Point by Point Response for Reviewer 1

General Comment:

The paper describes a set of drought projections for Australia developed by dynamically downscaling CMIP6 global climate models. A possible range of future drought conditions is considered that span multiple emissions pathways and model configurations. Future drought conditions are described through event frequency, duration, spatial extent and time spent in drought, in terms of changes in two commonly used drought metrics. The paper is well-structured, the information is clearly presented and the key results appropriately discussed. I recommend publication after minor revisions, which I describe below.

Response:

We thank the reviewer for the time spent on our manuscript and for the positive and constructive comments provided. Our comments below indicate where we have made changes to the manuscript to address these concerns.

Comment:

One key issue is the use of SPEI. This metric, being the difference between precipitation and potential evapotranspiration, is intended to reflect the atmospheric water balance and thereby give a complementary view to SPI-based drought. However, the use of potential evapotranspiration in the calculation of SPEI makes SPEI unrealistic in many water-limited parts of Australia, where actual evapotranspiration does not approach the potential upper limit. So, any projected worsening of PET-related conditions is merely an indication of an increase in atmospheric demand for moisture, rather than a conclusive reduction in water stores. I suggest this issue is more adequately discussed in the paper, including the implications in the interpretation of SPEI-based projections of drought.

Response:

In accordance with the reviewer's suggestion, we have strengthened the discussion of the SPEI-based drought projections. Specifically, we have added the following in our discussion of the differences between SPI and SPEI (refer to page 22 of our revised manuscript for implementation):

"However, further PET increases which drive SPEI in water-limited regions (Rangelands and Southern Australia) are unlikely to have as much consequence as in humid regions where the potential upper limit of actual evaporation has not already been met."

We further highlight the potential limitation of SPEI in water limited regions (refer to page 23 of our revised manuscript for implementation):

*"On the other hand, there is potential that the SPEI could overestimates future drought magnitudes, **especially in water-limited regions** and may better represent a conservative upper limit of potential future drought risk."*

Additionally, as suggested by the reviewer we have expanded on our discussion of the implications (refer to page 23 of our revised manuscript for implementation):

"It should be noted that increases to SPEI may not necessarily translate into on the ground changes, especially in water-limited environments where PET is already far greater than

precipitation. In these regions, which includes most of Australia the timing and magnitude of precipitation may be a more important consideration, and as such care must be taken when interpreting the SPEI-based drought projections."

<u>*Comment:*</u>
The second key issue is the lack of attention given to the uncertainty of the projections. While using a multi-model ensemble and multiple emissions pathways goes some way to addressing uncertainty, the drought projections should be presented along with quantified uncertainty estimates. Moreover, the issue of uncertainty propagation from GCM through to downscaling technique to RCM was not addressed.
<u>*Response:*</u>
We thank the reviewer for their comment. We had attempted to show the uncertainty from the multi-model ensemble and multiple emissions pathways using timeseries plots of all ensemble members (Fig. 3 and Fig. 4), probability density function plots (Fig. 5 and Fig. 6 and Fig. 8 and Fig. 9), and boxplots (Fig. 11). In accordance with the reviewer's comment, we have updated our spatial maps (Fig. 10 and Fig. S15) to include hatching based on the quantitative signal-to-noise ratio to determine where the climate change signal emerges from uncertainty of the projections. We have updated the caption for this figure and the following text has been added to the methodology to introduce the approach (refer to page 8 of our revised manuscript for implementation):
"To determine where there is confidence in the changes to the drought metrics, we adopt the signal-to-noise ratio to see where the climate change signal emerges over the 'noise' of the model ensemble (Hawkins et al., 2014). Here, the model uncertainty is considered as noise using the standard deviation of the projections (Hawkins and Sutton, 2011). We calculate the signal from the 11-model average, while the noise is derived from the standard deviation of all 15 projections (Chapman et al., 2024). Stippling is shown on the ensemble mean and median change maps where the signal-to-noise ratio is greater than 1.0 (Chapman et al., 2024; Hawkins et al., 2014; Hawkins & Sutton, 2011)."

Additionally, we have added figures to the supplementary materials, showing spatial maps of the 10^{th} and 90^{th} percentile of changes along with the multi-model average (Fig. S16 to Fig. S20). We have also included an additional figure of the changes to precipitation and PET from CCAM in the supplementary materials (Fig. S2). The results section of our manuscript has been updated to reflect these changes (refer to pages 18-19 of our revised manuscript for implementation):
"For the percent time in drought, frequency, and duration of extreme droughts, there were few regions where the signal-to-noise ratio was greater than one for SPI (Fig. 10). Significant increases can be noted in south-west Western Australia, in southern Victoria, southern South Australia and in western Tasmania under the high emissions scenario (SSP370), which are seen to reflect the spatial changes of mean precipitation (Fig. S2). In southwest Western Australia, SPI related extreme droughts were projected to occur both more frequently and last longer, leading to considerable increases in the percent time in drought. By contrast, the increases to the percent time in drought in southern Victoria, southern South Australia and in western Tasmania appears to be principally the result of increased drought frequency, with less clear

changes noted for drought duration. In addition to these regions, there were also significant increases to the percent time in moderate to extreme drought for the Gulf of Carpentaria and Northeastern Queensland for SSP370 by the 2090s (Fig. S15), which was not evident in the extreme droughts. For the remainder of the country, the results of SPI tended to be more uncertain. Interestingly, there were no regions of Australia where there was a significant reduction to the time spent in extreme drought.

For SPEI, there was wide model agreement for more frequent and longer drought events for the majority of the continent, particularly under SSP370 and for the end of the century (Fig. 10). This was especially true for the percentage time in drought, which is the result of both increasing drought frequency and duration. For parts of Northern Australia and Eastern Australia, there was generally less model agreement from the signal-to-noise ratio (as shown by the hatching) and the magnitude of the changes were typically smaller when compared to southern regions and the interior of the continent. Significant differences were noted between the 10th and 90th percentiles of projected changes to both SPI and SPEI, highlighting the uncertainty in these projections (Fig. S16 to Fig. S21)."

We have added the following text to the methodology to highlight how GCMs compare to the RCM used in this study (refer to page 5 of our revised manuscript for implementation):

"In the future, the climate change signal of the host GCMs from downscaling was shown to generally be preserved for precipitation, though with some differences in magnitudes in some regions, particularly in summer. For temperature changes, the downscaled models were shown to have good agreement with the host models across Australia (Chapman et al., 2024)." (p. 5)

We note that PET was derived offline from CCAM using Penman-Monteith reference crop approach using CCAM outputs of solar radiation, vapour pressure, maximum and minimum temperature, mean sea level pressure, and wind speed. As such, we are unable to compare PET projections from CCAM to the GCMs and unable to compare drought metrics derived from the GCMs to CCAM.

<u>*Comment:*</u>

The final key issue is that one of the most crucial findings of the study needs to be made more prominent. The results show that more time is projected to be spent under extreme conditions, both wet and dry, and less time under 'normal' conditions, for some parts of Australia (Table 3). This result should be made more prominent, for example by featuring in the abstract. This result is important because it suggests that the combination of projected changes in the climate system is shifting the dial towards more extreme climatic conditions and motivates future research in understanding the physical processes responsible for the shift.

<u>*Response:*</u>

We thank the reviewer for pointing this out. In accordance with their suggestion, we have added these key findings into the abstract (refer to page 1 of our revised manuscript for implementation):

"Increases to drought appear to have mostly come at the expense of 'normal' climatic conditions, with similar or increased time spent under extreme wet conditions, indicating an overall shift towards more extreme climatic conditions."

And the conclusion (refer to page 25 of our revised manuscript for implementation):
"These increases appear to have largely come at the expense of 'normal' climatic conditions, with little changes or small increases to time spent under extreme wet conditions, pointing towards an overall shift towards more extreme climatic conditions across Australia."

Furthermore, we have expanded on our discussion of future drought by adding the following section in bold (refer to page 22 of our revised manuscript for implementation):
*"Interestingly, the increase in extreme droughts did not lead to a decrease in extreme wetness, but rather mostly reduced time in near normal climate conditions (Table 3). **Indeed, in some regions there was an increase to the time spent in extreme wet conditions in the future, indicating an overall shift towards more extreme climatic conditions**. This was due to a shift in the mean and an overall flattening of the PDFs of SPI and SPEI as seen in Fig. 5 and Fig. 6, leading to more time in drought conditions. Similar PDFs changes have been noted in global assessments of soil moisture, runoff, and the Palmer drought index under CMIP5 and CMIP6 (Zhao and Dai, 2015, 2022)."*

Minor Comment:
L84: this is a bit of a throw away line. I suggest turning this around by stating that since RCMs have been shown to estimate regional rainfall features with higher precision than GCMs, RCMs are more appropriate to study drought on the regional scale.
Response:
In accordance with the reviewer's suggestion, we have changed this line to (refer to page 3 of our revised manuscript for implementation):
"However, while research to date has largely focussed on applying coarse GCM outputs to assess future droughts, RCMs have been shown to have more skill in representing key rainfall features and may therefore be better suited to study droughts at regional scales."

Minor Comment:
Inter-model variability (Figure 11) is shown to be higher for SPEI and some drought characteristics. Can an explanation be offered for why this is? What are the implications of this variability on the interpretation of future drought changes?
Response:
We believe the variability of the projected changes is related to the mean projected change (i.e. the range of changes approximately scales with the mean change). We have therefore added the following into the discussion (refer to pages 20-21 of our revised manuscript for implementation):
"The inter-model variability appears to approximately scale with the mean change in the projections, indicating greater uncertainty for larger changes."
"While the sign of the change is clear in these regions, especially for SPEI, there is considerable inter-model variability in the magnitude of the projected changes (Fig. 11), which may necessitate decision makers to adopt an adaptive approach to planning for these future eventualities."

Point by Point Response for Reviewer 2

General Comment:

The manuscript 'Meteorological Drought Projections for Australia from Downscaled high-resolution CMIP6 climate simulations' presents the future drought features (SPI and SPEI) based on the downscaled precipitation and potential evapotranspiration data. The work is well-presented. However, there are some issues that need to be clarified further before the publication.

Response:

We thank the reviewer for their time and constructive comments on our manuscript. Our comments below show where we have made changes to the manuscript to address these concerns.

Comment:

1. This study utilizes various drought characteristics, including duration, frequency, percent time (Figure 2), and shifts in the moving average, to predict future droughts. However, since the downscaling is applied only spatially, all temporal analyses could be conducted using GCM data. Yet, only Figure 10 presents a spatial map. What is the rationale for using downscaled data in this context?

Response:

We thank the reviewer for their comment. It is important to note that downscaling does improve the temporal and the spatial resolution of the projections (for instance CCAM has sub-daily data available). However, as this analysis was conducted using accumulated monthly precipitation and PET, outputs from GCMs could also be applied as suggested by the reviewer, though at a much coarser spatial resolution. We have found in previous work that downscaling improves the representation of precipitation and temperature, even when assessed at coarse spatial scales (Chapman et al., 2023), which we better highlight in our revised methodology (refer to page 5 of our revised manuscript for implementation):

"The downscaling approach adopted has been shown to significantly improve the performance over the host GCMs for precipitation and temperature in all seasons, with the largest improvements noted for climate extremes, even when assessed across the four Australian IPCC regions (Chapman et al., 2023), which are similar to the NRM super-clusters adopted in this study. Across Australia as a whole, seasonal precipitation was shown to improve in all models, with an ensemble average improvement of 43% using the Kling-Gupta Efficiency, while the annual cycle of precipitation improved in most models with an ensemble average improvement of 13% (Chapman et al., 2023). Downscaling also improved the fraction of dry days, reducing the bias for too many low-rain days. These improvements have clear beneficial effects for the simulation of future droughts."

The data visualization of such a complex analysis involving multiple sources of variation (i.e., emissions scenarios, time horizons, drought characteristics, drought severities and regions) is challenging and maps may not be the best type of graphic to convey the findings and communicate nuances under space constraints. For instance, we made a conscious choice in the manuscript to combine the spatial maps into subplots where possible to allow for an easy comparison of changes to drought characteristics from both SPI and SPEI. For instance, Fig. 10 highlighted by the reviewer contains subplots of 36 maps for extreme droughts. Additional maps of changes to moderate droughts can be seen in the supplementary materials (Fig. S14). We have added additional spatial maps of the 10th and 90th percentile changes to drought metrics to better understand the spatial uncertainty of the projections (Fig. S16 to Fig. S20), as well as maps of changes to precipitation and PET (Fig. S2).

We also wanted to highlight that one of the outputs of this contribution is the dataset of regionalised drought characteristics for Australian Local Government Areas and River Basin (https://doi.org/10.6084/m9.figshare.26343823), which is only possible due to the finer granularity of the downscaled projections. We better highlight this advantage in the methodology (changes in bold; refer to pages 8-9 of our revised manuscript for implementation):
*"Additional supplementary datasets tailoring projected drought impacts to Australian Local Government Areas (**566 sub-regions included**) and River Basins (**219 sub-regions included**) are also made available (Eccles, 2024), **thanks to the high-resolution projections used in this study**."*

Comment:
2. Why did the author choose to use downscaled data from the Conformal Cubic Atmospheric Model (CCAM)? What advantages does CCAM offer compared to other downscaled datasets? Additionally, how can you demonstrate that drought characteristics derived from the downscaled data are more reliable or accurate than those based on raw GCM data?
Response:
The reviewer is correct that there are other downscaled datasets available as part of the CORDEX CMIP6 experiment. However, at the time that this work was undertaken, only the CCAM dataset was available for analysis. This downscaled dataset is also advantageous over other datasets, as it is the largest ensemble available (15 model runs per emission scenario) and run at the highest resolution (10 km). We have added the following text to better highlight this advantage (refer to page 5 of our revised manuscript for implementation):
"This represents the largest downscaled ensemble of projections in Australia ran at the highest resolution."

We adopted reference crop evapotranspiration (PET) for calculating the SPEI, which was derived offline from CCAM requiring daily data for solar radiation, vapour pressure, maximum and minimum temperature, mean sea level pressure, and wind speed. This method for deriving PET is more data intensive and complex than alternatives but provides better estimations of PET compared to pan evaporation or simple temperature-based PET estimations. The approach is not available from other downscaled ensembles or from the raw GCM data. We have added the following to the introduction to better elucidate the advantages of this approach (refer to page 7 of our revised manuscript for implementation):
"This method for deriving PET is more intensive than simpler temperature-based approaches but is recommended where data is available (Beguería et al., 2014; Hosseinzadehtalaei et al., 2017; Sheffield et al., 2012)."

As we have derived our PET offline to CCAM no direct comparison to the host GCMs is possible. We have however, previously compared how downscaling improves the simulation of other variables such as precipitation and temperature, which will have clear benefits for the simulation of droughts. In line with the reviewer's comment, we have added the following to the introduction, which we also highlighted in response to comment 1 (refer to page 5 of our revised manuscript for implementation):
"Across Australia as a whole, seasonal precipitation was shown to improve in all models, with an ensemble average improvement of 43% using the Kling-Gupta Efficiency, while the annual cycle of precipitation improved in most models with an ensemble average improvement of 13% (Chapman et al., 2023). Downscaling also improved the fraction of dry days, reducing the bias for too many low-rain days. These improvements have clear beneficial effects for the simulation of future droughts."

Comment:
3. Is there any result about the comparison between the downscaled data and original data (such as precipitation and potential evapotranspiration) to evaluate the downscaling methods' performance?
Response:
As we note above, we have evaluated the added value of downscaling on precipitation and temperature, and undertaken comparisons with host models for historical (Chapman et al., 2023) and future (Chapman et al., 2024) projections, which we now highlight in the methodology (refer to page 5 of our revised manuscript for implementation):
"The downscaling approach adopted was shown to significantly improve the performance over the host GCMs for precipitation and temperature in all seasons, with the largest improvements noted for climate extremes, even when assessed across the four Australian IPCC regions (Chapman et al., 2023), which are broadly similar to the NRM super-clusters adopted in this study. Across Australia as a whole, seasonal precipitation was shown to improve in all models, with an ensemble average improvement of 43% using the Kling-Gupta Efficiency, while the annual cycle of precipitation improved in most models with an ensemble average improvement of 13%. These improvements have clear beneficial effects for the simulation of future droughts. Downscaling also improved the fraction of dry days, reducing the bias for too many low-rain days. In the future, the climate change signal of the host GCMs from downscaling was shown to generally be preserved for precipitation, though with some differences in magnitudes in some regions, particularly in summer. For temperature changes, the downscaled models were shown to have good agreement with the host models across Australia (Chapman et al., 2024)."

As also noted above, PET was derived offline from the model, and so we could not compare the performance from CCAM and the host GCMs.

Comment:
4. The study area was divided into four distinct regions—Eastern Australia, Northern Australia, the Rangelands, and Southern Australia—based on climatic and biophysical characteristics. However, the specific climatic and biophysical parameters used for this classification were not

explicitly defined. Including detailed information on climate patterns (e.g., precipitation regimes, seasonal variations), dominant vegetation types, and temperature ranges could enhance the clarity of the classification framework. Such specifications would facilitate a more comprehensive interpretation of the analytical results by providing critical contextual information about regional environmental variations.

Response:

We thank the reviewer for pointing out the lack of information regarding how the NRM regions were defined. It is important to note that we did not classify these regions ourselves. Rather, we adopt pre-defined regions classified by Australian Federal agencies to specifically assess climate change in Australia (CSIRO and Bureau of Meteorology, 2015). In accordance with the reviewer's recommendation, we have revised Fig. 1 in the revised manuscript to include the major climate regions as a background and have added a table in the supplementary materials which details the dominant climate and ecological characteristics within each of the super-clusters using information from (CSIRO and Bureau of Meteorology, 2015). We have added the following sentence to the methodology to reflect this change (refer to page 4 of our revised manuscript for implementation):

"Details of the dominant climate zones and ecological characteristics within each of these super clusters are presented in Table S1."

Comment:

5. The discussion's comparative analysis of the SPI and SPEI offers valuable methodological insights. However, stronger integration with region-specific climatic and biophysical drivers would benefit the interpretation. Additionally, the spatial specificity of distinctions between SPI and SPEI across sub-regions remains insufficiently delineated, limiting the granularity of conclusions.

The discussion should also explicitly articulate linkages between index disparities and potential localized environmental drivers, such as land cover status.

Response:

As the reviewer suggests we have expanded our discussion of how meteorological droughts interact with biophysical factors, including land cover in section 4.3 (refer to page 24 of our revised manuscript for implementation):

"Both positive and negative changes in landcover can influence meteorological droughts through changes in precipitation, temperature, and windspeed (due to changing surface roughness), which influence both SPI and SPEI. For instance, in southwest Western Australia largescale anthropogenic landcover changes were shown to partially drive long-term declines in precipitation along coastal regions and increases in inland regions (Pitman et al., 2004; Timbal and Arblaster, 2006). Further landcover changes as a result of climate change or other anthropogenic activities may therefore work to further exacerbate or mitigate future droughts depending on the region and the changes. The projections included in this study include landcover changes which are prescribed according to the emissions scenario (Eyring et al., 2016). These changes are, however, not dynamic or responsive to changes in the climate and as such could respond differently in the future, potentially impacting on the magnitude of the drought changes presented."

We assess NRM regions in the paper to enable the results to be interpretable (more regions require more subplots) and as NRM regions have commonly been used to assess climate change impacts in Australia. We have made available much more granular data as suggested by the reviewer which may be applied for these local-scale analyses. We have added the following text in our discussion to better highlight this fine scale dataset (refer to page 21 of our revised manuscript for implementation):
"We provide supplementary datasets tailoring these projections to Australian River Basins and Local Government Areas (Eccles, 2024). These datasets provide derived drought metrics at a much more granular scale, which may be useful for informing local and regional scale decisions on adaptation and drought preparedness."

Comment:
Can more spatiotemporal visualizations (e.g., seasonal or interannual variability in drought indices in different regions) be incorporated to elucidate sub-regional heterogeneity clearly?
Response:
In line with the reviewer's comment, we have included plots in the supplementary materials showing the interannual variability of projected droughts in each of the regions (Fig. S25 to Fig. S48). As each model has a different sequence of wet and dry events, we show all models so that the interannual variability of the projections is evident. We have added the following to the results section to reflect these changes (refer to page 10 of our revised manuscript for implementation):
"Interannual variability from the different projections in each of the regions are presented in Fig. S25 to Fig. S48."

The focus of our paper was on SPI-12 and SPEI-12 which includes the previous 12 months of accumulated of rainfall (and PET for SPEI), which is not suited to assessing seasonal variability. For this, a 3-month accumulation period would be better suited, which is broadly linked to agricultural droughts but outside the scope of this paper. We adopted a 12-month accumulation period for our assessments of SPI and SPEI as this was considered as a suitable timeframe for water deficits to impact various hydrological and agricultural systems (Zargar et al., 2011).

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