Comparison of BARRA and ERA5 in Replicating Mean and Extreme Precipitation over Australia

Kevin K. W. Cheung[1] kevin.cheung@nuist.edu.cn

Fei Ji[2,3] fei.ji@environment.nsw.gov.au

Nidhi Nishant[4] nidhi.nishant@transport.nsw.gov.au

Jin Teng[5] Jin.Teng@csiro.au

James Bennett[6] james.bennett@csiro.au

De Li Liu[7] de.li.liu@dpi.nsw.gov.au

[1]School of Emergency Management, Nanjing University of Information Science and Technology, Jiangsu 210044, China

[2] Science and Insights Division, NSW Department of Climate Change, Energy, the Environment and Water, Sydney, NSW 2150, Australia

[3] Australian Research Council Centre of Excellence for Climate Extremes, University of New South Wales, Sydney, Australia

[4]Climate Change Research Centre, University of New South Wales, Sydney, NSW, Australia

[5] CSIRO Environment, GPO Box 1700, Canberra, ACT 2601, Australia

[6] CSIRO Environment, Research Way, Clayton, VIC 3168, Australia

[7]NSW Department of Primary Industries, Wagga Wagga Agricultural Institute, Wagga Wagga, NSW 2650, Australia

Prepared for Hydrology and Earth System Sciences

First submission September 2024

Revised January 2025

Corresponding author: Dr. Kevin Cheung, School of Emergency Management, Nanjing University of Information Science and Technology, Jiangsu 210044, China. Email: kevin.cheung@nuist.edu.cn

Abstract

Reanalysis datasets are critical in climate research and weather analysis, offering consistent historical weather and climate data crucial for understanding atmospheric phenomena, and validating climate models. However, biases exist in reanalysis datasets that would affect their applications under circumstances. This study evaluates BARRA, which is a high-resolution reanalysis for the Australian region, and ERA5 in simulating mean precipitation and six selected precipitation extremes for their climatology, temporal correlation, coefficient of variation and trend. Both datasets reproduce spatial patterns of mean precipitation well with minor biases. ERA5 shows stronger temporal correlations, superior inter-annual precipitation accuracy, and lower biases in coefficient of variation compared to BARRA, especially in Northern Australia. However, both models exhibit substantial biases in trend, underestimating increasing trends in Northern Australia. ERA5 underestimates dry days and heavy rainfall, while BARRA tends to overestimate these extremes. Temporal correlations for extreme precipitation indices are weaker compared to mean annual precipitation. Notable differences exist in variability biases, with BARRA showing larger biases, especially for heavy precipitation in inland regions and Northern Australia. While both datasets replicate the main trends, biases persist. Overall, the evaluation results support application of both datasets for climatology analyses, but caution is advised for variability and trend analyses, particularly for specific extremes.

Key words: BARRA, ERA5, extreme indices, temporal correlation, coefficient of variation, trend

1. Introduction

Reanalysis dataset is created by combining historical observational data from various sources, such as weather stations, satellites, buoys, and more, with modern data assimilation techniques and numerical models (Kalnay, et al. 1996; Saha, et al. 2010; Dee et al. 2011; Kobayashi et al. 2015, Poli et al. 2016; Hersbach 2020). The fundamental aim of reanalysis is to construct a uniform and coherent historical archive of various atmospheric and environmental parameters, such as temperature, humidity and wind patterns, on either a regional or a global scale.

These datasets are invaluable for climate studies, weather analysis and model validation as they provide a uniform representation of historical climate conditions. For instance, Quagraine et al. (2020) used five global reanalysis datasets (European Centre for Medium-Range Weather Forecasts Reanalysis ERA-Interim, Dee et al. 2011; ERA5, Herbach et al. 2020; JRA-55, Kobayashi et al. 2015); MERRA2, (Gelaro et al. 2017); and NCEP-R2, Kanamitsu et al. 2002) to investigate the variability of West African summer monsoon precipitation, showing all datasets could represent the average rainfall patterns and seasonal cycle. Dai et al. (2023) utilized ERA5 data to estimate rainfall erosivity on the Chinese Loess Plateau, finding rainfall erosivity derived from ERA5 was highly consistent with those derived from the meteorological stations. Cheung et al. (2023) employed ERA5 to evaluate storm conditions in regional climate simulations, demonstrating regional climate models can capture climatology of measurements of storm severity over land including their spatial patterns and seasonality. Numerous studies have used reanalysis datasets as inputs for regional climate models (RCMs) to evaluate the models' capability in replicating observed climatic patterns (Solman et al., 2013; Ji et al., 2016; Fita et al., 2016, Di Virgilio et al., 2019; Capecchi et al., 2023; Di Virgilio et al., 2024; Ji et al., 2024).

While reanalysis datasets provide valuable insights into historical weather and climate conditions, they have limitations and uncertainties, given that they are modelled outputs rather than direct observations. Many studies have evaluated reanalysis data across various variables and regions. For instance, Betts et al. (2019) assessed ERA5 biases in near-surface variables over Canada, highlighting its improved performance over ERA-Interim (Dee et al. 2011), though precipitation biases remained significant. Similarly, Hu and Yuan (2021) and Jiang et al. (2021) found that ERA5 precipitation accurately captured rainfall pattern over the Eastern Tibetan Plateau and mainland China, but under-estimated intensity. Izadi et al. (2021) found ERA5 performed better at monthly and seasonal timescales in Iran, underestimating coastal summer precipitation and overestimating it in mountains. Jiao et al. (2021) and Qin et al. (2021) found ERA5 overestimated summer precipitation and frequency in China but underestimated intensity during the warm season. Lei et al. (2022) and Shen et al. (2022) noted ERA5's limitations in simulating extreme precipitation events in China, especially for high-end extremes.

Comparisons between reanalysis datasets have also been conducted. Wang et al. (2019) found that both ERA5 and ERA-Interim exhibited warm biases over Arctic Sea ice, with larger biases in cold season than warm season. Lei et al. (2020) showed ERA5 improved cloud cover simulation over eastern China but not over the Tibetan Plateau, when compared to ERA-Interim. Gleixner et al. (2020) found ERA5 reduced biases in temperature and precipitation over East Africa compared to ERA-Interim but still struggled with long-term trends. Song and Wei (2021) found both ERA5 and MERRA-2 (Gelaro et al. 2017) captured night precipitation peaks over North China, but only ERA5 accurately reflected the afternoon peak. Li et al. (2022) concluded that ERA5 performed better than ERA-Interim, JRA55 (Kobayashi et al. 2015), and MERRA-2 in capturing precipitation over the Poyang Lake Basin. A summary of the above literature review can be found in Table S1.

106   In Australia, reanalyses like NCEP (Kalnay et al., 1996), JRA-55 (Kobayashi et al.,

107 2015), ERA-Interim (Dee et al., 2011), and ERA5 (Hersbach et al., 2020) are commonly used,

108 alongside the Australian Bureau of Meteorology's high-resolution (12 km) BARRA reanalysis.

109 BARRA covers Australia, New Zealand, and Southeast Asia (Su et al., 2019), while BARRA-

110 C offers even higher-resolution (1.5 km) analysis for four capital cities (Su et al., 2021).

111   May et al. (2021) found BARRA reliable, though it showed seasonal and diurnal biases.

112 Other studies, like Pirooz et al. (2021), compared BARRA with global reanalyses, concluding

113 BARRA performed better for precipitation and temperature in New Zealand but lagged behind

114 ERA5 for high gust winds. Du et al. (2023) used BARRA for estimating daily precipitation in

115 ungauged Australian catchments, while Hobeichi et al. (2023) employed BARRA to train

116 statistical models for downscaling. Acharya et al. (2019, 2020) found BARRA's precipitation

117 performance varied by region, with poorer results in tropical areas. Nishant et al. (2022)

118 suggested higher resolution in BARRA-C didn't always improve precipitation simulations,

119 while Choudhury et al. (2023) noted ERA5 performed better for mean temperatures than

120 extremes in Australia. These previous studies on BARRA and BARRA-C have also been

121 summarized in Table S1.

122   However, there is a gap in the existing studies concerning the intercomparison of

123 various reanalyses, such as BARRA and ERA5, specifically in relation to precipitation

124 extremes over Australia. In this study, we aim to bridge this gap by evaluating and comparing

125 the performance of BARRA and ERA5 in capturing precipitation extremes. While the

126 traditional evaluation methods focusing on climatology (long-term mean), here we also include

127 temporal correlation, coefficient of variation and trend in evaluation to quantify their overall

128 performance, which have not been examined before in previous studies. By assessing climate

129 means and extremes and quantifying their biases, this study provides a valuable reference for

130 selecting appropriate datasets for specific applications and cautions against treating reanalysis

data as observations. The paper is organized as follows: Section 2 introduces the reanalysis datasets and observational data used for evaluation. Section 3 outlines the climate extreme indices and evaluation methodology. Results are presented in Section 4, followed by further discussion in Section 5. Finally, Section 6 offers a summary and conclusions.

2. Data

2.1 ERA5

ERA5 is a global atmospheric reanalysis dataset developed by ECMWF (Hersbach, et al. 2020). ERA5 provides hourly estimates of many atmospheric, land, and oceanic climate variables. The data is on a ~30 km horizontal grid and resolves the atmosphere using 137 levels from the surface up to a height of 0.01hPa (~80 km).

ERA5 is constructed upon the foundation of the Integrated Forecasting System (IFS) Cy41r2. This allows ERA5 to benefit from a decade's worth of development in areas such as model physics, core dynamics, and data assimilation techniques. ERA5 is a significant advancement over its predecessors (e.g., ERA-Interim) due to its higher spatial and temporal resolution, improved assimilation techniques, and more sophisticated modelling components. It provides a detailed and accurate representation of various atmospheric variables, such as temperature, humidity, wind speed, pressure, and more. The dataset covers the entire globe and spans from 1940 to the present, making it valuable for various applications in climate research, meteorology, environmental science, and more.

2.2 BARRA

BARRA is a high-resolution regional atmospheric reanalysis dataset developed by the Australian Bureau of Meteorology, which is available from January 1990 to February 2019 (Su, et al. 2019). BARRA was constructed based on the Australian Community Climate Earth-System Simulator (ACCESS) model with assimilation of a wide range of observational data to

156 create a coherent and consistent representation of past weather and climate conditions. BARRA

157 covers the Australian continent, New Zealand, part of Asia and some Pacific Islands with a

158 horizontal resolution of 12 km and 70 vertical levels from the surface up to a height of 80 km.

159 BARRA specifically focuses on providing detailed information about weather patterns and

160 atmospheric variables over the Australian region, which provides about 100 parameters at

161 hourly intervals.

162 The ACCESS model, which was applied to generate BARRA, originated from the

163 UKMO's Unified Model (UM), which can be configured in global mode or regional mode. For

164 regional simulations, the global version of ACCESS becomes ACCESS-R. ACCESS-R was

165 initialized by ERA-Interim reanalysis data, which also provides boundary conditions during

166 simulation. A series of observations have been assimilated into BARRA, including land and

167 ship (buoy) synoptic observations, upper-air observations from radiosondes and wind profilers,

168 satellite derived radiances and winds (Su et al. 2019). However, no precipitation observations

169 were directly assimilated.

170 **2.3 AGCD**

171 The observational data in the study are from the Australian Gridded Climate Dataset

172 (AGCD, Evans et al. 2020). The daily gridded maximum and minimum temperatures, and

173 precipitation data has a spatial resolution of 0.05° (~ 5km) and is interpolated from observations

174 at stations across the Australian continent. Most of those stations are in the more heavily

175 populated coastal regions with far fewer stations inland and over high elevation areas. For

176 example, there are very few station observations near the Gibson dissert region in Western

177 Australia, making the gridded observations unreliable over that region. Thus, in the following

178 figures that region has been masked and not considered for evaluation. Since observations and

179 reanalyses are not at the same spatial resolutions, we aggregate the observations to the native

180 grid of ERA5 and BARRA respectively for comparison, including the performance of

181 statistical significance tests. For comparison purpose, we also interpolate reanalysis to AGCD

182 grids using the conservative area weighted re-gridding scheme from the Climate Data

183 Operators (Schulzweida et al., 2006), which will be shown in the Supplementary Information.

184 The states and sub-regions in the Australian region we discuss in the following can be found

185 in Figure S1.

186

3. Methodology

188 **3.1 ET-SCI**

189 While extreme climate and weather events are generally multifaceted phenomena, in

190 this study we evaluate climate extremes based on daily precipitation and temperature as defined

191 by Expert Team on Sector-specific Climate Indices (ET-SCI; Alexander & Herold, 2015;

192 Herold and Alexander, 2016). We use the ClimPACT version 2 software to calculate the ET-

193 SCI indices (https://climpact-sci.org/), focussing on daily precipitation.

194 Although ClimPACT generates 14 precipitation-related core indices, we select seven

195 (Table 1) based on the following considerations: 1) To capture key aspects of climate extremes,

196 and 2) to capture extremes which have impacts on society and infrastructure such as agriculture,

197 water resources and economy (Tabari, 2020; Pei et al., 2021). Accordingly, we include absolute

198 indices such as the maximum 1-day precipitation (Rx1day) and total precipitation (PRCPTOT),

199 a threshold-based index (e.g., number of heavy rain days, R10mm), percentile indices (e.g.,

200 total annual precipitation from very heavy rain days, R99p), and duration indices such as the

201 consecutive wet (CWD) and dry days (CDD).

202 With the above consideration, the seven aforementioned precipitation-related indices

203 were calculated on native reanalysis grids and observation grids. While the availability of

204 AGCD and ERA5 starts much earlier, the analysis period is 1990–2018, which is the duration

205 of BARRA. Since the AGCD observations have the highest resolution, here we mainly show

206 the evaluation on the native grids of the reanalyses (i.e., the 12-km grid of BARRA and 30-km

207 grid of ERA5). The extreme indices calculated from reanalysis data have also been regridded

208 to the 5-km resolution using bilinear interpolation, which are included in the supplementary

209 information to demonstrate that our conclusions are insensitive to the choice of evaluation

210 resolution.

211

212 **3.2 Evaluation metrics**

213 We evaluate BARRA and ERA5 for their performance in capturing climatology (29

214 years in our case), coefficient of variation (CV), temporal correlation, and trends of seven

215 selected precipitation extreme indices. The CV is a valuable statistical tool representing the

216 ratio of the (yearly) standard deviation to the mean, allowing for the comparison of variation

217 between different data series, even when their means differ significantly. Temporal correlations,

218 which are computed at an annual time step, of climate extremes measure the similarities

219 between simulations and observations in terms of their inter-annual variabilities, with larger

220 temporal correlations indicating better performance. For trend analyses, we applied simple

221 linear trend line fitting to the yearly time series of climate indices. All the above metrics are

222 computed at each grid point in the datasets' native grids as well as the AGCD grid after re-

223 gridding. Differences between BARRA/ERA5 and AGCD then form the bias maps. After

224 averaging over all grid points, the domain averages will then be discussed in the following.

225 We use bias and domain-averaged absolute bias to quantify spatial differences between

226 reanalyses and observations. Temporal correlation, coefficient of variation, and trend are used

227 to quantify temporal similarities between reanalyses and observations. The non-parametric

228 Mann-Kendall test is used to assess the statistical significance of differences and trends. Biases

229 are assessed at an annual timescale for all extremes.

230

4. Results

4.1 Mean climate

This section evaluates and compares the annual mean of daily precipitation between BARRA and ERA5 against AGCD over Australia.

4.1.1 Bias and temporal correlation

We first evaluate precipitation simulated by BARRA and ERA5 against observations (AGCD). The mean annual precipitation from the three datasets and biases in BARRA and ERA5 compared to AGCD are shown in Figure 1 (and Figure S2 on the observation grid). Results show that both BARRA and ERA5 simulate the spatial patterns of mean annual precipitation very well with high rainfall in northern Australian, eastern Australia coast and western Tasmania and low rainfall inland, albeit with clear biases. Compared to AGCD, both BARRA and ERA5 underestimate precipitation up to 20% for Eastern Australian coast, southwest western Australia, and western Tasmania, but overestimate annual precipitation up to 30% inland (Figure S3). Some clear differences in biases between BARRA and ERA5 can be observed in central western Australia and northern Queensland where BARRA overestimate precipitation but ERA5 underestimate it. Domain averaged absolute bias in annual precipitation is about 0.17mm/day (~12.7% relative bias with respect to domain average) for BARRA and 0.15 mm/day (~10.5% relative bias) for ERA5 (Table 2).

The skill of simulated precipitation from BARRA and ERA5 are further demonstrated in the temporal correlations between BARRA/ERA5 and AGCD shown in Figure 2 (and Figure S4 on the observation grid). Temporal correlation of annual precipitation is larger in southeast Australia and northern Tasmania for both BARRA and EAR5, which is above 0.85. This indicates inter-annual variability of precipitation is well captured by BARRA and ERA5. In contrast, temporal correlation is weaker for western inland and northern Australia. ERA5 generally has larger temporal correlation when compared with BARRA, especially for northern

256 Australia, where temporal correlation for BARRA is below 0.5. On average, temporal

257 correlation for ERA5 is 0.85, which is larger than 0.77 for BARRA (Table 2).

4.1.2   CV (coefficient of variation) and trend

259   CV of annual precipitation for AGCD and biases between BARRA/ERA5 and AGCD

260 are presented in Figure 3 (and Figure S5 on the observation grid). By its definition, CV helps

261 capture the standard deviation in the dataset relative to its mean. In the observation, CV is

262 generally smaller for coastal regions including Tasmania except for northwest West Australia

263 ~~and Tasmania~~ than inland Australia, where annual rainfall is much smaller than coastal regions.

264 Alternatively, regions with higher annual precipitation generally have smaller CV. Both

265 BARRA and ERA5 reasonably capture the main feature of CV in observation. However, clear

266 biases can be observed, especially in BARRA that has more than 50% large positive biases in

267 Northern Australia, up to 20% positive biases for inland, and relatively smaller biases for

268 southeastern Australia, southwest West Australia and Tasmania. In contrast, ERA5 does not

269 have a clear bias pattern, and biases are relatively smaller when compared to BARRA.

270   To further investigate the variability evident in observations and BARRA/ERA5

271 simulations, we assess the trends in annual precipitation (Figure 4 and Figure S6 on the

272 observation grid). AGCD shows strong increasing trends over Northern Australia and

273 Northeast Australia coastal regions but decreasing trends over Northern Queensland,

274 southwestern West Australia and southern Great Dividing Range including Victoria, although

275 not all trends are significant. Most of inland regions have relatively small trend in annual

276 precipitation. Both BARRA and ERA5 reproduce the major trend pattern ~~reasonably well~~,

277 however, clear biases can be observed over Northern Australia where both BARRA and ERA5

278 underestimate trend more than 100% (i.e., trend of 0.08 mm/day per year with bias of similar

279 magnitude). BARRA overestimated decreasing trend over Northern Queensland but ERA5

280 underestimate it (even increasing trend instead).

281   In summary, evaluation of annual mean precipitation indicates both BARRA and ERA5

282   possess small biases (~20%) in the spatial precipitation patterns. ERA5 shows stronger

283   temporal correlations than BARRA, particularly in northern Australia. Overall, ERA5

284   demonstrates higher accuracy in capturing inter-annual precipitation variability. Both BARRA

285   and ERA5 captured spatial distribution of coefficient of variation reasonably well but with

286   large biases (~ 50%). BARRA shows much larger biases than ERA5 especially for Northern

287   Australia. Both BARRA and ERA5 roughly reproduce the pattern of trend but with very large

288   biases (~100%), especially for Northern Australia where both substantially underestimate the

289   increasing trend.

290

291   **4.2 Climate extremes**

292   This section evaluates the seven select precipitation extreme indices (Table 1) from

293   BARRA and ERA5 over Australia by comparing them against AGCD. Evaluations are

294   performed primarily using spatial bias maps and temporal correlations. We also assess the

295   interannual variability and trends in the simulated BARRA and ERA5 indices and compare

296   these with AGCD to further investigate any discrepancies.

297   **4.2.1   Bias and temporal correlation**

298   Annual mean biases in six precipitation extremes are shown in Figure 5 (and Figure S8

299   on the observation grid). For duration-related extremes (CDD and CWD), there is a clear north-

300   to-south gradient in AGCD (Figure S7) with longer duration of CDD and CWD in northern

301   Australia than southern Australia (CWD also has a clear west-to-east gradient in Tasmania),

302   which is well simulated in BARRA and ERA5 (Figure S7). While the spatial distributions are

303   well captured, clear biases are evident in them (Figure 5). BARRA generally underestimates

304   CDD especially for central inland and northwest West Australia where biases are up to 40%.

305   ERA5 also under-estimates CDD for central inland, but in contrast its over-estimates CDD for

most of northwestern Australia, overall ERA5 has smaller absolute bias in CDD (6.9 days) than BARRA (14.5 days) (Table 2). Both BARRA and ERA5 have similar bias pattern for CWD, which generally overestimate CWD over most of regions except for southern Australian coast, southwest West Australia and western Tasmania. The positive biases over Northern Australia may reach 30%. Overall BARRA has slightly larger biases in CWD (2.3 days) than ERA5 (1.7 days) (Table 2).

For threshold-based extremes (PRCPTOT, R10mm, R90p, R99p, Rx1day), both BARRA and ERA5 also generally match the spatial distribution of heavy precipitation days and R90p (Figure S7) in AGCD with large values in Northern Australia, eastern seaboard and Australian Great Dividing Range, and western Tasmania. However, clear biases can be observed in BARRA and ERA5 for both R10mm and R90p (Figure 5). BARRA and ERA5 have large negative biases in R10mm over Northern Australia, eastern seaboard, southwest Western Australia and western Tasmania, but biases in central inland and northwest West Australia are generally small. Overall, domain averaged absolute bias for ERA5 (1.7 days) is about half of that for BARRA (3.3 days). Both BARRA and ERA5 also have relatively large negative biases in R90p for most of northern Australia, eastern coasts, southwest West Australia and western Tasmania but small positive biases inland, especially for BARRA. Overall averaged absolute bias is 0.78 mm/day for BARRA and 0.44 mm/day for ERA5 (Table 2).

BARRA and ERA5 also reasonably captured the spatial patterns of R99p and Rx1day, however, quite large biases are in BARRA and ERA5 (Figure 5). BARRA generally overestimate R99p and Rx1day over northern Australia coasts and along the Great Dividing Range. In contrast, ERA5 generally underestimate R99p and Rx1day over northern and eastern coasts, southwest Western Australia and western Tasmania. The domain averaged bias in R99p

330 is at similar magnitude for BARRA (4.09 mm/day) and ERA5 (3.67 mm/day), however biases

331 in Rx1day is much larger for BARRA (20.3 mm/day) than ERA5 (7.9 mm/day) (Table 2).

332   Figure 6 (and Figure S9 on the observation grid) presents the temporal correlations

333 between BARRA/ERA5 and AGCD for the six precipitation extreme indices. Unlike the strong

334 temporal correlation between BARRA/ERA5 and AGCD for mean annual precipitation (Figure

335 2), the temporal correlations for these extreme indices are worse except for R90p (Figure 6).

336 For extremes like R10mm and R90p, the correlation ranges from reasonably good (above 0.6)

337 to pretty good (above 0.8) between BARRA/ERA5 and AGCD for most of the domain.

338 Temporal correlation for CDD, CWD and R99p are not as good as R10mm and R99p. CDD

339 has more regions with stronger correlations (0.5-0.6) or above than CWD and Rx1day, for the

340 latter correlation is about ~0.5 or less over most of the domain. Compared to BARRA, ERA5

341 has slightly stronger temporal correlations for those extremes (Table 2).

342

4.2.2   CV (coefficient of variation) and trend

344   The observed and simulated CV of precipitation extremes and biases in their CV for

345 BARRA and ERA5 are shown in Figure S10 and Figure 7 (and Figure S11 on the observation

346 grid), respectively. Generally, both BARRA and ERA5 have similar CV bias patterns and

347 magnitude for CDD, CWD and R10mm. In contrast, BARRA is quite different from ERA5 for

348 other three extremes. BARRA substantially under-estimated CV of R90p over most on inland

349 regions but ERA5 has much smaller negative biases, even small positive biases, although both

350 have small biases in CV of R90p along most coastal regions and Tasmania. BARRA

351 systematically overestimate CVs of R99p and Rx1day over northern Australia but ERA5 has

352 relatively small biases for them. Overall, BARRA has more than twice as much as CV biases

353 in ERA5 for R90p, R99p and Rx1day (Table 2).

Trends of each of the precipitation extreme indices for the three datasets and biases in trend for BARRA and ERA5 are shown in Figure S12 and Figure 8 (and Figure S13 on the observation grid), respectively. Generally, both BARRA and ERA5 simulate the main pattern of trends for those extremes but with large biases. BARRA and ERA5 simulated CDD trend well for southern Australia but BARRA generally under-estimated trend in CDD over inland Australia and overestimate trend in northwest Australia. ERA5 only has large positive trend biases in northern central Australia. The overall domain averaged biases are similar between BARRA (0.584) and ERA5 (0.566). Both BARRA and ERA5 have small biases in CWD in central and southern Australia but similar biases pattern in Northern Australia. They also have similar overall biases in CWD (0.064 for BARRA and 0.060 for ERA5). Both BARRA and ERA5 under-estimated increasing trend in R10mm in northern Australia, but BARRA overestimate trend in most of southeast Australia. In contrast, ERA5 under-estimate trend over there. Overall, ERA5 has slightly larger biases (0.094) than BARRA (0.085). Like R10mm, both BARRA and ERA5 also underestimate trend of R90p in most of northern Australia but have small biases in central and southern Australia. They have almost the same overall biases in R90p. BARRA/ERA5 has similar biases patterns for R99p and Rx1day but biases for rx1days are much larger. Both BARRA and ERA5 have large biases in R99p and Rx1day but biases in BARRA are generally larger than ERA5.

In summary, both BARRA and ERA5 reproduce spatial patterns of extremes well but display biases. ERA5 underestimates CDD and certain extreme precipitation indices (e.g., Rx1day), while BARRA tends to overestimate these extremes. Both reanalyses show discrepancies in various precipitation indices across different regions, with BARRA generally displaying larger biases compared to ERA5. Temporal correlations between BARRA/ERA5 and observations for extreme precipitation indices are weaker than those for mean annual precipitation, except for a few indices where ERA5 demonstrates slightly stronger correlations

379   compared to BARRA. Both BARRA and ERA5 align in CV patterns and biases for certain

380   extremes (CV, R10mm, R90p) but differ notably in others (PRCPTOT, trend, CDD, R99p,

381   Rx1day). BARRA significantly underestimates very heavy precipitation variability over inland

382   regions, while ERA5 presents smaller biases or even positive biases in these areas. Additionally,

383   BARRA tends to overestimate extreme precipitation variability in Northern Australia

384   compared to ERA5. Overall, BARRA shows more than double the biases in variability

385   compared to ERA5 for specific extreme precipitation indices. Both reanalyses generally

386   simulate the main trend patterns but exhibit considerable biases. BARRA underestimates or

387   overestimates trends in certain regions and indices, while ERA5 demonstrates different biases,

388   including smaller biases overall compared to BARRA across these precipitation extremes.

389

390   **5. Discussion**

391   In this study, we assessed the performance of BARRA and ERA5 in simulating mean

392   precipitation and six selected precipitation extremes. While most previous evaluations have

393   focused on the climatology of precipitation and its extremes, only a few studies have included

394   the coefficient of variation (CV) (Teng et al., 2024). Our evaluation encompassed annual

395   climatology, along with temporal correlation, CV, and trend analysis, providing a

396   comprehensive assessment of the performance of these two reanalysis datasets.

397   The results indicate that both BARRA and ERA5 demonstrate reasonable skill in

398   simulating mean precipitation and certain precipitation extremes (e.g., CWD and R90p).

399   However, they encounter challenges in accurately reproducing temporal correlation, CV, and

400   trends for certain extreme events, highlighting significant uncertainties in their representation

401   of extremes.

402   While acknowledging the capabilities of these reanalysis datasets, our study also

403   identifies specific limitations and suggests potential directions for future research. A crucial

404 consideration in model evaluation is the accuracy of observational data, which substantially

405 influences evaluation outcomes. In this study, we used the AGCD dataset as the observational

406 benchmark, which is based on interpolating data from in-situ stations (Evans et al., 2020).

407 However, the AGCD dataset presents several limitations: 1) Spatial coverage: Sparse station

408 coverage in northwest and central Australia, and limited observations in high-elevation areas,

409 result in a concentration of stations in southeastern Australia, southwestern Western Australia,

410 and eastern Tasmania. The arid interior is notably underrepresented. 2) Data completeness and

411 homogeneity: Incomplete and inhomogeneous observations due to missing data, changes in

412 observational techniques, or station relocations can affect the consistency of the dataset. 3)

413 Interpolation uncertainties: The interpolation method used in AGCD (splining), instead of the

414 ordinary kriging method used in its predecessor (AWAP), introduces uncertainties, particularly

415 in areas with sparse data coverage for extreme events like heavy rainfall.

416 These observational uncertainties may contribute to biases in the evaluation results. In

417 particular, the limited number of monitoring sites over the Great Dividing Range and inland

418 areas introduces significant uncertainties in estimated observed precipitation for these regions.

419 Independent studies, such as Chubb et al. (2016), found that daily precipitation is

420 underestimated by at least 15% in some areas, which could suggest similar underestimation in

421 BARRA and ERA5 for these regions. Similarly, the sparse gauge network in northwestern

422 inland areas might miss localized extreme precipitation events.

423 Our analysis focused on seven ET-SCI-defined precipitation extreme indices (including

424 mean precipitation), widely used in various evaluation studies (Nishant et al., 2020; Ji et al.,

425 2024). However, recognizing the need for region-specific indices, we suggest future studies

426 extend the analysis to incorporate additional extreme indices tailored to specific regions and

427 applications.

428   Our findings emphasize that while both BARRA and ERA5 are competent in simulating

429   the climatology of mean climate, temporal correlation, and CV, challenges remain in accurately

430   capturing trends, particularly for certain extremes. Notably, ERA5 shows better overall

431   performance compared to BARRA. Although higher resolution often correlates with better

432   performance, recent studies have shown that increasing resolution alone does not always

433   guarantee improvements (Nishant et al., 2022). Considering the critical role of driving data,

434   model physics, and data assimilation, it may be valuable to update BARRA using the latest

435   ERA5 data along with improved model physics and data assimilation techniques to enhance its

436   performance.

437   In this study, we evaluated ERA5 and BARRA on both their native resolutions and a

438   common resolution (5 km) to match AGCD. The results showed that the evaluations were

439   consistent across native and common resolutions, suggesting that the performance assessments

440   were not highly sensitive to changes in resolution.

441

442 **6. Summary and Conclusion**

443   Reanalysis datasets play a crucial role in climate research, weather analysis, and various

444   scientific investigations. Their ability to provide a consistent and comprehensive representation

445   of historical weather and climate conditions makes them invaluable. These datasets are

446   particularly essential for studying long-term climate trends, understanding atmospheric

447   phenomena, and validating climate models.

448   In this study, we evaluate BARRA and ERA5 for their capabilities to simulate mean

449   precipitation and six selected precipitation extremes for their climatology, temporal correlation,

450   coefficient of variation (CV) and trend to quantify their overall performance. We evaluated

451   BARRA and ERA5 at their native resolutions, as well as at a common resolution (i.e., the

452   observation resolution). Both analyses yielded consistent results, indicating that the evaluation

453   is not sensitive to the remapping process.

454   The assessment of annual mean precipitation reveals that both BARRA and ERA5

455   adeptly reproduce the spatial precipitation patterns, exhibiting minor biases of around 20%.

456   Particularly, ERA5 showcases stronger temporal correlations compared to BARRA, especially

457   evident in northern Australia. ERA5, overall, demonstrates superior accuracy in capturing

458   inter-annual precipitation variability. However, both models depict the spatial distribution of

459   the coefficient of variation reasonably well but with larger biases, roughly around 50%.

460   Particularly, BARRA displays significantly higher biases, especially in Northern Australia.

461   Regarding the replication of trend patterns, both models exhibit substantial biases,

462   reaching approximately 100%. This is especially notable in Northern Australia, where they

463   both notably underestimate the increasing trend. Furthermore, while both BARRA and ERA5

464   possess about the right spatial patterns of extremes, biases are evident. ERA5 tends to

465   underestimate consecutive dry days (CDD) and certain heavy rainfall events, while BARRA

466   tends to overestimate these extremes. Discrepancies in various precipitation indices across

467   regions are apparent, with BARRA generally displaying larger biases compared to ERA5.

468   When examining temporal correlations for extreme precipitation indices compared to

469   mean annual precipitation, both BARRA and ERA5 show weaker correlations, except for a

470   few indices (CDD, R10mm, R90p) where ERA5 slightly outperforms BARRA. While both

471   models align in coefficient of variation patterns and biases for certain extremes, notable

472   differences arise in others. BARRA notably underestimates very heavy precipitation variability

473   over inland regions, whereas ERA5 presents smaller biases or even positive biases in these

474   areas. Moreover, BARRA tends to overestimate extreme precipitation variability in Northern

475   Australia compared to ERA5. Specifically, BARRA showcases more than double the biases in

476   variability compared to ERA5 for specific extreme precipitation indices.

477   In terms of trend patterns, both models generally replicate the observed trends but

478 exhibit considerable biases. BARRA shows both underestimations and overestimations in

479 certain regions and indices, while ERA5 displays different biases, including overall smaller

480 biases compared to BARRA across these precipitation extremes.

481   In summary, our findings suggest that both ERA5 and BARRA are reliable for

482 climatological analyses, including mean precipitation and precipitation extremes, and can be

483 confidently used by end-users for such purposes. However, as discussed in the introduction,

484 caution is advised when using these datasets for variability and trend analyses, particularly for

485 specific extreme events like Rx1day. The performance of these reanalyses is regionally

486 dependent, and this should be considered when using them as observational references for

487 evaluating other model simulations. Additionally, the biases in the variability and trends of

488 climate extremes present in both datasets must be carefully accounted for when comparing

489 them with other data sources.

490

491

492 **Data Availability**

493 Details about AGCD are available at the Australian Bureau of Meteorology website
494 (http://www.bom.gov.au/metadata/catalogue/19115/ANZCW0503900567, (accessed on)).
495 The dataset is available on the NCI (National Computational Infrastructure) server in project
496 zv2. Detail on how to access the data can be found at http://climate-
497 cms.wikis.unsw.edu.au/AGCD, (accessed on). ERA5 data is available on the NCI in Project
498 rt52. BARRA data is available on the NCI in project cj37.

499 **Author Contributions**

500 KKWC and FJ conceptualized and implemented the research. KKWC, FJ and NN performed
501 the data analysis and prepared the figures. KKWC and FJ prepared the draft manuscript. All
502 authors contributed to the discussion of results, editing and finalization of the manuscript.

503 **Competing Interests**

504 The authors declare that they have no conflict of interest.

505

506 **Acknowledgments**

507 KKWC acknowledges support from The Startup Foundation for Introducing Talent of the
508 Nanjing University of Information Science and Technology. The modelling work was
509 undertaken on the National Computational Infrastructure (NCI) high performance computers
510 in Canberra, Australia, which is supported by the Australian Commonwealth Government.
511 The authors would like to thanks to the two anonymous reviewers for providing insightful
512 comments and detailed suggestions for us to improve the manuscript.

513

References

Acharya, S. C., Nathan, R., Wang, Q. J., et al.: An evaluation of daily precipitation from a regional atmospheric reanalysis over Australia. Hydrol. Earth Syst. Sci., 23, 3387–3403, https://doi.org/10.5194/hess-23-3387-2019 , 2019.

Acharya, S. C., Nathan, R., Wang, Q. J., et al.: Ability of an Australian reanalysis dataset to characterise sub-daily precipitation. Hydrol. Earth Syst. Sci., 24, 2951–2962, https://doi.org/10.5194/hess-24-2951-2020 , 2020.

Betts, A. K., Chan, D. Z., Desjardins, R. L.: Near-Surface Biases in ERA5 Over the Canadian Prairies. Front. Environ. Sci., 7, https://doi.org/10.3389/fenvs.2019.00129 , 2019.

Capecchi, V., Pasi, F., Gozzini, B., Brandini, C.: A convection-permitting and limited-area model hindcast driven by ERA5 data: precipitation performances in Italy. Clim. Dyn., 61, 1411–1437, https://doi.org/10.1007/s00382-022-06633-2 , 2023.

Cheung, K. K. W., Ji, F., Nishant, N., Herold, N., Cook, K.: Evaluation of Convective Environments in the NARCliM Regional Climate Modeling System for Australia. Atmosphere, 14, 690, https://doi.org/10.3390/atmos14040690 , 2023.

Choudhury, D., Ji, F., Nishant, N., Di Virgilio, G.: Evaluation of ERA5 simulated temperature and its extremes for Australia. Atmosphere, 14(6), 913. https://doi.org/10.3390/atmos14060913, 2023.

Chubb, T. H., Manton, M. J., Siems, S. T., Peace, A. D.: Evaluation of the AWAP daily precipitation spatial analysis with an independent gauge network in the Snowy Mountains. J. Southern Hemisphere Earth Systems Science, 66, 55-67, 2016.

Dai, W., Zeng, Y., Jing, T. G., et al.: Estimation of rainfall erosivity on the Chinese Loess Plateau: A new combination of the ERA5 dataset and machine learning. J Hydrol (Amst), 624, https://doi.org/10.1016/j.jhydrol.2023.129892, 2023.

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., et al.: The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. Q. J. R. Meteorol. Soc., 137, 553–597, https://doi.org/10.1002/qj.828, 2011.

Di Virgilio G., Evans J.P., Di Luca A., Olson R., Argueso D., Kala J., Andrys J., Hoffmann P., Katzfey J.J., Rockel B.: Evaluating reanalysis driven CORDEX regional climate models over Australia: model performance and errors. Climate Dynamics, 53, 2985-3005, 2019.

Di Virgilio, G., Ji, F., Tam, E., Evans, J., Kala, J., Andrys, J., Thomas, C., Choudhury, D., Rocha, C., Li, Y., Riley, M.: Evaluation of CORDEX ERA5-forced 'NARCliM2.0' regional climate models over Australia using the Weather Research and Forecasting (WRF) model version 4.1.2, Geosci. Model Dev. Discuss., https://doi.org/10.5194/gmd-2024-41 , 2024.

Du, Y. L., Wang, Q. J., Su, C. H., et al.: Estimating daily precipitation climatology by postprocessing high-resolution reanalysis data. Intl. J. Climatol., 43, 4151–4165, https://doi.org/10.1002/joc.8079, 2023.

Evans, A., Jones, D., Smalley, R., Lellyett, S.: An Enhanced gridded rainfall analysis scheme for Australia. Bureau Research Report No. 41, Bureau of Meteorology, Australia, 2020. Available at http://www.bom.gov.au/research/publications/researchreports/BRR-041.pdf

Fita, L., Evans, J. P., Argüeso, D., et al.: Evaluation of the regional climate response in Australia to large-scale climate models in the historical NARCliM simulations. Climate Dynamics, 1–15, https://doi.org/10.1007/s00382-016-3484-x, 2016.

Gelaro R, McCarty W, Suárez MJ, et al.: The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). J. Clim. 30, 5419–5454, https://doi.org/10.1175/JCLI-D-16-0758.1, 2017.

Gleixner, S., Demissie, T., Diro, G. T.: Did ERA5 Improve Temperature and Precipitation Reanalysis over East Africa? Atmosphere (Basel), 11, https://doi.org/10.3390/atmos11090996, 2020.

Herold, N., Alexander, L.: *Climpact 2*. https://github.com/ARCCSS-extremes/climpact2, 2016.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., et al.: The ERA5 global reanalysis. Q. J. R. Meteorol. Soc., 146, 1999–2049, https://doi.org/10.1002/qj.3803 , 2020.

Hobeichi, S., Nishant, N., Shao, Y. W., et al.: Using Machine Learning to Cut the Cost of Dynamical Downscaling. Earths Future, 11, https://doi.org/10.1029/2022EF003291 , 2023.

Hu, X. L., Yuan, W. H.: Evaluation of ERA5 precipitation over the eastern periphery of the Tibetan plateau from the perspective of regional rainfall events. Intl. J. Climatol. 41, 2625–2637, https://doi.org/10.1002/joc.6980 , 2021.

Izadi, N., Karakani, E. G., Saadatabadi, A. R., et al.: Evaluation of ERA5 Precipitation Accuracy Based on Various Time Scales over Iran during 2000-2018. Water (Basel), 13. https://doi.org/10.3390/w13182538, 2021.

Ji, F., Evans, J. P., Teng, J., Scorgie, Y., Argüeso, D., Di Luca, A.: Evaluation of long-term precipitation and temperature Weather Research and Forecasting simulations for southeast Australia. Climate Research 67, 99-115, 2016.

Ji, F., Di Virgilio, G., Nishant, N., Tam, E., Evans, J. P., Kala, J., Andrys, J., Thomas, C., Riley, M.: Evaluation of precipitation extremes in ERA5 driven regional climate simulations. Weather and Climate Extremes, https://doi.org/10.1016/j.wace.2024.100676 , 2024.

Jiang, Q., Li, W. Y., Fan, Z. D., et al.: Evaluation of the ERA5 reanalysis precipitation dataset over Chinese Mainland. J Hydrol (Amst), 595, https://doi.org/10.1016/j.jhydrol.2020.125660 , 2021.

Jiao, D. L., Xu, N. N., Yang, F., Xu, K.: Evaluation of spatial-temporal variation performance of ERA5 precipitation data in China. Sci. Rep. 11. https://doi.org/10.1038/s41598-021-97432-y, 2021.

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha, S., White, G., Woollen, J., et al.: The NCEP/NCAR 40-year reanalysis project. Bull. Am. Meteorol. Soc., 77, 437–472. https://doi.org/10.1175/1520-0477(1996)077<0437:TNYRP>2.0.CO;2 , 1996.

Kobayashi, S., Ota, Y., Harada, Y., Ebita, A., Moriya, M., Onoda, H., Onogi, K., Kamahori, H., Kobayashi, C., Endo, H., et al.: The JRA-55 Reanalysis: General Specifications and Basic Characteristics. J. Meteorol. Soc. Jpn. Ser. II, 93, 5–48, https://doi.org/10.2151/jmsj.2015-001 , 2015.

Lei, X. Y., Xu, W. L., Chen, S. T., et al.: How Well Does the ERA5 Reanalysis Capture the Extreme Climate Events Over China? Part I: Extreme Precipitation. Front. Environ. Sci., 10, https://doi.org/10.3389/fenvs.2022.921658 , 2022.

Lei, Y. H., Letu, H. S., Shang, H. Z., Shi, J.C.: Cloud cover over the Tibetan Plateau and eastern China: a comparison of ERA5 and ERA-Interim with satellite observations. Clim. Dyn., 54, 2941–2957. https://doi.org/10.1007/s00382-020-05149-x , 2020.

Li, X. X., Qin, X. C., Yang, J., Zhang, Y. Z.: Evaluation of ERA5, ERA-Interim, JRA55 and MERRA2 reanalysis precipitation datasets over the Poyang Lake Basin in China. Intl. J. Climatol. 42, 10435–10450. https://doi.org/10.1002/joc.7915, 2022.

May, P. T., Trewin, B., Su, C. H., Ostendorf, B.: Verification of moist surface variables over northern Australia in a high-resolution reanalysis (BARRA). J. Southern Hemisphere Earth Systems Science 71, 194–202. https://doi.org/10.1071/ES21007 , 2021.

Nishant N., Evans, J. P., Di Virgilio, G., Downes, S. M., Ji, F., Cheung, K. K. W., Tam, E., Miller, J., Beyer, K., Riley, M. L.: Introducing NARCliM1.5: evaluating the performance of regional climate projections for southeast Australia for 1950-2100. Earth's Future, https://doi.org/10.1029/2020EF001833, 2021.

Nishant, N., Sherwood, S., Prasad, A., Ji, F., Singh, A.: Impact of higher spatial resolution on precipitation properties over Australia, Geophysical Research Letters, DOI:10.1029/2022GL100717 , 2022.

Pei, F., Zhou, Y., Xia, Y.: Assessing the Impacts of Extreme Precipitation Change on Vegetation Activity. Agriculture, 11(6), 487, 2021.

Pirooz, A. A. S., Moore, S., Carey-Smith, T., et al.: Evaluation of global and regional reanalyses performance over New Zealand. Weather and Climate, 41, 52–70. https://doi.org/10.2307/27127989, 2021.

Poli, P., Hersbach, H., Dee, D.P., Berrisford, P., Simmons, A.J., Vitart, F., Laloyaux, P., Tan, D.G.H., Peubey, C., Thépaut, J.-N., et al.: ERA-20C: An Atmospheric Reanalysis of the Twentieth Century. J. Climate, 29, 4083–4097, https://doi.org/10.1175/jcli-d-15-0556.1 , 2016.

Qin, S., Wang, K. C., Wu, G. C., Ma, Z. S.: Variability of hourly precipitation during the warm season over eastern China using gauge observations and ERA5. Atmos. Res., 264, https://doi.org/10.1016/j.atmosres.2021.105872 , 2021.

632   Quagraine, K. A., Nkrumah, F., Klein, C., et al.: West African Summer Monsoon
633   Precipitation Variability as Represented by Reanalysis Datasets. Climate, 8,
634   https://doi.org/10.3390/cli8100111, 2020.

635   Saha, S., Moorthi, S., Pan, H.-L., Wu, X., Wang, J., Nadiga, S., Tripp, P., Kistler, R.,
636   Woollen, J., Behringer, D., et al.: The NCEP Climate Forecast System Reanalysis. Bull.
637   Am. Meteorol. Soc., 91, 1015–1058. https://doi.org/10.1175/2010BAMS3001.1., 2010.

638   Schulzweida, U., Kornblueh, L., Quast, R.: CDO user's guide. *Climate data operators,*
639   *Version*, *1*(6), 205-209, 2006..

640   Shen, L. C., Wen, J. H., Zhang, Y. Q., et al.: Performance Evaluation of ERA5 Extreme
641   Precipitation in the Yangtze River Delta, China. Atmosphere (Basel) 13,
642   https://doi.org/10.3390/atmos13091416, 2022.

643   Solman, S.A., Sanchez, E., Samuelsson, P., et al.: Evaluation of an ensemble of regional
644   climate model simulations over South America driven by the ERA-Interim reanalysis:
645   model performance and uncertainties. Climate Dynamics, 41, 1139–1157,
646   https://doi.org/10.1007/s00382-013-1667-2, 2013.

647   Song, Y. Y., Wei, J. F.: Diurnal cycle of summer precipitation over the North China Plain and
648   associated land-atmosphere interactions: Evaluation of ERA5 and MERRA-2. Intl. J.
649   Climatol. 41, 6031–6046, https://doi.org/10.1002/joc.7166 , 2021.

650   Su, C. H., Eizenberg, N., Jakob, D., et al.: BARRA v1.0: kilometre-scale downscaling of an
651   Australian regional atmospheric reanalysis over four midlatitude domains. Geosci.
652   Model Dev., 14, 4357–4378, https://doi.org/10.5194/gmd-14-4357-2021 , 2021.

653   Su, C. H., Eizenberg, N., Steinle, P., et al.: BARRA v1.0: the Bureau of Meteorology
654   Atmospheric high-resolution Regional Reanalysis for Australia. Geosci. Model Dev., 12,
655   2049–2068, https://doi.org/10.5194/gmd-12-2049-2019 , 2019.

656   Tabari, H.: Climate change impact on flood and extreme precipitation increases with water
657   availability. Scientific Reports, 10(1), 1-10, 2020.

658   Teng, J., Bennett, J. C., Charles, S., Chiew, F., Ji, F., Potter, N., Fu, G. B., Thatcher, M.,
659   Remenyi, T.: Trend and variance in regional climate models – validation and
660   hydrological implications, Journal of Hydrology, 642(11), 131817,
661   https://doi.org/10.1016/j.jhydrol.2024.131817 , 2024.

662   Wang C. X., Graham R. M., Wang, K. G., et al.: Comparison of ERA5 and ERA-Interim
663   near-surface air temperature, snowfall and precipitation over Arctic sea ice: effects on
664   sea ice thermodynamics and evolution. Cryosphere 13, 1661–1679.
665   https://doi.org/10.5194/tc-13-1661-2019 , 2019.

666

667

668

669 Table 1 List of ET-SCI indices evaluated in this study.

Index	Definition	Units	Timescale	Sectors
PRCPTOT	Total wet-day precipitation (Sum of daily precipitation >= 1.0 mm)	mm	Annual/Monthly	Agriculture and food security, water, water resources and food security, forestry/GHGs
CDD	Consecutive dry days (Maximum number of consecutive dry days (when precipitation < 1.0 mm))	days	Annual	Health, agriculture and food security, water resources and food security, disaster risk reduction, forestry/GHGs
CWD	Consecutive wet days (Maximum annual number of consecutive wet days (when precipitation >= 1.0 mm))	days	Annual	Coasts, agriculture, transport operations
R10mm	Days when precipitation is at least 10mm	days	Annual/Monthly	Coasts
R90p	Total annual precipitation from very heavy precipitation days (Annual sum of daily precipitation > 90th percentile)	mm	Annual	Coasts, transport operations
R99p	Total annual precipitation from very heavy precipitation days (Annual sum of daily precipitation > 99th percentile)	mm	Annual	Coasts, transport operations
Rx1Day	Amount of precipitation from very wet days (Maximum 1-day precipitation)	mm	Annual/Monthly	Agriculture and food security, water, coasts, disaster risk reduction, forestry/GHGs

670

671

672

673 Table 2 Domain-averaged absolute biases and temporal correlation between BARRA/ERA5
674 and AGCD for annual precipitation and precipitation extremes

Indices	Absolute biases in annual mean		Temporal correlation		Absolute biases in CV		Absolute biases in trend	
	BARRA	ERA5	BARRA	ERA5	BARRA	ERA5	BARRA	ERA5
Annual pr	0.169	0.149	0.771	0.854	0.063	0.037	0.008	0.007
CDD	14.543	6.913	0.578	0.650	0.050	0.045	0.584	0.566
CWD	2.346	1.714	0.446	0.527	0.061	0.059	0.064	0.060
R10mm	3.265	1.700	0.688	0.761	0.081	0.053	0.085	0.094
R90p	0.777	0.439	0.761	0.827	0.211	0.082	0.023	0.023
R99p	4.093	3.668	0.562	0.625	0.121	0.060	0.206	0.162
Rx1day	20.333	7.916	0.380	0.486	0.219	0.107	0.848	0.542

675

676

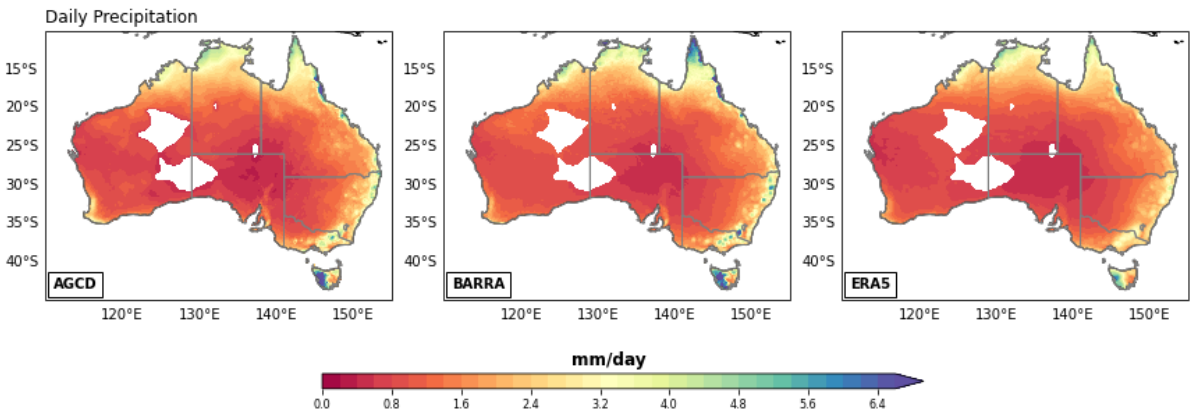
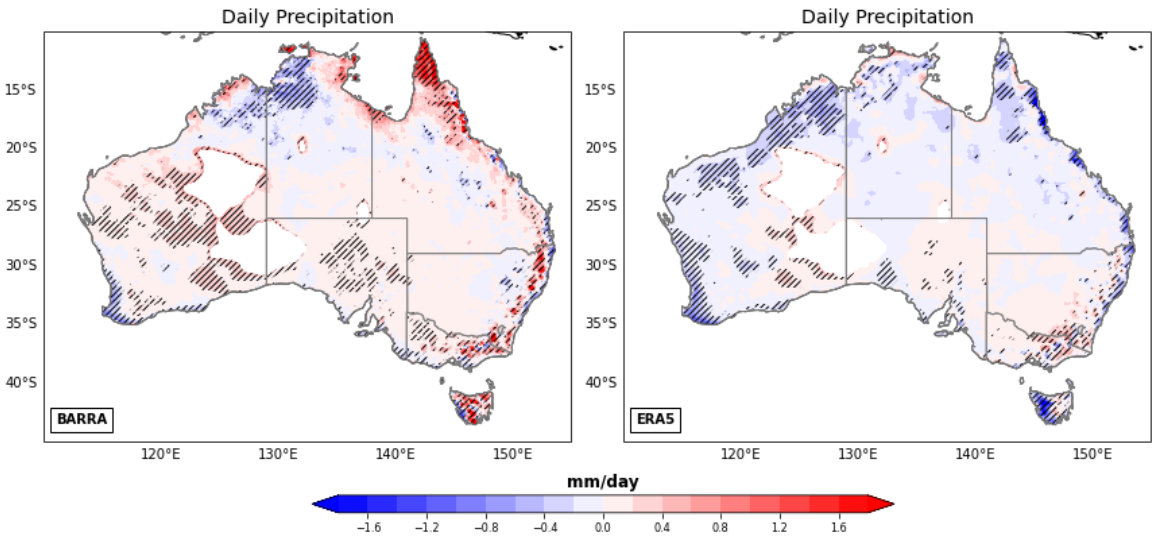



Figure 1 Annual mean precipitation of AGCD, BARRA and ERA5 (upper panels) and annual mean biases between BARRA/ERA5 and AGCD (lower panels). The regions with low density of station observations in AGCD has been masked and not considered in all subsequent evaluation. Unit: mm/day. Stippling indicates areas with biases that are statistically significant at 95% confidence level.

687

688

689

690

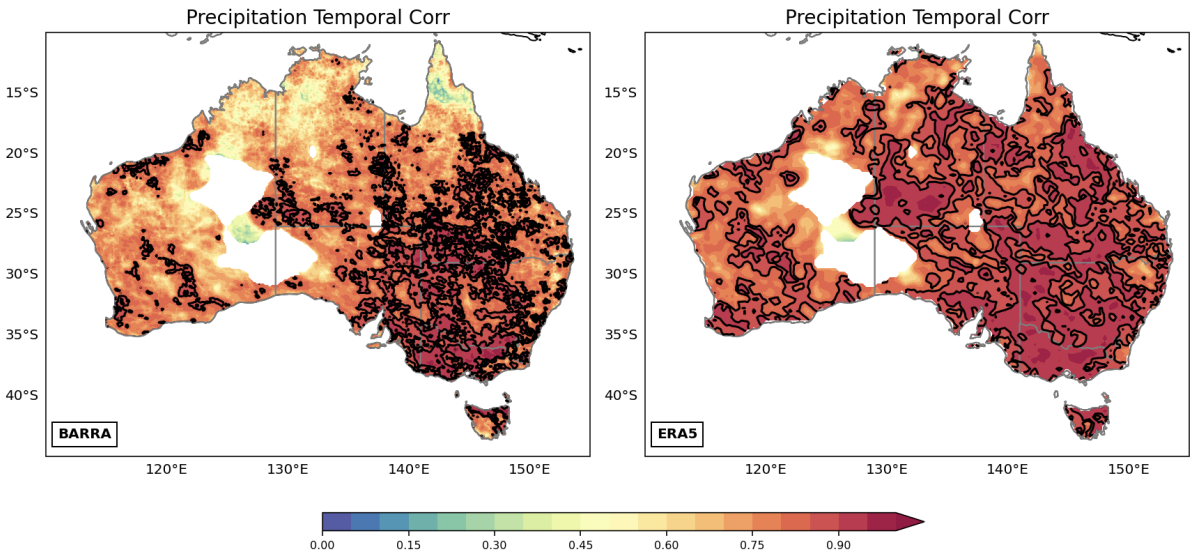
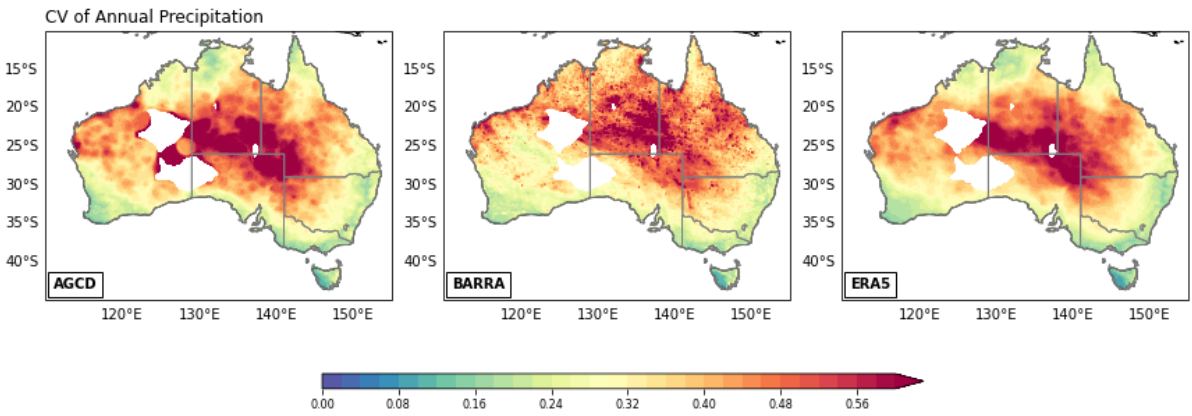
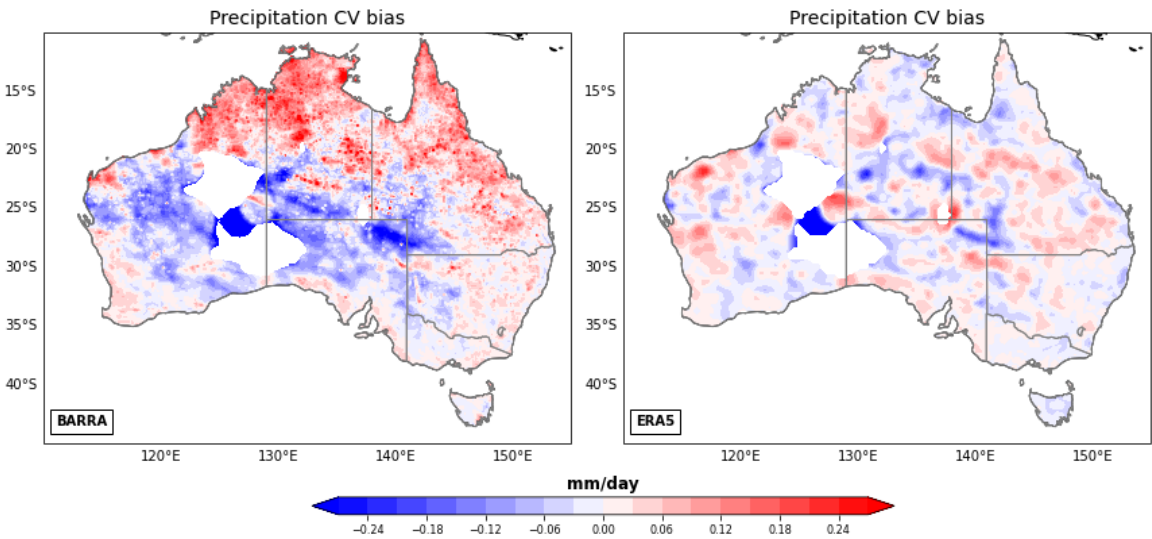



Figure 2 Temporal correlation coefficient of annual precipitation between BARRA/ERA5
and AGCD. A black contour at value 0.85 has been added for reference.

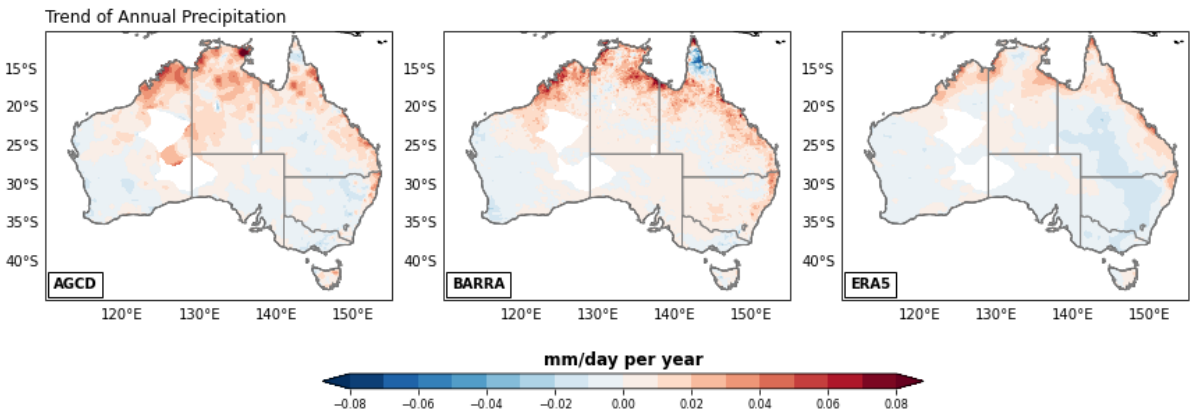
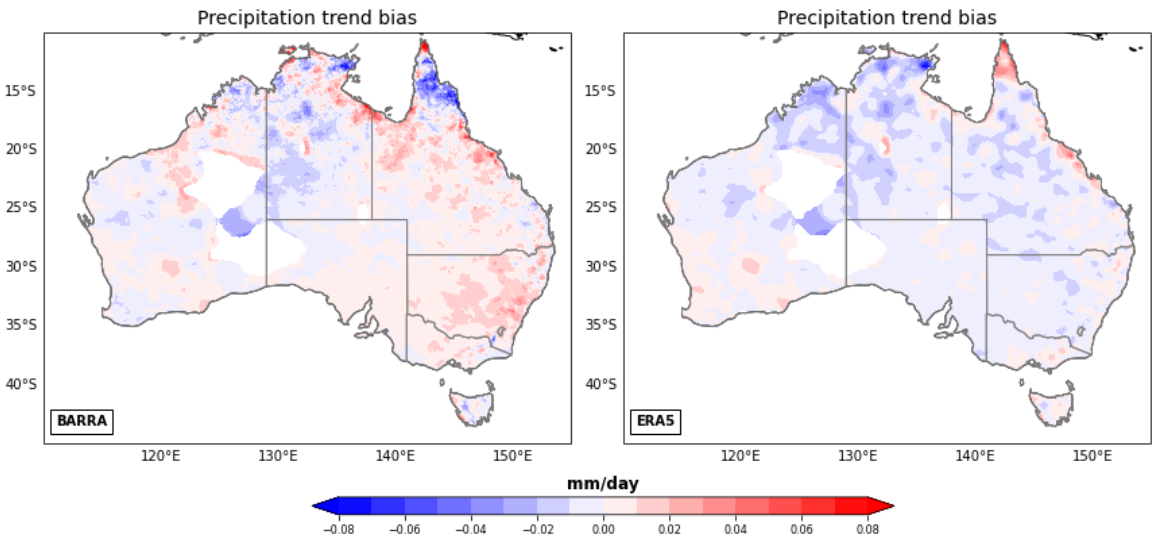
693

694

695

696

697

698   Figure 3 CV of annual precipitation for AGCD, BARRA and ERA5 (upper panels) and biases
699   in CV between BARRA/ERA5 and AGCD (lower panels).

700

701

702

703

704

705   Figure 4 Trend of annual precipitation for AGCD, BARRA and ERA5 (upper panels) and
706   biases in trend between BARRA/EAR5 and AGCD (lower panels).

707

708

709

710

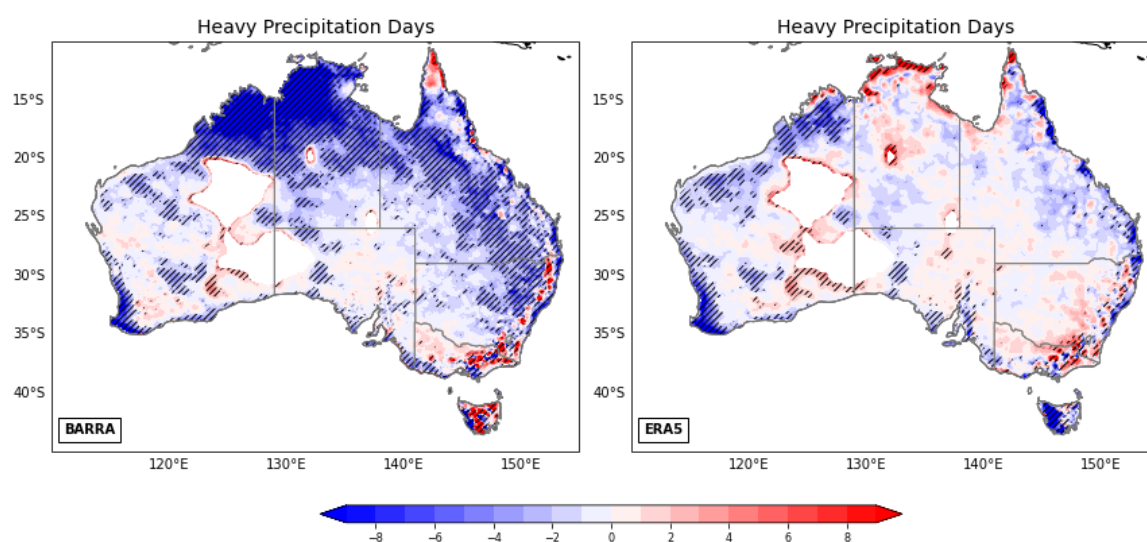
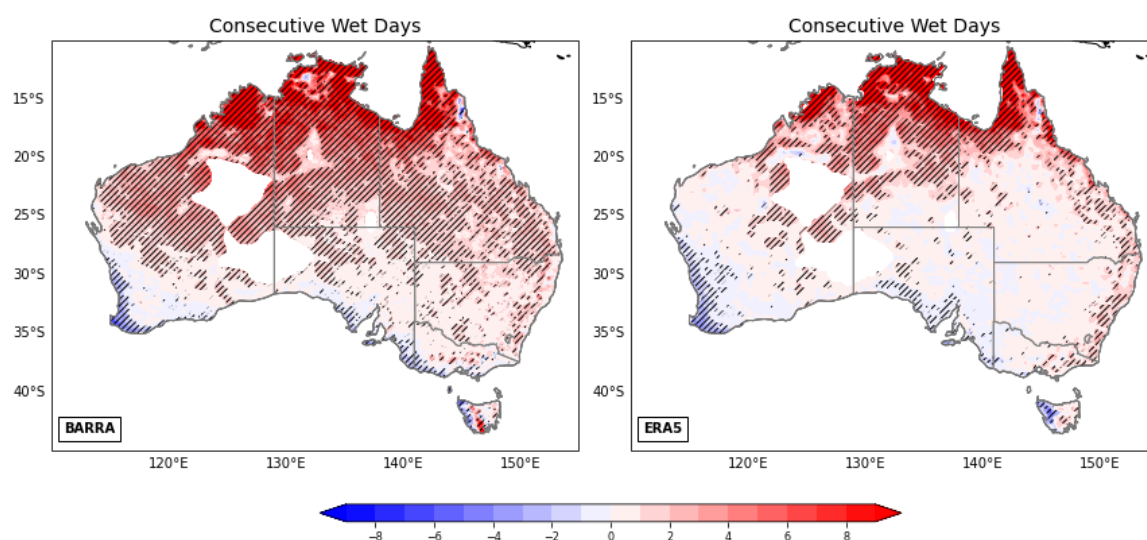
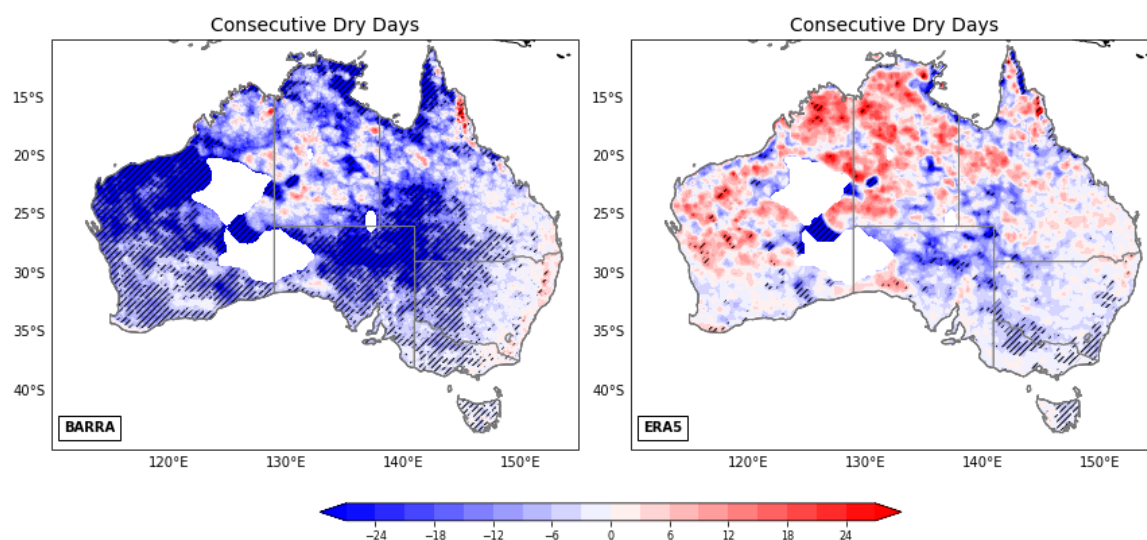



Figure 5 Biases in CDD, CWD, R10mm, R90p, R99p and Rx1Day in BARRA (left column) and ERA5 (right column). Stippling indicates areas with biases that are statistically significant at 95% confidence level. A black contour at 40% has been added to the panels for Rx1day (last row) for reference.

715

716

717

718

719

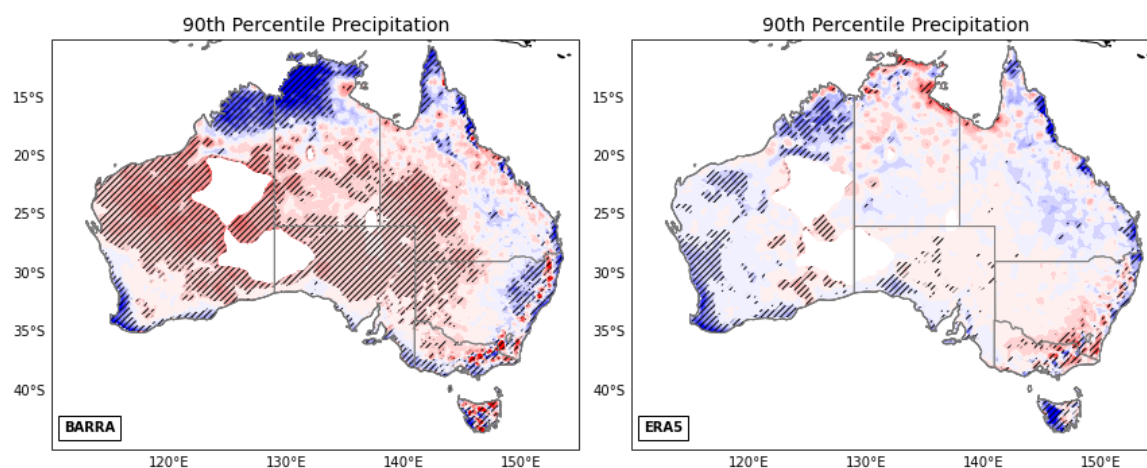
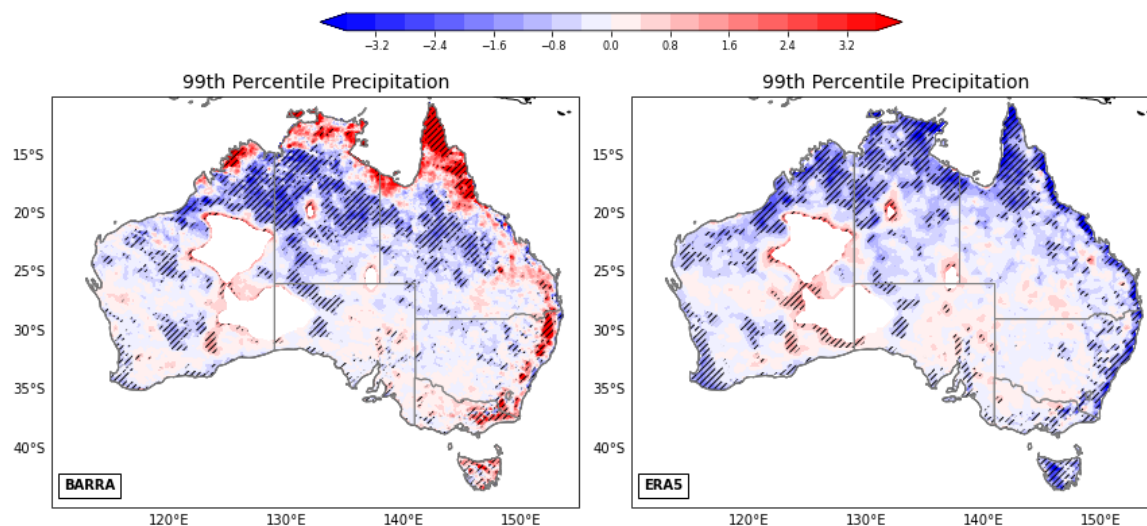
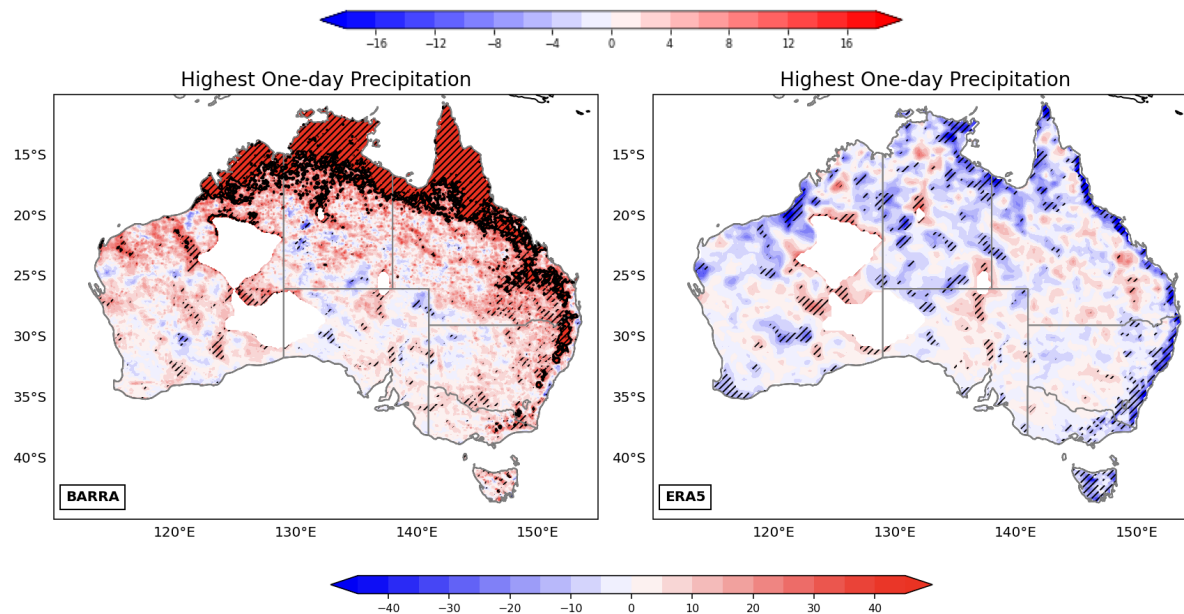



Figure 5 (continued).

721

722

723

724
725

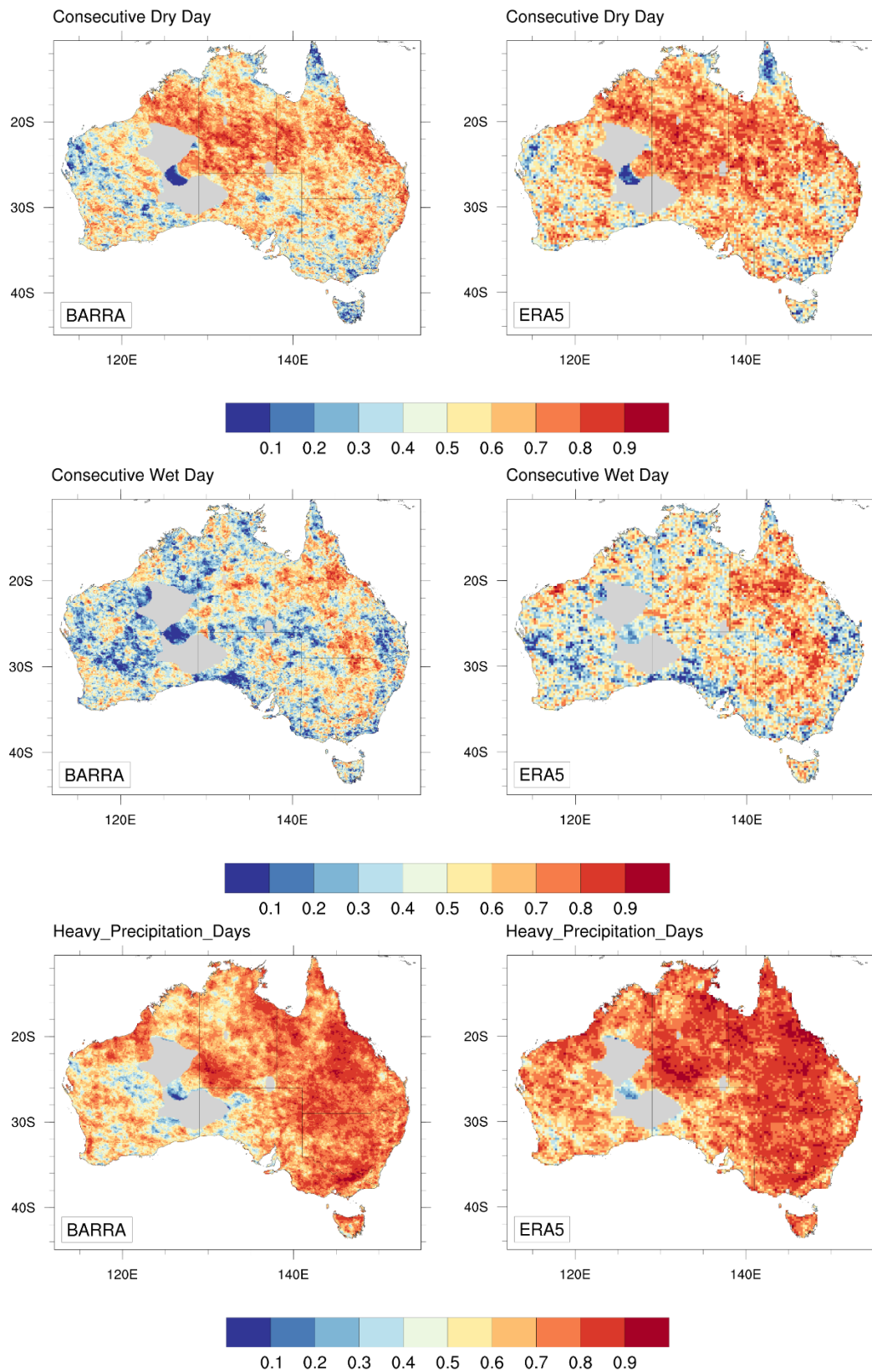



Figure 6 Temporal correlation of CDD, CWD, R10mm, R90p, R99p and Rx1Day between
BARRA and AGCD (left column) and between ERA5 and AGCD (right column).

728

729

730
731

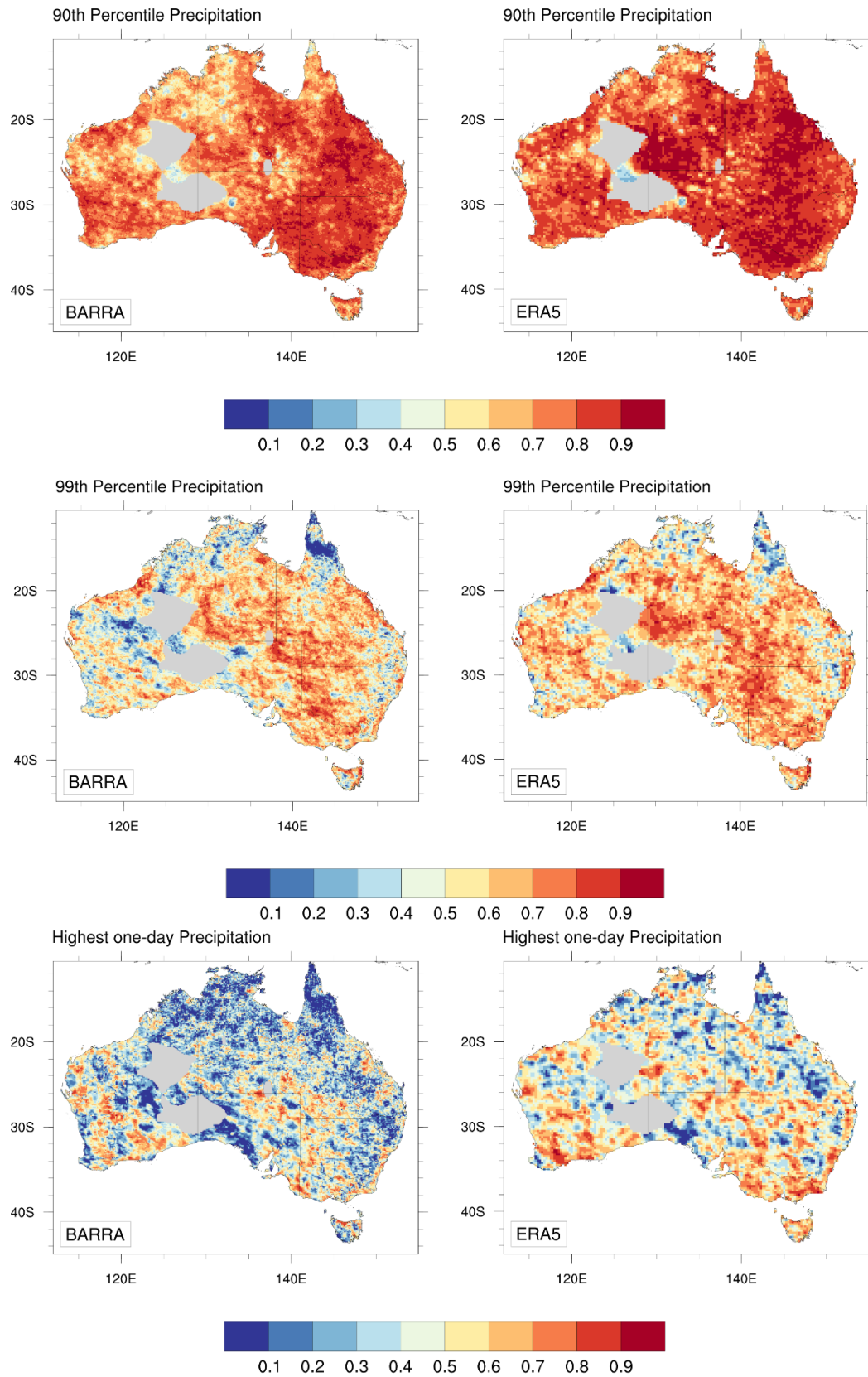
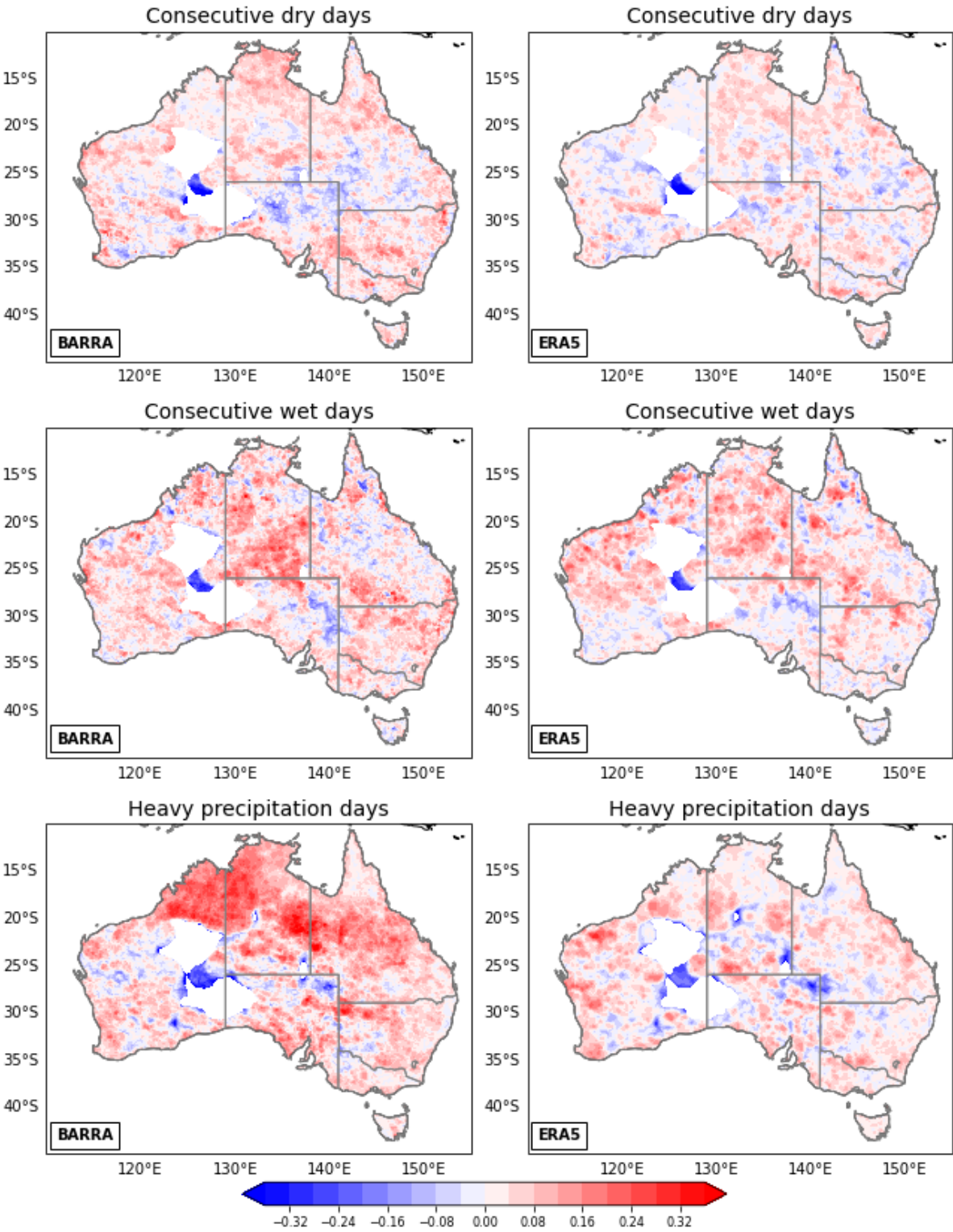



Figure 6 (continued).

733

734

735

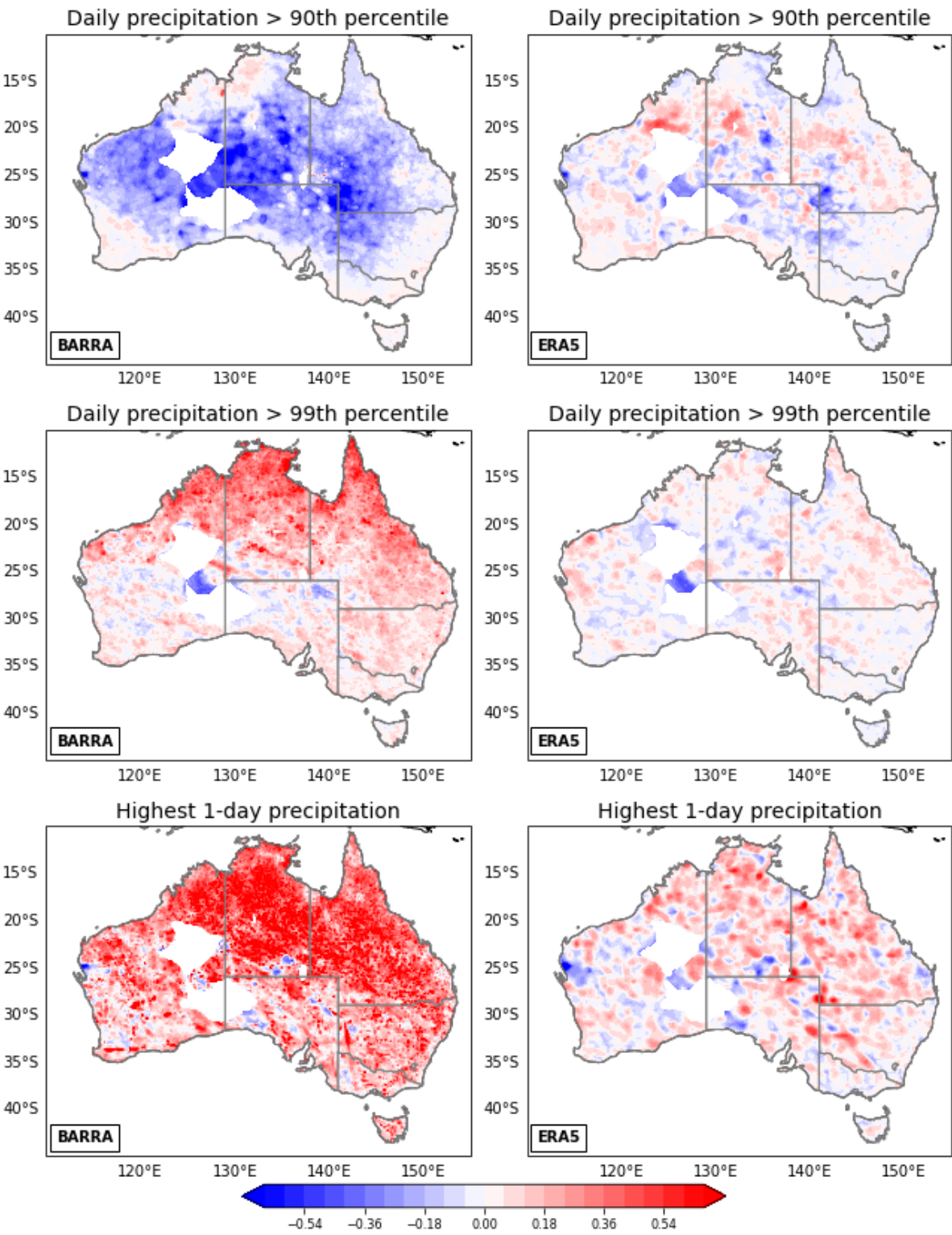
736

737   Figure 7 Biases in CV of CDD, CWD, R10mm, R90p, R99p and Rx1Day for BARRA (left
738   column) and ERA5 (right column) relative to AGCD.

739

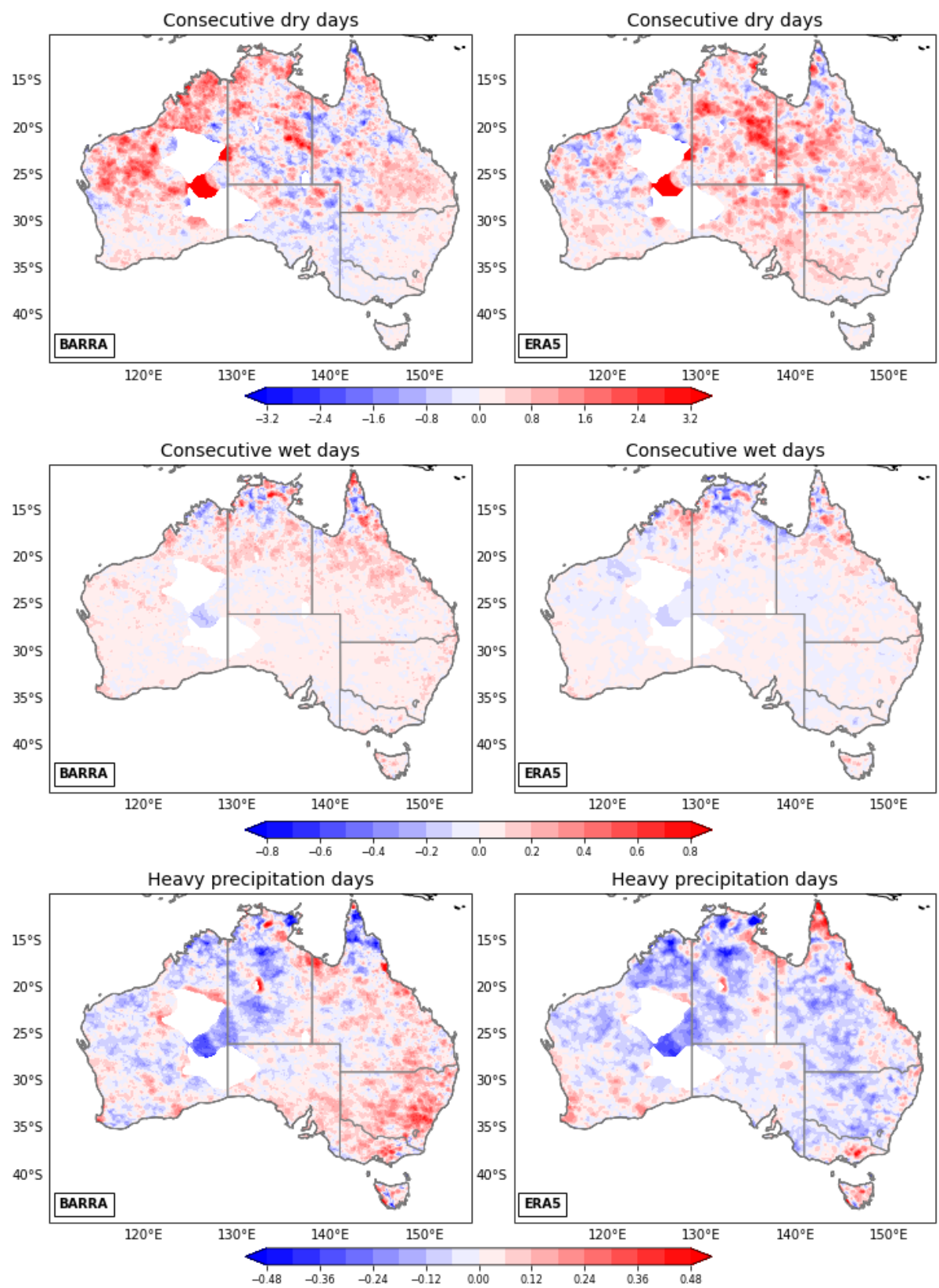
740

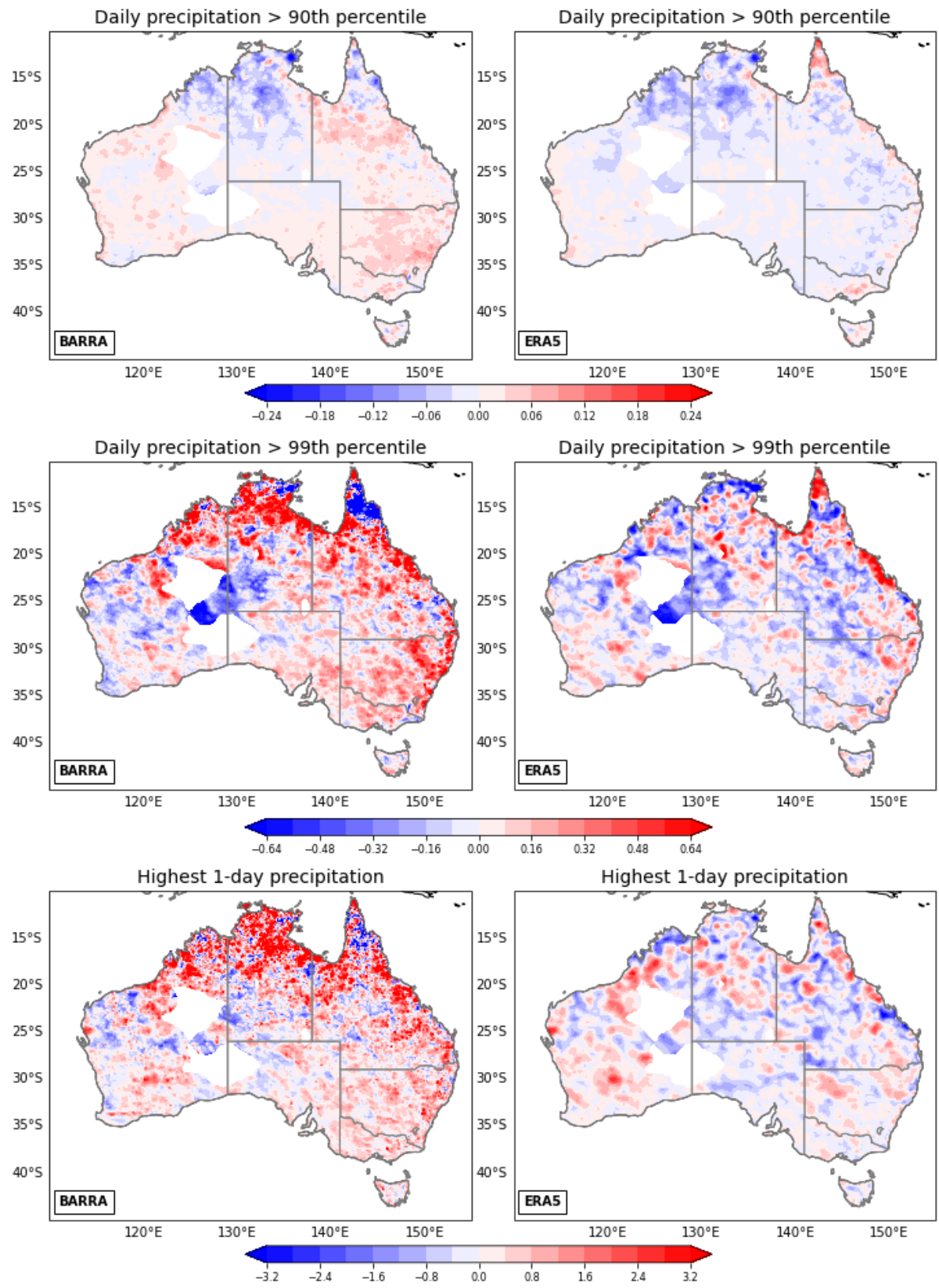
741

742

743   Figure 7 (continued).

744

745

746

747   Figure 8 Biases in trends of CDD, CWD, R10mm, R90p, R99p and Rx1Day for BARRA (left
748   column) and ERA5 (right column) relative to AGCD.

749

750

751

752   Figure 8 (continued).