# Flash Drought Indicator Intercomparison in the United States

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ABSTRACT: Increased flash drought awareness in recent years has motivated the development of numerous indicators for monitoring, early warning, and assessment. The flash drought indicators can act as a complementary set of tools by which to inform flash drought response and management. However, the limitations of each indicator much be measured and communicated between research and practitioners to ensure effectiveness. The limitations of any flash drought indicator are better understood and overcome through assessment of indicator sensitivity and consistency; however, such assessment cannot assume any single indicator properly represents the flash drought "truth." To better understand the current state of flash drought monitoring, this study presents an intercomparison of nine, widely used flash drought indicators. The indicators represent perspectives and processes that are known to drive flash drought, including evapotranspiration and evaporative demand, precipitation, and soil moisture. We find no single flash drought indicator consistently outperforms all others across the contiguous United States. We do find the evaporative demand- and evapotranspiration-driven indicators tend to lead precipitation- and soil moisture-based indicators in flash drought onset, but also tend to produce more flash drought events collectively. Overall, the regional and definition-specific variability in results supports the argument for a multi-indicator approach for flash drought monitoring, as advocated by recent studies. Furthermore, flash drought research—especially evaluation of historical and potential future changes in flash drought characteristics—should test multiple indicators, datasets, and methods for representing flash drought, and ideally employ a multi-indicator analysis framework over use of a single indicator from which to infer all flash drought information.

SIGNIFICANCE STATEMENT: Rapid onset or "flash" drought has been an increasing concern globally, with quickly intensifying impacts to agriculture, ecosystems, and water resources. Many tools and indicators have been developed to monitor and provide early warning for flash drought, ideally resulting in more time for effective mitigation and reduced impacts. However, there remains no widely accepted single method for defining, monitoring, and measuring flash drought, which means most indicators that are developed are compared with other individual indicators or conditions and impacts in one or two flash drought events. In this study, we measure the state of flash drought monitoring through an intercomparison of nine, widely used flash drought indicators that represent different aspects of flash drought. We find that no single flash drought indicator outperformed all others and suggest that a comprehensive flash drought monitor should leverage multiple, complementary indicators, datasets, and methods. Furthermore, we suggest flash drought research—especially that which reflects on historical or projected changes in flash drought characteristics—should seek multiple indicators, datasets, and methods for analyses, thereby reducing the potentially confounding effects of sensitivity to a single indicator.

KEYWORDS: Drought; Precipitation; Evapotranspiration; Soil moisture

## 1. Introduction

Flash drought is characterized by unusually rapid drought intensification over subseasonal time scales, which reduces lead time for preparation, response, and management to drought conditions (Otkin et al. 2022). Although precipitation deficits are a prerequisite for all types of drought, flash drought is often caused by concurrent precipitation deficit and elevated evapotranspiration due to high temperatures, low humidity, strong winds, abundant solar radiation, or a combination of these conditions (Otkin et al. 2018). The co-occurrence of limited precipitation and high evapotranspiration can cause a rapid depletion of soil moisture availability for plant use (Mozny et al. 2012; Otkin et al. 2013; Ford and Labosier 2017; Koster et al. 2019). Rapid soil drying can lead to vegetation moisture stress and the emergence of ecological and agricultural impacts. Because it results from insufficient precipitation and high evapotranspiration, flash drought is most likely to develop during the growing season

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when both evaporative demand and vegetation moisture requirements are high. Consequently, flash droughts have the potential to cause significant ecological, economic, and cultural impacts. For example, economic impacts from the 2012 flash drought in the central United States were estimated to be approximately $40 billion (Rippey 2015). The 2017 flash drought in the U.S. northern plains caused an estimated $240 million loss in recreation tourism in Montana alone (Hoell et al. 2020). These are just two of many examples of the adverse impacts of flash droughts on the environment and economy (e.g., Nguyen et al. 2019; Basara et al. 2019; Christian et al. 2020; Hunt et al. 2021).

The substantial impacts caused by recent flash drought events have motivated development of multiple indicators and indices for flash drought monitoring, identification, and early warning (Lisonbee et al. 2021). Mirroring the varied and complex processes through which flash drought occurs (e.g., Osman et al. 2022), indicators have been derived from a diverse set of meteorological and hydrological variables known to contribute to flash drought, including precipitation deficits (Noguera et al. 2020; Fu and Wang 2022), elevated evaporative demand or evapotranspiration (Otkin et al. 2013; Hobbins et al. 2016; Christian et al. 2019), and soil moisture depletion (Osman et al. 2021; Otkin et al. 2021). While individual indicators have been shown to effectively capture the onset and evolution of flash drought events (Otkin et al. 2016; Nguyen et al. 2019), they inherently represent only a single component of the interconnected processes that cause flash drought. The singular focus on precipitation, evapotranspiration, evaporative demand, or soil moisture, limits the extrapolation of these indicators beyond their test cases for monitoring compound multivariate hazards such as flash drought (e.g., Otkin et al. 2013).

The myriad limitations and caveats in any individual flash drought indicator can be better understood and overcome through a combination of case study and climatological assessment of their ability to capture flash drought onset and/or severity. Numerous prior studies have done this, evaluating the flash drought monitoring efficacy of individual indicators across a single or multiple flash drought events (e.g., Anderson et al. 2013; Ford et al. 2015; Christian et al. 2019; Chen et al. 2019; Hoffmann et al. 2021). The advantage of a case study assessment is that it tests an indicator in a real drought situation. However, differences in characteristics between flash droughts also necessitate a climatological assessment to ensure an indicator can perform well across a multitude of conditions and regions. In this study, we leverage the benefits of both climatological and case study assessments to test indicators.

The ideal validation of a drought indicator would be through its comparison with a tangible drought impact (e.g., crop yield loss, watering restrictions, excess wildlife mortality). However, drought impact assessment is a challenging endeavor partly because of the diversity of the impacts and when they occur. For example, the 2012 U.S. flash drought caused widespread mortality of seedlings on Christmas tree farms; however, this impact was not fully realized until several years later with a shortage of Christmas tree stock (Gutzmer 2018). The complexity of drought impacts has challenged impact monitoring and reporting, and our current infrastructure—while rapidly improving—is not sufficient to capture the breadth and depth of impacts from a severe drought (Bachmair et al. 2016). Consequently, most prior studies that evaluate one or more indicators of drought or flash drought determine a benchmark dataset or indicator that is assumed to represent the "truth." This approach may be reasonable in cases where the ultimate goal is improving monitoring or early warning for a specific result, such as soil moisture drought (e.g., Hoffmann et al. 2021; Parker et al. 2021). However, the results of such 1-to-1 indicator comparisons are limited by the uncertainties and limitations of the indicator that serves as the benchmark or "truth." This issue is exacerbated in the case of flash drought, where there is not a single dataset or indicator that is widely considered the benchmark to which other indicators can be compared.

From an operational monitoring perspective, the suite of potentially effective flash drought indicators can act as a complementary set of tools by which to inform flash drought response and management. However, the limitations and uncertainties with each tool must be well measured and communicated between research and operations to ensure proper use of any individual indicator (Otkin et al. 2022). Furthermore, we argue these limitations cannot be properly understood through 1-to-1 indicator comparisons.

Instead of assuming a single indicator or dataset represents the truth of flash drought, for our intercomparison we assume all indicators represent a version of the truth. In this way, we can evaluate a single indicator with respect to the multiple versions of the truth provided by the other indicators. Ideally, an indicator's version of the truth will closely match that of other indicators, providing confidence in a convergence of evidence toward operational flash drought monitoring. Osman et al. (2021) used a similar approach to study the sensitivity of flash drought climatology and trends in individual indicators and definitions. Our study is focused on providing a holistic set of evaluations by which to inform operational flash drought monitoring using a suite of indicators. In this way, the study highlights differences in indicator performance when compared with other indicators and by geographic region. The study's focus is the contiguous United States (CONUS) and evaluates flash drought monitoring over the period from 2002 to 2021, with flash drought case studies in 2012 and 2019.

## 2. Flash drought indicators

Since its inception in the scientific lexicon in the early 2000s, flash drought has been defined, studied, and monitored using many indicators and datasets. Most flash drought studies have used one or more indicators that can be broadly categorized as those representing 1) evapotranspiration, 2) soil moisture, and 3) precipitation (Lisonbee et al. 2021). Lisonbee et al. (2021) also include a category for temperature-based monitoring, but the effects of temperature on flash drought are captured by the evaporative demand-based indicators. For this study, we select indicators from these three categories, thereby representing many important processes and

TABLE 1. Flash drought indicators used in the study.

| Indicator | Native resolution | Period of record | Reference | Data source |
|---|---|---|---|---|
| EDDI (14 and 28 day) | 0.125° | 1979–present | Hobbins et al. (2016) | https://psl.noaa.gov/eddi/ |
| ESI (14 and 28 day) | 0.125° | 2002–present | Anderson et al. (2007) | https://climateserv.servirglobal.net/map |
| SMVI | 0.125° | 1979–present | Osman et al. (2021) | https://ldas.gsfc.nasa.gov/nldas/NLDAS2forcing.php |
| SPEI (14 and 30 day) | 4 km | 1979–present | Vicente-Serrano et al. (2010) | https://www.climatologylab.org/gridmet.html |
| SPI (14 and 30 day) | 4 km | 1979–present | McKee et al. (1993) | https://www.climatologylab.org/gridmet.html |
| USDM | — | 1979–present | Svoboda et al. (2002) | https://droughtmonitor.unl.edu/DmData/GISData.aspx |

impacts associated with flash drought. Within each category we select indicators that are both widely used in previous research and available for operational monitoring. The latter of these conditions is important as our intent is to remark on the current state of flash drought indicators for real-time monitoring applications. Table 1 contains more detailed information about each of the flash drought indicators used. Although the indicators selected for this study are not meant to be exhaustive, they do include at least one indicator from each of the major flash drought monitoring categories delineated by Lisonbee et al. (2021).

### *a. Evapotranspiration and evaporative demand indicators*

While there has been considerable disagreement among researchers as to how flash drought is characterized and defined, most agree evapotranspiration and evaporative demand play important roles in rapid onset drought and intensification (Otkin et al. 2018; Pendergrass et al. 2020; Nguyen et al. 2023; O and Park 2023). We use two widely studied evapotranspiration and evaporative demand-based indicators for this study: the evaporative demand drought index (EDDI; Hobbins et al. 2016) and the evaporative stress index (ESI; Anderson et al. 2007).

EDDI is a nonparametric percentile-based representation of evaporative demand anomalies. In this study, as in most applications of EDDI, evaporative demand is estimated using the American Society of Civil Engineers standardized reference evapotranspiration equation (Allen et al. 2005), based on the parameterized Penman–Monteith equation. Standardized evapotranspiration probabilities are derived using an inverse-normal approximation. Negative (positive) EDDI values indicate evaporative demand that is below (above) the climatological median values. A more detailed description of EDDI, and its derivation are provided in Hobbins et al. (2016). For this study, we obtained daily EDDI datasets from the NOAA/Physical Sciences Laboratory, where EDDI is also available for operational monitoring (https://psl.noaa.gov/eddi/). Reference evapotranspiration used to compute EDDI comes from the operational North American Land Data Assimilation System (NLDAS-2; Xia et al. 2012). Daily EDDI data are available at 0.125° spatial resolution across CONUS from 1979 to present. We use EDDI computed over 14-day (EDDI-14) and 28-day (EDDI-28) intervals to capture the typical duration of flash drought onset (e.g., Otkin et al. 2018). We also computed all results with 56-day EDDI, but the results did not significantly differ from the 28-day iteration, so we only show EDDI-28 results for brevity.

ESI is an evapotranspiration -based indicator, but unlike EDDI that uses only reference evapotranspiration, ESI is computed as the ratio of the actual evapotranspiration to a reference evapotranspiration. The Atmospheric Land Exchange Inverse (ALEXI; Anderson et al. 1997) model is used to estimate actual and reference evapotranspiration. Ratios of actual to reference evapotranspiration are standardized using a similar procedure as EDDI, based on climatological anomalies. A more detailed description of ESI and its derivation are in Anderson et al. (2007) and Otkin et al. (2013). ESI is available for operational monitoring at ClimateSERV (https://climateserv.servirglobal.net/map), but only the 28- and 84-day ESI products are available for download. For consistency with EDDI, we obtained 14-day (ESI-14) and 28-day (ESI-28) products directly from Dr. C. Hain at the NASA Marshall Space Flight Center. Daily ESI-14 and ESI-28 products are available at 0.125° resolution across CONUS from 2002 to present.

To identify flash droughts based on ESI and EDDI, we combine the methods of Pendergrass et al. (2020) and Parker et al. (2021). Specifically, a flash drought is identified with a ≥50-percentile change in EDDI or ESI (toward drying) over 14 days. This onset period must end with EDDI reaching at least the 80th percentile or ESI dipping to or below the 20th percentile. Last, the high EDDI or low ESI values must be sustained for another 14 days to imply drought conditions. A flash drought event was terminated when the EDDI fell below the 80th percentile (or ESI climbed above the 20th percentile) and remained there for at least another 14 days. This technique ensured the method did not identify two separate flash droughts within a 2-week period.

### *b. Soil moisture indicator*

Soil moisture is an important indicator of flash drought (Ford and Labosier 2017; Otkin et al. 2019) and is often used as a benchmark by which to compare other indicators (Christian et al. 2021; Hoffmann et al. 2021; Parker et al. 2021). For this study, we use 0–40-cm soil moisture from the NLDAS-2 Noah model to represent soil moisture conditions. The Noah model simulates hourly soil moisture at multiple depths, and we integrate conditions across 0–40 cm, matching the depths used in past studies (e.g., Ford and Labosier 2017; Osman et al. 2021). Daily NLDAS-2 soil moisture is available at a 0.125° resolution from 1979 to present, and we aggregate hourly soil moisture to daily averages. The NLDAS-2 Noah model was used in this study because it has been previously shown to have high soil moisture simulation fidelity (Xia et al. 2015), and it is available in near real-time for operational drought monitoring (https://ldas.gsfc.nasa.gov/nldas/drought-monitor).

To identify flash drought based on NLDAS-2 soil moisture, we adopt the soil moisture volatility index (SMVI; Osman et al. 2021). Based on the SMVI, a flash drought is identified if 1) the 5-day running average soil moisture falls below the 20-day running average soil moisture for at least 20 days, and 2) by the end of the 20-day period the soil moisture has dropped below its climatological 20th percentile for that time of the year. Soil moisture percentiles were calculated using a 30-day moving window over calendar years, thereby removing the effects of soil moisture seasonality (e.g., Ford and Quiring 2019). Osman et al. (2021) found the SMVI was more stable than previously proposed soil moisture-based metrics that relied solely on the "drop" in soil moisture from the 40th to the 20th percentile. The flash drought was considered to be terminated once the soil moisture climbed above the 20th percentile and remained there for at least 14 days.

## c. *Precipitation indicator*

As with any drought, precipitation deficits play an important role in determining the speed, intensity, and duration of a flash drought event. In this study, we use the standardized precipitation index (SPI; McKee et al. 1993) as a precipitation-based indicator of flash drought. Precipitation fields for SPI were taken from the gridMet dataset (Abatzoglou 2013), which is available daily at an approximately 4-km spatial resolution across CONUS from 1979 to the present. The precipitation fields were upscaled to the common 0.125° spatial resolution of the other indicators. SPI was then calculated as the gamma-standardized $n$-day precipitation accumulation. We derive SPI over 14-day (SPI-14) and 30-day (SPI-30) periods to capture the typical flash drought period of onset.

## d. *Combined indicator*

We use the standardized precipitation evapotranspiration index (SPEI; Vicente-Serrano et al. 2010) as an indicator of the combined effects of precipitation and evapotranspiration. Precipitation and reference evapotranspiration fields for SPEI were taken from the gridMet dataset, and upscaled to the common 0.125° spatial resolution of the other indicators. SPEI was calculated as the log-logistic standardized $n$-day accumulation of differences between precipitation and reference evapotranspiration. We derived SPEI over 14-day (SPEI-14) and 30-day (SPEI-30) periods.

We included both SPI and SPEI in this study to contrast the performance of similar metrics with and without the inclusion of reference evapotranspiration. This comparison is particularly important given the outsized role evaporative demand can plan in flash drought onset (Christian et al. 2020; Noguera et al. 2022). We adopt the method of Noguera et al. (2020) for identifying flash drought based on SPI and SPEI, where a flash drought requires a decrease in SPI or SPEI over 28 days with a total change in SPI or SPEI of 2 or greater and a final SPI or SPEI value of −1.28 or less.

## e. *The U.S. Drought Monitor*

The U.S. Drought Monitor (USDM; Svoboda et al. 2002) is a weekly map-based drought severity analysis produced by one of multiple authors with significant local input on drought conditions. The USDM uses a "convergence of evidence" approach to drought monitoring, such that USDM-depicted drought conditions in any given region on any given week will generally not be based on a single indicator. While somewhat subjective, this approach to drought monitoring reduces the negative impacts of biases in individual indicators and ensures local experts can inform the authors about conditions in their areas. USDM maps are produced each week on Tuesday and are released on Thursday.

We obtained weekly USDM maps in shapefile format and converted them to raster format with the common 0.125° spatial resolution of the other indicators. The shapefile-to-raster function assigned each grid cell the worst USDM drought category that encompassed at least 25% of the gridcell area. The once-weekly USDM dataset was then converted to a daily temporal resolution by assuming the same USDM value for each of the 6 days following the Tuesday on which the USDM map was produced. In this way we compare the USDM as it would be compared in an operational drought monitoring environment, assuming the map depicts drought accurately until the next USDM map is released. Flash drought is then identified in the daily USDM dataset using the Pendergrass et al. (2020) method of having a 2+-category decline in 2 weeks that is then sustained another 2 weeks.

## f. *Alternative EDDI indicator*

Methods used to identify flash drought for both operational monitoring and research applications generally follow the same guidelines irrespective of the indicator or variable used. Those guidelines tend to include a "flash" component where conditions change from nondrought to drought in a relatively short period of time, typically 2–6 weeks. Also included is a "drought" component where conditions must decline to at least drought status, and in many cases persist in drought status for another 2–6 weeks. However, differences in variables, thresholds, time periods, and standardization techniques can cause significant differences in the climatological frequency and intensity of flash drought across different regions. To better understand the sensitivity of our results to the method of identifying flash drought, we repeat the analysis using an alternative identification method based on EDDI-14.

Following a standardized change anomaly technique from Otkin et al. (2013) and Christian et al. (2019), we derive a "flash" component by calculating a standardized change in EDDI ($\mathrm{EDDI}_{ijd}z$), such that

$$\mathrm{EDDI}_{ijd}z = \frac{\mathrm{EDDI}_{ijd} - \overline{\mathrm{EDDI}_{ijd}}}{\sigma \mathrm{EDDI}_{ijd}}, \tag{1}$$

where $EDDI_{ijd}z$ is the daily change in EDDI-14 at grid cell $i$, $j$ and calendar day $d$, $\overline{EDDI_{ijd}}$ is the mean change in EDDI-14 for a specific grid cell and calendar day, and $\sigma EDDI_{ijd}$ is the standard deviation of EDDI-14 for a specific grid cell and calendar day. Therefore, $EDDI_{ijd}z$ represents the $z$ score of the change in EDDI-14 for a specific grid cell and calendar day. This method accounts for the mean and variability of day-to-day change in EDDI-14 in a specific location, thereby removing the background climatology of high frequency changes in EDDI-14.

Flash drought is identified based on $\overline{EDDI_{ijd}}z$ (herein referred to as $\Delta EDDI_z$) using the 4-part method proposed by Christian et al. (2019). Flash drought events are required to have 1) a minimum length of change of 30 days and 2) a final EDDI-14 value at or above its 80th percentile at the end of the 30-day "flash" period. Additionally, the $\Delta EDDI_z$ must be at or above the 60th percentile between individual days and there must be no more than 6 days in the 30-day period where the daily $\Delta EDDI_z$ value is below the 60th percentile. Christian et al. (2019) calculated flash drought at the pentad scale and required that at least 5 of 6 pentads during the "flash" period had a change above the 60th percentile. To match the daily scale of our analysis, we similarly require at least 24 of 30 days in the "flash" period to have $\Delta EDDI_z$ values above the 60th percentile. The $\Delta EDDI_z$ flash drought climatology and intercomparison statistics are compared with those from EDDI-14 to evaluate the sensitivity of our results to flash drought identification methods. The goal of this analysis is not to provide a comprehensive evaluation of all indicator sensitivity to flash drought, but instead demonstrate the importance of understanding threshold sensitivity when using a single indicator for flash drought monitoring and/or research.

Standardization and percentile calculation for EDDI, SPEI, SPI, and SMVI used statistics over the common period 1979–2021, while the ESI products used were standardized based on statistics from the 2002–21 period. The different time periods over which indicators were computed could introduce a bias ratio in the results; however, given all but 1 of the standardized products used the same common period 1979–2021, it would be unfair to restrict this period because the ESI solely uses a shorter period. All indicators were compared at a common 0.125° spatial scale and daily temporal scale over the common period of March–November 2002–21. Because flash drought is predominantly a warm-season phenomenon, we did not assess flash drought onset between December and February.

## 3. Intercomparison methods

### *a. Climatological assessment*

The goal of this study is to compare ten flash drought indicators to better understand the consistency between them when monitoring for flash drought. We hold a single indicator as the "comparison," which is the indicator we are evaluating. This indicator is then compared with each of the other nine indicators separately. In these comparisons, we assume each of the nine other indicators is the "benchmark" or truth. For each "comparison" and "benchmark" indicator evaluation, the 1-to-1 and aggregated comparison statistics are reported. This process is then repeated for each of the nine remaining indicators, iteratively holding one as the "comparison" and the others as the "benchmark." This process allows us to evaluate each indicator against other individual indicators as well as against the field of flash drought indicators in aggregate.

One-to-one indicator evaluations are done using a map comparison approach. This process is described using the following example comparing EDDI-14 to SMVI. In this case, EDDI-14 is selected as the "comparison" indicator (the indicator we want to evaluate) and the SMVI is selected as the "benchmark" indicator. For those more familiar with forecast verification, in this example the SMVI is practically denoted as the observation and EDDI-14 as the prediction. We then select a single day's field of EDDI-14 across CONUS and compare it with each single day's field of SMVI within 4 weeks before and after the EDDI-14 day selected. In this way, the EDDI-14 field is compared with every SMVI field from 28 days prior to 28 days after. Our 1-to-1 indicator comparisons lag and lead the benchmark indicator to capture the potential differences in the timing of flash drought onset between indicators. This approach more fairly evaluates indicators that may capture the same flash drought within a relatively small time window, and also allows us to measure the average lag or lead time with which the comparison indicator captures flash drought.

For each 1-to-1 comparison of daily flash drought fields, each grid cell in the comparison indicator across CONUS is compared with the corresponding grid cell in the benchmark indicator. The comparison produces a contingency table of hits $a$, false alarms $b$, misses $c$, and correct negatives $d$. A hit is when both indicators indicate a flash drought, and a correct negative is when both indicators indicate that there is not a flash drought. In the case of our analysis, there is no certified flash drought "truth," and therefore there are no true false alarms or misses. Instead, both false alarms and misses represent disagreement between the comparison and benchmark indicators. The contingency table of each 1-to-1 comparison is used to calculate the threat score (TS):

$$TS = \frac{a}{a + c + b}. \quad (2)$$

The TS is a measure of how well flash drought events in the comparison indicator, EDDI-14 in our example, correspond with flash drought events in the benchmark indicator, SMVI in our example. We also compute the bias ratio measure for each 1-to-1 comparison:

$$\text{bias ratio} = \frac{a + b}{a + c}. \quad (3)$$

Bias ratio is a measure of the ratio of flash drought events in the comparison indicator to the frequency of flash drought events identified by the benchmark indicator. We use bias ratio to indicate if the comparison indicator tends to identify fewer or more flash droughts with respect to other indicators. These comparisons and calculations of TS and bias ratio are repeated by comparing the EDDI-14 field on the single day to every SMVI field from 28 days prior to 28 days after. We then report the highest overall TS between EDDI-14 and SMVI across the 57-day comparison and the bias ratio on the day with the highest TS.

This approach has the benefit of simultaneously comparing two indicators over space and over time and producing 1) the overall strongest correspondence between the indicators (i.e., highest TS) and 2) the time at which the highest correspondence occurred. The timing of the strongest correspondence gives us important information on the lead or lag of the corresponding indicator relative to the benchmark indicator. For example, if the strongest correspondence between EDDI-14 and SMVI occurs when comparing EDDI-14 on day $n$ to SMVI on day $n + 3$, the implication is that EDDI-14 depiction of flash drought led SMVI flash drought by 3 days. The maximum TS, the bias ratio on the day of the maximum TS, and the timing of the maximum TS are recorded. The entire process is then repeated for each daily field between March 2002 and November 2021 excluding winter months. Results are reported as the overall average of daily maximum TS values and their corresponding bias ratio values, and the distribution of the timing of maximum TS between comparison and benchmark indicators. These aggregate statistics provide an overall summary of comparison between two indicators.

We use a "neighborhood maximum" approach (e.g., Sobash et al. 2011; Schwartz and Sobash 2017) to relax the requirement of an exact match between comparison and benchmark indicators at the grid cell for a hit. Specifically, a hit is recorded for a grid cell if both the comparison and benchmark indicators show flash drought anywhere in a surrounding 5 × 5 gridcell neighborhood. Such neighborhood-based approaches have been used widely in high-resolution precipitation forecast verification (e.g., Ebert 2008) to acknowledge the unrealistic expectation of a perfect 1-to-1 forecast at high resolution. While flash drought monitoring, and drought monitoring more broadly, is typically over coarser spatial scales, the same issues can arise from 1-to-1 gridcell comparisons that expect perfect matches between indicators. In most cases of flash drought monitoring, the precision of flash drought identification is on the order of tens of kilometers. Therefore, we selected a 5 × 5 gridcell neighborhood for our evaluation, with an approximate spatial footprint of 60 km × 60 km, which was deemed small enough to provide useable information for flash drought monitoring but coarse enough to provide a fair comparison between indicators. The neighborhood maximum approach was found to be the most consistent among 3 neighborhood-based comparison approaches for precipitation forecasting (Schwartz and Sobash 2017) and was deemed a good fit for our purpose.

One important detail to note is that we only calculated TS and bias ratio between two indicators when flash drought was indicated on at least 1% of the CONUS or CONUS region area in the comparison indicator. This was done to eliminate erroneously high TS values arising from shared flash drought between the two indicators in one or two grid cells, with no flash drought throughout the vast majority of CONUS. The comparisons were completed for all combinations of indicators across CONUS, and then repeated on a regional basis. Comparisons were also completed across each of the seven National Climate Assessment regions (defined in Fig. S1 in the online supplemental material), allowing evaluation of regional differences in performance.

### *b. Case studies*

We use two noteworthy flash drought events as case studies by which to compare the indicators. The first is the 2012 central U.S. flash drought, one of the most widely studied flash drought events globally (Otkin et al. 2016; Basara et al. 2019; Kam et al. 2021). The 2012 drought began in late spring following an extremely warm March and April, and, encompassed much of the central United States by July. Agricultural impacts from the 2012 event are estimated to have exceeded \$30 billion (Rippey 2015) and caused a shock to global food supply (Boyer et al. 2013). We examine the change in drought conditions represented in each drought indicator from 1 March to 1 September 2012 across a portion of the central United States that was significantly impacted by the drought event. The second flash drought we use as a comparison case study is the 2019 event in the southeastern United States. While not as infamous as the 2012 central U.S. event, the 2019 southeastern flash drought developed quickly and had significant impacts on agriculture and water resources (Di Liberto 2019). We examine the change in drought conditions represented in each drought indicator from 1 August to 1 November 2019 across a portion of the southeastern United States that was significantly impacted by the drought event.

The case study analyses include both map-based intercomparison across the lifetime of each flash drought and a time series analysis of flash drought spatial extent across the respective regions affected by each event.

## 4. Results

### *a. Flash drought climatological frequency*

The methods for identifying flash drought in all 10 indicators are based on a change in percentile or standardized anomaly over a 2–4-week period, persisting for another 2–4 weeks. Despite the similarity in flash drought identification methods, there are large differences in flash drought frequency between the 10 indicators (Fig. 1). In general, the indicators aggregated over 14-day periods had a higher frequency than the same indicators aggregated over 28- or 30-day periods. This is likely because 14-day aggregated indicators can respond more quickly to evolving environmental conditions, which produces overall more flash drought events. Specifically, the SPEI-14 shows the overall highest frequency of flash drought across CONUS over the 20-yr study period, with a domain average of 39 events, followed by EDDI-14 with 34 events on average, SPEI-30 with 29 events, and SPI-14 with 28 events. All indicators except the USDM (17 events on average) identified an average of at least 1 flash drought event per year per grid cell across CONUS. The EDDI-14 indicated a higher overall flash drought frequency than ESI-14, which is likely due to EDDI's use of reference evapotranspiration in contrast to ESI's actual evapotranspiration. Short-lived spikes in evaporative demand could induce a flash drought indication based on EDDI-14. But if soil moisture is sufficient to meet that additional demand, there may

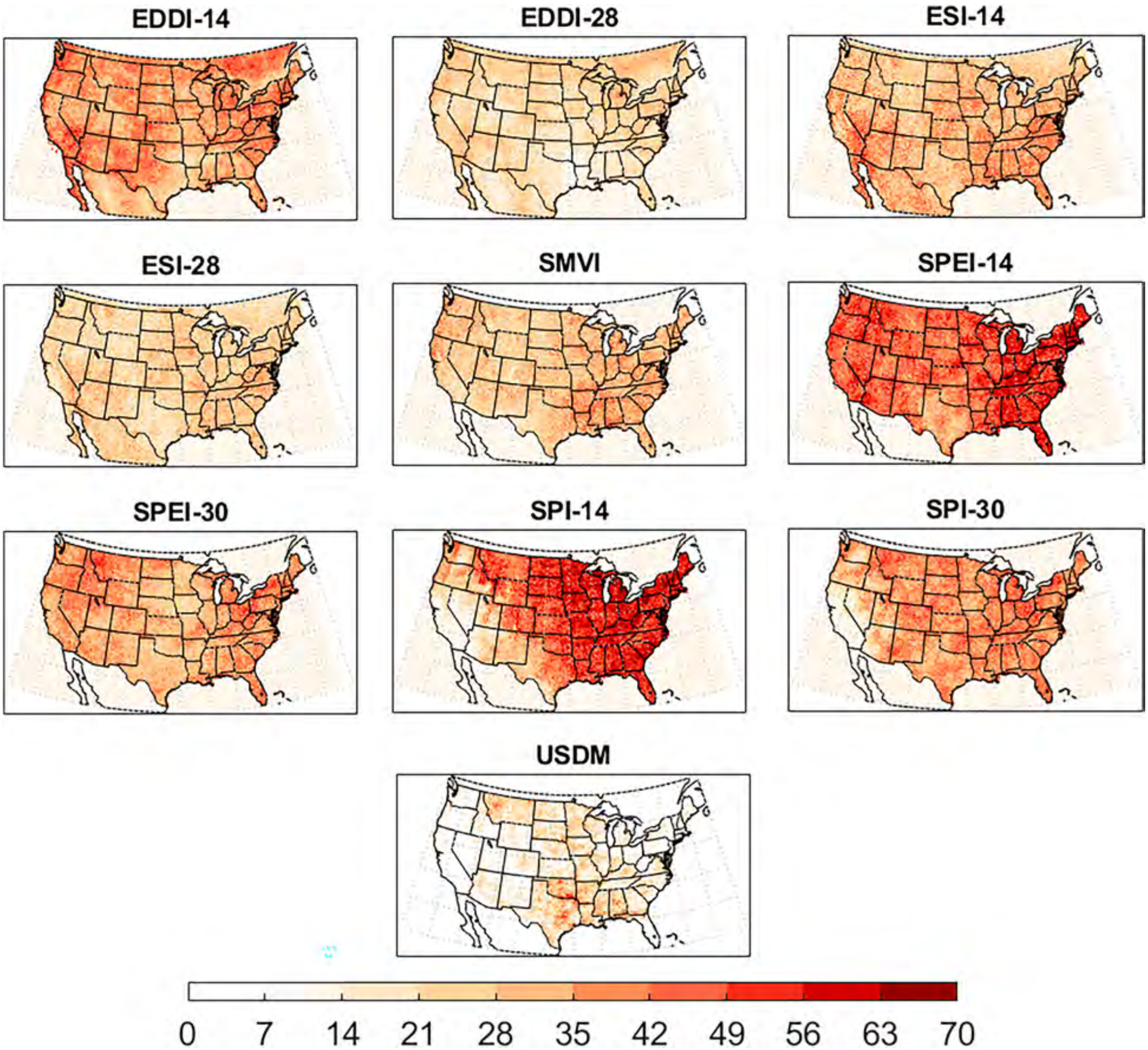


FIG. 1. Maps of the climatological frequencies of flash drought events between 2002 and 2021. The numbers shown are the flash drought event frequencies for each indicator.

not be an equivalent response in actual evapotranspiration, thereby producing a differential response between EDDI and ESI. These differences seem to be less apparent in the 28-day aggregation of EDDI and ESI, as their CONUS-wide climatological flash drought frequency is similar.

The maps of climatological flash drought frequency also show considerable regional variability for many indicators. EDDI-14 and EDDI-28 both exhibit a relatively low flash drought frequency over the southeastern United States, but in contrast, ESI-14, ESI-28, and SMVI all have relatively high frequency in the same region (Fig. 1). Both SPI-14 and SPI-30 identified fewer than 10 flash drought events in the southwest United States, including most of California and Nevada; however, their SPEI counterparts show relatively high flash drought frequency in that region. These differences are likely due to the SPEI's inclusion of potential evapotranspiration, which is a particularly important component to moisture balance and flash drought occurrence in dry regions. The USDM shows the highest frequency of flash drought in the Southern Plains and Southeast regions, with relatively few events identified in the Northwest, Southwest, and Northeast.

### b. *Indicator intercomparison across CONUS*

The daily maximum TS between two indicators is then averaged across all days of the comparison between 2002 and 2021. The overall TS results of all 1-to-1 indicator comparisons are shown in Fig. 2. Higher TS values indicate better correspondence, a TS value of 0 indicates no agreement and a TS value of 1 represents a perfect match. Overall, the various indicators are moderately well related to one-another, with TS

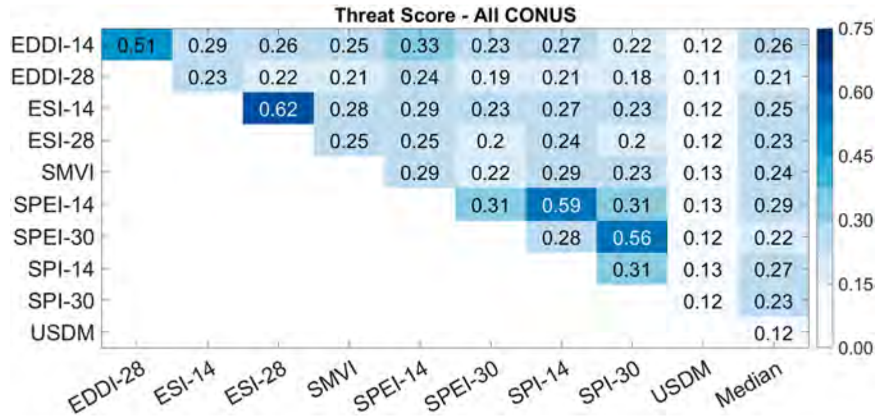


FIG. 2. Color table of the average TS from comparisons between two indicators across all comparisons. The far-right column shows the median of the nine TS values for each indicator.

values between 0.2 and 0.6. As expected, the different integration periods of the same indicator (e.g., EDDI-14 and EDDI-28) show good agreement, as are SPI and SPEI integrated over the same period (14 or 30 days). However, there is also a notably strong correspondence between EDDI-14 and SPEI-14 (0.33). Some of the indicators with relatively weak correspondence included EDDI-28 and SPEI-30 (0.19) and ESI-28 and SPI-30 (0.20). All indicators had a noticeably lower correspondence with the USDM, with TS scores ranging from 0.11 to 0.13. The far-right column of the table in Fig. 2 shows the median of the nine intercomparisons for each indicator. The SPEI-14 had the highest overall TS (0.29), followed by SPI-14 (0.27) and EDDI-14 (0.26). The EDDI, ESI, SPEI, and SPI indicators derived over 2 weeks consistently performed better than those derived over 4 weeks or 30 days. The only indicator based on soil moisture—the SMVI—had a higher correspondence to ESI-14 and SPEI-14 (0.28 and 0.29, respectively) compared with ESI-28 and SPEI-30 (0.21 and 0.22, respectively).

For each comparison, we report the bias ratio at the lead-lag comparison when the TS is maximized between indicators. For example, if the TS between SPEI-14 and SPI-14 is maximized at a 1-day lead time, we will report the bias ratio between the two indicators at that lead time. The bias ratio signals whether the comparison indicator tends to identify more or fewer flash drought events relative to the benchmark indicator. The bias ratio metric is then averaged over all daily comparisons between two indicators, with the results shown in Fig. 3. Bias ratio values over 1 (under 1) signify the comparison indicator indicates more (fewer) flash droughts relative to the benchmark indicator. The last column in Fig. 3 shows the median of the nine bias ratio values for each indicator. Overall, the indicators integrated over 14-day periods tend to have a higher flash drought frequency relative to other indicators. The ESI-14 has a bias ratio much closer to 1 (1.03). On the other hand, ESI-28 exhibited the lowest median bias ratio (0.69). SMVI and EDDI-28 also had lower bias ratio values, 0.75 and 0.76, respectively, which represents fewer flash drought events overall from those indicators (Fig. 3).

For each 1-to-1 indicator match, the map of the comparison indicator on day $n$ was compared with the maps of the benchmark indicator are days $n - 28$ to $n + 28$, and the day of the benchmark indicator that had the highest TS with the comparison

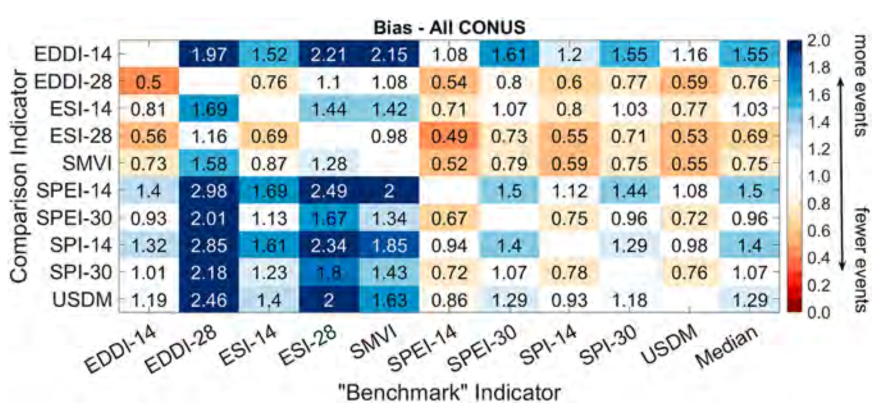


FIG. 3. Color table of the average bias ratio from comparisons between two indicators across all comparisons. The far-right column shows the median of the nine bias ratio values for each indicator.

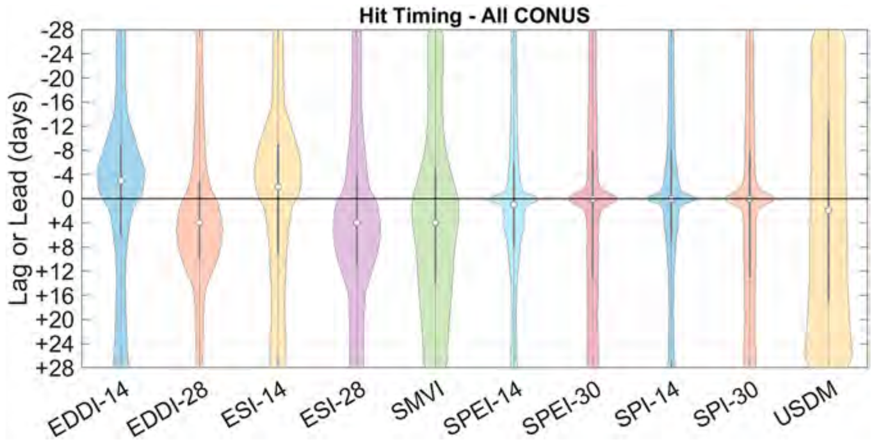


FIG. 4. Violin plots of the distribution of the timing of maximum correspondence between each indicator and all other indicators. Each point in the distribution represents one daily comparison. The white points in the plots represent the overall average timing, and the dark vertical line shows the interquartile range. Negative timing values represent a leading indicator; positive values represent a lagging indicator.

indicator was noted. The distributions of the timing of highest TS between indicators imply whether a given indicator tends to lead or lag other indicators' depiction of flash drought. Figure 4 shows violin plots of the distributions of the timing of highest TS by indicator. The shaded area in each violin plot represents the shape of the distribution of the lead or lag times at which hits occur. The width of the violin plot represents the density of the distribution for those values, such that a wider (narrower) shape indicates more (fewer) hits at that lead or lag time. The dark, vertical line in each plot represents the interquartile range and the white dot represents the distribution median. EDDI-14 and ESI-14 tend to be leading indicators meaning they had the strongest correspondence with other indicators prior to the other indicators showing flash drought. Specifically, the EDDI-14 and ESI-14 lead other indicators by, on average, 3.6 and 2.9 days, respectively. In contrast, the EDDI-28, ESI-28, and SMVI lagged other indicators by, on average, 4.1, 3.9, and 3.7 days, respectively. SPEI-14 tended to lag other indicators by less than 1 day, while the other three SPEI or SPI metrics tended to be leading indicators as often as they were lagging indicators. The USDM had the broadest distribution of timing, but on average tended to lag by 2.5 days.

Overall, the intercomparison of flash drought indicators across CONUS elucidated several important findings. Evapotranspiration and evaporative demand-based indicators integrated over 2-week periods (EDDI-14 and ESI-14) tend to lead other indicators in their identification of flash drought. However, while the EDDI-14 also produced many more flash droughts than most other indicators, ESI-14 tended to show approximately the same flash drought frequency as other indicators (i.e., bias ratio close to 1), and ESI-14 had a similar overall TS value as EDDI-14 (0.25 vs 0.26). SPEI-14 had the overall highest TS values, but also tended to identify many flash droughts that were not identified by other indicators and did not consistently lead other indicators in flash drought, as did EDDI-14 and ESI-14. The SMVI, based entirely on soil moisture, was consistently a lagging indicator, as is well documented in process-based flash drought studies (Otkin et al. 2016; Ford and Labosier 2017). Across CONUS, the EDDI-14, ESI-14, and all SPI and SPEI indicators tended to produce many more flash droughts than were identified by SMVI. For example, both EDDI-14 and SPEI-14 identified approximately 1.75 flash droughts for every 1 flash drought identified by SMVI. This result reflects the lack of definite translation of meteorological drought—driven by precipitation deficits and enhanced evaporative demand—to agricultural drought across CONUS.

### c. *Regional indicator intercomparisons*

Comparisons between flash drought indicators were repeated for each of the seven National Climate Assessment regions to evaluate regional variability in indicator performance. Figure 5a shows the average TS values by indicator for each of the seven regions. The SPEI-14, SPI-14, and EDDI-14 indicators consistently have the highest TS values across regions, while the USDM and, to a lesser extent, EDDI-28, ESI-28, and SPEI-30, have lower overall regional scores. There are differences in the overall performance of indicators by region. For example, the median TS value in the Southeast region is 0.27 as compared with a median of 0.21 in the Southwest. Practically, these differences represent stronger correspondence between indicators in the Southeast than in the Southwest region.

We also aggregate bias ratio between indicators by region (Fig. 5b). The patterns of flash drought frequency are mostly similar between regions. SPEI-14 identifies more flash droughts overall in every region, but most so in the Northeast and Southwest regions where the indicator shows 1.95 and 2.27 flash drought events for every 1 event in other indicators. EDDI-28, ESI-28, and SMVI tend to indicate fewer flash droughts in every region. All but the Northeast and Southwest regions have a median bias ratio value very close to 1. The individual region tables

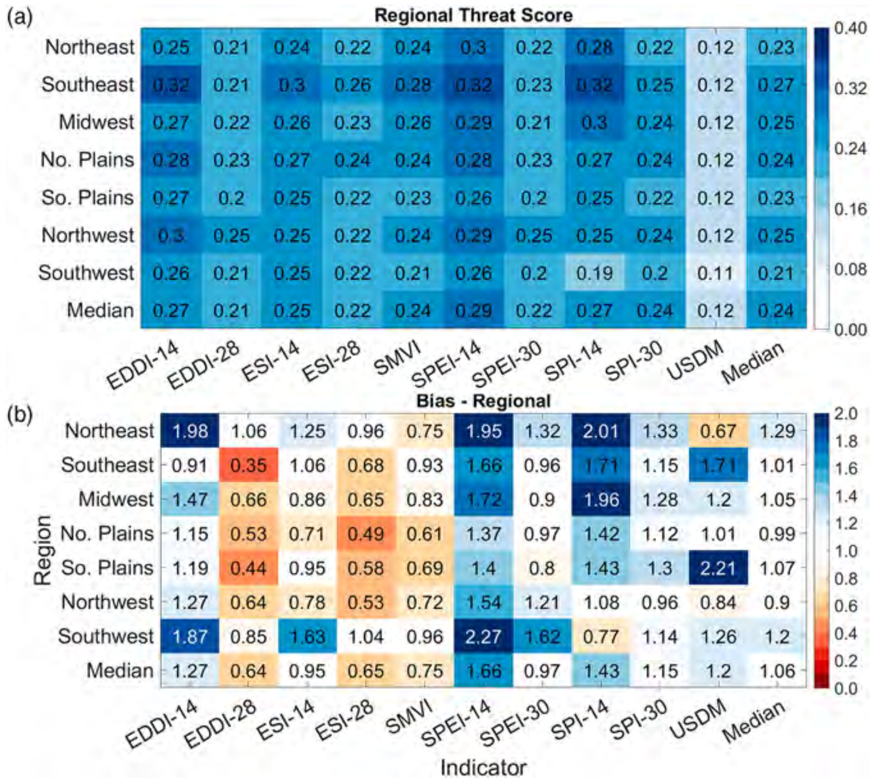


FIG. 5. Color tables of (a) average TS values and (b) bias ratio values by indicator for each of the seven National Climate Assessment regions.

of TS and bias ratio are available in Figs. S2 and S3 in the online supplemental material.

The overall patterns of timing of flash drought in each indicator are very similar between regions. In all regions, EDDI-14 and ESI-14 are leading indicators, with average lead times of 2 to 6 days. EDDI-28, ESI-28, and SMVI are lagging indicators in all regions, with lagging times of 2 to 8 days. SPI and SPEI indicators tend to lead and lag at roughly the same rate, and the USDM is a lagging indicator in every region except the Northwest, where it has an average lead time of just under 1 day.

The USDM flash drought method is based on categorical change over 2-week periods, suggesting the USDM changes more quickly in the Northwest region—relative to other indicators tested—than in other regions. This is particularly the case when compared with the Northeast region, where the USDM lags by an average of almost 8 days. It is worth mentioning that most flash droughts in the Northwest region in our study period are in Montana, with fewer than 10 flash droughts identified by the USDM in Washington, Oregon, and Idaho. Meanwhile, the USDM identified fewer than 10 flash droughts in most of the Northeast region. Therefore, these differences may also partly be a factor of relatively small sample sizes in these regions.

### d. Sensitivity to flash drought definitions

To better understand the sensitivity of our results to the method of flash drought identification, we repeat our analyses using an alternative flash drought method based on 14-day EDDI, the $\Delta EDDI_z$. The climatology and intercomparison results from $\Delta EDDI_z$ are compared with those from EDDI-14 (Fig. 6). The most striking difference between the two indicators, both based on the same 2-week EDDI dataset, is in the climatological frequency of flash drought over the 20-yr study period (Fig. 6a). While EDDI-14 tends to show higher flash drought frequency in the Northeast, western plains, and Southwest and lower flash drought frequency in the Southern Plains and Southeast, the climatological flash drought frequencies based on $\Delta EDDI_z$ are nearly opposite. $\Delta EDDI_z$ shows a hotspot of flash drought frequency in the Southern Plains, Southeast, and Midwest regions, with relatively few flash droughts in the Northeast, Northwest, and parts of the Southwest regions. For example, the average $\Delta EDDI_z$ flash drought frequency in the Southeast region is 45 events (approximately 2.25 events per year per grid cell), as compared with an average EDDI-14 frequency of just 23 events in the same region (approximately 1.15 events per year per grid cell). Meanwhile, EDDI-14 shows an average of 32 events in the Northeast region (1.6 events per year per grid cell) as compared with 5 events on average based on $\Delta EDDI_z$ (0.25 events per year per grid cell).

We compared $\Delta EDDI_z$ with all other indicators using the same methods as our other intercomparisons, calculating TS, bias ratio, and the timing of flash drought hits. Based on TS, the $\Delta EDDI_z$ slightly outperforms EDDI-14 in the Northeast, Southeast, Midwest, and Southern Plains regions, while slightly

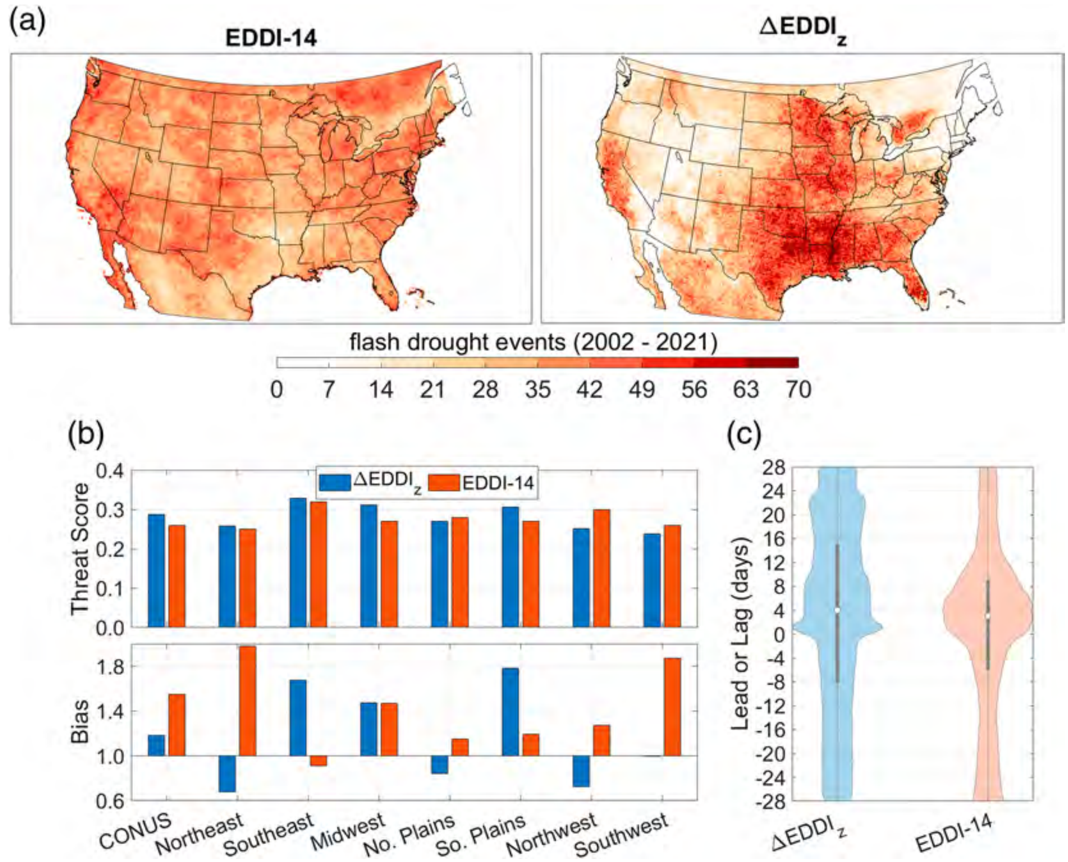


FIG. 6. (a) Maps of the climatological frequency of flash drought events between 2002 and 2021 identified by (left) EDDI-14 and (right) $\Delta EDDI_z$ definitions. (b) Bar plots of the CONUS- and region-average TS and bias ratio of flash drought identification of (blue) $\Delta EDDI_z$ and (red) EDDI-14. (c) Violin plots of the timing of hits of (blue) $\Delta EDDI_z$ and (red) EDDI-14 flash droughts in comparison with the other nine indicators.

underperforming in the northern plains, Northwest, and Southwest (Fig. 6b). Relative to the large bias ratio of EDDI-14 in the Northeast and Southwest regions, $\Delta EDDI_z$ has bias ratio much closer to 1 and has far fewer flash drought events identified in the Northeast region. The overall higher frequency of flash drought in the Southeast and Southern Plains regions result in higher bias ratio in $\Delta EDDI_z$ than in EDDI-14, but overall, across CONUS the $\Delta EDDI_z$ has a bias ratio closer to 1 than the EDDI-14. These results suggest the $\Delta EDDI_z$ may more closely match the other nine indicators in the study; however, these results vary considerably by region. Last, the violin plots in Fig. 6c show the distributions of the timing (i.e., lead or lag) of flash drought hits between $\Delta EDDI_z$, EDDI-14, and the other nine indicators. The $\Delta EDDI_z$ distribution tends to be broader than that of EDDI-14, with a longer average lead time of 4.1 days as compared with 3.6 for EDDI-14.

### e. *Case study intercomparison*

Our climatological analysis is complemented by an analysis of flash drought indicators based on two case study events, the 2012 central U.S. and 2019 southeastern U.S. flash droughts. For each case study we examine the intensity and spatial extent of drought across a subregion of the United States, and the change in characteristics during the drought evolution. The 2012 drought was preceded by a very warm early spring in the central United States that corresponded with elevated evaporative demand (Fuchs et al. 2012). EDDI anomalies were exceedingly high as early as 1 March 2012, representing strong evaporative demand (Fig. 7a). SPEI, SPI, and ESI-28 also showed somewhat- to very-dry conditions early in spring 2012, while SMVI only showed drier than normal soil conditions in the western half of the study region. EDDI, SPEI, and SPI indicated rapid drying across virtually the entire region between 1 May and 1 June in 2012, while SMVI, ESI, and USDM indicators only showed drought-like conditions in a fraction of the region (Fig. 7a). The SMVI and USDM showed rapid drought onset or intensification between 1 June and 1 July, better aligning with SPI and SPEI indicators; however, ESI did not show drought across most of the region until later in July. A brief reprieve from the very high evaporative demand reduced EDDI-based drought intensity around 1 July, but EDDI rapidly reintensified in August. By 1 September, rain from Hurricane Isaac had improved SPI and SPEI indicators in the southern half of the region, but the other indicators continued to show intense drought across much of the region.

We also include a time series of flash drought spatial extent across the region as an alternative way of visualizing the evolution

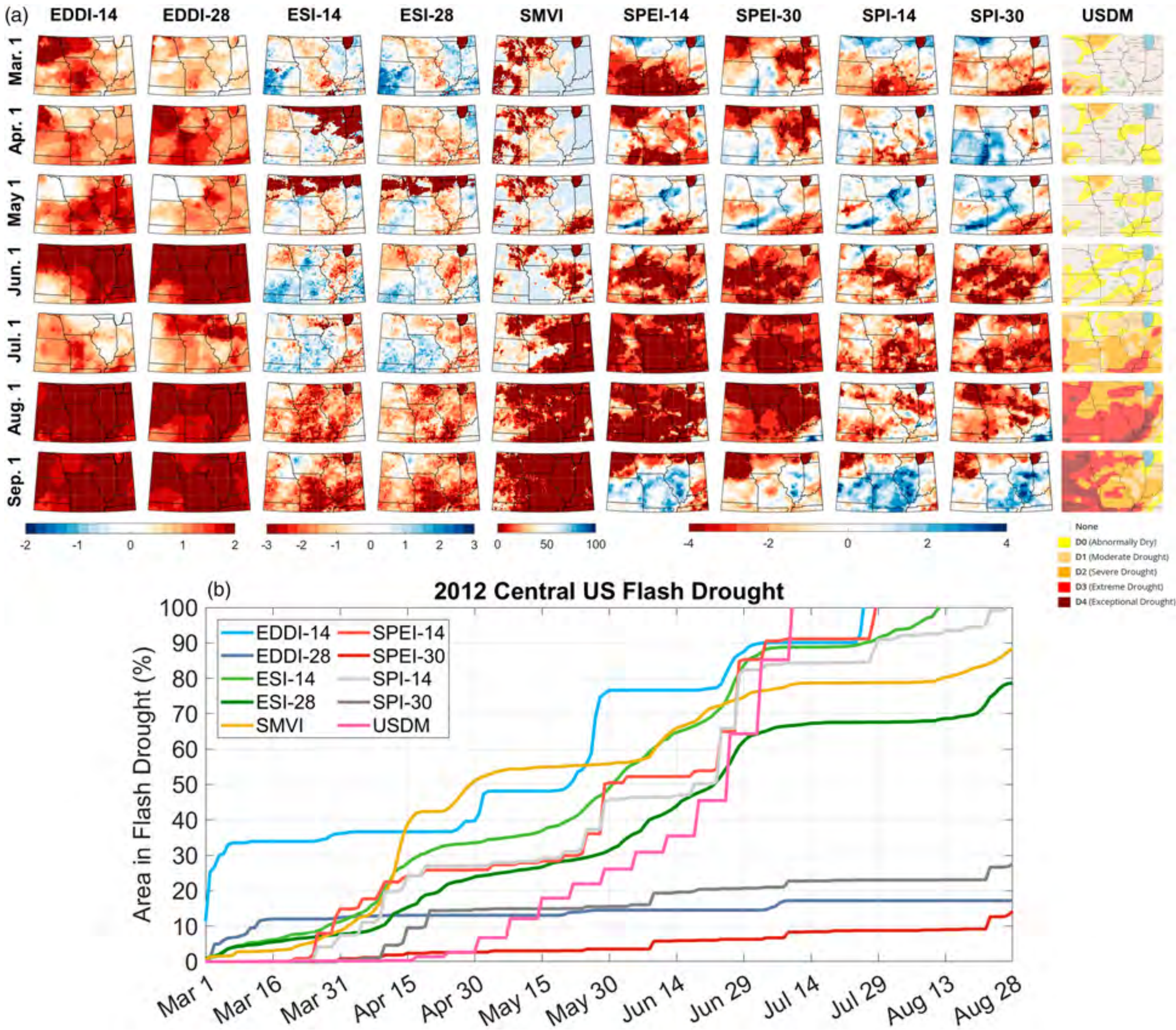


FIG. 7. (a) Maps of indicator conditions from 1 Mar to 1 Sep 2012 in the central United States. (b) The time series of flash drought spatial extent from 1 Mar to 1 Sep 2012. Flash drought extent is expressed as a percent of the central U.S. study region.

of flash drought in 2012 (Fig. 7b). The time series shows a rapid increase in flash drought in EDDI-14 in early March, followed by a plateau and reintensification in May and early June. EDDI-14 shows over 30% of the region in flash drought as of 5 March, which is more than a month before another indicator shows the same flash drought extent (SMVI, 11 April). In general, most indicators show flash drought expansion between mid-April and mid-June, with the SMVI, ESI-14, SPI-14, and SPEI-14 generally leading the ESI-28, SPI-30, and SPEI-30. The USDM lagged most of the other indicators by 2 to 4 weeks prior to 1 June, but then shows a rapid flash drought expansion between June and July and shows 100% of the region experienced a flash drought by 12 July. The EDDI-28, SPEI-30, and SPI-30 indicate flash drought in less than 30% of the region through the end of August, which is considerably less extensive than the other indicators. However, these three indicators do show extensive and intense dry conditions across the region as of 1 June and beyond (Fig. 7a). Therefore, the lack of flash drought extent—based on EDDI-28, SPEI-30, and SPI-30—is more likely due to the method of flash drought identification rather than the indicators themselves. Irrespective of these issues, there is a convergence of evidence from most indicators that the region experienced extensive flash drought between April and July 2012.

The second case studied differs from the first in many ways. First, the region affected—the Southeast—spans humid subtropical and humid continental climates with much less distinct precipitation seasonality than the central United States. Second, the drought occurred in late summer and autumn, spanning harvest of summer crops and planting of autumn and winter crops. August 2019 began with some small areas of very dry soil and low (dry) values of SPI, SPEI, and ESI in the southern parts of the region (Fig. 8a). Above normal temperatures increased evaporative demand in August and September,

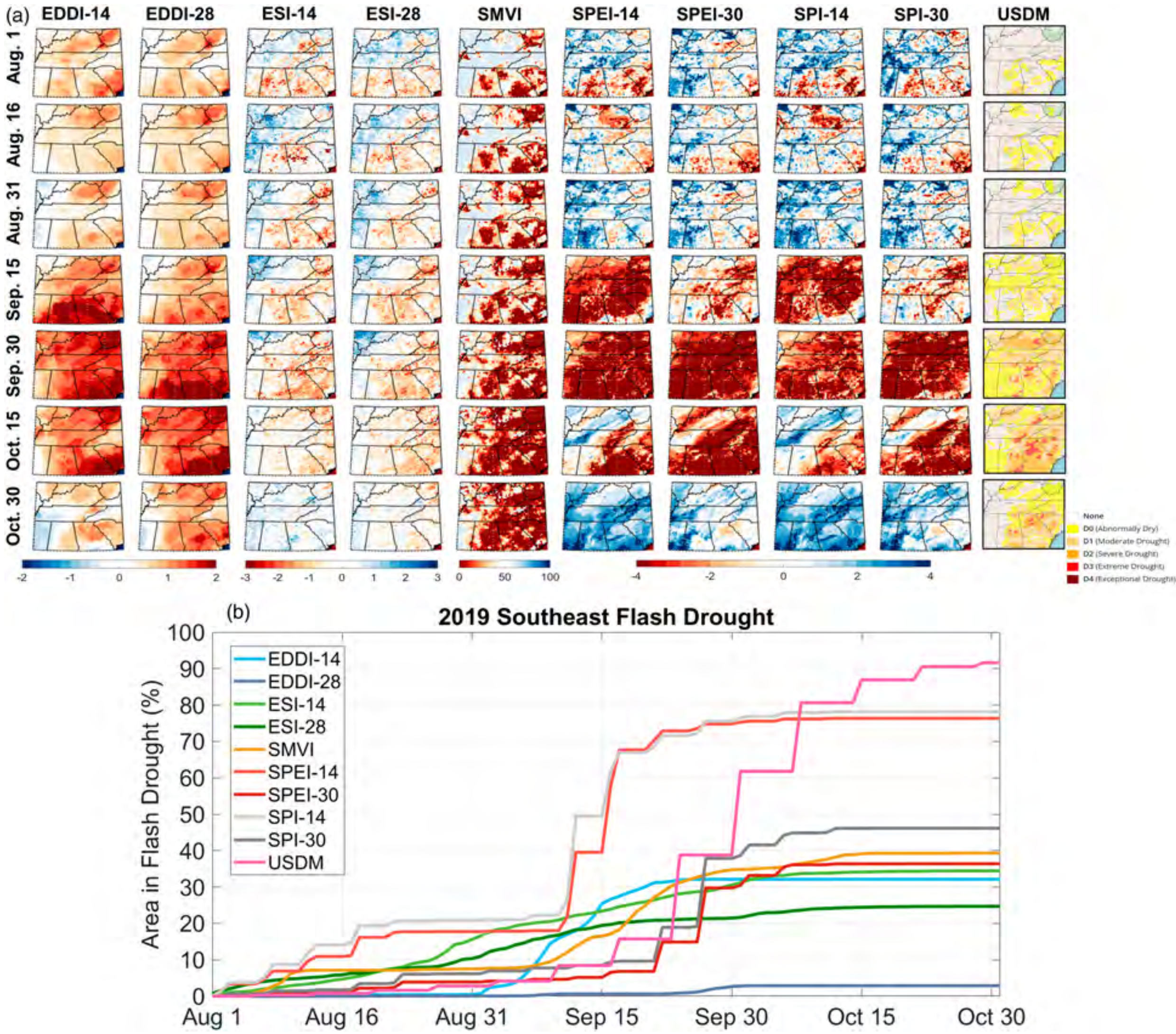


FIG. 8. (a) Maps of indicator conditions from 1 Aug to 30 Oct 2019 in the southeastern United States. (b) The time series of flash drought spatial extent from 1 Aug to 30 Oct 2019. Flash Drought extent is expressed as a percent of the southeastern U.S. study region.

as evidenced by positive EDDI-14 and EDDI-28 anomalies. Like the 2012 drought, EDDI indicated rapidly deteriorating conditions weeks ahead of most other indicators. However, SMVI, SPEI-14 and SPI-14 showed rapid expansion of very dry conditions in the first half of September (Fig. 8a). SPI-30, SPEI-30 and ESI and USDM indicators lagged in the expansion of drought conditions by 2–3 weeks, showing similar expansion in late September. Heavy precipitation from Tropical Storms Nestor and Olga in mid- to late October dramatically improved SPI- and SPEI-based conditions and reduced the extent of drought in the USDM. However, much of the region remained very dry through the end of October according to the SMVI and longer-term EDDI-28.

All indicators show a graduate increase in flash drought extent across the region in August 2019 (Fig. 8b). SPEI-14 and SPI-14 show the quickest increase in flash drought extent in August, followed by a rapid expansion in mid-September. EDDI-14, ESI-14, ESI-28, and SMVI show steady increasing flash drought extent between late August and late September, while SPEI-30, SPI-30, and USDM have very little expansion of flash drought prior to 15 September, followed by rapid expansion between 20 and 30 September. Despite showing extensive, severe dry conditions across most of the region, EDDI-28 identified flash drought in less than 10% of the region through the end of October, whereas USDM showed over 90% of the region experienced a flash drought between August and October. The SPI-14 and SPEI-14 indicators showed flash drought in at least 40% of the southeastern U.S. region approximately 2 weeks ahead of the USDM (Fig. 8b), as compared with a 3-week lag between SPI-14/SPEI-14 and USDM meeting the same 40% threshold in the 2012 drought (Fig. 7b).

## 5. Discussion

### a. Challenges of a single-indicator focus

Most flash drought studies characterize a noteworthy flash drought event or climatological characteristics of flash droughts using a single indicator (Ford and Labosier 2017; Koster et al. 2019; Christian et al. 2021). In these cases, even if other variables are assessed, the flash drought particulars of onset, duration, intensity, and spatial extent will be sensitive to the indicator used to characterize the event. The indicator-sensitivity is especially pernicious when assessing flash drought climatology on regional to global scales, as shown by Osman et al. (2021) and the EDDI comparison in this study (Fig. 6). In our case, the two different variations of EDDI-based flash drought indicators did not perform differently when compared with other indicators but did show large differences in regional frequency of flash drought. A climatological study of flash drought risk across CONUS using $\Delta \mathrm{EDDI}_z$ would identify the Southeast and Southern Plains regions as "hotspots" with high flash drought frequency (as in Christian et al. 2019), whereas the EDDI-14 indicator would characterize these regions as having relatively low flash drought frequency. Such discrepancies make it challenging to study, communicate, plan, and prepare for flash drought.

Similarly, we find the climatological assessment and case study analysis results were sensitive to the method of flash drought identification, even when using the same indicator. In the 2012 and 2019 flash drought case studies, the EDDI-28 and SPEI-30 indicated flash drought in only a small fraction of the study areas. However, both indicators showed widespread drought conditions that expanded and intensified over a 4–6-week period. These results highlight issues that arise when 1) treating flash drought as a binary event (i.e., occurrence or no occurrence) in climatology- or risk-focused studies and 2) using a single method for identifying flash drought with one indicator. Based on the case study analyses, it is possible the previously published methods used for identifying flash drought with EDDI-28 and SPEI-30 may be underestimating the frequency of events that can practically be considered rapid onset droughts. Result sensitivity to flash drought identification methods is therefore also important to consider for flash drought research and assessment.

While multivariate, multi-indicator approaches to flash drought early warning, monitoring, and communication are preferred (Otkin et al. 2022), studies and early warning/monitoring systems based on a single indicator can be useful to improving flash drought resilience if the biases, limitations, caveats of the indicator—and their implications for monitoring, early warning, and risk assessment—are well understood and communicated. Detailed assessments of flash drought indicators, datasets, and identification methods are particularly important in the context of evaluating projections and managing uncertainty of changes in flash drought frequency and severity in a warming climate because projected changes in flash drought risk greatly inform the development of adaptive management strategies (Ojima 2021). Therefore, future research on the historical or potential future hazard of flash drought should strive to either 1) use multiple indicators and variables to characterize the hazard; 2) test the sensitivity of the results to different indicators, datasets, and methods; or 3) ensure comprehensive understanding and communication of the limitations and assumptions of the single indicator, dataset, or method used in the study.

In lieu of a single dataset recognized as the flash drought "truth" or benchmark by which to evaluate all indicators, assessments must incorporate multiple, diverse indicators, datasets, and methods for intercomparisons. Many studies have relied on the USDM to provide the benchmark by which to evaluate an indicator's flash drought monitoring or early warning prowess. However, we find the USDM consistently underperforms when compared with the other nine indicators, with the overall lowest TS values. These results are not necessarily surprising because the USDM was not designed to monitor flash drought, and it regularly includes lagging indicators such as streamflow and reservoir levels, which will respond more slowly to evolving drought than evaporative demand, precipitation, or soil moisture. We see these lagging characteristics of the USDM in the flash drought case study analyses as well (Figs. 7b and 8b). Therefore, the USDM is a good benchmark to ensure a flash drought indicator captures the drought part of the event, but it should not be used as the sole verification of any flash drought indicator. Our results suggest the USDM is not as ideally suited for flash drought monitoring across CONUS as other indicators evaluated.

### b. Which indicator is "best"?

In this study, SPEI-14, SPI-14, and EDDI-14 had the highest overall TS values, attributable to the shorter window length and the indicators' ability to respond quicker to changing environmental conditions. These three indicators also consistently lead all others in depicting drought conditions in the 2012 and 2019 flash drought case studies. However, their relatively high biases suggest they may overestimate flash drought occurrence in most regions. For example, the SPEI-14 and EDDI-14 had bias ratio values of 1.97 and 1.84, respectively when compared with the soil moisture-based indicator (SMVI) in the Midwest region. The SPEI-14 and EDDI-14 indicate 1.8 and 1.5 flash drought events for every 1 event identified by SMVI in the Midwest, meaning 1 in every 3 flash droughts in EDDI-14 do not translate to soil moisture flash drought in the Midwest. Importantly, the flash drought frequency between indicators varied by region. For example, the same EDDI-14–SMVI comparison with a bias ratio of 1.84 in the Midwest had a bias ratio of only 1.02 in the Southeast, where the SMVI indicated a flash drought for every 1.1 flash droughts identified by EDDI-14. This suggests the rapidly increasing evaporative demand conditions captured by EDDI-14 more effectively translate to soil moisture depletion in the Southeast than in other regions. The regionality in the correspondence between indicators, such as EDDI-14 and SMVI, is a crucial consideration for researchers studying and recommending flash drought indicators for operational use across a region. In this case, our results would suggest that EDDI-14 may be a better fit for flash drought monitoring in the Southeast than in the Midwest.

Variations of EDDI, ESI, SPI, and SPEI indicators derived from 14-day periods consistently outperformed the same indicators derived from 28- or 30-day periods based on TS. In the cases of EDDI and ESI, the 14-day derivations also provided a more consistent lead time of 2–6 days compared with other indicators, while the 28-day derivations tended to lag other indicators. These results were in agreement with our case study analyses as well, such that the 14-day EDDI, SPI, and SPEI consistently lead the 28- or 30-day derivations for both the 2012 and 2019 events. However, from a climatological assessment the 14-day SPI and SPEI did not consistently lead flash drought indications compared with 30-day SPI and SPEI. Additionally, while EDDI-14, SPEI-14, and SPI-14 had higher TS values than their 4-week or 30-day counterparts, they also exhibited much higher bias ratio scores. The lone exception was ESI-14, which had a higher TS score than its 4-week counterpart but maintained a bias ratio near 1. The performance differences between composite window length using the same dataset and methodology (i.e., SPI-14 vs SPI-30) demonstrate the sensitivity of results to averaging windows. The time over which indicators are compiled—for example, 2 weeks, 4 weeks, or 1 month—is an important component of the indicator and should be tailored to its use case.

Specifically, when taken across CONUS, the ESI-14 had a much lower bias ratio (1.03) relative to EDDI-14 (1.55), suggesting the inclusion of actual evapotranspiration with reference or potential evapotranspiration, as ESI does, may help reduce the number of evaporative demand-identified flash droughts that do not necessarily translate to soil moisture impacts. As with most of our findings, the difference of biases between ESI and EDDI varied regionally, with large differences in the Northeast, Midwest, northern plains, and Northwest, but much smaller differences in the Southeast, Southern Plains, and Southwest regions. These regional differences in EDDI-14 and ESI-14 performance may relate to how well changes in evaporative demand lead to changes in actual evapotranspiration, which is partly attributed to the coupling between land (soil and vegetation) and atmosphere (Dirmeyer et al. 2018). Therefore, indicators using only potential evapotranspiration may sufficiently forewarn subsequent soil moisture and vegetation response to emerging flash drought in regions with strong land–atmosphere coupling, but inclusion of actual evapotranspiration may be more ideal in energy-limited environments with weaker coupling between actual and potential evapotranspiration. Additionally, increasing evaporative demand as a function of anthropogenic global warming could affect the relationship between actual and potential evapotranspiration, with consequences for the representativeness of a solely demand-based indicator like EDDI (Tomas-Burguera et al. 2020). More research is needed to understand 1) the magnitude of evaporative demand changes with continued, hastened, or slowed future warming; and 2) how those changes could affect drought monitoring indicators like EDDI and ESI.

Our case study analyses revealed the indicators generally show agreement in rapidly intensifying drought conditions in both 2012 and 2019 flash drought events. However, there are important differences in the timing and extent of the various drought depictions. In both case studies, EDDI-14 showed increasing dryness 2–3 weeks earlier than other indicators, followed by SPI-14 and SPEI-14. The SPI-30, SPEI-30, and USDM varied similarly through the evolution of both case study flash droughts and tended to lag other indicators by 2–3 weeks. The order of indicators showing drought expansion and flash drought occurrence generally follows the well documented physical processes underpinning flash drought across the United States (e.g., Otkin et al. 2018), with evaporative demand leading evapotranspiration leading soil moisture leading combined indicators like the U.S. Drought Monitor. A few indicators, including EDDI-28 and SPEI-30, did not show extensive flash drought in the 2012 and 2019 events, despite showing widespread drought conditions that intensified over time periods sufficiently short to practically be considered rapid. The lack of flash drought extent in these cases is therefore more likely attributable to fundamental limitations in the method of flash drought identification and less so to the indicator, itself.

### *c. Convergence toward diverse perspectives*

Multivariable or multi-indicator approaches to flash drought research, early warning, monitoring, and assessment are preferred over the use of a single indicator (Otkin et al. 2022). As also argued in Osman et al. (2021), our results provide evidence that research should not try to converge to a single indicator from which to infer information about flash drought across all regions. Instead, the inconsistency and regional variability in our results suggest a variety of perspectives—including evaporative demand, precipitation, soil moisture, and vegetation response—can provide a more holistic, representative, and actionable account of flash drought for operational early warning and monitoring. Likewise, research should not depend on a single indicator from which to infer historical and potential future characteristics of flash drought. Instead, the current and future risk of flash drought and resultant adaptive management and response strategies should be based on a multivariable perspective on flash drought. Additionally, the noteworthy differences in climatological flash drought frequency between EDDI-14 and $\Delta EDDI_z$ are evidence for the use of multiple datasets and methods when using a single indicator, like EDDI. Hazard mitigation, planning, and risk assessment based on either of the maps in Fig. 6a would result in very different conclusions, especially for the Southern Plains and Southeast regions where $\Delta EDDI_z$ shows almost double the number of flash drought events of EDDI-14 over the 20-yr study period.

### *d. Caveats and limitations*

Our study provides a novel intercomparison of flash drought indicators, many of which are used for operational flash drought monitoring. However, the results of this study come with multiple limitations and caveats, including the limited 20-yr study period. An ideal study period would span many decades to capture as many flash drought events as possible, but our study was limited by the availability of USDM and ESI indicators. Another limitation is the use of USDM for our analysis. Because the USDM is the only weekly updated product, its direct comparison with daily resolution indicators partly contributes to its relatively poor performance. With that said, we evaluate USDM from the perspective of operational flash drought monitoring, such that a product with a once-per-week update period will not be as responsive to rapid changes in precipitation, evaporative demand, or soil moisture as products that are updated daily. It is also worth noting that virtually all flash drought indicators identified 1–2 flash droughts per year per grid cell. The unusualness of flash drought celerity, by definition, would imply they are not necessarily frequent events. Therefore, while we cannot definitively conclude all indicators tested overestimated flash drought frequency, it is safe to say that only a fraction of the flash drought events identified by these indicators caused tangible and known drought impacts.

Flash drought identification methods were not identical across all drought indicators. We considered standardizing all indicators to the same dynamic range and using one method to identify flash drought to ensure the method of flash drought identification did not affect the results. However, flash drought studies, whether based on historical or projected climate information, often use different methods for identifying and characterizing flash drought, even if using the same variable, like precipitation or evaporative demand. Likewise, the myriad operational products that are part of the national or global drought monitoring infrastructure also have somewhat to very different methods for identifying and characterizing drought and flash drought. Because the ultimate goal of this study is to help improve operational flash drought monitoring through indicator evaluation and comparison, we eventually determined the best way forward was to evaluate each indicator as it is currently used or is proposed to be used for operational monitoring.

Last, our intercomparison was done without considering flash drought impacts. Ideally, indicators should be evaluated with documented flash drought impacts, such as water restrictions, ecological damage, or below trend crop yields. Drought impacts have always been a challenge to integrate into research and assessment. However, the advent of effective drought impact monitoring and reporting infrastructure portends an improved capability to use impacts directly when evaluating drought monitoring (Stahl et al. 2016; Otkin et al. 2018). All future research developing new or improved flash drought indicators should—as much as possible—integrate documented flash drought impacts in their assessments. Last, the regional averages of indicator comparisons may obscure other important differences in indicator performance within a given region.

## 6. Conclusions

We evaluate flash drought monitoring capability across CONUS through an intercomparison of nine flash drought indicators, most of which are currently used for operational monitoring. The indicators represent diverse perspectives and processes that are known to drive flash drought, including evapotranspiration and evaporative demand (ESI and EDDI), precipitation (SPEI and SPI), and soil moisture (SMVI). We also include the USDM, which is frequently used as a benchmark by which to evaluate flash drought indicators.

We find the precipitation and evaporative demand indicators derived over 14-day periods tended to have the highest correspondence overall to the other indicators and had the longest lead time, but also the highest flash drought frequency. The lone exception with a bias ratio closer to an ideal value of 1 was ESI-14, which tended to produce fewer flash droughts than similar indicators that do not incorporate actual evapotranspiration (e.g., EDDI-14 and SPEI-14). The 14-day SPI and SPEI indicators had consistently higher correspondence (TS) and higher bias ratio than their 30-day counterparts but did not provide consistently longer lead times for early warning. The USDM had the overall lowest correspondence with other indicators, which is partly attributable to the weekly update frequency of the USDM, relative to the daily update rates of the other indicators. The USDM also incorporates inherently lagging indicators of drought—such as streamflow and reservoir levels—that will not necessarily reflect flash drought as quickly as other indicators.

Importantly, we find considerable differences in indicator performance between CONUS regions. EDDI-14 had very high flash drought frequency in most regions, but less so in the Southeast and Southwest. We evaluated the sensitivity of the results to the definition used for identifying flash drought using an alternative method based on 14-day EDDI. The results showed large differences in the climatological frequency of flash drought between EDDI-14 and the alternative EDDI formation ($\Delta\mathrm{EDDI}_z$). The results suggest that 1) flash drought characteristics and climatological frequency (risk) are very sensitive to the definition of flash drought based on a single indicator (like EDDI) and 2) the sensitivity varies regionally.

Overall, we find no single flash drought indicator consistently outperforms across CONUS or any of the seven regions. Likewise, the regional and definition-specific variability in performance supports the argument for a multivariable and multi-indicator approach for flash drought early warning and monitoring advocated by Otkin et al. (2022). Flash drought research, especially evaluation of historical and potential future changes in flash drought climatological risk and characteristics, should seek multivariable frameworks for analysis, instead of using a single indicator from which to infer all flash drought information. In doing so, researchers can properly understand and communicate the complexity of flash drought and its impacts, and better guide effective adaptive management and response strategies.

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*Data availability statement.* EDDI, ESI, SMVI, SPI, SPEI, and USDM data used to identify flash droughts across the contiguous United States are made available online (https://drive.google.com/drive/folders/17f6l_6Q_8ZJO_4vouOx05N6GCQNaf2y1?usp=sharing).

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