Estimating Drought Conditions across the United States Using an Evapotranspiration-based Drought Index

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I. Introduction

Historically, the Palmer Drought Severity Index (PDSI; Palmer, 1965) was a landmark in the development of drought indices. However, several limitations of the PDSI were recognized as presented in Table 1. Because of these limitations, other indices such as the Standardized Precipitation Index (SPI; McKee et al., 1995) and the Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010) were developed. Recently, the Standardized Evapotranspiration Deficit Index (SEDI; Kim and Rhee, 2016) was developed by using actual evapotranspiration (ET) and the structure of SPI. Kim and Rhee (2016) showed the drought patterns of SEDI were consistent with the PDSI and SPI, and demonstrated that considering actual ET can provide a reliable measure for drought severity. However, the SEDI suffers from that it did not address the effect of precipitation.

Therefore, this study has focused on developing a drought index with an accurate ET method to consider the effects of temperature, precipitation and land surface coverage from remote sensing vegetation data. This study used the U.S. Drought Monitor (USDM; Svoboda et al., 2002) as another metric to assess the proposed index. Because the USDM is the most widely used for drought monitoring within the United States, and derived from a blend of drought metrics including the PDSI and SPI.

Table 1. Limitations of drought indices

Drought Index	Limitations
PSDI	• Inconsistent across diverse climate regions • Parameters were derived from small number of locations • Fixed temporal scale
SPI	• The variability of temperature is negligible
SPEI	• The use of reference ET for drought is questionable
SEDI	• The effect of precipitation is negligible

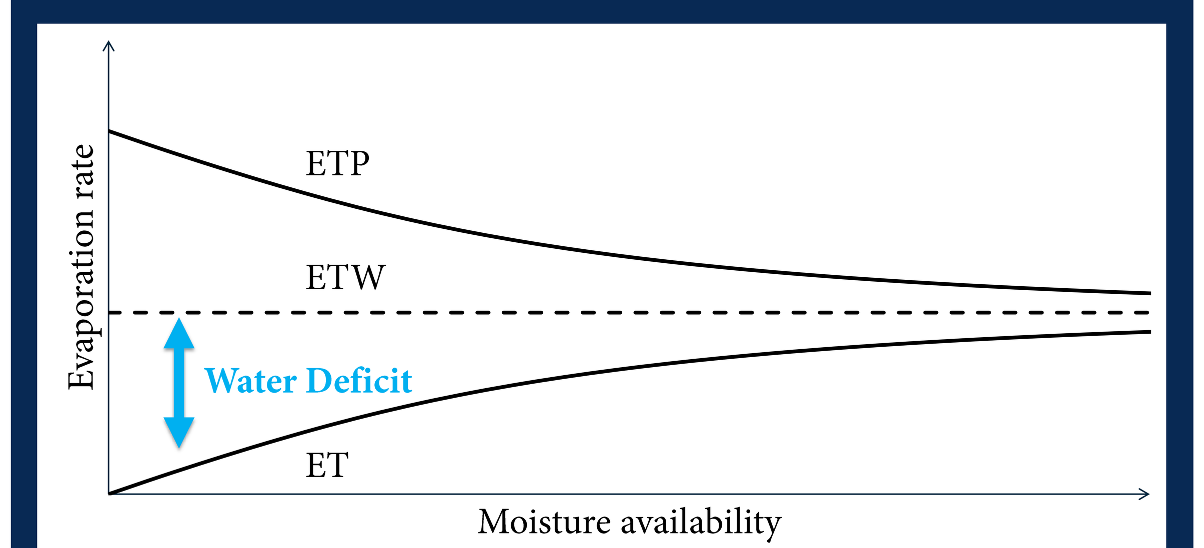
II. Method and Data

We proposed a simple drought index, the Evapotranspiration Water deficit Drought Index (EWDI), by using the monthly ET and the empirical probabilities of water deficit. The monthly ET estimated from the following complementary relationship formulation as given by Eq. (1) and illustrated in Fig. 1.

$$ET + ETP = f(G) \times ETW \qquad (1)$$

where ETP is the potential evapotranspiration, ETW is the ET rate for a wet surface and most often derived from the Priestley-Taylor expression (Priestly & Taylor, 1972), and $f(G)$ is a correction function and most often assumed to be 2. Kim and Kaluarachchi (2017) demonstrated that the inclusion of $f(G)$ greatly improved the model performance to estimate ET (details are available in the reference).

Figure 1 – Complementary relationship between ET, ETP and ETW with definition of water deficit



With an accurate ET value, we derived a water deficit (D_i) for month i using Eq. (2).

$$D_i = ETW_i - ET_i \qquad (2)$$

Given the monthly time series of D_i, the probability distribution function are obtained through the empirical Tuckey plotting position (Wilks, 2011). Then, EWDI is derived by the inverse normal approximation detailed in Vicente-Serrano et al. (2010)

We mainly used monthly gridded precipitation and temperature datasets from the PRISM climate Group that cover the contiguous United States (CONUS) at 4-km grid resolution from 2000 to 2015. As part of input data for the ET method, the Normalized Difference Vegetation index (NDVI) were retrieved from NASA Earth Observation. The USDM data were obtained from the National Drought Mitigation Center.

In this study, we estimated the EWDI with two different ET methods: GG-NDVI (Kim and Kaluarachchi, 2017) and the modified GG (Anayah and Kaluarachchi, 2014).

III. Results

Figure 2 – Correlation coefficients between EWDI-mod and EWDI-ndvi against USDM for 2001 to 2015. EWDI-mod was estimated from the modified GG (Anayah and Kaluarachchi, 2014), and EWDI-ndvi was estimated from Kim and Kaluarachchi (2017).

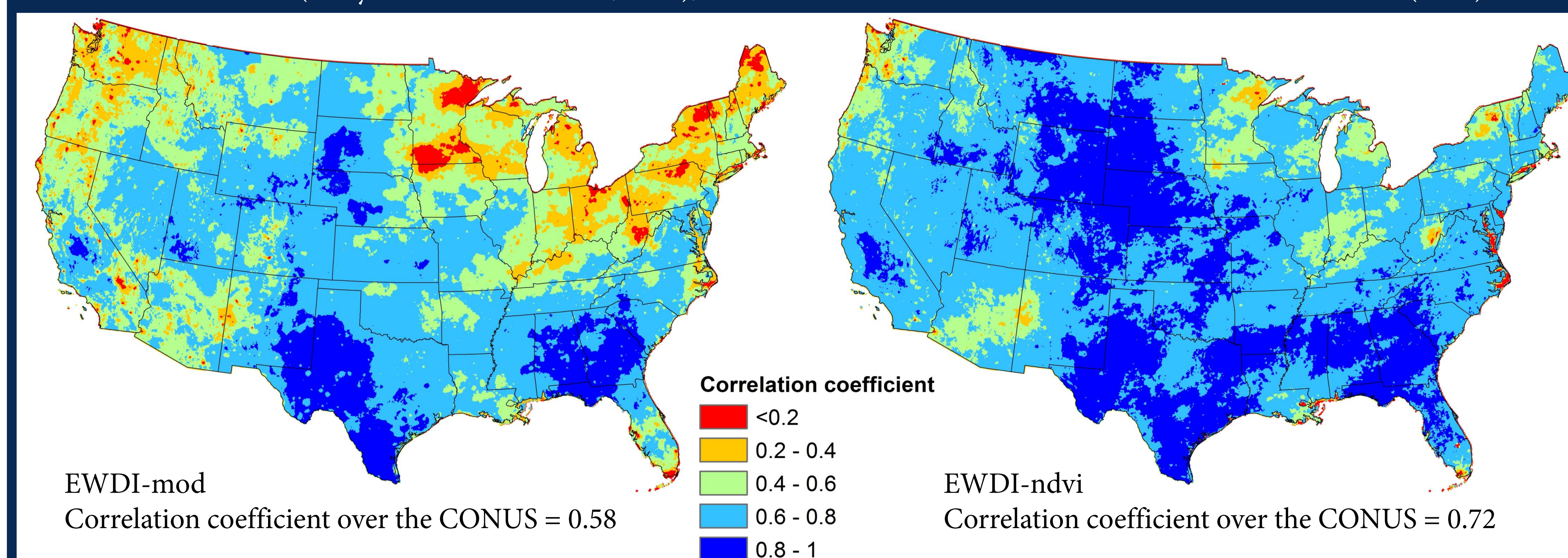


Figure 3 – (a) Percent area of San Bernardino County covered by at least D0, and (b) monthly estimated ET values with observed ET

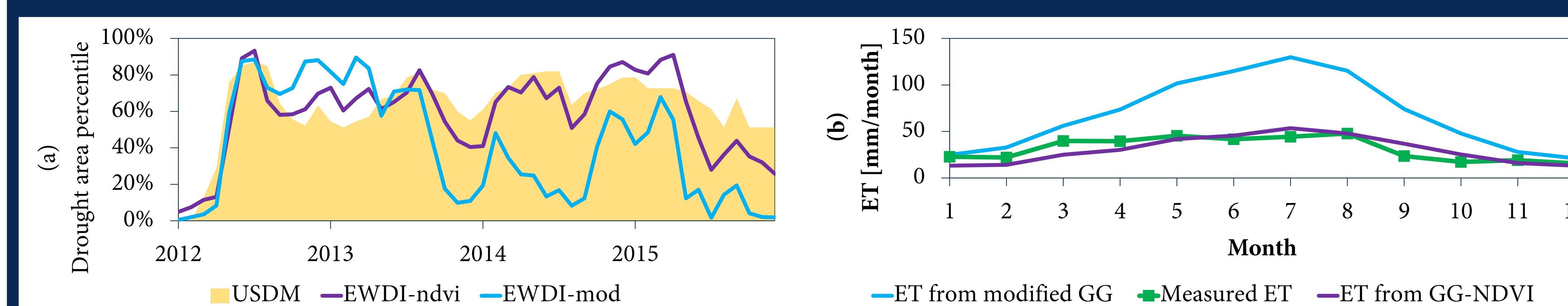


Figure 4 – Spatial comparisons of USDM and EWDI for major drought months in the CONUS

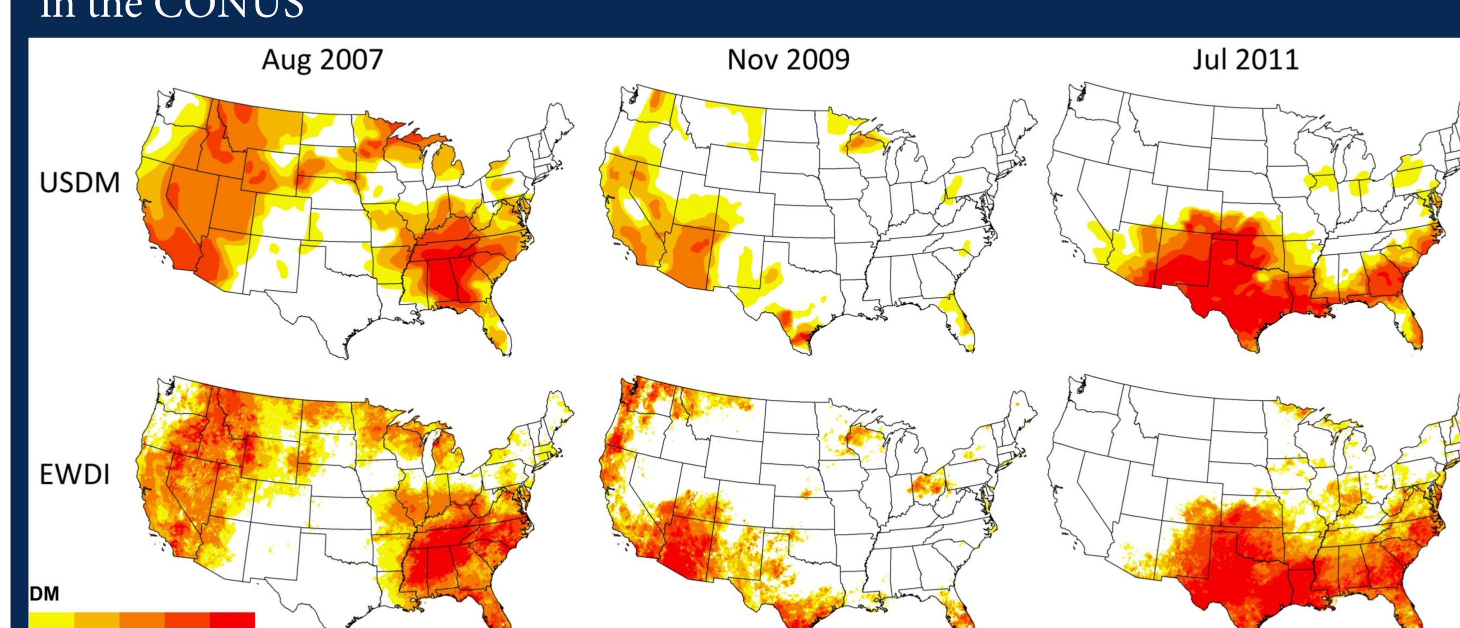
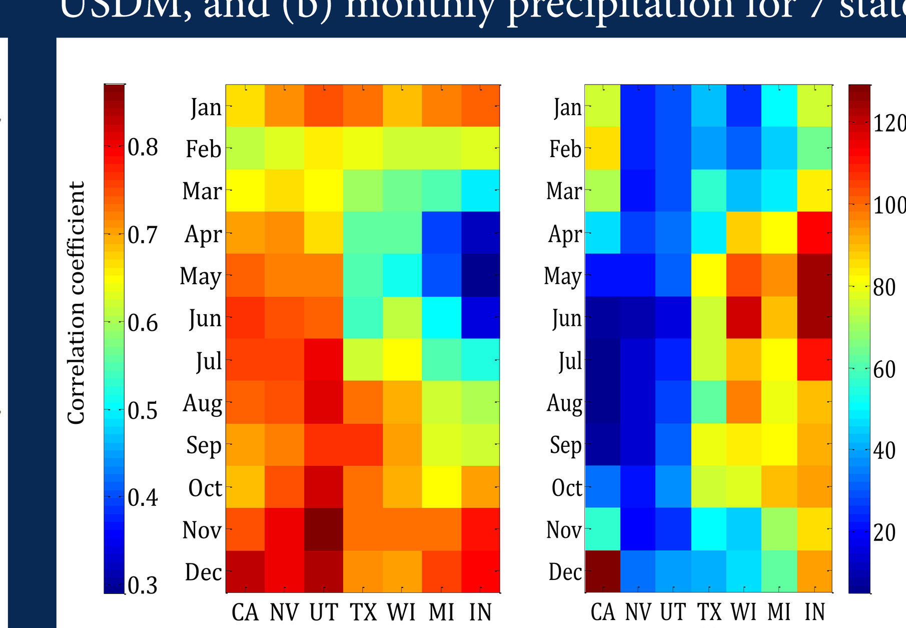


Figure 5 – (a) Correlations between EWDI and USDM, and (b) monthly precipitation for 7 states



IV. Conclusion

The EWDI is able to capture drought conditions over the CONUS and using the accurate ET method can improve the performance as a drought index. Moreover, the EWDI derived from GG-NDVI uniquely describes drought conditions with the land surface which has large impacts on drought compared to other drought indices.

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