~~Increased vulnerability~~ Vulnerability of European ecosystems to two compound dry and hot summers in 2018 and 2019

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Abstract. In 2018 and 2019, central Europe was ~~stricken~~ affected by two consecutive extreme dry and hot summers (~~DH2018 and DH2019~~DH18 and DH19). The ~~DH2018~~ DH18 had severe impacts on ecosystems and likely affected vegetation activity in the subsequent year, for example ~~though~~ through depletion of carbon reserves or damage from drought. Such legacies from drought and heat stress can further increase vegetation susceptibility to additional hazards. Temporally compound extremes such as ~~DH2018 and DH2019~~ DH18 and DH19 can, therefore, result in an amplification of impacts by preconditioning effects of past disturbance legacies.

Here, we evaluate how these two consecutive extreme summers impacted ecosystems in central Europe and how the vegetation responses to the first compound event (~~DH2018~~DH18) modulated the impacts of the second (~~DH2019~~DH19). To quantify ~~the modulating role of vegetation responses to the impacts of~~ changes in vegetation vulnerability to each compound event, we first train a set of statistical models for the period 2001-2017, which are then used to predict the impacts of ~~DH2018 and DH2019~~ DH18 and DH19 on Enhanced Vegetation Index (EVI) anomalies from MODIS. These estimates ~~can be seen as the~~ correspond to expected EVI anomalies ~~, had the impacts of DH2018 and DH2019 been consistent with~~ in DH18 and DH19 based on past sensitivity to climate. ~~These can then be~~ Large departures from the predicted values can indicate changes in vulnerability to dry and hot conditions, and used to identify modulating effects by vegetation activity and composition or other environmental factors ~~such as elevated CO$_2$ or warming trends~~on observed impacts.

We find two regions in which the impacts of the two DH events were significantly stronger than those expected based on previous climate–vegetation relationships. One region, largely dominated by grasslands and crops, showed much stronger

impacts than expected in both DH events due to an amplification of their sensitivity to heat and drought, possibly linked to changing background CO_2 and temperature conditions. A second region, dominated by forests and grasslands, showed browning from ~~DH2018 to DH2019~~ DH18 to DH19, even though dry and hot conditions were partly alleviated in 2019. This browning trajectory was mainly explained by the preconditioning role of ~~DH2018~~ DH18 to the observed response to ~~DH2019~~ DH19 through legacy effects, and possibly by increased susceptibility to biotic disturbances, which are also promoted by warm conditions.

Dry and hot summers are expected to become more frequent in the coming decades posing a major threat to the stability of European forests. We show that state-of-the-art process based models miss these legacy effects. These gaps may result in an overestimation of the resilience and stability of temperate ecosystems in future model projections.

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1 Introduction

Extreme dry and hot summers in western and central Europe have become more frequent over the past decades (Coumou and Rahmstorf, 2012; Seneviratne et al., 2014), a trend that is expected to continue as global mean temperatures rise (Barriopedro et al., 2011). Hot extremes in Europe are promoted by changes in atmospheric circulation (Coumou et al., 2015; Drouard et al., 2019) and amplified by strong feedbacks between the land-surface and the atmosphere, being therefore also associated with severe droughts (Miralles et al., 2014; Samaniego et al., 2018), i.e. compound ~~hot and dry~~ dry and hot events (DH).

In Europe, DH events have usually strong negative impacts on ecosystems, such as reduced ecosystem productivity (Ciais et al., 2005; Bastos et al., 2020b). After severe drought and heat stress, plant recovery can be lagged, for example due to ~~leaf shedding~~ reduced growth, or non-reversible losses in hydraulic conductance or carbon reserve depletion (Ruehr et al., 2019). This, in turn may increase vulnerability ~~if another DH~~ to another DH, if it occurs before complete recovery. ~~A second DH event~~ Repeated droughts have been linked to increased forest vulnerability in the northern mid-latitudes, although with variable responses (Anderegg et al., 2020). Impaired functioning during the recovery period can additionally increase the hazard of ~~other disturbances such as fires or insect outbreaks (Rouault et al., 2006; ?; ?). More frequent extremes may, therefore, threaten ecosystem stability by compounding multiple hazards and concurrent and lagged effects from highly impactful DH events~~ subsequent disturbances, e.g. insect outbreaks (Rouault et al., 2006). However, reductions in leaf area, increases in root allocation (McDowell et al., 2008) or reduced growth, by reducing evaporative tissue and enhancig water uptake capacity, could also confer an advantage to subsequent droughts (Gessler et al., 2020). It remains unclear whether the increased vulnerability to a subsequent drought can be explained by compounding hazards (e.g. accumulated water-deficits or compound heat) or modulating effects due to vegetation responses to the first event.

~~At European scale~~

In Europe, the summer ~~in~~ of 2018 was the hottest since 1500 (Sousa et al., 2020) ~~while at the same time leading to~~ and associated with an unprecedented area affected by drought (Albergel et al., 2019; Bastos et al., 2020a). ~~In 2019, central~~

50 ~~Europe was stricken by~~ This DH event resulted in decreases in ecosystem productivity by up to 50% in central Europe (Bastos et al., 2020a; Buras et al., 2019) and crop yield losses (Beillouin et al., 2020). Part of the central European region affected by DH18 registered another extremely hot and dry summer ~~(Boergens et al., 2020; Sousa et al., 2020).~~ in 2019 (Boergens et al., 2020; Sousa ~~.~~

From a hydrometeorological perspective, the dry and hot summers in 2018 and 2019 (~~DH2018 and DH2019~~DH18 and

55 DH19, respectively) could be considered individually as two compound events in that both high temperatures and strong drought conditions were observed (Zscheischler and Fischer, 2020). Taken together, they constitute a temporally compound event (Zscheischler et al., 2020)~~. For example,~~: Boergens et al. (2020) have shown that while soil-moisture deficits in summer 2019 were not as pronounced as in 2018, total water storage was lower in 2019 due to the water storage deficit resulting from the 2018 event.

60 ~~From an ecological perspective, these events are more complex as they constitute a combination of temporally (two consecutive extreme summers) and preconditioning (changes in ecosystem functioning) compound events. The DH2018 was one of the strongest in the past decades, leading to decreases in ecosystem productivity by up to 50% in central Europe (Bastos et al., 2020a; Buras et a . Compared to previous extreme summers, DH2018 was associated with increased sensitivity to temperature (Bastos et al., 2020b) . This can be a sign of increased plant vulnerability to "hotter" droughts (Allen et al., 2015), or of detrimental effects from

65 increased growth in response to the previous sunny and warm spring (Bastos et al., 2020a).~~ Given the unprecedented magnitude of ~~DH2018 and its severe impacts, it likely imposed such legacies throughout the subsequent year, for example through reduced growth or carbon reserve depletion that may have increased vulnerability to yet another dry and hot summer~~ DH18, it is likely that at least some ecosystems had not yet fully recovered in 2019.

~~Repeated droughts have been linked to increased forest vulnerability in the northern mid-latitudes, although with variable~~
70 ~~responses (Anderegg et al., 2020). It remains unclear whether the increased vulnerability to a subsequent drought can be explained by physical drivers (e.g. accumulated water-deficits or compound heat) or by modulating effects by vegetation responses during and following the first drought. Moreover, responses to drought are expected to~~ Therefore, from an ecological perspective, these two events are more complex, as their impacts can be preconditioned by seasonal (Bastos et al., 2020a) and inter-annual legacy effects. Finally, vulnerability to DH events can further be modulated by long-term ~~increase in CO$_2$, but the~~

75 ~~direction of this effect is not clear~~environmental changes: water-savings from reduced stomatal conductance should attenuate drought stress (Peters et al., 2018), but concurrent decrease in ~~evapotranspiration cooling~~ evapotranspirative cooling along with "hotter droughts" may amplify heat stress ~~(Obermeier et al., 2018)~~ (Allen et al., 2015; Obermeier et al., 2018) (Fig. 1).

Separating the modulating effects controlled by vegetation responses to global change or by legacies from past disturbances (Kannenberg et al., 2020) and seasonal legacy effects (Buermann et al., 2018) in observations is problematic as it requires
80 considering the compounding effects of multiple drivers (e.g., compound heatwave and drought) and separating the role of seasonal and inter-annual legacies both in physical variables (e.g., soil-moisture depletion) and in vegetation vulnerability to those drivers. ~~Such effects have been separated for seasonal legacies using model experiments and~~ This can be done by
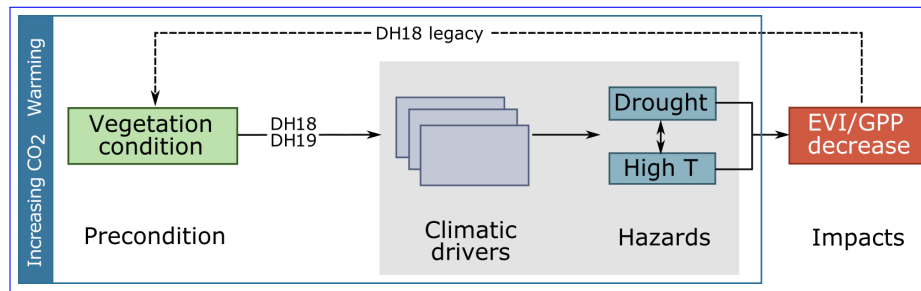
Figure 1. Conceptual description of the compound DH18 and DH19 events. Dry and hot conditions in both summers were a result of compouding atmospheric drivers (synoptic patterns, preceding climate anomalies, land-atmosphere interactions). The DH18 impacts were modulated by seasonal legacy effects in ecosystem functioning from a sunny and warm spring. We hypothesise that legacies from the DH18 event also contributed to modulate the response to DH19. These impacts can be further modulated by long-term changes in ecosystem vulnerability to drought and heat stress due to anthropogenic climate change and elevated CO_2.

designing counter-factual scenarios ((Lian et al., 2020; Bastos et al., 2020a)). to force process-based models, as recently done to evaluate seasonal legacy effects of hot and dry springs (Lian et al., 2020; Bastos et al., 2020a). However, it has been argued

85 that Earth System models have been reported to fail at modelling woody biomass trajectories following droughts (Anderegg et al., 2015), but so that they might miss inter-annual legacy effects from DH events, although no simulations designed to isolate the individual impact of drought over subsequent years have been conducted. The simulations by land-surface models (LSMs) in Bastos et al. (2020a) separated the individual impact of DH2018 on carbon and water fluxes by using an additional factorial simulation. When extended to 2019, these simulations allow evaluating how models simulate inter-annual legacy effects of

90 DH2018 and vulnerability to consecutive droughts (DH2018 and DH2019) performed. Alternatively, statistical models can be used to separate such effects based on observational data (Chan et al., 2021).

The occurrence of two consecutive hot and dry summers is uncommon in central Europe but may become more likely in the coming decades Barriopedro et al. (2011); Boergens et al. (2020). Therefore, the DH2018 and DH2019 can provide insights on how resilient might European ecosystems be

95 Here, we focus on DH18 and DH19 to gain insights on the resilience of European ecosystems to repeated hot and dry summers in the coming decades. Here, we attempt to answer this question by using both observations and models to:(i) evaluate the vulnerability of ecosystems to DH2018 and DH2019;(ii) detect fingerprints of global change and disturbance legacy effects in ecosystem vulnerability to DH2018 and DH2019;(iii) assess the ability of state-of-the-art LSMs to simulate the impacts on ecosystem of these two events.

100 Our results show an increasingly important contribution of vegetation condition, evaluated here by greenness and productivity, in preconditioning the response to both DH2018 and DH2019, suggesting that feedbacks between climate extremes and ecosystem functioning may increased vulnerability to climate change. Using both remote-sensing data and an update of the simulations by Bastos et al. (2020a), we first evaluate whether there are signs of increased vegetation vulnerability to repeated dry and hot summers of 2018 and 2019, and try to identify possible modulating effects. We then compare observation-based

results to updated simulations by state-of-the-art land-surface models and dynamic global vegetation models (for simplicity referred to as LSMs) designed to isolate the impacts of DH18 and legacy effects (Bastos et al., 2020a).

2 Data

2.1 Climate variables

~~For~~ In ecological studies, drought is better characterized by soil-moisture anomalies i.e. agricultural drought (Sherriff et al., 2011; Seneviratne et al., 2012; Samaniego et al., 2018) than atmospheric drought indices. We therefore base our drought assessment on two complementary soil-moisture datasets. The first is the observation-based soil moisture data obtained from SoMo.ml ~~(?)~~(Sungmin and Orth, 2021), used as reference in this study, and the second, for comparison with SoMo.ml, is ~~give~~ given by ERA5 volumetric soil-water content (Hersbach et al., 2020).

The SoMo.ml data are generated using a Long Short-Term Memory neural network model trained with meteorological forcing from ERA5 and land surface characteristics as inputs and global in-situ soil moisture measurements (Dorigo et al., 2011; Zeri, 2020) as target variables. The data cover ~~the period 2000-2019~~ soil-moisture in the first 50cm of the soil and are available at 0.25°lat/lon resolution and daily time-steps for the period 2000–2019. We remapped the fields to the finer resolution of the MODIS grid and aggregated the data to monthly means. We then subtracted the mean seasonal cycle and long-term linear trend, and divided by the corresponding standard deviation to obtain standardized soil-moisture anomalies (SM_{anom}).

~~We use monthly~~ Monthly temperature and volumetric soil-water content ~~(layers 1 and 2, top 28cm)~~ from the ECMWF ERA5 Reanalysis ~~. ERA5 uses an improved land-surface data-assimilation system that makes use of remotely-sensed and in-situ observations, and shows improved skill compared to previous reanalyses (Hersbach et al., 2020) and good temporal agreement with a range of global soil-moisture networks (?). Data~~ were obtained from the Copernicus Climate Change Service at 0.25°lat/lon resolution (Hersbach et al., 2020) at monthly time-steps and selected for the period 2000-2019 (common with SoMo.ml) and remapped to the finer resolution of the MODIS grid using conservative ~~regridding~~remapping. Standardized anomalies were calculated ~~by removing the mean seasonal cycle and long-term linear trend and then dividing by the corresponding standard deviation of~~ as described for SM_{anom} for ERA5 temperature and soil-moisture fields (T_{anom}, SM_{anom}^{ERA5}). Soil-moisture anomalies from ERA5 in layers 1–2 (top 28cm) are used for comparison of drought conditions with those estimated by SoMo.ml~~(SM_{anom} for simplicity), although it is worth noting that~~, although the two datasets are not fully independent.

2.2 Vegetation and soil data

We used the 16-day Enhanced vegetation Index (EVI) from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor from the MOD13C1 CMG product. The MOD13C1 CMG ~~follows a strict quality control and uses a gap-filling scheme to~~ provide continuous cloud-free spatial composites from 1km data ~~(Didan et al., 2015)~~ projected on a 0.05°lat/lon grid ~~. covering~~ (Didan et al., 2015), and were selected for the period 2001–2019. ~~MOD13C1 CMG is, therefore, a higher-quality product~~

especially suitable for spatiotemporal analysis and for comparison with LSMs as intended here. Standardized EVI anomalies (EVI_{anom}) were calculated by removing the mean seasonal cycle and long-term linear trend, and were then scaled by the corresponding pixel-level temporal standard deviation following the same approach as for climate variables. The standardization allows comparing the relative magnitude of anomalies for pixels with distinct temporal variability patterns and with vegetation productivity simulated by LSMs, which have different physical units.

For We used land-cover distribution we used in 2018 from the ESA Climate Change Initiative land-cover map (Kirches et al., 2014) (CCI-LC)for the year 2018. . The data are originally provided in land-cover classes at 300m spatial resolution and were converted to fractional cover at 0.05°lat/lon resolution for forest, grassland, crop classes using the LC-CCI user–tool.

Isohydricity We used isohydricity fields from global satellite measurements from Konings et al. (Konings et al., 2017) are available at 1°lat/lon resolutionfrom . Anisohydric plants (low isohydricity) show weak regulation of stomatal opening, and prioritize carbon assimilation over water savings during droughts. High isohydric plants show strong stomatal regulation of productivity and thereby preserve water at the cost of carbon assimilation during drought.

We use soil Available Water Capacity (AWC) from Ballabio et al. (2016) and Panagos et al. (2012), which used the Land Use and Cover Area frame Statistical survey (LUCAS) topsoil database to map soil properties at continental scale. The data are provided by the European Soil Data Centre (ESDAC) (esdac.jrc.ec.europa.eu).

2.3 Land-surface Outputs from land-surface and global dynamic vegetation models

Standardized anomalies of gross primary productivity (GPP_{anom}) and soil-moisture (SM_{anom}) were estimated by the mean of seven land-surface models (and dynamic global vegetation models (for simplicity referred to as LSMs) between 1979–2019 from an extension of Bastos et al. (2020a) simulations: a baseline simulation for comparison with observations and a factorial simulation to quantify the individual impact of summer 2018 and its legacy effects, when compared to the reference simulation.

For the reference simulation, the models were forced with observed CO_2 concentration from NOAA/ESRL and changing climate between 1979 A detailed description of the models used and 2019 from ERA5 and fixed land-cover map from 2010 from LUH2v2 (Hurtt et al., 2011). An additional simulation was ran where the models were forced with changing climate, except June–August 2018, where climatological summer climate conditions were used to force the models as described in Bastos et al. (2020a). This simulation allows evaluating the direct impact of DH2018 and its legacy effects. The model simulations were run for most models at 0.25 °spatial resolution for the European domain (32–75°N and -11–65°E), following a spin-up to equilibrate carbon-pools. For more details on the simulation protocol , we refer to (Bastos et al., 2020a). These simulations were extended here to 2019, using climate fields from ERA5. Here we analyse gross primary productivity (GPP) and simulated soil-moisturethe simulation protocol is provided in the Appendix A.

The seven LSMs followed the protocol and extended the simulations in Bastos et al. (2020a) up to 2019. These models are: ISBA-CTRIP (Joetzjer et al., 2015), JSBACH (Mauritsen et al., 2018), LPJ-GUESS (Smith et al., 2014), LPX-Bern (Lienert and Joos, 2018) , OCN (Zaehle et al., 2010), ORCHIDEE (Krinner et al., 2005) and SDGVM (Walker et al., 2017).

First, all ~~models~~ model outputs were remapped to a common 0.25 degree grid, and the multi-model ensemble mean was calculated for the common period with MODIS (2001–2019). The variables were then deseasonalized, detrended and standardized

170   as done for the other variables in the study.

3   Methods

3.1   Drought characterization

We use the observation-based SoMo.ml as a reference dataset to define agricultural drought conditions. Regions with average SM_{anom} below -1σ (Seneviratne et al., 2012) ~~,~~ during summer (JJA) are considered drought-affected areas during the DH

175   events. Then, a regional domain affected by both ~~DH2018 and DH2019~~ DH18 and DH19 events is selected to evaluate the impacts of two consecutive DH events. Within this region most pixels had negative SM_{anom} and the majority registered $SM_{anom} < -1.5\sigma$, but they differ in the magnitude of agricultural drought in ~~2019.~~ DH19. This allows comparing responses across pixels for different combinations of stress between ~~DH2018 and DH2019.~~ DH18 and DH19. Since we are interested in evaluating how recovery from DH18 affected impacts of DH19, we limit our analysis to pixels with negative EVI_{anom} in

180   DH18.

3.2   Compound ~~DH2018~~ DH18 and ~~DH2019~~ DH19 events

3.2.1   ~~DH2018~~ DH18 and ~~DH2019~~ DH19 impact characterization

To characterize different response ~~"types" to DH2018 and DH2019~~types to DH18 and DH19, we group pixels ~~in an unsupervised way (K-means clustering) based on the EVI impacts~~ using unsupervised clustering of EVI during the two extreme summers.

185   Using an unsupervised method allows avoiding making assumptions about the magnitude of impacts or the trajectory between ~~DH2018 and DH2019 (DH2018~~DH18 and DH19 (DH18→~~DH2019~~DH19) when grouping pixels. For this, we applied a K-means cluster analysis (Hamerly and Elkan, 2003) using two features, corresponding to the EVI_{anom} fields in ~~DH2018 and DH2019, for pixels with negative EVI_{anom} in DH2018~~DH18 and DH19. Four clusters captured the most significant differences in the impacts of ~~DH2018 and corresponding DH2018~~DH18 and corresponding DH18→~~DH2019~~ DH19 responses:

190   moderate/strong ~~DH2018~~ DH18 impacts and moderate/strong impacts by ~~DH2019~~DH19. These clusters were then used to evaluate how LSMs simulate the summer GPP_{anom} and SM_{anom}.

3.2.2   Detecting increased vulnerability to drought and heat stress

~~We propose that the two events can be considered~~ To better understand the impacts of the two events, we frame them as a combination of temporally and preconditioning compound events (Fig. 1): a sequence of two DH events, whose impacts

195   may be preconditioned by ecosystem vulnerability to DH, especially in the case of ~~DH2019. The DH impacts and ecosystem vulnerability, i.e. the propensity to be negatively impacted by a given event, are~~DH19. Vulnerability to DH is defined as the

impact of the physical hazard (hot and dry conditions) on vegetation and assessed by remotely-sensed EVI and modelled GPP anomalies.

~~Conceptual description of the compound DH2018 and DH2019 events. Dry and hot conditions in both summers were a~~ ~~result of compouding atmospheric drivers (synoptic patterns, preceding climate anomalies, land-atmosphere interactions). The~~ ~~DH2018 impacts were modulated by seasonal legacy effects in ecosystem functioning from a sunny and warm spring. We~~ ~~hypothesise that legacies from the DH2018 event also contributed to modulate the response to DH2019. These impacts can be~~ ~~further modulated by long-term changes in ecosystem vulnerability to drought and heat stress due to anthropogenic climate~~ ~~change and increasing CO_2.~~

The difference between the reference and factorial simulations by LSMs allow separating the modulating effects of ~~DH2018~~ DH18 legacies to the ~~DH2019~~ DH19 impacts (dashed arrow in Fig. 1). Separating the legacies in observations is more challenging, because the EVI signal at any time-step includes ~~both signals . We~~ signals from both concurrent climate and past legacies, and possibly also long-term global change. To do this, we hypothesise that preconditioning effects ~~from legacies from~~ ~~past disturbance (modulating DH2019) but also from~~ due to past disturbance legacies (modulating DH19) and global change (modulating ~~DH2018 and DH2019~~ DH18 and DH19) should be detectable by changes in ecosystem sensitivity to similar hazards. Increased vulnerability ~~can thus be detected if~~ corresponds thus to EVI_{anom} values ~~are~~ lower (more negative or less positive) than those expected for a given drought or temperature anomaly based on past sensitivities. Inversely, ~~acclimation to~~ ~~drought could~~ increased resistance would result in EVI_{anom} being less negative or more positive than expected for a given SM_{anom}.

We ~~test whether increased~~ assess whether changes in the sensitivity to climate anomalies is detected ~~for DH2018 and~~ ~~DH2019 in~~ in DH18 and DH19 using a statistical modelling approach to predict EVI_{anom} in DH18 and DH19 based on 2001–2017 climate–vegetation relationships. We do this in two steps: ~~a linear case, and another including non-linear and~~ first by fitting a linear regression model for mean EVI_{anom} in each cluster, and then, for more detailed insights, by fitting a random forest model at pixel scale, in which we include potential seasonal legacy effects. In both ~~steps, we characterize~~ ~~EVI-climate relationships for the period 2001–2017 and predict the EVI anomaliesin DH2018 and DH2019. In the~~ cases, the training period includes other DH events (Ciais et al., 2005; Orth et al., 2016), with similar climate anomalies, particularly 2003, thereby reducing the risk of attempting to predict EVI_{anom} based on "unseen" climatic conditions.

On a first step, ~~we estimate the EVI-climate relationships for each cluster by univariate linear regression modelsof using~~ for the spatially-averaged variables within each cluster, we fit the following models:

$$\overline{EVI}^{Ci}_{anom} = b_0 + b_1 \times \overline{VAR}^{Ci}_{anom} \tag{1}$$

Where $\overline{EVI}^{Ci}_{anom}$ and $\overline{VAR}^{Ci}_{anom}$ corresponds to the cluster (C_i) spatial average values of EVI_{anom} and climate variable (growing-season SM_{anom} or T_{anom}~~as predictors. Because impacts on EVI could~~), respectively. b_0, b_1 are the coefficients of each linear regression trained on 2001–2017 values. Each model is then used to estimate DH18 and DH19 EVI_{anom}. Negative

model residuals (observations minus predictions) can indicate increased vulnerability, while positive residuals can be a sign of increased resistance.

However, departures from a linear model could also result from non-linear interactions between soil-moisture and temperature or from legacy effects from spring (Bastos et al., 2020a; Lian et al., 2020), we extend this analysis by . To account for such effects and evaluate potential spatial asymmetries in the departures from long-term climate–vegetation relationships, we fit a random-forest (RF) regression using model using as target variable EVI_{anom} in each pixel (i) from 2001–2017, and the corresponding SM_{anom} and T_{anom} in spring (MAM) and summer SM_{anom} or T_{anom}. We in summer (JJA) as predictors:

$$EVI_{anom-i} = RF(T_{anom-i}^{spr}, SM_{anom-i}^{spr}, T_{anom-i}^{sm}, SM_{anom-i}^{sm}) \tag{2}$$

To reduce the risk of over-fitting due to the small sample size (17 years) and large number of predictors (4), we fit the RF model on a per-pixel basis but on 3x3 moving windows , in order to increase the sample size centered around each pixel (i.e. 17×9) for each regression and reduce over-fitting. To further control for possible over-fitting and poor predictive skill samples). We assess the model performance outside of the training samples , we calculate the RF model by calculating the out of bag scores in addition to the training sample scores. The importance of each predictor is then estimated by the Shapley additive explanation values (Lundberg and Lee, 2017). We then predict EVI_{anom} in DH18 and DH19 using the respective anomalies in $T_{anom}^{spr}, SM_{anom}^{spr}, T_{anom}^{sm}, SM_{anom}^{sm}$:

The EVI_{anom} predicted by the RF model for DH2018 and DH2019 DH18 and DH19 correspond to the expected DH impacts if no changes ecosystem vulnerability to drought and heat were present, i.e. considering only links between atmospheric drivers, from past relationships between the hazards and impacts in Fig. 1. It should be noted that the training period includes other DH events, particularly 2003 and 2015 (Ciais et al., 2005; Orth et al., 2016) thereby reducing the risk of attempting to predict anomalies out of the training sample. The As for the linear case, the difference between the RF model predictions and the actual EVI_{anom} (model residuals) provides thus an estimate of the contribution of an indication of changes in ecosystem vulnerability to the DH2018 and DH2019 DH18 and DH19 impacts.

For comparison with LSM simulations, the EVI_{anom} clusters were remapped to 0.25 degree by largest area fraction calculation, and subsequently GPP_{anom} and SM_{anom} model ensemble means for each cluster were compared with corresponding EVI_{anom} and ERA5 SM_{anom}. We first evaluate the linear relationships between the averaged GPP_{anom} for each cluster and the corresponding climate anomalies, for comparison with EVI_{anom}. Then, we estimate the legacy effects from DH2018 to 2019 DH18 on GPP_{anom} during 2019 based on the difference between the reference and factorial LSM simulations.

3.2.3 Modulating effects

To understand how land-cover can contribute to modulate the impacts of DH2018 and DH2019 DH18 and DH19 we analyse the land-cover composition of each cluster. Given that central Europe is characterized mostly by mixed pixels, we do this by calculating the a very heterogeneous landscape, we calculate land-cover selectivity in each cluster for forests, natural grasslands and croplands. Selectivity is defined as the difference between the probability a given land-cover class being present within

a cluster compared to its overall presence in the whole region. The probabilities are calculated by fitting a kernel-distribution function to the fractional cover fields for the whole region and for separate clusters. Positive (negative) selectivity means that a given land-cover type is more (less) ~~common~~ likely to be found in a given cluster ~~than~~ compared to its overall presence in the region.

265 ~~Finally, we try to explain the changes in ecosystem vulnerability, which are given by departures of EVI_{anom} residuals (EVI_{anom} observed minus predicted) from the range of residuals in the training period. To do this, we~~ For other modulating effects we evaluate how the spatial distribution of EVI_{anom} residuals for ~~DH2018 and DH2019~~ DH18 and DH19 relates to climatic and ecological variables: SM_{anom} and T_{anom} in spring and summer, number of dry months in the year of the DH event and the preceding year (i.e. 2017–2018 for ~~DH2018~~DH18, and 2018–2019 for ~~DH2019~~DH19), EVI_{anom} in the

270 preceding summer (EVI_{anom}^{yr-1}), the number of dry months in a given year and its preceding year (DM), ~~forest, cropland and grassland cover fractions from CCI-LC,~~ isohydricity (IsoH) and ~~AWC.~~ available water capacity (AWC, related to the maximum amount of water available for plants).

We include some of the drivers used to train the temporal climate-driven RF model to diagnose possible changes in the vulnerability ~~to climate, i.e. the impact is still driven by climate conditions, but vegetation responds more strongly~~ explained

275 by stronger vegetation sensitivity to climate anomalies than in the training period. EVI_{anom}^{yr-1} is used to evaluate the preconditioning role of ~~legacy effects from~~ past extreme summers or disturbances (summer is the peak of the growing season in this region). The number of dry months and AWC ~~(related to the maximum amount of water available for plants)~~ are also included as they may explain non-linear relationships between SM_{anom} and vegetation stress. Isohydricity provides a measure of the degree of stomatal regulation by plants. Since many of these variables have strong spatial ~~covariability~~ co-variation (e.g. T_{anom}

280 and SM_{anom}, ~~or to some extent tree/grassland cover and IsoH),~~ we evaluate their relationships with EVI_{anom} residuals by calculating the partial rank correlation (Spearman's ρ) between each variable, controlling for the others ~~.~~ separately. Since these effects might depend on land-cover type, we analyse separately pixels with high and low forest cover.

To further evaluate ~~long-term importance of~~ how inter-annual legacy effects ~~in vegetation activity~~ affect long-term vegetation dynamics, we apply a second temporal RF model to pixel-level EVI_{anom} (Section 3.2.2) ~~where we additionally include~~ with

285 EVI_{anom}^{yr-1} as ~~a predictor~~of the regression~~ an additional predictor. The model is trained for the period 2002–2017 ~~also~~ on 3×3 moving windows and ~~spring and~~ is then used to predict EVI_{anom} in ~~DH2018 and DH2019~~DH18 and DH19. The resulting model residuals were then compared to those of the climate–driven RF model.

4   Results

4.1   ~~DH2018~~ DH18 and ~~DH2019~~ DH19 impacts

290 Following the extreme summer in central Europe in 2018, mild temperatures and strong soil-moisture deficits remained until January 2019, when SM_{anom} returned to normal conditions (Fig. B1, Fig. B2). In central Europe, June 2019 was extremely hot, but July and August 2019 were milder (Fig. B1, (Sousa et al., 2020)), and soil-moisture deficits ~~were~~ became very pronounced in July (Fig. B2). In this region, ~~excepting~~ except April 2019, the months preceding summer were not particularly dry and

were even slightly wetter than average in February, March and May, the latter also colder than average. Therefore, the ~~DH2018~~

295 ~~and DH2019~~ DH18 and DH19 constitute more a sequence of two compound events than a ~~long~~ single drought. The areas experiencing severe dry and hot conditions in both summers correspond to a region covering central and eastern Europe and southern Sweden. This region is our study domain and indicated by the rectangle in Fig.2).

~~Spatial patterns of temperature (T_{anom}), soil-moisture (SM_{anom}) and EVI (EVI_{anom}) anomalies during summer 2018~~
~~(top panel) and summer 2019 (bottom panel) for the study region. The study region corresponds to a domain with dry and hot~~
300 ~~conditions in both 2018 and 2019 summers (DH2018 and DH2019).~~

Both DH events led to vegetation browning, though negative EVI_{anom} were more widespread in ~~DH2018 than DH2019~~ DH18 than DH19. Within the study region, 79% of the area showing negative EVI_{anom} in ~~DH2018 (EVI_{anom}^{DH2018}~~ DH18 (EVI_{anom}^{DH18}) also registered negative EVI_{anom} in ~~DH2019 (EVI_{anom}^{DH2019}), although greening can be found in some areas.~~ DH19 (EVI_{anom}^{DH19}).

305 ~~In this study, we limit our analysis to pixels negatively impacted by DH2018 and evaluate subsequent responses to DH2019~~
~~by grouping pixels based on (EVI_{anom}^{DH2018}, EVI_{anom}^{DH2019}) values using unsupervised clustering.~~

The spatial distribution of the ~~resulting clusters is shown in Fig. 3 (left panel) and the corresponding (EVI_{anom}^{DH2018}, EVI_{anom}^{DH2019})~~
~~pairs~~ clusters resulting from the unsupervised classification based on (EVI_{anom}^{DH18}, EVI_{anom}^{DH19}) pairs and corresponding centroids are shown in ~~the top right panel. For comparison, (SM_{anom}^{DH2018}, SM_{anom}^{DH2019}~~ Fig. 3 (left and top right panels), as well as the
310 corresponding (SM_{anom}^{DH18}, SM_{anom}^{DH19}) and (T_{anom}^{DH2018}, T_{anom}^{DH2019}) pairs are also shown.

~~Classification of impact groups within the study region in central Europe. The left panel shows the spatial distribution of the~~
~~four clusters from unsupervised classification of (EVI_{anom}^{DH2018}, EVI_{anom}^{DH2019}) values. The corresponding (EVI_{anom}^{DH2018}, EVI_{anom}^{DH2019})~~
~~distribution in each cluster are indicated in the top right panel (circles indicate the spatial mean and the lines spatial standard~~
~~deviation within each cluster). The corresponding distribution of SM_{anom} and T_{anom} pairs are shown in the centre right and~~
315 ~~bottom right panels respectively. The grey line, indicates similar anomalies in the two DH events.~~

The ~~T_{anom}^{DH18}, T_{anom}^{DH19}) (center and bottom right panels). The four~~ clusters aggregate pixels according to different impacts in ~~DH2018 and DH2019. Cluster C1 covers~~ DH18 and DH19. One cluster, covering 20% of the area~~and~~, includes pixels with moderate impacts in ~~DH2018~~ DH18 and further browning in ~~DH2019 (EVI_{anom}^{DH2019}~~ DH19, being therefore referred to as (C$_{Decline}$) (dark brown, EVI_{anom}^{DH19} below the 1:1 line in Fig.3, top right panel). This cluster is associated with mixed cover
320 of forests (10-40%, dominated by needle-leaved) and grasslands (15-60%), (Fig.B3). Cluster ~~C2 (~~C$_{HighV}$ (high vulnerability, covering 15% of the area) corresponds to pixels experiencing strong impacts in both events and is associated with high grassland and cropland fractions and low forest cover. Pixels with strong impacts in ~~DH2018 and~~ DH18 and weakly negative EVI_{anom}^{DH19}, i.e. partial recovery in ~~DH2019 (C3~~ DH19 (C$_{PRecov}$, 21% of the area), are mainly dominated by croplands. Finally, a group of pixels shows moderate EVI_{anom}^{DH18} and positive EVI_{anom}^{DH19} (C$_{Greening}$, ~~while pixels showing positive EVI_{anom}^{DH2019}~~
325 ~~(C4, 44%)~~correspond~~, corresponding mostly to mixed forest-grassland pixels (30-65% of forest, dominated by needle-leaved).

All clusters ~~have~~ align along proportional DH18:DH19 values of SM_{anom} and T_{anom}, with predominantly negative SM_{anom} and positive T_{anom} in both DH events ~~, but show~~ but alleviation of soil-moisture deficits and heat stress in ~~DH2019 compared~~
~~to DH2018~~ DH19 compared to DH18 (Fig. 3). ~~Clusters align along proportional SM_{anom} and T_{anom} in DH2018 vs DH2019~~
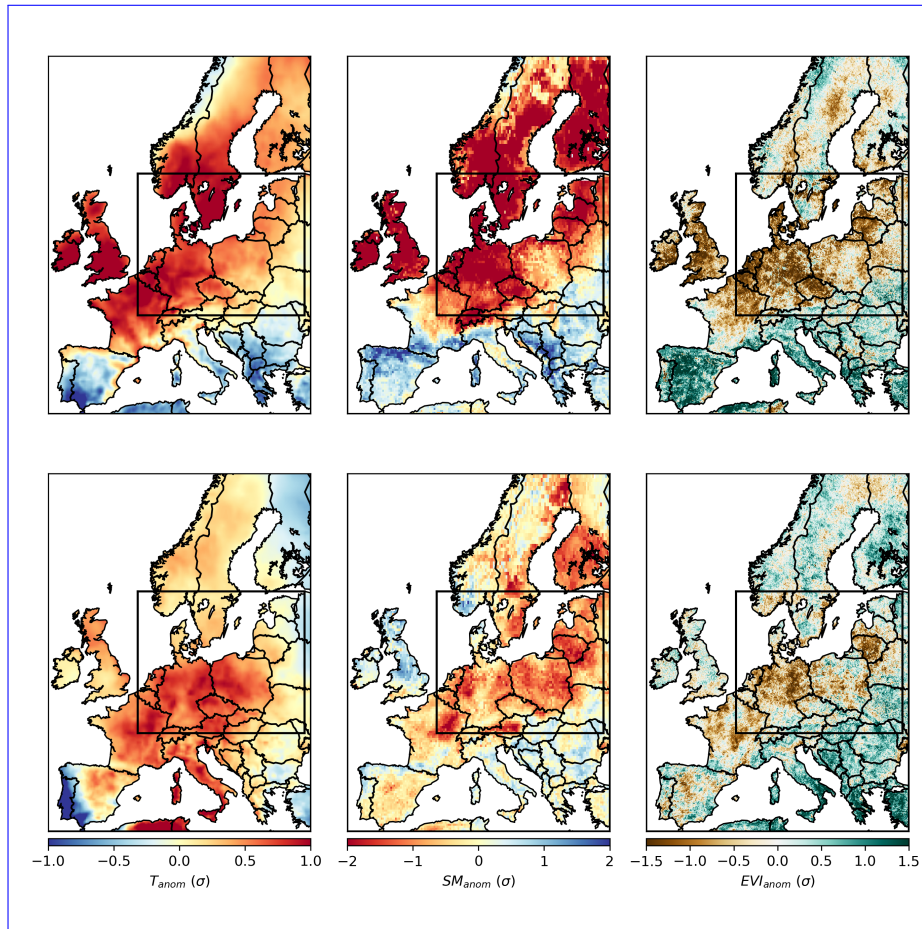
Figure 2. Spatial patterns of temperature (T_{anom}), soil-moisture (SM_{anom}) and EVI (EVI_{anom}) anomalies during summer 2018 (top panel) and summer 2019 (bottom panel) for the study region. The study region corresponds to a domain with dry and hot conditions in both 2018 and 2019 summers (DH18 and DH19).

~~with overlapping distributions.~~ The two recovery clusters (~~C3 and C4~~ C_{PRecov} and $C_{Greening}$) correspond to pixels with less se-

330   vere drought conditions and milder temperatures in ~~DH2019, and C4 (greening)~~ DH19, and $C_{Greening}$ corresponds to pixels where dry and hot conditions in ~~DH2018~~ DH18 were also more moderate. ~~C2~~ C_{HighV} corresponds to pixels experiencing drier and hotter anomalies in both summers and shows accordingly stronger impacts. Cluster ~~C1~~ $C_{Decline}$, however, shows increasing browning in ~~DH2019~~ DH19 in spite of drought and heat stress alleviation (Fig.3)~~, which suggests~~ . The distributions of climate anomalies for each cluster overlap each other and, in some cases, the 1:1 line, indicating that the intensity of the ~~hazard~~ hazards

335   (temperature, drought) ~~alone~~ cannot account for the resulting impacts ~~.~~ alone.

4.2   Ecosystem vulnerability to ~~DH2018~~ DH18 and ~~DH2019~~ DH19
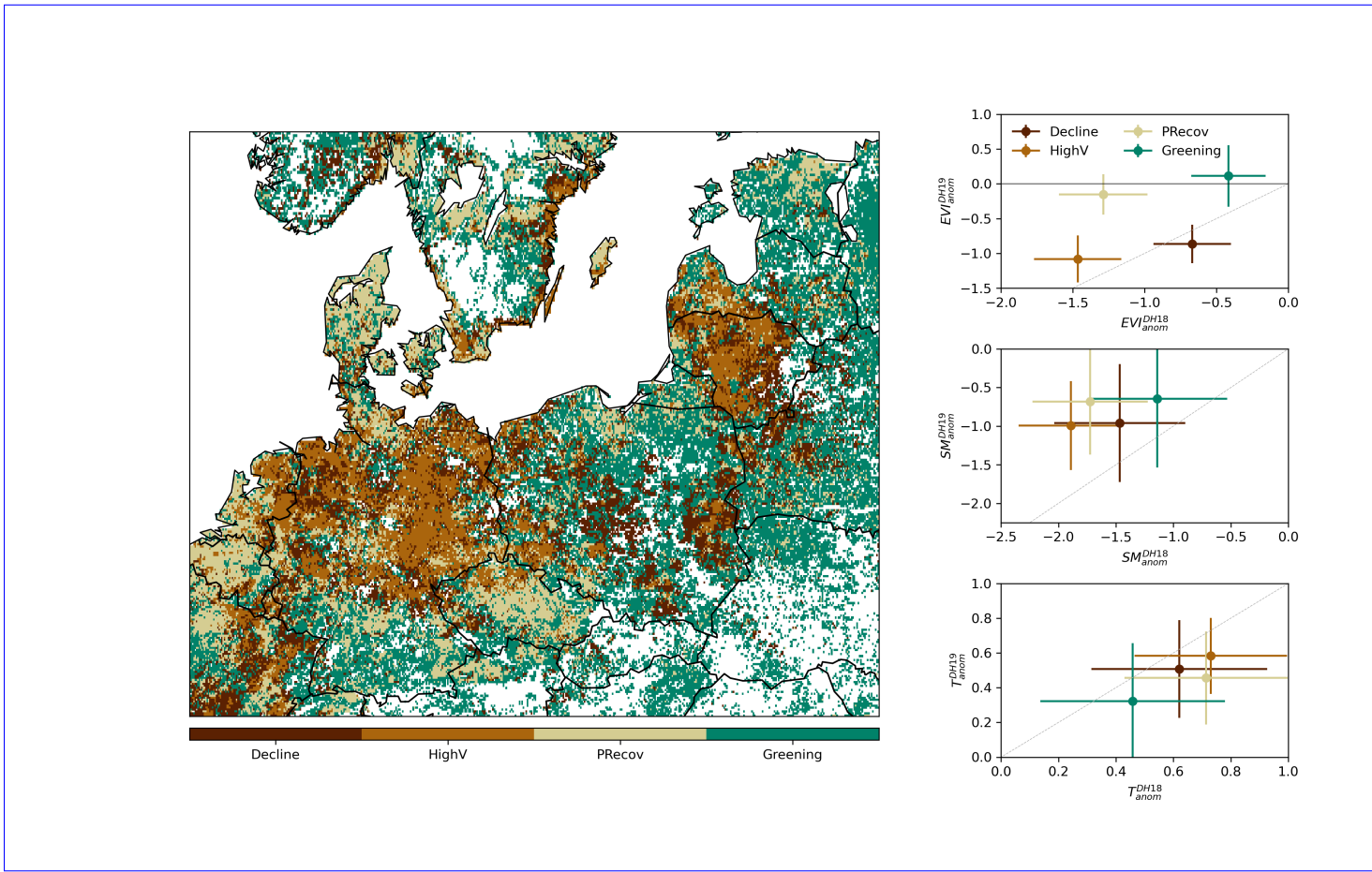
Figure 3. Classification of impact groups within the study region in central Europe. The left panel shows the spatial distribution of the four clusters from unsupervised classification of $(EVI_{anom}^{DH18}, EVI_{anom}^{DH19})$ values. The corresponding $(EVI_{anom}^{DH18}, EVI_{anom}^{DH19})$ distribution in each cluster are indicated in the top right panel (circles indicate the spatial mean and the lines spatial standard deviation within each cluster). The corresponding distribution of SM_{anom} and T_{anom} pairs are shown in the center right and bottom right panels respectively. The grey line indicates similar anomalies in the two DH events. Only pixels with negative EVI_{anom}^{DH18} are considered.

~~We evaluate ecosystem vulnerability to the two compound events by comparing EVI_{anom} in DH2018 and DH2019 with past~~ ~~EVI_{anom}–SM_{anom} and EVI_{anom}–T_{anom} relationships (Fig. 4) for each cluster separately.~~

All clusters show significant positive linear relationships between summer EVI_{anom} and SM_{anom} and negative linear

340   relationships with T_{anom} in 2001–2017 ~~, consistent with a general summer water-limited regime.~~ (Fig. 4). The relationships include the two extreme summers of 2003 and 2015 which had comparable T_{anom} and SM_{anom} to ~~DH2018 and DH2019~~ DH18 and DH19 in most clusters. The long-term sensitivities estimated are, though, robust even if these summers are excluded.

~~All three clusters with strong impacts in one event (C1 DH2019, C3 DH2018) or both (C2) show~~

The results correspond to a general summer water-limited regime, especially in clusters C_Decline, C_HighV and C_PRecov, which show stronger sensitivities to T_{anom} and SM_{anom} (slopes in Fig. 4) and higher variance explained by both models (R^2 0.58–0.68 for SM_{anom} and 0.49–0.55 for T_{anom}). For these clusters, EVI_{anom} is below the 95% confidence interval of the long-term linear ~~relationship with both~~ relationships for DH18 (C_PRecov and C_HighV) and DH19 (C_Decline and C_HighV). SM_{anom} ~~and T_{anom} for that event. These departures are not likely explained simply by compounding heat and drought impacts, as SM_{anom} and T_{anom} in 2003 are similar, or even stronger, than in DH2018 and DH2019.~~ DH18 and DH19 are generally similar to those of 2003, but DH18 was drier than 2003 in C_PRecov and C_HighV.

These departures may be related with seasonal legacy effects from the warm spring in ~~DH2018 and could also be linked to~~ DH18 and or the onset of non-linear responses to heat and drought~~under long-term changing environmental conditions~~. To account for these modulating effects, we model long-term (2001–2017) EVI_{anom}–climate relationships using spring and summer SM_{anom} and T_{anom} as predictors using random forest regression (see Section 3.2.2). ~~For most pixels, the~~ The model is able to ~~explain~~ predict 48 –90% (median and maximum out of bag score across pixels) of the pixel-level temporal variability of summer EVI_{anom} in 2001–2017 (Fig.B4)~~and consistently~~. Analysis of the variable importance shows that the model estimates summer water limitation and negative legacy effects from spring warming (Fig. B5), consistent with a summer water-limited regime and process-based modeling studies (Bastos et al., 2020a; Lian et al., 2020).

~~In DH2018~~ As in the linear case, the RF model estimates less negative or more positive EVI_{anom} in DH18 and ~~DH2019, the model has predominantly negative residuals, i.e. observed EVI_{anom} is more negative or less positive than predicted from past vegetation–climate relationships, as found in the linear case~~ DH19 than observations (Fig. 5). ~~Consistent with the results by the linear models, the~~ The residuals are below the range of the training period for the high impact clusters: ~~C1 and C3 in DH2019 and DH2018~~ C_Decline and C_PRecov in DH19 and DH18, respectively, and ~~C2~~ C_HighV in both (Fig. 5, bottom panel). In ~~the DH2019 "greening cluster" (C4)~~ C_Greening, residuals are predominantly positive (i.e. observed EVI_{anom} more positive than predicted), but still partly overlap with the range of residuals in the training period (Fig. 5).

~~We evaluate the role of diverse environmental variables in explaining the spatial distribution of residuals:~~
~~(i) the same climatic variables as used to train the RF model, indicating increased ecosystem sensitivity to climate;~~
~~(ii) EVI_{anom} in the previous summer to account for inter-annual legacy effects;~~
~~(iii) isohydricity and land-cover composition to evaluate the modulating role of vegetation functioning differences;~~
~~(iv) soil available-water capacity and number of dry months, which can impose thresholds in water limitation.~~

~~To do this, we calculate the~~ Pixels with high tree cover tend to show less negative or more positive residuals than pixels with low tree cover in both DH events (Fig. 6), but in DH19 the range of residuals is larger and includes pixels with strongly negative values. The partial rank correlation of the spatial distribution of EVI_{anom} residuals with respect to ~~the explanatory variables selected (~~ different explanatory variables is shown for pixels with high and low forest cover in Fig. 6~~)~~. Given the large number of pixels, all correlations are significant~~except those for croplands. In DH2018, vegetation condition in the previous year's growing season (i.e. summer 2017, +, positive effect), tree cover (+),~~.

In DH18, T_{anom} in spring (T_{anom}^{spr}, + for high and low tree cover) and summer SM_{anom} (SM_{anom}^{sm}, - ~~) show stronger~~ for high tree cover and + for low tree cover) show the strongest relationships with EVI_{anom} residuals. In ~~DH2019~~ DH19, EVI_{anom}^{yr-1}
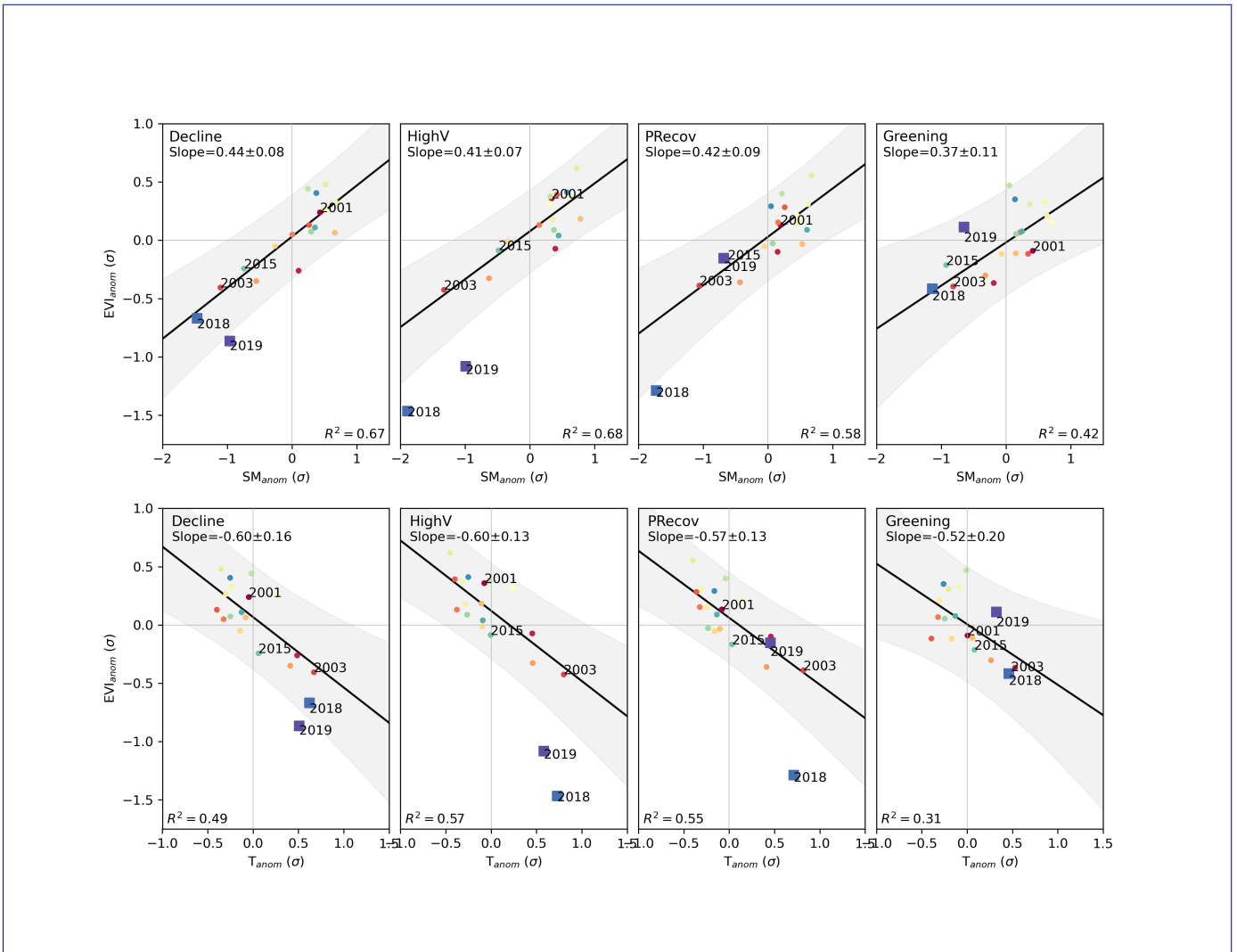
14

Figure 4. Departure of EVI_{anom} in ~~DH2018~~ DH18 and ~~DH2019~~ DH19 from long-term climate-driven variability. Relationship between EVI_{anom} and SM_{anom} (top panel) and between EVI_{anom} and ~~SM_{anom}~~ T_{anom} (bottom panel) for each individual summer between 2001 and 2019 over the study region. The results are shown separately for the four clusters defined in Fig. 3. The black line and shaded areas show the relationship and respective 95% confidence intervals obtained by ordinary least-squares linear regression between EVI_{anom} and the respective climate variable for all years between 2001–2017. Values of (EVI_{anom}, SM_{anom}) that deviate from the long-term relationships show increased sensitivity to climate anomalies, which can be a sign of increased vulnerability or ~~degradation trajectories~~ decline. The ~~colours~~ colors indicate individual years, ranging from 2001 (red) to 2019 (purple) ~~.~~ and square markers indicate 2018 and 2019.

~~and (+),~~ T_{anom}^{spr} ~~are also the most relevant variables, but~~ EVI_{anom}^{yr-1} ~~shows stronger correlation with~~ EVI_{anom} ~~residuals than~~ 380 ~~in DH2018, and~~ T_{anom}^{spr} ~~has an opposite sign~~ and T_{anom}^{sm} (-) show strong correlations, with consistent sign for both high and low tree cover pixels. DH19 residuals of pixels with high tree cover show strong correlation with SM_{anom} with opposite signs
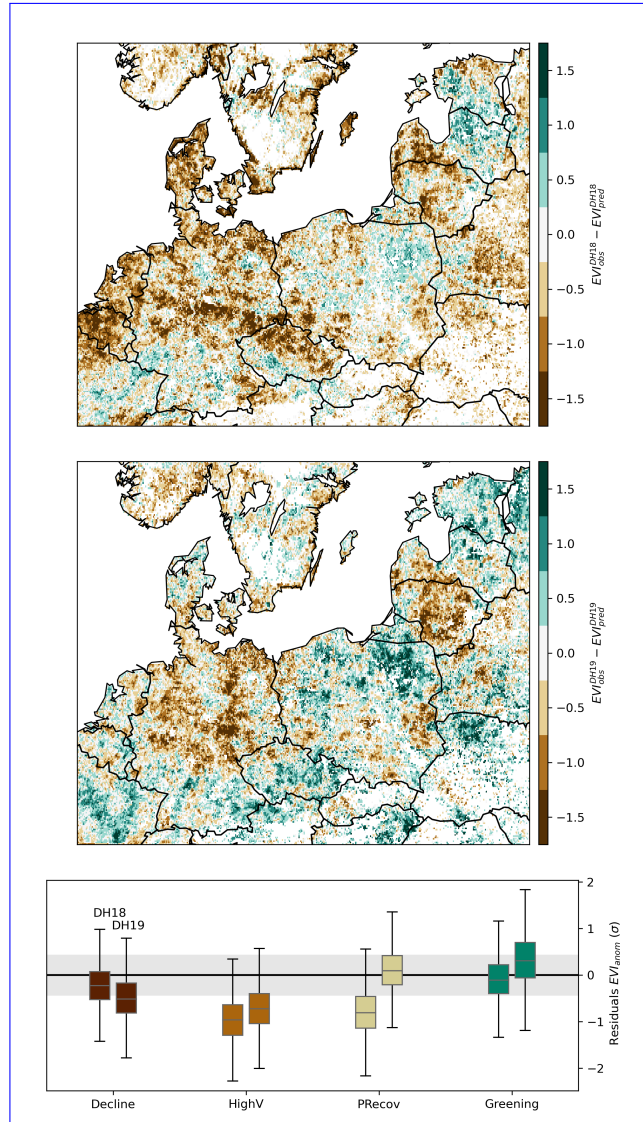
Figure 5. Spatial distribution of EVI_{anom} residuals in ~~DH2018~~ DH18 (top panel) and ~~DH2019~~ DH19 (central panel) estimated by the temporal RF model trained for 2001–2017 with spring and summer SM_{anom} and T_{anom} as predictors. The corresponding distribution per cluster for each DH event is shown by the boxplots in the bottom panel. The shaded grey envelope indicates the range of residuals in the training period.

Figure 6. Spatial partial correlation (spearman) between EVI_{anom} residuals and environmental variables in DH18 (top panels) and DH19 (bottom panels), for pixels with high (dark green, top 5% cover fraction) and low (light green, lower 5% cover fraction) tree cover (left panels). The variables considered are: spring and summer T_{anom} and SM_{anom} (indicated by superscripts *spr* and *sm*, respectively), EVI_{anom} in the previous growing season (EVI_{yr-1}), plant isohydricity (IsoH) and the number of dry months (DM). Because of the large number of pixels considered, all correlations are significant ($p-val \ll 0.01$). The right panels show the distribution of residuals for pixels with high and low tree cover.

in spring (+) and summer (-) ~~In DH2019, T^{sm}_{anom} and SM^{sm}_{anom} show stronger relationships with~~ and with AWC (-). In DH19, pixels with low tree cover show negative correlation between IsoH and EVI_{anom} ~~residuals as do the variables relating to water-availability (AWC , dry months and IsoH), all except T^{sm}_{anom} with opposite sign as in DH2018~~residuals.

385   To test whether the importance of EVI^{yr-1}_{anom} is particular to ~~the two DH events~~DH19, or if it may reflect long-term inter-annual legacy effects of anomalies in vegetation activity, we fit a second temporal RF model where EVI^{yr-1}_{anom} is used as an additional predictor (Figs. B4 and B6). Including vegetation condition in the previous summer improves the predictive power of the long-term RF model (72–97% out of bag score, compared to 48–90% for the model trained with climate drivers only). ~~However,~~ Even though the residuals for ~~DH2018 and DH2019 are comparable to those of~~ the training period are considerably

390 reduced relative to the climate–driven model, ~~while~~ the residuals for ~~the training period are considerably reduced~~DH18 and DH19 are comparable.

4.3   ~~DH2018~~ DH18 and ~~DH2019~~ DH19 impacts simulated by LSMs

The GPP from the LSM multi-model ensemble mean matches well the ~~relative differences in the impact of DH18 between clusters compared to EVI_{anom}~~ differences in impacts between clusters in DH18 (Fig. 7, top and middle panels) ~~. The~~ and the

395 temporal evolution of ~~monthly~~ GPP anomalies during the 2018 growing season (April to September, Table 1)~~also agrees with that of EVI_{anom}~~, with correlations ~~between~~ with EVI_{anom} of 0.74–0.90. ~~However, 2019 trajectories from GPP simulated by LSMs indicate above-average spring and early summer productivity for all clusters, and strong positive~~ Even though the root mean squared error (RMSE) is comparable in the two growing seasons, the correlations of GPP_{anom} ~~for both C3 and C4 during DH2019. However, correlations between~~ with growing-season EVI_{anom} ~~and GPP_{anom}~~ are much lower in ~~2019~~

400 DH19(-0.09 –0.43).

  ~~The disagreement in GPP_{anom}~~ by LSMs is above-average in spring and early summer 2019 ~~cannot be solely explained by errors in simulated soil-moisture anomalies , since simulated SM_{anom} shows very good agreement with both observation-based SM_{anom} from SoMo.ml and SM^{ERA5}_{anom} (correlations of 0.94–0.98, Table 1).~~ for all clusters, and anomalies in DH19 are either more positive or less negative, compared to EVI_{anom}.

405 LSMs simulate a stronger attenuation of drought compared to the observation-based SM_{anom}, though with consistent relative differences in SM_{anom} between clusters (compare Fig. B7 and Fig. 3). ~~The recovery simulated by LSMs in 2019 can be partly explained by too strong recovery of modelled soil-moisture (Fig. B7), but may also result from limited ability of LSMs in simulating changes in ecosystem vulnerability during the two DH events.~~LSMs simulate well the temporal evolution of SM_{anom} in the two growing seasons, with high correlation with both SoMo.ml and SM^{ERA5}_{anom} (correlations of 0.81–0.98).

410 The RMSE for simulated SM_{anom} is generally lower than that of GPP_{anom}.

  The sensitivity of GPP_{anom} ~~from LSMs to summer (JJA) soil-moisture anomalies (~~to simulated SM_{anom} and to T_{anom} (Fig. B8) is consistent with that of EVI_{anom} in all clusters (Fig. 4)~~. The sensitivity of GPP_{anom} to temperature is also consistent with that of EVI_{anom} for clusters C1 and C2, while for C3 and C4~~, although for C_{PRecov} and $C_{Greening}$ LSMs estimate non-significant negative relationships between GPP_{anom} and T_{anom}. ~~Simulated GPP agrees well with EVI_{anom}~~

415 ~~during the 2018 growing season (r=0.74–0.90, Table 1, Fig. 7) and the deviation~~ The deviations of GPP_{anom} from the linear
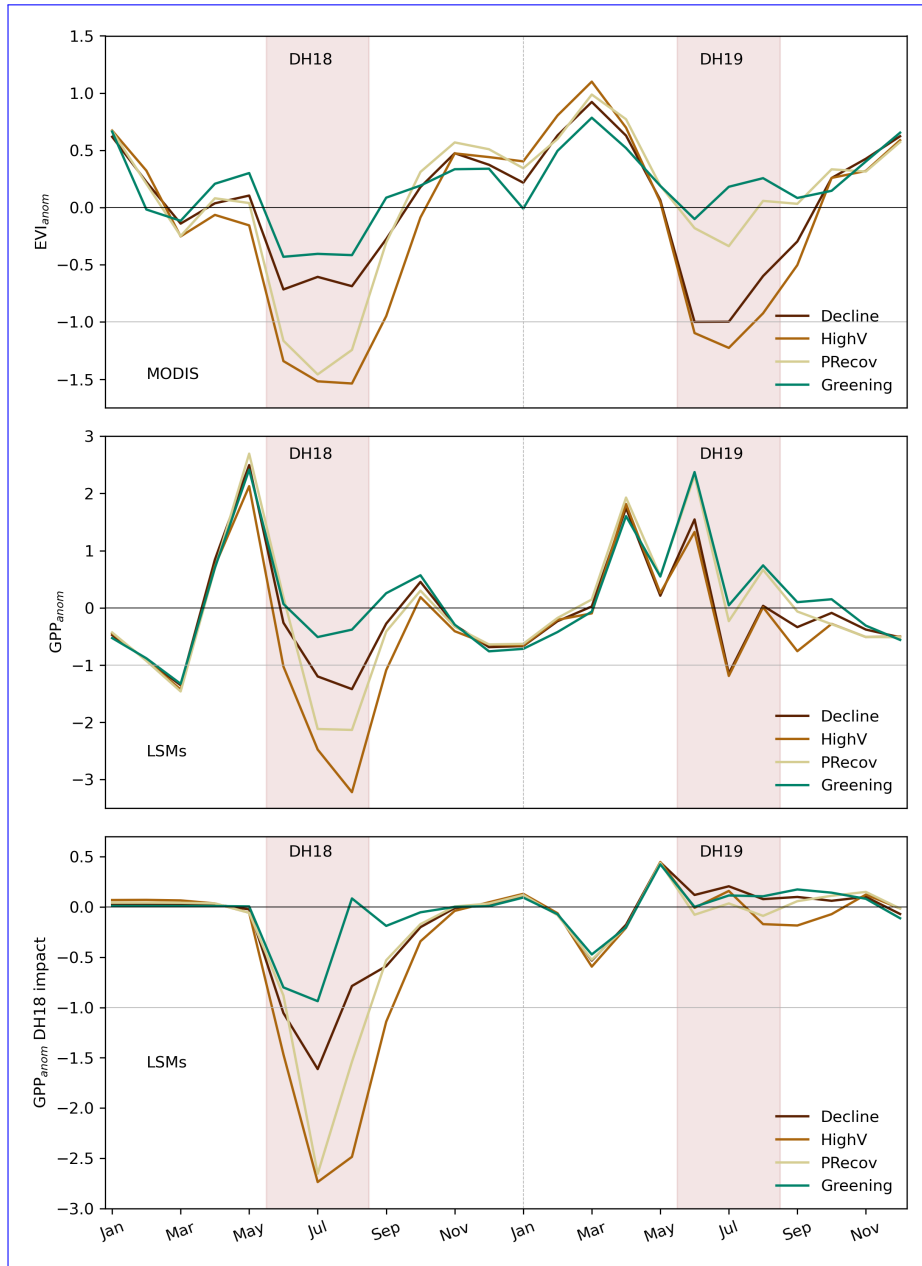
Figure 7. Observed and process-based model simulations of 2018/19 impacts. Seasonal evolution of EVI_{anom} (top panel) and standardized GPP anomalies (GPP_{anom}, central panel) over the two year period for each cluster (defined in Fig. 3 and shown for LSM grid in Fig. B7).The bottom panel shows the difference between the reference and factorial simulations, and indicates the impacts of ~~DH2018~~ DH18 on GPP_{anom} simulated by models during the event and in the subsequent months until December 2019.

Table 1. Correlation ~~of~~ between growing season (April–September) SM_{anom} simulated by LSMs with SM_{anom} from SoMo.ml and ERA5, and of EVI_{anom} with GPP simulated by LSMs.

height	~~C1~~ $C_{Decline}$		~~C2~~ C_{HighV}		~~C3~~ C_{PRecov}		~~C4~~ $C_{Greening}$	
	r	RMSE	r	RMSE	r	RMSE	r	RMSE
SM_{anom} gs. 2018	0.98	0.33	0.98	0.66	0.97	0.43	0.97	0.21
SM_{anom} gs. 2019	0.94	0.63	0.97	0.47	0.98	1.2	0.95	0.77
height SM_{anom}^{ERA5} gs. 2018	~~0.98~~ 0.87	~~0.97~~ 0.56	~~0.95~~ 0.92	~~0.98~~ 0.85	0.87	0.64	0.81	0.39
SM_{anom}^{ERA5} gs. 2019	~~0.93~~ 0.71	~~0.95~~ 0.72	~~0.94~~ 0.90	~~0.67~~ 0.52	0.91	1.2	0.70	0.82
height EVI_{anom} gs. 2018	0.80	1.0	0.90	1.2	0.74	1.2	0.79	0.86
EVI_{anom} gs. 2019	0.34	1.1	0.43	1.1	0.26	1.1	-0.09	1.1

response for ~~C2 and C3 in DH2018~~ C_{HighV} and C_{PRecov} in DH18 are correctly captured by LSMs~~. In 2019, though, simulated growing season GPP_{anom} shows low or even negative correlations with EVI_{anom} in all clusters (r=-0.09–0.43). This cannot be explained by poor simulation of SM_{anom}, which shows high correlation to both observation-based soil-moisture datasets.~~ but not that of DH19 in $C_{Decline}$.

5 Discussion

5.1 Early signs of increased vulnerability

~~Our results indicate that the extremely negative~~

For three clusters covering 56% of the pixels negatively impacted by DH18, the extremely low EVI_{anom} in response to ~~DH2018~~ DH18 and DH19 ~~cannot~~ could not be predicted from ~~past~~ EVI–climate relationships ~~, even when non-linear and seasonal legacy effects are considered~~ in 2001–2017 (Figs. 4, 5). ~~This suggests an important role of increased ecosystem vulnerability to climate (e.g., "hotter droughts") and of environmental factors (e.g. vegetation preconditioning effects), in explaining DH impacts.~~

~~The climatic variables used to train the temporal RF model still appear as relevant contributors to the spatial distribution of EVI_{anom} residuals (Fig. 6) which supports a contribution of climate–driven increased vulnerability under the two extreme summers. The sign of the correlation between T_{anom}^{spr} and SM_{anom}^{spr} with EVI_{anom} residuals indicates a positive effect of spring warming in partly offsetting vegetation growth (observed EVI_{anom} more positive or less negative than modelled), but with associated water depletion in spring amplifying the impacts of DH2018 in summer (Bastos et al., 2020a). This negative seasonal legacy effect through soil-moisture is also found in DH2019, but spring warming (or cooling, see Fig. B1) resulting in much stronger (weaker) impacts than those predicted by past vegetation–climate relationships (strong negative correlation).~~

~~The positive correlation of EVI_{anom} residuals in DH2018 with SM_{anom}^{spr} and T_{anom}^{spr} are also in line with increased sensitivity to water availability and temperature stress reported by Bastos et al. (2020b), i.e. stronger browning than predicted associated~~

with warmer and drier conditions. In DH2019, the negative impact of summer T_{anom}^{sm} was amplified, indicating increased vulnerability to heat stress, but the correlation of residuals with SM_{anom}^{sm} is the opposite as in DH2018. This is consistent with the results for clusters C1 and C4, where browning in DH2019 happened in spite of drought alleviation, in the case of C1, or

440 greeninghappened in spite of persisting soil-moisture deficits, in C4. However, these results indicate that other environmental effects may have an important role in modulating DH impacts, especially in DH2019.

The values of EVI_{anom} in the previous summer show the strongest correlations with the residuals in both years These departures reveal increased sensitivity to dry and hot conditions, and can be a sign of increased ecosystem vulnerability to such events. It should be noted, though, that we focused on pixels which were negatively impacted by DH18, but some pixels in the

445 regional domain selected showed greening, even in DH18 (Fig. 6). The higher correlation between EVI_{anom} residuals and EVI_{anom}^{yr-1} in DH2019 than DH2018 points to a stronger contribution of legacy effects preconditioning the impacts of DH2019, resulting from the heat/drought stress imposed by DH2018. Even though considering inter-annual legacy effects mediated by vegetation condition improves the predictive skill of the RF model, this does not reduce the residuals in DH2018 and DH2019. The strong spatial relationship between EVI_{anom}^{yr-1} with EVI_{anom} residuals suggests that the preconditioning role of vegetation

450 condition in DH2018 and DH2019 was amplified due a predominance of pixels with poorer vegetation condition before the DH events. This supports the important role of legacy effects from past stress conditions in impairing vegetation resistance to subsequent stressors, e.g. from to defoliation or damage from embolism (Ruehr et al., 2019) or higher susceptibility to diseases and pests due to reduced health (McDowell et al., 2020). The fact that EVI_{anom}^{DH2018} is the most relevant predictor for residuals in DH2019 further supports the importance of damage from past heat/drought stress in amplifying the impacts of a subsequent

455 DH event (Anderegg et al., 2020). 2). These regional asymmetries result in partial regional compensation of the DH18 impacts, as shown in Bastos et al. (2020b).

In both DH2018 and DH2019DH18 and DH19, higher tree cover fraction is associated with more positive or less negative residuals (Fig. 6), indicating that trees buffered the impacts of DH conditions on ecosystem activity. This is consistent with the were more resistant to DH than grasses and crops. The predominance of crops and grasslands in C2 and C3C_{HighV}, which had

460 strong negative residuals in DH2018both events, and of high tree cover in C4, where residuals are mostly within the range of residuals in the training period and even slightly positive (Figs. 4 and 5). Forests $C_{Greening}$ also support this effect. Trees can better cope with drought with their deeper rooting depth (Fan et al., 2017) and through the use of carbon reserves to support activity under stress conditions (Wiley, 2020). Moreover, some trees and grasses with stronger stomatal regulation can buffer the drought progression and its impacts by avoiding hydraulic failure (McDowell et al., 2020; Teuling et al., 2010). Even

465 though isohydricity is strongly species-dependent (Konings et al., 2017), this effect is This is reflected in the small but positive effect of isohydricity in explaining DH2018 residuals ..

The negative residuals in DH2019 for C2 are consistent with C2 showing the driest and hottest anomalies and predominantly cropland cover, but in C1 the strongly negative EVI_{anom}^{DH2019} are associated with mixed pixels (up to 40% forest relationship between isohydricity and 20–60% grassland cover) and higher isohydricity. This points to increased vulnerability and degradation

470 occurring mainly in natural ecosystems with stronger stomatal regulation, which is consistent with the negative relationship

of isohydricity with EVI_{anom}^{DH2019} residuals. The large negative EVI_{anom}^{DH2019} residuals and browning in response to DH2019 EVI_{anom} residuals in ~~C1 may be linked to impaired growth due to~~ pixels with high forest cover.

Increased vulnerability may be explained by modulating effects of global change on vegetation condition (e.g., "hotter droughts" (Allen et al., 2015), Fig. 1) and, in the case of DH19, it may be further linked to inter-annual legacies from the impact of DH18. The first should be expressed by relationships between EVI_{anom} residuals and climatic variables. The latter are more difficult to assess without comprehensive data about different competing factors, .e.g. defoliation or damage from embolism ~~, defoliation, or depletion of carbon reserves (Ruehr et al., 2019) under longer drought conditions (negative effect of dry months). However, increased~~ (Ruehr et al., 2019), higher susceptibility to diseases and pests due to reduced health (McDowell et al., 2020) or increased hazard of insect disturbances due to warm conditions (Rouault et al., 2006). The relationships between EVI_{anom} residuals and EVI_{anom}^{yr-1} provide an approximation, but do not allow to identify the underlying drivers.

In DH18, we find a positive effect of spring warming in vegetation growth, leading to weaker departures from long-term vegetation–climate relationships (observed EVI_{anom} more positive or less negative than modelled), but with associated water depletion amplifying the impacts of DH18 in summer in pixels with low tree cover. These results are in line with Bastos et al. (2020a) that showed contrasting seasonal legacy effects of warm springs in crop versus forest dominated regions.

On the contrary, spring and summer T_{anom}^{sm} in 2019 (or cooling, see Fig. B1) are negative correlated with EVI_{anom} residuals in both high and low tree cover pixels. This indicates increasing damage from heat stress, for example due to reductions in evapotranspirative cooling (Obermeier et al., 2018) or cascading ~~effects~~impacts of compound heat and drought, such as ~~the increased susceptibility of stressed trees to insect attacks and diseases cannot be excluded.~~ insect attacks (Rouault et al., 2006).

~~The~~ Including EVI_{anom}^{yr-1} in the long-term RF regression model improves the predictive skill for 2001–2017, but does not reduce the residuals in DH18 and DH19. The high correlation between EVI_{anom} residuals and EVI_{anom}^{yr-1} in DH19 can indicate either that pixels strongly impacted by DH18 were associated with amplified impacts by DH19 (negative residuals), or that pixels affected moderately by DH18 (less negative EVI_{anom}^{DH18}) were associated with positive residuals, i.e. stronger recovery. Damage to roots and tissues or depletion of carbon reserves from DH18 leading to higher vulnerability to DH19 could explain the positive correlation in high tree cover pixels in C$_{Decline}$. Conversely, the moderate DH18 impacts in C$_{Greening}$ may have resulted in increased resistance to DH19. The strong correlation found in low tree cover pixels is, though, surprising, as European crop species tend to be annual plants, and annual species can also be found in many grasslands. For these pixels, it is more likely that the positive correlation is explained by management practices, e.g. through earlier harvest or active reduction of stand density in DH19 (Bodner et al., 2015).

C$_{Decline}$ stands out from the other clusters, in that browning is found in spite of drought alleviation in DH19. The strong negative correlation of residuals with SM_{anom}^{sm} and AWC in forest dominated pixels is counter-intuitive and suggests that other environmental effects not considered in our analysis may modulate DH19 impacts. Insect outbreaks are a potential candidate to explain such effects: the stronger correlation of residuals with EVI_{anom}^{yr-1} in ~~DH2019~~DH19 could reflect increased susceptibility of impaired trees, combined with favourable climatic conditions for insect growth~~(,~~ reflected in stronger negative effects of

T_{anom}^{sm} in ~~DH2019, (Rouault et al., 2006)), indicates that such cascading effects could also have contributed to amplify the impacts of DH2019.~~ DH19 in high tree cover pixels.

Results from field inventories and forest plots support this hypothesis. ~~An increase in~~ Increased tree mortality and insect outbreaks in central Europe during 2018 ~~has~~ have been reported (Schuldt et al., 2020). A recent assessment by the German Federal Minister for Food and Agriculture (BMEL, 2020) reported crown damage in 36% of all tree types in summer 2019, a 7% increase compared to 2018 and predominating in trees over 60 years of age. According to this report, the mortality rate in both needle-leaved and broad-leaved trees almost tripled from 2018 to 2019. Although no large scale data on insect outbreaks is currently available, local authorities in regions where ~~C1~~ $C_{Decline}$ is prevalent report increase in tree mortality from bark-beetle infestations: the Environment Ministry of North Rhine Westphalia in western Germany reported soaring rates of spruce affected by severe bark-beetle infestations, from about 1% in 2018 to over 12% in 2019 (MULNV-NRW, 2019). In the Czech Republic, rates of spruce damaged by bark-beetles more than tripled, leading to increased mortality (Hlásny et al., 2021). In Belgium, a "bark bettle task force" was created in September 2018 by the economic office of Wallonia (OEW, 2018). Increased tree mortality and bark-beetle infestations have also been reported in eastern France (ONF, 2020).

5.2 Implications for earth system modelling

Temperate ecosystems are an important global sink of CO_2 (Pan et al., 2011) and are not usually considered hot-spots of drought risk and environmental degradation under climate change (Vicente-Serrano et al., 2020). Our results show that the past two extreme summers in central Europe reveal first signs of large-scale enhanced vulnerability in response to DH events (~~C2, C3~~ C_{HighV}, C_{PRecov}), and of potential degradation trajectories induced by consecutive events (~~C1~~ $C_{Decline}$). Even though limited to 20% of the study area, the patterns in ~~C1~~ $C_{Decline}$ highlight the risks associated with more frequent and intense droughts and heatwaves expected in the coming decades (Barriopedro et al., 2011; Boergens et al., 2020; Hari et al., 2020). At the same time progressive warming conditions ~~are likely to promote~~ can increase the likelihood of compound occurrence of multiple disturbances, such as droughts and insect outbreaks, both promoted by warm and dry conditions. Interactions between compounding disturbances can further contribute to forest C losses (Seidl et al., 2017; Kleinman et al., 2019). To anticipate such impacts, process-based modelling of ecosystem response to such events is needed.

The LSMs perform well in simulating the magnitude and evolution of productivity anomalies in 2018, but not in 2019. The recovery simulated by LSMs in DH19 can be partly explained by a strong recovery of modelled soil-moisture (Fig. B7), but may also result from limited ability of LSMs in simulating changes in ecosystem vulnerability during the two DH events. The latter is supported by the fact that simulated SM_{anom} shows good agreement in the temporal evolution of soil-moisture anomalies with both observation-based datasets but not of GPP_{anom} (Table 1).

The comparison of the reference and factorial simulations allows showing that the poor performance in 2019 may be related with interannual legacy effects. LSMs estimate legacies from ~~DH2018~~ DH18 only in the early growing season (March to May 2019), but do not estimate any legacy effects in summer (Fig. 7 bottom panel). The poor relationships between EVI_{anom} and simulated GPP_{anom} in response to ~~DH2019~~ DH19 indicate that processes controlling legacy effects such as damage from

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embolism, carbon-starvation and resulting tree-mortality or disturbances induced by drought and heat such as insect outbreaks,
currently missing in LSMs, likely explain the amplified impacts of ~~DH2019~~DH19.

LSMs are known to have limited ability to simulate drought-induced stress and tree mortality (Wang et al., 2012), and lack impacts of biotic disturbances, although rudimentary approaches have been attempted (Kautz et al., 2018). These model shortcomings add to limitations in simulating soil-moisture variability and transitions between energy-limited and water-limited regimes. Attributing the LSM errors to specific climatic or non-climatic processes here is challenging since up-to-date datasets on tree mortality, tree carbon reserves or spatially-explicit information on biotic disturbances are very limited. Nevertheless, our results show that LSMs can simulate well the impacts of one strong drought (~~DH2018~~DH18) on ecosystem dynamics but have limited skill in simulating the impacts of a subsequent compound extreme event (~~DH2019~~DH19) by missing important inter-annual legacy effects.

6 Conclusions

The two consecutive extreme dry and hot summers in central Europe (~~DH2018 and DH2019~~DH18 and DH19) had stronger impacts on vegetation activity than those expected by previous vegetation–climate sensitivity. This hints at large-scale increase in the vulnerability of ecosystems to compound heat and drought events, possibly modulated by ~~vegetation responses to the~~ long-term ~~warming and increasing CO₂ trends~~environmental changes. We find signs of degradation trajectories in 20% of the study area, where EVI decreased even with drought alleviation in the following year. We attribute these trajectories to legacies from ~~DH2018~~ DH18 amplifying the impacts of ~~DH2019 which indicate~~ DH19, which indicates that more frequent extreme summers may pose a major threat to the stability of temperate forests.

State-of-the-art land-surface models were able to simulate the exceptional impacts of ~~DH2018~~DH18, but they underestimated the impacts of ~~DH2019~~DH19. This is explained by LSMs missing the preconditioning effect of ~~DH2018 in DH2019~~ DH18 in DH19 impacts as they cannot simulate inter-annual legacy effects from DH events on ecosystem activity. In addition, LSMs also lack representation of biotic disturbances, which are triggered by DH conditions and further promoted by plant stress in response to DH. Because DH events may become more common in the coming decades, overlooking these effects may result in an overestimation of the resilience of the CO_2 sink to climate change in temperate regions.

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Appendix A: Supplementary ~~Figures~~ Methods

Land surface and global dynamic vegetation model simulations

We have used output of gross primary productivity (GPP) and simulated soil-moisture from seven models that followed the protocol and extended the simulations in Bastos et al. (2020a) up to 2019. These models are: ISBA-CTRIP (Joetzjer et al., 2015), JSBACH (Mauritsen et al., 2018), LPJ-GUESS (Smith et al., 2014), LPX-Bern (Lienert and Joos, 2018), OCN (Zaehle et al., 2010), ORCHIDEE (Krinner et al., 2005) and SDGVM (Walker et al., 2017).

The model simulations were run for most models at 0.25 °spatial resolution for the European domain (32–75°N and -11–65°E), following a spin-up to equilibrate carbon-pools. For the reference simulation, the models were forced with observed CO_2 concentration from NOAA/ESRL and changing climate between 1979 and 2019 from ERA5 and fixed land-cover map from 2010 from LUH2v2 (Hurtt et al., 2011). An additional simulation was ran where the models were forced with changing climate, except June–August 2018, where climatological summer climate conditions were used to force the models as described in Bastos et al. (2020a). This simulation, extended up to December 2019 allows evaluating the direct impact of DH18 and its inter-annual legacy effects.

For more details on the simulation protocol, we refer to (Bastos et al., 2020a).
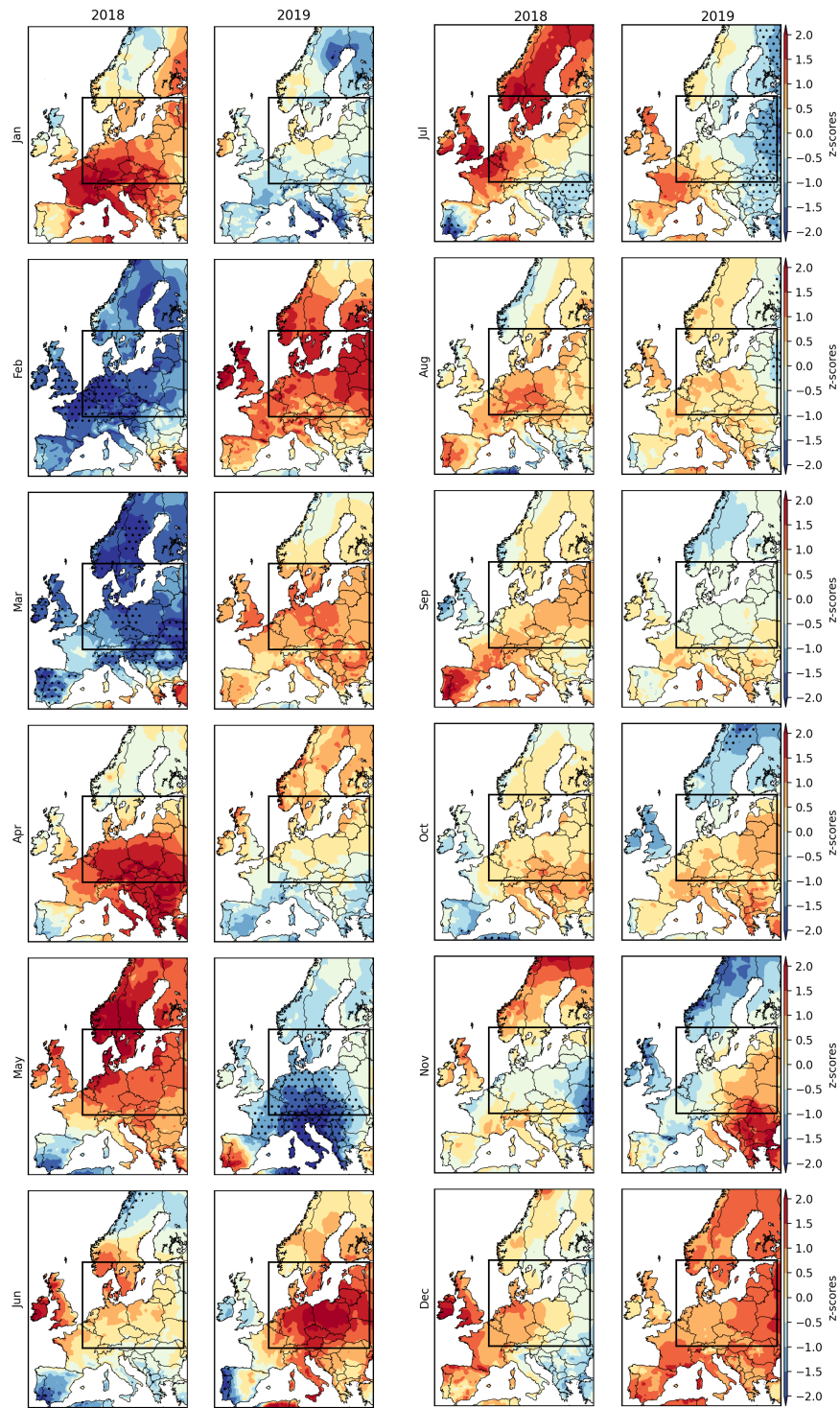
Appendix B: Supplementary Figures

Figure B1. Monthly temperature anomalies during 2018 and 2019. The rectangle indicates the study region.
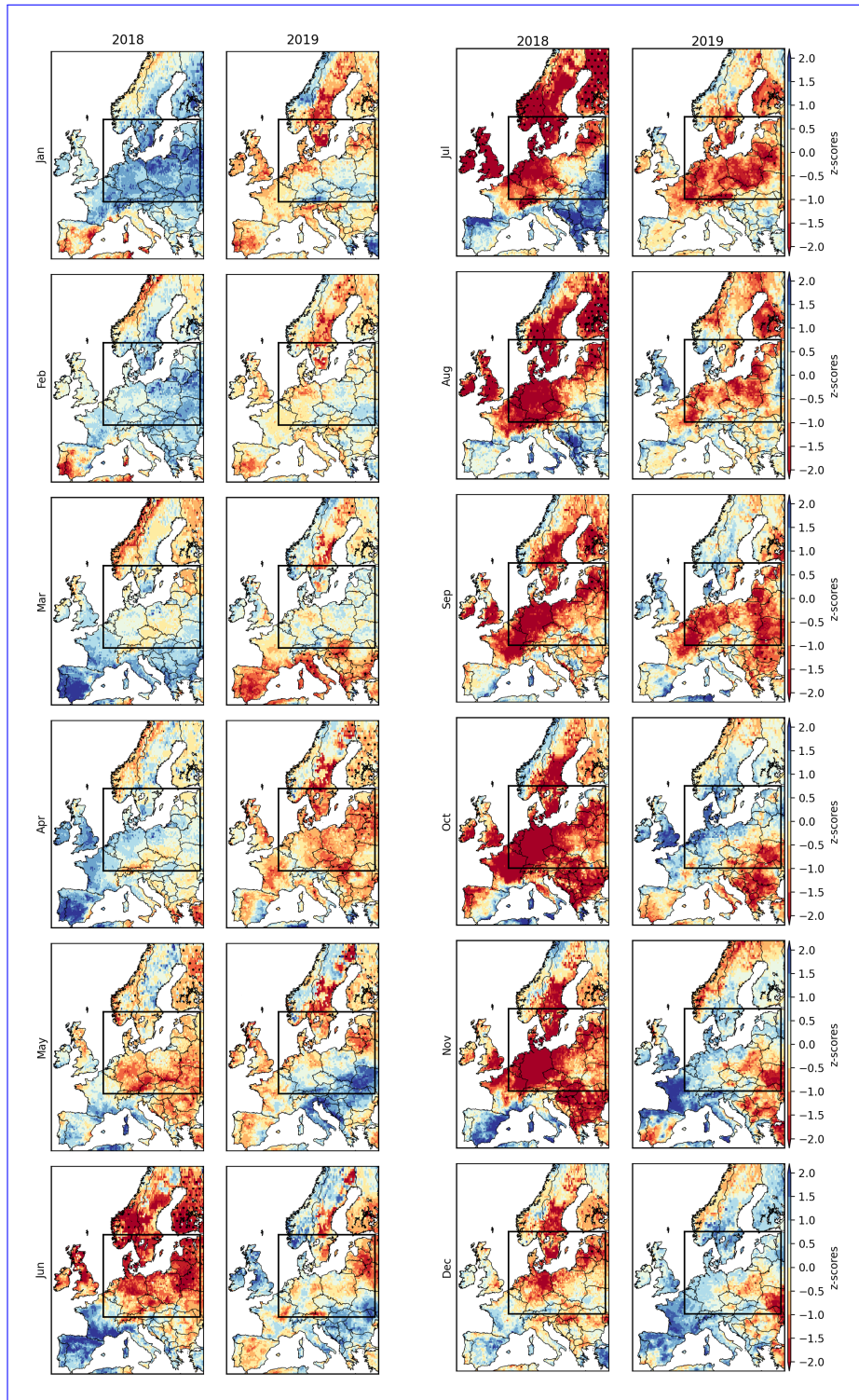
Figure B2. Monthly soil-moisture anomalies during 2018 and 2019. The rectangle indicates the study region, i.e. the areas experiencing drought conditions ($SM_{anom} < -1\sigma$) during both ~~DH2018~~ DH18 and ~~DH2019~~DH19. .
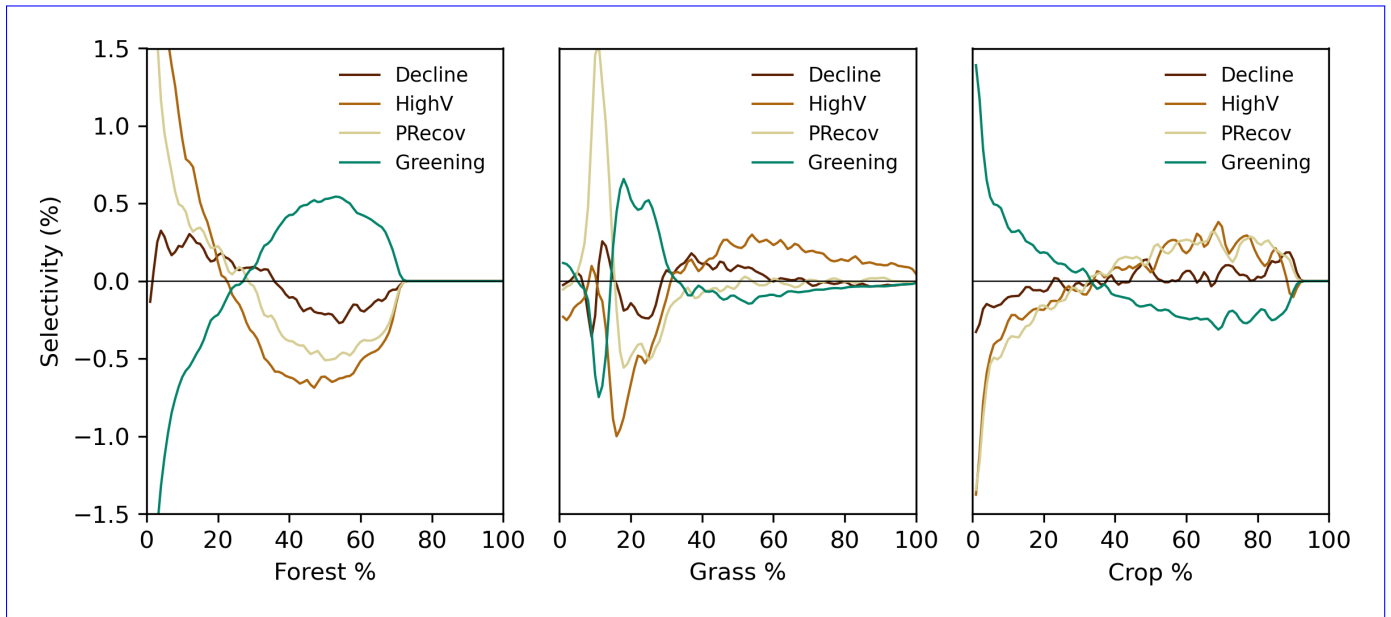
Figure B3. Selectivity of different land-cover composition for each cluster (Fig. 3). Selectivity is evaluated as the difference between the probability distribution of a given land-cover type (forest, left; grassland, middle; cropland, right) and the probability distribution of that land-cover type in the selected region. If selectivity is positive, the cluster is preferentially composed by the given land-cover type and the opposite for negative values. The 2018 land-cover classification maps from from ESA CCI-LC are used.
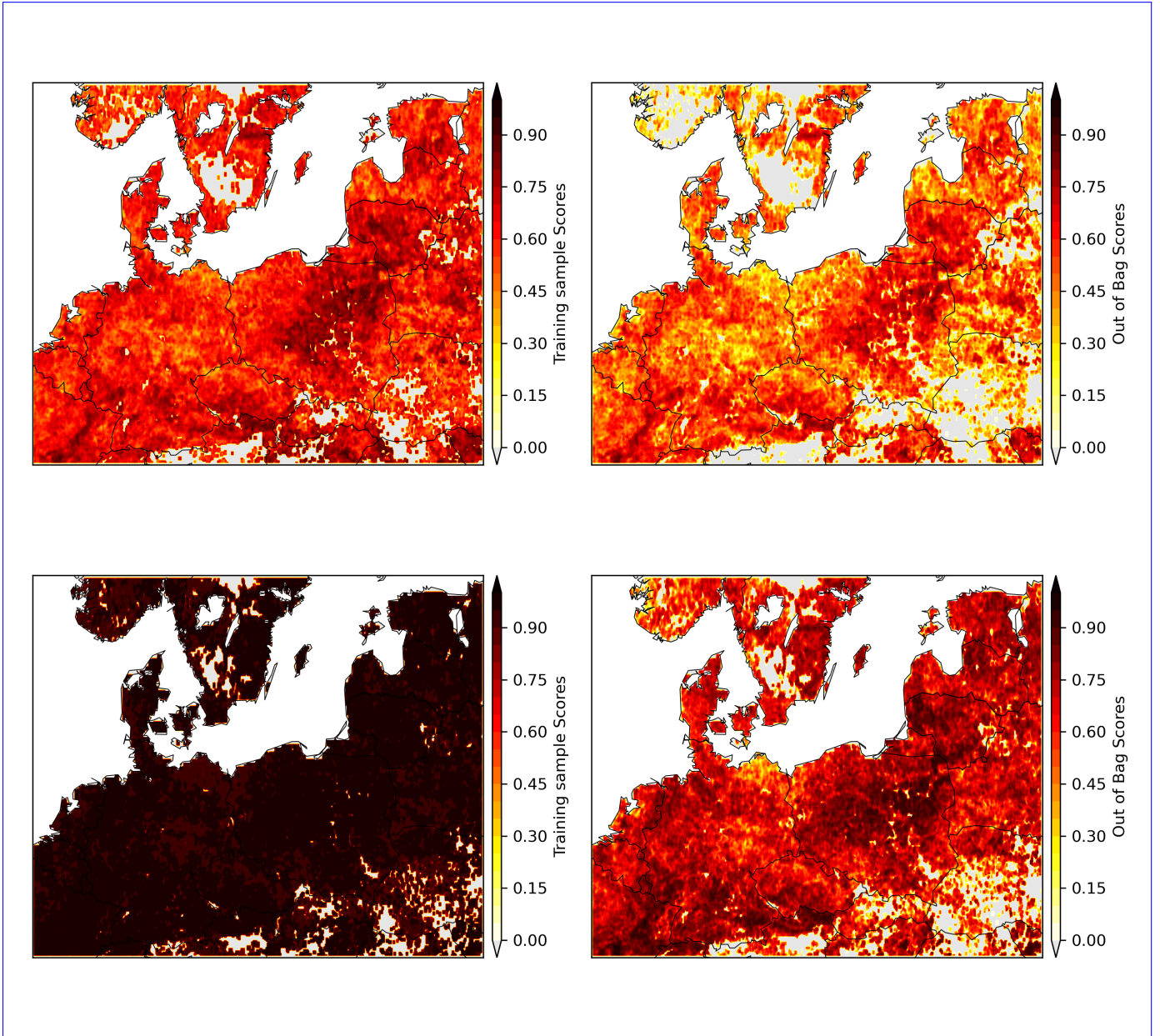
Figure B4. Performance of the temporal RF model in predicting EVI_{anom}, given by the out of bag scores. The top panel shows the scores for the climate-driven RF model and the bottom panel the corresponding results for the same model, but including EVI_{anom}^{yr-1} as an additional predictor.
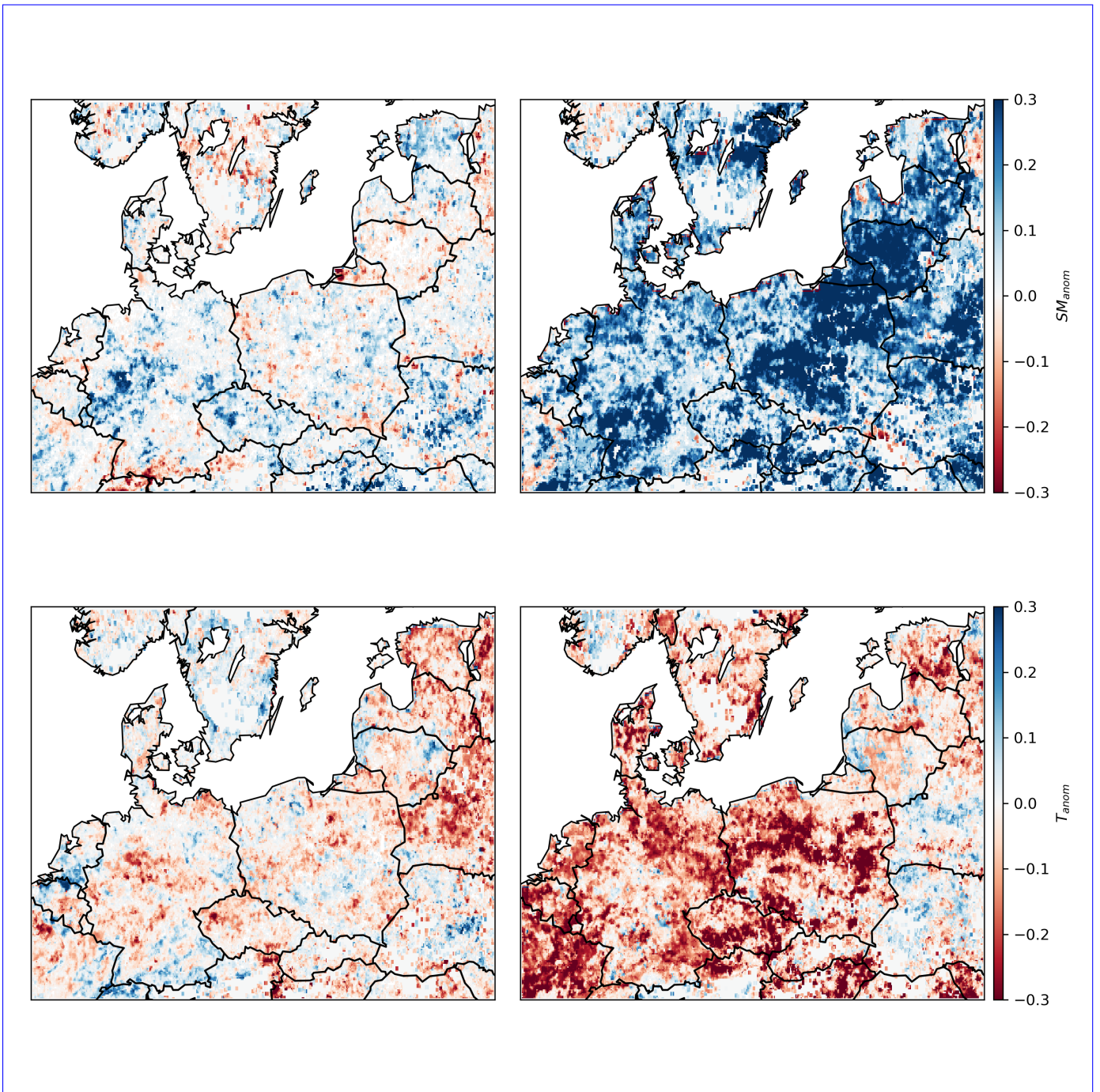
Figure B5. Importance of the four predictors used in the RF model to predict EVI_{anom}, spring (left) and summer (right), SM_{anom} (top) and T_{anom} (bottom), calculated from the Shapley additive explanation values (Methods).
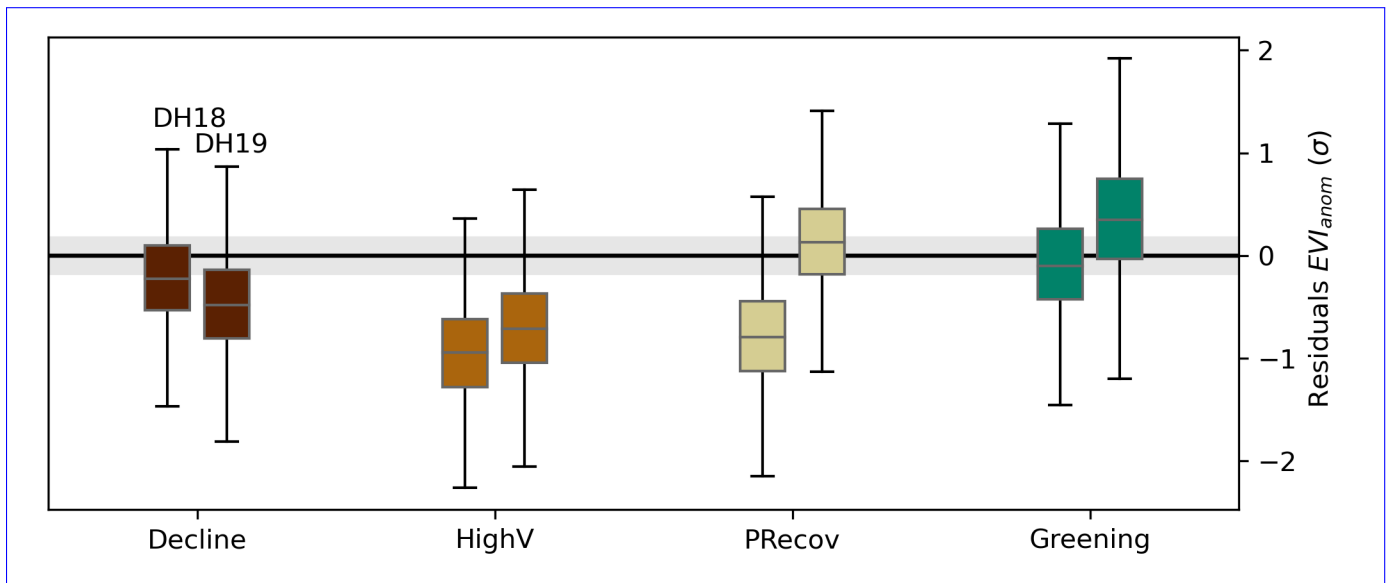
Figure B6. As in Fig. 5 bottom panel, but for the RF model trained using spring and summer SM_{anom} and T_{anom} as predictors, as well as EVI_{anom}^{yr-1}.
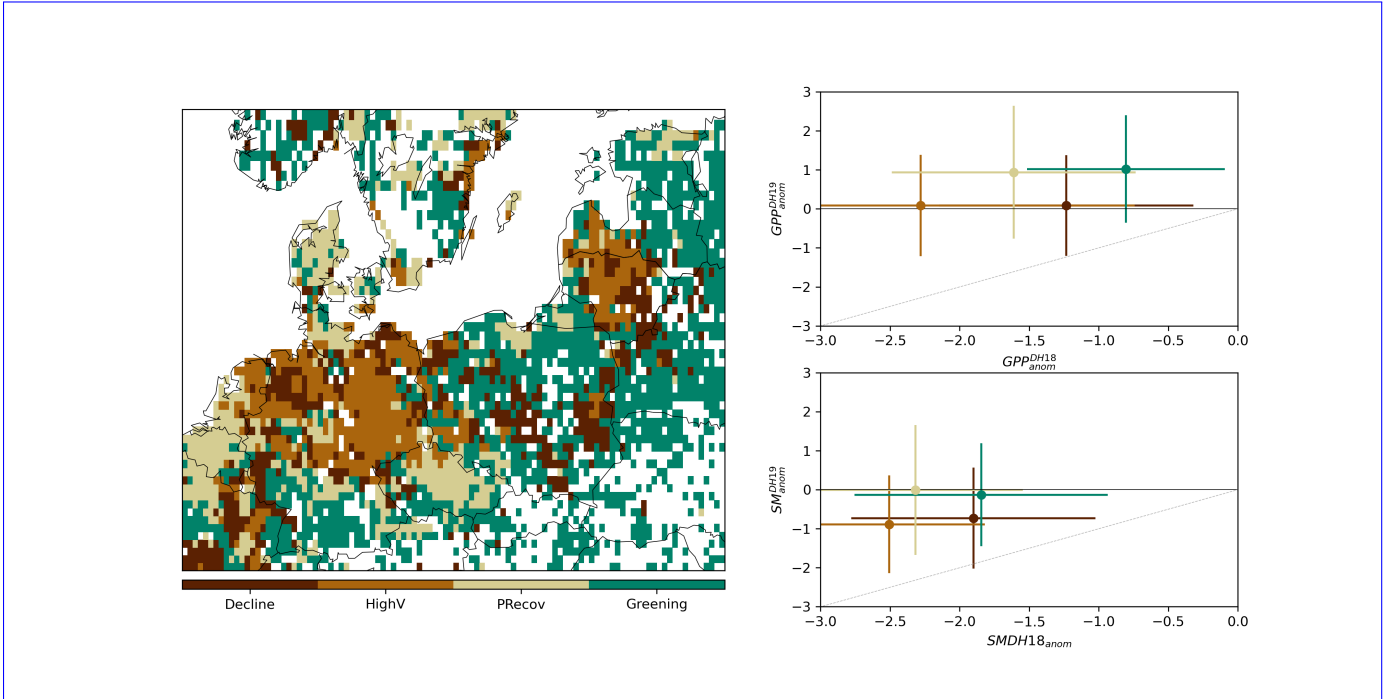
Figure B7. The left panel shows the spatial distribution of the four clusters from unsupervised classification of (EVI_{anom}^{DH2018} EVI_{anom}^{DH18}, EVI_{anom}^{DH2019} EVI_{anom}^{DH19}) values remapped to the coarser grid of LSMs. The corresponding (GPP_{anom}^{DH2018} GPP_{anom}^{DH18}, GPP_{anom}^{DH2019} GPP_{anom}^{DH19}) values simulated by the multi-model mean in each cluster are indicated in the top right panel (circles indicate the spatial mean and the lines spatial standard deviation within each cluster). The corresponding distribution of simulated SM_{anom} pairs in each cluster are shown in the bottom right panel. The grey line, indicates similar anomalies in the two DH events.
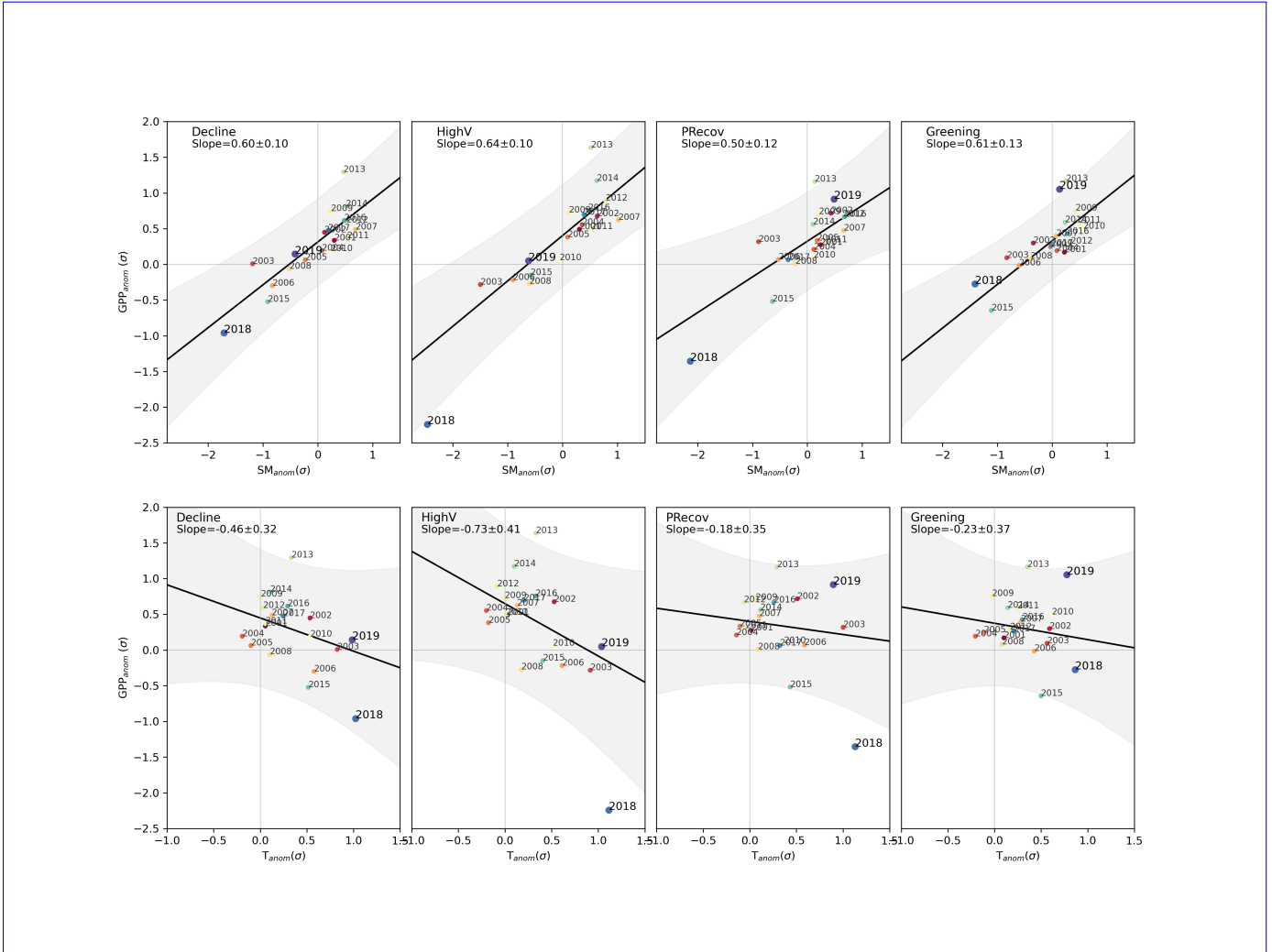
Figure B8. Same as Fig. 4 but for GPP and soil-moisture anomalies simulated by a subset of land-surface models from (Bastos et al., 2020a) extended up to December 2019.