Journal of Climate

Interannual coupling between summertime surface temperature and precipitation over land: processes and implications for climate change

--Manuscript Draft--

Manuscript Number:	JCLI-D-14-00324
Full Title:	Interannual coupling between summertime surface temperature and precipitation over land: processes and implications for climate change
Article Type:	Article
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Abstract:	Widespread negative correlations between summertime-mean temperatures and precipitation over land regions are a well-known feature of terrestrial climate. This behavior has generally been interpreted in the context of soil moisture-atmosphere coupling, with soil moisture deficits associated with reduced rainfall leading to enhanced surface sensible heating and higher surface temperature. The present study revisits the genesis of these negative temperature-precipitation correlations using simulations from the Global Land-Atmosphere Coupling Experiment - Coupled Model Intercomparison Project phase 5 (GLACE-CMIP5) multi-model experiment. The analyses are based on simulations with 5 climate models, which were integrated with prescribed (non-interactive) and with interactive soil moisture over the period 1950-2100. While the results presented here generally confirm the interpretation that negative correlations between seasonal temperature and precipitation arise through the direct control of soil moisture on surface heat flux partitioning, the presence of widespread negative correlations when soil moisture-atmosphere interactions are artificially removed in at least two out of five models suggests that atmospheric processes, in addition to land surface processes, contribute to the observed negative temperature-precipitation correlation. On longer timescales, the negative correlation between precipitation and temperature is shown to have implications for the projection of climate change impacts on near surface climate: in all models, in the regions of strongest temperature-precipitation anti-correlation on interannual timescales, long-term regional warming is modulated to a large extent by the regional response of precipitation to climate change, with precipitation increases (decreases) being associated with minimum (maximum) warming. This correspondence appears to arise largely as the result of soil-moisture atmosphere interactions.

We thank the reviewers for their comments on the manuscript. Below are our answers to the comments.
Please note that the manuscript has been reorganized, figures added or removed, their order changed. For the sake of consistency with the reviewers' comments, unless otherwise stated references to figure or section number in our reply below refer to the initial version of the manuscript.

The main changes brought to the manuscript are as follows:

- The manuscript was reorganized (section 4, figures order) and the steps of the analysis clarified to account for reviewer #1's comment on the perceived redundancy of the analysis in our initial manuscript;
- Following reviewer #3's recommendation, temperature-precipitation correlations from observations were added to the analysis;
- Following reviewer #1 and #3 comments, all figures were reworked; correlation maps use a different color scale emphasizing statistical significance, and where non-significant values are not shown. The field significance of temperature-precipitation correlations was assessed.

Reflecting these changes, the text has been modified extensively throughout the manuscript.
Also, note that observations of T-P correlations added to the study were found to be sensitive to linear detrending. Because the focus was on interannual variability, we show linearly detrended results. For the sake of consistency, all model results are then presented detrended as well in the revised manuscript. Small quantitative differences with the initial results thus exist, however the main results of the analysis remain qualitatively unaffected.
Please note that we also clarified the title of the manuscript, adding "over land".

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Reviewer Comments included in this letter:
Reviewer #1: The authors provide an analysis of long term climate simulations that isolate the mechanisms underlying precipitation-temperature correlations. The paper is well-written, and I don't have any real problem with the science. The paper, though, is much longer than it needs to be (comment #1), which detracts from its usefulness. I recommend publication subject to minor revision, though the length issue may, in some ways, suggest major revision.
1. The main result of the paper is that over much of the world, low (high) precipitation rates lead to low (high) evaporation rates which in turn lead to high (low) temperatures, while a secondary mechanism (cloudiness associated with both increased precipitation and reduced incident radiation) can also be important in some situations. That's fine, and the multi-model demonstration of this seems worthy of documentation. However, this result is effectively presented several times, through different methods of processing the same data (map comparisons, histograms, binning, examination of temperature/evaporation correlations, examination of radiation/precipitation correlations, etc.). The reader will be convinced very early on of the paper's main result and doesn't particularly benefit from seeing the same result pop out of additional processing methods. Personally, I didn't learn much of anything from Figures 3-8 that wasn't already demonstrated or implied reasonably well
in Figure 2.
Should the authors get rid of Figures 3-8? Maybe not all of them. Figure 3 is a nice summary and doesn't take up much room. Figures 4 and 5 show some potentially useful supporting information but do take up a lot of room; could multi-model averages be shown instead, given that model differences are not emphasized here, except for a few asides? As for Figures 6-7, I'll admit that they don't do anything for me. It's an interesting way to look at the data, but the information content is essentially the same as that of the earlier figures, so the reader has to do a lot of work for little gain. Figure 8 provides more supporting data, but again, the main findings were already presented, and I'm not fully convinced that the supporting data is needed.

While we agree with the reviewer's comment that Figure 2 already neatly contained the main results of the study, we still think figures 3-8 add value to the analysis and are actually necessary to explain the results in figure 2. We take the reviewer's comment here as showing that we failed to clearly define and separate the different parts of the analysis and their respective contributions:

- Figure 2 shows negative T-P correlations are reduced in all models from REF to expA, but subsist significantly in some models. Our *a priori* interpretation of Figure 2 is that soil moisture-atmosphere interactions have been disabled in expA by the suppression of interactive soil moisture, so that, while all processes represented on Figure 1 are active in REF and can contribute to simulated T-P covariability, only atmospheric processes play a role in these correlations in expA.
- Figure 4-5 confirm that in expA, the land only responds to the atmosphere (does not feed back to it) and Figure 8 provides some confirmation that in that context, negative T-P correlations in 1A seem to result from precipitation-radiation-temperature relationships (consistently with Figure 1).

- Figure 6-7 provide a separate but consistent line of analysis: the models that displayed negative T-P correlation in expA are also the ones that in simulation RF also display negative T-P correlations in regions of energy-limited evaporative regimes (in addition to displaying such correlations in soil moisture-limited regions); i.e., in both cases, they do so without soil moisture's feedbacks to the atmosphere. We feel this physical consistency between both simulations is worth presenting, as it reinforces the diagnosis of differences in model behavior. As a result we respectfully disagree with the reviewer's suggestion to remove Figure 6-7 and the corresponding analysis.

In response to the reviewer's comment, we have revised the manuscript to better separate the different stages of the analysis in the text and better underscore their respective contributions –e.g., lines 233-241, 294-299, 385-392 in the new manuscript. We also reorganized section 4 so that the text now follows the general plan outlined above, which we believe will be clearer than the initial version (that is, figures 4-5-6-7-8 have been rearranged as 4-5-8-6). To reduce the length of the manuscript, (former) Figure 7 was changed to Supplementary Material, as it helps understand Figure 6 but is not essential to the analysis. Note that Figure 3 now only shows Figure 3d, as surface areas of negative or positive correlations are now already shown on (former) Figure 2. We did consider showing multi-model averages for figures 4 and 5, but since these figures correspond to the axes on the binned plots on Figure 6, we think it is important to show them separately for each model to facilitate the understanding of Figure 6.

2. In any case, all of the figures need to be reworked. The caption in Figure 2, for example, says that blue and red contours indicate significance levels of 5%, but there are different shades of blue and red shown, so it's very difficult to interpret significance. The only approach that really makes sense here (in all the figures) is to mask out (i.e., plot as white) the values that are not significant at the 5% level.

The captions in the initial manuscript referred to the blue and red contour*, i.e. contour lines,* that showed 5% significance – not to the shading. We are sorry if that was unclear. In response to the reviewer's comment here (as well as to reviewer #3's comments), we have whited out non-significant correlations on all correlation maps; we have also changed the value-based color scale to a significance-based color scale: color thresholds now correspond to the 10%, 5%, 1%, 0.1% levels of correlation significance, so that readers can better assess the significance of the correlations displayed.

3. I like the climate change analysis (I even like the binned analysis in Figure 10), but I am confused about one thing. It looks like expA uses the 1971-2000 values even during the 2071-2100 period. Would the use of climatological values from the 2071-2100 period be more appropriate to address at least some aspects of the T-P correlation question (e.g., the use of these correlations on the x-axis of Figure 11b)? The authors should comment.

The reviewer is correct that expA uses 1971-2000 climatological soil moisture values throughout the simulation (1950-2100), including during 2071-2100. This was the design of the experiment (see Seneviratne et al. 2013 in the manuscript's references).
Figure 10 and 11 analyze the change in summertime temperature between present (1971-2000) and future (2071-2100) as a function of changes in precipitation between present and future, and of T-P correlations in the present. So by design plots on Figure 10b and 11b have 1971-2000 T-P correlations on the x-axis. In a way, what these figures are looking at is whether physical processes and feedbacks operating at short, interannual time scales (and responsible for present-time negative T-P correlations) bear any relevance for long term coupled temperature and precipitation change - figure 10b indicates that they do.
The GLACE-CMIP5 project includes another experiment expB, where a time-varying (over a 30-year window) climatology of soil moisture is prescribed (again, see Seneviratne et al. 2013). Thus, in that experiment, soil moisture at the end of the simulations is the climatology over 2071-2100 – as the reviewer suggests using here. However, in this experiment, prescribing soil moisture in this way means the long-term response of soil moisture to climate change, as well as the feedback of this long-term soil moisture change on surface climate, are already included (for instance, a long-term local decline in soil moisture will lead to average future warming); but the short-term feedbacks are not, since soil moisture is prescribed and not interactive. Thus we feel expB was not suited to investigate the issue we meant to analysis in this section (the consistency between short-term and long-term T-P coupling).

4. Line 251-252: "inform similarly on soil moisture versus energy-limited evaporative regimes". I don't see this. How can expA inform on soil moisture limited regimes?
What we meant was that radiation-evaporation correlations, in theory, reveal patterns of soil moisture and energy-limited evaporative regime, just like soil moisture-evaporation correlations do (see results for simulation REF). We cannot look at the latter in expA (since soil moisture is prescribed) but we can look at the former. They do reveal that evaporation is energy-limited nearly everywhere in expA.

Note that this sentence has been suppressed in the reorganization of the manuscript.

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Reviewer #2: The paper applies notions of climate response to land-atmosphere feedbacks to a set of CMIP5 simulations designed to isolate the role of such feedbacks in climate models in both historical and future climate scenarios. Important implications are found that, by elimination, certain areas are seen to have correlations symptomatic of land-atmosphere coupling that are in fact driven by the atmosphere alone. However, regions that do have direct feedbacks in effect demonstrate a modulation of climate warming signals via the water cycle that help explain some climate change results. The case is well presented, culminating in Fig 10.

Overall I recommend only minor revisions before publication.

L207: The "terrestrial pathway" was demonstrated by Guo et al. (2006) - this should be cited, and this idea/nomenclature should be introduced in the description of Fig 1.
We have edited the description of Figure 1 in the introduction accordingly (citing Guo et al. 2006, Dirmeyer et al. 2011).

L332-334: This statement is unsatisfyingly fuzzy. It seems this could be demonstrated with a basic slope calculation (linear regression) and/or correlation of temperature against surface energy balance terms.
We rephrased this statement. What we meant is that Figure 8b reflects the different model sensitivities of surface temperature to incoming solar radiation in the context of a non-soil moisture-limited evaporative regime (since evaporation in expA is essentially energy-limited) – i.e. how surface temperature is diagnosed in a model given solar radiation and water availability.

L346: These positive correlations can be meaningless if the variability is small, as it is typically for temperature in tropics. One needs to consider the magnitude of variability as well (cf. Guo et al. 2006, Dirmeyer 2011).

In general, precipitation variability and temperature variability vary in opposite ways with latitude: while temperature variability is indeed low in the Tropics and maximum (in summer) at high latitude, precipitation variability is higher in the Tropics (where mean precipitation is maximum) and lower at mid/high latitudes – see Trenberth and Shea (2005), Wu et al. (2013) (references in the manuscript). Thus precipitation and temperature act to offset each other (in terms of the impact of variability on the calculation of correlations). This point is now highlighted in the presentation of observed T-P correlations that was added to the manuscript.

L358-360: More specifically, ...sensitive to the way clouds and convection are parameterized. Please "go there" in the discussion, as this is a point that needs to be hammered home.
This topic is now mentioned in section 4c and in the discussion section.

Fig 7: Please label the columns with the pairs of correlation signs corresponding to the four quadrants.
Labels were added. Figure 7 was moved to Supplementary material, as Figure S1.

Fig 9 and discussion L385-390: Please give some tabular data or otherwise make these more quantitative. The reader cannot tell much from the figures - it is difficult to synthesize visually.
To provide a more quantitative and interpretable view of the change in correlations in the future, Figure 9 was replaced by a histogram of areas of significant positive or negative change in T-P, SM-ET-, ET-T correlations between present and future in the different models. The original Figure 9 was retained as Supplementary Figure S2, as it helps to interpret the spatial patterns behind the histogram.

Sec 6: But what can we say about nature? It is not directly shown here whether these models reflect observed relationships in these quantities (obviously such validation would only be possible in a limited way, but any degree of confidence that could be demonstrated would be helpful, even if taken from other literature). Perhaps a strong call needs to go out here to better validate the land-atmosphere interactions in these models (spur on the observational community).

The goal of our study was primarily to highlight the intermodel differences in the multivariate physical relationships that underlie an emerging behavior such as T-P covariability. While the evaluation of relevant processes (convection, clouds,

land-atmosphere coupling, etc.) in climate models has been the subject of many studies (e.g., Dirmeyer et al. 2006), we are not aware of studies systematically evaluating global, interannual relationships similar to those analyzed in the present study. We leave the corresponding evaluation of these relationships with observations or observation-based products (for evaporation, radiation, soil moisture, etc.) for future studies. We do note, however, that climate models (at least in CMIP5) seem to overestimate summertime temperatures over land (e.g., Christensen and Boberg 2012, Mueller and Seneviratne 2014). The comprehensive causes of such biases are being investigated (e.g., Ma et al. 2014), but there are indications that models in these regions are too dry (in terms of precipitation and/or evaporation) and that subsequent soil moisture-temperature coupling contributes to the warm bias (Christensen and Boberg 2012, Mueller and Seneviratne 2014). As we mention in the text, our view is that it is thus possible that these climate models, being biased towards a dry/warm state in summer, overestimate summertime soil moisture-atmosphere interactions in general, and the role of these interactions in T-P correlations in particular.
This discussion was modified in the text – lines 568-599 in the new manuscript.

Christensen, J. H., and F. Boberg (2012), Temperature dependent climate projection deficiencies in CMIP5 models, Geophys. Res. Lett., 39, L24705, doi:10.1029/2012GL053650.
Dirmeyer, Paul A., Randal D. Koster, Zhichang Guo, 2006: Do Global Models Properly Represent the Feedback between Land and Atmosphere?. J. Hydrometeor, 7, 1177–1198.
Ma, H.-Y., and Coauthors, 2014: On the Correspondence between Mean Forecast Errors and Climate Errors in CMIP5 Models. J. Climate, 27, 1781–1798.

Sec 6: Is there any indication of connections between model fidelity and any aspects of future projections (cf. Shukla et al. 2006)?
There seems to be a link between regional model biases and sensitivities. In summer, warm models tend to project more warming in some regions (Boberg and Christensen 2012). This kind of behavior is consistent with our Figure 10b, which shows that future warming depends on present-time land-atmosphere interactions (and precipitation change). Thus a correct representation of land-atmosphere interactions is crucial for accurate future surface climate projections.

Boberg F, Christensen JH (2012) Overestimation of summer temperature projections due to model deficiencies. Nat Clim Change 2:433–436. doi:10.1038/nclimate1454

Dirmeyer, P. A., 2011: The terrestrial segment of soil moisture-climate coupling. Geophys. Res. Lett., 38, L16702, doi: 10.1029/2011GL048268.

Guo, Z., and co-authors, 2006: GLACE: The Global Land-Atmosphere Coupling Experiment. 2. Analysis. J. Hydrometeor., 7, 611-625, doi: 10.1175/JHM511.1.

Shukla, J., T. DelSole, M. Fennessy, J. Kinter, and D. Paolino, 2006: Climate model fidelity and projections of climate change, Geophys. Res. Lett., 33, L07702, doi:10.1029/2005GL025579.

I do not wish to remain anonymous. -Paul Dirmeyer

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Reviewer #3: Review of "Interannual Coupling Between Summertime Surface Temperature and Precipitation: Processes and Implications for Climate Change" by A. Berg et al.

Summary

This manuscript includes analysis of multi-year summer-mean correlations of continental precipitation (P) and surface temperature (T) in five coupled OAGCM simulations of CMIP5 historical 20th century climate and projected 21st century climate, where the latter assumes an "RCP8.5 scenario " of greenhouse gas concentrations. For each model, the historical and projected future climate simulations are implemented in two experimental configurations, one which included interactive soil moisture ("REF") and the other with prescribed climatological soil moisture ("expA").

Major Comments

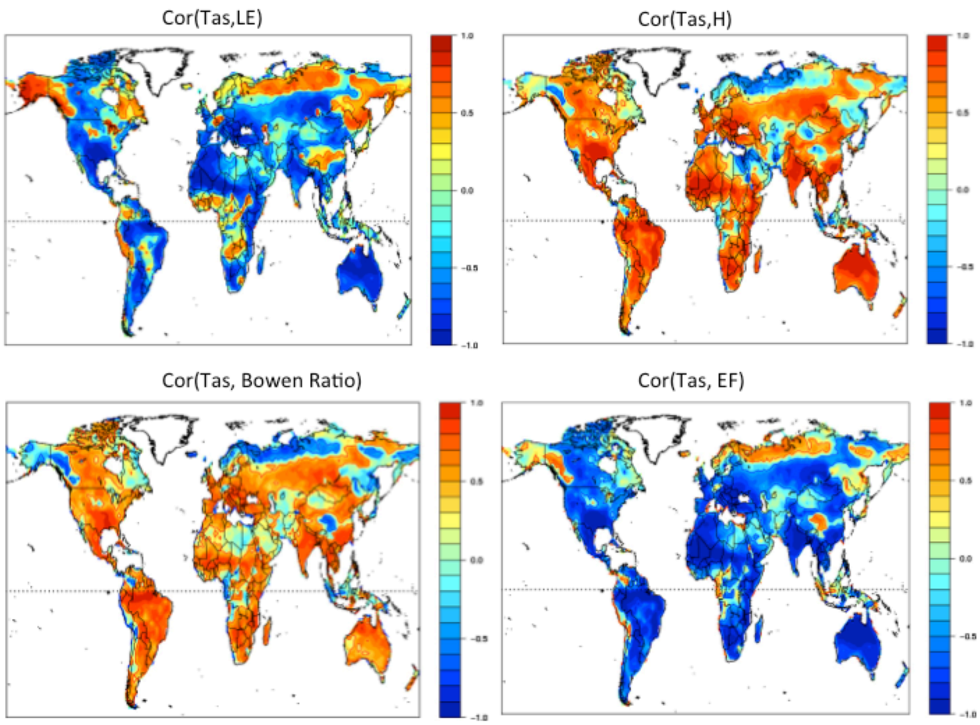
The analysis of these unique, paired simulations is quite interesting, and reflects considerable scientific insight. The description of results and their interpretation are also generally well written. However, in my opinion, the manuscript falls short in several respects:

1)There is no attempt to validate the historical simulations of P-T correlations relative to those determinable from the several continental P and T observational data sets (e.g. CRU, GPCP, University of Delaware, T products from reanalyses, etc.) that are now available. This also would require the remapping of model results to a common horizontal grid that is appropriate for comparison with the available observations. A validation relative to different observational P and T data sets also would convey the degree of observational uncertainty that currently exists. Such observational validation is a necessary prerequisite to further diagnosis of model processes, since it provides guidance on how important such processes are for obtaining a "good" simulation, and on how much "weight" to give the process relationships simulated by a particular model.

Since we refer to observed T-P correlations in the introduction, in the interest of clarity (and because the observational correlations displayed in Trenberth and Shea 2005 and other papers referenced in the initial manuscript are computed slightly differently than in our study), we have added our own calculation of T-P correlations from observations in the revised manuscript (Figure 1 and lines 81-100 in the new manuscript). As recommended by the reviewer here, different observational data sets (crossing different T and P products) were used; patterns are generally robust across datasets; significance of the correlations depends on record length.
We agree that adding observations facilitates the understanding of our study by the reader and provides some context to interpret our results. However, while we understand the reviewer's request to then validate simulated T-P correlations against these observations, we believe a thorough validation (beyond general visual comparison) is beyond the scope of the study (e.g., see Wu et al. 2013), and would not necessarily add much to the analysis of the underlying physical processes in the models. Indeed, in general, a model may display the "right" observable field for the "wrong" physical reasons (and vice-versa). Another issue is the limited number of models involved here. For instance here ESM2M and EC-EARTH display the strongest negative T-P correlations (in REF), but the analysis shows that they do so through different processes. Similarly, MPI-ESM, although it shares some process-level similarities with EC-EARTH, displays lower correlations. We thus do not believe, in particular given the limited number of models here, that T-P validation would be useful here to validate processes – rather, we emphasize in the discussion the need for process-level observational constraints on models in order to resolve these uncertainties.

2) The diagnosis of differences in P-T correlations among the model simulations is limited to consideration of their relationship to only a few other simulated processes (chiefly, surface evapotranspiration ET, downward shortwave radiation SW, and soil moisture SM), leaving the authors to speculate vaguely on other unexamined processes (e.g. clouds, precipitable water, surface turbulent fluxes) that might "explain" the model differences. It is puzzling why these variables, as well as other potentially relevant processes such as surface net radiation (the main energy forcing and proportional to potential evaporation) and Bowen ratio, are left unexamined.

We would like to underscore here that we analyzed more variables and processes than shown and discussed in the manuscript (including the ones mentioned in the reviewer's comment). We could not realistically show all variables analyzed (we note that reviewer #1 already finds the study too long); all the more that some of the variables are also clearly redundant: for instance, cloud cover and incoming shortwave radiation at the surface are strongly anti-correlated (at the spatio-temporal scales analyzed here), since cloud cover essentially blocks solar radiation. We thus showed the relationship of precipitation and temperature with solar radiation (figure 8, in the original manuscript) and chose not to show corresponding relationships with cloud cover (e.g., as indicated lines 331-335 in the original manuscript).
Similarly, we believe that surface turbulent fluxes are already an integral part of the study, given that i) we showed results for evapotranspiration ET, which is essentially interchangeable with the latent heat flux in this analysis, and ii) in the analysis of land evaporative regimes where ET is analyzed, the relationships between ET and soil moisture/atmosphere already carried most of the information on the 'terrestrial pathway' (Figure 1). This is because – at the time scale analyzed here – latent and sensible fluxes are significantly anti-correlated in soil –moisture limited regimes and positively correlated in energy-limited regimes. For instance below we show the correlations of temperature with, respectively, latent heat flux, sensible heat fluxes, Bowen Ratio and evaporative fraction in the GFDL model ESM2M. One can see the correlation patterns are essentially the same (with different signs). We thus feel the essential physical information is already provided by the analysis of ET in our study, without obvious need to display results for sensible heat flux or turbulent flux composites (EF, Bowen ratio).



Correlations between summer-averaged temperature (Tas) and latent heat flux (LE, upper left), sensible heat flux (H upper-right), Bowen Ratio (lower left) and Evaporative Fraction (EF=LE/(H+LE), lower right), over 1971-2000, in ESM2M; JJA in northern hemisphere and DJF in southern hemisphere. Contour lines indicate significant correlations (5% level, r=0.36).

We did also investigate net radiation in our analysis. However net radiation was not the most relevant variable for the processes analyzed here when we were interested in the role of radiation: for instance, the correlation of net radiation with ET does not reveal the patterns of soil moisture-limited and energy-limited evaporative regimes the way correlations between ET and solar radiation do (see fig.5a in the original manuscript, with negative and positive patterns – in contrast, net radiation-evaporation correlations tend to be positive everywhere). Similarly, the 'atmospheric pathway' for negative T-P correlations (e.g., Figure 8 in the original manuscript) involves the forcing effect of shortwave radiation on surface temperature (surface heating by radiation) and the anticorrelation between precipitation and shortwave radiation (clouds blocking radiation): other radiative fluxes cannot, a priori, play a similar role. We did investigate Figure 8 with different radiative terms (or combinations thereof, including net radiation) or directly with cloud cover: none provided a better fit (in terms of black contours and negative T-P correlations in expA on Figure 8c) than solar radiation. Note that incoming longwave radiation, for instance, tends to be positively correlated with precipitation and cloud cover, so cannot account for negative T-P correlations (since it is also positively correlated to surface temperature). Similarly, net radiation also includes the upward longwave radiation flux, function of surface temperature: thus it cannot be really considered as forcing surface temperature (which is what we were interested in our analysis here: how radiation forces surface temperature). For all these reasons we focused chiefly on solar radiation.
Finally, we do speculate in lines 353-356 about the role of precipitable water in positive T-P correlations in some models in the Tropics. Precipitable water was not a standard output in the GLACE-CMIP5 project, and therefore was not provided for the different models: investigating the related processes in the different models was thus impractical. In addition, the positive T-P correlations at equatorial latitudes were not the main focus of the present study and represent a small (and uncertain) part of the signal. In this context, we felt it was not unreasonable to limit the analysis to physical speculations. A more comprehensive study of the different positive and negative domains on Figure 6a is planned as a future study.

To account for the reviewer's comment, we have tried to clarify in the revised manuscript why we focus on particular variables in our analysis – e.g., lines 276-281 in the new manuscript. We also added a discussion of the role of longwave radiation in (former) Figure 8 (lines 317-327 in the new manuscript).

3) The related processes that are diagnosed are depicted in ingenious (although rather complicated) ways, but it is often not easy for the reader to interpret the results. For example, in some figures it is difficult to discern differences among the

models because statistically significant correlations are not clearly differentiated. The question of what constitutes a "significant" result is also not critically examined, especially when coherent spatial patterns of significant correlations are identified in some model fields. In such cases, "field significance" (e.g. see Livesey and Chen, 1983 Mon. Wea. Rev.) is potentially a pertinent issue, at least for precipitation and other variables that are correlated with temperature, which is likely to exhibit high spatial correlation on neighboring grid cells. More careful attention to such statistical complexities is called for.
Following the reviewer's suggestion (as well as reviewer #1's suggestion), we have whited out non-significant correlations (at the 10% level) on all correlation maps; in addition, we have also changed the value-based color scale to a significance-based color scale. Color thresholds now correspond to the 10%, 5%, 1%, 0.1% levels of correlation significance (instead of regular 0.1 increments), so the reader can more easily assess the significance of the correlations that are represented.
For T-P correlations (both in observations and in models), field significance was assessed, following Liveley and Chen 1983, by using a Monte Carlo approach: the 30 yearly maps of T and P (corresponding to summer averages) were shuffled randomly 1000 times, and the area of significant T-P correlations (as percentage of the land surface) calculated each time. The field-significance threshold was then estimated as the 95% quantile of the corresponding distribution of significant areas. Note that keeping yearly maps unchanged while shuffling years retains the spatial auto-correlation within each field. This is indicated in the caption of Figure 1 in the new manuscript.
We assessed the field significance for observational and model-simulated T-P correlations, given the exploratory nature of the analysis. We did not perform the calculations for process-level correlations in models (e.g., SM-ET correlations), given that they correspond to well-established climate processes in models and corresponding correlations are generally widespread.

These general points are elaborated in more detail below.

Details

Lines 159-160: Remapping to a common grid that is compatible with available observations (taking more than one combination of observed P and T) is recommended. This is essential for model validation purposes?see Major Comments, point 1 above.
Please see reply above (point 1).

Discussion and conclusion section: See Main Comments, point 2 above. A more comprehensive analysis of other model variables that are potentially relevant to T-P correlations is needed.
Please see reply above (point 2).

Fig. 2: In this and other figures where significant correlations are the focus of attention, the 5% significance value should be stated (see remarks above on field significance, which may require a more stringent significance level?see Major Comments, point 3 above). I also would recommend "whiting out" the regions where the correlations are not significant, rather than depicting them in shades of green, while retaining a monochrome red or blue color to denote positive or negative significant correlations, respectively. This will make it much easier for the reader to focus on what is really important in the maps.
Please see reply above (point 3). We do think there is value in showing how correlations vary above the significance level: as a result, instead of retaining a monochrome red or blue color to denote positive or negative significant correlations, we use different shades of red and blue to denote different significance levels.

Fig. 3: Using a different color scheme in panels b and d would help differentiate their content from that of panels a and c.
Because we now indicate areas of significant (positive or negative) T-P correlations on Figure 2, we only kept figure 3d in the revised version (Figure 3a and 3b would be redundant with these numbers).

Figs. 4 and 5: See Fig. 2 recommendations above. Adding labels to differentiate the map types of column a vs. column b also would be helpful for the reader.
Labels were added.

Fig. 6: These plots are quite difficult to interpret. To simplify, I'd recommend leaving out all non-significant points (again, the statistical significance level should be stated in the caption?see also remarks above on field significance) and using a different color scheme for the plots of column b (which are different in kind from those in column a).
We have tried to clarify the explanation for these plots in the text. For this particular plot (Figure 6a), we think it is interesting to show how T-P correlations behave in the 'phase space' (i.e., as a function of SM-ET and ET-T correlations) even below the significance level: how correlations become bluer (i.e., more negative) towards the bottom-right and upper-left corners, redder towards the bottom-left and upper-right corners (depending on models). As a result we did not white out

pixels below the 5% significance level (for T-P correlations).
The 5% significance level (for T-P correlations) was added in the captions.
Different color schemes are now used for columns a and b.

Fig. 7: Each column should be labeled--e.g. the leftmost column might be designated as "Fig. 6a Upper Left Quadrant (- , +) ", with corresponding modifications of the figure caption. See also remarks above concerning field significance. A continuous blue-to-red color bar need not be used--only monochrome blue or red to differentiate positive and negative P-T correlations.
Labels were added. Please note that Figure 7 has been changed to Supplementary Figure S1.
Pixels on Figure 7 already correspond to grid cells were SM-ET and ET-T correlations are both significant (either positive or negative, depending on the quadrant). These pixels are very few for the upper-right and lower-left quadrants (with variations between models): we mention so in the text, and that therefore significance may be an issue. Beyond this statement, however, we are not aware of a practical way to quantitatively assess the field significance of a field of joint correlations.
To facilitate the interpretation of these maps and their connection to the binned plots, we have contoured areas of significant T-P correlations on this quadrant maps. We believe it is also important to show the value of T-P correlations on these grid cells for each model (and not only monochrome colors), whether these correlations are significant or not, so that readers can understand why the different models display different average T-P correlation values in the corresponding quadrants of the binned plots. Background land maps were also changed to gray (and interior borders were suppressed) to make the plots more readable.

Fig. 8: See Fig. 2 recommendations above. In panel c), the black contours are difficult to discern, but this may become easier if the non-significant values are removed from the maps (again, field significance may be an issue here).
Non-significant pixels were whited-out. Background land maps were changed to gray (and interior borders were suppressed) to make the plots more readable.
The field significance of T-P correlations in exp1A is discussed earlier in the (revised) manuscript.

Fig. 9: Future-Present correlation differences are difficult to interpret (as evidenced by a color bar that extends to absolute values > 1.0 (what are these maximum/minimum values?). It may therefore be necessary to include maps of the future correlations as well, or to find a different means to communicate the intended results. See also Fig. 2 recommendations above.
This figure showed a plot of differences in 2 correlations (each with a [-1,1] range), therefore the potential range was [-2,2]: it was further narrowed to the range of actual correlation differences found in the models.
To provide a more quantitative and global view of the change in correlations in the future (as recommended by reviewer #2, too), Figure 9 was replaced by a histogram of surface area of significant positive or negative changes in T-P, SM-ET, ET-T correlations between present and future in the different models. The original Figure 9 was retained as Supplementary Figure S2, as it helps interpret the spatial patterns behind the histogram (non-significant changes were whited out).

Fig. 10: P units should be stated in the caption.
Added.

Minor Comments

Line 44, and elsewhere: Use of terms such as "interannual timescales", "interannual correlations", etc. is subject to misinterpretation. The quantities in question are zero-lag point-wise correlations of one seasonal-mean surface field against another, where these statistics are calculated over 30 years. Unless some care is taken in explaining this fact, a reader might erroneously think that "interannual correlations" are calculated with one variable field lagging the other by a whole year.
This was clarified in the text (new Figure 1 caption, Methods).

Line 139: The RCP8.5 scenario should be described in somewhat more detail.
A few words were added to remind readers that RCP8.5 is a high-energy consumption, no-climate policy and unabated-emissions scenario (akin to the SRES A2 scenario).

Line 146-147: The EC-EARTH model has been developed by a consortium, with coordinating headquarters located in Italy (see http://www.to.isac.car.it/ecearth). The atmospheric model component is that of the ECMWF.
Ok, changed.

Lines 221: This is the case in the Tropics?Is evapotranspiration energy-limited in the Tropics because rainfall is so plentiful, in spite of high net surface radiation?
Yes, evapotranspiration becomes energy-limited (or demand-limited) when it is no-longer soil water-limited (supply-limited). Water is no longer limiting for ET in the (deep) Tropics (e.g., see Jung et al. 2010).

Jung, Martin, et al. "Recent decline in the global land evapotranspiration trend due to limited moisture supply." Nature 467.7318 (2010): 951-954.

Line 228: "exactly complementary"?largely or mostly complementary is a more apt description
This sentence was removed in the reorganization of the manuscript.

Lines 349-352: We speculate that?In principle, it should be possible to demonstrate this supposition using model output variables. See Main Comments, point 2 above.
Please see reply above (point 2).

Line 374: The reader should be reminded here that it is an RCP8.5 future scenario that is being simulated.
OK, added.

Line 404: Suggested rewording: "Because maps of T-P correlations show regionally limited future changes, we investigate the relationship?in the models in a binned grid-cell framework."
We reworded this part for clarity (albeit differently than suggested here).

Lines 415-417: This statement doesn't seem to apply to the IPSL model.
As indicated in the text, this statement only applies to some models (mostly ESM2M, to a lesser extent MPI-ESM and EC-EARTH).
Lines 429-430: By "the most negative T-P correlations?" do you mean both the most numerous and the largest average negative value?
Yes, both in extent and intensity (see figure 3a, c, d).

Line 436: ?(except maybe in MPI-ESM). What is the basis for this statement?
MPI-ESM still seems to display maximum warming in the bottom-left part of Figure 11b.

Typographical Corrections

Line 291: A paragraph break is recommended at the sentence beginning "To help interpret?"
Added.
Line 296: (far-left column)
Added.
Line 306: energy-limited almost everywhere?
Changed.
Line 311: (originating either from?)
Edited.
Line 320: add phrase "than shown here" after ?with radiation.
This part was rephrased to clarify the meaning.
Line 350: Clapeyron
Edited.
Line 363: ?do not appear to be as significant?
Edited.
Lines 431-432: ?in the present-day climate
Edited.
Line 436: ?rather than radiation impacts
Edited.
Line 459: ?which shows the most extensive and strongest negative T-P correlations?
Edited.
Line 474: ?also inherently includes (strike "in itself")
Edited.
Line 549: Mitigation (remove hyphen)
Edited.

Interannual coupling between summertime surface temperature and precipitation over land: processes and implications for climate change

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Abstract. Widespread negative correlations between summertime-mean temperatures and precipitation over land regions are a well-known feature of terrestrial climate. This behavior has generally been interpreted in the context of soil moisture-atmosphere coupling, with soil moisture deficits associated with reduced rainfall leading to enhanced surface sensible heating and higher surface temperature. The present study revisits the genesis of these negative temperature-precipitation correlations using simulations from the Global Land-Atmosphere Coupling Experiment - Coupled Model Intercomparison Project phase 5 (GLACE-CMIP5) multi-model experiment. The analyses are based on simulations with 5 climate models, which were integrated with prescribed (non-interactive) and with interactive soil moisture over the period 1950-2100. While the results presented here generally confirm the interpretation that negative correlations between seasonal temperature and precipitation arise through the direct control of soil moisture on surface heat flux partitioning, the presence of widespread negative correlations when soil moisture-atmosphere interactions are artificially removed in at least two out of five models suggests that atmospheric processes, in addition to land surface processes, contribute to the observed negative temperature-precipitation correlation. On longer timescales, the negative correlation between precipitation and temperature is shown to have implications for the projection of climate change impacts on near surface climate: in all models, in the regions of strongest temperature-precipitation anti-correlation on interannual timescales, long-term regional warming is modulated to a large extent by the regional response of precipitation to climate change, with precipitation increases (decreases) being associated with minimum (maximum) warming. This correspondence appears to arise largely as the result of soil-moisture atmosphere interactions.

1) ***Introduction***

Temperature and precipitation are arguably the two most critical components of surface climate over land for both terrestrial ecosystems and human society. The covariability between these two variables and the processes that control or modulate it are thus of great interest to the study of the terrestrial climate variability and change and associated impacts on natural and human systems. One issue worth exploring is the extent to which mechanistic understanding of such relationships can inform the interpretation of climate model simulations across multiple temporal and spatial scales and enhance predictive skill.

Anti-correlation of terrestrial surface temperature and precipitation has been observed over a range of time scales and regions in many prior studies. Using station data over 1897-1960, Madden and Williams (1978) demonstrated that seasonal mean temperature and precipitation are negatively correlated in summer over most of North America, especially over the central Great Plains, while correlations of both sign were found roughly equally in other seasons. Similarly, over Europe correlations were found to be positive in winter and negative in summer. Analogous results have been reported using monthly data over North America for the period 1905-1984 (Zhao and Khalil 1993) and in regional studies over Europe (Trout 1987, Rebetez 1996) and South America (Rusticucci and Penalba, 2000). More recently, Trenberth and Shea (2005) employed reanalysis data and global precipitation observations to extend these results globally: while over the ocean interannual correlations between summertime-monthly temperature and precipitation anomalies tend to be positive, reflecting forcing of precipitation by ocean surface temperature, widespread negative correlations (from the Tropics to the high latitudes) are found over land in summer in both hemispheres. Adler et al. (2008) and Wu et al. (2013) have since demonstrated comparable results using different global observation datasets. Although the studies mentioned above indicate distinct behavior in terrestrial temperature-precipitation covariability for different seasons, Déry and Wood (2005) also report significant anti-correlations between annual-mean temperature and precipitation over land for observations over the 20th century. In addition, Madden and Williams (1978) and Déry and Wood (2005) indicate that such relationships hold across time scales ranging from monthly to decadal. It is thus possible that they modulate trends associated with climate variability or global warming. For instance, Portman et al. (2009) suggest that a positive trend in precipitation over recent decades may account for the postulated "warming hole" in the southeastern U.S.

Figure 1 illustrates these temperature-precipitation correlations over land in summer in a variety of observation datasets – including those used in the studies mentioned above (Trenberth and Shea 2005, Adler et al. 2008, Wu et al. 2013). All datasets are linearly detrended to remove effects of potential trends on correlations and focus on interannual variability. Extensive significant negative correlations dominate over land. The general patterns are robust across datasets: areas of strongest negative correlations include the Sahel, Southern Africa, Australia, India, parts of North America, South America and Eurasia. Correlations tend to be less significant for shorter records (30 years) than longer records (110 years). For shorter time periods, despite general pattern agreement, there are uncertainties between datasets regarding the total extent of these negative correlations (from 32.2% to 49.7% of land area). Where correlations are not negative, they are generally insignificant: this is the case mostly in deserts, in some regions at high latitudes and in the deep Tropics. Small areas of positive correlations can be found along the Equator, in particular in tropical Africa, in the longer records; however, these patterns appear less robust across datasets, and while field significance (e.g., Livezey and Chen 1983) is achieved for temperature-precipitation correlations as a whole in all datasets, positive correlations are not field-significant if considered separately (note that in that case, the threshold for field significance is slightly more than half the value indicated on Figure 1). Note that while temperature variability is lower at tropical latitudes, precipitation variability tends to be higher in absolute terms (the opposite being true at higher latitudes; e.g., Trenberth and Shea 2005): across latitudes precipitation and temperature thus act to balance each other in terms of the impact of variability on the calculation of correlations.

That summers over land tend to be either warm and dry or cold and wet—but typically not warm and wet or cold and dry—may be interpreted *a priori* as the result of several candidate processes, as depicted schematically in Figure 2. First, covariability between summertime temperature and precipitation may simply emerge from synoptic scale correspondence between decreased cloud cover/precipitation and increased incoming shortwave radiation heating the surface during clear-sky conditions, and conversely, increased cloud cover and decreased surface heating and associated temperatures during rainy conditions. Second, local land-atmosphere interactions, which are expected to play a stronger role in summer (Entekhabi et al. 1992, Koster et al. 2004, Seneviratne et al. 2010), may induce such relationships on seasonal scales through the effect of precipitation on soil moisture and attendant surface heat fluxes. Lower rainfall, for instance, is associated with reduced soil moisture and latent heat flux, and thus increased sensible heating at the surface, resulting in higher near-surface air temperatures (and conversely, higher precipitation is associated with lower temperature). Note that this pathway corresponds to the 'terrestrial branch' of soil moisture-atmosphere interactions (Guo et al. 2006, Dirmeyer et al. 2011). Positive feedbacks of modified surface heat flux partitioning on cloud cover/ radiation (e.g., Gentine et al. 2013) and large-scale circulation (e.g., Haarsma et al. 2009) may further amplify the effect of precipitation variability on temperatures.

The impact of soil moisture anomalies on subsequent temperatures has been highlighted in a number of mechanistic modelling studies that have isolated soil moisture variability as a source of daily surface temperature variability in summer, especially in transitions between humid and dry climates (Koster et al. 2006, Seneviratne et al. 2006, Koster et al. 2010). Observation-based estimates of soil moisture-temperature coupling are consistent with these patterns (Miralles et al. 2012). Soil moisture-atmosphere interactions have been shown to play an amplifying role in warm extremes, as noted for recent European heat waves in observational (Vautard et al. 2007, Hirschi et al. 2011, Quesada et al. 2012) as well as modelling (Fischer et al. 2007, Zampieri et al. 2009) studies. Observations provide support for antecedent soil moisture deficits enhancing the probability of subsequent summer hot conditions across different regions of the globe (Durre et al. 2000, Shinoda and Yamaguchi 2003, Mueller and Seneviratne 2012).

These lines of evidence point to coupled land-atmosphere processes as the source for the regionally widespread anti-correlations of summertime terrestrial temperature and precipitation (Trenberth and Shea 2005, Koster et al. 2009). However, whether local land-surface processes are solely responsible for the large-scale, interannual covariability between summertime-averaged temperature and precipitation as depicted in Figure 1 (see also Trenberth and Shea 2005, Adler et al. 2008 and Wu et al. 2013), remains to be determined. In their analysis of the relationship between mean summertime temperature and precipitation using a single climate model, Koster et al. (2009) indicate that these temperature-precipitation anti-correlations "essentially disappear" when simulated land-atmosphere interactions are disabled by prescribing surface fluxes; they thus identify land-atmosphere processes as the dominant driver of these relationships. Krakauer et al. (2009) also report reduced coupling of temperature and precipitation in another model when soil moisture-atmosphere coupling is suppressed through prescribing soil moisture, although they did not investigate this behavior in detail.

The aim of the present study is to explore more extensively, across several models, the correlations between mean temperature and precipitation in order to untangle the contribution of the different processes illustrated in Figure 2. To do so, we make use of simulations from the recent CMIP5 Global Land-Atmosphere Coupling Experiment (GLACE-CMIP5; Seneviratne et al.

2013), in which simulations spanning 1950-2100 were performed with a suite of current-generation models following an experimental set-up disabling land-atmosphere interactions. The manuscript is organized as follows: we describe the models and fields analyzed in Section 2. Section 3 presents the temperature-precipitation correlations in the GLACE-CMIP5 simulations. Land and atmospheric controls on these correlations are investigated in section 4, while section 5 describes the potential relevance of these correlations for climate change projections. The principal results and implications of our study are discussed in Section 6.

2) ***Methods and datasets***

In the context of the GLACE-CMIP5 experiment, five modeling centers performed a land-atmosphere-only transient climate change simulation (hereafter referred to as "expA") in which total soil moisture was overridden in the respective models by the climatological values over 1971-2000 from the corresponding historical, fully coupled CMIP5 simulation. ExpA extends over 1950-2100, with transient sea surface temperatures (SSTs), sea ice, land use, and radiative forcing agent concentrations prescribed from the corresponding CMIP5 simulations (using the historical simulations over 1950-2005 and the RCP8.5 scenario thereafter, characterized by high population and energy consumption growth, no climate policy and unabated emissions); however, soil moisture in each model is overridden by the 1971-2000 climatological seasonal cycle of soil moisture, and thus maintains a climatological seasonal cycle throughout the transient simulation. For each model, either the fully coupled CMIP5 simulation, or, in cases where there were minor differences in set-up, a new reference simulation identical to expA but with interactive soil moisture, was considered as a reference simulation (hereafter referred to as "REF"). The five models analyzed here are Geophysical Fluid Dynamic Laboratory's ESM2M, National Center for Atmospheric Research's CCSM4, the EC-EARTH model developed by a consortium of European research institutions[1], MPI-ESM from Max Planck Institute for Meteorology, and Institut Pierre Simon Laplace's IPSL-CM5A. The reader is referred to Seneviratne et al. (2013) for further discussion of the models and the experimental protocol of GLACE-CMIP5.

Here we compare interactive (REF) and prescribed (expA) soil moisture simulations over 1971-2000; we focus on correlations between temperature (T) and precipitation (P) in summer calculated, as in Figure 1, as zero-lag point-wise correlations of summertime-mean temperature against precipitation (hereafter referred to as T-P correlations). Although focusing on 1971-2000 limits sample sizes to 30 paired values (temperature and precipitation for 30 summers), it ensures that both simulations have identical soil moisture climatologies. The comparison thus isolates the effect on climate of soil moisture variability and associated soil moisture-atmosphere interactions only. June-July-August (JJA) means are used for the Northern Hemisphere and December-January-February (DJF) means for the Southern Hemisphere. Correlations between other variables are investigated similarly. As in Figure 1, 30-year time series of all climate variables analyzed were linearly detrended to remove any spurious effect of climate change-related trends on correlations and focus on interannual variability; such detrending was found to have little quantitative impact on the results for most models. Correlations are presented on the models' native grids, with resolution ranging from 1.125° x 1.125° for EC-EARTH to 3.75° x 1.875° for IPSL-CM5A. Antarctica and Greenland are removed from all datasets.

3) Temperature-Precipitation correlations

Figure 3a shows that T-P correlations are generally significantly negative over most of the land surface in REF in all models. The common patterns of negative T-P correlations that emerge across models - e.g., the US, the Sahel, a large swath of Eurasia and parts of Southeast Asia in JJA;

[1] See www.to.isac.cnr.it/ecearth/

the Amazon, South Africa and Northern Australia in DJF- are in qualitative agreement with calculations based on observations (Figure 1). Trenberth and Shea (2005) and Wu et al. (2013) indicate similar general agreement from other coupled climate models. Beyond common patterns, Figure 3a shows that the strength and extent of these correlations vary across models, from strong and widespread correlations (EC-EARTH) to weaker and more diffuse correlations (CCSM4). When combining correlation extent and strength, EC-EARTH shows the strongest negative correlations, followed by ESM2M, MPI-ESM, IPSL-CM5A and CCSM4 (Figure 4).

As in observations, areas of positive correlations in models are much reduced compared to areas of negative correlations. However, two models (ESM2M, CCSM4) exhibit coherent patches of significant positive correlations along the Equator, over Central Africa and Indonesia, which are reminiscent of areas of positive correlations found in some observational datasets (Figure 1). In ESM2M at least, positive correlations achieve field significance (4.2% of land surface area, above the 3.9% threshold). Thus, model uncertainty seems to parallel observation uncertainty regarding the covariability of temperature and precipitation over land in equatorial regions. Overall, both negative and positive correlations tend to be more significant in models (respectively, 55.4% and 2.4% of the land surface area on average across models) than in observations (respectively 42.8% and 0.5% on average across datasets) over comparable 30-year time periods. This difference may stem from observation uncertainty and the resulting difficulty in diagnosing process-level relationships in observation datasets; we note that results from longer observational record are more consistent with model results (respectively, 57.9% and 1.9% of land surface area significantly negatively or positively correlated; see Figure 1).

The results for simulation expA in Figure 3b indicate that when soil moisture is prescribed, negative T-P correlations are reduced, in all models, both in extent and intensity. However, while in some models these correlations essentially disappear, becoming less extensive and more disorganized (ESM2M, IPSL-CM5A and, to a lesser extent, CCSM4), in others extensive, spatially coherent and significant negative correlations persist (MPI-ESM, EC-EARTH), often in similar regions as in REF. Figure 4 indicates that in terms of combined extent and strength, negative T-P correlations in simulation expA reach 52.2% and 49.2%, respectively, of those in REF in MPI-ESM and EC-EARTH, but only 18.3%, 32.3% and 26.3% in ESM2M, CCSM4 and IPSL-CM5A, respectively. Using this index, correlations are stronger in EC-EARTH in expA than in CCSM4 in REF.

Positive correlations along the Equator in ESM2M and CCSM4 remain in expA, which indicates that they are unrelated to soil moisture variability. We further point out that the spatial extent of positive correlations increases from REF to expA (Figure 3); positive correlations achieve field significance in expA in three models (ESM2M, CCSM4 and IPSL-CM5A). Small patches of positive correlations appear in the Tropics in expA where insignificant or even negative correlations occurred in REF: this is the case over the eastern part of South America, southern Africa or Australia, in particular in IPSL-CM5A, CCSM4 and ESM2M. We note that overall, despite the reduction in negative correlations from REF to expA, T-P correlations remain field-significant in expA in all models.

Our general *a priori* interpretation of the differences between simulations REF and expA in Figure 3 is that soil moisture-moisture atmosphere interactions have been disabled in expA by the suppression of interactive soil moisture. Thus, while all processes represented on Figure 2 are active in REF and can contribute to simulated T-P covariability, only atmospheric processes play a role in these correlations in expA, and the differences between both simulations reflect the contribution of soil moisture-atmosphere interactions. To confirm this interpretation and further investigate the processes underlying negative T-P correlations in both simulations, we analyze in the following section the different relationships highlighted in Figure 2 in the different models, on the same interannual seasonal-mean timescales as for T-P correlations in Figures 1 and 3.

4) Land and atmospheric control on Temperature-Precipitation correlations

a. Evaporative regimes

To highlight the process-level differences between both simulations, we first investigate the different evaporative regimes in REF and expA. In general, evapotranspiration may be either limited by soil moisture availability or by atmospheric demand (temperature, net radiation, vapor pressure deficit, wind speed); soil moisture's feedbacks to the atmosphere are associated with the soil moisture-limited evaporative regime, when soil moisture controls surface turbulent fluxes and subsequent impacts on the low-level atmosphere (e.g., Seneviratne et al. 2010).

Correlations between seasonal mean soil moisture (SM) and evapotranspiration (ET) in Figure 5a highlight the average summertime evaporative regime in the different models in REF. Positive correlations indicate that, on average, ET is soil moisture-limited (higher soil moisture leading to larger ET). This is the case, generally, in the sub-Tropics and mid-latitudes. Conversely, negative correlations point out regions where ET is energy-limited: when water supply is sufficient, ET variability is then determined by variations in atmospheric demand, so that ET variability then drives soil moisture variability (e.g., higher ET depleting soil moisture, producing negative SM-ET correlations). This is the case in the Tropics, and in high latitude and high altitude regions. Large-scale patterns of SM-ET correlations are fairly consistent across models, but correlations vary in amplitude and regional differences can be important. MPI-ESM noticeably exhibits the most positive correlations, and shows almost no negative correlations in the Tropics. These intermodel differences arguably reflect the different parameterizations of soil hydrology in the models (Koster et al. 2009b).

Across models, patterns of correlations between summertime mean ET and atmospheric demand, represented here by temperature (Figure 5b) and incoming solar (shortwave) radiation (Rs, Figure 5c) are consistent with the above. ET-T correlations are negative where soil moisture limits ET (see Figure 5a): reduced ET is then offset by higher sensible heat flux, thus leading to higher temperatures (and vice-versa, higher ET damps temperature). In these regions, negative ET-Rs correlations (Figure 5c) reflect the fact that higher evapotranspiration results from higher rainfall, which is associated with lower solar radiation. Conversely, ET-T and Rs-ET correlations are positive where atmospheric evaporative demand, linked to temperature and surface net radiation, drives evapotranspiration. Comparison between Figure 5b and 5c shows that in most models, the effect of radiation seem to prevail at low latitudes and the effect of temperature at high latitudes. Overall, evaporative regimes in REF as diagnosed in Figure 5 are consistent with similar analyses using climate models (Seneviratne et al. 2006), observation-driven land surface models (Teuling et al. 2009) or observation-based datasets (Jung et al. 2010). Note that the analysis of the surface or atmospheric control on ET (i.e., latent heat flux) here illustrates the control on surface turbulent heat fluxes, since at the time scale considered here the surface sensible heat flux is strongly anti-correlated with ET in soil moisture–limited regimes and positively correlated in energy-limited regimes. Thus results for Figure 5 are similar with either surface heat flux, or composite thereof (e.g., Bowen Ratio, evaporative fraction).

Results from simulation REF show complementary patterns of soil moisture- and energy limited evaporative regimes; by contrast, results for simulation expA (Figure 6) show that when soil moisture variability is prescribed, only atmospheric control on surface ET remains. Figure 6 indicates that atmospheric demand (represented here by incoming shortwave radiation – results with temperature are similar) are driving ET variability nearly everywhere in the different models, except in desert and arid areas where there is little soil moisture to evaporate (note that since the seasonal cycle soil moisture is prescribed in expA and that soil moisture is thus constant from one summer to the next, correlations between soil moisture and ET, similar to Figure 5a, cannot be computed for expA). This atmospheric control reflects the absence of soil moisture depletion following evapotranspiration in expA, since soil moisture is overridden by climatological values at every time step in the models: in this context, soil moisture exerts no control on ET, and the atmosphere is left to drive ET variability.

The differences in evaporative regimes between REF and expA on Figures 5 and 6 confirm that while the land surface can feed back to the atmosphere in REF (in regions of soil moisture-limited regime), the atmosphere is entirely driving the land surface in expA. This confirms that soil moisture-atmosphere interactions are playing no role in T-P correlations in simulation expA in Figure 3 (in particular, in MPI-ESM and EC-EARTH). In the context of Figure 2, we thus interpret negative T-P correlations in expA as resulting from the "atmospheric" pathway.

b. Atmospheric control on T-P correlations in expA

The atmospheric pathway involves covariation of cloud cover and rainfall, with reduced rainfall and associated clouds (originated from either changes in large-scale circulation or in convection) leading to increased surface solar radiation and increased temperature, and conversely, increased precipitation/cloud cover leading to reduced incoming solar radiation and temperature. Figure 7 supports this interpretation by showing that regions of negative T-P correlations in simulation expA in Figure 3b are generally collocated (Figure 7c) with regions where precipitation anomalies are significantly anti-correlated with solar radiation anomalies (Figure 7a) and where, simultaneously, radiation anomalies are significantly (positively) correlated with surface temperature anomalies (Figure 7b). Admittedly, this colocation is not proof of causation: we cannot rule out that a separate, different mechanism may independently generate such negative T-P correlations in the models (in which case temperature-radiation and precipitation-radiation correlations of opposite sign may also independently be observed, as here). However, the good spatial match on Figure 7c (in particular for MPI-ESM and EC-EARTH) and the physical plausibility of the underlying processes are suggestive of a direct radiative control on the T-P correlation in expA. Note that radiative terms other than solar radiation play no similar direct role in negative T-P correlations. In particular, downwelling longwave radiation tends to be positively correlated with cloud cover and precipitation, so it would induce positive, instead of negative, T-P correlations (since it heats the surface as well). This effect may actually act to oppose the impact of cloud cover and solar radiation on T-P correlations: in particular, the lower negative T-P correlations actually simulated by CCSM4 over large parts of Eurasia compared to the patterns of precipitation-radiation-temperature covariations (black contours on Figure 7c) correspond to regions where surface temperature appears more strongly associated with downwelling longwave radiation in CCSM4 than in other models (not shown). Thus, our interpretation is that in this model and this region, positive anomalies of cloud cover/precipitation are not clearly correlated with negative temperature anomalies, because of the effect of the associated longwave radiation on surface temperature.

As shown in Figure 3b, negative T-P correlations in expA are wider and more coherent in MPI-ESM and EC-EARTH than in the other models. We interpret the differences between models as reflecting the differences between models in terms of cloud/radiative processes and impacts on the surface energy budget. Figure 7a shows that in simulation expA anomalies of precipitation across models are consistently and extensively associated with anomalies of incoming shortwave radiation of opposite signs. Differences between models mostly reflect different relationships between cloud cover and precipitation, and, to a lesser extent, differences in the strength of the link between cloud cover and radiation (not shown). On the other hand, positive correlations between incoming shortwave radiation and temperature are less extensive; they also show more differences between models (Figure 7b). These differences reflect the different sensitivities of surface temperature to incoming solar radiation in the models, in particular in a non-soil moisture-limited evaporative regime such as in expA (see previous subsection). For EC-EARTH, MPI-ESM and (to a lesser extent) CCSM4, these differences result in large swaths of positive correlations between summertime-mean shortwave radiation and surface temperature in the Tropics and high latitudes, whereas similar correlations are less extensive in ESM2M and IPSL-CM5A. As mentioned above, models also exhibit different relationships of surface temperature with downwelling longwave radiation (in particular CCSM4). The combination of these differences in longwave/shortwave radiation-temperature relationships with more minor differences in precipitation-radiation correlations explains the spread in T-P correlations between models in expA (Figure 3b). Overall, Figures 7a and 7b arguably reflect the aggregated effects of combined differences in parameterized cloud, convection, radiation, soil and turbulence schemes between models.

c. Land and atmospheric control on T-P correlations in REF

We now focus on the processes underlying T-P correlations in the context of interactive soil moisture, in simulation REF.

Soil moisture-atmosphere interactions arguably contribute to negative interannual T-P correlations in REF where correlation patterns in Figure 3a overlap with regions of positive SM-ET correlation (soil moisture controlling ET) and negative ET-T correlation (ET controlling temperature) in Figure 5. To analyze this relationship, we combine information from Figures 3 and 5 by binning T-P correlations along SM-ET correlations and ET-T correlations. Double histograms (or binned plots) on Figure 8a thus show T-P correlations in the different models in REF as a function of SM-ET and ET-T correlations (over land). For each model, for a given bin of SM-ET and ET-T correlation values, Figure 8a displays the average T-P correlation over all (map) pixels from Figure 5a and 5b that fall within this particular bin of SM-ET and ET-T correlations; Figure 8b indicates the number of map pixels from Figure 5 that fall in this bin. To help interpret Figure 8a in a spatial sense, Supplementary Figure S1 also displays the maps of pixels belonging to the different domains of the binned plots (i.e., upper-left, upper-right, lower-right and lower-left parts of the plots), showing the corresponding T-P correlations.

All models display negative T-P correlations in the bottom-right part of the plots, which corresponds to the soil moisture-limited evaporative regime: this quadrant corresponds to regions where, as mentioned above, soil moisture controls evapotranspiration (positive SM-ET correlations) and evapotranspiration controls temperature (negative ET-T correlations; see Figure 5). T-P correlations are overwhelmingly negative in these regions (see also Figure S1, far-right column). This indicates that in all models, soil moisture atmosphere interactions do contribute to negative T-P correlations (in REF).

A benefit of the binned analysis is that it shows that some models also produce negative T-P correlations in the upper-left part of the plots (EC-EARTH, MPI-ESM, CCSM4 to a lesser extent). This domain corresponds to the energy-limited evaporative regime: in this quadrant, temperature drives evapotranspiration (positive ET-T correlations) and evapotranspiration drives soil moisture (negative SM-ET correlation; see Figure 5). Figure S1 shows that, as mentioned in section 4a, these regions can be found at high latitudes and in the Tropics (far-left column). MPI-ESM displays negative T-P correlations predominantly at high latitudes, while EC-EARTH does so mostly in the Tropics (CCSM4 as well, but over the Amazon only). Since evapotranspiration in this regime is driven by atmospheric demand and drives soil moisture variability, negative T-P correlations in this quadrant clearly do not result from precipitation’s impact on soil moisture and soil moisture’s subsequent control on evapotranspiration and temperature. Rather, we interpret them as resulting from the same atmospheric processes as highlighted in the previous section in simulation expA. This interpretation is supported by the consistency between Figure 8a and Figure 3b: the models that show negative T-P correlations in the energy-limited evaporative regime in REF (upper-left part of the binned plots in Figure 8a) are the same ones that display significant negative T-P correlations in simulation expA in Figure 3b (EC-EARTH, MPI-ESM, and to a lesser extent, CCSM4). In both cases, the surface evaporative regime is controlled by the atmosphere (see section 4a). Figures 3b and 8a thus provide two independent yet consistent lines of evidence that these models are capable of producing negative T-P correlations that are not the product of soil moisture-atmosphere interactions, but which emerge through atmospheric processes only.

Figure 8b indicates that for most models, most (map) pixels (from Figure 3a) lie in the bottom-right part of the binned plots: that is, there are more map pixels that fall into the soil moisture–limited evaporative regime; pixels in the energy-limited regime are comparatively less numerous (except for IPSL-CM5A; see also Figure 5). More generally, Figure 8b shows that most pixels fall along a general bottom-right/upper-left line. This is to be expected, as the two axes are not independent: a positive SM-ET correlation for instance, reflecting a soil moisture-limited evaporative regime, will tend to be associated with a negative ET-T correlation (as more evapotranspiration will then cool the surface). However, Figure 8a also shows hints of coherent positive T-P correlation patterns emerging across models as one departs from this central line and moves towards the upper-right and lower-left quadrants, where SM-ET and ET-T correlations follow different behaviors. These tend to correspond to pixels in, respectively, equatorial latitudes and high latitudes (Suppl. Fig. S1). We note that these portions of the binned plots typically involve a small number of pixels (Figure 8b), which are often dispersed, so limited sample size may be an issue. On the other hand, as indicated in section 3, coherent patches of positive T-P correlations over equatorial latitudes exist in particular in Equatorial Africa and the Maritime

Continent in ESM2M and CCSM4; they correspond to the bottom-left quadrant in Figure 8 (see also Suppl. Fig. S1). The presence of positive correlations in both the interactive and prescribed soil moisture configurations (Figure 3) indicates that these are decoupled from interactive soil moisture processes. Rather, we speculate that such correlations reflect simulated Clausius-Clapeyron temperature scaling of precipitable water, which in turn is tightly associated with local precipitation, similar to corresponding relationships over ocean surfaces (Neelin et al. 2009, Muller et al. 2009, 2011). As discussed in the introduction, there is some ambiguity in the significance of the observed correlations over equatorial latitudes (Figure 1). In this context it is difficult to assess the validity or realism of the simulated regional covariability in the tropics. We note that the simulated tropical correlations are clearly model-dependent, likely reflecting differences in parameterizations of clouds and convective precipitation between models in these regions.

Small coherent areas of positive T-P correlations over high latitudes corresponding to the upper-right quadrant exist in particular in the IPSL-CM5A and CCSM4 models (Suppl. Fig. S1) – however these positive correlations do not appear to be as significant or extensive as those in the Tropics (see also Figure 3a). The upper-right quadrant corresponds to mean hydroclimatic conditions under which summertime mean evapotranspiration appears to be, on average, controlled by both soil moisture (positive SM-ET correlation) and temperature (positive ET-T correlation). One possible explanation for this model behavior is that precipitation over these areas is associated with advection of warmer, moister air: in this case, precipitation directly increases evapotranspiration (because of the positive SM-ET correlation), so the latter also appears associated with higher temperature.

5) Implications for climate change

In the previous section, we investigated the processes through which T-P correlations at the interannual time scale (i.e., from one summer to the next) arise in the different climate models. Taking advantage of the fact that both simulations REF and expA were simulated through 2100 using the RCP8.5 scenario after 2005, we now focus on how T-P correlations evolve in a warmer climate and what role they play in climate change projections.

a. Projected future T-P correlations

Figure 9 shows that in all models, parts of the land surface show significantly more negative T-P correlations at the end of the 21st century (2071-2100) compared to the end of the 20th century (1971-2000), while correlations also become significantly more positive in other areas (note that areas becoming more positive may still correspond to negative correlations). In MPI-ESM, CCSM4 and IPSL-CM5A, areas where correlations become significantly more negative clearly outweigh areas where significant positive changes occur, which reflects an increase in the total area of significant negative T-P correlations. Similar changes are less evident for ESM2M and EC-EARTH. Despite these changes, the overall spatial pattern of T-P correlations (Figure 3a) remains similar in the future in the different models (not shown). We note here that we cannot assess the field significance of these changes in T-P correlations between present and future through the same Monte-Carlo approach as used in Figure 1 and 3, as it would require sampling a control simulation with no changes in climate forcing agents. We point out that the net change (i.e., the area difference between areas becoming significantly more negative and areas becoming significantly more positive) remains smaller than 6% of the land surface in all models.

Because in all models, negative T-P correlations arise either partly or mostly as a result of soil moisture's feedbacks on surface temperature (see previous section), we analyze concurrent changes in SM-E and ET-T correlations. Figure 9 shows that in MPI-ESM, CCSM4 and IPSL-

CM5A, significant changes in SM-ET and ET-T correlations are, respectively, predominantly positive and negative, which reflect an increased control of soil moisture on evapotranspiration and increased control of evapotranspiration on temperature. Supplementary Figure S2 illustrates these changes spatially and shows that concurrent changes in SM-ET and ET-T mainly occur at high northern latitudes. This shift towards soil moisture-controlled conditions in summer in the future in regions like Eastern/Northern Europe and Siberia is consistent with previous modeling results (Seneviratne et al. 2006, Dirmeyer et al. 2012, Dirmeyer et al. 2013). This strengthening of the land-atmosphere pathway (Figure 2) is consistent with the more negative T-P correlations in these models; one must note, however, that areas of more negative T-P correlations do not necessarily overlap with areas of increased soil moisture control (e.g., Central Asia in MPI-ESM). In ESM2M, no such strengthening of the land-atmosphere pathway can be seen; rather, it seems that soil moisture's control on evapotranspiration becomes less pronounced in the future (Figure 9 and Suppl. Fig. S2). In EC-EARTH, a small shift towards more soil moisture controlled conditions is projected over Eastern Europe, which appears to result in stronger negative T-P correlations over this region.

b. Regional temperature change

We now investigate whether T-P covariability at the interannual time scale, such as diagnosed by T-P correlations, affects long-term temperature change over land in the models. Because patterns of T-P correlations show overall modest change in the future in the models (or become even more negative, see previous sub-section), we use present-climate T-P correlations to investigate how projected future warming is affected by interannual T-P covariability in the models. We do so using a binned grid-cell framework similar to Figure 8.

First, Figure 10a shows the mean summertime warming projected between 1971-2000 and 2071-2100 in the different models in simulation REF. Differences in the average temperature change reflect differences in climate sensitivities: IPSL-CM5A shows the largest overall warming, while ESM2M shows the smallest (with even some cooling in the Southern Ocean and the North Atlantic). In all models, summertime warming is greater over land than over the oceans, consistent with a land-sea warming ratio greater than unity (e.g., Sutton et al. 2007); however, patterns of changes over land differ between models. Figure 10b helps shed light on these differences by showing that the land regions of maximum warming in the models tend to correspond to regions that exhibit both the highest T-P summertime anti-correlations in current climate and negative projected precipitation changes. This pattern is particularly clear in ESM2M, MPI-ESM and EC-EARTH, somewhat less pronounced in CCSM4 and IPSL-CM5A. A few pixels of maximum warming also appear in regions of positive T-P correlations in Figure 10b (in general with positive precipitation change) corresponding to large warming in desert areas (see Figure 3a). In some models (ESM2M, MPI-ESM), conversely, minimum long-term warming is projected in regions that exhibit both the highest T-P summertime anti-correlations in current climate and positive projected precipitation changes.

This indicates that, consistently across models, T-P correlations have the potential to modulate long-term warming in conjunction with precipitation change. This is consistent with prior studies (Madden and Williams 1978, Déry and Wood 2005) showing that the T-P relationship holds over a range of time scales, including decadal variability and secular trends.

Figure 11a shows that in the absence of soil moisture change, long-term warming is largely reduced over land in expA compared to REF. This is consistent with the role of average soil moisture change (between present and future) in amplifying summertime warming over land, as shown in Seneviratne et al. (2013). This difference highlights the role of land-atmosphere interactions in the land-sea warming contrast projected by climate models (Sutton et al 2007). Figure 11b shows that in contrast to REF, no relationship similar to that in Figure 10b emerges between long-term warming, precipitation change and T-P correlations in simulation expA – to the exception of MPI-ESM. Interestingly, while EC-EARTH and MPI-ESM both display the most negative T-P correlations in expA over 1971-2000 (both in extent and intensity, Figure 4), they show different behaviors in terms of long-term warming (in expA): EC-EARTH does not exhibit a relationship between future warming and T-P correlations in this simulation, while MPI-ESM does. It thus appears unclear whether processes associated with the atmospheric pathway (Figure 2), which result in negative T-P correlations at the interannual time-scale, can also affect future surface warming through concurrent long-term changes in precipitation. At the very least, comparison between Figure 10b and 11b suggests that land-atmosphere interactions contribute to the warming patterns in Figure 10b to a large extent. In other words, our results indicate that through soil moisture feedbacks on near-surface climate, regional trends in precipitation may strongly modulate regional temperature change from global warming.

6) ***<u>Discussion</u>***

By comparing an ensemble of simulations with and without interactive soil moisture, we investigated the mechanisms responsible for negative T-P correlations for the first time in a suite of climate models. We have demonstrated that negative correlations between summertime-mean temperature and precipitation can arise through two mechanistic pathways in climate models, as described in Figure 2. The across-the-board decrease in T-P correlations between REF and expA in Figures 3a and 3b indicate that the terrestrial pathway, i.e. the control of soil moisture on surface heat fluxes and temperature, largely contributes to these correlations in all models. However, while soil moisture-atmosphere interactions are the main driver in some models, in others (mainly, MPI-

ESM, EC-EARTH) these correlations also emerge in the absence of soil moisture-atmosphere coupling (expA). Our analysis indicates that this comes in response to the stronger association in these models between cloud cover and precipitation on the one hand, and between solar radiation and surface temperature on the other hand. Consistently, Figure 8 shows that in the context of interactive soil moisture (REF), these models are capable of producing negative T-P correlations, not only in soil moisture-limited regions, but also in regions of energy-limited evaporative regime, where soil moisture variability does not feed back on surface temperature. This suggests that, in these models, the atmospheric pathway may also contribute to negative T-P correlations even in soil moisture-limited regions: in such regions, surface temperature may also be partly driven by the radiation anomalies associated with precipitation and soil moisture variability. This hypothesis is supported by the fact that in MPI-ESM and EC-EARTH, areas with atmosphere-driven negative T-P correlations in expA (Figure 3b) are found in the same regions that display land-driven correlations in REF (this is also the case in the other models over regions such as Australia or India). This suggests that atmospheric processes associating T and P (isolated in simulation expA) also contribute to the negative correlations in these regions in REF in Figure 2a. This is also consistent with the result that EC-EARTH, which shows the most extensive and strongest correlations in REF, also displays the strongest negative correlations in expA. In other words, in these models the two pathways appear to act in combination to produce strong negative T-P correlations over these regions. This additivity suggests that the contribution of soil moisture-atmosphere interactions to negative T-P correlations can be inferred from the difference between simulations REF and expA in Figure 4. Interestingly, some regions show positive T-P correlations in the absence of soil moisture-atmosphere interactions and negative T-P correlations otherwise (Figure 3). This suggests that in some cases these interactions can act to oppose the atmospheric regime: these regions appear to be mostly located on the eastern side of continents (in the Southern

Hemisphere), under the influence of air masses from the ocean; while this would result in positive T-P correlations if only the atmosphere was driving T-P covariability (as suggested by Figure 3b), the water-limited evaporative regime in these regions (Figure 5) reverses the relationship between T and P on average over the summer.

In this analysis one should be reminded that the soil moisture-atmosphere interactions pathway defined in Figure 2 also inherently includes the feedback of modified surface turbulent heat fluxes on cloud cover and radiation. For instance, in the case of a negative precipitation anomaly and subsequent soil moisture deficit, reduced evapotranspiration (which directly leads to higher surface temperature) may also negatively impact cloud cover and thus enhance incoming shortwave radiation, thereby further enhancing surface warming (Betts 2004, Ferranti and Viterbo 2006, Davin et al. 2011, Gentine et al. 2013); it may even further reduce precipitation (e.g., Berg et al. 2013). The GLACE-CMIP5 experimental set-up does not allow for separating these feedbacks from the direct impact of soil moisture on the surface energy budget and temperature. We note that some models (ESM2M) show increased interannual variability of mean summertime cloud cover between simulations REF and expA over some regions of negative T-P correlations, which suggests that feedbacks of surface fluxes to cloud cover are at play over these regions; however most models do not show such changes.

Overall, our analysis points to important uncertainties emerging at the seasonal-mean, interannual timescale between climate models with respect to various functional relationships, such as the control of soil moisture on evapotranspiration, the relationship of cloud cover with radiation and precipitation, or the impact of surface radiation on temperature. These differences are not unexpected, given that these emerging relationships are the result of small-scale parameterization schemes, such as cloud, convection, radiation, soil hydrology, and boundary-layer schemes. Through the interplay between these components, differences from the details of these parameterizations grow and result in different behaviors at larger and longer spatio-temporal scales. Consistent with our analysis, previous studies have noted, for instance, that climate models exhibit different apparent sensitivities of surface temperature variability to processes such as evapotranspiration and solar radiation (Lenderink et al. 2007, Fischer and Schar 2009). Such uncertainties ultimately undermine our ability to use these models to analyze observed climate phenomena such as T-P covariability: here, our multi-model analysis shows that model uncertainties hinder a clear and quantitative understanding and attribution of observed T-P correlations to particular processes, such as land-atmosphere interactions or cloud/radiative processes. There is thus a need to better evaluate process-level, multivariate relationships in climate models. We note, however, that while T-P correlations can readily be derived from observations, more uncertainties and limitations affect observations of the relevant underlying variables and their relationships at similar global and interannual scales (e.g., soil moisture, surface fluxes, radiation). It is thus difficult to constrain climate models regarding these processes. We note that recent studies indicate that climate models in CMIP5 tend to be too warm in summer over land (Christensen and Boberg 2012, Mueller and Seneviratne 2014). While the comprehensive causes of such biases are a subject of current investigation and may involve numerous physical processes (e.g., Ma et al. 2014), one possibility is that they overestimate summertime drying, and thus the subsequent feedback on surface temperature (Stegehuis et al. 2012). Locked in a dry and warm soil moisture-limited regime, models may then overestimate soil moisture-atmosphere interactions (Christensen and Boberg 2012). In contrast, some recent observational studies emphasize the role of cloud cover in the variance of summer temperature (Tang et al. 2012, Tang and Leng 2013). It is thus possible that models overestimate the contribution of soil moisture-atmosphere interactions to the negative T-P correlations investigated in this study. Future improvements in global land-atmosphere observational datasets, as well as point-wise land-atmosphere model evaluation exercises, may help further constrain such model uncertainties.

Conclusion

Widespread negative correlations between summertime-mean temperatures and precipitation have long been observed over land. Using simulations from the GLACE-CMIP5 multi-model experiment with and without interactive soil moisture, we explored for the first time the mechanisms responsible for such T-P covariability at the interannual time scale in a suite of climate models. Our results generally confirm the interpretation of such correlations arising largely through the direct control of soil moisture on surface heat flux partitioning: in all models soil moisture-atmosphere interactions contribute largely to these correlations. However in some models the association of cloud cover with precipitation on the one hand, and of solar radiation with surface temperature on the other hand, appears sufficient to generate significant negative correlations between temperature and precipitation, without feedbacks from the land surface. This range of model behavior suggests that observed temperature-precipitation anti-correlations may result from a combination of atmospheric and surface processes. Our results also underline the uncertainties between models regarding cloud/radiative processes and their link to surface temperature. Finally, we showed that on longer timescales, the negative correlation between precipitation and temperature over land has implications for the projection of climate change impacts on near surface climate: in all models, in regions of strong temperature-precipitation coupling, long-term regional warming is modulated to a large extent by projected precipitation changes. In most models this appears to be the result of soil moisture-atmosphere interactions. An important issue in climate sciences is the response of the global hydrologic cycle to global warming, in particular possible changes in precipitation patterns and amounts (e.g., Wentz et al.

2007). Our results demonstrate how regional-scale modifications to the water cycle can feed back on surface temperature changes through soil moisture control on evapotranspiration. These results imply that uncertainties in regional precipitation change, which are a well-documented issue of climate model projections, in particular in the Tropics (e.g., Neelin et al. 2006, Knutti and Sedlacek 2012), directly translate into uncertainties in temperature change. This arguably has compounding effects on uncertainties associated with climate change impacts on natural and human systems, but also suggests that reducing uncertainties in precipitation projections will help reduce the uncertainties in projected regional temperature change. This also implies that the correct representation of land surface hydrological processes in climate models is a key element to providing improved and more robust regional projections of global climate change.

Acknowledgments

Alexis Berg was supported by National Science Foundation (NSF) grants AGS-1035968 and AGS-1035843 and New Jersey Agricultural Experiment Station Hatch grant NJ07102, and is currently supported by NSF Postdoctoral Fellowship AGS-1331375. S.I.S. acknowledges support of the EU-FP7 EMBRACE project (European Commission's 7th Framework Programme, Grant Agreement number 282672), and the GEWEX (World Climate Research Programme, WCRP) and ILEAPS (Integrated Geosphere-Biosphere Programme, IGBP) projects, for the coordination and realization of the GLACE-CMIP5 experiment. S.M. acknowledges support from the National Oceanic and Atmospheric (US Department of Commerce) Grant NA08OAR4320752, US Department of Agriculture Grant 2011-67003-30373, and the Carbon Mitigation Initiative at Princeton University, sponsored by British Petroleum. Univ.Del., CMAP and GPCP datasets data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at http://www.esrl.noaa.gov/psd/. We thank Micah Wilhelm for his help with the GLACE-CMIP5 multi-model database.

REFERENCES

Adler, R. F., G. J. Gu, J. J. Wang, G. J. Huffman, S. Curtis, and D. Bolvin, 2008: Relationships between global precipitation and surface temperature on interannual and longer timescales (1979–2006), *J. Geophys. Res.-Atmos.*, **113**. D22104, doi:10.1029/2008JD010536.

Berg, A., K. Findell, B. Lintner, P. Gentine, C. Kerr, 2013: Precipitation Sensitivity to Surface Heat Fluxes over North America in Reanalysis and Model Data. *J. Hydrometeor*, **14**, 722–743.

Betts, A. K . 2004: Understanding hydrometeorology using global models, *Bull. Am. Met. Soc.*, **85** (11), 1673–1688.

Christensen, J. H., and F. Boberg (2012), Temperature dependent climate projection deficiencies in CMIP5 models, Geophys. Res. Lett., 39, L24705, doi:10.1029/2012GL053650.

Davin, E. L., R. Stöckli, E. B. Jaeger, S. Levis, and S. I. Seneviratne, 2011: COSMO-CLM^2: a new version of the COSMO-CLM model coupled to the Community Land Model. *Climate Dynamics*, **37**, 1889-1907, doi: 10.1007/s00382-011-1019-z.

Déry, S. J., and E. F. Wood, 2005: Observed twentieth century land surface air temperature and precipitation covariability, *Geophys. Res. Lett.*, **32**, L21414, doi:10.1029/2005GL024234.

Dirmeyer, P. A., 2011: The terrestrial segment of soil moisture-climate coupling. *Geophys. Res. Lett.*, **38**, L16702, doi: 10.1029/2011GL048268.

Dirmeyer, P. A, B. A. Cash, J. L. Kinter III, C. Stan, T. Jung, L. Marx, P. Towers, N. Wedi, J. M. Adams, E. L. Altshuler, B. Huang, E.K. Jin, and J. Manganello, 2012: Evidence for enhanced land-atmosphere feedback in a warming climate. *J. Hydrometeor.*, **13**, 981-995.

Dirmeyer, P A., Y. Jin, B. Singh, and X. Yan, 2013: Trends in Land–Atmosphere Interactions from CMIP5 Simulations. *J. Hydrometeor.*, **14**, 829–849.

Durre, I., J. M. Wallace, and D. P. Lettenmaier, 2000: Dependence of extreme daily maximum temperatures on antecedent soil moisture in the contiguous United States during summer. *J. Climate*, **13**, 2641–2651.

Entekhabi, D., I. Rodríguez-Iturbe, and R. L. Bras, 1992: Variability in Large-Scale Water-Balance with Land Surface Atmosphere Interaction. *Journal of Climate*, ***5***(8), 798–813.

Ferranti, L., and P. Viterbo, 2006: Sensitivity to soil water initial conditions. *J. Climate*, **19**, 3659–3680.

Fischer, E. M., S. I. Seneviratne, D. Luthi, and C. Schär , 2007: Contribution of land-atmosphere coupling to recent European summer heat waves, *Geophys. Res. Lett.*, **34**, L06707, doi:10.1029/2006GL029068.

Fischer, E., C. Schar, 2009: Future changes in daily summer temperature variability: driving processes and role for temperature extremes, *Climate Dynamics*, ***33***(7-8), 917-935, doi: 10.1007/s00382-008-0473-8.

Gentine, P., A. A. Holtslag, F D'Andrea, and M. Ek, 2013: Surface and atmospheric controls on the onset of moist convection over land. *J. Hydrometeor.*, **14**(5).

Guo, Z., and co-authors, 2006: GLACE: The Global Land-Atmosphere Coupling Experiment. 2. Analysis. J. Hydrometeor., 7, 611-625, doi: 10.1175/JHM511.1.

Haarsma, R.J., F. Selten, B. van den Huk, W. Hazeleger, and X. L. Wang, 2009: Drier Mediterranean soils due to greenhouse warming bring easterly winds over summertime central Europe. *Geophys. Res. Lett.*, **36**, L04705.

Hirschi, M., et al., 2011: Observational evidence for soil-moisture impact on hot extremes in southeastern Europe, *Nat. Geosci.*, **4**, 17.

Jung, M., and Coauthors, 2010: Recent decline in the global land evapotranspiration trend due to limited moisture supply. *Nature*, **467**, 951–954.

Knutti, R., and J. Sedláček, 2012: Robustness and uncertainties in the new CMIP5 climate model projections. *Nat. Climate Change*, **3**(4), 369-373.

Koster, R.D. et al. 2004: Regions of strong coupling between soil moisture and precipitation. Science, **305**, 1138-1140.

Koster, R.D., et al. 2006: GLACE: The Global Land-Atmosphere Coupling Experiment. Part I: Overview. *J. Hydrometeor.*, **7**, 590-610.

Koster, R.D., S.D. Schubert, and M.J. Suarez, 2009a: Analyzing the concurrence of meteorological droughts and warm periods, with implications for the determination of evaporative regime. *J. Climate*, **22**, 3331-3341.

Koster, R. D., Z. Guo, R. Yang, P. A. Dirmeyer, K. Mitchell, K., and M. J. Puma, 2009b: On the Nature of Soil Moisture in Land Surface Models. *J. Climate*, **22**(16), 4322–4335.

Koster, R.D., S. Mahanama, T. J. Yamada, G. Balsamo, M. Boisserie, P. A. Dirmeyer, F. Doblas-Reyes, C. T. Gordon, Z. Guo, J. H. Jeong, D. Lawrence, Z. Li, L. Luo, S. Malyshev, W. Merryfield, S. I. Seneviratne, T. Stanelle, B. van den Hurk, F. Vitart,and E.F. Wood, 2010: The contribution of land initialization to subseasonal forecast skill: First results from the GLACE-2 Project. *Geophys. Res. Lett.*, **37**, L02402.

Krakauer, N., B. Cook, and M. Puma, 2010: Contribution of soil moisture feedback to hydroclimatic variability. *Hydrol. Earth Syst. Sci.*, **14**, 505–520.

Lenderink, G., A. van Ulden, B. van den Hurk and E. van Meijgaard, 2007: Summertime inter-annual temperature variability in an ensembleof regional model simulations: analysis of the surface energy budget. *Climatic Change*, **81**, 233-247.

Livezey, R. E. and Chen, W. Y., 1983: Statistical field significance and its determination by Monte Carlo techniques. Monthly Weather Review, 111(1), 46-59.

Ma, H.-Y., and Coauthors, 2014: On the Correspondence between Mean Forecast Errors and Climate Errors in CMIP5 Models. J. Climate, 27, 1781–1798.

Madden, R. A., and J. Williams, 1978: The correlation between temperature and precipitation in the United States and Europe. *Mon. Weather Rev*., **106**, 142–147.

Miralles, D. G.; M. J. van den Berg, A. J. Teuling, and R. A. M. de Jeu, 2012: Soil moisture-temperature coupling: A multiscale observational analysis. *Geophys. Res. Lett.*, **39**, L21707

Mueller, B., and S. I. Seneviratne, 2012: Hot days induced by precipitation deficits at the global scale. *Proc. Natl. Acad. Sci. U.S.A.,* **109** (31), 12398-12403.

Mueller, B., and S. I. Seneviratne, 2014: Systematic land climate and evapotranspiration biases in CMIP5 simulations. *Geophys. Res. Lett*., **41**, doi:10.1002/2013GL058055.

Muller, C. J., L. E. Back, P. A. O'Gorman, and K. E. Emanuel, 2009: A model for the relationship between tropical precipitation and column water vapor. *Geophys. Res. Lett.*, ***36***, L16804. doi:10.1029/2009GL039667.

Muller, C. J., P. A. O'Gorman, and L. E. Back, 2011: Intensification of Precipitation Extremes with Warming in a Cloud-Resolving Model. *J Climate*, **24**(11), 2784–2800. doi:10.1175/2011JCLI3876.1.

Neelin, J. D., M. Munnich, H. Su, J. E. Meyerson, and C. E. Holloway, 2006: Tropical drying trends in global warming models and observations. *Proc. Natl. Acad. Sci. U. S. A.*, **103**(16), 6110–6115.

Portmann, R. W., S. Solomon, and G. C. Hegerl, 2009: Spatial and seasonal patterns in climate change, temperatures, and precipitation across the United States. *Proc. Natl. Acad. Sci. U. S. A.*, **106**, 7324–7329.

Quesada, B., R. Vautard, P. Yiou, M. Hirschi, and S. I. Seneviratne, 2012: Asymmetric European summer heat predictability from wet and dry southern winters and springs. *Nat. Climate Change*, **2**, 736–741.

Rebetez, M., 1996: Seasonal relationship between temperature, precipitation and snow cover in a mountainous region. *Theor. Appl. Climatol*., **54**(3–4), 99–106.

Rusticucci, M., and O. Penalba, 2000: Interdecadal changes in the precipitation seasonal cycle over southern South America and their relationship with surface temperature. *Climate Res*., **16**, 1–15.

Seneviratne, S. I., D. Lüthi, M. Litschi, and C. Schär, 2006: Land-atmosphere coupling and climate change in Europe. *Nature*, **443**, 205–209.

Seneviratne, S. I., T. Corti, E. L. Davin, M. Hirschi, E. B. Jaeger, I. Lehner, B. Orlowsky, and A. J. Teuling, 2010: Investigating soil moisture-climate interactions in a changing climate: A review. *Earth-Sci Rev*., **99**, 3-4, 125-161, doi:10.1016/j.earscirev.2010.02.004.

Seneviratne, S. I**.**, M. Wilhelm, T. Stanelle, B.J.J.M. van den Hurk, S. Hagemann, A. Berg, F. Cheruy, M. E. Higgins, A. Meier, V. Brovkin, M. Claussen, A. Ducharne, J.-L. Dufresne, K. L. Findell, J. Ghattas, D. M. Lawrence, S. Malyshev, M. Rummukainen, and B. Smith, 2013: Impact of soil moisture-climate feedbacks on CMIP5 projections: First results from the GLACE-CMIP5 experiment. *Geophys. Res. Lett.*, **40**, 5212-5217, doi:10.1002/grl.50956.

Shinoda, M., and Y. Yamaguchi, 2003: Influence of soil moisture anomaly on temperature in the Sahel: A comparison between wet and dry decades. *J. Hydrometeor*., **4**, 437–447.

Stegehuis, A., R. Vautard, P. Ciais, R Teuling, M. Jung, and P. Yiou, 2013: Summer temperatures in Europe and land heat fluxes in observation-based data and regional climate model simulations. *Climate Dynamics*, **41**, 455-477.

Sutton RT, B.-W. Dong, and J. M. Gregory, 2007: Land/sea warming ratio in response to climate change: IPCC AR4 model results and comparison with observations. *Geophys. Res. Lett*., **34**, L02701

Tang, Q., G. Leng, and P. Y. Groisman, 2012: European Hot Summers Associated with a Reduction of Cloudiness. *J. Climate*, **25**, 3637–3644.

Tang, Q., and G. Leng, 2013: Changes in Cloud Cover, Precipitation, and Summer Temperature in North America from 1982 to 2009. *J. Climate*, **26**, 1733–1744.

Teuling, A. J., and Coauthors, 2009: A regional perspective on trends in continental evaporation. *Geophys. Res. Lett.*, **36**, L02404, doi:10.1029/2008GL036584.

Trenberth, K. E., and D. J. Shea, 2005: Relationships between precipitation and surface temperature. *Geophys. Res. Lett*., **32**, L14703, doi:10.1029/2005GL022760.

Tout, D. G., 1987: Precipitation-temperature relation- ship in England and Wales summers. *Int. J. Clima-tol*., **7**(2), 181–184.

Vautard, R., P. Yiou, F. D'Andrea, N. de Noblet, N. Viovy, C. Cassou, J. Polcher, P. Ciais, M. Kageyama, and Y. Fan, 2007: Summertime European heat and drought waves induced by wintertime Mediterranean rainfall deficit. *Geophys. Res. Lett.*, **34**, L07711, doi:10.1029/2006GL028001.

Wentz, F. J., L. Ricciardulli, K. Hilburn, and C. Mears, 2007: How much more rain will global warming bring? *Science*, **317**, 233–235.

Wu, R. G., J. P. Chen, and Z. P. Wen, 2013: Precipitation–surface temperature relationship in the IPCC CMIP5 Models. *Adv. Atmos. Sci.*, **30**(3), 766–778, doi: 10.1007/s00376-012-2130-8.

Zampieri, M., F. D’Andrea, R. Vautard, P. Ciais, N. de Noblet-Ducoudré, and P. Yiou, 2009: Hot European summers and the role of soil moisture in the propagation of Mediterranean drought. *J Climate*, *22*(18), 4747–4758.

Zhao, W., and M. A. K. Khalil, 1993: The relationship between precipitation and temperature over the contiguous United States. *J. Climate*, **6**, 1232–1236.

Fig.1: Point-wise, zero-lag correlations of summertime-mean temperature (T) against precipitation (P), using different datasets. CRU: Climatic Research Unit (CRU) Time-Series (TS) Version 3.21; UoD: University of Delaware Monthly Temperature and Precipitation dataset V3.01; NASA: NASA Goddard Institute for Space Studies GISTEMP Surface Temperature Analysis; ERAI: ERA-Interim reanalysis; GPCP: Global Precipitation Climatology Project monthly precipitation dataset V.2.2; CMAP: CPC Merged Analysis of Precipitation V.1201. Top two plots (CRU and UoD) use full record lengths, at original resolution (0.5°x0.5°). All other plots use data regridded on a common 2.5°x2.5° grid (over 1979-2008). Increments on the color scale correspond to the 10%, 5%, 1%, 0.1% levels of correlation significance (for different record lengths); non-significant correlations (at 10%) are whited out. Antarctica and Greenland are removed from all datasets. Numbers within plots indicate, on the bottom-center: the land percentage with significant (5%) T-P correlations (in blue, negative correlations only, in red, positive correlations); on the bottom-right: the field-significance threshold, as estimated by a Monte-Carlo procedure in which yearly maps of T and P were randomly shuffled 1000 times; the threshold used is the 95% quantile of the corresponding 1000-member distribution of area percentage with significant (5%) correlations (e.g., Livezey and Chen 1983). The dashed equatorial line separates JJA (June-July-August) means which are used for the Northern Hemisphere and DJF (December-January-February) means used for the Southern Hemisphere.

Fig.2: Simplified representation of two pathways through which correlations between seasonal mean temperature and precipitation can occur in summer: red, atmospheric processes; blue, land-atmosphere interactions. Note that in the interest of clarity, not all physical relationships are depicted here (e.g., impacts of temperature on soil moisture, feedbacks of surface fluxes to cloud cover, etc., are not represented).

Fig.3: As in Figure 1, but for GLACE-CMIP5 models over 1971-2000, in simulation REF (**a**) and simulation expA (**b**). Color key corresponds to the 10%, 5%, 1%, 0.1% levels of correlation significance.

Fig.4: In simulation REF (red) and expA (blue), sum of the grid cell areas with significant negative T-P correlations (at the 5% level, i.e. r=0.36), weighted by the T-P correlation values on these grid cells.

Fig.5: (**a**) Correlation between summertime-mean total soil moisture and evapotranspiration (cor(SM,ET)); (**b**) correlation between summertime-mean temperature and evapotranspiration (cor(ET,T)); (**c**) correlation between summertime-mean incoming shortwave radiation and evapotranspiration (cor(Rs,ET)), over 1971-2000, in simulation REF, for the different models. Color key corresponds to the 10%, 5%, 1%, 0.1% levels of correlation significance.

Figure 6: Correlation between summertime-mean evapotranspiration and incoming shortwave radiation, over 1971-2000, for the different models in expA. Color key corresponds to the 10%, 5%, 1%, 0.1% levels of correlation significance.

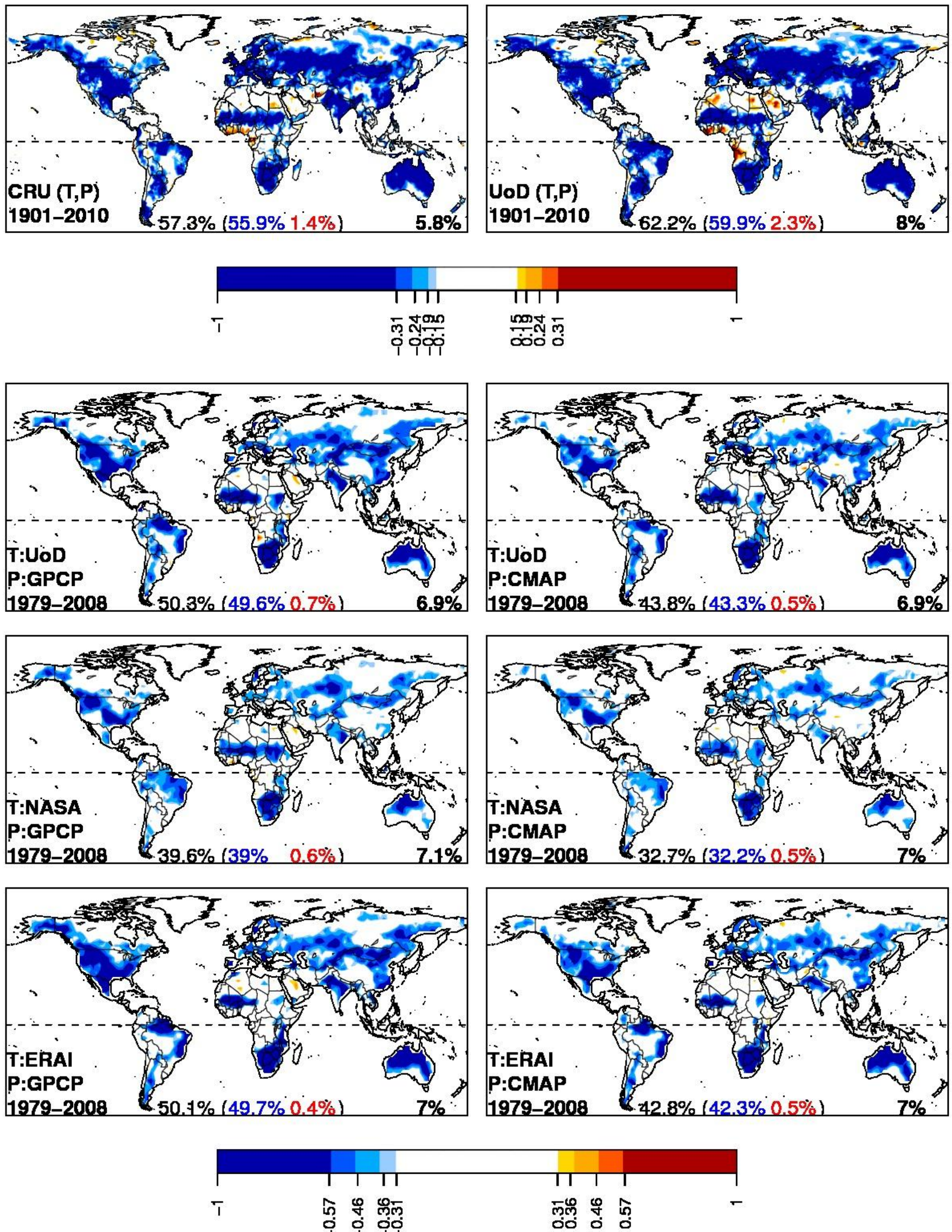
Fig.7: Correlation in simulation expA between summertime-mean incoming shortwave radiation and: (**a**) precipitation, and (**b**) temperature, over 1971-2000. (**c**) is the same as Figure 3b, i.e. T-P correlations in simulation expA, with black contours indicating where the correlations between summertime-mean temperature and radiation (seen in **b**) are significantly positive while the correlations between summertime-mean precipitation and radiation (seen in **a**) are significantly negative. Background land maps have been grayed (and interior borders were suppressed) in (c) to facilitate readability. Color key corresponds to the 10%, 5%, 1%, 0.1% levels of correlation significance.

Fig.8: (**a**) Correlation between summertime-mean temperature and precipitation, in simulation REF, binned as a function of correlations between soil moisture and evapotranspiration (cor(SM,ET), x-axis) and between evapotranspiration and temperature (cor(ET,T), y-axis), for the different models, over 1971-2000, over land. Blue and red contours indicate, respectively, negative and positive temperature-precipitation correlations significant at the 5% level (r=0.36); (**b**) percentage of total number of land pixels in each model that fall in each cor(SM,E)-(corE,T) bin.

Fig.9: Share of the land surface area (in %) where T-P, SM-ET and ET-T correlations become significantly more positive (positive bars) or significantly more negative (negative bars) between 1971-2000 and 2071-2100 (the difference being represented is future minus present) in different models in REF.

Fig.10: (**a**) Mean summer T change between 1971-2000 and 2071-2100, in K, in simulation REF; (**b**) mean summer T change between 1971-2000 and 2071-2100 from (**a**) (color key in K) binned along correlations between present-time (1971-2000) summertime-mean T and P (cor(T,P), x-axis) and mean summertime P change between 1971-2000 and 2071-2100 (y-axis, in mm/d), over land pixels only.

Fig.11: Same as Figure 10, for simulation expA. Note that temperature changes over the oceans in (a) are the same as in Figure 10 in simulation REF, since similar sea surface temperatures were prescribed in both experiments.



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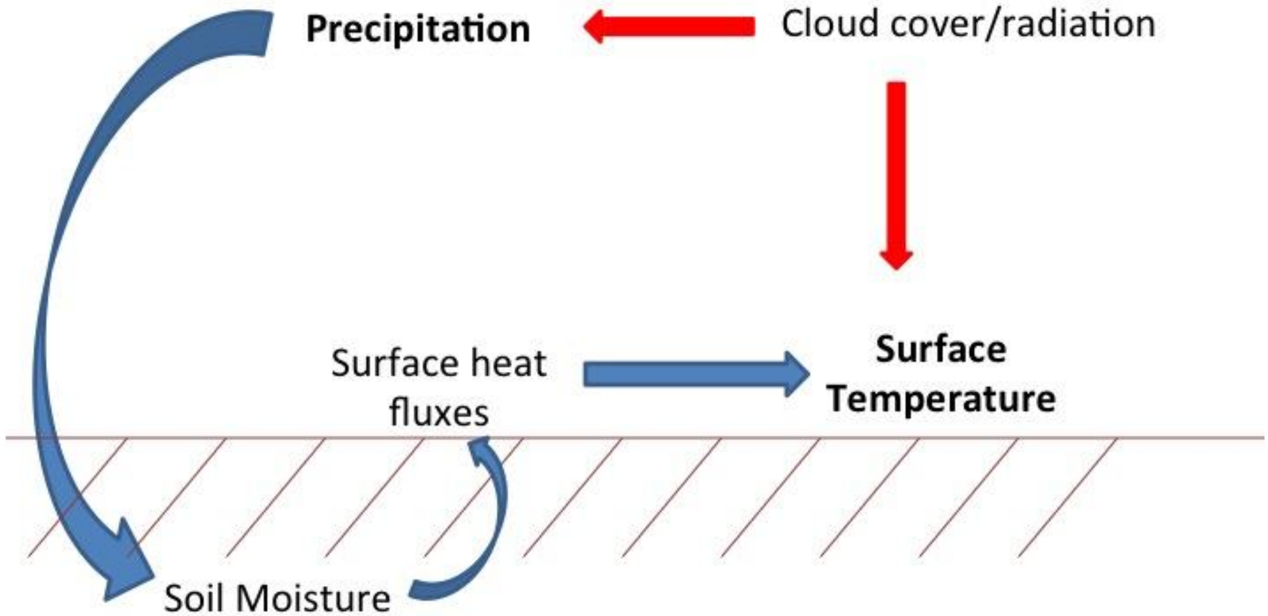

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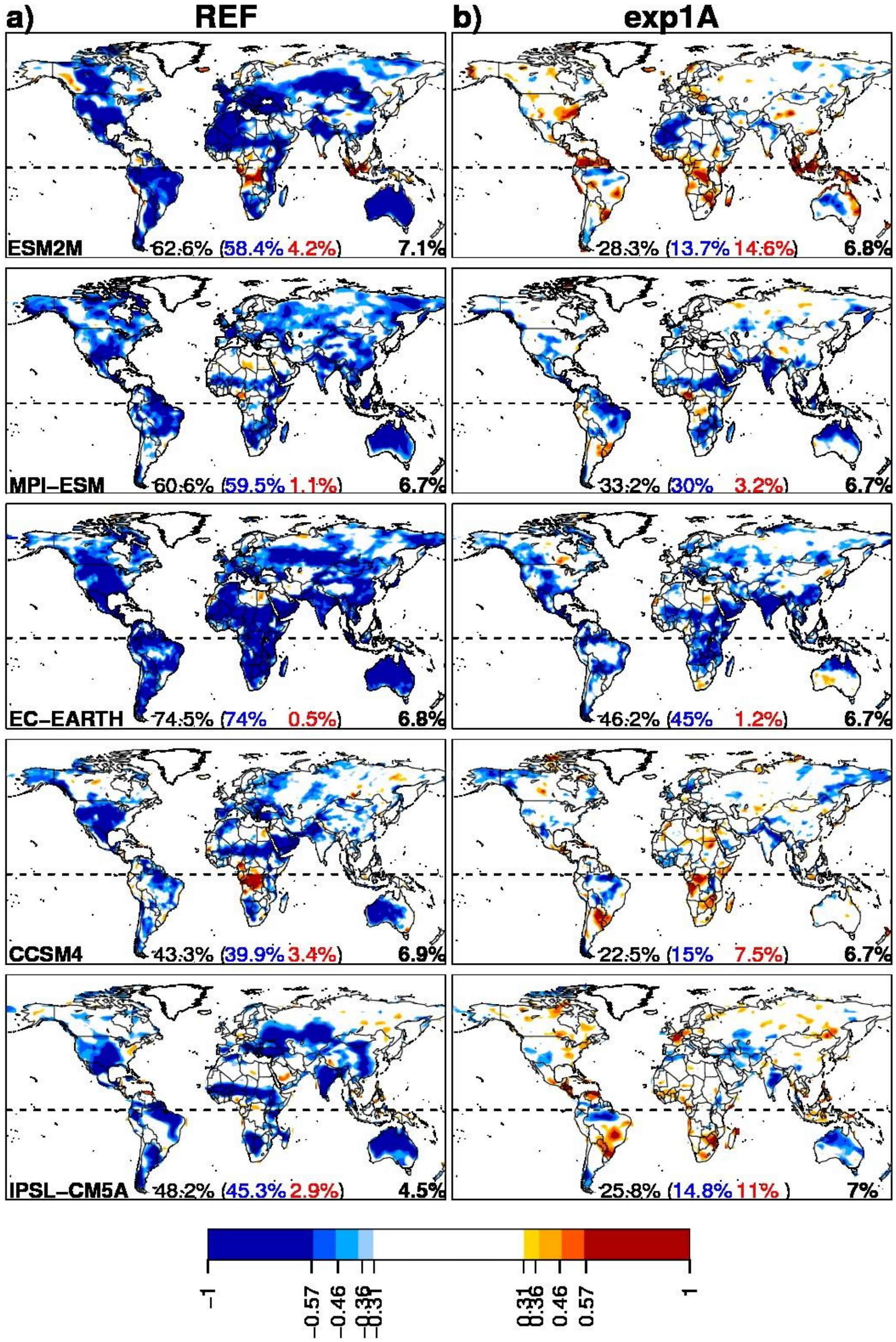

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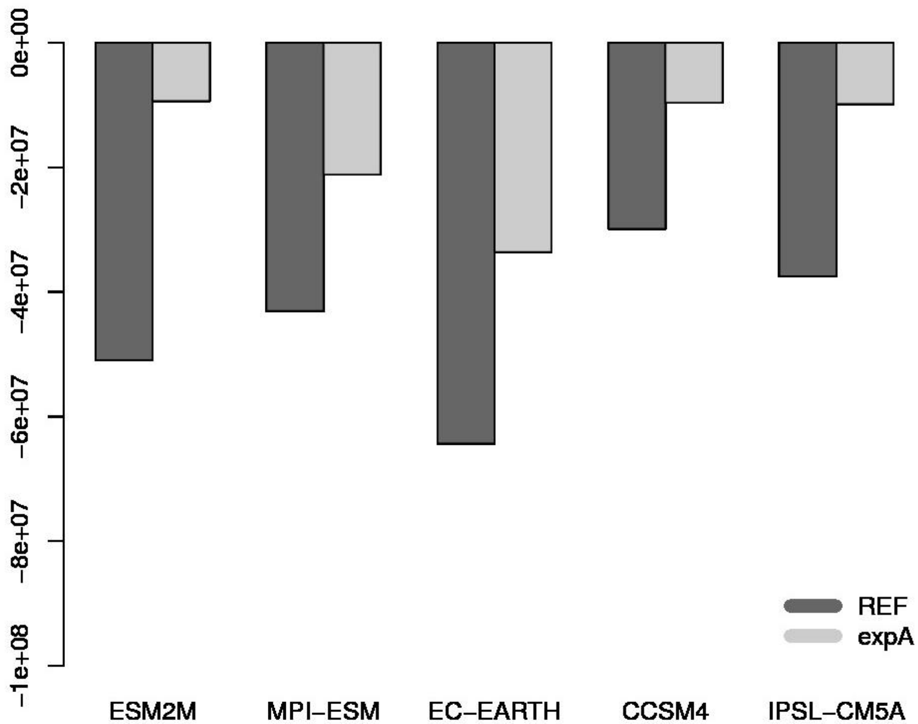

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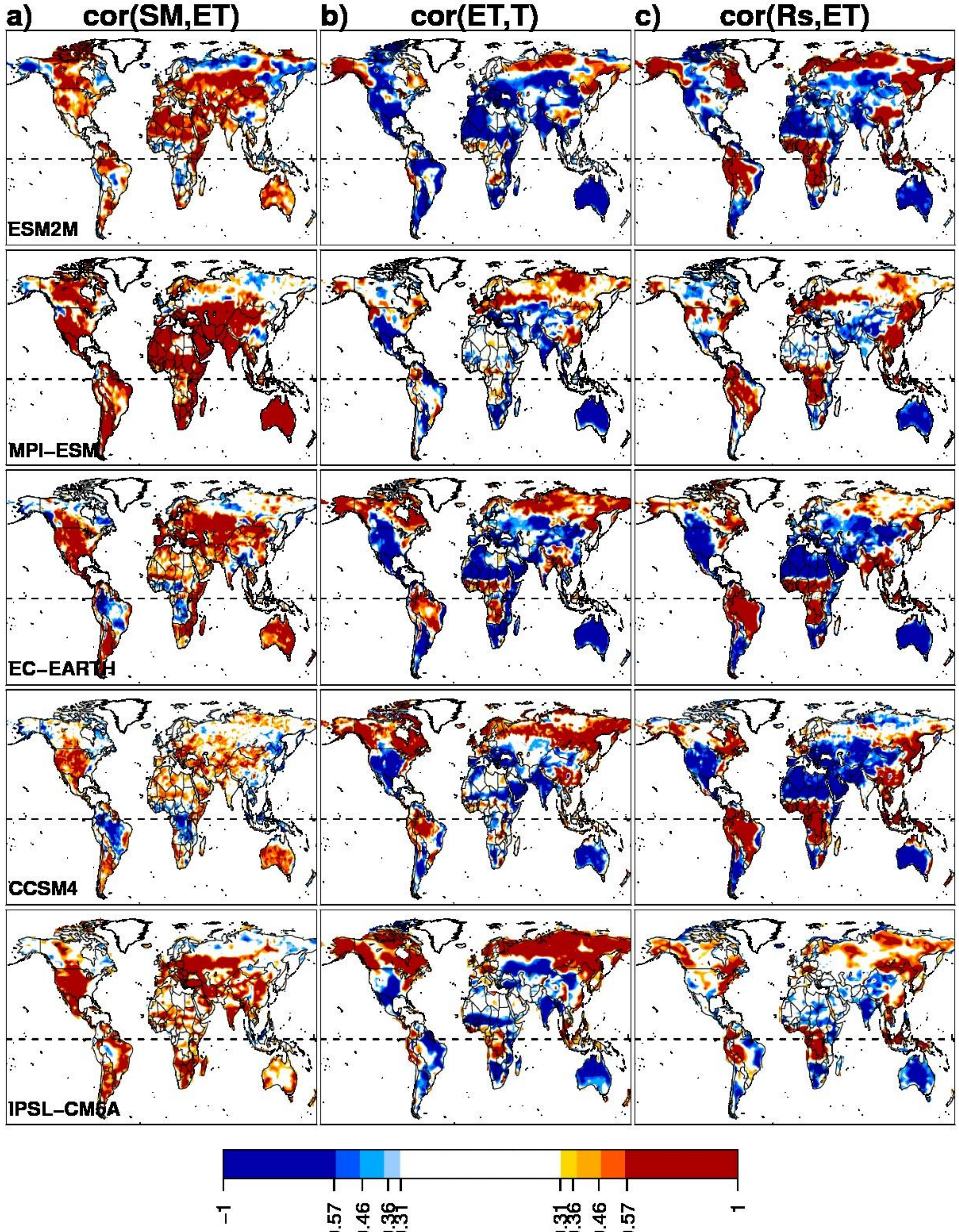

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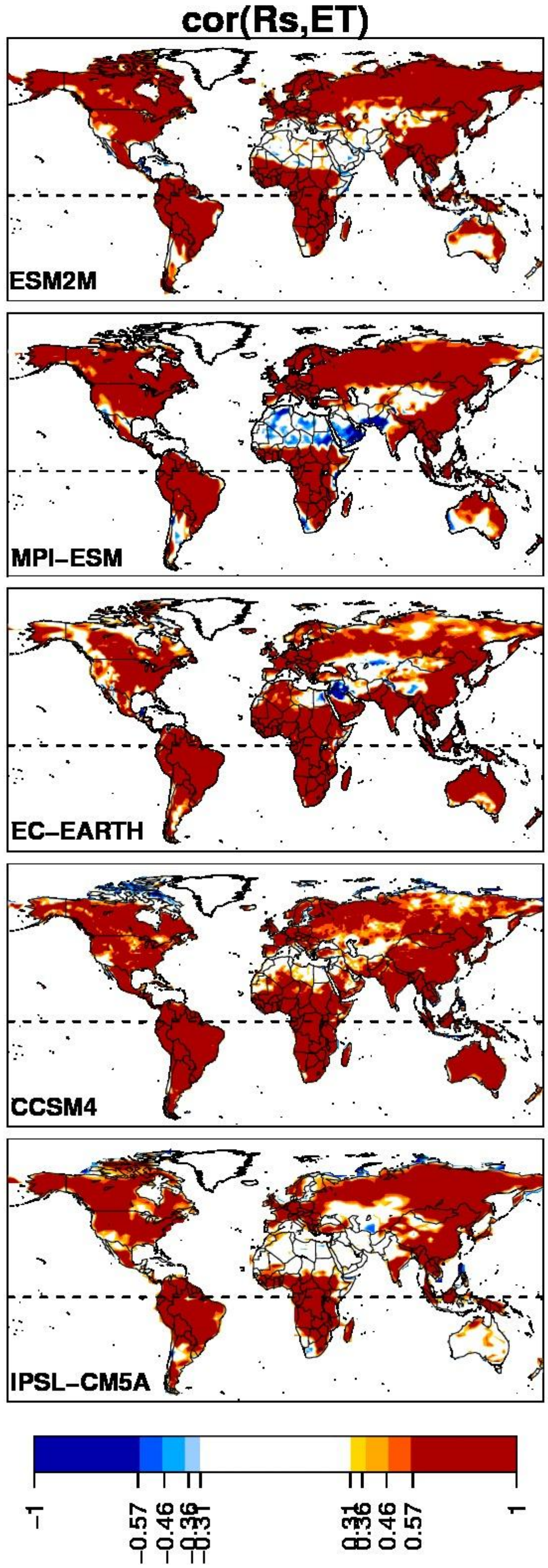

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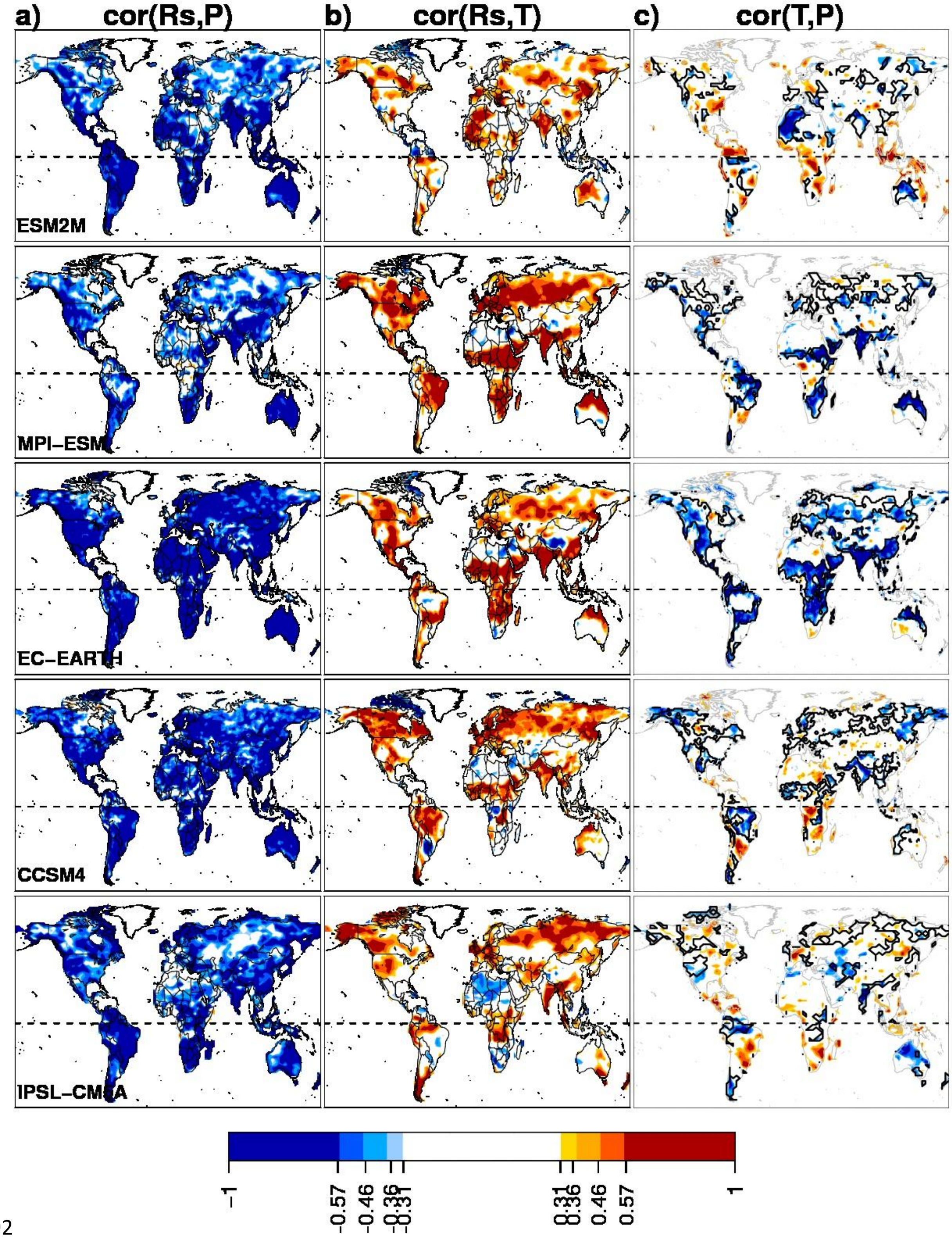

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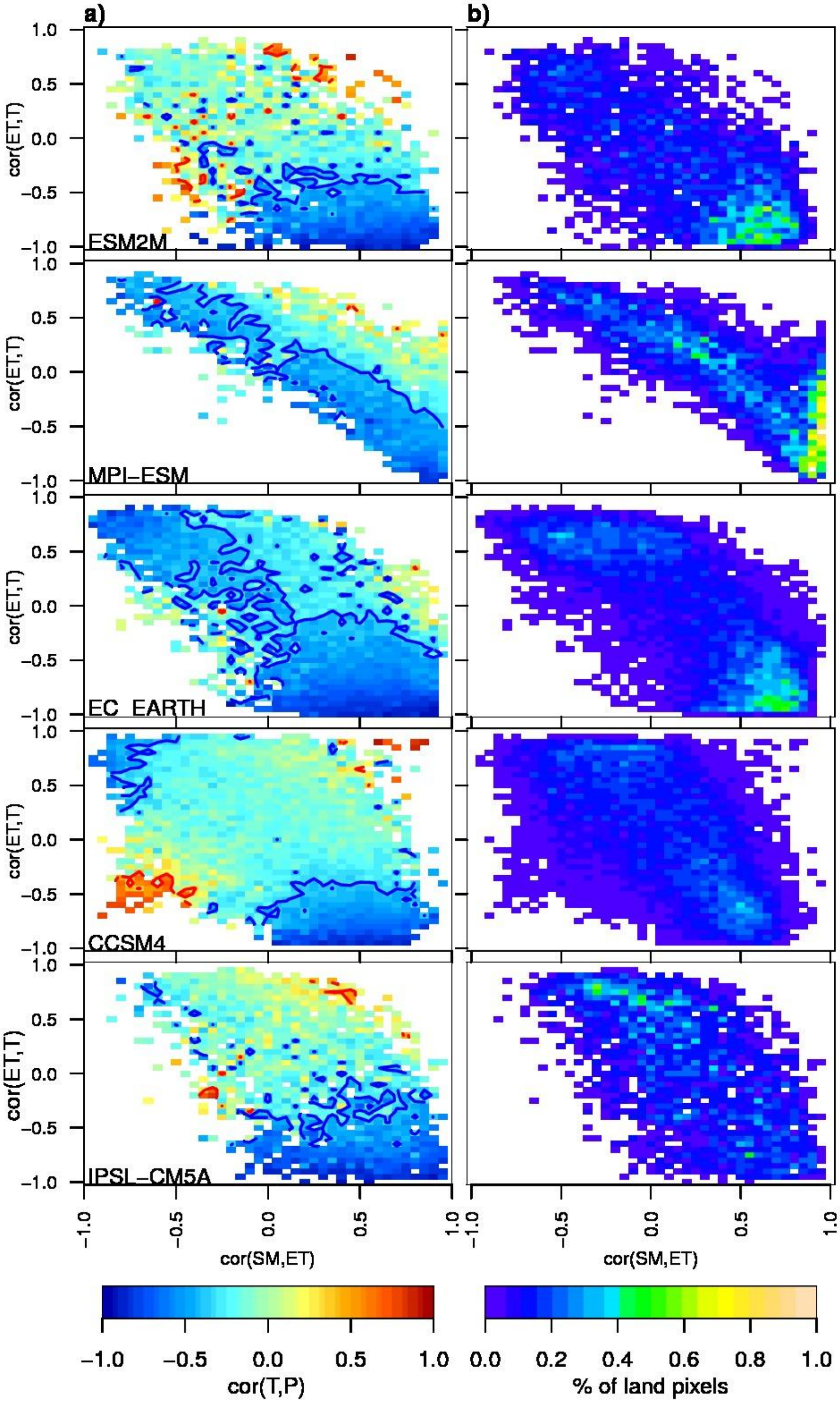

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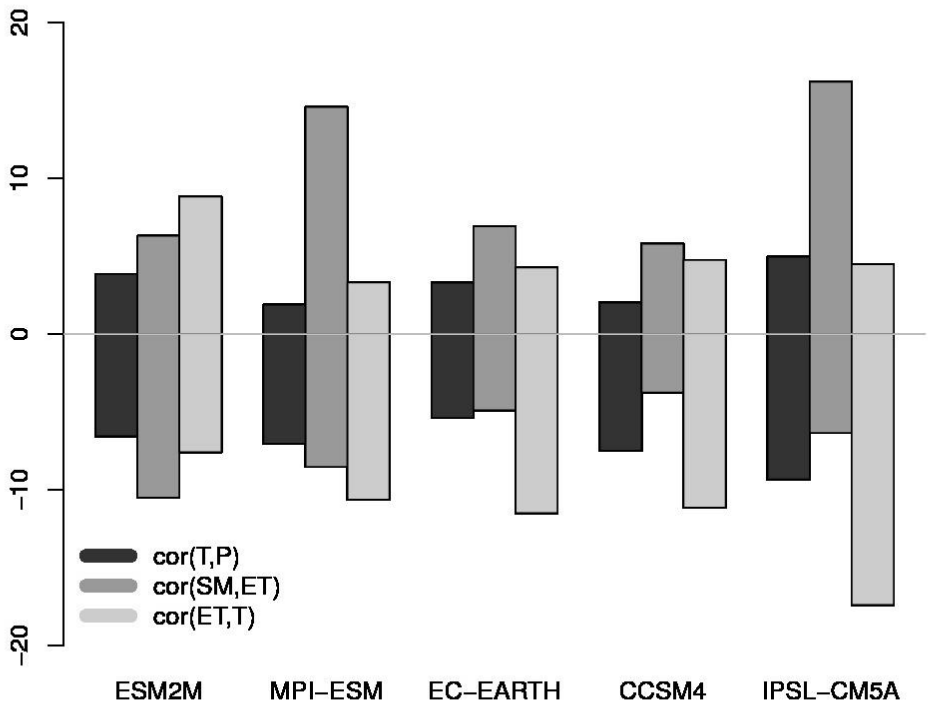

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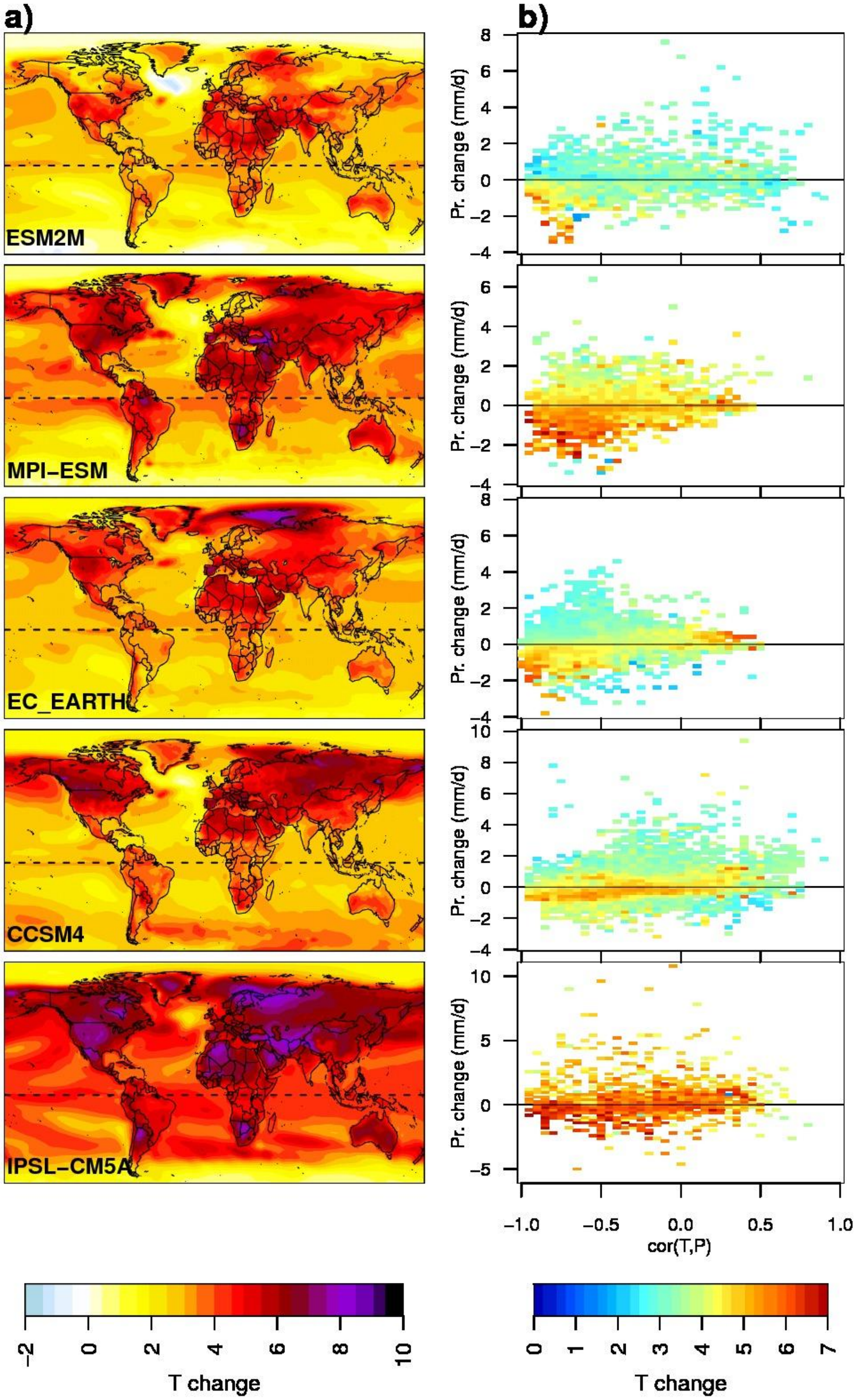

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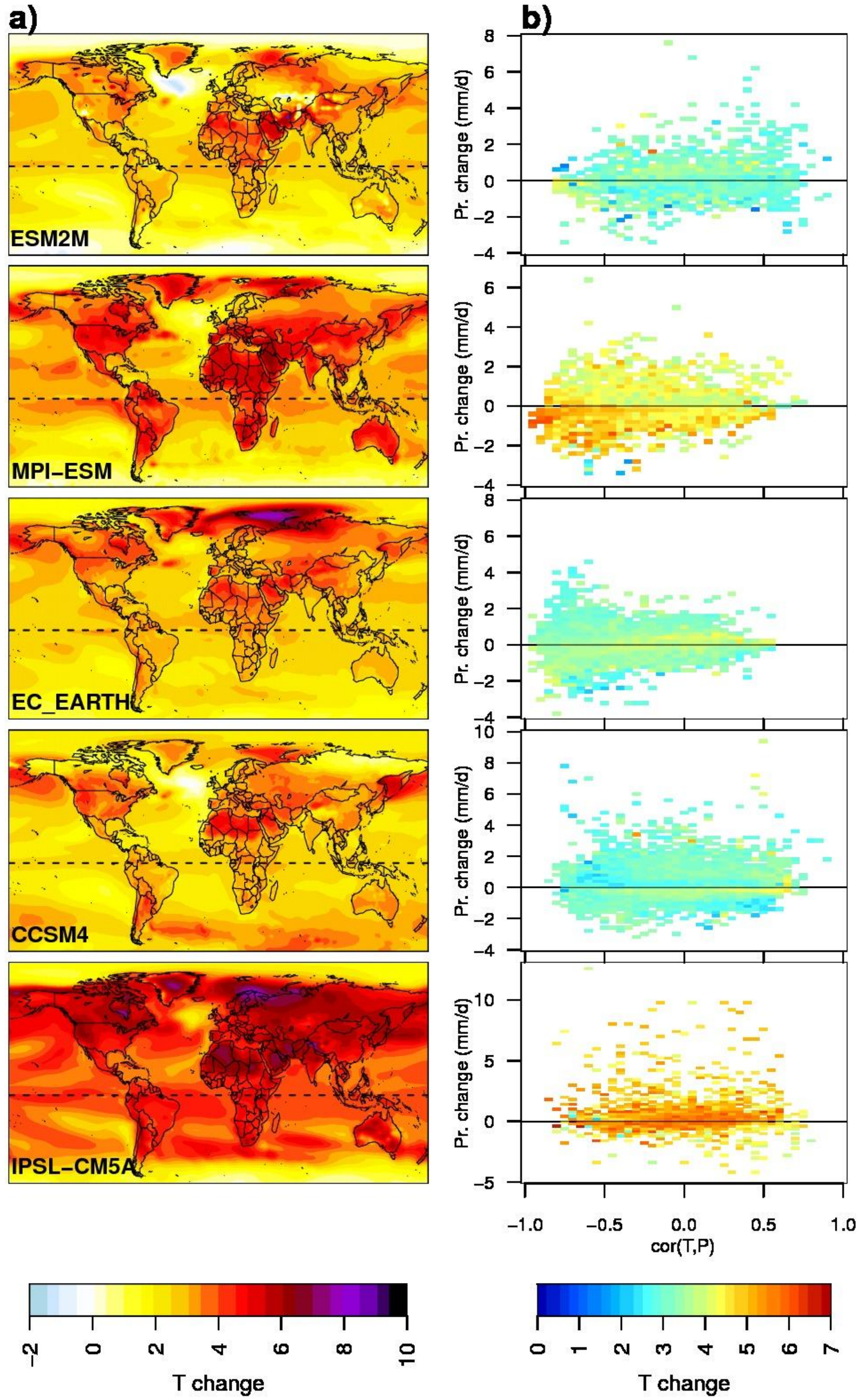

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Supplemental Material

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