Response to Reviewers' comments

We greatly appreciate the reviewers providing valuable and constructive comments on our manuscript HESS-2019-701. We seriously considered each comment and revised/improved the manuscript accordingly. The individual comments are replied below. In the following the reviewer comments are black font and our responses are blue and to assist with navigation we use codes, such as R1C2 (Reviewer 1 Comment 2).

To Anonymous Referee #1

R1C1: General comments: This paper analyzes projected changes in PDSI. It compares PDSI estimates obtained using potential evapotranspiration with and without accounting for the response of vegetation to increasing atmospheric CO2 concentration, as well as a direct estimate based on hydrological output from CMIP5 climate models. The main point is that there is no significant global drying trend based on PDSI, and the reason this was previously suggested is that offline impact models did not account for the response of vegetation to increased CO2. As noted by the authors (page 3, lines 54–57), several recent studies have already pointed out this problem when computing ET offline.

The valid point the authors make of refuting a general rule of "warming leads to drying" should not be interpreted as there will be no drying. The authors could try to make this even clearer by further emphasizing the projected increase in land area fraction under extreme conditions of water availability as well as the uncertainties in the projections.

Overall, the manuscript is well-structured and clearly conveys its main point. Nonetheless, it would be useful to further discuss some aspects of the methodology and address potential caveats of the PDSI.

Reply: Thanks for your encouraging and constructive comments. Your individual comments are replied below. We have changed the title and the text to avoid misleading the readers as "there will be no drying" and to focus on our key information that "we use direct climate model fluxes as inputs to PDSI and compare that with traditional PDSI. We find traditional PDSI overestimates projected drought. We also find that you can do a reasonable job using traditional PDSI but with CO_2 effects incorporated."

Specific comments

R1C2: Although PDSI has been a widely used index, it is not exempt from caveats.

When analyzing projected changes in drought (water availability) it would be beneficial to also directly show the changes in relevant variables like soil moisture and precipitation minus evapotranspiration. Although results for SPEI are presented in the supplement, a summary of trends in projected soil moisture anomalies would be a suitable complement to the manuscript. Particularly, maps of the trends would provide a more comprehensive picture as opposed to the global averages.
Reply: The maps of trends in soil moisture and precipitation minus evapotranspiration have been shown in a few previous publications (e.g., Berg et al., 2017; Greve et al., 2017; Swann et al., 2016; Yang et al., 2019); we have cited these papers and summarized/discussed their findings in the manuscript.

An important motivation of this study is actually based on these previous findings that total soil moisture (and root-zone soil moisture) does not show notable changes and precipitation minus evapotranspiration (or runoff) shows a slightly increase but estimated drought increases substantially in the coming century. The current study is designed to solve this contradiction. Several studies have pointed out the issue of ignoring the CO_2 effect in offline ET (and/or runoff) estimations (as noted by the reviewer), with the findings have important implications on drought changes. This study goes one step further by directly focusing on drought, using a widely used drought index – PDSI.

The spatial patterns of PDSI trend are shown in Figure 3. The global averaged PDSI series was intended to give an overall comparison between different PDSIs at the global scale (given comments by the editor and other reviewers, we removed this global average PDSI series from the main text in the revised manuscript).

R1C3: It appears that the climatically appropriate for existing conditions (CAFEC) coefficients are estimated for the entire period 1901–2100 (if this is the case, it should be explicitly stated). This seems counterintuitive to me when analyzing projected changes. Why would it not be more meaningful to estimate the soil moisture anomalies relative to some reference conditions from the past or present, e.g. 1901–1960 as for SPEI in Fig. S4?
Reply: Both PDSI and SPEI are calculated for the entire period 1901-2100 (both indices calculate the monthly departure from climatological means, and the climatological means are computed as the mean over 1901-2100). With the calculated SPEI series, in Fig. S4 (now supplementary Figure S3), we show the long-term SPEI change relative to the 1901-1960 mean to better highlight the changes.

In the revised manuscript, we have made this point clear in the method section (Line

116-117). In addition, we have removed the global average PDSI series (Figure 4 in the original submission) from the main text.

R1C4: It would be relevant to discuss and/or provide sensitivity tests to assumptions underlying the calculation of PDSI. For example, what value was selected for the available water capacity (AWC)? Is it constant in space? Are the values model dependent?
Reply: There is only one parameter (AWC) needed in PDSI calculation, and is derived from the Global Gridded Surfaces of Selected Soil Characteristics (https://webmap.ornl.gov/ogcdown/dataset.jsp?ds_id=569). We have described this in more detail in the revised manuscript (Line 117-119). The sensitivity of PDSI to AWC has been examined in a previous study (Sheffield et al., 2012), and the authors found that changes in AWC have only very minor impact on PDSI estimates. This is now mentioned in the revised manuscript (Line 119-120).

R1C5: It would be insightful to know more about the variability of PDSI given that all data is already available. For example, maps of change in the standard deviation of PDSI from a future period relative to present-day can be shown in the supplement.
Reply: Done. Revised as suggested (Supplementary Figure S4)

R1C6: The manuscript concludes (page 11, lines 273–274) highlighting the increased spatial variability in surface hydrological conditions. In this context, it could be appropriate to also discuss local changes in temporal variability, see Kumar et al. (2013). Kumar, S., Lawrence, D. M., Dirmeyer, P. A. & Sheffield, J. Less reliable water availability in the 21st century climate projections. Earth's Futur. 2, 152–160 (2013).
Reply: Done. Revised as suggested (Line 284), with the suggested paper now cited (thanks for the comment).

R1C7: Page 6, lines 129–132: Potential for discussion. Differences between total soil-depth representation in CMIP models may lead to systematic differences in PDSI estimates from individual models.
Reply: Done. We now mention this point in the revised manuscript (Line 137-139). In addition, we would like to point out although the absolute PDSI value might be different, differences in soil-depth are unlikely to affect the PDSI changes (as per Sheffield et al., 2012, see R1C4 above).

In addition, we updated our results by showing mean and range (estimates from all individual models) instead of standard deviation in the revised manuscript (Figure 5, S1-S3 in the revised manuscript). This better shows the difference between individual models.

R1C8: It should be noted that the discussed response of vegetation to increasing CO2 applies to transpiration, but not to evaporation from the soil and canopy as well as snow sublimation. In this case, increasing CO2 and temperature would have a direct effect towards increasing evaporation.
Reply: We agree with this point and we add a sentence in the revised manuscript to explicitly state that increasing CO_2 only impacts vegetation transpiration (Line 55-58).
Relevant text read: "This vegetation-[CO_2] response only impacts transpiration, not soil evaporation, interception from vegetation surfaces or sublimation in snow environments, however it should be noted that transpiration dominates (~ 65%) global terrestrial evaporation (Lian et al., 2018; Zhang et al 2016)."

R1C9: Fig. 3 shows that even for direct CMIP5 output there can be a considerable increase in the land fraction experiencing extreme drought/moist conditions. These areas could be even larger if we were to consider the full spread of the CMIP5 ensemble as opposed to plus/minus one standard deviation. Is it reasonable to consider that differences in how individual models represent the response of vegetation to increasing CO2 could explain the spread in CMIP5 projections? This may be an important discussion point for the paper.
Reply: We have updated our results by showing mean and range (estimates from all individual models) instead of standard deviation in the revised manuscript to better show the difference between individual models (Figures 5, S1-S3). However, it is beyond the scope of this manuscript to investigate how individual CMIP5 models deal with the response of vegetation to increasing CO_2. To the best of our knowledge, most (if not all) CMIP5 models adopt the Farquhar photosynthesis model to estimate assimilation rate, which is then coupled with the Ball-Barry model to estimate stomatal resistance. So, the response of vegetation to increasing CO_2 in most of the CMIP5 models is essentially the Farquhar response. So, the difference among models is unlikely caused by how the response of vegetation to increasing CO_2 represented in the model but more likely caused by the simulated difference in the controlling environmental factors (e.g., temperature, water availability, radiation, etc.) that modify the Farquhar response.

R1C10: What is the reason why this particular subset of 16 CMIP5 models was used and not all models that are available?
Reply: These particular 16 CMIP5 models were used because these 16 models

provide all outputs we need, in particular runoff estimations. We have explicitly stated this in the revised manuscript (Line 85-86).
Relevant text read: "These 16 CMIP5 models were selected as they output all variables, including runoff, that are needed for the analysis performed herein."

R1C11: Trends in vegetation greening are mentioned in the abstract. The following reference about hidden vegetation browning could be helpful. Pan, N., Feng, X., Fu, B., Wang, S., Ji, F. and Pan, S.: Increasing global vegetation browning hidden in overall vegetation greening: Insights from time-varying trends, Remote Sens. Environ., 214, 59–72, doi:10.1016/J.RSE.2018.05.018, 2018.
Reply: We have changed the relevant text as "the overall global greening", which implies that there are also scattered browning trend. We highlight greening here as it is the very big picture. However, the main text is all about climate model projections (which show an even more consistent greening trend across the globe), so the observed browning trend is not relevant here.

Technical comments
R1C12: In Palmer (1965), equation 26 appears to use monthly recharge (R) instead of long-term average R. This might be worth double checking since it seemed to me the average is used in the provided scripts.
Reply: The equation 26 in Palmer (1965) does not use monthly R but monthly climatological R: long-term mean R for each month. We follow that.

That equation is to estimate monthly weighting factors, so each month has only one weighting factor.

R1C13: Lines 45 and 225: Inconsistency in the reference Lehner et al., 2017 or 2018? There is only one reference entry.
Reply: Apology for the typo. It is Lehner et al., 2017. We have corrected it in the revised manuscript.

R1C14: Page 10, lines 23: I would delete the word "also" since the effects are opposite.
Reply: Done. Revised as suggested (Line 241).

R1C15: Page 11, line 273: Is Fig. 3b–f correct? Or Fig. 3b–c?
Reply: Done. We have renumbered the figures and carefully checked the text to ensure they are correctly referenced in the text.

R1C16: Figure 3: The selection criteria for where to have the black dots does not seem optimal. As it is now, it is showing all regions where the mean and median of PDSI have the same sign. I would suggest a different threshold for model agreement, e.g. black dots where at least 2/3 of the models agree in sign. Alternatively, it could be useful to include in the supplement maps of model agreement that are complementary to Figs. 3d–f.

Reply: There is a typo in the caption of Figure 3. The black dots actually show the same sign detected in at least 13 models (so >80%). We have corrected it in the revised manuscript (see caption of Figure 3).

R1C17: Page 8, line 194 and 196: It should be Fig. 4.

Reply: Apology for the typo. Since we have removed the global average PDSI series from the main text in the revised manuscript, this sentence has been deleted too.

References:

Berg et al., Divergent surface and total soil moisture projections under global warming, *Geophysical Research Letters*, 44, 236-244, 2017.

Greve et al., Simulated changes in aridity from the last glacial maximum to 4XCO2, *Environmental Research Letters*, 12, 114021, 2017.

Swann et al., Plant response to increasing CO2 reduce estimates of climate impacts on drought severity, *PNAS*, 113, 10019-10024, 2016.

Yang et al., Hydrological implications of vegetation response to elevated CO2 in climate projections, *Nature Climate Change*, 9, 44-48, 2019.

To Anonymous Referee #2:

R2C1: General Comments This report is a welcome contribution to the ongoing discussion in the literature regarding how to characterize changes in drought incidence under the changing climate. The paper is a follow-up to the paper by Yang et al (2019), which presents an equation that generally captures the variation of effective stomatal resistance within CMIP5 models as a function of atmospheric carbon dioxide concentration. In this paper, that relation is used to show how a popular drought index (the PDSI) can be adapted to characterize drought in our world of greenhouse warming. A readily available and simple offline alternative to the usual PDSI (and, in particular, to the Allen et al. form of the Penman-Monteith equation) will likely be of value to climate-change impacts analysts, many of whom may not be familiar enough with the biological processes in play or have the resources to model the processes with greater fidelity. That being said, it is important to evaluate the performance of the modified index carefully and to lay out clearly the assumptions and limitations in one place.

To some extent, the literature in this area has had a certain feel of X-vs-Y to it, X being increase of drought, and Y being no change in drought to speak of. This paper moves a bit toward the middle in acknowledging increases in drought incidence, but the overall presentation still has the feel of Y. Some specific suggestions for movement toward what might be a more balanced presentation are offered below for the authors' consideration.

Reply: Thanks for your encouraging and constructive comments. Your individual comments are replied below.

Specific Comments:

R2C2: The title "Little Change. . ." (which echoes that of Sheffield et al.) places the paper in the Y category mentioned in the General Comments above. To me, and perhaps to other readers, "little" implies something along the lines of "nothing to worry about." The authors might consider modifying the title to avoid that implication.

Reply: Thanks very much for the point. We have changed the title to: Comparing PDSI drought assessments using the traditional offline approach with direct climate model outputs.

R2C3: The reference to "PDSI" in the title, without qualification, is potentially confusing. Other publications (as well as this one) have shown that the usual PDSI equation applied to climate-change projections do imply increased drought. Would it be appropriate to change "PDSI" to "Co2-aware PDSI" or something else that

conveys that idea?
Reply: Please see our reply to R2C2.

R2C4: In general, the paper does a good job of citing the relevant literature. However, it's not clear to me that the abstract does justice to the previous literature (including the authors' own works) when it uses the phrase "resolve a paradox."
Reply: We have removed the phrase "resolve the paradox" in the revised manuscript.

R2C5: It's not immediately apparent what it means for the abstract to say that "global PDSI_CMIP5" remains generally unchanged. If this refers to the global average of the time average of the ensemble average of PDSI, then it is possible that the element of variability in space, in time, and across models could be lost in translation. It's hard to think about "drought" without considering variability.
Reply: We have revised the abstract to avoid any misunderstanding and/or misinterpretation of such. The new abstract reads:
"Anthropogenic warming has been projected to increase global drought for the 21st century when calculated using offline drought indices. However, this contradicts observations of the overall global greening and little systematic change in runoff over the past few decades and climate projections of future greening with slight increases in global runoff for the coming century. This calls into question the drought projections based on offline drought indices. Here we calculate a widely-used conventional drought index (i.e., the Palmer Drought Severity Index, PDSI) using direct outputs from 16 CMIP5 models (PDSI_CMIP5) such that the hydrologic consistency between PDSI_CMIP5 and CMIP5 models is maintained. We find that the PDSI_CMIP5-depicted drought increases (in terms of drought severity, frequency and extent) are much smaller than that reported when PDSI is calculated using the traditional offline approach that has been widely used in previous drought assessments under climate change. Further analyses indicate that the overestimation of PDSI drought increases reported previously using the traditional PDSI is primarily due to ignoring the vegetation response to elevated atmospheric CO_2 concentration ([CO_2]) in the offline calculations. Finally, we show that the overestimation of drought using the traditional PDSI approach can be minimized by accounting for the effect of CO_2 on evapotranspiration."

R2C6: The statement in the abstract that "projected increase in PDSI drought reported previously is primarily due to ignoring the vegetation response" seems somewhat overstated when I look at Figure 3, which suggests that the increase is about 50% or so due to ignoring the biological response, leaving another 50% that is not due to that.
Reply: We have revised the relevant text in the abstract to avoid any misunderstanding

and/or misinterpretation of such. In particular, in stead of saying “projected increase in PDSI drought reported previously”, we now use “the overestimation of PDSI drought increases reported previously” (Line 31).

R2C7: I did not carefully evaluate what was implied by lines 138-140: “The PDSIs were calculated using outputs of each CMIP5 model in turn, and the ensemble PDSIs (averaging PDSIs over models) were used in the following analyses,” but that passage gave me pause. Won’t averaging across models reduce both the temporal and spatial variability and thereby impact drought estimates?
Reply: We removed the global average PDSI series (Figure 4 in original submission) from the main text and updated (the new) Figure 5 to show the range of drought/moist areas projected by all individual models. In addition, results in Figure 5 are not ensembles but the results agreed in at least 8 models (as suggested by reviewer #3, i.e., R3C11).

R2C8: lines 208-210. The criterion for substantial increase in drought appears to based on the change in the average value of PDSI rather than the change in the exceedance of a threshold. Is that a good measure?
Reply: The focus here was the increase in drought (decrease in PDSI by definition). A place changes from extreme moist to mild moist is also considered as an indication of potential drought increase. The same analysis has been applied in a few previous studies (e.g., Liu et al., 2018) so we use the same approach to be able to compare with results from others.
Changes of PDSI exceeding a certain threshold indicate changes area under drought, and these results are given in Figure 5. In addition, we add a figure showing trends in months with PDSI exceeding a certain threshold to show changes in time under drought (Figure 4).

R2C9: lines 210-212. It was stated earlier that ensemble averages were used for the analysis. It’s quite possible I’ve read through the paper too quickly; the authors might consider taking precautions to avoid letting the casual reader get confused.
Reply: This is not the ensemble result (Figure 6 in the revised manuscript); instead, it is the result that shared by at least 8 of the 16 CMIP5 models (as suggested by reviewer #3, i.e., R3C11). This is now made clear in the revised manuscript (Line 217-219).

R2C10: lines 233-235. I am confused by “yet on the other hand” (which by the way sounds redundant in itself) combined with “also,” since both effects are working in the same direction. The “also” seems out of place here. I get that “also” here was

meant in the sense of "and here's another thing it does," but the current sentence structure doesn't work for me.
Reply: We have deleted "also" in the revised manuscript (Line 241).

R2C11: line 242-247. I think this is another place where the authors could relax away from the "Y" position mentioned in the general comments. It seems to me that the dryness near the surface might be important for wildfire risk and perhaps for various biological processes that take place close to the surface. This idea might even be allowed to bubble up into the abstract.
Reply: Following your suggestion, we have extended the discussion on possible impacts of surface soil moisture decline in the revised manuscript (Line 255-264).

R2C12: Figures 1 and 2. The creation of these figure to convey what's going on is appreciated. Figure 2 takes a while to understand. It might help if the four black arrows and the plus signs were removed. It also might help if there were another column for how Ep is computed.
Reply: Done. Revised as suggested. The second column from the left (under Meteorological Inputs) shows how E_P was computed for each PDSI.

R2C13: Figure 3. A map of trend in PDSI doesn't seem as useful as a map of trend in exceedance of some substantial value of PDSI.
Reply: The map of PDSI trend gives a general information on how PDSI changes. Per your comment we now also show the trend for the area under drought (defined by the PDSI exceeding a nominated threshold) (Figure 5). Following your suggestion, we have also added a map showing time (i.e., the number of months) in each year with a PDSI value exceeds a certain threshold (Figure 4).

R2C14: lines 435-436. "where the same sign of the PDSI trend is identified in at least 8 out of the 16 CMIP5 models.." Taken alone, without additional explanation in the caption, it seems like this would be true everywhere.
Reply: There is a typo in the caption of Figure 3. The black dots actually show the same sign detected in at least 13 models (so >80%). We have corrected this in the revised manuscript.

R2C15: Figure 4. This figure averages out a lot of information. Do the benefits of its inclusion outweigh the possible misunderstanding that it might generate? See also related comment above regarding "global PDSI_CMIP5" in abstract.
Reply: As also suggested by the editor, we removed this figure from the main text in the revised manuscript.

R2C16: Figure 5. As mentioned elsewhere, change in (expected value of) PDSI might not be the best metric for change in drought. Change in exceedance of thresholds might be better. I wouldn't be surprised if these were quite parallel, but to leave that taken for granted could weaken the overall impact of the paper.
Reply: Please see our reply to R2C8.
In addition, we understand this reviewer's concern of using changes in PDSI as the measure. However, using changes in exceedance of thresholds may also incur other issues. For example, if we chose PDSI = -1 as the threshold for drought, then locations having a PDSI = -2 in the baseline period and a PDIS = -1.5 in the future period (or PDSI = -1.5 in the baseline period and PDSI = -1.51 in the future period) will be identified as places with a substantial drought increase.

Technical Corrections
R2C17: line 93. Delete "and"
Reply: We have rewritten this part and this comment is not relevant in the revised manuscript.

R2C18: line 233. Change "increase" to "increases"
Reply: Done. Revised as suggested (Line 240).

R2C19: line 270-271. Consider changing "due to the ignorance of" to "due to ignoring."
Reply: Done. Revised as suggested (Line 279).

R2C20: line 285. Change semicolon to period.
Reply: Done. Revised as suggested (Line 271).

R2C21: line 433. Change "e-f" to "d-f"
Reply: The figures have been restructured and renumbers in the revised manuscript. We have carefully checked all figure captions to avoid such mistakes.

R2C22: line 287. Add period.
Reply: Done. Revised as suggested (Line 296).

References:
Liu et al., Global drought and severe drought-affected population in 1.5°C and 2°C warmer world, *Earth System Dynamics*, 9, 267-283, 2018

To Reviewer #3:

R3C1: This very innovative and important study shows that when the familiar Palmer Drought Severity Index (PDSI) is computed directly from global Earth System Model output of precipitation, evaporation, runoff and soil moisture storage (rather than box-modeling all those quantities from an offline-computed potential evaporation of questionable accuracy as is traditionally done), the dire projections of ubiquitous future global drought from those traditional studies vanish. Instead, the PDSI projections become both wetting and drying depending on region, consistent with the *direct* simulations of runoff, deep-layer soil moisture, etc. by the ESMs but not with the traditional PDSI studies.

This is a key methodological advance and shows that the PDSI index itself is not flawed under climate change, rather its known problems stem from the traditional potential evaporation input which is inaccurate, leading to inaccurate inferred water flux changes. The inaccuracy of the traditional potential-evaporation input is because leading-order biological effects of changing CO_2 and vapor pressure are taken into account in the ESMs but not in the potential-evaporation calculation, as the authors show well here.

I recommend only minor revisions before publication, since I was anonymous Reviewer #2 on the earlier version of this study that was originally submitted to Environ. Res. Lett., and I already had my concerns largely addressed during that review process at that journal. My strongly recommended minor revisions are listed below.

Reply: Thanks for your favorable evaluation of our study. Your individual comments are replied below.

R3C2: 30: This kind of parenthetical remark/qualification is appropriate for the body text, but I don't think is needed for the Abstract - it makes the Abstract too complicated and clunky. At least, that is how I read it. So I think you should either remove or greatly shorten this remark. You can put something like this in the body text instead.

Reply: Done. We have removed this additional remark in the revised manuscript.

R3C3: 54-57, 94-96, 122, 226, 271, 418: Should also mention the impact of increasing/elevated vapor pressure deficit, as you do in the Abstract. The direct effect of CO_2 is only part of the story, as you explain well at 235-237 but the text does not reflect here at all.

Reply: We have mentioned the VPD impact in Line 56 as you suggested. However, as we have carefully gone through other places you mentioned, we do not think they are biased statements. We use the term "CO_2 effects on vegetation" as a lumped impact including both direct and indirect pathways. Since we have explained them in the introduction and discussion, we prefer to keep using the "CO_2 effects on vegetation" as the overall impact to improve the flow of the manuscript.

R3C4: 88-89: It should be clarified here that this corresponds to the center stream in Figure 1, parallel to how you point out the right stream and left stream later in the paragraph.
Reply: Done. Revised as suggested (line 92). Noting that we use the word 'column' (or 'approach') rather than 'stream' to avoid any potential confusion for readers who are better reading languages other than English.

R3C5: 117-120: Similarly, this should mention that it is the right stream in Fig 1.
Reply: Done. Revised as suggested (line 125).

R3C6: 120-123: Similarly, this should mention that it is the left stream in Fig 1.
Reply: Done. Revised as suggested (line 130).

R3C7: 126-135: Similarly, this should mention that it is the center stream in Fig 1.
Reply: Done. Revised as suggested (line 133); and thanks for these (i.e., R3C4 to R3C7, inclusive) really good comments that mean Figure 1 becomes a 'backbone' for our analysis.

R3C8: 178: Should be 3d, not 3e.
Reply: Sorry for the typo. We have corrected in the revised manuscript (Line 180-183).

R3C9: 238: As stated in previous review for Environ. Res. Lett., "our results" on this line will be read by most readers as meaning "the current study" (even though that's not what you actually mean.) Since it's actually Yang et al (2019) that showed this key fact (not the current study), this needs to be rephrased to make that clear. It's largely the same authors, but different study, and the distinction is important.
Reply: Done. Revised as suggested (Line 247); thanks for the comment.

R3C10: Fig 2: Caption should point out which rows respectively correspond to the left, right and center streams of Fig 1.
Reply: Good suggestion; we have updated the caption of Figure 2 following your suggestion in the revised manuscript, noting (as per R3C4) we use the word 'column'

rather than ‘streams’.

R3C11: Fig 3d-f: Stippling when >50% of models agree on sign of change is trivial - this will almost always be true (unless exactly 8 models have increase and exactly 8 have decrease.) Rather, you should stipple when, say, >67% or >80% of models agree on sign of change. This better filters out changes that are just noise.

It is true that I suggested 50% threshold in previous review, but that was for models with dPDSI < -1, not for basic sign of change! 50% makes sense if the criterion is dPDSI < -1 because that’s not likely to occur by chance. But it doesn’t make sense for dPDSI < 0 or dPDSI > 0, since that occurs most of the time by chance (unless *exactly* 8 models happen to have a decrease!)
Reply: We are sorry about this but there is a typo in the caption of original Figure 3. The black dots actually show the same sign detected in at least 13 models (so >80%). We have corrected this in the revised manuscript; again we are sorry for the inconvenience.

R3C12: Supp Fig S1: This is greatly appreciated, but I think it would have an even greater impact if you reversed the color scale in panels b and c (i.e. make negative green/blue, and positive yellow/brown.) This is because in this context we are thinking of E as a loss term in the water budget, and so increasing trend of E -> more drying. (I know that in other contexts/purposes more E -> wetter, but here the purpose is clearly to indicate that panel c is not as "drying" as panel b, so the colors should intuitively reflect that!)
Reply: Done. Revised as suggested; and again thanks.

Comparing PDSI drought assessments using the traditional offline approach with direct climate model outputs

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Abstract. Anthropogenic warming has been projected to increase global drought for the 21st century when calculated using offline drought indices. However, this contradicts observations of the overall global greening and little systematic change in runoff over the past few decades and climate projections of future greening with slight increases in global runoff for the coming century. This calls into question the drought projections based on offline drought indices. Here we calculate a widely-used conventional drought index (i.e., the Palmer Drought Severity Index, PDSI) using direct outputs from 16 CMIP5 models (PDSI_CMIP5) such that the hydrologic consistency between PDSI_CMIP5 and CMIP5 models is maintained. We find that the PDSI_CMIP5-depicted drought increases (in terms of drought severity, frequency and extent) are much smaller than that reported when PDSI is calculated using the traditional offline approach that has been widely used in previous drought assessments under climate change. Further analyses indicate that the overestimation of PDSI drought increases reported previously using the traditional PDSI is primarily due to ignoring the vegetation response to elevated atmospheric CO_2 concentration ([CO_2]) in the offline calculations. Finally, we show that the overestimation of drought using the traditional PDSI approach can be minimized by accounting for the effect of CO_2 on evapotranspiration.

1 Introduction

Drought is an intermittent disturbance of the water cycle that has profound impacts on regional water resources, agriculture and other ecosystem services (Sherwood and Fu, 2014). By taking meteorological outputs from climate model projections as the inputs to offline drought indices/hydrological impact models, numerous studies have projected increases in future drought, in terms of severity, frequency and extent, mainly as a consequence of warming associated with anthropogenic climate change (Cook et al., 2014, 2015; Dai, 2011, 2012; Dai et al., 2018; Huang et al., 2015, 2017; Lehner et al., 2017; Liu et al., 2018; Naumann et al., 2018; Park et al., 2018; Samaniego et al., 2018; Sternberg, 2011; Trenberth et al., 2013). The scientific basis underpinning this drying trend projected using offline drought indices/hydrological impact models is that the calculated increases in evapotranspiration (*E*) are larger than the projected increase in precipitation (*P*) in many places (Sternberg et al., 2011), which results in an increasing water deficit and thus increasing simulated future drought. However, direct climate model outputs of E exhibit a much smaller increasing trend (Supplementary Figure S1) and the global land mean P is actually projected to increase faster than its E counterpart (Greve et al., 2017; Milly and Dunne, 2016, 2017; Roderick et al., 2015; Yang et al., 2018) leading to a very different conclusion.

Several recent studies have demonstrated that the drying bias in the offline calculated E trend is primarily due to neglecting the impact of increasing atmospheric CO_2 concentration ($[CO_2]$) (and its resultant vapor pressure deficit increase) on the water use efficiency of vegetation (Lemordant et al., 2018; Milly and Dunne, 2016, 2017; Roderick et al., 2015; Swann et al., 2016; Yang et al., 2019). This vegetation-$[CO_2]$ response only impacts transpiration, not soil evaporation, interception from vegetation surfaces or sublimation in snow environments, however it should be noted that transpiration dominates (~ 65%) global terrestrial evaporation (Lian et al., 2018; Zhang et al 2016). In existing hydrologic impact models/drought indices, P and potential evapotranspiration (E_P; the rate of evapotranspiration that would occur with an unlimited supply of water) are the two key input variables, which respectively represent water supply to, and water demand from, the land surface. While P is a direct climate model output, E_P is neither used nor produced by climate models. The traditional approach is to calculate E_P offline using the meteorological variables in the climate model output. The calculated E_P, together with the climate model projected P, are used to force an offline hydrologic impact model (or hydrologic calculations embedded in drought indices) that independently calculates E, runoff (Q), and storage change (ΔS), for assessing hydrologic changes under future climate scenarios (see Figure 1). Among various E_P models, the open-water-Penman model (Shuttleworth, 1993) and the reference crop Penman-Monteith model (Allen et al., 1998) have been most widely used in existing drought assessment studies, given their sound physical basis and relatively simple formulations. Nevertheless, both Penman-based models do not faithfully capture the biological processes embedded in the climate models. The open-water-Penman model was designed for water surfaces, where surface resistance (r_s) is, by definition, equal to zero. Allen et al's (1998) reference crop Penman-Monteith model prescribed a constant r_s at 70 s m^{-1}, which is appropriate for an idealized reference crop in the current climate but does not account for the fact that r_s increases with elevated $[CO_2]$ over vegetated surfaces in climate model projections (Yang et al., 2019). As a result, existing conventional offline hydrologic impact models/drought indices calculate estimates of E, Q and ΔS that are different from those same variables in the original fully-coupled climate model output. For that reason, the consequent assessments of drought changes in existing offline hydrologic impact models/drought indices do not correctly represent the projections in the underlying fully-coupled climate models. Figure 1 illustrates the inconsistency in the hydrologic predictions (also see Milly and Dunne 2017) that have resulted in different trends in projected future drought between climate models and offline hydrologic impact models/drought indices.

Here, we re-assess changes in future global drought using climate model projections from 16 Coupled-Model-Intercomparison-Project-Phase-5 (CMIP5) models under historical (1861-2005) and Representative Concentration Pathway 8.5 (RCP8.5; 2006-2100) experiments (Taylor et al., 2012). These 16 CMIP5 models were selected as they output all variables, including runoff, that are needed for the analysis performed herein. The Palmer Drought Severity Index (PDSI; Palmer, 1965) is adopted here to quantify drought as it has been widely used for operational drought monitoring and is increasingly used in studies assessing drought under climate change (Cook et al., 2014, 2015; Dai, 2011, 2012; Dai et al., 2018; Lehner et al., 2017; Liu et al., 2018; Sheffield et al., 2012; Swann et al., 2016; Trenberth et al., 2013). To maintain consistency between the calculated PDSI and the CMIP5 models, we first calculate PDSI using direct hydrologic outputs (i.e., P, E, Q, ΔS) from the CMIP5 models (PDSI_CMIP5; corresponds to the centre column in Figure 1; also see Methods). This procedure provides a reference for the PDSI projections. We then replicate the traditional PDSI calculation by using only meteorological data as inputs to calculate the reference crop Penman-Monteith E_P (PDSI_PM-RC) (the right-hand column shown in Figure 1). The inference is that this traditional offline approach that only responds to meteorological forcing will overestimate drought relative to the direct climate model output because it does not consider the biological effect of elevated [CO_2]. To evaluate that inference, we again re-calculate the PDSI using an offline formulation that considers both the meteorological forcing and the biological effects of elevated CO_2 (Yang et al., 2019) (the left-hand column in Figure 1).

2 Data and Methods

2.1 Climate model projections

We used outputs from 16 climate models participating in Phase 5 of the Coupled Model Intercomparison Project (CMIP5; Supplementary Table S1) under historical (1861-2005) and RCP 8.5 (2006-2100) experiments (Taylor et al., 2012). We used monthly series of runoff, precipitation, soil moisture, sensible and latent heat flux at the land surface along with near-surface air temperature, air pressure, wind speed and specific humidity. All outputs from 16 CMIP5 models were resampled to a common 1^{o} spatial resolution by using the first-order conservative remapping scheme (Jones, 1999).

2.2 Calculation of PDSI

The Palmer Drought Severity Index (PDSI) was used to quantify drought (Palmer, 1965). To minimize the impact of initial conditions on PDSI estimates, the first 40 years (1861-1900) are used for model spin-up with the analyses focused on the 1901-2100 period. Briefly, the PDSI model consists of two parts: (i) a two-stage bucket model that calculates the monthly water balance components (i.e., E, Q and ΔS) using P and E_P as inputs, and (ii) a dimensionless index that describes the moisture departure between the actual precipitation and the precipitation needed to maintain a normal soil moisture level for a given time (i.e., the climatically appropriate for existing conditions values; these values were calculated for the entire period of 1901-2100). The soil available water capacity (AWC) needed for PDSI calculation was derived from the Global Gridded Surfaces of Selected Soil Characteristics (https://webmap.ornl.gov/ogcdown/dataset.jsp?ds_id=569). While this parameter is inevitably subject to uncertainties, Sheffield et al (2012) demonstrated that the PDSI calculation is insensitive to AWC inputs. Detailed descriptions of PDSI can be found in Palmer (1965). A drought event is identified with negative PDSI values, with a more negative PDSI indicating a more severe drought, whereas moist events are associated with positive PDSI values.

We calculated PDSI following Palmer (1965) yet calculated E_P using the reference crop Penman-Monteith model (PDSI_PM-RC; the right-hand column in Figure 1). The Penman-Monteith model explicitly considers influences from both radiative and aerodynamic components and has been widely used in previous PDSI calculations (e.g., van der Schrier et al., 2011; Dai et al., 2011; Sheffield et al., 2012). In addition, we also used a modified Penman-Monteith model (PM[CO_2]; detailed later in the Methods and also see Yang et al., 2019) that accounts for the impact of elevated [CO_2] on r_s to calculate E_P and then PDSI (PDSI_PM[CO_2]; the left-hand column in Figure 1).

Additionally, instead of using hydrological simulations from the simplified water balance model embedded in the original PDSI model, we also calculated PDSI by using direct hydrologic outputs E, Q, ΔS from the 16 CMIP5 models (PDSI_CMIP5; the centre column in Figure 1). This approach ensures that PDSI_CMIP5 faithfully represented the CMIP5 output. As the original PDSI model depends on a two-stage ‘‘bucket’’ model of the soil, we correspondingly regarded the moisture in upper portion of soil column (integrated over the uppermost 10 cm) from CMIP5 models as the moisture in the first layer and the total soil moisture content as the available moisture in both layers (so differences between total soil-depth representation in CMIP5 models may lead to differences in PDSI estimates from individual models but are unlikely impact the PDSI changes). Moreover, since the estimation of the weighting factor that converts moisture anomalies into the PDSI index also requires knowledge of E_P, we used the E_P computed from a modified Penman-Monteith equation that explicitly considers the biological effect of elevated [CO_2] (i.e., PM[CO_2]) (Yang et al., 2019). To comprehensively document how the different PDSIs were calculated, we illustrate the calculation procedures of the different PDSIs in Figure 2. Additionally, Matlab codes with worked examples of the different PDSIs can be accessed through *https://github.com/zslthu/Calculate-PDSI-in-Matlab*. The PDSIs were calculated using outputs of each CMIP5 model in turn, and the ensemble PDSIs (averaging PDSIs over the 16 CMIP5 models) were used in the following analyses.

2.3 Calculation of Potential Evapotranspiration

Two potential evapotranspiration formulations were used to calculate E_P. The first is the reference crop Penman-Monteith E_P model, which computes E_P (mm day^{-1}) as (Allen et al., 1998):

$$E_P = \frac{0.408\Delta R_n^* + \gamma \frac{900}{T+273} uD}{\Delta + \gamma(1+0.34u)} \qquad (1)$$

where Δ (Pa K^{-1}) is the gradient of the saturation vapour pressure with respect to temperature, γ (Pa K^{-1}) is the psychrometric constant, R_n^* (MJ m^{-2} day^{-1}) is the surface available radiation (i.e., net radiation minus ground heat flux), D (Pa) is the vapour pressure deficit of the air at 2 m height, u (m s^{-1}) is the wind speed at 2 m height. In the reference crop Penman-Monteith model, r_s is prescribed as 70 s m^{-1} and this parameter value is embedded into the equation.

In addition, we used a modified reference crop Penman-Monteith E_P model (i.e., PM[CO_2]) that accounts for the impact of rising [CO_2] (expressed in ppm units) on r_s, as derived in Yang et al. (2019). The PM[CO_2] model calculates E_P as:

$$E_P = \frac{0.408\Delta R_n^* + \gamma \dfrac{900}{T+273} uD}{\Delta + \gamma\{1 + u[0.34 + 2.4\times 10^{-4}([CO_2] - 300)]\}} \qquad (2)$$

2.4 Determining the timing of global warming target

To demonstrate the impact of warming on drought changes, we assessed changes in PDSI_CMIP5 under two future warming targets: 1.5 ^{o}C and 2 ^{o}C warming above the pre-industrial level. The 1.5 ^{o}C and 2 ^{o}C warming levels have been extensively discussed (Huang et al., 2017; Lehner et al., 2017; Liu et al., 2018; Park et al., 2018; Samaniego et al., 2018), as they are the two key warming targets set in the Paris Agreement on climate change (UNFCCC, 2015). The timing when the global warming targets (i.e., $t_{1.5}$ and t_2) is reached in each of the 16 CMIP5 models was computed based on the model output of the near-surface air temperature (T_a). We first selected 1986-2005 as the baseline period, which is a widely used reference period for climate impact assessment (Lehner et al., 2017; Liu et al., 2018; Park et al., 2018). Then, we applied a 20-year moving average filter to the global mean annual T_a time series to remove the interannual fluctuations in annual T_a (Liu et al., 2018; Park et al., 2018). Each 20-year moving average is indexed to its final year (for example, the 20-year running mean T_a for 2080 is an average of T_a for 2061–2080). Finally, $t_{1.5}$ and t_2 are respectively determined at the times when global mean T_a reached 0.9 °C and 1.4 °C above the 1986–2005 baseline, as this period was at least 0.6 °C warmer than the pre-industrial level (Hawkins et al., 2017; Schleussner et al., 2016).

3 Results

3.1 Predicted drought changes

Figure 3 shows the global patterns of PDSI trends for the three PDSIs. Evident drought increases are depicted by PDSI_PM-RC across much of the North America, South America, central-to-south Europe, Congo Basin, southern Africa, southeast China and southern coastal areas of Australia (Figure 3a), as widely reported previously (Dai, 2011, 2012; Dai et al., 2018; Cook et al., 2014; Lehner et al., 2018; Liu et al., 2018). However, those broad scale trends are not identified by either PDSI_CMIP5 or PDSI_PM[CO_2] (Figures 3b and c). Compared with PDSI-PM-RC, both PDSI_CMIP5 and PDSI_PM[CO_2] show much smaller changes. This result clearly indicates an inconsistency between the PDSI_PM-RC that has been widely used in traditional offline calculations for drought assessment studies and the underlying CMIP5 models, as the PDSI_CMIP5 used here is based on the direct hydrologic outputs (E, Q and ΔS) from CMIP5 models.

To examine changes in drought frequency and extent, changes in months under drought within each year and changes in land area subject to dry and moist extremes are respectively shown in Figures 4 and 5. In applications, a PDSI < -3.0 is considered to be severe drought conditions while a PDSI > 3.0 is considered exceptionally moist (e.g., Palmer, 1965; Liu et al., 2018). We find that months with PDSI_PM-RC < -3.0 increase substantially over areas where PDSI_PM-RC evidently decreases, suggesting an increased drought frequency in these regions (Figure 4a). However, when assessed with PDSI_CMIP5 and PDSI_PM[CO_2], these drought frequency increases largely diminish (Figure 4b and 4c). Similar results are found for drought extent changes as severe drought during the 21st century increases by 0.2393 ± 0.0942% per year (p<0.01) for PDSI_PM-RC but only increases by 0.1099 ± 0.0228% per year (p<0.01) for PDSI_CMIP5 and 0.1178 ± 0.0308% per year (p<0.01) for PDSI_PM[CO_2], respectively (Figures 5a-c). By contrast, moist areas (i.e., PDSI > 3.0) are less divergent among the three different PDSIs, although the PDSI_PM-RC still shows the fewest wetting lands compared to the other two PDSIs (Figures 5a-c). Interestingly, both PDSI_CMIP5 and PDSI_PM[CO_2] depict the increase in drought area to be essentially equivalent as the increase in moist area (Figures 5a-c), which may suggest an overall unchanged PDSI_CMIP5 (PDSI_PM[CO_2]) series at the global scale (Supplementary Figure S2). The above results are largely retained when assessing changes at different thresholds (i.e., mild drought/moist events with PDSI < -1.0 and PDSI > 1.0, and moderate drought/moist events with PDSI < -2.0 and PDSI >2.0 (Figures 4d-4i and 5d-5i). The fact that the results based on PDSI_PM[CO_2] closely follow that of PDSI_CMIP5 highlights the importance of vegetation response to elevated [CO_2] in the control of future surface hydrological changes. This demonstrates the inconsistency between the PDSI_PM-RC and CMIP5 models is largely caused by ignoring the vegetation response to elevated [CO_2] in the PDSI_PM-RC calculations.

3.2 The effect of warming on drought changes

Warming has been identified as the key driver of the overall future drought increase in numerous studies (Cook et al., 2014, 2015; Dai, 2011, 2012; Dai et al., 2018; Huang et al., 2015, 2017; Lehner et al., 2017; Liu et al., 2018). To further understand the impact of warming on drought changes, we assessed changes in PDSI_CMIP5 at 1.5 ^{o}C and 2 ^{o}C warming above the pre-industrial level. The PDSI_PM-RC is also presented for comparison. Any substantial increase in drought is identified when PDSI for a future warming target decreased by 1.0 compared to PDSI during the 1986-2005 baseline (i.e., ΔPDSI < -1). Additionally, only places where the ΔPDSI < -1.0 threshold is reached in at least 8 CMIP5 model (out of the 16 CMIP5 models so 50% and more) are considered to be robust projections and thus used herein. Based on the PDSI_CMIP5, our results show that almost nowhere on earth (only 0.06% of the global land area) is projected to have a substantial drought increase at the 1.5 ^{o}C warming target, and this number only slightly increases to 0.77% at the 2 ^{o}C warming target (Figures 6a and b). In comparison, substantial increase in drought is identified at 5.10 % and 13.41 % of the global land area at the two warming targets, respectively, when PDSI_PM-RC is used (Figures 6a and c). More places are projected to have a substantial drought increase under future warming if we relaxed the threshold of PDSI change to -0.5 (i.e., ΔPDSI < -0.5) (Figures 6d-f). Nevertheless, the PDSI_CMIP5 still shows a considerable smaller percentage of drying lands (6.2% and 10.0%) than the PDSI_PM-RC (26.32% and 34.77%) under the two warming targets, respectively, particularly over North America, much of Amazonia, Europe, the Congo basin and southeast China.

4 Discussion and concluding remarks

The above results clearly demonstrate an overestimation of drought severity, frequency and extent using PDSI in many previous assessments of future drought (e.g., Cook et al., 2014, 2015; Dai, 2011, 2012; Dai et al., 2018; Lehner et al., 2017; Liu et al., 2018). The overestimation is primarily caused by neglecting the impact of elevated [CO_2] on r_s and consequently on E_P in the traditional offline calculation. As E_P is neither used nor produced by climate models, an offline intermediate E_P model is required to estimate E_P based on climate outputs of meteorological variables. However, conventional E_P models, such as the open-water Penman model and the reference crop Penman-Monteith model, involve an important assumption that r_s remains constant over time (Allen et al., 1998; Shuttleworth, 1993). This assumption is in general valid for water surfaces and/or wet bare soils but is not valid over vegetated surfaces. Over vegetated surfaces, on one hand, elevated [CO_2] leads to a partial stomatal closure that increases r_s (e.g., Ainsworth and Rogers, 2007) yet on the other hand, elevated [CO_2] has "fertilized" vegetation resulting in an increased foliage cover (e.g., Donohue et al., 2013; Zhu et al., 2016), which effectively suggests a reduction in r_s. In addition, elevated [CO_2] serves as the ultimate driver of climate warming in the CMIP5 models and consequently leads to an increase in atmospheric vapor pressure deficit, which also tends to increase r_s (Lin et al., 2018; Novick et al., 2016).

While the net effect of elevated [CO_2] on r_s is still uncertain in the real world, a recent study clearly showed that in CMIP5 models, elevated [CO_2] increases r_s, which, with all else equal, results in a decrease of E_P and thus E (Yang et al., 2019). Yang et al (2019) also showed that over vegetated surfaces, an increase in E_P caused by warming-induced vapor pressure deficit increase is almost entirely offset by a decrease in E_P caused by the increase in r_s driven by elevated [CO_2] in CMIP5 models. This suggests that climate change does not necessarily lead to a higher E_P over vegetated surfaces and hence increased drought under [CO_2] enrichment, which is consistent with CMIP5 model projections yet contradicts the perception that "warming leads to drying" presented in many previous studies (Cook et al., 2014, 2015; Dai, 2011, 2012; Dai et al., 2018; Huang et al., 2015, 2017; Lehner et al., 2018; Liu et al., 2018; Park et al., 2018; Samaniego et al., 2018; Sternberg, 2011; Trenberth et al., 2013).

Additionally, it is worthwhile mentioning that the CMIP5 models do project topsoil moisture (within the top 10 cm) declines with a very similar spatial pattern to changes in PDSI_PM-RC (Dai, 2012; Dai et al., 2018), which might be important for wildfire risk and various biological processes that take place close to the surface. However, since no systematic decline in runoff or in relevant vegetation parameters (e.g., leaf area index and gross/net primary production) seems to result from it (Greve et al., 2017; Milly and Dunne, 2016, 2017; Roderick et al., 2015; Swann et al., 2016; Yang et al., 2019), this decline in topsoil moisture has little influence from the vegetation and hydrological perspectives. This is likely as root-zone or deeper soil moisture that is of more agricultural/ecological and/or hydrological significance, is projected to remain more or less unchanged (Berg et al., 2017; Greve et al., 2017), consistent with PDSI_CMIP5 and PDSI_PM[CO_2] (Figures 3).

Here, we use PDSI as an illustrating case; but note that similar results were also found in another commonly used drought index (i.e., the Standardized Precipitation-Evapotranspiration Index, or SPEI; Vicente-Serrano, 2010) (Supplementary Figure S3). Nevertheless, both PDSI and SPEI, as well as other drought/aridity metrics, are secondary offline impact models. Since climate models are fully-coupled land (and ocean) – atmosphere models that are an internally consistent representation of the climate system (Milly and Dunne, 2016), a scientific prior of applying any offline hydrological impact models is that the adopted offline model must be able to recover the hydrological simulations generated by the climate models (Roderick et al., 2015; Milly and Dunne, 2017; Yang et al., 2019). Otherwise, any inconsistency in hydrological predictions between offline impact models and climate models themselves would lead to inconsistent predictions in other components of the climate system. Unfortunately, this important scientific prior has been largely ignored in many previous drought assessment studies, leading to biased drought predictions that are actually inconsistent with the climate model outputs.

In summary, we have shown that climate model projections of the global drought area under future climate change has been largely overestimated. Our results suggest that the “warming leads to drying” perception may be fundamentally flawed, primarily due to ignoring the vegetation response to elevated [CO_2] (also see Yang et al., 2019). However, despite a small overall trend globally, we find that both drying and wetting areas are simulated to increase towards the end of this century (Figures 5 and Supplementary Figure S4), suggesting an increased variability in surface hydrological conditions that will likely lead to increased droughts and/or floods and reduced reliability of available water at local/regional scales (e.g., Kumar et al., 2014). In this light, attention should be paid to regions where droughts and/or floods are projected to most likely increase (e.g., Mediterranean Europe and Central America) and more efforts may be needed to mitigate the consequent impact there under climate change.

Code availability

Matlab codes with worked examples of the different PDSIs can be accessed through *https://github.com/zslthu/Calculate-PDSI-in-Matlab*

Data availability

The data that support the findings of this study are openly available (http://cmip-pcmdi.llnl.gov/cmip5/).

Author contribution

Y. Yang and M. Roderick designed the study. S. Zhang and Y. Yang performed the calculation and drafted the manuscript. All authors contributed to results discussion and manuscript writing.

Competing interests

The authors declare that they have no conflict of interest.

Acknowledgements

This study was supported by the National Natural Science Foundation of China (Grant No. 41890821), the Qinghai Department of Science and Technology (Grant No. 2019-SF-A4), and the Ministry of Science and Technology of China (Grant No. 2019YFC1510604). M. Roderick ackonwledges the support of the Australian Research Council (CE170100023). T. McVicar acknowledges support from CSIRO Land and Water. We thank the HESS Editor and three reviewers for constructive comments that improved the study.

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Figure 2: **Flowchart of PDSI calculations.** Note that PDSI_PM-RC, PDSI_PM[CO_2] and PDSI_CMIP5 respectively follow the right-hand, left-hand, and centre columns in Figure 1.

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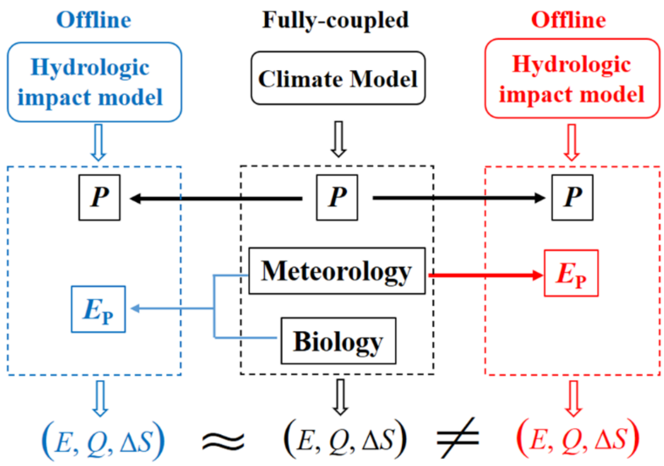

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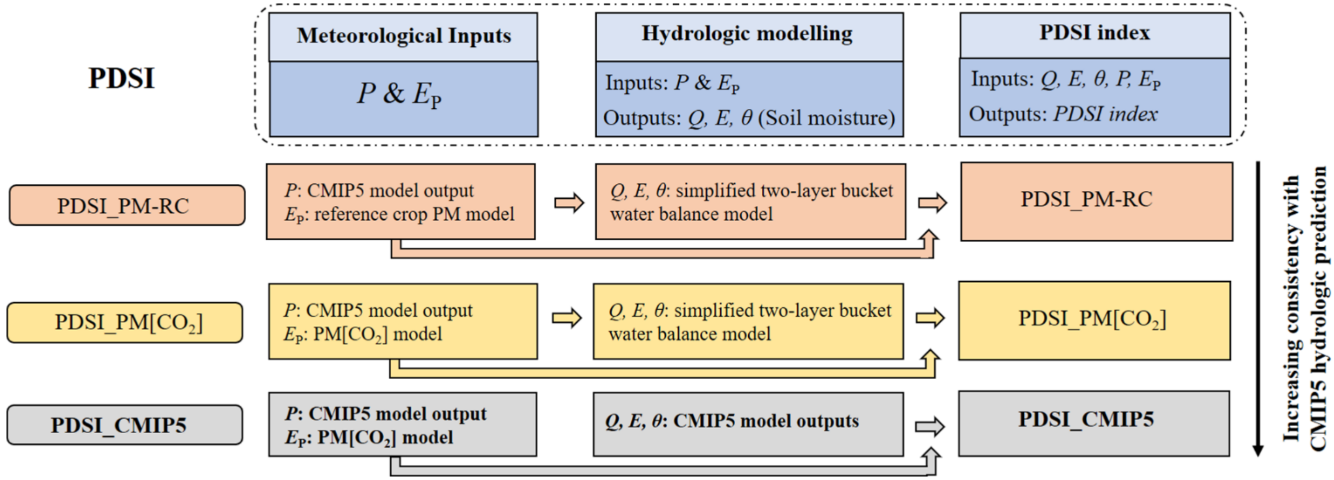

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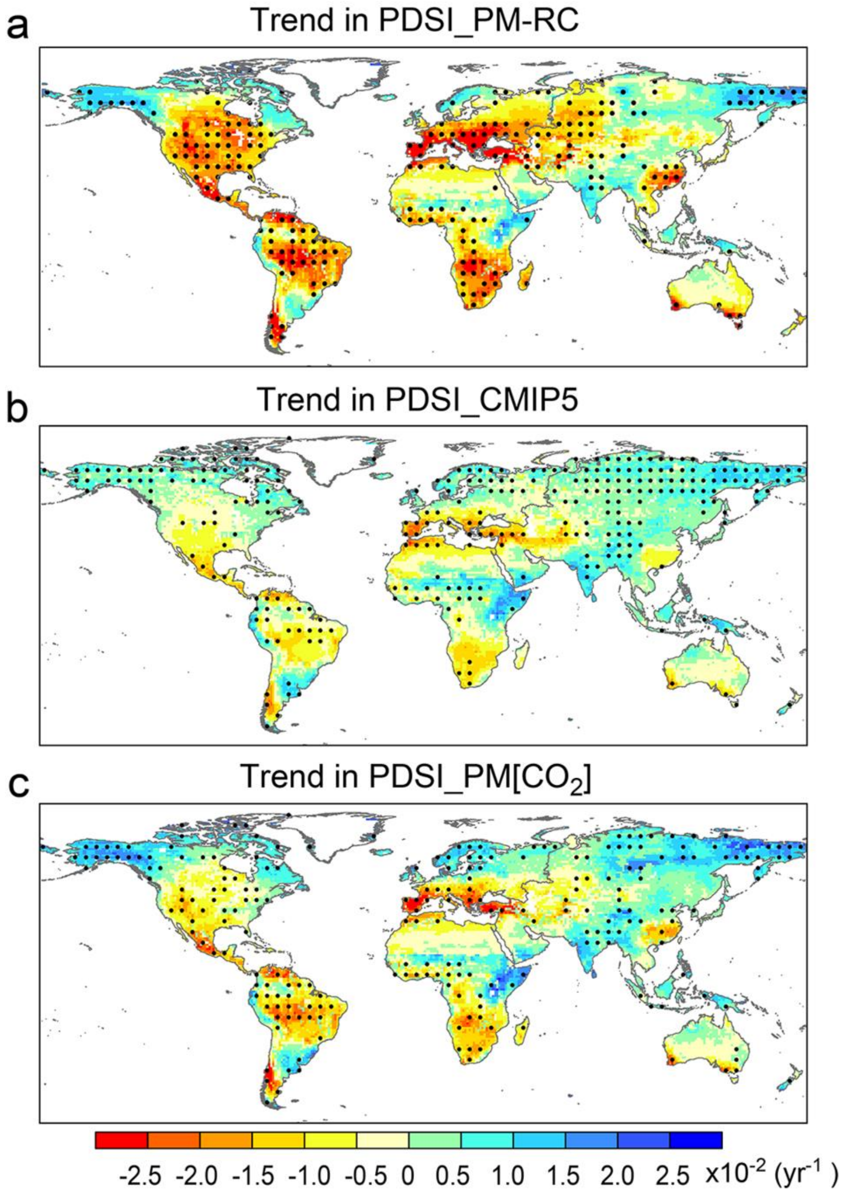

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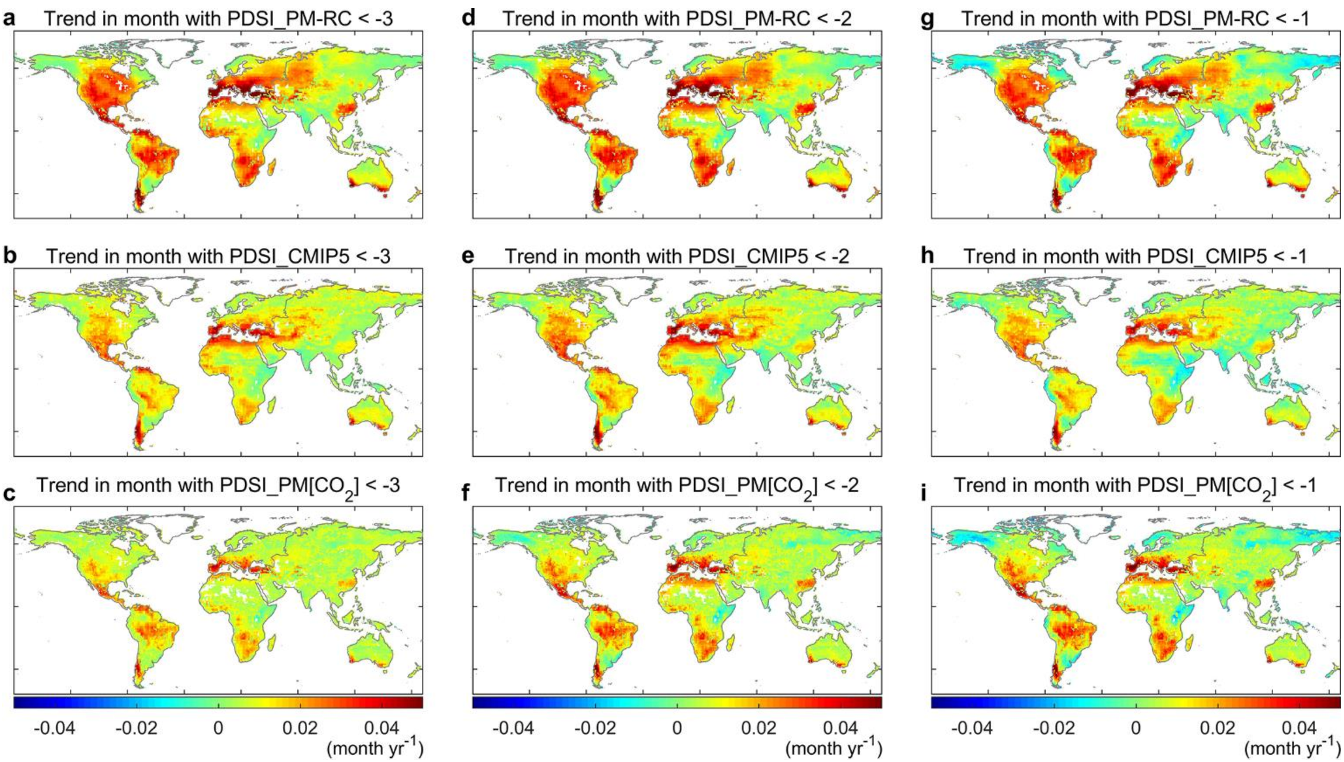

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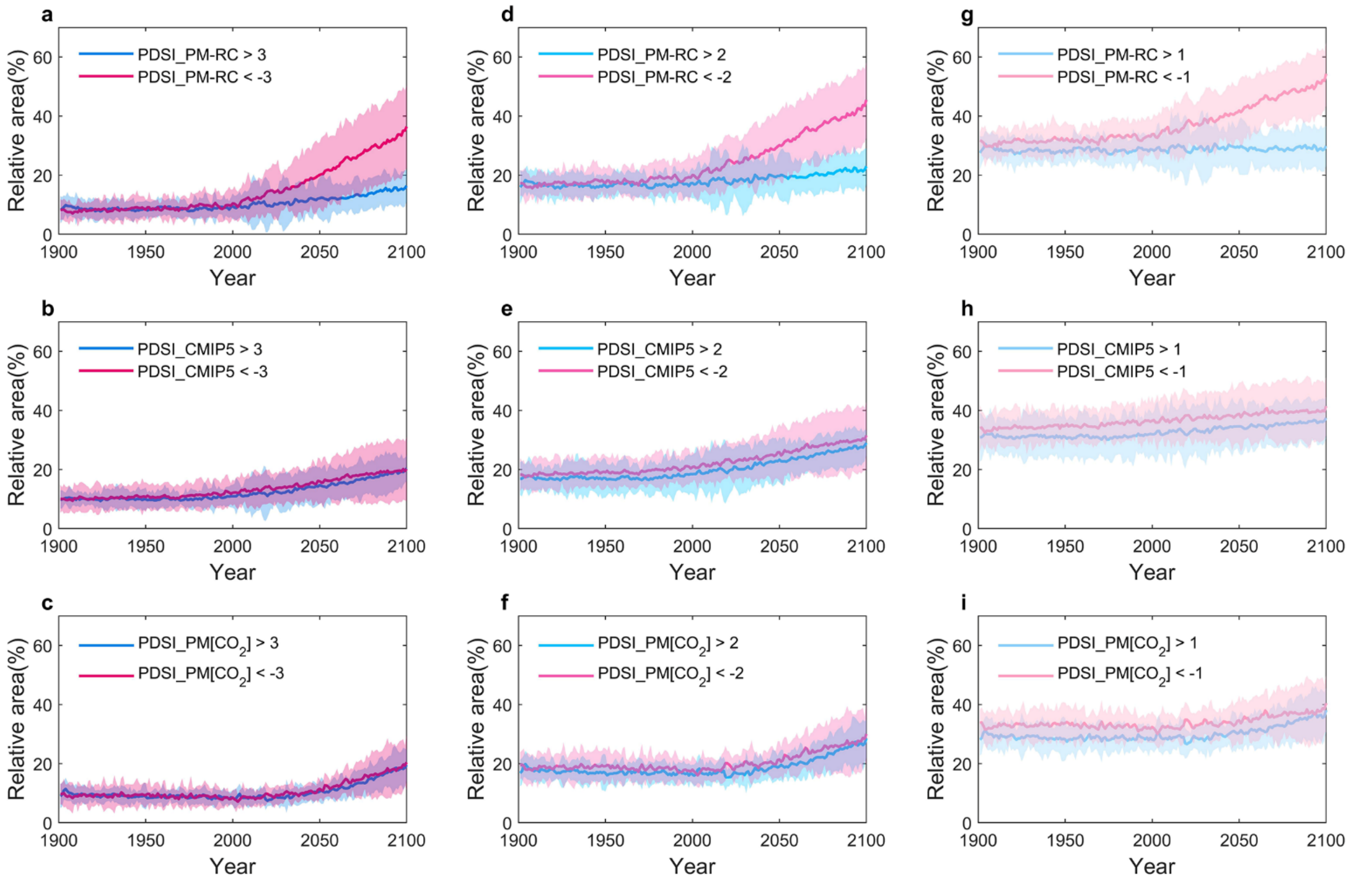

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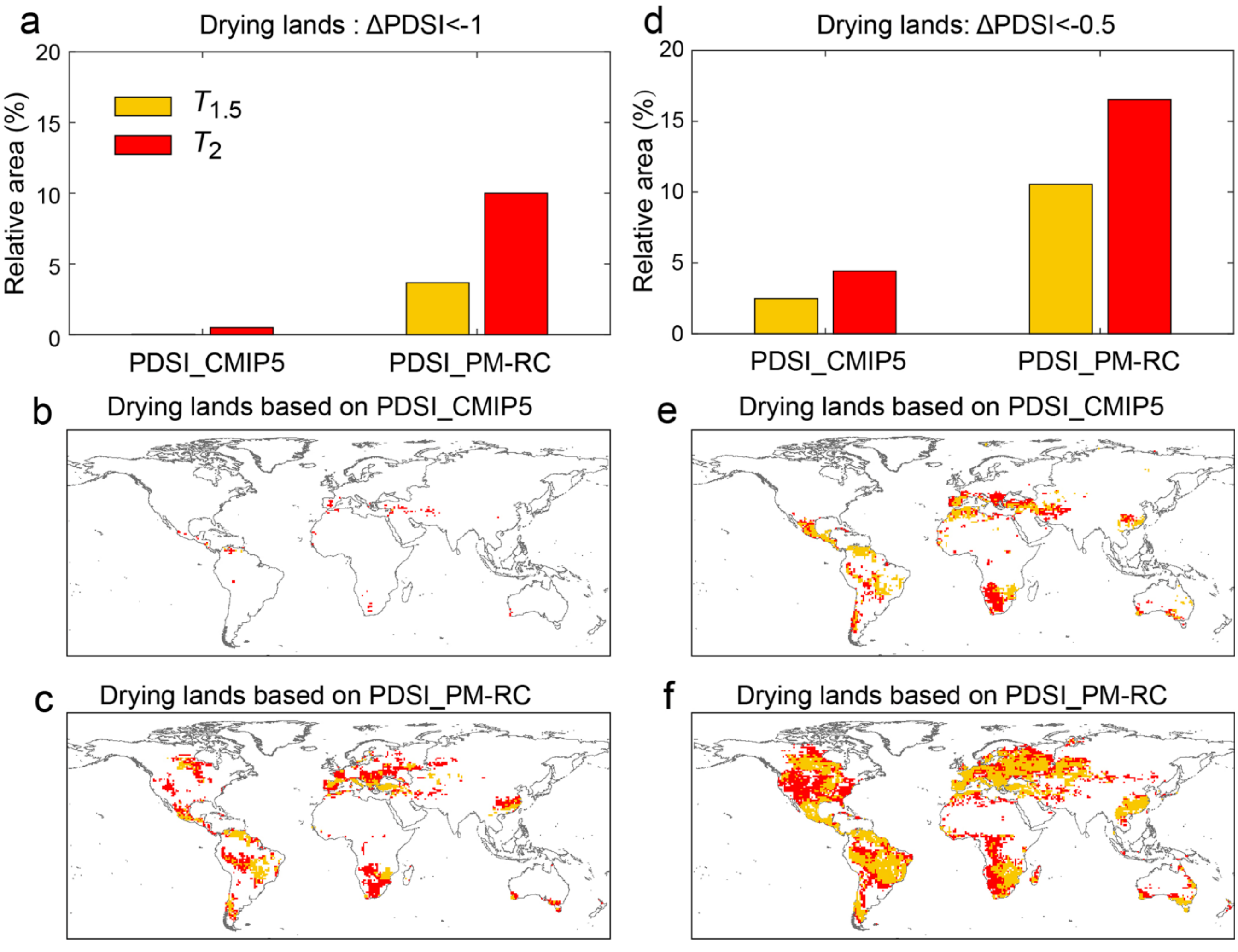

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