Responses to interactive comments on hess-2016-441

Original title: Sensitivity of potential evapotranspiration to changes in climate variables for different climatic zones
Revised title: Sensitivity of potential evapotranspiration to changes in climate variables for different Australian climatic zones

by Danlu Guo et al.

Reviewer #1

Overview

This paper does not present absolutely new findings but presents a systematic application of existing methods to assess sensitivity of models to compute potential evapotranspiration that is a relevant topic when dealing with climate change impacts analysis. So the paper is interesting, it is well written and matches the scope of this journal.

Comments

1. L1: the manuscript considers a wide area but not all the climatic zones as I would understand by reading the original title. I suggest to change it to: Sensitivity of potential evapotranspiration to changes in climate variables for different climatic zones of Australia

We agree with your suggestion and have changed the title to: "Sensitivity of potential evapotranspiration to changes in climate variables for different Australian climatic zones".

2. L452: Thus I would conclude that, as PET models are more sensitive to temperature data and climatic projections of all meteorological forcings except temperature show a high degree of uncertainty, it is better to use temperature based equations for assessing impacts of climate change. This is consistent with results shown in Ravazzani et al. (2014) in which they conclude that, in a humid alpine river basin, the bias introduced by the approximations from the method used to compute the evapotranspiration was less than the uncertainty associated with climate models, when you need to quantify climate change impacts.

   Ravazzani G, Ghilardi M, Mendlik T, Gobiet A, Corbari C, et al. (2014) Investigation of Climate Change Impact on Water Resources for an Alpine Basin in Northern Italy: Implications for Evapotranspiration Modeling Complexity. PLoS ONE 9(10): e109053. doi:10.1371/journal.pone.0109053

Thank you for the interesting point. These discussions focused on the sensitivity results of the two methods (Penman-Monteith and Priestley-Taylor) analysed in this paper, and therefore it was difficult to broaden out the discussion to other models in that section. However, in response to this comment, we have expanded the discussion of the potential advantages and disadvantages of using alternative PET formulations in the introduction, highlighting the tension between selecting more complex process-based PET models and simpler approaches (such as the temperature-based equations). We have also added a *citation to Ravazzani et al. (2014) in this section. The relevant discussion starts from L57 of the revised manuscript, as follows (with changes underlined):*

- *"Complex models such as the Penman-Monteith model are often recommended for their ability to <u>better</u> represent the physical processes that affect PET (McVicar et al., 2012;Donohue et al., 2010;Barella-Ortiz et al., 2013). <u>For example, the Penman-Monteith model can account for the effects of wind, and thus can assist to explain at least part of the observed decreases in pan evaporation with increases in temperature in many locations globally – the 'evaporation paradox' - as due to the observed decreases in wind speed (Roderick et al., 2007;McVicar et al., 2012;Lu et al., 2016)</u>. However, simpler empirical models may <u>also</u> be preferable under some conditions, as they require a smaller number of input climate variables, which might be able to be projected with greater confidence with GCMs<u>, and thus leading to greater confidence in the corresponding PET estimates</u> (Kay and Davies, 2008;Ekström et al., 2007;<u>Ravazzani et al., 2014</u>). For example, there is reasonable confidence in projections of temperature and relative humidity in Australia for a given emission scenario, but less confidence in projections of wind due to sub-grid effects of orography and other land-surface features (Flato et al., 2013;CSIRO and Bureau of Meteorology, 2015). In these situations, models such as the Priestley-Taylor model that do not depend on wind may produce more reliable estimates of PET compared to the more complex Penman-Monteith model. Thus, the choice of climate variables to include in climate impact assessments must be informed both by the relative importance of each variable on projections of PET (e.g. Tabari and Hosseinzadeh Talaee, 2014), and the likely confidence in the projections of each variable (e.g. Flato et al., 2013;Johnson and Sharma, 2009)."*

3. Fig.1: Legend displays much more zones than those illustrated in the map and this makes difficult to associate color to the proper class. i suggest to leave in the legend only climatic classes present in Australia

This figure has been reproduced from the Köppen classification data to fit the purpose of this study, in which all the 29 classes shown in the legend are presented in Australia. Please refer to the original version of the Australian Köppen classification map, available at: http://www.bom.gov.au/jsp/ncc/climate_averages/climate-classifications/index.jsp?maptype=kpn#maps.

4. Fig.4 to 8: captions of this and following figures use letter to describe figure content but letters are not present in figures. Also in the text authors use reference to specific panel within a figure (for example fig 3a) and the reader would benefit finding letter close to the panel. The same comment for figures 4 to 8.

We have labelled the separate panels in Figs. 3 to 8 following your suggestions in the revised manuscript, as follows:

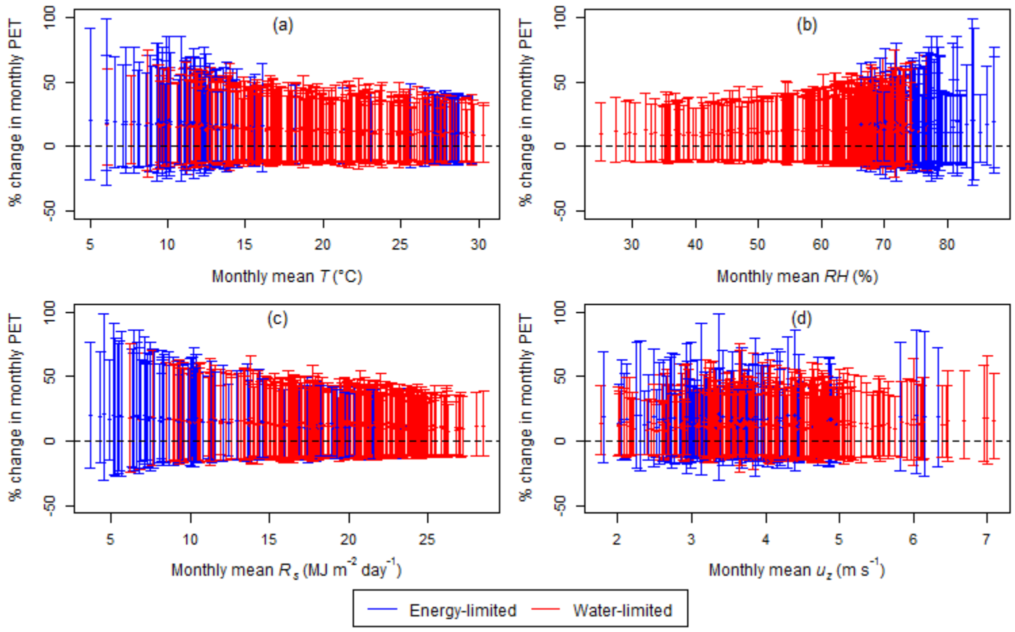


Figure 3: Monthly PET responses from the Penman-Monteith model, plotted against the monthly baseline levels of (a) temperature, (b) relative humidity, (c) solar radiation and (d) wind speed at 30 study sites. Each interval represents the range of all PET responses to the full set of climate perturbations for a single month at a single location, with the mean represented by the point on the line. The classification of energy- and water-limited months are based on the corresponding monthly PET/P ratios.

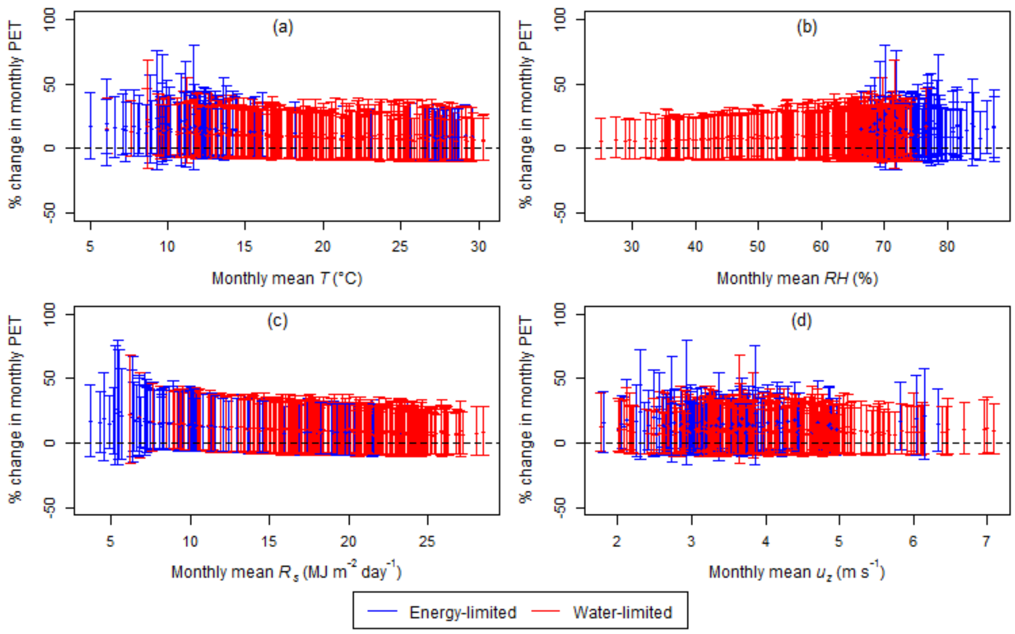


Figure 4: Monthly PET responses from the Priestley-Taylor model, plotted against the monthly baseline levels of (a) temperature, (b) relative humidity, (c) solar radiation and (d) wind speed at 30 study sites. Each interval represents the range of all PET responses to the full set of climate perturbations for a single month at a single location, with the mean represented by the point on the line. The classification of energy- and water-limited months are based on the corresponding monthly PET/P ratios.

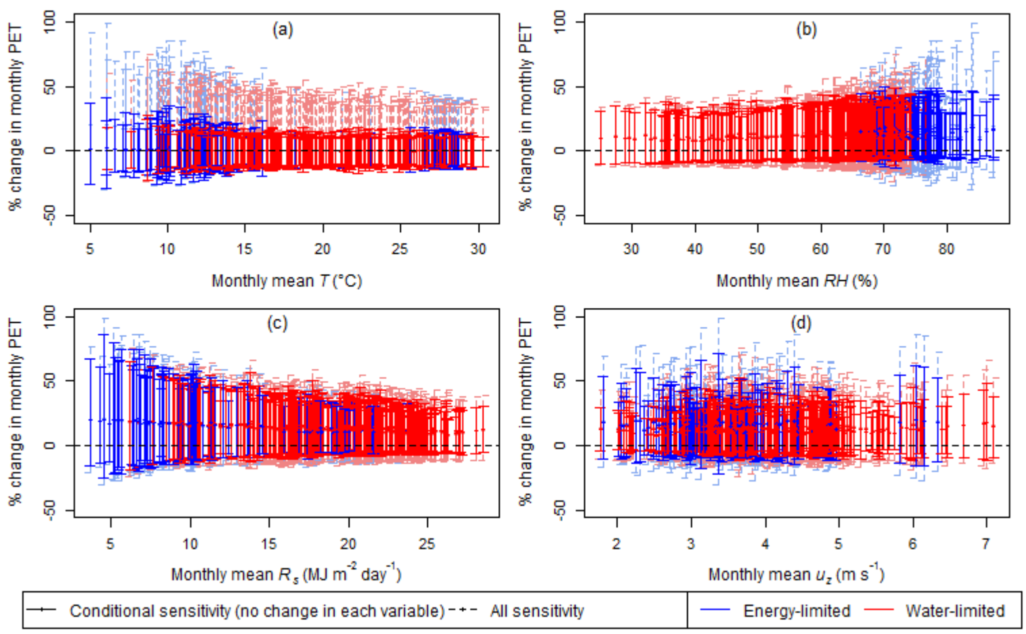


Figure 5: Monthly PET responses from the Penman-Monteith model, plotted against the monthly baseline levels of (a) temperature, (b) relative humidity, (c) solar radiation and (d) wind speed at 30 study sites. Each dashed (solid) line represents the range of all PET responses to the full set of climate perturbations (conditioned on no-change in each climate variable) for a single month at a single location. The corresponding means are represented by the points on the lines. The classification of energy- and water-limited months are based on the corresponding monthly PET/P ratios.

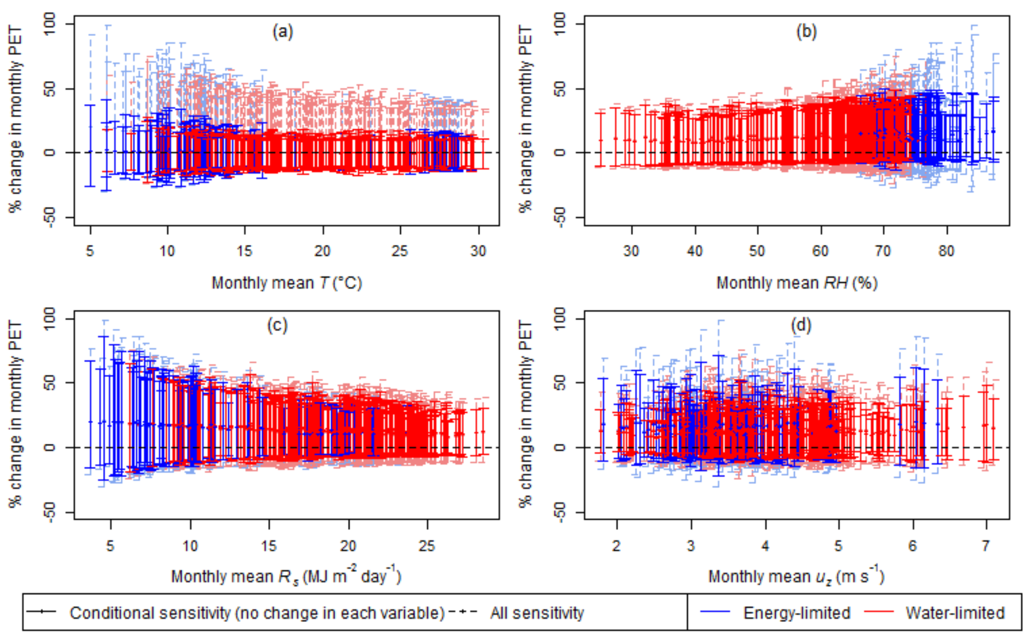


Figure 6: Monthly PET responses from the Priestley-Taylor model, plotted against the monthly baseline levels of (a) temperature, (b) relative humidity, (c) solar radiation and (d) wind speed at 30 study sites. Each dashed (solid) line represents the range of all PET responses to the full set of climate perturbations (conditioned on no-change in each climate variable) for a single month at a single location. The corresponding means are represented by the points on the lines. The classification of energy- and water-limited months are based on the corresponding monthly PET/P ratios.

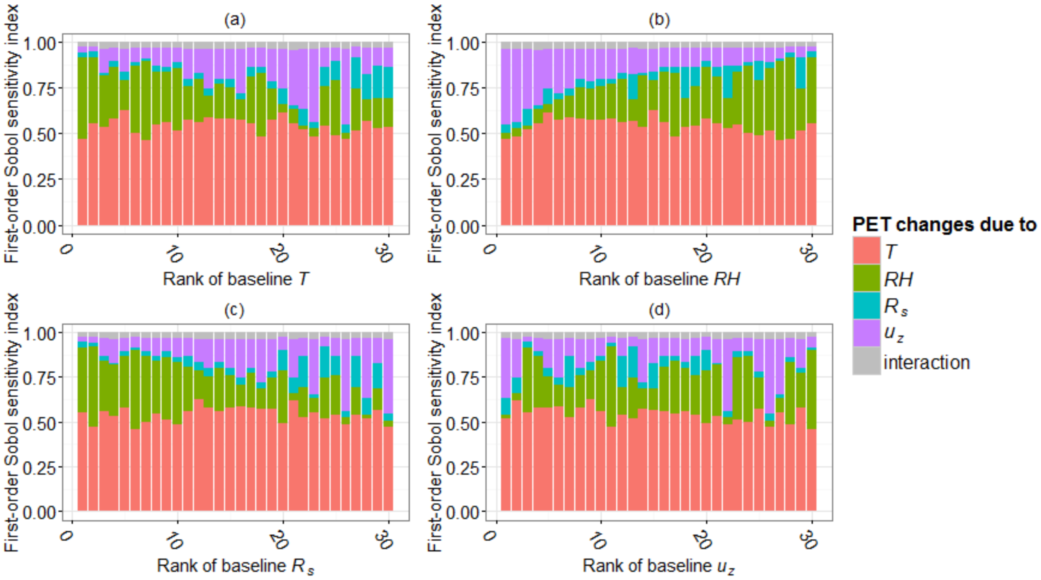


Figure 7: Sobol' first-order sensitivity indices of the Penman-Monteith model for changes in the four climate variables (colored) and their interaction effects (grey), plotted against the ranking of the average level of each climate variable at 30 study sites

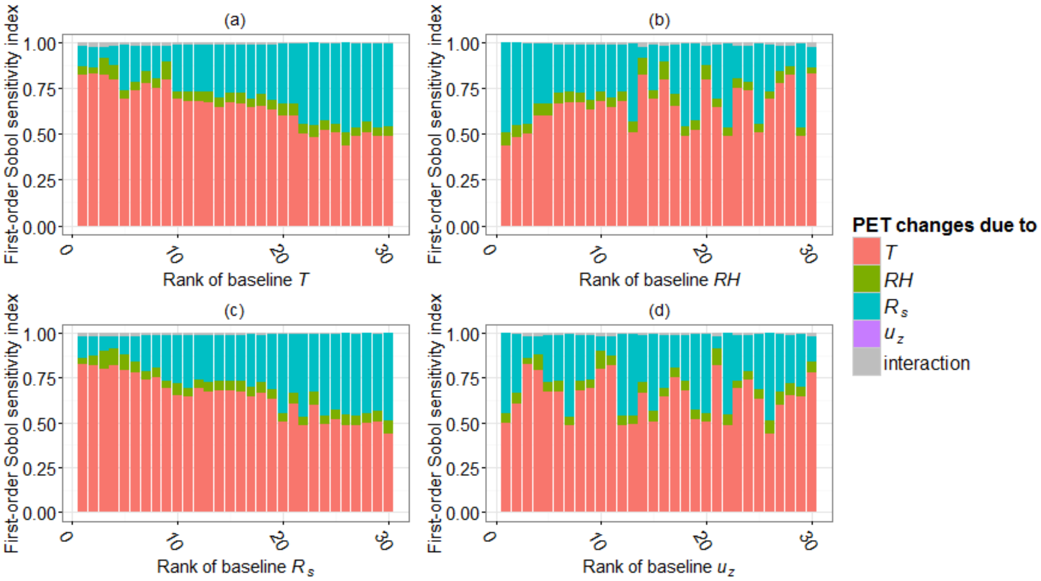


Figure 8: Sobol' first-order sensitivity indices of the Priestley-Taylor model for changes in the four climate variables (colored) and their interaction effects (grey), plotted against the ranking of the average level of each climate variable at 30 study sites

Reviewer #2

Overview

Overall, the paper is well written and concise. The goals of the paper are outlined well and the results are presented in a clear manner.

The purpose of this manuscript is to understand the possible implications of anthropogenic climate change on watershed-scale water budget through a global sensitivity analysis of PET. Several scenarios were analyzed in which baseline (current) climatic conditions were subjected to changes in: temperature; relative humidity; solar radiation; and, wind speed. The methods in this paper appear sound.

Comments

Specific comments

1. LINE 72: List the references to “number of recent studies”

These references can be found in sentences following this statement, which appear in L76 in the revised manuscript, as:

- *"For example, Goyal (2004) found that PET was most sensitive to perturbations in temperature, followed by solar radiation, wind speed and vapor pressure, at a single study site in an arid region in India. Tabari and Hosseinzadeh Talaee (2014) also looked at the sensitivity of PET to perturbations of historical climate data from eight meteorological stations representing four climate types in Iran, and concluded that the importance of wind speed and air temperature was lower while that of sunshine hours was higher for a humid location compared to an arid location. Gong et al. (2006) found that the differences in PET sensitivity across the upper, middle and lower regions of the Changjiang (Yangtze) basin in China were largely due to contrasting baseline wind speed patterns."*

2. LINES 72-86:
   (1) Were these analyses all specific to PET sensitivity? Which PET models did each use in their analysis?
   (2) How were they similar and different to this analysis?

(1) Yes, all of these analyses were specific to PET, although referred to as reference ET – which is the PET for a reference crop evaporative surface. All these studies were based on results from the Penman-Monteith model.
In the revised manuscript, we have added a clarification for the PET models used in these studies. This appears in L74 of the revised manuscript, as following (with changes underlined):

- *"Sensitivity analysis methods have been employed in a number of recent studies to assess the overall sensitivity of PET <u>estimated by the Penman-Monteith model</u> to potential changes in climate, as well as to better understand the relative importance of different climate variables on overall PET sensitivity.*

(2) The similarities/differences of these studies have been highlighted later in this section, which is in L84 of the revised manuscript:

- *"However, most of these PET sensitivity analysis studies focused on a limited number of study sites and/or climatic zones, so that the specific causes for varying PET sensitivity at different locations, such as the roles of climatic and hydrological conditions, remain unclear. Consequently, it is difficult to extrapolate our existing knowledge of PET sensitivity and the* *relative importance of each climate variable to new locations, which is essential for assessing the water balance at regional scales."*

Similar to these previous studies discussed, we focused on reference crop PET estimated with the Penman-Monteith model. However, to address the abovementioned limitations in the existing studies, we looked at a much broader range of climate zones. We also compared the results from the Penman-Monteith model with the Priestley-Taylor model, to understand the role of alternative model structures on climate sensitivity. Finally, to assess the sensitivity of PET, we conducted a global sensitivity analysis, which allowed to assess the responses of PET to potential changes in multiple climate variables at the same time, and thus to estimate the relative importance of each of these variables in affected PET.

3. LINES 87-90:
   (1) How are baseline hydrologic and climatic conditions affected by PET? Aren't the baseline conditions used as the baseline for comparison?
   (2) How is "…and how these sensitivity estimates are affected by baseline hydrologic and climatic conditions" in (i) different than "…and how this changes with the baseline hydrologic and climatic conditions" in (ii)? I am unclear what the difference is. Wouldn't the baseline hydrologic and climatic conditions be the baseline?

Thank you for highlighting these issues.

(1) We would like to take this opportunity to clarify the use of 'baseline hydrologic and climatic conditions' in our manuscript, which refers to the historical status of hydrology and climate at different locations. It is important to investigate the impact of different baselines on the overall PET sensitivity results as identified from previous literature, since this can affect the degree to which sensitivity values at one geographic location can be used to infer expected sensitivities for other locations. To clarify this, we have rephrased our study aims in L89 of the revised manuscript as following (with changes underlined):

- *"… this study aims to gain an understanding of (i) the sensitivity of PET estimates to changes in the key climatic variables which influence PET, and how these sensitivity estimates are affected by <u>varying</u> baseline hydrologic and climatic conditions <u>at different locations</u>; and (ii) the relative importance of these climatic variables for PET, and how this changes with the baseline hydrologic and climatic conditions <u>at different locations</u>."*

(2) In both study aims we were interested in the impact of varying baseline hydro-climatic conditions at different locations. The difference is that in study aim (i) we were interested in how the sensitivity of PET varies as a function of baseline hydro-climatic conditions at different locations. In contrast, in study aim (ii) we were interested in how the relative importance of each climate variable for PET varies as a function of baseline hydro-climatic conditions at different locations.

For example, one of the findings related to study aim (i) is in L280 of the revised manuscript, in which the sensitivity of PET at each study site was represented by the percentage change in PET in responses to plausible changes in the four climate variables:

- *"… with the Penman-Monteith model (Fig. 3), it is clear that the PET sensitivity displays a clear association with the baseline levels of climate variables, with higher sensitivity values for locations that are cooler (low T), more humid (high RH), and receiving less solar radiation (low Rs). The highest associations can be found with T (Fig. 3a), with the monthly changes in PET ranging from -30.2% to +98.3 % for the lowest baseline T value of 5.0 °C, compared to a range of -13.3 % to +46.6 % for the highest baseline T of 30.3 °C. Similarly, the range of Penman-*

Monteith PET sensitivity values also shows clear decreases with baseline Rs (Fig. 3c), and increases with baseline RH (Fig. 3b). The baseline uz (Fig. 3d) levels show no obvious impact on the PET sensitivity."

And one of the findings related to study aim (ii) is in L384 of the revised manuscript, in which the relative importance of each climate variable for PET at each study site was represented with the Sobol' first-order sensitivity index:

- *"Figure 7 shows the Sobol' first-order indices of the Penman-Monteith PET to changes in the four climate variables at the annual scale, as well as their interactions. The first-order indices are plotted against the baseline levels of each climatic variable to observe the impact of baseline climate conditions…. The Sobol' indices in the figure show that T is generally the most important variable for PET, with index values ranging from 0.46 to 0.62. Since the Sobol' indices suggest the partitioning of the total variance of PET, these results are consistent with Fig. 5a, which suggests that perturbations in T contribute to at least 45 % of the variation in the estimated changes in PET. The role of wind and humidity in affecting the sensitivity values is also evident, with wind being the second-most important variable (with Sobol' indices up to 0.42) for sites with low baseline humidity, and humidity being the second-most important variable (with Sobol' indices up to 0.47) for sites that have high humidity (Fig. 7b). Solar radiation is generally the variable with the lowest Sobol' indices, with the largest contributions (up to 18 %) can be observed for warm catchments (Fig. 7a)."*

4. LINE 96: What is meant by "climate-induced changes"?

We have removed this phrase in L99 of the revised manuscript, as follows:

- *"…the potential changes in one climate variable can be amplified or offset by changes in another variable…"*

5. LINE 97: Provide examples of how climate variables have been amplified or offset in the referenced literature.

A good example of these interactions is the observed decreases in pan evaporation with increasing temperature which is related to the decreases in wind (i.e. 'evaporation paradox'), which has been discussed earlier in the Introduction. To enable easier reference to this example in the discussion of how climate variables can amplify or offset each other, we have first highlighted the term 'evaporation paradox' in the earlier discussion in L59 of the revised manuscript, as:

- *"For example, the Penman-Monteith model can account for the effects of wind, and thus can assist to explain at least part of the observed decreases in pan evaporation with increases in temperature in many locations globally – the 'evaporation paradox' – as due to the observed decreases in wind speed (Roderick et al., 2007;McVicar et al., 2008;Lu et al., 2016)."*

And then L99 of the revised manuscript (the original L97) has been updated accordingly to refer to the example above, as follows (with changes underlined):

- *"It is worth noting that the potential changes in one climate variable can be amplified or offset by changes in another variable <u>(for examples see the discussions of 'evaporation paradox' in Lu et al., 2016;Roderick and Farquhar, 2002), which can affect the relative importance of each variable."</u>*

6. LINES 99-101: What is meant by the term "successful"? This sentence is unclear. Which environmental models is the author referring to?

To improve clarity we have removed the term 'successful', and have also specified the 'environmental models' used in literature. This statement is now in L102 of the revised manuscript, as follows (with changes underlined):

- *"… a global sensitivity analysis method was used, with similar methods being applied to account for the impact of joint variations in the input variables on the output <u>from a variety of environmental models, ranging from conceptual rainfall-runoff models (e.g. Tang et al., 2007a;Tang et al., 2007c) to complex models which consider a number of surface-groundwater processes (e.g. Guillevic et al., 2002;van Griensven et al., 2006;Nossent et al., 2011).</u>"*

7. LINES 101-102:
   (1) Which results? The analysis presented in this paper or the past studies referenced in this paragraph? Clarify which results are presented.
   (2) What does the author mean by "elucidate the specific roles of the baseline hydro-climatic condition on the PET sensitivity"? Earlier in the Introduction, the goal of the paper was stated to present how PET sensitivity changes with the baseline condition. Clarify this statement.

Thank you for highlighting these confusions.

(1) 'The results' referred to the results from the global sensitivity analysis of this study. To clearly specify the purpose and the expected outcomes from this sensitivity analysis, we have updated this statement in L106 of the revised manuscript, as follows (with changes underlined):
- *"The results <u>of the global sensitivity analysis in this study</u> were presented in terms of <u>both absolute sensitivity of PET and relative sensitivity indices of each climate variable</u> …"*

(2) We believe that this question is resolved with our response to your Comment #3(2), for which we have improved the clarity of our study aims in L89 of the revised manuscript, as following (with changes underlined):
- *"… this study aims to gain an understanding of (i) the sensitivity of PET estimates to changes in the key climatic variables which influence PET, and how these sensitivity estimates are affected by <u>varying</u> baseline hydrologic and climatic conditions <u>at different locations</u>; and (ii) the relative importance of these climatic variables for PET, and how this changes with the baseline hydrologic and climatic conditions <u>at different locations</u>."*

8. LINES 105-107: Do these two sets of results coincide with the study aims from LINES 87-90?

Yes. To highlight this alignment, we have rephrased these descriptions in the revised manuscript. These appear in L112 of the revised manuscript as following (with changes underlined):

- *"Section 4 presents and discusses two sets of results <u>which address the two study aims respectively, as:</u> (i) the estimated PET sensitivity to potential changes in temperature, solar radiation, humidity and wind, <u>and how this changes with location</u>; and (ii) the relative importance of the four climate variables for estimating PET, <u>and how this changes with location</u>."*

9. LINES 123-124: This data period seems to be pretty old. Can you provide explanation as to why more recent data was not selected?

The data period was selected according to the availability of high-quality climate observations in Australia (released by BoM 2013), which was mainly constrained by wind data that were only available up to the year 2005. In addition, the data period was also determined so that climate data were available for a consistent period at a number of case study locations within different climate zones in Australia, which is another factor limiting the data period that could be considered.

10. LINE 128: Instead of sunshine hour, sunrise-sunset?

The original data we obtained to calculate the solar radiation was in the form of sunshine hours, and were in the required format for the Ångström-Prescott equation in McMahon et al. (2013).

11. LINE 136: Instead of level, use elevation for land surface elevation, and values for the meteorological values listed in the table.

Thank you for the recommendation and we have replaced 'level' with 'value'. This appears in L142 of the revised manuscript, as:

- *"Table 1 shows the average values of the four PET-related climate variables, as well as the rainfall within the study period, at each of the 30 sites."*

12. LINE 140: What are the water-limited and energy-limited ratios based on? Provide a reference.

We have added two references which discussed the relevance of PET/P ratio and the water-/energy-limited status of catchments. This appears in L144 of the revised manuscript, as:

- *"… a quantity particularly relevant to ET processes is the long-term averaged ratio of PET to precipitation (PET/P), which describes whether a location is water-limited (PET/P >1) or energy-limited (PET/P < 1) (Gerrits et al., 2009;McVicar et al., 2010)."*

The full references are:

- *Gerrits, A., et al. (2009). "Analytical derivation of the Budyko curve based on rainfall characteristics and a simple evaporation model." Water Resources Research 45(4).'*
- *McVicar, T. R., et al. (2010). "The effects of climatic changes on plant physiological and catchment ecohydrological processes in the high-rainfall catchments of the Murray-Darling Basin: A scoping study." Prepared for the Murray-Darling Basin Authority (MDBA) by the Commonwealth Scientific and Industrial Research Organization (CSIRO) Water for a Healthy Country National Research Flagship, MDBA, Canberra, ACT, Australia.*

13. LINES 142-144: Penman and P-T estimates of PET can vary significantly, especially if wind is a factor and the P-T alpha-parameter is under- or over-estimated. Provide an example of the range of differences (i.e. uncertainty) between these two models for the climatic conditions you are presenting. In LINES 22-25 the authors mention there may be a need to select a different PET model based on the climatic conditions. I think the statements need to be revised to be more in line with the overall message.

Thank you. With regard to PET, the Priestley-Taylor model did suggest consistently lower estimates compared with the Penman-Monteith model. Please see the figure below, which summarizes the model uncertainty for the daily average PET estimates at the 30 sites within our study period:

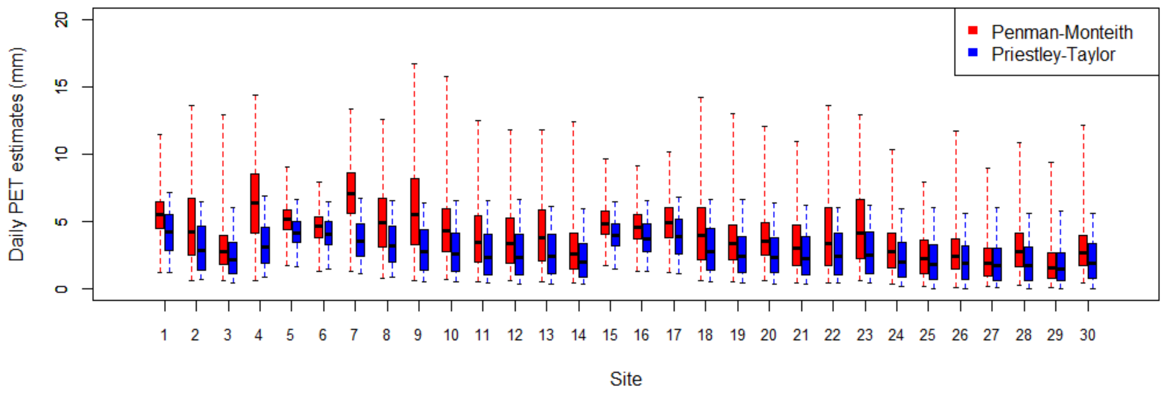


Figure 1. Ranges of estimates of average daily PET at each of the 30 study sites, obtained with both the Penman-Monteith model and the Priestley-Taylor model

The figure above illustrates that the impact of model choice is substantial on estimating PET, which justifies the significance of PET model selection, and is consistent with our suggestion of the necessity to select PET model in the abstract.

We would like to clarify that in the discussion which is related to this comment, we focused on the categorization of case studies into water- or energy-limited catchments, for which the PET model choice had minor effects, with only four sites showing different categorizations suggested from Penman-Monteith and Priestley-Taylor models (i.e. sites 6, 19, 20, 27).

We have added a clarification of the uncertainty in the categorization from using the Priestley-Taylor model in L150 of the revised manuscript, as following:

- *"Although the use of Priestley-Taylor model resulted in different PET estimates at each site, the categorization of water- and energy-limited catchments was generally consistent with those from Penman-Monteith, with different categories only shown at four out of the 30 study sites (sites 6, 19, 20 and 27)."*

Technical corrections/comments

1. Lines 67, 93, 144, etc.: Correct spelling throughout text: Priestley-Taylor, not Priestly-Taylor

Thank you. We have corrected this throughout the revised manuscript.

2. LINE 108: spell out Section

This abbreviation was used according to the formatting requirement for manuscript preparation for HESS (available from: http://www.hydrology-and-earth-system-sciences.net/for_authors/manuscript_preparation.html), which specified that: "the abbreviation "Sect." should be used when it appears in running text and should be followed by a number unless it comes at the beginning of a sentence."

3. LINE 166: remove extra "the"

We have corrected this in the revised manuscript.

Reviewer #3

Anonymous

Received and published: 22 November 2016

Comments

General comments

1. The manuscript presents a sensitivity analysis of potential evaporation (PE) estimates to changes in climate variables by using two different PE formulations. This issue is clearly not novel but to my opinion, the wide range of climatic settings of the studied sites and the fact that no clear consensus emerged from the literature on this issue justify the proposed manuscript. The paper is easy to follow and the discussion is interesting and nicely put into perspective with other related recent studies. My main concern is on the likelihood of the way the authors dealt with sampling the climate perturbations and on the potential impact of these choices on the proposed sensitivity analysis. In principle, Sobol analyses should be applied on models with non-correlated inputs, which is not the case of PE climate inputs. This does not mean that the analysis proposed is wrong but that a careful attention should be paid on these correlations and on the way they can be reduced/ taken into account. To shed light on this issue, I suggest the authors show the correlations between variables on the studied sites. The other related major comment is on the way the authors sampled the climate perturbations. As far as I understand, they sample individually the perturbation for each climate variable by ignoring the interactions between variables. This is a strong assumption since some perturbations are likely to be interdependent. For instance, RH is often estimated on the basis of dew-point and air temperatures. Consequently, the perturbations should concern dew-point temperature (or water vapour pressure) and air temperature rather than relative humidity and air temperature. Besides, the range of possible might be criticized since some perturbations might not be realistic (e.g. an increase of Rs will likely not be possible with a decrease in temperature).

Thank you for raising these issues. Our responses to each of your three concerns are as follows:

(1) ***Concern:*** *Sobol' method assumes independent inputs so it is not suitable for the PET-related variables as they are correlated.*
Response: *Our input variables for the Sobol' analysis in this study were actually the annual average changes in each climate variable (i.e. climate perturbations), rather than the daily data of each variable (where correlations can exist). These perturbations have been sampled with Latin hypercube sampling, which resulted in samples which ensured independence among the average changes of the four climate variables (see the figure below, which shows the average perturbation determined by the first 1000 samples out of the 5000 used in Sobol' analysis in this study, to allow easier visualization). The figure illustrates low pairwise correlations, and thus independence among the average changes in the four climate variables. Therefore, Sobol' was a suitable method for analysing the sensitivity of output PET to these average changes in each climate variable.*

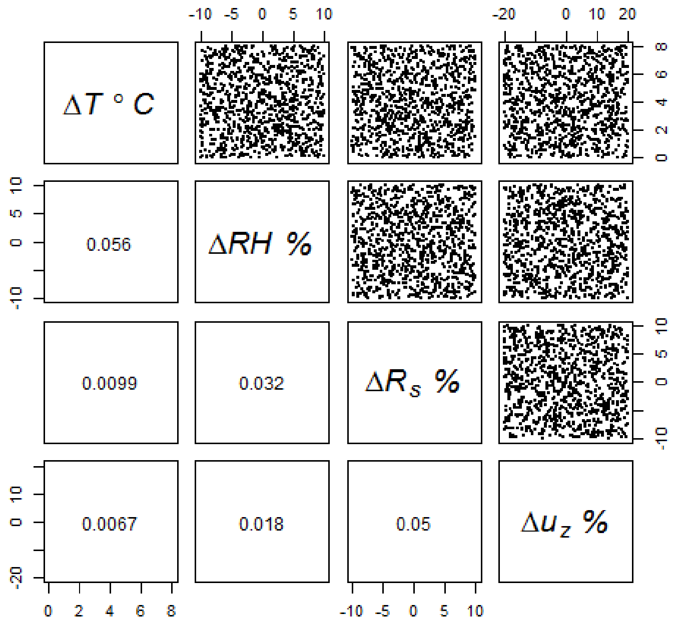
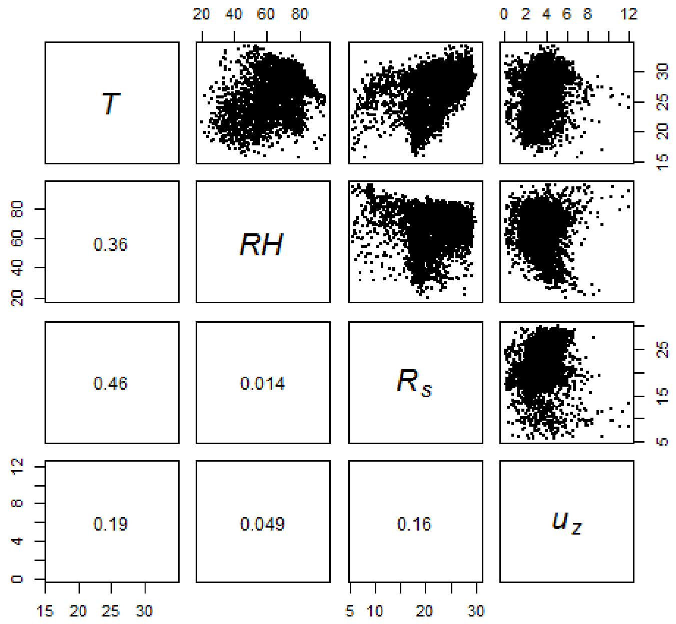


Figure 1. The first 1000 sets of perturbations in each of the four climate variables relative to the corresponding historical annual average levels, as used for the Sobol' analysis in this study. The lower-left triangle displays pairwise correlation coefficients.

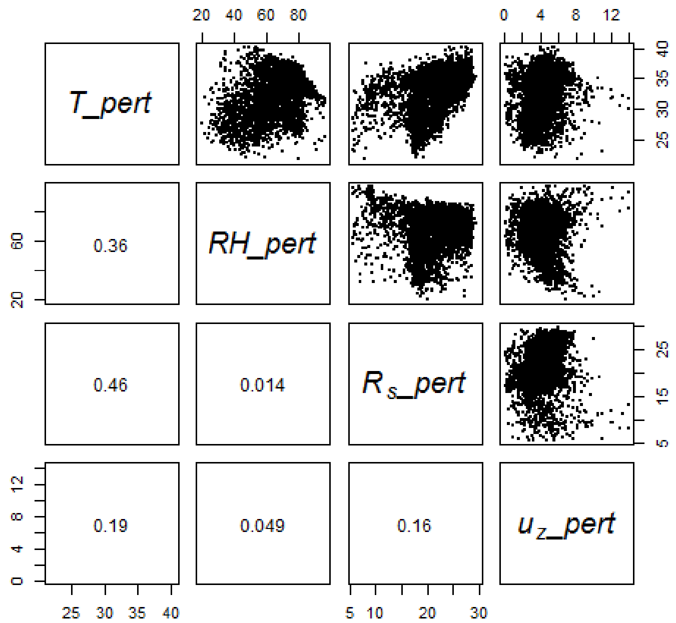
(2) Concern: *The perturbations of climate variables did not consider the historical correlation structures in the climate data.*

Response: *As we highlighted in the previous response, each of the climate perturbations in this study was applied to each climate variable as an overall annual average change factor, rather than being partitioned into daily variations. The resultant perturbed time-series of climate variables, therefore, were still able to preserve the correlation structures at the daily scale within historical data. For example, please refer to the two figures below, which show (i) pairwise correlation between the historical daily time-series of T, RH, R_s and u_z, for study site #1; and (ii) pairwise correlation between the perturbed daily time-series of T, RH, R_s and u_z, for study site #1, with the first perturbation used for Sobol' analysis, which was an average change of: +6.05 ºC, 1.14%, -1.74% and 16.9% for T, RH, R_s and u_z, respectively.*

It is evident from the figures that although our perturbation method changes the annual average values of these variables, they do not alter the historical correlation structures among the four climate variables at the daily scale.



(i)



(ii)

Figure 2. Pairwise correlation between (i) the historical daily time-series of T, RH, R_s and u_z, for study site #1; and (ii) the perturbed daily time-series of T, RH, R_s and u_z, for study site #1, with the first perturbation used for Sobol' analysis as an average change of: +6.05 °C, 1.14%, -1.74% and 16.9% for T, RH, R_s and u_z, respectively.

(3) Concern: *The perturbations of climate variables might yield physically infeasible climate condition.*

Response: *The climate perturbations were determined by the LHS to serve the sensitivity analysis to test the sensitivity of PET to all possible climate conditions. Therefore, although some perturbations might reflect climate conditions that are unlikely to occur in the future, they are still physically plausible. For example, although an increase in temperature is likely to lead to increasing R_s, both an increase or decrease in R_s are possible, as this is also related to cloud cover (e.g. Cubasch et al., 2013). Similarly, for all other pairs of climate variables, although some combinations of potential changes are more likely to happen than others, all combinations are physically plausible and thus should be considered in the sensitivity analysis.*

Note that although the above discussion concerns plausibility of different combinations of annual change factors applied as part of the sensitivity analysis, it is possible that application of such change factors can lead to physically implausible data points at the daily scale. For example, increasing annual average humidity in the sensitivity analysis may lead to daily values that exceed 100%. To avoid these changes, we have imposed an upper limit of 100%, and this issue is also the reason that we focus on changes in RH instead of T_{dew}.
In the revised manuscript, we have added a sentence to L211 to clarify how the physical limit of RH was applied, as:

- *"...to ensure physical plausibility of the perturbations, the daily maximum and minimum values of relative humidity were capped at a maximum of 100%."*

Specific comments

1. - I suggest the authors change the term potential evapotranspiration into potential evaporation that is more consensual.

We decided to keep the term 'potential evapotranspiration' ('PET') as this is a more widely used term in the literature assessing the hydrological impacts of climate change (e.g. New et al., 2007; Chiew et al., 2009; Prudhomme et al., 2010;), which is more relevant to the context of this study.

2. - There are some typos in the text, e.g. Priestly-Taylor is often used instead of Priestley-Taylor and Figure 1 includes many typos (equatorial, temperate).

Thank you. We have corrected these throughout the revised manuscript. We have also corrected the typos in Figure 1, which is now as follows:

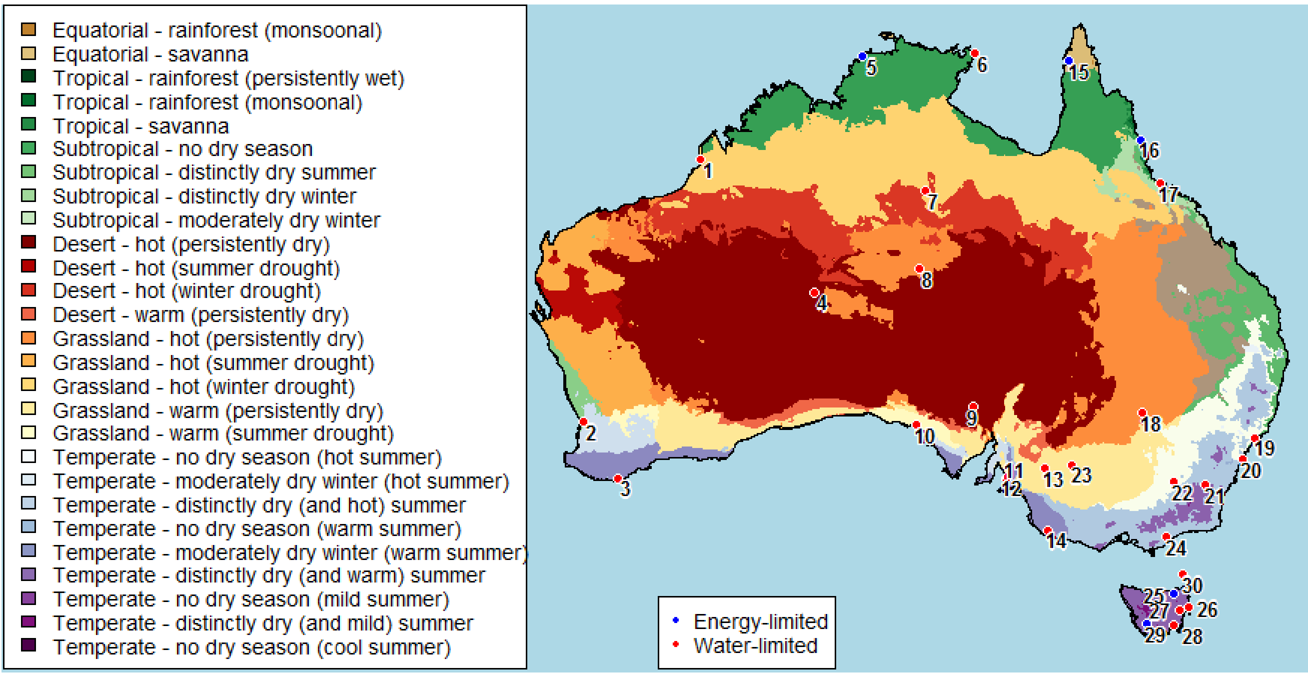


Figure 1: Locations of 30 Australian weather stations (see Table 1 for the full names of these weather stations) selected for analysis, with reference to their corresponding climate classes derived following the modified Köppen classification (reproduced with data from Stern et al., 2000).

3. - I suggest the authors include in the manuscript the equations of the two PE equations.

We agree with your suggestion. To address this we have added Appendix A.2. and Appendix A.3. in the revised manuscript, which include the main equation for each model, as well as other equations used to estimate the intermediate variables.

4. - Priestley-Taylor equation is simple and some results might be discussed on the basis of the equation directly (e.g. by deriving analytically sensitivity coefficients).

We have explained the zero-sensitivity of Priestley-Taylor PET to wind in the original manuscript. This appears in L370 of the revised manuscript, as:

- *"…wind is shown to have no impact as expected, since wind is not an input into the Priestley-Taylor model (Fig. 6d)."*

To strengthen the link between the results and the structure of the PET models, we have added the following explanation to the sensitivity of Priestley-Taylor PET to relative humidity in L366 of the revised manuscript, as follows:

- *"The lower impact of RH on Priestley-Taylor PET compared to the impact on Penman-Monteith PET can be related to the structure of Priestley-Taylor model, which does not consider the aerodynamic processes, so that the impact of RH on PET through these processes is not accounted (see Eqn. 2.7, 2.15 and 2.16 in Appendix A.2.)."*

The other two input variables, temperature and solar radiation, are incorporated into the Priestley-Taylor model in a highly non-linear manner, so it would be difficult to infer the corresponding sensitivity *directly from the model equation. For the same reason, it is difficult to explain the magnitude of PET sensitivity to these two variables with reference to the model structure.*

5. - The time period used as the baseline is relatively short and this might be helpful to give some information on the climatic specificity of the time period.

The selected study period aimed to reflect baseline near-recent climate conditions in Australia, and was selected according to the availability of high-quality climate observations in Australia (released by BoM 2013). The data period was mainly constrained by wind data, which were only available up to the year 2005. In addition, the data period was also determined so that climate data were available for a consistent period at a number of case study locations within different climate zones in Australia, which is another factor limiting the data period that could be considered.

As summarized in Table 1, the baseline included various climate conditions, with a wide range of values for each climate variable. Any uncertainty in specifying the baseline at individual locations due to the data length are therefore likely to be overshadowed by the wide ranges of each climate variable across the different study locations, as indicated by the varying ranges of average values of the four PET-related climate variables, given below:

- *T: 9.95 °C (Lake Leake) – 27.4 °C (Darwin)*
- *RH: 37.2 % (Tennant Creek) – 78.0 % (Strathgordon village)*
- *R_s: 11.7 MJ $m^{-2}day^{-1}$ (Strathgordon village)– 21.6 MJ $m^{-2}day^{-1}$ (Tennant Creek)*
- *u_z: 2.34 ms^{-1} (Alice Springs) – 6.40 ms^{-1} (Flinders Island)*

6. - Are wind speed and air temperature measured at 2m for all locations?

Air temperature data were measured at a height of approximately 1.2 metres above the ground, and wind speed data were normally measured at a height of 10 metres above the surface (http://www.bom.gov.au/climate/cdo/about/faq-data.shtml). The temperature observations were assumed to be close to the evaporative surface, while the height of wind speed measurements has been incorporated in the estimation of Penman-Monteith model to convert to a 2m height (the Priestley-Taylor model does not use wind as an input so this effect was not relevant).

7. - P.8 l.136 ET-related -> PET-related?

We agree with your suggestion and have reflected this change in L142 of the revised manuscript, as:

- *"Table 1 shows the average values of the four PET-related climate variables…"*

8. -P.14 l.260 ",." -> "."

This has been updated in the revised manuscript.

9. - The distinction between 'energy-limited' and 'water-limited' sites is interesting but not clearly defined: from the legends of Fig. 3-6, it appears that a studied site might be energy-limited for some months AND water-limited on some other month, which is non sense. From Fig 1, it appears that a given site is water-limited OR energy-limited. This need clarification and the threshold of aridity index value between the two classes should be defined.

Thank you for highlighting this confusion. We would like to take this opportunity to clarify that the water-/energy-limited status for each catchment presented in Fig. 1 was based on the long-term ratio of PET/P from the 10 years of data (as the PET/P ratios presented in Table 1), which was used to categorize the overall hydrological condition at the 30 case studies.

Due to the seasonal variation of PET and P, a catchment can switch between water- and energy-limited conditions for different months. Therefore, estimating the monthly PET/P ratios allowed us to discover more on how the PET sensitivities vary with these seasonal changes in hydrological conditions. The water- and energy-limited status shown in Fig. 3-6 were therefore based on monthly PET/T.

In the revised manuscript, we have improved the emphasis on the monthly scale for these figures in L305, as following (with changes underlined):

- *"In addition to assessing the impact of baseline climatic conditions, we are also interested in the role of baseline hydrological conditions (<u>represented by the PET/P ratio at each study site</u>) on PET sensitivity. <u>Since the hydrological conditions can vary substantially over the course of a year for each study site, for this analysis we focused on the PET/P ratios estimated on a monthly basis, and thus differ from the long-term PET/P ratios presented in Table 1.</u>"*

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Title: Sensitivity of potential evapotranspiration to changes in climate variables for different Australian climatic zones

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Abstract

Understanding the factors that have an impact on the sensitivity of potential evapotranspiration (PET) to changes in different climate variables is critical to assessing the possible implications of anthropogenic climate change on the catchment water balance. Using a global sensitivity analysis, this study assessed the implications of baseline climate conditions on the sensitivity of PET to a large range of plausible changes in temperature (T), relative humidity (RH), solar radiation (R_s) and wind speed (u_z). The analysis was conducted at 30 Australian locations representing different climatic zones, using the Penman-Monteith and Priestley-Taylor PET models. Results from both models suggest that the baseline climate can have a substantial impact on overall PET sensitivity. In particular, approximately ~~2~~two-fold greater changes in PET were observed in cool-climate energy-limited locations compared to other locations in Australia, indicating the potential for elevated water loss as a result of increasing actual evapotranspiration (AET) in these locations. The two PET models consistently indicated temperature to be the most important variable for PET, but showed large differences in the relative importance of the remaining climate variables. In particular, for the Penman-Monteith model wind and relative humidity were the second-most important variable for dry and humid catchments, respectively, whereas for the Priestley-Taylor model solar radiation was the second-most important variable, particularly for warmer catchments. This information can be useful to inform the selection of suitable PET models to estimate future PET for different climate conditions, providing evidence on both the structural plausibility and input uncertainty for the alternative models.

Keywords: climate impact assessment; evapotranspiration; climate zones; Penman-Monteith~~; climate zones~~; Priestley-Taylor; global sensitivity analysis

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1. Introduction

Evapotranspiration (ET) is critical in assessing the impacts of anthropogenic climate change on the catchment water balance, with ET fluxes accounting for about 62% of land-surface precipitation on average globally ~~(Dingman, 2015)~~(Dingman, 2015) and thus representing the dominant loss of water from a large proportion of catchments worldwide. ET fluxes are affected by climate change through a cascade of processes that begins with the increasing concentration of greenhouse gases, as well as their attendant impacts on large-scale circulation and associated changes to the global distribution of energy and moisture. These large-scale processes lead to local-scale changes in the atmosphere, which in turn influence the catchment water balance through a set of terrestrial hydrological processes by which precipitation is converted into actual ET (AET), runoff and groundwater recharge ~~(Oudin et al., 2005)~~(Oudin et al., 2005).

Climate impact studies that investigate the influence of climate forcings on the catchment water balance are usually based on projections of future climate represented by climate variables such as temperature and solar radiation from general circulation models (GCMs), which are converted into potential ET (PET) using one or several PET models. The PET projections are combined with GCM projections of precipitation (P), which together can be used to directly estimate the water deficit ~~(Chang et al., 2016; Taylor et al., 2013)~~(Taylor et al., 2013;Chang et al., 2016). Alternatively, rainfall-runoff models can be used to translate the changes in P and PET into changes in runoff ~~(e.g. Akhtar et al., 2008; Chiew et al., 2009; Koedyk and Kingston, 2016)~~(e.g. Akhtar et al., 2008;Chiew et al., 2009;Koedyk and Kingston, 2016), as well as associated information such as the impact on catchment yield ~~(Wilby et al., 2006)~~(Wilby et al., 2006), water supply security ~~(Paton et al., 2014, 2013)~~(Paton et al., 2014, 2013) and flood risk ~~(Bell et al., 2016)~~(Bell et al., 2016). Therefore, to quantify the specific impact of changes in ET on the water balance, a good understanding of the sensitivity of PET to potential changes in its key influencing climatic variables is required ~~(e.g. Goyal, 2004; Tabari and Hosseinzadeh Talaee, 2014)~~(Goyal, 2004;Tabari and Hosseinzadeh Talaee, 2014). This is particularly relevant given the recent focus on ~~“~~‘scenario-~~neutral”~~neutral’ (or ~~“~~‘bottom-~~up”)~~up’) approaches to climate impact assessment ~~(Brown et al., 2012; Culley et al., 2016; Prudhomme et al., 2010)~~(Brown et al., 2012;Prudhomme et al., 2010;Culley et al., 2016), which require the sensitivity of a given system to potential changes in climate forcings to be estimated ~~(Guo et al., 2016a; Kay et al., 2014; Prudhomme et al., 2013a; Prudhomme et al., 2013b; Steinschneider and Brown, 2013)~~(Prudhomme et al., 2013a;Steinschneider and Brown, 2013;Prudhomme et al., 2013b;Kay et al., 2014;Guo et al., 2016a).

Furthermore, the sensitivity of PET can provide critical evidence in relation to which models are most appropriate for PET estimation under climate change conditions, which is particularly relevant to the ongoing debate on the potential trade-off between model complexity and reliability. Complex models such as the Penman-Monteith model are often recommended for their ability to better represent the physical processes that affect PET ~~(Barella-Ortiz et al., 2013; Donohue et al., 2010; McVicar et al., 2012)~~(McVicar et al., 2012;Donohue et al., 2010;Barella-Ortiz et al., 2013)~~, such as potential compensating~~. For example, the Penman-Monteith model can account for the effects ~~between temperature~~ of wind, and ~~wind that may~~ thus can assist to explain ~~the paradox that decreasing~~ at least part of the observed decreases in pan evaporation ~~(which is closely related to PET) has been observed~~ with ~~increasing temperatures for~~ increases in temperature in many locations ~~worldwide (McVicar et al., 2008; Roderick et al., 2007).~~globally – the ‘evaporation paradox’ – as due to the observed decreases in wind speed (Roderick et al., 2007;McVicar et al., 2008;Lu et al., 2016). However, simpler empirical models may also be preferable under some conditions, as they require a smaller number of input climate variables, which might be able to be projected with greater confidence with GCMs~~.~~, and thus leading to greater confidence in the corresponding PET estimates ~~(Ekström et al., 2007; Kay and Davies, 2008)~~(Kay and Davies, 2008;Ekström et al., 2007;Ravazzani et al., 2014). For example, there is reasonable confidence in projections of temperature and relative humidity in Australia for a given emission scenario, but less confidence in projections of wind due to sub-grid effects of orography and other land-surface features ~~(CSIRO and Bureau of Meteorology, 2015; Flato et al., 2013).~~(Flato et al., 2013;CSIRO and Bureau of Meteorology, 2015). In these situations, models such as the ~~Priestly~~Priestley-Taylor model that do not depend on wind may produce more reliable estimates of PET compared to the more complex Penman-Monteith model. Thus, the choice of climate variables to include in climate impact assessments must be informed both by the relative importance of each variable on projections of PET ~~(e.g. Tabari and Hosseinzadeh Talaee, 2014)~~(e.g. Tabari and Hosseinzadeh Talaee, 2014), and the likely confidence in the projections of each variable (e.g. ~~Flato et al., 2013; Johnson and Sharma, 2009~~Flato et al., 2013;Johnson and Sharma, 2009).

Field Code Changed

Sensitivity analysis methods have been employed in a number of recent studies to assess the overall sensitivity of PET estimated by the Penman-Monteith model to potential changes in climate, as well as to better understand the relative importance of different climate variables on overall PET sensitivity. ~~For example, Goyal (2004)~~For example, Goyal (2004) found that PET was most sensitive to perturbations in temperature, followed by solar radiation, wind speed and vapor pressure, at a single study site in an arid region in India. ~~Tabari and Hosseinzadeh Talaee (2014)~~Tabari and Hosseinzadeh Talaee (2014) also looked at the sensitivity of PET to perturbations of historical climate data from eight meteorological stations representing four climate types in Iran, and concluded that the importance of wind speed and air temperature was lower while that of sunshine hours was higher for a humid location compared to an arid location. ~~Gong et al. (2006)~~Gong et al. (2006) found that the differences in PET sensitivity across the upper, middle and lower regions of the Changjiang (Yangtze) basin in China ~~are~~were largely due to contrasting baseline wind speed patterns. However, most of these PET sensitivity analysis studies focused on a limited number of study sites and/or climatic zones, so that the specific causes for varying PET sensitivity at different locations, such as the roles of climatic and hydrological conditions, remain unclear. Consequently, it is difficult to extrapolate our existing knowledge of PET sensitivity and the relative importance of each ~~atmospheric~~climate variable to new locations, which is essential for assessing the water balance at regional scales.

To address the shortcomings of existing studies outlined above, this study aims to gain an understanding of (i) the sensitivity of PET estimates to changes in the key climatic variables which influence PET, and how these sensitivity estimates are affected by varying baseline hydrologic and climatic conditions at different locations; and (ii) the relative importance of these climatic variables for PET, and how this changes with the baseline hydrologic and climatic conditions~~.~~ at different locations. These aims were achieved by analyzing the sensitivity of PET to perturbations in four of its driving climatic variables, namely temperature (*T*), relative humidity (*RH*), solar radiation (R_s) and wind speed (u_z), at 30 study sites across Australia representing a range of climate zones. Both the Penman-Monteith and ~~Priestly~~Priestley-Taylor models were used, as they represent different conceptualizations of the PET ~~process and also have been~~ -related processes, with both models being widely used for climate impact assessments ~~(Arnell, 1999; Donohue et al., 2009; Felix et al., 2013; Gosling et al., 2011; Kay et al., 2009; Prudhomme and Williamson, 2013)~~(Felix et al., 2013;Arnell, 1999;Gosling et al., 2011;Kay et al., 2009;Prudhomme and Williamson, 2013;Donohue et al., 2009). ~~Since~~It is worth noting that the ~~impact of climate-induced~~potential changes in one climate variable can be amplified or offset by changes in another variable ~~(for examples see Lu et al., 2016; Roderick and Farquhar, 2002; Su et al., 2015)~~(for examples see the discussions of 'evaporation paradox' in Lu et al., 2016;Roderick and Farquhar, 2002)~~,~~, which can affect the relative importance of each variable. To account for this effect, a global sensitivity analysis method was used, with similar methods being ~~successfully~~ applied to account for the impact of joint variations in the input variables on the output ~~of~~from a ~~range~~variety of environmental models, ranging from conceptual rainfall-runoff models ~~(e.g. Guillevic et al., 2002; Nossent et al., 2011; Tang et al., 2007a; van Griensven et al., 2006)~~(e.g. Tang et al., 2007a;Tang et al., 2007c)~~.~~ to complex models which consider a number of surface-groundwater processes (e.g. Guillevic et al., 2002;van Griensven et al., 2006;Nossent et al., 2011). The results of the global sensitivity analysis in this study were presented in terms of both absolute sensitivity of PET and relative sensitivity ~~scores~~indices of each climate variable, and ~~presented~~were used to elucidate the specific roles of ~~the~~varying baseline hydro-climatic ~~condition~~conditions on ~~the PET~~influencing these sensitivity measures.

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The subsequent sections of this paper are structured as follows. Section 2 introduces the data obtained from the 30 study sites required for the global sensitivity analysis. Section 3 describes the approach to the global sensitivity analysis of PET. Section 4 presents and discusses two sets of results ~~to assess~~which address the two study aims respectively, as: (i) the estimated PET sensitivity to potential changes in temperature, solar radiation, humidity and wind, and how this changes with location; and (ii) the relative importance of the four climate variables for estimating PET, ~~for each PET model~~and how this changes with location. The study is summarized and concluded in Sect. 5.

2. Data

To represent contrasting hydro-climatic conditions for assessing PET sensitivity, we selected case study locations within different Köppen classes in Australia. The original Köppen climate classification ~~(Köppen et al., 1930; Köppen, 1931)~~(Köppen et al., 1930;Köppen, 1931) provides a useful categorization of hydro-climatic conditions at specific locations, which is based on the long-term average levels and seasonal patterns of climatic and hydrologic variables, including temperature, relative humidity and rainfall. ~~The classification~~A 'modified Köppen classification' system has been ~~later~~ adapted for Australia~~, referred to as the "modified Köppen classification" (as in Stern et al., 2000)~~(as in Stern et al., 2000) and is now widely used in climatic and hydrologic studies to identify and categorize case study locations (e.g. ~~Johnson and Sharma, 2009; Li et al., 2014; Rustomji et al., 2009~~Johnson and Sharma, 2009;Rustomji et al., 2009;Li et al., 2014).

As mentioned in the Introduction, both the Penman-Monteith and the Priestley-Taylor models were used to estimate PET for the global sensitivity ~~analysis~~analyses. The estimation of PET with these models relies on temperature, relative humidity, solar radiation and (for the Penman-Monteith model only) wind speed. In addition, the rainfall data were also obtained to assess the aridity of the different locations. We limited the selection of study sites to those with 10 or more years of continuous climate data with no more than 5 % missing records over the study period. This led to a final selection of 30 weather stations (Fig. 1), with a consistent data period from 1 January 1995 to 31 December 2004. The data obtained at each site are detailed as below:

- **Daily maximum and minimum temperature (*T* in °C), maximum and minimum relative humidity (*RH* in %) and wind speed (u_z in m s^{-1}):** Data for each of these variables were obtained directly from each weather station.
- **Daily solar radiation (R_s in MJ m^{-2} day^{-1}):** Daily solar radiation was calculated from daily sunshine hour data (*n* in h) obtained from each weather station, using the Ångström-Prescott equation as in ~~McMahon et al. (2013)~~McMahon et al. (2013).
- **Daily rainfall (mm)**: Daily rainfall data were obtained from a rain gauge at each weather station.

Figure 1: Locations of 30 Australian weather stations (see Table 1 for the full names of these weather stations) selected for analysis, with reference to their corresponding climate classes derived following the modified Köppen classification (reproduced with data from Stern et al., 2000).

Table 1~~Table 1~~ shows the average ~~levels~~values of the four ~~ET~~PET-related climate variables, as well as the rainfall within the study period, at each of the 30 sites. As can be seen, there are large differences in the average values of each variable, highlighting large differences in the climatic conditions across the 30 sites. In addition, a quantity particularly relevant to ET processes is the long-term averaged ratio of PET to precipitation (PET/P), which describes whether a location is water-limited (PET/P >1) or energy-limited (PET/P < 1~~).~~) (Gerrits et al., 2009;McVicar et al., 2010). This ratio was ~~also~~ estimated for each site and is also shown in Table 1~~Table 1~~ (with the point colour in Fig. 1 indicating whether the location is water-limited or energy-limited). The range of PET/P values indicates substantial variations in the water availability conditions at different study sites. Note that these ratios were based on the estimates of PET from the Penman-Monteith model~~, which generally suggested similar PET/P ratios to those estimated from Priestly-Taylor.~~. Although the use of Priestley-Taylor model resulted in different PET estimates at each site, the categorization of water- and energy-limited catchments was generally consistent with those from Penman-Monteith, with different categories only shown at four out of the 30 study sites (sites 6, 19, 20 and 27).

Table 1: Names, locations and average climate conditions of the 30 weather stations over the study period (1995-2004).

3. Method

3.1. Overview

A schematic of the approach followed in study is shown in Fig. 2. As a required model input for the global sensitivity analysis, a large number of representative samples were first obtained for the four climate variables which influence PET (T, RH, R_s and u_z) at each study site, by perturbing the corresponding historical climate data (Sect. 3.2). The outputs of the global sensitivity analysis (i.e. the responses of PET) were estimated with the Penman-Monteith and Priestley-Taylor models (Sect. 3.3). ~~Using~~To understand the ~~perturbations~~ PET sensitivity and the relative importance of the four climate variables ~~and the responses of PET~~in influencing PET and how these change with location, a global sensitivity analysis was conducted with the responses of PET to the climate perturbations (Sect. 3.4~~), with the analysis divided into~~). This proceeded in two parts:

(1) To assess the sensitivity of PET to the climate variables, the percentage changes in PET in response to all the climate perturbations were estimated relative to the baseline PET at each location. ~~To generalize the results~~To observe the impact of varying baseline hydro-climatic conditions, the sensitivity obtained

from each PET model was also plotted against the baseline levels of each climate variable for all study sites.

(2) To assess the relative importance of each climate variable, the PET sensitivity to all climate perturbations in (1) was first compared to the conditional sensitivity when holding each variable constant. This comparison enables an assessment of the relative impact of each variable on the total PET sensitivity. An alternative presentation of the individual and interaction effects of the climate variables was achieved using the Sobol' method ~~(Sobol' et al., 2007), in which~~(Sobol' et al., 2007). Here, the total variance of PET was estimated based on different samples drawn from the perturbed ranges of each climate variable, and ~~was~~ then partitioned ~~the~~ into the individual contribution from each climate variable and their interactions (see Appendix A.1. for details). The Sobol' first-order sensitivity indices were estimated and plotted against the baseline levels of each climate variable for all study sites to explore the role of varying baseline ~~climate~~hydro-climatic conditions on the relative importance of each climatic variable for PET.

Figure 2: Schematic of the method used in this study.

3.2. Representing plausible changes in the climatic variables

As part of the global sensitivity analysis, a large number of representative combinations of the changes in the four climate variables ~~considered~~ (*T*, *RH*, R_s and u_z) were obtained. The upper and lower bounds for perturbing each climate variable were determined based on the uncertainty bounds of projections for 2100 for Australia ~~(Stocker et al., 2013)~~(Stocker et al., 2013). The selected bounds are given in Table 2~~Table 2~~, which are all slightly wider than those presented in Stocker et al. (2013) to encompass a comprehensive range of plausible future climate change scenarios. Within these bounds, samples were drawn for different combinations of changes in each climatic variable. Latin hypercube sampling (LHS) was used for this purpose due to its effectiveness in covering multi-dimensional input spaces ~~(Osidele and Beck, 2001; Sieber and Uhlenbrook, 2005; Tang et al., 2007b)~~(Osidele and Beck, 2001;Sieber and Uhlenbrook, 2005;Tang et al., 2007b).

Table 2: Plausible perturbation bounds for each climate variable relative to their current levels.

~~In accordance with the method suggested by Nossent et al. (2011), the sample size was selected to ensure the convergence of the first- and total-order Sobol'sensitivity~~According to Nossent et al. (2011) and Zhang et al. (2015), the sample size was selected to ensure the convergence of the first- and total-order Sobol' sensitivity indices, which occurs when the width of the 95 % confidence intervals from 1000-fold bootstrap resampling of the each index is below 10 % of the corresponding mean obtained from bootstrapping. Specifically, we generated different sizes of LHS samples of climate perturbations with the historical climate data from one study site, from which the PET responses were estimated using the Penman-Monteith model. The 1000-fold bootstrap estimates for the Sobol' first- and total-order sensitivity indices for each climate variable were then derived (as in Eqn. 1.2 and 1.5 in Appendix A.1., respectively) for each sample size. It was observed that both the Sobol' indices began to converge when the sample size exceeded 5000, ~~which~~and this was therefore used as the LHS sample size for all the sensitivity experiments in this study. Based on this sample size, a total of 30000 Sobol' samples were compiled as required to estimate the first- and total-order indices (as detailed in Appendix A.1.), which correspond to 30000 climate perturbations to be used to test PET sensitivity.

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~~The 5000~~To generate time series of perturbed climate data, the 30000 joint perturbations to the four climate variables obtained by LHS were treated as change factors, and applied to the time series of daily values of the corresponding historical data~~ in order to generate 5000 time series of climate affected daily data.~~. Rather than using a single daily mean value of temperature and relative humidity, the two PET models used in this study require both the daily minimum and maximum values; therefore each pair of temperature variables and relative humidity variables was considered jointly and thus perturbed by the same amount for each day. In addition, to ensure physical plausibility of the perturbations, the daily maximum and minimum values of relative humidity were capped at a maximum of 100%.

3.3. Estimating PET responses to climate perturbation

To represent the responses in PET as a result of the climate perturbations, we used both the Penman-Monteith and Priestley-Taylor models, which provide contrasting process representations to estimate PET. The Penman-Monteith model is often referred to as a combinational model, as it combines the energy balance and mass transfer components of ET, and takes into account vegetation-dependent processes such as aerodynamic and surface resistances~~.~~ (Eqn. 2.1 in Appendix A.2.). The model requires input of six climate variables, namely, T_{max}, T_{min}, RH_{max}, RH_{min}, R_s and u_z. The Priestley-Taylor model consists of a simpler structure, considering only the energy balance, without consideration of mass transfer or any impact from vegetation~~.~~ (Eqn. 3.1 in Appendix A.3.). Therefore, the Priestley-Taylor model is also referred to as a radiation-based model. The model only requires five climate variables, including T_{max}, T_{min}, RH_{max}, RH_{min} and R_s.

To minimize the potential confounding effects of differences in vegetated surface, the evaporative surface was assumed to be reference crop for all study sites, so that it was possible to use the FAO-56 version of the

Penman-Monteith model ~~(Allen et al., 1998)~~(Allen et al., 1998)~~. The detailed formulations of the two PET models, as well as use of constants and assumptions are included in McMahon et al. (2013). Both models were implemented using the R package *Evapotranspiration* (~~. The detailed formulations of the two PET models, as well as the relevant constants and assumptions, are included in McMahon et al. (2013). Both models were implemented using the R package *Evapotranspiration* (http://cran.r-project.org/web/packages/Evapotranspiration/index.html) ~~(Guo et al., 2016b).~~(Guo et al., 2016b). From each model, two sets of estimated PET were obtained: (i) a single set of baseline (historical) PET data at each study site with the historical climate data; (ii) ~~500~~30000 sets of perturbed PET data at each study site corresponding to the ~~500~~30000 sets of perturbed climate data obtained using LHS, as detailed in Sect. 3.2.

3.4. Analyses of PET sensitivity

To assess the overall sensitivity of PET to plausible climate change, we first estimated the annual average percentage changes in PET (relative to the baseline PET) using all climate perturbations at the 30 study sites, with estimates from both the Penmen-Monteith and Priestley-Taylor models. A closer investigation of how PET sensitivity varies with baseline climate was conducted by plotting all monthly PET responses against the average levels of each climate variable, for all study sites and all months. The reason for the choice of monthly timescale is that for some study sites, the climate can vary substantially by season, so that an annual analysis might obscure important sub-annual effects.

To assess the relative importance of each climate variable for PET estimation from each model, we first compared two sets of PET sensitivity, ~~including~~namely:

(1) The unconditional sensitivity of PET obtained from the entire ~~500~~30000 sets of climate perturbations from LHS; and

(2) The conditional sensitivity of PET ~~on~~assuming no ~~-change~~ changes in ~~each climatic variable~~one of the climate variables, obtained using a subset of all climate perturbations used in (1), for which the changes in the specific conditioning ~~climatic~~climate variable were close to zero (within ±0.1 ◦C for *T*, and within ±0.1 % for the other three variables).

In this way any difference between (1) and (2) was purely contributed by the impact of changing the specific conditioning climate variable. To quantify and compare the relative importance of each climate variable, we then utilized the Sobol' method, which was implemented within the R package *sensitivity* (https://cran.r-project.org/web/packages/sensitivity/index.html). We estimated the Sobol' first-order sensitivity indices (as in Eqn. 1.2, Appendix A.1.) to assess the role of each individual climate variable for each PET model, at the 30 study sites. The sum of all interaction effects was also calculated for each location as the difference between the sum of all first-order indices and one (Eqn. 1.6, Appendix A.1.). The Sobol' first-order indices were then plotted against the baseline levels of each climate variable at the 30 study sites, to assess how the relative importance changes with the baseline climatic conditions.

4. Results and discussion

4.1. Sensitivity of PET to potential climate change for different climate zones

We start by assessing the sensitivity of PET to the full set of climate perturbations at the 30 study sites at the annual timescale, using both the Penman-Monteith and Priestley-Taylor models. The sensitivity results are presented in Table 3 in terms of the minimum, maximum and average changes of PET relative to the 1995-2004 baseline based on the ~~5000~~30000 LHS replicates at each study site. The two models suggest similar average PET sensitivity at most locations, with the sensitivity of the Penman-Monteith model averaged across all the locations (+13.38 %) being slightly higher than that for the Priestley-Taylor model (+10.91 %). Greater differences between the two models were observed when considering the ranges of sensitivity values. In particular, the minimum and maximum values (averaged across all the 30 sites) were -13.66 % and +47.09 % for the Penman-Monteith model, respectively, compared to -7.39 % and +34.47 % for the Priestley-Taylor model. This corresponds to a range for the Penman-Monteith model being approximately 45 % wider than that of the Priestley-Taylor model.

Table 3: Annual average PET sensitivity to the full set of climate perturbations (as % changes to baseline PET) from the Penman-Monteith and Priestley-Taylor models at the 30 study sites relative to the 1995-2004 baseline. The maximum and minimum sensitivity values from each model are shaded in grey.

For each PET model, the sensitivity values display substantial variation across the locations, with both models suggesting the lowest PET sensitivity at arid locations and highest PET sensitivities at humid locations, as was also observed in ~~Tabari and Hosseinzadeh Talaee (2014),.~~Table 3. Specifically, the Penman-Monteith model identified the highest average PET sensitivity at Flinders Island (+17.15 %), with the lowest sensitivity at Alice Springs (+9.80 %). The Priestley-Taylor model identified the highest average PET sensitivity at Hobart (+17.77 %), with the lowest at Tennant Creek (+7.09 %).

To further investigate how PET sensitivity varies with different climatic conditions, we now focus on the associations between the PET sensitivity values and the baseline levels of the four climate variables for each month of the year and across the 30 study sites. Starting with the Penman-Monteith model (Fig. 3), it is clear that the PET sensitivity displays a clear association with the baseline levels of climate variables, with higher sensitivity values for locations that are cooler (low *T*), more humid (high *RH*), and receiving less solar radiation (low R_s). The highest associations can be found with *T* (Fig. 3a), with the monthly changes in PET ranging from -30.2% to +98.3 % for the lowest baseline *T* value of 5.0 °C, compared to a range of -13.3 % to +46.6 % for the highest baseline *T* of 30.3 °C. Similarly, the range of Penman-Monteith PET sensitivity values also shows clear decreases with baseline R_s (Fig. 3c), and increases with baseline *RH* (Fig. 3b). The baseline u_z (Fig. 3d) levels show no obvious impact on the PET sensitivity.

Figure 3: Monthly PET responses from the Penman-Monteith model, plotted against the monthly baseline levels of (a) temperature, (b) relative humidity, (c) solar radiation and (d) wind speed at 30 study sites. Each interval represents the range of all PET responses to the full set of climate perturbations for a single month at a single location, with the mean represented by the point on the line. The classification of energy- and water-limited months are based on the corresponding monthly PET/P ratios.

The sensitivity from Priestley-Taylor was also investigated (Fig. 4), and results are consistent with the results from the Penman-Monteith model, although the overall ranges were lower for each variable as anticipated from the results in Table 3. Interestingly, regardless of the choice of PET model, the range of sensitivity values at the monthly scale is higher than the range for the annual scale suggesting greater uncertainty at higher temporal resolutions.

Figure 4: Monthly PET responses from the Priestley-Taylor model, plotted against the monthly baseline levels of (a) temperature, (b) relative humidity, (c) solar radiation and (d) wind speed at 30 study sites. Each interval represents the range of all PET responses to the full set of climate perturbations for a single month at a single location, with the mean represented by the point on the line. The classification of energy- and water-limited months are based on the corresponding monthly PET/P ratios.

In addition to assessing the impact of baseline climatic conditions, we are also interested in the role of baseline hydrological conditions (represented by the PET/P ratio at each study site~~, calculated on a monthly basis as~~) on PET sensitivity. Since the hydrological conditions can vary substantially over the course of a year~~) on PET sensitivity.~~ for each study site, for this analysis we focused on the PET/P ratios estimated on a monthly basis, and thus differ from the long-term PET/P ratios presented in Table 1. These results are also shown in ~~Fig~~Figs. 3 and 4, with red-colored bars denoting water-limited conditions, and blue-colored bars denoting energy-limited conditions. These figures show that PET sensitivity is generally larger under energy-limited conditions, regardless of the choice of PET model. In contrast, for water-limited conditions, most sensitivity magnitudes only vary within approximately half of the entire range from each PET model. However, when exploring the association with temperature (~~Fig~~Figs. 3a and 4a) in more detail, the sensitivity is in fact lowest for energy-limited conditions during warm months (i.e. ~~as~~ when $T > 25$ °C, corresponding to the monsoonal summer months in the northern parts of Australia), and highest for the energy-limited conditions during cool months (i.e. ~~as~~ when $T < 15$ °C, corresponding to the wet winter months in southern Australia). This highlights that it is the atmospheric temperature, rather than the level of aridity, that appears to affect the overall sensitivity. This finding ~~lead~~leads to a different interpretation to previous studies, which indicated that the dominant drivers of spatially varying PET include aridity ~~(Tabari and Hosseinzadeh Talaee, 2014)~~(Tabari and Hosseinzadeh Talaee, 2014) and wind speed ~~(Gong et al., 2006)~~(Gong et al., 2006).

The above results also have potential implications on likely AET changes in a future climate. In particular, the above analysis shows that cool and humid regions and seasons appear to show the greatest sensitivity to PET, and given that water is not expected to be limited for these cases, the ratio between AET and PET is also likely to be the greatest for these cases. As such, one might expect a greater change to AET occurring at the locations and during times of the year where PET is most sensitive to changes in climate.

As a potential limitation to the above analysis, ~~reliability issues of the Penman-Monteith model discussed in a recent study (Milly and Dunne, 2016) suggest~~some reliability issues of the Penman-Monteith model have been discussed in a recent study by Milly and Dunne (2016), which suggested that the Penman-Monteith model may overestimate the sensitivity in these energy-limited regions relative to a GCM-based AET benchmark. They concluded that the potential changes in ET would be better described by GCMs than ~~“~~‘off-~~line”~~line’ PET models (such as the two models used in this study), as GCMs can explicitly consider more complex atmospheric processes, such as the interaction between CO_2 and stomatal conductance. Nevertheless, it should be noted that the current reliability of GCMs in simulating ET is also questionable, due to the uncertainty in representing soil moisture and radiative energy at the evaporative surface ~~(e.g. Barella-Ortiz et al., 2013; Boé and Terray, 2008; Seneviratne et al., 2013)~~(e.g. Seneviratne et al., 2013;Boé and Terray, 2008;Barella-Ortiz et al., 2013). In addition, due to the coarse scale of GCM output, downscaling is generally required to post-process output for use at local and regional scales, which often adds further bias and uncertainties to the GCM simulation and largely limits their applicability ~~(e.g. Chen et al., 2012; Diaz-Nieto and Wilby, 2005)~~(e.g. Chen et al., 2012;Diaz-Nieto and Wilby, 2005). Therefore, although GCM results may be more suitable for large-scale assessments, catchment-scale climate impact assessments are likely to be informed by ~~“~~‘off-~~line”~~line’ PET models for the foreseeable future. ~~-~~Consequently, the sensitivity results shown in this study ~~are likely to~~will remain relevant for climate impact assessments conducted using these models.

4.2. Relative importance of climate variables affecting PET for different climate zones

We now explore the relative importance of each climate variable on overall PET sensitivity, by first visualizing the conditional sensitivity of PET when holding each variable constant at its historical level while perturbing the remaining variables, and then comparing this to the unconditional sensitivity estimates (as shown in Fig. 3 and Fig. 4). Figure 5 shows the ranges of the monthly unconditional PET sensitivity (dashed lines) and the PET sensitivity conditioned on zero-change in each of T, RH, R_s and u_z (solid lines) for the Penman-Monteith model, plotted against the monthly baseline levels of the four climate variables at the 30 study sites.

Figure 5: Monthly PET responses from the Penman-Monteith model, plotted against the monthly baseline levels of (a) temperature, (b) relative humidity, (c) solar radiation and (d) wind speed at 30 study sites. Each dashed (solid) line represents the range of all PET responses to the full set of climate perturbations (conditioned on no-change in each climate variable) for a single month at a single location. The corresponding means are represented by the points on the lines. The classification of energy- and water-limited months are based on the corresponding monthly PET/P ratios.

The figure suggests that perturbations in T have the greatest impact on PET sensitivity compared to other climate variables (Fig. 5a), contributing to at least 45 % of the PET responses compared to the unconditional results. Humidity also plays a significant role, although only for higher humidity levels (contributing up to 57 % of PET responses) with relatively minor influence for the less humid catchments (Fig. 5b). In contrast, the role of solar radiation (Fig. 5c) and wind (Fig. 5d) is generally minor, with the unconditional sensitivities being only slightly wider than the conditional sensitivities.

A similar analysis was conducted for the Priestley-Taylor model (Fig. 6), and shows somewhat different results compared to those obtained for the Penman-Monteith model. Consistent with Fig. 5a, temperature has the greatest impact, but in this case contributes up to 85 % of the overall variability (Fig. 6a). As a result, the sensitivity values for the remaining variables are ~~correspondingly~~ much lower. Unlike in Fig. 5b, the role of relative humidity does not appear to increase significantly with increasing baseline humidity (Fig. 6b) and in general contributes less than 33 % of the overall variability. The lower impact of *RH* on Priestley-Taylor PET compared to the impact on Penman-Monteith PET can be related to the structure of Priestley-Taylor model, which does not consider the aerodynamic processes, so that the impact of *RH* on PET through these processes is not accounted (see Eqn. 2.7, 2.15 and 2.16 in Appendix A.2.). The role of solar radiation appears to be somewhat larger for high baseline solar radiation values (Fig. 6c) and wind is shown to have no impact as expected, since wind is not an input into the Priestley-Taylor model (Fig. 6d~~)~~). However, it is worth noting that although the Priestley-Taylor model does not consider wind as an input variable, the unconditional sensitivity is slightly wider than the sensitivity conditioned on no-change in wind. This is because the conditional sensitivity is estimated with only a subset of all climate perturbations (Sect. 3.4), which may not consist of the entire range of perturbation in each of the other three climate variables.

Figure 6: Monthly PET responses from the Priestley-Taylor model, plotted against the monthly baseline levels of (a) temperature, (b) relative humidity, (c) solar radiation and (d) wind speed at 30 study sites. Each dashed (solid) line represents the range of all PET responses to the full set of climate perturbations (conditioned on no-change in each climate variable) for a single month at a single location. The corresponding means are represented by the points on the lines. The classification of energy- and water-limited months are based on the corresponding monthly PET/P ratios.

A more formal ~~quantitive~~quantitative measure of the relative importance of each climate variable for PET is provided by the Sobol' indices. ~~The~~ Figure 7 shows the Sobol' first-order indices of the Penman-Monteith PET to changes in the four climate variables at the annual scale, as well as their interactions~~, are presented in Fig. 7 for~~

~~the Penman-Monteith model, which~~. The first-order indices are plotted against the baseline levels of each climatic variable to observe the impact of baseline climate conditions. For presentation purposes, the baseline levels are represented by the rank of the baseline annual average value of each variable, rather than the absolute level of each climate variable across the 30 study sites. The Sobol' indices in the figure show that *T* is generally the most important variable for PET, with index values ranging from 0.46 to 0.62. Since the Sobol' indices suggest the partitioning of the total variance ~~in~~of PET, these results are consistent with Fig. 5a, which suggests that perturbations in *T* contribute to at least 45 % of the variation in the estimated changes in PET. The role of wind and humidity in affecting the sensitivity values is also evident, with wind being the second-most important variable (with Sobol' indices up to 0.42) for sites with low baseline humidity, and ~~humdity~~humidity being the second-most important variable (with Sobol' indices up to 0.47) for sites that have high humidity (Fig. 7b). Solar radiation is generally the variable with the lowest Sobol' indices, ~~although~~with the largest contributions (up to 18 %) can be observed for warm catchments (Fig. 7a).

Figure 7: Sobol' first-order sensitivity indices of the Penman-Monteith model for changes in the four climate variables (colored) and their interaction effects (grey), plotted against the ranking of the average level of each climate variable at 30 study sites

The Sobol' sensitivity indices are also presented for the Priestley-Taylor model (Fig. 8), and show substantial differences compared to those for the Penman-Monteith model. Temperature exhibits the largest sensitivity score in most cases, and ranges from 0.44 to 0.83. The relative role of temperature varies most clearly as a function of both the baseline temperature (Fig. 8a) and the baseline solar radiation values (Fig. 8c), with temperature being particularly important for low temperature and low solar radiation sites. As temperature and radiation increase, the relative role of solar radiation becomes more important, reaching Sobol' index values of up to 0.49. In contrast, the role of relative humidity is generally minor (with Sobol' indices within the range 0.03-0.1) and does not appear to vary as a function of baseline conditions. Finally, the role of wind is absent, given that this variable is not included as part of the Priestley-Taylor equation.

Figure 8: Sobol' first-order sensitivity indices of the Priestley-Taylor model for changes in the four climate variables (colored) and their interaction effects (grey), plotted against the ranking of the average level of each climate variable at 30 study sites

The differences between the Penman-Monteith and Priestley-Taylor models highlight the different physical assumptions underpinning the models, with aerodynamic processes being important for the Penman-Monteith model as indicated by the relative importance of RH and u_z for this model, whereas R_s has a critical role in the Priestley-Taylor model, which is closely linked to the emphasis of radiative energy as the energy source for ET in the model.

Finally, comparing Fig. 7 and Fig. 8, it is apparent that the interactions among the four climate variables on PET (shown as grey bars) are greater in the Penman-Monteith model compared to the Priestley-Taylor model. Specifically, these interactions contribute ~~to~~fractions of 0.03-0.04, and 0-0.02 of the total variance in PET for the Penman-Monteith and Priestley-Taylor models, respectively. The relative magnitude of the interaction effects in the two models can be again related to their structural differences: the higher interaction effects in Penman-Monteith can be a result of the larger number of variables in this model compared with those in the Priestley-Taylor model.

It is difficult to assess the consistency of these sensitivity results with existing literature, given the different methodologies and datasets used in other studies. Although most PET sensitivity studies used only the Penman-

Monteith PET model, there is still substantial discrepancy in results depending on the specific implementations of sensitivity analysis. ~~For example, Gong et al. (2006)~~For example, Gong et al. (2006) perturbed each of temperature, wind speed, relative humidity and solar radiation within ±20 % for the Changjiang basin in China, and observed that that relative humidity was generally the most important variable driving PET, followed by solar radiation, temperature and wind speed. This contrasted with our results from the Penman-Monteith model, which showed temperature as the most important variable and solar radiation as the least important variable for almost all the stations analyzed, and may be attributable to the different baseline climates as well as the perturbation ranges used for the sensitivity analysis between the two studies.

The results of our study were more consistent with ~~Goyal (2004)~~Goyal (2004), who concluded that PET is most sensitive to potential changes in temperature for an arid region in India, by applying a ±20 % perturbation on each of temperature, solar radiation, wind speed and vapor pressure. ~~In contrast, Tabari and Hosseinzadeh Talaee (2014)~~In contrast, Tabari and Hosseinzadeh Talaee (2014) also used a ±20 % perturbation range, but on only three climate variables, ~~including~~namely temperature, wind speed and sunshine hours, for several climate regions in Iran. Their study concluded that the catchment aridity was a major ~~determinent~~determinant of the sensitivity to temperature, wind speed and humidity, whereas our analysis highlights the importance of baseline temperature and humidity, rather than the aridity (or water- or energy-limited status of the catchment) as a key driver.

~~PET sensitivity can be further diversified by the choice of PET models, as illustrated in McKenney and Rosenberg (1993)~~PET sensitivity can further diversify by the choice of PET models, as illustrated in McKenney and Rosenberg (1993), in which the percentage changes in PET due to a +6 ◦C change can differ up to around 40 %, when estimated with eight alternative PET models. This lack of consistency in the relative importance of the climate variables for PET is not surprising given the findings of our study, as the results are strongly dependent on the design of the sensitivity analysis experiment, including the choice of study sites and study periods, the input climate variables considered, and the ways to perturb them (i.e. the choice of global or local perturbation and the ranges of perturbation in different input variables).

Nevertheless, the sensitivity results from this study suggest some distinct spatial patterns of the relative importance of different climate variables in Australia. Since the Penman-Monteith model is the most comprehensive physically-based PET model, the above regionalization of the PET sensitivity from this model can be used as a benchmark to identify the key climate variables for estimating PET under potential climate change. This information can be particularly useful to suggest the potential suitability of specific PET models for regional applications. For example, since the Penman-Monteith PET showed higher sensitivity to wind at dry locations (Fig. 7b), it is expected that wind-dependent PET models (such as Penman and Penman-Monteith) would be more appropriate for predicting PET at these locations~~; in~~. In contrast, using simpler models that do not consider wind as an input (such as Priestley-Taylor) can be problematic for these locations. Although this study only examined two PET models, the results suggest that simpler empirical models are likely to ignore some potential dynamics and interactions within the climate variables, which makes them less preferred for PET estimation under changing climates.

Another particular issue in the selection of one or several PET models under a changing climate arises from considering the current reliability of available climate projections, as the models can show high levels of sensitivity to variables for which we currently do not have high-quality climate projections. For example, for a given emissions scenario, there is reasonable confidence in projections of temperature and relative humidity in Australia, but less confidence in projections of solar radiation and wind ~~(CSIRO and Bureau of Meteorology, 2015; Flato et al., 2013).~~(Flato et al., 2013;CSIRO and Bureau of Meteorology, 2015). However the radiation-based Priestley-Taylor model can show high sensitivity to solar radiation, particularly for warm locations with high baseline solar radiation (Fig. 8a and 8c), due to a particular emphasis on radiative energy and thus the empirical relationships between PET and solar radiation. Similarly, the Penman-Monteith model can exhibit higher sensitivity to wind for locations with low relative humidity (Fig. 7b). Therefore, the use of GCM projections at these locations may lead to significant uncertainty in PET estimates due to the uncertainty in the driving variables.

5. Summary and conclusions

In this study, we used a global sensitivity analysis to investigate the sensitivity of PET and the relative importance four climatic ~~variable~~variables which influence PET (*T*, *RH*, R_s and u_z) under plausible future changes in these variables. The sensitivity analysis was conducted at 30 Australian case study locations ~~with contrasting~~within different climate zones to understand the impact of varying baseline hydro-climatic conditions~~ for generalization of the results~~. For the sensitivity analysis, the historical climate data at each study site were first perturbed to represent a large number of plausible climate change conditions, and then the responses in PET were estimated with both the Penman-Monteith and Priestley-Taylor models, from which the sensitivity of PET was ~~analyzed~~analysed. The key results ~~were~~are as follows:

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- In general PET is most sensitive to potential changes in climate in regions with lower temperature, less solar radiation and greater humidity, where ~~2~~two-fold greater changes in PET are expected compared to other locations in Australia.
- Within the plausible perturbations in T, RH, R_s and u_z, PET is generally most sensitive to T. The relative importance of the other climate variables varies substantially with the PET models. R_s has a dominant role in the radiation-based Priestley-Taylor model, highlighting the importance of radiative energy in the model. In contrast, the importance of RH and u_z are comparable for the Penman-Monteith model, whereas R_s has only little impact, reflecting the contribution of aerodynamic energy.
- The relative importance of climate variables in influencing PET depends very clearly on baseline climatic conditions. From Penman-Monteith, locations that are warmer, drier and receiving more solar radiation generally show greater sensitivity to u_z and lower sensitivity to RH. For Priestley-Taylor, the importance of T increases while that of R_s decreases for cooler locations and locations receiving less solar radiation.

The global sensitivity analysis used in this study is a powerful tool for providing a comprehensive and consistent measure of PET sensitivity to different climatic variables, considering a wide range of possible changes in climate, across different models with different data requirements. However, we have identified space for improvements in further implementations. For example, the bounds of perturbation for each climate variable can have a substantial impact on PET sensitivity, and thus their selection requires careful justification ~~(for example see Shin et al., 2013; Whateley et al., 2014)~~(for example see Whateley et al., 2014;Shin et al., 2013)~~.~~ ~~Therefore, alternative lines of evidence on possible changes in climate should be considered in setting these bounds: for example, the results of ensemble climate models (e.g. Collins et al., 2013), the impact of low-frequency climatic modes~~ . Therefore, alternative lines of evidence on possible changes in climate should be considered in setting these bounds: for example, the results of ensemble climate models (e.g. Collins et al., 2013), the impact of low-frequency climatic modes ~~(e.g. Chen et al., 2013; Vincent et al., 2015)~~(e.g. Chen et al., 2013;Vincent et al., 2015), as well as findings from within paleoclimatology records (e.g. ~~Ault et al., 2014; Ho et al., 2015~~Ault et al., 2014;Ho et al., 2015).

The analysis in this study also lends itself to scenario-neutral analyses ~~(Brown et al., 2012; Prudhomme et al., 2010)~~(Brown et al., 2012;Prudhomme et al., 2010), although the full implications on specific impacts of hydrological systems (e.g. flood risk, water supply, etc) would require the sensitivity analysis to be propagated to runoff via explicitly modelling the interaction between ET and rainfall-runoff processes ~~(e.g. Garcia and Tague, 2015; Roy et al., 2016)~~(e.g. Garcia and Tague, 2015;Roy et al., 2016). Furthermore, potential changes to precipitation, which were not analyzed here but which can have a significant impact on future runoff, would need to be considered. Within this context, the incorporation of alternative lines of evidence can therefore not only be used to define the bounds of the perturbations, but can also be superimposed onto the exposure space ~~(e.g. as in Culley et al., 2016; Prudhomme et al., 2013a)~~(e.g. as in Prudhomme et al., 2013a;Culley et al., 2016) to provide insight into the likelihood of possible changes. The outcomes of our study can feed into such a scenario-neutral analysis by providing guidance on the variables that are likely to be most important for a particular location, as well as providing insights on the potential implications of using alternative PET models on the overall sensitivity results.

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Appendix

A.1. ~~Sobol~~Sobol’ sensitivity analysis ~~(Sobol’ et al., 2007)~~(Sobol’ et al., 2007)

Sobol’ is considered ~~as~~ a variance-based method, ~~in~~ which requires estimation of the total variance in ~~the output from~~ a model output due to changes in its inputs is estimated with ~~the~~a Monte-Carlo ~~method, using~~approach. To estimate the variances, a large number of ~~sampled perturbations in each of its~~ samples is firstly drawn by varying all input ~~variable~~variables simultaneously, and then a Sobol’ sequence is constructed by re-sampling from within these Monte-Carlo samples ~~(Saltelli et al., 2010)~~(Saltelli et al., 2010)~~. The total variance is then partitioned to the contribution of each individual input variable as well as their interactions, as following (equation adapted from Zhang et al., 2015):~~

. According to Sobol’ et al. (2007), to estimate the Sobol’ first-order and total-order indices with a Monte-Carlo sample size of *n* consisting of *p* input variables, a Sobol’ sequence with a total of *n*.(*p*+2) samples should be obtained, i.e. requiring *n.(p+2)* model evaluations.

Sobol’ analysis partitions the total variance in model output to the contribution of each individual input variable (i.e. first-order effects), as well as their interactions (i.e. higher-order effects), as follows (equation adapted from Zhang et al., 2015):

$$V_Y = \underbrace{\sum_{i=1}^{n} V_i}_{\textbf{Individual effects}} + \underbrace{\sum_{i<j} V_{ij} + \sum_{i<j<k} V_{ijk} \ldots + V_{1,2\ldots,n}}_{\textbf{Interactions}} \qquad (1.1)$$

~~The output from Sobol’ method include (equations adapted from Nossent et al., 2011)~~ The outputs from Sobol’ analysis include (equations adapted from Nossent et al., 2011):

1) First-order sensitivity index, which quantifies the individual contribution of each input variable to the total variance of the model's output;

$$S_i = \frac{V_i}{V_Y} \tag{1.2}$$

2) Second- and higher-order sensitivity index, which quantifies the contribution of interactions among two or more input variables to the total variance of the model's output;

$$\text{For second-order: } S_{ij} = \frac{V_{ij}}{V_Y} \tag{1.3}$$

$$\text{For higher-order: } S_{ij\ldots n} = \frac{V_{ij\ldots n}}{V_Y} \tag{1.4}$$

3) Total sensitivity index, which quantifies the total contribution of each input variable, including its individual effect as well as all its interactions with other input variables, to the total variance of the model's output.

$$S_{Ti} = S_i + \sum_{j \neq i} S_{ij} = 1 - \frac{V_{\sim i}}{V_Y} \tag{1.5}$$

From Eqn. 1.1 to 1.4, the sum of individual effects of all input variables and all their interactions equals one ~~(adapted from Zhang et al., 2015)~~(adapted from Zhang et al., 2015):

$$1 = \underbrace{\sum_{i=1}^{n} S_i}_{\textbf{Individual effects}} + \underbrace{\sum_{i<j} S_{ij} + \sum_{i<j<k} S_{ijk} \ldots + S_{1,2\ldots,n}}_{\textbf{Interactions}} \tag{1.6}$$

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A.2. Penman-Monteith PET model (FAO-56) (as in McMahon et al., 2013)

The Penman-Monteith PET model (FAO-56) is given as:

$$ET = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T_a+273}u_2(v_a^* - v_a)}{\Delta + \gamma(1 + 0.34u_2)} \qquad (2.1)$$

The process for estimating each of the variables in this equation are described in the following sections.

Estimating Δ in Equation 2.1

Δ is the slope of vapor pressure curve in kPa°C^{-1}, which is estimated by:

$$\Delta = \frac{4098[0.6108\exp(\frac{17.27 * T_a}{T_a + 237.3})]}{(T_a + 237.3)^2} \qquad (2.2)$$

In Eqn. 2.2, T_a is the average daily temperature in °C, calculated as:

$$T_a = \frac{T_{max} + T_{min}}{2} \qquad (2.3)$$

Estimating R_n in Equation 2.1

R_n is the net incoming solar radiation at the evaporative surface in MJ.m^{-2}.day^{-1}, which is estimated by:

$$R_n = R_{ns} - R_{nl} \qquad (2.4)$$

In Eqn. 2.4, R_{ns} is the net shortwave solar radiation, estimated by:

$$R_{ns} = (1 - \alpha)R_s \qquad (2.5)$$

In Eqn. 2.5, *α* is the albedo at evaporative surface which is fixed at 0.23 in this equation, and R_s is the measured or estimated incoming solar radiation in MJ.m^{-2}.day^{-1}. R_{nl} is the net outgoing longwave radiation, estimated as:

$$R_{nl} = \sigma(0.34 - 0.14v_a^{0.5})\frac{(T_{max}+237.2)^4 + (T_{min}+237.2)^4}{2}(1.35\frac{R_s}{R_{s0}} - 0.35) \qquad (2.6)$$

In Eqn. 2.6: *σ* is is Stefan-Boltzmann constant = = 4.903*10^{-9} MJ.m^{-2}.day^{-1} °K^{-4}, v_a is the mean daily actual vapor pressure in kPa, R_{s0} is the clear-sky radiation in MJ.m^{-2}.day^{-1}. v_a and R_{s0} estimated by Eqn. 2.7 and 2.8, respectively:

$$v_a = \frac{v_a^*(T_{max})^{\frac{RHmax}{100}} + v_a^*(T_{min})^{\frac{RHmin}{100}}}{2} \qquad (2.7)$$

$$R_{s0} = (0.75 + 2 \times 10^{-5}Elev)R_a \qquad (2.8)$$

In Eqn. 2.8, *Elev* is the ground elevation above sea level at the measurement location, and R_a is the extraterrestrial solar radiation in MJ.m^{-2}.day^{-1}, estimated as:

$$R_a = \frac{1440}{\pi} G_{sc} d_r^2 (\omega_s \sin(lat)\sin(\delta) + \cos(lat)\sin(lat)\sin(\omega_s)) \qquad (2.9)$$

In Eqn. 2.9, G_{sc} is the solar constant = 0.0820 MJ.m^{-2}.min^{-1}, *lat* is the latitude in radiance, d_r is the inverse relative distance between Earth and Sun, δ is the solar declination in radians, and ω_s is the sunset hour angle in radians, The d_r, δ and ω_s are estimated as follows:

$$d_r^2 = 1 + 0.033\cos(\frac{2\pi}{365} DoY) \text{ with } DoY \text{ as the day of the year} \qquad (2.10)$$

$$\delta = 0.409\sin(\frac{2\pi}{365} DoY - 1.39) \qquad (2.11)$$

$$\omega_s = arcos[-\tan(lat)\tan(\delta)] \qquad (2.12)$$

Estimating other variables in Equation 2.1

- *G* is negligible for daily time step.

- γ is the psychrometric constant in kPa°C^{-1}, estimated as:

$$\gamma = 0.00163\frac{P}{\lambda} \text{ where } P \text{ is the pressure at elevation } z \text{ meters} \qquad (2.13)$$

- u_2 is the daily average wind speed measured at 2 meters in m.s^{-1}, which can be estimated from the measured wind speed at *z* meters as:

$$u_2 = u_z \frac{\ln(\frac{2}{z_0})}{\ln(\frac{z}{z_0})} \text{ where } z_0 \text{ is the roughness height in meters} \qquad (2.14)$$

- (v_a^* - v_a) is the vapour pressure deficit in kPa, in which v_a is the mean daily actual vapor pressure in kPa, estimated as Eqn. 2.7; v_a^* is the daily saturation vapor pressure in kPa, estimated as:

$$v_a^* = \frac{v_a^*(T_{max}) + v_a^*(T_{min})}{2} \qquad (2.15)$$

In Eqn. 2.15, $v_a^*(T_{max})$ and $v_a^*(T_{min})$ are the vapor pressures at temperatures T_{max} and T_{min} in °C are estimated with:

$$v_T^* = 0.6108\exp[\frac{17.27T}{T+237.3}] \qquad (2.16)$$

A.3. Priestley-Taylor PET model (as in McMahon et al., 2013)

The Priestley-Taylor PET model is given as:

$$ET = \alpha_{PT} * [\frac{\Delta}{\Delta+\gamma}\frac{R_n}{\lambda} - \frac{G}{\lambda}] \qquad (3.1)$$

where:

- α_{PT} is the albedo specifically used for the Priestley-Taylor model, since an evaporative surface of reference crop was assumed, this has a value of 1.12 which was for a similar surface of short grass (See Table S8 of the supplementary of McMahon et al., 2013),

- Δ is the slope of vapor pressure curve in kPa°C^{-1}, estimated as Eqn 2.2.

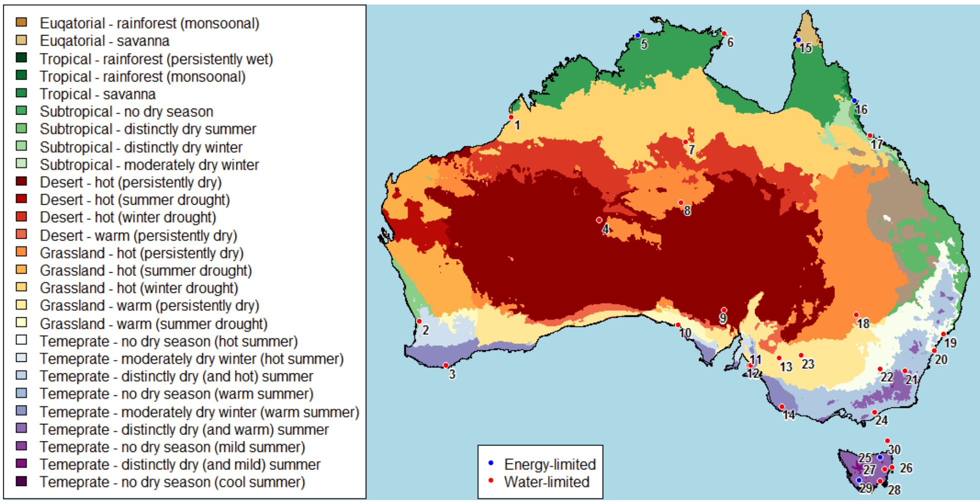
- γ is the psychrometric constant in kPa°C^{-1}, estimated as Eqn. 2.12.

- λ is the latent heat of vaporization, which is 2.45 MJ.kg^{-1} at 20°C.

- R_n is the net incoming solar radiation at the evaporative surface in MJ.m^{-2}day^{-1}, which is estimated in the same way as Eqn. 2.4.

- G is negligible for daily time step.

Figures and Tables



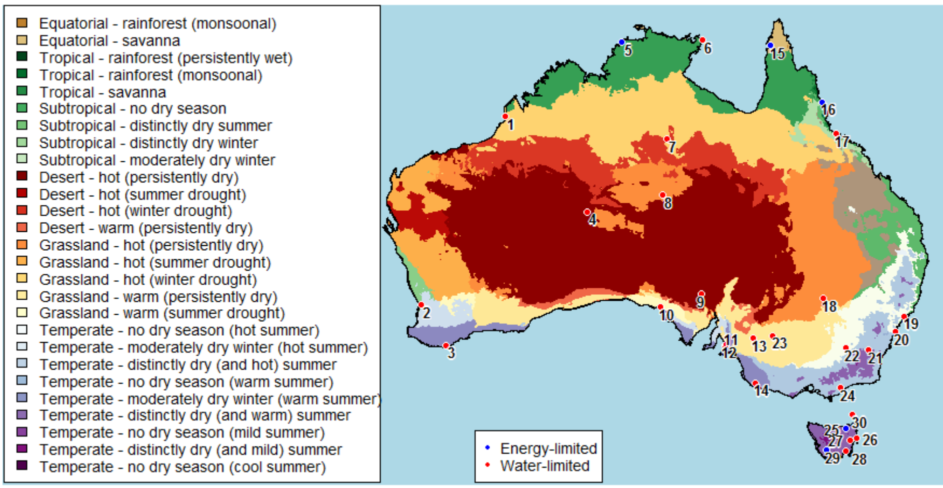


Figure 1: Locations of 30 Australian weather stations (see Table 1 for the full names of these weather stations) selected for analysis, with reference to their corresponding climate classes derived following the modified Köppen classification (reproduced with data from Stern et al., 2000).

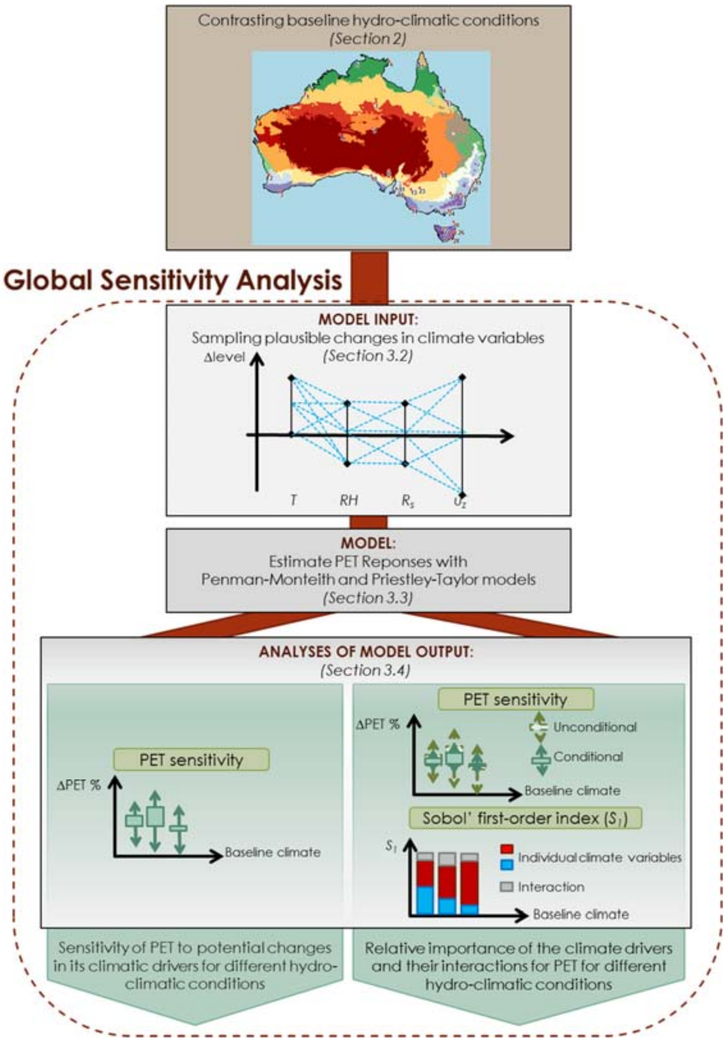
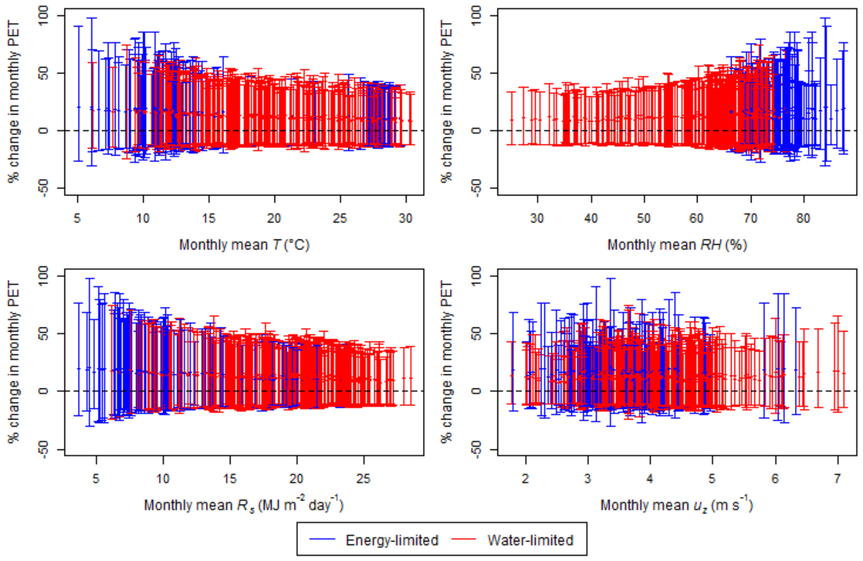

Contrasting baseline hydro-climatic conditions
(Section 2)
Global Sensitivity Analysis
MODEL INPUT:
Sampling plausible changes in climate variables
(Section 3.2)
Δlevel
T
RH
R_s
U_z
MODEL:
Estimate PET Reponses with
Penman-Monteith and Priestley-Taylor models
(Section 3.3)
ANALYSES OF MODEL OUTPUT:
(Section 3.4)
PET sensitivity
ΔPET %
Baseline climate
PET sensitivity
ΔPET %
Unconditional
Conditional
Baseline climate
Sobol' first-order index (S_1)
S_1
Individual climate variables
Interaction
Baseline climate
Sensitivity of PET to potential changes in its climatic drivers for different hydro-climatic conditions
Relative importance of the climate drivers and their interactions for PET for different hydro-climatic conditions

Figure 2: Schematic of the method used in this study.

919 
% change in monthly PET
Monthly mean T (°C)
Monthly mean RH (%)
Monthly mean Rs (MJ m-2 day-1)
Monthly mean uz (m s-1)
Energy-limited
Water-limited

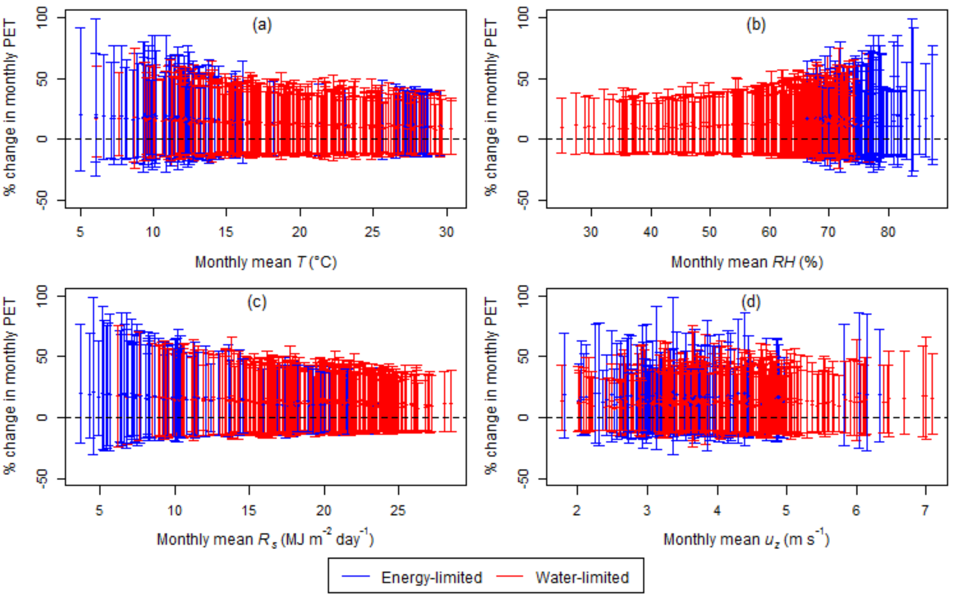
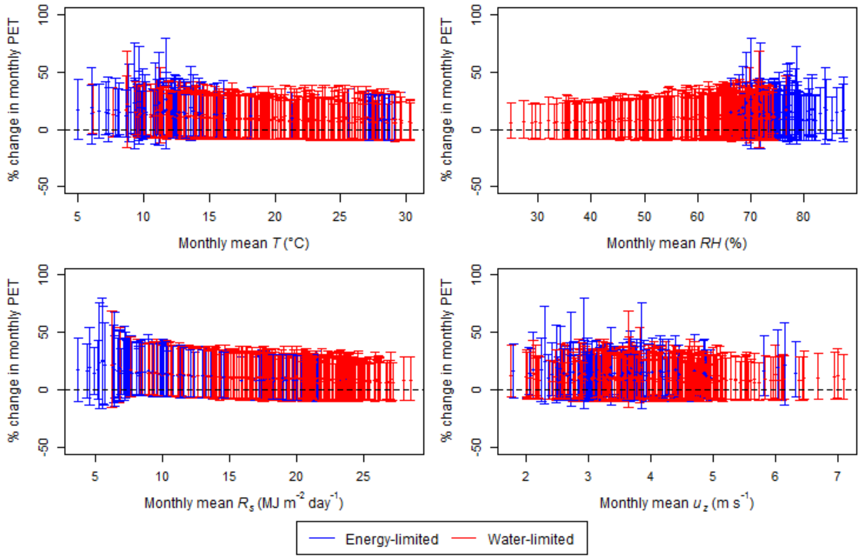


Figure 3: Monthly PET responses from the Penman-Monteith model, plotted against the monthly baseline levels of (a) temperature, (b) relative humidity, (c) solar radiation and (d) wind speed at 30 study sites. Each interval represents the range of all PET responses to the full set of climate perturbations for a single month at a single location, with the mean represented by the point on the line. The classification of energy- and water-limited months are based on the corresponding monthly PET/P ratios.



% change in monthly PET
Monthly mean T (°C)
Monthly mean RH (%)
Monthly mean R_s (MJ m^{-2} day^{-1})
Monthly mean u_z (m s^{-1})
Energy-limited
Water-limited

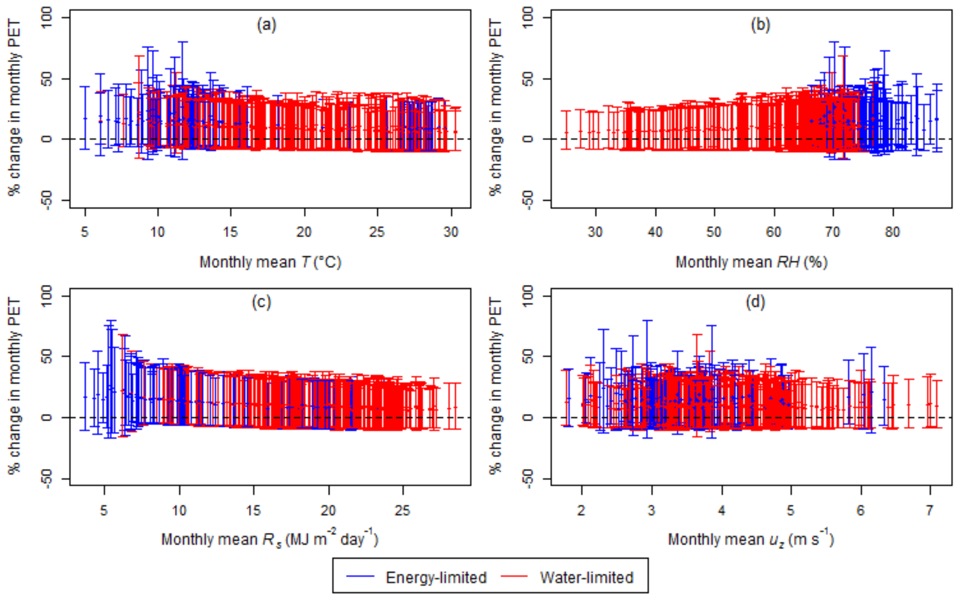
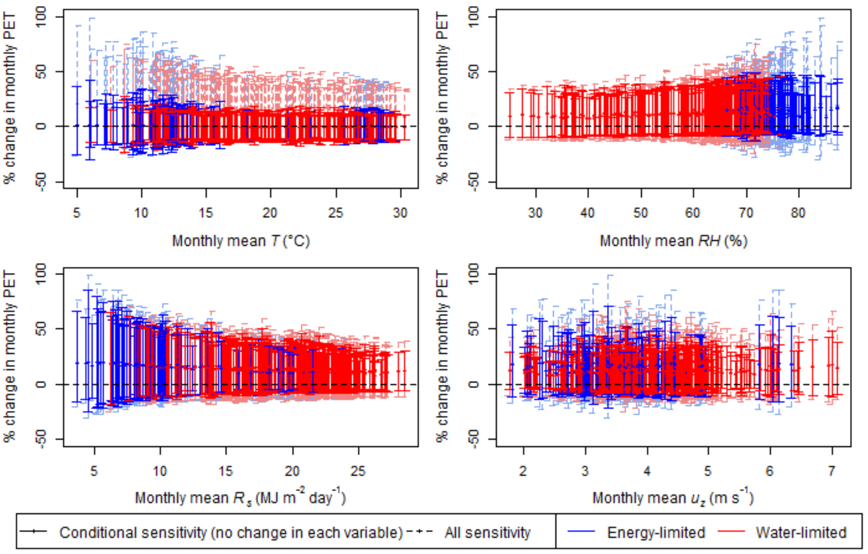


Figure 4: Monthly PET responses from the Priestley-Taylor model, plotted against the monthly baseline levels of (a) temperature, (b) relative humidity, (c) solar radiation and (d) wind speed at 30 study sites. Each interval represents the range of all PET responses to the full set of climate perturbations for a single month at a single location, with the mean represented by the point on the line. The classification of energy- and water-limited months are based on the corresponding monthly PET/P ratios.


% change in monthly PET
Monthly mean T (°C)
Monthly mean RH (%)
Monthly mean R_s (MJ m^{-2} day^{-1})
Monthly mean u_z (m s^{-1})
Conditional sensitivity (no change in each variable)
All sensitivity
Energy-limited
Water-limited

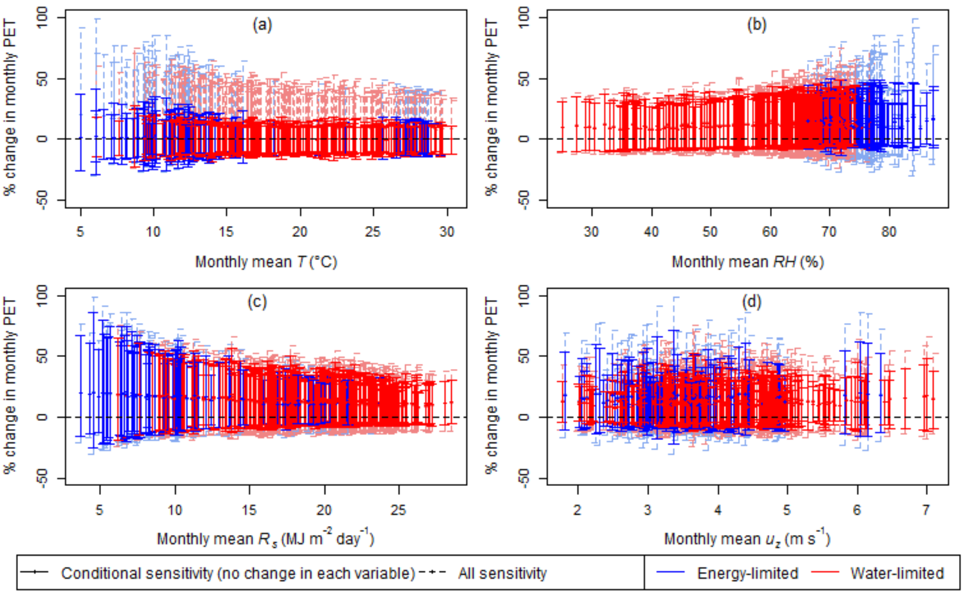


Figure 5: Monthly PET responses from the Penman-Monteith model, plotted against the monthly baseline levels of (a) temperature, (b) relative humidity, (c) solar radiation and (d) wind speed at 30 study sites. Each dashed (solid) line represents the range of all PET responses to the full set of climate perturbations (conditioned on no-change in each climate variable) for a single month at a single location. The corresponding means are represented by the points on the lines. The classification of energy- and water-limited months are based on the corresponding monthly PET/P ratios.

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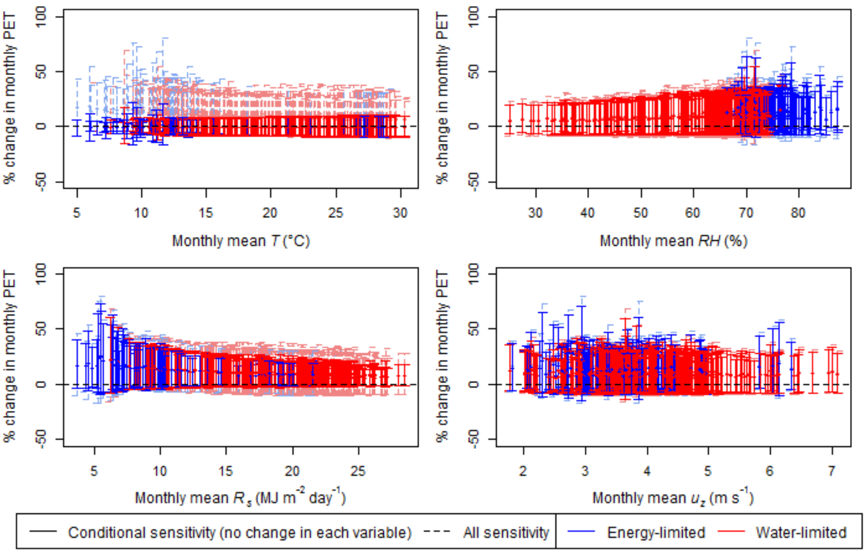

% change in monthly PET
Monthly mean T (°C)
Monthly mean RH (%)
Monthly mean R_s (MJ m^{-2} day^{-1})
Monthly mean u_z (m s^{-1})
Conditional sensitivity (no change in each variable)
All sensitivity
Energy-limited
Water-limited

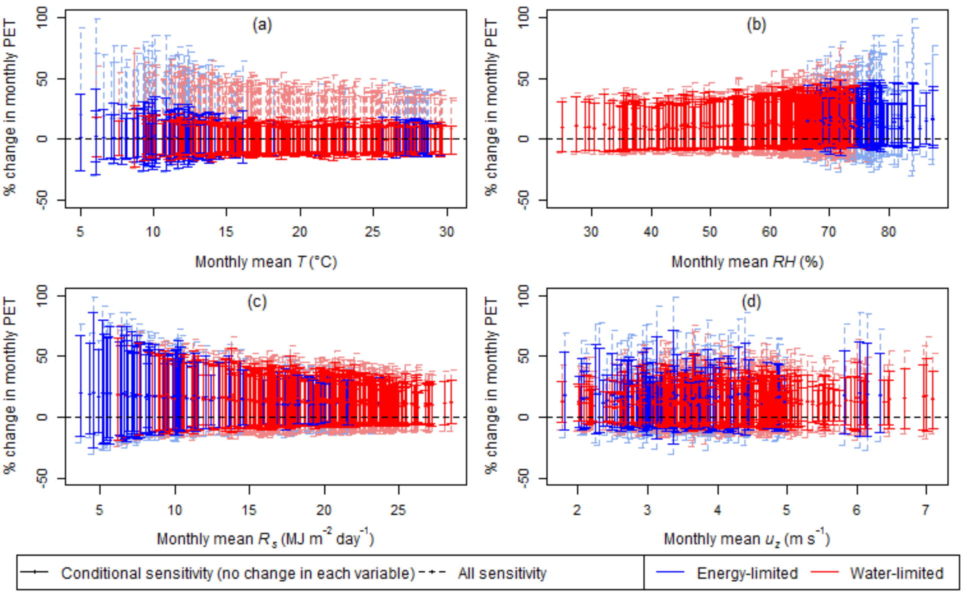
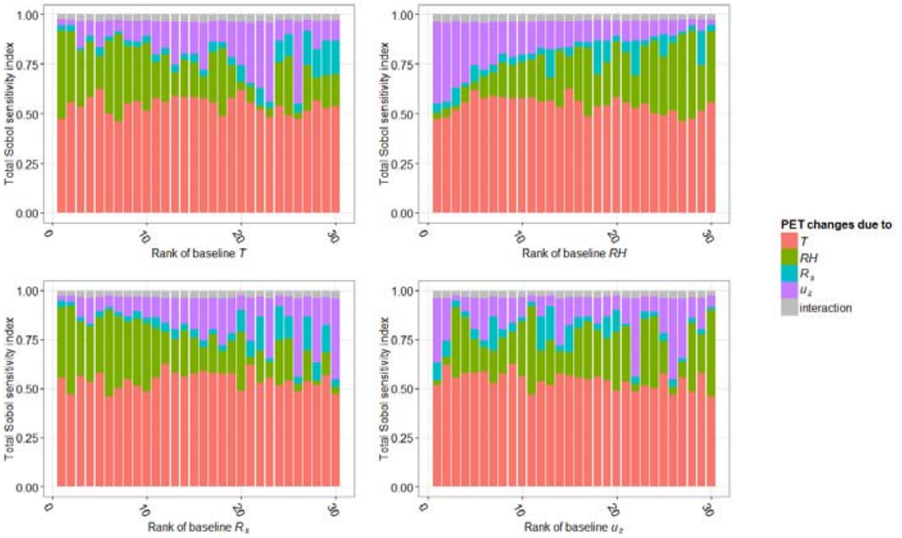


Figure 6: Monthly PET responses from the Priestley-Taylor model, plotted against the monthly baseline levels of (a) temperature, (b) relative humidity, (c) solar radiation and (d) wind speed at 30 study sites. Each dashed (solid) line represents the range of all PET responses to the full set of climate perturbations (conditioned on no-change in each climate variable) for a single month at a single location. The corresponding means are represented by the points on the lines. The classification of energy- and water-limited months are based on the corresponding monthly PET/P ratios.


Total Sobol sensitivity index
Rank of baseline T
Rank of baseline RH
Rank of baseline Rs
Rank of baseline uz
PET changes due to
T
RH
Rs
uz
interaction

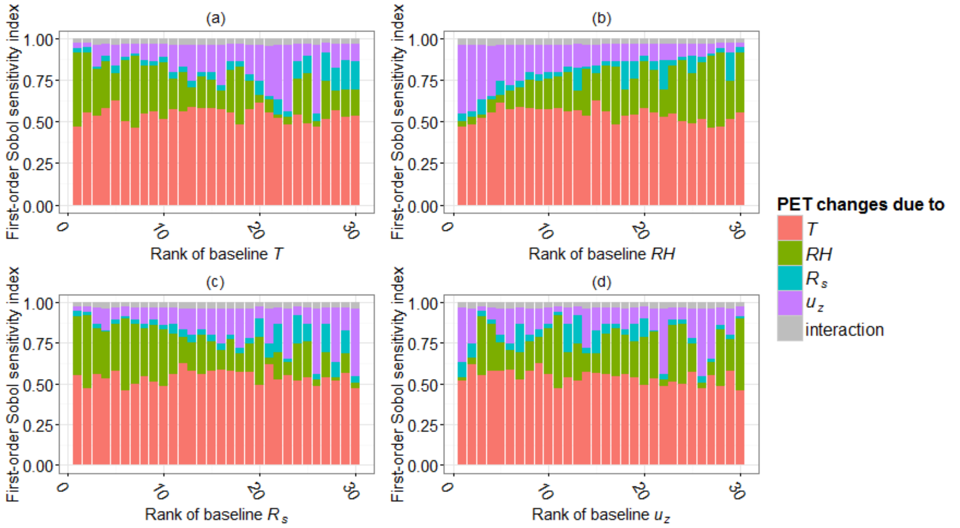


Figure 7: Sobol' first-order sensitivity indices of the Penman-Monteith model for changes in the four climate variables (colored) and their interaction effects (grey), plotted against the ranking of the average level of each climate variable at 30 study sites

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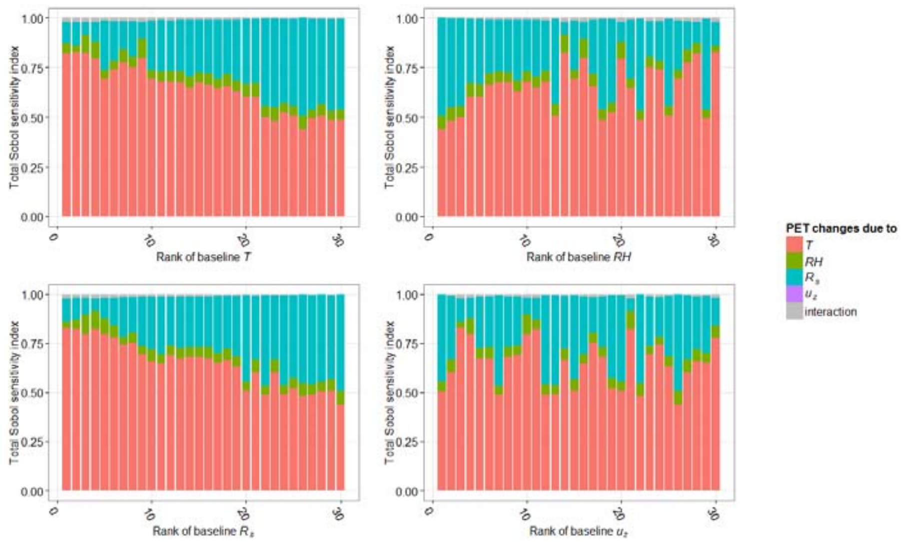
Total Sobol sensitivity index
Rank of baseline T
Rank of baseline RH
Rank of baseline Rs
Rank of baseline uz
PET changes due to
T
RH
Rs
uz
interaction

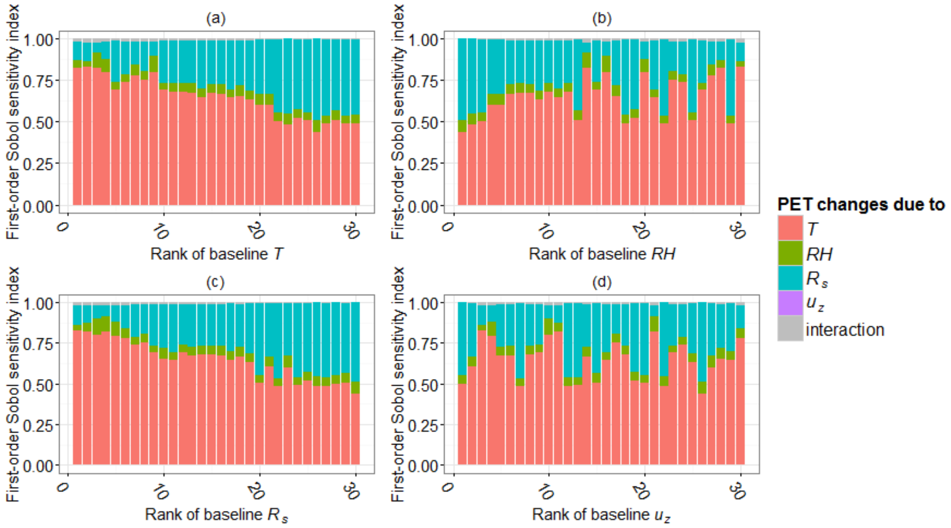

Figure 8: Sobol' first-order sensitivity indices of the Priestley-Taylor model for changes in the four climate variables (colored) and their interaction effects (grey), plotted against the ranking of the average level of each climate variable at 30 study sites

Table 1: Names, locations and average climate conditions of the 30 weather stations over the study period (1995-2004).

No.	Study site name	Köppen class[1]	Lat (°S)	Long (°E)	Elev (m)	*T* (°C)	*RH* (%)	R_s (MJ m^{-2} day^{-1})	u_z (m s^{-1})	Annual P (mm)	Annual PET (mm)	Annual PET/P
1	Broome airport	13	-17.95	122.2	7.4	26.37	65.15	21.55	3.684	865	2003	2.317
2	Perth	8	-31.93	116.0	15.4	18.54	61.72	18.95	4.519	721	1751	2.429
3	Albany	4	-34.94	117.8	68	15.08	73.59	15.20	4.382	752	1126	1.498
4	Giles	24	-25.03	128.3	598	22.70	38.40	20.29	4.380	394	2344	5.947
5	Darwin	35	-12.42	130.9	30.4	27.42	69.27	20.33	3.393	1976	1864	0.944
6	Gove	35	-12.27	136.8	51.6	26.29	75.93	19.45	3.500	1607	1660	1.033
7	Tennant Creek	13	-19.64	134.2	375.7	25.73	37.21	21.64	4.759	539	2634	4.886
8	Alice Springs	15	-23.80	133.9	546	21.18	44.53	20.79	2.352	331	1822	5.503
9	Woomera	24	-31.16	136.8	166.6	19.41	46.57	19.40	5.057	151	2153	14.24
10	Ceduna	11	-32.13	133.7	15.3	16.92	62.04	18.20	5.450	266	1723	6.478
11	Adelaide airport	12	-34.95	138.5	2	16.37	63.04	16.91	4.213	454	1410	3.107
12	Adelaide (kent town)	12	-34.92	138.6	48	16.95	61.20	16.88	3.161	569	1372	2.409
13	Loxton	12	-34.44	140.6	30.1	16.50	59.41	17.59	3.250	255	1490	5.847
14	Mount Gambier	4	-37.75	140.8	63	13.45	72.77	14.91	4.460	731	1116	1.526
15	Weipa	41	-12.68	141.9	18	26.87	72.21	19.31	3.271	2154	1782	0.827
16	Cairns	36	-16.87	145.7	3	24.80	73.00	18.98	4.352	1985	1678	0.845
17	Townsville	35	-19.25	146.8	4.3	24.53	69.45	20.27	4.304	1099	1802	1.641
18	Cobar	15	-31.48	145.8	260	19.08	50.64	19.05	2.458	398	1565	3.936
19	Williamtown	9	-32.79	151.8	9	17.84	70.57	16.07	3.927	1145	1309	1.143
20	Sydney	9	-33.94	151.2	6	18.19	67.69	15.97	5.311	1017	1393	1.369
21	Canberra	6	-35.30	149.2	578.4	13.36	65.82	16.86	3.302	590	1226	2.078
22	Wagga Wagga	9	-35.16	147.5	212	15.77	61.78	17.48	3.288	552	1436	2.602
23	Mildura	12	-34.24	142.1	50	17.11	55.62	18.24	3.604	246	1645	6.681
24	East sale	6	-38.12	147.1	4.6	13.77	72.32	14.92	4.062	529	1093	2.067
25	Scottsdale	3	-41.17	147.5	197.5	13.19	70.55	14.23	2.921	931	912	0.980
26	Bicheno	3	-41.87	148.3	11	14.69	66.68	13.69	3.319	690	966	1.401
27	Lake Leake	3	-42.01	147.8	575	9.96	75.40	13.44	3.358	732	774	1.056
28	Hobart	3	-42.83	147.5	4	12.77	65.67	14.04	4.367	483	1097	2.273

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29	Strathgordon village	3	-42.77	146.0	322	10.70	77.95	11.65	2.473	2626	699	0.266
30	Flinders Island	3	-40.09	148.0	9	13.54	73.59	14.34	6.399	654	1064	1.626

Note:

~~[1]The Köppen classes are presented with their corresponding identifiers from Stern et al. (2000)~~[1]The Köppen classes are presented with their corresponding identifiers from Stern et al. (2000), as: 3. Temperate - no dry season (mild summer); 4. Temperate - distinctly dry (and warm) summer; 6. Temperate - no dry season (warm summer); 8. Temperate - moderately dry winter (hot summer); 9. Temperate - no dry season (hot summer); 11. Grassland - warm (summer drought); 12. Grassland - warm (persistently dry); 13. Grassland - hot (winter drought); 15. Grassland - hot (persistently dry); 24. Desert - hot (persistently dry); 35. Tropical - savanna; 36. Tropical - rainforest (monsoonal); 41 Equatorial - savanna.

[2]*T* = temperature, *RH* = relative humidity, R_s = incoming solar radiation, u_z = wind speed, P = rainfall, PET = potential evapotranspiration calculated using the Penman-Monteith model.

Table 2: Plausible perturbation bounds for each climate variable relative to their current levels.

Climate variable	Perturbation range
T	0 to +8 °C
RH	-10 % to +10 %
R_s	-10 % to +10 %
u_z	-20 % to +20 %

Note: T = daily temperature, RH = daily relative humidity, R_s = daily incoming solar radiation, u_z = daily wind speed.

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Table 3: Annual average PET sensitivity to the full set of climate perturbations (as % changes to baseline PET) from the Penman-Monteith and Priestley-Taylor models at the 30 study sites relative to the 1995-2004 baseline. The maximum and minimum sensitivity values from each model are shaded in grey.

No.	Study site name	Penman-Monteith			Priestley-Taylor		
		Min.	**Max.**	**Avg.**	**Min.**	**Max.**	**Avg.**
1	Broome airport	-12.33	39.10	11.16	-9.61	33.75	9.59
2	Perth	-13.20	46.67	13.52	-7.98	34.17	10.62
3	Albany	-15.04	54.67	15.21	-7.28	35.49	11.63
4	Giles	-12.30	37.57	10.68	-7.73	25.83	7.27
5	Darwin	-12.73	39.10	10.92	-9.82	33.84	9.50
6	Gove	-13.10	41.34	11.53	-9.74	33.67	9.61
7	Tennant Creek	-12.28	36.45	10.21	-8.35	26.31	7.09
8	Alice Springs	-10.88	34.00	9.80	-8.00	27.41	7.92
9	Woomera	-12.84	43.48	12.73	-7.48	30.35	9.18
10	Ceduna	-13.97	49.61	14.39	-7.62	33.82	10.67
11	Adelaide airport	-14.47	49.80	14.17	-7.22	34.55	11.09
12	Adelaide (kent town)	-13.10	45.43	13.17	-7.15	33.70	10.78
13	Loxton	-12.55	44.05	12.96	-7.18	33.34	10.67
14	Mount Gambier	-15.33	57.97	16.00	-6.58	35.54	12.02
15	Weipa	-12.42	39.06	10.95	-9.66	32.98	9.36
16	Cairns	-14.80	44.74	12.08	-9.42	33.84	9.73
17	Townsville	-13.77	43.21	12.10	-9.43	34.26	9.90
18	Cobar	-10.62	37.49	11.36	-7.64	31.19	9.49
19	Williamtown	-13.64	47.99	13.68	-7.66	34.11	10.76
20	Sydney	-16.24	53.71	14.46	-7.61	35.24	10.98
21	Canberra	-12.41	46.17	13.85	-6.95	33.24	10.92
22	Wagga Wagga	-13.00	46.34	13.43	-7.09	33.27	10.74
23	Mildura	-12.61	44.50	13.05	-7.24	32.75	10.38
24	East sale	-14.43	53.82	15.34	-6.51	36.32	12.19
25	Scottsdale	-13.64	51.53	15.02	-5.42	40.00	13.47
26	Bicheno	-14.81	52.11	14.87	-4.91	46.38	15.68
27	Lake Leake	-16.06	60.36	16.45	-5.11	36.03	12.84
28	Hobart	-15.97	56.29	15.78	-4.57	50.36	17.77
29	Strathgordon village	-13.08	52.11	15.29	-4.66	33.83	12.35
30	Flinders Island	-18.05	64.07	17.15	-6.19	38.66	13.02
Average		**-13.66**	**47.09**	**13.38**	**-7.39**	**34.47**	**10.91**

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