

MS No.: ESD-2015-59

Title: Observationally based analysis of land–atmosphere coupling

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Review of the revised submission

Responses to the Editor, Reviewers #1 and #2

First of all, we would like to thank the Editor and the two reviewers for their work. Their comments were very helpful and we think they have significantly contributed to improve the quality of this paper. We have modified the manuscript addressing all the minor comments made by Reviewer #1 on the revised submission and we believe that the new revised manuscript is much improved. Please see below our detailed reply to the comments.

Responses to Reviewer #1

[22/02/2016]

Minor comments

1) P5 L8 Please also add this information “All grid points with a percentage of missing number larger than 30% (white areas in Fig. 1b) have not been considered in the analysis” to figure 1 caption.

Thank you for the suggestion. We included the sentence in Fig. 1 caption of the revised manuscript.

2) P5 23-30: Please adjust the format of Eq 1 to 3. Is “AS” a variable name or the product of A*S? Please use italic font for “A” in the text if it represents a variable name. I think journal may have its own guidance for the usage of mathematic terms. Please check that.

Thanks. AS is the product of A*S, where both A and S are matrices. We have double checked journal guidance for mathematical symbols and formulae and corrected the style of the variables in the text and equations accordingly. In particular, we have typeset all matrices in boldface in Section 3 of the revised manuscript. Please note that, due to unexpected problems with the word software, these changes are not evidenced in track-change.

3) P6. Please give reference to the SVD method.

We modified the sentence at P6 L23-24 of the revised paper to include reference to the SVD method.

original:

“This is not possible with other methods such as SVD (Singular Value Decomposition).”

new:

“This is not possible with other methods such as SVD (Singular Value Decomposition, [Bretherton et al., 1992]).”

4) Table 1. Please use proper capitalization form. The authors may consider listing the reference of each dataset at the last row of the table, instead of listing all of them in the title.

We appreciate the suggestion. We have corrected capitalization and we have listed the reference of each dataset at the last row of Table 1 in the revised manuscript.

5) P14 L3-5. This sentence is too long and hard to understand because it contains too many “and” which caused the problem of ambiguous meaning.

One can hardly tell what the correlation means for the structure like “correlation between A and B and C ”(it actually means corr of A and B, and corr of A and C). The usage of (a), (b) and “with”

in title of figure 8 can alleviate this problem. So please reorganize this sentence, for example, by inserting Fig 8a, Fig 8b like the description for figure 9 of the next paragraph, or by breaking it into two separate sentences.

Thanks for the suggestion. We have modified the sentence at P14 L4-10 in the revised manuscript as follows.

original:

“The point-by-point correlation coefficient between the second mode of variability (related to ENSO) of PRE forced by the SM and the total fields of PRE forced by the ET and PRE forced by the LAI is shown in Fig. 8 on panel a and b, respectively.”

new:

“The point-by-point correlation coefficient between the second mode of variability (related to ENSO) of PRE forced by the SM and the total field of PRE forced by the ET is shown in Fig. 8a. The correlation between the second mode of PRE forced by the SM and the total field of PRE forced by the LAI is shown in Fig. 8b.”

1 **Observationally based analysis of land-atmosphere** 2 **coupling**

3

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13

14 **Abstract**

15 The temporal variance of soil moisture, vegetation and evapotranspiration over land has been
16 recognized to be strongly connected to the temporal variance of precipitation. However, the
17 feedbacks and couplings between these variables are still not well understood and quantified.
18 Furthermore, soil moisture and vegetation processes are associated to a memory and therefore
19 they may have important implications for predictability.

20 In this study we apply a generalized linear method, specifically designed to assess the
21 reciprocal forcing between connected fields, to the latest available observational datasets of
22 global precipitation, evapotranspiration, vegetation and soil moisture content. For the first
23 time a long global observational dataset is used to investigate the spatial and temporal land
24 variability and to characterize the relationships and feedbacks between land and precipitation.

25 The variables considered show a significant coupling among each other. The analysis of the
26 response of precipitation to soil moisture evidences a robust coupling between these two
27 variables. In particular, the first two modes of variability of the precipitation forced by soil
28 moisture appear to have a strong link with volcanic eruptions and ENSO cycles, respectively,

1 and these links are modulated by the effects of evapotranspiration and vegetation. It is
2 suggested that vegetation state and soil moisture provide a biophysical memory of ENSO and
3 major volcanic eruptions, revealed through delayed feedbacks on rainfall patterns. The third
4 mode of variability reveals a trend very similar to the trend of the inter-hemispheric contrast
5 in SST and appears to be connected to greening/browning trends of vegetation over the last
6 three decades.

7

8 **1 Introduction**

9 Soil moisture (SM) is an important variable of the climate system, playing an important role
10 in the feedbacks between land-surface and atmosphere. SM is important in determining
11 climate variability at a wide range of temporal and spatial scales and controls hydrologic and
12 energy cycles (Seneviratne et al., 2010; Dirmeyer, 2011). Soil moisture-precipitation
13 feedbacks have been investigated at the global (Koster et al., 2004; Koster et al., 2009) and
14 the regional (Pal and Eltahir, 2003; Hohenegger et al., 2009) scale through numerical
15 simulations. Recent observational studies focused on local land-atmosphere coupling
16 (Santanello et al., 2009). However, a comprehensive observational study at the global scale of
17 the SM precipitation (PRE) coupling has never been performed. As shown by several
18 modelling studies, it is over transition zones between wet and dry climates that a strong
19 coupling between soil moisture and precipitation can be clearly identified and it is over these
20 regions that “soil moisture memory” can most probably contribute to subseasonal and longer
21 climate predictions (Koster et al., 2004; Ferranti and Viterbo, 2006). The term “soil moisture
22 memory” refers to the property of soil moisture to display persistent anomalies induced by
23 climatic events like ENSO or volcanic eruptions. Since slowly varying states of the land
24 surface can be predicted weeks to months in advance, the response of the atmosphere to these
25 land-surface anomalies can contribute to seasonal prediction. The large discrepancies among
26 model results evidence the need of observational analysis of soil moisture-precipitation
27 feedbacks (Seneviratne et al., 2010). The observational study by Alessandri and Navarra
28 (2008) clearly identified a link between rainfall and land surface-vegetation variability
29 indicating an important delayed feedback of the land surface to the precipitation pattern. In
30 this regard, a mechanism by which vegetation may provide delayed memory of El Niño and
31 La Niña events is identified.

1 Predictability of climate at seasonal and longer time scales stems from the interaction of the
2 atmosphere with slowly varying components of the climate system such as the ocean and the
3 land surface (Shukla and Kinter, 2006). However, much of the model improvements so far
4 have been obtained over ocean, where extensive availability of observations allowed model
5 progresses and reliable application of assimilation techniques (Rosati et al., 1997; Alessandri
6 et al., 2010; Alessandri et al., 2011). In contrast, forecasts performance over land is
7 substantially weaker compared to the ocean (Wang et al., 2009; Alessandri et al., 2011). Since
8 most of the applications of climate predictions would serve economic interests that are land-
9 based, there is an urgent need to improve climate forecasts over land. Long-term
10 improvements in understanding land-climate interactions and feedbacks over land must come
11 from the enhancement of the description of the physical processes on the basis of dedicated
12 process studies and observational databases. This can be suitably pursued firstly by analysing
13 the newest available satellite-derived observational datasets that can lead to a better
14 understanding and quantification of land surface-atmosphere feedbacks. The better knowledge
15 will then help us to conceive improved systems for the simulation of climate and for the
16 improvement of its prediction at seasonal and possibly longer time scales. Here a global array
17 of relevant up-to-date high quality datasets is acquired, harmonized and analysed. The
18 comprehensive dataset is analysed to characterize the seasonal-mean interannual variability of
19 land-surface variables and to improve understanding of the relationship and feedbacks
20 between land and climate. The analysis method is based on the Coupled Manifold (CM)
21 technique (Navarra and Tribbia, 2005) which has been specifically designed to analyse
22 covariation between fields considering both the local and remote forcing of one field to the
23 other. The CM has proved to be successful for the analysis of different climate fields, like
24 precipitation, vegetation characteristics, sea surface temperature, and temperature over land
25 (Alessandri and Navarra, 2008; Cherchi et al., 2007; Wang et al., 2011). Recently, the CM
26 technique has been also applied to investigate the relationship between surface temperature
27 and electricity demand in summer (De Felice et al., 2014). By taking advantage of the new
28 global array of relevant up to date high quality datasets, the present work substantially
29 extends the analysis previously performed by Alessandri and Navarra (2008) and, for the first
30 time, it includes SM and evapotranspiration (ET) feedbacks on PRE.

31 This paper is organized as follows: the observational datasets are described in Section 2.
32 Section 3 describes the analysis method and gives a brief introduction of the CM technique.

1 Section 4 presents the results. Summary and discussion of the main results of this study are
2 given in Section 5.

3

4 **2 The observational datasets**

5 The datasets used for this study are all observationally based, in order to make the analysis as
6 much as possible independent from global circulation model limitations and biases. High
7 quality up-to-date observational datasets of precipitation (PRE, from the Global Precipitation
8 Climatology Project [GPCP]), Evapotranspiration (ET, from University of Montana), soil
9 moisture (SM, from European Space Agency [ESA]) and Leaf Area Index (LAI, from Boston
10 University) have been acquired and prepared. The selection of the datasets is based mainly on
11 two criteria: 1) as long as possible period covered; 2) global spatial coverage. The observed
12 monthly PRE dataset is described in Adler et al. (2003). ET values are satellite-based
13 estimates from the Global Inventory Modeling and Mapping Studies [GIMMS] and MODIS
14 (Zhang et al., 2010). The SM dataset (Liu et al., 2011, 2012) is the most complete record of
15 this variable, based on active and passive microwave satellite sensors. The LAI dataset (Zhu
16 et al., 2013) is a long-term global data set resulting from the application of a neural network
17 algorithm to the NDVI3g product from GIMMS satellite data. All land-surface datasets (SM,
18 ET, LAI) are satellite products independent on the PRE dataset, which is based on rain
19 gauges. Despite both ET and LAI products have been acquired by using the AVHRR sensor,
20 the datasets have been produced by independent research groups which used completely
21 different methodologies. The LAI product has been generated by applying a neural network
22 algorithm on the NDVI satellite product while the ET dataset has been produced by using a
23 modified Penman-Monteith approach including eddy covariance and meteorological data
24 from the FLUXNET towers network. The time period, depending from the availability of the
25 datasets, is 24 years (1983-2006) for ET and 29 years (1982-2010) for the other variables.
26 Original datasets come with various sampling frequencies, ranging from daily to monthly. See
27 Table 1 for a summary of the characteristics of the retrieved datasets.

28 The data have been pre-processed and prepared for the subsequent analysis (Table 1). The
29 pre-processing included space and time averaging, analysis of the spatial coverage and gap
30 filling in order to minimize the effect of undefined values (hereinafter NaN). The gap filling
31 procedure is described in Section 3. ET and PRE datasets are observational products merged
32 with model information and so do not contain NaNs. Instead, LAI and SM are affected by

1 data gaps and present significant seasonal variation of the spatial coverage. Fig. 1a reports the
 2 seasonal cycle of the percentage of NaN values for LAI (full line) and SM (dashed line). Both
 3 variables show better spatial coverage during the summer season (June, July, August,
 4 September). On the other hand, mostly because satellite-based estimates of LAI and SM are
 5 unreliable in presence of snow cover (Zeng et al., 2013), during the winter season the
 6 coverage reduces substantially. The SM dataset derives from blending passive and active
 7 microwave satellite retrievals. Fig. 1b shows the percentage of SM missing data for each grid
 8 point. All grid points with a percentage of missing number larger than 30% (white areas in
 9 Fig. 1b) have not been considered in the analysis. Over regions characterized by particularly
 10 dense vegetation and high canopies, both satellite products are unable to provide reliable
 11 estimates (Liu et al., 2012). Conversely, non-vegetated areas are associated to NaN values in
 12 the LAI dataset.

13 In order to evaluate the effect of major volcanic eruptions on land-atmosphere coupling, we
 14 used the stratospheric Aerosol Optical Depth (AOD) at 550 nm, available from the NASA
 15 GISS dataset (Sato et al., 1993). To evaluate the effect of ENSO, we compute the NINO3
 16 index based on the HadISST 1.1 – Global sea-Ice coverage and Sea Surface Temperature
 17 (1870–present; Rayner et al., 2003) dataset.

18

19 **3 The Analysis Method**

20 The CM technique (Navarra and Tribbia, 2005) seeks linear relations between two
 21 atmospheric fields \mathbf{Z} and \mathbf{S} (that in general are assumed to be rectangular matrices) of the
 22 kind:

$$23 \quad \mathbf{Z} = \mathbf{Z}_{\text{for}} + \mathbf{Z}_{\text{free}} = \mathbf{A} \mathbf{S} + \mathbf{Z}_{\text{free}}, \quad (1)$$

$$24 \quad \mathbf{S} = \mathbf{S}_{\text{for}} + \mathbf{S}_{\text{free}} = \mathbf{B} \mathbf{Z} + \mathbf{S}_{\text{free}}, \quad (2)$$

25 The subscript $()_{\text{for}}$ indicates the component of the field forced by the other variable
 26 (hereinafter forced manifold), while $()_{\text{free}}$ indicates the free manifold. The free manifold
 27 contains the effects of nonlinearities. The linear operators \mathbf{A} and \mathbf{B} express the link between \mathbf{Z}
 28 and \mathbf{S} . \mathbf{A} expresses the effect of \mathbf{S} on \mathbf{Z} , while \mathbf{B} represents the effect of \mathbf{Z} on \mathbf{S} . In general, \mathbf{A}
 29 and \mathbf{B} are different. \mathbf{A} and \mathbf{B} are found by solving the Procrustes minimization problem:

$$30 \quad \mathbf{A} = \mathbf{Z} \mathbf{S}' (\mathbf{S} \mathbf{S}')^{-1}, \quad (3)$$

1 $\mathbf{B} = \mathbf{S} \mathbf{Z}' (\mathbf{Z} \mathbf{Z}')^{-1}$, (4)

2 Following Navarra and Tribbia (2005), the technique is applied to the principal components
3 of \mathbf{Z} and \mathbf{S} , therefore the coefficients of the linear operators \mathbf{A} and \mathbf{B} express the relations
4 between the modes of the two variables. CCA scaling (data scaled by the covariance matrices)
5 is applied to the Principal Components (PCs) of the variables before solving the Procrustes
6 problem:

7 $\hat{\mathbf{Z}} = (\mathbf{Z} \mathbf{Z}')^{-1/2}$, (5)

8 $\hat{\mathbf{S}} = (\mathbf{S} \mathbf{S}')^{-1/2}$, (6)

9 where $\hat{\mathbf{Z}}$ and $\hat{\mathbf{S}}$ are the CCA-scaled variables. Please refer to Navarra and Tribbia (2005) for
10 further details of the CM technique.

11 As explained in Cherchi et al. (2007), after applying the CCA scaling, the elements of \mathbf{A} and
12 \mathbf{B} are correlation coefficients and can be tested (with a significance test based on the Student t
13 distribution) to reject the null hypothesis of being equal to zero. To improve the robustness of
14 the analysis, each element of the \mathbf{A} and \mathbf{B} matrices has been verified to be different from zero
15 at the 1% significance level, following the method proposed by Cherchi et al. (2007).

16 The CM has two main advantages compared to other methods. The first one is that, when
17 applied to a couple of climate fields (i.e., PRE and SM), CM is able to separate one field (i.e.,
18 PRE) into two components: the first component (forced) is the portion of PRE variability that
19 is connected to the SM variability, whereas the second (free) is the part of PRE that is
20 independent from SM. Therefore, the CM technique enables to find robust relations between
21 fields in the presence of strong background noise. The second advantage is that the CM
22 technique is able to detect both local and remote effects of the forcing variable. This is not
23 possible with other methods such as SVD (Singular Value Decomposition [[Bretherton et al.,](#)
24 [1992](#)]).

25 In the present analysis the CM technique has been applied to the seasonal-mean inter-annual
26 anomalies. The climatological seasonal cycle has been removed and the data have been
27 stratified using the seasons: JFM (January-February-March), AMJ (April-May-June), JAS
28 (July-August-September) and OND (October-November-December). The JFM, AMJ, JAS,
29 OND stratification has been used by Alessandri and Navarra (2008) in their CM study of

1 vegetation and rainfall which we will use to compare our results. The trends are kept for their
2 relevance as possible indicators of climate change.

3 The LAI and SM datasets contain missing values, whose number and position significantly
4 vary with time. The application of the CM algorithms requires that the number and position of
5 the missing values is constant with time. Hence, if a NaN is present in a given grid-point at
6 any time, then it requires to mark as NaN that grid point, thus losing a great amount of
7 information. In order to keep as much information as possible from the data, we decided to
8 replace the missing values with climatological values provided that their total number,
9 considering a particular grid-point, does not exceed a given threshold. We selected different
10 thresholds for SM and LAI in order to obtain as similar as possible spatial coverage of the two
11 variables. The chosen threshold is 10% for LAI and 30% for SM. The results are robust with
12 respect to a $\pm 10\%$ change of the threshold values. As shown in Fig. 1b, the areas more
13 affected by the replacement of SM missing values (30% of values replaced by climatology)
14 are North-East Europe, East coast of Central-South America, East China and Korea. Since the
15 replacement of missing values with climatology reduces time variability, the coupling in these
16 regions may be underestimated as a consequence. We note that these gap-filled regions do not
17 correspond to transition zones between wet and dry climates (Koster et al., 2000). Therefore,
18 they are not expected to display a strong coupling between SM and PRE and to significantly
19 affect the main results of present study.

20 Since the main interest of the work is on the land-surface, the ocean values are masked out
21 from the PRE dataset. A preliminary analysis (not shown) revealed that their inclusion
22 resulted in a more difficult interpretation of the Empirical Orthogonal Functions (EOF)
23 patterns (Bretherton et al., 1992), due to the interaction of phenomena on different space and
24 time scales which are not connected to land variables.

25

26 **4 Results**

27 The CM technique has been applied to analyse the reciprocal forcing between PRE and the
28 observed surface variables (SM, ET, LAI). The global-scale reciprocally forced temporal
29 variances between PRE and the land surface variables is reported in Table 2. 19% of the PRE
30 variability is forced by SM. On the other hand, 17% of the SM variance appears to be forced
31 by PRE. 18% of the variability of PRE is forced by ET and 14% of the variance of ET is
32 forced by PRE. Considering the coupling between PRE and LAI, 17% of the variance of PRE

1 appears to be forced by LAI and 14% of the variability of LAI is forced by PRE. All the
2 variance ratios in Table 2 are significant at the 1% level. The chance of coincidentally getting
3 as high or higher ratios has been tested by means of a Monte Carlo bootstrap method (1000
4 repetitions).

5 Since SM is the most important land-surface parameter affecting seasonal to interannual
6 variability/predictability of precipitation (Koster et al., 2000; Zhang et al., 2008), the coupling
7 between SM and PRE will be analyzed in detail in the following.

8 **4.1 Reciprocal forcing between PRE and SM seasonal-mean anomalies**

9 Fig. 2 shows the ratio of the forced/total variance over land. The ratio of SM variance forced
10 by PRE is in panel a, while panel b shows the ratio of PRE variability which is accounted for
11 by the SM variability. For each grid point, the null hypothesis of coincidentally getting as
12 high or higher variance ratios has been tested using a Monte Carlo bootstrap method (1000
13 repetitions). The regions where the ratio values are not significantly different from zero at the
14 1% level are dotted. The observed SM variability appears to be intensely forced by PRE over
15 the Sahel and Central-eastern Africa, South Africa, Middle East, the semi-arid region of
16 Central West Asia, Indian Peninsula, Argentina, Eastern Brazil and Australia. Note that, due
17 to the limitations of the satellite estimates discussed in Section 2, large areas in Russia and the
18 Amazon basin are not covered in the SM dataset. The larger observed effects on PRE due to
19 SM inter-annual variability (Fig. 2b) occur in East Brazil, La Plata basin, Sahel, Asian boreal
20 forests, Middle East, Pakistan, Indonesia, northern and eastern Australia. Most of these
21 regions correspond to transition zones between dry and wet climates, where evaporation is
22 highly sensitive to soil moisture (Koster et al., 2000). Here we refer to the transition regions
23 between very dry and very humid environments, as individuated by Koster et al. (2000).

24 By using the CM technique (described in Section 3), the seasonal-mean PRE anomalies are
25 separated into forced and free components, where forced and free refers to the influence of the
26 SM variation. The variance explained by each mode of the PRE forced field is reported in
27 Table 3. The EOF analysis shows that the first three components of the variability of the
28 forced PRE field together account for 48% of total variance. The first two PCs does not
29 display trends while the third PC is dominated by a clear trend, as will be discussed later. The
30 first mode of variability of the forced PRE field explains 26% of the total variance. The
31 corresponding principal component displays two significant peaks at years 1983 and 1992

1 (Fig. 3a). The PC is significantly correlated (maximum correlation coefficient equal to 0.56 at
2 lag 0) to the stratospheric AOD. AOD peaks in correspondence of the two major eruptions of
3 the period: 1983 (El Chichon) and 1992 (Pinatubo). The peaks in the AOD time series
4 correspond to those of the forced PRE PC1, suggesting that this mode of variability is related
5 to changes in the solar radiation at the ground, confirming that absorption and reflection of
6 solar radiation by aerosol are particularly effective in reducing the hydrological cycle. The
7 fast response of the precipitation anomalies to the radiation change induced by large tropical
8 volcanic eruptions is in agreement with the results of the lag-correlation analysis by Gu and
9 Adler (2011), who found 0 time lag between stratospheric aerosol signal and PRE. The lagged
10 correlations of PC1 and AOD (Fig. 3b) show that significant (at 5% level) correlations endure
11 up to about 2 years after the aerosol peak (i.e: behind the autocorrelation period of AOD
12 itself; Fig. 3b dashed line). This result indicates that SM may provide a memory of the major
13 volcanic eruptions for PRE. Table 4 shows the variance explained by each EOF mode of the
14 whole original PRE field (that is, forced+free components). The link between PRE and
15 volcanic eruption signal is evident also in the first mode of variability of the total rainfall field
16 as confirmed by the correlation of the corresponding PC (explaining 10% of total PRE
17 variance) with AOD (Table 4).

18 Fig. 3c shows the spatial pattern of the first EOF of the PRE anomalies forced by the SM. A
19 clear negative signal is present over areas characterized by a wet climate (Amazon basin,
20 India and Indonesia). In these regions the stratospheric aerosol emitted during the volcanic
21 eruptions has the effect of reducing the intensity of the hydrological cycle (Alessandri et al.,
22 2012) with a consequent reduction of SM, PRE and continental discharge (Trenberth and Dai,
23 2007). In particular, according to Joseph and Zeng (2011) and Iles et al. (2013), the negative
24 signal over the monsoon regions may indicate a suppression of the monsoon linked to the
25 effects of the aerosol released during major eruptions. Further, differently from our results
26 and other observational (Trenberth and Dai, 2007) and modelling (Joseph and Zeng, 2011)
27 studies, the HadCM3 results of Iles et al. (2013) showed a wetting signal over India during the
28 summer season (although not significant in the observational dataset they used). On the other
29 hand, over transition zones (U.S. Great Plains, Argentina, Middle East) the dimming effect
30 may result in reduced evapotranspiration during the hot/dry season which drives an increase
31 of SM (Wild et al., 2009). During the following cool/wet season, the enhanced SM can induce
32 a lagged increase of the portion of PRE forced by SM. That can explain the increased PRE
33 over transition areas. On the other hand, the reduction of PRE over South Asia monsoon

1 region and the enhancement of PRE over the semi-arid areas of Central West Asia is
2 consistent with the monsoon-desert mechanism (Rodwell and Hoskins, 1996; Cherchi et al.,
3 2014): the reduction of radiation caused by the stratospheric aerosol drives a reduction of
4 convection over monsoon regions and a consequent reduction of PRE over South Asia
5 therefore abating Rossby wave induced subsidence over Middle East and East Mediterranean
6 (Cherchi et al., 2014).

7 The second PC of PRE forced by SM, explaining 14% of total variance, is dominated by a
8 large scale oscillation (Fig. 4a). The corresponding principal component (full line) displays an
9 high correlation coefficient of 0.60 with the NINO3 index (average of the Sea Surface
10 Temperature in the tropical Pacific region 5S–5N, 210–270E; dashed line) at lag 2 (significant
11 at the 1% level), indicating that EOF2 represents the portion of the rainfall forced by SM that
12 is related to the El Niño Southern Oscillation (ENSO; Philander, 1989) variability. The
13 second mode of forced PRE response due to SM variability appears to be lagged by one to
14 several seasons with respect to the ENSO phase (Fig. 4b), with the strongest correlations with
15 the NINO3 index two seasons after the maximum El Niño or La Niña intensity and significant
16 correlations enduring until the lag 5 season (i.e: behind the autocorrelation period of ENSO
17 itself; Fig. 5b dashed line). The results indicate that the effects related to ENSO in the SM
18 may induce a delayed forcing on PRE. Therefore, SM appears to provide a biophysical
19 memory of ENSO on the global precipitation pattern. The signal of ENSO can also be
20 evidenced in the second mode of variability of the total rainfall field as indicated by the
21 correlation of the corresponding PC (explaining 5% of total PRE variance) with NINO3
22 (Table 4). Again, the lag at which maximum correlation is attained is the same (lag 2) as in
23 the forced field but the correlation coefficient is 0.60 for the forced field and 0.43 for the total
24 PRE field.

25 The spatial pattern of the second EOF of the PRE anomalies forced by SM (Fig. 4c) displays
26 the signature of the tripole pattern over south America typical of ENSO teleconnections
27 (Ropelewski and Halpert, 1989). Similarly, negative PRE anomalies are shown over Brazil,
28 South Africa, North India and Indochina, displaying the land surface feedback to the reduced
29 rainfall related to the positive phase of ENSO there (Trenberth et al., 1998). On the other
30 hand, positive precipitation anomalies characterize the West and East Coasts of North
31 America, Central America, the dry and semi-arid region of North Venezuela, La Plata basin,
32 Horn of Africa, Sahel, Europe, Central and East Asia, South India and the East Coast of

1 Australia. Most previous research showed reduced precipitation over India during ENSO
2 years (Ropelewski and Halpert, 1989; Trenberth et al., 1998). The positive anomalies of PRE
3 forced by SM over South India related to the positive phase of ENSO evidence an interesting
4 negative feedback of the land-surface on the effect of ENSO on the rainfall over India.

5 The third PC of the PRE forced by the SM, explaining 8% of forced variance, displays a trend
6 (Fig. 5a) corresponding to a clear signal of increasing precipitation over the Sahel, South-East
7 Europe, Central Asia, North-East Asia, the Great Plains of North America, Nordeste and the
8 Northern part of South America (Fig. 5b). The trend of increasing precipitation is particularly
9 strong over the Sahel where, according to Hagos and Cook (2008), it can be related to a
10 warming of the northern tropical Atlantic Ocean which, through a modification of the
11 associated cyclonic circulation, enhances moisture transport over the region. In contrast, a
12 decrease of precipitation is evident over most of the Southern Hemisphere (SH), North West
13 Russia, East Russia, North India, China and West US, showing a north-south polarity of the
14 precipitation trend. The above trend pattern strongly resembles the trend pattern of global
15 rainfall annual mean anomalies described by Munemoto and Tachibana (2012, hereinafter
16 MT12). The authors associated this North-South polarity to a relatively larger warming of the
17 Northern Hemisphere (NH) compared to the SH that characterized the last three decades
18 starting from the early 1980s. MT12 found that the trend of the SST corresponds to an
19 increase of the specific humidity in the NH with respect to SH that enhances (reduces)
20 precipitation in the NH (SH). Although the focus of MT12 is on the Sahel region, the authors
21 defined a global index, the North South SST (NS-SST) polarity index, which successfully
22 captures the global signal of the precipitation trend. The NS-SST index is defined as the area
23 averaged NH SST annual mean anomalies minus the SH SST anomalies. The NS-SST index
24 (computed from HadISST), normalized by its standard deviation, and its trend are plotted in
25 Fig. 5a. Note that here the NS-SST index is computed from the seasonal mean anomalies
26 instead of the annual mean anomalies used in MT12, nonetheless the trend is not affected.

27 **4.2 Mediation effects of ET and LAI on the coupling between PRE and SM**

28 To investigate how the coupling between rainfall and soil moisture is mediated by
29 evapotranspiration and vegetation we further applied the CM technique between the
30 component of PRE forced by SM and ET (LAI), obtaining the component of PRE forced by
31 SM which is also forced by ET (LAI). As summarized in Table 5, 20% of the inter-annual
32 variability of the PRE anomalies forced by the SM is estimated to be globally forced by the

1 ET variation. It is important to note here that $19\% \times 20\% = 3.8\%$ represents only the ET forcing
2 on PRE mediated by SM and not the whole ET forcing on PRE which is actually 18% (Table
3 2). At the same time, 23% of the variance of PRE forced by SM is evaluated to be also forced
4 by LAI, therefore the LAI forcing on PRE mediated by SM corresponds to $17\% \times 23\% = 3.9\%$.

5 Fig. 6a shows the ratio of the variance of PRE forced by the SM which is also forced by the
6 ET with respect to the total forced rainfall variance. Fig. 6b shows the same plot but for the
7 LAI. The “hotspots” in Fig. 6a are similar to those found in Fig. 2b over Sahel, Horn of
8 Africa, East Europe, Asian boreal forests, Central Asia, West Coast of the US, East Brazil and
9 La Plata basin. This indicates that in all these regions the link between PRE and SM is at least
10 in part mediated by ET. Not surprisingly, the same regions also display a link with vegetation
11 (Fig. 6b). Furthermore, vegetation appears to significantly affect rainfall variability over the
12 semi-arid regions that are not dependent on ET such as Central West Asia, South-East Africa,
13 South-East Asia and West Australia, suggesting that in these regions the SM forcing on PRE
14 is mediated by vegetation state (e.g. stress of vegetation will affect PRE there).

15 To analyse how the response of PRE forced by SM to climate events and the trend are
16 mediated by ET (LAI), we applied the CM technique between each of the physical fields
17 corresponding to the first three modes of variability of PRE forced by the SM and ET (LAI).
18 Here we take the physical fields corresponding to the first three modes of variability of PRE
19 forced by SM and further decompose them to extract the parts of each mode that is forced by
20 ET and LAI, respectively. This analysis allows to figure out how ET and LAI contribute to
21 each component of PRE forced by SM which has been identified to be linked to external
22 climate forcing (volcanic eruptions, ENSO and trend). Overall, considering the global land,
23 21% of the variance displayed by the first mode (linked to volcanic eruptions) of PRE forced
24 by the SM is forced by the ET and 27% by LAI (Table 6). As for the second mode (connected
25 to ENSO), 38% of the variance is forced by ET and 36% by LAI. Concerning the third mode
26 (displaying a trend), 31% of the variance is forced by ET and 29% is forced by LAI. Rainfall
27 variability forced by the ET and LAI decomposed through EOF analysis is reported in Table
28 7. Interestingly, the third PC of the PRE forced by the ET (explaining 7% of the forced
29 variance) is correlated with AOD, with a maximum correlation coefficient of 0.41 at lag 6.
30 Analogously, the second PC of the PRE anomalies forced by the LAI (explaining 10% of the
31 forced variance) is correlated with AOD, with a maximum correlation coefficient of 0.41 at
32 lag 3, suggesting that both ET and vegetation contribute to provide memory of volcanic

1 eruptions, modulating at longer scales the effect of the SM forcing on PRE. The first PC of
2 PRE forced by ET (explaining 30% of the forced variance) is found to be significantly
3 correlated with the NINO3 index with a correlation coefficient of 0.52 at lag 0. The first PC
4 of PRE forced by LAI (explaining 27% of the forced variance) also has a maximum
5 correlation coefficient of 0.67 at lag 0 with the NINO3 index, indicating that vegetation acts
6 as the mediator at longer scales of the signal between SM and PRE. This result is consistent
7 with the relationship found by Alessandri and Navarra (2008) between precipitation forced by
8 vegetation (NDVI) and ENSO and with the delayed vegetation response to ENSO signal
9 found by Zeng et al. (2005). All the above correlation coefficients passed a significance test at
10 1% level.

11 To determine the regions where the mediating effects of ET and LAI have the larger influence
12 on the coupling with respect to the stratospheric volcanic eruptions, the first mode of
13 variability of PRE forced by the SM has been correlated with the total components of PRE
14 forced by the ET and LAI. The correlation coefficients are shown in Fig. 7a for PRE forced
15 by the ET and Fig. 7b for PRE forced by the LAI. Only the regions where correlations passed
16 a significance test at 5% level are shaded. Black upward (white downward) triangles denote
17 areas with positive (negative) values of the first EOF of the PRE anomalies forced by the SM
18 (Fig. 3c). The correlations are positive almost everywhere (i.e. the effects of both ET and LAI
19 tend to amplify the response of rainfall to large volcanic eruptions) and the patterns are very
20 similar for ET and LAI, indicating that the feedback of ET may be linked to the stress of
21 vegetation consequent to the effect of volcanic eruptions on radiative forcing. Large values
22 (up to 0.6) are seen over Central US, North West Brazil, La Plata basin, West Central Asia,
23 Horn of Africa, South Africa, the Asian monsoon region, Indonesia and Australia. Over these
24 regions evapotranspiration and vegetation activity are radiation limited (Seneviratne et al.,
25 2010). Nevertheless, while over some regions (Southern part of North America, La Plata
26 basin, Middle East, West Central Asia and Horn of Africa) ET and LAI contribute to an
27 increase of rainfall, over other regions (Northern South America, South Africa, Indian
28 monsoon region, Australia) they contribute to rainfall reduction. As discussed in Section 4.1,
29 over most of the SH (apart from La Plata basin and Horn of Africa) and the Asian monsoon
30 region there is a reduction of precipitation that can be associated to the dimming effect and
31 the consequent reduction of the hydrological cycle. In humid regions the rainfall reduction
32 can stress vegetation and may reduce its growth with effects lasting up to one year (Wang et
33 al., 2011b). On the other hand, over most of the arid and semi-arid regions (Middle East, West

1 Central Asia), the reduced evapotranspiration during past seasons induced by the dimming
2 effect may increase SM and therefore attenuate the stress on vegetation. This, in turn, has a
3 positive effect on precipitation.

4 The point-by-point correlation coefficient between the second mode of variability (related to
5 ENSO) of PRE forced by the SM and the total field of PRE forced by the ET is shown in Fig.
6 8a. The correlation between the second mode of PRE forced by the SM and the total field of
7 PRE forced by the LAI is shown in Fig. 8b.~~The point-by-point correlation coefficient between~~
8 ~~the second mode of variability (related to ENSO) of PRE forced by the SM and the total fields~~
9 ~~of PRE forced by the ET and PRE forced by the LAI is shown in Fig. 8 on panel a and b,~~
10 ~~respectively.~~ The sign of the feedback between PRE and SM is indicated by the second EOF
11 of PRE forced by the SM overlaid to the plot. Large positive correlations up to 0.6 are found
12 globally over most of the land areas. ET has a positive feedback on the increase of
13 precipitation over the West Coast of US, the dry and semi-arid region of North Venezuela, La
14 Plata basin, Sahel, North Europe, India, Central and East Asia and the South-East Coast of
15 Australia. Still a positive feedback is present over Brazil, South Africa and Indochina but in
16 this case ET leads to further reduction of PRE. A negative feedback of ET is seen over
17 Mexico. In this region the positive ENSO phase induces wet and cool conditions (Trenberth et
18 al., 1998) associated to an increase of PRE forced by SM that is contrasted by a reduction of
19 ET. As for vegetation, it contributes to rainfall enhancement over East and West Coasts of the
20 US, La Plata basin, North Europe, Horn of Africa, the semi-arid region of West Central Asia
21 and East Asia. Conversely, vegetation mediates precipitation reduction over Brazil, South
22 Africa and Indochina.

23 Fig. 9 shows the point-by-point correlation coefficient between the third mode of variability
24 of PRE forced by the SM (displaying a linear trend, see Fig. 5) and the total fields of PRE
25 forced by the ET (Fig. 9a) and PRE forced by the LAI (Fig. 9b) with the third EOF of PRE
26 forced by the SM overlaid on it. The feedback of ET on this mode of variability of PRE is not
27 significant over most of the NH. A positive effect of ET is seen over the semi-arid regions of
28 the SH but while over Sahel ET mediates an increase of rainfall, over Bolivia and Australia
29 ET leads to further reduction of PRE (Fig. 9a). On the other hand, ET has a negative feedback
30 over the humid region of Tanzania where it contrasts the reduction of PRE. The pattern of the
31 feedback of LAI (Fig. 9b) is very different from that of ET. Overall, the vegetation has a
32 positive feedback on the rainfall anomaly pattern forced by the SM. In particular, large

1 correlations up to 0.6 are seen over the Sahel, East Coast of the US, West South America,
2 East Europe, Tropical South Africa, West Central Asia, Asian boreal forests, Central and East
3 Asia, the Indian monsoon region and East Australia. The strong signal over the Sahel is in
4 agreement with Zeng et al. (1999) and Kucharski et al. (2013) who found that vegetation
5 feedback amplifies rainfall response to the SST variations on the decadal scale. LAI mediates
6 rainfall enhancement over the Sahel, East Coast of the US, Europe, the semi-arid region of
7 West Central Asia and the Indian monsoon region. Conversely, vegetation contributes to a
8 reduction of PRE over most of the SH (in particular over South America, South Africa and
9 East Australia), the West Coast of the US and East Asia. Fig. 9c shows the linear vegetation
10 trend over the period 1982-2010. Only areas where trend passed a significance test at the 5%
11 level are shown. Significant positive (greening) trend is seen in large parts of the NH (the East
12 Coast of the US, Sahel, Europe, West Central Asia, India and Asian boreal forests). A
13 negative vegetation trend (browning) appears over the West Coast of the US, West South
14 America, the tropical region of South Africa and East Asia. The greening/browning trends in
15 Fig. 9c are consistent with those found by de Jong et al. (2013). A comparison of panels b and
16 c of Fig. 9 evidences that most of the areas characterized by a positive trend of rainfall
17 anomalies are associated to a greening trend of vegetation while areas displaying a decrease
18 of PRE are regions associated to a browning trend. Therefore, the response of rainfall
19 anomalies forced by the SM to the inter-hemispheric SST trend appears to be coupled to a
20 greening/browning trend of vegetation activity. Furthermore, the third PC of PRE forced by
21 LAI displays a trend similar to that of the NS-SST index, analogously to the third PC of PRE
22 forced by SM, while no trends are found in the first five PCs of PRE forced by ET.

23

24 **5 Conclusions**

25 A global array of relevant up-to-date high quality datasets (soil moisture, evapotranspiration,
26 leaf area index and precipitation) is acquired, harmonized and analysed. For the first time a
27 long comprehensive global observational dataset is used to characterize the land variability as
28 a function of the space and time scales and to improve understanding of the relationships and
29 feedbacks between land and climate. By applying the Coupled Manifold technique on the
30 seasonal-mean inter-annual anomalies, the relationship and the coupling between the acquired
31 surface variables is assessed considering all the seasons.

1 The analysis shows a considerable degree of reciprocal forcing and coupling in the land
2 surface variables considered. The reciprocal forcing with precipitation is particularly strong
3 for the soil moisture, with 19% of the inter-annual variability of the precipitation over
4 continental areas that are forced by the SM variation. Conversely, 17% of the SM variance is
5 forced by PRE.

6 The PRE forced by the SM is dominated by a prominent decadal-scale drying, initiated by the
7 perturbation of the abrupt Mt. Pinatubo eruption. In 1991, the PC1 of the dominant forced
8 mode of PRE shows an abrupt decrease and the negative anomaly continues increasing in the
9 subsequent years until 1994. It is only after 1995 that the rainfall starts to slowly recover
10 towards the pre-eruption levels. In 1997, the signal sums-up with that of ENSO. It appears
11 that the persistence of the negative SM anomalies leads to increasing stress conditions for the
12 vegetation, thus leading to a larger ET response at longer time-lags after the perturbing event.
13 Our interpretation is that the persistence of the negative SM anomalies provides the memory
14 of the initial perturbing event and our analysis indicate that, through this mechanism, the
15 effect of Mt. Pinatubo eruption can last for several years and its memory appears to extend
16 and sum to the following 1997-1998 El Niño event. The second PC of the PRE forced by the
17 SM displays a large-scale oscillation correlated to ENSO variability with significant
18 correlations enduring behind the autocorrelation period of ENSO itself and up to more than
19 one year lag. This indicates that ENSO effects on SM induce a delayed forcing on PRE. The
20 third PC of the PRE forced by the SM is dominated by a trend, positive over most of the NH
21 and negative over most of the SH. This trend appears to be related to the inter-hemispheric
22 SST contrast to which corresponds an increase of the specific humidity in the NH with respect
23 to the SH that enhances (reduces) precipitation and SM in the NH (SH).

24 The combined analysis of the PRE modes related to the external climate forcings (volcanic
25 eruptions, ENSO, SST trend) and the rainfall forced by ET and LAI evidences the role of ET
26 and LAI as the mediators between SM forcing and rainfall. In particular, it appears that both
27 ET and LAI tend to provide a positive feedback on PRE over most of the regions,
28 contributing to further enhance or reduce rainfall depending on the regions of the globe, with
29 large differences between wet, transition and semi-arid climates. Nevertheless, the response to
30 ENSO is characterized by a negative feedback of ET over regions where the positive ENSO
31 phase induces wet and cool conditions (i.e. Mexico).

1 It is important to note that the coupling with SM revealed by the present analysis has to be
2 considered an underestimation of the real coupling, due to the incomplete cover of the SM
3 dataset. Nevertheless, the present investigation identifies the regions characterized by a strong
4 coupling and suggests most possible mechanisms linking the considered variables.

5 Since SM has been recognized as the most important land-surface parameter affecting
6 seasonal to interannual variability of precipitation (Koster et al., 2000; Zhang et al., 2008) the
7 present paper focused on the coupling between SM and PRE. Detailed analysis of the
8 reciprocal forcing between ET and LAI, LAI and SM and ET and SM will be the subject a
9 future paper that will further address the specific coupling among land-surface variables.

10

11 **Data availability**

12 Evapotranspiration dataset available from the Numerical Terradynamic Simulation Group
13 (NTSG) of the University of Montana. Web: <http://www.ntsg.umt.edu/project/et>

14 Leaf Area Index dataset available from the Department of Earth & Environment of Boston
15 University. Web: <http://sites.bu.edu/cliveg/datacodes/>

16 Soil Moisture dataset available from the European Space Agency (ESA) Climate Change
17 Initiative (CCI). Web: <http://www.esa-soilmoisture-cci.org/>

18 Precipitation dataset available from the Global Precipitation Climatology Project (GPCP).
19 Web: <http://precip.gsfc.nasa.gov/>

20 Aerosol Optical Depth dataset available from the National Aeronautics and Space
21 Administration (NASA) Goddard Institute for Space Studies (GISS). Web:
22 <http://data.giss.nasa.gov/modelforce/strataer/>

23 Sea Surface Temperature dataset available from the Hadley Centre for Climate Prediction and
24 Research (2006): Met Office HadISST 1.1 (Global sea-Ice coverage and Sea Surface
25 Temperature). Web: <http://catalogue.ceda.ac.uk/uuid/facafa2ae494597166217a9121a62d3c>

26

27 **Acknowledgements**

28 The research leading to these results has received funding from the European Union Seventh
29 Framework Programme (FP7/2007- 2013) under SPECS project (grant agreement n° 308378)

1 and by the LIFE10 ENV/FR/208 project FO3REST. We are grateful to the two anonymous
2 reviewers whose comments greatly improved the quality of the manuscript.
3

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6

1 Table 1. Evapotranspiration (ET) [~~Zhang et al., 2010~~], Leaf Area Index (LAI) [~~Zhu et al.,~~
2 ~~2013~~], Soil Moisture (SM) [~~Liu et al., 2011, 2012~~], Precipitation (PRE) [~~Adler et al., 2003~~]
3 datasets characteristics.

	ET	LAI	SM	PRE
T ype	satellite	satellite	satellite	gridded from rain gauges
V ersion	-	1.0	0.1	2.2
P roducer	University of Montana	Boston University	ESA	GPCP
Spatial resolution (original)	1° x 1°	8 km x 8 km	0.25° x 0.25°	2.5° x 2.5°
Spatial resolution (after pre-processing)	1° x 1°	0.5° x 0.5°	0.5° x 0.5°	2.5° x 2.5°
Temporal frequency (original)	monthly	15-days	daily	monthly
Temporal frequency (after pre-processing)	seasonal	seasonal	seasonal	seasonal
U nits	W m ⁻²	m ² m ⁻²	m ³ m ⁻³	mm d ⁻¹
P eriod	1983-2006	1982-2010	1979-2010	1979-2010
R eference	Zhang et al. (2010)	Zhu et al. (2013)	Liu et al. (2011, 2012)	Adler et al. (2003)

4
5

1 Table 2. Ratios of the global-scale forced and free variance with respect to the total variance
2 resulting from the application of the CM technique between PRE and SM, ET and LAI.

	Forced	Free
SM	0.17	0.83
PRE	0.19	0.81
ET	0.14	0.86
PRE	0.18	0.82
LAI	0.14	0.86
PRE	0.17	0.83

3

4

1 Table 3. PRE variability forced by the SM decomposed through EOF analysis. Each line
 2 displays the EOF explained variance (column 2) and the corresponding PC correlation with
 3 relevant climatic indices (column 3). AOD is the Stratospheric Aerosol Optical Depth.
 4 NINO3 index is defined as the average of the Sea Surface Temperature in the tropical Pacific
 5 region (5° S–5° N, 210–270° E). Here the maximum PC correlation is reported considering
 6 lagged correlations in the range -16 to +16. Only the correlation coefficients significant at 1%
 7 level are reported.

	Variance explained	Correlation with climate indices
PC 1	0.26	0.56 (AOD) at lag 0 (significant in the range: -4/+7)
PC 2	0.14	0.60 (NINO3) at lag 2 (significant in the range: 0/+5)
PC 3	0.08	-
PC >4	<0.07	-

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1 Table 4. Total rainfall variability decomposed through EOF analysis. Each line displays the
 2 EOF explained variance (column 2) and the corresponding PC correlation with relevant
 3 climatic indices (column 3). Here the maximum PC correlation is reported considering lagged
 4 correlations in the range -16 to +16. Only the correlation coefficients significant at 1% level
 5 are reported.

	Variance explained	Correlation with climate indices
PC 1	0.10	0.41 (AOD) at lag 0 (significant in the range: -2/+2)
PC 2	0.05	0.43 (NINO3) at lag 2 (significant in the range: +1/+4)
PC >3	<0.04	-

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1 Table 5. Ratios of the global-scale forced and free variance with respect to the total variance
2 resulting from the application of the CM technique between PRE forced by SM and ET, LAI.

	Forced	Free
PRE forced by SM (forced by ET)	0.20	0.80
PRE forced by SM (forced by LAI)	0.23	0.77

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1 Table 6. Ratios of the global-scale forced variance over the total variance resulting from the
 2 application of the CM technique between the first three modes of PRE forced by SM and the
 3 total fields of ET and LAI.

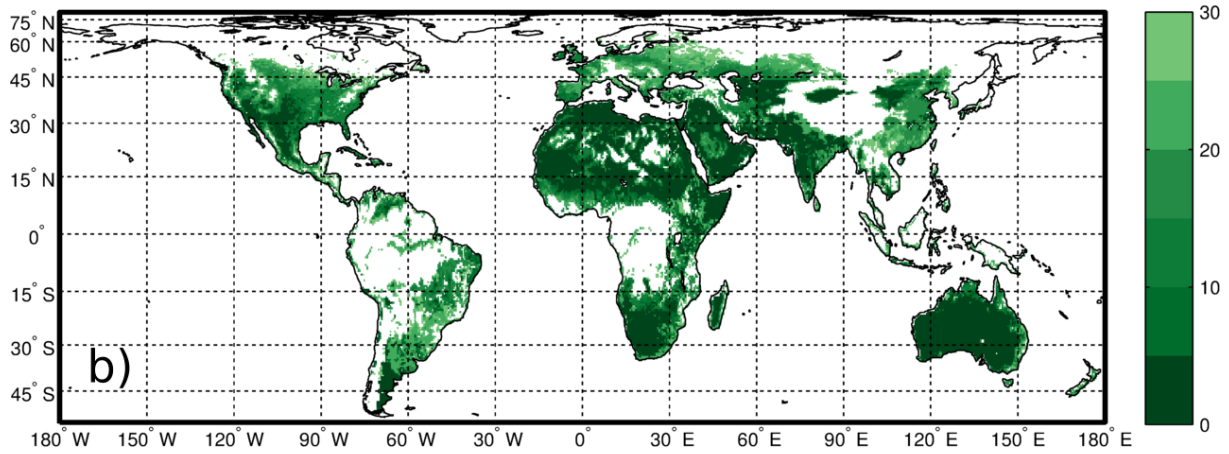
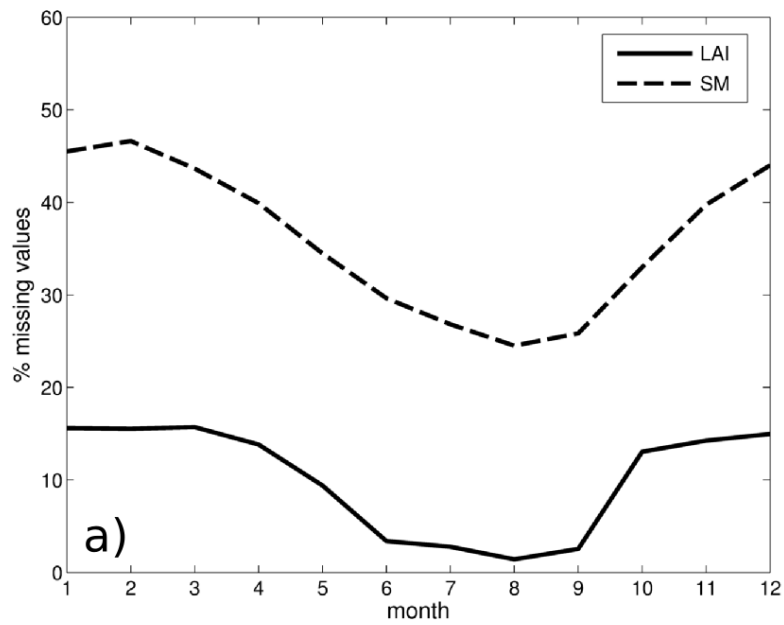
	ET	LAI
PRE forced by SM mode 1	0.21	0.27
PRE forced by SM mode 2	0.38	0.36
PRE forced by SM mode 3	0.31	0.29

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1 Table 7. Rainfall variability forced by the ET and LAI decomposed through EOF analysis.
 2 Each line displays the EOF explained variance (column 2) and the corresponding PC
 3 correlation with relevant climatic indices (column 3). Here the maximum PC correlation is
 4 reported considering lagged correlations in the range -16 to +16. Only the correlation
 5 coefficients significant at 1% level are reported.

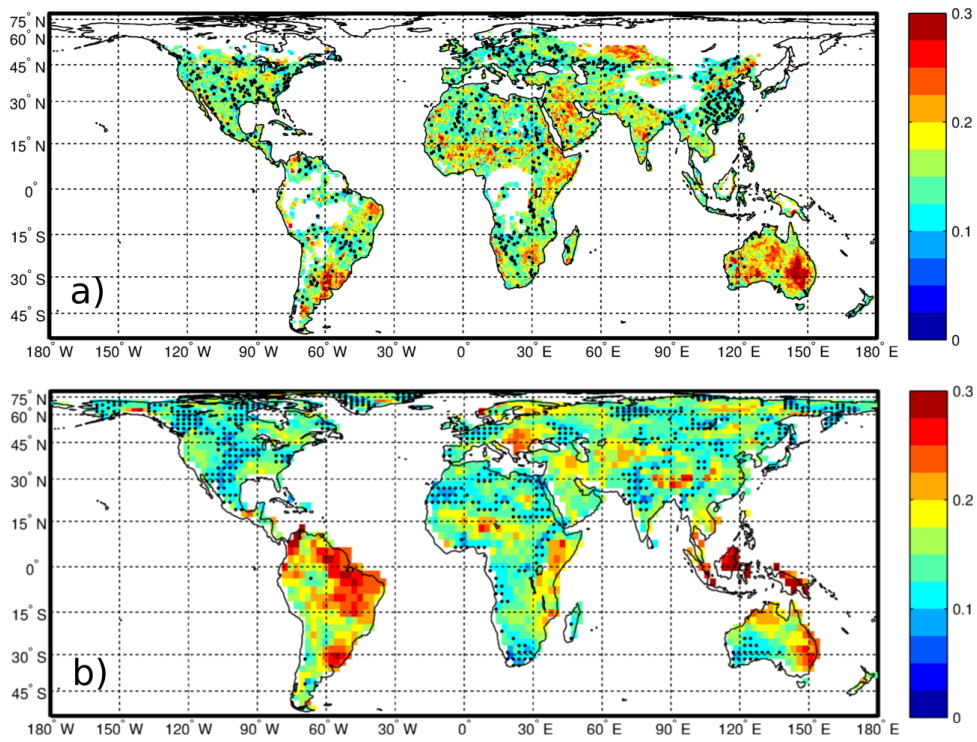
	Variance explained	Correlation with climate indices
PRE forced by ET		
PC 1	0.30	0.52 (NINO3) at lag 0 (significant in the range: -2/+2)
PC 2	0.13	-
PC 3	0.07	0.41 (AOD) at lag 6 (significant in the range: +3/+10)
PC >4	<0.05	-
PRE forced by LAI		
PC 1	0.27	0.67 (NINO3) at lag 0 (significant in the range: -2/+2)
PC 2	0.10	0.41 (AOD) at lag 3 (significant in the range: 0/+5)
PC 3	0.09	-
PC >4	<0.06	-

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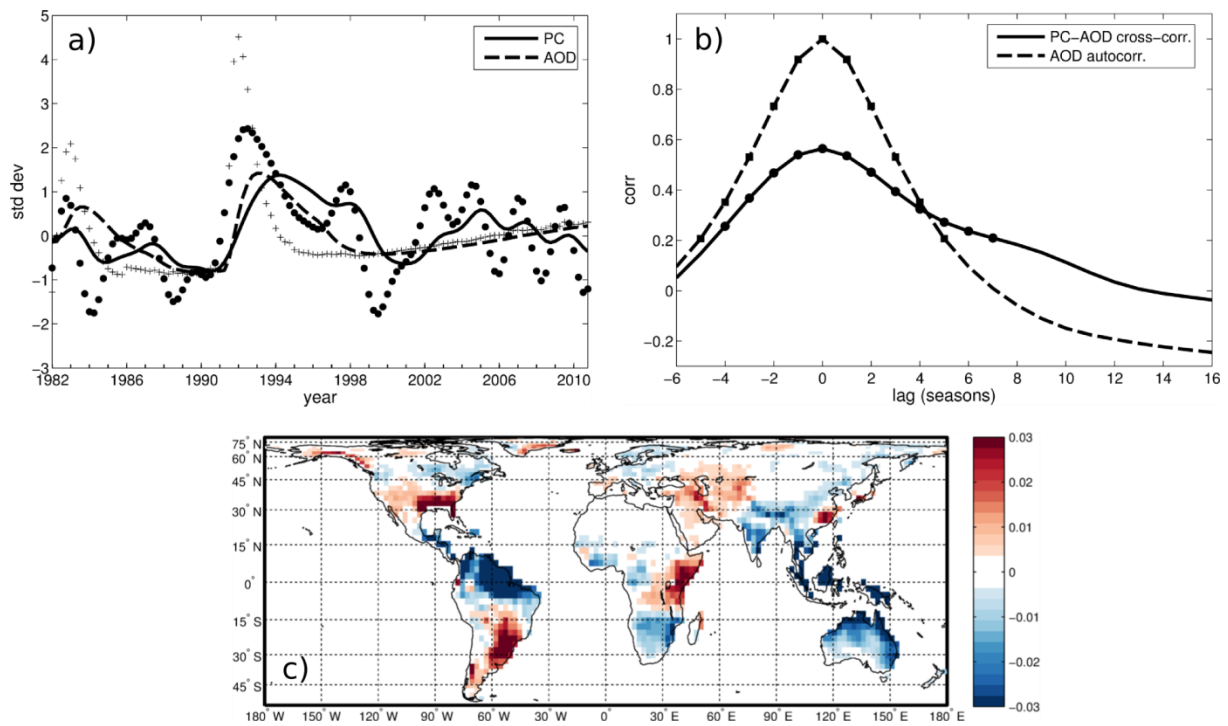
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Figure 1. (a) Global mean missing values in the time series (in %): LAI (full), SM (dashed).
 (b) Map of the percentage of SM missing data for each grid point. All grid points with a percentage of missing number larger than 30% (white areas in panel b) have not been considered in the analysis.



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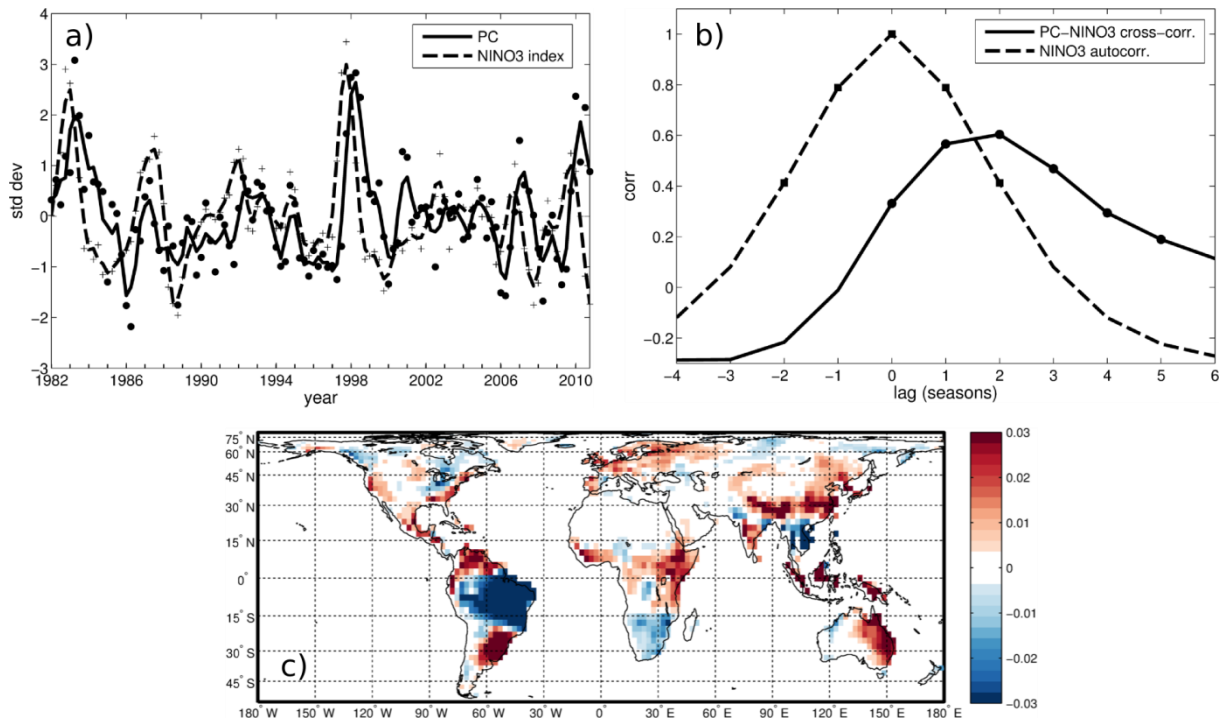
Figure 2. Ratio of the forced variance to the total variance. (a) The fraction of SM variance forced by PRE. (b) The fraction of PRE variance forced by the SM. Dots are placed over areas covered by the forced variable dataset but where variance ratio values did not pass a significance test at the 1% level.



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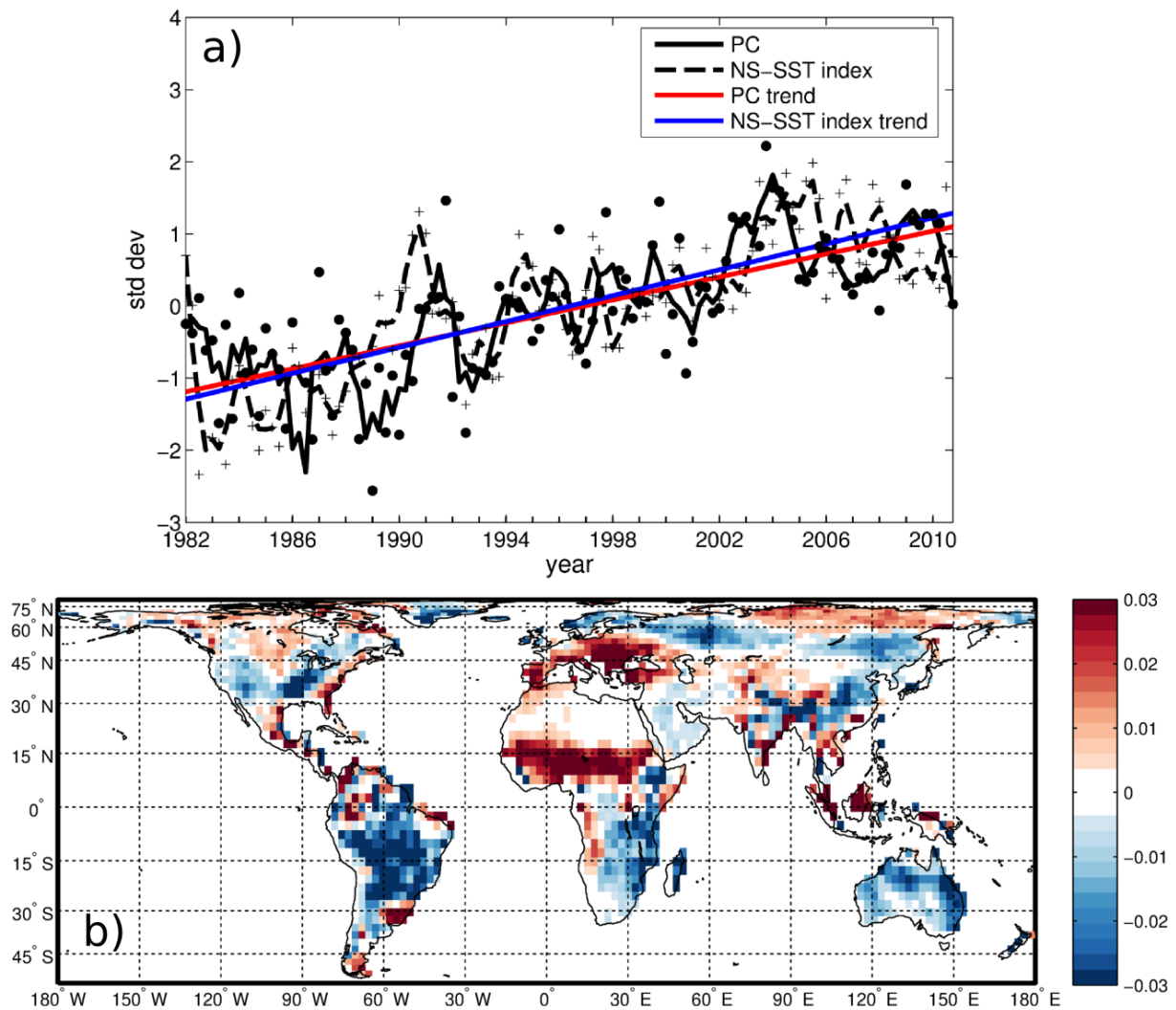
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3 Figure 3. (a) First normalized PC of the PRE anomalies forced by the SM (full line and filled
 4 circles), after cutoff low-pass filtering at 2 year-1 frequency. Dashed line (and cross marks)
 5 stands for the normalized stratospheric Aerosol Optical Depth (AOD). Lines stand for 5-years
 6 exponential moving average while marks represent each single season. (b) Lagged
 7 correlations between AOD and PC1 of the forced PRE. The dashed curve is the
 8 autocorrelation function of the AOD. Marks indicate significance at the 5% level. (c) First
 9 EOF of the forced PRE. Arbitrary units.



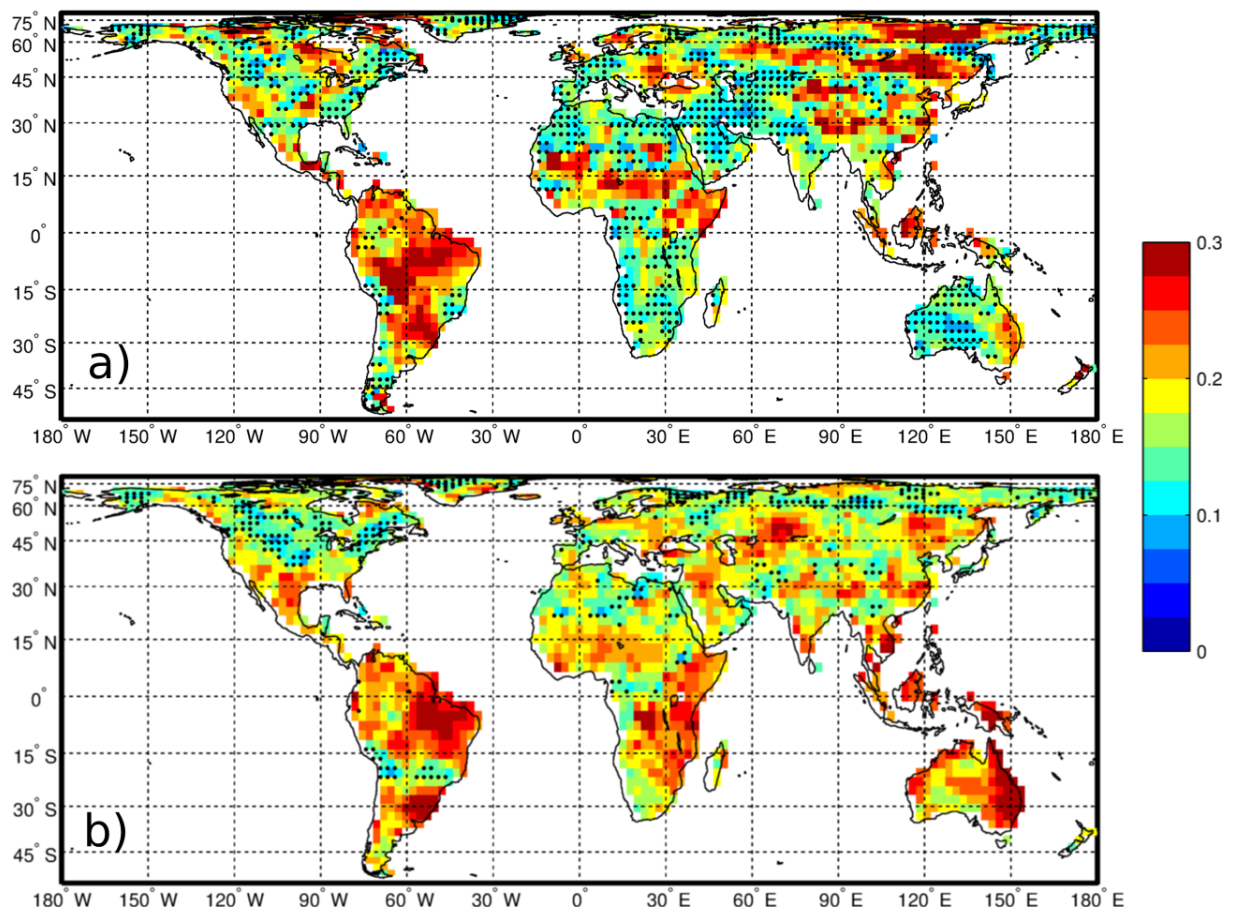
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Figure 4. (a) Second normalized PC of the PRE anomalies forced by the SM (full line and filled circles). Dashed line (and cross marks) stands for the normalized NINO3 index. Lines stand for 3-seasons running means while marks represent each single season. (b) Lagged correlations between NINO3 index and PC1 of forced PRE. The dashed curve is the autocorrelation function of the NINO3 index. Marks indicate significance at the 5% level. (c) Second EOF of the forced PRE. Arbitrary units.



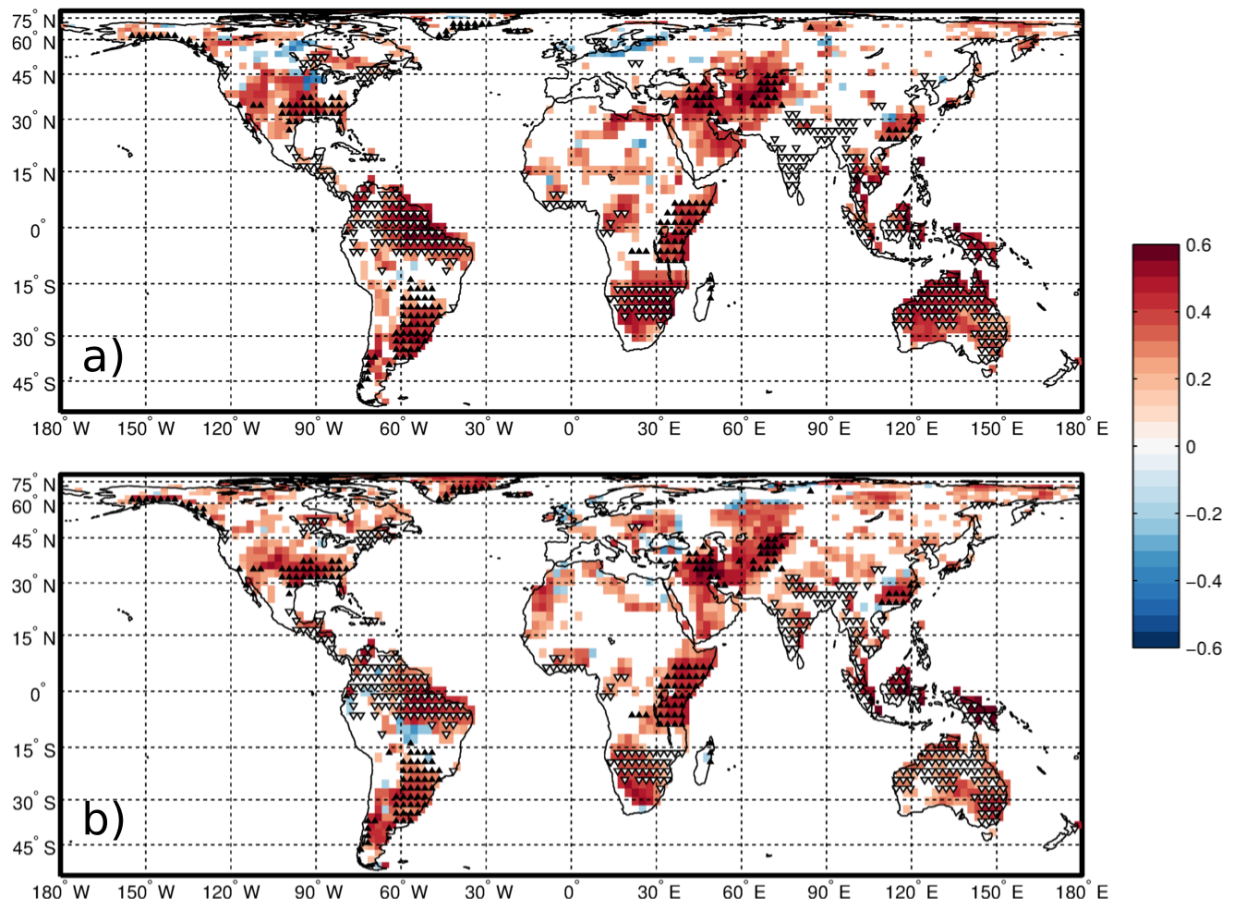
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Figure 5. (a) Third normalized PC of the PRE anomalies forced by the SM (full line and filled circles). Dashed line (and cross marks) stands for the normalized NS-SST index. Lines stand for 3-seasons running means while marks represent each single season. Coloured lines represent the trends (red for the PC, blue for the NS-SST index). (b) Third EOF of the forced PRE . Arbitrary units.



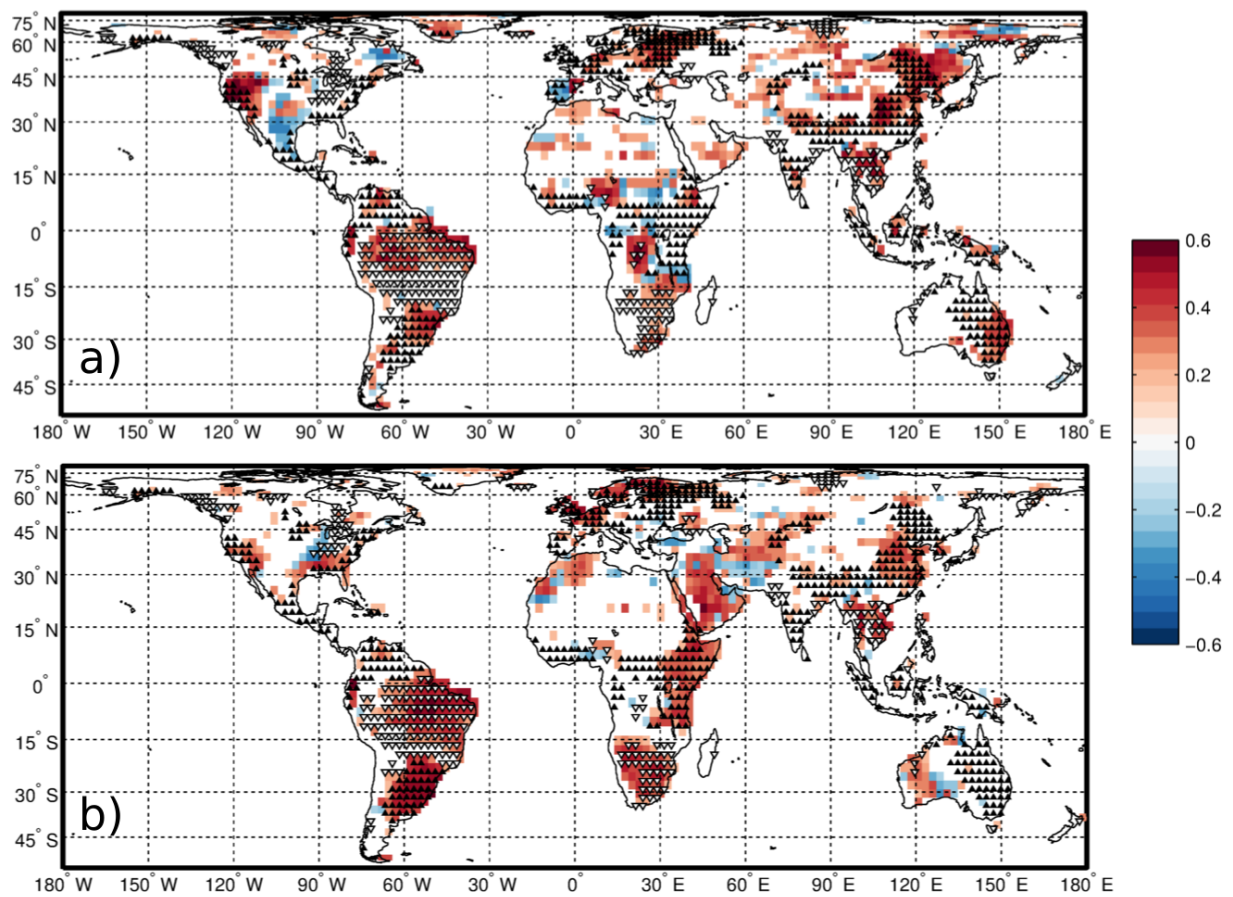
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Figure 6. Ratio of the forced variance to the total variance. (a) The fraction of PRE variance forced by the SM which is also forced by the ET. (b) The fraction of PRE variance forced by the SM which is also forced by the LAI. Dots are placed over areas where variance ratio values did not pass a significance test at the 1% level.



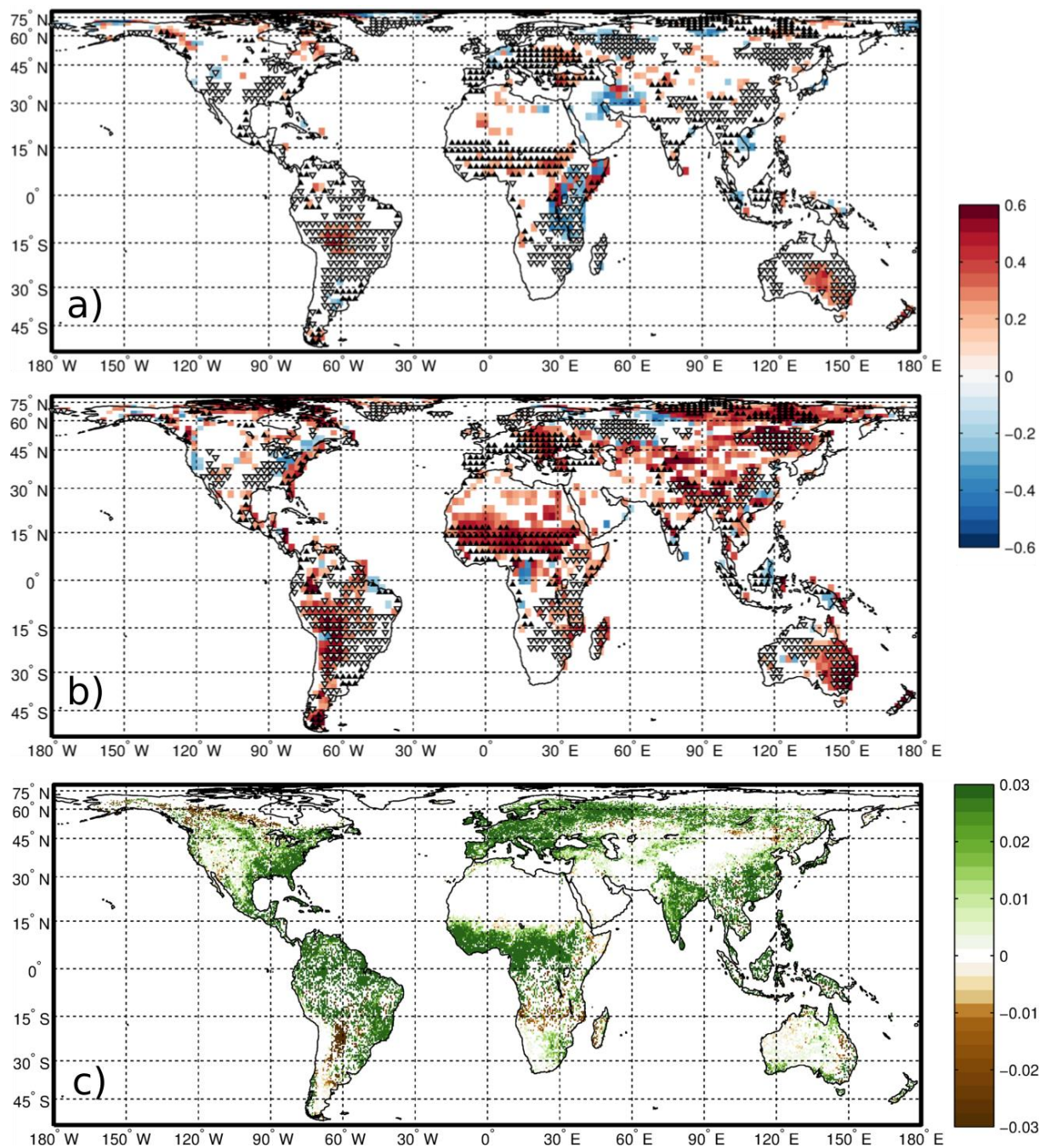
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Figure 7. Point-by-point correlation of the first mode of variability of PRE forced by SM with (a) the total fields of PRE forced by ET and (b) the PRE forced by LAI. Data have been filtered using a cutoff low-pass filter at 1 year frequency. Only areas where correlations passed a significance test at the 5% level are shown. Black upward (white downward) triangles denote areas with positive >0.01 (negative <-0.01) values of the first EOF of the PRE anomalies forced by the SM (Fig. 3c).



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Figure 8. Point-by-point correlation of the second mode of variability of PRE forced by SM with (a) the total fields of PRE forced by ET and (b) the PRE forced by LAI. Data have been filtered using a cutoff low-pass filter at 1 year frequency. Only areas where correlations passed a significance test at the 5% level are shown. Black upward (white downward) triangles denote areas with positive >0.01 (negative <-0.01) values of the second EOF of the PRE anomalies forced by the SM (Fig. 4c).



1

2

3 Figure 9. Point-by-point correlation of the third mode of variability of PRE forced by SM on
 4 the total field of (a) PRE forced by ET and (b) PRE forced by LAI. (c) Magnitude of the LAI
 5 change over 1982-2010, quantified using a linear model under the assumption of monotonic
 6 change. Data have been filtered using a cutoff low-pass filter at 1 year⁻¹ frequency. Only
 7 areas where correlations (panels a-b) and trend (panel c) passed a significance test at the 5%
 8 level are shown. Black upward (white downward) triangles denote areas with positive >0.01
 9 (negative <-0.01) values of the third EOF of the PRE anomalies forced by the SM (Fig. 5b).