Agro-meteorological risks to maize production in Tanzania: sensitivity of an adapted water requirements satisfaction index (WRSI) model to rainfall

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Abstract

The water requirements satisfaction index (WRSI) – a simplified crop water stress model – is widely used in drought and famine early warning systems, as well as in agro-meteorological risk management instruments such as crop insurance. We developed an adapted WRSI model, as introduced here, to characterise the impact of using different rainfall input datasets, ARC2, CHIRPS, and TAMSAT, on key WRSI model parameters and outputs. Results from our analyses indicate that CHIRPS best captures seasonal rainfall characteristics such as season onset and duration, which are critical for the WRSI model. Additionally, we consider planting scenarios for short-, medium-, and long-growing cycle maize and compare simulated WRSI and model outputs against reported yield at the national level for maize-growing areas in Tanzania. We find that over half of the variability in yield is explained by water stress when the CHIRPS dataset is used in the WRSI model (R^2 = 0.52-0.61 for maize varieties of 120-160 days growing length). Overall, CHIRPS and TAMSAT show highest skill (R^2 = 0.46-0.55 and 0.44-0.58, respectively) in capturing country-level crop yield losses related to seasonal soil moisture

deficit, which is critical for drought early warning and agro-meteorological risk applications.

Keywords: WRSI, Rainfall, Remote sensing, Tanzania, Maize

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1. Introduction

Inter-annual and seasonal rainfall and temperature variability affects cropland and pasture productivity, particularly in regions of rainfed agriculture. Understanding the impacts of agro-meteorological risks such as drought on crop production requires detailed evaluation of the sensitivity of yield indicators and crop models to different datasets providing model inputs. For example, a rainfall dataset that erroneously detects a delayed season onset would reduce the length of the growing season, subsequently leading to simulations of yield reduction or failure in years of 'normal' rainfall.

The WRSI Model. The Water Requirements Satisfaction Index (WRSI) is perhaps the most widely used crop water balance technique in operational drought monitoring, in which rainfall variability is the main driver of changes in yield. WRSI was developed by the United Nations (UN) Food and Agricultural Organization (FAO) for use with synoptic station data to monitor rainfed croplands throughout the growing season (Doorenbos and Kassam 1979 in Senay 2008; Frere and Popov 1979). Calibrated for a range of crops, WRSI, a.k.a. crop specific drought index (CSDI) (Melesse et al., 2007), provides an indication of crop performance on the basis of water availability during the growing season (Frere and Popov 1986 in McNally et al. 2015).

Through the relative relationship between water demand and supply, WRSI indicates the extent to which crop water requirements are met during the growing season (Patel et al., 2011).

WRSI Applications. WRSI forms the basis of the FAO AgroMet Shell tool (Patel et al., 2011) and the FAOINDEX software (Gommes 1993 in Rojas et al. 2005); a variation of WRSI is incorporated in the AquaCrop model (Steduto et al., 2012) and the European Commission's Joint Research Centre use WRSI for Africa and globally for in-house analyses. As part of an UN World Food Programme effort to set up in-country food security monitoring and early warning systems, WRSI is used in the Ethiopian Livelihood Early Assessment and Protection (LEAP) system - a platform for early warning owned by the Disaster Risk Management and Food Security Sector of the Ministry of Agriculture in Ethiopia. Since the 2000s, WRSI has supported the parametric agricultural insurance analysis of the Africa Risk Capacity, a Specialised Agency of the African Union supporting weather risk management (Bryla and Syroka, 2007; Bastagli and Harman, 2015). WRSI has been used perhaps most extensively by the growing international user community of the US Agency for International Development (USAID) Famine Early Warning System NETwork (FEWS NET), launched as FEWS in 1985 for five countries in the Sahel and Sudan (Verdin and Klaver, 2002) and renamed to FEWS NET in 2000. The FEWS NET community employs a 'convergence of evidence' approach where WRSI, alongside independent information from satellite-based records on rainfall and vegetation, provides information on agro-meteorological impacts on crop production (Verdin and Klaver, 2002).

GeoWRSI. Agencies concerned with drought monitoring and famine early warning, including FEWS NET, have increasingly moved toward grid-based use of WRSI, largely facilitated by the greater availability of gridded input data on rainfall and reference, or potential, evapotranspiration (PET) (Senay and Verdin, 2002, 2003; Verdin and Klaver, 2002). In 2002/03, FEWS NET set up the geospatial (gridded) version of WRSI, GeoWRSI (Magadzire 2009 in Jayanthi et al. 2014), for **operational crop monitoring and yield estimation** in 20 African countries, as well as in Central America, the Caribbean (Haiti), Central Asia, and the Middle East (Afgahnistan) with daily and dekadal outputs posted online at http://earlywarning.usgs.gov/adds (Verdin and Klaver, 2002; Melesse et al., 2007; Shukla et al., 2014). Unlike the WRSI in FAO's AgroMetshell software, GeoWRSI calculates water balance components on a grid-cell basis (Jayanthi et al., 2014). GeoWRSI uses satellite-based rainfall estimates, a potential evapotranspiration (PET) climatology derived using the Penman-Monteith equation, soil water holding capacity from digital soil databases, and published crop coefficient values (Kc) (Jayanthi and Husak, 2013).

Drought-related crop yield losses in response to water stress (rainfall and/or soil moisture deficit) were successfully assessed for maize in Kenya, Malawi, and Mozambique, and for millet in Niger through end-of-season WRSI, the ratio of seasonal crop actual evapotranspiration (AET) to seasonal crop water requirements, as an agricultural hazard index (Jayanthi et al., 2014). With the increasing availability of 30^+ years satellite-based rainfall datasets, GeoWRSI has been used to produce probabilistic estimates of rainfall-driven yield variations. For example, a novel **probablistic drought risk management** approach, considering the hazard, exposure, vulnerability, and risk components of agricultural drought risk profiling has helped to improve the statistical representation of hazards and risk exposures (Jayanthi et al., 2014). Alongside hydrologic and water balance models Noah and VIC, and other land surface models, WRSI is used in a **multi-model framework for seasonal agricultural drought forecasting** within the NASA FEWS NET Land Data Assimilation System (Shukla et al., 2014).

Previous Evaluations and Sensitivity Analysis. Although WRSI is widely used for operational crop performance monitoring, probabilistic drought risk management, and multi-model seasonal drought forecasting, a comprehensive absolute evaluation of WRSI relative to reported yield has not been carried out in many African countries, likely due to scarcity, or lack of, reliable agricultural statistics on crop yield, planted area, and seasonal production (Senay and Verdin, 2002, 2003). An overview of previous evaluations is given in Table 1. Regression correlations of WRSI with reported yields in the order of 0.75 are commonly reported (see references in Verdin and Klaver 2002), although these are usually for sub-national level and cover a time span between a single growing season and up to 10 years in one study.

Sensitivity of WRSI to inputs has been evaluated with the FAOINDEX

Table 1: Evaluations of WRSI against reported yield

Country (Crop)	**Findings (References)**
Ethiopia (sorghum)	Evaluated WRSI vs reported yield; district groups; 4 years (1996-1999); R^2=0.77 for years with WRSI below 98% (Senay and Verdin, 2002)
Ethiopia (maize)	Evaluated WRSI vs reported yield; 175 districts; 4 years (1996-1999); R^2=0.92 (Senay and Verdin, 2003)
Southern Africa (maize)	Higher correlation when yield reduction function considers long-term local average yield; 206 points; R^2=0.86 (Mattei and Sakamoto 1993 in Verdin and Klaver 2002)
Zimbabwe (maize)	Evaluated WRSI vs reported yield; 14 communal lands; 1996/97 season; R^2=0.8 (Verdin and Klaver, 2002)
India (maize, sorghum, pearl millet)	Evaluated WRSI vs reported yield; 7 years (1998-2004); mean significant R^2=0.52 (N=43); works well in drought-prone regions; higher R^2 for regions where proportion of area covered by each crop was higher; showed that drought stress can reduce season length by up to 20-30 days; observed declining trend in mean season length (Patel et al., 2011)
Kenya, Malawi, Mozambique (maize); Niger (millet)	WRSI used to develop crop yield loss functions (Jayanthi and Husak, 2013; Jayanthi et al., 2014); 10 years (2001-2010); R^2=0.52, 0.72, and 0.62 for Kenya, Malawi, and Mozambique, resp., and 0.64 for Niger

software (Gommes 1993 in Verdin and Klaver 2002) through simulations with varying planting dekad or start of season (SOS), soil water holding capacity (WHC), rainfall input, and PET. Results showed that ±10% change in rainfall or PET led to ±5% change in WRSI; similar sensitivity to shifting SOS was observed, and WRSI varied substantially in response to WHC changes with 25 mm and 50 mm increases leading to 10% and 16% increase of WRSI, respectively (Verdin and Klaver, 2002).

Motivation and Objectives. Inherently, models such as WRSI depend to a high degree on the quality of rainfall and reference evapotranspiration input data. Rainfall validations and inter-comparisons focus on assessing the performance of gridded rainfall data relative to point-based gauge observations of rainfall. However, what matters most for crop water stress modelling and weather index-based insurance products is the skill of rainfall datasets in capturing agricultural drought parameters such as season onset, duration, and cessation and the correlations between indicators such as WRSI with yield.

For example, in a West Africa study of rainfed cereal crops, Ramarohetra et al. (2013) showed that the choice of rainfall product – mainly via the product's skill in capturing seasonal rainfall total and distribution of wet days – can introduce large biases in crop yield simulations with the mechanistic crop growth models SARRA-H and EPIC. To our knowledge, a similarly comprehensive analysis of WRSI's sensitivity to rainfall inputs from different sources has not been carried out. Thus, the objective here is to evaluate the sensitivity of WRSI to different rainfall datasets and crop variety parameterisations, demonstrating the adapted WRSI developed here for a case study focused on maize production in Tanzania. With this study we also extend to Tanzania the evaluation of the WRSI method for assessing agro-meteorological risk on maize production, and characterise the spatial and temporal variation in the timing of the onset of rains and growing season duration defined using different methods (Senay and Verdin, 2003). The outcomes of this will help inform weather index-based insurance design on the variability in the correlation of WRSI and reported yield for different rainfall inputs.

2. Study Region

The United Republic of Tanzania (hereafter Tanzania) (total area: approx. 947,300 m^2; population: approx. 52 million) is situated on the eastern coast of Africa between 29-41°E and 1-12°S and has a diverse terrain with Africa's highest and lowest points, Mount Kilimanjaro (5,895 mASL) and the floor of Lake Tanganyika (352 mBSL), respectively.

Tanzania is dominated by tropical savanna, and warm semi-arid and arid climate zones. The eastern coastal region is hot and humid, while the high mountainous regions are cool. Mean annual temperatures in the highlands are between 10-20°C in the cold (May-August) and hot (November-February) seasons, respectively, and rarely fall below 20°C in the rest of the country.

Tanzania is characterised by two rainfall regimes. The unimodal zone in the central, southern, and western parts of the country has one main wet season 'Musumi' (October/November-April/May) prone to dry spells in February-April. The bimodal zone in the northeast mountainous region from Lake Victoria to the coast is defined by the seasonal north-south migration of the Inter-Tropical Convergence Zone (ITCZ) (Zorita and Tilya, 2002) with short 'Vuli' rains (October-November) and long 'Masika' rains (March-May).

Tanzania has diverse soils that are generally suitable for agricultural production. However, physical soil loss through erosion and decline in soil fertility due to continuous cropping practices without replenishment of soil nutrients and minerals present major challenges for increasing crop yield.

Apart from large zones under wildlife and biodiversity protection, agriculture contributes to about a quarter of the gross domestic product, providing 85% of exports and employing over half of the workforce. Agricultural production is mainly rainfed with only 1% of agricultural land currently under irrigated farming. The largest food crop is maize with 1.5 Mha under maize production and 5.17 Mt production in 2013. Longer maize varieties are grown in the unimodal rainfall zone, while double harvest of shorter varieties is common in the bimodal rainfall zone.

3. Data and Modelling Approach

The WRSI/GeoWRSI model is described in Senay and Verdin (2003) among others and summarised in Appendix A along with its key advantages and disadvantages. In order to address some of the model's disadvantages and to enable testing of its sensitivity to rainfall inputs from different sources and different crop growing cycle parameterisations, we developed an adapted WRSI model described here.

3.1. The Adapted WRSI model

The adapted version of WRSI developed here allows for sensitivity analysis to rainfall with phenology-relevant metrics such as start of season (SOS), length of the growing period (LGP), and end of season (EOS) through new capabilities to:

- drive the model with different rainfall input datasets,
- use a new, temporally-varying reference evapotranspiration input data, as opposed to climatological averages,
- use spatially-varying water holding capacity from a gridded soil database,
- apply different methods to define SOS and LGP, and
- calculate and output intra-seasonal variables such as cumulative rainfall at each crop development stage and seasonally, as well as water balance components such as soil moisture beyond the growing season.

3.1.1. Weather Data Inputs

Table 2 summarises the input reference evapotranspiration and rainfall data for the adapted WRSI model. Since the stochastic nature of climatic parameters plays a key role in the calculation of PET and AET, and subsequently WRSI and drought-related yield losses, using climatological PET values in WRSI may not be ideal (Kaboosi and Kaveh, 2010). Thus, we use a newly available, time-varying PET input dataset with each of three different rainfall data products (Table 2).

PET. Potential (reference) evapotranspiration (PET) data with the Penmann-Monteith equation (hereafter PET-PM) (Sperna Weiland et al., 2015) is available from the eartH2Observe tier-1 forcing dataset at 0.5° resolution globally

Table 2: Model input data (PET-PM = Potential (reference) EvapoTranspiraton with Penman-Monteith equation; ARC2 = African Rainfall Climatology v2; CHIRPS = Climate Hazards group InfraRed Precipitation with Station data; TAMSAT = Tropical Applications of Meteorology using SATellite data and ground-based observations)

Dataset	Spatial Resolution	Time Step	Time Period
Evapotranspiration			
PET-PM	0.083°($\approx 8km$)	daily	1979 - 2014
Rainfall			
ARC2	0.10°($\approx 10km$)	daily	1983 - present
CHIRPS	0.05°($\approx 5km$)	pentad, dekadal, daily	1981 - present
TAMSAT	0.0375°($\approx 4km$)	dekadal, daily	1983 - present

(Schellekens et al., 2016). Here, we use a downscaled PET-PM dataset at 0.083° resolution from the same source (PML, 2017), providing daily reference evaporation values in kg m^{-2} from 1979 to 2014 inclusive. The daily data were aggregated to dekadal time to drive WRSI calculations.

ARC2. The NOAA African Rainfall Climatology (ARC) Version 2 dataset (hereafter ARC2) (Novella and Thiaw, 2013) merges global precipitation index (GPI) information (3-hourly infrared data) with quality-controlled Global Telecommunication Systems (GTS) gauge observations of daily rainfall to provide daily rainfall estimates over Africa from 1983 to present. ARC2 is found to be consistent with two other satellite-based rainfall products, GPCP v2.2 and CMAP, with correlations of 0.86 over a 27-year overlap time period (Novella and Thiaw, 2013; Manzanas et al., 2014) and performed well for estimation of seasonal rainfall totals (Diem et al., 2014). ARC2 is also used for the R4 index based insurance in Ethiopia (Sharoff et al., 2015) and in Africa Risk Capacity's ARV software (ARC, 2017). The daily ARC2 data (NOAA-CPC, 2017) were aggregated to dekadal time step.

CHIRPS. CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) is an operational 35^+ years quasi-global rainfall dataset developed by the University of California, Santa Barbara (Funk et al., 2015). The data covers areas globally between 50°S-50°N from 1981 to the near-present, and incorporates 0.05° satellite imagery with *in situ* station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring. The CHIRPS version 2.0 final product provides information on daily and pentad (5-daily) rainfall. In addition to gauge data from GTS, CHIRPS-final uses all available sources of ground observations (such as GHCN, SASSCAL, SWALIM, etc.) at both the pentad and monthly time step with pentads re-scaled to match the monthly total. CHIRPS-final is generated once per month (in the third week of the month for the preceding month) as some station data are only available at the monthly time step. Daily CHIRPS data (UCSB-CHG, 2017) were aggregated to dekadal time step.

TAMSAT. The TAMSAT (Tropical Applications of Meteorology using SATellite and other data) research group at the University of Reading provides satellite-based rainfall estimates for the African continent and Madagascar in delayed near-real time. The TAMSAT rainfall estimation algorithm uses 15-min (30-min prior to June 2006) infrared imagery from the Meteosat geostationary satellites and a climatology-based calibration relationships (varying regionally and monthly) derived from a proprietary gauge dataset and historical gauge-satellite data (Maidment et al., 2014; Tarnavsky et al., 2014). The TAMSAT v3 daily rainfall estimates (TAMSAT, 2017), disaggregated from the pentad time step using cold cloud duration information (Maidment et al., 2017), were aggregated to dekadal time step for the analysis here.

3.1.2. Soil and Crop Parameters

Soil Data. The Harmonized World Soil Database (HWSD) combines information from existing regional and national updates of soil information worldwide with the 1:5,000,000 scale FAO-UNESCO Soil Map of the World (FAO, 1971-1981) and contains over 15,000 different soil mapping units at 30 arc-second spatial resolution (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2009a). Available water storage capacity ranging between 0-150 mm m^{-1} (estimated according to FAO procedures accounting for topsoil textural class and depth/volume limiting soil phases) from the HWSD v1.2 dataset (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2009b) is used to define spatially-varying water holding capacity (WHC) in the adapted WRSI model.

Crop Coefficients (Kc). Kc values provided by FAO are generally based on four crop growth stages: early (initial), vegetative (crop development), maturity (mid-season), and senescence (late season) where the early and mature stages are constant functions of time, and the vegetative and senescence stages are linear functions of time (Senay, 2008). Here, we use four-stage

K_c values for maize (*Zea mays* L.) (Steduto et al., 2012; Senay and Verdin, 2003) defined by 0.3, 1.2, and 0.35 at the early to vegetative, maturity to senescence, and harvest stages respectively (Allen et al., 1998).

Seasonal Parameters. The adapted WRSI model allows for definition of the start of season (SOS) from an external source or from rainfall input data using the AGHRYMET threshold approach of a given dekad with 25 mm rainfall followed by two dekads with 20 mm total rainfall as in the standard WRSI (see Appendix A). Although the AGHRYMET approach for SOS definition was developed for West Africa, Verdin and Klaver (2002) compared SOS detected by WRSI with field reports for the 1996/97 and 1997/98 growing seasons and showed that it is applicable for countries in southern Africa.

The length of the growing period (LGP) in the adapted WRSI can either be set as a constant, typically 80-180 days (e.g. 90 days for short-cycle maize, 160-days for long-cycle maize) or LGP can be defined from the persistence of rainfall over reference evapotranspiration, i.e. the length of time precipitation exceeds half of reference evapotranspiration as in the standard WRSI/GeoWRSI (see Appendix A). Since the adapted WRSI uses time-varying PET instead of climatology, LGP defined on the basis of rainfall persistence over PET varies from year to year. Specifically, LGP for each year is calculated from the SOS dekad while mean dekadal rainfall exceeds half of mean dekadal PET within the current LGP, or until there are six consecutive dekads without rainfall, indicating end of season. Using the average dekadal rainfall and PET within the current LGP allows for short dry spells to occur.

With either method for SOS and LGP definition, the end of season (EOS) is calculated as the sum of SOS and LGP in terms of dekad of the year (where 1-10 January is dekad 1 and 21-31 December is dekad 36).

Seasonal parameters are important, because crop variety and growing cycle length impact on the attainable yield with short-cycle crops sensitive to dry periods and long-cycle crops – to early EOS (Ramarohetra et al., 2013). Thus, with the adapted WRSI model we characterise and quantify the impact of seasonal parameters on WRSI as an indicator of crop yield.

3.2. Evaluation Data

For evaluation of WRSI simulations, we obtained yield data from the Statistics Unit of the Tanzanian Ministry of Agriculture Livestock and Fisheries (MALF) (http://www.kilimo.go.tz/). The data covers the time period between 1996 and 2009; however, from 2002 onwards, figures are reported for several new districts and contain estimates from national agricultural census for some years. Thus, only yield over the 1996-2002 time period is considered in the evaluation.

3.3. Model simulations and evaluation of sensitivity to rainfall

Here we describe the WRSI simulation scenarios and present the approach for evaluation of the model simulations.

3.3.1. Simulations

The adapted WRSI model, implemented in a spatially distributed mode, was applied for a total of 15 simulations, 5 model runs with each of the three rainfall data inputs and SOS identified using the WRSI threshold method. For model runs with each rainfall input dataset, simulations 1-4 use a constant LGP every season of 90, 120, 140, and 160 days, respectively, and simulation 5 uses LGP, which varies from year to year as it is defined using the WRSI approach based on rainfall persistence over time-varying PET.

The WRSI simulations cover the overlap time period between the rainfall and evapotranspiration input datasets, i.e. 1983-2014 for WRSI simulations with ARC2 and TAMSAT and 1981-2014 for those with CHIRPS rainfall input dataset. For all WRSI simulations, soil moisture was initialised as half of WHC after preliminary tests with values from dry soil to water at WHC showed little effect on the results. WRSI simulations were applied only to maize growing areas as of 2000 (You and Wood, 2006) and the evaluation against reported yield was carried out only for these areas at country level.

3.3.2. Evaluation

The evaluation of the impact of different rainfall input datasets on WRSI model simulations is carried out in three distinct parts.

The first part of the evaluation is focused on seasonal rainfall characteristics to support the identification of areas that are likely to experience similar agro-meteorological risk. Specifically, we evaluate the spatial patterns and temporal trends of SOS, LGP, and EOS across model simulations and relative to reported information on these.

In the second part, we examine the impact of different rainfall input datasets on the detection of WRSI below 80% spatially and over time (interpreted as below average crop production conditions). This is evaluated relatively among the three rainfall input datasets, as well as in relation to the five LGP scenarios (i.e. simulations 1-4 with 90, 120, 140, and 160 days fixed LGP and simulation 5 with variable LGP using the WRSI method).

Last, we assess the relationship of simulated seasonal WRSI and historically reported maize yield at the country level. As in previously reported comparisons (Table 1), seasonal WRSI values, as well as seasonal rainfall and median soil moisture for dekads in the season, over pixels in the maize growing areas (You and Wood, 2006) are averaged and compared through linear regression to reported national yield figures.

4. Results and Discussion

Here we present the results from the evaluation of rainfall seasonality, sensitivity of WRSI to rainfall input data, and correlations of WRSI, seasonal rainfall, and median soil moisture with reported yield for maize in Tanzania.

4.1. Evaluation of rainfall seasonality

Using the adapted WRSI model, we applied the standard rainfall threshold approach for SOS detection and the persistence of rainfall over evapotranspiration method for LGP determination to examine the spatial patterns and trends in the timing of SOS, the duration of LGP, and subsequently, the pattern and timing of EOS. It is worth noting that the focus is here on the main rainy season in the unimodal zone as capturing the two shorter rainfall seasons requires the use of two consecutive, and likely different, thresholds for SOS detection within the same agronomic year.

Figure 1 illustrates the differences in the spatial pattern of SOS, LGP, and EOS averaged over the time period covered by each rainfall product.

In the unimodal rainfall zone of Tanzania, the spatial patterns of SOS in ARC2, CHIRPS, and TAMSAT are similar, albeit with an earlier season onset in the ARC2 product on average across the country (dekad 28 corresponding to the first dekad of October, SD = 10.2) than in CHIRPS and TAMSAT (dekad 30 corresponding to dekad 3 of October with SD = 7.6 and 7.2, respectively).

With respect to LGP, the ARC2 product shows some artefacts likely due to the near-real time gauge-merging routine employed by the rainfall estimation algorithm (Novella and Thiaw, 2013) and results in an average LGP across the country of 14 dekads (SD = 3.1). CHIRPS reasonably well captures on average across the country a growing season of 15 dekads (SD = 2.6), which corresponds to the typical season length from October/November to April/May, and average LGP calculated from the TAMSAT product is 14.5 dekads (SD = 2.8).

As EOS is calculated by adding LGP to SOS, the spatial pattern of EOS reflects the above discussion with simulations using CHIRPS as input rain-

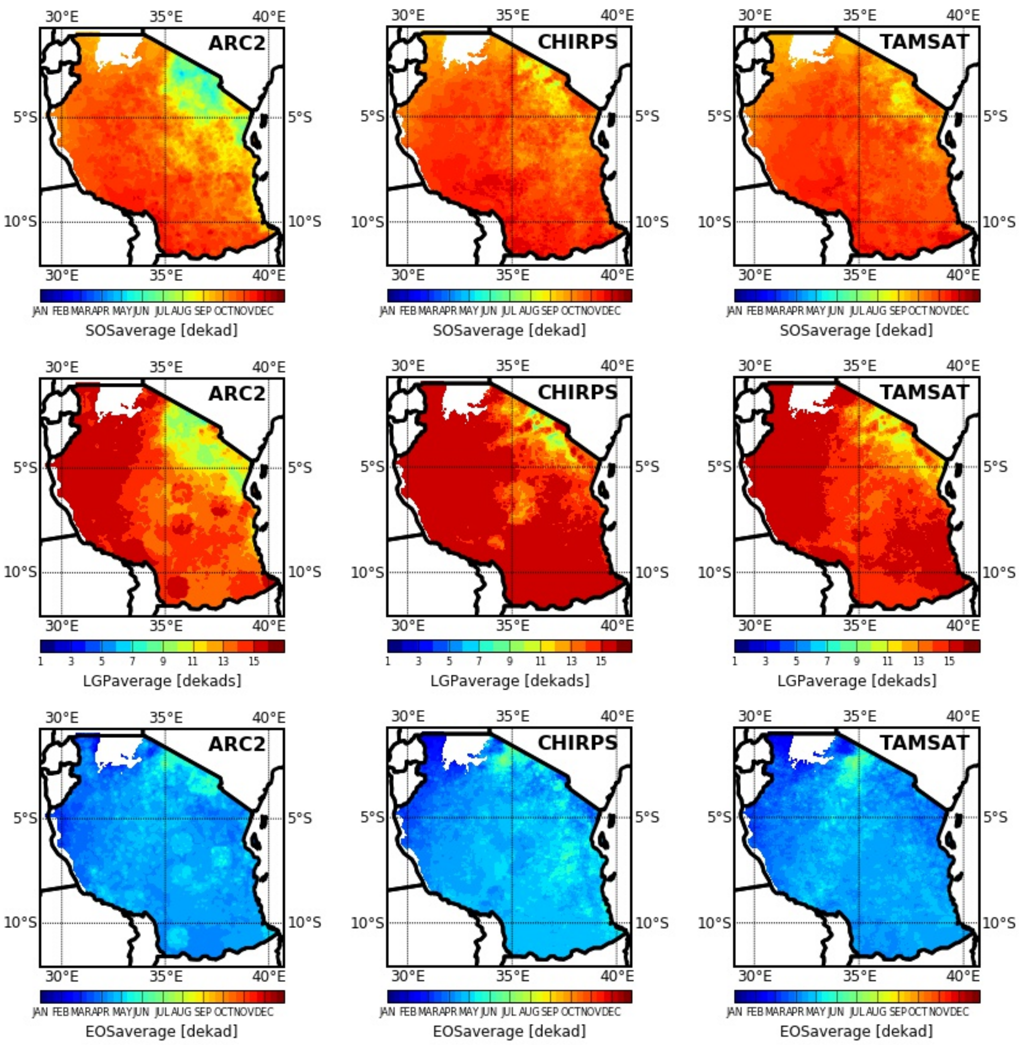

Figure 1: Average start of season (SOS) dekad determined using the WRSI rainfall threshold method (top), average length of growing period (LGP) defined using the WRSI method of rainfall $\geq$ 0.5 PET (middle), and average end of season (EOS) dekad (bottom) determined from the ARC2 (1983-2014), CHIRPS (1981-2014), and TAMSAT (1983-2014) rainfall products. Note: Inland water areas (Victoria, Tanganyika, and Nyasa lakes) are masked out.

fall data enabling to estimate the EOS reasonably well, i.e. on average in April/May. The spatial pattern of EOS also reflects the impact of artefacts in the ARC2 product discussed above, as well as the slightly earlier SOS and shorter LGP estimated by the ARC2 and TAMSAT products, as compared to the SOS and LGP estimated with the CHIRPS product.

Figure 2 illustrates the averaged across the country SOS, LGP, and EOS values over time as determined from the ARC2, CHIRPS, and TAMSAT rainfall products. Overall, ARC2 shows the lowest mean SOS dekad (dekad 28-29 corresponding to dekads 1-2 of October) and highest variability over time (SD = 3.6). For CHIRPS and TAMSAT these are dekad 30 (corresponding to dekad 3 of October) with SD of 2.8 and 2.7 respectively. With regard to LGP, CHIRPS shows the longest LGP of 15 dekads and the lowest SD of 0.6. For TAMSAT and ARC2 these are respectively LGP of 13.9 and 14.5 dekads with SD of 0.8 and 1.0. In terms of EOS, the variability is much less substantial with all rainfall input datasets producing average EOS around dekad 11 (corresponding to dekad 2 in April) and SD of 0.8, 0.9, and 1.0 for ARC2, CHIRPS, and TAMSAT, respectively.

The above analysis shows the relative differences between the skill of the three rainfall products in capturing the onset of rains, estimating the length and subsequently, the end of the growing season. The variability of SOS, LGP, and EOS detection has important implications for estimation of seasonal WRSI and subsequently, for crop yield monitoring and forecasting and agro-meteorological risk analysis on the basis of the WRSI model.

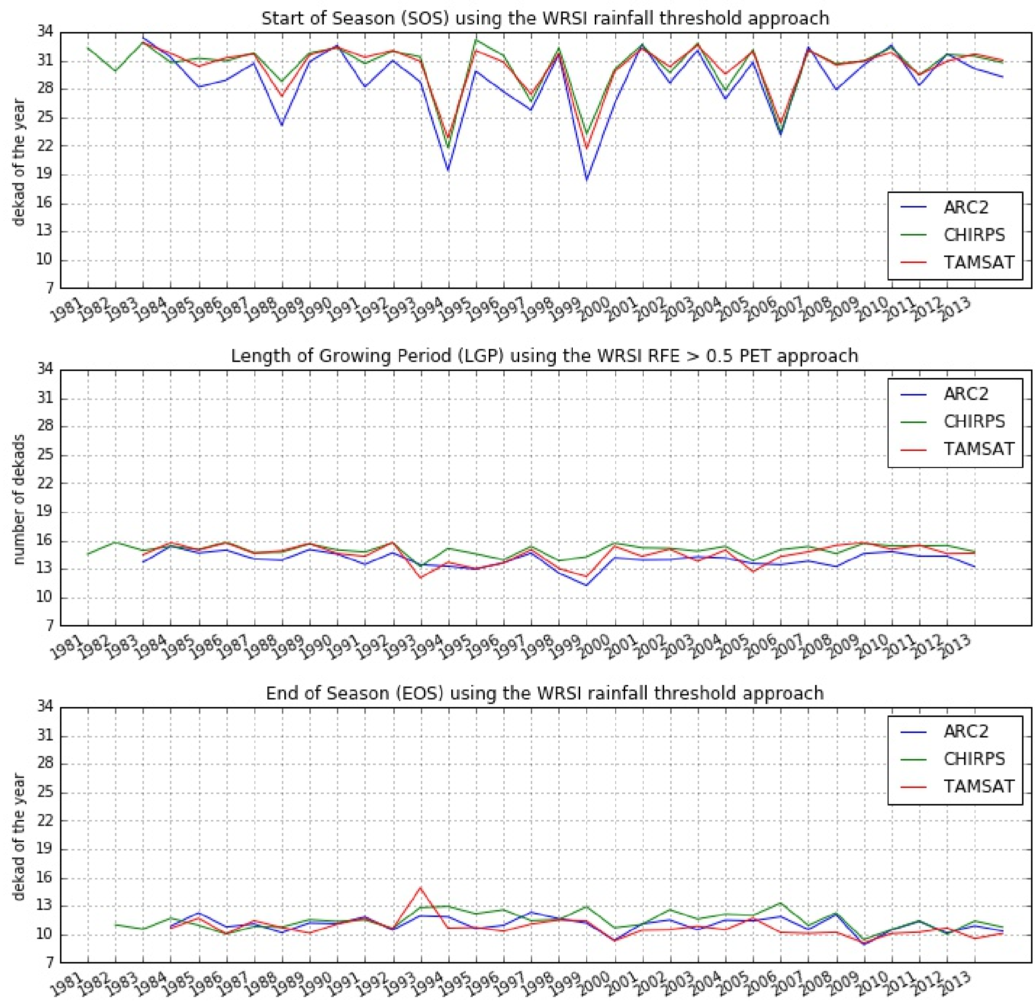

Figure 2: Regionally averaged start of season (SOS) determined using the WRSI rainfall threshold method, length of growing period (LGP) defined using the WRSI method of rainfall ≥ 0.5 PET, and end of season (EOS) determined from the ARC2, CHIRPS, and TAMSAT rainfall products.

4.2. Evaluation of WRSI sensitivity to rainfall inputs

Figure 3 shows the spatial pattern of average seasonal WRSI calculated with the standard WRSI approach for start of season based on rainfall threshold and the length of the growing period (LGP) defined on the basis of the persistence of rainfall over evapotranspiration. Across maize growing areas (You and Wood, 2006), for the unimodal zone similar average WRSI was calculated from simulations with ARC2 (1983-2014), CHIRPS (1981-2014), and TAMSAT (1983-2014). Average WRSI values over time from the simulations with all three rainfall data inputs are above 80%, indicating that on average the moisture requirements of maize are sufficiently met by available water. WRSI values fall below 80% for parts of the bimodal rainfall zone; however, this is not discussed as the adapted model cannot in its present form represent two short rainfall seasons within the same agronomic year.

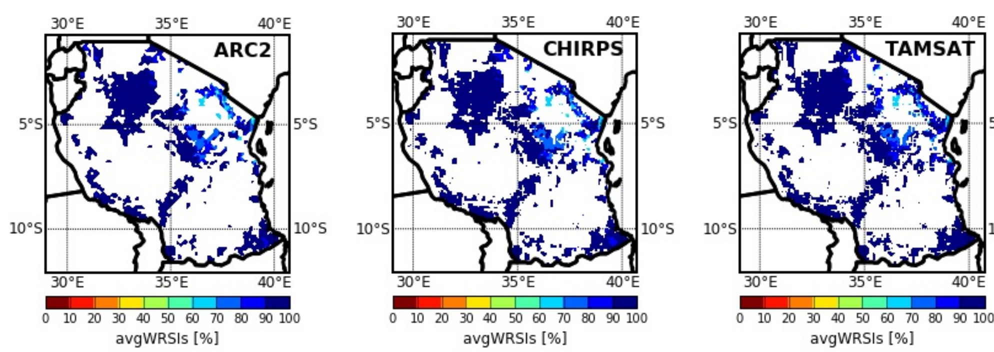

Figure 3: Average seasonal Water Requirements Satisfaction Index (WRSI) with the WRSI method for start of season (SOS) detection based on a rainfall threshold and length of growing period (LGP) defined as the length of time that rainfall ≥ 0.5 PET from the ARC2, CHIRPS, and TAMSAT rainfall products. Note: Areas not under maize production as of 2000 (You and Wood, 2006) are masked out.

Figure 4 illustrates the impact of rainfall input data on seasonal WRSI under the four scenarios of fixed length of the growing period (i.e. 90, 120, 140, and 160 days) and the scenario, under which LGP varies as a function of the persistence of rainfall over evapotranspiration. This results in lower variability over time of WRSI simulations with CHIRPS rainfall input and no years detected of regionally-averaged WRSI below 80% when CHIRPS and TAMSAT are used as rainfall input to WRSI simulations, while for ARC2 WRSI is below 80% for 160 days LGP in 1998 and 1999, and for 120, 140, and 160 days LGP in 1998, due to the earlier SOS and shorter LGP detected by ARC2. Overall, WRSI estimates based on CHIRPS and TAMSAT rainfall input data are higher than those with the ARC2 product. ARC2 based WRSI simulations also show the widest variation in standard deviation (SD) and CV respectively between 2.9 and 3% for the 90-days growing length simulation and 5.4 and 6% for the 160-days growing length simulation. CHIRPS based WRSI simulations result in the lowest SD and CV of 3.0 and 3% for the 90-days and WRSI method growing length scenarios and 4.0 and 4% for the 120-160 days growing length scenarios. WRSI results with TAMSAT as the rainfall input dataset are similar to those with CHIRPS, although less variable with SD and CV of 3.4 and 4% for the 90-days and WRSI method growing length scenarios and 4.8 and 5% for the 120-160 days growing length scenarios.

Table 3 shows the average total seasonal rainfall and WRSI using the ARC2, CHIRPS, and TAMSAT rainfall input datasets as an indication of

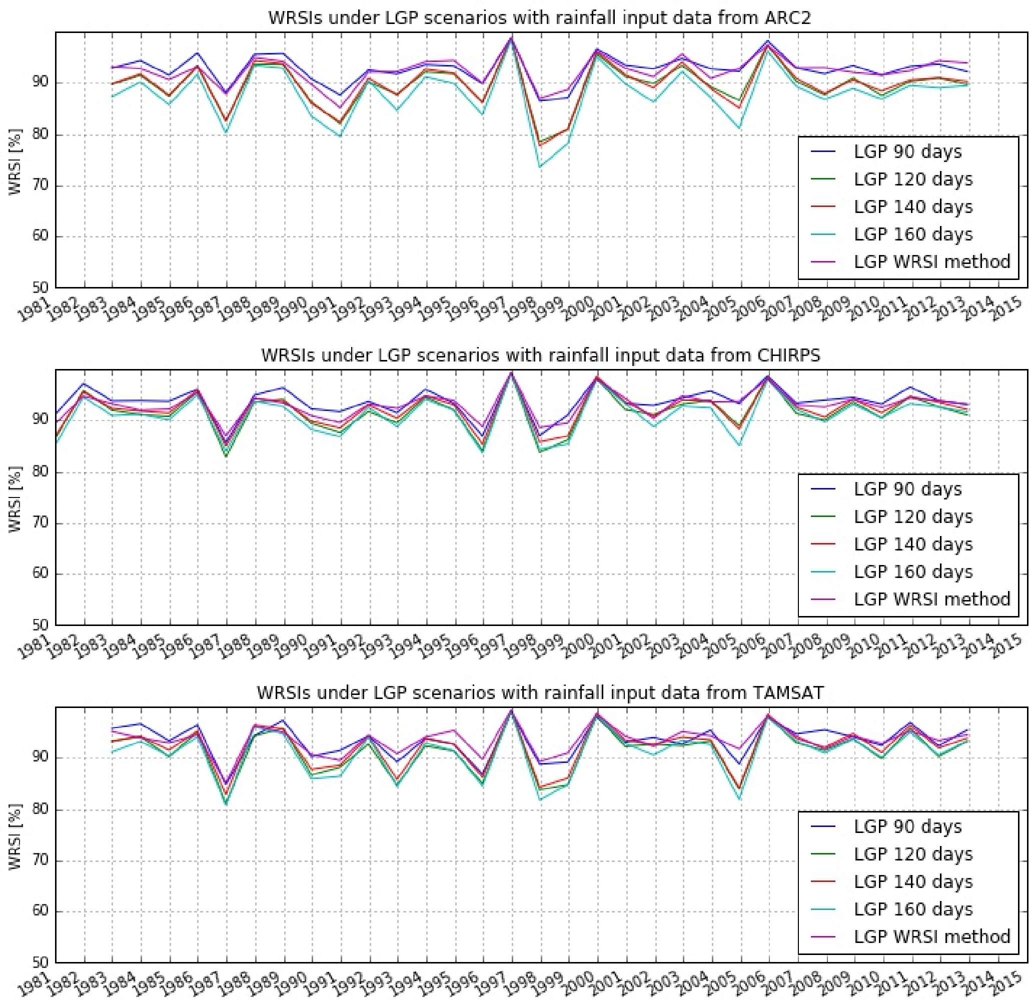

Figure 4: Regionally averaged WRSI defined with fixed length of the growing period (LGP) and using the WRSI method of rainfall ≥ 0.5 PET from the ARC2, CHIRPS, and TAMSAT rainfall products. Note: Inland water areas (Victoria, Tanganyika, and Nyasa lakes) are masked out, as well as areas not under maize production as of 2000 (You and Wood, 2006).

their skill in detecting the two years with lowest yield, i.e. 1996 and 1998 with 1.07 and 1.06 t ha^{-1}, respectively. Using either indicator, only CHIRPS detects both 1996 and 1999 as low-yield years, although due to spatial and temporal averaging all WRSI values are above 80%, indicating 'normal' (average) season conditions. It is worth nothing that while both total seasonal rainfall and WRSI are lowest for ARC2 and TAMSAT, and WRSI is lowest for CHIRPS in 1998, it was a relatively high-yielding year. This suggest the inadequacy of basing agricultural drought insurance on rainfall indices alone and the need to analyse additional information from a crop water stress model such as WRSI. Moreover, the correlation between low-yield years and low rainfall in particular, but also low WRSI, can break down due to factors not related to rainfall and/or not represented in the WRSI model such as changes in nutrient input or acreage planted with maize from year to year.

Table 3: Skill of detection of low-yield years in the 1996-2002 time period assessed using total seasonal rainfall from the ARC2, CHIRPS, and TAMSAT rainfall products and using these as input, the simulated WRSI with varying length of the growing period (LGP). Note: Two lowest values in bold font

	Yield	**Rainfall [mm]**			**WRSI [%]**		
Year	**[t ha^{-1}]**	**ARC2**	**CHIRPS**	**TAMSAT**	**ARC2**	**CHIRPS**	**TAMSAT**
1996	**1.07**	493	**459**	**495**	90	**89**	**90**
1997	1.19	597	869	753	99	99	99
1998	1.33	**377**	530	**473**	**87**	**89**	**89**
1999	**1.06**	**388**	**490**	506	**89**	**89**	91
2000	1.71	575	647	658	96	98	98
2001	1.46	536	632	625	93	94	94
2002	1.15	491	544	520	91	90	92

4.3. Evaluation of WRSI against yield at country level

Correlations from the regression analysis of WRSI, total seasonal rainfall, and median soil moisture (Median SMs) and reported yield figures for 1996-2002 are summarised in Table 4, although none had a significant p-value.

Table 4: Correlations between Water Requirements Satisfaction Index (WRSI), total seasonal rainfall, and median soil moisture (Median SMs) and yield data (1996-2002) from the Tanzanian Ministry of Agriculture, Livestock and Fisheries (MALF) across maize growing areas. WRSI simulations 1-4 use fixed length of the growing period (LGP) of 90, 120, 140, and 160 days, and simulation 5 uses variable LGP defined from the persistence of rainfall over evapotranspiration. Bold figures indicate highest correlation for each LGP scenario; underlined figures indicate highest correlation for each input rainfall dataset; no values are significant at $p \leq 0.05$

Product	**SIM1 LGP-90**	**SIM2 LGP-120**	**SIM3 LGP-140**	**SIM4 LGP-160**	**SIM5 WRSI**
WRSI vs Yield [t/ha]					
ARC2	0.42	0.40	0.41	<u>0.45</u>	0.40
CHIRPS	0.47	**0.52**	**0.57**	<u>**0.61**</u>	**0.56**
TAMSAT	**0.52**	0.51	0.52	0.52	<u>0.53</u>
Rainfall vs Yield [t/ha]					
ARC2	<u>0.47</u>	**0.42**	0.39	**0.38**	0.37
CHIRPS	0.31	0.30	0.33	0.31	<u>0.34</u>
TAMSAT	<u>**0.49**</u>	**0.42**	**0.43**	**0.38**	**0.41**
Median SMs vs Yield [t/ha]					
ARC2	0.26	0.30	0.33	0.36	<u>0.38</u>
CHIRPS	0.38	**0.46**	**0.52**	**0.53**	<u>0.55</u>
TAMSAT	**0.44**	**0.46**	0.48	0.48	<u>**0.58**</u>

For WRSI simulations using the ARC2 rainfall input dataset, correlations between WRSI and yield were lowest (R^2 <0.5) likely due to the earlier SOS and shorter LGP detected with the use of ARC2. This suggests that if ARC2 rainfall represents more realistically the spatial and temporal patterns of rainfall, its performance in WRSI can be improved to reflect more closely reported yield even when results are averaged across a country such as Tanzania with two distinct rainfall zones. The CHIRPS rainfall input dataset produced WRSI estimates that most closely correlate with yield figures for all LGP scenarios except the 90-days simulation. Correlations between WRSI simulations with TAMSAT and yield were highest for the variable LGP and 90-days LGP scenarios.

The evaluation of seasonal total rainfall and median soil moisture (Median SMs) relative to historical yield figures shows overall lower correlations with rainfall explaining less than half of the yield variance in all simulations (Table 4). Median soil moisture explains only 26-38% of yield variance with the ARC2 rainfall data input, while 46-53% of yield variance is explained by rainfall when CHIRPS is used as input for all fixed LGPs except the 90-day scenario and 55% for the time-varying LGP scenario. Using TAMSAT as rainfall input data 58% of yield variance is explained only for the simulation with time-varying LGP. This suggests that CHIRPS is well suited for use in the WRSI model, likely due to the realistic representation of seasonally-varying phenology-relevant parameters such as SOS, LGP, and EOS.

The results from a 7-year evaluation of WRSI and reported yield over Tanzania presented here are consistent with previous evaluations that covered 7 years in India (Patel et al., 2011) and 10 years in Southern and Western African countries (Jayanthi and Husak, 2013; Jayanthi et al., 2014), especially for areas where rainfall is the main limiting factor. Even though the area considered in the regression analysis includes parts of the bimodal zone with two rainfall seasons in the northeast part of Tanzania, the correlations achieved were similar to those reported in previous studies (see Table 1).

Discrepancies between simulated WRSI and other drought indicators and yield are to be expected due to the high uncertainty of areas under maize production in any given year historically, possibly a less stable acreage under maize production over the years considered here, and/or the limited 7-year historical production figures with sufficient reliability for analysis. It is worth noting that the aim of the evaluation of WRSI against yield is not to reproduce accurately historical yields at country level, but to characterise the impact of different rainfall datasets used as input to the WRSI model on WRSI outcomes through the evaluation of key dynamic modelling parameters such as season onset, cessation, and length of the growing period. This is important particularly where the ARC2, CHIRPS or TAMSAT rainfall datasets and WRSI are used as agro-meteorological risk and/or hazard indicators such as in weather index-based insurance and risk profiling frameworks based on statistical analysis of hazard, exposure, vulnerability, and risk.

Consistent with previous studies, some of the general challenges for historical validation of WRSI against reported yield include (i) staggered planting which is difficult to reproduce historically, i.e. farmers plant maize and if it fails, they plant sorghum, and if that fails, they may then re-plant with teff (Senay and Verdin, 2003), (ii) low production in normal rainfall conditions due to other factors such as floods, locust outbreaks, and nutrient inputs that are not represented in WRSI (McNally et al., 2015), (iii) different varieties grown in different agro-ecological zones, while national average data and simulations across the country with a single LGP are not expected to represent accurately the production/yield of mixed varieties, (iv) changes in crop management induced by government programmes (e.g. subsidised fertiliser), and (v) limited number of years with useable data after quality screening to detect outliers, and/or errors in historically reported figures of production-area-yield. The main challenge, however, is the uncertainty of reported area under maize production and changes in areas under maize production over time. Even though datasets on maize growing areas exist (You and Wood, 2006), they provide a snapshot in time as an estimate and not actual, field-based information over time that can be used for an absolute validation. Specific to the evaluation of WRSI for Tanzania is the challenge of rainfall variability in the unimodal and bimodal zones, as well as the limited availability of reliable long-term data on production-area-yield at sub-national level to distinguish between zones of unimodal and bimodal rainfall regimes.

5. Conclusions

We extended the evaluation of the WRSI method for assessing agro-meteorological risk such as drought on maize production through an adapted gridded version of the model and sensitivity analysis to rainfall inputs from three different sources, i.e. the ARC2, CHIRPS, and TAMSAT products. We characterised the spatial variation in the timing of the onset of rains and analysed the impact of using different rainfall input datasets, as well as the methods for definition of the start-of-season (SOS) and length of the growing period (LGP) on WRSI outputs.

The analysis showed that the CHIRPS and TAMSAT rainfall input datasets realistically represent season onset patterns, but CHIRPS performs best in detecting SOS patterns and assessing the LGP, resulting in highest correlations with WRSI. Understanding the impact of using different rainfall input datasets in WRSI helps to identify regions that are likely to experience similar agro-meteorological risks as relevant for the design and structure of risk management instruments such as weather index-based insurance. As a minimum, our results indicate that separate weather index-based insurance might be appropriate for the unimodal and bimodal zones in Tanzania.

Through WRSI simulations, we explored water-stressed regions in the maize growing area of Tanzania with other factors assumed constant (variety, fertiliser use, pests, diseases, etc.) and established the correlations between WRSI, seasonal rainfall, and median soil moisture and reported maize yield at the national level. CHIRPS-based WRSI and median soil moisture showed highest correlations with yield for the majority of simulations. This is despite the limitation of our study in that the country-level analyses of seasonality and WRSI response to different rainfall input datasets includes areas in the bimodal zone of the country in the northeast along the border with Kenya, while in its present form the adapted WRSI model is not set up to accommodate two short-duration rainfall seasons within the same agronomic year.

The results of this work suggest that CHIRPS is better suited for applications in weather index-based insurance and early warning monitoring with the WRSI model, while with ARC2 and TAMSAT the variability of the correlations between rainfall and WRSI model outputs and reported yield is greater and provides a less clear indication of their utility in structuring weather indices. Further work is required to build in capability in the WRSI model for representation of bimodal rainfall information so that the adapted WRSI model can be used to identify regions of similar rainfall season progression and climatology, and to account for the role of temperature in defining the growing season. Sub-national validation is desirable, provided the patterns of rainfall require higher spatial detail and reliable yield data are available, preferably over a longer period. Investigations in this area can be supported by analysis of the change of maize growing area over time. Overall, this can support the defining of risk areas and applying of risk management instruments accordingly.

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Appendix A.

The Water Requirements Satisfaction Index (WRSI) Model

WRSI requires as inputs information on rainfall and potential evapotranspiration, as well as soil water holding capacity and crop coefficients to calculate actual evapotranspiration, soil moisture, and WRSI during the crop growing season. Calculations are carried out on dekadal time step as defined by the World Meteorological Organisation (WMO), i.e. by dividing each month in three dekads with dekad 1 from 1st to the 10th inclusive, dekad 2 from the 11th to the 20th inclusive, and dekad 3 for the remaining 8-11 days depending on the month (WMO 1992 in Verdin and Klaver 2002). Since a daily time step makes modelling data-intensive without a proportional gain in information and a monthly time step fails to capture important vegetation growth stages, the dekadal time step has proved useful for agro-meteorological monitoring (Verdin and Klaver, 2002). Reference (potential) evapotranspiration, hereafter referred to as PET, represents the water demand for crop growth. Actual evapotranspiration (AET) is the actual soil water extracted used by the crop from its root zone (Jayanthi and Husak, 2013).

The USGS GeoWRSI in FEWS NET uses the following input datasets:

- Dekadal satellite-based rainfall estimates from the NOAA CPC RFE2.0 dataset at 0.1° (∼10 km) resolution (Verdin and Klaver, 2002).
- Dekadal PET at 1.0° (∼100 km) calculated with the Penman-Monteith equation (Shuttleworth 1992 in Senay and Verdin 2002, 2003; Verdin

and Klaver 2002) from 6-hourly numerical meteorological model output (Senay et al 2007b in Melesse et al. 2007, Verdin and Klaver 2002).

- Spatially varying soil information from FAO's digital database and topographical parameters from HYDRO-1K data based on Digital Elevation Model (DEM) (FAO 1988 and Gesch et al 1999 in Senay and Verdin 2002) or from the GTOPO30 DEM (Senay and Verdin, 2003).

- Crop coefficient values, varying throughout the growing season obtained from the FAO online database at http://www.fao.org/nr/water/cropinfo_maize.html (Jayanthi et al., 2014). For maize, Kc values are given as 0.30, 0.30, 1.20, 1.20, and 0.35 for the times corresponding to 0, 16, 44, 76, and 100% of LGP, respectively (Senay and Verdin, 2003).

Start of season (SOS). In WRSI, SOS for each pixel is defined, starting several dekads before the typical SOS, by identifying a dekad with at least 25 mm rainfall, followed by at least 20 mm rainfall total in the next two consecutive dekads (Senay and Verdin, 2002; Verdin and Klaver, 2002) according to the method defined by the Agriculture-Hydrology-Meteorology (AGHRYMET) Regional Center in Niger (AGHRYMET 1996 in Verdin and Klaver 2002). This method is used for monitoring with time-varying rainfall, although it can be too strict for semi-arid areas (Senay 2004 available at http://iridl.ldeo.columbia.edu/documentation/usgs/adds/wrsi/WRSI_readme.pdf). An alternative SOS detection method in WRSI is when the ratio between average rainfall and PET is grater than 0.5 (McNally et al. 2015; Hare and

Oglallo 1993 and Mersha 2001 in Senay 2004), although justification for selecting this threshold is not presented. This method is used with the climatological CHARM-WRSI dataset (Funk et al 2003 in Senay 2004). In WRSI, SOS indicates planting dates and triggers seasonal water balance calculations. Since irregularities in SOS have substantial impacts on early crop development (e.g. dry and hot conditions shorten the grain filling stage and decrease expected yields), realistic and skilful SOS detection is critical for successful crop performance monitoring.

Length of growing period (LGP). In WRSI, similarly to one of the methods for SOS detection, LGP is determined by the persistence, on average, above a threshold value of a climatological ratio between rainfall and PET (Senay and Verdin, 2002), i.e. crop growing period continues while average rainfall exceeds half of average PET (McNally et al., 2015). Thus, LGP does not vary year-to-year. Since WRSI values depend on the crop's LGP, the ratio of WRSI for current season over mean WRSI over the long-term is used as an indicator of drought-related yield loss.

End of season (EOS). EOS in WRSI is derived by adding LGP to SOS. Hence, EOS varies as a function of SOS and over time for every location, e.g. 9 dekads in arid and semi-arid regions to 18 dekads in wetter and mountainous regions (Melesse et al., 2007).

WRSI. End-of-season WRSI is computed as the ratio of supply, or demand met (i.e. total crop water requirement satisfied by rainfall and available moisture) and demand (i.e. seasonal crop water requirement) (Verdin and Klaver, 2002) with crop potential evapotranspiration (PETc) and seasonal crop actual evapotranspiration (AETc) expressed as percentage (Eq A.1). WRSI of 95-100% indicates no water deficit (i.e. adequate rainfall and moisture availability, or absence of yield reduction due to water deficit), values between 95% and 50% indicate varying degree of water stress and yield reduction due to inadequate water supply, and values below 50% indicate crop failure (Smith 1992 in Senay and Verdin 2002, 2003).

$$WRSI = \frac{\sum AETc}{\sum PETc} \times 100 \tag{A.1}$$

Where the crop water requirement PETc in [mm] is calculated at the dekadal time step during the growing season as follows:

$$PETc = Kc \times PET \tag{A.2}$$

PAW. In order to determine AETc, the actual amount of water withdrawn from the soil profile, dekadal precipitation (PPT) is added to soil water (SW) to calculate plant-available water (PAW) (see Eq A.3) and this is compared to the value of critical soil water (SWC) (see Eq A.4).

$$PAW_{\mathrm{d}} = SW_{\mathrm{d\text{-}1}} + PPT_{\mathrm{d}} \tag{A.3}$$

Soil Water Critical (SWC). Typically, for WHC somewhat arbitrary values such as 50 or 100 mm are used, esp. where reliable field data and digital soil maps are lacking (Verdin and Klaver, 2002). The operational FEWS NET WRSI version uses WHC for the top 100 cm from FAO digital soil map of the world (FAO 1994 in Verdin and Klaver 2002) to calculate SWC as follows:

$$SWC = WHC \times SW_{\mathrm{f}} \times RD_{\mathrm{f}} \tag{A.4}$$

Where WHC is water holding capacity of the soil, $\mathrm{SW_f}$ (0.45 for maize) is the fraction of WHC that defines the available soil water level, below which AETc becomes less than PETc, and $\mathrm{RD_f}$ is is the root depth fraction, which ranges between 0 and 1, and equals 1 when the crop is mature.

AETc. AETc is determined according to Eq A.5 on the basis of the relationship between PAW and SWC.

$$AETc = \begin{cases} PETc, & PAW \geq SWC \\ \frac{PAW}{SWC} \times PETc, & PAW < SWC \\ PAW, & AETc > PAW \end{cases} \tag{A.5}$$

Soil Water (SW). The final soil water content at the end of simulation period ($\mathrm{SW_d}$), is calculated as follows:

$$SW_{\mathrm{d}} = \begin{cases} WHC, & SW_{\mathrm{d}} > WHC \\ 0, & SW_{\mathrm{d}} < 0.0 \\ SW_{\mathrm{d}} = SW_{\mathrm{d\text{-}1}} + PPT_{\mathrm{d}} - AETc, & otherwise \end{cases} \tag{A.6}$$

Yield Reduction Response (Ky). Similarly to Kc, Ky is crop- and location-dependent (Reynolds 1998 in Senay and Verdin 2002) with published values (FAO1996); for example, Ky of 0.9 for sorghum means that a 10% reduction of WRSI from the optimal 100 is related to a 9% reduction of sorghum yield. It is also worth noting that Ky values were established using high-yielding varieties and field experiments and further explanation of Ky, as well as references to published values, are available elsewhere (Jayanthi and Husak, 2013). Kaboosi and Kaveh (2010) examined the sensitivity of the crop water production function to Ky, as well as PET and AET, and highlighted the importance of accurately defining crop growth stages (the length of which can be substantially different than those given by FAO 56 due to the diversity of crop varieties) and that high-yield varieties were more sensitive to water stress than low-yielding varieties.

WRSI Advantages

- Requires minimal data to initiate water budget processes and provides spatially continuous, near real-time info (Verdin and Klaver, 2002)

- Can help identify crop production decline/failure well before agricultural reports and statistics become available, i.e. several months after harvest (Verdin and Klaver, 2002); Effectively estimates yield reduction in dry years for drought-prone areas (Senay and Verdin, 2002)

- Can serve as a proxy of crop yield, i.e. can be related to crop production using a crop-specific linear yield reduction function (Doorenbos and Pruitt 1977 in Senay and Verdin 2002; Jayanthi and Husak 2013)

- Captures well inter-annual and spatial variability of water availability for crop production; good correlation with reported district-level yields, esp. for drought-prone rainfed agricultural areas (Patel et al., 2011)

- Captures impact of the timing of rainfall season, total seasonal rainfall, and seasonal rainfall distribution on crop yields (Syroka 2006 in Crowther 2007) with the causal link between weather and crop yield shortfall/loss being crucial for the success of index insurance schemes

- Tracks WRSI throughout the growing season, i.e. different role of rainfall deficit at the start of the season, and moisture deficits most critical at the flowering and crop development stages, i.e. stunted crop growth, reduced crop yield (Jayanthi and Husak, 2013)

- As WRSI considers yield variability relative to water availability, where WRSI is optimal, year-to-year variations can be attributed to other factors (heat stress, management practices, etc.), i.e. crop-specific effects of non-water drivers of yield variability (Senay and Verdin, 2002)

- Helps identify water-limited and water-unlimited areas for planning crops to be planted, e.g. high water requirements of maize, drought resistant sorghum, and flexible teff in Ethiopia (Senay and Verdin, 2003)

- Produces intermediate products that are useful in early warning and humanitarian aid planning/response, e.g. SOS map, soil water index (SWI) as a function/percentage of water holding capacity (WHC), spatial distribution of WRSI dekadal values, and dekadal anomalies in the form of observed (monitoring) and extended (forecasting) products (Melesse et al., 2007)

WRSI Disadvantages

- Spatial resolution of 10-km limited by inputs means that the model encompasses pixels containing different agro-ecological zones and more than one crop by several thousand smallholder farmers (Verdin and Klaver, 2002)

- Model performance varies spatially, i.e. model not equally reliable across large regions and continents

- High year-to-year variability of yield when WRSI is optimal ($\approx$100%) is attributable to other, non-rainfall drivers (Senay and Verdin, 2002)

- SOS defined from rainfall is limited by the skill of satellite rainfall datasets, and thus by sparse rain gauge networks (Patel et al., 2011)

- No indication of soil moisture outside growing season (Senay, 2008)
- Use of Kc poses limitations: 1) Kc values are crop-specific, i.e. require prior knowledge of crop planted in the region; 2) Kc values are region-specific, as crop growth is influenced by local climate, soils, etc; 3) requires knowledge of Kc values (or assumption of these) across the crop calendar at each crop development stage: initial, vegetative, mature, senescence (Senay, 2008); 4) LGP with Kc (spatial) adjustment does not work well for long growth cycle crops (e.g. sorghum); and 5) Kc breaks down for sparse crops, i.e. under non-standard conditions (Senay 2008; Fig 2, p 32 in Steduto et al. 2012)
- Calculations require WHC information as an arbitrary value (50-100 mm) or spatially-varying WHC from digital soil databases (Verdin and Klaver, 2002); In the latter, the accuracy of water budget calculations relies on WHC reflecting realistically field conditions
- Focused on water stress effects on crop production, while it would benefit from information on heat stress, e.g. growing degree days (GDD) concept used in WOFOST and other models
- Validation data is poor: 1) flux tower data (latent heat flux and point-based rainfall, for conversion of latent heat flux to daily AET, see p. 54 in Senay 2008), 2) EO data for validation have not been fully exploited, and 3) reported production-area-yield data are not available historically with consistent coverage and quality