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Key Points:
- A new drought index is developed based on estimated actual ET
- The new index equally performs with precipitation-dependent indices in areas of strong land-atmosphere coupling
- The new index spatially agrees with the Vegetation Health Index

Correspondence to:
D. Kim,
d.kim@apcc21.org

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A drought index based on actual evapotranspiration from the Bouchet hypothesis

Daeha Kim[1] and Jinyoung Rhee[1]

[1]Climate Application Department, APEC Climate Center, Busan, South Korea

Abstract Global drought assessment has mainly depended on precipitation-based drought indices that may also take into account potential evapotranspiration (ET_p). In this study, we combined the actual evapotranspiration (ET_a) estimated from the Bouchet hypothesis and the structure of the Standardized Precipitation-Evapotranspiration Index to develop a fully ET-based drought index, the Standardized Evapotranspiration Deficit Index (SEDI). We found that SEDI, without using precipitation data, produces results that are consistent with the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI) for drought identification in the South-Central United States. We also found a competitive performance of SEDI through comparisons between the Vegetation Health Index with SEDI, PDSI, and SPI. We suggest the high applicability of the SEDI based on the Bouchet hypothesis as an independent drought index for regions with strong land-atmosphere coupling or as an alternative drought index to fully precipitation-dependent indices for assessing agricultural droughts.

1. Introduction

Drought is a recurrent extreme climate event that may have detrimental consequences in human societies [*Dai*, 2011; *Heim*, 2002]. It is commonly characterized as the persistence of abnormally low precipitation, with general definitions including "a prolonged absence or marked deficiency of precipitation" [*World Meteorological Organization*, 1992] and "a period of abnormally dry weather sufficiently prolonged for the lack of precipitation to cause a serious hydrological imbalance" [*American Meteorological Society*, 1997]. From these definitions, the precipitation deficit is expected to play a central role in drought quantification and assessment. In several previous studies, the precipitation deficit was viewed as a main factor of increasing drought risk under climate change [e.g., *Sheffield and Wood*, 2008].

However, recent drought-related studies have focused mainly on evapotranspiration (ET) because it is coupled with atmospheric moisture demand and thus affects water availability on land surfaces [*Dai*, 2011]. *Vicente-Serrano et al.* [2010] proposed the Standardized Precipitation-Evapotranspiration Index (SPEI) by incorporating ET estimates into the structure of the Standardized Precipitation Index (SPI) [*McKee et al.*, 1993] and found more severe drought risks under global warming than are indicated by the precipitation deficit alone. Furthermore, a major controversy over global drought trends has originated from the discrepancy between the Thornthwaite and Penman-Monteith ET estimates [*Sheffield et al.*, 2012; *Dai*, 2013]. These studies suggest that ET could significantly affect drought severity, duration, and its spatial extent, and therefore, reliable ET estimates are essential for drought quantification.

Despite many attempts to include ET in drought assessment, most of previous studies have used ET with precipitation based on the concept of potential ET (ET_p), which is a hypothetical measure of the evaporative demand. Importantly, they over-relied on proportionality between ET_p and actual ET (ET_a), referred to as the Penman hypothesis [*Han et al.*, 2014], for estimating ET_a. Precipitation-based indices might be unsuitable for some practical purposes (e.g., drought forecasting) due to relatively higher uncertainty of precipitation than other climatic variables [*Gao et al.*, 2010]. In such a case, ET-based identification (i.e., comparison between ET_p and ET_a) may be good to track drought conditions [e.g., *Senay et al.*, 2013]. With Penman hypothesis, however, ET_a cannot be determined without soil moisture information or a land surface model because water availability on land surfaces itself is required for obtaining ET_a [*Allen et al.*, 1998]. The use of precipitation data is hence ultimately inevitable for estimating ET_a when using the Penman hypothesis. Indeed, the Penman hypothesis is often rejected by decoupled relationships or negative correlations between ET_p and ET_a [e.g., *Hobbins et al.*, 2004; *Ramírez et al.*, 2005; *Brutsaert*, 2006]. The proportionality between ET_p and ET_a is still an open question on a controversy [*Han et al.*, 2014].

On the other hand, the complementary relationship (CR) methods [e.g., *Morton*, 1983; *Granger and Gray*, 1989] have practical advantages. It is based on the complementary feedback mechanism between the atmosphere and unsaturated land surfaces introduced by *Bouchet* [1963], suggesting an inverse relation between ET_p and ET_a (referred to as the Bouchet hypothesis hereafter). The Bouchet hypothesis is theoretically acceptable from the perspective of energy conservation and allows a reliable estimation of ET_a by solely using commonly available climatic data [*Ma et al*., 2015]. The CR methods have been advanced for several decades [e.g., *Han et al*., 2011; *Anayah and Kaluarachchi*, 2014] as an alternative for the standard methods based on the Penman hypothesis [e.g., *Allen et al*., 1998] but nevertheless has been barely used for drought characterization or assessment [*Hobbins et al*., 2016; *McEvoy et al*., 2016].

The main objective of this study is to develop a new drought index that is fully dependent on the variability of ET estimates using a recently proposed CR method. We investigated the applicability of the newly proposed index at 9 month time scale over the conterminous United States (CONUS) by comparing it with two conventional drought indices. We also evaluated performance of the new index for monitoring droughts in vegetative spheres using a remotely sensed drought index.

2. Methodology and Data

2.1. The Modified Granger and Gray Method

In the Bouchet hypothesis as illustrated in Figure 1, the wet-environment ET (ET_w) is equal to ET_p and ET_a under saturated conditions, but the energy surplus increases ET_p as the surface dries (i.e., $ET_p > ET_w$). We used ET_w minus ET_a (referred to as ET deficit hereafter) to measure drought conditions because it should be closely related to surface water availability. Among the various CR methods used for estimating ET_w and ET_a, we selected the modified Granger and Gray (GG) method proposed by *Anayah and Kaluarachchi* [2014]. The modified GG method is a calibration-free method that was achieved through a comprehensive intercomparison study that considered modifications of the three classical CR methods of *Morton* [1983], *Brutsaert and Stricker* [1979], and *Granger and Gray* [1989]. It was validated by ET_a observations at 34 FLUXNET stations and showed statistically improved performance in ET_a estimation across a diverse range of climate conditions [see *Anayah and Kaluarachchi*, 2014].

The modified GG method uses the Priestley and Taylor equation [*Priestley and Taylor*, 1972] for estimating ET_w as

$$ET_w = \alpha \frac{\Delta}{\gamma + \Delta}(R_n - G_{soil}) \quad (1)$$

where α is a coefficient with a value of 1.28, Δ is the slope of the temperature-saturation vapor pressure curve (kPa °C^{-1}), γ is the psychrometric constant (kPa °C^{-1}), and R_n and G_{soil} are the net radiation (mm month^{-1}) and the soil heat flux (mm month^{-1}), respectively. R_n and G_{soil} are estimated with the maximum and minimum temperatures using the standard method of the American Society of Civil Engineers [*Allen et al*., 2005].

Granger and Gray [1989] developed an empirical relationship between ET_p and ET_a by defining the relative drying power (D) and the relative ET (G) as

$$D = \frac{E_a}{E_a + (R_n - G_{soil})} \quad (2a)$$

$$G = \frac{ET_a}{ET_p} = \frac{1}{1.0 + 0.028\exp(8.045\ D)} \quad (2b)$$

$$E_a = 10.6 \times (1 + 0.5U_2)(e_s - e_a) \quad (2c)$$

where E_a is the drying power of air (mm month^{-1}), U_2 is the wind speed at 2 m above the ground level, and e_s and e_a are the saturation and actual vapor pressures, respectively (mm Hg).

The symmetric CR of *Bouchet* [1963] is used in the modified GG method as

$$ET_a = 2ET_w - ET_p \quad (3)$$

ET_a is obtained from equations (2b) and (3) as

$$ET_a = \frac{2G}{G + 1}ET_w \quad (4)$$

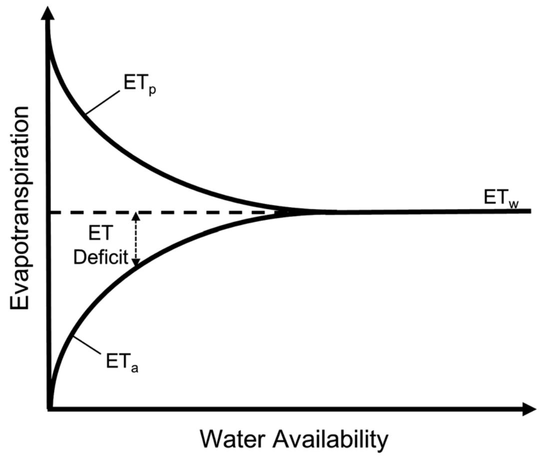

Figure 1. The complementary relationship between ET_p and ET_a and the ET deficit as drought indicator.

Further details and discussion about the modified GG method are available in *Anayah and Kaluarachchi* [2014].

2.2. Climatic Data and Drought Indices

We mainly used monthly gridded temperature data sets from the PRISM (Parameter-elevation Regressions on Independent Slopes Model) Climate Group (available at http://www.prism.oregonstate.edu/) that cover the CONUS at 4 km grid resolution from 1895 to 2014. The PRISM products are high-quality spatial climatic data acquired through a physiographical interpolation of point observations [*Daly et al*., 2008] and are regarded as enhanced climate data sets from knowledge-based mapping and a rigorous peer-review process [*Kangas and Brown*, 2007]. Detailed information about the PRISM data sets can be found at http://www.prism.oregonstate.edu/documents/PRISM_datasets.pdf.

Due to the difficulty of collecting quality wind speed data with the same length of the PRISM data sets, we used normal values of gridded wind speed for the 12 months (i.e., 12 typical spatial variations of January through December were only considered). The normal values were obtained by averaging the gridded daily wind speed data at 4 km resolution from 1979 to 2014 provided by the University of Idaho Gridded Surface Meteorological Data (available at http://climate.nkn.uidaho.edu/METDATA/). We converted the wind speed at 10 m above the ground level using the power law for calculating E_a.

For relative humidity, we used estimates of dew point temperature (T_d). T_d was estimated as the minimum temperature minus a temperature differential ranging from 0°C (for the lowest aridity) to 2.0°C (for the highest aridity) according to the recommendations for missing climatic data in *Allen et al.* [1998]. The aridity of each grid cell was identified by the ratio of annual precipitation to the Hargreaves ET, calculated using the 30 year normals of the PRISM data sets (available at http://www.prism.oregonstate.edu/normals/).

To evaluate drought indication of the new index, we additionally downloaded the Palmer Drought Severity Index (PDSI) and SPI data sets as per the official U.S. climate divisions from the National Climate Data Center (available at http://www1.ncdc.noaa.gov/pub/data/cirs/drd/). PDSI and SPI are highly or fully dependent on precipitation variability and have been commonly used for global and historical drought assessments [e.g., *Dai*, 2011]. We also collected the 4 km global Vegetation Health Index (VHI) products of advanced very high resolution radiometer from the Center for Satellite Applications and Research of the National Oceanic and Atmospheric Administration (available at http://www.star.nesdis.noaa.gov/smcd/emb/vci/VH/vh_ftp.php) to evaluate performance of the new index for indicating vegetation status. Global VHI products in the 30th week of each year (i.e., vegetation status in late July) from 1982 to 2014 were downloaded.

2.3. Drought Identification

We adopted the structure of SPEI [*Vicente-Serrano et al*., 2010] to produce a probability-based relative drought index. The precipitation minus the reference ET of SPEI was replaced with the ET deficit obtained from the modified GG method. Since SPI and SPEI show strong correlations with PDSI at 9 to 12 months of duration [e.g., *Vicente-Serrano et al*., 2010], we hypothesized that the 9 month duration for accumulating ET deficit would show high correlations with the precipitation-based indices. The accumulation of ET deficit considers influence of moisture availability in the previous months on the drought conditions of the current month. Hence, the series of 9 month ET deficit for each grid cell of the PRISM data sets over 119 years were fitted to a three-parameter log-logistic distribution (LL3) for each month using the probability-weighted moments [*Hosking*, 1990], as recommended by *Beguería et al.* [2014]. Using the fitted log-logistic distribution and the gridded 9 month ET deficit, monthly drought indices were produced from 1896 to 2014 at a 4 km grid resolution. While the SPEI uses the nonexceedance probability (p) of accumulated precipitation, the exceedance probability ($1 - p$) of the 9 month ET deficit was standardized because the ET deficit inversely indicates water availability. The novel drought index derived from the ET deficit will be referred to as the Standardized Evapotranspiration Deficit Index (SEDI) hereafter.

The time series of 9 month SEDI (referred to as SEDI9 hereafter) at 4 km grid resolution was spatially aggregated into the divisions for consistency with the downloaded PDSI and 9 month SPI (referred to as SPI9 hereafter) data sets. The global VHI images given at 4 km resolution were also spatially averaged with boundaries of the climate divisions for comparison.

3. Results and Discussion

3.1. Drought Identification by SEDI9

As shown in Figure 1, the ET deficit should be negatively related to surface moisture conditions and thus inversely expresses water availability (i.e., a larger value indicates less water availability). Because ET_a cannot exceed ET_w mathematically from equations (2b) and (4), the ET deficit is always positive as is precipitation. Hence, it would be possible to use a two-parameter probability density function, such as the gamma distribution, instead of LL3 when calculating the SEDI. It is noteworthy that the SEDI is an index that indirectly indicates moisture conditions on land surfaces with no involvement of precipitation.

Although several ET-based drought indices have been proposed using differences (or ratios) between ET_a and ET_p [e.g., *Anderson et al*., 2011; *Narasimhan and Srinivasan*, 2005], they have required remotely sensed images or land surface models. SEDI is distinguishable from the existing ET-based indices because it only uses common operational meteorological data. SEDI enables to extend ET-based drought identification up to the length of monthly temperature data sets when using typical wind speed values and minimum temperatures for relative humidity. However, all ET-based drought indices, including SEDI, have uncertainty. This assessment of uncertainty is beyond the scope of the current study, which aims to introduce the applicability of the Bouchet hypothesis in identifying droughts. Future efforts should be directed at further assessment of the reliability of ET_a estimates since this would inherently improve ET-based drought indices.

Figure 2 shows that the spatial distributions of the drought areas defined by the SEDI9, PDSI, and SPI9 were consistent for several major droughts in the CONUS. The months in 1934 and 1956 were part of the Dust Bowl and Southwest droughts, respectively, which are often documented as the worst multiyear droughts in the twentieth century [*Folger and Cody*, 2014]. The drought areas defined by the SEDI9 in July 1934 were similar to the divisions in drought areas defined by the PDSI. The SEDI9 captured the serious drought conditions in Montana during the Dust Bowl drought, which recorded great economic losses [*Cook et al*., 2007] as D2 or D3 areas, whereas the SPI9 did not. Interestingly, drought areas defined by the PDSI in the month of the Dust Bowl appeared to be an intermediate state between those of the SEDI9 and SPI9, which may be because the PDSI considers precipitation and ET_p together for drought quantification. The extreme drought centered in Texas and New Mexico in 1956 was captured by the SEDI9, albeit with less severity. Additionally, the SEDI9 clearly defined the severe droughts in the northern Great Plains that led to the widespread Yellowstone fire in 1988 as well as the critical drought experienced across Texas in 2011 [*Folger and Cody*, 2014].

Figure 3 shows the temporal correlations between the SEDI9 and the two conventional drought indices over the period of 1896–2014. The average of the temporal correlations over all climate divisions between the SEDI9 and PDSI was 0.52 (highest value was 0.72), and it was 0.51 between the SEDI9 and SPI9 (highest value was 0.78). Correlations between PDSI and SPI9 were very high with a range of 0.64–0.86 for all climate divisions as expected from the selected 9 month duration of SPI. From the correlation maps, it is indicated that consistency between ET deficit and precipitation deficiency is highest in the South-Central U.S. and decreases with increasing proximity to the Pacific or Atlantic Oceans. Importantly, the locations of high correlation to SPI9 (>0.6) approximately coincide with the regions of strong interactions between soil moisture and precipitation, namely, "hot spots" of land-atmosphere coupling [*Koster et al*., 2004, 2006]. *Guo et al*. [2006] found that the hot spots are likely to locate in the transition zones between arid and wet areas. The energy availability (not water availability) mainly controls ET_a in wet areas, while ET_a in arid areas is too small to entail significant effects on rainfall generation; thereby, the transition zones between humid and arid areas only can have ET_a sensitive to moisture conditions on land surfaces. The correlation maps in

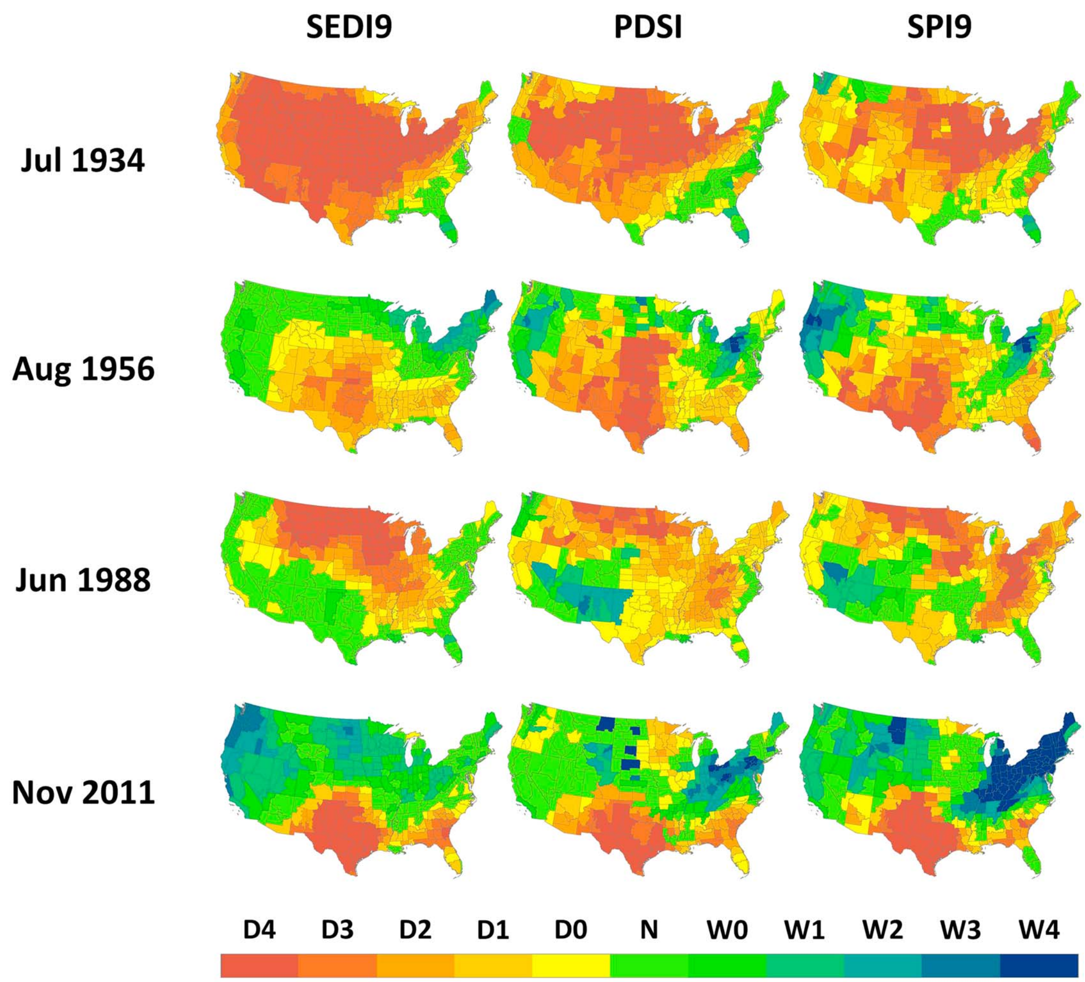

Figure 2. Maps of SEDI9, PDSI, and SPI9 for major drought months in the CONUS. The thresholds for classifying drought conditions (D4 to D0) were −2.0, −1.6, −1.3, −0.8, and −0.5 for the SEDI9 and SPI9, while those are −5.0, −4.0, −3.0, −2.0, and −1.0 for the PDSI. Wet conditions (W4 to W0) were categorized by the same numbers for D4 to D0 but with positive signs. *N* represents the normal condition.

Figure 3 confirm the hot spot locations of the prior studies [*Koster et al*., 2004, 2006; *Guo et al*., 2006] obtained from the atmospheric general circulation models. From the comparison between SEDI9, PDSI, and SPI9, we suggest that the combination of the modified GG method and the structure of SPEI can be a surrogate of precipitation-based drought indices in regions where the feedback mechanism between the atmosphere and land surfaces is expected to be strong.

Despite the ability for capturing drought conditions, the SEDI9 has caveats. First, it partially uses the CR since we defined droughts based on water availability (i.e., $ET_w - ET_a$), not on the evaporative demand (i.e., ET_p). For indicating drought conditions using the evaporative demand, the entire CR between ET_p and ET_a needs to be acknowledged [e.g., *Hobbins et al*., 2016; *McEvoy et al*., 2016]. It would be particularly important if an asymmetric CR is employed [e.g., *Zuo et al*., 2016]. Second, temporal variation of wind speed needs to be considered because declining rates of wind speed are globally present [*McVicar et al*., 2012]. We only considered spatial variation of wind speed for identifying the historical droughts in the early twentieth century, during which no quality wind speed data are available. However, impacts of the declining wind speed on the ET-based index should be further assessed since it gradually reduces the evaporative demand. In addition, the spatial scale should be appropriately selected for reliable estimation of ET_w and ET_a because the Bouchet hypothesis was developed under the assumption of negligible advection influences. At a very small or a continental scales, applying the same assumption could result in biased ET_a and ET_w estimates.

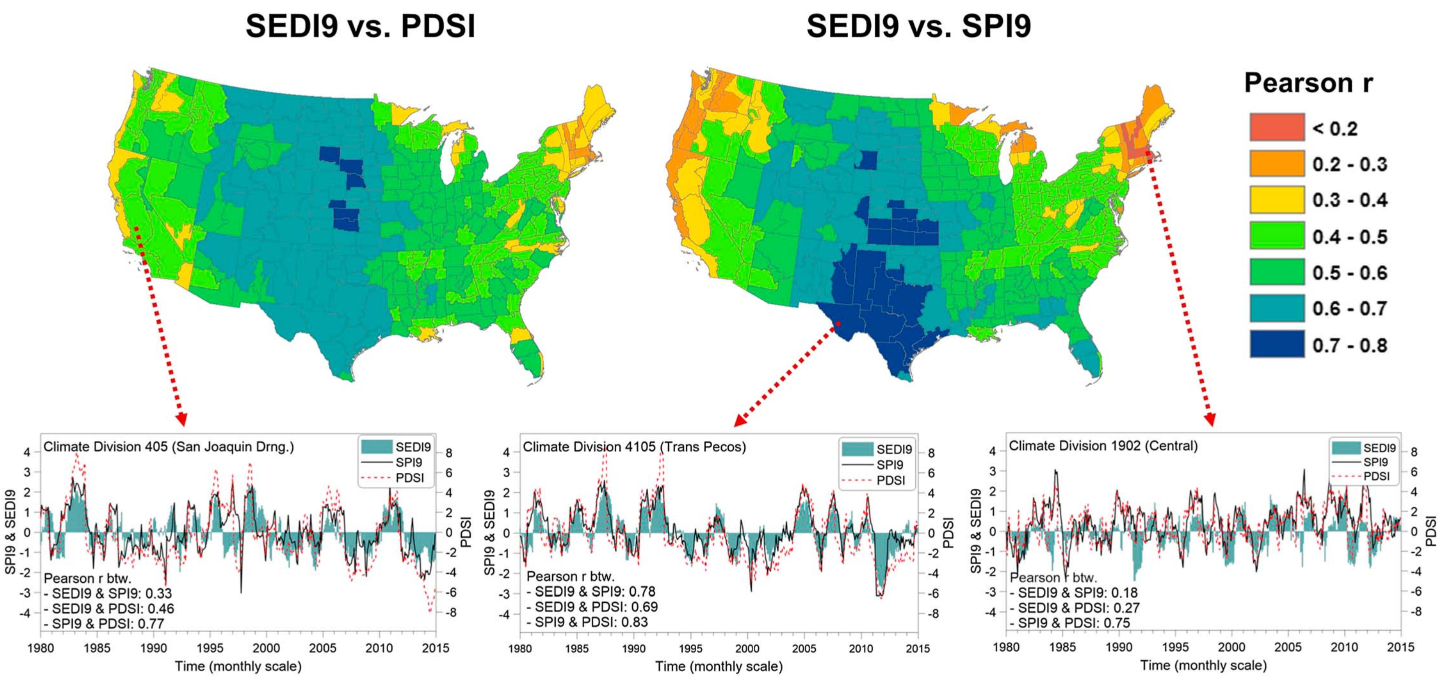

Figure 3. Distribution of temporal correlations (top left) between SEDI9 and PDSI and that (top right) between SEDI9 and SPI9 and (bottom) example time series of drought in three climate divisions.

3.2. Performance of SEDI for Vegetative Droughts

For evaluating performance of SEDI for indicating vegetative droughts, we compared VHI at the 30th week of the year (in the middle of growing season over the CONUS) with SEDI9, PDSI, and SPI9 in July from 1982 to 2014. VHI characterizes remotely sensed moisture and thermal conditions of vegetation surfaces. It is often used for assessing crop productivity, soil moisture conditions, and thus an indicator of agricultural droughts [*Kogan et al.*, 2004].

Figure 4 shows scatterplots between VHI and three indices of the climate divisions for the representative years with severe vegetative droughts [*Kogan and Guo*, 2015] and the time series of spatial correlations between VHI and the three drought indices. We found that SEDI9 was of clear positive correlations with VHI and generally outperforms SPI9 for indicating vegetative droughts. Average correlation coefficients for the period of 1982–2014 were 0.53, 0.60, and 0.41 between VHI and SEDI9, VHI and PDSI, and VHI and SPI9, respectively. Although PDSI was the best indicator of vegetation status on average, the performance of SEDI9 was comparable to PDSI. SEDI9 also performs better than the precipitation-dependent SPI9 in identifying agricultural droughts. In particular, the increasing trend in correlations between VHI and SEDI9 suggests that ET-based drought indices based on the Bouchet hypothesis could be better for monitoring agricultural and vegetative droughts in upcoming years. The upward correlation between VHI and SEDI9 may imply that the thermal condition is becoming relatively significant in indication of the vegetation health due to the globally rising temperatures.

4. Summary and Conclusions

A calibration-free method from the Bouchet hypothesis allowed us to estimate actual ET with readily available climatic data. A fully ET-dependent drought index was developed using the actual ET estimates in combination of the structure of a standardized drought index. The ET-based drought index was temporally consistent with conventional precipitation-based drought indices in identifying the historical droughts in the CONUS. High temporal correlations between the ET-based index and the precipitation-dependent indices were found in the regions with strong land-atmosphere coupling. From the comparison with the remotely sensed Vegetation Health Index, we also had an indication that the ET-based drought index well performs identifying vegetative or agricultural droughts.

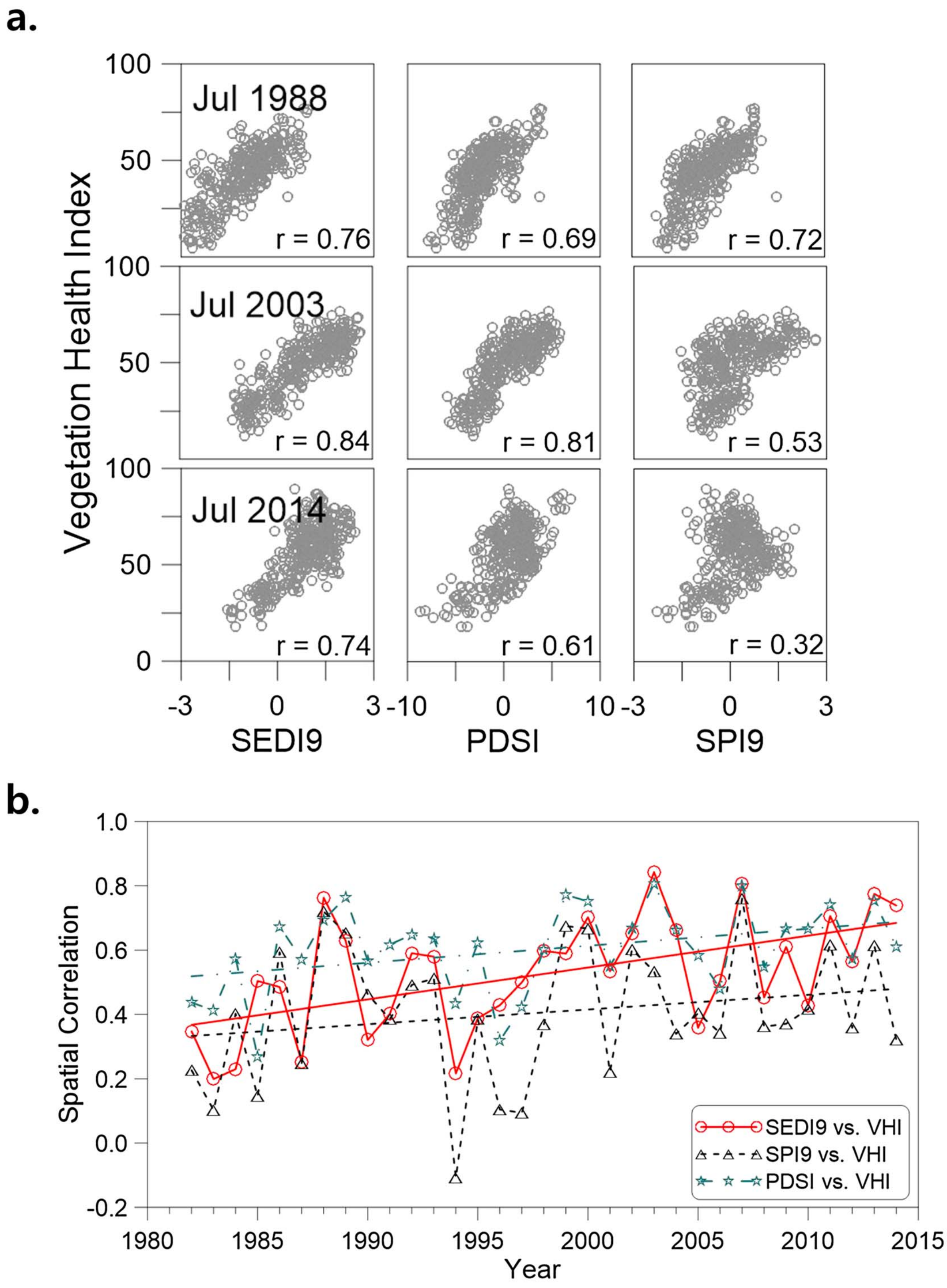

Figure 4. (a) Scatterplots between VHI and SEDI9, PDSI, and SPI9 for years with high correlation and (b) changes in spatial correlations between VHI and SEDI9, PDSI, and SPI9 over 1982–2014. The three straight lines inside the time series plots represent the linear trends of the spatial correlations.

ET has been central in recent scientific discussions on global and historical drought assessments, but most focus has been based on the application of the Penman hypothesis which depends on precipitation. The Bouchet hypothesis is an alternative approach for developing an ET-based index. In this study, we provided an example of a drought index based on the Bouchet hypothesis. Further studies could improve this work and apply it to other related relevant topics. These may include drought identification in areas of weak land-atmosphere coupling, determining time scales of the ET-based index and its effects on drought definitions, impacts of globally declining wind speed, and linkage to other natural phenomena.

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