Regional aspects of climate as produced by the CPTEC/COLA atmospheric GCM. Skill and Predictability assessment and applications to climate predictions

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ABSTRACT

The annual and interannual variability of regional rainfall produced by the CPTEC/COLA Atmospheric global climate model are studied here. The evaluation is made for a 9-member ensemble run of the model forced by observed global sea surface temperature (SST) anomalies for the 10-year period 1982-1991. The Brier skill score, Relative Operational Characteristic (ROC) and tercile categories are used to assess the predictability of rainfall and to validate rainfall simulations, in several regions around the planet. In general, the annual cycle of precipitation is well simulated by the model for several continental and oceanic regions in the tropics and mid latitudes. Interannual variability of rainfall during the peak rainy season is realistically simulated in Northeast Brazil, Amazonia, central Chile, and southern Argentina-Uruguay, Eastern Africa, and tropical Pacific regions, where it shows good skill. Some regions, such as Northwest Peru-Ecuador, and southern Brazil exhibit a realistic simulation of rainfall anomalies associated with extreme El Niño warming conditions, while in years with neutral or La Nina conditions, the agreement between observed and simulated rainfall anomalies is not always present.

1. Introduction

Because of the presence of non-linear processes in the climate system, deterministic projections of change are potentially subject to uncertainties arising from sensitivity to initial conditions or to parameter settings. Such uncertainties can be partially quantified from ensembles of runs from the same model (with slightly different initial condition for each ensemble member) or from ensembles of integrations from different climate models. In order to be able to make reliable forecasts of weather and climate in the presence of both initial conditions and model uncertainty, it is now becoming common to repeat the prediction many times from different perturbed initial states (Mason et al. 1999, Kumar et al. 2001). Based on the dispersion of the ensemble members ("inter-member spread") it is possible to establish confidence thresholds on the seasonal forecast and to determine the skill of the model at seasonal and interannual scales. For a number of predefined regions, inter-member spread may bear a relation to the accuracy of the prediction, and a climate signal in a regional prediction should appear as a discernible shift on the forecast distribution relative to the climatological distribution. The present study focuses on the validation of regional mean interannual variability of rainfall from an ensemble of 9 simulations of the atmospheric model of the CPTEC/COLA AGCM, forced with observed SST during a 10 year period (1982-91) (Cavalcanti et al. 2001).

2. Background

Seasonal and interannual climate variability comprise two components: (a) the externally forced component, which is the response to slowly varying external boundary forcing (SST, sea ice, albedo, soil moisture, and snow coverage) and radiative forcing (greenhouse gases and aerosol concentration); (b) the internally forced component, which is the atmospheric variability induced by internal dynamics and the weather noise (Brankovic et al. 1994, Koster et al. 2000). The externally forced component is potentially predictable at long-range assuming the forcings themselves are potentially predictable (Goddard et al. 2001). However, even if the SST anomalies could be predicted with no error, the associated atmospheric evolution could not be determined accurately due to the chaotic nature of the atmosphere. The internally forced component may be potentially predictable up to about two weeks. Even though a model can reproduce well the observed mean climate as an important and useful aspect of its performance, it is important to know its skill in reproducing the interannual variability at regional or global scales and to understand if the variability is externally forced (e.g. by SST) or if it results from internal dynamics with its characteristic chaotic behavior

Predictability of climate at seasonal-to-interannual time scales at both global and regional scale must include an analysis of sources of predictability (boundary conditions versus initial conditions, as well as sea surface versus land surface boundary conditions), the ENSO induced-predictability, as well as the ENSO induced-teleconnections and the influence of other ocean basins such as the Atlantic and Indian Oceans (Goddard et al. 2001). Much of the skill in predicting departures from normal seasonal totals or averages, often associated with atmospheric circulation patterns, has its origin in the slowly changing conditions at the earth’s surface that can influence the climate. The most important surface condition affecting climate is the SST, and particularly the SST in the tropical zones. Other, usually less influential, surface conditions is soil wetness and snow cover. Several studies have been devoted to simulations of the observed interannual variability of rainfall in several parts of the world, including regions where climate variability apparently is linked strongly to SST anomalies in tropical oceans besides the Pacific. The physical links between tropical and extra tropical SST variability, and the sensitivity of seasonal climate to this external forcing have been previously documented (see reviews in Goddard et al. 2001). Rainfall at the Indian subcontinent correlates better to tropical Pacific variability than to local Indian Ocean variability (e.g. Weare 1979). Land surface characteristics and processes also serve as slowly varying boundary conditions on climate simulations. Realistic representation of land surface-atmosphere interactions is essential to realistic simulation and prediction of continental scale climate and hydrology. Experiments on changes in land-surface, such as regional and large scale deforestation in the Amazon basin (see reviews in Zeng et al. 1999, Costa and Foley 2000) have identified the sensitivity of rainfall to changes in vegetation and soil moisture conditions in the region. The role of interannual changes in snow coverage in the Himalayas on the onset and intensity of the Indian monsoon has been studied by Matsuyama and Matsuda (1993). Goswami (1998) assessed the interannual variability of the Indian monsoon with focus on the internal and external forcing, and found that internal oscillations can account for a large part of the simulated monsoon variability.

In this paper, we present the highlights of the inter comparisons of the modeled and observed regional interannual variability of precipitation. We examine the statistical patterns of rainfall fields for the 1982-91 and also determine the skill of the model for several regions in the tropics and mid-latitudes. The inter-member spread is assumed as an indicator of model skill, and skill scores are calculated for several areas of the planet, with some of these regions known to be very sensitive to ENSO related warming in the tropical Pacific. If the skill is high and the dispersion among members is low, it suggests that the SST-forced component for the simulated seasonal rainfall mean is realistic.

However, low skill and high dispersion may still be a realistic SST-forced response of seasonal rainfall if reliability is reasonable.

3. The CPTEC/COLA AGCM: formulation and general climatology

Starting in 1995, seasonal predictions have been carried out using the CPTEC/COLA AGCM. This model is derived from the COLA AGCM (Kinter et al. 1997). The characteristics of formulation, physical parameterizations and the numerical aspects of the CPTEC/COLA AGCM are described in Satyamurti and Bittencourt (1999). The surface and upper-air climatology of the CPTEC COLA AGCM (Cavalcanti et al. 2001) shows that the model is capable of simulating the general large-scale atmospheric features, and also providing a reliable simulation of the regional-scale seasonal climate variability in both tropics and mid-latitudes. The major convergence zones and rainfall centers in the tropical region, surface and upper-level circulation features, intensity and location of storm tracks, the teleconnection patterns such as the PNA (Pacific North American), and the components of the energy and moisture balances are realistically depicted by the model. The ensemble approach used in this work is applied to validate the CPTEC/COLA AGCM against rainfall observations. This allows for an identification of the portion of the anomalous climate signal due to the external forcing (SST) and the portion that is due to internal variability or chaos in the atmosphere. Issues to be discussed include: (a) assessment of model's ability to simulate and predict regional rainfall variability due to SST forcing, taking into account systematic bias and errors of the model in reproducing regional aspects of climate; and (b) probabilistic climate forecasts during some extreme situations, such as El Niño and La Niña.

4. Experiment design, observational data sets and data processing, and assessment of skill of the model

The simulation of interannual climate variability consists of an ensemble of 9 integrations with different initial atmospheric conditions, for the period December 1982 to December 1991. Monthly-observed SST fields from the Climate Prediction Center/National Centers for Environmental Prediction (NCEP) Optimum Interpolated SST dataset are applied as forcing boundary conditions. The spin-up time for adjustments of the climate conditions of soil moisture is two and a half months. The model's seasonal and annual climatology is defined as the mean of all ensemble members of the experiment.

To validate the model regional interannual variability of global and regional rainfall, derived from the Climate Prediction Center [**C**PC] **M**erged **A**nalysis **P**recipitation (CMAP) data (Xie and Arkin 1998), was used for the observations. The CMAP data set is constructed on the 2.5°x2.5° latitude/longitude grid and covers a 20-year period from January 1979 to December 1998. For the selected regions (Fig. 1), rainfall indices based on both model and observations were constructed for each region's rainy season. They are expressed as departures from the 1982-91 long-term mean and then normalized by the standard deviation. The regions have been chosen for assessments of the annual cycle and interannual variability of simulated rainfall, as well as climate predictability and model skill, mainly because: (a) the dependence of rainfall variability of these regions to extreme SST forcing in tropical oceans, as documented in several studies and (b) the relatively low predictability in some regions (such as the monsoon regions) where the external forcing may be dominated by internal chaotic behavior of the climate system.

The skill of the CPTEC/COLA AGCM is assessed using the Relative Operating Characteristic (ROC) method is also used for representing the quality of categorical forecast. The ROC is a representation of the skill of a forecast system in which the hit rate and the false-alarm rate are compared. A ROC "event" is defined here as the "above-average"/"below-average"(i.e. 2-category). When the forecast system has some skill, the hit rate exceeds the false-alarm rate; negative skill is indicated when the false-alarm rate exceeds the hit rate. When there is no skill the hit and false-alarm rates are equal to the prior probability of warning being provided (Mason and Graham 1999).

5. Regional rainfall characteristics and time variability

5.1. Annual cycle of precipitation for several regions in the world

The behavior of the annual cycle of mean precipitation from the 9-member ensemble is discussed by analyzing regional patterns (Fig. 2). The discussion also includes the standard deviation of interannual variability and the inter-member spread shown in Fig. 2. However, it must be stressed that there is no reason why the dispersion and over- or under-estimation should be related. The model simulates quite well the annual cycle in several regions in the Americas, Indian subcontinent, Europe and tropical oceanic regions. In northern and southern Amazonia (Fig. 2a, b) the model underestimates rainfall during the January-May rainy season in contrast to the realistic depiction of the wintertime dry season. In Northeast Brazil (Fig. 2c, d) and Southern Chile (Fig. 2k) the model tends to overestimate rainfall systematically through the year, with the annual cycle well depicted in both northern and southern Northeast Brazil. Actually, in North Northeast Brazil (Fig. 2c) there is an obvious shift in the timing, with a longer rainy season in the model. The transition season from wet to dry conditions, which can often play an important role in seasonal variability, is April-June in the observations but is June-September in the model.

In Northwest Peru (Fig. 2f) the model shows a large overestimation (up to 300%) during the summer-fall rainy season. This overestimation in Northwest Peru and the underestimation in northern Amazonia may be connected through excess of convection (ascending motion) over Northwest South America and deficit of convection (descending motion) over Amazon region (direct thermal circulation). In Northwest Peru-Ecuador the annual cycle is stronger and in Amazonia weaker in the model than in CMAP data set.

In southern Brazil-Uruguay (Fig. 2e) the model underestimates the rainfall during January-September, and during the October-December rainy season the underestimation is of the order of the dispersion among members of the ensemble (1 STD). In the South American monsoon area (Fig. 2g) the model simulates quite well the annual cycle of rainfall. In Eastern Africa (Fig. 2h), the model reproduces realistically the double peak of the rainy season, even though the second peak is slightly overestimated. In India (Fig. 2i), the agreement between model and observations is remarkably good, in terms of amount and seasonal cycle; the dispersion among members is lower than in eastern Africa during the peak of the rainy season. In Europe (Fig. 2n) the model depicts well the annual cycle with a systematic overestimation. In the Pacific sector (Fig. 2l) the model overestimation of rainfall in the ITCZ contrasts with the underestimation of rainfall during the peak season in Indonesia (Fig. 2j).

5.2. Interannual variability of precipitation for several regions in the world

Precipitation normalized departures from 1982 to 1991 in the rainy season of the analyzed regions are displayed in Fig. 3. For Northern Amazonia (Fig. 3a), the scatter among members of the ensemble is larger than 1 STD (interannual STD), and the model and observations show the large negative rainfall departures due to ENSO 1982/1983 and 1986/1987. . The model produced wetter than normal rainy season in 1988 that is not depicted by the CMAP rainfall observations in northern Amazonia, while the model captures the positive rainfall departures in southern Amazonia (Fig. 3b). The dispersion among members of the ensemble for the FMAM peak in Northeast Brazil Amazonia (~1.5 STD in Fig 3c, d)) is not as large as in the Amazon, southern Brazil-Uruguay (Fig. 3e), or the South American monsoon region (Fig. 3g), where the scatter can reach more than 2 STD. In southern Brazil-Uruguay, despite this large dispersion, the model captures quite well the observed interannual variability, especially the more than normal observed rainfall in 1983 and the drought conditions in 1989. In Northwest Peru-Ecuador (Fig. 3f) the model reproduces quite well the large positive rainfall departures during the intense El Niño 1983 and 1987. Of all the regions in the Americas, Northeast Brazil (Fig. 3c, d) exhibits the best agreement between observed and modeled rainfall during the peak season over both the northern or southern sections. In particular, the positive rainfall departures during the La Niña events in 1985 and 1989 and the large negative rainfall departures during the El Niño events in 1983 and 1987 are well depicted by the model.

In Africa, the best depiction of the interannual rainfall variability belongs to Eastern Africa (Fig. 3h), especially for the extreme rainfall departures of 1984, 1985, 1987.1988 and 1990. In the Indian region, there is large spread among members (Fig. 3i), and the modeled rainfall has similar variability to the observations in 1986, 1988 and 1991. In the Pacific sector, interannual variability of rainfall along the Pacific ITCZ (Fig. 3l) is nicely depicted by the model, while along the SPCZ and the regions nearby the western Pacific the scatter among members is as high as 3 STD. In Indonesia (Fig 3j), the observed and modeled interannual variability does not coincide, and the model dispersion reaches up to 2 STD.

Based on discussions in Sections 5.1 and 5.2 we conclude that the CPTEC/COLA AGCM gives the phase of the annual cycle of precipitation reasonably well in area averages for tropical and subtropical South America, the North American monsoon area, and Africa. And in regions such as Amazonia, Northeast Brazil and along the Pacific ITCZ, the model reproduces the interannual variability of rainfall, showing in some of them the impacts of strong warming or cooling in the equatorial Pacific associated with ENSO, such as in 1983 and 1987 El Niño and 1985 and 1989 La Niña For regions where the modeled and observed interannual variability are very different, feedbacks that go beyond the SST external forcing may be more important, and this seems to be the case of the Indian monsoon region as explained by Goswami (1998).

As indicated The CPTEC/COLA AGCM consistently underestimates precipitation during the peak season in equatorial regions, with a relatively low spread among members during the whole year, and reproducing realistically the annual cycle of rainfall. The systematic underestimation of rainfall and convection in regions such as northern Amazonia or tropical western Africa is consistent with a systematic error in the location and intensity of the upper-tropospheric Bolivian High and on the convergence of the Atlantic trade winds. In compensation, the model generates overestimations of rainfall over northeast Brazil, eastern Amazonia, along the SACZ, and the Panama-Colombia coast. This underestimation of rainfall has also been observed in other tropical wet regions, such as western Africa and Indonesia-West Pacific, especially at the height of the rainy season and has been linked to some deficiencies on the Kuo’s convection scheme

In summary, over some regions, such as the Indian monsoon and southern Chile, and Europe the model simulates realistically the annual cycle of rainfall, even though the interannual variability is not well simulated, showing large spread among members or even simulating anomalies of opposite sign to those observed. In other regions the model shows under- or over-estimations of rainfall all year long, or during the peak of the rainy season. Some regions show a realistic simulation of the interannual variability during the whole 1982-91 periods, while over other regions the best simulation is detected only during extreme El Niño years.

Fig. 4a-n shows the ROC curves for several regions in the world. Buizza et al. (1999) suggest that an area under the ROC curve of more than 0.80 is an indication of a good prediction system, and an area of 0.70 is the limit for a useful prediction system. Fig. 4 shows that the area under the ROC curve for northeast Brazil is 0.91 and 0.82, Pacific ITCZ is 0.91, Indonesia is 0.70, Northwest Peru and Ecuador is 0.77, and eastern Africa is 0.74. Northern Amazonia falls almost on the limit of predictability, with 0.69. The areas under the ROC curve in southern Brazil, North and South American monsoon, Europe, Southern Brazil-Uruguay, Southern Chile and India fall below the 0.70 threshold value. Fig. 4a-d shows that for Amazonia and northeast Brazil, Pacific ITCZ (Fig. 4l), Northwest Peru-Ecuador (Fig. 4f), eastern Africa (Fig. 4h) and Indonesia (Fig. 4j), the ROC curve bends toward the top left, where hit rates are larger than false-alarm rates, and thus suggesting good model skill. Northern Amazonia (Fig. 4a) and eastern Africa (Fig. 4h) show the curve bend more to the central left side, while for the rest of regions, the curve lies close to the diagonal, suggesting that the forecasts system does not provide any useful information in those regions. In Europe (Fig. 4m) and northeastern USA (Fig. 4n) the line falls below the diagonal suggesting a negative skill.

In Eastern Africa and Northwest Peru-Ecuador, the relative good skill shown by the ROC curve and the large Brier score values for the same regions do not show a consistent figure of model skill for these regions. One way to reconcile those two results based on ROC and the Brier skill scores is to consider what the different skill scores are designed to measure. The Brier skill score is based on rainfall anomalies and the ROC is based on the hit and false-alarm rates. The effect of the strong warm forcing in the tropical Pacific may be contributing significantly to increase the ROC score (area under the ROC curve).

Based on the dispersion among members of the ensemble, and the correspondence between measures of model skill defined by the Brier score and the area under the ROC curve, as well as the correlation of seasonal anomalies, regions such as northeast Brazil (northern and southern sections), northern Amazonia and eastern Africa exhibit better predictability and good skill of the CPTEC/COLA AGCM in simulating the interannual rainfall variability, as compared to regions such as southern Brazil, India, or the North American monsoon. For those regions, the relatively poor predictability of rainfall during their peak season is evident due to the fact that the curve lies much closer to the diagonal. Work by Mason and Graham (1999) and Mason et al. (1999) have shown good skill of the ECHAM3-T42 AGCM (10 ensemble members for the 1950-94 period) in simulating wet conditions (MAM) in eastern Africa, even with the 0.58 area below the ROC curve. Fig. 4h shows that for the FMAM season the CPTEC/COLA model run (9 ensemble members for the 1982-91 period) presents area below the ROC curve of 0.74.

7. **Summary and conclusions**

In general, the model is successful in depicting the large-scale rainfall in the tropics in the presence of very large positive SST anomalies. In some regions

(Amazonia, Northeast Brazil, southern Brazil-Uruguay and northwestern Peru-Ecuador) the model simulates quite well regional rainfall anomalies during the El Niño years 1983 and 1987 and La Niña 1989. However, in the absence of significantly large SST anomalies, the model does not represent the observed rainfall variations with the same skill as during El Niño years. In areas, such as the monsoon areas of India and the Americas and in some other mid-latitude regions, there is a large spread among members of the ensemble and the simulated rainfall anomaly most of the time is not consistent with the observed one. For those regions, this apparent insensitivity of the model to large tropical SST anomalies may be responsible for the lower skill of the model over those regions. Better predictability and model skill is found in continental and oceanic tropical and equatorial regions.

Rainfall in northern Amazonia is systematically underestimated by the model at the peak of the rainy season, while in the adjacent Northeast Brazil the model tends to overestimate rainfall. However, in these regions the model depicts a realistic annual cycle as well as interannual variability of rainfall anomalies. The correct simulation of the annual cycle does not always guarantee a realistic simulation of the interannual variability of rainfall. This is the case of the Indian subcontinent, where the model depicts a very realistic annual cycle of rainfall, but the interannual variability is not well represented. In regions such as Northwest Peru and southern Brazil, the large scale forcing associated with large SST anomalies in the equatorial Pacific during El Niño determines a quite realistic simulation of rainfall anomalies in those regions, while during La Niña or neutral years the models does not always simulate the observed rainfall anomalies.

The ROC have been used to assess model skill and climate predictability in several regions of the globe. Northeast Brazil, northern Amazonia, southern Brazil, Northwest Peru-Ecuador (sensitive to El Niño's warming), Sahel, Indonesia-West Pacific, Central Australia, Europe and the Pacific ITCZ show lower Brier scores, indicative of better model skill. The South America regions also show the low spread among members of the ensemble for the interannual variability of rainfall anomalies. The area under the ROC curve is a simple index for summarizing the skill of a forecasts system. If we use an area of 0.70 as the limit for a useful prediction, Northeast Brazil (northern and southern sides), northern Amazonia, Northwest Peru and eastern Africa exhibit areas above this threshold value. This indicates that the CPTEC/COLA AGCM is able to simulate rainfall conditions at the height of the rainy season in those regions. In other regions, such as southern Brazil, India and the North American monsoon region the rainy season is considered relatively unpredictable in this model, even though for some of them the model may be able to simulate rainfall anomalies associated with extremely large SST forcing such as the strong El Niño during the run's period. The possibility that there may be some predictability of the FMAM rainfall in eastern Africa was not indicated by the Brier skill score, but is suggested by the ROC curve.

In summary, the model responds very well to large scale SST forcing in the tropical oceans, especially the warming during extreme El Niño or strong cooling during La Niña years, and hence can reproduce many aspects of interannual rainfall variability in several regions in the tropics, mid- and high-latitudes. As in several other climate models, simulations forced with observed SSTs could capture the most prevalent anomaly patterns observed in the atmosphere, with better skill in regions with high predictability such as Northeast Brazil, NW Peru-Ecuador, and northern Amazonia, Indonesia, the Pacific ITCZ region and Eastern Africa.

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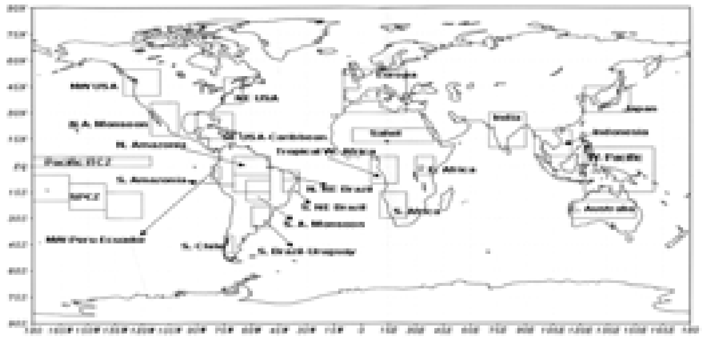


Figure 1. Selected land and oceanic regions for the computation of rainfall indices

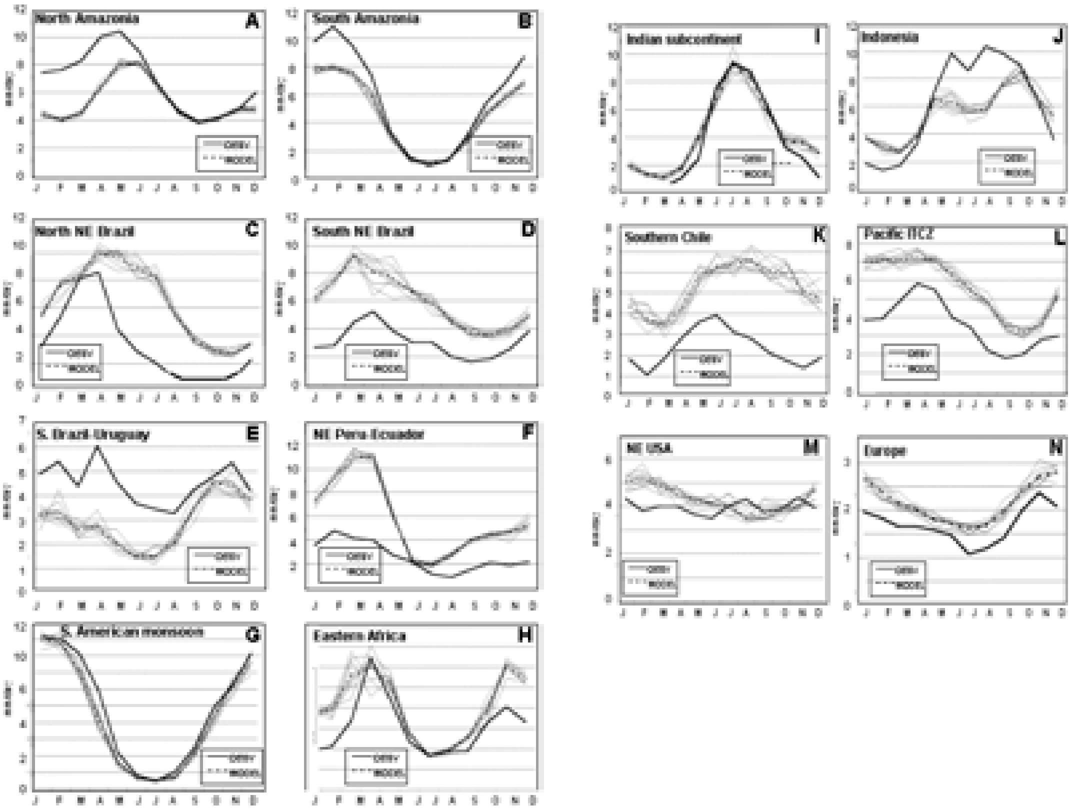


Figure 2. Annual cycle of observed and modeled rainfall in several regions of the globe (mm/day). Thick full line shows the observed rainfall. Thick broken lines represent the mean rainfall from the model ensemble. Thin full lines represent each one of the members of the ensemble.

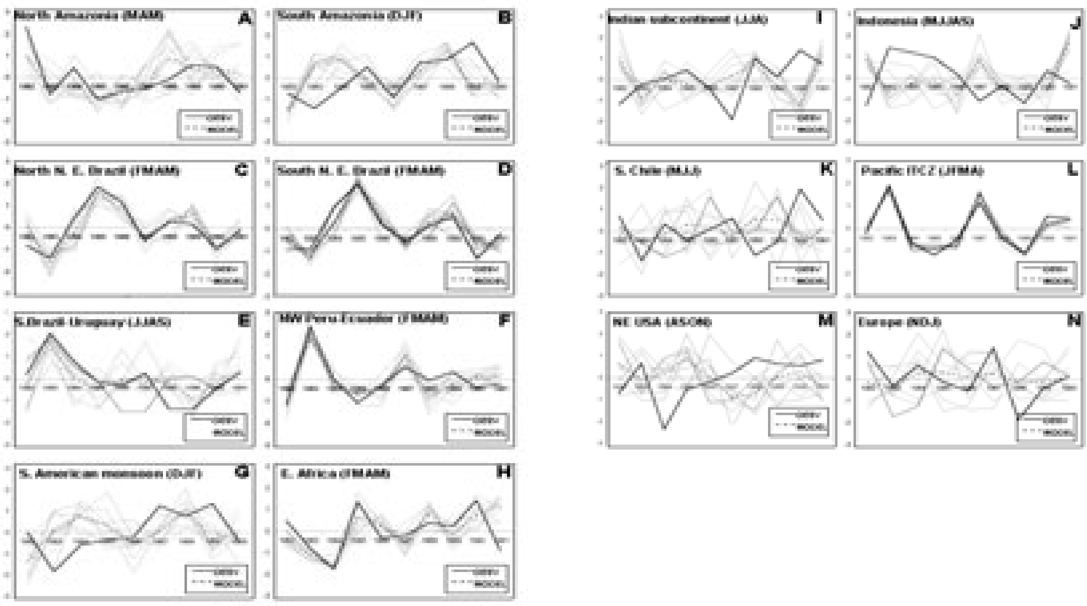
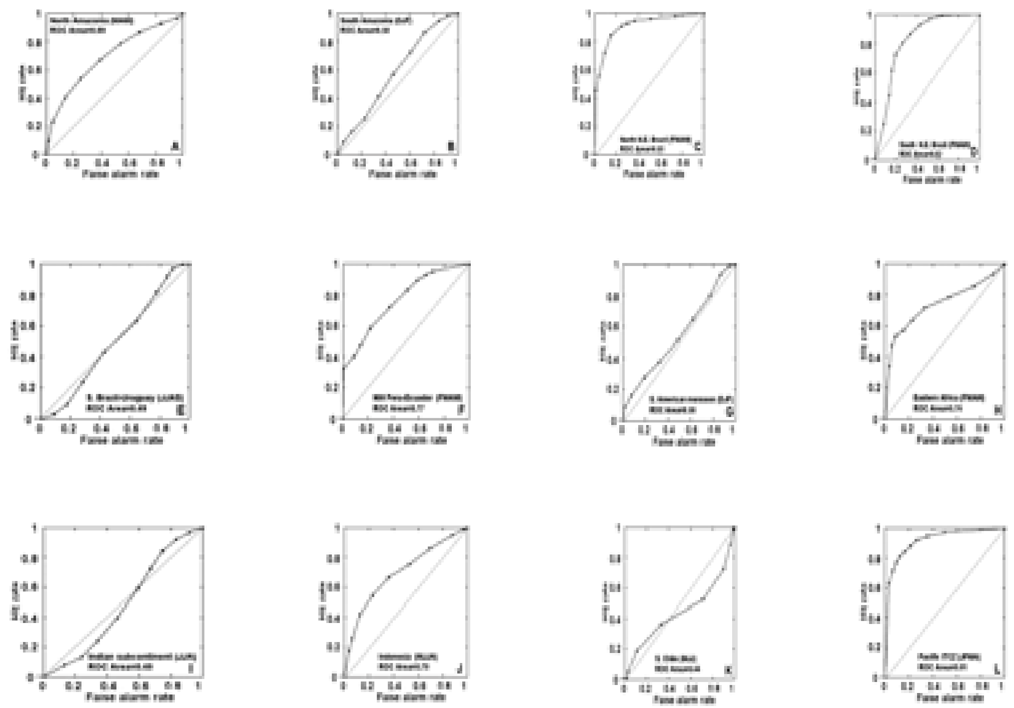


Figure 3. Interannual variability of observed and modeled normalized rainfall departures in several regions of the globe, during the peak of the rainy season. Thick full line shows the observed rainfall. Thick broken lines represent the mean rainfall from the model ensemble. Thin full lines represent each one of the members of the ensemble.



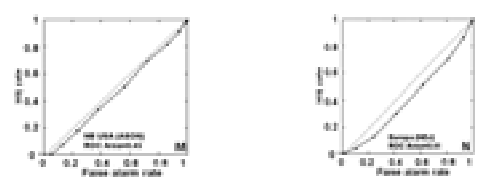


Figure 4. Hit rates versus false-alarm rates for rain averaged during the peak season for several regions of the world from 1982-91. The Hit and False alarm rates were calculated using rainfall simulated by the CPTEC/COLA AGCM