

Uncovering the critical soil moisture thresholds of plant water stress for European ecosystems

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Abstract

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88 Understanding the critical soil moisture (SM) threshold (θ_{crit}) of plant water stress and land surface energy partitioning is a basis to evaluate drought impacts and improve models for predicting future ecosystem condition and climate. Quantifying the θ_{crit} across biomes and climates is challenging because observations of surface energy fluxes and SM remain sparse. Here, we used the latest database of eddy covariance measurements to estimate θ_{crit} across Europe by evaluating evaporative fraction (EF)-SM relationships and investigating the covariance between vapor pressure deficit (VPD) and gross primary production (GPP) during SM dry-down periods. We found that the θ_{crit} and soil matric potential threshold in Europe are 16.5% and -0.7 MPa, respectively. Surface energy partitioning characteristics varied among different vegetation types; EF in savannas had the highest sensitivities to SM in water-limited stage, and the lowest in forests. The sign of the covariance between daily VPD and GPP consistently changed from positive to negative during dry-down across all sites when EF shifted from relatively high to low values. This sign of the covariance changed after longer period of SM decline in forests than in grasslands and savannas. Estimated θ_{crit} from the VPD-GPP covariance method match well with the EF-SM method, showing this covariance method can be used to detect the $\theta_{\text{crit}}.$ We further found that soil texture dominates the spatial variability of θ_{crit} while shortwave radiation and VPD are the major drivers in determining the spatial pattern of EF sensitivities. Our results highlight for the first time that the sign change of the covariance between daily VPD and GPP can be used as an indicator of how ecosystems transition from energy to SM limitation. We also characterized the corresponding θ_{crit} and its drivers across diverse ecosystems in Europe, an essential variable to improve the representation of water stress in land surface models.

Keywords: critical soil moisture threshold, surface energy partitioning, vapor pressure deficit, evaporative fraction, gross primary production, drought, Europe

The critical soil moisture (SM) threshold of plant water stress is the point when evapotranspiration starts to decrease due to the SM deficit (Feldman *et al.*, 2019, Seneviratne *et al.*, 2010). Below this threshold, exhaustion of SM leads to reduced evapotranspiration and increased partitioning towards sensible heat flux due to higher surface temperatures that lead to drier air and an increase in the vapor pressure deficit (VPD), which impairs important ecosystem functions like carbon dioxide uptake (Betts, 2004, Gentine *et al.*, 2019, Granier *et al.*, 2007, Seneviratne *et al.*, 2010). SM therefore plays a crucial role in partitioning of available between latent and sensible heat fluxes from the land surface (Schwingshackl *et al.*, 2017). This energy partitioning determines local climate and influences the terrestrial component of land-atmosphere coupling (Santanello Jr *et al.*, 2018). Thus, it is imperative to quantify the critical SM thresholds (θ_{crit}) of plant water stress and surface energy partitioning characteristics for evaluating the drought impacts on ecosystem function and improving models to predict future climate accurately.

The evaporative fraction (EF) is the ratio of latent heat flux to the sum of latent and sensible heat fluxes, and EF-SM relationships are commonly used to quantify θ_{crit} and surface energy partitioning characteristics (Budyko, 1974, Koster *et al.*, 2009, Seneviratne *et al.*, 2010). SM directly limits evapotranspiration under SM-limited conditions, which increase surface temperature at a given level of net radiation, driving a positive land-atmosphere climate feedback (Betts, 2004, Gentine *et al.*, 2019, Seneviratne *et al.*, 2010). At higher SM availability, the system is considered energy limited as more moisture does not necessarily lead to greater evapotranspiration, and the strength of the water, carbon, and energy cycle coupling is subdued (Feldman *et al.*, 2019, Pendergrass *et al.*, 2020). Evapotranspiration is at or near its potential value where net radiation and atmospheric resistance are instead limiting. This EF-SM framework is well established (Fig. 1) but quantifying the θ_{crit} that determines the transition from energy to water-limited regimes across biomes and climates is challenging because surface energy fluxes and SM observations remain sparse (Baldocchi *et al.*, 2004,

Budyko, 1974, Feldman *et al.*, 2019, Koster *et al.*, 2009). The extreme drought events that help quantify θ_{crit} are, by definition, rare, and often require long observational time series.

142 Attempts have been made to characterize these different evapotranspiration regimes at 143 sub-monthly scales using satellite greenness data and air temperature globally (Zscheischler et 144 al., 2015), for North America (Short Gianotti et al., 2019), and on weekly scales for Africa 145 using satellite remote sensing data of the diurnal amplitude of the land surface temperature 146 and surface soil moisture (Feldman et al., 2019). These studies did not investigate the role of 147 VPD, but recently, both observations and models showed that VPD increases tend to reduce 148 gross primary production (GPP) across a large range of SM conditions, whereas the reduction 149 of SM only reduces GPP below a critical SM threshold (Green et al., 2019, Grossiord et al., 150 2020, Kimm et al., 2020). GPP and evapotranspiration are tightly coupled on short time 151 scales (Gentine *et al.*, 2019), and we argue that the sign of the covariance between daily VPD 152 and GPP can be an indicator of the relative strength between the water and energy limitation 153 on ecosystem function. This is because VPD combines the effects of both water and enthalpy 154 (via temperature) on GPP (Grossiord et al., 2020, Kimm et al., 2020, Novick et al., 2016). 155 GPP is positively related to radiation under energy-limited regimes (Fig. 1), and positively 156 correlated with SM under water-limited regimes (Gentine et al., 2019, Seneviratne et al., 157 2010). However, it is unknown if the sign change of covariance between daily VPD and GPP 158 is also an effective metric to a describe surface energy partitioning characteristics between 159 water- and energy-limited regimes, and vice versa.

160 The dry-down periods following rainfall, i.e., long periods without rainfalls when soil 161 moisture decreases (Akbar et al., 2018, Feldman et al., 2018, Feldman et al., 2019), provide a 162 natural experiment for us to evaluate the EF-SM relationships and investigate how the sign of 163 the covariance between daily VPD and GPP changes as SM declines and ecosystems shift 164 from energy to water-limited states. During the course of a dry-down, an ecosystem with θ_{crit} 165 will transition from a regime during which higher VPD is driven by incoming radiation which 166 increases GPP, to another regime where SM reductions increase VPD but reduce GPP. During 167 a SM dry-down, there is generally an initial period of GPP increase due to available SM after

rainfall if the ecosystem is already water limited before the dry-down counting started, and is followed by a decline (Fig. 1); but VPD keeps increasing if the incoming solar radiation (RAD) remains stable, e.g., in the presence of anticyclonic conditions (Feldman *et al.*, 2020). During the initial increasing GPP period, energy-limitation (e.g., photosynthetically active radiation or temperature) is the major driver of GPP while SM becomes a key limiting factor during the following GPP decreasing stage (Seneviratne *et al.*, 2010). However, the relationships between VPD and GPP in these two different stages may be different. We hypothesize that the covariance between daily VPD and GPP can be used to detect these two regimes during dry-downs, i.e., one regime with energy limiting conditions (positive covariance) and one regime with water limiting conditions (negative covariance).

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178 During a dry-down, EF first remains constant but then decreases when SM becomes 179 lower than a given threshold (Fig. 1). The EF–SM relationship is characterized by a transition 180 point in SM separating the water and energy-limited regimes (Koster et al., 2009, Seneviratne 181 et al., 2010). There is limited opportunity to test the appearance of SM limitations during dry 182 episodes across a wide diversity of biomes and climates because EF-SM relationships are 183 infrequently characterized due to the challenge of directly measuring surface energy fluxes 184 and SM across sites (Baldocchi et al., 2004, Budyko, 1974, Feldman et al., 2019, Koster et al., 185 2009). To our knowledge, there is no observation-based assessment of the transition point of 186 SM between demand and soil water supply limitation across Europe. Even less is known 187 about the controlling factors and mechanisms in determining the θ_{crit} across diverse 188 ecosystems. Climate models, on the other hand, rely on a parametric representation of SM-189 evaporation relationships to describe associations between water and energy cycles and 190 predict future climate. However, due to difficulty in observing EF at large scales to constrain 191 model results, and the lack of model simulation output at daily or hourly time steps, these 192 relationships take different forms across climate models which contribute to divergences and 193 uncertainty in making climate projections (Dirmever et al., 2006, Feldman et al., 2019, 194 Schwingshackl et al., 2017).

195 The recently released ICOS (Integrated Carbon Observation System network of eddy 196 covariance observations)(Centre, 2019) dataset with continuously measured CO₂, water vapor, 197 and energy fluxes in Europe allows more direct observations of EF-SM relationships over 198 various biomes and climates. Further, this dense network provides a unique opportunity to 199 evaluate EF-SM relationships and change in the covariance between VPD and GPP during 200 dry-downs. In recent years, Europe has experienced a series of extreme summer drought and 201 heat events (e.g., 2003, 2010, 2015 and 2018), each characterized by record-breaking climate 202 anomalies and extensive dry-down periods (Bastos et al., 2020a, Bastos et al., 2020b, Fu et 203 al., 2020). We can thus investigate the surface energy partitioning-SM relationship during 204 these dry-downs (episodes with no rain for several consecutive days (Fig. 1)) where SM 205 shows a short term rise after rain and then decreases until the next rain event. There were 206 many 'dry-down' periods with no rain in Europe in recent years that can be used to detect the 207 critical moisture value at the onset of water stress.

208 Focusing on SM dry-downs, this study uses the latest eddy covariance measurements 209 from ICOS to quantify θ_{crit} across Europe and test the hypothesis that the sign change of 210 covariance between daily VPD and GPP can be used to detect θ_{crit} . By evaluating the EF-SM 211 relationships, we first quantify θ_{crit} values and the EF sensitivity to SM in the water-limited 212 regime. Then, we investigate the changes of covariance between daily VPD and GPP during 213 SM dry-downs and quantify θ_{crit} values with this second approach, which are compared with 214 the θ_{crit} from the first approach. Last, we explore what factors drive the spatial variability of 215 θ_{crit} and EF sensitivity to SM.

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217 2. Materials and Methods

218 2.1 Datasets

We used half-hourly SM, VPD, GPP, precipitation, latent heat flux, sensible heat flux and incoming shortwave radiation from the recently released ICOS (Integrated Carbon Observation System) dataset (Centre, 2019). ICOS includes 52 eddy covariance sites in Europe with energy, water, carbon fluxes and meteorological data, which were processed

following a consistent and uniform processing pipeline (Pastorello *et al.*, 2020). We selected 31 sites with measurements for all above variables, including 22 forests, 5 grasslands, 3 savannas and 1 shrubland (Table S1). Savanna sites include both trees and grasses and in our case are found in Mediterranean climate zones (El-Madany *et al.*, 2020, Luo *et al.*, 2018, Luo *et al.*, 2020). Croplands were excluded due to the effect of management on the seasonal timing of ecosystem fluxes, both from crop rotations and from the varying timing of planting and harvesting. Wetland sites were also removed because they have a high water table and infrequently show soil moisture limitations.

231 SM was measured as volumetric soil water content (percentage) at different depths, 232 varying across sites. Surface SM (SM 1: 0-5 cm) was measured at all sites and some sites 233 also provided deeper SM measurements (e.g., SM 2: 5-20 cm; SM 3: 20-60 cm). We mainly 234 used the surface SM observations but deeper SM measurements were also used when 235 available. GPP estimates from the night-time partitioning method were used for the analysis 236 (Reichstein et al., 2005). Data were quality controlled so that only measured and good-quality 237 gap filled data (QC = 0 or 1) were used. Daytime half-hourly data (9 am to 16 pm local 238 standard time) were averaged to daily values while SM values were averaged over the full day. 239

Measured soil texture, mean annual precipitation, summer average of VPD, incoming shortwave radiation and wind speed data at each site were also used to understand the drivers in determining the spatial variability of θ_{crit} and EF sensitivity to SM in water-limited stage.

243 2.2 Soil moisture dry-down identification

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Dry-downs following rainfall are episodes with no rain for several consecutive days during which SM shows a short term 'pulse' rise after rain and then decays until the next rain event. A dry-down is retained for our analysis when SM decreases consecutively for at least 10 days after rainfall (Akbar *et al.*, 2018, Feldman *et al.*, 2018, McColl *et al.*, 2017, Shellito *et al.*, 2018). Days with intermittent rainfall are excluded. We focused on the soil dry-downs during the summer (June–July–August) season for all available site-years. This resulted in 428 drydown events that form the basis of our study.

2.3 Critical SM threshold and evaporative fraction sensitivity to SM estimation

We calculated the daily evaporative fraction (EF) as the ratio of observed latent heat flux to the sum of latent and sensible heat fluxes during each soil dry-down. Then, we characterized the EF-SM relationship at each site using all available soil dry-downs, from a regression between these two variables with a linear-plus-plateau model:

$$EF = \begin{cases} a + b(SM - c) & \text{if } SM < \theta_{crit} \\ a & \text{if } SM \ge \theta_{crit} \end{cases}$$

8 where *a* is the maximum value of EF in absence of SM stress (energy-limited stage), *b* 9 represents the slope of the linear increase phase (water-limited stage), and *c* is the critical SM 1 threshold. These three parameters were simultaneously estimated by least squares fit with the 1 R software package 'nlstools' (Baty *et al.*, 2015) for each site, leading to site-specific 2 estimated values of peak EF, slope and θ_{crit} . θ_{crit} is the breakpoint until which EF increases 3 linearly as a function of SM (Figs. 1 and S1). The slope represents the EF sensitivity to SM in 4 the water-limited regime, indicating the magnitude of EF increase for each additional 1% 5 change in SM when SM is below its breakpoint. The plateau is the maximum EF value 6 reached when SM exceeds its threshold. The time spent in the water - limited stage was 7 computed as the ratio of the number of days with SM<threshold divided by the total duration 8 of the dry down as in Feldman *et al.* (2019). SM threshold values were converted to soil 9 matric potentials using soil retention curves and soil texture data (Table S1) (Gourlez de la 9 Motte *et al.*, 2020, Granier *et al.*, 2007, Marthews *et al.*, 2014).

There were 23, 16 and 12 sites with the critical SM threshold estimates based on the first (SM_1), second (SM_2), and third (SM_3) soil water content measurement depth (Figs. S1-3), respectively. For the rest of sites, it was not possible to estimate a SM threshold using the EF-SM relationship because samples were too infrequent, deep SM measurements were missing, or there were no thresholds.

2. 4 Covariance between daily VPD and GPP during dry-down

278 We also calculated the covariance between daily VPD and GPP across nine-day moving

279 windows during the dry-down (e.g., 1-9 days; 2-10 days; 3-11 days...). A positive covariance 280 indicates that higher VPD is associated with increases of GPP (which we term 'radiation 281 effects') while a negative covariance indicates that water stress limits GPP, i.e., with a higher 282 VPD caused by dryer soils results in a lower GPP. Here, we excluded some short dry-downs 283 because their covariances during the dry-down are all positive or negative, suggesting the 284 entire dry-down period is under energy-limited or water-limited stage. We only chose the 285 long soil dry-downs with at least 15 days (with at least 7 covariance values) and their 286 covariances must include both positive and negative values to see if the change of covariance 287 signs corresponds to the ecosystem transition from energy-limited into water-limited regime.

288 The evolution of covariance with moving window days during the dry-down periods 289 allowed us to evaluate the joint variability of daily VPD and GPP change. Across all soil dry-290 downs, the median value of the VPD-GPP covariance was calculated for equal bins of 1 day 291 change to identify the timing when the sign of covariance will change. Similar to the 292 covariance, the average of SM during the moving window (e.g., 1-9 days; 2-10 days; 3-11 293 days...) were also calculated to detect the critical SM threshold when the sign of covariance 294 changes. The correlation of Pearson and Spearman and their associated test were performed to 295 compare the θ_{crit} values from this covariance method with the EF-SM method.

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297 2.5 Drivers of the spatial variability of critical SM thresholds and EF slopes

298 We evaluated the relative importance of soil texture, mean annual precipitation, summer 299 average VPD, incoming shortwave radiation and wind speed in determining the spatial 300 variability of θ_{crit} and EF sensitivities to SM. We used a relative importance analysis approach 301 to quantify the relative contributions of each factor to the SM thresholds or EF slopes, 302 expressed as the Pearson correlation in a multiple linear regression (SM thresholds (or EF slopes)= $b_0 + b_1 \times MAP + b_2 \times Clay \text{ fraction} + b_3 \times VPD + b_4 \times radiation + b_5 \times wind + \varepsilon$). ε 303 304 represented other drivers that were not considered but might contribute to the variability of 305 SM thresholds or EF slopes. The algorithm was implemented with the 'relaimpo' package in 306 R (Grömping, 2006), which is based on variance decomposition for multiple linear regression

models. The 'relaimpo' package provides six different methods for analyzing the relative importance of each regressor in linear regression. We used 'LMG' to quantify the contribution of different correlated regressors in a multiple linear regression (Huang *et al.*, 2018). The LMG method estimates the relative importance (RI) of each variable by decomposing the sum of squares into non-negative contributions shared by each variable, and the LMG values were obtained by averaging the sequential sum of squares (r^2) for all possible orders. Finally, all RI values were normalized (divided by r^2) to sum to 1. We also repeated this analysis using the available energy (AE, the difference between net radiation and soil heat flux) instead of the incoming shortwave radiation to evaluate the relative role of AE.

3. Results

3.1 Surface energy partitioning characteristics and critical SM threshold of plant stress

EF behavior during all dry-downs within each vegetation type is plotted together in Figure 2. The general behavior is in line with that shown in Figure 1. Temperate grasslands and Mediterranean savannas showed stronger EF–SM coupling (greater slope) at low soil moisture values than boreal and temperate forests. The available energy is increasingly partitioned towards sensible heat flux with decreasing SM during the water-limited regime.

The surface SM thresholds (using SM_1) is highly correlated with the SM thresholds observed in deeper soil layers (using SM_2 and SM_3) (Fig. S4). As surface SM measurements are available at all sites, we focused on surface SM thresholds. Across all sites, we found that the critical SM threshold in Europe is $16.5 \pm 7.5\%$ (median \pm SD, Fig. 3a). Temperate grasslands ($27.0 \pm 10.6\%$) had higher SM thresholds than temperate forests ($16.5 \pm 5.5\%$) and Mediterranean savannas ($13.0 \pm 1.6\%$, Fig. 3c). We also found that the soil matric potential threshold in savannas (-1.22 ± 0.21 MPa) is more negative than in forests (-0.64 ± 0.45 MPa) and grasslands (-0.37 ± 0.49 MPa, Fig. 3c). Overall, we estimated that the critical soil matric potential threshold across all sites in Europe is -0.71 ± 0.46 MPa (Fig. 3b).

334 The sensitivities (slopes) of EF to SM, time spent in water-limited stage, and the peak 335 EFs are different among vegetation types (Fig. 4). Across all sites, EF decreased by 0.03 per 1% 336 SM decrease (Fig. 4a). Savannas showed a higher sensitivity of EF to SM (slope 0.05 ± 0.02) 337 than forests (slope 0.03 ± 0.02). We further found that the time spent in water-limited stage in 338 savannas ($82.9 \pm 9.7\%$ of all dry-down durations) was nearly two times as long as in forests 339 $(44.0 \pm 24.1\%)$; across all European sites, it was about $48.3 \pm 27.0\%$ of the dry-down period 340 duration (Fig. 4b). However, the peak EF in energy-limited stage in forests (0.5 ± 0.1) tended 341 to be higher than in savannas $(0.4 \pm 0.1, \text{Fig. 4c})$.

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3.2 Covariance between daily VPD and GPP during SM dry-down

344 As an alternative to the EF-SM relationships, the change in the sign of the covariance 345 between daily GPP and VPD during dry-down was used to detect the critical SM threshold. 346 To explore the dynamics of the VPD-GPP relationships during dry-down, we first illustrated 347 the changes in the covariance of daily GPP and VPD during a long soil moisture dry-down at 348 CH-Cha (grassland, Figs.5a, b), as well as the coincident changes in surface energy 349 partitioning–SM relationship (Fig. 5c). Both the original data and moving average data found 350 that daily GPP first increases but then decreases during the dry-down while daily VPD 351 increases steadily (Fig. 5a). The sign of covariance between daily VPD and GPP changed 352 from positive into negative around a SM threshold of 35% for this example (Fig. 5b). The 353 positive covariances suggested that positive radiation effects (VPD-radiation coupling) on 354 GPP are stronger while negative covariances showed that SM limiting effects on GPP are 355 stronger (VPD-SM coupling). The EF-SM relationship showed that the EF values remain 356 relatively high (about 0.75) at high SM (35-55%); however, under low SM (<35%), EF and 357 SM were positively related in the interval during which reduced SM lowers EF (Fig. 5c). 358 These observations are consistent with the notion that the ecosystem shifted from an energy-359 limited regime to a water-limited regime during this dry-down such that the sign of 360 covariance between daily VPD and GPP was related to surface energy partitioning. Another 361 example in a forest site, DE-Hzd, yielded similar results (Fig. S5).

362 We also examined the covariance between daily VPD and GPP for all soil dry-downs 363 (Fig. 6). All covariances consistently changed their signs from positive to negative during the 364 dry-down (Fig. 6a). We found that the median values of covariances across all dry-downs 365 revealed that the breakpoint often occurs around the 4th moving window (the covariance is 366 calculated using 9-day moving window, e.g., 1-9 days; 2-10 days; 3-11 days...). The changed 367 covariance signs are also found in different vegetation types consistently (Figs. 6b-d). The 368 timing of the breakpoint in forests (5th moving window, Fig. 6b) is larger than in grasslands (3rd moving window, Fig. 6c) and savannas (2nd moving window, Fig. 6d), suggesting that it 369 370 takes longer for the VPD-GPP covariance sign to change from positive to negative in forests 371 compared to grasslands and savannas. As the savanna sites have Mediterranean climate and 372 the peak growing season is mainly in spring (El-Madany et al., 2020, Luo et al., 2018, Luo et 373 al., 2020), we performed the same analysis using both spring and summer and obtained 374 similar results that the breakpoint in savannas is reached in shorter time than in forests (Fig. 375 S6).

376 Combining the SM data for each dry-down (Figs. 6e-h), we then quantified the critical 377 SM thresholds when the VPD-GPP covariance sign change at each site. We found that the θ_{crit} 378 estimated from the new covariance method match well with the EF-SM method (r=0.86, Figs. 379 6i-j). Compared with the θ_{crit} estimated from the EF-SM method, our results showed that the 380 VPD-GPP covariance method has potential to detect the critical moisture thresholds, although 381 the absolute magnitude of SM thresholds estimated from covariance method are a bit higher 382 than that of EF-SM methods (Figs. 6i-j).

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384 3.3 Drivers of the spatial variability of SM thresholds and EF slopes

The multiple linear regression model showed that the five factors studied (mean annual precipitation, clay fraction, summer VPD, incoming shortwave radiation and wind speed) can explain 74% and 65% of the spatial variability of SM thresholds (Fig. 7a) and EF sensitivities (Fig. 7b), respectively. However, the dominant predictors of the spatial variability of SM thresholds and reduction rates of EF were different. For the spatial variability of SM

390 thresholds, soil texture was the most important factor, and its relative importance was 76% 391 comparing with the other four factors (Fig. 7a), and clay fraction alone explained 65% of the 392 variability across all sites. For the spatial variability of reduction rates of EF, climate factors, 393 such as incoming shortwave radiation and VPD, were the major drivers, with relative 394 importance up to 53% and 26%, respectively (Fig. 7b). The same analysis using the available 395 energy (AE, the difference between net radiation and soil heat flux) instead of the incoming 396 shortwave radiation obtained similar results (Fig. S7). AE played an important role in 397 determining both the spatial variability of θ_{crit} (17%) and EF sensitivities (52%, Fig. S7).

399 4. Discussion

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400 Current water stress indicators typically hinge on the accuracy of evapotranspiration data, a 401 flux that is very difficult to measure globally and is often estimated with assumptions, thus 402 leading to high degrees of uncertainty (Wang & Dickinson, 2012). To our knowledge, we 403 demonstrate for the first time that the covariance between daily VPD and GPP changes its 404 sign from positive to negative during SM dry-downs as ecosystems transition from energy-405 limited regimes to water-limited regimes. Our results suggest that the sign of covariance 406 between daily VPD and GPP can capture shifts in the surface energy partitioning 407 characteristics and therefore has potential to be a new indicator of ecosystem water stress. For 408 global remote sensing data products, it becomes possible to have reasonable GPP products, 409 e.g., based Near-Infrared Reflectance of vegetation (NIR_v) (Badgley et al., 2017), normalized 410 difference vegetation index (NDVI) (Myneni et al., 1997), enhanced vegetation index (EVI) 411 (Huete et al., 2002) and daily FLUXCOM data (Jung et al., 2017, Tramontana et al., 2016), 412 and VPD is computed from directly observed temperature and relative humidity, whereas 413 global evapotranspiration products differ between datasets and are arguably more uncertain 414 (Badgley et al., 2015, Bai & Liu, 2018). Our covariance method provides a new option and 415 an independent tool to quantify the critical SM threshold and detect surface energy 416 partitioning characteristics over large regions, which we hope will be helpful to uncover the 417 SM thresholds of plant water stress at regional and global scales. One advantage of the

418 covariance indicator is that, from a remote sensing perspective, spatially resolved VPD and
419 GPP products have much lower levels of uncertainty than evapotranspiration products.
420 Another is that the type of stress is directly related to GPP, i.e., carbon uptake, and not only
421 indicative for stomatal conductance and transpiration.

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Although the critical SM thresholds estimated from VPD-GPP covariance method match well with the EF-SM method, we found that the absolute magnitude of SM thresholds estimated from the VPD-GPP covariance method are a bit higher than the EF-SM method (Figs. 6i-j), which may result from two reasons. First, the covariance method calculated the covariance and mean SM values using nine-day moving windows. The average values of SM across the window could lead to the difference of SM thresholds between the VPD-GPP covariance method and EF-SM method. Second, the eddy covariance evapotranspiration analysis measures not only plant transpiration but also soil evaporation (though it is often small) (Stoy *et al.*, 2019), which may also contribute to the differences found between approaches. To get a more plant-related estimate of the critical SM threshold, the response of plant functioning (GPP and transpiration) with atmospheric stress (VPD) under given soil moisture conditions needs to be taken into account.

434 The timing when the sign of the covariance between VPD and GPP changes from 435 positive to negative varies across vegetation types. Forests need more time for the sign of this 436 relationship to change after rain events than grasslands and savannas, showing that there is a 437 longer time during which VPD-radiation coupling is stronger than VPD-SM coupling in 438 forests compared to grasslands and savannas during SM dry-downs. The water storage in soil 439 and plants after rainfall in forests can be larger than in grasslands because forests have deeper 440 roots and access to moisture in deeper soils (Chapin III et al., 2011, Fan et al., 2017). Forests 441 often have stronger resistance to drought than grasslands and savannas (Konings & Gentine, 442 2017, Martínez-Vilalta & Garcia-Forner, 2017, Teuling et al., 2010), thus GPP rates are 443 maintained for a longer time after rainfall in forests.

The surface energy partitioning-SM relationship showed that grasslands and savannas
had stronger EF–SM coupling (slope) at low soil moisture values than that of forests (Figs. 2

446 and 4a). Grasslands have shallow roots and are more sensitive to SM decrease, leading to 447 abrupt drought, while forests have deep roots, access to deep soil water, and less sensitive to 448 surface soil moisture changes. The high sensitivity of EF to SM in water-limited periods in 449 grasslands and savannas will accelerate soil moisture depletion and quickly lead to large 450 water constraints on photosynthesis (El-Madany et al., 2020, Luo et al., 2018, Luo et al., 451 2020). The low sensitivity of EF to SM in forests is in line with our findings from covariance 452 analysis that showed it takes longer for the VPD-GPP covariance sign to change from positive 453 to negative in forests compared to grasslands and savannas, further supported the strong 454 resistance of forests to drought (Konings & Gentine, 2017, Teuling et al., 2010). We also 455 found that incoming shortwave radiation and VPD are the major drivers in determining the 456 spatial variability of EF sensitivity to SM, indicating that high radiation and VPD will 457 increase the sensitivity of EF to SM in water-limited stage. This will likely cause EF 458 sensitivity to increase in the future because increased exposure of plants to higher VPD from 459 warming and drier continental relative humidity is inevitable and widespread in future (Byrne 460 & O'Gorman, 2018, Novick et al., 2016).

461 Consistent with previous findings from satellite observations in Africa (Feldman et al., 462 2019), our results showed that savannas spend more time in the water-limited regime, but we 463 found that forests also spend almost 50% of the time in the water-limited regime, suggesting 464 that European forest ecosystems are exposed to drought. This time fraction spent in the water-465 limited regime may further increase in future with anthropogenic warming (Naumann et al., 466 2021), leading to greater drought damages in Europe. We also found that grasslands spend 467 more than 70% of the time in the energy-limited regime because these grassland sites are 468 mainly located in the northern Europe, which are limited by energy due to the high latitudes 469 or altitudes. Under energy-limited stage, the peak EF in grasslands was up to 0.79 (Fig. 4c), 470 indicating that grasslands allocate more energy for evaporative cooling, which suppresses 471 surface heating (Teuling et al., 2010).

472 Across all sites in Europe, our results showed that the critical SM threshold is 16.5% (Fig.
473 5), which is slightly higher than the value found in Africa (14%) using a different method

474 (Feldman et al., 2019) and an oak-grass savanna (15%) and an annual grassland (15%) in US 475 (Baldocchi et al., 2004). At the European sites, we found that soil texture is the most 476 important determining factor in controlling the spatial variability of SM thresholds (Fig. 7a), 477 which is in line with previous findings in Africa (Feldman et al., 2019) and the US (Akbar et 478 al., 2018), based on satellite data. We also converted the SM thresholds into soil matric 479 potentials, and found that the soil matric potential threshold in Europe is about -0.71 MPa. 480 The soil matric potential threshold in savannas is more negative than in forests and grasslands. 481 When we focused on the forest sites in Europe, we found that the soil matric potential 482 threshold is -0.64 MPa, which is very close from the -0.66 MPa value found by Granier et al. 483 (2007) across six forest ecosystems. We noted that the EF-SM relationship can be affected by 484 other factors, such as radiation and albedo (Haghighi et al., 2018). While several other factors 485 limit evapotranspiration besides soil moisture and the linear dependency is a simple 486 approximation, recent studies have highlighted that this EF-SM framework provides a good 487 first-order representation of regimes of land-atmosphere coupling, both in models and 488 observations (e.g., Koster et al. (2004a); Koster et al. (2004b); Seneviratne et al. (2006); 489 Teuling et al. (2006)). Here we provided a comprehensive analysis across representative 490 European ecosystems.

492 **5.** Conclusions

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493 Using a new database of flux tower observations across Europe, this study uncovered the 494 critical SM threshold and surface energy partitioning characteristics by evaluating EF-SM 495 relationships and examining the joint variability of daily VPD and GPP during SM dry-downs. 496 We carefully studied SM dry-downs to understand how ecosystems transition from energy-497 limited regimes to water-limited regimes. EF-SM relationships quantified the critical SM and 498 soil matric potential thresholds in Europe are 16.5% and -0.7 MPa, respectively. Surface 499 energy partitioning characteristics varied among different vegetation types; EF in savannas 500 had the highest sensitivities to SM in water-limited stage while it was the lowest in forests. 501 We found the sign of covariance between daily VPD and GPP changed after a longer period

502 in forests than in grasslands and savannas. The critical SM thresholds estimated from the 503 VPD-GPP covariance method match well with that of EF-SM method, suggesting that this 504 sign of VPD-GPP covariance can be used to detect the SM threshold. We further found that 505 soil texture dominates the spatial variability of SM thresholds while incoming shortwave 506 radiation and VPD are the major drivers in determining the spatial pattern of EF sensitivities. 507 The revealed critical SM threshold and its drivers across diverse biomes and climates in 508 Europe will be beneficial to improve climate models with parametric representations of 509 drought stress. Our results highlighted, for the first time, the important role of the sign change 510 of covariance between daily VPD and GPP in monitoring the surface energy partitioning 511 characteristics and quantifying the critical SM threshold, which opens its generalized 512 application using daily GPP estimates and VPD, e.g., from remote sensing data. The new 513 covariance method demonstrated here provides a new option and an independent tool to 514 quantify critical SM threshold and surface energy partitioning, which can help solve the 515 current challenge in uncovering the SM threshold of plant water stress at regional and global 516 scales.

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528 Conflict of interest

529 The authors declare no competing interests.

Data availability

The data that support the findings of this study are openly available in ICOS at (https://doi.org/10.18160/YVR0-4898).

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685 Figure legends

686 Fig. 1 Schematic of the typical relationship between evaporative fraction (EF) and soil moisture (SM), 687 as well as the changes in daily SM, gross primary production (GPP) and vapor pressure deficit (VPD) 688 during soil moisture dry-down. We hypothesize that the covariance between daily VPD and GPP can 689 be used to detect two regimes during dry-downs, i.e., one regime with energy limiting conditions 690 (positive covariance) and one regime with water limiting conditions (negative covariance). "+" and "-" 691 represent the positive and negative correlation, respectively. RAD: incoming shortwave radiation. 692 During a SM dry-down, there is generally an initial period of GPP increase due to available SM after 693 rainfall if the ecosystem is already water limited before the dry-down counting started.

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Fig. 2 EF-SM relationships for different vegetation types. Bold lines indicate binned median values
calculated in equal SM bins of 1% increments, while shading bounds the 25th and 75th percentiles of
EF values within soil moisture bins. EF: evaporative fraction; SM: soil moisture.

Fig. 3 Probability density function of estimated critical soil moisture (SM) threshold (a) and soil matric potential threshold (b). Estimated SM threshold and soil matric potential threshold among different vegetation types (c). For each box plot, the middle line indicates the median; the box indicates the upper and lower quartiles and the whiskers indicate the 5th and 95th percentiles of the data. The numbers in brackets indicate the number of sites.

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Fig. 4 The evaporative fraction (EF) sensitivity to soil moisture (SM) (a), time fraction spent in waterlimited stage (b) and the peak EF (c) among different vegetation types in Europe. For each box plot, the middle line indicates the median; the box indicates the upper and lower quartiles and the whiskers indicate the 5th and 95th percentiles of the data. The numbers in brackets indicate the number of sites.

Fig. 5 Daily soil moisture (SM), gross primary production (GPP) and vapor pressure deficit (VPD) during a soil dry-down at CH-Cha (grassland, a). Covariance between daily VPD and GPP changes with moving windows (b), and evaporative fraction (EF) changes with SM during the dry-down (c). The unit of covariance is μ mol CO₂ m⁻² s⁻¹ hPa. The color coding in panel (c) indicate the soil moisture values. Please note that the soil moisture scale is from high to low.

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Fig. 6 Covariance between daily vapor pressure deficit (VPD) and gross primary production (GPP)
across nine-day moving window changes with moving windows after rainfall during the dry-down (ad). Mean soil moisture (SM) during moving window for each dry-down (e-h). Comparison between
the critical SM thresholds estimated from the VPD-GPP covariance method and evaporative fraction
(EF) method (i-j). Covariance and mean soil moisture were calculated using 9-day moving window
(e.g., 1-9 days; 2-10 days; 3-11 days...). Each black line represents the covariance change at each dry-

down while the red line means the median value in equal bins of 1 day change (a-d). The shading bounds the 25th and 75th percentile of the distribution of covariance within the bin (a-d). The units of covariance is μ mol CO₂ m⁻² s⁻¹ hPa.

Fig. 7 Relative importance of mean annual precipitation (MAP), clay fraction, summer average vapor
pressure deficit (VPD), incoming shortwave radiation (RAD) and wind speed to the spatial variability
of soil moisture (SM) thresholds (a) and evaporative fraction (EF) slopes (b).













