**Plant access to belowground moisture allows sustained evapotranspiration during drought**

**Running Title: Belowground moisture allows sustained ET**

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**Abstract**

Subsurface water limitation is key to determine vegetation sensitivity to drought. There is evidence that water sources deeper than soil moisture exert a strong control on evapotranspiration (ET). However, these are impossible to observe directly at large scales and are not accounted for properly by land surface models. Here, we develop a method to study the impact of belowground water limitation on ET in progressing drought from ecosystem flux measurements. We train deep neural networks with 88,000 site-days of eddy-covariance data, meteorological data, multiple soil moisture datasets, and a remotely sensed greenness index. We derive a belowground water stress factor (fET) that isolates its ET reduction compared to atmospheric aridity, net radiation, air temperature and vegetation greenness. To investigate the sensitivity of ET impacts to progressing droughts, we regress fET against the cumulative water deficit (CWD), a normalized measure of whole-column water availability. We find that climate is the most important control on fET under drought, with much less variation induced by soil type or plant functional type. Evergreen needleleaf forests show the lowest sensitivity to belowground water stress, displaying almost negligible fET reductions up to a CWD of 300 mm. Savannahs and grasslands present an abrupt and progressive drop down to 10% fET after a CWD threshold of 50 mm. This variety of responses is not captured by a standard land surface model. We suggest this happens because models usually do not account for belowground water reservoirs. Our findings illuminate the understanding of vegetation sensitivity to drought and provide insight into modelling water stress effects.

**Keywords**: deep learning, root zone water storage capacity, climate change, data science, ecosystem fluxes, rock moisture, groundwater, soil moisture, vapor pressure deficit (VPD), potential evapotranspiration

# Introduction

Water availability controls evapotranspiration (ET) over most of the vegetated land surface (Ahlström et al., 2015; Beer et al., 2010; Schwalm et al., 2010; Seneviratne et al., 2010). Under increasingly dry conditions, plants can depend on belowground water reservoirs to sustain their activity (Hahm et al., 2019; McCormick et al., 2021; Milly, 1994) or rely on very resistant xylem (Mackay et al., 2015; Plaut et al., 2012). As droughts may become more severe and frequent in the future (Seneviratne et al., 2021), it is crucial to understand how plant function links subsurface water limitation and ecosystem evapotranspiration (ET). Here, we identify 'droughts' by water stress effects on vegetation and water balance deficits (Seneviratne et al., 2021).

Quantifying belowground water limitation effects on ET is challenged by the heterogeneity of the soil and bedrock structure, both vertically along the rooting zone and laterally across the landscape (Dralle et al., 2020; Gao et al., 2014; Thompson et al., 2011). We define the root zone water storage capacity (S0) as the maximum amount of soil moisture that can be accessed by vegetation for transpiration. A large S0 has been linked to a higher plant resistance to drought, sustained ET, and persistent vegetation cover during rain-free periods (Gao et al., 2014; Teuling et al., 2006). Recent studies have identified locally important contributions to S0 by water reservoirs below the soil layer, e.g., in fractured bedrock (Dawson et al., 2020; McCormick et al., 2021; Rempe & Dietrich, 2018; Stocker et al., 2021) or groundwater (Fan et al., 2017; Hain et al., 2015; Thompson et al., 2011). In settings with pronounced topographical gradients and in the proximity of water bodies, water-saturated zones can be within the reach of roots (Fan et al., 2013, 2017). This implies large variations in plant access to belowground water stores at multiple scales, as suggested also by inverse modelling (Fan et al., 2017; Hain et al., 2015). However, observations of the contributions of subsurface moisture to land-atmosphere exchanges are sparse and limited to a small number of individual field sites (Rempe & Dietrich, 2018).

Identifying the role of plant access to belowground water stores and its importance for ecosystem-atmosphere fluxes across vegetation types and climate zones has remained mostly unexplored. This is partly due to challenges in separating partial effects on ecosystem fluxes from multiple covarying drivers. In particular, soil moisture and vapor pressure deficit jointly affect ET but tend to covary (Giardina et al., 2018; Novick et al., 2016; Zhou et al., 2019). Although the soil moisture-VPD coupling is observed as a result of land-atmosphere feedbacks under relatively dry conditions (Seneviratne et al., 2010), this correlation fades under very dry or humid conditions (Ruddell & Kumar, 2009). This limits our understanding of belowground water availability effects on fluxes.

Indeed, the complexity of belowground water stores contrasts with their typical representation in land surface models (LSMs) (Fan et al., 2017). With a few exceptions, LSMs represent the land surface as a flat surface (Prentice et al., 2015), assume free drainage from the bottom soil layer which prevents the formation of water-saturated zones (Liang et al., 1994; Schlemmer et al., 2018), and do not account for the variety of bedrock lithology and its role as a moisture storage component (McCormick et al., 2021). Spatial variations of S0 are typically represented in models based on variations in soil type and in plant rooting depth assigned to plant functional types (PFTs) (Drewniak, 2019; Tumber-Dávila et al., 2022). These simplifications affect the accuracy at predicting water limitation effects on ET, particularly under drought conditions (Green et al., 2017; Kennedy et al., 2019) and at large spatial scales (K. Zhang et al., 2016). Taken together, this highlights the need to develop observational benchmarks for the role of belowground moisture limitation, separated from atmospheric aridity and other co-varying drivers (Giardina et al., 2018; Novick et al., 2016; Zhou et al., 2019), for a reliable ET modelling under a wide range of water limitation levels.

Here, we develop a method to diagnose the partial dependence of ET to belowground water limitation effects at eddy-covariance sites, whose footprint is typically on the range of a few hundred meters to two kilometers (Kljun et al., 2015). We use ecosystem-scale ET measurements, complemented by meteorological measurements, multiple soil moisture datasets and a remotely sensed greenness index. Using site-specific deep neural network (DNN) models, we estimate the fractional reduction in ET due to limiting belowground water stores (fET). fET isolates the control of belowground water availability on ET, factoring out effects of VPD and other drivers, i.e., vegetation greenness, air temperature and net radiation (Rn). We evaluate fET reductions due to belowground water availability by regressing it against the cumulative water deficit (CWD, the cumulative difference between observed ET and precipitation, see Box 1). In contrast to evaluating fET against surface soil moisture, evaluation against CWD reveals patterns of water stress effects even after drying out of the topsoil. It is therefore possible to identify the dependence of ET on belowground water reservoirs, below the relatively shallow soil layers, where measurement devices are commonly deployed.

# Methods

## Overview

For each site, we defined two separate deep neural network models (DNNPET and DNNET, respectively) for estimating potential and actual evapotranspiration (PET and ET, respectively). PET is estimated here as ET in absence of any belowground water limitations. The key difference between the two models is that DNNPET was trained using data from days with a relatively high soil moisture only, whereas DNNET was trained using all available data (see section 2.2). We defined a normalized measure of belowground moisture effects on ET (referred to as 'fET') by dividing the neural network estimate of ET (ETNN) by the neural network estimate of PET (PETNN). We then analyzed how fET evolves with increasing water stress by regressing it against the observed cumulative water deficit (CWD). Since the CWD is the integration of the water balance over time (see section 2.5), it constitutes a proxy for the depletion of belowground moisture. By definition, the CWD is independent from assumptions regarding soil depth or the total water storage capacity. It therefore implicitly includes contributions from both soil and subsurface water storage.

## Estimating potential ET

Our approach was based on a published method that separates soil moisture effects on light-use efficiency using FLUXNET2015 data (Stocker et al., 2018). Here, ETNN was estimated using observational ET (ETobs) as target variable and soil moisture, Rn, VPD, air temperature (T) and EVI as predictors:

PETNN was estimated using ETobs as target variable and Rn, VPD, T and EVI as predictors:

The choice of predictors was limited to a small number representing known environmental controls on ET and PET (Maes et al., 2019; Miralles et al., 2019). To avoid excessive model complexity and overfitting, the initial set of predictors was further subsampled based on a sensitivity analysis (not shown).

PETNN was derived by training the model with data from days when soil moisture was relatively high compared to the soil moisture time series of each site (‘moist days’). We thus defined PETNN as a soil-moisture unlimited ET. The method was only applied for sites where sufficient data above and below the soil moisture threshold were available. In contrast, the model for predicting ETNN was trained using all data and with soil moisture as an additional predictor. The threshold to divide data into ‘moist’ and ‘dry’ days was defined by running the model for a sequence of soil moisture thresholds. For each threshold, we calculated the median of the ratio in moist and dry days and determined the three models with the highest difference between these two ratios. Among these three models, the one with the smallest variance in fET during moist days was chosen.

We derived the belowground water stress factor (fET) as:

|  |  |
| --- | --- |
|  | Eq. 3 |

Using this method, we could quantify the control of belowground water reservoirs on ET, separated from other predictors (net radiation, VPD, vegetation greenness and air temperature). It has been shown that deeper soil moisture is strongly correlated with surface soil moisture (Salvucci & Entekhabi, 1994). Within this extent and considering that we evaluated fET against CWD (see section 2.5), we could therefore state that fET quantifies the control of belowground water reservoirs on ET.

The use of this neural-network based approach avoided the necessity to determine PET a priori based on possibly imperfect and theoretical estimations that are difficult to parameterize (Maes et al., 2019). It also allowed a data-driven determination of both PET and the effect of belowground water reservoirs that are consistent. Using ETNN instead of ETobs in Eq. 3 was expected to result in less noisy estimates, as ETNN and PETNN were affected by similar prediction errors, such as varying footprint and incorrect instantaneous energy balance closure. By definition, PETNN should agree with ETobs during ‘moist days’. On the contrary, PETNN was expected to overestimate ETobs during ‘dry days’, as the former was trained on ‘moist days’ data only (R2 = 0.40, RMSE = 1.095, Supplementary Fig. 1). With soil moisture as the only difference in predictors between PETNN and ETNN, fET could be interpreted as the separated control of subsurface available water on ET (Stocker et al., 2018).

We evaluated PETNN against an empirical Priestley-Taylor estimate of PET (PETPT) obtained from the SPLASH model (Davis et al., 2017) and against a linear model (lm) estimate of PET (PETlm). The site-specific linear regression models were defined as PETlm=k\*Rn, where Rn was converted to mass units (mm d-1) and k is a site-specific constant that scales Rn, calibrated against ETobs.

## Deep learning model architecture

The DNN models were built as feed-forward deep neural networks, implemented using R packages Tensorflow (Falbel et al., 2022) and Keras (Falbel, Allaire, Chollet, et al., 2021). The hyperparameter tuning was performed on the number of neurons per hidden layer (sampled among 8, 16, 32, 64), the number of hidden layers (sampled from 1 to 5), the optimizer (sampled among ‘adam’ or ‘rmsprop’), the activation function (“relu”, “leaky\_relu”, “linear”), the batch size (sampled among 16, 32, 64, 128, 256) and the learning rate (sampled among 0.01, 0.001, 0.0001) using the R packages ‘tfruns’ and ‘tfestimators’ (Allaire et al., 2018; Falbel, Allaire, Bostock, et al., 2021). We first ran the same tuning algorithm for a limited set of representative sites. To reduce the number of hyperparameters of the DNN, the ones that were giving consistent results from the beginning were removed from the final tuning across all sites, e.g., we retained only the activation function “relu” as it was clearly outperforming “linear” and “leaky\_relu”; we similarly kept a learning rate of 0.01.

We used the mean square error (MSE) as loss function during model training and the mean absolute percentage error as the error metric during model validation. Other error metrics were tested (e.g., mean absolute error) but resulted in a lower performance. To monitor the validation loss, we used the “EarlyStopping” callback function, with “patience” set to five. This function stopped the training process should the validation loss not improve after five epochs. This constrained the number of training epochs and avoided overfitting.

We then ran the hyperparameter tuning for a subset of 5% of the total hyperparameter combinations and chose the simplest model (i.e., the model with the lowest number of total parameters) among the five models with the lowest validation loss. We built one model per site, and the hyperparameters were tuned on a site-by-site basis. We then trained the feed-forward DNNs performing a five-fold cross-validation, with a 75%-25% split between training and validation data, respectively. The model with the lowest root-mean-square error was selected and the same procedure was repeated five times. We retained the mean prediction across the five ensemble neural network members. This was done to consider the variability caused by the inherent randomness of the initialization of the weights of the neural network neurons.

## Data

Half-hourly data was downloaded from the FLUXNET2015 website and filtered to keep only measured values (\*\_QC = 0) or values gap-filled with high confidence (\*\_QC = 1) (Pastorello et al., 2020). The latent heat flux was converted from energy units to mass units (ET) dividing it by the latent heat of vaporization as a function of air temperature, using the R package ‘Bigleaf’ (Knauer, El-Madany, et al., 2018)*.*

To reduce biases in ET predictions, we applied additional filters to the data, in accordance with other previous studies (Li et al., 2019; Medlyn et al., 2017; Zhou et al., 2016). We first applied a rainfall filter with a buffer of 6 hours after each rain event to exclude interception evaporation and to avoid sensor saturation with high relative humidity (Li et al., 2019). We further removed data with relative humidity higher than the 95% quantile to exclude the impact of dew evaporation on ET (Knauer, Zaehle, et al., 2018). To avoid stable boundary layer conditions, we excluded data where the sensible heat flux was smaller than 5 W m-2 and incoming shortwave radiation was smaller than 50 W m-2. Finally, only daytime data (GPP, ET and VPD > 0) were considered. Half-hourly data were aggregated into daily data to reduce noise and to avoid the ET-VPD hysteresis effect, observed at sub-daily timescales (Q. Zhang et al., 2014) (Q. Zhang et al., 2014). While aggregating to the daily level, the daily mean was calculated for all variables, except for VPD (for which we calculated the daily maximum), ET and precipitation (for which we used the daily sum). We only retained daily estimates with at least 8 measured half-hourly points, as in (Li et al., 2019).

The evaporative fraction (EF) was calculated using daily aggregates as . The soil heat flux was assumed to be negligible at the daily scale. EF was thus calculated as latent heat divided by Rn.

We used observational soil moisture data as available from the FLUXNET2015 dataset. To be consistent across all sites, we only used soil moisture data from the uppermost layer, as multiple depths were available only for a very limited number of sites. For many FLUXNET2015 sites, we found that observational soil moisture data was unavailable, incomplete, or inconsistent with ET observations. 'Incomplete' meant that the soil moisture timeseries had large data gaps (on the scale of >50% of the data, which made the calculation of CWD not possible). 'Inconsistent with ET observations' referred to the fact that soil moisture was not consistent with the soil water balance calculated using precipitation and latent heat flux, from the same FLUXNET2015 database. For these sites, we simulated soil moisture with SPLASH, a bucket-type soil water balance model (Davis et al., 2017). This model was based on a Priestley-Taylor formulation for ET estimation. We set the water-holding capacity (‘bucket depth’) to 220 mm (Davis et al., 2017; Orth et al., 2013). Using a modelled soil moisture represented a potential source of circularity in our analysis, since we were assuming a water-holding capacity specific to a rooting depth. However, we mostly used soil moisture to separate the training data into 'moist' and 'dry' days (see 'Estimating potential ET').

We downloaded MODIS EVI (MOD13Q1, 16 days, 250 m, Collection 5) with the ‘MODISTools’ R package (Tuck et al., 2014). Images with clouds, snow, ice or shadows were excluded. To get daily values, we applied a Savitzky–Golay smoothing filter (‘SIGNAL’ R package) with a 3rd order polynomial and frame length of 31 days. We could thus remove noise without altering the seasonal signal.

Before running the machine learning model, we excluded all NAs and soil moisture was normalized between 0 and 1 on a site-by-site basis for better comparison across sites. We centered and scaled all variables as part of the resampling process with the R package ‘caret’ (Kuhn et al., 2021).

We downloaded precipitation, ET and PET estimates of the GLDAS\_NOAH025\_3H product from the NASA Global Land Data Assimilation System Version 2 (GLDAS-2) (Beaudoing et al., 2020; Rodell et al., 2004). The product is based on an assimilation of ground- and space-based observations to model energy and water exchanges. We referred to ET and PET from this data product as ETGLDAS and PETGLDAS. We defined fETGLDAS = ETGLDAS/PETGLDAS to compare it with our deep learning estimate of fET. The data was originally available at a 3-hour time resolution and at a grid resolution of 0.25°x0.25°. After extracting the variables at the site level, we calculated daily means. Even if overestimated when compared to e.g., satellite products, PETGLDAS still displays good correlation with in-situ measurements (Zhan et al., 2019). Nevertheless, for comparison, PETGLDAS was scaled by dividing it by its median value in the lower CWD bin (CWD < 20 mm). This way, fETGLDAS was visually comparable with fET (roughly comprised between 0 and 1).

We extracted soil texture distribution data at FLUXNET2015 locations from the Regridded Harmonized World Soil Database v1.2 (Wieder et al., 2014). We downloaded mean annual temperature (MAT) and mean annual precipitation (MAP) from WorldClim version 2.1 and extracted their values at FLUXNET2015 sites (Fick & Hijmans, 2017).

The aridity index was calculated with FLUXNET2015 data as the ratio of annual precipitation (P) over potential evapotranspiration (PET), for all years in which data were available for the respective sites. Precipitation data are from the FLUXNET 2015 Tier 1 dataset; PET was calculated following the Priestley–Taylor equation (PETPT), as implemented in the SPLASH model (Davis et al., 2017).

To investigate the role of topography across sites, Global topographic index (GTI) values were downloaded from a high-resolution dataset and extracted at FLUXNET2015 locations (Marthews et al., 2015a, 2015b).

## Derivation of the cumulative water deficit

We derived the cumulative water deficit (CWD) as the cumulative difference of the actual evapotranspiration (ETobs) and precipitation (P), considered over continuous dry periods, i.e., periods where the difference *P – ETobs* was negative. The summation was stopped when the rain had compensated the water loss due to ET, i.e., the cumulative sum across days was zero (). We defined a ‘CWD event’ as the period between the start and the end of the summation, i.e., a dry-down event. We assumed that water stress is already mitigated when new precipitation is re-wetting the topsoil layers, even before the CWD is fully offset. For this reason, each ‘CWD event’ was terminated after rain had reduced the CWD to below 90% of its maximum value within the same event. To eliminate the noise caused by smaller CWD events, we retained only the period with the single largest CWD event each year. We used daily latent heat flux and precipitation timeseries from the FLUXNET2015 database. To calculate the CWD, it was important to focus on high quality observations. We therefore only retained values that had less than 80% of the original half-hourly data gap-filled according to the FLUXNET2015 data processing pipeline. At the same time, when calculating CWD, we must use a continuous time series of ET to avoid gaps that could offset the calculation. To avoid this, ET was gap-filled with single-layer neural networks, using temperature, PAR, VPD and ET simulated by the SPLASH model as predictors (Davis et al., 2017). To build this model, we used the R package ‘NNET’ (Venables & Ripley, 2002) and ‘CARET’ (Kuhn et al., 2021), and used a neural network with a single hidden layer, 20 nodes, 10-fold cross-validated. Note that we only used the gap-filled ET to calculate the CWD. Note also that this single hidden layer neural network used for gap filling ET is different from the deep learning model defined above. We trained the deep learning model with the ET timeseries cleaned as described in section 2.4 with no additional gap-filling.

## Site selection and binning

We evaluated fET for 135 sites of the total of 166 sites in the FLUXNET Tier 1 dataset, where observational soil moisture was consistent with ET and modelled soil moisture gave consistent results (as defined in section 2.4). The sites were filtered according to the final number of days after data cleaning (> 300 d) and to the performance of the DNN model. Mean PETNN had to be greater than or equal to ET during ‘dry days’ and the R2 between modelled ET and ETobs had to be > 0.5, retaining 58 sites. Nine sites were excluded upon visual inspection of the fET vs CWD relationship, which was not giving physically reasonable results. The remaining 49 sites are listed in Table 1 (Supplementary Information). We removed fET outliers, defined as any value that fell outside of the interval To categorize the behavior of different sites, we calculated the median of fET for every site, in the CWD interval comprised between 125 mm and 175 mm. We grouped all sites along this single dimension using a k-means algorithm, with predefined k = 3 (3 groups). We conducted a sensitivity analysis with k = 2 and k = 4. We retained the grouping with k = 3, as it captured more efficiently the inherent fET distribution. The resulting groups were: high fET (9 sites), medium fET (22 sites) and low fET (11 sites), and showed a consistent pattern in the decline of fET during drought. The CWD interval centered at 150 mm was a trade-off between using the largest possible CWD, thus capturing the most divergent responses across sites, and choosing a CWD value attained and exceeded in the largest number of sites. Sites that did not have a fET value in that CWD interval were manually assigned to the 'high fET' group, as their behavior was consistent with other sites in that group (Supplementary Fig. 3).

# Results

## Reliability of the deep neural network

Across all sites and days pooled, ETNN achieved consistent results against ETobs (R2 = 0.78, Fig. 1a). To evaluate the accuracy of PETNN, we compare it against ETobs during moist days only (R2 = 0.77, Fig. 1b). This method gave better results compared to PETPT (R2 = 0.45, Fig. 1c) or PETlm (R2 = 0.40, Fig. 1d), both evaluated for moist days only. Although the general patterns are robust across the three different methods, they emerge clearer when using DNNs for modelling PET. We thus retained PETNN for further analyses.

To analyze the timing and magnitude of water limitation on ETobs, we evaluated its seasonality compared to ETNN and PETNN (Fig. 2). We chose two sample sites for contrasting behavior: DK-Sor, a humid deciduous broadleaf forest, and US-Ton, a dry woody savannah site. At DK-Sor, PETNN and ETobs almost perfectly overlap, meaning that belowground moisture limitation has little to no effect on ET, allowing it to be almost always at its potential rate, i.e., energy-limited and without belowground moisture limitations (Fig. 2a, red and black lines). At US-Ton, PETNN departs substantially from ETobs during the dry season, indicating significant impacts of belowground moisture (Fig. 2b, red and black lines). In both cases, ETNN is consistent with ETobs (black and blue lines) and the ET trend is confirmed by Rn converted to mass units (Fig. 2, dashed green line).

## Binning of fET vs CWD responses

In the fET vs CWD density plot for all site, we observe a variety of responses (Fig. 3b). For CWD values up to approximately 100 mm, there is an accumulation of points centered at fET equal to one. At higher CWD values, fET declines gradually. We can distinguish two other smaller clouds of points, one centered at around fET equal to 0.4 and another one at 0.2.

We can see a variety of fET responses at a CWD interval of around 150 mm (red dotted lines in Fig. 3b). To investigate commonalities of the fET-CWD relationship across sites, we divided them into three groups based on the fET median in this interval (Fig. 3a). Sites were thus grouped into low, medium, and high fET. Each group exhibits different fET vs CWD behavior (Supplementary Figs. 3-4).

## Patterns of fET vs CWD responses across sites

At 'high fET' sites, there is almost no effect of water stress on plants, as fET is almost always near one for CWD values up to 300 mm (Fig. 4a). In contrast, when predicted by a standard land surface model, after a CWD threshold of around 150 mm, fETGLDAS is decreasing linearly with progressing drought (Fig. 4b). At 'medium fET' sites (Fig. 4c), the bulk of fET values is equal to one, up to a CWD of around 100 mm. At a CWD greater than 100 mm, we observe a tail of fET that is slowly decreasing with progressing CWD, reaching an fET of around 0.5 at a corresponding CWD of 250 mm. In contrast, fETGLDAS displays several tails, which decrease linearly with progressing CWD, down to zero (Fig. 4d). At 'low fET' sites, fET stays equal to one until a CWD of 50 mm. After that, we observe an abrupt drop followed by a levelling-off, approaching but not reaching zero (Fig. 4e). Interestingly, in the same fET group, fETGLDAS is decreasing almost linearly with progressing drought, reaching values around zero (Fig. 4f). Compared to observations, models also tend to overestimate water stress (Fig. 4e,f). In the 'low fET' group, the drop in fET followed by a levelling-off is present also when plotting sites individually (Fig. 5). This confirms that the observed trend is not due to plotting several sites pooled together. The general trends observed for fET vs CWD are confirmed by a model-independent indicator of ET stress, the evaporative fraction (EF), plotted as a function of CWD (Supplementary Fig. 2).

## Relationship to other soil and climate variables

To gain insight into what factors drive the different fET behaviors, we investigated the relationship between fET groups and other soil and climate variables (Fig. 6). The sand fraction is higher and the silt fraction is lower in the 'low fET' group (Fig. 6a). Sites in the 'high fET' group are usually found in humid climates (Fig. 6c). They consist mostly of forests, and in particular evergreen needleleaf forest (ENF, 7 sites over 16, Fig. 6b). We found that sites with intermediate fET reductions are found in mesic regions (Fig. 6c). They are mostly characterized by forests (14 sites over 22) and croplands (4 sites over 22, Fig. 6b). Sites with the strongest reduction in fET are found in the driest climates (Fig. 6c). These sites are composed of savannahs (5 sites over 11), grasslands (4 sites over 11) and shrublands (1 sites over 11, Fig. 6b). Topographic effects and mean annual precipitation do not vary significantly across fET groups (Fig. 6d,e). In contrast, the mean annual temperature decreases from low to high fET groups (Fig. 6f).

# Discussion

Almost no effect of water stress was detected even for substantial CWD at 'high fET' sites (Fig. 4a). This means that belowground moisture is rarely limiting, allowing evapotranspiration to be almost always at its potential rate. At 'medium fET' sites, the effect of water stress on plants becomes visible at a CWD greater than 100 mm (Fig. 4c). At 'low fET' sites, the effect of water stress on plants during dry conditions shows an abrupt response at a CWD of 50 mm followed by a levelling-off to fET values of around 0.5 to 0.1 (Fig. 4e). Even at high CWD values, vegetation activity is never completely shut off. This is likely accompanied by extremely low water potentials along the water transport pathways in the roots, xylem, and leaves, but without further losses of their hydraulic conductivity or further reductions in stomatal conductance (Jacobsen et al., 2007; Martínez-Vilalta & Garcia-Forner, 2017; Stojnić et al., 2018). Water continues to be supplied to maintain a base ET level without further reductions in plant access to moisture, a pattern not reflected by a standard land surface model (Fig. 4b,d,f). This suggests that plants may have access to deep water or have a low xylem potential cavitation point that allows them to sustain ET even during the unfolding of a drought event. Field studies could be devised to discriminate between these alternative hypotheses using measurements that are linked to ET and can directly sample water in the soil-plant-atmosphere continuum (SPAC, i.e., sap flow and leaf water potential measurements).

## Drivers of the abruptness of the fET decrease with CWD

Our findings are consistent with the notion that forests are more resistant to drought than grasslands and can support vegetation activity over longer dry periods (Konings & Gentine, 2017; Martínez-Vilalta & Garcia-Forner, 2017; Teuling et al., 2010). Grasslands tend to have shallower roots and thus are more likely to experience water stress when the topsoil dries out. Forests tend to have deeper roots that can access deeper water stores, and therefore are more resilient to high CWD (Fan et al., 2017).

The different behavior observed in grasslands and forests could explain the drop in fET after a certain CWD threshold (Fig. 4e). In the 'low fET' group, the dominant PFT is woody savannah, a tree-grass ecosystem characterized by a herbaceous understory (grassland) scattered with sufficiently spaced trees, so that the canopy is never continuous (Fig. 6b) (El-Madany et al., 2020; Luo et al., 2018). After a certain CWD value (around 50 mm), we hypothesize that the herbaceous layer loses access to water, and thus stops contributing to ET. In turn, trees can have a more resistant xylem allowing them to pull water at lower water potentials or, alternatively, they can rely on deep roots to access deeper water reservoirs. These strategies allow trees to keep transpiring even at higher CWD. This could explain why we observe an abrupt change in fET, followed by a levelling-off which never reaches zero (Fig. 4e). In this framework, the levelling-off corresponds to a period where activity of the understory ceases and mostly trees contribute to a base evapotranspiration.

The cavitation resistance found in arid plant communities could also explain the levelling-off of the fET vs CWD relationship, which almost never reaches zero, even at the highest CWD (Jacobsen et al., 2007). In particular, when the belowground moisture availability across the root zone decreases in such a way that the root water potential decreases, one would also expect the xylem potential to decrease, and in turn the leaf water potential and the stomatal conductance. The relatively flat fET curve suggests that either a) plants access deep belowground moisture and maintain relatively high water potentials along the SPAC while water is continuously consumed (thus continuously increasing the cumulative water deficit), b) conductance along the SPAC is relatively insensitive to the range of water potentials experienced by plants under the conditions investigated here. That insensitivity would thus correspond to a specific range in the Weibull curve, where the water potential is varying without dramatically affecting the conductance (Wolf et al., 2016).

The correlation between fET groups and the aridity index (Fig. 6c) indicates different adaptive plant strategies to water stress. At intermediate to low aridity, woody vegetation invests in green tissue to be more drought-resistant, i.e. deeper rooting depth, and lower minimum leaf water potentials (Van der Molen et al., 2011). At high aridity, carbon uptake is limited so that increased allocation to deep roots is not possible, as indicated by the prevalence of drought-deciduous vegetation at arid sites. These plants have a more resistant xylem and typically have tracheid rather than vessels, allowing a smaller leaf area index (LAI) which in turn reduces the maximum transpiration (Mcdowell et al., 2008). Semi-arid regions are a key driver of the interannual variability of the terrestrial carbon cycle (Ahlström et al., 2015; Poulter et al., 2014). The seasonal reductions in ET found at arid sites suggest that a more accurate account of drought conditions of these areas in global models could improve the prediction of the variability of the carbon cycle (Biederman et al., 2017).

There was no significant difference in topographic index across fET groups (Fig. 6d). This is consistent with the fact that most flux towers are located in flat areas and valleys, so that most sites cluster into similar topographic index values (Thompson et al., 2011).

We can observe a clear correlation between the median fET (as defined above) and the aridity index (Fig. 7). At the same time, fET is also dependent on soil texture, which regulates climate conditions. In particular, the clay fraction exerts a strong control on the fET vs aridity index relationship (Fig. 7a). The higher the silt fraction, the stronger the relationship between fET and the aridity index (slopes of the regression lines, Fig. 7c). The opposite can be said for the sand fraction: the higher the sand fraction, the weaker the relationship between fET and the aridity index (Fig. 7b). Overall though, climate is the prime factor controlling the spectrum of fET medians (i.e. ET), but soil texture is regulating the intensity of the response. Indeed, soil texture modulates the water retention curve and thus the response of plants, which are mostly sensitive to water potential (Novick et al., 2022).

## Possible explanations of the discrepancy between models and observations

The hypothesis that trees access deeper water reservoirs is consistent with recent findings, which highlight the often-neglected importance of deep, non-soil water stores for root water uptake (Dawson et al., 2020). The occurrence of the high-sensitivity sites in arid climates characterised by savannahs and shrublands indicates that a large fraction of S0 could be stored in weathered bedrock (rock moisture) (McCormick et al., 2021). Rock moisture is usually accessible to plants, but is essentially not quantified by models, and is especially important during drought, after soil moisture is depleted (Rempe & Dietrich, 2018). This could explain why the lower tail of the fET vs CWD relationship in the 'low fET' group never reaches zero, even at very high CWD (i.e. under ongoing drought, Fig. 4e). The same behaviour is not captured by models, which cannot quantify rock moisture (Fig. 4f).

Groundwater could also explain the discrepancy between models and observations. Groundwater is commonly not taken into account by global models (Condon et al., 2021; Hain et al., 2015), but it has been shown to have a pivotal effect in sustaining additional transpiration during drought (Mu et al., 2021). The neglect of groundwater in many land surface models could thus explain why they tend to overestimate water stress effects compared to observations (Fig. 4b,d,f). This is consistent with the fact that quantifying plant access to groundwater and its regulation of ET can improve ET prediction (Thompson et al., 2011). Our observation-driven approach implictly accounts for plant access to groundwater, thus diminishing the bias in ET estimation.

In our anaysis, we compared our results to a standard land surface model, the GLDAS\_NOAH025\_3H product. GLDAS uses vegetation tiling to represent sub-grid heterogeneity of vegetation types, so the fluxes in a grid box are a weighted average of land cover tiles at 1 km resolution. NOAH assigns a rooting depth to each vegetation type (Beaudoing et al., 2020; Rodell et al., 2004). This could explain why GLDAS data does not capture some of the water stress responses highlighted by our approach, as the rooting depth has been shown to vary strongly even within the same species and climate (Fan et al., 2017). The GLDAS product does not account for heterogeneity in rooting depth within the same vegetation type.

The different tails of the fETGLDAS vs CWD relationship approaching zero (Fig. 4d) seem to reflect different rooting depths at different sites. This difference with our approach (Fig. 4c) could be exacerbated due to a scale mismatch between GLDAS and FLUXNET2015. The GLDAS value extracted at the FLUXNET location represents a weighted average of the vegetation types within the 0.25-degree grid cell. Hence a small apparent rooting depth (i.e. a small decrease in the fETGLDAS vs CWD) may suggest that in that grid cell there is a small water holding capacity in the soil or a high grass fraction. In contrast, each PFT present in a FLUXNET2015 tower footprint contributes to the overall flux. The tower footprint is also generally below 1 km, much smaller than 25 km (i.e. 0.25 degrees on a global grid).

The almost linear signal found in high-sensitivity sites when using GLDAS data (Fig. 4f) could be linked to large scale heterogeneity. There is an intrinsic problem in ET prediction related to the fact that soil moisture, and by extension belowground water availability, varies in nature at scales in the order of 1-10 m, while models have grid cell sizes at scales as big as one to several hundred kilometers. The upscaling would naturally smooth out the stress response (Baker et al., 2017). The fact that the GLDAS model uses vegetation tiles to simulate low-scale heterogeneity could entail an ecosystem response more linear than what it really is. In other words, large scale averaging could lead to a less abrupt regulation of fET (Baker et al., 2017). More research is needed to resolve the apparent model-observation bias in light of the role of belowground water availability.

# Conclusions

Our observation-driven statistical approach is used here to evaluate the effects of belowground water stress on ET, separated from the contribution of other drivers, such as radiation, VPD and vegetation greenness. We demonstrated that it is crucial to account for belowground water availability effects to diagnose ET responses to drought. We highlighted substantial differences in plant responses to water stress across biomes. Differences are related to vegetation type, mean climate at the site, and soil texture. Forests tend to show little sensitivity to water stress, whereas savannahs, shrublands and grasslands show an abrupt drop in ET after an initial stress-free phase. In both cases and in contrast with a representative land surface model, ET is almost never completely shut off during drought. Access to belowground water reserves could explain the bimodal behavior observed in arid sites. The fact that most models do not account for belowground water availability and use a simplified approach to represent subgrid spatial heterogeneity leads to a general overestimation of water stress effect on plants. Future research should address this observation-model bias, focusing on the role of deep unquantified water stores.

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**Author contributions**

F.G., B.D.S., P.G. and A.G.K. designed the study and wrote the manuscript text. F.G. performed the research and prepared figures.

**Conflict of interest**

The authors declare no conflicts of interest.

**Data and code availability statement**

All datasets used in this study are freely available from the following sources:

* Ecosystem fluxes and meteorological data: https://fluxnet.org/data/fluxnet2015-dataset/
* MODIS EVI (from MOD13Q1, 16 days, 250 m): https://lpdaac.usgs.gov/products/mod13q1v006/
* Precipitation, ET and PET estimates from the GLDAS\_NOAH025\_3H product: https://disc.gsfc.nasa.gov/datasets/GLDAS\_NOAH025\_3H\_2.1/summary?keywords=gldas
* Soil texture distribution data: https://daac.ornl.gov/SOILS/guides/HWSD.html
* Mean annual temperature (MAT) and mean annual precipitation (MAP): https://www.worldclim.org/data/worldclim21.html
* Global topographic index (GTI): https://data-search.nerc.ac.uk/geonetwork/srv/api/records/6b0c4358-2bf3-4924-aa8f-793d468b92be
* All other intermediate data, final modelled output and computer code that support this study are available from the Zenodo Digital Repository (Giardina et al. 2022).

**References**

Ahlström, A., Raupach, M. R., Schurgers, G., Smith, B., Arneth, A., Jung, M., Reichstein, M., Canadell, J. G., Friedlingstein, P., Jain, A. K., Kato, E., Poulter, B., Sitch, S., Stocker, B. D., Viovy, N., Wang, Y. P., Wiltshire, A., Zaehle, S., & Zeng, N. (2015). The dominant role of semi-arid ecosystems in the trend and variability of the land CO2 sink. *Science*, *348*(6237), 895–899.

Allaire, J., Tang, Y., Ushey, K., Kuo, K., & Falbel, D. (2018). *tfestimators: Interface to “TensorFlow” Estimators* (1.9.1).

Baker, I. T., Sellers, P. J., Denning, A. S., Medina, I., Kraus, P., Haynes, K. D., & Biraud, S. C. (2017). Closing the scale gap between land surface parameterizations and GCMs with a new scheme, SiB3-Bins. *Journal of Advances in Modeling Earth Systems*, *9*(1), 691–711. https://doi.org/10.1002/2016MS000764

Beaudoing, H., Rodell, M., & NASA/GSFC/HSL. (2020). *GLDAS Noah Land Surface Model L4 3 hourly 0.25 x 0.25 degree V2.1*. Greenbelt, Maryland, USA, Goddard Earth Sciences Data and Information Services Center (GES DISC). https://disc.gsfc.nasa.gov/datasets/GLDAS\_NOAH025\_3H\_2.1/summary

Beer, C., Reichstein, M., Tomelleri, E., Ciais, P., Jung, M., Carvalhais, N., Rödenbeck, C., Arain, M. A., Baldocchi, D., Bonan, G. B., Bondeau, A., Cescatti, A., Lasslop, G., Lindroth, A., Lomas, M., Luyssaert, S., Margolis, H., Oleson, K. W., Roupsard, O., … Papale, D. (2010). *Terrestrial Gross Carbon Dioxide Uptake: Global Distribution and Covariation with Climate*. *329*(August), 834–839.

Biederman, J. A., Scott, R. L., Bell, T. W., Bowling, D. R., Dore, S., Garatuza-Payan, J., Kolb, T. E., Krishnan, P., Krofcheck, D. J., Litvak, M. E., Maurer, G. E., Meyers, T. P., Oechel, W. C., Papuga, S. A., Ponce-Campos, G. E., Rodriguez, J. C., Smith, W. K., Vargas, R., Watts, C. J., … Goulden, M. L. (2017). CO2 exchange and evapotranspiration across dryland ecosystems of southwestern North America. *Global Change Biology*, *23*(10), 4204–4221. https://doi.org/10.1111/gcb.13686

Condon, L. E., Kollet, S., Bierkens, M. F. P., Fogg, G. E., Maxwell, R. M., Hill, M. C., Fransen, H. J. H., Verhoef, A., Van Loon, A. F., Sulis, M., & Abesser, C. (2021). Global Groundwater Modeling and Monitoring: Opportunities and Challenges. In *Water Resources Research* (Vol. 57, Issue 12, p. e2020WR029500). John Wiley and Sons Inc. https://doi.org/10.1029/2020WR029500

Davis, T. W., Prentice, I. C., Stocker, B. D., Thomas, R. T., Whitley, R. J., Wang, H., Evans, B. J., Gallego-Sala, A. V., Sykes, M. T., & Cramer, W. (2017). Simple process-led algorithms for simulating habitats (SPLASH v.1.0): Robust indices of radiation, evapotranspiration and plant-available moisture. *Geoscientific Model Development*, *10*(2), 689–708. https://doi.org/10.5194/gmd-10-689-2017

Dawson, T. E., Hahm, W. J., & Crutchfield-Peters, K. (2020). Digging deeper: what the critical zone perspective adds to the study of plant ecophysiology. *New Phytologist*, *226*(3), 666–671. https://doi.org/10.1111/nph.16410

Dralle, D. N., Jesse Hahm, W., Rempe, D. M., Karst, N., Anderegg, L. D. L., Thompson, S. E., Dawson, T. E., & Dietrich, W. E. (2020). Plants as sensors: Vegetation response to rainfall predicts root-zone water storage capacity in Mediterranean-type climates. *Environmental Research Letters*, *15*(10). https://doi.org/10.1088/1748-9326/abb10b

Drewniak, B. A. (2019). Simulating Dynamic Roots in the Energy Exascale Earth System Land Model. *Journal of Advances in Modeling Earth Systems*, *11*(1), 338–359. https://doi.org/10.1029/2018MS001334

El-Madany, T. S., Carrara, A., Martín, M. P., Moreno, G., Kolle, O., Pacheco-Labrador, J., Weber, U., Wutzler, T., Reichstein, M., & Migliavacca, M. (2020). Drought and heatwave impacts on semi-arid ecosystems’ carbon fluxes along a precipitation gradient: Drought and Heatwave Impacts. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *375*(1810). https://doi.org/10.1098/rstb.2019.0519

Falbel, D., Allaire, J., Bostock, M., Tanaka, M., Bowe, S., You, Y., Decker, K., Fernandes, R., Sagalaev, I., & Pakala, Y. (2021). *tfruns: Training Run Tools for “TensorFlow”* (1.5.0).

Falbel, D., Allaire, J., Chollet, F., RStudio, Google, Tang, Y., Bijl, W. Van Der, Studer, M., & Keydana, S. (2021). *keras: R Interface to “Keras”* (2.4.0).

Falbel, D., Allaire, J., RStudio, Yuan Tang, Dirk Eddelbuettel, Golding, N., Kalinowski, T., & Inc., G. (2022). *Package ‘tensorflow’* (2.8.0).

Fan, Y., Li, H., & Miguez-Macho, G. (2013). Global patterns of groundwater table depth. *Science*, *339*(6122), 940–943. https://doi.org/10.1126/science.1229881

Fan, Y., Miguez-Macho, G., Jobbágy, E. G., Jackson, R. B., & Otero-Casal, C. (2017). Hydrologic regulation of plant rooting depth. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(40), 10572–10577. https://doi.org/10.1073/pnas.1712381114

Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: new 1‐km spatial resolution climate surfaces for global land areas. *International Journal of Climatology*, *37*(12), 4302–4315. https://doi.org/10.1002/joc.5086

Gao, H., Hrachowitz, M., Schymanski, S. J., Fenicia, F., Sriwongsitanon, N., & Savenije, H. H. G. (2014). Climate controls how ecosystems size the root zone storage capacity at catchment scale. *Geophysical Research Letters*, *41*(22), 7916–7923. https://doi.org/10.1002/2014GL061668

Giardina, F., Konings, A. G., Kennedy, D., Alemohammad, S. H., Oliveira, R. S., Uriarte, M., & Gentine, P. (2018). Tall Amazonian forests are less sensitive to precipitation variability. *Nature Geoscience*, *11*(6), 405–409. https://doi.org/10.1038/s41561-018-0133-5

Green, J. K., Konings, A. G., Alemohammad, S. H., Berry, J., Entekhabi, D., Kolassa, J., Lee, J.-E., & Gentine, P. (2017). Regionally strong feedbacks between the atmosphere and terrestrial biosphere. *Nature Geosci*, *advance on*(May). https://doi.org/10.1038/ngeo2957

Hahm, W. J., Dralle, D. N., Rempe, D. M., Bryk, A. B., Thompson, S. E., Dawson, T. E., & Dietrich, W. E. (2019). Low Subsurface Water Storage Capacity Relative to Annual Rainfall Decouples Mediterranean Plant Productivity and Water Use From Rainfall Variability. *Geophysical Research Letters*, *46*(12), 6544–6553. https://doi.org/10.1029/2019GL083294

Hain, C. R., Crow, W. T., Anderson, M. C., & Tugrul Yilmaz, M. (2015). Diagnosing neglected soil moisture source-sink processes via a thermal infrared-based two-source energy balance model. *Journal of Hydrometeorology*, *16*(3), 1070–1086. https://doi.org/10.1175/JHM-D-14-0017.1

Jacobsen, A. L., Pratt, R. B., Davis, S. D., & Ewers, F. W. (2007). Cavitation resistance and seasonal hydraulics differ among three arid Californian plant communities. *Plant, Cell and Environment*, *30*(12), 1599–1609. https://doi.org/10.1111/j.1365-3040.2007.01729.x

Kennedy, D., Swenson, S., Oleson, K. W., Lawrence, D. M., Fisher, R., Lola da Costa, A. C., & Gentine, P. (2019). Implementing Plant Hydraulics in the Community Land Model, Version 5. *Journal of Advances in Modeling Earth Systems*, *11*(2), 485–513. https://doi.org/10.1029/2018MS001500

Kljun, N., Calanca, P., Rotach, M. W., & Schmid, H. P. (2015). A simple two-dimensional parameterisation for Flux Footprint Prediction (FFP). *Geoscientific Model Development*, *8*(11), 3695–3713. https://doi.org/10.5194/gmd-8-3695-2015

Knauer, J., El-Madany, T. S., Zaehle, S., & Migliavacca, M. (2018). Bigleaf - An R package for the calculation of physical and physiological ecosystem properties from eddy covariance data. *PLoS ONE*, *13*(8), 1–26. https://doi.org/10.1371/journal.pone.0201114

Knauer, J., Zaehle, S., Medlyn, B. E., Reichstein, M., Williams, C. A., Migliavacca, M., De Kauwe, M. G., Werner, C., Keitel, C., Kolari, P., Limousin, J. M., & Linderson, M. L. (2018). Towards physiologically meaningful water-use efficiency estimates from eddy covariance data. *Global Change Biology*, *24*(2), 694–710. https://doi.org/10.1111/gcb.13893

Konings, A. G., & Gentine, P. (2017). Global variations in ecosystem-scale isohydricity. *Global Change Biology*, *23*(2), 891–905. https://doi.org/10.1111/gcb.13389

Kuhn, M., Wing, J., Weston, S., Williams, A., Keefer, C., Engelhardt, A., Cooper, T., Mayer, Z., Kenkel, B., Team, R. C., Benesty, M., Lescarbeau, R., Ziem, A., Scrucca, L., Tang, Y., Candan, C., & Hunt, T. (2021). *caret: Classification and Regression Training* (6.0-88). https://doi.org/10.1887/0750303123/b365c43

Li, X., Gentine, P., Lin, C., Zhou, S., Sun, Z., Zheng, Y., Liu, J., & Zheng, C. (2019). A simple and objective method to partition evapotranspiration into transpiration and evaporation at eddy-covariance sites. *Agricultural and Forest Meteorology*, *265*(May 2018), 171–182. https://doi.org/10.1016/j.agrformet.2018.11.017

Liang, X., Lettenmaier, D. P., Wood, E. F., & Burges, S. J. (1994). A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *Journal of Geophysical Research*, *99*(D7), 14415. https://doi.org/10.1029/94JD00483

Luo, Y., El-Madany, T. S., Filippa, G., Ma, X., Ahrens, B., Carrara, A., Gonzalez-Cascon, R., Cremonese, E., Galvagno, M., Hammer, T. W., Pacheco-Labrador, J., Martín, M. P., Moreno, G., Perez-Priego, O., Reichstein, M., Richardson, A. D., Römermann, C., & Migliavacca, M. (2018). Using Near-Infrared-Enabled Digital Repeat Photography to Track Structural and Physiological Phenology in Mediterranean Tree–Grass Ecosystems. *Remote Sensing*, *10*(8), 1293. https://doi.org/10.3390/rs10081293

Mackay, D. S., Roberts, D. E., Ewers, B. E., Sperry, J. S., McDowell, N. G., & Pockman, W. T. (2015). Interdependence of chronic hydraulic dysfunction and canopy processes can improve integrated models of tree response to drought. *Water Resources Research*, *51*(8), 6156–6176. https://doi.org/10.1002/2015WR017244

Maes, W. H., Gentine, P., Verhoest, N. E. C., & Miralles, D. G. (2019). Potential evaporation at eddy-covariance sites across the globe. *Hydrology and Earth System Sciences*, *23*(2), 925–948. https://doi.org/10.5194/hess-23-925-2019

Marthews, T. R., Dadson, S. J., Lehner, B., Abele, S., & Gedney, N. (2015a). *High-resolution global topographic index values*. NERC Environmental Information Data Centre. (Dataset).

Marthews, T. R., Dadson, S. J., Lehner, B., Abele, S., & Gedney, N. (2015b). High-resolution global topographic index values for use in large-scale hydrological modelling. *Hydrology and Earth System Sciences*, *19*(1), 91–104. https://doi.org/10.5194/hess-19-91-2015

Martínez-Vilalta, J., & Garcia-Forner, N. (2017). Water potential regulation, stomatal behaviour and hydraulic transport under drought: deconstructing the iso/anisohydric concept. *Plant Cell and Environment*, *40*(6), 962–976. https://doi.org/10.1111/pce.12846

McCormick, E. L., Dralle, D. N., Hahm, W. J., Tune, A. K., Schmidt, L. M., Chadwick, K. D., & Rempe, D. M. (2021). Widespread woody plant use of water stored in bedrock. *Nature*, *597*(7875), 225–229. https://doi.org/10.1038/s41586-021-03761-3

Mcdowell, N., Pockman, W. T., Allen, C. D., Breshears, D. D., Cobb, N., Kolb, T., Plaut, J., Sperry, J., West, A., Williams, D. G., & Yepez, E. A. (2008). Mechanisms of Plant Survival and Mortality during Drought: why do survive while others succumb plants drought ? to. *New Phytologist*, *178*(4), 719–739.

Medlyn, B. E., De Kauwe, M. G., Lin, Y. S., Knauer, J., Duursma, R. A., Williams, C. A., Arneth, A., Clement, R., Isaac, P., Limousin, J. M., Linderson, M. L., Meir, P., Martin-Stpaul, N., & Wingate, L. (2017). How do leaf and ecosystem measures of water-use efficiency compare? *New Phytologist*, *216*, 758–770. https://doi.org/10.1111/nph.14626

Milly, P. C. D. (1994). Climate, soil water storage, and the average annual water balance. *Water Resources Research*, *30*(7), 2143–2156. https://doi.org/10.1029/94WR00586

Miralles, D. G., Gentine, P., Seneviratne, S. I., & Teuling, A. J. (2019). Land–atmospheric feedbacks during droughts and heatwaves: state of the science and current challenges. *Annals of the New York Academy of Sciences*, *1436*(1), 19–35. https://doi.org/10.1111/nyas.13912

Mu, M., De Kauwe, M. G., Ukkola, A. M., Pitman, A. J., Guo, W., Hobeichi, S., & Briggs, P. R. (2021). Exploring how groundwater buffers the influence of heatwaves on vegetation function during multi-year droughts. *Earth System Dynamics*, *12*(3), 919–938. https://doi.org/10.5194/esd-12-919-2021

Novick, K. A., Ficklin, D. L., Baldocchi, D., Davis, K. J., Ghezzehei, T. A., Konings, A. G., MacBean, N., Raoult, N., Scott, R. L., Shi, Y., Sulman, B. N., & Wood, J. D. (2022). Confronting the water potential information gap. *Nature Geoscience*, *15*(3), 158–164. https://doi.org/10.1038/s41561-022-00909-2

Novick, K. A., Ficklin, D. L., Stoy, P. C., Williams, C. A., Bohrer, G., Oishi, A. C., Papuga, S. A., Blanken, P. D., Noormets, A., Sulman, B. N., Scott, R. L., Wang, L., & Phillips, R. P. (2016). The increasing importance of atmospheric demand for ecosystem water and carbon fluxes. *Nature Climate Change*, *6*(11), 1023–1027. https://doi.org/10.1038/nclimate3114

Orth, R., Koster, R. D., & Seneviratne, S. I. (2013). Inferring soil moisture memory from streamflow observations using a simple water balance model. *Journal of Hydrometeorology*, *14*(6), 1773–1790. https://doi.org/10.1175/JHM-D-12-099.1

Pastorello, G., Trotta, C., Canfora, E., Chu, H., Christianson, D., Cheah, Y.-W., Poindexter, C., Chen, J., Elbashandy, A., Humphrey, M., Isaac, P., Polidori, D., Ribeca, A., van Ingen, C., Zhang, L., Amiro, B., Ammann, C., Arain, M. A., Ardö, J., … Papale, D. (2020). The FLUXNET2015 dataset and the ONEFlux processing pipeline for eddy covariance data. *Scientific Data*, *7*(1), 225. https://doi.org/10.1038/s41597-020-0534-3

Plaut, J. A., Yepez, E. A., Hill, J., Pangle, R., Sperry, J. S., Pockman, W. T., & Mcdowell, N. G. (2012). Hydraulic limits preceding mortality in a piñon-juniper woodland under experimental drought. *Plant, Cell & Environment*, *35*(9), 1601–1617. https://doi.org/10.1111/j.1365-3040.2012.02512.x

Poulter, B., Frank, D., Ciais, P., Myneni, R. B., Andela, N., Bi, J., Broquet, G., Canadell, J. G., Chevallier, F., Liu, Y. Y., Running, S. W., Sitch, S., & Van Der Werf, G. R. (2014). Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle. *Nature*, *509*(7502), 600–603. https://doi.org/10.1038/nature13376

Prentice, I. C., Liang, X., Medlyn, B. E., & Wang, Y. P. (2015). Reliable, robust and realistic: The three R’s of next-generation land-surface modelling. *Atmospheric Chemistry and Physics*, *15*(10), 5987–6005. https://doi.org/10.5194/acp-15-5987-2015

Rempe, D. M., & Dietrich, W. E. (2018). Direct observations of rock moisture, a hidden component of the hydrologic cycle. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(11), 2664–2669. https://doi.org/10.1073/pnas.1800141115

Rodell, M., Houser, P. R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C. J., Arsenault, K., Cosgrove, B., Radakovich, J., Bosilovich, M., Entin, J. K., Walker, J. P., Lohmann, D., & Toll, D. (2004). The Global Land Data Assimilation System. *Bulletin of the American Meteorological Society*, *85*(3), 381–394. https://doi.org/10.1175/BAMS-85-3-381

Ruddell, B. L., & Kumar, P. (2009). Ecohydrologic process networks: 1. Identification. *Water Resources Research*, *45*(3). https://doi.org/10.1029/2008WR007279

Salvucci, G. D., & Entekhabi, D. (1994). Equivalent steady soil moisture profile and the time compression approximation in water balance modeling. *Water Resources Research*, *30*(10), 2737–2749.

Schlemmer, L., Schär, C., Lüthi, D., & Strebel, L. (2018). A Groundwater and Runoff Formulation for Weather and Climate Models. *Journal of Advances in Modeling Earth Systems*, *10*(8), 1809–1832. https://doi.org/10.1029/2017MS001260

Schwalm, C. R., Williams, C. A., Schaefer, K., Arneth, A., Bonal, D., Buchmann, N., Chen, J., Law, B., Lindroth, A., Luyssaert, S., Reichstein, M., & Richardson, A. D. (2010). Assimilation exceeds respiration sensitivity to drought: A FLUXNET synthesis. *Global Change Biology*, *16*(2), 657–670. https://doi.org/10.1111/j.1365-2486.2009.01991.x

Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., Orlowsky, B., & Teuling, A. J. (2010). Investigating soil moisture-climate interactions in a changing climate: A review. *Earth-Science Reviews*, *99*(3–4), 125–161. https://doi.org/10.1016/j.earscirev.2010.02.004

Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Luca, A. Di, Ghosh, S., Iskandar, I., Kossin, J., Lewis, S., Otto, F., Pinto, I., Satoh, M., Vicente-Serrano, S. M., Wehner, M., & Zhou, B. (2021). Weather and Climate Extreme Events in a Changing Climate. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, *Cambridge*(In Press.).

Stocker, B. D., Tumber-d, S. J., Konings, A. G., Anderson, M. B., Hain, C., & Jackson, R. B. (2021). Global distribution of the rooting zone water storage capacity reflects plant adaptation to the environment. *BioRxiv*. https://doi.org/https://doi.org/10.1101/2021.09.17.460332

Stocker, B. D., Zscheischler, J., Keenan, T. F., Prentice, I. C., Peñuelas, J., & Seneviratne, S. I. (2018). Quantifying soil moisture impacts on light use efficiency across biomes. *New Phytologist*, *218*(4), 1430–1449. https://doi.org/10.1111/nph.15123

Stojnić, S., Suchocka, M., Benito-Garzón, M., Torres-Ruiz, J. M., Cochard, H., Bolte, A., Cocozza, C., Cvjetković, B., De Luis, M., Martinez-Vilalta, J., Ræbild, A., Tognetti, R., & Delzon, S. (2018). Variation in xylem vulnerability to embolism in European beech from geographically marginal populations. *Tree Physiology*, *38*(2), 173–185. https://doi.org/10.1093/treephys/tpx128

Teuling, A. J., Seneviratne, S. I., Stöckli, R., Reichstein, M., Moors, E., Ciais, P., Luyssaert, S., Van Den Hurk, B., Ammann, C., Bernhofer, C., Dellwik, E., Gianelle, D., Gielen, B., Grünwald, T., Klumpp, K., Montagnani, L., Moureaux, C., Sottocornola, M., & Wohlfahrt, G. (2010). Contrasting response of European forest and grassland energy exchange to heatwaves. *Nature Geoscience*. https://doi.org/10.1038/NGEO950

Teuling, A. J., Seneviratne, S. I., Williams, C., & Troch, P. A. (2006). Observed timescales of evapotranspiration response to soil moisture. *Geophysical Research Letters*, *33*(23), 0–4. https://doi.org/10.1029/2006GL028178

Thompson, S. E., Harman, C. J., Konings, A. G., Sivapalan, M., Neal, A., & Troch, P. A. (2011). Comparative hydrology across AmeriFlux sites: The variable roles of climate, vegetation, and groundwater. *Water Resources Research*, *47*(7), 1–17. https://doi.org/10.1029/2010WR009797

Tuck, S. L., Phillips, H. R. P., Hintzen, R. E., Hudson, J. P. W. S., Purvis, A., & N., L. (2014). MODISTools - downloading and processing MODIS remotely sensed data in R. *Ecology and Evolution*, *4*(24), 4658–4668. https://doi.org/10.1002/ece3.1273

Tumber-Dávila, S. J., Schenk, H. J., Du, E., & Jackson, R. B. (2022). Plant sizes and shapes above and belowground and their interactions with climate. *New Phytologist*. https://doi.org/10.1111/nph.18031

Van der Molen, M. K., Dolman, A. J., Ciais, P., Eglin, T., Gobron, N., Law, B. E., Meir, P., Peters, W., Phillips, O. L., Reichstein, M., Chen, T., Dekker, S. C., Doubková, M., Friedl, M. A., Jung, M., van den Hurk, B. J. J. M., de Jeu, R. A. M., Kruijt, B., Ohta, T., … Wang, G. (2011). Drought and ecosystem carbon cycling. In *Agricultural and Forest Meteorology* (Vol. 151, Issue 7, pp. 765–773). Elsevier. https://doi.org/10.1016/j.agrformet.2011.01.018

Venables, W. N., & Ripley, B. D. (2002). *Modern Applied Statistics with S* (Fourth). Springer.

Wieder, W. R., Boehnert, J., Bonan, G. B., & Langseth., M. (2014). *Regridded Harmonized World Soil Database v1.2*. ORNL DAAC, Oak Ridge, Tennessee, USA.

Wolf, A., Anderegg, W. R. L., & Pacala, S. W. (2016). Optimal stomatal behavior with competition for water and risk of hydraulic impairment. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(46), E7222–E7230. https://doi.org/10.1073/pnas.1615144113

Zhan, S., Song, C., Wang, J., Sheng, Y., & Quan, J. (2019). A Global Assessment of Terrestrial Evapotranspiration Increase Due to Surface Water Area Change. *Earth’s Future*, *7*(3), 266–282. https://doi.org/10.1029/2018EF001066

Zhang, K., Kimball, J. S., & Running, S. W. (2016). A review of remote sensing based actual evapotranspiration estimation. *Wiley Interdisciplinary Reviews: Water*, *3*(6), 834–853. https://doi.org/10.1002/wat2.1168

Zhang, Q., Manzoni, S., Katul, G., Porporato, A., & Yang, D. (2014). The hysteretic evapotranspiration—Vapor pressure deficit relation. *Journal of Geophysical Research: Biogeosciences*, *119*(2), 125–140. https://doi.org/doi:10.1002/ 2013JG002484

Zhou, S., Yu, B., Zhang, Y., Huang, Y., & Guangqian, W. (2016). Partitioning evapotranspiration based on the concept of underlying water use efficiency. *Water Resources Research*, *52*, 1160– 1175. https://doi.org/10.1111/j.1752-1688.1969.tb04897.x

Zhou, S., Zhang, Y., Williams, A. P., & Gentine, P. (2019). Projected increases in intensity, frequency, and terrestrial carbon costs of compound drought and aridity events. *Science Advances*, *5*(1), 1–9. https://doi.org/10.1126/sciadv.aau5740