EXAMINING SPATIOTEMPORAL TRENDS OF DROUGHT IN THE CONTERMINOUS UNITED STATES USING SELF-ORGANIZING MAPS

A Thesis
by
MARIA C. MORENO

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APPROVED BY:

____
Margaret M. Sugg
Chairperson, Thesis Committee

____
Johnathan W. Sugg
Member, Thesis Committee

____
Baker L. Perry
Member, Thesis Committee

____
Saskia van de Gevel
Chairperson, Department of Geography and Planning

____
Mike McKenzie, Ph.D.
Dean, Cratis D. Williams School of Graduate Studies

Abstract

EXAMINING SPATIOTEMPORAL TRENDS OF DROUGHT IN THE CONTERMINOUS UNITED STATES USING SELF-ORGANIZING MAPS

Maria Moreno
B.A., Appalachian State University
M.A., Appalachian State University

Chairperson: Margaret M. Sugg

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 and prolonged temporal scale. The evolution of drought and its impacts are typically region specific; the West and Southwest U.S. have experienced severe droughts at a higher frequency than the East and parts of the Midwest. While these regions do experience drought, intensified precipitation variability also obscures how drought may be changing in these locations. To better understand these trends, we examine the spatiotemporal trends of drought using self-organizing maps (SOM). SOMs are a novel, 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 1895-2016. After training, we created cartographic visualizations of the SOM output and conducted a subsequent time-

series analysis to link with our spatial observations. Our results concur with other observed trends which identify no significant increase in drought over the last century. Over the last 40 years, we observed increased precipitation in the Northeast, Midwest, and upper Great Plains across several nodes. Of particular interest, we noted a statistically significant increase in drought patterns in Southwestern and Western U.S. over the study period. These findings further support the notion that drought is region-specific and may manifest in certain regions more severely.

Acknowledgments

This work would not have been able to reach completion without the unwavering support of my research advisors, Dr. Margaret Sugg, and Dr. Johnathan Sugg, who have both played integral roles in my success as a master's thesis student. Dr. Maggie Sugg has been an especially wonderful mentor as we both navigated through completing a thesis virtually. Her encouragement and attentiveness provided me the tools I needed to succeed during uncertain times, and for this I am sincerely grateful. Dr. Johnathan Sugg has also been a dedicated advisor, whose guidance in my methods was an essential component to the completion of my thesis. I am thankful for his contributions during this process. I would like to acknowledge, and thank fellow committee member, Dr. Baker Perry, whom without I would not have found my passion for research and climatology and embark on the journey of obtaining a masters in Geography. I would also like to recognize and thank Ronnie Leeper with the North Carolina Cooperative Institute for Climate and Satellites (NCICS) for providing the data used to complete this work.

Given the unusual circumstances, I was unable to present this work at the Association of American Geographers (AAG) 2021. Regardless, I would still like to recognize the Office of Student Research, an on-campus organization which offered to provide funding for an opportunity to present at the AAG. I would also like to offer special recognition to the Department of Geography and Planning at Appalachian State University for providing a safe, and open environment where students and faculty support each other, both morally and academically. Despite the challenges the department has been faced with, our department has shown admirable resilience. A special thanks to our program director Dr. Derek Martin, and our department chair Dr. Saskia Van de Gevel whose devotion to students and higher education have made my experience welcoming and enjoyable.

Finally, I would like to acknowledge my family, and my husband who have been patient and caring throughout this entire journey. My mother and father Cristina and Beto, who have only shown me to persevere and challenge myself, I am grateful for their ongoing inspiration. A special thanks to my husband, Brandon Cox, for always encouraging me to pursue all my academic dreams.

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Foreword

The main body of this thesis is formatted in accordance with the guidelines for manuscript submission to *International Journal of Climatology*, a journal which aims to expand and stimulate research in climatology, covering a range of topics, including climate and society interactions, climatic variability, and climate change, and local to global scale climate observations and modeling.

Introduction

Droughts are one of the costliest natural hazards; over the last 40 years, 26 droughts have cost at least $249 billion USD in the United States, averaging about $9 billion of annual loss in damages per event (NIDIS, 2020). Despite this, drought events are not easily quantified; on a global scale, there is much debate on whether drought frequency and severity has increased, and more contention prevails regarding the extent of anthropogenic forcing's on drought (IPCC, 2014; Trenberth et al. 2014). Unlike other natural hazards, drought onset is insidious and often affects a greater spatial extent and prolonged temporal scale. In accordance, continuous direct observations of drought are necessary to understand how projected increasing temperature and shifting precipitation trends will influence drought's natural variability.

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 are less understood (Easterling et al. 2007; Trenberth et al. 2014). In the United States, the spatiotemporal variations of drought differ geographically due to climate forcing's unique regional characteristics (Ficklin et al. 2015). In the U.S., the West has seen a greater frequency and severity of droughts, while a great majority of the country including the East and parts of the Midwest, have seen intensified precipitation variability. Data inconsistencies due to limited availability or access to high quality long-term precipitation data, varying baseline periods, and techniques have amplified the uncertainties in our understanding of climate extremes such as drought (Alexander 2016; Trenberth et al. 2014).

Consequently, as droughts are expected to increase in frequency and severity, the current body of literature seeks to better understand climate forcing's, or the internal regional variability that drive anomalous drying or wetting trends. To our knowledge, there is no other study that examines the spatiotemporal trends of drought using self-organizing maps (SOM). SOM's have been an exceptionally useful tool in meteorological and atmospheric research (Hewitson and Crane 2002; Skific and Francis 2012; Sheridan and Lee 2011; Sugg and Konrad 2017). The objective of this study is to observe the general trends of drought of the conterminous United States (CONUS), identify anomalous drying or wetting patterns, and assess how they have changed over time across different regions. Results documented here will inform future studies exploring drought trends by providing a new way to examine geographic patterns associated with meteorological drought over the last century.

EXAMINING SPATIOTEMPORAL TRENDS OF DROUGHT IN THE CONTERMINOUS UNITED STATES USING SELF-ORGANIZING MAPS

Camila Moreno[1], Dr. Margaret Sugg[1], Dr. Johnathan Sugg[1], Dr. Baker L. Perry[1], Jennifer Runkle[2], Ronnie Leeper[2]

1 Department of Geography & Planning, Appalachian State University, Boone, NC, USA
[2] North Carolina Institute for Climate Studies, North Carolina State University, NC, USA

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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 and prolonged temporal scale. The evolution of drought and its impacts are typically region specific; the West and Southwest U.S. have experienced severe droughts at a higher frequency than the East and parts of the Midwest. While these regions do experience drought, intensified precipitation variability also obscures how drought may be changing in these locations. To better understand these trends, we examine the spatiotemporal trends of drought using self-organizing maps (SOM). SOMs are a novel, 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 1895-2016. After training, we created cartographic visualizations of the SOM output and conducted a subsequent time-series analysis to link with our spatial observations. Our results concur with other observed trends which identify no significant increase in drought over the last century. Over the last 40 years, we observed increased precipitation in the Northeast, Midwest, and upper Great Plains across several nodes. Of particular interest, we noted a statistically significant increase in drought patterns in Southwestern and Western U.S. over the study period. These findings further support the notion that drought is region-specific and may manifest in certain regions more severely.

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 $249 billion USD 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 has increased, and even more uncertainty regarding the extent of anthropogenic forcing's on drought exists (IPCC, 2014; Trenberth et al. 2014).

Uncertainties concerning drought in the CONUS are ongoing as scientific consensus of *regional* drought trends in the United States is lacking. Regions characterized as naturally dry, such as the Southwest, have experienced increased persistence of droughts, and naturally wet regions have experienced increased precipitation variability, i.e., increased intensity when it rains (Andreadis and Lettenmaier 2006; Groisman et al. 2004, 2008; Li, et al. 2013). 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 are less understood (Easterling et al. 2007; Trenberth et al. 2014). Accordingly, continuous direct observations of drought are necessary to understand how projected increasing temperature and shifting precipitation trends will influence drought's natural variability.

The pervasiveness of drought negatively impacts a wide variety of sectors, including agriculture, energy, ecosystem viability, and public health (Crausbay et al. 2017; Sugg et al. 2020; Vicente-Serrano et al. 2020). Drought is understood to have occurred when there is a deficit or total absence of precipitation over a prolonged period (IPCC, 2007). However, unlike other natural hazards, drought onset is insidious and often affects a greater spatial extent and prolonged temporal scale. Droughts can be described in many ways and are typically characterized by their impacts, which largely drives how they are framed. *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). Plant available water shortages resulting from prolonged drought eventually lead to what is known as *agricultural drought*, where crop yields are significantly depleted per reduced soil moisture (Heim, 2002). Much like agricultural drought, *hydrological drought* becomes evident when sustained low levels of precipitation begin to reduce streamflow, groundwater supply, reservoir availability, and lake levels (Heim, 2002). *Socioeconomic drought* encompasses the relationship between the supply of an economic good that cannot meet societal demands due to the impacts of meteorological, agricultural, and hydrological drought (Heim, 2002). According to the National Oceanic and Atmospheric Administration (NOAA), these are the four universally recognized drought types; however, there has been a recent push to 'redefine drought' to capture the ecological dimensions of drought (Crausbay et al. 2017). With an emphasis on the human-nature relationship, Crausbay et al. 2017 defines *ecological drought* as "an episodic deficit in water availability that drives ecosystems beyond thresholds of vulnerability, impacts ecosystem services and triggers feedback in natural and/or human systems." Unlike other drought definitions, *ecological drought* attempts to encapsulate the complexity of drought; however, quantification of such relationships remains complex and becomes increasingly difficult to capture without a comprehensive drought index.

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). Many early indices are specific to one region or application, thus are inadequate for capturing geographical differences of drought (Heim, 2002). One of the most widely used drought indices is the Palmer Drought Severity Index (PDSI), developed in 1965, based on the water-balance model. Other popular drought metrics include the Standardized Precipitation Index (SPI), which only considers precipitation. As an extension of SPI, the Standardized Precipitation Evapotranspiration Index (SPEI) was developed by Vicente Serrano et al. (2010) to account for the effect of temperature on potential evapotranspiration (PET). 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. The consequences of these varying drought metrics make the quantification of drought challenging and inherently subjective. Depending on the chosen drought index, the emphasis placed on the relative roles of precipitation, evapotranspiration, and available water content vary, thus can change the interpretation of observed drought trends (Trenberth et al. 2014).

Tree-ring reconstructions of drought have revealed that the United States has experienced recurrent *megadrought*s (severe drought lasting longer than two decades) over the last 1000 years, although this type of drought has not yet been documented in the 20th century (Cook et al. 2007). Other notable droughts include the most severe since 1700, the 1930's Dust Bowl (Cook et al. 1999), and the Southwest drought of 1950-56 (Cook et al.

2007), and more recently 2012 where 65.5% of the U.S. experienced moderate to severe drought according to the USDM (Heim, 2017). 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 and 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. 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 and Labosier 2014; Wang et al. 2010; Seager et al. 2009). Moreover, drought variability is naturally influenced by teleconnections such as El Niño-Southern Oscillation, in which the warm phase (El Niño) promotes increased precipitation in the winter across the Gulf Coast, and Southeast and in contrast creates warmer, and drier conditions in Northern and Western parts of the U.S. (Trenberth et al. 2014). In comparison, the opposite is true during the cold phase of ENSO (La Niña), which normally is associated with drier conditions and increased temperatures across the Southeast, and Gulf Coast, and wetter conditions in the Northern U.S., and Pacific Coast. The North Atlantic Subtropical High, also known as the Bermuda High, further influences the probability of drought during the warm season because it promotes increased air temperatures and decreased precipitation events when it is displaced inland over the Southeastern US (USDA, 2017). Projected warming trends augment the many concerns regarding how an increase in temperature will affect droughts' persistence.

Climate extremes such as drought have been the subject of many scientific studies to better understand their associated climatic conditions and their impacts. Nonetheless, drought trends as compared to the historical record remain contested given notable gaps across metrics used to define drought. The IPCC Synthesis Report (2014) attributed increased global aridity since the 1950's to warming trends, i.e., climate change, although with low confidence due to difficulties discerning decadal-scale variability from long-term trends of drought, as well as regional differences of observed drought trends. Some studies have supported the claim that drought trends have been increasing since the 1950's (Dai 2011b; Dai, 2013; 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 forcing's (Sheffield et al. 2012). Data inconsistencies due to limited availability or access to high quality long-term precipitation data, varying baseline periods, and techniques have amplified the uncertainties in our understanding of climate extremes such as drought (Alexander 2016; Trenberth et al. 2014). 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. 2014).

Higher air temperatures allow the atmosphere to hold more moisture; therefore, in regions such as the Southeast, there is an expected probable increase and intensification of rainfall (Wang et al. 2010, Li et al. 2013); however, precipitation variability may mask how drought has changed in these locations (Easterling et al. 2007). Consequently, as droughts are expected to increase in frequency and severity, there is a growing need to continue monitoring drought to identify salient, and significant trends for improved planning measures in the future. The current body of literature seeks to better understand climate forcing's, or the internal regional variability that drive anomalous drying or wetting trends. However, anthropogenic forcing's that may enhance droughts are less understood and may alter natural patterns of drought.

Previous studies examining patterns of drought have relied on simulated datasets of various hydro-climatic factors (e.g., soil moisture, runoff) to reconstruct past drought in the 20th century (Andreadis and Lettenmaier 2006). Ficklin (2015) tested spatial trends of drought using Mann-Kendall trends analysis and found four grouped regions showing increasing (upper Midwest, Lousianna, Southeast and Southwest), and four grouped regions displaying decreasing trends (New England, Pacific Northwest, upper Great Plains, and the Ohio River Valley). While these studies revealed that regional differences were driven by local variations in precipitation and temperature patterns, results have been limited by technical limitations of multiple regression, including the assumption of linearity, estimating multicollinearity, and the inability to determine causality.

Self-organizing maps are a novel, 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 and Crane 2002; Skific and Francis 2012; Sugg and Konrad 2017), and have quickly gained traction across a variety of climatological applications (Sheridan and Lee 2011). 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). 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 and Francis 2012). SOMs are used for pattern detection in data sets that may otherwise be too great in the scope of analysis and subject to human error (Kohonen, 1990) and are particularly useful for analysis that considers spatial variations across temporal scales guided by human expertise (Andrienko et al. 2010). SOMs also associate separate groups with similar or adjacent patterns (Hewitson and Crane 2002).

To our knowledge, there is no other study that examines the spatiotemporal trends of drought using self-organizing maps (SOM). The objective of this study is to observe the general trends of drought of the conterminous United States (CONUS) from 1895-2016 to identify anomalous drying or wetting patterns and quantify how they have changed over time across U.S. regions. To satisfy these objectives, we will be using self-organizing maps, a sophisticated and powerful technique used to characterize groups or clusters similar (or dissimilar) to each other from large datasets and derive diagnostic inferences from such maps. Results documented here will inform future studies exploring drought trends by offering a new way to examine geographic patterns associated with meteorological drought over the last century.

Methods

Data

Data used in this study are derived from the North Carolina Cooperative Institute for Climate and Satellites (NCICS). The data consists of monthly observations of county-level Palmer Drought Severity Index (PDSI) values from 1895-2016 for the conterminous United States. The total number of counties in our data is 3,103 with 1,464 corresponding drought observations per county. The PDSI index was chosen as the primary drought metric for this study owing to its prominence as a measure for long-term meteorological drought (Keyantash and Dracup 2002), and comprehensive consideration of the availability of atmospheric moisture in the water balance model (Palmer, 1965). The PDSI is computed based on local climatic conditions, and available data; inputs consist of available water content in the top layer of soil, temperature, and precipitation at the monthly interval. The PDSI index can also be modified to include potential evapotranspiration using either the Thornthwaite or Penman-Monteith equation, although the former method has been attributed to overestimating dryness (Sheffield et al. 2012). 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.

There are several limitations to the PDSI that have been addressed in previous papers (Alley, 1984; Karl, 1986; Karl et al. 1985). The original formulation of the PDSI index was based on climatic conditions in the central United States, which have a semi-arid climate unique to the region, therefore widespread applicability requires some extrapolation. 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). Nonetheless, modified variants of the PDSI have been developed that address some of these drawbacks, including the self-calibrated PDSI (scPDSI). Proposed by Wells et al. (2004), scPDSI extends the index to dynamically represent actual local climate characteristics in real-time, thereby improving comparability across different regions. Our PDSI algorithm considers daily minimum and maximum temperature, and precipitation, as well as available water content (AWC) in the top layer of soil. Potential evapotranspiration (PET) was estimated using the *Thornthwaite* equation, which is based on monthly mean surface air temperature, latitude, and month (Thornthwaite, 1948). The need for a scPDSI and other modified variants of PDSI is beyond the scope of this paper, which seeks only to examine the historical spatiotemporal trends of meteorological drought in the United States.

Self-Organizing Maps

In this study, the SOM was trained with PDSI values on a 3x4 Kohonen array with 12 resultant nodes. The SOM output shows a spatially coherent representation of patterns detected within the input data. We iteratively tested several other array sizes (i.e., [3x3, 4x4], not shown) to determine the optimal number of nodes that best captured the variability of historical patterns and provided spatial coherence across the array, a common practice used to assign optimal SOM dimensions (Sheridan and Lee 2011, Hewitson and Crane 2002, Kohonen, 2013). In our sensitivity analysis, SOMs with fewer nodes were inadequate at capturing all the data's variability, while larger sized networks presented many similar patterns with few discernible differences.

The unsupervised training process for the SOM begins with what is known as 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 twelve 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. The remaining monthly PDSI observations were then presented to the SOM to approximate the first guess, or approximate arrangement of patterns across the nodes. 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. Patterns in each node are therefore theoretical representations of all the best matched observations which resemble the distributions of the raw PDSI data from 1895-2016.

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 arbitrarily 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 longer-duration persistence and lower values indicate shorter duration trends. In this study, analyses were completed in RStudio (R Core Team

2020) using the Kohonen package (Wehrens and Buydens 2007; Wehrens and Kruisselbrink 2018); final maps were created using the Maps package (Brecker and Wilks 2018) and statistical analyses performed using the modified MK package (Patakamuri S. K., and O'Brien, N. 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 1895-2016. The MK trend test is commonly employed to detect monotonic trends in a time series of climate or hydrologic data (Pohlert et al. 2015; Kendall, 1975; Mann, 1945). Time-series data are typically limited by their sensitivity to seasonality and other existing covariates, also known as serial correlation. Initially the MK test without adjusting for seasonality was performed with statistical significance level determined at $p \leq 0.10$ for a two-sided test. Observed trends appeared promising, but to account for seasonal dependence, we carried out a seasonal Mann-Kendall trend test (Hirsch et al. 1982) with statistical significance level remaining the same. As a final sensitivity analysis, a modified MK that adjusts for serial correlation 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 (Hamed and Rao 1998).

Results

Fig. 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 and Crane 2002) and expresses extremes in each of the four corners of the SOM, with more smooth continuous patterns in between (Sheridan and Lee 2011).The resultant SOM nodes (Fig. 1) exhibits a continuum of spatial patterns over time 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, overall persistence of wet trends were greater than drought conditions (Fig. 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.

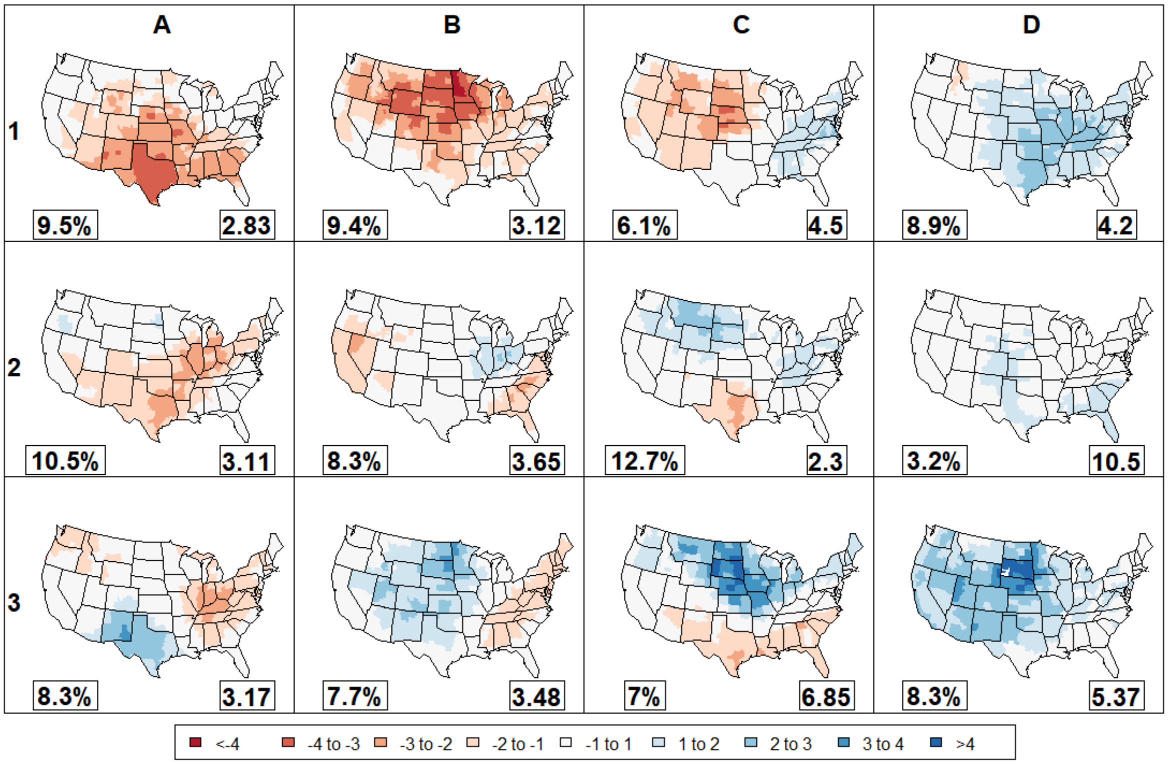

Figure 1: Self-Organizing Cartographic Maps (1-12). Percentage value (lower left) indicates the percentage of total months within the study period. Values in the lower right represent persistence of trends, where higher values indicate longer durations, and lower values indicate shorter duration trends (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, C3) and Midwest (A1, A2, B1, 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 (Fig. 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. 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. In addition, nodes with drier conditions predominantly concentrated in the Western portion of the CONUS (B2, C1) were less frequent, but more

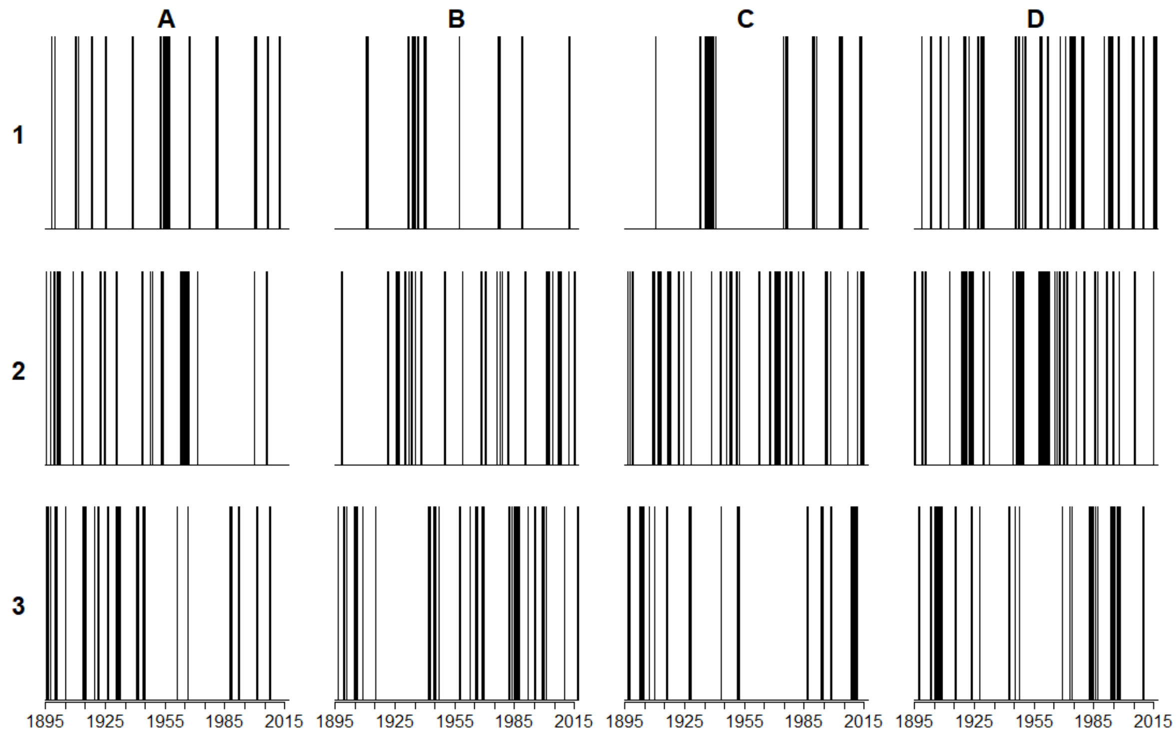

Figure 2. For each cartographic visualization (Fig. 1) a corresponding absence and presence bar plot was generated to visually characterize both the return periods and persistence (duration) of patterns from 1895-2016. Thicker bands represent longer persistence.

persistent than other drought patterns. The most frequent of drought patterns is shown in node A2, at 10.5%, the drought pattern extends from eastern Texas up into the Ohio Valley. Moreover, the most severe PDSI patterns of drought (widespread -3 to -4 values) fall over places 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 (Fig. 1), nodes A1 and B1 show widespread extreme drought conditions, however, corresponding plots A1 and B1 in Fig. 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 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 Fig. 2 are more scattered over the study period than widespread drought (A1-C1), and wet patterns (B3-D3). Overall, the proportion of frequency was revealed to be homogeneous (between 8 and 10%) across the SOM, however, map C2 at 12.7% was the most common pattern.

Both Mann-Kendall and the seasonal Mann-Kendall trend tests showed that trends in our study were statistically significant (alpha < 0.10). While this non-parametric test is a common, widely accepted measure of trends in climatological studies, the novel nature of this study required further analysis to ensure robustness of results. From the seasonal MK test, we observed a total of 10 statistically significant increasing and decreasing trends (Table 1). In Fig. 1, PDSI patterns with decreasing drought trends in nodes (D1 and D3) were found in the Northeast, Southeast and some of South-Central U.S with decreasing wet trends in the Pacific Northwest, Southwest, and South-Central U.S (nodes A2, A3, and C2). Increasing trends were found for nodes A1 and B1 that exhibit extreme drying patterns across most of the U.S. (Fig. 1) centered over the northern and southern Plains, respectively. Other nodes with increasing trends included C1 with moderate to severe drying concentrated in the West and parts of the Midwest, whereas B3, and C3 displayed increasing wetting trends over the upper Great Plains, Midwest, and Northeast (Fig. 1). After the modified Mann-Kendall test, which accounts for serial correlation, many significant trends across the SOM became insignificant apart from node A1 (alpha < .10), which exhibited a significant increasing trend over the entire study period (Table 1). These results suggest that neither of the nodes are becoming more common over the other with an exception for A1, which tends to persist over several consecutive years (thicker bands in Fig. 2) since 1915.

Table 1: Mann Kendall (Tau), Seasonal Mann Kendall (Tau), and Hamed and 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	-0.05	0.019	-0.0511	0.018	-0.018741	0.394
B3	0.0463	0.030	0.0469	0.031	.014527	0.634
C3	0.0694	0.001	0.0698	0.001	0.026811	0.312
D4	-0.0898	0.0000	-0.0907	0.0000	-.03349843	0.215
A2	-0.0797	0.0001	-0.0803	0.0002	-0.34983	0.161
B2	-0.0221	0.300	-0.0222	0.303	-0.009703	0.6608
C2	-0.0677	0.001	-0.0686	0.001	-0.02449	0.4098

D2	0.0157	0.461	0.0157	0.466	0.005887	0.7994
A1	0.103	0.0000	0.104	0.0000	0.0466	0.075
B1	0.0813	.0001	0.082	0.0001	0.03166	0.227
C1	0.0416	0.051	0.042	0.051	0.016382	0.378
D1	-0.0567	0.007	-0.0572	0.008	0.020497	0.4737

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 most SOM patterns. However, our time-series analysis showed increased persistence of wet trends over the latter half of the 20th century, primarily concentrated in the Northeast, Midwest, and upper Great Plains. Droughts were found to generally occur at a higher frequency but did not persist for long durations. In contrast, wet trends occurred slightly less frequently, but persisted for longer when they did occur. We also observed a minor statistically significant increase of moderate to severe drought conditions across the Southwest, the Great Plains and Southeast.

After performing the modified MK test to account for serial correlation, the only significant increasing trend identified is expressed in node A1, which resembles drought conditions of the 1950-57 drought episode that affected areas across the U.S, from the West coast to the Mississippi Valley. This finding does not necessarily imply that future droughts will share identical characteristics (severity, intensity, spatial extent) of the 1950s, but instead suggests this pattern of drought is likely to manifest more frequently in these regions. Heim (2017) compared regional 1998-2014 droughts across the U.S. to historical national-scale droughts of the 1930's and 1950's. His 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. Moreover, as compared to the 1930s and 1950s the 1998-2014 drought episodes were found to be much warmer and wetter, i.e., 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 (Fig. 1).

Previous assessments of historical drought trends have described a sensitivity of the significance of trends on temporal scaling and regional variability (Alexander 2016; Soulé 1993; Soulé and Yin 1995). 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. When compared to middle and later 30-year intervals, these same regions exhibited above-normal moisture conditions. Yet, Soulé (1993) found no significant differences of 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 analysis. The prevalence of statistically insignificant trends in our study could also be attributed to both the temporal and geographic scale of analysis applied. Statistically significant increasing drought patterns exhibited in node A1 indicates that severe drought conditions will be more likely in these regions, but the greater persistence of wet conditions revealed by our time-series analysis suggests that both may be valid but are not captured in our sample.

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. The vacillation regarding 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).

Strengths and Limitations

The spatial distribution of trends documented in this study qualitatively concur with previously observed general drying and wetting trends in the United States (Andreadis and Lettenmaier 2006; Easterling et al. 2007; Ficklin et al. 2015; Soulé and Yin 1995). Direct comparability is limited, however, due to differences of timescales between studies, as well as climate variables and metrics applied to characterize trends, e.g., measures of soil moisture conditions versus long-term precipitation data.Our findings coincide with other studies where we see that a greater number of wetting trends predominantly took place after 1970, of which are largely concentrated across the Pacific Northwest, Midwest, upper Great Plains, and the Northeast portions of the U.S (Andreadis and Lettenmaier 2006; Balling and Goodrich 2011; Groisman et al. 2004; Ficklin et al. 2015; Soulé 1993). 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.

Results described in this study should not be used to support any claims of causality as this paper is observational in nature, focusing only on historical meteorological drought trends. It should also be noted that our PDSI calculation may have influenced the relative estimate of wetness or dryness captured in the SOM, as the *Thornthwaite* method was applied instead of the more physically based *Penman-Monteith* equation, which may mean that the severity of drying trends described here could be exaggerated (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). Despite these differences, 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 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) teleconnections (Ford and Labosier 2014).

Conclusion

Global increases in temperature and precipitation variability have been well documented (IPCC, 2007, 2014; Dai 2013; Alexander et al. 2006; Groisman et al. 2004; Groisman et al. 2008; 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 et al. 2004, 2011a; Sheffield et al. 2012), a notable amount of uncertainty surrounding future trends continues to exist (Trenberth et al. 2014; Seneviratne 2012).

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 trend 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).

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Vita

Camila Moreno is the daughter of Cristina Ordonez and Beto Moreno, Colombian immigrants that moved to North Carolina in 2004. Camila moved to Boone, North Carolina in 2016 after transferring from the University of North Carolina at Greensboro to finish the remainder of her undergraduate studies in Spanish and political science. Upon graduating in 2018, she decided to continue the path of higher education and pursue a master's degree in Geography at Appalachian State.

Coming into the graduate program, Camila was a true novice having a background in language and humanities. With minimal experience in research, statistics and analysis, Camila participated in many classes to learn about a variety of topics. Dr. Margaret Sugg provided several opportunities to take part in research outside of the classroom, which encouraged Camila to pursue a thesis. The support from both Dr. Johnathan and Margaret Sugg that Camila received was invaluable to carrying out research on climatic extremes, such as drought. Camila will graduate in May 2021 magna cum laude and plans to pursue a Ph.D. in Geography focusing on climatological impacts on society in hopes of one day becoming a professor.