Southern hemisphere climate variability as represented by an ocean-atmosphere coupled model

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1. INTRODUCTION

Southern Hemisphere (SH) climate variability has been the focus of several researchers (e.g., Wallace and Hsu, 1983). According to these early studies, the SH is characterized by quasistationary oscillations and zonally propagating waves in the atmospheric circulation. The ability of predicting these modes of climate variability on longer timescales is vital. Potential predictability is usually measured as a signal-to-noise contrast between the slowly evolving and chaotic components of the climate system. Such measures are certainly sensitive to how the variance decomposition is performed. One way of separating the variance is using a temporal filtering technique which assumes that weather noise dominates much shorter timescales (e.g., Basher and Thomosph, 1996). Notwithstanding, weather noise includes not only high-frequency, day to day fluctuations but also low-frequency intraseasonal fluctuations that give rise to chaotic, unpredictable variability through temporal fluctuation. The aim of this study is, therefore, to assess the ability of a coupled global climate model in reproducing observed SH climate variability using a variance decomposition procedure recently suggested by Zheng and Frederiksen (2004) and Zheng *et al. (*2009).

2. DATA AND METHOD

Model 500 hPa Geopotential height (GH) produced by an Ocean-Atmosphere Coupled Climate Model (OAGCM; Beraki *et al.,* 2011) hindcast integrations for the period spanning 1982 to 2009 (28yrs) are considered here. The National Centers for Environmental Prediction Reanalysis II (NCEP-R2) dataset (Kanamitsu *et al.,* 2002) is used as a proxy data for observations.

We adopted here the variance decomposition technique (Zheng and Frederiksen, 2004) that uses mean monthly fields as input. The procedure is suitable for isolating the interannual (*BSy*) and intraseasonal covariability (*Esyo*) matrices. To overcome the pitfall in estimating the covariance matrix when the number of grid points considered in the computation exceeds the temporal sample size (which is the case here), we applied a variant of the Empirical Orthogonal Function (EOF) truncation approach of Zheng and Frederiksen (2004) in conjunction with the "*sample space*" formalism postulated by Preisendorfer (1988). The covariance matrix of the interannual component is further decomposed into a *boundary-forced* (Bsy) and a *slow varying internal source component (Ssy;* Zheng *et al.*, 2009). The latter gives an important insight in the understanding of the source of variation within the GCM ensemble prediction system. Following the estimation of covariance matrices for the different components, an EOF analysis is conducted to derive patterns related to the various intraseasonal and interannual components.

3. RESULTS AND DISCUSSIONS

The OAGCM ability to reproduce observed modes of climate variability is assessed here using a basic covariance decomposition statistical model. The analysis has been conducted for the austral summer season (DJF) 500hPa GH using 10 ensemble realizations of the OAGCM (lead-1) and NCEP. Fig. 1 shows the intraseasonal and interannual components for the first two leading EOF modes (see caption). Generally the NCEP EOF patterns (fig. 1(a)) share a great deal of similarities with the results of Grainger *et al.* (2011; see their fig. 1 and 2) despite that there are also some differences in terms of patterns apparently attributed to the source of data and sample size differences; Grainger *et al.* (2011), for example, used 49yrs of NCEP-R1 500hPa GH. Comparing the OAGCM with NCEP, it adequately captures some of the dominant SH modes of variability. Notwithstanding, the model is seemingly underestimating the amplitude of the spatial loadings relatively. It is worth noting that differences in sign signature are presumably caused by the sample space formalism treatment adopted here and should not be considered as a weakness of the OAGCM.

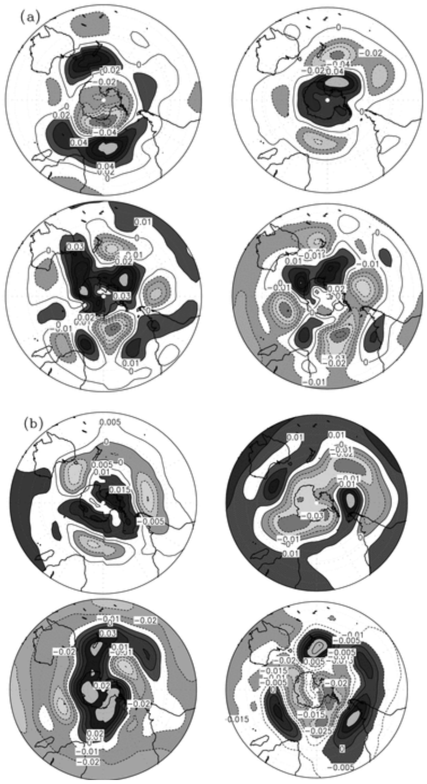

Figure 1: First two dominant EOF modes for weather noise (left panel) and slow more predictable interannual component (right panel). (a) NCEP Reanalysis and (b) OAGCM 500hPa GH for the austral summer respectively. Light (dark) shades highlight –ve (+ve) signature of the spatial loadings.

Table1: Variance explained by the first 6 leading EOFs for the intraseasonal and interannual variability. Included also is contribution of the slow internal dynamics (*Sy*) and boundary forcing (*By*; highlighted).

NCEP		OAGCM			
Esy	BSy	Esyo	BSy	By	Sy
22.78	36.60	21.65	50.38	31.63	43.39
18.59	19.63	15.59	22.76	26.95	16.04
10.72	10.79	9.58	8.96	11.44	10.80
8.51	6.15	6.80	4.24	7.26	7.62
7.69	5.46	5.01	2.79	6.11	5.40
4.42	4.36	4.66	2.13	3.07	3.97

The variance explained by the first 6 leading EOF modes for the NCEP and OAGCM is given in Table1. It implies that the major portion of the predictable component of the model is coming from the slow internal dynamics. One point correlation (not included) between Optimum Interpolation Sea Surface Temperature (OI SST) and the leading NCEP and AOGCM (Principal Component) PC-1 yield consistent results. Both of them show strong correlation with the El Niño Southern Oscillation (ENSO), Southern Annular Mode (SAM) and equatorial Indian Ocean Dipole (IOD) where the latter is stronger in the model.

4. ACKNOWLEDGEMENT

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