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Hydrology and Earth System Sciences
Discussions

Impact of hydro-meteorological conditions and flash drought duration on post-flash drought recovery time patterns

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Abstract. Recovery time, which refers to the duration an ecosystem needs to revert to its pre-drought state, is a fundamental aspect of ecological resilience. Recently, flash droughts (FDs) characterized by rapid onset and development have been gained recognition. Nevertheless, the spatiotemporal patterns of recovery time and the factors that affect it remain largely unknown. In this study, we set up a novel method to investigates the recovery time patterns of terrestrial ecosystem in China based on gross primary productivity (GPP) by employing the Random Forest (RF) regression model and the Shapley Additive Prediction (SHAP) method. A random forest regression model was developed for analysing the factors influencing recovery time and establish response function functions through partial correlation for typical flash drought recovery periods. Additionally, the dominant driving factors of recovery time determined by using the SHAP method. Results reveal an average recovery time of approximately 37.5 days across China, with central and southern regions experiencing the longest recovery time. Post-flash drought radiation emerges as the primary environmental factor, followed by aridity index and post-flash drought temperature, particularly in semi-arid/sub-humid areas. Temperature exhibits a non-monotonic relationship with recovery time; with excessively cold or overheated temperatures leading to longer recovery times. Herbaceous vegetation recovers more rapidly than woody forests, with deciduous broadleaf forests demonstrating the shortest recovery time. This study provides valuable insights into comprehensive water resource and ecosystem management, and it will be helpful in large-scale drought monitoring.

https://doi.org/10.5194/hess-2024-128
Preprint. Discussion started: 17 May 2024

Hydrology and Earth System Sciences
Discussions

1 Introduction

Climate change has exacerbated drought, which could have significant implications for the achievement of Sustainable Development Goals (SDGs) (Lindoso et al., 2018). Among the 17 SDGs proposed in the 2030 Agenda, at least 5 of them are directly associated with drought, including Goal 6 “Clean water and sanitation”, Goal 11 “Sustainable cities and communities”, Goal 12 “Responsible production and consumption”, Goal 13 “Climate action”, and Goal 15 “Life on land” (Zhang et al., 2019; Nilsson et al., 2016). Flash droughts, characterized by rapid onset and intensification, have recently gained recognition by hydrologist and general public worldwide (Yuan et al., 2023). These have a significant impact on the productivity, photosynthesis, and latent heat flux of the ecosystem (Zhang et al., 2020a; Yang et al., 2023). The impacts of flash droughts are not only reflected during the events but also have legacy effects post the events (Liu et al., 2023). Recovery time, defining the duration an ecosystem requires to recover its pre-drought state, is a fundamental aspect of ecological resilience (Schwalm et al., 2017; Wu et al., 2017). It is related to ecological states as it may trigger a critical "tipping point" in the ecosystem leading to a transition to a new state (Lenton et al., 2008). With the anticipation of more frequent and severe flash droughts in the future (Sreeparvathy & Srinivas, 2022), it is of paramount importance to explore post-flash drought recovery trajectories (Jiao et al., 2021).

Drought recovery characteristics have been widely observed at the ecosystem scale, usually determined through tree ring records, productivity or greenness observation, and satellite retrieval (Gazol et al., 2017; Kannenberg et al., 2019). These studies have found varied recovery times across different regions and ecosystems. For different ecosystem types, grasslands have a longer recovery time compared to other land covers due to their shallow-rooted plants and lower soil water retention capacity (Hao et al., 2023). In contrast, the recovery time in croplands is more susceptible to interference by human farming systems (Darnhofer et al., 2016). For forests, mixed forests can recover quickly, while deciduous broadleaf forests have the longest recovery time (He et al., 2018). When comparing hydro-meteorological conditions, semi-arid and semi-humid regions have a longer recovery time compared to humid and arid regions (Zhang et al., 2021).

However, the contribution of driving factors in flash drought recovery remains unclear in previous studies. For example, some results reveal that the background value, drought return interval, post-drought meteor-hydrological conditions, and drought attributes (duration, intensity, etc.) play an important role in regulating drought recovery (Kannenberg et al., 2020). This may be due to the fact that the lower the background value, the more severe the damage to the ecosystem, the more abnormal the meteor-hydrological conditions after drought, and the longer the required drought recovery time (Fu et al., 2017). Greater intensity and longer duration can lead to substantial drought losses (Godde et al., 2019). Additionally, more favorable post-drought meteor-hydrological conditions (e.g., increased precipitation and suitable temperature) increase the probability of complete recovery (Jiao et al., 2021). The physiological regulation of plants, including alterations in leaf water potential and phenology, also plays a crucial role in this process (Miyashita et al., 2005).

https://doi.org/10.5194/hess-2024-128
Preprint. Discussion started: 17 May 2024


Hydrology and Earth System Sciences
Discussions

Although the impact of flash droughts on ecosystems and their subsequent damage has been extensively studied, the recovery process requires more attention for a better understanding of flash droughts. It has been reported that both SIF and SIF yield values showed a declining trend post-flash drought (Yao et al., 2022), while 95% of the GPP in the Indian region responded to flash droughts, with an average response time of 10-19 days (Poonia et al., 2021). However, these studies predominantly focus on the response of ecological indicators, particularly the decrease caused by flash droughts, with limited attention given to the recovery process (Otkin et al., 2019). Notably, a substantial contrast exists in the definition of recovery stages between flash droughts and traditional slow droughts (Wang et al., 2016). These results lead to the conclusion that recovery is a part of the former, while the recovery phase of the latter usually occurs at the end of the event (Qing et al., 2022). Furthermore, some studies have concluded that the determination of flash drought recovery relies on changes in soil moisture or peak evapotranspiration intensity, while for traditional slow drought, it is mainly based on ecological or hydrological indicators (Xu et al., 2023). If we take China as a typical area for studying flash droughts, there were frequent flash drought events in China from southwest to central China from 1980 to 2021 (Wang et al., 2022a). Moreover, there may be more severe and frequent flash droughts in the future (Christian et al., 2023). Wang et al. (2023) conducted a study on the recovery of flash droughts in the Xiang River Basin and Wei River Basin in China and revealed that the majority of flash drought events in both basins recover within 28 days. However, to the best of our knowledge, there is currently a lack of studies on the recovery of flash drought and the factors influencing its spatiotemporal patterns across China.

Drought can lead to water shortages, reducing access to clean drinking water. Therefore, effective drought management is crucial for achieving SDGs. By collecting newly available datasets as well as hydro-meteorological variables in China, this study assesses the extent of the impact of flash drought post-flash drought, documents the time taken for recovery post-flash drought, and analyzes the factors contributing to variations in ecosystem recovery. The objectives of this study are to: (1) investigate the spatial pattern of post-flash drought recovery; (2) identify the most critical determinants of recovery; and (3) analyze the impact of various factors on flash drought recovery times. In the following sections, Section 2 provides a brief description of data and methods, followed by Section 3, which presents the results presented by novel methods applied. Then, we provide a detailed discussion in Section 4. Section 5 gives the conclusions with some more information presented in supplementary materials.

2 Data and methods

2.1 Data

2.1.1 Soil moisture datasets

Daily root-zone soil moisture (SM) data for the period of 2001-2018 are obtained from Global Land Evaporation Amsterdam Model (GLEAM) (https://www.gleam.eu/). GLEAM estimates root-zone soil moisture using a multi-layer water balance approach. The depth of the root zone varies based on the type of land cover. For tall vegetation (e.g. trees), the depth is

https://doi.org/10.5194/hess-2024-128
Preprint. Discussion started: 17 May 2024


Hydrology and Earth System Sciences
Discussions

96 divided into three layers (0-10 cm, 10-100 cm, and 100-250 cm); For low vegetation (e.g. grass), there are two layers (0-10
97 cm and 10-100 cm); Bare soil only has one layer (0-10 cm) (Martens et al., 2017; Miralles et al., 2011). It has been widely
98 applied in the identification and impact assessment of flash drought events (Zha et al., 2023). We utilized the bilinear
99 interpolation method to resample SM from a spatial resolution of 0.25° to 0.1°, aligning it with the accuracy of other
100 datasets. This method is appropriate for continuous input values, easy to implement, and generally effective in converting
101 coarse input data into spatially refined output (Chen et al., 2020).

102 **2.1.2 Hydro-meteorological datasets of affecting variables of recovery time**

103 We analyze the recovery time considering multiple influencing factors such as meteorological variables, drought-related
104 variables, and land cover (He et al., 2018). Meteorological data from the China Meteorological Forcing Dataset (CMFD),
105 accessible at https://westdc.westgis.ac.cn/, is utilized for the period spanning 2001 to 2018 (Yang et al., 2019). The near-
106 surface air temperature, downward shortwave radiation, downward longwave radiation, precipitation rate and wind speed are
107 used in this study. VPD is calculated based on temperature, and specific humidity using Eq. (1) - (3) (Peixoto & Oort. 1996)
108 (Zotarelli et al., 2020).

109 $$SVP = 0.618\exp\left(\frac{17.27T}{T+273.73}\right) \quad (1)$$

110 $$AVP \approx \frac{q_s \cdot p}{\varepsilon} \quad (2)$$

111 $$VPD = SVP - AVP \quad (3)$$

112 where SVP and AVP is saturated vapor pressure and actual vapor pressure (kPa), respectively. And T is temperatures
113 (°C),q_s is the specific humidity, p is the atmospheric pressure (kPa), ε= 6.22 is the ratio of water vapor molecular weight to
114 dry air weight.

115 Aridity index is calculated as the ratio of precipitation to potential evapotranspiration. Typically, the multi-year average of
116 the aridity index serves as an indicator of water availability and drought timing within a particular region (Huang et al.,
117 2016). Aridity index is obtained from https://doi.org/10.6084/m9.figshare.7504448.v5 (Zomer et al., 2022). To analyze the
118 distinct responses of different vegetation types, we employ the MODIS dataset from the International Geosphere-Biosphere
119 Programme (IGBP) MCD12C1 (Friedl et al., 2002) (Fig. S1).

120 **2.1.3 Gross primary productivity**

121 Gross Primary Productivity (GPP) is a commonly employed indicator for monitoring photosynthesis dynamics post drought
122 (Gazol et al., 2018). This study uses the GPP datasets from Global MODIS and FLUXNET-derived Product. It has a spatial
123 resolution of 0.1° and a daily time resolution (Joiner et al., 2021). To match the flash drought event, daily soil moisture data
124 were aggregated to pentad-mean (five-days) data. This study chooses the growing seasons (April to October) from 2001 to
125 2018 as the study period.

https://doi.org/10.5194/hess-2024-128
Preprint. Discussion started: 17 May 2024

Hydrology and Earth System Sciences
Discussions

2.2 Method

2.2.1 The identification of flash drought events and recovery time

In this study, we identify flash drought events by analyzing changes in soil moisture, taking into account their rapid intensification and duration. Evaporation demand is often used as a warning indicator for flash droughts (Rigden et al., 2020). Because it may overestimate flash droughts (Lesinger & Tian. 2022). To identify flash drought events, the daily soil moisture data is aggregated into pentad-mean data. These averages are then converted into percentiles based on the climatology of each pentad period during the growing season. According to the definition proposed by Yuan et al. (2019) and Zhang et al. (2020a), we identify the flash drought event (Fig. 1 a&b). The speed of flash drought (Ospd) is the ratio of the difference between the 40th percentile and the lowest percentile of the onset stage to the length of onset. The frequency refers to the overall number of occurrences within a given time frame (e.g., per year or per decade). Severity is the accumulated soil moisture percentile deficits from the threshold of 40%. On the basis of Wang et al. 2023 's definitions, we defined the recovery time of vegetation production after a flash drought (Fig. 1):

$$\text{GPP anomaly} = \frac{GPP-\mu_{GPP}}{\sigma_{GPP}} \quad (4)$$

where, $\mu_{GPP}$and σ_{GPP} are mean and standard deviation of the pentad time series of GPP.

When the GPP anomaly of post-flash drought is negative and reaches its minimum, it indicates the beginning of the recovery stage. The recovery stage ends when the GPP anomaly returns to a positive value. However, if no flash drought event occurs during the period of negative GPP anomaly or if the GPP anomaly is already negative before the onset of the flash drought event, the GPP data series should be excluded.

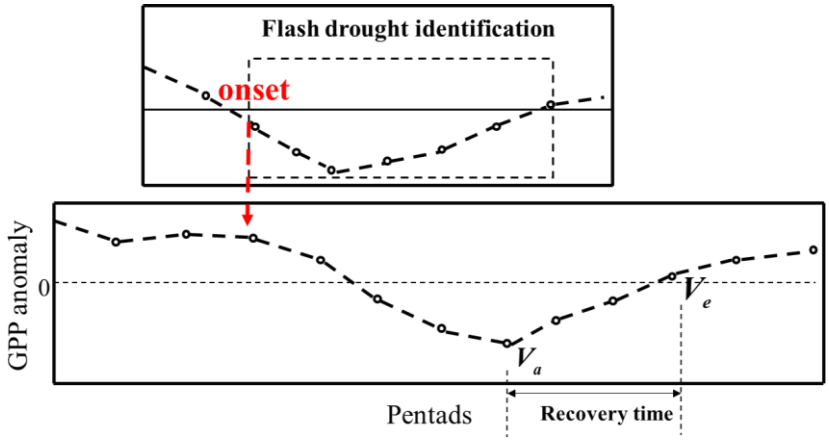

Figure 1. The identification of flash drought and recovery time. (a) and (b) are flash drought identification base on SM percentile. (b) Is detrended vegetation production index on a time series, 0 is defined as the threshold of a negative anomaly. Below the dashed line represents that vegetation production is in a negative abnormal state. We quantify recovery time as:

https://doi.org/10.5194/hess-2024-128
Preprint. Discussion started: 17 May 2024


Hydrology and Earth System Sciences
Discussions

148 the recovery time begins when the vegetation production loss reaches the maximum and ends when the detrended vegetation
149 production index is above 0.

150 **2.2.2 Response functions**

151 Partial dependence plots based on the random forest algorithm are utilized for visualizing response functions (Schwalm et
152 al., 2017; Sun et al., 2016). The analysis of partial dependence focuses on evaluating the marginal impact of a covariate (or
153 independent variable) on the response variable, while keeping other covariates constant (Liaw & Wiener. 2002). It facilitates
154 the exploration of insights within large datasets, particularly when random forests are primarily influenced by low-order
155 interactions (Martin, 2014). In addition, it is valuable tools for identifying significant features, detecting non-linear
156 relationships, and gaining insights into the overall behavior of a predictive model.

157 **2.2.3 Attribution analysis of ecosystem recovery**

158 In order to better understand the potential factors driving vegetation productivity recovery after flash droughts, we conduct
159 attribution analysis. We selected downward radiation (the sum of downward shortwave radiation and downward shortwave
160 radiation), temperature, wind speed, precipitation rate, VPD, flash drought speed (Ospd), flash drought severity (Osev), flash
161 drought duration (Odur), aridity index, land cover types as explanatory variables. The feature importance of random forest
162 can only indicate the extent to which the input variables influence the model's output, but it does not reveal how these input
163 variables specifically impact the model's output (Wang et al., 2022b). The Shapley Additive Prediction (SHAP) method has
164 emerged as a valuable tool that addresses the limitations of traditional machine learning methods
165 (Štrumbelj&Kononenko,2014). As a result, the SHAP method is widely utilized in attribution analysis of variables (Wang et
166 al., 2022b; Lundberg & Lee, 2017).

167 $$\varphi_{\mathrm{m}}(v)=\sum_{S\subseteq N\setminus\{m\}}\frac{|S|!(|N|-|S|-1)!}{|N|!}(v(S\cup\{m\})-v(S)) \quad (5)$$

168 where,$\varphi_m(v)$ represents the contribution of covariate m, N denotes the set of all covariates, S is a subset of N, and $v(S)$
169 represents the value of that subset.

170 We utilized a random forest model and employed these variables as predictive factors to estimate the productivity recovery
171 time for all study grid cells. Then, we used the SHAP value to quantify the marginal contribution of each predictive variable
172 and rank their relative importance based on the average absolute SHAP value.

https://doi.org/10.5194/hess-2024-128
Preprint. Discussion started: 17 May 2024

Hydrology and Earth System Sciences
Discussions

3 Results

3.1 Characteristics of flash droughts

Figure 2 presents the frequency, duration, severity, and speed of flash droughts over China during 2001-2019. Approximately 7% of grids did not experience a flash drought event, while the remaining 93% of grids experienced at least one event. The middle and lower reaches of the Yangtze River exhibited a high frequency value with above 12 events/decade, whereas other regions mainly ranged from 0 to 9 events/decade. There is a clear spatial pattern for the duration, ranging from 0 to 20 days over China. The Southwestern and the middle and lower reaches of the Yangtze River had longer durations, exceeding 90 days (Fig. S2). In addition to the higher severity of flash droughts in the southwest region, a similar spatial pattern was observed for severity and speed. Regarding speed, areas with faster speed were primarily concentrated in the lower reaches of the Yangtze River. Overall, the middle and lower reaches of the Yangtze River and the southwestern region are considered hot spots, although the latter's speed is not rapid.

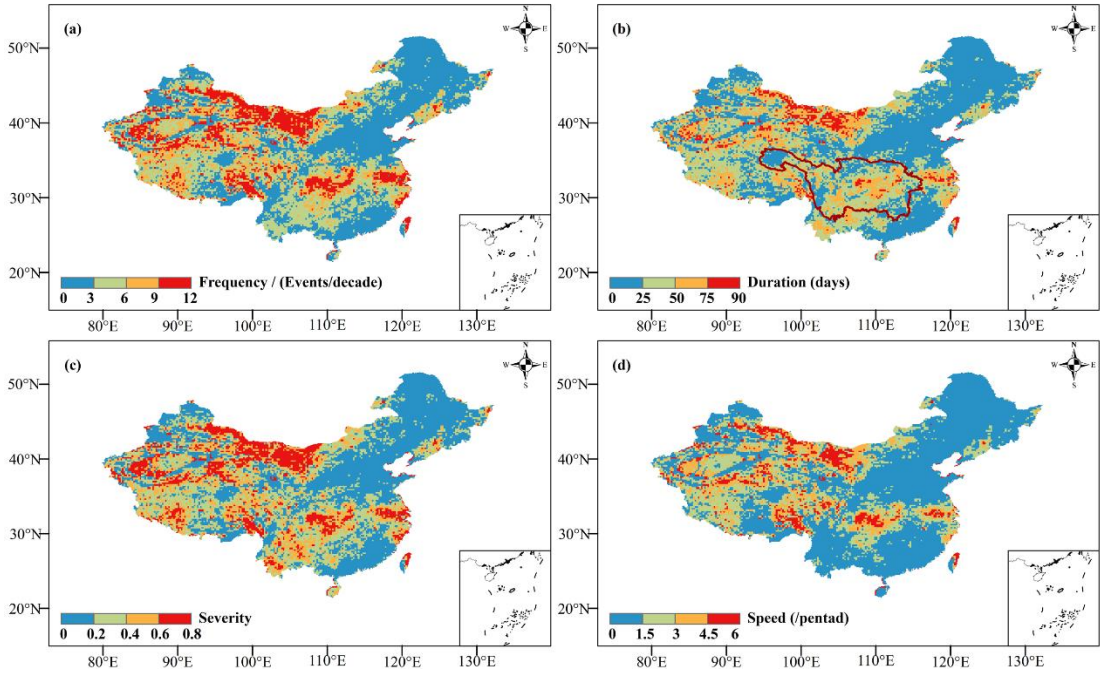

Figure 2. Frequency (a), duration (b), severity (c), speed (d) of flash drought over China during 2001–2019.

3.2 Spatial pattern of ecosystem recovery time and recovery rate

Vegetation productivity showed a clear response to flash droughts, and this response typically had a certain lag (Fig. S3). Ecosystems exhibited distinct spatial differences in recovery times to flash droughts (Fig. 3). The mean recovery time for Chinese ecosystems was 37.5 days (7.5 pentads) calculated by GPP. Most regions were able to recover to their normal state within 50 days. However, certain areas, such as central China and southern China, required 90 days or more to recover. In

https://doi.org/10.5194/hess-2024-128
Preprint. Discussion started: 17 May 2024

Hydrology and Earth System Sciences
Discussions

terms of time series, there was no evident trend in the mean recovery time, with fluctuations occurring within 7.5 pentads. On average, the recovery rate of grids in China ranged from 0 to 2 per pentad, and approximately 90% of grids had a recovery rate of less than 1 per pentad. There is no significant trend in recovery rate over time. To further illustrate the impact and recovery of flash droughts on different vegetation types, we calculated the recovery time and recovery rate for each type (Fig. 4). Among the different vegetation types, DBF had a shorter recovery time and a higher recovery rate. Additionally, CRP showed moderate recovery rates, while GRS had relatively low rates of recovery. This reflects the fact that flash droughts had a more significant impact on GRS and resulted in greater productivity losses.

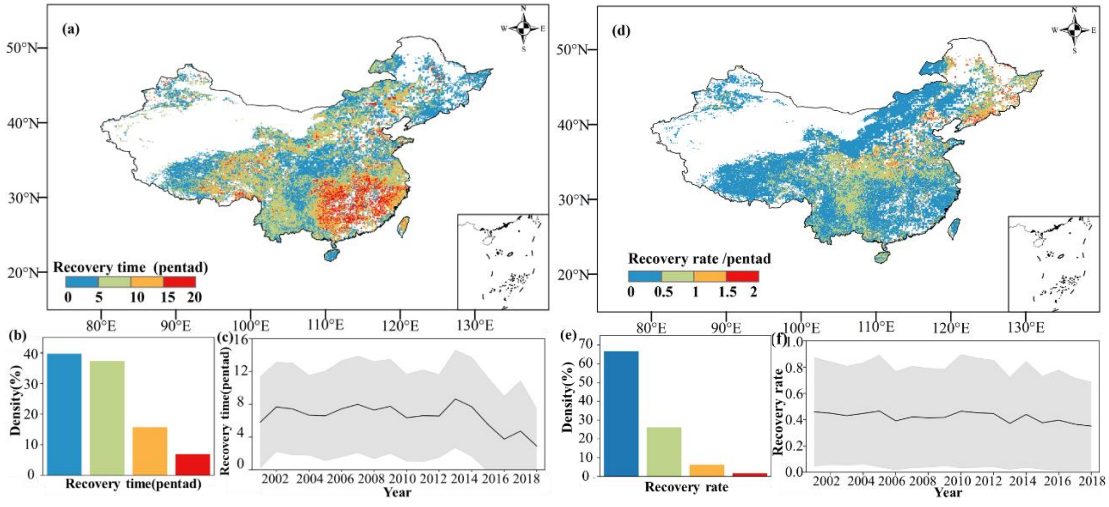

Figure 3. Spatial pattern of recovery time (a-c) and recovery rate (d-f). (a) and (d) represent the recovery time (pentad) and recovery rate (/pentad) calculated by using GPP data respectively. (b) and (e) represent the density of different recovery times and recovery rate respectively, the horizontal axis represents the recovery time (pentad), recovery rate (/pentad) and the vertical axis is the density. Regions with sparse GPP or no droughts are masked with white.

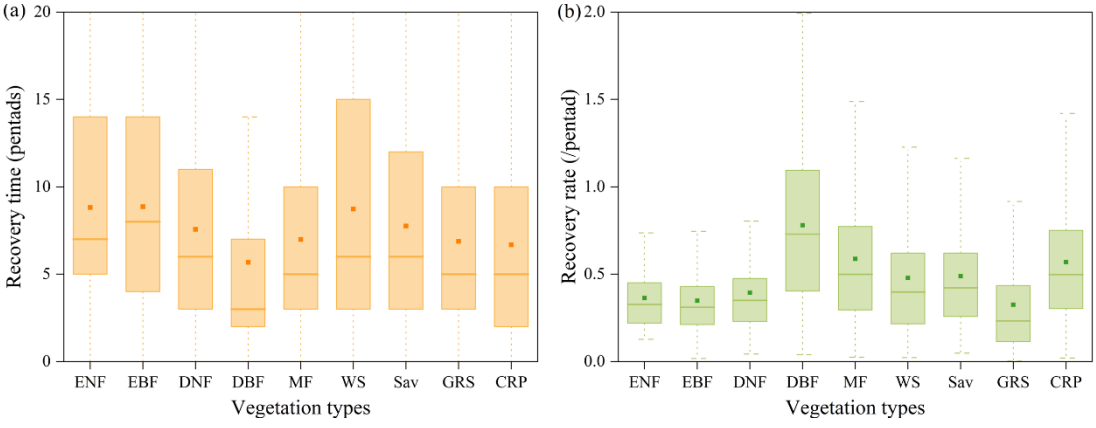

Figure 4. The recovery time and recovery rate across different vegetation types. The vegetation types are: ENF (evergreen coniferous forest), EBF (evergreen broad-leaved forest), DNF (deciduous coniferous forest), DBF (deciduous

https://doi.org/10.5194/hess-2024-128
Preprint. Discussion started: 17 May 2024


Hydrology and Earth System Sciences
Discussions

broad-leaved forest), MF (mixed forests), WS (closed shrubland, open shrubland, and woody savannas), SAV (savannas (temperate)), GRS (grasslands), CRP (croplands).

3.3 Response functions for flash drought recovery time

The random forest regression model explained 55% of the out-of-bag variance in recovery time (Fig. 5). Radiation emerged as the most influential factor impacting flash drought recovery time, with lower solar radiation conditions leading to prolonged the recovery time (Fig. 5a). Temperature did not exhibit a monotonic response in relation to recovery time. Excessively cold or overheated temperatures resulted in longer recovery times, whereas slightly higher temperatures promoted vegetation recovery (Fig. 5b). Specifically, a slight increase in temperature facilitated vegetation restoration, while higher temperatures extended the recovery time of flash droughts. This suggests that the projected rise in extreme high temperatures will further lengthen the recovery time (Li et al., 2019). In terms of flash drought characteristics, the difference in recovery time was related to the discrepancy in severity and duration, albeit to a lesser extent than speed (Fig. 5c, h & i). Recovery time increased in a stepwise manner as the duration increased. Ecosystems experiencing prolonged durations of flash droughts typically exhibit longer recovery times. In addition, semi-arid/sub-humid areas ($0.2<AI<0.65$) have longer recovery times (Fig. 5d). The wind speed exhibited a bimodal pattern, indicating that the recovery time was shortest when it closely aligned with the multi-year average or was 3.5 times higher than the multi-year average (Fig. 5e). Adequate precipitation following a flash drought assisted in recovery, although excessively extreme precipitation could also hinder it (Fig. 5f). Extreme vapor pressure deficit (VPD), whether high or low, prolonged the recovery time (Fig. 5g). Among different vegetation types, herbaceous vegetation recovered more rapidly than woody forests. Deciduous broadleaf forests (DBF) demonstrated the shortest recovery time (Fig. 5j).

https://doi.org/10.5194/hess-2024-128
Preprint. Discussion started: 17 May 2024

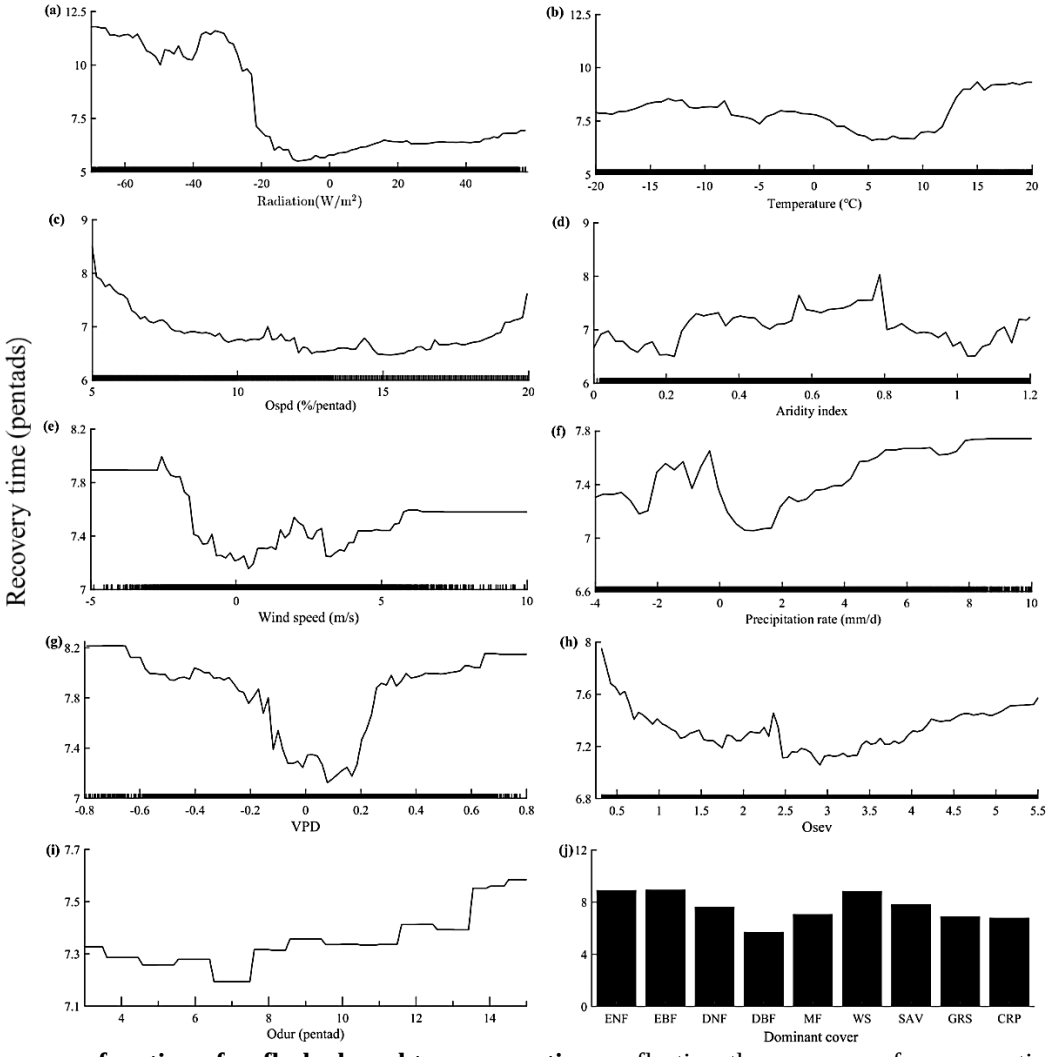

Figure 5. Response functions for flash drought recovery time, reflecting the response of recovery time to a single dependent variable when others are unchanged. Note difference in the y-axis scales. The covariates a to j are the deviations from the baseline. Positive (negative) indicates above (below) the average value.

3.4 Drivers of flash drought recovery time

We then performed an attribution analysis using SHAP method to quantify the relative importance of the considered variables. The results were consistent with the results of section 3.3. In general, radiation and aridity index were the most relevant controls of spatial variations of post-flash drought recovery time (Figure 6). Temperature was the third most impactful variable overall, primarily due to its high impact in predicting the recovery time where it has an absolute mean SHAP value of 0.62. Compared to other variables, the impact of speed and duration of flash droughts were relatively low. In addition, during the process of flash drought recovery, the losses caused by flash droughts can also affect productivity

https://doi.org/10.5194/hess-2024-128
Preprint. Discussion started: 17 May 2024

Hydrology and Earth System Sciences
Discussions

recovery. The relationship between recovery time and the attributes of flash drought (speed, severity, duration) is usually negative. That is to say, faster, more severe, and longer lasting flash droughts often have a longer recovery time. Specifically, the speed of flash droughts characteristics is one of the main controlling factors for recovery time.

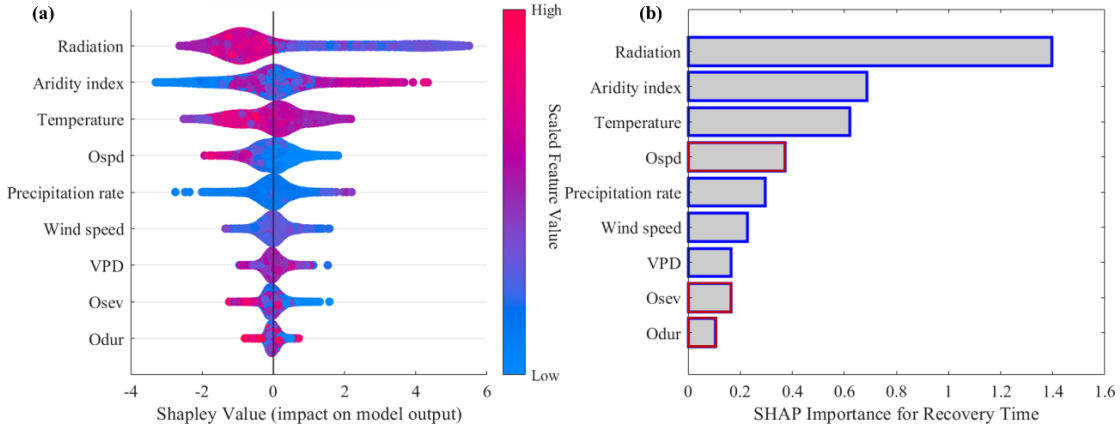

Figure 6. Identifying drivers of patterns of post-flash drought recovery time. (a) The summary plot of SHAP values in random forest machine learning. (b) The SHAP Importance (averaged absolute SHAP values) for recovery time. Considered drivers include flash drought characteristics (in red), post-flash drought hydro-meteorological conditions (in blue).

4 Results

4.1 Assess flash drought recovery time based on vegetation productivity

Given the prevalence of drought in regions over the past few decades, drought is a major natural disaster worldwide (WMO. 2021). In addition, its exposure, vulnerability, and risk are expected to further increase under future climate and socio-economic changes (Tabari & Willems. 2018; Cook et al., 2020). Flash drought is widely recognized as a sub-seasonal phenomenon that develops rapidly (Tyagi et al., 2022). Flash droughts have varying degrees of impact on the photosynthesis, productivity, and respiration of ecosystems (Mohammadi et al., 2022). Reducing drought risks and strengthening social drought resistance are also important tasks in order to achieve SDGs by 2030 (Tabari et al., 2023). The response frequency of Solar-Induced Fluorescence (SIF) in the China basin to flash droughts exceeds 80%, with 96.85% of the regional response occurring within 16 days (Yang et al., 2023). Previous studies have calculated the recovery time of flash drought based on changes in soil moisture, ranging from 8 to 40 days (Otkin et al., 2019). Additionally, the recovery time is generally longer in humid areas compared to arid areas. However, not all flash drought events result in a decrease in ecosystem productivity (Liu et al., 2019). For instance, a study conducted by Zhang et al. (2020b) revealed that between 2003 and 2018, 81% of flash droughts in China displayed negative normalized anomalies in GPP, while the remaining 19% of the events did not exhibit such negative anomalies. Therefore, GPP serves as a more appropriate indicator for monitoring post-drought photosynthesis-related dynamics and evaluating ecosystem recovery time (Yu et al., 2017). Based on GPP, most flash

https://doi.org/10.5194/hess-2024-128
Preprint. Discussion started: 17 May 2024


Hydrology and Earth System Sciences
Discussions

drought events in the Xiangjiang River Basin (XRB) and Weihe River Basin (WRB) recovered within 2 to 8 days. Moreover, the recovery time in the XRB, which is located in a humid area, tends to be longer (Wang et al., 2023). It should be noted that this study only investigated the aforementioned two watersheds and did not include semi-humid/semi-arid areas. Our study revealed that the average recovery time for flash droughts in the China is approximately 37.5 days (7.5 pentads) (Figure 3).

4.2 The factors that affect drought recovery time

The solar radiation and aridity index were the primary factors that influence the recovery time (Figures 5 & 6). The recovery time was regulated by a combination of drought characteristics (drought return interval, severity, duration), post-drought hydro-meteorological conditions, and vegetation physiological characteristics (Fathi-Taperasht et al., 2022; Liu et al., 2019). In the case of flash droughts characterized by rapid development, the speed is one of the most important factors controlling the recovery time (Figure 6). Ecosystems experienced stress fatigue, which means that the restoration of the ecosystem progressively deteriorates due to repeated exposure to stressors that occur at frequencies outside the evolutionary history of the affected system (Hacke et al., 2001; Schwalm et al., 2017). Previous studies have shown that the spatial patterns of flash drought recovery were similar to those of precipitation, temperature, and radiation (Wang et al., 2023). Increased radiation energy and precipitation post a drought can promote vegetation photosynthesis (Zhang et al., 2021). Additionally, there are regional variations in the time required for drought recovery. Generally, semi-arid and semi-humid areas took longer to recover to their pre-drought state (Figure 5). Ecosystems in these areas exhibited higher overall sensitivity to drought (Vicente et al., 2013; Yang et al., 2016). Vegetation in arid areas adapted to long-term water deficit through various physiological, anatomical, and functional mechanisms, resulting in high drought resistance (Craine et al., 2013). In humid areas, sufficient water storage helped resist drought (Liu et al., 2018). Vegetation also played a crucial role in regulating the recovery trajectory. The drought resistance of plants was determined by various traits such as stomatal conductance, hydraulic conductivity, and cell turgor pressure (Bartlett et al., 2016; Martínez-Vilalta et al., 2017). Grasslands and shrublands could quickly recover from drought, while forest systems require longer periods of time (Gessler et al., 2017). This may because those have relatively simple vegetation structures, shorter life cycles, and faster growth rates (Ru et al., 2023). In contrast, forest systems have more complex vegetation structures and ecological processes (Tuinenburg et al., 2022).

4.3 Limitations and perspectives

We emphasized that the post-flash drought recovery trajectory of ecosystem is influenced by several factors, including post-flash drought hydrological conditions, flash drought characteristics, and the physiological characteristics of vegetation. However, we should note that in this study, the same percentile threshold (20%, 40%) was used to identify flash drought events based on empirical values from previous research findings. Further investigation should investigate how to determine region-specific thresholds and examine the sensitivity of these thresholds to flash drought recognition (Gou et al., 2022).

https://doi.org/10.5194/hess-2024-128
Preprint. Discussion started: 17 May 2024


Hydrology and Earth System Sciences
Discussions

Furthermore, it is important to consider that plant strategies for coping with flash drought can vary due to species differences (Gupta et al., 2020). There is still a need for improvement in understanding the physiological and ecological mechanisms involved in flash drought recovery. Flash droughts can have multiple impacts on ecosystems, and it is worth noting that our approach in this study focused primarily on GPP. To gain a more comprehensive understanding, future research should explore the mechanism of ecosystem restoration from multiple perspectives, such as evaluating greenness and photosynthesis. In future water resource management, we should recognize the importance of adopting measures to reduce the risk of drought disasters.

5 Conclusions

Effectively reducing drought risk and reducing drought exposure are crucial for achieving sustainable development goals (SDGs) related to health and food security. This study applied a random forest regression model to analyze the factors influencing recovery time and the response functions settled up by partial correlation for typical flash drought recovery time. The most important environmental factor affecting recovery time is post-flash drought radiation, followed by aridity index and post-flash drought temperature. Recovery time prolongs with lower solar radiation conditions. Semi-arid/sub-humid areas have longer recovery time. Temperature does not exhibit a monotonic response in relation to recovery time; excessively cold or overheated temperatures lead to longer recovery times. Herbaceous vegetation recovers more rapidly than woody forests, with deciduous broadleaf forests demonstrating the shortest recovery time.

Our study assessed the recovery time of ecosystems to flash droughts based on GPP dataset and identified the dominant factors of recovery time. Results show that 78% of ecosystems could recover within 0 to 50 days. However, certain areas, such as central China and southern China, required 90 days or more to recover. The analysis of the response functions showed that radiation emerged as the most influential factor impacting flash drought recovery time, with lower solar radiation conditions leading to prolonged recovery time. Additionally, temperature did not exhibit a monotonic response in relation to recovery time. In terms of flash drought characteristics, the difference in recovery time is more associated with speed than severity and duration.

Although this study provides a good basis for further investigation of flash drought characteristics, it is important to note that the further extension of this study may lead to more understanding of flash drought for hydrological application or worldwide practices. It is important to determine region-specific thresholds and examine the sensitivity of these thresholds to flash drought recognition. Furthermore, plant strategies for coping with flash drought can vary due to species differences. To gain a more comprehensive understanding of flash drought recovery, future research should also explore the mechanism of ecosystem restoration from multiple perspectives, such as evaluating greenness and photosynthesis.

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Hydrology and Earth System Sciences
Discussions

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Global Land Evaporation Amsterdam Model (GLEAM) soil moisture data is available from https://www.gleam.eu/. The China Meteorological Forcing Dataset (CMFD) can be accessed via https://westdc.westgis.ac.cn/zh-hans/data/7a35329c-c53f-4267-aa07-e0037d913a21/. Global MODIS and FLUXNET-derived Product GPP dataset is available from https://daac.ornl.gov. The MODIS land cover dataset MCD12C1 is available from https://doi.org/10.24381/cds.f17050d7.

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