18.14 MODEL OUTPUT STATISTICS APPLIED TO MULTI-MODEL ENSEMBLE FORECASTS FOR SOUTHERN AFRICA

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1. INTRODUCTION

General Circulation Models (GCMs) typically exhibit systematic spatial and temporal errors in their representation of rainfall over southern Africa. The existence of systematic biases suggests the need to recalibrate GCM rainfall simulations. It has been shown before that a Model Output Statistics (MOS) (Wilks 1995) approach improved on a single GCM's deterministic (ensemble mean) rainfall forecasts over southern Africa (Landman and Goddard 2002). However, the inherent variability of the atmosphere requires seasonal climate forecasts to be expressed probabilistically. There are advantages in combining ensemble members of a number of GCMs into a multi-model ensemble since GCMs differ in their parameterizations and therefore differ in their performance under different conditions: using a suite of several models not only increases the effective ensemble size, it also leads to probabilistic forecasts that are skillful over a greater portion of the region and a greater portion of the time series. In this paper, MOS is applied to a super-ensemble from five GCMs, subsequently removing remaining systematic biases, leading to the most reliable forecasts possible.

2. DATA AND METHOD

Reynold's reconstructed sea-surface temperature (SST) data (Smith et al, 1996) serve as the simultaneous observed boundary forcing for the respective GCM experiments. Archived (1965/66 to 1997/98) December to February (DJF) GCM rainfall records from five models (CCM3.2, ECHAM4.5, NCEP-MRF9, COLA T63 and NASA-NSIPP1) are the predictors used in the respective sets of linear MOS equations. Regional DJF rainfall indices for the corresponding 33-year period, computed for nine homogeneous rainfall regions shown in Figure 1 (southwestern Cape [SWC], south coast [SCO], Transkei [TRA], KwaZulu-Natal coast [KZC], Lowveld [LOW], northeastern [NEI], central [CIN] and western interior [WIN] regions and northern Namibia/western Botswana [NWB]), form the predictands.

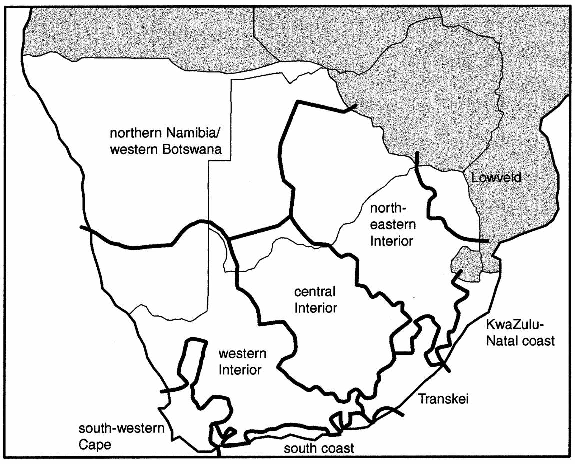

FIG. 1. Location map of the rainfall regions.

Optimal MOS models for each GCM are designed that produce the highest average cross-validation correlation between the rainfall indices and the recalibrated ensemble mean of each GCM. Once the optimal MOS models are determined, cross-validated recalibrated forecasts for each ensemble member (9 members from each GCM) are produced leading to a probability forecast for each season of the 33 years.

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Probabilities are assigned to each of three equi-probable categories (above-normal, near-normal and below-normal) by calculating the number of times a category is hit by any of the nine ensemble members. The Ranked Probability Skill Score (RPSS) (Wilks 1995) is the metric used here to quantify the relative confidence of forecasting the observed category. A collection of perfect forecasts, predicting the observed category with 100% probability, would have an RPSS of 1, and a perpetual forecast of climatological probabilities would yield a RPSS of 0.

3. RESULTS

Figure 2 shows the RPSS of each MOS model forecast, as well as the RPSS of a combined forecast obtained by simply averaging the forecast probabilities (Mason and Mimmack 2002) from the five MOS models. When averaging the probabilities various uncorrected errors cancel since these errors often have opposing directions. The improvements over the individual GCM-MOS forecasts are therefore attributed to the collective information of all the models used in the mean of probabilities algorithm. Combining algorithms that weight the probabilities from the different models by a measure of model skill (e.g., Krishnamurti et al. 2000) will also be presented, as well as multi-model MOS forecasts based on additional MOS model optimization schemes (i.e., optimizing the MOS models through highest cross-validation RPSS scores instead of correlations).

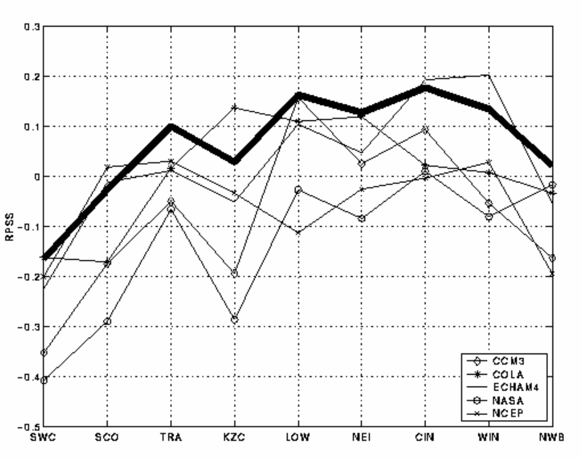

FIG. 2. RPSS for each rainfall region of southern Africa and for each of the five MOS models (thin lines) and the combining algorithm (thick line).

4. REFERENCES

Krishnamurti, T. N., C. M. Kishtawal, Z. Zang, T. LaRow, D. Bachiochi, E. Williford, S. Gadgil, and S. Surendran, 2000: Multimodel ensemble forecasts for weather and seasonal climate. *J. Climate*, **13**, 4196-4216.

Landman, W. A., and L. Goddard, 2002: Statistical recalibration of GCM forecasts over southern Africa using model output statistics. *J. Climate*, **15**, 2038-2055.

Mason, S. J., and G. M. Mimmack, 2002: Comparison of some statistical methods of probabilistic forecasting of ENSO. *J. Climate*, **15**, 8-29.

Smith, T. M., R. W. Reynolds, R. E. Livezey, and D. C. Stokes, 1996: Reconstruction of historical sea surface temperatures using empirical orthogonal functions. *J. Climate*, **9**, 1403-1420.

Wilks, D. S., 1995: *Statistical Methods in the Atmospheric Sciences*. Academic Press, 467 pp.