On the impact of increasing drought on the relationship between soil water content and evapotranspiration of a grassland

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Abstract
Weighable lysimeters were used to study the relation between soil water content (SWC) and the actual evapotranspiration (ETa) of grassland under two different climate regimes of Rollesbroich and Selhausen but for an identical soil from Rollesbroich. All components of the water balance were determined from 2012 until 2018. Budyko analysis was used to characterize the hydrological status of the studied sites. Wavelet analysis was also applied to study the power spectrum of ETa, vegetation-height-adjusted reference evapotranspiration (ETcrop), and water stress index (WSI) defined as ETa/ETcrop, as well as SWC at three different depths and the coherence between SWC and ETa and WSI. The Budyko analysis showed that 2018 resulted in a shift of both locations towards more water-limited conditions, although Rollesbroich remained an energy-limited system. Based on the power spectrum analysis, the annual timescale is the dominant scale for the temporal variability of ETa, ETcrop, and SWC. The results also showed that increasing dryness at the energy-limited site led to more temporal variability of SWC at all depths at the annual timescale. Wavelet coherence analysis showed a reduction of the phase shift between SWC and ETa at an annual scale caused by the increase in dryness during the measurement period. We found that phase shifts between SWC and ETa and SWC and WSI were stronger at the water-limited site than at the energy-limited site. The wavelet coherence analysis also showed that from 2014 to 2018, the control of ETa and WSI on SWC increased due to higher dryness of soil.

1 | INTRODUCTION

The interaction between soil water content (SWC) and actual evapotranspiration (ETa) plays a key role in ecohydrological and land-surface processes (Robinson et al., 2008; Scanlon et al., 2006; Wang & Dickinson, 2012; Wang, Wang, & Zhang, 2019). Although the relationship between SWC and ETa is critical for land–atmosphere coupling and management of agroecosystems, the key processes are not yet well understood (Miralles, Gentine, Seneviratne, & Teuling, 2019). Land surface energy dynamics, regional runoff dynamics, and vegetation productivity can be strongly affected by variations in SWC (Moran, Peters-Lidard, Watts, & McElroy, 2004).
particular, the effect of longer drought periods on the interaction between SWC and \( \text{ET}_a \) requires further analysis, and its improved understanding is key for sustainable management of agricultural production systems such as grass- and arable lands.

Several studies, based on observations and model predictions, pointed out the major impact of SWC on \( \text{ET}_a \) (Jung et al., 2010; Seneviratne et al., 2010; Teuling et al., 2009) across spatial scales. At a global scale, Jung et al. (2010) showed that limited soil water supply led to a decline in global land \( \text{ET}_a \). They based their analysis on meteorological observations, using remotely sensed SWC and ET measurements obtained from the global FLUXNET in combination with ensemble calculations of different land surface models. The time period that a soil, as a large reservoir, is able to remember past anomalies of SWC is considered as SWC persistence or memory (Orth, 2013). Orth and Seneviratne (2013) used data from >100 catchments across Europe to study the impact of SWC memory (persistence characteristic) on \( \text{ET}_a \) and runoff. Memory effects are typically studied using autocorrelation of observed or modeled SWC time series (McColl, He, Lu, & Entekhabi, 2019). Orth and Seneviratne (2013) found higher memory effects for monthly averaged data of SWC and ET than for daily averaged values, because the monthly aggregation takes out the daily variations of meteorological effects. They also showed that SWC memory is stronger during drying anomalies and that SWC memory acts as an upper limit for ET memory. Graf et al. (2014) applied wavelet coherence analysis on SWC and all major water budget components including precipitation (\( P \)), reference evapotranspiration (\( \text{ET}_0 \)), \( \text{ET}_a \), and runoff in an energy-limited site (Wüstebach, Germany) for a period of 3 yr from 1 May 2010 to 30 Apr. 2013. They found out that at weekly resolution, soil water storage (SWS) is correlated to the residual of \( P - \text{ET} - \text{runoff} \) and that the variation in the coherence between SWC and \( \text{ET}_a/\text{ET}_0 \) in time is responding to changes in soil water availability.

Although the abovementioned studies outline the importance of SWC control on \( \text{ET}_a \) and the control of SWC memory on \( \text{ET}_a \), the strength of SWC control on \( \text{ET}_a \) is uncertain. To address this, Seneviratne et al. (2010) reviewed the role of SWC on land surface–climate interactions in a changing climate with a specific focus on SWC–temperature (\( T \)) and SWC–\( P \) feedbacks. They identified three climate or SWC regimes that control the SWC–\( \text{ET}_a \) coupling: a wet SWC regime with SWC values above a critical value, a dry SWC regime with SWC below wilting point (WP), and a transitional climate regime between a critical SWC and WP where SWC strongly controls \( \text{ET}_a \). The dry and transitional regimes correspond to the water-limited \( \text{ET}_a \) regime defined in the Budyko theory (Budyko & Miller, 1974), whereas the wet regime corresponds to the energy limited \( \text{ET}_a \) regime in this theory. Seneviratne et al. (2010) concluded that there is still a large uncertainty with respect to the impact of geographi-

### Core Ideas
- Both examined sites shifted toward more water-limited conditions in dry year 2018.
- The yearly phase shift between SWC and \( \text{ET}_a \) decreased by greater dryness of 2014–2018.
- The control of \( \text{ET}_a \) and WSI on SWC increased by greater dryness of 2014–2018.

### 2 MATERIALS AND METHODS

#### 2.1 Study sites

The data were collected at the experimental field sites Rollesbroich (50°37′12″ N, 6°18′15″ E) and Selhausen...
(50°52'7" N, 6°26'58" E) located at the Eifel/Lower Rhine Valley Observatory of the German Terrestrial Environmental Observatories (TERENO) in Germany (Figure 1; Bogena et al., 2018; Pütz et al., 2016). Hereafter, for convenience we will call Rollesbroich the energy-limited site and Selhausen the water-limited site (see Section 3). We used nine weighable high-precision grassland lysimeters taken at the energy-limited site, which are part of the TERENO-SOILCan lysimeter network in Germany (Pütz et al., 2016). Six of the lysimeters filled with soil monoliths were installed in spring 2010 at their original location in winter 2010, and three monolithic lysimeters were transferred from energy-limited site to the water-limited site, to subject them to a drier and warmer climate, in winter 2010. Lysimeter data for 2011 were not included in the evaluation because at least one hydrological year is necessary for the lysimeters to adapt to the prevailing site conditions. The transfer from an elevated site (Rollesbroich, 515 m asl) along an altitudinal gradient to a lowland site (Selhausen, 104 m asl) corresponded to an increase of the average daily temperature of 2.9 °C and a decrease of the average annual precipitation of 395 mm during the study period (2012–2018).

All lysimeters have a surface area of 1 m² and a depth of 1.5 m. The extensively managed grassland ecosystem consists mainly *Lolium perenne* L. and *Trifolium repens* L. In order to prevent the disruption of the natural hydraulic gradient and water flow by the lysimeter vessel, tensiometers (TS1, UMS) were installed at 1.4-m depth in the lysimeters and in the surrounding field soil. The field tensiometers controlled a bidirectional pump to transport water upwards (capillary rise) or downwards (drainage) between a suction rake at the lysimeter bottom and the seepage water tank and ensured that the lysimeter water dynamics were adjusted to the observed field dynamics (Groh, Vanderborght, Pütz, & Vereecken, 2016). Further information of the test site and the lysimeter setup is available in Pütz et al. (2016).

### 2.2 | Time series data

Seven-year time series data (1 Jan. 2012–31 Dec. 2018; i.e., 2,557 d) were obtained from different sources in this study. The ET₄ data were calculated from weight changes of lysimeters, which provide 1-min mass changes with resolution of 10 g. The raw data underwent an extensive manual and automated plausibility check. For more details, see Küpper et al. (2017) and Pütz et al. (2016). Consequently, the adaptive window and threshold filter (AWAT; Peters et al., 2017) was used for further noise reduction, which negatively affects the
determination of land surface water fluxes. The AWAT filter applies an adaptive smoothing window and adaptive threshold value to the lysimeter data, which are both dependent on the noise and signal strength of measurements. To further omit an underestimation of fluxes during changes in flow direction, a snap routine was implemented in the AWAT filter routine, which adds an additional anchor point between the original points, based on the 75th quantile of the neighboring moving average data. This routine has been shown to reliably estimate water fluxes, especially for flux events like dew formation or small ET in winter (Groh, Pütz, Gerke, Vanderborght, & Vereecken, 2019; Groh et al., 2018). We used the procedure referred to above to obtain daily $ET_a$ data from energy-limited site and water-limited site for 2013–2018 and 2015–2018, respectively. To obtain $ET_a$ for the remaining years (2012 in the energy-limited site and 2012–2014 in the water-limited site), the $ET_a$ was calculated based on the daily water balance equation (Groh et al., 2020):

$$ET_a = P - ΔSWS - Q_{net}$$

where $P$ is daily precipitation, $Q_{net}$ is the daily sum of net water flux across the lysimeter bottom ($Q_{net} > 0$: drainage; $Q_{net} < 0$: capillary rise) and $ΔSWS$ is the daily SWS change in the soil profile, which was obtained by analyzing the changes of lysimeter weight at night (mean value of weight between 12:00 a.m. and 2:00 a.m.) between two consecutive days. This approach was necessary, because the sealing covering the gap between the lysimeter cylinder and the collar affected the intra-daily weight measurement of the lysimeters due to changes in properties of the sealing by sunlight. However, measurements at night were accurate.

We obtained the daily $Q_{net}$ values from mass changes of the leachate from the lysimeters, collected with a weigheable reservoir tank (resolution = 1 g). The SWC of the lysimeters is measured at three different depths (10, 30, and 50 cm) using time-domain reflectometry probes (CS610, TDR100, Campbell Scientific) with a 30-min time interval.

We obtained the meteorological data from the TERENO data portal (https://teodoor.icg.kfa-juelich.de/ibg3searchportal2/index.jsp). The stations of the used data are listed in Supplemental Material 1. The meteorological data comprised $T$ and wind speed measured at 2-m height, as well as relative and specific humidity, air pressure, and global radiation. All variables were averaged daily prior to any further analysis. Then, crop adjusted reference evapotranspiration ($ET_{crop}$, Equation 2), as well as the reference grass surface evapotranspiration with a reference height of 12 cm ($ET_0$, Equation 3), were calculated using the Penman–Monteith model on a daily basis after Allen, Pereira, Raes, and Smith (1998). Equation 3 is derived from the original Penman–Monteith Equation 2 to estimate $ET_0$ (Allen et al., 1998):

$$ET_{crop} = \frac{Δ(R_n - G) + ρ_s c_p (e_s - e_a)/r_a}{λ[Δ + γ(1 + r_s/r_a)]}$$  

$$ET_0 = \frac{0.408 Δ(R_n - G) + γ \frac{900}{T + 273} u_2 (e_s - e_a)}{Δ + γ(1 + 0.34 u_2)}$$

where $ET_{crop}$ and $ET_0$, respectively, are vegetation-height-adjusted and reference grass evapotranspiration (mm d$^{-1}$), $λ$ is latent heat of vaporization (MJ kg$^{-1}$), $R_n$ is net radiation at the crop surface (MJ m$^{-2}$ d$^{-1}$), and $G$ is soil heat flux density (MJ m$^{-2}$ day$^{-1}$). $Δ$ is the slope of saturation vapor pressure curve (kPa °C$^{-1}$), $γ$ is psychrometric constant (kPa °C$^{-1}$), $ρ_s$ is mean air density (kg m$^{-3}$), and $c_p$ is specific heat (MJ kg$^{-1}$ °C$^{-1}$). $T$ is mean daily air temperature at two meters height (°C) and $u_2$ is wind speed at 2-m height (m s$^{-1}$). The $r_s$ and $r_a$ respectively are (bulk) surface or canopy and aerodynamic resistances (s m$^{-1}$).

The plant heights of the grassland varied considerably during the season. In the case of $ET_{crop}$, the variables of $r_s$, $r_a$, and leaf area index (LAI) (Allen et al., 1998) were estimated based on measured height of the grassland vegetation:

$$r_a = \frac{\ln \left( \left( \frac{z_m - 2/3 h_{plant}}{0.123 h_{plant}} \right) \times \ln \left( \left( \frac{z_m - 2/3 h_{plant}}{0.123 h_{plant}} \right) \right) \right)}{k^2 u_2}$$

$$r_s = r_a / LAI_{act}$$

$$LAI_{act} = 0.5LAI = 0.5 \left( 24 h_{plant} \right)$$
where $z_m$ and $z_h$ are the heights of the wind and humidity measurements (L), respectively, $h_{plant}$ is the grass height (m) at the lysimeter, and $K$ is the von Karman constant (\text{--}). The stomatal resistance, $r_s$ (s m$^{-1}$), was fixed to 100 s m$^{-1}$ assuming a well-watered grass cover according to Allen et al. (1998). The LAI$_{act}$ is the active leaf area index taking into account that only the upper grass surface contributes to heat and vapor transfer (\text{--}). We measured the grass heights at the lysimeters by measuring stick and linearly interpolated the heights between two measurements intervals on a daily basis.

### 2.3 Data gap filling

Missing meteorological data were gap-filled using an Empirical Orthogonal function (EOF) approach after Beckers and Rixen (2003) and modified by Graf (2017). We used the local TERENO network of 18 meteorological stations to set up a correlation matrix between sites for each variable, and filled the missing data by iterative re-estimation based on the significant EOFs, which were in turn determined by cross-validation.

Missing ET$_a$ and SWC data were gap filled by applying the group method of data handling (GMDH; Hecht-Nielsen, 1990), which has been successfully used to gap fill series of soil hydrological state variables (Pachepsky & Rawls, 1999; Rahmati, 2017). In the case of ET$_a$, we used available ET$_0$ data for the same day, as well as available ET$_a$ data for 2 d before and 2 d after missing dates as predictors. For SWC, we used the available SWC data from neighboring stations as predictors from the TERENO platform. The details about the gap filling of the time series data, as well as the quality of the gap-filled data, are provided in Supplemental Material 2.

### 2.4 Data analysis

#### 2.4.1 Data averaging

In our analysis, we used lysimeter-averaged daily data of the soil water balance at the energy-limited site (six lysimeters) and water-limited site (three lysimeters). We used the CV to quantify the variability between lysimeters. The CV values of SWC were calculated for the three depths by averaging the values over the whole measurement period and deriving an averaged SD. At the energy-limited site, the CV values of SWC were 5, 4.5, and 7.0% at the depths 10, 30, and 50 cm, respectively. At water-limited site, the CV values were 8.2, 7.1, and 3.1% at 10, 30, and 50 cm. In the case of ET$_a$, the CV values at energy-limited and water-limited sites were 10.5 and 8.2%, respectively. The SWC and ET$_a$ are therefore slightly more variable at the water-limited site than at the energy-limited site. Overall, given the low CV values, the mean values are a good representation of SWC and ET$_a$ of single lysimeters.

#### 2.4.2 Consistency check of actual evapotranspiration data

Prior to averaging across lysimeters, we applied a consistency check on daily ET$_a$ data obtained from the different lysimeters at each site. To do this, we conducted an ANOVA on ET$_a$ data based on a completely randomized design with the factors lysimeter and time. Then, we analyzed the residuals ($e$) obtained from ANOVA analysis. The hypothesis was that the residuals are normally distributed. To check this, we first calculated the cumulative probability ($p$) of the $e$ values. Then, taking the mean and SD of the $e$, we recomputed the normally distributed residuals ($\hat{e}$) for the obtained $p$ values. Then, we considered the data with $e < \min(\hat{e})$ or $e > \max(\hat{e})$ as outliers and removed them. This led to the removal of 32 daily lysimeter ET$_a$ values in the energy-limited site and 75 in the water-limited site. Finally, we used the mean value of the remaining lysimeters for each day to gap fill those data, or a simple regression between ET$_a$ and ET$_{crop}$ was used to replace them in the case that all lysimeters of a given day were taken out.

#### 2.4.3 Budyko plot

We used the Budyko framework (Budyko, 1958; Budyko & Miller, 1974) to characterize the hydrological status of both sites. In a Budyko plot, the evaporative index (EI = ET$_a$/P) is plotted against the aridity index (AI = ET$_{crop}$/P) for annual or long-term averages.

#### 2.4.4 Soil water storage and water stress index

In order to quantify the SWS, we used SWC measured at three different depths of 10, 30, and 50 cm. To do this, we used the following equation:

$$
SWS = SWC\{10 \text{ cm}\} \times d_1 + SWC\{30 \text{ cm}\} \times d_2 + SWC\{50 \text{ cm}\} \times d_3
$$

where SWS is soil water storage (L) of the entire soil profile (150-cm depth), SWC is soil water content (L$^3$ L$^{-3}$) at different depths specified by {10 cm}, {30 cm}, and {50 cm}, and $d_1$–$d_3$ represent the layer thickness. We assume that SWC{10 cm} is reflecting the soil water status in Layer 1 from soil surface to 20-cm depth ($d_1 = 20$ cm), SWC{30 cm} is reflecting the soil water status in Layer 2 from 20- to 40-cm
depth, and finally SWC(50 cm) is reflecting the soil water status in the last layer from 40- to 150-cm depth.

To characterize the occurrence of water stress, we used the ratio between ETa and ETcrop as the water stress index (WSI) (Eden, 2012; Speich, 2019). Water stress index values <1 reflect conditions when the plant can no longer transpire optimally and reduces its transpiration rate. Our calculations showed large variability in WSI values, especially in winter-time, including values >1. This is likely the result of comparatively large error to signal ratios on both the numerator and denominator, as both ETa and ETcrop are small in winter-time. For example, winter P is occurring at times when plants are senesced or are not transpiring. During the summer time (1 July–30 September), 95% of WSI values were between 0.05 and 1.2 in both sites. Therefore, as it is unrealistic to have WSI values >1, we limited all WSI values >1 to 1.

### 2.4.5 Wavelet analysis

Continuous wavelet coherence analysis (Si, 2008) was used to quantify the strength of correlation and phase shift (delay) between SWC and ETa and between SWC and WSI for each point in the time and in the frequency domain. The software package described in Grinsted, Moore, and Jevrejeva (2004) was used to conduct the wavelet coherence analysis, where a Monte Carlo approach is used to determine the significance of localized coherence (Graf et al., 2014). The continuous, nonorthogonal Morlet wavelet is selected as the mother wavelet function (Graf et al., 2014; Grinsted et al., 2004).

According to Si (2008), the integral wavelet transform, W(s, τ) of a time series y(t) measured at time t is defined by

\[
W(s, \tau) = \int y(t) \frac{1}{\sqrt{s}} |\psi^*(\frac{t-\tau}{s})| dt
\]

(8)

where \(\psi^*\) is the mother wavelet function, s is the dilation (s > 1) or contraction (s < 1) factor of the wavelet function \(\psi^*\), and \(\tau\) is the temporal translation or shift of the function \(\psi^*\) (Si, 2008). The squared amplitude of the wavelet transform, |W(s, \tau)|^2, gives the wavelet power spectrum (Torrence & Compo, 1998). One can plot this spectrum against time, providing delocalized information of the power at a certain moment in time, or against frequency or period. We must note that in addition to the original signals, we also conducted a power spectrum analysis on normalized signals (dividing signals by their SD). In this case, the SWC spectra almost coalesce. The larger variance at 10-cm depth leads to a normalized spectrum that is slightly lower at the period of 365 d compared with the normalized spectra obtained at 30 and 50 cm. The cross-wavelet spectrum can be computed from the wavelet transform of the two simultaneously sampled variables and is comparable with the covariance in ordinary correlation-regression analysis and the cross spectrum in Fourier analysis (Graf et al., 2014). The normalized real part of the cross wavelet spectrum is comparable with an \(R^2\) value. Other than \(R^2\) values obtained from conventional correlation analysis, it is localized in both the time and frequency domains. It indicates the maximum correlation after removing any potential phase shift (also called delay, which is the difference in timing of two consecutive maximal values of investigated signals) between the variables at this particular time and frequency (Graf et al., 2014). This phase shift is reported independently. Supplemental Material 3 provides a simple analysis of several artificial signals using wavelet coherence analysis to describe the concepts of perfect correlation, anticorrelation, and phase shift or phase angle, which is used below in the manuscript. We evaluated the phase shift between the SWC and ETa time series using cross-wavelet analysis. The following equation is used to quantify the phase shift between a base signal (e.g., SWC) and a second signal (e.g., ETa):

\[
\text{Phase shift} = \frac{\text{Phase angle}}{2\pi} \times n
\]

(9)

where phase shift (in days) and phase angle (in radians) refer to the difference in timing of two consecutive maximal values of the base and second signals (e.g., between the maxima of SWC and ETa), and n represent the period (1/frequency) of the signals. The phase angle is quantified by wavelet coherence analysis through the cross-wavelet spectra.

In order to determine whether SWC controls ETa or WSI or vice versa, we introduce the concept of “lag” defined as:

\[
\text{lag} = \begin{cases} 
\text{Phase shift, if } -n/4 \leq \text{Phase shift} \leq +n/4 \\
-n/2 - \lfloor|\text{Phase shift}|\rfloor, \text{ if Phase shift} < -n/4 \\
\text{Phase shift} - n/2, \text{ if Phase shift} > +n/4
\end{cases}
\]

(10)

Negative lag values mean that the second signal controls the base signal (e.g., ETa controls SWC), whereas positive lag values mean that the base signal controls the second one. Based on the above equation, abs(lag) values quantify the length of the time window for which a signal at time \(t\) is controlled by the status of the other signal during that time window, \(t - \text{abs(lag)}\).

In order to evaluate whether the reduction in yearly phase shift between ETa and SWC is caused by a shift in ETa or SWC (and/or both), cross-wavelet spectra were calculated between each of the signals and a benchmark signal with a constant frequency (365 d) and a constant phase (\(\pi/2\)). As a benchmark signal \(y\), we used

\[
y = \sin(2\pi t/365 + \pi/2)
\]

(11)

The use of the above equation ensures the fluctuations of an imaginary signal at yearly cycle with a period of 365 d, and which has its maximal values at start of each period (first day of each period). Therefore, any phase shift occurring between
the benchmark signal and two other signals of $E_{Ta}$ and SWC quantifies the shift in $E_{Ta}$ and SWC signals.

In addition, in order to support the interpretation of the wavelet analyses, we carried out simple soil water balance simulations for a few scenarios. The simulations are used to show that precipitation might be an important control on the observed change in phase shift between $E_{Ta}$ and SWC. In each scenario, we assumed that the precipitation, $P$, is constant over time. This assumption is supported by an ANOVA analysis performed on the seasonal $P$ data at both sites. At a .05 significance level, there is an observed seasonality at both sites (Table 1). The difference in $P$ between both sites is mainly caused by higher winter and spring rainfall at the energy-limited site compared with the water-limited site.

We distinguished four scenarios each with a different yearly precipitation: 1,277.5, 1,095, and 912.5 mm. These values span the ranges of precipitation amount observed at both sites. We also assumed that the annual fluctuations of $E_{Tcrop}$ over time could be represented using a sine function:

$$E_{Tcrop}(t) = \langle E_{Tcrop}(t) \rangle \left[ 1 + \sin\left(2\pi t/365 + \pi/2 \right) \right]$$

(12)

where $\langle E_{Tcrop}\rangle$ is the yearly averaged $E_{Tcrop}$.

Yearly averaged $E_{Tcrop}$ was selected based on the observed values at the energy-limited and water-limited sites. The water balance model was a simple bucket model that assumed that the SWC could not exceed the water content at field capacity, and that excess water percolated rapidly out of the root zone. To model the reduction of evapotranspiration when the soil dried out, we used a reduction function that assumes a linear relation between the ratio of $E_{Ta}$ and $E_{Tcrop}$ and the SWC, as is often applied in ecohydrological models or crop models (Allen et al., 1998).

We simulated the annual fluctuations of the SWC in the root zone for a period of 7 yr using the algorithms below. We simulated the water content in the root zone as

$$\text{if } \text{SWC} \leq \text{SWC}_{\text{crit}}, \text{then}$$

$$\text{dSWC}/\text{d}t = 1/L_{\text{root}} \left\{ P - E_{Ta} \left[ E_{Tcrop}(t), \text{SWC} \right] \right\}$$

$$\text{else } \text{dSWC}/\text{d}t = 0$$

(13)

where FC is the water content at field capacity and $L_{\text{root}}$ is the root zone depth. The $E_{Ta}$ is a function of the $E_{Tcrop}$ and of the

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**TABLE 1** ANOVA test to check the seasonality of the precipitation

| Site            | Winter Mean ± SD | Spring Mean ± SD | Summer Mean ± SD | Fall Mean ± SD | $F_p$ | $p$ |
|-----------------|-----------------|-----------------|-----------------|---------------|------|-----|
| Energy-limited  | 252.0 ± 72.2    | 241.7 ± 73.6    | 278.1 ± 106.9   | 287.9 ± 43.0  | 0.53 | .66 |
| Water-limited   | 127.3 ± 52.9    | 157.5 ± 46.6    | 209.8 ± 89.1    | 170.6 ± 21.5  | 2.45 | .08 |

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**TABLE 2** Parameters used in the simulation of the soil water balance. The notation $x:y:z$ for the applied range of precipitation indicates that precipitation intensities from $x$ to $z$ were modeled in steps of $y$

| Parameter        | Energy-limited site | Water-limited site |
|------------------|----------------------|--------------------|
| Applied range of precipitation, mm d$^{-1}$ | 2.0:5:3.5 | 1.25:0.5:2.75 |
| FC, % (v/v)      | 29.8                | 29.8              |
| WP, % (v/v)      | 8                   | 8                 |
| Root depth, mm   | 500                 | 500               |
| SWC$_{\text{crit}}$ | 20                  | 20                |
| Avg. reference evapotranspiration, mm d$^{-1}$ | 1.964 | 2.299 |

*FC and WP, soil water content at field capacity and wilting point, respectively. SWC$_{\text{crit}}$, critical soil water content.

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**RESULTS AND DISCUSSIONS**

3.1 **Climatic and hydrological conditions at energy-limited and water-limited sites**

We used the Budyko framework (Figure 2) to plot the yearly and 7-yr water balance of the energy-limited and water-limited sites for the period 2012–2018. For the 7-yr period, we assumed that the underlying assumption (zero change in
FIGURE 2 Budyko plots for (a) energy-limited and (b) water-limited sites during 2012–2018. The $\omega$ stands for free model parameter of Budyko function, $ET_{\text{crop}}$ stands for crop height-adjusted evapotranspiration, and $P$ stands for precipitation.

TABLE 3 Yearly values of soil water balance components at both energy-limited and water-limited sites for the measurement period of 2012–2018

| Year   | $P$   | $ET_a$ | $ET_{\text{crop}}$ | Capillary rise | Drainage | $dSWS/dt$ | Net influx |
|--------|-------|--------|--------------------|----------------|----------|----------|------------|
|        | mm    | mm     | mm                | mm yr$^{-1}$   | mm       | mm       | mm         |
| Energy-limited site |       |        |                    |                |          |          |            |
| 2012   | 1,035.7 | 605.2  | 678.9              | 13.1           | 480.0    | −36.4    | −466.9     |
| 2013   | 982.3  | 642.4  | 705.3              | 26.1           | 425.7    | −59.6    | −399.5     |
| 2014   | 1,098.2| 683.2  | 728.6              | 25.4           | 416.8    | 23.6     | −391.3     |
| 2015   | 1,148.7| 670.5  | 704.6              | 43.4           | 564.4    | −42.8    | −521.0     |
| 2016   | 1,102.7| 614.4  | 685.6              | 38.0           | 526.8    | −0.5     | −488.7     |
| 2017   | 1,133.1| 654.4  | 716.9              | 42.1           | 537.3    | −16.4    | −495.2     |
| 2018   | 917.6  | 650.2  | 801.9              | 42.1           | 375.9    | −66.3    | −333.8     |
| Sum    | 7,418.3| 4,520.3| 5,021.9            | 230.3          | 3,326.8  | −198.4   | −3,096.4   |
| Mean   | 1,059.8| 645.8  | 717.4              | 32.9           | 475.3    | −28.3    | −44.2      |
| SD     | 85.0   | 28.1   | 41.0               | 11.6           | 71.0     | 32.4     | 68.3       |
| CV     | 8.0    | 4.4    | 5.7                | 35.1           | 14.9     | 114.5    | 15.4       |
| Water-limited site |       |        |                    |                |          |          |            |
| 2012   | 722.5  | 689.9  | 728.0              | 47.9           | 12.8     | 67.7     | 35.1       |
| 2013   | 588.0  | 731.0  | 771.5              | 107.8          | 87.3     | −122.5   | 20.5       |
| 2014   | 710.9  | 736.8  | 785.3              | 133.3          | 45.2     | 62.2     | 88.1       |
| 2015   | 749.1  | 784.3  | 886.0              | 71.2           | 42.2     | −6.3     | 29.0       |
| 2016   | 713.7  | 663.6  | 832.5              | 44.6           | 56.0     | 38.6     | −11.4      |
| 2017   | 648.9  | 679.3  | 918.3              | 126.9          | 51.7     | 44.8     | 75.2       |
| 2018   | 523.4  | 588.1  | 957.3              | 82.5           | 62.4     | −44.7    | 20.1       |
| Sum    | 4,656.4| 4,872.9| 5,878.9            | 614.1          | 357.5    | 40.0     | 256.5      |
| Mean   | 665.2  | 696.1  | 839.8              | 87.7           | 51.1     | 5.7      | 36.6       |
| SD     | 82.3   | 62.8   | 83.9               | 36.0           | 22.5     | 69.2     | 34.2       |
| CV     | 12.4   | 10.9   | 9.0                | 41.0           | 44.1     | 121.1    | 93.5       |

Note. $P$, precipitation; $ET_a$, actual evapotranspiration; $ET_{\text{crop}}$, crop-height-adjusted reference evapotranspiration; $dSWS/dt$, the change in soil water storage over time; net influx, capillary rise minus drainage.
water storage) for the Budyko analysis is fulfilled, as the change in water storage in this period is 2.6% of the P at the energy-limited site and 0.8% of the P at the water-limited site (Table 3). At the energy-limited site, total P exceeds ET_a, leading to an EI of 0.58, whereas at the water-limited site, ET_a slightly exceeds P, resulting in an EI of 1.04. The aridity index (AI) for the 7-yr period is 0.66 for the energy-limited site and 1.26 at the water-limited site.

The yearly calculation of the Budyko values (Figure 2) shows a smaller variability at the energy-limited site compared with the water-limited site, indicating a larger climatic and hydrological variability at the water-limited site. Values of the different components of the soil water balance in Table 3 reflect this. The CV values of P, ET_{crop}, and ET_a are smaller at the energy-limited site compared with the water-limited site. The largest differences between the sites occur, however, for drainage and change in SWS. At the water-limited site, the yearly change in SWS ranges between −122.5 and 67.7 mm, and the yearly drainage ranges between 12.8 and 87.3 mm. These values occur in two consecutive years, namely 2012 and 2013. At the water-limited site, EI was the lowest at only 1.26 at the water-limited site.

Figure 3 shows the SWC at three depths, ET_{crop}, and ET_a at the energy-limited and water-limited sites for the studied period. The results show that the mean wintertime (1 January–31 March) SWC(10 cm) values at the energy-limited site are higher (42.2 ± 2.2%) than at the water-limited site (35.5 ± 1.9%), as more rainfall water is available and ET_a is lower for both locations. Differences in SWC during wintertime between both sites are less pronounced at deeper depths. The SWC(30 cm) is 37.1 ± 1.2% at the energy-limited site and 39.2 ± 0.6% at the water-limited site. At 50-cm depth, SWC is 36.6 ± 0.2 and 34.1 ± 1.8% for the energy-limited and water-limited sites, respectively.

After 2015, the minimal SWC during summer at the water-limited site decreases from an average of 22.6% to a value of 15%. At deeper depths, we observe no clear decline in the minimal SWC during summer over the different years. At the energy-limited site, minimal SWC decreases both in the surface layer and at 30-cm depth from 2015 on (Figure 3). Major controls are most likely the different climatic conditions, since soil, vegetation, and management are the same.

Figure 3 also shows that at the water-limited site, the rewetting of the soil profile in 2017 and 2018 occurs slower than that at the energy-limited site. This can be seen by comparing the SWC data of 2017 and 2018 between the summer and winter period at the energy-limited and water-limited sites. The change in SWC is much slower (the curves remain flat for longer) at the water-limited site Selhausen than at the energy-limited site.

Despite the fact that the soil profiles are rewetted in late summer, ET_a at the water-limited site does not increase. Based on the plant hydraulics, it can be assumed that the transpiration rate is linearly dependent on the difference between a weighted average of the soil water potentials in the root zone and the leaf water potential (Javaux, Couvreur, Vanderborght, & Vereecken, 2013). Assuming that the plants control the leaf water potential during stress periods and keep it constant when a critical leaf water potential is reached, ET_a should increase when the soil water potential increases during stress periods.

However, we do not observe this at the water-limited site in 2017 and 2018. One possible explanation might be that the vegetation was not able to recover as soil was wetting, because the grass was slightly dried and brown and therefore did not transpire. If P is occurring during these times, a larger portion of it is partitioned into percolation and soil rewetting, and a smaller fraction than usual is routed into ET_a.

Figure 4 shows the global (time-averaged) power spectrum of ET_a, ET_{crop}, WSI, and SWC at the energy-limited and water-limited sites. Panel (a) presents the global power spectrum of ET_a and ET_{crop} at both sites showing uniquely centered signals at a period of 365 d (the yearly ET cycle). The strength of the ET_{crop} power in the yearly cycle is lower at the energy-limited site [918 (mm d^{-1})^2] compared with the water-limited site [1,188 (mm d^{-1})^2]. The ET_{crop power in the yearly cycle [with mean value of 1,053 (mm d^{-1})^2 is considerably larger than the ET_a power [with mean 639 (mm d^{-1})^2] at both sites. The latter signal (ET_a) shows the opposite trend between the two sites, where its yearly power is higher at the energy-limited site [709 (mm d^{-1})^2] than at the water-limited site [569 (mm d^{-1})^2].

Panel (b) shows the global power spectrum of WSI vs. examined periods at both sites. The energy-limited site shows a weak global maximum at a period of 365 d with a power value of 1.03 [(mm d^{-1})/(mm d^{-1})]^2 that is more pronounced at the water-limited site with a power value of 2.12 [(mm d^{-1})/(mm d^{-1})]^2. This maximum corresponds to the drought stress that occurs during summer time.

Panels (c) and (d) of Figure 4 present the global power spectra of SWC at 10-, 30-, and 50-cm depths vs. the period of the measured signals at the energy-limited and water-limited sites, respectively. First, we see two dominant periods in the SWC signals at all depths and for both sites, with the strongest SWC signal occurring at 365 d and a second signal that is less strong occurring at 600 d. The power of the
SWC signals at a period of 365 d is almost half (on average) that at the energy-limited site [with mean power values of 6,854(%)^2] compared with the water-limited site [with mean power values of 1,2576(%)^2], indicating the presence of stronger amplitudes in the SWC signal at the water-limited site. The strength of this signal is smaller for all depths at the energy-limited site than at the water-limited site. Panels (c) and (d) also show that the strength of the signal is depth dependent at both sites: the deeper the measurement level, the lower is the strength of the signal. At deeper depths, SWC is typically more stable due to less immediate meteorological effects.

Wavelet analysis also allows inspecting the time evolution of the power spectra for SWC, ET_a, ET_c, and WSI. As already shown in Figure 3, we see an intensification of the SWC signal from 2015 onwards at the energy-limited site. This intensification of the SWC, caused by an increase in climatic forcing, which is stronger at the water-limited site than at the energy-limited site, occurs in all three depths but is less pronounced at deeper depths. We have illustrated this in

**FIGURE 3** Time series data of daily actual (ET_a) and vegetation-height-adjusted reference (ET_c) evapotranspiration, as well as soil water contents (SWC) at 10-, 30-, and 50-cm depths, of energy-limited and water-limited sites. The \( \theta_{\text{mean}} \) stands for average of minimal SWC during different years, and \( \theta_y \) and \( \theta_{y-1} \) stand for minimum SWC values at given year of \( y \) and \( y-1 \), respectively.
**Figure 4** The global power spectra of (a) actual (ET\(_a\)) and vegetation-height-adjusted reference (ET\(_{crop}\)) evapotranspiration, (b) water stress index (WSI), and soil water content (SWC) at (c) energy-limited and (d) water-limited sites.

**Figure 5** The power spectra of soil water content (SWC) at 10-cm depth at (a) energy-limited and (b) water-limited sites and water stress index (actual evapotranspiration [ET\(_a\)]/vegetation-height-adjusted reference evapotranspiration [ET\(_{crop}\)]) at (c) energy-limited and (d) water-limited sites.

Figure 5 (Panels a and b), which shows the time and period variant power spectrum of SWC at 10 cm at the energy-limited and water-limited sites. We have presented the power spectrum maps of the SWC at other depths in Supplemental Material 4.

Although the power spectrum analysis of ET\(_{crop}\) and ET\(_a\) shows the constant strength of them at both sites for the measurement period (shown in Supplemental Material 4), there are decreasing and increasing intensities in the WSI over time at the energy-limited and water-limited sites,
The evolution of $ET_{\text{crop}}$, $ET_a$, and $P$ from 2012 to 2018 for both sites is shown in Figure 6. At the water-limited site, the differences between $ET_{\text{crop}}$ and $ET_a$ remain constant in the first 3 yr. After 2014, the difference increases and reaches a maximum in 2018. At the energy-limited site, the difference is minimal in 2014 and increases over the next 4 yr to reach a maximum, but its value is much smaller compared with the water-limited site.

3.2 Coherence between soil water content, evapotranspiration, and water stress index

We used wavelet coherence analysis to explore the relationship between SWC and $ET_a$ or WSI for different times and frequencies. Since our analysis showed that the coherence between SWC{10 cm} and $ET_a$ or between SWC{10 cm} and WSI is nearly identical for the other depths (30 and 50 cm), we present the detailed results for the first depth only, and for two other depths, we only report the averaged coherence values. The same applies to the coherence between total SWS in the profile and $ET_a$ and/or between the SWS and WSI. Figures for SWC at 30 and 50 cm, as well as SWS, are reported in Supplemental Material 5.

The coherence between SWC and $ET_a$ at all three depths at both sites is particularly strong at periods between 200 and 512 d (Figure 7a), suggesting a strong correlation between both signals at the annual cycle. The coherence between SWC and $ET_a$ at other time cycles or periods (weekly, monthly, and/or seasonally) is unstable and erratic (Figures 7a and 7b).
Figure 7 also shows that the shorter the period, the higher the variation in coherence $R^2$ values. This can be explained by the fact that at shorter periods (daily to weekly), other environmental controls affect the SWC and $E_{Ta}$ relationship. At high frequencies, the coherence between SWC and $E_{Ta}$ observed at the yearly timescale gets lost because only factors determining $E_{Ta}$ are subject to fast changes (e.g., short-term fluctuations in rainfall, temperature, humidity, and the presence of cloudy days with low radiation). Soil water content, in contrast, changes slowly, especially during dry-down events, whereas rapid and strong changes are only possible after strong rain events.

The coherence between SWC and WSI shows a clearly different picture between the energy-limited and water-limited sites (Figure 7c and 7d). At the energy-limited site, high coherence values only occur in the middle of 2014 (change from blue to yellowish color). At the water-limited site, SWC and WSI remain highly correlated in the period of 2012–2018. This happens because any change in WSI index at the water-limited site will affect the status of the SWC and/or vice versa, and consequently a high correlation could be assumed between them for entire examined period. At the energy-limited site, in contrast, the variation in $E_{Ta}$ is mainly controlled by $E_{Ta}$ rather than SWC. Therefore, a low correlation between SWC and WSI is reasonable.

Figure 8 represents the evolution of the coherence between SWC at three depths and $E_{Ta}$, as well as between SWC and WSI at the yearly cycle (365 d), showing a clear difference between the energy-limited and water-limited sites. Panel (a) of Figure 8 shows that at the energy-limited site, the yearly coherence between SWC and $E_{Ta}$ ranges between 0.9 and 0.97 for all depths and the full measurement period. Clearly, SWC and $E_{Ta}$ are highly correlated at this period that corresponds to the yearly cycle.

Panels (c) and (d) of Figure 8 show the evolution of the coherence of SWC and WSI at the energy-limited and water-limited sites, respectively. The energy-limited site shows an increase in the coherence over time, starting around the middle of 2014 and reaching a value of 1.0 at the beginning of 2017, indicating high correlation between SWC and the
WSI. The phase shift (see discussion in Section 3.3) shows SWC and WSI to be fully in phase with a positive correlation indicating that a high value of ET_a/ET_c occurs when SWC in the profile is high. In contrast, at the water-limited site, the coherence decreases from 0.9 down to 0.6 at the end of the measurement period, indicating a weakening correlation between SWC and WSI. Around the beginning of 2015, the coherence already fell to its minimum value of 0.6, but increased to a maximum of 0.75 in the beginning of 2017.

3.3 | Phase shift analysis between soil water content, evapotranspiration, and water stress index

The wavelet coherence analysis allows analyzing the phase shifts between SWC and ET_a and between SWC and WSI. The arrows in Figure 7 indicate the phase shifts. More explanation on the meaning of arrow directions is provided in Supplemental Material 3. The direction of the arrows (mostly left aligned) in Panels (a) and (b) of Figure 7 indicates an anti-correlation between SWC (depth-independently) and ET_a at a yearly cycle at both sites. Perfect left-aligned arrows mean that the examined variables lag behind each other with a phase shift of, in the case of an annual cycle, 6 mo. However, inspection of the arrow direction in the yearly cycle in Panels (a) and (b) of Figure 7 shows nearly identical left-aligned arrows in 2014. Before or after 2014, arrows point downward for the SWC–CET_a relations and upward for the SWC–WSI relation, indicating that ET_a is lagging behind SWC and SWC is lagging behind WSI. In general, downward arrows indicate positive (second variable lags) phase shifts and upward arrows negative (first variable lags) phase shifts. Figure 9 shows the annual-period phase shifts for SWC–ET_a (Panels a and b) and SWC–WSI (Panels c and d) over time for the energy-limited and water-limited sites, respectively. For a more intuitive interpretation, we converted the phase angles in radians to phase shifts in days.

Panel (a) of Figure 9 shows phase shifts between SWC and ET_a at the energy-limited site. We observe a positive phase shift between SWC and ET_a, indicating that ET_a is lagging behind the SWC. The phase shift between SWC and ET_a at
the energy-limited site reaches a maximum of $\sim 160$ d (i.e., the maximum of the $ET_a$ occurs 160 d later than the maximum of SWC, or the minimum of SWC occurs $183 - 160 = 23$ d later than the maximum $ET_a$) around the middle of 2014, and this is the case for all depths. This means that the rate of $ET_a$ occurring during the previous 23 d ($t - 23$) is influencing SWC at time $t$. After the middle of 2014, the phase shifts decrease up to the end of the measurement period (2018), with values ranging between 140 and 115 d being equal to lag times of $-43$ and $-68$ d. This means that by advancing in time from the middle of 2014 toward 2018, the time window in which $ET_a$ controls SWC is longer than before. We also observe that the differences between the maximum values and the final values are in the same range, indicating that the change in phase shift over time is depth independent.

Panel (b) of Figure 9 shows that the phase shift between $ET_a$ and SWC at the water-limited site obtains its maximum in the middle of 2014, and this is for all depths. This finding corresponds to the observations at the energy-limited site. In addition, changes in phase shift from the middle of 2014 to the end of 2018 are almost identical for the three depths. We also observed this at the energy-limited site. Two things are fundamentally different, however. First, the decrease in phase shifts after the middle of 2014 is much stronger than at the energy-limited site, indicating that water stress also occurs at larger depths. Second, the absolute differences in phase shifts between depths are more pronounced.

Panel (c) of Figure 9 shows the phase shifts between SWC and WSI at the energy-limited site. The phase shift between SWC and WSI at the energy-limited site reaches a maximum of zero at the middle of 2014 for the first two depths. The deepest layer shows a slightly negative value at this time. This means that SWC and WSI are perfectly to almost perfectly in phase and are positively correlated. We can explain this by the fact that high SWC values lead to $ET_a$ values being equal to $ET_{crop}$, a situation typically occurring in wintertime. Before or after 2014, any increase in soil dryness causes negative phase shifts between SWC and WSI, indicating that WSI is lagging behind the SWC. This means that WSI controls SWC by a lag time of $<40$ d. The interesting thing at the energy-limited site is that before 2014, SWC controlled WSI, whereas after mid-2014, WSI started controlling SWC.

Panel (d) of Figure 9 shows the phase shift between SWC and WSI at the water-limited site for three depths. The maximum phase shift occurs in the middle of 2014, but it is lower than zero and depth dependent. This is what we have also observed at the energy-limited site. The negative phase shifts after the middle of 2014 until 2018 indicate that the summer minimum of WSI occurs before the one of SWC. The presence of water stress at the water-limited site leads also to larger negative phase shifts than at the energy-limited site after the middle of 2014. This means that towards 2018, WSI starts controlling SWC by a lag time of $\sim 60$ d in the surface soil and 90 d in the deeper layer (which is longer than the lag times at the
There can be three reasons for the change in phase shift between SWC and ET\textsubscript{a} over the years. First, the maximum SWC occurs later in winter because the soil was drier than usual (e.g., dry autumn or early winter) and requires more time to wet again. Second, maximum ET\textsubscript{a} occurs earlier in the season (late spring or early summer) because the soil water stock is depleted earlier due to the small amount of water stored in the soil after winter and/or because there is less $P$ in spring and summer. Third, a combination of the two previous cases is possible. Finally, changes in rooting depth and root mass, as well as changes in species composition and grass canopy, due to the translocation from an energy- to a water-limited site might theoretically affect coherence and phase shift between
The phase shift between the benchmark signal and SWC, as well as ET$_{a}$, is generally smaller in the energy-limited site than in the water-limited site and increases with depth (Figures 10a–10c). The phase shift of 10–40 d for the energy-limited site indicates that the annual SWC reach their maxima around 10–40 d after the start of the year. In the drier climate of the water-limited site, this phase shift ranges between 10 and 60 d and is larger for deeper soil layers. We can explain the increase of phase shift with depth by the delay of soil rewetting when ET$_{a}$ starts to decrease due to water infiltrating from the top surface. The smaller precipitation at the water-limited site leads to a slower rewetting and hence a larger phase shift between the benchmark signal and SWC. Looking at the evolution of the phase shift over time, a minimal phase shift between the benchmark signal and the SWC occurs around mid-2014 at both locations. As the drying becomes stronger after 2015, the phase shift increases at both sites, indicating that the observed SWC signal is occurring later in the year.

Panel (d) of Figure 10 shows a consistent shift of the ET$_{a}$ maxima towards earlier in the season (by ∼20 d at the energy-limited site and ∼25 d at the water-limited site) during the measurement period. As a conclusion, at both sites, the occurrence of maximal ET$_{a}$ is shifted to earlier times, whereas the maximal SWC is shifted to later times, and these shifts are more pronounced at the drier site (water-limited site). However, the shift in maximum SWC is much more pronounced than the shift in maximum ET$_{a}$. The net effect of these shifts at both sites leads to a decrease in the phase shift between the SWC and ET$_{a}$ signals, as observed from the phase shift analysis between SWC and ET$_{a}$ (Figure 9).

In order to evaluate whether the changes in the SWC and ET$_{a}$ signals, and their change in phase shift against the reference signal, can be explained by changes in annual precipitation at both sites using a simple water balance model, we analyzed the simulated SWC and ET$_{a}$ for both sites for a range of yearly precipitation rates (Figure 11). We show the
simulated SWC and ET$_a$ for both sites for a range of yearly precipitation rates in Figure 11. We also present the average phase shift (over both period and time) between the benchmark signal and the simulated SWC and ET$_a$ in Figure 12 vs. the simulated annual precipitation rate. These simulations show how phase shift increases with decreasing precipitation. The time when the maximal SWC is reached moves from early January to late January or early February. However, the phase shifts of the simulated ET$_a$ with respect to the benchmark signal are similar to the observed ones. The phase shifts of the simulated ET$_a$ with respect to the reference signal are similar to the observed ones. They show the same difference between the sites and a similar change in function of changing precipitation. In the case of SWC, the simulated phase shifts do not vary so strongly with annual precipitation as the measured one. However, the change of the phase shift with precipitation is qualitatively the same with larger phase shifts for smaller precipitation. The reason for this difference between observed and simulated SWC phase shifts could be the constant SWC (i.e. equal to SWC at field capacity [SWC$_{FC}$]) during the winter period.

The fact that 2014 appears to be a turning point with respect to the impact on the phase shift between SWC and ET$_a$ and between SWC and WSI is related to the presence of wetter summer conditions, with high rainfall amounts compared with earlier and later years (Figure 13).

4 | SUMMARY AND CONCLUSIONS

The relationship between SWC and ET$_a$ at water-limited and energy-limited sites under grassland in Germany was investigated for the observation period of 2012–2018. We used nine weighable lysimeters to quantify all terms of the soil water balance. In addition, we performed SWC measurements at three depths. From the nine lysimeters, three lysimeters were translocated from the Rollesbroich (energy-limited) to the Selhausen (water-limited) site. The observation period between 2012 and 2018 provided daily values of the soil water balance. We applied continuous wavelet transform to investigate the power spectrum, the coherence, and the phase shift between SWC, ET$_a$, and the WSI (defined as the ratio between ET$_a$ and ET$_{crop}$). Power spectrum analysis showed a strong power of all signals (ET$_a$, ET$_{crop}$, WSI, and SWC) in the yearly cycle at both sites. The ET$_{crop}$ and WSI both had a higher power in the annual period at the water-limited site than at the energy-limited site, indicating the higher water stress at the water-limited site. Contrary to ET$_a$ and ET$_{crop}$, which showed a unimodal power spectrum, the SWC signals showed a bimodal power spectrum centered on periods of around 365 and 600 d. The power in the annual cycle was particularly visible at the water-limited site. The strength of the SWC signals was depth dependent at both sites, with signal strength decreasing with soil depth. A key finding of this paper is the presence of a decreasing trend in the phase shift between SWC and ET$_a$, and an increasing phase shift between SWC and WSI. This was derived from a wavelet coherence analysis. At both sites, the change in phase shift started in 2014 after a wet summer (Ionita et al., 2017; Orth, Zscheischler, & Seneviratne, 2016). The decrease in phase shift between SWC and ET$_a$ at both sites was caused by a shift in maximum ET$_a$ towards earlier times in the summer season and a shift in the SWC towards later times in the winter season. The observed phase shifts between SWC and ET$_a$ and between SWC and WSI were depth dependent, especially at the water-limited site. The change in phase shift between both sets (SWC–ET$_a$ and SWC–WSI) indicated that the lag time between SWC and ET$_a$ and between SWC and WSI were increasing. Therefore, the more negative lag values obtained between both sets (SWC–ET$_a$ and SWC–WSI) showed that the duration of the time that ET$_a$ and WSI control SWC was increasing as we approached 2018. Using a conceptual model, we demonstrate that the increasingly dry conditions from 2014 onwards are likely the reason for the change in phase shift over time. The extremely dry year of 2018 increased the aridity index at both the water- and energy-limited sites. At the energy-limited site, we observed an increase in the EI, whereas at the water-limited site, the EI = 1 for all years. Finally, we noticed a change in phase shift between SWC and ET$_a$ due to the occurrence of increasing drought in a grassland. The maximum of ET$_a$ occurs earlier as dry conditions prevail over the years. This might have implications for the management of grasslands in terms of the amount and timing of fertilizer application and the timing and number of cutting periods. This effect might become more severe as climate change proceeds and droughts become more frequent. Most likely, this phenomenon of change in phase shift may also be relevant for cropped systems. The other interesting finding is that when ET$_a$ is reduced due to drought, an increase in SWC towards the end of the growing season is not followed by an increase in evapotranspiration. We would expect such an increase when we assume that under stress conditions, the water potential in the leaves is regulated by stomata and kept at constant value (isohydric plants). Using plant hydraulics to calculate the water flow through the plant from the soil to the leaves based on the difference between the soil and the leaf water potential should lead to a higher water flow when the soil water potential increases. A further decrease in transpiration when the soil is rewetted after a dry period indicates that either the plant hydraulic conductance is further declining during this wetting phase and/or the leaf water potential is increasing more strongly than the soil water potential. During droughts, the grass leaves die off and the grass surface turns brown. Such a die off suggests a decrease in plant hydraulic conductance. A stronger increase in leaf water potential with increasing soil water potential would imply a hysteretic relation between
stomatal conductance and leaf water potential. This behavior is not captured well by most root water uptake models. More detailed studies on the impact of dryness and drought on the rooting system and canopy composition of the grass cover might be helpful in better understanding the observed changes in coherence and phase shifts between SWC and ETa. Further studies are needed at larger scales and including different soil systems, climate, and vegetation regimes to assess the generality of the observed phase shift during longer periods of water stress and climate-relevant timescales.

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CONFLICT OF INTEREST
The authors declare no conflict of interest.

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Additional supporting information may be found online in the Supporting Information section at the end of the article.

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