A COMPARISON OF SATELLITE DATA-BASED DROUGHT INDICATORS IN DETECTING THE 2012 DROUGHT IN THE SOUTHESTERN US

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Abstract

The drought of 2012 in the North America devastated agricultural crops and pastures, further damaging agriculture and livestock industries and leading to great losses in the economy. The drought maps of the United States Drought Monitor (USDM) and various drought monitoring techniques based on the data collected by the satellites orbiting in space such as the Gravity Recovery and Climate Experiment (GRACE) and the Moderate Resolution Imaging Spectroradiometer (MODIS) are inter-compared during the 2012 drought conditions in the southeastern United States. The results indicated that spatial extent of drought reported by USDM were in general agreement with those reported by the MODIS-based drought maps. GRACE-based drought maps suggested that the southeastern US experienced widespread decline in surface and root-zone soil moisture and groundwater resources. Disagreements among all drought indicators were observed over irrigated areas, especially in Lower Mississippi region where agriculture is mainly irrigated. Besides, we demonstrated that time lag of vegetation response to changes in soil moisture and groundwater partly contributed to these disagreements, as well.

Keywords: Drought monitoring; Drought indicators; MODIS; GRACE; USDM.

1. Introduction

Drought is one of the devastating natural hazards, which often recurs when plants cannot sustain their growth as a result of water deficit. Its occurrence interferes with agricultural production by significantly reducing crop yields, in turn damaging the global economy. As the world population has been steadily growing, food supply must keep up with this increasing demand.

In this regard, several drought monitoring tools such as United States Drought Monitor (USDM) (Svoboda et al. 2002) and Global Agricultural Drought Monitoring and Forecasting System (GADMFS) (Deng et al. 2013) have been developed to detect onset, duration, extent and severity of drought and timely inform state and government agencies, stake-holders, farmers and public so that its devastating effects can be mitigated.

Observations obtained by satellites orbiting in space are indispensible to routinely track the Earth's ground and surface water resources and natural hazards such as droughts and floods, etc. In the last decade, many efforts have been devoted to drought monitoring. Drought is relatively defined natural phenomenon, generally identified by the deviations of precipitation (e.g., meteorological drought), soil water (e.g., agricultural drought) and ground water and streamflow (e.g., hydrological drought) from their long-term average condition (Wilhite 2000).

Remotely-sensed vegetation indices such as the Normalized Difference Vegetation Index (NDVI) have been extensively used to track droughts (Kogan 2001), especially from the NOAA’s Advanced Very High Resolution Radiometer (AVHRR) because of its long record (e.g., ≈ 30 years). Vegetation indices are good surrogate measures of photosynthetically functioning vegetation

(Tucker and Choudhury 1987). Because drought hinders the photosynthetic activity of plants, large-scale reduction in NDVI over a region (e.g., statewide) can be associated with droughts. After completing the 10 years in orbit, the products of NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) have been also used to monitor droughts (Yagci et al. 2012; Deng et al. 2013). MODIS acquires observations in narrower bands than the AVHRR instrument, successfully avoiding the water vapor absorption in the Visible-RED (RED) and Near-Infrared (NIR) region of the electromagnetic spectrum. Therefore, MODIS-NDVI products attain relatively larger values and better accuracy in exhibiting temporal profiles of forests than the AVHRR-NDVI data (Huete et al. 2002).

In addition to NDVI, ability of surface brightness temperature (Tb) or land surface temperature (LST) to track drought has been successfully tested and validated against the crop yields in the state of Texas, U.S.A (Yagci et al. 2011) and around the globe (Kogan 2001). LST is better indicator of surface temperature conditions than Tb since it is corrected for surface emissivity and estimated from surface radiance, i.e., atmospherically corrected surface radiance reaching the sensor. LST is a proxy for moisture availability and evapotranspiration conditions such that water depletion in the plant root zone leads to stomatal closure, reduced transpiration and subsequently elevated canopy temperatures (Anderson and Kustas 2008). Drought detected by NDVI and LST products is referred to as vegetative drought or agricultural drought.

In recent years, a new way has surfaced to monitor drought through analysis of the terrestrial water storage (TWS) anomalies. The monthly variations in the Earth's gravitational signal measured by twin satellites of the Gravity Recovery and Climate Experiment (GRACE) have been shown to relate to monthly TWS changes with roughly 1.5 cm accuracy at regional scales (Wahr et al. 2004). GRACE-derived TWS is coarsely resolved and contains vertically-integrated information about surface and sub-surface water conditions, therefore its spatial, temporal, and vertical decomposition into soil moisture and groundwater components achieved through data assimilation into the Catchment Land Surface Model (CLSM) aids in its interpretation and application to drought monitoring (Houborg et al. 2012; Rodell 2012). The resulting groundwater and soil moisture wetness fields are appropriate for hydrological and agricultural drought monitoring applications, respectively.

USDM is a collaborative effort by the National Drought Mitigation Center of the University of Nebraska—Lincoln, the Departments of Commerce and Agriculture and outside experts to summarize weekly drought conditions across the U.S. (Svoboda et al. 2002). Despite the fact that USDM is the premier drought product for the U.S., it does have certain shortcomings such as a tendency towards overestimation of drought areal coverage and difficulty in representing the local-scale (e.g., county-scale) conditions, which have been highlighted by several studies (Brown et al. 2008; Tadesse, Brown, and Hayes 2005).

The conterminous U.S. experienced a vast costly drought in 2012 which caused disastrous impacts on agriculture and livestock industries, totaling nearly $30 billion losses (Rippey 2015). The drought of 2012 was similar to the drought of 1988 in terms of cost and the mega-drought of the 1950s in terms of areal coverage (Rippey 2015). In this study, characteristics of the 2012 drought are examined using the drought maps derived from the aforementioned approaches. Each method is rather distinct in terms of input type and source, theoretical background and level of complexity. Their results are inter-compared in 2012, and their similarities and discrepancies are also highlighted in Southeast US.

2. Data and Methods

2.1. NDVI

NDVI is a measure of vegetation greenness, ranging from -1 to 1. Presence of chlorophyll pigments in plant leaves causes visible sunlight in RED region of the spectrum to be absorbed for photosynthesis and sunlight in NIR region of spectrum is substantially reflected due to cell structure of the leaves. Therefore, green healthy functioning vegetation, always attains larger NDVI value than brown stressed vegetation. Swain et al. (2011) demonstrated that NDVI in the drought year of 2002 was considerably smaller than NDVI during the non-drought year, 2007 over the croplands and grasslands of Nebraska, U.S. The 16-day composite MODIS-NDVI products (Collection 5) were retrieved from the NASA's Land Processes Distributed Active Archive Center (LP DAAC). The level-3 NDVI products, abbreviated as MOD13A2.005, are compiled from radiometrically-, geometrically- and atmospherically-corrected surface reflectances and have 1-km spatial resolution. The compositing algorithm, the constrained view angle maximum value composite (CV-MVC), picks the best available NDVI observation that is non-cloudy and closest to nadir view to represent the vegetation conditions during the 16-day period (Solano et al. 2010).

2.2. LST

LST is a proxy variable for moisture availability and evapotranspiration conditions (Anderson and Kustas 2008). Elevated LSTs are typical during drought years as opposed to LSTs observed in normal or wet years since plants are not transpiring to cool off the canopy. Likewise, Swain et al. (2011) demonstrated that LST increased during the 2002 drought year in comparison to the 2007 normal year in the croplands (corn) and grasslands of Nebraska. The collection 5 daytime MODIS-

LST products were retrieved from the NASA's LP DAAC. The level-3 LST products, abbreviated as MYD11A2.005, are composited over a 8-day period with 1-km spatial resolution and calculated from radiometrically-, geometrically- and atmospherically-corrected surface radiances. Unlike 16-day NDVI composites, the 8-day LST composite is the average of all non-cloudy LSTs during the 8-day period (Wan 2007).

2.3. Vegetation Condition Index (VCI)

The Vegetation Condition Index (VCI) was introduced to separate the annually varying NDVI component due to prevailing weather conditions from long-term component of NDVI (e.g., climate, soil and land cover type) (Kogan 1997). The index ranges from 0 to 100 and can be calculated with the following formula:

$$VCI_c = 100 \times \frac{NDVI_c - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (\mathbf{1})$$

where $NDVI_{min}$ and $NDVI_{max}$ are the multi-year minimum and maximum NDVI values, respectively, and $NDVI_c$ is the NDVI value of the compositing period of interest. For instance, if VCI of the 177th day of 2012 is the interest, then $NDVI_c$ is the NDVI value of the 177th day of 2012. VCI values of 0 and 100 indicate the worst and best vegetation conditions, respectively. Prior to VCI calculation, low-quality NDVI pixels that are covered with cloud, cloud shadows and adjacent to clouds were removed based on quality flags in the corresponding quality assurance (QA) layers that come with the NDVI products. The resulting gaps in NDVI products were filled by interpolation. NDVI observations from two preceding and following 16-day periods along with their corresponding day of year (DOY) information were used to interpolate gaps and downscale to 8-day temporal resolution. The VCI-based drought maps were compiled by the percentile-based classification scheme given in Table 1.

2.4. Temperature Condition Index (TCI)

Similar to VCI, TCI was designed to highlight LST changes due to prevailing weather conditions (Kogan 1997). It ranges from 0 to 100 and can be calculated with the following formula:

$$TCI_c = 100 \times \frac{LST_{max} - LST_c}{LST_{max} - LST_{min}} \quad (\mathbf{2})$$

where LST_{min} and LST_{max} are the multi-year minimum and maximum LST values, respectively, and LST_c is the LST value of the compositing period of interest. For instance, if TCI of the 177th day of 2012 is the interest, then LST_c is the LST value of the 177th day of 2012. Minimum and maximum TCI values (e.g., 0 and 100) indicate the worst and best vegetation conditions, respectively. Prior to TCI calculation, LST products underwent a masking process where all cloudy LST observations were removed. The incomplete LST time series were filled by temporal interpolating using LST observations from two preceding and following 8-day compositing periods. The TCI-based drought maps were categorized by the drought classification scheme in Table 1 to identify drought-affected areas.

2.5. United States Drought Monitor (USDM)

The team of roughly 15 authors of the USDM combines meteorological, agricultural and hydrological drought indicators such as Palmer Drought Severity Index (PDSI), Climate Prediction Center (CPC) soil moisture model, US Geological Survey (USGS) weekly streamflow, Standardized Precipitation Index (SPI) and other drought indices to produce weekly drought maps, by focusing on broad-scale conditions (e.g., state-level). In turn, it may not be used to infer local-scale (e.g., county-level) conditions. Drought is classified by percentiles into 5 different severities, abnormally dry, moderate, severe, extreme and exceptional drought, as outlined in Table 1 (The National Drought Mitigation Center 2016). In the end, a blend of drought indicators with different weights determined subjectively by the experts contributes to the final drought map (Svoboda et al. 2002), and this map is updated weekly and disseminated via the USDM website (http://droughtmonitor.unl.edu/Home.aspx).

Table 1 - USDM Drought Classification Scheme

Category	Description	Percentiles
D0	Abnormally Dry	21 to 30
D1	Moderate Drought	11 to 20
D2	Severe Drought	6 to 10
D3	Extreme Drought	3 to 5
D4	Exceptional Drought	0 to 2

2.6. GRACE-based Drought indicators

Earth's gravity field varies in space and time as a result of heterogeneities and movements of mass at the surface, including redistribution of terrestrial water storage (TWS). GRACE detects these gravitational variations as they perturb the orbits of its twin satellites (Tapley et al. 2004; Wahr et al. 2004), and uses them to infer monthly changes in TWS at regional scales (>150,000 km^2) (Swenson et al. 2006). In addition to its coarse spatial and temporal resolutions, GRACE alone cannot separate changes in groundwater, soil moisture, surface waters, and snow/ice (Rodell and Famiglietti 1999). Zaitchik, Rodell, and Reichle (2008) proposed a data assimilation method based on the Catchment Land Surface Model (Koster et al. 2000) to downscale and vertically decompose GRACE-based TWS. Later, Houborg et al. (2012) applied this data assimilation approach to GRACE-derived TWS and produced drought indicators for surface soil moisture (SFSM), root-zone soil moisture (RTSM) and ground water storage (GWS) in 0.125 degree resolution, which conformed to the percentile ranges proposed by the USDM (Table 1), thus delineating drought-affected areas across the continental U.S.. SFSM and RTSM are indicative of agricultural drought, whereas GWS can be used to map the extent and severity of hydrological drought. These experimental GRACE-based products are now incorporated into the USDM and disseminated weekly via this website, http://drought.unl.edu/monitoringtools/nasagracedataassimilation.aspx.

2.7. Study area

The study area is the southeastern U.S., where a humid warm temperate climate is prevalent according to Köppen-Geiger climate classification (Kottek et al. 2006). The land cover is mainly dominated by forests (mostly deciduous), cultivated crops and hay/pasture according to the National Land Cover Database 2011 (NLCD 2011). Summers are characteristically hot and wet with frequent thundershowers. Evaporative demand is high during summers, which makes the region very susceptible to drought when seasonal rainfall is delayed.

Basins in the study area (Figures 1 and 2) were retrieved from the website of the Watershed Boundary Dataset (WBD) (http://nhd.usgs.gov/wbd.html) to compare the drought indicators on the basin-level. The WBD contains boundaries of drainage areas developed by the collaborative effort among the US federal agencies in consistent with national federal standards, and topographic and hydrologic features across the US and territories (U.S. Geological Survey and the U.S. Department of Agriculture, Natural Resources Conservation Service 2013). Each basin in the WBD is defined as the level-3 hydrological unit and assigned a unique identifier, hydrological unit code (HUC). In this paper, we follow the naming conventions of hydrological units established in the WBD, Region (Level-1), Basin (Level-3) and Watershed (Level-5), in the descending order with respect to areal size.

Various crops such as corn, soybeans, rice, winter wheat, sorghum, cotton and peanuts are grown in the study area, particularly in lower Mississippi region along Mississippi river (Figure 1). During hot seasons, crops are irrigated to support crop growth and ensure high crop yields, and irrigation is primarily concentrated over Lower Mississippi region (Figure 3) according to the irrigation map, extracted from the MODIS Irrigated Agriculture Dataset for the US (MIrAD-US). Pervez and Brown (2010) developed a geospatial model by combining remote sensing inputs such as MODIS-NDVI and NLCD products with US Department of Agriculture (USDA) Census of Agriculture irrigated area statistics to produce 2012 irrigated-agriculture areas dataset at 250-m resolution.

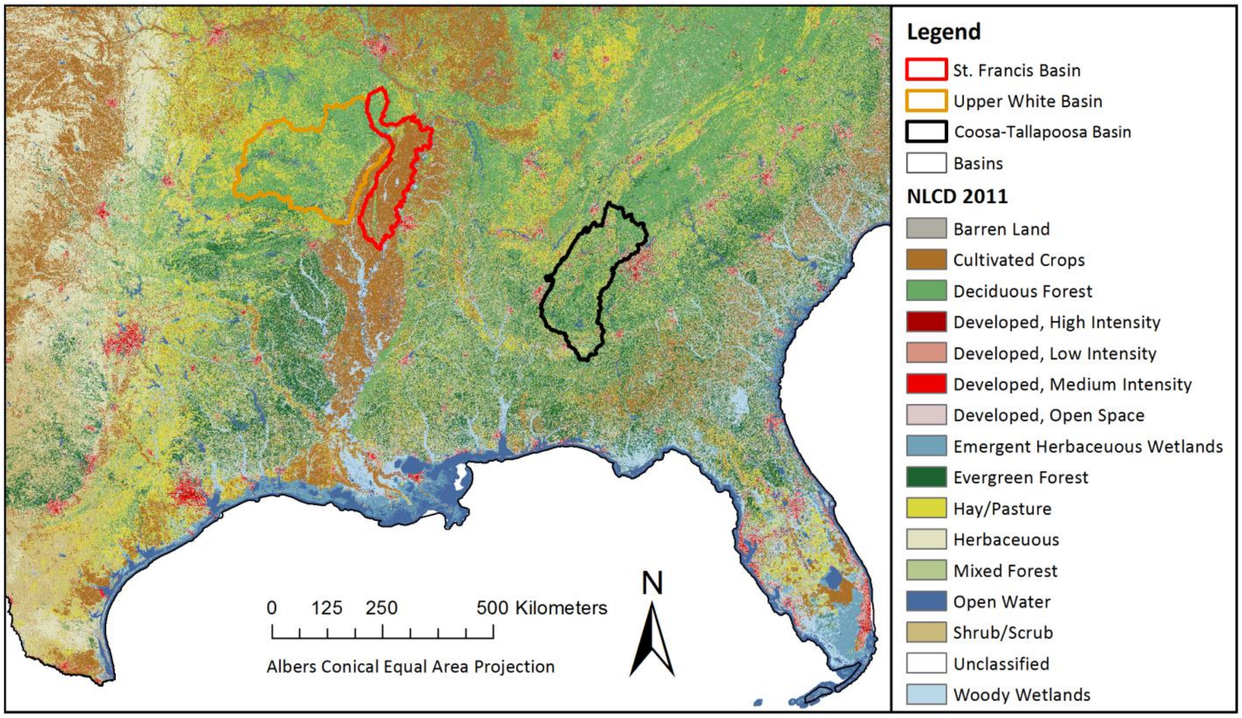

Figure 1 - Study area and boundaries of basins defined in the Watershed Boundaries Dataset (WBD). The background image is the land cover/land use subset from the National Land Cover Database 2011 (NLCD 2011).

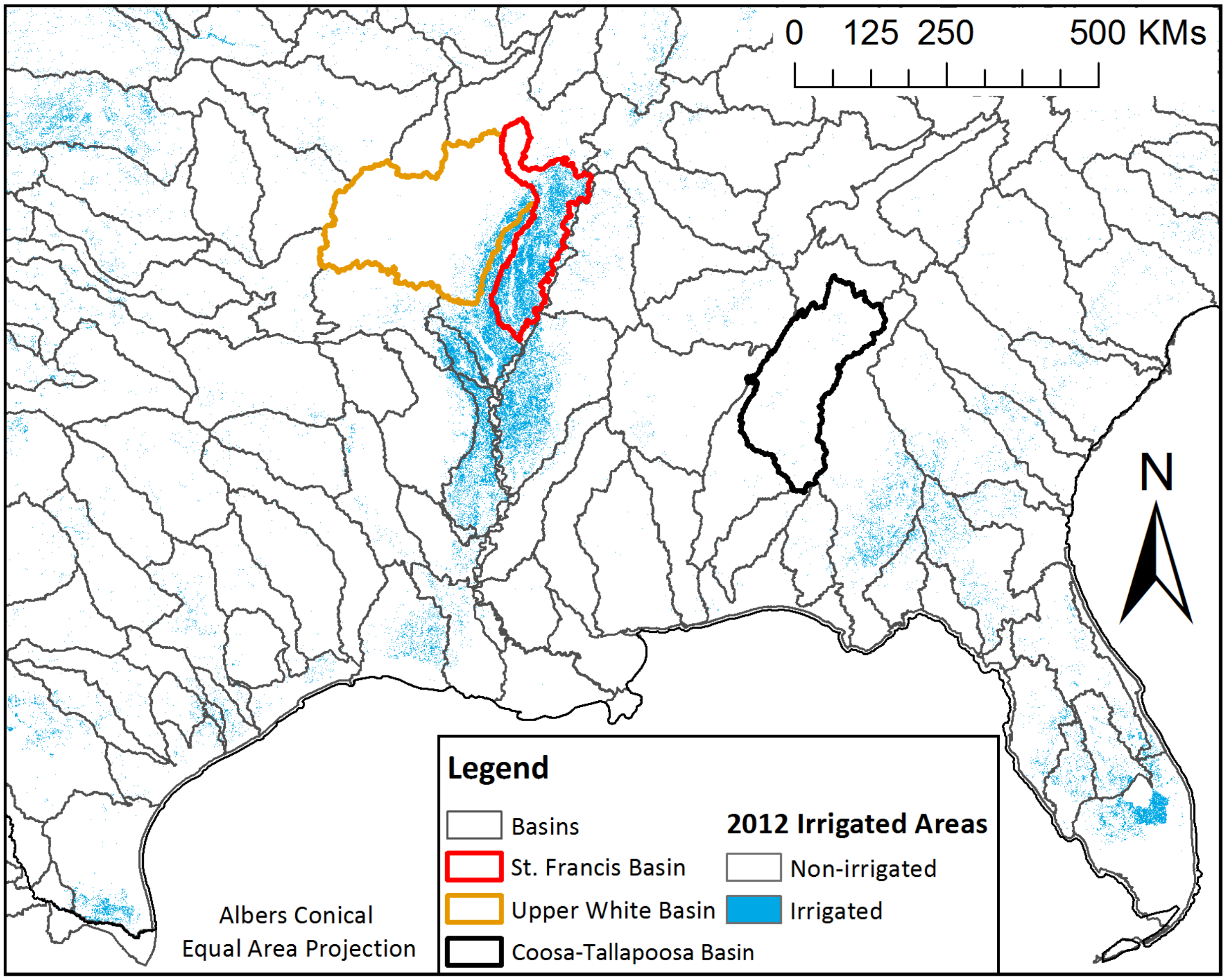

Figure 2 - Irrigated areas in 2012 with respect to basins in the study area. Irrigation map is the subset of the MODIS-based Irrigated Areas Database (MIrAD 2012)

3. Results

The spatial extent and severity of the 2012 drought are mapped by all drought indicators as described in Section 2. The identical classification scheme (Table 1) is employed to indentify drought-affected regions and quantify severity of drought, ensuring that they are all in same units. Therefore, percentile-based classification allows us to visually and quantitatively analyze the drought results and draw meaningful conclusions. Visual comparison is necessary to analyze the spatial extent of drought reported by all drought indicators, while quantitative examination enables to inter-compare results with respect to drought onset, end and intensity. It is crucial to re-emphasize that drought maps based on GWS percentiles is an indicator of hydrological drought, while VCI-, TCI-, RTZSM- and SFSM-based drought maps provide agricultural drought conditions. On the other hand, USDM-based drought maps collectively contain information about hydrological, meteorological and agricultural drought.

3.1. Spatial Representation of Drought

GRACE- and MODIS-based maps are shown side-by-side in Figure 3 along with the USDM map on August 6, 2012. These maps are valid for the week of 6-12 August, 2012, except that USDM map is valid for the week of 7-13 August, 2012. Good correspondence between TCI- and VCI-based maps was observed, although VCI indicated relatively large drought extent. Both maps were also generally in good agreement with the USDM map and GRACE-SFSM, although they displayed more extensive drought extent than MODIS-based drought indices. One stark discrepancy among all indicators was seen in Georgia where both GRACE-derived indices and USDM suggested severe-to-exceptional agricultural drought, while VCI and TCI did not indicate any drought. Over Central US, drought extent reported by all indicators were in complete agreement. Of all the indicators, the largest drought extent was reported by GRACE-GWS and -RTZSM on August 6, 2012 (Figure 3).

Another disagreement in indices was observed over Lower Mississippi region where the land is cultivated for agricultural production. Crops in this region were irrigated in 2012 according to irrigated agriculture map (Figure 2). Over this region, VCI did not report widespread reduced vegetation activity (Figure 4), and TCI did not indicate elevated LST in comparison to other years, both indicating a response of the respective index to the irrigation signal. On the other hand, severe-to-exceptional drought was reported in the USDM and GRACE-derived SFSM over the St. Francis basin (Figure 4), indicating that their broader-scale indices did not capture the local irrigation practices that were taking place in 2012.

According to GRACE-based maps, ground water, root-zone and surface soil moisture all deviated negatively from their historical averages throughout the study area, further signaling both agricultural and hydrological drought throughout Southeast US. In Georgia where VCI and TCI did not detect drought on August 6, 2012, both USDM and GRACE-based drought indicators detected severe-to-exceptional drought. Over irrigated agriculture of Lower Mississippi region, GRACE-based drought indicators were in agreement with USDM, but not with the MODIS-based indicators (Figure 3 and 4). Disagreements between MODIS and GRACE indices were generally situated along Appalachians Mountains (e.g., Blue Ridge mountains, and Ridge and Valley), Piedmont Plateau and Atlantic Coastal Plains. Over these regions, GRACE drought indicators reported severe-to-exceptional groundwater and soil moisture depletion in 2012. Drought reported by GRACE-SFSM was not seen in VCI and TCI maps along Appalachians Mountains. Broadly, discrepancies between GRACE-SFSM and MODIS indices seemed to be concentrated over highly elevated areas along Appalachians Mountains (i.e., Blue Ridge Mountains).

There is a well-known lagged response of vegetation (i.e., NDVI) to precipitation (Di, Rundquist, and Han 1994), and Ji and Peters (2003) suggested 3-month lag of NDVI to precipitation deficit. For this reason, 3-month Percent of Normal Precipitation for the time period of June-August of 2012 (Figure 5) was retrieved from the NOAA's National Climatic Data Center (NCDC) (http://www.ncdc.noaa.gov/temp-and-precip/). This precipitation deficit map broadly matched drought extent indicated by VCI on August 6, 2012, while smaller drought extent was reported by TCI. Both USDM and GRACE-SFSM indicated comparatively larger drought extent.

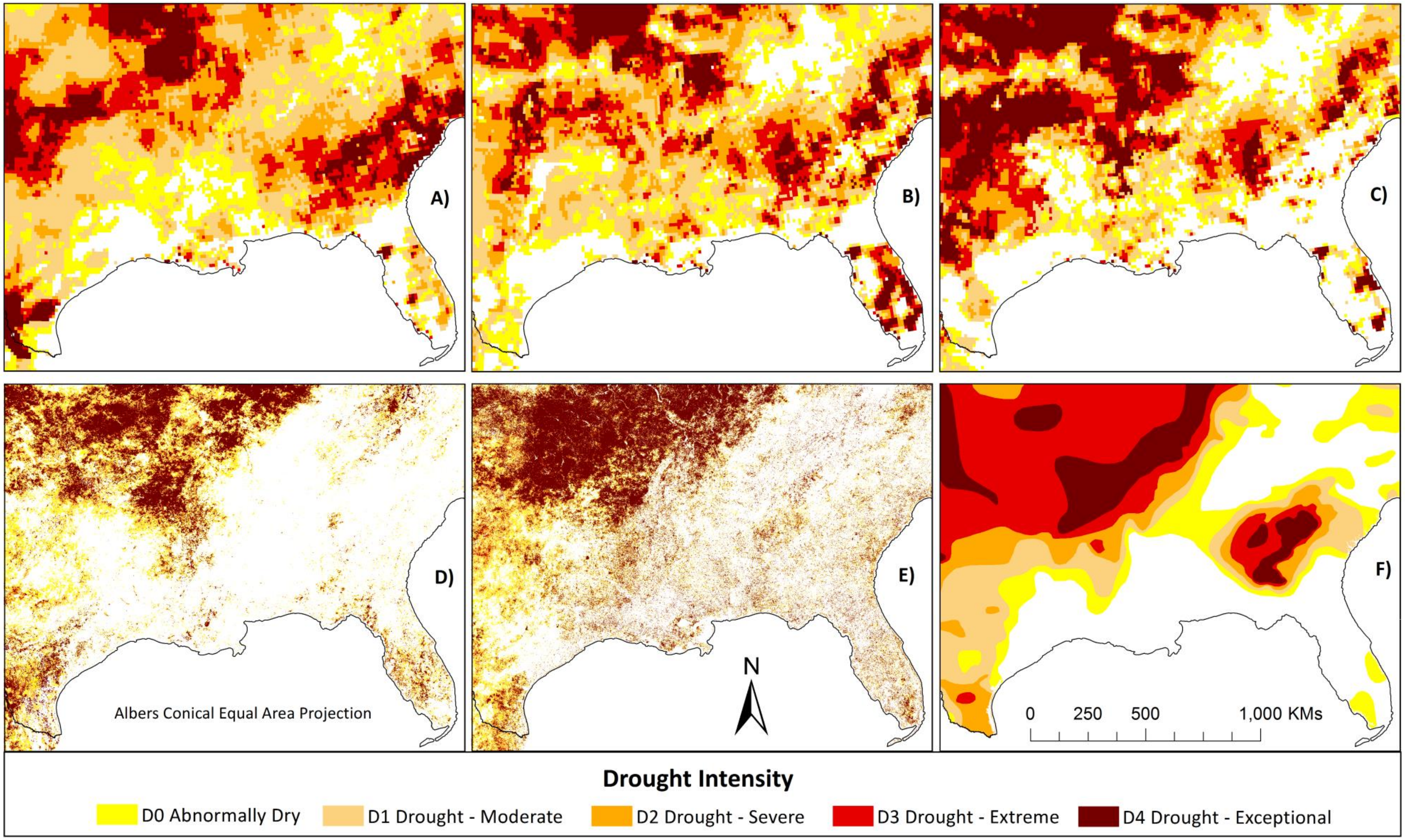

Figure 3 - GWS-based (A), RTZSM-based (B), SFSM-based (C), TCI-based (D), VCI-based (E) and USDM (F) drought maps. The USDM drought map is valid from August 7 to August 13, 2012, and all other maps are valid between August 6 and August 12, 2012.

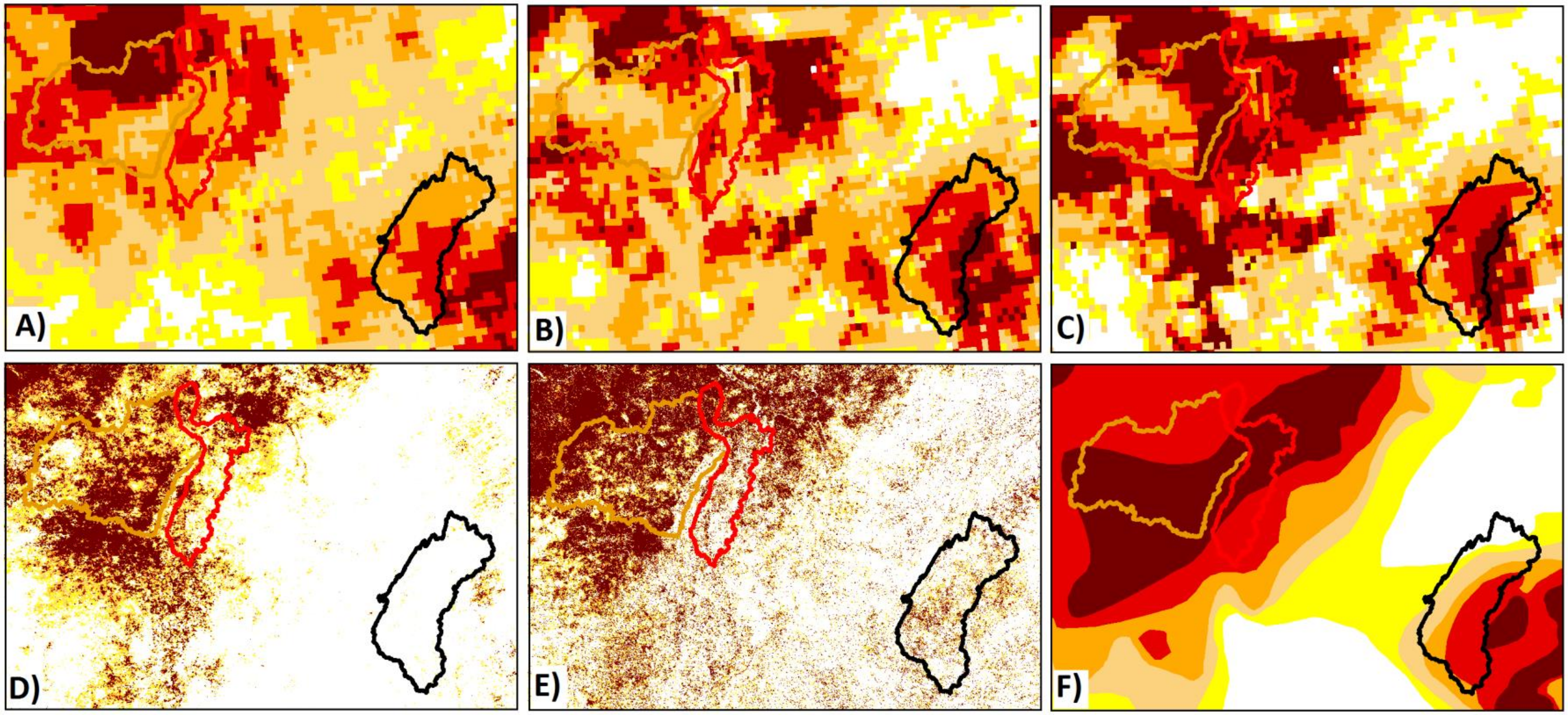

Figure 4 - The close-up view of the drought maps over three basins on August 6, 2012 (USDM map is on August 7, 2012). Basin names are given in both Figures 1 and 2. The order of drought maps is same as the order in Figure 3.

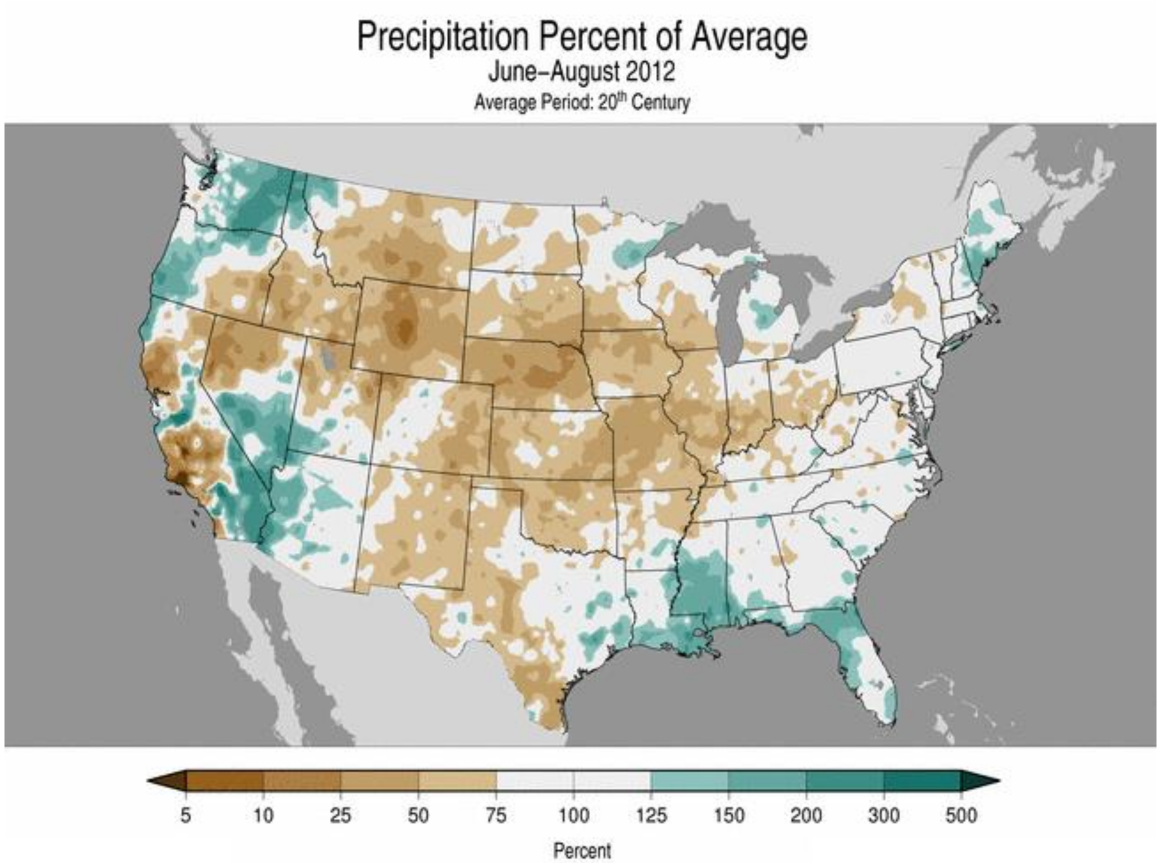

Figure 5 - 3-month Percent of Normal Precipitation for the time period of June- August, 2012 (NOAA-National Climatic Data Center 2012).

3.2. Drought intensity

Aside from analysis of spatial extent of drought, quantitative examination of drought intensity is essential to reveal similarities and differences across indices. The comparison is conducted based on the basin-level averages of drought indicators. The location of three basins in the study area, Coosa-Tallapoosa (HUC6=031501), St. Francis (HUC6= 080202) and Upper White (HUC6= 110100) can be seen in both Figures 1 and 2. Coosa-Tallapoosa basin was selected for analysis because MODIS-based drought indicators did not indicate any drought on August 6, 2012, in contrast to USDM and GRACE-derived indicators (Figure 4). St. Francis basin was impacted by the irrigation signal seen only in VCI and TCI, and all drought indicators were in good agreement in

Upper White basin. Using basin boundaries, time series of VCI, TCI, RTZM, SFSM and GWS were constructed between April 30, 2012 and October 1, 2012 on a weekly basis (Figures 6 and 7).

The results (Figure 6a) show that VCI was relatively constant above the drought threshold (>30, Table 1) in St. Francis basin throughout 2012 where agriculture is irrigated (Figure 2). Similarly, VCI didn't report any drought throughout the 2012 growing season in Coosa-Tallapoosa basin where precipitation deficit was not seen between June and August of 2012 (Figure 5). However, TCI fluctuated substantially around the drought threshold throughout 2012 in St. Francis basin (Figure 7a) unlike Upper White (Figure 7b), indicating drought from May 14 to May 27, no drought from May 28 to June 17, drought from June 18 to July 8 and no drought from July 9 to July 15. Moreover, TCI was reported drought during the late June and early July of 2012 (Figure 7c) and at other times, no drought was indicated by TCI in Coosa-Tallapoosa basin. From early June to late August in 2012, good correspondence was observed between all GRACE-based and MODIS-based drought indicators in Upper White basin (Figure 6b and 7b), identifying drought conditions. GRACE-derived indicators implied that all three basins experienced severe-to-exceptional drought during the 2012 growing season.

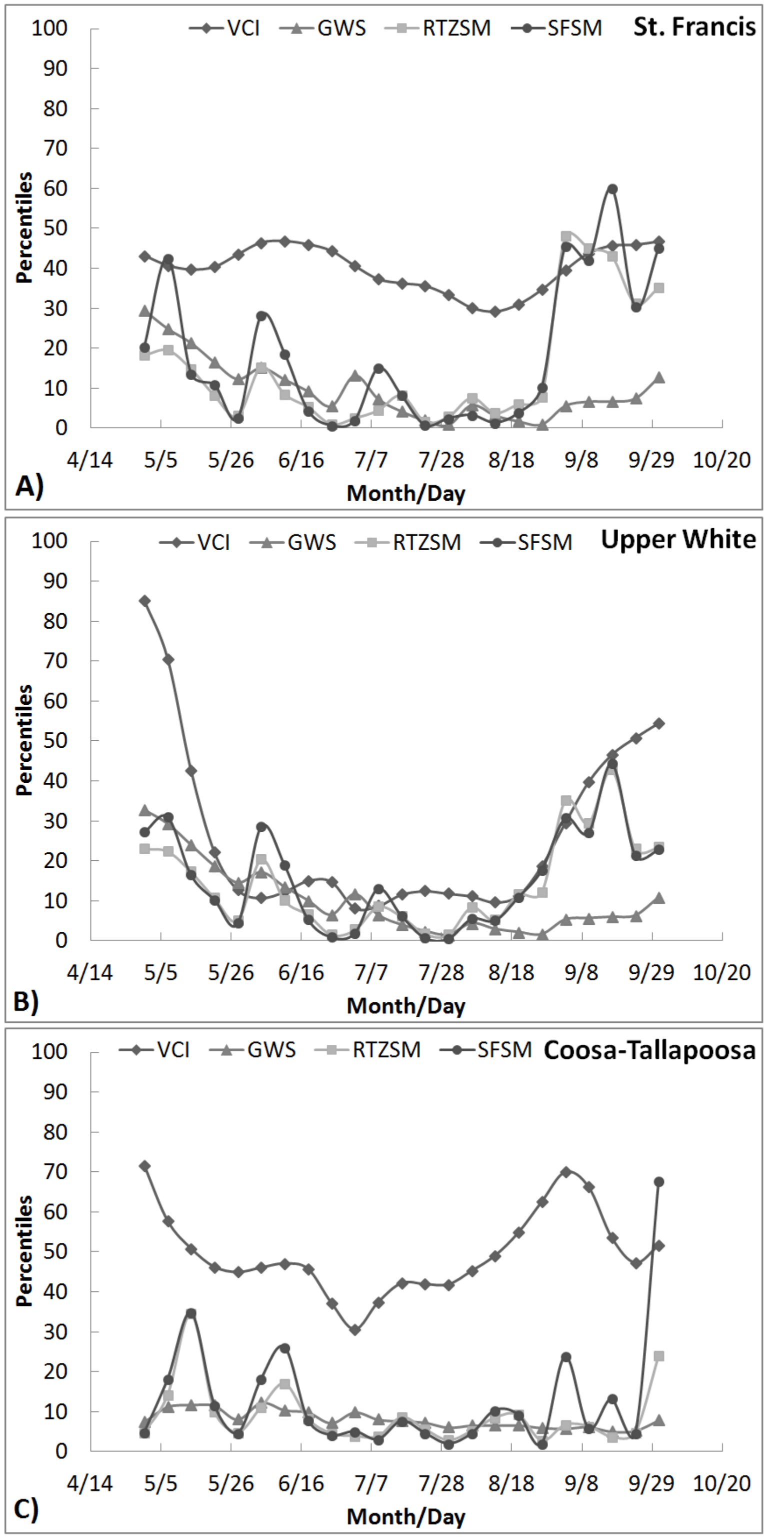

Figure 6 - Basin averages of Vegetation Condition Index (VCI), Groundwater Storage (GWS), Root-Zone Soil Moisture (RTZSM) and Surface Soil Moisture (SFSM) in St. Francis (A), Upper White (B) and Coosa-Tallapoosa (C).

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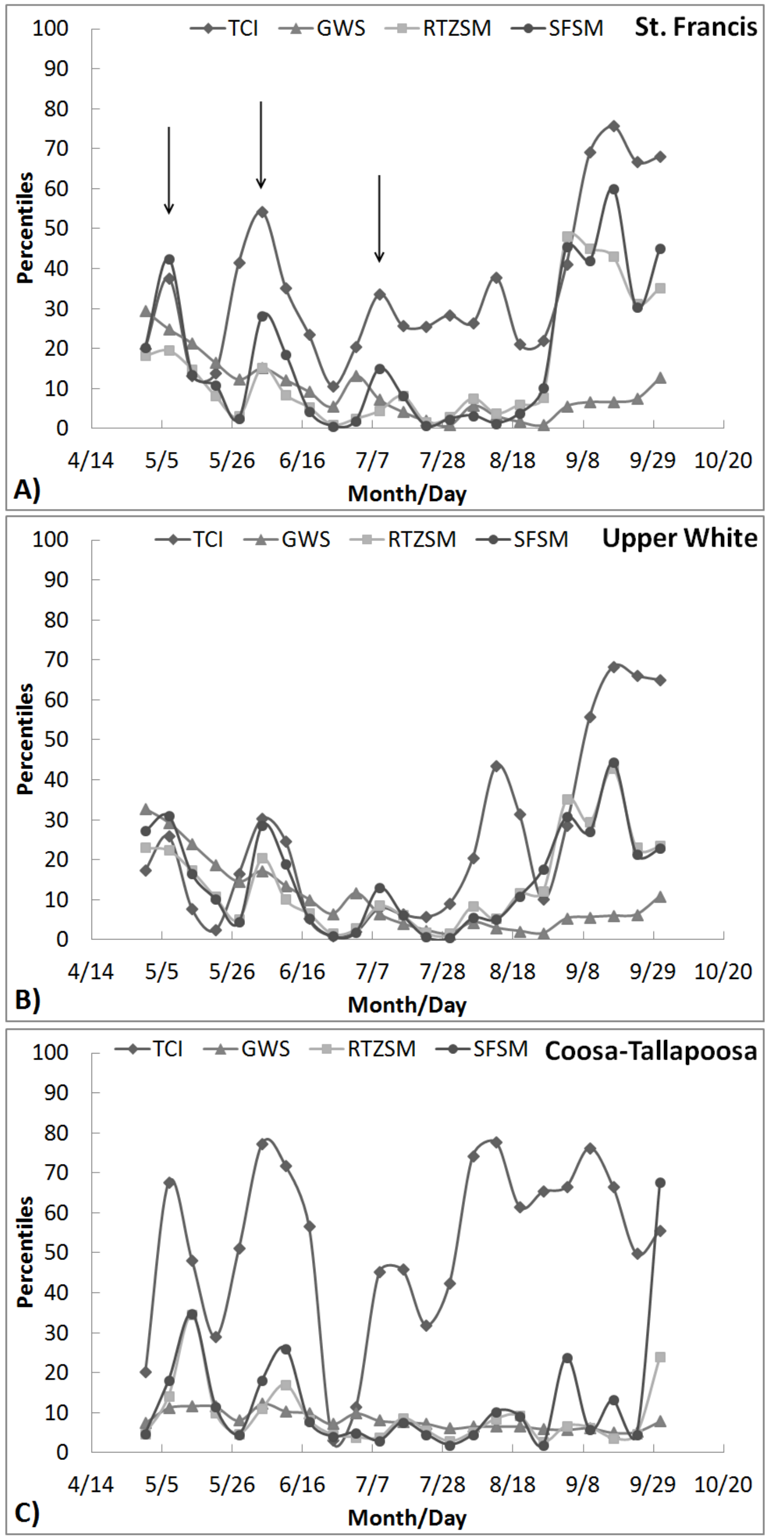

301 **Figure 7 - Basin averages of Temperature Condition Index (TCI), Groundwater Storage (GWS), Root-Zone Soil**
302 **Moisture (RTZSM) and Surface Soil Moisture (SFSM) in St. Francis (A), Upper White (B) and Coosa-Tallapoosa (C).**

Correlation analysis was conducted using the time series of drought indicators in 2012. Each time series is composed of 23 weekly observations spanning from April 30 to October 1, 2012. The results revealed that TCI had higher statistically significant relationship at 0.01 significance level with both SFSM and RTZSM than GWS in St. Francis and Upper White basins (Table 2). TCI did not display any relation to groundwater variations in all basins. On the other hand, VCI exhibited statistically significant relationship with GWS, RTZSM and SFSM only in Upper White basin. Finally, there was no statistically significant correlation among any MODIS- and GRACE-based indicators in Coosa-Tallapoosa basin.

Lagged response of NDVI and NDVI-based drought indices to soil moisture at various depths up to 100cm was reported by other studies (Peng, Deng, and Di 2014; Adegoke and Carleton 2002) such that response of plants to soil moisture changes is not concurrent, rather exhibits some time lag. Time lags up to 7 weeks are considered, and additional basin averages of GRACE-derived GWS, RTZSM and SFSM are computed starting from January 16 until October 1, 2012, ensuring that correlation coefficients are always computed from 23 weekly observations of all drought indicators and the time period matches the growing season when vegetation is not dormant (i.e., April 30 to October 1). The results (Table 3) show that correlations among drought indicators improved considerably, thus suggesting that VCI exhibited lagged response to changes in surface and root-zone soil moisture in St. Francis and Upper White basins. On the other hand, no lag was found between TCI and GRACE-based RTZSM and SFSM, thus suggesting that LST varies simultaneously with SFSM and RTZSM during dry years. Again, there was no significantly lagged relationship among all indicators in Coosa-Tallapoosa basin. Overall, VCI lagged behind RTZSM and SFSM about 2 weeks in St. Francis and Upper White basins. Therefore, TCI responded to changes in SFSM and RTZSM more quicker than VCI in St. Francis and Upper White basins. Furthermore, the results pointed out that VCI and TCI had positive relationship in all basins, yet only statistically significant at 0.01 level in Upper White basin (Table 3). Time delay of 3 weeks between VCI and TCI was observed in Upper White basin.

Table 2- Correlation coefficients (r) between VCI, TCI, SFSM, RTZSM and GWS in St. Francis, Upper White and Coosa-Tallapoosa basins. Time series are composed of observations time series between April 30 and October 1, 2012. Statistically significant r at 0.01 significance level (α = 0.01) are underlined. The critical r value is 0.53 at 0.01 significance level.

N=23	St. Francis		Upper White		Coosa-Tallapoosa	
r=0.53	VCI	TCI	VCI	TCI	VCI	TCI
GWS	0.46	-0.08	0.64	-0.13	-0.26	-0.08
RTZSM	0.43	0.75	0.67	0.71	0.07	0.17
SFSM	0.52	0.78	0.67	0.64	0.17	0.23
TCI	0.44		0.44		0.40	

Table 3 - The lags and their correlation coefficients (r) between VCI, TCI, SFSM, RTZSM and GWS in St. Francis, Upper White and Coosa-Tallapoosa basins. Statistically significant r and lag at 0.01 significance level (α = 0.01) are underlined. The critical r value is 0.53 at 0.01 significance level.

N=23	St. Francis				Upper White				Coosa-Tallapoosa			
r=0.53	VCI		TCI		VCI		TCI		VCI		TCI	
	lag	r	lag	r	lag	r	lag	r	lag	r	lag	r
GWS	0	0.46	0	-0.08	0	0.64	0	-0.13	7	0.14	0	-0.08
RTZSM	2	0.55	0	0.75	2	0.87	0	0.71	0	0.07	0	0.17
SFSM	1	0.57	0	0.78	2	0.83	0	0.64	0	0.17	0	0.23
TCI	1	0.46	-	-	3	0.84			1	0.50		

The correlation analysis among GRACE-derived SFSM, RTZSM and GWS revealed that SFSM was strongly correlated with RTZSM and GWS in all basins (Table 4), although relationship was relatively less strong in Coosa-Tallapoosa basin in 2012. SFSM relation to RTZSM was concurrent, while time lag of 4 weeks was observed between SFSM and GWS in all basins (Table 4). The results also suggested that there was a strong lagged-relationship between RTZSM and GWS in all basins, and the lag was 5 weeks in St. Francis and Upper White basin and 3 weeks in Coosa-Tallapoosa basin.

Table 4 - The lags and their correlation coefficients (r) among GRACE-derived drought indicators in St. Francis, Upper White and Coosa-Tallapoosa basins. The critical r value is 0.46 at 0.01 significance level.

N=31	**SFSM**					
r=0.46	**St. Francis**		**Upper White**		**Coosa-Tallapoosa**	
	lag	**r**	**lag**	**r**	**lag**	**r**
RTZSM	0	0.93	0	0.97	0	0.75
GWS	4	0.89	4	0.89	4	0.69
	RTZSM					
GWS	5	0.94	5	0.93	3	0.81

4. Discussion

Over irrigated agriculture in Lower Mississippi region, VCI did not report any drought although USDM clearly indicated drought in 2012. Especially in St. Francis basin, VCI provided more consistent results as opposed to TCI because LST responds more rapidly to prevailing weather conditions and irrigation events than NDVI. Furthermore, there was no discernible variation in SFSM, RTZSM and GWS unlike that observed in TCI over irrigated fields of St. Francis basin. It can be concluded that when agricultural fields were irrigated in 2012, LST decreased rapidly, and subsequently TCI signaled no drought. When the surface became dry before the next irrigation event, TCI reported drought after the sudden increase in LST (Figure 7a). In conclusion, discrepancy between MODIS- and GRACE-based results in St. Francis can be easily explained by irrigation, where irrigation is not considered in the decomposition of GRACE-based TWS into SFSM, RTZSM and GWS (Houborg et al. 2012).

Correlation analysis revealed that the relationship between VCI and GRACE-based SFSM and RTZSM is not concurrent, rather lagged in St. Francis and Upper White basins, whereas TCI had concurrent positive relationships with both GRACE-derived SFSM and RTZSM. Approximately, VCI exhibited 2-week lag to surface and root-zone soil moisture in 2012. Such conclusions with NDVI-based indices were achieved by other studies (Peng, Deng, and Di 2014; Adegoke and Carleton 2002), as well. Correlations between VCI and other drought indicators were statistically significant at 99% confidence level and improved considerably when lag effect is taken into consideration in St. Francis and Upper White basins. However, the results of the correlation analysis in St. Francis basin should be interpreted with caution since transfer of groundwater to surface through irrigation and subsequently infiltration of that water down to root-zone is not explicitly handled in CLSM. Besides, the land is heavily subject to anthropogenic effects (e.g., irrigation, harvesting of crops and farming practices) and timing of these events can vary annually. Therefore, such drivers could be partly responsible for poorer correlation of VCI to SFSM, RTZSM and TCI in St. Francis basin in comparison to Upper White basin. In Coosa-Tallapoosa, no statistically significant relationship observed between VCI and TCI could be attributed to frequent thundershowers, a common weather activity in summers across this region. We demonstrated that TCI fluctuated substantially throughout the 2012 growing season as opposed to VCI because LST responds wetting events (e.g., irrigation and thundershowers) more quicker than NDVI.

We theorize that the timing of irrigation events can be detected by LST or TCI where LST responds rapidly to irrigation event as sharp changes were seen in TCI time series in St. Francis as opposed to Upper White basin. The methodology developed by Pervez and Brown (2010) only decides whether or not a pixel is irrigated, but doesn't supply any information about the timing of watering events. We suspect that sudden changes in the time series could be sign of irrigation as depicted with arrows in Figure 6-A. However, LST products must be combined with MIrAD irrigation dataset to eliminate likely errors because sharp fluctuations observed in Coosa-Tallapoosa (Figure 7c) could lead to false-positives (i.e., Type I error). More research is needed to validate our claim.

Utility of VCI to monitor meteorological drought was investigated by Quiring and Ganesh (2010), however we demonstrated that although USDM indicated drought conditions (i.e., meteorological drought) over irrigated agriculture in Lower Mississippi region, drought was not reported by VCI during the 2012 growing season (Figure 6-A). Therefore, VCI may not be a reliable indicator of meteorological drought, but agricultural drought.

Our analysis of the 2012 drought in the Southeastern US demonstrated that the agreements and disagreements over the extent and intensity of the 2012 drought exist among USDM, GRACE- and MODIS-based drought indicators. We demonstrated that precipitation between June and August (Figure 5) was at normal levels where disagreements between MODIS, GRACE and USDM were seen over Georgia. Additionally, two principal factors, irrigation and lagged response of vegetation to variations in soil moisture, could be partially responsible for these disagreements.

Another factor that may contribute to these disagreements is the type of drought reported by these indicators such that GRACE-GWS is a measure of hydrological drought indicator, while the rest could be more suitable in depicting agricultural drought conditions.

5. Conclusions

USDM, GRACE- and MODIS-based drought maps were successful in depicting the drought of 2012 despite disagreements over its extent and intensity, and they all indicated that Southeast US experienced severe-to-exceptional drought in 2012. Both MODIS-based and GRACE-SFSM drought maps closely mimicked the surface conditions depicted in the USDM maps except over irrigated areas, Georgia and along Appalachians Mountains (e.g., Blue Ridge mountains, and Ridge and Valley). However, short-term precipitation deficit map agreed with MODIS indices in these regions, indicating normal precipitation conditions compared to long-term average conditions. GRACE-based GWS implied that majority of the southeastern US experienced moderate-to-extreme hydrological drought, thus suggesting that groundwater sources severely depleted during the drought of 2012. We demonstrated that disagreements over the extent and intensity of the 2012 drought across all drought indicators could result from irrigation, complex lagged response of vegetation to precipitation and soil moisture and the type of drought these indicators report (e.g., meteorological, agricultural and hydrological drought).

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