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, and they were named as 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 "*Flash drought simulation based on machine learning technologies with time-adjacent meteorological conditions*". 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 17-18:

"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 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 33:

"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 119-122:

"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 274-276:

"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 282-284:

"…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 286-287:

"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 300:

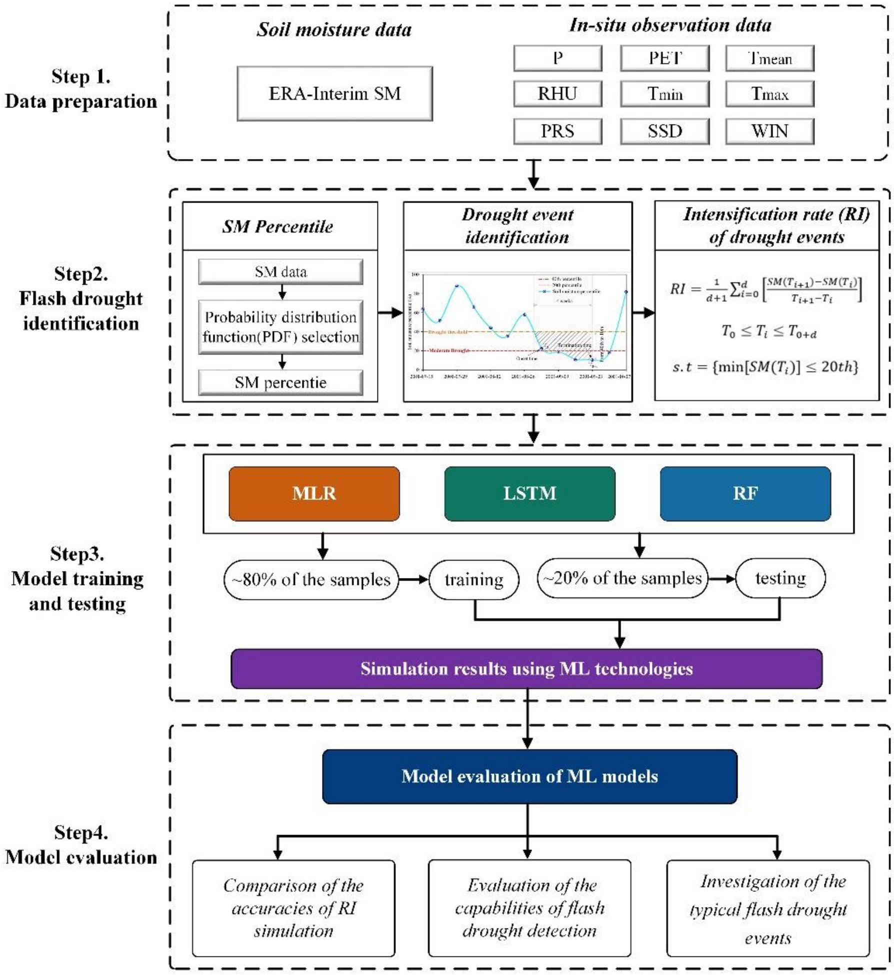

Figure 2: The flow chart of evaluating the performances of ML models for flash droughts detection.

In Page 12 Line 301:

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

In Page 12 Lines 304-305:

"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 313:

"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 319:

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

In Page 16 Line 347:

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

In Page 17 Lines 378-379:

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

Page 20 Lines 391-392:

"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 417-419:

"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 467-468:

"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 517:

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

In Page 28 Lines 526-527:

"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. 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) and was similar to the previous literature (Yuan et al., 2017; Ford et al., 2015) 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.

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 predictors 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.

References:

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.

Hao, Z., Singh, V. P., Xia, Y.: Seasonal drought prediction: Advances, challenges, and future prospects, Rev. Geophys., 56, 108–141, https://doi.org/10.1002/2016RG000549, 2018.

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.

Nicolai-Shaw, N., Gudmundsson, L., Hirschi, M., Seneviratne, S. I.: Long-term predictability of soil moisture dynamics at the global scale: Persistence versus large-scale drivers, Geophys. Res. Lett., 43, 8554–8562, https://doi.org/10.1002/2016GL069847, 2016.

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.

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.

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 will discuss the influences of different definitions on simulation results in the discussion section.

References:

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, 2020.

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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.

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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.

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 142-145 include 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:

Ling, X., Huang, Y., Guo, W., Wang, Y., Chen, C., Qiu, B., Ge, J., Qin, K., Xue, Y., Peng, J.:

Comprehensive evaluation of satellite-based and reanalysis soil moisture products using in situ observations over China, Hydrol. Earth Syst. Sci., 25, 4209–4229, https://doi.org/10.5194/hess-25-4209-2021, 2021.

Liu, Z., Liu, Y., Wang, S., Yang, X., Wang, L., Baig, M. H. A., Chi, W., Wang, Z.: Evaluation of Spatial and Temporal Performances of ERA-Interim Precipitation and Temperature in Mainland China,31:4347–4365, https://doi.org/10.1175/JCLI-D-17-0212.1, 2018.