Response to reviewer RC1 (reviewer in black Open Sans 11, **response in blue, Calibri,11)**

"The study addresses a drought analysis in the Ebro River basin in Spain by using remote sensing (RS) data of evapotranspiration from MOD16A2ET and soil moisture data from SMOS1km 20 as well as SURFEX-ISBA land-surface model (LSM) data to calculate the Evapotranspiration Deficit Index (ETDI) and the Soil Moisture Deficit Index (SMDI) for the period 2010-2017. Also, SAFRAN data are used to calculate the Standardized Precipitation Index (SPI) at different aggregation time scales. The drought indices are computed both at the monthly and weekly scales. In particular, the study investigates the mechanisms of drought propagation in the land-atmosphere system by analyzing the temporal lags between the drought indices to identify the synchronicity and memory of the anomalies between precipitation, evapotranspiration and soil moisture to interpret factors involved in drought onset.

Overall, the study is interesting and well written. A few comments follow.

1) In the Introduction, the bibliographic review of previous studies on the use of remote sensing products in drought analysis at the weekly scale focused on rainfed agriculture could be extended. I suggest referring to the following study and reference therein: https://doi.org/10.5194/nhess-20-471-2020:"

We thank the reviewer for the insights of the suggested article about the multiple studies tackling the development of drought indices and the use of remote sensing products in drought analysis. The text has been of great help to significantly reform the introduction to further explain and clarify the aim of the study in the context of previous works. The first paragraph is now divided in two expanding the reasoning for the use of specific indices and the need to address evapotranspiration and soil moisture as relevant variables:

"Drought is a major natural hazard for the societies in semi-arid climates (Van Loon, 2015) which demands increasing levels of adaptation and resilience measure to guarantee water supply (Watts et al., 2012), particularly in water-stressed environments. Rain-fed agriculture (Tigkas and Tsakiris, 2015), and even the enduring natural vegetation are very exposed to drought, especially under climate change, which has long-lasting implications to the local environment (Gudmundsson et al., 2014). Knowing that complex interactions take place in the land-atmosphere system under drought, the traditional meteorological or hydrologic approach may overlook drought-relevant interactions between evapotranspiration and soil moisture (Teuling et al., 2013).

This explains why modern drought monitoring combines evapotranspiration, soil moisture and even vegetation anomalies to track drought status, such as the Objective Drought Indicator (OBDI) integrated in the U.S. Drought Monitor (Svoboda et al., 2002) or the Combined Drought Indicator within the framework of the European Drought Indicator Observatory (Sepulcre-Cantó et al, 2012). This approach is on the upward trend, since even parsimonious composite drought indices like the probabilistic precipitation vegetation index (PPVI) (Monteleone, Bonacorso and Martina, 2020) outperform the capabilities of common indices to characterize drought. Therefore, composite indices facilitate the characterization of drought from multiple perspectives (e.g. Meteorological, Hydrological or Agricultural) but can be impractical to explore the mechanisms of drought due to complex calculations or missing data. Even though long-term anomalies of rainfall, and other meteorological, hydrological or vegetation condition variables evapotranspiration and soil moisture are currently regularly monitored, evapotranspiration and soil moisture ones still face challenging monitoring. Not only the indirect nature of these variables' data but also their limited spatial and temporal availability limit the number of studies adopting them, even despite and their known to play a relevant role in the recurrence of drought and heat waves (Zampieri et al., 2009; Dasari et al., 2014), often short-term anomalies are overlooked, Provided that especially regarding interactions of evapotranspiration and soil moisture operate on short time scales (Teuling et al, 2018), there is need to address dedicated exploration of *their relevance on the evolution of drought at the shortest time scale available, which for the soil moisture and evapotranspiration data is currently the weekly scale."*

In the fourth and fifth paragraph we have expanded on the reasoning of using remote sensing products with special reference to previous experience on this matter: *"Space agencies have released multiple RS products in the last decades facilitating the distributed analysis of drought (AghaKouchak et al., 2015). Optical spectrometry of the atmospheric (rainfall, temperature, water vapor) and surface (vegetation reflectance) variables have often been the basis for distributed characterization of drought indicators. Surface vegetation indices such as the widespread NDVI (Liu and Kogan, 1996) pioneered on the application of RS data to assess the impacts of drought, but thereafter the increasing availability of RS data of multiple meteorological variables has increased its usage on drought indices (West et al., 2019), While even common indices like the SPI can now rely on RS data (Sahoo et al, 2015), the many advantages of RS data facilitate integrating multiple data sources into the increasingly operative composite drought indices for weekly drought monitoring (USDM, Svovoda et al., 2002; CDI, Sepulcre-Cantó et al., 2012) even below the weekly scale (Monteleone, Bonaccorso and Martina, 2020). Beyond precipitation, temperature and other directly observable meteorological variables, evapotranspiration and soil moisture represent components of the land-atmosphere system which are difficult to measure on the ground, and consequently suitable for the focus of RS. Recent years have seen a rise in the availability of RS-based evapotranspiration databases such as the global dataset included in GLEAM (Miralles et al., 2011; Martens et al, 2017) or the soil moisture global database CCI (Dorigo et al., 2017). However, the still coarse spatial resolution of these global datasets limit the use of these databases for regional scale analysis or processes understanding.*

Fortunately, in parallel to the RS missions, the development of processing techniques has improved the applicability of RS -derived data products (Wagner et al., 2007). On this basis, there are soil moisture datasets of increasing high resolution available from the combination of passive microwave sensors such as those from SMOS and SMAP missions (Kerr et al., 2010; Entekhabi et al., 2010; respectively) and active microwave sensors such as ASCAT or Sentinel-1 (Bartalis et al., 2007; Hornacek et al., 2012; respectively). This is the case of the high-resolution soil moisture and evapotranspiration products SMOS1km (Merlin et al., 2013; Molero et al., 2016, Escorihuela and Quintana-Seguí., 2016; Escorihuela et al., 2018). Similarly, high-resolution RS evapotranspiration products such as and the MOD16A2 (Mu et al., 2013) used in this study are currently available. Therefore, it is worth exploring the capabilities and limitations of high-resolution RS data for drought monitoring at regional scale. Both remote sensing products represent components of the land-atmosphere system which are difficult to measure on the ground, particularly under extreme conditions such as drought (Miralles et al., 2019). To date, relatively few works have used satellite data for drought analysis in the IP (Vicente-Serrano, 2006; Scaini et al, 2015, Martínez-Fernández et al., 2016; Sánchez et al., 2016; Ribeiro et al., 2019), especially at the spatial and temporal resolution of this study (Pablos et al., 2019)." With these additions we hope the introduction provides a better idea on the background of the discipline and the purpose of the study.

2) "The complex interactions between drought indices, investigated by means of a throughout correlation analysis, highlights feedbacks among the considered variables, with a preeminent role of evapotranspiration in the link between rainfall and soil moisture. The study is carried out by calculating the Pearson correlation coefficients between pair of series of the three drought indices at weekly scale, introducing lags from -104 weeks to +104 weeks. The use of the Pearson correlation coefficient implies that the underlying variables are normal distributed. This is true, by definition, for the SPI, but what about the ETDI and SMDI? In case the normal hypothesis is rejected, the Spearman rank correlation statistic must be used instead. "

We sincerely appreciate the warning that ETDI and SMDI might differ from the normal distribution of the SPI. We are aware this difference implies a tendency to over-represent extremes by ETDI and SMDI compared to the SPI. There are several reasons of our choice of these indices despite this disadvantage: The use of r

Spearman was initially adopted but the data-intensive calculations required for the large amount of data made it impractical. The analysis of lags using Pearson, which took weeks for each interaction (i.e. SPI-4-SMDI), provided results in an order of magnitude quicker than the Spearman ones. To test the representativity of the results of r Pearson coefficient presented in the manuscript, we have compared the lags calculated by Pearson and Spearman coefficients using a subset of the data (~1/4 of the total 10129 pixels: 2580 pixels, for the full range of lags from -104 to +104 weeks, chosen over a representative area of the basin, the north central region in between Pre-Pyrenees and the Ebro Depression). In this way, after several weeks of reanalysis we can indicate the similarity between coefficients is remarkable. Correlation between the r Pearson and r Spearman results for the subset showed higher than 0.9 in all subsets based on RS data and lower for the case of the LSM data: 0.37-0.79. Therefore, considering the limitations of using Pearson under non-normal conditions, the notably higher computational cost of adopting Spearman instead of Pearson for such a big dataset (computational time in the order of months compared to in the order of weeks), but also the absence of characteristics of the data enhancing the difference between the two methods such as the existence of outliers (Orth et al., 2015), we assume r Pearson can be considered a reliable alternative to Spearman rank coefficient to evaluate the characteristics of the lags of our interest: timing, duration and magnitude. The results of the comparison between r Pearson and r Spearman are illustrated below for the SPI13w-ETDIw (r Pearson in blue, r Spearman in orange).

RS SPIw13-ETDIw

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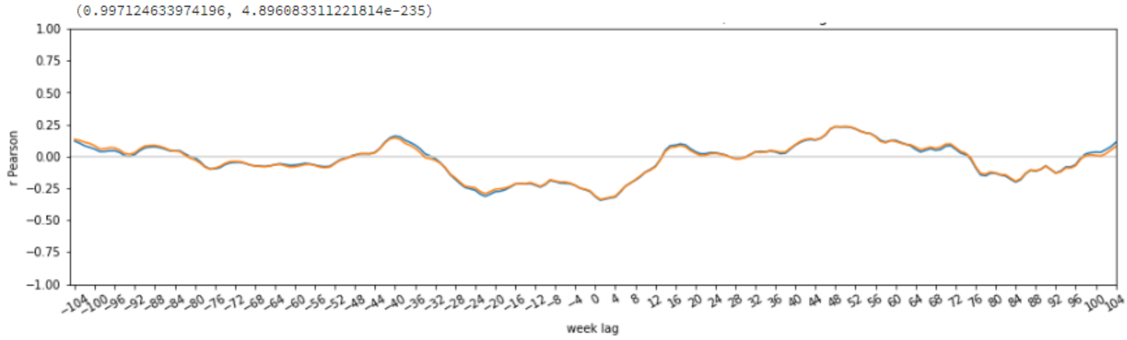
In [80]: spearmanr(aux18nz, aux28nz)
Out[80]: SpearmanrResult(correlation=0.9933240986822622, pvalue=4.470966505320416e-197)

In [81]: r, p = stats.pearsonr(aux18nz, aux28nz)
         print(r,p)

(0.997124633974196, 4.896083311221814e-235)
```



LSM SPIw13-ETDIw

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In [92]: spearmanr(aux19nz, aux29nz)
Out[92]: SpearmanrResult(correlation=0.5406522408855433, pvalue=2.446830167209659e-17)

In [93]: r, p = stats.pearsonr(aux19nz, aux29nz)
         print(r,p)

(0.6730341415628398, 4.619938995690008e-29)
```
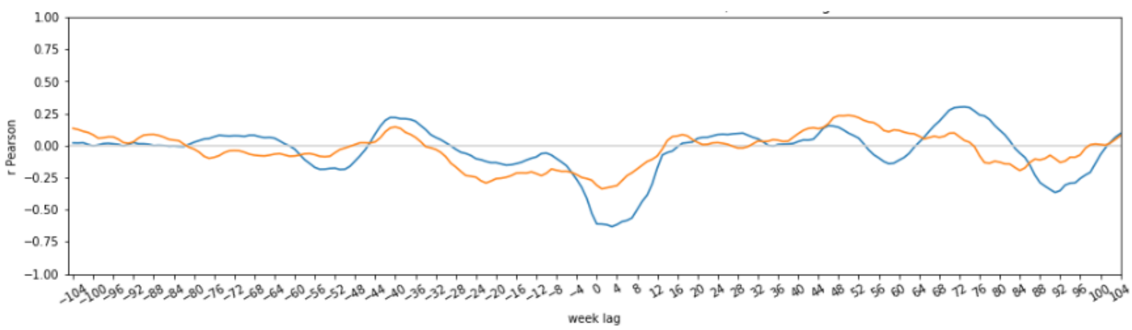
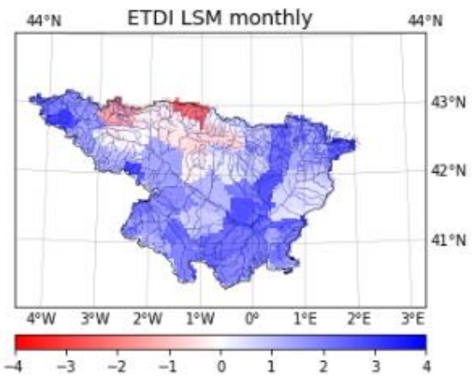



3) "Lag analysis show a remarkable disagreement between RS and LSM for the SMDI - SPI interactions, with SMDI obtained with the LSM showing substantially lower correlations than the ones of RS, while also differing in the timing of the clusters of correlation. The authors state that they expected that the LSM, as being simpler than reality, had stronger SPI – ETDI - SMDI correlations than the RS dataset and justify this result by the accumulation of uncertainties of modelling, inputs and LSM structure. I suggest the authors to better argue this point. Why should the adopted LSM work only for SPI and ETDI? "

The model simulations are run offline, this is, the meteorological data forces the LSM, but the LSM does not affect the forcing data. Thus, the feedbacks are lost. Some of them remain implicitly, as the meteorological observations include the feedback, as observed. For instance, previous works have shown that soil moisture is further influenced by additional factors beyond rainfall, such as groundwater and redistribution of soil moisture depending on topography, which are underrepresented in the LSM. This was reported from multiple other works such as the articles indicated by the reviewer (Teuling et al., 2006; Samaniego et al., 2018) and is a matter of improvement in the current versions of the model.

Beyond the causes commented above and already discussed in Section 6.3 we can further illustrate for the reviewer the impact of the input and LSM structure. The parametrization of the model assumes a semi-distributed approach by sub-basins of the catchment on which each subbasin is defined based on average values of land cover and soil characteristics of the ECOCLIMAP2 database in the subbasin. In consequence, the patchiness of LSM results due to the partial aggregation of the input (see figure below), may cause the loss of spatial variability compared to the remote sensing results and induce the mismatch on RS-LSM results we see on Figs. 3-7.



3b) Furthermore, gridded soil moisture datasets are available at the global and European scale (see for instance the Copernicus climate data service). These datasets can be a valid alternative to the LSM soil moisture data and deserve some references in the study.

The reviewer is right when indicating the many virtues of gridded soil moisture datasets available at multiple scales to further compare the performance of land surface models and remote sensing data in the characterization of soil moisture. Data from assimilated reanalysis models like ERA5 [0.1x0.1º], CCI [0.25x0.25º], LISFLOOD [5x5 km], to mention some, are available at spatial resolution over or nearly an order of magnitude coarser than the ones required for this study.

The reviewer must bear in mind, neither observational nor grided databases of comparable resolution of soil moisture and evapotranspiration are available in the area. Alternatives such as SMAP1 have very short series available (2015-onwards) despite their similar capabilities to SMOS1km (Dari et al., 2021).Previous studies have validated SMOS1km in the area of study *(Merlin et al., 2013, RSE)* [1x 1km resolution] or in nearby areas for MOD16A2 (Pasquato et al. 2015; Sanchez-Ruiz et al., 2016; García-Llamas et al., 2019).

Alternative coarser databases of similar remote sensing, reanalysis or modelling sources may incur in similar nature of the sources of uncertainties and consequently may incur in similar uncertainties to the evapotranspiration (MOD16A2ET) and soil moisture (SMOS1km) databases used in this study.

The use of the LSM SURFEX-ISBA in comparison to remote sensing data is a main aim of the study. Despite the limitations of this LSM, as offline model, it has been validated in the area before and successfully reported to provide useful evaluation of water resources (Escorihuela and Quintana-Seguí, 2016; Quintana-Seguí and Barella-Ortiz, 2020). Also in nearby areas like Portugal and France, the LSM SURFEX-ISBA has repeatedly shown great capability to simulate land-surface processes (Nogueira et al., 2020; Le Moigne et al., 2020). The comparison aims to detect the factors impacting the model performance to further improve the capabilities of the model.

4) With reference to the feedback mechanisms depicted in Figure 8, the Discussion can be enriched by a comparison with previous studies investigating the same mechanism, such as:

- In section 6.2 where the feedback mechanisms are discussed we considered valuable expanding (*in italics*) the clarification about the reason that supports defining the distinct mode of evolution of anomalies under high or low energy characteristics in the Mediterranean climate:

"…compared to the prevalence of local soil moisture recycling common in more continental areas of Europe (Bisselink and Dolman, 2008). The advective explanation is supported by the contrast between the few weeks of precedent influence of soil moisture on rainfall we observe in the Ebro basin and the up to 250 days of precedent influence of continental areas prone to soil moisture recycling (Rowntree and Bolton, 1983; Bisselink and Dolman, 2008). Some studies focused on continental climates of relevant summer rainfall described the implications of the alteration of the recycling due to soil moisture depletion during heatwaves and drought (Rasmijn et al., 2018). In the Iberian Peninsula, though, due to the Mediterranean climate characterized by the lack of summer rainfall, soil moisture annually reaches such low levels that we can expect annual summer mechanisms of dry weather in the near atmosphere. Differences between areas where soil moisture plays a role, like central Europe, and areas where soil moisture is unable to control the evolution of the system under high-energy conditions, like the Iberian Peninsula, have been reported before in the Mediterranean-like western Australia in comparison to eastern Australia (Herold, Kala and Alexander, 2016)."

- While regarding the mechanisms of the feedbacks, we appreciate the proposal of the reviewer about enriching the discussion, we find it appropriate and has been widely clarified and expanded accordingly partly to the suggested articles and some others into the text of section 6.2.

5) Please check Figure 7 since you wrote the same thing for both negative and positive lags.

Thanks for pinpointing the mistake in labels in the Figure 7 and when describing the lags in the caption "for the -104 leading and for the +104 lagged time steps of SMDIw in reference to the ~~SPIw-4~~ ETDIw" in Line 799. It has been corrected