Asynchrony of recent European soil moisture and vegetation droughts

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Abstract

Climate change will likely lead to more regular and more severe drought events in the near future, with large impacts on agriculture, especially during long-lasting precipitation deficits or heat waves. This study focuses on agricultural droughts, which are generally defined as soil moisture deficits so severe, that vegetation is negatively impacted. However, during short soil moisture drought events, vegetation is not always negatively affected, and sometimes even thrives under increased solar input. Because of this duality in agricultural drought impacts, the use of the term *agricultural droughts* is a potential issue. Here we show that, in major European droughts over the past two decades, clear asynchronies did occur between soil moisture and vegetation anomalies. A wrong use of the term agricultural droughts could lead to misclassification of drought events and false drought alarms, and for that reason, a distinction is necessary between soil moisture and vegetation droughts.

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Key Points:

- Substantial asynchronies between soil moisture and vegetation droughts were found over European droughts in the past two decades
- Asynchrony in drought is most important in humid regions and/or early summer
- Instead of using agricultural drought, a distinction should be made between soil moisture and vegetation drought

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Abstract

Climate change will likely lead to more regular and more severe drought events in the near future, with large impacts on agriculture, especially during long-lasting precipitation deficits or heat waves. This study focuses on agricultural droughts, which are generally defined as soil moisture deficits so severe, that vegetation is negatively impacted. However, during short soil moisture drought events, vegetation is not always negatively affected, and sometimes even thrives under increased solar input. Because of this duality in agricultural drought impacts, the use of the term *agricultural droughts* is a potential issue. Here we show that, in major European droughts over the past two decades, clear asynchronies did occur between soil moisture and vegetation anomalies. A wrong use of the term agricultural droughts could lead to misclassification of drought events and false drought alarms, and for that reason, a distinction is necessary between soil moisture and vegetation droughts.

Plain Language Summary

Climate change impacts large parts of our society, not in the least water reservoirs, as drought conditions are expected to aggravate. Many definitions for droughts exist, but here we focus on *agricultural droughts*, which occur when the water content of the soil diminishes to such a level that vegetation is negatively impacted. In some cases, however, vegetation profits from drought conditions. For example, droughts often coincide with more hours of sun, and if the vegetation is not (yet) water limited, this can enhance vegetation growth, rather than counteract it. A drought in soil moisture can thus lead to two opposite effects in vegetation. This duality is not included in the term *agricultural drought*, and thus is a potential issue in drought research. Here we show that, although they are classified as the same type of drought, substantial differences between soil water droughts and vegetation droughts exist. This risks misclassification of droughts and false drought alarms, and for that reason, a distinction should be made between soil moisture and vegetation drought events.

1 Introduction

Due to climate change and enhanced land-atmosphere feedbacks, the impact of droughts will likely become more severe over the coming decades (Teuling, 2018). Droughts are generally considered to be induced by a precipitation deficit relative to normal conditions, which, when persisting over longer time periods, results in insufficient water supply to meet demands of both human activities and the environment (Hayes et al., 2011). As a result, impacts of droughts can range from decreased crop yield, damage to ecosystems, and land subsidence, to insufficient drinking water and disruption of transport. To monitor and quantify drought across the terrestrial part of the hydrological cycle, numerous drought indices are available. These can be divided into indices for meteorological, agricultural, and hydrological drought in line with the three main drought types. Meteorological droughts are defined as a prolonged period with below-normal precipitation, and they are typically quantified with the Standardized Precipitation Index (SPI) (McKee et al., 1993). Meteorological droughts can propagate into hydrological droughts, which entail below-normal (ground)water levels or river discharge (Seneviratne et al., 2012), and are generally evaluated using e.g. reservoir levels, Standardized Runoff Index or the Streamflow Drought Index (Shukla & Wood, 2008; Hayes et al., 2011). Lastly, agricultural droughts are defined as a soil moisture deficit severe enough to hamper vegetation growth (Wilhite & Glantz, 1985). Due to their direct relation to food production (through crop yield) and water management (through irrigation), agricultural drought is often the key focus of drought monitoring and forecasting.

Agricultural droughts have traditionally been quantified based on soil moisture conditions in the root zone. The well-known and widely-used Palmer Drought Severity Index (PDSI, see Palmer, 1965) calculates a simple water budget based on monthly values of precipitation and potential evapotranspiration, in combination with parameters that have been optimised to ensure similar PDSI values correspond to similar impacts on vegetation and crop yield even in different climate conditions. The development of high-resolution land surface models applied at continental scales now also allows to have a more physically-based alternative to PDSI, which can account for local soil and vegetation properties. In other cases, standardised in situ or remotely sensed soil moisture observations have been used directly as agricultural drought index (Mozny et al., 2012). Helped by the readily available satellite observations of vegetation indices like NDVI, EVI, SIF, fPAR, NIRv and VOD, other studies have been focusing on the use of these vegetation indices to quantify agricultural drought (Anyamba & Tucker, 2012; Hu et al., 2019). The question remains whether soil moisture and vegetation indices reflect the same agricultural drought.

Whereas soil moisture and vegetation-based indices both aim to quantify agricultural drought, the relation between soil moisture and vegetation is characterised by considerable complexity and nonlinearity. Although combined indices have been proposed as a solution (Yurekli & Kurunc, 2006; Sivakumar et al., 2010; Sepulcre-Canto et al., 2012), it can be questioned whether agricultural drought should be quantified by a single index. From the small scale to the continental scale, distinct water- and energy limited soil moisture regimes can be identified (Denissen et al., 2020), with the relation between soil moisture and evaporative fraction often being represented by a bilinear relation (Seneviratne et al., 2010). Above the so-called critical moisture content, evapotranspiration and plant functioning will not be limited or affected by a lack of precipitation. In fact, increased incoming solar radiation can even enhance evapotranspiration, leading to positive anomalies in vegetation indices despite prolonged meteorological drought conditions (Jolly et al., 2005; Teuling et al., 2006; Mastrotheodoros et al., 2020). Because of this duality in the drought impacts, the use of the term *agricultural drought* is ambiguous, even more so as the term *drought* bears a negative connotation to it, though its impacts are not necessarily negative.

To address the issues surrounding the definition of agricultural drought, we aim to quantify the synchrony between droughts in soil moisture and vegetation using readily available long-term gridded datasets of precipitation, vegetation functioning, and soil moisture. Based on the concept of critical soil moisture, we hypothesise that the link between soil moisture and vegetation droughts is more direct in the water-limited Mediterranean region, whereas a more complex behaviour is expected in the more humid Northern Europe. We investigate the relation between soil moisture and vegetation drought for six widespread meteorological drought events that occurred over the past two decades in Europe, including the severe 2003 and, more recent, 2018 events, that occurred in water- as well as energy-limited regions. In addition, we test the ability of soil moisture to predict observed agricultural drought (i.e. vegetation impact).

2 Methods

The most severe droughts over Europe (here 11° W-45° E, 35-72° N) during growing seasons over the past two decades were selected to study the relation between soil moisture and vegetation anomalies. The selection was based on the 6 month aggregated Standardized Precipitation Index (SPI6, derived from monthly NASA GPM IMERG precipitation data, McKee et al., 1993; Huffman et al., 2019) in September of each year, so that the SPI6 reflects the rainfall deficit over the entire growing season. Interconnected pixels over relatively large areas with a strong precipitation deficit (SPI6 $<$ -1) were chosen, resulting in the six events as indicated in Figure 1: the 2002 drought over the Baltic states and north-western Russia (Rimkus et al., 2017), the 2005 event on the Iberian Peninsula (Sepulcre-Canto et al., 2012) and the infamous 2003, 2015 and 2018 events over central Europe (Ionita et al., 2017; Hanel et al., 2018; Buras et al., 2020). Because of the

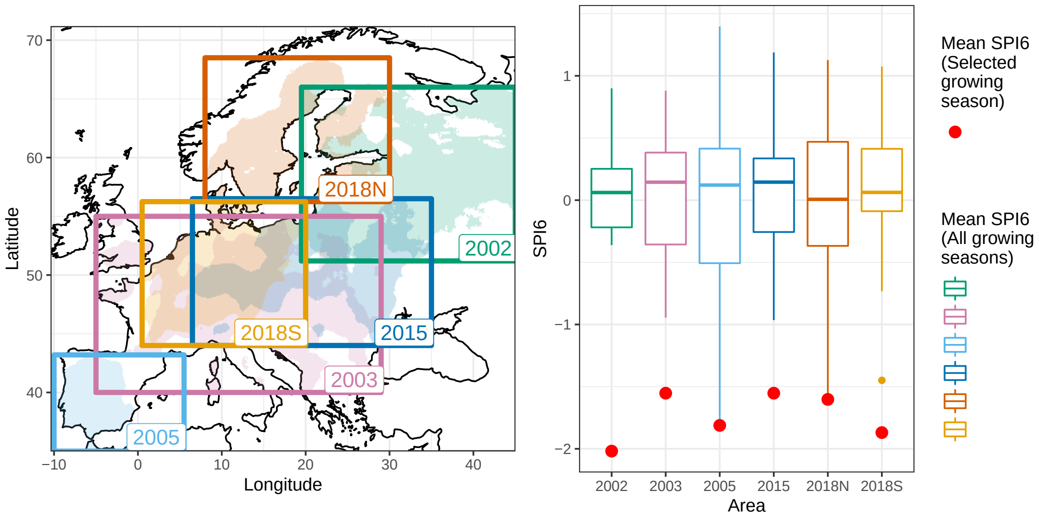

Figure 1. Properties of the selected summer droughts. Left: location and spatial extent, right: SPI6 over the selected growing season (red), compared to the distribution of SPI6 in the remaining growing seasons for the same region.

large North-South extent of the 2018 drought event, this event was split in two parts (referred to as *2018N* and *2018S*).

To allow for a fair comparison between anomalies of different variables, normalisation was used. Monthly soil moisture (SM, ESA CCI SM v04.5, Gruber et al., 2017; Dorigo et al., 2017; Gruber et al., 2019) and Normalized Difference Vegetation Index (NDVI, MODIS MOD13C2, Tucker, 1979; Didan, 2015) data were thus standardised by subtracting the long-term monthly mean from the SM/NDVI at each time step, and subsequently divided by the long-term monthly standard deviation. This resulted in values between approximately -3 and $+3$, indicating negative and positive anomalies, respectively, that can be directly compared with SPI6. Other indices, such as the ESSMI (Carrão et al., 2016) for soil moisture data, or the VCI (Kogan, 1990) for NDVI data, are available and comparable to normalisation, but a more general approach was adopted here to increase comparability of two different variables. We recognise anomalies in SM (SMA) and NDVI (NDVIA) below -1 as pixels in drought. To account for seasonality in the variables, data for each month of the year were taken separately, and pixels with less than 7 data points were removed from the analysis. The datasets have been extensively validated (e.g. Lahoz et al., 2018; Navarro et al., 2019), and, as such, a validation has not been conducted here.

After the data normalisation, for each drought event, the fraction of the selected SPI6 pixels with an anomaly lower than -1 was determined for each variable. Then, for each event and time step, the Pearson correlation between SMA and NDVIA was quantified. Though correlation is useful for an overview of similarity between two variables, it is not sensitive to bias or scale errors (Brier & Allen, 1951; Murphy & Epstein, 1989). Skill scores, on the other hand, give a more in-depth and well-rounded view on the use of SM as a predictor for agricultural impact. It should be noted that, because soil moisture drought is often used as a proxy for vegetation drought, predictions using soil moisture drought are implicitly assumed to be skilful. Therefore, the number of Hits (H), Misses (M), Correct Rejections (CR) and False alarms (FA) were determined, and converted to five skill scores, each highlighting a different aspect of prediction accuracy. First, the

Frequency Bias (FB) is given by:

$$\mathrm{FB} = \frac{\mathrm{H+FA}}{\mathrm{H+M}}, \tag{1}$$

and expresses the difference between mean drought frequencies. Next, the frequency of hits (FOH) is a measure of discrimination, showing the fraction of forecasted vegetation droughts that were correct, which is given by:

$$\mathrm{FOH} = \frac{\mathrm{H}}{\mathrm{H+FA}}. \tag{2}$$

The frequency of misses (FOM) is given by:

$$\mathrm{FOM} = \frac{\mathrm{M}}{\mathrm{H+M}}, \tag{3}$$

and expresses the fraction of observed vegetation droughts that are incorrectly forecasted by the soil moisture anomaly. The Hanssen-Kuipers score (HK Hanssen & Kuipers, 1965) measures the ability of the soil moisture drought to discriminate between (or correctly classify) vegetation drought events and non-events:

$$\mathrm{HK} = \frac{\mathrm{H}}{\mathrm{H+M}} - \frac{\mathrm{FA}}{\mathrm{FA+CR}}. \tag{4}$$

Lastly, the Odds Ratio (OR, Stephenson, 2000) is used to measure the strength of the association between soil moisture and vegetation drought:

$$\mathrm{OR} = \frac{\mathrm{H} \cdot \mathrm{CR}}{\mathrm{FA} \cdot \mathrm{M}} \tag{5}$$

We refer to Hogan and Mason (2011) for an overview of these, and more, skill scores, and their (dis-)advantages.

3 Results

A general check of the full data time series revealed that during each event, asynchronies between spatial patterns in soil moisture and vegetation anomalies are widespread. Figure 2 serves as an illustration for these asynchronies, which occur in all green and purple pixels (See Fig. S1-S5 for other events). Regionally more humid areas such as mountain ranges and high latitude regions can easily be distinguished by their relatively low Pearson correlations between SMA and NDVIA (Fig. S6), in line with our hypothesis. Furthermore, correlations between the anomalies were low in April and generally increased towards September, though in some areas, correlations peak in August.

Not all of the six studied events were equally affected by deficits in SM and/or NDVI. A comparison between drought extents using the fraction of the area affected by a SM/NDVI deficit is given in Fig. 3. The 2002, 2015 and 2018N events are characterised by a clear overlap between the *NDVI* and *Both* lines, indicating that an area affected by an NDVI deficit also has a soil moisture deficit. Interestingly, in 2003, 2005 and 2018S, some vegetation deficits occur in absence of a SM drought. In these cases, vegetation growth was thus not obviously limited by current water content, but possibly by other factors, e.g., energy, heat stress, antecedent low soil moisture conditions, or pests and diseases. Since these three events are located further south than most other selected events, energy limitations can be ruled out. Heat stress could well have been the limiting factor for vegetation, as well as antecedent soil moisture anomalies, which had been negative long before the growing season in 2003 and 2005 (Fig. S9), though NDVI anomalies (Fig. S11) were negative even before that, indicating a poor state of vegetation all-together. For the 2018S event, antecedent SM conditions are ruled out, as its anomalies only become negative in May 2018.

Figure 4 shows the severity of each drought event for both vegetation and soil moisture and the Pearson correlation between NDVIA and SMA. Asynchrony between the

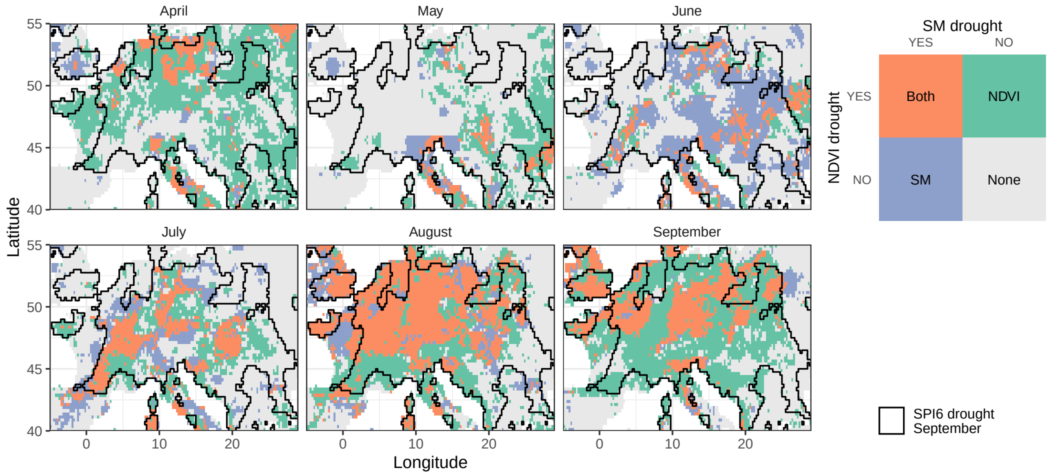

Figure 2. Synchronicity between soil moisture and vegetation droughts during the 2003 growing season. Note the asynchronous development of soil moisture and vegetation drought, with soil moisture drought dominating in June, and vegetation in April and September. Similar figures for the other drought events are included in the Supporting Information (Fig. S1-S5)

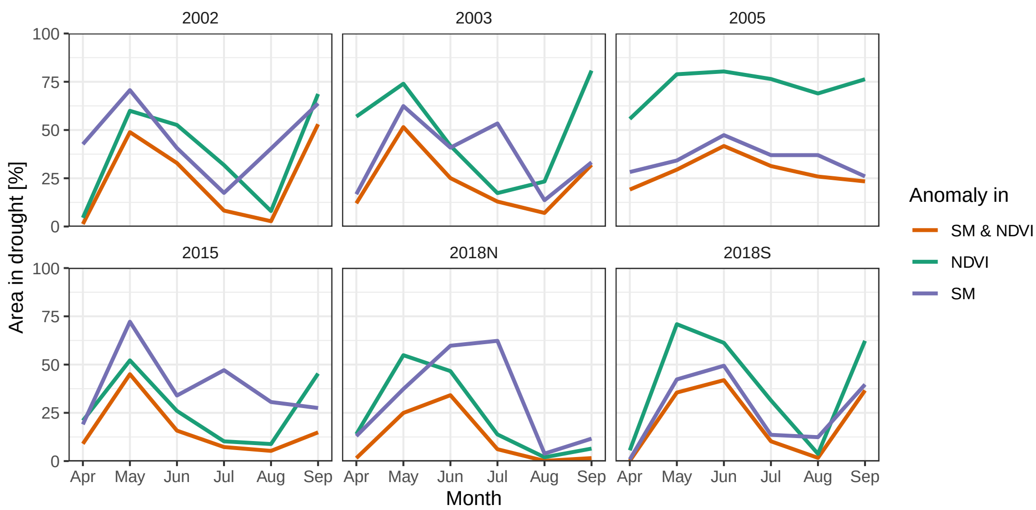

Figure 3. Growing-season evolution of percentage of area in drought. Panels show the six drought events, with drought defined as anomaly < -1. NDVI (green) and SM (purple) pixels are shown separately, and the percentage of pixels affected by droughts in both variables simultaneously (orange).

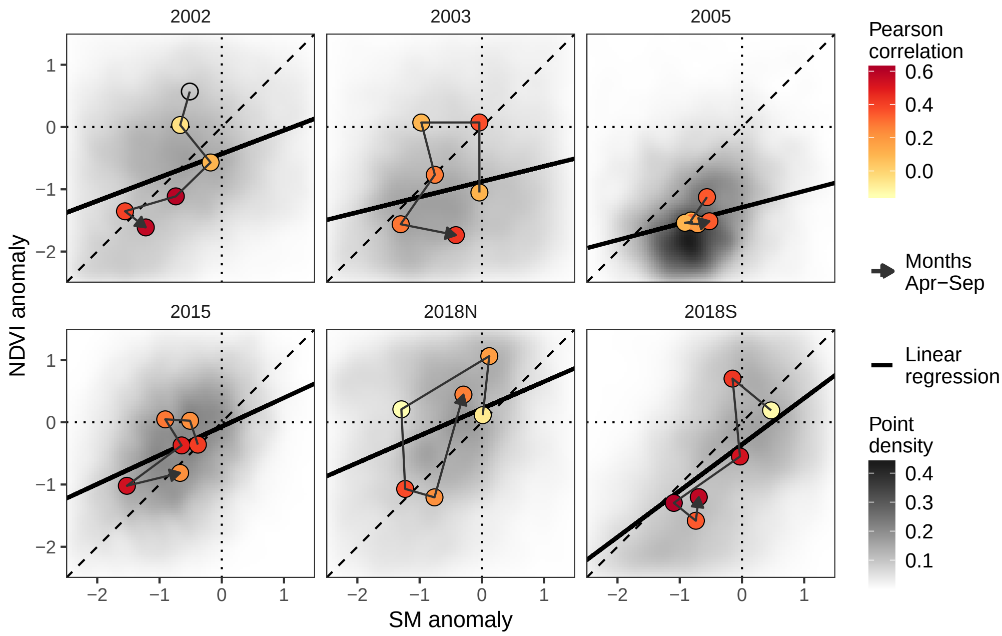

Figure 4. Relation between soil moisture and vegetation drought anomalies. Panels show the six drought events, with drought defined as anomaly < -1. Centroids of each month are chronologically connected with an arrow, and shaded by the Pearson correlation in that month, if $p \leq 0.05$.

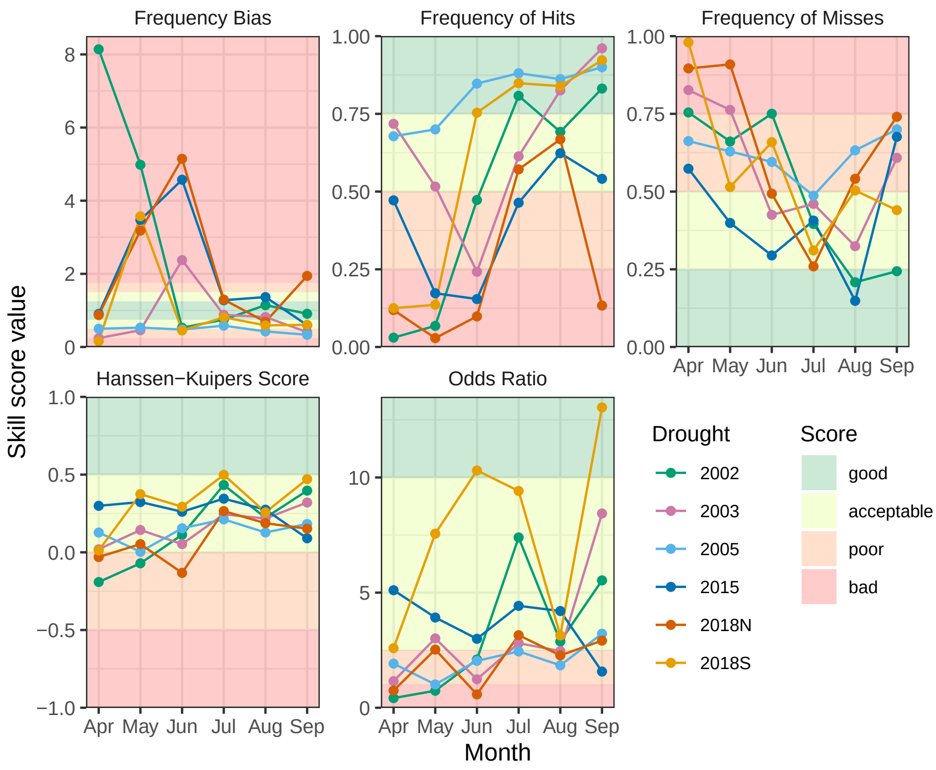

Figure 5. Skill scores for soil moisture drought as a proxy for vegetation drought. Background colours indicate the quality of the skill scores (see Methods for an, and the lines show different drought events.

two variables is visible in the irregular shape of the arrows, and the deviation of the linear regression from the 1:1 line. Generally, a delay can be distinguished between negative SMA and NDVIA values. This delay was expected, since the information contained in satellite soil moisture data mainly contains surface soil moisture content, rather than root-zone soil moisture content (Nicolai-Shaw et al., 2017). Interestingly, though, positive anomalies are more common in NDVIA than in SMA, showing that impacts of soil moisture droughts do not always show in the vegetation, and can sometimes even lead to opposite, i.e. positive, impacts in vegetation. High monthly correlations between SMA and NDVIA generally occur late in the growing season, as shown by redder colours in Fig. 4. It seems that there is a general pattern that, when vegetation is energy limited, it remains largely unaffected by small anomalies in soil moisture content, whereas under water limited conditions, which are more likely to occur near the end of the growing season, higher correlations are found, consistent with results of Jolly et al. (2005).

Given the clear asynchrony in soil moisture and vegetation under water-limited conditions, it is relevant to question how well soil moisture-based indices, such as the widely-used SSMI and PDSI, perform when targeting to quantify vegetation drought. The skill scores of agricultural drought impacts, as reflected in NDVI and as predicted using SMA, is shown in Figure 5. From the low density of lines in the parts of the skill score plots shaded green, it is clear that the overall skill is rather low. Moreover, similar to the Pearson correlation, skill scores generally increase in August, though we expect the usefulness of end-of-season NDVIA prediction to be limited for agricultural purposes. Over-forecasting, i.e. when more droughts are forecasted using soil moisture than there are droughts observed in vegetation, as seen in a FB > 1, generally occurs in the beginning of the growing season, whereas underforecasting (FB < 1) occurs near the end of the growing season. The respective in- and decrease in FOH and FOM show the result of the changing frequency bias. The HK, showing the accuracy of events minus the accuracy of non-events, is rather stable throughout the growing season, though it peaks in the second half, just as the OR, which shows the number of correct forecasts. None of the drought events stand out in all of the skill scores. A sensitivity analysis showed that different thresholds for the drought selection and skill scores did not substantially change the results.

4 Discussion

The complexity of agricultural droughts is not a local or regional issue, but a global one, and thus should be considered that way. While this study was performed over the European continent, it covers a range of climates found around the globe: from arid regions in the Mediterranean to boreal regions in northern Scandinavia. It is therefore expected that the behaviour will be similarly asynchronous in other regions. Limitations of this approach are on a local scale, rather than the global scale, due to the low spatial resolution of the used datasets. Even though each dataset was carefully selected based on their length, spatial resolution and validation results over Europe, resulting in a selection of datasets best suited for this analysis, uncertainties are inherent to any type of data and results should therefore be interpreted with care. In complex landscapes, high-resolution information can sometimes reveal a range in anomalies, even containing contrasting signs, that is not visible at coarser scale (Buitink et al., 2019). The normalising of soil moisture data in this study can be criticised, because soil moisture data are often bimodal (Teuling et al., 2005; Vilasa et al., 2017). In addition, a dataset length of 18 years can be considered short compared to a traditional 30-year reference period, as recommended by the WMO (2017). On the other hand, uncertainties due to areal properties are decreased, because pixel values are compared to other values of the exact same pixel, while the resulting anomalies can easily be compared to other pixel values. This, next to the possibility to fairly compare different variables, led to the decision to use a standard normalisation for both vegetation and soil moisture data, regardless of this method's limitations.

In this research we used available long-term satellite records of soil moisture and NDVI. Whereas current satellite soil moisture products are limited to the top few cm, a soil moisture drought assessment is ideally based on observations over the entire root zone. However, such observations are currently only available in several regional-scale observation networks (Mittelbach et al., 2011). Besides NDVI, numerous other products exist that reflect vegetation water status and/or productivity. These include other indices based on optical (NIR, RED and BLUE) imagery (e.g. NIRv, EVI, etc.) or on microwave data (e.g. VOD). Though each of these different indices might give slightly different results, their application should not affect the fundamentally different response of soil moisture and vegetation to drought.

The inherently complex and nonlinear relation between soil moisture and vegetation status has important implications for drought monitoring, where traditionally a distinction is made between meteorological, agricultural, and hydrological drought events. Whereas traditionally soil moisture has been used to indicate agricultural drought, our research highlights that a distinction is necessary between soil moisture drought (reflecting water status) and vegetation drought (reflecting its impact on the vegetation). This is particularly true when evaluating droughts across climate zones. The distinction between soil moisture and vegetation drought is important, because shorter soil moisture droughts can even have a positive rather than negative impact on productivity, risking misclassification of drought events and false drought alarms.

5 Conclusions

Agricultural droughts are generally quantified using soil moisture anomalies, but our results show that a clear asynchrony exists between these anomalies and their effects on vegetation. occasionally, negative anomalies in soil moisture even lead to positive anomalies in vegetation. In some of the studied events, vegetation drought could not be attributed to a soil moisture deficit alone. This leads to a discrepancy between the definition of agricultural droughts and the synchrony of soil moisture and vegetation deficits. To overcome this duality in the definition of agricultural droughts, and to prevent false drought alarms, drought monitoring and prediction may benefit from a move away from the combined term *agricultural drought*, that can lead to mixing up of soil moisture and vegetation effects, towards two separate terms: soil moisture drought and vegetation drought, each with their own indices and use in drought monitoring and forecasting.

Acronyms

CR Correct Rejections
FA False Alarms
FB Frequency Bias
FOH Frequency of Hits
FOM Frequency of misses
H Hits
HK Hanssen-Kuipers score
M Misses
NDVI(A) Normalized Difference Vegetation Index (Anomaly)
OR Odds Ratio
SM(A) Soil Moisture (Anomaly)
SPI Standardized Precipitation Index

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Supporting Information for "Asynchrony of recent European soil moisture and vegetation droughts"

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Contents of this file

Introduction This document is intended to provide a more detailed background information on the separate drought events discussed in the paper and to visualise the data underlying the results.

S1-S5 Figures S1 to S5 provide illustrations of each drought event, with separate colours for pixels that are identified as in a soil moisture drought (SM < -1, purple), a vegetation drought (green, NDVI < -1) or both (orange).

S6 Figure S6 is included in this document to provide an overview of spatial differences in correlation between soil moisture and NDVI anomalies.

S7-S8 Figures S7 and S8 show the reaction of different land use types on drought conditions. Figure S7 contains all pixels in drought areas which have at least 90% coverage in the CCI landcover dataset from 2018 in one of the following categories:

- Cropland, rainfed, tree or shrub cover
- Tree cover, broadleaved, evergreen, closed to open (>15%)
- Tree cover, broadleaved, deciduous, closed to open (>15%)
- Tree cover, broadleaved, deciduous, closed (>40%)
- Tree cover, broadleaved, deciduous, open (15-40%)
- Tree cover, needleleaved, deciduous, closed to open (>15%)
- Tree cover, needleleaved, deciduous, closed (>40%)
- Tree cover, needleleaved, deciduous, open (15-40%)
- Tree cover, needleleaved, evergreen, closed to open (>15%)
- Tree cover, needleleaved, evergreen, closed (>40%)
- Tree cover, needleleaved, evergreen, open (15-40%)
- Tree cover, mixed leave type (broadleaved and needleleaved)
- Mosaic T and shrub (>50%) / herbaceaous cover (<50%)

Figure S8 contains all pixels in drought areas which have at least 90% coverage in the CCI landcover dataset from 2018 in one of the following categories:

- Cropland, rainfed
- Cropland, rainfed, herbaceous cover
- Cropland irrigated or post-flooding

- Mosaic cropland (>50%) / natural vegetation (Tree, shrub, herbaceous cover) (<50%)
- Mosaic natural vegetation (Tree, shrub, herbaceous cover) (>50%) / cropland (<50%)
- Grassland
- Sparse vegetation (tree, shrub, herbaceous cover) (<15%)

S9-S12 Figures S9 to S12 show average time series of soil moisture (S9, S10) and NDVI (S11, S12), from May in the year prior to the event until the end of the event (September) in the selected pixels. All values in the selected event extent, according to the SPI6 rule as discussed in the main document, were averaged per monthly time step. Figures are provided both for the anomalies (S9, S11) and the original values (S10,S9).

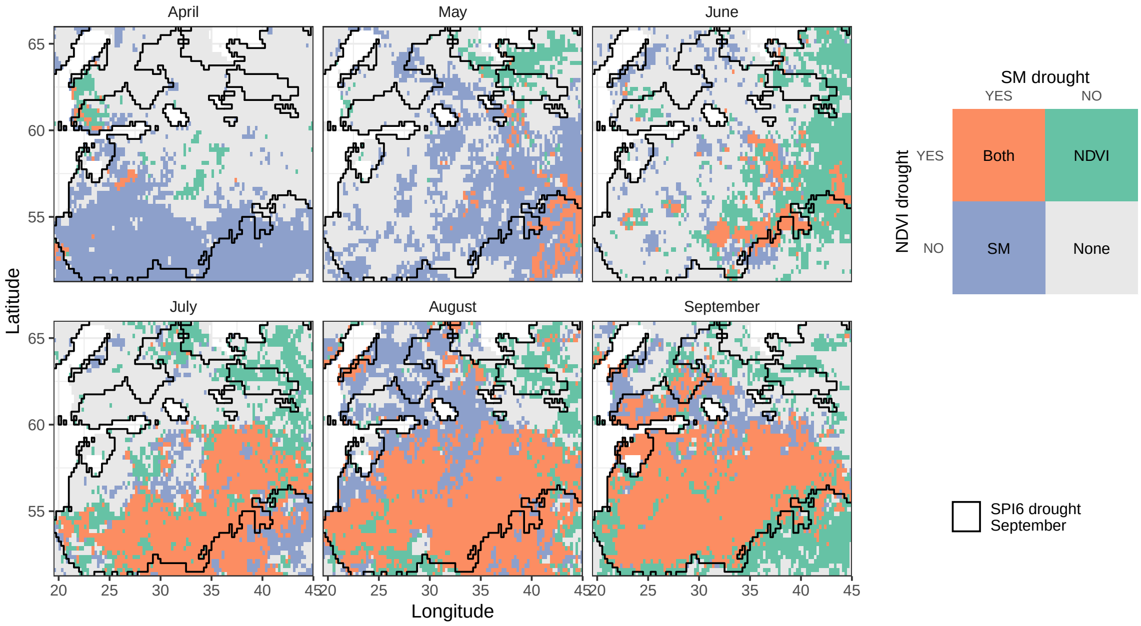

Figure S1. Soil moisture and vegetation anomalies during the 2002 growing season, produced in the same way as Figure 2 in the main document.

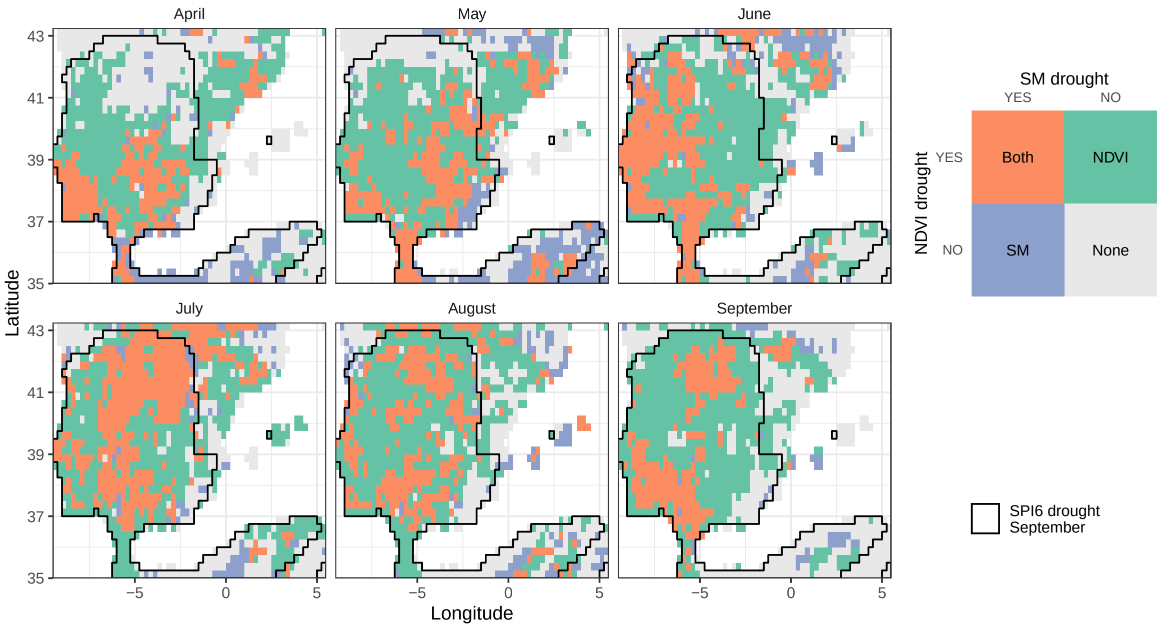

Figure S2. Soil moisture and vegetation anomalies during the 2005 growing season, produced in the same way as Figure 2 in the main document.

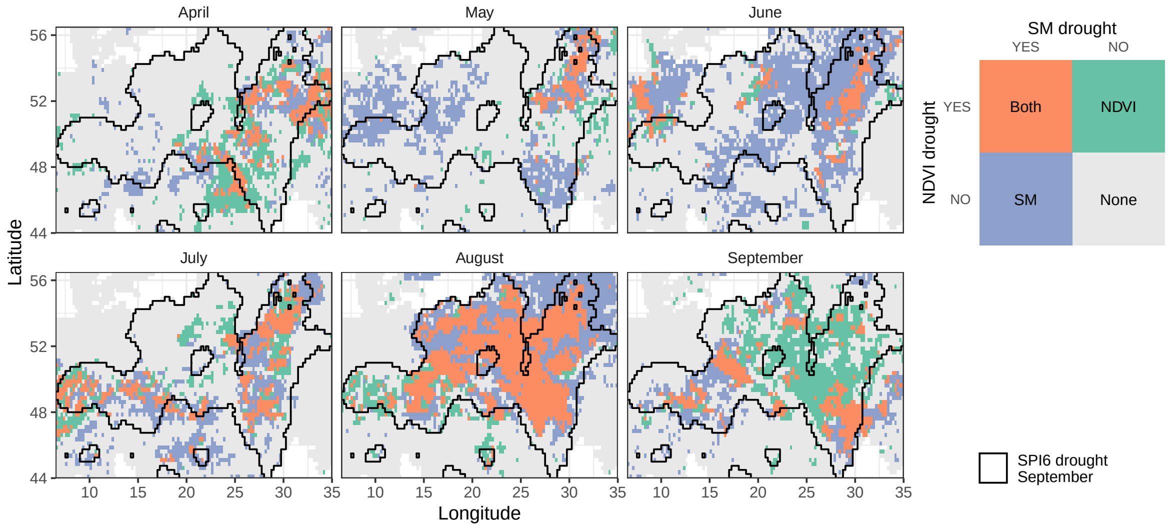

Figure S3. Soil moisture and vegetation anomalies during the 2015 growing season, produced in the same way as Figure 2 in the main document.

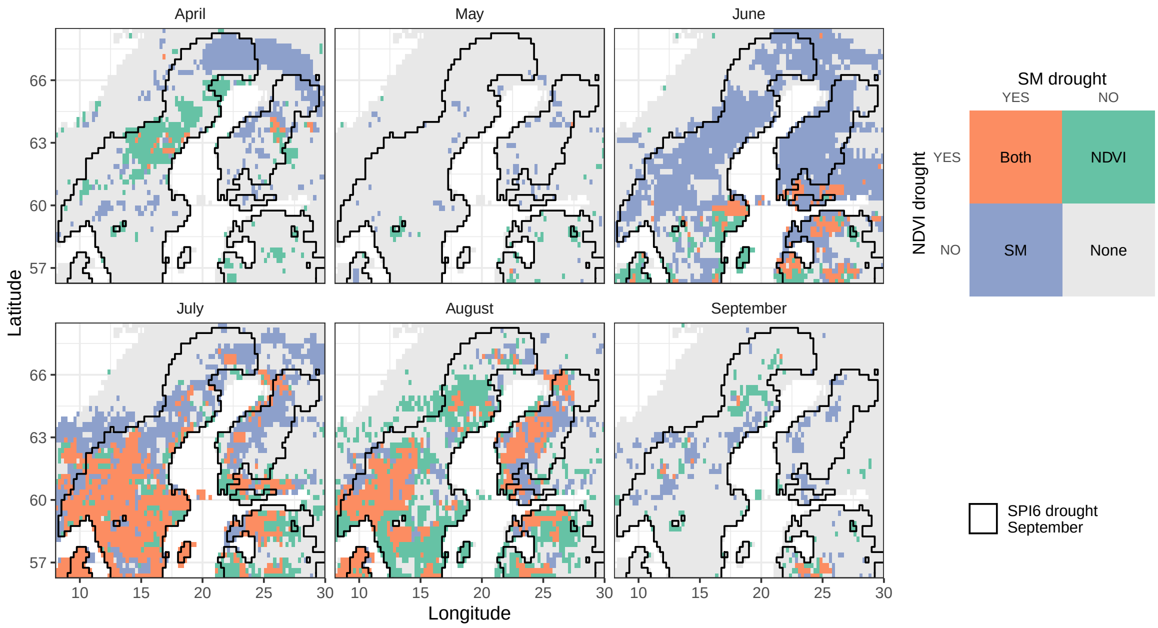

Figure S4. Soil moisture and vegetation anomalies during the 2018 growing season (northern part of drought event), produced in the same way as Figure 2 in the main document.

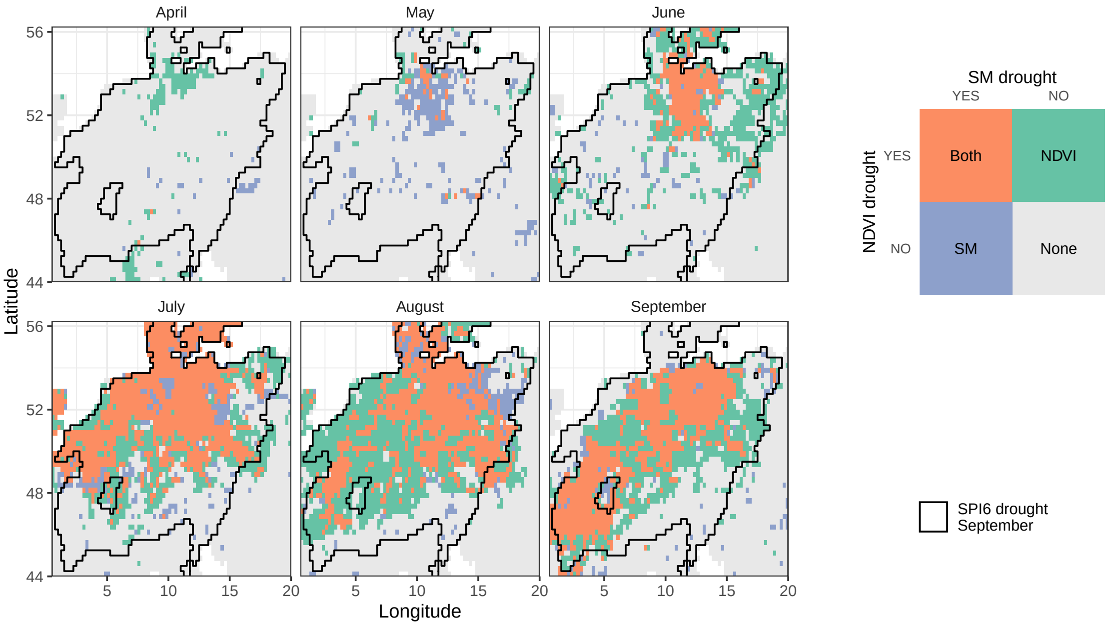

Figure S5. Soil moisture and vegetation anomalies during the 2018 growing season (southern part of drought event), produced in the same way as Figure 2 in the main document.

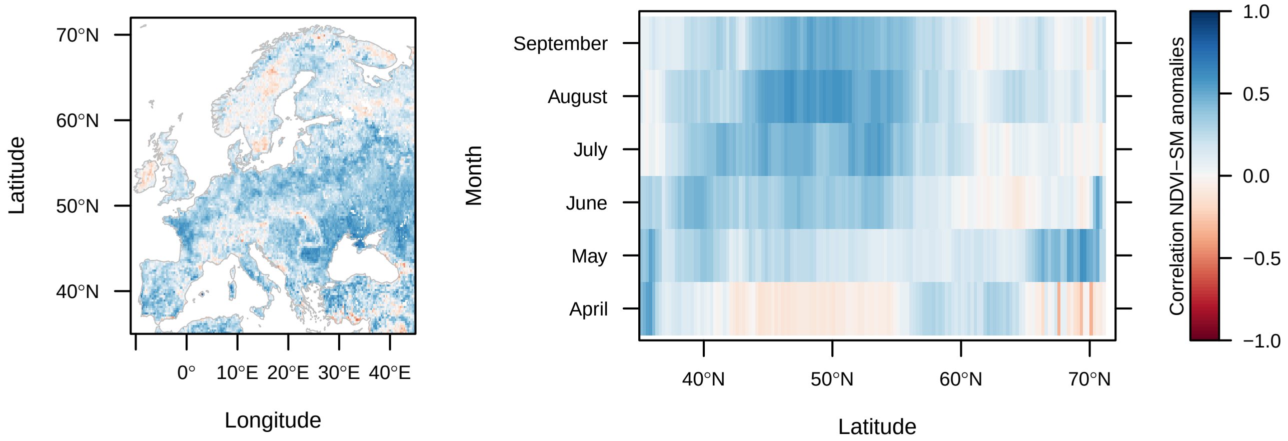

Figure S6. Correlation between soil moisture and NDVI, in space (left), and zonal averages throughout the growing season (right).

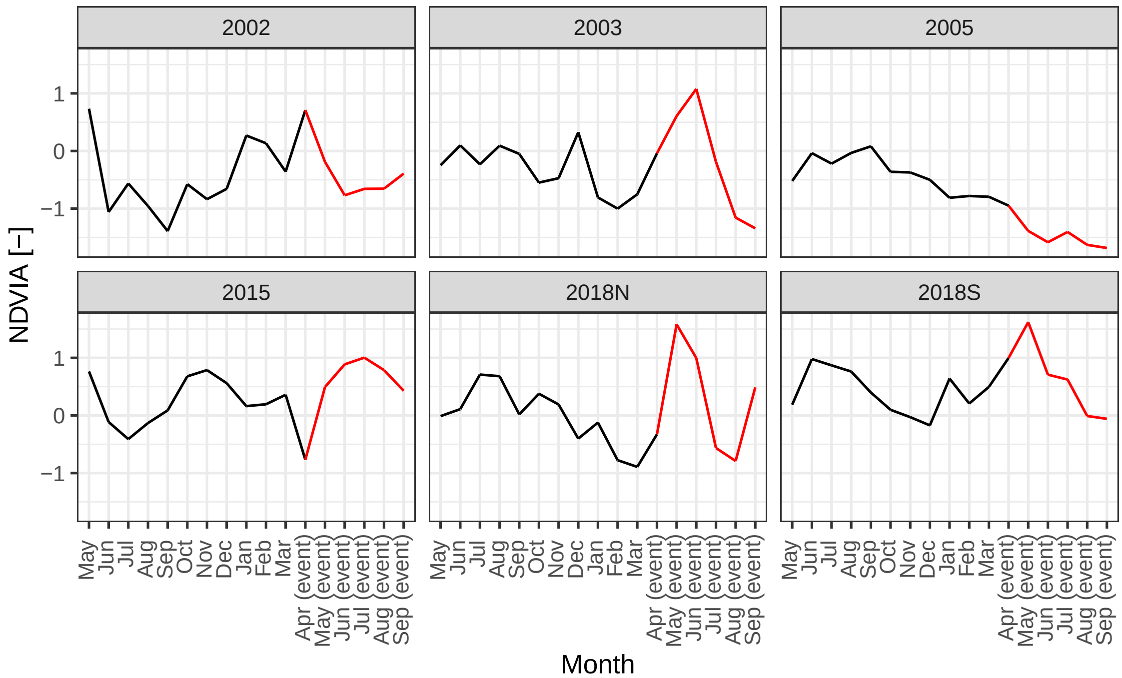

Figure S7. Average NDVI anomalies in forested pixels in event areas prior to (black) and during (red) each event.

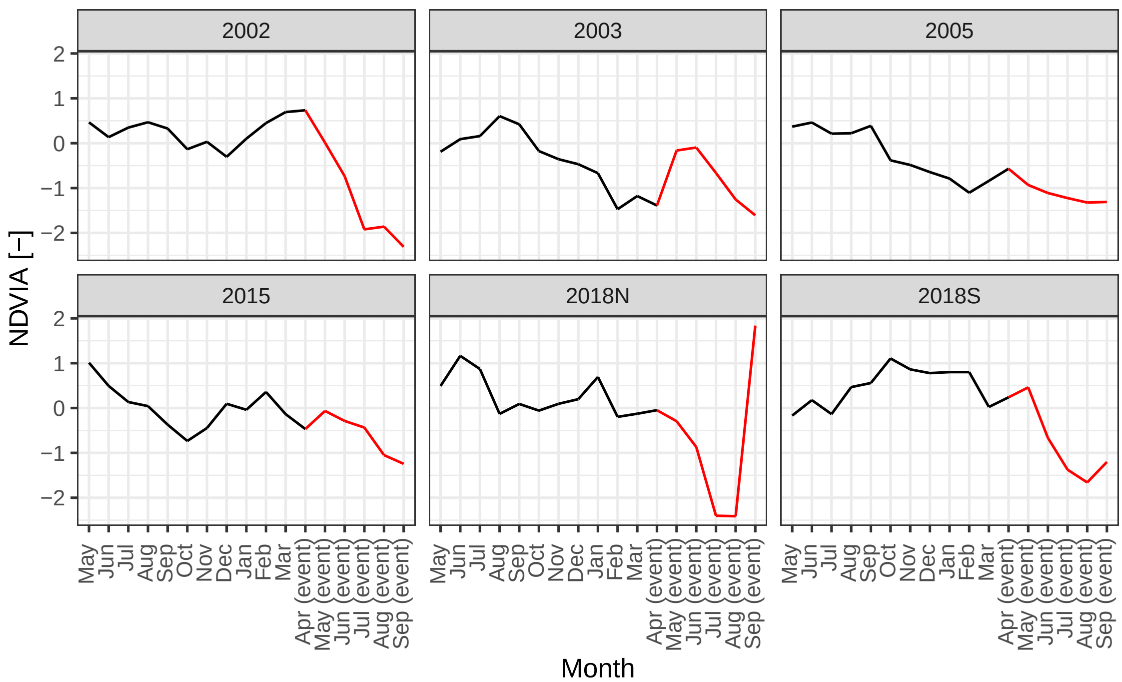

Figure S8. Average NDVI anomalies in grassland pixels in event areas prior to (black) and during (red) each event.

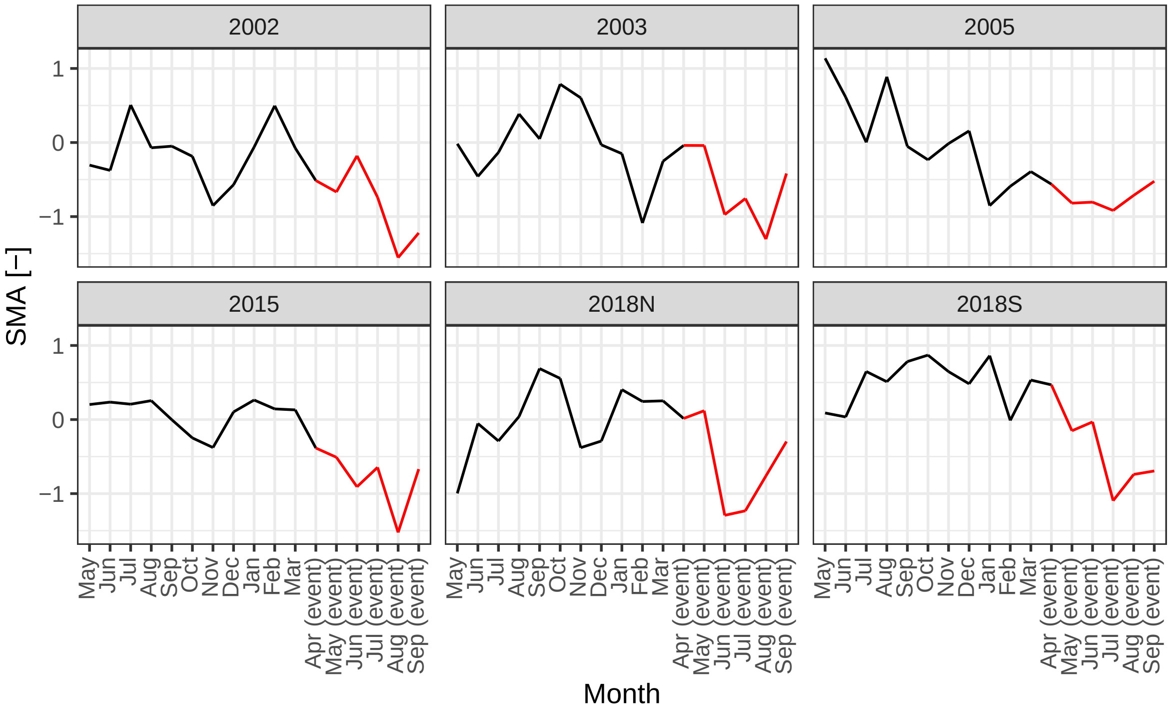

Figure S9. Average soil moisture anomalies in event areas prior to (black) and during (red) each event.

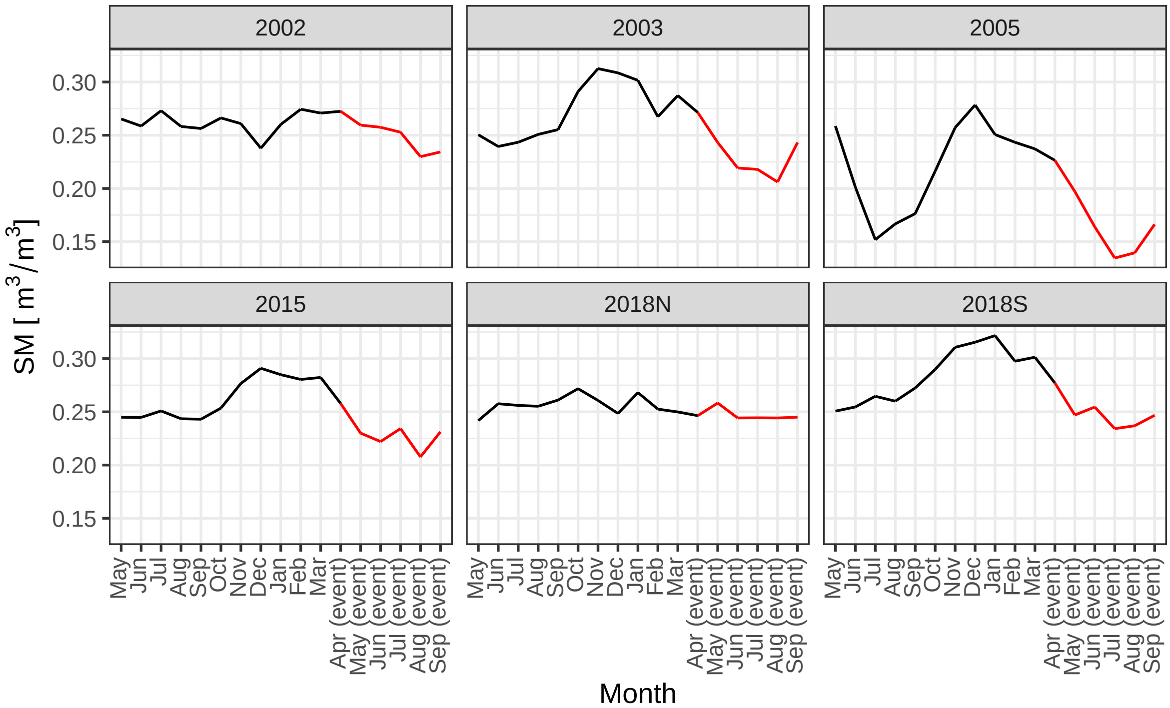

Figure S10. Average soil moisture in event areas prior to (black) and during (red) each event.

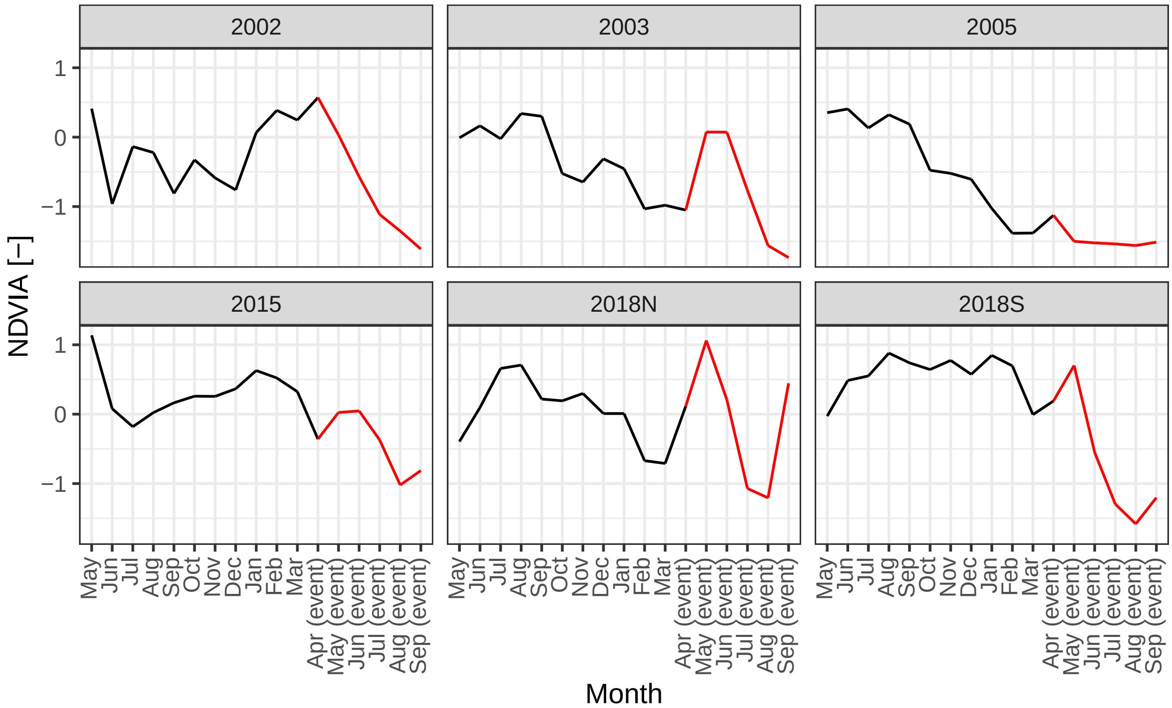

Figure S11. Average NDVI anomalies in event areas prior to (black) and during (red) each event.

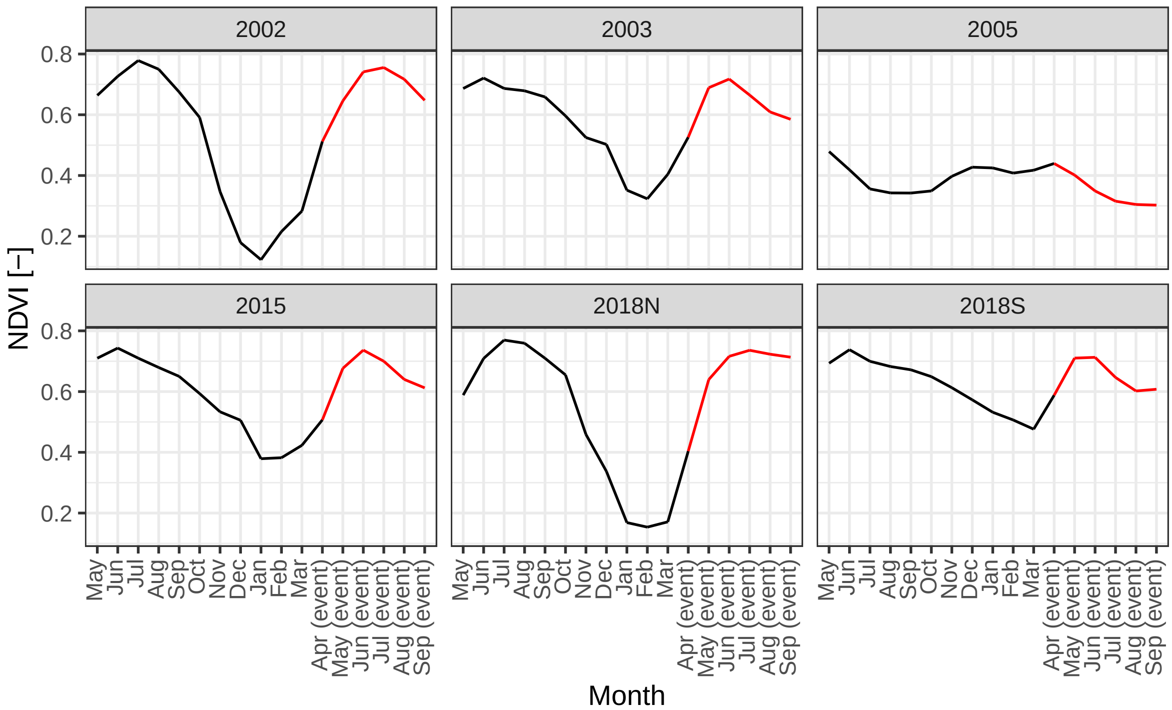

Figure S12. Average NDVI in event areas prior to (black) and during (red) each event.