Answer to Anonymous Referee #1

We would like to thank the anonymous reviewer for the comments.

The reviewer raised concerns regarding a) the quality of soil moisture data, b) the spatial aggregation of land cover classes and Mediterranean subregions and c) the standardization technique.

The satellite-based soil moisture data set from ESA CCI is a state of the art data set, which underwent validation and quality assessment and has been used frequently for similar purposes in the scientific literature. Furthermore, the results from the reanalysis soil moisture data set from ERA5 Land are in agreement with the ones from ESA CCI in general. For details, we refer to our answer regarding the comments on lines 45-54 / 75-80.

The broad aggregation of land cover classes is common at such large spatial scales and a significantly more detailed land cover product is not available for the entire Mediterranean Basin to our knowledge. We argue that the classification of Mediterranean subregions allows visualizing certain large-scale patterns, while more detailed at pixel scale can be retrieved from the spatial maps provided in the article. For details, we refer to our answers regarding the comments on lines 69, Figure 5 and Figure 6.

The z-score standardization technique used here is commonly applied and does not bias our results. We additionally performed the analysis by dividing by the interquartile range instead of the standard deviation, however differences in the results of both approaches are negligible. For details, we refer to our answer regarding the comment on lines 100-105.

A detailed answer to all comments follows below.

Major comments

Lines 45-54 / 75-80:

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).

Line 69:

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.

Lines 100-105:

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).

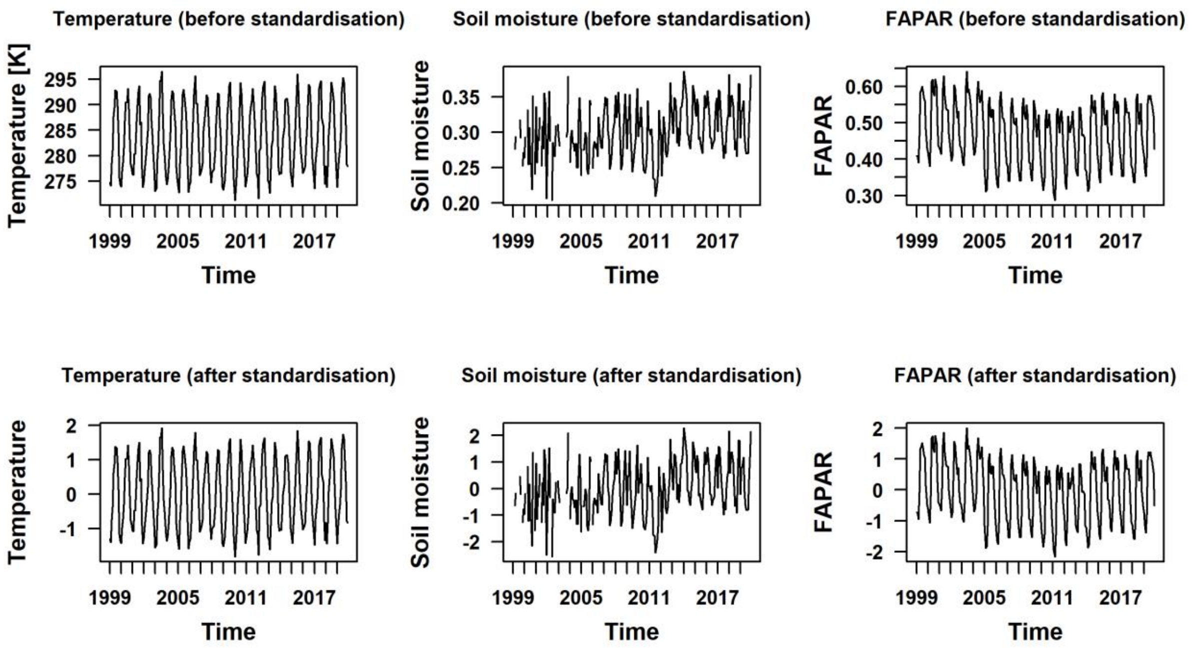

Figure R1: Time series of temperature, soil moisture and FAPAR from 1999-2019 before (upper row) and after standardisation (lower row) for an exemplary pixel

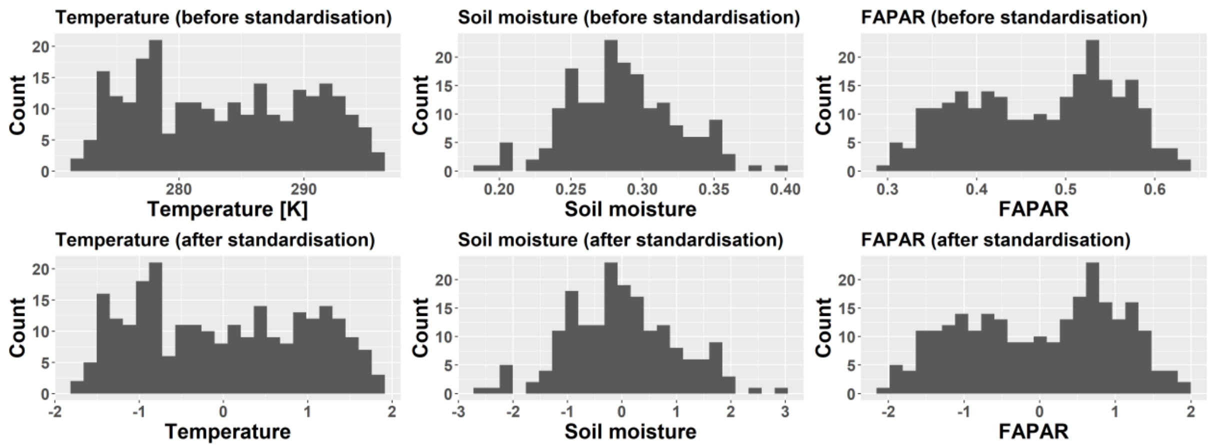

Figure R2: Histograms of temperature, soil moisture and FAPAR from 1999-2019 before (upper row) and after standardisation (lower row) for an exemplary pixel

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.

Figure 5:

High temperatures favor grain filling only for a certain temperature range. The relationship is nonlinear, so high temperature may favor crop growth until a certain threshold, where temperatures become too hot and limit crop growth (Hatfield and Prueger 2015). A variaty of crops is particularly vulnerable to temperature extremes during reproductive stages such as anthesis and grain filling (Luo 2011). The optimum and maximum temperature for grain filling for wheat is at 20.7 and 35.4°C, respectively (Porter and Gawith, 1999). We analysed the daily maximum temperature from ERA5 in May from 1999-2019 at all pixels with landcover “Crops (rainfed)” in the Mediterranean Basin west of 40°E and the optimum temperature is exceeded 62% of the time on average and the maximum temperature is exceeded at least once within this time span in 35% of the pixels. 31°C is stated as the physiological limit for wheat beyond which sterile grains are produced (Porter and Gawith, 1999). This temperature is exceeded on average 5% of the time and at least once within the time 1999-2019 for 74% of the grid points. This shows that relevant physiological temperature thresholds for crops are exceeded in the Mediterranean Basin in May and vulnerability to hot conditions is therefore plausible. For a detailed overview on crop sensitivity to temperature extremes during anthesis we refer to Hatfield and Prueger (2015).

We agree that crops such as maize and wheat are vulnerable to dry conditions in their reproductive phase (see e.g. Zhang and Oweis 1998, Daryanto et al., 2016). As we point out in lines 362-364, significant vulnerability to dry conditions in May is detected for various land cover classes in the ERA5 Land soil moisture data set, while there is no significant vulnerability in the ESA CCI data set. We will add a sentence in line 364, stating that the ERA5 Land soil moisture data set is presumably more realistic for the month of May.
“For land cover classes such as “Crops (rainfed)” vulnerability to dry conditions in May seems realistic, as various crops are prone to drought in their reproductive phase (Zhang and Oweis 1998, Daryanto et al., 2016), which indicates that ERA5 Land might give more plausible results for the month of May.”

Figure 6:

In addition to the time series plots spatial maps are provided to give further detail on the spatial patterns. Therefore, we argue that this division is still justified. It allow to quickly spot large-scale patterns (such as the prolonged vulnerability to hot and dry conditions in Turkey), while details which are not apparent in subregion aggregation can still be seen in the spatial maps.

Minor comments

Line 20 and lines 26-30:

Land abandonment has indeed lead to increasing biomass and forest cover in the Mediterranean within the past decades (Spano et al. 2013, Peñuelas et al. 2017). We rather refer to to increased tree mortality, growth reduction, extended fire risk, agricultural yield decline and vegetation shifts connected to increasing aridity and rising temperatures. Thank you for the remark, we will add more details on climatic impacts on ecosystems in the introduction.

We would further like to point out that ecosystems impacts are repeatedly addressed in the Discussion as well, e. g. in lines 232-237, 241-242, 261-274 and 312-320.

Lines 24-25:

Note that most of NE Spain is excluded from the study since it does not have a Mediterranean climate according to the Köppen-Geiger classification (see section 2.1 Study area and Fig. 1). Furthermore, we mention seasonal differences e.g. in lines 242-243.

Lines 40-41:

We will mention the linkage of extreme heat waves and Saharan air intrusions.

Lines 45-46:

We agree that soil moisture is important for crops during winter and spring and that it reaches its annual minimum in summer. High winter temperatures have been demonstrated to have both positive (see e.g. Sippel et al. 2018 for an example in Spain) and negative (see e.g. Ben-Ari et al. 2018 for an example in northern France) impacts on vegetation in combination with wet springs. This demonstrates that high winter temperatures can play a relevant role for crop productivity.

Introduction in general:

The research gap we address here is the inclusion of seasonality in the assessment of ecosystem vulnerability (see lines 31-33 and 59-63).

The introduction is structured in the following way: In the first paragraph (lines 20-30), we address characteristics of the Mediterranean Basin and why it is important to investigate the impacts of climate anomalies on ecosystems in the Mediterranean. In the second paragraph (lines 31-43), we introduce the importance of considering seasonality in the analysis of ecosystem vulnerability. In the third paragraph (lines 44-58), we state that soil moisture is an important variable for ecosystem producitivity and explain the potential of long-term satellite soil moisture products, which emerged within the last years for this purpose. We will add information on the FAPAR here in the resubmitted version. In the final paragraph (lines 59-63), we give details on our research aims.

Lines 75-76:

Long-term observation data sets such as the ESA CCI soil moisture data set usually contain inhomogeneities (Preimesberger et al. 2020). Single satellites only cover a limited time span; therefore inhomogeneities at transition times cannot be fully avoided. Such inconsistencies have been carefully investigated and the merging scheme of ESA CCI is considered to provide a viable long-term product (Su et al. 2016, Preimesberger et al. 2020).

Lines 80-81:

ESA CCI soil moisture is a satellite-based data set, while ERA5 Land is a reanalysis data set. We apply both data sets here for verification of our obtained results. Both data sets are commonly used in the scientific literature and have been compared various times (see e.g. Preimesberger et al. 2020, Beck et al. 2021 or Albergel et al. 2013 and Dorigo et al. 2017 for their predecessor data sets).

Lines 83-84:

The bands of SPOT/VGT and PROBA-V cover similar spectral ranges (Smets et al. 2019). For the overlapping period from October 2013 to May 2014, the FAPAR from SPOT/VGT and PROBA-V show high agreement for all biome types (Verger et al. 2019).

Line 86:

We will write "Mediterranean climate" instead of "Mediterranean Basin" to be more precise. Note that we only investigate those regions of the Mediterranean Basin, which have a Mediterranean climate according to the Köppen-Geiger classification. We also mention that crops are affected by soil moisture in winter (see lines 241-242) in the discussion.

Lines 85-96:

We will move the information in this section to the introduction to improve readability, so that the background information is gathered jointly in this part of the manuscript.

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.

References

Ahlström, Anders; Raupach, Michael R.; Schurgers, Guy; Smith, Benjamin; Arneth, Almut; Jung, Martin et al. (2015): Carbon cycle. The dominant role of semi-arid ecosystems in the trend and variability of the land CO2 sink. ***Science*** *(New York, N.Y.)* 348 (6237), pp. 895–899. DOI: 10.1126/science.aaa1668.

Akbar, R., Short Gianotti, D., McColl, K.A., Haghighi, E., Salvucci, G.D., Entekhabi, D., 2018. Hydrological Storage Length Scales Represented by Remote Sensing Estimates of Soil Moisture and Precipitation. ***Water Resour. Res.*** 54, 1476–1492.

Albergel, C., Dorigo, W., Reichle, R.H., Balsamo, G., Rosnay, P. de, Muñoz-Sabater, J., Isaksen, L., Jeu, R. de, Wagner, W., 2013. Skill and Global Trend Analysis of Soil Moisture from Reanalyses and Microwave Remote Sensing. ***J. Hydrometeor*** 14, 1259–1277.

Baumbach, Lukas; Siegmund, Jonatan F.; Mittermeier, Magdalena; Donner, Reik V. (2017): Impacts of temperature extremes on European vegetation during the growing season. In ***Biogeosciences*** 14 (21), pp. 4891–4903. DOI: 10.5194/bg-14-4891-2017.

Beck, H.E., Pan, M., Miralles, D.G., Reichle, R.H., Dorigo, W.A., Hahn, S., Sheffield, J., Karthikeyan, L., Balsamo, G., Parinussa, R.M., van Dijk, A.I.J.M., Du, J., Kimball, J.S., Vergopolan, N., Wood, E.F., 2021. Evaluation of 18 satellite- and model-based soil moisture products using in situ measurements from 826 sensors. ***Hydrology and Earth System Sciences*** 25, 17–40.

Ben-Ari, T., Boé, J., Ciais, P., Lecerf, R., van der Velde, M., Makowski, D., 2018. Causes and implications of the unforeseen 2016 extreme yield loss in the breadbasket of France. ***Nature communications*** 9, 1627.

Berg, A., Sheffield, J., Milly, P.C.D., 2017. Divergent surface and total soil moisture projections under global warming. ***Geophys Res Lett*** 44, 236–244.

Boeck, H.J. de, Dreesen, F.E., Janssens, I.A., Nijs, I., 2011. Whole-system responses of experimental plant communities to climate extremes imposed in different seasons. ***The New Phytologist*** 189, 806–817.

Bonan, G.B., 2016. Ecological climatology: Concepts and applications, 3rd ed. Cambridge University Press, New York.

Buitenwerf, R., Sandel, B., Normand, S., Mimet, A., Svenning, J.-C., 2018. Land surface greening suggests vigorous woody regrowth throughout European semi-natural vegetation. ***Global Change Biology*** 24, 5789–5801.

Bulut, B., Yilmaz, M.T., Afshar, M.H., Şorman, A.Ü., Yücel, İ., Cosh, M.H., Şimşek, O., 2019. Evaluation of Remotely-Sensed and Model-Based Soil Moisture Products According to Different Soil Type, Vegetation Cover and Climate Regime Using Station-Based Observations over Turkey***. Remote Sensing*** 11, 1875.

Cailleret, M., Jansen, S., Robert, E.M.R., Desoto, L., Aakala, T., Antos, J.A., Beikircher, B., Bigler, C., Bugmann, H., Caccianiga, M., Čada, V., Camarero, J.J., Cherubini, P., Cochard, H., Coyea, M.R., Čufar, K., Das, A.J., Davi, H., Delzon, S., Dorman, M., Gea-Izquierdo, G., Gillner, S., Haavik, L.J., Hartmann, H., Hereş, A.-M., Hultine, K.R., Janda, P., Kane, J.M., Kharuk, V.I., Kitzberger, T., Klein, T., Kramer, K., Lens, F., Levanic, T., Linares Calderon, J.C., Lloret, F., Lobo-Do-Vale, R., Lombardi, F., López Rodríguez, R., Mäkinen, H., Mayr, S., Mészáros, I., Metsaranta, J.M., Minunno, F., Oberhuber, W., Papadopoulos, A., Peltoniemi, M., Petritan, A.M., Rohner, B., Sangüesa-Barreda, G., Sarris, D., Smith, J.M., Stan, A.B., Sterck, F., Stojanović, D.B., Suarez, M.L., Svoboda, M., Tognetti, R., Torres-Ruiz, J.M., Trotsiuk, V., Villalba, R., Vodde, F., Westwood, A.R., Wyckoff, P.H., Zafirov, N., Martínez-Vilalta, J., 2017. A synthesis of radial growth patterns preceding tree mortality. ***Global Change Biol*** 23, 1675–1690.

Ceccherini, G., Gobron, N., Migliavacca, M., 2014. On the Response of European Vegetation Phenology to Hydroclimatic Anomalies. ***Remote Sensing*** 6, 3143–3169.

Chen, T., Jeu, R. de, Liu, Y.Y., van der Werf, G.R., Dolman, A.J., 2014. Using satellite based soil moisture to quantify the water driven variability in NDVI: A case study over mainland Australia. ***Remote Sensing of Environment*** 140, 330–338.

Ciabatta, L., Massari, C., Brocca, L., Gruber, A., Reimer, C., Hahn, S., Paulik, C., Dorigo, W., Kidd, R., Wagner, W., 2018. SM2RAIN-CCI: a new global long-term rainfall data set derived from ESA CCI soil moisture. ***Earth Syst. Sci. Data*** 10, 267–280.

Daryanto, S., Wang, L., Jacinthe, P.-A., 2016. Global Synthesis of Drought Effects on Maize and Wheat Production. ***PloS one*** 11, e0156362.

De Rosnay, P., Drusch, M., Vasiljevic, D., Balsamo, G., Albergel, C., Isaksen, L., 2013. A simplified Extended Kalman Filter for the global operational soil moisture analysis at ECMWF. ***Q.J.R. Meteorol. Soc.*** 139, 1199–1213.

Denissen, J.M., Teuling, A.J., Reichstein, M., Orth, R., 2020. Critical Soil Moisture Derived From Satellite Observations Over Europe. ***J. Geophys. Res. Atmos***. 125.

Dorigo, W.A., Gruber, A., Jeu, R. de, Wagner, W., Stacke, T., Loew, A., Albergel, C., Brocca, L., Chung, D., Parinussa, R.M., Kidd, R., 2015. Evaluation of the ESA CCI soil moisture product using ground-based observations. ***Remote Sensing of Environment*** 162, 380–395.

Dorigo, W., Jeu, R. de, 2016. Satellite soil moisture for advancing our understanding of earth system processes and climate change. ***International Journal of Applied Earth Observation and Geoinformation*** 48, 1–4.

Dorigo, W., Jeu, R. de, Chung, D., Parinussa, R., Liu, Y., Wagner, W., Fernández-Prieto, D., 2012. Evaluating global trends (1988-2010) in harmonized multi-satellite surface soil moisture. ***Geophys Res Lett*** 39.

Dorigo, W., Wagner, W., Albergel, C., Albrecht, F., Balsamo, G., Brocca, L., Chung, D., Ertl, M., Forkel, M., Gruber, A., Haas, E., Hamer, P.D., Hirschi, M., Ikonen, J., Jeu, R. de, Kidd, R., Lahoz, W., Liu, Y.Y., Miralles, D., Mistelbauer, T., Nicolai-Shaw, N., Parinussa, R., Pratola, C., Reimer, C., van der Schalie, R., Seneviratne, S.I., Smolander, T., Lecomte, P., 2017. ESA CCI Soil Moisture for improved Earth system understanding: State-of-the art and future directions. ***Remote Sensing of Environment*** 203, 185–215.

Gruber, Alexander; Scanlon, Tracy; van der Schalie, Robin; Wagner, Wolfgang; Dorigo, Wouter (2019): Evolution of the ESA CCI Soil Moisture climate data records and their underlying merging methodology. In ***Earth Syst. Sci. Data*** 11 (2), pp. 717–739. DOI: 10.5194/essd-11-717-2019.

Hatfield, J.L., Prueger, J.H., 2015. Temperature extremes: Effect on plant growth and development. ***Weather and Climate Extremes*** 10, 4–10.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R.J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., Thépaut, J.-N., 2020. The ERA5 global reanalysis. ***Q.J.R. Meteorol. Soc.*** 146, 1999–2049.

Luo, Q., 2011. Temperature thresholds and crop production: a review. ***Climatic change*** 109, 583–598.

Maggioni, V., Houser, P.R., 2017. Soil Moisture Data Assimilation. In: Park, S.K., Xu, L. (Eds.) Data Assimilation for Atmospheric, Oceanic and Hydrologic Applications (Vol. III). Springer International Publishing, Cham, pp. 195–217.

Mohanty, B.P., Cosh, M.H., Lakshmi, V., Montzka, C., 2017. Soil Moisture Remote Sensing: State-of-the-Science. ***Vadose Zone Journal*** 16, vzj2016.10.0105.

Nicolai-Shaw, N., Zscheischler, J., Hirschi, M., Gudmundsson, L., Seneviratne, S.I., 2017. A drought event composite analysis using satellite remote-sensing based soil moisture. ***Remote Sensing of Environment*** 203, 216–225.

Orth, R., Destouni, G., Jung, M., Reichstein, M., 2020. Large-scale biospheric drought response intensifies linearly with drought duration in arid regions. ***Biogeosciences*** 17, 2647–2656.

Peñuelas, J., Sardans, J., Filella, I., Estiarte, M., Llusià, J., Ogaya, R., Carnicer, J., Bartrons, M., Rivas-Ubach, A., Grau, O., Peguero, G., Margalef, O., Pla-Rabés, S., Stefanescu, C., Asensio, D., Preece, C., Liu, L., Verger, A., Barbeta, A., Achotegui-Castells, A., Gargallo-Garriga, A., Sperlich, D., Farré-Armengol, G., Fernández-Martínez, M., Liu, D., Zhang, C., Urbina, I., Camino-Serrano, M., Vives-Ingla, M., Stocker, B., Balzarolo, M., Guerrieri, R., Peaucelle, M., Marañón-Jiménez, S., Bórnez-Mejías, K., Mu, Z., Descals, A., Castellanos, A., Terradas, J., 2017. Impacts of Global Change on Mediterranean Forests and Their Services. ***Forests*** 8, 463.

Phillips, Nathaniel D. (2018): YaRrr! The Pirate's Guide to R. Available online at https://bookdown.org/ndphillips/YaRrr/standardization-z-score.html.

Porter, J.R., Gawith, M., 1999. Temperatures and the growth and development of wheat: a review***. European Journal of Agronomy*** 10, 23–36.

Preimesberger, W., Scanlon, T., Su, C.-H., Gruber, A., Dorigo, W., 2021. Homogenization of Structural Breaks in the Global ESA CCI Soil Moisture Multisatellite Climate Data Record. ***IEEE Trans. Geosci. Remote Sensing*** 59, 2845–2862.

Seddon, A.W.R., Macias-Fauria, M., Long, P.R., Benz, D., Willis, K.J., 2016. Sensitivity of global terrestrial ecosystems to climate variability. ***Nature*** 531, 229–232.

Sippel, S., El-Madany, T.S., Migliavacca, M., Mahecha, M.D., Carrara, A., Flach, M., Kaminski, T., Otto, F.E.L., Thonicke, K., Vossbeck, M., Reichstein, M., 2018. Warm Winter, Wet Spring, and an Extreme Response in Ecosystem Functioning on the Iberian Peninsula. ***Bull. Amer. Meteor. Soc.*** 99, S80-S85.

Smets, Bruno; Verger, A.; Camacho, F.; van der Goten, R.; Jacobs, T. (2019): Copernicus Global Land Operations "Vegetation and Energy". Product User Manual. Leaf Area Index (LAI) Fraction Of Absorbed Photosynthetically Active Radiation (FAPAR) Fraction Of Vegetation Cover (FCOVER) Collection 1km Version 2 Issue 1.33. *Copernicus Global Land Operations*. Available online at https://land.copernicus.eu/global/products/fapar, checked on 4/17/2020.

Spano, D., Snyder, R.L., Cesaraccio, C., 2013. Mediterranean Phenology. In: Schwartz, M.D. (Ed.) Phenology: An Integrative Environmental Science. Springer Netherlands, Dordrecht, pp. 173–196.

Su, C.-H., Ryu, D., Dorigo, W., Zwieback, S., Gruber, A., Albergel, C., Reichle, R.H., Wagner, W., 2016. Homogeneity of a global multisatellite soil moisture climate data record. ***Geophys Res Lett*** 43, 11,245-11,252.

Szczypta, C., Calvet, J.-C., Maignan, F., Dorigo, W., Baret, F., Ciais, P., 2014. Suitability of modelled and remotely sensed essential climate variables for monitoring Euro-Mediterranean droughts. ***Geosci. Model Dev.*** 7, 931–946.

Teuling, A.J., Seneviratne, S.I., Stöckli, R., Reichstein, M., Moors, E., Ciais, P., Luyssaert, S., van den Hurk, B., Ammann, C., Bernhofer, C., Dellwik, E., Gianelle, D., Gielen, B., Grünwald, T., Klumpp, K., Montagnani, L., Moureaux, C., Sottocornola, M., Wohlfahrt, G., 2010. Contrasting response of European forest and grassland energy exchange to heatwaves. ***Nature Geosciences*** 3, 722–727.

Ummenhofer, Caroline C.; Meehl, Gerald A. (2017): Extreme weather and climate events with ecological relevance: a review. In ***Philosophical transactions of the Royal Society of London. Series B, Biological sciences*** 372 (1723). DOI: 10.1098/rstb.2016.0135.

Verger, Aleixandre; Baret, Frederic; Weiss, Marie (2019): Copernicus Global Land Operations "Vegetation and Energy" "CGLOPS-1". Algorithm Theorethical Basis Document. Leaf Area Index (LAI) Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) Fraction of green Vegetation Cover (FCover) Collection 1km Version 2 Issue I1.41. *Copernicus Global Land Operations*. Available online at https://land.copernicus.eu/global/products/fapar, checked on 4/17/2020.

von Buttlar, J., Zscheischler, J., Rammig, A., Sippel, S., Reichstein, M., Knohl, A., Jung, M., Menzer, O., Arain, M.A., Buchmann, N., Cescatti, A., Gianelle, D., Kieley, G., Law, B.E., Magliulo, V., Margolis, H., McCaughey, H., Merbold, L., Migliavacca, M., Montagnani, L., Oechel, W., Pavelka, M., Peichl, M., Rambal, S., Raschi, A., Scott, R.L., Vaccari, F.P., van Gorsel, E., Varlagin, A., Wohlfahrt, G., Mahecha, M.D., 2018. Impacts of droughts and extreme temperature events on gross primary production and ecosystem respiration: a systematic assessment across ecosystems and climate zones. ***Biogeosciences*** 15, 1293–1318.

Zhang, H., Oweis, T., 1999. Water–yield relations and optimal irrigation scheduling of wheat in the Mediterranean region. ***Agricultural Water Management*** 38, 195–211.