The Predictive Skill and the Most Predictable Pattern in the Tropical Atlantic: 
The Effect of ENSO

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ABSTRACT

This work investigates the predictive skill and most predictable pattern in the NCEP Climate Forecast System (CFS) in the tropical Atlantic Ocean. The skill is measured by the sea surface temperature (SST) anomaly correlation between the predictions and the corresponding analyses, and the most predictable patterns are isolated by an empirical orthogonal function analysis with a maximized signal-to-noise ratio. On average, for predictions with initial conditions (ICs) of all months, the predictability of SST is higher in the west than in the east. The highest skill is near the tropical Brazilian coast and in the Caribbean Sea, and the lowest skill occurs in the eastern coast. Seasonally, the skill is higher for predictions with ICs in summer or autumn and lower for those with ICs in spring. The CFS poorly predicts the meridional gradient in the tropical Atlantic Ocean. The superiority of the CFS predictions to the persistence forecasts depends on IC month, region, and lead time. The CFS prediction is generally better than the corresponding persistence forecast when the lead time is longer than 3 months. The most predictable pattern of SST in March has the same sign in almost the whole tropical Atlantic. The corresponding pattern in March is dominated by the same sign for geopotential height at 200 hPa in most of the domain and by significant opposite variation for precipitation between the northwestern tropical North Atlantic and the regions from tropical South America to the southwestern tropical North Atlantic. These predictable signals mainly result from the influence of the El Niño–Southern Oscillation (ENSO). The significant values in the most predictable pattern of precipitation in the regions from tropical South America to the southwestern tropical North Atlantic in March are associated with excessive divergence (convergence) at low (high) levels over these regions in the CFS. For the CFS, the predictive skill in the tropical Atlantic Ocean is largely determined by its ability to predict ENSO. This is due to the strong connection between ENSO and the most predictable patterns in the tropical Atlantic Ocean in the model. The higher predictive skill of tropical North Atlantic SST is consistent with the ability of the CFS to predict ENSO on interseasonal time scales, particularly for the ICs in warm months from March to October. In the southeastern ocean, the systematic warm bias is a crucial factor leading to the low skill in this region.

1. Introduction

Early studies have demonstrated the impact of the tropical Atlantic sea surface temperature (SST) on the climate variability in the surrounding regions, such as the precipitation over northeast Brazil (e.g., Hastenrath and Heller 1977; Moura and Shukla 1981) and sub-
years. However, the analyses of predictability of TAV are few and the predictive ability of current climate models in the tropical Atlantic Ocean is still unclear. Most prediction studies focused on the variability of the North Atlantic Oscillation (e.g., Hu and Huang 2006c) or on the influence of prescribed SST anomalies (SSTA) on the atmosphere. Prediction experiments of Chang et al. (1998) using a regional coupled ocean–atmosphere model of the tropical Atlantic indicated that the SST decadal variability in the subtropics of the northern Atlantic Ocean is predictable several years ahead with modest levels of skill. They suggested that atmosphere–ocean interactions enhance the predictability of low-frequency SST variation beyond the time scale of persistence. They showed that the low-frequency SST variability in the tropical North Atlantic has significant predictability using statistical models at short lead times (less than 1 yr), and using a coupled atmosphere model for long-range forecasts with lead times up to about 3 yr. Using linear inverse modeling, Penland and Matrosova (1998) quantified the predictability of tropical Atlantic SST on seasonal to interannual time scales. They found that predictability of the Caribbean Sea and tropical North Atlantic SSTA is enhanced when using global tropical SSTA as predictors compared with using only the tropical Atlantic Ocean as predictors. This predictability advantage does not carry over into the equatorial and south tropical Atlantic Ocean where persistence becomes a competitive predictor in those regions.

It has been noted previously that TAV is closely linked to the El Niño–Southern Oscillation (ENSO) phenomenon. The global temperature and precipitation response to ENSO have been well documented (e.g., Yulaeva and Wallace 1994; Tourre and White 1995; Chiang and Sobel 2002). In an El Niño year, warming dominates the whole tropical troposphere (Chiang and Sobel 2002). Previous investigations have also demonstrated the impact of ENSO on TAV. For example, Tourre et al. (1985) and Katz (1987) pointed out that tropical Atlantic wind forcing induced by ENSO is linked with equatorial Atlantic warm events. Carton and Huang (1994) showed the dependence of enhanced equatorial Atlantic trade winds during ENSO on variations of the thermocline in the western equatorial Atlantic. Delecluse et al. (1994) suggested that ENSO may force the Atlantic equatorial mode. Enfield and Mayer (1997) indicated that ENSO is a major remote forcing of TAV anomalies. Latif and Grötzner (2000) identified an internal equatorial Atlantic oscillation, which is strongly influenced by ENSO with the equatorial Atlantic SST lagging by about 6 months. Huang et al. (2002) found that the SSTA in the tropical North Atlantic Ocean is substantially affected by ENSO, with enhancement from local coupling in their model. Merkel and Latif (2002) demonstrated a southward shift of the North Atlantic low pressure systems in the winter season during El Niño events. Wang (2002) suggested that an El Niño can affect the tropical North Atlantic through the Walker and Hadley circulations, favoring the tropical North Atlantic warming in the subsequent spring of the El Niño year. Wang (2002) also indicated that the tropical South Atlantic does not significantly correlate with Pacific El Niño. Recently, Tourre and White (2005) examined the space–time evolution of the dominant ENSO signal of SST, upper-ocean heat storage, zonal surface wind, and sea level pressure (SLP) in 3.4–5.7-yr band period in the tropical eastern Pacific–Atlantic domain. They found that slow SST–SLP coupled waves propagate eastward from the eastern Pacific Ocean into the tropical Atlantic Ocean basin at a speed of about 20 cm s$^{-1}$. As a result, a peak signal in the equatorial Atlantic lags that in the eastern equatorial Pacific by 12–18 months. It has also been noted in some previous studies that the influence of ENSO on TAV is seasonally dependent. For example, Huang (2004) showed a distinct progression of the ENSO signals in the tropical Atlantic Ocean from season to season with different mechanisms. During the boreal winter of a maturing El Niño year, a basinwide warming occurs in the tropical Atlantic with a major center in the southern subtropical Atlantic. In following boreal spring, the warming occurs mainly in the northern tropical Atlantic Ocean.

The robustness of these results needs to be further examined, although it is clear that knowledge of the ENSO condition ahead of time would provide reasonable opportunities to predict TAV. These studies have shown promise for TAV predictions. However, there is no consensus regarding how ENSO affects the predictive skill, and what the most predictable pattern in TAV is in a real climate prediction system of a coupled general circulation model (CGCM). This work examines the predictive skill and the most predictable pattern in the tropical Atlantic Ocean in a real climate prediction system. The paper is organized as follows. In section 2, the data and analysis strategy are briefly described. Section 3 examines the predictability of TAV, the dependence on lead month and initial condition (IC) month. Section 4 investigates the most predictable patterns and their connection with ENSO. Section 5 is a summary and gives further discussion.

2. Data and analysis strategy

The predictions, analyzed in this work, were conducted by the National Centers for Environmental Pre-
diction (NCEP) Climate Forecast System (CFS), which cover predictions initialized in all calendar months from 1981 to 2003. In a given start month, 15 predictions of 9-month length from lead month 0 to 8 are produced with different oceanic and atmospheric ICs. The oceanic ICs are chosen as the three Global Ocean Data Assimilation System (GODAS) analyses at the 11th and 21st of lead month 0 and 1st of lead month 1 (Saha et al. 2006). The atmospheric ICs are from the NCEP reanalysis II (Kanamitsu et al. 2002). In addition to the atmospheric ICs at the same time as the oceanic ICs, each of the three oceanic states is also paired with other four atmospheric ICs, namely, those within two days before and after at a daily interval to form a five-member local cluster. Therefore, there are total 15 ocean–atmosphere ICs spread from the ninth of lead month 0 to the third of lead month 1. Details of the ICs are given in Saha et al. (2006) and Huang et al. (2007). The datasets of these monthly mean predictions of the 15 individual members as well as their ensemble mean are available from the NCEP Web site (online at http://nomad6.ncep.noaa.gov/cfs/monthly).

The atmospheric component of the CGCM used to conduct the predictions is a lower-resolution version of the global weather forecast system of NCEP. The horizontal resolution is T62, and there are 64 vertical levels. The subscale physical parameterizations have been modified from the model used to produce the NCEP–National Center for Atmospheric Research (NCAR) reanalysis (Kalnay et al. 1996), as described in Saha et al. (2006). The oceanic component is the Geophysical Fluid Dynamics Laboratory Modular Ocean Model (version 3; Pacanowski and Griffies 1998). The ocean model domain extends across the world oceans from 74°S to 64°N with a horizontal grid of 1° × 1° poleward of 30°S and 30°N and with gradually increased meridional resolution to 1/3° between 10°S and 10°N. The ocean model has 40 levels vertically with 27 of them in the upper 400 m. The atmospheric model is coupled with the oceanic component on a daily basis without flux adjustment or correction. ENSO and its associated features are realistically reproduced by this model in long-term simulations (Wang et al. 2005) and are well captured in predictions.

For the CFS prediction validation, we used the monthly mean data from the NCEP–NCAR reanalysis I and II (Kalnay et al. 1996; Kanamitsu et al. 2002). We also used monthly SST data on a 2° × 2° grid (Reynolds and Marsico 1993; Reynolds and Smith 1994; Reynolds et al. 2002), and precipitation field data on a 2.5° × 2.5° resolution (Xie and Arkin 1996, 1997). The SST dataset is the second version of the optimally interpolated (OI) SST dataset (Reynolds and Marsico 1993; Reynolds and Smith 1994; Reynolds et al. 2002). This SST dataset is referred to as OIv2-analyzed SST in the following text. The precipitation fields are a combination of satellite retrievals, in situ rain gauge stations, and atmospheric model products (Xie and Arkin 1996, 1997). All the data used this work span the period from January 1981 to December 2004, except that OIv2-analyzed SST are from November 1981 to December 2004. We first examine the evolution of averaged SST predictability and signal-to-noise ratio of SST variance as a function of lead time and also the predictability for some typical regional mean SST indices. The most predictable patterns of SST, geopotential height at 200 hPa (H200), and precipitation, as well as the effect of ENSO on these patterns, are investigated. The predictable patterns are isolated by applying an empirical orthogonal function (EOF) analysis with maximized signal-to-noise ratio (MSN EOF hereafter) to the predicted time series of 1981–2003 with given lead time of the predictions.

The MSN EOF is a method to derive patterns that optimize the signal-to-noise ratio from all ensemble members. This approach was developed by Allen and Smith (1997) and discussed in Venzke et al. (1999). It has also been used by Sutton et al. (2000), Chang et al. (2000), and Huang (2004) in extracting the dominant MSN EOF patterns in ensemble GCM integrations. This method minimizes the effects of noise in a moderate ensemble size. An ensemble mean is supposedly composed of a forced and a random part, which may be attributed, respectively, to the prescribed external boundary conditions and the unpredictable internal noise. In our case, the forced part is associated with the predictable signals, which show certain consistency among different members of the ensemble predictions because of the memories contained in the ICs. The leading MSN EOF mode is the one with the maximum ratio of the variance of the ensemble mean to the deviations among the ensemble members. In this work, we only analyze the leading MSN EOF mode, which is defined as the most predictable pattern and is significant at the 95% level using an F test. Details of this method were documented in Allen and Smith (1997), Venzke et al. (1999), and Huang (2004).

3. Predictability of TAV

In this section, we analyze the evolution of the CFS predictive skill as a function of lead time and its variation with region in the tropical Atlantic Ocean. The predictive skill is defined as the correlation between the CFS-predicted and OIv2-analyzed SST. The predictive
The correlations between CFS-predicted and OIv2-analyzed SST in the tropical Atlantic Ocean vary with regions and lead time (left column of Fig. 1). In a 1-month lead, the correlations between the predictions and analyses are generally larger than 0.5. The predictions in the current work are the ensemble mean of 15 individual prediction members. Beyond 5-month lead, the correlations are below 0.5 in most regions of the domain, except for some areas in the western ocean. Spatially, the SST predictive skill of CFS is higher in the west than in the east. The highest predictive skill is near the tropical Brazilian coast and in the Caribbean Sea, and the lowest skill occurs in the eastern coast and in the regions near the northern and southern boundary of the domain. As we will see later, the higher skill in the west is associated with a stronger ENSO influence there. In contrast to that ENSO is the major source of predictability of TAV in CFS; the model systematic error is one of the factors that limits the model predictive skill. For example, the large positive SST bias in the southeastern Atlantic (Fig. 2) may modify the west–east SST gradient and change the trade winds in the region. This affects the atmosphere–ocean interaction features in this region.

On average, the correlation patterns of the CFS prediction (left column of Fig. 1) are similar to those of persistence forecast of SSTA (middle column of Fig. 1). The correlations of persistence forecast are larger than those of the CFS prediction when the lead time is less than 3 months (right column of Fig. 1). The CFS prediction is superior to the persistence forecast in most regions of the tropical Atlantic when the lead time is beyond 3 months (see right column of Fig. 1), although the differences of the corrections are small between the CFS prediction and the persistence forecast. The superiority of the CFS prediction to the persistence forecast grows when the lead month increases.

The features of the spatial and temporal evolution of the predictability of TAV in Fig. 1 are elucidated by examining the predictability of some indices that characterize TAV. Following Servain (1991), the TB index is the averaged SSTA from 20°S to 30°N; the NB index represents the averaged SSTA in the north (5°–28°N), the SB index expresses the averaged SSTA in the south (20°S–5°N), and the dipole index is defined as NB–SB. The correlations between the CFS-predicted and analyzed indices are shown in the left column of Fig. 3, the corresponding ones for the persistence forecast are shown in the middle column, and the right column is the difference. The predictability is the largest for the TB index (Fig. 3a) and the smallest for the dipole index (Fig. 3d). The predictability of the NB and SB indices is in between. This result suggests that although CFS is successful in predicting the basinwide fluctuation, the predictions of the anomalous meridional SST gradients are relatively poor. Figure 3 shows that the predictive skill is dependent on when the predictions are initiated. The predictive skill is highest when ICs are in boreal spring and summer for the TB index (Fig. 3a) and the SB index (Fig. 3c), from boreal summer to winter for the NB index (Fig. 3b), and in boreal spring and early summer for the dipole index (Fig. 3d). The dependence of the skill on the season for the NB and SB indices may imply that the skill is generally higher for prediction with ICs in a cold season than in a warm season.

Although the correlation patterns are different between the CFS prediction and persistence forecast, and also vary with the indices, there are some similarities in the differences of the predictive skill between the CFS prediction and persistence forecast (right column of Fig. 3). When the lead is less (greater) than 3 months, the CFS prediction is worse (better) than the persistence forecast. The superiority of the CFS prediction to the persistence forecast enlarges with increase of the lead month. That is consistent with Fig. 1 (right column). For the dipole index, mainly because of the very low persistence, the predictability difference of the dipole index between the CFS prediction and persistence forecast is high when ICs are in boreal spring and early summer, although the correlation between the CFS predicted and analyzed dipole index is small. It is shown in Fig. 3 that persistence beats the CFS skill in the first three months. This is probably because the SST from the forecast IC are different than the verifying SST analysis; it probably would not happen if the NCEP GODAS (Behringer et al. 1998; Behringer and Xue 2004) SST analysis were used as verifying dataset. Therefore, there is room for improving the forecast skill in the first three months by improving the ocean initialization. After all, it is interesting to note that high predictive skill up to 8 months can be achieved for those indices. In the next section, we will identify the source of this high predictability.

The decay of the correlation between the CFS-predicted and OIv2-analyzed SST (left columns of Figs. 1 and 3) with lead time is also demonstrated by the decline in the ratio of the CFS-predicted signal-to-RMS

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Fig. 1. Correlations between (left) OIv2-analyzed and predicted SST anomalies, (middle) persistence correlations of OIv2-analyzed SST anomalies, and (right) the differences at different lead months for all ICs in 1981–2003. The contour interval is 0.1, and the shading represents values greater than 0.5 or less than 0.3 in the left and middle columns, and positive values in the right column.
Mean Errors of SST (Predicted–Observed) (All ICs, 1981–2003)

Fig. 2. Mean errors of SST (predicted–Olv2 analyzed) for all ICs in different lead months. The contour interval is 0.4°C, and the shading is for values greater than 0.4°C or less than −0.4°C.
Fig. 3. Correlations of regional mean SST indices between (left) OIv2-analyzed and predicted, (middle) persistence correlations of OIv2-analyzed anomalies, and (right) the differences at different lead months and all ICs for 1981–2003 in the Atlantic. (a) TB (SST averaged in 20°S–30°N), (b) NB (SST averaged in 5°–28°N), (c) SB (SST averaged in 20°S–5°N), and (d) dipole (NB–SB) indices. The contour interval is 0.1, and the shading represents values greater than 0.7 or less than 0.5 in the left and central columns, and positive values in the right column. The small black squares in the left and right columns of (a) are the target month of March in the following analyses.
error. The ratio is calculated as the standard deviation (std dev) of the OIv2-analyzed SST multiplying the correlation between the CFS ensemble mean and the analyzed SST then divided by the RMS error. Figure 4a (first row) is an example, showing the predicted signal-to-RMS error ratios of SST in March with 0- (left panel), 4- (middle panel), and 8-month (right panel) leads. It is noted that almost all the ratios are positive, consistent with the positive correlation between the CFS-predicted and the analyzed SST (see left column of Fig. 1 for the situation of the tropical Atlantic and all ICs). The ratio is generally smaller than 1 without maximum center in the tropical central and eastern Pacific, resulting from a similar distribution of RMS error (Fig. 4d) and the std dev of the forecast ensemble mean (Fig. 4e) with a maximum center in the tropical central and eastern Pacific. Except for some regions in the southeastern oceans, the similar spatial distribution patterns of Figs. 4d and 4e, particularly in the tropical Pacific, may suggest that CFS RMS error evolves similarly to that of the std dev of the forecast ensemble mean. Because the amplitudes in Fig. 4d are slightly larger than that in Fig. 4e and the correlation between CFS ensemble mean and the analyzed SST is less than 1.0, the ratio of the CFS-predicted signal-to-RMS error is smaller than 1.0.

The evolution pattern of the ratio of the predicted signal to ensemble noise (Fig. 4a) is different from that of the signal-to-noise ratio (Fig. 4b), in both the spatial pattern and amplitudes. The ensemble signal and noise are calculated following Rowell et al. (1995). The ratio is a measurement for the skill and spread relationship in the model. Figure 4b shows a clear maximum center in the tropical central and eastern Pacific, indicating that the CFS ensemble spread (noise) is smaller than the signal (std dev of forecast ensemble mean) in these regions. From Figs. 4c and 4d, we see that the model ensemble noise and the RMS error are largest in the 4-month lead prediction and smallest in the 0-month lead prediction, and also the RMS error is larger than the model ensemble noise. Thus, the decline of the model signal-to-noise ratio in Fig. 4b may be mainly due to the decrease of the signal, suggesting that the decline of the CFS predictive skill is mainly due to the decrease of the signal instead of the increase of the ensemble spread (noise). In addition, the evolution of the RMS error in the southeastern Atlantic is consistent with the result of Huang et al. (2007). They found that the error of the CFS prediction in the southeastern tropical Atlantic grows much faster for the prediction starting in boreal summer and autumn than that starting in late winter and spring.

4. The most predictable patterns of TAV and the effect of ENSO

In this section, the most predictable patterns in the tropical Atlantic Ocean are extracted by applying MSN EOF, and the effect of ENSO on these patterns is examined. In this section, March is chosen as the targeted month for the most predictable pattern study, since it is the month with largest variability and strongest lag relation between ENSO and TAV (Tourre and White 2005). Anomalous atmospheric circulation patterns over the north tropical Atlantic are phase locked to the seasonal circle, and boreal spring is the season having the strongest signal of out-phase variation between the northern and southern tropical Atlantic (Nobre and Shukla 1996). Moreover, for the target month in March, on average in the tropical Atlantic, there are the highest correlations between the CFS predictions and the OIv2 analyses (see the small black squares in the left panel of Fig. 3a), and also the superiority of the CFS prediction to the persistence forecast is generally larger for March than for any other target months, except for ICs in January, February, and March (see the small black squares in the right panel of Fig. 3a). Separating calculations indicate that the most predictable pattern is generally similar for different target months (not shown), implying independence of the results to the target month. The MSN EOF is calculated in this work based on forecast ensemble mean and forecast ensemble spread. It should be noticed that each member in an ensemble prediction is treated equally in the MSN EOF calculation. This means that there is no consideration given to the fact that some members are better predictions than others.

a. The most predictable pattern of SST

Figure 5 shows the first mode of MSN EOF (MSN EOF1) of SST in the tropical Atlantic Ocean for (a) a March IC at a 0-month lead, (b) a November IC at a 4-month lead, and (c) a July IC at an 8-month lead. It should be pointed out that the predicted anomalies are the ensemble mean, which are calculated with respect to different monthly climatology means for the two periods 1981–90 and 1991–2003 to remove the influence of the systematically warm bias in CFS during 1981–90 (Peng et al. 2005). It has been found that the warm bias was caused by a coding problem, which results in about 0.5°C warmer on average in 1981–90 than in 1991–2003 in the tropical and subtropical SST of the GODAS ocean analysis. Its impact on the CFS is a discontinuity of the tropical SSTA prediction, which was systematically warmer in 1981–90 than in 1991–2003. It is rea-
Fig. 4. (a) Predicted signal-to-RMS error, (b) signal-to-ensemble noise ratio of standard deviation, (c) CFS ensemble noise, (d) CFS RMS error, and (e) the standard deviation of forecast ensemble mean for March SST averaged over 1981–2003. (left) 0-month lead and the March IC; (middle) 4-month lead and the November IC; and (right) 8-month lead and the July IC. The contour interval is (a) 0.3, (b) 0.5, (c) 0.25°C, and (d), (e) 0.5°C. The shading represents values greater than (a) 0.6, (b) 1.0, (c) 0.5°C, and (d), (e) 1.0°C.
Fig. 5. (left) Time series and (right) spatial patterns of MSN EOF1 of March SST: (a) 0-month lead and the March IC, (b) 4-month lead and the November IC, and (c) 8-month lead and the July IC. The contour interval is 0.2, the zero lines are omitted, and the shading is for values greater than 0.2 or less than −0.2 for the spatial patterns. The real magnitude of the SST anomalies (°C) can be restored by multiplying the values in the spatial patterns with the corresponding time series. The percentage of the explained variance for the ensemble mean anomalies is indicated in each panel.
sonable and necessary to compare the predictions with the corresponding GODAS data, which were used to make the predictions.

There are obvious similarities among the leading modes derived from different leads for both the patterns and time series (Fig. 5). The percentages of the variance of the ensemble mean SSTA explained by the MSN EOF1 are 45%, 46%, and 50% in Figs. 5a, 5b, and 5c, respectively. In general, positive values dominate most of the domain with some negative signals existing in the northwestern corner of the domain (Fig. 5). It is interesting to note that the MSN EOF1 for the July IC is the only one that has a maximum in the Gulf of Guinea (Fig. 5c), which may be due to the relatively small ensemble noise in this region (see right panel of Fig. 4c). For the time series, large positive values correspond to El Niño years, such as 1983, 1988, 1998, and 2003, and large negative values generally correspond to La Niña years, such as 1989 and 1999–2001. This result is consistent with the ENSO influence on TAV indicated by previous studies mentioned in the introduction [e.g., Wang (2002), Chiang and Sobel (2002), etc.]. However, the relationship between ENSO and the MSN EOF1 mode does not always hold for all warm and cold years of ENSO. The relationship is more representative for strong ENSO years, such as 1983, 1998, and 1989, than for weak ENSO years. For instance, 1992 is distinct in that it has a little warming in the tropical Atlantic in boreal spring in 0- (Fig. 5a) and 4-month (Fig. 5b) lead predictions and a substantial warming in 8-month lead predictions. The complicated relationship between ENSO and the most predictable patterns may be because ENSO is just one of the factors affecting TAV.

The relationship between the most predictable patterns of TAV and global SST is demonstrated by calculating the regressions of the CFS-predicted (left column) and OIv2-analyzed (right column) global SST onto the time series of MSN EOF1 with the November IC at 4-month leads (Fig. 6). It is seen that the general regression patterns for CFS-predicted (left column) and OIv2-analyzed (right column) SST are similar, particularly in the Pacific and Indian Oceans, although the regressions are stronger and more significant in the former. The regressions in the Pacific are dominated by ENSO in both the predicted and OIv2-analyzed SST. That suggests that ENSO, both in the real world and in the model, is related to the TAV predictability. For the predicted SST, there are little changes for the connection between the most predictable patterns of TAV and ENSO from preceding December until April (left column of Figs. 6a–d). This is consistent with the simultaneous correlations between the time series in Fig. 5 and the corresponding Niño-3.4 index in the predictions (see the second row in Table 1). However, for the OIv2-analyzed SST, the strongest regressions occur in the preceding December (right panel of Fig. 6a); then the regressions are weakened continuously in the following months (right panels of Figs. 6b–e). From the regressions in Fig. 6, we also note that the association of the most predictable patterns of TAV with the predicted SST variations in the tropical Indian Ocean is similar to but stronger than the association with the OIv2-analyzed SST.

In the Atlantic, the differences of the regressions for using the predicted and OIv2-analyzed SST are clear, particularly in the South Atlantic. In the preceding December (Fig. 6a), the significant signals are confined to the equatorial and South Atlantic for the predicted SST, but there are almost no significant regressions for the OIv2-analyzed SST. In the following months (Figs. 6b–e), the significant regressions occupy the whole tropical Atlantic for the predicted SST. In contrast, the significant regressions mainly exist in some regions of the subtropical North Atlantic for the OIv2-analyzed SST. The area with significant regressions in the tropical Atlantic Ocean reaches its maximum in simultaneous and 1-month-lag regressions for both the OIv2-analyzed and predicted SST (Figs. 6c,d). After that the regression in the tropical Atlantic Ocean weakens with a reduced area of significance (Fig. 6e).

Besides the differences of the regressions between the predicted and OIv2-analyzed SST in Fig. 6, the differences are also seen between the most predictable patterns in Fig. 5 and the regression patterns with the OIv2-analyzed SST in the Atlantic in Fig. 6 (right column), particularly for the southeastern tropical Atlantic Ocean. In contrast to the most predictable pattern with an almost whole domain positive values (Fig. 5), which is similar to the regression patterns using the predicted SST (left column of Fig. 6), for the regressions using the OIv2-analyzed SST (right column of Fig. 6), the significant positive signals are mainly in the tropical North Atlantic and the regression has little significance in the South Atlantic. The discrepancy between the CFS predictions and the OIv2 analyses may reflect a flaw in the prediction system; that is, although the Atlantic meridional SST gradient is influenced by ENSO in reality, the ENSO response in the CFS in the Atlantic sector suggests a symmetric mode with respect to the equator. This is consistent with the evidence indicated in the previous section that the model is unable to predict the meridional gradient (dipole index) very well. This distinction may impact the atmospheric cir-
FIG. 6. (left) CFS-predicted and (right) OIv2-analyzed SST regression onto SST MSN EOF1 time series for a 4-month lead and November IC (Fig. 5b) at different leading and lagging months. The contour interval is 1.0°C per std dev of the MSN EOF1 time series, the zero lines are omitted, and the shading is for significant regression at the 95% level.
calculation over the Atlantic. The possible reasons for the differences will be further discussed in next section.

To further analyze the relationship between the most predictable pattern of TAV and ENSO, Fig. 7 shows the simultaneous regressions of global SST, H200, and total precipitation in the tropical Atlantic Ocean onto the Niño-3.4 index in March by using reanalysis and other observational data. The regression patterns in Fig. 7a are almost identical to Fig. 11 of Chiang and Sobel (2002). The basic features in Fig. 7a are also similar to that in Fig. 6c with the OIv2-analyzed SST, confirming the connection between the most predictable pattern of TAV and ENSO. The major difference between Figs. 7a and 6c (right panel) is that the regressions in the Atlantic are more significant in Fig. 6c (right panel) than in Fig. 7a.

b. The most predictable patterns of H200 and precipitation

The simultaneous regression pattern of H200 onto Niño-3.4 (Fig. 7b) is similar to the MSN EOF1 of H200 (Fig. 8). The percentages of the variance of the ensemble mean H200 anomalies explained by the MSN EOF1 are 68%, 82%, and 70% in Figs. 8a, 8b, and 8c, respectively. Both Figs. 7b and 8 are dominated by positive values symmetric about the equator, implying that the model reproduces this symmetric response to ENSO in the upper atmosphere quite realistically. This result seems to tell a quite different story from the SST; that is, that the upper-atmospheric response to ENSO is symmetric about the equator in the Atlantic sector. This is consistent with the previous finding of Yulaeva and Wallace (1994) based on the temperature in the upper atmosphere. They showed that warming (cooling) in the tropical Atlantic Ocean and the tropical Pacific corresponds to positive (negative) H200 over the Tropics.

The spatial pattern and time series of MSN EOF1 of total precipitation are shown in Fig. 9. The percentages of the variance of the ensemble mean total precipitation anomalies explained by the MSN EOF1 are 45%, 44%, and 60% in Figs. 9a, 9b, and 9c, respectively. There are clear differences between the spatial patterns (Fig. 9) and the simultaneous regression pattern of analyzed total precipitation onto Niño-3.4 (Fig. 7c). The main differences are in the tropical Americas and the tropical western Atlantic. The regression value in this region is small (Fig. 7c) and strong negative values dominate this region for the most predictable pattern (Fig. 9). The negative regression is confined to the northeastern coast of Brazil (Fig. 7c), but in the model the negative is shifted northward and the area with negative regressions is enlarged (Fig. 9). The patterns of Figs. 7c and 9 agree in showing positive and significant values along the equatorial eastern Pacific and around the Caribbean Sea and the Gulf of Mexico, which implies that the rainfall variation in these regions may be associated with ENSO. The regression pattern is similar when calculating the regressions of the analyzed precipitation onto Niño-3.4 or onto the time series of MSN EOF1 (Figs. 7c, 10a). It is also the case when using the CFS-predicted precipitation (Figs. 9, 10b). However, the clear difference is seen in the regression between using the analyzed (Figs. 7c, 10a) and predicted precipitation (Figs. 9, 10b).

Comparing with Figs. 7c and 10a, we found that the CFS overestimates the contrast of precipitation between regions from tropical South America to the tropical southwestern North Atlantic and the tropical eastern Pacific (Figs. 9, 10b). The overestimation of the contrast of the precipitation variation (Figs. 9, 10b) is associated with too-strong divergence and convergence in the CFS. On average, the CFS has excessive divergence (convergence) at low (high) levels over the region from tropical South America to the tropical southwestern North Atlantic and excessive convergence (divergence) at low (high) levels in the tropical eastern Pacific (Figs. 10d,f), compared with the corresponding fields from the reanalyses data (Figs. 10c,e). It seems that the influence of ENSO on the tropical Atlantic precipitation is overestimated and misplaced.

The large values in the time series of Figs. 8 and 9 are connected with ENSO. This is consistent with the high correlation between the time series and the Niño-3.4 index in the prediction (third and fourth rows of Table 1). However, it is interesting to note that the correlation is insignificant at the 95% level between the time series of MSN EOF1 of SST (Fig. 5a) and that of precipitation

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**Table 1.** Simultaneous correlations between the predicted Niño-3.4 index and the MSN EOF1 time series in Figs. 5, 8, and 9. Correlations are significant at the 95% level using a Student’s *t* test, when it is larger than 0.41.

<table>
<thead>
<tr>
<th>Indices</th>
<th>Mar IC, 0-month lead</th>
<th>Nov IC, 4-month lead</th>
<th>Jul IC, 8-month lead</th>
</tr>
</thead>
<tbody>
<tr>
<td>Niño-3.4 and SST MSN EOF1</td>
<td>0.41</td>
<td>0.76</td>
<td>0.92</td>
</tr>
<tr>
<td>Niño-3.4 and H200 MSN EOF1</td>
<td>0.84</td>
<td>0.90</td>
<td>0.92</td>
</tr>
<tr>
<td>Niño-3.4 and precipitation MSN EOF1</td>
<td>0.86</td>
<td>0.95</td>
<td>0.89</td>
</tr>
</tbody>
</table>
(Fig. 9a) for the predictions of the March IC at 0-month lead (third row of Table 2). The simultaneous correlation between the predicted Niño-3.4 index and the time series of MSN EOF1 of SST for the predictions of the March IC at 0-month lead (Fig. 5a) is only marginally significant at the 95% level (second row of Table 1). The low correlations for the predictions in 0-month lead may be a symptom of a nonbalanced initialization in the model. From Table 2, we also note that the correlations between the model most predictable patterns
in different fields generally grow with lead months. This suggests an increase of the ENSO contribution to the ensemble mean anomalies with lead time. This is confirmed by the general increase of the correlations between the Niño-3.4 index and the model most predictable patterns with lead time (Table 1). This interesting phenomena may be explained as follows: the model usually produces more partitions unrelated to ICs for

![Diagram](image)

**Fig. 8.** Same as in Fig. 5, but for H200. The contour interval is 1, the zero lines are omitted, and the shading is for values greater than 4 or less than 0 for the spatial patterns. The real magnitude of the H200 anomalies (gpm) can be restored by multiplying the values in the spatial patterns with the corresponding time series. The percentage of the variance of the ensemble mean anomalies explained by the MSN EOF1 is given in each panel.
the prediction with a longer lead time. The IC-unrelated partition will be largely erased by averaging the members in the ensemble. As a result, the ENSO-related signal becomes more dominant in the prediction with a longer lead time.

5. Summary and discussion

This work investigates the predictive skill and most predictable pattern in the CFS in the tropical Atlantic Ocean. The skill is measured by SSTA correlation be-
Simultaneous Regression onto MSN EOF1 March Precipitation
(CFS: Nov. IC; Lead=4Mon; 1981–2003; Shading: 95% F-test)
(Contour: mm/day/STDV for Precip and $10^{(-6)}$/s/STDV for div)

(a) Xie–Arkin Precip
(b) CFS Predicted Precip
(c) NCEP/NCAR 200 hPa Div
(d) CFS Predicted 200 hPa Div
(e) NCEP/NCAR 850 hPa Div
(f) CFS Predicted 850 hPa Div

Fig. 10. Simultaneous regression on the time series in Fig. 9b. (a) Xie–Arkin precipitation, (b) CFS-predicted ensemble mean precipitation, (c), (d) divergence at 200 and 850 hPa, respectively, of NCEP–NCAR reanalysis data, and (e), (f) divergence at 200 and 850 hPa, respectively, of CFS-predicted ensemble means. The contour interval is 4 mm day$^{-1}$ per std dev of the time series for precipitation and $3 \times 10^{-6}$ s$^{-1}$ per std dev for divergence at 200 hPa and $2 \times 10^{-6}$ s$^{-1}$ for divergence at 850 hPa, the zero lines are omitted, and the shading is for significant regression at the 95% level.
between the predictions and the corresponding analyses, and the most predictable patterns are isolated by an EOF analysis with maximized signal-to-noise ratio. On average, for the predictions with ICs of all months, the predictability of SST is higher in the west than in the east. The highest skill is near the tropical Brazilian coast and in the Caribbean Sea, and the lowest skill occurs in the eastern coast. Seasonally, the skill is higher for predictions with ICs in summer or autumn and lower for those with ICs in spring. CFS poorly predicts the meridional gradient in the tropical Atlantic Ocean. The superiority of the CFS predictions to the persistence forecasts depends on the IC month, region, and lead time. The CFS prediction is generally better than the corresponding persistence forecast when the lead time is longer than 3 months. The most predictable pattern of SST in March has the same sign in almost the whole tropical Atlantic. The corresponding pattern in March is dominated by the same sign for geopotential height at 200 hPa in most of the domain and by significant opposite variation for precipitation between the northwestern tropical North Atlantic and the regions from tropical South America to the southwestern tropical North Atlantic. These predictable signals mainly result from the influence of ENSO. The significant values in the most predictable pattern of precipitation in the regions from tropical South America to the southwestern tropical North Atlantic in March are associated with excessive divergence (convergence) at low (high) levels over these regions in CFS.

The predictive skill of the CFS in the tropical Atlantic Ocean is largely determined by its ability to predict ENSO. This is because of the strong connection between ENSO and the most predictable patterns in the tropical Atlantic Ocean in this model. Fortunately, the CFS predictions for ENSO are quite skillful on interseasonal time scales (Fig. 11). On average, the CFS prediction is better than the persistence forecast beyond a 1-month lead, particularly for the ICs from January to July.

The warm bias in the southeastern Atlantic (Fig. 2) may also lead to excessive atmosphere convection in the model. According to Chiang and Sobel (2002), the existence of atmospheric convection is crucial for temperature variations to propagate from the troposphere to the surface. This is confirmed by the zonal and vertical cross section averaged between 12°S and 8°S for temperature regression onto the time series of MSN EOF1 of precipitation (Fig. 12). The figure shows that the precipitation pattern in Fig. 9b is associated with temperature variations at all levels over the tropical southeastern Atlantic in CFS (Fig. 12b). In contrast, in the reanalysis data, the association over the tropical southeastern Atlantic is constricted to the upper tropo-

### Table 2. Simultaneous correlations among the MSN EOF1 time series in Figs. 5, 8, and 9. Correlation is significant at the 95% level using a Student's t test, when it is larger than 0.41. Insignificant correlations are in italics.

<table>
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<th>Jul IC, 8-month lead</th>
</tr>
</thead>
<tbody>
<tr>
<td>SST and H200</td>
<td>0.64</td>
<td>0.93</td>
<td>0.98</td>
</tr>
<tr>
<td>SST and precipitation</td>
<td>0.20</td>
<td>0.78</td>
<td>0.86</td>
</tr>
<tr>
<td>H200 and precipitation</td>
<td>0.84</td>
<td>0.94</td>
<td>0.86</td>
</tr>
</tbody>
</table>

![Figure 11](image-url) (a) Correlations between analyzed and CFS-predicted Niño-3.4 (5°S–5°N, 170°–120°W) index at different lead months and all ICs for 1981–2003 in the Atlantic, (b) the corresponding correlations of persistence forecast, and (c) the difference of (a) minus (b). The contour interval is 0.1, and the shading represents values greater than 0.7 or less than 0.5 in (a) and (b), and greater than 0.0 in (c).
sphere and the regressions become negative for the lowest levels in the southeastern tropical Atlantic (Fig. 12a). Therefore, the theory of Chiang and Sobel (2002) can explain why the most predictable pattern of SST in the CFS is an almost homogeneous pattern in the tropical Atlantic Ocean (see Fig. 5), different from that in the southeastern Atlantic regions shown in Fig. 7a of this work and in Fig. 11 of Chiang and Sobel (2002). This result suggests that the systematic warm bias in the southeastern ocean is a crucial factor leading to the low skill and unrealistic most predictable pattern in this region. The impact of this error on the interannual variability has also been demonstrated by Huang (2004).

Recently, Huang and Hu (2007) analyzed the observed monthly mean cloud cover data, which were produced by the International Satellite Cloud Climatology Project using a series of satellite radiance measurements (Rossow and Dueñas 2004). They demonstrated the impact of a cloud–radiation–SST feedback on the interannual variability of climate in the southeastern tropical Atlantic Ocean. It is found that the leading pattern of the low-cloud anomalies over the southeastern tropical Atlantic Ocean from June to August (JJA) is a modulation of its climatological center off the Angola and Benguela coasts on both interannual and longer time scales. The anomalous JJA low-cloud pattern is influenced by SST anomalies off the western coast of Africa near 15°S in January and February. In an anomalous warm SST event, the slow expansion of warmer surface water into the open ocean is conducive to deficit low-cloud cover in the subsequent JJA. The reduced low-cloud in turn increases the amount of the local solar radiation reaching the sea surface and forces a positive SST tendency in the southeastern ocean. This moves the center of the SST anomalies away from the coast and closer to the equator. This feedback affects the evolution of the southeastern tropical Atlantic anomalous events. By comparing this observed cloud–SST feedback with the CFS simulation, Hu et al. (2007, manuscript submitted to J. Climate) found that this cloud–radiation–SST feedback is not well simulated in CFS. The major problem is that the model underestimates low-cloud cover in the southeastern tropical Atlantic Ocean, causing an overestimated amount of the local solar radiation reaching the sea surface and resulting in the warm SST bias in Fig. 2.

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In Hu and Huang (2007), the values of the regression coefficients shown in Figs. 6 and 10 are incorrect because of a coding error. The correct values should be divided by the square root of the sample size. For the sample size of 23, the amplitudes of the regression coefficients in these figures should be smaller by a factor of 4.8 than shown in the figures. All the regression patterns and significance tests remain the same. The conclusions are not affected by this error.

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