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Key Points:

- Agricultural drought in the contiguous United States was identified by high-resolution standardized soil moisture index
- Drought in the East Coast are likely to get exacerbated due to climate condition although tropical storm (TS) landfall
- Drought in the Gulf of Mexico are rarely affected by TS

Supporting Information:

Supporting Information may be found in the online version of this article.

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Unraveling the Relationship Between Tropical Storms and Agricultural Drought

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Abstract Drought and tropical storm (TS) are associated with water deficit and surplus, respectively. Soil moisture is a key component in the hydrological cycle that plays an important role in monitoring drought and reflects the infiltrated or stored water due to TS rainfall. Therefore, soil moisture information can be used for the assessment of whether TS can ameliorate severe drought conditions. Here, we use downscaled 1 km Soil Moisture Active Passive data set generated at the Center for Complex Hydrosystems Research at the University of Alabama, and Hurricane Database 2nd generation to examine the coincidence of extreme events between agricultural droughts and Atlantic TS in the contiguous United States from 2015 to 2019. The Cumulative Distribution Function (CDF) matching approach is employed to correct the bias using the root zone soil moisture data provided by the North American Land Data Assimilation System Phase 2 (NLDAS-2), and then weekly Standardized Soil Moisture Index is calculated for characterization of agricultural drought. As a result, we estimate the frequency of TS impacted regions in the US, the ratio of droughts ameliorated and exacerbated by TS, and the regions where TS highly affect the offset of drought. Our findings indicate detailed spatial information of the offset of drought conditions based on a high-resolution data set and provide potential information in terms of mitigating drought and TS for the future.

1. Introduction

Droughts are extreme events associated with water deficiency for an extended period that causes economic and environmental losses and can be classified into four types: meteorological drought (precipitation deficit), agricultural drought (soil moisture deficit), hydrological drought (streamflow deficit), and socioeconomic drought (social responses in terms of water supply and demands) (Wilhite & Glantz, 1985). Drought studies are steadily conducted to understand the causes, to plan for future drought, and to characterize different types of droughts (Folger et al., 2013; Gavahi et al., 2020; Kuwayama et al., 2019; Madadgar & Moradkhani, 2013; Staudinger et al., 2014). The southeast US is gaining more attention for drought risk due to more frequent and severe droughts (Engström et al., 2020; Martin et al., 2020). For example, the agricultural losses from Texas 2011 drought were around $7.6 billion, making it the costliest drought in the state's history (Fannin, 2012).

Tropical storm (TS) is another extreme event frequently landfalls in the US that causes substantial economic and environmental damages and fatalities (Elsner et al., 2008; Emanuel, 2005). TS with wind speed greater than or equal to 74 mph is classified as tropical cyclone (TC) by the Saffir-Simpson scale (Simpson, 1974). TCs are becoming more severe due to warmer ocean water temperatures under climate change (Elsner, 2020; Emanuel, 2020; Kossin et al., 2020). Indirect hazards such as flooding and storm surges occur in coastal regions due to the strong winds and heavy rainfalls from TC (Rappaport, 2014; Touma et al., 2019). Although TCs are well known for their devastating wind storm and torrential rainfall, in some cases, they result in interacting positively with drought (Maxwell et al., 2013).

Several studies in the past sought the contribution of TC to drought conditions: TC that causes a pendulum swing from drought (Palmer Drought Severity Index (PDSI) ≤ -2.0) to near normal or wet (PDSI ≥ -0.50) is known as Drought-Busting TCs (Maxwell et al., 2013, 2012; Palmer, 1965). TC occasionally leads to shorter and less severe droughts with a belated initiation (Kam et al., 2013). Frequent landfalls of TC during warm seasons are also found to mitigate droughts (Brun & Barros, 2014). Drought in coastal regions is highly affected by anomaly in TC rainfalls when compared to inland regions (Y. Jiang et al., 2016). Additionally, rainfall-induced by landfalling TC plays a critical role in crop yield in agriculture dominating states in the US (Kellner et al., 2016). The above-mentioned studies are focused on TC rainfall. Whereas, Song et al. (2020) identified that rainfall is not always proportional to the wind scale of the TC and therefore, in some cases TS events may accompany more rainfall relative to TC. Moreover, a plethora of studies have looked into TC weakening the drought intensity while drought worsened despite the presence of TC has received less attention. Furthermore, the contribution of TS on the drought intensity in the US at the continental scale is not often investigated.

Soil moisture is known as a key variable for agricultural drought monitoring in a multitude of studies (Berg & Sheffield, 2018; Gavahi et al., 2020; Hao & AghaKouchak, 2013; Martínez-Fernández et al., 2016; L. Xu et al., 2020, 2019; Y. Xu et al., 2018; Yin et al., 2020). Moreover, soil moisture is an important component in the hydrological cycle, which is estimated through in situ stations, satellite remote sensing, or hydrologic modeling. In addition, soil moisture is often used in drought-TC-related studies in order to derive storage capacity, define drought, and calculate drought index (i.e., PDSI; Brun & Barros, 2014; Kam et al., 2013; Maxwell et al., 2013). Since soil moisture is related to rainfall in most locations (i.e., soil moisture increases with rainfall) (Sehler et al., 2019), we applied soil moisture as a linkage between TS and agricultural droughts. Several historic rainfall events associated with Atlantic TC have resulted in a sudden transition from severe drought to significant flooding over just a few days and therefore end the drought. Examples are TS Imelda (2019) in September and Hurricane Harvey (2017) in late August over southeastern Texas; Hurricane Florence (2018) in September over North Carolina; Hurricane Joaquin (2015) in early October over South Carolina (Case et al., 2021). It is important to note that although the rainfall associated with the TS directly affects the soil moisture condition, some studies showed that the antecedent soil moisture anomalies contribute to the intensification of TS as the storm moves inland and meets favorable environmental conditions to evolve (Kellner et al., 2012). However, in conditions of insufficient soil moisture, such TS when landfall may decay more rapidly since there is no surface latent heat flux to sustain the system.

Global soil moisture product is available owing to the advanced technology of remote sensing such as the Soil Moisture Active Passive (SMAP), Soil Moisture and Ocean Salinity, Soil Moisture Operational Product System, etc. Spatial resolution of the soil moisture data derived by satellite are still coarse while hydrological- and agricultural applications require finer-scale (kilometer or sub-kilometer) soil moisture data due to spatial heterogeneousness (i.e., land use, vegetation, and topography) in regional or local areas (Hssaine et al., 2021; Tian et al., 2020). Different downscaling approaches are developed based on the need of high-resolution soil moisture data (Guevara & Vargas, 2019; Montzka et al., 2018; Yin et al., 2020). Moreover, recent studies have utilized 1 km scale soil moisture data for drought monitoring and revealed finer resolution data provide more detailed information in heterogeneous areas (Abbaszadeh et al., 2021, 2019; Fang et al., 2021; Gavahi et al., 2020; Yin et al., 2020). Literature indicates the inefficacy of previous studies in identifying the TS-drought relationship at regional or local level as they did not use the soil moisture data at kilometer or sub-kilometer scales which are crucial for effective agricultural practices and farm-level studies (Brun & Barros, 2014; Kam et al., 2013; Maxwell et al., 2013). In addition, these studies have not considered the root zone soil moisture which is important from an agricultural point of view since agricultural drought is best characterized by deficiencies in soil moisture in the root zone (Ajaz et al., 2018; Mladenova et al., 2020).

Therefore, with the given background the novelty of this study is the quantification of agricultural droughts that are ameliorated or exacerbated when Atlantic TS occurred in the contiguous United States (CONUS) using high spatial resolution soil moisture data. Our study broadens the knowledge of drought-TC related researches by (a) a wider range of the storm data considering TS instead of TC, (b) utilizing high spatial resolution soil moisture data considering root zone soil moisture, and (c) assessing the droughts weakened by TS as well as the ones worsened after TS landfall. The present study seeks to answer the following research questions: (a) Can root zone soil moisture reflect the relationship between TS and agricultural drought? (b) How to link TS events with agricultural droughts to evaluate the droughts weakened and worsened by TS? (c) To what extent the agricultural droughts have been ameliorated or exacerbated by Atlantic TS? (d) In which regions do the TS events contribute more to agricultural droughts?

This article is organized as follows. Descriptions of the data and method are included in Section 2. Section 3 presents the results including standardized soil moisture index (SSI) map, frequency of TS events in the US, drought ameliorated or exacerbated by TS, the contribution of TS in each state, and impact of TS in drought duration. At the same time, we discuss the results, uncertainties in this research, and highlight the findings comparing to previous studies. Finally, Section 4 provides a summary of our findings with the conclusion.

2. Data and Method

We use two different soil moisture data: the 1 km downscaled SMAP data and the SMERGE_RZSM0_40CM data. The 1 km downscaled SMAP data is generated at the Center for Complex Hydrosystems Research (CCHR) at the University of Alabama (Abbaszadeh et al., 2019, 2021). This data provides surface daily soil moisture data of the top 5 cm soil layer at 1 km spatial resolution from March 2015 to February 2020 over the CONUS. The SMERGE_RZSM0_40CM data is developed by merging the North American Land Data Assimilation System land surface model output with surface satellite retrievals from the Europeans Space Agency Climate Change Initiative. This data provides root zone daily soil moisture of 0–40 cm layer at 0.125° × 0.125° from January 1979 to May 2019 over the CONUS (Hasenauer, 2010; Tobin et al., 2017).

We used the downscaled SMAP soil moisture data (surface soil moisture) from 2015 to 2019, and bias corrects it with the SMERGE_RZSM0_40CM data (root zone soil moisture). Although SMERGE is available since 1979 to May 2019, we used only five years of it (2015–2019) in order to be consistent with the SMAP data which is available since 2015. The Cumulative Distribution Function (CDF) matching, a bias correction method, is used to reduce the systematic bias and to create a homogenous time-series from the two soil moisture data (Kornelsen & Coulibaly, 2015; Wang et al., 2018). This method allows capturing the spatiotemporal dynamics of the soil moisture retrievals with respect to the reference data set. The downscaled SMAP data, comparing to the SMERGE_RZSM0_40CM data, advantages on its finer spatial resolution which is better for regional- and local studies while the surface layer depth is inappropriate for agricultural drought analysis. We expect to obtain a data set with high spatial resolution considering the root zone layer soil moisture by CDF matching which advantages from both soil moisture data. The CDF matching is performed as follows:

$$\boldsymbol{d}_1 = \overline{\boldsymbol{\Theta}}_{\boldsymbol{SMAP}} - \boldsymbol{d}_2\overline{\boldsymbol{\Theta}}_{\boldsymbol{RZSM}} \tag{1}$$

$$\boldsymbol{d}_2 = \frac{\boldsymbol{stddev}(\boldsymbol{\Theta}_{\boldsymbol{SMAP}})}{\boldsymbol{stddev}(\boldsymbol{\Theta}_{\boldsymbol{RZSM}})} \tag{2}$$

$$\boldsymbol{\Theta}_{\boldsymbol{BCSM}} = \boldsymbol{d}_1 + \boldsymbol{d}_2\boldsymbol{\Theta}_{\boldsymbol{RZSM}} \tag{3}$$

where $\overline{\boldsymbol{\Theta}}_{\boldsymbol{SMAP}}$ denotes the 1 km downscaled SMAP data, $\overline{\boldsymbol{\Theta}}_{\boldsymbol{RZSM}}$ the SMERGE soil moisture data, $\boldsymbol{d}_1$ and $\boldsymbol{d}_2$ are parameters, and $\boldsymbol{\Theta}_{\boldsymbol{BCSM}}$ is the bias-corrected soil moisture data.

The SSI is a drought index calculated from soil moisture and represents the agricultural drought. SSI is defined in a similar way to the commonly used standardized precipitation index (SPI; McKee et al., 1993). The detailed calculation of the empirical probability and the standardized index can be found in Gringorten (1963). First, the empirical probabilities ($\boldsymbol{p}$) for each grid are obtained by Equation 4:

$$\boldsymbol{p} = \frac{\boldsymbol{i} - 0.44}{\boldsymbol{n} + 0.12} \tag{4}$$

where $\boldsymbol{n}$ is the sample size and $\boldsymbol{i}$ is the rank of the soil moisture data from the smallest to the largest. Then, the empirical probabilities are converted into the standard normal distribution function:

$$\boldsymbol{SSI} = \boldsymbol{\Phi}^{-1}(\boldsymbol{p}) \tag{5}$$

where $\boldsymbol{\Phi}^{-1}$ is the inverse of the standard normal distribution function.

We generate a weekly drought map using the SSI and classify them similarly to the drought classification of the US Drought Monitor (Svoboda et al., 2002). According to the US Drought Monitor, drought magnitude is classified into D0, D1, D2, D3, and D4 indicating abnormal dry, moderate-, severe-, extreme-, and exceptional-drought, respectively (Svoboda et al., 2002). We define D0, D1, D2, D3, and D4 when the SSI ranges −0.5 to −0.7, −0.8 to −1.2, −1.3 to −1.5, −1.6 to −1.9, and less than or equal to −2.0, respectively.

Hurricane Data 2nd generation (HURDAT2) provides a track record of date/time, location, and 6-hourly wind speed information when a TS event has occurred (Landsea & Franklin, 2013). The status of system such as TC, TS, and tropical depression are categorized by the sustained wind speed greater than or equal to 74, 39, and less than 38 mph, respectively. We broaden the range of storm-scale from TC to TS since the amount of rainfall from TS should not be treated the same as their lower wind speed (Song et al., 2020) while previous studies focused on only TC (Brun & Barros, 2014; Kam et al., 2013; Maxwell et al., 2013). The movement of storms is recorded in the latitudes and longitudes of its center. We generate a 5° radius buffer to the trajectory of each event to assume the impacted area according to the TS event (H. Jiang & Zipser, 2010; Nogueira & Keim, 2010). Here, we assume that the TS-related rainfall will fall in the buffered area and it will interact with the soil moisture in the same area and may change the drought condition. We look at the frequency of TS and impacted regions in the US by overlaying the buffered trajectory of each TS events which landfall over the CONUS.

We look into the change in the weekly drought conditions after TS landfall to determine whether the drought was affected by TS. In preparation for changing drought conditions, we designate the drought weakening week when the week has a severe, extreme, or exceptional condition (D2–D4) and when the following week has a moderate drought or wetter condition (D1, D0, and no drought). On the contrary, we designate the drought worsened week when the week has a moderate drought or wetter condition (D1, D0, and no drought) followed by a week with severe, extreme, or exceptional drought condition (D2–D4). Drought weakened week coincided with TS are defined as "drought ameliorated by TS". On the other hand, drought worsened week coincided with TS are defined as "drought exacerbated by TS". Note that we use the term "drought exacerbated by TS" to identify the concurrent event when the two extremes coincide, however, this does not mean that TS is the main cause of drought exacerbation.

Following the above evidence, we assessed the relationship between droughts and the TS in the CONUS. We calculated the percentage of drought ameliorated (exacerbated) by the TS using the ratio of the number of droughts ameliorated (exacerbated) by the TS to the total number of drought weakened (worsened) weeks in the area. Then, we averaged the percentage of the droughts ameliorated (exacerbated) by the TS for each state and rank them in order. We computed the mean drought duration for the whole study period and evaluated the mean drought duration of the droughts ameliorated by TS for further analysis.

We use an unsmoothed version of the monthly Atlantic Multidecadal Oscillation (AMO) index to investigate whether the climate variability is related with the droughts in this study (Enfield et al., 2001). The AMO contains information of the sea surface temperature anomalies relative to the long-term average and positive AMO is strongly associated with the increased drought frequency in the east coast (McCabe et al., 2004). In addition, we look into the annual corn yield data from the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) to analyze the impact of TS in corn yield during the drought (USDA NASS, 2017).

3. Results and Discussions

The SSI is widely used to detect the extent of soil moisture and monitor agricultural drought. The SSI plays an important role in our study as a linkage between TS and agricultural drought events. Figure 1 shows an example of one of the weekly drought maps among 213 weeks for the week in September 14–21, 2016. The pixel size (spatial resolution) is 1 km which contains information of the SSI. The dark red, red, orange, light orange, yellow, and white colors in the figure represent the exceptional (D4), extreme (D3), severe (D2), moderate (D1) drought, abnormal dry (D0), and no drought, respectively. As for the specific week shown in Figure 1, severe-, extreme-, and exceptional-droughts were observed in the East coast (i.e., North Carolina, Virginia, West Virginia, and Pennsylvania) while moderate drought and wetter conditions were observed relatively in the South US (i.e., Texas, Louisiana, and Florida) and Midwestern US (i.e., Missouri, Illinois, and Indiana). The presented drought map for this specific week also matches the drought map provided by the US Drought Monitor which strengthens the validity of the results in the current stage. The drought map for each week is different as the drought intensity derived by SSI is unevenly distributed over the CONUS considering time and space. The weekly drought map will be used to examine the drought weakened (worsened) weeks, then it will be overlayed with TS to define the drought ameliorated (exacerbated) by TS.

Based on our selection of TS from HURDAT2, 62 events were found to have the intensity of TS while 27 events among the 62 events have landfall or reached near the coastline of the CONUS during the study period. Thirty four states in the US have experienced a TS event at least once while some of the areas have experienced 17 TS during the study period (Figure 2). Some of the areas in North Carolina, Virginia, Tennessee, Georgia, Delaware, and Maryland are found to be frequently impacted by TS, while Texas, Louisiana, and Mississippi are relatively less impacted by the number of TS during the whole study period.

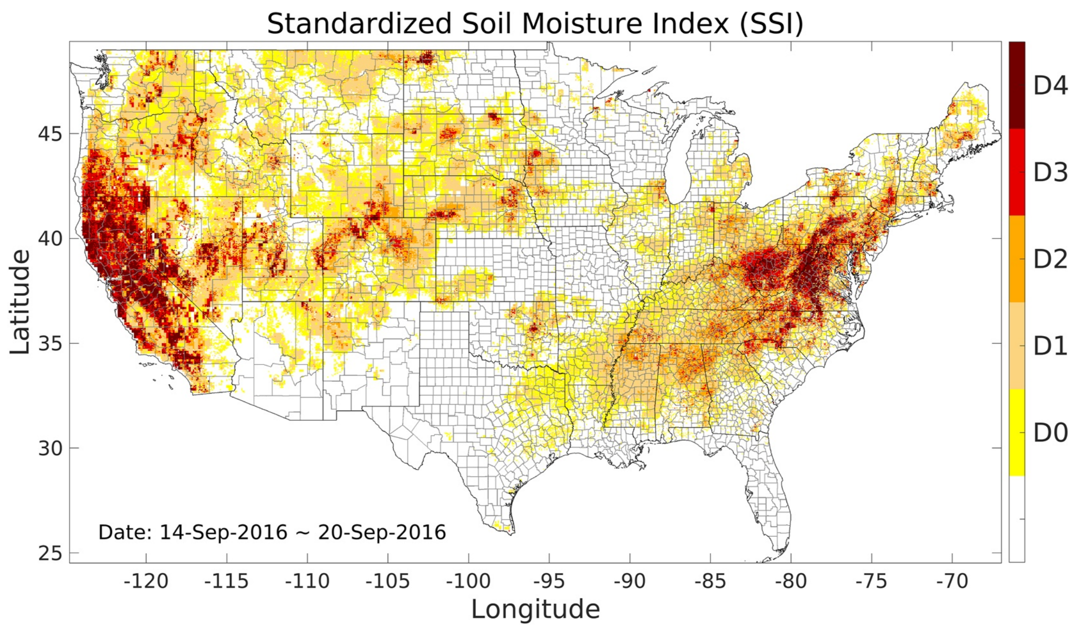

Figure 1. Drought spatial distribution map based on weekly SSI for September 14–20, 2016.

We combine the buffered trajectories of the TS with the drought weakened (worsened) weeks and compute the percentage of the drought ameliorated (exacerbated) by TS (Figure 3). Dark red to yellow colors show the criteria of different percentages and the gray color shows regions where there were no TS events at all. Droughts ameliorated by TS are widespread in the eastern US (Figure 3a). The droughts ameliorated by TS are observed at a higher rate (over 25%) in some of the areas in Georgia, Tennessee, Kentucky, and Virginia. Comparing to the droughts ameliorated by TS, the droughts exacerbated by TS are similarly widespread but more shifted to the Eastside (Figure 3b). We found that TSs which are affecting droughts occur relatively in a higher latitude and inland, while the coastal areas in the Gulf of Mexico are showing a low rate of droughts recovered by TS. For example, 25% of droughts ameliorated by TS in Georgia (e.g., total number of experienced TS is 12) indicates

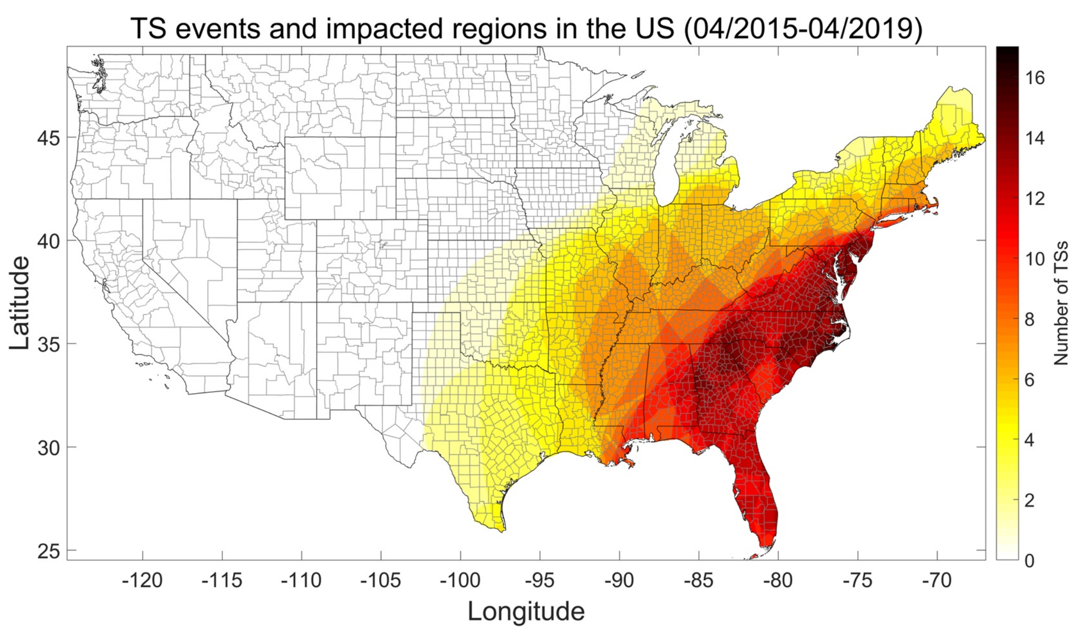

Figure 2. Frequency of TS events and the impacted regions in the US based on HURDAT2 track records with 5° radius buffer.

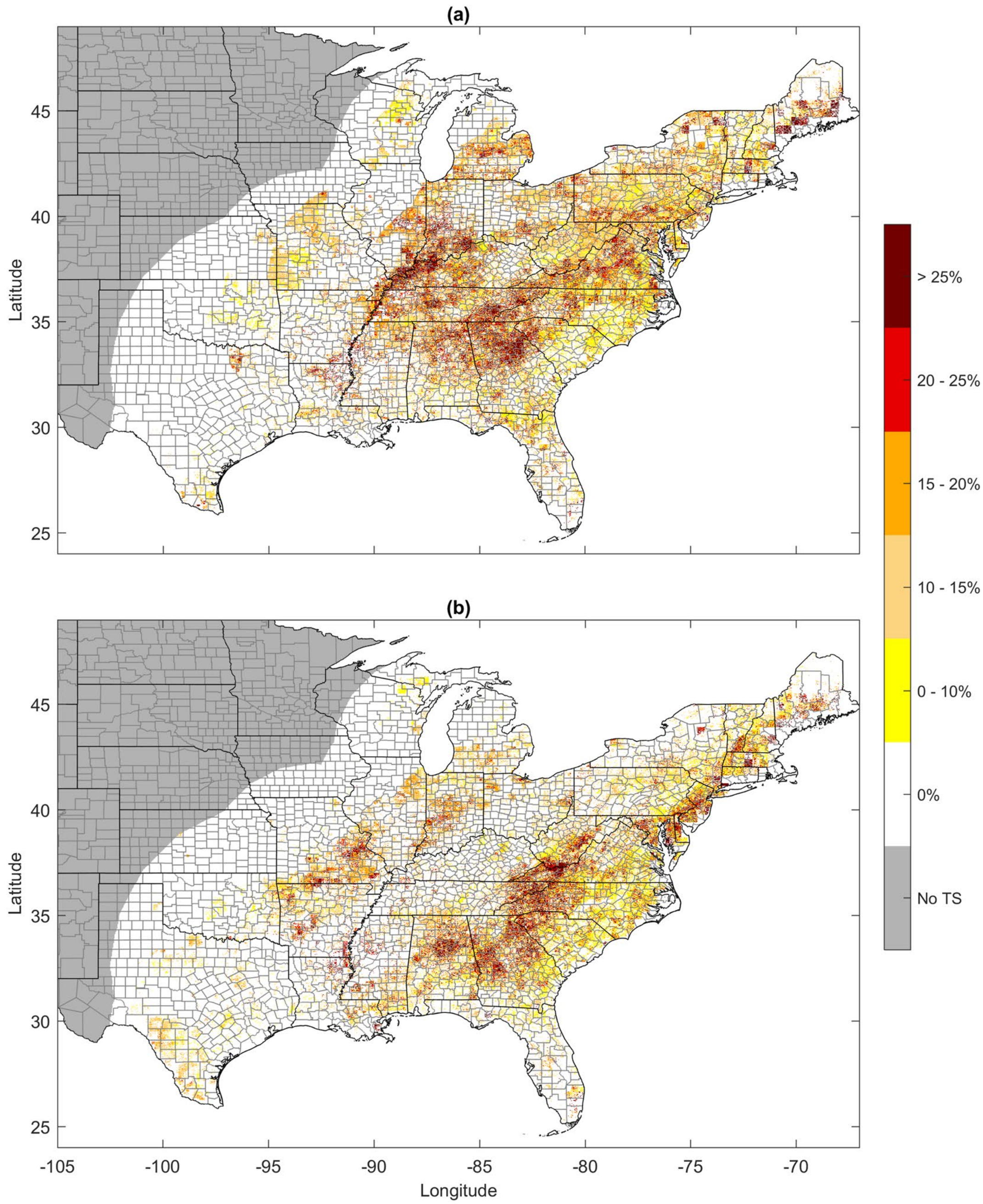

Figure 3. Percentage of drought ameliorated and exacerbated by TS in the US.

either 1 TS event out of 12 TS events ameliorated drought when drought condition has weakened 4–48 times during the study period.

To investigate the contribution of TS in drought amelioration (exacerbation) in each state in the US, we average the group of pixels for each state (Figure 4). Here, we obtain the rank of states where drought was affected by TS. Droughts in Virginia (13.6%) are most weakened by TS and are followed by Tennessee (13.5%) and Maryland (12.6%) when averaging the percentage of drought ameliorated by TS for each state (Figure 4a). States in the eastern coastline in the US are more likely to be affected by TS and weaken droughts, including Tennessee and Kentucky. As for the drought exacerbated by TS, New Jersey (16.0%) have the highest rate and is followed by Delaware (15.8%) and the District of Columbia (14.1%) (Figure 4b). According to the plot, we find that droughts in Texas, Louisiana, Mississippi, and Florida are less influenced by TS, and the white-colored area shows that

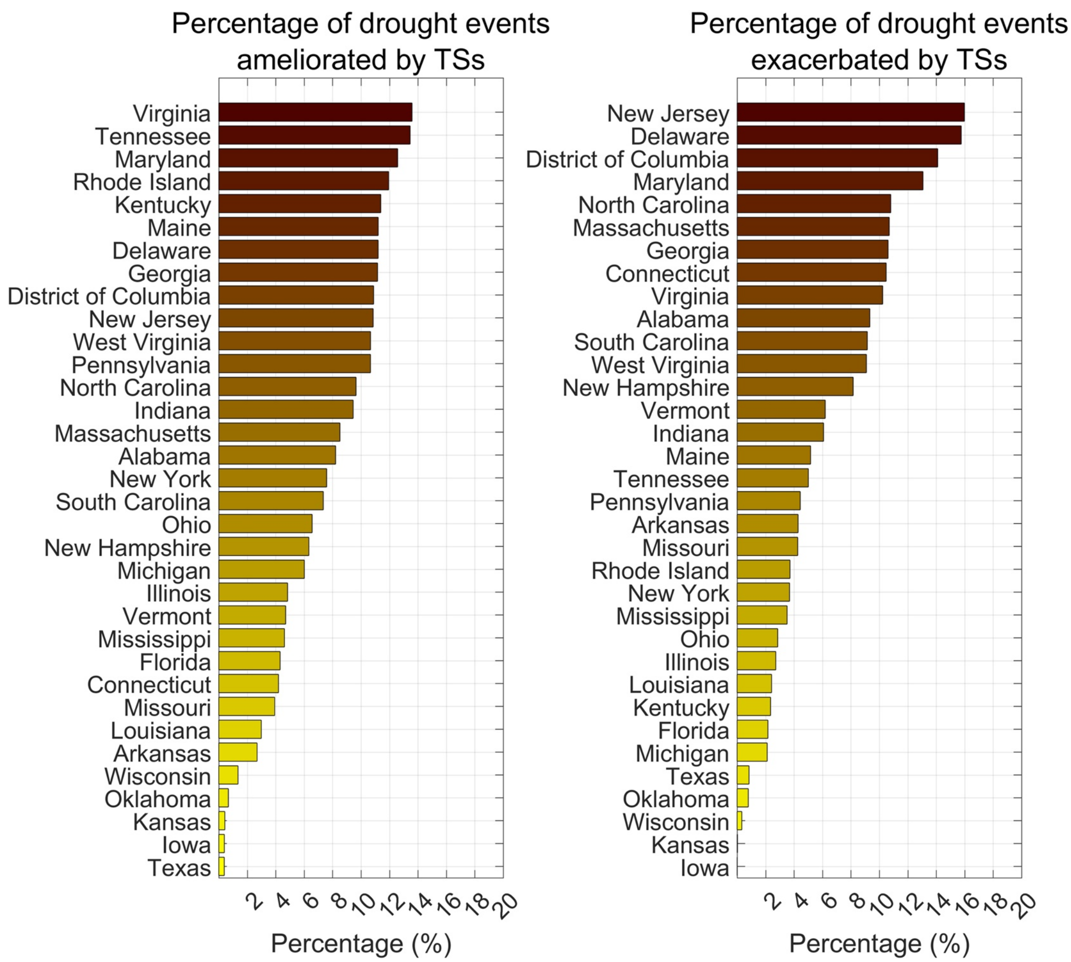

Figure 4. Percentage of drought ameliorated and exacerbated by TS in each state in the US.

none of the TS have affected drought in these areas (Figure 3). These states are near to the location where some of the powerful and destructive TS landfall (i.e., Hurricane Harvey (2017) and Michael (2018)). This implies the drought in the Gulf of Mexico is relatively irrelevant to TS. On the other hand, droughts in the eastern coastal states such as Virginia, Delaware, Maryland, New Jersey, and the District of Columbia are more likely to be affected by TS in either a positive or a negative way.

Our results indicate that how frequent the TS landfall in the CONUS is and show the ratio of drought amelioration and exacerbation during the study period. A low rate (less than 14%) of agricultural droughts turned out to be ameliorated by TS in the US (Figure 4a). On the other hand, a low rate (less than 16%) of agricultural droughts turned out to be exacerbated by TS (Figure 4b). These percentages are calculated by averaging the percentage of drought events affected by TS for each state and thereby we conclude that not many agricultural droughts are affected by TS in the US. Especially, states in the Gulf of Mexico were found to have a relatively low percentage of drought ameliorated (exacerbated) by the TS. The reason for the difference in the response of droughts to TS landfall (either amelioration and exacerbation) is potentially due to that the amount of precipitation and wind speed is not proportionally associated with the TS (Song et al., 2020) and the variable intensity of the droughts across space and time. Our results corroborate with the findings of the other studies that indicated the percentage of droughts ended by TS are relatively higher in the East coast states than the South coast states (Maxwell et al., 2013, 2012).

Although the infrequent droughts are affected by TS, based on the order of the states in Figure 4, one can tell in which states the TS events contribute more to agricultural droughts. Droughts in some of the inland states (Tennessee and Kentucky) and the East coast states (Virginia, Maryland, and Rhode Island) have a relatively higher

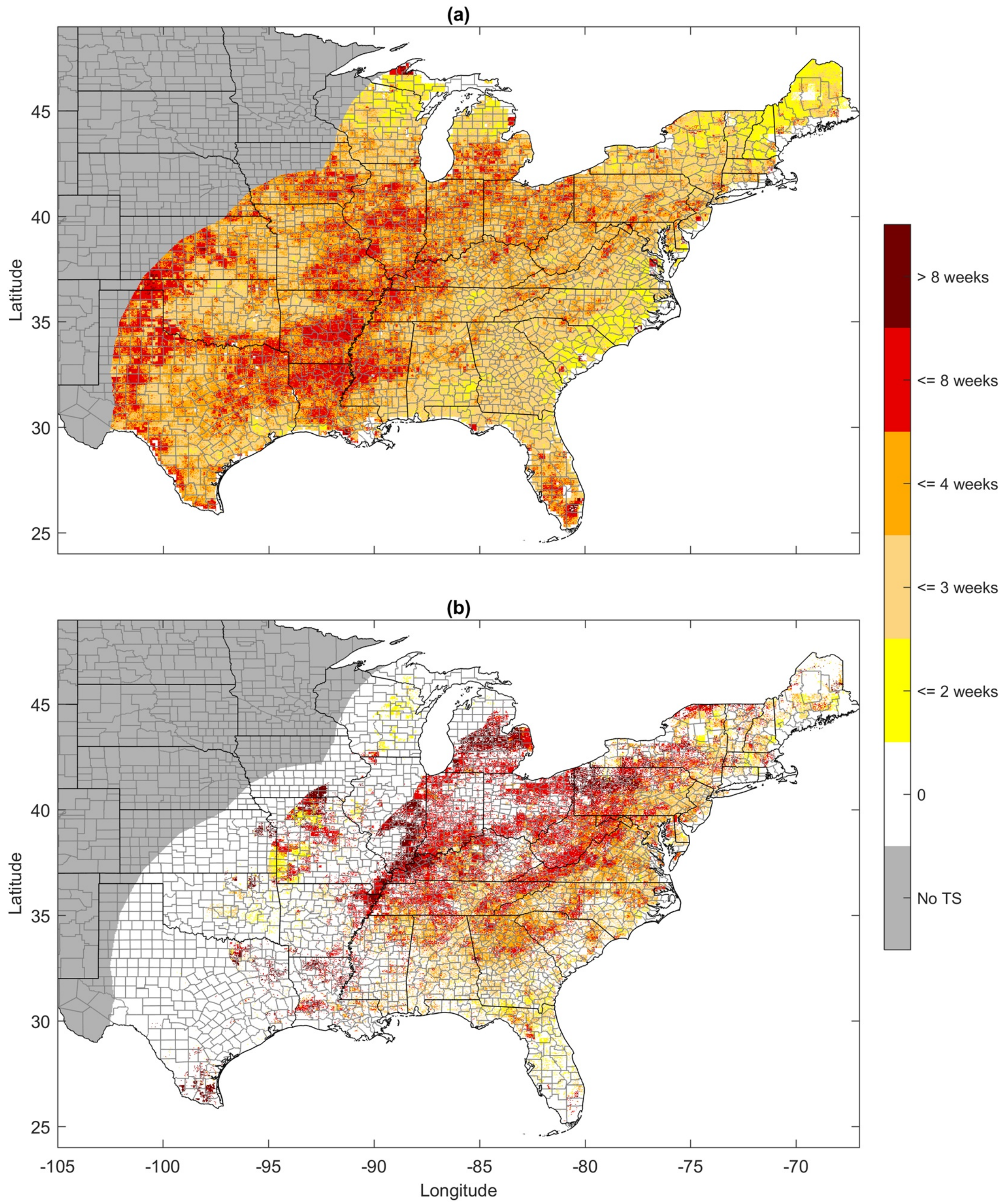

Figure 5. Mean drought duration in the US during April 2015 to April 2019 and the mean drought duration for the drought events ameliorated by TS during the same period.

probability to be recovered by the TS. However, it is to be noted that in this study we also found that many of the droughts were also exacerbated in the East Coast states. In the same East Coast states including New Jersey, Delaware, District of Columbia, Maryland, and North Carolina we noticed that the droughts are also worsened after TS.

We further examine the drought duration, one of the drought characteristics, to compare the difference between the drought duration for the whole study period and the drought ameliorated by TS. Here, we focused only on the drought duration ameliorated by TS because the drought recovering TS associate with the drought offset while exacerbating TS associated with the drought onset, and it is difficult to discuss the drought duration with only the onset of drought. Figure 5a illustrates the drought duration during the study period for the TS impacted regions with color legend describing the length of the duration in weeks while Figure 5b presents the drought duration of

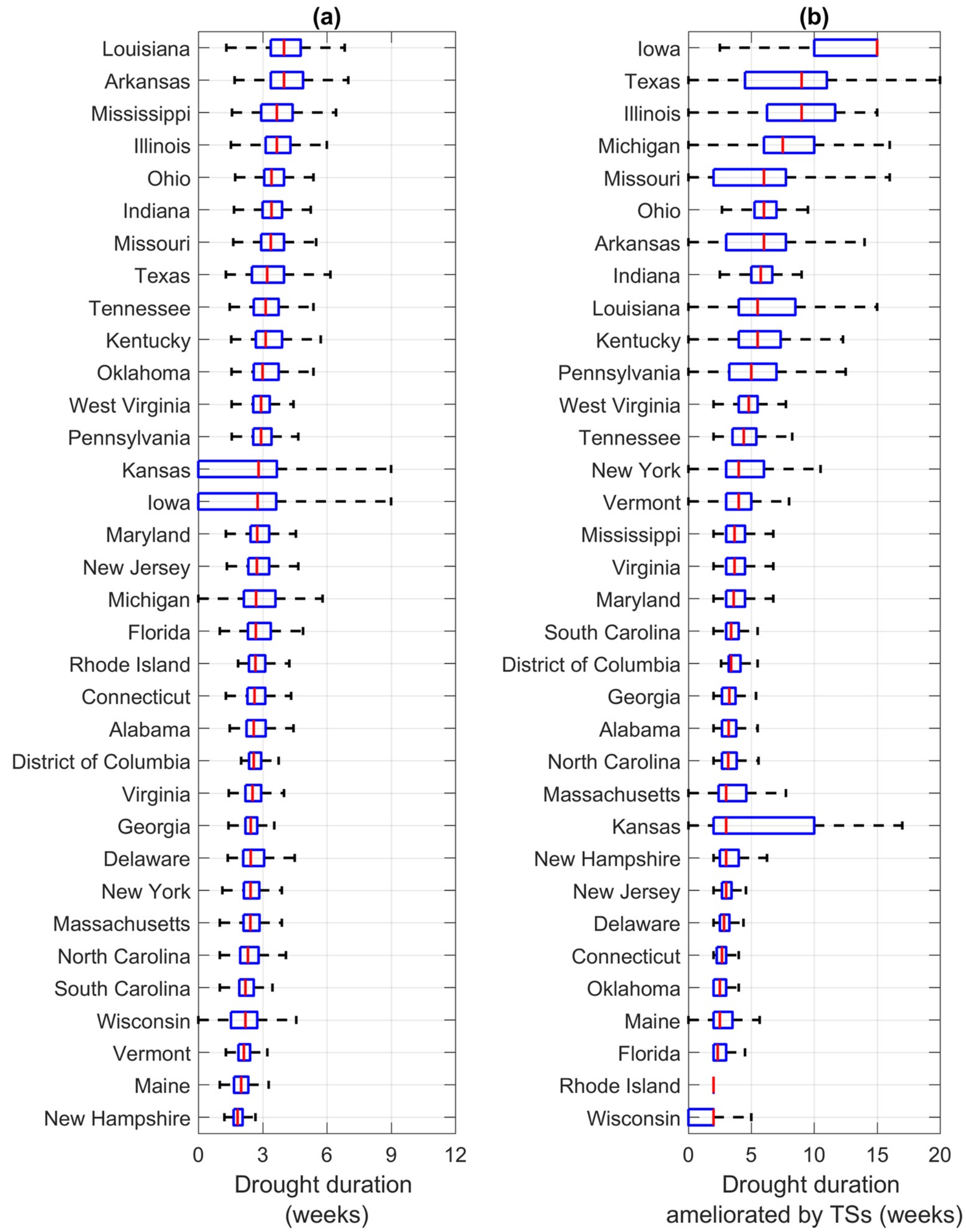

Figure 6. Box plot of the drought duration and drought duration ameliorated by TS in each state in the US.

the drought ameliorated by TS. Note that the white colored area means that none of the droughts were ameliorated by TS. In addition, we generate box plots to look in details of the drought duration for each state (Figure 6). The order of the states is given by the median drought duration (red), and the dashed lines (black) extend to the most extreme data points not considered outliers.

According to the mean drought duration map, the droughts ameliorated by TS have longer mean drought durations (Figure 5). Relatively darker colors are observed in the location where TS have ameliorated droughts (Figure 5b) when compared to the mean drought durations estimated for the whole study period (Figure 5a). This implies that the drought duration of some of the droughts ended by TS might last longer if there were no TS to end them and TS have positively affected droughts. For example, Illinois was found to have approximately 1-month median drought duration during the whole study period (Figure 6a), while the median drought duration of droughts ameliorated by TS was approximately 9 weeks (Figure 6b). Iowa, Texas, Illinois, Michigan, Missouri,

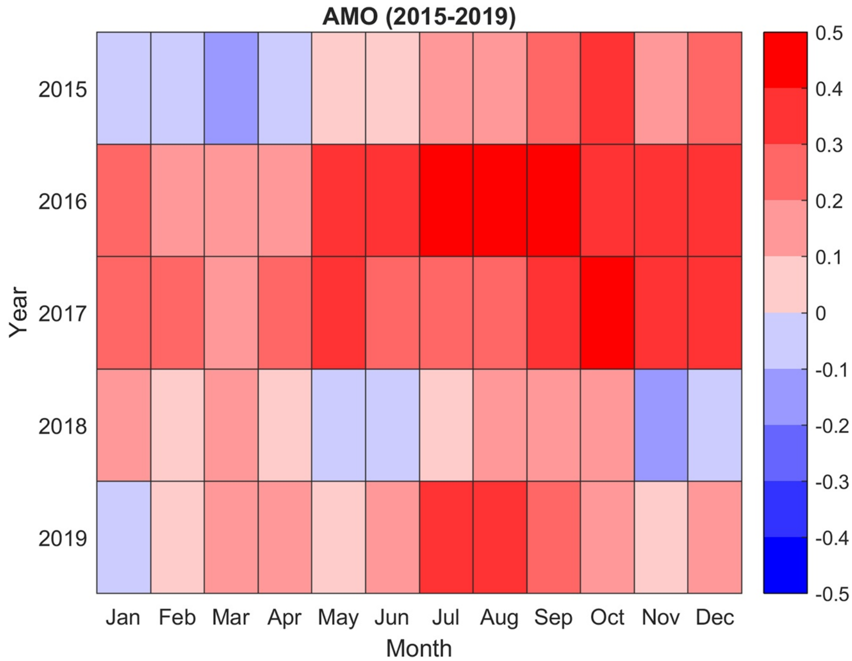

Figure 7. Unsmoothened monthly AMO index from 2015 to 2019.

Ohio, Arkansas, and Indiana are found to be the states with longer drought duration affected by TS, although these states have less experienced TS. Some of the results might be contradictory when comparing the percentage of droughts ameliorated by TS and the drought durations ameliorated by TS. For example, Texas is one of the states with a relatively small number of TS impacted and lower percentage of droughts were recovered by TS, however, the drought duration ameliorated by TS in this state is longer than other states. This indicates that inland states (Iowa, Illinois, Michigan, Missouri, and so on) are less affected by TS, but some areas in the inland states are positively affected by TS in terms of drought duration since the median drought duration from droughts ameliorated by TS are relatively longer than the median drought duration for the study period. States in the East coastline (e.g., District of Columbia, Maryland, South Carolina, and North Carolina) are more affected by TS, and the drought duration ameliorated by TS (Figure 6b) is similar to the normal drought duration (Figure 6a).

While there is a consensus that the landfall resulting from the TS can potentially ameliorate droughts, in this study we found that in the states New Jersey, Delaware, District of Columbia, Maryland, North Carolina, Massachusetts, Georgia, Connecticut, and Virginia over 10% of the droughts are exacerbated after TS. Although in some cases, drought in the East coast states was exacerbated after TS landfall, the drought exacerbation was not able to be explained only by the TS since TS accompanies with either large or small amount of precipitation and raise the soil moisture. If we have to find the reason from TS, we could only assume that the amount of precipitation related to TS was not enough to meet the level to raise the soil moisture to weaken the drought.

As for an alternative approach, we look into the AMO index and create a heat map to see if the drought exacerbated by TS is related with climate variability (Figure 7). The heat map shows that AMO index was positive most of the time during the study period (from April 2015 to April 2019) except for few months in 2018 and 2019. The possible explanation for the exacerbation of the drought post-TS can be due to positive AMO (Figure 7) during the majority of the months within the study period (April 2015 to April 2019). Positive AMO is strongly associated with the increased drought frequency in the east coast (McCabe et al., 2004). Moreover, at a given location the TS landfalls are generally intense and short-lived (Zhou et al., 2018). Therefore, these landfalls provide a short-term reduction in drought intensity (since the majority of the water flow into drainage channels, rather than infiltrating into the soil), but the impacts of AMO during the positive phase is long-term which is often more than a month (Murgulet et al., 2017). Similar results of insignificant amelioration of monthly droughts due to TS landfall is also reported by Misra and Bastola (2016) across 28 catchments in the southeast US.

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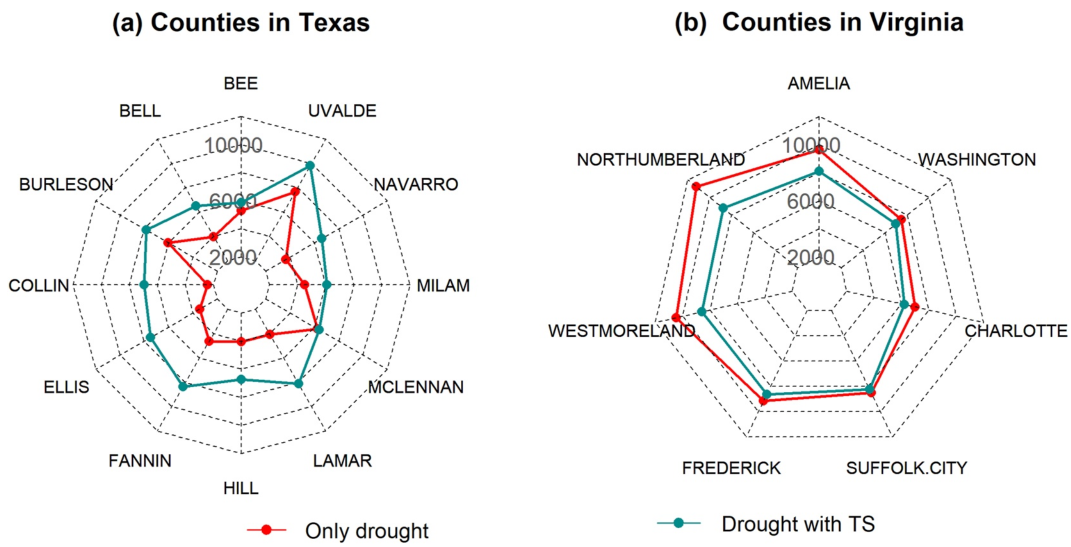

Figure 8. Corn yield derived from USDA for 12 and 7 counties in Texas and Virginia, respectively.

To investigate whether the drought amelioration (exacerbation) associated with TS have any positive (negative) impact on agriculture, we evaluated the relationship between droughts with and without TS at county scale corn yield (derived from USDA). In our analysis, we compared corn yield for several counties which were under drought conditions (but no TS events) against corn yield under drought conditions with TS events for the corresponding counties. Here, the temporal interval for pre- and post-TS is weekly, and the corn yield is annual. In general, the corn planting starts in April and harvesting season ends by November. We only consider the TS that landfall between April and November so that the TS is involved in the middle of the corn growing period and check the drought condition accordingly. For demonstration here, we present the corn yield for 12 and 7 counties from Texas and Virginia, respectively, during drought and drought with TS events (Figure 8). Based on our analysis, we found that counties in both states were affected by droughts during 2015 (no TS), 2017 (TS Harvey landfall in Texas during drought), and 2016 (TS Hermine landfall in Virginia during drought) (Figures S1 and S2 in Supporting Information S1). According to our analysis, corn yield increase for all the counties in 2017 (post-Harvey in Texas) (Figure 8a), whereas, the yield reduces in Virginia in 2016 (post-Hermine) (Figure 8b) relative to corn yield in 2015. As for Bee and McLennan counties in Texas, the reason of insignificant corn yield is likely due to flooding and strong winds from Hurricane Harvey (Perroni, 2017). Furthermore, student's *t* test conducted for the corn yield for pre- and post-TS years suggest the rejection of null hypothesis (p-value <0.05) that the corn yields are same. Therefore, statistically, we observe different corn yields at both states for pre- and post-TS. These results are consistent with the findings of our study and illustrate that droughts ameliorated or exacerbated by TS have severe positive and negative implications respectively on crop yield. Our analysis demonstrates how the associated TS and drought relates to crop yield which is a step ahead relative to the existing studies where analysis of the previous studies are limited only to the relationship between drought and TC.

In this study, the high-resolution root zone soil moisture data plays an important role in characterizing agricultural drought, representing the water-related to TS in terms of drought amelioration, and linking the two extremes. However, there is a limitation that affects the derivation of agricultural drought: short data length (4 yr). Since SSI is a statistical index, the values are highly dependent on the length of the data. Fortunately, as for the South and East US regions, the weekly drought map we created matches well to the weekly drought map provided by the US Drought Monitor. The 1 km downscaled SMAP data would be more useful in the future as the length of the data is getting longer since it is adding up current records to the data set starting from March 2015.

Here, we list some other factors that have uncertainties in terms of connecting the Atlantic TS to agricultural drought. First, we assumed that the precipitation from TS is correlated with soil moisture although they are not always positively correlated. According to recent studies, most of the locations in the CONUS have shown a positive relation between precipitation and soil moisture (Guillod et al., 2015; Sehler et al., 2019; Yang et al., 2018). With the assumption, we were able to utilize the soil moisture data as a linkage for TS and agricultural drought and conclude that the amelioration of drought is due to TS-related precipitation. Other than that the probability of drought ameliorated (exacerbated) by TS would not be valid. Second, the 5° radius buffer, which represents the impacted area from TS, is another source that could create uncertainty. We assumed TS-related precipitation falls all over the buffered area while precipitation does not always fall all over the place in practice (H. Jiang & Zipser, 2010). A shift in the buffer size or location will lead to a difference in the TS impacted regions in the US (Figure 2) and change the subsequent results one after another. For example, states or counties will be limited when a smaller buffer is applied. Third, the difference of the temporal resolution of the two extremes may create uncertainty. In this study, the difficulty of evaluating the shorter lifetime of landfalling TS (generally a few days to weeks) on longer remaining droughts (generally months to annual) are alternatively compromised utilizing weekly drought conditions to deal with the disputed lifespan of two different extreme events in this study. Finally, we used soil moisture and an empirical method to derive the SSI when there are other hydrological variables (i.g. precipitation), multivariate indices, parametric approach, and other conditions such as climate change and land use that can be considered to improve this study (Karimiziarani et al., 2022; Liu et al., 2017; Shukla & Wood, 2008; Waseem et al., 2015; Xing et al., 2020; L. Xu et al., 2020; L. Xu, Chen, Yang, Zhang, & Yu, 2021).

The percentage of drought ameliorated or exacerbated by TS based on the drought map ranges widely from 0 to more than 25%. When we group the percentage of drought ameliorated or exacerbated by TS into states, it shows a low rate where drought amelioration is less than 14% and drought exacerbation is less than 16%. This is because we considered all the 0% (white colored area in Figure 3) when averaging the drought ameliorate (exacerbated) by TS. For example, the probability of drought ameliorated by TS in Texas is 0% in more than half of the area in Texas. Some of the areas in Texas shows rate which is more than 10% (light orange, orange, red, and dark red colored area in Figure 3a). If we only consider the areas with positive percentage, the rank of the states shown in Figure 4 will be different. Nevertheless, we cannot generalize the information for the whole state based on a small portion of area nor conclude Texas has a higher probability of drought ameliorated by TS. In addition, the diverse characteristics of drought in a single state was inevitable due to the high spatial resolution data. This implies that some of the areas in the states with low percentage of drought amelioration may have chance of relatively higher probability of drought ameliorated by TS.

Overall, droughts in the East coast states (Delaware, District of Columbia, Maryland, New Jersey, and Virginia) including Georgia are more likely to be ameliorated or exacerbated after TS landfall when considered a threshold level of 10% for both amelioration and exacerbation. Droughts in Kentucky, Maine, Pennsylvania, Rhode Island, Tennessee, and West Virginia have relatively higher probability to be ameliorated than exacerbated by TS while Connecticut, Massachusetts, and North Carolina have relatively higher chance of exacerbation than amelioration.

The outcomes of this study are widely applicable for agricultural and water resources management studies and policymaking. The general perception that TS events are likely to ameliorate droughts is not true for all TS and droughts, especially in the East coast states. Therefore, the state governments/farmers might rely on the TS forecast for their crop planning, but drought may be persistent even after the TS during droughts. This might result in more water allocation for the irrigation and hence robust planning including modeling is paramount.

4. Conclusions

Our study is conducted to quantify the role of Atlantic TS in agricultural drought in the US. We generated a weekly drought map using SSI based on a high-resolution root zone soil moisture data set and then combined the drought events with TS events considering time and space to find whether the drought condition changes after TS occurs. We investigated whether the agricultural droughts are ameliorated or exacerbated by TS, and if so, how many of them are affected by Atlantic TS. Our study reveals that Atlantic TS are weakening and worsening agricultural drought in the US and that states are affected by TS from different perspectives. We were able to understand the characteristics of agricultural drought based on the weekly SSI map, and how each state is exposed to the risk of TS based on the frequency of TS and impacted regions in the US. We found that agricultural droughts in the East coast states are relatively experiencing more frequent and have more probability to be exacerbated after TS landfall due to climate conditions. Agricultural droughts in the Gulf of Mexico are infrequently ameliorated or exacerbated by Atlantic TS although TS offset droughts with longer duration in part of the states. Our research can be further studied and improved by composing a parametric multivariate drought index, extending the length of data, adding more details in evaluating the relationship between agricultural drought and TS. Our findings indicate detailed spatial information of the offset of drought conditions based on a high-resolution data set and provide potential information in terms of mitigating drought and TS for the future.

Data Availability Statement

One km downscaled SMAP soil moisture product can be accessed by CCHR website (https://moradkhani.ua.edu/smap). Rootzone soil moisture (SMERGE_RZSM0_40CM) is available at NASA Goddard Earth Sciences (GES) Data and Information Services Center (DISC) (https://disc.gsfc.nasa.gov/datasets/SMERGE_RZSM0_40CM_2.0/summary). Atlantic tropical storm data (HURDAT2) can be downloaded from the National Hurricane Center Data Archive (https://www.nhc.noaa.gov/data/#hurdat).

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