



# Technical note: A stochastic framework for identification and evaluation of flash drought

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Abstract. The rapid development of droughts, referred to as flash droughts, can pose serious impacts on agriculture, ecosystem, human health, and society. However, its definition using pentad-average soil moisture could result in low accuracy of assessing the drought occurrence, making it difficult to analyze various factors controlling the formation of flash drought. Here we used a stochastic water balance framework to quantify the timing of drought as the first passage time of soil moisture dropping from

- a higher level to a lower one. Based on this framework, we can theoretically examine the nonlinear relationship between the 5 timing of drought and various hydrometeorological factors and identify possible flash drought risks caused by less rainfall (e.g., long dry spells), higher evapotranspiration (e.g., extreme heatwaves), lower soil water storage capacity (e.g., deforestation), or a combination thereof. Applying this framework to the global datasets, we found that flash drought risks also exist in humid regions such as southern China and the northeastern United States, calling for particular attention to flash drought monitoring and mitigation.
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#### Introduction 1

Drought, usually defined as a prolonged period of water scarcity, is one of the major natural disasters that influenced nearly 40% of the population over the world (Hamdy et al., 2003) the rapid intensification of drought is particularly detrimental such as the drought in 2012 in the central United States, which has long-term impacts on agriculture, animal husbandry, navigation,

- 15 and employment (Hoerling et al., 2014), and was estimated to be the costliest drought event in U.S. history with total losses of 35 billion U.S. dollars (Grigg and Neil, 2014). The timing of drought occurrence has recently received much research attention and various indices have been proposed to define the rapid intensification of drought or 'flash drought'. Based on hydrometeorological variables such as evapotranspiration and precipitation, Mo and Lettenmaier (2015) identified two types of flash drought primarily caused by heatwaves and precipitation deficit, both of which can be accurately characterized as rapid-
- intensification of drought conditions (Liu et al., 2020). Moreover, soil water capacity is associated with vegetation dynamics 20 and water balance, thus also influencing the timing of drought (Wang et al., 2013; Gao et al., 2014). While traditional drought indices and monitoring systems (e.g., standardized precipitation evapotranspiration index) do not promptly respond to the rapid occurrence of drought events (Ford et al., 2015; Zhang et al., 2017; Mohammadi et al., 2022), soil moisture has been argued





to be a useful indicator in characterizing flash drought (Hunt et al., 2009; Mozny et al., 2012; AghaKouchak et al., 2015). A
flash drought event is usually identified when the pentad-average (5-day average) soil moisture percentile dropped from 40 percentile (a drier than normal soil condition) to 20 percentile (the onset of moderate drought) in 20 days or less (Otkin et al., 2016; Ford and Labosier, 2017; Basara et al., 2019; Nguyen et al., 2019; Zhang et al., 2022) and subsequent studies have also refined the onset and end of flash drought events (Yuan et al., 2018, 2019). A comprehensive review of the flash drought definitions is given by Lisonbee et al. (2021).

- 30 While these indices based on pentad-average soil moisture reduce the impacts of extreme soil moisture fluctuation and are valuable for characterizing drought behaviors, the timing of soil moisture crossing any thresholds has a coarse temporal resolution of 5 days. This may be less accurate for drought occurrence within 20 days or less, resulting in a relative bias of higher than 25% and thus further complicating the assessment and identification of hydrometeorological factors contributing to the flash drought. An illustrative example based on a water balance model introduced in Sec. 2 is given in Fig. 1, which shows
- both the time series of instantaneous soil moisture (s, solid lines in Fig. 1a) and pentad-average soil moisture ( $s_5$ , solid lines in Fig. 1c). For the prescribed hydrometeorological factors, it takes 15 days for s to decrease from 40 to 20 percentile but 15-20 days for  $s_5$ . When varying soil water capacity  $w_0$  (Fig. 1b) or total rainfall rate by a factor of k (Fig. 1d), one can find zigzag lines of  $s_5$  crossing the threshold, suggesting insensitive response of traditional flash drought index to these parameters. While this problem may be partially solved by using smoothing technique or changing averaging windows, the problem essentially
- 40 stems from the probabilistic structure of the soil moisture evolution, which requires further exploration for accurate assessment of flash drought.

Toward this goal, here we provide a stochastic framework as well as its crossing properties to quantify the rapid intensification of drought. Without counting drought events and justifying the proper smoothing windows for eliminating extreme fluctuations of soil moisture, it allows us to describe the whole probabilistic structure of soil moisture crossing different thresh-

- 45 olds, which theoretically counts infinitely many drought events and smooths the extreme fluctuations over the whole spectrum of soil moisture levels. Based on this framework, we can precisely calculate the ensemble mean time required for soil moisture to decline from 40 to 20 percentiles and compare the timing of drought under different hydrometeorological conditions, thus providing an efficient and objective tool for analyzing the rapid intensification of drought. The paper is organized as follows: section 2 introduces the stochastic framework, section 3 analyzes the effects of various hydrometeorological factors contribut-
- 50 ing to the timing of drought occurrence and then the framework is applied to identify global patterns of flash drought risks. The conclusions are summarized in section 4.

#### 2 Theory

To characterize the 'flash' behavior drought, we use, without loss of generality, the minimalist soil water balance framework (Porporato et al., 2004; Porporato and Yin, 2022)

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$$w_0 \frac{\mathrm{d}x(t)}{\mathrm{d}t} = R(t) - E(x(t), t) - \mathrm{LQ}(x(t), t),$$
 (1)





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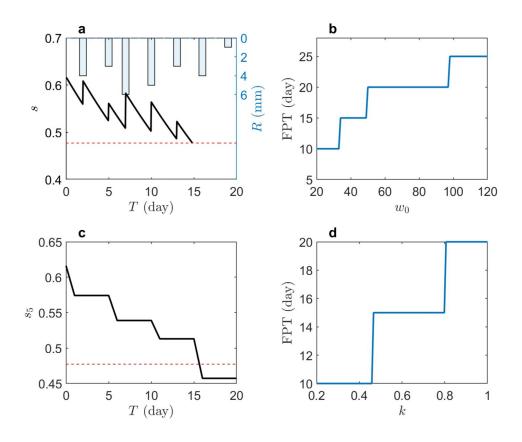


Figure 1. An illustrative example of drought occurrence. Time series of (a) rainfall, instantaneous soil moisture s, and (c) pentad-average soil moisture  $s_5$ . First passage time (FPT) from 40 to 20 percentile is calculated (b) by varying soil water capacity  $w_0$  and (d) by changing rainfall rate by a factor of k. Simulated soil moisture is based on a water balance model in Sec. 2. The parameters: potential evapotranspiration  $E_{\text{max}} = 4 \text{ mm day}^{-1}$ , water storage capacity  $w_0 = 80 \text{ mm in (a), (c) and (d)}$ .

where x is the relative soil moisture ranging from 0 at the wilting point to 1 around field capacity,  $w_0$  is water storage capacity in the rooting zone, R, E, and LQ are rainfall, evapotranspiration, and deep leakage/runoff, respectively. In the minimalist framework, we assume E linearly increases from 0 at x = 0 to  $E_{\text{max}}$  at x = 1, and excessive parts of rainfall at x = 1 are converted to LQ. When assuming the rainfall is a Marked Poisson process with rainfall rate  $\lambda$  and exponentially distributed rainfall depth of mean  $\alpha$ , we can express the probability density function (PDF) of x at steady state, p(x), as (Porporato et al., 2004)

$$p(x) = \frac{\gamma^{\lambda/\eta}}{\Gamma(\lambda/\eta) - \Gamma(\lambda/\eta, \gamma)} e^{-\gamma x} x^{\lambda/\eta - 1}$$
(2)





where  $\gamma = w_0/\alpha$ ,  $\eta = E_{\text{max}}/w_0$ , and  $\Gamma(\cdot)$  and  $\Gamma(\cdot, \cdot)$  are the complete and incomplete gamma functions, respectively. The cumulative distribution function (CDF) of x can be found by integrating Eq. (2) as

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$$P(x) = \frac{\Gamma(\lambda/\eta) - \Gamma(\lambda/\eta, \gamma x)}{\Gamma(\lambda/\eta) - \Gamma(\lambda/\eta, \gamma)}$$
(3)

The inverse of CDF is the quantile function of x, providing soil moisture values for the given percentiles.

Following the flash drought definition given by Ford and Labosier (2017) and many others, we measure the timing for the drop of relative soil moisture from a high level  $x_1$  (e.g., 40 percentile) to a low level  $x_2$  (e.g., 20 percentile). In our stochastic framework, this timing is also a random variable,  $t_{x_1 \downarrow x_2}$ . While its whole distribution is difficult to obtain, its mixed feature with both continuous and discrete parts is evident (Gardiner, 1985). When there is no rainfall, the soil moisture decreases

70 with both continuous and discrete parts is evident (Gardiner, 1985). When there is no rainfall, the soil moisture decreases following the fast routine from  $x_1$  to  $x_2$  with minimal  $t_{x_1 \downarrow x_2}$ , which can be found by solving Eq. (1) without rainfall and runoff (i.e., R = LQ = 0),

$$t_{\min} = \frac{1}{\eta} \ln\left(\frac{x_2}{x_1}\right). \tag{4}$$

The atom probability of this no rainfall condition in a Poisson process is e<sup>-λt<sub>min</sub></sup>. In the minimalist case, the continuous part
tends to be an exponential distribution shifted by t<sub>min</sub> as demonstrated in Fig. 2. Therefore, we can approximate the whole distribution of t<sub>x1 \plack x2</sub> as

$$f(t_{x_1 \downarrow x_2}) \approx e^{-\lambda t_{\min}} \delta(t_{x_1 \downarrow x_2} - t_{\min}) + (1 - e^{-\lambda t_{\min}}) \beta e^{-\beta(t_{x_1 \downarrow x_2} - t_{\min})},$$

$$(5)$$

where  $\delta()$  is the Dirac delta function, and  $\beta$  is the parameter. Moreover, the expectation is often referred to as the mean first passage time (MFPT),  $\bar{t}_{x_1 \downarrow x_2}$  (Rodríguez-Iturbe and Porporato, 2004)

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$$\bar{t}_{x_1\downarrow x_2} = \int_{x_2}^{x_1} \frac{1}{\eta^2 u^2 p(u)} [\lambda - \lambda P(u) + \eta u p(u)] \mathrm{d}u,$$
 (6)

which does not have explicit solution due to the presence of P(u)/p(u) in the integral. Codes for the numerical integration with different parameters are available at github.com/yxshot/MFPT. Matching this mean value with its PDF in Eq. (5) yields the parameter  $\beta$ 

$$\beta = \frac{1 - e^{-\lambda t_{\min}}}{\text{MFPT} - t_{\min}}.$$
(7)

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Therefore, the distributions of  $t_{x_1 \downarrow x_2}$  in Eq. (5) and its mean  $\bar{t}_{x_1 \downarrow x_2}$  in Eq. (6) provide comprehensive metrics for quantifying the rapid intensification of drought. It should be noted that more complicated loss functions for E and LQ can be used in Eq. (1) to formulate more realistic metrics. As a starting point for applying this framework, here we only use  $\bar{t}_{x_1 \downarrow x_2}$  (i.e., MFPT), and the whole distribution for describing the risks of the flash drought will be the subject of future research.





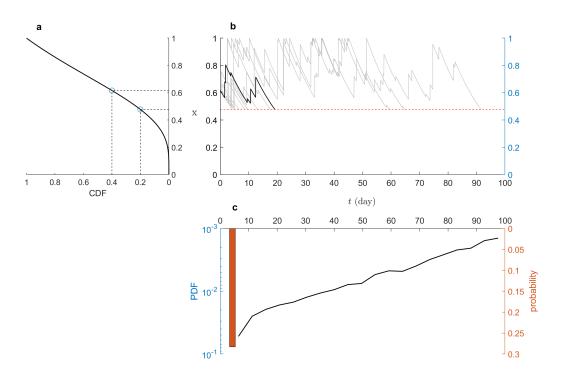


Figure 2. (a) Quantile function for soil moisture (i.e., inverse of Eq.(3)), (b) numerical simulation of Eq. (1) for relative soil moisture x from 40 to 20 percentiles, and (c) the corresponding distribution of first passage time (sample size of 1000). The parameters are set as follows: average rainfall depth  $\alpha = 12$  mm, rainfall rate  $\lambda = 0.3$  day<sup>-1</sup>, water storage capacity  $w_0 = 83.2$  mm, and potential evapotranspiration  $E_{\text{max}} = 5 \text{ mm day}^{-1}$ . Note the left y-axis for the continuous part of the distribution is in logarithmic scale.

# 3 Results

### 90 3.1 Hydrometeorological impacts on the timing of drought

The interaction among climate, soil, and vegetation controls the water balance and influences the timing of drought (Mishra and Singh, 2010; Chen et al., 2021; Hu et al., 2021). This is theoretically analyzed here by using the framework developed in the last section with four hydrometeorological factors, i.e., rainfall frequency ( $\lambda$ ), average rainfall depth ( $\alpha$ ), potential evapotranspiration ( $E_{\text{max}}$ ), soil water storage capacity ( $w_0$ ).

- 95 By fixing two factors and varying the other two, we can find how hydrometeorological factors influence the mean first passage time of soil moisture dropping from 40 to 20 percentiles. It is clear that ensemble average soil moisture is more sensitive than pentad-average soil moisture in response to the environmental factors (see Figs. 1 and 3), highlighting the importance of exploring the probabilistic behaviors of water balance for assessing flash drought. Using this stochastic framework, we found less precipitation (e.g., long dry spells), stronger evapotranspiration (e.g., heatwave-induced high evaporation), and lower water
- 100 storage capacity (e.g., large-scale deforestation) can speed up the loss of soil moisture, resulting in shorter MFPT (see Fig. 3a-





c). While the first two factors have been identified in previous studies, the last one is less extensively investigated probably due to the low resolution of the traditional pentad-average soil moisture (although rooting depth or soil water storage capacity is one of the critical factors considered in the general drought events, e.g., Passioura, 1983; Padilla and Pugnaire, 2007; Sehgal et al., 2021).

- 105 Specifically, low water storage capacity accelerates the loss of water even in wet regions where plenty of water is converted into runoff (Fig. 3a) or in cold regions where potential evaporation is low (Fig. 3b), quantifying its role in controlling flash drought. In contrast to water storage capacity, the impacts of rainfall frequency or potential evapotranspiration on MFPT tend to be less nonlinear (Fig. 3c). In arid regions of high potential evapotranspiration rate, neither increasing water storage capacity nor rainfall rate can significantly slow down the rate of moisture decline (e.g., upper right corners of Fig. 3 b and c), because
- 110 the evaporated moisture is always greater than the gained. In semi-arid or semi-humid regions, the occurrence of flash droughts may require the combined effects of several hydrological conditions (e.g., moderate rainfall frequency and high potential evapotranspiration or low water storage capacity, see Fig. 3 a and c).

Moreover, the interplay between the frequency and the depth of rainfall can be analyzed by considering a fixed total precipitation  $\alpha \lambda = \text{const.}$  Therefore, increasing  $\lambda$  means frequent yet lighter rainfall, lowering the overall uncertainty of the rainfall

115 process. For saturation excess runoff, lower rainfall uncertainty tends to reduce the runoff generation and thus increase the MFPT as shown in Fig. 3d. Similarly, larger soil water capacity provides deeper buffering zones for uncertain rainfall, also increasing MFPT and delaying the timing of drought. Note that canopy interception is not considered here, which may reduce water infiltrated into the soil and shorten the MFPT.

# 3.2 Timing of global drought occurrence

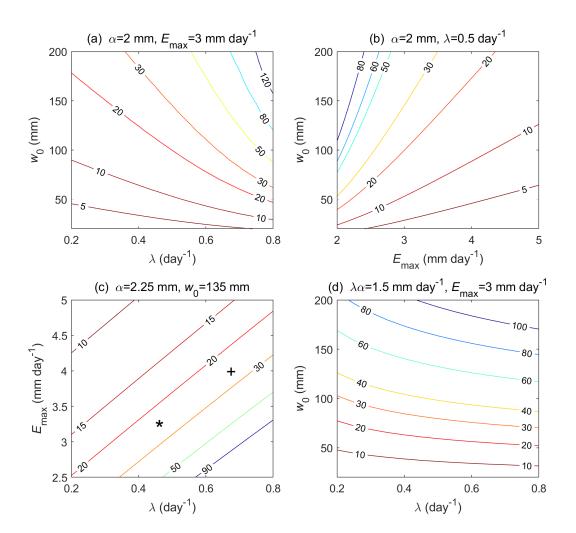
- 120 Besides the theoretical analysis of the drought occurrence, our framework can also be used to diagnose the timing of drought for specific sites. Towards this goal, here we used global datasets of soil water capacity, precipitation, and potential evapotranspiration. The daily precipitation in the boreal summer of 2009-2018 was obtained from the Global Precipitation Climatology Project (GPCP) to calculate the rainfall frequency and average depth. GPCP is part of the World Climate Research Program (WCRP), which combines satellite infrared, microwave, and sounding observation data and precipitation observation data from
- 125 more than 6,000 ground stations at the spatial resolution of 1° (Huffman et al., 1997, 2001). We calculated the average potential evapotranspiration by using the Climate Research Unit (CRU) TS v4, which is one of the most widely used observed climate datasets at the spatial resolution of 0.5° (Harris et al., 2020). The global soil water storage capacity of the rooting zone is from the International Satellite Land Surface Climatology Project, Initiative II (ISLSCP II) with a resolution of 1°, which is derived from the assimilation of NDVI-fPAR and atmospheric forcing data (Kleidon, 2011).

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We rescaled all these datasets to 0.5° spatial resolution and substituted them into Eq. (6) to find the global MFPT (see Fig. 4). Our calculations do not include hyper-arid regions, which may be better characterized as permanent drought conditions. The results show that in summer soil moisture in southern China and the United States decreases rapidly, making these regions prone to flash drought risks. This is consistent with some recent observations and analyses, which have shown increasing trends







**Figure 3.** The influence of hydrometeorological factors on mean first passage time (days) of soil moisture dropping from 40 to 20 percentiles. The unit of MFPT is day.  $w_0$  is water storage capacity in the rooting zone,  $\lambda$  is rainfall rate,  $\alpha$  is average rainfall depth, and  $E_{\text{max}}$  is potential evapotranspiration. '+' and '\*' correspond to the for sites in Guangdong, China and New York State, USA respectively (see Fig. 4).



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of flash drought events in humid areas in China (Wang et al., 2016; Yuan et al., 2019; Qing et al., 2022). Chen et al. (2019) also found flash drought events occurred mainly in the central United States during the warm season.

It is also possible to identify different types of flash droughts from our stochastic framework. The flash drought in the central United States in Fig. 4 is caused by a combination of high evapotranspiration and low rainfall rate, while the rapid decline in soil moisture in several areas of the southern hemisphere may be associated with the seasonal drought. Specifically, we focused on one site in the eastern United States and another in southeastern China, which are both marked in Fig. 3(c) according to their MFPT and hydrological conditions and in Fig. 4 based on their geographical locations. While the decline in soil moisture

- at both sites is around 25 days, the causes are somehow different. With approximately the same water storage capacity, the site in southeastern China has adequate precipitation but higher evaporation, whereas the site in the eastern United States has relatively lower evapotranspiration but less precipitation. These fall in the two categories of flash drought described by Mo and Lettenmaier (2015, 2016), namely heat-wave flash drought caused by increased evapotranspiration and the precipitation-
- 145 deficit flash drought caused by insufficient precipitation. It is clear that from our stochastic framework it might be interesting to define a third type of flash drought related to low water capacity in regions undergoing rapid urbanization or deforestation. This requires further investigation and remains an exciting and open area of research in hydrometeorology.

# 4 Conclusions

This study aimed at providing a stochastic framework to quantify the rapid intensification of drought. Within the minimalist soil
water balance framework, the mean first passage time for the relative soil moisture dropping from different levels was obtained, which was then used to identify different types of flash drought. We found that not only precipitation and evapotranspiration frequently mentioned in previous studies but also water storage capacity discussed here could all play major roles in controlling the timing of drought. By applying this framework and analyzing various hydrometeorological factors, we identified a rapid decline of soil moisture in some wet areas due to high evapotranspiration rates, such as southern China and the northeast United
States.

In response to global warming, the frequency of flash droughts may increase, posing great risks to our society. Understanding the causes of these drought events is a necessary step for drought warning, preparation, and mitigation. The stochastic framework developed here is efficient at diagnosing the impacts of hydrometeorological factors and thus could provide an objective tool for monitoring flash drought events. Future work could focus on applying this stochastic framework and using

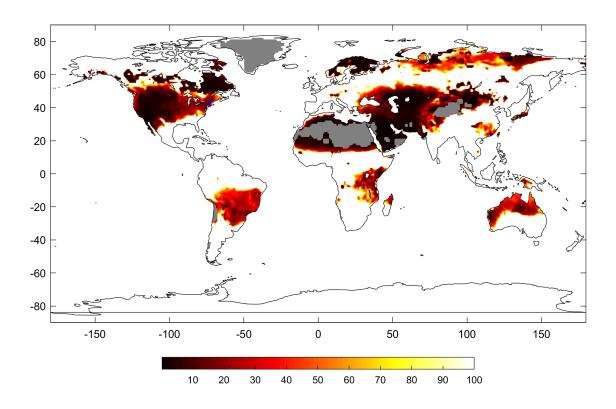
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0 the upcrossing properties of the stochastic process to evaluate the drought-mitigation strategies by quantifying the timing of recovering from a low soil moisture level to a higher level (e.g., setting  $x_1 < x_2$  for  $\bar{t}_{x_1\uparrow x_2}$ ).

Code availability. Codes for calculating MFPT are available at github.com/yxshot/MFPT.







**Figure 4.** Global distribution of mean first passage time (MFPT) in summer. The two points marked in blue are New York State, USA ( $74^{\circ}W$ ,  $44^{\circ}N$ ) and Heyuan City, Guangdong Province, China ( $115^{\circ}E$ ,  $24^{\circ}N$ ). The gray areas are hyper-arid regions, other colored areas are those where MFPT of soil moisture dropping from 40 to 20 percentiles in less than 100 days. Desert regions (grey areas) are excluded in this analysis.

*Data availability.* GPCP data were obtained from doi.org/10.7289/V5RX998Z, CRU data were from crudata.uea.ac.uk/cru/data/hrg/, ISLSCP II data were from daac.ornl.gov/ISLSCP\_II/.

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Competing interests. The authors declare no competing interests.





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