Interdecadal Variations in AGCM Simulation Skills

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(Manuscript received 31 March 2005, in final form 18 November 2005)

Abstract

Global climate models forced by sea surface temperature are standard tools in seasonal climate prediction and in projection of future climate change caused by anthropogenic emissions of greenhouse gases. Assessing the ability of these models to reproduce observed atmospheric circulation given the lower boundary conditions, and thus its ability to predict climate, has been a recurrent concern. Several assessments have shown that the performance of models is seasonally dependent, but there has always been the assumption that, for a given season, the model skill is constant throughout the period being analyzed. Here, it is demonstrated that there are periods when these models perform well and periods when they do not capture observed climate variability. The variations of the model performance have temporal scales and spatial patterns consistent with decadal/interdecadal climate variability. These results suggest that there are unmodeled climate processes that affect seasonal climate prediction as well as scenarios of climate change, particularly regional climate change projections. The reliability of these scenarios may depend on the time slice of the model output being analyzed. Therefore, more comprehensive model assessment should include a verification of the long-term stability of their performance.

1. Introduction

Global climate models forced by persisted and/or forecast sea surface temperature (SST) are standard tools in seasonal climate prediction. They are also used in higher-resolution projections of future climate change caused by anthropogenic emissions of greenhouse gases, in which case they are forced by SST fields provided by lower-resolution coupled atmosphere-ocean models. Assessing the reliability of these dynamical atmospheric general circulation models (AGCMs) in reproducing the observed atmospheric circulation given the lower boundary conditions has been a recurrent concern in seasonal-to-interannual climate prediction. The assessments have been carried out in several ways, including the computation of several indices, and the comparison between the leading modes of variability obtained from the observations and the models’ outputs. Some studies have shown that the performance of models is seasonally dependent (e.g., Peng et al. 2000). The seasonal variation of the climate models’ performance is related to seasonal variations in the ability of the ocean boundary to influence a particular region as well as seasonal variations in the atmosphere modes of variability. For example, Kumar et al. (2003), using a perfect model assumption, found differences in the spatial patterns of the predictability in summer and winter. Apart from variation in skill with seasons, for a given season the models’ skill has always been assumed to be constant with time.

As the atmosphere and the oceans undergo interdecadal variations (e.g., Enfield and Mestas-Nuñez 1999; Vimont et al. 2002), it is natural to ask whether this multiyear variability also influences the skill of the models in reproducing the observed atmospheric circulation. The response is important both for seasonal-to-interannual climate prediction and for projections of

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future climate change. This question is only now starting to be addressed.

Nakaegawa et al. (2004) analyzed the long-term variation of a potential prediction skill, based on AGCM integration with observed SST. The potential skill is based on the perfect model assumption, in which one of the members of the ensemble is assumed to be true, and is the maximum skill a model can reach in reproducing the observed atmospheric fields. A trend in this potential skill was found in boreal winter [December–January–February (DJF; hereafter, 3-month periods are denoted by the first letter of each respective month)] and attributed to the positive trend in the temporal variance of SST.

In the present study, we focus on the actual skill of models in order to take into account the possible inability of AGCMs in reproducing correctly the observed interdecadal variability. Seasonal responses of two AGCMs to prescribed observed SST are compared to observed seasonal fields to examine long-term variations in performance as measured by correlations between the AGCMs outputs and observations characterized by the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis. These variations are then related to decadal/interdecadal modes of SST variability. Variations in performance by season, variable, and pressure level are also examined. Although we suggest some reasons for the long-term behavior of the models, this study intends mainly to call the attention to temporal variations of the models’ performance that have not been stressed in the literature thus far.

2. Data and methodology

We examine the behavior of two AGCMs for which ensembles of multiple realizations are available for the period 1950–94: the ECHAM3 (Version 3.6, Max Planck Institute) and the NCEP (MRF9) models. The two models have comparable resolution: NCEP has truncation T40 with 18 sigma levels; ECHAM3 has T42 truncation with 19 sigma levels. There are, however, several differences in their parameterization schemes (Kumar et al. 1996; Deutsches Klimarechenzentrum 1992). Both models are forced by reconstructed observed SST (Smith et al. 1996) for the lower boundary, although the NCEP model used the optimum interpolation (OI) data (Reynolds and Smith 1994) for the 1982–94 period. The two datasets are very similar in this period. The data from 7 runs of the ECHAM3 model and 13 runs of the NCEP model are examined. Observed fields are based on the NCEP–NCAR reanalysis (Kalnay et al. 1996). Although this reanalysis uses a version of the NCEP model, there are considerable differences in their resolution and parameterization schemes (Peng et al. 2000).

Monthly means were obtained for four variables (zonal component of wind, meridional component of wind, streamfunction, and velocity potential) at four levels (850, 700, 500, and 200 hPa) for the period 1950–94. Then 81 (9 × 9) area-averaged 45-yr time series were made by averaging the data over each 20° latitude × 40° longitude region over the globe for each of the 12 months. The data were further averaged to form seasonal means (MAM, JJA, SON, and DJF). The analysis is based on the simultaneous temporal anomaly correlation coefficients (CCs) between area-averaged time series of seasonal mean model responses and reanalysis data. We use CCs between the models ensemble means and the NCEP–NCAR reanalysis as a simple indicator of model “skill.” We note that the correlation analysis will not account for any mean bias between the model and observations.

Before focusing on the long-term variations of model skill, we assessed the sensitivity of the skill to other factors. The influence of seasonal variations is examined through seasonal (3-month) anomaly CCs calculated for the whole 45-yr period (1950–94). The CCs for each season were calculated relative to the 45-yr mean. The comparison of these CCs for different seasons shows if there is a season in which there is clearly a better skill of the models in reproducing the observed circulation. A similar procedure is followed to verify whether there is a particular best simulated circulation parameter or whether circulation anomalies are best simulated at a particular atmospheric level.

The interdecadal variation of the models’ performance over the globe is assessed through the computation of simultaneous seasonal CCs between 11-yr running series of the NCEP–NCAR reanalysis data and model output. For computing the 11-yr running CCs the seasonal anomalies were calculated relative to each 11-yr running mean. Although we expect some variations in the CCs due to sampling, we assume that the overall variation of these CCs is an indication of the interdecadal variation of the models’ skill.

We also examined the long-term variations of model performance by comparing the temporal variability of the observed response of the atmosphere to the El Niño–Southern Oscillation (ENSO) with the temporal variability of the model response to ENSO. To this end, CCs between 11-yr running series of SST in the Niño-3 region (5°S–5°N, 90°–150°W) and observed seasonal 200-hPa zonal wind component are compared with the corresponding sliding correlations between Niño-3 SST and zonal wind from each AGCM. First, 11-yr sliding
CCs were calculated for each of the 7 members of the ECHAM3 run and each of the 13 members of the NCEP run, and then they were averaged for each model. Computing mean CCs rather than CCs with the ensemble means provides a more realistic view of the model’s response to Niño-3 SST. The CCs computed from the ensemble means would be higher because the variance of the nondeterministic noise in the relationship between the model’s wind and SST decreases when using ensemble means.

The interdecadal variations of the models’ skill are further examined through the empirical orthogonal function (EOF) analysis of the sliding CCs between observed and modeled fields. The EOF analysis is applied to the projection matrix of the CC data onto itself, without removing the mean. The resulting EOFs will then be dominated by regions where the CCs are large (positive or negative), thus enhancing regions with higher predictability. The relationship between the interdecadal variability of the models’ skill and the interdecadal variability of SST is disclosed by the covariance of the first two principal component (PC) series with SST. Using covariance instead of correlation highlights the ocean basins where amplitude of SST variability is stronger. The statistical significance of the covariances is assessed by using a Monte Carlo procedure: 10 000 random permutations of the SST field data are generated and the covariance with the principal component series is calculated. Then the number of times in which the absolute value of the covariance with the random permutations exceeds that with the original data is counted. This value, divided by 10 000, gives the level of significance.

It is recognized that the procedure of averaging over 20° × 40° regions gives a poor spatial resolution, but it allows a global and comprehensive view, and an easy visualization of the results.

3. Analysis

a. Dependence of the models’ skill on the season, parameter, region, and level

The influence of seasonal variations on model skill, as represented by the correlation between the model’s output and the observed data, is shown in Figs. 1a,b. These figures show the CCs for the zonal wind at 200 hPa for each season. It is worth noting that the best correlations for all seasons occur in the Tropics and subtropics, particularly in the subtropical region of the Northern Hemisphere (NH; 10°–30°N). These are statistically significant in most of the areas (boxes) and seasons. Over this subtropical region, the differences in CCs, that is, skill, for different seasons is larger in the NCEP model than in ECHAM3. The best overall performance for both models occurs in JJA (Table 1). The performance is not that good in the subtropical region of the Southern Hemisphere (SH; 10°–30°S). The best average performance in this region occurs in DJF. Therefore, summer is the season with best performance in the subtropics of both hemispheres based on CCs with upper-level zonal wind. In the equatorial belt (10°S–10°N) the average performance is better than in the SH subtropics, and although there is no strong seasonality, the CCs tend to follow the behavior observed in the NH (Table 1). In the Southern Hemisphere extratropics the correlations are significantly positive only in spring and winter. The ECHAM3 model seems to reproduce the 200-hPa zonal wind variations slightly better than NCEP model.

The performance, that is, the correlation structure of the models, is strongly parameter dependent (Fig. 2). Only the results for the ECHAM3 model, for the MAM season, are shown, since the general conclusions drawn from them are the same for the NCEP model and the other seasons. On average, the best-simulated parameter at 200 hPa is streamfunction. There is, however, a great spatial variability concerning the best-simulated parameter. In the tropical belt (30°S–30°N) the zonal wind seems to be the best-represented parameter, while the streamfunction is best represented outside this belt. However, in certain longitudinal sectors with strong tropical heat sources (80°–160°E and 40°–120°W) the skill for the velocity potential is generally even better. Figures 1 and 2 show clearly that the performance of the models depends on the region. The difference is not so great when different levels of the troposphere are considered (Fig. 3), although some differences are visible. For instance, the zonal wind at 200 hPa is better reproduced than at other levels, on average, especially in the subtropics of both hemispheres (10°–30°). Thus, the remainder of the analysis in this paper will concentrate on the 200-hPa level.

b. Interdecadal variation of the models’ skill

The analysis of the sliding CCs between observed and simulated parameters is focused on 200-hPa zonal wind, which is usually the best-simulated parameter in the Tropics, according to our assessment. However, the results presented here are also supported by the analysis of other parameters, for example, the 200-hPa streamfunction, the best-simulated parameter in the extratropics (not shown). The contrasting seasons of DJF and JJA will be analyzed to stress the interseasonal differences.
Figures 4 and 5 confirm that the performance for 200-hPa zonal wind is usually better in the Tropics and show clearly that the model skill undergoes decadal/interdecadal variations in several regions. When comparing the results for both models (Fig. 4a with Fig. 4b, Fig. 5a with Fig. 5b), it is evident that there are similarities in the fluctuations of the sliding correlations between the observed and modeled 200-hPa zonal winds, especially in the tropical belt for both the DJF and JJA seasons. This indicates that, in spite of the differences in skill, the two models show consistent interdecadal variations of their performance.

The comparison between results for different seasons, but considering the same model and parameter (Figs. 4a and 5a, Figs. 4b and 5b), discloses more differences than similarities. This highlights the seasonally dependent performance that exists in both models.

c. Interdecadal variation of the models’ skill in responding to ENSO

We also test the long-term variations of the models’ performance by looking at the temporal variability in the models’ response to ENSO, and comparing it to the observed response of the atmosphere in the NCEP–NCAR reanalysis. This analysis is carried out for both the winter and summer. In DJF the 200-hPa zonal winds in the tropical belt (30°N–30°S), in both models, are more strongly correlated with the Niño-3 SST index than the reanalysis zonal winds (Fig. 6). In addition, the CCs with the model winds do not show much temporal
TABLE 1. Number of boxes with 20° latitude × 40° longitude, in each latitude band, in which correlation between observed and simulated 200-hPa zonal wind is maximum, for each season. The seasons with maximum number of boxes in one or both models are boldface. In parentheses is the number of boxes with significant positive correlation. Only for the NCEP model output in the extratropics are the maximum values of these two numbers not in the same season.

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FIG. 2. Simultaneous CCs between the observed and modeled (ECHAM3) variables at 200 hPa for the MAM season, in the period 1950–94. Before calculating the CCs, values were averaged over 20° × 40° latitude–longitude regions. In each grid region the bars represent, from left to right, values of CCs (from −1 to +1) for zonal wind, meridional wind, velocity potential, and streamfunction, respectively. The threshold for two-sided statistical significance at the 0.05 level is 0.29. The bars representing statistically significant (nonsignificant) CCs are black (gray).

FIG. 3. Same as in Fig. 2, but for zonal wind at different levels. The bars represent, from left to right, values of CCs (from −1 to +1) for 850 hPa, 700 hPa, 500 hPa, and 200 hPa, respectively.
variation, and do not reproduce well most of the inter-decadal variability seen in the Niño-3 SST and reanalysis correlations. This is especially noticeable for the NCEP model. This suggests that the model atmospheres are more sensitive to the tropical SST than the real atmosphere; that is, the model’s tropical response appears to be less variable than the observed response to ENSO forcing in DJF. In JJA the ECHAM model zonal winds are less strongly correlated with the Niño-3 SST than the reanalysis winds, although the correlations with the NCEP model zonal winds in the tropical belt are still strong, at least in the Western Hemisphere (Fig. 7). Overall, the simulated response to ENSO does not reproduce well the temporal evolution of the observed response in both seasons. Although this is particularly important in the tropical regions, where the predictability is higher, it is also important to point out that the periods of observed strong response in the extratropics are also generally not reproduced by the models (cf. Fig. 6a with Figs. 6b,c, and Fig. 7a with Figs. 7b,c).

The temporal variations in the response to ENSO seem to be a little stronger in DJF (Fig. 6a) than in JJA (Fig. 7a). The ECHAM3 model output reproduces the observed variations a little more faithfully (Fig. 6b). The response of the NCEP model is rather uniform throughout the years, especially in the subtropics (Fig. 6c).

Fig. 4. Simultaneous 11-yr sliding CCs between the observed and modeled DJF 200-hPa zonal wind in the period 1950–94. Before calculating the CCs, values were averaged over 20° × 40° latitude-longitude regions. In each grid region, values of CCs (from −1 to +1) are on the y axis, and the central years of the sliding windows (from 1955 to 1989) are on the x axis. The threshold for two-sided statistical significance at the 0.05 level is 0.52. The bars representing statistically significant (nonsignificant) CCs are black (gray). The modeled zonal wind used was (a) the ECHAM3 model output and (b) the NCEP model output.
d. Connection between interdecadal modes of SST variability and the interdecadal variations of the models’ skill

An EOF analysis is performed on the series of 35 CCs between sliding 11-yr periods of reanalysis data and model outputs shown in Fig. 4 and Fig. 5. The EOF analysis, spanning the period 1955–89, provides the modes of variability in the relationship between observed and simulated zonal winds. These modes are described by spatial patterns of coherent variations (Figs. 8a,b), and their evolution in time (Fig. 8c). This analysis is shown here for the 200-hPa zonal winds in the boreal winter (DJF) because in this season the SST main modes of variability are considered to have larger components and the tropospheric associations are stronger (e.g., Venegas et al. 1997; Enfield and Mestas-Nuñez 1999). This is consistent with our Figs. 4 and 5, which show that the correlations between observed and modeled zonal wind are stronger in DJF than in JJA.

The analysis was also carried out for the boreal spring (MAM) that demonstrated similar, but weaker, factor loadings as those for DJF (not shown). Since both the NCEP and ECHAM3 models show similar results, we only show the ECHAM3 results analysis.

As the EOF analysis is applied to the projection matrix of the CC data onto itself, without removing the mean, the resulting spatial patterns will be dominated by regions where the CCs are large (positive or negative), thus enhancing regions with higher predictability. The PC time series (with the mean removed) indicates how the skill in these regions varies.

The first principal component explains 69% of the variance, and its factor loadings (Fig. 8a) indicate mainly coherent variations of the model’s skill in response to the tropical Pacific SST. More specifically, the dominant pattern of the model’s skill variability is related with the zonal wind response to the tropical eastern Pacific SSTs. The subtropical patterns represent variations in the ability of the models to respond to
Fig. 6. Same as in Fig. 4, but for simultaneous 11-yr sliding CCs between the Niño-3 SST index and DJF 200-hPa zonal wind. The 200-hPa zonal wind used was (a) from the NCEP–NCAR reanalysis, (b) from the ECHAM3 model output, and (c) from the NCEP model output.
SST anomalies that enhance/reduce the zonal mean Hadley circulation. The skill in simulating the subtropical upper-level zonal winds influences the skill in the extratropics, especially of the winter hemisphere, as these winds are related to Rossby wave propagation into the extratropics. In fact, the first mode pattern resembles somewhat the pattern of 200-hPa anticyclones associated with ENSO, and there is even hint of

Fig. 7. Same as in Fig. 6, but for JJA.
a Pacific–North America (PNA)-like pattern. There are patterns of strong skill variability in the extratropics of the winter hemisphere poleward of the two maxima of skill variability in the subtropics. Figures 8a and 8c show that there was an overall increase in the model’s performance in the 1970s and 1980s, when the ENSO-related variability and anomalies were stronger. As our analysis is emphasizing the regions with higher predictability, and these are generally associated with ENSO impacts, it is natural to expect some resemblance between the first EOF pattern of the model skill (Fig. 8a) and the response in the zonal wind to ENSO (Figs. 6a, b). The strongest values are in the same regions in both figures, mainly in the Tropics/subtropics of the eastern Pacific, in both hemispheres, and in the subtropics of the Southern Hemisphere. It is also possible to see that in these regions there are variations in the response of the observed zonal winds to Niño-3 SST (Fig. 6a) that are not reproduced in the model (Fig. 6b). This is why the components of the first EOF of the model skill are so strong in these regions (Fig. 8a).

The second principal component explains 10% of the
The highest factor loadings feature model skill variability of opposite signs in the equatorial Indian Ocean and in the subtropics and midlatitudes in both hemispheres (Fig. 8b). This mode underwent a transition of phase in the 1960s. The modes obtained for the NCEP model (not shown) present the same general characteristics, except for some minor differences.

To understand possible physical mechanisms behind the variability of the models’ performance, we calculate the covariance between the first and second PCs and SST averaged over $10^\circ \times 10^\circ$ latitude-longitude regions. The patterns of covariance indicate regions where SST varies coherently with the modes of model skill. The covariance with the first PC features higher correlation in the North Pacific and the North Atlantic, with correlation of opposite sign prevailing in the SH (Fig. 9a). These patterns resemble a mode of non-ENSO low-frequency SST variability reported by Enfield and Mestas-Nuñez (1999): the Atlantic multidecadal variability, which had a change of phase in the early 1970s, as our first PC. It is worth stressing the similarities that exist between the patterns in Fig. 9a and Fig. 5 of Enfield and Mestas-Nuñez (1999), in spite of the very different periods of analysis in both studies. Among them is the pattern in the North Atlantic [characteristic of the SST anomalies associated with the North Atlantic Oscillation (NAO)] and the patterns in the tropical east Pacific and South Atlantic with opposite sign to those in the North Atlantic and North Pacific, and the same sign as those in the Indian Ocean and west Pacific. The anomalies in the tropical east Pacific are probably the reason for the interdecadal modulation of ENSO-related variability, which affects the skill, as shown by the first EOF in Fig. 8a. On the other hand, part of these patterns indicates SST anomalies that in nature are predominantly forced by the atmosphere (instead of forcing it), especially those in the North Atlantic. Forcing the AGCMs with these observed SST anomalies will not reproduce completely the atmospheric interdecadal variations, which is part of the reason for the variations in their skill.

The covariance between global SST and the second PC (Fig. 9b) displays patterns resembling features of
4. Discussion and conclusions

The present analysis of the ECHAM3 and NCEP model outputs during the period 1950–94 confirms that there are interseasonal variations in the skill of the models, and that this skill is also dependent on the location and the parameter being simulated. Furthermore, it discloses interdecadal variations in the skill of the models and shows, for the first time, that these variations are coherent with interdecadal fluctuations of SST anomalies. For example, Fig. 9a suggests that the first mode of the skill variability (Fig. 8a) varies coherently with a global mode of interdecadal SST variability, the Atlantic multidecadal variability, which, in turn, is related to the NAO. Besides the North Atlantic and North Pacific, this mode also has strong components in the eastern Pacific, and thus may be related to the modulation of ENSO strength on interdecadal scales as reflected in the main features of Fig. 8a.

The interdecadal variations of model skill are also apparent in the atmosphere response to ENSO. In the NH winter, when the ENSO signal in the central/eastern Pacific is stronger, the model response to Niño-3 SST in the tropical/subtropical region tends to be stronger and more uniform throughout the years than the response of the observations, that is, the reanalysis (Fig. 6). It suggests that in this region the models’ atmosphere is more directly controlled by the tropical SST than the real atmosphere. In the extratropics the models’ response is generally weak, and even where it is strong, it does in general not coincide with the periods in which the observed response is strong. This means that in most of the periods in which the Niño-3 SST provided predictability to certain regions in the extratropics, there is much less skill in the models. On the other hand, there are extratropical regions and periods of strong models’ response to Niño-3 SST, without an observational counterpart. Figure 6 shows some examples in the northern and southern Pacific.

Some of the fluctuations in the correlations of Figs. 4 and 5 may be influenced by temporal changes in the input data to the NCEP–NCAR reanalysis such as the introduction of satellite data in the late 1970s. However, there is little evidence of a general change in the nature of the correlations associated with these changes in inputs in the analyses presented here.

Several factors might be associated with the long-term variations in the models’ skill.

1) The models may not be able to reproduce correctly the anomalous tropospheric heat sources (resulting from convection) associated with interdecadal modes of variability (Allan and Slingo 2002).

2) The misrepresentation of these sources may impact significantly the atmospheric circulation, both in the Tropics and in the extratropics.

3) The models may not be able to reproduce the interdecadal changes in the basic state of the atmosphere (as, for instance, those related to the NAO), which may modify their ability to represent well some processes, such as the propagation of Rossby waves generated by tropical heat sources into the extratropics.

4) Even if the models reasonably reproduced the changes in the tropospheric heat sources and the basic state of the atmosphere, their best adjustment for simulating observed fields and their variations during one phase of an interdecadal oscillation might not be the best one during the opposite phase.

Changes in the basic state of the atmosphere–ocean system may occur naturally as well as part of greenhouse gas–related variations. The analysis presented here suggests that models do not adequately reproduce the interdecadal changes in the basic state and their consequences. The influence of the atmospheric basic state in the propagation of Rossby waves is demonstrated by analysis of the influence functions of a vorticity equation model at 200 hPa (Grimm and Silva Dias 1995). The influence function allows the diagnoses of the upper-level divergence (associated with convection in the Tropics/subtropics) responsible for the circulation anomaly at a given location. Figures 10a,b show the December influence function for a target point in southern South America computed with basic states for two different 30-yr periods: 1949–78 and 1973–2002.
The amplitude of the influence function is stronger in the second period than in the first one in the equatorial eastern Pacific, and the signs are opposite. This indicates that upper-level divergence (associated with heat sources) in this region was much more efficient in producing rotational circulation anomalies around the target point in the more recent decades, consistent with Fig. 8. There are also other differences, especially in the NH, again suggesting that changes in the basic state result in variations in the atmospheric teleconnections.

The differences between the fluctuations of the sliding correlation for different seasons, disclosed by the comparison of Figs. 4 and 5, are expected on the basis that the basic state of the atmosphere varies seasonally, and so does the impact of the low-frequency modes of SST on the atmosphere. Also these SST modes vary from one season to another.

The long-term fluctuations of the ability of the AGCMs forced with observed SST in reproducing the variability of the atmosphere seem to reflect fluctuations in the ocean–atmosphere links related to decadal/interdecadal climate variability. This suggests inability of these models to operate properly in climate regimes different from those for which they were developed and calibrated. The existence of unmodeled interdecadal climate variations is likely due to unmodeled, poorly modeled or not-well-understood climate processes. Given the use of these models in seasonal climate predictions and similar models in projections of future climate change, the long-term variations in their perfor-
mance may have serious implications. The long-term variations of models’ skill indicate that the regional reliability of long climate model runs may depend on the time slice in which the output of the model is analyzed. Therefore, more comprehensive model assessments should include a verification of the long-term stability of their performance.

Acknowledgments. We wish to thank the two anonymous reviewers for their helpful suggestions. This work has been supported by CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico, Brazil) and the Inter-American Institute for Global Change Research (IAI—CRN055). The IRI was established by agreement between the NOAA Climate Program Office and Columbia University. This paper is funded by the cooperative agreement from the National Oceanic and Atmospheric Administration NA050AR431004. The views expressed herein are those of the authors and do not necessarily reflect the views of NOAA or any of its subagencies.

REFERENCES


