**General Reponses**

We appreciate the referee's time given to this manuscript. To avoid misunderstanding we clarify our aims and objectives first and then continue with our responses to more detailed comments.

From the 1950s on the ten hottest summers over Europe were found to have succeeded to a rainfall deficit in late winter. This finding was first reported and highlighted by Vautard et al., (GRL, 2007), and later highlighted in *Nature* with the suggestive title 'rainfall rules' (Nature, 2007). This suggested scope for improved seasonal predictability of summer climate over Europe. Intensive numerical simulations have suggested that the suggested linkage is dynamically maintained by feedback loops between soil moisture and the atmosphere (not soil moisture memory solely), as cited in our paper. Key questions arising are thus: can this mechanism contribute to interannual variability of summer temperature and if so, by how much? We intended to provide an answer to this question from observations to further substantiate modeling results such as Seneviratne et al (2006, *Nature*) who suggested that initial soil moisture states in spring could explain roughly two thirds of summer temperature variance, but that these states were not necessarily linked to winter or spring precipitation.

For this purpose, obtaining the robust summer $T_{mean}$ ($T_{max}$) part in response to the winter $P_{JFM}$ is critical. Using rigorous statistics, we have obtained the expected robust relations with unit correlation. To assure that the obtained linkage is not a statistical coexistence, we further analyzed the soil moisture fields (scPDSI), which play a key role in partitioning the available solar energy into sensible and latent heat. As we emphasize in our manuscript, our statistics show that all the analyzed summer fields ($T_{mean}$, $T_{max}$ and scPDSI) robustly co-fluctuate in response to winter $P_{JFM}$. We thus suggest that the relations we have obtained are extremely likely to be maintained by the same climate dynamics. Furthermore, these statistical relations are also found in the modeling studies previously reported, and we wished to substantiate with observational analysis. This reasoning forms the basis of our conclusion that we might have found a climate regime where there is strong interaction of the water cycle interaction with temperature. Although this regime explains only 5-25% of the analyzed summer climate fields, this is not small for climate prediction purpose.

**Detailed Reponses**

**Comment #1**

"On general grounds the statement that a statistical technique can determine the direction of influences cannot be true. If all the information available is two covarying fields, no statistical technique can ever show causality. In particular, one can never exclude that a third factor influences both fields. As an example, El Niño causes both drought in September–October in Indonesia, and often fewer hurricanes over the Atlantic Ocean. Given precipitation fields of Indonesia and hurricane tracks over the Atlantic Ocean, no statistical method can ever show that both are influenced by El Niño as this is information not available to the analysis.

In particular, the method of Eqs (1)–(4) reduces to linear regression in the case of 1×1 fields, i.e., time series. Linear regression of time series does not have the property of isolating directional influence. This is in contrast to the general remark that for all cases this method detects directional interactions, which is therefore false."

**Response:**

Some general comments on statistics are not directly related to the content of our manuscript; and we can only give some general arguments as responses. We need to clarify first that what we are discussing in the manuscript are functional relations, i.e., the driver-response relations in statistical sense. We fully understand and appreciate that functional relations cannot be interpreted directly as physical causal chains; neither did we interpret these that way.

It is common to disentangle from observations the directions and quantify the strength of directional interactions, i.e., the driver-response relations, of bivariate or multivariate signals. This is a very general topic if we look broader into other fields of science, for example, in econometrics, physics, neuroscience, biology, artificial intelligence, and many others. There exist numerous statistical techniques for this purpose, for example, the well established Granger causality. Various other methodologies exist, such as the phase slope index, transfer entropy, phase-synchrony-based techniques, structural equation modeling, Bayesian interface, directed transfer function, directed coherence, … and many more (references can be obtained on request). These are only tools for time series analysis.

For climate fields containing variability in both time and space, Navarra and Tribbia (2005) proposed a Procrustes formulation that generalizes the traditionally used regression and variance based methods, such as CCA and SVD. This technique has been successfully used to investigate the ocean-air coupling and land-atmosphere coupling. We have cited some clear examples of this method in our manuscript, for example, Alessandri and Navarra (GRL, 2008). Obviously, variables that are not incorporated into the statistical fields cannot be represented in the output, and the statistical results cannot be interpreted directly as physical causal chains. That is not to say that they do not exist. We will thus have to combine the statistical results with existing knowledge; hence we compared the results in our manuscript with some published numerical simulations. To come back to the referee's example, even if a high correlation between Indonesian precipitation and hurricane tracks exists, this cannot be interpreted directly as physical relations. For an interpretation of physics, we have to combine with the existing knowledge. Researchers with expertise can hypothesize a driver of El Niño to exist and easily show with a partial correlation that there is actually no statistical correlation between Indonesian precipitation and hurricane tracks.

The referee is right that the Eqs (1)-(4) can reduce to traditionally used linear regression with regard to time series. However, this technique is designed for analyzing climate "fields" as we addressed, not for time series. The concept of field is not ambiguous, which essentially involves the distribution of one variable in climate space. Time series or data points can not be called fields. We do not claim this technique is valid for all cases, neither did the authors who proposed this technique. The referee's statement, "Linear regression of time series does not have the property of isolating directional influence", is unfortunately not quite right. The property of linear regression depends on how it is formalized. For example, the well established Granger causality and directed transfer function are linear regressions on a vector base. Vector regression is also widely used in other statistics to infer directional influences (references can be obtained on request).

Exogenous as well as latent variables are the central concern of statistics. There doesn't exist such techniques that can generally satisfy these concerns, neither does the CMT technique. However, from a viewpoint of reality there exists no such an external mechanism that uniformly influences winter precipitation and summer temperature. From a viewpoint of statistics, in this case the CMT is indeed a significant step forward towards disentangling directional influences. We give below some mathematical and practical justifications.

In our paper, of interest is only the influence of winter precipitation on summer climate; therefore the inverse direction was not included. Let $\boldsymbol{S}$ and $\boldsymbol{Z}$ be two fields. In case the reciprocal influences are desired, using the concept of forced and free manifold, as we have described in the paper, the two fields can be separated into:

$$\boldsymbol{Z}=\boldsymbol{Z}_{for}+\boldsymbol{Z}_{free}=\boldsymbol{AS}+\boldsymbol{Z}_{free}, \text{ and} \quad\quad (1)$$
$$\boldsymbol{S}=\boldsymbol{S}_{for}+\boldsymbol{S}_{free}=\boldsymbol{BZ}+\boldsymbol{S}_{free},$$

where $\boldsymbol{A}$ represents the influence of $\boldsymbol{S}$ on $\boldsymbol{Z}$, and $\boldsymbol{B}$ represents the influence of $\boldsymbol{Z}$ on $\boldsymbol{S}$. Generally the A and B are not equivalent, which differs from cross correlation. The $\boldsymbol{AS}$ portion is a combination of directional influence from $\boldsymbol{S}$ to $\boldsymbol{Z}$ and the possible influences exerted on both $\boldsymbol{S}$ and $\boldsymbol{Z}$ fields by external mechanisms. We can further decompose the forced manifolds ($\boldsymbol{AS}$ and $\boldsymbol{BZ}$) by writing $\boldsymbol{Z}$ and $\boldsymbol{S}$ into the right-hand side of the two equations in (1),

$$\boldsymbol{Z}=\boldsymbol{A}(\boldsymbol{BZ}+\boldsymbol{S}_{free})+\boldsymbol{Z}_{free}=\boldsymbol{ABZ}+\boldsymbol{AS}_{free}+\boldsymbol{Z}_{free} \text{ and} \quad\quad (2)$$
$$\boldsymbol{S}=\boldsymbol{B}(\mathrm{AS}+\boldsymbol{Z}_{free})+\boldsymbol{S}_{free}=\boldsymbol{BAS}+\boldsymbol{BZ}_{free}+\boldsymbol{S}_{free}.$$

The $\boldsymbol{ABZ}$ and $\boldsymbol{BAS}$ represent the fully coupled portions in the $\boldsymbol{Z}$ and $\boldsymbol{S}$ fields (See Figure 1 for a graphical explanation). Since $\boldsymbol{S}_{free}$ is independent from $\boldsymbol{Z}$, $\boldsymbol{AS}_{free}$ represents a portion of $\boldsymbol{Z}$ purely forced by $\boldsymbol{S}$. So does the $\boldsymbol{BZ}_{free}$.

We take an example of $P_{JFM}$ -$T_{max}$ relations. Let $\boldsymbol{S}$ stand for winter $P_{JFM}$ and $\boldsymbol{Z}$ stand for summer $T_{max}$. According to equation (2), the $\boldsymbol{Z}$ field was first decomposed into the forced manifold ($\boldsymbol{AS}$) and the free manifold ($\boldsymbol{Z}_{free}$) with regard to $\boldsymbol{S}$; and the $\boldsymbol{AS}$ portion was then further decomposed into $\boldsymbol{BAS}$ and $\boldsymbol{AS}_{free}$. The variance ratios of $\boldsymbol{AS}$, $\boldsymbol{ABZ}$, $\boldsymbol{AS}_{free}$ portions to $\boldsymbol{Z}$ respectively are computed, shown in Figure 2 of this response. It appears that 6.7% of the total $T_{max}$ variance on average is contained in the $\boldsymbol{AS}$ portion. However, $\boldsymbol{ABZ}$ contains less than 1% of the total $T_{max}$ variance, which indicates that there doesn't exit an external mechanism forcing both winter precipitation and summer $T_{max}$. The $\boldsymbol{AS}_{free}$ portion of $T_{max}$, which is purely forced by $P_{JFM}$, contains most of the $\boldsymbol{AS}$ variance. Compare the panels of Figure 2 in this response. Clearly, this indicates what we have presented in our manuscript are indeed directional influences, and our claims are reasonable. We will insert this justification in the revised version.

**Comment #2**

"Doing a normal MCA analysis on the fields without the CMT technique (and without EOF pre-filtering) gives pretty much the same results. The first SVD mode explains 28% of variance and looks very similar to Figs 1bc, see Fig.1 of this review.

The JFM precipitation pattern is highly correlated with the NAO time series (r = 0:73). Still, the linear correlation of the JFM NAO index on JJA Tmean is compatible with zero, and on Tmax about 0.2 in France, in contrast with the title of the manuscript, see Fig.2 of this review.

The analysis of the authors therefore just recovered the well-known weak local correlations between JFM precipitation and Tmean and Tmax in France, Fig.3 of this review. The same holds for the scPDSI index, which is higher if there has been lower precipitation in winter at the same grid point.

To summarise, the authors use a novel statistical technique with improbable claims, but essentially recover simple results that can just as easily be shown using simple correlation analysis: late winter precipitation is correlated to locally drier summer soils in large parts of Europe, which in turn are correlated to local higher mean and maximum temperatures in France. The NAO can be a source of this precipitation variability."

**Response:**

**The** spatial patterns are truly similar with or without the CMT. However, this doesn't necessarily conflict with the concept of directional influence. Given two fields A and B with information flowing only from A to B, the cross correlation must be identical with the directional influence from A to B if the coupling directions are completely disentangled. This is quite close to our case for physical reasons. In other words, if the spatial patterns of our results were essentially different from those of only SVD cross correlation, there must have been something wrong.

Unfortunately, the referee appears to have missed the point that our technique has significantly and largely increased the accuracy of the derived relations even with only regard to the SVD analysis. For SVD as well as CCA analysis, the reliability of derived modes (associations) are not determined by the spatial patterns, but determined only by the PC time series. Performing SVD to any twin field can result in spatial patterns, and we can conclude a linkage only when the PC time series are highly correlated, for example, r>0.7. Applying the SVD without CMT is also what we actually did. We have addressed this in our original manuscript:" The time coefficient series of the 1st MCA mode without CMT exhibit a correlation of 0.40 (not shown), which is clearly insufficient to conclude a significant linkage. The same situation also holds in the following analysis of *T*max as well as soil moisture proxy of scPDSI". The CMT helps to improve this correlation to unit value, so that we can safely and statistically significantly (!) draw a conclusion of the existence of this linkage. The unit correlation of PC time series indicates an obvious advantage using CMT. Besides the directional influence, the superiority of using CMT in our analysis, as we have shown in our manuscript also includes:

a. The summer climate fields ($T_{mean}$, $T_{max}$ and scPDSI) are functionally separated into two portions: free from or functionally forced by the $P_{JFM}$ (See previous discussions). This enables us to estimate the percentage of total variance (passing a 5% significance test) of summer climate fields as a function of $P_{JFM}$. This is what other techniques can't do.

b. By a strict control on the elements in the functional operator $\boldsymbol{A}$, the CMT enables us to find very robust relations between fields in the presence of very strong background noise. In our case, we can conclude little from the direct correlation values of 0-0.2, as shown by the referee. We improve substantially the correlation to unit using the CMT, and thus conclude that a robust linkage exists.

The referee correlated the NAO index with summer $T_{mean}$ and $T_{max}$ in the presence of strong background noise, showing low correlation values. However, we are correlating the NAO index with one persistent climate mode/regime, which explains significantly 5-25% of the total summer temperature variance. Again, these values are not small for climate prediction purposes. Finding deterministic modes/regime in climate fields is a general approach for climate diagnostics, because we can then make climate predictions based on deterministic modes/regime rather than on the noise. Our correlation between NAO and the derived climate regime is r=0.65, indicating a strong linkage between winter NAO circulation and the deterministic climate mode in summer. Our results suggest this is an important and deterministic factor we have to take into account when making climate prediction.

We agree with the referee that correlation coefficient between winter NAO and summer temperature is very low. However, such a correlation depends on the data length and possibly also data preprocessing. For example, as we have cited, Qian et al. (J. Clim., 2003) reported significant correlation between winter NAO and summer temperature over part of Europe (see our response to referee 2).

The comments, "…and on Tmax about 0.2 in **France**" and "…between JFM precipitation and Tmean and Tmax in **France**" and "local higher mean and maximum temperatures in **France**", are not comments to our content. These seem to be comments to the referee's own correlation maps with only but weak correlation values over France. Our results are essentially different. In our results, significant signals are found over large area of south Europe; while over France, the signals are relatively weak, actually. See the figures in our paper.

The referees comment that "The same holds for the scPDSI index, which is higher if there has been lower precipitation in winter at the same grid point." This is opposite to our content throughout the paper. More importantly, this misunderstanding has apparently clouded the pathway how we are stepping towards the underlying dynamics of the derived linkages between the fields, that is, winter precipitation influences summer temperature via soil moisture.

In the referee comments, the words "local", "locally" and "on the same grid point" etc are repeatedly used to emphasize the 'locality' of our results. Again these are not comments to our content. Physically, we are fully aware the land-atmosphere coupling is non-local with northward and eastward propagation from the current literature as we cited. Technically, we are using the CMT technique that takes into account both local and remote forcing (Alessandria and Navarra, GRL, 2008). Graphically, we have clearly presented this non-locality in our figures (Figure 1 and Figure 2). And literally, large space in our paper was used to discuss this non-local coupling. See for instance lines (Page 5085, Line 25-27; Page 5087, Line 17-18; Page 5090, Line 1-19).

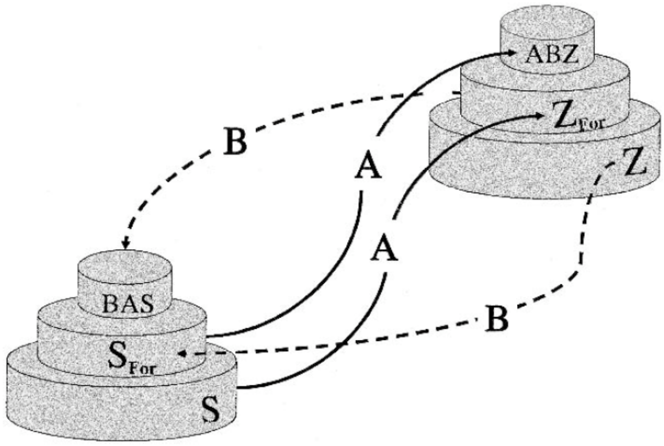


Figure 1: A graphical explanation of the coupled manifold technique. Same as figure 6 in Navarra and Tribbia (2005).

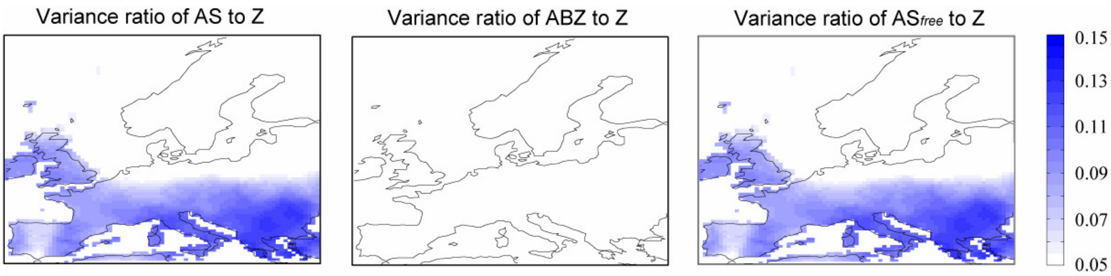


Figure 2: Variance ratios of ***AS***, ***ABZ***, $\boldsymbol{AS_{free}}$ portions to ***Z*** respectively. See text for the abbreviations.