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

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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 "Ready, Set & Go!", aims to proactively address impending droughts by setting predefined thresholds, triggers, and funding mechanisms for anticipatory actions. The system uses seasonal forecasts 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. 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. 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 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.

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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 multi natural 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 multi natural hazards (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 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.

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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.

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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 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.

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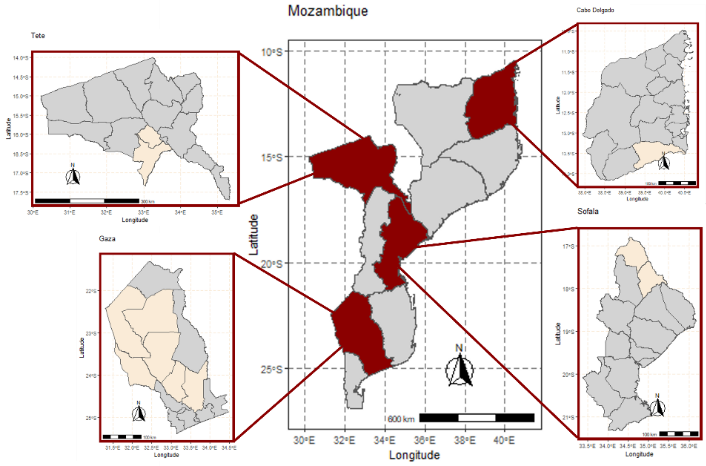

Figure 1: Districts in Mozambique with government-approved anticipatory action plans.

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.

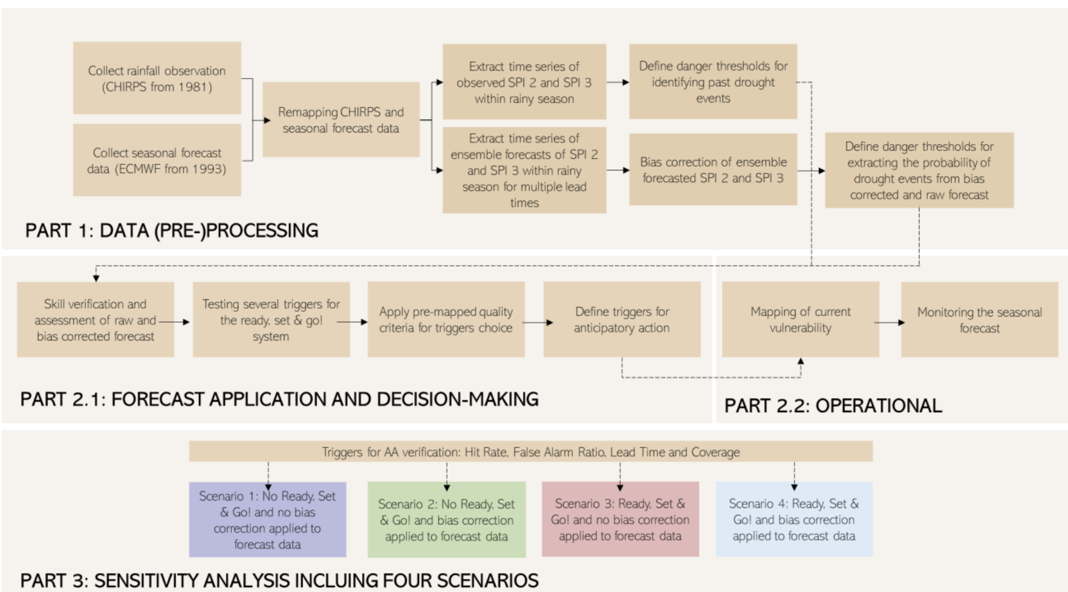

Figure 2: Flowchart of the methodological framework applied in this study, handled in three stages: (1) data pre-processing; (2) forecast application and decision-making; and (3) sensitivity analysis.

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2.2.1 Data pre-processing

Collection of datasets and rescaling

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).

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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.

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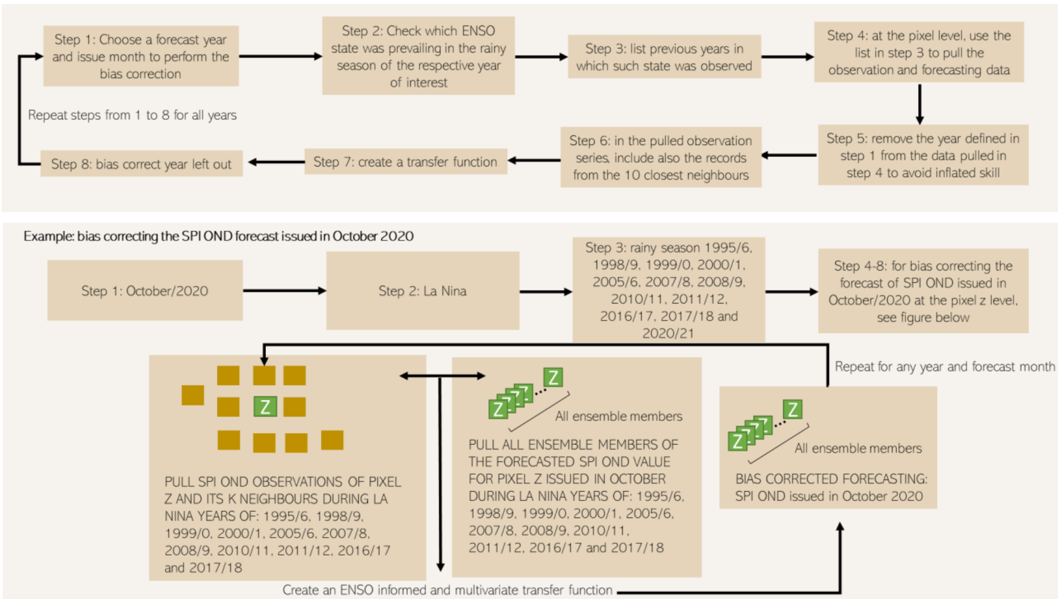

Figure 3: Bias correction methodology and illustrative example.

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 Forecast application and decision-making

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 triggers for the Ready, Set & Go! drought alert

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.

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

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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	

Defining triggers for anticipatory action

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

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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. 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 province and 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, 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 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.

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2.2.4 Sensitivity analysis including four scenarios

We test the strength of our methods by performing a sensitivity analysis considering four scenarios. For each scenario, four metrics are extracted:

1. **Hit Rate:** percentage of past severe droughts captured by the AA trigger(s).
2. **Tolerant False Alarm Ratio:** false alarms can occur when the trigger for AA is exceeded but the exact threshold of the drought is not met. For instance, 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 better contextualization of false alarms, we calculate 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). 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 difference between the starting month of the SPI indicator and the month in which the forecast was issued. For instance, the 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 a found AA trigger, which satisfies criteria highlighted in Table 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 Severe drought years according to adopted threshold

In Figure 4, we display the frequency in which the extracted SPI 2 and SPI 3 indicators were per zone and window (see Table 2) exceeded or equaled the severe threshold since 1981. The results are first computed at the district level, and then subsequently aggregated at the zonal level. The top 5 highest years with the largest number of 2- and 3-month periods and districts under severe drought conditions are highlighted. In addition, bars are colored according to the ENSO dominant phase during the past rainy seasons in Mozambique (see classification in Supplementary Material S2). In general, we observe that large-scale severe drought conditions can happen during any of the three phases of ENSO for all zones. Therefore, there is a need for establishing an AA system against droughts that is operationally feasible regardless of the ENSO state. However, we observe that during El Niño phases, the frequency of severe droughts (M = 66) is significantly larger than during Neutral phases (M = 41) and La Niña phases (M = 31) measured with a t-test ($p < .01$). The increased frequency of droughts during El Niño phases have been also found by

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other previous studies (Araneda-Cabrera et al., 2021; Lyon & Mason, 2007). In addition, we observe that top 5 years from window 1 and window 2 varies substantially. In the North zone, only the rainy season of 2004-05 is ranked as top 5 for both windows whereas in the Central zone only the rainy season of 1991-92. In the South zone, the rainy seasons of 1991-92 and 2015-16 are ranked as top 5 for windows 1 and 2. This also supports the importance of developing an AA system that considers the different intra-seasonal variability in rainfall, and therefore designing operations around stages of the rainy cycle. Furthermore, we provide a similar overview at the province level (see Supplementary Material S2), where we observe similar patterns to what was found in the zones. At the district level, an overview of the years and individual SPI 2 and SP3 indicators in which the severe threshold was exceeded are shown (see Supplementary Material S2). These are the events of relevance in which the seasonal forecast is expected to provide reliable alerts for the AA triggering system.

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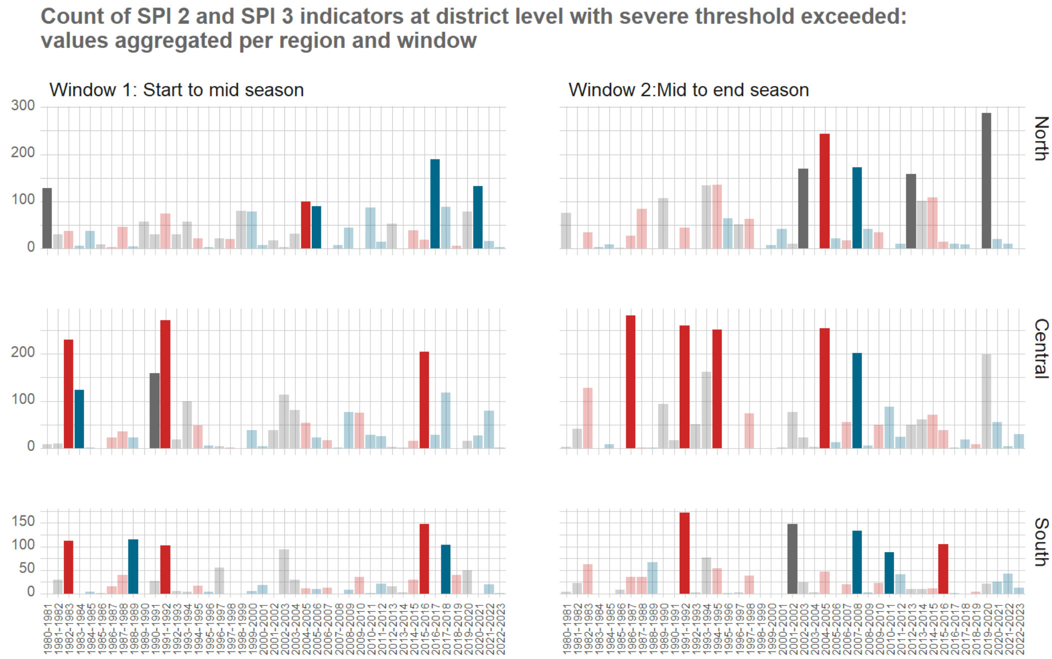

Figure 4: Frequency in which the extracted SPI 2 and SPI 3 indicators were per zone and window exceeded or equaled the severe threshold since 1981. First, the counting is done per district and subsequently aggregated at the zonal level within window 1 (left) and window 2 (right). For an overview of the 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.

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3.2 Zonal based overview of bias correction

In Figure 5, we show the percentage of areas per zone and forecast month with an improved AUROC score after bias correction. It is important to note that the evaluation of the bias correction methodology is based mainly in the outcome of the AUROC score as it provides a practical view to users whether the forecast of severe droughts benefits or not from this process. Our goal with this approach is to identify opportunities for avoiding the waste of anticipatory action resources given an inaccurate prediction. For a spatial overview, we display similar results in a series of maps in Supplementary Material S3. Overall, the zone with the highest percentage of area of improved forecasts is the North (38%), followed by the Central (19%) and South (19%) zones. For the North zone, the single forecast month with highest and lowest found improvement are July (56%) and February (20%), respectively. For the Central zone, these are the months of January (26%) and August (10%), respectively and for the South zone, these are the months of July and August (26%) and December and January (14%), respectively. Across all forecast months, the SPI indicators that most increased in skill are SPI ON, DJ and SPI NDJ (58%) for the North zone, SPI JFM (43%) for the Central zone and, SPI ON (47%) for the South zone. At the district level, we find that 24% of all forecasted SPI gain skill (measured by the AUROC score) in comparison to the raw forecast. A detailed overview of the AUROC scores is provided in section 3.3.

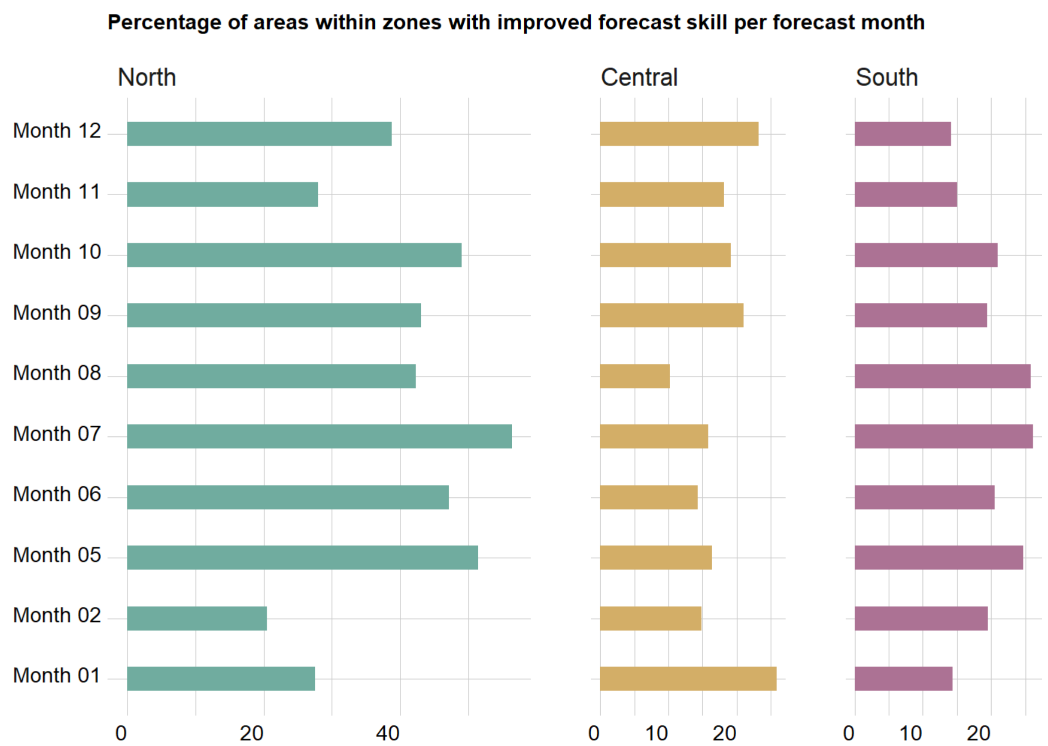

Figure 5: Percentage of zonal areas in which skill has gained using bias correction for different lead times of the forecast.

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3.3 Overview of the maximum AUROC score

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.

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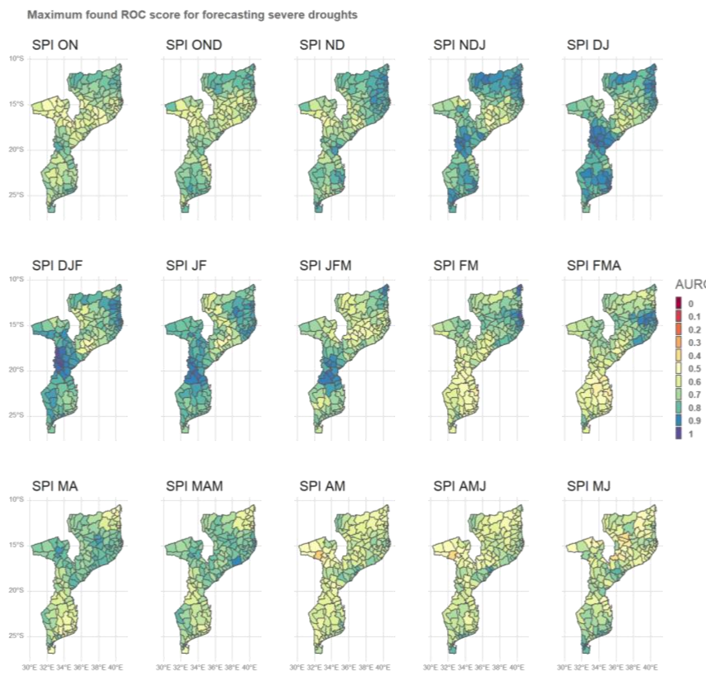

Figure 6: Overview of the maximum AUROC score across lead times combining outcomes of both raw and bias corrected forecast.

3.4 Sensitivity Analysis

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. 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.

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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	Scenario 2: single drought alert and bias correction applied to forecast data	Scenario 3: Ready, Set & Go! and no bias correction applied to forecast data	Scenario 4: Ready, Set & Go! and bias correction applied to forecast data
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%
	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

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

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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 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.

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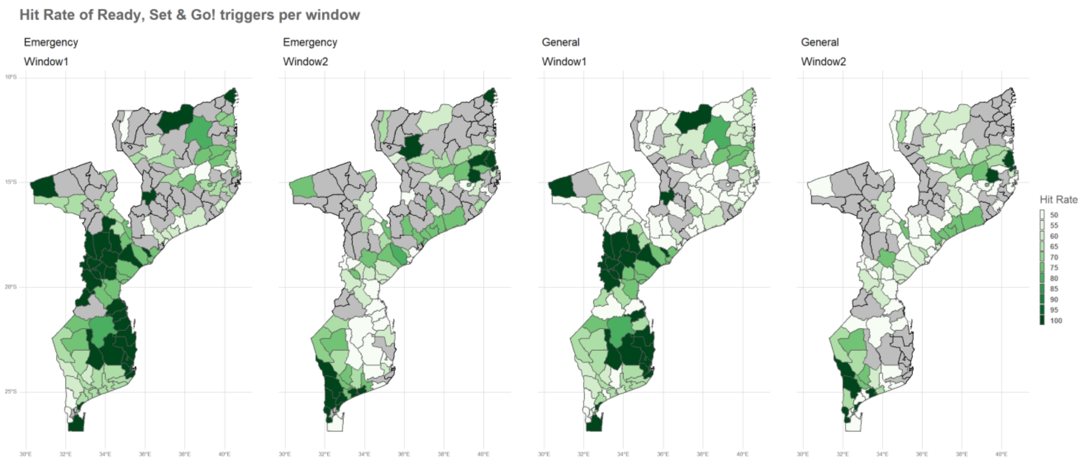

Figure 7: Hit rate of the Ready, Set & Go! Trigger system for severe droughts for two trigger menu (emergency and general) and two windows of intervention (window 1 and window 2). No trigger for the Ready, Set & Go! for severe droughts were found for the districts in grey.

Regarding the average false alarm ratio of the triggers across 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.

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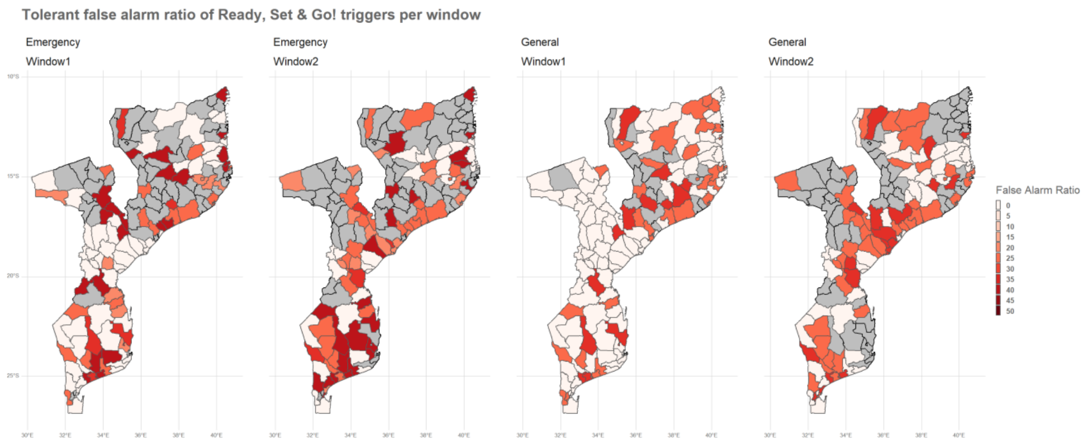

Figure 8: False Alarm ratio of the Ready, Set & Go! Trigger system for severe droughts for two trigger menu (emergency and general) and two windows of intervention (window 1 and window 2). No trigger for the Ready, Set & Go! for severe droughts were found for the districts in grey.

4. DISCUSSION, LIMITATIONS AND NEXT STEPS

In this study, we present the technical approach adopted by the Ready, Set & Go! trigger system which is used by Mozambican governmental institutions and their implementing partners for supporting AA activities against droughts. We show that the Ready, Set & Go! optimizes the use of seasonal forecast information by finding triggers for AA based on a double confirmation process, which combines longer lead time with shorter lead time forecast information for issuing alerts. We observe that by using ensemble bias corrected and raw rainfall forecasts, AA activities against droughts could be scaled up, on average, to 76% of Mozambican districts. National coverage against severe droughts could be reached to 87% of all districts if targeting only the first window of the rainy season (general triggers). This means that seasonal forecasts are able to reliably inform AA, as per multi-institutional criteria, several months ahead of the onset of severe droughts. This shows a potential for a major national scale up of current AA pilots, contributing to the ambitious goals of the Maputo Declaration in which governments committed to expand early warning systems in Southern Africa region (SADC, 2022). At the global level, our Ready, Set & Go! System also partially contributes to the *Early Warning for All* initiative that seeks to ensure that everyone 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 increased climate information portfolio for the National Meteorological and Hydrological Services with a direct application downstream. However, there are limitations and opportunities for further improvements of the system, which we discuss in the paragraphs below.

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With the Ready, Set & Go! Trigger system, we ultimately seek to bring AA and reliable early warning information for all districts in Mozambique. Although we are not yet fully able to achieve this goal with the techniques adopted, we believe that refining the bias correction methodology may further leverage the system. Bias correction is considered a key component of precipitation forecasts and QM is one of the most commonly technique applied. For setting up the AA trigger' system, we developed and assessed a bias correction methodology in order to identify opportunities for increasing the skill of the seasonal forecast in predicting severe droughts. Despite increasing skill for 24% of all forecasted SPI (at the district level) and increasing AA coverage by 4% (Table 3, scenario 3 compared to 4), there are currently improvements that can be taken to advance the bias correction approach, which we describe below.

Firstly, our method uses an ENSO-informed process for selecting samples to build the bias correction transfer function. This seeks to ensure that the bias correction adjusts rainfall quantities according to the climatology of rains during different ENSO phases and therefore capturing relevant global processes (Manzanas & Gutiérrez, 2019; Maraun et al., 2017). In practice, this means that the time series of SPIs, extracted from both CHIRPS and ECMWF ensemble forecasts, are split into Neutral, La Niña and El Niño years depending on the actual and retrospective prevalent phase of ENSO (overview in Supplementary Material S1). However, for some regions in Mozambique, the ENSO-rainfall signal is less present, such as the rainfall from October to December in parts of Tete (WFP, 2018). Therefore, using only an ENSO informed process may not be the ideal approach given the weak ENSO-rainfall link. In addition, there are other modes of climate variability such as the Indian Ocean Dipole which is well known to drive year to year rainfall variability in the country (B. A. et al., 2021; Ficchì et al., 2021; Harp et al., 2021). This creates the need for further investigating the suitability of other modes of teleconnections to the Mozambican climate in the bias correction approach. 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).

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Furthermore, we show the potential for scaling up AA using rainfall seasonal forecast from the ECWMF. In our setup, seasonal forecast is downscaled from 1 to 0.25 degrees via bilinear interpolation, which enables forecasting skill to be assessed at the district level. Being able to extract drought alerts at the district level is key in order to match the geographical targeting of AA interventions. However, further investigation could be done to evaluate other suitable downscaling techniques, such as ML, which was shown to increase the skill of forecasts (Jin et al., 2023). Furthermore, ECMWF was initially chosen as the main source of forecasting information mainly motivated by the known higher skill in predicting precipitation over the African continent in comparison to other centers (Gebrechorkos et al., 2022). However, future studies could benefit from moving from a single center to a Multi-Model Ensemble (MME) approach. MME links independent models emerging from different producing centers of forecasting information, and its key at reducing the effect of individual model errors which in turn can improve 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

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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 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.

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 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).

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5. CONCLUSIONS AND RECOMMENDATIONS

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 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:

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- 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.

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