GLOBAL-SCALE EVALUATION OF DIFFERENT PRECIPITATION DATASETS USED IN DEVELOPING METEOROLOGICAL DROUGHT INDEX FOR AGRICULTURAL APPLICATION

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1. INTRODUCTION

In recent years, drought has contributed to some of the world's severe famines that might affect food security and human livelihoods. Understanding drought and its potential impact are key points towards future mitigation, especially in agriculture (FAO, 2018).

Hundreds of drought indexes and indicators representing different types of drought have been developed (Mishra and Singh, 2010). Among them, the most used drought indexes are known as SPI (Standardized Precipitation Index) (McKee et al., 1993), SPEI (Standardized Precipitation Evapotranspiration Index) (Vicente‐Serrano et al., 2010), and PDSI (Palmer Drought Severity Index) (Palmer, 1965). Numerous studies and applications employed such indexes and, however, conclude that no index is outperforming others significantly. Moreover, a recent report by Hoffman et al. (2020) indicated that larger uncertainty results from different main inputs used in each index, i.e., precipitation, rather than between the drought indexes.

The evaluation of different input data in drought index calculation for agricultural impact is less discussed, whereas it is necessary to estimate the hazard and its implication to livelihood more accurately. Therefore, this study aims to evaluate the performance of various precipitation datasets used in deriving the meteorological drought index. SPI is used since it is suitable for this study purpose, given its sole input, i.e., precipitation, for detecting its significance variation. Their performance to capture agricultural variable variations is assessed by comparing dry SPI with global crop yield anomaly estimates from the historical global yield dataset.

2. MATERIALS AND METHODS

2.1 Materials

Datasets used in this study are shown in Table 1 and Table 2. All data are set in a 0.5-degree spatial resolution and subset over 1983 to 2014 (32 years).

Table 1 Precipitation dataset used in this study

Type	Dataset	**Type**	Dataset
Gauge observation	GPCC, CRU, CPC, UDEL, PRECL	**Reanalysis**	ERA-5, MERRA, JRA-55
Merging	MSWEP		

Table 2 Crop-related dataset used in this study

Name	Data	Use	References
Crop calendar	Planting and harvesting date (Day of Year)	Drought exposure	(Sacks et al., 2010)
The global dataset of historical yield (GDHY)	Crop yield (t/ha)	Crop yield anomaly	(Iizumi et al., 2020)

2.2 Methods

SPI development

SPI is standardization of fitted precipitation time series to a probability distribution, transforming to a normal distribution (McKee et al., 1993). We computed the monthly SPI from 1 to 12-month time scales to assess seasonal to interannual droughts.

Drought model during crop growing season

The monthly SPIs then are a subset within the crop growing period, with the reference of harvesting month of each year (Kim et al., 2019). Then drought magnitude at year t (H_t) were obtained using Eq.1.

$$H_t = -\sum_{j=0}^{k} S_{C-j,\ t} \tag{1}$$

where $S_{j,t}$= k-month aggregated SPI (SPI<0) in month j and year t and C is the harvest-related month in 2000 (Sacks et al., 2010;). It should be noted that the minus operator is to make negative SPI absolute (higher Ht, higher drought magnitude).

Crop yield anomaly

The agricultural response to drought stress is represented by crop yield anomaly obtained from the crop yield dataset (Iizumi et al. 2020). The average yield used to get anomaly along time series is represented by 5-year centered moving average.

Drought-yield anomaly correlation

Pearson correlation coefficient was calculated to assess the correlation between drought and crop yield anomaly over 32 years.

3. RESULT AND DISCUSSION

3.1 SPI development

Fig. 1 gives the example of how SPI calculation based on different datasets can vary spatially and temporally in some parts of the region (i.e., Congo). It should be taken into consideration when performing drought estimates

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for various aims. Fig. 2 shows the spread in spatial scale over a global scale. The highest variations are found in developing regions where observations are scarce (i.e., African countries), higher latitude, and high elevation region. Consequently, it indicates high uncertainty (of drought index) in the area where crop sensitivity to drought has been profound (Miyan, 2015).

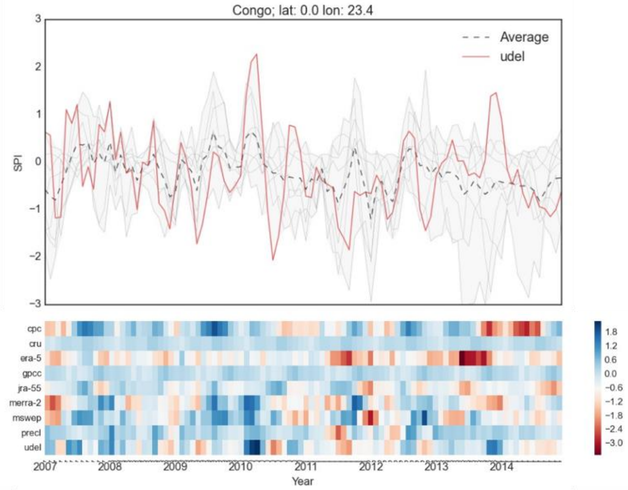

Fig. 1 SPI values in time series at one grid

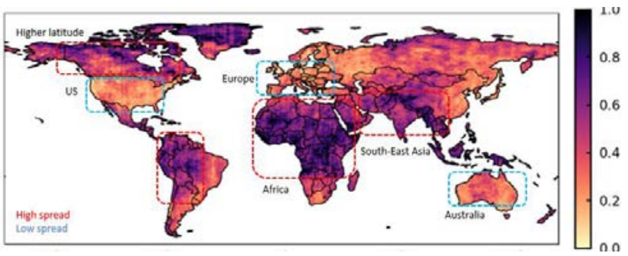

Fig. 2 Spread of SPI results from different datasets in over global scale

3.2. Drought-yield anomaly correlation

Fig.3 shows the example of drought and crop yield anomaly correlation in Maize crop using SPI12 derived from mean dataset ensemble. This study obtained scaled mean SPI values from all datasets to test its suitability to represent drought conditions. Red pixels show drought affect yield loss (negative correlation), while the pie chart shows proportions of global crop area (0-100%) weighted using global crop area fraction (Portmann et al. 2010). Drought-induced yield loss is evident in some regions (maize crop in this example), e.g., US, Europe, South Africa, and South America.

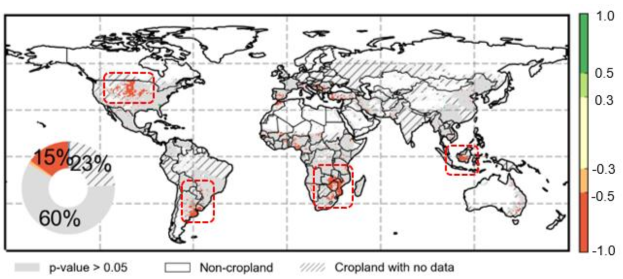

Fig. 3 Drought-crop yield anomaly correlation example in case of maize using SPI12 ensemble mean

Comparing the SPI performance derived from different datasets in terms of their ability to explain crop yield variation, Fig. 4 shows the total global area fraction of strong negative correlation (indicating drought impact to crop yield loss). Mean ensemble, CRU, and MERRA based drought index is highly correlated with crop yield anomaly (higher fraction global grids), while JRA-55 correlation yields a quite different result with other (much less). The impact of the drought is not significant to wet crops (i.e., rice). It might be due to the support of irrigation or less drought given in the monsoon environment.

This signifies the importance of other disruption's impact analysis to rice in particular (e.g., flood). In addition, these results indicate the most correlated SPI time scale related to more prolonged drought and slow drought propagation (representing agricultural to hydrological drought). This can explain how crop is affected by drought.

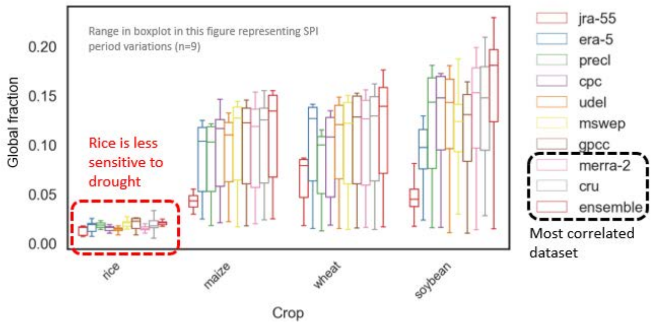

Fig. 4 Fraction of global crop area (-1 ≤ r ≤ -0.5) weighted by global crop area (Portmann et al. 2010)

4. CONCLUSION

Variation of SPI derived from different datasets can vary significantly in data-scarce region, higher latitude, and higher elevation (given its common understanding from precipitation uncertainty as its main input). Attention is required when selecting datasets for computing drought indices (emphasized in the observation-scarce regions).

By using different input dataset, 4-10% total global crop areas are negatively affected by drought (vary within around 6% in average (varies between crop types and SPI time scale).

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