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Assessment of the performance of drought indices for explaining crop yield variability at the national scale: methodological framework and application to Mozambique

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Highlights

- A method to identify indices (DIs) for monitoring drought impact on crops is proposed.
- SPEI and SSI were the DIs that best detected historical droughts in Mozambique.
- Percentage area affected by drought (PAA) better indicates crop yield variability than nationally averaged DIs values.
- PAA of SPEI-3 and SSI-12 explained the variability of most crop yields.
- The usefulness of regional disaggregated data for such impact analysis is recognized.

ABSTRACT

Droughts are one of the most damaging and complex natural disasters in the world, and they frequently affect agricultural production. Drought monitoring is essential for decision-makers seeking to minimize the socio-economic impacts related to drought events. In this study, we propose a methodology to identify the most suitable drought indices and data sources for monitoring the impact of drought on crops. Mozambique is used as a case study, as it represents a challenging example because of its poor hydroclimatic monitoring network and a lack of disaggregated data for agricultural production. A total of seven standardized drought indicators (SPI, SPEI, SSI, SVCI, STCI, SVHI, and STWS) at different scales (1, 3, 6, and 12 months) were obtained from global databases and evaluated as possible predictors of the annual variability of agricultural yields at the national level. A statistical model of crop yields based on time series was used to measure the explanatory capacity of each index. SPEI and SSI were the most effective at detecting the country's historical drought records regardless of whether nationally averaged values or the percentages of area affected by drought (PAA) were used. However, PAA was found to be a more accurate predictor of variability in crop yields. The variability of most cereals (maize, millet and sorghum) was adequately explained by the PAA of SPEI-3, with that of other crops (cashew nuts, cassava, potatoes, tea, tobacco and vegetables) being explained by the PAA of SSI-12. Specific indicators were proposed for monitoring wheat and sugar cane. These results can directly support managers and decision makers in developing drought contingency plans in Mozambique. To further demonstrate the potential of this methodology, it should be tested in other regions with a greater availability of agricultural data, including spatial disaggregation.

Keywords
Drought index, drought impacts, crop yield, statistical model, Mozambique.

1. Introduction
Droughts represent one of the most extensive, costly, recurrent, and complex types of natural disasters worldwide (Bryant et al., 2005; Mishra and Singh, 2010). Given that it is related to water availability, the agricultural sector is especially sensitive to this natural phenomenon. Negative impacts, like a decrease in quantity and/or quality of crops, directly affect food security and consequently, the quality of life within a region or country (Backlund et al., 2008). Such impacts are more perceptible in high drought risk regions (e.g., Southern Africa) and rainfed agriculture systems (Tigkas et al., 2019).

Droughts are classified into four widely accepted types: Meteorological, agricultural, hydrological, and socio-economic (Wilhite and Glantz, 1985). Each type is typically characterized and described through drought indices (DIs) (Hayes et al., 2011); several DIs have been developed over the last century (World Meteorological Organization and Global Water Partnership, 2016). Most DIs require climatic and/or hydrological data with at least 30 years of observation as inputs for a reliable temporal drought analysis, whereas at least one data station per 5000 km^2 is recommended for spatial analyses (AghaKouchak et al., 2015).

In recent decades, different institutions have constructed and updated various large-scale climate and hydrological data sets (e.g. Abatzoglou et al., 2018; Beck et al., 2017a; Harris et al., 2020; Thomas et al., 2014). These products provide gauge-based, satellite-derived, or reanalysis-based estimates, and can constitute a suitable alternative for calculating DIs in data-scarce regions (e.g., Nashwan et al., 2020). Though these global products are not without limitations (Beck et al., 2017b; Sun et al., 2018), they have been used in several drought and agriculture-related studies worldwide and constitute a reliable data source (Agutu et al., 2017; Champagne et al., 2019; Du et al., 2018; García-León et al., 2019; Jayanthi et al., 2013; Lawal et al., 2019; Potopová et al., 2020; Rojas et al., 2011).

Drought studies related to agriculture usually use correlation tests and statistical models to explain the relationship between farming yields and drought indicators (Shi et al., 2013). These models can be based on a single point or area (time series methods), spatial and temporal variations (panel methods), or solely spatial variations (cross-section methods) (Lobell and Burke, 2010). The type of model can be chosen depending on the spatial and temporal detail of the crop yield series (Shi et al., 2013). García-León et al. (2019) and Peña-Gallardo et al. (2019a) researched the relationships between drought indices and crop yields at the provincial and regional scale in Spain using panel methods. For the same purpose, Jayanthi et al. (2013) used the time series method in Malawi because they only had data on agricultural yields at the national level. Regardless of the method chosen, crop yields are frequently subject to a detrending process to extract the yield trend and remove the variability in productivity caused by non-climate factors (e.g., improvements in farming techniques, seed hybrid development, and irrigation optimization) (Champagne et al., 2019; Peña-Gallardo et al., 2019b), before developing the statistical model.

The above studies showed that site- and crop-specific studies are required to identify the most suitable DI and data sources for monitoring the impact of drought on crops. However, there is currently no standard methodology to assess the performance of DIs in explaining crop yield variability. To fill this research gap, in this study we propose a methodological framework to be applied at the national scale, comprising three steps. First, we use global gauge-based and satellite-derived datasets to calculate several well-known DIs and validate them with historical drought records. In addition to nationally average drought indicator values, new aggregated descriptors based on the areas affected by drought are considered to better capture regional variability when working at this scale. Second, we analyse the time variability among DIs to identify those that are strongly correlated and potentially provide redundant information. Then, we develop a time-series based statistical crop model to predict national yields using DIs as predictors. Building on the above analysis, we identify a DI or set of DIs, as well as the data sources to compute them, that can be used to monitor crop yields.

The proposed methodology is applied to Mozambique as a case study, with an emphasis on determining a climatic drought-related explanation of the national crop yield variability. The case study is challenging because this country does not currently have an operational measurement network that meets optimum criteria (Easterling, 2013), data on agricultural yields are limited, and previous research on drought impacts is scarce. However, it is also of considerable interest because of the role played by agriculture in the sustainable development in this region and the concerns raised by climate change. Mozambique is one of the poorest and least developed countries in the world. Approximately 70% of the population works in agriculture, representing 24% of the GDP (Ministério da Agricultura e Segurança Alimentar, 2015). It is also located in one of the most drought- and climate change-prone areas (Eriksen and Silva, 2009; IPCC, 2014; Osbahr et al., 2008; Patt and Schröter, 2008), which increases the vulnerability of its agricultural sector. For these reasons, this country is immersed in several development programs led by the Food and Agricultural Organization (FAO) (Midgley et al., 2012) and the World Food Programme (WFP) (WFP, 2007), among others, aimed at implementing climate change adaptation strategies to enhance the resilience and sustainability of agriculture. It is in this context that this work explores the impact of drought on agricultural production in Mozambique.

The overall aim of this study is to develop a methodology of general applicability to identify the most suitable DIs and data sources for monitoring the impact of drought on crops at national scale. Two methodological aspects are worth noting: (1) the reliance on freely global-scale datasets to obtain a comprehensive set of potential DIs, and (2) the exploration of alternatives to averaging DI values over the entire country, that are intended to better capture the local and regional drought conditions when working at such scale. The proposed methodology may thus be of special interest in countries with data scarcity, where ground data observations are neither sufficient nor timely available for drought monitoring, and countries with significant regional variability in drought occurrence, where nationally average drought indicator values may conceal regional differences. The methodology is tested in Mozambique. To the knowledge of the authors, this is the first study that compares drought indices for an agricultural drought risk assessment in this country. This study endeavours to act as a tool for supporting decision-makers, focusing on the performance of DIs in explaining yields and yield variability at the national scale. The results can help assess drought-related risks to crop production and are ultimately intended to contribute to developing an agricultural drought monitoring system in this country. As such, we acknowledge the need to reconcile the demands for highly detailed analysis with the extent of the resource requirements (infrastructure, operational needs, etc.) and data availability.

2. Materials and methods

2.1. Study area

Mozambique lies in southeast Africa (Fig. 1a) and covers a continental area of 801.590 km². The weather system is dominated in the north by the Inter-Tropical Convergence Zone and in the south by Antarctic Polar Fronts and Tropical Temperate Troughs (Manhique et al., 2011). The climate is tropical, with a hot and rainy summer season from November to March, and a cool and dry winter season from April to October (Midgley et al., 2012). The annual average temperature varies from 17.8°C to 32.8°C (Fig. 1e), and has increased by 1.25–2.0°C in the last 60 years (Ragab and Prudhomme, 2002). The annual average precipitation is 1032 mm, 75% of which occurs during summertime.

Owing to these conditions, the sowing and harvesting season generally extends from November to April (Rojas et al., 2011). Farming is one of the main activities in the country (70% of the population depending on subsistence farming), with over 80% of the total cultivated area used to produce staple food crops. Because of the lack of hydraulic infrastructure for irrigation, over 95% of this agricultural production is mainly rainfed and without fertilizer consumption (FAO, 2016).

The country is prone to drought, which has caused temporary food insecurity in the past (FAO, 2016). According to the International Disaster Database (EM-DAT, 2019) and the International Research Institute for Climate and Society (IRI) (Hellmuth et al., 2007), Mozambique has experienced various annual and interannual drought episodes in recent decades. In terms of socio-economic impacts, the most important were the droughts that occurred in 1979–1980, 1983–1984, 1987, 1991–1992, 1994–1995, 1998, 2001–2003, 2005, 2007–2008, 2010, and 2016.

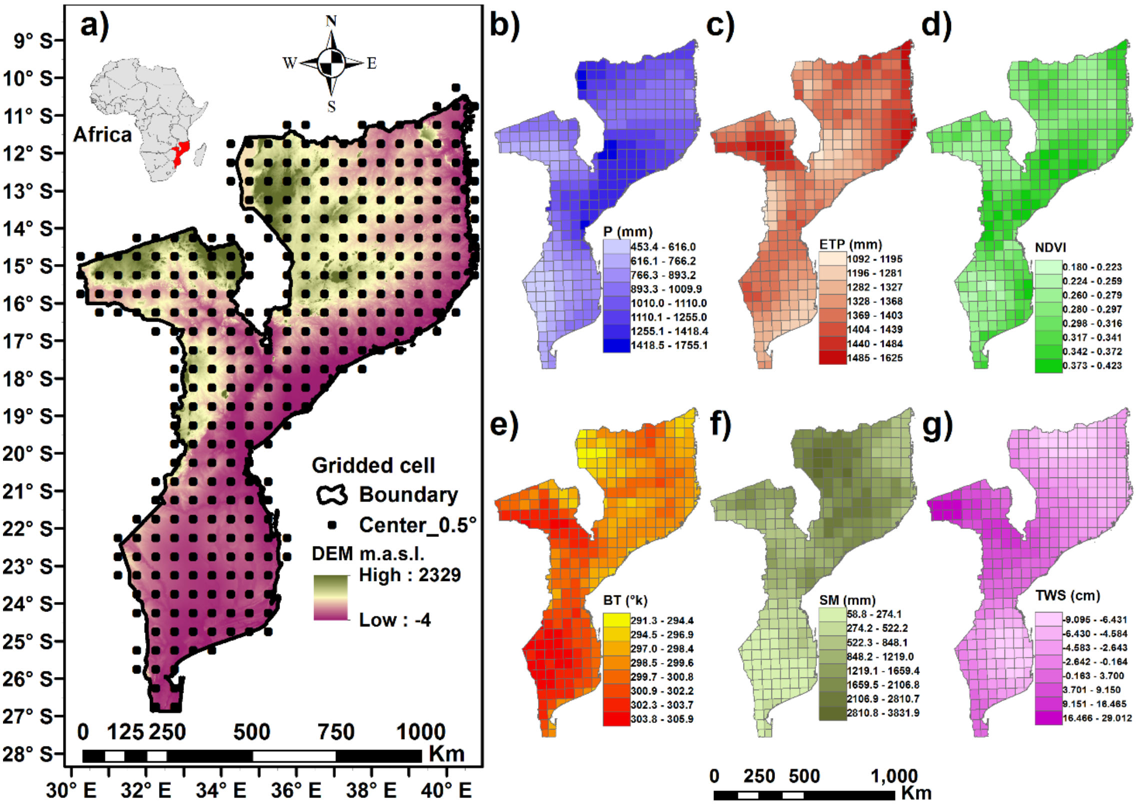

Fig. 1. a) Location of Mozambique in Africa and its topography. Black dots illustrate the CRU grid points (0.5°×0.5°). Spatial distribution of annual mean values of: b) precipitation (1973–2017), c) potential evapotranspiration (ETP, 1973–2017), d) Normalized Difference Vegetation Index

(NDVI, 1983–2017), e) Brightness Temperature (BT, 1983–2017), f) Soil moisture (1973-2017), and g) Terrestrial Water Storage (TWS, 2002–2017), across the country.

2.2. Meteorological, hydrological and vegetation data

The data used for calculating the DIs (Table 1) comprises Precipitation (P) and Potential Evapotranspiration (ETP) as meteorological information, the Normalized Difference Vegetation Index (NDVI) and Brightness Temperature (BT) related to vegetation conditions, and the Soil Moisture (SM) and Terrestrial Water Storage (TWS) as hydrological measures.

Index	Input	Data source	Original temporal resolution	Original spatial resolution	Time span
SPI-n	P	CRU	Monthly	0.5^{o}	1973–2017
SPEI-n	P, ETP	CRU	Monthly	0.5^{o}	1973–2017
SSI-n	SM	TerraClimate	Monthly	$1/24^{o}$	1973–2017
SVCI-n	NDVI	NOAA STAR	Weekly	$1/24^{o}$	1982–2017
STCI-n	BT	NOAA STAR	Weekly	$1/24^{o}$	1982–2017
SVHI-n	VCI, TCI	NOAA STAR	Monthly	0.5^{o}	1982–2017
STWS-n	TWS	GRACE	Monthly	1^{o}	2002–2017

Table1. Summary of drought indices and data sources used in this study. The temporal accumulations (n) were 1, 3, 6, and 12 months.

Monthly P and ETP were obtained from Climatic Research Unit CRU TS3.10 (CRU) at the University of East Anglia (Harris et al., 2020) for the period between 1973 and 2017 (https://crudata.uea.ac.uk/cru/data/hrg/) at a 0.5° resolution. A total of 343 CRU grid points covering the entire Mozambican territory were used for the study (Fig. 1).

NDVI and BT are derived from spectral reflectance at the blue, red, and near-infrared (NIR) wavelengths observed from space by orbiting satellites (Deering, 1978). These data were obtained from the Center for Satellite Applications and Research (STAR) and the environmental satellites for the U.S. Oceanic and Atmospheric Administration (NOAA). Datasets consist of 7-day value composites at 8 km resolution from 1982 to 2017 (https://www.star.nesdis.noaa.gov/smcd/emb/vci/VH/vh_ftp.php). Monthly SM time series from 1973 to 2017 and a 1/24° resolution were obtained from the TerraClimate dataset (https://climate.northwestknowledge.net/TERRACLIMATE/index_directDownloads.php) (Abatzoglou et al., 2018). These values have been derived using a one-dimensional soil water balance model based on the primary climate variables of this dataset.

The GRACE satellites can accurately observe and measure the TWS changes over global land areas (Tapley et al., 2004). Monthly TWS data at a 1° resolution (https://grace.jpl.nasa.gov/data/get-data/monthly-mass-grids-land/) from 2003 to 2016 were used in this study. The gridded TWS data were scaled following the process explained by Landerer and Swenson (2012).

To establish consistency with the CRU spatial and temporal resolution, the NDVI, BT and SM data were resampled to a 0.5° resolution and monthly scale. Four-point bilinear resampling was applied to TWS data for the same reason. The spatial distribution of the annual mean values of each variable for the study period is shown in Fig. 1b-g.

2.3. Drought indices and area affected by droughts

The drought indices (DIs) used in this study (Table 1) rely on the meteorological, vegetation condition, and hydrological data described in the previous section. Although several DIs exist (Dai, 2011; World Meteorological Organization and Global Water Partnership, 2016), we selected seven widely known DIs that have been successfully used in drought and agriculture-related investigations (Agutu et al., 2017; Sun et al., 2012).

The Standardized Precipitation Index (SPI-n) (McKee et al., 1993) shows precipitation anomalies with respect to the long average of P, considering a window period of n months. Its computation consists of fitting P time series accumulated at a chosen n-months period with a two-parameter gamma probability distribution and later standardizing this result. The Standardized Precipitation and Evapotranspiration Index (SPEI-n) (Vicente-Serrano et al., 2010), the Standardized Soil Moisture Index (SSI-n) (Hao and AghaKouchak, 2013), the Standardized Vegetation Condition Index (SVCI-n), the Standardized Temperature Condition Index (STCI-n), the Standardized Vegetation Health Index (SVHI-n) and the Standardized Terrestrial Water Storage (STWS-n) (Agutu et al., 2017) were calculated following the same mathematical procedure as the SPI, but used the corresponding variables as inputs rather than P. The SPEI-n uses the difference between P and ETP, which is understood as the climatic water balance. SSI, SVCI-n, STCI-n, and SVHI-n used the SM, VCI, TCI, and VHI, respectively, as previously calculated according to Kogan (1995), whereas the STWS-n used the TWS. The SPEI-n and STWS-n were fitted to a three-parameter log-logistic probability distribution following Vicente-Serrano et al. (2010). The seven indices were calculated for four temporal accumulations (n) of 1, 3, 6 and 12 months, considering that farming periods for selected crops are less than one year. The indices were evaluated according to the categories explained in Table 2 for standardized indexes, following the recommendations of McKee et al. (1993).

Standardized Indices	**Category**
< -2.00	Extreme drought
< -1.50	Severe drought
< -1.00	Moderate drought

Table 2. Intensity categories of droughts used in this study for standardized indices.

We computed the DIs time series for each CRU cell and then aggregated them into a single national time series. For this purpose, we averaged the DIs values over the entire territory (343 cells), weighted by cell area in the country (a), to obtain a single national monthly time series for each DI. We also calculated the percentage area affected by droughts (PAA) by considering the intensity thresholds indicated in Table 2. We determined the percentage of cells under the different intensity categories using the DIs time series for each cell on a monthly scale. The annual PAA was obtained through aggregating from a monthly to annual series over the calendar year. The idea behind the calculation of the PAA is to evaluate alternatives to national averaged DI values that can better capture, in a single value, subnational differences in drought conditions. The spatial averaging performed for computing the national DI values can, in some cases, hide extreme drought conditions occurring at a more regional scale, which is not the case with the PAA computation. The time span covered by the DIs and PAA series depended on the availability of main data, as indicated in Table 1.

2.4. Crop yield data

The country-level annual crop yield data (Y) for Mozambique was obtained from the FAO data portal (http://www.fao.org/faostat/en/#data/QC) for the period of 2002–2017 (Fig. 2). Crops included maize, millet, sorghum, wheat, cashew nuts, cassava, potatoes, sugar cane, tea, tobacco, and vegetables. According to Kasnakoglu and Mayo, (2004), this data source represents one of the most credible, readily available Y dataset because of its monitoring data quality and statistical process. More recently, Agutu et al. (2017) used it successfully in a nearby region to characterize agricultural drought.

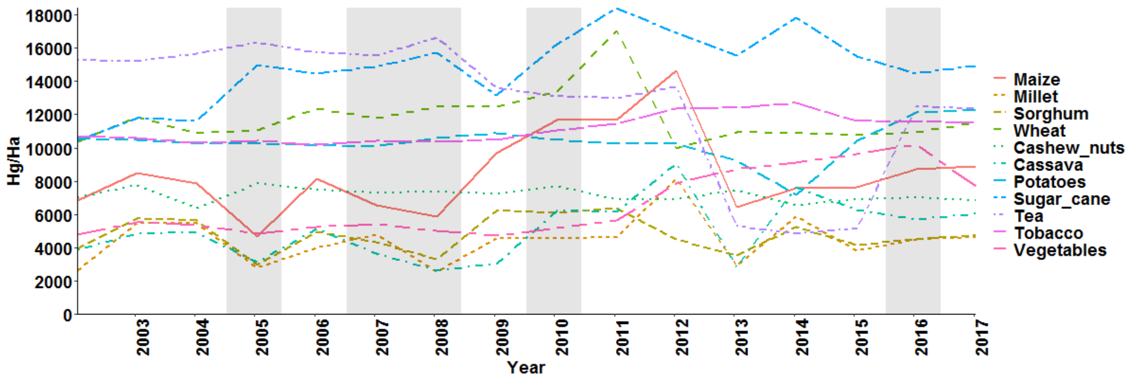

Fig. 2. Time series of the main yield crops in Mozambique after applying a detrending process (Source: FAO data portal http://www.fao.org/faostat/en/#data/QC). Drought years according to the records are shaded in grey. NOTE: Yields of cassava, potatoes and vegetables are divided by 10, and that of sugar cane is divided by 40 for visualization.

Crop statistics are not routinely compiled in Mozambique at the sub-national level (e.g., by agroecological zones or provincial levels). The availability of sub-national production statistics is, in fact, very limited in the majority of sub-Saharan African countries (You et al., 2009). At present, regional yields in Mozambique are available for around 8 non-consecutive years (depending on the specific crop and region) from sources like the FAO Agro-MAPS database (http://kids.fao.org/agromaps) (George, 2006) or the Agricultural Statistics Yearbooks (Ministério da Agricultura e Segurança Alimentar, 2015). However, these data are insufficient to support the type of analysis proposed in this paper and were, therefore, not considered in this study.

Mozambique has only recently started to improve its farming techniques. This could be attributed to the social, economic and political issues Mozambique has faced in recent decades, causing limited developments in agriculture (FAO, 2016). However, we decided that it might be necessary to apply a detrending process to the crop data in order to eliminate variations that may result from abiotic factors (market prices, government policy, etc.). Y trends were calculated using the Mann-Kendall (MK) trend test method (Mann, 1945): Millet, cashew nuts, cassava, potatoes, sugar cane, tobacco, and vegetables had positive and significant trends; tea showed a negative and non-significant trend, whereas the other crops had positive and non-significant trends. The crop yield series were detrended by fitting a linear regression model and extracting the residuals. The average crop yield was added to the residual series to produce the detrended yield data. The analyses shown in this paper were conducted on the detrended data series, and the detrending process was applied only for Y with significant trends (hereafter detrended crops yield are simply referred as Y).

2.5. Skill assessment and benchmarking of drought indices

In the first step of the proposed methodology, the performance of the different drought indices for drought detection was analysed. For this purpose, the historical drought record from EMDAT and IRI was compared with the time series of the average national DIs values and the annual PAA for each DI. The EMDAT is part of the Centre for Research on the Epidemiology of Disasters (CRED), which initiated its active disaster data collection in 1973 (Guha-Sapir et al., 2015); hence, skill assessment was conducted from 1973 to 2017 on a yearly basis. In this work, a year qualified as a drought year if at least two consecutive months were under moderate drought intensity (Table 2) according to the DIs series. This two-month criterion allows the exclusion of short droughts, which are presumably of minor importance, as done in previous studies (Spinoni et al., 2019). In the case of the PAA series, a drought year was designated if the annual PAA value reached 30%. Although this is an arbitrary threshold, the percentage of land impacted by drought is directly related to the number of agricultural households affected, and therefore with the drought impact on productivity (Rojas et al., 2011). The performance metrics used were the probability of detection (POD) or hit rate, and the probability of false detection (POFD) or false alarm rate, computed according to Wilks (2006):

$$POD = 100\frac{H}{H+M} \tag{1}$$

$$POFD = 100\frac{FA}{CN+FA} \tag{2}$$

where H are hits, M misses, FA are false alarms, and CN are correct negatives. H represents the coincidence of drought of both series (historical records and DIs/PAA series), and M corresponds to the presence of a drought in the records and the absence of this event in the DIs/PAA series. FA occurs if there is no drought in the records, but one occurs in the DIs/PAA series, and finally, CN represents the years in which there is no drought in both series. The Euclidean distance between the point (x_1=POFD, y_1=POD) of each DI and PAA series and the point with the best possible performance (x_2=POFD=0, y_2=POD=100) was used to benchmark performance. Shorter distances thus indicated better performance.

A correlation analysis between the DIs series was performed in the second step of the methodology. We calculated the Pearson correlation coefficients between all monthly DIs series averaged at the country scale. The correlation coefficients were analysed to assess if the information provided by the different DIs was redundant.

2.6. Statistical crop yield model

In the third step of the methodology, we developed a statistical crop yield model for Mozambique by assuming that Y was the response of a function of k independent variables X which, in this context, included the DIs and PAA as possible predictors. Given $Y \in [0, \infty)$, and following Shi et al. (2013), an exponential (time series) model was adopted as follows:

$$\ln(Y_t) = f(X_{t1}, X_{t2}, ..., X_{tk}) = \beta_0 + \sum_{j=1}^{k} \beta_j (X_{tj}) + \varepsilon_t \tag{3}$$

where Y is the vector of annual crop yields (Fig. 2), *t* is the year, X represents the vector with the candidate predictors, β_j are the constant coefficients and ε the error.

Both single and multiple candidate predictors are considered to develop the models. Equation (3) transforms in a simple linear regression model with one explanatory variable or in a multiple linear regression, respectively. The times series considered as candidate predictors for the models are: 1) The national average DIs of all months of the year (January to December), 2) the annual national average DIs, 3) the annual average PAA under a certain intensity category (moderate, severe, or extreme). The multiple linear regression models use the annual average PAA under the three aforementioned intensity categories as candidate predictors (i.e., three independent variables). Fig. 3 summarizes the steps in a methodological flow-chart.

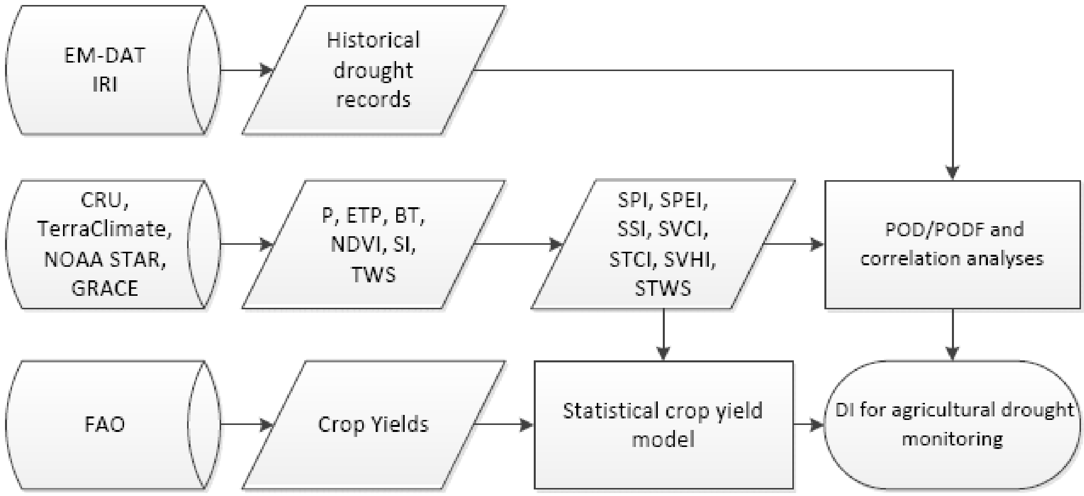

Fig. 3. Methodological flow-chart of the study.

3. Results and Discussion

3.1. Comparison with historical drought records

The temporal patterns of the national averaged DIs series are plotted in Fig. 4. Each DI detected several droughts of different intensity categories: Moderate (green), severe (orange), and extreme (red). The longer the temporal accumulation (n) for each DI is, the later the dry periods are detected, and they are also less frequent. This result can be explained by the time scale of the DI and the drought propagation through the hydrological cycle. The historical droughts of 1987, 1991–1992, 1994–1995, 2005, and 2016 were the main drought events detected by the majority of DIs. According to the DI linked to soil moisture (SSI), an extreme intensity was reached in up to four of these events. The DIs related to vegetation conditions (SVCI, STCI, and SVHI) also classified the 1991–1992 event as extreme. The remaining DIs (SPI, SPEI, and STWS) distinguished several drought events (including the five named above), but the intensities were lower (moderate and severe). In these DIs, extreme intensities were completely smoothed out by the spatial averaging process.

STCI-n and STWS-n indicated drought conditions in Mozambique between 12.0% and 14.1% during the analysed period. SPI-n and SVCI-n reported the shortest time under drought conditions (less than 7.2%). When the extreme drought threshold was considered, SCVI-n indicated that such conditions were present less than 2.1% of the time, whereas less than 0.4% of the time was classified in this intensity category, according to SPI-n.

Similar to the DIs time series observations, the historical droughts in 1987, 1991–1992, 1994–1995, 2005, and 2016 were the events that were most clearly detected by majority of the PAA series. These drought periods have also been highlighted in previous studies (Brida and Owiyo, 2013; Jayanthi et al., 2013; Trambauer et al., 2014). In these significant events, the total area affected by drought and its distribution in intensity categories differed between DIs. In 1992, up to 74 % of the Mozambican territory was below the moderate drought threshold, and 53 % reached the extreme intensity according to SPEI-12. In 2016, STWS-6 showed that 90 % of the country was facing a moderate drought, 5% of which corresponded to an extreme intensity; however, SPEI-12 indicated a PAA greater than 20% in the extreme category.

To benchmark the capacity of detection of historical drought events by the different indices, the POD and POFD metrics were computed, as described in Section 2.5. Table 3 shows the skill assessment of the national averaged DIs series and PAA series according to the distance (d) to the point with the best possible performance. The rankings of DIs according to their performances were quite similar for both series (DIs and PAA). In both cases, the best performance was obtained by SPEI-3 and SPEI-6, with more than 50% of POD and with POFD ranging from 7% to 26%. Similar performances were obtained with these two indices when considering thresholds for drought detection between 20 and 35 % of the annual PAA value, demonstrating that the indexes are robust with respect to slight variations in the definition of a drought year. These results are consistent with previous studies that found that EMDAT drought disasters were best matched with severe droughts identified using meteorological DIs for mid-high temporal accumulations (United Nations, 2009). The worst detection performance was provided by the DIs related to vegetation conditions (SVHI and SVCI). Nonetheless, all the DIs detected the most important drought events because they affected the entire hydrological cycle.

DIs	**H**	**M**	**FA**	**CN**	**POD**	**POFD**	**d**	**PAA**	**H**	**M**	**FA**	**CN**	**POD**	**POFD**	**d**
SPEI-6	9	9	2	25	50.00	7.41	50.55	**SPEI-3**	9	9	2	25	50.00	7.41	50.55
SPEI-3	10	8	7	20	55.56	25.93	51.45	**SPEI-6**	9	9	2	25	50.00	7.41	50.55
STCI-3	8	8	4	16	50.00	20.00	53.85	**SPEI-12**	8	10	2	25	44.44	7.41	56.05
SPEI-12	8	10	1	26	44.44	3.70	55.68	**SSI-3**	8	10	2	25	44.44	7.41	56.05
STCI-1	8	8	5	15	50.00	25.00	55.90	**SSI-6**	8	10	2	25	44.44	7.41	56.05
SPI-6	7	11	1	26	38.89	3.70	61.22	**SPI-6**	7	11	0	27	38.89	0.00	61.11
SSI-1	7	11	1	26	38.89	3.70	61.22	**SPI-12**	7	11	1	26	38.89	3.70	61.22
SSI-3	7	11	1	26	38.89	3.70	61.22	**SSI-1**	7	11	1	26	38.89	3.70	61.22

Table 3. Skill assessment results according to POD and POFD. The DIs not included in the table have distances (d) to the point with the best possible performance larger than 62.

The national averaged DIs series are likely missing some climatic, hydrological, or vegetative information of specific regions within the country. For example, drought conditions that affect an area of the country might be concealed by wet conditions in another region. This is not the case for the PAA series, which a priori makes them a better option for working at a national scale. However, both the DIs and the PAA series showed a similar detection capability of historical records. Overall, the meteorological indices (SPEI and SPI) most closely matched the historical records. However, none of the DIs were able to perfectly capture all the drought periods collected from historical records (i.e., POD lower than 100), and they identified drought conditions outside the drought years recorded in the historical disaster databases (i.e., POFD greater than 0).This may be attributed to the following reasons: On the one hand, unrelated circumstances might have worsened the consequences of what would otherwise be considered as a mild drought, being recorded as drought year in the records. For example, a) other natural disasters occurring between dry periods, such as the heavy floods in 1981 and 1985 and between 2000 and 2001 (Brida and Owiyo, 2013; Midgley et al., 2012; Patt and Schröter, 2008), b) civil war and conflicts, such as the conflict from 1982–1984 against Zimbabwe (Hellmuth et al., 2007), c) epidemics, such as the cholera outbreak in 1983–1984 (Eriksen and Silva, 2009), or d) food security crises, as in the 2001–2005 period (FAO, 2006). On the other hand, the drought events in Mozambique were reported at the national level, even if they occurred only in a specific region of the country. Therefore, the national DIs series obtained after averaging at national level and the PAA may not adequately reflect regional information.

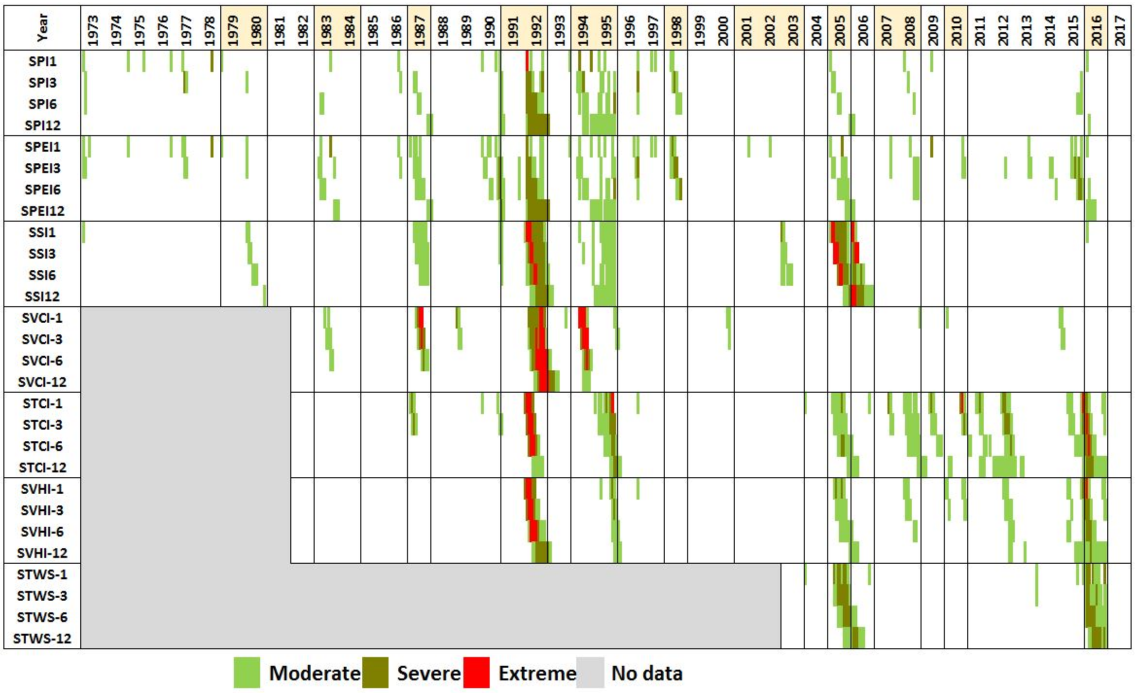

Fig. 4. Monthly temporal evolution of SPI, SPEI, SSI, SVCI, STCI, SVHI, and STWS at the national scale (-1, -3, -6, and -12-month aggregations). Intensity levels can be interpreted in conjunction with Table 2. Historical drought years according to the records are highlighted in yellow.

3.2. Correlation between drought indices

The occurrence, intensity, and duration of drought periods in Mozambique showed some variability between the different DIs. In this step, we compared the drought variation patterns between each DI. Fig. 5 shows the Pearson coefficients between the DIs time series; the strongest correlations are painted blue, and non-significant (ρ>0.05) correlations are denoted as struck through.

Overall, the strongest correlations were found between the indices associated with meteorological variables (SPI and SPEI) and between those related to soil moisture (SSI). These were followed by those associated with soil conditions and temperature (STCI and SVHI). In general, a DI with a temporal accumulation of 1 month had a very high or nearly perfect correlation with the same DI at a 3-month scale. The same was observed between the temporal aggregations of 3 and 6 months, and between 6 and 12 months.
The indexes associated with the vegetation condition, albeit without meteorological variables such as temperature in their calculation (SVCI), as well as STWS exhibited considerably different variabilities from the rest of DIs, with low correlation values. These two DIs also had the most non-significant correlations with other DIs. The SVCI is an index that indicates the condition of the vegetation, and thus can reflect other factors external to the climate (e.g., irrigation, forestation, and afforestation). STWS, on the other hand, characterizes the total availability of surface and underground water, so its variation depends on the complete hydrological process of the area and not solely on one or two climatological parameters. The lowest correlations were found for the highest temporal accumulation (SWT-12), which could be related to multiannual droughts (not analysed in this paper).

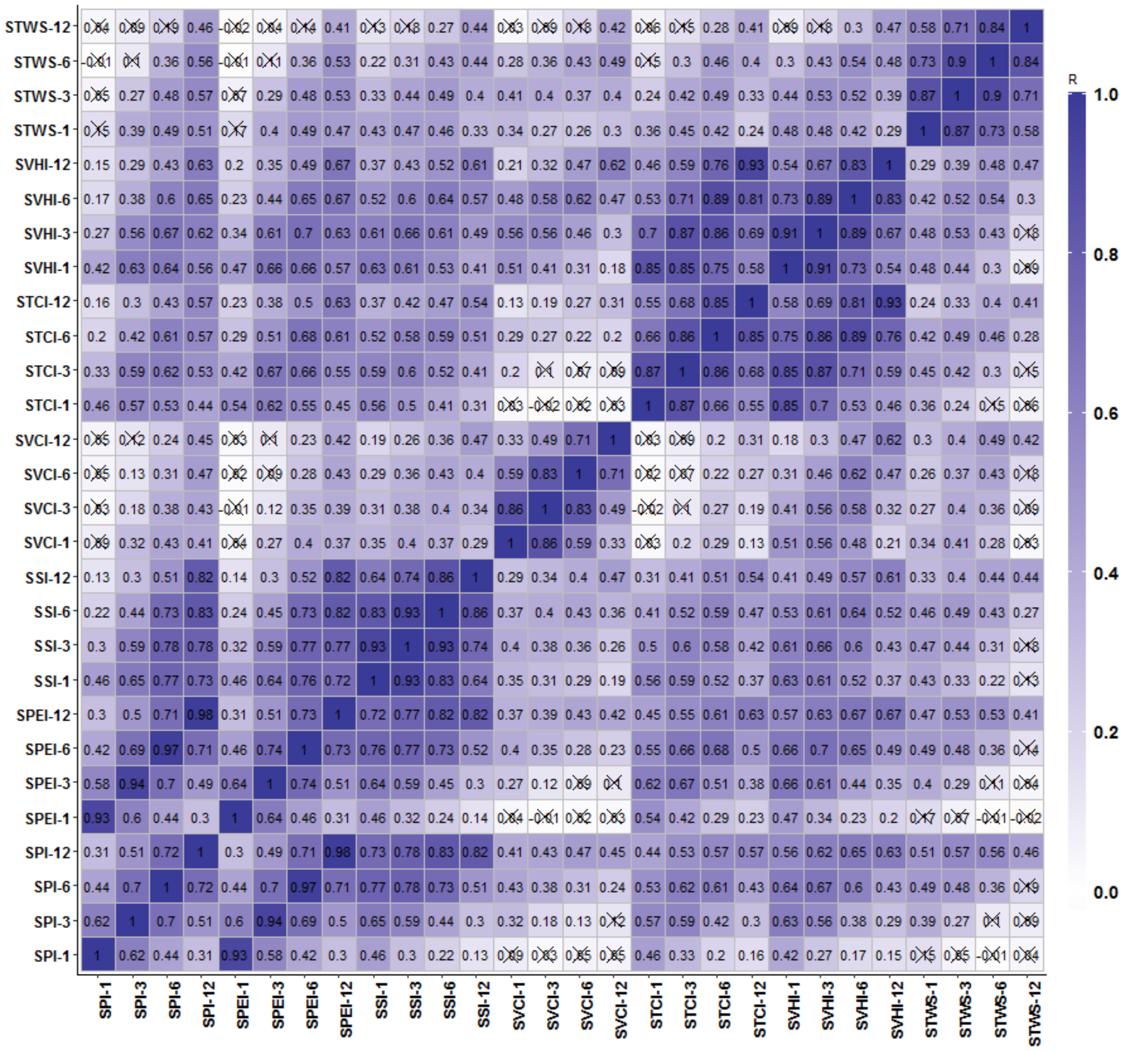

Fig. 5. Correlation coefficients (R) between the DIs, where the non-significance level (ρ>0.05) is indicated by strikethrough.

The results of the correlation analyses are consistent with the physical meaning of the different DIs. Although there is a time lag between the meteorological forcing and the hydrological responses, DIs based on meteorological variables with 6- and 12-month accumulations showed strong correlations with DIs based on vegetation/hydrological data. The results suggest that only one of these meteorological DIs (SPI and SPEI with n=6 and n=12 months) could be used alone in any subsequent analysis, as they provided very similar information and had high correlations with other DIs. SCVI may be used but considering that it does not have an important correlation with hydroclimatic indicators, it should be used in conjunction with another DI.

3.3. Explanation of crop yield variability

Because of the close relationship between Y and drought conditions, especially in areas with little hydraulic infrastructure such as Mozambique (non-irrigated agriculture), a time-series statistical model was proposed to find the DI that better explains the annual yield variability of the 11 selected crops, as explained in Section 2.6. The candidate predictors were the averaged national DIs of each month (Jan to Dec), the annual averaged national DIs (annual), the annual PAA at moderate (a_mod), severe (a_sev) and extreme (a_ext) intensities, and the sum of the annual PAA at moderate, severe, and extreme intensities (a_sum), totalling 17 time estimates for each DI. Because 28 DIs were analysed, this created a total of 17x28=476 candidate predictors for each type of crop. Fig. S1 (supplementary materials) shows all R^2 values of the statistical model results for each crop. The crop types are represented on the y-axis and the candidate predictors are on the x axis. The strongest positive correlations are plotted as red. Many of the estimates were non-significant ($p < 0.05$).

The main reason for such low coefficients has already been mentioned: there are no regional data on crops. Droughts can, however, affect specific regions of the country that contribute little to the overall national yield. The use of national aggregated estimates in these cases means that we are searching for correlations between droughts affecting one area of the country and yields produced in others. It is also worth noting that this study is focused on rainfed agriculture, but some crops (e.g., vegetables or sugar cane) might be irrigated in some areas, adding noise to the yield data. Mozambique is thus a highly complex scenario. Area-based analysis in countries where disaggregated data are available will certainly improve the results.

However, if a certain number of indicators containing reasonable correlations with crops are determined, this can act as a valuable tool for decision-makers, who currently do not have objective data to guide their policies. As more data become available, the same methodology can be applied to improve drought monitoring.

The best candidate predictors of Y were different for each crop. This is because not all crops are equally sensitive to drought, nor do they have the same water harvesting or storage capacities. In general, the best predictors were those based on the PAA and related to agricultural and hydrological droughts. Being predictors that incorporate spatial information below the national level, they showed a better relationship with Y than national indicators that lost spatial information in their computation. Again, we note that introducing spatial disaggregation improved the results. If, in addition to incorporating spatial information from the DIs, data for the evolution of crops by area were available, the results would be much more accurate.

Considering that some of the indicators had high correlations between themselves, which meant that their spatial-temporal drought patterns were similar, the determination coefficients resulting from the proposed model were understandably similar between themselves. For example, SPI-6 and SPEI-3 best explained the variability of the sorghum, with R^2 values of 0.70 and 0.67, respectively (with a correlation of 0.70 between them). To limit the number of indicators, the predictive capacities between these two DIs can be considered highly similar; SPEI-3 can ultimately be chosen, as it also provides reasonable results in other crops such as millet and maize. Thus, the proposal of indicators should be compacted to a minimum number that can explain the variability of the 11 crops. Fig. S1 (supplementary materials) allows for an analysis of which DI reasonably explains the evolution of each of the crops.

Of the 11 crops analysed, 8 of them showed a high correlation with 2 predictor candidates: SPEI-3_a_sum reasonably explained the evolution of cereals (maize, millet, and sorghum) and SSI-12_a_sum explained the rest of the crops (cashew nuts, cassava, potatoes, tea, tobacco and vegetables) (Fig. 6). This suggests that DIs that consider not solely precipitation but soil moisture conditions, either directly or indirectly, can provide a better assessment of the potential impacts on agricultural production. The differences in the phenological characteristics and the cultivation period of the studied crops can justify the need for considering different DIs (SPEI and SSI) at both short and long timescales (3 months and 12 months). The variability of the cereal yields is typically best explained by short term meteorological DI (Chen et al., 2016; Peña-Gallardo et al., 2019a), whereas other crops such as tubers and vegetables respond to soil moisture drought conditions at a longer timescale (Daryanto et al., 2016; Sorensen, 2005). It should also be noted that the choice of a limited set of indices, for the sake of simplicity and operational use, comes at the cost of more difficult physical interpretation of the results.

There were some crops that did not neatly fit into these general trends. Wheat also responded well to SPEI, as did all other cereals, but SPEI-6_Aug presented a much better fit than SPEI-3_a_sum, used for all other cereals; thus, the former predictor stands out. One possible reason may be a widespread or uniform distribution of wheat crops, where the zoning provided by PAA-based indicators does not offer an added value. This is however a hypothesis, as disaggregated data are not available.

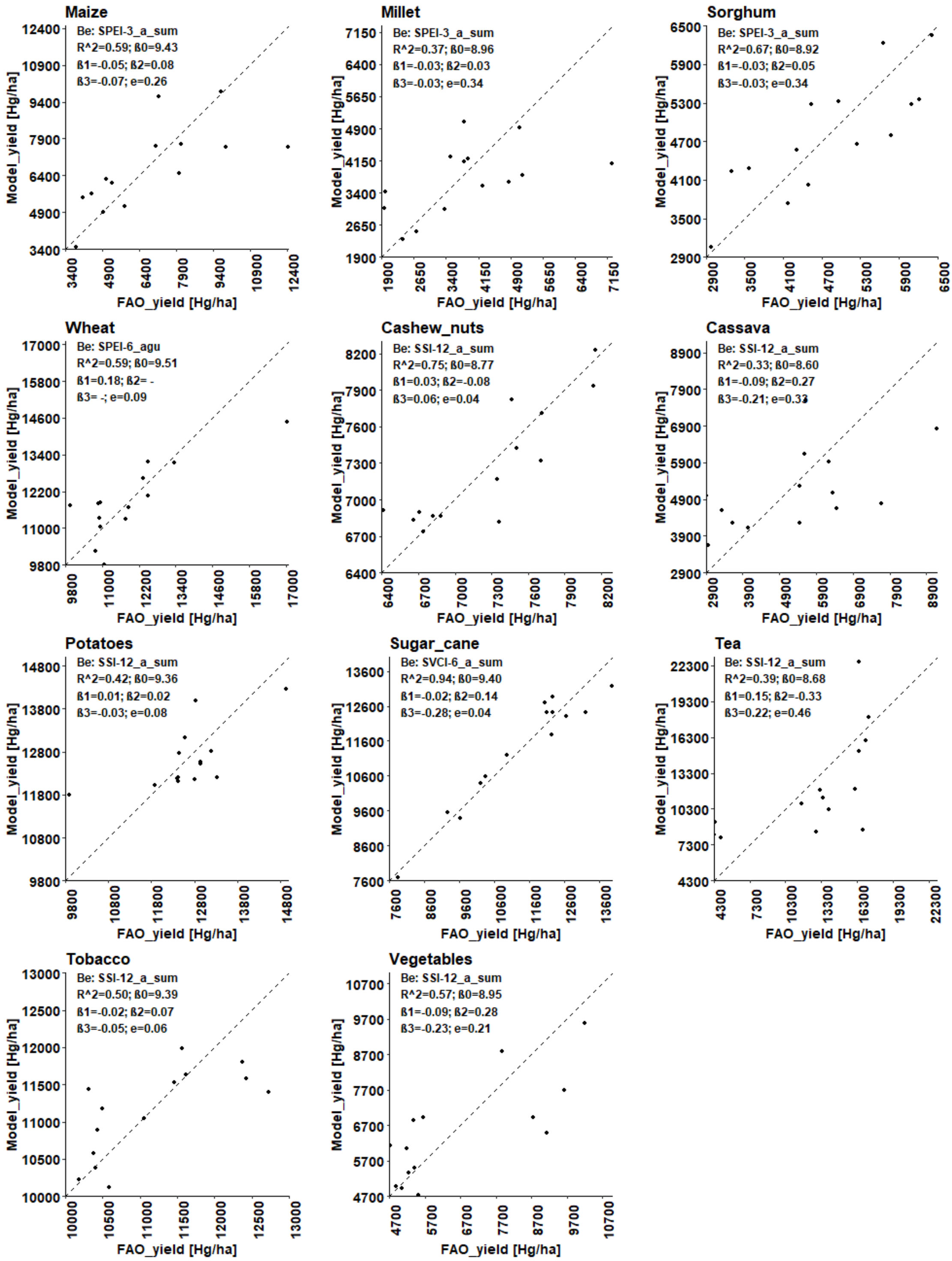

Fig. 6. Crop yields as measured by FAO versus crop yields as calculated using the best explanatory variable candidate (indicated as Be). Fitted parameters are also shown. The dashed line corresponds to the 1:1 line.

The last peculiarity is that of sugar cane. This crop had acceptable correlations with other indicators, so it could have been included within the general block. However, sugar cane also had an excellent correlation with the SVCI-6_a_sum indicator, as demonstrated in Fig. 6, so the best-fit DI was selected in this case. It is difficult to estimate the reason for the adjustment, although Lisboa et al. (2018) highlighted the good strong predictive capacity of sugarcane yields using NDVI data. The modelled and measured Y are compared for all crops in Fig. 6.

The lack of spatially detailed agricultural data made Mozambique a difficult place to find relationships between Y and DIs. Nevertheless, the method applied here discovered relationships that adequately explained the variance of Y for some crops, proving that it can be used in other regions or countries. However, as these are national approximations for a considerable territory, these results should be considered with care.

4. Concluding remarks

The aim of this research was to test a methodology that could evaluate various drought indices as tools for monitoring drought and to test their ability to explain the annual variability of crop yields. The case study was carried out for Mozambique, which was especially challenging given its poor monitoring system and lack of local/regional data on crop yields; thus, data from global databases and national agricultural data were used.

The proposed indicators successfully detected the main drought events from 1973 to 2017 according to historical records, and accurately noted their duration and intensity. The SPEI and SSI indicators had the best capacity to detect historical droughts through using both nationally averaged time series and the PAA.

Variability in crop yields was associated with agricultural and hydrological droughts. This variability was explained for the majority of crops using two generic indicators: SPEI-3_a_sum explained the performance of various cereal crops (maize, millet, and sorghum), whereas SSI-12_a_sum correlated well with several other crops (cashew nuts, cassava, potatoes, tea, tobacco, and vegetables). Some specific indicators were proposed for two specific crops: SPEI-6 of August (wheat) and SVCI-6_sum (sugar cane). SPEI and SSI also offered the best results in terms of their ability to explain historical drought events. In addition, because the state level agricultural data were used, the annual area affected by drought (PAA used in both SPEI-3_a_sum and SSI-12_a_sum) explained the variance of agricultural yields more effectively than the national level drought indicators.

In summary, the proposed methodology allowed us to confirm the use of these drought indicators—in their different temporal accumulations—as a tool to monitor and characterize droughts and model the annual yields of specific crops in Mozambique. This methodology should be tested in other regions with a greater availability of agricultural data, including spatial disaggregation. These results can be used as a support mechanism by managers and decision makers for drought contingency plans in Mozambique. However, there is a need to deepen the analysis of droughts in this country at the regional level, to provide an improved basis for drought management at the local level.

Declaration of interest

The authors declare that they have not conflict of interest.

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Appendix A: Supplementary materials

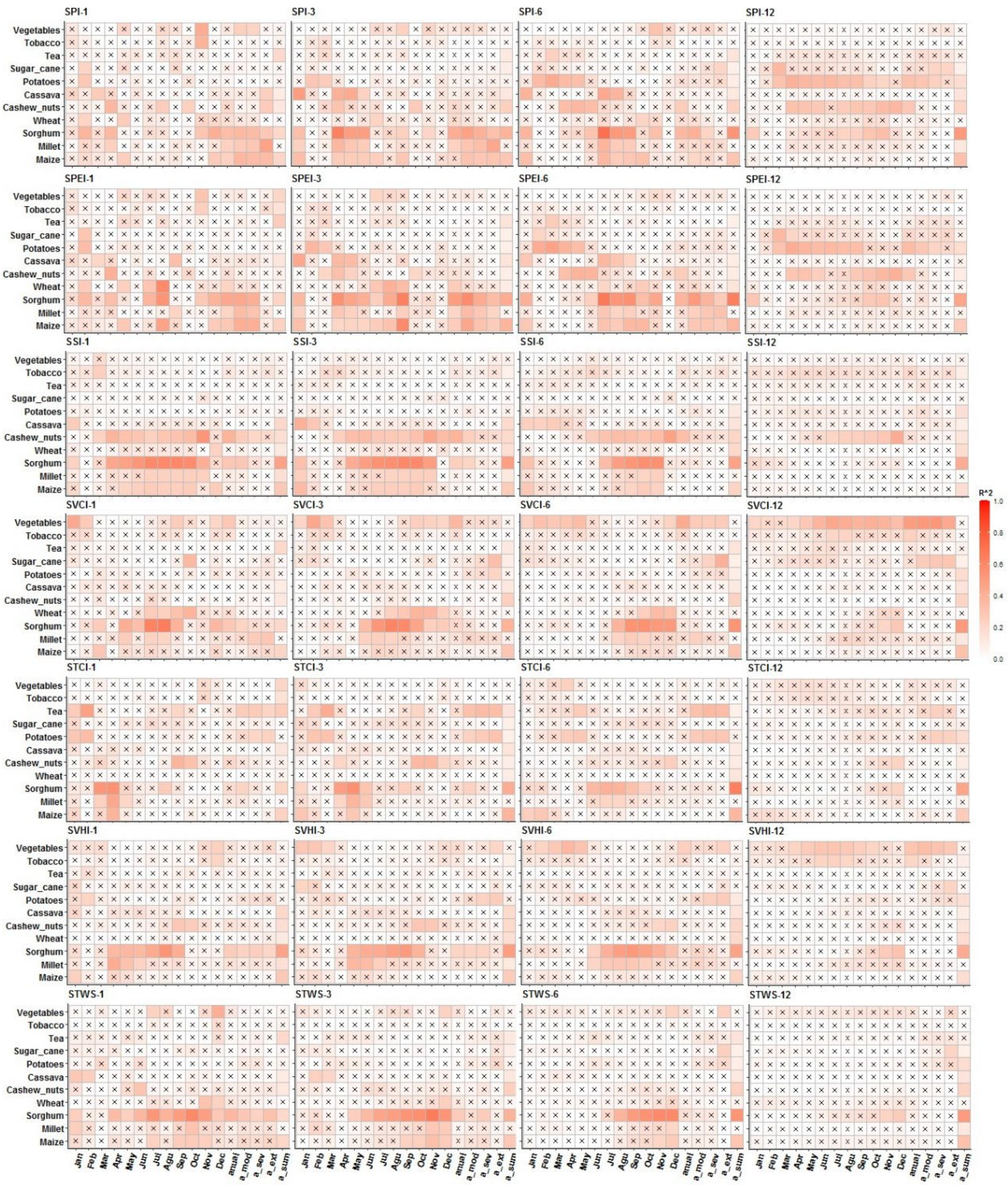

Fig. S1. Determination coefficients (R^2) of the statistical crop models. The different candidate predictors (x-axis) represent the monthly DI values (Jan to Dec), the average annual values (annual), and the PAA for the multilinear regression model (a_sum) and each intensity category: moderate (a_mod), severe (a_sev), and extreme (a_ext). The strongest positive correlations are shown in red. Non-significance values ($p > 0.05$) are marked with a cross.