A linear tendency correction technique for improving seasonal prediction of SST

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[1] A methodology is presented to linearly correct the tendency of sea surface temperature (SST) anomalies in a coupled model. Using an atmospheric general circulation model (AGCM) coupled to a slab ocean as an example, we demonstrate the effectiveness of the linear correction methodology in improving the model's skill predicting SST in the tropical Atlantic Ocean during boreal spring. For this particular coupled model, the correction mainly takes into consideration the linear ocean dynamics absent in the slab ocean, thereby improving the skill in the tropical south and equatorial Atlantic. The corrected coupled model is further shown to produce a skillful rainfall forecast in the intertropical convergence zone (ITCZ) region during the boreal spring. *INDEX TERMS:* 4215 Oceanography: General: Climate and interannual variability (3309); 4263 Oceanography: General: Ocean prediction; 3339 Meteorology and Atmospheric Dynamics: Ocean/atmosphere interactions (0312, 4504). **Citation:** Barreiro, M., and P. Chang (2004), A linear tendency correction technique for improving seasonal prediction of SST, *Geophys. Res. Lett.*, *31*, L23209, doi:10.1029/2004GL021148.

1. Introduction

[2] Systematic errors in coupled atmosphere-ocean models are known to be one of the major obstacles to seasonal climate prediction. Various techniques have been developed to reduce these coupled model systematic errors. *Yang and Anderson* [1999], for example, develop a method in which the systematic initial tendency error of the model is subtracted from the prognostic equations. *Chen et al.* [2000] describe an approach to correct the bias of a coupled model when the errors are linearly related to the model state. Here, we propose a technique based on Linear Inverse Modeling (LIM) [*Penland and Sardeshmukh*, 1995]. It assumes that the systematic error in the tendency can be separated linearly into a deterministic part that can be linearized around the state vector and a random part that can be parameterized as a white noise process. Therefore, the tendency error of the coupled model is corrected by adding a term that is linearly related to the state vector. This methodology can be applied to any coupled model, provided that the model's deterministic physics obeys approximately linear dynamics.

[3] To best illustrate how this technique works, in this paper we show some results of a prediction study in the tropical Atlantic sector using an AGCM coupled to a slab ocean. By construction, the model has systematic biases in its deterministic dynamics because the slab ocean has no ocean dynamics. We show that the linear correction procedure successfully corrects the model biases in the regions where ocean dynamics are expected to be important.

[4] In a recent study, *Chang et al.* [2003] (hereafter CSJ) show that SST anomalies in the tropical north Atlantic (TNA) can be predicted two seasons in advance using an AGCM coupled to a slab ocean, owing to the combined effect of the remote ENSO influence and local thermodynamic air-sea feedbacks. But in the tropical south and equatorial Atlantic, the simple coupled model revealed poor skills and under-performed the persistence forecast. Here we use CSJ's results as a reference with the exception that the prediction and verification period is expanded from 1959 to 2000. We focus on February–May, the peak months of the gradient mode of variability in the tropical Atlantic [*Chiang et al.*, 2002], allowing us to investigate the importance of ocean dynamics in its evolution.

2. Linear Tendency Correction Technique

[5] The general approach for correcting the tendency error of a coupled model consists of introducing a term to the prognostic equations, which is assumed to be linearly related to the prognostic variables. The dynamical operator governing the correction is derived based on LIM. Here we illustrate the methodology by correcting the SST tendency of an AGCM coupled to a slab ocean.

[6] The governing equation for the SST anomaly, $\mathbf{T}$, is given by $\frac{\partial \mathbf{T}}{\partial t} = \mathbf{Q}$, where $\mathbf{Q}$ is the net surface heat flux anomaly divided by the heat capacity of the mixed layer (variables denote ensemble mean quantities). We assume the following: (i) the predicted $\mathbf{Q}$ can be separated additively into two parts: one that is related to the SST ($\mathbf{Q_S}(\mathbf{T})$), and a second part that is due to internal atmospheric variability ($\mathbf{Q_N}$) considered here as white noise; (ii) the observed SST anomaly obeys a similar equation with $\hat{\mathbf{Q}}_\mathbf{S}(\hat{\mathbf{T}})$ (the "hat" denotes observed quantities); and (iii) the heat flux anomaly is linearly related to the SST anomaly according to $\mathbf{Q_S}(\mathbf{T}) = \mathcal{A}\mathbf{T}$ and $\hat{\mathbf{Q}}_\mathbf{S}(\hat{\mathbf{T}}) = \hat{\mathcal{A}}\hat{\mathbf{T}}$, where $\mathcal{A}$ and $\hat{\mathcal{A}}$ are the linear operators (matrices) in the model and observations, respectively. These matrices are different because $\hat{\mathcal{A}}$ includes not only ocean-atmosphere feedbacks, but also a contribution from ocean dynamics. Our goal is to derive a matrix $\mathcal{B}$, such that $\mathcal{A} + \mathcal{B}$ approximates $\hat{\mathcal{A}}$ as close as possible.

[7] To find $\mathcal{B}$ we first construct an equation for the prediction error $\epsilon = \hat{\mathbf{T}} - \mathbf{T}$ by taking the difference

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between the equations for observed and predicted SST. This leads to

$$\frac{\partial \epsilon}{\partial t} = \hat{\mathcal{A}}\epsilon + \mathcal{B}\mathbf{T} + \zeta, \qquad (1)$$

where ζ is white noise. Since the initial prediction error is zero, evaluating (1) at $t = 0$ states that the initial tendency of the prediction error is linearly related to the initial temperature ($\mathbf{T}(0)$), and the operator that links the two quantities is the undetermined linear ocean dynamics. In reality, $\mathcal{B}$ also represents systematic errors in the atmospheric fluxes of the model and the use of a constant mixed layer. We assume that these are smaller, so that $\mathcal{B}$ mainly represents the missing ocean dynamics. Integrating (1) between zero and a small lead time τ, and multiplying the result by $\mathbf{T}(0)$ allows to calculate $\mathcal{B}$ as the coefficient matrix of a multivariate linear regression

$$\mathcal{B} = \frac{1}{\tau}\left(\epsilon(\tau)\mathbf{T}(0)^t\right)\left(\mathbf{T}(0)\mathbf{T}(0)^t\right)^{-1}. \qquad (2)$$

Once $\mathcal{B}$ is determined, we incorporate it into the model as a linear correction. Thus, in a linear framework

$$\frac{\partial \mathbf{T}}{\partial t} = \mathcal{A}\mathbf{T} + \mathcal{B}\mathbf{T} + \mathbf{Q_N} \simeq \hat{\mathcal{A}}\mathbf{T} + \mathbf{Q_N}. \qquad (3)$$

Matrix $\mathcal{B}$ is generally non-diagonal, and thus the correction introduced in the slab ocean is non-local. That is, changes of SST in one location due to $\mathcal{B}\mathbf{T}$ depend on SST anomalies in other locations. This property is essential to represent dynamical ocean processes, which can affect remote areas through advection or wave propagation.

3. Model and Present Application

[8] We used (as CSJ) the CCM3 AGCM developed at NCAR coupled to a slab ocean with annual mean mixed layer depth taken from *Levitus* [1994]. The CCM3 has T42 horizontal resolution and 19 vertical levels [*Kiehl et al.*, 1998]. To assure a correct simulation of the annual cycle of SST, the slab ocean uses a ‘‘Q-flux’’ correction that accounts for the missing climatological ocean dynamics.

[9] CSJ performed two sets of prediction experiments. They initialized the coupled model with global (PGIC experiment) and Atlantic-only (30°S–60°N, PAIC experiment) observed December SST and integrated forward for 9 months. A 10-member ensemble was constructed for each case using different initial atmospheric conditions derived from the NCEP reanalysis dataset. To test the correction technique we repeated the 10-member ensemble of predictions initialized with global SST but with the term $\mathcal{B}\mathbf{T}$ in the equation of the slab ocean. This new experiment, hereafter called CPGIC, was carried out only for the period 1981 to 2000, because of concern over data quality in the southern hemisphere prior to 1981 when satellite-derived SST was not available.

[10] Calculating $\mathcal{B}$ involves choosing τ and finding the inverse of the December SST covariance matrix (see equation (2)). This matrix is singular because we only have 20 years of data, and the degree of the singularity increases with the spatial domain considered. To avoid spurious numerical errors, it is necessary to invert the matrix in a truncated state vector space and limit the spatial domain to a manageable size. This prompts us to choose carefully the region to correct. We decided to focus on the equatorial and tropical south Atlantic (ETSA) region, where ocean dynamics are expected to be most important and the standard coupled model of CSJ shows the lowest skill. The results shown below are based on the correction applied to an ETSA region defined by (50°W–20°E, 20°S–5°N), which contains 167 spatial points.

[11] We truncated the SST in terms of Empirical Orthogonal Functions (EOFs) of the December observed SST. We then found the best $\mathcal{B}$ in the parameter space of EOFs and τ as follows. Assuming SST obeys (3), the SST at time t, $\mathbf{T}(t)$, can be predicted from the initial condition $\mathbf{T}(0)$ as

$$\mathbf{T}(t) = e^{(\mathcal{A}+\mathcal{B})t}\mathbf{T}(0). \qquad (4)$$

We calculated $\mathcal{A}$ from a 100-year control run of the CCM3/slab ocean model applying LIM. Matrix $\mathcal{B}$, in turn, is calculated following (2) for several pairs of EOF truncation and τ values. The SST prediction error of the PAIC experiment is used to avoid possible remote influences from the tropical Pacific. Next we use (4) to predict SST. We choose τ and EOF truncation such that this linear prediction is best optimized according to the following two measures of prediction skill in the ETSA region: the normalized error variance of predicted SST, and the correlation skill during April-May-June. These criteria lead to an EOF truncation number of four (82% of total variance), and a lead time of one month, $\tau = 1$. The resulting matrix $\mathcal{B}$ is non-diagonal. Moreover, the leading normal mode has largest weight in the cold tongue and equatorial regions, and is similar to the SST pattern of the zonal mode, which has been largely attributed to ocean dynamics [*Zebiak*, 1993]. These results were found using the prediction error from 1959 to 2000. Using a jackknifing procedure, where estimates of the correction matrix $\mathcal{B}$ were calculated leaving out the years for validation did not significantly change the indices of prediction skill and led to the same choice of parameters. After several sensitivity tests, we concluded that the characteristics of matrix $\mathcal{B}$ are robust, and decided to calculate it using all available years. The ‘‘a posteriori’’ result that the best $\mathcal{B}$ is found for the smallest possible value of τ is satisfying, because (2) was derived in the limit of very small τ. Since $\mathcal{B}$ is calculated using the prediction error at $\tau = 1$, the predicted January SST from the standard model is used. Thus, the corrected predictions, strictly speaking, can be considered to start in January, because one needs both December and January to construct $\mathcal{B}$. Note, however, that we focus on the months of February to May, which are not used for training the model. Moreover, we show below that the effect of the correction is not just a one-month shift in the prediction skill of the model, but the corrected model performs consistently better than the standard one.

[12] The next section compares CPGIC with PGIC from 1981 to 2000. The skill of the models is obtained

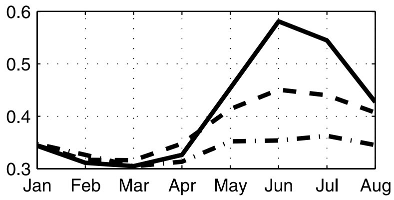

Figure 1. Standard deviation of SST in the region (30°W–5°E, 5°S–5°N) for observations (solid line), PGIC (dashed-dotted line), and CPGIC (dashed line). The standard deviation in the experiments is calculated over the concatenated 10 ensemble members.

by validating the ensemble mean against observations, focusing on SST and precipitation. We use the data set of *Smith et al.* [1996] for SST, and the Xie-Arkin data set for precipitation.

4. Results

[13] Figure 1 shows the standard deviation of SST for PGIC, CPGIC and observations in the equatorial region. The correction enhances the SST variance along the equator with the right seasonality, peaking in June like the observations, although it is not able to capture the full amplitude. The prediction experiments begin to differ at the end of the boreal spring season, hinting at the importance of ocean dynamics in this period. Variability is also enhanced along the Angolan coast in the CPGIC experiment.

[14] We considered February–March (FM) and April–May (AM) as the growing and decaying phases of the gradient mode, respectively. The SST correlation skill of PGIC and CPGIC during FM and AM is shown in Figure 2. In the TNA the experiments show very similar skill. In the ETSA, on the other hand, CPGIC is clearly superior to PGIC. This is particularly true during AM when CPGIC shows large areas with correlations larger than 0.45 (95% significance level) which are absent in PGIC. The higher skill of CPGIC in the ETSA also holds into the following season (not shown).

[15] To further compare the predictions we constructed an index to characterize the gradient mode. This so-called gradient index is defined as the SST difference between the regions defined by (50°–20°W, 4°–14°N) and (35°–5°W, 4°–14°S). Figure 2e compares the correlation between the predicted and observed gradient index against the skill of the persistence forecast. Both experiments beat persistence after February. The standard prediction (PGIC), however, shows a correlation skill of about r = 0.44 from February to July that is just below the 95% significance level. The corrected prediction (CPGIC), on the other hand, is able to predict the gradient index up to July with a peak correlation value of $r \simeq 0.75$ during April–May (99% significant). CPGIC also has smaller root mean square (RMS) error (Figure 2f). The higher skill in predicting the SST gradient improves the predicted equatorial wind stress, particularly the meridional component (τ_y). The correlation between predicted and NCEP reanalysis τ_y averaged over (50°–10°W, 5°S–5°N) peaks in late spring with a correlation of 0.61 (0.44) and 0.56 (0.39) in CPGIC (PGIC) during April and May, respectively. These anomalous cross-equatorial winds change the location of moisture convergence shifting the ITCZ toward warm waters, a characteristic of the gradient mode [*Chiang et al.*, 2002]. To describe this shift we constructed a rainfall index as the difference between anomalies in the centers of action of the leading EOF of precipitation in the tropical Atlantic from February to May. As for SST and τ_y, the correlation between predicted and observed rainfall indices is largest in late spring with values of 0.64 (0.23) and 0.71 (0.44) in CPGIC (PGIC) during April and May, respectively. Figure 3 shows the rainfall correlation maps in the period 1982–2000. During FM the experiments have similar skill, with CPGIC showing larger correlations overall. In AM, the corrected experiment predicts the variability of the Atlantic ITCZ across the whole basin with significant skill. PGIC, on the other hand, shows some skill in predicting rainfall variations associated with the ITCZ mainly north of the equator, and in northeastern Brazil. The better prediction of SST, τ_y and rainfall suggests that CPGIC captures the dynamics of the gradient mode very well.

[16] We next looked at the covariability of rainfall and SST prediction errors during March-April-May [*Goddard and Mason*, 2002], using a joint singular value decomposition (SVD) analysis. Rainfall prediction errors are defined as the difference between the predicted rainfall and the simulated rainfall when observed SST is imposed as a boundary condition for the CCM3 (GOGA runs). The SST error is defined as the predicted SST minus the observed SST. The analysis is performed from 1982 to

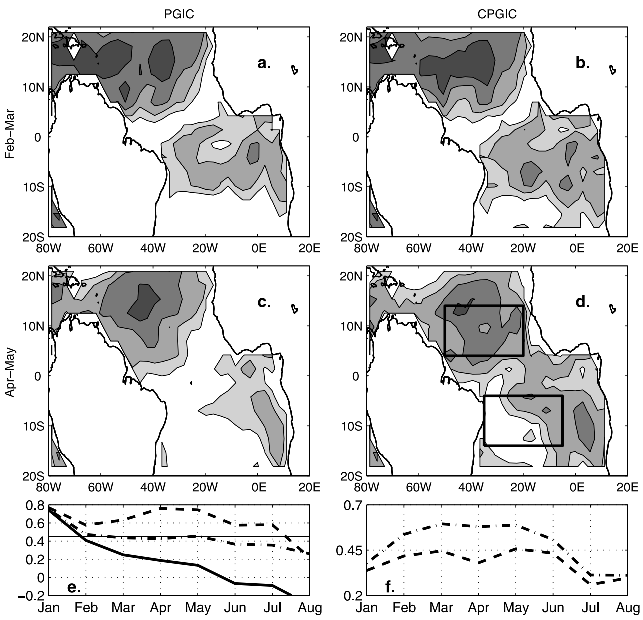

Figure 2. SST correlation skill of PGIC and CPGIC for Feb–Mar (upper panels), and Apr–May (middle panels). Shaded contours are 0.3, 0.45, 0.6 and 0.75. The boxes in (d) indicate the regions used to construct the gradient index. (e) Correlation between predicted and observed gradient index for PGIC (dashed-dotted line), and CPGIC (dashed line). Persistence forecast is shown as a solid line. The horizontal line denotes the 95% significance level. (f) RMS error of the gradient index for PGIC (dashed-dotted line) and CPGIC (dashed line).

1994, the common period shared by the prediction runs and the GOGA integrations.

[17] The leading SVD of covarying prediction errors for PGIC is shown in Figures 4a and 4b (61% of squared covariance). The associated time series are correlated at r = 0.95, but show no correlation with SST outside the tropical Atlantic. Thus, errors in the predicted rainfall are, to first order, dependent on the local SST, and consist of a shift of the ITCZ driven by a large cross-equatorial gradient. Since the standard model lacks ocean dynamics, it tends to exaggerate the importance of feedbacks between the SST and surface heat fluxes, thus favoring SST evolution with dipole-like characteristics. The leading SVD of prediction errors for CPGIC explains 71% of the squared covariance and the time series are correlated at r = 0.84. The error in the predicted rainfall no longer shows a dipole pattern, and the covarying SST error has an SST gradient confined west of 20°W (Figures 4c and 4d). This suggests that ocean dynamics tend to oppose the thermodynamic feedback, reducing the SST errors in the equatorial and cold tongue regions. The time series associated with the SVD are correlated (95% significant) with simultaneous SST prediction errors in the tropical Pacific. Also, the symmetric rainfall pattern of Figure 4d is reminiscent of the direct ENSO influence on the Atlantic ITCZ through an anomalous Walker circulation [*Chiang et al.*, 2002], further suggesting that first order rainfall errors in CPGIC involve not only local processes, but also remote influences.

5. Summary

[18] This study presents a new general technique to correct the tendency of SST anomalies of a coupled model. Here, we applied the approach to a system consisting of an AGCM coupled to a slab ocean designed to predict tropical Atlantic SST during boreal spring. In this case, the technique introduces a statistical correction to the slab ocean that parameterizes the heat transport due to anomalous linear ocean dynamics. Results indicate that the correction is successful in improving the prediction in the ETSA, and points to the importance of ocean dynamics in the prediction of tropical Atlantic SST.

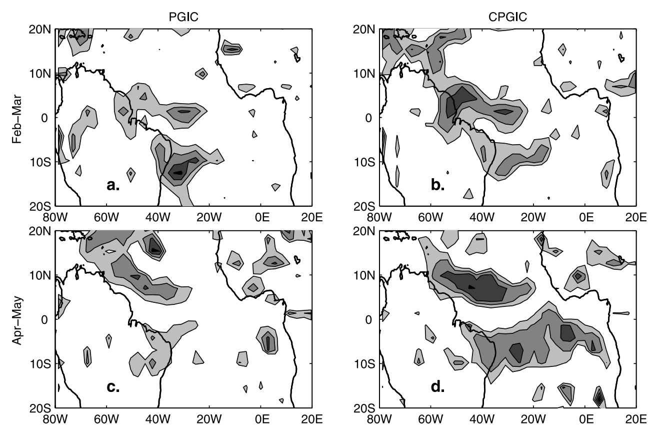

Figure 3. Rainfall correlation skill of PGIC and CPGIC for Feb–Mar (upper panels), and Apr–May (middle panels). Shaded contours as in Figure 2.

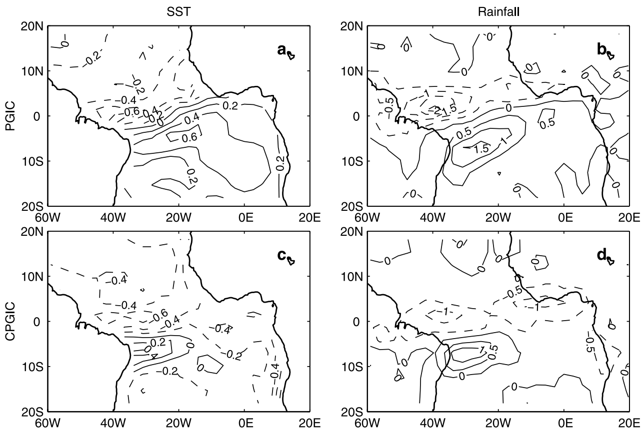

Figure 4. Leading SVD of covarying errors in predicted SST and rainfall during March-April-May for (a–b) PGIC, and (c–d) CPGIC.

[19] The experiments further suggest that the role of ocean dynamics (correction) during boreal spring is that of weakening the thermodynamic air-sea coupling between SST and heat flux in the equatorial region. The effect is strongest toward the end of the spring season, and seems to be important for the decay of the gradient mode. This is consistent with previous studies of the role of ocean dynamics in regulating the SSTs associated with the gradient mode of variability [*Chiang et al.*, 2002]. *Barreiro et al.* [2004] further investigate the dynamics included in the correction.

[20] As a consequence of the improved SST prediction, particularly the cross-equatorial gradient, the corrected coupled model shows high skill in predicting rainfall anomalies in the ITCZ region during spring across the Atlantic basin. This offers an encouraging perspective for seasonal climate prediction in the tropical Atlantic sector during boreal spring using a one-tier prediction system.

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