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Satellite-observed changes in vegetation sensitivities to surface soil moisture and total water storage variations since the 2011 Texas drought

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Abstract

We combine soil moisture (SM) data from AMSR-E and AMSR-2, and changes in terrestrial water storage (TWS) from time-variable gravity data from GRACE to delineate and characterize the evolution of drought and its impact on vegetation growth. GRACE-derived TWS provides spatially continuous observations of changes in overall water supply and regional drought extent, persistence and severity, while satellite-derived SM provides enhanced delineation of shallow-depth soil water supply. Together these data provide complementary metrics quantifying available plant water supply. We use these data to investigate the supply changes from water components at different depths in relation to satellite-based enhanced vegetation index (EVI) and gross primary productivity (GPP) from MODIS and solar-induced fluorescence (SIF) from GOME-2, during and following major drought events observed in the state of Texas, USA and its surrounding semiarid area for the past decade. We find that in normal years the spatial pattern of the vegetation–moisture relationship follows the gradient in mean annual precipitation. However since the 2011 hydrological drought, vegetation growth shows enhanced sensitivity to surface SM variations in the grassland area located in central Texas, implying that the grassland, although susceptible to drought, has the capacity for a speedy recovery. Vegetation dependency on TWS weakens in the shrub-dominated west and strengthens in the grassland and forest area spanning from central to eastern Texas, consistent with changes in water supply pattern. We find that in normal years GRACE TWS shows strong coupling and similar characteristic time scale to surface SM, while in drier years GRACE TWS manifests stronger persistence, implying longer recovery time and prolonged water supply constraint on vegetation growth. The synergistic combination of GRACE TWS and surface SM, along with remote-sensing vegetation observations provides new insights into drought impact on vegetation–moisture relationship, and unique information regarding vegetation resilience and the recovery of hydrological drought.

Introduction

The state of Texas and surrounding areas have experienced multiple severe drought events during the last decade (NOAA 2007, 2011, Dong et al 2011, Combs 2012, Hoerling et al 2013, Long et al 2013). A severe hydrological drought occurred from 2011–2013 over Texas and surrounding areas, exacerbating regional water supply shortages, wildfire disturbance, and drought-induced tree mortality; it also decreased agricultural productivity and raised energy demand (Combs 2012, Scanlon et al 2013, Schwantes et al 2013). Severe and extensive drought has direct impact on both terrestrial water and carbon cycles. Vegetation
gros primary production (GPP) from canopy photosynthesis is the primary conduit of carbon transfer between the land and atmosphere. The GPP reduction in response to declining water supply and drought stress weakens the terrestrial carbon sink (e.g. Zhao and Running, 2011, Schaefer et al 2012, Schwalm et al 2012). Thus to assess and reduce drought impact, it is essential to monitor and understand how drought disturbance influences the water supply pattern and affects vegetation productivity.

The development of a severe drought starts from changes in atmospheric processes and the deterioration of climatic water supply, which in turn affects surface soil moisture replenishment and deeper groundwater storage recharge. Drought recovery also involves the same top-to-bottom changes in each of these water storage components (e.g. Van Loon, 2015). A complete characterization and understanding of drought and its impact therefore require an assessment of terrestrial water storage (TWS) components covering the entire water column.


Here we study how drought affects vegetation sensitivities to inter-annual changes in surface soil moisture and the overall water storage using a suite of synergistic overlapping global satellite sensor observations. We use GRACE observation of TWS as proxy of TWS conditions of the entire water column and surface soil moisture retrievals from AMSR-E/2 satellite microwave sensors as an indicator of the dynamic surface (within ~5 cm depth) SM signal. We use MODIS enhanced vegetation index (EVI), GOME-2 solar-induced fluorescence (SIF) and MODIS GPP as a proxy of vegetation growth changes. The domain of our investigation centers on the state of Texas and surrounding semiarid areas within the southwest USA; this region features water-limited vegetation growth conditions representative of the southern Great Plains and has experienced severe and persistent drought conditions in the last decade.

We first evaluate the 2011 drought condition by analyzing the corresponding water supply deficit from GRACE TWS and AMSR-E/2 SM, and the associated reduction in vegetation growth estimated from MODIS EVI, GOME-2 SIF and MODIS GPP. We then examine drought-induced changes in the temporal correlations between vegetation growth and water storage variations, in relation to plant functional types and changes in water supply pattern. We investigate how drought modulates the variability and persistence of shallow-depth surface SM and overall TWS, and its implication for vegetation-moisture relationship and drought recovery. We also evaluate the vegetation sensitivity to surface and overall water storage changes for each season in the analyzed area. We conclude on the implication of combining synergistic satellite observations to characterize drought evolution across the soil-vegetation-atmosphere system for improving understanding of vegetation sensitivity to water storage changes from surface soil and deeper groundwater sources.

**Data and method**

We use 131 monthly GRACE solutions from the Center for Space Research at the University of Texas (Tapley et al 2004), between August 2002 and December 2013. Each gravity solution consists of spherical harmonic coefficients up to degree and order 60. We replace GRACE-derived degree-2 and order-0 coefficients with those estimated from satellite laser ranging (Cheng et al 2013) and include degree-1 coefficients calculated following Swenson et al (2008).

We correct GRACE solutions for the glacial isostatic adjustment (GIA) signal following A et al (2013). GRACE-derived TWS anomalies are calculated relative to the period from August 2002-December 2013. To reduce the random error components, we apply a Gaussian smoothing with a 400 km radius (Wahr et al 1998) and then generate a monthly TWS time series over a half-degree latitude-longitude grid.

For the long-term SM record, we use a consistent global surface soil moisture record derived from similar calibrated, overlapping microwave brightness temperature (Tb) retrievals from AMSR-E (Advanced Microwave Scanning Radiometer for EOS), FY3B-MWRI (Microwave Radiation Imager) and AMSR-2 (AMSR follow-on instrument onboard the JAXA GCOM-W1 satellite) sensor records (Du et al 2014). The SM record has global coverage and 1–3 d temporal fidelity as derived from AM orbit Tb observations, while an iterative retrieval algorithm is used with multiple Tb frequencies and polarizations to account for potential negative impacts on the soil moisture retrievals from atmosphere precipitable water vapor, open water inundation, vegetation biomass cover and surface temperature variations (Du et al 2014). The resulting 10.7 GHz SM retrievals are primarily
sensitive to moisture conditions within the surface (0–2 cm depth) soil layer under low to moderate vegetation biomass cover characteristic of semiarid grassland and shrubland vegetation within the domain (Du et al 2016). The SM retrievals are mapped to a consistent 25 km resolution global grid and daily time step with well characterized accuracy and performance (Du et al 2014, 2016, Mladenova et al 2014).

We use three sets of satellite records to represent vegetation growth condition, including NASA EOS MODIS MOD13C2 (Collection 5) enhanced vegetation index (EVI) record (Huete et al 2011), MOD17A2 (Collection 5) GPP record (Zhao et al 2005, Zhao and Running, 2011) and GOME-2 (Global Ozone Monitoring Experiment-2) (Version 26, Level 3) 740 nm solar induced fluorescence (SIF) record (Joiner et al 2013). The MOD13 EVI record has been widely used to represent both vegetation state and productivity (e.g. Sims et al 2006, Seddon et al 2016). The MOD17 GPP record used for this investigation has undergone five major reprocessing improvements and has well documented global accuracy (e.g. Heinsch et al 2006, Turner et al 2006, Huntzinger et al 2012). Both MODIS EVI and GPP records extend from Feb 2000 to present and are produced at 1 km resolution and 8 d temporal fidelity. The GOME-2 measurement provides longest SIF record since 2007. Recent studies have shown that the flux of chlorophyll fluorescence emitted from canopy photosynthetic process is a more direct indicator of GPP (Joiner et al 2013, Frankenberq et al 2014). The SIF record is generated monthly at a spatial resolution of 0.5°. For consistency, all vegetation metrics are composited to a monthly time step at a 0.5°×0.5° global grid. We also use the MODIS MCD12Q1 (Collection 5) land cover type product to define the vegetation distribution in the study domain (Friedl et al 2010).

A satellite microwave remote sensing based global record of daily landscape freeze-thaw status is used to define the annual non-frozen (NF) season for each grid cell over the domain (Kim et al 2011, 2014). We then treat the NF period, which spans most of the year in the study domain, as the potential growing season for evaluating vegetation-moisture relationships. We use ERA-Interim monthly 2 m height air temperature (Dee et al 2011) for removal of the temperature dependency on vegetation growth in the partial correlation analysis; we also include precipitation from the Global Precipitation Climatology Project (Adler et al 2003, Huffman et al 2009) to represent water inputs to the analyzed system. For consistent comparison, all data-sets are processed in the same way as the GRACE data unless otherwise noted (text S1 available at stacks.iop.org/ERL/12/054006/mmedia). The GRACE processing provides regionally averaged time series but largely preserves the inter-annual variability from the finer-scale time series (text S1, figure S1).

In this study, we utilize a z-score standardization approach for comparison of the vegetation-moisture relationships across different spatial and temporal domains. There is both spatial and temporal variability in local climate, and therefore the same amount of water deficit may have significantly different impact on biomes at one location or time period than another (e.g. Ji and Peters, 2003, Vicente-Serrano et al 2013). To account for this, we apply z-score standardization to the time series of interest as follows:

\[
    z_{ij} = \frac{x_{ij} - \bar{x}_j}{\sigma_j}
\]

where \(i\) is the year ranging from 2002 to 2013, \(j\) is the month ranging from January to December, \(\bar{x}_j\) and \(\sigma_j\) are the mean and standard deviation of time series \(x\) at month \(j\) (e.g. Zhao et al 2017). This procedure effectively removes the climatology from the original time series and normalizes the time series according to its monthly standard deviation. We generate z-score time series to represent both vegetation state and productivity (e.g. Huffman et al 2009), nonetheless, we can also use the z-score time series to represent both vegetation state and productivity (e.g. Huffman et al 2009) with different time periods (e.g. Zhao et al 2017). This procedure effectively removes the climatology from the original time series and normalizes the time series according to its monthly standard deviation. We generate z-score time series to represent both vegetation state and productivity (e.g. Huffman et al 2009) with different time periods (e.g. Zhao et al 2017). This procedure effectively removes the climatology from the original time series and normalizes the time series according to its monthly standard deviation. We generate z-score time series to represent both vegetation state and productivity (e.g. Huffman et al 2009) with different time periods (e.g. Zhao et al 2017). This procedure effectively removes the climatology from the original time series and normalizes the time series according to its monthly standard deviation. We generate z-score time series to represent both vegetation state and productivity (e.g. Huffman et al 2009) with different time periods (e.g. Zhao et al 2017). This procedure effectively removes the climatology from the original time series and normalizes the time series according to its monthly standard deviation. We generate z-score time series to represent both vegetation state and productivity (e.g. Huffman et al 2009) with different time periods (e.g. Zhao et al 2017). This procedure effectively removes the climatology from the original time series and normalizes the time series according to its monthly standard deviation. We generate z-score time series to represent both vegetation state and productivity (e.g. Huffman et al 2009) with different time periods (e.g. Zhao et al 2017). This procedure effectively removes the climatology from the original time series and normalizes the time series according to its monthly standard deviation. We generate z-score time series to represent both vegetation state and productivity (e.g. Huffman et al 2009) with different time periods (e.g. Zhao et al 2017). This procedure effectively removes the climatology from the original time series and normalizes the time series according to its monthly standard deviation. We generate z-score time series to represent both vegetation state and productivity (e.g. Huffman et al 2009) with different time periods (e.g. Zhao et al 2017). This procedure effectively removes the climatology from the original time series and normalizes the time series according to its monthly standard deviation. We generate z-score time series to represent both vegetation state and productivity (e.g. Huffman et al 2009) with different time periods (e.g. Zhao et al 2017). This procedure effectively removes the climatology from the original time series and normalizes the time series according to its monthly standard deviation. We generate z-score time series to represent both vegetation state and productivity (e.g. Huffman et al 2009) with different time periods (e.g. Zhao et al 2017). This procedure effectively removes the climatology from the original time series and normalizes the time series according to its monthly standard deviation. We generate z-score time series to represent both vegetation state and productivity (e.g. Huffman et al 2009) with different time periods (e.g. Zhao et al 2017).
functions for the z-score time series of SM and TWS. Again we de-trend the time series to obtain more conservative estimate of the correlation coefficients (online supplementary text S2, figure S2). We define a characteristic time scale for each time series data record as the lag time when the amplitude of the autocorrelation function decreases to $1/e$.

Results

We show in figures 1(a)–(e) the annual anomalies (up to 1-$\sigma$) of EVI, SIF, GPP, SM and TWS in 2011 relative to the pre-drought common period of 2007–2010. We find strong spatial agreement among EVI, SIF and GPP observations, all indicating vegetation growth

![Figure 1](image_url). The 2011 mean anomalies of (a) EVI in %, (b) SIF in mWm$^{-2}$nm$^{-1}$sr$^{-1}$, (c) GPP in gCm$^{-2}$month$^{-1}$, (d) SM in % cm$^{-3}$ and (e) TWS in mm, relative to the 2007–2010 (pre-drought) means. Only results significant up to 1-$\sigma$ are shown. (f) Land cover type in the analyzed area. Results (except for TWS) are shown at a 0.5$^\circ$ grid without Gaussian spatial averaging.
reduction in the analyzed domain, with the largest decrease occurring in the grassland region (figures 1 (a)−(c), (f)). SIF results show notable speckling compared to EVI and GPP, likely due to its high retrieval noise in low productivity grassland region. Both SM and TWS observations capture the deteriorated water supply condition in 2011, where surface SM shows significant decrease in the northern grasslands and the overall TWS shows large deficit in the grassland and forest areas from central to eastern Texas (figures 1(d)−(f)).

Figures 2(a) and (b) show the vegetation-moisture correlations calculated using the de-trended EVI, TWS and SM z-score time series during the common period of 2007−2013; here we consider only areas where the partial correlation coefficient is statistically significant at more than 98% confidence level ($p < 0.02$). We find strong correlations over majority of the analyzed domain for each pair of vegetation-moisture observables. EVI shows strong correspondence with SM changes in the central grassland band (figure 2(a)), same area where we observe largest EVI reduction during the 2011 drought (figure 1(a)). The EVI correlation with TWS is strongest in the grassland and forest area spanning from central to eastern Texas (figure 2(b)), same area where we observe largest TWS deficit in 2011 (figure 1(e)). To illustrate vegetation-moisture relationships prior to the hydrological drought, we show in figure 2(c) and (d) correlations calculated using time series from 2003–2009; this period has a 7 yr duration (same duration as for 2007–2013) and samples the pre-drought condition. We find congruent EVI responses to changes in surface SM and to overall TWS. Both correlations are strongest in the drier shrubland and grassland to the west, and are weaker or insignificant in the moist east, consistent with the annual precipitation gradient over the analyzed domain (figure S6).

Figure 3 shows the same comparison but using SIF and GPP as the vegetation metrics. We find the same GPP correlations as those using EVI during 2003−2009 (figures 3(e) and (f)). Correlations involving SIF are not shown for this pre-drought period due to its short record length. During 2007−2013, $R_{\text{SIF-SM}}$ and $R_{\text{SIF-TWS}}$ show strong agreement with those using EVI (figures 3(a)−(b)). $R_{\text{GPP-SM}}$ is strongest in the center and western portion of the analyzed domain (figure 3(c)). $R_{\text{GPP-TWS}}$ is significant and of same magnitude over most of the analyzed domain (figure 3(d)). The 2007–2013 period includes relatively normal years before the drought. When we focus on a shorter 2010–2013 period (online supplementary text S3, figure S3) covering exclusively the onset, peak and recovery of the hydrological drought, we find the same spatial pattern for $R_{\text{EVI-SM}}$, $R_{\text{EVI-TWS}}$, $R_{\text{SIF-SM}}$ and $R_{\text{SIF-TWS}}$ as those shown in figures 2 and 3, but with a slightly larger magnitude. The GPP correlations are now in agreement with those using EVI and SIF, with stronger $R_{\text{GPP-SM}}$ in the grassland region and significant $R_{\text{GPP-TWS}}$ in the center and east.
As shown in figures 2 and 3, vegetation growth shows different responses to surface SM and overall TWS changes since the initiation of the hydrological drought, and we find a transition in the spatial pattern of vegetation-moisture correspondence: vegetation sensitivity to SM variations weakens slightly in the shrub-dominated west and strengthens in the central grassland band; and regions with strong TWS dependency has experienced a shift from the west to the grassland and forest area in the center and east. Notably in the western portion of the domain, vegetation growth shows small or insignificant correlation with TWS during the drought period (figure 2(b), figures 3(b) and (d), figures S3(d)–(f)) while the correlation with SM is still significant. Indeed, drought disturbance influences SM and TWS differently, which would in turn impact vegetation sensitivities to SM and TWS. Before 2010, TWS variation is significantly correlated with surface SM changes over the entire domain (figure 4(a)), implying that in the normal years shallow-depth SM changes, that are directly accessible to plant, dominate overall TWS variability. After 2010, the SM-TWS correlation weakens significantly in the western shrub-dominated area (figure 4(b)), suggesting a decoupling between shallow-depth and overall water variations. To analyze the changes in this shrub-dominated area, we outline a 400 km-radius sub-region centered at (32°N, 104°W) (figure 4(a)), and we show the time series of each observable averaged in the sub-region and filtered for seasonal dependence using a 13 m window (figures 4(c) and (d)). Vegetation growth shows congruent correspondence with both SM and TWS before 2010. Since mid-to-late 2010, SM and TWS decline rapidly.

Figure 3. Similar to figure 2, panels (a)–(d) show the partial correlation coefficients (significant up to 98% confidence level) for $R_{\text{SIF-SM}}, R_{\text{SIF-TWS}}, R_{\text{GPP-SM}}$, and $R_{\text{GPP-TWS}}$, respectively, using the NF seasons during 2007–2013. Panels (e) and (f) show $R_{\text{GPP-SM}}$ and $R_{\text{GPP-TWS}}$ for the NF seasons during 2003–2009.
followed by reduction in EVI, SIF and GPP; vegetation metrics start to show greater sensitivity to SM than TWS. After 2011, we observe episodic increases in growth associated with precipitation-driven surface wetting while TWS shows a consistent declining trend through the 2010–2013 record. Correlations computed using the de-trended time series before and after 2010 also show a decrease in $R_{\text{EVI-TWS}}$ from 0.66 ($p < 0.001$) to 0.36 ($p = 0.03$), while $R_{\text{EVI-SM}}$ is relatively stable (from 0.63 to 0.61; $p < 0.001$) (See also Text S3).

In this shrub-dominated region, we attribute the contrasting response of vegetation to SM and TWS to different drought impacts on the characteristic time scale and persistence of each hydrological component. As shown in figure 4(d), SM exhibits similar sensitivity to precipitation through the entire analyzed period, consistent with dynamic wetting and drying of surface SM. In contrast, TWS is less sensitive to precipitation during the hydrological drought than the earlier record. This implies that the persistence or memory effect in TWS is enhanced during the
exceptional drought. To investigate this further, we compute the autocorrelation functions using the de-trended TWS and SM z-scores before and after 2010. TWS and SM show a similar autocorrelation function for 2003–2009 (figure 4(e)). If we define a characteristic time scale using the lag time when the amplitude of the autocorrelation decreases to 0.368 (or 1/e), we find that TWS and SM have a time scale of 2.9 and 3.2 m, respectively, implying that the persistence of TWS and SM both extend up to about 3 m over the initial record. During the 2010–2013 period, however, we find a notable difference between the SM and TWS autocorrelations: the SM shows a time scale of 2.7 m, while the TWS shows stronger autocorrelation, especially at the 7–9 m time scale (figure 4(f)). The longer TWS time scale during the hydrological drought likely reflects temporal variability in deeper groundwater storage that is less accessible to local shrub growth, consistent with previous studies based on a multi-scalar drought index (e.g. Vicente-Serrano et al 2010, 2013, Wang et al 2015). We have also compared SM and TWS autocorrelations before and after drought in the central grassland band; there the SM and TWS time scales are less sensitive to drought, and TWS generally shows stronger persistence than SM (−4−5 m for TWS, −3 m for SM) through the entire period. In our analysis, autocorrelation functions are calculated during 2003–2009 and the drier 2010–2013, involving different sample sizes. We have tested the sensitivity of the autocorrelation analysis to the sample size and find that it does not affect our results (online supplementary text S4, figure S4).

To evaluate possible seasonal dependency of the vegetation-moisture relationships in the analyzed domain, we have examined the annual z-score time series of EVI, SIF, GPP, TWS and SM averaged for each of the four seasons (online supplementary figure S5). Despite the occurrence of 2011 drought, we find consistent seasonal vegetation-moisture correspondence through the entire period: vegetation sensitivity to water is strong from spring to fall, and weaker only in the winter months. Indeed, in semi-arid/arid climate zones, seasonal temperature and energy constraints on vegetation growth are less important than available water supply as the main driver of vegetation productivity.

Discussion

This study focuses on the state of Texas and surrounding semi-arid grassland and shrubland areas. This region features an east-west gradient in mean annual precipitation with generally drier conditions in the western portion of the domain. Some of the areas in the west receive less than 400 mm of annual precipitation, contrasting with up to 1000 mm of annual rainfall for some eastern areas of the domain. We find that this climate gradient largely determines the regional pattern of vegetation-moisture relationships in normal years (before the 2011 hydrological drought). In the drier portion of the domain, variations in vegetation productivity are strongly correlated with changes in both surface soil moisture and total water storage, whereas in wetter areas, vegetation dependency on water supply is less significant (figures 2(c) and (d), figures 3(e) and (f)). This general relationship is consistent with previous studies based on water supply pattern at both regional scale and site level (e.g. Nemani, 2003, Huxman et al 2004).

However we find that drought disturbance affects this regional pattern of vegetation-moisture relationships, depending on the underlying plant functional types. In the central grassland band, vegetation growth under drought manifests enhanced sensitivity to surface SM variations (figures 2, 3 and S3), implying strong susceptibility of semi-arid grassland to drought disturbance (Knapp and Smith, 2001, Moran et al 2014). This is also consistent with the larger SIF, EVI and GPP reductions observed in the grassland area during the 2011 drought (figures 1(a)–(c)). On the other hand, this enhanced sensitivity to SM variations also leads to rapid recovery of vegetation growth following the replenishment of surface SM after the drought disturbance, implying strong drought resilience for the grassland.

In the shrub-dominated west, vegetation growth under drought show slightly smaller but significant correlation with surface SM, and the sensitivity to TWS weakens significantly compared to the earlier record (figures 2, 3 and S3). It is likely that in this area, the TWS variations during the exceptional drought occur at a depth beyond the local plant root zone. The 2011 hydrological drought in Texas is reported to have caused widespread mortality in woody vegetation (Schwantes et al 2016), which might also weaken regional vegetation-moisture correspondence.

In the eastern Texas, plant water sensitivity transitions from low to strong after the hydrological drought. This is due to the deteriorated water supply condition caused by the exceptional TWS anomaly (figure 1(e)). We also find stronger vegetation sensitivity to changes in overall TWS than surface SM in this region. This may be attributed to deeper rooting systems associated with the abundant tree coverage (e.g. Schenk and Jackson, 2002) and also indicates that the recovery of vegetation growth in this region relies on the water replenishment in the entire soil column, rather than only in the surface layer.

The differential vegetation drought response is also linked to drought-induced changes in the hydrological cycle. The GRACE TWS signal detects water storage changes over the entire water column, extending from surface to deeper groundwater sources, with each storage component featuring different characteristic time scales of variability.
The time scale estimate derived from autocorrelation measures the inertia of the time series, or how long an anomaly can persist. Our results show that an exceptional drought disturbance can modulate this inertia. The longer TWS time scale during the hydrological drought indicates that larger or more persistent water replenishment are required to alter the deficit status of water supply, which implies a longer recovery time and prolonged constraint on vegetation growth following a major drought.

Previous studies have suggested that an increase in temporal autocorrelation and decrease in recovery rate may indicate a system approaching an ecological tipping point (e.g. Dakos et al 2008, Scheffer et al 2009, Seddon et al 2016). Our results demonstrate that the GRACE TWS time series can be used to evaluate changes in the characteristic time scale of the underlying water supply variations influencing vegetation growth, and the slowing recovery rate in TWS may serve as a warning signal to detect critical transitions in the terrestrial hydrological cycle affecting ecosystem service.

Natural grassland and shrubland in semi-arid and arid climate zones have drought tolerant adaptations, including relatively deep rooting systems allowing plant access to groundwater to sustain productivity under dry surface SM and atmosphere conditions (McDowell et al 2008). It is, however, a challenge to understand how vegetation under drought stress responds to changes in hydrological components at different soil depths and with varying temporal signatures, which has important implications for drought resilience associated with each plant species (Wang et al 2007, Vicente-Serrano et al 2013, Zhao et al 2017). This study utilizes AMSR-E/2 SM and GRACE TWS to provide respectively estimates of shallow-depth and overall water supply influencing vegetation growth. Subsequent partitioning of the GRACE TWS is needed to fully distinguish water supply variations within the entire soil column. Future studies may benefit by incorporating lower frequency (e.g. L-band) satellite microwave remote sensing to enable enhanced delineation of surface to root zone soil moisture changes affecting vegetation productivity (Entekhabi et al 2014).

Conclusions

We use synergistic overlapping satellite environmental data records to investigate recent drought related impacts on terrestrial water storage and ecosystem productivity in the state of Texas and surrounding semi-arid areas over the past decade (2003–2013). The satellite data examined included bulk terrestrial water storage (TWS) from GRACE, surface soil moisture (SM) from AMSR-E/2, enhanced vegetation index (EVI) and vegetation gross primary production (GPP) from MODIS, and solar-induced fluorescence (SIF) from GOME-2, with each of them featuring unique spatial and temporal signature. We expect that the same methodology of aggregation and normalization (Text S1, figure S1) adopted in this work may facilitate future dataset inter-comparison using other remote-sensing products including the SMAP data (Entekhabi et al 2014).

We find both SM and TWS capture water supply constraints to vegetation growth, distinguishing relatively rapid SM wetting and drying of the surface soil layer from TWS variations including larger and deeper groundwater sources. In relatively normal years, vegetation growth shows congruent sensitivity to changes in surface and overall water storage, and the spatial pattern of vegetation-moisture relationship follows the regional gradient in mean annual precipitation. Following the hydrological drought, vegetation growth in the central grassland shows enhanced sensitivity to SM variations. Vegetation sensitivity to TWS variations weakens in the western shrubland, and strengthens in the grassland and forest area spanning from center to the east. Together these results show contrasting vegetation sensitivity to surface SM and total water storage in the drier period, implying different drought susceptibility and resilience associated with each plant functional type.

In the analyzed region, the inter-annual variability of total water storage is closely associated with changes in surface soil moisture, while the relationship between TWS and SM diverges under drought conditions. We find that in relatively normal years TWS shows strong coupling and similar characteristic time scale to surface SM, while TWS manifests longer temporal variability and stronger persistence than surface SM under severe drought, implying longer recovery time and sustained water constraint to plant growth.

The ongoing SMAP mission and planned GRACE-FO/2 mission will provide enhanced observations of surface to root zone SM and TWS, including model enhanced assessment of soil moisture related water supply constraints affecting GPP (Kimball et al 2015). The current array of complimentary satellite Earth observations provides new opportunities for global drought monitoring and better understanding of hydrological and ecosystem interactions.

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