Responses to Reviewer #3

Point #1

Author(s): Qichun Yang et al.

MS No.: hess-2021-69

This paper focuses on the comparison of two calibration strategies to provide short-term reference crop evapotranspiration (ETo). ETo forecasting is still a relatively new area of research, in Australia and elsewhere, and has received more attention in the past few years. Skilful ETo forecasts in Australia would help support efficient water use and water management. Two strategies to calibrate ETo forecasts have emerged: i) the calibration of raw ETo forecasts and ii) bias-correcting input variables first before calibrating ETo forecasts. Little work to date compares the two approaches, it is unclear which method might be more advantageous or skilful. This paper therefore addresses a topical subject with a large audience interest.

I have some reservations regarding some methodological choices and justifications (purpose and inclusion of experiment 3 and 4), as well as a lack of interpretations of the results overall. I recommend revision to strengthen this paper.

Response: Thank you for the valuable suggestions and careful review. We revise this work carefully based on your constructive suggestions.

Point #2

The authors re-grid the weather forecast variables of ACCESS-G2 to match the timeframe and resolution of the gridded data AWAP. They perform four experiments: experiments 1) and 2) are based on the ETo anomaly and climatological mean, whereas experiment 3 and 4) use the ETo values directly. Furthermore, experiment 1) and 3) use raw inputs to calculate and calibrate ETo forecasts whereas experiments 2) and 4) first bias-correct inputs before ETo calibration. The SCC calibration method is used for ETo forecast while a quantile mapping method is used to bias-correct input forecasts. The authors evaluate the forecasts using three metrics for the theoretical assessment of bias, reliability and accuracy. Overall results suggest that the second strategy (bias-correction of inputs before ETo calibration) provides more skilful forecasts.

Response: We appreciate the reviewer's thorough review. The work has been substantially improved based on the valuable comments.

Point #3

Major comments:

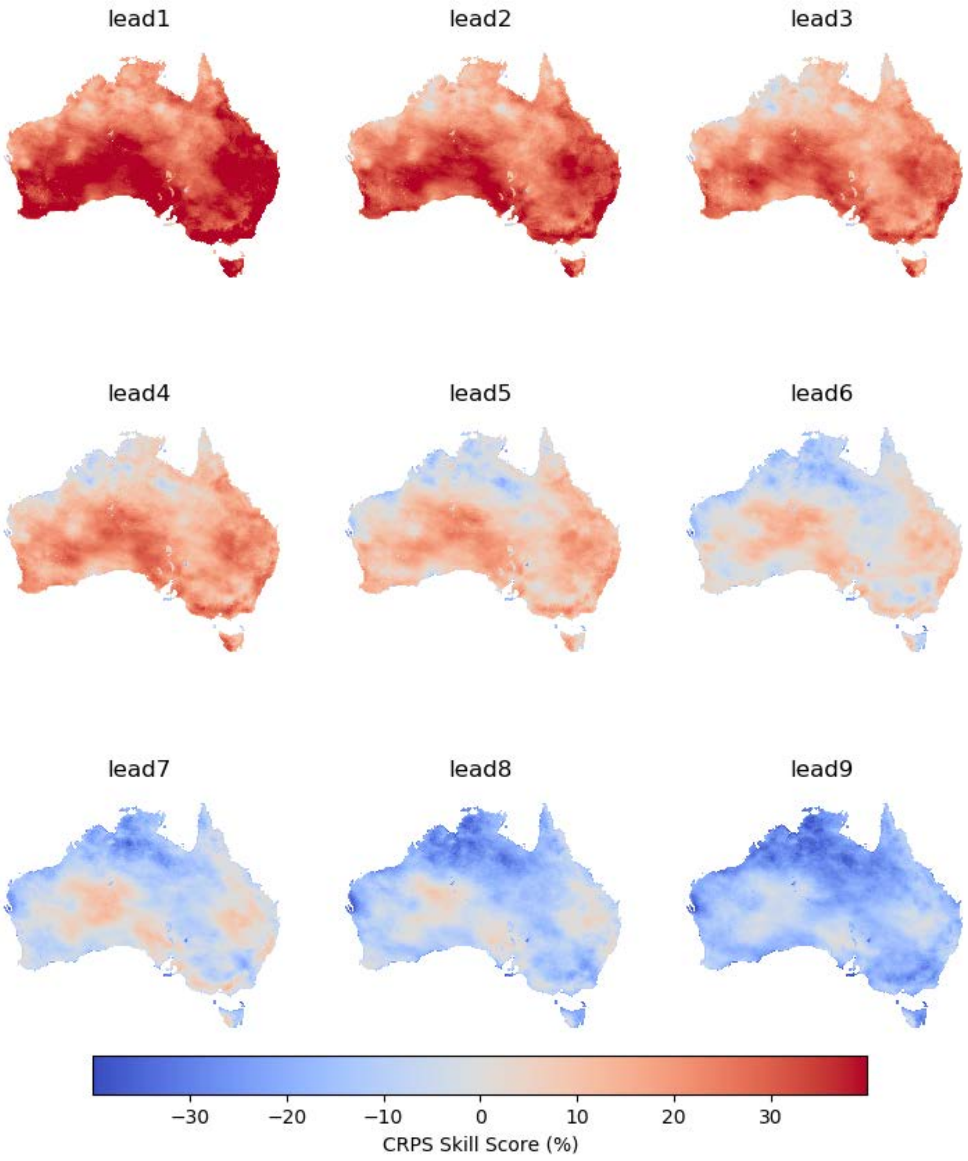
Methodology:

P4 section 2.3: Why not compare the calibration method used SCC to other methods tested in the literature which would enable to place this work in context to other studies on ETo forecasting?

Response: We appreciate the constructive comments. We understand that comparing the performance of SCC with existing methods will help readers better understand the strengths of SCC. We did not compare the SCC model directly with other models in the original submission for a couple of reasons:

First, this investigation addresses a common challenge faced by NWP-based ETo forecasting, rather than developing a new calibration model for ETo forecasting. The primary objective of this investigation is to evaluate the necessity of correcting forecasts of input variables prior to calibrating ETo forecasts. As we introduced in the main text, the calibration strategy developed in this study is expected to benefit ETo forecast calibrations broadly, rather than improving an individual model. As suggested by the model experiments in our investigation (Calibrations 1-4), the developed strategy could potentially be applied to other calibration models.

Second, we feel it is not necessary to compare the performance of SCC against calibration models with widely used but less sophisticated algorithms. Simple calibration models, such as quantile mapping (QM), have been widely used in calibrating hydroclimate forecasts. These models are often readily available, or could be easily coded and implemented. However, the limitations of these models have been reported (Zhao et al., 2017). When we started this investigation, we used quantile mapping to calibrate ETo forecasts (raw ETo forecasts constructed with raw forecasts of input variables). As demonstrated in the following figure, the CRPS skill score of quantile mapped ETo forecasts is not only lower than the SCC-calibrated forecasts for each corresponding lead time, but also becomes negative (worse than climatological forecasts) in parts of Australia starting from lead time 4. As a result, calibration of ETo forecasts with quantile mapping further confirms the limitations of this model. Using such models as a reference to evaluate the performance of SCC is not fair, since their limitations have been reported. As a result, we decide not to include a comparison with quantile mapping in this manuscript.



CRPS skill score of calibrated ETo forecasts using Quantile Mapping

Third, we have limited access to sophisticated calibration models. There is no global post-processing software library archiving these models. As a result, we found it was hard to access the source code of these models and to directly compare SCC with them. In addition, previous comparisons suggest that the performance of these models varied with study areas, NWP models, and choice of evaluation metrics (Wilks, 2018), and there is no conclusion regarding which group of post-processing models has the best performance. Our indirect comparison with other models confirms the above study. Details will be presented in the following paragraphs.

Fourth, the short-achieved NWP forecasts (3-year) used in this study represent a challenge for conducting the calibration using other models. Many calibration models, particularly those based on models of the joint probability of forecasts and observations (Krzysztofowicz and Herr, 2001; Wang and Robertson, 2011)**, require long hindcasts (20-30 years) to establish a joint distribution to link observations and forecasts. Applying such models to short-archived forecasts such as those used in this study will substantially undermine the statistical assumption of these models. The advantages of SCC in calibrating short-archived forecast has been explained in our recent publications** (Wang et al., 2019; Yang et al., 2021)**.**

As a result, we did not compare SCC directly with other models. However, we totally agree with the reviewer that comparison of model performance with other models will help readers better understand the reliability of this work. For example, we extract our results at three sites in Australia where ETo forecasts were also calibrated based on the Bayesian joint probability (BJP) model (Zhao et al., 2019)**, and compare the results of the two investigations. In addition, we also compare our results with investigations in other regions of Australia and the U.S. We add the following paragraph to discuss findings of our work relative to existing investigations to the Discussion section (section 4.1):**

"This investigation further highlights the importance of statistical calibration in improving the quality of raw ETo forecasts (Medina and Tian, 2020). In the ETo forecasting across 40 sites in Australia, although raw ETo forecasts constructed with NWP outputs reasonably captured the magnitude and variability of ETo, forecast skills better than climatology were only found for the first 6 lead times (Perera et al., 2014). Our investigation suggests that statistical calibration could substantially improve forecast skills and outperform the climatology forecasts for all 9 lead times across Australia. The findings of this investigation agree well with the site scale short-term ETo forecasting based on GCM outputs (Zhao et al., 2019a) in terms of improvements in forecast skills. Calibrated forecasts from Calibration 2 demonstrate similar skills as those of Zhao et al. (2019a). However, our calibration achieves the improvements using much shorter archived raw forecasts (3-year vs. 23-year) than Zhao et al. (2019a), thanks to the capability of SCC in calibrating short-archived forecasts (Wang et al., 2019). Calibrated forecasts from Calibration 2 also demonstrate comparable biases (0.32-0.95%) with calibrated ETo forecasts (0.49-0.63%) in the U.S. based on the Bayesian model averaging (BMA) model and weather forecasts from three NWP models during 2014-2016 (Medina and Tian, 2020)."

In addition, we also highlight the importance of further testing the proposed calibration strategy (strategy ii) based other calibration models. We add the following content to section 4.2:

"Second, further investigations based on other calibration models are needed to validate the conclusions of this investigation. Our analyses based on two different methods (based on ETo anomalies vs. based on original ETo) find similar improvements in calibrated ETo forecasts with the adoption of bias-correction of input variables. Additional evaluations using other calibration models will be needed to ascertain whether the improvements will be achieved when the calibration is conducted with a different model.**"**

Reference:

Medina, H. and Tian, D.: Comparison of probabilistic post-processing approaches for improving numerical weather prediction-based daily and weekly reference evapotranspiration forecasts, Hydrol. Earth Syst. Sci., 24, 1011–1030, 2020.

Perera, K. C., Western, A. W., Nawarathna, B. and George, B.: Forecasting daily reference evapotranspiration for Australia using numerical weather prediction outputs, Agric. For. Meteorol., 194, 50–63, doi:10.1016/j.agrformet.2014.03.014, 2014.

Wilks, D.S., 2018. Chapter 3. Univariate Ensemble Forecasting, in: Vannitsem, S., Wilks, D.S., Messner, J.W. (Eds.), Statistical Postprocessing of Ensemble Forecasts. pp. 49–89. https://doi.org/https://doi.org/10.1016/C2016-0-03244-8

Krzysztofowicz, R., Herr, H.D., 2001. Hydrologic uncertainty processor for probabilistic river stage forecasting: precipitation-dependent model. J. Hydrol. 249, 46–68.

Wang, Q.J., Robertson, D.E., 2011. Multisite probabilistic forecasting of seasonal flows for streams with zero value occurrences. Water Resour. Res. 47, 1–19. https://doi.org/10.1029/2010WR009333

Wang, Q.J., Zhao, T., Yang, Q., Robertson, D., 2019. A Seasonally Coherent Calibration (SCC) Model for Postprocessing Numerical Weather Predictions. Mon. Weather Rev. 147, 3633–3647. https://doi.org/10.1175/MWR-D-19-0108.1

Yang, Q., Wang, Q.J., Hakala, K., 2021. Achieving effective calibration of precipitatioAn forecasts over a continental scale. J. Hydrol. Reg. Stud. 35, 100818. https://doi.org/10.1016/j.ejrh.2021.100818

Zhao, T., Wang, Q.J., Schepen, A., 2019. A Bayesian modelling approach to forecasting short-term reference crop evapotranspiration from GCM outputs. Agric. For. Meteorol. 269–270, 88–101. https://doi.org/10.1016/j.agrformet.2019.02.003

Point #4

Presentation of summary statistics. Why not use boxplots to present overall statistics and across lead times (for example next to figure 4 and so on)? Reliability diagrams for particular ETo thresholds would be helpful to communicate when the forecasts are reliable.

Response: Thank you for the constructive suggestions. We created boxplots for results shown as maps (Figures 1 to 9 in the main text). For Figures 1 and 7, which already include many subplots, we present the corresponding boxplots in the Supplementary Material. For other map figures (Figures 2-6, and 8-9), which have extra zoom for adding new subplots, we combine these boxplots with maps. We also update the main text accordingly. Please find the boxplots as follows:

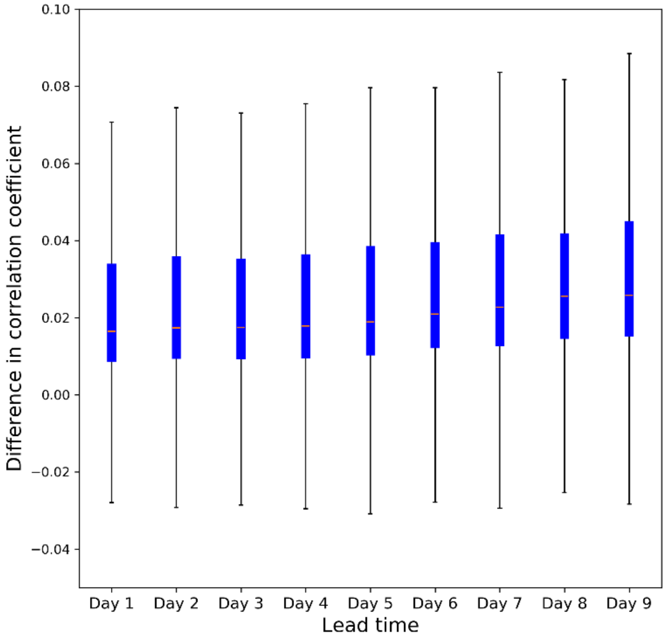


Figure 2 The boxplot summarizing improvements in correlation coefficient between raw ETo forecasts and AWAP ETo with the adoption of bias-correction to input variables

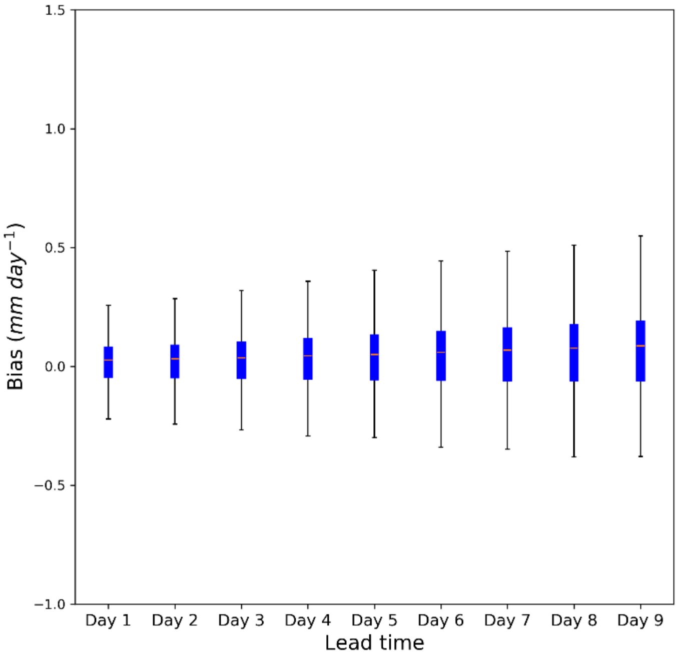


Figure 3 The boxplot summarizing bias in calibrated ETo forecasts from Calibration 2

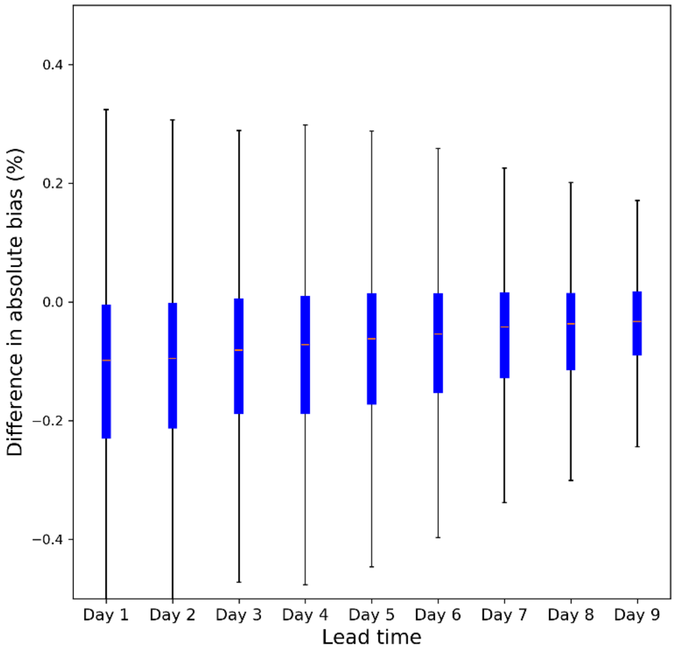


Figure 4 The boxplot summarizing differences in absolute bias between calibrated ETo forecasts from Calibration 2 with Calibration 1

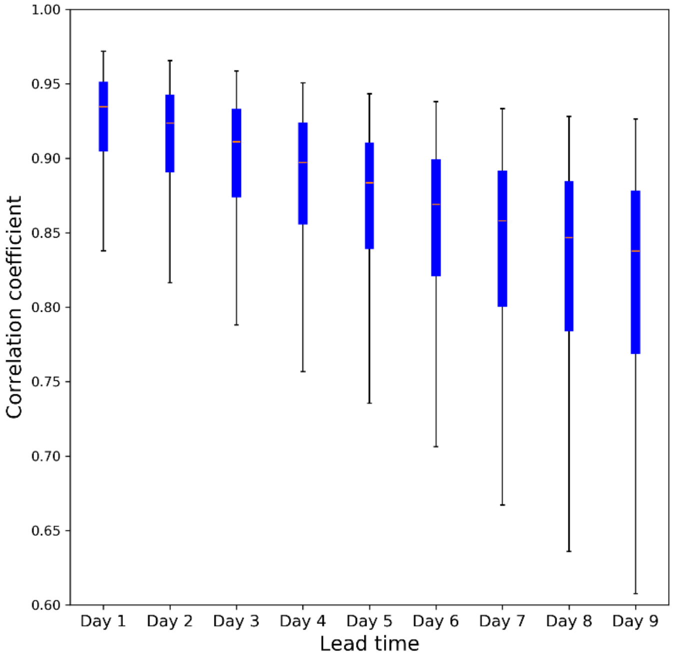


Figure 5 The boxplot summarizing correlation coefficient between calibrated ETo forecasts from Calibration 2 and AWAP ETo data

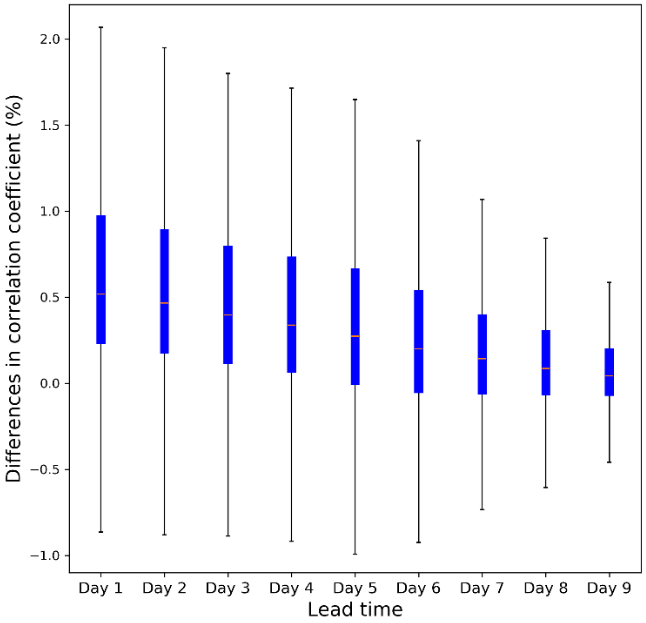


Figure 6 The boxplot summarizing differences in the correlation coefficient (calibrated forecasts vs. AWAP ETo) between Calibrations 2 and 1

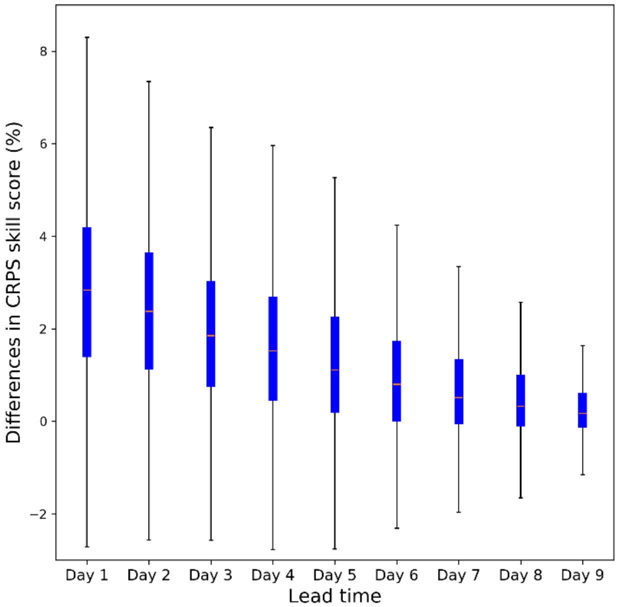


Figure 8 The boxplot summarizing differences in CRPS skill scores between the calibrated forecast from Calibration 2 with those from Calibration 1

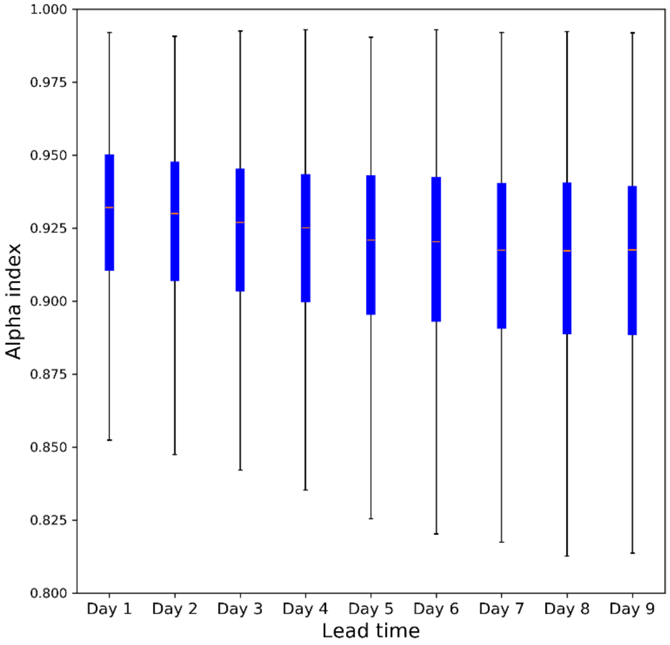


Figure 9 The boxplot summarizing the alpha index in the calibrated ETo forecasts

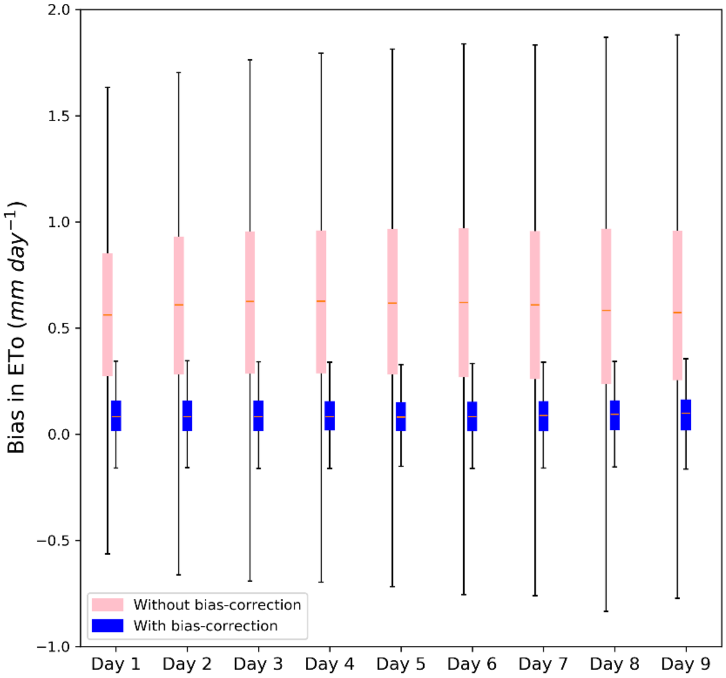


Figure S12. The boxplot of biases in raw ETo forecasts constructed without bias-corrected input variables (pink) and correct inputs (blue)

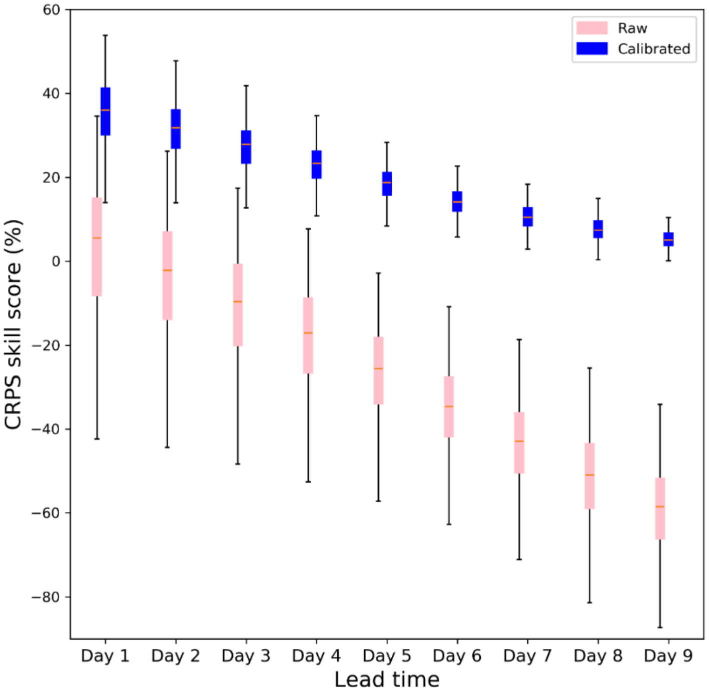


Figure S14. The boxplot of CRPS skill score in raw (pink) and calibrated ETo forecasts (blue)

We also created reliability diagrams to summarize to evaluate the calibrated ensemble forecasts from Calibration 2. The three thresholds used to generate the reliability diagram are 3 mm/day, 6mm/day, and 9 mm/day. This diagram (Figure 10) is added to the main text to further evaluate the reliability of calibrated ETo forecasts

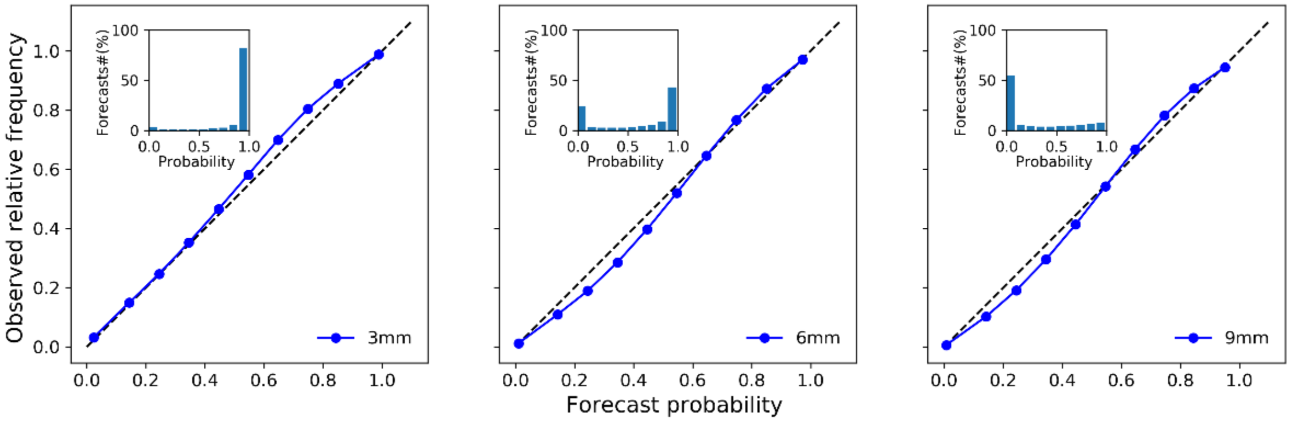


Figure 10: Reliability diagrams of calibrated ETo forecasts during 4/2016-3/2019 with thresholds of 3, 6, and 9 mm day^{-1}.

We updated the Method section to introduce how the reliability diagram is created and how to understand the diagram:

"We evaluate the reliability of calibrated ETo forecasts from calibration 2 using the reliability diagram (Hartmann et al., 2002), which assesses how well the predicted probabilities of an event corresponding to their observed frequencies. We convert the calibrated ensemble ETo forecasts to forecast probabilities exceeding three thresholds, including 3, 6, and 9 mm day^{-1}. We pool forecasts of different grid cells, days, and lead times together in the calculation of forecast probability. In the reliability diagram, perfectly reliable forecasts will demonstrate a curve along the diagonal. A plotted curve above the diagonal indicates underestimations and vice versa."

We add the following sentence to section 3.5 (Reliability of calibrated ETo forecasts) to introduce the reliability diagram.

"The reliability diagram further confirms the consistency between forecast probabilities and observed frequencies (Figure 10). The plotted curves based on three thresholds (3, 6, and 9 mm day^{-1}) are mainly distributed along the 1:1 line, indicating high reliability of calibrated ETo forecasts."

Point #5

Authors present experiments 1-4 in the method but then only present some results one experiment 3) and 4) in the last section of results (CRPSS in 3.5). No explanation are provided of why calibration 3) and 4) are only briefly introduced. Why is there a big gap with no results on calibration 3) and 4) on the bias and reliability results? Could the authors please expand on the purpose of including these at all in? At p17 l350-354, 'a further evaluation based on a different way of implementing the calibration demonstrate similar improvements in calibrated ETo forecasts with the adoption of bias-correction to input variables'. Is the purpose of including experiment 3) and 4) to test the generalisation of the method? If so, it needs to be clearly stated and justified earlier.

Response: Thank you for the valuable comments. The reviewer is correct that adding calibrations 3 and 4 is to further evaluate that whether our strategy could be generally applied to future NWP-based ETo forecasting, and will the strategy be independent of calibration models. We further explain the reason by adding the following sentences to clarify why Calibrations 3 and 4 are included in this study in Method (section 2.3):

"The comparison between Calibrations 1 and 2 is to investigate whether the bias-correction of input variables would further improve ETo forecasts when the calibration is conducted based on ETo anomalies and climatological mean. We also conduct additional calibrations which post-process ETo forecasts directly (Calibrations 3 and 4), to test whether the contribution of improving the input variables to ETo forecast calibration, if there is any, will depend on how ETo forecasts are calibrated (based on anomalies vs. based on original ETo forecasts). Calibrations 3 and 4 will help evaluate the feasibility of strategy ii for the general application in NWP/GCM-based ETo forecasting. Key steps of the four calibrations could be found in the schematic diagram (Figure S1). In the main text, we primarily analyze results from Calibrations 1 and 2. Improvements with the adoption of bias-correction to input variables in Calibrations 3 and 4 are very similar to those of Calibrations 1 and 2 (see the Supplementary Material). To avoid redundancy, we present results from Calibrations 3 and 4 in the Supplementary Material.**"**

In the original submission, we did not present all results from Calibrations 3 and 4 because these two calibrations were complementary for supporting findings from Calibrations 1 and 2. This is an extra step to further evaluate the robustness of the calibration strategy developed in this study. In addition, differences in bias, reliability, and correlation coefficient between Calibrations 3 and 4 are very similar to those between Calibrations 1 and 2. We thought it might be a bit redundant and may confuse readers if we present all results from Calibrations 3 and 4 in the main text. However, we also agree with the reviewer that it is necessary to present results from Calibrations 3 and 4 if readers may be interested in them. In the revised manuscript, we present them in the supplementary material (See the figures below), in order not to distract readers from understanding key objectives (e.g., the necessity of bias-correcting input variables prior to ETo calibration) of this investigation. Specifically, in addition to the figure showing improvements in CRPS skill score, we also add figures demonstrating differences in absolute bias (Figure S15), correlation coefficients (Figure S16), and alpha index (Figure S18) between Calibrations 3 and 4 in the Supplementary Material:

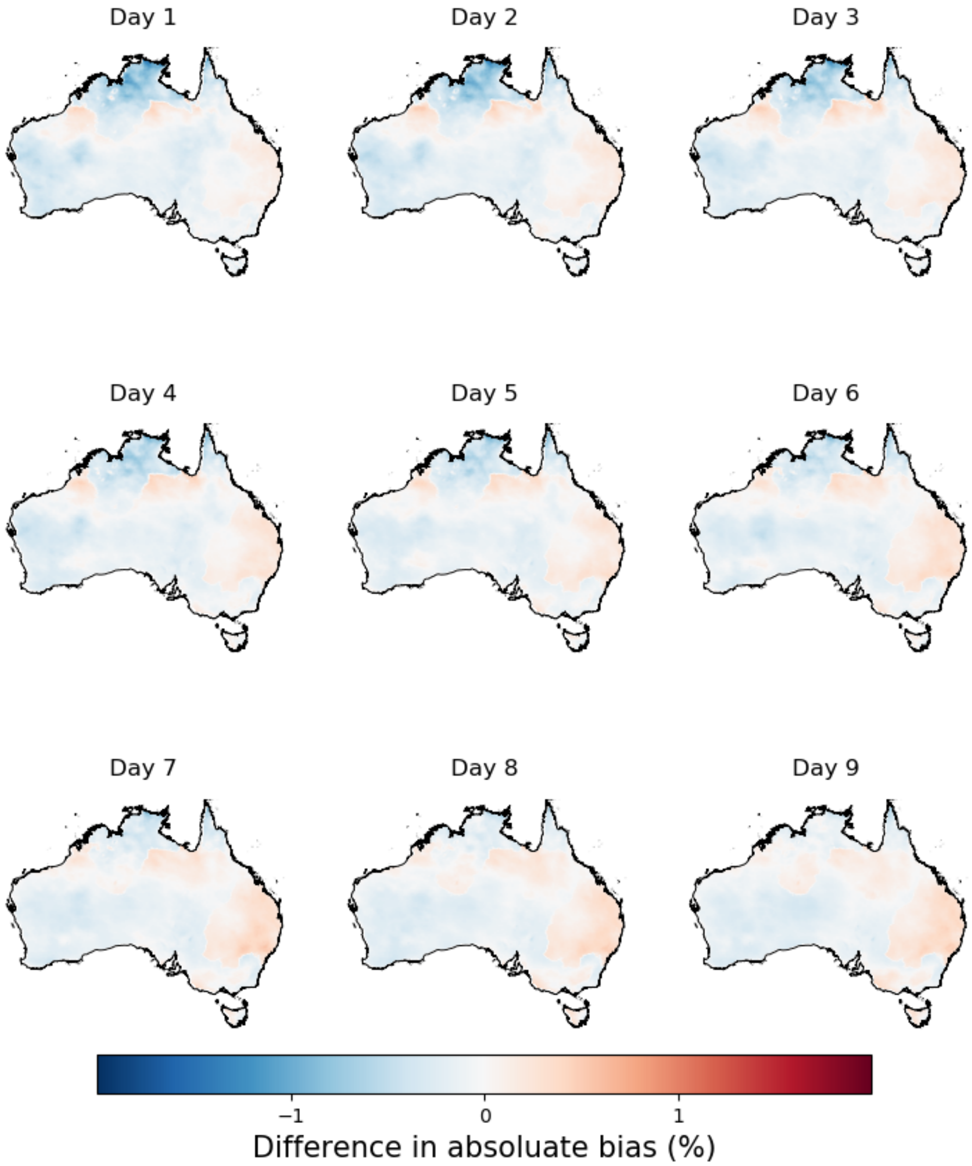


Figure S15. Differences in absolute bias between Calibrations 3 and 4

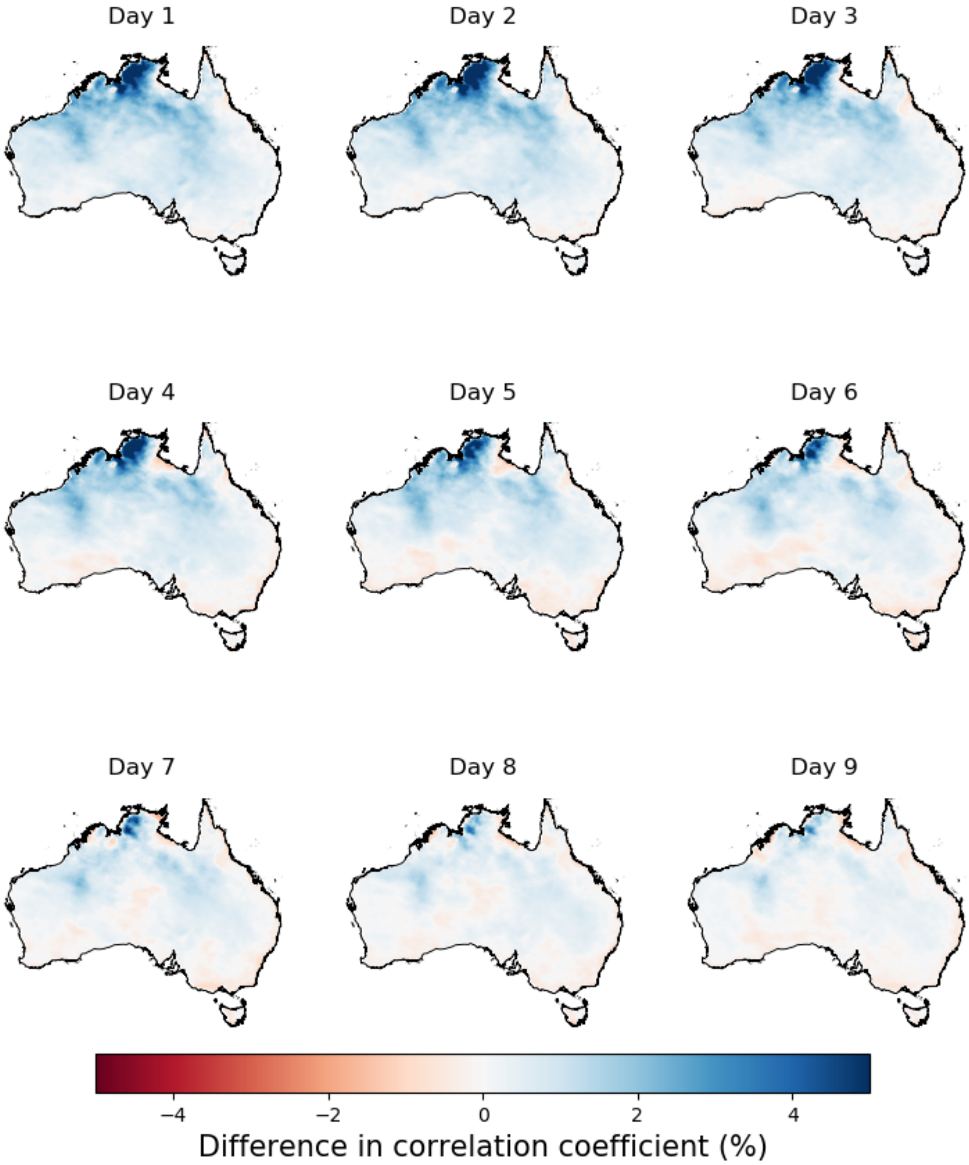


Figure S16. Differences in correlation coefficient between Calibrations 3 and 4

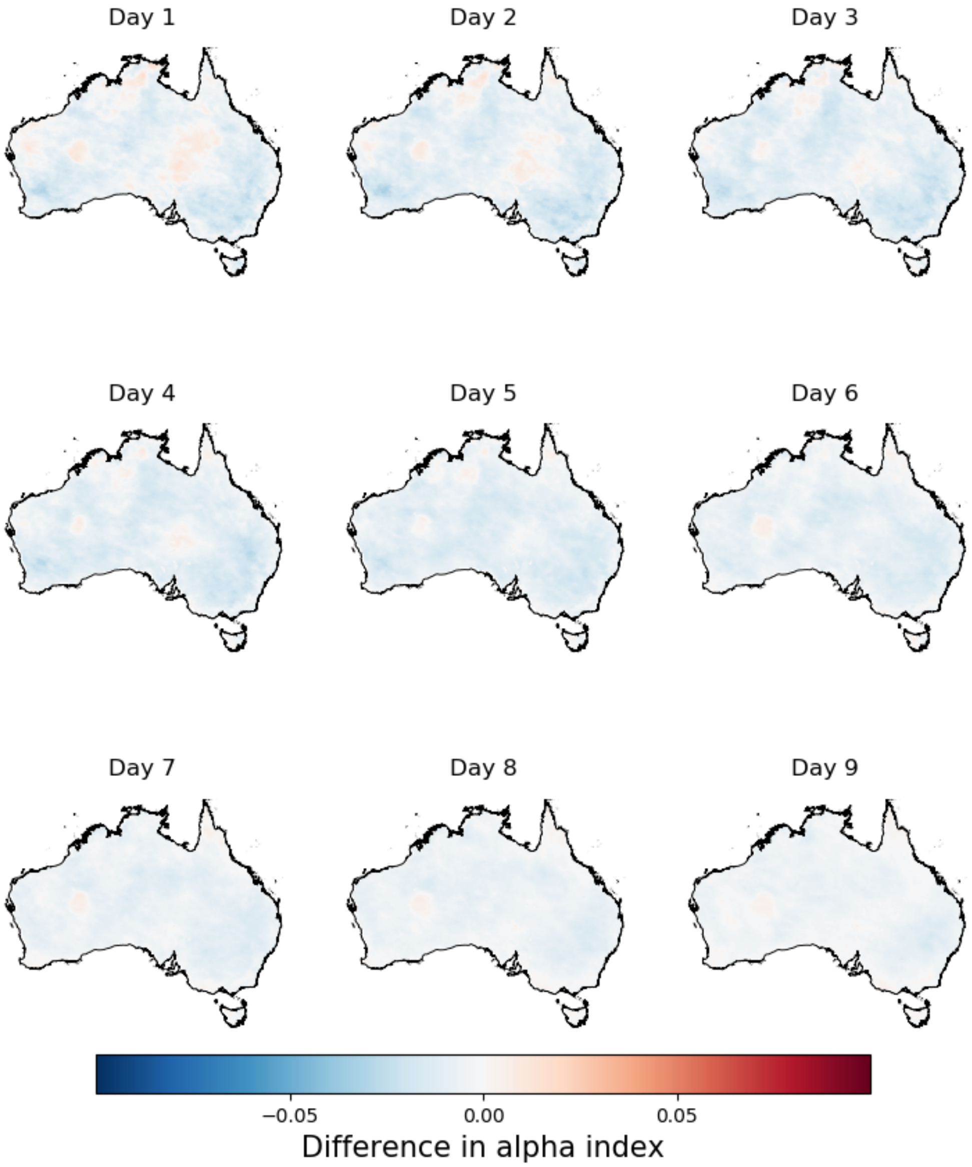


Figure S18. Differences in alpha index between Calibrations 3 and 4

We add one new section in Results to introduce results from Calibrations 3 and 4

3.6 Results from Calibrations 3 and 4

"We also compare the bias, reliability, correlation coefficient, and CRPS skill score of calibrated forecasts from Calibrations 3 and 4, to evaluate whether we can obtain similar improvements through the bias-correction of input variables if we conduct the ETo forecast calibration in a different way (without using climatological mean and anomalies). Results show that the adoption of bias-correction also leads to lower bias, higher correlation coefficient, and higher CRPS skill score in terms of magnitude, spatial patterns, and trend along the lead times, when ETo forecasts are calibrated directly (Figure S10, and S12-S13). In addition, the alpha index was only slightly different between Calibrations 3 and 4 (Figure S11). This additional comparison further confirms the general applicability of strategy ii for enhancing NWP-based ETo forecasting."

Point #6

Methodological choices for evaluation:

P7 l 180-185 : why choosing the absolute bias and over a relative measure e.g. percentage bias? This choice makes it difficult to compare the magnitude of the errors in the results across different variables and studies. For example, figure 1 shows a bias between -2 to 2mm/day which does not seem like much compared to other input variables such as precipitation. Figure 3 with a range of -0.1 to 0.1 seems very small. Conversely, percentages are used for the correlation coefficient in Figure 6 so why not use it for the bias?

Response: We appreciate the reviewer's valuable comments. Bias shows differences with the observed mean, and could be either positive or negative. Larger departures from mean, no matter the bias is positive or negative, suggest larger inconsistencies with observations. Using absolute bias will help measure the departure, rather than indicating overestimations or underestimations. As a result, using absolute bias, we can compare results from two different calibrations, with smaller absolute bias indicating closer to the mean, and thus suggesting better performance.

We agree with the reviewer that using percentages will make the results more comparable with other variables, or with other studies. As a result, we change the unit of bias in figures 1, S12, 3, 4 to percentage:

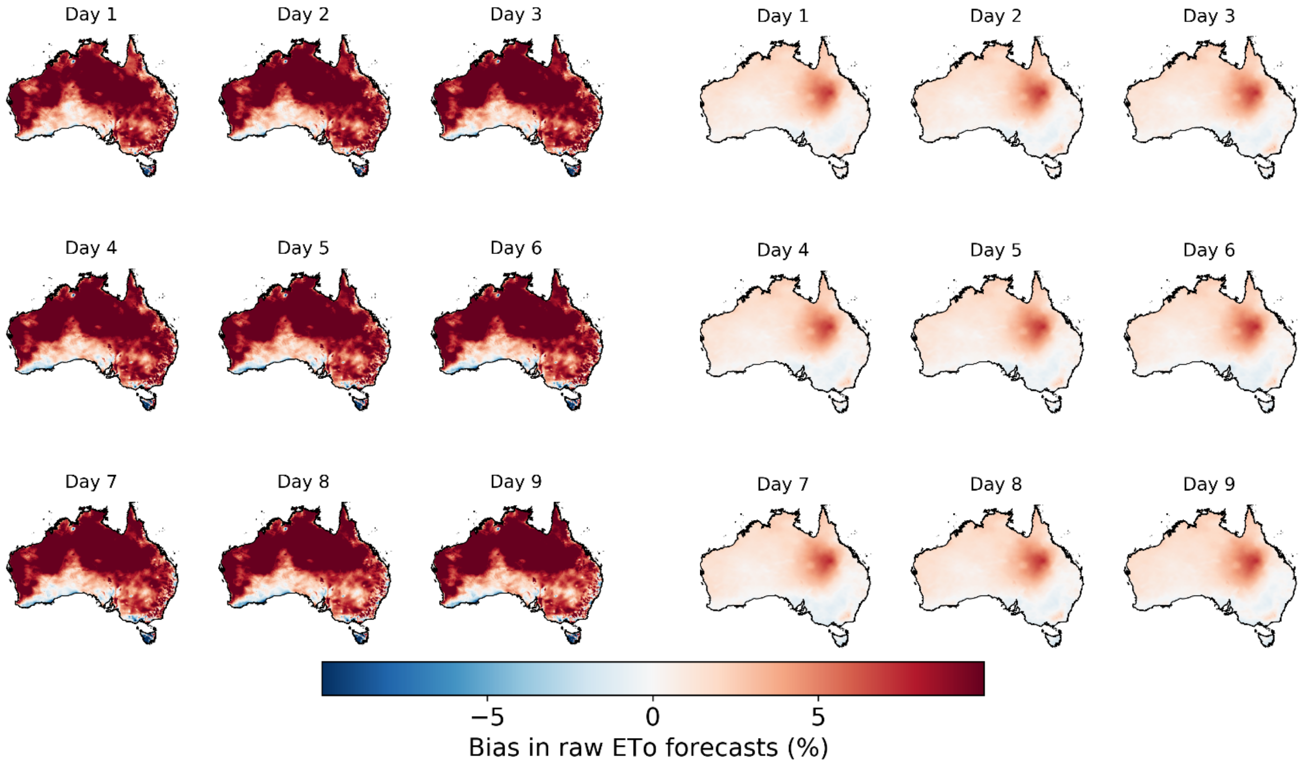


Figure 1: Bias in (three panels on the left) raw ETo forecasts constructed with raw forecasts of input variables and (three panels on the right) raw ETo forecasts constructed with bias-corrected input variables.

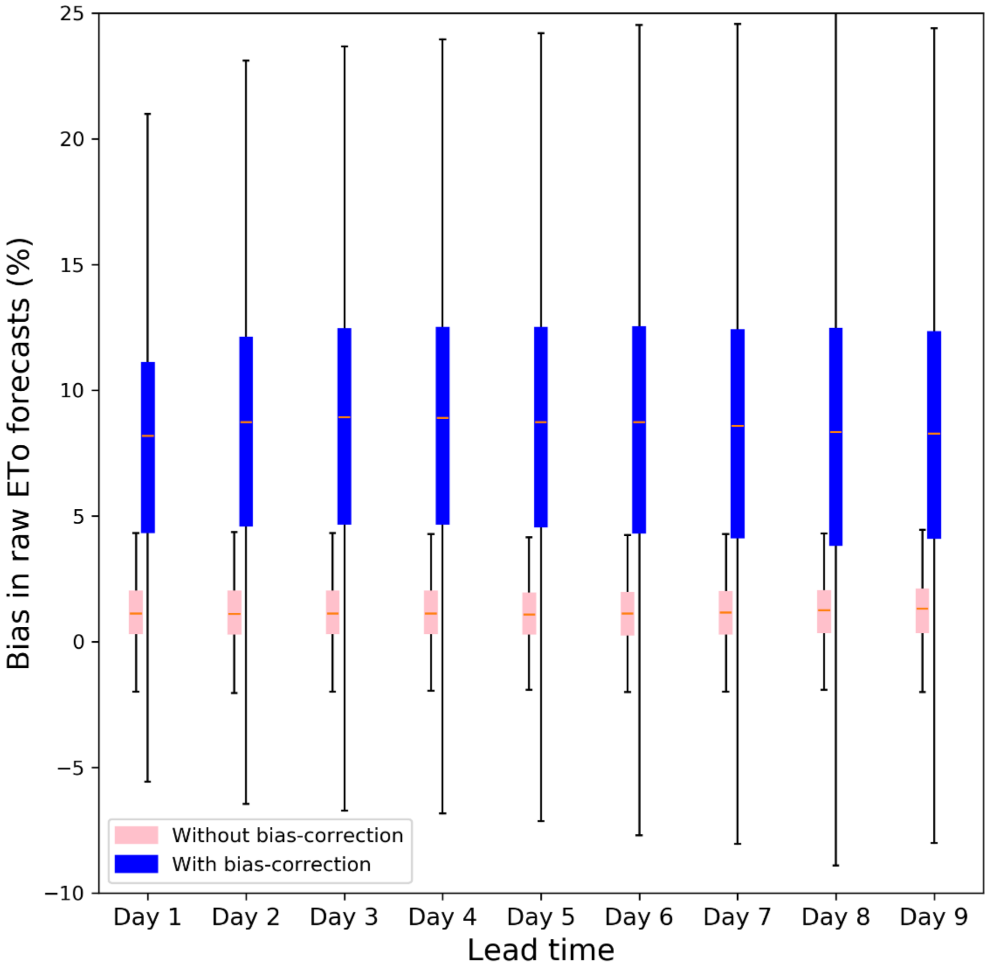


Figure S12. Boxplot of biases in raw ETo forecasts constructed without bias-corrected input variables (pink) and correct inputs (blue)

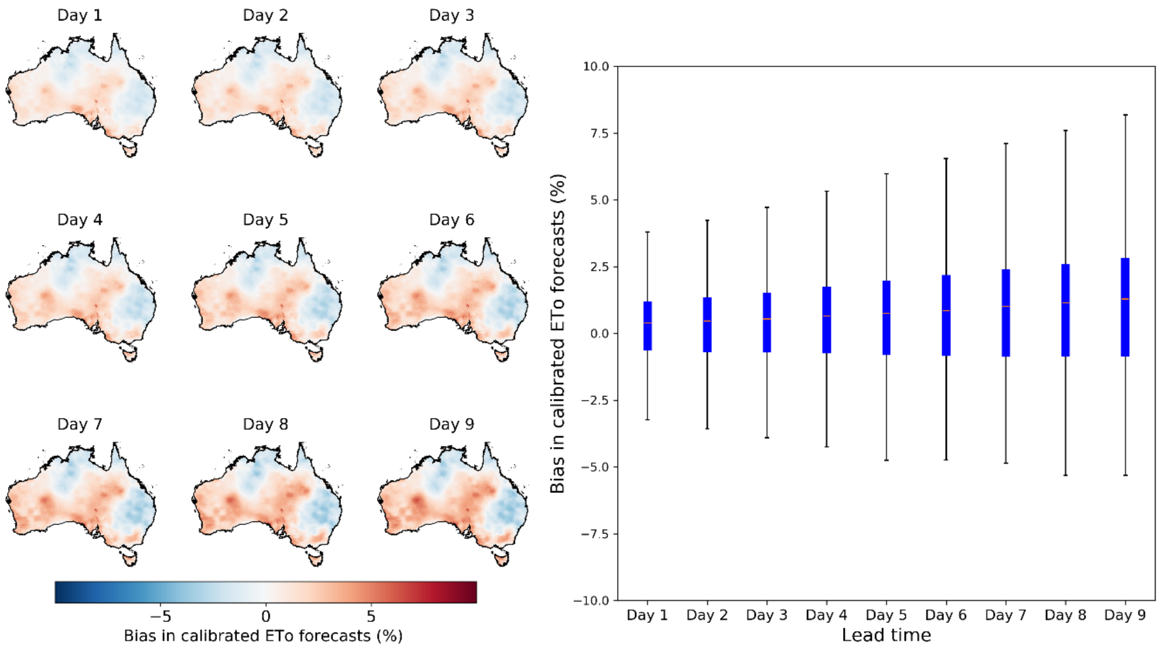


Figure 3: Bias in calibrated ETo forecasts of 9 lead times from Calibration 2, in which raw ETo forecasts are constructed with bias-corrected input variables. Maps on the left show the spatial patterns of bias, and the boxplot on the right summarizes results for all grid cells.

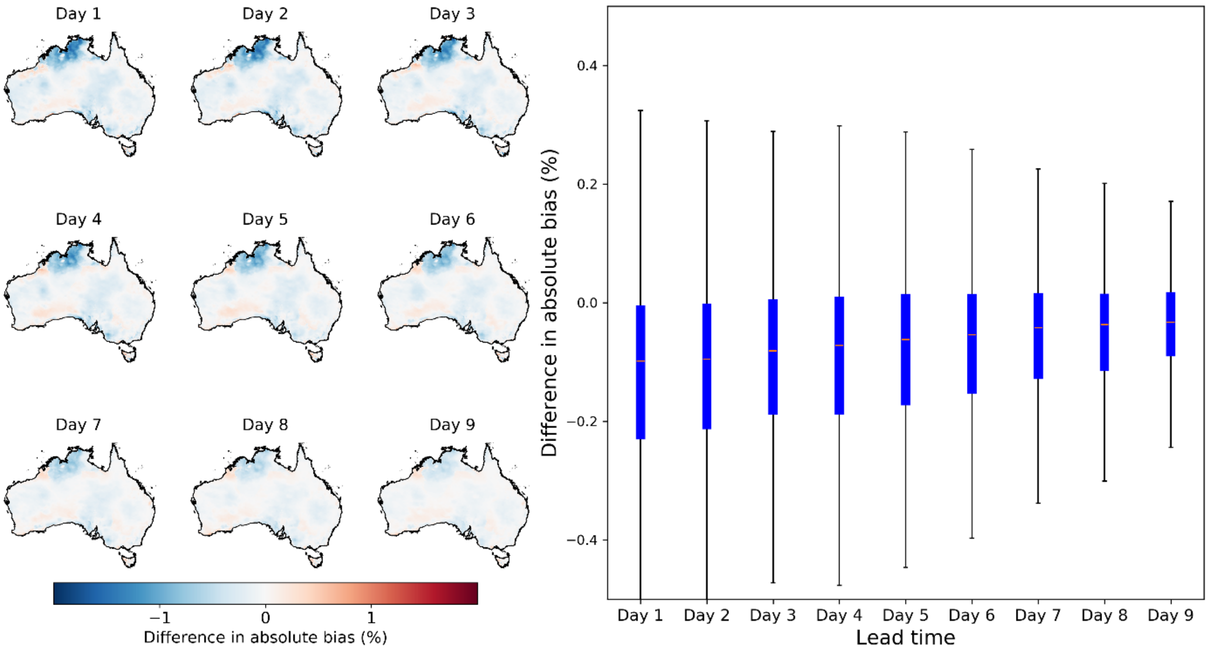


Figure 4: Differences in absolute bias between calibrated ETo forecasts from Calibration 2 with Calibration 1. Maps on the left show the spatial patterns of difference in absolute bias, and the boxplot on the right summarizes results for all grid cells.

Point #7

P8 l205-2015: why is climatology used as reference forecast for the skill score? In hydrological forecasting persistence is typically used for short lead times, whereas climatology would be used for longer lead times, see fore example (Pappenberger, Ramos et al. 2015). Could you please expand and justify the choice of reference forecast used and implication of interpretation of results?

Response: We really appreciate the reviewer's valuable suggestion and the introduction of this classic paper. We choose the climatology forecasts as the reference rather than using persistency for several reasons:

1, Climatology forecasts have been widely used as the reference in the calculation of CRPS skill score for short-term hydroclimate forecasts. One advantage of climatology forecasts is that it often has similar error across all lead times (Bennett et al., 2014), and will be useful to evaluate forecasts skills among different lead times. Therefore, climatology forecasts could be used to show to decreasing skills of the calibrated forecasts as lead time advances (Academies, 2014; Zhao et al., 2019).

2, Persistence is also a good reference, but it's been mainly used for the first two lead times. As demonstrated in figure 5 of Bennett et al. (2014), errors in persistency could increase quickly with lead time. As a result, multiple studies suggested that persistence could be good for skill discrimination for the short lead times (Pappenberger et al., 2015; Thiemig et al., 2015).

Since we investigate 9 lead times in this study, errors in persistency are expected to be large at long lead times. As a result, we think the use of climatology forecasts as the reference for the calculation of the CRPS skill score is acceptable.

We add the following sentence to section 2.4.4 (Skills of the raw and calibrated forecasts) to explain the use of climatology forecasts as the reference for the calculation of CRPS skill score

"In the calculation of CRPS skill score, both climatology forecasts or the last observations (persistence) have been used as reference forecasts (Pappenberger et al., 2015; Thiemig et al., 2015). However, reference forecasts based on persistence are more suitable for evaluating the performance of forecasts shorter than two days. As a result, we choose climatology forecasts as the reference since errors in climate forecasts are similar among all lead times and thus could be used to evaluate the increasing errors in raw and calibrated forecasts as lead time advances."

Reference:

Academies, N.: The science of NOAA'S Operational Hydrologic Ensemble Forecast Service, Bull. Am. Meteorol. Soc., (January), 79–98, doi:10.1175/BAMS-D-12-00081.1, 2014.

Bennett, J. C., Robertson, D. E., Lal, D., Wang, Q. J., Enever, D., Hapuarachchi, P. and Tuteja, N. K.: A System for Continuous Hydrological Ensemble Forecasting (SCHEF) to lead times of 9 days, J. Hydrol., 519, 2832–2846, doi:10.1016/j.jhydrol.2014.08.010, 2014.

Pappenberger, F., Ramos, M. H., Cloke, H. L., Wetterhall, F., Alfieri, L., Bogner, K., Mueller, A. and Salamon, P.: How do I know if my forecasts are better? Using benchmarks in hydrological ensemble prediction, J. Hydrol., 522, 697–713, doi:10.1016/j.jhydrol.2015.01.024, 2015.

Thiemig, V., Bisselink, B., Pappenberger, F. and Thielen, J.: A pan-African medium-range ensemble flood forecast system, Hydrol. Earth Syst. Sci., 19, 3365–3385, doi:10.5194/hess-19-3365-2015, 2015.

Zhao, T., Wang, Q. J. and Schepen, A.: A Bayesian modelling approach to forecasting short-term reference crop evapotranspiration from GCM outputs, Agric. For. Meteorol., 269–270(January), 88–101, doi:10.1016/j.agrformet.2019.02.003, 2019.

Point #8

P8 l214. Why is the definition of CRPSS using percentage? As far as I am aware, most studies do not present the CRPSS in terms of percentage, could you please comment on the reason of this choice with references that also use percentages and if there is any advantages?

Response: Thank you for the comments. We agree with the reviewer that many studies use ratios when presenting the CRPS skill score. Meanwhile, we also notice that some studies (see the reference list at the bottom of our response to this comment) use percentage as the unit of CRPS skill score. No matter which unit is used, CRPS skill score could effectively demonstrate higher skills in calibrated forecasts relative to the raw forecasts (Figure 7), and quantify improvements in forecast skill (Figures 8, S9, S12) with the adoption of the calibration strategy.

As shown in Figure 7, skills of calibrated forecasts decreased quickly with lead time. As a result, the CRPS skill score decreases to small numbers and approaches zero at lead time 9. One advantage of using percentages as the unit for CRPS skill score is that these small numbers will be expressed as integers rather than small decimals.

We add the following sentence to explain why the percentage is used for CRPS skill score:

“We use percentage as the unit of CRPS skill score so low skill scores at long lead times will be expressed as integers. **”**

Here are some investigations using % as the unit of CRPS skill score

Brown, J. D. and Seo, D. J.: A nonparametric postprocessor for bias correction of hydrometeorological and hydrologic ensemble forecasts, J. Hydrometeorol., 11(3), 642–665, doi:10.1175/2009JHM1188.1, 2010.

Kumar, L. G. A., Smith, A. S. D., Gonzalez, G. B. P., Merryfield, V. K. W. and Newman, A. S. Á. M.: A verification framework for interannual-to-decadal predictions experiments, Clim. Dyn., 40, 245–272, doi:10.1007/s00382-012-1481-2, 2013.

Munkhammar, J., van der Meer, D. and Widén, J.: Probabilistic forecasting of high-resolution clear-sky index time-series using a Markov-chain mixture distribution model, Sol. Energy, 184(January), 688–695, doi:10.1016/j.solener.2019.04.014, 2019.

Robertson, D. E. and Wang, Q. J.: Seasonal Forecasts of Unregulated Inflows into the Murray River , Australia, Water Resour. Manag., 27, 2747–2769, doi:10.1007/s11269-013-0313-4, 2013.

Schepen, A., Wang, Q. J. and Robertson, D. E.: Seasonal Forecasts of Australian Rainfall through Calibration and Bridging of Coupled GCM Outputs, Mon. Weather Rev., 142, 1758–1770, doi:10.1175/MWR-D-13-00248.1, 2014.

Point #9

Analysis and interpretation of results:

P11 l259-261: why the higher difference in bias in approaches for the Nothern Territory? How does this relate to the biases, errors and assumptions of the NWP? Is it correlated to the biases of specific input variables? How is it correlated to the nonlinear relationship in calculatint ETo? Why are the biases most pronounced for shorter lead times? Please comment.

Response: Thank you for the valuable comments. To answer these questions, we present more results to explain how quantile mapping to input variables contributes to improving calibrated ETo forecasts. Specifically, we (1) calculate the correlation coefficients (*r*) between raw/bias-corrected forecasts of the five input variables and AWAP data to further analyze how quantile mapping has improved input variables, in addition to correcting bias (shown in figure 1); (2) investigate the improvements in correlation coefficients between raw ETo forecasts following the bias-correction to input variables and AWAP ETo, to examine how improvements in each variable are translated into the resultant raw ETo forecasts; (3) explain how improvements in raw ETo forecasts through bias-correcting input variables lead to improvements in calibrated ETo forecasts. Please find more details as follows:

1, In addition to correcting bias (Figures S2 to S6), quantile mapping also generally improves the temporal patterns of raw forecasts of the input variables. Following figures shows *r* between raw forecasts of the input variables and their corresponding AWAP data (three columns on the left), and improvements in *r* by quantile mapping (three columns on the right):

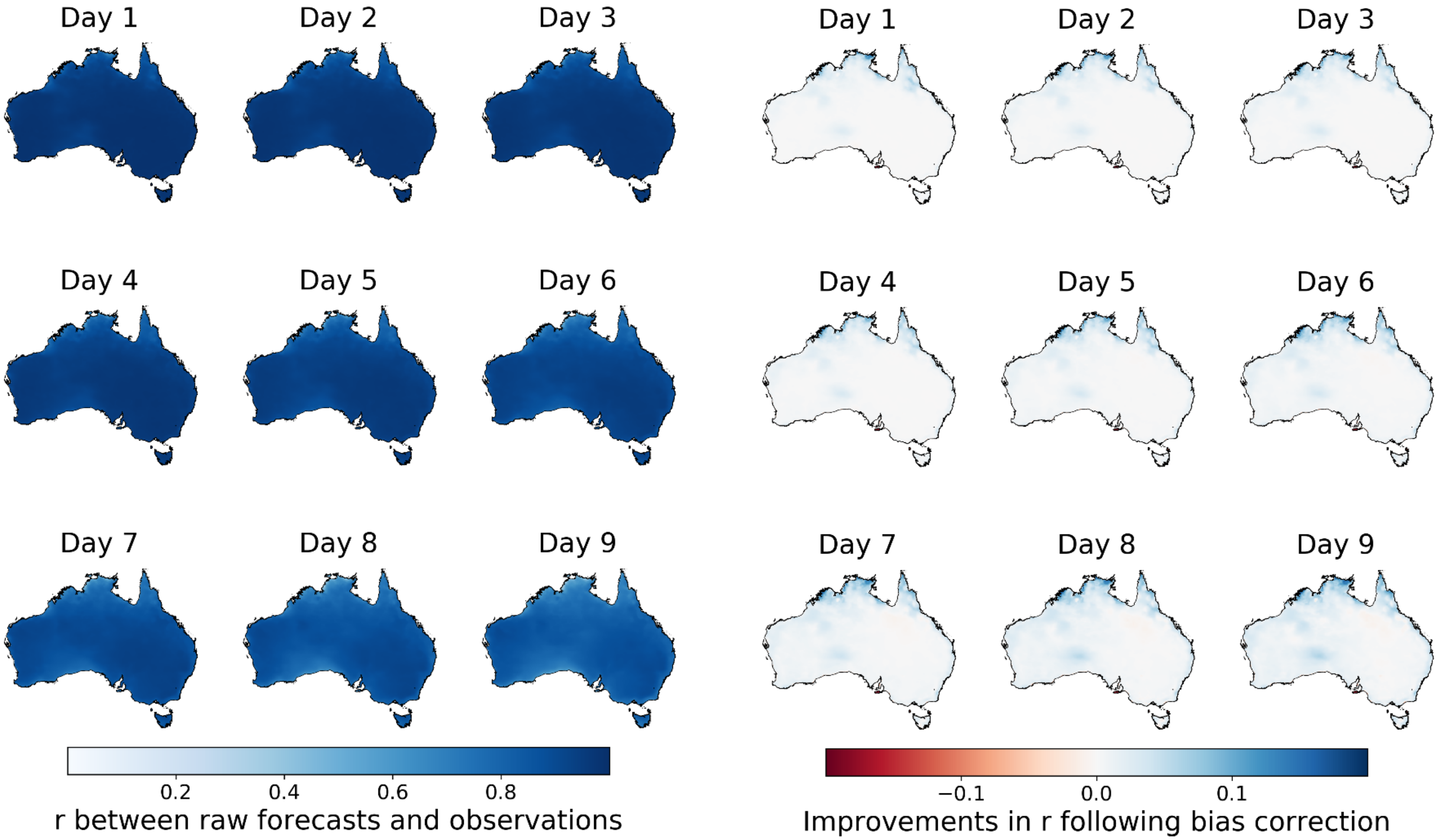


Figure S7. Correlation coefficients (r) between raw Tmax forecasts and AWAP data (three panels on the left), and improvements in r (three panels on the right) through quantile mapping

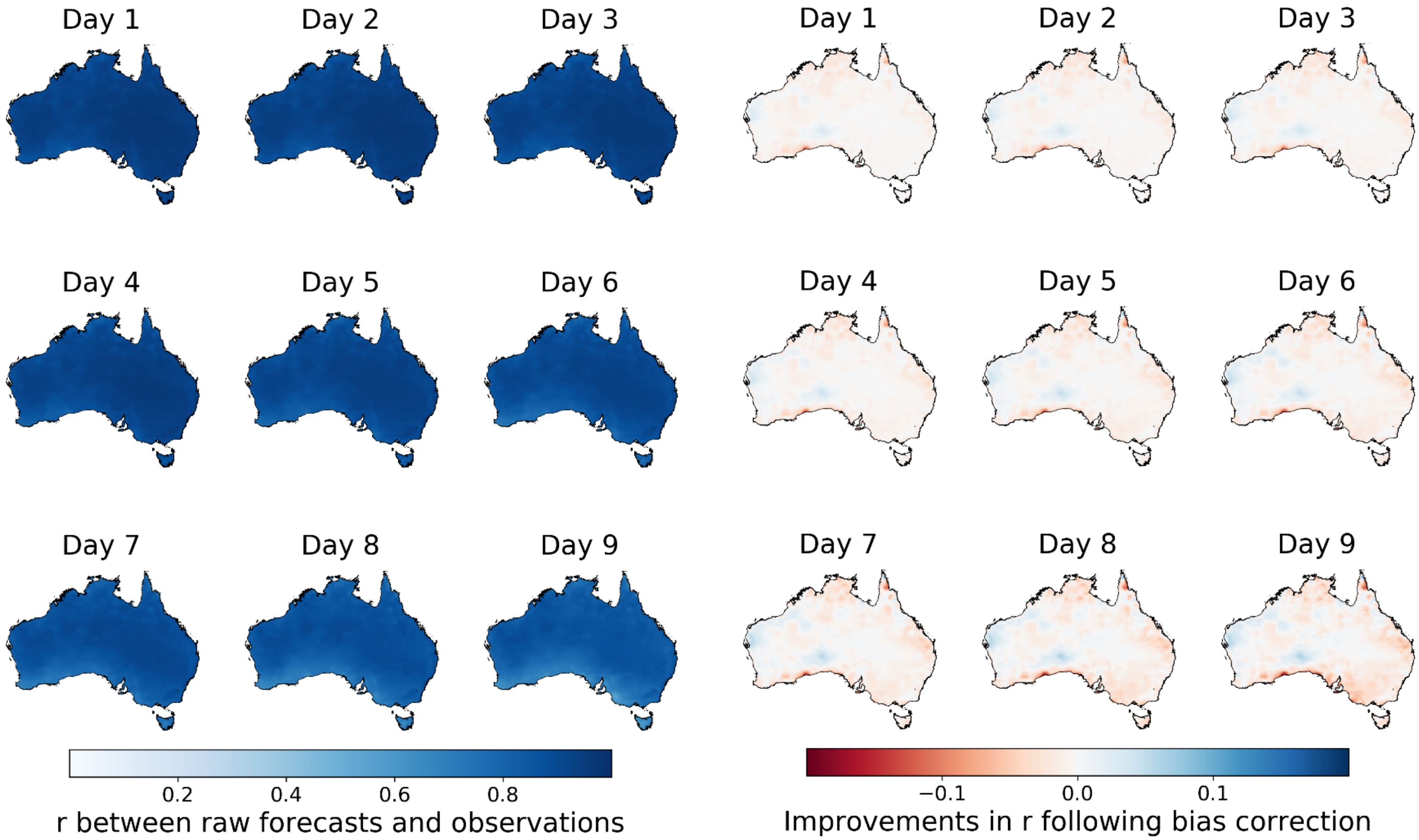


Figure S8. Correlation coefficients (r) between raw Tmin forecasts and AWAP data (three panels on the left), and improvements in r (three panels on the right) through quantile mapping

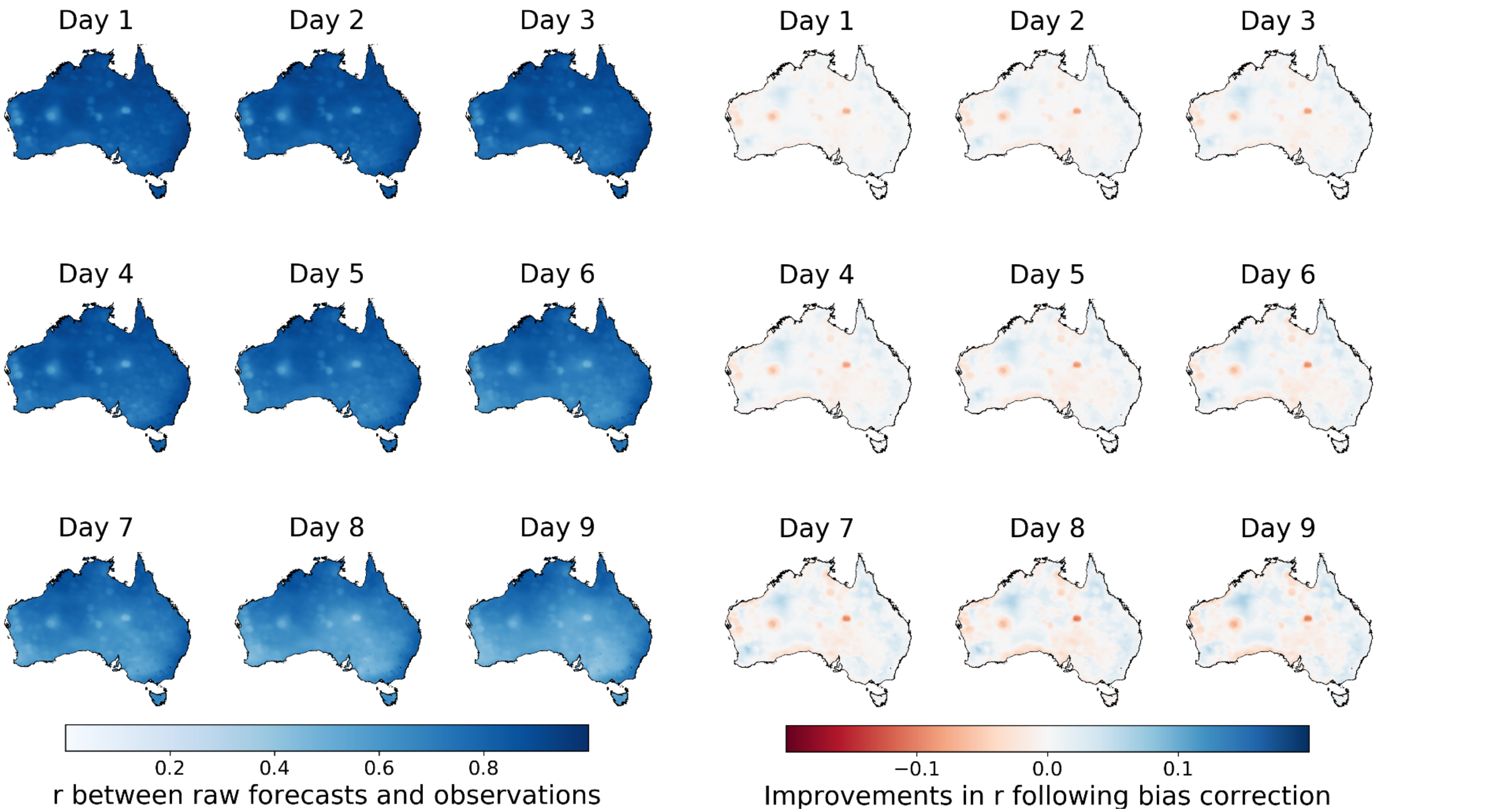


Figure S9. Correlation coefficients (r) between raw vapor pressure forecasts and AWAP data (three panels on the left), and improvements in r (three panels on the right) through quantile mapping

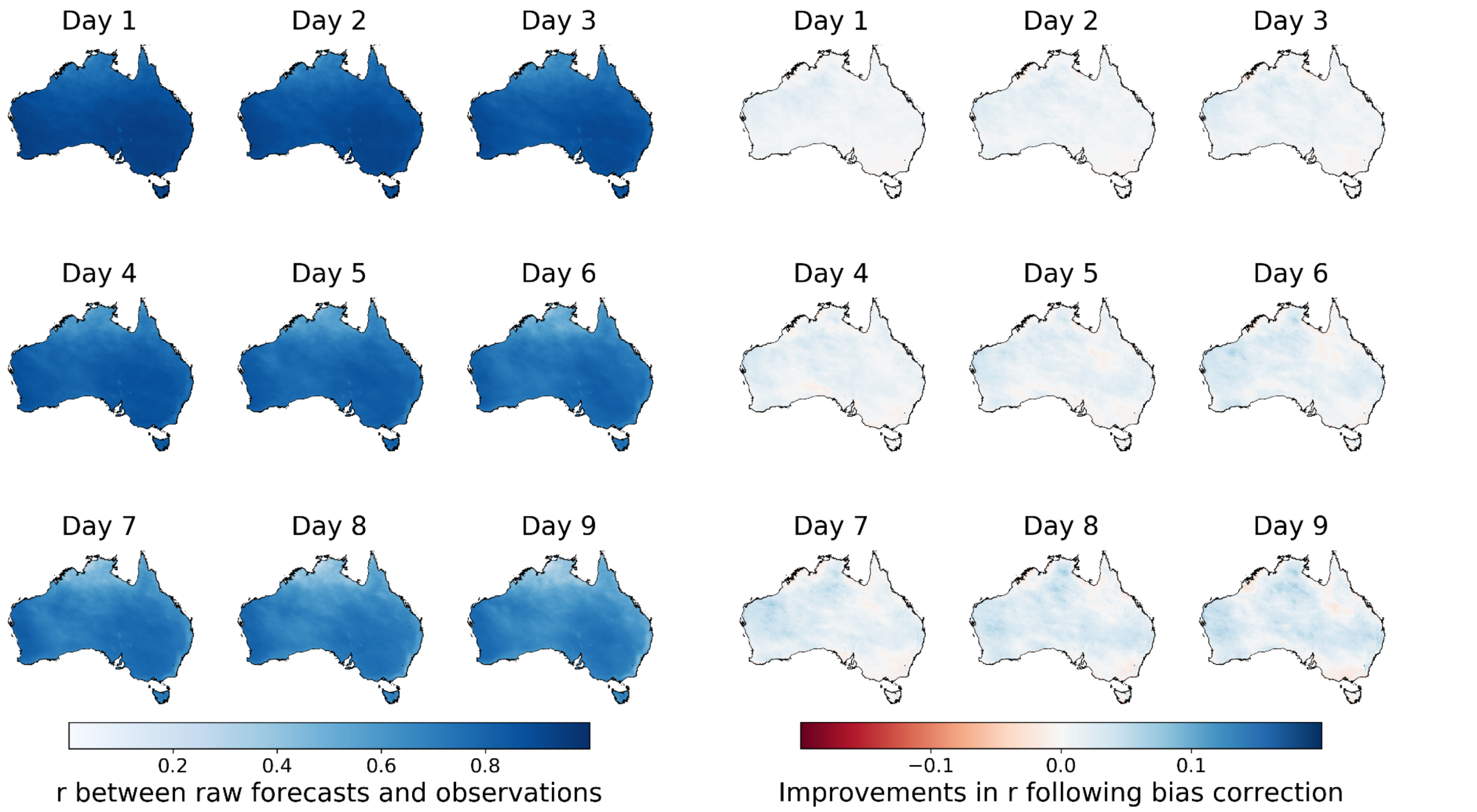


Figure S10. Correlation coefficients (r) between raw solar radiation forecasts and AWAP data (three panels on the left), and improvements in r (three panels on the right) through quantile mapping

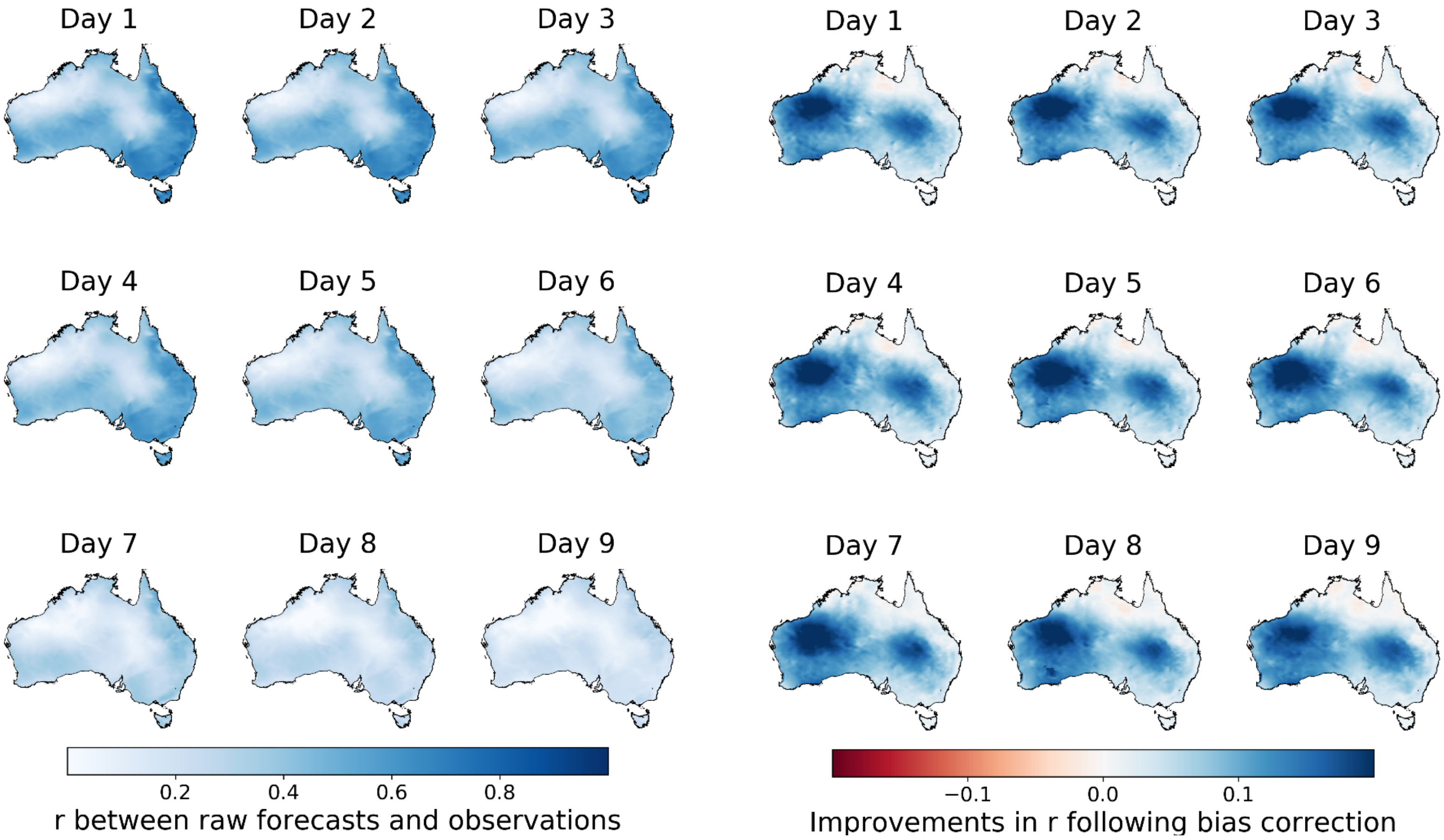


Figure S11. Correlation coefficients (r) between raw wind speed forecasts and AWAP data (three panels on the left), and improvements in r (three panels on the right) through quantile mapping

As shown in the above figures, *r* between raw forecasts of the input variables and AWAP data varies with the input variables. The two temperature variables have higher r values than the other three variables, and wind speed forecasts demonstrate the lowest correlation with AWAP data. For all variables, the *r* values decrease with lead time, indicating higher uncertainties in raw forecasts at longer lead times.

Quantile mapping generally improves the correlation between forecasts and AWAP data. The above figures show that bias-corrected forecasts demonstrate higher *r* for Tmax, solar radiation, and wind speed across most parts of Australia; for Tmin and vapor pressure, changes in *r* are less significant and both improvements and slight decreases in *r* are observed.

We add the above figures to the supplementary. We also add following descriptions to section 3.1:

"Raw forecasts of the input variables generally agree with the AWAP data in temporal patterns during the study period, but the *r* varies with variables (Fig. S7-S11). The two temperature variables (Tmax and Tmin) have higher *r* values (>0.9) than the other three variables, and wind speed forecasts demonstrate the lowest correlations with AWAP data. For all variables, the *r* decreases with lead time, indicating higher uncertainties in raw forecasts at longer lead times.**"**

"In addition, quantile mapping also improves the correlation between forecasts and AWAP data (Fig. S7-S11). The most significant improvements are found in wind speed forecasts, showing increases in *r* by up to 0.2 in central and southern parts of Australia. Forecasts of Tmax and solar radiation also demonstrate higher *r* with the adoption of quantile mapping. Both increases and slight decreases were found for vapor pressure and Tmin, showing that temporal patterns of forecasts of these two variables are not changed much through the bias-correction. **"**

2, With the adoption of quantile mapping to raw forecasts of individual variables, raw ETo forecasts (Calibrations 2 or 4) also show higher *r* with observations, than the raw ETo forecasts constructed with the original raw forecasts of input variables (Calibrations 1 or 3):

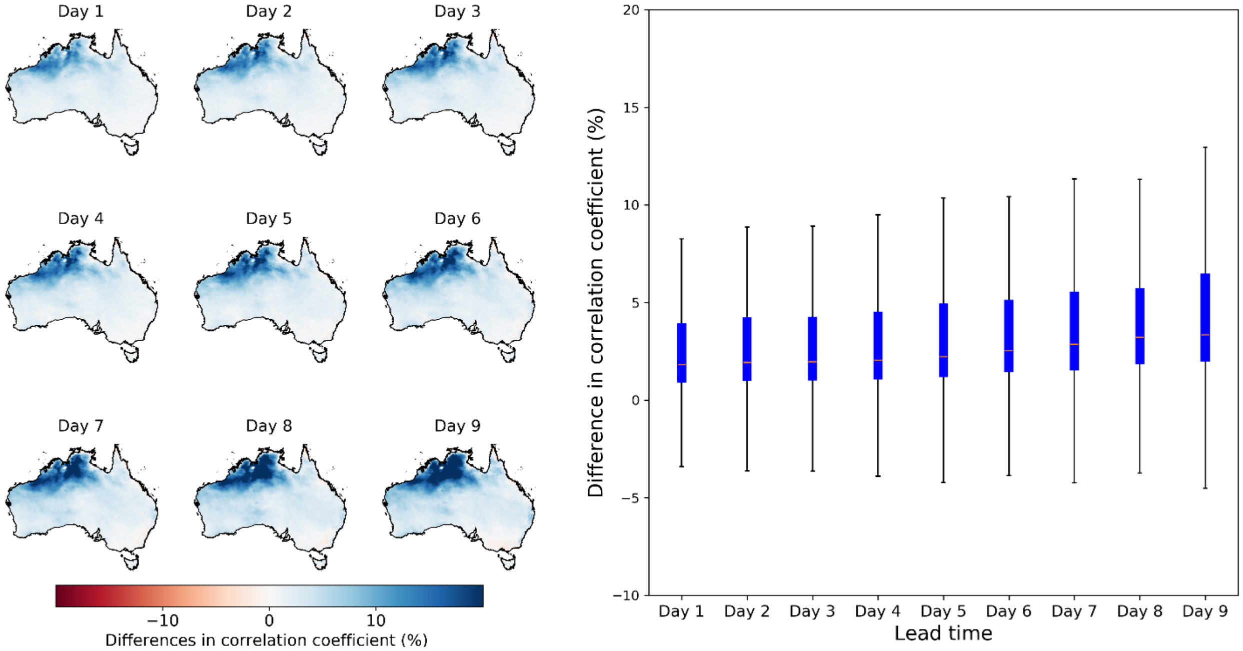


Figure 2: The comparison between the correlation coefficient of AWAP ETo and raw ETo forecasts constructed with the bias-corrected inputs vs. the correlation coefficient of AWAP ETo and raw ETo forecasts constructed with the uncorrected inputs. The boxplot on the right summarizes results for all grid cells.

As is shown in the above figure, the quantile mapping also improves the temporal patterns of raw ETo forecasts, for all the lead times. More significant improvements are found in northern Australia. However, due to the nonlinearity in the calculation of ETo using the input variables, spatial patterns of improvements in *r* (Figure 2) does not resemble that of any individual input variables. Although both Tmax and wind speed show more significant improvements in northern Australia, where the *r* improvements are greater than other regions (Figure 2), the spatial patterns of *r* improvements in ETo forecasts are different from these two variables in other parts of the country. As a result, we believe that improvements in *r* of raw ETo forecasts are contributed jointly by these input variables and their interactions.

We add the above figure (Figure 2) to the manuscript and add the following contents to the manuscript:

“The adoption of quantile mapping to improve input variables also improves the temporal patterns of raw ETo forecasts (Figure 2). Compared with the raw ETo forecasts constructed with uncorrected input variables, the raw ETo forecasts based on bias-corrected inputs generally shows higher correlation coefficients with AWAP ETo, particularly in northern Australia. However, due to the nonlinearity in the calculation of ETo using the input variables, spatial patterns of improvements in *r* (Figure 2) does not resemble improvements in any individual input variables (Figures S7 to S11). The improvements in *r* of raw ETo forecasts seem to be contributed jointly by these input variables and their interactions.**”**

3, We add the following contents to section 3.2 to explain the spatial patterns of changes in *r* and absolute bias:

“Larger reductions in absolute bias in northern Australia coincide with the improvements in the correlation between raw ETo forecasts and AWAP ETo (Figure 2). However, unlike the improvements in *r* for all lead times in raw ETo forecasts, the improvements in absolute bias are more pronounced for short lead times (Days 1-3) than long lead times (Days 7-9). The uneven improvements may reflect that intrinsic uncertainties at long lead times have hindered the manifestation of improvements to the raw ETo forecasts in calibrated ETo forecasts.**”**

Based on the above analyses, we can then answer the questions the reviewer raised regarding the figure of absolute bias in this comment.

More significant reductions in absolute bias in northern Australia show similar spatial patterns with that of the improvements in correlation coefficient between raw ETo forecasts and AWAP ETo. As we further explained in our response to your next comment (#10), deficiencies in NWP models in simulating weather dynamics in tropical regions have been reported. However, improvements to raw ETo forecasts in r with the application of quantile mapping could not be explained by any individual variable. The nonlinearity in calculating ETo based on the individual variables may have combined improvements in each variable and lead to more significant improvements in northern Australia. Less significant improvements in ETo forecasts at longer lead times may be caused by the more significant intrinsic uncertainties than short lead times. These uncertainties have inhibited the translation of improvements in raw ETo forecasts to calibrated forecasts.

Point #10

P13 l282-285: Why lowest score of correlation coefficient in northern Territory? Is it linked to the NWP (and if so how?) or is it linked to observations? E.g. differneces in observations compared to rest of country?

Response: Thank you for the comments. We believe the correlation results from the NWP forecasts rather than from observations for several reasons:

1, Evaluation of the observations (AWAP data) did not show larger errors in this region, than other areas of Australia (Jones et al., 2009). As a result, we do not have evidence that the quality of observations in this region is lower than in other regions

2, Deficiencies of NWP forecasts in tropical regions in Australia have been well documented. Due to its highly dynamic nature, tropical regions often demonstrate larger errors than other climate zones. In the evaluation of NWP forecasts in Australia, tropical zones often show lower skills than other regions (Ebert and Mcbride, 2000; Mcbride and Ebert, 2000; Roux et al., 2010). According to Huang et a. (2018), ACCESS models have been suffering from low skills in simulating the convective processes in tropical zones of Australia.

3, Raw ETo constructed with the ACCESS outputs showed higher RMSE in Northern Territory than other regions (Perera et al., 2014), further confirms that lower correlation coefficient is mainly caused by the NWP forecasts.

We add the following sentences to the section 3.3:

"Deficiencies in ACCESS models in simulating dynamics of tropical climate systems may have resulted in low correlation coefficients in Northern Territory.**"**

Reference:

Ebert, E. E. and Mcbride, J. L.: Verification of precipitation in weather systems : determination of systematic errors, J. Hydrol., 239, 179–202, 2000.

Huang, J., Rikus, L. J., Qin, Y. and Katzfey, J.: Assessing model performance of daily solar irradiance forecasts over Australia, Sol. Energy, 176(November), 615–626, doi:10.1016/j.solener.2018.10.080, 2018.

Jones, D. A., Wang, W. and Fawcett, R.: High-quality spatial climate data-sets for Australia, Aust. Meteorol. Oceanogr. J., 58, 233–248, 2009.

Mcbride, J. L. and Ebert, E. E.: Verification of quantitative precipitation forecasts from operational numerical weather prediction models over Australia, Weather Forecast., 15(1), 103–121, doi:10.1175/1520-0434(2000)015<0103:VOQPFF>2.0.CO;2, 2000.

Perera, K. C., Western, A. W., Nawarathna, B. and George, B.: Forecasting daily reference evapotranspiration for Australia using numerical weather prediction outputs, Agric. For. Meteorol., 194, 50–63, doi:10.1016/j.agrformet.2014.03.014, 2014.

Roux, B., Seed, A., Pagano, T. and Roux, B.: Improved use of precipitation forecasts in short-term water forecasting – progress report, The Centre for Australian Weather and Climate Research A partnership between CSIRO and the Bureau of Meteorology Improved., 2010.

Point #11

P14 l294-297: The geographical patterns of the correlation performance is very similar to the patterns of the bias performance. Could you please comment why and if the reasons are the same? Are these related to either the NWP or observations?

Response: Thank you for the valuable comments. We add the following figure to the manuscript to demonstrate how bias-correction of input variables improves correlations between raw ETo forecasts and AWAP ETo:

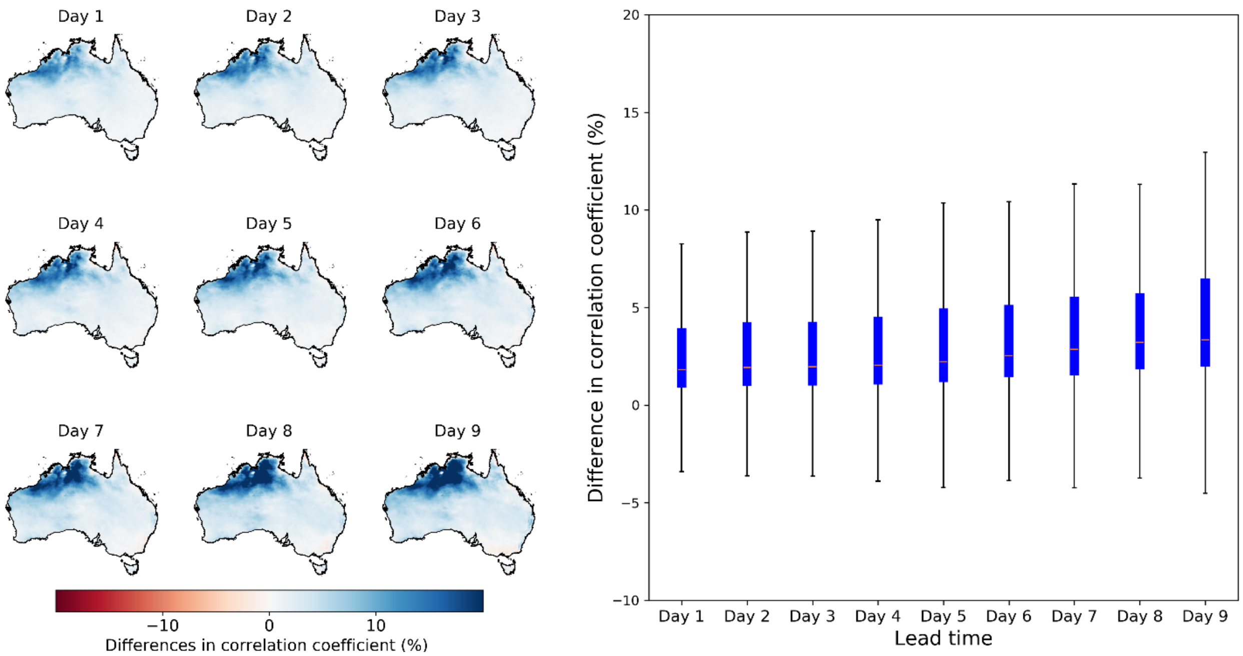


Figure 2: The comparison between the correlation coefficient of AWAP ETo and raw ETo forecasts constructed with the bias-corrected inputs vs. the correlation coefficient of AWAP ETo and raw ETo forecasts constructed with the uncorrected inputs. The boxplot on the right summarizes results for all grid cells.

The above figure shows that when input variables are bias-corrected, the resultant raw ETo forecasts show higher correlation coefficients, than raw ETo forecasts constructed with uncorrected inputs. Spatial patterns of the improvements in *r* in raw forecasts for short lead times are consistent with the improvements in *r* in calibrated forecasts (Figure 6). As a result, we believe this is how the new calibration strategy improves the calibration of ETo forecasts. Less significant improvements in ETo forecasts at longer lead times may be caused by the more significant intrinsic uncertainties in raw forecasts than short lead times. These uncertainties have inhibited the translation of improvements in raw ETo forecasts to calibrated forecasts. We have explained the connections between improvements in raw forecasts and calibrated forecasts in response to your comment #9.

As we introduced in the manuscript, when we calibrate the raw ETo forecasts (f(t)), we built a conditional distribution ($\tilde{o}(\mathrm{m}(t))$**) for observations (**$\mathrm{o(t)}$**), and 100 values will be drawn from this conditional distribution to generate the calibrated ensemble forecasts:**

$$\tilde{o}(\mathrm{m}(t))\sim N\left(\mu_o(\mathrm{m}(t))+r\frac{\sigma_o(\mathrm{m}(t))}{\sigma_f(\mathrm{m}(t))}(f(t)-\mu_f(\mathrm{m}(t))),(1-r^2)\sigma_o^2\right)$$

in which where $\mathbf{m}(\boldsymbol{t})$ returns the month k (k=1 to 12) of daily forecasts or observations of day $\boldsymbol{t}$; $\boldsymbol{\mu_f}(\mathbf{m}(\boldsymbol{t}))$ and $\boldsymbol{\sigma_f}(\boldsymbol{m}(\boldsymbol{t}))$ refer to the marginal distribution's mean and standard deviation of $\boldsymbol{f}(\boldsymbol{t})$ in month $\mathbf{m}(\boldsymbol{t})$, respectively; $\boldsymbol{\mu_o}(\mathbf{m}(\boldsymbol{t}))$ and $\boldsymbol{\sigma_o}(\boldsymbol{m}(\boldsymbol{t}))$ are the mean and standard deviation of the

marginal distribution of $o(t)$ in month $\mathrm{m}(t)$; r is the correlation between $f(t)$ and $o(t)$ in the transformed space.

As a result, when the correlation is improved, it will help improve the estimation of the mean and standard deviation of the above conditional distributions. As a result, bias in calibrated forecasts will be further reduced. That is why improvements in bias demonstrate a similar spatial pattern as those of the correlation coefficient.

To explain improvements in r in calibrated forecasts, we add the following sentence to the section 3.3:

"Spatial patterns of improvements in r of calibrated ETo forecasts (Figure 6) are similar to the improvements in *r* of raw ETo forecasts (Figure 2), particularly for the short lead times. The improvements in *r* of calibrated ETo forecasts (Figure 6) may also lead to more reliable conditional distributions for a given raw forecast (equation 4). As a result, regions showing improvements in *r* in calibrated ETo forecasts (Figure 6) often demonstrate reductions in absolute bias (Figure 3).**"**

Point #12

P16 l320-328. Please comment on why the accuracy has larger differences in terms of geographical patterns than for the bias and PIT performance which had very strong localised performance.

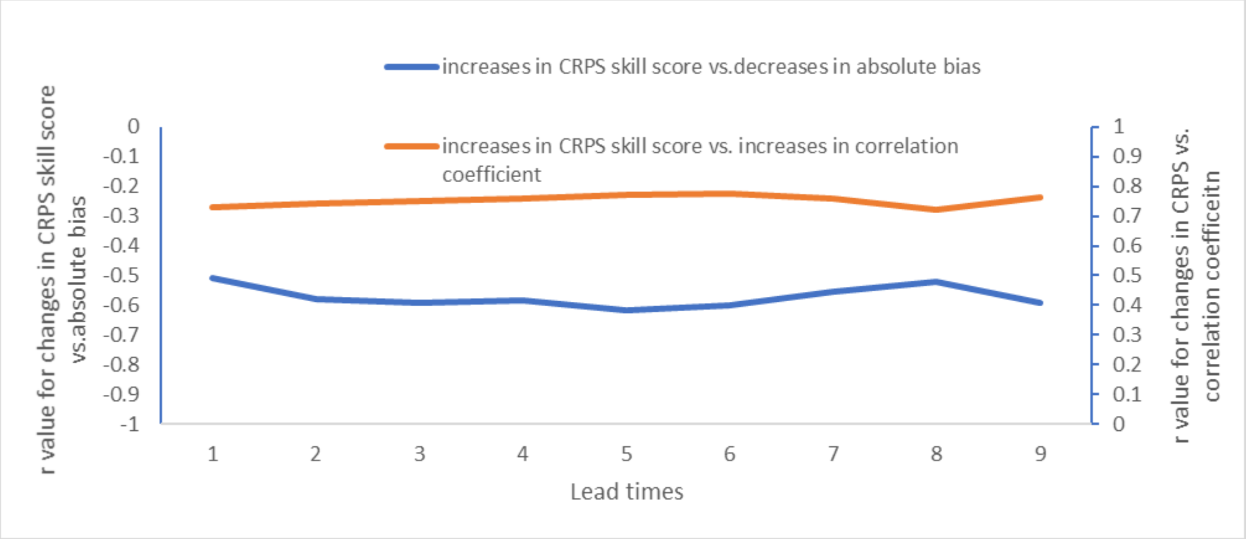
Response: Thank you for the comments. We believe there are four reasons for the differences in spatial patterns of CRPS skill score (Figure 8) with changes in bias (Figure 4), correlation coefficient (Figure 6), and alpha index (Figure S13):

1, The metrics measure different features of the quality of forecasts, and may have different sensitivities to changes in calibrated forecasts. As a result, it is not unexpected that their spatial patterns show differences. The CRPS skill score measures the performance of calibrated forecasts relative to the climatology forecast; correlation coefficient shows consistency between observations and forecasts; bias measures average differences; the alpha index is an indicator showing whether the distribution of calibrated forecasts is overconfident or underconfident. As a result, improvements indicated by these metrics do not necessarily show exactly the same spatial patterns.

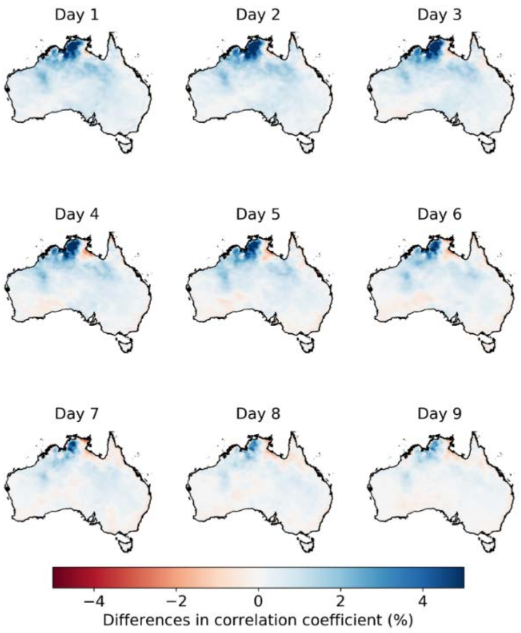
2, The alpha index is less sensitive to changes in forecasts than other metrics. It is well known that the quality of forecasts often declines with lead time, even for calibrated forecasts. This tendency can be seen from the correlation coefficient (Figure 5) and CRPS skill score (Figure 7). However, the same trend is not shown by the alpha index. As demonstrated by figure 9, the alpha index demonstrates similar magnitudes and spatial patterns among the 9 lead times. As was introduced in equations 13 and 14, PIT value and alpha index are mainly used to measure the consistency between distributions of forecasts and observations. Cmprovements achieved through the adoption of calibration strategy ii (e.g., Calibrations 2

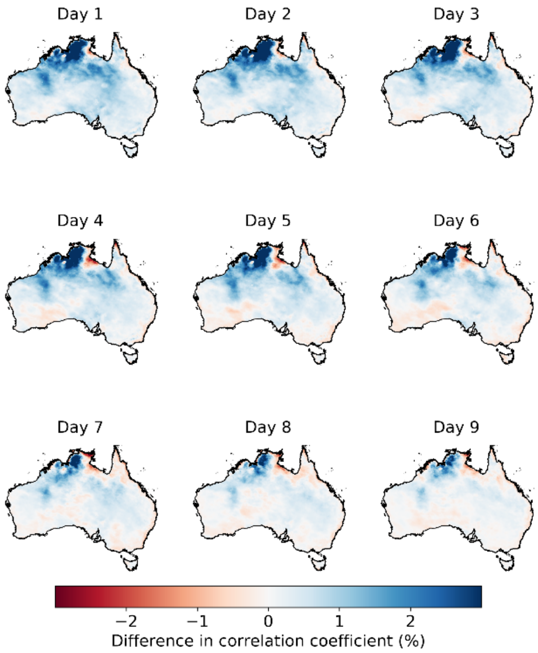
and 4) may not significantly change the statistical distributions of the calibrated forecasts. As a result, differences in alpha index (Figure 13) between Calibrations 2 and 1 do not show spatial patterns resembling absolute bias (Figure 4), correlation coefficient (Figure 6), and CRPS skill score (Figure 8). In addition, the t-test suggested that differences in alpha index between Calibrations 2 and 1 are not statistically significant for most lead times (Table S2).

3, Although Improvements in absolute bias, correlation coefficient, and CRPS skill score measures different features of the improvements (explain in our point 1 of the our response to this current comment), their spatial patterns are generally consistent. We calculate the spatial correlation for changes in CRPS skill score vs. changes in absolute bias (figure 8 vs. figure 4), and the spatial correlation for changes in CRPS skill score vs. changes in correlation coefficients (figure 8 vs. figure 6). As is shown in the following figure, the spatial patterns of CRPS skill score improvements are generally consistent with the reduction in absolute bias (negative r values), and increases in *r* (positive r values).



4, The upper and lower limits used for the maps may have affected our understanding of the spatial patterns of the evaluation metrics. Following comparison shows that when using narrower limits (-3% to 3%, rather than -5% to 5%) for the color bar of the maps showing improvements in correlation coefficients (figure on the right), the spatial pattern is more consistent with the maps showing increases in CRPS skill score (Figure 8). In the revised manuscript, we use the plot with narrower color bar limits in the revised manuscript.





To explain spatial patterns of the evaluation metrics, we add a new subsection to the Results section (3.7 Summary of results):

"Although the selected metrics measure different aspects of forecast quality, they generally agree with each other in demonstrating improvements in calibrated ETo forecasts with the adoption of the Strategy ii. As introduced in the Method section, the CRPS skill score measures the performance of the calibrated forecasts relative to climatology forecast; correlation coefficient shows consistency between observations and forecasts in temporal variability; bias measures average differences; the α-index is an indicator showing whether the distribution of calibrated forecasts is overconfident or underconfident. As a result, these metrics differ from each other when used to measure differences between different calibrations (Figures 4, 6, and 8). However, these three metrics are generally consistent in the spatial patterns of improvements. As demonstrated in Figure 4, the alpha index showed fewer decreases at longer lead times than other metrics, indicating that α-index is less sensitive to changes in the quality of calibrated forecasts. That is why the adoption of calibration Strategy ii did not lead to significant changes in the α-index."

Point #13

P16 l329: Results on calibration 2 and 4: what is the comparison between 2 and 4? Why are these only addressed in the evaluation of forecast accuracy section? Why is there no mention of these for the bias and reliability evaluation? I suggest changing the section order and moving this section first. Then, add a sentence in the bias and reliability section to explicitly communicate what results of experiment 3) and 4) are not presented and why.

Response: Thank you for the valuable suggestions. We check the original submission and believe your comments refer to Calibrations 3 and 4 here.

As we explain in our response to your comment #5, calibrations 3 and 4 are to further confirm that whether our strategy is suitable for general application. We further explain the reason of by adding the following sentences to clarify why Calibrations 3 and 4 are included in this study in Method:

“The comparison between Calibrations 1 and 2 is to investigate whether the bias-correction of input variables would further improve ETo forecasts when the calibration is conducted based on ETo anomalies and climatological mean. We also conduct additional calibrations which post-process ETo forecasts directly (Calibrations 3 and 4), to test whether the contribution of improving the input variables to ETo forecast calibration, if there is any, will depend on how ETo forecasts are calibrated (based on anomalies vs. based on original ETo forecasts). Calibrations 3 and 4 will help evaluate the feasibility of strategy ii for the general application in NWP/GCM-based ETo forecasting. Key steps of the four calibrations could be found in the schematic diagram (Figure S1). In the main text, we primarily analyze results from Calibrations 1 and 2. Improvements with the adoption of bias-correction to input variables in Calibrations 3 and 4 are very similar to those of Calibrations 1 and 2 (see the Supplementary Material). To avoid redundancy, we present results from Calibrations 3 and 4 in the Supplementary Material.**”**

As we introduced in our response to your comment point #5, we add more results (bias, correlation, and alpha-index) from Calibrations 3 and 4 to the Supplementary material and one new subsection (3.6) to briefly introduce these figures (Figures S15-S18).

Point #14

Discussion:

There are little to no direct comparison of results and calibration work presented here to any previous methods or studies (which were mentioned in the introduction). To address a research closure, please put the work presented in this paper in context with other studies applying strategy 1 and strategy 2.

Response: We appreciate the reviewer’s valuable suggestion. We explain in detail why we do not compare our calibration directly with calibrations using other models in our response to your comment #3. However, we totally agree with the reviewer that it is necessary to compare our results with previous investigations in ETo forecasting to help the audience better understand the performance of our model. Therefore, we add the following contents to the Discussion:

“This investigation further highlights the importance of statistical calibration in improving the quality of raw ETo forecasts (Medina and Tian, 2020). In the ETo forecasting across 40 sites in Australia, although raw ETo forecasts constructed with NWP outputs reasonably captured the magnitude and variability of ETo, forecast skills better than climatology were only found for the first 6 lead times (Perera et al., 2014). Our investigation suggests that statistical calibration could substantially improve forecast skills and outperform the climatology forecasts for all 9 lead times across Australia. The findings of this investigation agree well with the site scale short-term ETo forecasting based on GCM outputs (Zhao et al., 2019a) in terms of improvements in forecast skills. Calibrated forecasts from Calibration 2 demonstrate similar skills as those of Zhao et al. (2019a). However, our calibration achieves the improvements using much shorter archived raw forecasts (3-year vs. 23-year) than Zhao et al. (2019a), thanks to the capability of SCC in calibrating short-archived forecasts (Wang et al., 2019). Calibrated forecasts from Calibration 2 also demonstrate comparable biases (0.32-0.95%) with calibrated ETo forecasts (0.49-0.63%) in the U.S. based on the Bayesian model averaging (BMA) model and weather forecasts from three NWP models during 2014-2016 (Medina and Tian, 2020)."

In addition, we also highlight the importance of testing the proposed calibration strategy (strategy ii) in the future in section 4.2, in the hope that this strategy will be tested b based on other calibration models:

“Second, further investigations based on other calibration models are needed to validate the conclusions of this investigation. Our analyses based on two different methods (based on ETo anomalies vs. based on original ETo) find similar improvements in calibrated ETo forecasts with the adoption of bias-correction of input variables. Additional evaluations using other calibration models will be needed to ascertain whether the improvements will be achieved when the calibration is conducted with a different model.”

Point #15

It is unclear whether authors recommend the use of experiment 2) or 4), when and why. In that sense, I question again the inclusion of these experiments without further elaborating and discussing these results.

Response: Thank you for the valuable suggestion. As we explain in our response to your comments #5 and #13, the objective of this study is to evaluate the necessity of correcting the input variables prior to ETo calibration. We also further explain that including Calibrations 3 and 4 was to further evaluate whether the strategy could be generally applied to other calibration models in the revised manuscript. In addition, we add results from Calibrations 3 and 4 and discussed implications from these two calibrations:

“We also compare the bias, correlation coefficient, CRPS skill score, and reliability of calibrated forecasts from Calibrations 3 and 4, to evaluate whether we can obtain similar improvements through the bias-correction of input variables if we conduct the ETo forecast calibration in a different way (without using climatological mean and anomalies). Results show that the adoption of bias-correction also leads to lower bias, higher correlation coefficient, and higher CRPS skill score in terms of magnitude, spatial patterns, and trend along the lead times, when ETo forecasts are calibrated directly (Figure S15-S17). In addition, the alpha index was only slightly different between Calibrations 3 and 4 (Figure S18). This additional comparison further confirms the general applicability of strategy ii for enhancing NWP-based ETo forecasting.”

Point #16

Structure:

The introduction is well structured and appropriately present previous work studies and existing strategies.

Response: We appreciate your constructive comments.

Point #17

The title is a bit lengthy, authors could consider shortening it.

Response: We change the title from:

“Bias-correcting individual inputs prior to combined calibration leads to more skillful forecasts of reference crop evapotranspiration**”**

to:

"Bias-correcting individual inputs enhances forecasting of reference crop evapotranspiration."

Point #18

As noted above, I suggest authors consider the order of results presented in the context of results from experiment 3) and 4).

Response: As we explained in our response to your comments #5 and #13, we add a new subsection (3.6) to present results from calibrations 3 and 4 and discuss implications of these two Calibrations.

Point #19

Minor comments:

P4 l106: I suggest adding a diagram clearly explaining steps and differences of procedure between the calibration experiments.

Response: We appreciate the valuable suggestions and create a diagram to show the key steps of the four calibrations

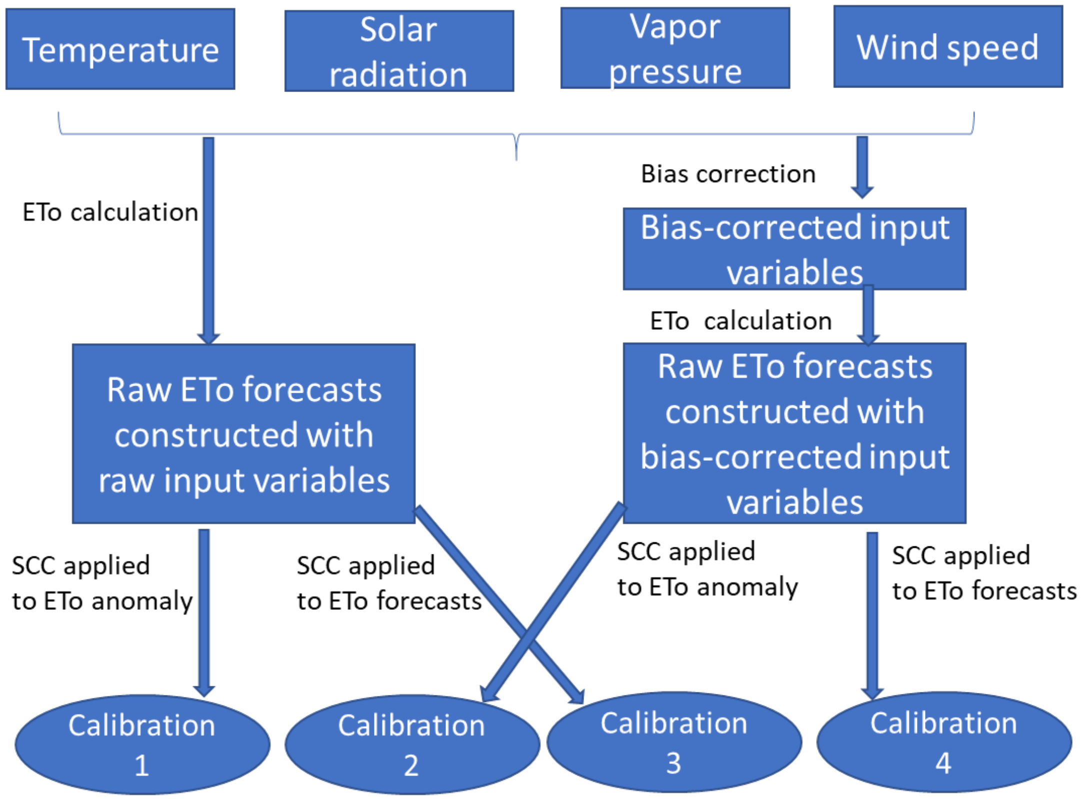

Temperature
Solar radiation
Vapor pressure
Wind speed
ETo calculation
Bias correction
Bias-corrected input variables
ETo calculation
Raw ETo forecasts constructed with raw input variables
Raw ETo forecasts constructed with bias-corrected input variables
SCC applied to ETo anomaly
SCC applied to ETo forecasts
SCC applied to ETo anomaly
SCC applied to ETo forecasts
Calibration 1
Calibration 2
Calibration 3
Calibration 4

Figure S1. Schematic of the four calibrations

Point #20

P3 l68: '…pressing need to investigate.' Please expand why it is pressing?

Response: Thank you for the comments. ETo forecasts have been increasingly used in planning of farming activities (e.g., amount and timing of irrigation) in Australia. We improve this sentence as follows:

"Since NWP/GCM-based ETo forecasting is increasingly conducted to support water resource management, there is a need to investigate the necessity of correcting raw forecasts of the input variables as part of ETo forecast calibration, to provide high-quality ETo forecasts."

Point #21

P3 l74: Calibrate should be calibrate with small cap letter.

Response: Thank you for the careful review. We correct this typo.

Point #22

P3 l80-84: There are many efforts to develop downscaling methods, please comment on what was been done here to downscale ACCESS-G2 to the AWAP grid. Why not scaling AWAP to the match the forecast grid?

Response: Thank you for the valuable suggestions. In the revised manuscript, we further introduce that we used bilinear interpolation to remap ACCESS-G2 forecasts. Meanwhile, we agree with the reviewer that sophisticated methods have been developed to downscale coarse resolution forecasts to match observations.

In this study, the purpose of the regridding is to connect forecasts with the corresponding observations so we can calibrate the forecasts, rather than trying to reconstruct the spatial patterns of forecasts at a finer scale.

We conducted a literature review on the remapping methods used in forecasts post-processing. It is common that raw forecasts and references data have different spatial resolutions. We found that bilinear interpolation of forecasts from a coarser resolution to a finer resolution has been widely used in forecast post-processing and verification. For example, Hamill et al. (2015) used bilinear interpolation to downscale the resolution of Global Ensemble Forecast System (GEFS) forecasts from 1° to 1/8° to match observations before post-processing with an analogy-based model. Yuan et al. (2014) used bilinear interpolation to remap the Global Ensemble Forecast System (GEFS, with resolutions of ~0.469° and ~0.625°) to match the North-American Land Data Assimilation System (NLDAS, with the resolution of 1/8°), before the forecasts were post-processed with a quantile mapping method. Zeng and Yuan (2018) used bilinear interpolation to remap sub-seasonal to seasonal forecasts from ECMWF (0.25°X0.25°to 0.5°X0.5° for different lead times), NCEP (1°X1°), China Meteorological Administration (CMA, 1°X1°), Hydrometeorological Centre of Russia (HMCR, 1.1°X1.4°), and Australian Bureau of Meteorology (BoM, 2°X2°) to a common resolution of 0.7°, in order to match the reanalysis data. James et al. (2017) regridded the wind forecasts with bilinear interpolation from the 3-km High-Resolution Rapid Refresh (HRRR) NWP model to an observation tower in Colorado to evaluate forecast quality. Bowler et al. (2008) interpolated the ECMWF forecasts with a grid spacing of 1.5° bilinearly to the site scale for forecast verification. Yuan and Wood (2012) used bilinear interpolation to match forecasts from the Euro- Mediterranean Centre for Climate Change (CMCC-INGV), the European Centre for Medium-Range Weather Forecasts (ECMWF), the Leibniz Institute of Marine Sciences at Kiel University (IFM-GEOMAR), Météo France, and UK Met Office (UKMO), which have a spatial resolution of 2.5° to match the observation of 1°.

As a result, previous investigations suggested that downscaling with a sophisticated method could potentially be useful, but that is not necessarily essential in forecast post-processing, and bilinear interpolation is acceptable.

However, we agree with the reviewer that it is necessary To acknowledge this need, we add the following sentence to section 4.2 Implications for forecasting of integrated variables and future work:

"In the future, more sophisticated remapping method should be adopted to investigate the impacts of grid cell regridding on forecast calibration."

Reference:

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James, E.P., Benjamin, S.G., Marquis, M., 2017. A unfied high-resolution wind and solar dataset from a rapidly updating numerical weather prediction model. Renew. Energy 102, 390–405. https://doi.org/10.1016/j.renene.2016.10.059

Monteiro, J.A.F., Strauch, M., Srinivasan, R., Abbaspour, K., Gucker, B., 2016. Accuracy of grid precipitation data for Brazil : application in river discharge modelling of the Tocantins catchment. Hydrol. Process. 30, 1419–1430. https://doi.org/10.1002/hyp.10708

Yuan, X., Wood, E.F., 2012. On the clustering of climate models in ensemble seasonal forecasting. Geophys. Res. Lett. 39, 1–7. https://doi.org/10.1029/2012GL052735

Yuan, X., Wood, E.F., Liang, M., 2014. Integrating weather and climate prediction: Toward seamless hydrologic forecasting. Geophys. Res. Lett. 5891–5896. https://doi.org/10.1002/2014GL061076.Received

Zeng, D., Yuan, X., 2018. Multiscale Land – Atmosphere Coupling and Its Application in Assessing Subseasonal Forecasts over East Asia. J. Hydrometeology 19, 745–760. https://doi.org/10.1175/JHM-D-17-0215.1

Point #23

P4 l100: please add a comment that SCC model will be described in section 2.3.2

Response: We added the following sentence to this section:

"Details of the SCC model are presented in section 2.3.2**"**

Point #24

P5 l134 climatological means or mean? Please rephrase and clarify this sentence.

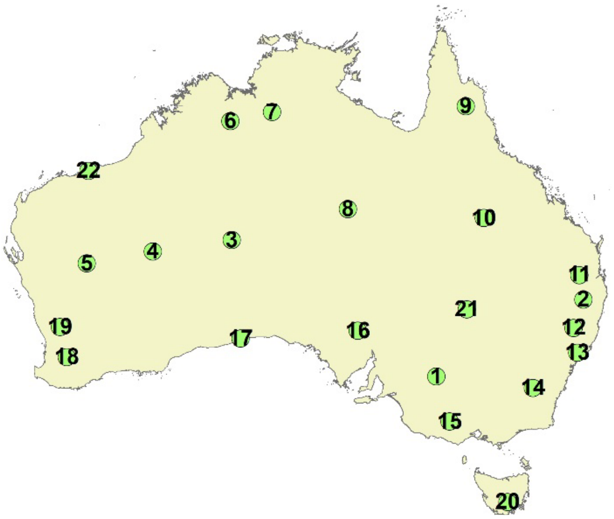
Response: Thank you, and we change it to 'climatological mean'

Point #25

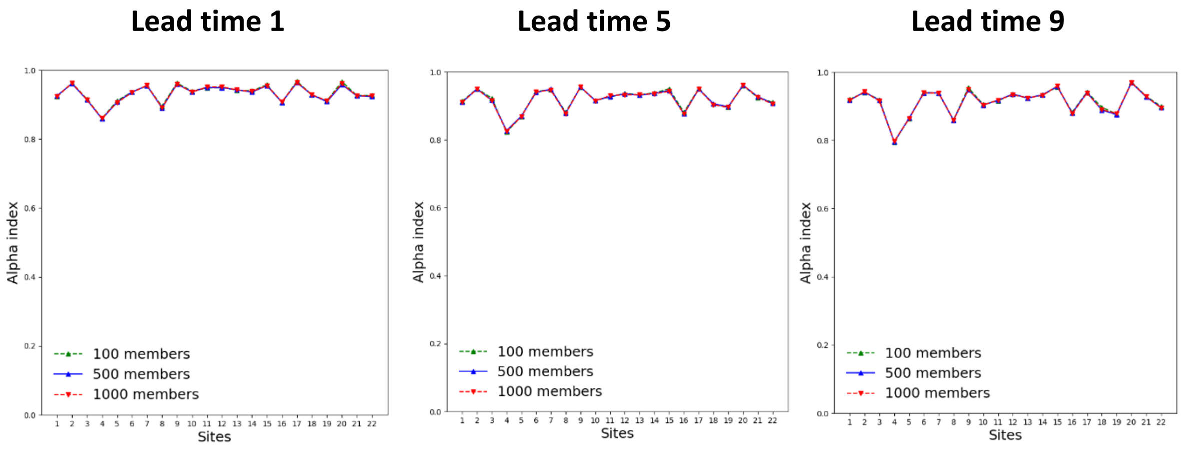
P6 l165: Why are only 100 members drawn, is there any difference with a varying number of ensemble members for forecast reliability?

Response: Thank you for the comments. We use 100 members because the computation cost is more affordable than using a larger ensemble size.

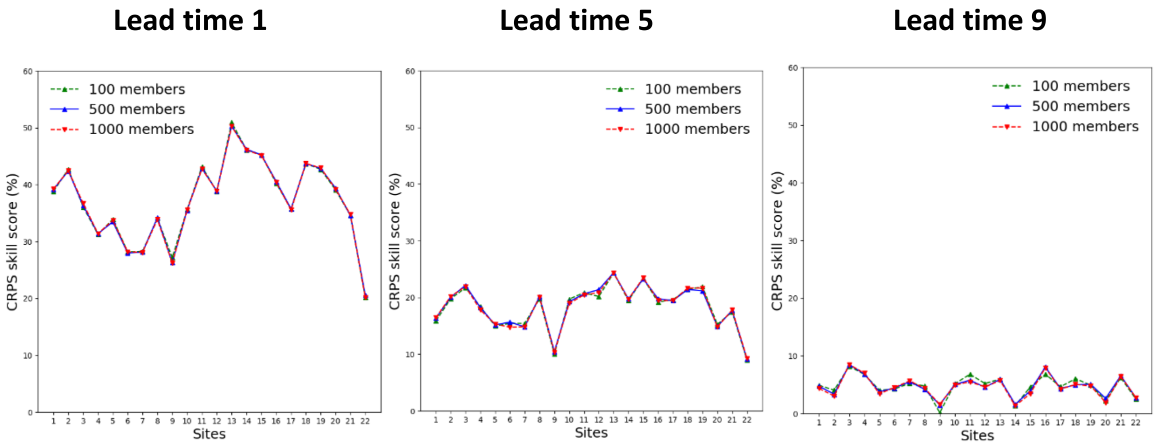
In order to evaluate how different ensemble sizes would affect the reliability and skills of forecasts, we choose 22 sites randomly across Australia and compare the alpha index and CRPS skill score across these sites using 100, 500, and 1000 ensemble sizes. The following map shows the locations of the 22 sites.



The following figure shows the alpha index is almost identical across the selected sizes for the three ensemble sizes:



Comparison of CRPS skill score shows that different ensemble sizes have negligible impacts on the score:



As a result, we conclude that the ensemble size used in this study is reasonable.

Point #26

Is there a need or a reason to verify accumulated Eto forecast values across lead times (as is often the case for streamflow forecasting)? Please comment.

Response: Thank you for the comments. For short-term weather forecasts, which are issued on a daily basis, users are often interested in the short-lead-time forecasts (e.g., lead times 1 to 3). Accumulated forecasts across all lead times will not provide the information that users are particularly interested.

In addition, the evaluation by lead time shows that improvements with the adoption of the new calibration strategy (Calibrations 2 and 4) decrease with lead time, but still show better

performance than the calibrations (Calibrations 1 and 3) without correcting input variables, event at lead time 9. As a result, we are confident that evaluation based on accumulated ETo will not change the conclusion of this study.

Point #27

P8 l225: 'wind speed is higher than 1m/s than the reference in Australia'. Could you please translate that in terms of percentage so that this statement can be more easily compared to other locations.

Response: We add more quantitative information in the evaluation of raw forecasts of input variables:

“The daily minimum temperature (Tmin) is underpredicted by more than 15 °C in western and central parts of Australia by the raw forecasts, but is overpredicted by ca. 1 °C in eastern and southern Australia. Forecasted wind speed is higher than the reference data by more than 1m/s (or by ca. 63%) in most parts of Australia. Similarly, raw solar radiation forecasts are about 5% higher than AWAP data across Australia. Vapor pressure is underpredicted in western and central regions by ca.14%, but is overpredicted by ca. 6% in coastal areas of south-eastern Australia by the raw forecasts.**”**

Point #28

P18 l380' NWP outputs have been increasingly used for ETo forecasting.' For which applications? Please finish the sentence.

Response: We modify this sentence as follows:

" NWP outputs have been increasingly used for ETo forecasting to support water resource management."

Point #29

P18 l385 Addition 'of' in … skill 'of' the calibrated ETo forecasts.

Response: We add the missing ‘of’ to this sentence:

“With this extra step, the bias, correlation coefficient, and skills of the calibrated ETo forecasts are all improved, particularly for the short-lead-time forecasts.**”**

Point #30

References:

Pappenberger, F., M. H. Ramos, H. L. Cloke, F. Wetterhall, L. Alfieri, K. Bogner, A. Mueller and P. Salamon (2015). "How do I know if my forecasts are better? Using benchmarks in hydrological ensemble prediction." Journal of Hydrology 522: 697-713.

Response: We cited this paper in the revised manuscript in introducing the CRPS skill score.