On the link between mean state biases and prediction skill in the tropics – An atmospheric perspective

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ABSTRACT

The present study examines how mean state biases in sea-surface temperature (SST), surface wind and precipitation affect model skill in reproducing surface wind and precipitation anomalies in the tropics. This is done using theoretical arguments, atmosphere-only experiments in the Coupled Model Intercomparison Project Phase 5 (CMIP5), and customized sensitivity tests with the SINTEX-F general circulation model. Theoretical arguments suggest that under certain conditions the root mean square error (RMSE) of a variable can be related to its variance and its mean, which indicates a direct link between bias and skill. The anomaly correlation coefficient (ACC), on the other hand, is generally not related to either the mean state or its variance, as several examples document. Multi-model atmosphere-only experiments with prescribed SST warming suggest that both ACC and RMSE of surface wind and precipitation are rather insensitive to warming on the order of 4 K. When SST biases from a free-running control simulation are prescribed in SINTEX-F, the ACC of surface wind is almost unaffected in the equatorial Pacific and Atlantic, while that of precipitation decreases noticeably in some regions but also increases in others. The RMSE of both fields shows widespread deterioration. There is a tendency for warm SST biases to increase the signal-to-noise ratio and sometimes ACC as well. The results suggest that, in the context of atmosphere-only simulations, improving SST and precipitation biases does not necessarily improve the skill in reproducing anomalies of surface wind and precipitation.

1. Introduction

The numerical simulation of weather and climate has made substantial progress over the last several decades (Edwards 2000; Richter et al. 2016). Nevertheless, systematic errors continue to pose a challenge to general circulation models (GCMs; de Szoeke and Xie 2008; Bellenger et al. 2013; Nagura et al. 2015; Richter et al. 2014a). While computational power has increased tremendously over the last few decades most climate models still cannot resolve scales below 100 km and even numerical weather prediction typically cannot resolve scales below 10 km. Due to these limitations to model resolution, many processes that occur on small spatial scales have to be parameterized. Among these processes are cumulus convection, boundary layer turbulence, and cloud microphysics. While such parameterizations have been reasonably successful, as demonstrated by the success of numerical weather prediction (NWP) in predicting weather and that of climate models in reproducing past and current climates, they necessarily involve the use of approximations, simplifications and ad-hoc assumptions, and also suffer from the limited availability of observational data. Thus deficiencies in parameterizations are thought to be the main cause of some of the persistent biases in GCMs, which, in the tropics, include errors in the mean position of the intertropical convergence zone (ITCZ; Li and Xie 2014), underrepresentation of low-level stratocumulus clouds (Richter 2015), and inadequate representation of the intraseasonal oscillation (Hung et al. 2013).

With the continuing increase in computing power it is possible that cumulus convection, whose representation requires a resolution of 5 km or higher, will be explicitly resolved over the next one to two decades, thus eliminating the need for cumulus parameterization. Boundary layer turbulence and cloud microphysics, on the other hand, require

67 a model resolution that is several orders of magnitude higher and therefore will need to
68 be parameterized even in the long term. This is one of the reasons why systematic model
69 errors (or biases) will likely continue to be an issue in GCMs.

70 Much work has been done to identify biases and alleviate them. By way of motiva-
71 tion, such studies often state that GCM biases deteriorate the skill of seasonal predictions
72 (as well as undermine confidence in global change projections). The often implicit as-
73 sumption is that alleviating biases will lead to a more realistic representation of variabil-
74 ity and more skillful predictions. Few studies, however, have thoroughly investigated this
75 link between mean state bias and prediction skill. The ones that have been performed do
76 point to a link but results are sometimes ambiguous. Perhaps the clearest evidence for a
77 link comes from a study by Manganello and Huang (2009), who used a heat flux correc-
78 tion scheme to reduce sea-surface temperature (SST) errors in the eastern tropical Pacific.
79 The flux correction, by design, drastically reduced the SST errors in the model but also
80 led to more realistic SST variability in the eastern Pacific, with a peak in boreal winter, as
81 observed, whereas the control simulation produced spurious peaks in spring and summer.
82 Moreover, the improvement in mean and variability were accompanied by improved El
83 Niño/Southern Oscillation (ENSO) prediction skill from lead month 6 onward. The au-
84 thors linked the relatively poor skill in their control model to the spurious variability peak
85 in summer: predictions initialized in January managed to grow SST anomalies until July
86 but could not maintain them afterward. Similar results were obtained by Ding et al.
87 (2015b) who found that climatological surface heat flux correction in a model with pre-
88 scribed surface momentum anomalies dramatically increased the model's ability to re-

produce SST anomalies. They attributed the increased simulation skill to the influence of SST bias reduction on the climatology of surface wind stress and subsurface temperature.

Gualdi et al. (2005) show that increased atmospheric resolution in their model leads to both a reduced easterly surface wind bias over the equatorial Pacific and generally improved ENSO prediction skill. Lee et al. (2010) used a pattern correlation metric to examine the relation between mean state and prediction skill at 1-month lead time in the global tropics for a multi-model ensemble of reforecasts. They find that models with higher pattern correlation for the mean state also tend to have higher pattern correlation for the anomalies. This intermodel relation varies considerably depending on the season, and is more pronounced for SST than for precipitation. Magnusson et al. (2013) study the impact of heat and momentum flux correction on the prediction skill of a version of the European Centre for Medium Range Weather Forecasts (ECMWF) model. They obtain a slight improvement in SST anomaly correlation coefficient (ACC) in the eastern tropical Pacific at lead months 6 and 7 for the reforecasts with flux correction.

DelSole and Shukla (2010) used the DEMETER multi-model reforecasts to examine the related issue of whether skill is affected by model drift (i.e. the model's transition from observation-based initial conditions toward its biased equilibrium state during the forecast period). Based on the intermodel correlation between skill and bias over the first three forecast months they concluded that there is a robust inverse relation, particularly for the tropical Pacific. However, due to the fact that the intermodel correlations were based on only 7 models, there is some uncertainty regarding the results. It is also not clear to what extent the drift during the first three forecast months resembles the equilibrium bias.

There is no shortage of studies on the link between mean state biases and variability errors (e.g. Sperber and Palmer 1996; Guilyardi 2006; Spencer et al. 2007; Jin et al. 2008; Richter et al. 2014a; Ding et al. 2015a; Deppenmeier et al. 2016) but these studies typically do not examine how variability errors affect prediction skill. Thus it appears that much work remains to be done to study the link between seasonal prediction skill and model performance in terms of mean state and variability. This is an important issue with practical implications because a deeper understanding of the link between bias and prediction skill can help the community understand which improvement efforts are likely to yield the highest return in terms of added prediction skill. It might also inform us that some regions are not likely to benefit much from further model improvement, at least as far as seasonal prediction skill is concerned. The tropical Atlantic may turn out to be such a region. On the one hand, SST and surface wind biases are severe there (Davey et al. 2002; Richter et al. 2008; Richter et al. 2014a) and many prediction models still struggle to beat persistence forecasts, as can be seen in Fig. 1 for a model ensemble from the Climate Historical Forecast Project (CHFP) intercomparison (Kirtman and Pirani 2009). On the other hand, it has been shown that, despite severe biases, some models produce relatively realistic variability patterns (Richter et al. 2014a) and that the theoretical predictability may be much lower than in the tropical Pacific (Richter et al. 2014b). This suggests that some models are able to capture the relevant atmosphere-ocean coupling and that the limiting factor for forecast skill in the region might not be model biases but predictability. In this context it is instructive to consider the results of Tompkins and Feudale (2010), who showed that an enhanced network of ocean observations could improve the ECMWF

forecast skill for the West African monsoon in the absence of any major model improvement.

Considering the issues discussed above we argue that it is important to obtain a deeper understanding of the link between mean state biases and prediction skill. The present study aims to take a first step in this direction by focusing on the ability of models to reproduce surface wind and precipitation anomalies when forced with observed SSTs, i.e. in an Atmospheric Model Intercomparison Project (AMIP)-style setting. One could consider this as a forecast at lead time 0, and it may provide an upper limit of the prediction skill one would expect to achieve. This statement should be qualified, however, because it has been shown that atmosphere-only experiments may misrepresent surface heat fluxes (Wang et al. 2005; Wu and Kirtmann 2005) and therefore coupling may increase precipitation skill at short lead times (Kang et al. 2004; Lee et al. 2010; DelSole and Shukla 2012).

Before examining model simulations, we will introduce the models and experiments used in section 2 and discuss some general considerations in section 3. To understand the impact of mean state SST warming on prediction skill we will examine three experiments from the Coupled Model Intercomparison Project Phase 5 (CMIP5) in section 4. These experiments prescribe observed SST from 1979-2008 but one experiment adds a spatially uniform 4K warming, while another one adds a patterned warming typical of global warming simulations. The purpose is to test the mean state dependence of the atmospheric response to SST anomalies. The impact of mean state biases will be further examined in dedicated sensitivity experiments with one particular model in section 5, while summary and conclusions will be given in section 6.

2. Method and experiment description

We examine the influence of biases on skill using two strategies. In the first, we study how skill is affected by intrinsic atmospheric biases, i.e. how a model's ability to reproduce surface wind and precipitation anomalies is affected by the respective biases in those fields. The second method is to examine how skill (in surface wind and precipitation) is affected by errors in the climatology of the SST boundary forcing. Details are given in the following.

2.1. CMIP5 experiments

We use AMIP-type simulations performed by several modeling centers for the CMIP5 model intercomparison. The basic experiment, called AMIP, consists of an atmospheric GCM (AGCM) forced with observed SST for the period 1979-2008. Monthly mean SSTs are interpolated to daily values. This experiment will be used to pursue the first strategy, i.e. exploring the influence of intrinsic atmospheric biases on skill. The SST boundary forcing is essentially the same in all models (except for interpolation errors) and thus we expect bias and skill of our fields of interest to be determined mainly by the atmospheric model component. It is, of course, possible that extraneous influences, e.g. from the land surface model obscure the bias-skill relation.

Two additional AMIP-type experiments in the CMIP5 archive allow us to pursue the second strategy, i.e. examining the sensitivity of skill to errors in the SST boundary forcing. In experiment amip4K a constant value of 4 K is added to the AMIP SST everywhere over the ice-free oceans. Experiment amipFuture adds a warming pattern that is also constant in time, but varies in space. The pattern is derived from the ensemble average of several global warming simulations and thus includes, among others, warming that

180 is enhanced at the equator. The original purpose of amip4K and amipFuture was to ex-
181 plore various aspects of climate change. In the present study, on the other hand, we are
182 not concerned with climate change, but rather use these experiments as a convenient way
183 to investigate how the surface wind and precipitation responses are affected by unrealistic
184 SST values ("unrealistic" in the sense of being inconsistent with the present-day green-
185 house gas forcing applied in the models), with the standard AMIP experiment serving as
186 our control.

187 To compare experiments, we calculate the ensemble average over a set of 11 models
188 (Table 1), which is the largest subset that performed all three experiments. The resulting
189 time series spans the period 1979-2008 (360 monthly means). The multi-model climatol-
190 ogy and anomalies are calculated based on this ensemble average. For experiment AMIP,
191 we also analyze intermodel correlations, with climatology and anomalies calculated for
192 each model separately.

193 **2.2. Sensitivity experiments with SINTEX-F**

194 While the SSTs in amip4K and amipFuture provide a good opportunity to explore
195 surface wind and precipitation sensitivity to the mean state, the SST distributions are
196 quite different from typical model biases. To test specifically how SST biases affect the
197 ability of a model to reproduce surface wind and precipitation we perform experiments
198 with one particular model, the SINTEX-F GCM. This model was developed under the
199 European Union-Japan collaboration project (Luo et al. 2003) and is based on the Euro-
200 pean SINTEX model (Gualdi et al. 2003). The version used here consists of the ECHAM
201 4.6 AGCM (Roeckner et al. 1996), the OPA 8.2 oceanic GCM (OGCM; Madec et al.
202 1998), and the OASIS 2.4 coupler (Valcke et al. 2000). The atmospheric resolution is
203 T106 (approximately 1.1°), with 19 vertical levels, 4-5 of which are inside the planetary

204 boundary layer. The oceanic resolution is 2° x 2° with the meridional resolution increas-
205 ing to 0.5° at the equator. The OGCM has 31 vertical levels, 19 of which lie within the
206 top 400m.

207 The control experiment (CTRL hereafter) is a simulation in which SSTs are strongly
208 restored to the Optimally Interpolated SST (OISST; Reynolds et al. 2002) observations
209 from 1982 to 2014. The strong restoring results in SST boundary conditions that are very
210 similar to an AMIP-type simulation but may differ from observations on the order of 0.1
211 K. CTRL comprises 9 ensemble members, which are generated by using three restoring
212 time scales (1-day, 2-day, 3-day) and three settings for the surface momentum flux for-
213 mulation (Luo et al. 2005).

214 We perform two sensitivity tests, both of which use SSTs from a free-running 500-
215 year control simulation (FR-CTRL). In the first experiment (Atl_bias), SST biases from
216 FR-CTRL are imposed on the tropical Atlantic between 30°S and 30°N. This is achieved
217 by subtracting OISST climatology (stratified by calendar month) from the original SST
218 boundary conditions and adding the corresponding FR-CTRL climatology values. Thus
219 the SST anomalies are the same as in OISST but the mean state in the tropical Atlantic is
220 that of FR-CTRL and therefore features all the biases of the latter. In the second experi-
221 ment (Pac_bias), an analogous procedure is applied to the tropical Pacific between 30°S
222 and 30°N. Experiments with SST restoring in various regions using SINTEX-F were also
223 performed by other authors, e.g. Sasaki et al. (2015), but none of these restored the SST
224 to a biased state. The sensitivity experiments also consist of 9 ensemble members, which
225 were generated by perturbing the SST boundary conditions with random values of 0.01 K
226 amplitude.

Our reference data set for surface wind is the European Centre for Medium Range Weather Forecasts (ECMWF) Interim reanalysis (Dee et al. 2011). For precipitation we use the Global Precipitation Climatology Project (GPCP) version 2.2, which is a blend of satellite and station data (Adler et al. 2003).

3. General considerations

3.1. Relation between MSE, ACC, and biases

Here we examine whether there is an explicit mathematical link between biases (in both mean and variability) on the one hand and prediction skill on the other. The measures of prediction skill examined here are the anomaly correlation coefficient (ACC) and the mean square error (MSE). ACC is defined as the Pearson correlation coefficient between the predicted (p) and observed anomalies (o):

$$r(p,o) = \frac{\sum_{i=1}^{n}(p_i - \bar{p})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^{n}(p_i - \bar{p})^2}\sqrt{\sum_{i=1}^{n}(o_i - \bar{o})^2}}$$

where the overbar denotes the seasonally stratified climatological time average, p_i and o_i are the seasonally stratified total values, and i is the time index. Likewise, MSE is defined through the following equation:

$$MSE^*(p,o) = \frac{1}{n}\sum_{i=1}^{n}(p_i - o_i)^2,$$

where the asterisk indicates the use of total fields in the calculation of MSE. ACC and MSE* are related through the following equation (e.g. Barnston 1992):

$$MSE^*(p,o) = std^2(p) + std^2(o) - 2std(p)std(o)r(p,o) + b^2(p) \quad (1)$$

where p and o denote the total fields, *std* is standard deviation, and b(p) is the mean bias of the prediction, i.e. $b = \bar{p} - \bar{o}$. In (1), MSE* and bias are explicitly related because

248 the total fields are used. Once the seasonal mean is removed, as is routinely done in sea-
249 sonal prediction, the bias term drops out and (1) becomes

250 $$MSE(p,o) = std^2(p) + std^2(o) - 2std(p)std(o)r(p,o) \quad (2)$$

251 Eq. 2 shows that MSE decreases with increasing ACC. Further, if the predicted vari-
252 ance is much larger than the observed one, it is easy to see that the first term on the right-
253 hand side of (2) dominates (independent of ACC). In this case, MSE is essentially deter-
254 mined by the standard deviation of the prediction model. Likewise, if *std(o)* >> *std(p)*
255 then *std(o)* dominates MSE.

256 In the case of *std(p)* = *std(o)*, i.e. predicted standard deviation is error-free, (2) can
257 be rearranged to give $MSE(p,o) = 2std^2(o)[1 - r(p,o)]$, which states that MSE is a
258 simple function of ACC and the observed variance (which equals the predicted variance).

259 Last, if ACC is close to 1, (2) can be approximated as $MSE(p,o) = std^2(p) +$
260 $std^2(o) - 2std(p)std(o)$, or, after some manipulation,

261 $$\text{RMSE(p,o)} = |std(p) - std(o)| \quad (3)$$

262 where RMSE is the root mean square error and the vertical bars denote the absolute
263 value function. (3) suggests that, for ACC close to 1, RMSE is proportional to the abso-
264 lute difference between the predicted and observed standard deviations. We test this rela-
265 tion for precipitation in the Niño 3.4 region (170º-120º W, 5º S-5ºN) using the AMIP
266 multi-model ensemble. Figure 2a scatters RMSE versus the RHS of (3). The ACC is 0.9
267 or higher in most models so that the approximation used to derive (3) holds reasonably
268 well. This is borne out by the high intermodel correlation coefficient of 0.96. RMSE is a
269 little higher than what would be expected if (3) were to hold exactly, presumably due to
270 the ACC being less than one (see Fig. 3a).

It is intuitively obvious that errors in the predicted variance will affect RMSE and so the high degree of intermodel correlation is essentially down to the ACC being consistently high across models. However, for an intermittent, positive definite variable like precipitation there is another aspect to Eq. (3), which may link skill to the mean state. Since precipitation is often zero but never less than zero, areas of high precipitation in the mean are also often areas of high precipitation variability. We thus suspect that regions with a wet precipitation bias also feature excessive variance and a high RMSE. Assuming an exact relation between mean and variance, Eq. (3) can be transformed into

$$RMSE(p,o) = c \cdot |\bar{p} - \bar{o}| = c \cdot |b(p)| \quad (4)$$

where c is a constant relating standard deviation of precipitation to its mean. To what extent this simple relation holds is examined in Fig. 2b, where, for each model, the RMSE of precipitation is scattered against the bias in the Niño 3.4 region. The intermodel correlation is 0.61, which is significant above the 99% level. As in Fig. 2a, there is an offset in the relation, which indicates the influence of the ACC.

3.2. Empirical link between ACC and bias

We have seen that, for the Niño 3.4 region, there is a moderately strong relation between mean state bias and RMSE of precipitation in regions where ACC is high. A more interesting question is whether there also is a relation between mean state and ACC. It can be seen from the definition of ACC that any linear transformation of the operands (i.e. observed and predicted time series) will leave its value unchanged. Intuitively one might expect severe biases (such as an ITCZ location bias) to affect ACC but such mean state biases do not figure into the mathematical definition of ACC (excepting the pathological case in which at least one of the time series is constant). Thus, based on the definition of ACC, there is no a-priori reason to expect that it should be influenced by errors in the

295 mean state or variance. We can nevertheless examine whether there is empirical evidence
296 for a link. To get a global view we show (seasonally unstratified) ACC and the annual
297 mean bias of precipitation for the AMIP multi-model mean (Fig. 3a). There is a tendency
298 for high ACC to be accompanied by small biases, particularly in the central and eastern
299 equatorial Pacific and northern Indian Ocean. Other areas, like the equatorial Atlantic,
300 tend to show the opposite behavior, i.e. high ACC accompanied by strong biases. The
301 pattern correlation is 0.15, which is not significant at the 5% level. Surface zonal wind
302 (Fig. 3b) also shows a variety of patterns, with high ACC in the eastern Indian Ocean al-
303 most collocated with the maximum easterly wind bias, while in the western equatorial
304 Atlantic high ACC exists where the bias is very small. The pattern correlation between
305 the two fields is -0.20, which is significant at the 5% level.

306 We further examine the relationship between bias and ACC in terms of intermodel
307 spread. The Niño 3.4 June-July-August (JJA) precipitation is overestimated in most
308 AMIP models and this anticorrelates with ACC at -0.68 (Fig. 4b). For precipitation over
309 the equatorial Atlantic, on the other hand, the intermodel correlation is weakly positive,
310 indicating a slight tendency for models with larger biases to have higher ACC (Fig. 4a, c).
311 No significant relation exists for the equatorial Indian Ocean. Precipitation indices over
312 monsoon regions (West Africa, South America, and India) show a similarly weak inter-
313 model correlation (Fig. 4d-f). Furthermore, the general lack of useful prediction skill is
314 striking. If the threshold is set at 0.5, a rather generous value, useful skill is only reached
315 by one model each for West Africa and South America, while no model shows useful
316 skill over India. As shown by previous studies, the absence of coupled feedbacks in
317 AMIP experiments reduces the models' ability to reproduce precipitation patterns (Kang

et al. 2004; Lee et al. 2010; DelSole and Shukla 2012) and thus skill may be somewhat higher in a seasonal prediction setting. Nevertheless, the generally low skill in these state-of-the-art models underscores the challenge of predicting rainfall in the monsoon regions, consistent with the study by Wang et al. (2009). As stated in their study, land surface initialization may be one way of improving skill for those regions.

A few examples of the ACC-bias relation for surface zonal wind are given in Fig. 5. For the western equatorial Atlantic (40-20ºW, 2ºS-2ºN; WEA hereafter) most models show the familiar westerly bias in March-April-May (MAM; Fig. 5a) as documented in Richter et al. (2008) and Richter et al. (2014a). Despite noticeable biases many models achieve an ACC of 0.8 or higher. A systematic relation between bias and ACC is not discernible. For the Niño 4 region (160ºE-150ºW, 5ºS-5ºN) in MAM, models are about evenly split into groups of westerly and easterly biases (Fig. 5b). There is a weak tendency for models with stronger easterly mean wind to have higher ACC (as indicated by the intermodel correlation of -0.44), even when the mean wind is more easterly than observed. The JJA surface zonal winds over the equatorial Indian Ocean (50-95ºE, 5ºS-5ºN) are too easterly in most models (Fig. 5c) and this is moderately correlated with a decrease in ACC (intermodel correlation 0.48). Overall, both precipitation and surface zonal wind tend to have higher ACC in those models with smaller biases but this is true only in some regions of the global tropics and many counter examples exist, most notably the equatorial Atlantic.

The tropical Pacific is known to have worldwide teleconnections (e.g. Horel and Wallace 1981) and thus one might expect to find that tropical Pacific precipitation biases adversely affect skill in other regions of the world. We examine this by repeating the

341 analysis in Figs. 4 and 5 but with precipitation averaged over the Niño 3.4 region on the
342 x-axis (not shown). Of the six regions shown in Fig. 4, only three show significant inter-
343 model correlations. Apart from the tropical Pacific (see Fig. 4b) these are the tropical In-
344 dian Ocean and the Indian monsoon index (inter model correlations -0.42 and -0.37, re-
345 spectively). For the latter, individual ACCs are low (see Fig. 4f), so that the tropical Indi-
346 an Ocean relation appears to be the most interesting. According to this relation, models
347 with pronounced positive precipitation bias in the Niño 3.4 region during boreal fall tend
348 to have very low ACC for precipitation over the tropical Indian Ocean. Relating the sur-
349 face wind ACCs shown in Fig. 5 to mean precipitation in the Niño 3.4 region does not
350 produce any significant correlations. A more detailed investigation into the remote impact
351 of tropical Pacific biases, particularly for the Indian Ocean, might produce interesting re-
352 sults but is out of scope for the present study.

353 ## 4. Comparison of AMIP, amip4K, and amipFuture

354 In this section we examine multi-model ensemble means of three experiments in the
355 CMIP5 archive (see Table 1 for a list of ensemble members). In amip4K, the prescribed
356 SSTs are uniformly warmed by 4 K, relative to AMIP (Fig. 6b). This leads to a noticeable
357 precipitation increase over the tropical Pacific and a more moderate increase over the
358 tropical Atlantic and Indian Oceans. In amipFuture a typical global warming pattern is
359 added to the AMIP SST, with enhanced warming in the deep tropics that is about 1 K
360 warmer than in amip4K. Precipitation appears to respond in a non-linear way as values
361 over the equatorial regions increase markedly compared to amip4K. Perhaps the most
362 striking difference is seen over the eastern equatorial Pacific, where precipitation above 3
363 mm/day extends much farther east than in either AMIP or amip4K. The non-linear re-

sponse in amipFuture is consistent with the result of previous studies that demonstrate the importance of the equatorial warming enhancement to rainfall patterns (Xie et al. 2010; Sobel and Camargo 2012; Huang et al. 2013).

4.1. Impact of SST warming on skill in the tropical Pacific

The ACC of Niño 4 surface zonal wind is almost unchanged in amip4K and amipFuture (Fig. 7a), despite pronounced precipitation changes (Fig. 6). In all experiments ACC is quite high and generally ranges between 0.8 and 0.9. This illustrates the strong influence of SSTs on surface winds in the tropical Pacific (consistent with Lindzen and Nigam 1987, and Zebiak and Cane 1987), an important part of the ENSO feedback loop (Bjerknes 1969; Neelin et al. 1998). ACC is even higher for precipitation in the Niño 3.4 region (Fig. 7b) with values up to 0.98 in AMIP and amip4K. Here amipFuture shows a noticeable decrease relative to the other two experiments, with ACC reduced by as much as 0.1 in April and May though this decrease is not statistically significant at the 95% level, based on Fisher's z transformation.

The higher SSTs in amip4K and amipFuture give rise to more intense precipitation over the tropics, which should increase variability and thus RMSE (see section 3). Moreover, since convection enhances the surface wind response to SST anomalies (Zebiak 1986; Richter et al. 2016) we also expect to see an increase in surface wind variability and, potentially, its RMSE. There is an opposing effect from the increase of atmospheric moisture and the stabilization of the atmospheric column (Held and Soden 2006). In the experiments under consideration, however, the variance of surface zonal wind does increase in the tropics (not shown). Consequently, the RMSE of surface zonal wind in the Niño 4 region (Fig. 7c) shows a more obvious skill deterioration as was the case for ACC, particularly for amipFuture. Nevertheless, the increase of RMSE relative to AMIP does

388 not exceed 25% and none of the differences are significant at the 95% level, according to
389 an F-test. For Niño 3.4 precipitation, the RMSE is more seriously affected (Fig. 7d), with
390 values increasing by about a factor of 3 in amipFuture (statistically significant for all
391 months). In amip4K the increase is only 10-20% and is only statistically significant in
392 December.

393 The deterioration of precipitation RMSE in amipFuture points to a nonlinear re-
394 sponse of precipitation and its variability in the equatorial Pacific region. Such nonlinear-
395 ity is considered to play an important part in the skewness of ENSO (e.g. An and Jin
396 2004; Frauen and Dommenget 2010) and in the changes of ENSO variability under glob-
397 al warming (Power et al. 2013; Zheng et al. 2016). It is remarkable, however, that ACC is
398 not much affected by this nonlinearity.

399 The area with the strongest decline in ACC is the central equatorial Pacific in MAM
400 (not shown). Analysis of this area (160-120ºW, 5ºS-5ºN) reveals that observations, amip
401 and amip4K all feature a highly non-linear relationship between precipitation and under-
402 lying SST (not shown): as SSTs exceed 28 ºC (32 ºC in the case of amip4K) the precipi-
403 tation response becomes much more pronounced. In amipFuture, on the other hand, the
404 relation is approximately linear, which leads to its decreased ACC.

405 **4.2. Impact of SST warming on skill in the tropical Atlantic**

406 In the WEA, the ACC of surface zonal wind anomalies is above 0.7 from April
407 through June (Fig. 8a), with substantially lower values in other months. For the most part,
408 ACC is very similar across experiments though AMIP tends to have higher values in bo-
409 real fall. These differences, however, are not statistically significant and, furthermore,
410 skill in all three experiments is well below the usefulness level.

411 The ACC of precipitation over the equatorial Atlantic (50ºW-10ºE, 5ºS-5ºN; EQATL
412 hereafter) exceeds 0.8 from May through July in all three experiments (Fig. 8b), which
413 indicates a robust response to the pronounced SST anomalies that occur in that season
414 (e.g. Carton and Huang 1994; Xie and Carton 1994; Richter et al. 2014a). In other
415 months, ACC in the warming experiments both rises above and drops below the AMIP
416 reference so that, on the whole, SST warming appears to have no systematic effect on the
417 ACC of equatorial Atlantic precipitation.

418 RMSE of surface zonal wind over the western equatorial Atlantic tends to improve in
419 the warming experiments from March through June (Fig. 8c), while in other months dif-
420 ferences tend to be very small. None of these changes are statistically significant.

421 The RMSE of precipitation, on the other hand, increases significantly in the warming
422 experiments, as expected from the increased mean (Fig. 6) and variability (not shown).
423 This is particularly evident in amipFuture, where differences are statistically significant
424 in several months.

425 5. Sensitivity tests with SINTEX-F

426 We first discuss the annual mean climatology of the SINTEX-F experiments. Biases
427 generally have significant seasonal variability, particularly in the tropical Atlantic (Rich-
428 ter and Xie 2008). Nevertheless, the annual mean biases already feature many of the sali-
429 ent model errors. In the interest of brevity, we therefore discuss the annual mean biases
430 only.

431 In experiment Atl_bias the tropical Atlantic SST of the SINTEX-F AMIP-like CTRL
432 experiment is replaced with the biased climatology of the free running control simulation.
433 This leads to annual mean SST in the eastern tropical Atlantic being up to 3 K warmer

than in either CTRL or the observations (Fig. 9c). The Atlantic ITCZ responds by broadening meridionally, as can be seen from the increased precipitation south of the equator in Fig. 9c. Precipitation also changes in some other regions, with increase in the equatorial Indian Ocean and decrease in the South Pacific Convergence Zone (SPCZ).

In experiment Pac_bias (Fig. 9d) the equatorial Pacific SSTs are warmer than observed, particularly in the eastern basin. The SPCZ intensifies, extends further eastward, and becomes more zonally oriented, while the north-equatorial ITCZ weakens. This leads to a pronounced double ITCZ structure, a common bias in GCMs (de Szoeke and Xie 2008; Li and Xie 2014). Precipitation in other basins is not affected much.

Tropical precipitation is overestimated in all three experiments, a common problem in GCMs (Richter et al. 2016) that is most apparent over the Pacific warm pool. Note that for the latter region the precipitation differences across the experiments are relatively small compared to their difference from observations.

Surface zonal wind is biased westerly over the central and eastern equatorial Pacific in CTRL (Fig. 9b). A westerly bias is also seen over the equatorial Atlantic, which is typical of most GCMs (Richter et al. 2008). When SST biases are prescribed in the tropical Atlantic the westerly bias intensifies (Fig. 9c). This demonstrates the amplification of westerly wind biases in AGCMs by SST biases, as shown for CMIP3 (Richter et al. 2008) and CMIP5 (Richter et al. 2014a) models. In Pac_bias the westerly wind bias over the equatorial Pacific deteriorates noticeably (Fig. 9d). This is consistent with the surface winds responding to the reduced zonal SST gradient.

5.1. Impact of SST biases on skill in the Tropical Pacific

The ACC of surface zonal wind in the Niño 4 region (Fig. 10a) shows that the skill of CTRL is comparable to that of the AMIP ensemble (Fig. 7a). Overall, skill scores in

458 the equatorial Pacific are relatively robust to the presence of SST biases (Fig. 10). The
459 ACC of Niño 4 surface zonal wind is essentially the same in all three experiments, with
460 differences less than 0.05 that are not statistically significant at the 95% level (Fig. 10a).
461 The ACC of Niño 3.4 precipitation (Fig. 10b) decreases significantly in January, May,
462 and August but never by more than 0.1.

463 A horizontal map of ACC for precipitation in MAM is presented in Fig. 11. CTRL
464 shows maximum ACC in the eastern equatorial Pacific. The difference plot (Fig. 11b)
465 reveals that the Niño 3.4 region chosen for Fig. 10 includes areas of both significant in-
466 crease and decrease in ACC. The most evident decrease is in the eastern tropical Pacific,
467 where CTRL had high skill (Fig. 11a). Significantly increased ACC is found in the west-
468 ern equatorial Pacific, and in the far eastern Pacific centered at 10ºS and 10ºN. The
469 changes in ACC very roughly correspond to those in mean precipitation in that both tend
470 to decrease on the equator and increase away from it (Fig. 11b).

471 We examine the region of the largest ACC decrease (140-105ºW, 5ºS-5ºN; EEP
472 hereafter) by scattering simulated vs. observed MAM precipitation (Fig. 12a). It is evi-
473 dent that both mean and variability of precipitation are reduced in Pac_bias (see also Fig.
474 11b). The two points with the highest precipitation in the GPCP observations correspond
475 to the years 1983 and 1998, both of which followed exceptionally strong El Niño events.
476 CTRL reproduces these high precipitation events fairly well while Pac_bias does not,
477 which contributes to the drop of ACC from 0.95 in CTRL to 0.55 in Pac_bias.

478 Convection in the tropics is thought to be sensitive to the absolute value of the under-
479 lying SST (Graham and Barnett 1987) though there may be no critical threshold (Zhang
480 1993). We examine to what extent background SST changes in the EEP contribute to the

481 drop in ACC by scattering precipitation versus SST, both averaged over the EEP (Fig.
482 12b). While the EEP has a warm bias in the annual mean (Fig. 9d), in MAM it is cooler
483 than observed by about 0.3 K (Fig. 12b). Convection in the tropics can be sensitive to
484 small SST changes, but closer inspection of Fig. 12b shows that, even for the same SST
485 values, Pac_bias has much lower precipitation than CTRL or the observations. Further-
486 more, in Pac_bias, precipitation for some SST values below 28ºC turns out to be higher
487 than that for SST above 28ºC. Thus the local SST change does not seem sufficient to ex-
488 plain the drastic reduction of mean precipitation in the region (Fig. 11b).

489 A meridional section averaged from 140-105ºW (Fig. 13) reveals an SST decrease of
490 almost 1 K just north of the equator, which is partially offset by an increase south of the
491 equator and therefore not apparent in the area average. Additionally, there is a warm bias
492 of almost 2 K further poleward in both hemispheres for Pac_bias (Fig. 13). This is ac-
493 companied by anomalous subsidence and lower tropospheric divergence over the equato-
494 rial region and anomalous rising motion off the equator in both hemispheres. The analysis
495 suggests that SST biases both in the EEP and in the subtropics create an environment in
496 the EEP that is less conducive to convection. This makes it more susceptible to factors
497 other than the underlying SST.

498 The RMSE of surface zonal wind in the Niño 4 region is almost unchanged in
499 Pac_bias (Fig. 10c), with no significant differences in any month. The RMSE of precipi-
500 tation in the Niño 3.4 region (Fig. 10d) significantly decreases in April and October. This
501 improvement in RMSE is explained by the decreased variability in Pac_bias (not shown,
502 but inferable from the precipitation decrease in Fig. 11b; see Eq. 3). There also is a pro-
503 nounced and significant increase of RMSE in December.

504 It is interesting to note that the RMSE of precipitation consistently increases in the
505 Atl_bias experiment (Fig. 10d) though this is only statistically significant in January and
506 August. The result suggests remote influences on the Pacific from the severe tropical At-
507 lantic SST bias.

508 **5.2. Impact of SST biases on skill in the Tropical Atlantic**

509 CTRL reproduces the surface zonal wind anomalies in the WEA with an ACC of ap-
510 proximately 0.8 from April through June (Fig. 14a), comparable to the performance of
511 the AMIP multi-model ensemble (Fig. 8). Atl_bias features slightly lower ACC in those
512 months but also higher ACC in other months. None of the differences are statistically
513 significant. The ACC of precipitation for the EQATL index in CTRL is highest from
514 May through July (Fig. 14b). The ACC in Atl_bias reduces in most months (significantly
515 so in April, May and December). An increase of ACC occurs in August and September
516 but is not statistically significant.

517 RMSE deteriorates more markedly than ACC (Fig. 14cd), with significant differ-
518 ences in many months. This is a consequence of the warm SST bias in Atl_bias, which
519 increases both mean (Fig. 15) and variability (not shown) of precipitation, exacerbating
520 the biases in CTRL. Excessive variability in precipitation directly leads to a high RMSE
521 (Eq. 3) and, through its impact on wind variability, indirectly contributes to the high
522 RMSE of that quantity.

523 The horizontal map of climatological precipitation in CTRL, averaged over April
524 through June (AMJ; Fig. 15a), shows maximum precipitation off the West African coast
525 at about 5ºN. ACC, on the other hand, is highest over the central equatorial Atlantic. In
526 response to the warm bias in Atl_bias, the ITCZ shifts southward, resulting in precipita-
527 tion decrease north of the equator and increase south of it (Fig. 15b). This behavior is

528 roughly mirrored by the ACC, similarly to the Pacific case. Only some areas feature sta-
529 tistically significant changes. For the ACC of surface zonal wind, the horizontal map
530 shows the highest skill in the western equatorial Atlantic off the coast of Northeast Brazil
531 (Fig 15c). In Atl_bias, this area only shows a slight decrease (Fig. 15d and Fig. 14a) but
532 further east the impact is more visible, though still not statistically significant.

533 We examine how the SST biases affect the precipitation response to equatorial warm
534 events by compositing SST and precipitation anomalies in July for Atlantic Niño years
535 (1984, 1988, 1991, 1995, 1996, 1999, 2008) and plot horizontal maps for the observa-
536 tions and the two experiments (Fig. 16). The observations show wet precipitation anoma-
537 lies between the equator and 10ºN extending over northeast Brazil to the west and Africa
538 to the east (Fig. 16a). The most pronounced rain anomalies occur off Northwest Africa
539 and over the central equatorial Atlantic, while maximum SST anomalies occur in the
540 eastern equatorial Atlantic (ATL3 region). Large areas of warm SST anomalies in the
541 tropical southeast Atlantic are not accompanied by increased precipitation. CTRL, which
542 is forced with essentially the same SST field, reproduces the precipitation response fairly
543 well although precipitation anomalies are too intense (by a factor 3 approximately) and
544 too narrow in the meridional direction (Fig. 16b). Precipitation anomalies are unrealistic
545 in Atl_bias because, in addition to being excessive, they are shifted southeastward (Fig.
546 17c). To a first approximation, the precipitation response in Atl_bias just follows the un-
547 derlying SST anomaly pattern, which is not the case in the observations and CTRL. Pat-
548 tern correlation with observations for the area 50ºW-10ºE, 10ºS-10ºN yields 0.72 and -
549 0.02 for CTRL and Atl_bias, respectively, thus confirming the visual impression. The
550 drastic deterioration of the precipitation response in Atl_bias thus appears to be due to the

551 unrealistic sensitivity to the underlying SST anomalies. This in turn, directly relates to the
552 mean state SST bias, which is most severe in the southeastern tropical Atlantic (Fig. 9c)
553 and thus creates an environment that is unrealistically conducive to deep convection.

554 The increased sensitivity to SST anomalies in Atl_bias, however, can also lead to in-
555 creased skill by allowing a robust precipitation response to emerge that would otherwise
556 be drowned out by atmospheric internal noise and remote influences. This is suggested by
557 the increased ACC of precipitation over the tropical southeast Atlantic (Fig. 15b). We
558 quantify this by calculating the signal-to-noise ratio (SNR) for the tropical Atlantic. An
559 easy way to estimate SNR is to calculate ensemble mean variance divided by intra-
560 ensemble variance. The result for AMJ confirms that SNR is indeed increased over the
561 southeastern tropical Atlantic (shading in Fig. 17). This roughly corresponds with the
562 SST bias during the season (contours in Fig. 17), though this relation is certainly compli-
563 cated by other factors. Compositing events with anomalously high precipitation over the
564 southeastern tropical Atlantic (10ºW-10ºE, 10ºS-0) confirms higher skill in Atl_bias for
565 this particular region (not shown).

566 # 6. Summary

567 ## 6.1. Summary

568 We have investigated the link between GCM biases and prediction skill in the tropics
569 through theoretical considerations and AMIP-style sensitivity tests. Our metrics for mod-
570 el skill have been RMSE and ACC, and we have applied these to the variability of sur-
571 face winds and precipitation.

572 Taking the well-known relation among RMSE, standard deviation and ACC as our
573 starting point (Eq. 2), we have shown that, if ACC is close to 1, there is a simple relation

574 between RMSE and the observed and simulated standard deviations that holds for any
575 field. Thus, RMSE becomes a simple function of the simulated standard deviations. For
576 areas in which models have consistently high skill, such as the equatorial Pacific, this re-
577 lation clearly emerges in a multi-model scatter plot of AMIP models (Fig. 2a). For a posi-
578 tive definite field like precipitation, there is a relatively close relation between mean and
579 variability. This establishes a link between the mean and RMSE of precipitation or, in
580 other words, bias and skill. A multi-model scatter plot suggests that this relation holds
581 reasonably well for the equatorial Pacific.

582 By definition, ACC is not explicitly related to the mean state and, consistently, mul-
583 ti-model plots scattering the ACC against bias of precipitation do not reveal a systematic
584 link, except for the equatorial Pacific (Figs. 3, 4b). For the three monsoon regions exam-
585 ined, the scatter plots also suggest a general absence of useful prediction skill, although
586 the lack of coupled feedbacks in AMIP may contribute to this. Equatorial surface zonal
587 winds do not show a strong relation between mean and ACC either, though there is some
588 suggestion of a link for the equatorial Indian Ocean (Fig. 5c). Biases over the tropical Pa-
589 cific appear to have some negative remote impact on skill over the Indian Ocean but
590 more analysis will be needed to substantiate this relation.

591 Multi-model AMIP-style simulations with prescribed warming patterns over the
592 global oceans indicate that ACC and RMSE are rather insensitive to SST changes on the
593 order of 4 K. Only for precipitation the RMSE deteriorates noticeably due to the exces-
594 sive variability that results from the warming.

595 In two sensitivity experiments with the SINTEX-F GCM, SST biases from a free-
596 running control simulation were prescribed over either the tropical Atlantic or the tropical

Pacific, while leaving the anomalies as in the control simulation. The ACC of surface zonal wind is mostly unaffected in some key equatorial regions. Precipitation shows some more obvious decrease, particularly over the equatorial Atlantic. The RMSE of precipitation and surface zonal wind deteriorates noticeably over the equatorial Atlantic because the variability of these fields increases. Conversely, RMSE is not affected significantly over the equatorial Pacific, where mean precipitation and its variability tend to decrease.

Composite analysis of equatorial Atlantic warm events (Atlantic Niños) reveals that the warm SST biases in the eastern tropical Atlantic are associated with excessive sensitivity of precipitation anomalies to the underlying SST. This suggests that the unrealistically warm SST produce an environment conducive to deep convection that reacts very sensitively to warm SST anomalies, even when observations show no such sensitivity.

While the excessive sensitivity to local SST anomalies often deteriorates the skill of precipitation, it can also increase it under certain circumstances. This appears to be the case for the southeastern tropical Atlantic where the signal-to-noise ratio is increased over warm SST biases. The spatial pattern of ACC (15ab) supports this notion because it shows increased skill in the southeastern tropical Atlantic. In the eastern equatorial Pacific, on the other hand, cold SST biases are accompanied by a reduction in mean precipitation during MAM, and ACC decreases (Fig. 11). Recent studies indicate that the signal-to-noise ratio is underestimated in climate models (e.g. Eade et al. 2014; Scaife et al. 2014) and thus warm SST biases may be able to compensate for this deficiency in some scenarios.

6.2. Discussion

Our results indicate that there is generally no straightforward linear correspondence between mean state biases in SST, precipitation and surface wind on the one hand, and the ability of a model to reproduce surface wind and precipitation anomalies on the other. Particularly the skill for surface wind seems largely unaffected by the mean state SST. For precipitation, there is some indication that cool SST biases reduce the signal-to-noise ratio and skill. This relation, however, can also work in the opposite direction, i.e. skill increases when the mean SSTs are positively biased. To summarize this, our results indicate that reducing the amplitude of SST biases does not necessarily lead to increased skill.

That SST biases affect precipitation more than surface wind can be explained by the non-linearity of precipitation. Changes in the SST distribution have a strong influence on whether a region permits or does not permit deep convection. This was evident in the Pacific bias experiment, where local cold biases and off-equatorial warm biases conspired to effectively suppress the precipitation response to warm SST anomalies in eastern equatorial Pacific. Conversely, the warm SST bias in the southeast Atlantic produced an environment that was unrealistically conducive to convection, leading precipitation to respond to SST anomalies where it would not in nature.

Our sensitivity tests assess the impact of mean state SST biases only and thus assume that variability patterns remain unaffected. This will generally not be the case for coupled seasonal predictions because mean state wind biases will change, among others, the simulated temperature stratification of the oceans and therefore the areas of strong air-sea coupling. Thus SST variability patterns and their timing may change significantly in coupled prediction experiments and, for the case of free running coupled simulations, such changes are well documented (e.g. Richter et al. 2014a for the tropical Atlantic, and Bel-

643 lenger et al. 2013 for the tropical Pacific). Therefore, the impact of model biases on cou-
644 pled prediction runs cannot be addressed here.

645 We stress that our results do not suggest that reducing surface wind and precipitation
646 biases is futile. Rather we have shown that, in the narrow context of AMIP-like experi-
647 ments, one cannot necessarily expect increased skill from improving mean state biases.

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818

Captions

Table 1 AMIP models used in this study. The "symbol" column shows the symbol used in the multi-model scatter plots. The "ensemble" column shows which models were used for the ensemble mean. The SINTEX-F model (first row) is not part of AMIP but was run in an AMIP-like configuration.

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Fig. 2 AMIP multi-model scatter plots of quantities calculated from JJA mean precipitation in the Niño 3.4 region. (a) Absolute difference of predicted and observed standard deviation versus root mean square error (RMSE). (b) Absolute difference of predicted and observed mean versus RMSE. Each model is marked by a letter, with "a" in the origin denoting observations. The model names can be looked up in Table 1. All quantities are calculated for the period 1979-2008.

Fig. 3 ACC (shading) and bias (contour lines; interval 0.5) of the ensemble average of 11 AMIP models for (a) precipitation (mm/day), and (b) surface zonal wind (m/s). The reference data are GPCP for precipitation and ERA-Interim for surface zonal wind. Dashed lines indicate negative values. The zero contour line has been omitted. The ACC is calculated for the entire time series (1979-2008; no seasonal stratification).

Fig. 4 AMIP multi-model scatter plot of mean precipitation versus its ACC for several regions and seasons: (a) equatorial Atlantic (50°W-10°E, 5°S-5°N) in MAM, (b) Niño 3.4 (170-120°W, 5°S-5°N) in JJA, (c) equatorial Indian Ocean (50-95°E, 5°S-5°N) in SON, (d) Sahel (land points in 20°W-40°E, 5-15°N) in JJA, (e) South American monsoon region (land points in 90-30°W, 25-5°S) in JJA, and (f) Indian monsoon region (land points in 65-95°E, 5-25°N) in JJA. Each letter corresponds to one model, with "a" denoting observations.

Fig. 5 AMIP multi-model scatter plot of surface zonal wind ACC and mean for the following regions and seasons: (a) western equatorial Atlantic (40-20°W, 2°S-2°N) in MAM, (b) Niño 4 (160°E-150°W, 5°S-5°N) in MAM, and (c) equatorial Indian Ocean (50-95°E, 5°S-5°N). Each letter corresponds to one model, with "a" denoting observations.

Fig. 6 Climatological annual mean of SST (shading; °C) and precipitation (contour lines; interval 3 mm/day) for an 11-member model ensemble in three experiments: (a) AMIP, (b) amip4K, and (c) amipFuture.

Fig. 7 Skill metrics in the equatorial Pacific for three AMIP-style experiments (amip, amip4K, and amipFuture), stratified by month, for the following quantities, and regions: (a) ACC of Niño 4 surface zonal winds, (b) ACC of Niño 3.4 precipitation, (c) RMSE of Niño 4 surface zonal winds, and (d) RMSE of Niño 3.4 precipitation. The reference data is ERA-Interim for winds and GPCP for precipitation. The dots indicate values that are significantly different from experiment AMIP at the 95% confidence level based on a Fisher's z transformation for ACC and an F-test for RMSE.

Fig. 8 As in Fig. 7, but for WEA surface zonal winds and equatorial Atlantic precipitation (50°W-10°E, 5°S-5°N).

Fig. 9 Climatological annual mean of SST (shading; °C), precipitation (contour lines; contour interval 2 mm/day) and surface winds (vectors; reference 5 m/s) in observations and the three AMIP-style experiments conducted with SINTEX-F. (a) Total fields for OISST (SST), GPCP (precipitation) and ERA-Interim (surface winds), (b) biases in CTRL, (c) biases in Atl_bias, and (d) biases in Pac_bias. The biases in panels b-d are with reference to the observations in panel a. The reference period is 1982-2014.

Fig. 10 As in Fig. 7 but for the following SINTEX-F experiments: CTRL (green line), Atl_bias (blue line), and Pac_bias (orange line). Skill scores are calculated from the 9-ensemble mean of each experiment for the period 1982-2014.

Fig. 11 (a) ACC (shading) and climatological mean (contours; interval 3 mm/day) of MAM precipitation in CTRL. (b) The difference between Pac_bias and CTRL for ACC (shading) and climatological mean precipitation (contours; interval 2 mm/day; negative contours dashed). In panel b, values significant at the 95% level are stippled.

Fig. 12 MAM total precipitation (mm/day) averaged over the eastern equatorial Pacific (140-105°W, 5°S-5°N) scattered against (a) GPCP observations averaged in the same way, and (b) underlying SST (°C) averaged in the same way. Green indicates observations, blue CTRL, and orange Pac_bias. Regression lines are calculated for individual data sets and plotted in the corresponding colors. The correlation coefficient (r) and slope (m) are shown in the upper left.

Fig. 13 Difference between Pac_bias and CTRL. The upper panel shows a latitude-pressure section of geopotential height (shading; m), and meridional and vertical velocity (arrows; units: m/s for meridional velocity and hPa/hr (multiplied by -10) for pressure velocity; upward arrows indicate rising motion and vice versa), averaged over the eastern Pacific (140-105°W). The lower panel shows the SST difference averaged over the same longitude range.

Fig. 14 As in Fig. 10 but for the WEA (panels a and c) and EQATL (panels b and d) indices.

Fig. 15 (a) ACC (shading) and climatological mean (contours; interval 3 mm/day) of MAM precipitation in CTRL. (b) The difference between Atl_bias and CTRL for ACC (shading) and climatological mean precipitation (contours; interval 2 mm/day; negative contours dashed). (c) and (d) As in (a) and (b) but for surface zonal wind. In (b) and (d), values significant at the 95% level are stippled. The precipitation contour lines are repeated in (c) and (d) to facilitate assessing their collocation with the ACC of surface zonal wind.

Fig. 16 SST (shading; ºC) and precipitation anomalies (contours; mm/day) in July, composited on Atlantic Niño years (1984, 1988, 1991, 1995, 1996, 1999, 2008) for (a) GPCP observations, (b) CTRL, and (c) Atl_bias. The precipitation contour interval is 0.5 mm/day in (a), and 1 mm/day in (b) and (c). The zero-contour line has been omitted.

Fig. 17 April-May-June (AMJ) difference of Atl_bias and CTRL in terms of Signal-to-noise-ratio (SNR; shading), and SST (contours; ºC). SNR is estimated as the ensemble mean variance divided by the inter-ensemble variance. The SST difference between the two experiments is essentially identical to the bias in Atl_bias because SSTs in CTRL are strongly restored toward observations.

A. Tables

model	horizontal grid	# vertical levels	symbol	ensemble
SINTEX-F	T106 (1.1 º)	19	b	
ACCESS1-0	1.875º x 1.25º	38	c	
ACCESS1-3	1.875º x 1.25º	38	d	
bcc-csm1-1	T42 (2.8º)	26	e	yes
bcc-csm1-1-m	T42 (2.8º)	26	f	
BNU-ESM	T42 (2.8º)	26	g	
CanAM4	T63 (1.8º)	35	h	yes
CCSM4	1.25º x 0.9º	26	i	yes
CESM1-CAM5	1.25º x 0.9º	26	j	
CMCC-CM	T159 (0.75º)	31	k	
CNRM-CM5	T127 (1.5º)	31	l	yes
CSIRO-Mk3-6-0	T63 (1.9º)	18	m	
EC-EARTH	T159 (1.25º)	62	n	
FGOALS-g2	2.8125º x 2.8125º	26	o	
FGOALS-s2	R42 (2.8º x 1.7º)	26	p	
GFDL-CM3	200 km (2º)	48	q	
GFDL-HIRAM-	C180 (0.5º)	32	r	
GFDL-HIRAM-	C360 (0.25º)	32	s	
GISS-E2-R	2º x 2.5º	29	t	
HadGEM2-A	1.875º x 1.25º	60	u	yes
inmcm4	2º x 1.5º	21	v	
IPSL-CM5A-LR	3.75º x 1.9º	39	w	yes
IPSL-CM5A-	1.25° x 2.5°	39	x	
IPSL-CM5B-LR	3.75º x 1.9º	39	y	yes
MIROC5	T85 (1.4º)	40	z	yes
MIROC-ESM	T42 (2.8º)	80	0	
MPI-ESM-LR	T63 (1.8º)	47	1	yes
MPI-ESM-MR	T63 (1.8º)	95	2	yes
MRI-AGCM3-	T319 (60km)	64	3	
MRI-AGCM3-	T959 (20km)	64	4	
MRI-CGCM3	T159 (1.125º)	35	5	yes
NorESM1-M	2.5º x 2.9º	26	6	

Table 1 AMIP models used in this study. The "symbol" column shows the symbol used in the multi-model scatter plots. The "ensemble" column shows which models were used for the ensemble mean. The SINTEX-F model (first row) is not part of AMIP but was run in an AMIP-like configuration.

B. Figures

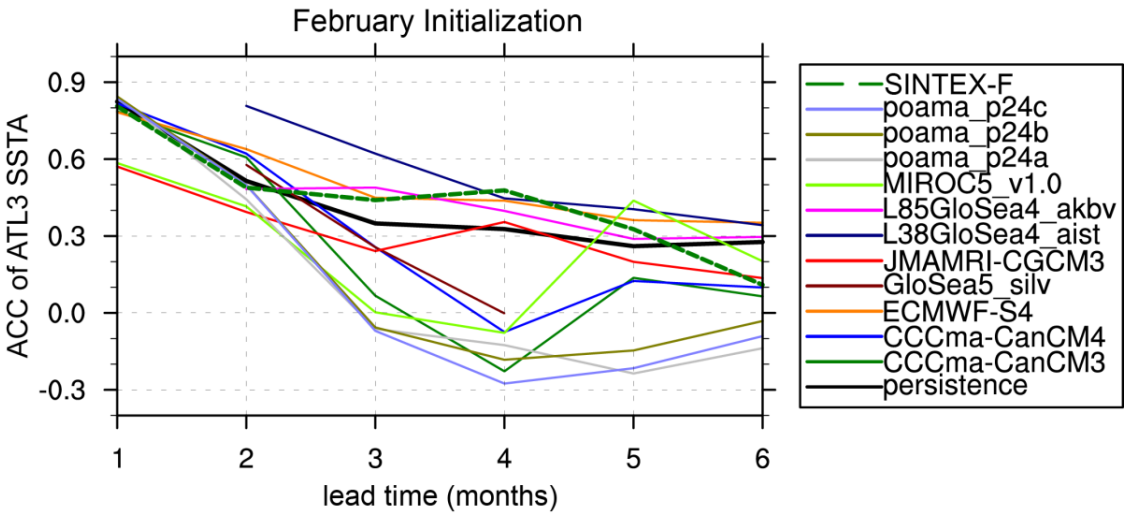
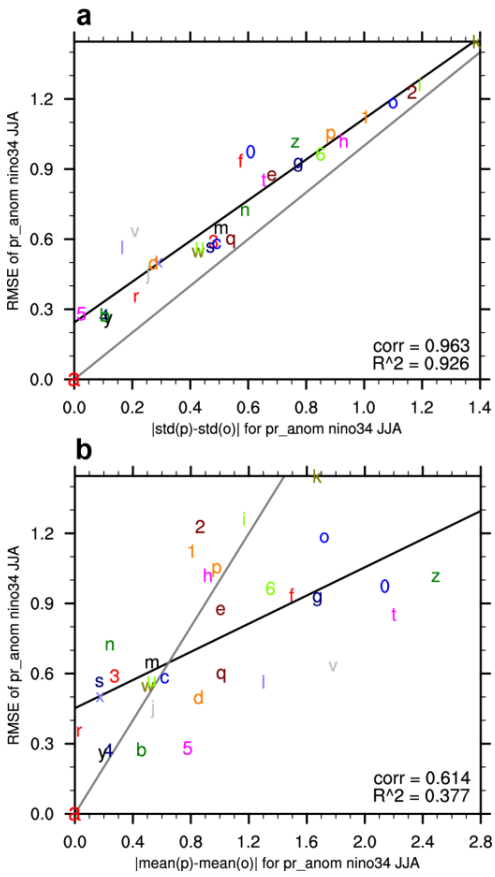
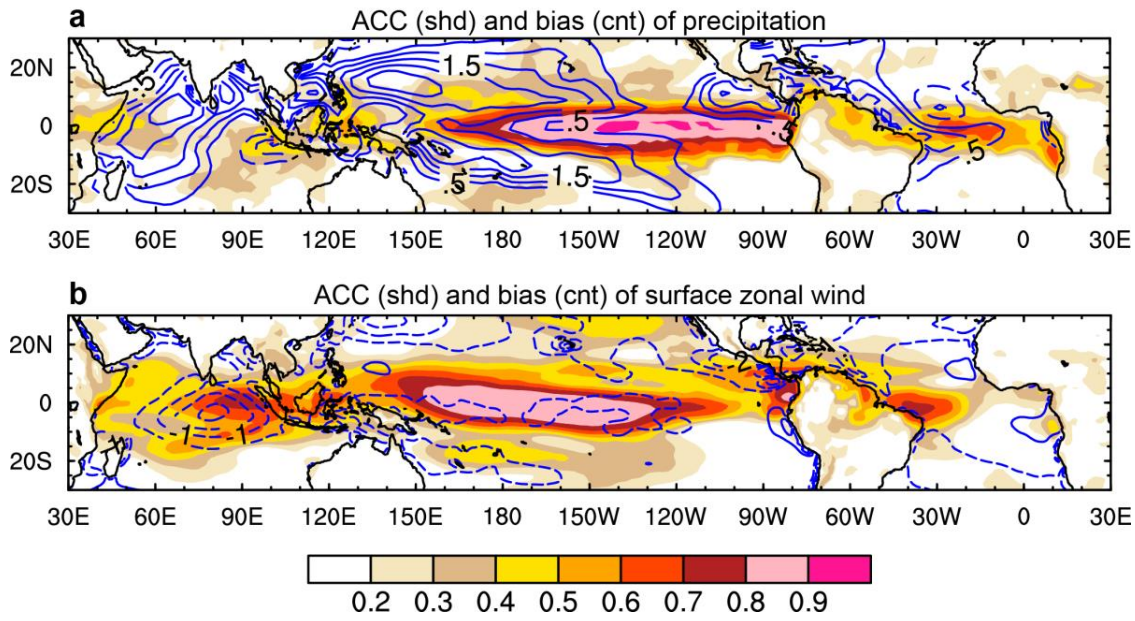


Fig. 1 Anomaly correlation coefficient (ACC) for SST in the ATL3 region as function of lead time for seasonal predictions from the CHFP model intercomparison (solid lines) and the SINTEX-F prediction system (dashed green line). The skill of the persistence reference prediction is indicated by the black solid line. All predictions were initialized on 1 February so that lead time 1 is centered on the middle of February, 2 on the middle of March etc. For some models, not all lead times were available.



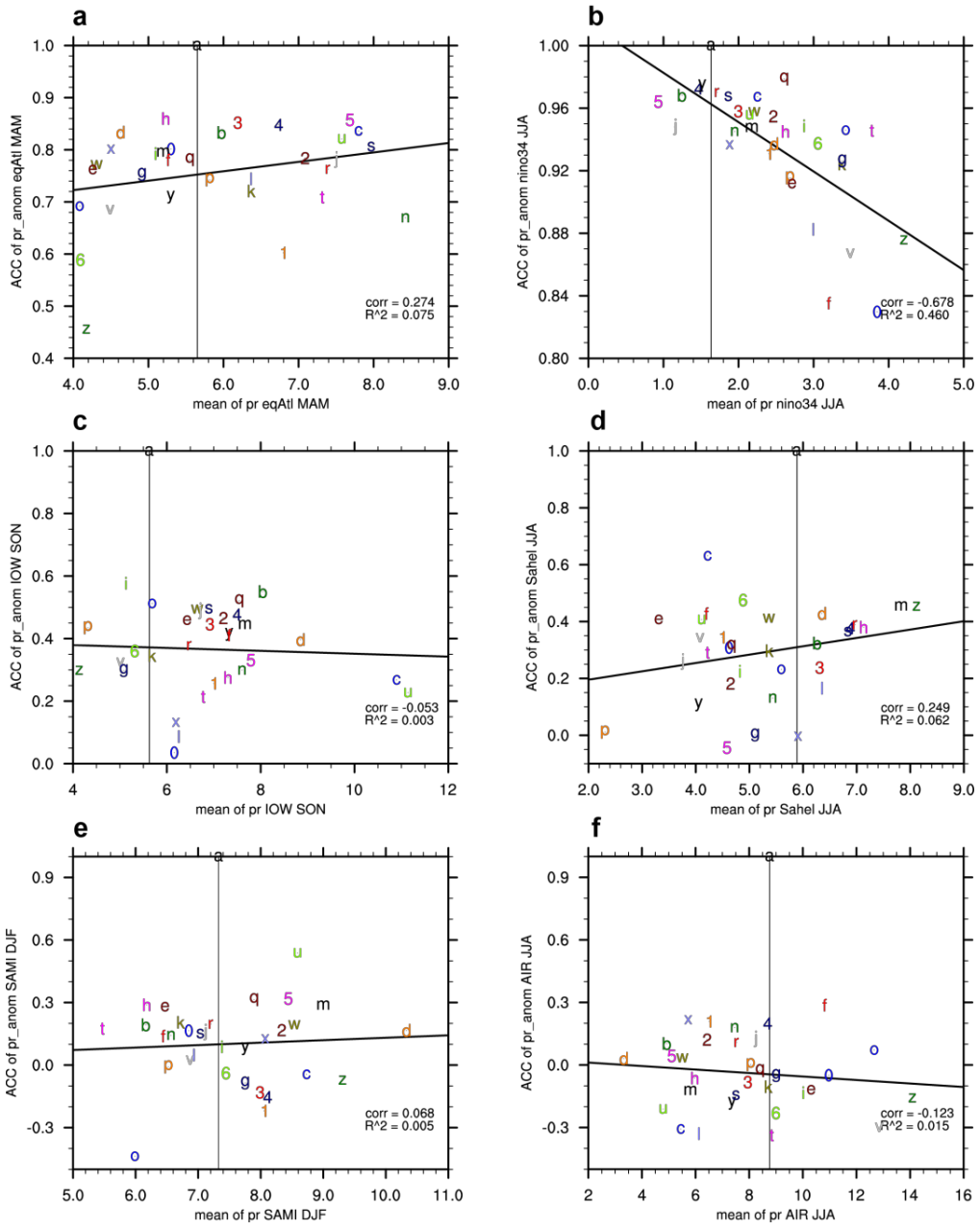
939

940 **Fig. 2** AMIP multi-model scatter plots of quantities calculated from JJA mean precipitation in the
941 Niño 3.4 region. (a) Absolute difference of predicted and observed standard deviation versus root mean
942 square error (RMSE). (b) Absolute difference of predicted and observed mean versus RMSE. Each model
943 is marked by a letter, with "a" in the origin denoting observations. The model names can be looked up in
944 Table 1. All quantities are calculated for the period 1979-2008.



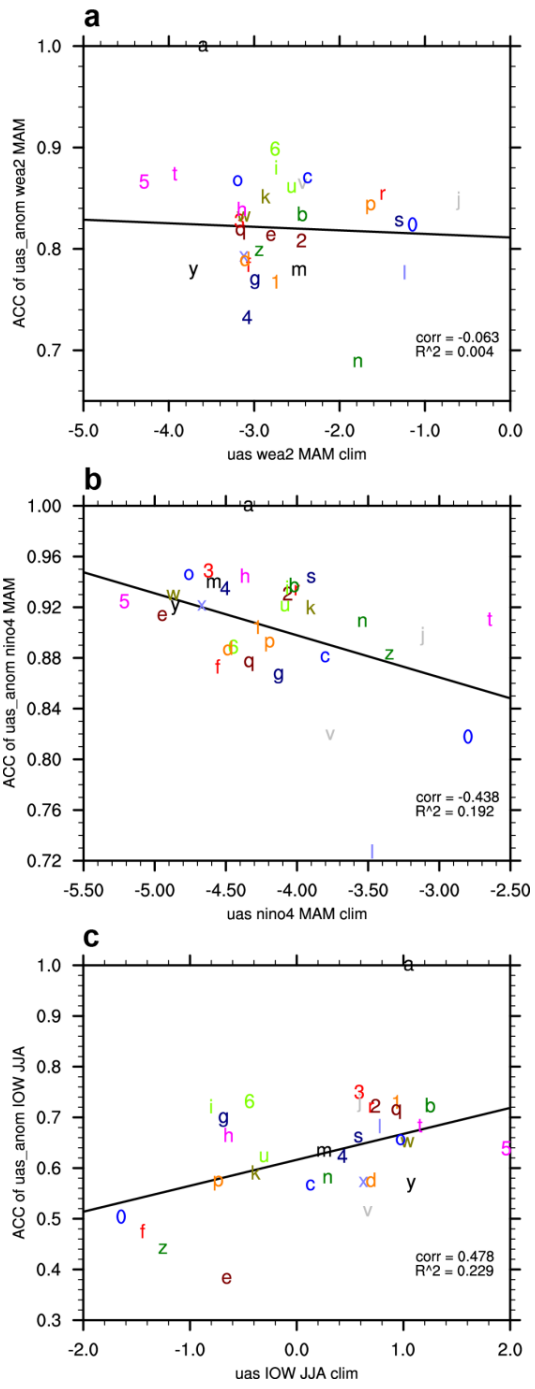
945

946 **Fig. 3** ACC (shading) and bias (contour lines; interval 0.5) of the ensemble average of 11 AMIP
947 models for (a) precipitation (mm/day), and (b) surface zonal wind (m/s). The reference data are GPCP for
948 precipitation and ERA-Interim for surface zonal wind. Dashed lines indicate negative values. The zero con-
949 tour line has been omitted. The ACC is calculated for the entire time series (1979-2008; no seasonal strati-
950 fication).



951

952 **Fig. 4** AMIP multi-model scatter plot of mean precipitation versus its ACC for several regions and
953 seasons: (a) equatorial Atlantic (50°W-10°E, 5°S-5°N) in MAM, (b) Niño 3.4 (170-120°W, 5°S-5°N) in
954 JJA, (c) equatorial Indian Ocean (50-95°E, 5°S-5°N) in SON, (d) Sahel (land points in 20°W-40°E, 5-
955 15°N) in JJA, (e) South American monsoon region (land points in 90-30°W, 25-5°S) in JJA, and (f) Indian
956 monsoon region (land points in 65-95°E, 5-25°N) in JJA. Each letter corresponds to one model, with "a"
957 denoting observations.



958

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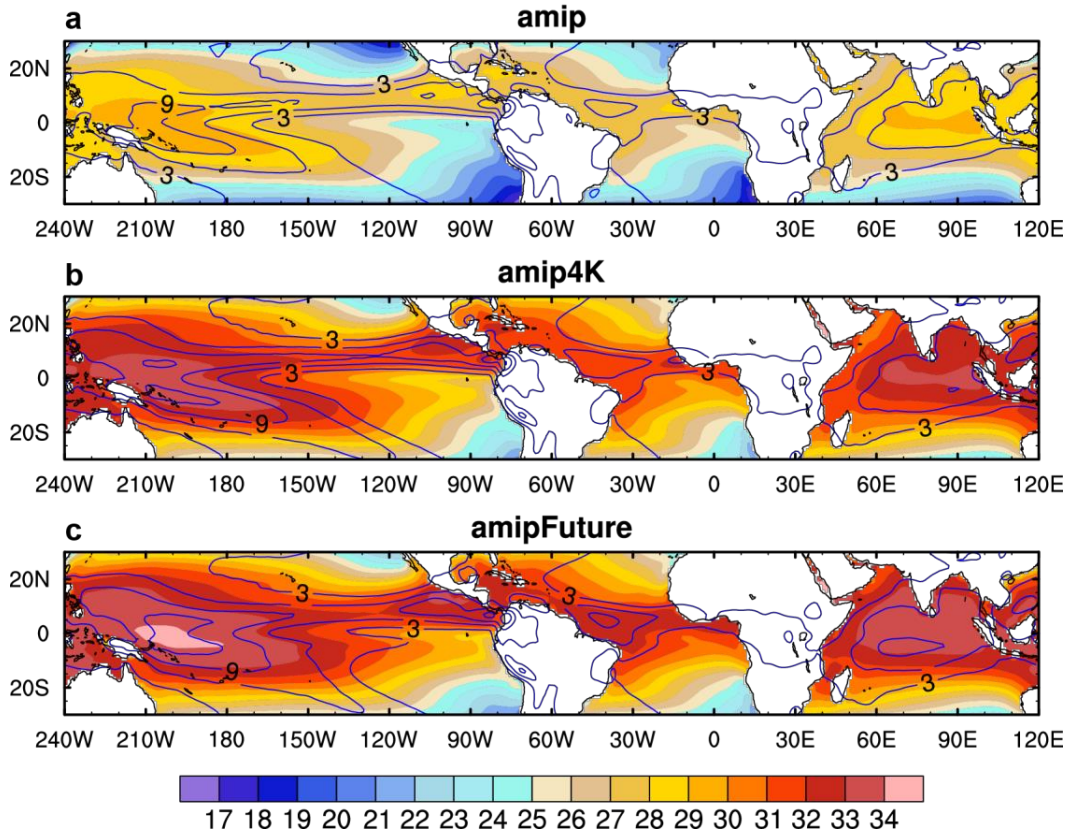
960 and seasons: (a) western equatorial Atlantic (40-20°W, 2°S-2°N) in MAM, (b) Niño 4 (160°E-150°W, 5°S-
961 5°N) in MAM, and (c) equatorial Indian Ocean (50-95°E, 5°S-5°N). Each letter corresponds to one model,
962 with "a" denoting observations.



963

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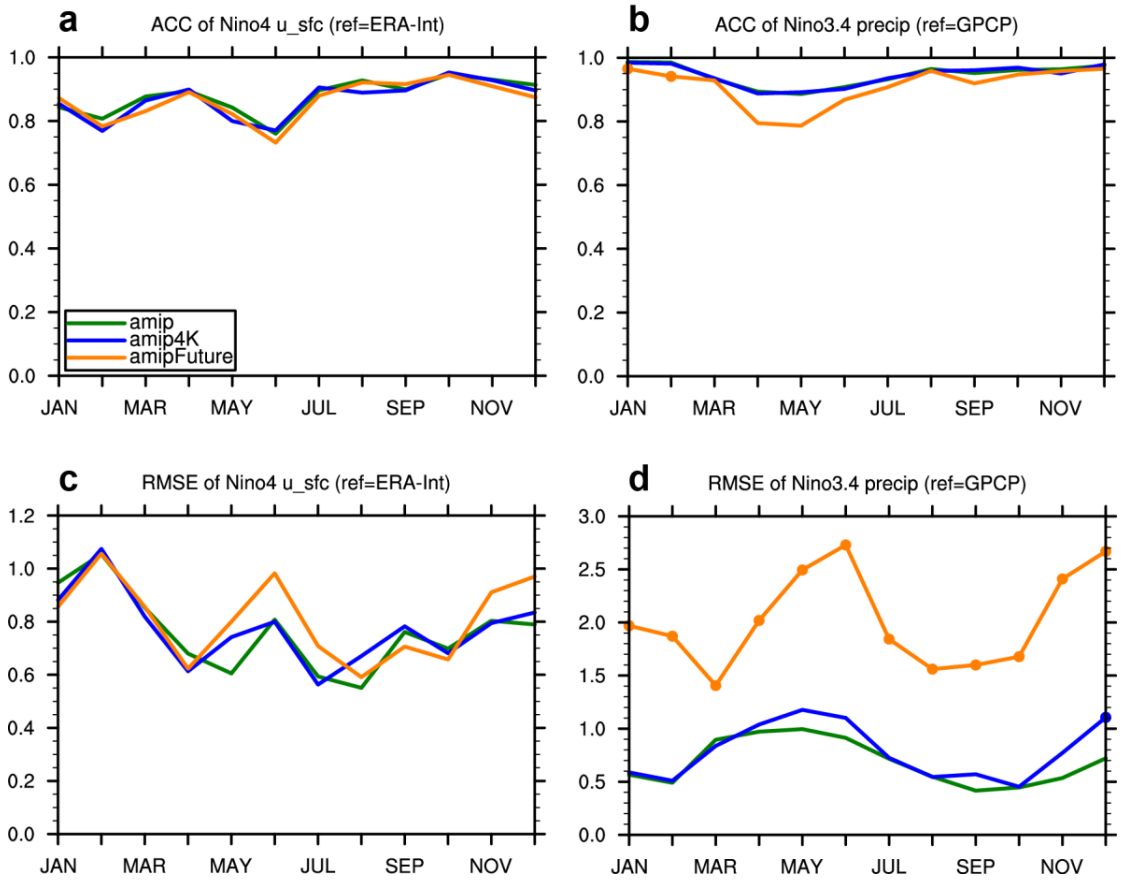
966 Future.



967

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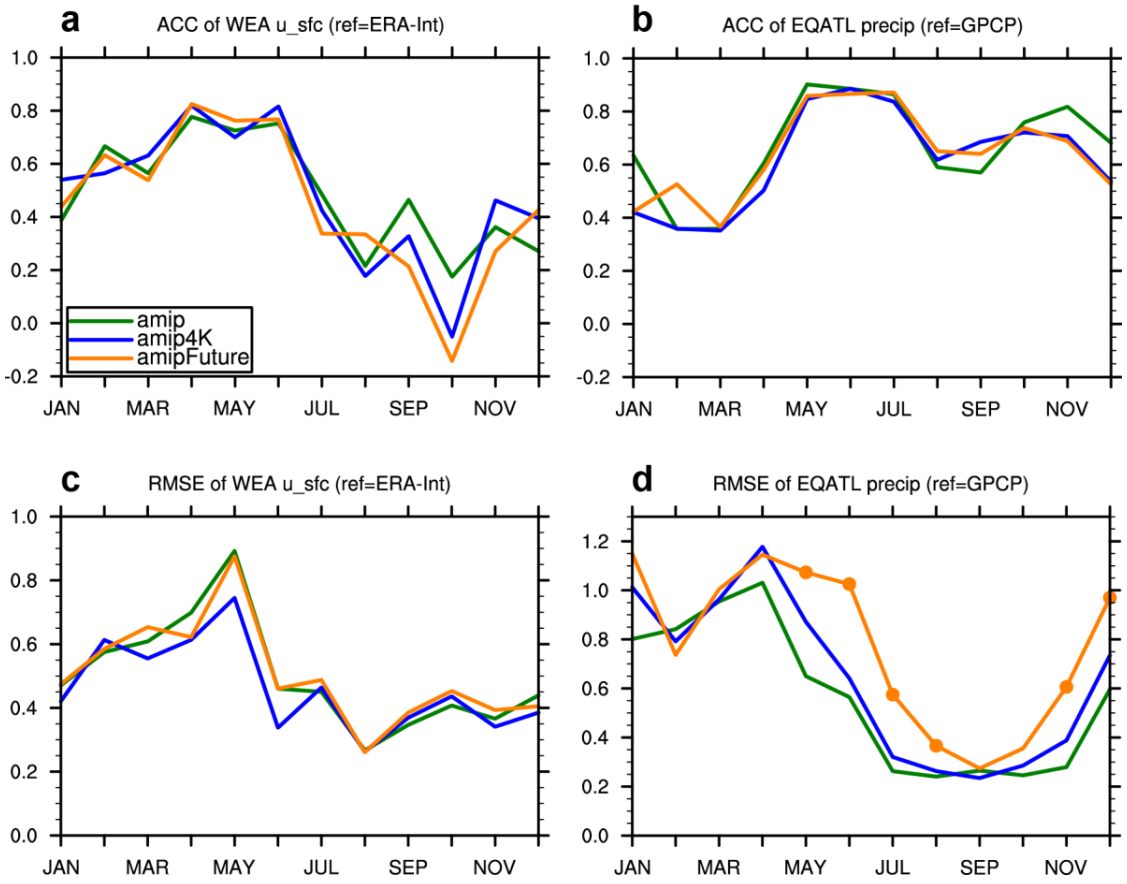
972 cate values that are significantly different from experiment AMIP at the 95% confidence level based on a
973 Fisher's z transformation for ACC and an F-test for RMSE.



974

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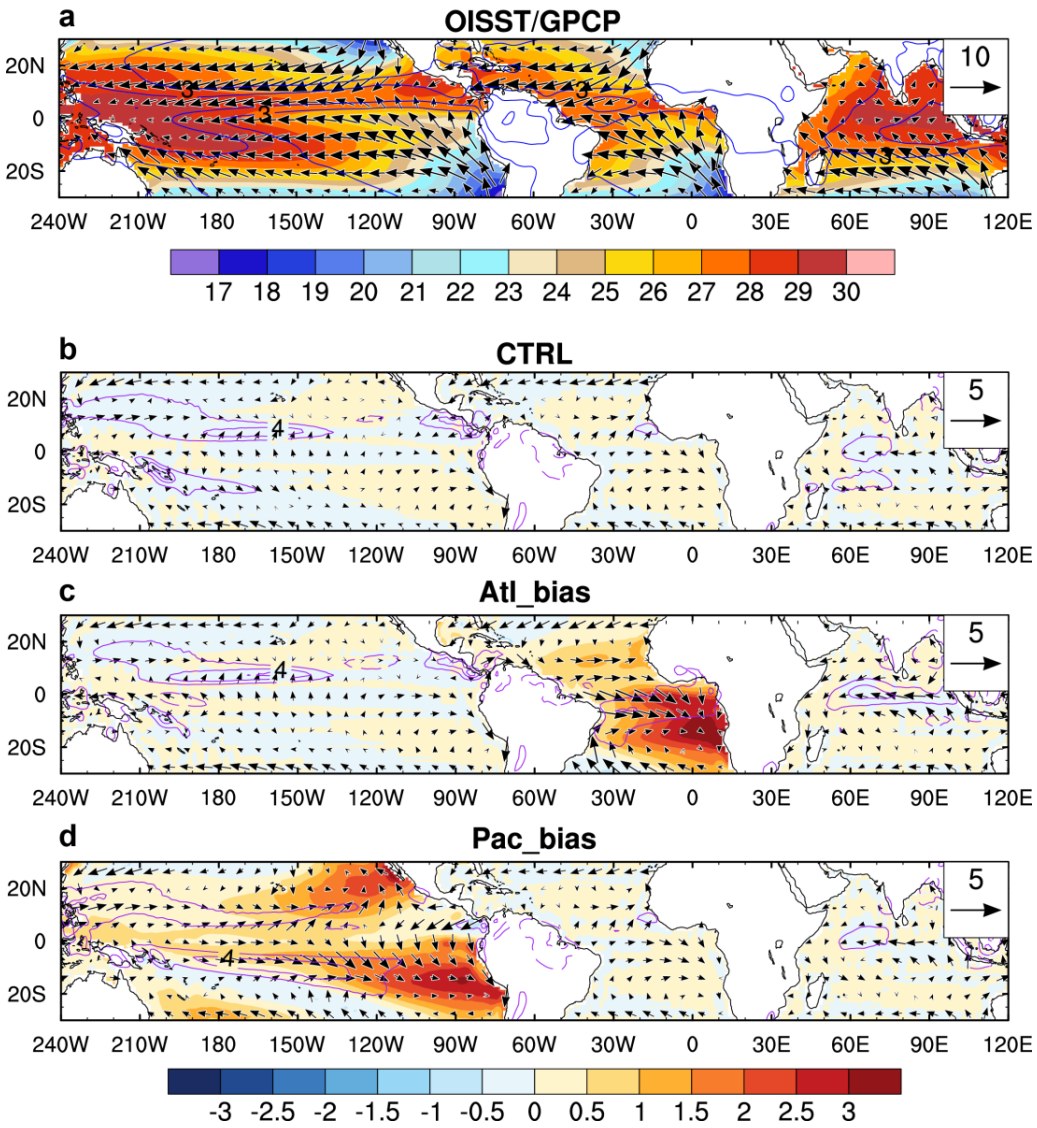
976 10°E, 5°S-5°N).



977

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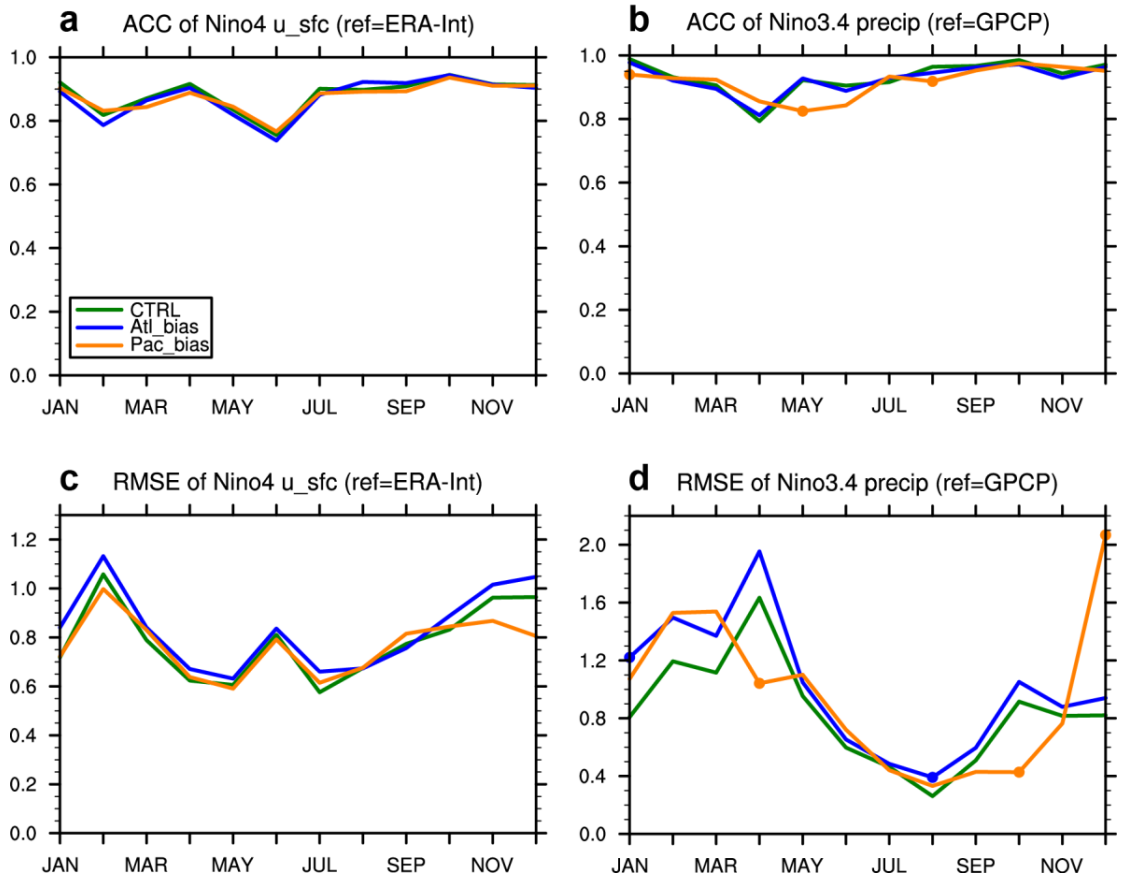
981 Interim (surface winds), (b) biases in CTRL, (c) biases in Atl_bias, and (d) biases in Pac_bias. The biases
982 in panels b-d are with reference to the observations in panel a. The reference period is 1982-2014.



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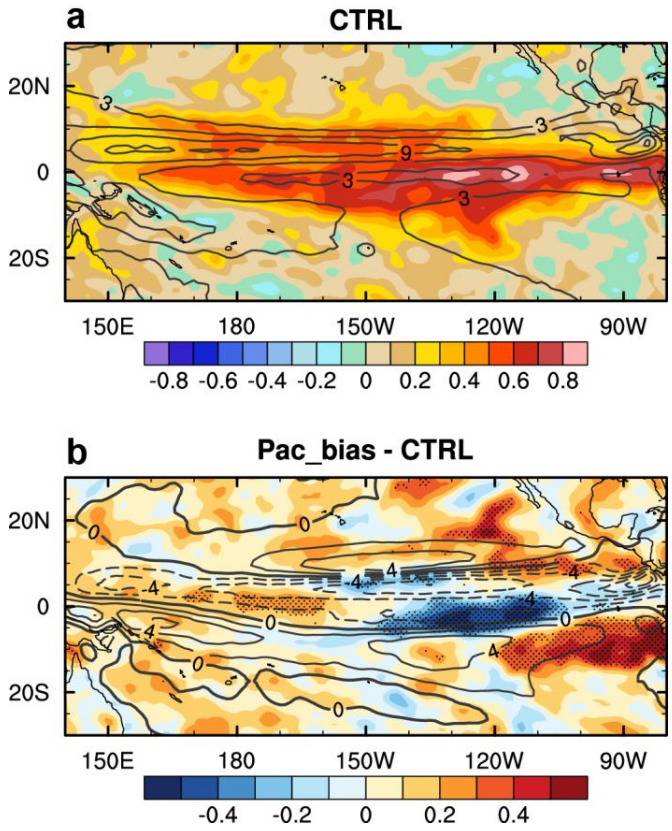
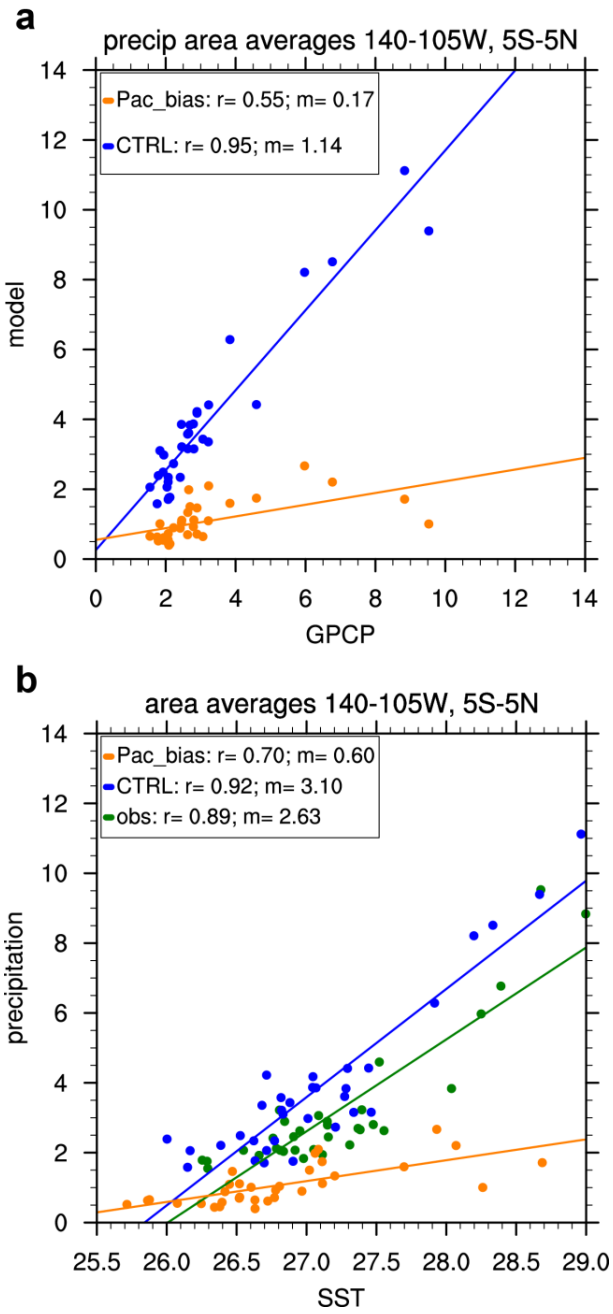


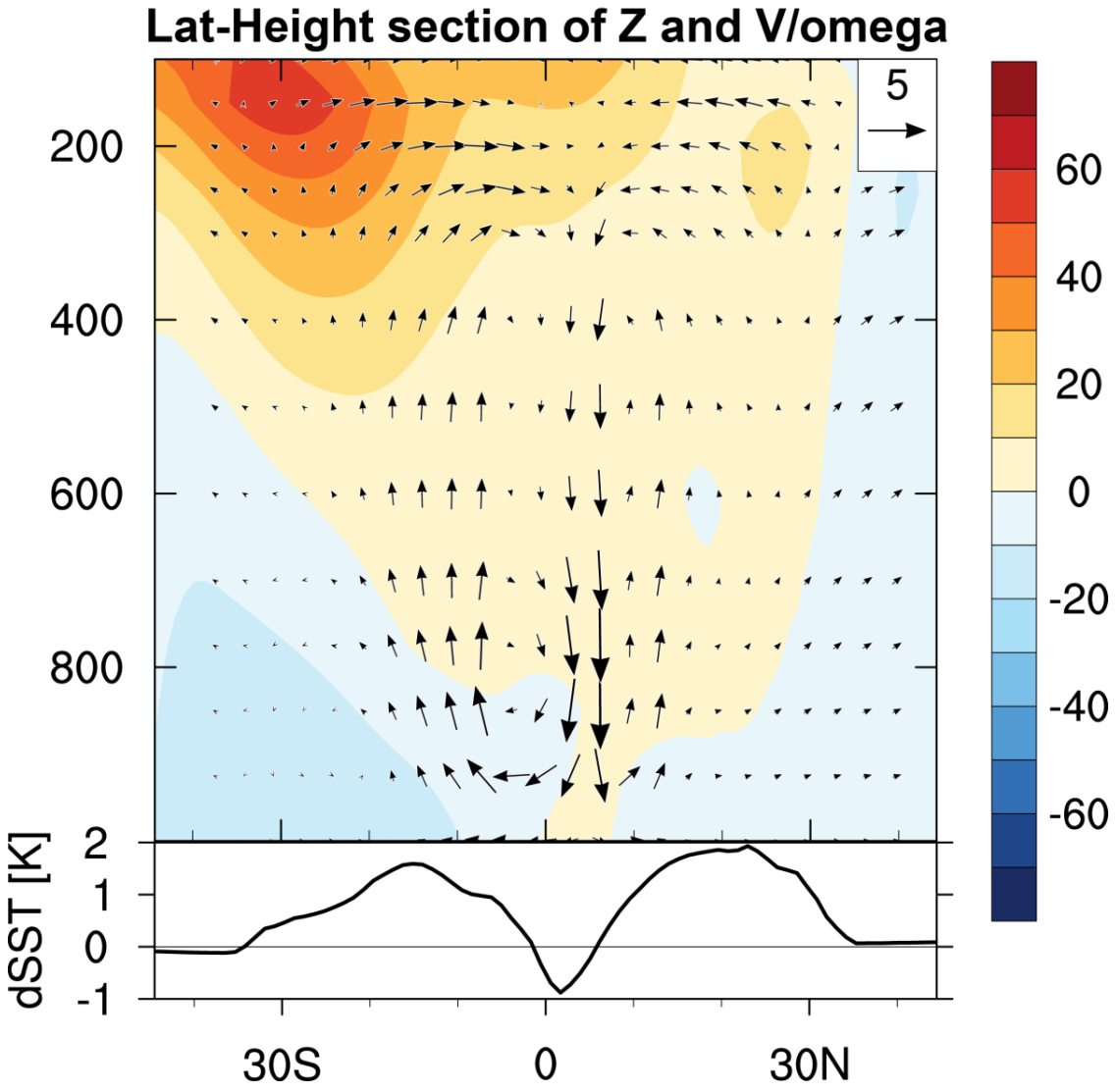
987

988 **Fig. 11** (a) ACC (shading) and climatological mean (contours; interval 3 mm/day) of MAM precipi-
989 tation in CTRL. (b) The difference between Pac_bias and CTRL for ACC (shading) and climatological
990 mean precipitation (contours; interval 2 mm/day; negative contours dashed). In panel b, values significant
991 at the 95% level are stippled.



992

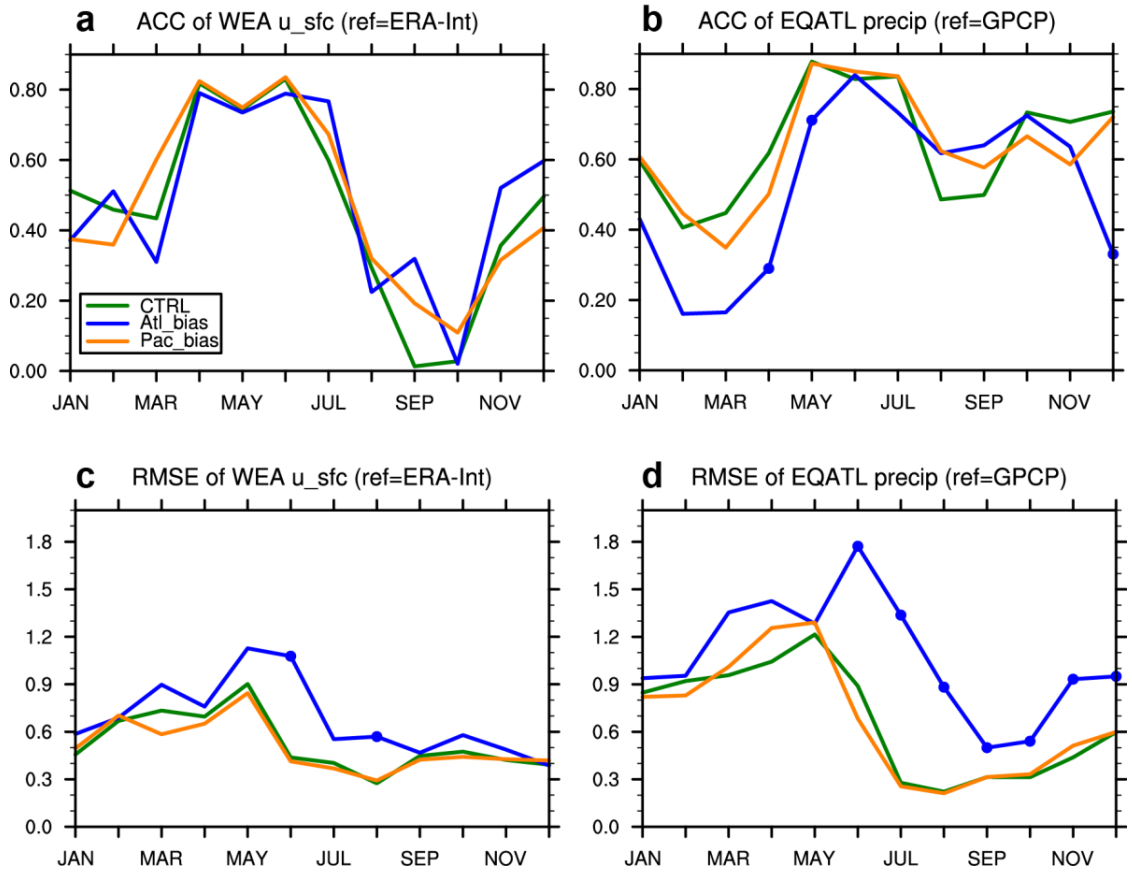
993 **Fig. 12** MAM total precipitation (mm/day) averaged over the eastern equatorial Pacific (140-105°W,
994 5°S-5°N) scattered against (a) GPCP observations averaged in the same way, and (b) underlying SST (°C)
995 averaged in the same way. Green indicates observations, blue CTRL, and orange Pac_bias. Regression
996 lines are calculated for individual data sets and plotted in the corresponding colors. The correlation coeffi-
997 cient (r) and slope (m) are shown in the upper left.



998

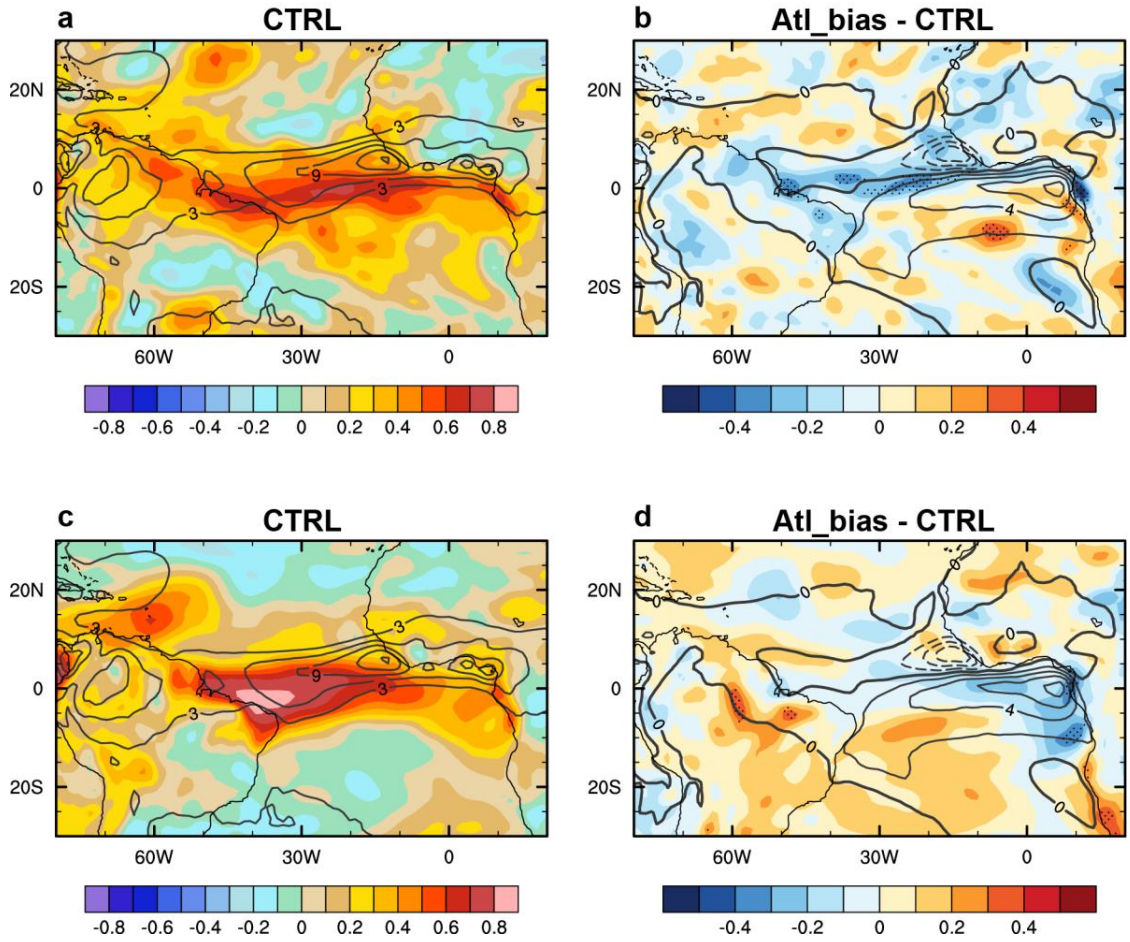
999 **Fig. 13** Difference between Pac_bias and CTRL. The upper panel shows a latitude-pressure section
1000 of geopotential height (shading; m), and meridional and vertical velocity (arrows; units: m/s for meridional
1001 velocity and hPa/hr (multiplied by -10) for pressure velocity; upward arrows indicate rising motion and
1002 vice versa), averaged over the eastern Pacific (140-105°W). The lower panel shows the SST difference av-
1003 eraged over the same longitude range.

1004



1005

1006 **Fig. 14** As in Fig. 10 but for the WEA (panels a and c) and EQATL (panels b and d) indices.



1007

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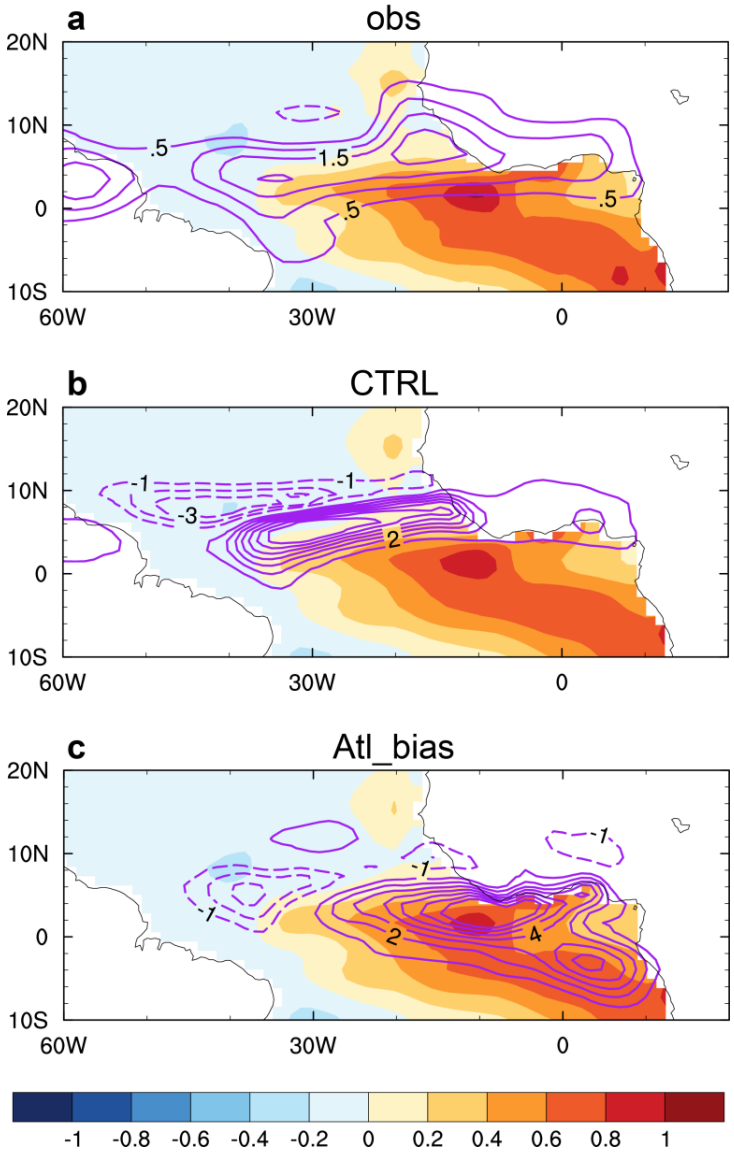
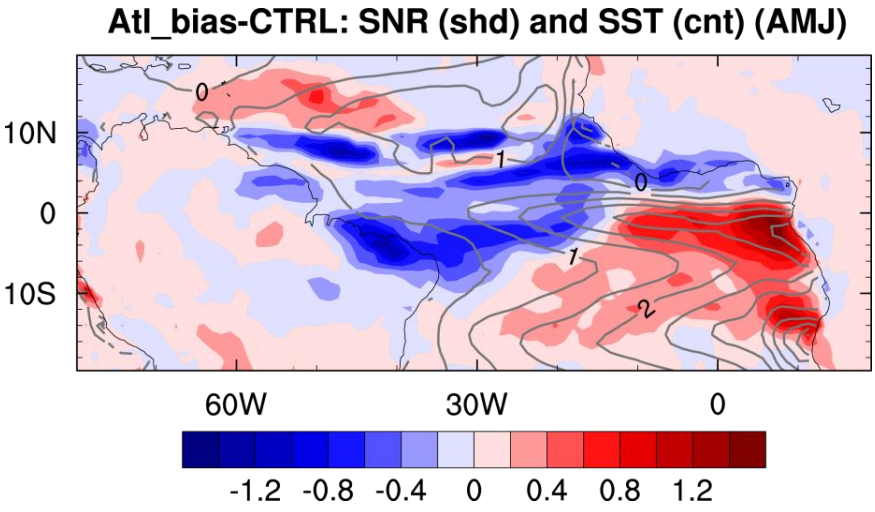
1012 contour lines are repeated in (c) and (d) to facilitate assessing their collocation with the ACC of surface
1013 zonal wind.



1014

1015 **Fig. 16** SST (shading; ºC) and precipitation anomalies (contours; mm/day) in July, composited on
1016 Atlantic Niño years (1984, 1988, 1991, 1995, 1996, 1999, 2008) for (a) GPCP observations, (b) CTRL, and
1017 (c) Atl_bias. The precipitation contour interval is 0.5 mm/day in (a), and 1 mm/day in (b) and (c). The zero-
1018 contour line has been omitted.



1019

1020 **Fig. 17** April-May-June (AMJ) difference of Atl_bias and CTRL in terms of Signal-to-noise-ratio
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1022 inter-ensemble variance. The SST difference between the two experiments is essentially identical to the
1023 bias in Atl_bias because SSTs in CTRL are strongly restored toward observations.