Response to reviewer RC2 (reviewer in black Open Sans 11, **response in blue, Calibri,11)**

" by Gaona et al. submitted to NHESS-discussion an analysis of the atmosphere-soil-vegetation interaction, performed through a time correlation analysis among indices of precipitation anomalies (SPI computed at weekly scale), evapotranspiration deficit index (ETDI) and soil moisture deficit index (SMDI) for the period 2010-2017. ETDI e SMDI input data are provided from both remote sensing and from modelling approaches. The study area is the Ebro basin (Spain). The goal of the work is to get more insights into the drought propagation mechanisms.

The manuscript is within the scope of the Journal and potentially of interest for the readers of NHESS. However, I have some main concerns that prevent from publishing the manuscript in its present form. Here below my general comments:

1. I found very interesting the adopted methodology. My main concern is on the use in the specific case study of standardized indexes. The time span analysed is 8 years. This means that whatever the adopted method for standardization, the statistical population is 8 (maximum). In the original work by Narasimhan and Srinivasan (2005) the ETDI and SMDI are computed on a dataset covering a time span of 70 years (1911-1980), making robust the statistical approach necessary to compute SPIn (fitting of the gamma or Pearson III distribution), ETDI and SMDI (setting the range of variation through the definition of the min and max values, as well as the median to compute the deviation). In my opinion the authors should wide the database extending the time span to 2021 in order to perform an uncertainty analysis on the robustness of the adopted statistical approach.

   For example, it would be interesting to study the variability of the fitting for SPI and of the min-med-max values necessary to compute the ETDI and SMDI by considering n subset of n-1 elements (12 subset of 11 y data if you consider the time span 2010-2021) and studying how the statistical metrics and the indexes themselves vary in relation to the subset. I know that it is a lot of work, but in my opinion, this is mandatory to ensure a sound and robust time lag analysis. Therefore, my concerns are not on the methodology adopted for the analysis of the relationships among the indexes, but on the indexes themselves."

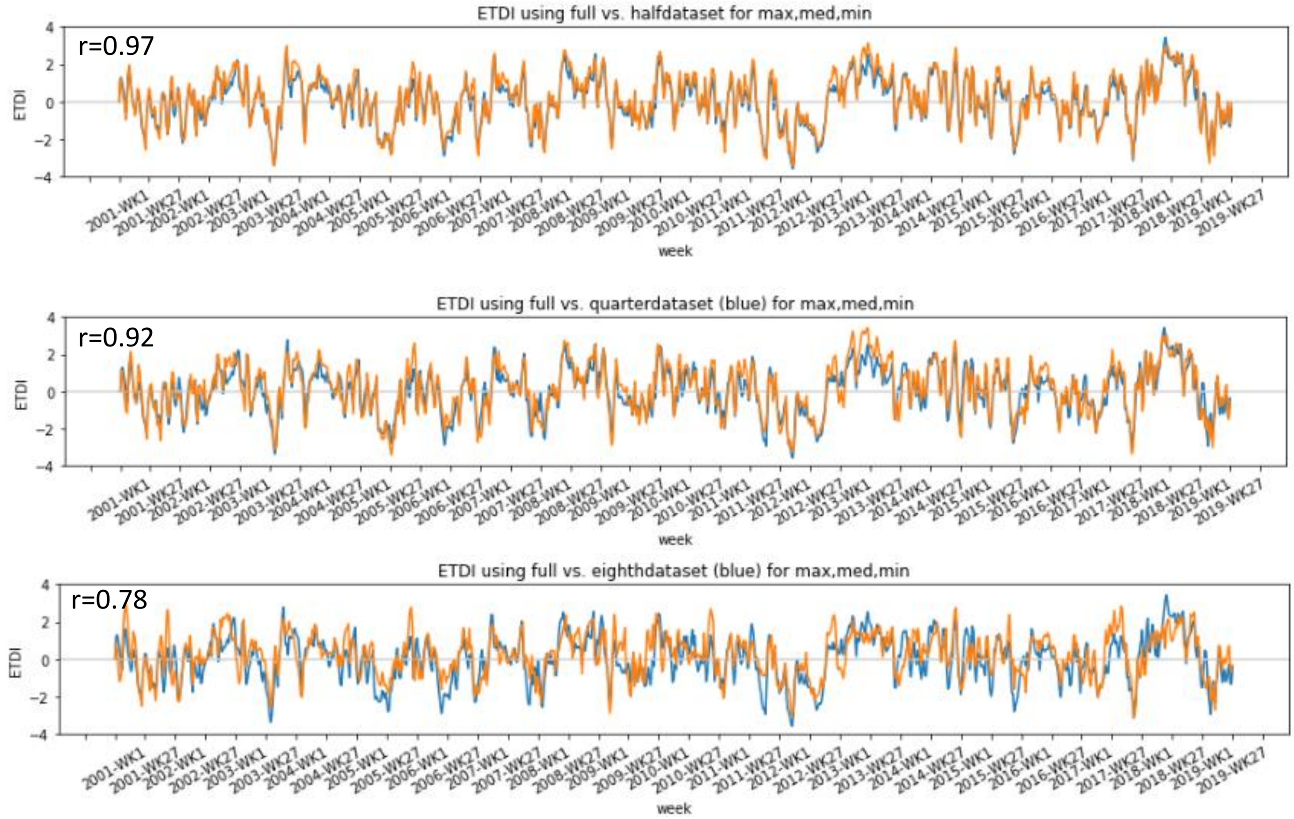
   We sincerely appreciate the rigorous and accurate comments of the reviewer about the temporal constraints of the study and the sub-optimal application of drought indices for short time series. We are aware of the narrow timespan available for the analysis of soil moisture data but SMOS1km is the longest reliable data series available. Certainly, there are remote sensing databases with long-term time series of the variables of this study, even for soil moisture (e.g. CCI). However, apart from the coarse spatial resolution of CCI (0.25º instead of the 1km of SMOS1km), CCI inherits multiple inhomogeneities due to the different remote sensing data sources used to generate such long series. ASCAT and AMRS-E have been tested in the area of study in comparison with SMOS1km and despite their notable performance, SMOS1km outperforms them both in resolution and due to its lack of roughness and vegetation effects (Escorihuela and Quintana-Seguí, 2016). The SMOS1km dataset generated using the DisPATCh Algorithm (Merlin et al., 2013) has been also reported of remarkable reliability in similar studies in the area (Dari et al., 2021). Equal resolution SMAP and Sentinel-1 options are of much shorter data series and consequently not appropriate for the focus on lags of this study. Therefore, SMOS1km dataset was the longest and optimal remote sensing option for soil moisture analysis. In the case of evapotranspiration remote sensing data, MOD16A2 is also the best option considering the spatial or the temporal constraints of the alternative databases of longer duration or similar spatial resolution (e.g. ERA5Land of 0.1x0.1º resolution spatial resolution, GLEAM 0.25x0.25º, Tomas-Burguera et al., 2019 only spans to 2014…etc.). Provided these constraints, we support the validity of considering SMOS1km + MOD16A2 as well as ETDI and SMDI as the best available options for the analysis of interactions of the selected variables, to evaluate the interactions between rainfall, evapotranspiration, and soil moisture.

Regarding indices, and following the previous clarification, the study aims to underline the convenience of addressing single-variable analysis of drought factors to promote the understanding of water exchanges under drought instead of discussing global indices only able to partially characterize drought but not specific mechanisms of interaction. That's the reason for adopting individual indices to assess the anomalies of relevant variables involved in drought's evolution. In view of this, there are multiple aspects of incompatibility between drought indices focused on different variables. In fact, the SMDI and ETDI are among the few indices defined for different relevant variables of the system exactly in the same way, which would be an advisable aspect for studies focused on the multivariate analysis of drought.

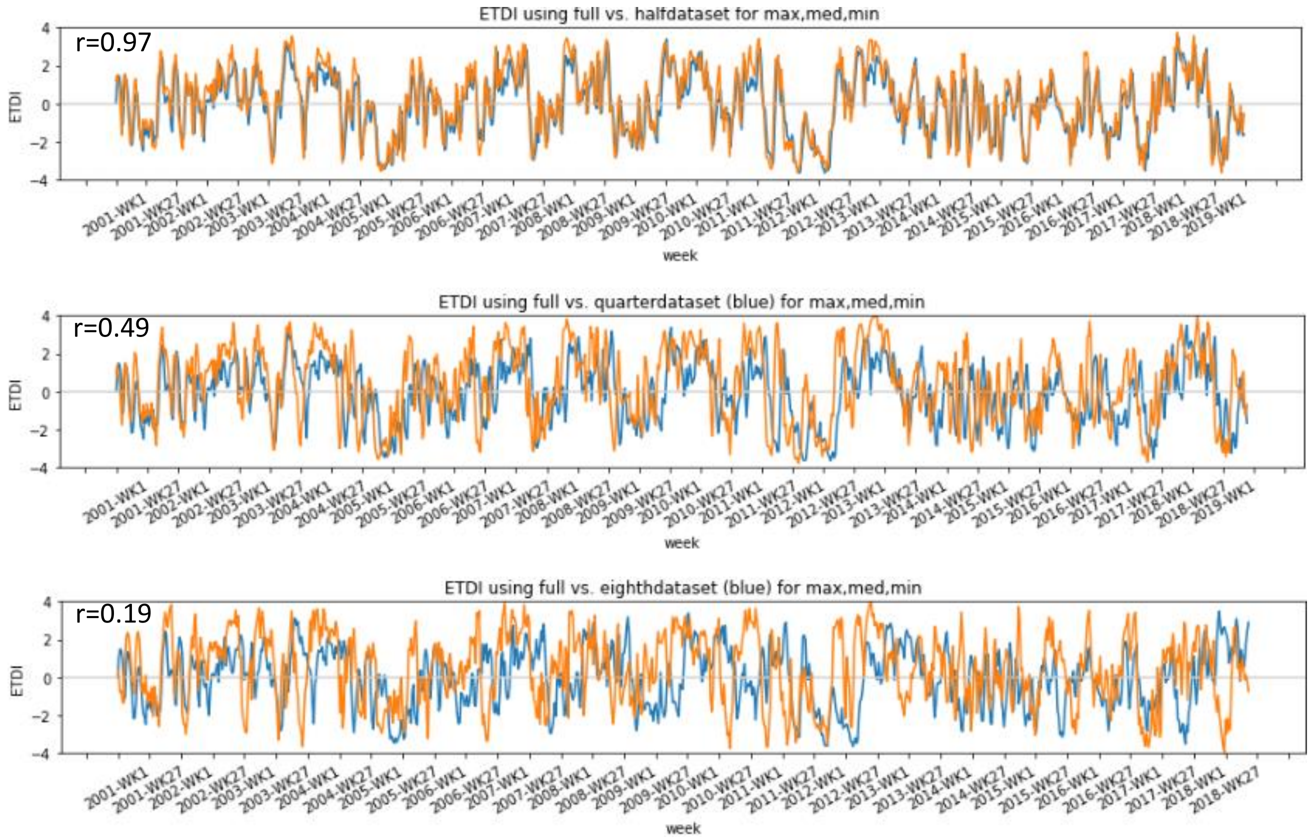
Following the recommendation of the reviewer, we tested the sensitivity of the ETDI and SMDI (they have the same definition based on calculating max, min, median annual weekly values of the data) to the number of years of data used to obtain the maximum, minimum and median values of the series necessary to calculate the indices. We adopted the ETDI because it has a longer series (~18years) than SMDI (~8 years) so that the results of half the length of the series of ETDI can give an idea of how the restricting length of the SMDI series impacts the outcomes of the study. Firstly, taking the full spatial dataset (all pixels of data: 10129px) we constrained the temporal data available to generate the mean annual max/med/min weekly values of the series to a half, a quarter and an eighth of the length of the series. The comparison of the correlation between the ETDI obtained using the full spatial and temporal dimension compared to the half, quarter and an eight length of the series using ¼ of the data (case A) indicate there is little impact due to the shortening of the timeseries. Adopting the length of 8 years of SMDI compared to 18 years would keep ETDI and SMDI values above r=0.95. Even an eighth of the 18y series length keeps r=0.78. The reason for such low impact is the high spatial resolution of the dataset, whose spatial heterogeneity contributes to compensate the risk of sensitivity of the ETDI/SMDI series to the shortening of the temporal dimension. This statement is supported by the results of the increased sensitivity of the ETDI to the shortening of the series when a fraction of the pixels instead of the full range of basin pixels is used (case B, with 1/20 of the pixels). Using 1/4 of all pixels (case B, not shown) causes a slight degradation of the series, while using a 1/20 fraction (case C) causes a sharp decline in the correlation, particularly for the biggest shortening of the timeseries (1/8 of length). Therefore, we can assume the ETDI and SMDI series are sufficiently representative despite their short length of the dataset thanks to the spatial resolution providing enough heterogeneity of the MOD16 and SMOS values to define sufficiently representative max, median and min values to generate the ETDI and SMDI series.

SENSITIVITY ANALYSIS OF ETDI		**Spatial dimension**		
r Spearman coefficient	r Pearson of full time series vs.	**10129px (full)**	**2580px (1/4)**	**516px (1/20)**
Temporal dimension	**1/2 length**	0,97	0,97	0,97
	1/4 length	0,92	0,81	0,49
	1/8 length	0,78	0,73	0,19

A) ETDI sensitivity to series length with full spatial dataset (10129 px)



C) ETDI sensitivity to series length with 1/20 of the spatial dataset (516 px)



2. "In my opinion, results on table 1 could be presented in a more effective way. I suggest presenting four different correlation matrixes (2010-2017m, dry periods m, 2010-2017 w, dry periods w). Each matrix has on the rows [ETDI RS; SMDI RS; SPIm-1; SPIm-3; SPIm-6; SPIm-12] and on the columns [ETDI RS; ETDI LSM; SMDI RS; SMDI LSM]. A colour code to highlight the Pearson correlation, ranging [0,1] would help the readability of the tables, supporting the presentation of the outcomes."

We thank the reviewer for the suggestions to improve the visualization of Table 1 which has been completely reformed following the indications. We realize the matrix format and the color code helps interpreting the magnitude of the correlation. (At Lines 845-850).

2010-2017 - Monthly scale

		ETDI		SMDI	
		RS	LSM	RS	LSM
ETDI	RS		0,77	0,58	
	LSM	0,77			0,32
SMDI	RS	0,58			0,27
	LSM		0,32	0,27	
SPI	SPIm-1	0,39	0,51	0,42	0,45
	SPIm-3	0,62	0,80	0,61	0,41
	SPIm-6	0,72	0,78	0,58	0,30
	SPIm-12	0,81	0,71	0,63	0,24

2010-2017 - Monthly scale - Dry periods

		ETDI		SMDI	
		RS	LSM	RS	LSM
ETDI	RS		0,60	0,50	
	LSM	0,60			0,43
SMDI	RS	0,50			0,13
	LSM		0,43	0,13	
SPI	SPIm-1	0,23	0,37	0,52	0,59
	SPIm-3	0,42	0,67	0,41	0,32
	SPIm-6	0,45	0,39	0,19	0,17
	SPIm-12	0,75	0,53	0,40	0,22

2010-2017 - Weekly scale

		ETDI		SMDI	
		RS	LSM	RS	LSM
ETDI	RS		0,55	0,50	
	LSM	0,55			0,21
SMDI	RS	0,50			0,19
	LSM		0,21	0,19	
SPI	SPIw-4	0,57	0,68	0,57	0,33
	SPIw-13	0,63	0,74	0,51	0,21
	SPIw-26	0,57	0,60	0,40	0,16
	SPIw-52	0,48	0,45	0,43	0,15

2010-2017 - Weekly scale - Dry periods

		ETDI		SMDI	
		RS	LSM	RS	LSM
ETDI	RS		0,34	0,46	
	LSM	0,34			0,18
SMDI	RS	0,46			0,12
	LSM		0,18	0,12	
SPI	SPIw-4	0,30	0,49	0,57	0,25
	SPIw-13	0,32	0,47	0,36	0,29
	SPIw-26	0,21	0,30	0,40	0,02
	SPIw-52	0,31	0,16	0,39	-0,03

* Dry periods considered when SPI<0, ETDI<0, SMDI<0

Table 1: Matrices of significant (in bold) correlation coefficients considering p-values=0.05 for pairs of indices at monthly and weekly scale for the period 2010-2017 of the SPI I, ETDI and SMDI series, and the corresponding dry period subsets. Higher correlation values show a more intense red color. Since the correlations of interest refer to comparing the same type of data sources for different indices, dark grey cells identify unsuitable combinations for the analysis such as comparing RS results from one index with LSM results from another index

3. "Figures 4-7. These are the core business of the work, but the outcomes did not convince me. I focus on the bars showing statistically significant correlations (blue or red coloured bars). It is clear that the fraction of the basin presenting high correlations lasts approximately for a time span equal to the time scale of the SPI: more or less 4 weeks when I use SPI1, more or less 13 weeks when I use SPI12 and so on. I'm not convinced that this is not simply due to time autocorrelation of the pairs SPIn(t), SPIn(t+n) and not to real physical processes as proposed in the discussions. Please, clarify this point as it is very important"

Regarding the concerns of the reviewer about the "potential autocorrelation" of the ETDI - SPI at 13, 26 and 52 weeks of aggregation, firstly, its mainly caused by the effect of the period of aggregation, and secondly, the purpose was in fact to illustrate the impact of the period of aggregation used for SPIw-13, w26 and w52 indices (of monthly focus as SPI-3, -6 and-12) instead of using the weekly-focused results of SPIw-4 (SPI-1) to elucidate the interactions.

Since the Section 5.1 in results and 6.1 in discussion focus on the advantage of the week scale, we show the range of results from SPI-4w as supportive evidence of the pertinence of using the week scale, less prone to aggregated outcomes, particularly for this type of interactions and geographical context, than the commonly used monthly scale. In fact, many any times the SPI-3 is used to debate anomalies in the atmospheric system, like when referred to meteorological drought. We argue, based on the studies focused on flash droughts and drought on semi-arid environments, that the scale of analysis should be weekly, even when referring to interactions between atmosphere and land surface like SPI-ETDI or SPI-SMDI. For this reason, discussion in section 6.1 based on Figures 3,4,5,6 was written in that sense:

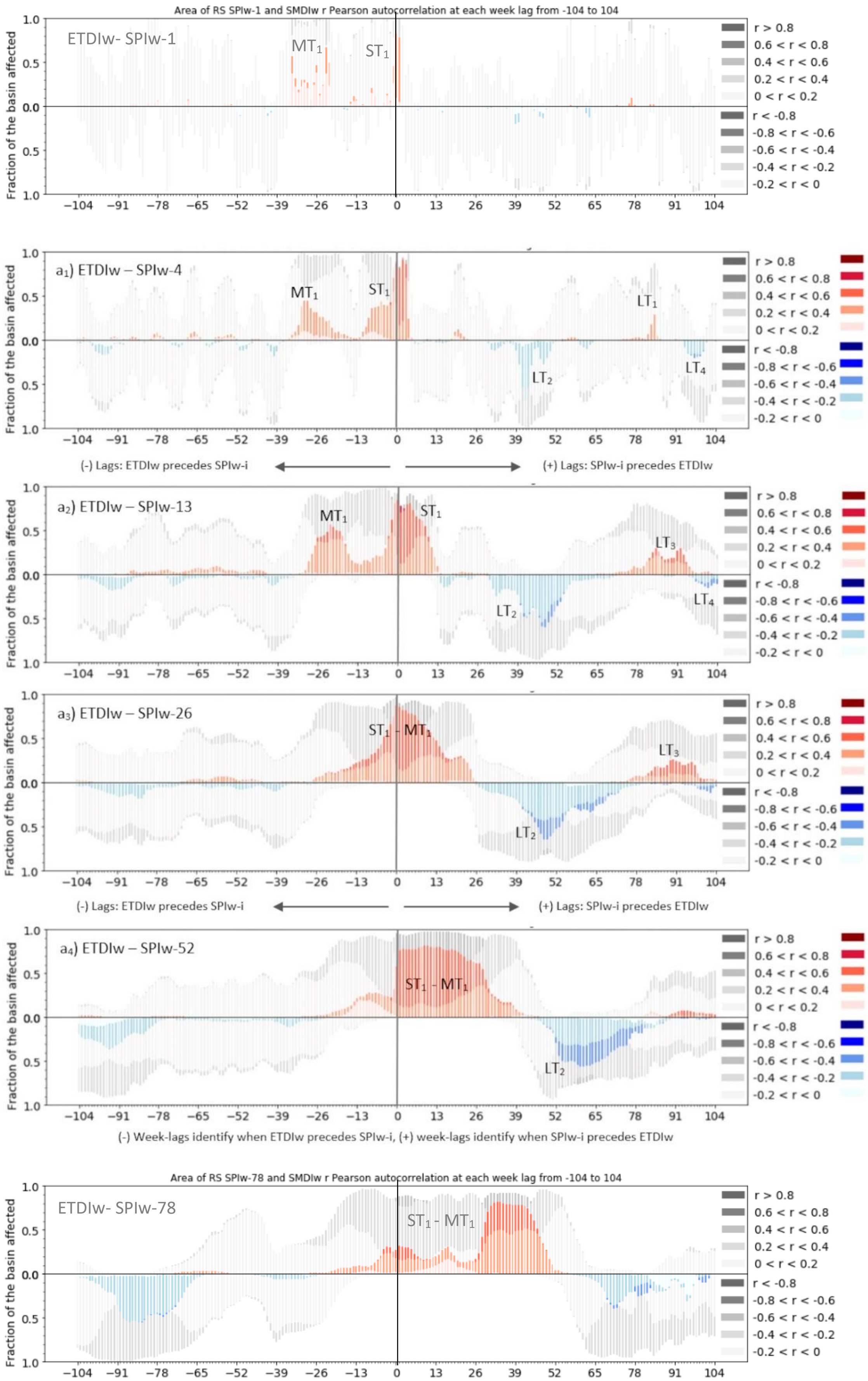
L429-433 "The clusters of moderate to high correlation between indices mostly occur within the first month preceding or following an anomaly (Figs. 3-7), particularly in the short to very short-term. Apart from the tendency of high correlations to peak and plunge in the interval of a few weeks, the information about its delay or precedence can only be observed when the weekly scale is adopted."

The range of subplots of Figs. 3 to 6, as well as the ones of aggregation period of 1 week and 78 weeks attached below, show in fact that the aggregation period mostly impacts results when using aggregations over 3 months, as it is the case of SPI-3 (SPIw-13), both in timing and duration of the clusters of lags. Therefore, the panel of aggregation periods of Figs. 3-6 provided two subplots below and two subplots over this midpoint of the range of aggregation to show the sensitivity of results to the aggregation period.

The additional plots of SPIw-n – ETDIw attached below (SPIw-1 and SPIw-78) show that the clusters of lags MT_1 and ST_2, primarily of precedent lags, appear clearly separated in the first three subplots of SPIw-1 - ETDIw, SPIw-4 - ETDIw and SPIw-13 - ETDIw while they become merged and largely distorted by the increasing period of aggregation (i.e. SPIw-26 and -52 – ETDIw). The longer the period of aggregation, the more the clusters increase the magnitude of the correlation, the length of the cluster and the significance of the correlations. Additionally, we can observe that the shortest period of correlation, the SPIw-1 – ETDIw shows very fragmented signals of interactions which is logical when analyzing results at the weekly scale. However, the timing of the fragmented clusters of correlation match well those shown until aggregation periods of 13 weeks, so that we can say, results are consistent in between weekly and the firsts months scale of aggregation of the SPIw. In consequence, the two upper ETDIw - SPIw-n subplots of Figure 3 and 4 aimed to illustrate the range of temporal scales at which the interactions between rainfall and evapotranspiration anomalies are within the range of observability. The lower ones of SPIw-26 and SPI-52 – ETDIw alternatively illustrate the temporal scales (seasonal, annual) at which the interactions between SPI and ETDI cannot be further discerned. In the case of SPI-n – SMDI, again the range of lag suitable for the interpretation of SPIw-ETDIw remains consistent until the seasonal scale of aggregation of the SPI.

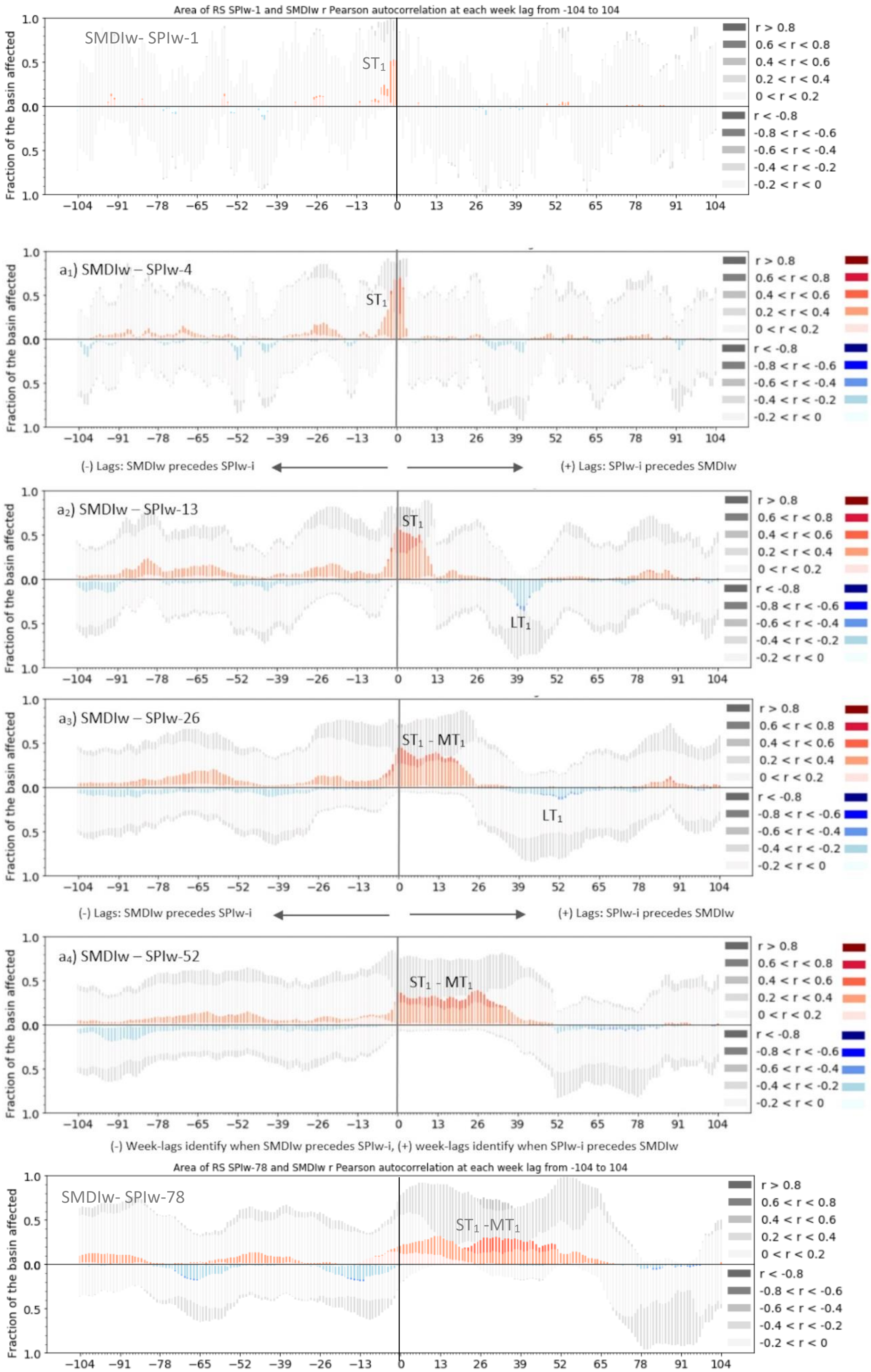
The range of subplots in figs 3-6, aimed to illustrate how the weekly scale (dominating the clustering configuration in between SPIw-1 and SPIw-13) is the most suitable for the interpretation of the short-term interactions. For this reason, the results described in Section 5 mostly referred to the short-term aggregation periods to interpret the clusters of lags, stating that the higher SPIw26 and SPIw52 results tend to dampen, merge and later the clustering of lags indicated by SPIw4 and SPIw13. We are open to include SPIw1 in Figs 3-6 for better illustration of our purpose, while we refrain ourselves to include it due to the reluctance of the scientific community to refer to aggregations of the SPI index below the monthly scale. Therefore, we have further clarified this scope of showing the sensitivity of results to the aggregation period in the description of results (lines L331-332, L350-351, L393-395) and discussion section (L437-L440).

SPIw-n – ETDI



Area of RS SPIw-1 and SMDIw r Pearson autocorrelation at each week lag from -104 to 104
ETDIw- SPIw-1
MT1
ST1
Fraction of the basin affected
r > 0.8
0.6 < r < 0.8
0.4 < r < 0.6
0.2 < r < 0.4
0 < r < 0.2
r < -0.8
-0.8 < r < -0.6
-0.6 < r < -0.4
-0.4 < r < -0.2
-0.2 < r < 0
a1) ETDIw – SPIw-4
LT1
LT2
LT4
(-) Lags: ETDIw precedes SPIw-i
(+) Lags: SPIw-i precedes ETDIw
a2) ETDIw – SPIw-13
LT3
a3) ETDIw – SPIw-26
ST1 - MT1
a4) ETDIw – SPIw-52
(-) Week-lags identify when ETDIw precedes SPIw-i, (+) week-lags identify when SPIw-i precedes ETDIw
Area of RS SPIw-78 and SMDIw r Pearson autocorrelation at each week lag from -104 to 104
ETDIw- SPIw-78

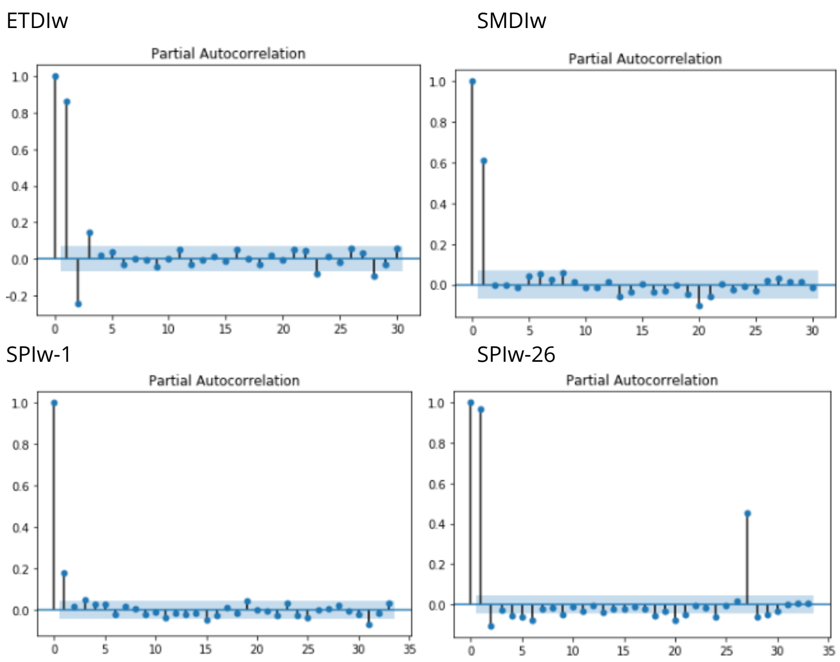
SPIw-n - SMDI



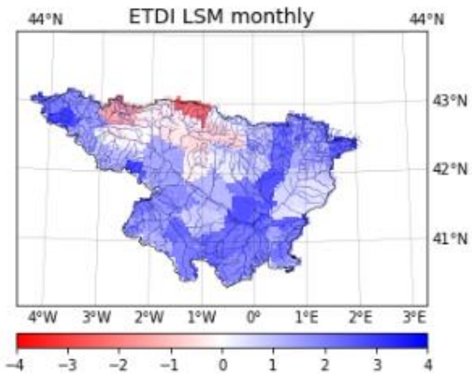
Area of RS SPIw-1 and SMDIw r Pearson autocorrelation at each week lag from -104 to 104
SMDIw- SPIw-1
ST1
a1) SMDIw – SPIw-4
ST1
(-) Lags: SMDIw precedes SPIw-i
(+) Lags: SPIw-i precedes SMDIw
a2) SMDIw – SPIw-13
ST1
LT1
a3) SMDIw – SPIw-26
ST1 - MT1
LT1
(-) Lags: SMDIw precedes SPIw-i
(+) Lags: SPIw-i precedes SMDIw
a4) SMDIw – SPIw-52
ST1 - MT1
(-) Week-lags identify when SMDIw precedes SPIw-i, (+) week-lags identify when SPIw-i precedes SMDIw
Area of RS SPIw-78 and SMDIw r Pearson autocorrelation at each week lag from -104 to 104
SMDIw- SPIw-78
ST1 -MT1
Fraction of the basin affected
r > 0.8
0.6 < r < 0.8
0.4 < r < 0.6
0.2 < r < 0.4
0 < r < 0.2
r < -0.8
-0.8 < r < -0.6
-0.6 < r < -0.4
-0.4 < r < -0.2
-0.2 < r < 0

Regarding the possibility of autocorrelation, once checked the series are stationary (by Augmented Dickey-Fuller (ADF) test) we tested the autocorrelation results of each drought index series. ETDI and SMDI mainly show autocorrelations in the range from 7 to 10 weeks of significant autocorrelation. The autocorrelation values of series of SPI, while depending on the period of aggregation, differ notably (2 weeks on SPIw-1, 5 weeks on SPIw-4, 10 weeks for SPIw-13, 18 on SPIw-26, 35 on SPIw-52, 40 on SPI-78, 45 on SPIw-104) from those of ETDI and SMDI, while the range of ones of importance (ACF>0.5) barely reach half of them. The increasing values of autocorrelation with the increasingly aggregated SPI are compatible with the effect of the moving average of SPI. The evaluation of partial autocorrelation is more informative. Partial autocorrelations of ETDI and SMDI show mostly two (to four) week-lags as significant. An AR(2) configuration can be explained as a combination of growing and decaying exponentials. We assume the first term causes the direct relation and the second one inverse relation, supports our interpretation that the interactions between indices have a dominant positive interaction limited in time by a secondary inverse interaction, which we define as the energy-limiting shift from high-energy conditions (evapotranspiration-mediated) to low-energy conditions (rainfall-inhibited). The autoregression terms at 4, 13, 26, 52 of SPIw-n again refer to remnants of the moving average of the aggregation period of SPIw-n.

Therefore, since the duration of the autocorrelation of ETDI, SMDI and ETDI differs (except for the combination SPIw13-ETDI or SMDI) the results of significant interactions commented based on SPI-ETDI or SPI-SMDI interactions remain consistent from the weekly to the below-seasonal scale (SPIw-13), which is the scale at which we underline the importance of identifying the interactions between indices. Therefore, we can say that despite the evident increasing lengthening of the impact of the moving average (aggregation period) on the significant clusters of correlation between indices in subplots c) and d) of Figs.3-6, the duration of the lags shown in Figs. 3-6 does seem to be defined by true interaction between the anomalies of the indices beyond autocorrelation artifacts.



Regarding the apparent mismatch of RS and LSM of causes 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.



4. "Line 162 "In order to fill the gaps … interpolation". Please, specify the methodology adopted to interpolate and the maximum time span interpolated (this may strongly affect the results if the original time series is very fragmented, or the missing data interval are long)"

   The interpolation was applied pixel by pixel on a temporal basis. The maximum time span for the temporal interpolation fed from the last previous data within two weeks. No spatio-temporal interpolation was applied. This clarification has been included in the same L162 of the manuscript.

5. "Equations 1 and 3. I would suggest indicating the median with an overbar, avoiding MWS"

   Unlike other authors applying the ETDI and SMDI, we considered worthwhile keeping the notation shown by the authors of the indices SMDI and ETDI (Narasimhan and Srinivasan, 2005, AFM) expressed in the Equations 1 and 10 of their article to avoid confusion in the formula defining these indices.

6. "Equation 1. As written, the first equation is always positive and the second is always negative. Is it correct? Shouldn't it be the opposite?"

   The notation is that of Narasimhan and Srinivasan (2005, AFM) and is correct. We understand the misunderstanding of the reviewer since both the ETDI and SMDI may require an example to interpret their meaning. This is the case for Equation 1 of the water stress anomaly formula fed by the water stress ratio. The water stress ratio (WS=(PET-AET)/PET) for an area experiencing AET close to that of the PET (i.e. under wet conditions, e.g. 75% of PET) generates a water stress of WS=0.25. Using this value in the first equation of Equation 1, when WS<=MWS (assuming MWS may be 0.5, maxWS=0.9, minWS=0.1), we get the WSA=(MSW0.5-WS0.25)/(MWS0.5-minWS0.1)*100=62.5. This is a positive WSA that may tend to keep ETDI in + values, indicating wet conditions. It is the water stress ratio of values in between 0 (dry) and 1 (wet) which mislead the interpretation of the sign.