

Responses to RC1 of “Comparison of BARRA and ERA5 in Replicating Mean and Extreme Precipitation over Australia” by Cheung et al.”

The authors have evaluated BARRA and ERA5 reanalysis data against observed precipitation across Australia, following a comprehensive literature review of previous evaluations of ERA5/ERA Interim and BARRA. Unlike earlier assessments of BARRA that primarily focused on precipitation climatology, this study emphasizes precipitation extremes, temporal correlation, and long-term trends. The evaluation provides valuable guidance for users regarding data analysis and model evaluation based on BARRA data. The manuscript concludes that BARRA exhibits a larger overall bias than ERA5 concerning precipitation extremes. However, the authors do not explain the potential sources of this bias. More analysis or discussions are necessary before the manuscript can be considered for publication in HESS. Detailed comments are as follows:

Responses:

We appreciate the comment from RC1 that our study would provide valuable guidance for users applying BARRA data. We accept your suggestion to increase discussion on the potential sources of biases in BARRA. Following your comments in the following, we will add more analysis and discussion to enhance our manuscript in this aspect, as detailed in responses to the specific comments.

Major Comments:

1. Clarification of BARRA Data: Please provide additional information about the BARRA dataset. For instance, is ACCESS, used to construct BARRA, a regional climate model? What large-scale forcing data was used to drive the regional climate model? What observational data were assimilated into the BARRA dataset? Specifically, was observational precipitation included in the assimilation process? This information is crucial for understanding the results presented in the manuscript.

Responses: The following discussion on BARRA’s background information has been added to the revised manuscript.

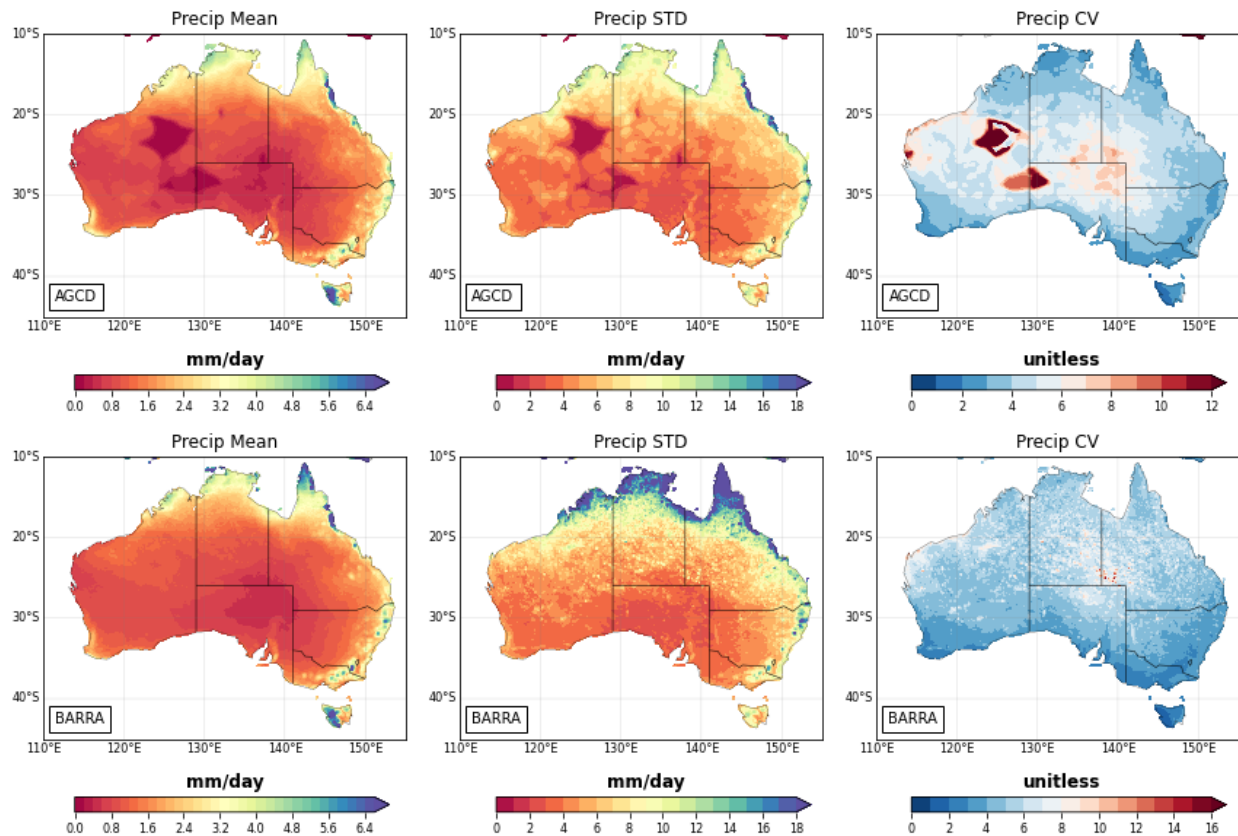
The Bureau of Meteorology (BoM)’s ACCESS model, which was applied to generate BARRA, originated from the UKMO’s Unified Model (UM), which can be configured in global mode or regional mode. For regional simulations, the global version of ACCESS becomes ACCESS-R. ACCESS-R was initialized by ERA-Interim reanalysis data, which also provides boundary conditions during simulation. A series of observations have been assimilated into BARRA, including land and ship (buoy) synoptic observations, upper-air observations from radiosondes and wind profilers, satellite derived radiances and winds (Su et al. 2019). However, no precipitation observations were directly assimilated.

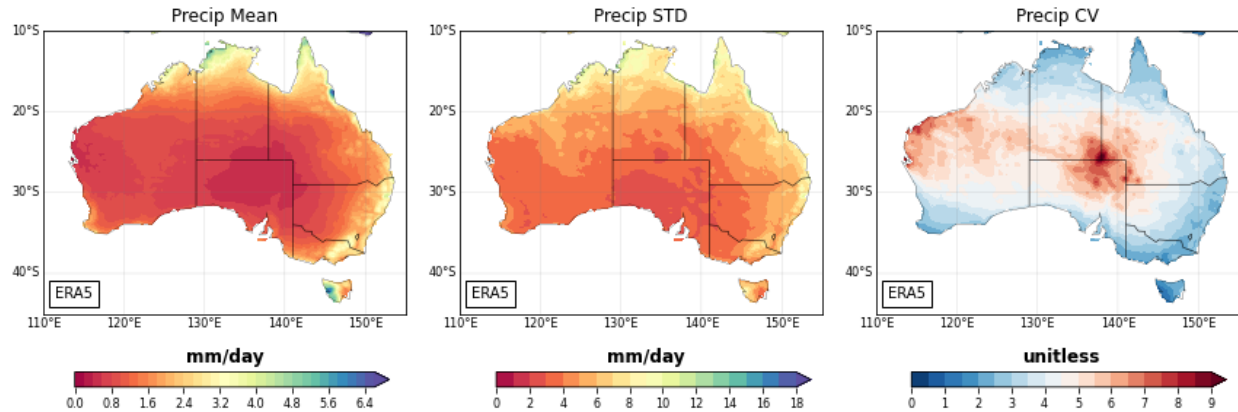
2. Evaluation of Precipitation Extremes: Section 4.1 evaluates the annual mean precipitation derived from BARRA and ERA5, which is partly related to precipitation extremes. It would be desirable to further assess precipitation on a day-to-day basis, such as the correlation and

variance of daily precipitation. From a probability density distribution perspective, both the mean and variance influence extremes. To what extent is the bias in precipitation extremes related to mean and variance biases?

Responses:

Thank you for this comment. In our study, the mean bias and CV do measure the accuracy of mean and standard deviation in the density distribution of precipitation on interannual timescale. We agree that it is highly desirable to examine day-to-day variability of precipitation based on our evaluation measures, a timescale of which influences from transient synoptic to mesoscale weather systems are important. However, it is quite outside the original scope of our study. Out of curiosity, we have examined mean precipitation, standard deviation and CV based on daily data from AGCD, BARRA and ERA5, as shown in the following figures. It can be seen that on daily timescale their patterns of standard deviation and CV deviate from each other quite substantially. We will put such a daily evaluation as a follow-up study of the current one.





3. Investigation of Reanalysis Biases: The manuscript lacks an investigation or discussion regarding the sources of reanalysis biases. BARRA was constructed based on the ACCESS model with the assimilation of observational data. It appears that the regional climate model (RCM) used to construct BARRA was driven by ERA-Interim. Do ERA-Interim and BARRA exhibit similar biases in precipitation extremes? To what extent does the BARRA inherit biases from ERA-Interim? What role does the parameterization scheme of the RCM play in precipitation biases?

Responses:

To further our response to point #1, the RCM used in BARRA (i.e., ACCESS-R) was driven by ERA-Interim reanalysis. Detailed comparison between the biases in BARRA and ERA-Interim, when evaluated against BoM's in-situ observations, have been performed in Su et al. (2019). In general, BARRA shows better agreement with point-scale observations of 2-m temperature, 10-m wind speed and surface pressure. Some biases of BARRA are indeed inherited from ERA-Interim, such as negative biases in strong wind speed. Monthly time series from BARRA and ERA-Interim (e.g., for maximum and minimum temperature and precipitation) during the evaluation period in Su et al. (2019) (2003–2016) also show similarities. Both BARRA and ERA-Interim did not assimilate observed precipitation directly, and in the 12-km grid BARRA did apply convection parameterization (the mass flux convection scheme of Gregory and Rowntree 1990). BARRA have better similarities with AWAP, the gridded observational dataset of BoM's rain gauges, than ERA-Interim, especially in terms of frequency statistics for heavy rain events and annual mean.

Other Comments:

L42 and elsewhere: Since ERA5 and BARRA are not solely model outputs but also results of extensive observational data assimilation, the statement "Both 'models' reproduce spatial patterns of mean precipitation well" is misleading. The authors may consider replacing "model" with "dataset."

Responses: We have replaced “model” by “dataset” in the revised manuscript.

L232-234 and Figure 2: To my understanding, Figure 2 illustrates the correlation coefficient of annual precipitation between reanalysis and AGCD over the period from 1990 to 2019. This

assesses the ability of reanalysis data to reproduce interannual variation of annual precipitation. How well do the reanalysis datasets reproduce observed day-to-day precipitation variability in various seasons?

Responses: Please see our response to major comments #2.

L259: What is meant by "underestimate biases"?

Responses: Thanks for picking this up. "underestimate biases" was incorrect - we meant both BARRA and ERA5 underestimate the trend. This has been corrected in the revised manuscript.

Figures 3, 4, 6, 7, 8: Please also indicate the significance of bias, trend, or correlation in these figures.

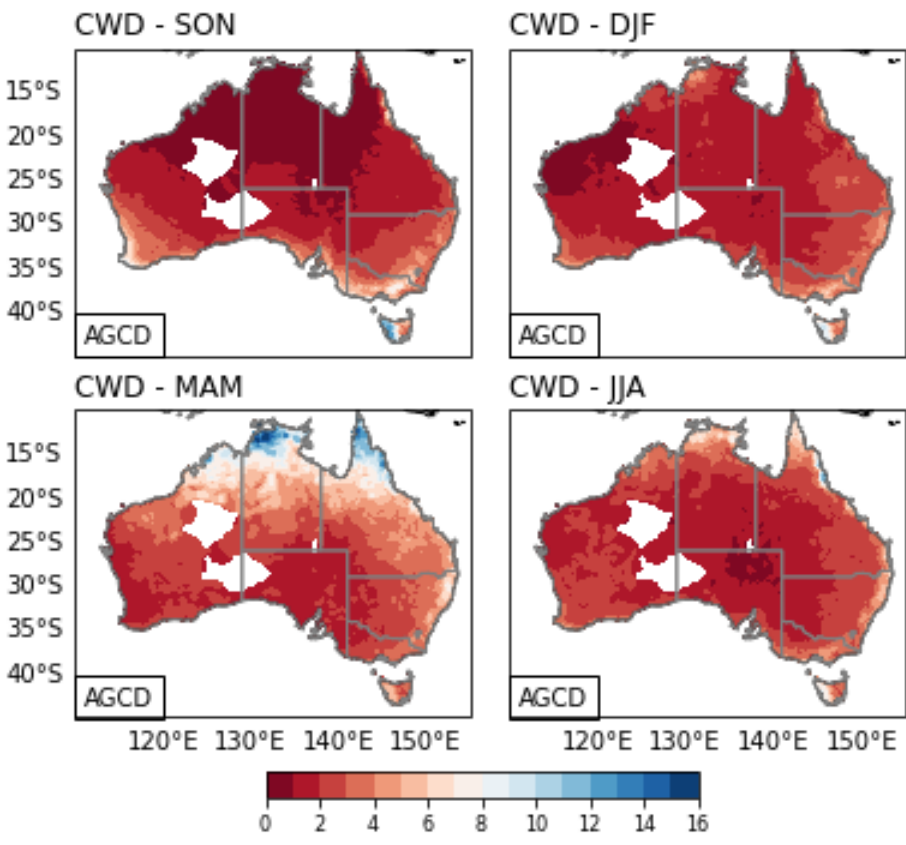
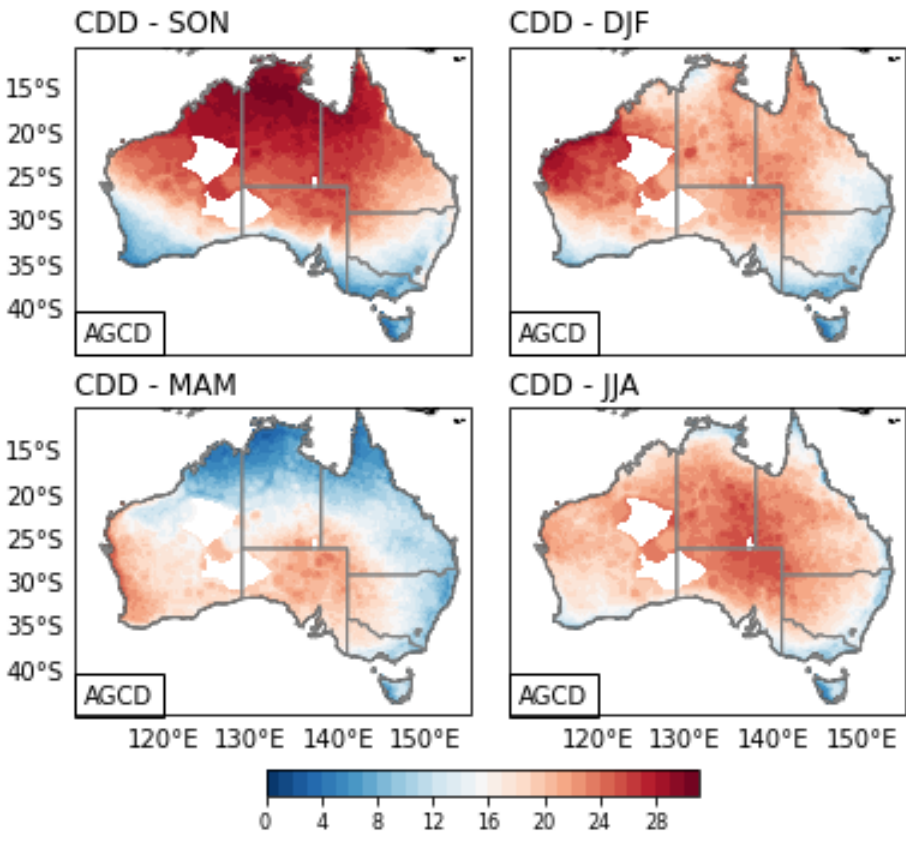
Responses: Thanks for this suggestion. Unfortunately, we have only retained the mean values of trend and CV during the evaluation period but not the entire sample, and thus not able to compute significance of trend and their biases.

Figure 7: Please also evaluate the coefficient of variation (CV) of day-to-day precipitation in different seasons.

Responses: Please see our responses to major comment #2.

L279-281, Figure S7: Both consecutive dry days (CDD) and consecutive wet days (CWD) exhibit longer durations in northern Australia compared to the southern regions. Why is this the case? CDD and CWD usually exhibit opposite changes. Are the CDD and CWD values illustrated in Figure S7 the maximum values observed over one year? The authors may want to evaluate climate extreme indices in different seasons, as northern Australia is influenced by the Asian-Australian monsoon, which presents a distinct annual cycle in precipitation. The climate extreme indices, such as CDD and CWD, can vary significantly across seasons.

Responses: Northern Australia is monsoonal, with very strongly delineated wet and dry seasons. In general, wet seasons (approximately Nov-Mar) are intensely wet, while it seldom rains in the dry season (Apr-Oct). This is why CDD and CWD can both be longer than in southern Australia, which exhibits something like a mediterranean climate. The CDD and CWD values shown in Figure S7 are averaged over the 29-year period. We have examined their values (based on AGCD observations) in four seasons respectively. From the figure below, the clear seasonal variation of the two indices is evident. The highest CDD values at northern Australia occur during spring (SON), which is close to the annual mean pattern. CWD has highest values during autumn (MAM) also at northern Australia and that has been shown in the annual mean as well.



L409-412: Why does BARRA generally perform worse than ERA5? BARRA was produced using a limited-area meteorological forecast model driven by ERA-Interim (Su et al., 2019, GMD). How does BARRA's performance compare with its large-scale forcing data, ERA-Interim, in terms of precipitation? Does BARRA inherit biases from ERA-Interim?

Responses: In our response to major comments #1 and #3 we have briefly summarized the findings in Su et al. (2019) in evaluating BARRA and comparing with the driving reanalysis ERA-Interim. The key points are that BARRA generally agree better with station observations (for surface temperature, winds and precipitation) than ERA-Interim. Indeed, bias patterns and interannual trends in BARRA can be seen to have inherited from ERA-Interim. In this study, on the other hand, we compare BARRA versus ERA5. Thus, relative biases between the two datasets may be related to improvements (in resolution, data assimilation and process representation) of ERA5 over ERA-Interim. Impacts from these improvements are highly complex and inter-related. We will extend our scope in a further study to investigate factors behind differences between BARRA and ERA5. Since ERA5 is currently the most popular dataset for climate evaluation studies, our work has clarified the added-value and inadequacy of BARRA in terms of climate extremes.