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Key Points:
- GPS shows terrestrial water storage changes from 2012 High Plains drought
- Drought-induced TWS anomalies are long-lived compared to other drought effects
- GPS could be used for real-time monitoring of TWS variations during drought

Supporting Information:
- Readme
- Figure S1
- Table S1

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Terrestrial water storage response to the 2012 drought estimated from GPS vertical position anomalies

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Abstract Historically, drought monitoring systems have not incorporated observations of terrestrial water storage (TWS). Global Positioning System (GPS) instruments can be used to estimate TWS variations in near real time because the solid Earth responds elastically to changes in hydrologic loading. Here GPS vertical position data, *u*, are used to assess the timing and duration of TWS anomalies in the High Plains caused by the 2012 drought; *u* indicates an initial TWS minimum in 2012, consistent with GRACE TWS, several months after the most severe meteorological forcing. Standard drought indices show recovery from drought during spring 2013. In contrast, *u* indicates that the TWS anomaly intensified by approximately 15% during summer 2013, an interval when no GRACE data are available. Hydrologic observations indicate that depletion of groundwater, not soil moisture, is the source of the persistent TWS anomaly. These results show that GPS data could be used to monitor drought-induced variations in TWS in near real time.

1. Introduction

The 2012 drought in the central U.S. was the most severe since the Dust Bowl and resulted in billions of dollars in damages [*Basara et al.*, 2013; *Hoerling et al.*, 2013]. Drought severity may increase in the future [*Dai*, 2012], and near real-time monitoring of drought conditions would mitigate losses [*Hayes et al.*, 2011]. Characterization of drought intensity depends upon the application [*Dai*, 2010]. Meteorological, agricultural, and hydrological drought are quantified with different data that may be blended to produce a drought index, such as United States Drought Monitor (USDM) [*Svoboda et al.*, 2002].

Until recently, drought monitoring systems did not consider changes in terrestrial water storage (TWS)–the amount of water stored as soil moisture, groundwater, snow, and in surface water bodies. For example, the USDM relied primarily on meteorological and shallow soil moisture data [*Svoboda et al.*, 2002]. Measuring changes in TWS is difficult. In situ networks do not provide collocated measurements of all TWS components [*Rodell and Famiglietti*, 2001]. Combining data from disparate networks is challenging because most measurements represent small sampling areas ($< 10\ m^2$). Most land surface models depict variations of soil moisture and snow but do not account for water stored more than ~2 m beneath the surface. GRACE satellite data can be used to retrospectively analyze TWS variations caused by drought [*Thomas et al.*, 2014]. However, GRACE is not optimal for real–time monitoring: the latency period is 2–6 months, repeat frequency is monthly, and there are data gaps [*Famiglietti and Rodell*, 2013]. Only recently have GRACE TWS data been made available for USDM analyses (M. Svoboda, personal communication, 2014) using a data assimilation system designed for this purpose [*Houborg et al.*, 2012].

GPS data have been used to estimate variations in TWS, and many studies have shown that GPS and GRACE fluctuations are well correlated [*Davis*, 2004; *Tregoning et al.*, 2009; *Nahmani et al.*, 2012]. The Earth's crust and uppermost mantle respond elastically to changes in TWS [*Becker and Bevis*, 2004; *Tsai*, 2011]. A decrease (increase) in TWS yields upward (downward) motion, which is apparent in GPS vertical position anomalies, *u*. GPS vertical position anomalies have been compared to the seasonal cycle of hydrologic loading [*Blewitt et al.*, 2001; *van Dam et al.*, 2001; *Bevis*, 2005; *Ouellette et al.*, 2013; *Argus et al.*, 2014]. However, these data have not been used to monitor TWS fluctuations caused by drought, even though they have attributes that make them well-suited for this application: (1) availability in near real time (data latency of 1 day), (2) widespread spatial distribution, and (3) sensitivity to both local (~10 km) and regional loading [*Bevis*, 2005; *Ouellette et al.*, 2013; *Amos et al.*, 2014; *Argus et al.*, 2014].

In some locations, GPS vertical position also records deformation associated with changes in groundwater levels and pore pressure in aquifers. Poroelastic adjustments are instantaneous and reversible [*Galloway et al.*, 1999],

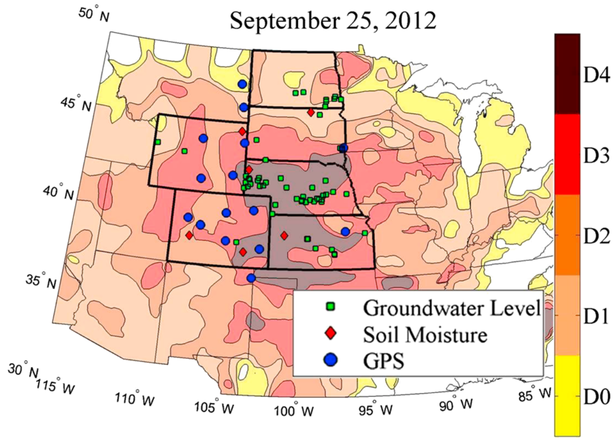

Figure 1. USDM severity map and location of GPS stations (blue circles), groundwater monitoring wells (green squares), and Climate Reference Network soil moisture stations (red diamonds). Drought classifications increase in severity from D0 to D4. The High Plains region is outlined.

yielding variations that could obfuscate the effects of TWS on position [*Munekane*, 2004; *Ji and Herring*, 2012]. GPS sites affected by poroelastic effects cannot be used to study variations in TWS. These sites can be identified based on a positive correlation between u and depth to water table [*Argus et al.*, 2014], with positive u anomalies indicating downward motion. Poroelastic effects are limited to the pumped area, so GPS data from distant (~10 km) sites can be used to study how changes in groundwater affect TWS [*Amos et al.*, 2014].

Here we use GPS vertical position time series to characterize the dynamics of TWS variations associated with the 2012 High Plains drought. The GPS data are compared to GRACE TWS and hydrologic observations. We transform the position time series into a drought metric and then compare it to two drought indices. This analysis was completed retrospectively but could have been completed in near real-time to monitor TWS anomalies during the drought.

2. Methods

We focus on the "High Plains" region as delineated by the USDM (Figure 1). This is the area that was most severely affected by the drought: more than 20% of the region experienced "exceptional drought" (category D4) for more than 2 months. The duration and extent of severe drought conditions was limited further east.

2.1. GPS Data

We use data from 15 GPS stations distributed across the High Plains region that had near-continuous records since 2006 (Figure 1). Additional stations exist in this region, but their records were either much shorter, had significant missing data, or contained offsets suggesting instrument problems. GPS data were accessed using University NAVSTAR Consortium, Boulder, Colorado's (UNAVCO) Data Archive Interface v2 Portal. The position solutions include removal of the effects of the ionosphere and tidal displacements [*Anderson et al.*, 2006]. We removed expected vertical displacements due to atmospheric loading using data provided by the Global Geophysical Fluid Center [*van Dam*, 2010].

We removed a linear trend from the vertical position time series for each site, using data from the time period 2006–2013 (Table S1 in the supporting information). The trends are assumed to be due to isostatic or tectonic effects and not from changes in water storage. However, there is no direct method to assess if this assumption is accurate. Therefore, we repeated all analyses without removing linear trends. These results are discussed below. Next, we applied a low-pass filter on each record because the raw data exhibit high-frequency noise typical of GPS time series [e.g., *Ouellette et al.*, 2013] (Figure 2).

Vertical position time series were converted to anomalies by subtracting the mean. We consider the vertical position anomalies, u (positive deviations indicating downward motion), as indicators of changes in TWS. These two quantities are known to be linearly related [*Becker and Bevis*, 2004; *Bevis*, 2005; *Tsai*, 2011]:

$$\Delta u = \alpha \Delta \text{TWS} \quad (1)$$

where α depends on crust and mantle properties. We do not estimate absolute changes in TWS from u. This requires assumptions about the pattern of loading. Instead, we focus on the magnitude of anomalies relative to fluctuations observed throughout the record, yielding a region-specific measure of drought severity. The u data from the stations are averaged to produce a vertical position record for the High Plains.

We next transform u to a metric of drought intensity, DI_{GPS}. We first remove the seasonal cycle from each u time series. This is standard when producing drought indices, as it allows for comparisons of drought

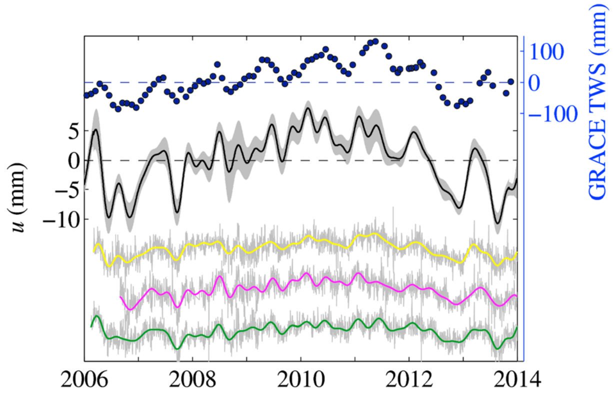

Figure 2. GPS vertical position, *u*, and GRACE TWS (blue circles) shown as anomalies relative to the period 2006–2013. The mean of the 15 detrended filtered GPS time series is shown in black, with positive anomalies indicating downward motion. The grey-shaded region shows the standard deviation of *u* between the 15 stations. Three examples of low-pass filtered (colored) and unfiltered (light grey) time series are shown at the bottom. The *y* axis for the example time series is compressed by a factor of 4.

intensity at times of the year that are climatologically wetter or dryer. The GPS time series used here do not have strong seasonal cycles (Figure 2) compared to time series from stations situated near mountains with seasonal snowpacks [*Argus et al*., 2014]. We estimated seasonal amplitude and phase parameters for each site using least squares (Table S1). The seasonal component (S) was modeled as

$$S = A\cos\ (2\pi ft - \phi) \tag{2}$$

where A is the estimated amplitude, t is time, f is the frequency (1 year), and ϕ is the estimated phase in radians.

We then convert the seasonally adjusted position anomalies to percentiles based on each station's observed cumulative distribution function (CDF). The average of the seasonally adjusted u time series is similarly converted to percentiles based on the corresponding CDF, yielding $\mathrm{DI_{GPS}}$ for the region. $\mathrm{DI_{GPS}}$ represents how likely each u observation is compared to the full time series. Low percentiles correspond to dry periods. This transformation yields a metric comparable to other drought indices, which also use percentiles to characterize severity [*Svoboda et al*., 2002; *Thomas et al*., 2014].

2.2. Hydrologic Data

We compare the u time series to hydrologic data to explore the causes of the TWS variations during and after the 2012 drought. We use North American Land Data Assimilation System project phase 2 (NLDAS-2) daily precipitation data, a spatially interpolated product based on gauge data, to describe the meteorological forcing of drought [*Xia et al*., 2012]. We use the mean precipitation corresponding to the 15 GPS sites, as variations during the drought were consistent across the region. We show the monthly precipitation anomalies (percent) calculated using observed precipitation compared to the months' means from 2006 to 2013. We also show the cumulative precipitation deficit: the running sum of daily precipitation anomalies (in millimeter), relative to the average daily precipitation from 2006 to 2013. The cumulative deficit was set to zero in January 2011. Choosing a different date would shift the cumulative precipitation deficit curve but would not change its shape.

We compare u time series to TWS anomalies based on GRACE Release 05 Level 2 data, which considers monthly estimates of spherical harmonic coefficients of the Earth gravity field [*Tapley et al*., 2004]. Raw data were processed by the University of Texas Center for Space Research. We used GRACE TWS anomalies that represent changes in loading for a disk with a radius of 500 km, centered over the High Plains.

We also compare u to the timing and magnitude of fluctuations in groundwater and soil moisture, as these are the primary components of TWS fluctuations in the High Plains [*Strassberg et al*., 2007]. It is not possible to close the water balance for the region given the paucity and distribution of soil moisture sites and groundwater monitoring wells (Figure 1), which is typical [*Rodell and Famiglietti*, 2001]. We use U.S. Geological Survey well data from all wells in the High Plains that had complete records during 2011–2014 ($n = 65$, Figure 1). We assume a specific yield of 0.15 to convert changes in water table depth to water storage [*Strassberg et al*., 2007] and ignore intermediate zone storage [*Rodell and Famiglietti*, 2001]. We selected soil moisture sites from the Climate Reference Network (CRN), instead of the Soil Climate Analysis Network, as the former had more continuous records and observations to a greater depth. Only six CRN sites from the High Plains had nearly continuous records between 2011 and 2014 (Figure 1). Changes in soil moisture were calculated using observations at five depths (down to 1 m) by weighting observations according to the spacing between sensors.

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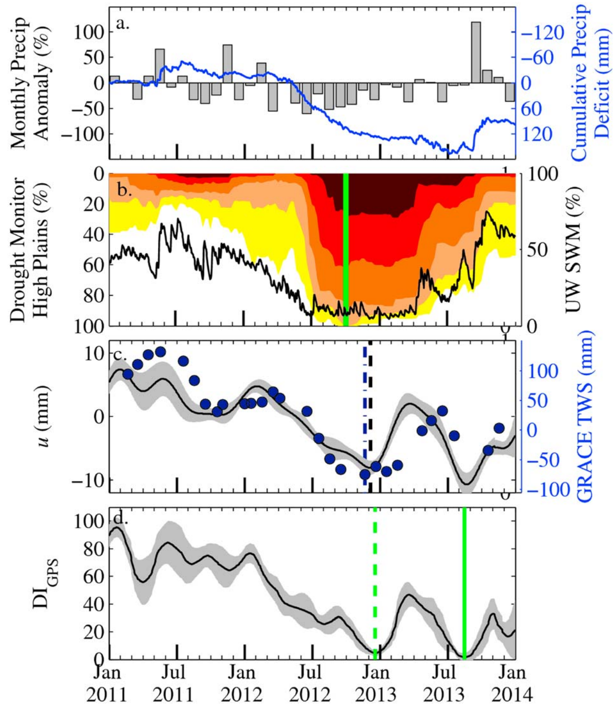

Figure 3. (a) NLDAS precipitation averaged for 15 GPS stations. Grey bars indicate monthly precipitation anomalies, and the blue line shows the cumulative precipitation deficit, set to zero in January 2011. (b) USDM (colored areas) and SWM (black line) for the High Plains. Colors indicate the percent of the High Plains in each USDM category. The green line is the date when the greatest percentage of the High Plains was classified in any drought category. (c) Comparison of average *u* (black line) and GRACE TWS anomalies. The standard deviation of *u* across the sites is shown by the shaded area. The average *u* (black dashed) and GRACE TWS (blue dash dotted) 2012 minimum lines are shown. (d) Time series of average DI_{GPS} from the 15 sites, with the grey-shaded region showing the standard deviation between sites. The dashed (solid) green line shows the timing of the 2012 (2013) minimum.

2.3. Drought Indices

We compare DI_{GPS} to two different drought indices. The USDM is a composite index based on a variety of meteorologic, hydrologic, and related data [*Svoboda et al.*, 2002]. The weekly USDM values are adjusted for seasonality to facilitate interseasonal comparisons. The USDM intensity is reported as one of five categories, D0–D4, corresponding to abnormally dry through exceptional drought conditions. The categories translate to percentiles; for example, a D4 drought is considered to be in the 0–2 percentiles.

Given the limited soil moisture data available, we also use a modeled soil moisture product. The University of Washington Surface Water Monitor (SWM) integrates information from five hydrologic models to produce combined soil moisture and snow water equivalent percentile time series on a $0.5 \times 0.5°$ grid [*Wang et al.*, 2009]. First, a percentile time series is calculated for each model at each grid point. The empirical probability distribution used to generate each daily percentile is determined from the simulated climatology, so SWM values include a seasonal adjustment. Percentile time series for each model are then averaged to produce the multimodel estimate. SWM variations are representative of total soil moisture fluctuations over the top 1 or 2 m of the soil profile, with second-order effects from snow. SWM data were averaged for the 15 grid cells that included the GPS stations.

3. Results

3.1. Precipitation and Drought Indices

Before March 2012, precipitation was roughly average across the 15 High Plains GPS sites (Figure 3a). The cumulative precipitation deficit (starting January 2011) was close to zero. The persistent anomalies that caused the drought began in March 2012. By the end of 2012, the cumulative precipitation deficit was more than 120 mm, equal to 26% of the average annual total. The dry conditions persisted into 2013, although they were not as severe. Through August 2013, the cumulative precipitation deficit grew by an additional 40 mm. Much of the deficit was erased by the historic rainfall event that occurred in mid-September 2013.

High Plains USDM severity increased dramatically starting in July and reached its maximum in October 2012 (Figure 3b). At this time, 100% of the High Plains was in drought and more than 20% of the region was under “extreme” conditions (category D4). The USDM indicates that recovery from the drought began in April 2013, although less severe conditions did persist throughout 2013. Variations in drought intensity based on SWM are similar (Figure 3b). The SWM shows that drought intensity increased steadily over 18 months

10.1002/2014GL061206

Table 1. Water Cycle Variables and Drought Metrics During December 2012 and August 2013, the Times of the *u* Minima and the Change Between the 2 Months[a]

	Mean December 2012	Mean August 2013	Δ 2012, 2013
Cumulative precipitation deficit (mm)	126.4	151.3	−24.9
CRN soil moisture (mm)	170	215	45
Mean Δ groundwater storage (mm)	−85	−154	−69
GRACE TWS (mm)	−61.7	No data	—
u position (mm)	−7.8	−10.4	2.6
USDM, area not in D0–D4 (%)	1.5	25.1	−23.6
University of Washington SWM (%)	7.6	39.6	−32
u (%)	5.2	2.0	3.2

[a]For water cycle variables, a positive change indicates an increase in water storage or precipitation between December 2012 and August 2013. For drought metrics and *u*, a positive change indicates an increase in drought severity between December 2012 and August 2013. Groundwater data and cumulative precipitation deficit data are relative to January 2011.

until December 2012. SWM shows nearly continuous recovery starting in April 2013, synchronous with the USDM. There is a short-term intensification of both SWM and USDM drought during summer 2013.

3.2. GPS and GRACE Time Series

We first describe variations in *u* over the 8 yearlong record and compare these variations to fluctuations in GRACE TWS. The *u* time series exhibit a coherent regional signal (Figure 2): average *u* for the High Plains varies by nearly 20 mm, while the standard deviation across the 15 stations is usually less than 3 mm. Relatively low positions (positive *u* anomalies) observed between 2009 and 2011 indicate high TWS. Average *u* is low at the beginning and end of the record, indicating times with low TWS. The *u* minima in 2012 and 2013 are particularly noticeable. This nearly decadelong pattern of *u* is consistent with GRACE TWS. However, variations in *u* differ from GRACE at higher frequencies, partly because GRACE data are only monthly. GRACE TWS exhibits a clear seasonal cycle with consistent amplitude from year to year. Although a seasonal cycle is apparent in *u*, it is often dominated by higher-frequency variations.

We now describe the variations in GRACE TWS, *u*, and DI_{GPS} during the development and recovery from the drought. GRACE TWS decreased rapidly during the spring and summer of 2012, reaching a minimum in November 2012 that was the lowest value since 2006 (Figure 3c). Consistent with the typical seasonal cycle, GRACE TWS increased in early 2013 and then started to decrease again during July of 2013. We cannot gauge the magnitude of the 2013 summer minimum because there are no GRACE data available for August or September.

All 15 GPS stations exhibited a steady decrease in *u* during development of the drought (Figure 3c). The lowest average *u* (indicating lowest TWS) in 2012 was observed at the end of the fall, similar in timing to the GRACE minimum and after the peak USDM intensity (Figure 3b); *u* then increased in winter 2013, consistent with the typical seasonal cycle. During the following spring and summer, *u* decreased strongly until mid-August, again indicating diminished TWS. At this time, average *u* was lower than at any other time in the record (2006–2013) and was 3 mm lower than observed in 2012. This suggests that the TWS anomaly was ~15% stronger in 2013 than 2012, given the observed range of *u* (20 mm); *u* increased rapidly starting in September 2013, when the precipitation deficit finally started to diminish.

Variations of DI_{GPS} are similar to those shown by *u* (Figure 3d). However, the seasonality adjustment included in calculating DI_{GPS} yields two differences. First, the *u* minima in both 2012 and 2013 are short-lived compared to the USDM record. In contrast, the corresponding intervals with extreme DI_{GPS} are longer in duration. Second, the temporary recovery from drought during early 2013 is not as strong based on DI_{GPS}, because *u* typically increases during winter and spring. The differences between *u* and DI_{GPS} would be more dramatic in locations with stronger seasonal cycles. DI_{GPS} also shows the likelihood of the observed anomalies: DI_{GPS} stayed below 5% in late 2012 and fell below 2% during summer of 2013. The latter was one of the driest periods of the record.

4. Discussion

Was High Plains TWS lower during the summer of 2013 than in 2012, more than a year after the onset of the drought? The vertical position time series suggest that this is the case: all 15 stations exhibit more extreme anomalies in 2013. However, the difference in u is not large (3 mm) compared to uncertainty of position estimates, so drawing a conclusion based on the GPS data alone is not possible. The TWS minima in 2012 and 2013 cannot be compared using GRACE, as there are no data during the 2 month interval in 2013 when u is lowest. We turn to hydrologic data to assess if the 2013 TWS minimum suggested by GPS data is reasonable. The cumulative precipitation deficit was greater in late summer 2013 than any time during the preceding year (Table 1). If this resulted in lower TWS in 2013, it should be apparent in soil moisture or groundwater data. Although it is not possible to close the regional water balance, we do compare changes in soil moisture and groundwater between 2012 and 2013.

Soil moisture, averaged over the top 1 m of the soil column, varied consistently at the six CRN stations in the High Plains. Observed CRN soil moisture reached a minimum in December 2012. Soil moisture in August 2013 was higher than observed at that time by the equivalent of 45 mm of water storage (Figure S1 and Table 1). Considering these observations and the SWM, TWS anomalies during drought development were likely caused in part by soil moisture deficits. However, persistence of TWS drought through summer 2013 must have had a different source.

Observations of water table elevation in shallow aquifers indicate that a decrease in groundwater storage could have yielded lower TWS in 2013. The average depth to water table was greater in August 2013 than at any time in 2012 and about 0.5 m greater than during the first u minimum in December 2012. This is equivalent to a 70 mm decrease in water storage (Figure S1 and Table 1). This should be considered a maximum estimate of the change for the region. Many of the wells are in the High Plains aquifer, where withdrawals are greater than in other parts of the region. The portion of the observed groundwater depletion caused by the 2012 drought, instead of long-term groundwater mining, is unknown. Drought conditions would lead to increased pumping for irrigation. Concurrently, the water table likely dropped due to the natural response to the precipitation deficit. Regardless, the combination of anthropogenic and natural effects yielded lower groundwater storage in 2013, which is the likely explanation for why u reached a minimum more than a year after the most severe meteorological forcing.

Although groundwater levels were changing throughout the drought period, poroelastic effects do not noticeably impact the GPS position data. Poroelastic effects from decreasing groundwater level lowers the land surface [*Galloway et al.*, 1999]. This is the opposite of what was observed during the drought: the land surface increased in height, consistent with a response to lower TWS. In fact, there is a strong negative correlation between depth to water table and u throughout the drought interval ($r^2 = -0.70$), suggesting changes in groundwater is an important source of TWS variations. Variations in u from the 15 GPS sites are remarkably consistent across the High Plains (Figures 2 and 3), even though site monuments are installed in a various bedrock types and in different hydrogeologic settings. This provides further evidence that poroelastic adjustments were negligible.

Our results were generated after removing a linear trend from each record. The trend at most of the stations shows that elevation is decreasing ($u > 0$) by 1 to 4 mm yr^{-1} (Table S1), slightly faster than expected due to glacial isostatic rebound [*Peltier*, 2004]. Differences between observed trends and modeled rebound could be due to tectonics, long-term changes in TWS, or uncertainty in trend estimation. The results describing u and DI_{GPS} during development and recovery from the drought are largely insensitive to trend removal. For example, if trends are not removed, average u (DI_{GPS}) is still lower in August 2013 than in December 2012 by several millimeters (several percent).

Our results show how GPS vertical position records can be used to monitor TWS during drought. Here the GPS data show that TWS anomalies persisted for more than a year after the most severe meteorological forcing due to depleted groundwater storage. In contrast, standard drought indices show a more rapid recovery. TWS based on u complements GRACE data, given their differences in latency, sensing footprint, and error sources. Two main obstacles exist when using GPS data for drought monitoring. First, characterizing the magnitude of anomalies is challenging given the short period of record of most GPS data series. Linking u variations to products with longer records would be helpful [e.g., *Houborg et al.*, 2012]. Second, isostatic and tectonic effects obfuscate long-term changes in TWS, making it difficult to isolate these secular changes from the shorter-term fluctuations associated with drought. Even with these complications, data from thousands of GPS stations operating worldwide could provide valuable information to enhance drought monitoring systems. No other measurement provides near real-time data that characterize TWS variations, a key descriptor of how the hydrologic cycle responds to drought.

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