Response to Editor and Reviewers

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Article title: Analysis of flash droughts in China using machine learning technologies

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Dear reviewers and editor:

Thank you so much for valuable comments and kind suggestions on our paper. Your illuminating comments and suggestions give us the possibility to properly fix several questionable issues, and to improve the overall quality of the paper. We highly appreciate your time and effort. Please find our point-to-point responses to your comments below.

Response to reviewer #1

1. This paper studies the predictability of flash drought over China using machine learning methods. The starting point is ERA5 soil moisture over China for the period 1979-2021. They use a definition of flash drought based on changes in soil moisture percentiles (SMP) which they term the rate of intensification (RI) during periods when SMP is decreasing. They define flash droughts as occurring when SMP crosses the 40th percentile and is decreasing at a rate of at least 6.5 percent per week (time step is weekly). There is some confusion in Figure 1 and text surrounding it as to whether crossing of the 20th percentile of SMP is also required (the figure implies this, but text does not). There also is a criterion for a termination time Tn "when the rapid decline of soil moisture ceases", but this is not shown in Figure 1 nor are specifics in the text.

Response: We thank the reviewer's comment. In the revised manuscript (no marks), we added some descriptions in Page 5 Lines 159-160 to clarify two detailed requirements for extracting drought events: "*Specifically, the drought events are extracted from the entire period by following two requirements below: (1) soil moisture falls below the 40th percentile, and (2) soil moisture should decay to below the 20th percentile.*". The original symbol T_n which represents the termination time of the onset-development phase was replaced by T_{0+d} in order to keep its consistency between Fig. 1(a) and Fig. 1(b). We adjusted the formula of the intensification rate of drought events and revised some related descriptions as below:

In Page 6 Lines 173-177:

$$RI = \frac{1}{d+1}\sum_{i=0}^{d}\left[\frac{SM(T_{i+1})-SM(T_i)}{T_{i+1}-T_i}\right], \quad T_0 \leq T_i \leq T_{0+d}, \tag{1}$$

$$s.t = \{\min[SM(T_i)] \leq 20th\}, \tag{2}$$

"Where T_0 is the onset time, T_{0+d} denotes the termination time for the onset-development phase, d is the duration of onset-development phase, $SM(T_i)$ is the soil moisture percentile at time T_i in the rapid intensification process of drought."

In Page 6 Lines 168-170:

"*T_{0+d} denotes the termination time for the onset-development stage when the rapid decline of soil moisture ceases…*"

"T_{0+d} can be determined through a polynomial function and located when the first derivative of the constructed polynomial equals zero in calculus."

Besides, we revised Figure 1 in the original manuscript to show the termination time T_{0+d} clearly. For the specific identification method of the termination time, we added one sentence in Page 6 Lines 170-171: *"The detailed determination process of T_{0+d} is presented in our previous study (Liu et al. 2020a)."*

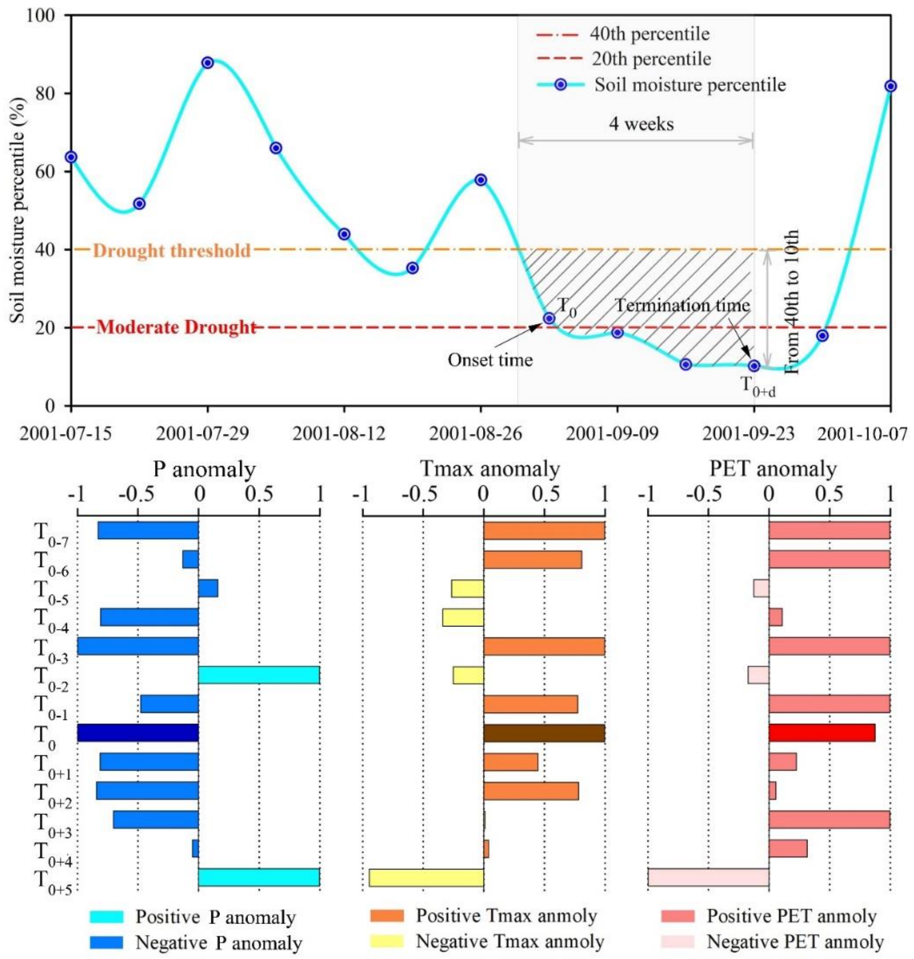

Fig.1 A concept map for identifying flash droughts.

2. My main problem with this paper is philosophical. Why are you using machine learning at all? It reflects no physical process understanding water – you just throw a bunch of variables that you think could possibly have something to do with RI and turn the crank. Rather obviously, flash droughts are going to occur during dry periods (during precipitating periods, presumably soil moisture increases rather than decreases). So given that it's dry, it must have to do with evaporative demand, and the soil moisture you start with. We do understand those processes (albeit imperfectly), so surely you could use a physically based model to predict the RI. Now, if you did that first, and then applied ML and could somehow (not clear at all to me how) use the ML predictions to diagnose the physically based ones so as to improve them, I would be interested. But I don't really see where the hydrologic content is in this paper.

Response:

Thanks for your comments. We agree that a physically-based model is helpful to understand the physical process of flash drought. Flash drought is an emerging and ongoing topic in the drought community during the past ten years. It has a rather complicated evolving process and is influenced by a variety of factors in its different development stages. A variety of studies have analyzed the characteristics of flash drought at global and regional scales, though there is no consistent notion on how we define flash droughts in the community (e.g., Ford et al. 2015; Otkin et al. 2018; Liu et al., 2020a). Especially, the physically driven mechanism of flash drought is still uncertain. Given the current progresses of the flash drought field, it is difficult to predict RI using physical-based models. The three machine learning (ML) technologies (i.e., MLR, RF, and LSTM) were used to establish the relationship between RI and predictors, which can be served as references for recognizing and understanding the physical formation and development features of flash droughts.

We agree that it is difficult to use ML technologies to reflect the physical process of flash drought. However, these ML technologies have advantages in providing a fast and direct mapping pathway between the independent and dependent variables based on a combination of abundant data and advanced model architectures (Feng et al., 2021; Sahoo et al., 2017; Yang et al., 2020). Also, they can provide an accurate estimation of soil moisture, though the input samples are limited (Long et al., 2019). Given this, we considered using the ML models to evaluate the feasibility of flash droughts simulation over China. Our current study is to figure out the statistical interaction between RI and the anomalies of meteorological factors, which is beneficial for understanding the physical mechanism of flash droughts.

Besides, we appreciate the reviewer for providing a good idea that we can diagnose the physical-based models using machine learning technologies to improve the performance of the former models. This might be a study direction in the future flash drought field. However, considering the reason for the unclear physical mechanism of flash droughts, we applied the ML models to analyze the potential relationship between the RI and anomalies of climate factors in the current work. This is the first step before we effectively construct physical-based models to simulate and predict the RI in the future. The advantages for using machine learning algorithms have been supplemented in the introduction section in Page 4 Lines 105-111:

"*These ML technologies have superiorities in providing a fast and direct mapping pathway between the independent and dependent variables without further a priori knowledge about, or assumptions on, underlying physical processes (Feng et al., 2021; Sahoo et al., 2017; Yang et al., 2020). They can capture key information hidden in historical data, and then apply these patterns to predict target data in future scenarios.*

Also, they can provide an accurate estimation of soil moisture, though the input samples are limited (Long et al., 2019; Almendra-Martín, et al., 2021). However, limited studies focused on flash droughts simulation based on ML technologies."

References:

Almendra-Martína, L., Martínez-Fernandez´, J., Piles, M., ´Gonzalez-Zamora´, A.: Comparison of gap-filling techniques applied to the CCI soil moisture database in Southern Europe, Remote Sens. Environ., 258, 112377, https://doi.org/10.1016/j.rse.2021.112377, 2021.

Feng, Z., Niu, W., Tang, Z., Xu, Y., Zhang, H.: Evolutionary artificial intelligence model via cooperation search algorithm and extreme learning machine for multiple scales nonstationary hydrological time series prediction, J. Hydrol., 595, 126062, https://doi.org/10.1016/j.jhydrol.2021.126062, 2021.

Ford, T. W., McRoberts, D. B., Quiring, S. M., Hall, R. E.: On the utility of in situ soil moisture observations for flash drought early warning in Oklahoma, USA, Geophys. Res. Lett., 42:9790–9798, https://doi.org/10.1002/2015GL066600, 2015.

Liu, Y., Zhu, Y., Ren, L., Otkin, J., Jiang S.: Two Different Methods for Flash Drought Identification: Comparison of Their Strengths and Limitations, J. Hydrometeorol., 21: 691-704, https://doi.org/10.1175/JHM-D-19-0088.1, 2020a.

Long, D., Bai, L., Yan, L., Zhang, C., Shi, C., Yang, W., Lei, H., Quan, J., Meng, X., Shi, C.: Generation of spatially complete and daily continuous surface soil moisture of high spatial resolution, Remote Sens. Environ., 233, 10.1016/j.rse.2019.111364, 2019.

Otkin, J. A., Svoboda, M., Hunt, E. D., Ford, T. W., Anderson, M. C., Hain, C., Basara, J. B.: Flash Droughts: A review and assessment of the challenges imposed by rapid onset droughts in the United States, Bull. Am. Meteorol. Soc., 99(5), 911-919, https://doi.org/10.1175/BAMS-D-17-0149.1, 2018.

Sahoo, S., Russo, T. A., Elliott, J., Foster, I.: Machine learning algorithms for modeling ground water level changes in agricultural regions of the U.S., Water Resour. Res., 53, 3878–3895, https://doi.org/10.1002/2016WR019933, 2017.

Yang, S., Yang, D., Chen, J., Santisirisomboon, J., Zhao, B.: A physical process and machine learning combined hydrological model for daily streamflow simulations of large watersheds with limited observation data, J. Hydrol., 590(1): 125206, http://doi.org/10.1016/j.jhydrol.2020.125206, 2020.

3. My other complaint is that key information needed to understand the results is either buried in text or missing altogether. For instance, were flash drought periods extracted from the entire period of record, without regard for season? Ordinarily, one would expect such events to occur primarily in summer, when evaporative demand is the highest. But RI is determined in terms of soil moisture percentage changes, which

complicates the picture considerably. In winter, for instance, evaporative demand will be reduced, but the range of soil moisture percentages likely is also reduced, so it could be that the statistics of RIs are being dominated by events that in a practical sense aren't really droughts at all. I don't know if this is true but constraining the analysis to a window in the summer (if this hasn't already been done – I searched the document and didn't find any indication that it was) would make the most sense.

Response:

Thanks for pointing out that. Yes, we extracted flash drought from the entire period of record. When we designed the manuscript, we also first focused on flash droughts in the summertime as the reviewer suggested. We analyzed the identification results carefully and found flash droughts are prone to occur during the cross seasons (e.g., spring-summer or the summer-autumn). Constraining the analysis to a window in the summer may miss the continuous development process of flash drought. Given the above considerations, we preferred to analyze flash droughts by using the entire period. The main reasons are listed below: Firstly, our method relies on continuous time series of soil moisture percentile. The intermittent data makes it hard to capture the onset, or termination of drought events accurately, and the continuity and integrity of the datasets are important for identifying the development process of drought. Secondly, some important information related to flash droughts might be ignored if we merely focus on them in the summer. Previous studies showed that flash droughts may coexist with the seasonal drought and cross-seasonal drought due to the diverse climatic conditions and underlying surface (i.e., the soil texture and vegetation cover) of China (Liu et al., 2020b). Meanwhile, according to their study, cross-season drought events easily started from spring (April and May) and summer (June and July). We also analyze the frequency of flash drought occurrence (FOC, Mo et al., 2016) in different seasons, as shown in Fig. 2. According to our identification results, the frequency of flash drought occurrence in winter is the lowest, and for 84% of the study area, the FOC is no more than 5% (Fig. 2a). This low value may have tiny influences on the simulation results. Based on the above analysis, we were more inclined to use the entire period for RI simulation and prediction of flash droughts. We considered your suggestion carefully and supplemented some expressions in Page 6 Lines 178-185 in the revised manuscript to explain the reason why we focused on the entire period.

"In this method, we extracted flash droughts from the entire period of records, the

main reasons are listed: Firstly, our method relies on continuous time series of soil moisture percentile. The intermittent data makes it hard to capture the onset, or termination of drought events accurately, and the continuity and integrity of the datasets are important for identifying the development process of drought. Secondly, enough important information related to flash droughts need be included in the ML models because flash droughts may coexist with the seasonal drought and cross-seasonal drought due to the diverse climatic conditions and underlying surface (i.e., the soil texture and vegetation cover) of China (Liu et al., 2020b). Thirdly, the occurrence of flash drought in winter is limited, which may have tiny influences on the simulation results."

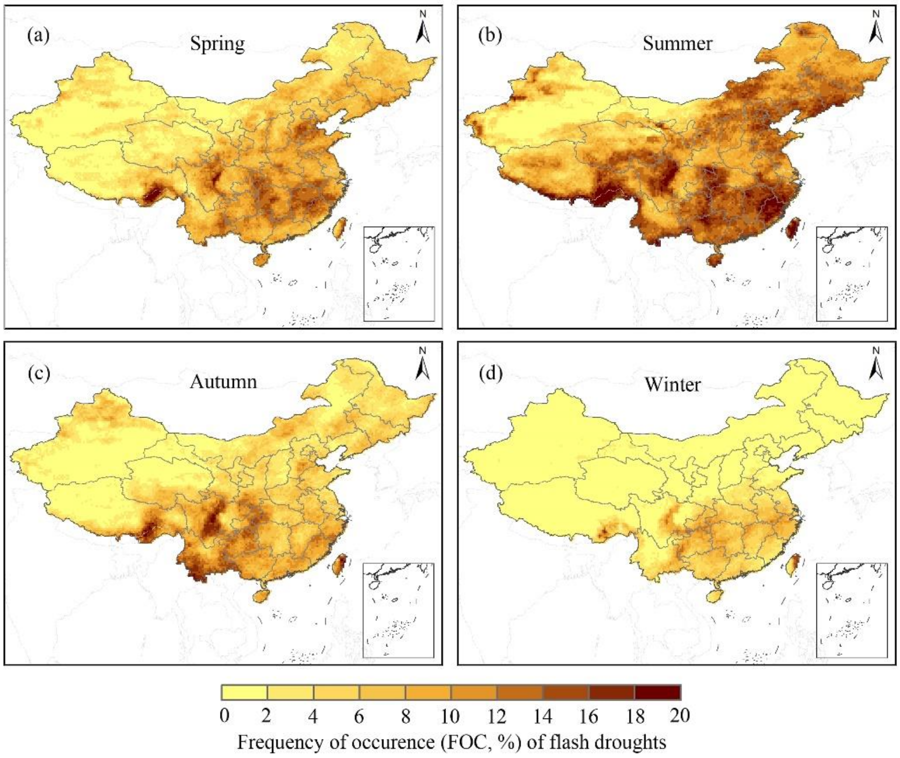

Fig.2 Spatial distribution of frequency of occurrence of flash droughts in different seasons over China

References:

Mo, K. C., Lettenmaier, D, P.: Precipitation deficit flash droughts over the United States, J. Hydrometeorol., 17(4): 1169-1184, https://doi.org/10.1175/JHM-D-15-0158.1, 2016.

Liu, Y., Zhu, Y., Zhang, L., Ren, L., Yuan, F., Yang, X., Jiang, S.: Flash droughts characterization over China: From a perspective of the rapid intensification rate, Sci. Total Environ., 704,135373, https://doi.org/10.1016/j.scitotenv.2019.135373, 2020b.

Response to reviewer #2

Overall, I consider this to be a worthwhile contribution to the rapidly expanding flash drought literature. The authors provide a new definition that can be compared to other proposed definitions and they examine association with a range of potential drought predictors. My two major comments are on the framing and the comparison between flash droughts and "slow droughts."

Response: We thank the reviewer for the positive comments to our study and please see our responses in detail below.

Major comments:

1. The methods applied in the study are, formally, supervised statistical learning algorithms. While one can debate what "AI" means, I think it's fair to assume that very few people think of linear regression, or even nonparametric statistical approaches like Random Forest, as AI. LTSM does sometimes get put in the AI basket, but it's no longer really a leading edge, advanced AI application. All that to say, I was surprised by the content of the manuscript after reading the title, and I suspect others may be as well. The paper simply does not provide an AI-oriented methodological advance, nor does it present results that are interesting because of novel application of relatively new methods. For this reason I recommend retitling and reframing the paper to focus on the flash drought findings, and removing the prominent use of the term AI in title, abstract, and throughout the paper. There are many published studies in many fields that compare performance of parametric and nonparametric methods for various applications, sometimes including NN as well, and at this point I really think that the difference in performance between those methods is best presented as a comparison of statistical methods that is useful but not particularly innovative. Instead, I recommend that the authors focus on their actual flash drought results in the framing of the paper, as those results are quite interesting for the flash drought community.

Response:

Thank you for pointing out that. We agree with the reviewer's comment that these three methods (i.e., MLR, RF, and LSTM) are inappropriate to consider as artificial intelligence (AI) technologies. As you mentioned, these parametric and nonparametric methods were named machine learning (ML) technologies in previous studies (Bouras et al., 2021; Liakos et al., 2018; Schwalbert et al., 2020). Following your suggestions and previous studies, we classified these methods i.e., MLR, RF, and LSTM into machine learning technologies and modified the original title to "Analysis of *Flash Droughts in China using Machine Learning*". The new title would be better to reflect the key point of flash drought in this work. We corrected sentences containing AI terms and replaced them with descriptions of machine learning technologies. The detailed revisions are shown as below:

In Page 1 Lines 16-17:

"The relationship between the rate of intensification (RI) and nine related climate variables is constructed using three machine learning (ML) technologies, namely, multiple linear regression (MLR), long short-term memory (LSTM), and random forest (RF) models."

In Page 1 Line 22-23:

"For drought detection, all three ML technologies presented a better performance in monitoring flash droughts than in conventional slowly-evolving droughts."

In Page 1 Line 32:

"This study is valuable to enhance the understanding of flash drought and highlight the potential of ML technologies in flash droughts monitoring."

In Page 4 Lines 118-121:

"In Section 4, we present the evaluation of RI simulation results, the performance comparison of ML technologies in terms of flash droughts and slow evolving droughts, as well as a specific investigation on typical flash drought events. Section 5 discusses the potential reasons for the varied performances of ML models in RI estimation, and their feasibilities in flash droughts detection."

In Page 10 Lines 273-276:

"In addition, three skill scores, including the probability of detection (POD), false alarm ratio (FAR), and critical success index (CSI), were employed to measure the performances of three ML technologies in flash droughts detection. All these three metrics indices range between 0 and 1. POD and CSI show the ratio of detected flash droughts by the ML technologies to observed flash droughts, and the higher values, the better performances of ML technologies in flash droughts detection."

In Page 10 Lines 281-283:

"…where H (Hits) represents flash droughts both detected by the ML methods and observations; F (False alarms) represents the case when flash droughts captured by ML approaches but not recorded in observations. M (Misses) represents flash

droughts recorded in observations but not captured by ML approaches."

In Page 11 Lines 285-286:

"The general flowchart for evaluating the performances of ML technologies (i.e., MLR, LSTM, and RF model) in flash drought detection is presented in Fig. 2."

In Page 12 Line 299:

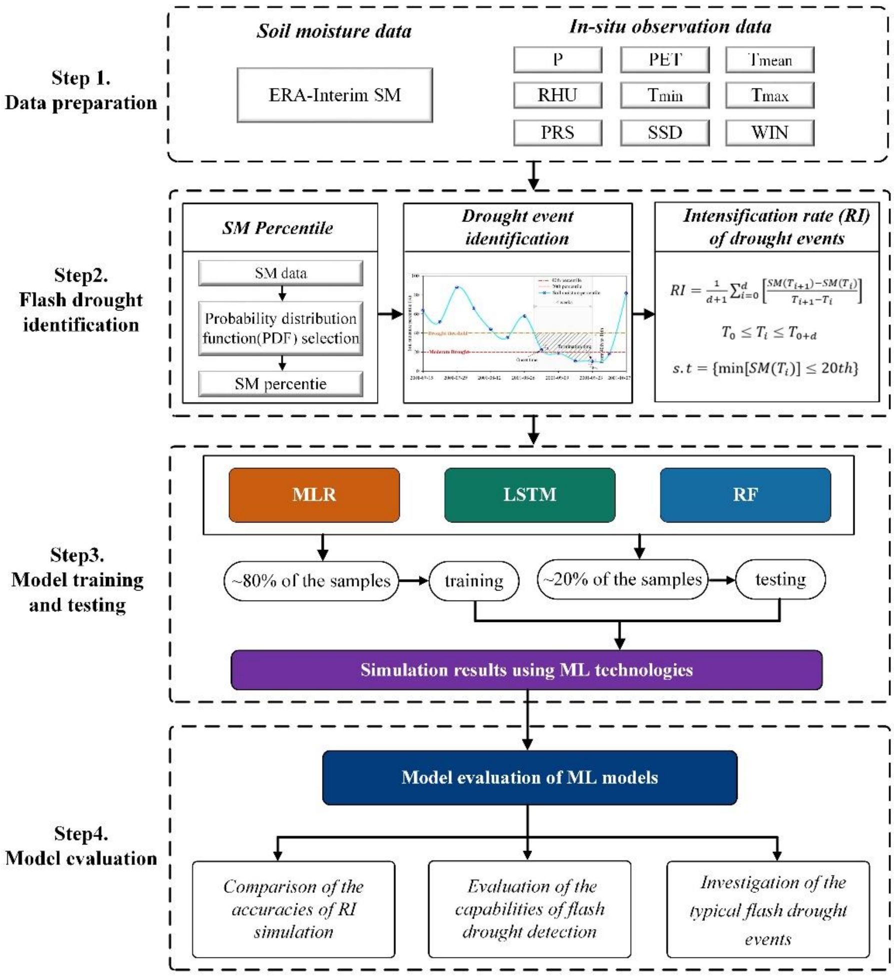

Figure 2: The flow chart of evaluating the performances of ML models for flash droughts detection.

In Page 12 Line 300:

"Figure 2: The flow chart of evaluating the performances of ML models for flash droughts detection."

In Page 12 Lines 303-304:

"The capabilities of ML technologies in simulating the RI of soil moisture were assessed through intercomparison with the observed RI derived from ERA soil moisture."

In Page 13 Line 312:

"Based on the observed RI and simulations from three ML technologies (i.e., MLR, LSTM, and RF), Fig. 4 shows the…."

In Page 13 Line 318:

"Among the three ML models, the RF performed best, as shown in Figs. 5e and f, …"

In Page 16 Line 346:

"To evaluate the capabilities of three ML models in detecting drought events, we analyzed…"

In Page 17 Lines 377-378:

"In general, all three ML models provided more reliable information in detecting flash droughts than slowly-evolving droughts."

Page 20 Lines 390-391:

"The ability of capturing the migration trajectories of droughts over time and space is also important for evaluating the capabilities of candidate ML models in drought detection."

In Page 22 Lines 416-418:

"5.1 Performance of ML technologies for RI estimation

In this study, we evaluated three ML technologies, and found RF provided the best estimations of RI with higher CC and lower RMSE comparing to the observed RI (Figs. 4 and 5)."

In Page 26 Lines 466-467:

"5.2 Comparison of ML technologies for flash droughts and slowly-evolving droughts

In this study, all three ML models produced better RI estimations of flash droughts than those of conventional droughts…"

In Page 28 Line 546-547:

"Furthermore, these ML methods displayed a relatively higher detection capacity of flash droughts than that of traditional slowly evolving droughts."

In Page 29 Lines 554-556:

"This work would help enhance the understanding of flash droughts and provide a reference for the application of ML models on simulating flash droughts."

Reference:

Bouras, E. h., Jarlan, L., Er-Raki, S., Balaghi, R., Amazirh, A., Richard, B., Khabba, S.: Cereal Yield Forecasting with Satellite Drought-Based Indices, Weather Data and Regional Climate Indices Using Machine Learning in Morocco, Remote Sens., 13, 3101, https://doi.org/10.3390/rs13163101, 2021.

Liakos, K. G., Busato, P., Moshou1, D., Pearson, S., Bochtis, D.: Machine Learning in Agriculture: A Review, Sensors, 18, 2674, http://doi.org/10.3390/s18082674, 2018.

Schwalbert, R. A., Amado, T., Corassa, G., Pott, L. P., Prasad, P. V. V., Ciampitti, I. A.: Satellite-based soybean yield forecast: Integrating machine learning and weather data for improving crop yield prediction in southern Brazil, Agric. For. Meteorol., 284, 107886, http://doi.org/10.1016/j.agrformet.2019.107886, 2020.

2. I appreciate the section of the manuscript that compares the predictability of flash drought to conventional drought. But in making this distinction the authors implicitly assume that flash and slow droughts, as distinguished using the RI threshold employed in this paper, are meaningful and relatively homogeneous types of drought with respect to the predictor variables. Are the flash droughts and slow droughts in the inventory relatively homogeneous and separable with respect to these predictors, when evaluated using standard clustering or homogeneity tests? And is there evidence of the greater spread in meteorological predictors for slow drought relative to flash drought, as the authors suggest when explaining poorer performance in predicting slow droughts as a function of meteorology?

Response:

We thank the reviewer for their work and the positive comments. Yes. Flash droughts and slowly-evolving droughts are relatively homogenous and separable with respect to these predictors. Figure 3 shows the anomalies of meteorological elements (i.e., average temperature (Tmean), maximum temperature (Tmax), potential evapotranspiration (PET), precipitation (P), and relative humidity (RHU)) at the onset phase of flash droughts and traditional droughts across China. It shows that the climate driving of two types of droughts is significantly different. For energy-related meteorological elements, their average anomalies of flash droughts are more than 1-fold of standard deviation, which is generally larger than that of conventional droughts. As for the moisture-related climate factors, their anomalies of rapid intensification droughts are lower than that of slowing developing droughts. For the RI threshold method used in this study, we first identified drought events and calculated the decline rate of soil moisture. Our identification method followed the suggestion of Otkin et al. (2018) was similar to the previous literature (Ford et al., 2015; Yuan et al., 2017) which focused on two key characteristics of flash drought, namely the intensification rate to reflect how fast the drying status proceeds, and the upper (40th) and lower (20th) limits of soil percentile to guarantee the event really falls into drought. Then, the RI of different drought events (including both flash droughts and traditional slowly-evolving droughts, and flash droughts can be distinguished from conventional droughts based on the RI threshold of "-6.5th percentile/week"), as well as relevant predictors, were employed as inputs to the ML models. Finally, the feasibilities of flash drought and slowly-evolving drought simulation were evaluated.

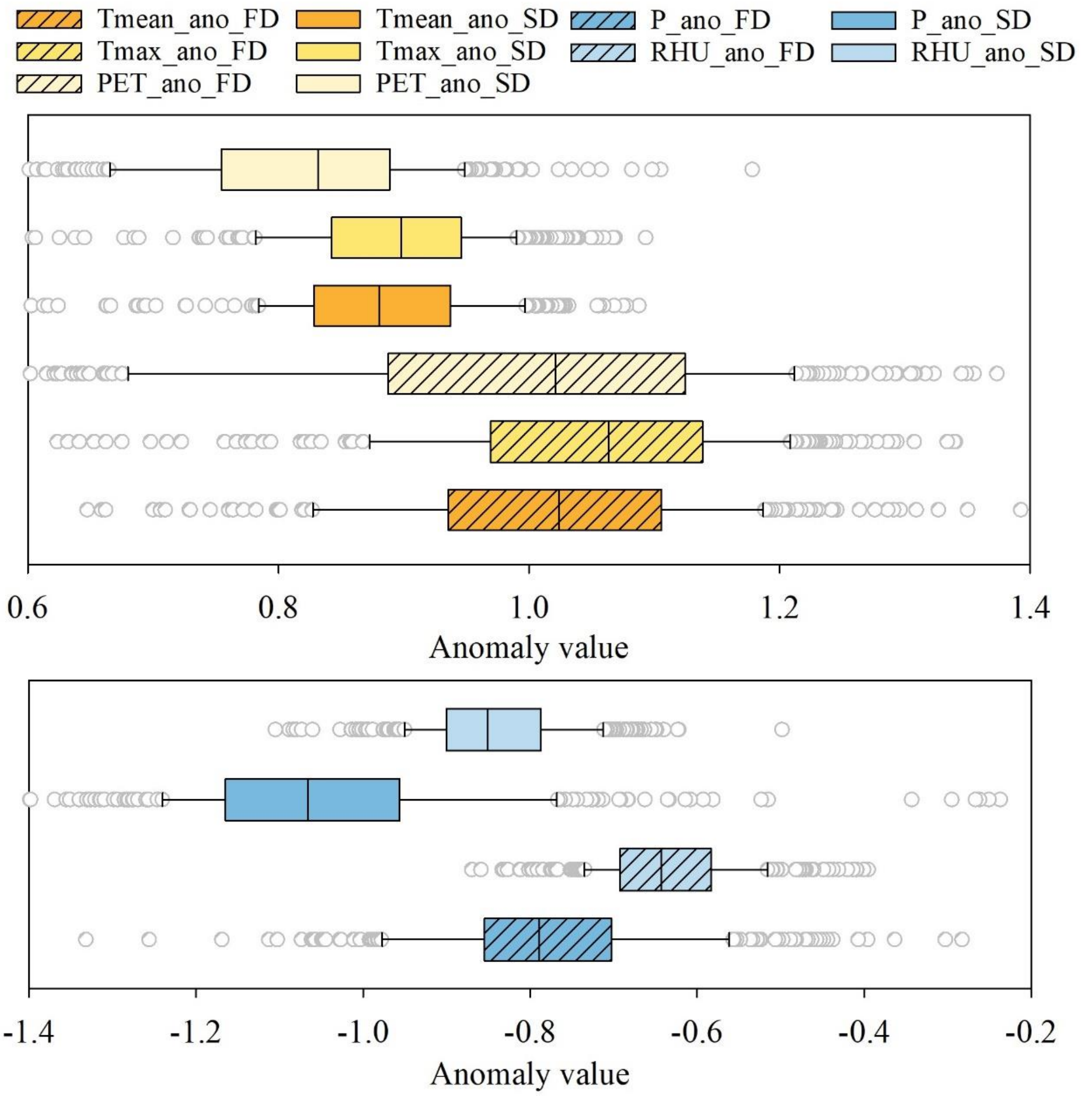

Figure 3 Meteorological anomalies of flash droughts and slowly developing droughts at the onset phase over China.

Traditional drought is influenced by a variety of predictors actively involved in the physical processes of the atmosphere, ocean, and land (Hao et al., 2018), which bring great challenges for the prediction of drought. These predictors can be divided into three types: (1) The first type of predictors is the large-scale climate indices, for instance, Surface Sea Temperature (SST), Southern Oscillation Index (SOI), Pacific Decadal Oscillation (PDO), and North Atlantic Oscillation (NAO). The large-scale teleconnection factors have been shown to be an important driving force for the occurrence and development of drought in different areas of the world (Hoerling et al., 2003; Nicolai-Shaw et al., 2016; Trambauer et al., 2013). (2) The second type of predictor refer to the local climate variables (e.g., precipitation, temperature). For example, under the joint effects of precipitation deficit and high temperature, soil moisture may be declined and persistent moisture deficits may lead to agricultural drought (Otkin et al., 2018; Yuan et al., 2019). (3) The land initial conditions (e.g., the persistence of soil moisture) can also be used as predictors for the prediction of drought (Wu et al., 2021). Especially for flash droughts, relevant studies showed that they have a stronger meteorological driving demand than conventional droughts (Ford and Labosier, 2017; Liu et al., 2021). This suggests a close interaction between RI and these local meteorological conditions, and this may be one reason for the relatively high efficiencies of these meteorological variables for RI prediction. By contrast, the formation of traditional drought involves complicated atmosphere-land surface feedbacks at multiple scales, and it is difficult to efficiently capture the variation of RI for slowly-evolving drought from a meteorological perspective. The revisions are listed as below:

In Page 5 Line 155-158:

"*Following the suggestion of Otkin et al. (2018) and the methodology of Liu et al., (2020a), we adopt a quantitative method to identify flash droughts by focusing on the rate of intensification (RI) during their onset-development phase. The soil moisture decline rate-based approach was similar to methods of the previous literature (Ford et al., 2017; Yuan, et al., 2017).*"

In Page 26 Line 470-473:

"*For instance, precipitation deficits, enhanced evaporative demand (high temperature or heatwave), their joint or alternant effects are all possible to impose cumulative effects on soil moisture and lead to agricultural drought (Otkin et al., 2018; Yuan et al., 2019).*"

In Page 26 Line 476-484:

"*The large-scale circulation can modify precipitation's frequency and intensity,* *increase wind speed, temperature, and evaporative demand. Several studies showed that the occurrence of droughts is related to large-scale circulation factors (Hoerling et al., 2014; Mo and Lettenmaier, 2016). Wang et al., (2016) found that under the background of El Niño of 2015/2016, a positive summer Eurasian teleconnection pattern is beneficial to anomalous northerly currents and weakening the East Asia summer monsoon, then leading to extreme droughts over northern China. The 2017 drought in north-eastern China was caused by a strong positive phase of Arctic Oscillation (AO) in March (Zeng et al., 2019). Also, 2000-2012 interdecadal drought in Eastern Africa is closely linked to the anomalies of Surface Sea Temperature (SST) in the tropical Pacific basin (Lyon and De Witt, 2012).*"

In Page 26 Line 492-494:

"*Meanwhile, they have a stronger meteorological forcing than conventional droughts (Ford and Labosier, 2017), indicating a close interaction between RI of flash drought and these local meteorological conditions. This may be one possible reason for the higher accuracies of RI prediction for flash droughts.*"

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Ford, T. W., Labosier, C. F.: Meteorological conditions associated with the onset of flash drought in the Eastern United States, Agric. For. Meteorol., 247, 414-423, https://doi.org/10.1016/j.agrformet.2017.08.031, 2017.

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Liu, Y., Zhu, Y., Zhang, L., Zheng, L., Ren, L., Jia, Y.: Precedent meteorological driving forces of flash drought and their feasibility for flash drought simulation, Adv. Water Sci., 32(4): 497-507, https://doi.org/10.14042/j.cnki.32.1309.2021.04.002, 2021.

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Otkin, J. A., Svoboda, M., Hunt, E. D., Ford, T. W., Anderson, M. C., Hain, C., Basara, J. B.: Flash Droughts: A Review and Assessment of the Challenges Imposed by Rapid-Onset Droughts in the United States, Bull. Am. Meteorol. Soc., 99(5), 911-919, https://doi.org/10.1175/bams-d-17-0149.1, 2018.

Trambauer, P., Maskey, S., Winsemius, H., Werner, M., Uhlenbrook, S.: A review of continental scale hydrological models and their suitability for drought forecasting in (sub-Saharan) Africa, Phys. Chem. Earth., 66, 16–26, https://doi.org/10.1016/j.pce.2013.07.003, 2013.

Wang, S. S., Yuan, X., Li, Y. H.: Does a strong ElNio imply a higher predictability of extreme drought? Sci Rep, 7:40741, https://doi.org/10.1038/srep40741, 2017.

Wu, H., Su, X., Singh, V. P., Feng, K., Niu, J.: Agricultural drought prediction based on conditional distributions of vine copulas, Water Resour. Res., 57, e2021WR029562. https://doi.org/10.1029/2021WR029562, 2021.

Yuan, X., Wang, L. Y., Wood, E. F.: Anthropogenic intensification of southern African flash droughts as exemplified by the 2015/16 season, Bull. Am. Meteorol. Soc., 98, S86-S90, https://doi.org/10.1175/BAMS-D-17-0077.1, 2017.

Yuan, X., Wang, L., Wu, P., Ji, P., Sheffield, J., Zhang, M.: Anthropogenic shift towards higher risk of flash drought over China, Nat. Commun. 10 (1), 1–8, https://doi.org/10.1038/s41467-019-12692-7, 2019.

Zeng, D. W., Yuan, X., Roundy, J. K., Effect of teleconnected land-atmosphere coupling on Northeast China persistent drought in spring-summer of 2017, J. Climate, 32(21):7403-7420, https://doi.org/10.1175/JCLI-D-19-0175.1, 2019.

Other comments:

1. I have no issue with the authors using their own, new definition to define flash drought events in their inventory, but it would be useful to, at a minimum, see a discussion of how the choice of definition is expected to influence results. Ideally, a comparison of inventories generated using one or two other definitions would be included.

Response:

Thanks for your constructive suggestion. For the definition of flash drought, Mo and Lettenmaier (2015, 2016) first proposed an identification method by combing several thresholds of hydrometeorological variables including soil moisture, precipitation, temperature, and evapotranspiration (hereafter denoted multiple thresholds method). On this basis, two types of flash drought were distinguished: the precipitation deficit flash drought (PDFD) and the heat wave flash drought (HWFD). The multiple threshold method provides some insights for understanding flash droughts from the aspect of their driving mechanism. Oktin et al. (2018) argued that the multiple threshold method may have intrinsic drawbacks and they stated that the approach of flash drought identification should account for two aspects, one refers to the rapid intensification, and the other is the actual moisture limitation condition (hereafter denoted soil moisture decline rate-based threshold method). Liu et al. (2020) evaluated the flash drought results derived from different identification methods and found that the unreasonable thresholds associated with PDFD and HWFD limited their ability to capture the spatiotemporally continuous variation of drought. Mo et al. (2020) agreed that the multiple threshold method in some cases may lead to misjudgments of flash drought. In this study, we followed the suggestions of Otkin et al. (2018): (1) soil moisture percentile needs to be below the 20th percentile, which can guarantee the drought status to reach the actual moisture limitation condition; (2) the average RI exceeded a predetermined threshold (absolute value of the RI threshold is 6.5th percentile per week), which can reflect the feature of rapid intensification of drought. The soil moisture decline rate-based method is the main identification measurement for flash drought in recent years. And this threshold criterion is similar to studies conducted by Ford et al. (2015) which defined the decline of soil moisture percentile from 40th to 20th within 4 pentads as a flash drought event. The comparisons between our method and the multiple threshold method had been conducted in the previous study (Liu et al., 2020), along with the sensitivities of RI threshold on the identification results of flash droughts. We carefully considered your suggestions. In the revised manuscript, we discussed the influences of different definitions on simulation results in the discussion section in Page 28 Line 514-534.

“5.3 Influence of definitions on RI simulation results

As we mentioned before, two main definitions of flash drought were proposed by Mo et al., (2015, 2016) and Otkin et al., (2018). The two definitions were compared in several former studies in their effects on identifying flash droughts. Wang et al., (2018) investigated PDFD and HWFD over China during the growing seasons in 1979-2010 and found that PDFD tends to occur in southern China, where moisture supply is sufficient, while HWFD is more likely to occur in semi-arid regions (e.g., northern China). Liu et al., (2020a) showed the strengths and limitations of the soil moisture rapid-intensification approach and the multiple variables threshold methods (i.e., identification methods for PDFD and HWFD events). For flash drought based on the rate of intensification approach (RIFD), the average frequency of occurrence (FOC) varied between 3% and 10%, while the average FOC of HWFD and PDFD was less than 3% and ranged from 4% to 6%, respectively, suggesting different identification ways would affect results of FOC to some extent. Even though the choice of definition may lead to different results of flash drought frequency, the difference wouldn't be significant no matter which kinds of definitions are applied. Osman et al., (2021) compared several definitions (e.g., soil moisture percentiles drop (SMPD), standardized evaporative stress ratio (SEER), heat-wave-driven (HWD), and precipitation-deficit-driven (PDD)) to investigate the sensitivity of identification results to the choice of definition, and the research showed that the spatial distribution of some typical flash drought events is well captured by most of the evaluated definitions. In short, diverse definitions of flash drought wouldn't affect the feasibility of analyzing the flash droughts simulation from the perspective of meteorological forcing. In this study, we focused on evaluating the performance of three ML algorithms on RI simulation and their ability in identifying flash droughts. Indeed, the ML models have a weak advantage in discovering the physical mechanism of flash droughts. However, the interaction between flash drought and corresponding meteorological anomaly was first analyzed, which would provide a reference to develop a physical-based model to simulate flash drought in the future."

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Droughts: A review and assessment of the challenges imposed by rapid onset droughts in the United States, Bull. Am. Meteorol. Soc., 99(5), 911-919, https://doi.org/10.1175/BAMS-D-17-0149.1, 2018.

2. The authors use a combination of ERA5 and meteorological station data. Can they show or cite a study that shows how consistent ERA5 is with meteorological station data in China?

Response:

Thanks for the reviewer's comment. In our study, we applied ERA-interim soil moisture data and anomalies of multiple meteorological elements as the input to machine learning models for analyzing the feasibilities of flash droughts simulation over China. For the ERA-interim dataset, many efforts have been conducted to assess its quality based on limited in-situ observations. For example, Ling et al. (2021) compared satellite-based and reanalysis soil moisture products (i.e., the European Space Agency's Climate Change Initiative (ESA CCI), ERA-interim, National Centers for Environmental Prediction (NCEP), the 20th Century Reanalysis Project from National Oceanic and Atmospheric Administration (NOAA), and ERA5) using ground observations in China during 1981-2013. Compared to other soil moisture datasets, ERA-interim and ERA5 products can better show the decreasing trend from the southeast to northwest, and they are able to reproduce the variabilities tendency of time series compared to that of in-situ observations. Meanwhile, ERA-interim precipitation and temperature data showed better consistencies with the interpolated ground station (STA) data in eastern China than in western China during 1980-2012 (Liu et al., 2018). At the regional and seasonal scales, ERA-interim temperature and precipitation both present a good agreement with STA temperature, and the former is better than the latter. Therefore, ERA-Interim is generally consistent with the in-situ observation and can be used to combine ground observations to simulate flash droughts. We have added some descriptions in the revised manuscript in Page 5 Lines 140-144 including the following sentences:

"For the reliability of the ERA-interim soil moisture dataset in China, it can well present the decreasing trend from the southeast to the northwest and reproduce the variability tendency of the time series of soil moisture compared to the in-situ soil moisture observations (Ling et al., 2021). Thus, ERA-Interim SM can be used to identify drought events and combined with meteorological station data to simulate

flash droughts in this study."

References:

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