Answer to editor

We would like to thank you for your valuable comments and the five points of criticism and your suggestions how to address them. We will discuss these points below: a) standardisation technique, b) maturity of remotely sensed soil moisture data, c) spatial aggregation of land cover data, d) ground truth and e) trend analysis (these answers are also part of the individual responses to the reviewers).

a) Standardisation technique

Calculating z-scores is a commonly applied standardisation technique (Phillips 2018). It does not lead to a bias in the tails of the distribution, but merely rescales the data. The purpose of this transformation here is to rescale soil moisture and temperature to a common scale, so they can be analysed and displayed jointly on this standardised scale (while maintaining their original distribution shape) (Orth et al. 2020). For illustration, we show time series and histograms for an exemplary pixel for all three variables before and after the transformation below (Figs. R1 and R2).

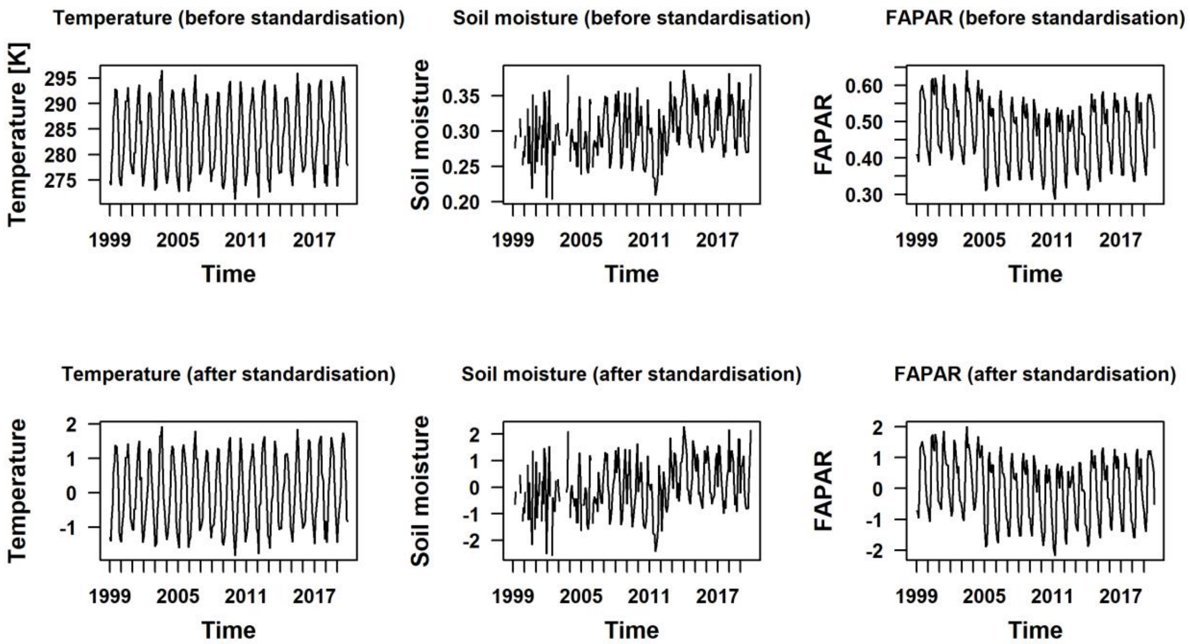

Figure R1: Time series of temperature, soil moisture and FAPAR from 1999-2019 before (upper row) and after standardisation (lower row) for an exemplary pixel

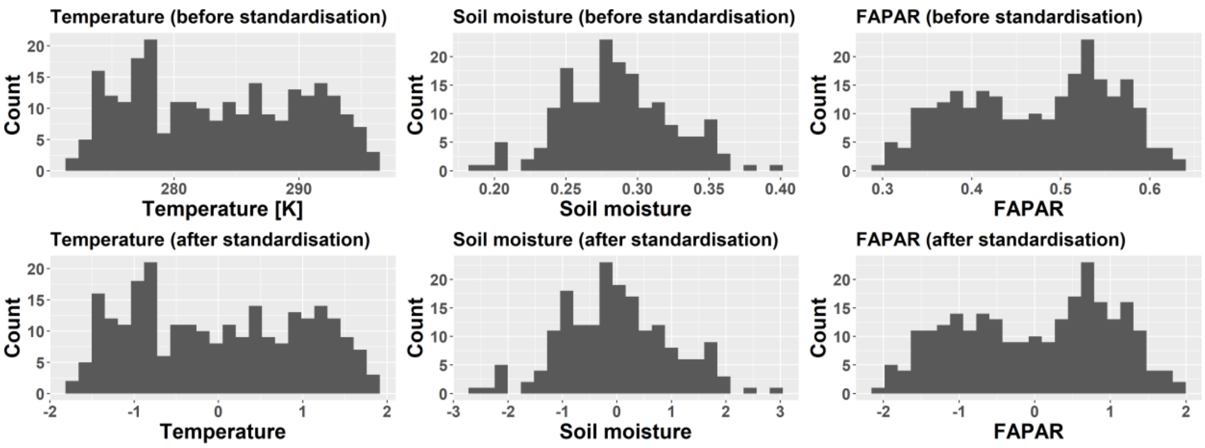

Figure R2: Histograms of temperature, soil moisture and FAPAR from 1999-2019 before (upper row) and after standardisation (lower row) for an exemplary pixel

Many time series are not normally distributed (according to the Shapiro-Wilk test the assumption of normality is rejected for 23.3%, 66.7%, 69,6% of the time series of deseasonalised temperature, soil moisture and FAPAR used in this study, based on a p-value of 0.05, respectively). However, normally distributed data is not a prerequesite for standardizing the time series to z-scores. This transformation has been applied in similar contexts for a variety of data sets (von Buttlar et al. 2018 and Orth et al. 2020, both published in *Biogeosciences*, Seddon et al. 2016, published in *Nature)* including non-normally distributed data such as precipitation, as it was carried out e.g. in the Ahlström et al. 2015, published in *Science*.

We repeated the entire analysis, standardizing by dividing by the interquartile range instead of the standard deviation. The differences in the results of the vulnerability analysis are negligible: statistical significance changes in 3 out of the 504 cases displayed for the land covers classes and subregions as despicted in Figs. 5, 6, A1 and A2 of the article. For all other combinations of land covers, subregions at the 12 months of the year, statistical significance remains unchanged. The standardisation using z-scores is statistical sound in the context of our study, but we can provide our findings based on division by the interquartile range instead of the standard deviation if required.

b) Maturity of remotely sensed soil moisture data

To address the uncertainties of the satellite-based soil moisture data set from ESA CCI, we additionally used the soil moisture reanalysis data set from ERA5 Land for the layers 0-7 cm, 7-28 cm and 28-100 cm (corresponding to the soil moisture data sets used in Nicolai-Shaw et al. 2017) to assess the soundness of our results. Both data sets show agreement in the overall patterns (see Appendix A). We only show the first layer (0-7 cm) from ERA5 Land in the submitted manuscript, because it is rather well correlated with deeper layers and there are only subtle changes in vulnerability between these layers. This is in line with findings by Orth et al. (2020) who also found only minor difference between surface and deep layers. In addition to Figure A1 and A2, we will add corresponding figures for the layers 7-28 cm and 28-100 cm, to enable the reader to assess how vulnerability to soil moisture varies within the top 100 cm of the soil according to the reanalysis data set from ERA5 Land. We appreciate that the additional usage of the soil moisture data set from ERA5 Land should be described more prominently in the manuscript (currently in lines 5-6, 80-81 and 200-202). We will further mention its usage in line 58 in the introduction.

The optimal hydrologic variable referring to ecosystem vulnerability is plant available water within the root zone. However, observations of this variable are not available for large spatial scales. Therefore, it is necessary to use either related observational data as proxies such as precipitation or satellite surface moisture data or data resulting from land surface models or assimilation of model and observations, all of which have specific constraints.

Soil moisture values are included in the land-data assimilation in the ERA5 Land reanalysis data set based on a point-wise Simplified Extended Kalman Filter (de Rosnay et al. 2013, Hersbach et al. 2020). Surface soil moisture is linked to root-zone soil moisture via soil water redistribution to deeper layers and therefore remotely sensed surface soil moisture is used for the approximation of root zone soil moisture in land data assimilation systems (Maggioni and Houser 2017, Orth et al. 2020). We are well aware that the dynamics of surface soil moisture are directly linked to wetting and drying processes, i.e. rainwater infiltration and soil evaporation. Thus, soil water dynamics of deeper soil layers show a dampened and delayed dynamics compared to the surface layer, but still there is a significant correlation between them (Akbar et al. 2018). ERA5 is the first ECMWF reanalysis data set, which includes satellite information for the derivation of soil moisture estimates (Hersbach et al. 2020).

We will add a further sentence on the delayed connection of surface and deeper soil layers in line 297:

"For example, it takes some time for the propagation of surface drying to deeper soil layers, because of the slow capillary flow (Berg et al. 2017)."

We further argue that using satellite-based soil moisture data in large-scale ecological applications is a state-of-the art method. We want to emphasize that remote sensing soil moisture products have significantly improved over the last years (Mohanty et al. 2017, Gruber et al. 2019) (see lines 199-200), are increasingly being used to assess the impact of droughts on plant productivity (Dorigo and de Jeu 2016) and the ESA CCI soil moisture has been applied succesfully in a large number of studies for ecological applications. For an overview we refer e.g. to Table 5 and section 4.3 in Dorigo et al. (2017). This shows that surface soil moisture – despite its undisputed limitation – can give valuable insights on the state of the ecosystems. Denissen et al. 2019 state that satellite surface soil moisture is well suited to infer the state of the vegetation and corresponding land-atmosphere interactions during climate extremes. The transition from an energy- to a water-limited regime is marked by the critical soil moisture regions (Denissen et al. 2019), which makes soil moisture an appropriate variable especially in Mediterranean environemnets (Szczypta et al. 2014). Chen et al. (2014) assessed variability in the NDVI over Australia and conclude that not only precipitation but also remotely sensed soil moisture data from ESA CCI can be a good predictor for vegetation growth. A further example where ESA CCI soil moisture is used for biospheric drought effect assessment can be found in Orth et al. (2020) (published in *Biogeosciences*). Nicolai-Shaw et al. (2017) emphasize that remotely sensed soil moisture is a valuable addition or might even be able to replace other soil moisture proxies for the investigation of land-vegetation-atmosphere-dynamics (see lines 54-55). The authors highlight the usage of remote sensing based soil moisture for the assessment of drought development. They found strong responses of grasslands to soil moisture droughts, while forests showed weaker responses and relate this to the shallower rooting depth of grasslands compared to forests.

We will add a sentence on this at line 298:

"Nicolai-Shaw et al. (2017) found that soil moisture data from ESA CCI was a good indicator for drought in grasslands, while forests exhibited weaker responses, probably due to access to deeper soil layers for forests compared to grasslands."

For a comparison of the ESA CCI soil moisture data set with gridded precipitation, see e.g. Dorigo et al. (2012, 2017). Furthermore, the ESA CCI soil moisture data set was even used to create a global precipitation product, which was compared to state-of-the-art precipitation data sets and showed relatively good performance (Ciabatta et al. 2018). We also would like to emphasize that ESA CCI soil moisture has been validated succesfully with in situ observations e.g. in Spain and France at depths from 5 to 30 cm (see lines 299-301; Albergel et al. 2013, Dorigo et al. 2015) and Turkey (Bulut et al. 2019).

Finally, precipitation does not directly translate into plant available water within the root zone (de Boeck et al. 2011; see lines 47-49) and is thus not necessarily superior to surface soil moisture data for the assessment of plant available soil water. Several other processes play a role, such as evapotranspiration (especially important in the Mediterranean), runoff, topography, soil properties and irrigation (Mohanty et al. 2017).

c) Spatial aggregation of land cover data

A general remark on the data used in this study: There is a certain mismatch between the desirable spatial scale for assessing ecological impacts and the actually available climatic and land cover data sets (Ummenhofer et al. 2017). So, while remote sensing offers consistent large spatial and temporal coverage, there remains a trade-off regarding their coarse spatial resolution.

A more detailed land cover classification map would be beneficial, but is not available for the Mediterreanean Basin to our knowledge (CORINE Land Cover would show greater detail but is only available for the European side of Mediterranean basin).

We argue that it is common to use such rather broad categories, which rather resemble plant functional types than specific plant communities, for the analysis of the impact of climatic extremes on ecosystems. Plant functional types are partially based on climatic preferences (Bonan 2016). While there are certain simplifications, their distinctions nevertheless provide valuable insights on key ecological properties. For example, when comparing broadleaf and needleleaf forests, the former have high photosynthetic rates and stomatal conductance, the latter have lower photosynthetic rates and conductance (Bonan 2016), and it has been shown, that they show differences in drought-induced growth reductions leading to tree mortality (Cailleret et al. 2016). As a further example, Teuling et al. (2010) investigate the differing responses to heatwaves for forests and herbaceous perennial vegetation using data from various European flux tower sites. Furthermore, dynamic global vegetation models are usually based on plant functional types and these models are built with the intent to investigate the feedback of ecosystems and climate (Bonan 2016).
Therefore, we argue that we use an adequate state of the art classification scheme for investigating interactions of ecosystems and climate at such spatial scales for our type of research.

Land cover classification schemes like the one in our study are commonly applied; examples of studies using the same or similar land cover classifications in such a context include Ceccherini et al. (2014), Baumbach et al. (2017) (published in *Biogeosciences*), Nicolai-Shaw et al. (2017) and Buitenwerf et al. (2018).

We would further like to point out that we only include grid points belonging to the Köppen-Geiger classes Csa (“Warm temperate climate with dry and hot summer”) or Csb (“Warm temperate climate with dry and warm summer”), i.e. areas with alpine grasslands and semiarid steppes are not considered in the study.

d) Ground truth

We agree that validation with ground truth is generally desirable.
We would like to point out that all data sets have been validated using both ground truth and model data and underwent quality assessment see e.g. Dorigo et al. (2015), Dorigo et al. (2017) for ESA CCI, Sanchez-Zapero (2019), Fuster et al. (2020) for FAPAR and Hersbach et al. (2020) for ERA5. We would like to emphasize that ESA CCI soil moisture has been validated succesfully with ground observations e.g. in Spain, France (see lines 299-301; Albergel et al. 2013, Dorigo et al. 2015) and Turkey (Bulut et al. 2019) and the FAPAR has been validated with observation data from e.g. Tunisia, Italy, Spain and France primarily for a variety of crop types (Fuster et al. 2020). In addition to the already mentioned validation of ESA CCI soil moisture in Spain and France, we will mention its validation in Turkey and the validation of the FAPAR in line 301.

It is usually challenging to validate satellite data with ground truth, as ground truth does not exist in such a consistent form in space and time, as it would be desirable (Preimesberger et al. 2020). A full-fledged validation of our analysis remains therefore hardly feasible, as there is no ground truth data set available, which is consistently available for the representative land cover classes and subregions for all months of year for the entire time span to our knowledge. Because a comparison with in-situ data was not feasible in our case, we rather used ERA5 reanalysis data as an independent additional source for comparison to the soil moisture product from ESA CCI (see lines 199-202 and Appendix A), which is common practice in cases where sufficient in-situ data is not available (Preimesberger et al. 2020).

We argue that it is beyond the scope of our study to incorporate ground truth and it is common in the scientific literature to rely on validated data sets without carrying out an independent validation for the specific case study (for examples of similar studies without ground truth validation see e.g. van Oijen et al. 2013, Rolinski et al. 2015, Ivits et al. 2016, Baumbach et al. 2017, Nicolai-Shaw et al. 2017).

For the points raised regarding lines 231, 311 and 325 we refer to the corresponding sections below.

e) Trend analysis

We quantify vulnerability (after Rolinski et al. 2015) as the average deviation of the environmental variable under hazardous ecosystem conditions from values under non-hazardous ecosystem conditions for a specific time span (e.g. the vulnerability to temperature for all months of July in a grid point in central Spain regarding the time span 1999-2019). Thus, ecosystem vulnerability is based on the comparison of non-extreme to extreme conditions within a given time span, i.e. it is always related to a certain reference period and cannot be assigned for a single point in time. Therefore, a trend analysis investigating year-to-year changes is not directly feasible, but a trend anaylsis can be carried out by analysing several time spans, if time series are available for a sufficient length (e.g. comparing vulnerability for the periods 1999-2019, 1999-2024, 1999-2029).

A certain number of years encompassing a few extremes is required to obtain a meaningful baseline value. For only a small number of years, stochasticity is still too high for such a trend analysis. The time span we investigate has a length of 21 years from 1999 onwards (the year where the applied FAPAR product is first available), which is considered too short for a vulnerability trend analysis, as a reference period of 30 years is commonly suggested as a baseline in climatological settings (Stocker et al. 2013).

We will add the following text in line 282:

“The time series used here encompasses 21 years and is thus still too short for analyzing long-term trends. Nevertheless, our approach can potentially be used to monitor how vulnerability changes in future for the 12 months of the year by comparing vulnerability during different time spans if time series of sufficient length are available.”

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