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Seasonal and regional biases in CMIP5 precipitation simulations

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ABSTRACT: This study provides insight into how CMIP5 climate models perform in simulating summer and winter precipitation at different geographical locations and climate conditions. Precipitation biases in the CMIP5 historical (1901 to 2005) simulations relative to the Climatic Research Unit (CRU) observations are evaluated over 8 regions exhibiting distinct seasonal hydroclimates: moist tropical (Amazonia and central Africa), monsoonal (southern China), moist continental (central Europe), semi-arid (western United States and eastern Australia), and polar (Siberia and Canada). While the bias and monthly quantile bias (MQB) reflect no substantial differences in CMIP5 summer and winter precipitation simulations at the global scale, strong seasonality and high inter-model variability are found over the selected moist tropical regions (i.e. Amazonia and central Africa). In the semi-arid regions, high inter-model precipitation variability is also displayed, especially in summer, while the median of simulations is an overestimate of both winter and summer precipitation. In Siberia and central Europe, most CMIP5 models underestimate summer precipitation, and overestimate it in winter. Also, the MQB values decrease as the choice of quantile thresholds increase, implying that the underestimation of summer precipitation is primarily associated with biases in lower quantiles of the precipitation distribution. While the CMIP5 models exhibit similar behaviors in simulating high-latitude winter precipitation, they differ substantially in summer simulations for the selected Canadian and Siberian regions. Finally, in the monsoonal southern China region, CMIP5 models exhibit large overall precipitation biases in both summer and winter, as well as at higher quantiles.

KEY WORDS: Precipitation · Climate · CMIP5

1. INTRODUCTION

Global climate models have been used to simulate historical and projected precipitation for climate change and variability studies. Several modeling groups and international collaborative activities, such as the Intergovernmental Panel on Climate Change (IPCC 2007), provide data sets of historical and future climate simulations. However, climate model simulations are subject to uncertainties and biases because of errors in model parameterization, boundary conditions, simplifying assumptions, model structure, and input variables (Feddema et al. 2005, Tebaldi et al. 2006, John & Soden 2007, Reichler & Kim 2008, Liepert & Previdi 2012).

Water resources are particularly sensitive to changes in precipitation, which is a key variable in understanding the global water cycle and analyzing water availability (Kharin et al. 2007, Seager et al. 2007, Cayan et al. 2010, Madani & Lund 2010, Azarderakhsh et al. 2011, Sivakumar 2011, Stoll et al. 2011, Wehner 2012, AghaKouchak et al. 2013, Hassanzadeh et al. 2013, Mirchi et al. 2013, Nazemi et al. 2013). However, GCM-based precipitation simulations are inherently uncertain and subject to systematic and unpredictable (random) biases (Feddema et al. 2005, Min et al. 2007, Mehrotra & Sharma 2012, Brekke & Barsugli 2013). Quantification and characterization of biases and uncertainties in GCM-based precipitation climate simulations are therefore nec-

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essary for understanding the available data sets and their potential applications in water cycle analysis and future water resources management.

Recently, the Coupled Model Intercomparison Project Phase 5 (CMIP5) has provided the climate community with a suite of coordinated climate model simulations to facilitate addressing science and policy questions relevant to the IPCC 5th Assessment Report (AR5) (Meehl & Bony 2011, Taylor et al. 2012). Compared to the Phase 3 of the project (CMIP3), which contributed to the IPCC 4th Assessment Report, the CMIP5 simulations incorporate more advanced treatments of land use change and anthropogenic aerosols forcings (Knutti 2010, Taylor et al. 2012, Stott et al. 2013). By considering multiple climate models with different model physics and/or forcings, the CMIP5 experiment provides an ensemble of opportunity to explore uncertainty in climate model simulations (Stott et al. 2013).

Given the uncertainties in forcings, initial conditions, and model structures, one cannot expect climate models to accurately replicate historical observations in every respect. Since the development of the first climate models, evaluation of historical climate simulations against ground-based observations has become an ongoing activity of the climate community (Bony et al. 2006), since future improvements in climate model simulations largely rely on extensive and targeted evaluation studies. Gleckler et al. (2008) has introduced a number of performance metrics for evaluation of climate model simulations against observations. AghaKouchak & Mehran (2013) also have proposed several volumetric indicators and skill scores for assessing biases in climate model simulations.

A myriad of studies have focused on validation of climate model historical precipitation simulations (e.g. Dai 2006, Phillips & Gleckler 2006, Sun et al. 2007, Chen & Knutson 2008, Moise & Delage 2011, Schaller et al. 2011, Balan Sarojini et al. 2012, Deser et al. 2012, Flaounas et al. 2012, Liu et al. 2012, Watanabe et al. 2012, Catto et al. 2013, Gaetani & Mohino 2013, Hirota & Takayabu 2013, Kharin et al. 2013, Knutti & Sedláček 2013, Kumar et al. 2013, Schubert & Lim 2013, Sillmann et al. 2013). In a recent study, Mehran et al. (2014) evaluated a wide range of CMIP5 historical precipitation simulations and concluded that over many regions most CMIP5 precipitation simulations were in fairly good agreement with satellite observations. However, over deserts and certain high latitude regions, there were major discrepancies between model simulations and observations. Mehran et al. (2014) also showed that while removing the mean-field bias improves the overall bias, it does not lead to a significant improvement at higher quantiles of precipitation simulations. Hao et al. (2013) evaluated changes in joint precipitation and temperature extremes in CMIP5 simulations against ground-based observations. Their results showed that model simulations agreed with ground-based observations on the sign of the change in occurrence of joint extremes; however, discrepancies were observed on regional patterns and magnitudes of change in individual CMIP5 climate models.

The present study evaluates the seasonal and regional biases in CMIP5 historical (1901 to 2005) simulations of continental precipitation with respect to the observational Climatic Research Unit (CRU; Mitchell & Jones 2005) data set, using several quantitative statistical measures. Furthermore, the cumulative distribution functions (CDFs) of the CMIP5 precipitation simulations are investigated, especially at higher quantiles of precipitation. The seasonal (summer and winter) biases are evaluated against observations over 8 regions across the globe. The selected regions have distinct climate and seasonality; hence the study provides insight into how models perform at different geographical locations and climate conditions.

2. DATA

The CRU (New et al. 2000, Mitchell & Jones 2005) monthly precipitation data are used as reference observations. CRU data sets have been widely applied in many regional and global studies, and have been validated against other observational data sets (precipitation, Tanarhte et al. 2012; temperature, Jones et al. 2012, Morice et al. 2012). In this study, 34 CMIP5 precipitation simulations (Table 1) and their multimodel ensemble median for the period 1901–2005 are evaluated relative to CRU observations. In addition to simulations by physical climate models that include prescribed historical atmospheric CO_2 concentrations, runs of 'Earth Systems Models' with a prognostic global carbon cycle that are driven by the corresponding prescribed historical CO_2 emissions (designated by the suffix _esm) are also considered here. The CMIP5 simulations are archived in the Global Organization for Earth System Science Portals (GO-ESSP) coordinated by the United States Department of Energy (DOE) Program for Climate Model Diagnosis and Intercomparison (PCMDI). For consistency, the CMIP5 precipitation simulations and CRU observations are all re-gridded to a common 2° × 2° spatial resolution.

Table 1. List of 34 CMIP5 models and their related institutions and countries. AOR (UoT): Atmosphere and Ocean Research Institute (The University of Tokyo); CAS: Chinese Academy of Sciences; CMA: China Meteorological Administration; CNRM: Centre National de Recherches Meteorologiques; CSIRO: Commonwealth Scientific and Industrial Research Organisation; DOE: Department of Energy; JAMSTEC: Japan Agency for Marine-Earth Science and Technology; MPI: Max Planck Institute; NCAR: National Center for Atmospheric Research; NSF: National Science Foundation; NIES: National Institute for Environmental Studies; TU: Tsinghua University

Models	Institution	Country
BCC-CSM1-1_esm	Beijing Climate Center, CMA	China
CanESM2_esm CanESM2	Canadian Centre for Climate Modelling and Analysis	Canada
CCSM4	NCAR	USA
CESM1-BGC_esm CESM1-BGC CESM1-CAM5 CESM1-WACCM	NSF, DOE, and NCAR	USA
CNRM-CM5	CNRM	France
CSIRO-ACCESS1-0 CSIRO-ACCESS1-3 CSIRO-MK3-6-0	CSIRO and Bureau of Meteorology	Australia
FGOALS-g2	Institute of Atmospheric Physics, CAS, TU	China
GFDL-CM3 GFDL-ESM2G_esm GFDL-ESM2M_esm GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory	USA
GISS-E2-H GISS-E2-R	NASA Goddard Institute for Space Studies	USA
HadGEM2-CC HadGEM2-ES_esm HadGEM2-ES	Met Office Hadley Centre	UK
INMCM4_esm	Institute for Numerical Mathematics	Russia
IPSL-CM5A-LR_esm IPSL-CM5A-LR	Institut Pierre-Simon Laplace	France
MIROC5 MIROC-ESM_esm MIROC-ESM	JAMSTEC, AOR (UoT), NIES	Japan
MPI-ESM-LR_esm MPI-ESM-LR	MPI for Meteorology	Germany
MRI-CGCM3 MRI-ESM1_esm	Meteorological Research Institute	Japan
NorESM1-M NorESM1-ME	Norwegian Climate Centre	Norway

3. METHODOLOGY

In this study, summer is defined as June, July, and August (JJA) in the Northern Hemisphere (NH) and December, January, and February (DJF) in the Southern Hemisphere (SH), whereas winter is defined as DJF in the NH and JJA in the SH. First, summer and winter biases (B) in CMIP5 climate model simulations are estimated for the entire distribution of precipitation as:

$$B = \Sigma_{i=1}^{n}(\mathrm{SIM}_i) \,/\, \Sigma_{i=1}^{n}(\mathrm{OBS}_i) \qquad (1)$$

where SIM and OBS denote simulations and observations, while $i = 1, \ldots, n$ refer to a particular sample of the observations and corresponding simulations. Then, the monthly quantile bias (MQB; AghaKouchak et al. 2011) is derived for a number of areas around the globe, in order to further study the corresponding regional summer and winter biases. The MQB is defined as the mean ratio of CMIP5 simulations (hereafter, SIM) over CRU observations (hereafter, OBS) above the quantile, q:

$$\mathrm{MQB} = \frac{\sum_{i=1}^{n}(\mathrm{SIM}_i \mid \mathrm{SIM}_i \geq q)}{\sum_{i=1}^{n}(\mathrm{OBS}_i \mid \mathrm{OBS}_i \geq q)} \qquad (2)$$

An MQB of 1 corresponds to no bias in model simulations versus ground-based observations above the choice of quantile threshold (e.g. the 75th or 90th percentiles of non-zero precipitation data for each model separately). Note that in all models, small values below the typical precipitation detection limits (here, 10 to 5 mm s^{-1} or ~0.9 mm d^{-1}) are assumed to be zero. The MQB values are computed for selected regions in the western US, Australia, Amazonia, Europe, Canada, Siberia, southern China, and central Africa (Fig. 1) for summer and winter. The selected boxes cover regions with different climatic conditions. The regional climates can be broadly described as (1) moist tropical (Amazonia and central Africa), (2) monsoonal (southern China), (3) moist continental (central Europe), (4) semi-arid (western USA and eastern Australia), (5) and polar (Siberia and Canada).

The designations of regional climates follow a hydroclimatic schema: moist tropical implies that summer and winter rainfall is associated with shifts in the convective Intertropical Convergence Zone (ITCZ); monsoonal regions occur where the prevail-

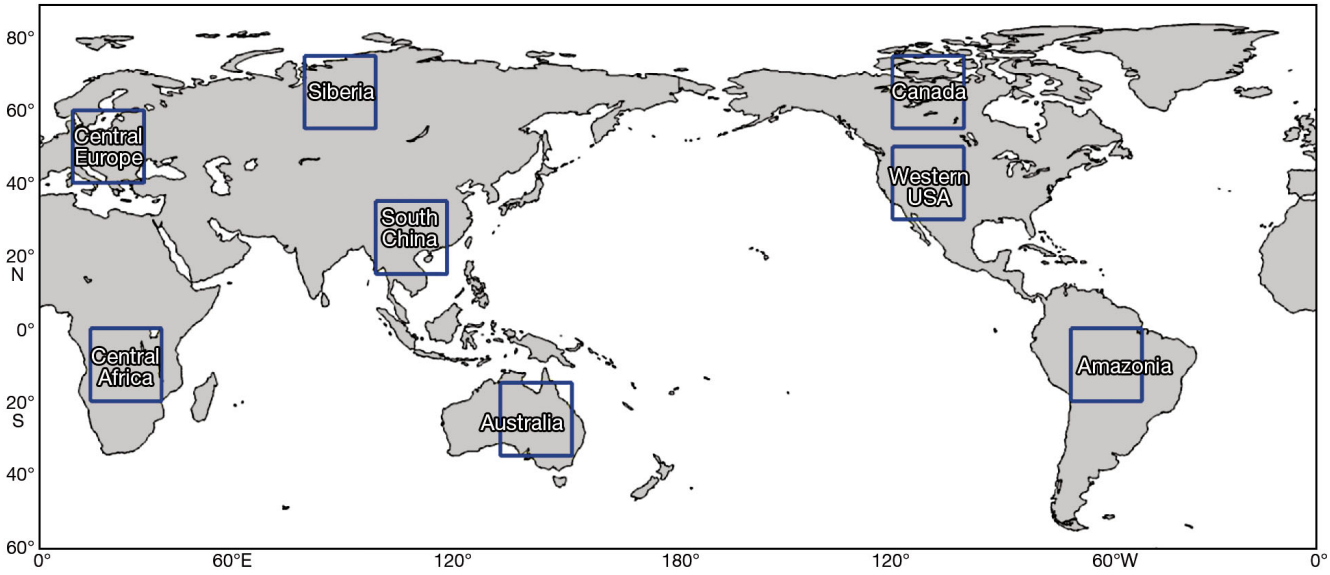

Fig. 1. Continental regions selected for this study

ing seasonal winds produce a wet summer but a relatively dry winter; moist continental describes regions having both moist summers and winters; semi-arid suggests generally drier seasons, especially in summer; and polar regions are associated with cold, snowy winters and cool, moist summers. In the selected regions, only simulations over land are evaluated where ground-based observations are available.

4. RESULTS

The bias ratios of 12 selected CMIP5 simulations are presented in Fig. 2 for summer, and in Fig. 3 for winter (white areas correspond to no data in simulations or observations). We can see that several models show distinct differences (overestimation or underestimation) in summer and winter. For example, most models underestimate summer precipitation in Europe, while they overestimate winter precipitation. Over Amazonia, on the other hand, most models overestimate summer precipitation, while they underestimate winter precipitation. In several parts of the globe, including the western USA, most models tend to overestimate precipitation in both summer and winter. Fig. 4 displays the global averages of the overall bias, MQB above the 75th (Q75) and 90th quantile (Q90) for all 34 CMIP5 models as well as their ensemble median. All panels in Fig. 4 show a consistent positive bias, in that none of the climate models global averages underestimate precipitation relative to observations. With respect to global averages, all CMIP5 climate models and their ensemble median overestimate precipitation in summer and winter by ~2 to 33%. As shown, the bias and MQB values of summer and winter global averages are similar, though overall, slightly higher in summer than those of winter.

Unlike global averages of summer and winter, the regional summer and winter biases over the selected geographical and climatic regions are substantially different. Fig. 5 displays the regional summer and winter biases for all the CMIP5 models and their ensemble median over (a) Europe, (b) Amazonia, (c) central Africa, (d) Australia, (e) western USA, (f) Siberia, (g) Canada, and (h) south China. Figs. 6 & 7 show similar figures for MQB Q75 and Q90, respectively.

We can see that most models and their ensemble median underestimate summer precipitation and overestimate winter precipitation over Europe (Fig. 5a; see also Scoccimarro et al. 2013). As shown, model biases are less (closer to 1) at higher quantiles (Figs. 6a & 7a), suggesting that the overall summer and winter biases are associated more with lower quantiles of precipitation. This result can be understood as a general tendency for today's climate models to simulate light rainfall too frequently and intense rainfall too rarely (Sillmann et al. 2013). Such an excessive 'drizzle' phenomenon, presumably associated with unrealistic representation of the microphysics of precipitation, was previously noted as a common error in earlier-generation models (Dai 2006, Sun et al. 2007, Stephens et al. 2010). This error

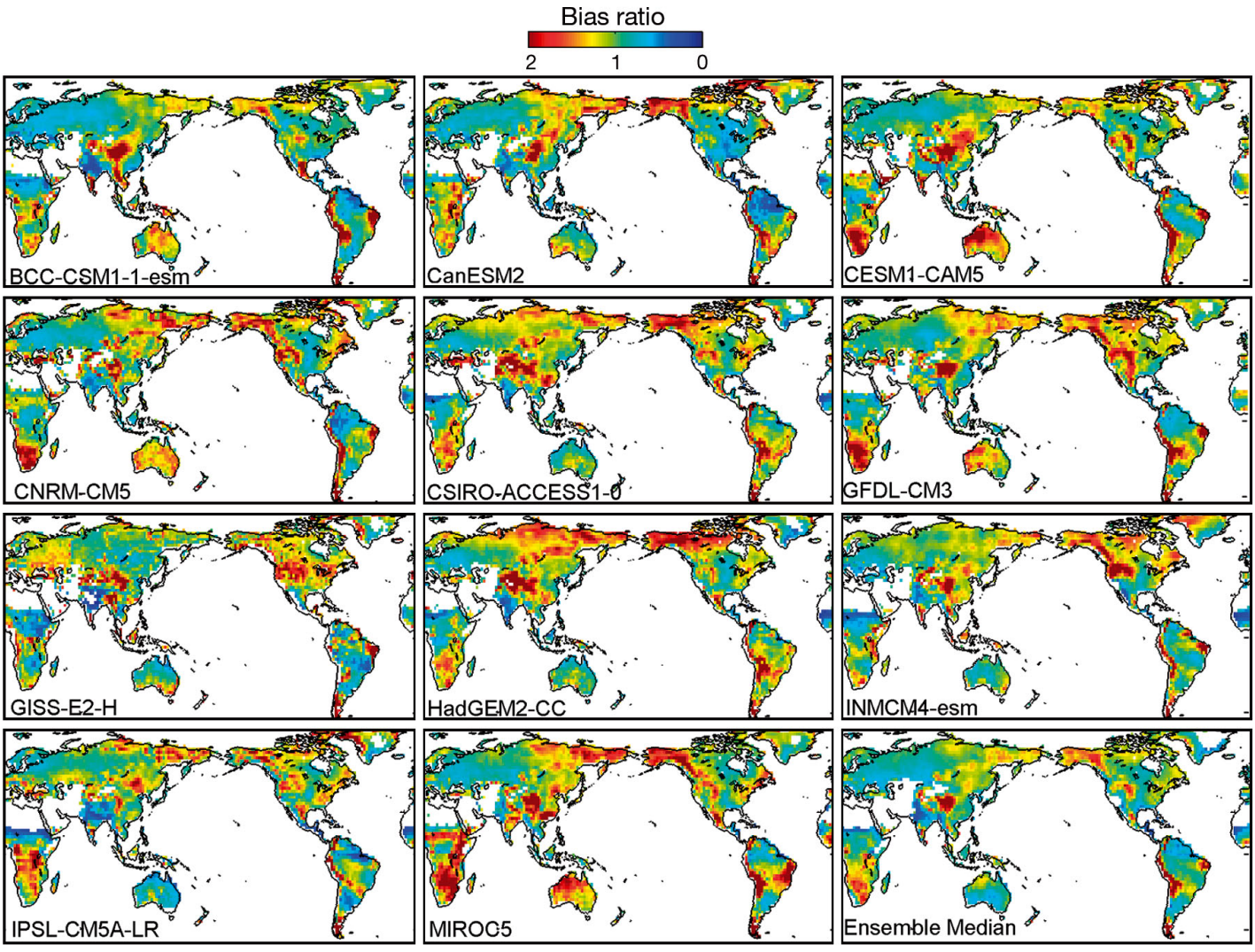

Fig. 2. Bias ratio (CMIP5:CRU) of selected climate model simulations of summer precipitation: Jun–Aug in the Northern Hemisphere, and Dec–Feb in the Southern Hemisphere. CRU: Climatic Research Unit

apparently carries over to the CMIP5 models as well, but will be shown to vary with region in the analysis that follows.

In contrast to central Europe, most CMIP5 model simulations underestimate winter precipitation over the Amazonia region (Fig. 5b). The overall bias (Fig. 5b) and MQB values (Figs. 6b & 7b) for the CMIP5 models, as well as for their ensemble median, indicate that CMIP5 climate models simulate precipitation here somewhat more reliably in summer than in winter. It should be noted that winter MQB values also are higher than those of summer (e.g. compare MQB above Q90 in summer and winter in Fig. 7b).

The regional bias and MQB over central Africa are plotted in Figs. 5c, 6c & 7c. As shown, the CMIP5 inter-model variability with respect to bias is substantial in both summer and winter precipitation simulations. The overall bias values are somewhat higher in summer, while the MQB values are higher in winter, indicating that there are substantial biases associated with high quantiles of winter precipitation simulations in central Africa. On the other hand, the overall summer biases can be attributed more to light rainfall events, as the overall biases are larger than corresponding MQB values.

Both Amazonia and central Africa can be categorized as moist tropical regions in which summer or winter rainfall is associated with shifts in the convective ITCZ (Waliser & Gautier 1993). In the SH summer (DJF) the ITCZ, a narrow band of intense convective rainfall, moves south of the Equator, and both Amazonia and central Africa receive heavier convective precipitation than in the SH winter (JJA). In both regions, the inter-model variability of precip-

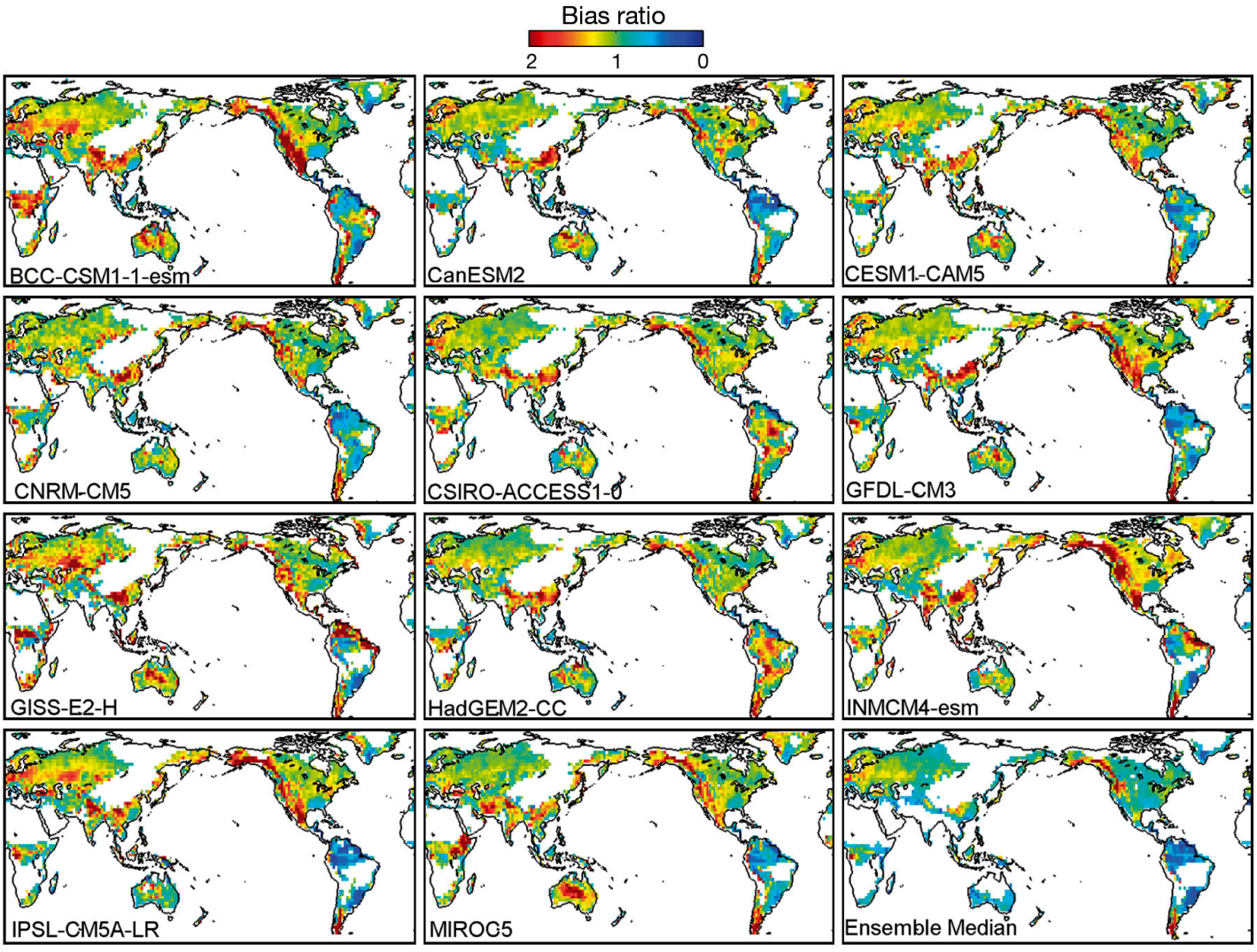

Fig. 3. Bias ratio (CMIP5:CRU) of selected climate model simulations of winter precipitation: Dec–Feb in the Northern Hemisphere, and Jun–Aug in the Southern Hemisphere. See Fig. 2

itation is high, which is probably associated with the varying ability of the models to correctly simulate the ITCZ precipitation. It is well-known that climate models' precipitation errors tend to be large in tropical regions such as Amazonia and central Africa, where shortcomings in model representations of convection are most apparent (Randall et al. 2007). For this reason, numerous studies have focused on improving sub-grid scale parameterizations of convective events.

Figs. 5d, 6d & 7d display the CMIP5 models' overall summer and winter biases and MQB values for semi-arid eastern Australia. In both seasons, most models overestimate precipitation, but since the summer biases deviate more from the optimum value of 1 (B = 1 indicates 'no bias'), it can be concluded that the models display somewhat better skill in simulating winter precipitation. A possible physical explanation for this seasonal asymmetry is that convective precipitation, which is prevalent in summer, is more poorly simulated than winter frontal precipitation, which is more realistically represented in today's climate models (e.g. Catto et al. 2010). The inter-model variability of the biases is also more substantial in summer than winter: although several CMIP5 models substantially underestimate Australian summer precipitation, a few models overestimate it by >180%, yielding an overall ensemble-median overestimation of summer precipitation. The MQB values are of similar magnitude for summer and winter, however, suggesting that the larger overall biases in summer are attributable to errors in simulating lighter rainfall events over eastern Australia.

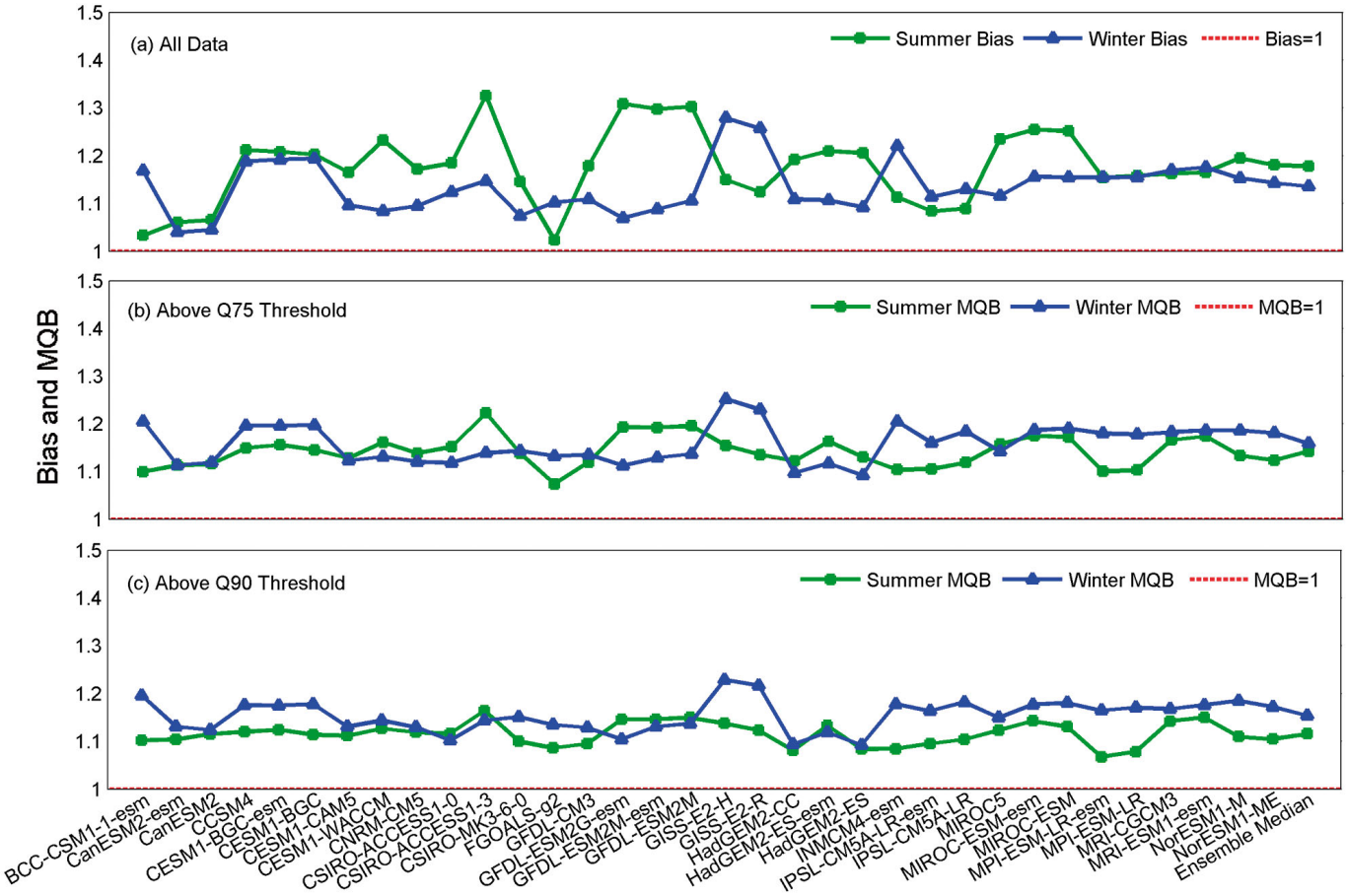

Fig. 4. Global averages of the overall bias, monthly quantile bias (MQB) above 75th (Q75) and 90th quantile (Q90) for CMIP5 models and their ensemble median

Figs. 5e, 6e & 7e present the overall bias and MQB values for the CMIP5 models and their ensemble median over another semi-arid region, the western USA. Here almost every CMIP5 model is seen to overestimate both summer and winter precipitation, characteristics that are displayed by the corresponding ensemble medians as well (with precipitation overestimated by ~31 and 37%, respectively). As their MQB values demonstrate, the CMIP5 models also substantially overestimate precipitation at high quantiles in both seasons. It is noteworthy that the winter biases, in particular, display somewhat more inter-model variability than in eastern Australia (Figs. 5d, 6d & 7d), possibly because of the more important role played by topography in determining the climate of the western USA. In this respect also, there are inter-model variations in the placement of the high/low biases ($B > 1$ / $B < 1$) in the western USA (see Fig. 3). Few of the models display high precipitation biases over the steep but spatially narrow Sierra Nevada mountain chain of California, for example, while most models exhibit a high bias over the broader Rocky Mountain Cordillera near the center of the western USA region defined in Fig. 1. These spatial variations in precipitation bias are mainly a consequence of the relatively coarse horizontal resolution of the typical CMIP5 model (a 2° × 2° latitude/longitude grid) which effectively smooths and flattens topography, thereby distorting its impact on precipitation. Hence, increased horizontal resolution and improvements in the dynamics of atmospheric flow over topography in climate models could substantially improve their simulation of precipitation (Ghan et al. 2002, Wehner et al. 2010).

The overall bias and MQB values for the CMIP5 models and for their ensemble median over the polar Siberian region are displayed in Figs. 5f, 6f & 7f. It can be seen that the inter-model variability of simulated summer precipitation biases are much higher than in the winter simulations, but the ensemble median result is very close to the CRU observations in this region. The winter simulations generally over-

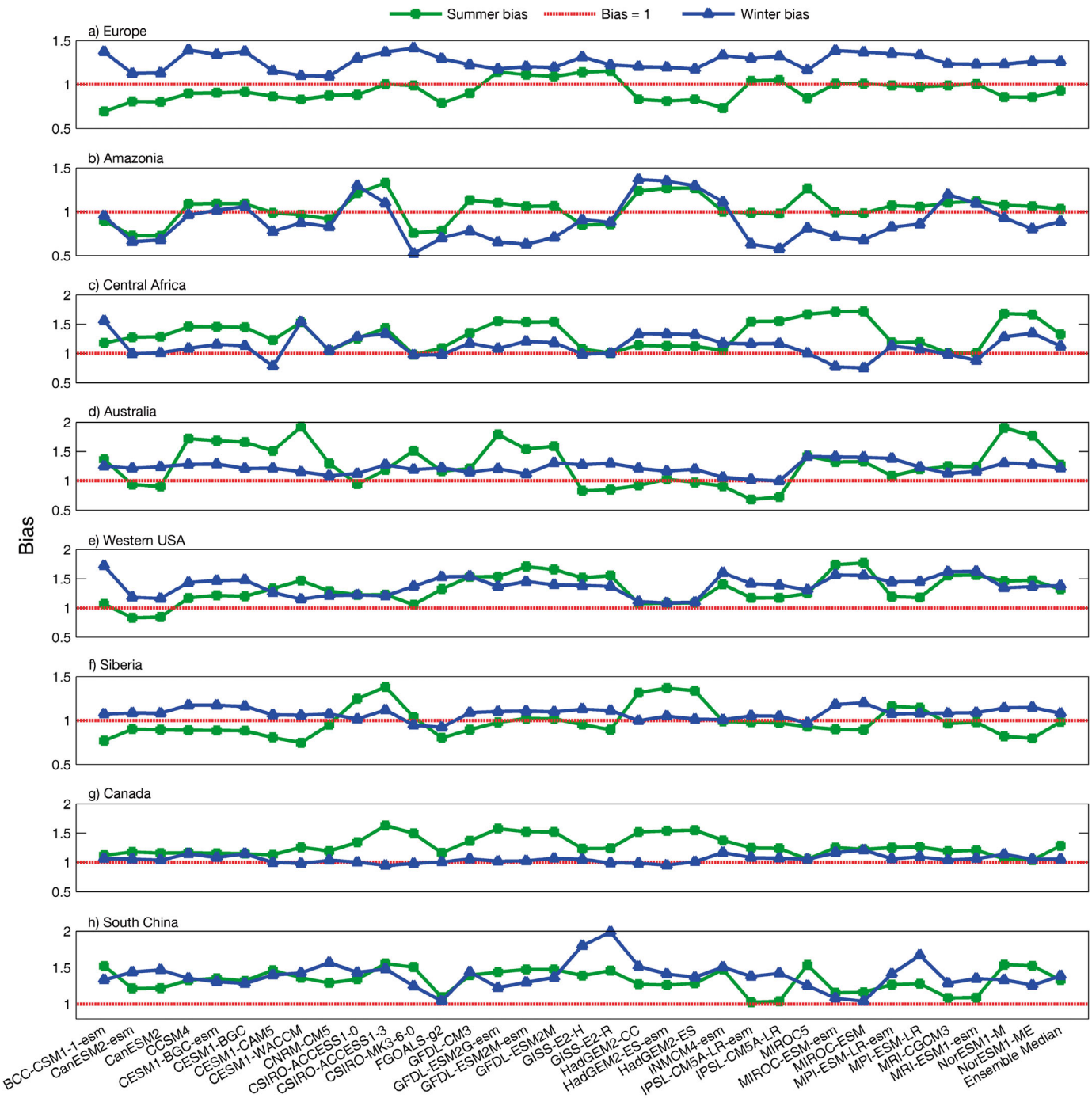

Fig. 5. Regional summer and winter biases over (a) Europe, (b) Amazonia, (c) central Africa, (d) Australia, (e) western United States, (f) Siberia, (g) Canada, and (h) south China in CMIP5 precipitation simulations

predict the observations, but by relatively small amounts. In contrast to the semi-arid western USA, the MQB of precipitation simulations over Siberia are less than the corresponding *B* values, indicating that lower quantiles of precipitation contribute more to the overall bias. The Siberian simulations thus exemplify the common problem of excessive light and mid-range precipitation, but they display this tendency more in summer when frontal systems (i.e. extratropical cyclones) are weaker and when convective processes contribute a greater fraction of the total precipitation.

In contrast to their Siberian precipitation simulations, CMIP5 models and their ensemble median

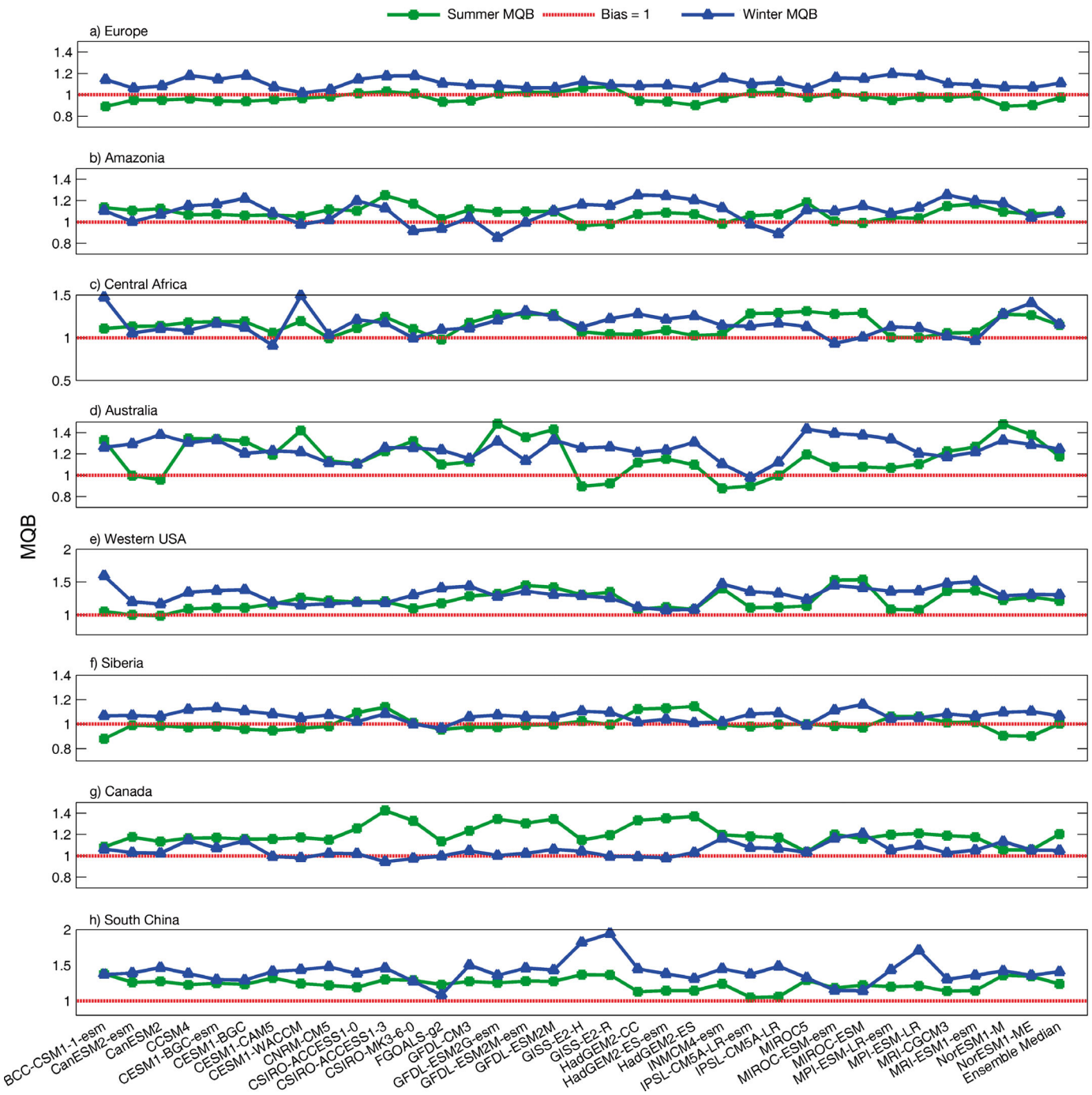

Fig. 6. Regional summer and winter monthly quantile bias (MQB) above 75th percentile threshold (Q75) over (a) Europe, (b) Amazonia, (c) central Africa, (d) Australia, (e) western United States, (f) Siberia, (g) Canada, and (h) south China in CMIP5 precipitation simulations

generally overestimate summer precipitation in the polar region of northern Canada (see Fig. 5g). The overall bias and MQB values for summer precipitation simulations also are substantially greater than those in Siberia (compare Figs. 6g & 7g with Figs. 6f & 7f), indicating more problematical simulation of heavy precipitation. Here, topography (e.g. the Canadian Rocky Mountain chain) may be partly responsible for the differences in summer biases with respect to Siberia. In winter, however, the overall biases and MQB values for Canada and Siberia are quite similar, suggesting a generally satisfactory CMIP5 simulation of the frontal systems that predominate in these polar regions.

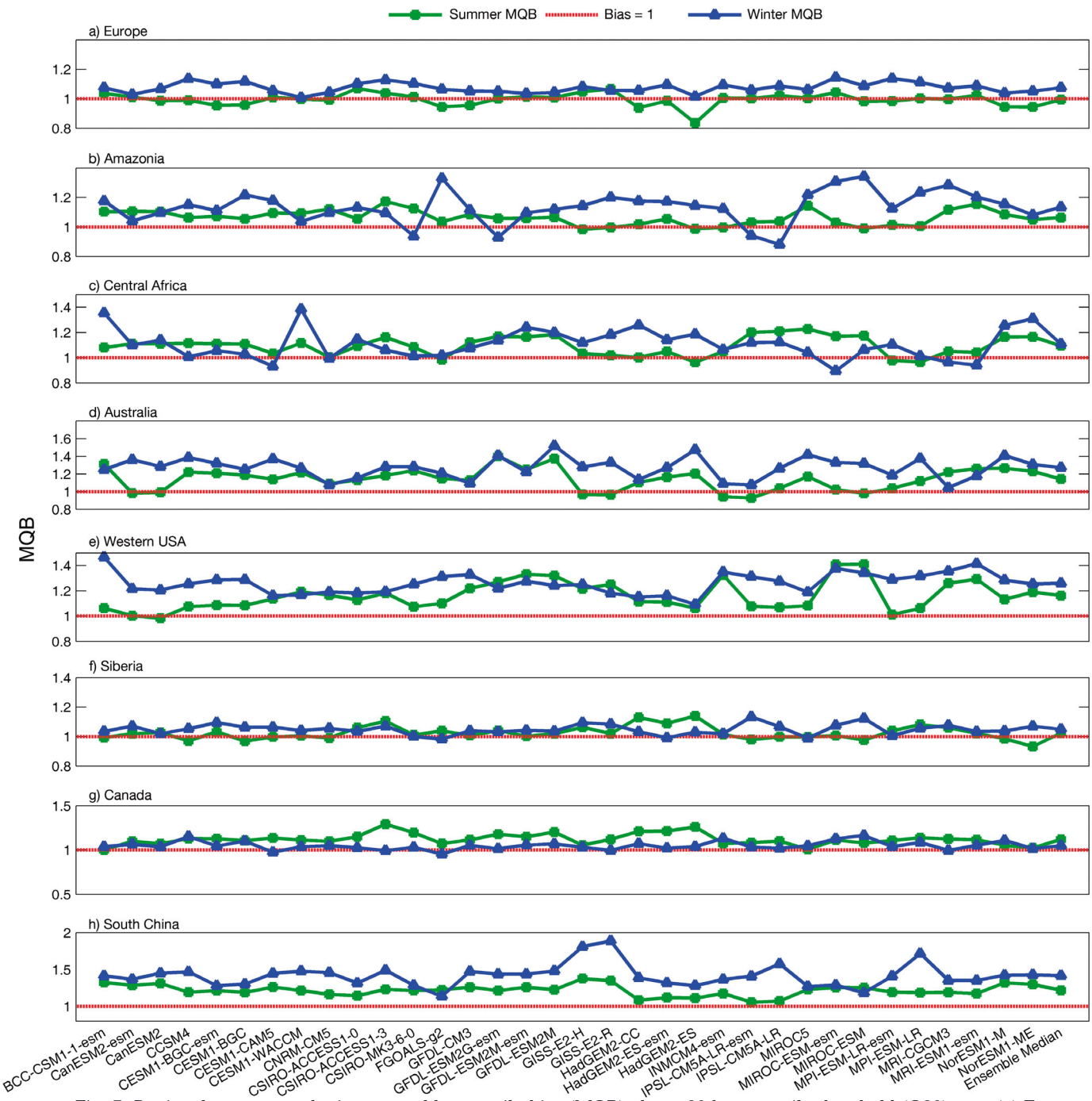

Fig. 7. Regional summer and winter monthly quantile bias (MQB) above 90th percentile threshold (Q90) over (a) Europe, (b) Amazonia, (c) central Africa, (d) Australia, (e) western United States, (f) Siberia, (g) Canada, and (h) south China in CMIP5 precipitation simulations

In the monsoonal southern China region, the CMIP5 models and their ensemble median clearly overestimate precipitation in both summer and winter (Figs. 5h, 6h & 7h). Unlike, most other selected regions, the overall summer and winter precipitation biases are also reflected consistently at high quantiles of precipitation, indicating a general overestimation of intense precipitation events, but also with a fairly high degree of inter-model variability. In summer, southern China is subject to monsoonal convective systems, but in winter, more to frontal systems with generally drier 'background' conditions. Limitations of climate models in capturing monsoonal and convective events have been recognized in previous publications (e.g. IPCC 2007), but the general overestimation of winter pre-

cipitation implies that the CMIP5 simulations of frontal systems and/or the parameterization of microphysical processes may also be problematical in this region.

The study results indicate that the biases of CMIP5 simulated summer and winter precipitation are qualitatively different across regions. Fig. 8 provides further insights into the distinct differences in the empirical CDFs (F(x)) of the observed (black lines) and CMIP5 simulations (gray lines) in summer and winter, respectively (gray simulation lines to the right/below the observations black line imply the overestimation of precipitation, and vice versa). For example, it is seen that the lower quantiles of simulated summer precipitation are generally underestimated relative to CRU observations in central Europe and Amazonia, but they are overestimated in the western United States and Siberia.

Fig. 8 also highlights structural differences in the regional CDFs, providing insights into how the midrange values (near $F(x) = 0.5$) of the CMIP5 simulations vary across different regions. For example, the CDFs of the summer precipitation in the selected moist tropical regions are inflected in this midrange, possibly indicating marked differences in the physical processes that are operative in lighter versus heavier precipitation events. In polar regions, it is also apparent that the midrange values of summer

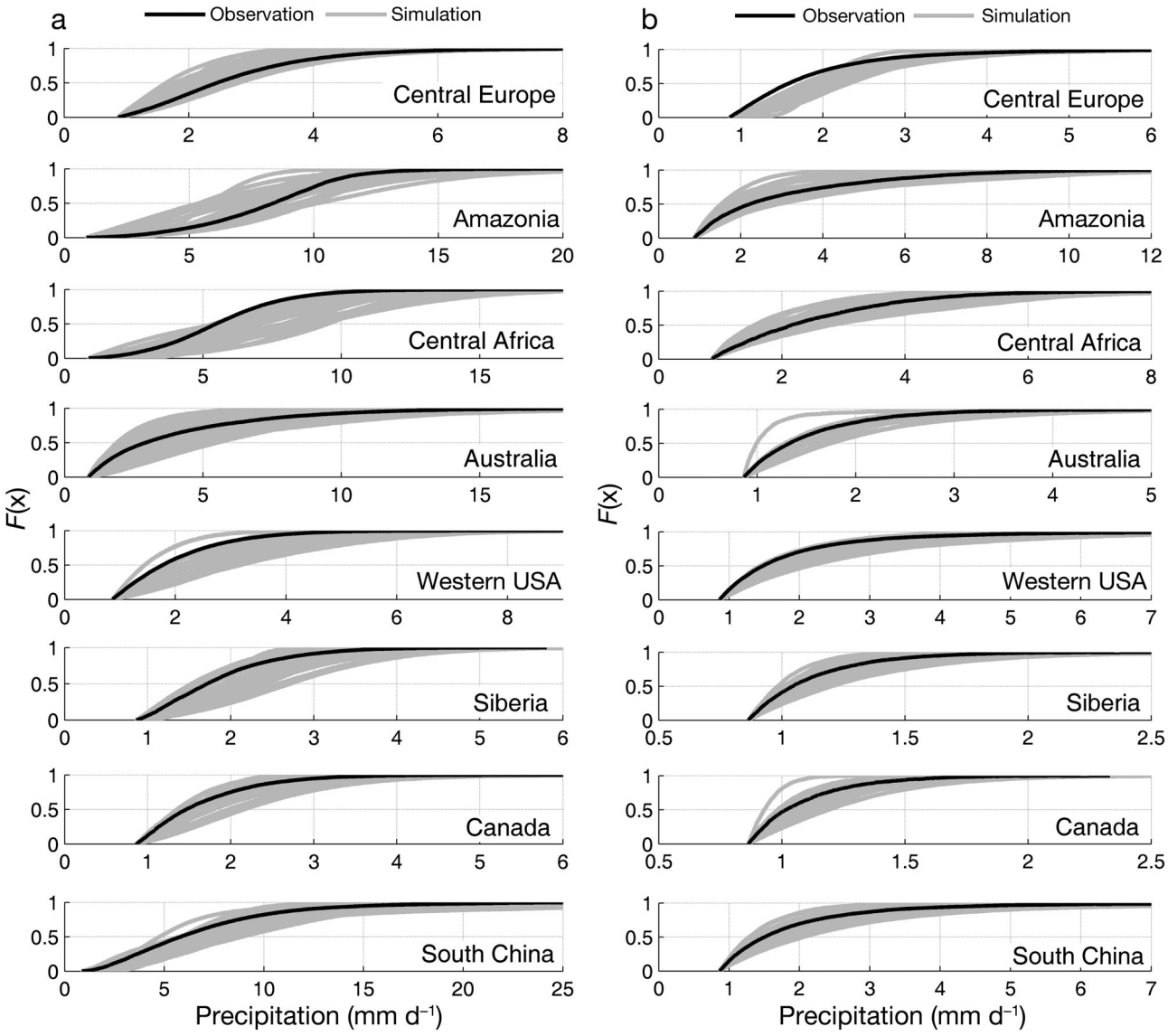

Fig. 8. Empirical cumulative distribution functions (CDFs; F(x)) of observed (black lines) and CMIP5 precipitation simulations (gray lines) in (a) summer and (b) winter for each region

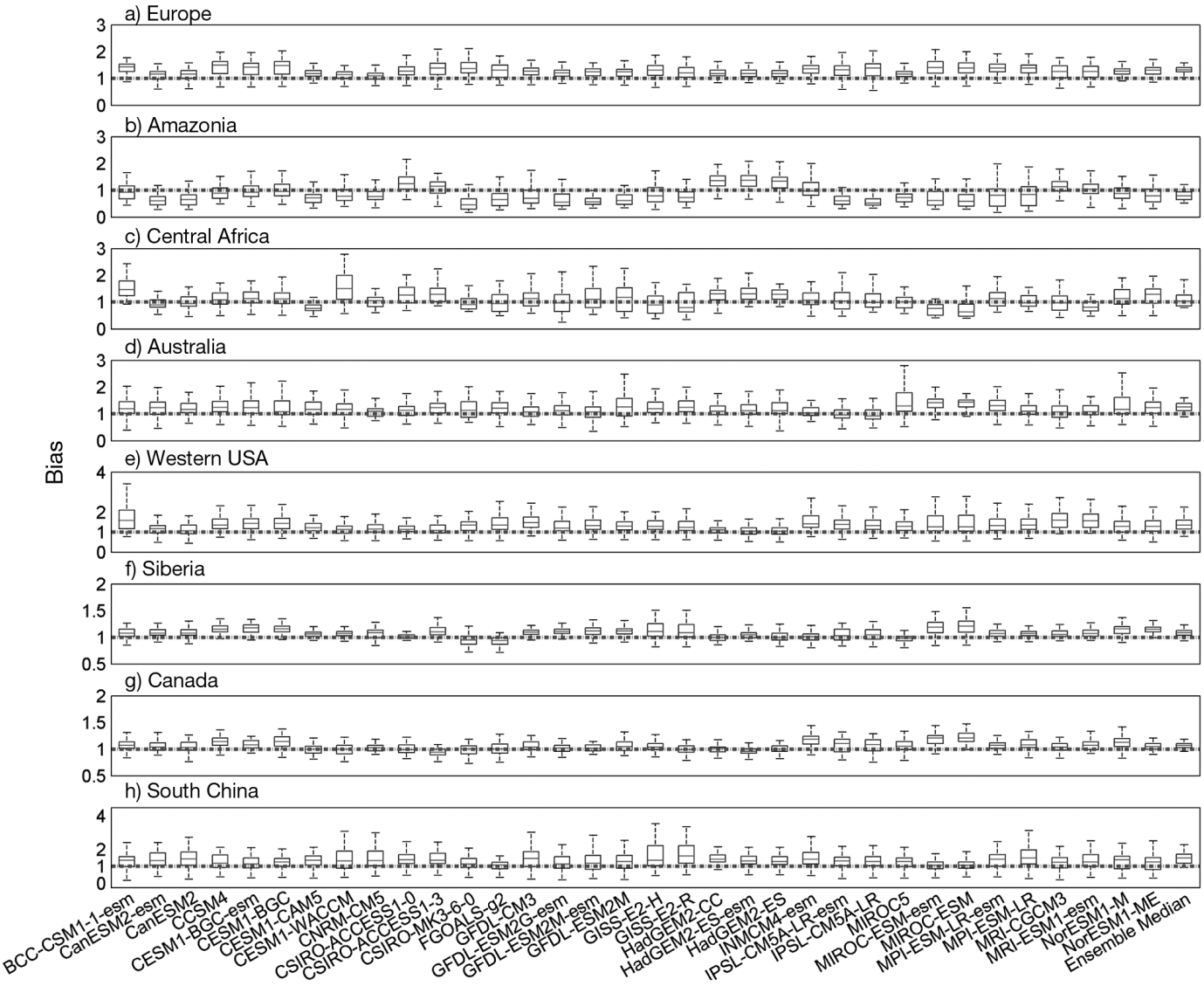

Fig. 9. Medians (midlines in boxes), 25th and 75th percentiles, and whiskers (variability outside respective percentiles) of the biases of each CMIP5 summer precipitation simulation over 8 different hydroclimatic regions

precipitation are overestimated in CMIP5 simulations relative to CRU observations.

To show the variability and robustness of the biases across the models and regions, boxplots of biases values in summer and winter are presented in Figs. 9 & 10. The figures display the median, 25th and 75th percentile edges, and whiskers (variability outside respective percentiles) of simulated precipitation biases for each model and region separately. One can see that there is substantial variability, not only model-to-model, but also region-to-region. In these figures, where the ensemble median stands relative to the inter-model range gives an indication of how consistent the simulation biases are across the selected CMIP5 models.

It is acknowledged that observational (CRU) data are subject to uncertainties, especially in the first half of the 20th century, when the spatial coverage of available observations was quite limited (New et al. 2000, Ferguson & Villarini 2012). To assess the robustness of the results, the analyses presented in this paper have been tested for the more reliable observations from the period 1951–2005. The results are provided in the Supplement (see Figs. S1–S6 in the Supplement at www.int-res.com/articles/suppl/c061p035_supp.pdf), corresponding to Figs. 4–7. As shown, the results do not change substantially when data from the first half of the 20th century are eliminated from the analysis. To further examine the robustness of the statistics, the same analyses are

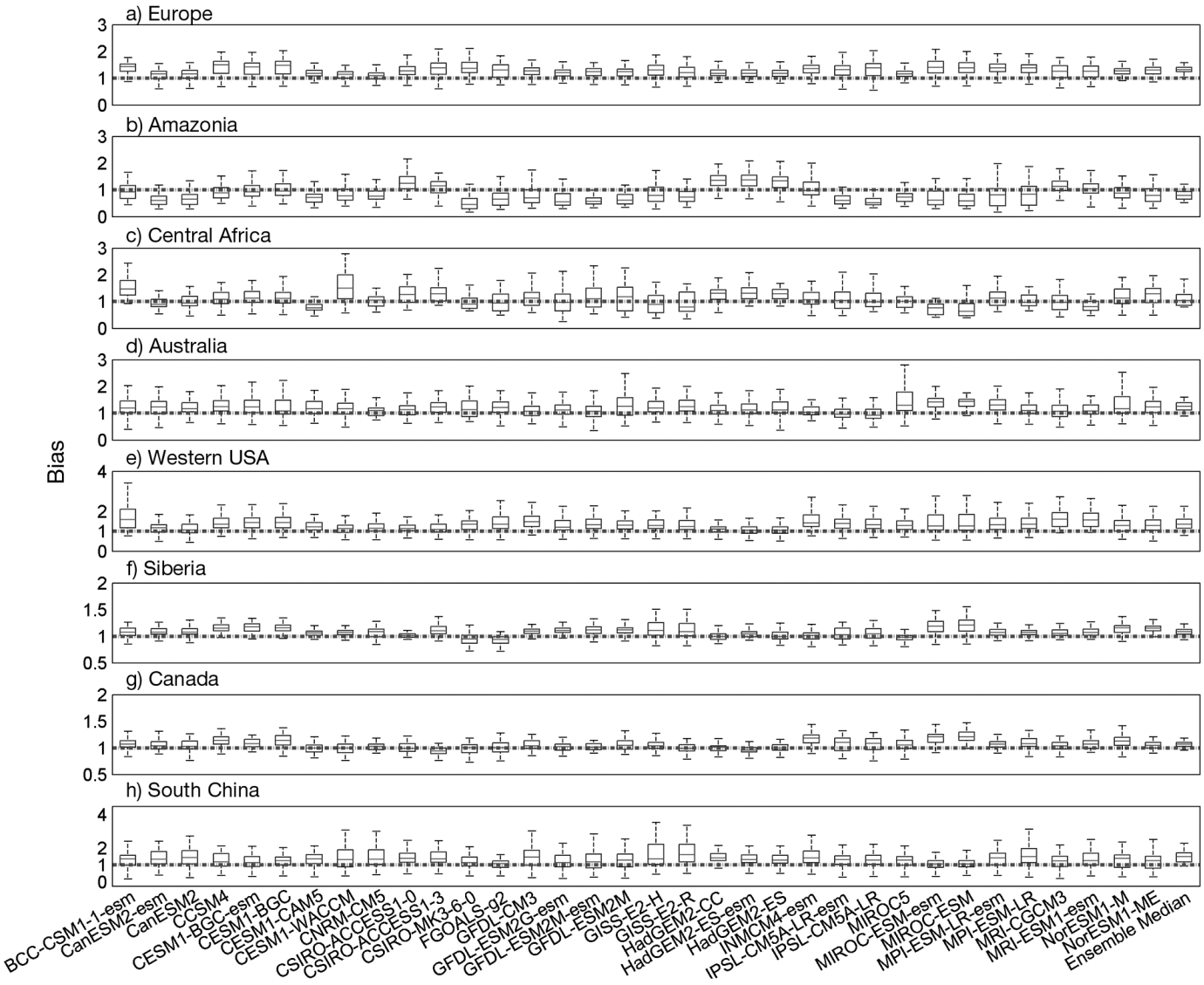

Fig. 10. Median (midlines in boxes), 25th and 75th percentiles, and whiskers of the biases of each CMIP5 winter precipitation # simulation over 8 different hydroclimatic regions

performed using the University of Delaware precipitation data (Nickl et al. 2010). As an example, Fig. S7 (in the Supplement) displays the global averages of the overall bias, MQB above 75th (Q75) and 90th quantile (Q90) for all the CMIP5 models and their ensemble median relative to the University of Delaware (UD) global precipitation data (as in Fig. 4, but with the UD precipitation as reference observation). One can see that the global average statistics are very similar using both CRU and UD observations. Fig. S8 (in the Supplement) shows the Regional summer and winter relative to the UD precipitation data over (a) Europe, (b) Amazonia, (c) central Africa, (d) Australia, (e) western USA, (f) Siberia, (g) Canada, and (h) south China (as in Fig. 5, but with UD precipitation as reference observation). We can see that even at the regional scale, the presented statistics using 2 different observational data sets are consistent.

5. CONCLUDING REMARKS

Recent advances in numerical computing and climate models have led to an increase in climate simulations of the past and future. However, climate model simulations are inherently subject to many uncertainties, and thus diverse methods are needed to comprehensively quantify simulation biases and the physical errors associated with them. The United

States Global Change Research Program (USGCRP 2009) identifies areas in which uncertainties limit our ability to estimate future climate change and its regional impacts that will entail mitigation and adaptation policy decisions. The quantification of biases in climate model simulations is therefore a prerequisite for future advances in both model development and policy formulation.

In this paper, the seasonal and regional biases in CMIP5 historical (1901 to 2005) simulations are evaluated against the CRU ground-based observations. The selected regions exemplify moist tropical, monsoonal, moist continental, semi-arid, and polar hydroclimatic regimes. The cumulative distribution functions (CDFs) of the CMIP5 precipitation simulations are also investigated, especially at higher quantiles (i.e. 75th and 90th percentiles) that are relevant to the analysis of heavy precipitation events (Benestad 2003, 2006).

The global averages of overall bias (*B*) and MQB values indicate no substantial difference in summer versus winter precipitation simulations. In fact, at a global scale, all models overestimate the total precipitation amount as well as its higher quantiles (e.g. 75th and 90th percentiles). However, strong seasonality in bias values is observed over the selected moist tropical regions (Amazonia and central Africa). Furthermore, the models exhibit high inter-model variability in the selected tropical regions, particularly in winter precipitation simulations. In both regions, substantial biases are observed at high quantiles of precipitation. Moreover, the CDFs of summer precipitation in the selected Amazonian and central African tropical regions (in contrast to those of other regions) are more inflected in their midrange, possibly reflecting marked differences in the physical processes that are operative for lighter versus heavier precipitation events.

Of the selected regions, 3 (central Europe, Siberia, and Canada) experience cold winter climates, and warm-to-cool, moist summers. In the selected regions over Siberia and Europe, many CMIP5 models underestimate precipitation in summer, while overestimating it in winter. In both areas, the MQB values decrease as the choice of quantile threshold increases, suggesting that the model underestimations of summer precipitation are primarily associated with biases in lower quantiles of precipitation. In contrast, in the selected Canadian region, the CMIP5 models and their ensemble median overestimate summer precipitation. Furthermore, the overall biases of summer precipitation are substantially higher than those of the selected region in Siberia. However, the CMIP5 models exhibit a similar behavior in simulating winter precipitation over the selected cold regions.

In the 2 semi-arid areas (the western United States and Australia) considered, the CMIP5 simulations show high inter-model variability, particularly in summer, while the ensemble median overestimates precipitation in both summer and winter. Here the MQB values of summer and winter precipitation also are similar.

Finally, the CMIP5 models exhibit substantial biases both in summer and winter in the selected southern China region, which is dominated by monsoonal regimes. Further improvements in sub-grid scale convective and cloud microphysical parameterizations are probably necessary to substantially improve precipitation simulations in this region.

The authors stress that the above conclusions are based on an exploratory analysis that exploits some of the available ground-based observations to evaluate the CMIP5 seasonal simulations of continental precipitation. It is acknowledged that the CRU data sets, similar to all other observational data, are also subject to uncertainties that may affect the results. Furthermore, observational biases and uncertainties may have both systematic and random statistical characteristics. Efforts by the authors are underway to decompose the observed biases into systematic and random components using methods introduced by AghaKouchak et al. (2012) to further analyze CMIP5 model uncertainties. It should be obvious that the biases and errors of climate model simulations are not limited to those discussed in this paper. The authors thus advocate that more effort should be devoted to the quantification and characterization of the details of biases exhibited by climate model simulations. It is hoped that further research to develop metrics for evaluating model performance will lead to more reliable precipitation simulations.

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