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3 Bias correction of multi-ensemble simulations from the 4 HAPPI model intercomparison project

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22

23 Abstract

24

25 Prior to using climate data as input for sectoral impact models, statistical bias correction is
26 commonly applied to correct climate model data for systematic deviations. Different
27 approaches have been adopted for this purpose, however the most common are those based
28 on the transfer functions, generated to map the distribution of the simulated historical data
29 to that of the observations. Here, we present results of a novel bias correction method,
30 developed for Inter-Sectoral Impact Model Intercomparison Project Phase 2b (ISIMIP2b) and
31 applied to outputs of different GCMs generated within the HAPPI (Half A degree Additional
32 warming, Projections, Prognosis and Impacts) project. We have employed various analysis
33 measures including mean seasonal differences, ensemble variability, annual cycles, extreme
34 indices as well as a global hydrological model to assess the performance of ISIMIP2b bias
35 correction technique. The results indicate substantial improvements after the application of



1 bias correction when compared against observational data. Moreover, the extreme indices as
2 well as output of global hydrological model also reveal a marked improvement. At the same
3 time, the ensemble spread of the original data is preserved after the application of bias
4 correction. We find that the bias corrected HAPPI data can provide a reliable basis for sectoral
5 climate impact projections.

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7

8 **Introduction**

9

10 Global climate models (GCMs) are the most commonly used tools to assess changes in future
11 climate. However, due to their coarser resolution (~ 200 km), many regional and local scale
12 climate features go beyond the scope of GCMs and give rise to biases in different climate
13 variables against observation in historical period (Flato *et al* 2013). Besides resolution,
14 imperfect representation of physical processes, incorrect initialization or errors in the
15 parameterization chain etc., can also act as contributing factors to these biases (Ehret *et al*
16 2012). Global models are benchmarked against global datasets and a set of comprehensive
17 variables, not for specific regions or sector relevant outputs. Despite biases in absolute values,
18 relative changes in GCMs have been shown to resemble observed trends well (Flato *et al*
19 2013). However, when GCM output is directly used to force impact models (e.g. crop models,
20 hydrological models etc.), which are often certain processes are based on specific thresholds,
21 these absolute biases limit the applicability of the climate data by affecting the calibration and
22 validation process, which is an important aspect of impact modeling (Warszawski et al 2013).

23

24 Different approaches have been adopted to overcome the biases generated by GCMs. One of
25 them is the stochastic downscaling in which a functional relationship is established between
26 the most robust and reliable fields provided by GCMs and the observed meteorological
27 variables for a specific region. However, this approach is criticized due to one critical
28 assumption implicit to all statistical downscaling methods which is ‘statistical stationarity’
29 (Dixon et al 2016). Moreover, in certain cases (e.g. ISIMIP experiment) in which the global
30 impact models are forced with the GCM data, stochastic downscaling does not remain a very
31 useful option (Warszawski et al 2013). Another physically more consistent approach to
32 overcome these biases is regional climate modelling (Giorgi and Mearns 1999). A regional



1 climate model (RCM) can not only bridge the resolution gap for the better representation of
2 regional scale features, but it also gives the flexibility for the representation of characteristic
3 processes of a certain region (Saeed et al 2012). However, despite improvements during
4 recent years, the output of RCMs is still afflicted with biases (systematic errors) to a degree
5 that preclude their direct use in the impact models (Piani et al 2010).

6

7 Another well-established approach to overcome the biases of GCMs to make them suitable
8 for their use in impact models is the post-processing of GCM data by correcting with and
9 towards observations (Sippel et al 2016). This approach has become standard in impact
10 studies and is known as bias correction (or bias adjustment). There are different methods
11 which have been published in earlier literature ranging from simple adjustment of the means
12 to flexible, potentially multivariate, quantile mapping approaches (Maraun et al 2017).
13 However, like other methods, there have been many problems associated with the bias
14 correction methods. Few of those already identified include alteration of spatiotemporal field
15 consistency, relations among variable and violation of conservation laws (Ehret et al 2012).
16 Therefore this approach is prone to misuse and hence a careful practice of the bias correction
17 is generally recommended (Maraun et al 2017).

18

19 For this study, we have used the applied bias correction technique developed for ISIMIP (Inter
20 Sectoral Impact Modelling Inter-comparison Project) and recently extended for ISIMIP2b
21 (Frieler et al 2016), hereafter referred to as ISIMIP2b-BC approach. ISIMIP bias correction is a
22 trend preserving statistical bias correction approach which adjusts the monthly mean and
23 daily variability of simulated climate data to observations (Hempel et al 2013)(Lange 2017).
24 Here we applied the ISIMIP2b-BC to GCM output from the HAPPI (Half a degree Additional
25 warming, Projection, Prognosis and Impacts) model intercomparison project (Mitchell et al.
26 2017).

27

28 Following the adoption of the Paris Agreement, there has been a growing interest for
29 quantifying impacts at discrete levels of global mean temperature (GMT) increase such as
30 1.5°C and 2.0°C above pre-industrial levels (Schleussner et al 2016). By now, there has been a
31 dearth of research to address this issue because many available experiments in the CMIP
32 (Couple Model Inter-comparison Project) are not specifically designed for informing this



1 report. This has led to the HAPPI experiment, an international effort specifically designed to
2 provide a framework for the generation of climate data describing how the climate, in
3 particular extreme weather, might differ from the present day in worlds those are 1.5° and
4 2.0°C warmer than pre-industrial conditions (Mitchell et al 2017). The quasi-stationary multi-
5 ensemble design also allows for assessments of climate change signals against a highly
6 variable background.

7

8 In this paper, we present the performance of ISIMIP2b-BC in correcting the biases associated
9 with different variables from four different GCMs analyzed in the HAPPI experiment. Besides
10 validation, this paper also focuses on whether the application of ISIMIP2b-BC preserves the
11 ensemble spread of the original simulations. This paper also provides a reference document
12 for the future users of HAPPI data.

13

14 **Data and Methodology**

15

16 The HAPPI modelling setup considers three time periods (historical, +1.5°C and +2.0°C) each
17 spanning over 10 years (Mitchell et al 2017). All the runs are executed atmosphere only under
18 prescribed sea-surface temperatures and sea-ice forcing conditions. For each of the three
19 periods considered, multi-ensemble GCM realizations are provided. The ‘historical period’
20 taken through 2006-2015 for HAPPI. We employed ISI-MIP2b bias correction methodology to
21 bias correct HAPPI data in order to improve the representation of regional features using
22 (Hempel et al 2013), (Lange 2017). Following the modelling protocol of the Intersectoral
23 Impact Model Intercomparison Project (Frieler et al 2016), the resultant projections are re-
24 gridded to a 0.5°x0.5° regular grid and then bias corrected using the EWEMBI dataset (Lange
25 2017). In total 20 ensemble members per GCM have been bias corrected.

26

27 In previous applications, bias correction was generally applied on a single transient simulation
28 by generating transfer functions for a variable in the base period. These transfer functions
29 were then applied to the projected data of the transient simulation. In HAPPI, the transfer
30 functions have been derived for one long-term member over a climatological time scale of
31 more than 25 years (Table 1). This long-time frame is chosen in order to capture the effects of
32 natural variability. The GCM specific transfer function is then applied to each ensemble
33 member (of 10 years period) to attain the bias corrected data. It is noteworthy that the



1 individual ensemble members of the different periods are initialised stochastically. This
2 implies that numbering of ensemble members is purely statistical and does not imply any
3 physical relationship in terms of natural variability. Table 2 shows the HAPPI variables which
4 are bias corrected using ISIMIP2b-BC in the present study.

5

6 Different analysis approaches, including mean seasonal differences, mean standard deviation
7 across ensemble, annual cycle and extreme indices, are employed to find out the performance
8 of ISIMIP2b-BC. In addition, both the original (non-bias corrected) and the bias corrected data
9 sets have been used to force WaterGAP (Müller Schmied *et al* 2014), a global water use and
10 availability model, which calculates freshwater fluxes and storages for all continents except
11 for Antarctica. A detailed and comprehensive model description of WaterGAP can be found in
12 (Müller Schmied *et al* 2014) and (Müller Schmied 2017). The version used here is
13 WaterGAP2.2c.

14

15 Results

16

17 Mean Seasonal Differences:

18

19 Seasonal plots of ISIMIP2b-BC of 5 variables for different GCMs are shown in Figure 1, which
20 are plotted by taking the mean of 20 ensemble members for each variable and compared
21 against the EWEMBI dataset (2001-2010). Moreover, the complete results for all the variables
22 across all the 4 GCMs are presented in Figure S1-S8. MIROC5 exhibits the strongest bias for
23 temperature over most parts of the globe (Figure 1 and Figure S1). For certain regions, like
24 Russia, the sign of the seasonal bias is swapped between MAM and JJA (Figure 1). Moreover,
25 the direction of the bias is also different among different GCMs over different regions (Figure
26 S1). Application of ISIMIP2b-BC improved the results drastically by bringing the biases down
27 to 0.5°C over most of the globe, irrespective of the direction of the bias. A similar behavior is
28 observed for the results of tasmin and tasmax where large biases are reasonably corrected by
29 ISIMIP2b-BC (Figure S2 and S3). A common feature across all the GCMs is are systematic biases
30 over the high latitude sea ice regions (warm bias over the Arctic, cold bias over Antarctica) for
31 the three temperature variables (i.e. tas, tasmin and tasmax) during boreal autumn and
32 winter, which stays consistent even after the application of ISIMIP2b-BC. This feature might
33 be the result of the substantial alterations in sea ice coverage between the bias correction



1 period and the recent past (decrease in the Arctic, increase in the Antarctic (Nghiem et al.
2 (2016)) that will ultimately alter affect the applicability of the transfer function. Despite visible
3 improvements in terms of model bias, we identify the high latitudes as a region where the
4 assumption of a time invariant transfer function is of limited validity.

5

6 A similar behavior is observed for precipitation as in Figure 1 for ECHAM6 (and full set of
7 models in Figure S4). Once again, the bias correction yielded substantial improvement of
8 precipitation. A few differences remain over the tropical and subtropical arid regions which is
9 attributed to the lack of precipitation in those regions, and therefore a small difference
10 appears substantial when looking at relative changes for certain seasons. The results for other
11 GCMs also show similar patterns (Figure S4).

12

13 CAM4-2degree shows an overestimation of near surface wind speed over most of the land
14 area which is substantially reduced by ISIMIP2b-BC across all the seasons (Figure 1). ECHAM6
15 and NorESM1 show better results for surface wind speeds which is further improved after the
16 application of ISIMIP2b-BC (Figure S5). A special case is MIROC5 which shows underestimation
17 of near surface wind speeds over tropical forested regions of Africa and South America, which
18 remains the same after the application of ISIMIP2b-BC. It appears that in MIROC5, the wind
19 speeds are calculated inside the rainforest canopy and, therefore, are one to two orders of
20 magnitude too weak in the original model data (Tatsuo Suzuki (Personal Communication)).

21

22 For other variables, such as rsds, rlds and hurs, ISIMIP2b-BC has also done a very satisfactory
23 job in reducing the biases for all the seasons across all the four GCMs (Figure 1 and Figure S5-
24 S8).

25

26 **Seasonal variability across the ensemble:**

27

28 A key research question for HAPPI simulations are changes in the extremes. Although the
29 ISIMIP2b-BC methodology should leave the stochastic ensemble variability unaffected, we
30 therefore explicitly assessed its effects. The seasonal ensemble standard deviation of daily
31 data for selected variables is presented in Figure 2. The complete results for all the variables
32 across all the 4 GCMs are presented in Figure S9-S16.

33



1 All the GCMs have simulated higher temperature variability over higher latitudes as compared
2 to tropics, especially during the corresponding winter season (Figure 2 and Figure S9).
3 ISIMIP2b-BC has ably kept the ensemble variability for all the GCMs. There are few small
4 differences between the original and bias corrected data over some region, however the
5 overall spatial pattern of the variability is reasonably kept after the application of ISIMIP2b-
6 BC. Similar results are obtained for tasmax and tasmin, and are presented in Figure S10 and
7 S11 respectively.

8

9 In comparison to temperature variable, precipitation shows different behavior with the
10 monsoon regions showing highest variability in the original simulation with varying magnitude
11 among different GCMs (Figure 2 and Figure S12). The variability is prominent especially during
12 the rainy season. ISIMIP2b-BC has largely kept the variability of the original data with
13 consistent spatial pattern, however there are few differences at regional scale (for example
14 over the South Asian Summer Monsoon region (SASM)). Looking at the summer season plot
15 (JJA) in Figure S12, it can be noticed that all the GCMs have different spatial patterns of
16 variability over land as well as Indian ocean in the original data. High and low variability over
17 India can be seen for MIROC5 and ECHAM6 respectively. Moreover, magnitude and location
18 of high variability spot over the Arabian Sea vary between the GCMs. Application of ISIMIP2b-
19 BC resulted in consistent pattern for all the four GCMs with highest variability occurring over
20 central India for JJA. Therefore, change in variability for precipitation arise as the result of the
21 modification of highly dynamical features of the climate system, such as Monsoon, that are
22 not equally represented in the GCMs. While ISIMIP2b-BC is affecting the ensemble variability
23 in regions where dynamical features dominate, this to some extent is more correcting for
24 misrepresentations of these features in the underlying GCMs without changing their
25 dynamical characteristics. However, it presents a limitation to the applicability of a purely
26 thermodynamic and statistical correction in the presence of strong dynamical features.

27

28 For rsds, the highest variability follows the seasonal march of the sun in northern and southern
29 hemisphere in the original data for all the GCMs (Figure 2 and Figure S14). ISIMIP2b-BC has
30 once again done a good job in keeping the seasonal spatial pattern as well as magnitude of
31 the variability. However, ISIMIP2b-BC show a small reduction in the ensemble variability of
32 rlds towards higher latitudes, by keeping the spatial pattern consistent (Figure S15).



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2 Furthermore, a satisfactory performance of ISIMIP2b-BC in correcting the hurs and sfcWind
3 fields have been observed which can be seen from the Figure S13 and S16 respectively.

4

5 **Annual Cycle:**

6

7 In order to further ascertain the ability of ISIMIP2b-BC in keeping the spread of the original
8 simulation, annual cycle of all the 8 variables have been plotted in Figure 3 and Figure S17 to
9 S20 averaged only over the land areas. The temperature (tas, tasmax, tasmin) and radiation
10 (rsds, rlds) variables show small ensemble spread for both original and bias corrected data.
11 ISIMIP2b-BC has done a satisfactory job in bringing these variables closer to the EWEMBI
12 annual curve while keeping the spread reasonably intact. For other variables ISIMIP2b-BC not
13 only corrects the bias, but also the shape of the mean curve (e.g. hurs for MIROC5 and pr for
14 CAM4-2degree in Figure 3). ECHAM6 has reasonably captured the annual cycle of
15 precipitation over the land areas, however ISIMIP2b-BC has shown a marked improvement for
16 the rest of the three GCMs. GCMs have also shown varying performances in capturing the
17 annual cycle of sfcWind with CAM4-2degree and NorESM1 a systematic overestimation which
18 is also corrected by ISIMIP2b-BC quite reasonably (Figure 3 and Figure S17 to S20).

19

20 **Extreme Indices:**

21

22 Climate extremes are one of the parameters which are likely to get affected by bias corrections
23 especially if the resolution simulation and the observations are considerably different from
24 each other (Maraun et al 2017). Moreover, the climate extremes are also reported to perform
25 not as good as long-term means and trends after the application of ISIMIP bias correction
26 (Hempel et al 2013). Therefore, it becomes imperative to analyze how does ISIMIP2b-BC
27 perform with HAPPI data in representing climate extremes. For this purpose, we consider
28 different extreme indices based on the recommendation of the Expert Team on Climate
29 Change Detection and Indices (Zhang et al 2011). For each extreme, all the indices are
30 calculated for each individual ensemble member for both bias corrected and original data and
31 the ensemble mean is taken afterwards across all the four GCMs. The presented results in
32 Figure 4 to 7 are the differences from EWEMBI data.

33



1 Consecutive Summer Days (CSD):

2

3 CSD is defined as the number of instances for which the maximum temperature remains
4 greater than certain threshold for consecutive period of 5 days or more. Results for each
5 model are presented in Figure 4 for the thresholds 30°C, 35°C and 40°C. Figure 4 shows general
6 improvement in the simulation of CSD after the application of ISIMIP2b-BC, bringing the
7 results closer to the EWEMBI data. Understandably, most of the differences occur in the lower
8 latitudes where these high temperature thresholds are attained more often. ECHAM6 and
9 MIROC5 simulate higher number of CSD instances than EWEMBI which are reasonably
10 corrected by ISIMIP2b-BC.

11

12 Consecutive Frost Days (CFD):

13

14 CFD is defined as the number of instances for which the minimum temperature remains less
15 than 0°C for consecutive period of 5 days or more. Results for each model for CFD are
16 presented in Figure 5. Contrary to CSD, most of the differences occur in the higher latitudes
17 for CFD. Once again, ECHAM6 has simulated much higher number of CFD than EWEMBI data
18 which is corrected to a large extent after the application of ISIMIP2b-BC. Altogether, ISIMIP2b-
19 BC has brought the CFD results closer to EWEMBI.

20

21 Consecutive Dry Days (CDD):

22

23 CDD is defined as the number of instances for which the daily precipitation remains less than
24 certain threshold for consecutive period of 5 days or more. Figure 6 shows the CDD results for
25 thresholds of 1mm/day, 1.5 mm/day and 2.0 mm/day. Once again, improvements in CDD after
26 the application of ISIMIP2b-BC can be seen. Although irrelevant in terms of impact model
27 application, however most obvious improvement is in the correction of overestimation and
28 underestimation for MIROC5, over most of the ocean region. Improvements can also be seen
29 over land regions for all the models.

30

31 Consecutive Wet Days (CWD):

32



1 CWD is defined as the number of instances for which the daily precipitation remains higher
2 than certain thresholds for consecutive period of 5 days or more. Results for CWD days for
3 thresholds of 1 mm/day, 2 mm/day and 3 mm/day are shown in Figure 7. Like other indices
4 discussed earlier, a general improvement in the results after the application of ISIMIP2b-BC
5 can be witnessed. Similar to CDD, application of ISIMIP2b-BC has shown a marked
6 improvement in the MIROC5 simulation over the ocean areas. Moreover, improvement can
7 also be noticed in the results of CWD for all the models over land areas.

8

9 **Simulated Streamflow:**

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11 The streamflow is calculated by WaterGAP for the bias corrected and non-bias corrected
12 ensemble members and compared to a reference run forced with EWEMBI data. In figure 8
13 we present the simulation results at outlets of three major river systems (Rhine, Mississippi
14 and Amazon). Due to the bias correction, the annual discharge and the seasonal flows fit
15 better to the reference simulations. Next to the general better fit of discharge the range of
16 the ensemble members is predominantly maintained in the three basins. Some further
17 streamflow simulation results can be found in figure S21, which also support the
18 aforementioned findings.

19 **Summary and Conclusions:**

20

21 Bias correction of climate model output has remained a controversial issue among the
22 scientists. A vast variety of bias correction methods are already in use in the field of climate
23 and impact modeling, however many problems with the bias correction methods have also
24 been identified. For example, bias correction not only alters the underlying physical
25 characteristics among variables, but also e.g. for extreme tails for the same variable (Sippel et
26 al., 2016). On the other hand, climate scientists are confronted with growing pressure to
27 translate their modeling information into informed adaptation decision by using the impact
28 models. Impact models, in which certain processes are based on threshold, are sensitive to
29 large systematic biases in the climate data making bias correction an essential step. We have
30 assessed the performance of ISIMIP2b-BC in correcting 8 variables simulated under HAPPI
31 project across 4 different GCMs.

32



1 An overall satisfactory performance of ISIMIP2b-BC is witnessed in correcting the seasonal
2 means as well ensemble spread across the GCMs. A marked improvement in the annual cycle
3 of the variable is also achieved. The results for extreme indicators also come closer to the
4 observations although they have not been explicitly bias corrected. All these improvements
5 are translated into the results of the impact model (WaterGAP), which show significant
6 improvements after the application of ISIMIP2b-BC. Few limitation have also been identified,
7 for example ISIMIP2b-BC failed to correct the deviations in strong dynamical features of the
8 monsoon regions.

9
10 The results of this study indicate that the application of bias correction technique is mandatory
11 when forcing the impact models with the data of climate models. Besides an orthodox
12 validation, this study will also serve as a reference document to analyze the performance of
13 bias corrected against the original (non-bias corrected) data for the future HAPPI data users.

15 Data availability:

16 The data used in this paper is freely available from the link
17 <http://portal.nersc.gov/c20c/data/ClimateAnalytics/>

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Table 1: Table of GCMs which are bias corrected in HAPPI, with their specifications.

Model	Horizontal Resolution	Time-Period for construction of Transfer Functions	References
CAM4	2x2 ^o	1979-2005	Neale et al. (2013)
MIROC5	150x150 km	1979-2010	Shiogama et al. (2014)
MPI-ECHAM6.3	T63	1979-2010	--
NorESM1-Happi	1.25x0.94 ^o	1986-2010	Bentsen et al. (2013)

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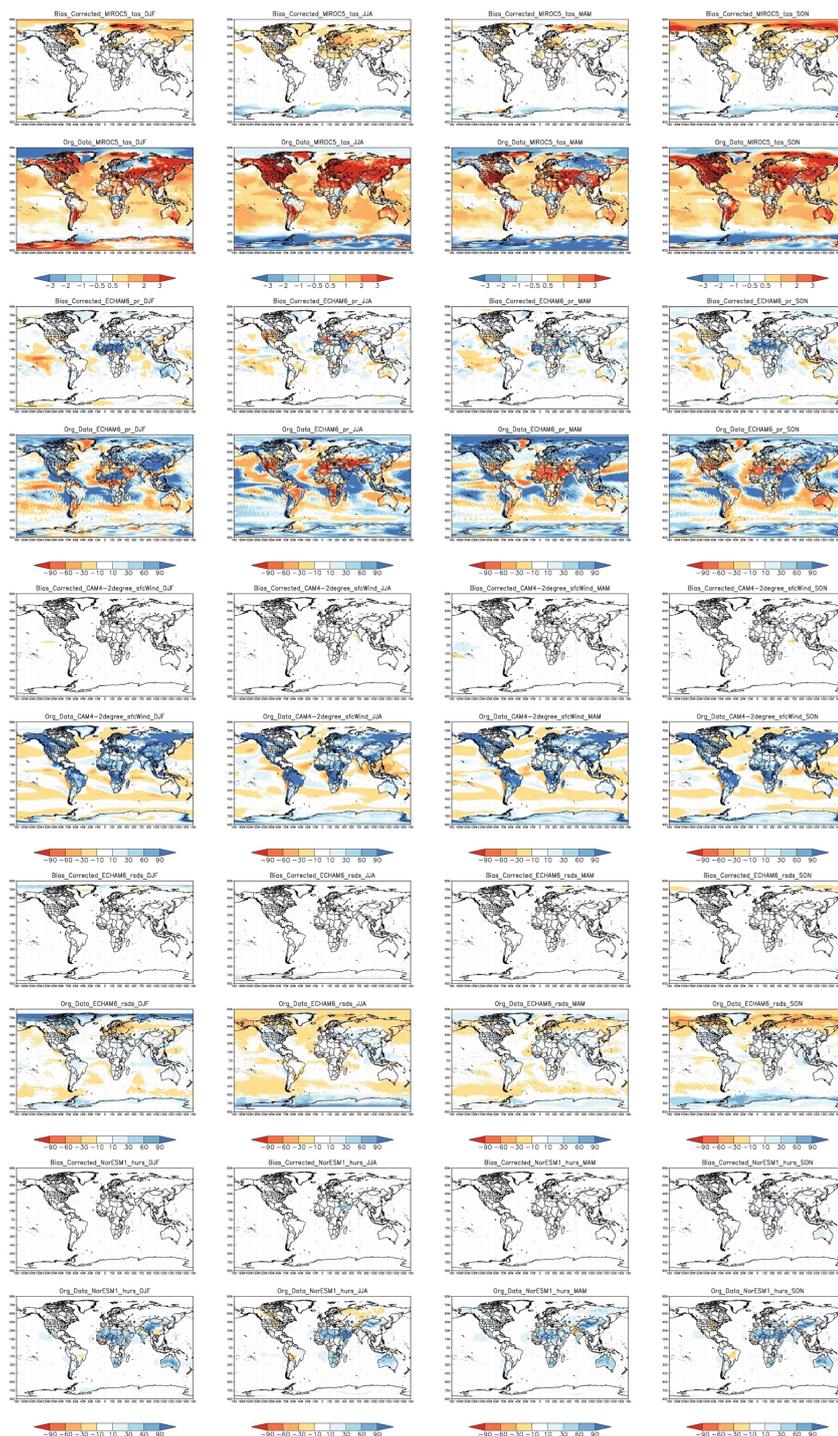
Table 2: List of HAPPI variables which are bias corrected using ISIMIP2b-BC.

Variable	Short name	Unit
Precipitation	pr	Kg m ² s ⁻¹
Near surface air temperature	tas	K
Near surface maximum air temperature	tasmax	K
Near surface minimum air	tasmin	K

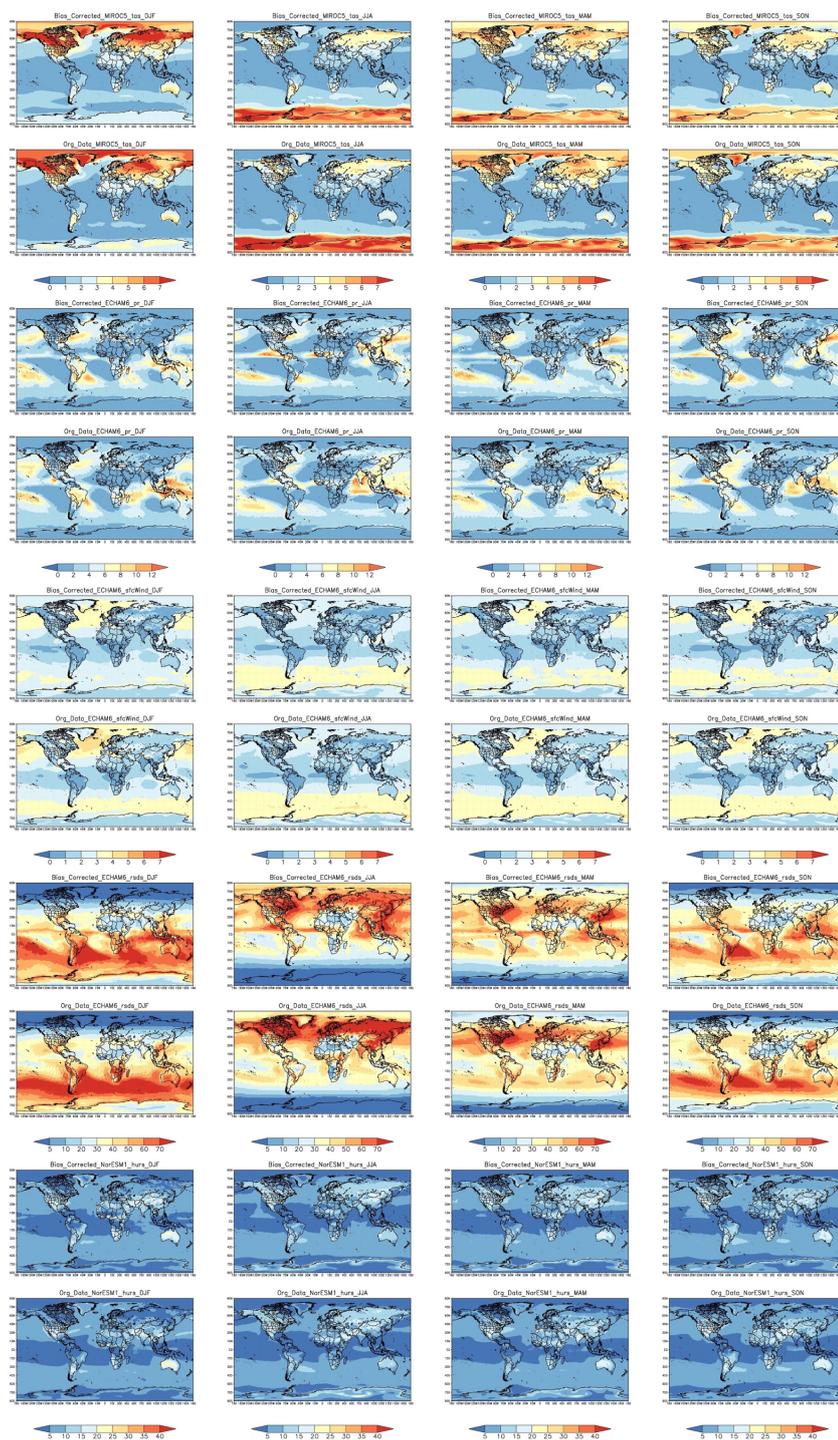


temperature		
Surface downwelling longwave radiation	rlds	W m^{-2}
Surface downwelling shortwave radiation	rsds	W m^{-2}
Near surface wind speed	sfcWind	m s^{-1}
Near surface relative humidity	hurs	%

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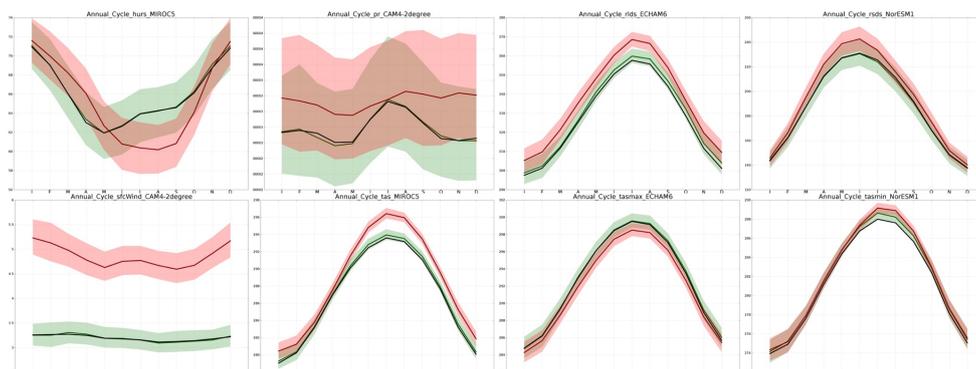


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 2 *Figure 1: Seasonal absolute (tas) and relative (pr,rds,hurs,sfcWind) differences against EWEMBI data for different GCMs.*
 3 *For each variable, upper and lower panels show the results of bias corrected and original (non-bias corrected) data*
 4 *respectively.*

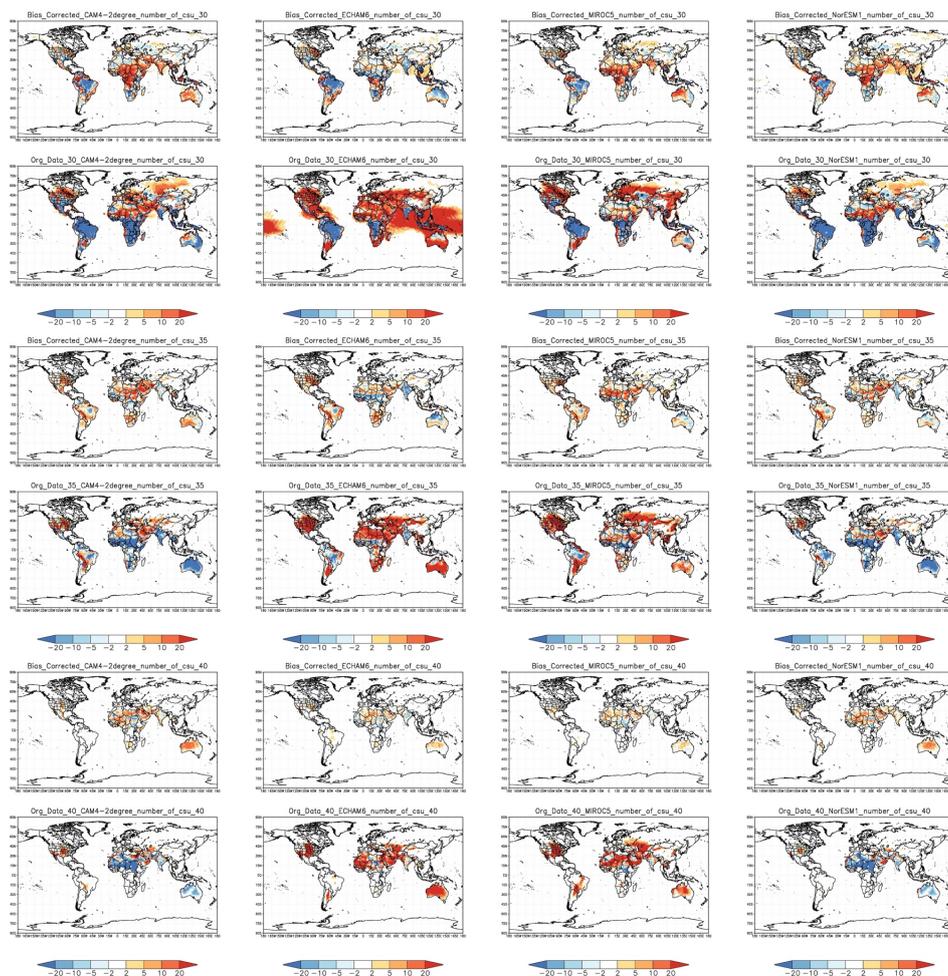


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Figure 2: Seasonal ensemble standard deviation across different GCMs for different variables. For each variable, upper and lower panels show the results of bias corrected and original (non-bias corrected) data respectively.

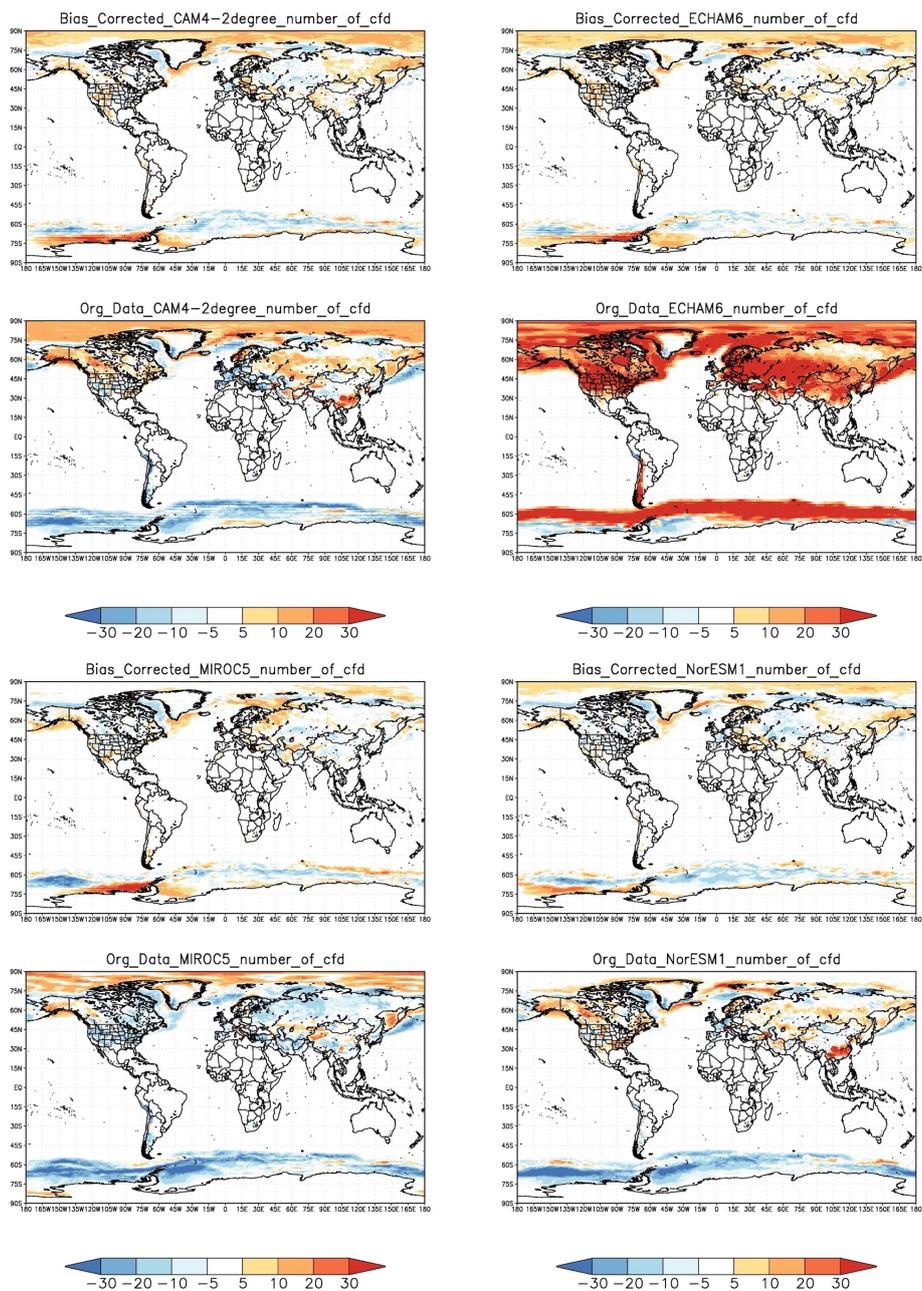


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2 Figure 3: : Annual Cycle for different variables averaged over the land areas across different GCMs. Red, green and black
3 curves represent ensemble median for original (non-bias corrected), bias-corrected and EWEMBI data. The respective
4 coloured band around original and bias corrected curves represent the spread of the 20 Ensemble member for each variable.

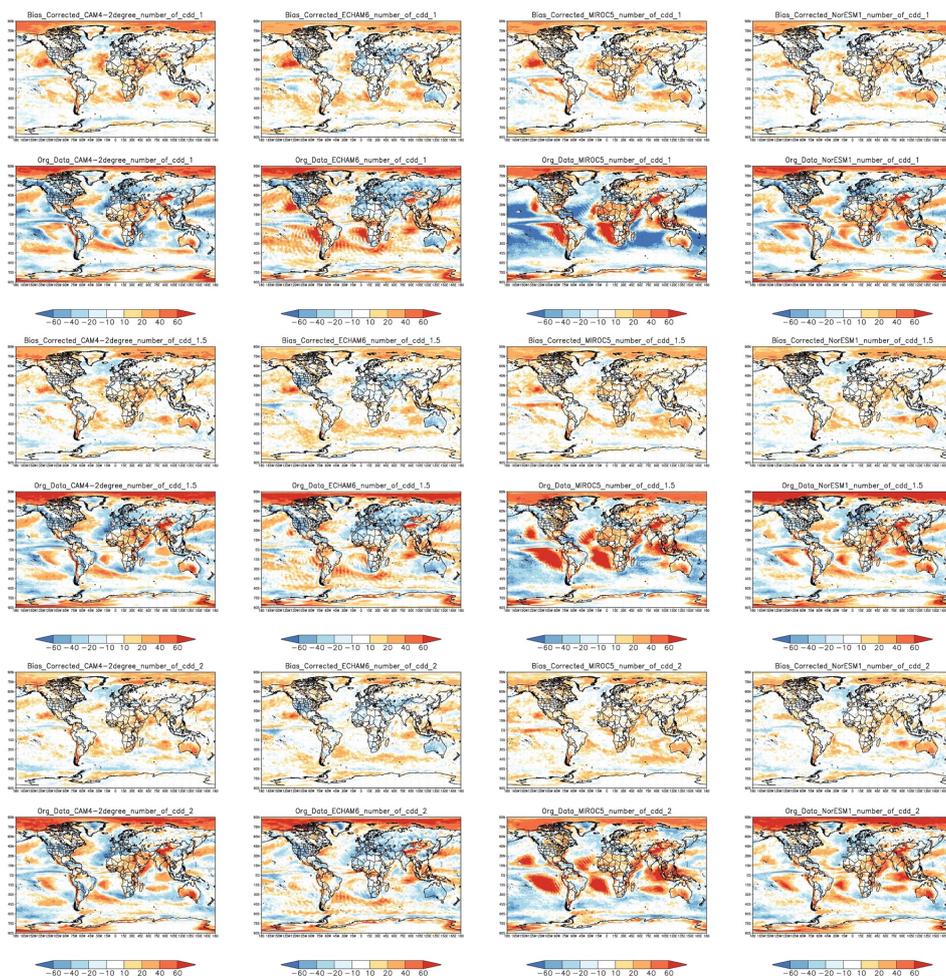


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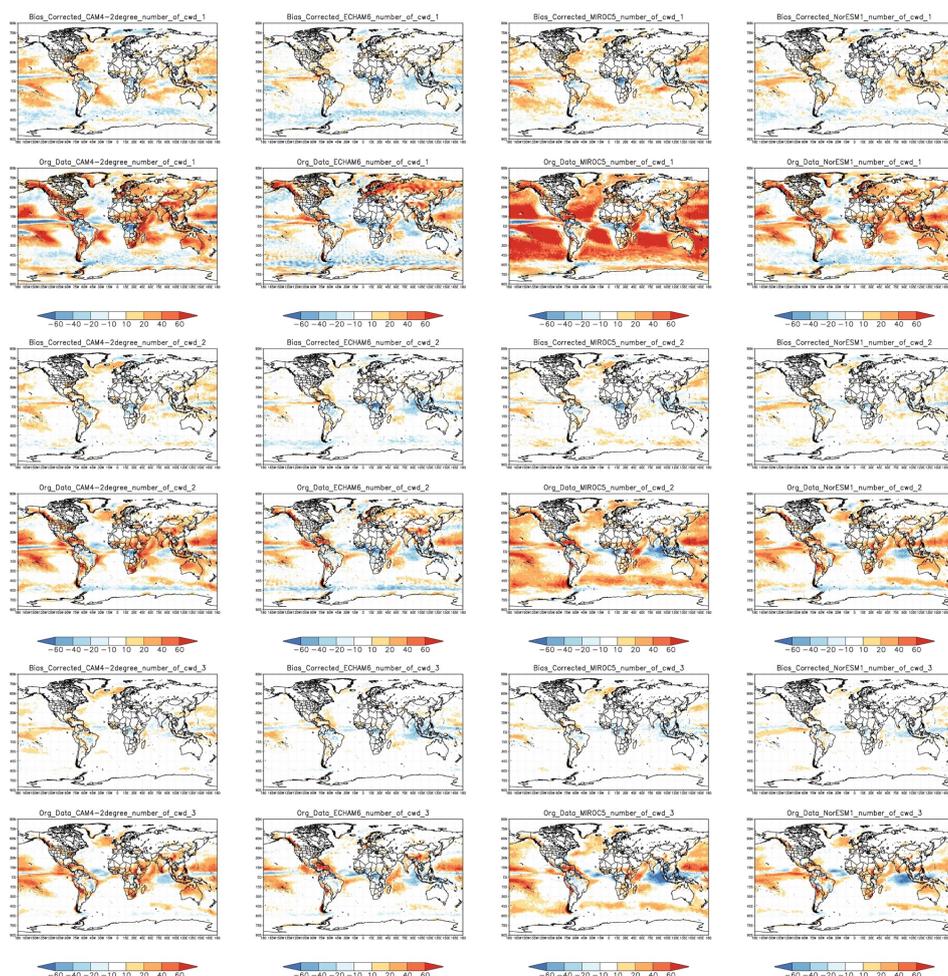
2 *Figure 4: Consecutive Summer Days (CSD) index at the thresholds of 30°C, 35°C and 40°C presented as a difference from*
 3 *EWEMBI data. Presented are the number of instances during which the maximum temperature remains equal or more than*
 4 *the respective thresholds consecutively for 5 days or more. Upper and Lower panels show the results for bias corrected and*
 5 *original (non-bias corrected) data across all the four GCMs.*



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 2 *Figure 5: Consecutive Frost Days (CFD) index presented as a difference from EWEMBI data. Presented are the number of*
 3 *instances during which the minimum temperature remains equal or less than 0°C consecutively for 5 days or more. Upper*
 4 *and Lower panels show the results for bias corrected and original (non-bias corrected) data across all the four GCMs.*



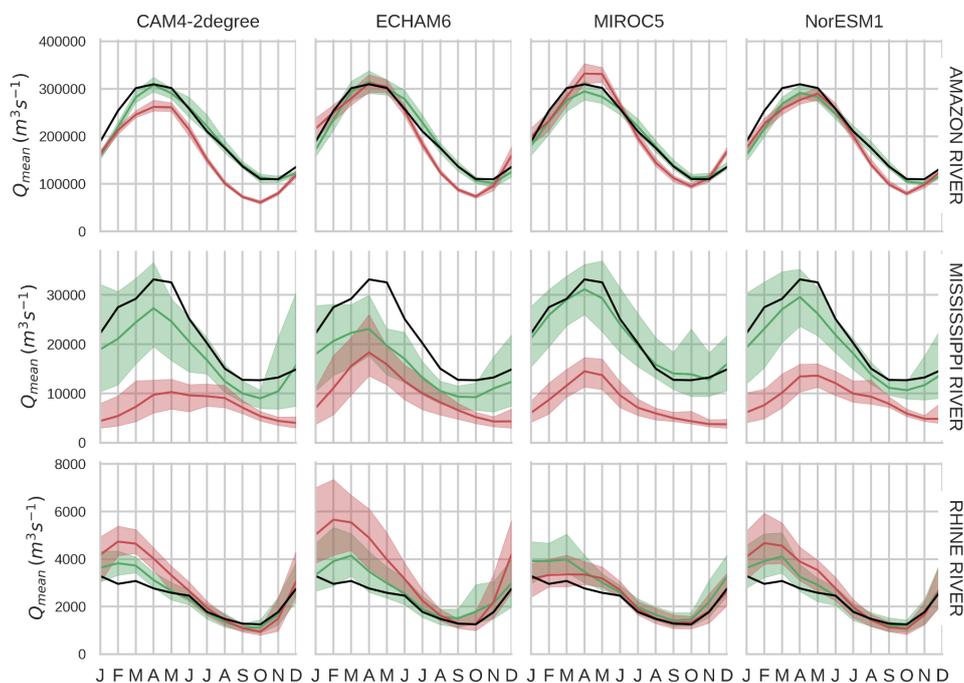
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 2 *Figure 6: Consecutive Dry Days (CDD) index at the thresholds of 1mm/day, 1.5 mm/day and 2.0 mm/day presented as a*
 3 *difference from EWEMBI data. Presented are the number of instances during which the daily precipitation remains more*
 4 *than the respective thresholds consecutively for 5 days or more. Upper and Lower panels show the results for bias corrected*
 5 *and original (non-bias corrected) data across all the four GCMs.*



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 2 *Figure 7: Consecutive Wet Days (CWD) index at the thresholds of 1mm/day, 2 mm/day and 3 mm/day presented as a*
 3 *difference from EWEMBI data. Presented are the number of instances during which the daily precipitation remains more*
 4 *than the respective thresholds consecutively for 5 days or more. Upper and Lower panels show the results for bias corrected*
 5 *and original (non-bias corrected) data across all the four GCMs.*



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Figure 8: Seasonal discharge at the outlet of Amazon river basin (first row), Mississippi river basin (second row) and Rhine river basin (third row) for 2006 – 2013 for the analysed GCMs. The black line represents the reference simulation forced with EWEMBI, whereas the green and red coloured lines represent the bias corrected and the original (non-bias corrected) ensemble mean. The coloured bands around original and bias corrected curves show the spread of the 20 ensemble members.