INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. **21**: 1–19 (2001)

RETRO-ACTIVE SKILL OF MULTI-TIERED FORECASTS OF SUMMER RAINFALL OVER SOUTHERN AFRICA

WILLEM A. LANDMAN[a,*], SIMON J. MASON[b], PETER D. TYSON[a] and WARREN J. TENNANT[c]

[a] *Climatology Research Group, PO Wits, Johannesburg, 2050, South Africa*
[b] *International Research Institute for Climate Prediction, Scripps Institute of Oceanography, University of California San Diego, Mail Code 0235, La Jolla, CA 92093-0235, USA*
[c] *South African Weather Bureau, Private Bag X097, Pretoria, 0001, South Africa*

Received 25 November 1999
Revised 29 June 2000
Accepted 29 June 2000

ABSTRACT

Sea-surface temperature (SST) variations of the oceans surrounding southern Africa are associated with seasonal rainfall variability, especially during austral summer when the tropical atmospheric circulation is dominant over the region. Because of instabilities in the linear association between summer rainfall over southern Africa and SSTs of the tropical Indian Ocean, the skilful prediction of seasonal rainfall may best be achieved using physically based models. A two-tiered retro-active forecast procedure for the December–February (DJF) season is employed over a 10-year period starting from 1987/1988. Rainfall forecasts are produced for a number of homogeneous regions over part of southern Africa. Categorized (below-normal, near-normal and above-normal) statistical DJF rainfall predictions are made for the region to form the baseline skill level that has to be outscored by more elaborate methods involving general circulation models (GCMs). The GCM used here is the Centre for Ocean–Land–Atmosphere Studies (COLA) T30, with predicted global SST fields as boundary forcing and initial conditions derived from the National Centres for Environmental Prediction (NCEP) reanalysis data. Bias-corrected GCM simulations of circulation and moisture at certain standard pressure levels are downscaled to produce rainfall forecasts at the regional level using the perfect prognosis approach.

In the two-tiered forecasting system, SST predictions for the global oceans are made first. SST anomalies of the equatorial Pacific (NIÑO3.4) and Indian oceans are predicted skilfully at 1- and 3-month lead-times using a statistical model. These retro-active SST forecasts are accurate for pre-1990 conditions, but predictability seems to have weakened during the 1990s. Skilful multi-tiered rainfall forecasts are obtained when the amplitudes of large events in the global oceans (such as El Niño and La Niña episodes) are described adequately by the predicted SST fields. GCM simulations using persisted August SST anomalies instead of forecast SSTs produce skill levels similar to those of the baseline for longer lead-times. Given high-skill SST forecasts, the scheme has the potential to provide climate forecasts that outscore the baseline skill level substantially. Copyright © 2001 Royal Meteorological Society.

KEY WORDS: baseline skill; canonical correlation analysis; downscaling; general circulation model; perfect prognosis; seasonal rainfall forecasts; southern Africa

1. INTRODUCTION

Droughts and floods have long been distinctive features of the climate of southern Africa (Tyson, 1986). Variability of the climate has been accentuated by the occurrence of El Niño–Southern Oscillation (ENSO) events, but is by no means dominated by them (Mason and Jury, 1997). Climate variations have an important impact on agriculture, housing, water supply, industry and tourism. With an ever-increasing population that is putting an associated increase in demand on fresh water resources, effective water management has become essential. The need for providing accurate forecasts of rainfall a season ahead, or at least a few months in advance, is becoming more and more necessary in the region. Since

* Correspondence to: South African Weather Bureau, Private Bag X097, Pretoria, 0001, South Africa; e-mail: willem@iri.ldeo.columbia.edu

understanding the predictability of the atmosphere at seasonal-to-interannual time-scales has improved considerably during the past decade, the provision of such forecasts has become a possibility in general (Carson, 1998) and may prove feasible for southern Africa (Mason and Tyson, 2000). It is this notion that is explored in this paper.

Variability in sea-surface temperatures (SSTs) has been shown to be related to southern African climate variability (Nicholson and Entekhabi, 1987; Walker, 1990; Jury and Pathack, 1991; Mason *et al*., 1994; Mason, 1995; Makarau and Jury, 1997; Mason and Jury, 1997; Rocha and Simmonds, 1997; Reason and Lutjeharms, 1998; Reason, 1999) and provides the main source of atmospheric predictability at seasonal time-scales (Palmer and Anderson, 1994). Inclusion of anomalous SSTs, in the areas surrounding southern Africa, into seasonal prediction models has enabled predictions of climate variability to be made for the region (Cane *et al*., 1994; Hastenrath *et al*., 1995; Barnston *et al*., 1996; Mason, 1998; Mattes and Mason, 1998; Jury *et al*., 1999; Landman and Mason, 1999a; Mason and Tyson, 2000). Much effort has gone into constructing seasonal forecast algorithms (Wilks, 1995), but most of these prediction algorithms make extensive use of linear statistics. Many important climate processes demonstrate strong non-linearities and the forecast skill of statistical models is restricted owing to the exclusion of these processes (Barnston *et al*., 1994; Carson, 1998). Furthermore, the inherent assumptions of most statistical models, such as that of Gaussian probability distributions, are frequently invalid. Purely statistical methods of seasonal forecasting, especially those that are linear, are unable to take instabilities within SST–southern African rainfall associations into account. However, such changing associations may be simulated by a general circulation model (GCM), at least qualitatively (Landman and Mason, 1999b). Further improvements to the prediction of southern Africa's summer rainfall on a seasonal scale will be best achieved by using GCMs.

Physically based dynamical models should outscore statistical models if the ocean-atmosphere system contains sufficient inherent predictability (Barnston *et al*., 1994). Forecast skill using dynamical models of the atmosphere can be achieved by first predicting SSTs for regions known to be partly responsible for the rainfall variability over land. These predicted SST fields are then incorporated in a two-tiered forecasting system to force an atmospheric GCM (Bengtsson *et al*., 1993; Barnett *et al*., 1994; Hunt *et al*., 1994; Graham and Barnett, 1995; Bengtsson *et al*., 1996; Hunt, 1997; Mason *et al*., 1999). GCM forecasts can never be perfect because of errors unavoidably present in initial conditions and because of model deficiencies (Holton, 1979). The use of parameterization schemes adds to the uncertainty of GCM forecasts of rainfall. Rainfall over southern Africa typically is overestimated by GCMs (Joubert and Hewitson, 1997; Mason and Joubert, 1997). Despite these limitations, GCMs have been used to provide skilful seasonal rainfall forecasts for many parts of the globe, but especially in the tropics (Hunt *et al*., 1994; Hunt, 1997; Shukla, 1998; Stockdale *et al*., 1998; Mason *et al*., 1999). It remains to be seen if there is operational skill for southern Africa, which generally lies outside the tropics, where seasonal predictability is relatively low because of the greater inherent chaotic instability of the extratropical atmosphere (Palmer and Anderson, 1994). Tropical atmospheric circulation becomes dominant only during the peak summer rainfall months of December–February (DJF) creating the prospect of higher forecast skill over southern Africa in this season (Mason *et al*., 1996). The rainfall variability over southern Africa at this time of year is related to atmospheric circulation and moisture fields (Taljaard, 1986; D'Abreton and Lindesay, 1993; Taljaard, 1994; D'Abreton and Tyson, 1995; Taljaard, 1995; D'Abreton and Tyson, 1996; Mason and Jury, 1997).

In this paper, the skill of statistical and GCM summer rainfall forecast systems for southern Africa is compared over a 10-year retro-active period from 1987/1988 to 1996/1997. The aim is to assess whether a GCM-based approach to seasonal rainfall estimation can produce rainfall forecasts with skill that outscores that of statistical modelling. Only when this is so is operational regional forecasting using GCMs justified because of the much greater expense involved. The statistical model used here is canonical correlation analysis (CCA), and evolutionary features of SSTs, such as a warming or cooling equatorial Pacific Ocean, are used as the only predictors (Landman and Mason, 1999a). The GCM that is used is the Centre for Ocean–Land–Atmosphere Studies (COLA) T30 18-layer spectral model with a resolution of roughly 400 km over the study area (Kirtman *et al*., 1997). The lower boundary conditions of the GCM are monthly-mean SSTs, predicted using a CCA-based statistical model. The GCM-simulated circulation and moisture fields are bias-corrected and downscaled to regional rainfall forecasts (Karl *et al*., 1990; Cui *et al*., 1995; von Storch and Navarra, 1995; Rummukainen, 1997). Although GCMs demonstrate significant skill at global or even continental scale (Mason *et al*., 1999), they are unable to represent local subgrid-scale features (Joubert and Hewitson, 1997; Mason and Joubert, 1997). Instead, the bias-corrected GCM fields are used as predictors in CCA-based perfect prognosis equations, developed from the relationship between observed circulation and moisture, and summer rainfall over southern Africa. The multi-tiered forecast system presented here is used to define reliable skill estimates over the retro-active forecast period. Retro-active forecasts are compared to the baseline skill level set by the statistical model in order to determine whether operational GCM-based seasonal rainfall forecasting is a realistic option for improved categorized (below-normal, near-normal, above-normal) seasonal rainfall estimation in southern Africa.

2. DATA

2.1. SSTs

SSTs were used as the only predictors in both the CCA seasonal rainfall and SST forecasting models. Reconstructed SST fields using empirical orthogonal functions are available for the period 1950–1995 (Smith *et al*., 1996). Optimum interpolation (OI) SST data (Reynolds and Smith, 1994) were obtained from 1996 to date to form a set of 3-month means. During operational predictions, the latest OI data are used to update the SST data set. Both the reconstructed (2° latitude × longitude) and the OI (1° latitude × longitude) sets were reduced to a 6° latitude × 4° longitude grid (1078 points) to reduce the large matrices involved in the statistical forecast models. However, large oceanic features, such as El Niño or La Niña events, are still adequately represented by the coarser grid.

2.2. Rainfall

DJF rainfall totals for 510 South African stations, 56 stations in Namibia, 7 stations in Lesotho and 25 stations in Botswana were obtained for the period 1950/1951 to 1996/1997. Regional rainfall indices were computed in a manner similar to that of Mason (1998) for nine homogeneous rainfall regions (Landman and Mason, 1999a) defined as: southwestern Cape; south coast; Transkei; KwaZulu–Natal coast; Lowveld; northeastern Highveld; central interior; western interior; northern/western Botswana (Figure 1).

2.3. NCEP reanalysis data

For the initial conditions used to construct an ensemble of GCM forecasts, and for constructing optimal equations relating rainfall and atmospheric variables such as circulation and moisture, the National Centers for Environmental Prediction (NCEP) reanalysis data (Kalnay *et al*., 1996) were used. For initial conditions, global reanalysis data are available for every 24 h; for circulation and moisture monthly mean data were used for the window 10°–45°S; 10°W–60°E spanning most of southern Africa and adjacent oceans. The 24 hourly data for the period 1987/1988 to 1996/1997 were used to obtain the initial conditions. The monthly data for 1950/1951–1996/1997 were used to relate circulation and moisture at standard pressure levels to rainfall. The data have a 2.5° horizontal resolution.

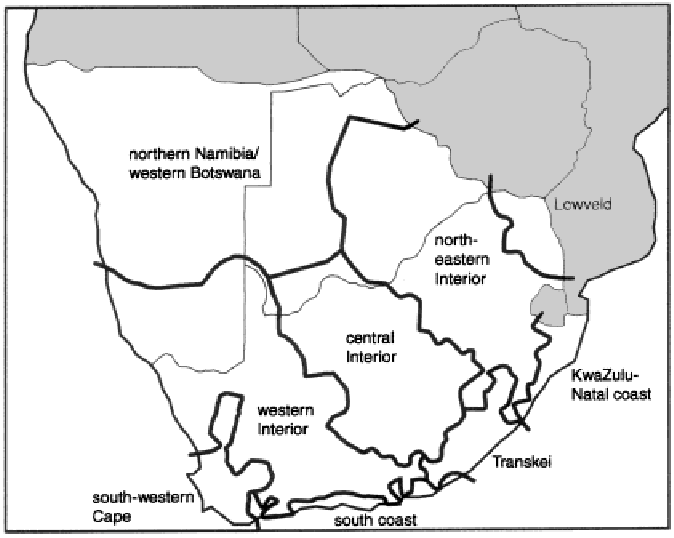

Figure 1. The nine rainfall regions used in this study. Countries shaded grey were not included

3. METHODS

3.1. The statistical seasonal rainfall forecast model

A CCA-based model for forecasting southern African rainfall has been developed for operational use at the South African Weather Bureau. It is described in detail by Landman and Mason (1999a). Often used as a forecast technique, CCA (Barnett and Preisendorfer, 1987; Graham *et al.*, 1987a,b; Barnston and Ropelewski, 1992; Barnston, 1994; Chu and He, 1994; Barnston and Smith, 1996; Shabbar and Barnston, 1996; Landman and Klopper, 1998) was used here to set the baseline statistical model skill level that must be exceeded to demonstrate the usefulness of a GCM approach to seasonal rainfall forecasting. The Landman and Mason (1999a) model used in this paper was constructed to relate global-scale SSTs, forming the predictor set, to the regional rainfall indices of DJF that form the predictand set. SSTs were used as predictors of seasonal rainfall over southern Africa in the CCA model because of the memory they impart to the climate system (Palmer and Anderson, 1994) and because of their role in ocean–atmosphere interaction in the region (Nicholson and Entekhabi, 1987; Walker, 1990; Jury and Pathack, 1991; Mason *et al.*, 1994; Mason, 1995; Mason and Jury, 1997; Rocha and Simmonds, 1997; Reason and Lutjeharms, 1998; Reason, 1999).

The model was used to produce regional rainfall forecasts at 1- and 3-months lead-times. A lead-time of 1-month implies that the forecast/hindcast is for the season beginning 1 month after the end of the predictor period. The following schematic illustrates the definition of predictor seasons for hindcasting DJF rainfall of 1982 for different lead-times using the CCA model:

1981 1982 1982/1983
<u>*SON DJF MAM JJA*</u> SON ⇒ DJF (3-month lead)

SO <u>*NDJ FMA MJJ ASO*</u> N ⇒ DJF (1-month lead)

The underlined months indicate the 3-month periods for which observed 3-month SST means were calculated to produce a forecast of DJF rainfall.

3.2. The SST forecast model

CCA was likewise used to predict near-global (45°N–45°S) SST anomalies. Such an approach has been shown to work in the prediction of equatorial SSTs in the Pacific Ocean (Barnston and Ropelewski, 1992). As with the rainfall forecasting model, the preceding four seasonal (3-month) mean near-global SSTs were used as predictors. The predictands were the subsequent monthly near-global SSTs. For rainfall forecasts for the DJF season issued at the beginning of September, SST forecasts for the 7 months leading up to March are required. For forecasts made in early November, the SSTs of 5 consecutive months are required. The following schematic illustrates the lead-times involved in making forecasts during early September and early November, respectively, for the 1982/1983 season:

1981 1982 1983
SON DJF MAM JJA SO $\Rightarrow$ S, O, N, D, J, F, M (3-month lead)

SO *NDJ FMA MJJ ASO* $\Rightarrow$ N, D, J, F, M (1-month lead)

Although the lead-times refer to the number of months leading up to the target season of DJF, much longer leads are involved in predicting the SSTs at the end of the predictand period, i.e. forecasts made in early September for February have a 5-month lead.

In constructing the CCA model, pre-orthogonalization using empirical orthogonal function (EOF) analysis (Barnston, 1994) was performed on the standardized predictor and predictand fields. The number of EOF modes to be retained in the CCA eigenanalysis was determined to account for about 60% of the variance of both predictand and predictor fields, following Jolliffe's (1972) modification of the Guttman–Kaiser criterion (Jackson, 1991). The predictand fields, which are an integration of several 1-month fields, were separated after the prediction to obtain forecasts for each 1-month period contained in the combined predictand field. Subsequently the predicted fields were filtered to reduce the noise associated with the CCA forecasts (Press *et al*., 1992) and were then interpolated to the GCM grid resolution of 3.75° × 3.75°. The anomaly fields were smoothed using a grid–spectral–grid conversion at triangular truncation at 15 waves. Anomalies over land grid-points were set to zero for this purpose and areas of sea-ice were set to 271.4 K. SST anomalies poleward of 45° were decayed exponentially to 0.5 K or less at 2 months.

3.3. The GCM

The COLA GCM was forced by the predicted monthly SSTs from the CCA model detailed above. Initial conditions for the GCM forecasts were derived from the NCEP reanalysis data (Kalnay *et al*., 1996). Each case of the monthly GCM forecasts consisted of the average of five ensemble members generated using the lagged (24-h) average forecasting technique (Hoffman and Kalnay, 1983). In the absence of an independent model climatology, GCM mean biases were removed by subtracting the 3-month mean forecast errors in the remaining 9 years of the retro-active period. The ideal would be to have a longer and completely independent GCM model climatology of 20–30 years, but for computational reasons it was not practical to build a sufficiently long climatology forced with hindcast SST. Although Atmospheric Model Intercomparison Project (AMIP)-style model climatologies are available, because of the relatively weak variances of forecasts compared to observed SSTs, the forecast atmospheric anomalies are likewise likely to be weak. While prognostic fields over the 10-year period can not, therefore, be considered as truly retro-active, they do not use any information of the target season when the correction is made for that season. By removing only the GCM bias, it has been assumed that the variances of the GCM-simulated fields are correct. Because the target season is excluded when calculating the GCM's mean bias, the effect of not using an earlier independent climatology on forecast skill is expected to be minimal. Probably the strongest impact will be to underestimate the skill of the GCM because of the removal of any potentially predictable mean bias of precipitation over the retro-active period.

3.4. Downscaling approach

Rather than using model-simulated grid-point rainfall, the *perfect prognosis* approach (Wilks, 1995) for downscaling dynamical model quantities was used in this paper. Using CCA (von Storch *et al*., 1993), observed (NCEP reanalysis) 850, 700, 500 and 200 hPa geopotential heights, 700 hPa relative humidity, 850–500 hPa thickness and 500–200 hPa thickness were related to the DJF seasonal indices of the nine homogeneous rainfall regions shown in Figure 1. These downscaling equations can be used to produce rainfall forecasts by applying them to the GCM-simulated atmospheric fields obtained by forcing the GCM with the predicted SSTs at long (3-month) and short (1-month) lead-times. Usually, a perfect prognosis approach makes no attempt to compensate for systematic errors of the dynamical model and assumes that the dynamical model quantities are perfect. Notwithstanding, bias corrections can be, and were, applied before use in the perfect prognosis equations.

In designing the optimal CCA downscaling model, EOF analysis was performed on the predictor and predictand sets. The number of modes to be retained in the CCA eigenanalysis problem was determined, as before, using cross-validated forecast skill sensitivity tests. The sensitivity tests were conducted with a varying number of retained predictor and predictand EOF modes to obtain the combination producing the highest average correlation of the summer rainfall regions. The optimal combination involved predictor modes explaining about 90% of the variance and predictand modes explaining about 70% of the variance. The truncation for the number of CCA modes retained was determined by using the Guttman–Kaiser criterion (Jackson, 1991). For each of the four training periods, two CCA modes were retained. Table I shows the cross-validation correlations for each of the training periods.

With high cross-validated and statistically significant correlations for the summer rainfall regions, it should prove possible to achieve good forecast skill, provided that the GCM simulated circulation and moisture fields are accurate. Due to model deficiencies in both the COLA T30 GCM (Xue and Shukla, 1998) and the SST model, perfect prognostic fields are unlikely. Notwithstanding, if there is a SST signal in the climate, a well designed GCM forced with skilful SST forecasts should lead to significant reproducibility of climate anomalies among ensemble members and, hence, predictability (Ward and Navarra, 1997). It is this notion that remains to be tested for southern Africa.

3.5. Estimating forecast skill

There are several methods for determining model output performance (Wilks, 1995). For the statistical models, performance was first estimated over the training period involved in setting up the CCA prediction equations by employing the method of cross-validation (Barnett and Preisendorfer, 1987; Michaelsen, 1987; van den Dool, 1987; Barnston and van den Dool, 1993; Elsner and Schmertmann, 1994). For cross-validation, the value that is to be predicted is omitted from the training period. Here, only 1 year was removed from the training period. Cross-validation was employed to:

Table I. Perfect prognosis cross-validation correlations between observed and downscaled regional rainfall for each of the respective training periods

Region	1951/1952–1986/1987	1951/1952–1989/1990	1951/1952–1992/1993	1951/1952–1995/1996
Southwestern Cape	0.09	0.07	0.03	0.06
South coast	0.04	−0.02	−0.06	−0.16
Transkei	0.53*	0.58*	0.61*	0.61*
KwaZulu–Natal coast	0.49*	0.36*	0.38*	0.36*
Lowveld	0.79*	0.78*	0.77*	0.73*
Northeastern interior	0.68*	0.69*	0.70*	0.66*
Central interior	0.81*	0.78*	0.80*	0.80*
Western interior	0.74*	0.72*	0.71*	0.69*
N Namibia/W Botswana	0.77*	0.79*	0.81*	0.77*

Correlations significant at the 95% level of confidence are marked with an asterisk.

(i) estimate the optimal number of global-scale SST EOF modes and DJF rainfall EOF modes for the CCA rainfall model by maximizing the cross-validated skill;
(ii) estimate the optimal number of combined DJF circulation- and moisture-fields EOF modes and DJF rainfall EOF modes by maximizing the cross-validated skill;
(iii) estimate the skill of grid-point SST predictions;
(iv) bias-correct the GCM prognostic fields by removing the mean of the GCM simulations during 9 years of the retro-active period from the simulation of the remaining year.

Cross-validation may indicate biased skill levels (Barnston and van den Dool, 1993). In order to obtain skill levels that are unbiased, model validation should be conducted over a test period that is independent of the training period. This method of model validation is referred to as retro-active forecasting and involves the evaluation of predictions compared to observations excluding any information following the target year (Wilks, 1995). The retro-active procedure can be illustrated by considering forecasts for DJF during the 10-year period 1987/1988–1996/1997. The model was first trained with information leading up to and including 1986/1987. Three consecutive years were then predicted using this trained model, and predictions of DJF rainfall for 1987/1988, 1988/1989 and 1989/1990 were made. The model was subsequently retrained using data leading up to and including 1989/1990 to predict 1990/1991, 1991/1992 and 1992/1993 conditions. This procedure was continued until the 1996/1997 DJF rainfall was predicted using a model trained with data up to 1995/1996. Thus, statistical-model retro-active DJF rainfall forecasts for the 10-year period starting in 1987/1988 used a training period of 36 years (1951/1952 to 1986/1987) for predicting 1987/1988, 1988/1989 and 1989/1990 conditions. Likewise, a training period of 39 years (1951/1952–1989/1990) was used for predicting 1990/1991–1992/1993 conditions, a 42-year period (1951/1955–1992/1993) for predicting 1993/1994–1995/1996 and, finally, a 45-year period (1951/1952–1995/1996) for predicting 1996/1997 conditions.

Retro-active forecast validation gives skill levels that are unbiased and gives the best indication of how a model would perform operationally. The retro-active CCA forecasts were variance-adjusted (Ward and Folland, 1991), with the variance defined over the appropriate training periods. The variance-adjustment ensures that near-perpetual forecasts of near-normal rainfall are avoided. Retro-active forecasting was employed to establish the performance of the CCA model over the test period in order to obtain the baseline skill level. It was used also to construct SST forecast fields that constitute the boundary forcing in the GCM during the 10-year testing period. Finally, the performance of the rainfall prediction algorithms involving the GCM over the retro-active test period was established. The GCM-derived rainfall forecasts are not strictly retro-active because of the way in which the model biases were removed, but computational constraints precluded a fully retro-active process.

In estimating the skill in predicting the DJF rainfall, each of the observed and predicted fields was separated into three equiprobable terciles defining above-normal, near-normal or below-normal conditions. For each homogeneous region of the predictand set, the categorical forecast was compared with that of the observed in order to calculate the model skill. Skill levels may be variously defined by the linear error in probability space (LEPS) scores (Ward and Folland, 1991; Potts *et al.*, 1996), hit scores (the number of times a correct category is forecast) (von Storch and Navarra, 1995) and the false alarm ratio (FAR), i.e. the fraction of forecast events that failed to materialize (best possible FAR is zero and worst possible FAR is one) (Wilks, 1995). Sometimes the false alarm ratio is called the false alarm rate (Wilks, 1995; Mason and Graham, 1999).

3.6. Significance testing

In order to see if the hit-scores and LEPS scores are statistically significant, a Monte Carlo test was performed (Livezey and Chen, 1983; Wilks, 1995). This was done by randomly creating above-normal, near-normal or below-normal rainfall categories for both a predicted and observed rainfall set, calculating the number of hits and the LEPS scores and repeating the procedure 1000 times. For skill determined by hit scores, the 90% confidence level is associated with five hits out of a possible ten, the 95% level with six hits and the 99% level with seven hits. A LEPS score of 35% defines the 90% confidence level, a score of 46% the 95% level and a score of 62% the 99% level.

4. RESULTS

4.1. Setting a baseline skill level

By quantifying a level of forecast skill, the baseline skill level using the CCA linear statistical model can be set and, hence, compared to forecasts generated by the GCM. Table II represents a summary of the categorised (above-normal, near-normal or below-normal) CCA rainfall forecasts made in early November for the DJF rainfall season for the 10-year period 1987/1988–1996/1997. Rainfall for three of the 1-month lead-time retro-active years (1988/1989, 1991/1992 and 1994/1995) is predicted accurately, while poor accuracy is found for 1987/1988 and 1995/1996 (La Niña event). The number of hits is poorer for the 3-month lead, made in early September, than for the 1-month lead forecasts. Despite the improvement in skill at the shorter lead-time, forecasts made in September frequently are consistent with those made in November: forecasts of dry (wet) conditions do not change to wet (dry) with increasing lead-time and years that are predicted skilfully (1988/1989, 1991/1992 and 1992/1993) with a 1-month lead are equally skilfully predicted with a 3-month lead. For both lead-times, there is a strong indication that the model has a bias towards forecasting below-normal rainfall conditions. It is possible that this may be the result of warming of tropical SSTs over recent years (Kawamura, 1994). Notwithstanding the low skill and the bias, the baseline skill level has been set that has to be outscored by the GCM-based forecasts.

4.2. SST forecasts

The CCA model for forecasting of SST anomalies that are used as boundary forcing for the GCM was tested for the equatorial Indian Ocean as well as for the equatorial Pacific Ocean, where useful skill has been demonstrated for similar models (Barnston *et al.*, 1994). Area-averaged indices were calculated for the Indian Ocean from 3°N to 3°S and 48°E to 104°E and the NIÑO3.4 region of the Pacific Ocean. The assessment of predictability was made for the 10-year retro-active period from 1987/1988 to 1996/1997. For comparison, model forecast skill is also compared with the skill that would be obtained using persisted SST anomalies as a forecast.

Cross-validated correlations between January predicted and observed Indian Ocean SSTs for 1- and 3-month lead-times are 0.73 and 0.69. The January forecast anomalies of the retro-active test period are shown in Figure 2(a, b). Good forecasts were produced for 1988, 1989 and 1994–1997. Only 1990 and 1993 were poor. Owing to the importance of the influence of the Indian Ocean SSTs on the climate of southern Africa (Mason and Jury, 1997; Goddard and Graham, 1999), the predictability of this ocean needs to be further improved. The CCA SST prediction model outperforms persistence forecasting in the Indian Ocean. The correlations between predicted and persisted SST indices are in the vicinity of 0.5 or less (Figure 2(c, d)). Given that the CCA SST prediction model outperforms persistence in the Indian Ocean, and that it has been shown that accurate Indian Ocean SST forecasts are essential for the reliable simulation of climate variability over southern Africa (Goddard and Graham, 1999), model SST forecasts are used as boundary conditions to force the COLA GCM in the multi-tiered scheme being advocated.

For the equatorial Pacific Ocean, 1- and 3-month forecasts give cross-validation correlations between predicted and observed January SSTs of 0.85 and 0.76 for the NIÑO3.4 region. The January forecast anomalies of the retro-active test period are shown in Figure 2(e, f). The La Niña event of 1989 was well predicted, but the strength of the 1992 El Niño event was underestimated by about a half. The subsequent El Niño event was predicted with improved accuracy, but the predicted anomaly of the 1996 La Niña event was very close to zero at 1-month lead, and was positive at a 3-month lead. Poor predictability during the 1990s has been found with other models and may be because of inherent poor predictability during the early part of the decade (Goddard and Graham, 1997; Philander, 1998; Barnston *et al.*, 1999). Since the test period used here is from 1987/1988 to 1996/1997, many of the retro-active predictions are

Table II. Categorized CCA retro-active 1-month (left of /) and 3-month (right of /) lead forecasts (lower case) and observations (upper case) for the nine regions

Region		La Niña			El Niño			El Niño	La Niña		Hit score	LEPS
	1987/1988	1988/1989	1989/1990	1990/1991	1991/1992	1992/1993	1993/1994	1994/1995	1995/1996	1996/1997		
Southwestern Cape	a/a N	a/a N	a/a N	a/a N	b/b B	a/a B	b/b N	b/b N	n/b A	n/a A	1(0)/2(1)	−20/−12
South coast	a/n N	a/a N	a/a N	n/b N	b/b A	n/n B	b/b A	b/b A	b/b N	n/a N	2(2)/1(1)	−65/−74
Transkei	b/b A	a/a A	a/a B	b/b N	b/b B	b/b B	n/b N	b/b N	b/b A	b/b N	3(1)/3(1)	−2/−14
KwaZulu–Natal coast	n/n A	a/a A	a/a N	b/b A	b/b B	b/b B	n/b B	b/n B	b/b A	b/b N	4(1)/4(2)	21/21
Lowveld	n/n A	n/n N	n/n N	b/b N	b/b B	b/b N	n/n B	b/n B	b/b A	b/b N	4(1)/3(1)	16/−3
Northeastern interior	b/n A	a/n A	n/b N	b/b A	b/b B	b/b N	n/n N	b/n B	b/b A	b/b N	5(2)/2(1)	9/−22
Central interior	b/b A	a/n A	n/b B	b/b A	b/b B	b/b B	a/n A	b/n B	b/b A	b/b N	5(2)/3(2)	23/−2
Western interior	b/b N	a/a A	n/b B	b/b N	b/b B	b/b N	a/n A	b/n N	b/b A	b/b N	3(1)/4(1)	22/28
N Namibia/W Botswana	b/b A	n/n A	b/b N	b/b A	b/b B	b/b N	n/n N	b/n B	b/b N	b/b N	3(1)/2(1)	−3/−25
Hits	0/1	6/4	2/3	1/0	8/8	3/3	4/3	5/1	0/0	1/1		

A and a refer to above-normal; N and n refer to near-normal; B and b refer to below-normal.
The hit score is the number of correct forecast categories over the 10 years for each region. Numbers in brackets are the number of hits associated with neither an El Niño nor a La Niña event. Hits refer to the number of correct forecasts during a particular year.

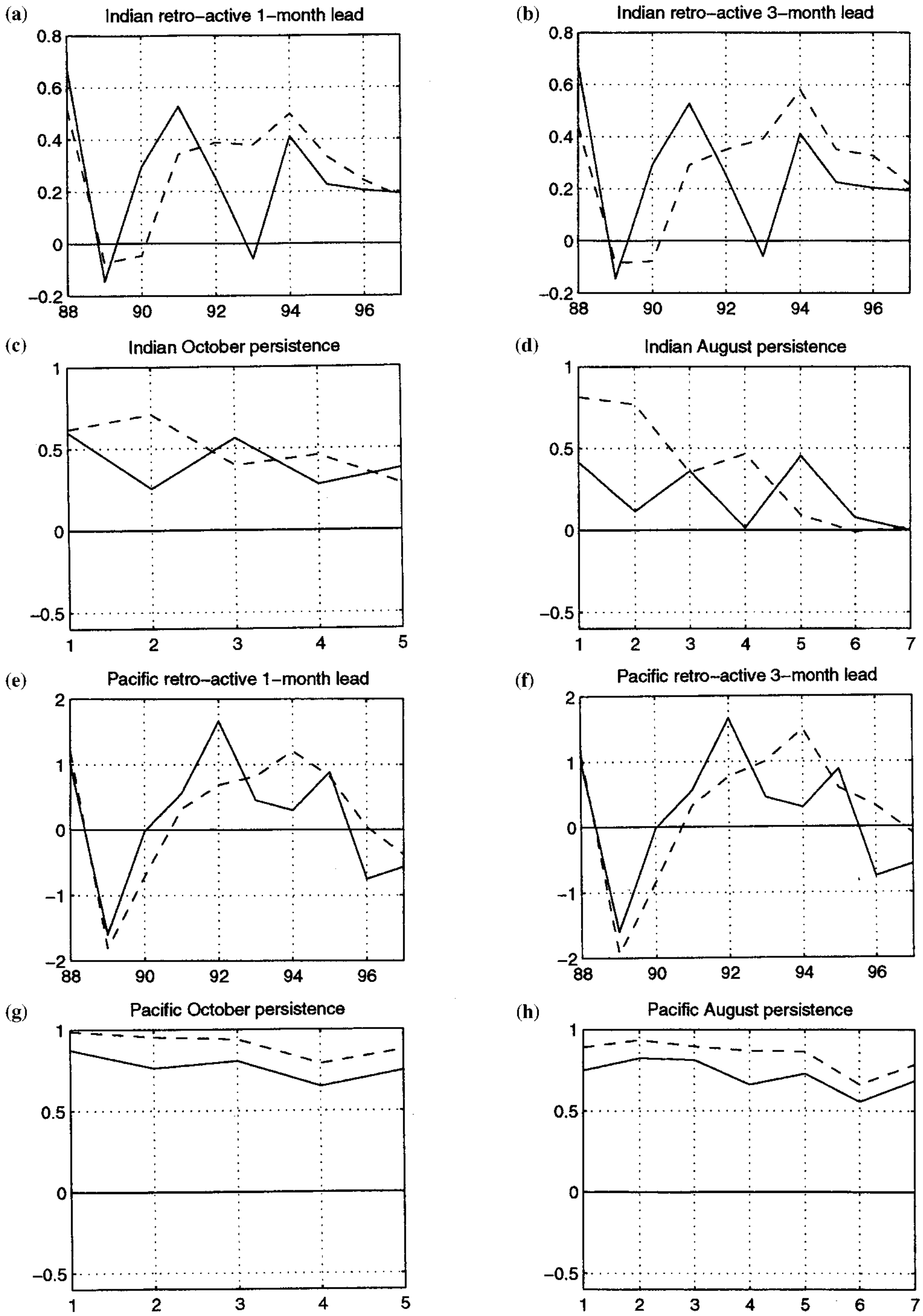

Figure 2. Observed (solid line) and retro-active forecasts (dashed line) of the Indian Ocean SST anomalies (°C) for (a) 1-month and (b) 3-month lead-times; correlations between predicted (solid line) and persisted (dashed line) Indian Ocean SSTs for (c) 1-month lead-times (i.e. using October SSTs) and (d) 3-month lead-times (i.e. using August SSTs); observed (solid line) and forecast (dashed line) SST anomalies for the NIÑO3.4 domain for (e) 1-month and (f) 3-month lead-times; correlations between predicted (solid line) and persisted (dashed line) NIÑO3.4 domain SSTs for (g) 1-month lead-times (i.e. using October SSTs) and (h) 3-month lead-times (i.e. using August SSTs)

Table III. Categorized multi-tiered retro-active 1-month (left of /) and 3-month (right of /) forecasts (lower case) and observations (upper case) for the nine regions

Region		La Niña			El Niño			El Niño	La Niña		Hit score
	1987/1988	1988/1989	1989/1990	1990/1991	1991/1992	1992/1993	1993/1994	1994/1995	1995/1996	1996/1997	
Southwestern Cape	a/b N	a/a N	a/a N	n/a N	a/b B	b/b B	b/b N	b/a N	a/b A	a/a A	4(3)/3(2)
South coast	a/a N	a/a N	a/a N	a/a N	a/b A	b/b B	b/b A	b/a A	a/b N	a/a N	2(1)/2(1)
Transkei	n/n A	a/a A	a/a B	a/n N	n/n B	b/b B	b/n A	b/a N	a/n A	a/a N	3(1)/3(2)
KwaZulu–Natal coast	b/b A	a/n A	n/n N	a/n A	n/n B	b/b B	b/n B	b/a B	a/n A	a/n N	7(4)/3(3)
Lowveld	n/n A	a/n N	n/n N	n/n N	n/n B	n/n N	n/n B	n/n B	n/n A	n/n N	4(4)/5(4)
Northeastern interior	n/b A	a/n A	n/n N	a/n A	n/n B	n/n N	n/n N	n/a B	a/n A	n/n N	7(5)/4(4)
Central interior	n/n A	a/a A	a/a B	a/n A	n/n B	n/n B	n/n A	n/a B	a/n A	n/n N	4(2)/2(1)
Western interior	a/a N	a/a A	a/a B	a/n N	n/a B	n/n N	n/n A	n/a A	a/n A	a/n N	4(1)/4(3)
N Namibia/W Botswana	a/n A	a/a A	a/a N	n/n A	n/n B	n/n N	n/n N	n/n B	n/n N	n/n N	6(4)/5(3)
Hits	1/0	6/5	3/3	5/3	1/1	8/8	3/2	2/1	7/1	5/7	

A and refer to above-normal; N and n refer to near-normal; B and b refer to below-normal.
The hit score is the number of correct forecast categories over the 10 years for each region. Numbers in brackets are the number of hits associated with neither an El Niño nor a La Niña event. Hits refer to the number of correct forecasts during a particular year.

likely to suffer from this inherent poor predictability. The correlations between the predicted NIÑO3.4 indices of the 1- and 3-month lead-times and the persisted October and August indices, respectively, are only slightly lower than those using persistence (Figure 2(g,h)). However, persistence forecasts for the equatorial Pacific Ocean are normally outscored with lead-times exceeding two seasons (Barnston *et al.*, 1994).

4.3. Forecast skill of the multi-tiered scheme

For the 1-month lead multi-tiered forecasts (Table III), the hit scores for the KwaZulu–Natal coast and the northeastern interior are significant at the 99% level of confidence (hit score of seven), and those of northern Namibia/western Botswana at the 95% level of confidence (hit score of six). Hit scores for the southwestern Cape, Lowveld, central interior and western interior outscore chance (hit scores larger than three). The skill of the 3-month lead rainfall forecasts is less than that of the 1-month lead forecasts. The hit scores for the 3-month lead rainfall forecasts (Table III) for the Lowveld and northern Namibia/western Botswana outscore chance and are significant at the 90% level of confidence. For many of the regions, five or more one-category misses are seen for both lead-times, partly because of the large number of near-normal rainfall forecasts issued for some regions, which occur as a result of the underestimation of the strength of SST anomalies. In general, the multi-tiered approach outperforms the baseline CCA statistical model, in some cases significantly so (cf. Tables II and III).

Drier than normal conditions frequently prevail over southern Africa during El Niño Pacific warm events and wetter than normal conditions during La Niña cold events (Ropelewski and Halpert, 1987, 1989; Mason and Jury, 1997; Rocha and Simmonds, 1997). The El Niño years of 1991/1992 and 1994/1995 were particularly dry and the La Niña years of 1988/1989 and 1995/1996 particularly wet. During the La Niña event of 1988/1989, the downscaling model predicted the widespread above-normal rainfall conditions accurately over both lead-times (Table III). For the La Niña event of 1995/1996, the 1-month lead rainfall forecasts were accurate, but near-normal rainfall conditions were predicted for the El Niño event of 1991/1992 (both lead-times) and for the El Niño event of 1994/1995 (1-month lead). Forecasts of the strength of the 1991/1992 El Niño event are only about half of the observed anomaly, while the rainfall forecasts were for near-normal over the summer rainfall regions. Even with weak SST anomalies during the 1995/96 La Niña, 1-month lead rainfall forecasts proved accurate. The 3-month lead forecasts for the event predicted near-normal rainfall over the summer rainfall regions. These forecasts were accurate for northern Namibia/western Botswana, but not for the other regions.

The skill scores of GCM-derived forecasts (Table IV) are better than those for the CCA rainfall model. In the latter case, no significant LEPS scores were achieved for any of the regions (Table II). In contrast,

Table IV. Summary of the multi-tiered model skill scores for the nine regions for a 1-month (left of /) and a 3-month (right of /) lead-time

Regions	A	N	B	Hit score	LEPS
Southwestern Cape	0.7/0.8	0.0/1.0	0.7/0.6	4/3	32/25
South coast	0.9/0.8	1.0/1.0	0.7/0.8	2/2	−12/−12
Transkei	0.6/0.8	1.0/0.8	0.7/0.0	3/3	8/8
KwaZulu–Natal coast	0.3/1.0	0.5/0.7	0.3/0.5	7/3	60*/1–12
Lowveld	1.0/1.0	0.6/0.5	1.0/1.0	4/5	4/10
Northeastern interior	0.0/1.0	0.4/0.5	1.0/1.0	7/4	52*/−22
Central interior	0.3/0.7	0.8/0.9	1.0/1.0	4/2	19/−16
Western interior	0.7/0.8	0.5/0.4	1.0/1.0	4/4	16/−10
N Namibia/W Botswana	0.3/0.5	0.4/0.5	1.0/1.0	6/5	40/22

The false alarm ratios are shown for the different categories (A denotes above-normal, N near-normal and B below-normal).
LEPS scores significant at the 95% level of confidence are marked with an asterisk.

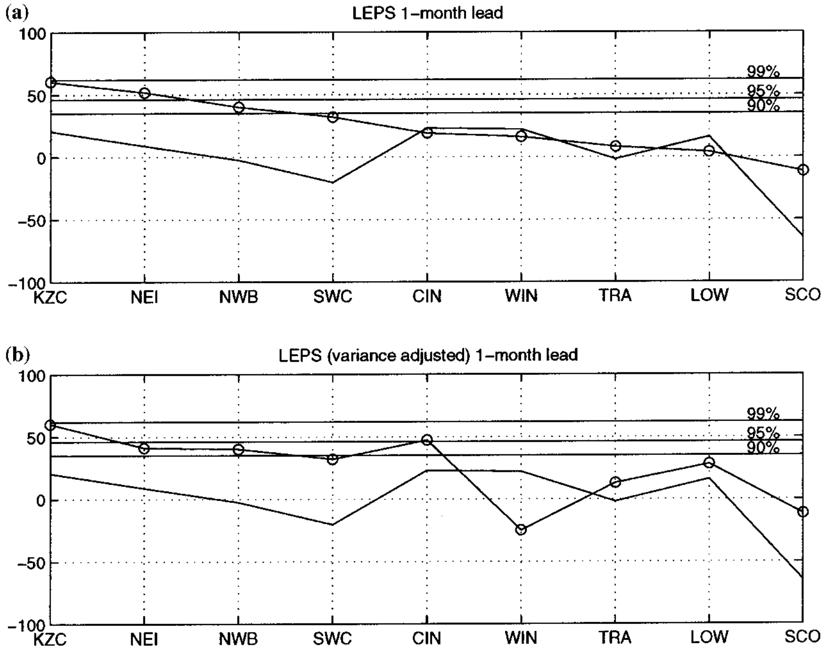

Figure 3. (a) LEPS scores for retro-active forecasts for the nine regions (KZC: KwaZulu–Natal coast; NEI: northeastern interior; NWB: northern Namibia/western Botswana; SWC: southwestern Cape; CIN: central interior; WIN: western interior; TRA: Transkei; LOW: Lowveld; SCO: south coast) with a 1-month lead-time; (b) LEPS scores for variance-adjusted retro-active forecasts with a 1-month lead-time. The solid line represents the CCA model scores; the circled line multi-tiered model scores. Horizontal lines indicate 90, 95 and 99% confidence levels

the GCM-downscaled forecasts gave higher hit scores than the CCA model for all the regions except for the central interior. The multi-tiered method produced hit scores that outscore chance for seven of the nine regions at 1-month lead-time and for four regions at 3-month lead-time. Even for years that are not associated with strong equatorial Pacific forcing, the GCM forecasts are associated with high numbers of hits, for example 1992/1993 and 1996/1997. A few cases can be presented that have FAR values of zero (best possible FAR is zero and worst possible FAR is one), while high FAR values are associated mostly with below-normal rainfall forecasts.

Comparison of CCA and multi-tiered LEPS scores for a 1-month lead (Figure 3(a)) reveals that the multi-tiered model outperforms its statistical counterpart in all regions except the western and central interior and the Lowveld. However, even in these regions, skill levels are only marginally worse than those of the CCA model. This is so despite lack of variance-adjustment (Ward and Folland, 1991) in the multi-tiered forecasts. When variance-adjustment is applied to the multi-tiered model, LEPS scores improve in most cases, in particular for the central interior and the Lowveld (Figure 3(b)). The forecast skill for both the multi-tiered and CCA techniques are poor for 3-month lead forecasts (Figure 4(a)). None of the LEPS scores are significant at the 90% level of confidence. Applying variance-adjustment to the 3-month lead-time multi-tiered forecasts (Figure 4(b)) does little to improve skill. For longer lead forecasts, the CCA statistical model continues to outperform the GCM-based approach.

Downscaled categorized forecasts at a 1-month lead-time (left entries) derived from forcing the GCM during ENSO years with observed rather than predicted SSTs are presented in Table V. Much improved forecasts are found for the 1991/1992 season when widespread drier than normal conditions are simulated successfully. Likewise, the favourable rainfall of the 1995/1996 season is accurately predicted. The forecasts for 1994/1995 are less satisfactory. For a 1-month lead-time, the LEPS scores from observed SSTs are not much better than those obtained from predicted SSTs (Figure 5(a) and Figure 3(a)), but a substantial improvement in skill for 3-month lead forecasts results from the use of observed SSTs (Figure 5(b) and Figure 4(a)).

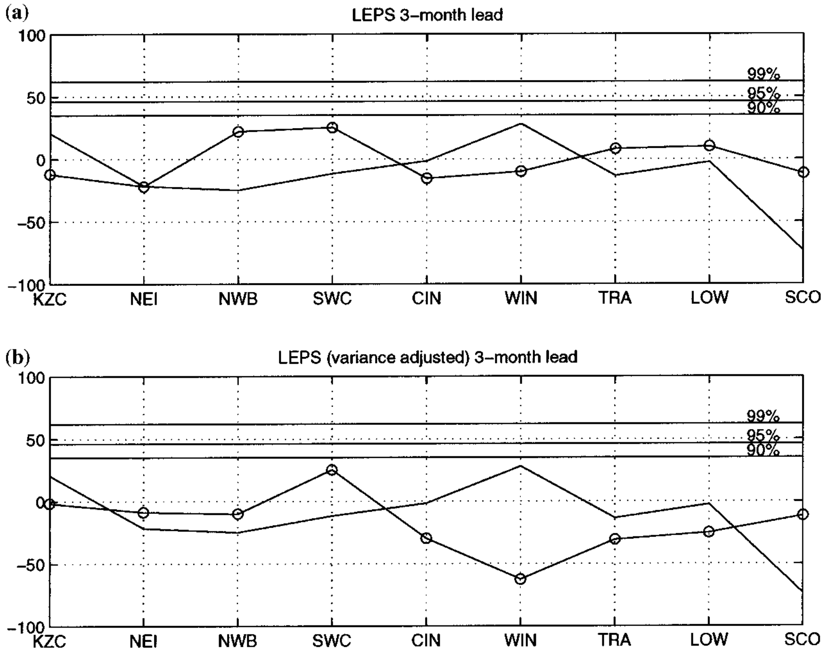

Figure 4. As for Figure 3, but for a 3-month lead-time

Table V. Categorized forecasts (lower case) at a 1-month lead of selected years in the retro-active period, produced from observed DJF SSTs (left of /) and forecasts produced from persisted August SST anomalies (right of /) and observations (upper case) for the nine regions

	1991/1992	1994/1995	1995/1996
	El Niño	El Niño	La Niña
Southwestern Cape	b/b B	a/a N	a/b A
South coast	b/b A	n/a A	a/b N
Transkei	b/n B	n/n N	a/b A
KwaZulu–Natal coast	b/n B	n/n B	a/b A
Lowveld	b/n B	n/b B	n/b A
Northeastern interior	b/n B	n/n B	n/b A
Central interior	b/n B	n/b B	a/b A
Western interior	b/a B	n/n N	a/b A
N Namibia/W Botswana	b/n B	n/n B	n/b N
Hits	8/1	2/5	6/0

A and a refer to above-normal; n and N refer to near-normal; b and B refer to below-normal. Hits refer to the number of correct forecasts during a particular year.

One of the main problems with the multi-tiered approach is that the CCA model used to predict the SST fields underestimates the strength of major ENSO events, particularly in the early stages of an evolving ENSO event. Likewise, the SST anomalies are under-predicted at longer lead-times for the peak of the event. Persisting observed SST anomalies produces amplitudes comparable to the predicted amplitudes. In the foreseeable future, over the longer lead-times, multi-tiered rainfall forecasts from persisted SST anomalies will, thus, produce forecasts that are at least as skilful as those using predicted anomalies. Multi-tiered forecasts derived from forcing the GCM during ENSO years with August persisted SSTs were satisfactory for the 1994/1995 El Niño, but underestimated the drought of 1991/1992

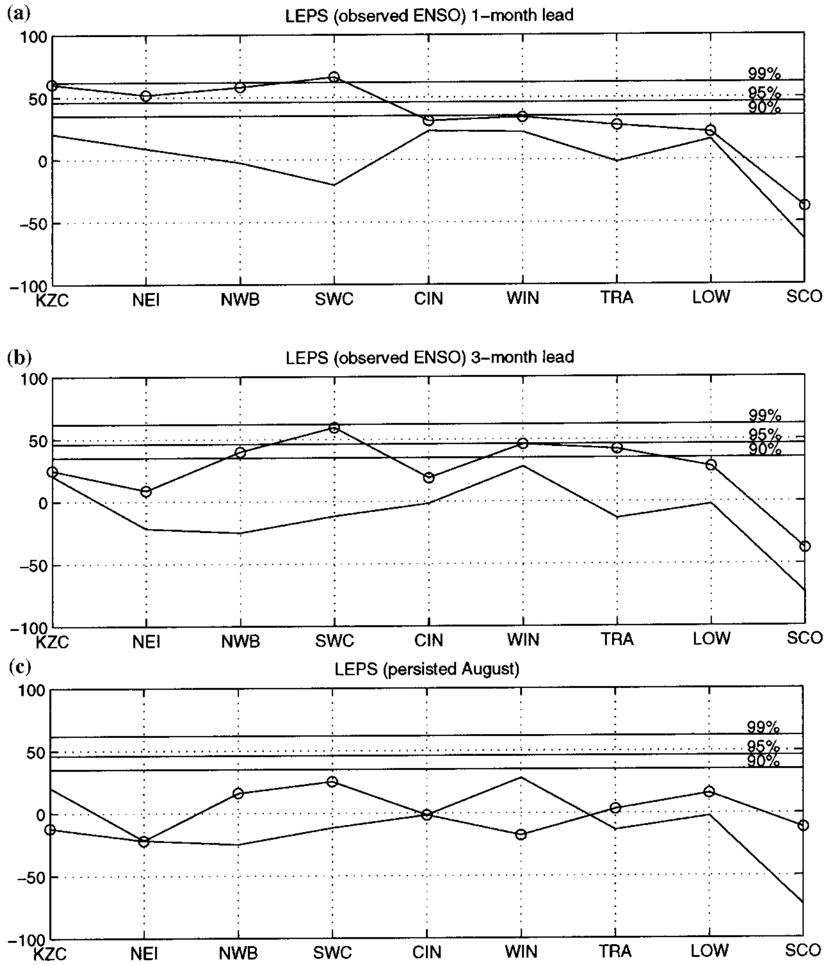

Figure 5. LEPS scores for retro-active forecasts with (a) 1-month and (b) 3-month lead-times using observed DJF SSTs during ENSO events; (c) LEPS scores of forecasts produced from persisted August SST anomalies during ENSO events. The solid line gives the CCA model scores; the circled line multi-tiered model scores. Confidence levels and regions are as defined in Figure 3

and the wet conditions of 1995/1996 (right entries of Table V). Persisting observed August global SST anomalies during these ENSO events produced rainfall forecast skill scores (Figure 5(c)) that are comparable to those of the 3-month lead forecasts using CCA-derived SST boundary conditions (Figure 4(a)). LEPS scores associated with forecasts from observed SSTs during ENSO years outscore those using persisted SST anomalies (Figure 5(b,c)).

5. DISCUSSION

Until recently, efforts to model southern African seasonal rainfall have been mainly statistical. Some success has been achieved in this manner. However, given that statistical models do not take into account the non-linearities associated with air–sea interactions responsible for interannual rainfall variability over southern Africa, and that linear SST and rainfall associations have become unstable during recent decades, alternative means of forecasting seasonal rainfall has become an urgent necessity. In this paper, an attempt has been made to develop a physically based prediction algorithm for operational application to the summer rainfall of southern Africa. To do this, a baseline skill level has been established using a statistical model. The COLA GCM has been used to simulate non-linearities in the climate system and to investigate whether it can improve on statistical predictions. In a multi-tiered approach, the SSTs have been predicted statistically in a CCA model with lead-times of a few months and used as boundary forcing in the GCM. The GCM-simulated fields have been downscaled to regional level to compare skill levels with the baseline skill and to test the utility of operational seasonal rainfall forecasts on a regional level.

Evolutionary global SSTs have been used successfully in a CCA model to predict SST anomalies of the equatorial Indian and Pacific (NIÑO3.4) Oceans. The scheme works well retro-actively for pre-1990 conditions, but predictability seems to have weakened during the 1990s. After accurate predictions of the 1988/1989 La Niña event, the model underestimated the strength of the subsequent El Niño event of 1991/1992 and the La Niña event of 1995/1996. Likewise loss of predictability occurred in the tropical Indian Ocean after 1989, but appears to have improved from 1994/1995. Forecasts of the tropical Indian Ocean anomalies, particularly for the later part of the austral summer rainfall season, are better than those predicted with persistence. On this basis the use of the SST forecasts to force the GCM appears justified. The NIÑO3.4. forecast scores are close to those found using persisted SST anomalies as a forecast. Although the retro-active skill levels appear disappointing, in general the 1990s are considered to have been a period of poor inherent predictability. Thus, the fact that positive skill was indicated for the period, and that the cross-validated skill levels of the SST model were high, are encouraging results.

Downscaled bias-corrected GCM-produced forecasts in many regions of southern Africa are significantly better than the statistical predictions over lead-times of 1 and 3 months. At worst, the GCM-based forecasts are at least comparable with those of the statistical model. Forecasts for a 1-month lead-time produced higher skill levels than those for 3-months lead-times particularly in the eastern regions of the KwaZulu–Natal coast and the northeastern interior. Both multi-tiered and statistical models produce poorer skill levels with longer lead-times.

A number of possibilities have been explored to improve multi-tiered forecast skill. The first was the adjustment of the forecast variance over the retro-active period, which produced somewhat increased skill scores, but only for short lead-times. The longer lead forecast skill remained unaltered and poor rainfall forecasts for three of the four ENSO events occurred because of the inability of the statistical SST forecast model to correctly estimate anomalies that form the boundary conditions for the GCM. The SST amplitudes for the ENSO events were always underestimated. Given improved SST forecasts, rainfall forecast skill should improve significantly. Forcing the GCM with observed rather than predicted SSTs (i.e. perfect SST forecasts) resulted in smaller discrepancies between predicted and observed rainfall for the ENSO seasons considered. The 3-month lead-time skill using observed SST improved substantially. However, the use of observed conditions is useful only for analysing what actually happened and not for predicting what might happen in a future situation. When using persisted anomalies for predicting the future SST field, the skill did not necessarily improve when forcing the GCM with persisted August (the month associated with 3-month lead-times) SST anomalies.

6. CONCLUSIONS

The COLA T30 GCM has been used successfully to predict seasonal rainfall over the summer rainfall region of southern Africa. It has been found that the multi-tiered approach can be applied in an operational environment, provided that the spatial characteristics and amplitudes of the SST forcing fields are described adequately. The multi-tiered scheme is able to produce skill levels that are better than chance and to outscore the baseline skill level of a linear statistical model. With improved prediction of SST fields, the multi-tiered scheme has the potential to improve seasonal rainfall forecasts significantly. Until that time, forecasts produced for long lead times with persisted SST anomalies must suffice. Significantly, the potential for GCM seasonal forecasting of rainfall over southern Africa is high. In the past, statistical modelling offered the best prospects for seasonal climate forecasting; in future, GCMs will undoubtedly provide the best basis for doing so. At present, both methods are needed and are best blended in a multi-tiered approach to offer pragmatic and cost-effective solutions to a complex problem.

ACKNOWLEDGEMENTS

The rainfall data used were obtained from the South African Weather Bureau and the National Meteorological Services of Botswana, Namibia and Lesotho. The utilization of the South African Weather Bureau's computer resources is acknowledged with gratitude. This paper was funded in part by a grant/cooperative agreement from the National Oceanic and Atmospheric Administration (NOAA). The views expressed herein are those of the authors and do not necessarily reflect the views of NOAA or any of its sub-agencies.

REFERENCES

Barnett TP, Preisendorfer RW. 1987. Origins and levels of monthly and seasonal forecast skill for United States air temperature determined by canonical correlation analysis. *Monthly Weather Review* **115**: 1825–1850.

Barnett TP, Bengtsson L, Arpe K, Flügel M, Graham N, Latif M, Ritchie J, Roeckner E, Schlese U, Schulzweida U, Tyree M. 1994. Forecasting global ENSO-related climate anomalies. *Tellus* **46A**: 381–397.

Barnston AG. 1994. Linear statistical short-term climate predictive skill in the Northern Hemisphere. *Journal of Climate* **7**: 1513–1564.

Barnston AG, Ropelewski CF. 1992. Prediction of ENSO using canonical correlation analysis. *Journal of Climate* **5**: 1316–1345.

Barnston AG, Smith TM. 1996. Specification and prediction of global surface temperature and precipitation from global SST using CCA. *Journal of Climate* **9**: 2660–2697.

Barnston AG, van den Dool HM. 1993. A degeneracy in cross-validated skill in regression-based forecasts. *Journal of Climate* **6**: 963–977.

Barnston AG, van den Dool HM, Zebiak SE, Barnett TP, Ji M, Rodenhuis DR, Cane MA, Leetmaa A, Graham NE, Ropelewski CR, Kousky VE, O'Lenic EA, Livezey RE. 1994. Long-lead seasonal forecasts—where do we stand? *Bulletin of the American Meteorological Society* **66**: 2097–2114.

Barnston AG, Thiao W, Kumar V. 1996. Long-lead forecasts of seasonal precipitation in Africa using CCA. *Weather and Forecasting* **11**: 506–520.

Barnston AG, Glantz MH, He Y. 1999. Predictive skill of statistical and dynamical climate models in SST forecasts during the 1997/98 El Niño episode and the 1998 La Niña onset. *Bulletin of the American Meteorological Society* **80**: 217–243.

Bengtsson L, Schlese U, Roeckner E, Latif M, Barnett TP, Graham NE. 1993. A two-tiered approach to long-rang climate forecasting. *Science* **261**: 1026–1029.

Bengtsson L, Arpe K, Roeckner E, Schulzweida U. 1996. Climate predictability experiments with a general circulation model. *Climate Dynamics* **12**: 261–278.

Carson DJ. 1998. Seasonal forecasting. *Quarterly Journal of the Royal Meteorological Society* **124**: 1–26.

Cane MA, Eshel G, Buckland RW. 1994. Forecasting Zimbawean maize yield using eastern Pacific sea surface temperatures. *Nature* **370**: 204–206.

Chu P-S, He Y. 1994. Long-range prediction of Hawaiin winter rainfall using canonical correlation analysis. *International Journal of Climatology* **14**: 659–669.

Cui M, von Storch H, Zorita E. 1995. Coastal sea level and the large-scale climate state. A downscaling exercise for Japanese Islands. *Tellus* **47A**: 132–144.

D'Abreton PC, Lindesay JA. 1993. Water vapour transport over southern Africa during wet and dry early and summer months. *International Journal of Climatology* **13**: 151–170.

D'Abreton PC, Tyson PD. 1995. Divergent and non-divergent water vapour transport over southern Africa during wet and dry conditions. *Meteorology and Atmospheric Physics* **55**: 47–59.

D'Abreton PC, Tyson PD. 1996. Three dimensional kinematic trajectory modelling of water vapour transport over southern Africa. *Water SA* **22**: 297–305.

Elsner JB, Schmertmann CP. 1994. Assessing forecast skill through cross-validation. *Weather and Forecasting* **9**: 619–624.

Goddard L, Graham NE. 1997. El Niño in the 1990s. *Journal of Geophysical Research* **102**: 10423–10436.

Goddard LM, Graham NE. 1999. The importance of the Indian Ocean for simulating rainfall anomalies over eastern and southern Africa. *Journal of Geophysical Research* **104**: 19099–19116.

Graham NE, Barnett TP. 1995. ENSO and ENSO-related predictability. Part II: Northern Hemisphere 700-mb height predictions based on a hybrid coupled ENSO model. *Journal of Climate* **8**: 544–549.

Graham NE, Michaelsen J, Barnett TP. 1987a. An investigation of the El Niño–Southern Oscillation cycle with statistical models. 1. Predictor field characteristics. *Journal of Geophysical Research* **92**: 14251–14270.

Graham NE, Michaelsen J, Barnett TP. 1987b. An investigation of the El Niño-Southern Oscillation cycle with statistical models. 2. Model results. *Journal of Geophysical Research* **92**: 14271–14289.

Hastenrath S, Greischar L, van Heerden J. 1995. Prediction of summer rainfall over South Africa. *Journal of Climate* **8**: 1511–1518.

Hoffman RN, Kalnay E. 1983. Lagged average forecasting, an alternative to Monte Carlo forecasting. *Tellus* **35A**: 100–118.

Holton JR. 1979. *Numerical Prediction. An Introduction to Dynamic Meteorology* (2nd edn). Academic Press: San Diego; 173–213.

Hunt BG. 1997. Prospects and problems for multi-seasonal predictions: some issues arising from a study of 1992. *International Journal of Climatology* **17**: 137–154.

Hunt BG, Zebiak SE, Cane ME. 1994. Experimental predictions of climate variability for lead times of twelve months. *International Journal of Climatology* **14**: 507–526.

Jackson JE. 1991. *A User's Guide to Principal Components*. Wiley: New York.

Jolliffe IT. 1972. Discarding variables in principal component analysis. I: Artificial data. *Applied Statistics* **21**: 160–173.

Joubert AM, Hewitson BC. 1997. Simulating present and future climates of southern Africa using general circulation models. *Progress in Physical Geography* **21**: 51–78.
Jury MR, Pathack BMR. 1991. A study of climate and weather variability over the tropical southwest Indian Ocean. *Meteorology and Atmospheric Physics* **47**: 37–48.
Jury MR, Mulenga HM, Mason SJ. 1999. Exploratory long-range models to estimate summer climate variability over southern Africa. *Journal of Climate* **12**: 1892–1899.
Karl TR, Wang W-C, Schlesinger ME, Knight RW, Portman D. 1990. A method of relating general circulation model simulated climate to the observed local climate. Part I: Seasonal statistics. *Journal of Climate* **3**: 1053–1079.
Kalnay E, Kanamitsu M, Kistler R, Collins W, Deaven D, Gandin L, Iredell M, Saha S, White G, Woollen J, Zhu Y, Chelliah M, Ebisuzaki W, Higgins W, Janowiak J, Mo KC, Ropelewski C, Wang J, Leetmaa A, Reynolds R, Jenne R, Joseph D. 1996. The NCEP/NCAR 40-year reanalysis project. *Bulletin of the American Meteorological Society* **77**: 437–471.
Kawamura R. 1994. A rotated EOF analysis of global sea surface temperature variability with interannual and interdecadal scales. *Journal of Physical Oceanography* **24**: 707–715.
Kirtman BP, Shukla J, Huang B, Zhu Z, Schneider EK. 1997. Multiseasonal predictions with a coupled tropical ocean–global atmosphere system. *Monthly Weather Review* **125**: 789–808.
Landman WA, Klopper E. 1998. 15-year simulation of the December to March rainfall season of the 1980s and 1990s using canonical correlation analysis (CCA). *Water SA* **24**: 281–285.
Landman WA, Mason SJ. 1999a. Operational long-lead prediction of South African rainfall using canonical correlation analysis. *International Journal of Climatology* **19**: 1073–1090.
Landman WA, Mason SJ. 1999b. Change in the association between Indian Ocean sea-surface temperatures and summer rainfall over South Africa and Nambia. *International Journal of Climatology* **19**: 1477–1492.
Livezey RE, Chen WY. 1983. Statistical field significance and its determination by Monte Carlo techniques. *Monthly Weather Review* **111**: 46–59.
Makarau A, Jury MR. 1997. Predictability of Zimbabwe summer rainfall. *International Journal of Climatology* **17**: 1421–1432.
Mason SJ. 1995. Sea-surface temperature–South African rainfall associations, 1910–1989. *International Journal of Climatology* **15**: 119–135.
Mason SJ. 1998. Seasonal forecasting of South African rainfall using a non-linear discriminant analysis model. *International Journal of Climatology* **18**: 147–164.
Mason SJ, Graham NE. 1999. Conditional probabilities, relative operating characteristics, and relative operating levels. *Weather and Forecasting* **14**: 713–725.
Mason SJ, Joubert AM. 1997. Simulated changes in extreme rainfall over southern Africa. *International Journal of Climatology* **17**: 291–301.
Mason SJ, Jury MR. 1997. Climate variability and change over southern Africa: a reflection on underlying processes. *Progress in Physical Geography* **21**: 23–50.
Mason SJ, Tyson PD. 2000. The occurrence and predictability of drought over southern Africa. In *Drought Volume 1: A Global Assessment*, Wilhite DA (ed.). Routledge: New York; 113–134.
Mason SJ, Lindesay JA, Tyson PD. 1994. Simulating drought in southern Africa using sea surface temperature variations. *Water SA* **20**: 15–22.
Mason SJ, Joubert AM, Cosijn C, Crimp SJ. 1996. Review of seasonal forecasting techniques and their applicability of southern Africa. *Water SA* **22**: 203–209.
Mason SJ, Goddard L, Graham NE, Yelaeva E, Sun L, Arkin PA. 1999. The IRI seasonal climate prediction system and the 1997/98 El Niño event. *Bulletin of the American Meteorological Society* **80**: 1853–1873.
Mattes M, Mason SJ. 1998. Evaluation of a seasonal forecasting procedure for Namibian rainfall. *South African Journal of Science* **94**: 183–185.
Michaelsen J. 1987. Cross-validation in statistical climate forecast models. *Journal of Climate Applied Meteorology* **26**: 1589–1600.
Nicholson SE, Entekhabi D. 1987. Rainfall variability in equatorial and southern Africa: relationships with sea surface temperatures along the southwestern coast of Africa. *Journal of Climate and Applied Meteorology* **26**: 561–578.
Palmer TN, Anderson DLT. 1994. The prospects of seasonal forecasting—a review paper. *Quarterly Journal of the Royal Meteorological Society* **120**: 755–793.
Philander SG. 1998. Learning from El Niño. *Weather* **53**: 270–274.
Potts JM, Folland CK, Jolliffe IT, Sexton D. 1996. Revised 'LEPS' scores for assessing climate model simulations and long-range forecasts. *Journal of Climate* **9**: 34–53.
Press WH, Teukolsky SA, Vetterling WT, Flannery BP. 1992. *Numerical Recipes in Fortran. The Art of Scientific Computing* (2nd edn). Cambridge University Press: Cambridge; 963 pp.
Reason CJC. 1999. Interannual warm and cool events in the subtropical/mid-latitude south Indian Ocean region. *Geophysical Research Letters* **26**: 215–218.
Reason CJC, Lutjeharms JRE. 1998. Variability of the south Indian Ocean and implications for southern African rainfall. *South African Journal of Science* **94**: 115–123.
Reynolds RW, Smith TM. 1994. Improved global sea surface temperature analyses using optimum interpolation. *Journal of Climate* **7**: 929–948.
Rocha A, Simmonds I. 1997. Interannual variability of south-eastern African summer rainfall. Part I: relationships with air–sea interaction processes. *International Journal of Climatology* **17**: 235–266.
Ropelewski CF, Halpert MS. 1987. Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation. *Monthly Weather Review* **115**: 1606–1626.
Ropelewski CF, Halpert MS. 1989. Precipitation patterns associated with the high index of the Southern Oscillation. *Journal of Climate* **2**: 268–284.
Rummukainen M. 1997. *Methods for statistical downscaling of GCM simulations*. Swedish Meteorological and Hydrological Institute Report Nr RMK 80. p. 29.

Shabbar A, Barnston AG. 1996. Skill of seasonal climate forecasts in Canada using canonical correlation analysis. *Monthly Weather Review* **124**: 2370–2385.

Shukla J. 1998. Predictability in the midst of chaos: a scientific basis for climate forecasting. *Science* **282**: 728–731.

Smith TM, Reynolds RW, Livezey RE, Stokes DC. 1996. Reconstruction of historical sea surface temperatures using empirical orthogonal functions. *Journal of Climate* **9**: 1403–1420.

Stockdale TN, Anderson DLT, Alves JOS, Balmaseda MA. 1998. Global seasonal rainfall forecasts using a coupled ocean-atmosphere model. *Nature* **392**: 370–373.

Taljaard JJ. 1986. Change of rainfall distribution and circulation patterns over southern Africa in summer. *Journal of Climatology* **6**: 579–592.

Taljaard JJ. 1994. Atmospheric circulation systems, synoptic climatology and weather phenomena of South Africa. Part 1: Controls of the weather and climate of South Africa. *South African Weather Bureau Technical Paper No* 27: 45.

Taljaard JJ. 1995. Atmospheric circulation systems, synoptic climatology and weather phenomena of South Africa. Part 3: The synoptic climatology of South Africa in January and July. *South African Weather Bureau Technical Paper No* 29: 64.

Tyson PD. 1986. *Climate Change and Variability in Southern Africa*. Oxford University Press: Cape Town.

van den Dool HM. 1987. A bias in skill in forecasts based on analogues and antilogues. *Journal of Climate and Applied Meteorology* **26**: 1278–1281.

von Storch H, Navarra AEDS. 1995. *Analysis of Climate Variability. Application of Statistical Techniques*. Springer–Verlag: Berlin.

von Storch H, Zorita E, Cubasch U. 1993. Downscaling of global climate change estimates to regional scales: An application to Iberian rainfall in wintertime. *Journal of Climate* **6**: 1161–1171.

Walker ND. 1990. Links between South African summer rainfall and temperature variability of the Agulhas and Benguela currents systems. *Journal of Geophysical Research* **95**: 3297–3319.

Ward MN, Folland CK. 1991. Prediction of seasonal rainfall in the north Nordeste of Brazil using eigenvectors of sea-surface temperature. *International Journal of Climatology* **11**: 711–743.

Ward MN, Navarra A. 1997. Pattern analysis of SST-forced variability in ensemble GCM simulations: examples over Europe and the tropical Pacific. *Journal of Climate* **10**: 2210–2220.

Wilks DS. 1995. *Statistical Methods in the Atmospheric Sciences*. Academic Press: San Diego; 467.

Xue Y, Shukla J. 1998. Model simulation of the influence of global SST anomalies on Sahel rainfall. *Monthly Weather Review* **126**: 2782–2792.

