**Belowground moisture allows sustained evapotranspiration during drought**

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**Abstract**

Subsurface water limitation is key in determining 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 measure directly at large scales and are thus not quantified properly by land surface models. Here, we define a method to study the impact of belowground water limitation on ET in progressing drought. We train a deep neural network with 88000 site-days of eddy covariance 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 a normalized measure 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 than 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. The 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**: potential evapotranspiration, climate change, deep learning, data science, ecosystem fluxes, rock moisture, drought stress, groundwater, machine learning, soil moisture, vapor pressure deficit (VPD), root zone water storage capacity

**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; Sonia I. 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 (S.I. Seneviratne et al., 2021), it is crucial to understand plant physiological controls that link subsurface water limitation and ecosystem evapotranspiration (ET). Here, we refer to 'droughts' as agricultural droughts, identified by water stress effects on vegetation and water balance deficits (S.I. Seneviratne et al., 2021).

Quantifying belowground water limitation effects on ET is challenged by a range of complexities that are heterogeneous both vertically along the rooting zone and laterally across the landscape (Dralle et al., 2020; Gao et al., 2014; Thompson et al., 2011). The root zone water storage capacity (SR) is defined as the maximum amount of soil moisture that can be accessed by vegetation for transpiration. A large SR has been linked to a higher plant resistance, sustained ET, and persistent vegetation cover during rain-free periods (Gao et al., 2014; A. J. Teuling et al., 2006). Recent studies have emphasized locally important contributions to SR by water reservoirs below the soil layer, e.g. in fractured bedrock (rock moisture, Dawson et al., 2020; McCormick et al., 2021; Rempe & Dietrich, 2018) or groundwater (Ying 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 (Y Fan et al., 2013; Ying Fan et al., 2017). This implies large dissimilarities at multiple scales in plant access to belowground water stores, as suggested by inverse modelling (Ying Fan et al., 2017; Hain et al., 2015). However, the quantification of belowground water availability effects on ET across biomes has remained largely 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 (Novick et al., 2016; Zhou et al., 2019). The soil moisture-VPD coupling is only observed as a result of land-atmosphere feedbacks under relatively dry conditions (Sonia I. Seneviratne et al., 2010), but this correlation fades under very dry or humid conditions (Ruddell & Kumar, 2009). This limits our understanding of belowground water availability effects on fluxes. It also hinders our ability to find generalizations valid across a wide range of conditions to properly inform models.

Indeed, the complexity of belowground water stores and plant access to them contrasts with their typical representation in land surface models (LSMs). With a few exceptions, LSMs represent a flat surface (Prentice et al., 2015), assume free drainage from the bottom soil layer which prohibits the formation of water-saturated zones (Liang et al., 1994; Schlemmer et al., 2018), focus on VPD effects ignoring the role of belowground water availability in determining ET responses to drought (Fisher et al., 2008), do not account for the variety of bedrock lithology and its role as a moisture storage component (McCormick et al., 2021), and rely on prescribed and often underestimated plant rooting depths (Drewniak, 2019; Tumber-Dávila et al., 2022). Spatial variations of SR are typically represented in models as a result of the spatial distribution of plant functional types (PFTs) across biomes (Drewniak, 2019) and variations in soil type. 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 a need to accurately describe the effects of belowground moisture limitation, separated from atmospheric aridity and other co-varying drivers, for a reliable ET modelling at all scales (Novick et al., 2016; Zhou et al., 2019).

Here, we develop a method to diagnose the partial dependence of ET to belowground water limitation effects. We use ecosystem-scale observations where multiple drivers of vegetation activity are measured continuously. Using site-specific deep neural network (DNN) models trained on eddy-covariance data, multiple soil moisture datasets and a remotely sensed greenness index, 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 an increasing cumulative water deficit (CWD, the cumulative difference of ET and precipitation, see Box 1). In contrast to evaluating fET against soil moisture, evaluation against CWD has the advantage to reveal patterns of water stress effects even after drying out of the topsoil. It is thus possible to identify the dependence of ET on belowground water reservoirs, below the relatively shallow soil layers, where measurement devices are commonly deployed. We find that, contrary to most models, the sensitivity of plants to water stress does not show a gradual decline during drought, but rather a variety of responses across biomes, with some abrupt responses. Models cannot reproduce the shape of the relationship between a normalized measure of ET impacts (fET) and a normalized measure of whole-column water availability (CWD).

**Methods  
Overview**

The first step of our approach consisted in building site-specific DNN models estimating ET and potential evapotranspiration (PET), defined here as ET without any belowground water limitations. For each site, we defined two separate models (DNNPET and DNNET, respectively). The key difference between the two models is that DNNPET was trained using site-days with a relatively high soil moisture, whereas DNNET was trained using all available site-days (see 'Estimating Potential ET'). We defined a normalized measure of ET impacts (fET) dividing the neural network estimate of ET (ETNN) by the neural network estimate of PET (PETNN). We then analysed how fET evolves with increasing water stress by regressing it against the cumulative water deficit (CWD). Since the CWD is the integration of the water balance over time (see 'Derivation of the cumulative water deficit'), it constitutes a proxy for belowground water availability.

**Estimating Potential ET**

Our approach is based on an earlier method that separates soil moisture effects on light-use efficiency (LUE; defined as the amount of CO2 assimilated by plants per unit of absorbed light) using FLUXNET2015 data (Stocker et al., 2018). 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 made based on a sensitivity analysis guided by the results of a previous study (Maes et al., 2019). To avoid excessive model complexity and overfitting, the predictors were limited to a small number representing known controls on ET (Miralles et al., 2019). 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 smallest variance in fET during moist days was chosen.

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

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

We can thus quantify the control of belowground water reservoirs on ET, separated from other predictors (net radiation, VPD, vegetation greenness and air temperature). Note that we used half-hourly data from the FLUXNET2015 dataset (see 'Data'). The use of this neural-network based approach avoids the necessity to determine PET a priori based on possibly imperfect and difficult to parameterize theoretical estimations (Maes et al., 2019). It also allows a data-driven determination of both PET and the effect of belowground water reservoirs. Using ETNN instead of ETobs in Eq. 3 resulted in a lower signal-to-noise ratio, as ETNN and PETNN are 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’ (R2 = 0.769, Fig. 1b). On the contrary, PETNN is expected to overestimate ETobs during ‘dry days’, as the former is trained on ‘moist days’ data only (R2 = 0.362, RMSE = 1.095, Supplementary Fig. 1b). With soil moisture as the only difference in predictors between PETNN and ETNN, fET can be interpreted as the separated control of subsurface available water on ET (Stocker et al., 2018). Note that it has been shown that soil moisture profiles follow the same spectra at different depths, in case of a relatively deep water table (Salvucci & Entekhabi, 1994).

We benchmarked 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 linear model was defined as PET=k\*Rn, where Rn was converted to mass units (mm d-1) and k is a site-specific constant that scales Rn, calibrated to ETobs.

**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 tuning algorithm for a limited set of sites (15). To reduce the number of hyperparameters, 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 stops the training process should the validation loss not improve after five epochs. This constraints the number of epochs and avoids overfitting.

We then ran the hyperparameter tuning for a subset of 5% of the total combinations and chose the simplest model (i.e. with 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 deep neural networks using five-fold cross validation, with a 75%-25% split between training and validation data, respectively. The model with 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 take into account 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)*.*

A difference with Stocker et al. (2018) is that, to reduce biases in ET prediction vs GPP prediction, we applied additional filters to the FLUXNET2015 data set, 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 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 with sensible heat flux smaller than 5 W m-2 and incoming shortwave radiation 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). 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, two quantities directly downloaded from the FLUXNET2015 dataset that are not model dependent.

We used observational soil moisture data as available from the FLUXNET2015 dataset, measured in volume water per volume soil. 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' means 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' refers to the fact that soil moisture was not consistent with the soil water balance simulated 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). The model is 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 represents a potential source of circularity in our analysis, since we are 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'). ~~Our deep learning model (see 'Model Architecture') mostly uses information about the relative magnitude and the timing of soil moisture variations. The absolute magnitudes, that are directly connected to the rooting depth, are rather irrelevant for our deep learning model.~~

We downloaded MODIS EVI (MOD13Q1, 16 days, 250 m, Collection 5) with the ‘MODISTools’ R package (Tuck et al., 2014). We excluded images with clouds, snow, ice or shadows. 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 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).

To benchmark the results of our observations-driven statistical model, 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 a fusion of ground and space based observations using land surface assimilation techniques to model energy and water exchanges. We will refer 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 is 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 accuracy, PETGLDAS was scaled by dividing it by its median in the lower CWD bin (CWD < 20 mm). This way, fETGLDAS is 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 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 is calculated following the Priestly–Taylor equation (PETPT), as implemented in the SPLASH model (Davis et al., 2017). 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. The CWD timeseries is calculated as the cumulative sum of for days when there is a net water loss from the surface (). The summation is stopped when the rain has compensated the water loss due to ET, i.e. the cumulative sum across days is zero (). We define a ‘CWD event’ as the period between the start and the end of the summation, i.e. a dry-down event. We consider 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, within each ‘CWD event’, we removed all data after rain has 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 data that fell into the biggest CWD instances each year. We used daily latent heat flux and precipitation timeseries from the FLUXNET2015 database. To calculate the CWD, it is important to focus on high quality observations. For this reason, we 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 gapfilling ET is different from the deep learning model defined above. We trained the deep learning model with the ET timeseries cleaned as described in the ‘data’ subchapter 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 'Data'). 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 modelled PET had to be greater or equal to ET during ‘dry days’ and the R2 between modelled ET and ETobs had to be > 0.5, leaving 59 sites. Seven sites were excluded upon visual inspection of the fET vs CWD relationship, which was not giving consistent results. The remaining 52 sites are listed in Table 1. 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, medium fET and low fET, and showed a consistent pattern in the decline of fET during drought. Sites that did not have a fET value in that CWD interval were manually assigned to the 'high fET' group, as their behavior was more consistent with other sites in that group (Supplementary Fig. 3). We chose this grouping based on the fET median at a CWD of 150 mm, because this is where there was the most variability in the fET vs CWD response (see Fig. 4).

**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, to have conditions where water is not limiting (R2 = 0.76, Fig. 1b). This method gave more reliable results compared to the empirical Priestley-Taylor estimates of PET (PETPT, R2 = 0.45, Fig. 1c) or to PET predicted with a simple linear model based on net radiation (PETlm, R2 = 0.40, Fig. 1d). We can see that, 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 in detail the accuracy of PETNN, we evaluated its seasonality compared to ETNN and ETobs (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 without belowground moisture limitations (Fig. 2a, red and green lines). At US-Ton, PETNN departs substantially from ETobs during the dry season, indicating substantial impacts of soil moisture (Fig. 2b, red line). In both cases, predicted values are consistent with the trend of Rn converted to mass units (Fig. 2, dashed gray line).

**Insensitivity of ET to soil moisture drying**

To gain further insight into the effects of soil moisture regulation on ET, we evaluated fET as a function of soil moisture (Fig. 3a,b). We chose two sample sites for contrasting behavior: BE-Vie, a humid mixed-forest, and IT-CA3, a Mediterranean deciduous broad leaf forest.

At BE-Vie, fET is around one even at the lowest soil moisture bin (Fig. 3a). For this site, we used simulated soil moisture with a water-holding capacity of 220 mm (see Methods), as there were no other sites available with observed soil moisture deeper than 50 cm. The insensitivity of fET to soil moisture drying, even when soil moisture is defined with a bucket depth of 220 mm, may indicate access to deeper water stores. At IT-CA3, we used observational soil moisture at a depth of 1 m available from the FLUXNET2015 dataset. We find increasingly small fET values for small soil moisture values (Fig. 3b). Looking at fET for lower soil moisture bins at IT-CA3, we can observe that its increase may not follow a linear trend. We may have a high concentration of data points in the lowest soil moisture bins, thus masking some effects of water stress on ET. Focusing on results across all sites, the fET median is significantly different from zero for about one third of sites, and it decreases to be around zero for the rest of the sites (Fig. 3c). This means that for about two third of sites the vegetation is still transpiring at near potential rates. To sustain their activity in such conditions, plants must have access to deeper water stores.

**Binning of fET vs CWD responses**

To avoid conflating data points into a single low soil moisture bin, we turn to analyzing fET as a function of CWD. When soil moisture approaches its minimum value, the CWD can still increase, as long as ET is non-null. Therefore, CWD is a metric more sensitive to dry conditions (see Methods and Box 1). In other words, evaluating ET relationships in response to CWD illuminates plant responses to water stress under continued dry downs, even below the topsoil. We thus plotted fET as a function of CWD for all sites (Fig. 4b). We observe a variety of responses across sites. For CWD values up to approximately 100 mm, there is an accumulation of points centered at fET equal to one. At higher CWD values, we can see a rather gradual decline in fET. 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 infer that fET is varying as a function of CWD following a certain hockey-stick pattern. We can observe a variety of fET responses at a CWD interval of around 150 mm (Fig. 4b). The distribution of fET median values in this CWD interval shows three distinct groups (Fig. 4a). To highlight this pattern, we divided the sites based on this distribution (Fig. 4a,c,e). Sites were thus grouped into low, medium, and high fET. Each group exhibits a definite fET vs CWD behavior (Supplementary Fig. 4-5-6).

**Patterns of fET vs CWD responses across sites**

At 'high fET' sites, there is almost no effect of water stress on plants, as they show an fET value almost always near one for CWD values up to 300 mm (Fig. 5a). In contrast, when predicted by models, after a CWD threshold of 150 mm, water stress (fETGLDAS) is decreasing linearly with progressing drought (Fig. 5b). At 'medium fET' sites (Fig. 5c), we see that 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. 5d). 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. 5e). Interestingly, in the same fET group, fETGLDAS is decreasing almost linearly with progressing drought, down to zero (Fig. 5f). Compared to observations, models also tend to overestimate water stress (Fig. 5e,f). The general trends observed for fET vs CWD are confirmed when plotting a model-independent indicator of ET stress, the evaporative fraction (EF), as a function of CWD (Supplementary Fig. 2).

**Relationship to other soil and climate variables**

To interpret the different sensitivities of fET to CWD in each fET group, we investigated their relationship with other soil and climate variables (Fig. 6). The sand fraction is higher in the 'low fET' group, at the expense of the silt fraction (Fig. 6a). Forests prevail in the 'high fET' group, followed by croplands (Fig. 5b). The 'medium fET' group has a similar distribution of vegetation classes. In the 'low fET' group, treeless PFTs are dominant (savannahs, shrublands and grasslands, Fig. 5b). The aridity index shows a decreasing trend across the fET groups, with the 'low fET' one being the most arid (Fig. 5c). Topographic effects and mean annual precipitation could not explain much of the variance across fET groups (Fig. 5 d,e). The mean annual temperature is increasing across fET groups (Fig. 5f).

**Discussion**

We demonstrated that we can derive belowground water limitation effects on ET from aboveground measurements of fluxes. Analysing a normalized measure of ET impacts as a function of CWD captures more than the effects of depleted moisture stores in soils. Our approach highlights the control of groundwater, deep water and potentially rock moisture on ET.

At 'high fET' sites, there is almost no effect of water stress on plants (Fig. 5a). This means that soil moisture is limiting only under the most extreme conditions, allowing evaporation to be almost always at potential rate. At 'medium fET' sites, the effect of water stress on plants become visible at CWD greater than 100 mm (Fig. 5c). At 'low fET' sites, the effect of water stress on plants during drought shows an abrupt response at a CWD of 50 mm followed by a levelling-off to fET values comprised between 0.5 and 0.1 (Fig. 4e). Even at high CWD values, vegetation activity is never completely shut off. This could imply that plants may have deep roots that can access the saturated zone or can reach very low water potentials before they could lose their xylem hydraulic conductivity (Jacobsen et al., 2007; Martínez-Vilalta & Garcia-Forner, 2017; Stojnić et al., 2018). In all cases, even at the highest water deficit, fET is almost never going down to zero, unlike in models (Fig. 5b,d,f). This suggests that plants may have access to deep water or low potential surface reservoirs that allow them to sustain ET even during the unfolding of a drought event.

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

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, 9 sites over 20, Fig. 5b). They maintain a relatively high, near potential, ET even under dry conditions, showing only little reductions associated with belowground moisture availability (Fig. 5a). 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). They keep a relatively high ET in mild drought, and even under the highest CWD they show a maximum fET decline of about 50% (Fig. 5c). Sites with the strongest reduction in fET are found in the driest climates (Fig. 6c). This is consistent with the strong soil moisture effects detected in arid and semi-arid regions (He et al., 2016; Nicolai-Shaw et al., 2017; Sonia I. Seneviratne et al., 2010). These sites are composed mostly by nontree vegetation: savannahs (5 sites over 11), grasslands (4 sites over 11) and shrublands (1 sites over 11, Fig. 5b).

Our findings are consistent with the fact 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 have shallower roots and they are thus more likely to experience water stress when the topsoil dries out. Forests have deeper roots that can access deeper water stores, and they are thus more resilient to high CWD (Ying Fan et al., 2017). The different behaviour observed in grasslands and forests could explain the drop in fET after a certain CWD threshold (Fig. 5e). In the 'low fET' group, the dominant PFT is savannah, a tree-grass ecosystem characterised by a herbaceous understory (grassland) interrupted by sufficiently spaced trees, so that the canopy is never continuous (Fig. 5b) (El-Madany et al., 2020; Luo et al., 2018). After a certain CWD value (around 50 mm), the herbaceous layer loses access to water, and thus stops contributing to ET. In turn, trees can have a very resistant xylem allowing them to pull water at low water potentials or they can rely on deep roots to access deeper water reservoirs. These strategies allow trees to keep transpiring even at high CWD. This could explain why we observe an abrupt change in fET, followed by a levelling-off which never reaches zero (Fig. 5e). In this framework, the levelling-off corresponds to a period where the understory is shut off and mostly trees are transpiring. 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). The abrupt transition (high slope) at CWD of 50 mm may be a sign of a strong coupling between ET and belowground water stores, i.e. in that interval ET is sensitive to even small variations in CWD. After a certain CWD value, savannahs show a stronger dependence on belowground water availability than forests (Fu et al., 2022).

The correlation between fET groups and 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-resilient, i.e. deeper rooting depth, and lower 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 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 effects 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 are in similar topographic conditions (Thompson et al., 2011).

We can observe a clear correlation between the minimum fET and the aridity index (Fig. 7), as expected. At the same time, fET is also dependent on soil texture, which regulates climate conditions. In particular, the clay fraction is exerting 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). Climate is the prime factor controlling the spectrum of fET minima (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).

**Explanation of the discrepancy between models and observations**

The hypothesis of trees accessing deeper water reservoirs is consistent with recent findings, which highlight the often-neglected importance of deep, non-soil water stores (Dawson et al., 2020). The occurrence of the high-sensitivity sites in arid climates characterised by savannahs and shurblands indicates that a large fraction of SR could be stored in weathered bedrock (rock moisture) (Extended Data Table 1 in McCormick et al., 2021). Rock moisture is usually accessible to plants but essentially not quantified by models, and it 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. 5e). The same behaviour is not captured by models, which cannot quantify rock moisture (Fig. 5f).

Groundwater (or rock moisture) 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. 5b,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. A limit of this product is how it handles subgrid variability. 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. The vegetation tiles are created from the modified IGBP land cover dataset at 1 km resolution (Beaudoing et al., 2020; Rodell et al., 2004). 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 dramatically even within the same species and climate (Ying Fan et al., 2017). The GLDAS product does not account for heterogeneity in rooting depth within the same vegetation type.

The different tails going to zero of the fETGLDAS vs CWD relationship (Fig. 5d) seem to reflect different rooting depths at different sites. This difference with our approach (Fig. 5c) could be 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 PFTs present in a FLUXNET2015 tower footprint contribute 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. 5f) 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 on the order of 1-10 m, while models have grid cell sizes on scales as big as 1 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 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.

In conclusion, our observation-driven statistical approach is able 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 a functional difference in plant responses to water stress across biomes. Forests tend to show little sensitivity to water stress, whereas savannahs and other treeless PFTs show an abrupt drop in ET after an initial stress-free phase. In both cases and in contrast with most models, ET is almost never completely shut off during drought. We found that this difference is mostly explained by climate, yet the intensity of the response is modulated by soil texture. 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 could address this observation-model bias focusing on the role of deep unquantified water stores.

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