo, B. J., & Mavume, A. F. (2021). Seasonal to Interannual Variability of Vertical Wind Shear and Its Relationship with Tropical Cyclogenesis in the Mozambique Channel. *Atmosphere*, *12*(6), 739. https://doi.org/10.3390/atmos12060739

Manzanas, R., & Gutiérrez, J. M. (2019). Process-conditioned bias correction for seasonal forecasting: a case-study with ENSO in Peru. *Climate Dynamics*, *52*(3), 1673–1683. https://doi.org/10.1007/s00382-018-4226-z

Maraun, D., Shepherd, T. G., Widmann, M., Zappa, G., Walton, D., Gutiérrez, J. M., Hagemann, S., Richter, I., Soares, P. M. M., Hall, A., & Mearns, L. O. (2017). Towards process-informed bias correction of climate change simulations. *Nature Climate Change*, *7*(11), 764–773. https://doi.org/10.1038/nclimate3418

Mawren, D., Hermes, J., & Reason, C. J. C. (2020). Exceptional Tropical Cyclone Kenneth in the Far Northern Mozambique Channel and Ocean Eddy Influences. *Geophysical Research Letters*, *47*(16). https://doi.org/10.1029/2020GL088715

Nahar, J., Johnson, F., & Sharma, A. (2018). Addressing Spatial Dependence Bias in Climate Model Simulations—An Independent Component Analysis Approach. *Water Resources Research*, *54*(2), 827–841. https://doi.org/10.1002/2017WR021293

OCHA. (2017). *Report on the RIASCO Action Plan for the El Niño - Induced Drought in Southern Africa 2016/2017*. https://reliefweb.int/report/world/report-riasco-action-plan-el-ni-o-induced-drought-southern-africa-20162017

Rapolaki, R. S., Blamey, R. C., Hermes, J. C., & Reason, C. J. C. (2019). A classification of synoptic weather patterns linked to extreme rainfall over the Limpopo River Basin in southern Africa. *Climate Dynamics*, *53*(3–4), 2265–2279. https://doi.org/10.1007/s00382-019-04829-7

Ratri, D. N., Whan, K., & Schmeits, M. (2019). A Comparative Verification of Raw and Bias-Corrected ECMWF Seasonal Ensemble Precipitation Reforecasts in Java (Indonesia). *Journal of Applied Meteorology and Climatology*, *58*(8), 1709–1723. https://doi.org/10.1175/JAMC-D-18-0210.1

Reason, C. J. C., & Keibel, A. (2004). Tropical cyclone Eline and its unusual penetration and impacts over the southern African mainland. *Weather and Forecasting*, *19*(5), 789–805.

Richard, Y., Fauchereau, N., Poccard, I., Rouault, M., & Trzaska, S. (2001). 20th century droughts in Southern Africa: Spatial and temporal variability, teleconnections with oceanic and atmospheric conditions. *International Journal of Climatology*, *21*(7), 873–885. https://doi.org/10.1002/joc.656

Rozante, J. R., Moreira, D. S., Godoy, R. C. M., & Fernandes, A. A. (2014). Multi-model ensemble: technique and validation. *Geoscientific Model Development*, *7*(5), 2333–2343. https://doi.org/10.5194/gmd-7-2333-2014

SADC. (2022). *Maputo Declaration on the Commitment by SADC to enhance Early Warning and Early Action in the Region*. https://au.int/sites/default/files/pressreleases/42156-other-Maputo_Declaration_Final_AUC_11_Sept-2022.pdf

Saji, N. H., Goswami, B. N., Vinayachandran, P. N., & Yamagata, T. (1999). A dipole mode in the tropical Indian Ocean. *Nature*, *401*(6751), 360–363. https://doi.org/10.1038/43854

Silva, J. A., & Matyas, C. J. (2014). Relating Rainfall Patterns to Agricultural Income: Implications for Rural Development in Mozambique. *Weather, Climate, and Society*, *6*(2), 218–237. https://doi.org/10.1175/WCAS-D-13-00012.1

Svoboda, M., Hayes, M., Wood, D. A., & others. (2012). *Standardized precipitation index user guide*.

Toté, C., Patricio, D., Boogaard, H., Wijngaart, R. Van der, Tarnavsky, E., & Funk, C. (2015). Evaluation of Satellite Rainfall Estimates for Drought and Flood Monitoring in Mozambique. *Remote Sensing 2015, Vol. 7, Pages 1758-1776*, *7*(2), 1758–1776. https://doi.org/10.3390/RS70201758

Trambauer, P., Werner, M., Winsemius, H. C., Maskey, S., Dutra, E., & Uhlenbrook, S. (2015). Hydrological drought forecasting and skill assessment for the Limpopo River basin, southern Africa. *Hydrology and Earth System Sciences*, *19*(4), 1695–1711.

Weingärtner, L., Pforr, T., & Wilkinson, E. (2020). *The evidence base on Anticipatory Action*.

WFP. (2016). *WFP Regional Bureau for Southern Africa SPECIAL OPERATION 200993*. https://documents.wfp.org/stellent/groups/internal/documents/projects/wfp285532.pdf

WFP. (2018). *MOZAMBIQUE: A Climate Analysis*. https://doi.org/10.54302/mausam.v71i4.50

WFP. (2023). *Building systems to anticipate drought in Mozambique*. https://reliefweb.int/report/mozambique/anticipatory-action-building-systems-anticipate-drought-mozambique-impact-assessment-wfps-capacity-strengthening-interventions-national-systems-september-2023

Winsemius, H. C., Dutra, E., Engelbrecht, F. A., Archer Van Garderen, E., Wetterhall, F., Pappenberger, F., & Werner, M. G. F. (2014). The potential value of seasonal forecasts in a changing climate in southern Africa. *Hydrology and Earth System Sciences*, *18*(4), 1525–1538. https://doi.org/10.5194/hess-18-1525-2014

WMO. (2022). *Early Warnings For All: The UN Global Early Warning Initiative for the Implementation of Climate Adaptation*. https://library.wmo.int/records/item/58209-early-warnings-for-all

World Bank. (2018). *Mozambique food market monitoring and resilient agriculture planning. Policy Report, 645 Washington D.C*.

Yoshikane, T., & Yoshimura, K. (2023). A downscaling and bias correction method for climate model ensemble simulations of local-scale hourly precipitation. *Scientific Reports*, *13*(1), 9412. https://doi.org/10.1038/s41598-023-36489-3

Zarei, M., Najarchi, M., & Mastouri, R. (2021). Bias correction of global ensemble precipitation forecasts by Random Forest method. *Earth Science Informatics*, *14*(2), 677–689. https://doi.org/10.1007/s12145-021-00577-7