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Key Points:

- Increasing the horizontal resolution alone did not help address problems with simulating regional precipitation in this case study
- Significant model developments are required to reap the benefits of high horizontal resolution

Supporting Information:

Supporting Information may be found in the online version of this article.

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Impact of Higher Spatial Resolution on Precipitation Properties Over Australia

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Abstract Coarse resolution datasets often poorly capture precipitation properties. It is commonly expected that skill at the local level should increase by refining spatial resolution. Here, we examine the influence of spatial resolution on the accuracy of means and extremes in precipitation by comparing high-resolution dynamically downscaled data against the driving lower-resolution reanalysis. We show that the higher-resolution data are less accurate than lower-resolution data for both mean and extreme precipitation. The quantitative deterioration (increase in the domain averaged relative error) from coarse to high resolution varies typically between 1%–8% and 5%–30% for mean and extreme precipitation, respectively. We also find that the finer-scale variability resolved only by the higher-resolution system and successfully predicted by that system is of negligible magnitude compared to the overall error (less than 1%). We conclude that finer-scale resolution by itself does not necessarily bring a meaningful improvement in local simulation accuracy.

Plain Language Summary In this study, we examined the impact of spatial resolution on means and extremes in precipitation using high-resolution dynamically downscaled data against the driving lower-resolution reanalysis over Australia. We report that high-resolution data are less accurate than lower resolution data for standard statistics of precipitation. We also discuss the possible reasons for the deterioration and variations between previous studies. The results highlight that increasing the horizontal resolution alone will not help address problems with precipitation. Significant model developments and data assimilation techniques are required to reap the benefits of high horizontal resolution.

1. Introduction

Changes in global and regional precipitation characteristics are among the most relevant aspects of climate change in a warming world (IPCC, 2021). Climate models are valuable tools for studying climate variability and climate change; however, the current state-of-the-art climate models generally show significant biases in simulating precipitation, especially its extremes (Grose et al., 2020; Kao & Ganguly, 2011; Toreti et al., 2013). Climate models represent small-scale processes such as convection using sub-grid models known as parameterizations, and these parameterizations contribute substantially to uncertainty in precipitation projections (Bony et al., 2015; Daleu et al., 2016; Wilcox and Donner, 2007). Precipitation characteristics are also greatly dependent on topography, orography, and spatial variations, which the coarse resolution of climate models fail to represent accurately.

There are broadly two reasons why a finer grid might improve an atmospheric or climate simulation. First, better numerical resolution of processes such as atmospheric convection, eddies or land-atmosphere interactions and topographic effects could produce *more accurate* calculations on all scales, even to global-scale circulations or phenomena like El Nino. Second, for a given large-scale accuracy, a more refined grid could add *local detail* that a coarser grid cannot resolve. How valuable this detail will depend on the situation; for initial-value numerical weather prediction, for example, any detail that observations can constrain is important, and forecast centers run at the highest affordable resolutions (now approaching 10 km for global domains). For climate applications, the benefits are harder to verify and may derive mainly from detail in the boundary conditions (land surface and orography).

From an ensemble of regional and global climate simulations (RCM and GCM, respectively), previous studies have concluded that precipitation intensity increases with increases in spatial resolution (Bador et al., 2020;

Caldwell, 2010; Kopparla et al., 2013; Rauscher et al., 2016). These studies evaluate outputs from climate models run independently at high and low resolution, respectively. Although these studies provide valuable insights on model performance for simulating precipitation properties based on spatial resolution, the finest spatial resolution of any of the models examined in these studies was 25 km, which is insufficient to resolve convection. The recent intercomparison project on global storm-resolving models, that is, Dynamics of the Atmospheric general circulation Modeled on Non-hydrostatic Domains (DYAMOND), provides 40-day (1 August–10 September 2016) global simulations at less than 5 km spatial resolution (Stevens et al., 2019). Recent studies have evaluated the impact of higher resolution on climate statistics like the diurnal cycle of precipitation, water and energy budgets, location, and width of the Intertropical Convergence Zone (ITCZ), the position of the polar jet and land-sea contrast (Arnold et al., 2020; Hohenegger et al., 2020) using DYAMOND simulations, however, the impact of spatial resolution on precipitation extremes in DYAMOND simulations remains unexplored due to the short period of the available data.

In the last two decades, there has been a growing demand for high-resolution regional climate data using dynamical downscaling (Cabos et al., 2019; Dosio et al., 2015; Evans et al., 2014; Nishant et al., 2021). One of the reasons for producing high resolution regional climate data is that it enables diverse applications ranging from traditional climate studies to industrial applications, including regional climate change impact assessments (Fall et al., 2010) and extreme event reconstructions (Zick & Matyas, 2016).

Sharma and Huang (2012) evaluated climate downscaling experiments driven by NCEP Global Analysis using the Weather Research and Forecasting (WRF) model in a nested setup, that is, where the fine resolution child domain is embedded within the coarse resolution parent domain. They found that refinement of spatial resolution does not guarantee better results and that finer resolution (6 and 3 km) nested runs produced excessive, mean rainfall while the coarser resolution (12 km) simulations were the closest to the observations in terms of relative bias. On the other hand, Jeworrek et al. (2021) evaluated WRF simulations driven by the Global Deterministic Prediction System (GDPS) model. They simulated three nested domains of spatial resolution of 27, 9, and 3 km over the complex terrain of southwest British Columbia. They found that high resolution produced lower relative biases and a more accurate spread in the precipitation intensity distribution, yet higher relative standard deviations of errors (i.e., the RMS difference between forecasts and observations). Similarly, Qiu et al. (2020) using a WRF nested modeling system consisting of a 20 and 5 km domain and driven by ERA-Interim reanalysis, found that high-5-km simulations have lower biases and RMS errors than low-20-km simulations for intensity and frequency of precipitation.

The large-scale drivers in GCMs running independently at fine and coarse resolution can show variance, as these models are designed to balance model resolution, physics complexity and computational requirements. Therefore, disentangling the benefits of spatial resolution from other variabilities in the GCMs running independently at fine and coarse resolution is challenging. However, with nested domain dynamical downscaled simulations, the large-scale drivers remain the same for both resolutions, and thus, such an approach can focus on the impact of finer detail and possible improvements in local accuracy given the same continental-scale conditions. It will not, however, reveal any improvements to continental-scale circulations that could result from using higher global resolution.

Despite the many model-based studies evaluating the impact of spatial resolution on precipitation characteristics, only a few studies have evaluated this with convection-permitting resolution dynamically downscaled data against the driving lower-resolution data (Jeworrek et al., 2021; Qiu et al., 2020). All these studies are moreover based on free-running dynamical downscaled simulations, which gradually deviate from the driving fields due to the accumulation of simulated errors, known as "climate drift" (Mai et al., 2020).

Fortunately, over the Australian continent, there exists high-resolution dynamical downscaled and lower-resolution driving reanalysis data, known as the Bureau of Meteorology Atmospheric high-resolution Regional Reanalysis for Australia (BARRA; Su et al., 2019). The BARRA project delivers Australia-wide (identified as BARRA-R) reanalysis data with approximately 12 km horizontal resolution and additional convection-resolving scale (1.5 km horizontal grid-length) downscaling (BARRA-SY, BARRA-PH, BARRA-AD, and BARRA-TA), nested within BARRA-R, centered on major Australian cities (Sydney, Perth, Adelaide, and Tasmania) generating additional high-resolution information needed for local-scale applications. BARRA-SY, BARRA-PH, BARRA-AD, and BARRA-TA are together referred to as BARRA-C (Su et al., 2021). BARRA-C is like a typical downscaling simulation, except it has a better way of incorporating observed large-scale driving field through initial and boundary conditions (Su et al., 2021). For this reason, BARRA-C should be more accurate than typical climate downscaling (even using reanalysis as a driver), let alone a free-running GCM. This allows a more incisive test of the benefit of resolution, assuming the large-scale fields are close to reality.

Therefore, in this study, we evaluate the impact of spatial resolution on precipitation properties using convection permitting-resolution dynamical downscaled BARRA-C data against the driving lower-resolution BARRA-R reanalysis data over Australia. We examine two research questions. First, does higher resolution improve the accuracy at the coarser scales and by how much? Second, how much finer scale variability, which is not predicted by a lower resolution system, is successfully predicted by a high-resolution system?

2. Data and Methods

2.1. Bureau of Meteorology Atmospheric High-Resolution Regional Reanalysis for Australia (BARRA)

BARRA is the first atmospheric regional reanalysis over Australia, New Zealand, and Southeast Asia available between 1990 and 2019. BARRA-R, which is at a 12 km resolution over Australia, New Zealand and the maritime continent, is produced using version 10.2 of the Unified Model (UM; Davies et al., 2005). The atmospheric model uses a non-hydrostatic, fully compressible, deep-atmosphere formulation. Its dynamical core solves the equations of motion using mass-conserving, semi-implicit, semi-Lagrangian, and time-integration methods. BARRA-R is configured with 70 vertical levels extending from near the surface to 80 km above sea level: 50 model levels below 18 km and 20 levels above this. BARRA-R uses a community land-surface model, the Joint UK Land Environment Simulator (JULES; Best et al., 2011). The land-surface model simulates rainfall partitioning into canopy interception, surface runoff, and infiltration and uses Richards' equation and Darcy's law to model soil hydrology. BARRA-R uses the mass flux convective parameterization scheme of Gregory and Rowntree (1990).

The BARRA-R sequential data assimilation process is initialized using ERA-Interim reanalysis fields (Dee et al., 2011). After the initialization, the only relationship with ERA-Interim is solely through the lateral boundary conditions. Hourly lateral boundary conditions for BARRA-R are interpolated from ERA-Interim's 6-hourly analysis fields at $0.75° \times 0.75°$ resolution. BARRA-R assimilates observations from land-surface stations, ships, drifting buoys, aircrafts, radiosondes, wind profilers, and satellite observations, namely retrieved wind, radiances, and bending angle. Before being assimilated, observations are screened to select the best-quality observations, remove duplicates, and reduce data redundancy (Rawlins et al., 2007).

BARRA-R drives convection permitting (1.5 km) downscaling models over smaller subdomains centered over the Australian capital cities (Su et al., 2021), which will be the regions of study here. These domains are BARRA-SY, BARRA-PH, BARRA-AD, and BARRA-TA, centered on Australian capital cities Sydney, Perth, Adelaide, and Tasmania, respectively. In contrast to statistical or parametric downscaling, BARRA-SY, BARRA-PH, BARRA-AD, and BARRA-TA, that is, BARRA-C, uses dynamical downscaling and incorporates equivalent-resolution 6-hourly BARRA-R data as initial conditions to generate 1.5 km horizontal grids that satisfy dynamical equations of the atmosphere and honor the land surface characteristics and heterogeneity.

BARRA-C is constrained by BARRA-R at the lateral boundaries using the method of relaxation and blending (Bush et al., 2020; Davies et al., 2005). The boundary conditions force the development of the larger-scale features within the BARRA-C domains and ensures the benefits of the BARRA-R reanalysis (i.e., incorporating equivalent-resolution observational data) are inherited by BARRA-C, wherein the nested model is treated as a physically consistent interpolator of the driving model (Su et al., 2021). BARRA-C is run without convection parameterization and relies on the model dynamics to represent convective motions. While convection is still not fully resolved at 1.5 km resolution, removal of the cumulus parameterization has been shown to result in more realistic behavior (Clark et al., 2016).

BARRA-C offers higher resolution in space and time than existing global reanalyzes and has been developed specifically for Australia. Studies have shown that BARRA-C provides a realistic depiction of the meteorology at and near the surface over land as diagnosed by temperature, wind speed, surface pressure, and precipitation (Su et al., 2021).

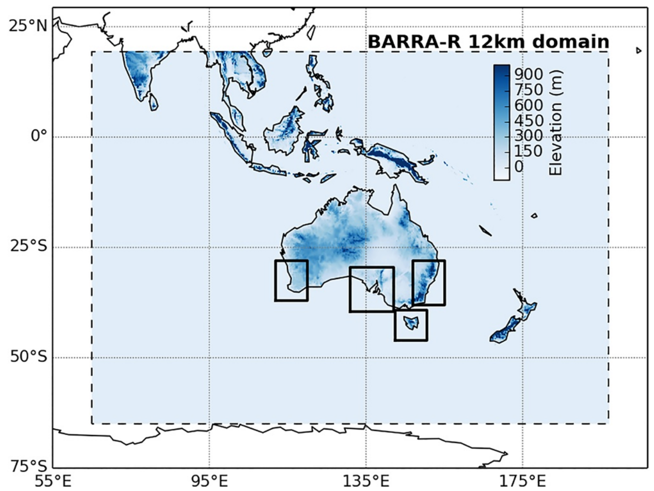

Figure 1. Bureau of Meteorology Atmospheric High-Resolution Regional Reanalysis for Australia (BARRA) domain map. BARRA-R Regional 12 km domain within the light blue dotted box covers all of Australia, New Zealand and the maritime continent. Smaller black boxes are the 1.5 km subdomains centered over some major Australian cities, Sydney, Tasmania, Adelaide and Perth. Source (http://www.bom.gov.au/research/projects/reanalysis/).

2.2. Australia Gridded Climate Data (AGCD)

We use observational precipitation estimates from the AGCD data (Jones et al., 2009; previously known as Australian Water Availability Project [AWAP]) to compare precipitation from BARRA with observations for the historical period, that is, 1990–2019. This daily, gridded precipitation data set has a spatial resolution of 0.05° and is obtained from an interpolation of station data across the Australian continent. Most of these stations are in the more heavily populated coastal areas with a sparser representation inland.

2.3. Methodology

This study focuses primarily on data over the four Australian capital cities using the 1.5 km data from dynamically downscaled domains (BARRA-SY, BARRA-PH, BARRA-AD, and BARRA-TA) and the 12-km reanalysis data over the BARRA-R domain (Figure 1). We perform the analysis for both mean and extreme precipitation. We calculate four annual extreme precipitation indices based on the daily precipitation data. These indices are the annual maximum of daily precipitation (Rx1Day [mm]), annual 99th percentile of precipitation (R99p [mm]), annual 95th percentile of precipitation (R95p [mm]), and number of days when precipitation is greater than 10 mm (R10mm [days]). Each index is computed for each location within the domain using the ensemble of all observing times. These four indices are chosen to capture the intensity, frequency, and duration aspects of the precipitation extremes.

The "Skill metric" we used to evaluate the performance of reanalysis data is simply the relative error in an index, defined in Equation 1, which measures the absolute error relative to the magnitude of the observable.

$$\text{Skill metric}_{ij} = \left|\left(X_{\text{Reanalysis}_{ij}} - X_{\text{Observation}_{ij}}\right) / X_{\text{Observation}_{ij}}\right| * 100 \tag{1}$$

$X_{\text{Reanalysis}_{ij}}$ and $X_{\text{Observation}_{ij}}$ in Equation 1 are the values of one of the above-listed statistics at a single grid point "*ij*" from the BARRA reanalysis and AGCD observation, respectively. The skill metric is calculated on either the 12-km or 1.5-km grids (see below). To address the first research question, that is, whether higher resolution improves the accuracy seen at the coarser scales, we re-gridded all data to 12-km resolution using bilinear interpolation. We use the climate data operator bilinear interpolation tool for re-gridding. To measure the "Accuracy premium," that is, the added value of high resolution, we subtract the skill metric of the re-gridded 1.5-km resolution data from that of the 12-km data at each grid point, as shown in Equation 2.

$$\text{Accuracy Premium}_{ij\cdots 12\text{km grid}} = \left(\text{Skill Metric}_{\text{LR}_{ij}} - \text{Skill Metric}_{\text{HR}_{ij}}\right) \tag{2}$$

Here, $\text{Skill Metric}_{\text{HR}_{ij}}$ and $\text{Skill Metric}_{\text{LR}_{ij}}$ are the skill metric at each 12-km grid point of the high and lower resolution data, respectively. The accuracy premium gives the quantitative measure of the added accuracy of high resolution, with positive values denoting improvement of accuracy relative to the natively 12-km simulation. We also compare the higher- and lower-resolution data for their skill in capturing the domain averaged absolute bias and pattern correlation.

To address the second research question—that is, if the higher resolution data have any skill in predicting the extra detail not predicted by the coarser scales—we instead re-gridded the lower-resolution data to higher resolution (again using bilinear interpolation). We then calculate the accuracy premium again at each 1.5-km grid point using the same methodology as above, that is, subtract the skill metric of the lower resolution data with the skill metric of the higher resolution data (Equation 3).

$$\text{Accuracy Premium}_{ij\cdots 1.5\text{km grid}} = \left(\text{Skill Metric}_{\text{LR}_{ij}} - \text{Skill Metric}_{\text{HR}_{ij}}\right) \tag{3}$$

Here, $\text{Skill Metric}_{\text{HR}_{ij}}$ and $\text{Skill Metric}_{\text{LR}_{ij}}$ are the skill metric at each 1.5-km grid point of the high and lower resolution data, respectively. This accuracy premium ($\text{Accuracy Premium}_{ij\cdots 1.5\text{km grid}}$) is then re-gridded back to coarse resolution that is, 12 km (Equation 4).

$$\left(\text{Accuracy Premium}_{ij\cdots 1.5\text{km grid}}\right)_{\text{regridded to 12km}} = \text{Regridded}\ \left(\text{Accuracy Premium}_{ij\cdots 1.5\text{km grid}}\right) \tag{4}$$

The "geographical skill premium" (Equation 5) is then calculated on the coarse grid by subtracting this re-gridded, 1.5-km skill score (Equation 4) from the previous, 12-km skill score (Equation 2).

$$\text{Geographical Skill Premium} = \Big(\left(\text{Accuracy Premium}_{ij\cdots 1.5\text{km grid}}\right)_{\text{regridded to 12km}} - \text{Accuracy Premium}_{ij\cdots 12\text{km grid}}\Big) \tag{5}$$

Positive values of geographical skill premium indicate that higher resolution has skill in predicting the finer scale variability that is not resolved by the lower-resolution system. To examine the impact of gridding method on the results, we re-did the entire analysis by using climate data operator flux-conserving method and found that re-gridding method has no impact on the results.

3. Results

For mean precipitation (Figures 2a–2d), the high-resolution data show added accuracy (i.e., positive accuracy premium) over the lower-resolution data only over mountains regions in BARRA-SY and BARRA-TA, and western coastlines in BARRA-PH. For most of the inland regions, the high-resolution data shows deterioration in skill (i.e., negative accuracy premium). These results are consistent for all the sub-domains (BARRA-SY, BARRA-AD and BARRA-PH) except BARRA-TA where the skill premium shows large spatial variation in sign and magnitude for both means and extremes in precipitation. The noise over BARRA-TA can be partly explained by the complex terrain over this region which results in uneven distribution of precipitation which both high- and low-resolution data is unable to capture (Figures S1 and S2 in Supporting Information S1).

For extreme precipitation indices we see higher resolution data are typically more inaccurate than lower-resolution data for all the regions (Figures S3–S10 in Supporting Information S1). For R99p and Rx1Day, high resolution BARRA-SY, BARRA-PH, and BARRA-AD data show substantially larger error in comparison to coarse resolution data. Due to this, the skill premium consistently shows large deterioration (more than 20%). Like R99p and Rx1Day, R10 mm also shows similar results that is, deterioration in skill with high resolution for BARR-PH and BARRA-AD. However, here BARRA-SY and BARRA-TA show added accuracy over most part of the domain. For R95p, there is no consistent added accuracy or deterioration throughout the domain, however domain average shows slight decline in skill with high resolution. BARRA-TA shows similar results, that is, noisy spatial pattern of skill premium as mean precipitation for all the extremes.

Overall, high resolution data are less accurate than lower-resolution data for both means and extremes in precipitation. The similarity between the results in mean and extremes of precipitation can be attributed to the fact that model uncertainty in mean and extreme precipitation is tightly coupled (Nishant & Sherwood, 2021). These results are also consistent with Su et al. (2021), who showed that high resolution BARRA-C that is, BARRA-SY, BARRA-TA, BARRA-AD, and BARRA-PH produce too much heavy rain and not enough light rain in comparison to driving lower resolution BARRA-R data. Thus, BARRA-C brings no added value for wet extremes like 95th to 99th percentile of precipitation. Their study was, however limited to added value analysis only at the domain mean level. In contrast, we in this study examine the spatial pattern of added value and find similar results. The authors also argued that the uncertainly in BARRA-C can be potentially due to the still under-resolved convection and the model's inability to resolve detrainment from convective updrafts.

Some of the errors in high-resolution data over the topographically complex areas might be attributable to the limitations in observations over these regions. Chubb et al. (2016) compared AGCD data against a spatially dense independent gauge network in the Snowy Mountains regions of the BARRA-SY domain. Their results suggested that AGCD data underestimated the precipitation amount by about 15% over these regions. They attributed this dry bias to a lack of stations in the area needed to represent the precipitation climatology empirically and the inability of the AGCD analysis to account for the steep topography exposed to the prevailing winds. Due to the uncertainties in the observational data, it is difficult to ascertain whether high-resolution data add information initially missing in the observations or if they add noise over the topographically complex areas.

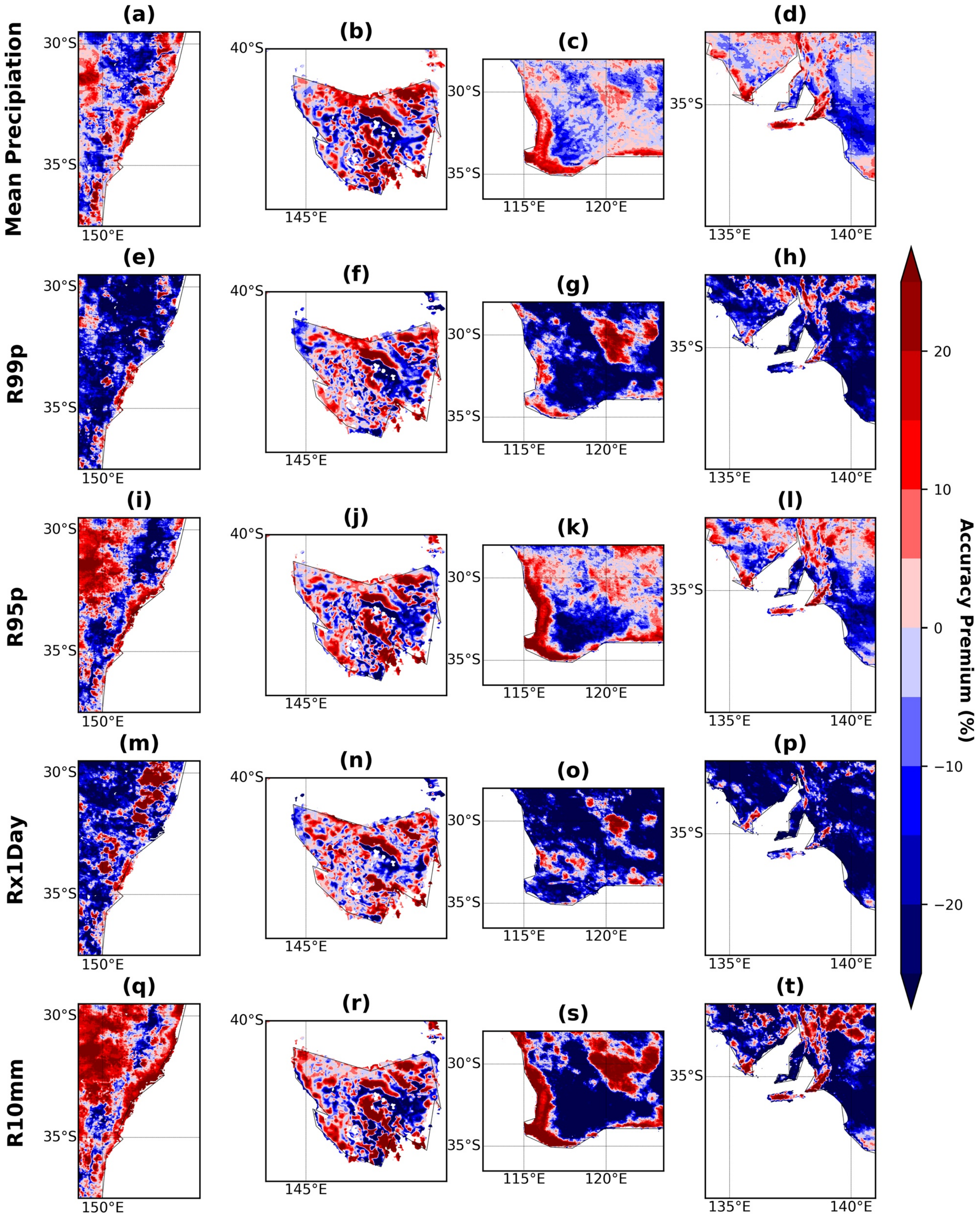

Figure 2. Spatial variation of accuracy premium (added accuracy) added by high-resolution for mean and extremes in precipitation for the BARRA-SY (a, e, i, m, q), BARRA-TA (b, f, j, n, r), BARRA-PH (c, g, k, o, s) and BARRA-AD (d, h, l, p, t). Here, positive values mean added accuracy. Here the first, second, third, fourth and fifth rows show mean, 99th and 95th percentile, maximum 1-day and number of days greater than 10 mm of precipitation, respectively.

Quantitatively for mean precipitation and the extreme measures R99p, R95p, Rx1day, and R10 mm, we see no added accuracy of high-resolution data for all the subdomains except BARRA-SY and BARRA-TA for R10mm. The geographical skill premium, that is, the finer scale variability which is not predicted by a lower resolution system but is successfully predicted by a high-resolution system, is found to be very small (less than ∼1%) and spatially noisy for both mean and extreme precipitation, with no systematic positive tendency except in BARRA-AD (Figure 3).

The evaluation of domain-averaged statistics suggests that high-resolution data deteriorates mean absolute bias and relative bias, whereas it slightly improves pattern correlation (Figure 4). The deterioration in biases is smallest for mean precipitation (between 1% and 8% deterioration in relative bias) and largest for R99p and Rx1Day (between 5% and 30% deterioration in relative bias). R10mm and R95p show similar deterioration as mean precipitation, except for BARRA-SY and BARRA-TA, which show improvement in bias from coarse to high resolution for R10mm. BARRA-SY records the highest biases for both means and extremes in precipitation (Figures 4a–4e), potentially due to the topographical complexity in the domain.

High-resolution data show a slightly stronger pattern correlation with observations than the lower-resolution data for all the analyzed variables (Figures 4k–4o). However, the improvement in pattern correlation between the two resolutions is found to be small. The most significant improvement in pattern correlation from lower to high resolution is seen over the BARRA-SY domain for the same reason discussed earlier in the paper. There are however some exceptions to this pattern. For example, BARRA-TA, shows negligible improvement to slight deterioration in pattern correlation from coarse to high resolution for mean precipitation, R99p and R95p whereas BARRA-AD shows deterioration in pattern correlation for Rx1day. There is minimal difference between lower to high resolution when the data is either re-gridded to 12 or 1.5 km resolution (solid and dotted lines: Figure 4) for all the three metrics, that is, mean absolute and relative bias and pattern correlation.

4. Conclusion and Discussion

In this work, we evaluated the impact of spatial resolution on means and extremes in precipitation using high-resolution dynamical downscaled data (BARRA-C; 1.5 km) against the driving lower-resolution reanalysis data over Australia (BARRA-R; 12 km). We find that high-resolution data are less accurate than low resolution data typically for both mean and extremes in precipitation. Standard statistics of the precipitation distribution (mean precipitation, R99p, R95p, Rx1Day, and R10mm) show negative skill improvement: ∼1%–8% and 5%–30% increase in relative error for mean and extreme precipitation from lower to high resolution. This result occurs even though the higher-resolution simulation incorporates equivalent-resolution BARRA-R data (which is guided by a suite of observations) as initial and boundary conditions, which would not be the case for a global and regional climate model prediction. We also find that finer scale detail, which is represented only by the higher-resolution grid, is a negligible source of additional skill at the local level, either because there is little detail in the rainfall statistics, or it is not well predicted.

These results agree with those of past studies that examined increasing resolution of global simulations (down to ∼25 km) which also found decreasing accuracy (i.e., closeness with observations) in the simulation of precipitation extremes (Bador et al., 2020; Caldwell, 2010; Kopparla et al., 2013; Rauscher et al., 2016). Past downscaling studies with non-parametrized, convection-permitting inner grids have also shown a typical tendency of excessive precipitation extremes and worse bias than with coarser grids, suggesting no added value for precipitation statistics (Chan et al., 2013; Fosser et al., 2020; Kendon et al., 2014; Sharma & Huang, 2012). Our results, however, do not agree with some of the regional model-based studies with a typical high resolution of ∼3–10 km (Jeworrek et al., 2021; Olsson et al., 2015; Qiu et al., 2020; Torma et al., 2015). These studies which kept the convective parameterizations on at the higher resolution, found that higher-resolution model data simulated some precipitation characteristics better than coarse resolution, especially in terms of biases.

We speculate that the differences in findings between the two groups of studies can be attributed to the modeling design. In particular, studies finding added value were based on models in which convective parameterization is used at both finer and coarser scales (Jeworrek et al., 2021; Olsson et al., 2015; Qiu et al., 2020; Torma et al., 2015). On the other hand, the above studies finding no added value are based on models in which convective parameterization is used at the coarser scale but switched off at the finer scale.

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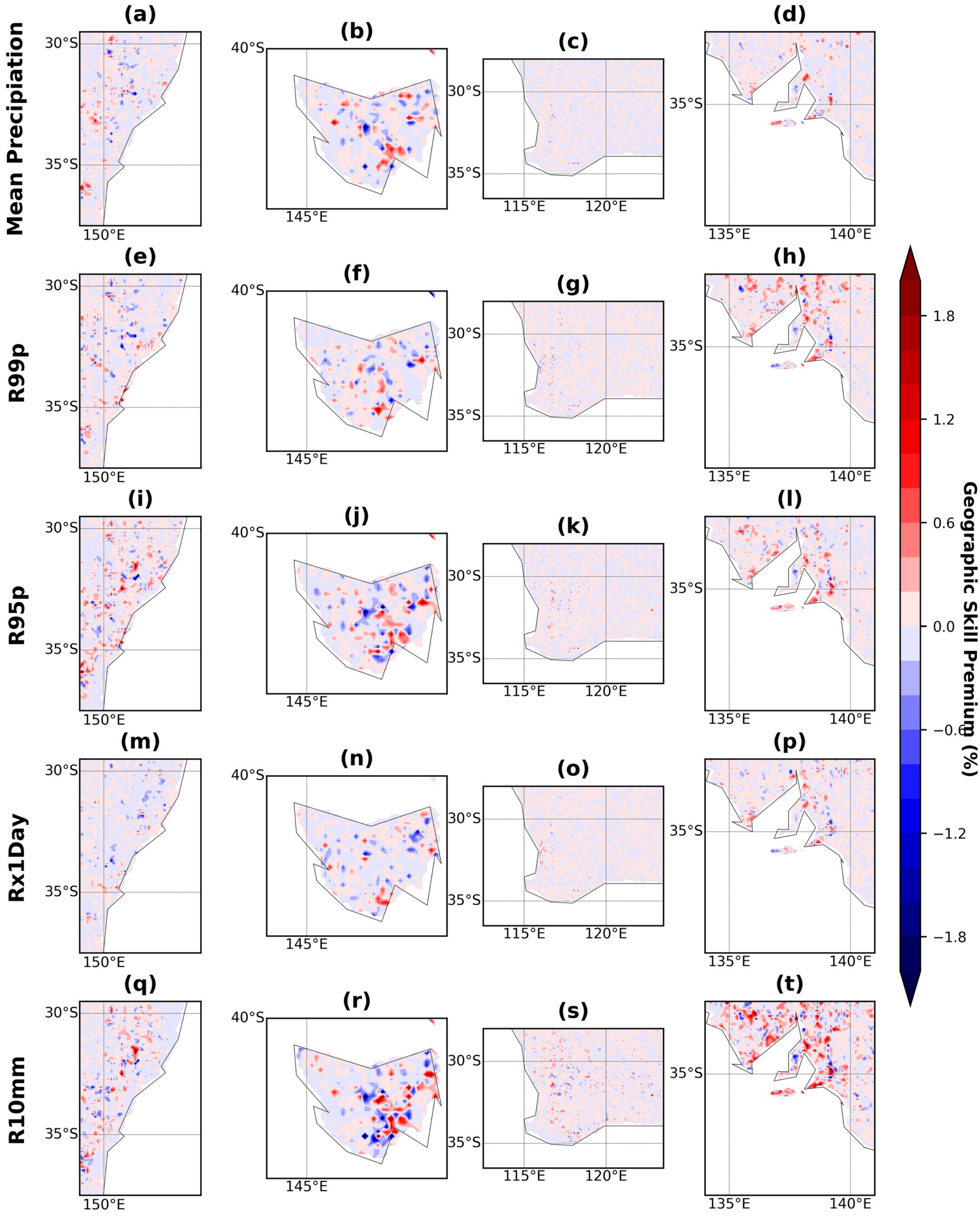

Figure 3. Spatial variation of geographical skill premium added by high-resolution for mean and extremes in precipitation for the BARRA-SY (a, e, i, m, q), BARRA-TA (b, f, j, n, r), BARRA-PH (c, g, k, o, s) and BARRA-AD (d, h, l, p, t). Here, positive values indicate that higher resolution has skill in predicting the finer scale variability that is not resolved by the lower-resolution system. Here the first, second, third, fourth and fifth rows show mean, 99th and 95th percentile, maximum 1-day and number of days greater than 10 mm of precipitation, respectively.

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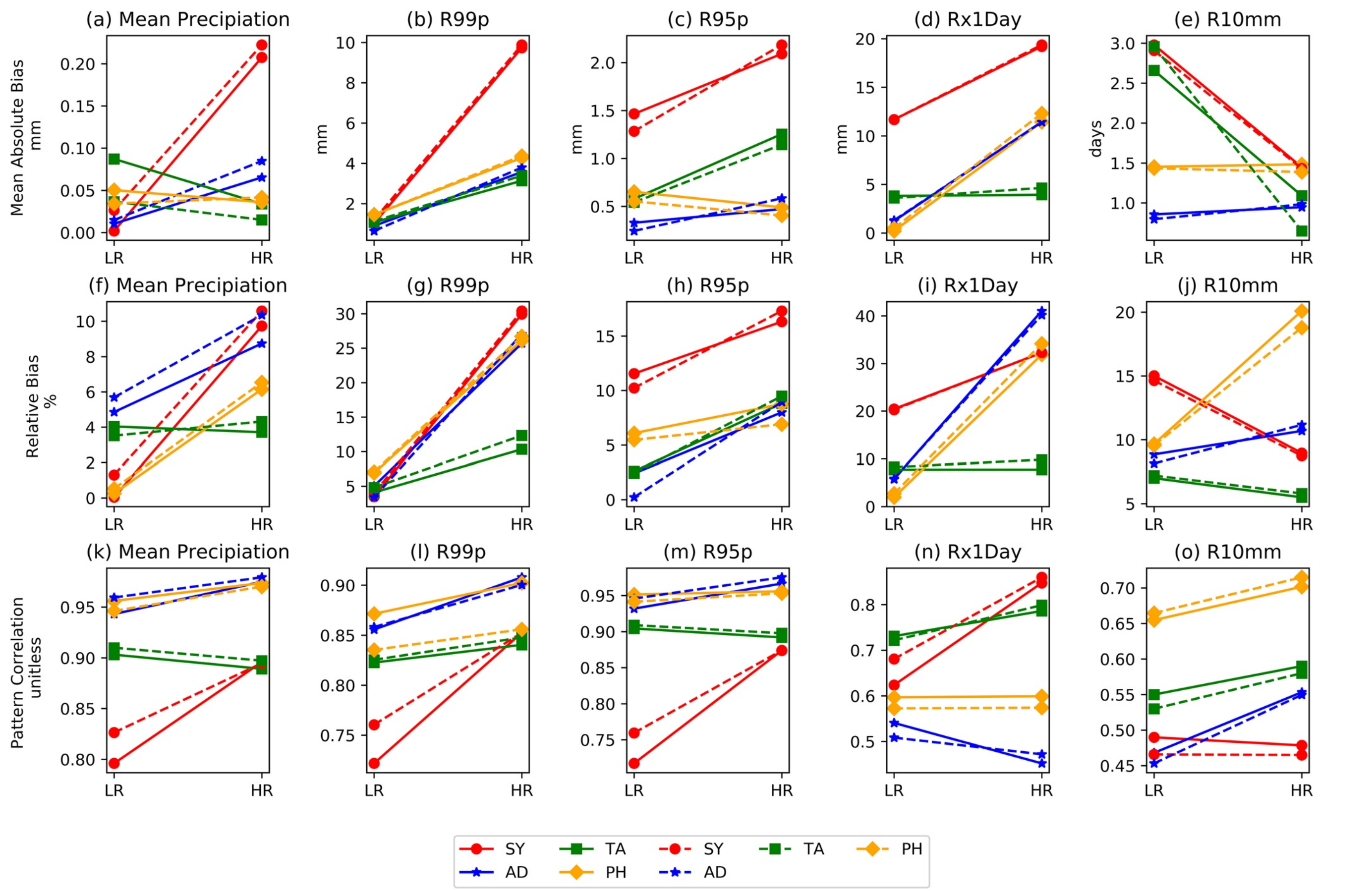

Figure 4. Domain averaged error metrics for averages of high- and lower-resolution reanalysis data. Here (a–e), (f–j) and (k–o) show mean absolute bias, relative bias and pattern correlation, respectively. In contrast, red, blue, green and yellow color represents BARR-SY, BARRA-AD, BARRA-TA, and BARRA-PH regions, respectively. LR and HR are abbreviations for lower and high resolution, respectively. Here solid and dashed line represents data re-gridded to 12 and 1.5-km resolution, respectively. Here the first, second, third, fourth and fifth columns show the mean, 99th percentile, maximum one day, number of days greater than 10 mm and 95th percentile of precipitation, respectively.

A model design can be challenging at grid resolutions that are not fine enough (between 1 and 5 km) to fully resolve processes explicitly, yet much finer than is assumed in the approximating schemes. At such grid resolution, the model is still insufficient to adequately trigger and represent small convective showers, individual convective cells, or updrafts (e.g., Bryan et al., 2003; Clark et al., 2016), and may require parameterized convection at least to some degree (e.g., Deng & Stauffer, 2006; Lean et al., 2008; Roberts & Lean, 2008). Although it remains debatable, based on the results of this study and the studies cited above, we can argue that convective parametrization should be turned on at scales that are not fine enough to gain the advantage of higher resolution on precipitation properties.

We also suggest that more tests of optimization are required for high-resolution RCMs. For example, RCMs in nested-domain setups are typically tested and selected based on their performance at the coarser scales. The selected model configuration is then used to run the higher resolution model. We suggest that RCM selection for dynamical downscaling should be based on the evaluation of performance of high-resolution model. We recommend future studies to investigate this with a properly designed experiment.

We must note certain caveats of our results. First, they are purely based on means and extremes of precipitation. It can be argued that added value could appear for other climate variables. For example, we did not examine sub-daily precipitation, hydrological variability, and extremes like drought. Second, this study only used three standard metrics (i.e., relative bias, mean absolute bias, and pattern correlation) to determine skill and did not examine the joint distribution of multiple variables or strong morphology. Third, we use a single observational data set to validate the reanalysis data. Over topographically complex regions, AGCD data have been found to show dry bias due to a lack of stations in the area needed to represent the precipitation climatology empirically and the inability of the AGCD analysis to account for the steep topography exposed to prevailing winds (Chubb et al., 2016). We acknowledge that observational uncertainties should be considered carefully while determining whether high-resolution data adds information initially missing in the observations or if it adds noise over these areas.

Nonetheless, deterioration of accuracy at higher horizontal resolution for standard statistics of the precipitation distribution shows that increasing the horizontal resolution alone will not help address problems with precipitation. More progress in the data assimilation processes of the driving reanalysis datasets requires significant improvement in the precipitation properties to get proper global-scale circulations and climate variability. These improvements in the driving reanalysis datasets, together with the improvement in the representation of physical processes in the dynamical downscaling, will add to the benefits of increasing spatial resolution. Therefore, there remains enormous scope for significant model developments and data assimilation techniques to reap the benefits of high horizontal resolution. In a future study, it would be crucial to analyze in detail the physical processes (e.g., large scale vs. convective precipitation, precipitation associated with frontal systems or tropical cyclones, orographic precipitation over steep terrain, etc.) associated with extreme precipitation in low- and high-resolution models to gain a better understanding of where the model improvements can be focused for better results.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

BARRA data that support the findings of this study can be accessed by emailing helpdesk.reanalysis@bom.gov.au and requesting access to NCI (National Computational Infrastructure) Gadi project data cj37. More details about the BARRA data set can be found on the following website: http://www.bom.gov.au/research/projects/reanalysis/, "How to get access" section. Data from AGCD are available freely at the Bureau of Meteorology website http://www.bom.gov.au/climate/data/. The data set is also available on the NCI Gadi project zv2. Detail on how to access the data can be found http://climate-cms.wikis.unsw.edu.au/AGCD.

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