Predicting southern African summer rainfall using a combination of MOS and perfect prognosis

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[1] A statistical-dynamical approach to probabilistic precipitation forecasts of southern African summer rainfall is described and validated. An ensemble of seasonal precipitation and circulation fields is obtained from the ECHAM4.5 atmospheric general circulation model (AGCM). Model output statistics (MOS) then spatially recalibrate the AGCM fields relative to observations. Although the MOS equations are built using the simulation data, in which observed SSTs force the AGCM, the same set of equations can be applied to the predicted data, in which predicted SSTs force the AGCM. The use of prediction data in a set of equations developed for simulations, assumes that the AGCM forecast skill approximates its simulation skill and that the systematic biases of the AGCM do not change in a prediction setting; this assumption is analogous to a perfect prognosis (PP) approach. Probabilistic forecast skill is assessed using this MOS-PP-recalibration scheme for 3 equi-probable categories using a 3-year-out cross-validation approach. High skill scores are found over the north-eastern interior of the region, with marginal skill over the remainder of the austral summer rainfall regions. When skill is assessed for only the wettest and driest of the years, high skill appears over most of the region. **Citation:** Landman, W. A., and L. Goddard (2005), Predicting southern African summer rainfall using a combination of MOS and perfect prognosis, *Geophys. Res. Lett.*, *32*, L15809, doi:10.1029/2005GL022910.

1. Introduction

[2] Recent emphasis on research to determine the future behaviour of the climate system has shifted from purely empirical-statistical approaches to dynamical approaches based on the first principles of the processes governing the climate system. However, both methods have merit, and most forecasts systems will benefit from their combined use. The approach of statistically interpreting AGCM output to improve 3-month seasonal rainfall simulations over southern Africa has already been demonstrated [*Landman et al.*, 2001; *Landman and Goddard*, 2002].

[3] Two methods employed to statistically relate GCM fields to observations are perfect prognosis (PP) and model output statistics (MOS). In PP the same system of equations used to map observed or simulated variability in one field, or set of fields, to variability in another is applied in a forecast setting. PP assumes that the relationships between the variables do not change in the forecast setting. Perfect prognosis (PP) [*Wilks*, 1995] performed over a 10-year retro-active period demonstrated useful operational forecast skill over the austral summer rainfall period of southern Africa [*Landman et al.*, 2001]. In MOS a system of equations maps variability in model field(s) to variability in observed fields in order to minimize biases in model output. Model output statistics (MOS) [*Wilks*, 1995] recalibration has shown improved skill over both raw AGCM-simulated rainfall and over a simple statistical forecasting technique using global sea-surface temperature (SST) patterns as predictors [*Landman and Goddard*, 2002]. Strictly speaking, the MOS equations applied to AGCM simulation data are not the same set of MOS equations applied to AGCM forecast data. In a pure MOS approach a different set of equations would be developed for each lead-time, for a given season. Although MOS is the technique preferred over PP recalibration for the region [*Bartman et al.*, 2003], the MOS approach is potentially much more computationally expensive because separate MOS equations are constructed for the AGCM forecasts required at different lead-times owing to the decrease in AGCM skill with increasing lead-time. The pure MOS approach also requires hindcasts for the AGCM that coincide with the real-time prediction system, such as SST prediction methodology.

[4] A new forecast method is presented here, which combines the attributes of MOS and PP into a single forecast system. This system uses AGCM simulation data to construct MOS equations and subsequently uses forecast fields of the same AGCM at various lead-times in the simulation-MOS equations. The AGCM biases are therefore taken into account in a much more representative way than the case of a "pure" PP system. This process of using retrospective forecast data in a set of equations based on simulation data makes the assumption that the skill with which the AGCM can produce forecasts at certain lead-times is as good as skill obtained from simulation data and also that the model biases do not change in a forecast setting. This new system is henceforth referred to as MOS-PP. The probabilistic forecast skill of the MOS-PP during austral summer is subsequently demonstrated in this paper.

2. Data and MOS-PP Description

[5] December–February (DJF) rainfall totals for approximately 600 southern African rainfall stations, including South Africa, Namibia, Lesotho and Botswana, were obtained for the period 1950/51 to 1999/2000. DJF is

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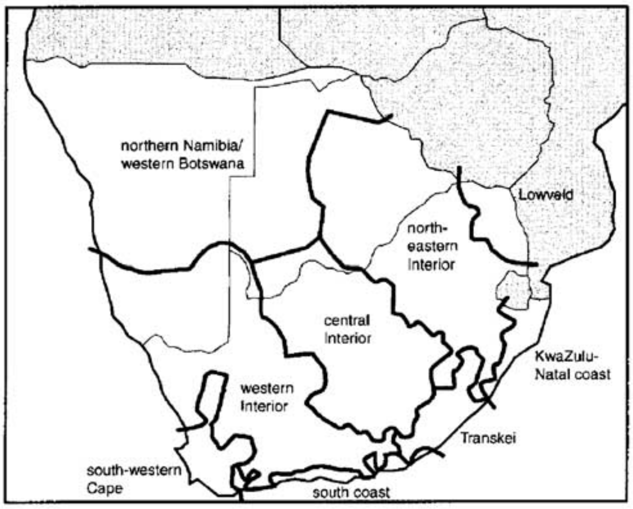

Figure 1. The 9 homogeneous rainfall regions used in the study. Countries shaded grey are not included.

selected as the period to demonstrate the MOS-PP skill, because AGCMs demonstrate potential predictability of the circulation over the region in DJF when a tropical atmosphere dominates [*Mason et al.*, 1996]. Moreover, this season is important for farmers, as, for example, flowering and grain filling occurs then [*Mjelde et al.*, 1997]. Thus, potentially skilful information can be provided at a time when climate sensitive decisions need to be made.

[6] Regional rainfall indices were computed for nine homogeneous rainfall regions (Figure 1) [*Landman et al.*, 2001]. The south-western Cape is predominantly an austral winter rainfall region and the south coast receives rain throughout the year. These two regions are therefore not included in the analyses presented in the paper because they are not strongly influenced by the tropical circulation in DJF, resulting in lower predictability during austral summer there. Integrations were performed using the ECHAM4.5 AGCM [*Roeckner et al.*, 1996]. An ensemble of 24 runs was forced with simultaneous observed SSTs (SSTs occurring during the same season as the simulated rainfall season) [*Reynolds and Smith*, 1994; *Smith et al.*, 1996] from 1950 to present but only used until 1999/2000 in this study. At initialization ensemble members differ from each other by one model day at the beginning of the integration. No observed atmospheric conditions are inserted into the runs at any time. The resulting AGCM fields are referred to as *simulation* mode fields. The GCM is successful in simulating the overall pattern of maximum rainfall over the north-east of South Africa decreasing towards the south-west, but it displaces slightly the local maximum over these regions and simulates lower rainfall totals than found in the observed climatology. A second ensemble of 12 members forced with persisted November SST anomalies was also produced, referred to as *hindcast* mode fields, constituting a 0-month lead-time. In this study the hindcast fields of only 1973/74 to 1999/2000 are used (27 years). Identical initial conditions were used for both sets, but they differ because of the different prescribed SST anomalies: In the simulation experiment, the DJF simulation sees the observed evolution of December, January and February SSTs. In the hindcast experiment, the DJF simulation sees the observed SST anomalies of November persisted on the climatological seasonal cycle.

[7] Canonical correlation analysis (CCA) [e.g., *Barnett and Preisendorfer*, 1987] is the mathematical technique used to set up the simulation MOS recalibration equations. This technique identifies patterns of variability that are highly correlated. The MOS equations are applied to each of the 12 ensemble members from the retrospective forecasts. The probabilistic precipitation forecasts then are constructed from the MOS-corrected ensembles. The following schematic illustrates the training period involved in making 27 0-month lead-time forecasts for the DJF season:

1950/51 – 1972/73(23-year training period) → forecasting DJF rainfall of 1973/74
1950/51 – 1973/74(24-year training period) → forecasting DJF rainfall of 1974/75
etc.
1950/51 – 1998/99(49-year training period) → forecasting DJF rainfall of 1999/2000

[8] The first step in designing the optimal MOS model is to develop the CCA regression equations. Empirical orthogonal function (EOF) analysis is performed first on the predictor (DJF ECHAM4.5 *ensemble mean* simulated total precipitation field) and predictand sets (DJF observed rainfall). The domain used is from 9.8°S to 40.5°S, and 11.3°E to 70.3°E, large enough to include the part of the south-western Indian Ocean that has an effect on southern African austral summer rainfall [*Reason*, 2001]. The number of modes retained in the CCA eigen-analysis problem is determined over a 48-year period produced from using 3-year-out cross-validated skill sensitivity tests. For cross-validation, the value that is to be predicted is omitted from the training period. Here, three years are removed from the training period and the middle year is forecast. The number of retained predictor and predictand EOF modes of the fields that produced the highest averaged cross-validation correlation for the rainfall regions of southern Africa (Figure 1) is subsequently identified. The number of CCA modes is determined by using the Guttman-Kaiser criterion [*Jackson*, 1991], but with a minimum of two CCA modes.

[9] MOS-PP forecasts are made for three equi-probable categories of below-normal, near-normal and above-normal rainfall. Because the variance of the ensemble mean is lower than that of the individual ensemble members, a variance inflation factor [*Wilks*, 1995] is introduced into the forecasts. The terciles are subsequently calculated from the ensemble mean: the DJF simulated total precipitation is ranked and divided into three equal parts. The ranked probability skill score (RPSS) [*Wilks*, 1995; *Mason*, 2004] determines the probabilistic forecast skill of the MOS-PP system.

3. Results

[10] Figure 2 shows the cross-validated correlation values for the 7 pure summer rainfall regions for the various combinations of predictor and predictand EOF modes. The highest correlation values are found for the Lowveld and north-eastern interior regions. Similar, albeit lower, values are seen for the central and western interior regions.

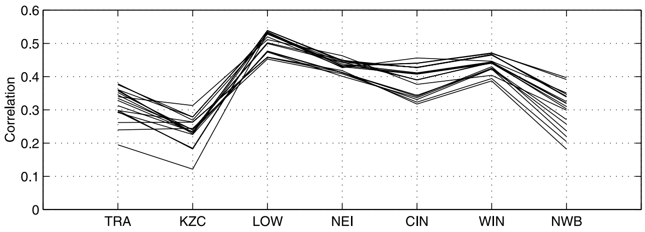

Figure 2. Correlations obtained from the various predictor and predictand EOF mode combinations over the 48-year 3-year-out cross-validated ECHAM4.5-MOS simulations for the 7 rainfall regions (TRA: Transkei; KZC KwaZulu-Natal coast; LOW: Lowveld; NEI: north-eastern interior; CIN: central interior; WIN: western interior; NWB: northern Namibia/western Botswana).

However, the optimal MOS model produces marginally higher correlation values for the central interior than for the western interior. The combination producing the best overall results is for 3 predictand and 4 predictor EOF modes, respectively explaining 80% and 65% of the variance. CCA patterns analysis [*Barnett and Preisendorfer*, 1987] (not shown) of DJF precipitation for the 48-year period using the ensemble mean of the simulation data, shows the most dominant CCA predictor pattern associated with above-normal rainfall resembles a tropical-temperate trough system. A significant proportion of austral summer rainfall over much of southern Africa is a result of these synoptic-scale systems that link tropical lows and westerly waves [*Todd and Washington*, 1999; *Todd et al.*, 2004]. When these systems are well developed, above-normal summer rainfall is generally produced by them as they extend over southern Africa and into the adjacent Indian Ocean [*Mason and Jury*, 1997]. The second CCA predictor mode shows a dipole pattern over the north-eastern interior of the region and the channel between Mozambique and southern Africa. This feature may be attributed to the influence of tropical troughs or cyclones which sometimes find their way into, or develop in, the channel and can occasionally persist there for extended periods of time. These storms occur mostly in January and February. With the presence of these tropical systems, rainfall over the north-eastern interior of the forecast region is suppressed owing to the associated subsidence on the periphery of these systems [*Tyson and Preston-Whyte*, 2000]. However, it has been found that the influence from tropical cyclones over the south-western Indian Ocean results in poor model forecast performance over the Lowveld [*Mason et al.*, 1996]. Owing to the relative high cross-validation MOS skill found over the north-east (Figure 2), it can be concluded that most of the skill comes from the AGCM's ability to simulate tropical-temperate trough systems. This is also supported by the fact that the tropical-temperate trough mode is the dominant CCA predictor mode and that the CCA predictand mode 1 (not shown) show similar loadings over both the Lowveld and north-eastern interior.

[11] Similar to the highest cross-validation correlations found over the north-east, the RPSS values of Figure 3 also show that the best 0-month lead-time MOS-PP forecast are found for the Lowveld area, followed by the north-eastern interior. The same conclusion about the origin of forecast skill therefore holds when using the MOS-PP forecast system. The high skill found over this area is encouraging since important agricultural activities such as corn, tea, citrus and other fruit production take place there. Negative RPSS values are found for both the KwaZulu-Natal coast and the northern Namibia/western Botswana regions. The latter region receives most of its rainfall in the months immediately following the DJF season, with very little rainfall during December and January. Forecast skill over the KwaZulu-Natal regions is not stationary in time, however, and improves significantly over the most recent decade [*Landman and Goddard*, 2002]. By considering only the 6 wettest and 6 driest years (12 in total) of the 27-year forecast period, high RPSS values are seen (Figure 4). These high values are the result of the forecast system being better able to predict for "extreme" years as opposed to "average" years and because of the small number of years considered extreme. The largest RPSS increase is found for Northern Namibia/western Botswana where the predictability of extremes may be higher owing to the low recorded DJF rainfall totals over this area. As was found when considering all the years (48) (Figure 2) and all the forecast years (27) (Figure 3), the highest "extreme" season (12 years) forecast skill is again evident over the north-eastern interior (Figure 4).

4. Discussion and Conclusions

[12] Previous work has demonstrated recalibrated AGCM forecast skill over the region, and has shown that recalibrated forecasts are superior to raw AGCM forecasts [e.g., *Landman and Goddard*, 2002]. However, using a pure MOS forecast system for all lead-times may be too expensive to develop and run operationally. In this paper, ECHAM4.5 archived simulation DJF rainfall fields have been statistically recalibrated using a MOS approach to observed DJF rainfall indices for 7 summer rainfall regions of southern Africa. Retrospective forecasts from ECHAM4.5 with 0-month lead-time are subsequently used as predictors in the simulation-MOS equations to produce MOS-PP forecasts for the 7 regions over a 27-year retro-active [*Landman et al.*, 2001] forecast period. The MOS-PP system combines the advantages of the MOS and PP techniques by better addressing the GCM biases problem found with PP techniques, and requiring only one set of prediction equations for all lead-times as apposed to a new

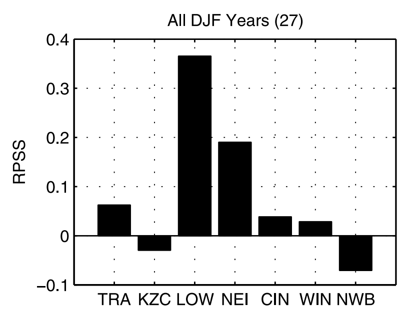

Figure 3. RPSS over the 27-year retro-active forecast period for the 7 rainfall regions (for region definitions, see Figure 2).

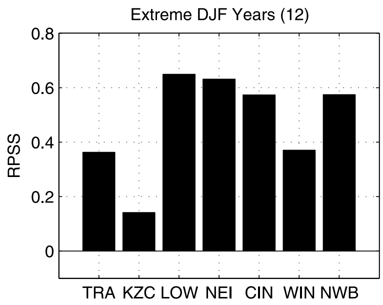

Figure 4. RPSS over the 6 wettest and 6 driest years of the 27-year retro-active forecast period for the 7 rainfall regions (for region definitions, see Figure 2).

set for each forecast lead-time when using a traditional MOS system. The main disadvantage of the MOS-PP system is that the AGCM forecast fields are generally not as good as the simulation fields. However, previous work [*Landman and Goddard*, 2002; *Goddard and Mason*, 2002] has shown that at short lead-times, little skill is lost for the austral summer rainfall season over southern Africa. Importantly, the MOS-PP system's high forecast skill derives from a physical mechanism - the AGCM's ability to correctly simulate tropical-temperate trough systems over the region. High skill is particularly evident when forecasting the 6 wettest and 6 driest years of the 27-year forecast period, again with the north-eastern interior exhibiting the highest skill values. One can therefore conclude that the existence or absence of modelled tropical-temperate trough systems mostly contributes to extreme season forecast skill. This conclusion is supported by the CCA predictor pattern of the 6 wettest and 6 driest years that shows similar features as mode 1 CCA predictor for the entire period discussed above (not shown).

[13] This paper has demonstrated the usefulness of using a hybrid dynamical-statistical system. More work will be conducted to investigate the predictability of rainfall using a MOS-PP system for rainfall seasons additional to DJF and for lead-times that can be considered more beneficial to the users of these forecasts than the 0-month lead-time demonstrated here. In addition, the predictability of extreme seasons in particular should be investigated.

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