Effect of Ocean Boundary Conditions on South America Rainfall Seasonal Prediction

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INTRODUCTION

Sea surface temperature, soil moisture, snow cover and sub-surface ocean temperature are currently believed to be the main sources of predictive information for seasonal predictions. This study aims to compare the potential predictability of ocean heat content versus sea surface temperature as predictor variables for South America austral summer (DJF) seasonal rainfall, which is a way of assessing the additional predictive skill from the ocean subsurface.

INVESTIGATION APPROACH

We use an empirical (statistical) multivariate regression model (see the following session) based on maximum covariance analysis (also known as singular value decomposition) with the following predictors for DJF rainfall:
a) previous October Pacific and Atlantic sea surface temperature (1-month lead SST based);
b) previous August Pacific and Atlantic ocean heat content (3-month lead OHC based);
c) previous August Pacific alone ocean heat content (3-month lead OHC based);
where ocean heat content (OHC) is defined as the average ocean temperature in the upper 300 metres (T300).

THE EMPIRICAL MODEL

As in Coelho *et al.* (2006) empirical predictions are produced with the following multivariate regression model:

$$Y|Z \sim N(M(Z - Z_o), T)$$

$$M = S_{YZ} S_{ZZ}^{-1}$$

$$\overline{Y} = M(\overline{Z} - Z_o)$$

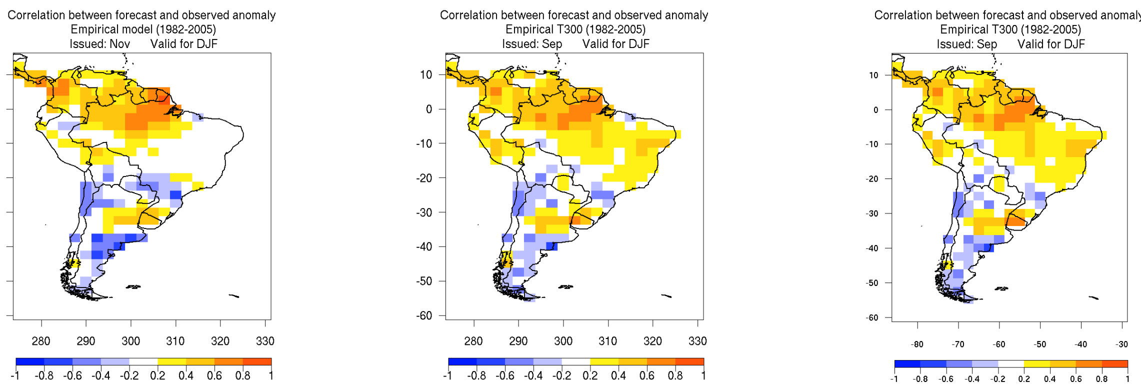
$$T = S_{YY} - S_{YZ} S_{ZZ}^{-1} S_{YZ}^{T}$$

where Y is a n x q matrix containing the predictand variable (DJF rainfall), Z is a n x v matrix containing the predictor variable (i.e. SST or OHC), S_{YZ} is a q x v cross-covariance matrix of the predictor and predictand variables, S_{YY} is a q x q covariance matrix of the predictand variable and S_{ZZ} is a v x v covariance matrix of the predictor variable. Because of large data dimensionality and spatial dependence between neighbouring data points a data reduction technique based on the maximum covariance analysis (MCA) of the cross-covariance matrix between the predictor and predictand variables is applied prior to performing the regression. A small number of covariate modes are selected and the time series (indices) of these modes are used to build the regression model. For the selection of modes, the spatial patterns (loadings) and the amount of covariance accounted for each mode are examined. This approach has the advantage of isolation covariate patterns that summarize the main sources of seasonal predictability.

Empirical models are constructed using the first two leading modes of the cross-covariance matrix between the predictor variable (i.e. SST or ocean heat content) and the predictand variable (rainfall). All models are built using 24 years of data from 1982 to 2005. Skill measures are computed in cross-validation mode, where data for the year to be predicted is left out when building the regression model. Sea surface temperature data used in this study is from Reynolds *et al.* (2003). The ocean heat content is from the recently produced ECMWF oceanic reanalysis (Balmaseda *et al.*, 2008). Rainfall estimates are from the Global Precipitation Climatology Project (Adler *et al.,* 2003). Both SST and OHC data are at 1^{o} latitude by 1^{o} longitude resolution. Rainfall data is at 2.5^{o} latitude by 2.5^{o} longitude resolution.

SKILL ASSESSMENT

Figure 1 shows correlation maps of the three austral summer rainfall anomaly predictions here investigated. Maps show the correlation between observed and mean predicted anomalies at each grid point during the period 1982-2005. Figures 1a and 1b show that the two regression approaches that use simultaneous Pacific and Atlantic SST or OHC as predictors have positive skill with correlation coefficients superior to 0.4 in tropical and southeast South America. Figure 1a shows that 1-month lead Pacific and Atlantic SST-based predictions have nearly null skill over the northeast region of Brazil. Figure 1b shows that when Pacific and Atlantic ocean heat content is used to produce 3-month lead predictions a much larger area has positive skill. Parts of the northeast region of Brazil now have positive skill with correlation between 0.4 and 0.6. Central and southeast Brazil, which previously had nearly null skill (Fig 1a) now have positive skill. These results show that subsurface ocean temperatures are useful predictors for producing improved long lead seasonal predictions. Figure 1c shows that 3-month lead Pacific alone OHC-based predictions have similar skill to 3-month lead simultaneous Pacific and Atlantic OHC-based predictions (Fig 1b), indicating that part of the predictive skill over tropical and southeastern South America is realized by Pacific ocean subsurface temperatures.



(a) (b) (c)

Figure 1: Correlation maps of a) 1-month lead Pacific and Atlantic SST-based, b) 3-month lead Pacific and Atlantic OHC-based, and c) 3-month lead Pacific OHC-based austral summer rainfall predictions for the period 1982–2005. Correlation values above 0.4 are statistically significant at the 5% level.

SOURCES OF SKILL

The sources of skill for the 3-month lead Pacific and Atlantic OHC-based predictions are summarized in Figure 2. This figure shows the spatial patterns of the two leading modes of the maximum covariance analysis between August OHC and DJF rainfall anomalies over the period 1982-2005. Maps shown in Fig. 2 are obtained by correlating the time series (indices) of one field (e.g., rainfall) with the grid point values of the other field (e.g., OHC). Correlations with magnitude 0.4 or higher are statistically significant at the 5% level. This first mode (Figs. 2a and 2b) accounts for 51.4% of the squared covariance between OHC and rainfall. The OHC pattern (Fig. 2a) shows basinwide correlations in the equatorial Pacific related to the El Nino-Southern Oscillation (ENSO) phenomenon. The associated rainfall pattern (Fig. 2b) has negative correlations over northern South America and positive correlations over southern Brazil, Uruguay and northern Argentina. During El Nino years, when the equatorial Pacific is warmer than normal, northern South America is marked by deficits of rainfall and southeastern South America by excesses of rainfall. During La Nina years, when the equatorial Pacific is colder than normal, this pattern is reversed. Similar leading maximum covariance analysis patterns to Figs. 2a and 2b have been found for the Pacific and Atlantic SST-based regression model presented in the previous section (not shown). ENSO is the main source of predictive skill for South America, as can be noted by the similarity between the skill maps of Fig. 1 and the map of Fig. 2b. The most skillful regions coincide with regions where ENSO atmospheric teleconnections are mostly pronounced.

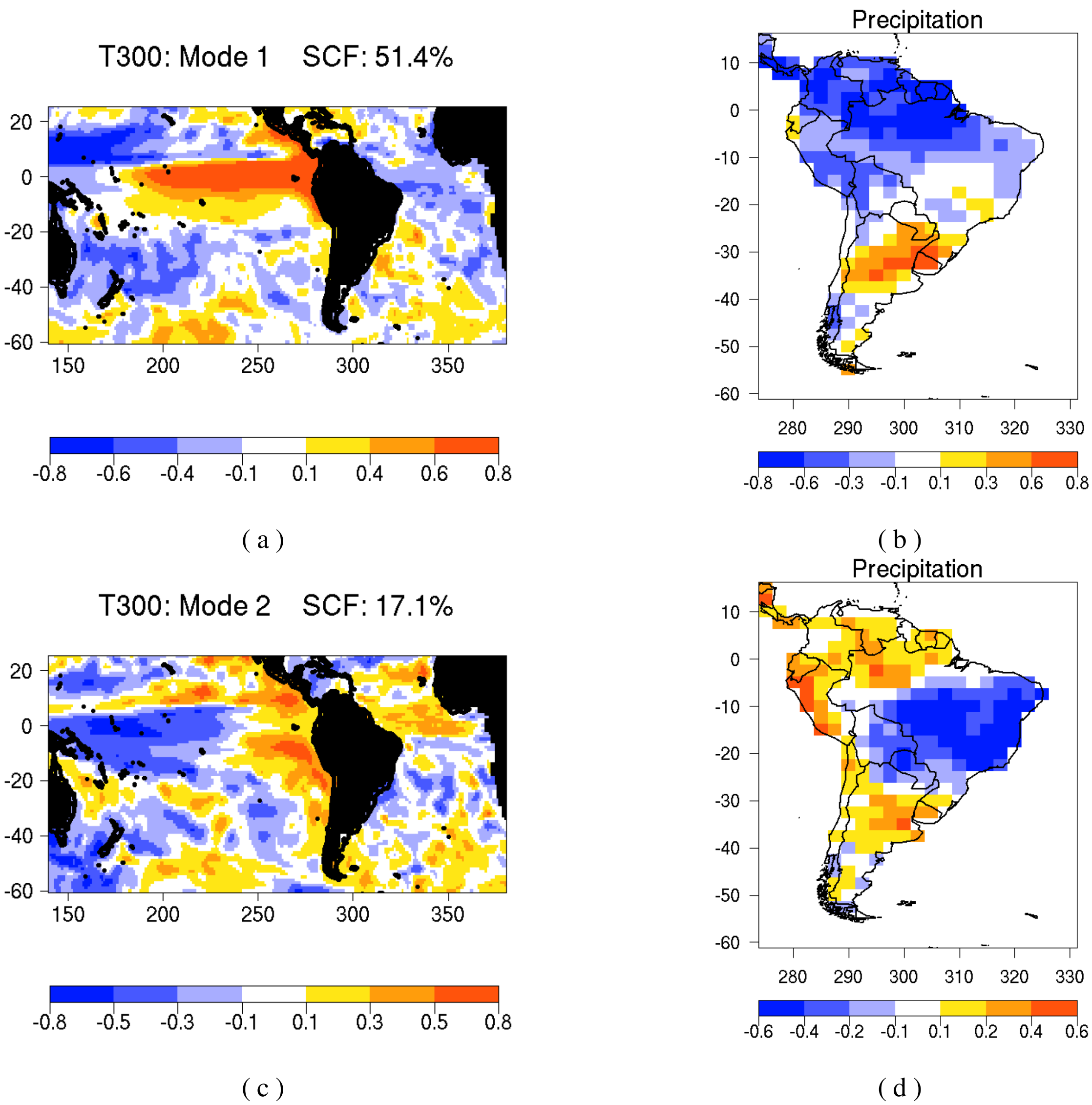


Figure 2: Correlation patterns of the first (panels a and b) and second (panels c and d) MCA modes between August Pacific and Atlantic ocean heat content anomalies and austral summer (DJF) rainfall anomalies for the period 1982-2005. Correlation values above 0.4 are statistically significant at the 5% level.

The second mode (Figs. 2c and 2d) accounts for 17.1% of the squared covariance and relates OHC variability in the equatorial Pacific near the west coast of South America to rainfall over South America. The OHC structure in the equatorial Pacific has positive correlation near the west coast of South America resembling a coastal ENSO signature (Fig. 2c). OHC anomalies in this region produce rainfall anomalies with the same signs in neighboring northwest South America as noted in Ecuador, northern Peru and the Brazilian Amazon region (Fig. 2d).

Figure 3 shows spatial patterns of the two leading modes of the maximum covariance analysis between August Pacific alone OHC and DJF rainfall anomalies over the period 1982-2005. The spatial patterns over the Pacific and South America of these two leading models and the correlation skill for this empirical model (Fig. 1c) are remarkably similar to the ENSO patterns shown in Fig. 2 and the correlation skill of Fig 1b. This finding provides supportive evidence for ENSO being the main source of predictive skill for austral summer South American rainfall. Skill improvements of 3-month lead OHC-based austral summer predictions when compared to 1-month lead SST-based predictions is therefore realized by the Pacific sub-surface temperature signal via ENSO atmospheric teleconnections.

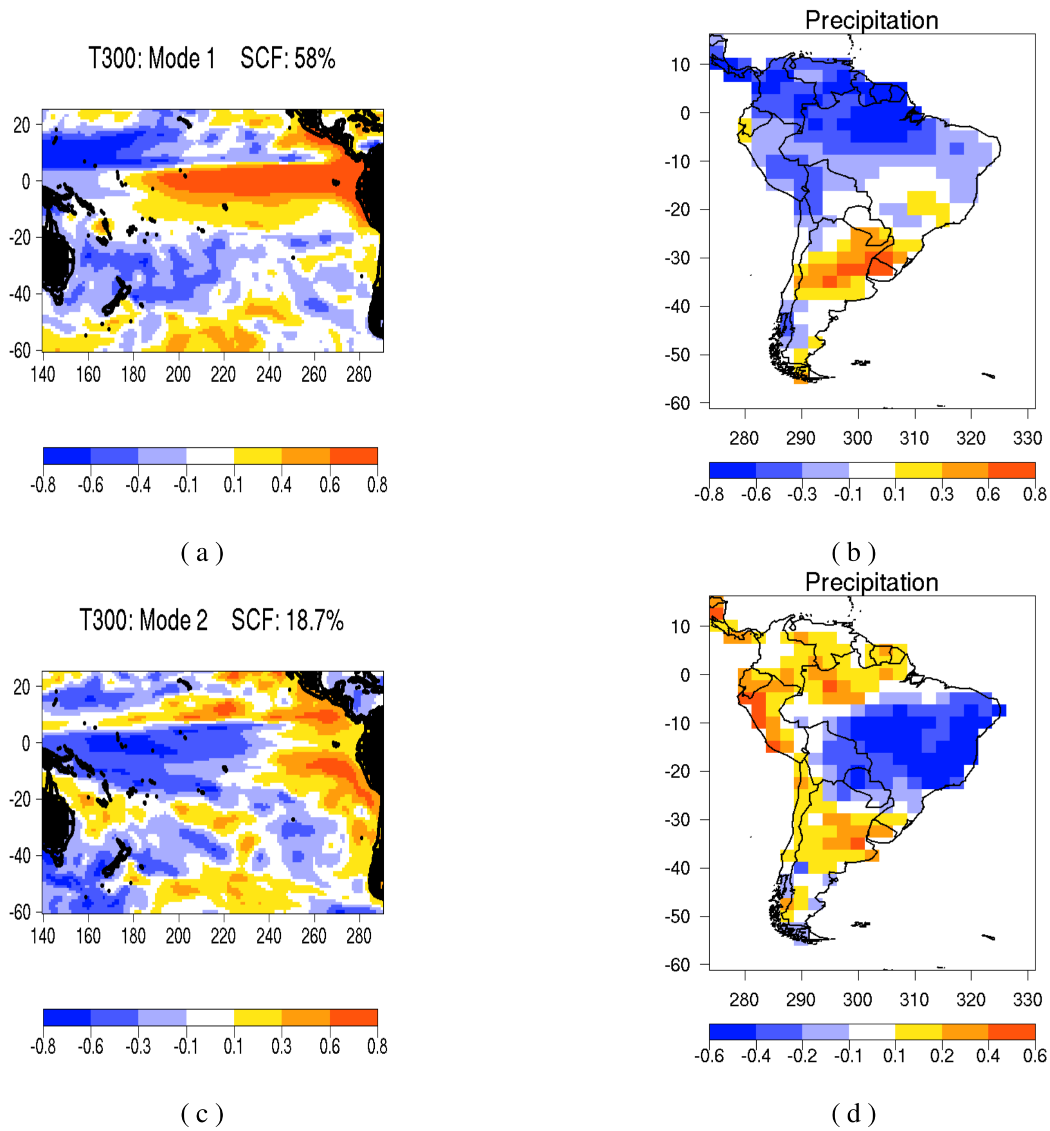


Figure 3: Correlation patterns of the first (panels a and b) and second (panels c and d) MCA modes between August Pacific alone ocean heat content anomalies and austral summer (DJF) rainfall anomalies for the period 1982-2005. Correlation values above 0.4 are statistically significant at the 5% level.

CONCLUSIONS

This study has investigated the effect of ocean boundary conditions on South America austral summer rainfall seasonal predictions. The main findings can be summarized as follows:

- Austral summer rainfall predictions are skilful in tropical and southeast South America
- Tropical Pacific ocean ENSO variability is the main source of skill for South American rainfall predictions during the austral summer
- Tropical Pacific provides predictive information for producing long lead (3-month lead) ocean heat content based predictions of comparable or superior level of skill to short lead (1-month lead) predictions based on SST

Tropical Atlantic climate variability has previously been reported to affect seasonal rainfall over the northeast region of Brazil. The comparative effect of Atlantic alone sea surface temperature and Atlantic alone subsurface temperatures on South America rainfall predictions will be discussed elsewhere.

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