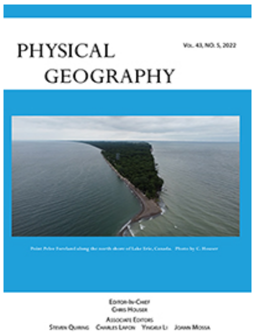

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Examining spatiotemporal trends of drought in the conterminous United States using self-organizing maps

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ABSTRACT

Droughts are a natural, recurrent climate extreme that can inflict long-lasting devastation on natural ecosystems and socio-economic sectors. Unlike other natural hazards, drought onset is insidious and often affects a greater spatial extent over a prolonged temporal scale. In the United States the evolution of drought and its impacts are typically region-specific and intensified precipitation variability may obscure how drought may manifest. In this study, we examine the spatiotemporal trends of drought using self-organizing maps (SOM), competitive learning subset of artificial neural networks (ANN), requiring unsupervised training of inputs. We introduced monthly Palmer Drought Severity Index (PDSI) values to the SOM to identify existing clusters of wetting and drying patterns from 1895 to 2016. After training, we created cartographic visualizations of the SOM output and conducted a subsequent time-series analysis to link with the geographic patterns of drought. Over the last 40 years, precipitation intensified in the Northeast, Midwest, and upper Great Plains across several nodes. Across the majority of SOM patterns, we identified no significant changes of drying or wetting patterns over the last century for the greater part of the CONUS.

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Drought; self-organizing maps; climatic extremes; spatial analysis; Drought; PDSI

Introduction

Droughts are a natural, recurrent climate extreme that can inflict long-lasting devastation on natural ecosystems and socio-economic sectors. Droughts are one of the costliest natural hazards; over the last 40 years, 26 droughts have cost at least USD 249 billion in the United States, averaging about $9 billion of annual loss in damages per event (Smith, 2020). Despite this, drought events are not easily quantified. On a global scale, there is much debate on whether drought frequency and severity have increased as interactions between temperature, precipitation, and potential evapotranspiration (PET) are not uniform across various spatial and temporal scales (McCabe & Wolock, 2015; Trenberth et al., 2013). Notwithstanding, the most recent IPCC report on climate change attributes anthropogenic forcings with high confidence as a catalyst for intensification of the effects of drought and other climate extremes at varying localized scales (Williams et al., 2019, 2020).

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In the United States (CONUS), there is scientific consensus concerning the historical spatial patterns of drought where distinct geographic differences between drought occurrence and drought severity, intensity, and duration have been identified (Ge et al., 2016; Kangas & Brown, 2007; Karl & Koscielny, 1982; Ortegren et al., 2011; Soulé, 1992). Regional drought risk assessments have found significant increasing trends across the southwest and southern Plains (Andreadis & Lettenmaier, 2006; B. I. Cook et al., 2015; Williams et al., 2013). Regions characterized as naturally dry, such as the southwest, have experienced increased persistence of droughts, and naturally wet regions have experienced increased precipitation variability, that is, increased intensity when it rains (Andreadis & Lettenmaier, 2006; Groisman & Knight, 2008; Groisman et al., 2004; Li et al., 2013). Kangas and Brown (2007) found that the southeast and southern gulf were the least susceptible to prolonged drought, while the northern Rockies and southern Plains were most susceptible. However, projections of the nature and causes of prolonged drought in regions like the southeast, midwest, and northern/central plains remain somewhat uncertain given influences of seasonality, PET, precipitation variability, and warming sea surface temperatures (SST; Easterling et al., 2007; Ge et al., 2016; Ortegren et al., 2011). While there is broad agreement that temperature and precipitation variability have increased over the latter half of the 20th century, the regional effects of these trends on evaporative demand have become increasingly prevalent under the context of future water availability (Easterling et al., 2007; Trenberth et al., 2013).

Drought impacts are extensive and can have devastating effects on agriculture, energy, ecosystem viability, and public health (Crausbay et al., 2017; Sugg et al., 2020; Vicente-Serrano et al., 2020). Drought onset is insidious and often affects a greater spatial extent and prolonged temporal scale. Droughts can be broadly classified as either meteorological, hydrological, agricultural, or socio-economic (Wilhite & Glantz, 1985). *Meteorological drought* is the most common or "quantifiable" form of drought, which describes atmospheric conditions that lead to a reduced or complete absence of precipitation (Heim, 2002) and is the definition we implement to describe drought in our analysis.

Background

State of the drought literature

The diversity of drought definitions has prompted the development of more than 150 drought indices for drought characterization, monitoring, and analysis (Zargar et al., 2011). One of the most widely used drought indices is the Palmer Drought Severity Index (PDSI), developed in 1965, based on the water-balance model. Most indices are better applied to specific regions and smaller temporal scales, but there is not one drought metric that captures the full scope of drought. Depending on the chosen drought index, the emphasis placed on the relative roles of precipitation, evapotranspiration, and available water content varies, thus can change the interpretation of observed drought trends and related impacts (Trenberth et al., 2013).

Tree-ring reconstructions of drought, using PDSI, have revealed many regions across North America have experienced recurrent *megadrought*s (severe drought lasting longer than two decades) over the last 500–1000 years (E. R. Cook et al., 2007; Stahle et al., 2007).

Notably, three "megadroughts" have been identified across the western sector of the continental U.S. from A.D. 1300 to 1900 (Stahle et al., 2007). While this drought type has not yet been recorded in modern societies, the U.S. has previously experienced intense and prolonged droughts, including the most severe since 1700, the 1930′s Dust Bowl (E. Cook et al., 1999), and the Southwest drought of 1950–56 (E. R. Cook et al., 2007). In addition, more recently, in 2012, about 65.5% of the U.S. experienced moderate-to-severe drought, according to the USDM (Heim, 2017). Mechanisms which lead to severe drought are complex; however, changes to land cover and land use have been identified as potential drivers of alterations to precipitation, temperature, and water availability (Shukla et al., 2019). Modifications across the landscape due to agriculture, urbanization, and deforestation significantly affect feedback between energy, water, and greenhouse gas emissions (GHGs) between land and the atmosphere (Sleeter et al., 2018). For example, urbanization has led to an increase of impervious surfaces and a reduction of vegetative cover; these factors minimize the cooling effect of evapotranspiration and promote what is known as the "urban heat Island effect," making these areas warmer than locations with greater vegetative cover (Sleeter et al., 2018). In addition, accelerated runoff and reduced infiltration capabilities due to soil compaction result in disturbances to the hydrologic cycle (Kaushal et al., 2017). The outcome of these interactions are presented as localized changes to weather patterns compounded by the effects of climate change (Sleeter et al., 2018).

In the United States, the spatiotemporal variations of drought differ geographically due to climate forcing's unique regional characteristics (Ficklin et al., 2015). The West and Southwest have experienced severe, more intense, prolonged droughts (Andreadis & Lettenmaier, 2006; Ficklin et al., 2015), whereas the Eastern and Southeastern regions have not experienced such long-lasting deficits (Li et al., 2013; Wang et al., 2010). In the West, increased heat is expected to amplify the duration and severity of a drought. Warmer atmospheric temperatures promote an increase in moisture or water vapor in the air; therefore, in regions such as the southeast, there is an expected increased intensification of rainfall (Li et al., 2013; Wang et al., 2010). Despite this, precipitation variability may mask how the drought has changed in these locations (Easterling et al., 2007). The Southeastern region typically experiences frequent tropical cyclones and flooding, but internal atmospheric variability and projected increased evaporation are likely to enhance drought in these locations (Ford & Labosier, 2013; Seager et al., 2009; Wang et al., 2010).

Some studies have supported the claim that drought trends have been increasing since the 1950′s (Dai, 2013a; Vicente-Serrano et al., 2010); however, this has been refuted by studies that argue that the magnitude of drought changes over time is attributed to methods used to estimate potential evapotranspiration (PET) and other climate forcings (Sheffield et al., 2012). Data inconsistencies due to limited availability or access to high-quality long-term precipitation data, varying baseline periods, and analytic techniques have amplified the uncertainties in our understanding of drought (Alexander, 2016; Trenberth et al., 2013). While it is widely recognized that drought is invariably linked to heat (Vicente-Serrano et al., 2010), other climatic indicators, such as precipitation, soil moisture, evapotranspiration, wind speed, cloud cover, and solar radiation, also play significant roles in regional drought cycles (Ficklin et al., 2015; Trenberth et al., 2013).

The current body of literature seeks to better understand climate forcings or the internal regional variability that drives anomalous drying or wetting trends. Previous studies examining patterns of drought have relied on simulated datasets of various hydro-climatic factors (e.g. soil moisture or runoff) to reconstruct past drought in the 20th century (Andreadis & Lettenmaier, 2006). For example, Ficklin et al. (2015) tested spatial trends of drought using Mann-Kendall trends analysis and found four grouped regions showing increasing (upper Midwest, Louisiana, Southeast, and Southwest), and four grouped regions displaying decreasing trends (New England, Pacific Northwest, upper Great Plains, and the Ohio River Valley).

Self-organizing maps (SOM) are a competitive learning subset of artificial neural networks (ANN), requiring unsupervised training of nodes (inputs). SOMs have been an exceptionally useful tool in meteorological and atmospheric research (Hewitson & Crane, 2002; Skific & Francis, 2012; Sugg & Konrad, 2017) and have quickly gained traction across a variety of climatological applications (Sheridan & Lee, 2011). The appeal of SOMs stem from their ability to work with large datasets to derive salient clusters across a multidimensional space, while retaining the original data space continuum (Skific & Francis, 2012). In the climate literature, SOMs have become a popular method for the characterization of the physical conditions behind extreme climatic events (Gibson et al., 2017). This method has been previously used to discern drought types and find linkages between episodes of drought and associated synoptic patterns (Gibson et al., 2016; Harrington et al., 2016).

The objective of this study is to observe the general spatial patterns of drought of the conterminous United States from 1895 to 2016 using the PDSI and quantify how they have changed over time. Here, we present monthly PDSI values over 1895–2016 to the SOM to identify clusters of extreme trends and describe the temporal and spatial behavior of meteorological drought. SOM outputs were then tested to delineate statistically significant increasing or decreasing trends. As a secondary aim, we also examined if SOM patterns were moderated by extratropical cyclone precipitation using a novel ETC data set. Results will inform future studies exploring drought trends by offering a new analytic tool to examine geographic patterns associated with meteorological drought over the last century.

Methods

Data

The Palmer Drought Severity Index (PDSI) was chosen as the primary drought metric for this study owing to its prominence as a measure for long-term meteorological drought (Keyantash & Dracup, 2002) and comprehensive consideration of the availability of atmospheric moisture in the water balance model (Palmer, 1965). PDSI is based on local climatic conditions and computed using monthly averages of available water content in the top layer of soil, temperature, and precipitation observations. The PDSI is then modified to evaluate monthly potential evapotranspiration using either the *Thornthwaite* or *Penman-Monteith* equation, although the former method has been attributed to overestimating dryness (Sheffield et al., 2012). Even so, because the *Penman-Monteith* method is more physically realistic, it also requires more complex inputs; and previous work has shown that estimation of PET using either method is quite similar in terms of identifying extreme drying or wetting trends (Dai, 2011a; Van der Schrier et al., 2011). These calculations are used to reconstruct dryness or wetness changes over the long term and can then be standardized to allow for the comparison across regions at various timescales.

Data used in this study are derived from the North Carolina Cooperative Institute for Climate and Satellites (NCICS) and the National Centers for Environmental Information (NCEI). We used monthly observations of county-level PDSI values from 1895 to 2016 for the CONUS, which includes 1,464 drought observations per county. Unlike other clustering algorithms, the SOM method does not adhere to a priori assumptions about the distributions of the original data (Hewitson & Crane, 2002), meaning PDSI observations for all counties were introduced to the SOM randomly, and its corresponding weighting coefficient was iteratively updated within the data space until the best representation of the underlying distribution was identified.

There are several limitations to the PDSI that have been addressed in previous papers (Alley, 1984; Karl, 1986). The original formulation of the PDSI index was based on climatic conditions in the central United States, which has a semi-arid climate unique to the region. For instance, the PDSI scale theoretically ranges from −10 (dry) to 10 (wet) but varies depending on how PDSI is calculated. Thus, interpretations of relative wetness or dryness for a given PDSI value in one geographical location could hold a different meaning in another (Dai et al., 2004). Moreover, the PDSI has been criticized for its sensitivity to available water content. For example, it does not reflect seasonal differences owing to its inability to account for the effect of snow cover and frozen ground (Karl et al. 1985) and for not incorporating a lag period between water accumulation and runoff (Alley, 1984).

Perhaps the most prominent critique of the PDSI has been the arbitrary establishments of the start and end period of a drought event and subjective weighting factors used for standardization (Heim, 2002). In addition, another aspect of the PDSI critique is related to the baseline period chosen for inputs. Nonetheless, the PDSI is a common proxy-based metric used to examine historical trends of drought. This study evaluated monthly PDSI conditions using NCEI's 5-km NClimGrid dataset of monthly temperature and accumulated precipitation (Vose et al., 2014). Potential evapotranspiration (PET) was estimated using the *Thornthwaite* equation, which is based on monthly mean air temperature, latitude, and month (Thornthwaite, 1948).

Self-organizing maps

In this study, the SOM was trained with PDSI values on a 3 × 4 array with 12 nodes. The selected number of nodes determines the degree to which such groupings are generalized; therefore, a subjective criterion is often employed depending on the application of interest (Hewitson & Crane, 2002). As a measure of the SOM's sensitivity to various array dimensions, we tested several other array sizes (i.e. [3 × 3, 4 × 4], not shown) to determine the optimal number of nodes that best captured the variability of historical patterns and provided spatial coherence across the array. In our sensitivity analysis, SOMs with fewer nodes were inadequate at capturing the range of pattern variability, while larger-sized networks presented many similar patterns with few discernible differences.

The unsupervised training process for the SOM begins with random initialization, in which a random monthly PDSI observation from the input data is presented to the network and is forced to join one of the 12 nodes. The remaining monthly PDSI observations are then presented to the SOM to approximate the first guess or approximate arrangement of patterns across the nodes. Because the SOM is topologically organized, neighboring nodes are also updated as observations are assigned to particular nodes. In this study, a neighborhood radius size of .66 is used, and the learning rate declined linearly from 0.05 to 0.01 during SOM training. Over a series of 100 iterations, the weight vector is updated until the best match is found for each monthly PDSI observation using Euclidean distance. After approximately 50 iterations, the mean distance of each pattern to its closest unit decreased, indicating an improvement in the SOM training process. Patterns in each node are, therefore, theoretical representations of all the best-matched observations, which resemble the distributions of the raw PDSI data from 1895 to 2016.

After training, spatiotemporal analysis was conducted by mapping the representative PDSI vectors to each county in the CONUS for all 12 nodes. Each node contains the monthly timestamp for all the best matching observations throughout the study period, which provides a valuable way to diagnose whether there are any temporal trends among the patterns. First, we calculated the frequency of each pattern as a percentage of total months within the study period. This step provided a means of assessing the return periods of each pattern. Second, we calculated a persistence metric in each node to determine the duration of each pattern relative to its frequency of occurrence. Typically, this criterion is established with the drought metric used to quantify severity based on an accumulation of precipitation deficits. We defined persistence as the total number of times in which a spatial pattern occurred two or more consecutive months in a row, divided by the number of times where the node duration was only one month. Following Gibson et al. (2016), this value is a unitless number where higher values indicate a persistence with longer-duration and lower values indicate shorter duration. In this study, analyses were completed in RStudio (R Core Team, 2020) using the Kohonen package (Wehrens & Buydens, 2007); final maps were created using the Maps package (Wehrens & Kruisselbrink, 2018) and statistical analyses were performed using the modified MK package (Patakamuri & O'Brien, 2020).

As a final statistical measure of these trends, we applied the Mann-Kendall (MK) nonparametric trend test to determine the nature of trends from 1895 to 2016. The MK trend test is commonly employed to detect monotonic trends in a time series of climate or hydrologic data (Kendall, 1975; Mann, 1945; Pohlert, 2015). To account for seasonal dependence, we carried out a seasonal Mann-Kendall trend test with statistical significance determined at $p < 0.10$ for a two-sided test as a secondary measure for robustness (Hirsch et al., 1982). Autocorrelation influences the statistical significance of the MK test by increasing the probability of detecting trends when actually none exist (Yue et al., 2002). Despite this well-known assumption, studies often fail to address the issue of autocorrelation. In our study, as a final sensitivity analysis, a modified MK that adjusts for autocorrelation using a variance correction approach, was applied to address potential issues of serial correlation in the trend analysis and to ensure the robustness of trend observations across a long time period (Hamed & Ramachandra Rao, 1998).

Extratropical cyclone track anomalies

To evaluate the spatial patterns of synoptic activity (i.e. frequency of frontal passages) associated with PDSI's SOMs, monthly extratropical cyclone (ETC) track anomalies from 1948 to 2018 were evaluated against each of the SOM nodes. The ETC tracks were extracted from the National Centers for Environmental Prediction (NCEP) reanalysis of one dataset (Kalnay et al., 1996) by associating nearby successive low-pressure centers between each 6-hourly timestep. ETCs were assumed to have dissipated if no low-pressure center was found within 750 km of the last timestep. This approach closely mirrored the one used in Klotzbach et al. (2016) in their ETC analysis based on the 20th Century Reanalysis. In an effort to ensure spurious tracks were excluded from the analysis, only ETCs with a duration of 48 hours (8-time steps) or more were included. Monthly counts of ETC tracks were then placed onto a 20 km resolution grid such that every pixel within a 250 km radius of a track was considered to have had an ETC pass by. The mean and standard deviation of ETC track counts were evaluated for each of the 12 months of the year from 1948 to 2018. This allowed for the derivation of monthly standardized ETC track anomalies by subtracting the month's ETC track counts from the historical (1948 to 2018) mean and dividing through by the historical standard deviation. These track anomalies were used to spatially compare areas of the U.S. that had higher or lower levels of atmospheric activity with the distinct drought patterns identified using self-organized maps.

Results

Figure 1 presents a 2D topological overview of multidimensional groupings within our input PDSI dataset arranged by similarity. The SOMs spatial organization aligns similar patterns in proximity to each other, and dissimilar patterns further apart (Hewitson & Crane, 2002) expressing extremes in each of the four corners of the SOM, with more smooth continuous patterns in between (Sheridan & Lee, 2011). The resultant SOM nodes (Figure 1) exhibits a continuum of spatial patterns from 1895 to 2016, where we see more extreme drought intensity beginning at the top-left quadrant, and as we transition towards the bottom right, more extreme wet trends are clustered together. Persistence of trends (lower right value) appears to increase across each row from left to right indicating that across time, the overall persistence of wet trends were greater than drought conditions (Figure 1). Notably, there appears to be an inverse relationship between pattern frequency (lower left value) and how long trends persist (lower right value), where conditions that occurred at a higher frequency persisted for shorter durations, and vice versa. Nodes displaying widespread drought patterns occurred at a greater frequency but persisted less. In contrast, nodes with above normal moisture conditions primarily concentrated across the Great Lakes, the Midwest, the North and Southeast, and parts of the upper Great Plains occurred less often but persisted for longer.

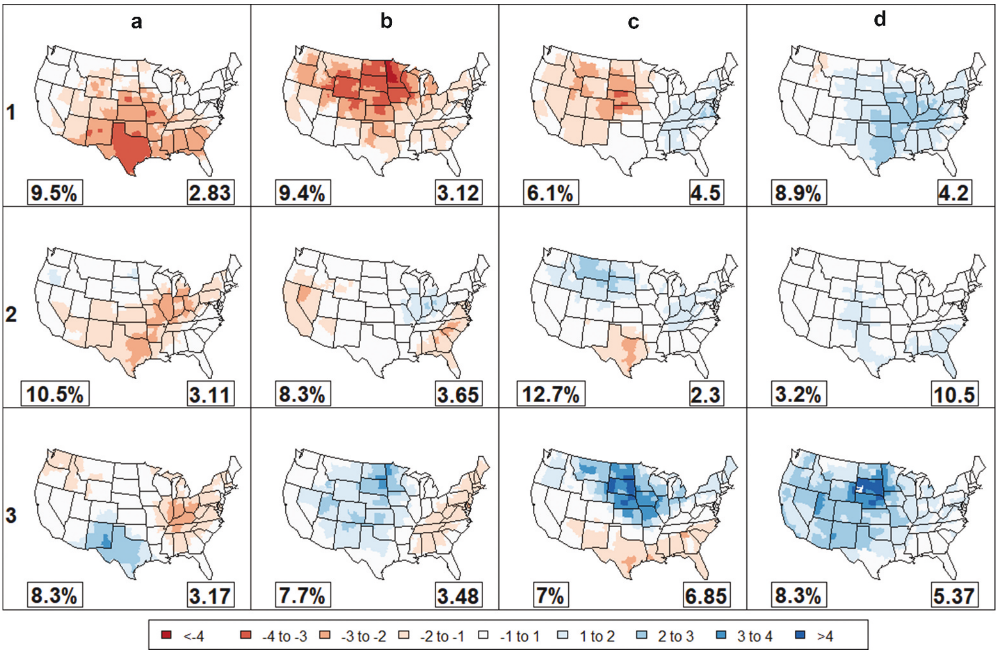

Figure 1. Self-Organizing Cartographic Maps (1–12). Percentage value (lower left) indicates the percentage of total months within the study period. Values in the lower right represent the persistence of trends, where higher values indicate longer duration, and lower values indicate shorter duration trends (Gibson et al., 2016).

As expected, drought trends are predominantly located in the West and Southwest regions. However, drought conditions in the Southeast (A3, B2, B3, and C3) and Midwest (A1, A2, B1, and C1) are also displayed in several maps. Node D1 exhibits above normal wetness in the Northeast, Southeast, and Midwest, with similar trends displayed in node D3 (Figure 1). This wetting trend occurred at a higher frequency and persisted for longer durations when compared to apparent drought conditions in the same locations as seen in nodes A3 and B3. In addition, nodes with drier conditions predominantly concentrated in the Western portion of the CONUS (B2, C1) were less frequent but more persistent than other drought patterns. The most frequent of drought patterns is shown in node A2, at 10.5%, extending from eastern Texas up into the Ohio Valley. Moreover, the most severe PDSI patterns of drought (widespread −3 to −4 values) fall over regions that were impacted by the 2012 drought.

Results from the time series analysis provide a more comprehensive explanation of observed spatial distributions. In one corner of the SOM (Figure 1), nodes A1 and B1 show widespread extreme drought conditions. However, corresponding plots A1 and B1 in Figure 2 reveal that these events occurred relatively infrequently over time and persisted the most during the 1950′s and the 1930′s respectively. Similarly, of the nodes displayed in the SOM, C1 was found to be less common over the study period, primarily observed in the 1930s and early 1980s. At the other extreme of the SOM continuum, nodes B3, C3, and D3 displaying widespread above normal moisture conditions were more prevalent during and after the mid-1980′s. The organizational structure of the SOM

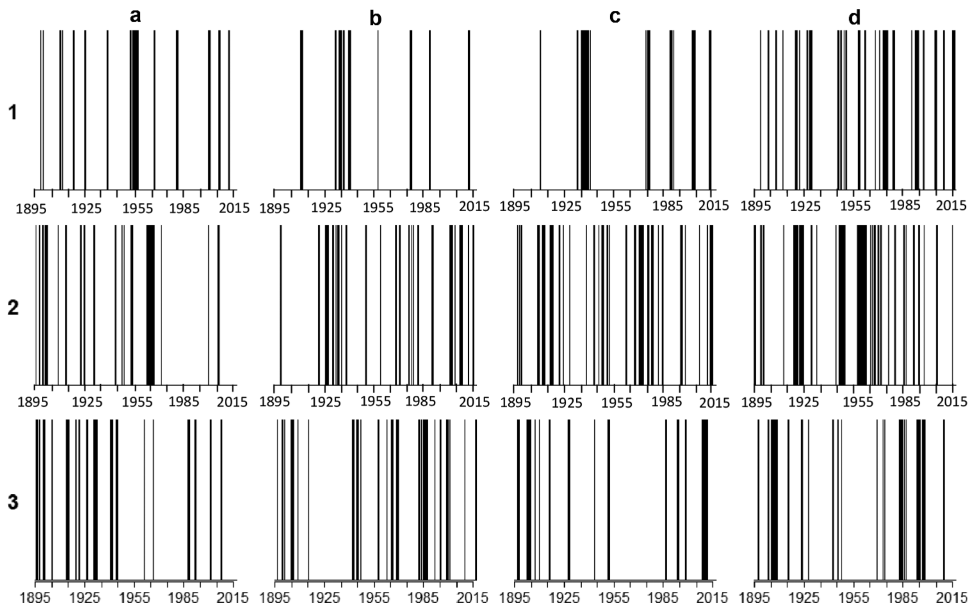

Figure 2. For each cartographic visualization (Figure 1) a corresponding absence and presence bar plot was generated to visually characterize both the return periods and persistence (duration) of patterns from 1895 to 2016. Thicker bands represent longer persistence.

suggests that nodes across the center (row 2) represent transitional patterns in the continuum between more extreme patterns with greater severity (higher absolute values of PDSI) and/or spatial extent. For instance, patterns of concurrent wet and dry conditions (A2-D2) shown in Figure 2 are more evenly distributed over the study period than widespread drought (A1-C1), and wet patterns (B3-D3). Overall, the proportion of frequency was revealed to be fairly homogeneous (between 8 and 10%) across the SOM. However, map C2 at 12.7% was the most common pattern.

As a secondary measure of persistence, we also examined the average length of consecutive months for SOM patterns. Across nodes, the average length of consecutive months remained similar with B1, a pattern of extreme drought, having the largest mean number of consecutive months in the same node, followed by A1, C3, and D4. On average, when a node is established, it persists for approximately 4 to 5 months, and once established, it will repeat the following month approximately 72 to 85% of the time. The most extreme drought patterns (B1, A1), common among the historical 1930s and 1950s droughts, had a longer period of five to six mean consecutive months of the pattern. However, these severe drought patterns (B1, A1, and C3) do not occur often but persist across months (i.e. a greater number of consecutive months with SOM pattern).

Both Mann-Kendall and the seasonal Mann-Kendall trend tests showed that trends in our study were statistically significant across 8 of the 12 nodes (alpha < 0.10). From the seasonal MK test, we observed a total of eight statistically significant trends; specifically, four significant increasing and four significant decreasing trends (Table 1). While this nonparametric test is common in climatic and hydrologic time series trend analysis, few studies address the issue of autocorrelation (Hamed & Ramachandra Rao, 1998). To

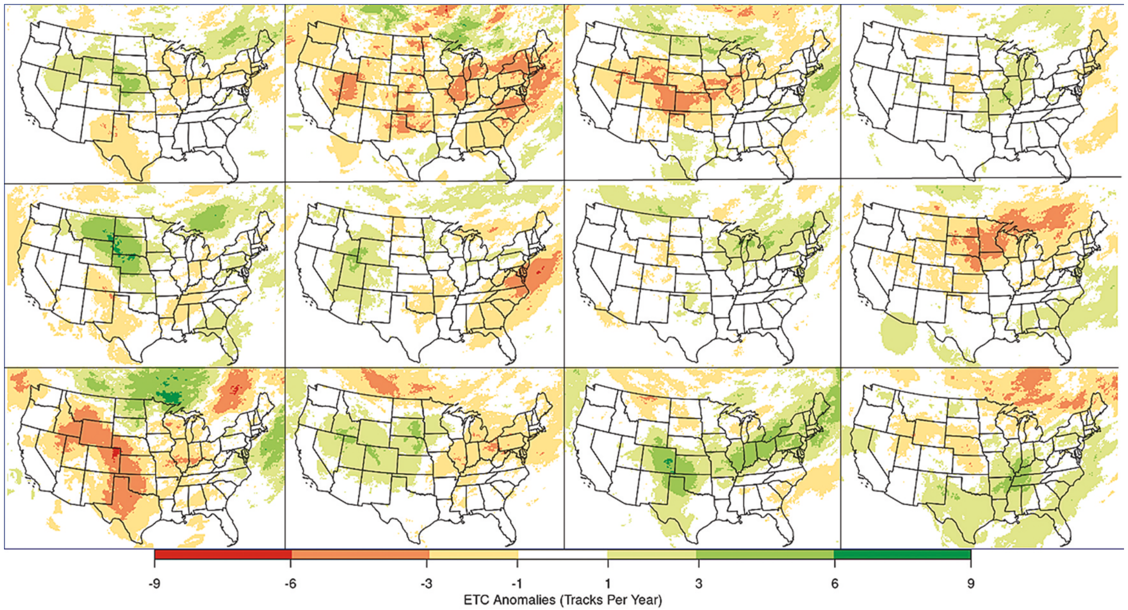

Figure 3. Extratropical cyclone track anomalies for each SOM node from 1948 to 2018.

Table 1. Mann Kendall (Tau), Seasonal Mann Kendall (Tau), and Hamed and Ramachandra Rao (1998) approach for adjusting for serial correlation in Mann Kendall time-series analysis. A positive Tau statistic indicates that a trend is increasing over time. A negative Tau statistic indicates that a trend is decreasing over time. Statistical significance level determined at $p \leq 0.10$.

	Mann Kendall (Tau)	2-sided *p*-value	Seasonal Mann Kendall	2-sided *p*-value	Mann Kendall (Tau) Variance Correction Approach	*p*-value
A3	−0.108	0.000	−0.109	0.000	−0.042	0.146
B3	0.060	0.005	0.060	0.005	0.023	0.336
C3	−0.004	0.847	−0.004	0.844	−0.001	0.960
D4	−0.009	0.672	−0.009	0.661	−0.003	0.901
A2	−0.076	0.000	−0.078	0.000	−0.029	0.300
B2	0.075	0.000	0.076	0.000	0.027	0.214
C2	0.002	0.897	0.002	0.897	0.001	0.960
D2	−0.052	0.014	−0.052	0.015	−0.023	0.425
A1	0.011	0.592	0.011	0.594	0.004	0.849
B1	−0.058	0.005	−0.059	0.006	−0.019	0.451
C1	0.076	0.000	0.078	0.000	0.026	0.319
D1	0.104	0.000	0.104	0.000	0.046	0.137

ensure trends were robust to the effects of serial autocorrelation we also included results from the Hamed and Ramachandra Rao (1998) approach (Yue et al., 2002). After variance correction with the modified Mann Kendall (Hamed & Ramachandra Rao, 1998), no trends were statistically significant, alpha < 0.10, highlighting the influence of autocorrelation in the Mann Kendall statistic and the probability of detecting trends when none exist. Nodes A3 and D1 were the nearly significant p-value < 0.15 and had higher tau values than other nodes (Table 1). In Figure 1, these PDSI patterns correspond with decreasing drought trends in the eastern US (D1) and southern US (D1, A3) and increasing drought in the Midwestern US (A3). Overall these trend results suggest that neither of the nodes are becoming more common over the other node values.

The ETC track anomalies were found to be in general agreement with most of the PDSI SOM patterns, with positive and negative track count anomalies spatially associated with areas of wetter and drier PDSI conditions. This pattern was particularly true of SOM node B1 (node 10), which had widespread negative PDSI and ETC anomalies across the CONUS (Figure 3). In a similar way, the positive and negative PDSI regions of SOM B3 (node-2) were spatially associated with the positive and negative ETC track anomalies across the western and eastern portions of the US, respectively. However, this was not the case for SOM nodes A3 (node-1), D4 (node-4), D2 (node-8), and A1 (node-9), which had areas with inversely related patterns between wet and dry PDSI conditions and fewer (negative) and greater (positive) anomalies, respectively. In A3 (node-1), for instance, the reduction in ETC tracks over the eastern edge of the Rockies and south through Texas was not well matched with the wetter PDSI conditions over New Mexico and Texas despite a good agreement over Illinois, Indiana, and Washington State. Similarly, a reduction in ETC tracks over the eastern edge of the Rockies was not well matched with widespread wetter PDSI conditions over much of western half of the US. The mismatch between the PDSI patterns and ETC tracks could be related to a number of factors such as the quantity of precipitation associated with a single ETC or a sharp drop in temperature conditions, which would reduce evaporative demand and result in wetter PDSI conditions. It should also be noted here that there are other sources of drought ameliorating precipitation (wetter PDSI conditions) beyond ETC tracks, such as those associated with atmospheric rivers, tropical cyclones, and monsoonal activity. That said, the spatial patterns of the PDSI-based SOMs were well matched with ETC track anomalies.

Discussion

In this study, we examined the large-scale spatiotemporal patterns of meteorological drought over the CONUS and described how they have changed over time using self-organizing maps. Our findings revealed no statistically significant changes in moisture across the majority of SOM patterns for the entire sample period 1895 to 2016. Yet, our time-series analysis (Figure 2) showed increased persistence of wet trends over the latter half of the 20th century, primarily concentrated in the Northeast, Midwest, and upper Great Plains. These findings coincide with other studies where we see that a greater number of wetting trends predominantly took place after 1970, of which are primarily concentrated across the Pacific Northwest, Midwest, upper Great Plains, and the Northeast portions of the U.S. (Andreadis & Lettenmaier, 2006; Balling & Goodrich, 2011; Ficklin et al., 2015; Groisman et al., 2004; Soulé, 1993).

Droughts were found to occur at a higher frequency generally but did not persist for long durations, with the expectation of the 1930′s and 1950′s droughts. In contrast, wet trends occurred slightly less frequently but persisted for longer when they did occur. The spatial distribution of trends documented here qualitatively concur with previously observed general drying and wetting trends in the United States (Andreadis & Lettenmaier, 2006; Easterling et al., 2007; Ficklin et al., 2015; Soulé & Yin, 1995). However, direct comparability is limited due to differences in timescales between studies and climate variables and metrics applied to characterize trends, for example, measures of soil moisture conditions versus long-term precipitation data. Extreme drying trends concentrated in the West, Southwest, Central Plains, and the southeast demonstrated a statistically significant increase, suggesting that an increase of precipitation frequency across much of the U.S. may be outweighed by an increase in evapotranspiration caused by temperatures in these locations.

Our results revealed notable wetting trends in concurrence with extreme drying trends, suggesting that replication of the analysis using the *Penman-Monteith* method would produce similar results. Nonetheless, testing these differences is necessary to confirm this and further strengthen the findings described here. In addition, our subjective persistence criteria may have overestimated or underestimated the duration of overall trends. The PDSI has a lag period of about 12–18 months thus cannot capture the effect of snowmelt and runoff. In turn, this limits our ability to quantify seasonal changes that precede or follow extreme drying or wetting patterns. Seasonal influences on drought have been shown to vary regionally and can be further linked to atmospheric and oceanic influences, such as warm-phase (El-Niño) and cold-phase (La Niña) ENSO teleconnections (Ford & Labosier, 2013), as well as other large-scale oceanic oscillations like the Atlantic Multidecadal Oscillation and the Pacific Decadal Oscillation, which may interact with ENSO to influence regional precipitation (Dai 2013b, 2013a).

In this study, ETC track densities were generally found to be lower than usual (i.e. less active weather pattern) over areas with dryer PDSI conditions or more drought. This trend was particularly true for PDSI indicated drought conditions over the eastern half of the U.S. (A2, A3, B1, B2, B3, and C3). A majority of the ETCs that impact this region originate from an area of cyclone genesis along the eastern edge of the Rocky Mountains. In general, the eastern half of the U.S. is a moisture-rich environment where the presence of ETCs increases the potential for precipitation and large temperature swings that can impact PDSI conditions. In contrast, the Western U.S. (west of the Rockies including west Texas) is a moisture scarce region where precipitation is mainly seasonal and is not always associated with ETCs (i.e. atmospheric rivers or monsoon rains). As a result, wet PDSI conditions may not align with ETC anomalies, and other precipitation sources should be considered outside of ETC to explain PDSI patterns. For instance, many of the drought patterns over North America and the Desert Southwest (Cole & Cook, 1998) have been largely associated with La-Nina conditions (E. R. Cook et al., 2007), which is the presence of cooler waters in the eastern tropical Pacific. The cooler ocean waters off of southern California and Baja Mexico have been associated with subsidence and limited moisture transport (Namias, 1955), weakening the North America Monsoon (NAM). The NAM is a crucial source of precipitation for the U.S. Desert Southwest that includes Arizona, New Mexico, Utah, Colorado, and western Texas. In these circumstances, moisture available for precipitation would be diminished in this region for any extra-tropical cyclones that may develop. These trends highlight the importance of moisture availability on regional differences in drought evolution.

After performing the modified MK test to account for serial correlation, we observed no statistically significant trends in moderate-to-severe drought conditions during the 1895 to 2016 time period. Nodes A3 and D1 had the lowest alpha values (alpha < 0.20), which resembled increasing drought in the midwest and decreasing drought in the south and the eastern US. These nodes did not encompass the significant drought periods of the 1930s and 1950s droughts, which A1 and C1 dominated, but rather short-duration droughts in the latter part of the study period. Heim (2017) compared regional 1998–2014 droughts across the U.S. to historical national-scale droughts of the 1930′s and 1950′s. Their analysis revealed that the 1950s drought was the most severe regarding areas characterized by long-duration dryness, whereas the 1998–2014 drought episodes expressed more frequent short-duration trends. This phenomenon concurs with the recent literature on flash droughts, which characterizes the conditions that led to the 2012 drought across much of the U.S. (Otkin et al. 2018). Flash drought is a more recent seasonal to sub-seasonal climatic phenomenon characterized by rapid intensification of dryness driven by coupled atmospheric extremes (high temperatures, increased radiation, high wind, no precipitation) that dramatically increases evaporative stress on the environment (Pendergrass et al. 2020). As compared to the 1930s and 1950s the 1998–2014 drought episodes were found to be much warmer and wetter, that is, more regions were experiencing wet conditions concurrently with dry conditions in others and had persisted the longest, which is strikingly consistent with patterns displayed in nodes B3, C1, and C3 (Figure 1).

Previous assessments of historical drought trends have described the sensitivity of the significance of trends on temporal scaling and regional variability (Alexander, 2016; Soulé, 1993; Soulé & Yin, 1995). Our results confirm previous work in the Continental US that highlights no increasing frequency, spatial extent, or severity of droughts during the twentieth century despite considerable decadal variability (Karl & Heim, 1990). In addition, our results confirm regional work in the southeastern US, which found infrequent drought persistence using SPI (Ford & Labosier, 2013). However, Easterling et al. (2007) found that although the contiguous U.S. had experienced an increase in temperature, the tendency of drought in the southeast has been obscured by the coupled increase in precipitation variability. Node A1, a pattern of extreme drought in the southeastern US, was one of the least persistent patterns in our sample (2.83; Figure 1). Yet, a pattern of moderate drought in the southeastern US (Node C3) was found to be one of the more persistent patterns (6.85) in contrast to Ford and Labosier's (2013) main finding. However, it accounted for a small portion of the sample size (7%) and suggests the importance of differentiating between moderate and severe forms of droughts when comparing results across studies.

Similar to drought patterns found by Ganguli and Ganguly (2016), we noted that the drought patterns in our study (C1 and A1) in the 1930s and 1950s are common in recent years (2010–2016). However, Ganguli and Ganguly (2016) found the spatial coverage of the most recent droughts (the 2010s-2016) exceeded the iconic droughts of the 1930s and 1950s. In contrast, we found that the iconic drought patterns (node A1, B1, and C3) were not as persistent in modern times compared to the 1930s and 1950s (Figure 2). However, once these patterns were set up in the 1930s and 1950s they did continue, on average, for consecutive months (4 to 5-month periods).

Soulé (1993) compared three discrete 30-year intervals over a 90-year period and found an inverse relationship of mean moisture conditions between periods. During the early 30-year period, regions such as the Great Plains and Midwest displayed below-normal moisture conditions. Compared to middle and later 30-year intervals, these same regions exhibited above-normal moisture conditions. Yet, Soulé (1993) found no significant differences in mean moisture conditions in over 50% of climatic divisions for all 30-year interval comparisons. Alexander (2016) further elaborates on the challenges faced by the IPCC when managing existing inhomogeneities on monthly time-series data and attempting to delineate climatic extremes. As such, indications of significant changes to moisture are subject to the chosen temporal and spatial scale of the analysis. The prevalence of statistically insignificant trends in our study could also be attributed to both the temporal and geographic scales of our analysis.

Lastly, our study also highlights the necessity of accounting for autocorrelation in time series analysis, as many studies may be finding significant trends as the result of positive autocorrelation rather than significant increases in precipitation (Hamad and Rao). After correcting for correlation, none of our trends were statistically significant despite significant MK and Seasonal MK tests. Future analysis should account for variance correlation methods like Hamed and Ramachandra Rao (1998) to ensure trends are robust.

Future work could expand on our findings by verifying the significance of increasing or decreasing trends at regional to local scales, as well as applying the SOM to the self-calibrated PDSI to aid a more refined understanding of current drying trends in these locations. Future studies seeking to understand seasonal differences of drought could then extract linkages between dates of occurrence and the synoptic conditions associated with common drought patterns. Differences in SOMs based on other popular drought metrics such as the Standardized Precipitation Index (SPI) or the Standardized Evapotranspiration Index (SPEI) can provide additional insight using differing perspectives of drought and comparing geographic similarities of drying and wetting trends. The SPI is recommended as the best measure of drought for its simplicity (Hayes et al., 2011), and the SPEI further extends this metric to calculate potential evapotranspiration (PET), a known driver of drought across the Western U.S. The vacillation regarding the optimal formulation of PET is evident across the literature, and more research is necessary to capture the complexities that lead to the development of drought (Seneviratne, 2012).

Conclusion

Global increases in temperature and precipitation variability have been well documented (Dai 2013a; Alexander et al., 2006; Groisman et al., 2004; Pal et al., 2013); however, the extent to which such climatic shifts will exacerbate extremes in the U.S. remain somewhat unclear given regional drought variability. In addition, because of limited access to high-quality long-term climatic datasets and divergent findings proposed in the drought literature (Dai, 2011a; Dai et al., 2004; Sheffield et al., 2012), a notable amount of uncertainty surrounding future trends continues to exist (Seneviratne, 2012; Trenberth et al., 2013).

Our findings showed that self-organizing maps can be successfully applied to a trend analysis of historical drying and wetting patterns. Our time-series analysis showed that the occurrence of patterns was evenly distributed, but patterns of greater persistence were revealed to be wet conditions. Moreover, the only statistically significant increasing trend was related to drought, suggesting that both conditions (increased drought and intensified precipitation) are occurring, but the drivers behind these trends remain ambiguous. Results further corroborate the notion that drought is increasingly region-specific and should be observed exclusively at the regional scale to account for the unique forcing's influencing trends (Ficklin et al., 2015).

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability

The data that support the findings of this study are openly available at the National Center for Environmental Information (NCEI) and the National Integrated Drought Information System (NIDS).

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