The Diagnosis about Spatiotemporal Characteristics and Driving Factors of Flash Drought and Its Prediction over Typical Humid and Semiarid Basins in China

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ABSTRACT: Flash drought is a rapid-onset drought, which has greatly threatened the agricultural production and economic development. However, the unclear development mechanism of flash droughts brings challenges for its monitoring, forecasting, and mitigation. This study investigates the spatiotemporal characteristics, driving factors, and the prediction of flash drought over typical humid and semiarid basins. The main objectives and findings are as follows. 1) The patterns of flash drought are compared under different climate types. The results show that flash drought is more serious in the chosen humid basin than that in the semiarid basin, with more events, longer duration, and larger frequency of occurrence (FOC). 2) The development mechanisms of flash drought are explored by analyzing the anomalies of seven meteorological variables in the evolution of flash drought. The results indicate that the main driving factors are the negative anomalies of precipitation and the positive anomalies of temperature, which usually occur at two pentads before the onset of flash drought. 3) The prediction of soil moisture as a key variable in flash droughts' developing process is conducted using support vector machine (SVM), with meteorological variables and a remote sensing soil moisture, namely, Soil Moisture Active Passive (SMAP), as inputs. In this study, about 65%–70% of flash droughts can be captured by the prediction. However, some events are missed, and false alarms also exist in most stations in both basins. This study can provide some references for monitoring and early warning of flash drought, which is important to reduce the losses and risks in agricultural production.

SIGNIFICANCE STATEMENT: As a new type of drought, the spatiotemporal characteristics and evolutionary mechanisms of flash drought are still not completely understood, and the short onset time brings unique challenges for its monitoring, prediction, and mitigation. Currently, studies that investigate flash drought prediction are at the exploratory stage. To the best of our knowledge, very limited studies have been conducted to predict flash drought based on the predicted soil moisture with the SVM model. Therefore, we investigate and compare the spatiotemporal characteristics, driving factors of flash drought over typical humid and semiarid basins in China. The prediction of flash drought is also conducted using an indirect method, which identifies flash drought using the predicted soil moisture with SVM. This study is meaningful for risk management in agricultural production and economic development.

KEYWORDS: Drought; Soil moisture; Support vector machines

1. Introduction

Drought is a natural disaster that affects agricultural production, ecological environment, and economic development, especially for the agriculture-dominant regions (Torres et al. 2013). The traditional droughts usually develop slowly and take months or even longer to reach the maximum intensity (Zhang et al. 2020). However, droughts that develop in a fast way have frequently been observed in recent years (Otkin et al. 2018), and the term “flash drought” has been popularized to describe this kind of drought (Ford et al. 2015).

Flash drought refers to the rapid-onset drought event, which usually reflects the quick decrease of soil moisture (Yuan et al. 2019). Flash droughts are likely to occur during the growing seasons with extreme meteorological conditions (e.g., lack of precipitation and extreme heat) (Wang and Yuan 2018; Wang et al. 2016). In recent years, the increasing heat resulting from global warming may make the events more prevalent than expected (Wang et al. 2016). Compared with the traditional

drought, the short onset time (less than one month) of flash drought significantly reduces the time allowed for disaster prevention and mitigation, which potentially results in greater harm to agricultural production and economic development (Ford and Labosier 2017; Liu et al. 2020a; Otkin et al. 2018; Wang and Yuan 2018). To reduce its damage, the investigation for its definition, spatiotemporal characteristics, and evolutionary mechanisms has become a focus in the research field of flash drought (Otkin et al. 2018; Wang et al. 2016; Yuan et al. 2019; Zhang et al. 2017).

There are multiple approaches to define and identify flash drought, which are based on soil moisture changes, precipitation deficits, temperature anomalies, evapotranspiration, and some other related variables (Christian et al. 2020; Li et al. 2020b; Mahto and Mishra 2020; Nguyen et al. 2019; Osman et al. 2021; Otkin et al. 2013; Christian et al. 2019b). Until now, new definitions and identification methods were constantly being proposed, but were inconsistent (Li et al. 2020b; Christian et al. 2019b). The differences and inconsistency in definitions of flash drought reflect different aspects of flash drought, but also bring some challenges to its monitoring (Liu et al. 2020b; Osman et al. 2021). The definition proposed

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by Mo and Lettenmaier (2015, 2016) classifies flash drought into precipitation deficit and heat wave flash droughts based on the anomalies of meteorological variables. This definition is widely used in the investigations of flash drought (Wang and Yuan 2018; Zhang et al. 2017). However, it lacks the rapid intensification that reflects the core process of flash drought, which may end up capturing a dry period rather than a flash drought (Liu et al. 2020b; Osman et al. 2021; Otkin et al. 2018). Therefore, the newly proposed definitions usually focus on the short duration and rapid rate of intensification, which can better describe the core process of the event. In this study, the definition proposed by Yuan et al. (2019) is applied, which is based on the rapid intensification rate of soil moisture.

Compared with traditional droughts, flash drought shows some unique characteristics in its physical mechanisms. A traditional drought is usually caused by long-term (months or longer) changes in both precipitation and evapotranspiration (Zhang et al. 2020). For flash drought, extreme atmospheric anomalies that last for a short duration can attribute to its occurrence (Ford and Labosier 2017; Zhang et al. 2020). Its specific physical mechanisms are still not completely understood, which brings difficulties for the monitoring of flash drought (Pendergrass et al. 2020). Therefore, it is of great importance to explore driving factors to the occurrence of flash drought for further monitoring. Studies have been conducted to discuss the anomalies of the meteorological variables prior to the onset of flash drought (Ford and Labosier 2017; Li et al. 2020a; Liu et al. 2020a; Wang and Yuan 2018; Zhang et al. 2017). Close relationships between most meteorological variables and the occurrence of flash drought have been found in previous studies (Ford and Labosier 2017; Liu et al. 2020b; Otkin et al. 2016). However, the investigation about the evolution of meteorological conditions based on the definition using rapid intensification rate of soil moisture is limited (Liu et al. 2020a,b). In addition, the meteorological conditions related to flash drought in most regions of China in recent years are still unknown. Therefore, it is essential to figure out the driving factors to the occurrence of flash drought in typical regions of China.

Furthermore, to ensure the safety of food and water resources and promote the sustainable development of the ecological environment, reliable flash drought prediction is of great importance. However, the prediction of flash drought is still a challenge (Pendergrass et al. 2020). Although some studies investigate the flash drought prediction (Chen et al. 2020; DeAngelis et al. 2020; Ford et al. 2015; Mo and Lettenmaier 2020), most of these prediction methods cannot be directly adopted in the studies based on other identification methods. Additionally, limited to the data availability, to predict flash drought directly based on long time series of flash droughts is difficult to achieve. Therefore, some studies obtain flash drought predictions though an indirect method, which means flash drought is identified based on the predicted variables, which are the key variables in the process of flash drought (DeAngelis et al. 2020; Mo and Lettenmaier 2020). In this study, flash drought is defined by the intensification rate of soil moisture. Therefore, reliable soil moisture is the key for the accurate prediction of flash drought. As a traditional data

source, in situ measurement can provide high-precision soil moisture values at different temporal scales (Santi et al. 2018). However, the in situ measurement at many regions is difficult to access, due to the uneven distribution of the measuring stations (Mishra et al. 2017). Remote sensing technology provides the possibility to effectively obtain soil moisture by frequently and continuously sensing surface characteristics (Su et al. 2003). It has high resolution, wide measurement range, long time span, and low cost (Mishra et al. 2017; Peng et al. 2015). However, the remote sensing method usually can only provide soil moisture at the surface layer. Therefore, it may be effective to obtain root zone soil moisture predictions by coupling the remote sensing soil moisture with prediction models (Ford et al. 2014). SVM is a data-driven model, which shows great performance in classification, regression, and forecasting (Bordoni et al. 2017). Compared with hydrological models, it has comparable or even better prediction efficiency but needs much fewer input variables (Jajarmizadeh et al. 2014; Koycegiz and Buyukyildiz 2019). The investigation on its application is meaningful for data-limited regions. In addition, it very rarely has been adopted for flash drought prediction, although it is considered as a useful method for traditional drought monitoring and prediction (Bordoni et al. 2017; Liu et al. 2016; Roodposhti et al. 2017; Yu et al. 2012).

Generally, the occurrences of traditional drought are paid great attention to in the arid regions (Zhang et al. 2020; Zou and Ren 2010). However, studies show that flash droughts occur more frequently in humid regions due to significantly driven effects by high temperature (Li et al. 2020a; Wang et al. 2016; Zhang et al. 2017). Therefore, it is meaningful to diagnose and predict the onset of flash droughts over basins with different climate types. Two agriculture dominant basins with different typical climate conditions, namely, Xiang River basin and Wei River basin, are selected as the study areas. Xiang River basin belongs to the subtropical humid monsoon climate zone, affluent in light, heat, and water resources. It is the most densely populated region with the highest level of urbanization in Hunan Province. On the other hand, Wei River basin has a temperate continental semiarid monsoon climate, with limited water and heat resources. Its climate pattern is typical for large areas in north China. Drought is one of the most frequent natural disasters in these two regions, which has been paid great attention (Huang et al. 2014; Zou et al. 2017). However, the flash drought has rarely been investigated and compared in the regions of China because the difficulties in data availability (Wang et al. 2016; Zhang et al. 2017). It is meaningful to investigate the flash drought in these two regions as case studies to provide reference for the other humid and semiarid basins in China. Additionally, the investigations on flash drought prediction are rarely based on the definition applied in this research (Liu et al. 2020a,b).

Based on the above, three main objectives of this study are as follows: 1) to compare the spatiotemporal characteristics of flash droughts between the semiarid and humid basins within China by focusing on the events in Xiang River basin and Wei River basin during 2017–19 as examples; 2) to investigate the meteorological conditions related to the evolution of

FIG. 1. DEM and river network of (a) Xiang River basin and (b) Wei River basin and the spatial distribution of the meteorological stations.

these flash drought events; and 3) to predict the soil moisture conditions leading to flash drought onset using SVM method. The remaining structure of the paper is organized as follows: the study area and data are described in section 2; the methodology and evaluation indices are introduced in section 3; sections 4 and 5 present the results and discussions, respectively; and the conclusions are summarized in section 6.

2. Study area and data

a. Study area

Two agriculture dominant basins are selected as study areas, which are Xiang River basin and Wei River basin. Xiang River basin (24.5°–28.5°N, 110°–114°E) is located in southern China with a subtropical humid monsoon climate (Juan et al. 2006). It is one of the largest tributaries of the Yangtze River, which has about 82 375 km² surface area above Xiangtan Station, which is the outlet of the basin. The Pacific monsoon climate is the dominate climate type in this basin, with 1400–1700 mm average annual precipitation and 16°–18°C average annual temperature (Zhu et al. 2019). In this study, it is selected as a typical basin in humid regions.

Wei River basin (33.5°–37.5°N, 103.5°–110.5°E), located in north China, is the largest tributary of the Yellow River (Zou et al. 2017). Wei River basin has a continental climate (Huang et al. 2014). It is cold and rainy in winter, and hot and rainy in summer. The average annual temperature is 7.8°–13.5°C and the annual precipitation is 500–800 mm (Zhao et al. 2015). It is chosen as a typical case to investigate the characteristics of flash drought in semiarid/arid regions.

Figure 1 shows the digital elevation maps (DEM) and the river network of Xiang River basin (Fig. 1a) and Wei River basin (Fig. 1b), and the spatial distribution of the 35 meteorological stations used in this study.

b. Datasets

1) IN SITU DATA

Meteorological variables from 2017 to 2019 at the above 35 stations can be achieved from the National Meteorological Information Center (<https://data.cma.cn/site/index.html>). The meteorological variables including daily precipitation (P), average temperature (T), maximum temperature ($T_{\max}$), average relative humidity (R_h), wind speed (W_s), and solar radiation (R_s) are selected to probe the driving factors of flash drought in this study. The potential evapotranspiration (PET) is calculated using the Penman–Monteith equation (Chiew et al. 1995).

2) SMAP SOIL MOISTURE RETRIEVALS

The SMAP satellite, which was developed by NASA (National Aeronautics and Space Administration), was launched on 31 January 2015 (Entekhabi et al. 2010). Its main mission is to provide the global surface soil moisture using the L-band radiometer (Chan et al. 2018). The top 0–5-cm soil moisture data with a high-target accuracy ($0.04 \text{ m}^3 \text{ m}^{-3}$) can be achieved (<https://earthdata.nasa.gov/>) (Chan et al. 2016). In this study, the passive SMAP Level 2 L-band radiometer descending soil moisture product (SMAP L2 Radiometer Global 36-km EASE-Grid soil moisture version 6, SMAP_L2_SM_P) is selected to provide daily surface soil moisture.

3) REFERENCE SOIL MOISTURE FROM CHINA LAND SOIL MOISTURE DATA ASSIMILATION SYSTEM (CLSMDS)

The CLSMDS product is a gridscale analysis product fusing multisource observed data. It has a temporal resolution of 1 h and a spatial resolution of $0.0625^\circ \times 0.0625^\circ$ (Shi et al. 2011). Specially, the daily/hourly multilayer soil moisture data (0–5, 0–10, 10–40, 40–100, 100–200 cm) are provided over Asia

(<http://data.cma.cn/>) (Shi et al. 2011). The dataset is in good agreement with in situ observations, with the national regional average correlation coefficient equal to 0.89 and the bias equal to $0.01 \text{ m}^3 \text{ m}^{-3}$ (Shi et al. 2011). It has been proved to be reliable as the reference data and applicable for drought monitoring (Zhu et al. 2019). In this study, the gridded root zone layer soil moisture (0–10, 10–40, 40–100 cm) are interpolated to station scale to identify the flash drought events at the 35 stations mentioned above.

4) GPM IMERG FINAL PRECIPITATION

The Integrated Multisatellite Retrievals for GPM (IMERG), which combines information from the Global Precipitation Measurement (GPM) satellite constellation to estimate precipitation, is used to illustrate the precipitation pattern with a high spatial resolution. GPM IMERG Final Precipitation L3 V06 is selected in this study, the spatial and temporal resolutions of which are 0.1° and one month, respectively. The data from 2017 to 2019 during the growing seasons (April–October) are adopted. The data can be accessed from https://disc.gsfc.nasa.gov/datasets/GPM_3IMERGM_06.

5) ERA5 TEMPERATURE DATA

The temperature data with a high spatial resolution is provided by the latest ECMWF (European Center for Medium-Range Weather Forecasts) global reanalysis data (ERA5). The spatial and temporal resolutions of the dataset are 0.1° and one month, respectively. In this study, the data from 2017 to 2019 during the growing seasons (April–October) are adopted. The data can be accessed from <https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5>.

3. Methodology

As mentioned above, the aim of this study is to investigate and compare the spatiotemporal characteristics and driving factors of flash drought over typical humid and semi-arid basins, and to explore the prediction of flash drought events for the possibility of flash drought early warning and forecasting. First, the flash drought events are identified over two basins based on the reference soil moisture data, namely, CLSMDAS, as case studies to analyze their spatiotemporal characteristics. Second, the anomalies of meteorological variables are analyzed to investigate the driving factors of these flash droughts. Third, predictions of flash droughts are obtained based on the predicted root zone soil moisture with SVM model.

a. Support vector machine (SVM)

The SVM model is a generalized linear classifier that based on supervised learning (Cortes and Vapnik 1995). After the kernel method being adopted in this algorithm, it can also be used for nonlinear classification and regression. In this study, the radial basis function (RBF) is selected as the kernel function. It can estimate one dependent variable with several independent variables as inputs (Yu et al. 2012). The basic idea of the model is to achieve the largest regressions by constructing an optimal hyperplane in the sample space or feature

space which maximizes the distance between itself and different types of sample sets. The regularized function $f(x)$ is set through the following formulations:

The minimization

$$\frac{1}{2}\|w\|^2 + C \sum_{i=1}^L (\xi_i + \xi_i^*) \quad (1)$$

is subject to

$$\begin{cases} y_i - \sum_{j=1}^M \sum_{i=1}^L \mathbf{w}_j x_{ji} - b \leq \varepsilon + \xi_i \\ \sum_{j=1}^M \sum_{i=1}^L \mathbf{w}_j x_{ji} + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \quad (2)$$

$$f(x) = \sum_{j=1}^M \mathbf{w}_j x_j + b, \quad \mathbf{w} \in R^M, b \in R, \quad (3)$$

where M is the number of the support vectors, b is the bias, $\mathbf{w}$ represents the vector weights for inputs to the output, C is the penalty parameter that determines the trade-off between the complexity of the function f and the tolerance for error in the prediction, ε is the insensitive parameter, and ξ_i, ξ_i^* are slack variables that determine the degree to which input samples with error greater than ε will be penalized.

This is known as the ε -insensitive loss function, which is different from the traditional loss function (e.g., least squares or least modulus), as the errors less than ε are ignored. Any (absolute) error smaller than ε does not require ξ_i and ξ_i^* to be nonzero and therefore does not enter the objective function.

In this study, the SVM model is adopted to predict the root mean (0–1 m) soil moisture for the subsequent flash drought identification. The training set and the testing set are 2 April 2017–31 March 2019 and 1 April 2019–31 October 2019, respectively. The input variables of SVM are in-site meteorological variables (P , T , Ws , PET , Rs , Rh) and SMAP remote sensing soil moisture dataset, which have been evaluated to be suitable for soil moisture prediction in our previous study (Zhu et al. 2021). Then, the flash droughts can be identified based on the predicted soil moisture.

b. The definition of flash drought events

Pentad, which means five days, is applied as a unit for the duration of flash drought events. We focus on pentads from April to October (49 pentads per year). According to the definitions provided by Yuan et al. (2019), a flash drought is identified when it meets the following three conditions: (i) the pentad mean root zone (top 1 m) soil moisture decreases from above the 40th percentile to the 20th percentile in four pentads; (ii) the drought terminates when the declined soil moisture rises up to the 20th percentile again; (iii) and the duration of the drought, which refers to the entire length of flash drought event, should be three pentads at least.

The onset of a flash drought is defined as the first pentad when the soil moisture falls below the 40% percentile. The frequency of occurrence (FOC), which defined as the percentage of pentads of flash droughts, can be calculated with the following equation (Zhang et al. 2017):

$$\text{FOC} = \frac{N}{N_{\text{total}}} \times 100\%, \quad (4)$$

where N_{total} is the total number of pentads and N is the number of pentads of flash drought in each station occurred from 2017 to 2019.

The severity of flash drought can also be explicitly estimated using the soil moisture percentile deficit during the flash drought. The severity is calculated with the accumulated soil moisture percentile deficits from the threshold, which is 40th percentile of soil moisture (red shaded area in Fig. 2) (Yuan et al. 2019).

c. Evaluation indices

The correlation coefficient (R value), the relative bias (BIAS), and the root-mean-square error (RMSE) between the predicted values and reference values are used to evaluate the performance of SVM in root mean soil moisture prediction:

$$R = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \times \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}}, \quad (5)$$

$$\text{BIAS} = \frac{\sum_{i=1}^n (Y_i - X_i)}{\sum_{i=1}^n X_i} \times 100\%, \quad (6)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (X_i - Y_i)^2}{n}}, \quad (7)$$

where X_i and Y_i represent the reference soil moisture and predicted soil moisture, respectively, and $\bar{X}$ and $\bar{Y}$ represent the mean value of these two datasets, respectively.

The probability of detection (POD), false alarm ratio (FAR), and the threat score (TS) are adopted to evaluate the performance of SVM in flash drought prediction (Mo and Lettenmaier 2020):

$$\text{POD} = \frac{N_A}{N_A + N_C}, \quad (8)$$

$$\text{FAR} = \frac{N_B}{N_A + N_B}, \quad (9)$$

$$\text{TS} = \frac{N_A}{N_A + N_B + N_C}, \quad (10)$$

where N_A , N_B , and N_C represent the number of the hits, the false alarms, and the misses, respectively.

FIG. 2. Schematic overview of the evolution process of flash drought indicated by soil moisture percentile.

4. Results

a. Characteristics of flash droughts over the two typical basins

The occurrence of flash droughts over Xiang River basin during the three years range from 1 to 6 times, with an average value of 3 times (Fig. 3a). The flash droughts that occurred at Zhuzhou station during the three years have the shortest mean duration of 17 days, while those that occurred at Daoxian station have the longest mean duration of 50 days. The average duration of the flash droughts in Xiang River basin is about 30 days. The FOC ranges from 5% to 25%, with the average value of 14.3%. In general, the flash droughts are more likely to occur at Pingjiang, Mapoling, Yichun and Daoxian stations than the other stations. The flash droughts usually occur in summer (June–August) and autumn (September–November) in these three years, with almost all events are in July–October (Fig. 3c). Compared to the north part, the stations at the south part are likely to experience flash droughts earlier. The severity of these events obviously varies over Xiang River basin, which shows relatively higher values at the stations located at the north-east and southwest corners.

The onset times of flash droughts occurred in the Wei River basin during 2017–19 range from 1 to 4 (Fig. 4a). The mean duration of these flash droughts at different stations ranges from 15 to 40 days, with which at 76% of stations below 25 days. And the average duration over Wei River basin is about 20 days. The total duration of flash droughts accounts for 2%–17% of the entire study period, and its mean value is 9.2%. Figure 4d also shows that the flash droughts are more likely to occur in the southeast part than in the northwest part. The flash droughts in Wei River basin mainly occur in spring (March–May) and summer (June–August), 57.6% of which occur in April–June and 81.4% in April–July. In addition, the flash drought events usually occur earlier in the southeast part of the basin (Fig. 4c). The severity of these events also varies over Wei River basin, with relatively higher values at the stations located at the east boundary.

All stations at both basins have flash droughts during the period from 2017 to 2019, with more than half of the stations

FIG. 3. (a) The onset times, (b) the mean duration, (c) the mean onset day of the year, (d) the frequency of occurrence (FOC), and (e) the mean severity of the flash droughts during the growing seasons in Xiang River basin.

in both regions have FOC values ranging from 5% to 15%. The duration of these events ranges from 3 pentads to 10 pentads, which indicates that the flash drought is a submonth-to month-scale event in both basins. Apart from the similarities, there are also some obvious differences in the pattern of flash drought between these two basins. The number of events that occurred, mean duration, and severity of flash droughts are all larger in Xiang River basin than that in Wei River basin. The flash droughts usually occur earlier in Wei River basin than Xiang River basin. In addition, the flash droughts present more obvious spatial variability in Wei River basin than that in Xiang River basin, which is mainly illustrated via the differences of onset time and FOC.

b. Meteorological conditions related to the development of flash droughts

To explore the driving factors of flash droughts, the meteorological conditions related to the development of these events in the two basins are analyzed. Six meteorological variables (P , $T_{\max}$, W_s , RH , R_s , PET) are selected to explore their characteristics before and during the development stage of flash drought. Figure 5 shows that the soil moisture condition varies among different events at 2–4 pentads before the onset, with the mean value around the 50th percentile. From 1 pentad before the onset to 2 pentads

after the onset, soil moisture of most events rapidly declines from normal status (above the 40th percentile) to moderate drought (below the 20th percentile).

Therefore, the anomalies of the meteorological variables (P , $T_{\max}$, W_s , RH , R_s , PET) are analyzed between 4 pentads before and 2 pentads after the onset of flash drought to explore the driving factors of the flash drought development (Figs. 6 and 7). At 3–4 pentads prior to the onset, there are no significant anomalies can be found in Wei River basin. The values of meteorological variables, including P , $T_{\max}$, R_s , and PET , show abnormality at 3 pentads prior to the onset of flash drought in Xiang River basin. However, the anomalies obviously decrease at 2 pentads prior to the onset and increase again at 1 pentad prior to the onset. Generally, the significant anomalies usually appear 1–2 pentads prior to the occurrence of flash drought, and reach their maximum at the onset period. RH even exhibit a rapid transition from positive anomalies to negative anomalies in a period of 1–2 pentads. PET also rapidly transfers from the negative anomalies to the positive anomalies within 1–2 pentads. During the development stage, the anomalies of P , RH , R_s , $T_{\max}$, and PET almost remain unchanged at the first 5 days after the onset of flash drought. Within 2 pentads after the onset of flash drought, the anomalies of P and RH generally remain negative, while the anomalies of R_s , $T_{\max}$, and PET generally remain

FIG. 4. (a) The onset times, (b) the mean duration, (c) the mean onset day of the year, (d) the frequency of occurrence (FOC), and (e) the mean severity of the flash drought events during the growing seasons in Wei River basin.

positive. Their anomalies are attributed to the continuous decreasing of the soil moisture.

In general, the P and RH in the two basins before and during the development stage of the flash drought show significant negative anomalies, while the T_{max} , R_s , and PET present significant positive anomalies. In addition, W_s prior to and during the development stage of flash drought does not show clear positive or negative pattern. The maximum negative anomalies of P reach 0.5 deviation in both basins. The maximum positive anomaly of T_{max}

reaches 1.5 deviations and 2 deviations in Xiang River basin and Wei River basin, respectively. In the evolution of PET , the maximum value of anomaly is observed in Xiang River basin, which is 2 deviations. Since P and PET shows obvious anomaly and has direct relationship with soil moisture, the anomalies of $P - PET$ are calculated (Fig. 8). The negative anomaly can also be observed from 1 pentad prior to the onset to 2 pentads after the onset, with maximum anomaly (about 1 deviation) observed at the onset pentad for both basins.

FIG. 5. Variation of soil moisture percentile for flash drought events (gray lines) of all stations in both basins. The black line represents the ensemble-mean of all flash drought events. The labels lag-1 to lag-4 represent 1–4 pentads prior to the onset pentad, while lag+1 to lag+4 represent the lagged 1–4 pentads of the onset pentad, respectively.

FIG. 6. Pentad anomalies of meteorological variables (P , $T_{\max}$, W_s , R_h , R_s , and PET) prior to and after the flash drought onset in Xiang River basin.

c. Flash drought prediction over Xiang and Wei River basins with SVM

1) THE PERFORMANCE OF SVM IN ROOT ZONE SOIL MOISTURE PREDICTION

According to the definition of flash drought event used in this study, the prediction of flash drought is based on unusually rapid intensification rates of the root zone soil moisture. And as we mentioned above, the SVM with SMAP and meteorological variables as inputs are adopted for root zone soil moisture prediction. Then, the flash drought events are identified based on the predicted soil moisture

values. The performance of SVM at station scale is evaluated using three indices, namely, R , $BIAS$, and $RMSE$.

In terms of its performance in Xiang River basin, the prediction efficiency varies at different stations but shows generally good performance both in the training and the test stages (Table 1). In the training stage, the correlation coefficients between the predicted soil moisture and the reference soil moisture at 14 stations are all above 0.55, with 85.6% of values above 0.7. The p values are all below 0.01, which shows the good significance of the model at these stations. The $BIAS$ and $RMSE$ values are below 1% and $0.03 \text{ m}^3 \text{ m}^{-3}$, respectively, which indicates the high accuracy of the soil moisture prediction.

FIG. 7. Pentad anomalies of meteorological variables (P , $T_{\max}$, W_s , R_h , R_s , and PET) prior to and after the flash drought onset in Wei River basin.

FIG. 8. Pentad anomalies of P -PET prior to and after the flash drought onset in (a) Xiang River basin and (b) Wei River basin.

In the test stage, absolute BIAS values are all below 10%, with 71.4% of values below 6%, which is relatively higher than that in the training stage. However, the correlation is higher than that in the training stage ($R > 0.7$, $p < 0.01$). And the RMSE shows comparable performance with that in training stage, with 71% of values below 0.035. Therefore, the performance in the training and test stages indicates that the SVM model is capable to predict root mean soil moisture with SMAP and meteorological variables as inputs in Xiang River basin.

In Wei River basin, the prediction efficiencies at the 21 stations are also satisfactory in general, but show lower correlation and higher bias than that in Xiang River basin (Table 2). The R values are above 0.7 at 66% of stations in the training stage, while above 0.6 at 81% of stations in the test stage. The p values are below 0.01 both at the training stage and the test stage, which indicate the high significance of SVM. The BIAS and RMSE values in the training stage are similar to that in Xiang River basin, which are below 15% and $0.055 \text{ m}^3 \text{ m}^{-3}$, respectively. The SVM model underestimates the root mean

soil moisture in the test stage at all stations, with BIAS around 10%. Above all, the SVM model also can be considered reliable for root mean soil moisture prediction in Wei River basin.

2) FLASH DROUGHT PREDICTION WITH SVM

For Xiang River basin, there are 43 flash droughts during 2017–19 at 14 stations, 10 of which occurred in the testing stage (April 2017–October 2018). Based on the predicted soil moisture with SVM, 25 flash drought events in the training stage and 7 in the test stage can be identified, respectively (Table 3). The POD at the training stage and the test stage are 0.76 and 0.70, respectively (Table 4). In addition, 10 false alarms exist, with 0.22 and 0.3 FAR at the training and test stages, respectively. For Wei River basin, 59 flash droughts occurred at the 21 stations during 2017–19, with 23 events in the test stage. Among them, 24 events can be captured using the predicted soil moisture in the training stage, while 15 events can be captured in the test stage. Also, 20 events are missed, 8 of which are in the test stage (Table 3). Therefore, the POD at

TABLE 1. The performance of SVM for root mean soil moisture prediction in Xiang River basin. The correlation coefficients pass the significance test with $p < 0.01$.

	Training			Test		
	R	BIAS (%)	RMSE ($\text{m}^3 \text{ m}^{-3}$)	R	BIAS (%)	RMSE ($\text{m}^3 \text{ m}^{-3}$)
Changning	0.732	0.257	0.022	0.897	−5.301	0.031
Changsha	0.784	−0.208	0.022	0.830	−8.222	0.044
Chenzhou	0.752	0.057	0.016	0.900	−3.799	0.024
Daoxian	0.840	0.257	0.019	0.898	−4.791	0.028
Hengyang	0.755	0.014	0.025	0.816	−10.537	0.049
Jinggangshan	0.551	0.173	0.020	0.720	−0.775	0.029
Lianzhou	0.811	−0.143	0.016	0.907	−4.089	0.022
Mapoling	0.698	−0.077	0.025	0.764	−1.571	0.034
Nanyue	0.801	−0.072	0.023	0.709	−9.263	0.049
Pingjiang	0.761	0.433	0.023	0.823	−2.877	0.030
Shuangfeng	0.777	−0.048	0.021	0.809	−8.339	0.044
Yichun	0.758	−0.053	0.016	0.857	−0.405	0.029
Yongzhou	0.843	0.393	0.020	0.909	−5.274	0.030
Zhuzhou	0.777	0.548	0.025	0.821	−5.191	0.033

TABLE 2. The performance of SVM for root mean soil moisture prediction in Wei River basin. The correlation coefficients pass the significance test with $p < 0.01$.

	Training			Test		
	R	BIAS (%)	RMSE ($\text{m}^3 \text{m}^{-3}$)	R	BIAS (%)	RMSE ($\text{m}^3 \text{m}^{-3}$)
Changwu	0.788	0.537	0.023	0.644	-9.309	0.034
Fengxiang	0.697	-0.386	0.019	0.625	-10.866	0.037
Guyuan	0.787	1.086	0.027	0.650	-9.479	0.042
Huajialing	0.876	1.663	0.028	0.550	-3.138	0.021
Huanxian	0.794	0.962	0.028	0.745	-6.025	0.025
Jinghe	0.648	-0.369	0.018	0.682	-15.168	0.054
Kongtong	0.813	0.017	0.023	0.656	-10.100	0.036
Liupanshan	0.889	1.147	0.031	0.683	-10.074	0.040
Longxian	0.659	0.374	0.022	0.532	-13.190	0.043
Luochuan	0.766	0.009	0.017	0.672	-10.681	0.035
Maiji	0.605	-1.257	0.027	0.688	-12.404	0.043
Pucheng	0.726	-0.611	0.017	0.646	-8.615	0.028
Qindu	0.628	-0.939	0.021	0.672	-13.907	0.051
Shangzhou	0.724	0.056	0.022	0.542	-5.287	0.027
Taibai	0.858	1.573	0.036	0.498	-6.155	0.031
Wugong	0.558	-2.252	0.027	0.608	-15.017	0.054
Wuqi	0.812	0.602	0.032	0.653	-4.024	0.024
Xifeng	0.753	1.393	0.031	0.625	-9.892	0.037
Xiji	0.847	1.074	0.027	0.706	-7.163	0.028
Yaozhou	0.720	-0.517	0.016	0.695	-10.135	0.033
Yongshou	0.674	-0.373	0.021	0.631	-13.609	0.043

training stage and test stage are 0.67 and 0.65, respectively (Table 4). And 18 events identified by soil moisture predictions did not actually occur in this basin, which means they are false alarms. The FAR are 0.35 and 0.16 at training and test stages, respectively.

In general, over 67%–76% of events in the training stage and over 65%–70% of events in the test stage can be identified using the predicted soil moisture. However, above 25% of flash drought events are not captured in both basins. And false alarms also exist. To better evaluate the prediction performance, TS is also adopted as an overall indicator (Table 4). The TS at the training stage and the test stage are 0.63 and 0.54 over Xiang River basin. As for Wei River basin, TS are slightly lower, with 0.49 and 0.58 for the training and test stages. Therefore, the prediction method that using SVM to predict soil moisture for flash drought identification can be considered to have a moderate prediction skill.

To further illustrate the performance of flash drought prediction based on the predicted soil moisture, the spatial distributions of the predicted flash drought events are shown in Figs. 9 and 10. In Xiang River basin, the predictions overestimate the occurrence times of flash drought at two stations, while underestimate them at one station. The FOC of predicted flash droughts shows good performance at most stations except at Jinggangshan, Yichun, Pingjiang, and Hengyang stations. In Wei River basin, it can be observed that the occurrence times of predicted flash droughts are underestimated at four stations and overestimated at eight stations. The FOC of predicted flash droughts shows some biases, ranging from 0% to 6%. The maximum bias presents at Huanxian station.

5. Discussion

a. Comparison of spatiotemporal characteristics of flash droughts between two basins

The above results show that more flash droughts occur in Xiang River basin during 2017–19, with longer duration, larger FOC, and worse severity than that in Wei River basin. To explore the reasons for the different characteristics of these flash droughts in the two basins, several factors of the two basins are taken into consideration, including land use types, vegetation coverage, temperature, and precipitation patterns. The land use maps are achieved from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (<http://www.resdc.cn>). Considering the study period ranges from 2017 to 2019, the land use data in 2018 is adopted in this study. The land use at the stations over Xiang River basin is dominated by forest and agricultural land (Fig. 11a). The main land use types at the stations over Wei River basin are agricultural land and grassland (Fig. 11b).

TABLE 3. The comparison between the flash drought events identified by the predicted soil moisture and the reference soil moisture.

	Xiang River basin		Wei River basin	
	Training stage	Test stage	Training stage	Test stage
Hits	25	7	24	15
Misses	8	3	12	8
False alarm	7	3	13	3

TABLE 4. The POD, FAR, and TS for the flash drought event prediction based on the predicted soil moisture.

	Xiang River basin		Wei River basin	
	Training stage	Test stage	Training stage	Test stage
POD	0.76	0.70	0.67	0.65
FAR	0.22	0.30	0.35	0.16
TS	0.63	0.54	0.49	0.58

There are a few stations over Wei River basin dominated by forest. In addition, the southeast corner of Wei River basin is dominated by the urban and built-up land, as well as the agricultural land, which means the stations located at the northwest and southeast corners of Wei River basin has relatively lower vegetation coverage (Fig. 12).

Considering the land use types and vegetation coverage of these two basins, it can be found that the forest land usually has a high normalized difference vegetation index (NDVI) value. The grassland and the agriculture land, which also account for considerable area in these two basins, usually have relatively low NDVI values. Therefore, it reveals that the more onset times of flash drought at the stations over Xiang River basin may be due to the dense vegetation. This finding is also consistent with some previous studies (Li et al. 2020a; Wang et al. 2016; Zhang et al. 2017). Another possible reason for flash drought to occur more frequently in agricultural/grasslands versus forested locations is that the former land use has a shallower root zone, while forested regions have deeper root zones that can access more subsoil moisture and limit rapid intensification toward drought (Christian et al. 2019a, 2020). However, contrary to the finding, it is interesting that the frequency of flash drought occurrence at the southeast corner of Wei River basin, which has a low NDVI value, is relatively higher than other parts of the basin (Fig. 4). Therefore, some

other factors probably also contribute to the characteristics of flash drought.

To further explore the other factors related to the spatial distribution of the occurrence of flash drought, the spatial distribution of the mean temperature alongside precipitation patterns during the April–October months from 2017 to 2019 are illustrated in Fig. 13. As mentioned above, GPM_3IMERGM and ERA5 are used to illustrate the pattern of precipitation and temperature. Figure 13 shows that precipitation in the central part of Xiang River basin mainly ranges from 1000 to 1100 mm, and precipitation in most parts of the basin is around 1000–1200 mm. The southwest and the northeast corners have relatively higher precipitation, where the FOC of flash drought is also higher. The temperature of most parts of the basin is around 23°–25°C. On the other hand, the precipitation and temperature in Wei River basin show a pattern of gradually decreasing from the southeast to the northwest (Fig. 14). The spatial distribution of the FOC of flash droughts in Wei River basin also presents a similar pattern with that of precipitation and temperature. According to the temperature mode, precipitation pattern and FOC of flash droughts in the two basins, it indicates that the flash drought is more likely to occur in warm and humid regions, which is consistent with the conclusions in other related studies (Liu et al. 2020a; Zhang et al. 2017). It is because the rapid soil moisture decline should be a result of the intensification of ET driven by higher temperature (Wang et al. 2016; Zhang et al. 2017). However, whether the rising temperature causes ET to increase or decrease is uncertain because drought conditions usually inhibit ET, especially in arid and semiarid regions (Yuan et al. 2019). Therefore, humid and semihumid regions are more likely to sustain high ET amount in a few pentads, which can subsequently lead to the rapid decrease of soil moisture. Above all, the results show that the occurrence of flash drought is related to both the land coverage factors and

FIG. 9. (a) The onset times and (b) the frequency of occurrence (FOC) of the flash drought events identified based on the predicted with SVM during the growing seasons in Xiang River basin.

FIG. 10. (a) The onset times and (b) the frequency of occurrence (FOC) of the flash drought events identified based on the predicted with SVM during the growing seasons in Wei River basin.

the meteorological factors. In general, flash drought is more likely to occur in a humid and warm basin with dense vegetation, such as Xiang River basin, which is also consistent with the results found in some other studies (Ford and Labosier 2017; Otkin et al. 2013).

b. Driving mechanism of flash drought development

The results in section 4b reveal that the development of flash drought is closely related to all the selected meteorological variables in this study, except Ws. The negative anomalies of P show that precipitation deficit causes decrease in Rh, soil moisture and evapotranspiration. The decreased evapotranspiration in turn results in the increase in temperature (Zhang et al. 2017). The abnormal elevation of T , which also reflects on the elevated Rs, causes PET to increase. The deficit between P and PET further leads to the rapidly decreasing soil moisture. Therefore, it can be concluded that the driving factors of flash drought are similar over two basins with different climate types, which mainly are precipitation deficit and abnormally high temperature.

As for the lead time, the quick evolution of flash drought conditions observed in these two regions indicates that a long-term

anomaly of meteorological condition is not necessary for the occurrences of flash drought. The lack of precipitation and extreme heat that last for 1–2 weeks could lead to the beginning for the occurrence of flash drought. And the anomaly needs to persist for 2 pentads for flash drought to develop. Therefore, it suggests that the development flash droughts in these two basins are associated with relatively short-period (15–25 days) anomaly of the meteorological conditions. This finding is consistent with the conclusions in some other studies (Ford and Labosier 2017; Wang and Yuan 2018).

In addition, when comparing the anomalies in these two basins, an interesting difference can be found. The anomalies of precipitation at 3 pentads prior to the onset are negative in Xiang River basin, while positive in Wei River basin. It may be due to the drier climate in Wei River basin, compared to Xiang River basin. If the antecedent soil condition is dry, it is difficult for the soil moisture to drop rapidly because of the limited evaporation (Ford and Labosier 2017; Mo and Lettenmaier 2016; Zhang et al. 2017). Proper precipitation may temporarily increase soil moisture and provide conditions for occurrences of flash drought. It also indicates that the anomalies of

FIG. 11. Land use of 2018 in (a) Xiang River basin and (b) Wei River basin.

FIG. 12. Spatial distribution of annual normalized difference vegetation index (NDVI) in some regions of China.

precipitation and temperature in only one pentad do not necessarily lead to the onset of flash drought, because the anomalies need to remain positive/negative for a few pentads for the flash drought to develop. Otherwise, the dry condition of soil can be quickly recovered with the meteorological conditions back to the normal level.

The findings are meaningful and can provide reference for future studies on flash drought. But there are still some limitations. The research period selected this study is three years due to the limitation of the reference dataset. Therefore, the driving mechanism is discussed based on limited events, which may have difficulty to reveal a comprehensive evolutionary mechanism related to meteorological conditions. More data sources with long time series, such as reanalysis soil moisture datasets, may be adopted to further investigate the characteristics and influence factors of flash drought in the future studies.

c. The early warning for flash drought

The early warning of flash drought is paid much attention to in recent years (Ford et al. 2015; Pendergrass et al. 2020). The flash drought prediction shown in the above results is based on the meteorological variables and remote sensing surface soil moisture dataset. The results indicate that flash drought can be identified by combining appropriate model and reliable datasets. Therefore, the prediction of flash drought is capable to bring possibility for the early warning of flash drought.

Nevertheless, the misses and false alarms in the prediction of flash drought cannot be ignored. There are overestimation or underestimation in the occurrence times of flash drought at about half stations in Wei River basin. The difficulties in flash drought prediction proposed by Pendergrass et al. (2020) still remain big challenges. The performance of flash drought prediction in Xiang River basin is obviously better than that in Wei River basin, due to the more accurate prediction of root mean soil moisture. Therefore, the early warning of flash drought may be achieved by obtaining more accurate prediction of soil moisture and meteorological variables.

Since the accuracy of soil moisture prediction may be limited to the efficiency of SVM, a deep learning method, for instance, the long short-term memory (LSTM) model, is also applied to probe its potential in soil moisture prediction (Shen 2018; Shen et al. 2018). We selected three typical stations as examples, namely, Longxian, Jinggangshan, and Yongzhou, to compare the performance of SVM and LSTM in root mean soil moisture prediction (Table 5). Compared with SVM in the training stage, LSTM shows better performance in terms of R and RMSE. However, their performance is comparable in the test stage, with LSTM outperforming SVM slightly. It justifies the use of SVM, and indicates that deep learning method can be an alternative way to improve the prediction of soil moisture for flash drought identification, which can be explored in future studies.

In addition, it can be observed that misses and false alarms both exist in the prediction. Apart from utilizing deep learning

FIG. 13. Spatial distribution of (a) precipitation and (b) mean temperature during April–October (2017–19) in Xiang River basin.

FIG. 14. Distribution of (a) precipitation and (b) mean temperature during April–October (2017–19) in Wei River basin.

method to improve the prediction of soil moisture, as mentioned above, it is possible to reduce the misses by changing the identification frame in the prediction process. Ford and Labosier (2017) states that the main reason for the less identified flash drought in their study than that reported in Mo and Lettenmaier (2015, 2016) is that the lower selection of the threshold of soil moisture percentile. Zhang et al. (2017) also compared the frequency of occurrence for flash drought under different percentile thresholds of soil moisture. The results show that the higher percentile thresholds lead to higher frequency of the identified flash drought. Therefore, increasing the percentile thresholds of soil moisture in the identification process in prediction can probably increase the captured events. Although some of these predicted events maybe false alarms, the decrease in misses is meaningful for the early warning of the disasters.

6. Conclusions

This study diagnosed the spatiotemporal characteristics of flash drought and its driving factors in two agriculture-domain basins with different typical climate conditions in China. The drought patterns in one semiarid region, namely, Wei River basin, and one humid region, Xiang River basin, were compared. Additionally, soil moisture was predicted by SVM coupled with SMAP for flash drought identification to explore the possibility for its early warning. The main conclusions can be summarized as follows:

1) The flash droughts occurred in Xiang River basin usually have the longer duration, larger FOC, and higher severity

than that in Wei River basin. Additionally, flash drought events are more likely to occur in July–October in Xiang River basin, while they are more likely in April–July in Wei River basin.

- 2) The spatial distribution of flash drought is attributable to vegetation coverage and the pattern on precipitation and temperature. It is more likely to occur in humid and subtropical regions with dense vegetation.
- 3) The development mechanism of flash drought is closely related to the meteorological conditions. The P and RH present negative anomalies prior to the onset of flash drought, while $T_{\max}$, R_s , and PET show positive anomalies. The deficit in precipitation and the high temperature are the main driving factors for flash drought development over Xiang River basin and Wei River basin. The evolution of meteorological conditions from two pentads before the onset to two pentads after that shows similar pattern in both basins.
- 4) According to the R , BIAS, and RMSE, SVM can be considered as a reliable method for root zone soil moisture prediction at daily scale at the stations in Wei River basin and Xiang River basin.
- 5) The accuracy of flash drought prediction is generally acceptable, with TS ranging from 0.49 to 0.63. About 65%–70% of events can be captured based on the predicted soil moisture with SVM in the training stage and the testing stage. However, false alarms exist in most stations in both basins, with FAR lower than 0.35. The prediction of flash drought still faces some difficulties and challenges.

TABLE 5. The performance of SVM and LSTM for root mean soil moisture prediction. The correlation coefficients pass the significance test with $p < 0.01$.

		Training			Test		
		R	BIAS (%)	RMSE ($\text{m}^3 \text{m}^{-3}$)	R	BIAS (%)	RMSE ($\text{m}^3 \text{m}^{-3}$)
Longxian	SVM	0.659	0.374	0.022	0.532	−13.190	0.043
	LSTM	0.889	−0.371	0.013	0.647	−6.753	0.028
Jinggangshan	SVM	0.551	0.173	0.020	0.720	−0.775	0.029
	LSTM	0.807	−0.219	0.014	0.788	−1.859	0.025
Yongzhou	SVM	0.843	0.393	0.020	0.909	−5.274	0.030
	LSTM	0.941	−1.238	0.013	0.959	−0.915	0.019

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Data availability statement. SMAP soil moisture data and GPM 3IMERGM precipitation data are provided by National Aeronautics and Space Administration (NASA) from <https://earthdata.nasa.gov/>. CLSMDAS soil moisture data and the in-situ meteorological data are provided by the China Meteorological Administration from <http://data.cma.cn/>. The land use maps and NDVI data are provided by the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) from <http://www.resdc.cn>. The ERA5 reanalysis temperature data are provided by European Center for Medium-range Weather Forecasts (ECMWF) from <https://www.ecmwf.int>.

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