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Predictability of Dry Season Reforecasts over the Tropical South American Region

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1. Introduction

The potential predictability of the dry phase of South American monsoon (SAM) has been studied relatively little when compared to the wet phase. In fact it was not until Zhou and Lau (1998) that South America (SA) was recognized as having a monsoon climate. The SAM went unrecognized for such a long period due to the fact that it does not exhibit a distinct seasonal reversal of winds. It is not until the annual mean is removed from the seasonal mean that a wind reversal appears. Although the SAM does not exhibit a seasonal reversal in the wind field, it does exhibit a distinct seasonal cycle in precipitation; a wet phase occurs during Austral summer [December-February (DJF)] and a dry phase occurs during the winter [June-August (JJA)]. A rapid increase in precipitation occurs during the spring [September-November (SON)] and a decrease during March-May (MAM). Additionally, the SAM exhibits large-scale land-sea temperature differences, a large-scale thermally direct circulation with a continental rising branch and an oceanic sinking branch, land-atmosphere interactions associate with elevated terrain and land surface conditions, surface low pressure and an upper level anticyclone, and intense low-level inflow of moisture to the continent (Vera *et al.* 2006).

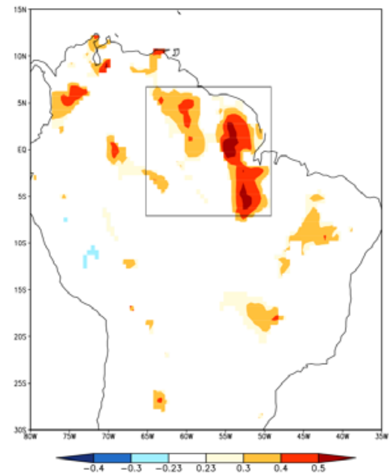

Fig. 1 Correlation of JJA rainfall with the following DJF rainfall. Only statistically significant values are shaded. The box represents the middle-lower reaches of the Amazon River.

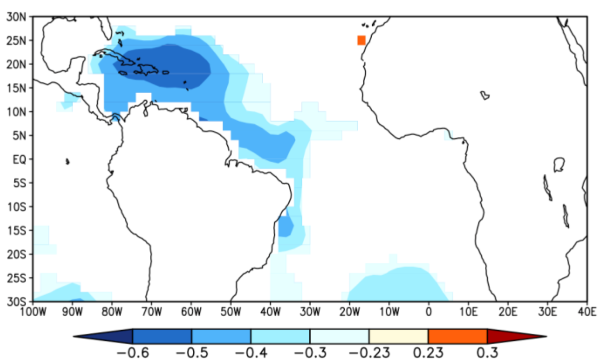

Fig. 2 Correlation of JJA ERSSTv3 with DJF Climate Research Unit (CRU) Rainfall. Only statistically significant values are plotted.

In this study we wish to investigate the predictability of the dry phase of the SAM (JJA) in two climate models and the potential improvement that dynamical downscaling and bias correction processes can have on forecasts. New research suggests that the dry phase of the SAM may be more significant than previously anticipated. Strong positive correlations exist between JJA rainfall and the following DJF rainfall particularly over north east Brazil (Figure 1). Additionally, strong negative correlations exist between DJF rainfall within the box in Figure 1 and JJA SSTs in the region of the Atlantic Warm Pool (AWP; Figure 2). This implies that higher than normal precipitation during JJA is followed by higher than normal precipitation during the following DJF and a cooler than normal AWP during the following JJA.

Prior research has shown that dynamical downscaling can improve model output primarily through improved resolution and model physics (Chan and Misra 2009). Anomaly nesting (i.e. bias correction) should

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also improve model output by reducing the bias of the global climate model (GCM) before the downscaling is performed with the regional climate model (RCM) (Misra and Kanimitsu 2004).

2. Data and Methodology

Model reforecasts from eight dry seasons (2000-2007) are analyzed in this study. Reforecasts are performed using the NCEP Climate Forecast System (CFS) and the NCEP Scripps Regional Spectral Model (RSM). A second integration of the RSM (RSM-AN), which uses a bias correction process, is also used for comparison. The bias correction process used in this study is based on the Anomaly Nesting method from Misra and Kanamitsu (2004). This method replaces the GCM climatology with the climatology from reanalysis before the downscaling process is performed. In this study, CFS climatology is replaced with NCEP NCAR Reanalysis I (atmosphere) and ERSSTv2 (ocean). The CFS is run at triangular spectral truncation T62 and the RSM is run at a 60km resolution. Both models use six ensemble members which are generated by perturbing the initial atmospheric conditions. Atmospheric conditions are perturbed by resetting the initial date of the atmospheric restart file after integrating the model for a week. Land and ocean states remain unchanged between ensemble members.

The fidelity of the three models' reforecasts is investigated. Particular attention is paid to the two regions outlined in figure 3 (Amazon River Basin (ARB) and the subtropical region (ST)). Using CFSR (temperature and precipitation) and TRMM 3B-43 (not shown) and CMAP (not shown) regions of significant model bias for the fields of temperature and precipitation are identified. Fields are averaged over JJA, 2000-2007 so as to provide an eight-year seasonal average. Relative Operator Characteristic (ROC) curves plotted and the area under the curve (AUC) is calculated as a measure of the model's skill at predicting an event (Mason and Graham, 1999). ROC curves are scatter plots of hit rate to false alarm rate for varying thresholds of accuracy. In this study, events are defined as above normal, normal, and below normal temperature and precipitation. The threshold used to determine whether or not a model will predict a "yes" or "no" occurrence of an event is the number of ensemble members required to have correctly identified an event. For example, if the threshold were "4 ensemble members" and observations identified a particular year to have had above average precipitation, we would require 4 or more members to predict above average precipitation in order to say that the model got a "hit". A model can "perfectly" predict an event for a given threshold if it gets a "hit" for each of the 8 years in our study.

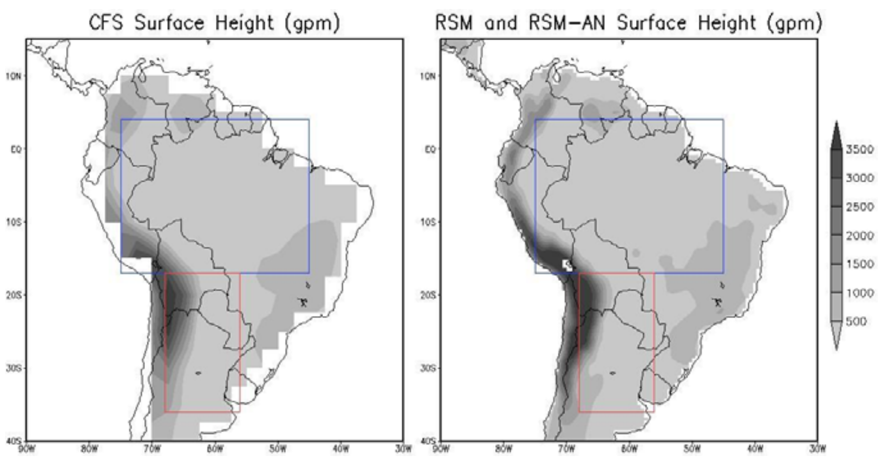

Fig. 3 Topography (gpm) is plotted with the land surface mask applied for the CFS (left) and RSM (right). The blue box represents the Amazon River Basin region and the red box represents the subtropical region.

3. Results

a. Model Bias

Precipitation patterns are realistic in all three models (Figure 4). Both the ITCZ and the SACZ are well defined. All models also show precipitation minima over a majority of the ARB and the ST regions as well as over the equatorial South Pacific Ocean.

When compared to the CFSR, regions of significant model bias become evident (Figure 5). All three models show a significant positive bias over mountainous terrain and large negative biases over the tropical South Pacific Ocean. The CFS and the RSM-AN have similar patterns of bias. Both have large negative bias in the northern SA, negative bias in the La Plata Basin, and weak positive bias over southeastern Brazil. The anomaly nesting process in the RSM-AN is potentially responsible for the observed reduction in the magnitude of positive and negative biases in the CFS in southeastern Brazil and points further south. The RSM has large positive bias over most of Brazil, with the exception of extreme northeastern coastal regions. At first glance, it appears that the bias in the models is very large, with many regions having over 100% difference when compared to CFSR. However, it is important to remember that the precipitation rates in many of these regions are very small (*i.e.* <1mm/day) and a large percentage difference is easily achieved.

Bias maps of temperature are much nosier than precipitation (Fig. 6). One similarity between all three models is positive biases in equatorial regions. Both the RSM and RSM-AN have less bias than the CFS in this region. Interestingly, the RSM reduces the bias more than the RSM-AN. All models also show small negative biases in southern Brazil. In subtropical regions the CFS has primarily negative biases while the RSM and RSM-AN have positive biases.

b. Model Skill

In this study the RCM shows some improvement over the GCM at forecasting temperature but not necessarily when forecasting precipitation. In the ARB the CFS predicts above average temperatures most skillfully (Table 1; AUC=0.667). While the RSM and RSM-AN also forecast above normal temperatures best, they improve upon the CFS with scores of 0.792 and 1 respectively. In the ST region, the CFS has AUCs of 0.5 for all 3 events, which indicates no skill. The RSM and RSM-AN again improve upon the CFS; both have AUCs around 0.9 when predicting below normal temperatures.

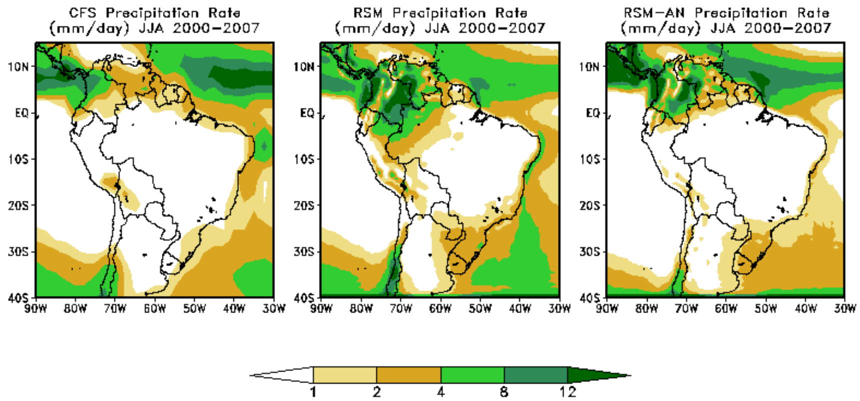

Fig. 4 Precipitation rate (mm/day) averaged over JJA and over all eight years (2000-2007). Values less than 1mm/day are masked. CFS (left), RSM (center) and RSM-AN (right).

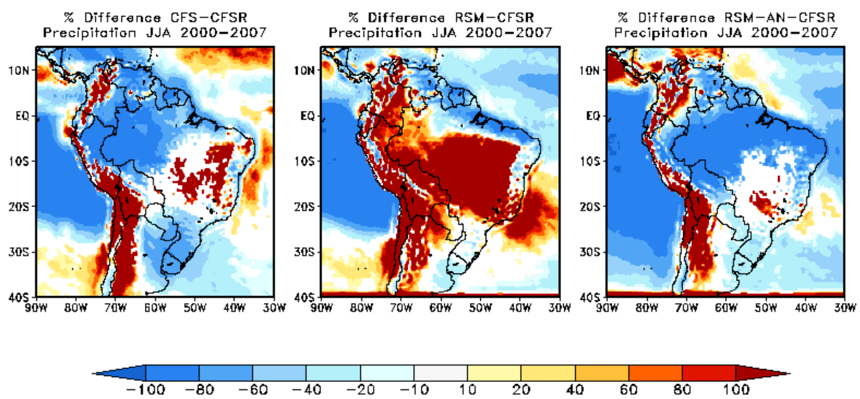

Fig. 5 Shows the percentage difference between the climatologically averaged JJA precipitation rate of the model (CFS[left], RSM[center], RSM-AN[right]) and CFSR averaged over the same period. Only significant values are plotted. Each plot is normalized using the CFSR.

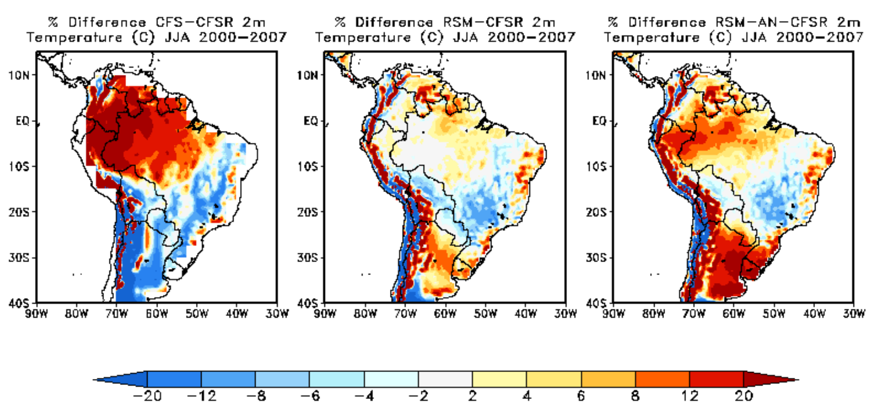

Fig. 6 Same as Figure 5 except for temperature (°C).

AUCs are generally much less when predicting precipitation due to the random nature of this field. This characteristic is replicated in our results. In the ARB the CFS predicts only below normal precipitation with some skill (AUC=0.792). It is interesting to see that the RSM shows very little skill in this region for any event while the RSM-AN improves upon the CFS significantly with an AUC of 0.958 when forecasting above normal precipitation. In the ST, only the RSM achieves an AUC above 0.5, with a score of 0.67 when forecasting above normal precipitation. The fact that no model has high AUCs in the ST is consistent with signal to noise ratio plots (not shown), which show significantly more signal in the ARB than the ST during the dry season.

Area Under The ROC Curve Amazon River Basin	CFSR					
	Temperature			Precipitation		
	A	N	B	A	N	B
8 Years of CFS 6 ensembles	0.667	0.438	0.625	0.458	0.5	0.792
8 years of RSM, 6 Ensembles	0.792	0.75	0.75	0.583	0.22	0.458
8 Years of RSM-AN, 6 Ensembles	1	0.969	0.625	0.958	0.59	0.708

Area Under The ROC Curve Subtropical Region	CFSR					
	Temperature			Precipitation		
	A	N	B	A	N	B
8 Years of CFS 6 ensembles	0.5	0.5	0.5	0.417	0.438	0.5
8 years of RSM, 6 Ensembles	0.5	0.75	0.958	0.67	0.5	0.208
8 Years of RSM-AN, 6 Ensembles	0.542	0.34	0.917	0.167	0.5	0.167

Table 1 Shows the area under the ROC curves for the ARB (top) and ST (bottom). Areas are calculated by comparing models with CFSR. Areas are calculated for three events, above normal (A; orange), normal (N; white), and below normal (B; blue) and are calculated for temperature and precipitation. Values less than or equal to 0.5 indicate that the model has no skill at forecasting the variable for that particular event and the user would be better off using climatology as a forecast. A value of 1 means that the model is close to being perfect.

4. Concluding Remarks

All 3 models produced realistic looking fields of temperature and precipitation. However, bias plots show that all models are strongly biased in particular regions when compared to CFSR. As expected, biases of precipitation were significantly larger than those of temperature. This is most likely due to two factors. Precipitation is a noisy field that is not resolved well, particularly in climate models. Additionally, values of rain rate during the dry season are low; therefore, large percentage differences between data sets are easily achieved.

We have found that for both regions of interest, the downscaling process improves predictability of temperature, but not necessarily precipitation. In both the ARB and ST, AUCs for temperature increased from the CFS, to the RSM and RSM-AN. The anomaly nesting process improved upon the RSM, but only in the ST. It was not as clear whether the downscaling and anomaly nesting processes significantly improve the predictability of precipitation.

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