# UC Davis
## UC Davis Previously Published Works

**Title**

A drought indicator reflecting ecosystem responses to water availability: The Normalized Ecosystem Drought Index

**Permalink**

**Authors**

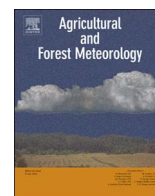Chang, Kuang-Yu
Xu, Liyi
Starr, Gregory
et al.

**Publication Date**

**DOI**

ELSEVIER

# A drought indicator reflecting ecosystem responses to water availability: The Normalized Ecosystem Drought Index

Kuang-Yu Chang[a,b,c,*], Liyi Xu[d], Gregory Starr[e], Kyaw Tha Paw U[a]

[a] Department of Land, Air and Water Resources, University of California, Davis, CA, USA
[b] Earth System Research Center, University of New Hampshire, Durham, NH, USA
[c] Climate and Ecosystem Sciences Division, Lawrence Berkeley National Laboratory, Berkeley, CA, USA
[d] JJoint Program on the Science and Policy of Global Change, Massachusetts Institute of Technology, Cambridge, MA, USA
[e] Department of Biological Sciences, University of Alabama, Tuscaloosa, AL, USA

## ARTICLE INFO

## ABSTRACT

Drought, one of the most destructive natural disasters is projected by numerous studies to become more severe and widespread under climate change. These water limitations will have profound effects on terrestrial systems across the globe. Yet, most of the existing drought monitoring indices are based on drought stress derived from environmental conditions rather than ecosystem responses. Here, we propose using a new approach, the Normalized Ecosystem Drought Index (NEDI), coupled with modified Variable Interval Time Averaging (VITA) method, to quantify drought severity according to ecosystem transitional patterns with water availability. The method is inspired by Sprengel's and Liebig's Law of the Minimum for plant nutrition. Eddy covariance measurements from 60 AmeriFlux sites that cross 8 International Geosphere–Biosphere Programme (IGBP) vegetation types were used to validate the use of NEDI coupled to VITA. The results show that NEDI can reasonably depict both drought stress posed by the environment and drought responses presented by various ecosystems. Water availability becomes a dominant limiting factor for ecosystem evapotranspiration when NEDI falls below zero, and normalized evapotranspiration strength generally decreases with decreasing NEDI under this regime. The widely used self-calibrating Palmer Drought Severity Index (sc-PDSI) and Standardized Precipitation Index (SPI) have difficulty capturing ecosystem responses to water availability, although they can reasonably represent drought conditions detected in the environment. The normalization feature employed in NEDI makes it feasible to compare drought severity over different regions, seasons and vegetation types. The new drought index also provides a valuable tool for irrigation and water distribution management practices which may enhance water conservation efforts as drought conditions become more prevalent.

## 1. Introduction

Drought is one of the most devastating natural disasters that can cause serious agricultural, economic and social impacts in the world (Wilhite, 2000). Several studies project increased aridity over land and more widespread droughts associated with changing climate, which could have profound impacts on agriculture, ecosystem structure and function, and human welfare (Mpelasoka et al., 2008; Feyen and Dankers, 2009; Seager et al., 2007, 2009; Dai, 2011a,b). Therefore, it is imperative to define more robust drought measures that can objectively quantify its characteristics, such as onset, severity and duration. Current drought measures often label drought into four categories: meteorological or climatological drought, agricultural drought, hydrological drought, and socioeconomic drought (Wilhite and Glantz, 1985;

Heim, 2002; Dai, 2011a,b).

Several drought indices have been developed to consider drought monitoring demands across diverse group of users. Some drought indices define droughts as the departures of soil water balance from normal conditions, such as the Palmer Drought Severity Index (PDSI) (Palmer, 1965), the self-calibrating Palmer Drought Severity Index (sc-PDSI) (Wells et al., 2004) and the Soil Moisture Deficit Index (SMDI) (Narasimhan and Srinivasan, 2005). Other drought indices define droughts as the deviations from normal precipitation patterns, such as the Standardized Precipitation Index (SPI) (McKee et al., 1993), and fractional decreases in precipitation compared to climatological averages (Shi et al., 2014; Hoover and Rogers, 2016). The Standardized Precipitation Evapotranspiration Index (SPEI) includes the effect of evapotranspiration demand caused by temperature variability into the

SPI framework, which combines the features in PDSI and SPI (Vicente-Serrano et al., 2010; Beguería et al., 2014).

These drought indices can serve as useful tools for drought monitoring, although these approaches may only reflect potential drought stress imposed on an ecosystem rather than actual drought responses. Thus, such drought indices may miss potential phenological and morphological impacts on ecosystems, since ecosystems can have various adaptation and acclimation mechanisms in regards to limited water availability (Lu and Zhuang, 2010; Liu et al., 2011; Starr et al., 2016). At the canopy scale, stomatal conductance could decrease to reduce water loss from a water stressed ecosystem (Reichstein et al., 2002; Ponce Campos et al., 2013). Total leaf area and net primary production of an ecosystem could be regulated in response to limited water availability (Huxman et al., 2004; Saleska et al., 2007; Zhao and Running, 2010). This reduction in leaf level physiological activity in evergreen systems has been observed at least a year following the alleviation of the water stress (Starr et al., 2016). Water use efficiency was found to increase with moderate drought and decrease under severe drought (Lu and Zhuang, 2010).

At the biome scale, a particular ecosystem found at any location has an assemblage of species that are in their specific ecological niche (Peterson, 2003), and has experienced climatological conditions like periodic droughts. These ecosystem responses are able to regulate local and regional circulation patterns, which could have significant influence on water cycles (Foley et al., 2003; Levis 2010). Failure to represent this type of ecosystem regulation may increase the uncertainty in quantifying drought characteristics for real time monitoring and future prediction. In addition to the regulations of soil water availability, ecosystem water and carbon fluxes are also controlled by atmospheric demand for water, indicated by vapor pressure deficit (Whelan et al., 2013; Novick et al., 2016). Therefore, drought index development should not only focus on environmental dryness, but also on ecosystem responses to different limiting factors. Novick et al. (2016) presented a synthesis analysis of drought effects on ecosystem responses, but the dryness index used in their study was based on the ratio of annual potential evapotranspiration and annual precipitation that represents ecosystem characteristics rather than ecosystem transitional responses.

Here, we propose an ecosystem drought indicator called the Normalized Ecosystem Drought Index (NEDI) that can measure drought severity to relate to the effects of ecosystem responses to limited water availability. The NEDI provides a measure of ecosystem responses to drought, which is often not discussed in current drought perspectives (Wilhite and Glantz, 1985). The main difference that distinguishes NEDI from the existing drought indices is the use of normalized surface water balance in quantifying drought conditions, which incorporates ecosystem characteristics in drought severity estimation. With the incorporation of these ecosystem characteristics, we hypothesize that the inclusion of normalization feature can facilitate the inter-comparison of drought severity across different geographical regions and ecosystem types. Ecosystem responses to drought are depicted by the measured changes in normalized evapotranspiration strength (hereafter K) defined as the ratio between actual evapotranspiration (hereafter ET) and potential evapotranspiration (Thornthwaite, 1948). The $K$ defined here is conceptually similar to the Evaporative Stress Index (*ESI*, Anderson et al., 2007), and the crop coefficient $K_c$ (Allen et al., 1998). A modified Variable Interval Time Averaging (VITA) technique traditionally used in detecting turbulence ramp events (Blackwelder and Kaplan, 1976) is applied to identify ecosystem responses to water availability and determine drought severity. The variations of K are analyzed by the modified VITA in drought index domain to illustrate the relationship between measured ecosystem drought response and estimated drought severity. We examined the applicability of NEDI with field measurements taken at 60 AmeriFlux eddy covariance (EC) towers (489 site years in total) across 8 different vegetation types that were defined by the International Geosphere–Biosphere Programme classification

(IGBP). The drought conditions commonly identified by sc-PDSI, SPI1 and SPI12 were analyzed and compared with the NEDI to determine the differences among the indices, and show the importance of ecosystem function in quantifying drought severity.

## 2. Methodology

### 2.1. Normalized Ecosystem Drought Index (NEDI)

We use the difference between monthly precipitation (P) and monthly potential evapotranspiration (hereafter PET) to estimate water availability (W), similar to the Standardized Precipitation Evapotranspiration Index (Vicente-Serrano et al., 2010), and related to the Reconnaissance Drought Index (Tsakiris and Vangelis, 2005). However, we represent water supply with total precipitation collected in the previous months (j = 1 for 1 month lag, j = 2 for 2 months lag, and so forth) instead of the value in the current month to account for legacy effects for precipitation to become an available water source. Therefore, the water availability for the month $i$ can be represented as

$$W_i = P_{i-j} - PET_i, \tag{1}$$

which is positive with water surplus, neglecting groundwater storage and runoff. The monthly NEDI is then defined by normalizing the $W_i$ series with the maximum absolute value of water availability shown in the $W_i$ series of $I$ months, which can be represented as

$$NEDI_i = \frac{W_i}{\max(abs(W_{i=1,I}))}. \tag{2}$$

NEDI can quantify water availability at each ecosystem from $-1.0$ (driest condition; maximum water shortage) to 1.0 (wettest condition; maximum water surplus).

The Thornthwaite PET (Thornthwaite, 1948), which requires only the mean monthly surface air temperature and latitude, was used to estimate the monthly water demand required in NEDI. Despite its limitations (Jensen et al., 1990; Donohue et al., 2010; van der Schrier et al., 2011), Dai (2011a) showed that using the more sophisticated Penman-Monteith PET only reduced uncertainties slightly in the PDSI calculation. Therefore, the Thornthwaite PET was used in our NEDI calculation to bypass the extensive amount of data required for using Penman-Monteith PET, allowing us to examine NEDI with a greater number of eddy covariance stations.

### 2.2. Modified Variable Interval Time Averaging (VITA)

Based on a running variance concept, VITA (Blackwelder and Kaplan, 1976) has been widely applied to detect turbulence characteristics in unsteady flows (Shaw et al., 1989). The localized variance used in VITA for each time interval window T is calculated as

$$var(t_i, T) = \frac{1}{T} \int_{t_i-T/2}^{t_i+T/2} p(t)^2 dt - [\frac{1}{T} \int_{t_i-\frac{T}{2}}^{t_i+\frac{T}{2}} p(t) dt]^2, \tag{3}$$

where $p$ and $t_i$ stand for the variable to be used for detection of some phenomenon and observation time, respectively. When the streamwise velocity is used for the variable $p$, turbulence patterns are identified if rapid changes are detected in the localized variance, suggesting the existence of high velocity fluctuations associated with coherent turbulent structures, as originally used by Blackwelder and Kaplan (1976).

We extend this running variance concept to drought monitoring by using NEDI values in place of time (the variable $t_i$ in Eq. (3)), that is NEDI (the variable $n_i$ in Eq. (4)) was used instead of the time on the abscissa. The variable to be used in detection is then labeled and sorted by the corresponding NEDI value, instead of sorted by time series. This modified VITA is thus defined as

$$var(n_i, N) = \frac{1}{N} \int_{n_i}^{n_i+N} p_{(n)}^2 dn - [\frac{1}{N} \int_{n_i}^{n_i+N} p_{(n)} dn]^2, \tag{4}$$

where $n_i$ and $N$ stand for the $i^{th}$ NEDI value and the number of NEDI analyzed in each localized window, respectively. The analysis window size $N$ was set as 30 to smooth out high frequency variations. Different values of window size $N$ were tested, and all results were similar to those presented here (SI1 and SI2).

The modified VITA in Eq. (4) was used to detect ecosystem transitional responses to drought conditions following the general concept of Sprengel's and Liebig's Law of Minimums for plant nutrition (van der Ploeg et al., 1999). For field ecosystems studies, a variety of variables that affect ecophysiological response are constantly changing, and unlike laboratory studies, cannot be constrained or controlled to readily separate the effects of a single variable of interest. That ecophysiological response will show variance when plotted against any particular single variable of interest when other variables are naturally changing and affecting the ecophysiological response also (i.e. photosynthetic radiation, time of year and temperature). However, when the variable of interest is at some threshold, such as the limited water availability of drought conditions, then the ecophysiological response will be invariant since it is being constrained by the limiting factor, and the variance will therefore be low.

When limited water availability is a dominant factor limiting ecosystem ET, $K$ is mainly determined by water availability and thus localized variance would be low and comparable between neighboring windows. When other variables come into play, because sufficient water is available, $K$ is a function of other variables (i.e. photosynthetic radiation, soil moisture and environmental temperature) that are changing quasi-independently of the water availability, thus resulting in an increased variance of $K$. Under this scenario, localized variance could present rapid fluctuations that would be detectable by the modified VITA. The NEDI values at which localized variance starts presenting rapid fluctuations show the transition between lower NEDI identifying drought sufficiently severe to be the limiting variable, and higher NEDI when the ecosystem is not under drought conditions and other variables jointly control $K$. This method could be applied to detect and quantify ecosystem responses as measured by other ecophysiological variables, such as stomata conductance and gross primary productivity (GPP).

The modified VITA (Eq. (4)) can also be applied to other drought indices besides NEDI. We compare VITA for NEDI and using VITA for three other indices described later: the Self-Calibrating Palmer Drought Severity Index (sc-PDSI); the Standardized Precipitation Index over 1 month duration (SPI1); and the Standardized Precipitation Index over 12 months duration (SPI12).

## 3. Data

### 3.1. AmeriFlux dataset

Half-hourly eddy covariance datasets for 60 AmeriFlux sites from 1991 to 2015 (489 site years) were used in this study (http://ameriflux.lbl.gov/). These sites encompass a variety of ecosystem types and climatological conditions (Fig. 1; Appendix A), and should be representative enough to examine NEDI. The Thornthwaite PET (Thornthwaite, 1948), precipitation anomaly, ET deficit, normalized ET strength $K$, and NEDI were calculated at monthly scale based on the half-hourly measurements taken at each AmeriFlux site. ET deficit was calculated as measured ET minus Thornthwaite PET. The precipitation anomaly was computed as total precipitation measured at each month minus the monthly mean precipitation calculated by the available measurements recorded at each site (Appendix A).

### 3.2. Self-Calibrating Palmer Drought Severity Index (sc-PDSI)

The monthly $2.5^{\circ} \times 2.5^{\circ}$ self-calibrating Palmer Drought Severity Index (sc-PDSI) from the National Center for Atmospheric Research Climate Analysis Section (Dai, 2011a) was used in this study. The sc-PDSI measures the cumulative departure in surface water balance in terms of moisture supply (precipitation) and demand (potential evapotranspiration) (Palmer, 1965; Wells et al., 2004; Dai, 2011a,b). The sc-PDSI calculation involves precipitation, evapotranspiration, soil moisture loss and recharge, and runoff, and more details of its formulations can be found in Wells et al. (2004). Studies have shown that the sc-PDSI performs better than the original PDSI over Europe and North America because of the inclusion of dynamically calculated and spatially based climatic characteristics and duration factors (van der Schrier et al., 2006a, 2006b, 2007). The sc-PDSI values for the AmeriFlux sites were extracted from the nearest grid cells of the sc-PDSI dataset where the AmeriFlux sites are located. Drought conditions indicated by sc-PDSI were compared to those in SPI (Section 3.3) and NEDI at the same time periods and locations.

### 3.3. Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) is a multi-timescale drought index that requires only precipitation data. The SPI represents abnormal wetness and dryness with user defined time durations by comparing precipitation departure from the cumulative probability distribution of precipitation over the same region and period (McKee et al., 1993). The low data requirements, simple calculation and flexible time duration employed in the SPI enable its wide range of applications such as drought monitoring at variable timescales and water supply management (Guttman, 1998, 1999). Because the SPI is only based on precipitation data, it is limited in its ability to represent drought conditions when other environmental components like temperature are not stationary (Vicente-Serrano et al., 2010). Nevertheless, studies have shown that drought conditions are mainly determined by the variability of precipitation, and the SPI is reasonably correlated with the Palmer Index at time scales of 6–12 months (Heim 2002; Redmond 2002). The SPI series used in this study was calculated at the 60 AmeriFlux sites based on the calculation procedure described in McKee et al. (1993). The monthly precipitation data required for SPI calculation was aggregated from the half-hourly measurements taken at each AmeriFlux site. The temporal sensitivity of the time interval selection of SPI was examined, and the results show that ecosystem responses to SPI are consistent across different time intervals (SI 3). Results from one month SPI (SPI1) and twelve months SPI (SPI12) were presented in this study for the brevity of our discussion.

Drought conditions indicated by SPI1 and SPI12 were compared to those indicated by sc-PDSI and NEDI at the same time periods and locations. Specifically, precipitation anomaly, ET deficit and normalized ET strength $K$ were examined in relationship to the different drought indices. In addition to time series analysis, we also applied the modified VITA (Section 2.2) to evaluate ecosystem responses to water availability in drought index space (Eq. (4)).

## 4. Results and discussions

### 4.1. Precipitation anomaly and ET deficit

The precipitation legacy effects on delaying water input to ecosystem were examined by applying different values of time lag (j) in the water availability ($W_i$) calculation (Eq. (1)). Lags between 0 and 6 months (j from 0 to 6) were tested, and ecosystem responses to drought show the greatest association with one-month lag in precipitation (j = 1) (SI 4; SI 5). Studies have found that the intensity and variability of precipitation is one of the most important climate drivers of drought stress that causes changes in ecosystem productivity (Craine et al.,
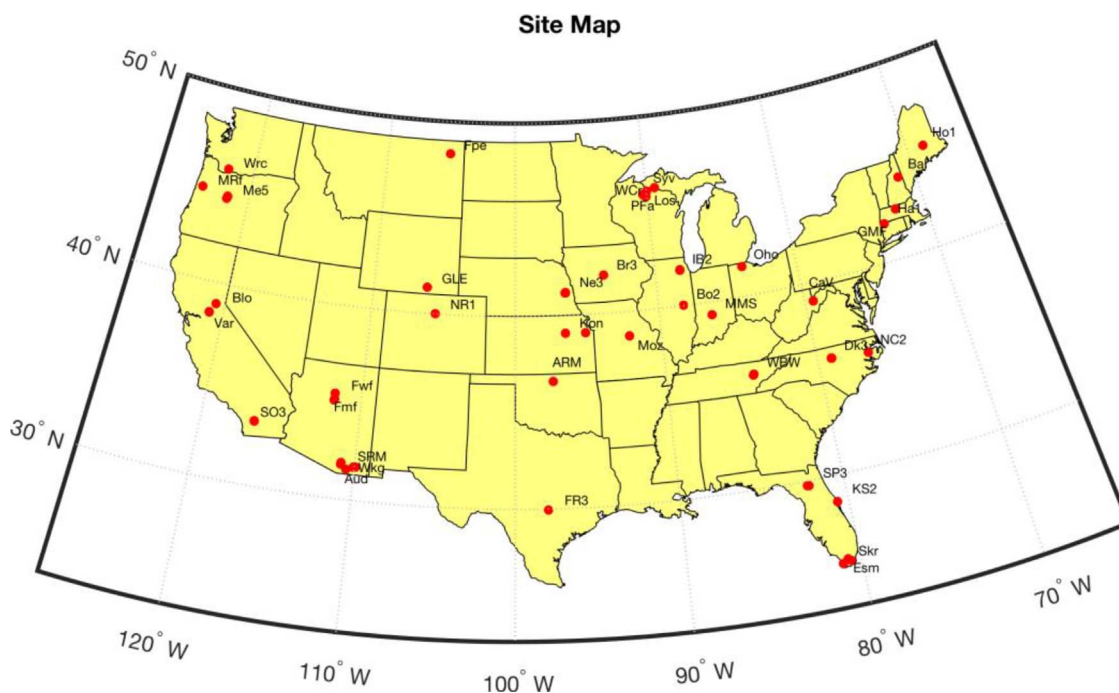
## Site Map



**Fig. 1.** The locations of the Ameriflux sites used in this study, denoted in red dots. The corresponding site names are indicated on the map. More detailed information of the AmeriFlux sites is summerized in Appendix A. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2012; Williams et al., 2013; Barnes et al., 2016). This sensitivity of precipitation shown in NEDI calculation suggests that ecosystem ET is not only responsive to the amount of precipitation, but also the timing of precipitation becomes an available water source for ecosystem. In addition, the use of precipitation from the previous month provides a valuable tool for users and decision makers to modify management practices accordingly. For example, one can estimate ecosystem drought conditions without introducing uncertainties in predicting precipitation in current or future months, and apply a suitable irrigation and water distribution management plan to optimize the amount of water consumption.

Continuous time series records of NEDI, sc-PDSI, SPI1 and SPI12 were compared to investigate temporal variability represented by the different indices. The transitions between wet and dry regimes were described by the precipitation anomaly and ecosystem ET deficit. Analysis was performed across all 60 AmeriFlux sites and results are consistent for all. We also conducted and present more in-depth results from a more detailed study of Howland Forest (US-Ho1) because it is one of the sites that has relatively long-term continuous quality controlled eddy covariance measurements.

The time series of the calculated monthly precipitation anomaly and the drought indices for US-Ho1 (data from 1997 to 2009) and the correlation coefficients between the anomaly and the indices, are shown in Fig. 2. Dry regimes indicated by negative drought indices generally coincide with negative monthly precipitation anomaly and vice versa. Monthly precipitation anomaly is positively correlated with the drought indices, and the correlation coefficient is highest for SPI1 (C = 0.7048) and lowest for SPI12 (C = 0.1955). These results suggest that all of these drought indices can reasonably depict environmental drought stress posed on ecosystem, such as below normal precipitation, consistent with Heim (2002) and Keyantash and Dracup (2002). The differences between the correlation coefficients indicate that different drought indices reflect different temporal scales, suggesting that the temporal scale represented by a drought index is as important as the physics embedded in it. Therefore, it is critical to have a proper drought index with a suitable temporal scale to depict the environmental condition of the system, since different ecosystems are sensitive to different aspects of climate variability (Craine et al., 2012; Vicente-Serrano et al.,

2013; Barnes et al., 2016).

Similar analysis was performed with ET deficit to evaluate ecosystem responses to drought indicated by these indices. ET deficit should become more negative as an ecosystem responds to limited water availability, with ET being much lower than PET under drought conditions. The time series of the ET deficit and the drought indices at US-Ho1 from 1997 to 2009 show that all indices correlate poorly with ET deficit, except the proposed NEDI (Fig. 3). The correlation coefficient is 0.6314 with NEDI, but its magnitude is less than 0.05 with sc-PDSI, SPI1 and SPI12. The results suggest that ecosystems may not necessarily suppress ET to reduce water loss in the presence of environmental drought (negative drought indices). Therefore, the commonly used sc-PDSI and SPI may have difficulty in representing ecosystem responses to limited water availability, although they can be used in detecting drought conditions in the environment.

NEDI, on the other hand, may have advantages in drought monitoring because it can identify both environmental drought conditions and ecosystem responses to limited water availability. Within these indices, drought conditions are identified as below normal water balance, which does not necessarily correspond to a water deficit (negative water balance) environment that poses drought stress to ecosystems (Vicente-Serrano et al., 2013). Our results suggest that drought conditions identified by NEDI correlate with ecosystem responses to a water deficit environment, owing to the use of normalized water balance in its calculation.

In addition to the time series analysis, we aggregated the drought indices and ET deficit series from the all sites. Density scatter plots for the associated composite results (Fig. 4) show that data points are more concentrated in regimes with moderate water availability, no matter which drought index is used. This behavior indicates that all the drought indices can effectively categorize normal and extreme events, although their methods and objectives are different. All of the drought indices present an asymmetric pattern between wet (positive) and dry (negative) regimes, which shows that ET deficit in the dry regime can be significantly higher than those in the wet regime. In the wet regime, the scatter patterns between ET deficit and drought indices are similar for all of the indices. There is no clear ET deficit trend in response to changing water availability in the wet regime, suggesting that ET is not
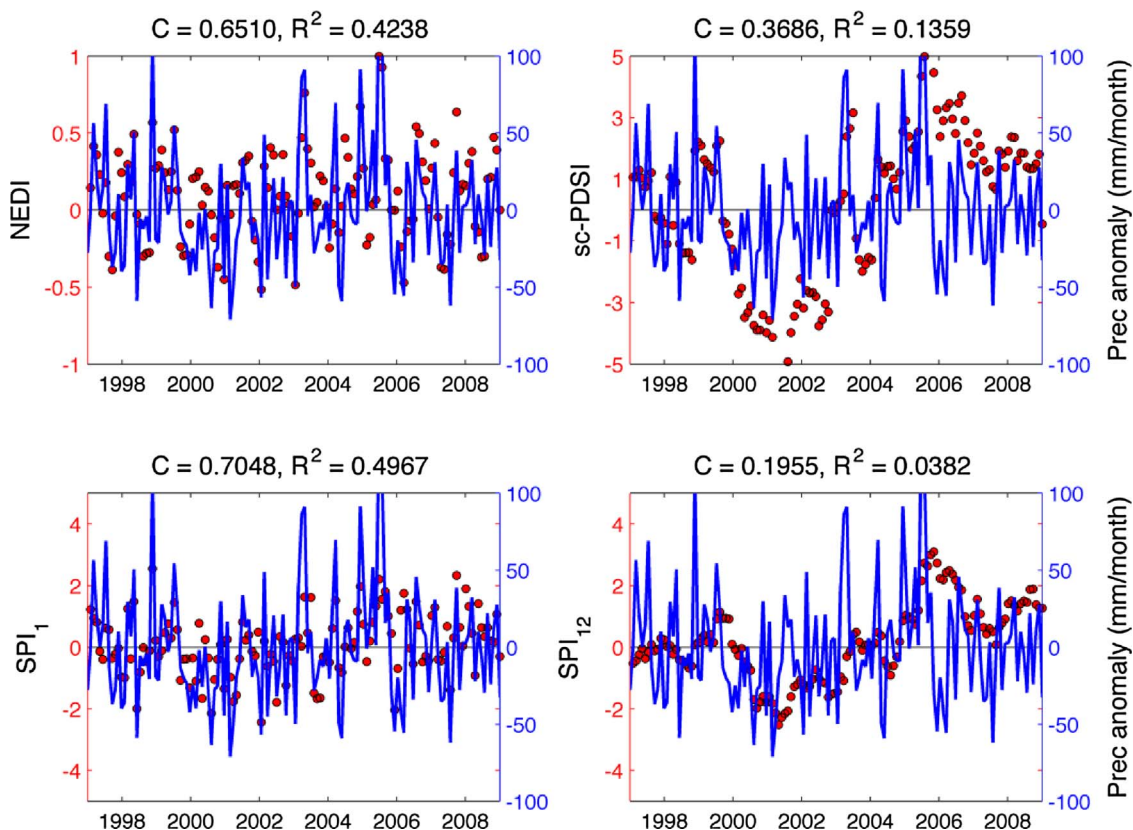
**Fig. 2.** Time series for drought indices (red dots; left axes) and precipitation anomaly (blue lines; right axes) plotted at the Howland Forest from 1997 to 2009. The corresponding correlation coefficient and $R^2$ values are written on top of each subplot. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
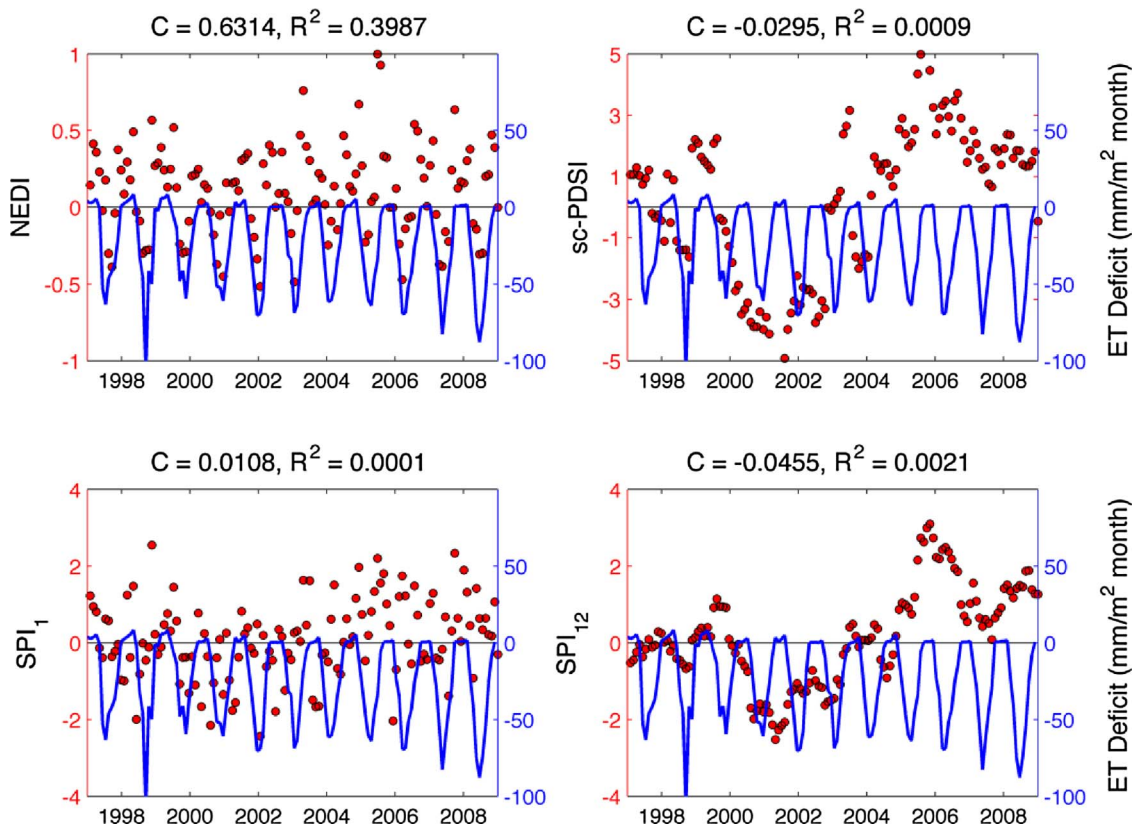


**Fig. 3.** Time series for drought indices (red dots; left axes) and ET deficit (blue lines; right axes) plotted at the Howland Forest from 1997 to 2009. The corresponding correlation coefficient and $R^2$ values are written on top of each subplot. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
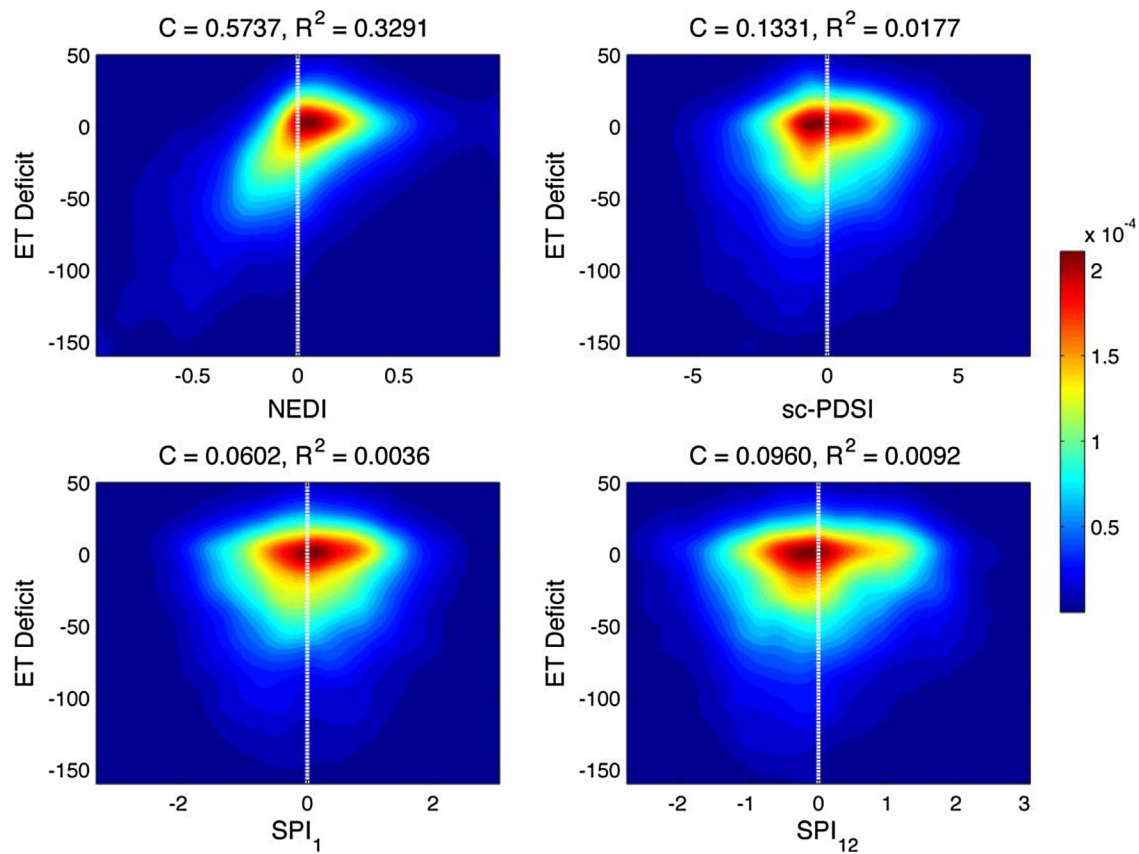
**Fig. 4.** Density scatter plots between ET deficit and drought indices aggregated from 60 AmeriFlux sites used in this study. Color bar represents the density of the data points presented in the dataset. The corresponding correlation coefficient and $R^2$ values are written on top of each subplot.

sensitive to excessive amount of water input when enough water availability is present. In the dry regime, drier conditions described by lower values of sc-PDSI, SPI1 and SPI12 are not necessarily associated with lower ET deficits, and most of the lowest ET deficit events are in a moderate drought regime as defined by these drought indices. On the other hand, there is a clear relationship that lower NEDI usually comes with lower ET deficit, and this pattern holds true throughout the entire dry regime. Therefore, the composite results again show that NEDI can represent ecosystem responses to drought, while sc-PDSI, SPI1 and SPI12 have difficulty in relating water availability with actual ecosystem responses.

The reduction in ET depicted by sc-PDSI, SPI1 and SPI12 are similar to those presented in Novick et al. (2016), where growing season surface conductance and ET were analyzed in a range of dryness index (the ration of annual PET to annual precipitation). Novick et al. (2016) observed considerable variability of ET deficit when hydrologic stress starts affecting ecosystem functions (dryness index < 4), and ET deficit stops growing as drought increased (dryness index > 4). This pattern was observed no matter hydrologic stress is caused by decrease in soil moisture supply or increase in atmospheric demand. These results suggest that drought indices based on surface water balance may not reflect the status of water availability used by an ecosystem under extreme drought events. This finding adds support that normalized surface water balance used in NEDI can better portray ecosystem responses to hydrologic stress.

### 4.2. The modified VITA and drought severity

To avoid biases from varying magnitudes of site-dependent ET deficit, the transitional signals of ecosystem responses to water availability were analyzed in terms of the nondimensional normalized ET strength ($K$, Section 1). The density scatter plots between different sets

of drought index and $K$ were again aggregated from the 60 sites (Fig. 5). Our results show that higher values of $K$ are more likely to be in the wet regimes as defined by the drought indices, which indicates that ecosystem ET can reach its potential value when sufficient water is provided. The use of NEDI presents an asymmetric pattern between wet and dry regimes, and normalized ET strength generally reduces with decreasing NEDI. Similar patterns can be found with the other drought indices, although the decreasing trend of $K$ is less prominent under drought conditions detected by sc-PDSI, SPI1 and SPI12. These results suggest that the use of NEDI is preferable to detect ecosystem responses to limited water availability.

The distribution patterns shown in Fig. 5 provide a way to characterize ecosystem responses over wet and dry regimes, although the magnitude of $K$ could vary significantly over a zone with similar drought indices. The modified VITA (Section 2.2) was employed to filter out this type of variation and to clarify the relationships between $K$ and different sets of drought index. The modified VITA successfully transforms the distribution patterns into variable space, and effectively filters out noisy parts of the signal (Fig. 6). When represented in variable space, there is a rapid transition signal in localized variance of $K$ when NEDI changes sign, suggesting that ecosystem responds differently to water availability between wet and dry NEDI regimes. When NEDI is positive, localized means of $K$ are relatively high with strong localized variances of $K$ fluctuating over the wet regime. When NEDI is negative, localized means of $K$ are relatively low with weak and steady localized variances of $K$, and localized means of $K$ generally decrease with decreasing NEDI under the dry regime. Such features cannot be found with the use of sc-PDSI, SPI1 and SPI12 (Fig. 6). Instead, localized variances of $K$ jump randomly over the entire domain of the selected drought index (sc-PDSI, SPI1 or SPI12), and there is no clear transitional pattern that separates wet and dry regimes based on the modified VITA. Although localized means of $K$ are relatively low when
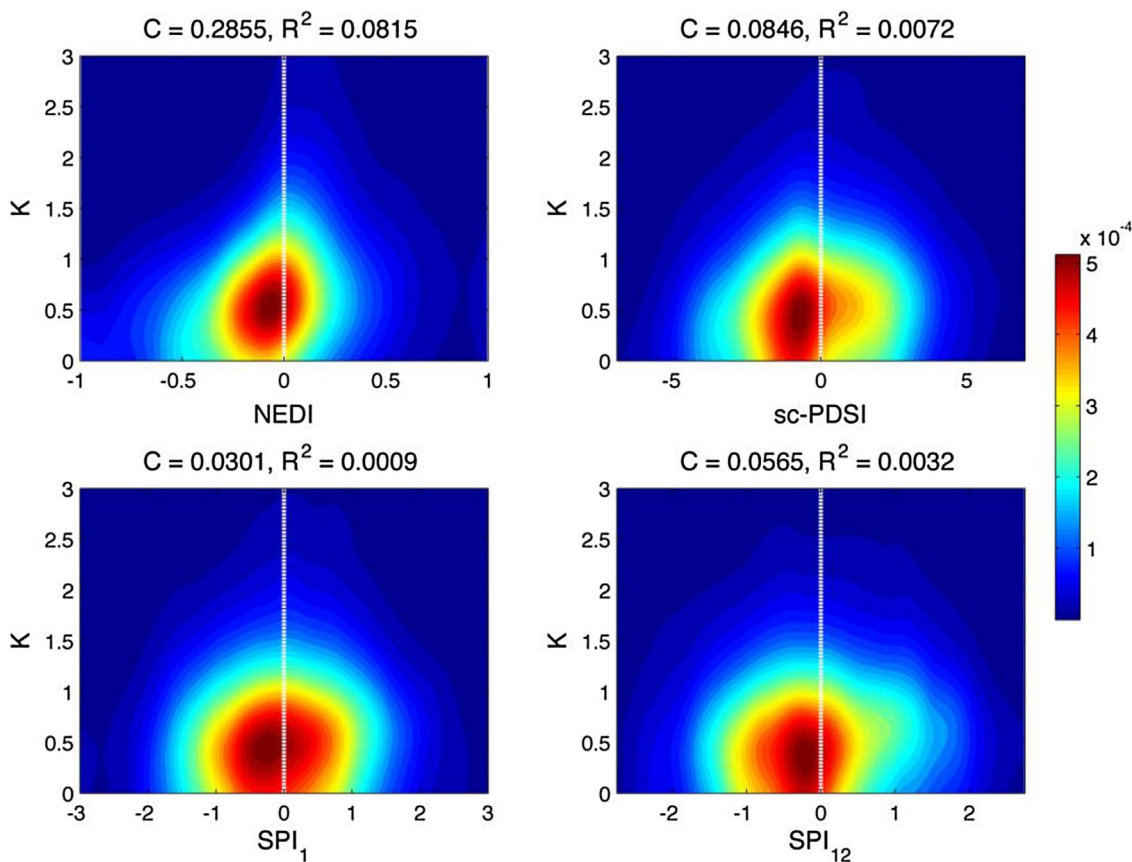
**Fig. 5.** The density scatter plots between normalized ET strength ($K$) and drought indices aggregated from 60 AmeriFlux sites used in this study. Color bar represents the density of the data points presented in the dataset. The corresponding correlation coefficient and $R^2$ values are written on top of each subplot.

the selected drought index (sc-PDSI, SPI1 or SPI12) is negative, they lack a coherently decreasing trend with decreasing value in the selected drought index. These results suggest that NEDI can be a better indicator to represent ecosystem ET ecophysiological regulation effects when compared to the widely used sc-PDSI, SPI1 and SPI12.

The strong and fluctuating localized variances of $K$ with positive NEDI indicate that water availability is not a limiting factor controlling ET. Other factors like environmental temperature, solar radiation and soil moisture may be as important as water availability in controlling ecosystem ET (Jung et al., 2010; Zhang et al., 2016). On the contrary, the weak and steady localized variances of $K$ with negative NEDI indicate that lack of water availability is a dominant limiting factor controlling ET, i.e. the supply of water falls short of ecosystem demand.

Based on this relationship, we could derive a numerical representation that directly links normalized ET strength with drought severity, since both normalized ET strength and water availability can be represented by NEDI. After examining a series of regression models, we selected the ninth order polynomial fit for estimating normalized ET strength with NEDI due to its acceptable performance and complexity (Fig. 7). Lower order of regression models result in larger root mean square errors, and higher order of regression models do not necessarily improve the estimated normalized ET strength. The relationships between estimated normalized ET strength ($K'$) and NEDI ($x$) can thus be represented as

$$K' = A_1 x^9 + A_2 x^8 + A_3 x^7 + A_4 x^6 + A_5 x^5 + A_6 x^4 + A_7 x^3 + A_8 x^2 + A_9 x + A_{10}, \tag{5}$$

where $A_1$ to $A_{10}$ are shown in Table 1. This regression line was plotted with localized means of normalized ET strength under drought conditions defined by NEDI (Fig. 8).

As shown in Fig. 8, the normalized ET strength reduced by 20%,

50% and 75% when NEDI was $-0.05$, $-0.3$ and $-0.9$, respectively. We can define moderate drought ($K = 0.8$), severe drought ($K = 0.5$) and extreme drought ($K = 0.3$) when NEDI falls below $-0.05$, $-0.3$ and $-0.9$, respectively. The NEDI drought severity may not be easily compared with the drought intensity described by PDSI (Palmer, 1965) and SPI (McKee et al., 1993), because these drought indices do not reliably identify drought characteristics as indicated by the ET deficit and normalized ET strength ($K$) that are used in our study (Figs. 4 and 6). The NEDI drought severity defined here was based on measured ET regulation patterns encompassing a variety of ecosystem types and climatological conditions, suggesting that it can objectively reflect water availability under different biogeographical, climatological and ecological paradigms.

### 4.3. Sensitivity to vegetation types

In addition to the distribution patterns shown in Figs. 4 and 6, drought conditions as measured by NEDI, sc-PDSI and SPI were further examined to evaluate their sensitivity to vegetation types. The 60 AmeriFlux sites were categorized into 8 IGBP vegetation types: needleleaf forest; broadleaf forest; mixed forest; grasslands; savannas; shrublands; croplands; and wetlands. The ET deficit versus NEDI density scatter plots (Fig. 9) show that the distribution patterns in Fig. 4 hold true for all of the vegetation types, and ET deficit generally decreases with deceasing NEDI. Therefore, NEDI can represent ecosystem responses to limited water availability for every vegetation type, although its relationship to ET deficit is most prominent for shallow rooted vegetation (grassland, savannas and shrublands), indicated by higher frequency of occurrence shown in Fig. 9. The sc-PDSI has difficulty representing a realistic relationship to ET deficit (Fig. 10). These results show that ET deficit does not necessarily respond to changes in
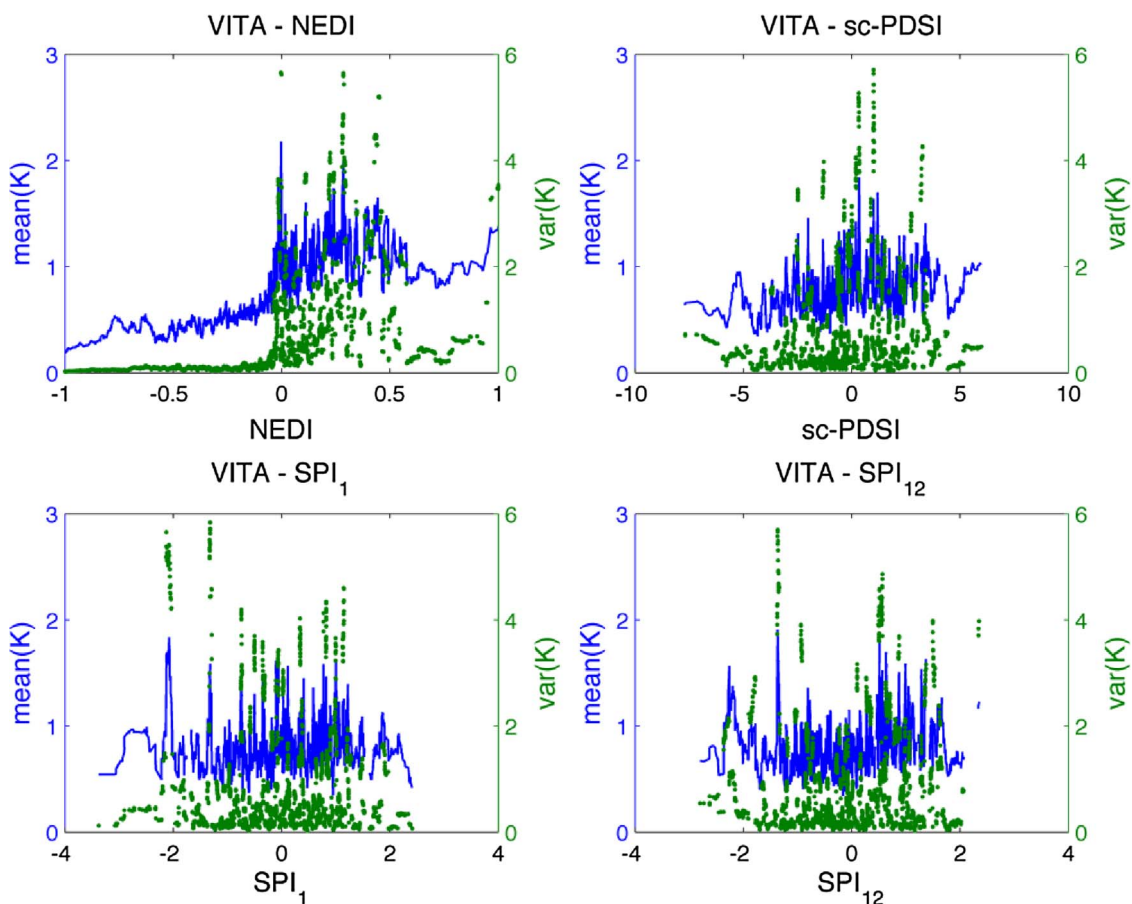
**Fig. 6.** The localized mean (left axes; blue lines) and the localized variance (right axes; green dots) of normalized ET strength ($K$) calculated by the modified VITA. Results were aggregated from 60 AmeriFlux sites used in this study for each of the investigated drought indices. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
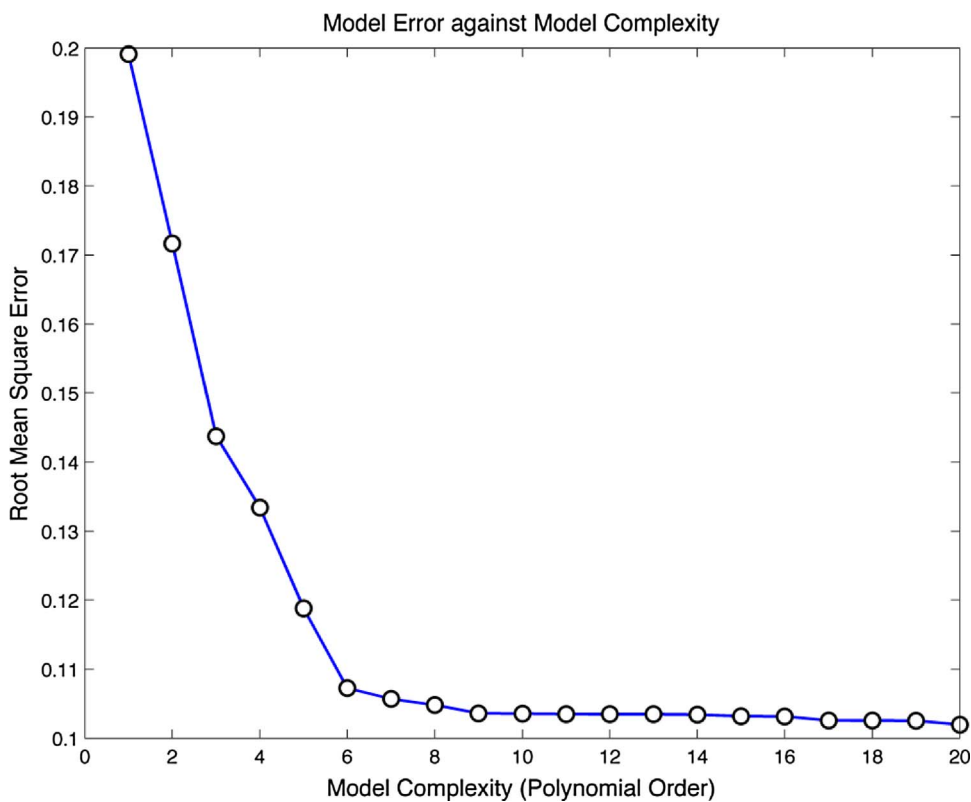


**Fig. 7.** The root mean square error of normalized ET strength associated with different order of polynomial fit when NEDI is negative.

**Table 1**
Coefficients used for the ninth order regression model. $A_1$ through $A_{10}$ are the coefficients for the seventh through the zero order terms, respectively.

| Coefficient | Value |
| --- | --- |
| $A_1$ | 3829.5520 |
| $A_2$ | 17419.8063 |
| $A_3$ | 33336.2779 |
| $A_4$ | 35023.9484 |
| $A_5$ | 22154.0019 |
| $A_6$ | 8721.1720 |
| $A_7$ | 2134.3419 |
| $A_8$ | 313.7211 |
| $A_9$ | 25.7850 |
| $A_{10}$ | 1.5050 |

sc-PDSI, although lower ET deficit is generally correlated with drought conditions detected by sc-PDSI for shallow rooted vegetation. Similar insensitivity of PDSI to actual ET was reported in van der Schrier et al. (2011). The results for SPI1 and SPI12 exhibit similar patterns as for sc-PDSI (results not shown), suggesting that these types of drought indices may not reflect ecosystem responses to limited water availability.

The NEDI threshold separating wet and dry regimes was applied to the 8 IGBP vegetation types to investigate its sensitivity to vegetation types, based on the modified VITA. The results (Fig. 11) indicate that localized means and variances of $K$ with positive NEDI are higher than the negative NEDI counterparts, which agrees with the aggregated results presented in Fig. 6. The NEDI threshold separating wet and dry regimes, indicated by the modified VITA applied to $K$, varied with different vegetation types. For example, water availability becomes a dominant limiting factor when NEDI is around 0.14 for shrublands, and when NEDI is around 0.26 for savannas and wetlands. These results suggest that different vegetation types can have different tolerance to water stress, which could arise from their structural and functional differences in response to changing environmental conditions. Despite

the variation in NEDI threshold, all of the ecosystem types show that localized means of $K$ start decreasing upon the onset of rapid change in localized variances of $K$, regardless of the actual NEDI value. This suggests that ecosystem ET is mainly determined by water availability when NEDI falls below the threshold where rapid change in localized variances of $K$ is detected through the modified VITA, consistent with the composite results shown in Fig. 6. Therefore, efforts to quantify specific ecosystem responses to limited water availability should focus on detecting rapid fluctuations in localized variances of $K$. The NEDI drought severity scale defined in Section 4.2 can be a useful tool for practical drought monitoring, since water availability is a dominant factor controlling ET for all 8 vegetation types when NEDI is negative (Fig. 11).

We performed the same analysis for the other drought indices, and the results for each IGBP category from sc-PDSI (Fig. 12) are similar to the composite results shown in Fig. 6. Rapid changes in localized variances of K were often detected during both dry and wet conditions that are defined by sc-PDSI. Alternatively, this variance was only detected in the wet regime of NEDI. Moreover, localized means of K are often comparable between the dry and wet regimes defined by sc-PDSI, which is different from the decreasing trend of K detected in NEDI estimates. These results suggest that the use of sc-PDSI may not necessary present contrasting behavior of ecosystem responses to different levels of water availability for most of the 8 vegetation types. Nevertheless, the results show that rapid changes in localized variances of $K$ followed by decreasing localized means of $K$ can be found when sc-PDSI is used at grasslands and savannas, although the transitional signal is less evident than the NEDI counterparts. This type of transitional signal occurs when sc-PDSI is around −4 (extreme drought; Wells et al., 2004), suggesting that water availability may not be a dominant limiting factor controlling ET until ecosystem is under extreme drought as measured by sc-PDSI. Similar patterns can be found in SPI1 and SPI12 (results not shown), indicating that sc-PDSI and SPI could represent ecosystem responses to varying water availability for some vegetation types, although their transitional signal is not as prominent as the NEDI
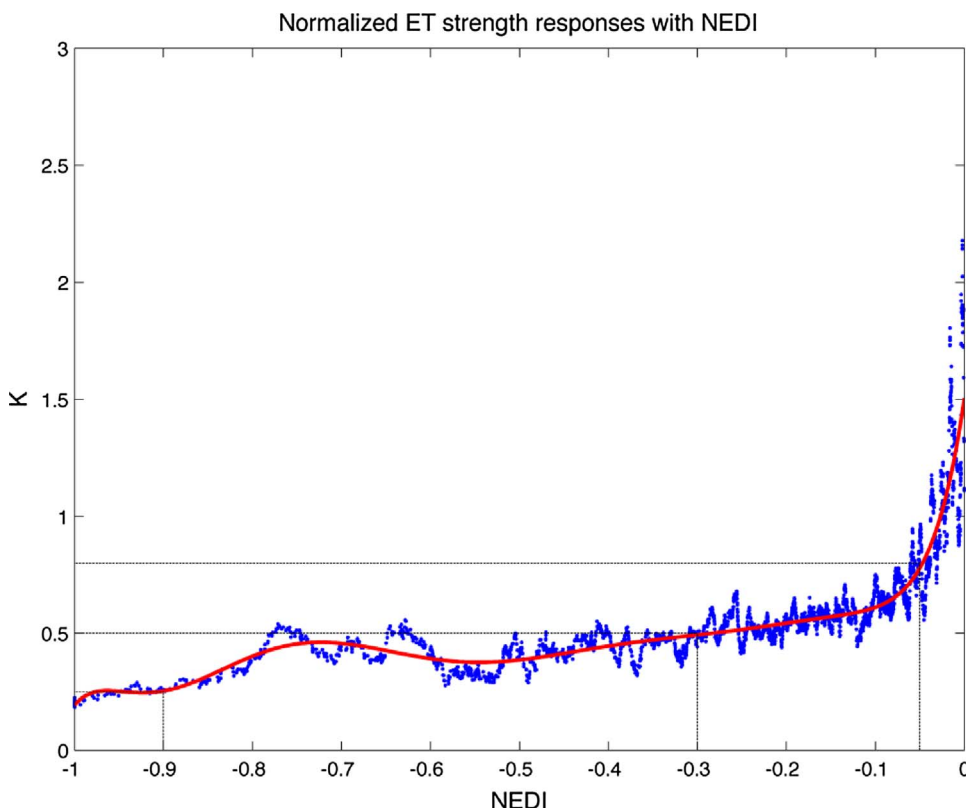


Fig. 8. Blue dots are the scatter plot between localized means of normalized ET strength ($K$) and NEDI. Red line represents the localized means of $K$ estimated by the ninth order polynomial fit. Black dash lines indicate the normalized ET strength along with NEDI. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
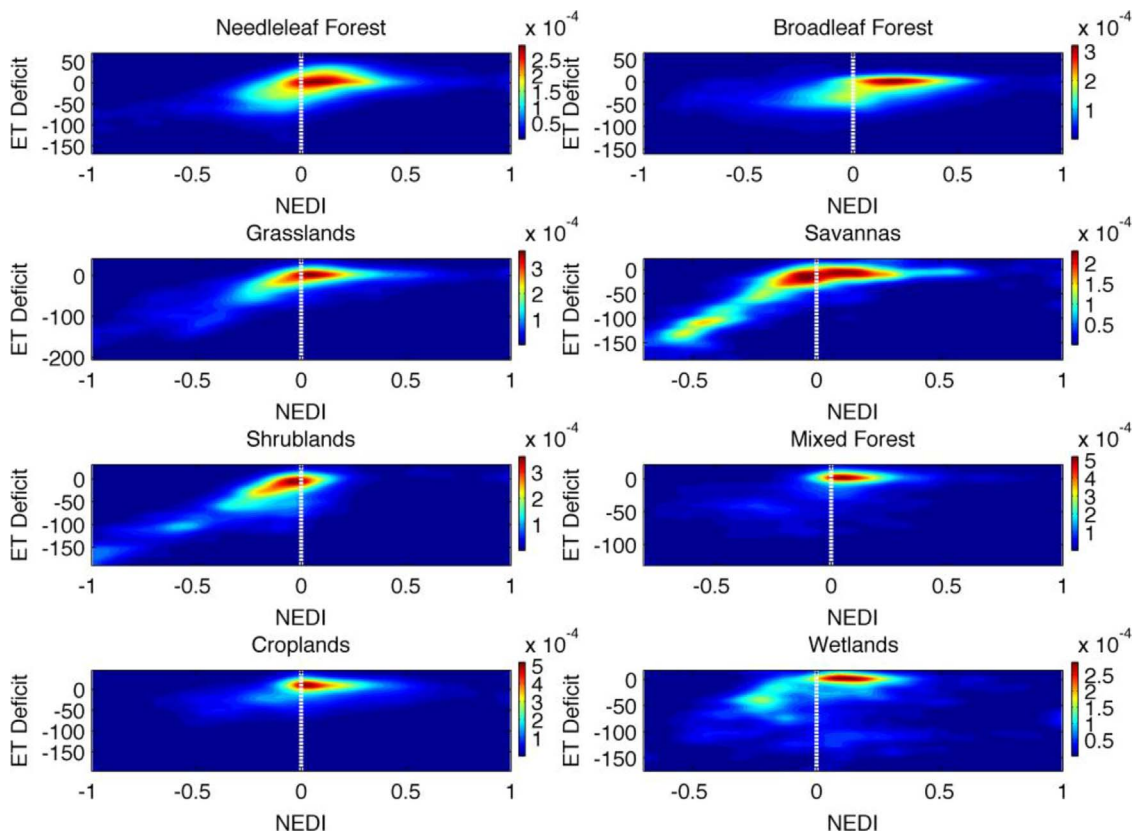
**Fig. 9.** Density scatter plots between ET deficit and NEDI for the 8 IGBP vegetation types examined in this study. Color bar represents the density of the data points presented in the dataset.
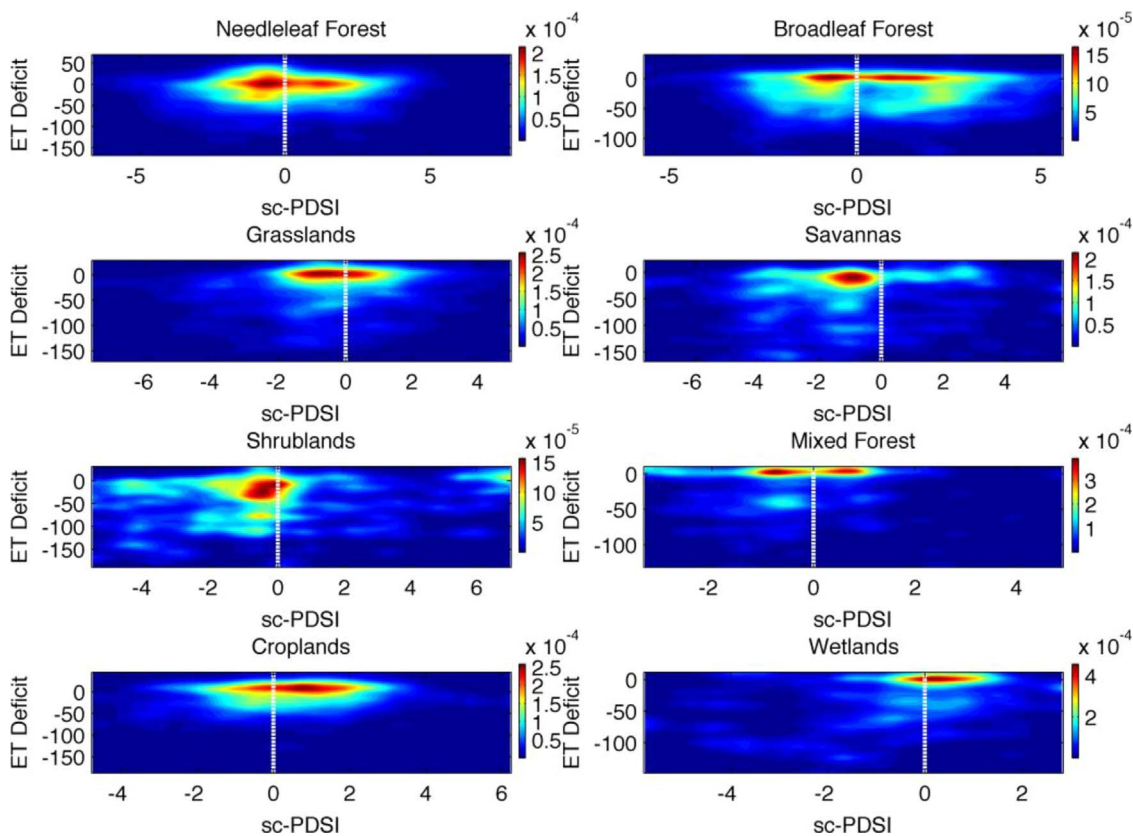


**Fig. 10.** Density scatter plots between ET deficit and sc-PDSI for the 8 IGBP vegetation types examined in this study. Color bar represents the density of the data points presented in the dataset.
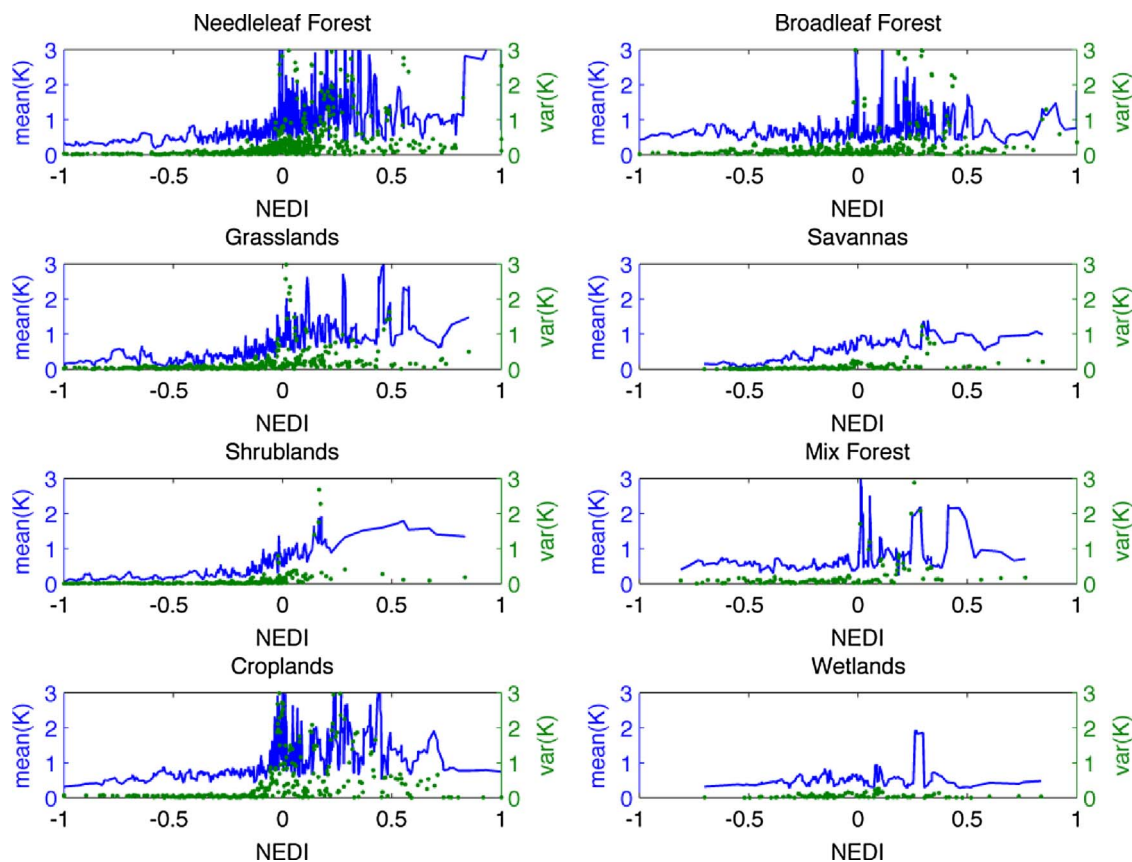
**Fig. 11.** The localized mean (left axes; blue lines) and the localized variance (right axes; green dots) of normalized ET strength (K) calculated by the modified VITA with NEDI under different vegetation types. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

proposed here. The relatively weak sensitivity to ecosystem responses found in sc-PDSI and SPI may be associated with the fact that this type of atmosphere-centric drought index does not include the effects of plant physiological responses to changing environmental conditions (Swann et al., 2016).

## 5. Conclusions

We developed the Normalized Ecosystem Drought Index (NEDI) to quantify drought severity in terms of ecosystem transitional responses to limited water availability. Eddy covariance measurements from 60 AmeriFlux sites (489 site years in total) across 8 IGBP vegetation types were used to examine the validity of NEDI. The results show that NEDI can successfully depict environmental drought stress like the negative precipitation anomaly, and ecosystem ET reduction in response to limited water availability. Using a modified VITA, we found that water availability becomes a dominant factor controlling ET when NEDI falls below the point where rapid change in localized variances of normalized ET strength is detected. The NEDI threshold is generally around zero, which separates environmental conditions into a wet regime with stronger ET (positive NEDI) and a dry regime with weaker ET (negative NEDI). The use of sc-PDSI, SPI1 and SPI12 may not necessarily reflect this type of ecosystem transitional response, and normalized ET strength may not drop significantly under drought conditions identified by these drought indices.

The new drought index NEDI has several advantages. The low data requirement and simple nature of NEDI make it straightforward for application to different scientific disciplines or drought detection and analysis at various spatial and temporal scales. The normalization feature of NEDI enables it to perform drought severity comparison across different regional, seasonal and ecological conditions. The modified VITA developed in this study can be applied to detect ecosystem responses to other limiting factors, such as environmental temperature, plant tissue temperature and photosynthetic active radiation.

In addition, drought conditions suggested by NEDI can be used to optimize irrigation plans and facilitate studies interested in ecosystem physiological responses to water availability, as they reflect ecosystem responses to drought. The framework develop in this study should be able to apply at any spatial scales, since NEDI calculation does not involve any site-specific parameters or ecosystem dependent properties. This can be done with proper air temperature and precipitation datasets at user defined study region, as they are the only intrinsic variables needed in NEDI calculation. This easy of using this new index will provide a valuable tool for users and decision makers to modify water management practices accordingly.
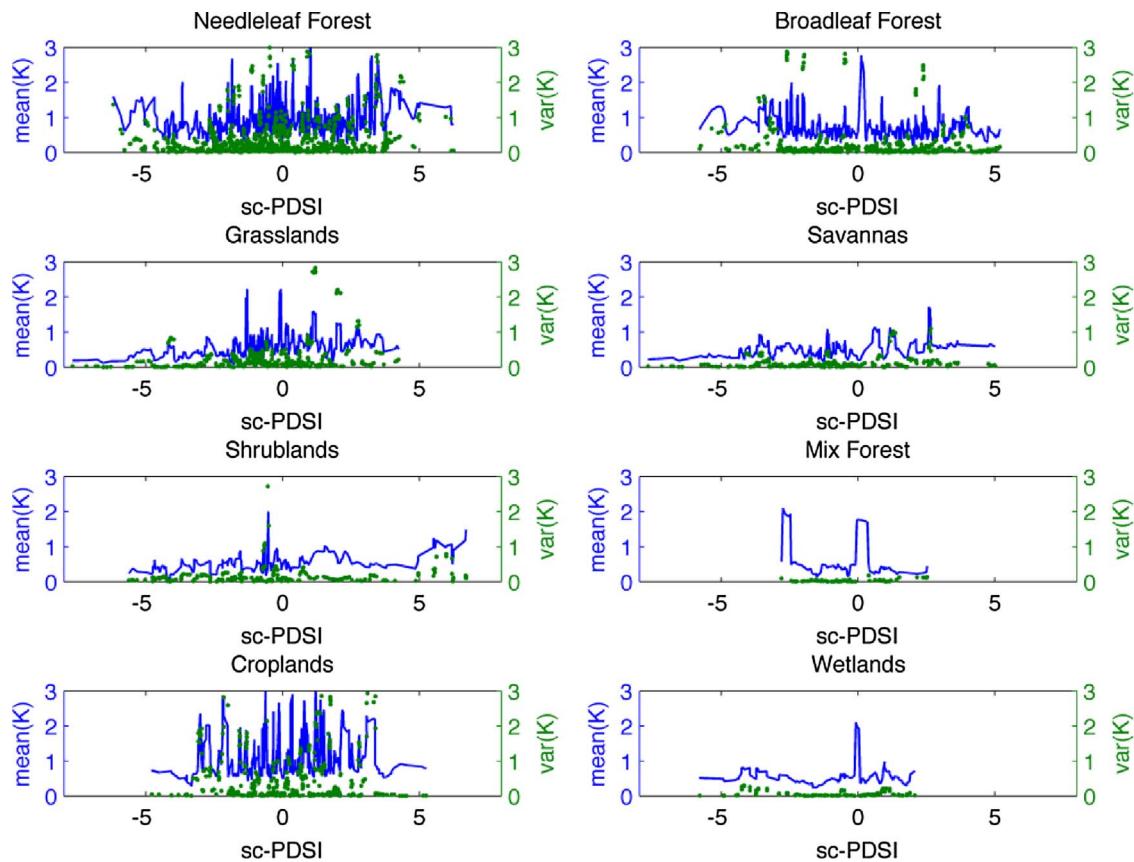
Fig. 12. The localized mean (left axes; blue lines) and the localized variance (right axes; green dots) of normalized ET strength (K) calculated by the modified VITA with sc-PDSI under different vegetation types. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

## Appendix A. The AmeriFlux sites used in this study

| Site name | Vegetation type (IGBP) | Climate condition (Köppen) | Data period |
|---|---|---|---|
| ARM SGP Main (US-ARM) Fischer et al. (2007) | Croplands | Humid Subtropical (Cfa) | 12/31/2000–01/27/2013 |
| Bondville (US-Bo1) Meyers and Hollinger (2004) | Croplands | Humid Continental (Dfa) | 08/25/1996–12/30/2010 |
| Bondville Companion (US-Bo2) Bernacchi et al. (2005) | Croplands | Humid Continental (Dfa) | 05/13/2004–12/28/2008 |
| Brooks Field Site 10 (US-Br1) Cammalleri et al. (2014) | Croplands | Humid Continental (Dfa) | 01/01/2005–11/09/2011 |
| Brooks Field Site 11 (US-Br3) Sakai et al. (2015) | Croplands | Humid Continental (Dfa) | 01/01/2005–11/09/2011 |
| Fermi Agricultural (US-IB1) Matamala et al. (2016) | Croplands | Humid Continental (Dfa) | 03/28/2005–12/31/2011 |
| Mead Irrigated (US-Ne1) Suyker et al. (2004) | Croplands | Humid Continental (Dfa) | 05/25/2001–05/31/2013 |
| Mead Irrigated Rotation (US-Ne2) Suyker et al. (2004) | Croplands | Humid Continental (Dfa) | 06/04/2001–05/31/2013 |
| Mead Rainfed (US-Ne3) Suyker et al. (2004) | Croplands | Humid Continental (Dfa) | 06/04/2001–05/31/2013 |
| Bartlett Experimental Forest (US-Bar) Richardson et al. (2007) | Deciduous broadleaf forest | Warm Summer Continental (Dfb) | 12/31/2003 −01/14/2013 |
| Chestnut Ridge (US-ChR) Cammalleri et al. (2014) | Deciduous broadleaf forest | Humid Subtropical (Cfa) | 05/11/2005–01/13/2011 |
| Harvard Forest (US-Ha1) Moore et al. (1996) | Deciduous broadleaf forest | Warm Summer Continental (Dfb) | 10/28/1991–12/31/2014 |
| Morgan Monroe State Forest (US-MMS) Pryor et al. (1999) | Deciduous broadleaf forest | Humid Subtropical (Cfa) | 01/01/1999–12/31/2014 |

| | | | |
|---|---|---|---|
| Missouri Ozark (US-MOz) Gu et al. (2006) | Deciduous broadleaf forest | Humid Subtropical (Cfa) | 01/01/2004–12/31/2014 |
| Ohio Oak Openings (US-Oho) DeForest et al. (2006) | Deciduous broadleaf forest | Humid Continental (Dfa) | 01/01/2004–12/31/2013 |
| Walker Branch (US-WBW) Hanson et al. (2005) | Deciduous broadleaf forest | Humid Subtropical (Cfa) | 12/31/1994–06/06/2007 |
| Willow Creek (US-WCr) Desai et al. (2005) | Deciduous broadleaf forest | Warm Summer Continental (Dfb) | 01/01/1998–12/31/2014 |
| Florida Everglades Shark River Slough Mangrove Forest (US-Skr) Barr et al. (2009) | Evergreen broadleaf forest | Humid Subtropical (Cwa) | 01/01/2004–09/12/2011 |
| Blodgett Forest (US-Blo) Goldstein et al. (2000) | Evergreen needleaf forest | Mediterranean (Csa) | 06/02/1997–10/10/2007 |
| Duke Forest Loblolly Pine (US-Dk3) Katul et al. (2003) | Evergreen needleaf forest | Humid Subtropical (Cfa) | 01/01/1998–12/31/2008 |
| Flagstaff Managed Forest (US-Fmf) Dore et al. (2010) | Evergreen needleaf forest | Mediterranean (Csb) | 07/29/2005–12/31/2010 |
| Flagstaff Unmanaged Forest (US-Fuf) Dore et al. (2008) | Evergreen needleaf forest | Mediterranean (Csb) | 09/06/2005–12/31/2010 |
| GLEES (US-GLE) Zeller and Nikolov (2000) | Evergreen needleaf forest | Subarctic (Dfc) | 10/01/2004–12/31/2012 |
| Howland Forest Main (US-Ho1) Hollinger et al. (1999) | Evergreen needleaf forest | Warm Summer Continental (Dfb) | 01/01/1996–12/31/2009 |
| Metolius Intermediate Pine (US-Me2) Law et al. (2004) | Evergreen needleaf forest | Mediterranean (Csb) | 01/01/2002–12/31/2014 |
| Metolius Second Young Pine (US-Me3) Sun et al. (2004) | Evergreen needleaf forest | Mediterranean (Csb) | 01/01/2004–12/31/2009 |
| Metolius First Young Pine (US-Me5) Law et al. (2003) | Evergreen needleaf forest | Mediterranean (Csb) | 06/17/1999–12/31/2002 |
| Marys River Fir Site (US-MRf) He et al. (2015) | Evergreen needleaf forest | Mediterranean (Csb) | 01/01/2005–02/17/2012 |
| North Carolina Loblolly Pine (US-NC2) Noormets et al. (2010) | Evergreen needleaf forest | Humid Subtropical (Cfa) | 01/01/2005–12/31/2010 |
| Niwot Ridge (US-NR1) Turnipseed et al. (2002) | Evergreen needleaf forest | Subarctic (Dfc) | 11/01/1998–12/31/2014 |
| Austin Cary (US-SP1) Fang et al. (1998) | Evergreen needleaf forest | Humid Subtropical (Cfa) | 07/01/2000–12/31/2011 |
| Mize (US-SP2) Fang et al. (1998) | Evergreen needleaf forest | Humid Subtropical (Cfa) | 01/01/1999–12/31/2008 |
| Donaldson (US-SP3) Fang et al. (1998) | Evergreen needleaf forest | Humid Subtropical (Cfa) | 01/01/1999–12/31/2010 |
| Wind River Field Station (US-Wrc) Paw U et al. (2004) | Evergreen needleaf forest | Mediterranean (Csb) | 01/01/1998–12/31/2015 |
| Audubon Research Ranch (US-Aud) Qi et al. (2000) | Grasslands | Steppe (Bsk) | 06/07/2002–09/26/2011 |
| Canaan Valley (US-CaV) Yang et al. (2007) | Grasslands | Marine West Coast (Cfb) | 01/06/2004 −11/18/2010 |
| Duke Forest Open Field (US-Dk1) Katul et al. (2003) | Grasslands | Humid Continental (Dfa) | 01/01/2001–12/31/2008 |
| Fort Peck (US-FPe) Cammalleri et al. (2014) | Grasslands | Steppe (Bsk) | 01/01/2000–12/28/2008 |
| Flagstaff Wildfire (US-Fwf) Dore et al. (2008) | Grasslands | Mediterranean (Csb) | 06/15/2005–12/31/2010 |
| Fermi Prairie (US-IB2) Matamala et al. (2016) | Grasslands | Humid Continental (Dfa) | 10/06/2004–12/31/2011 |
| Kansas Field Station (US-KFS) Cochran et al. (2016) | Grasslands | Humid Subtropical (Cfa) | 06/16/2007–12/31/2012 |
| Konza Prairie (US-Kon) Logan and Brunsell (2015) | Grasslands | Humid Subtropical (Cfa) | 08/22/2006–12/31/2012 |
| Vaira Ranch (US-Var) Baldocchi et al. (2004) | Grasslands | Mediterranean (Csa) | 01/01/2000–12/31/2014 |
| Kendall Grassland (US-Wkg) Scott et al. (2010) | Grasslands | Steppe (Bsk) | 05/06/2004–12/31/2015 |
| Duke Forest Hardwoods (US-Dk2) Katul et al. (2003) | Mixed forest | Humid Subtropical (Cfa) | 01/01/2001–12/31/2008 |
| Great Mountain Forest (US-GMF) Lee et al. (2001) | Mixed forest | Warm Summer Continental (Dfb) | 05/19/1999–12/31/2004 |

| Park Falls (US-PFa) Desai (2014) | Mixed forest | Warm Summer Continental (Dfb) | 01/01/1995–12/31/2014 |
|---|---|---|---|
| Sylvania Wilderness (US-Syv) Desai et al. (2005) | Mixed forest | Warm Summer Continental (Dfb) | 01/01/2001–12/31/2014 |
| Kennedy Space Center Scrub Oak (US-KS2) Powell et al. (2006) | Closed shrublands | Humid Subtropical (Cwa) | 06/29/1999–12/31/2006 |
| Sky Oaks Old (US-SO2) Stylinski et al. (2002) | Closed shrublands | Mediterranean (Csa) | 01/01/1997–12/31/2006 |
| Sky Oaks Young (US-SO3) Stylinski et al. (2002) | Closed shrublands | Mediterranean (Csa) | 01/01/1997–12/31/2006 |
| Santa Rita Creosote (US-SRC) Crow et al. (2015) | Open shrublands | Unknown | 01/01/2008–12/31/2014 |
| Lucky Hills Shrubland (US-Whs) Scott (2010) | Open shrublands | Steppe (Bsk) | 06/29/2007–12/31/2015 |
| Florida Everglades Shark River Slough Long Hydroperiod Marsh (US-Elm) Schedlbauer et al. (2012) | Permanent wetlands | Unknown | 07/22/2008–12/31/2013 |
| Florida Everglades Taylor Slough Short Hydroperiod Marsh (US-Esm) Schedlbauer et al. (2012) | Permanent Wetlands | Unknown | 01/01/2008–12/31/2013 |
| Lost Creek (US-Los) Sulman et al. (2009) | Wetlands | Warm Summer Continental (Dfb) | 01/01/2000–12/31/2014 |
| Freeman Ranch Mesquite Juniper (US-FR2) Heinsch et al. (2004) | Woody savannas | Humid Subtropical (Cfa) | 01/01/2005–12/29/2008 |
| Freeman Ranch Woodland (US-FR3) Heinsch et al. (2004) | Woody savannas | Humid Subtropical (Cfa) | 07/17/2004–12/31/2012 |
| Santa Rita Mesquite Savanna (US-SRM) Scott et al. (2008) | Woody saccvannas | Steppe (Bsk) | 12/31/2003–12/31/2015 |
| Tonzi Ranch (US-Ton) Baldocchi et al. (2004) | Woody savannas | Mediterranean (Csa) | 01/01/2001–12/31/2014 |

## Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.agrformet.2017.12.001.

## References

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration: guidelines for computing crop requirements. Irrig. Drain. Pap. No. 56. FAO http://dx.doi.org/10.1016/j.eja.2010.12.001. 300.

Anderson, M.C., Norman, J.M., Mecikalski, J.R., Otkin, J.A., Kustas, W.P., 2007. A climatological study of evapotranspiration and moisture stress across the continental United States based on thermal remote sensing: 2. Surface moisture climatology. J. Geophys. Res. 112, D11112. http://dx.doi.org/10.1029/2006JD007507.

Baldocchi, D.D., Xu, L., Kiang, N., 2004. How plant functional-type, weather, seasonal drought, and soil physical properties alter water and energy fluxes of an oak-grass savanna and an annual grassland. Agric. For. Meteor. 123, 13–39. http://dx.doi.org/10.1016/j.agrformet.2003.11.006.

Barnes, M.L., et al., 2016. Vezgetation productivity responds to sub-annual climate conditions across semiarid biomes. Ecosphere 7, 1–20. http://dx.doi.org/10.1002/ecs2.1339.

Barr, J.G., Fuentes, J.D., Engel, V., Zieman, J.C., 2009. Physiological responses of red mangroves to the climate in the Florida Everglades. J. Geophys. Res. 114, 1–13. http://dx.doi.org/10.1029/2008JG000843.

Beguería, S., Vicente-Serrano, S.M., Reig, F., Latorre, B., 2014. Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. Int. J. Climatol. 34, 3001–3023. http://dx.doi.org/10.1002/joc.3887.

Bernacchi, C.J., Hollinger, S.E., Meyers, T., 2005. The conversion of the corn/soybean ecosystem to no-till agriculture may result in a carbon sink. Glob. Chang. Biol. 11, 1867–1872. http://dx.doi.org/10.1111/j.1365-2486.2005.01050.x.

Blackwelder, R.F., Kaplan, R.E., 1976. On the wall structure of the turbulent boundary layer. J. Fluid Mech. 76, 89. http://dx.doi.org/10.1017/S0022112076003145.

Cammalleri, C., Anderson, M.C., Kustas, W.P., 2014. Upscaling of evapotranspiration fluxes from instantaneous to daytime scales for thermal remote sensing applications. Hydrol. Earth Syst. Sci. 18, 1885–1894. http://dx.doi.org/10.5194/hess-18-1885-2014.

Cochran, F., Brunsell, V.N.A., Suyker, A.E., 2016. A thermodynamic approach for assessing agroecosystem sustainability. Ecol. Indic. 67, 204–214. http://dx.doi.org/10.1016/j.ecolind.2016.01.045.

Craine, J.M., Nippert, J.B., Elmore, A.J., Skibbe, A.M., Hutchinson, S.L., Brunsell, N.A., 2012. Timing of climate variability and grassland productivity. Proc. Natl. Acad. Sci. 109, 3401–3405. http://dx.doi.org/10.1073/pnas.1118438109.

Crow, W.T., Lei, F., Hain, C., Anderson, M.C., Scott, R.L., Billesbach, D., Arkebauer, T.,

2015. Robust estimates of soil moisture and latent heat flux coupling strength obtained from triple collocation. Geophys. Res. Lett. 42, 8415–8423. http://dx.doi.org/10.1002/2015GL065929.

Dai, A., 2011a. Characteristics and trends in various forms of the Palmer Drought Severity Index during 1900–2008. J. Geophys. Res. Atmos. 116, 1–26. http://dx.doi.org/10.1029/2010JD015541.

Dai, A., 2011b. Drought under global warming: a review. Wiley Interdiscip. Rev. Clim. Change 2, 45–65. http://dx.doi.org/10.1002/wcc.81.

DeForest, J.L., Noormets, A., McNulty, S.G., Sun, G., Tenney, G., Chen, J., 2006. Phenophases alter the soil respiration-temperature relationship in an oak-dominated forest. Int. J. Biometeorol. 51, 135–144. http://dx.doi.org/10.1007/s00484-006-0046-7.

Desai, A.R., Bolstad, P.V., Cook, B.D., Davis, K.J., Carey, E.V., 2005. Comparing net ecosystem exchange of carbon dioxide between an old-growth and mature forest in the upper Midwest, USA. Agric. For. Meteor. 128, 33–55. http://dx.doi.org/10.1016/j.agrformet.2004.09.005.

Desai, A.R., 2014. Influence and predictive capacity of climate anomalies on daily to decadal extremes in canopy photosynthesis. Photosynth. Res. 119, 31–47. http://dx.doi.org/10.1007/s11120-013-9925-z.

Donohue, R.J., Mcvicar, T.R., Roderick, M.L., 2010. Assessing the ability of potential evaporation formulations to capture the dynamics in evaporative demand within a changing climate. J. Hydrol. 386, 186–197. http://dx.doi.org/10.1016/j.jhydrol.2010.03.020.

Dore, S., Kolb, T.E., Montes-Helu, M., Sullivan, B.W., Winslow, W.D., Hart, S.C., Kaye, J.P., Koch, G.W., Hungate, B.A., 2008. Long-term impact of a stand-replacing fire on ecosystem CO2 exchange of a ponderosa pine forest. Glob. Chang. Biol. 14, 1801–1820. http://dx.doi.org/10.1111/j.1365-2486.2008.01613.x.

Dore, S., Kolb, T.E., Montes-Helu, M., Eckert, S.E., Sullivan, B.W., Hungate, B.A., Kaye, J.P., Hart, S.C., Koch, G.W., Finkral, A., 2010. Carbon and water fluxes from ponderosa pine forests disturbed by wildfire and thinning. Ecol. Appl. 20, 663–683. http://dx.doi.org/10.1890/09-0934.1.

Fang, C., Moncrieff, J.B., Gholz, H.L., Clark, K.L., 1998. Soil CO2 efflux and its spatial variation in a Florida slash pine plantation. Plant Soil 205, 135–146. http://dx.doi.org/10.1023/a:1004304309827.

Feyen, L., Dankers, R., 2009. Impact of global warming on streamflow drought in Europe. J. Geophys. Res. Atmos. 114, 1–17. http://dx.doi.org/10.1029/2008JD011438.

Fischer, M.L., Billesbach, D.P., Berry, J.A., Riley, W.J., Torn, M.S., 2007. Spatiotemporal variations in growing season exchanges of CO2, H2O, and sensible heat in agricultural fields of the Southern Great Plains. Earth Interact 11. http://dx.doi.org/10.1175/EI231.1.

Foley, J.A., Costa, M.H., Delire, C., Ramankutty, N., Snyder, P., 2003. Green surprise? How terrestrial ecosystems could affect earth's climate. Front. Ecol. Environ. 1, 38–44. http://dx.doi.org/10.2307/3867963.

Goldstein, A.H., Hultman, N.E., Fracheboud, J.M., Bauer, M.R., Panek, J.A., Xu, M., Qi, Y., Guenther, A.B., Baugh, W., 2000. Effects of climate variability on the carbon dioxide, water, and sensible heat fluxes above a ponderosa pine plantation in the Sierra Nevada (CA). Agric. For. Meteorol. 101, 113–129. http://dx.doi.org/10.1016/S0168-1923(99)00168-9.

Gu, L., Meyers, T., Pallardy, S.G., Hanson, P.J., Yang, B., Heuer, M., Hosman, K.P., Riggs, J.S., Sluss, D., Wullschleger, S.D., 2006. Direct and indirect effects of atmospheric conditions and soil moisture on surface energy partitioning revealed by a prolonged drought at a temperate forest site. J. Geophys. Res. 111, 1–13. http://dx.doi.org/10.1029/2006JD007161.

Guttman, N.B., 1998. Comparing the palmer drought index and the standardized precipitation index. J. Am. Water Resour. Assoc. 34, 113–121. http://dx.doi.org/10.1111/j.1752-1688.1998.tb05964.x.

Guttman, N.B., 1999. Accepting the standardized precipitation index: a calculation algorithm1. J. Am. Water Resour. Assoc. 35, 311–322. http://dx.doi.org/10.1111/j.1752-1688.1999.tb03592.x.

Hanson, P.J., Wullschleger, S.D., Norby, R.J., Tschaplinski, T.J., Gunderson, C.A., 2005. Importance of changing CO 2, temperature, precipitation, and ozone on carbon and water cycles of an upland-oak forest: incorporating experimental results into model simulations. Glob. Chang. Biol. 11, 1402–1423. http://dx.doi.org/10.1111/j.1365-2486.2005.00991.x.

He, Y., Yang, J., Zhuang, Q., Harden, J.W., Mcguire, A.D., Liu, Y., Wang, G., Gu, L., 2015. Incorporating microbial dormancy dynamics into soil decomposition models to improve quantification of soil carbon dynamics of northern temperate forests. J. Geophys. Res. Biogeosci. 120, 2596–2611. http://dx.doi.org/10.1002/2015JG003130.

Heim, R.R., 2002. A review of twentieth-century drought indices used in the United States. Bull. Am. Meteorol. Soc. 83, 1149–1165. http://dx.doi.org/10.1175/1520-0477(2002)083<1149:AROTDI>2.3.CO;2.

Heinsch, F.A., Heilman, J.L., McInnes, K.J., Cobos, D.R., Zuberer, D.A., Roelke, D.L., 2004. Carbon dioxide exchange in a high marsh on the Texas Gulf Coast: Effects of freshwater availability. Agric. For. Meteorol. 125, 159–172. http://dx.doi.org/10.1016/j.agrformet.2004.02.007.

Hollinger, D.Y., Goltz, S.M., Davidson, E.A., Lee, J.T., Tu, K., Valentine, H.T., 1999. Seasonal patterns and environmental control of carbon dioxide and water vapour exchange in an ecotonal boreal forest. Glob. Change Biol. 5, 891–902. http://dx.doi.org/10.1046/j.1365-2486.1999.00281.x.

Hoover, D.L., Rogers, B.M., 2016. Not all droughts are created equal: the impacts of interannual drought pattern and magnitude on grassland carbon cycling. Glob. Change Biol. 22, 1809–1820. http://dx.doi.org/10.1111/gcb.13161.

Huxman, T.E., et al., 2004. Convergence across biomes to a common rain-use efficiency. Nature 429, 651–654. http://dx.doi.org/10.1038/nature02561.

Jensen, M., Burman, R.D., Allen, R.G. (Eds.), 1990. Evapotranspiration and Irrigation Water Requirements. ASCE Manuals and Reports on Engineering Practices. New York, NY, USA, ASCE No. 70, 360 pp.

Jung, M., et al., 2010. Recent decline in the global land evapotranspiration trend due to limited moisture supply. Nature 467. http://dx.doi.org/10.1038/nature09396.

Katul, G., Leuning, R., Oren, R., 2003. Relationship between plant hydraulic and biochemical properties derived from a steady-state coupled water and carbon transport model. Plant Cell Environ. 26, 339–350. http://dx.doi.org/10.1046/j.1365-3040.2003.00965.x.

Keyantash, J., Dracup, J.A., 2002. The quantification of drought: an evaluation of drought indices. Bull. Am. Meteorol. Soc. 1167–1180. http://dx.doi.org/10.1175/1520-0477(2002)083<1191:TQODAE>2.3.CO;2.

Law, B.E., Sun, O.J., Campbell, J., V.T.S, Thornton, P., 2003. Changes in carbon storage and fluxes in a chronoseuence of ponderosa pine. Glob. Change Biol. 4, 510–524. http://dx.doi.org/10.1046/j.1365-2486.2003.00624.x.

Law, B.E., Turner, D., Sun, O.J., Van Tuyl, S., Ritts, W.D., Cohen, W.B., 2004. Disturbance and climate effects on carbon stocks and fluxes across Western Oregon USA. Glob. Change Biol. 10, 1429–1444. http://dx.doi.org/10.1111/j.1365-2486.2004.00822.x.

Lee, X., Bullock Jr, O.R., Andres, R.J., 2001. Anthropogenic emission of mercury to the atmosphere in the northeast United States. Geophys. Res. Lett. 28, 1231–1234.

Levis, S., 2010. Modeling vegetation and land use in models of the Earth System. Wiley Interdiscip. Rev. Clim. Chang. 1, 840–856. http://dx.doi.org/10.1002/wcc.83.

Liu, Y., Xiao, J., Ju, W., Zhou, Y., Wang, S., 2011. Water use efficiency of China ' s terrestrial ecosystems and responses to drought. Nat. Publ. Gr 1–12. http://dx.doi.org/10.1038/srep13799.

Logan, K.E., Brunsell, N.A., 2015. Agricultural and Forest Meteorology Influence of drought on growing season carbon and water cycling with changing land cover. Agric. For. Meteorol. 213, 217–225. http://dx.doi.org/10.1016/j.agrformet.2015.07.002.

Lu, X., Zhuang, Q., 2010. Evaluating evapotranspiration and water-use efficiency of terrestrial ecosystems in the conterminous United States using MODIS and AmeriFlux data. Remote Sens. Environ. 114, 1924–1939. http://dx.doi.org/10.1016/j.rse.2010.04.001.

Matamala, A.R., Jastrow, J.D., Miller, R.M., Garten, C.T., 2016. Temporal changes in C and N stocks of restored prairie: implications for C sequestration strategies. Ecol. Appl. 18, 1470–1488. Stable URL: http://www.jstor.org/stable/40062268.

McKee, T.B., Doesken, N.J., Kleist, J., 1993. The relationship of drought frequency and duration to time scales. Preprints, Eighth Conf. on Applied Climatology. Amer. Meteor. Soc., Anaheim CA, pp. 179–184.

Meyers, T.P., Hollinger, S.E., 2004. An assessment of storage terms in the surface energy balance of maize and soybean. Agric. For. Meteorol. 125, 105–115. http://dx.doi.

org/10.1016/j.agrformet.2004.03.001.

Moore, K.E., Fitzjarrald, D.R., Sakai, R.K., Goulden, M.L., Munger, J.W., Wofsy, S.C., 1996. Seasonal variation in radiative and turbulent exchange at a deciduous forest in central Massachusetts. J. Appl. Meteorol. 35, 122–134. http://dx.doi.org/10.1175/1520-0450(1996)035<0122:SVIRAT>2.0.CO;2.

Mpelasoka, F., Hennessy, K., Jones, R., Bates, B., 2008. Comparison of suitable drought indices for climate change impacts assessment over Australia towards resource. Int. J. Climatol. 1292, 1283–1292. http://dx.doi.org/10.1002/joc.

Narasimhan, B., Srinivasan, R., 2005. Development and evaluation of soil moisture deficit index (SMDI) and evapotranspiration deficit index (ETDI) for agricultural drought monitoring. Agric. For. Meteorol. 133, 69–88. http://dx.doi.org/10.1016/j.agrformet.2005.07.012.

Noormets, A., Gavazzi, M.J., McNulty, S.G., Domec, J.-C., Sun, G.E., King, J.S., Chen, J., 2010. Response of carbon fluxes to drought in a coastal plain loblolly pine forest. Glob. Chang Biol. 16, 272–287. http://dx.doi.org/10.1111/j.1365-2486.2009.01928.x.

Novick, K.A., et al., 2016. The increasing importance of atmospheric demand for ecosystem water and carbon fluxes. Nat. Clim. Chang. 1, 1–5. http://dx.doi.org/10.1038/nclimate3114.

Palmer, W., 1965. Meteorological drought. Res. Pap. 1–65.

Paw U, K.T., Matthias, F., Suchanek, T.H., Ustin, S.L., Chen, J., Park, Y.-S., Winner, W.E., Thomas, S.C., Hsiao, T.C., Shaw, R.H., King, T.S., Pyles, R.D., Schroeder, M., Matista, A.A., 2004. Carbon dioxide exchange between an old-growth forest and the atmosphere. Ecosystems 7, 513–524. http://dx.doi.org/10.1007/s10021-004-0141-8.

Peterson, A.T., 2003. Predicting the geography of species' invasions via ecological niche modeling. Q. Rev. Biol. 78, 419–433.

Ponce Campos, G.E., et al., 2013. Ecosystem resilience despite large-scale altered hydroclimatic conditions. Nature 494, 349–352. http://dx.doi.org/10.1038/nature11836.

Powell, T.L., Bracho, R., Li, J., Dore, S., Hinkle, C.R., Drake, B.G., 2006. Environmental controls over net ecosystem carbon exchange of scrub oak in central Florida. Agric. For. Meteorol. 141, 19–34. http://dx.doi.org/10.1016/j.agrformet.2006.09.002.

Pryor, S.C., Barthelmie, R.J., Jensen, B., 1999. Nitrogen dry deposition at an AmeriFlux site in a hardwood forest in the midwest. Geophys. Res. Lett. 26, 691. http://dx.doi.org/10.1029/1999GL900066.

Qi, J., Marsett, R.C., Moran, M.S., Goodrich, D.C., Heilman, P., Kerr, Y.H., Dedieu, G., Chehbouni, A., Zhang, X.X., 2000. Spatial and temporal dynamics of vegetation in the San Pedro River basin area. Agric. For. Meteorol. 105, 55–68. http://dx.doi.org/10.1016/S0168-1923(00)00195-7.

Redmond, K.T., 2002. The depiction of drought. Bull. Am. Meteorol. Soc. 83, 1143–1147. http://dx.doi.org/10.1175/1520-0477(2002)083<1143:TDODAC>2.3.CO;2.

Reichstein, M., Tenhunen, J.D., Roupsard, O., Ourcival, J.-M., Rambal, S., Miglietta, F., Peressotti, A., Pecchiari, M., Tirone, G., Valentini, R., 2002. Severe drought effects on ecosystem CO2 and H2O fluxes at three Mediterranean evergreen sites: revision of current hypotheses? Glob. Chang. Biol. 8, 999–1017. http://dx.doi.org/10.1046/j.1365-2486.2002.00530.x.

Richardson, A.D., Jenkins, J.P., Braswell, B.H., Hollinger, D.Y., Ollinger, S.V., Smith, M.L., 2007. Use of digital webcam images to track spring green-up in a deciduous broadleaf forest. Oecologia 152, 323–334. http://dx.doi.org/10.1007/s00442-006-0657-z.

Sakai, T., Iizumi, T., Okada, M., Nishimori, M., Grünwald, T., Prueger, J., Cescatti, A., Korres, W., Schmidt, M., Carrara, A., Loubet, B., Ceschia, E., 2015. Varying applicability of four different satellite-derived soil moisture products to global gridded crop model evaluation. Int. J. Appl. Earth Obs. Geoinf. 48, 51–60. http://dx.doi.org/10.1016/j.jag.2015.09.011.

Saleska, S.R., Didan, K., Huete, A.R., da Rocha, H.R., 2007. Amazon forests green-up during 2005 drought. Science 318, 612. http://dx.doi.org/10.1126/science.1146663.

Schedlbauer, J.L., Munyon, J.W., Oberbauer, S.F., Gaiser, E.E., Starr, G., 2012. Controls on ecosystem carbon dioxide exchange in short- and long-hydroperiod Florida everglades freshwater marshes. Wetlands 32, 801–812. http://dx.doi.org/10.1007/s13157-012-0311-y.

Scott, R.L., Cable, W.L., Hultine, K.R., 2008. The ecohydrologic significance of hydraulic redistribution in a semiarid savanna. Water Resour. Res. 44, 1–12. http://dx.doi.org/10.1029/2007WR006149.

Scott, R.L., Hamerlynck, E.P., Jenerette, G.D., Moran, M.S., Barron-Gafford, G.A., 2010. Carbon dioxide exchange in a semidesert grassland through drought-induced vegetation change. J. Geophys. Res. Biogeosci. 115, 1–12. http://dx.doi.org/10.1029/2010JG001348.

Scott, R.L., 2010. Using watershed water balance to evaluate the accuracy of eddy covariance evaporation measurements for three semiarid ecosystems. Agric. For. Meteorol. 150, 219–225. http://dx.doi.org/10.1016/j.agrformet.2009.11.002.

Seager, R., Ting, M., Held, I., Kushnir, Y., Lu, J., Vecchi, G., Huang, H.-P., Harnik, N., Leetmaa, A., Lau, N.-C., Li, C., Velez, J., Naik, N., 2007. Model projections of an imminent transition to amore arid climate in southwestern North AmericScience. Science 1475, 1181–1184. http://dx.doi.org/10.1126/science.1139601.

Seager, R., Ting, M., Davis, M., Cane, M., Naik, N., Nakamura, J., Li, C., Cook, E., Stahle, D.W., 2009. Mexican drought: an observational modeling and tree ring study of variability and climate change. Atmosfera 22, 1–31.

Shaw, R.H., Paw, U.K.T., Gao, W., 1989. Detection of temperature ramps and flow structures at a deciduous forest site. Agric. For. Meteorol. 47, 123–138.

Shi, Z., Thomey, M.L., Mowll, W., Litvak, M., Brunsell, N.A., Collins, S.L., Pockman, W.T., Smith, M.D., Knapp, A.K., Luo, Y., 2014. Differential effects of extreme drought on production and respiration: synthesis and modeling analysis. Biogeosciences 11, 621–633.

Starr, G., Staudhammer, C.L., Wiesner, S., Kunwor, S., Loescher, H.W., Baron, A.F., Whelan, A., Mitchell, R.J., Boring, L., 2016. Carbon dynamics of Pinus palustris

ecosystems following drought. Forests 7. http://dx.doi.org/10.3390/f7050098.

Stylinski, C.D., Gamon, J.A., Oechel, W.C., 2002. Seasonal patterns of reflectance indices, carotenoid pigments and photosynthesis of evergreen chaparral species. Oecologia 131, 366–374. http://dx.doi.org/10.1007/s00442-002-0905-9.

Sulman, B.N., Desai, A.R., Cook, B.D., Saliendra, N., Mackay, D.S., 2009. Contrasting carbon dioxide fluxes between a drying shrub wetland in Northern Wisconsin, USA, and nearby forests. Biogeosciences 6, 1115–1126. http://dx.doi.org/10.5194/bg-6-1115-2009.

Sun, O.J., Campbell, J., Law, B.E., Wolf, V., 2004. Dynamics of carbon stocks in soils and detritus across chronosequences of different forest types in the Pacific Northwest, USA. Glob. Chang. Biol. 10, 1470–1481. http://dx.doi.org/10.1111/j.1365-2486.2004.00829.x.

Suyker, A.E., Verma, S.B., Burba, G.G., Arkebauer, T.J., Walters, D.T., Hubbard, K.G., 2004. Growing season carbon dioxide exchange in irrigated and rainfed maize. Agric. For. Meteorol. 124, 1–13. http://dx.doi.org/10.1016/j.agrformet.2004.01.011.

Swann, A.A.L.S., Hoffman, F.M., Koven, C.D., Randerson, J.T., 2016. Plant responses to increasing CO2 reduce estimates of climate impacts on drought severity. Proc. Natl. Acad. Sci. 113, 10019–10024. http://dx.doi.org/10.1073/pnas.1604581113.

Thornthwaite, C.W., 1948. An Approach toward a Rational Classification of Climate. Geogr. Rev. 38, 55–94.

Tsakiris, G., Vangelis, H., 2005. Establishing a drought index incorporating evapotranspiration. Eur. Water 9 (10), 3–11.

Turnipseed, A.A., Blanken, P.D., Anderson, D.E., Monson, R.K., 2002. Energy budget above a high-elevation subalpine forest in complex topography. Agric. For. Meteorol. 110, 177–201. http://dx.doi.org/10.1016/S0168-1923(01)00290-8.

van der Ploeg, R.R., Bohm, W., Kirkham, M.B., 1999. On the origin of the theory of mineral nutrition of plants and the law of the minimum. Soil Sci. Soc. Am. J. 63, 1055–1062.

van der Schrier, G., Briffa, K.R., Osborn, T.J., Cook, E.R., 2006a. Summer moisture availability across north america. J. Geophys. Res. Atmos. 111, 1–10. http://dx.doi.org/10.1029/2005JD006745.

van der Schrier, G., Briffa, K.R., Jones, P.D., Osborn, T.J., 2006b. Summer moisture variability across Europe. J. Clim. 19, 2818–2834. http://dx.doi.org/10.1175/JCLI3734.1.

van der Schrier, G., Efthymiadis, D., Briffa, K.R., Jones, P.D., 2007. European alpine moisture variability for 1800–2003. Int. J. Climatol. 27, 415–427. http://dx.doi.org/10.1002/joc.1411.

van der Schrier, G., Jones, P.D., Briffa, K.R., 2011. The sensitivity of the PDSI to the Thornthwaite and Penman-Monteith parameterizations for potential evapotranspiration. J. Geophys. Res. Atmos. 116, 1–16. http://dx.doi.org/10.1029/2010JD015001.

Vicente-Serrano, S.M., Beguería, S., López-Moreno, J.I., 2010. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. J. Clim. 23, 1696–1718. http://dx.doi.org/10.1175/2009JCLI2909.1.

Vicente-Serrano, S.M., et al., 2013. Response of vegetation to drought time-scales across global land biomes. Proc. Natl. Acad. Sci. 110, 52–57. http://dx.doi.org/10.1073/pnas.1207068110.

Wells, N., Goddard, S., Hayes, M.J., 2004. A self-calibrating Palmer drought severity index. J. Climate 17, 2335–2351.

Whelan, A.R., et al., 2013. The cyclic occurrence of fire and its role in carbon dynamics along an edaphic moisture gradient in longleaf pine ecosystems. PLoS One 8 (1), e54045. http://dx.doi.org/10.1371/journal.pone.0054045.

Wilhite, Glantz, 1985. Understanding the drought phenomenon: the role of definitions. Water Int. 10, 111–120.

Wilhite, D.A., 2000. Drought as a natural hazard: concepts and definitions. In: In: Donald, A., Wilhite, A. (Eds.), Drought: A Global Assessment, vol. I. Routledge, New York, pp. 3–18 (Chapter 1).

Williams, A. Park, et al., 2013. Temperature as a potent driver of regional forest drought stress and tree mortality. Nat. Clim. Change 3, 292–297. http://dx.doi.org/10.1038/nclimate1693.

Yang, F., Ichii, K., White, M.A., Hashimoto, H., Michaelis, A.R., Votava, P., Zhu, A., Huete, A., Running, S.W., Nemani, R.R., 2007. Developing a continental-scale measure of gross primary production by combining MODIS and AmeriFlux data through Support Vector Machine approach. Remote Sens. Environ. 110, 109–122. http://dx.doi.org/10.1016/j.rse.2007.02.016.

Zeller, K.F., Nikolov, N.T., 2000. Quantifying simultaneous fluxes of ozone, carbon dioxide and water vapor above a subalpine forest ecosystem. Environ. Pollut. 107, 1–20. http://dx.doi.org/10.1016/S0269-7491(99)00156-6.

Zhang, Y., et al., 2016. Multi-decadal trends in global terrestrial evapotranspiration and its components. Sci. Rep. 6. http://dx.doi.org/10.1038/srep19124.

Zhao, M., Running, S.W., 2010. Drought-Induced reduction in global terrestrial net primary production from 2000 through 2009. Science 329, 940–943. http://dx.doi.org/10.1126/science.1192666.