CROP RESPONSE PATTERN TO DIFFERENT METEOROLOGICAL DROUGHT TIMESCALES: A GLOBAL-SCALE ANALYSIS

Tohoku University Student Member ○Vempi Satriya Adi Hendrawan
Tohoku University Member ○Daisuke Komori

1. INTRODUCTION

Drought has contributed to some of the world's most severe famines (e.g. a severe drought in India affecting 300 million people in 2002). Agriculture is the most affected sector by drought in developing countries, absorbing about 80% of all direct impacts (FAO 2017). Therefore, understanding drought and its impact are vital points towards the rising incidence of weather extremes and its negative impacts on agriculture.

The nature of drought impact on crops depends on how drought is defined (i.e., timescale, duration, and severity) (Mckee *et al* 1993) and the characteristic of crop resistance (Daryanto *et al* 2016). Numerous previous studies have assessed drought impact to crop by using multiple drought timescales (Peña-Gallardo *et al* 2019). Drought timescale can be referred to as the length of time (e.g., months) during which the drought event develops (Hayes 2001).

This study assesses crop sensitivity based on different drought timescales. This study aims to understand the global pattern of crop response to different drought timescales. This study contributes to existing drought-related studies for agricultural systems to understand how different drought timescales are associated with crop yield anomalies.

2. MATERIALS AND METHODS

The different drought timescale was modelled by a multiscalar meteorological drought index (i.e., SPI) with 1 – 12-month timescales based on the global gridded precipitation datasets. All analysis was done for each major crop (maize, rice, soybean, and wheat) in 0.5° grid resolution during 1981 – 2016 (36 years).

2.1. Materials

Datasets used in this study are shown in Table 1. The primary input dataset in this study is the global precipitation datasets for the drought model and crop yield data for assessing drought risk on crops.

Table 1 Dataset used in this study

Name	Data	Use	References
Drought Index (SPI)	Precipitation from ensemble historical global dataset	Drought model	(Hendrawan *et al* 2022)
Crop calendar	Planting and harvesting date (Day of Year)	Exposure model	(Sacks *et al* 2010)
The global dataset of historical yield (GDHY)	Crop yield (t/ha)	Risk model	(Iizumi and Sakai 2020, Kim *et al* 2019)

2.2. Methods

SPI was calculated by transforming monthly accumulated precipitation (i.e., within 1 – 12-month) to standardized value (mean 0 standard deviations 1) based on the specific distribution (i.e., gamma distribution) (Guttman, 1998).

Drought Index (DI) was then calculated based on the ensemble mean of several SPI data, obtained from the ensemble mean of several datasets (GPCC, CRU, PRECL, UDEL, CPC, MSWEP, MERRA-2, ERA-5, JRA-55). Then, Eq. 1 was used to convert monthly SPI to annual drought index based on harvesting month obtained from Sacks et al. (2010) dataset. To see the detailed method, refer to Hendrawan et al. (2022).

$$DI_{n,t} = \begin{cases} |SPI\text{-}n_{j,t}| & SPI < 0, \\ null & SPI \geq 0, \end{cases} \qquad (1)$$

where $SPI\text{-}n_{j,t}$ is the SPI of n-month precipitation accumulation in harvested month j in year t. oor example, $SPI\text{-}3_{aug,2015}$ is calculated using precipitation sum within 3-month: June, July, and August in 2015.

We assessed the relationship between each 12-timescales DI and crop yield anomaly estimated by detrending the gridded global dataset of crop yields for major crops (maize, rice, soybean, and wheat) for the four crops types using the Pearson correlation. Thus, we obtained 12 different correlations in each grid independently for each crop and obtained a DI timescale in which crop yield anomaly shows the highest correlation (Hendrawan *et al* 2022, Peña-Gallardo *et al* 2019).

3. RESULT AND DISCUSSION

3.1 SPI development

The result shows that medium timescale shows a stronger correlation for maize and soybean by around

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Contact Address: Tohoku University, 6-6 Aoba, Aramaki, Aoba-ku, Sendai 980-8579, Japan, Tel: +81-22-795-7455

24% and 31% of the total global crop area, respectively, followed by long and short timescale. Meanwhile, for wheat, long-timescale shows the highest global proportion by around 27%. In the case of rice, the dominant response is shown in the short timescale for around 17% global crop area. Medium responses to drought in maize and soybean are profound, while in contrast, wheat indicates a longer response to drought, and rice is more sensitive to short drought timescale despite its less share of global cropland (Fig. 1).

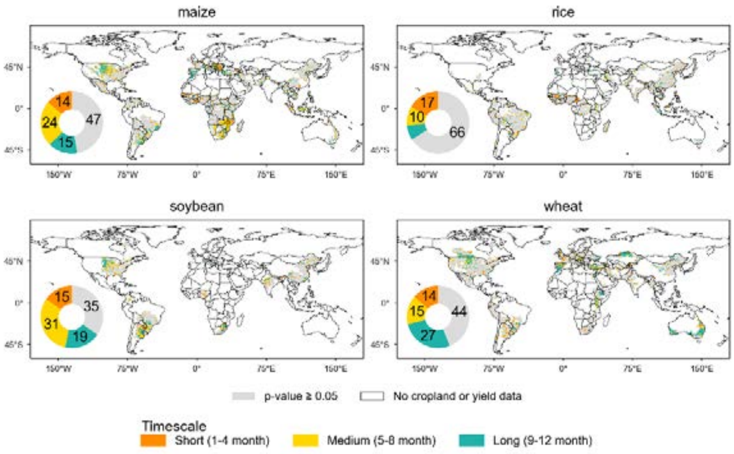

Figure 1 Drought timescales (short, medium, and long) at which the most negative correlation between DI and crop yield anomaly is obtained.

Considering the different climatic regions that may govern the response of crop yield to drought, we summarized the results by categorizing cropland into the main classes (tropical, arid, temperate, cold, and polar) and the sub-types based on precipitation types (rainforest, monsoon, dry savannah, wet savannah, steppe, desert, dry summer, dry winter, without dry season, ice cap, and tundra) (Fig. 2). Results show that crop response to drought varies depending on the crop types among different climatic regions. For example, in the case of maize, medium response timescale become dominant for arid, cold, and temperate, followed by a long and short response. However, for the tropical region, the short response has more control in maize. Regarding the classification based on the sub-types, medium response timescale still dominates in all regions followed by a long and short response, except in savannah and wet region dominated by the short response. In dry summer, monsoon, and rainforest extended response slightly higher than short and medium timescale response.

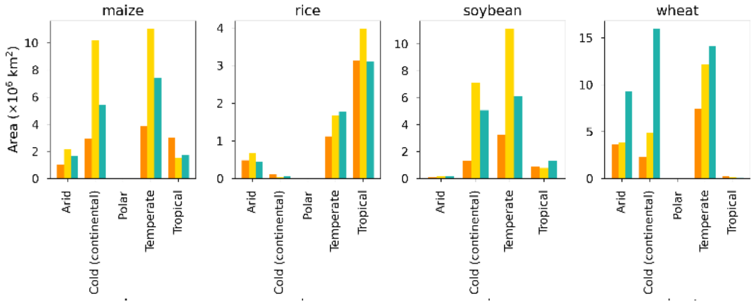

Figure 2 Area proportion of each different response timescale to drought (short, medium, and long) in different climatic regions based on Köppen-Geiger climate classification.

4. CONCLUSION

This study reveals that crop yield loss is generally more sensitive to medium (5-8 months) to long (9-12 months) drought timescales globally, compared to short timescale (1-4 months). Various determinants might control the different spatial of crop response which is essential for further consideration.

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