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Key Points:

- Daily and 500-m resolution vegetation optical depth (VOD) was derived through multi-sensor data fusion
- Optical-infrared and microwave synergy resolves heterogeneous vegetation water conditions within 25-km grid cells
- Re-constructed VOD can improve understanding and monitoring of vegetation water potential at plant-to-stand scales

Supporting Information:

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

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Enhanced Satellite Monitoring of Dryland Vegetation Water Potential Through Multi-Source Sensor Fusion

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Abstract Drylands are critical in regulating global carbon sequestration, but the resiliency of these semi-arid shrub, grassland and forest systems is under threat from global warming and intensifying water stress. We used synergistic satellite optical-Infrared (IR) and microwave remote sensing observations to quantify plant-to-stand level vegetation water potentials and seasonal changes in dryland water stress in the southwestern U.S. Machine-learning was employed to re-construct global satellite microwave vegetation optical depth (VOD) retrievals to 500-m resolution. The re-constructed results were able to delineate diverse vegetation conditions undetectable from the original 25-km VOD record, and showed overall favorable correspondence with in situ plant water potential measurements (R from 0.60 to 0.78). The VOD water potential estimates effectively tracked plant water storage changes from hydro-climate variability over diverse sub-regions. The re-constructed VOD record improves satellite capabilities for monitoring the storage and movement of water across the soil-vegetation-atmosphere continuum in heterogeneous drylands.

Plain Language Summary Drylands provide ecosystem services to more than two billion people but are under threat from global warming and intensifying water stress. We used a machine-learning method to combine multi-satellite observations for estimating vegetation water status and seasonal changes over drylands. Our enhanced-resolution satellite vegetation retrievals (known as vegetation optical depth) were able to delineate diverse vegetation water conditions undetectable from the original 25-km data record, and showed strong correspondence with in situ plant water measurements. Our approach improves satellite capabilities for monitoring the storage and movement of water across the soil, vegetation, and atmosphere layers in heterogeneous drylands.

1. Introduction

Drylands are critical ecosystems, encompassing up to 45% of the Earth's land surface (Právělie, 2016), providing ecosystem services to more than two billion people (Smith et al., 2019) and regulating variability in global carbon sequestration (Poulter et al., 2014). Despite their importance, drylands are among the most vulnerable ecosystems to climate change due to the high sensitivity of plant functions to moisture and thermal stress (Kannenberg et al., 2024; Maestre et al., 2016; Smith et al., 2019). Considering the high spatial and temporal heterogeneity of dryland cover and environmental conditions, more effective methods for global monitoring of dryland ecosystems are needed to resolve the complexity of vegetation responses to rainfall pulses, dry spells, and long-term climate trends down to the local plant community level (e.g., meters-to-kilometers and hours-to-years) (Feldman et al., 2024; Smith et al., 2019).

Satellite microwave remote sensing is highly sensitive to water content in vegetation and soil (Du, Kimball, et al., 2019; Du, Watts, et al., 2019), and can provide insights into vegetation function complementary to that of optical and thermal indices. Vegetation optical depth (VOD) represents the slant-path opacity of vegetation to the propagation of microwave energy (Du et al., 2017). VOD is sensitive to the above-ground biomass water content and has been widely used in monitoring global vegetation dynamics from satellite microwave sensors (Frappart et al., 2020). VOD is generally determined by sensor configuration (e.g., microwave frequency and observation geometry) and vegetation properties, including vegetation water content (VWC) and aboveground dry biomass (Frappart et al., 2020; Konings & Gentile, 2017). Complementary to greenness-based vegetation indices derived

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from optical-infrared (IR) remote sensing, VOD allows for measurements of VWC beyond the top-of-canopy, encompassing both leafy and woody biomass even on cloudy days. VOD has been used to track the storage and movement of water within the soil-plant-atmosphere continuum (Konings et al., 2019), as an index of plant water potential (Holtzman et al., 2021; Momen et al., 2017), to understand plant traits and responses to water stress (Konings & Gentine, 2017; Li et al., 2017; Moesinger et al., 2022), monitor vegetation phenology (Du, Kimball, et al., 2019; Du, Watts, et al., 2019; Jones et al., 2014), and infer long-term trends in above-ground biomass (Dou et al., 2023; Konings et al., 2021; Rodríguez-Fernández et al., 2018). For example, VOD is proportional to VWC, and thus can be formulated as a function of water potential and total aboveground dry biomass for estimating these vegetation parameters (Momen et al., 2017). Satellite VOD-based estimation of plant water potential (Ψ) is of particular importance considering the critical role of Ψ in regulating canopy stomatal controls on photosynthesis and gas exchange with the atmosphere, determining the risk of xylem embolism and mortality, and driving water flows through the soil-plant-atmosphere continuum (Novick et al., 2022). VOD derived retrievals also have the potential to augment sparse in situ Ψ measurements of individual plants to reveal broader vegetation water storage changes and behavior of entire plant communities. Despite the potential of satellite VOD in monitoring plant water dynamics, it remains challenging to separate the diurnal to synoptic signals in plant water status from dry biomass disturbances and long-term changes (Dou et al., 2023; Konings et al., 2021).

For monitoring landscape-level vegetation dynamics, a variety of global VOD products have been developed utilizing space-borne microwave radiometers such as the Advanced Microwave Scanning Radiometer (AMSR) for EOS and AMSR2 (Du et al., 2017; Liu et al., 2011; Owe et al., 2008; Wang et al., 2021), Soil Moisture and Ocean Salinity (SMOS) (Cui et al., 2015; Wigneron et al., 2021), and Soil Moisture Active Passive (SMAP) missions (Chaubell et al., 2021). Compared with L-band SMAP and SMOS retrievals, the relatively high-frequency observations (e.g., C- and X-band) from AMSR-E/2 have a shallower penetration depth and are therefore useful for evaluating vegetation with low to moderate cover and above-ground biomass typical of semi-arid shrub and grassland environments (Jones et al., 2012; Li et al., 2021). In addition, AMSR provides a multi-decade VOD record (since 2002) with frequent sampling (up to twice-daily) and continuing observations enabled from planned next generation microwave radiometers including AMSR3 (to be launched in 2024; Shimoda, 2018) and the Copernicus Imaging Microwave Radiometer (CIMR) (Kilic et al., 2018). However, there are two major drawbacks associated with passive microwave VOD. First, its coarse spatial resolution (generally ≥ 10 km) results in spatial-scale mismatch with traditional ground-based biomass and Ψ measurements at plant-to-stand scales (Holtzman et al., 2021; Konings et al., 2019). A second related issue is the mixed-pixel problem, where contrasting VOD component signals from different land covers (e.g., forest and shrublands) within the same satellite footprint remain unseparated. Finer-scale VOD records are therefore needed to interpret the relationships between satellite passive microwave observations over large regions and plant physiological measurements for individual plants and plant communities (Humphrey & Frankenberg, 2023; Yao et al., 2024).

Alternatively, satellite optical-IR and synthetic aperture radar (SAR) sensors are capable of delineating vegetation conditions at sub-meter to sub-kilometer resolutions, but are constrained by limited temporal frequency and missing observations (Du, Kimball, et al., 2019; Du, Watts, et al., 2019). For example, major data gaps in optical-IR records commonly occur during the shoulder seasons at higher latitudes; the global revisit for Sentinel-1 SAR and upcoming National Aeronautics and Space Administration - Indian Space Research Organisation SAR (NISAR) missions range from 6 to 12 days (Kellogg et al., 2020). These timescales can be too long to fully capture the intermittent wetting and drydown behavior in vegetation (Feldman et al., 2024; Noy-Meir, 1973). Nevertheless, the higher resolution (< 1 km) allows evaluation of vegetation productivity, evapotranspiration (ET), and water stress conditions from optical-IR retrievals of land surface temperature, vegetation greenness, or solar-induced canopy fluorescence. These optical-IR retrievals complement passive-microwave observations of soil moisture and VOD (Guan et al., 2017; Jones et al., 2012). SAR-based VOD (El Hajj et al., 2019) and Radar Vegetation Index (RVI; Kim et al., 2011) retrievals also offer similar sensitivity to vegetation microwave attenuation properties and water storage changes as passive-microwave sensors, but with a trade-off: higher spatial and lower temporal resolution.

Considering the respective constraints of different satellite sensors, and the need to resolve dryland vegetation water status at the local plant community level, our objective was to integrate multi-sensor vegetation observations (Mohite et al., 2022) using machine-learning (ML) approaches to build (a) VOD data with enhanced spatial (500-m) and temporal (daily) resolution, and to (b) improve linkages between global satellite VOD observations and detailed plant-to-stand level water potential measurements in selected dryland systems.

2. Data and Methods

2.1. Study Regions

We focused on re-constructing an existing global 25-km AMSR VOD record to 500-m resolution and comparing the spatially enhanced results with detailed in situ measurements of stem water potential (Ψ_{stem}) for two dryland locations in the southwestern U.S. The first site is located within the National Ecological Observatory Network (NEON) Santa Rita Experimental Range (latitude 31.91°, longitude −110.84°; AmeriFlux site ID: US-xSR) in southern Arizona where continuous Ψ_{stem} measurements were made on locally dominant creosote shrubs (*Larrea tridentate* sp.). The 0.25° by 0.25° area surrounding this site was used for VOD re-constructing and mapping, and the overlying 5° by 5° area for training the ML model and integrating multi-source satellite data (Figures S1a and S1c in Supporting Information S1). The major vegetation type over the sampling site is desert shrubland (Fiorella et al., 2021), although substantial urban areas, trees, and croplands are located within the surrounding re-constructing area (Figure S1c in Supporting Information S1).

The second study region is defined by a ML training area (5° by 5°) surrounding Cedar Mesa (latitude 37.5241°, longitude −109.7471°; AmeriFlux site ID: US-CdM) in southeastern Utah where continuous measurements of Ψ_{stem} were collected from locally dominant Utah Junipers (*Juniperus osteosperma* sp.) within the associated VOD re-constructing area (0.25° by 0.25°) (Figures S1a and S1b in Supporting Information S1). The woody vegetation within this sampling site is primarily composed of Utah juniper and two-needle piñon, which are scrubby trees with an average tree height of ~3 m (Kannenberg et al., 2023). There exists a sparse understory consisting of great basin sage, bunchgrasses, and cacti, while the occasional coverage of ponderosa pine also occurs within the re-constructing area (Figure S1b in Supporting Information S1).

2.2. Data Sets

We re-constructed the original 25-km VOD record to 500-m resolution using a random forest (RF) (Breiman, 2001) ML approach to improve spatial consistency between the satellite VOD retrievals and in situ Ψ_{stem} measurements. The RF model was trained using satellite observations from 25-km grid cells and then applied at finer (500-m) spatial resolution.

Variations in water storage and movement along the soil-plant-atmosphere continuum are controlled by hydraulic pressure and water potential gradients largely driven by canopy evaporative water losses and other plant metabolic activities. Plant water storage and movements are also influenced by plant traits including canopy biomass structure and phenology, and water-use strategies (Gou & Miller, 2014; Kannenberg et al., 2022). Passive microwave VOD is proportional to VWC, a function of relative water content (RWC) or water potential and total aboveground dry biomass (AGB) (Momen et al., 2017). Accordingly, VOD is related to other vegetation metrics derived from optical-IR and SAR observations such as NDVI, Normalized Difference Water Index (NDWI), and RVI, and also inter-connected with environmental controls such as ET, precipitation and soil moisture.

For 25-km RF predictions, the target variable is the 25-km Land Parameter Data Record (LPDR) VOD (Du et al., 2017). The predictors include Sentinel-1 RVI (for US-CdM site only), Moderate Resolution Imaging Spectrometer (MODIS) NDVI, NDWI (Gao, 1996), ET data set (MOD16A2 Version 6.1; Mu et al., 2011), and Daymet (version 4) gridded precipitation (Thornton et al., 2022), which were aggregated over the 25-km grid cells. For 500-m RF predictions, the predictors include the original MODIS NDVI, NDWI, and ET data at 500-m resolution, Daymet 1-km precipitation resampled to 500-m resolution, and the Sentinel-1 RVI data (for US-CdM site only) aggregated over the 500-m pixels. The corresponding target variable is 500-m resolution VOD. In addition, the LPDR 25-km volumetric soil moisture (VSM; Du et al., 2017) were added as a common predictor for both the 25-km and 500-m RF predictions, which described the background soil dry-wet dynamics for further model constraining.

2.2.1. Satellite Passive Microwave VOD and VSM

The LPDR VOD and VSM data set derived from AMSR X-band (10.7 GHz) brightness temperature (T_b) observations provides global coverage at 25-km resolution and 1–3 days sampling frequency, and represents the vegetation and surface (~1 cm depth) soil wetness conditions at around 1:30 a.m. (descending pass) and 1:30 p.m. (ascending pass) local time (Du et al., 2017). The data set has been widely used for studying vegetation phenology (Du, Kimball, et al., 2019; Du, Watts, et al., 2019; Jones et al., 2014), plant water-use strategies

(Konings & Gentine, 2017; Li et al., 2017), drought-driven tree mortality (Rao et al., 2019), the global carbon budget (Natali et al., 2019), and comprehensive drought assessment (Du, Kimball, et al., 2019; Du, Watts, et al., 2019). The X-band LPDR is well-suited for monitoring dryland ecosystems, indicated by the best correlations with optical vegetation indices at seasonal timescales among the major satellite VOD records (Li et al., 2021).

2.2.2. MODIS Vegetation Products

For resolving the spatial heterogeneity within 25-km VOD grid cells, finer-scale vegetation information is used in the re-constructing process. The ML predictors for VOD re-constructing included vegetation features derived from MODIS. The NDVI and NDWI were adopted to quantify the respective vegetation greenness and water content conditions. In addition, NDVI was more capable of capturing the VOD temporal dynamics relative to active-microwave proxies, which are sensitive to vegetation structures (Zhong et al., 2024). Considering the inter-connections between VOD and ET (Yao et al., 2024), the MODIS ET 8-day composites (MOD16A2 Version 6.1; Mu et al., 2011) were also included as a predictor.

2.2.3. Radar Vegetation Index

In addition to MODIS vegetation features, the RVI derived from Sentinel-1 A/B SAR (10-m resolution) data was used as another predictor and proxy for vegetation biomass and water content (Kim & Van Zyl, 2009). Different from the original RVI definition where VV, HH, and VH polarizations were utilized (Kim & Van Zyl, 2009), the RVI was adapted for Sentinel-1 observations here by assuming HH and VV equivalence over vegetation (Equation 1).

$$RVI = \frac{8VH}{VV + HH + 2VH} \approx \frac{8VH}{2VV + 2VH} \quad (1)$$

Additionally, the RVI data were not utilized as a predictor for the US-xSR site due to the temporal sparsity of SAR observations since December 2021 when data transmission failure of Sentinel-1B resulted in a reduced sampling frequency.

2.2.4. Stem Water Potential Measurements

Automated stem psychrometers were used to measure Ψ_{stem} over the US-xSR site in Arizona and US-CdM site in Utah. Stem psychrometers (ICT International) measure xylem water potential through a dual-thermocouple design that generates a wet bulb depression and corrects for temperature gradients in the chamber (Guo et al., 2020; Kannenberg et al., 2023). At US-xSR, psychrometers were installed on two branches each of six individual *L. tridentata* shrubs from 18 February 2023, to 2 November 2023. At US-CdM, psychrometers were installed on one branch of seven individual *J. osteosperma* trees, which comprised 92% of the basal area at that site, from 24 May 2021 to 5 November 2021. Psychrometers were calibrated prior to installation, rotated between branches every 1–5 months depending on sensor contact, and Ψ_{stem} was logged every 30 min. After initial quality check to account for installation equilibration and sensor drift, half-hourly measurements were aggregated into daily stand-level means for predawn (2 hr prior to sunrise) and midday (2 hr spanning solar noon) conditions.

2.2.5. Satellite Data Processing

Google Earth Engine (GEE), a cloud-based platform for efficient processing and analysis of multi-petabyte geospatial data (Gorelick et al., 2017), was used for pre-processing the selected data sets, aligning the predictor and predictand data spatially and temporally, and implementing the ML model (Section 2.3).

The ML model training was performed over the training areas where all data sets were aggregated to 8-day temporal resolution consistent with the MODIS ET product, and 25-km spatial resolution consistent with LPDR VOD product. Different from the original LPDR VOD where a 30-day median filter was applied (Du et al., 2017), un-smoothed VOD data were first uploaded to GEE as an asset with daily variations preserved and then 8-day averaging was performed for temporal consistency with the MODIS-based predictors. The MODIS NDVI and NDWI were calculated from the MODIS Nadir BRDF-Adjusted surface Reflectances (NBAR) daily product (MCD43A4 Version 6.1) (Schaaf et al., 2002), and then composited to the 8-day time step in GEE. The

NBAR data set is suitable for capturing dryland phenology dynamics by minimizing uncertainties associated with the sensor viewing geometry (Walker et al., 2012).

For de-speckling and correcting for incidence angle effects, the Sentinel-1 SAR Ground Range Detected (GRD) images were first filtered using a 3-by-3 median filter, and local incidence angles were calculated based on Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM) data. The RVI data were calculated using VV and VH backscatter (Equation 1), empirically corrected using the cosine correction method and local incidence angle (Mladenova et al., 2012), and aggregated to the 8-day time step.

Finally, all of the fine-resolution predictors were spatially averaged into 25-km grid cells consistent with the VOD data sets over the ML training areas and study periods (1 February 2023 to 30 November 2023; and 1 May 2021 to 30 November 2021). In addition, the RVI data within the re-constructing areas were also aggregated to 500-m resolution and combined with the original MODIS products for building the relatively high-resolution predictor data sets for VOD re-constructing over the US-CdM site.

2.3. Methods for Re-Constructing VOD and Estimating Ψ_{stem}

ML approaches have shown promise in resolving remote sensing problems by discovering and leveraging the subtle or hidden patterns and relationships in multi-source and multi-scale geospatial data (Maxwell et al., 2018). We adopted the RF approach for building relationships among the multi-source satellite vegetation observations (Breiman, 2001). RF regression trees have demonstrated high efficiency and robustness in enhancing satellite estimates in terms of accuracy and spatio-temporal resolution (Du et al., 2022).

For facilitating the data processing and analysis, three RF models with a 50-tree structure were assessed using five-fold cross-validation, which involves randomly splitting the data set into five bins for training (80% of the data) and validation (20% of the data) in each of the five iterations. For the US-xSR site, two RF models were trained over the respective 5-month periods (February–June 2023 and July–November 2023) for addressing the impacts of vegetation biomass seasonality on VOD. For the US-CdM site, one RF model was trained on a shorter data period (late May 2021 to early November 2021) corresponding with less than 6-months of available Ψ_{stem} measurements at this site.

The trained model was subsequently applied to the re-constructing area for deriving higher-resolution VOD utilizing the 500-m resolution predictors. Considering the RF models were built based on 8-day composites, the resulting 500-m VOD time series were corrected to restore the daily variation by multiplying the derived 500-m data against the ratio of the original daily VOD and 8-day VOD composite from each 8-day period. Here we assumed daily VOD variations within each 8-day period are the same at coarse (25-km) and fine (500-m) scales. Finally, a 7-day moving average was applied to both the re-constructed and original VOD time series to suppress potential higher temporal frequency noise (Du et al., 2017) while keeping smoothed temporal variations within the 7-day time window. The original 25-km and re-constructed 500-m VOD data sets for 1:30 a.m. and PM local times were then compared with the respective pre-dawn and mid-day Ψ_{stem} measurements in terms of spatial distribution pattern and correlation coefficients.

Moreover, VOD is proportional to VWC, which is the product of the AGB and RWC (Momen et al., 2017). The AGB and RWC can be linearly approximated from the respective optical vegetation indices and vegetation water potential (Momen et al., 2017). Accordingly, Ψ_{stem} can be approximated from the satellite-derived VOD and NDVI variables as:

$$\Psi_{\text{stem}} = (\text{VOD} - a - b \cdot \text{NDVI}) / (c + d \cdot \text{NDVI}) \quad (2)$$

where a , b , c , and d are fixed parameters for a given location and time (AM or PM). Finally, non-linear surface fitting was performed for estimating parameters a , b , c and d in Equation 2 using Levenberg-Marquardt (LM) optimization, and the correlation between fitted and measured Ψ_{stem} data was used to examine the feasibility of satellite retrieval of vegetation physiological parameters.

3. Results

The ML model results derived using the selected predictors effectively reproduced VOD with root mean square error (RMSE) of approximately 0.09 Np, coefficient of determination (R^2) of 0.92, and bias of 0.000 Np for the

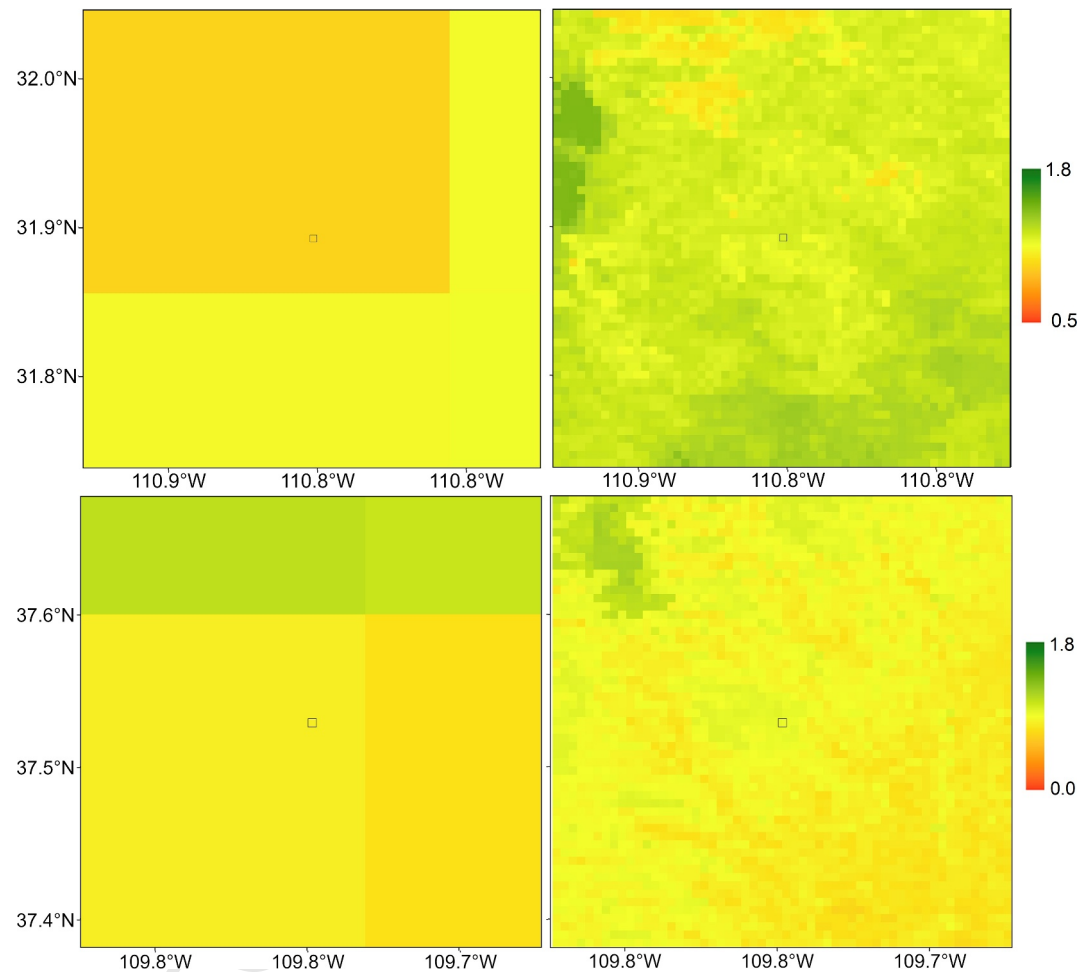


Figure 1. Comparisons between the vegetation optical depth (VOD) spatial distributions of the original 25-km (a) and the re-constructed 500-m (b) data sets over the re-constructing area surrounding the US-xSR site for 28 August 2023; and comparisons between the 25-km (c) and 500-m (d) VOD for the US-CdM site on 29 August 2021. Rectangular symbols centered in the re-constructing areas represent site locations.

US-xSR site. Similar VOD performance was attained at the US-CdM site, with RMSE of 0.11 Np, R^2 of 0.86, and bias of 0.002 Np. For both sites, VSM made the greatest contribution to the VOD prediction ($\sim 29\%$ for US-xSR; $\sim 22\%$ for US-CdM), followed by NDVI ($\sim 24\%$ for US-xSR; $\sim 20\%$ for US-CdM), while precipitation contributed the least ($\sim 10\%$ for US-xSR; $\sim 12\%$ for US-CdM) (Table S4 in Supporting Information S1). For each site, the above statistics and predictor importance are also consistent between RF models developed using the AM and PM data sets and different time periods.

For each re-constructing area, the original VOD maps rely on four 25-km grid cells to provide a broad overview of the regional vegetation pattern (Figures 1a and 1c). In contrast, the respective 500-m VOD results over the US-xSR site for 28 August 2023 (Figure 1b) and the US-CdM site for 29 August 2021 (Figure 1d) provide a 50-fold increase in spatial resolution for better delineating vegetation heterogeneity. The associated enhancement in spatial detail reveals more pronounced landscape variability in VOD. For example, although the northwestern grid cell exhibits the lowest vegetation level among the four 25-km grid cells of the re-constructing area surrounding the US-xSR site (Figure 1a), the re-constructed data indicate the highest VOD along its western edge (Figure 1b), aligning with trees (e.g., irrigated pecan orchards) identified in the land cover map (Figure S1c in Supporting Information S1). Similarly, the singular high VOD observed in the northwestern 25-km grid cell of the re-constructing area surrounding the US-CdM site corresponds with overall high but diverse VOD values in the re-constructed map (Figure 1d), where elevated VOD areas mainly align with the forested sky islands (Van Leeuwen et al., 2010) within the grid cell (Figure S1b in Supporting Information S1). The high-elevation sky

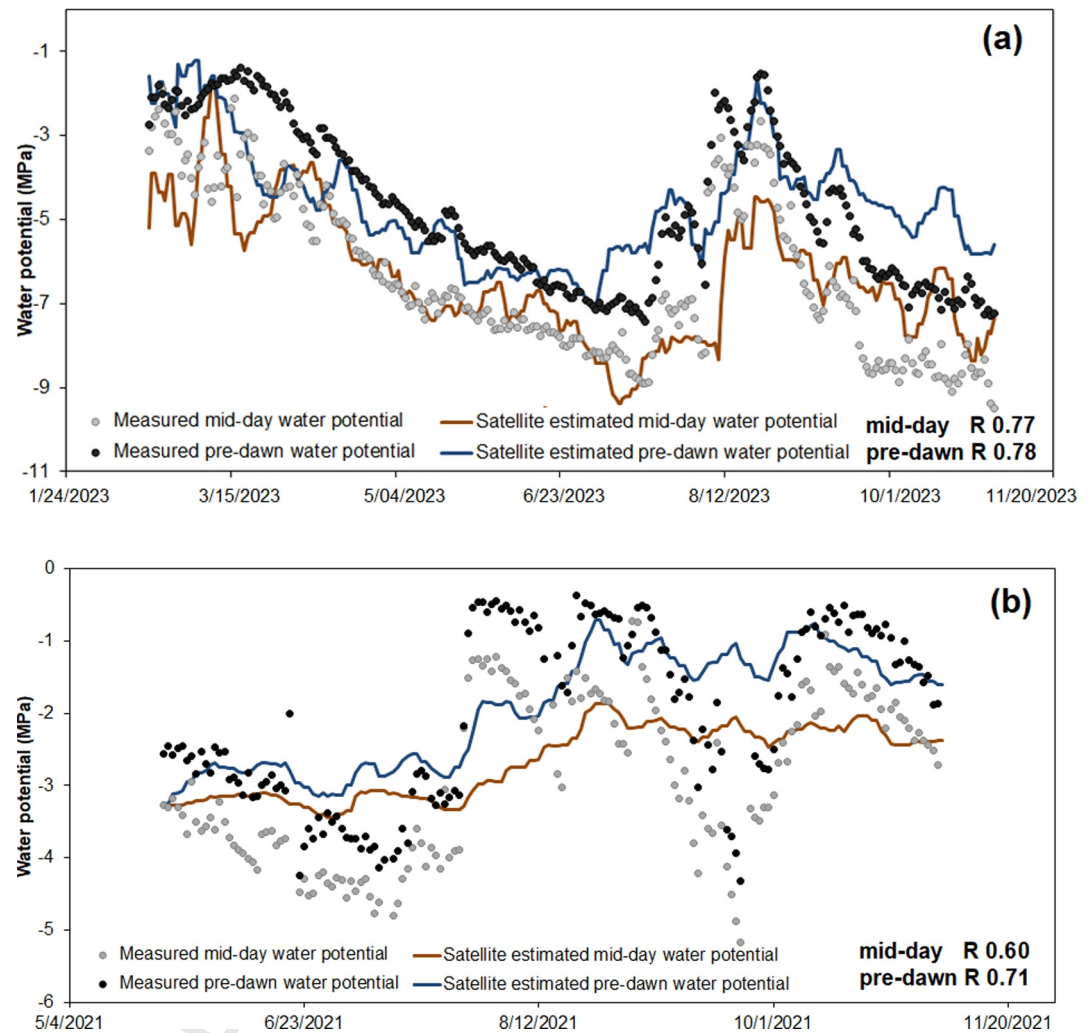


Figure 2. Comparisons between the water potential measurements and satellite-based estimation for the US-xSR site in Arizona (a) and the US-CdM site in Utah (b).

islands and surrounding low-elevation arid areas represent steep environmental gradients and large vegetation variability and play a crucial role in regional carbon sequestration, but remain inadequately resolved from global satellite and reanalysis data (Van Leeuwen et al., 2010).

The original and re-constructed VOD data sets at 1:30 a.m. and PM local time were compared with the respective pre-dawn and mid-day Ψ_{stem} measurements from each site. For all comparisons, the Ψ_{stem} measurements showed stronger correspondence with the re-constructed VOD than the original 25-km data; and the respective correlation coefficients consistently improved from 0.65 to 0.75 (US-xSR site; pre-dawn time; Figure S2a in Supporting Information S1), 0.41 to 0.76 (US-xSR site; mid-day time; Figure S2b in Supporting Information S1), -0.10 to 0.69 (US-CdM site; pre-dawn time; Figure S2c in Supporting Information S1), and -0.44 to 0.49 (US-CdM site; mid-day time; Figure S2d in Supporting Information S1).

Considering the inter-connections among water potential, aboveground dry biomass, and VOD (Momen et al., 2017), the parameters of Equation 2 were numerically estimated from the re-constructed VOD, 500-m NDVI and measured Ψ_{stem} time series for the respective pre-dawn and mid-day conditions at the two sites. The estimated Ψ_{stem} data demonstrated strong agreement with the measurements for the US-xSR site (R of 0.77 and 0.78 for respective mid-day and pre-dawn data) whereas the correspondence was lower for the US-CdM site (R of 0.60 and 0.71 for mid-day and pre-dawn) (Figure 2).

4. Discussion

Plant water storage and movement along the soil-plant-atmosphere continuum is controlled by moisture gradients, plant metabolic activities, and plant traits including canopy biomass structure and phenology, and water-use strategies (Gou & Miller, 2014; Kannenberg et al., 2022). Canopy (leaf and xylem) water potential is a key plant physiological parameter essential to regulating water transport and carbon assimilation by directly affecting canopy stomatal conductance to CO₂ and water vapor, and photosynthesis (Nikinmaa et al., 2014). Direct quantification of canopy water potential has traditionally involved controlled field experiments and labor-intensive measurements at plant-level and plot-scale (Guo et al., 2020, 2024). Our study indicates that the satellite VOD retrievals can contribute important information enhancing the delineation and monitoring of plant water status in drylands. However, remaining challenges exist in establishing a clear link between VOD and leaf-to-stand level water potentials, including spatial scale inconsistency (Holtzman et al., 2021) and confounding effects of aboveground dry biomass and VWC (Konings et al., 2021).

Our study suggests that high-resolution direct satellite retrieval of the plant water status in dryland ecosystems is achievable using complementary optical-IR and microwave remote sensing. The ML-based multi-sensor fusion is able to reproduce VOD from optical-IR and SAR observations ($R^2 \geq 0.86$) enabling the delineation of vegetation water potentials at 500-m resolution and closer to the scale of individual plant communities and in situ field measurements. This level of spatial delineation in vegetation physiology is indistinguishable in the original 25-km VOD record (Figure 1). The RF-based approach generally exhibits minimal biases across the entire training or validation data set but may under-/over-estimate over individual data points. Both optical-IR and SAR vegetation retrievals are important to the VOD prediction, although the relatively low contribution from RVI for the sparsely vegetated US-CdM site might stem from the impacts of soil moisture and surface roughness on RVI vegetation sensitivity (Kim et al., 2011). In addition, the MODIS ET product is derived from the Penman-Monteith equation using both MODIS observations and meteorological reanalysis data (Mu et al., 2011). Uncertainties related to underlying model assumptions and coarse-resolution (~50-km) reanalysis data may propagate into the ET retrieval (Mu et al., 2011) and affect the VOD re-constructing. Considering diverse water-stress conditions and varying responses from different vegetation species may exist within a given 25-km grid cell, the original VOD could show either high (e.g., Figure S2a in Supporting Information S1; US- xSR site) or low (e.g., Figure S2c in Supporting Information S1; US-CdM site) correlation with stand-level water potential measurements. In contrast, the re-constructed VOD data allow for comparisons at more consistent spatial scales, and show major improvement in VOD- Ψ_{stem} relationships for both sites and both AM and PM sample times. While the focus of this study is on drylands, supplementary results suggest the approach may also be extended to forests in mesic areas (Figure S4 in Supporting Information S1; Table S1 in Supporting Information S1).

As an initial effort to estimate water potential directly from satellite retrievals, re-constructed VOD and MODIS NDVI were used to fit the Ψ_{stem} measurements based on Equation 2. The fitted results showed strong correlations (R from 0.60 to 0.78) with detailed ground measurements across sites and AM/PM sample periods, suggesting the feasibility of satellite quantification of VWC. While the RF predictors generally showed good correspondence with the site Ψ_{stem} measurements (Table S2 in Supporting Information S1), permutation importance analysis further confirmed that VOD generally dominates the variations of estimated Ψ_{stem} relative to NDVI, with the VOD importance exceeding 83% in all cases except for the mid-day water potential estimates at the US-CdM site (Table S3 in Supporting Information S1). However, for the US-CdM site, the major drop of measured water potential in late September 2021 was largely missing from the re-constructed VOD (Figures S2c and S2d in Supporting Information S1) and estimated water potential (Figure 2b). Uncertainties in stem psychrometer measurements during dry conditions may cause deviations in the expected VOD- Ψ_{stem} linkage (Kannenberg et al., 2023), especially considering the largest standard deviations of Ψ_{stem} measurements were identified over the same period (late September 2021) (Figure S3 in Supporting Information S1). Another possible reason for this discrepancy may stem from the 500-m gridding and 8-day compositing of satellite data used in the RF model development, which may fail to capture finer-scale (e.g., 1–100 m) heterogeneity and more dynamic changes in water potential. The estimated and measured water potential data sets represent different spatial scales (e.g., 500 m vs. individual trees) and in situ measurement has its own uncertainties, which also likely contribute to the discrepancies between the two data sets. GNSS-based measurements of VWC with improved (~100-m) spatial scale consistency could be utilized for further assessment (Feldman, 2024). For the US-xSR site, occasional frost events in late February may affect satellite land surface observations and the associated water potential estimates. We further estimated water potential using the averages of the site- and pass-specific parameters of Equation 2

(Table S3 in Supporting Information S1), which showed an overall similar correlation with the in situ measurements (R 0.71), but a much larger bias (1.85 MPa) compared with the previous results (R 0.71; bias 0.08 MPa). This indicates the potential of using the re-constructed VOD for monitoring the relative changes of water potential at sites lacking in situ measurements and highlights the need for calibrating data levels.

While similar ML approaches have been widely used in satellite soil moisture and solar-induced fluorescence studies (Malbêteau et al., 2016; Zhang et al., 2018), re-constructing fine-scale VOD is relatively new and needs to be carefully interpreted due to the confounding effects from biomass and VWC (Konings et al., 2019; Zhong et al., 2024). Potential improvements may include (a) integrating additional complementary satellite observations, including from NISAR and commercial CubeSat constellations in the ML models for improved representation of temporal dynamics, (b) optimizing the RF training by targeting shorter time periods and weighting toward variables more related to water stress than biomass changes, (c) assessing temporally decomposed VOD signals (Dou et al., 2023) for inferring water potential without prior knowledge contributed from NDVI and other sources, and (d) exploring how Equation 2 parameters vary across space and time for further assessing satellite capabilities of monitoring vegetation water potential over different regions.

In addition, daily water and carbon fluxes of dryland ecosystems were found to be highly sensitive to fluctuations in soil water availability as well as other environmental controls (Guo et al., 2024; Kannenberg et al., 2023). Additional analysis is needed in future studies to clarify the inter-connections among re-constructed VOD, water and carbon fluxes, and ecosystem processes.

5. Conclusions

Plant water potential is a key physiological parameter influencing water storages and movements along the soil-vegetation-atmosphere continuum. The fusion of synergistic observations from optical-IR and microwave sensors can more effectively resolve the heterogeneous vegetation conditions within 25-km passive microwave VOD grid cells, and enable improved monitoring of plant water potential at plant-to-stand levels. Our initial assessment showed that plant water potential can be estimated using re-constructed VOD and optical-IR vegetation indices, while further enhancement is possible through ongoing calibration refinements to the satellite data and the additional use of other complementary remote sensing data.

Data Availability Statement

The AMSR VOD data were produced by NTSG, UM and accessed from NSIDC (Du & Kimball, 2021). MODIS nadir BRDF-adjusted reflectance (C. Schaaf and Wang, 2021) and ET (Running et al., 2021) data were provided by NASA's Land Processes Distributed Active Archive Center (LP DAAC) and accessed from GEE. ESA COPERNICUS Sentinel-1 SAR data (ESA, 2024) were accessed from GEE. The script used in this study is available at Zenodo (Du & Kimball, 2024).

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