Seasonal Comparison of the Response of CCM3.6, ECHAM4.5 and COLA2.0 Atmospheric Models to Observed SSTs

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Abstract

The main features of three atmospheric general circulation models forced with monthly-mean, observed sea surface temperature for the 1979-1995 period are analyzed and compared with observational data. The ensemble means and intra-ensemble standard deviations of several variables were investigated for the two seasons December-January-February and June-July-August. Correlations of the ensemble mean anomalies with observational data and with the indices Nino-3 and the Atlantic Dipole were also calculated. The probability distribution function of the precipitation at different regions was also examined, as well as the internal and external variance of the precipitation in the three models. No model has uniformly better characteristics than the others. On the contrary, each model has strengths and weaknesses that depend on the region and season.
1 Introduction

The purpose of this work is to study the main features of three atmospheric general circulation models (AGCMs) and compare them with observational data. The response of these three AGCMs forced with the monthly mean observed sea surface temperature (SST) for the 1979-1995 period [16] is analyzed, in analogy to the AMIP II (Atmospheric Model Intercomparison Project) integrations [3, 4]. Ensembles of 10 members of the three models were performed, using the same horizontal resolution (T42) for the three models. The AGCMs used in this study were the CCM3.6 (from NCAR - National Center for Atmospheric Research, Boulder CO) [5, 6], the ECHAM4.5 (from Max-Planck Institute for Meteorology, Hamburg, Germany) [14] and the COLA 2.0 (from the Center of Ocean-Land-Atmosphere Studies, Calverton, MD) [7], which are newer versions of these models than were used in the AMIP I project [3]. We compared these models with different observational data and with NCEP Reanalysis data. Using different atmospheric initial conditions derived from balanced AGCM states, all the integrations have a common period from January 1979 to December 1995.

The analysis was done on different variables of the models, most of them important to atmosphere-ocean coupling. We analyse these variables for the two extreme seasons: December, January and February (DJF) and June, July, and August (JJA). The seasonal ensemble means of the chosen variables were calculated and also the standard deviations within the ensembles. Finally, correlations of the ensemble mean anomalies with observational data and with the indices Nino-3 and the Atlantic Dipole were also obtained. The probability distribution function (PDF) of the precipitation at different regions was also examined, as well as a comparison of the internal and external variance of the precipitation in the three models.

We used the observational data from the University of East Anglia for surface temperature and precipitation over land [10, 11]. The Xie-Arkin dataset was used for precipitation over land and ocean [17, 18]. Most of the other variables were compared with the NCEP Reanalysis data [8].
2  Near Surface Temperature

2.1  Ensemble Mean Seasonal Temperature

In Figs. (1) and (2) the difference between the ensemble mean seasonal temperature at 2m for the models and the observational data (UEA dataset [10, 11]) is shown for DJF and JJA, respectively. Most results are presented in four or three panels, with each of the models and the observations or the differences of each model and observations (e.g. CCM3.6 minus UEA), respectively.

Fig. (1) shows that in DJF, CCM3.6 has a cold bias over Northern Africa, South Asia, Australia, most of South America and the northeast of North America, while it is too warm over Central Asia and Siberia. In Fig. (2) we see that in JJA the CCM3.6 has a cold bias over all continents, with the exception of Greenland. In contrast, the COLA2.0 model has a warm bias over most of the Northern Hemisphere, with the exception of South Asia in DJF. The COLA model has a weaker and less expansive warm bias in JJA, compared to DJF. ECHAM4.5 has a cold bias over Africa, Asia and Greenland, and a warm bias over Western North America and Southern South America in DJF. The ECHAM4.5 has very similar error patterns for DJF and JJA, but the cold bias over Africa, Asia and Australia is weaker in JJA than in DJF, while the warm bias over North America is stronger. There is also a warm bias in JJA in Central South America for the ECHAM4.5 model. A bias with an absolute value larger than $2^\circ C$ is significant in a t-test comparing the models and the observations.

2.2  Temperature Intra-ensemble Standard deviation

In Figs. (3) and (4) the time-mean intra-ensemble standard deviation of the near surface temperature (within the ensembles) for DJF and JJA are shown for the three models. The largest values of the near surface temperature standard deviation occurred at the hemisphere that was at winter season at extra-tropical regions. For both seasons the COLA model had the smallest standard deviation within the ensemble, while CCM and ECHAM have comparable ones. In JJA though, the COLA model has a larger intra-ensemble standard deviation in USA.
Figure 1: DJF mean near surface temperature difference between (a) CCM and UEA, (b) ECHAM and UEA, (c) COLA and UEA.
Figure 2: JJA mean near surface temperature difference between (a) CCM and UEA, (b) ECHAM and UEA, (c) COLA and UEA.
Figure 3: DJF mean near surface temperature intra-ensemble standard deviation for (a) CCM, (b) ECHAM, (c) COLA.
Figure 4: JJA mean near surface temperature intra-ensemble standard deviation for (a) CCM, (b) ECHAM, (c) COLA.
2.3 Correlation of Models and Observed Temperature Anomalies

Figs. (5) and (6) show the correlation of the ensemble mean temperature anomalies between the models and the UEA observational data for DJF and JJA, respectively. The correlation is significant with 95% (90%) confidence, when larger than 0.5 (0.4), and the model is considered to have a good skill over those regions. In DJF, the three models have skill over the Northern part of South America, Caribbean, southern North America (with the exception of the ECHAM model), most parts of Africa, Indonesia, New Zealand, Japan, Greenland, southern India and southern and northern Europe. The COLA model has good skill over Eastern Asia, while ECHAM shows high correlations for the Near East, Australia, and Alaska, and CCM has good skill over western US in DJF. In JJA, CCM and ECHAM models have poorer skill over Greenland. COLA is the only model with good skill over most parts of Asia in both seasons, while ECHAM has a larger region with positive correlations over Africa. In South America CCM and COLA have a better skill in JJA than DJF, while for North America CCM and ECHAM have a larger correlation pattern in JJA.

In Table 1 the area average temporal correlation values (x100) of the anomalous near surface temperature between the models and the UEA data is shown for DJF and JJA. The three models have comparable correlation values for the Globe, with correlation values that are below the significance minimum with 90% of confidence. When the separate continents are considered, some models show skill over certain continents the others do not. CCM has skill in South America for both seasons and ECHAM in Australia and Europe in DJF. In the other continents the area average correlation values are not significant with 90%; although smaller regions in these continents have skill. The lowest correlation values are in Asia (CCM and ECHAM for DJF) and North America (CCM - DJF/JJA and ECHAM - DJF).

2.4 Signal to noise ratio of temperature anomalies

We can estimate the signal to noise ratio associated with major events of the different models for temperature anomalies by comparing the intra-ensemble standard deviation of the mean anomalous temperature with the absolute value of the ensemble mean temperature anomaly. We chose the El Niño of 1982-1983 and analysed the Northern Hemisphere winter season (December 1982, January and February 1983). In order for the models to have a deterministically predictable
Figure 5: DJF anomalous near surface temperature correlation with UEA observational data with (a) CCM, (b) ECHAM, (c) COLA.
Figure 6: JJA anomalous near surface temperature correlation with UEA observational data with (a) CCM, (b) ECHAM, (c) COLA.
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Table 1: Area averaged simulation skill of the CCM3.6, ECHAM4.5 and COLA models for DJF and JJA, expressed as a temporal correlation (x100) of the near surface temperature anomalies of the models and UEA data. Only correlations larger than 0.426 (DJF) or 0.412 (JJA) are significant (90% level of confidence).

signal in that event, the values of the absolute ensemble temperature anomaly should be larger than the standard deviation of the anomalous temperature.

We show in Figs. (7) and (8) respectively two regions: North America and South America. By examining Fig. (7) we notice that the models have in general a weak signal over North America, with the standard deviation within the ensemble being much larger than the mean ensemble anomaly for DJF over most of the region, especially in Alaska, for all the models. CCM shows a signal on the East Coast of US, while ECHAM has a strong signal in California, and the Midwest and the COLA model over the mid-Atlantic states. Fig. (8) shows that the three models have high signal to noise ratio over the Northern part of South America, especially ECHAM. In the Southern part of South America, the signal of the three models is much weaker than in Northern part of South America.

3 Precipitation

3.1 Ensemble Mean Seasonal Precipitation over Land

In Figs. (9) and (10) the difference between the ensemble mean precipitation for the three models and the UEA data for DJF and JJA are shown. The three models disagree with the observations of rainfall over mountain regions with different degrees of error, as in Alaska, Rocky Mountains, Western Mexico, Andes, and Central Australia. The models frequently show higher rainfall amount than the
Figure 7: Intra-ensemble standard deviation from temperature anomaly (a) C-CM, (c) ECHAM, (e) COLA and absolute temperature anomaly (b) CCM, (d) ECHAM, (f) COLA for the winter 82/83 (D82JF83).
Figure 8: Intra-ensemble standard deviation from temperature anomaly (a) C-CM, (c) ECHAM, (e) COLA and absolute temperature anomaly (b) CCM, (d) ECHAM, (f) COLA for the winter 82/83 (D82JF83).
observations in the summer hemisphere. The three models show lower rainfall than the observations over Indonesia in DJF in and Northern South America and the Guinea Coast in JJA.

### 3.2 Ensemble Mean Seasonal Precipitation over Ocean and Land

In Figs. (11) and (12) the mean precipitation is shown for the three models and the Xie-Arkin dataset [17, 18] for DJF and JJA. The Xie-Arkin dataset has a very high quality over land areas and comparison with other merged analysis showed close agreement over tropical and subtropical ocean areas, while significant differences were found over the extratropical oceans [18]. The three models have an excess in quantity and spread of rainfall over the Northern Atlantic and the Caribbean in DJF, especially the COLA model, however most of this rainfall excess pattern is north of 30N, where the rainfall data is still uncertain. The ECHAM model rainfall pattern in JJA over the Northern Atlantic and the Caribbean reasonably similar to the Xie-Arkin dataset. In the Southern Atlantic CCM and COLA rain too much near the Brazilian Northern coast in JJA. Over the Indian Ocean, all models reproduce the main monsoon features, with the rainfall over the Indian Ocean in DJF and over the Asian continent in JJA. However, there is an excess of rainfall North of Equator and not enough rainfall South of the Equator for the CCM and the COLA model in DJF. The ITCZ (intertropical convergence zone) is present and well defined in the three models, however the pattern is more spread than the observations for both branches and the spectral characteristic of the models lead to a wavelike pattern that does not appear in the data.

### 3.3 Precipitation Variance

In Figs. (13) and (14) the intra-ensemble variance of the precipitation (within the ensemble) for the three models in DJF and JJA are shown. The largest variations occur in the tropics, especially over the ITCZ region. ECHAM has the largest internal standard deviations while CCM has the smallest values in both DJF and JJA. CCM and COLA show larger intra-ensemble variances over the continents than ECHAM especially in the Southern Hemisphere in DJF. The pattern of variability in the ensemble is mostly located in the summer hemisphere reaching the South of the Asian Continent for the three models in JJA.

In Figs. (14),(15),(16) the intra-ensemble, external, and total variance of the precipitation of the three models for DJF are shown. ECHAM4.5 is the model with the largest values of intra-ensemble variance over the ocean, while CCM3.6...
Figure 9: DJF mean precipitation difference between (a) CCM and UEA, (b) ECHAM and UEA, (c) COLA and UEA.
Figure 10: JJA mean precipitation difference between (a) CCM and UEA, (b) ECHAM and UEA, (c) COLA and UEA.
Figure 11: DJF mean precipitation for the AGCM models (a) CCM, (b) ECHAM, (c) COLA and (d) Xie-Arkin data.
Figure 12: JJA mean precipitation for the AGCM models (a) CCM, (b) ECHAM, (c) COLA and (d) Xie-Arkin data.
has the smallest intra-ensemble variance over the ocean. Over land though, COLA is the model with the largest intra-ensemble variance. The three models have a large external variance over the Pacific Ocean due to the ENSO signal, as expected. COLA has a large external variance over the Indian Ocean too, besides in coastal regions (northwestern Australia, Mexico east coast) large values of variance appear, that are not present in the other two models. The external variance over land also reaches large values for the COLA model. The total variance of the both ECHAM and COLA are large over the Pacific and Indian Oceans, while the CCM has a pattern that is more similar to the Xie-Arkin dataset. Over land ECHAM is the model with a total variance most similar in pattern and values to the Xie-Arkin dataset.

3.4 Correlation of Models and Observed Precipitation Anomalies

Figs. (17) and (18) show the correlation of the anomalous precipitation of the models with the UEA precipitation data [10, 11] in DJF and JJA, respectively. The three models have the largest values of correlation at the tropics, for both seasons. Northern South America, the Caribbean, the West Africa coast and Indonesia are the tropical regions where most skill is found. Alaska and the West Coast of North America are regions that all the models have skill, especially in DJF. Asia is the region with the least skill for the three models, with many parts presenting negative skill for the three models in both seasons.

Table 2 shows the area averaged correlation values of the anomalous precipitation. As expected, the correlation values for the anomalous precipitation are much lower than for the anomalous temperature (table 1) and in all continents the area average values are below the minimum for significance at 90% of significance. The ECHAM model has area averaged correlation values much higher than CCM and COLA for the precipitation, globally and in most regions in both seasons. Globally, ECHAM has a larger correlation in JJA than in DJF, while COLA and CCM have largest values occur in DJF. The region with largest correlation values for all the models is South America, while in Asia all the models have their smallest values, having even a negative area average correlation in JJA, for CCM and COLA. ECHAM correlation values for Europe are much higher than those of the other two models. In Asia and North America, CCM and COLA have different correlation values in these between the seasons, much larger than in JJA, while ECHAM show much more comparable correlation values in these regions.
Figure 13: JJA precipitation intra-ensemble variance for (a) CCM, (b) ECHAM, and (c) COLA.
Figure 14: DJF precipitation intra-ensemble variance for (a) CCM, (b) ECHAM, and (c) COLA.
Figure 15: DJF precipitation external variance in the ensemble for (a) CCM, (b) ECHAM, and (c) COLA.
Figure 16: DJF precipitation total variance for (a) CCM, (b) ECHAM, (c) COLA, (d) Xie-Aarkin dataset.
Figure 17: DJF anomalous precipitation correlation with UEA observational data with (a) CCM, (b) ECHAM, (c) COLA.
Figure 18: JJA anomalous precipitation correlation with UEA observational data with (a) CCM, (b) ECHAM, (c) COLA.
for both seasons.

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Table 2: Area averaged simulation skill of the CCM3.6, ECHAM4.5 and COLA models for DJF and JJA, expressed as a temporal correlation (x100) of the precipitation anomalies of the models and UEA data. Only correlations larger than 0.426 (DJF) or 0.412 (JJA) are significant (90% level of confidence).

### 3.5 Signal to noise ratio of precipitation anomalies

In Figs. (19) and (20), the intra-ensemble standard deviation and the absolute value of the mean anomalies for the models are shown for North America and South America, respectively, for the winter 82-83 (December 1982, January, February 83). The three models have large values of the standard deviation on both coasts of North America and these are in larger than those of the absolute precipitation anomaly, indicating a very weak ratio of signal to noise for the models in North America. ECHAM though has a ratio of signal to noise stronger in California and Florida than in the rest of the North America. The three models have stronger ratio of signal to noise in South America than in North America, in particular in the Northern region of South America, with all the models having very strong ratios of signal to noise in Northeast Brazil.

### 3.6 Precipitation Anomalies Probability Distribution Function

The probability distribution of the precipitation anomaly for two regions: Northeast Brazil (43W-36W, 8S-4S) and South Africa (14E-34E, 35S-25S) in their respective rainy seasons, FMAM (February, March, April and May) and DJF, was also analysed. Following [1], we used the binned probability ensemble technique.
Figure 19: Intra-ensemble standard deviation from precipitation anomaly (a) C-CM, (c) ECHAM, (e) COLA and absolute precipitation anomaly (b) CCM, (d) ECHAM, (f) COLA for the winter 82/83 (D82JF83).
Figure 20: Intra-ensemble standard deviation from precipitation anomaly (a) CCM, (c) ECHAM, (e) COLA and absolute precipitation anomaly (b) CCM, (d) ECHAM, (f) COLA for the winter 82/83 (D82JF83).
These two regions have reasonable skill for the three models in these regions in their rainy seasons, as shown in Figs. (21), (22).

3.6.1 Distribution of Individual Ensemble Members Precipitation Anomalies

Figs. (23) and (24) show the range of values the individual ensemble members of the precipitation anomaly and where the observations fall relative to that range for Northeast Brazil (FMAM) and South Africa (DJF), respectively. The seasonal precipitation anomaly averaged in each area is calculated for each of the ensemble members (open blue dots) and the ensemble mean (green dots) of the three models, besides the UEA observational data (red crosses). The three models show a larger spread within the ensemble for Northeast Brazil than for South Africa. Comparing the three models, in both regions we can notice that COLA is the model with the largest spread and CCM with the smallest one for NE Brazil in FMAM, and ECHAM having a very small spread for South Africa in DJF. This difference in spread among the models is consistent with the large intra-ensemble variance of the COLA model over land shown in Figs. (14) and (13) for DJF and JJA and that is also true for other seasons. In Fig. (14) it is clear that in DJF ECHAM is the model with the smallest intra-ensemble variance in South Africa. The spread of the individual members of the ensemble of the CCM model is the most similar to the spread of the observations for both regions. The ECHAM model has a spread that is larger than the observations for NE Brazil in FMAM, while the spread of the COLA model has a bias towards dry years for both regions.

3.6.2 Binned Probability Distribution of Precipitation Anomalies

The binned probability distribution function in these two regions was also calculated following [1]. This method evaluates the entire probability distribution, not just the mean or a few low-order moments, it does not give all possible information though, as climatology or a perfect model would have a uniform binned probability distribution. The anomalous precipitation of each grid point for each season in the region considered is sorted by values for all the ensemble members (\(N = 10\)). There is a \(1/N\) probability that the observed anomalous precipitation in that grid point in that season will be in each of the intervals (bins) considered. By doing the same analysis for all the seasons, all ensemble members and all grid points in the chosen regions, we can obtain a binned probability distribution. So instead of using the precipitation anomaly for the whole area, as was used in Figs.
Figure 21: FMAM anomalous precipitation correlation with UEA observational data with (a) CCM, (b) ECHAM, (c) COLA for South America.
Figure 22: DJF anomalous precipitation correlation with UEA observational data with (a) CCM, (b) ECHAM, (c) COLA for Africa.
Figure 23: FMAM anomalous seasonal area average precipitation distribution for (a) CCM, (b) ECHAM, (c) COLA for Northeast Brazil. Blue open dots are the different ensemble members, green dots are the ensemble means for each season and red cross is the UEA seasonal area average.
Figure 24: DJF anomalous seasonal area average precipitation distribution for (a) CCM, (b) ECHAM, (c) COLA for South Africa. Symbols as in Fig. 23.
In this case we consider the precipitation anomaly in each grid point and compare with the observations.

The binned probability distribution of precipitation anomalies for the three models for Northeast Brazil is shown in Fig. (25). In this case, the model with the most uniform probabilistic distribution is the ECHAM4.5, while the COLA and the CCM3.6 models have a large concentration of the population on the two outermost bins, suggesting a lack of variability for these models in Northeast Brazil in FMAM. These models produce either too much or too little precipitation, as is also clear for the COLA model from Fig. (23) for the COLA model. For the CCM model, when the region as a whole is considered (Fig. (23)), the observations in most cases fall inside the model individual members range. In contrast, the ECHAM4.5 has a slight larger concentration on the middle bins, suggesting that this model has a too large intra-ensemble variance, which was also be noticed in Fig. (23). Fig. (26) shows the Binned Probability distribution for South Africa in DJF. In South Africa (DJF) the model with the most uniform binned probability distribution is the COLA model. The ECHAM4.5 has the two outermost bins most heavily populated especially, bin 1, indicating that most times the observed precipitation anomaly is smaller than the smallest ensemble member and that the model has a bias towards wet. The other bin that is heavily populated for ECHAM4.5 is bin 11, the other extreme, indicating that most time the observation anomaly is wetter than the wettest ensemble member. This leads us to conclude that ECHAM4.5 does not have enough variability in South Africa in DJF. This could also be seen in Fig. (24), in which is clear that ECHAM is the model with the smallest intra-ensemble variability. The CCM3.6 presents the lowest bin also heavily populated (too much precipitation in the model) The binned probability distribution of the precipitation anomaly for CCM3.6 is very irregular with too local maxima in intermediate states, besides the outmost smallest bin. This distribution indicates that CCM3.6 has a few “preferred” states in South Africa in DJF, leading to the conclusion of a insufficient variability in this case too. One has to remmber though that we are considering here only 17 years of model integration, so it is plausible that these conclusions could be modified using a larger time sampling for the models.

**3.6.3 Chi-square Test of Precipitation Anomalies**

The chi-square test was then used to determine if the observations are uniformly distributed in the bins and the significance of the chi-square test was then evaluated. When we find a small values of the chi-square significance, this means
Figure 25: Binned probability distribution of anomalous precipitation for (a) C-CM, (b) ECHAM, (c) COLA for Northeast Brazil in FMAM.
Figure 26: Binned probability distribution of anomalous precipitation for (a) C-CM, (b) ECHAM, (c) COLA for South Africa in DJF.
that the distribution of the observations in the bins is significantly different from uniform, leading to the conclusion that the model binned probabilistic distribution is inconsistent with the observations. The chi-square test measures the statistical significance of the difference between the model and observation distributions, but not the strength of this difference [1].

Figs. (27) and (28) show the chi-square test for the anomalous precipitation in DJF and FMAM, respectively for the three models. Grid points which have a chi-square different from a uniform distribution with 90% (99%) significance or more are shaded in yellow (orange), the grid points in green are not significantly different from an uniform distribution. For South Africa in DJF, the ECHAM4.5 has 22% of its grid points which differ from an uniform distribution at the 90% significance level, while the COLA model just has 6% of its grid points different from an uniform distribution. For Northeast Brazil in FMAM the situation is exactly the opposite, with 27% of the grid points of the COLA model different from uniform at the 90% significance level, while none of the ECHAM grid points differ from an uniform distribution at this significance level.

From what we discussed until now, we are led to the conclusion that in order to obtain better skill in a forecast using AGCMs, only a multi-model approach can lead to the best possible forecast, as the different models have such different distributions in different areas in their rainy seasons.

4 Geopotential Heights

The geopotential heights at 500mb for DJF and JJA are shown in Figs. (29) and (30) for the three models and for NCEP Reanalysis data during the same period.

The ECHAM model has a pattern of high values of geopotential heights in the tropics both in DJF and JJA, which is either absent in the other models and NCEP Reanalysis (case of DJF) or has a much smaller spatial extent (case of JJA). The ECHAM model has then in both seasons in most parts of the globe (with the exception of the southern high latitudes) as bias towards high values of the geopotential heights at 500mb, while COLA and CCM have their differences from NCEP Reanalysis mainly restricted to middle and high latitudes with a bias towards low values of the geopotential heights, mainly being displaced towards more equatorial latitudes than the NCEP Reanalysis. The bias of the ECHAM model in the tropics is also present at the 200mb geopotential heights (not shown), the ECHAM model having a wave pattern too strong also at this height in both seasons, while the wave pattern is too weak in the extratropics, as happens with
Figure 27: Chi-square test for the anomalous precipitation binned probability distribution for (a) CCM, (b) ECHAM, (c) COLA for South Africa in DJF. Orange (yellow) grid points differ from an uniform distribution with 99% (90%) significance level, green grid points are not statistically different from an uniform distribution at these levels.
Figure 28: Chi-square test for the anomalous precipitation binned probability distribution for (a) CCM, (b) ECHAM, (c) COLA for the Northeast Brazil in FMAM. Orange (yellow) grid points differ from an uniform distribution with 99% (90%) significance level, green grid points are not statistically different from an uniform distribution at these levels.
CCM and COLA.

Figs. (31) and (32) show the error of the Geopotential Heights at 500mb for the three models compared with the NCEP Reanalysis data [8] for DJF and JJA, respectively. The model error is defined as the difference between the simulated and the observed values at each grid point. The error pattern indicates that the planetary waves were incorrectly simulated by the three GCM models. Large errors can be seen, especially at high latitudes for the three models in both seasons. The heights over the northern high latitudes in DJF and JJA for CCM and COLA is are low, while for the ECHAM model north of 60°N the height values are too high. The error pattern of CCM and COLA are very similar, with geopotential heights in most regions smaller than the observed ones, and the largest magnitude of the errors being at extra-tropical regions (Antarctica, Alaska, and North of the Eurasian Continent). ECHAM, on the other hand, has geopotential heights larger than the observed and the error pattern is also of considerable magnitude in tropical and mid-latitudes regions.

5 Surface Winds

Figs. (33) and (34) show the average seasonal surface winds for DJF and JJA, respectively. The three models have too strong winds on the zonal belt around Antarctica in DJF seasons, especially COLA and CCM. The seasonal shifts of the subtropical anti-cyclones in direction of the pole during the summer are captured by the models. The large seasonal variation of the winds over the Asian continent due to the Asian monsoons are also well described by the models. In the region of the ITCZ in the Pacific, the southeasterly trade winds are too strong in the COLA model for both seasons.

Figs. (35) and (36) show the difference between the models and NCEP Reanalysis surface winds. ECHAM and COLA have more differences from the NCEP Reanalysis winds in the northern hemisphere. The error patterns of CCM and COLA in JJA are very similar, with COLA having a bigger magnitude, while ECHAM has the smallest magnitude of errors. The three models have problems simulating the winds in the tropical Pacific in the northern summer, mainly due to an excess of cross equatorial flow that is not present in the NCEP Reanalysis. In general, the three models have too strong winds in most parts of the globe in the two extreme seasons compared with the NCEP Reanalysis winds.
Figure 29: DJF Geopotential Heights at 500mb for (a) CCM, (b) ECHAM, (c) COLA, (d) NCEP Reanalysis.
Figure 30: JJA Geopotential Heights at 500mb for (a) CCM, (b) ECHAM, (c) COLA, (d) NCEP Reanalysis.
Figure 31: DJF difference of model and NCEP Reanalysis Geopotential Heights at 500mb for (a) CCM, (b) ECHAM, (c) COLA.
Figure 32: JJA difference of model and NCEP Reanalysis Geopotential Heights at 500mb for (a) CCM, (b) ECHAM, (c) COLA.
Figure 33: DJF mean surface winds for the AGCM models (a) CCM, (b) ECHAM, (c) COLA and (d) NCEP Reanalysis data.
Figure 34: JJA mean surface winds for the AGCM models (a) CCM, (b) ECHAM, (c) COLA and (d) NCEP Reanalysis data.
Figure 35: DJF difference of model and NCEP Reanalysis Surface Winds for (a) CCM, (b) ECHAM, (c) COLA.
Figure 36: JJA difference of model and NCEP Reanalysis Surface Winds for (a) CCM, (b) ECHAM, (c) COLA.
6 Wind stress

The mean ensemble wind stress for DJF and JJA for the models and NCEP Reanalysis data is shown in Figs. (37) and (38). As expected, the wind stress patterns are very similar to those of the surface winds. The wind stress is stronger in the winter hemisphere, particularly over the North Atlantic, North Pacific and in the Southern Hemisphere westerly belt. All models capture the strong seasonal changes in the Indian Ocean off the Somali coast due to the Indian monsoon. The three models have zonal wind stress values larger than the NCEP Reanalysis data at midlatitudes, especially COLA. The low windstress values at the tropics are well captured by the three models. The meridional wind stress patterns are very well described by the models, with the exception of COLA, which shows a stronger windstress at the Southern Hemisphere belt (northerly) and the North Atlantic and North Pacific (southerly) than NCEP Reanalysis data in both seasons.

7 Net Heat Flux

The net heat flux at the surface (from the atmosphere to the land/ocean surfaces) for the Northern Hemisphere winter (DJF) and summer (JJA) are shown in Figs. (39) and (40). The models can describe well the main features of the net surface heat flux: positive net heat flux at the summer hemisphere, and negative at the winter hemisphere, larger heat flux gains and losses over the ocean, largest heat flux losses in DJF at the North Pacific east coast, and North Atlantic, but not in the vicinity of the poles. The comparison of the models with data in this case, shows a large difference among the models in relation to NCEP Reanalysis data. COLA model has an extra amount of heat flux in both seasons in the summer Hemisphere between midlatitudes and the pole. In contrast, CCM and ECHAM have a small deficiency of heat flux in the Southern Hemisphere belt in both seasons, particularly for DJF. The values of the surface heat flux near the coastal areas are problematic in all the models, especially COLA, which has much larger values than NCEP Reanalysis. The spectral nature of the models is clear, especially off the west coast of South America, due to the Andes, especially ECHAM in DJF. It is important to mention that when comparing the NCEP Reanalysis heat fluxes to other datasets, e.g. Oberhuber [12] or da Silva [2], there is a large difference among them, so is hard to access the confiability of the heat fluxes in the NCEP Reanalysis dataset, since this dataset is also effectively a model product.
Figure 37: DJF mean windstress for the AGCM models (a) CCM, (b) ECHAM, (c) COLA and (d) NCEP Reanalysis data.
Figure 38: JJA mean windstress for the AGCM models (a) CCM, (b) ECHAM, (c) COLA and (d) NCEP Reanalysis data.
Figure 39: DJF mean net surface heat flux for the AGCM models (a) CCM, (b) ECHAM, (c) COLA and (d) NCEP Reanalysis data.
Figure 40: JJA mean net surface heat flux for the AGCM models (a) CCM, (b) ECHAM, (c) COLA and (d) NCEP Reanalysis data.
8 Correlations with the Nino-3 Index

The near surface temperature and the precipitation correlation with the Nino-3 index was calculated monthly and seasonally (DJF and JJA). The Nino-3 index was obtained using monthly anomalous sea surface temperature from Reynolds [13] in the Pacific from 1979 - 1995, averaged over the latitudes 5S - 5N and longitudes 90W - 150W.

8.1 Monthly Correlation of Temperature with Nino-3

The monthly correlation was calculated in two different ways. First, we calculated the correlation of the monthly index Nino-3 with the anomalous temperature of each integration and then the ensemble mean correlation was obtained, this is shown in Fig. (41). We also performed the calculation, obtaining first the mean anomalous temperature of all the integrations and then calculating the correlation with Nino-3, shown in Fig. (42). By comparing Figs. (41) and (42), we see that by calculating first the ensemble mean anomalous temperature the correlation values increase, as the signal to noise ratio is increased.

All the models show a positive correlation over northern South America, which also appears in the UEA data, however ECHAM shows a negative correlation pattern in southern South America that does not show up in the data. This negative pattern is present in the observations and in other models, when the extreme seasons correlations (DJF) are calculated (see Figs. (43) and (44), but ECHAM carries this correlation to the annual correlation, while the other models and the observational data do not. Over North America, the observed correlation pattern is captured roughly by all the models, with a negative correlation over Mexico and Southern US, a positive correlation over Canada and a negative correlation over Greenland that is very weak for CCM and COLA. In Africa, the observed data has a positive correlation pattern south of the Equator, while CCM and COLA show a positive pattern spread over the whole continent. Over Europe the UEA data show a weak positive correlation, while COLA shows a negative correlation. The three models have a positive correlation over South Asia, in agreement with the UEA data. The eastern Asian continent negative pattern is better described by COLA and ECHAM, while the ECHAM and COLA capture the negative correlation over the Himalaya and the positive anomaly over Central Asia is shown in different degrees in the three models. COLA shows a strong positive correlation over Australia, that does not appear in the data.
Figure 41: Ensemble mean correlation of index Nino-3 with the anomalous near surface temperature for the AGCM models (a) CCM, (b) ECHAM, (c) COLA and (d) UEA data.
Figure 42: Correlation of Nino-3 index with the ensemble mean anomalous near surface temperature for the AGCM models (a) CCM, (b) ECHAM, (c) COLA and (d) UEA data.
### 8.2 Seasonal Correlation of Temperature with Nino-3

Figs. (43) and (44) show the correlation of Nino-3 with the ensemble mean anomalous temperature in the extreme seasons (DJF and JJA). Though most of the correlation pattern in the extreme season is very similar to that for the annual correlation, some characteristics are different. In both seasons, a negative correlation in southern South America is present in the observations, and this also appears in the models. In North America, the correlation pattern in JJA is very different in the models and the observations, where a East/West pattern appears, instead of a North/South pattern, which is present in the three models. In DJF, a negative correlation pattern appears in Northern Africa and Near East, which does not appear in any of the models. The positive correlation in Africa in the models has a much larger spatial extent in both seasons for all the models than occur in reality. The correlation pattern in Europe is not well captured in COLA and ECHAM, with even opposite correlations appearing in the whole continent (COLA), or only in the Baltic coutries (ECHAM in JJA). In contrast CCM has a positive correlation over Europe in JJA.

### 8.3 Seasonal Correlation of Precipitation with Nino-3

Figs. (45) and (46) show the correlation between Nino-3 and the ensemble mean anomalous precipitation for DJF and JJA. In DJF, the three models have a much larger area with negative correlation over North America extending from Alaska than appears in the observations. The positive correlation over southern North America in DJF was well captured by the three models. The northern South America negative correlation is very well described by the models, especially in DJF, while in JJA the models tend to have a smaller negative pattern than the observations. The negative pattern over South Africa for DJF appears well in ECHAM and COLA. In the same region in JJA, while we have an almost neutral correlation for the data, the models range from too wet (ECHAM) to dry (COLA). The observations show in DJF a positive correlation in the northern part of Europe and most of Asia, with exception of Siberia and India. The large positive correlation pattern over central and eastern Europe and Asia is captured by the three models in DJF, but not the details. All models have a positive correlation over India in DJF, while the observations indicate a negative correlation. In JJA, the correlation pattern is much weaker in Central Asia than DJF in the observations, in contrast ECHAM shows a positive correlation. COLA has a strong correlation signal in DJF and JJA over Australia that does not occur in reality, and the same happens
Figure 43: Correlation of Nino-3 index with the ensemble mean anomalous near surface temperature for the AGCM models in DJF (a) CCM, (b) ECHAM, (c) COLA and (d) UEA observational data.
Figure 44: Correlation of Nino-3 index with the ensemble mean anomalous near surface temperature for the AGCM models in JJA (a) CCM, (b) ECHAM, (c) COLA and (d) UEA observational data.
Correlation with Atlantic Dipole

The Atlantic Dipole index was defined following Servain [15]. Using Reynolds monthly anomalous sea surface temperature (SST) [13] from 1979 - 1995, the average anomalous SST for each March - May (MAM) season is obtained. These are then averaged on two boxes North (5N - 30N) and South (20S - 5N) of the Equator from 60W to the African coast. The North and South box values are then normalized by their standard deviation and finally their difference is defined as the Atlantic Dipole Index.
Figure 46: Correlation of Nino-3 index with the ensemble mean anomalous precipitation for the AGCM models in JJA (a) CCM, (b) ECHAM, (c) COLA and (d) UEA observational data.
9.1 Correlation of the Temperature Anomaly with the Atlantic Dipole

Figure (47) shows the correlation of the Atlantic Dipole index with the ensemble mean anomalous temperature in MAM for the observational data and the three models. The three models capture the positive correlation over northern South America, but the pattern is too broad compared with the observed correlation pattern. ECHAM has a strong negative correlation in southern South America that does not appear in the observations. The negative correlation pattern observed over southern North America is clearly defined in the three models. There is a positive correlation pattern over western Africa, both north and south of the Equator, with a negative correlation pattern on the northeast, in the observed correlation. In the three models, the positive correlation is clear, however the pattern is spread over almost all the continent, and the negative correlation does not appear in any of the models.

9.2 Correlation of the Precipitation Anomaly with the Atlantic Dipole

The correlation of the anomalous precipitation and the Atlantic Dipole index in MAM is shown in Fig. (48). The three models show correlation patterns very similar to the observed correlation pattern over most of the Americas, with a positive correlation pattern in Southern US and northern South America, and a negative correlation pattern over Northeast Brazil. The positive correlation pattern over southern South America is too strong in the models, and they do not capture the weak negative pattern around 25S. In Central America the CCM and ECHAM show a negative correlation not present in the observations. Over Africa the observational correlation of the precipitation with the Atlantic Dipole does not show a very strong signal, as occurred in the Americas. The models show very strong patterns that appear only weakly in the observations (positive over the Guinea and the Great Horn, negative over Angola). ECHAM and COLA have positive and negative correlation patterns correctly localized over these regions, but the correlation pattern is too strong and spreads over a region much larger than the observations. CCM has a pattern similar to the other two models, but displaced to the North, and showing a negative correlation over the Guinea region and positive correlation over Angola.
Figure 47: Correlation of Atlantic Dipole index with the ensemble mean anomalous surface temperature for the AGCM models in MAM (a) CCM, (b) ECHAM, (c) COLA and (d) UEA observational data.
Figure 48: Correlation of Atlantic Dipole index with the ensemble mean anomalous precipitation for the AGCM models in MAM (a) CCM, (b) ECHAM, (c) COLA and (d) UEA observational data.
10 Conclusions

In this work, an intercomparison of three AGCMs is performed. The three models capture the general patterns of the atmospheric and surface characteristics in the seasons analysed. However, some regional characteristics are still problematic and need some modelling improvement. It is not possible to point out a model with characteristics outstandingly better than the others, on the contrary, each model has strong and weak points in different regions within different seasons. It is clear that a multi-model approach should lead to a better forecast than any of the current models studied here.
A.1 Definition Intra-ensemble, External and Total Variances

Following [9] and references therein, any variable is defined as $x(n, y)$, where $n$ represents the ensemble member with $N = 10$ being the total number of ensemble members, and $y$ represents the year with $Y = 17$ being the total number of years considered. We can then define two averages: the ensemble mean and the climatological mean. The ensemble mean is defined with the respect to the integration member in the ensemble:

$$x_e(y) = \frac{1}{N} \sum_{n=1}^{N} x(n, y).$$

(1)

The climatological mean is taken to respect to the integrations and years:

$$x_c = \frac{1}{NY} \sum_{n=1}^{N} \sum_{y=1}^{Y} x(n, y) = \frac{1}{Y} \sum_{y=1}^{Y} x_e(y).$$

(2)

The interannual variability signal can be described by the yearly variation in respect to the ensemble mean $x_e(y)$:

$$\sigma_e^2 = \frac{1}{Y} \sum_{y=1}^{Y} [x_e(y) - x_c]^2.$$  

(3)

The variance $\sigma_e^2$ then measures the external, or forced signal. On the other hand, the dispersion within the ensemble members, can be defined as:

$$\sigma_i^2 = \frac{1}{Y} \sum_{y=1}^{Y} \left[ \frac{1}{N} \sum_{n=1}^{N} [x(n, y) - x_e(y)]^2 \right],$$

(4)

which measures the internal model variability. Finally, the total variance, is the sum of the internal and the external variance:

$$\sigma_t^2 = \frac{1}{NY} \sum_{n=1}^{N} \sum_{y=1}^{Y} [x(n, y) - x_c]^2 = \sigma_e^2 + \sigma_i^2.$$  

(5)
References


