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# Thirstwaves: Prolonged Periods of Agricultural Exposure to Extreme Atmospheric Evaporative Demand for Water

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**Key Points:**
- Regional hotspots of thirstwaves do not necessarily align with areas of high overall evaporative demand
- Intensity, duration, and frequency of thirstwaves have increased significantly ($p < 0.05$) over 17%, 7%, and 23% of US cropland area, respectively
- The likelihood of no thirstwaves occurring during the growing season has significantly decreased

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## Abstract

Global atmospheric evaporative demand has increased, impacting agricultural productivity and water use. Traditionally, trend assessments have been limited to total evaporative demand, overlooking shifts in daily extremes, which are meaningful for agrohydrological outcomes yet largely unknown. Here, using a fully physical metric of evaporative demand, that is, standardized short crop reference evapotranspiration, we introduce the concept of thirstwaves—prolonged periods of extremely high evaporative demand—and analyze their characteristics during 1981–2021 growing seasons for the conterminous US. Findings show that long-term mean spatial patterns demonstrated by thirstwave characteristics do not follow that of total or mean evaporative demand. Weighted for cropland area harvested, thirstwave intensity, duration, and frequency have increased by 0.06 mm $d^{-1}$ decade$^{-1}$, 0.10 days decade$^{-1}$, and 0.39 events decade$^{-1}$, respectively during 1981–2021. Statistically significant trends appear across 17%, 7%, and 23% of cropland area for intensity, frequency, and duration. Not only have thirstwaves increased in severity, but the likelihood of no thirstwaves occurring during the growing season has significantly decreased. Our work proposes a novel metric to describe periods of extremely elevated evaporative demand and presents a systematic analysis of such conditions historically for US croplands.

## Plain Language Summary

The atmosphere is getting more demanding for water around the world, and this affects water use and farming outcomes. Previously, studies mainly looked at the overall atmospheric demand for water, but little is known about changes in occurrence of very high atmospheric demand for water over consecutive days. In this study, we use introduce the idea of "thirstwaves," which are long periods of very high atmospheric demand for water. We looked at these thirstwaves that have occurred during 1981–2021 in the US and analyzed them for how intense and how frequent they were and how many days they lasted. We found that the worst thirstwaves happened in places that do not see the highest demand. Over time, all aspects of these thirstwaves have gotten worse. It has also become much less likely that a growing season will pass without any thirstwaves. These findings suggest that in addition to monitoring overall atmospheric demand for water, it's important to track, measure, and report thirstwaves to those managing agriculture and water resources.

## 1. Introduction

Evaporative demand of the atmosphere serves as a critical link between many disciplines including but not limited to hydrology, climate science, biometeorology, plant physiology, and agronomy. Evaporative demand represents the thirst or evaporating power of the atmosphere, or the maximum possible (not actual) flux of water into the atmosphere with unlimited water availability (Vicente-Serrano et al., 2020). For agricultural crops, evaporative demand is typically represented by the standardized short crop evapotranspiration $ET_{os}$ (Allen et al., 1998; Jensen & Allen, 2016; Walter et al., 2005), assuming an unlimited supply of water to a uniform grass surface. $ET_{os}$ encapsulates the radiative and aerodynamic drivers of actual evapotranspiration. $ET_{os}$ exerts a strong control on land-atmospheric interactions across the entire hydroclimatic spectrum, since $ET_{os}$ drives actual evapotranspiration in energy-limited ecosystems and $ET_{os}$ is driven by actual evapotranspiration in water-limited ecosystems (Hobbins et al., 2016; Vicente-Serrano et al., 2020). It is a strong determinant of terrestrial hydrological and energy budgets and impacts a multitude of critical processes including but not limited to vegetation water stress (Grossiord et al., 2020), consumptive water use of ecosystems (Jensen & Allen, 2016), streamflow (Das et al., 2011), and wildfire burned area (Abatzoglou & Kolden, 2013).

There is sufficient evidence to establish that $ET_{os}$ has been increasing historically (Albano et al., 2022; Anabalón & Sharma, 2017; Kukal et al., 2023; Roderick et al., 2009; Vicente-Serrano et al., 2020; Wang et al., 2012), and

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has been attributed to spatially varying contributions from air temperatures, humidity, solar radiation, and wind speeds (Albano et al., 2022; Kukal et al., 2023). These assessments are largely focused on trend detection and quantification in total and/or mean $ET_{os}$ for annual, seasonal, and calendar month periods. However, it is well established that effects of anthropogenic climate change extend beyond changes in the means and totals and are more importantly characterized by substantial shifts in extremes (Mearns et al., 1984). Such an extreme-centric perspective has been largely lacking in research and discussions around evaporative demand, and therefore we understand virtually nothing about how $ET_{os}$ extremes have evolved historically in different regions. Understanding the nature of prolonged periods of extremely high $ET_{os}$ is imperative for stakeholders in agriculture, water resources, and ecosystem functioning and arguably more meaningful than measuring change in total and mean $ET_{os}$. As with other environmental and hydrological metrics, comprehensively addressing $ET_{os}$ extremes entails that their intensity, duration, and frequency are quantified and evaluated for changes in space and time.

This study provides such an assessment of extreme $ET_{os}$ periods for conterminous United States (CONUS) during the recent past (1981–2021). Here, for the first time, we propose the concept of thirstwaves, which are prolonged periods of extreme $ET_{os}$. Consequently, we measure the intensity, frequency, and duration of historically observed thirstwaves with an emphasis on agricultural footprint within CONUS.

## 2. Materials and Methods

### 2.1. Data

Our analysis used daily short crop (grass) reference evapotranspiration ($ET_{os}$) as an indicator of evaporative demand. $ET_{os}$ represents standardized reference evapotranspiration from well-watered and clipped cool-season grass such as fescue or perennial ryegrass having a height of 0.12 m, a leaf area index of approximately 3.0 and albedo of 0.23. The formulation of $ET_{os}$ considered here follows the recommendations provided by American Society of Civil Engineers-Environmental & Water Resources Institute (ASCE-EWRI) (Jensen & Allen, 2016; Walter et al., 2005) and the FAO Irrigation and drainage paper 56 (Allen et al., 1998). As opposed to temperature-based evaporative demand formulations such as Thornthwaite (1948), Hargreaves (Hargreaves & Samani, 1985), Hamon (1961), and Blaney-Criddle (Blaney & Criddle, 1962), this combination-based formulation of $ET_{os}$ is sensitive to all radiative and aerodynamic drivers and is a fully physical metric of evaporative demand.

We obtained $ET_{os}$ for the spatial extent of CONUS during 1981–2021 from gridMET (Abatzoglou, 2013a) data set hosted on Google Earth Engine. The original data are available at a 4-km spatial resolution and were rescaled to a county scale for this analysis using Spatial Reducer, which is a directly employable function in Google Earth Engine that serves to aggregate data over space. The gridMET data set is a hybrid of NLDAS-2 and the Parameter-Elevation Regressions on Independent Slopes Model (Daly et al., 2008) and is widely employed for applications in water resources management (Albano et al., 2022; Kukal et al., 2023; Melton et al., 2022).

### 2.2. Defining and Detecting Thirstwaves

Thirstwaves were defined following the widely used definition of a heatwave that is based on air temperatures (Perkins & Alexander, 2013), but employing $ET_{os}$ as the central metric. A thirstwave was deemed to have occurred when during at least three consecutive days, daily $ET_{os}$ was greater than the 90th percentile of $ET_{os}$ corresponding to each Julian day. The 90th percentile used in this definition was based on a 15-day moving window over a baseline period, that is, 1981–2000. The 15-day moving window was centered on the Julian day being evaluated. $ET_{os}$ data during 1981–2000 were used as baseline records for establishing climatologically extreme thresholds. These thresholds were used to detect thirstwaves through the study period. The definition uses a minimum of 3-day period for qualification as a thirstwave, which is consistent with the heatwave criteria (Perkins & Alexander, 2013), however, the physiological impacts of different thresholds remain uninvestigated. The analysis was limited to the warm season (April until October inclusive) representing an extended agricultural growing season in the CONUS.

### 2.3. Assessing Thirstwave Characteristics

We used three characteristics of thirstwaves (Figure 1) to assess historical thirstwaves within individual growing seasons in the CONUS:

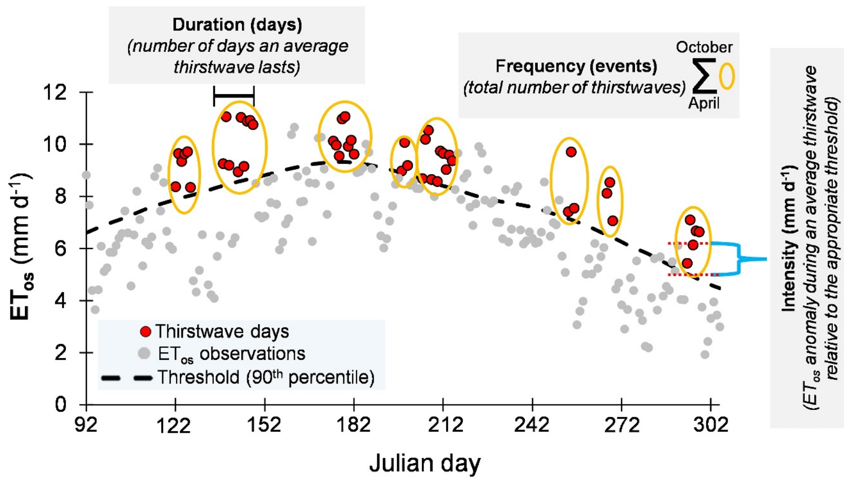


**Figure 1.** A schematic that conceptualizes the three thirstwave characteristics (intensity, duration, and frequency) using example observations.

1. Thirstwave intensity: mean magnitude of $ET_{os}$ anomaly (relative to the 90th percentile threshold) across all days that belong to thirstwaves detected during the growing season. Thirstwave intensity is reported as mm $d^{-1}$ for simplicity, but it is important to note the distinction between $ET_{os}$ units (mm $d^{-1}$) and intensity units (mm $d^{-1}$ above the 90th percentile), the latter being an anomaly.
2. Thirstwave duration: The mean length (in days) of all thirstwaves detected during the growing season.
3. Thirstwave frequency: The total number of thirstwaves (discrete events) detected during the growing season.

Each characteristic was calculated for every growing season during 1981–2021 at the county level. Using counties as the fundamental spatial unit allows for interpretation of findings with respect to agricultural cropland footprint. We obtained total cropland acreage for each county reported in the most recent US Agricultural Census of 2022 (USDA, 2022) using the USDA NASS Quick Stats Database (USDA, 2024). All statistics were aggregated to nine farm resource regions (FRRs) (Heimlich, 2000), which are also based on county boundaries. Regional statistics were weighted using county-level cropland acreage.

### 2.4. Trend Calculations

We calculated trends in each thirstwave characteristic for all counties, FRRs, and at the CONUS-level following the nonparametric Theil-Sen slope estimator (Sen, 1968). The resulting trends in the characteristic were reported as rate of change over a decade. All trends reported for any given region were weighted using county-level cropland acreage (USDA, 2022). The statistical significance for each of the monotonic trends was tested using the Mann–Kendall trend test (Kendall, 1975; Mann, 1945).

## 3. Results

### 3.1. Long-Term Mean Thirstwave Characteristics

When weighted using county-level crop harvested area, thirstwaves observed across CONUS during 1981–2021 had a mean intensity of 0.8 mm $d^{-1}$, duration of 4 days, and frequency of 2.9 events per growing season. Maximum thirstwave intensity, duration, and frequency observed in the observational record were 2.8 mm $d^{-1}$, 17 days, and 20 events, respectively. Mapping of long-term (1981–2021) mean county-level thirstwave characteristics revealed considerable spatial heterogeneity (Figure 2), with intensity, duration, and frequency ranging from 0.3 to 1.3 mm $d^{-1}$, 3.2–5.1 days, and 1.3–4.7 events, respectively. All thirstwave characteristics demonstrate signature mean spatial patterns, underscoring the critical need for measuring severity of prolonged extreme $ET_{os}$ conditions using each specialized characteristic. Thirstwave intensity is relatively greater (>1 mm $d^{-1}$) in the High Plains region, indicating that this region is subject to significantly greater $ET_{os}$ magnitude beyond the 90th percentile threshold. Thirstwaves have relatively lasted longer (i.e., duration) on average (>4.5 days) in parts of

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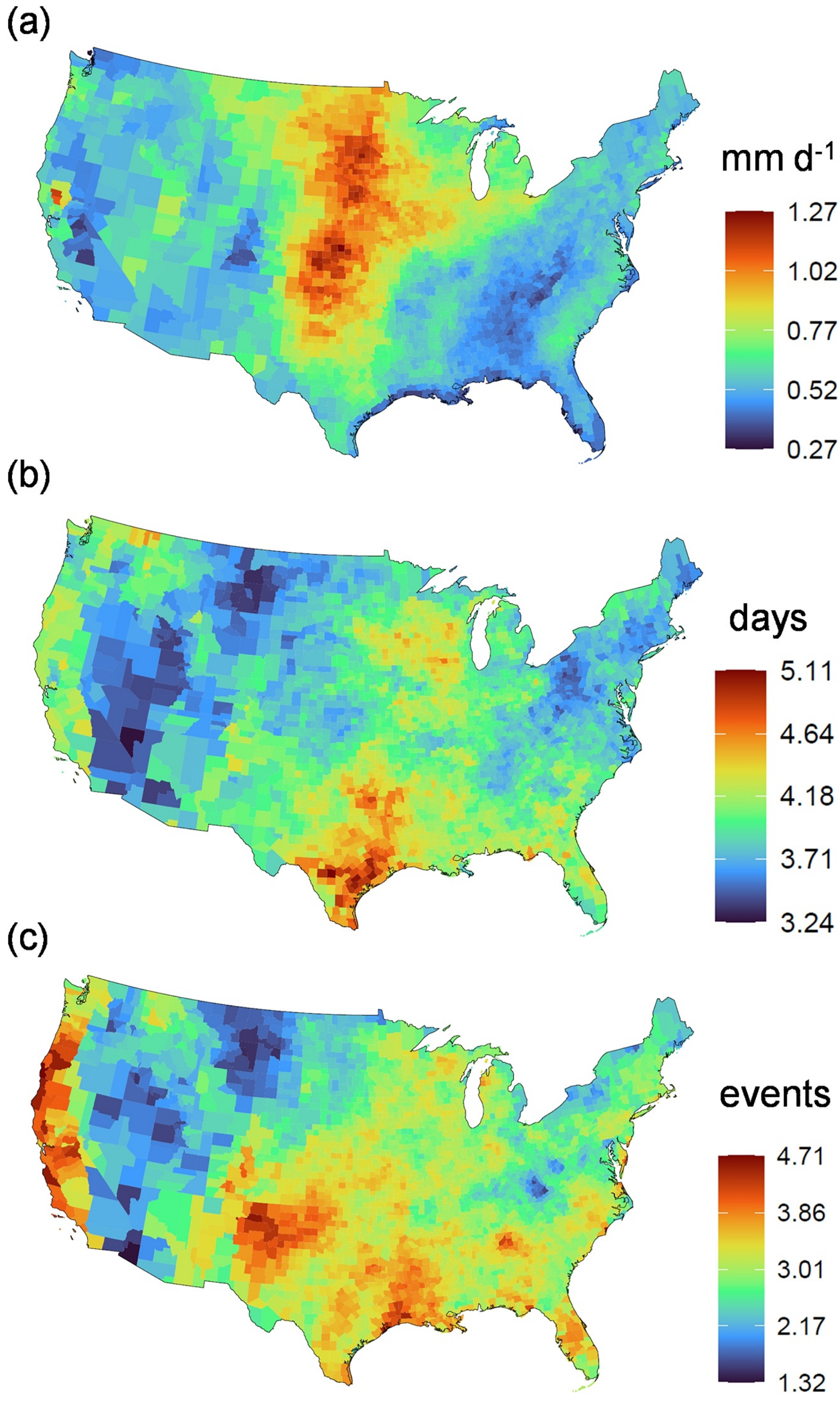


**Figure 2.** (a) Long-term mean county-level thirstwave intensity, (b) duration, and (c) frequency over the period 1981–2021.

Southern US Upper Midwest, west coast, and the Pacific Northwest. The west coast, and the Southern US have had relatively greater number (>3.5 events) of thirstwaves (i.e., frequency) than the national average.

For all three characteristics, the spatial patterns were quite dissimilar to those observed for total (April through October inclusive) $ET_{os}$ (Figure 3). Total $ET_{os}$, whether aggregated over the warm season (Figure 3) or calendar year (Kukal et al., 2023) is minimum in the Northeast, gradually increases to maximum in the Southwest, except for low values at higher elevations. This implies that variability-centric and extreme measures of $ET_{os}$ including

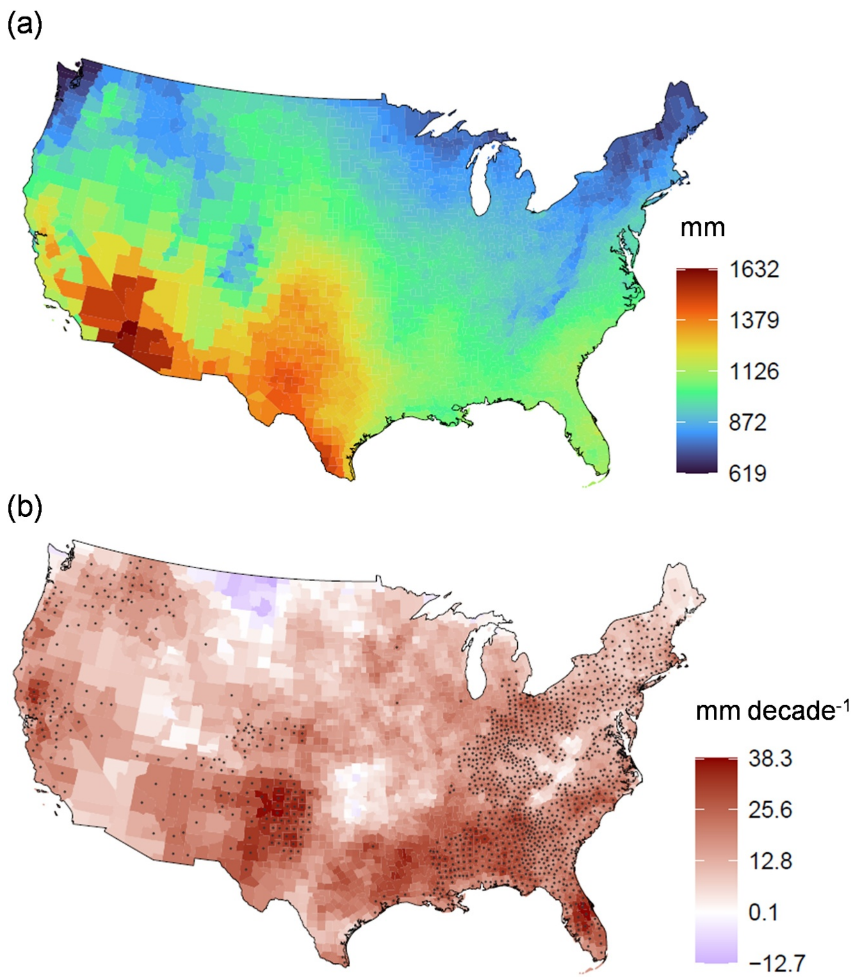


**Figure 3.** (a) Long-term (1981–2021) mean county-level total short-crop reference evapotranspiration, $ET_{os}$ (mm) during the growing season; (b) trend in growing season $ET_{os}$ (mm decade$^{-1}$) during 1981–2021. The growing season considered here is identical to what is considered for thirstwave analysis, that is, 1st April until 31st October. The dots overlaid on a county depict that the trend is significant at the 95% confidence level.

thirstwaves have not historically followed the patterns exhibited by mean or aggregate $ET_{os}$. In fact, most regional hotspots for severe thirstwaves (i.e., higher values of either or all characteristics) are not in the US Southwest (region with highest total $ET_{os}$).

### 3.2. Trends in Thirstwave Characteristics

Harvested area-weighted thirstwave intensity, duration, and frequency for CONUS have increased at the rate of 0.06 mm d$^{-1}$ decade$^{-1}$, 0.10 days decade$^{-1}$, and 0.39 events decade$^{-1}$, respectively during 1981–2021. While these are CONUS-aggregated trends, not all counties report significant ($p < 0.05$) trends (shown as black dots in Figure 4). Approximately one-quarter (23%) of the national harvested area experienced a statistically significant increase in thirstwave frequency, while 17% saw a significant rise in thirstwave intensity. Only 7% of the area experienced an increase in thirstwave duration. The significant trends observed in thirstwave intensity, duration, and frequency for individual counties are much greater in magnitude (Figure 4). When considering only the counties that experienced significant trends (shown as black dots in Figure 4), mean rates of increase were 0.11 mm d$^{-1}$ decade$^{-1}$, 0.36 days decade$^{-1}$, and 0.81 events decade$^{-1}$, respectively, however, trend values as high as 0.29 mm d$^{-1}$ decade$^{-1}$ (Ellis County, Oklahoma), 1 day decade$^{-1}$ (Sandoval County, New Mexico), and 2.2 events decade$^{-1}$ (Osceola County, Florida) were documented. Although significant trends were found in distinct regions (Figure 4), it is noteworthy that the Southern Plains and parts of Southwest saw an increase in all three characteristics.

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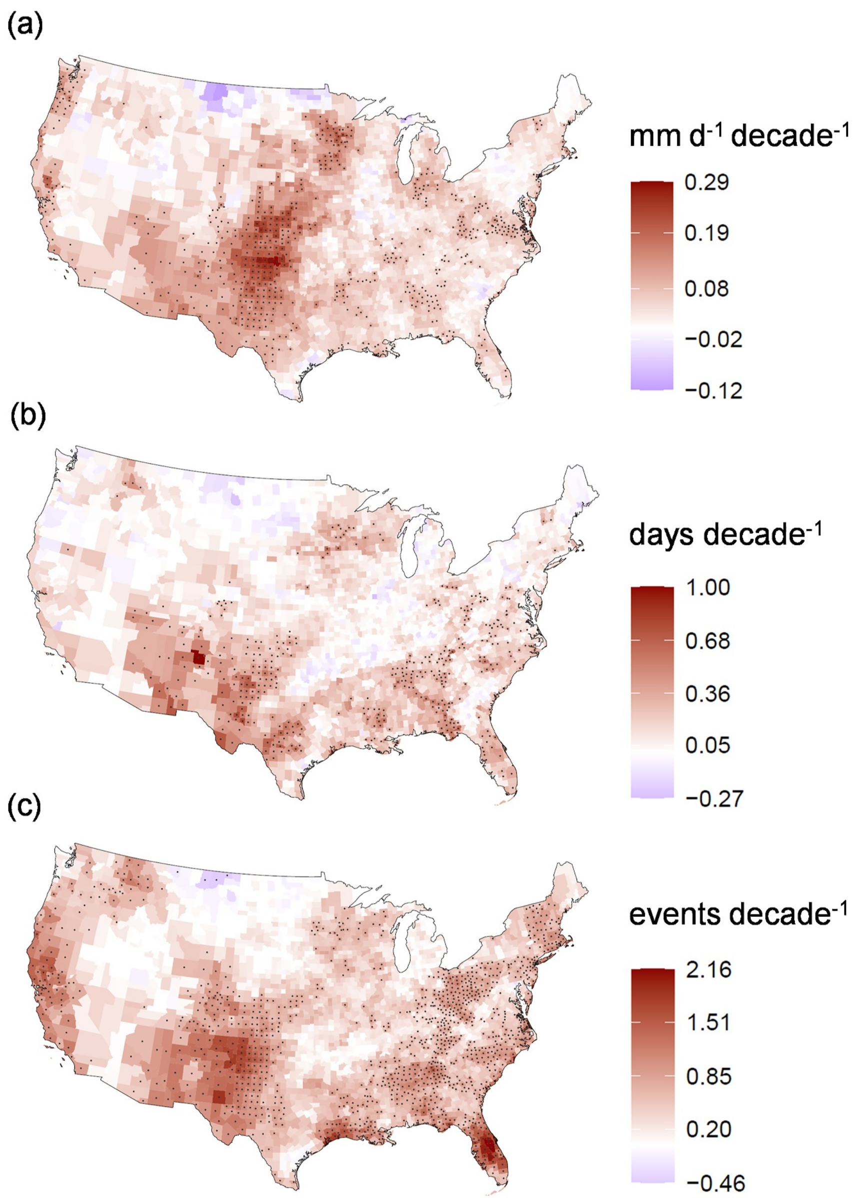


**Figure 4.** (a) Trends (rate of change per decade) in county-level thirstwave intensity, (b) duration, and (c) frequency over the period 1981–2021. The dots overlaid on a county depict that the trend is significant at the 95% confidence level.

### 3.3. FRR-Level Assessment of Thirstwaves

Given the potential impacts of thirstwaves on agricultural productivity and water use, it is useful to interpret thirstwave climatology and trends against region-specific contribution to national agricultural output. To this end, we aggregated thirstwave characteristics and related statistics to FRRs (shown in Figure 5a) which account for several attributes relevant to agricultural production, that is, climate, soil, water, topography, commodity types etc. (Heimlich, 2000). Harvested area-weighted long-term intensity was the highest for Prairie Gateway, Northern Great Plains, and Heartland; duration was the highest for Mississippi Portal and Heartland; and frequency was the highest for Prairie Gateway and Mississippi Portal. Relative dominance of these FRRs was also observable for individual growing seasons during 1981–2021 (Figures 5b–5d).

Trends in frequency accounted for the greatest footprint (Table 1) amongst all characteristics, with 40%–50% of area harvested in Southern Seaboard, Fruitful Rim, and Basin and Range regions showing significant increase. Similarly, 43% of harvested area in Prairie Gateway underwent significant increase in intensity. The share of

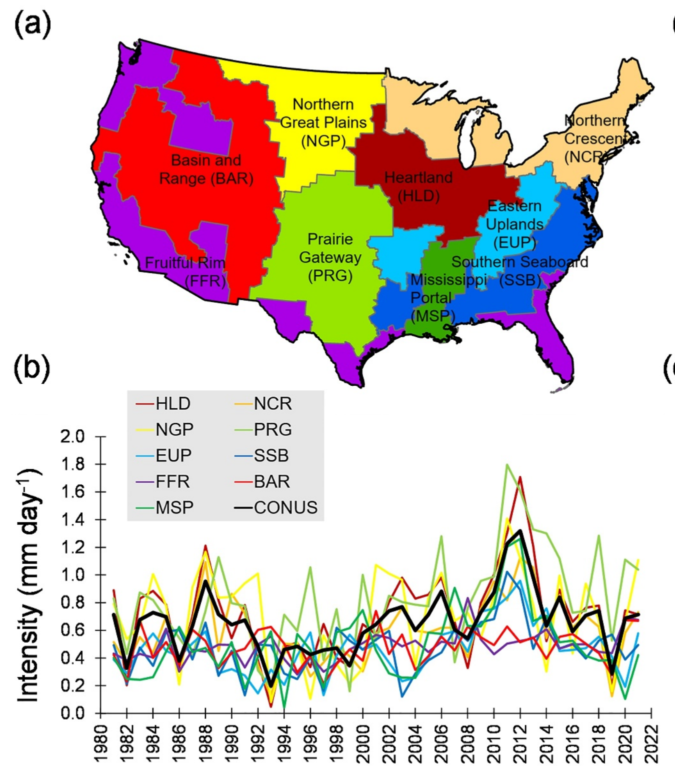


**Figure 5.** (a) Map showing each of the nine Farm Resource Regions (FRRs). (b) Time series of cropland area-weighted thirstwave intensity; (c) duration; and (d) frequency for the nine FRRs and CONUS during 1981–2021.

harvested area that saw significant increase in duration within any of the FRRs was not greater than 15% (Prairie Gateway, Eastern Uplands, and Southern Seaboard). Although each FRR has distinctive agricultural attributes, they are subject to significant distribution of actual harvested cropland within their boundaries, necessitating weighting county-level trends using crop harvested area. Across entire individual regions, observed weighted

**Table 1**
*Climatological (1981–2021) and Trend (1981–2021) Statistics for Thirstwave Characteristics Specific to the Nine Farm Resource Regions (FRRs) and the Conterminous US (CONUS)*

| | | | Climatology | | | Trend | | | % Acreage with significant trends | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Cropland share (%) | Value share (%) | Intensity (mm $d^{-1}$) | Duration (days) | Frequency (events) | Intensity (mm $d^{-1}$ $decade^{-1}$) | Duration (days $decade^{-1}$) | Frequency (events $decade^{-1}$) | Intensity | Duration | Frequency |
| Heartland | 27 | 23 | 0.8 | 4.1 | 3.0 | 0.06 | 0.10 | 0.37 | 11 | 3 | 12 |
| Northern Crescent | 9 | 15 | 0.7 | 4.0 | 2.8 | 0.05 | 0.12 | 0.39 | 13 | 8 | 24 |
| Northern Great Plains | 17 | 6 | 0.9 | 3.7 | 2.3 | 0.02 | 0.00 | 0.02 | 5 | 0 | 5 |
| Prairie Gateway | 17 | 12 | 1.0 | 4.0 | 3.4 | 0.13 | 0.14 | 0.60 | 43 | 14 | 35 |
| Eastern Uplands | 6 | 5 | 0.5 | 3.9 | 2.9 | 0.04 | 0.10 | 0.46 | 11 | 15 | 36 |
| Southern Seaboard | 6 | 9 | 0.6 | 4.0 | 3.2 | 0.04 | 0.16 | 0.61 | 16 | 15 | 47 |
| Fruitful Rim | 8 | 22 | 0.6 | 4.0 | 3.0 | 0.04 | 0.10 | 0.63 | 30 | 6 | 45 |
| Basin and Range | 4 | 4 | 0.6 | 3.8 | 2.4 | 0.03 | 0.09 | 0.39 | 8 | 6 | 44 |
| Mississippi Portal | 5 | 4 | 0.6 | 4.2 | 3.3 | 0.05 | 0.17 | 0.53 | 17 | 11 | 35 |
| CONUS | 100 | 100 | 0.8 | 4.0 | 2.9 | 0.06 | 0.10 | 0.39 | 17 | 7 | 23 |

*Note.* The climatology and trends are weighted using county-level cropland harvested area. Also provided are the FRR-level share of the national cropland and production value.

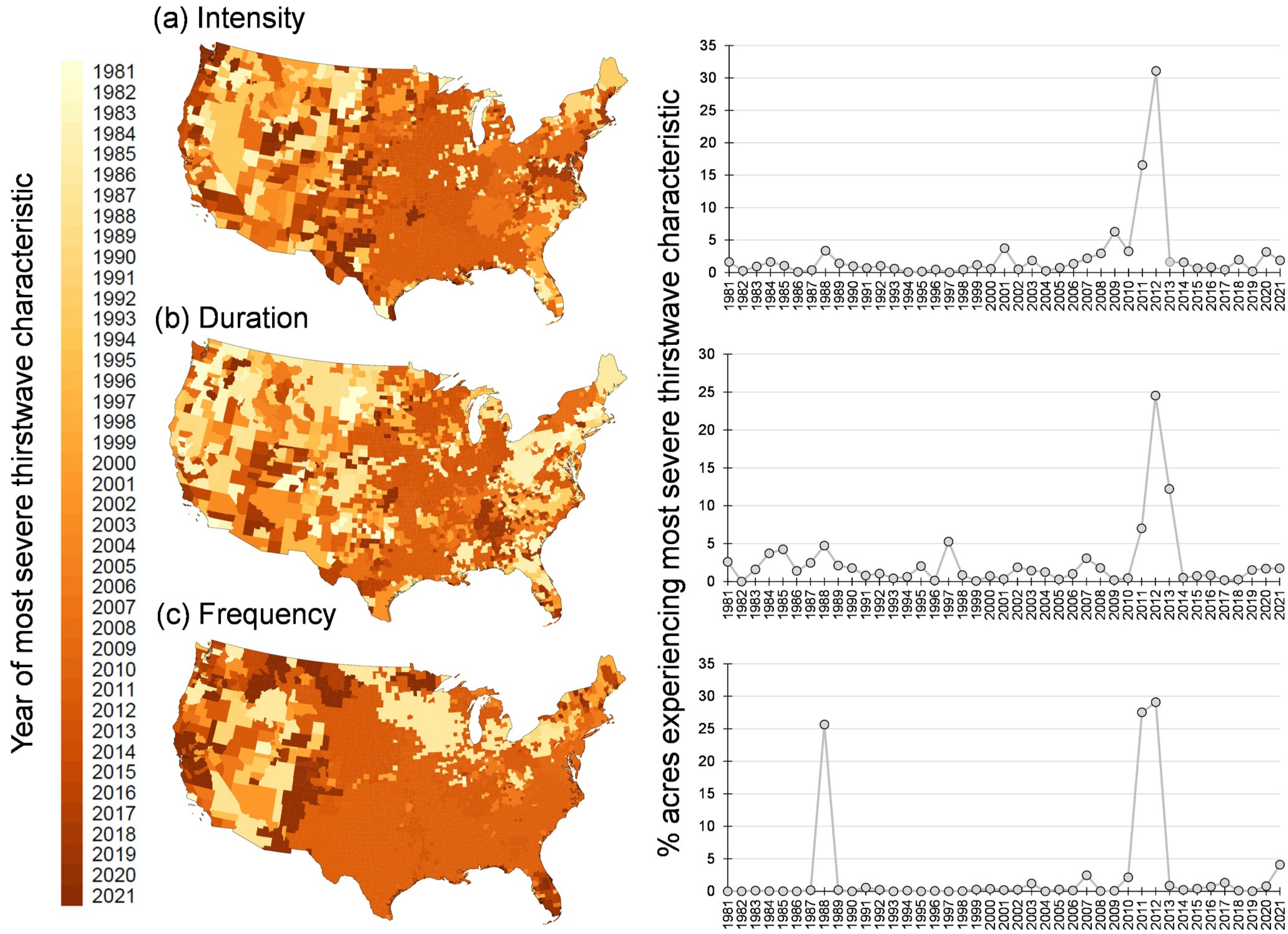


**Figure 6.** (a) The year in which the most severe thirstwaves occurred for each county when defined by intensity; (b) duration; (c) and frequency. Also shown alongside each map is the percentage of acreage experiencing the most severe thirstwave for each year.

increase in intensity was greatest for Prairie Gateway (0.13 mm $d^{-1}$ $decade^{-1}$) by a large margin. For duration, Mississippi Portal had the highest increase (0.17 days $decade^{-1}$), closely followed by Southern Seaboard (0.16 days $decade^{-1}$). Fruitful Rim had the greatest increase in frequency (0.63 events $decade^{-1}$), closely followed by Southern Seaboard (0.61 events $decade^{-1}$), and Prairie Gateway (0.60 events $decade^{-1}$). Since there is considerable disparity in FRR-level contributions to national cropland acreage and production value (Table 1), an increase in thirstwave severity for certain FRRs such as Heartland, Northern Great Plains, and Prairie Gateway may be more consequential for agricultural productivity and water management implications. In this regard, Prairie Gateway holds particular significance with not only its substantial national contribution, but also its higher acreage footprint of severely affected thirstwaves (Table 1). Such findings aggregated to meaningful scales (FRRs) allow for interpreting and dissemination of sector-specific (agricultural) impacts of extreme weather.

### 3.4. Most Severe Thirstwaves: Revisiting 2011–2012 Droughts Via the Thirstwave Lens

Besides long-term change, we also assessed when the most severe thirstwaves have been recorded. The vast majority of the most severe thirstwaves with large agricultural footprints across much of CONUS have occurred since 2000 (Figure 6). When severity is defined using intensity (Figure 6a), duration (Figure 6b), and frequency (Figure 6c), a large proportion (83%, 63%, and 72%, respectively) of harvested cropland area nationally has had its most severe thirstwaves occur since 2000. Further, a sizable fraction (72%, 81%, and 90%, respectively) of this proportion further has had the most severe thirstwaves occur after 2010. Overall, the most severe thirstwave characteristics observed over large swaths of CONUS (Figure 6) mostly corresponded to the historically worst 2011–2012 drought (Rippey, 2015). 2012 demonstrated the most severe thirstwaves observed in CONUS when

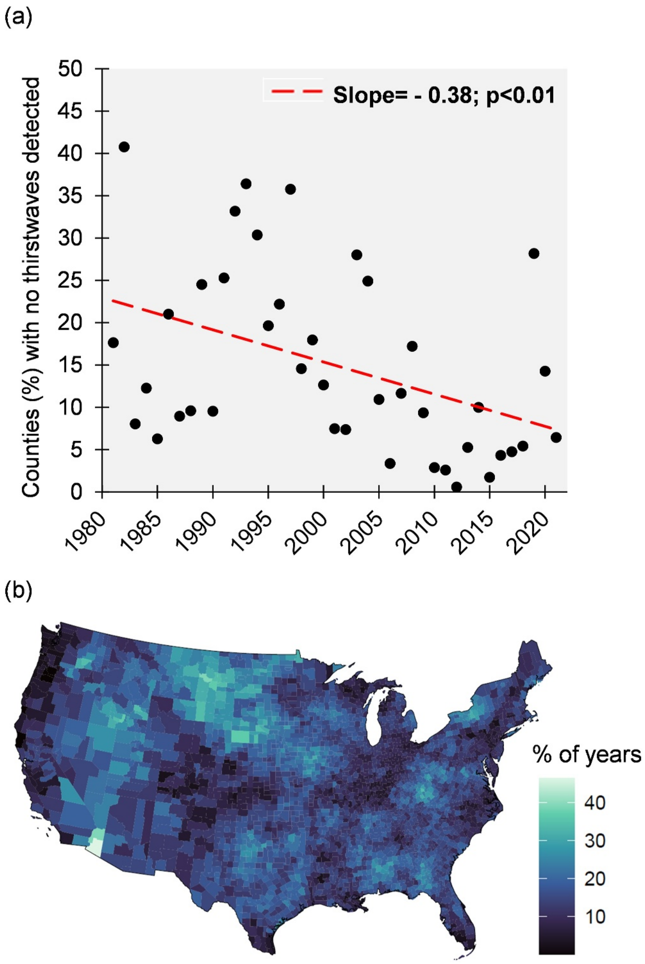


**Figure 7.** (a) Share (percent) of counties where no thirstwaves were detected for each year; and (b) percent of years for each county where no thirstwaves were detected during 1981–2021. The linear fit in panel (a) is significant at the 99% confidence level.

represented by any of the three characteristics. Aggregated across CONUS, thirstwaves during 2012 had an intensity, duration, and frequency of 1.32 mm $d^{-1}$, 5.8 days, and 8.5 events, respectively. Thirstwaves during 2012 had the highest intensity in one-third of nationally harvested area, while also demonstrating the highest duration and frequency in about more than a quarter (25% and 29%, respectively) of nationally harvested area (Figure 6). In fact, the combined period of 2011–2012 accounted for the most severe thirstwave intensity, duration, and frequency recorded in 48%, 32%, and 57% of cropland area, respectively.

The 2012 thirstwave was the most severe from a frequency standpoint (2.8 times the long-term mean), followed by intensity (2 times the long-term mean), and duration (1.7 times the long-term mean). FRR-specific differences in severity of the 2011–2012 thirstwaves relative to long-term behavior were much higher (Table 1). Thus, the 2011–2012 drought is in fact the most severe manifestation of thirstwaves, corroborated by the fact that evaporative demand drought index (EDDI), which is a $ET_{os}$-based tool, has been shown to provide exceptional early warning for this event (Hobbins et al., 2016).

### 3.5. Decreased Likelihood of Experiencing No Thirstwaves

Not every county experienced a thirstwave event every season. In fact, 18% of county-growing seasons did not encounter any thirstwaves at all during 1981–2021. Over time, percentage of counties that did not experience a thirstwave in the year has ranged from 1% to 41%, and has declined significantly ($p < 0.01$) over time (Figure 7a), at a rate of ~4% per decade. Thus, not only have thirstwaves become more severe over time, but regions and seasons that historically experienced few or no thirstwaves now face a significantly higher likelihood of encountering at least one thirstwave. The Southwest, Northern Rockies and Northern Plains are primary examples of such regions (Figure 7b).

## 4. Discussion

A consistent framework for defining, detecting, and measuring thirstwaves was proposed and employed in this study to characterize prolonged periods of extremely elevated evaporative demand. The framework, while original in application, is coherent with techniques commonly used to measure extreme air temperature periods, that is, heatwaves (Perkins & Alexander, 2013; Perkins-Kirkpatrick & Lewis, 2020). For accurate interpretation of our findings, it should be noted that the basis of our analysis is $ET_{os}$, as defined by FAO (Allen et al., 1998) and ASCE (Jensen & Allen, 2016; Walter et al., 2005). Evaporative demand is typically reported using diverse formulations depending on meteorological data availability (McMahon et al., 2016), and our choice of $ET_{os}$ was driven by a need for wide reach, physical soundness, and relevancy to US water management and practice. It incorporates both radiative and aerodynamic influences that determine water use in agriculture.

Our proposition of thirstwaves is motivated by the outstanding need to address current gaps associated with quantifying and reporting "extended exposure" of ecosystems to extreme evaporative demand. A large body of environmental extremes research has investigated the impacts of heatwaves on crop loss, agricultural water use, and water productivity globally (Belleza et al., 2023; Lu & Kueppers, 2015; Souri et al., 2020; van der Velde et al., 2010; Zampieri et al., 2017). However, an emphasis on heatwaves completely overlooks impacts from humidity, wind, and radiation. Although heatwave definitions have evolved over time to account for these (primarily humidity), their targeted applications are limited to human/animal thermal comfort (Cvijanovic et al., 2023; X.-X. Li, 2020; D. Li et al., 2020; Nairn et al., 2022). Agricultural stakeholders and audiences lack tailored metrics for quantifying and reporting prolonged periods of acute environmental conditions that are meaningful for water management and stress monitoring. The thirstwave concept differs fundamentally from heatwaves, both in physics as well as impacts on vegetation. By using $ET_{os}$ as its core measure, thirstwaves inherently capture extreme environmental conditions comprehensively, considering factors beyond air temperature, which is the sole driver in heatwave metrics. As a result, thirstwaves are better suited for explaining alterations in stomatal behavior and transpiration during extreme conditions than heatwaves (Damour et al., 2010). Hobbins (2016) found that during the growing season, temperature accounts for only part of daily evaporative demand variability in the CONUS; wind speed often dominates in the southwestern US in summer, solar radiation in the southeastern US, and humidity along the eastern seaboard in winter. In areas where temperature does dominate the signal of evaporative demand variability, it does so only partly. These fundamental differences also imply that spatiotemporal variability of thirstwaves does not follow those of heatwaves that have been presented in the literature (Oswald, 2018; Smith et al., 2013).

The thirstwaves concept also presents unique advantages to currently deployed metrics for measuring demand-side drivers of drought. To assess our work against current tools, it is essential to draw distinctions between them and thirstwaves. The potential of drought emergence and monitoring using EDDI has been evaluated to be a robust practice for early warning (Hobbins et al., 2016, 2019, 2022, 2023; McEvoy et al., 2016; Parker et al., 2021). As an operational tool, the primary function of EDDI is to classify regions and periods into drought categories based on $ET_{os}$ anomalies (Lukas et al., 2017). It is not intended to identify and quantify discrete multi-day events of extreme $ET_{os}$ anomalies, limiting its utility in systematically assessing how such events evolve over space and time. Analyzing thirstwaves requires a daily timeseries of $ET_{os}$, whereas the finest resolution timeseries of $ET_{os}$ percentiles available from EDDI are weekly. The thirstwave framework offers the capability to identify individual "waves" of extreme $ET_{os}$ that may begin and end at any time, providing greater flexibility, responsiveness, and adaptability compared to the EDDI, which relies on fixed calendar timescales (e.g., weekly, monthly). More recently, a global study showed drastic increase in very rare extremes of evaporative demand by employing vapor pressure deficit (VPD) as the core metric (Hermann et al., 2024). While it is not uncommon to represent evaporative demand using VPD (Gamelin et al., 2022; Nwayor et al., 2024; Yuan et al., 2019), it is noteworthy that VPD does not account for radiative energy's influence. In contrast, $ET_{os}$ explicitly accounts for both VPD as well as net radiation available at the surface, both of which govern transport of water vapor from surface to the environment.

Our findings show that the severity of thirstwaves has increased during the last four decades in many parts of the CONUS, when assessed using either of the three characteristics (higher intensity, frequency and duration). These changes are possibly a consequence of shifts in $ET_{os}$ distribution whereby even a small change in mean $ET_{os}$ can induce disproportionally large changes in $ET_{os}$ extremes, as is suggested in the case of extreme temperatures (Boer & Lambert, 2001; Katz & Brown, 1992; Mearns et al., 1984; Nicholls et al., 1996). Additionally, regions where thirstwaves have been historically severe (Figure 2) and where they are changing (intensifying, getting longer and frequent) are distinct (Figure 4) from changes in total warm season $ET_{os}$ (Figure 3). More importantly, thirstwave climatology and trends are especially dominant over agriculturally relevant regions (Heartland, Northern Great Plains, and Prairie Gateway). Although targeted investigations are required, a greater number of longer and more intense thirstwaves may hold important ramifications for local producer-level adaptation and regional policy. These conditions may likely translate into more frequent and longer episodes of greater crop water stress and loss of productivity in rainfed/dryland crop production (Singh et al., 2021). Consequently, these evolving conditions might increase the perceived value of investing in supplemental irrigation (Dalton et al., 2004), aligning with recent trends in irrigation adoption in the eastern US (Zeng & Ren, 2022). Since irrigated systems are typically designed to meet historical peak demand, extreme $ET_{os}$ persisting over multiple days during full canopy cover conditions could lead to soil water deficits and crop water stress, posing challenges for regions reliant on groundwater with limited pumping capacities (Foster et al., 2015; Steward et al., 2013) or those with restricted surface water rights (Deitch & Kondolf, 2004). Near real-time adaptation of on-farm management to these extreme conditions by producers will require translating $ET_{os}$ observations and forecasts into operational decision support systems. While not available currently, delivery of extreme $ET_{os}$ warnings/reports is a viable future avenue as a climate service that is supported by growing reference agricultural weather monitoring networks (collecting all four meteorological inputs necessary to calculate $ET_{os}$) in the country (Marek et al., 2020; Palmer, 2008; Shulski et al., 2018).

Having conceptualized and characterized historical thirstwaves for CONUS for the first time, we advocate for more research in this direction that can resolve and elucidate thirstwaves' multidimensional impacts within and beyond the agriculture sector. Future research should investigate translation of thirstwaves into changes in the soil water balance components, crop water stress, and irrigation requirements at regional to global scales and historical to future time periods. Other relevant areas of investigation should include impact of data set choices (Blankenau et al., 2020; Coughlan de Perez et al., 2023), threshold definitions (Vogel et al., 2020), and reference periods (Perkins-Kirkpatrick & Lewis, 2020) on thirstwave characteristics. Changes in methodological choices may influence spatiotemporal behavior of thirstwaves, as shown in the context of heatwaves. For instance, two heatwaves have been considered independent if they are 4 days apart and considered a single event otherwise (Tripathy et al., 2023). Similarly, significantly complicated multi-criteria relative and absolute thresholds have been investigated to define heatwaves (Smith et al., 2013). The proposition of an initial standardized definition in this research lays the foundation for similar developmental work for improving and targeted finetuning of the metric for application within various industries.

## Data Availability Statement

The study uses short crop reference evapotranspiration gridded data contained within the gridMET data sets hosted on Google Earth Engine (Abatzoglou, 2013b).

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