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Key Points:
- Statistical downscaling improves the current climatology but does not reduce the intermodel spread of future rainfall projections
- Models with more similar base climates yield more similar projections of change both with and without statistical downscaling
- Screening models provides a simple method for constraining future projections and is insensitive to the choice of observational data sets

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Constraining Climate Model Projections of Regional Precipitation Change

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Abstract As communities prepare for the impacts of climate change, policy makers and stakeholders increasingly require locally resolved projections of future climate. Statistical downscaling uses low-resolution outputs from climate models and historical observations to both enhance the spatial resolution and correct for systematic biases. By examining the downscaled rainfall over land, we show that although bias corrections are effective in reducing biases in the current climate, they do not reduce the intermodel spread in future rainfall projections. This failure stems from the strong dependence of future rainfall change upon the current climatological rainfall patterns. Even after bias corrections are applied, the downscaled projections of precipitation change retain this dependence upon their native climatology. However, we show that this dependence can be exploited; even very simple methods to subset models according to their ability to resolve the observed rainfall climatology can substantially reduce the intermodel spread in rainfall projections.

Plain Language Summary To prepare for future climate change, policy makers and stakeholders require reliable model projections with high spatial resolution. To meet this need, statistical methods have been developed to postprocess the model output so correct for systematic biases and enhance the spatial resolution. We focus on rainfall over land and find that the postprocessing only yields consistent values for the current climate and no reduction in the uncertainty is obtained for future projections even after the postprocessing. We show that patterns of future rainfall change exhibit a strong dependence on the current climate. This dependence can be exploited by selecting models based on their ability to reproduce the observed climate. We show that this screening of models can significantly reduce the uncertainty in future rainfall projections. The success of this simple method emphasizes the importance of model evaluation in reducing the uncertainty of multimodel climate change projections.

1. Introduction

Our knowledge of future climate change comes mostly from general circulation models (GCMs) that typically have spatial resolutions of ~100–200 km. However, the application of these projections for future adaptation planning and decision making often requires information with much higher spatial resolutions (Giorgi & Mearns, 1991; Gleick, 1986; Huth et al., 2000; Snover et al., 2013; Wigley et al., 1990). This is particularly true for rainfall which is highly variable in both space and time, and has a tremendous impact on a wide range of human activities. However, the direct use of the GCM output is often hampered by its low spatial resolution and systematic biases in its mean state (Benestad et al., 2008). To reduce biases and improve spatial resolution, downscaling has been developed to make the projections more suitable for regional applications. There are two general types of downscaling: dynamical downscaling (Giorgi et al., 2001; Mearns et al., 2003) and statistical downscaling (Benestad et al., 2008; Hewitson et al., 2014; Maraun et al., 2010; Piani et al., 2010; Teutschbein & Seibert, 2012; Wilby & Wigley, 1997). This study evaluates data sets processed by statistical downscaling methods.

Statistical downscaling methods usually start with a training step, in which a transfer relationship is derived between model output and observation that are common to some past period. Next, an application step follows, in which the derived transfer relationship is applied to the model output of a different period (e.g., future projections). The two-step procedure finally yields refined model output that is more suitable for adaptation planning and decision making because of its higher spatial resolution and reduced biases.

Bias correction procedure implicit in statistical downscaling methods has been shown to improve the mean state of variables such as precipitation and temperature (Maraun et al., 2010; Piani et al., 2010; Teutschbein

& Seibert, 2012). However, many concerns arise when performing statistical downscaling. For example, statistical downscaling methods can inflate the magnitude of trends, leading to a misrepresentation of future climate changes (Cannon et al., 2015; Hagemann et al., 2011; Maraun, 2013; Vannitsem, 2011). In addition, downscaling methods struggle with any region with significant subgrid-scale variability (Dixon et al., 2016; Lanzante et al., 2018; Maraun & Widmann, 2015). Perhaps most importantly, several studies have shown that statistical downscaling methods are unable to overcome the impacts of circulation biases that are deeply rooted in a GCM's climatology (Addor et al., 2016; Eden et al., 2012; Maraun et al., 2017; Stocker et al., 2015). Since the atmospheric circulation exerts a strong control on regional climate (Shepherd, 2014), the circulation biases are also reflected in regional biases in other fields (e.g., temperature and rainfall) and lead to implausible patterns of future climate change (Hall, 2014). To address such problems, Maraun et al. (2017) suggested that a careful model selection be performed, in which GCMs with lower circulation biases are given more weight, to improve the fidelity of the climate projections. This study further explores this recommendation.

We first evaluate the impact of several statistical downscaling methods on model projections of future rainfall change. We find that while they are effective in correcting for systematic biases in the current climatology, they are generally ineffective at reducing the intermodel spread in projections of rainfall change. We demonstrate that this ineffectiveness results from the dependence of the patterns of projected rainfall change upon the model's native rainfall climatology, and that this dependence persists even after bias corrections are applied. We then highlight how the strong dependence between the model's mean rainfall climatology and its projections of rainfall change can be exploited to reduce the intermodel spread in future projections.

2. Data and Method

We assess the effectiveness of statistical downscaling methods using the downscaled precipitation over land (Brekke et al., 2013) from phase 5 of the Coupled Model Intercomparison Project (Taylor et al., 2012). In the original phase 5 of the Coupled Model Intercomparison Project ensemble, there can be multiple models from one institution in which they share similar model physics but may vary in other aspects such as spatial resolution. To remove possible influences from those duplicate models, we consider only one model from each institution and retain the model with higher spatial resolution or greater complexity. A list of the modified phase 5 of the Coupled Model Intercomparison Project models used is shown in Table S1 in the supporting information.

In this study, we focus on one of the most common downscaling methods—a two-step method called Bias Correction and Spatial Disaggregation (BCSD; Wood et al., 2004). The first step (referred to as bias correction) adjusts GCM output based on a statistical comparison between historical simulations and observations over a common period. Typically, the observation's original resolution is the targeted downscaled resolution; however, the observations need to be interpolated to the GCM's spatial resolution (referred to as REGRID OBS) for a direct comparison. At each grid point and time step, biases are assessed by a "quantile map" (Panofsky et al., 1958) that combines cumulative distribution functions (CDFs) from the historical simulations and REGRID OBS. To correct the biases, the CDFs from the historical simulations are adjusted to match the CDF from REGRID OBS at each rank probability in the quantile map. For example, for each month two CDF curves are constructed, one based on the daily observations over the chosen reference period and the other based on the corresponding historical model simulations. At each rank probability, the CDF from model is adjusted to the same value as the CDF from the observation. Figure 1a from Pierce et al. (2015) illustrates how this adjustment works. This process is repeated for each model; thus, the number of model CDF curves is the same as the ensemble size. The reader is referred to Brekke et al. (2013) for further details regarding this and other downscaling methods used here.

The second step, referred to as spatial disaggregation, increases the spatial resolution of the GCM output. At each time step, factor values are computed as the ratio of the adjusted output to REGRID OBS, and then spatially interpolated to the downscaled resolution. The original observations are multiplied by the interpolated factor values to produce the bias-corrected and spatially disaggregated output. In addition, we also use model simulations that have been downscaled using the same spatial disaggregation method, but have not been bias corrected. This set of model output is referred to as Spatial Disaggregation, no Bias Correction (SD_noBC).

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Table 1
A Comparison of the Effectiveness of the Selection of Models for Different Statistical Downscaling Methods Applied

	Spatial resolution	Temporal resolution	Coverage	Reduction in $\sigma dlnP$
SD_noBC	1/2°	Monthly	Global	19%
			Contiguous United States	20%
BCSD	1/2°	Monthly	Global	17%
			Contiguous United States	19%
BCCA	1/8°	Daily	Contiguous United States	19%
LOCA	1/16°	Daily	Contiguous United States	16%

We also summarize results using two other statistical downscaling methods that are only available over the contiguous United States. The first of these is called Bias Correction Constructed Analogues (Maurer, 2010), in which the first step is still the bias correction as described above, but uses daily values that are 15 days before and after each time step to construct the CDFs. The second step best approximates the adjusted precipitation at each time step using a linear combination of the 30 daily values in REGRID OBS, which is referred to as the constructed analogue (Van den Dool, 1994). Weights retrieved from the linear combination are applied to the original observations to produce the statistically downscaled outputs. The other method is Localized Constructed Analogs (Pierce et al., 2014). Compared to Bias Correction Constructed Analogues, this method selects the locations at which 30 analog days are chosen rather than use the same analog days at all grid points. Thus, different locations can use different analog days to get a better approximation. Spatial resolution of the statistically downscaled data sets used in this study is shown in Table 1.

To investigate connections between the models' native climate and their projected patterns of rainfall change, we define the current climatology, P_1, computed by a 20-year average of historical simulations from 1986 to 2005, and the future projection, P_2, computed also by a 20-year average of Representative Concentration Pathway 4.5 from 2080 to 2099. Previous studies have shown that the intensity of extreme precipitation increases as the climate warms (Kharin et al., 2007; Sun et al., 2007). However, such increase exhibits heterogeneity, in which moderate precipitation events change more slowly than the rate of moisture increase while the most extreme events might increase at or above the rate of atmospheric moisture increase (Pendergrass, 2018). Regional changes in the precipitation are dominated by regions of heaviest rainfall. From a societal perspective, however, the regions of greatest vulnerability to rainfall changes often experience the least amount of rainfall. With this in mind, we quantify the changes using the *fractional* precipitation difference between the two climatologies, $dlnP = lnP_2 - lnP_1 \approx dP/P$, rather than the absolute difference,$dP = P_2 - P_1$. To avoid indeterminate changes, we limit our analysis to regions where P_1,P_2 > 0.1 mm/day. We use the observed historical data from Maurer et al. (2014) to quantify a model's ability to reproduce the observed climatology P_o, which is computed by a 20-year average for consistency. The CPC Merged Analysis of Precipitation (Xie & Arkin, 1997) is also used to assess the robustness of the results.

3. Results

In this section, we examine the uncertainty in model projections of future rainfall change and the impact of statistical downscaling methods in reducing this uncertainty. Figure 1 depicts the multimodel ensemble mean distribution of *dlnP* for both the SD_noBC (Figure 1a) and BCSD (Figure 1b). In the ensemble mean, the models project increased rainfall over tropical Africa, Asia, and North America, and decreased rainfall over Australia and South Africa. Broadly speaking, these changes tend to reflect a “wet get wetter, dry get drier” pattern of increased rainfall over the tropics and midlatitudes and decreased rainfall over the subtropics. Note that spatial distributions of the ensemble mean *dlnP* are nearly identical between the SD_noBC and BCSD, indicating that bias corrections do little to alter the spatial patterns of rainfall change.

Next we compute the intermodel standard deviation in *dlnP* (referred to as $\sigma dlnP$) to provide a measure of the intermodel spread or uncertainty in precipitation change between model projections (Figures 1c and 1d). The largest spread between models is generally found in the tropics with smaller spread found in higher

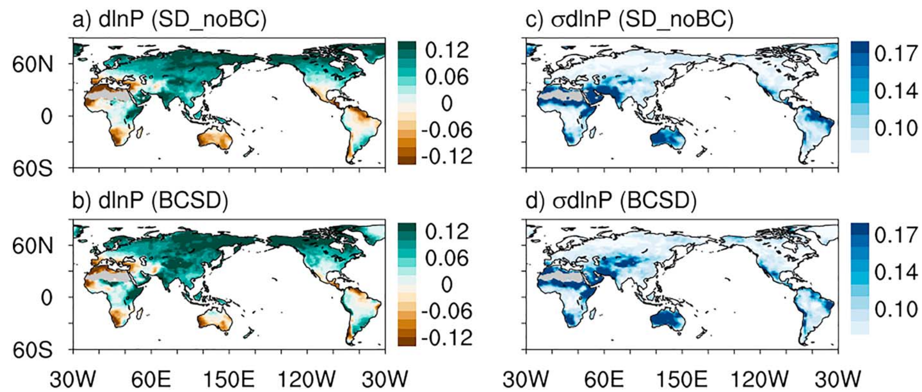

Figure 1. Maps of (a and b) the ensemble mean *dlnP* and (c and d) *σdlnP*. (a) and (c) are computed from the data set with only spatial disaggregation applied (SD_noBC), whereas (b) and (d) from the data set with both bias correction and spatial disaggregation applied (BCSD). The units of *dlnP* and *σdlnP* are dimensionless. Regions where P_1,$P_2 < 0.1$ mm/day are masked with gray shading.

latitudes. Comparison of Figures 1c and 1d illustrates the similar values of *σdlnP* between the SD_noBC and BCSD results. Indeed, the area-mean value of *σdlnP* is nearly identical for BCSD (0.102) and SD_noBC (0.104). This indicates that the bias correction, while improving the climatology of the model output, has little if any impact in reducing the intermodel spread of the projected changes in precipitation. Therefore, even if bias corrections are applied to the model output, the projected changes exhibit no reduction in uncertainty as measured by the intermodel spread.

Large intermodel spread reduces credibility in the model projections and makes it more difficult for stakeholders to determine which of the model projections are most suitable for their applications. While model output with severe biases are largely unusable for many applications, there are numerous issues related to bias correction (e.g., Maraun, 2013) and the application of bias correction itself is even questioned (Ehret et al., 2012). One way of reducing this dilemma is to improve the statistical methodology. Recent developments on bias correction focus on better matching variability and extremes (Haerter et al., 2011; Johnson & Sharma, 2012; Michelangeli et al., 2009; Piani et al., 2010), identifying the dependence between different variables (Piani & Haerter, 2012; Vrac & Friederichs, 2015), correcting feature location (Levy et al., 2013), and retaining simulated trends (Haerter et al., 2011; Hempel et al., 2013; Li et al., 2010). However, it is the credibility of climate model projection itself that ultimately provides the limiting factor in the resulting downscaled products (Adams et al., 2015; Barsugli et al., 2013; Hewitson et al., 2014).

In consideration of this, Maraun et al. (2017) suggested that models with large circulation biases should be excluded from consideration. For example, substantial biases have been found in the large-scale atmospheric circulation, which can result from insufficient resolution of the atmospheric model (Davini et al., 2017), unrealistic topography (Pithan et al., 2016; van Niekerk et al., 2017), or biases in the sea surface temperature (Ashfaq et al., 2011; Keeley et al., 2012; Scaife et al., 2011). It has also been shown that the intermodel spread in rainfall change is due neither to uncertainty in climate sensitivity (Kent et al., 2015) nor the patterns of sea surface temperature change (He & Soden, 2016). However, diagnosing simulations run by an ensemble of atmosphere-only models with a uniform sea surface temperature warming, He and Soden (2016) showed that climatological biases strongly affect future projections of rainfall change. In particular, they demonstrated that models with more similar climatologies of rainfall yield more similar projections of future rainfall change.

The results from He and Soden (2016) suggest that if we can reduce the climatological biases in models, the uncertainty in their projections of future rainfall change should be reduced accordingly. Motivated by this, we first explore if similar relationships between the mean climatology and patterns of projected change exist in the SD_noBC and BCSD data sets. To quantify the impact of climatological biases on projections of rainfall change, we compute cross-model spatial correlations of climatology and those of projections of rainfall change. We find that before bias corrections are applied, the strong dependence of the patterns of projected change on the mean climate noted in He and Soden (2016) also holds true here.

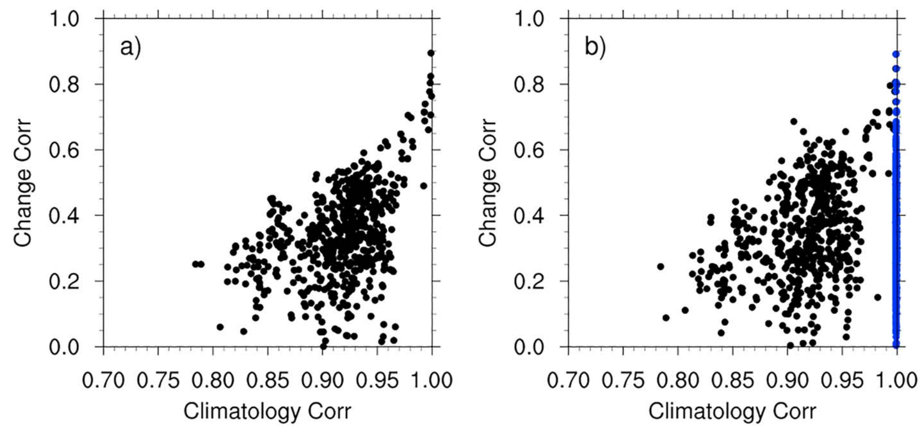

Figure 2. To illustrate that models with more similar mean climates tend to have more similar patterns of regional change, we plot the cross-model spatial correlation of the climatology (*x* axis) versus the cross-model spatial correlation of the precipitation change (*y* axis). Black dots in (a) are correlations computed using the uncorrected climatology from SD_noBC and the uncorrected precipitation change from SD_noBC. Blue dots in (b) are correlations computed using the corrected climatology from BCSD versus the corrected precipitation change from BCSD. Black dots in (b) are correlations computed by the uncorrected climatology (SD_noBC) versus the corrected precipitation change (BCSD). The similarity between the black dots in (a) and (b) highlights that regional patterns of precipitation change tend to retain their dependence upon the uncorrected climatology even after bias corrections are applied.

Namely, models with more similar climatology also tend to have more similar patterns of change (black dots in Figure 2a).

The blue dots in Figure 2b depict the same analysis after the bias corrections are applied. As expected, the climatological differences are greatly reduced; that is, all model cross correlations are ~1 since the climatologies are bias corrected to be identical. However, despite the perfect agreement in the climatologies, the spread between model projections of rainfall change remains large. To further explain the nearly unchanged spread between model projections of rainfall change, we match the cross-model spatial correlations of the uncorrected climatology with those of bias-corrected projections of rainfall change (black dots in Figure 2 b). The distribution of spatial correlations is almost identical to that in Figure 2a, indicating that the model-projected rainfall change, even after the bias corrections are applied, retains its dependence on the model's native uncorrected climatology. Similar results are also found in the Bias Correction Constructed Analogues and Localized Constructed Analogs data sets (not shown).

As noted above, BCSD or other statistical downscaling methods are ineffective in reducing the intermodel uncertainty in projections of rainfall change. However, the dependence of the regional patterns of rainfall change on the mean climatology offers a simple way to exclude models with large climatological biases and thereby reduce the spread in future projections. Indeed, Maraun et al. (2017) argued that selecting models with lower circulation biases can be a practical way to avoid implausible patterns of future climate change. Models with significant circulation biases means a failure to get other relevant processes correct, and such models should not be trusted for future projections. Here we explore the effectiveness of this philosophy by applying a simple screening method that exploits the dependence of regional patterns of future rainfall change upon the current rainfall climatology.

First we compute the spatial correlations between each model's native climatology and the observed climatology. This spatial correlation provides a simple metric of the models' ability to reproduce the observed climatology. Then, the five “best” models (i.e., those with the highest spatial correlation to the observed climatology) are selected. The aim of such a selection is to see if removing models with demonstrably large biases from observations can reduce the intermodel spread in future projections—something that statistical downscaling alone fails to accomplish.

This method is first implemented at the global scale using the SD_noBC data set. After the screening of models, the models with a more realistic climatology show an overall decrease in their intermodel spread compared to the full ensemble of models (Figure 3). The reduction in $\sigma dlnP$ varies regionally but on a global

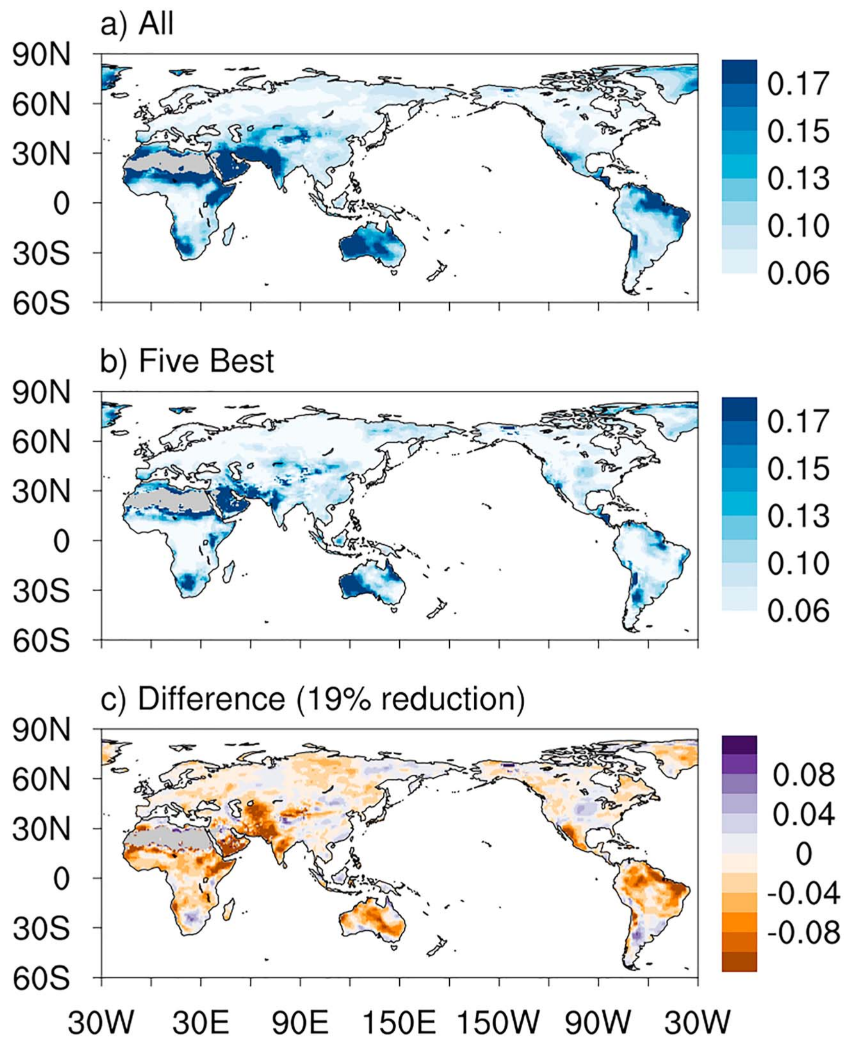

Figure 3. Maps of the intermodel spread in precipitation change ($\sigma dlnP$) for (a) all models, (b) five "best" models, and (c) the difference (five "best"—all models). Units are dimensionless. Regions where P_1,P_2 < 0.1 mm/day are masked with gray shading.

average is reduced by ~20% (Figure 3c). Such a reduction confirms that even simple methods can exploit the dependence between the mean state and projections of future rainfall change. Similar reductions are obtained when the screening method is applied to the other downscaled data sets (Table 1).

To ensure that the reduction in $\sigma dlnP$ for the five best models is not a statistical artifact of using a smaller sample size, we also consider the intermodel spread computed from all possible five-model combinations of the full ensemble. The estimate of $\sigma dlnP$ from this method is similar to that obtained if one uses the full model ensemble (not shown).

Model biases can vary regionally, in which case the best models are also likely to depend on the region under consideration. One might expect that subsetting models would be more effective when performed regionally, rather than globally. To test this, we repeat the above procedure for select continental subregions (Figure 4). A comparison of the top five models used at the global and regional scales is shown in Table S2. When selecting the top five models for each continental subregion, the intermodel spread is reduced significantly in all cases compared to the full model ensemble (Figure 4, the left and middle columns). In all cases, the reduction in the intermodel spread is equal to or greater than that obtained globally. Also, a comparable level of reduction in the intermodel spread is obtained using CPC Merged Analysis of Precipitation, suggesting that the screening method is insensitive to the choice of observational data sets.

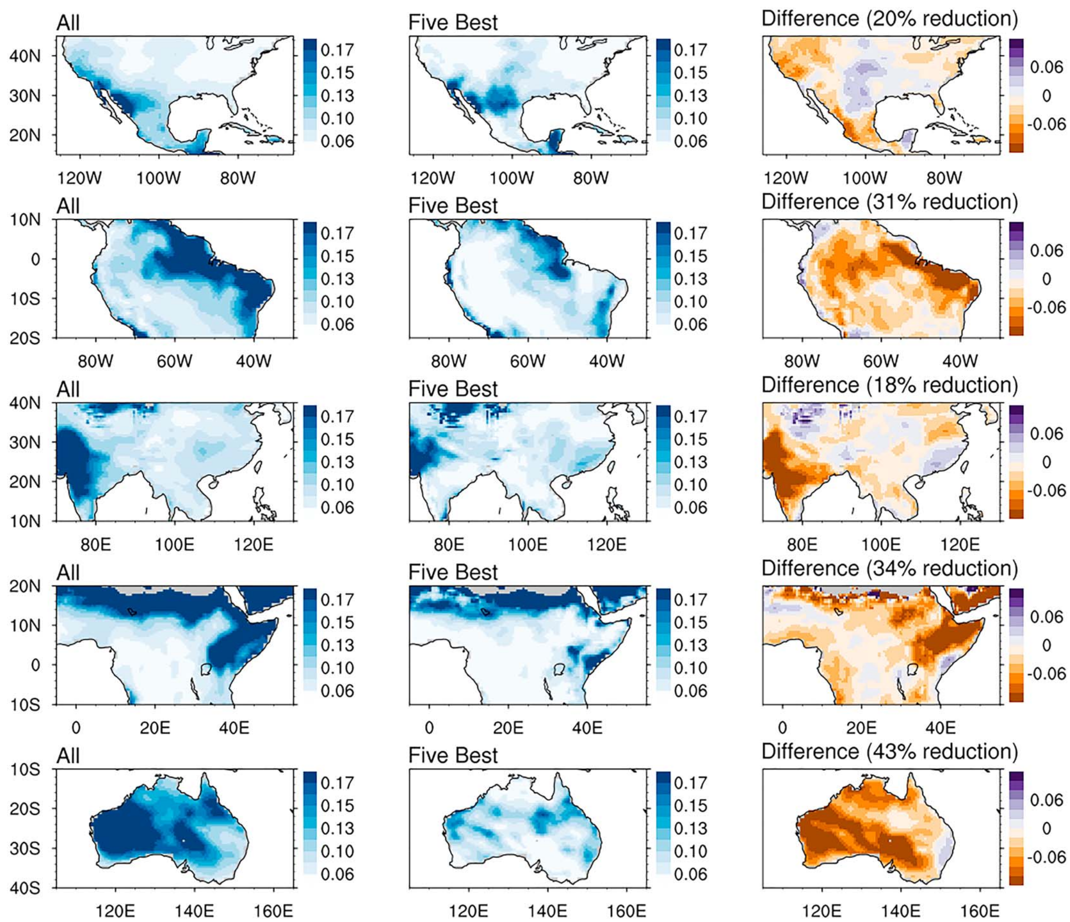

Figure 4. Maps of the intermodel spread in precipitation change (*σdlnP)* across (left column) all models, (middle column) five different "best" models, and (right column) their difference for selected continental-scale regions. Units are dimensionless.

4. Summary and Discussion

Statistical downscaling methods are widely used to reduce biases and improve the spatial resolution of model output (Maraun et al., 2010; Piani et al., 2010; Teutschbein & Seibert, 2012). In this study, the impact of statistical downscaling methods on future projections of rainfall change is assessed. We show that, although bias corrections improve the mean climate, they have little impact in reducing the intermodel uncertainty in projections of precipitation change. This failure stems from a strong dependence of future rainfall change upon the base climatology. Even after bias corrections are applied, the downscaled projections of precipitation change retain this dependence upon the model's native climatology. However, this dependence also provides a mechanism to reduce uncertainty in future rainfall projections. Even simple methods to eliminate models with large biases relative to the observed climatology provide an effective strategy for reducing the intermodel spread in rainfall projections. By excluding models with low similarity to the observed rainfall climatology, the intermodel spread in projected rainfall changes can be significantly reduced at both global and regional scales. However, it is worth mentioning that this method is from a climatological perspective and does not necessarily ensure that relevant modes of internal variability are accurately represented. In addition, one recent study has shown that the observations used in the downscaling process can influence the downscaled products (Alder & Hostetler, 2019). Uncertainties do exist among different observational data sets (Sun et al., 2018). Here an overall reduction of the intermodel spread has been achieved using two different observational data sets, indicating that the results are not sensitive to the uncertainties in observational data sets. Even the uncertainties in observations vary regionally, the screening method can still constrain future projections. One reason is that the original intermodel spread is much larger than the uncertainties in observations.

The success of even the simplest level of screening used here supports the arguments for selecting (or excluding) models based upon their ability to reproduce relevant aspects of the observed climate. A wide range of diagnostics and performance metrics can provide more insight into the origins of model biases and identify better ways to constrain regional projections (Eyring et al., 2016). Our study provides evidence of how even basic model evaluation helps to reduce the intermodel spread in future projections. Certainly, more sophisticated methods for selecting or weighting models exist and are likely to further reduce the intermodel spread. Rather than being subject to one single variable, comprehensive model evaluation that takes different variables' characteristics into consideration could enhance credibility. In that sense, individual metrics are synthesized into an overall index that can be used in screening models. With this in mind, model evaluation should proceed toward a standardized framework that emphasizes user-oriented diagnostics of relevance to stakeholders and the impact community (Eyring et al., 2016).

Acknowledgments
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