SEASONAL MAXIMUM TEMPERATURE PREDICTION SKILL OVER SOUTHERN AFRICA: 1- VS. 2-TIERED FORECASTING SYSTEMS

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1. Introduction

Sea-surface temperature (SST) anomalies can nowadays be predicted with great accuracy. Due to the seasonal evolution in the estimation of these SST anomalies it is possible to generate seasonal-average forecasts by integrating them in atmospheric global circulation models (AGCMs) (Graham *et al*., 2000; Goddard & Mason, 2002). Using such a two-tiered modelling system to forecast the seasonal outcome of an area has been employed in South Africa for several years already (e.g., Landman *et al*., 2001). Coupled ocean-atmosphere models, or one-tiered systems, aim to produce more reliable seasonal forecasts due to them being able to explain the feedback between the atmosphere and the ocean. Whereas two-tiered systems assume that the atmosphere rather responds to SST's and does not affect the oceans.

General circulation models (GCMs) have confirmed skill at a global or even continental scale. However, GCM's are unable to show local sub-grid features, resulting in overestimating rainfall over southern Africa. Such systematic biases have created the need to downscale GCM simulations over southern Africa. One method is to employ a model output statistics (MOS) approach. Global models are employed in this study to predict seasonal maximum temperature extremes over southern Africa. Comparisons are drawn between the downscaled seasonal 850hPa geopotential height field forecasts of a two-tiered system versus the downscaled height forecasts from a coupled system. The ECHAM4.5 (Roeckner et al., 1995) atmospheric general circulation model is used for both the one-tiered and two-tiered systems. The application of this study may include the potential of health hazards associated with extremely hot summer seasons over the region.

2. Data and Method

All data required are obtained from the data library of the International Research Institute for Climate and Society (IRI). UEA CRU TS3p0 2m maximum temperature data are the predictand fields. 850hPa geopotential height field data from both the ECHAM4.5 AGCM and coupled model, ECHAM4.5-MOM3-DC2, are the predictor fields from the two- and one-tiered systems respectively. Data are extracted for the five 3-month seasons of OND, NDJ, DJF, JFM and FMA from 1982-2005. Forecast lead-times of up to three months for all seasons are taken into account for both models.

The hindcasts from both the one-and two-tiered forecasting systems were subsequently statistically downscaled to southern African resolution. MOS equations are implemented to compensate for any systematic deficiencies in the global models directly in the regression equations (Landman and Beraki, 2011; Landman and Goddard, 2002). MOS equations are developed by using the canonical correlation analysis (CCA) option of the Climate Predictability Tool (CPT) of the IRI. The forecast fields (predictors) for each of the global models that are used in the MOS are confined over a domain that covers equator to 45˚S and 15˚W to 60˚E. The 2m maximum temperature data (predictand) covers a domain of 12˚S to 35˚S and 11˚W to 41˚E.

Verification is performed over a test period independent of the training period. This period is obtained through a retro-active forecasting approach consequently producing an independent forecast data set of 12 years. In estimating the maximum temperature forecast skill of the different seasons of interest, the observed and predicted fields are put into three categories defining above-normal, near-normal and below-normal temperatures. These three categories are not equi-probable due to the above- and below-normal threshold values respectively representing the 75th and 25th percentile values of the climatological record. This categorization set the scene to test the models' ability to predict seasonal maximum temperature extremes..

Due to seasonal climate being inherently probabilistic, it needs to be verified probabilistically. Therefore the relative operating characteristic (ROC) (Mason and Graham, 2002) and reliability diagram (Hamill, 1997) are used to verify the downscaled forecasts. ROC scores applied to probabilistic forecasts indicated a higher probability when an event occurred (ROC >0.5) opposed to when it did not occur. Therefore ROC identified whether the set of forecasts had the attribute of discrimination. The forecasts are reliable if there is consistency between predicted probabilities and observed frequencies of such an event.

3. Results

Figure 1 shows the ROC scores of the above (75th percentile) and below (25th percentile) normal categories for both the one- and two-tiered modelling systems. 2m temperature data was initally used as the predictor, however, 850hPa geopotential height fields proved to generate more skill as the predictor of 2m maximum temperature over southern Africa.

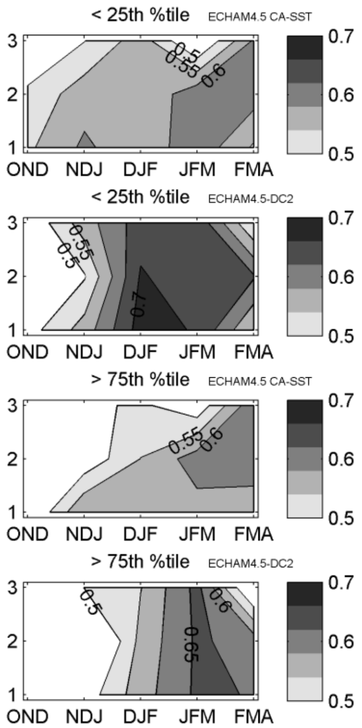

FIG 1: ROC scores of above (75th) and below (25th) normal percentiles for both the 1- and 2-tiered systems for the seasons OND, NDJ, DJF, JFM and FMA with lead-times up to 3 months.

From Figure 1 it can be deduced that the coupled model has the best chance to capture seasonal maximum temperature extremes. Moreover, the seasons that showed the highest ROC values are DJF and JFM, which coincide with the period of highest seasonal temperatures normally found over southern Africa. The below-normal percentile of the one-tiered system indicates the highest overall skill, which implies that the coupled model is able to skilfully predict when there is a high likelihood of not experiencing extremely high seasonal maximum temperatures during mid-summer. The coupled system is also useful to predict the likelihood of extremely high maximum temperatures during the second half of the summer season, i.e., January to March.

4. References

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