Answer to Anonymous Referee #2

We would like to thank the anonymous reviewer for the detailed feedback, which helped to improve the article further. We will address all raised points below.

Major comments

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.

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."

Minor comments

Lines 90-96:

To avoid redundancy between "Introduction" and "Methods" we will move the information on FAPAR and ESA CCI soil moisture in the second and third paragraph of 2.2 to the introduction at line 59 and remove redundant parts.

Line 105:

Yes, σ is calculated for the whole year. The months of the year have different variabilities and we aim to preserve this intraannual variability (whereas a monthly calculation of σ would artificially produce months with equal variability). We will add the word "year-round".

"dividing by the **year-round** standard deviation of the deseasonalised time series"

Section 2.4:

Van Oijen et al. (2013) (which our definition is based on) also denote that vulnerability is sometimes referred to as sensitivity. Weißhuhn et al. (2018) define sensitivity as a "measure of susceptibility" to a hazard and according to Ionescu et al. (2009) sensitivity is "characterising how much a system's state is affected by a change in its input". These definitions are applicable to the notion of vulnerability in our article. We investigate if extreme reductions in ecosystem productivity are linked to significant deviations in temperature and soil moisture. Hence, only if temperature or soil moisture deviations are related to low FAPAR values, significant ecosystem vulnerability will be detected.

Smith 2011 states, "we must be able to attribute the extreme ecological response to the period of climate extremity. [… This is] critical for elucidating what factors may contribute to differential sensitivity of ecosystems to climate extremes."
According to the framework by Smith 2011, vulnerability to extreme climatic events is defined as a climate extreme leading to an extreme ecological response. The definition used in our article involves extremeness in the response, as well as a significant deviation of the climatic driver (to the climatic driver during non-extreme ecosystem conditions). Therefore, our definition differs in that regard that it includes extremeness only for the ecological response, not necessarily for the driver (but extremes in the driver usually are significant deviations and thus they are included, so our definition is broader than the one by Smith 2011). In our case, ecosystem vulnerability rather shows if the ecosystem variable is susceptible to certain climatic conditions (which do not need to be extreme).

It should be noted that our approach is impact-based (see lines 132-133); following the definition of Rolinski et al. 2015 who "[…] define hazardous conditions from an ecosystem perspective to quantify the probability of weather conditions determining ecosystem vulnerability". This means, we are asking which are the climatic conditions leading to extreme ecosystem response (perpective from the ecosystem: define ecological extreme and attribute it to climatic drivers) rather than asking what are ecological impacts of climate extremes (perspective from the climatic driver: defining a climatological extreme and attribute it to ecological response).

Risk is not assessed in our approach. This could be done in principal by using a qualitative instead of a distributional threshold (Rolinski et al. 2015). Risk is related to hazard probability, i.e. the proportion of exceedances of the hazard-threshold. In our case, this threshold is a percentile, which means each pixel has the same hazard probability (10%), so risk analysis is not directly applicable here. We chose to use a relative threshold (a percentile) rather than an absolute threshold, because it is not straightforward to determine a meaningful absolute threshold for extremeness of the FAPAR with validity for all land covers and subregions.
We contacted one of the authors of Rolinski et al. 2015, who confirmed that a percentile-based approach is an appropriate choice for our setting.

We will make the following changes to the manuscript:

We will replace lines 112-114

"The ecosystem vulnerability methodology serves to attribute drivers to their impact and identify whether a univariate or bivariate driver can be attributed to the respective impact."
by
"Ecosystem vulnerability shows if ecosystems are susceptible or sensitive to a certain hazard. It allows to attribute states of low ecosystem productivity to certain climatic conditions by linking such states to corresponding deviations in temperature and soil moisture."

We will add in line 132:

"Every grid point has the same number of months with hazardous ecosystem conditions, i.e. the same risk of exceeding such a threshold is assumed uniformly for all grid points."

We will move

"Our approach is impact-based, i.e. it focusses on the extremeness of the impact rather than the extremeness of the driver because this enables relating multiple drivers to a single outcome (Zscheischler et al., 2014, 2018)."

from line 132-133 to line 145 and add:

"According to the framework by Smith (2011), vulnerability to extreme climatic events is defined as a climate extreme leading to an extreme ecological response. Therefore, our definition differs in that regard that it comprises extremeness only for the ecological response, not necessarily for the climatic driver. The definition used here is broader than the one by Smith (2011), because it includes significant deviations of the driver variable in general, not only extremes. In our case, ecosystem vulnerability rather shows if the ecosystem variable is susceptible to certain climatic conditions (which do not need to be extreme). "

Line 171:

Yes, in each case 10% are classified as extreme. Extremes are defined by the FAPAR, not the driver variables (temperature and soil moisture). Therefore, these FAPAR extremes do not necessarily have to be linked to any anomalies in the driver variables. So, in the case of sparse vegetation the subset of temperature at times with FAPAR extremes (times where FAPAR is below the 10% percentile) is not significantly different from the subset of temperature at other times without FAPAR extremes (times where FAPAR is above the 10% percentile). Our approach is designed this way – identifying first the impacts and then relate them to potential drivers (see lines 132-133) –, so it specifically leaves the option that the regarded driver variables are not relevant in certain cases (which is also an important finding).

You also additionally mention that vegetation might be dormant. This is another affect, which can occur. It is important to note that the 10% defined as extremes in each time series are not equally distributed within the months of the year. As pointed out above in the comment on line 171, σ is calculated for the entire time series, not seperately for each month. Therefore, months with higher variability are more likely to have a higher number of extremes. Because dormant months have low variability in the FAPAR, they thus will have few (if any) FAPAR extremes. Our approach is designed like this because this implicitly minimizes extremes outside of the growing season (without the need to explicitly define a growing season). See also lines 329-339 in the article.

We will write:
"Sparse vegetation is probably well adapted to hot conditions, as it never shows vulnerability to hot conditions, which means that temperature during extreme ecosystem conditions is not significantly higher than during non-extreme ecosystem conditions."

Figure 6:

Thank you for pointing this out. We will adjust it accordingly.

Line 222:

Thank you, yes we mean indeed "…or dry system".

Line 231:

In Fig. R1 we show three example plots for the Iberian Peninsula (first row), northwestern Africa (second row) and the southeastern Mediterranean (third row). The months of August are marked by red vertical lines.

We will delete the word "presumably" in line 231. We will add "and the FAPAR values are usually at their annual minimum at this time of the year." in line 232.

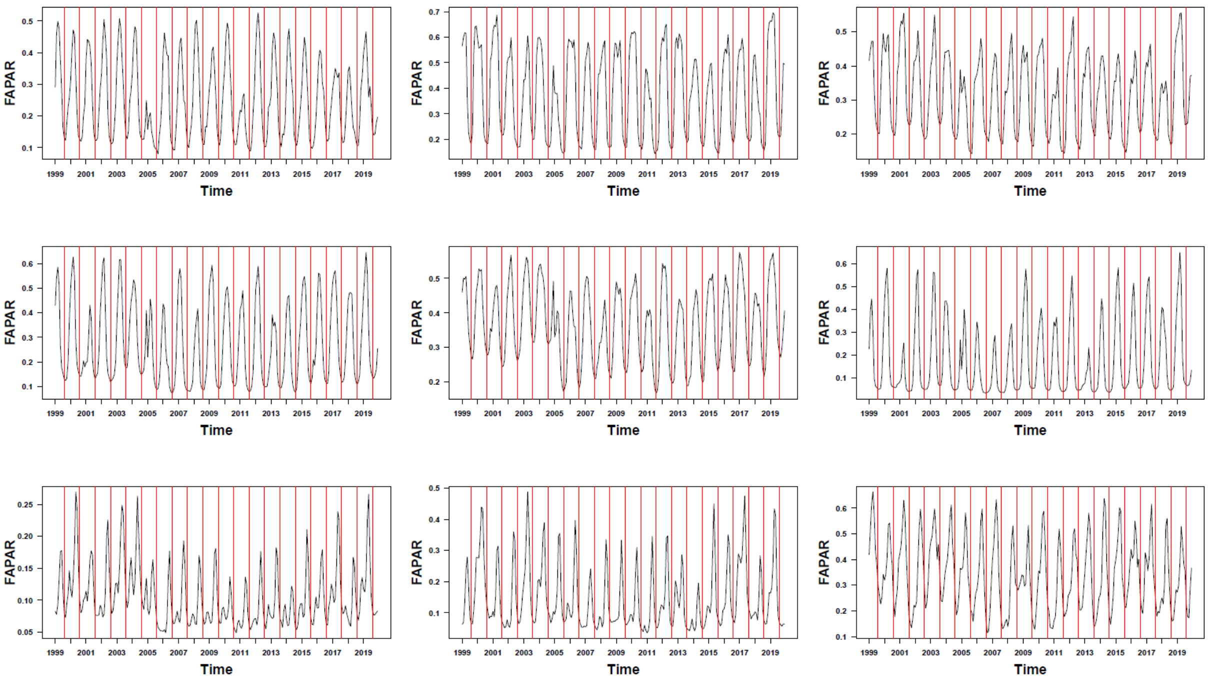

Figure R1: Time series of FAPAR from 1999-2019 for three example plots for the Iberian Peninsula (first row), northwestern Africa (second row) and the southeastern Mediterranean (third row). The months of August are marked by red vertical lines.

Line 267:

We will write:

"The sensitivity to heat varies with phenophase (Hatfield and Prueger, 2015) and the effect on the carbon cycle can differ seasonally. High temperatures might e.g. increase carbon uptake by advancing spring onset, but may lead to uptake reductions in summer (Piao et al., 2019)."

Lines 311 / 325:

We considered this and ran the analysis with various time lags and moving average lengths. The article in its current form includes already many components: a bivariate setting (temperature and soil moisture), soil moisture from two sources (satellite and reanalysis data), various land covers and subregions at all months of the year. Therefore, we investigate (3 driver variables x 12 months x (6 subregions + 8 land covers) 504 cases currently, which lead to several thousand cases if multiplied additionally with various time lags. This makes it challenging to add further complexity.
As we pointed out (lines 311-328), finding the optimal time lag is particularly cumbersome, as the optimal time lag might differ depending on the driver variable (temperature or soil moisture) and the specific land cover.
Therefore, we decided to use only one time lag in our article because a thorough analysis of the influence of time lags might add too much complexity to the article and makes it also challenging to display all these cases visually in a comprehensive way.

Error correction

We noticed an error in our code. The percentiles defining hazardous conditions were wrongly indexed, leading to slightly different percentiles throughout. The changes are generally minor and all conclusions from our article can be inferred as before. Figures and text will be adjusted where needed. We would like to apologize for this inconvenience.

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