AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER
10.1002/2015GL064799

Key Points:
- SST bias corrupts the simulation of equatorial Atlantic SST variability
- Fifty percent of Atlantic Nino is captured by a flux-corrected model driven by real winds
- Only a flux-corrected model captures the observed role of ocean dynamics

Supporting Information:
- Text S1, Figure S1, and Table S1

Correspondence to:
H. Ding,
hding@geomar.de

Citation:
Ding, H., R. J. Greatbatch, M. Latif, and W. Park (2015), The impact of sea surface temperature bias on equatorial Atlantic interannual variability in partially coupled model experiments, *Geophys. Res. Lett.*, *42*, 5540–5546, doi:10.1002/2015GL064799.

Received 2 JUN 2015
Accepted 16 JUN 2015
Accepted article online 20 JUN 2015
Published online 14 JUL 2015

The impact of sea surface temperature bias on equatorial Atlantic interannual variability in partially coupled model experiments

Hui Ding[1], Richard J. Greatbatch[1,2], Mojib Latif[1,2], and Wonsun Park[1]

[1]GEOMAR Helmholtz Centre for Ocean Research Kiel, Kiel, Germany, [2]Faculty of Mathematics and Natural Sciences, University of Kiel, Kiel, Germany

Abstract We examine the impact of sea surface temperature (SST) bias on interannual variability during boreal summer over the equatorial Atlantic using two suites of partially coupled model (PCM) experiments with and without surface heat flux correction. In the experiments, surface wind stress anomalies are specified from observations while the thermodynamic coupling between the atmospheric and oceanic components is still active as in the fully coupled model. The results show that the PCM can capture around 50% of the observed variability associated with the Atlantic Niño from 1958 to 2013, but only when the bias is substantially reduced using heat flux correction, with no skill otherwise. We further show that ocean dynamics explain a large part of the SST variability in the eastern equatorial Atlantic in both observations (50–60%) and the PCM experiments (50–70%) with heat flux correction, implying that the seasonal predictability potential may be higher than currently thought.

1. Introduction

Equatorial Atlantic variability in boreal summer is dominated by the Atlantic zonal mode or Atlantic Niño, and corresponding sea surface temperature (SST) anomalies can exceed 1°C in the eastern equatorial Atlantic [*Xie and Carton*, 2004]. Fluctuations in equatorial Atlantic SST exert a significant impact on surrounding countries [*Chang et al.*, 2006] and were shown to affect SST variability in the southeastern tropical Atlantic [e.g., *Hu and Huang*, 2007] and El Niño–Southern Oscillation (ENSO) [e.g., *Rodríguez-Fonseca et al.*, 2009; *Ding et al.*, 2012; *Keenlyside et al.*, 2013]. Thus, it is of great socioeconomic interest to study equatorial Atlantic variability.

The importance of ocean dynamics for Atlantic Niño is still not as clear as for its counterpart in the tropical Pacific. Many studies have shown that Atlantic Niño arises from the Bjerknes positive feedback and delayed negative feedback, suggesting that ocean dynamics have a role to play [e.g., *Zebiak*, 1993; *Keenlyside and Latif*, 2007; *Ding et al.*, 2010; *Hu et al.*, 2013]. But other studies suggest that ocean dynamics may be less important [*Trzaska et al.*, 2007; *Wang and Chang*, 2008]. *Trzaska et al.* [2007] reported that the leading mode in the tropical Atlantic simulated by an atmospheric general circulation model coupled to a slab ocean model resembles the spatial pattern of Atlantic Niño in observations, despite the lack of ocean dynamics. *Wang and Chang* [2008] argue that atmospheric stochastic forcing plays a dominant role in defining the spatial patterns of tropical Atlantic variability, whereas the contribution of ocean dynamics is moderate.

Most state-of-the-art coupled general circulation models (GCMs) exhibit a large warm SST bias in the eastern tropical Atlantic [e.g., *Richter et al.*, 2014; *Wang et al.*, 2014]. The SST bias is typically on the order of several degrees Celsius so that many models simulate a reversed SST gradient along the equator. The bias has been attributed to a westerly wind bias [e.g., *Richter et al.*, 2014], excessive shortwave radiation at the surface [*Huang et al.*, 2007; *Hu et al.*, 2008], excessive southward migration of the Intertropical Convergence Zone [*Doi et al.*, 2012; *Richter et al.*, 2014], and lack of sufficient vertical atmospheric model resolution [*Harlaß et al.*, 2015]. The warm bias may deteriorate the simulation of equatorial Atlantic interannual SST variability in CGCMs [*Liu et al.*, 2013; *Richter et al.*, 2014; *Ding et al.*, 2015]. Nevertheless, several models are still able to capture some aspects of Atlantic Niño, including the amplitude, pattern, phase locking, and duration of events [e.g., *Richter et al.*, 2014].

In this study, we explore the potential to capture observed equatorial Atlantic SST variability in partially coupled model experiments in which SST is a fully prognostic variable. Our results show that the experiments can capture about 50% of observed Atlantic Niño events only when the mean state error in SST is greatly reduced

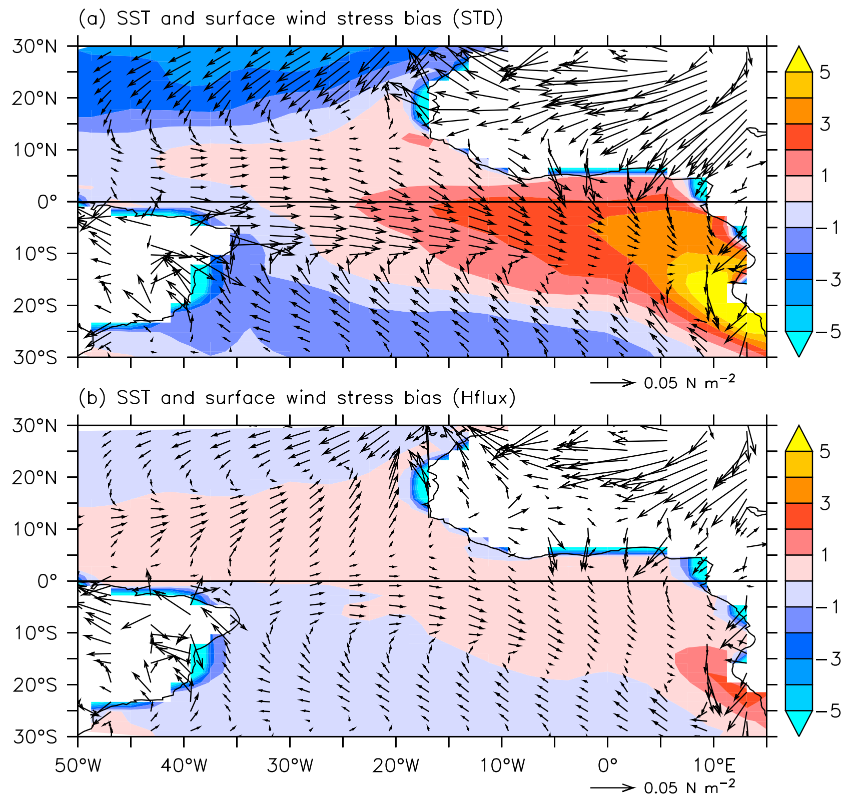

Figure 1. Sea surface temperature (shading) and surface wind stress (vectors) annual mean bias in (a) STD and (b) Hflux with respect to observations. Here observed reconstructed SST [*Rayner et al.*, 2003] and surface wind stress of ERA-Interim [*Dee et al.*, 2011] are employed. The units of SST and surface wind stress are °C and N m^{-2}, respectively.

using a surface heat flux correction. We further show that ocean dynamics explain a large part of Atlantic Niño in observations and the experiments in which heat flux correction is employed. In section 2, the model setup and the experiments are described. Sections 3 and 4 present the results and summary.

2. Model, Experiments, and Methodology

A fully coupled atmosphere/ocean/sea ice model, the Kiel Climate Model (KCM) [*Park et al.*, 2009], is employed. The atmosphere component uses T31 horizontal resolution (3.75° × 3.75°) with 19 vertical levels up to 10 hPa; the ocean resolution is 2° in latitude and longitude with an equatorial latitudinal refinement to 0.5° within 10° of the equator.

Two versions of the KCM are employed: (1) a standard version (STD) which suffers from a large tropical Atlantic annual mean bias (Figure 1a) similar to most state-of-the-art CGCMs [e.g., *Richter et al.*, 2014; *Wang et al.*, 2014] and (2) a heat flux-corrected version (Hflux) in which the annual mean SST bias is greatly reduced (Figure 1b). To derive the latter, the KCM (as in STD) is first integrated for 470 years with ocean model temperature in the first level (of depth 10 m) restored to observed monthly climatological SST globally with a relaxation time scale of 10 days. The last 70 years of the model run, when the integration reaches a state of equilibrium in the upper ocean, is employed to diagnose the monthly climatological heat flux associated with the restoring term. In Hflux, this diagnosed heat flux is added back to the KCM globally in the first model level as an external forcing and the integration runs for 80 years without significant trend in global mean SST. We note that the surface heat flux correction not only reduces the SST bias (Figure 1b) but also improves the upper ocean temperature and the surface wind stress fields (Figure 1b), which in turn enhances the thermocline tilt along the equator (Figure S1 in the supporting information). It is important to note that in Hflux, the correction to the heat flux is independent of the state of the model.

Our partial coupling strategy is that the ocean/sea ice component of the KCM is driven by the time series of observed monthly mean wind stress anomalies that are added globally to the respective wind stress monthly

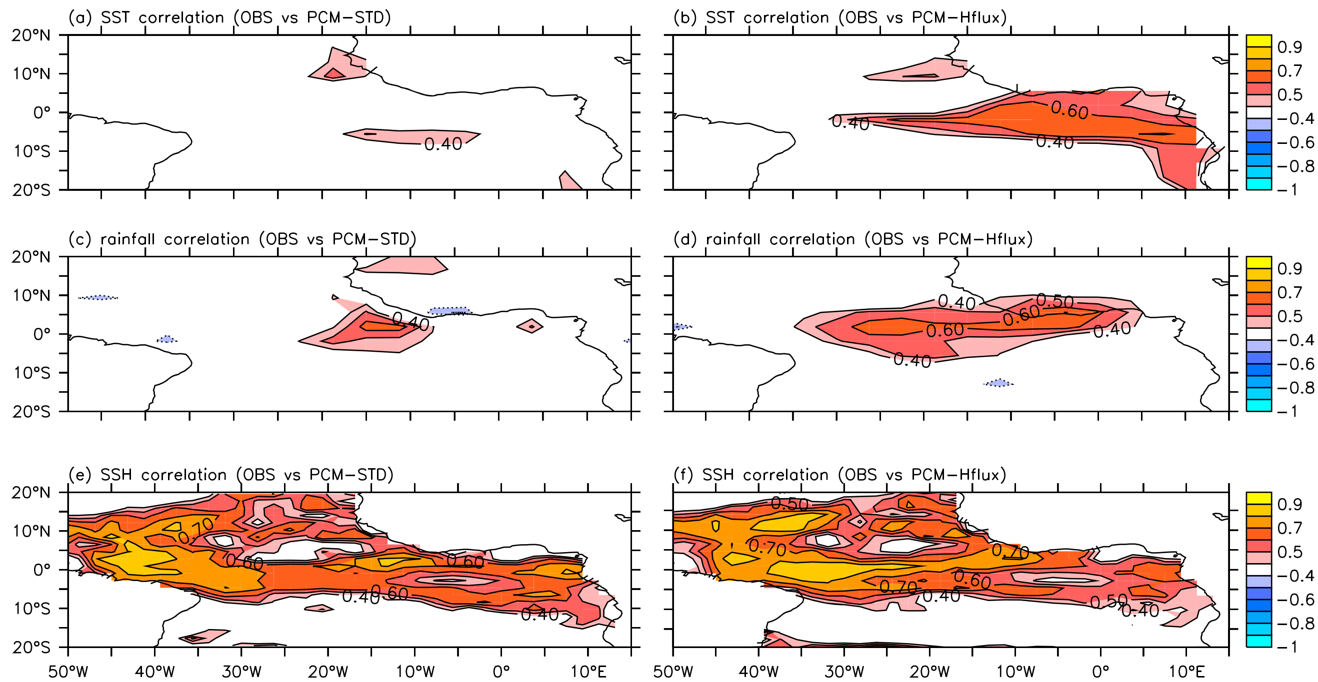

Figure 2. Pointwise correlation for seasonal mean (JJA) anomalies against observations in (a, b) SST from 1958 to 2013, (c, d) rainfall from 1979 to 2013, and (e, f) sea surface height from 1993 to 2013 using PCM-STD (Figures 2a, 2c, and 2e) and PCM-Hflux (Figures 2b, 2d, and 2f). In Figures 2a–2f, observations from HadISST [*Rayner et al.*, 2003], GPCP rainfall [*Adler et al.*, 2003], and satellite-observed SSH (http://www.aviso.oceanobs.com/) are employed, respectively.

climatology calculated from STD and Hflux while still maintaining the thermodynamic coupling between the atmosphere and ocean/sea ice components [see *Ding et al.*, 2013, 2014]. Note that no account is taken of the submonthly fluctuations of wind stress. Here we emphasize that SST is a fully prognostic variable and is not directly constrained by observations, which is a big advantage compared to ocean-only experiments in which some form of surface restoring is retained [*Zhang et al.*, 1993; *Greatbatch et al.*, 1995]. It is worth noting that the climatology of the partially coupled model in STD (Hflux) changes only a little with respect to fully coupled version of STD (Hflux). The reason is because observed wind stress anomalies are used for the partially coupled experiments and not the total observed wind stress.

Partially coupled model (PCM) experiments are carried out using both the STD and Hflux versions in order to explore the impact of the warm bias in the tropical Atlantic. In the experiments, wind stress anomalies calculated from the ERA-40 reanalysis [*Uppala et al.*, 2005] from 1958 to 2001 and the ERA-Interim reanalysis [*Dee et al.*, 2011] from 2002 to 2013 are used. We believe that there would be little change to our results if we employed wind stress from the ERA-Interim reanalysis in the period of 1979–2001 because the two wind stress products closely resemble each other in the tropical Atlantic during this period. An ensemble of six (seven) PCM runs using the STD (Hflux) model version is driven by the corresponding wind stress product, differing only in their initial conditions. In this study, the ensemble mean of the six (seven) model runs, denoted as PCM-STD (PCM-Hflux), is analyzed and shown in the figures unless stated otherwise. The small difference in ensemble size does not affect the results (see Table S1). Finally, it should be noted that in all model runs, the concentration of greenhouse gases is fixed at late twentieth century levels (348 ppm) and does not increase with time [*Park et al.*, 2009].

3. Results

The PCM experiments are assessed by calculating the correlation between model and observed seasonal mean SST anomalies during boreal summer (June-July-August, JJA) when Atlantic Niño variability peaks [*Xie and Carton*, 2004]. It is obvious that PCM-Hflux (Figure 2b) performs much better than PCM-STD (Figure 2a) at reproducing observed SST variability in the tropical Atlantic. PCM-STD shows skill only in a very small area, while PCM-Hflux clearly shows skill in a large area over the central and eastern tropical Atlantic (correlation as high as 0.6). Correspondingly, PCM-Hflux is also superior to PCM-STD at capturing observed Atlantic

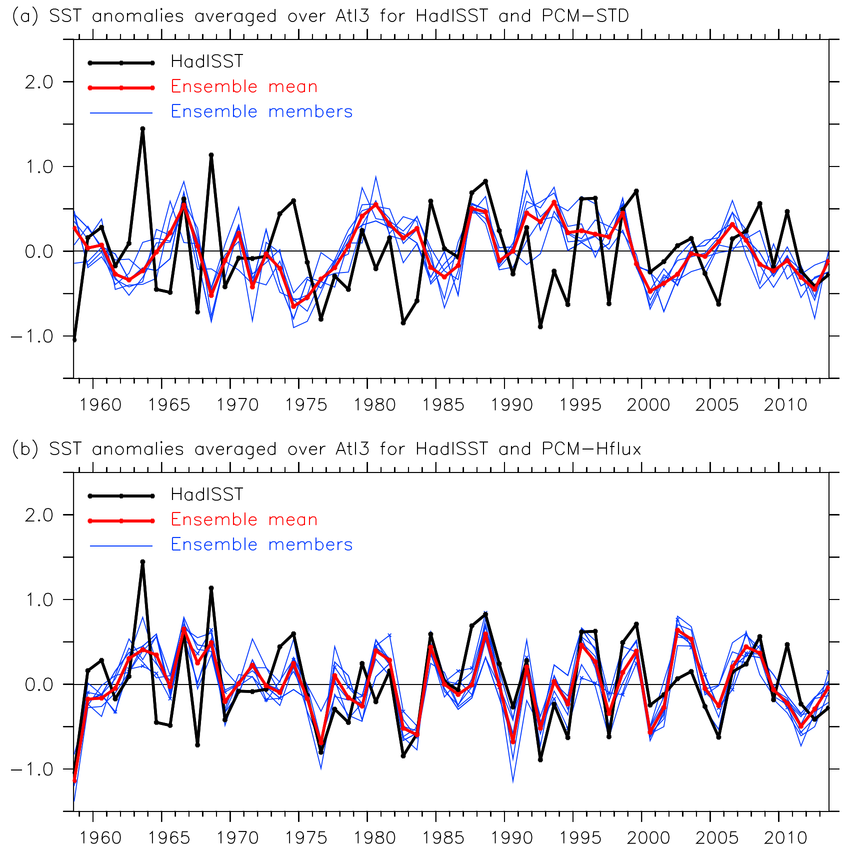

Figure 3. (a) Seasonal mean (JJA) SST anomalies averaged over the Atl3 box (20°W–0°W, 3°S–3°N) from HadISST (black line) [*Rayner et al.*, 2003], the ensemble mean (red line), and individual ensemble members (blue lines) of PCM-STD and (b) SST anomalies averaged over the Atl3 box (20°W-0°W, 3°S-3°N) from HadISST (black line) [*Rayner et al.*, 2003], the ensemble mean (red line), and individual ensemble members (blue lines) of PCM-Hflux.

Niño events, as reflected in the SST anomalies averaged over the Atl3 region (20°W–0°W, 3°S–3°N; Figure 3). PCM-STD seldom captures observed Atlantic Niño events (Figure 3a). The correlation in Atl3 SST between observations and PCM-STD is −0.05 from 1958 to 2013 and 0.1 after 1979 (the satellite era). On the contrary, PCM-Hflux simulates observed Atlantic Niño remarkably well and captures almost all events (Figure 3b). The correlation in Atl3 SST between observations and PCM-Hflux is 0.67 from 1958 to 2013 and up to 0.71 after 1979. It follows that a model that employs surface heat flux correction is able to reproduce up to 50% of the variance of Atlantic Niño as seen in observations using knowledge only of the observed wind stress anomalies that drive the ocean, whereas the same model run without surface heat flux correction shows no skill. It is noticeable that each ensemble member in PCM-Hflux also simulates an Atl3 SST time series very close to the observations (Figure 3b and Table S1).

Consistent with the better performance at simulating observed SST variability, PCM-Hflux (Figure 2d) also performs better than PCM-STD (Figure 2c) at capturing observed rainfall (Global Precipitation Climatology Project, GPCP) [*Adler et al.*, 2003] variability during boreal summer from 1979 to 2013. The area with correlation equal to or larger than 0.4 in rainfall is much larger in PCM-Hflux than in PCM-STD.

The PCM experiments are also compared against observations in subsurface temperature variations (Figures 2e and 2f). Here sea surface height (SSH) variations are employed as a proxy for subsurface temperature variations since in the equatorial oceans, SSH is closely related to the depth of the 20°C isotherm (Z20) [e.g., *Cane*, 1984]. Obviously, PCM-STD and PCM-Hflux show similar performance when simulating observed SSH variations in the tropical Atlantic. This is interesting and means that the anomalous upper ocean circulation in the two model versions, driven by the same imposed wind stress anomalies, is similar despite the presence of the warm bias in PCM-STD.

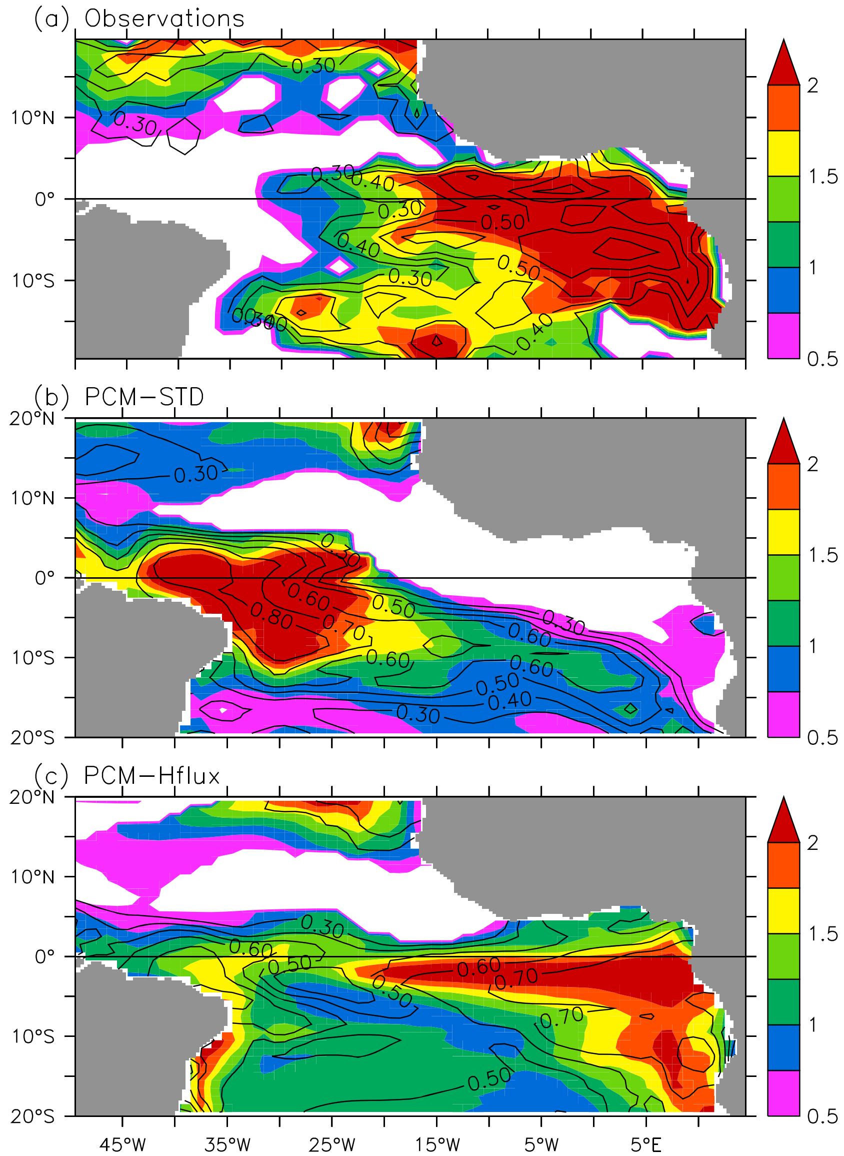

Figure 4. The regression (shading) of seasonal mean (JJA) SST anomalies onto local seasonal mean (JJA) sea surface height (SSH) anomalies calculated from (a) observations, (b) PCM-STD, and (c) PCM-Hflux. The contours are the explained variances, and their interval is 0.1. In Figure 4a, observed reconstructed SST [*Rayner et al.*, 2003] is employed and SSH from satellite (http://www.aviso.oceanobs.com/) is used. The unit of the regression coefficients is C/(10 cm).

We now turn our attention to the impact of subsurface temperature anomalies on local SST variations. This is estimated by calculating the regression of SST anomalies onto local SSH anomalies during boreal summer (Figure 4). SSH is again used as a proxy for subsurface temperature variations. Regression values calculated from observations show a link between subsurface and surface temperature variations (Figure 4), consistent with previous studies [e.g., *Keenlyside and Latif*, 2007]. A 10 cm rise in SSH corresponds to a warming of 2.0°C in SST with an explained variance of about 50%–60% in observations (Figure 4a). In contrast to the observations, subsurface and surface temperature variations in PCM-STD are coupled in the western tropical Atlantic but not in the east (Figure 4b). This seems to be associated with the climatological mean surface winds being biased westerly in the east (not shown), implying Ekman downwelling along the equator, meaning that subsurface temperature anomalies cannot easily impact SST variability in the east [*Ding et al.*, 2015]. Different from PCM-STD, PCM-Hflux (Figure 4c) captures the observed relation between subsurface temperature and SST variability in the eastern equatorial Atlantic in both amplitude and explained variance. In PCM-Hflux (Figure 4c), a 10 cm increase in SSH corresponds to a warming of SST of about 2°C, and explained variances are in the range of 50–70%, roughly consistent with those seen in observations (Figure 4a). The success for capturing the link is probably because of the reduced westerly wind bias (Figure 1b) and the improved upper ocean temperature structure (Figure S1) in Hflux compared to STD (Figures 1a and S1). It is obvious that PCM-Hflux (Figure 4c) still exhibits an unrealistic link between SST and SSH in the western equatorial Atlantic similar to but weaker than in PCM-STD (Figure 4b). This is probably because it is not possible to cure model bias in all aspects through only reducing the warm bias at the sea surface using surface heat flux correction.

In the present paper, we have focused on the role of subsurface temperature variations, an important element of the Bjerknes feedback [e.g., *Keenlyside and Latif*, 2007]. Nevertheless, some other dynamics may also contribute to equatorial Atlantic interannual variability, for instance, the advective-reflective oscillator [*Wang*, 2001] and links between the equatorial and subtropical Atlantic [*Richter et al.*, 2012]. To derive a complete picture of the contribution of ocean dynamics requires a full heat budget analysis, which should be investigated in future studies.

4. Summary and Conclusions

We have shown that the tropical Atlantic warm SST bias in coupled climate models severely inhibits the ability of these models to correctly reproduce both the observed SST variability in the equatorial Atlantic and the dynamics governing that variability. Using partially coupled model (PCM) experiments in which the ocean component of the coupled model is driven by observed wind stress anomalies, we are able to reproduce up to 50% of the variance of the observed SST variability but only in the model version in which the SST bias has been substantially reduced using surface heat flux correction (PCM-Hflux). The standard model version without heat flux correction (PCM-STD) exhibits essentially no skill. Furthermore, it is only in PCM-Hflux that the observed relationship between SST and subsurface temperature variations is reproduced. The observed relationship indicates an important role for ocean dynamics for determining the SST variability in the equatorial Atlantic, a mechanism that operates in PCM-Hflux but not in PCM-STD with the implication that thermodynamic forcing plays a much more important role in the latter. These results are important because virtually all climate models suffer from a tropical Atlantic SST bias similar to that in the model used here. Thus, the role of thermodynamic processes may be overestimated when such biased models are used in assessing the origin of equatorial Atlantic SST variability and its predictability.

Nevertheless, the heat flux-corrected version of the KCM (PCM-Hflux) is still deficient in many aspects. This is not surprising given that it is not possible to correct errors in all aspects by only reducing temperature bias at the sea surface alone. In addition, the KCM is a low-resolution model and cannot resolve, for example, the equatorial deep jets which have been shown to be important for variability in the equatorial Atlantic [*Brandt et al.*, 2011]. Large reduction in tropical Atlantic SST bias and considerable improvements in the subsurface thermal structure in the eastern tropical Atlantic were reported by *Harlaß et al.* [2015] conducting experiments with KCM versions employing higher horizontal and vertical resolution only in its atmospheric component. We argue that PCM experiments might perform even better than reported here using an improved coupled climate model with enhanced physics and reduced bias.

We noted that a substantial part of SST variability in the eastern equatorial Atlantic is explained by subsurface temperature variability in both observations (50–60%) and PCM-Hflux (50–70%), implying that there is a potential predictability for SST in the equatorial Atlantic with consequences for the surrounding continents. Nevertheless, the contribution of subsurface temperature variations to SST variability is generally lower for the Atlantic Niño than for ENSO [*Keenlyside and Latif*, 2007, Figure 2c], implying that potential predictability is lower in the Atlantic than in the Pacific. In the eastern equatorial Pacific (not shown), SSH explains 70–80% of the variance of local SST variations in observations and PCM-Hflux as well as in PCM-STD. The standard version of the KCM simulates the mean state in the Pacific well so that heat flux correction plays only little role. Correspondingly, both PCM-STD and PCM-Hflux capture around 80% of the variance of the observed Nino3 time series (not shown). However, it seems clear that a prerequisite for predictability in the Atlantic sector is the alleviation of the tropical Atlantic warm bias in models.

Acknowledgments
This work was supported by the BMBF SPACES/SACUS (grant 03G0837A) projects and by the GEOMAR and EU FP7 projects PREFACE (grant agreement 603521). Data shown in this paper are available by email from corresponding author (hding@geomar.de).

The Editor thanks two anonymous reviewers for their assistance in evaluating this paper.

References

Adler, R. F., et al. (2003), The Version-2 Global Precipitation Climatology Project (GPCP) Monthly Precipitation Analysis (1979 present), *J. Hydrometeorol.*, *4*, 1147–1167, doi:10.1175/1525-7541(2003)004<1147:TVGPCP>2.0.CO;2.

Brandt, P., A. Funk, V. Hormann, M. Dengler, R. J. Greatbatch, and J. M. Toole (2011), Interannual atmospheric variability forced by the deep equatorial Atlantic Ocean, *Nature*, *473*(7348), 497–500, doi:10.1038/nature10013.

Cane, M. A. (1984), Modeling sea level during El Niño, *J. Phys. Oceanogr.*, *14*(12), 1864–1874, doi:10.1175/1520-0485(1984)014<1864:MSLDEN>2.0.CO;2.

Chang, P., Y. Fang, R. Saravanan, L. Ji, and H. Seidel (2006), The cause of the fragile relationship between the Pacific El Nino and the Atlantic Niño, *Nature*, *443*(7109), 324–328, doi:10.1038/nature05053.

Dee, D., et al. (2011), The ERA-Interim reanalysis: Configuration and performance of the data assimilation system, *Q. J. R. Meteorol. Soc.*, *137*(656), 553–597, doi:10.1002/qj.828.

Ding, H., N. Keenlyside, and M. Latif (2010), Equatorial Atlantic interannual variability: The role of heat content, *J. Geophys. Res.*, *115*, C09020, doi:10.1029/2010JC006304.

Ding, H., N. S. Keenlyside, and M. Latif (2012), Impact of the equatorial Atlantic on the El Niño southern oscillation, *Clim. Dyn.*, *38*(9–10), 1965–1972, doi:10.1007/s00382-011-1097-y.

Ding, H., R. J. Greatbatch, M. Latif, W. Park, and R. Gerdes (2013), Hindcast of the 1976/77 and 1998/99 climate shifts in the Pacific, *J. Clim.*, *26*(19), 7650–7661, doi:10.1175/JCLI-D-12-00626.1.

Ding, H., R. J. Greatbatch, W. Park, M. Latif, V. A. Semenov, and X. Sun (2014), The variability of the East Asian summer monsoon and its relationship to ENSO in a partially coupled climate model, *Clim. Dyn.*, *42*(1–2), 367–379, doi:10.1007/s00382-012-1642-3.

Ding, H., N. Keenlyside, M. Latif, W. Park, and S. Wahl (2015), The impact of mean state errors on equatorial Atlantic interannual variability in a climate model, *J. Geophys. Res. Oceans*, *120*, 1133–1151, doi:10.1002/2014JC010384.

Doi, T., G. A. Vecchi, A. J. Rosati, and T. L. Delworth (2012), Biases in the Atlantic ITCZ in seasonal-interannual variations for a coarse- and a high-resolution coupled climate model, *J. Clim.*, *25*(16), 5494–5511, doi:10.1175/JCLI-D-11-00360.1.

Greatbatch, R., G. Li, and S. Zhang (1995), Hindcasting ocean climate variability using time-dependent surface data to drive a model: An idealized study, *J. Phys. Oceanogr.*, *25*(11), 2715–2725, doi:10.1175/1520-0485(1995)025<2715:HOCVUT>2.0.CO;2.

Harlaß, J., M. Latif, and W. Park (2015), Improving climate model simulation of tropical Atlantic sea surface temperature: The importance of enhanced vertical atmosphere model resolution, *Geophys. Res. Lett.*, *42*, 2401–2408, doi:10.1002/2015GL063310.

Hu, Z., and B. Huang (2007), Physical processes associated with the tropical Atlantic SST gradient during the anomalous evolution in the southeastern ocean, *J. Clim.*, *20*(14), 3366–3378, doi:10.1175/JCLI4189.1.

Hu, Z.-Z., B. Huang, and K. Pegion (2008), Low cloud errors over the southeastern Atlantic in the NCEP CFS and their association with lower-tropospheric stability and air-sea interaction, *J. Geophys. Res.*, *113*, D12114, doi:10.1029/2007JD009514.

Hu, Z.-Z., A. Kumar, B. Huang, and J. Zhu (2013), Leading modes of the upper-ocean temperature interannual variability along the equatorial Atlantic Ocean in NCEP GODAS, *J. Clim.*, *26*(13), 4649–4663, doi:10.1175/JCLI-D-12-00629.1.

Huang, B., Z.-Z. Hu, and B. Jha (2007), Evolution of model systematic errors in the tropical Atlantic basin from coupled climate hindcasts, *Clim. Dyn.*, *28*(7–8), 661–682, doi:10.1007/s00382-006-0223-8.

Keenlyside, N., and M. Latif (2007), Understanding equatorial Atlantic interannual variability, *J. Clim.*, *20*(1), 131–142, doi:10.1175/JCLI3992.1.

Keenlyside, N. S., H. Ding, and M. Latif (2013), Potential of equatorial Atlantic variability to enhance El Niño prediction, *Geophys. Res. Lett.*, *40*, 2278–2283, doi:10.1002/grl.50362.

Liu, H., C. Wang, S.-K. Lee, and D. Enfield (2013), Atlantic warm pool variability in the CMIP5 simulations, *J. Clim.*, *26*(15), 5315–5336, doi:10.1175/JCLI-D-12-00556.1.

Park, W., N. Keenlyside, M. Latif, A. Ströh, R. Redler, E. Roeckner, and G. Madec (2009), Tropical Pacific climate and its response to global warming in the Kiel Climate Model, *J. Clim.*, *22*(1), 71–92, doi:10.1175/2008JCLI2261.1.

Rayner, N., D. Parker, E. Horton, C. Folland, L. Alexander, D. Rowell, E. Kent, and A. Kaplan (2003), Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century, *J. Geophys. Res.*, *108*(D14), 4407, doi:10.1029/2002JD002670.

Richter, I., S. K. Behera, Y. Masumoto, B. Taguchi, H. Sasaki, and T. Yamagata (2012), Multiple causes of interannual sea surface temperature variability in the equatorial Atlantic Ocean, *Nat. Geosci.*, *6*(1), 43–47, doi:10.1038/ngeo1660.

Richter, I., S.-P. Xie, S. K. Behera, T. Doi, and Y. Masumoto (2014), Equatorial Atlantic variability and its relation to mean state biases in CMIP5, *Clim. Dyn.*, *42*(1–2), 171–188, doi:10.1007/s00382-012-1624-5.

Rodríguez-Fonseca, B., I. Polo, J. García-Serrano, T. Losada, E. Mohino, C. Mechoso, and F. Kucharski (2009), Are Atlantic Niños enhancing Pacific ENSO events in recent decades?, *Geophys. Res. Lett.*, *36*, L20705, doi:10.1029/2009GL040048.

Trzaska, S., A. W. Robertson, J. D. Farrara, and C. R. Mechoso (2007), South Atlantic variability arising from air-sea coupling: Local mechanisms and tropical-subtropical interactions, *J. Clim.*, *20*(14), 3345–3365, doi:10.1175/JCLI4114.1.

Uppala, S., et al. (2005), The ERA-40 re-analysis, *Q. J. R. Meteorol. Soc.*, *131*(612), 2961–3012, doi:10.1256/qj.04.176.

Wang, C. (2001), A unified oscillator model for the El Niño–Southern Oscillation, *J. Clim.*, *14*(1), 98–115, doi:10.1175/1520-0442(2001)014<0098:AUOMFT>2.0.CO;2.

Wang, C., L. Zhang, S.-K. Lee, L. Wu, and C. R. Mechoso (2014), A global perspective on CMIP5 climate model biases, *Nat. Clim. Change*, *4*(3), 201–205, doi:10.1038/nclimate2118.

Wang, F., and P. Chang (2008), Coupled variability and predictability in a stochastic climate model of the tropical Atlantic, *J. Clim.*, *21*(23), 6247–6259, doi:10.1175/2008JCLI2283.1.

Xie, S., and J. Carton (2004), Tropical Atlantic variability: Patterns, mechanisms, and impacts, in *Earth's Climate: The Ocean-Atmosphere Interaction, Geophys. Monogr. Ser.*, vol. 147, edited by C. Wang, S.-P. Xie, and J. A. Carton, pp. 121–142, AGU, Washington, D. C.

Zebiak, S. (1993), Air–sea interaction in the equatorial Atlantic region, *J. Clim.*, *6*(8), 1567–1586, doi:10.1175/1520-0442(1993)006<1567:AIITEA>2.0.CO;2.

Zhang, S., R. Greatbatch, and C. Lin (1993), A reexamination of the polar halocline catastrophe and implications for coupled ocean-atmosphere modeling, *J. Phys. Oceanogr.*, *23*(2), 287–299, doi:10.1175/1520-0485(1993)023<0287:AROTPH>2.0.CO;2.