## *New Phytologist* Supporting Information

Article title: Diagnosing evapotranspiration responses to water deficit across biomes using deep learning

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The following Supporting Information is available for this article:

**Fig. S1** Performance of the deep-learning model at predicting evapotranspiration (ET) across sites.

**Fig. S2** EF vs CWD for sites grouped according to their median fET

**Fig. S3** fET vs CWD for sites grouped according to their median fET. High fET group.

**Fig. S4** fET vs CWD for sites grouped according to their median fET. Medium fET group.

**Fig. S5** Seasonality of predicted and observed evapotranspiration (ET) at two sample dry sites.

**Fig. S6** Performance of the deep-learning model at predicting evapotranspiration (ET) and potential evapotranspiration (PET), using the four predictors retained in the study vs a set of seven predictors.

**Fig. S7** Evolution of the fractional reduction in evapotranspiration (fET) vs transpiration (fT) with the cumulative water deficit (CWD) and performance of the deep-learning model at predicting evapotranspiration (ET) vs transpiration (T).

**Fig. S8** Range and distribution of EVI for ‘moist’ and ‘dry’ days.

**Fig. S9** Distribution of cumulative water deficit (CWD) calculated with GLDAS and FLUXNET data in the ‘low fET’ group.

**Fig. S9** Cumulative water deficit (CWD) time series at sample site US-Ton.

**Fig. S10** Evolution of the fractional reduction in evapotranspiration (fET) with the cumulative water deficit (CWD) using observational vs modelled soil moisture data at US-Ton, US-Var, IT-CA3 and US-MMS.

**Fig. S11** Seasonality of predicted and observed evapotranspiration (ET), fractional reduction in evapotranspiration (fET) and enhanced vegetation index (EVI) at US-Ton and US-SRG.

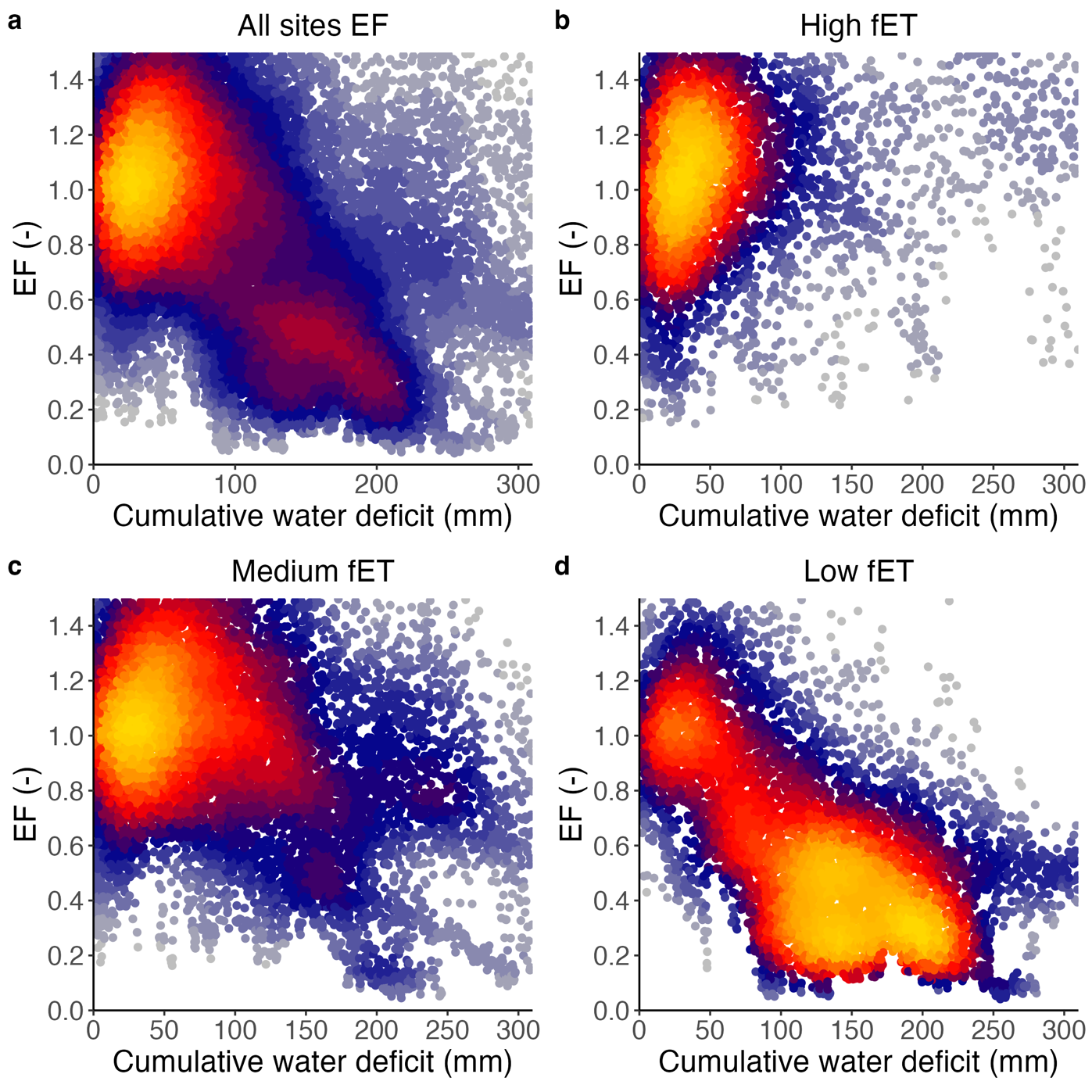
**Table S1** FLUXNET Tier 1 sites included in the analysis.

**Methods S1** Extended description of data processing, deep learning models and GLDAS product.

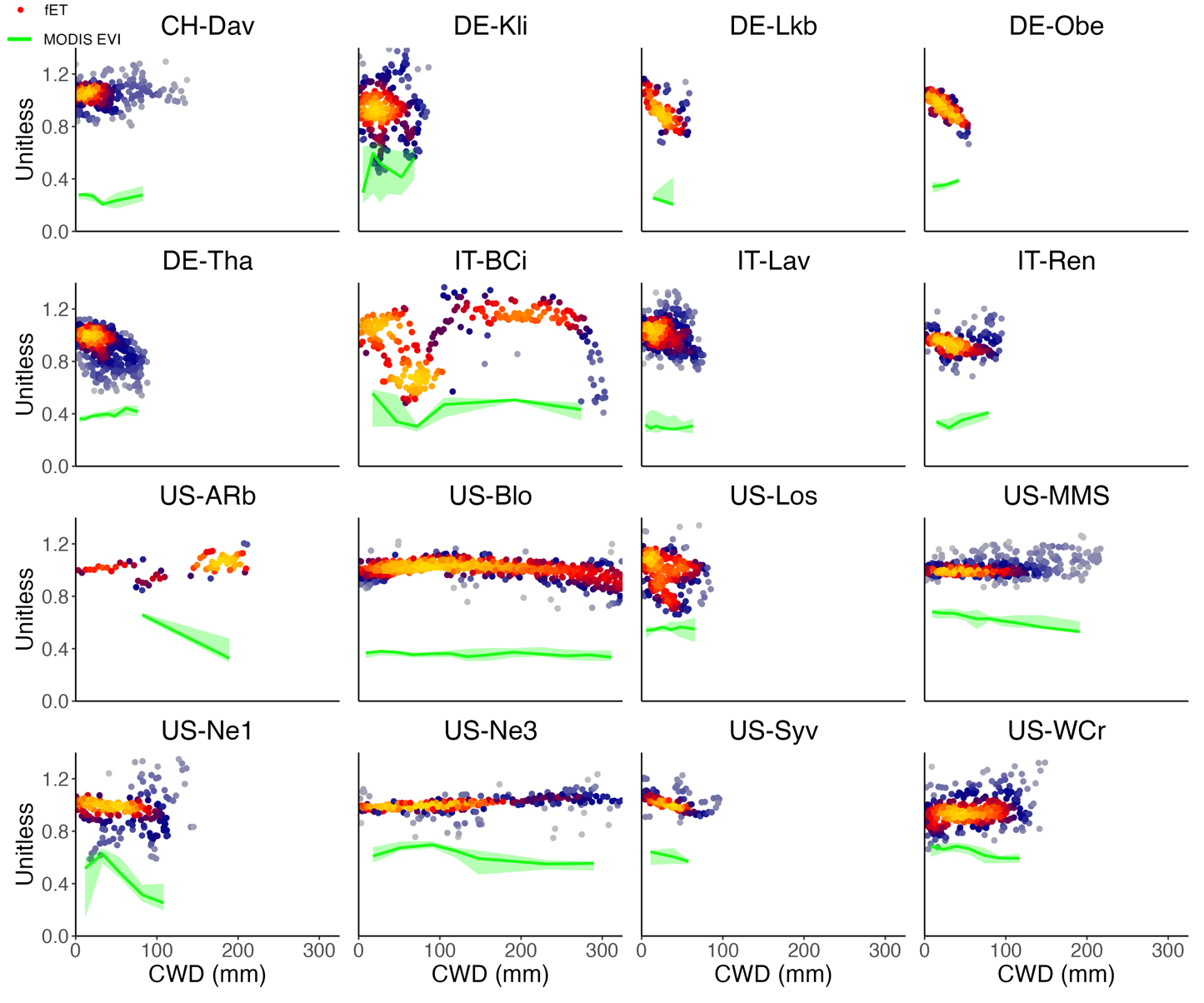
**Figures  
Fig. S1** Performance of the deep-learning model at predicting evapotranspiration (ET) across sites.ETNN and PETNN are respectively ET and PET predicted with our deep learning model. ETobs corresponds to observational ET from FLUXNET2015. **a**,PETNN vs ETNN, evaluated on moist days. **b**, PETNN vs observational ETobs, evaluated on dry days. Red line: regression line between modelled and observed data. Dashed black line: *y = x* line. RMSE, root-mean-square error. R package ‘LSD’ was used to plot the point density (Schwalb et al., 2020).

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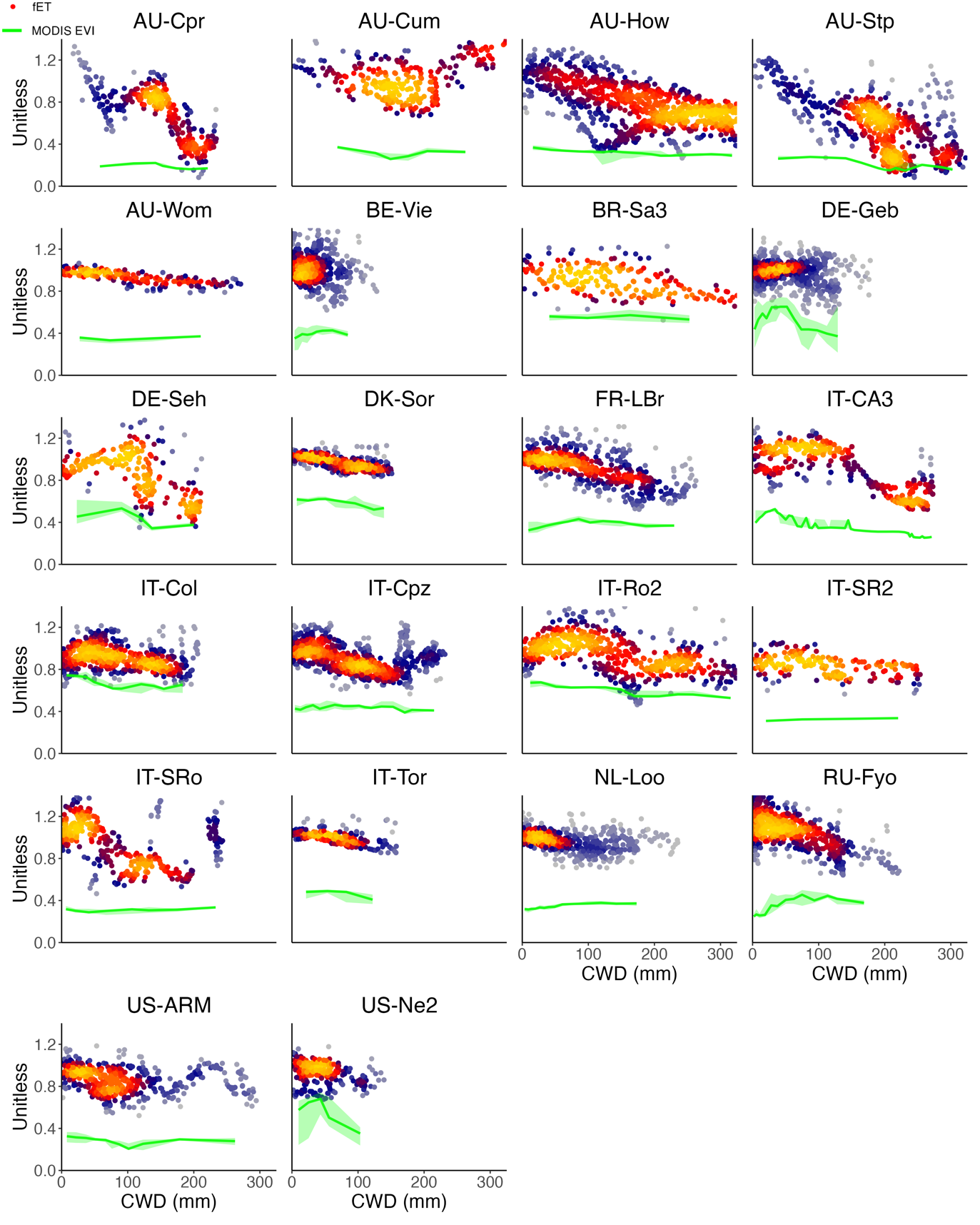
**Fig. S2** EF vs CWD for sites grouped according to their median fET. a, All sites. b, High fET. c, Medium fET. d, Low fET. The clustering is consistent with Figure 3. EF was scaled by dividing it by the median in its lower CWD bin (CWD < 20 mm). EF was calculated as latent heat divided by net radiation, two quantities directly downloaded from the FLUXNET2015 dataset that do not depend on any model. R package ‘LSD’ was used to plot the point density (Schwalb et al., 2020).

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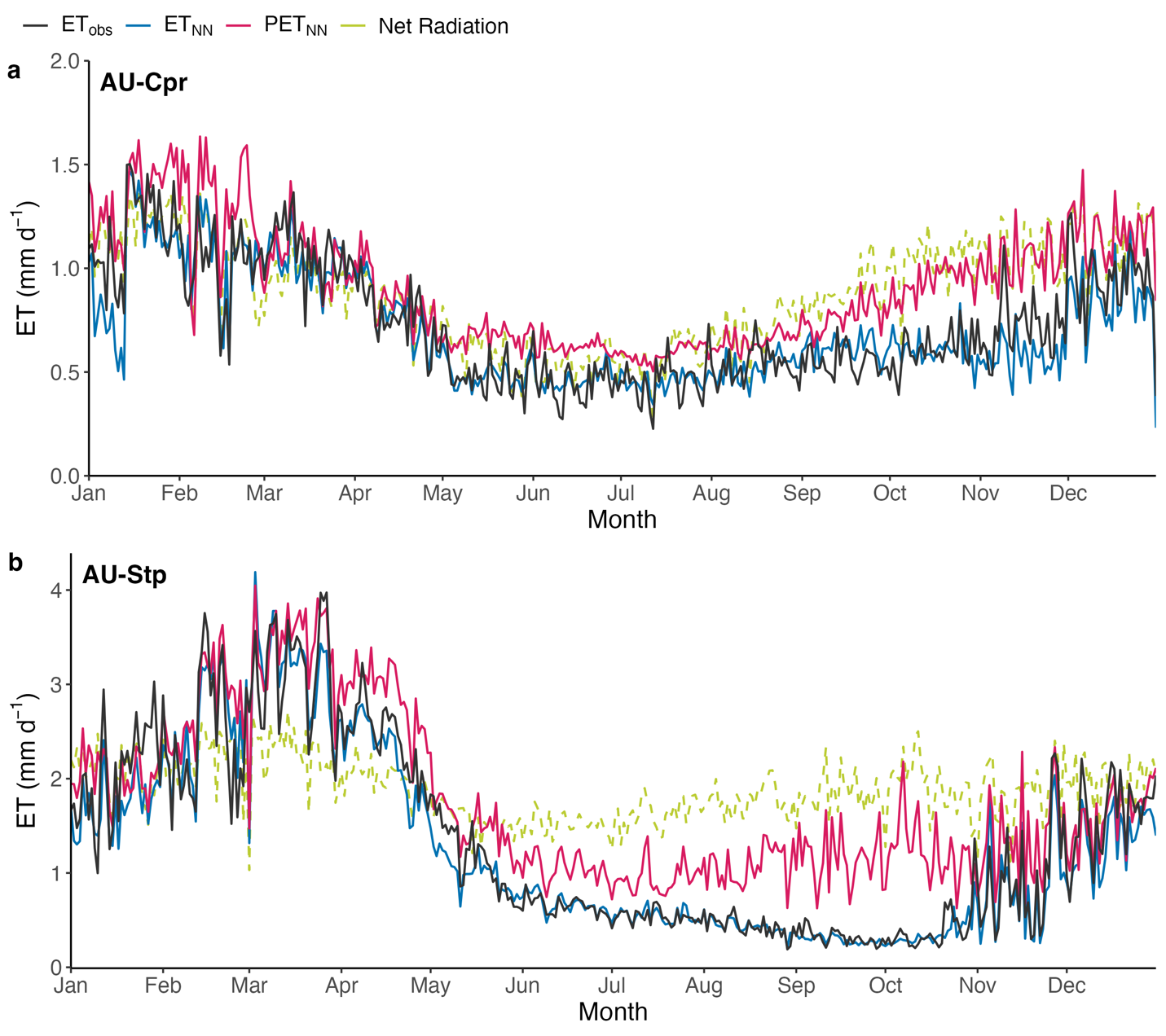
**Fig. S3** Evolution of the fractional reduction in evapotranspiration (fET) with the cumulative water deficit (CWD) for sites classified in the **‘**high fET’ group. Colored dots: fET. Green line: MODIS Enhanced Vegetation Index (EVI). EVI was binned by CWD intervals of 50 points. Shading represents the lower and upper quartiles, and the solid line the median in every bin. R package ‘LSD’ was used to plot the point density (Schwalb et al., 2020).



**Fig. S4** Evolution of the fractional reduction in evapotranspiration (fET) with the cumulative water deficit (CWD) for sites classified in the **‘**medium fET’ group. Colored dots: fET. Green line: MODIS Enhanced Vegetation Index (EVI). EVI was binned by CWD intervals of 50 points. Shading represents the lower and upper quartiles, and the solid line the median in every bin. R package ‘LSD’ was used to plot the point density (Schwalb et al., 2020).

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**Fig. S5** Seasonality of predicted and observed evapotranspiration (ET) at two sample dry sites. **(a)** AU-Cpr. (**b)** AU-Stp. ETNN and PETNN are respectively ET and PET predicted with our deep learning model. ETobs corresponds to observational ET from FLUXNET2015. Blue line: ETNN. Red line: PETNN. Black line: ETobs. Dashed green line: Net radiation converted to mass units (mm d-1). We derived the seasonality by calculating the mean across all years for every day of the year.



**Fig. S6** Performance of the deep-learning model at predicting evapotranspiration (ET) and potential evapotranspiration (PET), using the four predictors retained in the study vs a set of seven predictors at US-Ton. *obs* corresponds to observational ET from FLUXNET2015. *nn\_act* and *nn\_pot* are respectively ET and PET predicted with our deep learning model.

|  |  |
| --- | --- |
| Four predictors: net radiation, VPD, air temperature, EVI | Seven predictors: net radiation, VPD, air temperature, EVI, wind speed, soil temperature, U\* |
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**Fig. S7** Evolution of the fractional reduction in evapotranspiration (fET) vs transpiration (fT) with the cumulative water deficit (CWD) and performance of the deep-learning model at predicting evapotranspiration (ET) vs transpiration (T) at US-Ton, US-Var and DK-Sor. Transpiration data (Tobs) are from a from a published dataset (Li et al., 2019a). ETobs corresponds to observational ET from FLUXNET2015. ETNN and TNN are respectively ET and T predicted with our deep learning model.

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| **US-Ton** | |
| **ET** | **T** |
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| **US-Var** | |
| **ET** | **T** |
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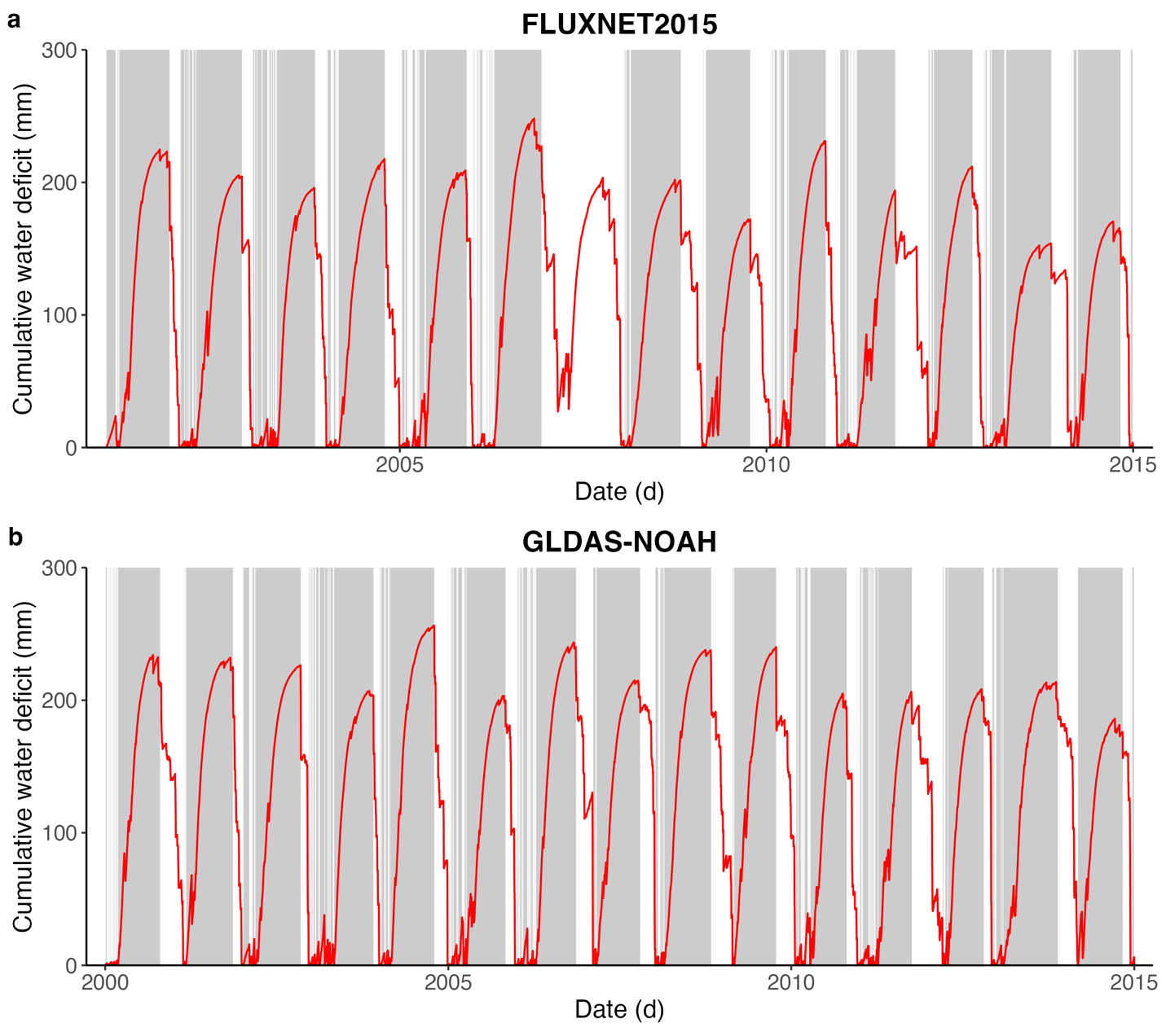
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| **DK-Sor** | |
| **ET** | **T** |
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|  | Chart, scatter chart  Description automatically generated |

**Fig. S8** Range and distribution of EVI for ‘moist’ and ‘dry’ days. **(a)** Boxplot of EVI for all sites. Blue: ‘moist days. Red: ‘dry days’. **(b)** Histogram of EVI for all sites. Blue: ‘moist days. Red: ‘dry days’. **(c)** Boxplots of EVI at individual sites showing all data**. (d)** Boxplots of EVI at individual sites showing ‘moist days’ data only**.**

**Chart

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**Fig. S9** Cumulative water deficit (CWD) time series at sample site US-Ton. Red line: time series of CWD. Grey bands correspond to intervals of progressively increasing CWD, denoted as ‘CWD events’. **(a)** CWD calculated using evapotranspiration and precipitation from the FLUXNET2015 dataset **(b)** CWD calculated using evapotranspiration and precipitation from the GLDAS-NOAH dataset (see Methods). Note that in a) the CWD accumulated in the year 2006 is not fully compensated by the wet season of the following year.



**Fig. S10** Evolution of the fractional reduction in evapotranspiration (fET) with the cumulative water deficit (CWD) and performance of the deep-learning model at predicting evapotranspiration (ET) at US-Ton, US-Var, IT-CA3 and US-MMS, using observational soil moisture data from FLUXNET2015 vs modelled soil moisture data from a published dataset (Davis et al., 2017). ETobs corresponds to ET used to train the model. ETNN corresponds to ET estimated with our deep learning model.

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| --- | --- |
| **US-Ton** | |
| **Observational SM** | **Modelled SM** |
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| --- | --- |
| **US-Var** | |
| **Observational SM** | **Modelled SM** |
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| **US-MMS** | |
| **observational SM** | **modelled SM** |
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**Fig. S11** Seasonality of predicted and observed evapotranspiration (ET), fractional reduction in evapotranspiration (fET) and enhanced vegetation index (EVI) at US-Ton and US-SRG. PETNN corresponds to potential ET predicted with our deep learning model. ETobs corresponds to observational ET from FLUXNET2015. Green line: EVI. Blue line: fET. Red line: PETNN. Black line: ETobs. We derived the seasonality by calculating the mean across all years for every day of the year. Chart, histogram

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**Tables**

**Table S1** FLUXNET Tier 1 sites included in the analysis. Group refers to the grouping of sites according to their median fET (see Methods). Coordinates in decimal degrees. IGBP is the vegetation class (GRA, grasslands; SAV, savannah; WSA, woody savannah; ENF, evergreen needleleaf forest; EBF, evergreen broadleaf forest; DBF, deciduous broadleaf forest; CSH, closed shrubland; WET, wetland; CRO, cropland; MF, mixed forest). MAT, mean annual temperature (°C). MAP, mean annual precipitation (mm).

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| --- | --- | --- | --- | --- | --- | --- |
| **Site** | **Coordinates** | **Years** | **IGBP** | **fET group** | **MAT (**°C) | **MAP (mm)** |
| **AU-Cpr** | 140.59, -34 | 2010 - 2014 | SAV | medium fET | 17.35 | 269 |
| **AU-Cum** | 150.72, -33.61 | 2012 - 2014 | EBF | medium fET | 17.28 | 850 |
| **AU-DaP** | 131.32, -14.06 | 2007 - 2013 | GRA | low fET | 27.22 | 1175 |
| **AU-DaS** | 131.39, -14.16 | 2008 - 2014 | SAV | low fET | 27.13 | 1134 |
| **AU-Gin** | 115.71, -31.38 | 2011 - 2014 | WSA | low fET | 18.53 | 697 |
| **AU-How** | 131.15, -12.49 | 2001 - 2014 | WSA | medium fET | 27.03 | 1640 |
| **AU-RDF** | 132.48, -14.56 | 2011 - 2013 | WSA | low fET | 26.98 | 958 |
| **AU-Stp** | 133.35, -17.15 | 2008 - 2014 | GRA | medium fET | 26.39 | 639 |
| **AU-Wom** | 144.09, -37.42 | 2010 - 2012 | EBF | medium fET | 10.70 | 1071 |
| **BE-Vie** | 6, 50.31 | 1996 - 2014 | MF | medium fET | 8.01 | 1085 |
| **BR-Sa3** | -54.97, -3.02 | 2000 - 2004 | EBF | medium fET | 25.50 | 1856 |
| **CH-Dav** | 9.86, 46.82 | 1997 - 2014 | ENF | high fET | 3.53 | 1053 |
| **DE-Geb** | 10.91, 51.1 | 2001 - 2014 | CRO | medium fET | 8.96 | 496 |
| **DE-Kli** | 13.52, 50.89 | 2004 - 2014 | CRO | high fET | 7.61 | 839 |
| **DE-Lkb** | 13.3, 49.1 | 2009 - 2013 | ENF | high fET | 4.20 | 1364 |
| **DE-Obe** | 13.72, 50.78 | 2008 - 2014 | ENF | high fET | 6.09 | 820 |
| **DE-Seh** | 6.45, 50.87 | 2007 - 2010 | CRO | medium fET | 10.17 | 709 |
| **DE-Tha** | 13.57, 50.96 | 1996 - 2014 | ENF | high fET | 8.26 | 754 |
| **DK-Sor** | 11.64, 55.49 | 1996 - 2014 | DBF | medium fET | 8.48 | 614 |
| **FR-LBr** | -0.77, 44.72 | 1996 - 2008 | ENF | medium fET | 12.52 | 908 |
| **FR-Pue** | 3.6, 43.74 | 2000 - 2014 | EBF | low fET | 13.35 | 683 |
| **IT-BCi** | 14.96, 40.52 | 2004 - 2014 | CRO | high fET | 16.10 | 1035 |
| **IT-CA3** | 12.02, 42.38 | 2011 - 2014 | DBF | medium fET | 14.52 | 328 |
| **IT-Col** | 13.59, 41.85 | 1996 - 2014 | DBF | medium fET | 6.95 | 789 |
| **IT-Cpz** | 12.38, 41.71 | 1997 - 2009 | EBF | medium fET | 15.54 | 757 |
| **IT-Lav** | 11.28, 45.96 | 2003 - 2014 | ENF | high fET | 6.79 | 502 |
| **IT-Noe** | 8.15, 40.61 | 2004 - 2014 | CSH | low fET | 15.85 | 748 |
| **IT-Ren** | 11.43, 46.59 | 1998 - 2013 | ENF | high fET | 3.98 | 664 |
| **IT-Ro2** | 11.92, 42.39 | 2002 - 2012 | DBF | medium fET | 14.54 | 380 |
| **IT-SR2** | 10.29, 43.73 | 2013 - 2014 | ENF | medium fET | 14.02 | 888 |
| **IT-SRo** | 10.28, 43.73 | 1999 - 2012 | ENF | medium fET | 14.02 | 888 |
| **IT-Tor** | 7.58, 45.84 | 2008 - 2014 | GRA | medium fET | 1.56 | 1317 |
| **NL-Loo** | 5.74, 52.17 | 1996 - 2013 | ENF | medium fET | 9.38 | 839 |
| **RU-Fyo** | 32.92, 56.46 | 1998 - 2014 | ENF | medium fET | 4.51 | 693 |
| **US-AR2** | -99.6, 36.64 | 2009 - 2012 | GRA | low fET | 14.22 | 600 |
| **US-ARb** | -98.04, 35.55 | 2005 - 2006 | GRA | high fET | 15.29 | 793 |
| **US-ARM** | -97.49, 36.61 | 2003 - 2012 | CRO | medium fET | 14.90 | 861 |
| **US-Blo** | -120.63, 38.9 | 1997 - 2007 | ENF | high fET | 11.04 | 1510 |
| **US-Los** | -89.98, 46.08 | 2000 - 2014 | WET | high fET | 4.12 | 833 |
| **US-MMS** | -86.41, 39.32 | 1999 - 2014 | DBF | high fET | 11.13 | 1097 |
| **US-Ne1** | -96.48, 41.17 | 2001 - 2013 | CRO | high fET | 10.24 | 799 |
| **US-Ne2** | -96.47, 41.16 | 2001 - 2013 | CRO | medium fET | 10.21 | 799 |
| **US-Ne3** | -96.44, 41.18 | 2001 - 2013 | CRO | high fET | 10.20 | 793 |
| **US-SRG** | -110.83, 31.79 | 2008 - 2014 | GRA | low fET | 17.57 | 537 |
| **US-SRM** | -110.87, 31.82 | 2004 - 2014 | WSA | low fET | 18.53 | 459 |
| **US-Syv** | -89.35, 46.24 | 2001 - 2014 | MF | high fET | 3.76 | 844 |
| **US-Ton** | -120.97, 38.43 | 2001 - 2014 | WSA | low fET | 16.14 | 656 |
| **US-Var** | -120.95, 38.41 | 2000 - 2014 | GRA | low fET | 16.20 | 639 |
| **US-WCr** | -90.08, 45.81 | 1999 - 2014 | DBF | high fET | 4.23 | 828 |

**Methods**

**Methods S1** Extended description of data processing, deep learning models and GLDAS product.

## 1 Data processing

In accordance with previous studies, we filtered the data to reduce biases in ET prediction (Li et al., 2019b; Liu et al., 2022; 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., 2019b). We further removed data with relative humidity higher than the 95% quantile to exclude the impact of dew evaporation on ET (Knauer et al., 2018). Please note that this is a simplification, given that dew formation is technically associated with cooler surface temperature compared to air temperature. However, this filter, together with the filter below on shortwave radiation, should be robust enough to exclude conditions with dewfall. 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.

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 (soil moisture >> ET − P or soil moisture << ET − P) calculated using precipitation and latent heat flux, from the same FLUXNET2015 database.

## 2 Derivation of the soil moisture threshold

The threshold to divide data into ‘moist’ and ‘dry’ days was determined by building site-specific models for a sequence of soil moisture thresholds. The sequence of thresholds was sampled from 0.1 to 0.7 with an increment of 0.05. 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. The method was only applied for sites where sufficient data above and below the soil moisture threshold were available.

## 3 Hyperparameter tuning of the deep neural networks

The site-specific 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). Before training the machine learning models, we excluded all NAs and centered and scaled all variables with the R package ‘caret’ (Kuhn 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.

In hyperparameter tuning, 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. This function stopped the training process should the validation loss not improve after five epochs. This limited the number of training epochs and avoided overfitting. We ran hyperparameter tuning for a subset of 5% of the total hyperparameter combinations. We then retained five sets of hyperparameters that achieved the lowest validation loss. Among the five models with the lowest validation loss, we chose the simplest model (i.e., the model with the lowest number of total features). We repeated this procedure for every site.

Once we had defined the site-specific set of hyperparameters, we trained the feed-forward DNNs performing a five-fold cross-validation, with a 75%-25% split between training and testing 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.

## 4 Gap-filling of ET for the calculation of the cumulative water deficit

We gap-filled ET based on site-specific 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 packages ‘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. We only used the gap-filled ET to calculate the CWD. Note that this single hidden layer neural network used for gap filling ET is different from the DNN model defined in section 1 of Methods S1. We trained the DNN model with the ET timeseries cleaned as described in section 2.2 with no additional gap-filling.

## 5 The GLDAS\_NOAH025\_3H\_2.1 product

We downloaded precipitation (variable ‘Rainf\_tavg’), ET (variable ‘Evap\_tavg’) and PET (variable ‘Rainf\_tavg’) estimates of the GLDAS\_NOAH025\_3H\_2.1 product from the NASA Global Land Data Assimilation System Version 2 (GLDAS-2), which provides data from 2000 to present (Beaudoing et al., 2020; Rodell et al., 2004). Consistently with our processing of FLUXNET2015 data, we calculated daily averages and removed negative ET and PET values (see section 2.2. of Methods and section 1 of Methods S1). The GLDAS\_NOAH025\_3H\_2.1 product is a GLDAS simulation using the Noah land surface model version 3.6. Since GLDAS is an offline land surface modeling system, GLDAS\_NOAH025\_3H\_2.1 is not coupled to an atmospheric model (Beaudoing et al., 2020; Rodell et al., 2004). Instead, the Noah 3.6 model within GLDAS uses meteorological forcings (e.g. precipitation, temperature), obtained from reanalysis and satellite sources, to predict surface energy fluxes including ET (Ek et al., 2003). Noah 3.6 describes ET as the sum of transpiration from the plant canopy, direct evaporation of soil water from the uppermost soil layer, and direct evaporation of canopy-intercepted water. These components are determined based on the evaluation of a single surface energy budget for a specific model gridbox (Chen et al., 1996). To calculate soil moisture stress effects on ET, the model scales the soil moisture content based on the maximum water-holding capacity and the wilting point, which are specified per soil type (Chen et al., 1996). In particular, Noah uses an empirical non-linear soil moisture stress function, enabling the sustenance of base evapotranspiration levels even beyond the wilting point, while simultaneously decreasing evapotranspiration rates when the soil moisture approaches its field capacity (Chen et al., 1996). As detailed in chapter 3.1.2 of Chen et al., 1996, within the Oregon State University model (part of Noah 3.6), the empirical soil moisture stress function is used to calculate canopy resistance, which is a multiplier of canopy evapotranspiration. The soil moisture stress function is formulated as (from Eqn 14 of Chen et al., 1996):

Where is the empirical soil moisture stress function comprised between 0 and 1, is the volumetric soil water content (fraction of unit soil volume occupied by water) at the *i*th soil layer, 0.11 and 0.27 are empirically determined coefficients, is the *i*th soil layer thickness, and and represent the thickness of the two soil layers between which canopy transpiration is partitioned in the model’s representation of soil moisture.

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