Assessment of the effects of spatiotemporal characteristics of drought on crop yields in southwest China

Author

Mokhtar, Ali, He, Hongming, Alsafadi, Karam, Mohammed, Safwan, Ayantobo, Olusola O, Elbeltagi, Ahmed, Abdelwahab, Ossama MM, Zhao, Hongfei, Quan, Ye, Abdo, Hazem Ghassan, Gyasi-Agyei, Yeboah, Li, Yu

Published

2021

Journal Title

International Journal of Climatology

DOI

10.1002/joc.7407

Rights statement

Downloaded from

Griffith Research Online

Assessment of the effects of Spatiotemporal Characteristics of Drought on Crop Yields in Southwest China

Ali Mokhtar[1,2†], Hongming He[1,3*], Karam Alsafadi[4†], Safwan Mohammed[5], Olusola O. Ayantobo[6,7], Ahmed Elbeltagi[8], Ossama M.M. Abdelwahab[2], Hongfei Zhao[1], Ye Quan[3], Hazem Ghassan Abdo[9], Yeboah Gyasi-Agyei[10], Yu Li[*11]

[1]State of Key Laboratory of Soil Erosion and Dryland Farming on Loess Plateau, Institute of Soil and Water Conservation, Northwest Agriculture and Forestry University; Chinese Academy of Sciences and Ministry of Water Resources, Yangling 712100, China.

[2]Department of Agricultural Engineering, Faculty of Agriculture, Cairo University, Giza 12613, Egypt.

[3]School of Geographic Sciences, East China Normal University, Shanghai 210062, China.

[4] School of Geographical Sciences, Nanjing University of Information Science and Technology, Nanjing 210044, China.

[5]Institution of Land Utilization, Technology and Regional Planning, Faculty of Agricultural and Food Sciences and Environmental Management, University of Debrecen, Debrecen 4032, Hungary.

[6]State Key Laboratory of Hydroscience and Engineering, Department of Hydraulic Engineering, Tsinghua University, Beijing, China

[7]Department of Water Resources Management and Agricultural-Meteorology, Federal University of Agriculture, Abeokuta, Nigeria.

[8]Agricultural Engineering Dept., Faculty of Agriculture, Mansoura University, Mansoura; 35516, Egypt

[9]Geography Department, Faculty of Arts and Humanities, Tartous University, Tartous, Syria.

[10]School of Engineering and Built Environment, Griffith University, Nathan QLD 4111, Australia.

[11]Institute of Geographic Sciences and Natural Resources, Chinese Academy of Sciences, Beijing 101400, China

[†]These two authors contributed equally.

*****Correspondence: hongming.he@yahoo.com; liyuljy@163.com Tel.: (+86-29-87012884; 712100).

Abstract: There are limited literature on the impacts of drought on crop yields in warm regions such as southwest China. Drought vulnerability of four different crops (wheat, rice, maize and sugarcane) cultivated in three provinces (Sichuan, Guizhou and Yunnan) within southwest China were investigated in this study. It was based on the drought index of standardized precipitation evapotranspiration index (SPEI) for -3- and -6-months timescales (SPEI-3 and SPEI-6). The correlation between the SPEI and the standardized yield residuals series (SYRS) index for the individual crops was estimated for the period from 1960 to 2018. The highest drought duration was recorded in the southern part of the study area especially in the Yunnan Province. For SPEI-3, 60% of the total area was affected by drought mainly during the months from August to December for about 13 years (2005-2018). In terms of SPEI-6, the total affected area by the drought exceeded 80% during the timeframe from 2009 to 2013. Among the studied crops, winter wheat had the highest annual crop yield losses particularly in 2010 when the loss exceeded 50%. The results of this study have implications for agricultural management and climate policymaking in minimizing the influence of drought under the warming climate in southwest China. Further, it provides greater insight into crop–climate interactions and sustainable crop production.

Keywords: SPEI; drought; crop yield losses; crop resilience; standardized yield residuals series; climate variables.

1. Introduction

The world’s population is increasing at a rate of 1.13% per year, and is expected to reach 9.6 billion by 2050 (Tripathi et al., 2019). Thus, there is a need to increase crop production to meet the expected global food demand. However, global and regional climate change poses a major threat to food security and sustainability of land resources (Godfray et al., 2010, Kang et al., 2009). In the last few decades, studies on the direct and indirect impacts of climate change on terrestrial ecosystem and water balance, e.g., on agriculture (Chandio et al., 2020) and potential evapotranspiration (Dinpashoh et al., 2019), have become some of the major interests of scientists. Extreme climate events such as floods and drought, which significantly correlates with global warming, have led to major environmental damage and extinction of some animal species and agricultural sectors (Hansen et al., 2019, Wang et al., 2017, Lobell et al., 2011a, Mehrabi and Ramankutty, 2017). For example, at the global scale, (Lesk et al., 2016) estimated the loss of 1820 million Mg of maize, rice and wheat due to drought events during the past four decades. Climate change caused a decrease in yield of around 3.8% and 5.5% for wheat and maize respectively, during the period of 1980-2008 (Lobell et al., 2011a). (Mehrabi and Ramankutty, 2017) estimated a loss of $237 billion in global crop production due to drought and heat related events between 1961 and 2014.

More than 150 drought indices have been developed for drought assessment, classification and monitoring (Svoboda and Fuchs, 2016). Some common indices are the Palmer Drought Severity Index *(*PDSI) (Palmer, 1968), Standardized Precipitation Index (SPI) (McKee et al., 1993), Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), Rainfall Anomaly Index (RAI) (Van Rooy, 1965), and

Precipitation Evapotranspiration Difference Condition Index (PEDCI) (Tian et al., 2020). A detailed review of drought indices can be found in (Mishra and Singh, 2010). Among the indices, the SPEI has been proposed for detecting and monitoring drought (Vicente-Serrano et al., 2010). This index combines the sensitivity of the PDSI to changes in evaporation demand under a warming climate and the multi-temporal nature of the SPI. Moreover, SPEI is one of the most widely used indices for tracking drought evolution at different time scale of interest (Vicente-Serrano et al., 2010, Potop and Možný, 2011). Examples on the global use of SPEI are in China (Gao et al., 2017), Hungary (Alsafadi et al., 2020), southern Africa (Manatsa et al., 2017), Bangladesh (Miah et al., 2017), India (Das et al., 2016), and Poland (Somorowska, 2016). However, there is no general consensus on the most suitable drought index for studying the impact of drought on crop yields (Esfahanian et al., 2017). Moreover, only a very few investigations (Peña-Gallardo et al., 2018, Tian et al., 2018) have compared drought indices for the identification of their appropriateness for monitoring drought impacts on various crop types. Some previous studies have recommended applying SPEI index to study the relation between drought and global agricultural production (Peña-Gallardo et al., 2019, Chen et al., 2016, Wang et al., 2018, Potopová et al., 2016). Since our study focuses mainly on meteorological drought during the whole crop growth period, SPEI was selected to characterize the drought events in the study area.

In China, drought poses a major threat to the sustainability of socio-economic activities, costing more than US$12 billion between 1949 and 1995 (Jia et al., 2016). Xu et al. (2015) reported that drought covered more than half of the non-arid areas in China between 1963 and 2011. Southwest China has been projected to be the most drought prone area under the current (Zhai et al., 2010) and future climate scenarios (Wang and Chen, 2014). Recently, southwest China experienced serious drought episodes which severely impacted the socioeconomic, ecosystems, and agricultural sector, especially in 2006 where 0.3 million hectares of crops failed and about 18 million people faced water scarcity (Yang et al., 2012b, Zhang et al., 2012, Wang et al., 2015a). The main objectives of this research were (1) to detect and characterize the temporal–spatial distribution of drought characteristics (duration, intensity, and severity) from 1960 to 2018, (2) to identify the temporal response of four crops (maize, wheat, rice, and sugarcane) to drought, and (3) to evaluate the resilience and yield sensitivity of the four crops to drought events in southwest China.

2. Material and methods

2.1 Study area

The study area covers 105.5×10^4 km^2 of southwest China, consisting of Yunnan (39.4×10^4 km^2), Guizhou (17.6×10^4 km^2) and Sichuan provinces (48.5×10^4 km^2). The Sichuan basin is surrounded by mountains with elevation between 1000 and 3000 m, while the Yunnan-Guizhou plateau has an average elevation of 2000 m (Figure 1). Southwest China has a typical monsoonal climate which frequently fluctuates in the climate variables. The average annual temperature is 14^0C but has a significant increasing trend, especially in the south of the Yunnan province. The slope change of precipitation has decreased during the last five decades (Mokhtar et al., 2020a). The mean annual precipitation is 1000 mm, and with a significant decreasing trend (Mokhtar et al., 2020a, Zhang et al., 2019a), further, it is reported that the spatial distribution of precipitation was varied over the study area with increasing from north to south, especially, in southwest Yunnan province that reached 2200mm/year (Mokhtar et al., 2021a). Forest is the dominant ecosystem type, occupying about 46% of the study area. Grass ecosystem is the second major ecosystem type, accounting for about 28% of the study area (Table 1). The third major ecosystem type of agriculture occupies an average area of 23% (Mokhtar et al., 2020a, Zhang et al., 2019b).

2.2 Data sources

The climate datasets were retrieved from stations data which capture local conditions and show the deviation between the local station (high resolution to meet spatial resolution requirement). Further, rain gauges are universally considered as the reference data for precipitation observations as they provide a direct physical record of the precipitation at a given station. In the same study area, (Mokhtar et al., 2020a) used the Penman-Monteith equation ET_0 values that were calculated based on climate variables for each meteorological station during the period 1960-2016. Moreover, the SPEI index has been calculated based on meteorological station over the Tibetan Plateau, China, during the period 1980-2018 (Mokhtar et al., 2021b). Thus, the daily precipitation; minimum, maximum and average temperature; sunshine hours; wind speed and relative humidity were obtained from 90 meteorological stations (1960–2018) through China National Meteorological Data Sharing Platform *(http://data.cma.cn/en)*. The monthly evapotranspiration was calculated over the study area using the Penman-Monteith equation (Allen, 2000, Suleiman et al., 2007, Suyker and Verma, 2009, Fan and Thomas, 2013, Mokhtar et al., 2020a).

Rice, winter wheat, maize and sugarcane crops were selected for the study because of their dominance in the region. Rice, winter wheat and maize compose of 75% of all calories consumed by humans (Lobell et al., 2011b, Leng and Hall, 2019). Wheat is the second most important grain crop after rice, and the third highest crop produced for food in China, its production and sown area being 12.74×10^6 ton and 22.62×10^6 ha, respectively (China Statistical Yearbook, *http://www.stats.gov.cn/*). Southwest China is one of the five major ecological regions for wheat production in China (Li et al., 2019). The planting area of wheat in Southwest China is about 2.2 million ha, accounting for about 9.2% of the national total of China, nearly 80% of which come from Sichuan and Yunnan provinces (National Bureau of Statistics of China, 2009). Rice and maize are the dominant crops accounting for about 90% of the total cereal grain output and around 83% of the food crop sown in the area in 2017 (Fan et al., 2020). The crop yield and sown area data were extracted from the National Bureau of Statistics of China (*www.epschinadata.com/*). The growing season for winter wheat in southwest China is from November to April, for summer maize is from May to September, for sugarcane is from January to October, and for rice is from May to September. The land use cover change with 1 km resolution was retrieved from *earthdata.nasa.gov/* (MCD12Q1.A2013001.h26v05.051).

2.3 Methods

2.3.1 SPEI calculations and characteristics

Southwest China is characterized by increasing temperature and reducing total precipitation, resulting in more frequent and severe drought episodes (Mokhtar et al., 2020a, Li et al., 2011b, Zhen-Feng et al., 2013, Liu et al., 2015). Moreover, the region has experienced an increase in reference crop evapotranspiration (ET_0) with a gradual warming trend (Mokhtar et al., 2020a, Yang et al., 2015). Thus, it is important to combine the increasing temperature with increasing ET_0 in order to better understand the characteristics and the spatial–temporal variabilities of drought within the southwest China under a warming climate using the SPEI.

The detailed calculation steps of SPEI are as follows. Firstly, we calculated the monthly potential evapotranspiration using the Penman-Monteith model and climate data for 90 stations during the study period from 1960 to 2018. Secondly, we calculated the monthly water balance (D_i) as the difference between the total monthly precipitation (P_i) and the potential evapotranspiration (PET_i) for each month (i) as:

$$D_i = P_i - PET_i \tag{1}$$

SPEI was calculated from the standardized values as:

$$SPEI = W - \frac{c_0 + c_1 W + c_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \tag{2}$$

$$W = \sqrt{-2\ln\left(P\right)} \qquad for \quad P \le 0.5 \tag{3}$$

where the constants are c_0=2.5155, c_1=0.8028, c_2=0.0103, d_1=1.4328, d_2=0.1892, d_3=0.0013 and P is the probability of exceeding a determined D value (Vicente-Serrano, 2010). Detailed information on the principle and definitions of SPEI can be found in Vicente-Serrano, (2010), Liu et al. (2018), Gao et al. (2017). In this study, the monthly water balance was developed by calculating the difference between monthly precipitation and potential evapotranspiration. The R package SPEI (http://cran.r-project.org/web/packages/SPEI) was used to calculate the SPEI values at multiple time scales.

While SPEI can be calculated for multiple monthly timescales (i.e. 1, 3, 6, 9, 12 month) (Wang et al., 2015c, Wang et al., 2015b), we restricted our study to 3 (SPEI-3) and 6 (SPEI-6) months. SPEI-3 and SPEI-6 are generally used to represent agricultural drought where rainfall shortage for a short period is the main cause of drought (Park et al., 2018). In order to detect changes in SPEI-3 and SPEI-6 series, the non-parametric Mann-Kendall statistic (M-K) was applied (Mann, 1945, Kendall, 1948), while the Sen's slope method was used to estimate the change value by time (Sen, 1968). Table 2 presents the SPEI category classification (Agnew, 2000).

Once a specific drought event was identified over the three provinces, the drought characteristics of duration (*DD*), intensity (*DI*), and severity (*DS*) were analyzed (Wang et al., 2015b). *DS* is the absolute sum of SPEI values during a drought event calculated as:

$$DS = \left| \sum_{i=1}^{DD} SPEI_i \right| \tag{4}$$

where $SPEI_i$ is the value in month i, and *DI* is the lowest SPEI values during the specific drought event. The total drought duration (*TDD*) for all drought events having SPEI < 0 over the whole study period is given as (Alsafadi et al., 2020):

$$TDD\ (\%) = \frac{n_i}{N_i} \times 100 \tag{5}$$

where n_i is the number of drought events for location i, N_i is the total number of months for the study period. The percentage spatial extent of drought (SEoD) was determined for the different drought categories as (Li et al., 2012, Tan et al., 2015):

$$SEoD \quad (\%) = \frac{m_i}{M_i} \times 100 \qquad (6)$$

where m_i is the number of drought time points when SPEI < 0 for month i, and M_i is the total number of points of the timeseries.

2.3.2 The Standardized Yield Residuals Series (SYRS)

Crop yield is affected by many variables besides climate, and shows a positive trend (Vicente-Serrano et al., 2010, Potopová et al., 2016). Moreover, mechanization and innovation in agriculture have increased in the last century due to the following factors (Potopová et al., 2016):

- non-climatic factors, such as new varieties, fertilizers, mechanization and water management practices, which have created a growing trend in the yield;
- agro-meteorological conditions (e.g., dryness and wetness episodes) during the growing season;
- the yield sensitivity to dryness/wetness conditions; and
- residual error.

To remove bias introduced by non-climate factors, and to enable comparison of yields between the four crop types, the original yield timeseries were transformed to standardized yield residuals series (SYRS) (Lobell and Asner, 2003, Wu et al., 2004). The indicator of agricultural drought risk is given by the residuals of the detrended yield y_i^T as (Potopová et al., 2016):

$$y_i^T = y_i^0 - y_i^{(\tau)} \tag{7}$$

where y_i^0 is the observed crop yield and $y_i^{(\tau)}$ is the value of the fitted quadratic polynomial regression model. The SYRS is computed as:

$$SYRS = \frac{y_i^{(T)} - \mu}{\sigma} \tag{8}$$

where μ is mean of the yield residuals and σ is the standard deviation of the yield residuals. Table 2 shows the yield categories according to the SYRS (Potopová et al., 2016).

The percentage of annual yield loss was based on equation 8. SPEI-3 and SPEI-6 were analyzed to assess the effect of drought severity and to evaluate the vegetation response to drought (Tigkas et al., 2019). To assess the impacts of drought on crop yields, changes in the percentage of annual yield loss (Y_L%) was estimated as:

$$Y_L = \frac{Y_i^0 - Y_i^{(\tau)}}{Y_i^{(\tau)}} \times 100 \tag{9}$$

2.3.3 Resilience Analysis

Crop resilience is the ability of a crop to tolerate external disturbances (drought) and sustain the same structure and functions under changing conditions (Sharma and Goyal, 2018a). A dimensionless index (R_d) was used to quantify crop resilience to drought as:

$$R_d = \frac{y_i^o}{y_i^{(\tau)}} \tag{10}$$

The value of R_d is classified into four categories; slightly non-resilient for $0.9 < Rd < 1$, moderately non-resilient for $0.8 < Rd < 0.9$, and severely non-resilient for $Rd < 0.8$. (Guo et al., 2019, Sharma and Goyal, 2018a, Sharma and Goyal, 2018b). Figure 2 shows the schematic diagram of the methodology.

3. Results

3.1 Spatiotemporal characteristics *of drought over the past decades*

In order to establish drought episodes which have characterized the southwestern China, and to detect the temporal evolution of dry-wet events, the SPEI-3 and SPEI-6 were analyzed for the 90 climatic stations using the M–K test and Sen's slope estimator. The M-K test results showed a positive trend in 29 stations (32%) that covered the east of Guizhou and the northwest of Sichuan provinces (Fig. 3). A negative trend prevails in the rest of the studied stations which concentrated within the Yunnan province. However, the significant positive trend ($p < 0.05$) resulted from only 11 stations (12%). For SPEI-6, the significant trend ($p < 0.05$) occurred in 9 stations (10%). Furthermore, the SPEI-3 and SPEI-6 results indicated a significant change during the periods from 2009 to 2013 and from 2014 to 2018. The temporal evolution of SPEI series at 3- and 6-months timescales fluctuated during the study period. During the period from 2009 to 2015 the drought can be classified as extreme. For SPEI-3, the drought covered 63.5% of the study area during 2009-2013 and 52% during 2014-2018, while for SPEI-6 the spatial extent was 66% and 54%, respectively. During the two periods of 2009-2013 and 2014-2018, extreme and very extreme droughts combined reached 19% and 14% of the study area, respectively, for SPEI-3 and 22% and 15% for SPEI-6. More than 28% of the total area can be categorized as mild and moderate drought (Fig. 4).

Figures 4c and 4d show the spatial extent of drought (SEoD) of the monthly SPEI-3 and SPEI-6 series. During the last two decades (2000 to 2018) more than 80% of the total area was subjected to drought (i.e., SPEI < 0), especially from August to December. Meanwhile, high SEoD values > 80% was observed between spring and early summers within the last half of the 20th century. This result indicates that drought extent spatially will not only change in severity, intensity and frequency, but also in the period of occurrence and duration in a vast majority of the study area.

Five drought events (D_S) within the period of study were extracted and mapped (D1:1960-1964, D2:1966-1970, D3:1983-1987, D4: 2009-2013, and D5: 2014-2018) for assessment (Figure 5). D4 is ranked as the worst drought episode to hit the study area. It has the highest total drought duration, more than 80% (> 50 months) occurring in the southern part (largely in central Yunnan). The drought duration for D5 ranged from 40% to 60% of the total duration for SPEI-3 and SPEI-6 but limited to 70% in the western parts of study area. The spatial distribution of TDD of the D_S over the Sichuan province ranged from 20 to 40%. The TDD was higher in the southern part than in the northern part, and reached 70% in the central Yunnan during the highest drought event of D4. For the drought intensity, the highest values occurred in the southeast regions during D4. D1 and D2 events seem to have similar drought characteristics.

3.2 Variability of crop yields

As shown in Figure 6, the crop yield exhibits a significant increasing trend from 1960 to 2018. More than 75% of the crop yield variability is explained by the year variable. Wheat yield increased remarkably during the first and second periods by 0.154

and 0.004 t/ha per decade, respectively, for the Guizhou province. Meanwhile, wheat yield decreased during the second period by 0.008 and 0.006 t/ha per decade for Sichuan and Yunnan provinces, respectively. By contrast, maize yield declined on the second period within Guizhou and Sichuan provinces by 0.011 and 0.005 t ha^{-1} per decade, respectively. However, the yield of rice and sugarcane sharply increased during the first period but showed a declining trend during the second period for all provinces.

Within Guizhou province, the highest wheat yield losses occurred in 2003, 2016 and 2018, while maize yield losses were observed in 1988, 2011 and from 2013 to 2015 (Figure 6 and Table 3). On the other hand, the years with high yield increment of wheat were 1993 followed by 2015 and 2014, whereas they were 2002 and 1961 for maize (Fig. 6b). For rice, the high yield increment was in 1998 and 2004, but for sugarcane the highest yield occurred in 1984 followed by 2012 and 2014. In Yunnan province, the high yield losses were documented in 1986 and 2010 for wheat, in 2008 and 2010 for maize, in 1977 followed by 2002 for rice, and from 1975 to 1979 for sugarcane. Within Sichuan province, the highest yield losses of wheat were recorded in 1975 and 1977, in 1961 for maize, and for rice the yield losses were highest in 1976 followed by 2006. Also, there was sharp losses in 1976 and 1977 for sugarcane. The highest yield increments occurred in 1960, 1965, 1980, and 1984, for wheat, maize, rice, and sugarcane, respectively, in Sichuan province.

3.3 Crop yields respond to occurrence of droughts over the past decades

The correlation coefficient between SYRS of winter wheat and SPEI is the highest among all crops, revealing that winter wheat yield is more prone to drought (Fig 7b). For example, in Yunnan, the Pearson correlation coefficient *r* for SYRS-wheat vs. SPEI-6 reached 0.58 ($p \leq 0.05$; *R* =0.61), with a maximum value occurring during (February, March and April as 0.49, 0.58 and 0.42, respectively). In Sichuan, *r* for SYRS-wheat vs. SPEI-3 ranged from -0.24 to 0.27, with the highest value for February. For Yunnan, the Pearson correlation coefficient from the first node to flowering (end of April to May) ranged from 0.36 to 0.42 for SPEI-6. A significant correlation for the SPEI-6 (*r* =0.29) was observed from early to mid-grain filling (June). For SPEI-3, and in Schiuan, the correlation between sugarcane and drought was significant during August and September and reached 0.35 in August (Fig. 7b3). For SYRS of rice within Sichuan, the correlation ranged from -0.01 to 0.44 during the growing season with the highest correlation in August (*R* = 0.44) under SPEI-3 (Fig. 7b2). For sugarcane and rice, the highest correlation was observed in August for (SYRS vs. SPEI-3) as 0.35. It was recommended that the precipitation and temperature are climatic factors that affect SPEI (Guo et al., 2019). Based a critical value, the Pearson correlation coefficient can be described as significant or not. In this study, the critical value was set to 0.25, so any value more than 0.25 is considered a significant correlation. The significance of the correlation is a better indicator than high or low correlation.

A stepwise regression method was applied to determine the effect of the individual climate variable on SYRS. The multivariate regression method based on historical data has been widely used, and it can capture the net climate effects of combined climate variables (Prabnakorn et al., 2018, Li et al., 2020, Zhou et al., 2020). Table 3 shows the individual effects of each climate variable on SYRS for the selected four crops over the three provinces. Based on Table 3, wheat depends mainly on four sets of climate variables; 1) temperature, 2) precipitation 3) temperature, precipitation and sunshine, and 4) temperature, wind, sunshine and drought. In Yunnan, temperature, wind and drought are responsible for wheat yield variations, while for Sichuan and Guizhou temperature and sunshine are the main responsible variables. For SPEI-3, set 4 is the most significant one impacting on SYRS of wheat ($R=0.64, p<0.001$) followed by SPEI-3 in Sichuan ($R=0.48, p=0.000$). By contrast, precipitation only affected the SYRS of wheat in Sichuan and Guizhou over the 3 months' timescale. Maize is affected by 1) drought and temperature, 2) drought and sunshine, 3) drought and wind speed and 4) drought, relative humidity, sunshine and wind. Set 4 significantly impacted on maize SYRS for SPEI-3 in Yunnan ($R=0.45, p<0.01$). Rice and sugarcane show similar tendencies by depending on 1) drought and relative humidity, 2) drought, relative humidity and wind speed, and 3) drought, relative humidity, temperature and sunshine. Generally, both wheat and maize show sharp response to climate variables in Yunnan especially on the 3 months' timescale. Rice and sugarcane are highly affected by climate variables in Sichuan on 3 months' timescale as well.

3.4 Resilience analysis of crop yields

Table 4 presents the crop yield losses (Y_L) due to both drought duration (DD) and severity (DS). It is observed that the degree of yield losses varies among the crops due to drought/wet impact on the various crop stages. In Yunnan, 1977 ranked as the year with the highest failure of sugarcane and rice. Winter wheat recorded the highest crop losses, especially in 2010 when the losses exceeded 50%. The annual Y_L of winter wheat varied between 21% and 50%, occurring from the sowing stage to the harvest stage (9 months).

The total accumulation of the negative SPEI for the two timescales was 9.8 during the whole season. For Sichuan, the highest crop losses were noticed in 1976 and 1977, sugarcane and rice failures reaching 44.9% and 25.3%, respectively. The annual Y_L of winter wheat ranged from -19% to 45%, maize varied from -23% to 32%, rice ranged from -25% to 20%, and sugarcane ranged from -45% to 42% (Fig. 8d). Clearly, the drought in 2011 had the worst impact on maize, rice and sugarcane, causing more than 25% of Y_L in Guizhou. Within this context, DD for maize was 5 months and associated with 7.3 of DS (2011). Interestingly, rice was also vulnerable to drought with the DD being 6 months and associated with 8.3 of DS.

The dynamic interaction between drought and crop resilient is shown in Fig. 8e. Most of studied crops seem to be resilient or slightly non-resilient to drought having R_d greater than 0.9. With the exception of wheat (R_d = 0.49), all crops in Yunnan province were resilient or slightly affected by drought. For Guizhou, wheat was moderately non-resilient to drought, maize was resilient, but both rice and sugarcane were severely non-resilient to drought. The correlation matrix between drought (SPEI-3 and SPEI-6) and the affected agriculture area (%) is presented in Table 5. High negative correlation was detected in Guizhou during the summer season revealing that most of the agricultural land in Guizhou was affected by drought events that occurred between 1978 and 2018. For Yunnan, highly negative correlation is concentrated within the winter months. However, the drought impact was less pronounced over SPEI-3 and SPEI-6 in Sichuan. Within Guizhou, the highly negative correlation was reported in the autumn months for SPEI-6.

Figure 9 shows the correlation coefficient between SYRS and the SPEIs for the various drought events and crops. Winter wheat was positively correlated with SPEI-3 and SPEI-6 for all D_S events during September in the Yunnan province. During January and February within Yunnan there was significant positive correlation for drought events of D4 (2009-2013) and D4+D5 (2009-2018) for SPEI-3. In contrast, rice showed a significant positive correlation within Sichuan for SPEI-6 during D1(1960-1964) in August (Fig. 9c). For sugarcane, slight correlation was observed with the SPEI during all drought events except within Sichuan during D3 (1983-1987) that a highly positive correlation with SPEI-3 in September was observed (Fig. 9d).

4. Discussion

During the past few decades, drought events occurring in many parts of China, and globally, have resulted in severe damage to terrestrial ecosystems (Leng et al., 2015). Of particular note are the successive drought events during 1997-2003 years (Wang et al., 2011), in 2006 (Li et al., 2011a) and from 2009 to 2010 (Yang et al., 2012a) that has caused tremendous damages to the ecosystems, especially in the agricultural sector (Leng et al. 2015). Southwest China is one of the vulnerable zones to climate change due to the downward airflows which is impacting on water vapor flux associated with anomalies of the atmospheric circulation (Li et al., 2011). Our results indicate clearly a significant negative trend for SPEI-3 SPEI-6 within the study period. In this regard, adaptation strategy of a national scale should be implemented to minimize the direct impact of the drought cycles.

Crop yields are mainly influenced by climatic parameters. Chen et al. (2013) highlighted the possible impact of global warming on southwest China crop production where temperature is higher than the optimal limit for plant growth (Mokhtar et al., 2020a, Mokhtar et al., 2020b). Nonetheless, the negative impact of drought is highly correlated with the crop phenological stage (Mavromatis, 2007, Li et al., 2009, Wu et al., 2004). Our findings revealed that extreme drought events badly affected maize yield during the different phenological stages (Table 3). Wheat yield was highly sensitive to drought from March to May within the Yunnan province, indicating that the severe yield failure could be attributed to the spring drought, corroborating the findings of (Xianfeng et al., 2018). There is a weak correlation between rice yield and drought as rice cultivation is mainly under irrigation systems (Wang et al., 2014). In contrast, the yields of maize were significantly sensitive to drought conditions during the summer period within the Guizhou province as observed by previous studies (Otegui et al., 1995, Xianfeng et al., 2018). Within the Yunnan and Sichuan provinces, the correlation between the SYRS of maize and SPEI during the growing season was low, especially at the end of the growing season, the reason being the rational allocation of water resources and progress made in drought resistance (Geng et al., 2018). In the northeast China the main climatic variables impacting on maize yield are temperature, followed by precipitation, and dryness/wetness conditions (Zhou et al., 2020).

Our results are consistent with previous research which have proven that SPEI-3 is responsible for most of the yield losses or its increment during the late growth stage (Ming et al., 2015, Xu et al., 2018), especially the maturation and grain formation stages that are the key yield determinant period. It implies that short-term SPEI-3 and SPEI-6 values are strongly correlated with the rainfed wheat yield and other crops because they reflect the soil water content which influences the water balance of the crops, water absorption by roots, physiological and biochemical mechanism, and growth and yields of crops. Meanwhile, the negative correlation coefficients indicate that the main limitation factor of wheat yields in the rainy provinces is the wet stress (Xu et al., 2018, Wu et al., 2012) as in some regions of Guizhou. Increased humidity and wetness events during the growth period enhance the possibility of fungal diseases. Wheat crop is susceptible to infection, such as the occurrence of wheat rust and other pathogens, especially during the growth period, causing significant yield losses (El-Orabey and Elkot, 2020). The asymmetric yield response implies a weak adaptability of crop production to water surplus in some regions as in Guizhou. Nevertheless, the low level of moisture and mild droughts may be favorable and useful to the improvement of wheat yields as reported in (Xu et al., 2018). By contrast, Liu, 2018 reported that agricultural drought risk increased for wheat but decreased for maize within the north China Plain (Liu et al., 2018). This could be attributed to a less pronounced impacts of drought on maize yield, which may be related to rational allocation of water resources and advances in drought resistance (Geng et al., 2018), and are consistent with the results of our study.

The sharp growth of water demand within the study area is due to increasing planting areas for rice and maize, and the rapid evolution of drought cycle (Xu et al., 2013). Full irrigation is not a possible solution to alleviate the impact of drought risks on crop yields due to the limited water resources and associated pumping costs. Rice consumes two to three times more water than the other cereal crops, thus reducing rice planting is one solution to mitigate the water deficit (Bouman et al., 2007). However, this option is not valid due to growing food demand, and rice contributes to more than 60% of staple food for Chinese people. Therefore, the most economical and sustainable solution would be to develop new varieties of crops with decreased sensitivity to water deficits.

5. Conclusion

In this study, the key issue was to understand crop yield responses to drought within southwest China. Four crops were assessed for the period from 1960 to 2018. Drought evolution was analyzed using SPEI at 3- and 6- months timescales within the study area. The spatiotemporal variations and long-term trends of agricultural droughts and crop yields were investigated. The main findings of the study are summarized as below.

- SPEI-3 and SPEI-6 were useful for assessing drought risk of crop yields within southwest China provinces of Yunnan, Guizhou and Sichuan.
- In Yunnan, the highest total drought duration greater than 80% (> 50 months) occurred in the southern part during the period from 2009 to 2013.
- The spatial distribution of crop yield responses to drought was clear at the provincial scale. Moreover, the relationship between SYRS and SPEI explained more than 75% of the crop yield variability for the four crops (wheat, rice, maize and sugarcane) within the three provinces.
- Winter wheat has the highest annual crop losses among the crops during the study period, especially in 2010 when the loss exceeded 50%.

- Generally, both wheat and maize exhibit sharp response to climate variables in Yunnan, especially looking at the 3 months’ timescale. This is also the case for rice and sugarcane in Sichuan.

One disadvantage of SPEI is that it does not account for soil water storage that can be carried over from one month to the other, thus as an additional water source for the agroecosystems. Future research should incorporate soil water storage accounting, one such approach has been demonstrated by (Feng et al., 2017). Trends in crop yield may not be wholly attributed to climatic variables. Future research should also consider model evaluations using first differences of yield and climate to ascertain whether climate is solely responsible for the observed trends in crop yield. It is recommended that future research should consider also using available global datasets for comparison since interpolating station data across space has limitations, particularly where very few stations data exist.

Acknowledgement: This research work was financially supported by the National Key Research and Development Program (Grant No. 2017YFC0505200; 2017YFC0505205), the National Natural Science Foundation of China (Grant No. 41672180 Project of the Integrated Scientific Expedition of the Ailao-Wuliang Mountains National Park (Grant No. 2019IB018), Key Platforms and Scientific Research Projects in Universities in Guangdong Province of China (Grant No. 2018KTSCX212), Guangdong Rural Science and Technology Commissioner Project of China (Grant No. 319B0203), and the Second Tibetan Plateau Scientific Expedition and Research Program (Grant No. SQ2019QZKK2003).

Author Contributions: AM and HH collected the research data, analysed the data, and drafted the paper. AM, HH and KA designed the research and provided suggestions to data analysis. AM, SA and KA generated the figures in the main text. OA and YGA edited and provided suggestions to improve the paper's content and structure. All authors read and edited the final manuscript.

Conflicts of interest: The authors declare no conflicts of interest.

Reference

AGNEW, C. 2000. Using the SPI to identify drought.

*ALLEN, R. G. 2000. Using the FAO-56 dual crop coefficient method over an irrigated region as part of an evapotranspiration intercomparison study. Journal of Hydrology, 229***,** *27-41.*

*ALSAFADI, K., MOHAMMED, S., AYUGI, B., SHARAF, M. & HARSÁNYI, E. 2020. Spatial–Temporal Evolution of Drought Characteristics Over Hungary Between 1961 and 2010. Pure and Applied Geophysics***,** *1-18.*

*BOUMAN, B., HUMPHREYS, E., TUONG, T. & BARKER, R. 2007. Rice and water. Advances in agronomy, 92***,** *187-237.*

CHANDIO, A. A., JIANG, Y., REHMAN, A. & RAUF, A. 2020. Short and long-run impacts of climate change on agriculture: an empirical evidence from China. International Journal of Climate Change Strategies and Management.

*CHEN, T., XIA, G., LIU, T., CHEN, W. & CHI, D. 2016. Assessment of drought impact on main cereal crops using a standardized precipitation evapotranspiration index in Liaoning Province, China. Sustainability, 8***,** *1069.*

*DAS, P. K., DUTTA, D., SHARMA, J. & DADHWAL, V. 2016. Trends and behaviour of meteorological drought (1901–2008) over Indian region using standardized precipitation–evapotranspiration index. International journal of climatology, 36***,** *909-916.*

*DINPASHOH, Y., JAHANBAKHSH-ASL, S., RASOULI, A., FOROUGHI, M. & SINGH, V. 2019. Impact of climate change on potential evapotranspiration (case study: west and NW of Iran). Theoretical and Applied Climatology, 136***,** *185-201.*

*EL-ORABEY, W. M. & ELKOT, A. F. 2020. Prediction of leaf rust severity and yield loss in wheat based on environmental factors. Journal of Plant Diseases and Protection***,** *1-13.*

*ESFAHANIAN, E., NEJADHASHEMI, A. P., ABOUALI, M., ADHIKARI, U., ZHANG, Z., DANESHVAR, F. & HERMAN, M. R. 2017. Development and evaluation of a comprehensive drought index. Journal of environmental management, 185***,** *31-43.*

*FAN, Z. X. & THOMAS, A. 2013. Spatiotemporal variability of reference evapotranspiration and its contributing climatic factors in Yunnan Province, SW China, 1961–2004. Climatic Change, 116***,** *309-325.*

*FENG, W., ABATZOGLOU, J. T., HICKE, J. A. & LIAO, F. H. 2017. Interannual county-level climate yield relationships for winter wheat on the Columbia Plateau, USA. Climate Research, 74***,** *71-79.*

*GAO, X., ZHAO, Q., ZHAO, X., WU, P., PAN, W., GAO, X. & SUN, M. 2017. Temporal and spatial evolution of the standardized precipitation evapotranspiration index (SPEI) in the Loess Plateau under climate change from 2001 to 2050. Science of the Total Environment, 595***,** *191-200.*

*GENG, S., YAN, D., YANG, Z., ZHANG, Z., YANG, M. & KAN, G. 2018. Characteristics analysis of summer maize yield loss caused by drought stress in the northern Huaihe Plain, China. Irrigation and Drainage, 67***,** *251-268.*

*GODFRAY, H. C. J., BEDDINGTON, J. R., CRUTE, I. R., HADDAD, L., LAWRENCE, D., MUIR, J. F., PRETTY, J., ROBINSON, S., THOMAS, S. M. & TOULMIN, C. 2010. Food security: the challenge of feeding 9 billion people. science, 327***,** *812-818.*

*GUO, L., SUN, F., LIU, W., ZHANG, Y., WANG, H., CUI, H., WANG, H., ZHANG, J. & DU, B. 2019. Response of ecosystem water use efficiency to drought over China during 1982–2015: Spatiotemporal variability and resilience. Forests, 10***,** *598.*

*HANSEN, B. B., GAMELON, M., ALBON, S. D., LEE, A. M., STIEN, A., IRVINE, R. J., SÆTHER, B.-E., LOE, L. E., ROPSTAD, E. & VEIBERG, V. 2019. More frequent extreme climate events stabilize reindeer population dynamics. Nature communications, 10***,** *1-8.*

*JIA, J.-Y., HAN, L.-Y., LIU, Y.-F., HE, N., ZHANG, Q., WAN, X., ZHANG, Y.-F. & HU, J.-M. 2016. Drought risk analysis of maize under climate change based on natural disaster system theory in Southwest China. Acta Ecologica Sinica, 36***,** *340-349.*

*KANG, Y., KHAN, S. & MA, X. 2009. Climate change impacts on crop yield, crop water productivity and food security–A review. Progress in natural Science, 19***,** *1665-1674.*

KENDALL, M. G. 1948. Rank correlation methods.

*LENG, G. & HALL, J. 2019. Crop yield sensitivity of global major agricultural countries to droughts and the projected changes in the future. Science of the Total Environment, 654***,** *811-821.*

*LENG, G., TANG, Q. & RAYBURG, S. 2015. Climate change impacts on meteorological, agricultural and hydrological droughts in China. Global and Planetary Change, 126***,** *23-34.*

*LESK, C., ROWHANI, P. & RAMANKUTTY, N. 2016. Influence of extreme weather disasters on global crop production. Nature, 529***,** *84-87.*

*LI, N., LIN, H., WANG, T., LI, Y., LIU, Y., CHEN, X. & HU, X. 2020. Impact of climate change on cotton growth and yields in Xinjiang, China. Field Crops Research, 247***,** *107590.*

LI, Y., XU, H. & LIU, D. 2011a. Features of the extremely severe drought in the east of Southwest China and anomalies of atmospheric circulation in summer 2006. Acta Meteorologica Sinica, 25, *176-187.*

LI, Y. P., YE, W., WANG, M. & YAN, X. D. 2009. Climate change and drought: a risk assessment of crop-yield impacts. Climate Research, 39, *31-46.*

LI, Z., HE, Y., AN, W., SONG, L., ZHANG, W., CATTO, N., WANG, Y., WANG, S., LIU, H. & CAO, W. 2011b. Climate and glacier change in southwestern China during the past several decades. Environmental Research Letters, 6, *045404.*

LI, Z., ZHENG, F.-L. & LIU, W.-Z. 2012. Spatiotemporal characteristics of reference evapotranspiration during 1961–2009 and its projected changes during 2011–2099 on the Loess Plateau of China. Agricultural and Forest Meteorology, 154, *147-155.*

LIU, B., CHEN, C., LIAN, Y., CHEN, J. & CHEN, X. 2015. Long-term change of wet and dry climatic conditions in the southwest karst area of China. Global and Planetary Change, 127, *1-11.*

LIU, X., PAN, Y., ZHU, X., YANG, T., BAI, J. & SUN, Z. 2018. Drought evolution and its impact on the crop yield in the North China Plain. Journal of hydrology, 564, *984-996.*

LOBELL, D. B. & ASNER, G. P. 2003. Climate and management contributions to recent trends in U. S. agricultural yields. Science, 299, *1032-1032.*

LOBELL, D. B., BAENZIGER, M., MAGOROKOSHO, C. & VIVEK, B. 2011a. Nonlinear heat effects on African maize as evidenced by historical yield trials. Nature Climate Change, 1, *42-45.*

LOBELL, D. B., SCHLENKER, W. & COSTA-ROBERTS, J. 2011b. Climate trends and global crop production since 1980. Science, 333, *616-620.*

MANATSA, D., MUSHORE, T. & LENOUO, A. 2017. Improved predictability of droughts over southern Africa using the standardized precipitation evapotranspiration index and ENSO. Theoretical and applied climatology, 127, *259-274.*

MANN, H. B. 1945. Nonparametric Tests Against Trend. Econometrica, 13, *245-259.*

MAVROMATIS, T. 2007. Drought index evaluation for assessing future wheat production in Greece. International Journal of Climatology, 27, *911-924.*

MCKEE, T. B., DOESKEN, N. J. & KLEIST, J. The relationship of drought frequency and duration to time scales. Proceedings of the 8th Conference on Applied Climatology, 1993. Boston, 179-183.

MEHRABI, Z. & RAMANKUTTY, N. 2017. The cost of heat waves and droughts for global crop production. bioRxiv, *188151.*

MIAH, M. G., ABDULLAH, H. M. & JEONG, C. 2017. Exploring standardized precipitation evapotranspiration index for drought assessment in Bangladesh. Environmental monitoring and assessment, 189, *547.*

MING, B., GUO, Y., TAO, H., LIU, G., LI, S. & WANG, P. 2015. SPEIPM-based research on drought impact on maize yield in North China Plain. Journal of Integrative Agriculture, 14, *660-669.*

MISHRA, A. K. & SINGH, V. P. 2010. A review of drought concepts. Journal of hydrology, 391, *202-216.*

MOKHTAR, A., HE, H., ALSAFADI, K., LI, Y., ZHAO, H., KEO, S., BAI, C., ABUARAB, M., ZHANG, C., ELBAGOURY, K., WANG, J. & HE, Q. 2020a. Evapotranspiration as a response to climate variability and ecosystem changes in southwest, China. Environmental Earth Sciences, 79, 312.

MOKHTAR, A., HE, H., ALSAFADI, K., MOHAMMED, S., HE, W., LI, Y., ZHAO, H., ABDULLAHI, N. M. & GYASI-AGYEI, Y. 2021a. Ecosystem Water Use Efficiency Response to Drought Over Southwest China. Ecohydrology, e2317.

MOKHTAR, A., HE, H., ZHAO, H., KEO, S., BAI, C., ZHANG, C., MA, Y., IBRAHIM, A., LI, Y. & LI, F. 2020b. Risks to water resources and development of a management strategy in the river basins of the Hengduan Mountains, Southwest China. Environmental Science: Water Research & Technology.

MOKHTAR, A., JALALI, M., ELBELTAGI, A., AL-ANSARI, N., ALSAFADI, K., ABDO, H. G., SAMMEN, S. S., GYASI-AGYEI, Y., RODRIGO-COMINO, J. & HE, H. 2021b. Estimation of SPEI Meteorological Drought using Machine Learning Algorithms. IEEE Access.

OTEGUI, M. E., ANDRADE, F. H. & SUERO, E. E. 1995. Growth, water use, and kernel abortion of maize subjected to drought at silking. Field Crops Research, 40, 87-94.

PALMER, W. C. 1968. Keeping track of crop moisture conditions, nationwide: The new crop moisture index.

PARK, J., LIM, Y.-J., KIM, B.-J. & SUNG, J. H. 2018. Appraisal of drought characteristics of representative drought indices using meteorological variables. KSCE Journal of Civil Engineering, 22, 2002-2009.

PEÑA-GALLARDO, M., VICENTE-SERRANO, S. M., DOMÍNGUEZ-CASTRO, F. & BEGUERÍA, S. 2019. The impact of drought on the productivity of two rainfed crops in Spain. Natural Hazards & Earth System Sciences, 19.

PEÑA-GALLARDO, M., VICENTE-SERRANO, S. M., DOMÍNGUEZ-CASTRO, F., QUIRING, S., SVOBODA, M., BEGUERÍA, S. & HANNAFORD, J. 2018. Effectiveness of drought indices in identifying impacts on major crops across the USA. Climate Research, 75, 221-240.

POTOP, V. & MOŽNÝ, M. 2011. The application a new drought index–standardized precipitation evapotranspiration index in the Czech Republic. Mikroklima a mezoklima krajinných structur a antropogenních prostředí, 2, 2-14.

POTOPOVÁ, V., BORONEAN, C., BOINCEAN, B. & SOUKUP, J. 2016. Impact of agricultural drought on main crop yields in the Republic of Moldova. International Journal of Climatology, 36, 2063-2082.

PRABNAKORN, S., MASKEY, S., SURYADI, F. & DE FRAITURE, C. 2018. Rice yield in response to climate trends and drought index in the Mun River Basin, Thailand. Science of the Total Environment, 621, 108-119.

SEN, P. K. 1968. Estimates of the regression coefficient based on Kendall's tau. Journal of the American statistical association, 63, 1379-1389.

SHARMA, A. & GOYAL, M. K. 2018a. Assessment of ecosystem resilience to hydroclimatic disturbances in India. Global change biology, 24, e432-e441.

SHARMA, A. & GOYAL, M. K. 2018b. District-level assessment of the ecohydrological resilience to hydroclimatic disturbances and its controlling factors in India. Journal of Hydrology, 564, 1048-1057.

SOMOROWSKA, U. 2016. Changes in drought conditions in Poland over the past 60 years evaluated by the Standardized Precipitation-Evapotranspiration Index. Acta Geophysica, 64, 2530-2549.

SULEIMAN, A. A., SOLER, C. M. T. & HOOGENBOOM, G. Determination of the FAO-56 crop coefficients for peanut under deficit irrigation in a humid climate. 2007 ASAE Annual Meeting, 2007. American Society of Agricultural and Biological Engineers, 1.

SUYKER, A. E. & VERMA, S. B. 2009. Evapotranspiration of irrigated and rainfed maize–soybean cropping systems. Agricultural & Forest Meteorology, 149, 0-452.

SVOBODA, M. & FUCHS, B. 2016. Handbook of drought indicators and indices.

TAN, C., YANG, J. & LI, M. 2015. Temporal-spatial variation of drought indicated by SPI and SPEI in Ningxia Hui Autonomous Region, China. Atmosphere, 6, 1399-1421.

TIAN, L., LEASOR, Z. T. & QUIRING, S. M. 2020. Developing a hybrid drought index: Precipitation Evapotranspiration Difference Condition Index. Climate Risk Management, 100238.

TIAN, L., YUAN, S. & QUIRING, S. M. 2018. Evaluation of six indices for monitoring agricultural drought in the south-central United States. Agricultural and forest meteorology, 249, 107-119.

TIGKAS, D., VANGELIS, H. & TSAKIRIS, G. 2019. Drought characterisation based on an agriculture-oriented standardised precipitation index. Theoretical and Applied Climatology, 135, 1435-1447.

TRIPATHI, A. D., MISHRA, R., MAURYA, K. K., SINGH, R. B. & WILSON, D. W. 2019. Estimates for world population and global food availability for global health. The role of functional food security in global health. Elsevier.

VAN ROOY, M. 1965. A RAINFALL ANOMALLY INDEX INDEPENDENT OF TIME AND SPACE, NOTOS.

VICENTE-SERRANO, S. M., BEGUERÍA, S. & LÓPEZ-MORENO, J. I. 2010. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. Journal of climate, 23, 1696-1718.

WANG, A., LETTENMAIER, D. P. & SHEFFIELD, J. 2011. Soil moisture drought in China, 1950–2006. Journal of Climate, 24, 3257-3271.

WANG, J., WANG, K., ZHANG, M. & ZHANG, C. 2015a. Impacts of climate change and human activities on vegetation cover in hilly southern China. Ecological Engineering, 81, 451-461.

WANG, L. & CHEN, W. 2014. A CMIP5 multimodel projection of future temperature, precipitation, and climatological drought in China. International Journal of Climatology, 34, 2059-2078.

WANG, Q., SHI, P., LEI, T., GENG, G., LIU, J., MO, X., LI, X., ZHOU, H. & WU, J. 2015b. The alleviating trend of drought in the Huang-Huai-Hai Plain of China based on the daily SPEI. International Journal of Climatology, 35, 3760-3769.

WANG, Q., WU, J., LI, X., ZHOU, H., YANG, J., GENG, G., AN, X., LIU, L. & TANG, Z. 2017. A comprehensively quantitative method of evaluating the impact of drought on crop yield using daily multi-scale SPEI and crop growth process model. International journal of biometeorology, 61, 685-699.

WANG, S., MO, X., HU, S., LIU, S. & LIU, Z. 2018. Assessment of droughts and wheat yield loss on the North China Plain with an aggregate drought index (ADI) approach. Ecological Indicators, 87, 107-116.

WANG, W., ZHU, Y., XU, R. & LIU, J. 2015c. Drought severity change in China during 1961–2012 indicated by SPI and SPEI. Natural Hazards, 75, 2437-2451.

WANG, Y., WU, P., ENGEL, B. & SUN, S. 2014. Application of water footprint combined with a unified virtual crop pattern to evaluate crop water productivity in grain production in China. Science of the total environment, 497, 1-9.

WU, H., GAO, P., XU, W. & BAO, Y. 2012. Risk division on winter wheat suffering from spring wet damages in Jiangsu Province. Acta Ecologica Sinica, 32, 1871-1879.

WU, H., HUBBARD, K. G. & WILHITE, D. A. 2004. An agricultural drought risk-assessment model for corn and soybeans. International Journal of Climatology, 24, 723-741.

XIANFENG, L., YAOZHONG, P., XIUFANG, Z., TIANTIAN, Y., JIANJUN, B. & ZHANGLI, S. 2018. Drought evolution and its impact on the crop yield in the North China Plain. Journal of Hydrology, S0022169418305912-.

XU, X., GAO, P., ZHU, X., GUO, W., DING, J. & LI, C. 2018. Estimating the responses of winter wheat yields to moisture variations in the past 35 years in Jiangsu Province of China. Plos one, 13, e0191217.

XU, X., GE, Q., ZHENG, J., DAI, E., ZHANG, X., HE, S. & LIU, G. 2013. Agricultural drought risk analysis based on three main crops in prefecture-level cities in the monsoon region of east China. Natural hazards, 66, 1257-1272.

YANG, H., LUO, P., WANG, J., MOU, C., MO, L., WANG, Z., FU, Y., LIN, H., YANG, Y. & BHATTA, L. D. 2015. Ecosystem evapotranspiration as a response to climate and vegetation coverage changes in Northwest Yunnan, China. Plos one, 10, e0134795.

YANG, J., GONG, D., WANG, W., HU, M. & MAO, R. 2012a. Extreme drought event of 2009/2010 over southwestern China. Meteorology and Atmospheric Physics, 115, 173-184.

YANG, J., GONG, D., WANG, W., HU, M. & MAO, R. 2012b. Extreme drought event of 2009/2010 over southwestern China. Meteorology & Atmospheric Physics, 115, 173-184.

ZHAI, JIANQING, BUDA, S. U., KRYSANOVA, VALENTINA, VETTER, TOBIAS, GAO, C. & JIANG, T. 2010. Spatial Variation and Trends in PDSI and SPI Indices and Their Relation to Streamflow in 10 Large Regions of China. Journal of Climate, 23, 649-663.

ZHANG, C., HE, H. & MOKHTAR, A. 2019a. The Impact of Climate Change and Human Activity on Spatiotemporal Patterns of Multiple Cropping Index in South West China. Sustainability, 11, 5308.

ZHANG, C. J., HE, H. M. & MOKHTAR, A. 2019b. The Impact of Climate Change and Human Activity on Spatiotemporal Patterns of Multiple Cropping Index in South West China. Sustainability, 11, 21.

ZHANG, J., JIANG, L., FENG, Z. & LI, P. 2012. Detecting Effects of the Recent Drought on Vegetation in Southwestern China. Journal of Resources & Ecology, 3, 43-49.

*ZHEN-FENG, M., JIA, L., SHUN-QIAN, Z., WEN-XIU, C. & SHU-QUN, Y. 2013. Observed climate changes in southwest China during 1961–2010. Advances in Climate Change Research, 4***,** *30-40.*

*ZHOU, Z., SHI, H., FU, Q., LI, T., GAN, T. Y. & LIU, S. 2020. Assessing spatiotemporal characteristics of drought and its effects on climate-induced yield of maize in Northeast China. Journal of Hydrology***,** *125097.*

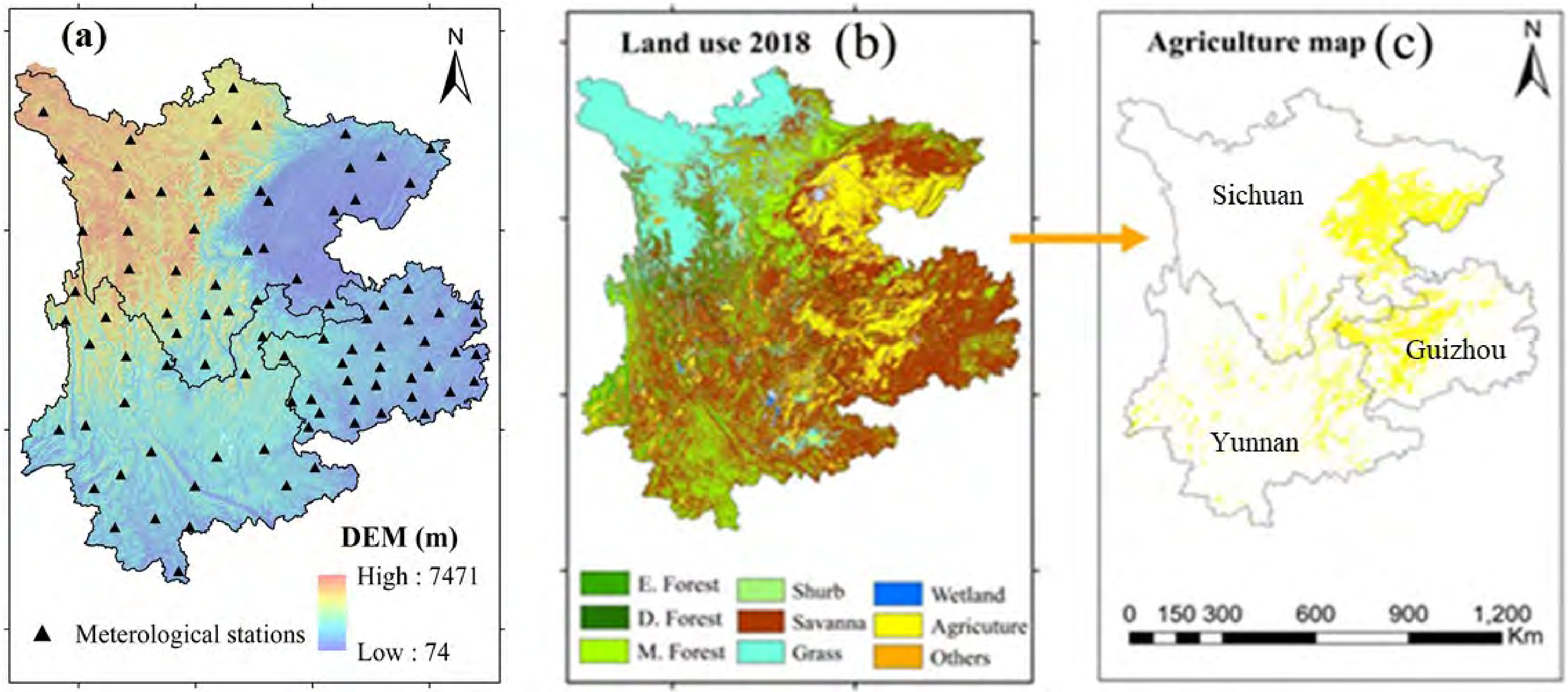


Fig. 1: a) Location of the study area in southwest China showing the meteorological stations, b) land use in 2018 and c) agriculture map derived from land use map 2018.

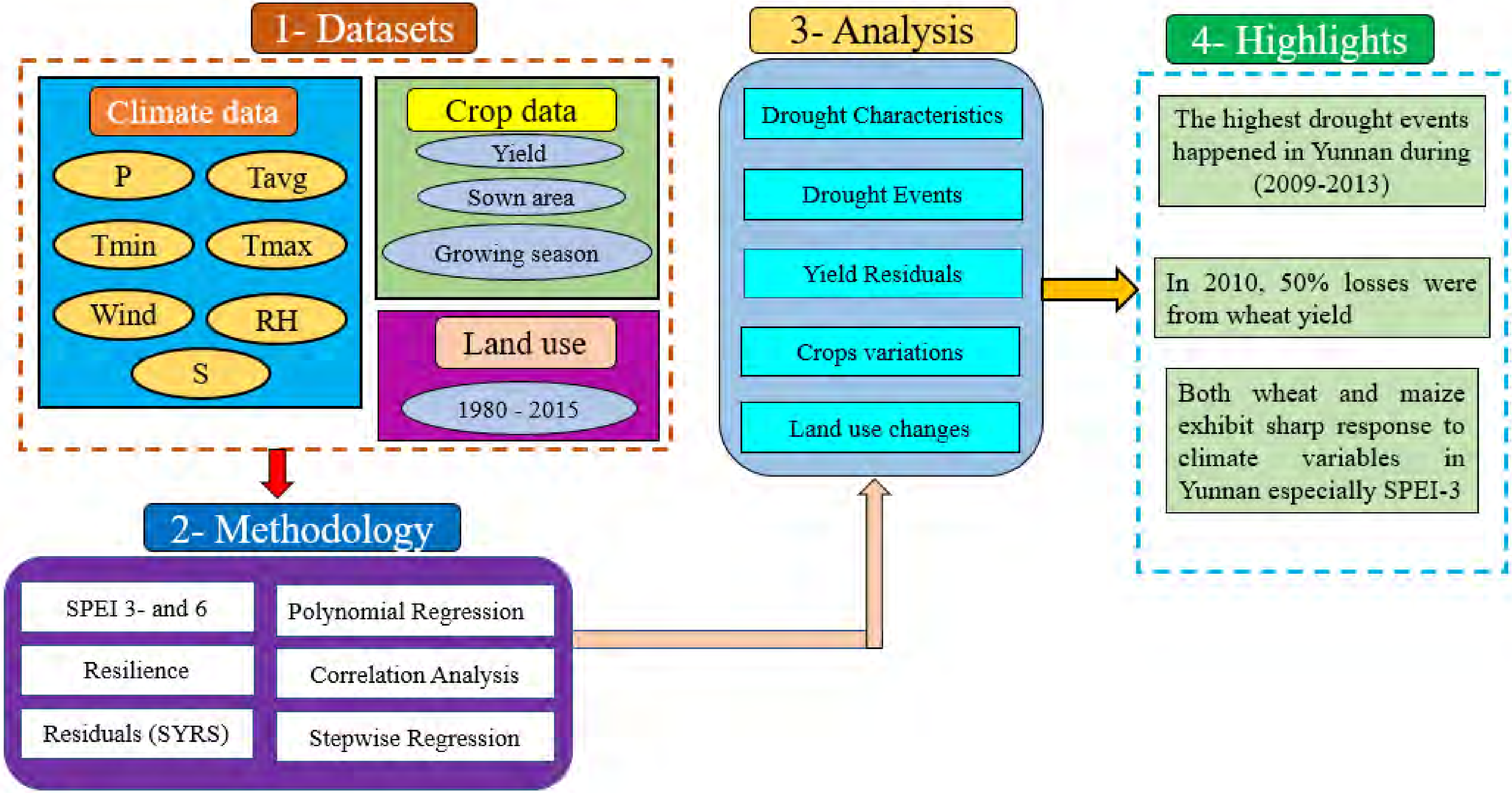


Fig. 2: Flowchart of the methodology adopted for this study

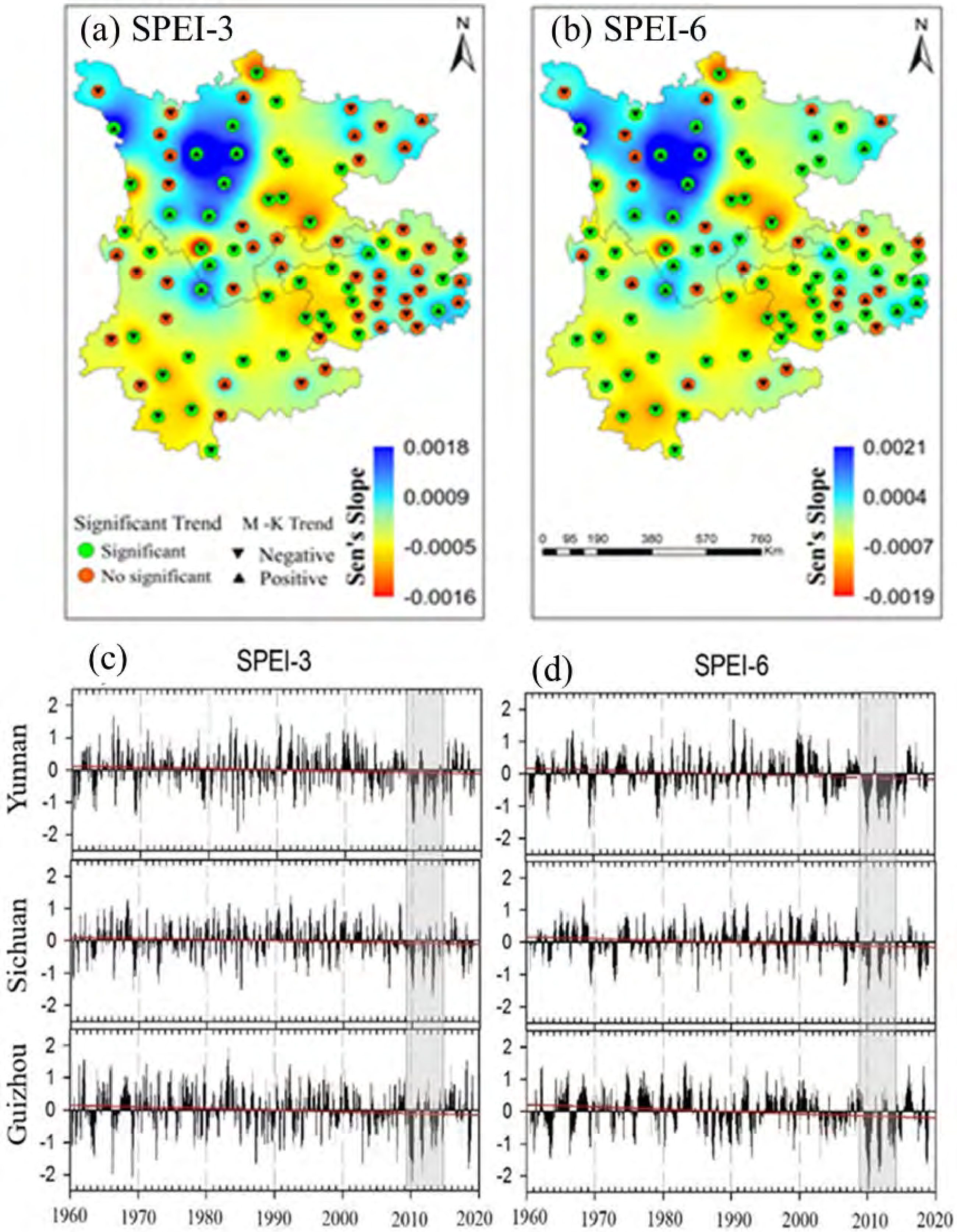


Fig. 3: Trends and magnitude of change of SPEI (a, b), temporal evolution of SPEI-3 and SPEI-6 (c, d).

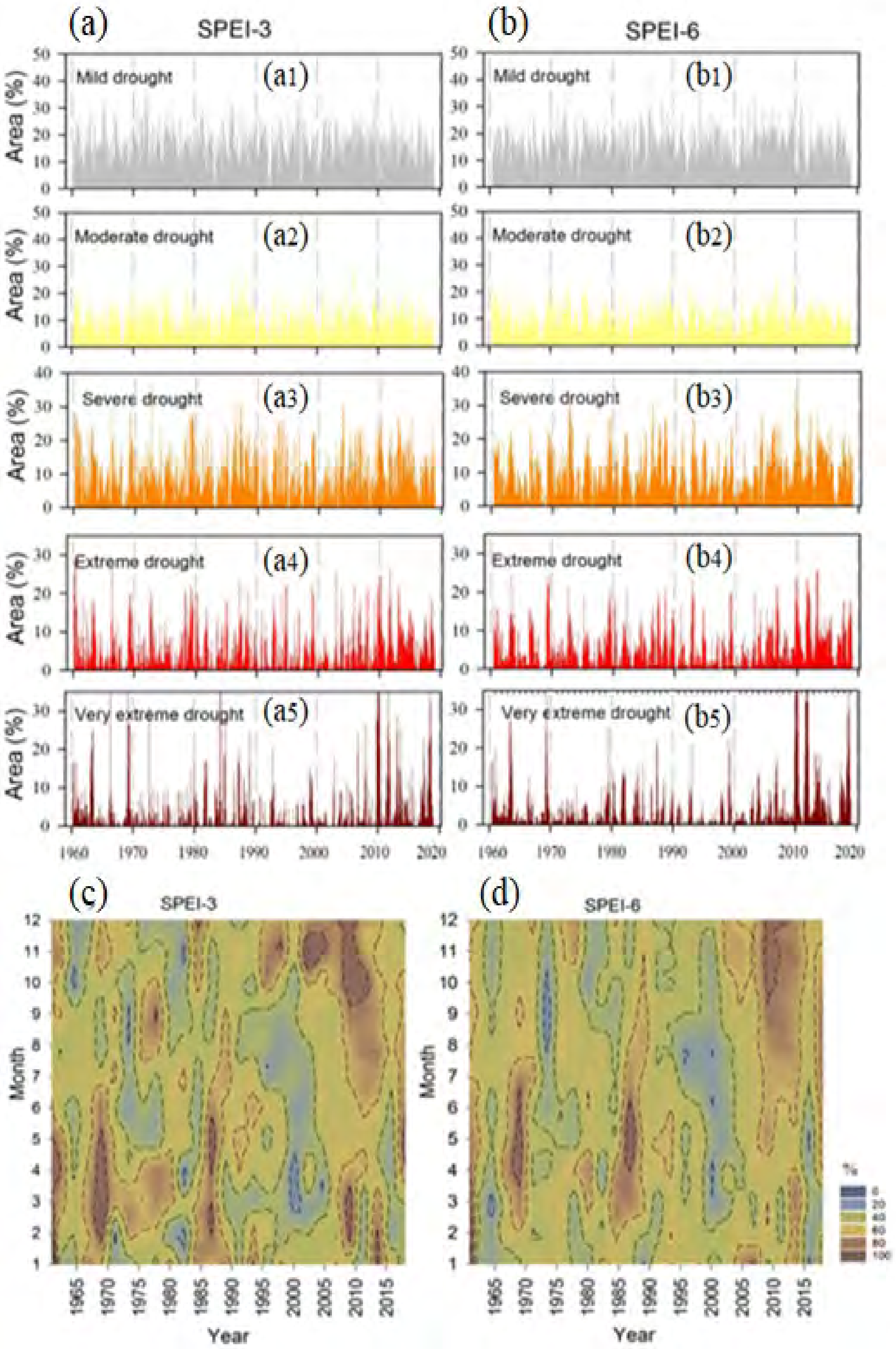


Fig. 4: Temporal evolution of percentage of areas affected by different drought categories for SPEI series at 3- and 6-month timescale during 1960-2018 (a, b for annually and c, d for monthly).

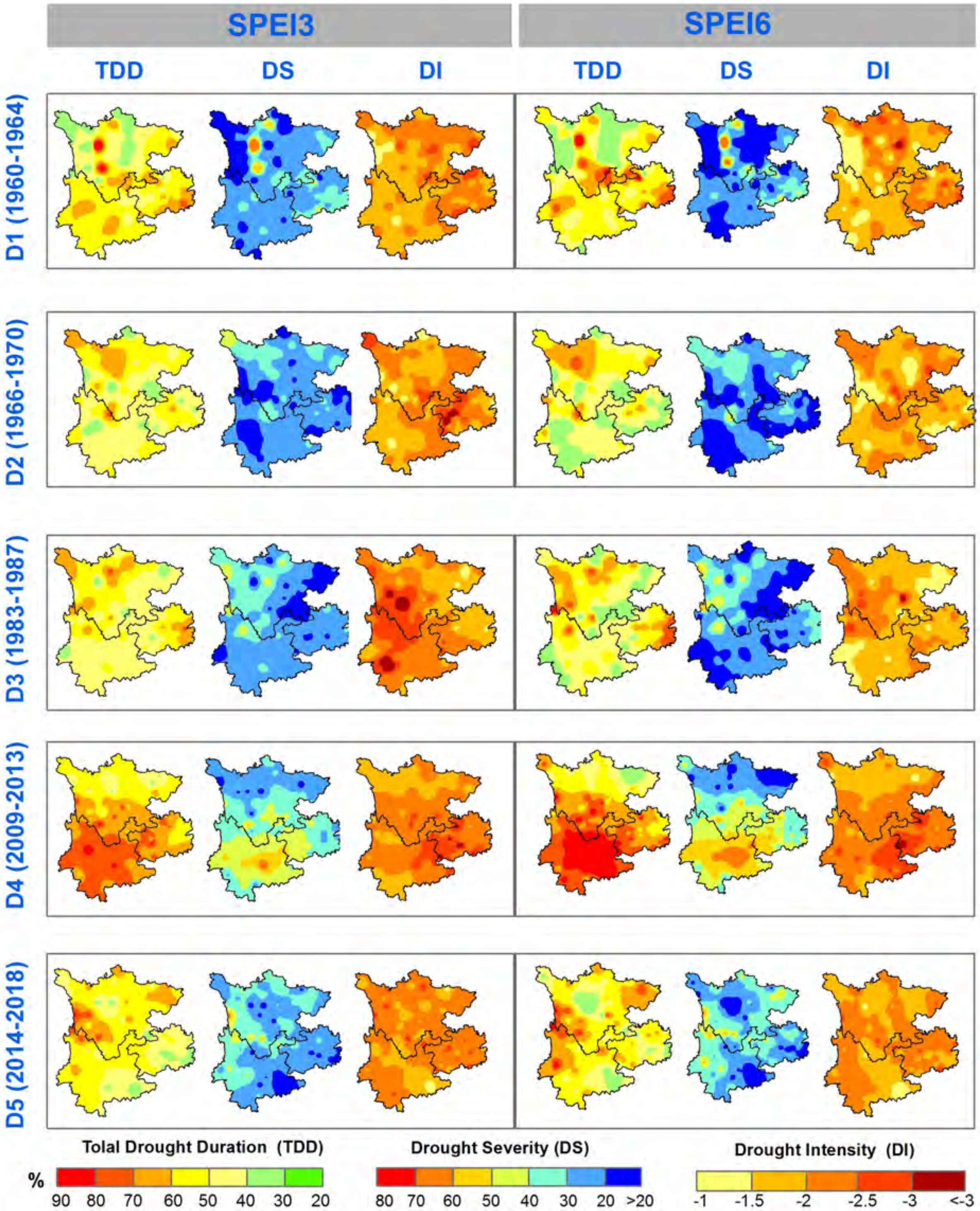


Fig. 5: Spatial extent of total drought duration (TDD), drought severity (DS), and the minimum values of SPEI or the drought intensity (DI) for SPEI-3 and SPEI-6 for the specific drought events.

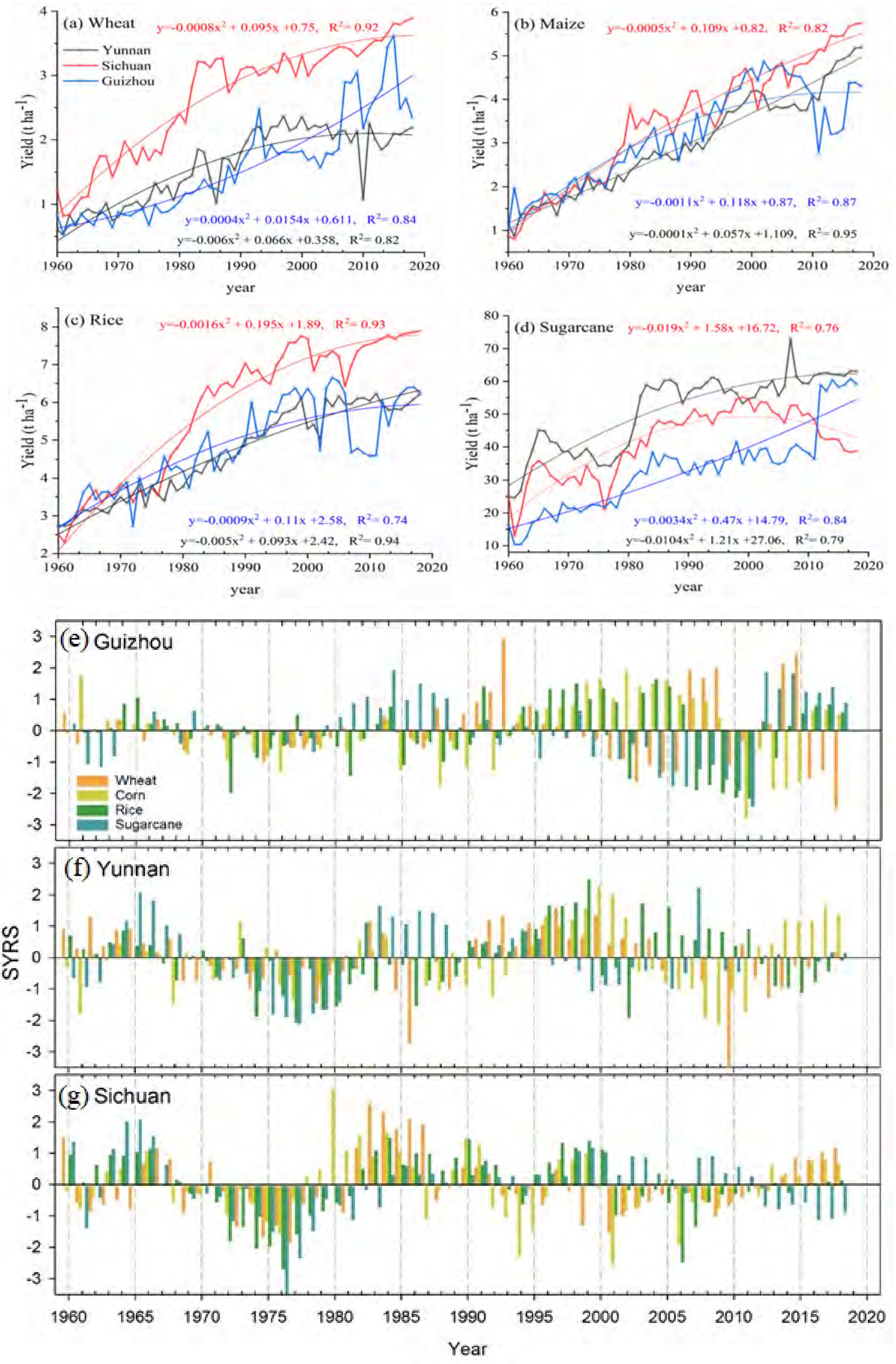
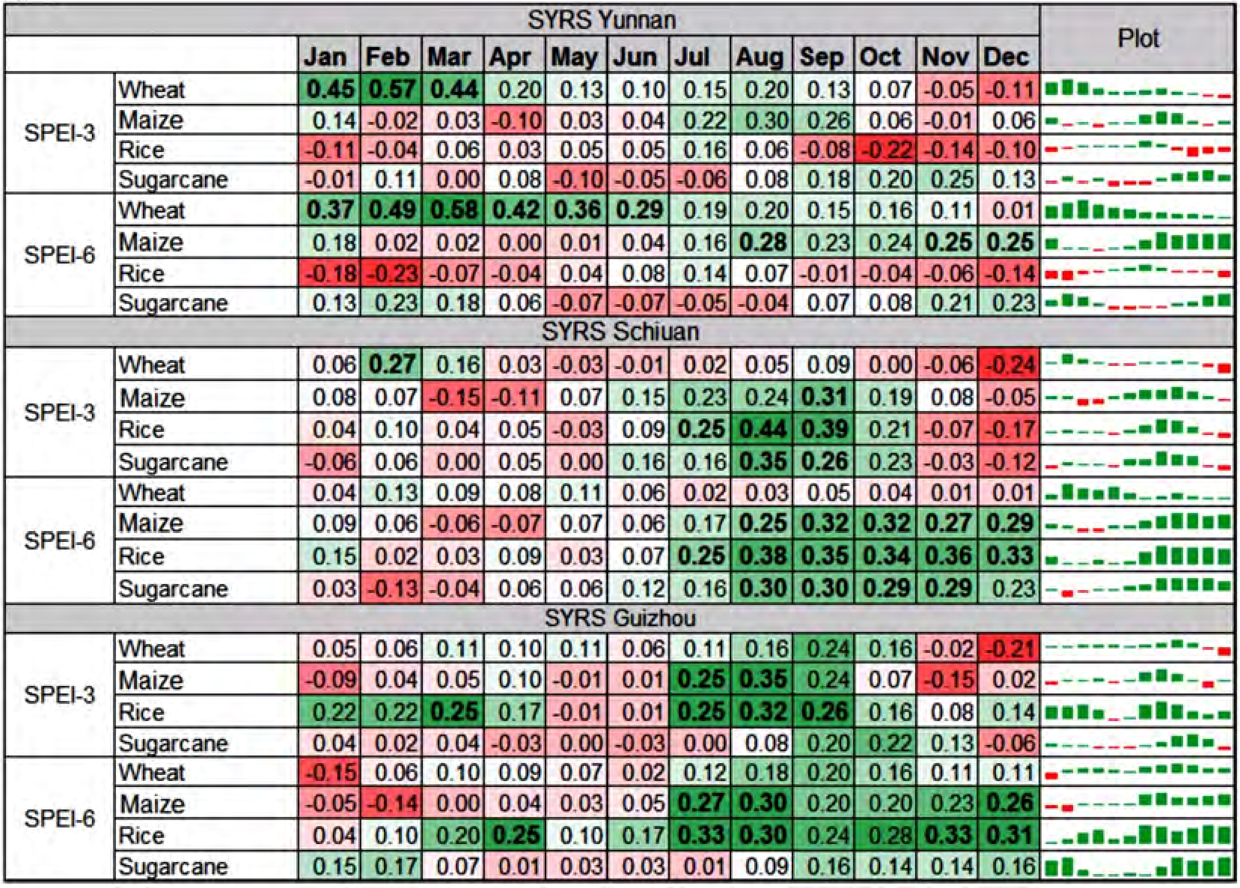


Fig. 6: Time evolution of crop (wheat, maize, rice and sugarcane) yields with fitted quadratic trend model, and the temporal change of SYRS for the crops.

(a)



		SYRS Yunnan												Plot
		Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	
SPEI-3	Wheat	**0.45**	**0.57**	**0.44**	0.20	0.13	0.10	0.15	0.20	0.13	0.07	-0.05	-0.11	
	Maize	0.14	-0.02	0.03	-0.10	0.03	0.04	0.22	0.30	0.26	0.06	-0.01	0.06	
	Rice	-0.11	-0.04	0.06	0.03	0.05	0.05	0.16	0.06	-0.08	-0.22	-0.14	-0.10	
	Sugarcane	-0.01	0.11	0.00	0.08	-0.10	-0.05	-0.06	0.08	0.18	0.20	0.25	0.13	
SPEI-6	Wheat	**0.37**	**0.49**	**0.58**	**0.42**	**0.36**	**0.29**	0.19	0.20	0.15	0.16	0.11	0.01	
	Maize	0.18	0.02	0.02	0.00	0.01	0.04	0.16	**0.28**	0.23	0.24	**0.25**	**0.25**	
	Rice	-0.18	-0.23	-0.07	-0.04	0.04	0.08	0.14	0.07	-0.01	-0.04	-0.06	-0.14	
	Sugarcane	0.13	0.23	0.18	0.06	-0.07	-0.07	-0.05	-0.04	0.07	0.08	0.21	0.23	
		SYRS Schiuan												
SPEI-3	Wheat	0.06	**0.27**	0.16	0.03	-0.03	-0.01	0.02	0.05	0.09	0.00	-0.06	-0.24	
	Maize	0.08	0.07	-0.15	-0.11	0.07	0.15	0.23	0.24	**0.31**	0.19	0.08	-0.05	
	Rice	0.04	0.10	0.04	0.05	-0.03	0.09	**0.25**	**0.44**	**0.39**	0.21	-0.07	-0.17	
	Sugarcane	-0.06	0.06	0.00	0.05	0.00	0.16	0.16	**0.35**	**0.26**	0.23	-0.03	-0.12	
SPEI-6	Wheat	0.04	0.13	0.09	0.08	0.11	0.06	0.02	0.03	0.05	0.04	0.01	0.01	
	Maize	0.09	0.06	-0.06	-0.07	0.07	0.06	0.17	**0.25**	**0.32**	**0.32**	**0.27**	**0.29**	
	Rice	0.15	0.02	0.03	0.09	0.03	0.07	**0.25**	**0.38**	**0.35**	**0.34**	**0.36**	**0.33**	
	Sugarcane	0.03	-0.13	-0.04	0.06	0.06	0.12	0.16	**0.30**	**0.30**	**0.29**	**0.29**	0.23	
		SYRS Guizhou												
SPEI-3	Wheat	0.05	0.06	0.11	0.10	0.11	0.06	0.11	0.16	0.24	0.16	-0.02	-0.21	
	Maize	-0.09	0.04	0.05	0.10	-0.01	0.01	**0.25**	**0.35**	0.24	0.07	-0.15	0.02	
	Rice	0.22	0.22	**0.25**	0.17	-0.01	0.01	**0.25**	**0.32**	**0.26**	0.16	0.08	0.14	
	Sugarcane	0.04	0.02	0.04	-0.03	0.00	-0.03	0.00	0.08	0.20	0.22	0.13	-0.06	
SPEI-6	Wheat	-0.15	0.06	0.10	0.09	0.07	0.02	0.12	0.18	0.20	0.16	0.11	0.11	
	Maize	-0.05	-0.14	0.00	0.04	0.03	0.05	**0.27**	**0.30**	0.20	0.20	0.23	**0.26**	
	Rice	0.04	0.10	0.20	**0.25**	0.10	0.17	**0.33**	**0.30**	0.24	0.28	**0.33**	**0.31**	
	Sugarcane	0.15	0.17	0.07	0.01	0.03	0.03	0.01	0.09	0.16	0.14	0.14	0.16	

(b)

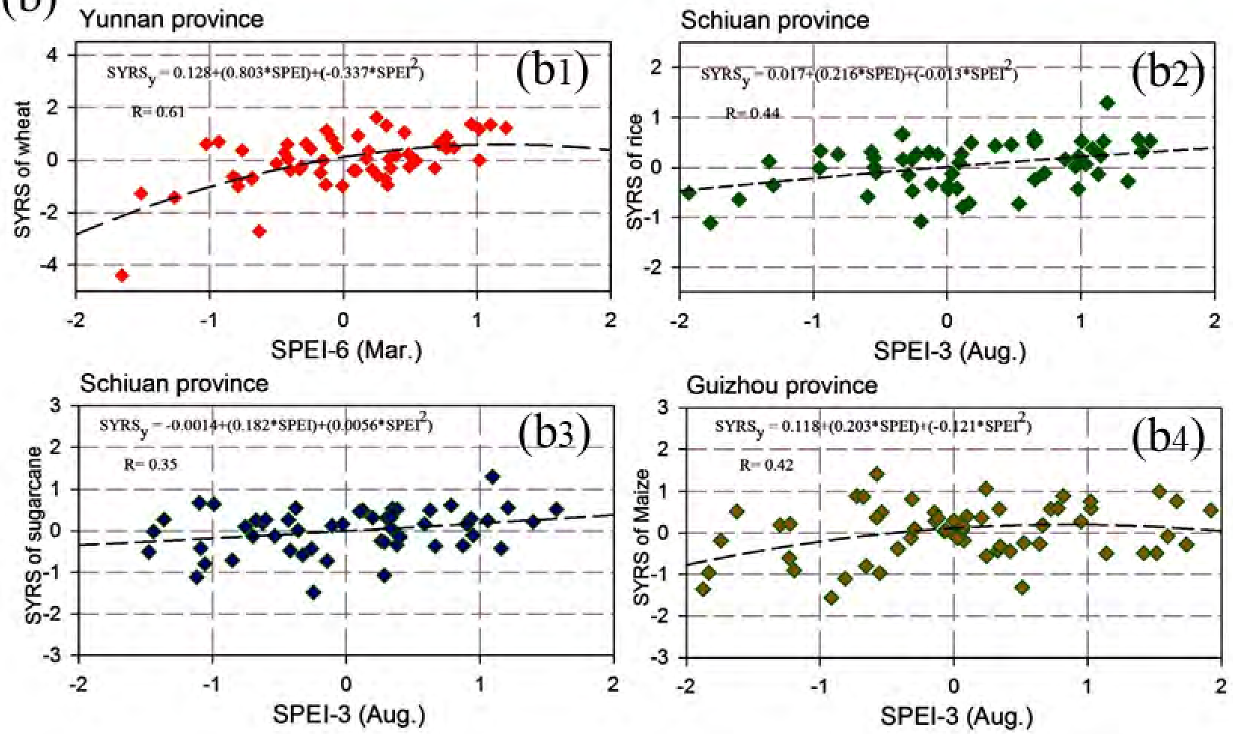


Fig. 7: The Pearson correlation coefficient (r) of the linear regression between the averages of SPEIs at 3- and 6-month timescale and the SYRS of wheat, maize, rice and sugarcane in the 3 provinces for the period of 1960–2018 (a). The graphs denote the trends of second-order polynomial fitted to the SYRS of the crops against SPEI-3 and SPEI-6 for March and August as illustrative examples (b1-b4).

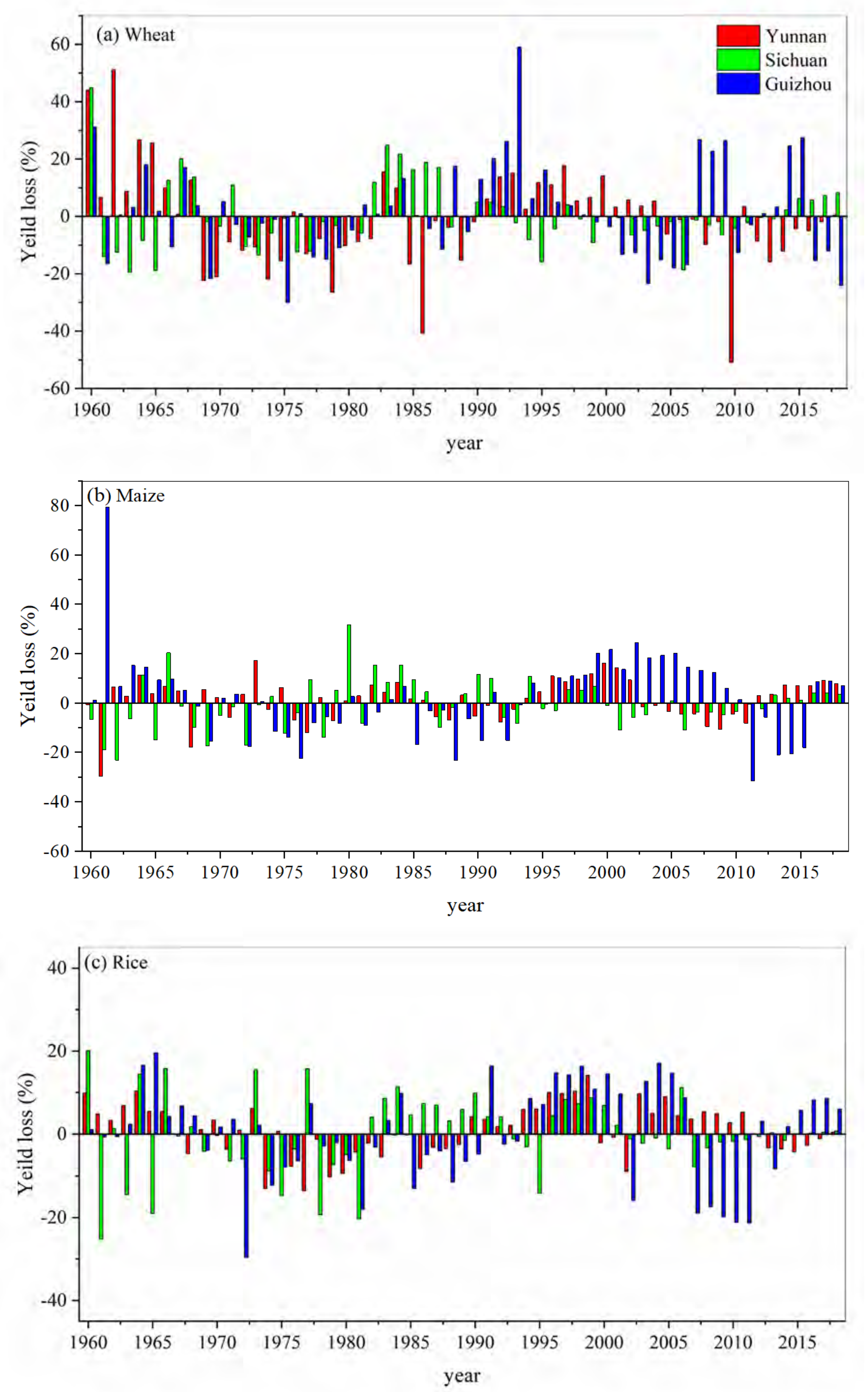


Figure 8 continue

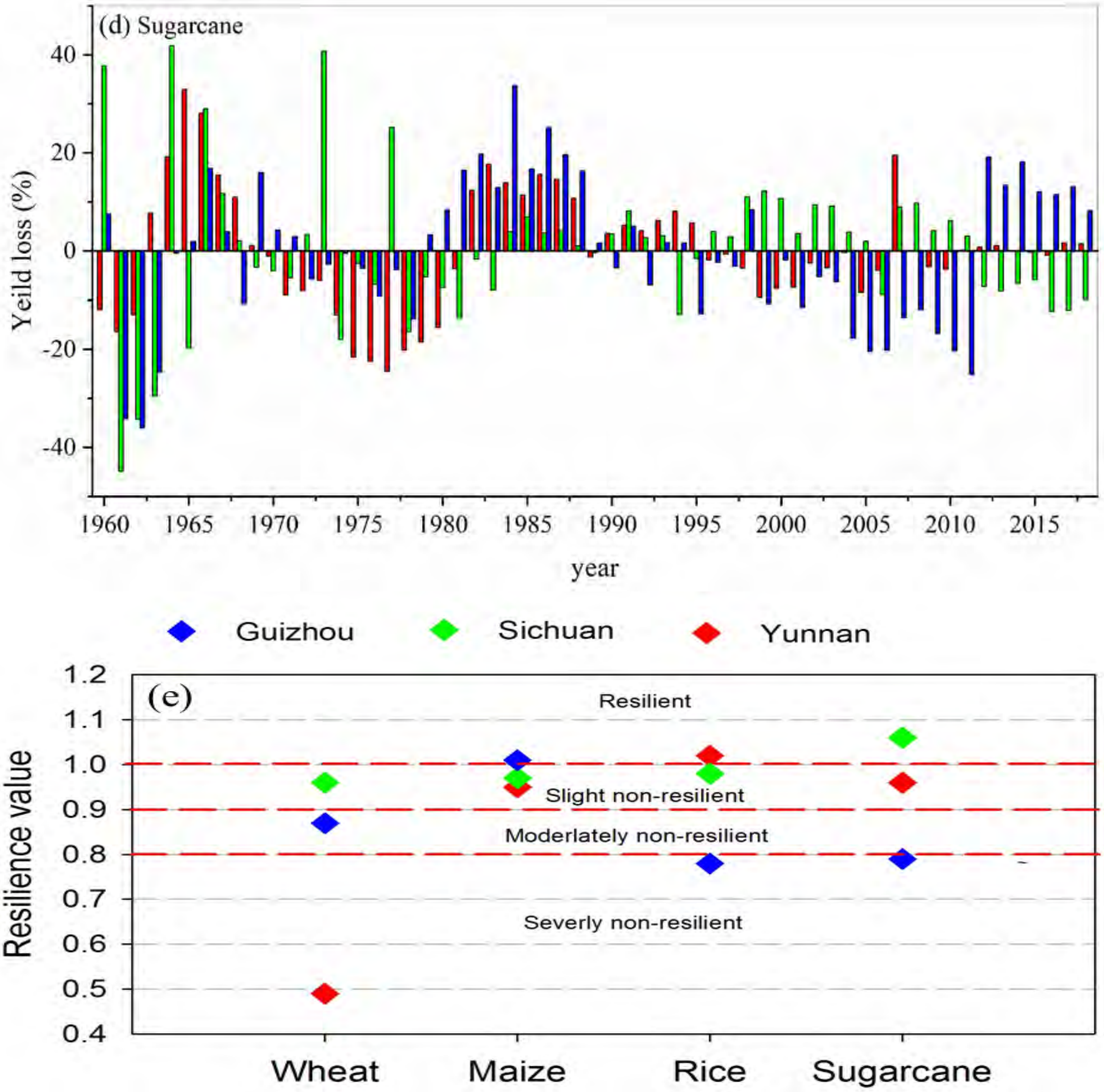
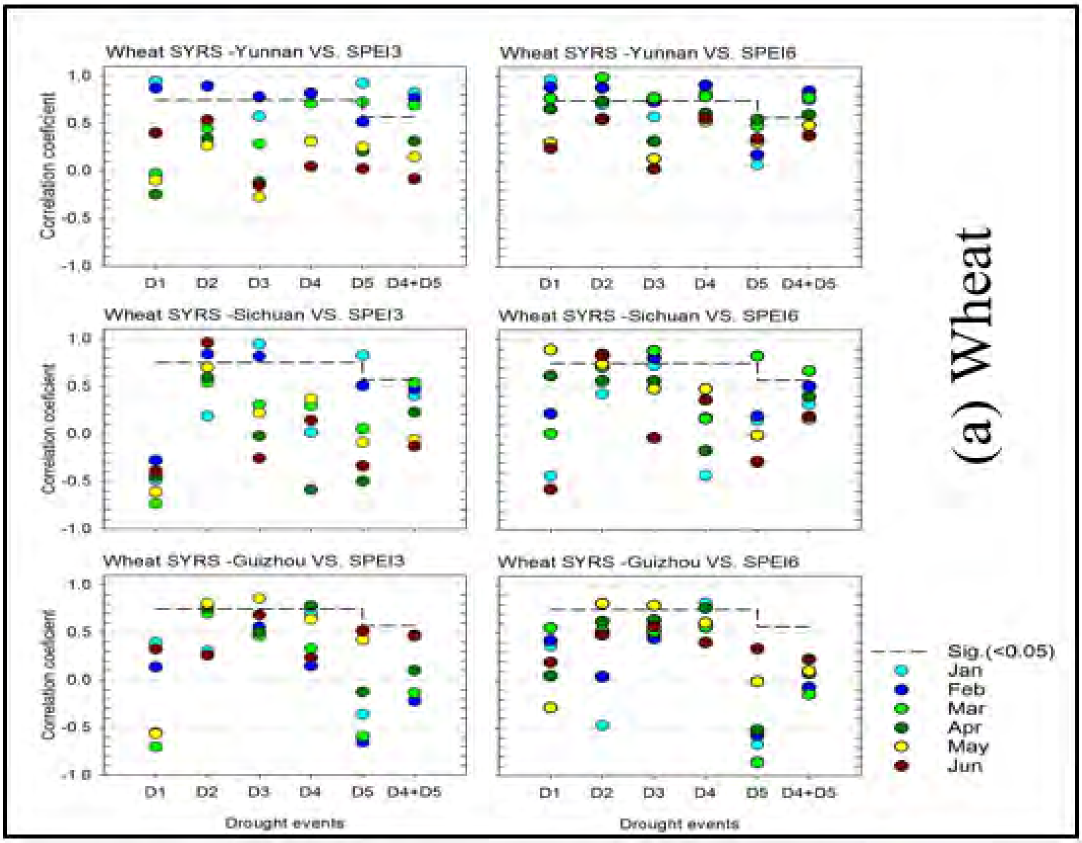
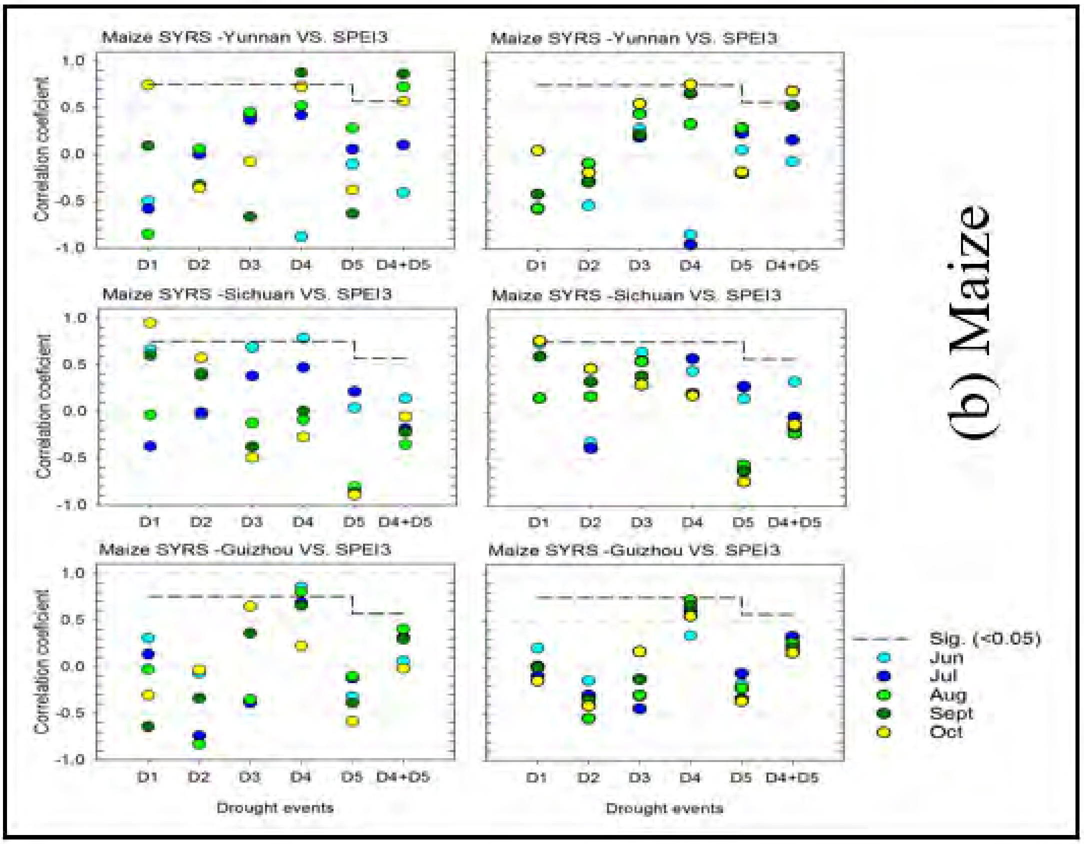


Fig. 8: Annual percentage of yield loss over the three provinces during the period from 1960 to 2018 (a-d) and the regional mean R_d for the different crops (e).

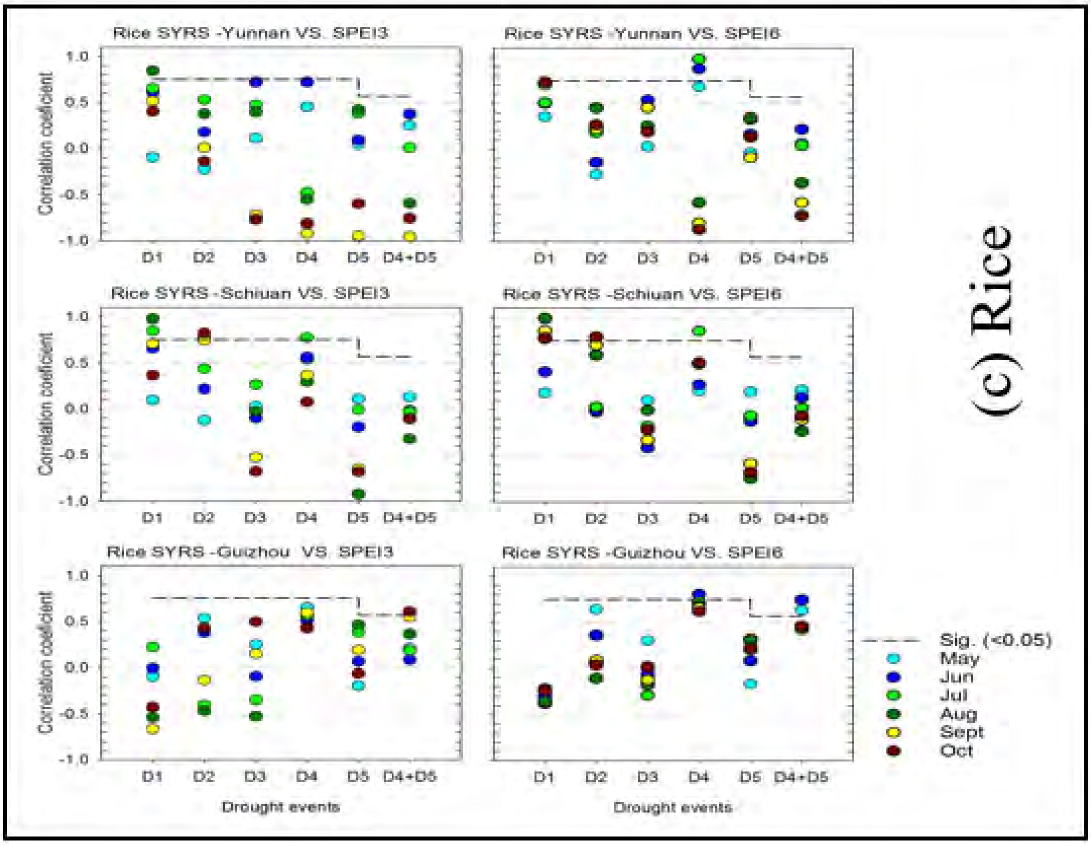


(a) Wheat



(b) Maize

Figure 9 continue



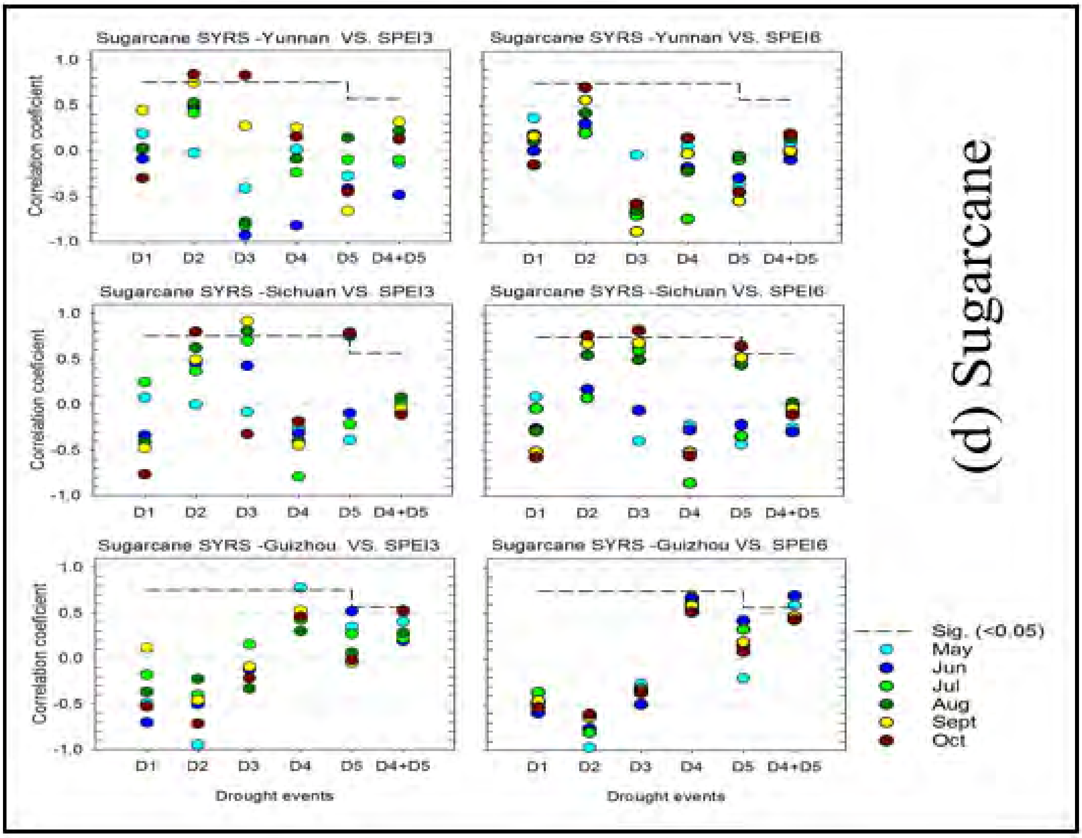


Fig. 9: Pearson correlation between SYRS and drought events during the period of 1960-2018 within the three provinces.

Table 1: The ecosystem cover changes (km^2) in southwest China during the period from 1980 to 2015

	Agriculture	Forest	Grass	Wetland	Others
1980	240471	479351	289681	13163	19365
1990	240836	480486	289704	10461	21075
1995	234031	486652	289802	10198	21732
2000	239472	476927	293421	10659	21550
2005	238293	478179	292570	10721	7885
2010	237471	478691	292299	10867	22704
2015	235431	477852	291707	11703	10885
Percentage %	22.93	46.22	28.06	1.07	1.72

Table 2: SPEI drought classification and yield categories according to the SYRS (Vicente-Serrano et al., 2010; Potopová et al., 2015).

Drought group	SPEI values	Yield category	SYRS
No drought	> 0	High yield increment	≥ 1.50
Mild drought	0 to -0.5	Moderate yield increment	1.00–1.49
Moderate drought	-0.5 to -0.84	Low yield increment	0.51–0.99
Severe drought	-0.84 to -1.28	Normal	0.50 to −0.50
Extreme drought	-1.28 to -1.65	Low yield losses	−0.51 to −0.99
Very extreme drought	> -1.65	Moderate yield losses	−1.00 to −1.49
		High yield losses	≤ −1.50

Table 3: Stepwise regression models developed over the three provinces for the different four crop yield

	Scale	Crop	Regression model
Yunnan	3-months	Wheat	$y=13.147+0.879SPEI\text{-}3_2-1.97W_1-2.01W1_2-0.34Tave_5+0.076T_{min4}-0.012S_8$, $(R=0.64, p=0.000)$
		Maize	$y=-2.36+0.041RH_5+0.025S_{10}-2.725W_1+0.877SPEI\text{-}3_9$, $(R=0.45, p=0.000)$
		Rice	$y=1.164+0.070RH_9+0.737Tave_2-0.016S_2-0.015S_7+0.184T_{min4}+0.011P_4-0.129T_{min5}$, $(R=0.602, p=0.000)$
		Sugarcane	$y=4.866-0.067RH_{12}+0.386SPEI\text{-}3_{11}$, $(R=0.287, p=0.000)$
	6-months	Wheat	$y=1.17+1.01SPEI\text{-}3_3+0.145T_{min4}-1.23W_6$, $(R=0.43, p=0.000)$
		Maize	$y=-1.16-2.56W_5+0.05RH_{12}+0.65SPEI\text{-}6_{12}+0.018S_{12}$, $(R=0.39, p=0.000)$
		Rice	$y=4.96-0.067RH_{11}+128Tave_3-0.043S_6-0.58Tave_1-0.393SPEI\text{-}3_{10}$, $(R=0.50, p=0.000)$
		Sugarcane	$y=4.84-0.067RH_{12}+0.369SPEI\text{-}6_2$, $(R=0.28, p=0.000)$
Sichuan	3-months	Wheat	$y=5.95-0.697T_{max4}+0.038S5+0.584T_{min3}-0.303T_{min4}$, $(R=0.48, p=0.000)$
		Maize	$y=-2.696+0.73SPEI\text{-}3_9+0.025*S_{11}$, $(R=0.146, p=0.005)$
		Rice	$y=10.96-0.064RH_{12}+0.838SPEI\text{-}6_8-0.068T_{min12}+0.699T_{max4}+0.245T_{min3}-1.37W_2+0.024S_3+0.265T_{max11}-0.064T_{min5}$, $(R=0.69, p=0.000)$
		Sugarcane	$y=10.51-3.73W_1-0.071RH_6$, $(R=0.55, p=0.000)$
	6-months	Wheat	$y=8.66-0.396T_{max7}$, $(R=0.13, p=0.004)$
		Maize	$y=5.1+0.76SPEI\text{-}6_9-0.314T_{ave7}$, $(R=0.15, p=0.005)$
		Rice	$y=15.96-0.07RH_1+0.81SPEI\text{-}6_8-0.091T_{min12}-0.32T_{max7}-1.73W_3$, $(R=0.47, 0.000)$
		Sugarcane	$y=11.62-2.87W_4-0.06RH_4-0.02S_{10}$, $(R=0.49, p=0.000)$
Guizhou	3-months	Wheat	$y=-2.025+0.015P_3+0.162T_{min6}+0.011S_9$, $(R=0.23, p=0.001)$
		Maize	$y=2.879-1.2W_4+0.378SPEI\text{-}3_8$, $R=0.152, p=0.004$
		Rice	$y=4.689+0.454SPEI\text{-}3_8+0.446SPEI\text{-}3_3-0.06RH_1$, $R=0.211, p=0.001$
		Sugarcane	$y=6.594-0.018S_9-0.051RH_1$, $(R=0.203, p=0.001)$
	6-months	Wheat	$y=-1.516+0.002P_9$, $(R=0.084, p=0.016)$
		Maize	$y=4.932-2.21W_5+0.363SPEI\text{-}6_{12}$, $(R=0.17, P=0.002)$
		Rice	$y=9.73+0.5SPEI\text{-}6_7-0.021S_{10}-0.067RH_1-0.227T_{min3}$, $(R=0.295, p=0.000)$
		Sugarcane	$y=4.785-0.227T_{max12}+0.442SPEI\text{-}6_9$, $(R=0.185, p=0.001)$

Note: $T_{avg\text{-}i}$, $T_{max\text{-}i}$ and $T_{min\text{-}i}$ are the average temperature, maximum temperature, and minimum temperature in i^{th} month, respectively. Pi is the precipitation in i-th month, Si is the sunshine hours in i-th month, Wi is wind speed in i-th month, RH_i is relative humidity in i-th month, p is the P-value and R is the adjusted R^2.

Table 4: Percentage of crop yield loss (Y%) due to both drought duration (DD) and drought severity (DS)

	Wheat					Maize					Rice					Sugarcane				
	Year	Y (%)	G	DS	DD	Year	Y (%)	G	DS	DD	Year	Y (%)	G	DS	DD	Year	Y (%)	G	DS	DD
Yunnan	2010	-50.8	S-H	9.8	9	1961	-29.5	S-H	0	0	1977	-13.6	S-F	1.16	4	1977	-24.5	S-F	1.16	4
	1986	-40.8	V-H	2.9	7	1968	-17.7	S-H	0	0	1974	-13	S-H	0	0	1976	-22.5	F	0.4	2
	1979	-26.5	S-H	7.6	9	1977	-11.8	S-F	1.03	3	1979	-10.2	S-J	2.5	3	1975	-21.6	S-H	2.8	6
	1969	-22.4	V-H	7.1	7	2009	-10.6	J-H	3	4						1978	-20.1	H	1	2
	1974	-21.9	V	1.1	2											1979	-18.5	S-F	2.5	4
	1970	-21	S-F	2.9	6											1961	-16.4	S-H	0	0
Sichuan	1977	-19.5	H	0.6	1	1961	-23	S-H	0	0	1976	-25.3	J-F	1.03	3	1976	-44.9	F-H	1	3
	1975	-18.8	V-H	1.95	7	1976	-18.8	J-H	1.03	3	1974	-20.4	S-H	0	0	1961	-34.2	S-H	-	0
	1962	-18.7	F-H	2.4	3	1994	-17.2	S-H	3.5	5	1972	-19.3	J-H	3.6	4	1977	-29.5	V-H	2.5	5
	1973	-15.8	S-F	4.1	7	2001	-17.1	S-H	0	0	1975	-19	S-H	1.4	5	1975	-19.8	S-H	1.5	5
	1976	-14.1	V-F	0.8	3	1975	-14.8	S-H	1.05	4	2006	-14.7	S-H	5.15	6	1978	-18.0	F-H	0.4	3
	1965	-13.4	V	0.15	1	1972	-13.7	J-H	3.6	4	1977	-14.5	J-H	2.5	5	1972	-16.4	F-H	3.6	4
	1961	-12.5	S-V	2.4	5	2006	-12	S-H	5.1	5	1973	-14.2	J-H	3.6	4					
Guizhou	1975	-30.1	V	2.4	4	2011	-31.5	S-H	7.33	5	1972	-29.6	F-H	3.1	3	1962	-36.1	S-H	1.1	6
	2018	-24.1	H	3.1	2	1988	-23.2	S-F	1.8	3	2011	-21.3	S-H	8.3	6	1961	-34.1	S-V	1.5	2
	2003	-23.4	S-H	3.2	8	1976	-22.2	S-H	0	0	2010	-21.3	S-H	1.7	6	2011	-25.2	S-H	8.3	6
	1969	-21.6	V-H	5.9	6	2013	-20.9	S-H	4.7	5	2009	-19.9	S-H	3.5	6	1963	-24.7	**S-H**	**4.7**	**6**

2005	-18	S-V	3.8	5	2014	-20.4	S-H	2.9	5	2007	-19	S	0.5	1	2005	-20.4	S-H	1.8	6
2006	-17	S-V	2	4	2015	-17.9	S-H	0	0	1981	-18.1	S-H	3.2	6	2010	-20.3	S-H	3.2	6
1961	-16.5	S-V	3.4	5	1972	-17.5	J-H	3.1	4	2008	-17.4	S-H	0	0	2006	-20.2	S-H	2.2	6
2016	-15.5	S-H	0	0	1985	-16.7	H	0.63	2	2002	-15.8	H	0.3	2	2004	-17.7	V-H	1.9	5
2004	-15.2	S-V	2.7	3	1969	-15.3	H	0.15	1						2009	-16.8	S-H	3.5	6

Note: G: Growing cycle stages: S; sowing, J; joining, V; vegetative, F; flowering, H: harvest and mature. Shaded gray to represent the crop yield losses (YCL) during wet events.

Table 5: Correlation matrix between agriculture area (%) affected by drought and SPEI values at the 3 and 6 monthly timescales for the period of 1978-2018.

		Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
Yunnan	SPEI-3	-0.33	-0.37	-0.24	-0.15	-0.24	-0.28	-0.32	-0.36	-0.21	-0.04	-0.02	0.08
	SPEI-6	-0.47	-0.50	-0.41	-0.29	-0.33	-0.37	-0.36	-0.39	-0.38	-0.34	-0.29	-0.13
Guizhou	SPEI-3	-0.24	-0.28	-0.32	-0.31	-0.27	-0.20	-0.38	-0.48	-0.52	-0.43	-0.15	0.01
	SPEI-6	-0.22	-0.31	-0.30	-0.35	-0.38	-0.39	-0.49	-0.57	-0.55	-0.51	-0.48	-0.51
Sichuan	SPEI-3	-0.18	0.04	0.18	0.22	0.17	0.22	0.18	0.08	-0.04	0.02	0.14	0.16
	SPEI-6	-0.07	-0.13	0.08	0.08	0.15	0.28	0.26	0.14	0.10	0.15	0.14	0.01

Note: The critical value for Pearson Correlation is 0.31, df (40,2), significant value < 0.05.