Food and Agriculture Organization of the United Nations

Technical Working Paper

Exploring the application of Artificial Intelligence for triggering drought anticipatory action:

A Timor-Leste case study

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Abbreviation

AA	Anticipatory Action
AI	Artificial Intelligence
ASEAN	Association of Southeast Asian Nations
C3S	Copernicus Climate Change Service
CDI	Combined Drought Index
DMI	Dipole Mode Index
ECMWF	European Centre for Medium-Range Weather Forecasts
ENSO	El Niño-Southern Oscillation
FAO	Food and Agriculture Organization of the United Nations
FGD	Focus Group Discussions
GCF	Green Climate Fund
GFFO	German Federal Foreign Office
GIEWS	Global Information and Early Warning System
HSS	Heidke Skill Score
IOD	Indian Ocean Dipole
IPC	Integrated Food Security Phase Classification
KII	Key Informant Interviews
MALLF	Ministry of Agriculture, Livestock, Forestry, and Fisheries
NGO	Non-government organization
RMSD	Root mean square difference
SFERA	Special Fund for Emergency and Rehabilitation Activities
SMAPI	Soil Moisture Anomaly Percentage Index
SPI	Standard Precipitation Index
SPI1	Standardized Precipitation Index 1
SPI3	Standardized Precipitation Index 3
TCI	Temperature Condition Index
UNEP	United Nations Environmental Programme
UNRCO	United Nations Resident Coordinator's Office
VCI	Vegetation Condition Index
WASH	Water, sanitation and hygiene
WMO	World Meteorological Organization

Executive summary

For many decades, humanitarian assistance has focused on response, initiating both funding and operational activities only after disaster impacts had been recorded. In recent years, numerous humanitarian actors have united their efforts to complement traditional, reactive mechanisms with a proactive approach that can be activated before a disaster strikes. Anticipatory Action (AA) leverages forecasts of extreme weather events, coupled with risk information, to identify and implement locally led actions. The ultimate goal is to protect lives and livelihoods more efficiently and with greater dignity for populations at risk of predictable disasters. AA remains a relatively novel approach, with much still being explored on how it can be deployed and scaled up.

This research describes the process of developing an agricultural drought-triggering methodology for AA within the context of Timor-Leste, an Indo-Pacific nation grappling with limited observation data. Drought is a severe and recurring natural hazard in Timor-Leste, significantly impacting livelihoods and exacerbating food insecurity due to the compounding effects of the climate crisis. This study provides a comprehensive understanding of the methodology's development, highlighting the collaborative establishment of an AA protocol with the government and the humanitarian community, spearheaded by the Food and Agriculture Organization of the United Nations and the Government of Timor-Leste. Overall, this study aims to facilitate a transition towards a preemptive approach for disaster risk management and highlight the advances of the introduction of Artificial Intelligence (AI) moving forward.

1. Introduction

Climate change poses various challenges to agriculture and water, sanitation and hygiene (WASH). The frequent incidence of extreme weather and climate events, including heatwaves, droughts, heavy rainfall with landslides, and floods in recent years, serves as compelling evidence of climate change (Isaev, Ermanova, *et al*., 2022). Timor-Leste is one of the most vulnerable countries in the Indo-Pacific region – and among the top 20 in the world – in terms of climate change impacts, according to the World Risk Report 2020 (Behlert *et al*., 2020). This vulnerability arises primarily from its climate-sensitive agricultural systems and a lack of adaptive capacity (Secretariat of State for Environment, Coordinating Minister for Economic Affairs, 2021). More than 70 percent of the population relies on climate sensitive, rain-fed agriculture as their main source of income. Food security is a primary challenge due to low yields and post-harvest losses, likely to be compounded by higher temperatures, rainfall intensity and sea level rise (Agency for International Development, 2017). Overall, 79 percent of all households are engaged in crop production, with maize, rice, cassava and vegetables being the most common crops. When only accounting for the rural population, this number rises to 95 percent (National Statistics Directorate of the Timor-Leste, 2015). Of the total population, 36.8 percent live in urban areas, while 63.2 percent reside in rural regions (Population and Housing Census, 2023).

Production of maize and rice, the country's staple crops, is already insufficient to meet current domestic demand (U.S. Agency for International Development, 2017). Drought and higher temperatures have had devastating impacts on the yields of crops such as maize. In coastal areas, high temperature induces evaporation from rising groundwater levels, which increases salt concentration in the rooting zones of plants and stunts their growth and productivity (Barnett, Dessai and Jones, 2007). For example, maize production fell by 40 percent and rice production by 57 percent during the 2016 El Niño, which marked one of the most severe cycles on record (U.S. Agency for International Development, 2017). According to assessments carried out in 2016 by the United Nations Resident Coordinator's Office (UNRCO) in Timor-Leste, the worst affected areas have been the coastal plains in the eastern and southwestern parts of the country, where population density is high. These are the municipalities of Covalima, Lautem, Viqueque, Baucau and the special economic zone of Oé-Cusse (UNRCO, 2016). After crop production, livestock rearing constitutes the second most important income source. A Rapid Drought Impact Assessment by the Food and Agriculture Organization of the United Nations (FAO) in 2016 found that 48 percent of the respondents reported at least one dead animal and the 21 percent had one sick animal, particularly in the municipalities of Baucau, Ermera and Viqueque.

Timor-Leste's vulnerability and exposure to drought impacts is exacerbated by multiple climate hazards and compounding socioeconomic factors. Alongside long-term structural issues, such as low incomes and poverty, the floodings in 2021, 2022 and 2023, as well as the COVID-19 pandemic, have stretched community resilience, negatively impacting agricultural production. In 2023, more people were in the crisis level of food insecurity, based on the Integrated Food Security Phase Classification (IPC), than before the 2015–2016 drought (IPC, 2023). Timor-Leste imports roughly 60 percent of its food, providing a high level of exposure to inflation in the regional and global food market (IPC, 2023). Food inflation is being influenced by the war in Ukraine, with the FAO All Rice Price Index reporting a 31.2 percent increase in August 2023 from August 2022 (FAO, 2023). A decrease in agricultural production due to drought, coupled with an increase in regional and global demand risks, exacerbates the problem of affordability of food for communities in Timor-Leste, increasing food insecurity.

Another sector that is vulnerable to drought is WASH. Limited access to safe drinking water is and will continue to be a significant challenge in Timor-Leste (Secretariat of State for Environment, Coordinating Minister for Economic Affairs, 2021). Groundwater resources are replenished by rainfall during the wet season, serving as storage for year-round use. However, increased demand for domestic, industrial and agricultural purposes is straining this resource. For instance, access to water sources is a key concern, as nearly 40 percent of the population relies on water sources that are 30 minutes or more away on foot (Secretariat of State for Environment, Coordinating Minister for Economic Affairs, 2021).


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Drought significantly impacts livelihoods and exacerbates food insecurity due to the compounding effects of climate change and population growth in Timor-Leste. However, there is no existing sustainable drought monitoring, forecasting, and triggering system in place to enable Anticipatory Action (AA) in the small island country. Compared to late responses to disasters, the AA approach can provide a higher return on investments (Global Commission on Adaptation, 2019). Empirical studies suggest that every USD 1 invested in AA can have a return of up to USD 7.1 in avoided losses and added benefits (FAO, 2023).

Also known as Forecast-based Financing or Early Warning Early Action, AA is an increasingly common approach to disaster risk management that allows for the release of funding and the triggering of actions before a hazard or impact occurs, based on scientific forecasts. Advances in technology, meteorology, and data availability and sharing have enabled increasingly accurate predictions of the occurrence and impact of disasters. With this comes the impetus to adopt approaches that are preventive and protective to shield household assets, livelihoods, and economic gains. The goal of AA is to support risk-exposed groups in building resilience over time by investing in predictable and effective assistance mechanisms that are activated prior to an event occurring.

As of early 2023, Timor Leste also started its ascension to the Association of Southeast Asian Nations (ASEAN). This comes at an opportune time as the intergovernmental body released in mid-2022 the ASEAN Framework on Anticipatory Action in Disaster Management, which sets out three essential building blocks that must be functional for an AA system to be effective: 1) risk information, forecasting, and early warning systems with a clear triggering methodology and thresholds; 2) planning, operations, and delivery with appropriate activities that can be executed promptly; and 3) pre-arranged finance with sufficient funds available when needed, which are flexible and agile (ASEAN, 2022). The Framework is the first globally to recognize AA into intergovernmental systems, leading the way to support ASEAN Member States in crafting a common language, objectives and ambition for the global community working on AA (ASEAN, 2022).

The scope of this study explores the development of an AA protocol – a standard operating tool for bringing the AA concept from theory to reality – for drought in Timor-Leste. It incorporates the three building blocks, but inherently, our core focus is on the first two. This AA protocol is planned to be tested with the Government of Timor-Leste and FAO, with an open invitation for partners to test the AA protocol as well.
This research pioneers the description of the process involved in developing an agricultural drought-triggering methodology for AA within the context of Timor-Leste, a country with limited observation data but with the potential to showcase how innovative methods can be applied to ensure drought risk is adequately monitored and managed. The authors have also developed a framework to assess how these methodologies can be utilized effectively for lead time-dependent decision-making, incorporating different phases based on the crop calendar.
The methods and the results support the development of drought AA protocols and other AA guidelines for the Indo-Pacific region.

2. Materials and methods

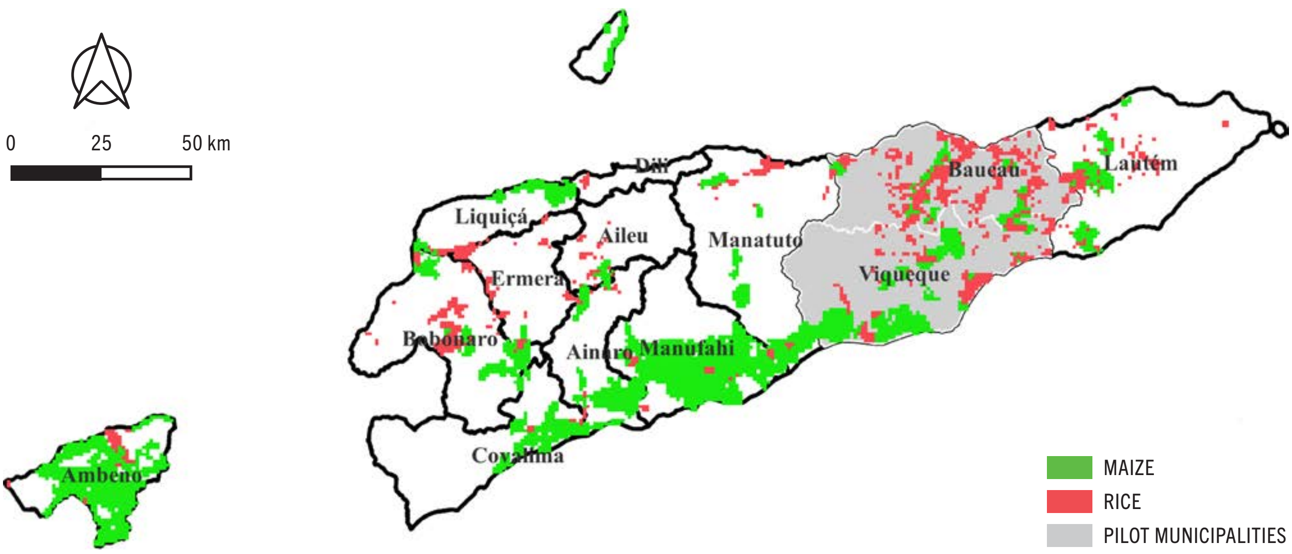
2.1 Study site

Timor-Leste is a small country situated between 8.1 and 9.5°S and 125.0 and 127.3°E (Figure 1). It also encompasses the small enclave of Oecussi, located between 9.2 and 9.5°S and 124.1 and 124.5°E, situated in the western half of the island within West Timor (Molyneux *et al*., 2012). The total land area is 14 874 km². Majority of the land has a slope of 8–25 percent, and 44 percent of the land has a slope higher than 40 percent (Barnett, Dessai and Jones, 2007). While there is minimal land leveling, slopes as steep as 40 percent are cultivated for crops such as maize, cassava, peanuts, sweet potatoes, rice and beans (U.S. Agency for International Development, 2017).

Timor-Leste has two seasons in terms of the rainfall regime. The wet season is December–May, and the dry season is June–November. Depending on the rainfall, the staple crop season, such as for maize and rice, is approximately 70 percent during the wet season and 30 percent during the dry season. However, the proportion of the crop calendar may change from municipality to municipality (Timor-Leste's National Adaptation Plan, 2021):

An analysis of historical drought impacts using yield data and consultations with the Ministry of Agriculture, Livestock, Forestry, and Fisheries (MALFF) of Timor-Leste revealed that during previous drought years, the Baucau and Viqueque municipalities (Figure 1) were the most severely affected areas in terms of agriculture. Hence, the decision was made to pilot and develop a drought-triggering methodology for AA in these two municipalities.

FIGURE 1: STAPLE CROP PLANTING LANDS, TIMOR-LESTE



NOTE: LANDS PLANTED TO MAIZE ARE SHADED IN GREEN; LANDS PLANTED TO RICE ARE SHADED IN RED. THE BAUCAU AND VIQUEQUE PILOT MUNICIPALITIES ARE SHADED IN GREY.

SOURCE: AUTHORS' OWN ELABORATION. MAP CONFORMS WITH UN. 2011. MAP OF TIMOR-LESTE. NEW YORK, UNITED STATES OF AMERICA

2.2 Data

Two sources of impact data were used in this research. One source is the loss and damage data for Timor-Leste, obtained from the reported damage in various reports (UNRCO, 2016; USAID, 2017; *Timor-Leste's National Adaptation Plan*, 2021). The other is from MALFF, resulting in several weather and climate events, with damage expressed in terms of affected area and production loss at regional and subregional levels. Events of relevance to this work include El Niño, erratic rainfall, water stress and drought. The dataset covers the period 2000–2020. The summary of drought events identified in this dataset is presented in Table 1. The second source utilized municipality-level harvest area and production volume data for maize and rice obtained from MALFF for the period 2011–2022 for both Baucau and Viqueque municipalities. In addition, the country level yield data of coffee, maize and rice were obtained from FAOSTAT portal (https://www.fao.org/faostat/en/#data/QV) for the period 1993–2022. These data were used for verification of drought triggering methodology.

TABLE 1: DAMAGE REPORTED FOR DROUGHT EVENTS

Year	Impact events
2002–2003	The El Niño event resulted in a severe drought, which caused failed harvests across almost the entire country. It is considered the worst drought in the past 30 years.
2004–2005	Erratic rains led to failed harvest.
2005–2006	Late, scarce and erratic rains forced farmers in many rural communities to replant their crops at least three times – in November, December and January – with insignificant difference in results.
2006–2007	In 2006, El Niño caused delays in the typical wet season throughout the country for more than one month. Rainfall pattern remained erratic, and dry spells were reported in some areas until late February 2007, leading to a 30-percent drop in production.
2015–2016	The El Niño event was one of the most intense and widespread, affecting farming communities severely. It put many crops and animals under much water stress and caused thousands of farmers to lose their animals and crops.
2017	As consequence of the El Niño phenomenon, the rainy season of December 2016 – April 2017 was delayed.
2019	Below-average rainfall during the wet period caused localized dry conditions.

SOURCE: AUTHORS' OWN ELABORATION.

Due to the absence of historical rainfall and soil moisture observations, we used the Climate Hazards Group InfraRed Precipitation with Station data, version 2.0 (CHIRPS v2.0). The rainfall estimates from rain gauge satellite observations of the Climate Hazards Center–UC Santa Barbara were found to be adequate to analyze the climate of Timor-Leste for a United Nations Environment Programme (UNEP) feasibility study report (UNEP, 2021). In addition to the UNEP report, we conducted a verification analysis comparing CHIRPS rainfall data with 4.8 km spatial resolution and the fifth generation European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis data (ERA5-Land) with 11.1 km spatial resolution. This analysis aimed to identify the most accurate rainfall dataset for analysis in Timor-Leste. ERA5-Land data is freely available from the Copernicus Climate Data Store.

In Timor-Leste, the longest historical *in situ* observations are available only for the Manufahi and Dili meteorological stations from 2004 to 2022, which were used in the verification of CHIRPS and ERA5-Land rainfall datasets.

This limitation informed our choice to use either CHIRPS or ERA5-Land rainfall data in developing the drought-triggering methodology in the pilot municipalities of Baucau and Viqueque. We also used the satellite observations data at a resolution of 9 km surface (0–10 cm); the root-zone (0–100 cm) Soil Moisture Anomaly Percentage Index (SMAPI) (Dorigo *et al*., 2017; Das *et al*., 2018); the Vegetation Health Index (VHI) based on satellite observations with a 1 km spatial resolution from the FAO portal (Global Information and Early Warning Sysyem (GIEWS), 2023); and the monthly indices for modes of climate variability such as El Niño (Nino 3.4) and Indian Ocean Dipole Mode Index (DMI) from the Tokyo Climate Center (Tokyo Climate Center, 2023), were used.

The seasonal forecasts of ECMWF's SEAS5 that were used for this study were retrieved from the Copernicus Climate Change Service (C3S) through the Climate Data Store. The monthly total rainfall reforecasts (or hindcasts) from 1993 to 2016 and the forecast from 2017 to 2023 were used with spatial resolution 1°×1°.

2.3 Methods

2.3.1 Agricultural drought indices

Agricultural drought, a severe agrometeorological phenomenon, and an integral part of climate variability, often affects various regions in Timor-Leste. However, it is difficult to establish the frequency of occurrence of droughts in the country due to the lack of historical data.
To perform a drought analysis, an indicator for forecast and monitoring is needed to accurately determine wet and dry periods. Many researchers have proposed several indicators of drought, which were all given in the guide to indicators and the indicators of aridity of the World Meteorological Organization (WMO), according to Svoboda and Fuchs (2016). The agricultural drought-triggering methodology analyses are framed towards understanding two aspects: the precursors of impact and the predictors of drought. The first allows an understanding of the historical impact, which helps in recognizing the initial stages of drought and potentially informing timely intervention strategies to mitigate its impacts on agriculture. By identifying these predictors, analysts can anticipate with confidence the probability of drought events occurring in the coming seasons. The variables reflecting the precursors of impact do not necessarily have to show a direct relationship between their status and future drought, although they might signify vulnerability to droughts and thus affect the magnitude of impact of an eventual climatological drought. These variables include soil moisture, vegetation, and vegetation index, as well as current rainfall anomalies. Variables considered as predictors of future drought include the El Niño-Southern Oscillation (ENSO) Index and the IOD Index. To address the methodology for triggering drought, we propose a Combined Drought Index (CDI) in this research. We employ rainfall, soil moisture and vegetation monitoring indices, as well as a 3-month rainfall forecast enhanced by rainfall predictors such as ENSO and IOD indices. This approach is necessary due to the limited accuracy of seasonal rainfall forecasts.

Many drought indices derived from remote sensing data have been developed and used to effectively detect drought conditions all over the world (Park *et al*., 2021; Chang *et al*., 2024). Because drought stresses vegetation, the extent of a drought can be reflected by changes in the vegetation index. A combination of different indices representing vegetation stress, water deficit and soil moisture status can describe the severity of and changes in drought better than each index in isolation. A typical drought indicator, the VHI, was proposed by Kogan (Kogan, 1995; Kogan *et al*., 2004) and was based on the combination of Vegetation Condition Index (VCI) and Temperature Condition Index (TCI).
For example, the User-Centred Integrated Early Warning System for Drought in Papua New Guinea (Bhardwaj *et al*., 2021) used the VHI and Standard Precipitation Index (SPI) (Beguería *et al*., 2013; Svoboda and Fuchs, 2016). As Papua New Guinea is located in close proximity to Timor-Leste and shares the same atmospheric circulation patterns, in this research we utilized previously verified VHI indices (Bhardwaj *et al*., 2021) with the meteorological drought index SPI. Table 2 presents the drought classes used for SPI (Svoboda and Fuchs, 2016), VHI (Kogan *et al*., 2004), and SMAPI (Luong, Hiep and Bui, 2021).

TABLE 2: DROUGHT CLASSES FOR VARIOUS INDICES

Drought indices	No drought	Mild drought	Moderate drought	Severe drought	Extreme drought
SPI	0.00 <	-0.99 to 0.00	-1.49 to -1.00	-1.99 to -1.5	-2.00 >
SMAPI	-0.05 <	-0.15 to -0.05	-0.30 to -0.15	-0.50 to -0.30	-0.50 >
VHI	0.40 <	0.30 to 0.40	0.20 to 0.30	0.10 to 0.20	0.00 to 0.10

NOTE: SPI = STANDARD PRECIPITATION INDEX; SMAPI = SOIL MOISTURE ANOMALY PERCENTAGE INDEX; VHI = VEGETATION HEALTH INDEX.

SOURCE: SVOBODA, M. AND FUCHS, B.A. (2016) HANDBOOK OF DROUGHT INDICATORS AND INDICES | WORLD METEOROLOGICAL ORGANIZATION. GENEVA: WMO. AVAILABLE AT: https://public.wmo.int/en/resources/library/handbook-of-drought-indicators-and-indices.

Moreover, in 2009, the WMO recommended using SPI for drought monitoring, which has been adopted in research or operational practices by more than 70 countries (Svoboda and Fuchs, 2016). "SPI depth" denotes the precipitation sum for the number of months used in the calculation. The WMO recommends using the following SPI depth classification for detecting different drought types: 1 to 2 months for meteorological drought; 3 to 6 months for agricultural drought; 6 to 12 months or more for hydrological drought. In this study, the anticipatory action is set up with a focus on agricultural drought. We propose to use a 1-month standard precipitation forecast (SPI1), which measures meteorological drought, monthly mean VHI, and monthly mean SMAPI, along with a 3-month standard precipitation forecast (SPI3) that provides a 3-month lead time before the crisis reaches its peak. For historical CDI calculations, the SPI3 forecasted index is derived from bias-corrected ECMWF seasonal forecast.

The main idea behind the CDI for identifying agricultural drought is an idealized cause–effect relation between rainfall deficit and yield. There are different steps in this relationship: a rainfall deficit (step 1) leads initially to soil moisture deficit (step 2), which, if prolonged over time, will result in crop water stress and be reflected in the VHI observed (step 3). This finally generates a reduction in yields (step 4). That's why the CDI aims to monitor the current condition of the rainfall deficit with SPI1, the monthly soil moisture with SMAPI, and the vegetation condition with VHI, along with the forecasted 3-month rainfall with SPI3. In Table 3, the proposed and tested CDI classes are presented. This approach monitors meteorological drought and predicts agricultural drought, involving processes spanning more than 4 months in the atmosphere and Earth surface interaction. In its simplest form, this CDI would allow us to identify which cause–effect relationship phase the agricultural system has reached in the event of a drought and when to start the activation of the Anticipatory Action (AA) protocol.

TABLE 3: COMBINED DROUGHT INDEX CLASSES

CDI	No drought	Mild drought	Moderate drought	Severe drought	Extreme drought
SPI3	0.00 ≤	0.00 >	-1.00 ≥	-1.00 ≥	-1.50 ≥
SPI1	0.00 ≤	0.00 >	0.00 >	-1.00 ≥	-1.00 ≥
SMAPI	0.00 ≤	0.00 >	-0.05 ≥	-0.15 ≥	-0.30 ≥
VHI	0.40 <	0.40 to 0.50	0.40 to 0.50	0.40 >	0.40 >

NOTE: SPI = STANDARD PRECIPITATION INDEX; SMAPI = SOIL MOISTURE ANOMALY PERCENTAGE INDEX; VHI = VEGETATION HEALTH INDEX; CDI = COMBINED DROUGHT INDEX.

SOURCE: AUTHORS' OWN ELABORATION.

2.3.2 Bias-correction of the seasonal forecast

Different statistical approaches have been applied in these bias-corrections of the seasonal forecasts. Several studies have employed machine learning methods to solve different earth- and climate-related problems (Nabavi, Haimberger and Abbasi, 2019; Chang *et al*., 2020; Bolourani *et al*., 2021; Czernecki, Marosz and Jędruszkiewicz, 2021; Park *et al*., 2021; Isaev, Ajikeev, *et al*., 2022). Our research is the first to use machine learning methods in Timor-Leste to bias-correct seasonal rainfall forecast by using rainfall observation, ENSO index and IOD index. Machine learning algorithms can analyze incoming information and look for explicit and hidden patterns in these data. Thus, they represent an extremely powerful modelling approach that facilitates the reproduction of extremely complex dependencies (Isaev, Ermanova, *et al*., 2022). In the machine learning approach used for the monthly parameters with period 1993–2023 (n = 369), 30 percent of the data were allocated for the test and 70 percent for training.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We used machine learning XGBoost Regressor (XGBR) algorithm (Bolourani *et al*., 2021) with Hyperparameter Tuning (HPT), which was found in previous research (Isaev, Ajikeev, *et al*., 2022; Isaev, Ermanova, *et al*., 2022) to be suitable for time–series meteorological data applications. This approach was employed to estimate the dependent 3-month rainfall forecast from a set of potential predictors: rainfall observations, ENSO index and IOD index.

2.3.3 Verification methods

As historical rainfall observations were lacking in the pilot municipalities, we verified the best reanalysis dataset by using available meteorological data from the Manufahi and Dili stations in another municipality then piloting areas for the period 2004–2022 through the calculation of monthly BIAS. Moreover, the Taylor diagram (Taylor, 2001) was then applied to verify the CHIRPS and ERA5 rainfall observations. Taylor diagrams show correlation statistics of CHIRPS and ERA5 rainfall observations, such as the Pearson correlation coefficient, root mean square difference (RMSD), and standard deviation; thus, they can be used to summarize remote sensing and reanalysis rainfall observation accuracy and consistency (Funk *et al*., 2015). The seasonal rainfall forecast bias-correction model was evaluated using statistical methods to assess errors between actual and bias-corrected data. This evaluation included employing measures such as BIAS and the Taylor diagram.

For the validation of CDI, plots with national yield data for the period 1993–2022 and municipality-level data for the period 2011–2022, along with retrospectively calculated CDI, were analyzed. The Heidke Skill Score or HSS (Heidke, 1926), also known outside of meteorology as kappa (Cohen, 1960), measures the fractional improvement of the forecast over the standard forecast. It was used to evaluate the CDI with SMAPI for the period 1993–2023. The range of the HSS is $-\infty$ to 1. Negative values indicate that the chance forecast is better, 0 means no skill, and a perfect forecast obtains an HSS of 1. For 2×2 contingency tables, following the terminology of Jolliffe and Stephenson (2012) and Table 4, the calculation of HSS is:

$$HSS = \frac{2\,(ad-bc)}{[(a+c)(c+d)+(a+b)(b+d)]} \quad (1)$$

TABLE 4: COMPARISON BETWEEN FORECASTS AND OBSERVATIONS

Event forecast	Event observed	
	Yes	No
Yes	a (hit)	b (false alarm)
No	c (miss)	d (correct rejection)

NOTE: THE SYMBOLS A–D REPRESENT THE DIFFERENT NUMBERS OF CASES OBSERVED TO OCCUR IN EACH CATEGORY.
SOURCE: HEIDKE, 1926.

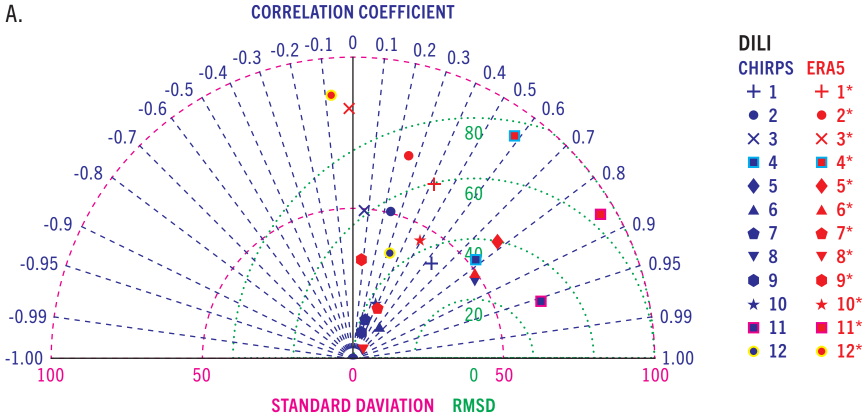
3. Results and discussion

3.1 Verification of rainfall datasets with *in situ* observations

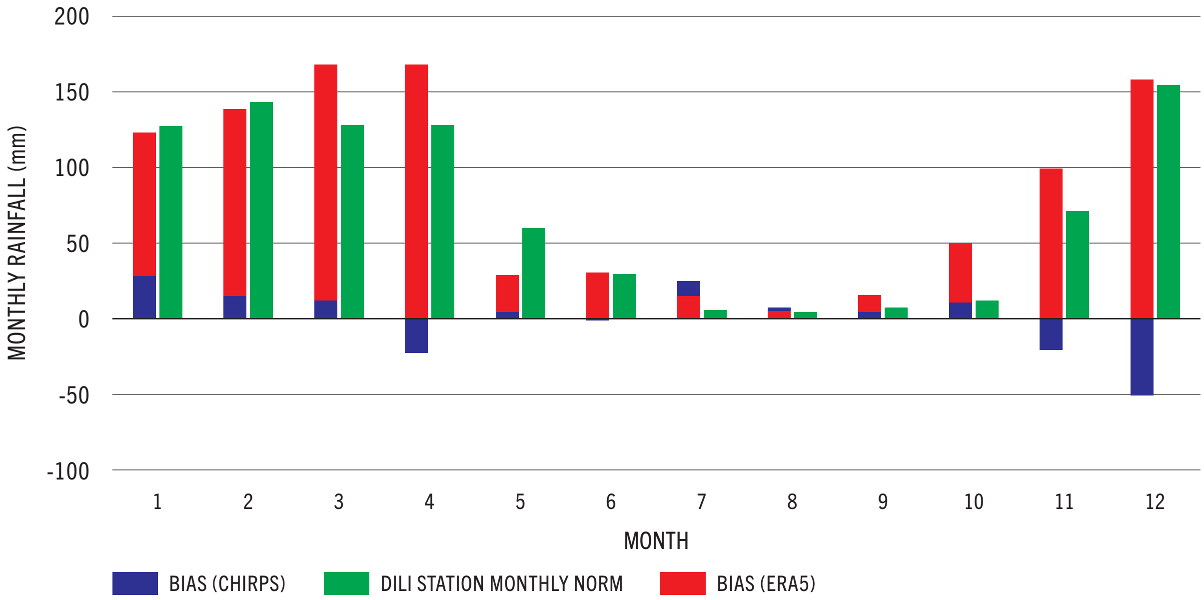
To verify the monthly rainfall from CHIRPS and ERA5, we calculated standard deviation, RMSD correlation coefficient, and BIAS for the Dili meteorological station for the period 2004–2023 (Figures 2A and 2B), and for the Manufahi meteorological station (Figures 2C and 2D). The analysis of the verification statistic metrics shows better accuracy in CHIRPS observations than ERA5 rainfall data. From November to May, both rainfall datasets become less accurate. This can be explained by the cloudy conditions corresponding to these rainy season months. As the CHIRPS rainfall dataset shows better quality, and due to the lack of rainfall observations in the pilot Baucau and Viqueuqe municipalities, we used CHIRPS rainfall data in the later analysis.

FIGURE 1: VERIFICATION OF RAINFALL DATASETS

A.



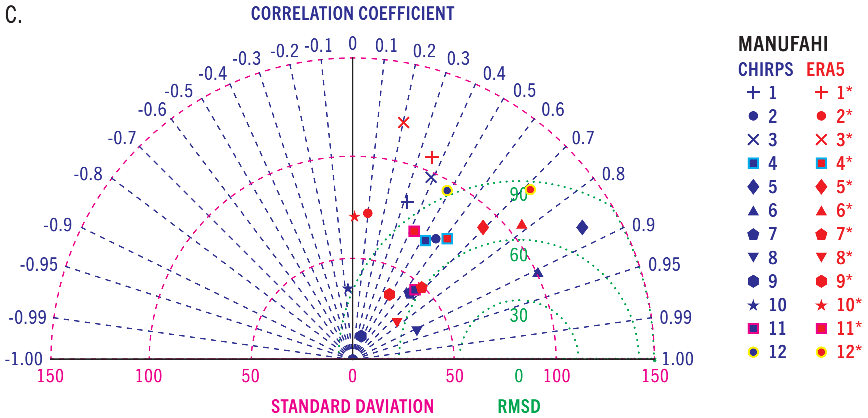
B.



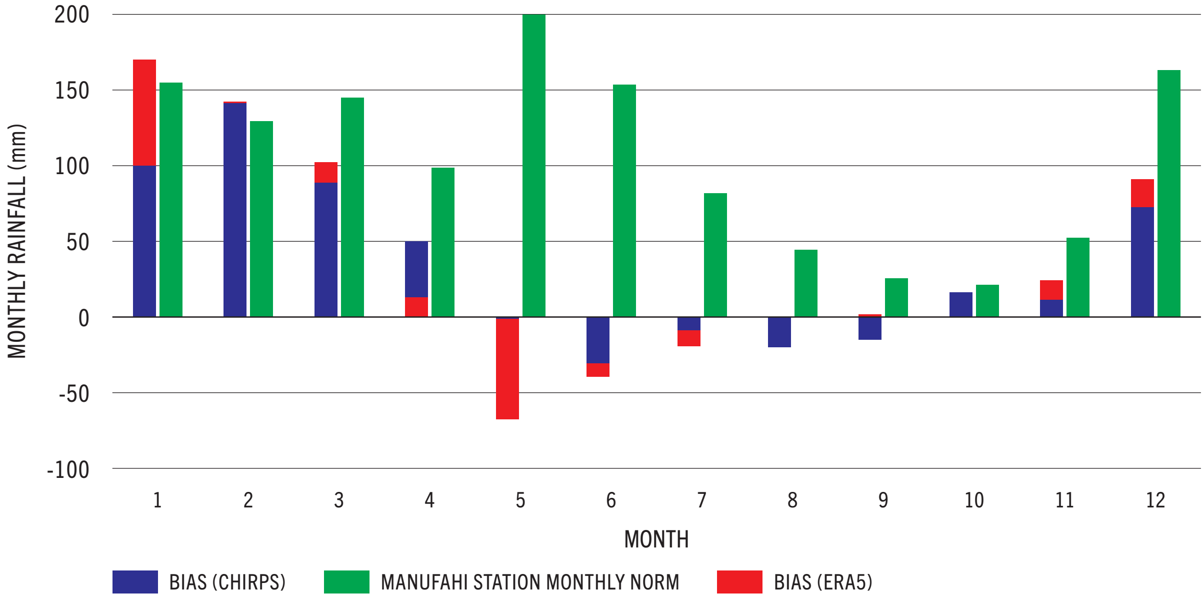
SOURCE: AUTHORS' OWN ELABORATION.

FIGURE 1 *(CONTINUED)*

C.



D.



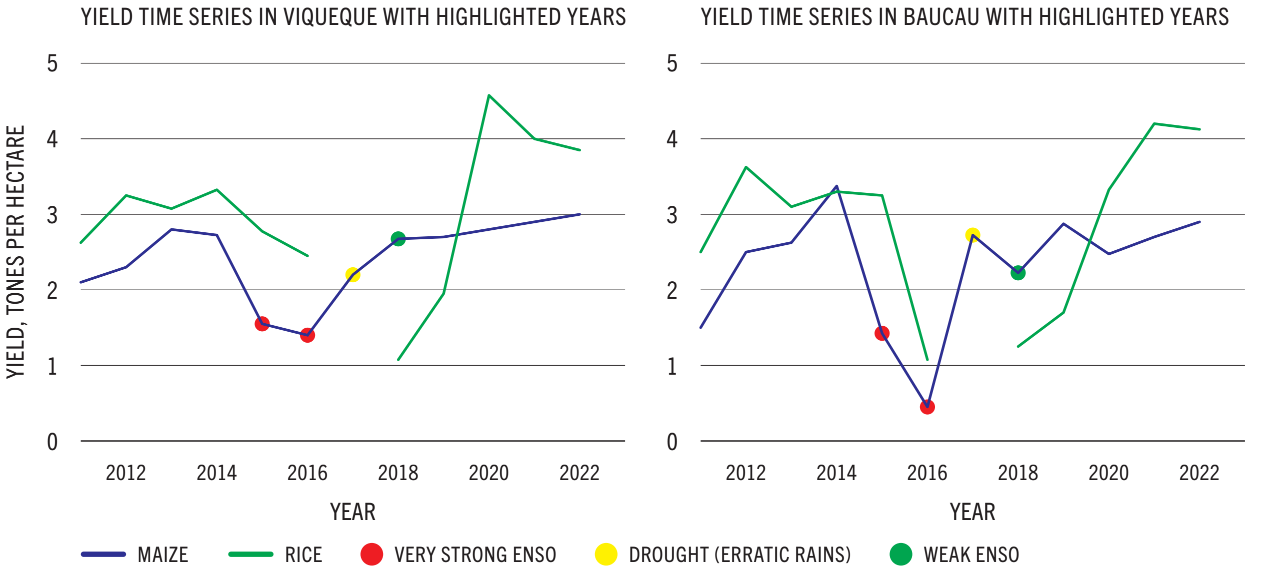
SOURCE: AUTHORS' OWN ELABORATION.

Figure 2A shows a Taylor diagram of the correlation, centred RMSD, and standard deviation between monthly rainfall from CHIRPS and ERA5, as well as monthly data from the Dili meteorological station. The different symbols (1–12) represent months, and the sample period is 2004–2023. Figure 2B shows the BIAS of monthly rainfall derived from CHIRPS in blue and ERA5 in red, and the monthly rainfall norms from the Dili meteorological station in green. Figure 2C shows a Taylor diagram of the correlation, the centred RMSD, and standard deviation between monthly rainfall from CHIRPS and ERA5 and from the Manufahi meteorological station. The different symbols (1–12) represent months, and the sample period is 2004–2023. Figure 2D shows the BIAS of monthly rainfall derived from CHIRPS in blue and ERA5 in red. The monthly rainfall norms of Manufahi meteorological station are in green color, and the sample period is 2004–2023.

3.2 Relationship between drought years and drought impacts reported in yield data

Due to the limited data length, a qualitative assessment of the relationship between drought and yield reduction was conducted instead of a correlation analysis. Overall, there is an agreement between data on rice and maize yield productivity and drought related to ENSO, as shown in Figure 3. Yield was reduced significantly during the severe ENSO years of 2015 and 2016, with a slight impact during the weak ENSO event of 2018.

FIGURE 3: RELATIONSHIP BETWEEN DROUGHT YEARS AND DROUGHT IMPACTS REPORTED IN YIELD DATA FOR VIQUEQUE AND BAUCAU MUNICIPALITIES



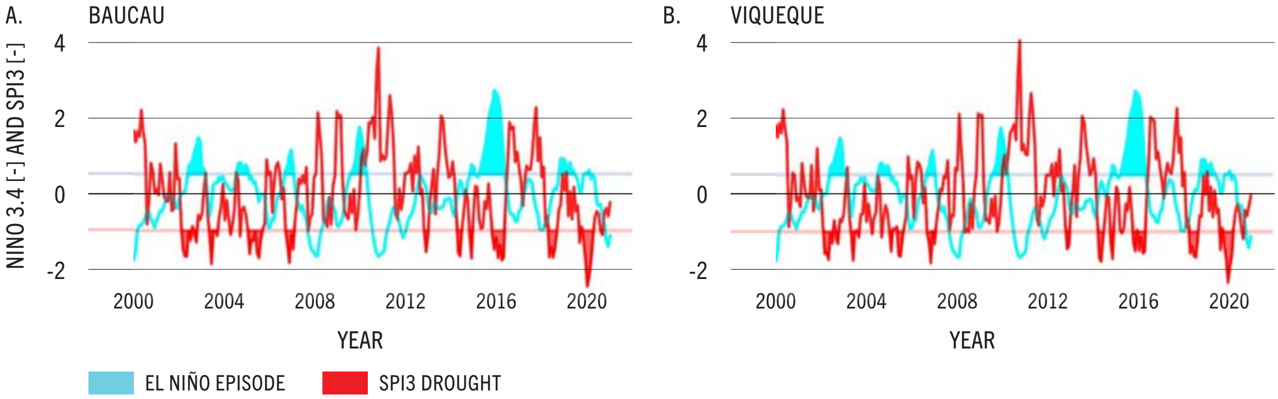
NOTE: ENSO = EL NIÑO-SOUTHERN OSCILLATION.

SOURCE: AUTHORS' OWN ELABORATION.

3.3 El Niño-Southern Oscillation and Indian Ocean Dipole as predictors of drought

It is well known that ENSO, or sea-surface temperature anomalies in the El Niño region of the Pacific Ocean, exerts a very strong influence on atmospheric circulation and, consequently, rainfall in some regions of the world, including Timor-Leste. There appears to be a strong relationship between the state of ENSO and concurrent rainfall in Baucau and Viqueque municipalities, as depicted in Figures 4A and 4B. ENSO is one of the most important sources of climate predictability at seasonal time scales because it varies and evolves relatively slowly, over a time scale of months to a year.

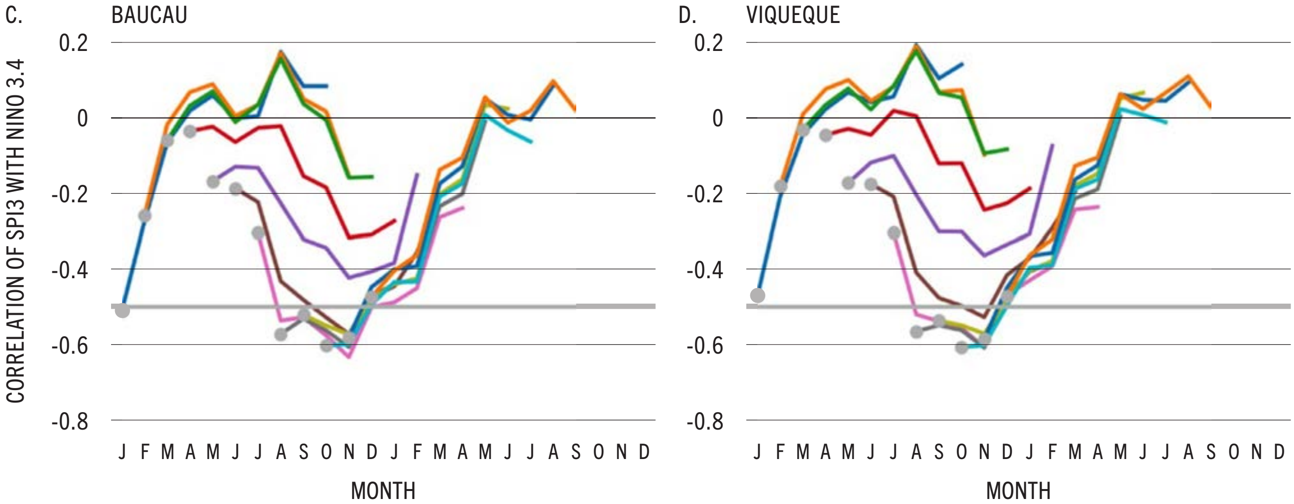
FIGURE 4: TIME SERIES OF NINO 3.4 AND SPI3



NOTE: SPI3 = Standardized Precipitation Index 3

SOURCE: AUTHORS' OWN ELABORATION.

FIGURE 4 *(CONTINUED)*



NOTE: SPI3 = Standardized Precipitation Index 3

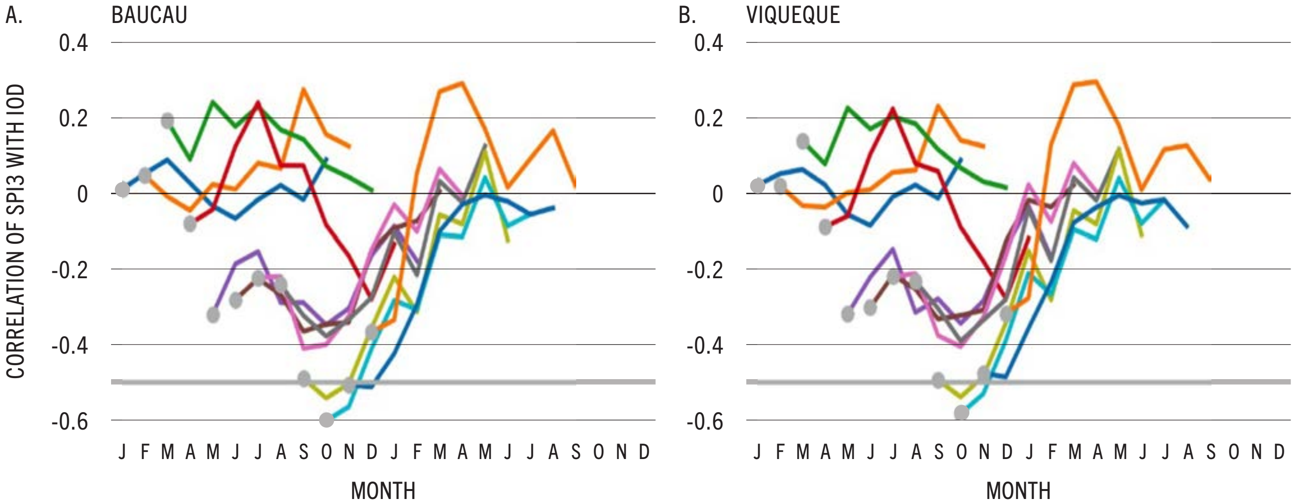
SOURCE: AUTHORS' OWN ELABORATION.

Figures 4A and 4B show a time series of NINO 3.4 with highlighted El Niño episodes, and SPI3; SPI values of -1 or less denote a moderate or stronger drought; The NINO 3.4 Index employs the commonly used threshold of 0.5 to mark El Niño conditions. Figures 4C and 4D show the correlation between NINO 3.4 and SPI3 at various lead times. SPI3 for the nominal month represents data from 3 subsequent months (i.e. data for January will be SPI3 over January–March). Each line represents a correlation between the NINO 3.4 Index on the month marked and the given month's SPI3. Correlation level indicates practically applicable predictive power (-0.5) marked with a grey line.

In Figures 4C and 4D, the NINO 3.4 Index and its relationship with rainfall anomalies over Baucau and Viqueque municipalities, indexed by SPI3, are analyzed. This analysis is conducted to evaluate the role of ENSO as a potential predictor of drought in these areas. We consider two approaches: using the current ENSO as a predictor of future meteorological drought and using the forecasted state of future ENSO as a predictor of future meteorological drought. The strength of the relationship between NINO 3.4 and SPI3 varies significantly between seasons and lead times, with strong relationships enabling practical application in predictive models during the period of August to January in Baucau (Figure 4C) and August to December in Viqueque (Figure 4D).

The IOD is another mode of global climate variability known to influence rainfall over Timor-Leste. Similar to ENSO, it is characterized by persistence at a seasonal time scale. However, the relationship between IOD and rainfall anomalies is weaker compared to ENSO (Figure 5). Only near-concurrent (short lead times) relationships during September–December show potential predictability.

FIGURE 5: CORRELATION BETWEEN THE INDIAN OCEAN DIPOLE AND STANDARDIZED PRECIPITATION INDEX 3



NOTE: SPI3 = STANDARDIZED PRECIPITATION INDEX 3. SP13 FOR THE NOMINAL MONTH REPRESENTS DATA FROM 3 SUBSEQUENT MONTHS (I.E. DATA POINT FOR JANUARY WILL BE SPI3 OVER JANUARY–MARCH). EACH LINE REPRESENTS A CORRELATION BETWEEN IOD ON THE MONTH MARKED AND THE GIVEN MONTH'S SPI3. THE CORRELATION LEVEL INDICATING PRACTICALLY APPLICABLE PREDICTIVE POWER (-0.5) IS MARKED WITH A GREY LINE.

SOURCE: AUTHORS' OWN ELABORATION.

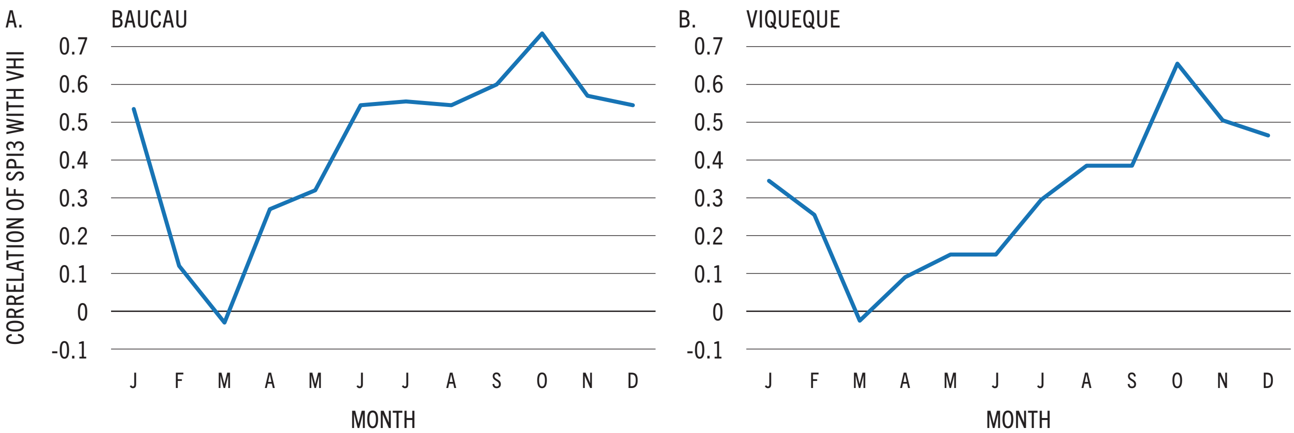
3.4 Antecedent conditions as precursors of impacts of drought

Building towards a CDI, this section evaluates variables that are not predictors of drought but rather reflect antecedent drought conditions. These conditions can lead to the moderation or aggravation of the impact of a meteorological drought. We consider two variables: the VHI and soil moisture content. The purpose of these analyses is to identify whether a signal of the antecedent conditions expressed by these variables can be observed in the available impact indices. As a first step, to provide a backdrop for the analyses of the association between the indices considered here and the impacts, we examine their relationship with meteorological drought as indexed by SPI3. This analysis only considers rainfall anomalies as a driver of these variables, with SPI preceding VHI and soil moisture.

3.4.1 Relationship between Vegetation Health Index and drought

The VHI varies in a similar pattern to SPI3, with a similar character of variability (Figure 6). Correlations between antecedent SPI3 and VHI are relatively strong in June–January but weak in February–May in Baucau. For Viqueque, correlations are strong in September– January and weak in February–August (Figure 6).

FIGURE 6: CORRELATION BETWEEN VEGETATION HEALTH INDEX AND STANDARDIZED PRECIPITATION INDEX 3



NOTE: VHI = VEGETATION HEALTH INDEX; SPI3 = STANDARDIZED PRECIPITATION INDEX 3.

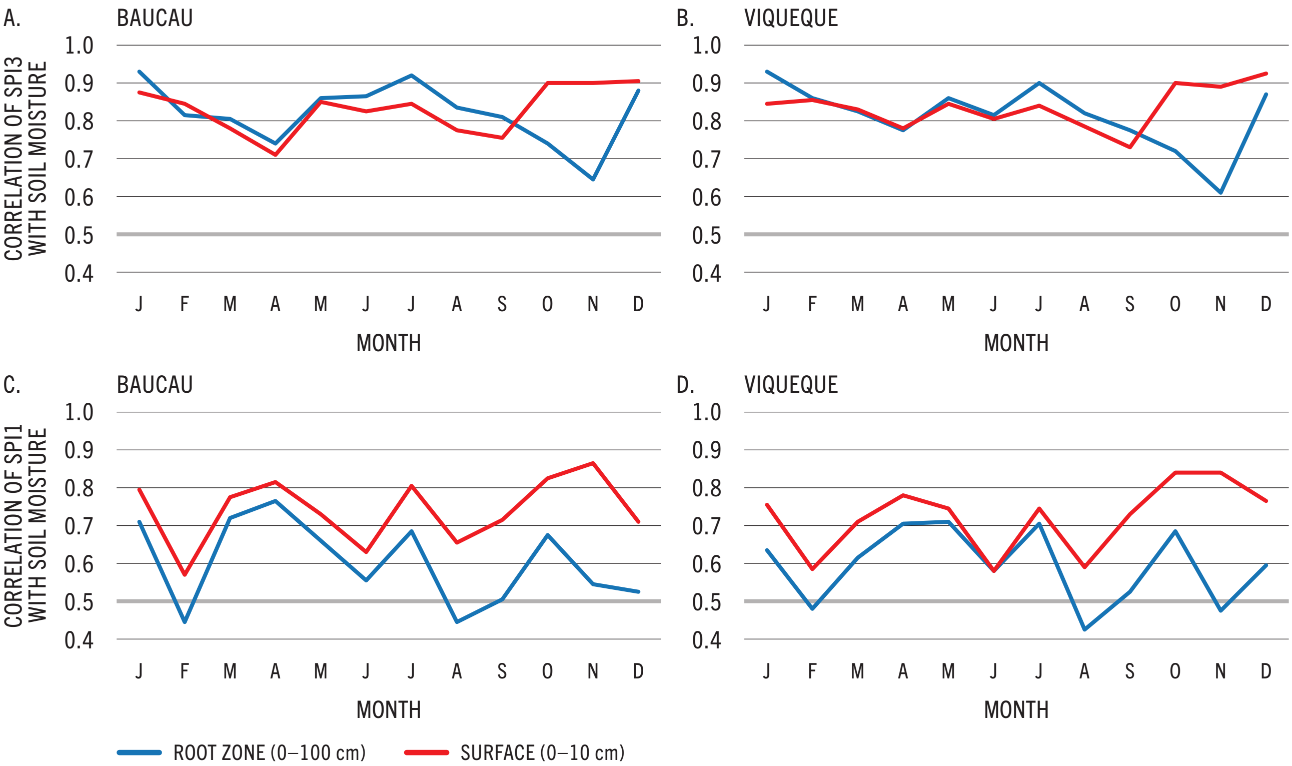
SOURCE: AUTHORS' OWN ELABORATION.

3.4.2 Relationship between soil moisture status and Standardized Precipitation Index

The correlations between SPI3, SPI1 and soil moisture are relatively good overall (Figure 7). From here, we can conclude that soil moisture provides valuable observational data for regions where meteorological observations do not exist.

The surface soil moisture (0-10 cm) exhibits a better correlation with SPI3 during the period October–December compared to root-zone soil moisture (0-100 cm) (Figures 7C and 7D). Similarly, SPI1 and surface soil moisture demonstrate a stronger correlation for all months than root-zone soil moisture (Figure 7) while utilizing root-zone soil moisture is beneficial for agricultural drought monitoring. Therefore, in this analysis, we prioritize the use of root-zone soil moisture, serving as a good indicator of the previous month's rainfall and soil conditions.

FIGURE 7: CORRELATION BETWEEN SOIL MOISTURE ANOMALY AND STANDARDIZED PRECIPITATION INDEX



NOTE: SPI = STANDARDIZED PRECIPITATION INDEX. FIGURES 7A AND 7B SHOW THE CORRELATION BETWEEN SOIL ANOMALY AND SPI3; FIGURES 7C AND 7D SHOW THE CORRELATION BETWEEN SOIL ANOMALY AND SPI1. THE CORRELATION LEVEL INDICATING PRACTICALLY APPLICABLE PREDICTIVE POWER (+0.5) IS MARKED WITH A GREY LINE.

SOURCE: AUTHORS' OWN ELABORATION.

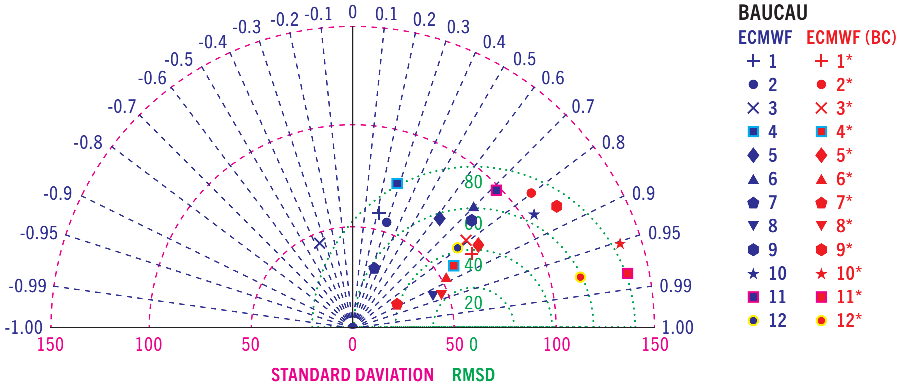
3.5 Verification of the European Centre for Medium-Range Weather Forecasts seasonal rainfall forecast and bias-correction method

To analyze the performance of ECMWF seasonal rainfall forecast and bias-corrected seasonal rainfall forecast with the ML XGBR-HPT algorithm in modeling 3-month rainfall forecasts, we calculated standard deviation, RMSD, and correlation coefficient for the period 1993–2022 (Figures 8A and 8C), and for BIAS from January 2023 to September 2023 (Figures 8B and 8D).

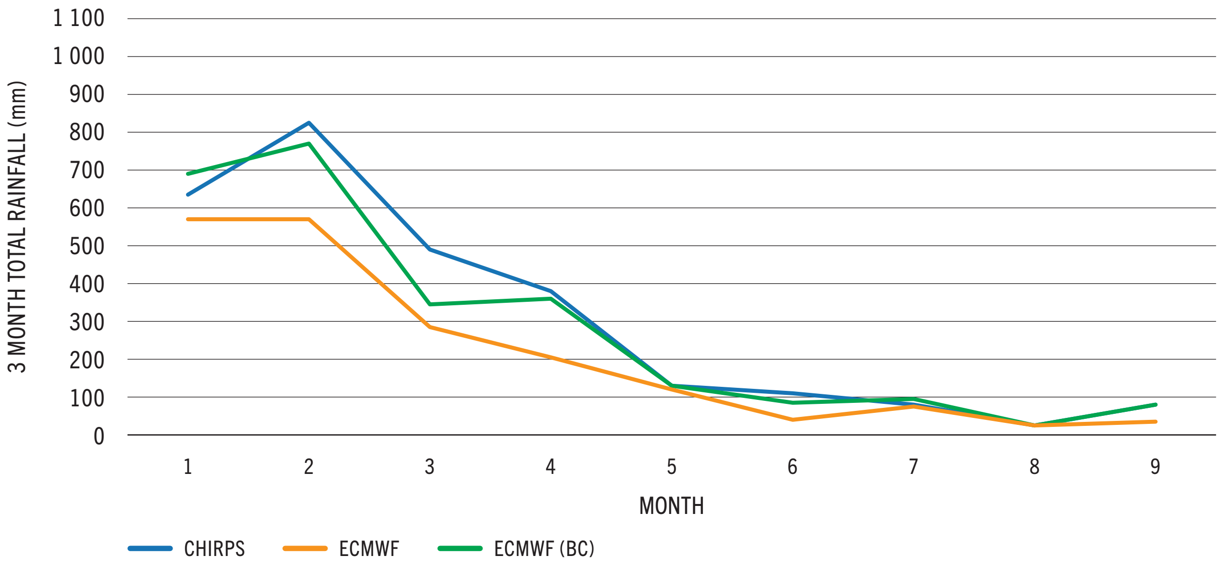
The results of statistical estimations show a higher correlation coefficient and smaller standard deviation with RSMD for bias-corrected ECMWF (BC), indicating better performance than ECMWF. The increased performance in rainfall forecasts was more pronounced during the rainy season from December to May (Figures 8A and 8C).

FIGURE 8: VERIFICATION OF THE EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FORECASTS SEASONAL RAINFALL FORECAST AND BIAS-CORRECTION METHOD

A.



B.

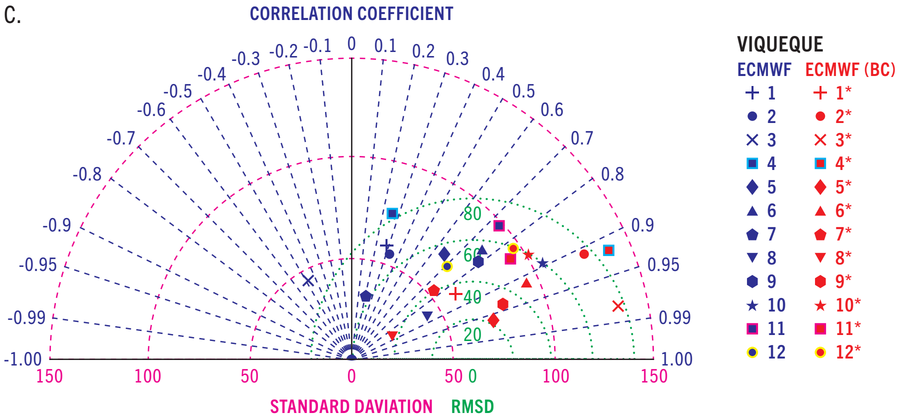


NOTE: ECMWF = EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FORECASTS; RMSD = ROOT MEAN SQUARE DIFFERENCE; BC = BIAS-CORRECTED. FIGURE 8A IS A TAYLOR DIAGRAM OF THE CORRELATION, CENTERED RMSD, AND STANDARD DEVIATION BETWEEN 3-MONTH TOTAL RAINFALL FROM ECMWF IN RED, ECMWF(BC) IN BLACK, AND DATA FROM THE CHIRPS FOR BAUCAU. THE DIFFERENT SYMBOLS (1–12) REPRESENT MONTHS, AND THE SAMPLE PERIOD IS 1993–2023. FIGURE 8B SHOWS THE 3-MONTH TOTAL RAINFALL FORECASTED BY ECMWF IN ORANGE, 3-MONTH TOTAL RAINFALL BIAS-CORRECTED ECMWF(BC) IN GREEN, AND DATA FROM CHIRPS IN BLUE FOR 2023. FIGURE 8C IS THE CORRESPONDING TAYLOR DIAGRAM FOR VIQUEUQE, AND FIGURE 8D IS THE FORECAST WITH OBSERVATION.

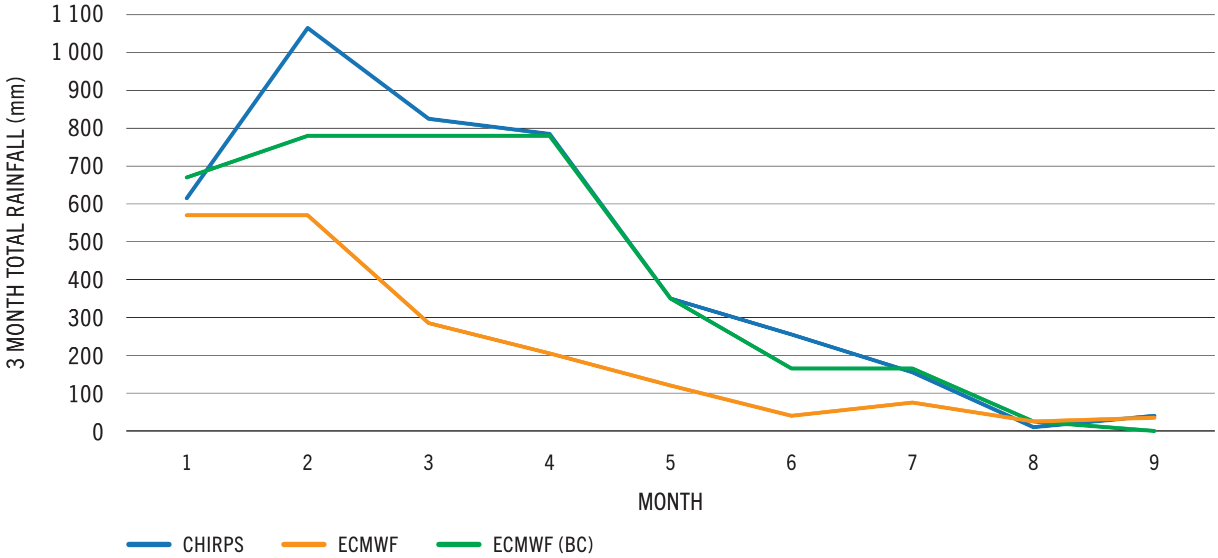
SOURCE: AUTHORS' OWN ELABORATION.

FIGURE 8 *(CONTINUED)*

C.



D.



NOTE: ECMWF = EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FORECASTS; RMSD = ROOT MEAN SQUARE DIFFERENCE; BC = BIAS-CORRECTED. FIGURE 8A IS A TAYLOR DIAGRAM OF THE CORRELATION, CENTERED RMSD, AND STANDARD DEVIATION BETWEEN 3-MONTH TOTAL RAINFALL FROM ECMWF IN RED, ECMWF(BC) IN BLACK, AND DATA FROM THE CHIRPS FOR BAUCAU. THE DIFFERENT SYMBOLS (1–12) REPRESENT MONTHS, AND THE SAMPLE PERIOD IS 1993–2023. FIGURE 8B SHOWS THE 3-MONTH TOTAL RAINFALL FORECASTED BY ECMWF IN ORANGE, 3-MONTH TOTAL RAINFALL BIAS-CORRECTED ECMWF(BC) IN GREEN, AND DATA FROM CHIRPS IN BLUE FOR 2023. FIGURE 8C IS THE CORRESPONDING TAYLOR DIAGRAM FOR VIQUEUQE, AND FIGURE 8D IS THE FORECAST WITH OBSERVATION.

SOURCE: AUTHORS' OWN ELABORATION.

3.6 Early warning and Anticipatory Action

One of the objectives of this research is to ensure the proper monitoring of the likelihood of drought and its potential impact on livelihoods and food security, enabling timely AA. To achieve this, the nature and severity of potential drought will be estimated based on several indicators and corresponding thresholds provided by various sources. It is crucial to acknowledge that while this system has been established, it will require regular testing, revision and calibration in collaboration with stakeholders.

3.6.1 Crisis timelines – a phased approach to slow-onset Anticipatory Action

Crisis timelines serve as tools for untangling the complexities of slow-onset AA. Alongside the drought triggering methodology, this is a critical tool to help launch and provide the blueprint for the AA approach (Levine *et al*., 2020). For the drought hazard, they form the foundation of a phased approach by pinpointing AA windows and suitable interventions. These timelines enable stakeholders to understand how drought triggering can be coupled with actions to mitigate or articulate impacts of the forecast event. These provide an indication on how much time is required for AA implementation, and ultimately, the growing phases of action over time for slow-onset hazards. These timelines further indicate the timing of preparedness and response measures, guiding the integration of AA and facilitating scaled-up support.

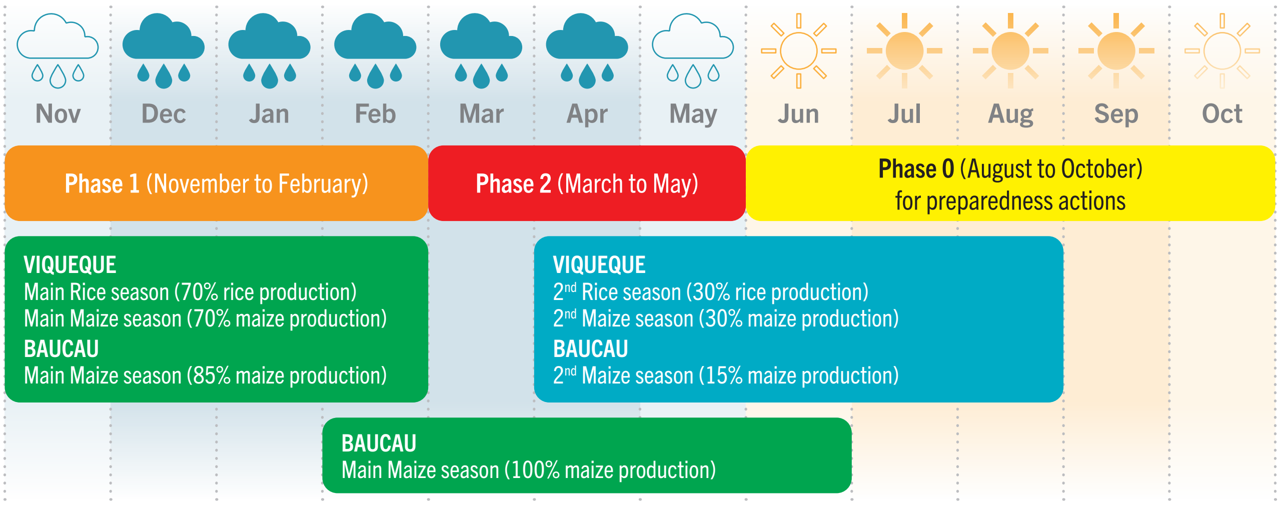
In applying the AA approach to slow-onset hazards, a crucial initial step involves analyzing how seasonal calendars align with the natural hazard in question, including agricultural cycles and livestock movement patterns. After this analysis, determining which activities would be most beneficial during each cycle becomes imperative for effective interventions. This is because different actions need to be taken depending on the phenological stage of the crops.

In Timor-Leste, a crisis timeline was developed in early 2023. Based on consultations with MALFF and an updated crop calendar provided by government counterparts, the following phases were proposed and agreed (visualization provided in Table 5):

- Phase 0 (June–October): The dry season is critical to observe to understand the total output of production, as lower yields have the potential to exacerbate food insecurity in the upcoming phases if they do not suffice. It is mainly growing and harvesting for a second season of maize (30 percent from all annual production) and rice (30 percent from all annual production) in Viqueque and second season for maize (15 percent from all annual production) in Baucau.
- Phase 1 (November–February): This time marks the onset of the rainy season. It provides an opportunity to assess the performance of the dry season and to anticipate the conditions that could persist into the wet season. A mix of both forecast and observation data is recommended. It is mainly growing and harvesting for the first season of maize (70 percent from all annual production) and rice (70 percent from all annual production) in Viqueque, and first season for maize (85 percent from all annual production) in Baucau.
- Phase 2 (March–May): This is the main planting and growing season for rice in Baucau (100 percent) and planting for second season of maize (30 percent from all annual production) and rice (30 percent from all annual production) in Viqueque, and second season for maize (15 percent from all annual production) in Baucau.

TABLE 5: DROUGHT ANTICIPATORY ACTION CRISIS TIMELINE WITH UPDATED CROP CALENDAR

Month		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Seasonality	Main rice season	Sowing			Harvest								
	Second rice season							Growing					
	Main maize season		Harvest								Sowing		
	Second maize season				Sowing				Harvest				
Impact analysis On agriculture and fisheries		Emergence of water shortages					Crop loss/ livestock mortality				Delay in main crop planting		
Emergency response timings Typical peak of need													
Early warning and anticipatory action timings	Early warning monitoring			Phase 2					Phase 0			Phase 1	
	Anticipatory action			Phase 2						Phase 0		Phase 1	



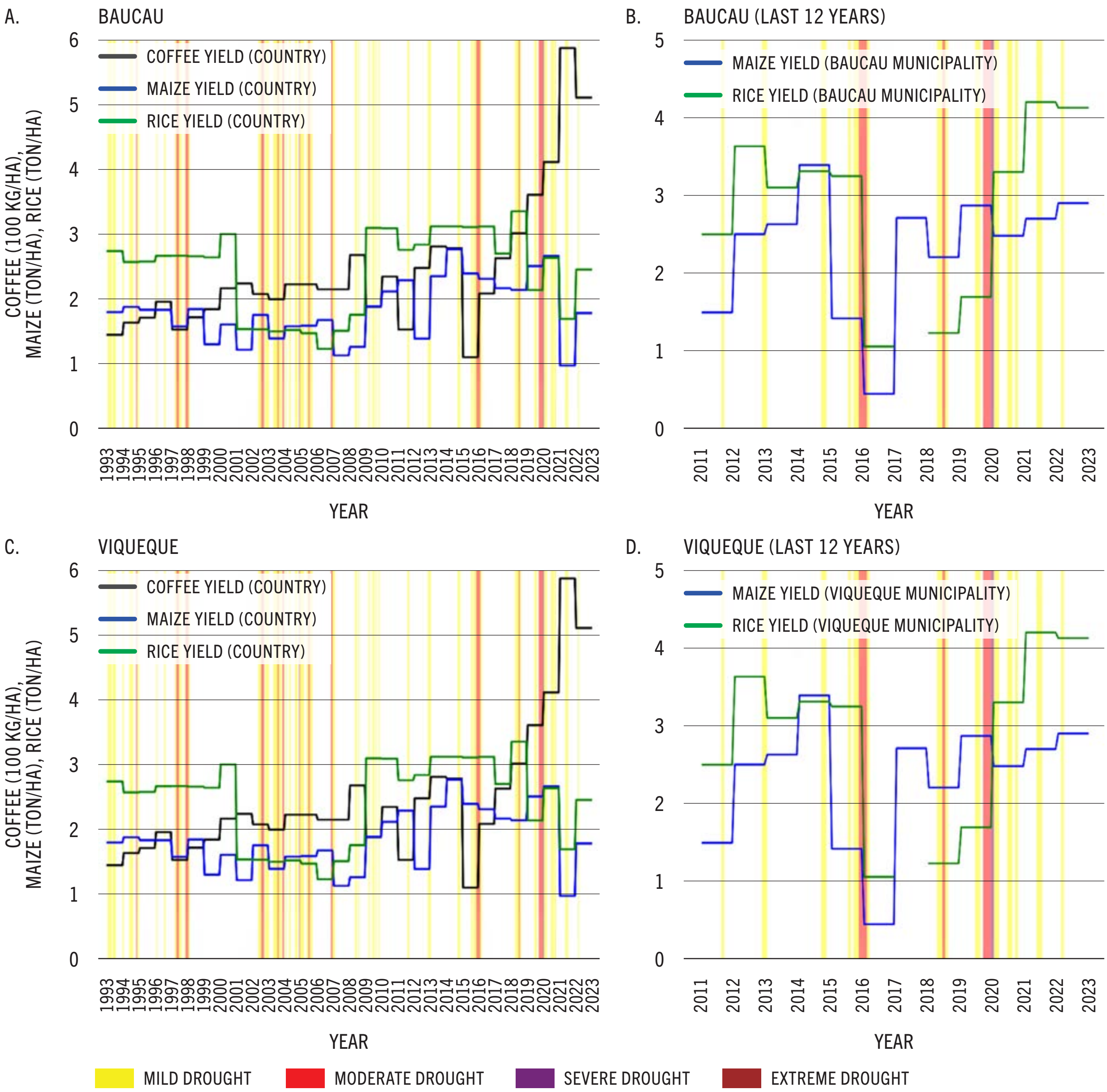
SOURCE: AUTHORS' OWN ELABORATION.

3.6.2 Triggering of drought and Anticipatory Action activation thresholds

The main challenges of drought-triggering for AA are, first, that drought forecasting is currently nonexistent for Timor-Leste, and second, there is a lack of historical agrometeorological observations data. To address these challenges, the indicators listed in Table 2 can help determine whether an agricultural drought is approaching. A CDI value (Table 3) depending on seasonal and temporal relations incorporates the following key indicators: ENSO, SPI1, SPI3, SMAPI, IOD and VHI. The vegetation response relative to precipitation takes time to manifest, and the drought impact value chain process goes through rainfall to soil moisture and then to VHI (Isaev, Kulikov, *et al.*, 2022). That is why we used SPI1, calculated from rainfall observations, to complement the current monitoring of soil moisture and VHI. We also used SPI3, calculated from seasonal forecasts as recommended by (Bhardwaj *et al.*, 2021), because it provides more accurate forecasts compared to 6-month rainfall forecasts and SPI6.

By using historical data, the CDI was calculated for the period 1993–2023, and the national yield data for the period 1993–2022. Municipal-level data for the period 2011–2022 were overlaid (Figure 10). From the CDI calculation result (Figure 10), we can conclude that significant yield reductions were observed during moderate and severe droughts.

FIGURE 9: COMBINED DROUGHT INDEX AND YIELD TIME SERIES



NOTE: FIGURE 10A SHOWS DATA FOR BAUCAU, WHILE FIGURE 10C SHOWS VIQUEQUE WITH CDI AND NATIONAL-LEVEL DATA ON COFFEE, MAIZE AND RICE YIELDS FOR THE PERIOD 1993–2022. FIGURE 10B SHOWS DATA FOR BAUCAU, WHILE FIGURE 10D SHOWS VIQUEQUE WITH CDI AND MUNICIPAL-LEVEL DATA ON MAIZE AND RICE YIELDS FOR THE PERIOD 2011–2022.

SOURCE: AUTHORS' OWN ELABORATION.

Additionally, the HSS was calculated to evaluate the forecasting skills of the CDI for the period 1993–2023 (Table 5). In the calculation of HSS, forecast hits were considered when CDI predicted one drought class, and during the predicted 3 months if one of them reached the same class of drought by SMAPI. Overall, the HSS shows the capability of the CDI to capture and predict agricultural drought with a lead time of 3 months (Table 5). Better performance was shown during no drought (HSS = 82) and moderate drought (HSS = 65–68). As described in the methodology, negative values indicate that the chance forecast is better, 0 means no skill, and a perfect forecast obtains a HSS of 1.

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TABLE 6: HSS for the Combined Drought Index with a forecast lead time of 3 months, 1993–2023

Combined Drought Index (CDI), with a lead time of 3 months	Heidke Skill Score (HSS)	
	Baucau	Viqueque
CDI = No drought	0.82	0.82
CDI = Mild drought	0.46	0.42
CDI = Moderate drought	0.65	0.68
CDI = Severe drought	0.33	–

NOTE: CDI = COMBINED DROUGHT INDEX.
SOURCE: AUTHORS' OWN ELABORATION.

To better analyze and examine the evaluation of drought, the CDI values during the drought years and the corresponding 3-month SMAPI are presented for the period 2011–2022 in Table 6. Values indicating forecast hits are highlighted in green, forecast misses (underestimated forecast) in orange, forecast misses (overestimated forecast) in white. From the analysis of the CDI (Table 6) and SMAPI, the forecasted CDI overall hits more than 80 percent.

From the analysis of CDI results (Figure 10, Tables 5 and 6), we can conclude that the combination of IOD and ENSO led to moderate to severe drought, even during weak ENSO years like 2006 and 2019, which were comparable to the 1997–1998 and 2015–2016 very strong ENSO years. Based on yield reduction and SMAPI (Figure 10, Tables 5 and 6), the AA activation threshold for moderate drought is proposed. Hence, there are three critical times that should be considered for deciding on a drought AA activation (Figure 9). During consultations with the municipal-level extensions of MALFF, the tentative drought AA timeline, depending on the phenological stage of the main staple crop and a combination of drought indices, was proposed using the updated crop calendar (Figure 9).

TABLE 7: CDI CALCULATIONS AND MONTHLY SMAPI DURING DROUGHT YEARS FOR THE PERIOD 2011–2022

Year	Month	Combined Drought Index (CDI), with a lead time of 3 months	Observed monthly SMAPI for the CDI forecasted month (%)			Combined Drought Index (CDI), with a lead time of 3 months	Observed monthly SMAPI for the CDI forecasted month (%)		
			1	2	3		1	2	3
2011	8	Mild drought	-1	-2	-2	Mild drought	-1	-1	-1
2012	11	Mild drought	-3	-15	0	Mild drought	-1	-14	-1
	12	Mild drought	-15	0	0	Mild drought	-14	-1	-2
2014	10	Mild drought	-5	-11	-11	Mild drought	-5	-10	-10
2015	7	Mild drought	-1	-3	-4	Mild drought	-4	-4	-5
	10	Mild drought	-4	-11	-18	Moderate drought	-6	-10	-15
	11	Moderate drought	-11	-18	-27	Moderate drought	-10	-15	-16
	12	Moderate drought	-18	-27	-10	Moderate drought	-15	-16	-7
2016	1	Moderate drought	-27	-10	-7	Moderate drought	-16	-7	-8
	2	Mild drought	-10	-7	-12	Mild drought	-7	-8	-12
2018	4	Mild drought	-4	-12	-20	Mild drought	-2	-9	-15
	5	Mild drought	-12	-20	-24	Moderate drought	-9	-15	-17
	6	Moderate drought	-20	-24	-21	Moderate drought	-15	-17	-16
	7	Mild drought	-24	-21	-15	Mild drought	-17	-16	-15
2019	6	Mild drought	-2	-6	-8	Mild drought	-3	-5	-6
	7	Mild drought	-6	-8	-7	Mild drought	-5	-6	-5
	10	Moderate drought	-6	-12	-34	Moderate drought	-5	-10	-30
	11	Moderate drought	-12	-34	-21	Moderate drought	-10	-30	-15
	12	Severe drought	-34	-21	-14	Mild drought	-30	-15	-9
2020	1	Mild drought	-21	-14	-7	Mild drought	-15	-9	-8
	2	Mild drought	-14	-7	-3	Mild drought	-9	-8	-5
	6	Mild drought	-6	-12	-12	Mild drought	-5	-9	-9
2021	5	Mild drought	-7	-14	-3	Mild drought	-7	-10	1
	6	Mild drought	-14	-3	-3	Mild drought	-10	1	0
2022	2	Mild drought	-2	-2	-1	Mild drought	0	-2	-2

NOTE: CDI = COMBINED DROUGHT INDEX; SMAPI = SOIL MOISTURE ANOMALY PERCENTAGE INDEX. GREEN HIGHLIGHTS = VALUES INDICATING FORECAST HITS; ORANGE HIGHLIGHTS – FORECAST MISSES (UNDERESTIMATED FORECAST); WHITE HIGHLIGHTS = FORECAST MISSES (OVERESTIMATED FORECAST).

SOURCE: AUTHORS' OWN ELABORATION.

3.6.3 Types of Anticipatory Action interventions

As highlighted in the introduction, the ASEAN Framework on AA in Disaster Management (2022) emphasizes three key building blocks of AA. This study primarily delves into building block 1: risk information and forecasting early warning systems. However, this section also explores building block 2: planning, operations, and delivery, as well as building block 3: pre-arranged finance. Given the tight time constraints for AA, planning and operations for implementation must be conducted well in advance, preceding drought-triggering alerts.

In particular, engaging communities and local governments in the design of AA activities is crucial for ensuring the relevance, efficiency, and effectiveness of AA protocol formulation. Leveraging the historical analysis of past drought events combined with risk and vulnerability data, FAO Timor Leste pinpointed the most at-risk locations. Should the drought trigger thresholds be met, a range of AA interventions are tied to this alert for implementation with the goal to mitigate humanitarian impacts for communities reliant on livelihoods and are vulnerable to drought in these identified areas. To select such activities however, it is essential to ground them (a) community insights, ensuring their relevance to anticipated needs and explore options for local action (b) local government capacities to ensure the activities being implemented have a scalability and replicability potential.

In July 2023, Focus Group Discussions (FGDs) were deployed in 6 *sucos* across Viqueque and Baucau municipalities. FAO conducted 12 FGDs with 134 participants, among them 60 participants were female while 74 were male. In addition, 7 Key Informant Interviews (KIIs) were held with local government staff from Civil Protection Authority, MALFF and community leaders. To provide context and guidance to the discussion, a four-step principal model for selecting AA was outlined for stakeholders highlight they should be: timebound, having a protective intent, being implemented prior to impact, and guided by a 'no regrets' and 'do no harm' approach. Through these consultations the following actions were selected:

- Phase 0:
    - Conduct training on water preservation techniques, crop and livestock management, and other agricultural drought management approaches to use during a drought event.
    - Facilitate the dissemination of early warning messages tailored to specific audiences, including households and groups engaged in agricultural production, local authorities, and non-government organizations (NGOs).
    - Distribute drought-tolerant rice and maize seeds.
    - Establish rain-harvesting infrastructure for drinking water and agricultural support ahead of the rainy season.
- Phase 1:
    - Enhance water storage using water tanks or by rehabilitating ponds.
    - Rehabilitate and clear irrigation systems.
    - Provide vouchers for agricultural inputs, such as shade cloth, and offer support with mulching and fertilizers.
    - Offer pest control assistance to manage the potential outbreak of mice and rats.
    - Implement cash-for-work programmes to increase access to cash for targeted individuals and communities. These funds can be utilized to rehabilitate water sources, dig or deepen handmade wells, and repair hand pumps.
    - Distribute livestock fodder.
- Phase 2:
    - Provide cash assistance for the most at-risk farmers and daily workers.
    - Supply feed and health kits (vitamins and minerals) for livestock.
    - Offer water purification tablets to increase access to clean water.
    - Explore the potential to scale up the government's Bosla Da Mae programme and school feeding programme.

Pre-arranged finance stands as the final cornerstone for successful AA implementation. While AA budgets need not match those of response efforts, funding must be adaptable and readily accessible following a drought trigger for AA. Plans lacking adequate resources will falter in delivering successful AA activities. In the case of Timor-Leste, the FAO office, alongside CPA and MALFF, has agreed to leverage FAO's Special Fund for Emergency and Rehabilitation Activities (SFERA) and the German Federal Foreign Office (GFFO) contribution, to pilot this approach. The drought trigger was activated in September 2023, linked to a moderate-to-strong El Niño and positive IOD. Accordingly, the scenario outlined above came into reality and at the time of writing evidence collection is underway. Insights gained will inform ongoing investments from the Green Climate Fund (GCF), enhancing government capacities for future events.

4. Conclusions and recommendations

This study introduced a drought-triggering methodology for AA in Timor-Leste, utilizing a combination of six indicators. These triggers have been implemented and tested in five municipalities: Baucau, Viqueque, Oecusse, Covalima, and Liquica. The two main challenges in creating this methodology for AA are the low accuracy of seasonal forecasts and the sparse hydrometeorological observation network in data-scarce Timor-Leste. Therefore, seasonal rainfall forecasts should be complemented by potential predictors such as El Niño and IOD indices. To fill gaps in hydrometeorological ground monitoring, remote sensing-derived indices should be incorporated. This study derives quantitative relationships between climatic and environmental indicators used to inform potential AA initiatives at different time scales for Timor-Leste. These indicators include observed (SPI1) and forecasted (SPI3) anomalies of rainfall, soil moisture anomalies, VHI and El Niño (Nino 3.4), and IOD (DMI) indices. They form the basis for designing a prototype of the CDI which characterizes the different stages of the cause-and-effect relationship of agricultural drought.

The CDI illustrates the spatial extent of a drought situation and provides an overview of the possible consequences for agriculture. It classifies the drought process, where rainfall deficit leads to a soil moisture deficit. These conditions subsequently result in a reduction of vegetation production. The CDI also takes into account a 3-month rainfall forecast complemented with drought predictors such as El Niño (Nino 3.4) and IOD (DMI) by using machine learning algorithms for bias-correction of the seasonal rainfall forecast. Thresholds and decision rules were defined based on these inputs to trigger early warnings and Anticipatory Action. The lead time detected by this CDI indicates the significance of a 3-month window of action and highlights how proactive action could be operationalized and enabled systematically.

The authors conclude that the developed CDI demonstrated an ability to detect both severe and mild drought events, and this study illustrates the promising potential for its operational implementation in Timor-Leste. The system's conceptually simple design and its openly sourced satellite and forecasting inputs provide a valuable proof of concept for use in other drought-vulnerable countries in Asia and the Pacific. However, such a system would need further testing, verification and community engagement before operationalization.

This methodology is in the testing period and will be further developed and improved by addressing identified gaps during this phase. Following the proposed AA crisis timeline, during the first week of every month, FAO, in collaboration with the government and partners, will monitor the CDI. If the threshold (CDI = moderate drought) is reached in the target municipalities, field verification will be carried out within 3–5 days. If the threshold is confirmed through local observations and consultations with local farmers and municipal extensions, AA will be activated as outline in section 3.6.3.

Future investigations in this domain should delve into the performance of the testing period, as previously emphasized, and deepen our understanding of how this process is implemented and has responded to challenges on both national and local fronts. This research could encompass the perspectives of disaster risk management communities regarding AA and their willingness to embrace future scaling efforts, while also scrutinizing the tool's precision.

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