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Comparison of Meteorological and Agricultural Drought Indicators across Ethiopia

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Abstract

Meteorological drought indicators are commonly used for agricultural drought contingency planning in Ethiopia. Agricultural droughts arise due to soil moisture deficits. While these deficits may be caused by meteorological droughts, the timing and duration of agricultural droughts need not coincide with the onset of meteorological droughts due to soil moisture buffering. Similarly, agricultural droughts can persist even after the cessation of meteorological droughts due to delayed hydrologic processes. Understanding the relationship between meteorological and agricultural droughts is therefore crucial. An evaluation framework was developed to compare meteorological and agricultural droughts using a suite of exploratory and confirmatory tools. Receiver operator characteristics (ROC) was used to understand the covariation of meteorological and agricultural droughts. Comparisons were carried out between SPI-2, SPEI-2 and Palmer Z-index to assess intra-seasonal droughts and between SPI-6, SPEI-6 and PDSI for full-season evaluations. SPI was seen to correlate well with selected agricultural drought indicators but did not explain all the variability noted in agricultural droughts. The relationships between meteorological and agricultural droughts exhibited spatial variability which varied across indicators. SPI is better suited to predict non-agricultural drought states more so than agricultural drought states. Differences between agricultural and meteorological droughts must be accounted for better drought-preparedness planning.

Key Words: PDSI, Z-index, Receiver Operating Characteristics (ROC), SPI, SPEI, GIS, food security, droughts

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Introduction

Ethiopia is a predominantly rural country with a high dependence on rainfed agriculture and pastoral activities. Agriculture and animal husbandry contribute significantly to the nation's Gross Domestic Product (42% of GDP) and 85% of the nation's export earnings and account for over 85% employment [1]. The vulnerability of the agriculture sector (broadly defined here to include pastoral activities as well) to drought risks is particularly high due to lack of irrigation infrastructure. Droughts are known to cause death and disease due to malnutrition, unemployment, migration, social unrest and even violence in the greater horn of Africa [2]. From an economic standpoint, droughts are noted to reduce the GDP of Ethiopia by 1% - 4% [3].

The government of Ethiopia has recognized that drought management is essential to the sustainable development of the nation. In 2013, the government of Ethiopia adopted national policy and strategy for disaster risk management (DRM) which calls for decentralized stakeholder-based approaches to deal with recurring disasters such as droughts. Woredas (districts or third level administrative units) are required to develop drought contingency plans (DCP) to build local resilience to recurring droughts and thus mitigate harmful social effects associated with drought events [4].

Understanding drought characteristics is a critical first step towards its management. However, drought is a complex phenomenon with no universally accepted definition. They can broadly be classified into meteorological, agricultural, hydrological and socio-economic droughts [5]. Fundamentally, meteorological droughts imply precipitation anomalies and the first trigger of a drought event. Reduced precipitation, in turn, leads to low relative humidity and greater evapotranspiration which removes water from surficial soils. The deficits in soil moisture (i.e., green water) are referred to as agricultural droughts as they reduce the amount of water available for crops including native vegetation necessary for animal husbandry. As precipitation is the fundamental driver of hydrology, precipitation deficits further manifest as reduced recharge and runoff and lead to a reduction in surface water and groundwater reserves (i.e.,

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blue water) causing hydrologic droughts. The relationships between meteorological, agricultural and hydrological droughts are not always straightforward. The onset and cessation of agricultural and hydrological droughts do not typically coincide with meteorological droughts as the former are affected by other factors (e.g., soil and watershed characteristics) that control the rate of water movement and storage in soil, surface water, and groundwater compartments [6].

Understanding the relationship between meteorological and agricultural droughts is important for proper drought contingency planning in rural areas of Ethiopia. As most of the agriculture is rainfed, a strong correlation between meteorological and agricultural drought is to be expected. However, meteorological and agricultural droughts need not be coincident nor the relationships between these two types of drought be perfect or even strong. The soil moisture at any time can be affected by precipitation in previous months or seasons and is also affected by other factors including but not limited to soil type and atmospheric temperature. In Ethiopia, while many farmers grow crops during the Meher growing season that coincides with the longer Kerimt (June – October) rainy season, the shorter Belg (February – May) rains often provides the soil moisture necessary for tillage and planting activities and also improve pastures for livestock [7]. Therefore, lagged relationships between agricultural and meteorological drought indicators are of interest as well.

Understanding the spatio-temporal characteristics of agricultural droughts and the importance of characterizing the differences between meteorological and agricultural droughts has been recognized in recent times. Using downscaled climate projections in conjunction with calibrated models, Wang et al. [8], conclude that agricultural droughts (as measured using standardized soil water index or SSWI) are more sensitive to climate change than the Standard Precipitation Index (SPI) an indicator of meteorological drought. Hernandez and Uddameri [9] utilized SPI and the standardized precipitation evapotranspiration index (SPEI), a measure of agricultural droughts, in conjunction with global downscaled model projections to conclude that droughts in the early part of the 21st century are likely

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dominated by temperature increases (moisture deficits and water demands) while those in the latter part are controlled by both supply deficits (meteorological droughts) and increased water demands in South Texas. Using short-term (15 years) meteorological and remote-sensed vegetation data from Morocco, Ezzine et al. [10], concluded that the relationship between meteorological and agricultural droughts to be low to moderate. Duan and Mei [11] used SPI, SSWI and standardized surface runoff (SSRI) indices to study meteorological, agricultural and hydrological droughts in Huai river basin in China and concluded that agricultural and meteorological droughts have a greater impact on local water resources management issues.

Dhakar et al. [12], studied the relationship between SPI (meteorological drought indicator) and satellite derived vegetation condition index (VCI) (an indicator of agricultural droughts). They concluded that the relationship between meteorological and agricultural drought indicators improves with seasonal progression indicating a time-varying relationship between the two variables. Gunda et al. [13], compared SPI and PDSI at 13 stations across Sri Lanka. They concluded that these indicators performed better as agricultural drought indicators under different climatic conditions. Portela et al. [14], compare meteorological and agricultural droughts using SPI and SPEI indicators in Eastern Slovakia. Their results indicate that SPI (meteorological) and SPEI (agricultural) droughts show similar trends but SPI is more sensitive to water shortages and surpluses in this humid region. Tirivarombo et al. [15], compared meteorological (SPI) and agricultural drought indicator (SPEI) in Zambia and concluded that SPEI indicated droughts of greater duration and severity and cautioned the use of SPI as a sole indicator of drought. These studies from across the world indicate that there are differences between meteorological and agricultural droughts which must be recognized for proper planning and management of agricultural water resources. The literature review also highlighted that agricultural and meteorological drought comparisons were often ad hoc and qualitative. A statistical evaluation framework is generally missing to

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perform consistent comparisons across multiple scales at which droughts manifest and across spatial regions of interest.

National scale comparison of recent meteorological droughts using SPI have been undertaken in recent times in Ethiopia (e.g., Viste et al. [16]; Suryabhagavan [17]). However, to the best of our knowledge, a detailed comparison of meteorological and agricultural droughts has not been undertaken in Ethiopia. The information generated from such a comparison is vital to understand how precipitation deficits propagate through agricultural systems and affect a nation's food security and economic vitality. Such a comparison can help identify whether supply-side deficits (precipitation anomalies) or demand side increases (greater evapotranspiration) control agricultural droughts. This information is fundamental to developing future monitoring programs within a region. Furthermore, conducting such a comparison on a national (Ethiopia-wide) scale would also identify regional differences and help policy makers and governmental agencies prioritize areas of critical need and help guide the proper allocation of scarce fiscal and logistic resources for the improvement of water resources.

The primary goal of this study is to compare the evolution of meteorological and agricultural droughts at various temporal scales across Ethiopia at a high spatial resolution. To accomplish this goal, the study proposes a comprehensive drought comparison framework using a suite of evaluation metrics covering both exploratory and confirmatory testing methods that can be consistently applied across multiple spatio-temporal scales. While the results of the study are directly beneficial to water planners and policy makers in Ethiopia, the developed drought evaluation framework is generic and can be applied to any other region.

Methodology

The proposed agricultural and meteorological drought comparison framework begins with the selection of appropriate indicators to quantify agricultural and meteorological droughts. Time-series of these indicators over a common time-period are then used to make comparisons. Drought indicators provide

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numerical values whose magnitude indicates the (moisture) state the system is in. This continuous drought indicator time-series can also be used directly to understand cross-correlation between agricultural and meteorological droughts as well as perform confirmatory hypothesis tests to establish their relationships under various lags. For most indicators, negative values below a pre-specified threshold indicate drought. Therefore, indicator time-series can be transformed into a binary (drought/no-drought) time-series using appropriate thresholds. These binary time-series can be compared to determine the agreement between them and can also be used to construct contingency tables and perform a wide array of statistical analysis to compare meteorological and agricultural droughts. The proposed framework provides a suite of exploratory and confirmatory tests that can be used to evaluate continuous and discrete (binary) meteorological and agricultural drought time-series, which are illustrated using Ethiopia as a case-study.

Selection of Meteorological and Agricultural Drought Indicators

As stated earlier, the first step of the evaluation framework is to select appropriate meteorological and agricultural drought indicators. While there are many meteorological drought indicators, the Lincoln declaration recommended the adoption of the Standardized Precipitation Index (SPI) as a universal indicator of meteorological droughts [18]. Several studies have adopted this indicator to study meteorological droughts in Ethiopia [16,17,19-23] and as such it has been adopted here for that purpose as well.

While the quantification of meteorological droughts using SPI has become a standard practice worldwide, no universally acceptable indicator for characterizing agricultural droughts exist today. It is widely recognized that agricultural droughts are best defined using soil moisture as the master variable [24]. However, soil moisture has not been extensively monitored in most parts of the world (Ethiopia included) as doing so has proven to be challenging due to the high level of spatio-temporal variability of this parameter [25] and lack of reliable methods for upscaling point level measurements to larger spatial scales

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[26]. While agricultural drought indices based on model derived soil moisture estimates have been proposed [27], calculating them is usually infeasible for large-scale (regional and national) studies spanning over multiple watersheds. Crop stress and vegetative health indices (e.g., the normalized difference vegetation index or NDVI) have also been used to assess agricultural droughts [28,29]. However, these methods do not yield standardized measures that can be consistently compared in space and time and are also affected by the limited length of the records as they rely on satellite derived data [16,30] and as such are not suitable for evaluating long-term droughts to capture natural climatic and hydrologic variability that manifest over multi-decadal scales due to limited data availability [31,32].

To overcome the limitations of short temporal records, drought indices that utilize temperature based potential evapotranspiration, in addition to rainfall, to indirectly capture the effects of soil moisture deficits have been proposed and are often used to characterize agricultural droughts [33]. The standardized precipitation evapotranspiration index (SPEI) which uses the standardized measure of precipitation (P) minus evapotranspiration (PET) [34] over short accumulation periods (typically 1 – 6 months) has been widely used as an indicator of agricultural droughts [34-38]. In this regards, Vicente-Serrano et al. [34], indicate the method used to estimate PET has little bearing on the computation of SPEI and recommend using the Thornthwaite model which allows the use of the SPEI agricultural drought index with minimal data requirements.

The Palmer Drought Severity Index (PDSI) originally proposed by Palmer [39] is another widely used drought indicator that has been employed to monitor agricultural droughts and estimating soil moisture deficits [40]. It is now computed using the self-calibrating procedure (SC-PDSI) proposed by Wells et al. [41], which removes certain rigid empirical assumptions in the original formulation and allows PDSI values to be compared across spatial scales. PDSI (implied to mean SC-PDSI here for brevity) is based on an idealized two-bucket model conceptualization of the watershed and requires monthly precipitation (P) and evapotranspiration (PET) data. Dai [42] found that the choice of the method for estimating PET had

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a small effect on PDSI and the indicator exhibits a strong correlation with soil moisture, particularly in summer and autumn months. Its reliability is also likely to be higher in warm climates (such as Ethiopia) where the hydrology is not affected by spring snowmelt. PDSI has also been used widely to characterize agricultural droughts [13,43,44]. Studies have shown that PDSI correlates strongly with SPI values computed using higher accumulations [45, 46]. Therefore, PDSI can be considered as a seasonal indicator of agricultural droughts.

The $PDSI_t$ (at any time, t) is a weighted sum of previous month $PDSI_{t-1}$ value which indicates climate spell and the moisture anomaly, Z_t which measures the dryness (or wetness) over the current month, t. Mathematically,

$$PDSI_t = p\dot{P}DSI_{t-1} + q\dot{Z}_t \quad (1)$$

Where, p and q are duration factors obtained from the self-calibration procedure outlined by Wells et al. [41], at any given location. The Z-index exhibits greater volatility than PDSI as it largely depends upon the monthly soil moisture without the effect of antecedent months. It is seen as a good indicator for characterizing agricultural droughts [47]. As Z-index removes the effects of previous months, it is a useful indicator of intra-season (short-term) droughts. Again, a long calibration period (> 50 years) is recommended for calculating PDSI and Z-index [48].

Given the focus on agricultural droughts, the proposed framework recommends computing SPI and SPEI indices computed at 2- and 6-month accumulations to compare droughts within (intra-season or short-term) and over the entire growing seasons (full-season or long-term) in Ethiopia. PDSI and the associated Z-index are also recommended to indicate full-season and short-term drought impacts over the growing seasons. Thus, the framework recommends the comparison of meteorological and agricultural droughts at two temporal scales – 1) Intra-seasonal comparison of meteorological and agricultural droughts using SPI-2, SPEI-2 and Palmer Z-index and 2) full season comparison of meteorological and agricultural

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droughts using SPI-6, SPEI-6, and PDSI. Preliminary investigations indicated that the use of SPI-1 could pose challenges due to months with no rainfall which can be ameliorated using SPI-2 without loss of representativeness of short-term climate dynamics. SPI and SPEI computed at 2- and 6-month scales effectively bracketed the evaluation results noted at intermediate scales (i.e., 3-,4- and 5-month accumulations). Therefore, evaluations at 2- and 6-month scales reduces computational burden without any loss of information at least in the context of Ethiopia, which is the focus of this study. Similar empirical evaluations will be necessary to select appropriate scales when the proposed framework is to be applied at other locations.

Metrics for Comparing Meteorological and Agricultural Droughts

A consistent set of metrics are essential to compare the selected meteorological and agricultural drought indicators. The proposed framework recommends exploratory data analysis (EDA) as a first step of the evaluation process. Visual explorations of agricultural and meteorological time-series plots, autocorrelation and cross-correlation functions are recommended to obtain preliminary insights on the behavior of agricultural and meteorological droughts. While these EDA methods are useful to obtain station-level insights, they are limited use when comparing agricultural and meteorological droughts across large (nation-wide) spatial scales. Exploratory comparative metrics which summarize the differences (or similarity) between meteorological and agricultural drought indicators and amenable to mapping are valuable for spatial assessments. Two such metrics are identified as part of the proposed evaluation framework and discussed below.

The Time Series Distance Measure (TSDM) calculates the Euclidian distance between two series. If two time-series are coincident then TSDM will assume the minimum possible value. The larger the value of TSDM the greater is the divergence between two time-series. TSDM provides an initial picture with regards to the simultaneous occurrence of meteorological and agricultural droughts. As the drought indicators are measured over different scales (units), they need to be normalized on a common (0 – 1)

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scale to identify areas where the two indicators are more coincident and areas where they are less so. The normalization of TSDM also allows for a consistent comparison across drought indicators.

Previous studies have indicated that agricultural and meteorological droughts need not be coincident [6]. However, agricultural drought indicators may correlate to lagged values of a meteorological indicator or vice-versa. This situation arises because meteorological droughts are precipitation dependent while agricultural droughts depend on both temperature and precipitation. The cross-correlation function (CCF) evaluates the similarity between two series across various lags. CCF varies between -1 and 1 where 0 implies no similarity and negative values indicate inverse relationship. The maximum value of CCF (regardless of the sign) indicates the maximum strength of the relationship between the two indicators which could occur at a lag different than zero. While CCF plots are useful for station-level evaluation, the absolute maximum CCF value can be mapped and used in an exploratory mode to compare the lagged behavior of agricultural and meteorological time-series across the region of interest to understand the spatial variations in the maximum possible correlation between agricultural and meteorological droughts

While EDA is important to obtain critical insights related to agricultural and meteorological droughts, confirmatory analysis making use of statistical hypothesis tests is necessary to provide critical evidence with regards to the joint behavior of meteorological and agricultural droughts. The Granger test of causality [49] evaluates whether the lagged variables of one timeseries (X or meteorological drought indicator) is useful to predict the values of the other time-series(Y or an agricultural drought indicator). The null hypothesis assumes the two time-series X and Y are completely independent and therefore lagged variables of X timeseries has no bearing on Y. The alternative hypothesis implies adding lagged variables of X enhances the prediction of Y which in turn indicates a significant correlation between the two time-series (albeit at different lags). Mathematically, the test compares the following two models:

$Y_t = a + bY_{t-1} + \cdots + kY_{t-k}$ (Null Hypothesis is a k-lag endogenous model) (2)

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$$Y_t = a + bY_{t-1} + \cdots + kY_{t-k} + \propto X_{t-1} + \cdots + \lambda X_{t=k} \text{ (Alternate Hypothesis -exogenous model)} \quad (3)$$

And assesses whether the addition of any exogenous parameters is warranted. The Granger test is useful to evaluate the influence of X (meteorological drought indicator) on Y (agricultural drought indicator). The test will find in favor of the null hypothesis when the addition of the independent parameter (X) leads to no improvement in the model estimates (indicating X is not a good predictor of Y). Only when X improves the model estimate significantly will the model find in favor of the alternative hypothesis, rejecting the null. However, as linear models are fit (see equations 2 and 3), the test will fail when the added exogenous variables (X) have a very strong relationship with Y as this causes multicollinearity in the model. The Granger test of causality confirms (or helps analyze) the exploratory CCF plots as they both work directly with time-series of drought indicator values directly. Granger test of causality is recommended as part of the proposed framework to assess the strength of the association between meteorological drought time-series and agricultural drought timeseries.

While the magnitude of the drought indicator is useful to assess the severity of the drought, a coarser indication of whether the system is in drought (regardless of the severity) or not is often enough in long-term planning applications. Furthermore, the drought indicator value does not directly indicate whether the system is under drought unless it is compared to a pre-specified drought threshold [50]. Therefore, binary (drought/no-drought) time-series developed using pre-specified cut-offs are valuable to compare agricultural and meteorological droughts. For the recommended drought indicators here, the cut-off values can be taken as ≤ -1 for SPI and SPEI, ≤ -2 for PDSI and ≤ -1.25 for Z-Index based on the recommendations of the US Drought Monitor [50]. The binary agricultural and meteorological timeseries can be organized as a 2 x 2 contingency tables to evaluate their drought classification characteristics.

The chi-square test evaluates the null hypothesis that the classifications of meteorological and agricultural droughts are independent of each other against the alternative hypothesis that there is a correlation

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between agricultural and meteorological droughts and can be used as a first-line of evidence to assess the potential correlation of agricultural and meteorological droughts. The Cohen Kappa test [51,52] uses Cohen Kappa statistic as a measure of agreement between agricultural and meteorological time-series and evaluates the null hypothesis of no agreement between the two series against the alternative of statistically significant agreement between the two. In addition to hypothesis testing, the magnitude of the Cohen Kappa statistic is useful to evaluate the strength of the agreement when the null hypothesis is rejected. The proposed evaluation framework recommends that this statistic be mapped (with non-significant values set to zero) to understand the spatial variability of the strength of association between agricultural and meteorological drought indicators.

Receiver Operator Characteristics (ROC) provides another useful set of metrics to compare agricultural and meteorological drought classifications. A variety of metrics measuring the degree of similarity (or lack thereof) using the 2 x 2 contingency table designed from binary drought time-series [53]. The false positive rate (FPR) and the true positive rate (TPR) are two fundamental measures for evaluating the coincidence between meteorological and agricultural droughts. The area under the ROC curve (AUC) provides a good single measure to summarize the strength of relationship between agricultural and meteorological droughts. In a similar vein, accuracy, specificity, and recall also evaluate the nature and extent of correlation between agricultural and meteorological droughts [53] and can be mapped to make spatial comparisons. Table 1 further describes the various terms used in ROC analysis and explain how they pertain to the evaluation of meteorological and agricultural droughts. ROC metrics are all amenable to spatial mapping making them valuable to compare spatial differences between agricultural and meteorological droughts. As such, the proposed framework recommends ROC analysis as an integral component for comparing agricultural and meteorological droughts and its utility is illustrated by comparing meteorological and agricultural droughts in Ethiopia.

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Table 1: Contingency Table and Receiver Operator Characteristics (ROC) as they Pertain to Agricultural and Meteorological Drought Evaluations

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Ag</td><td rowspan="2">D: Drought, ND: Nodrought</td><td rowspan="2"></td><td rowspan="2"></td></tr>
<tr><td>D</td><td>ND</td></tr>
<tr><td rowspan="2">Met</td><td>D</td><td>TP</td><td>FP</td><td>P = TP + FN</td><td>TP – True Positive</td><td>Coincident Ag and Met droughts</td></tr>
<tr><td>ND</td><td>FN</td><td>TN</td><td>N = FP + TN</td><td>FP = False Positive</td><td>Met. Drought but no Ag. drought</td></tr>
<tr><td colspan="5">P + N = Total data points used for classification</td><td>FN = False Negative</td><td>Ag. Drought but no Met. drought</td></tr>
<tr><td colspan="5"></td><td>TN – True Negative</td><td>No Met. Drought and No Ag. droughts</td></tr>
<tr><td colspan="5">False Positive Rate (FPR) or Recall</td><td>TP/P</td><td>Coincidence of Ag and Met. Droughts over all Ag.droughts</td></tr>
<tr><td colspan="5">True Positive Rate (TPR)</td><td>FP/N</td><td>Fraction of met droughts over all Ag. Non-droughts</td></tr>
<tr><td colspan="5">Accuracy</td><td>(TP +TN)/(P + N)</td><td>Fraction of co-occurrence of both met and ag droughts and non-droughts</td></tr>
<tr><td colspan="5">Precision</td><td>TP/(TP + FP)</td><td>Fraction of times Ag and Met droughts are coincident over all met droughts</td></tr>
<tr><td colspan="5">Specificity</td><td>TN/(FP + TN)</td><td>Fraction of coincident Ag. and Met No-drought states over all Ag. No drought states</td></tr>
</table>

Illustrative Application – Comparison of Meteorological and Agricultural Droughts in Ethiopia

Data Compilation

Following Asfaw et al. [7], gridded monthly precipitation dataset extracted from GPCC Full Data Monthly Product Version 2018 produced by Global Precipitation and Climatology Center (GPCC) and available on 0.5° x 0.5° grid [54] were used along with temperature data from Climate Research Unit (CRU TS 4.21) as described in Harris et al. [55]. GPCC Full Data Monthly Product is the most comprehensive gridded precipitation dataset available today and is based on measurements from over 80,000 stations worldwide. It covers a period ranging from January 1891 – December 2016 when this study was conducted. The GPCC Full Data Monthly Product is the most accurate in situ precipitation reanalysis data set of GPCC and

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aims to support regional climate monitoring, model validation, climate variability analysis and water resources assessment studies (e.g., Becker et al. [56]; Zeise et al. [57]). It is also noted to provide representative coverage in Ethiopia [7] and as such was deemed suitable for this study.

The CRU Climate Dataset is produced by the Climate Research Unit at the University of East Anglia and is gridded at a resolution of 0.5^{o} x 0.5^{o} over the land mass and was available on a monthly time-step from 1901-2017 at the time of this study. The CRU dataset is also based on observations from several thousand stations worldwide. The principal data sources come from the World Meteorological Organization (WMO) and the National Oceanic and Atmospheric Administration (NOAA through its National Climate Data Center, NCDC). This dataset has also been used several hundred climate change assessment studies and known to provide reasonable estimates for temperature [55] and as such was used to obtain temperature data across Ethiopia and to compute potential evapotranspiration needed for SPEI and was also used as an input for PDSI and Z-index calculations.

Data for the common period of both GPCC precipitation and CRU temperature datasets (January 1901 – December 2016) were extracted for 377 grid locations across Ethiopia (shown in Figure 1) and used to calculate the drought indicators – SPI, SPEI, PDSI-SC (referred to as PDSI for brevity).

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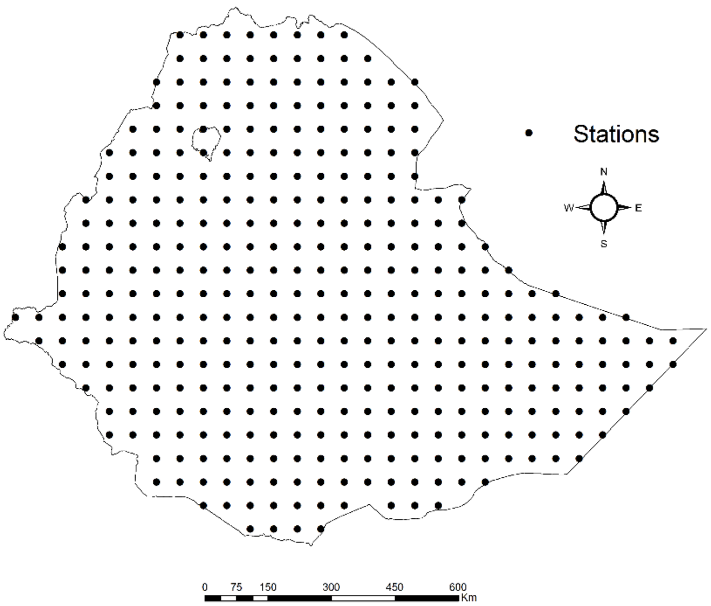

Figure 1: 0.5° x 0.5° degree grid used for evaluation of meteorological and agricultural droughts across Ethiopia

Short-term SPI calculations could be affected by the presence of months with no rainfall. Therefore, SPI and SPEI indices were computed using the procedures presented in Stagge et al. [58], to correct for zero precipitation values. The standard procedures for computing self-calibrating PDSI and Z-index were used [41]. Customized scripts were developed in R programming environment [59] using existing packages [60-62] as appropriate.

Results and Discussion

Exploratory Data Analysis

The maximum cross-correlation coefficient for various agricultural and meteorological indicators is plotted in Figure 2 and represents the maximum possible correlation between agricultural and meteorological drought indicators regardless of the lag at which they occurred. In the short-term, the relationship between SPI-2-SPEI-2 exhibits considerable variability as compared to SPI2-Z-index values. This result highlights that SPEI-2 is controlled by different mechanisms in different parts of Ethiopia. When

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the correlation between SPI-2 and SPEI-2 is strong, precipitation has a higher role in controlling intra-season droughts (as measured using SPEI-2). Surficial soil dryness (caused by temperatures) plays a greater role in other areas where the SPI-2 and SPEI-2 relationship is weaker. In contrast, the relationship between SPI-6 and SPEI-6 is near perfect. Higher precipitation accumulations (6 months) in effect dampen the short-term 'temperature' dominant signals seen in SPI-2. In other words, the ability to store moisture from previous months can help alleviate short-term droughts brought forth by surficial soil dryness and points to the need for irrigation systems in Ethiopia.

The cross-correlation between SPI-2 and Z-index (intra-season) is good (0.6-0.8) over most of Ethiopia and does not exhibit significant spatial variability. The Z-index is computed using a two-bucket model which accounts for soil moisture dynamics over a 1 m soil. This tends to mask the surficial drying effects noted in SPEI-2. The correlation between SPI-6 and PDSI is also good but not as strong as SPI-6 and SPEI-6 and exhibits some variability likely due to differences in parameterizations across different locations obtained using the self-calibration process. Overall, based on CCF, SPI serves as a better surrogate for simulating long-term (seasonal) agricultural droughts then short-term (intra-season) droughts. In both cases, SPI does not explain all the noted variation in agricultural droughts (except perhaps those computed using SPEI-6).

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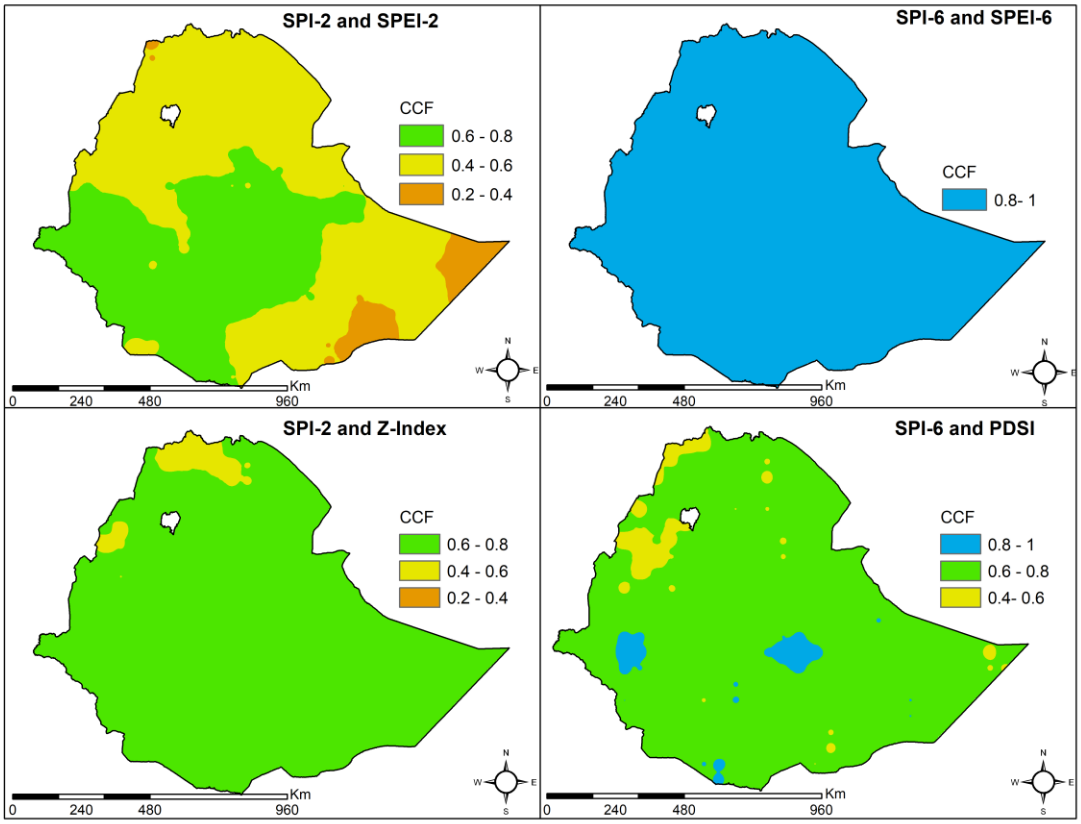

Figure 2: Maximum Cross-Correlation Coefficient between Meteorological (SPI) and Agricultural (SPEI, Z-index, PDSI) Droughts in Ethiopia

Time series distance measure (TSDM) evaluates the aggregated distance between agricultural and meteorological drought indicators. As the measurement scale of different indicators is different, Figure 3 plots the normalized distance (normalization was done such that smallest distance has a value of unity while largest distance has a value of zero and intermediate values are on a linear 0-1 scale). As TSDM measures the distance at any given point in time (and not on lags), it is akin to lag-0 cross-correlation coefficient. Therefore, the comparison of spatial patterns of CCF presented in Figure 2 and TSDM in Figure 3 shows where the relationship between meteorological and agricultural indicators are strongest at lag-0 or likely to covary. It can be noted that the region where the SPI-2 and SPEI-2 correlation is strongest also exhibits a strong TDSM correlation. Low to moderate CCF values shown in Figure 2 for SPI-2 and SPEI-2

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CCF correspond to areas where the relationship between the indicators is stronger at other lags. A comparison of TSDM (Figure 3) and CCF between SPI-2 and Z-index (Figure 2) shows that the maximum strength between these two variables occurs at non-zero lags. This suggests that short-term soil moisture dynamics are not affected by changes in precipitation alone.

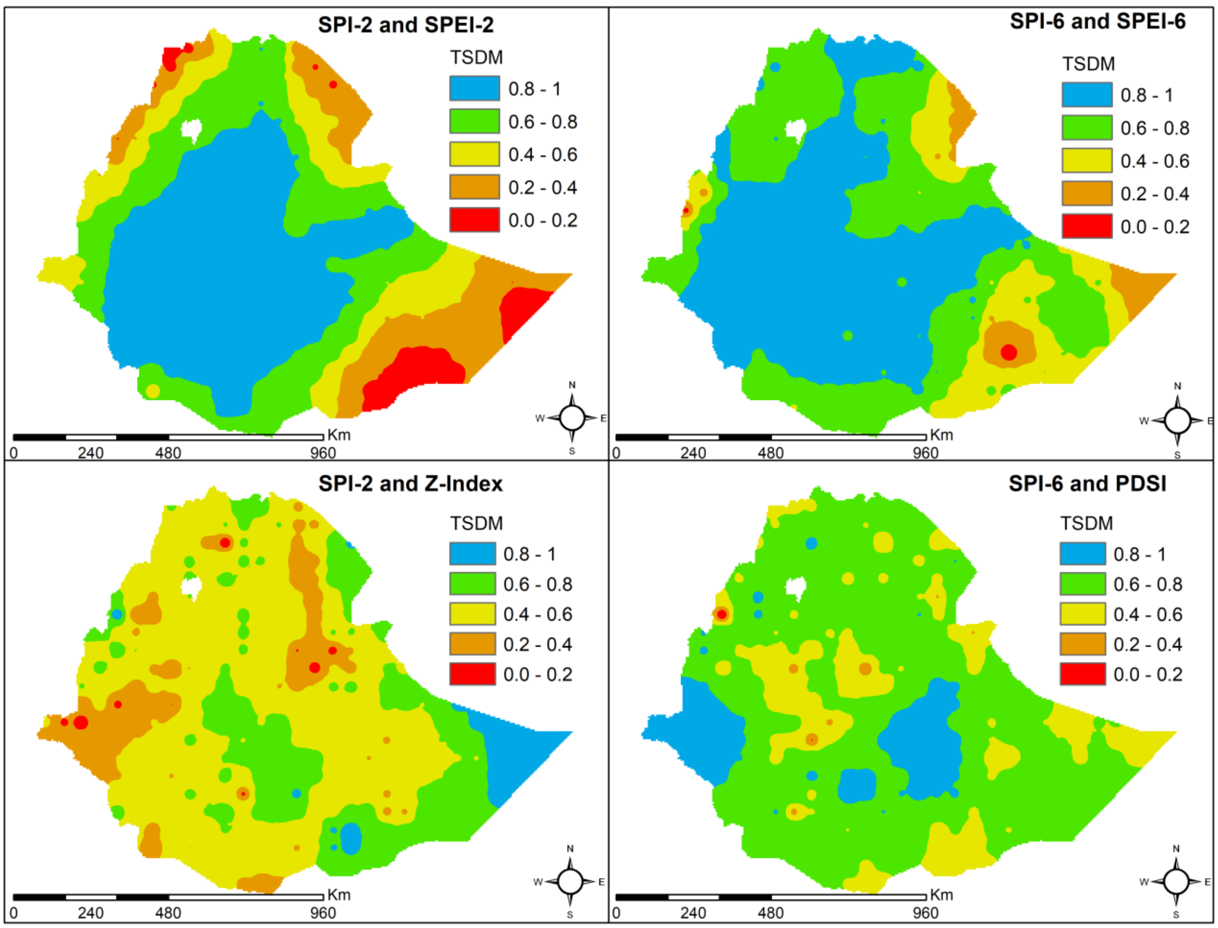

Figure 3: Normalized Timeseries Distance Measure (TSDM) between Agricultural and Meteorological Indicators

A comparison of short-term (SPI-2 and SPEI-2) and long-term (SPI-6-SPEI-6) indicates that as accumulation periods increase, so does the area over which lag-0 becomes higher. This result is to be expected because,

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at longer timescales, there is a greater possibility of a parcel of land experience both meteorological and agricultural droughts. Again, a comparison of CCF (Figure 2) and TDSM (Figure 3) for SPI-6 and SPEI-6 shows regions where the relationship between meteorological droughts (SPI-6) and agricultural drought (SPEI-6) may be strong but the droughts need not be coincident. The degree of coincidence between SPI-6 and PDSI as measured using TDSM is much lower when compared to SPI-6 and SPEI-6 relationship, indicating a lagged relationship between SPI and PDSI which likely arises due to greater moisture buffering capacity in PDSI as compared to SPEI.

Exploratory data analysis using CCF and TSDM metrics indicate that agricultural and meteorological droughts exhibit moderate to strong correlation over much of Ethiopia. However, these droughts need not always be coincident. SPEI indicates a greater degree of spatial coincidence with SPI as compared to Z-Index and PDSI, especially at higher accumulation levels (i.e., for seasonal droughts). The coincidence or lack thereof is important to evaluate whether SPI (a meteorological drought indicator) can serve as a useful surrogate for capturing agricultural droughts and the results suggest that the suitability of SPI as a surrogate for agricultural droughts depends upon the choice of the agricultural drought indicator, the assessment scale (short- or long-term) and the location within the country.

Confirmatory Hypothesis Testing

The exploratory data analysis indicated that the relationship between agricultural and meteorological droughts was strong not always coincident. Granger test of causality was performed to statistically confirm this result the results of which are presented in Figure 4.

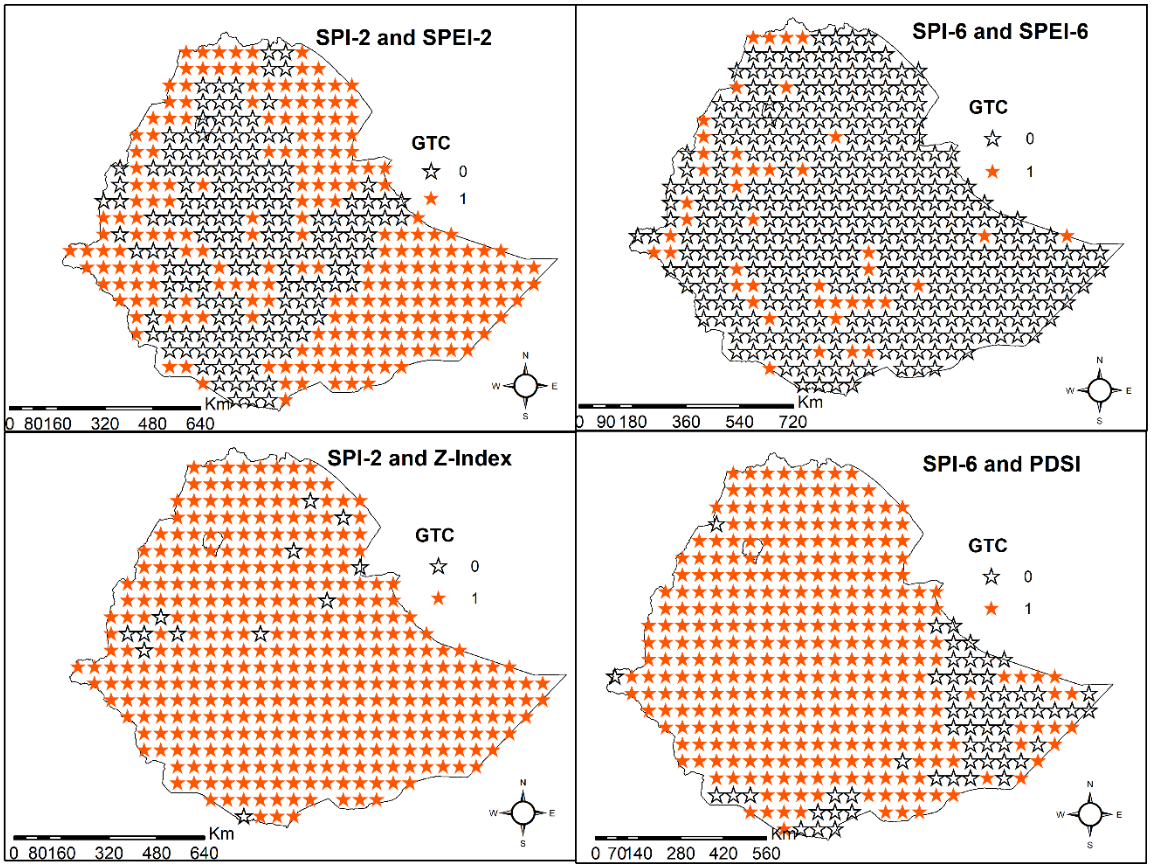

Figure 4: Spatial Locations in Ethiopia where Granger Test Rejected the Null Hypothesis of No Correlation between Meteorological and Agricultural Droughts (1 - Null Hypothesis was Rejected at 0.05 significance; 0 - Null hypothesis was not rejected or Multicollinearity issues were found)

The Granger test of causality indicated that adding meteorological drought indicator generally improves the prediction of agricultural droughts, indicating that SPI can be a lagged indicator of SPEI (i.e., moisture deficits from previous precipitation events do impact current agricultural droughts). However, the Granger test was inconclusive at many places, especially for SPEI-6. The locations where SPI and SPEI were strongly correlated caused multicollinearity issues during the application of the Granger Test. Overall, it can be inferred that the Granger test generally found that lagged values of SPI can be useful to predict (or improve the prediction of) agricultural drought indicators when the strength of the relationship

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is not so strong to cause multicollinearity effects. This result generally confirms the qualitative assessment that a relationship between lagged SPI and agricultural drought indicators is noted at many locations across Ethiopia.

The chi-square test was performed to evaluate the correlation between binary-encoded (drought/no=drought) agricultural and meteorological drought time-series. The results from the chi-square test were significant at all locations and for all combinations of agricultural-meteorological drought indicators. While Chi-square test is commonly used, one of its limitations is its tendency to reject the null hypothesis of independence even when the correlations are small, especially for large sample sizes. Some correlation between the indicators is to be expected because they all, to some degree or another, depend upon precipitation. While the chi-square test may be capturing this result, it does not help tease out the effects of how various agricultural drought indicators modify the precipitation signal. As such, chi-square test, while common, is of limited value for comparing agricultural and meteorological drought indicators (therefore the results of the test are not presented here for brevity).

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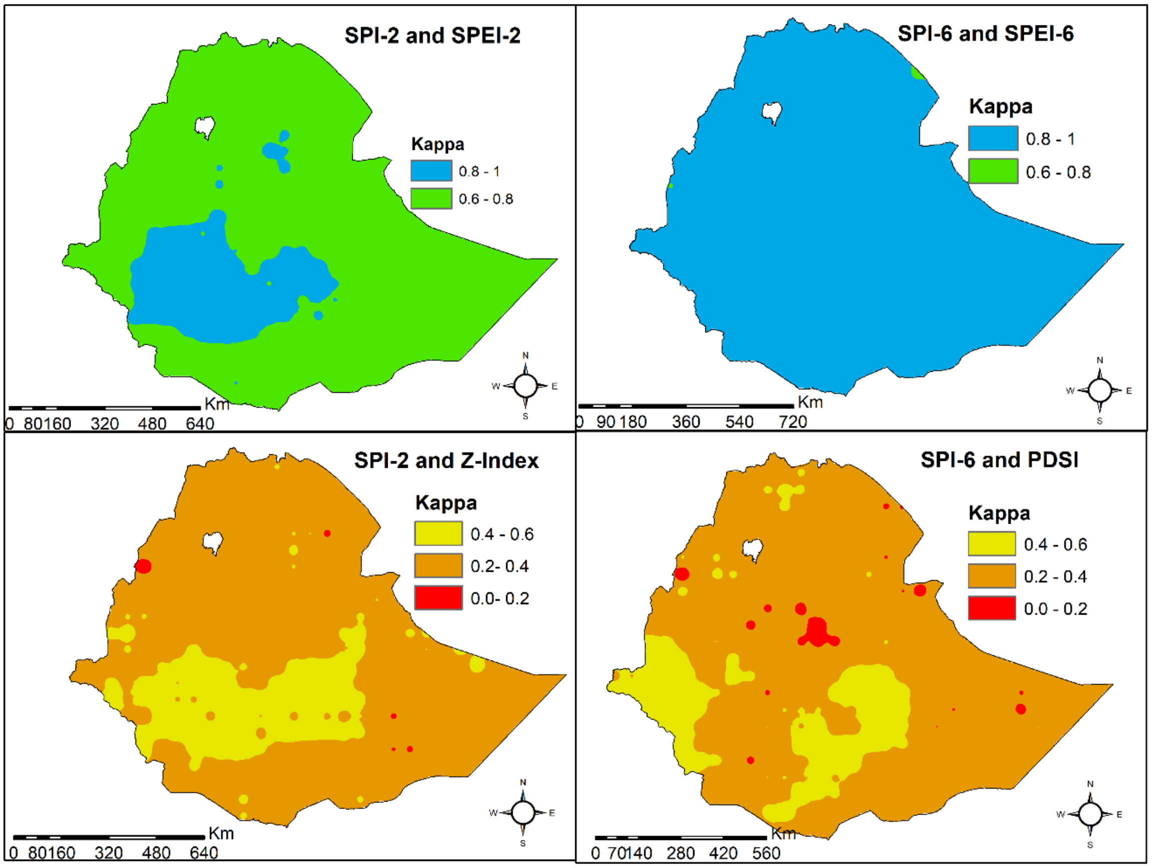

Figure 5: Cohen kappa Values Across Ethiopia for Agricultural and Meteorological Drought Indicator Combinations here

The Cohen kappa test rejected the null hypothesis of independence between agricultural and meteorological droughts at all locations (at 5% significance level). Figure 5 presents the Cohen kappa values and comparison with Figure 2 (CCF plot) indicates considerable similarities. The Cohen kappa is, however, more conservative (except perhaps for SPI-6 and SPEI-6 combination) in defining the degree of agreement between agricultural and meteorological indicators. This result arises because unlike CCF, the Cohen kappa is computed using binary (drought/no-drought) time-series and therefore the comparison is simply on magnitudes but on classified drought states.

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The degree of association as measured using kappa statistic is higher for SPI-SPEI combinations more so then SPI-PDSI (Z-Index) combinations. It is important to recognize the Cohen kappa statistic was computed on classified time-series while CCF was calculated using raw indicator values. As the thresholds for categorizing between drought and no-drought are different for each indicator, the kappa measure provides a more realistic picture of concordance between agricultural and meteorological droughts. PDSI and Z-index exhibit a lower level of agreement with SPI when their values are encoded into drought and no-drought climate states suggesting that the duration of droughts predicted by SPI is not consistent with those predicted by PDSI and Z-index.

Receiver Operator Characteristics (ROC) Analysis

The true positive rate (TPR), or sensitivity, denotes the fraction of times the meteorological droughts are coincident with agricultural droughts. Therefore, TPR provides a direct evaluation of how well SPI based meteorological drought indicators capture the agricultural droughts predicted by SPEI and PDSI (Z-Index).

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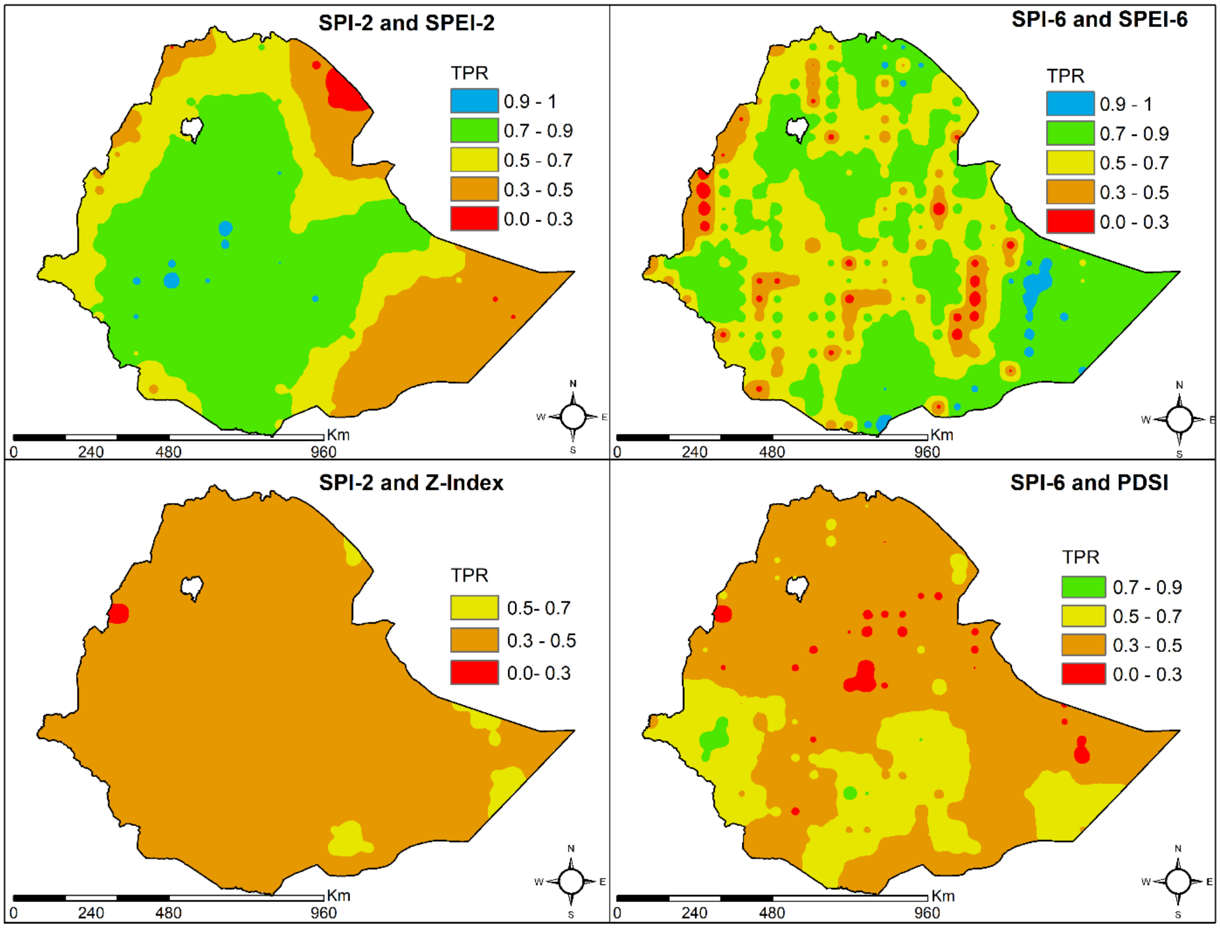

Figure 6: True Positive Rate (TPR) for Various Agricultural-Meteorological Drought Combinations in Ethiopia

Figure 6 depicts the TPR computed TPR values across Ethiopia. It is evident that coincident meteorological and agricultural droughts occur at different frequencies across the nation and depend upon the choice of the indicator for characterizing meteorological droughts. While SPI can better predict SPEI based short-term and long-term droughts over much of the country, the TPR rates for these combinations also exhibit the greatest variability. In general, SPI and SPEI are coincident 50% - 80% of the time but their coincidence can be lower than 30% in some regions. Short-term SPI2-SPEI2 are highly non-coincident in the Somali Region of Ethiopia (Southeastern sections) where belg (short-rainy season) rainfall is prominent and the

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region has greater aridity then other parts of the country. The covariation of SPI (meteorological) and PDSI and Z-index (agricultural) is lower with most regions of the country being in meteorological and agricultural drought states 30% – 70% of the time. While the covariation between SPI and PDSI (Z-index) is lower compared to SPEI based agricultural drought indicators, they also exhibit much more homogeneity across the nation. Thus, SPI may only capture a smaller fraction of the agricultural drought (as predicted by PDSI and Z-index) but it does so consistently across the nation. On the other hand, SPI may be able to capture agricultural droughts predicted by SPEI better in some locations it does not do so consistently. Furthermore, Figure 6 also indicates that the accumulation period plays a critical role in defining the covariation between SPEI and SPI based indicators.

The false positive rate (FPR) denotes the fraction of time there is meteorological drought but not agricultural drought and is mapped across Ethiopia for various indicator combinations of interest in Figure 7. Agricultural systems may exhibit a delay in responding to the onset of meteorological droughts, especially if the soil moisture is buffered from previous rainfall events that occurred prior to the initiation of droughts. Smaller values of FPRs indicate a greater coincidence of agricultural and meteorological droughts.

Again, the SPI-SPEI combinations indicate greater coincidence in some parts of Ethiopia but also exhibit considerable variability. The extent of precipitation accumulation is particularly significant in the southeastern (Somali) region of the county for SPI-SPEI combination. The SPI-6 and PDSI and SPI-2 and Z--index combinations generally show a greater divergence, but the noted deviation is more uniform across the nation. In general, meteorological droughts exist without the onset of agricultural droughts no more than 15% of the time regardless of the indicator used but can be less than 4% of the time (with 4% - 10% being a typical range).

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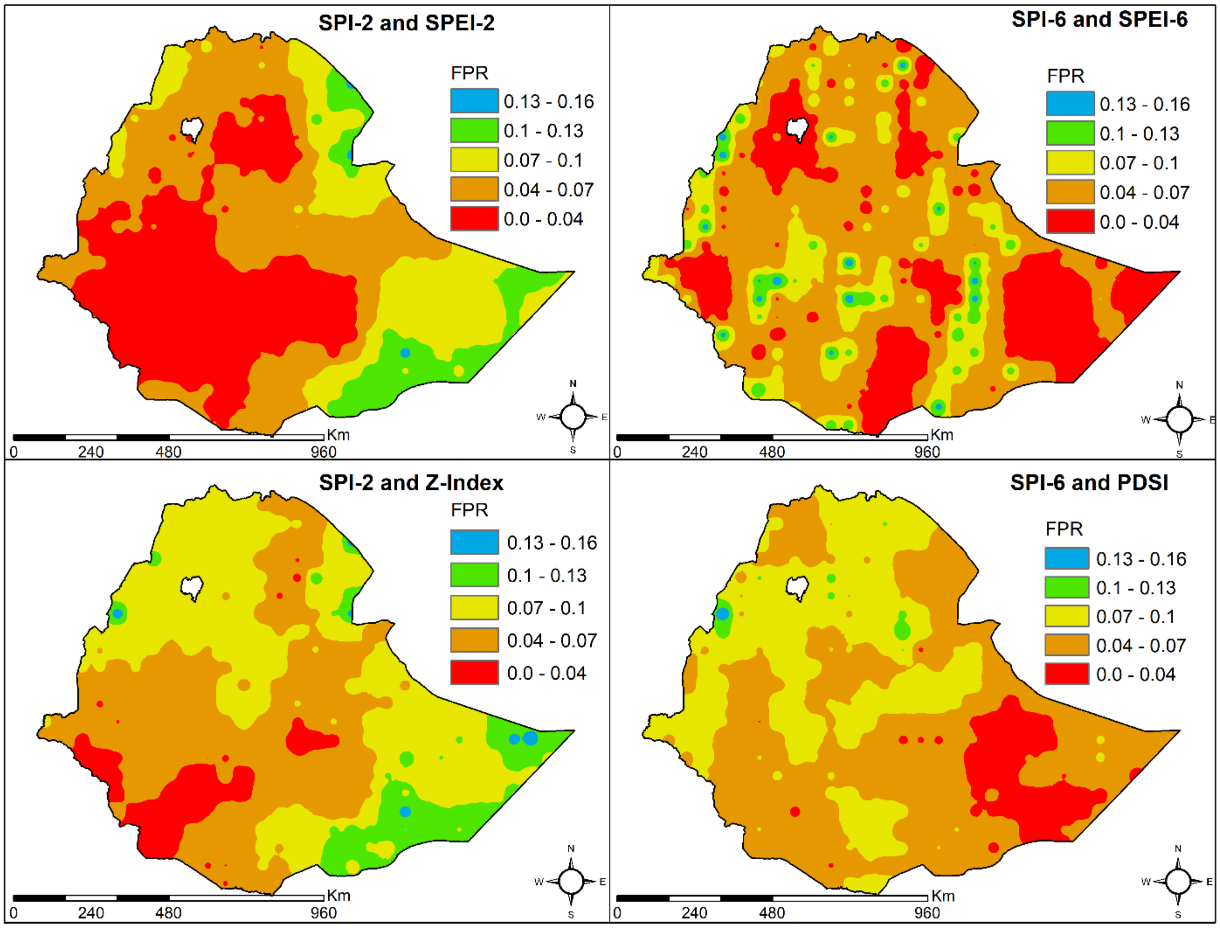

Figure 7: False Positive Rate (FPR) For Various Drought Indicator Combinations Across Ethiopia here

The Receiver Operating Characteristics (ROC) Curve is depicted in Figure 8 and plots the FPR and TPR values for each location. The 45° degree line on the ROC curve indicates the line of equal FPR and TPR. The coincidence of a meteorological and agricultural droughts increases (due to non-random relationships) when points fall in the upper triangular portion shown in Figure 7. The point (0,1) indicates a perfect coincidence (i.e., 100% of the time) between meteorological and agricultural droughts. As almost all points fall in the upper triangle, a reasonably strong, non-random relationship between agricultural and meteorological droughts can be ascertained regardless of the indicators.

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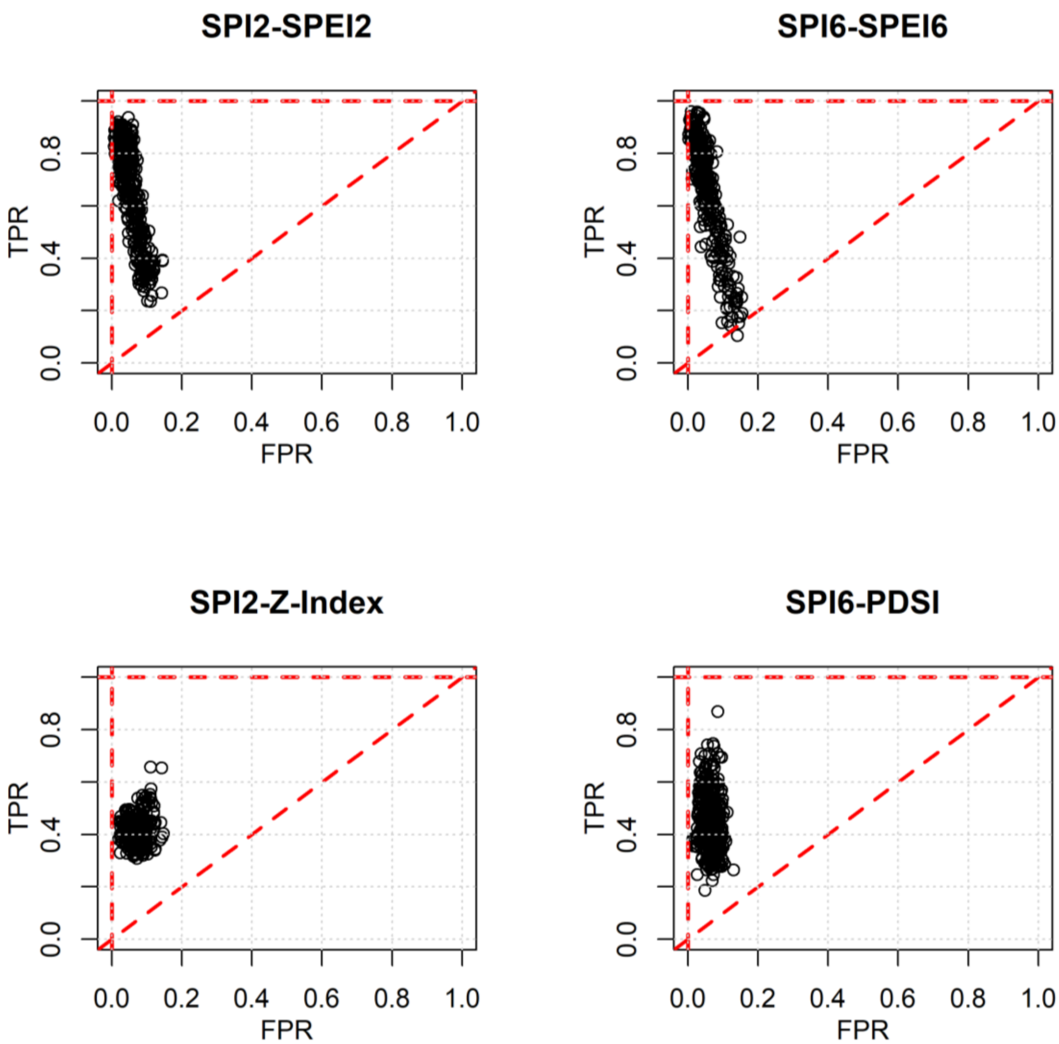

Figure 8: Receiver Operator Characteristics (ROC) Curve for various Meteorological-Agricultural Drought Combinations

While the covariance of Z-index and SPI-2 is not strong, there is also less variability across the nation. The strength of the relationship between SPI-2 and SPEI-2 can vary widely and a similar behavior can be seen for SPI-6 and SPEI-6 (long-term) drought combination as well. This result again states that if SPEI is chosen as an agricultural drought indicator, SPI may or may not serve as a useful surrogate to signify agricultural droughts depending upon the location of interest. On the other hand, If Z-Index and PDSI are chosen as

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drought indicators, SPI is likely to be a poorer but consistent surrogate across the nation for characterizing agricultural droughts.

The AUC values shown in Figure 9 not only reconfirm the findings from earlier metrics but are also helpful in evaluating areas where meteorological indicators covary to a higher extent with a selected agricultural indicator. It is evident from Figure 9 that SPI-2 can be useful as a surrogate in some portions when SPEI-2 is selected as an agricultural drought indicator. However, along the northern and western borders and southeastern portions of the country, the level of surrogacy offered by SPI-2 is the same regardless of which agricultural indicator is used. GIS mapping of AUC allows one to ascertain the minimum level of surrogacy that SPI provides regardless of the choice of the agricultural indicator.

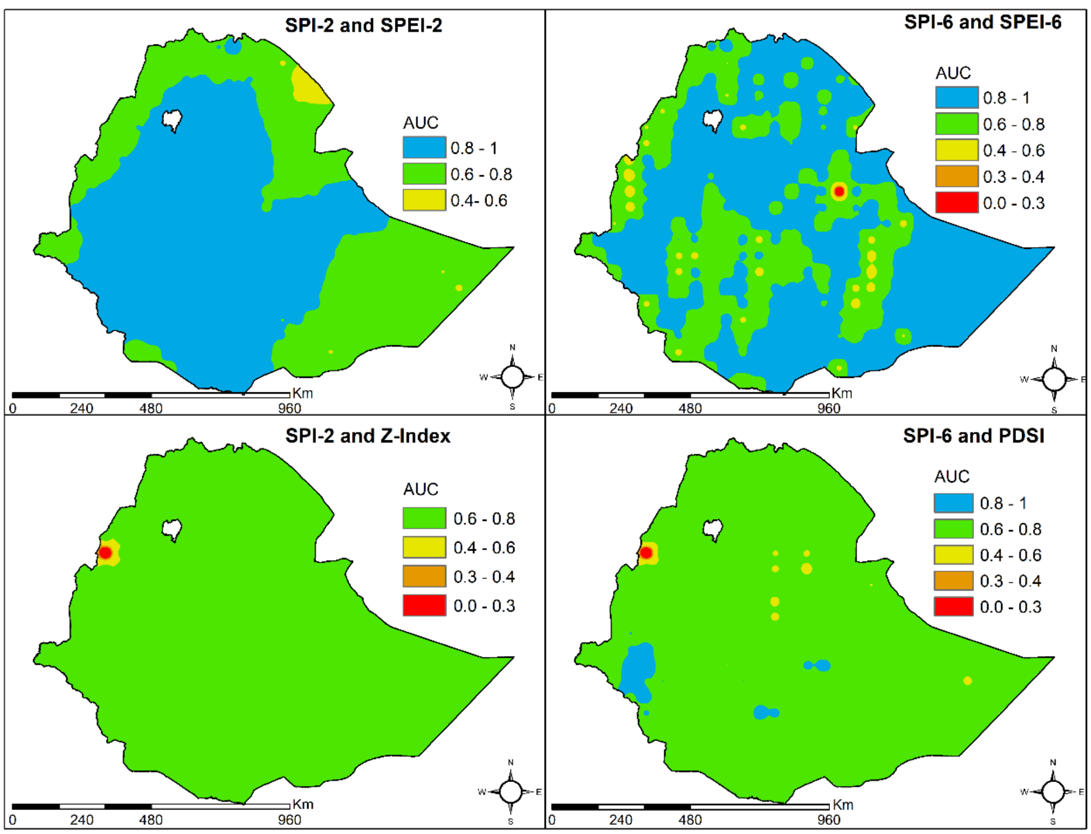

Figure 9: Area Under the Curve (AUC) for Intra-Season and Full-Season Agricultural and Meteorological Drought Comparisons

Precision provides an estimate of the fraction of times meteorological and agricultural droughts are coincident over all meteorological droughts. Precision is another measure that helps evaluate the concordance of agricultural and meteorological droughts and thus help evaluate the suitability of SPI in capturing agricultural droughts being predicted by SPEI, PDSI (Z-index). Figure 10 illustrates that the precision values exhibit extreme variability across Ethiopia. Not all meteorological drought conditions translate to agricultural drought conditions. Various factors such as antecedent soil moisture (water stored from previous rainfall events) and plant adaptations to water stresses help buffer agricultural systems against meteorological droughts. However, in areas with higher values of precision, the buffering capacity is low, and the onset of a meteorological drought quickly causes agricultural droughts. Therefore, SPI can serve as an useful early-warning detector of agricultural droughts.

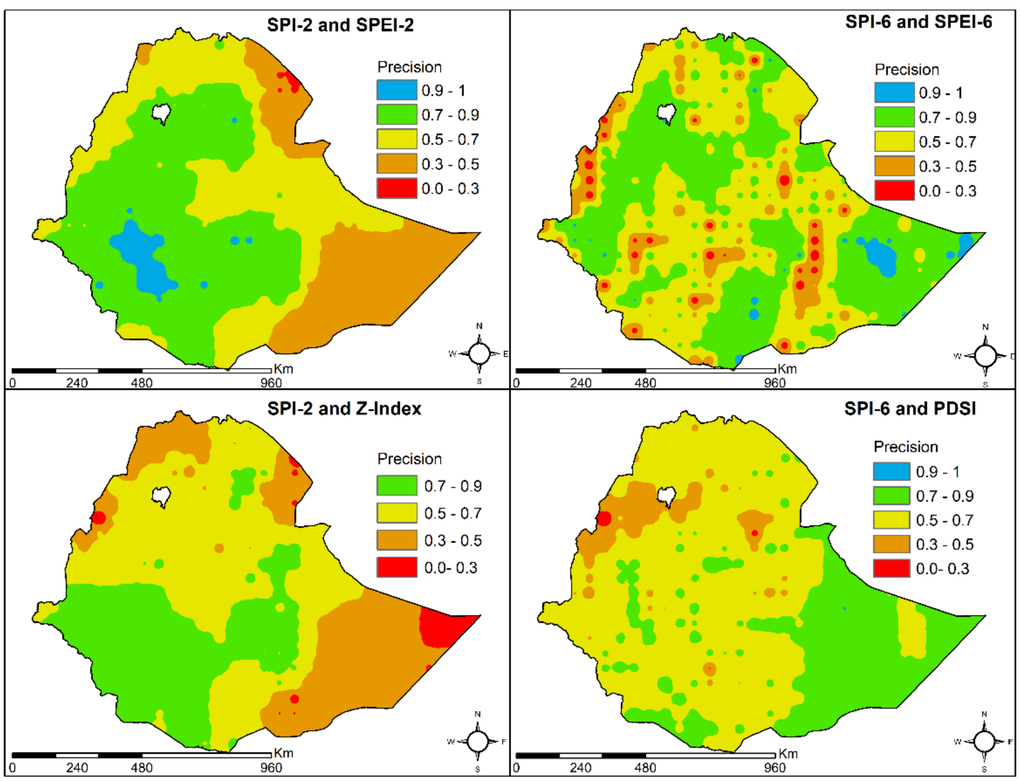

Figure 10: Precision Measures of Agricultural and Meteorological Droughts

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While the focus so far has been on the drought climate state, it is equally important to consider both agricultural and meteorological non-drought states. Specificity can be viewed as a complement to the False Positive Rate (FPR). While FPR looks at coincident times of both agricultural and meteorological droughts across all agricultural droughts, Specificity is the fraction of time both meteorological and agricultural systems are in non-drought states over all times the agricultural system is in a non-drought state. Specificity is useful to assess the fraction of time when there are no climate related water stresses on the agricultural system.

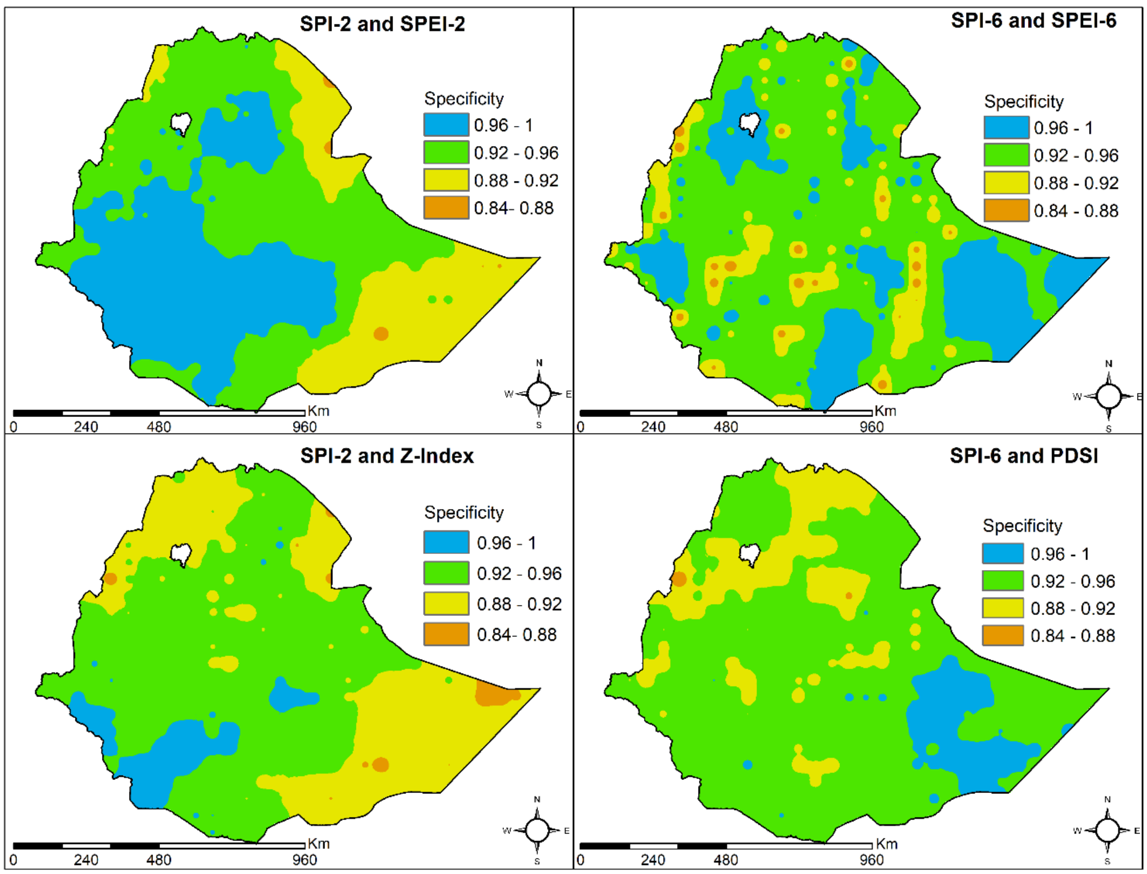

Figure 11: Specificity Measures of Agricultural and Meteorological Droughts

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Figure 11 depicts specificity measures for various meteorological-agricultural drought indicator combinations. The results suggest that the specificity across Ethiopia is reasonably high regardless of the agricultural drought indicator used. Where there is no meteorological drought there is unlikely to be an agricultural drought. According to these results, SPI can be a very useful indicator to highlight agricultural non-drought states. Comparison of the False Positive Rate (Figure 7) and Specificity (Figure 11) suggests that SPI is much better suited to indicate when the agricultural system is not in a drought state, more so that when it is in the drought state.

Accuracy measures the total number of coincident agricultural and meteorological drought and non-drought states against all possible states. Accuracy thus provides a comprehensive evaluation of using SPI as a surrogate for other agricultural drought indicators considering both drought and non-drought states.

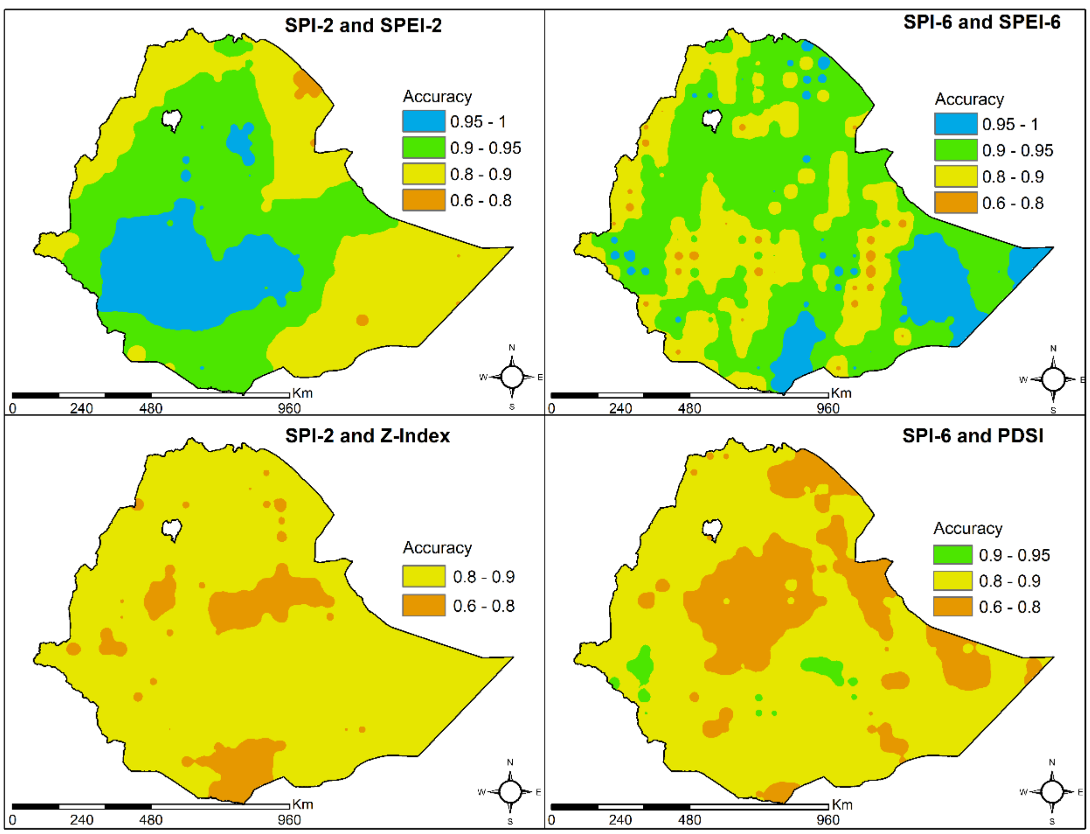

Figure 12: Accuracy Measure Measures of Agricultural and Meteorological Droughts

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Figure 12 suggests that SPI has at least 60% accuracy in predicting agricultural (drought and non-drought) states and it can be over 95% in some instances. Again, the spatial variability of accuracy for different agricultural drought indicators is evident from Figure 12. In general, the accuracy is better for SPI-SPEI combinations more so than SPI-PDSI (Z index) combinations. However, as seen from Figure 11, the accuracy is high because of the ability of SPI to better predict agricultural non-drought states, more so than its ability to predict agricultural drought states. Therefore, a stand-alone evaluation of accuracy does not provide the full picture with regards to the ability of SPI to predict agricultural droughts and accuracy results must be viewed in the context of false positive rate (recall) and precision estimates to assess which states (drought or non-drought) are being better predicted by SPI.

Closing Remarks

Rainfall undoubtedly plays a significant role in sustaining agricultural and pastoral activities in predominantly rural Ethiopia. Meteorological droughts arise due to deficits in precipitation and propagate through agricultural systems to create agricultural droughts. However, meteorological and agricultural droughts need not be coincident. Antecedent soil moisture (stored water supply) and plant water regulation (demand management) may help plants withstand some meteorological droughts. On the other hand, as soil moisture dynamics are affected by a variety of slow hydrologic processes such as evapotranspiration (ET), exfiltration and deep percolation, agricultural droughts may persist long after the cessation of meteorological droughts. Which brings up the question of whether meteorological drought indicators can serve as effective surrogates for prescribing agricultural droughts?

The standardized precipitation index (SPI) is now recognized as a de facto standard for characterizing meteorological droughts. While a de facto standard agricultural drought indicator does not exist, drought indicators that account for both precipitation (supply) and evapotranspiration (demand) are used to characterize agricultural droughts. In this context, the standardized precipitation evapotranspiration index (SPEI), Palmer drought severity index (PDSI) and Palmer Z-index are commonly used to model

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agricultural droughts. As agricultural seasons are short (typically < 6 months), these drought indicators are computed for 1 – 6 months accumulation times. Is SPI a useful surrogate to model agricultural droughts as defined using SPEI and PDSI (Z-index)?

An evaluation framework comprising of a suite of exploratory and confirmatory data analysis methods was postulated and used to evaluate the covariation of SPI (meteorological droughts) and agricultural droughts (as defined using SPEI and PDSI (Z-index). SPI-2, SPEI-2, and Z-index were used to quantify short-term droughts, while SPI-6, SPEI-6, and PDSI were used to characterize full season behavior. The results indicate that agricultural droughts are indeed correlated to meteorological droughts. However, the strength of this relationship not only depends upon the choice of the agricultural drought indicator but also the location (i.e., spatial variability) and if the interest is on intra-seasonal or full season droughts (accumulation time-period). In general, SPI is better correlated to SPEI, but the relationship is highly variable. SPI is less correlated to PDSI and Z-index, but the relationship is spatially homogeneous. Knowledge of SPI can help improve our predictions of agricultural droughts, but the lag (lead) between meteorological and agricultural droughts must be properly accounted for. Contingency table analysis indicated that agricultural droughts can exist when there are no meteorological droughts and not all meteorological droughts cause agricultural droughts. Based on overall assessment metrics (accuracy and AUC), there is a strong to moderate relationship between SPI and agricultural drought indicators. The SPI exhibits high specificity but much lower recall (false positive rate), indicating that SPI is useful in defining agricultural non-drought states more than predicting drought states.

In the Ethiopian context, SPI has been widely used to quantify agricultural droughts under the assumption that most of the agriculture in the country is rainfed and therefore meteorological droughts should have a direct impact on agricultural production. However, as this study suggests, agricultural and meteorological droughts need not be coincident, and SPI does not provide a full picture of agricultural droughts. Efforts should be made to initiate a nationwide soil moisture network, which in the long run

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will provide direct evidence of agricultural droughts and in the short term, help farmers make better farming choices. In the interim, water planners and policy makers must make use of multiple drought indicators that indirectly capture the soil moisture dynamics when developing their drought preparedness schemes. In general, SPEI-2 and PDSI were seen to be more aggressive indicators of short- and long-term agricultural droughts. SPI can potentially be used as an early-warning indicator of agricultural droughts, but it cannot used for defining the cessation of agricultural droughts. The postulated framework provides useful tools to elucidate the relationships between meteorological and agricultural droughts and in conjunction with spatial mapping provide an intuitive visualization of how these two droughts vary over large regional scales. The presented framework in conjunction with high-resolution gridded precipitation and temperature data available in the public-domain provide necessary tools to conduct century-scale national-scale drought assessments and visualize results across large spatial scales.

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Author Contributions

Conceptualization, Venkatesh Uddameri and Elma Hernandez; Data curation, Farhang Forghanparast; Formal analysis, Dawit Teweldebirhan Tsige and Venkatesh Uddameri; Funding acquisition, Stephen Ekwaro-Osire; Investigation, Dawit Teweldebirhan Tsige; Project administration, Venkatesh Uddameri; Resources, Elma Hernandez; Software, Venkatesh Uddameri; Visualization, Dawit Teweldebirhan Tsige; Writing – original draft, Venkatesh Uddameri and Farhang Forghanparast; Writing – review & editing, Elma Hernandez and Stephen Ekwaro-Osire.

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