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Key Points:
- Granger causality tests are used to identify environmental drivers of plant water stress based on satellite observations across African drylands after rainfall events.
- Soil moisture loss and diurnal surface heating drive plant drying across African drylands.
- Land-atmosphere interactions and feedbacks reinforce this plant water loss during soil moisture drydowns.

Supporting Information:
- Supporting Information S1

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Abstract
Plant water content observations using microwave remote sensing measurements allow monitoring of landscape-scale plant water stress. During soil drying following rainfall events, we use Granger causality framework to quantify the degree to which environmental factors drive satellite-based plant water content loss across Africa's diverse biomes. After soil drying into the water-limited regime, satellite observations show that plants dry while solar radiation, vapor pressure deficit, and diurnal temperature amplitude increase. We find that soil drying primarily drives plant water content loss across African drylands, though with regional effects of diurnal temperature amplitude increases (found to indicate vapor pressure deficit increases here). We also detect interactions between these factors that reinforce plant drying during periods of soil moisture loss. Our results provide observational evidence across Africa that individual and interactive components of surface drying and heating can all drive plant water stress, especially during intermittent poststorm drying periods.

Plain Language Summary
Plant water content represents the amount of water within the volume of vegetation canopy, and its dynamics can capture plant water stress. Since plant water content can now be monitored at large spatial scales using satellites, we use a rigorous statistical framework to quantify how the climatic factors soil water content, daily temperature range, light intensity, and atmospheric dryness individually drive plant drying across the expanse of diverse biomes across Africa. We specifically conduct our analysis on water-limited periods about a week after rainfall events, where we show that plant water content progressively declines while soil dries and light intensity, heat, and atmospheric dryness increase. We find that plant drying after rainfall is driven by soil water loss across Africa's drier ecosystems and regionally by daily temperature range increases. Additionally, the interconnectedness of the plant, soil, and atmospheric conditions evaluated here reinforces plant drying in these ecosystems. We conclude that surface drying and heating can individually and interactively drive plant water stress at landscape scales.

1. Introduction
Plant water content plays a fundamental role in whole-plant function, such as in modulating root water uptake and transpiration loss and participating in carbohydrate transport. When plant water content is progressively lost due to increased transpiration demand and/or reduced root water uptake (Katul et al., 2012), predawn water potential becomes more negative, and typically photosynthesis decreases and mortality risk increases (Kramer & Boyer, 1993; McDowell et al., 2008). Given these considerations and its role as a state variable, plant water content dynamics carry information about plant water stress (Bartlett et al., 2012; Konings et al., 2019; Martínez-Vilalta et al., 2019) beyond that of less direct indicators like soil moisture and carbon flux (Kennedy et al., 2019). As such, plant hydraulic schemes with plant water status are increasingly parameterized in dynamic global vegetation models to predict drought-induced mortality and leaf gas exchanges (Fisher et al., 2018; Tai et al., 2017; Xu et al., 2016). With vegetation's dominant role in the climate system, modulating land-atmosphere exchanges (Green et al., 2017; Jasechko et al., 2013), it is important to understand the climatic drivers of plant water content and stress at the landscape scale.

Plant water content has been challenging to widely monitor with only related measurements of predawn water potential sparsely available in space and time. Now available satellite remote sensing observations...
of Earth’s low-frequency microwave emission allow global monitoring of plant water content (via vegetation optical depth [VOD]) (Entekhabi et al., 2010; Kerr et al., 2010). These satellite measurements are most apt to monitor plant water stress at large scales because they observe within-canopy water content as opposed to top-of-canopy indices (i.e., greenness). As such, these observations have been shown to be a viable indicator for drought-driven mortality (Rao et al., 2019) and terrestrial carbon loss (Brandt et al., 2018).

With few studies evaluating drivers of the satellite-based plant water content (Konings, Williams, et al., 2017), it is unclear how much climatic factors individually drive landscape-scale plant water stress. There is currently no consensus on the degree to which vapor pressure deficit (VPD), soil moisture, and/or their coupled effects control ecosystem-scale plant function and how their effects on plant water stress should be modeled (L. Liu et al., 2020; Y. Liu et al., 2020; Novick et al., 2016; Rigden et al., 2020; Stocker et al., 2018). Temperature and light intensity can further drive plant water stress through interacting with soil and atmospheric moisture and influencing stomatal function (Grossiord et al., 2020; Jarvis, 1976).

Here, we evaluate climatic drivers of plant water content dynamics during soil drying periods between rain events, specifically following the transition from the energy- to water-limited evaporative regime when plants can experience water stress. Previous work showed that, following rainfall in the water-limited regime, soil moisture dries and surface temperature, solar radiation, and VPD increase (Feldman et al., 2019; Gallego-Elvira et al., 2016). Meanwhile, plants lose water content (Feldman et al., 2018). These processes are shown in Figure 1 using satellite observations. Given concurrent soil drying and increasing light intensity, surface heating, and atmospheric vapor demand, these factors may be driving this observed plant drying (Figure 1).

Once conditions dry into the water-limited regime (drier than θ*; Figure 1 and supporting information Figure S1), rates of change are typically slower (Figure 1 middle column), but land-atmosphere coupling is known to be greater because the surface energy balance depends more on soil moisture (Eagelson, 1978; Koster et al., 2004; Seneviratne et al., 2010). Additionally, greater vegetation-climate coupling occurs in this regime (Zscheischler et al., 2015). Therefore, we expect that interactions within the soil-plant-atmosphere system, especially in the water-limited regime, further drive the plant water content losses.

We ask: To what degree do climatic factors drive plant water content loss following rainfall across climates and biomes? Given land-atmosphere coupling in the water-limited regime, does land-atmosphere coupling intensify plant water content loss during soil drying cycles?

Our approach presents several advantages and novelties for quantifying climatic drivers of landscape-scale plant function and plant water stress. (1) We use Granger causality (GC) statistical tests which detect stronger temporal linkages between climatic factors than correlative analyses. (2) Satellite-observed plant water content is used allowing closer evaluation of plant water stress than superficial satellite-based canopy parameters used in similar studies (Green et al., 2017; Kaufmann et al., 2003; Madani et al., 2017). (3) Conditioning on soil moisture drydowns in the water-limited regime isolates likely conditions of plant water stress when plant drying is occurring (Figure 1) and surface drying and warming are prolonged for multiple days after rainfall. (4) Interactions are evaluated at 3-day timescales, made possible due to 1- to 3-day cloud contamination-free satellite microwave observations, as opposed to common vegetation function evaluations at monthly scales using optical/infrared satellite observations (Claessen et al., 2019; Green et al., 2017; Papagiannopoulou et al., 2017). While monthly scale GC studies are valuable in identifying biosphere-climate interactions, the variables considered here (Figure 1) are less coupled on subweekly scales allowing more confident partitioning of predictors’ effects in regressions (Novick et al., 2016). This is partly because these variables’ covariability can be inflated by confounding seasonal periodicity common among all variables beyond weekly timescales (Tuttle & Salvucci, 2017). (5) Using only observations avoids prescribed relationships between variables in modeled data sets.

2. Methods
2.1. Space and Time Domain Selection
We are interested in uncovering patterns in the climatic drivers of plant water stress across ecosystem type and select Africa as our study domain due to its diversity of biomes (from semiarid grassland to humid
Subweekly biometeorological processes have been understudied in Africa due to sparse surface observation networks, but the landscape is conducive for remote sensing with limited mountainous regions, standing water bodies, frozen ground, and microwave interference. Furthermore, the Spinning Enhanced Visible and Infrared Imager (SEVIRI) geostationary satellite provides high-quality observations of the surface-canopy temperature, diurnal cycle, and daily light intensity—essential for determining short-term drivers of plant water content loss and not available on other continents.

We condition our analysis on post-rainfall behavior to evaluate drying conditions that promote water stress and to exclude water inputs that bias our analysis toward rainfall prediction at the expense of evaluating short-term drivers of plant water content loss.
drying dynamics. These drydowns are defined as at least 9 days (three, 3-day intervals) of consecutive soil moisture (δ) decreases. We further condition on the water-limited regime using δ* estimates from Feldman et al. (2019) (Figure S1) providing several advantages: (1) these periods allow evaluation of likely plant water stress conditions because plant drying typically begins in this regime (Figures 1 and S1); these periods occur 6 days after rainfall on average where soil drying and surface warming have been prolonged (Figure S2), and energy fluxes (i.e., transpiration) are water limited (Short Gianotti, Salvucci, et al., 2019). (2) Relationships between variables are approximately linear allowing use of linear statistical frameworks (Feldman et al., 2019). (3) Land-atmosphere interactions are theoretically most active in this regime. This conditioning results in 90 observations per pixel on average, which are distributed throughout all identified drydowns throughout the year, especially in Africa’s drylands where nearly all drydowns transition into water limitation. Pixels with less than 40 observations are removed due to increased regression uncertainty. Results are insensitive to specific δ* definitions with nearly identical results obtained for varied δ* across all pixels.

Our study domain is thus defined as African regions with nonzero time spent in the water-limited regime, significant vegetation presence (nonbare soil), and low water body coverage (>5% pixel area).

2.2. Data Sets

δ are used from the National Aeronautics and Space Administration's (NASA) Soil Moisture Active Passive (SMAP) satellite at a 9-km grid with 1- to 3-day sampling (O’Neill et al., 2019). VOD is also obtained from SMAP but using a different algorithmic approach (Konings et al., 2016). Therefore, VOD and δ retrieval errors are uncoupled. While SMAP δ estimates are considered to theoretically represent the top 5 cm of soil, they have been empirically shown to observe a soil water column down to 50 cm (Akbar et al., 2018; Short Gianotti, Rigden, et al., 2019). VOD is used synonymously here with plant water content due to their linear relationship, since VOD represents microwave emission attenuation due to the water volume in the canopy (Jackson & Schmugge, 1991). VOD is also a proxy for leaf water potential (Momen et al., 2017; Zhang et al., 2019). δ and VOD uncertainty increase in forested regions, though these regions are primarily excluded due to no time spent water limited.

Daily downwelling shortwave radiation (Rs) and 15-min surface temperatures (representing both surface and canopy) are obtained from SEVIRI on-board European and EUMETSAT space agency’s Meteosat Second Generation geostationary satellite series at a 3-km resolution (Trigo et al., 2011). The SEVIRI observation disc primarily covers Africa. We compute diurnal temperature amplitude (dT) or difference in temperatures at 1:30 p.m. and 6:00 a.m. local time when temperatures are typically at their maximum and minimum (Holmes et al., 2015). dT is known to be directly linked to land surface energy fluxes, being negatively related to latent heat flux (Figure S3, Bateni & Entekhabi, 2012; Panwar et al., 2019). Rs and dT errors are not expected to be correlated because they are retrieved from different measurement frequencies.

VPD is computed from daily 1:30 p.m. local time measurements of boundary layer temperature and humidity from the Atmospheric Infrared Sounder (AIRS) on-board NASA’s Aqua satellite at a 1° resolution (Teixeira, 2013). Though we averaged VPD between 1,000 and 850 mb, it is mostly representative of 850 mb (upper boundary layer) due to lower-quality observations nearer to the surface. However, this VPD is still well correlated with near-surface reanalysis VPD (Figure S3).

Data set uncertainty is further discussed in Text S2. More detailed evaluations of these data sets can be found in previous works (Chan et al., 2016; Feldman et al., 2019, 2018; Konings, Piles, et al., 2017).

Given that SMAP is available for the shortest period, all data sets are obtained over the 5-year SMAP period between 1 April 2015 and 31 March 2020. All data sets are regridded to SMAP’s 9-km Equal Area Scalable Earth 2 grid. Finally, all variables are averaged to 3-day periods for a constant sampling frequency with SMAP’s 1- to 3-day sampling and SEVIRI temperatures often not available daily due to cloud contamination. Mean annual precipitation from GPM IMERG V6 (Huffman et al., 2019) from 2015 to 2019 is used to evaluate climatic gradients.

2.3. Vector Autoregression

Vector autoregression (VAR) is a predictive regression approach used here to quantify the lagged linear influence of each variable on the others (Hamilton, 1994). The approach allows for GC testing of variable
interactions and does not require specifying which variables are dependent. The system of equations is as follows:

\[ Y_t = \alpha + \sum_p \beta_p Y_{t-p} + \varepsilon_t \]  \hspace{1cm} (1)

\[ Y_t = [VOD_t, \theta_t, R_{st}, dT_t, VPD_t]' \]  \hspace{1cm} (2)

where \( \alpha \) and \( \beta \) are the regression constant and slope vectors. \( \varepsilon_t \) are the residuals. \( p \) is the lag order (where one lag refers to the previous 3-day period). Equation 1 is solved using ordinary least squares. All variables in \( Y \) are deseasonalized using a 30-day moving average climatology (Dong & Crow, 2018) to remove the influence of seasonal connections between factors that may bias detection of interactions at subweekly timescales (Tuttle & Salvucci, 2017). Deseasonalized predictor variables are not overly correlated (\( \rho < |0.5|; \) Figure S4), and therefore, multicollinearity between predictors (causing \( \beta \) magnitude inflation) is not likely. Augmented Dicky-Fuller tests reveal that all variables across our study region are stationary, a requirement of VAR approaches. A single lag (\( p = 1 \)) was found to be optimal based on a tenfold cross-validation approach (Figure S5 and Text S1). For VOD, the main focus variable of the study, the VAR model sufficiently fits the data across the study area with mean \( R^2 \) of 0.61 and model residual variability about half of the observation variability (Figure S6).

2.4. Granger Causality Tests

GC tests whether variable \( X_1 \)'s past values influence another variable, \( X_2 \), beyond \( X_2 \)'s own history (Granger, 1969; Salvucci et al., 2002). A variable “Granger causes” another when its estimated \( \beta \) values in Equation 1 are significantly nonzero (Hamilton, 1994). Note that GC only detects a few elements of causality and thus cannot be explicitly interpreted as detecting physical causality, but it provides a stronger statistical, predictive link between two variables than correlational analyses (Hamilton, 1994). The GC test is performed by restricting a given variable’s \( \beta \) values to zero (restricted model) and testing whether the residual sum of squares (RSS) is significantly higher than that of the full, unrestricted model (Hamilton, 1994). The test statistic is as follows:

\[ S = n \left( \frac{RSS_{Restricted} - RSS_{Full}}{RSS_{Full}} \right) \]  \hspace{1cm} (3)

where \( n \) is the sample size and \( S \) is asymptotically a chi-square statistic with 1 degree of freedom. RSS is determined using tenfold cross validation with out-of-sample validation to avoid overfitting (James et al., 2014). The procedure here is nearly identical to standard GC tests in previous geophysical studies (Green et al., 2017; Kaufmann et al., 2003; Mosedale et al., 2006). Based on additional tests, we found our results to be robust to residual nonnormality, autocorrelation, and heteroscedasticity, which are critical assumptions of ordinary least squares approaches (Figures S7 and S8; Greene, 2003). See Text S3 for discussions of GC interpretation and uncertainties due to measurement error, nonrandomly missing data, and assumptions of linearity.

2.5. Quantifying Interactions Between Factors

To quantify the direct impact of variable \( X \) on VOD holding other variables constant, an impulse response formulation is used (Hamilton, 1994):

\[ \frac{\Delta VOD}{\Delta t} \bigg|_{X_t \rightarrow VOD_t} = \frac{\partial X}{\partial t} \beta_{X_{t-1} \rightarrow VOD_t} \]  \hspace{1cm} (4)

where \( \beta \) is computed in Equation 1 and the partial derivative is estimated with \( X \)'s median change during drydowns in the water-limited regime (Figure 1 right column). The influence of multiple variable
interactions on VOD is also quantified considering collocation of direct interactions in a given pixel from Equation 4. This is equivalent to quantifying multiple factor interactions using recursion:

$$\frac{\Delta VOD}{\Delta t} \rightarrow \beta_{Xt-1 \rightarrow Zt-1 \rightarrow VOD} = \frac{\partial X}{\partial t} \beta_{Xt-1 \rightarrow Zt-1 \rightarrow VOD}$$ (5)

where the indirect impact of X on VOD via X’s impact on variable Z is computed (see Text S4 for derivation). The feedback of VOD on itself is a special case of Equation 5 when X equals VOD. Given stationary time series, $\beta_{Xt-1 \rightarrow Zt-1}$ and $\beta_{Xt-1 \rightarrow Zt}$ are equal. Only interactions with both statistically significant $\beta$ in Equation 5 are reported. While the recursion here inherently relies on two time steps to detect the interaction in this predictive framework, the physical interaction may still occur at shorter timescales. We ultimately refrain from using contemporaneous statistics (i.e., structural VAR and correlation) that would quantify within-time step interactions because they invalidate the predictive, GC framework.

3. Results and Discussion

3.1. Direct Drivers of Plant Water Content Loss

We find widespread plant water content (via VOD) loss driven by surface soil drying in the water-limited regime, especially in drier regions of Africa (Figure 2a; computed using Equation 4). Because plant water potential typically comes to equilibrium with soil water potentials overnight (predawn equilibrium), plant water loss is likely occurring because plant rehydration following previous day transpiration is progressively reduced due to soil moisture loss (Slatyer, 1967). We expect that SMAP’s 5-cm (and deeper; see section 2.2) soil moisture loss dynamics are relevant to the typically shallower root distributions of grass and tree species in the semiarid domains of Africa (Holdo & Nippert, 2015; Kulmatiski & Beard, 2013).

While solar radiation regionally shows statistically significant influences on VOD, its sign of influence is inconsistent and effect magnitude is small (Figures 1 and 2b). Solar radiation increases occur primarily during the initial 2–3 days of drying when cloud cover dissipates after a mesoscale event and remain nearly constant thereafter (Figure 1; Feldman et al., 2019). Solar radiation is instead likely driving large-scale plant dynamics on longer, seasonal timescales (Papagiannopoulou et al., 2017).

dT increases regionally drive plant drying primarily in Southern Africa (Figure 2c). While VPD surprisingly shows no discernable impact on plant drying here (Figure 2d), we assert that dT is likely serving as a closer proxy for VPDleaf (or VPD across the leaf interface) than the AIRS boundary layer VPD used here based on three lines of evidence. First, repeating the VAR implementation using afternoon temperature, used to calculate dT, shows nearly identical results (Figure S9). This soil-canopy temperature is likely representative of leaf temperature, directly related to VPDleaf. Second, removing dT from the VAR implementation leads to an increased effect size for AIRS boundary layer VPD on plant drying in the same regions of Southern Africa (Figures S10 and S11). Finally, boundary layer VPD can potentially be uncoupled from VPDleaf (Grossiord et al., 2020; Lin et al., 2019). Therefore, AIRS boundary layer VPD still provides VPD information driving plant water loss, but dT likely primarily reflects VPDleaf effects on plant water content in the regression. It is ultimately unclear why dT (and VPD) does not influence Sahel vegetation though we suspect it is due to weaker dT dynamics and vegetation-type differences (Text S5).

Our results suggest that increased temperatures (and higher VPD) promote landscape-scale plant drying (Figures 2c and S9), at least for the semiarid vegetation of Southern Africa and Morocco. This drying occurs despite the potential suppressing effect of stomatal closure at higher VPD (Massmann et al., 2019; Medlyn et al., 2011). This result is consistent with previous findings that transpiration increases with VPD in many species, even if stomatal resistance decreases (Cunningham, 2004; Lansu et al., 2020; Monteith, 1995; Mott & Parkhurst, 1991; Teuling et al., 2010; Urban et al., 2017). Additionally, greater soil temperatures are associated with higher conductance and transpiration (Cochard et al., 2000).

While VPD is expected to have an increasing impact on plant function under climate change (Konings, Williams, et al., 2017; Novick et al., 2016), soil moisture limitations on vegetation have been found to be widespread, especially in drier environments (Grossiord et al., 2020; L. Liu et al., 2020; Novick et al., 2016; Stocker et al., 2018). At subweekly scales here, our results show that the effects of soil moisture are twice more widespread than dT on an areal basis, though dT effects are still prevalent and individually
dominant in regions like that near the Kalahari Desert. Moreover, soil moisture and dT both have similar magnitudes of influence on plant water loss in the regions where they respectively show significant effects. While statistical partitioning of effects is limited by mutual information between these variables, we expect these to be the dominant controlling variables because the analysis is based on near-daily timescales when these factors are less coupled, especially after removal of the seasonal cycle. Furthermore, the regions where soil moisture and dT impact on plant water content largely remain the same when removing the other regressor from the VAR implementation (Figures S10 and S12).

Soil moisture and dT influences on VOD become more widespread in drier regions (black line in Figures 3a, 3b, and S13). These effects may weaken in more humid biomes (approaching Congo Basin) because the vegetation may rely more on light availability, even under water-limited conditions (Nemani et al., 2003).

### 3.2. Effects of Soil-Plant-Atmosphere Interactions on Plant Water Content

We find that soil moisture loss and dT increases, which both influence plant drying, are enhanced by interactions with other variables (Figure 3; using Equation 5). Two such interactions are relatively widespread and larger in magnitude. First, soil moisture drying tends to increase dT which further reduces plant water content ($\theta_{t-1} \rightarrow \Delta dT_{t-1} \rightarrow VOD_t$ in Figure 3b). This represents a known land-atmosphere coupling mechanism where more available energy is progressively partitioned into increasing surface heating as soil moisture.
dries (Seneviratne et al., 2010). While previous studies show strong land-atmosphere coupling across these water-limited regions (Dirmeyer, 2011; Koster et al., 2006; Miralles et al., 2012), we show how this specific mechanism drives plant drying with observations in a GC framework. Additionally, a VOD feedback occurs with soil moisture \((\theta_{t-1} \rightarrow \text{VOD}_t)\) where presumably plant water uptake reduces soil moisture resulting in reduced rehydration capacity and further plant water loss (Figure 3a). Both mechanisms occur more frequently in drylands (Figures 3a and 3b). While solar radiation shows a statistically significant indirect influence on VOD, the magnitude of this impact is smaller than that of other interactions (Figure 3b). Furthermore, VPD interactive effects on VOD are infrequent, though we suspect that \(dT\) is a closer proxy for VPD_{leaf}.

These interactions show that a direct influence of a variable on VOD is often influenced by interactions with other variables. For example, soil moisture influences \(dT\)'s direct impact on VOD in many dryland locations (Figure 3b). This interconnectedness reinforces plant drying. Therefore, models or analyses which neglect these interactions (i.e., no land-atmosphere interactions) may bias the rate at which plants dry.

Ultimately, the sum of all interactions shows a net tendency to enhance plant drying primarily through \(dT\) and \(\theta\) (Figure S14). The magnitude of total interaction impacts on VOD is inherently small as it is computed

Figure 3. Interactions between soil-plant-atmosphere factors contribute to plant water content (VOD) loss. Figure shows the prevalence and relative magnitude of two-step Granger "causal" interactions across the study region (using Equation 5), computed based on single interactions in Figures 2, S15, and S16. (a) Soil moisture interactions' impact on VOD. (b) Diurnal temperature amplitude interactions' impact on VOD. An interaction pathway's areal percentage (left) and relative magnitude (right) are represented by the same color. Soil moisture and \(dT\) direct effects on VOD are almost entirely plant drying effects (>95% of region; see Figure 2 insets). Therefore, relative magnitudes greater than zero signify that the respective interaction enhances plant drying.
4. Conclusions and Implications

We use a statistical framework and remote sensing observations from several satellite instruments to quantify the individual and interacting environmental factors that drive plant water content loss patterns after rainfall events. Evaluating plant water content responses to climatic factors provides implications for plant water stress drivers beyond commonly used satellite photosynthetic metrics that evaluate top-of-canopy properties. The GC framework provides strong statistical evidence for the role of soil drying and diurnal temperature amplitude increases (but not solar radiation) as well as land-atmosphere interactions on plant water stress during soil moisture drydowns in the water-limited regime.

We address the debate on the degree to which soil moisture and air VPD influence plant function at landscape scales. We show that soil moisture has the most widespread effects on plant water content which is consistent with previous studies that show dominant soil moisture effects on dryland vegetation (L. Liu et al., 2020; Novick et al., 2016; Stocker et al., 2018). However, dominant effects of land diurnal temperature amplitude (likely representing VPDleaf; see section 3.1) are also regionally prevalent in Southern African and Moroccan drylands and have similar magnitudes of effect on plant drying as soil moisture. Widespread soil moisture and diurnal temperature amplitude individual effects as well as interactions that reinforce plant drying suggest that a single factor is not always stronger or more dominant in its influence on landscape-scale plant function, at least for drylands here. The results suggest that soil moisture and VPD as well as their interactions should be explicitly considered in models that use empirical stress functions and in plant hydraulic schemes with plant water storages being implemented in dynamic global vegetation models (Fisher et al., 2018; Kennedy et al., 2019; Rigden et al., 2020).

Our study further indicates that satellite microwave VOD observations show notable responses to surface and atmospheric variability not only at seasonal but also at subweekly timescales (Feldman et al., 2018; Konings & Gentine, 2017).

Poststorm plant drying can represent transpiration under nonstressed conditions co-occurring with photosynthesis. However, we assert that we are evaluating plant water stress conditions here because our analysis is conditioned on drydown periods in the water-limited regime that occur about 1 week after the last rain event (Figure S2). These periods result in prolonged soil drying and surface warming that occur when plant water content subweekly anomalies are continuously negative and energy fluxes (including transpiration) are soil moisture limited. Our results thus show that surface drying and warming both individually and interactively can drive plant water stress in African drylands depending on the location. These stress conditions, if prolonged, may be the precursor to more severe stress with compound dry-warm events (Bastos et al., 2020; Zhou et al., 2019). The results also suggest that with interstorm periods lengthening under climatic changes of less frequent, more intense rainfall (Giorgi et al., 2019; Knapp et al., 2008), plants can experience more prolonged water stress conditions even without changing rainfall totals. Our results suggest that these considerations may have widespread effects on dryland vegetation, which covers 40% of the globe and is a dominant driver of the global carbon cycle's interannual variations (Poulter et al., 2014).

Data Availability Statement

SMAP L1C brightness temperature used to retrieve vegetation optical depth (https://nsidc.org/data/SPL1CTB_E) and SMAP L2 soil moisture (https://nsidc.org/data/SPL2SMP_E Versions/3) are available from the National Snow and Ice Data Center. All LandSAF data sets are available from EUMETSAT (https://landsaf.ipma.pt). Vapor pressure deficit data are available from NASA JPL (airs.jpl.nasa.gov/data/get-data). Generated maps plotted in this study are publicly available online (https://github.com/afeld24/VARVODDrivers).

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