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Comparison of hydrological and vegetation remote sensing datasets as proxies for rainfed maize yield in Malawi

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ABSTRACT

Weather Index-based Insurances (WIIs) have emerged as a promising risk coping mechanism to compensate for weather-induced damage to rainfed agriculture. Remote sensing may provide cost-effective information capable of discriminating the weather spatial variability thus reducing the *spatial basis risk*, i.e., the mismatch between the weather-based index triggering the insurance payout and the actual damage experienced by the farmers, which is often one of the causes hindering the wide implementation of WIIs. In this work we assess which indices based on remote sensing datasets are the best proxy indicators for rainfed maize yield in Malawi. We analyse the spatial (district scale) and temporal (monthly) correlations of historical maize yield data and several remote sensing datasets including the Climate Hazards group Infrared Precipitation with Stations (CHIRPS) dataset, the ESA CCI Soil Moisture combined dataset (version 4.2), the Evaporative Stress Index (ESI) from the Atmosphere-Land Exchange Inversion model (ALEXI), the MOD13Q1 Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI). With respect to the previous literature, this work exploits a historical crop yield dataset at the sub-national level which allows us to analyse the correlation of the hydro-meteorological and vegetation variables at a higher spatial resolution than what is commonly done (i.e., at the national level using FAO national yield statistics) and ultimately explore the issues related to WII spatial basis risk. Results show that the correlations between crop yield and satellite datasets show high spatial and temporal variability, making it difficult to identify a unique WII index that is at the same time simple and effective for the entire country. Precipitation, particularly the standardized March precipitation anomaly, has the highest correlations with maize yield (with Pearson correlation values higher than 0.55), in Central and South Malawi. Soil moisture and NDVI do not add much value to precipitation in anticipating historical maize yield at the district scale. From a methodological perspective, our work shows that WII indexes are best identified by: *i)* considering datasets with fine spatial resolution, whenever possible; *ii)* accounting for the vulnerability of the different crop growing stages to water-stress; *iii)* distinguishing between water scarce and water abundant events.

1. Introduction

Almost 95% of the agriculture in Africa is rainfed thus making crop production highly vulnerable to weather and climate related risks, such as droughts and heat waves (Rockström et al., 2009; Biradar et al., 2009; Godfray et al., 2010). Extreme weather events can adversely impact agricultural production and threaten food security particularly in those communities whose livelihoods rely on subsistence food production, such as in the majority of smallholder farming systems (Barnett et al., 2008; Vogel et al. (2019); He et al. (2019) and references therein). Weather Index-based Insurances (WIIs) emerged as a promising risk coping mechanism to compensate for weather-induced damage to crop yield, especially for rainfed agriculture (Mills, 2007; World Bank, 2011). Instead of relying on crop loss assessment, as traditional agricultural insurances, the WII payoff is proportional to an index representing the weather conditions experienced by farmers. This eliminates the burden and cost of on-the-ground crop-loss assessment, thus making WII affordable to low income households and enabling faster payouts. Because of these features, many WII schemes were tested in sub-Saharan Africa in the last decades and few of them have been implemented,

Abbreviations: WII, Weather Index-based Insurance.

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including those supported by ACRE-Africa and R4 Rural Resilience Initiative (Barnett et al., 2008; Ntukamazina et al., 2017).

WII are effective and sustainable only if a good correlation between the index triggering the insurance payout and the actual damage experienced by the farmers exists (Mills, 2007; World Bank, 2011; Carter et al., 2015). The mismatch between these two is known as *basis risk* and represents one of the main challenges that hinders the success of WII. The *spatial basis risk* particularly (i.e., the mismatch between the weather-based index and the actual crop damage caused by the spatial variance of the weather-crop relationship) is one of the major concerns for farmers (Hess and Syroka, 2005; Leblois and Quirion, 2013). In fact, most of the WII ensuring crop loss due to water stress and droughts relies on indexes expressing (deficit or lack of) precipitation measured at ground stations (Barnett et al., 2008; World Bank, 2011; Ntukamazina et al., 2017; Möllmann et al., 2020). Given the high spatial variability of precipitation events, the station records may not represent the actual meteorological conditions experienced by the farmers the further from the station. The decline of gauging networks worldwide (Vorosmarty et al., 2001; Pagano et al., 2014) and the lack of long-term and widespread records particularly in developing countries (Sheffield et al., 2014) challenge the wide applicability of WII (Leblois et al., 2014). There has been a recent effort to introduce new gauging networks in sub-Saharan Africa, e.g., the Trans-African Hydro-Meteorological Observatory (TAHMO) launched in 2014 (van de Giesen et al., 2014), which, although promising, provide short observational records which hinder robust statistical analysis.

Remote sensing represents a good alternative data source for WII because of its large spatial coverage, range of spatial and temporal resolutions, and long record length (De Leeuw et al., 2014). The remote sensing features which could add value when used in the design of WII instead of gauges are that: *i)* remote sensing provides cost-effective information available automatically and in near real-time; *ii)* the data accuracy does not depend on the density and distribution of the gauging network; *iii)* the remote sensing datasets are global and, in principle, capable to discriminate the weather spatial variability. These features, in turns, could potentially contribute to reducing the spatial basis risk and upscaling the WII applicability thus including farmers in remote and/or data scarce regions (Carter et al., 2015; De Leeuw et al., 2014). On the other hand, the main issues with using remote sensing in the design of WII are that: *i)* contrary to ground stations, which provide direct measurements of the weather variables (e.g., the precipitation amount), the satellite sensors measure proxy variables, thus potentially increasing the uncertainty of the weather estimation and eventually the basis risk; *ii)* as a result the WII design may become less transparent and trustworthy to the farmers, thus, leading to more resistance in the uptake of the insurance.

A number of studies have explored the potential for remote sensing datasets in the design of WII in sub-Saharan Africa although their actual use in pilot or operational insurance schemes is still rare. In their review paper, De Leeuw et al. (2014) report that remote sensing data has been used for assessing weather-related risk in crop (traditional and index-based) insurances against flood, drought, and fire and, sometimes, it has also been used for verifying the damages claimed in traditional insurances. Most of the literature concerning drought risk assessment is based on indexes derived by rainfall monitoring, hydrological modelling, crop monitoring or a combination of them, which can address the different aspects of droughts, i.e., the meteorological, hydrological, and agricultural drought (Tarnavsky and Bonifacio, 2020; Benami et al., 2021). The simplest indexes include rainfall anomalies (Tarnavsky et al., 2014), temporal rainfall attributes, such as the duration and or the onset of the rainy season (Wakjira et al., 2021), or short-term dryness indicators, such as the number of non-rainy days (Senay et al., 2014). More complex indexes rely on the integration of the precipitation estimates with water mass balance estimates or crop yield estimates (Tadesse et al., 2008). Most of the literature concerning the use of WII against drought risk adopts remote sensing estimate of precipitation or NDVI (Normalized Difference Vegetation Index) to define the weather index (Barnett et al., 2008; Funk and Budde, 2009; De Leeuw et al., 2014; Awondo et al., 2020). A large part of the studies using these indexes as part of WIIs ensure livestock, while the use of WIIs for crop insurance is less extensive. The reason is likely that the relationship between water availability, vegetation greenness, and crop yield is more complex than the relationship between water availability, vegetation greenness, and forage yield in rangelands and it is influenced by agricultural management practices which may vary largely among individual farmers. Some previous works (e.g., Hoffman et al., 2018; Enenkel et al., 2018, 2019) have thus claimed the need to define more sophisticated WII indexes, for example by accounting for hydrological or weather variables which influence crop growth dynamics more closely than precipitation (e.g., soil moisture, evaporative stress index, extreme degree days, and vapour pressure deficit). However, these studies often find that variables different than precipitation only slightly improve the prediction of national statistics of crop yield in sub-Saharan Africa. On the other hand, the adoption of more complex regression techniques, with respect to the widely used linear regression (e.g., multivariate, non-linear, or black-box relations identified via machine-learning algorithms), have been shown to improve the prediction performance (see Vogel et al. (2019); Hoffman et al. (2018)) and references therein). It is nevertheless unclear if such performance increase can compensate for the more complex WII design which may undermine the farmers' understanding of the insurance product and perception of the associated benefits, which in turn may weaken their willingness to purchase the insurance (Gine and Yang, 2009; Patt et al., 2010; Binswanger-Mkhize, 2012; Cole et al., 2013; Carter et al., 2015; Osgood et al., 2018; Möllmann et al., 2020).

In this work we explore the potential of several remote sensing datasets in reducing the spatial basis risk of a possible WII ensuring maize yield against water scarcity in Malawi. We analyse the spatial correlations of several indexes representing hydrological variables and vegetation greenness and historical records of maize yield at the sub-national level, i.e., county level. We focus particularly on rainfed maize, which is the most important food crop in Malawi and, more generally, an indicator for food security in sub-Saharan Africa (FAO, IFAD, WFP, 2015; Stevens and Madani, 2016). Our research questions are:

- which indexes can reliably represent the exposure of Malawi rainfed maize yield to water scarcity at the sub-national level?
- what is the added value in considering indexes based on hydrological variables and vegetation greenness other than the commonly used precipitation?
- what is the spatial basis risk associated with the different indexes?

With respect to the previous literature, this work exploits a historical crop yield dataset at the sub-national level which allows us to analyse the correlation of the hydro-meteorological and vegetation variables at a higher spatial resolution than what is commonly done (i.e., at the national level using the FAO national yield statistics) and ultimately explore the issues related to WII spatial basis risk. We consider the following remote sensing datasets: Climate Hazards group Infrared Precipitation with Stations (CHIRPS) dataset (Funk et al., 2015), ESA CCI Soil Moisture combined dataset (version 4.2), Evaporative Stress Index (ESI) from the Atmosphere-Land Exchange Inversion model (ALEXI) (Wardlow et al., 2012), MOD13Q1 dataset, including both the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) (Didan, 2015). We compute standardized anomalies for the annual yield records and monthly remote sensing variables (also considering consecutive months during the maize growing season to possibly account for cumulative processes which may influence crop growth). We then analyse the spatio-temporal correlation of the datasets (quantified by median Pearson correlation coefficient) to understand how water scarcity propagates from meteorological (i.e., precipitation) to hydrological variables (i.e., soil moisture) and, finally, how it impacts vegetation growth as measured by ESI, NDVI and EVI, and historical maize yield data. We repeat this analysis by removing the years when a flood occurred according to the Emergency Events Database (EM-DAT) (Guha-Sapir, 2019) so to focus specifically on drought risk only.

2. Study area: Malawi

Malawi has an heterogeneous landscape with elevations spanning from approximately 20 to 2900 m a.s.l. and different land cover, from forest, mostly in the north, to cropland (Fig. 1). Malawi has a tropical climate with a wet season from November to April, which usually receives 95% of the total annual precipitation, and a dry season between May and October (Jayanthi et al., 2013). The mean annual temperature shows a clear trend from north to south while the annual average precipitation is quite homogeneous across the country (about 700 mm on average), but for the high altitude areas where mean annual precipitation can be up to 2500 mm (Ngongondo et al., 2011).

Malawi is divided into three administrative regions, North, Central and South, comprising 28 districts in total. Agriculture is the main economic sector in the country representing about 40% of the Gross Domestic Product (GDP) (Syroka and Nucifora, 2010). The majority of the agriculture is rainfed and the food production is almost entirely consumed within the country. The agricultural economy of Malawi, strongly dedicated to the subsistence of the population, is among the most sensitive to climatic shocks in Southern Africa (Minot, 2010; Clay et al., 2003; Aragie et al., 2018). Malawi is indeed prone to experiencing food crisis, which have affected around 17 million people from the beginning of the century (Hess and Syroka, 2005; Harrigan, 2008; Pourazar, 2017). In particular, Malawi faced a severe drought in 2005 which, together with a change in agricultural policy, led to food shortage and a consequent increase in maize price in 2005 and 2006 (Harrigan, 2008). To tackle this food crisis, the government introduced a new Malawi Agricultural Input Subsidy Programme which was centred around the distribution of vouchers to approximately 50% of the smallholder farmers for buying fertilizers and improved maize seeds (Dorward and Chirwa, 2011). The main difference with respect to previous programmes was to specifically target the most productive farmers with resources (i.e., fertilizers and seeds) to improve their food self-sufficiency and agricultural income which could in turn boost the national food self-sufficiency (Chinsinga, 2008; Levy, 2005). The Malawi Agricultural Input Subsidy Programme was successful in fulfilling and sometime even exceeding the national requirements in the following years (Chibwana et al., 2013).

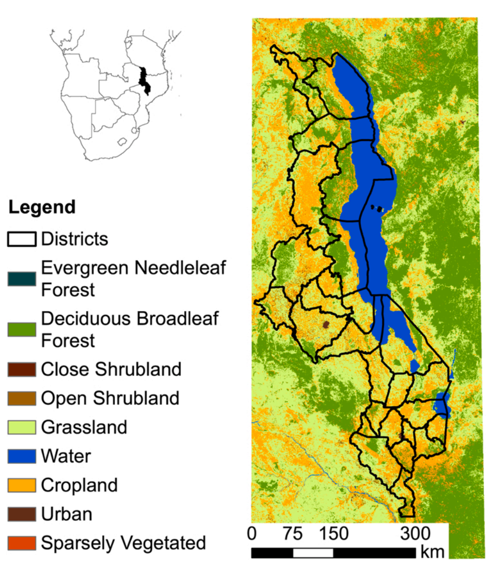

Fig. 1. Malawian districts and land cover map.

In this study, we focus on maize which is the dominant crop in Malawi followed by cassava, tabacco and rice (Clay et al., 2003). According to the Fourth Integrated Household Survey IHS4 conducted by the World Bank and the Malawian National Statistical Office, approximately 83% of the households were engaged in agricultural activities in 2016 and 75% of the crop fields were cultivated with maize (National Statistical Office, 2017). Maize is thus a good indicator of households food security in the country. Maize is mostly cultivated in the south and central-south districts (see Fig. 2a). The sowing period spans from mid November to the end of December and the harvesting period spans from the end of April to the end of July. The actual crop season in each field depends on the farm location, the local weather conditions, and the individual farmers' management practices. Extreme weather events could negatively impact the maize production depending on the plant growing stage. Maize is very sensitive to water stress during the flowering stage (which occurs about 8 weeks after plants emerge, i.e, in February or March) while the early vegetative stages are more vulnerable to floods (Clay et al., 2003; Çakir, 2004; Osgood et al., 2007; Ransom and Endres, 2014; Comas et al., 2019).

There have been previous studies and implementations of WII against droughts in Malawi for groundnuts and maize (Hess and Syroka, 2005; Chavula and Gommes, 2006; Osgood et al., 2007; Barnett et al., 2008). Most of these studies analyse the relations between precipitation (recorded at ground stations) and crop yields. Hellmuth et al. (2009) specifically acknowledge that the spatial variability of the rainfall and the lack of rainfall stations with reliable and long term-records limit the upscaling of the pilot studies and suggest that remote sensing may help in this respect. Gine and Yang (2009) conducted randomized field experiments with maize and groundnut farmers in Malawi to understand which conditions favour the uptake of WII insurances. Almost 70% of the interviewed farmers reported that the amount of rainfall was the most important risk factor for crop production. Interviews and simulation games conducted with farmers in Ethiopia and Malawi reported in Patt et al. (2010) suggests that a better understanding of the WII scheme correlates with higher willingness to purchase it. Finally, Reeves (2017) critically discusses the experience of the African Risk Capacity drought insurance policy in Malawi.

3. Materials and methods

3.1. Maize yield dataset

Local maize is the maize variety that is most consistently cultivated across Malawi (Gine and Yang, 2009; Lunduka et al., 2012). We use yearly yield data from official Agricultural Statistical bulletins provided by the Ministry of Agriculture in Malawi. The dataset has a yearly temporal resolution, a district spatial resolution (for a total of 28 districts in the whole Malawi), and it spans the period 1984–2016 (Table 1). Fig. 2a shows the average percentage of cropland harvested with maize for each district in the period 1984–2016. Maize is mostly cultivated in Central and South Malawi with districts having up to 12% of their cropland cultivated with maize. Fig. 2b shows the average yield computed over the whole of Malawi and in the three regions. A shift in the mean yield is recognizable in the year 2005 (breakpoint resulted from the Pettitt test with p-value lower than 0.001) which corresponds to the introduction of the agricultural policy mentioned in Section 2.

3.2. Remote sensing datasets

We consider precipitation and soil moisture as the main hydrometeorological variables that influence crop growth, and NDVI, EVI, and ESI as variables representing crop health status (Table 1). The Climate Hazards group Infrared Precipitation with Stations (CHIRPS) dataset is a quasi-global precipitation dataset which combines satellite and ground

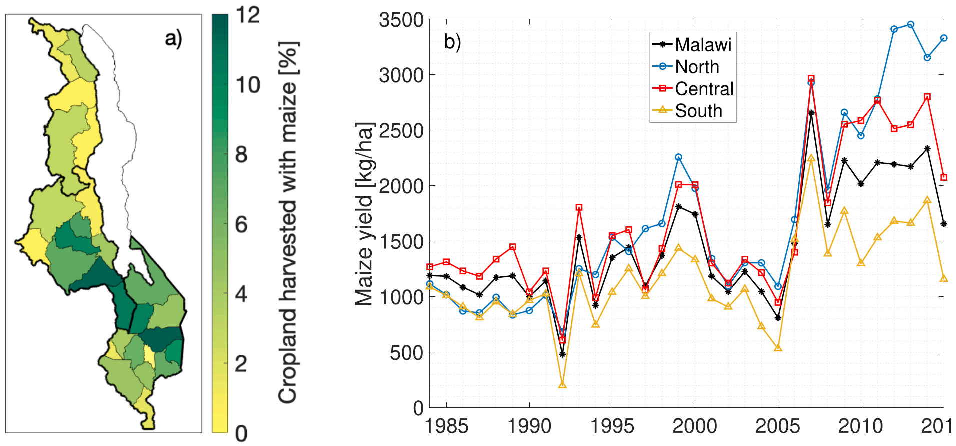

Fig. 2. a) Average percentage of cropland harvested with maize in each district in the period 1984–2016. b) Time series of average maize yield in the whole Malawi and in the three administrative regions, i.e., North, Central and South Malawi, in the period 1984–2016.

Table 1
Summary of the datasets used in this work.

Dataset	Variable	Spatial resolution	Temporal resolution	Period of availability
Maize yield	Yield	District	Yearly	1984–2016
CHIRPS	Precipitation	5×5 km^2	Monthly	1981–2019
ESA CCI SM	Soil Moisture	25×25 km^2	Monthly	1979–2015
MODIS NDVI	Normalized Difference Vegetation Index	1×1 km^2	Monthly	2001–2017
MODIS EVI	Enhanced Vegetation Index	1×1 km^2	Monthly	2001–2017
Alexi ESI	Evaporative Stress Index	5×5 km^2	Monthly	2001–2019

measurements (Funk et al., 2015). It spans the period from 1981 to near real-time with a spatial resolution of 5×5 km^2. With respect to other remote sensing precipitation datasets, CHIRPS has shown to be the most accurate in Africa (Gebrechorkos et al., 2018; Dinku et al., 2018). We use the ESA CCI Soil Moisture combined dataset (version 4.2), which spans the period 1979–2015 with a spatial resolution of 25×25 km^2. This dataset is derived by the combination of measurements from two active and four passive microwave sensors, and represents the moisture in the upper few centimetres of soil (Dorigo et al., 2015; Gruber et al., 2019). The Evaporative Stress Index (ESI) represents the monthly anomaly of the ratio between actual evapotranspiration (ET) and potential evapotranspiration (PET). We use it to identify water-stressed vegetation. The dataset spans the period 2001–2019 with a spatial resolution of 5×5 km^2. ET and PET are derived from satellite datasets and the Atmosphere-Land Exchange Inversion model (ALEXI) (Wardlow et al., 2012). Finally, we use the MOD13Q1 dataset, including both the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI). These datasets span the period 2001–2016 with a spatial resolution of 1×1 km^2 (Didan, 2015). We disregard NDVI and EVI values smaller than 0.1 to exclude non-vegetated or sparsely vegetated pixels.

3.3. Land cover map

We use the ESA CCI Land Cover map (Defourny et al., 2017) to identify cropland areas in Malawi. It refers to 2015 and has a spatial resolution of 300×300 m^2. In this work, we define cropland as the aggregation of three classes in the original ESA CCI classification, namely, “Rainfed Cropland", “Mosaic cropland ($>$ 50%)/natural vegetation", and “Mosaic natural vegetation ($>$ 50%)/cropland". Most of the cropland is located in Central and South Malawi, while North Malawi is mostly covered with forest (Fig. 1). We use this cropland map to mask the remote sensing datasets in some of the analysis, as detailed in Section 3.5.

3.4. Emergency Events Database (EM-DAT)

The Emergency Events Database (EM-DAT) (Guha-Sapir, 2019) records various types of disasers worldwide from 1900 to nowadays. It is used for vulnerability assessment by various research and governmental institutions and organizations. The definition of disaster event adopted in EM-DAT requires that at least one of the following criteria is met: 10 or more people reported killed; 100 or more people reported affected; declaration of a state of emergency; call for international assistance. We considered the events belonging to the following categories: Natural disaster - Hydrological - Flood - Riverine flood or Flash flood. In the period of analysis, 2001–2015, North Malawi experienced 21 events, Central Malawi experienced 41 events and Southern Malawi experienced 76 events (corresponding to 1.4, 2.73 and 5.0 events per year respectively). We use this dataset for a comparative analysis on the exposure of maize yield to both flood and drought risk, and to drought risk only, as detailed in Section 3.5.

3.5. Spatio-temporal correlation of statellite datasets and maize yield data

Our analysis concerns the period 2001–2015 (for a total of 15 years) as this represents the largest overlapping period of all the datasets. We preprocess the datasets in Table 1 by computing standardized anomalies for each dataset as follows. The crop yield data have an annual time resolution and a spatial resolution corresponding to the administrative districts of Malawi. For each district i and year j, we compute the standardized anomaly $z_{i,j} = (x_{i,j} - \mu_{i,p})/\sigma_{i,p}$, where $z_{i,j}$ is the standardized maize yield, $x_{i,j}$ is the original maize yield, $\mu_{i,p}$ and $\sigma_{i,p}$ are the mean and standard deviation of maize yield computed over the period p. To account for the step change in the mean yield due to the changes in the agricultural policy (see Fig. 2b and Section 2), we consider two time periods, namely, $p = 2001 - 2005$ if $j \leq 2005$ and $p = 2006 - 2015$ if $j > 2005$. No change is, instead, detectable in the time series of either the hydrometeorological variables or the vegetation greenness variables. For each pixel k and aggregation period m (corresponding to one month or a sequence of consecutive months), we compute the standardized anomaly $z_{k,m} = (x_{k,m} - \mu_k)/\sigma_k$ where the mean and standard deviations account for the entire period of analysis, i.e., 2001–2015. We aggregate consecutive months during the maize growing season to possibly account for cumulative processes which may influence the crop growth.

We then analyse the spatio-temporal correlation of the datasets to understand how water scarcity propagates from meteorological (i.e., precipitation) to hydrological variables (i.e., soil moisture) and, finally, how it impacts vegetation growth (i.e., ESI, NDVI and EVI) and historical maize yield data. We quantify the correlations by means of the Pearson correlation coefficient $\rho_{ab} = \sigma_{ab}/(\sigma_a\sigma_b)$, where σ_{ab} is the covariance between the variable a and b and σ_a, σ_b is the standard deviation of the variable a and b respectively. In particular, we analyse the spatial variability of the Pearson correlation coefficients for different time lags between precipitation and the other remote sensing variables. When the spatial resolution of the datasets do not match the spatial resolution of CHIRPS (i.e, 5×5 km^2), we aggregate the dataset with the finest resolution to the coarsest resolution. In other words: *i)* we average CHIRPS to 25×25 km^2 when analysing the correlation between precipitation and soil moisture; *ii)* we average NDVI and EVI to 5×5 km^2 when analysing the correlation between precipitation and vegetation health. We disregard pixels where more than 30% of the data are missing, for example because of cloud cover. When we analyse the spatio-temporal correlation of the remote sensing datasets and historical maize yield data, we mask the remote sensing datasets using the cropland mask described in Section 3.3 and we compute the median of all the resulting pixels in each district. We repeat the correlation analysis by removing the flood years listed in the EM-DAT so to focus specifically on crop yield damage possibly caused by water scarcity only.

4. Results

4.1. Correlation between precipitation and the other remote sensing datasets

Precipitation and soil moisture present on average the highest pixel-to-pixel Pearson correlation coefficients (Fig. 3). In particular, the correlations computed for January, February, and March are the highest. The results show a clear spatial trend with increasing correlation values from North (approximately 0.4) to Central (approximately 0.6) and South Malawi (approximately 0.7).

Precipitation and ESI show the highest correlations in March in South Malawi and in April in Central and North Malawi. As in the previous case, there is a clear spatial trend between the 3 regions, but the correlation coefficients are in general below 0.4. We acknowledge, however, that ESI has a percentage of missing data up to 85% due to cloud cover in January and February, which may affect the correlation results in those months.

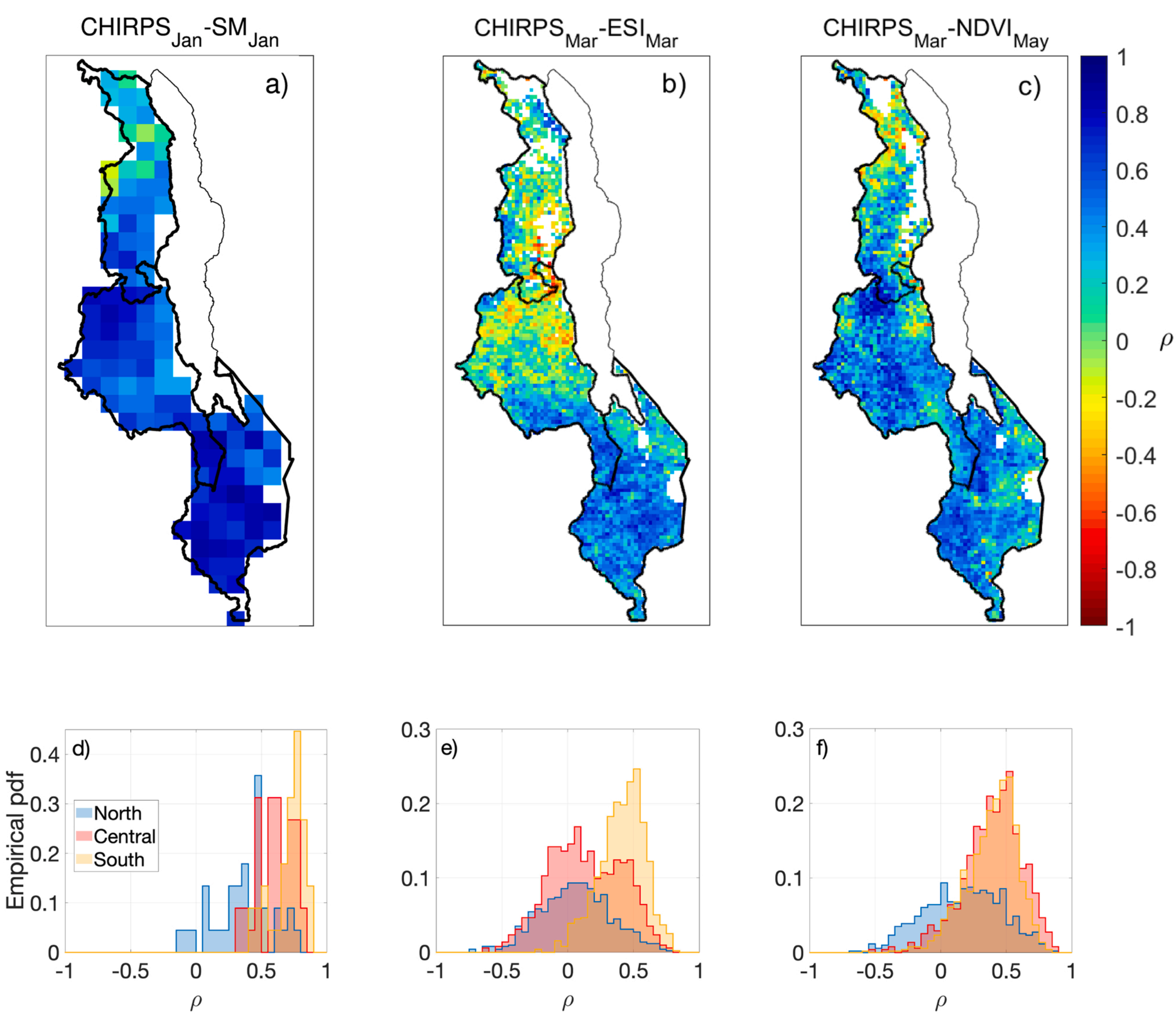

Fig. 3. Pixel-to-pixel Pearson correlation values and their empirical distribution between a,d) precipitation and soil moisture in January; b,e) precipitation and ESI in March; c,f) precipitation in March and NDVI in May.

The correlation analysis between precipitation and NDVI and precipitation and EVI show very similar results although NDVI presents slightly higher correlation values. Differently from the previous cases, the highest correlation coefficients are obtained when considering a time lag of two months, i.e., when considering precipitation in February or March and NDVI in April or May respectively. The spatial trend is visible also in this case with lower and more variable correlation values in North Malawi (approximately 0.2) and higher and less variable correlation values in South Malawi (approximately 0.5).

4.2. Correlation between remote sensing datasets and historical maize yield

Table 2 shows the median Pearson correlation coefficients between each remote sensing dataset and the historical maize yield computed over the 3 Malawian regions. As detailed in Section 3.5, we analyse the correlation for each month and sequence of consecutive months in the maize growing season when considering all the years in the period 2001–2015 and when removing the flood events to focus on the relation between water scarcity and maize yield only. Only the most interesting results for each remote sensing variable are reported in the table. When considering the entire period (i.e., with flood years), only precipitation and soil moisture show correlation values larger than 0.5, particularly in March and when considering the aggregation of January, February, and March in South Malawi only. When removing flood years from the datasets, precipitation and soil moisture show higher correlation values with maize yield both in Central and South Malawi. In addition, also NDVI and ESI show correlation values higher than 0.5 in Central Malawi. NDVI has generally higher correlation values than EVI. The spatial differences are noticeable, as it was the case in the previous analysis, with North Malawi showing lower correlation values than Central and South Malawi.

Fig. 4 further explores, within each region, the spatial variability of the relations which showed the highest correlations reported in Table 2. For all the variables, the correlation values vary from district to district in each of the 3 regions. Nevertheless, districts in Central and South Malawi tend to behave more homogeneously than districts in North Malawi. The degree of spatial variability is however dependent on the variable considered. For example, precipitation in South Malawi and ESI in Central Malawi show the lowest variance.

Table 2
Median regional Pearson correlation coefficients between remote sensing datasets and maize yield data, including or not flood years. Only the most relevant aggregation periods for each variable are included. Correlation values larger than 0.5 are highlighted in bold. Significant correlations with a p-value lower than 0.05 are identified with an asterisk.

		with floods			without floods		
		North	Central	South	North	Central	South
CHIRPS	**Feb**	0.15	0.38*	0.25*	0.34	0.31*	0.29*
	Mar	0.43*	0.29*	**0.65***	0.41	**0.56***	**0.55***
	FM	0.39*	0.42*	**0.50***	0.45	**0.55***	**0.50***
	JFM	0.37	0.38*	**0.65***	0.26	0.34*	**0.54***
SM	**Feb**	0.24	0.30*	0.10*	0.09	0.32*	0.44*
	Mar	0.28	**0.56***	0.43*	0.06	**0.67***	0.38*
	Apr	0.29	0.36*	0.35*	0.15	**0.50***	0.32*
	FM	0.36*	0.44*	0.39*	0.25	**0.53***	**0.54***
	JFM	0.28	0.23*	0.33*	0.18	0.16	**0.55***
ESI	**Mar**	0.01	0.09	0.28*	-0.06	0.25*	0.44*
	Apr	0.01	0.01	0.42*	-0.09	0.21	0.36*
	May	-0.08	0.32*	0.14*	-0.05	0.43*	0.15*
	Jun	-0.18	0.31*	0.09	-0.17	**0.54***	0.16
NDVI	**Apr**	0.19	0.38*	0.40*	0.22	**0.53***	0.42*
	May	-0.02	0.42*	0.37*	-0.12	**0.54***	0.32*
	Jun	0.14	0.31*	0.39*	0.03	0.43*	0.29*
EVI	**Apr**	0.04	0.25*	0.39*	-0.12	0.46*	0.46*
	May	-0.12	0.30*	0.29*	-0.25	0.41*	0.29*
	Jun	0.04	0.23*	0.26*	-0.09	0.37*	0.23

As precipitation shows in general higher correlation values to maize yield than the other variables, we further explored its relationship with historical maize yield on an annual basis. Fig. 5 shows the scatterplot between March precipitation standardized anomalies and maize yield standardized anomalies in the three regions. Each point correspond to a district and year in the entire period of analysis and when removing flood years. Negative March precipitation standardized anomalies clearly correlate with negative crop yield standardized anomalies. Positive precipitation standardized anomalies, instead, do not show a clear trend. In most cases (but not all) they are associated with positive maize yield standardized anomalies. The cases in which they are associated with negative yield standardized anomalies tends to correspond with years when at least one flood event happened (filled circles in the figure). The number of flood events are higher in Central and South Malawi. When the flood years are removed, monotonic relations are visible in all the 3 regions: the water-stress effect on the crop yield becomes clearer, as well as the saturation of crop yield with increasing precipitation.

5. Discussion

5.1. On the spatial and temporal resolution of the remote sensing datasets

We analyse the correlation between precipitation and other remote sensing variables to investigate how water availability propagates from meteorological (i.e., precipitation) to hydrological variables (i.e., soil moisture) and, finally, how it impacts vegetation growth (i.e., ESI, NDVI and EVI). Precipitation and soil moisture have the highest correlation coefficients during the peak of the rainy season, i.e., in January, February, and March, with no time lag between the two variables (Section 4.1 and Fig. 3). Even if it is reasonable to expect a delay between precipitation events and the accumulation of moisture in the soil, this dynamic is masked by the monthly resolution of our analysis and by the fact that the remote sensed soil moisture is representative of the water storage in the first few centimeters of soil only which dries out quickly after rainfall events. The lower correlations in North Malawi are likely due to the extensive presence of forests which, on the one hand, intercept precipitation and, on the other hand, shade the soil from direct radiation thus affecting the soil moisture accumulation and depletion (Fig. 1). This is confirmed by the correlation analysis between precipitation and ESI, which show lower values in the north. When considering the correlation between precipitation and vegetation indexes, the time lag of the maximum correlation increase up to two months, which indicates the response time on vegetation growth processes to precipitation. This analysis suggests that the remote sensing datasets at the time and spatial resolution adopted in this study are adequate for analysing the effect of water availability to vegetation growth processes, although a finer time resolution would likely allow a better detection of hydro-meteorological and vegetation dynamics happening on shorter scales than one-month. This is likely one of the reasons why, the soil moisture and ESI datasets are less informative than precipitation in anticipating maize yield, as discussed in Section 5.2.

5.2. On potential WII indexes

Precipitation and soil moisture have the highest and most spatially consistent correlations with crop yield among the variables we have analysed (Table 2 and Fig. 4). For both variables, we find the highest correlations in March or in the aggregation of February and March, in Central and South Malawi particularly. This result is consistent with previous literature, e.g., Jayanthi et al. (2013) which report that crop in South Malawi is most vulnerable to water-stress in February and March. As mentioned in Section 2, this period corresponds to maize flowering in Malawi which is one of the most sensitive growing stages to water-stress

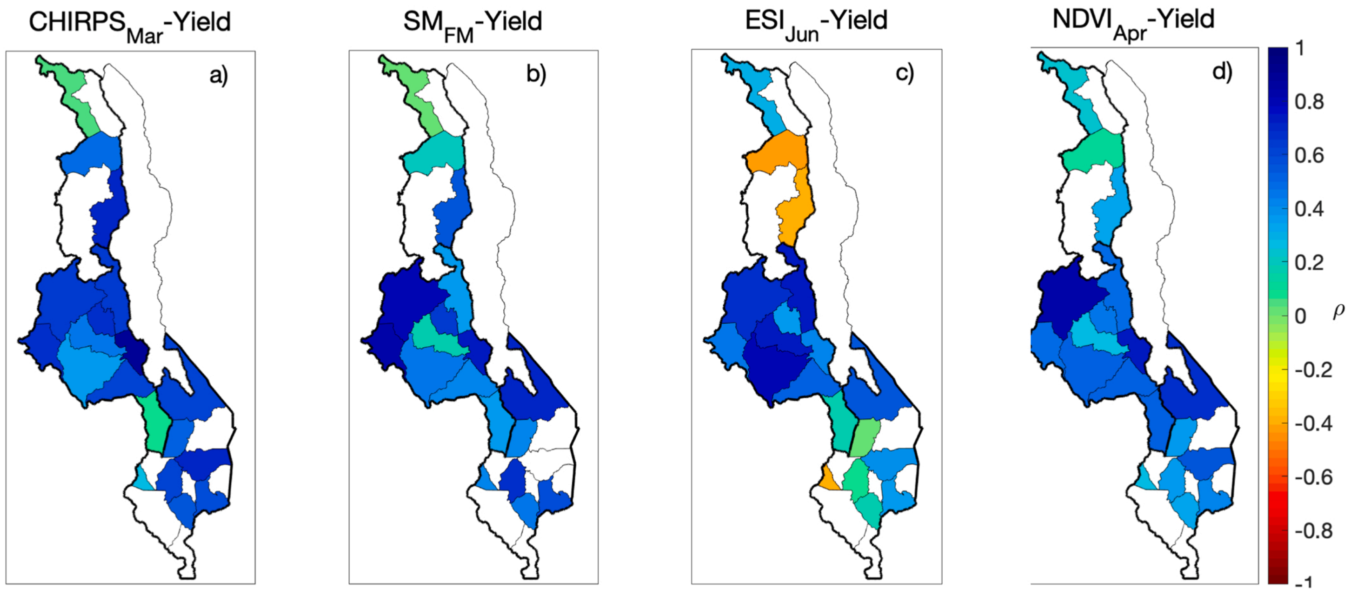

Fig. 4. Median district Pearson correlation values between maize yield and a) March precipitation, b) February-March soil moisture, c) June ESI, d) April NDVI. Flood years in each district are removed.

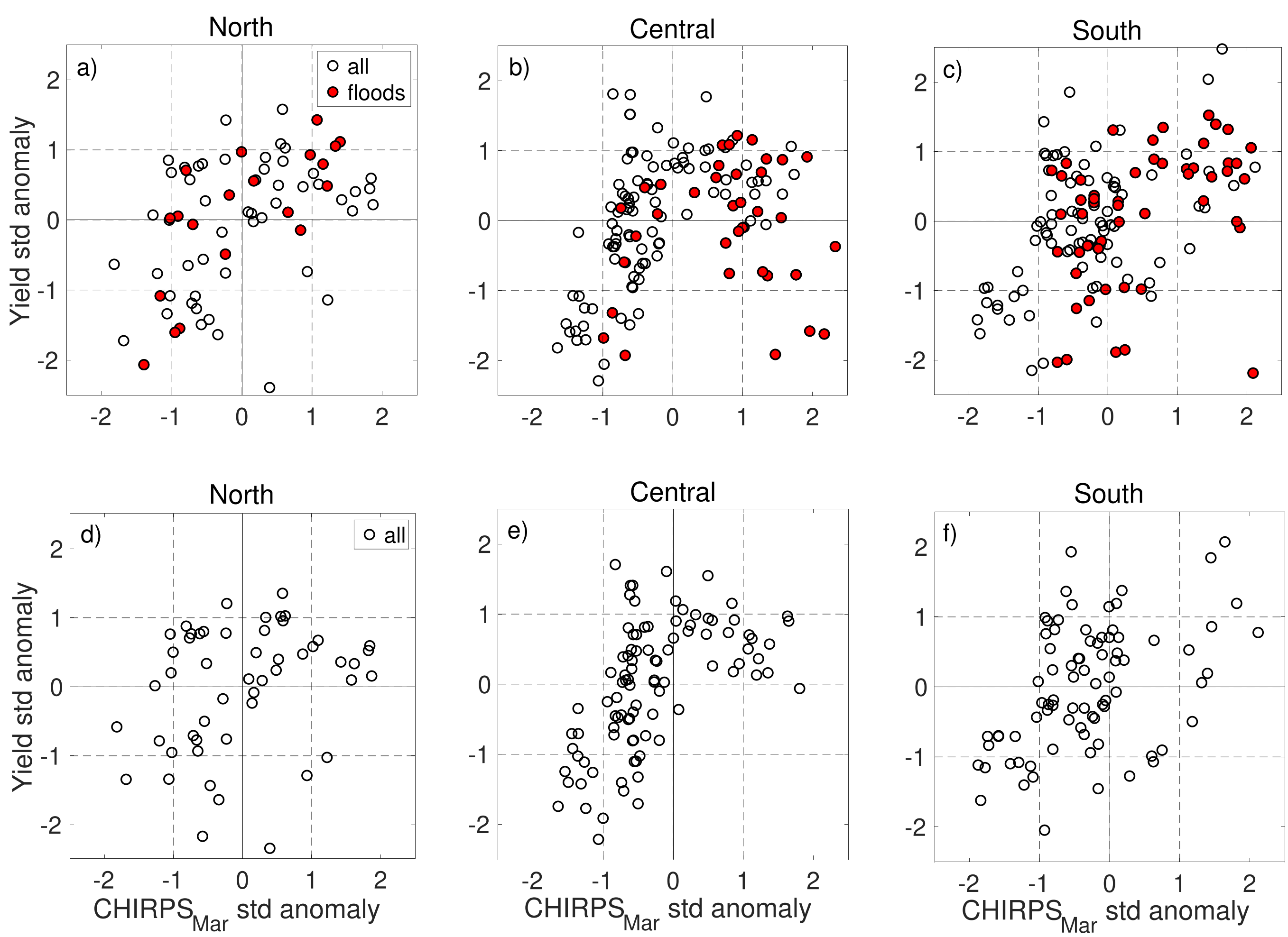

Fig. 5. Scatterplot between March precipitation standardized anomaly and maize yield standardized anomaly in North Malawi (a,d), Central Malawi (b,e), and South Malawi (c,f). Each point corresponds to a district and year in the entire period of analysis (upper panels) and when removing flood years (lower panels).

(Clay et al., 2003; Çakir, 2004; Comas et al., 2019). Our analysis suggests instead that ESI is not a good proxy for rainfed maize yield. This result may be driven by the high percentage of missing data during the high precipitation months (December–February) which are also critical for maize growth. Indeed, ESI can be estimated under clear sky conditions only (Anderson et al., 2007). NDVI generally shows higher correlation values than EVI. Our results show that the correlation values of NDVI in April and May (corresponding roughly to the harvesting period, as commented in Section 2) are comparable to the ones obtained when considering precipitation and soil moisture. This is however limited to Central Malawi. NDVI could thus be considered a satisfactory proxy for maize yield only in parts of the country . The literature is not unanimous on this point (see for example Möllmann et al. (2020) and references therein) as the correlation between NDVI and crop yield may be very location specific (Turvey and McLaurin, 2011; Bokusheva et al., 2016). For example, according to Turvey and McLaurin (2011), vegetation greenness is not necessarily a proxy for crop yield, while Lopresti et al. (2015) suggest that NDVI is a satisfactory predictor for wheat yield in a case study in Argentina, and Makaudze and Miranda (2010) conclude that NDVI is a more effective WII index than precipitation for maize and cotton yield in Zimbabwe.

Contrary to other works (e.g., Enenkel et al., 2018, 2019), our analysis suggest that evapotranspiration, soil moisture, and vegetation variables do not add much value with respect to precipitation in anticipating historical maize yield at the district spatial resolution in Malawi. Precipitation seems thus to be the most promising candidate for a WII index among the remote sensing datasets we have analysed in this work. In fact, it not only shows higher correlation coefficients for a wide portion of the country, but it has the most straightforward and intuitive connection to crop growth thus increasing the potential for the acceptance and uptake of the insurance from both the insured farmers and the insurance company (Hess and Syroka, 2005; Osgood et al., 2007; World Bank, 2011).

5.3. On the effect of water stress and excess

There is a theoretical parabolic relationship (an inverted U) between crop growth and water availability as both water scarcity and excess inhibit plant growth (Clay et al., 2003). Nevertheless, the sensitivity of maize to water scarcity or excess can be different depending on the growth stages (see the discussion in Section 2). Our analysis suggests that it is important to account for these differences when analysing the correlations of hydrometeorological variables and crop yield. Fig. 5 suggests that below-average precipitation in March is critical for the final maize yield. When removing flood years from the analysis, the water-stress effect on the crop yield becomes clearer, as well as the saturation of crop yield with increasing precipitation. Although most floods are associated with positive precipitation anomalies, as expected, some are associated with below-average precipitation. This may descend from the rough details about the flood location, extent, and duration recorded in the EM-DAT database: a flood may have affected a sub-portion of the district, while the precipitation anomaly is computed on the entire district, or may not have been so intense to damage the crops.

Table 2 supports our conclusion because identifying and removing flood events from the analysis generally improves the correlations. Nevertheless, the Pearson correlation coefficients do not exceed 0.7. This partly reflects the fact that crop yield depends on many factors that are not necessarily water-related such as soil fertility, crop management practices, pests, labour availability among others (World Bank, 2011; Sutcliffe et al., 2016). Concerning the 2005 Malawi food crisis, the FAO reported, for example, that: “[the 2005 food crisis was] the result of a combination of factors, including drought, floods, consecutive poor harvests, endemic poverty and the effects of the HIV/AIDS pandemic" (FAO Newsroom, 2005). This multi-driver dependence is evident from the scatterplots in Fig. 5 which show a considerable spread in crop yield, particularly when March precipitation is slightly below-average. This suggests that a small water deficiency in that period is not always critical and may be compensated by other factors. The drivers that may cause this spread should be further investigated as they may suggest possible structural and/or policy interventions to increase the yield and reduce its variability.

5.4. On the spatial basis risk

The maize yield dataset we use in this work is quite unique because it spans a relatively long time period for all the districts across Malawi. In fact, most of the literature adopts the FAO national statistics on crop yields (e.g., Hoffman et al., 2018; Enenkel et al., 2018; Vogel et al., 2019). This allows us to analyse the spatial variability of the correlations with the remote sensing datasets. For all the analysed relations, a clear spatial trend is visible. This is likely induced by the elongated shape of the country, the landscape of which presents clear gradients in elevation, temperature, and land cover. North Malawi usually shows lower correlation values than Central and South Malawi. Even among the districts in each region, the correlations show high variability. Our analysis suggests that considering a unique index for the entire Malawi may be challenging, as the highest correlations in each district are associated to different variables and months.

Unfortunately, we do not have historical maize yield records at finer spatial resolution. Still we could have a sense of this finer spatial variability by considering NDVI prior to the maize senescence (approximately around April-May) as a proxy for maize yield. Fig. 3c,f suggests that the spatial heterogeneity of the correlation when considering precipitation may be high even within each district. Our results show that remote sensing datasets may be very valuable for representing the spatial heterogeneity of precipitation and reducing the spatial basis risk. As such it could be interesting to further explore its role within a WII pilot scheme. The next generation of high-resolution remote sensing datasets, e.g., NDVI at 10×10 m^2 could allow for a better characterization of the spatial variability of cropland extension and yield estimate that could improve the effectiveness of the insurance contracts (Bokusheva et al., 2016).

5.5. Limitations and future works

Althought we use an interesting maize yield dataset, as commented in Section 5.4, it is difficult to assess how reliable the data is. World Bank (2011) claims that national and district crop yield statistics may be of limited quality, consistency and only available for brief periods of time. Covering large areas, they usually summarize different environmental conditions and farmers adopting different practices which may not be adequately recorded during the data collection process (Osgood et al., 2013). Clay et al. (2003) reports that there might be an issue with overestimation of yield and production of tuber, cassava, and sweet potatoes in the reports of the National Statistical Office of the Ministry of Agriculture in Malawi. For these reasons, there is limited research about WII considering historical crop yield data (Enenkel et al., 2018). The uncertainty associated with these data is, however, difficult to quantify.

The monthly time aggregation we adopted in this study may mask some more complex relationship between hydrometeorological variables and crop growth. Repeating the analysis using a finer time resolution is potentially interesting for further refining the identification of a possible WII index. This would allow also to overcome another limitation of the study, i.e., considering a fixed average maize growing season for the entire Malawi and for each year. It would be instead interesting to account for the spatial variability and interannual variability of the growing season. For example, the FAO guidelines use the dekad (i.e., a period of 10 consecutive days) as unit of time to analyse the crop growth dynamics and indicate that there is some difference in the start and lenght of the maize growing season depending on whether the field is located in low, medium, or high elevation zones. These analyses could further explain the spatial variability of the results shown in this paper and contribute to reduce the spatial basis risk.

We considered a fixed landcover map in this work, corresponding to the year 2015, to identify cropland in Malawi. Cropland expansion is, however, happening in all sub-Saharan Africa for meeting the growing food demand of the local smallholder farmers (Chamberlin et al., 2014; Ordway et al., 2017; Li et al., 2021). A more precise and time varying mapping of cropland location and extent could improve the accuracy of the correlations explored in this work. This is, however, a field of ongoing research as most of the studies so far estimate cropland expansion at the national level only (Evenson and Gollin, 2003; Grassini et al., 2013).

As the identification of flooding events is important to focus on the specific impact of water scarcity on maize yield, it may be interesting to better characterise the time, duration, and spatial extent of the floods. Remote sensing datasets could be used to validate and possibly improve the EMDAT records. As in the previous cases, this additional information could contribute to improve the correlations between the precipitation index and maize yield thus ultimately reducing the spatial basis risk.

6. Conclusions

In this work we explored the suitability of using remote sensing datasets as proxy for maize yield in the 28 administrative districts of Malawi. We analysed the spatial and temporal correlations of the historical maize yield data and several remote sensing datasets including the Climate Hazards group Infrared Precipitation with Stations (CHIRPS) dataset, ESA CCI Soil Moisture combined dataset (version 4.2), the Evaporative Stress Index (ESI) from the Atmosphere-Land Exchange Inversion model (ALEXI), the MOD13Q1 Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI).

Our analysis shows that indexes based on precipitation (particularly precipitation standardized anomaly in March) provides the highest (Pearson correlation coefficient higher than 0.55) and most spatially consistent correlations across the districts in Malawi. Soil moisture and NDVI show correlations similar to precipitation in some months and areas, but contrary to what is suggested by some recent literature, they do not improve significantly the correlations with maize yield at the spatial and temporal resolution adopted in this study. NDVI shows higher correlations than EVI, and ESI is not a suitable proxy for rainfed maize yield in Malawi because of the high percentage of missing values in the months of February and March. Overall, the use of remote sensing dataset allowed us to discriminate the spatial variability of the relation between water availability and crop yield. The strength of the relations are location dependent: the highest and less variable correlation values are found in Central and South Malawi. We conclude that the spatial basis risk can be addressed by adopting remote sensing datasets in the definition of a WII index, but the variability of the correlations across and within the 3 Malawian regions still prevents an identification of a unique index which could be regarded as the most suitable maize crop yield proxy in the whole country.

From the methodological point of view, we recognize the importance of distinguishing between water scarce and water abundant events which, if considered together, may confound the strength of the relations investigated. It is also important to test the specific area for the suitability of NDVI as a proxy for crop yield as this is very location dependent. Also considering a-priori field or laboratory based knowledge on the vulnerability of the different crop growing stages to water-stress (cause by either water scarcity or abundance) is helpful in identifying possible WII indexes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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