A MONTHLY FORECAST STRATEGY FOR SOUTHERN AFRICA

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ABSTRACT

Various techniques and procedures suited to monthly forecasting are investigated and tested. These include using the products generated by atmospheric general circulation models during a 17-year hindcast experiment, and downscaling the forecast circulation to regional rainfall in South Africa using circulation indices and canonical correlation analysis. The downscaling methods are evaluated using the cross-validation technique. Various model forecast bias-correction methods and skill-enhancing ensemble techniques are employed to improve the 30-day prognosis of the model. Forecasts from the general circulation model and each technique are evaluated. Those demonstrating reasonable skill over the southern Africa region, and which are feasible when considering available resources, are adopted into a strategy which can be used operationally to produce monthly outlooks. Various practical issues regarding the operational aspects of long-term forecasting are also discussed.

I declare that this dissertation is my own, unaided work,
and that it has not been submitted previously
as a dissertation or thesis for any degree
at any other University.

31 July 1998

University of the Witwatersrand, 1998

To my wife,

Melanie

PREFACE

The prediction of atmospheric processes may be attempted on the basis of three types of forecast: short-range forecasts that are nearly entirely dependent on initial conditions, long-range forecasts largely independent of initial conditions and intermediate forecasts that are dependent on initial conditions and boundary forcing. The decreasing dependence of forecasts on initial conditions with forecast length is demonstrated by the observation that the predictability limit of the instantaneous state of the atmosphere is two weeks. This is because random errors are unavoidably present in the initial conditions. Owing to the nonlinearity and instability of atmospheric flow these errors grow with time. Gradually the larger scales of motion are affected causing the forecast fields to diverge from the actual fields.

Whereas the predictability limit of wave numbers 5 - 12 is two weeks, that of wave numbers 0 - 4 is more than a month. This provides a basis for longer-range forecasts. Moreover, ensemble techniques increase predictability and produce a probability distribution of outcomes. These probabilistic forecasts which are distinct from the traditional deterministic forecasts made from one model simulation form the basis of the present study.

A set of monthly hindcasts over 17 years using the COLA T30 18-layer atmospheric general circulation model is used to establish model skill on the monthly time scale over the southern African region. The lagged average forecasting technique, the method of breeding initial perturbations and the cluster analysis of ensemble suites are various aspects of ensemble forecasting that are studied. A multivariate statistical technique is used to downscale synoptic scale circulation to rainfall and surface temperature over South Africa.

Various techniques and procedures that can be used to produce monthly outlooks of rainfall are examined in the dissertation. The chief objectives of the research are to:

(i) study previous work on predictability of the atmosphere over southern Africa and adjacent areas,

(ii) develop and test techniques that can be used to produce monthly outlooks,

(iii) filter and process general circulation model output to include ensemble forecasting techniques and bias correction,

(iv) evaluate and verify techniques and forecasts using case studies, and

(v) develop ways of constructing and presenting forecasts in a user-friendly fashion.

The dissertation is divided into seven chapters. **Chapter One** introduces the field of monthly forecasting within the scope of current shorter-range and longer-range forecasting capabilities. Monthly forecasting activities at other centres are summarized. **Chapter Two** discusses the global general circulation with a focus on southern Africa. Literature on the deviations of the circulation from climate means and resulting changes in rainfall is reviewed. In **Chapter Three** the tools and techniques used to generate information to make forecasts are discussed. Resources needed to operate these tools are also listed. Interpretation of the data generated by processes in Chapter 3 is described in **Chapter Four**. Evaluation results of forecasts and techniques are presented in **Chapter Five**. **Chapter Six** presents a practical view of monthly forecasting and a summary is given in **Chapter Seven**.

An article on the verification of 17 years of hindcasts covered in Chapters 4 and 5 has been submitted to the *International Journal of Climatology* and was presented at the Dynamical Extended Range Forecast (DERF) workshop held in Toulouse, France, in 1997. Two downscaling methods described in the same chapters have been submitted to the *International Journal of Climatology* in an article discussing operational extended-range forecasts for South Africa during the 1997/98 El Niño/Southern Oscillation event. The circulation index work was presented earlier at the Twelfth Conference of the *South African Society of Atmospheric Sciences* in Cape Town, 1996. A summary of Chapters 3 to 5 can be found in the preprints of the *Fifth International Conference on Southern Hemisphere Meteorology and Oceanography*, which was held in Pretoria in April 1997. Operational products generated by the methods described in this thesis are included in an article that has been accepted for publication in the *Water SA* journal.

Model input data were derived from the NCEP reanalysis dataset. Rainfall observation data were extracted from the South African Weather Bureau (SAWB) climate database. Sea surface temperature data were downloaded from the Climate Prediction Center's Internet Website. Models used include the COLA T30 18-layer general circulation model (GCM) purchased from the Center for Ocean-Land-Atmosphere Studies (COLA), and the T126 and T62 versions of the 28-layer global forecasting model developed at the National Centers for Environmental Prediction, Washington, D.C.. Model simulations were done on the SAWB Cray-J90 computer. Special thanks go to Karin Marais and Elda Stewart of the SAWB library for assistance in obtaining various literature used in the thesis and to Mike Haslam who assisted in the running of GCMs on the Cray-J90 computer. Without the sterling supervision and valuable proofing of articles for scientific journals by Professor Peter Tyson this thesis would not have reached its current level. My gratitude is extended to him and others in the Climatology Research Group at the University of the Witwatersrand.

CONTENTS

CHAPT"R 1

BACKGROUND

Introduction

Weather impacts humans in many ways. The outcome includes affecting social events, determining lifestyles and causing success or failure of activities, such as agriculture, that are vital to the economy. For this reason man has been trying to forecast the weather for thousands of years. Successful forecasting is often a function of the scale of atmospheric motion. John von Neumann suggested three different categories of atmospheric motion, depending on the time scale of the prediction (Pfeffer, 1960). The first included motions that are mainly determined by initial conditions and forecasts are done by extrapolating tendencies over short times. The second category includes the opposite extreme of motions that are largely independent of initial conditions. Forecasts of such motions are done by using observed characteristics of low-frequency variability. Motions occurring between these two extremes make up a third category, where initial conditions are becoming less important, but still relevant, and low-frequency modes increasing in importance. Logically, it is best to consider these prediction problems in the order in which they are listed.

Forecasts dependent only on initial conditions

For a long time short-range forecasts were restricted to only one day. As communication and observation improved from late in the nineteenth century forecasts of two and three days ahead could be attempted (Pfeffer, 1960). However, most early attempts were unsuccessful. This is mainly b ause the two requirements to make forecasts were not met adequately. These are, first, the state of the atmosphere at some given time needs to be known and, secondly, the physical laws governing any change to the initial state must be formulated (Wickham, 1970). Problems that had to be overcome, and still need to be today, albeit to a lesser degree, were obtaining a complete knowledge of the state of the entire atmosphere in real-time, and being able to simulate the atmosphere using a model that contains the exact time-dependent equations governing changes in the atmosphere. The latter problem has been resolved to a large extent since the advent of the modern supercomputer. Model resolutions are continually being made finer and larger amounts of data can be processed in shorter periods of time.

The procedure of obtaining a gridded field of atmospheric data from irregularly spaced observations is called analysis (Daley, 1991). Subjective analysis began in the nineteenth century. Synoptic charts with lines of constant pressure (isobars), temperature (isotherms) and other meteorological values were drawn by hand. The judgements of the analyser were heavily relied upon and hence the term *subjective analysis*. Digitization of the synoptic chart was attempted, but the analysis took longer than the forecast. An automatic procedure of arriving at an analysis was needed. The process had to work without human intervention and at the same time not use excessive computer time. Panofsky (1949) made the first serious attempt at this. He used a scheme of fitting a polynomial expansions to all the observation points. The coefficients of the polynomial were determined by a least squares fit. Such a p became known as an *objective analysis* because the judgement of a hum had been eliminated. Knowledge and expertise in this field increased rapidl, ...er Panofsky. Gilchrist and Cressman (1954) fitted the polynomials to observations close to the grid point instead of globally. They also suggested an automatic quality control of the observation data and that a *background field* or first *guess field* be used as a starting point to which an analysis increment be added. The background field is obtained from a previous forecast or taken from a climatological database. Initialization was later introduced to prevent the excitation of inertia-gravity waves in models during integrations. These steps have been grouped together in the data assimilation cycle. The South African Weather Bureau (SAWB) global data assimilation system uses global observations every six hours (Fig 1.1).

The exact state of the entire atmosphere cannot be known. There are several reasons for this. First, there are vast data voids in areas of the globe where no in-situ observations are done. Secondly instrument error may be present. The error of representativeness arises from a local phenomenon at an observing station, e.g. a thunderstorm, being interpreted as a much larger-scale phenomenon (Daley, 1991).

The second requirement for making weather forecasts has been realized in the form of Numerical Weather Prediction (NWP) models. These will be discussed in detail in Chapter 3. Daily forecasts of weather conditions with a lead time of up to seven days are now fairly good (Table 1.1).

Table 1.1: Root mean square error of the 500 hPa and 1000 hPa heights (m) and of the 850 hPa temperature (K) averaged over the area between 20°S and 90°S for forecasts up to seven days for January 1996 by the European Centre for Medium-Range Weather Forecasts (ECMWF) operational forecasting system. 7-day persistence forecast errors are given in the last column. (WMO/TD - No. 815, 1997)

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Persist
500hPa height	17	32	47	62	75	88	97	126
1000hPa height	15	26	37	46	55	63	69	85
850hPa temp	1.2	1.9	2.5	3.0	3.4	3.8	4.1	5.0

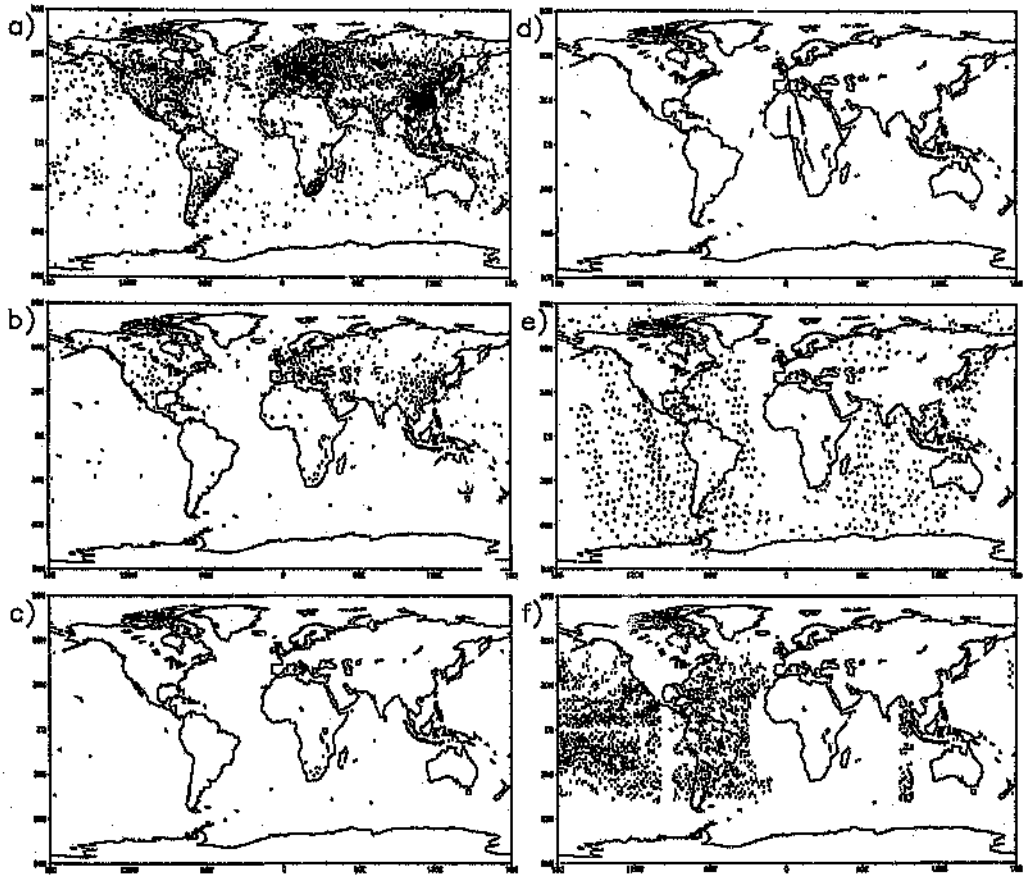


Figure 1.1: Global coverage of six observation types, a) Surface, b) Radiosondes, c) Pilot Balloons, d) Aircraft reports, e) Vertical temperature soundings and f) Cloud drift winds, for the six-hour period from 2100-0300 UTC on 21/22 January 1997.

Despite these advances the predictability limit of the instantaneous state of the atmosphere is not more than two weeks. This is because of the random errors unavoidably present in the initial conditions. Owing to the non-linearity and instability of atmospheric flow these errors grow with time (Holton, 1979). Gradually the larger scales of motion are affected causing the forecast fields to diverge from the actual fields. This is clear from the drop in skill of the ECMWF model as the forecast lead time increases.

Forecasts independent of initial conditions

The science of producing seasonal forecasts is very young relative to short-range forecasting. However, global observing systems and computing power are already advanced so this area of research has progressed rapidly. A comprehensive summary of current long-lead seasonal forecasting capabilities is found in Barnston *et al.* (1994). Purely statistical methods include Canonical Correlation Analysis (CCA; Graham *et al.*, 1987a,b; Barnston and Ropelewski, 1992) Principal Oscillation Patterns (POPS) (Xu and von Storch, 1990; Penland and Magorian, 1993) and Optimal Climate Normals (OCN) (Wilks, 1996). Dynamical methods include the Cane-Zebiak simple coupled model of the Lamont-Doherty Earth Observatory and the complex fully coupled model of the National Centers for Environmental Prediction (NCEP). A combination of statistical and dynamical methods yield hybrid models. One such model is the Scripps Institution for Oceanography-Max Planck Institute for Meteorology full ocean general circulation model coupled to a statistical atmosphere model. These methods have all achieved a moderate level of mean skill in predictions of the tropical Pacific Sea Surface Temperature (SST) at a lead time of two seasons (Barnston *et al.*, 1994).

Forecasts dependent on both initial conditions and boundary conditions

The attempt to use general circulation models to simulate the atmosphere beyond the classic two-week predictability limit is based on the findings of Shukla (1981). The earth's surface serves as a lower boundary to the atmosphere. Sea surface temperature, snow, soil moisture and vegetation act as slowly varying external forcing. They are considered slowly varying since the time scale of change of these parameters is much larger than the time scale of synoptic instabilities. The time evolution of the atmosphere is then a function of the initial conditions, which determine the nature of the instabilities and how they interact, and the boundary forcing. The relative contribution of each factor needs to be understood to determine the predictability of time-averaged fields. Shukla (1981) ran a number of 60-day integrations of a general circulation model (GCM) with different initial conditions but the same lower boundary fields. He showed that the predictability limit of wave numbers 5 - 12 (*synoptic scale*) is two weeks and wave numbers 0 - 4 (planetary scale) more than a month. Therefore, time averages, which are governed by low-frequency planetary waves, have a predictability limit beyond the classical two weeks. These time-averaged fields are well-suited to monthly forecasting.

Model integrations made from the initial conditions that differ very slightly will produce different forecasts (Lorenz, 1982) (Fig 1.2). The rate of divergence of these forecasts depends on various factors rooted in the initial conditions. Instead of using one model integration to make a forecast, an ensemble of forecasts should be used. Leith (1974) showed that the average of an ensemble of forecasts will have better skill than the control forecast provided perturbed initial conditions are representative of the initial probability distribution of the basic circulation in the control analysis. Gilman (1985) suggested using a mixture of techniques when producing monthly forecasts because these forecasts are not deterministic. Thus, monthly forecasts that suggest a scope of possible outcomes with probabilities attached to each outcome ought to be strived for.

Long-term Forecasting Activities around the World

Monthly forecasting needs to be defined in the context of the full range of forecasting. At the shortest end of the spectrum there is *nowcasting* which extrapolates current trends up to two or three hours ahead. Short-term forecasting continues on to 48 hours and medium-range forecasting up to five days

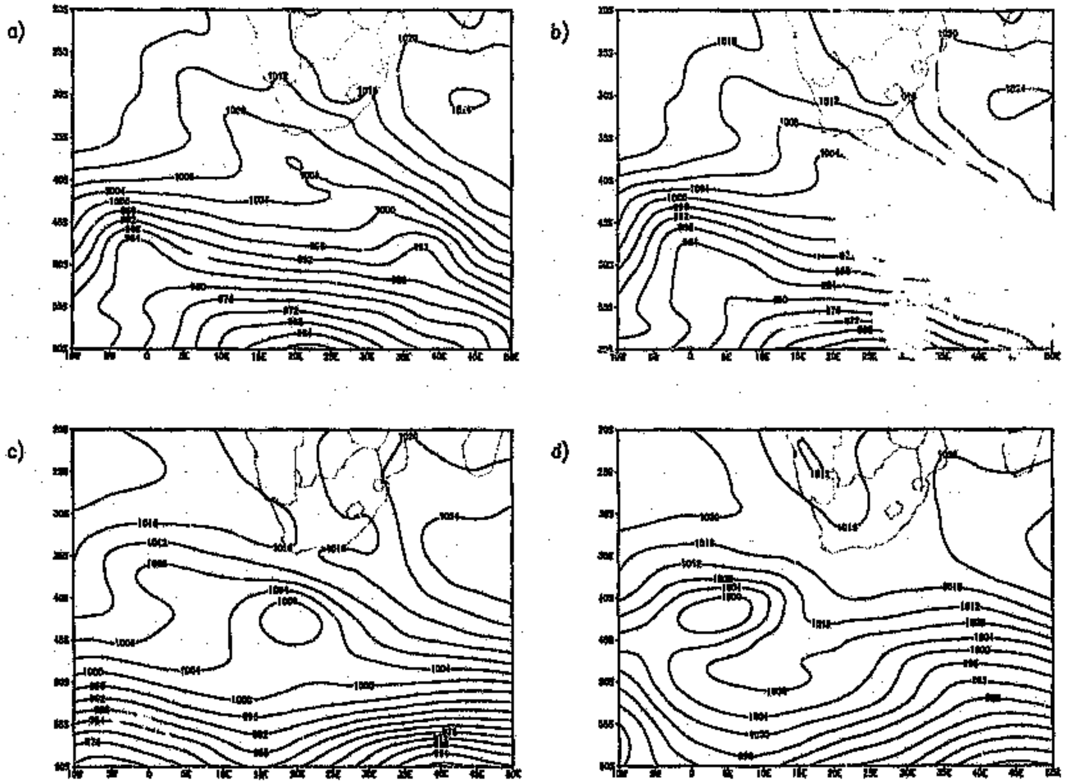


Figure 1.2: 500 hPa heights at a) control analysis and b) perturbed analysis and five day forecast c) control, d) perturbed.

(Meteorological Office, 1991). Long-term forecasts are for periods greater than five days. Seasonal forecasts usually begin at a lead time of one to two months and extend up to several seasons. In this dissertation monthly forecasts bridge the gap between medium-term forecasts and seasonal forecasts and are defined as *intra-monthly forecasts extending from 5 to 30 days ahead.*

Seasonal forecasting has achieved success in recent years and may have a high level of skill in many areas. The Climate Prediction Center (CPC) at NCEP issues long-lead forecasts of 3-month mean temperature and precipitation. ECMWF, Météo France and the United Kingdom Meteorological Office (UKMO) are producing coordinated experimental seasonal predictions from ensemble simulations for each season. Many other weather services including, the Bur-- -f Meteorology Research Centre Climate Group in Australia, the Canadian Weath.. Service, and the National Climate Center of the China Meteorological Administration, are active in the field of seasonal forecasting (WMO, 1996).

Monthly forecasting activities are also practised at many weather centres. The United Kingdom Meteorological Office produces deterministic and probabilistic forecasts from 30-day ensembles every two weeks. Specification equations relate the numerical output to surface climate anomalies (Richardson and Harrison, 1994). The National Centers for Environmental Prediction (NCEP), formerly the National Meteorological Center (NMC), use the method of breeding growing modes (BGM) to generate ensembles for two-week forecasts (Toth and Kalnay, 1993) (Fig. 1.3). The Chinese National Meteorological Centre used their T42L10 model for operational monthly forecasting and research into the monthly forecasting problem (Zheng *et al.*, 1993). The European Centre for Medium-range Weather Forecasts produced a set of 30-day integrations with the operational ECMWF model from 1985 to 1988. They found modest skill which became marginal beyond day 20 and that model resolution has a large effect on the model climate drift (Palmer *et al.*, 1990; Tibaldi *et al.*, 1990). At Mètèo-France a global T42 version of the French numerical prediction model has been used to produce monthly mean forecasts of the northern hemisphere winter months from 1983 to 1990. They found the presence of skill even beyond day 30 but concluded that statistical post-processing is necessary to produce useful forecasts (Deque and Royer, 1992). Other centres that have experimented with dynamical extended range forecasting are the Canadian Weather

Service (Ritchie *et al.*, 1994) and the Japanese Meteorological Agency (Yamada, 1991; Takano *et al.*, 1995).

A recent investigation into the utility of dynamical extended-range prediction formed part of the Atmospheric Model Intercomparison Project (AMIP) (Gates, 1992). This international effort was to determine the systematic climate errors of various atmospheric models by simulating the climate of the decade 1979-1988 using the same set of sea surface temperature and sea ice boundary conditions. Results were directed at obtaining a comprehensive evaluation of atmospheric models at the time and to provide useful information for further model development. Results from an analysis of the ability of 15 GCMs to simulate the tropical intra-seasonal oscillation show that a wide range of model skills exist, with no single model being capable of capturing successfully the full extent of the oscillation (WCRP, 1995).

Extended-range prediction in South Africa is still in its infancy. Most research groups are attempting categorical forecasts of monthly and seasonal averages of rainfall and temperature. Statistical methods used include a CCA model, run by the Research Group for Seasonal Climate Studies (RGSCS) at the SAWB (Landman, 1997), and a non-linear discriminant analysis model developed at the Climatology Research Group (CRG) at the University of the Witwatersrand (Mason, 1995; Mason *et al.*, 1996). GCMs, run at the SAWB, are beginning to prove useful as monthly forecasting tools (Tennant, 1997). The Monthly Outlook Development Group (MODG) at the SAWB, of which the author is the leader, has been experimenting with techniques to produce monthly outlooks. MODG was incorporated into the RGSCS in March 1997. All the groups mentioned are members of the South African Long Lead Forecast Forum (SALFF). The forum operates under the auspices of the SAWB and requires that each member uses a tested, scientific methodology in arriving at an outlook.

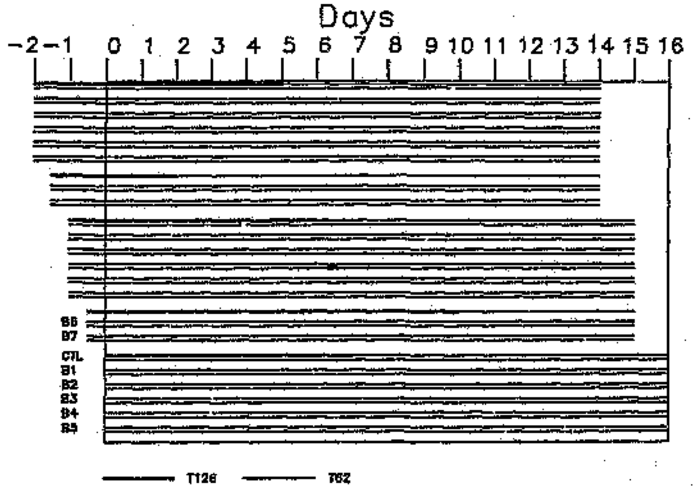


Figure 1.3: Schematic of the configuration of the operational ensemble forecasting at NCEP (1994). Each horizontal line represents a numerical forecast. High resolution, T126 forecasts are marked with heavy lines while other forecasts are run at T62 resolution. Pairs of perturbed forecasts based on the breeding method are marked B1-B7. Control runs are marked CTL. High resolution forecasts starting at 00Z are truncated to T62 after 7 days and those starting at 12Z are truncated after 3 days (after Toth and Kalnay,1993).

Hypotheses

Various techniques and procedures that can be used to produce monthly outlooks of rainfall and temperature will be examined in the dissertation.

The hypotheses to be tested are:

a) that atmospheric general circulation models are able to simulate the general circulation and various other variables around South Africa to an acceptable degree of accuracy;

b) that ensemble methods improve the skill of atmospheric general circulation models

c) that methods exist to interpret data generated by atmospheric general circulation models in an objective way when constructing a monthly forecast;

d) that skilful categorical forecasts of rainfall ahead one month for South Africa are possible.

CHAPTER 2

GENERAL CIRCULATION AND RAINFALL OF SOUTH AFRICA

Introduction

To be able to predict something one needs to understand its characteristics as fully as possible. Rainfall is controlled by the general circulation, and seeing as the general circulation is simulated by atmospheric models, the skill of forecasts depends on how well the GCM can simulate the general circulation and how well the link between rainfall and general circulation is understood. In this chapter the approach that should be taken for monthly forecasting in South Africa is considered. The literature of rainfall and general circulation over South Africa is reviewed. These studies explain most of the controls of the weather in the region and contrast circulation patterns when rainfall deviates from the normal.

Southern Hemisphere General Circulation

Atmospheric circulation in the southern hemisphere is quite distinct from that in the northern hemisphere (Hoskins and Pearce, 1983). The differences extend from surface and upper troposphere circulations to the magnitude of seasonal variations. In the northern hemisphere large amplitude long-waves occur and blocking is common (Hoskins and Pearce, 1983). However, standing waves and blocking occur less frequently in the southern hemisphere (Trenberth and Mo, 1985). Duration of blocking events is also shorter. This is because there are generally stronger westerlies throughout the southern hemisphere troposphere at the middle and high latitudes. Another reason for differences between the circulation in the two hemispheres is that the proportion of water to land in the southern hemisphere (4:1) is much greater than that in the northern hemisphere (1.5:1) (Pickard and Emery, 1990).

A wealth of publications describing the features of the atmosphere in the southern hemisphere are available. Foremost among these are atlases showing the climate of the upper air in the southern hemisphere by Taljaard *et al.* (1969), Van Loon *et al.* (1971), Jenne *et al.* (1971) and Crutcher *et al.* (1971) and books by Sturman and Tapper (1996). Major hemispheric features are discussed below.

The upper troposphere circulation is mainly zonal with small amplitude long-waves (Fig. 2.1a). During winter the concentric contours of upper troposphere pressure surfaces enlarge as the atmosphere cools (Fig. 2.1b). This strengthens the upper westerlies to as far north as 15°S. The maximum subtropical jet stream is found over Australia. At the surface three semi-permanent anticyclones are situated in the South Atlantic, Indian and eastern Pacific Oceans (Fig. 2.1c). These constitute the sub-tropical high pressure belt. During the austral summer this belt is broken by low pressure areas that develop on the western side of the continents because of thermal heating. Mid-latitude cyclones occur poleward of this belt in the prevailing westerly winds. Surface pressures rise substantially in the subtropics, especially over the continents with the approach of winter (Fig 2.1d). However, further south pressure changes from summer to winter are small and irregular and a tight pressure gradient between the tropics and the South Pole is maintained throughout the year.

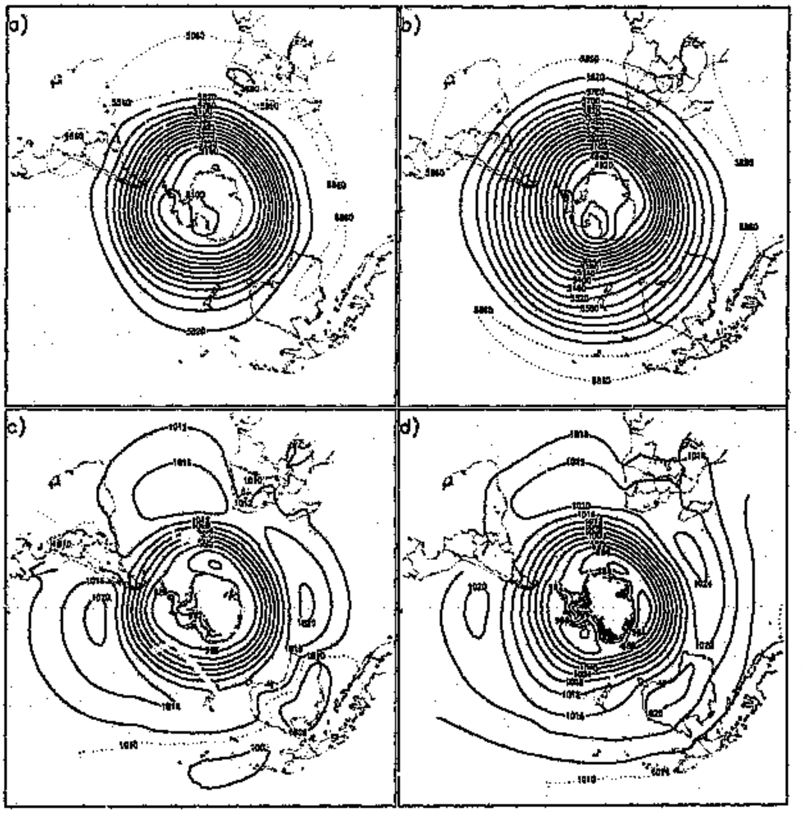


Figure 2.1: Climatological maps of 500 hPa heights (a) and mean sea-level pressure (c) for summer (DJF) and winter (JJA) (b) and (d) from the NCEP reanalysis data from 1979 - 1995. Sea-level pressure over topography exceeding 2500 m is masked out.

Synoptic Weather Patterns Affecting Southern Africa

The general circulation over southern Africa is described comprehensively by Schulze (1965), Taljaard *et al.* (1969), Tyson (1986), van Heerden and Hurry (1987), Preston-Whyte and Tyson (1988), and Taljaard (1994; 1995a; 1995b and 1995c).

South Africa is situated at the southern tip of the African continent between the South Atlantic and Indian Oceans in the latitudes of the sub-tropical high pressure belt. The strength and movement of these anticyclones are a major control of the weather in the area (Taljaard, 1994). During the eastward progression of the South Atlantic anticyclone the system often becomes elongated as it passes south of the continent. This process is commonly referred to as ridging by forecasters (Tyson, 1986). The resulting onshore flow causes cooler weather, usually with rain, to move along the coast and inland as far as the escarpment (Taljaard, 1995b). Once the anticyclone becomes established in the Indian Ocean the air moving westward along its northern flank over now warmer waters carries large amounts of moisture inland.

The surface cyclonic circulation over the western parts of the country is often in the shape of a trough which extends southward from Namibia. This, in conjunction with the Indian Ocean anticyclone, helps draw moisture westward into the interior. Widespread rain with many areas east of the surface trough receiving in excess of 10 mm is common with this circulation type (Taljaard, 1995a).

Mid-latitude cyclones occur in principal storm tracks, of which one lies south of the African continent (Physick, 1981) (Fig. 2.2). During the austral winter these cyclones shift equatorward and when they pass near the continent there is rainfall over the south-western Cape (van Heerden and Hurry, 1987). Much of the rain is as a result of topographic uplift of maritime air over the mountains in the region.

During late summer months some of the tropical cyclones in the southwest Indian Ocean move close to South Africa and occasionally make landfall on the northern Kwazulu-Natal coast. Flooding usually occurs in the areas directly affected by the cyclone with dry conditions in adjacent areas (Poolman and Terblanche, 1984). Predicting the frequency and tracks of tropical cyclones has proved difficult in South Africa (de Coning, 1992) and in Australia (Fraedrich and Leslie, 1989).

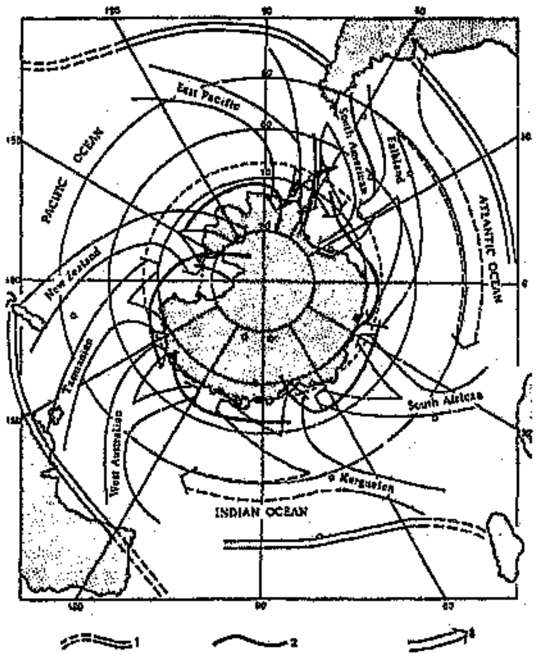


Figure 2.2: Cyclone trajectories over the ocean and position of major fronts in winter. 1 Polar front; 2 Antarctic front; 3 meridional cyclone trajectories. (after Physick, 1981).

Characteristics of Rainfall in South Africa

Annual rainfall amounts range from less than 200 mm in the far western areas to in excess of 1000 mm over the mountainous areas in the east (Fig. 2.3). Ocean temperatures around South Africa play a big role in the observed east-west gradient of the rainfall (Fig. 2.4). The Benguela Ocean Current brings cold water to the west coast while warm water moves southward along the east coast driven by the Agulhas Current. Another major controller of rainfall is the topography. The interior of South Africa lies on a high-altitude plateau surrounded by an escarpment that slopes steeply to a narrow coastal belt (Fig. 2.5). The escarpment is highest in the east and acts as the major watershed, with rivers on the plateau draining westwards into the Atlantic Ocean.

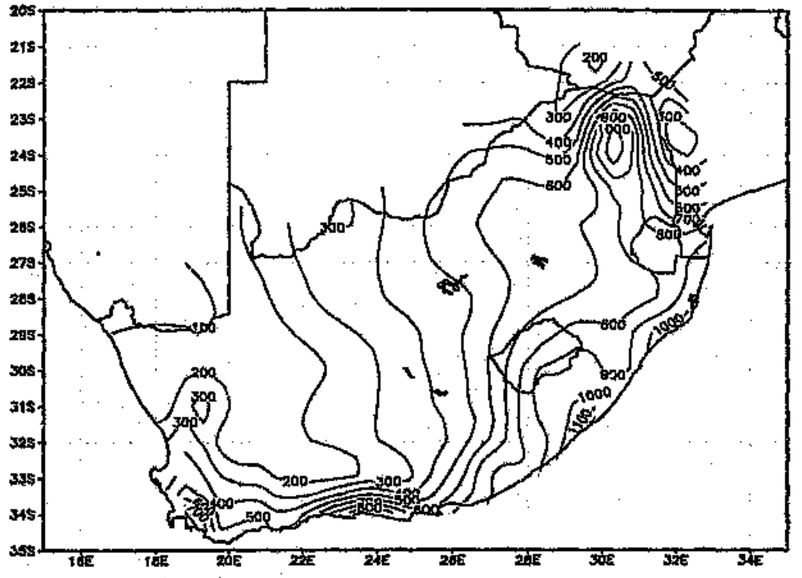


Figure 2.3: Annual rainfall for South Africa derived from 510 rainfall stations over the period 1930 to 1995 (South African Weather Bureau climate database).

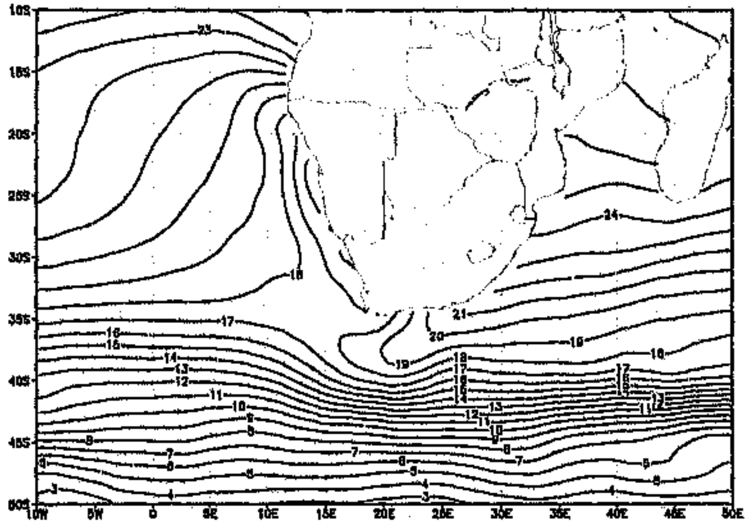


Figure 2.4: Annual mean sea-surface temperatures over the period 1981 to 1996 (°C) (Reynolds and Marsico, 1993).

The annual cycle of rainfall is demonstrated by studying the change of mean monthly rainfall at monthly intervals. Increases follow an anti-clockwise path, beginning with maximum increases in the Eastern Cape during August, northern Botswana in December and the south-western Cape by April (Taljaard, 1986) (Fig. 2.6).

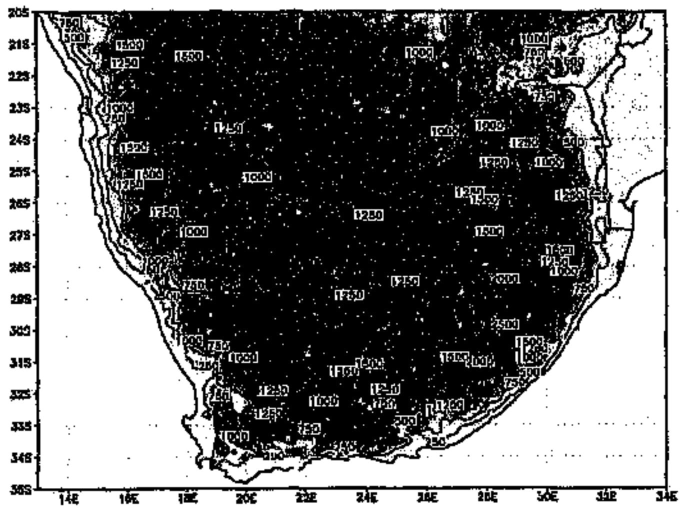


Figure 2.5: Topography of southern Africa (United States Navy dataset).

The quasi-stationary cloud bands, often present over the central parts of the country, account for more than 50% of the rainfall over the Free State province (Harrison, 1984a) (Fig. 2.7a). Conditions favourable for the development of such cloud bands are anticyclonic activity south of the continent and cyclonic activity over Botswana (Barclay *et al.*, 1993) (Fig. 2.7b). Simultaneously, a 500 hPa trough over the west coast is usually present, forcing upper winds with a northerly component. This provides necessary dynamics to lift the warm, moist air and form precipitating clouds (Taljaard, 1995a). Influx of moist air from the Indian Ocean often forms a sharp boundary with the dry continental air and aids in the development of thunderstorms (Harrison, 1984b). Much of the convective activity over Southern Africa owes its origin to the interaction between mid-latitude wave disturbances in the westerlies and quasi-stationary tropical upper tropospheric troughs in the south-west Indian Ocean (Lyons, 1991).

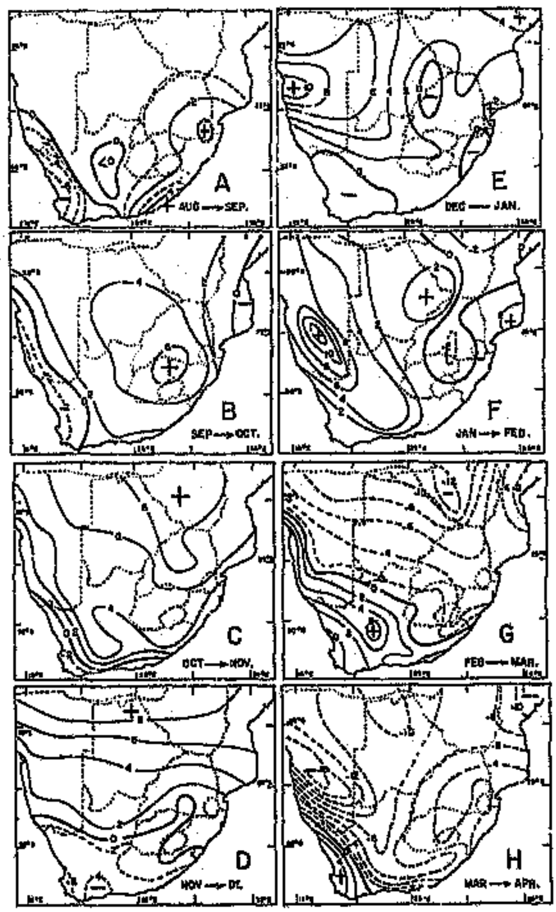
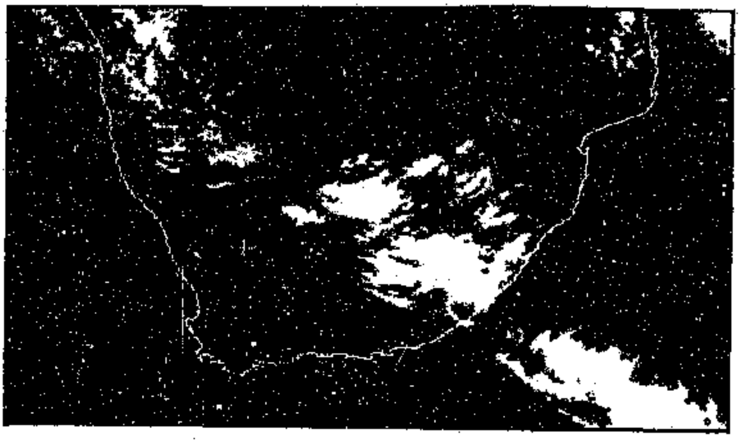


Figure 2.6: Change of percentage mean monthly rainfall at monthly intervals starting with August to September and ending with March to April (after Taljaard, 1986).

a)



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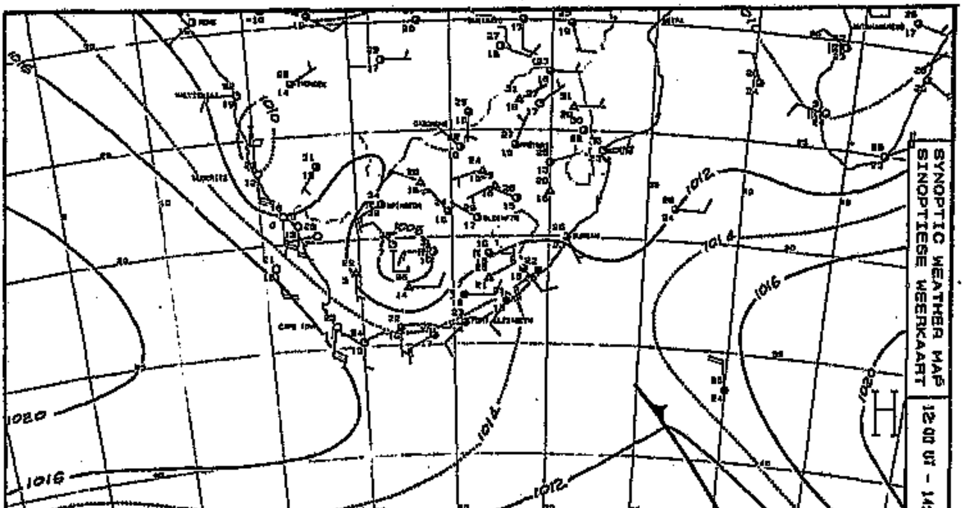


Figure 2.7: Infrared satellite image (a) and associated synoptic chart (b) at 12Z on 20 January 1997.

Changes in the Circulation during Wet and Dry Years

During dry years in South Africa, the cloud bands shift eastward over Madagascar (Harrison, 1986). Taljaard (1989) and Taljaard and Steyn (1991) have found that the circulation during dry years consists of less frequent and less intense anticyclonic activity south of the country with upper winds being zonal or having a southerly component. This is supported by Miron and Tyson (1984). The surface pressure anomaly fields during dry years are negative south, and positive east and west of the continent (Fig. 2.8). In the mid-troposphere geopotential heights are anonymously low south of the continent. Jury *et al.* (1992) found that above normal convective activity across equatorial Africa, North-East Madagascar and the south-west Indian Ocean coincides with below normal convective activity over southern Africa. Dry spells in Zimbabwe have similar controls to those of South Africa. Here, an increase in mid-latitude cyclones off the south-west coast of Africa and tropical cyclones near Madagascar are associated with dry weather (Matarira and Jury, 1990). Surface air flow patterns over South Africa have a more northerly or easterly component during wet years and a more westerly component during dry years (Miron and Lindesay, 1983).

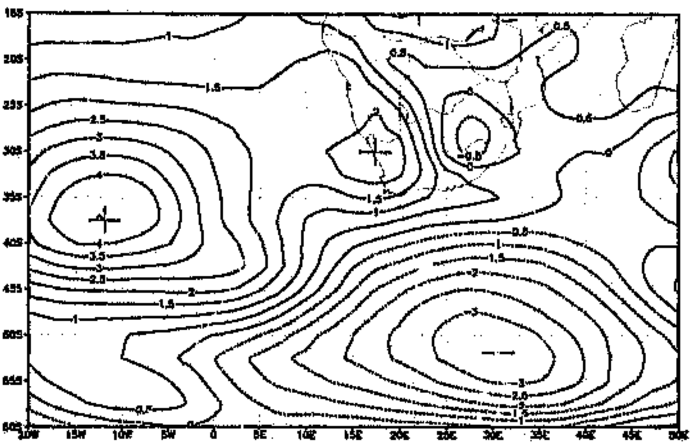


Figure 2.8: Average sea-level pressure anomaly for February 1983.

CHAPTER 3

TECHNIQUES USED IN MONTHLY FORECASTING

Introduction

Monthly forecasting lies somewhere between an initial value problem and a boundary value problem (Shukla, 1981). Therefore the techniques used to generate guidance for monthly forecasts should include both initial values and boundary values. To this end general circulation models of the atmosphere and ocean provide an obvious choice. These models consist of discrete, time-dependent equations of motion, thermodynamics and continuity which integrate the initial conditions forward in time. In atmospheric models the lower boundary is forced from SSTs and from snow and ice coverage. In ocean models the upper boundary is forced by surface winds and temperature. Recent experiments have coupled ocean and atmospheric models so that the boundary forcing is updated at regular time-steps simultaneously in both models (Ji *et al.*, 1994). A number of GCM simulations are usually performed for each forecast case creating an ensemble of forecasts. This technique is used to improve forecast skill and move away from deterministic forecasts towards probabilistic ones.

General Circulation Models

Historical development of numerical models

The first serious attempt at numerical weather forecasting was by the British scientist Richardson in 1922 (Holton, 1979). He showed how the governing differential equations of the atmosphere could be approximated at discrete points and written as tendencies which could be extrapolated ahead in time at small time increments. The main constraint at the time was computing power. Richardson estimated that he would need 64000 people to solve the simplest equations over a small domain to keep up with the atmosphere on a real-time basis. Unfortunately Richardson's experiment failed because fast-growing gravity waves contaminated his forecast. In 1948 Charney simplified the governing equations by making geostrophic and hydrostatic assumptions which filtered gravity waves out. As computers became more powerful and the observation network improved, more complex models could be used. Today global models use the closed set of primitive equations making only the hydrostatic assumption. The primitive equations consist of three prognostic equations (two horizontal components of the momentum equation and the thermodynamic energy equation) and three diagnostic equations (the continuity equation, the hydrostatic approximation and the equation of state). Non-hydrostatic, limited-area, meso-scale models have been recently introduced (Gallus and Rancic, 1996) to provide finer detail over smaller regions for short-term forecasts.

GCMs used at the SAWB

Two GCMs are used at the SAWB for monthly forecasting. The T30 version of the Center for Ocean-Land-Atmosphere Studies (COLA) GCM (hereafter COLA

T30) is used for 30-day forecasts and the T62 version of the National Centers for Environmental Prediction (NCEP) GCM, implemented locally as the Global Spectral Model (hereafter GSM T62), is used for daily 14-day forecasts.

The GSM T62 model (Sela, 1980) is used operationally at NCEP for global medium-range forecasts. Prognostic variables are represented by spherical harmonics of legendre polynomials with triangular truncation at wave number 62. This corresponds to a horizontal grid of 192 by 94 points, about 200 km. The vertical coordinate is the sigma parameter which is the pressure at a level normalized by the surface pressure below that point. There are 28 unevenly spaced sigma levels (Fig. 3.1). Physical processes included in the model are deep and shallow convection, large-scale precipitation, radiation, surface physics, vertical diffusion and gravity wave drag.

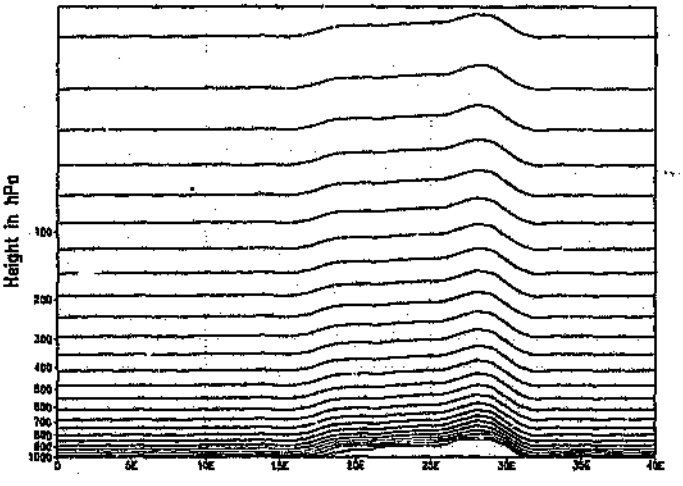


Figure 3.1: Vertical coordinate levels in the GSM T62 model at 30°S over South Africa.

The COLA T30 model is a spectral model with triangular truncation at wave number 30. This corresponds to a horizo: .l Gaussian grid of 96 by 48 points, roughly 400 km resolution. Physical processes included in this GCM are similar to those of the GSM T62 GCM. A simple biosphere model is also included to enable the model to be used for climatological studies. Data processed in this part of the model are deep soil temperature, ground temperature, canopy temperature, soil moisture, liquid water storage, latest computed precipitation, roughness, maximum mixing length and sea-ice temperature (COLA, 1995; Kirtman *et al.*, 1997). This model is used mainly to study ocean-atmosphere processes.

Input data

Real-time initial conditions for GCM runs are available from the operational GDAS at the SAWB. High quality global analysis fields are not readily available in real-time from modelling centres, therefore the SAWB GDAS data is vital to the operational monthly forecasting programme. Global observation data is collected from the Global Telecommun..:ation System via Washington, D.C. and passed through quality control routines and prepared for the GDAS which runs every six hours. Boundary condition data for the GCMs, including SSTs, snow and ice cover, are collected in real-time from NCEP via the Internet and prepared for each model.

Initial conditions for hindcasts were derived from NCEP reanalysis data (Kalnay *et al.*, 1996). These global analyses were created using a fixed data assimilation method for homogeneity and are available for every six hours from 1 January 1979 to 31 December 1995. They have a horizontal resolution of 2.5° latitude by 2.5° longitude and 17 constant pressure levels in the vertical. Archived boundary data include optimum interpolatión (OI) SST data (Reynolds, 1988; Reynolds and Marsico, 1993). In forecast mode initial observed sea-surface temperature anomalies are persisted for the duration of the forecast. To date this is the best method for forecasting sea-surface temperatures up to one month owing to ocean model initialization difficulties (Latif *et al.*, 1993). Remaining boundary data used by the GCMs are climatological fields created for the specific model resolution.

Resources

GCMs are computationally expensive, needing large amounts of computer memory and CPU time. The COLA T30 GCM requires 32 MBytes of memory and requires 5400 billion floating point operations to complete a 30-day forecast. The GSM T62 model uses 88 MBytes of memory and undergoes 300 billion floating point operations to produce a 24 hour forecast. Available resources used at the SAWB include a Cray J916-8/1024 model J90 classic supercomputer with eight CPUs (Cray-J90), each performing 200 million floating point operations per second and a memory capacity of 1024 MBytes, a Silicon Graphics IRIX-Indigo workstation, laser printers with Post-script capabilities, and the Grid Analysis and Display System (GrADS) to produce maps of forecast data.

Ensemble Methods

The basic requirement of guidance used to construct forecasts is that the forecast has to have the best possible skill. Ensemble forecasting methods have long been one of the best ways of improving GCM skill (Leith, 1974; Murphy, 1988b). The skill of single numerical forecasts is limited by uncertainties present in initial conditions (Holton, 1979), the predictability of the atmosphere in a geographical region during that season (Colucci and Baumhefner, 1992; Dalcher *et al.*, 1988) and how well the GCM simulates the atmosphere (Shukla, 1981). Ensemble forecasting addresses the first problem of initial condition errors. Hoffman and Kalnay (1983) introduced the lagged average forecasting (LAF) technique which generates an ensemble of forecasts by initializing a GCM successively six or twelve hours later. This method does not require any additional computation of perturbations. A further milestone in ensemble forecasting was reached when Toth and Kalnay (1993) developed a method for breeding initial perturbations. The perturbations are intended to optimally sample the initial error probability distribution and provide a realistic scope of possible errors in the control analysis. The breeding method outperformed the Monte Carlo method which used random perturbations (Toth and Kalnay, 1993). Ensemble forecasting is extremely expensive computationally. Thus there is a limit to the number of perturbations that can be run for each analysis. Toth and Kalnay (1995) studied the question of how many ensemble members are needed to improve on the skill of the control forecast. The largest improvements are found when increasing the ensemble size to ten members. Only minimal increases in forecast skill are obtained beyond 20 members. However, Barker (1991) found that the relationship between ensemble spread and forecast error improves with more ensemble members. Toth and Kalnay (1995) showed that this relationship can still be improved upon when using more than 40 members. The breeding method and LAF method can be combined to produce such a large number of forecasts. The SAWB 14-day forecast ensemble suite consists of 43 members (Fig. 3.2).

Apart from improving forecast skill by averaging ensemble forecasts, additional information about forecast skill (Kalnay and Dalcher, 1987; Barker, 1991) and the probability of outcomes is also generated. If the initial conditions are representative of the real state of the atmosphere, then the array of forecasts should, in most cases, span the correct forecast (Fig 3.3). Probabilities of outcomes may be calculated as a function of the number of ensemble members supporting each outcome.

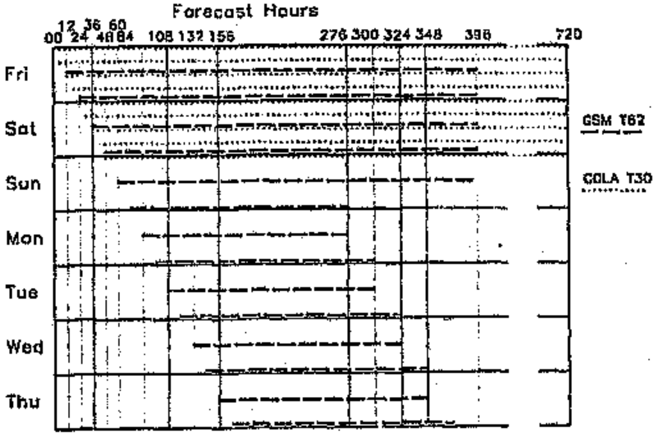


Figure 3.2: SAWB ensemble suite of the GSM T62 model.

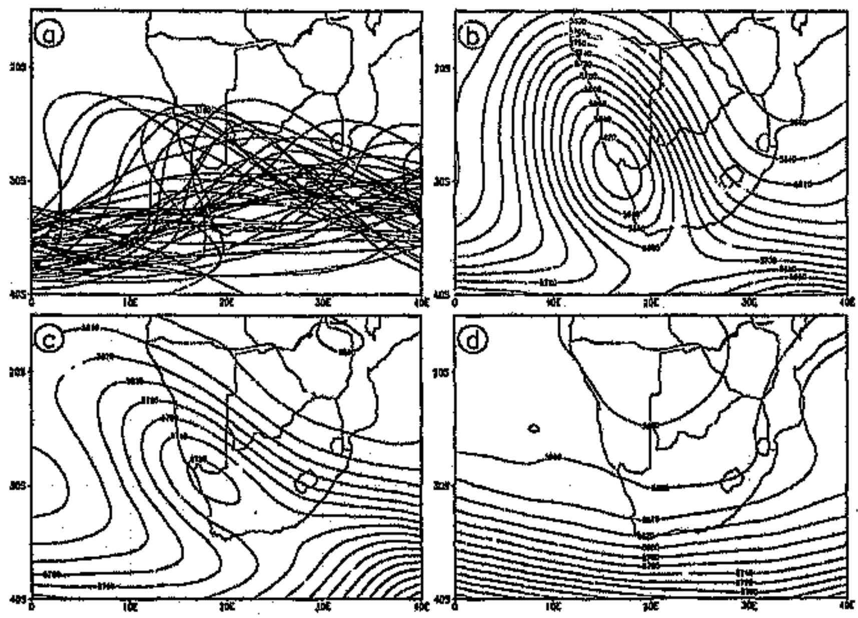


Figure 3.3: a) Spaghetti diagram of 5760 gpm contours of the 500 hPa field forecast by the SAWB operational ensemble forecasts for 12Z 25 May 1997 with b) the verifying analysis, c) best ensemble forecast (9-day) and d) worst ensemble forecast (8-day)

Preparation of a Forecast Database

Evaluation of the techniques described in this chapter requires a large set of GCM forecasts because the statistical measures used become more reliable as the number of experiments increase. Data and resource constraints allow a set of COLA T30 GCM hindcasts and a selection of operational GSM T62 forecasts.

COLA T30 forecasts

Initial conditions for the COLA T30 GCM for the hindcast experiment were prepared from the NCEP reanalysis dataset. Each forecast case consists of nine forecasts initialized at successive six hour intervals and combined using the LAF technique. The first run in each case is separated by 28 days. Using the full reanalysis dataset 221 cases could be done comprising 1989 model simulations in total. Forecast daily conditions of sea-level pressure, 500 hPa heights, surface temperature, rainfall and outgoing long-wave radiation (OLR) for 30-day periods were archived for evaluation. The LAF method requires that a nine-member 30-day forecast ensemble consists of a 32-, 31.75-, 31.5-, 31.25-, 31-, 30.75-, 30.5-, 30.25- and a 30-day model simulation.

GSM T62 forecasts

Owing to limited computer resources and the finer resolution of this model, hindcasts have not yet been done. Instead, output from the operational model runs (see Fig 3.2) from October 1997 to March 1998 have been used for verification purposes. This is in excess of 1000 individual simulations for 26 cases.

CHAPTER 4

INTERPRETATION OF FORECAST GUIDANCE

Introduction

GCMs produce vast amounts of information ranging from global, three-dimensional prognostic fields (temperature, geopotential height, humidity, wind and surface pressure), fields derived from the prognostic variables (vertical velocity) to diagnostic fields (rainfall, outgoing long-wave radiation, surface temperature and cloud cover). Some of the model output fields can be used directly, e.g. rainfall. Others, e.g. sea-level pressure, need to be interpreted by some method to produce usable parameters. The interpretation is done in two steps. First, the various output fields are filtered and combined to provide the best possible guidance. Secondly, model parameters have to be converted and downscaled to forecast parameters over desired regions. Extended-range forecast parameters are typically rainfall and surface temperatures.

Diagnostic model variables have an additional uncertainty brought about by parameterization schemes. Model simulated rainfall over southern Africa is frequently overestimated by low-resolution GCMs. An example is given by the COLA T30 GCM (Fig. 4.1). The overestimation occurs despite the fact that the GCM-simulated mean sea-level pressure and 500 hPa height climate compare well with the observed climatology (Fig. 4.2). Model simulated surface temperature also suffers from biases, while smoothed model topography makes it difficult to obtain site specific temperature forecasts from model output owing to adiabatic effects.

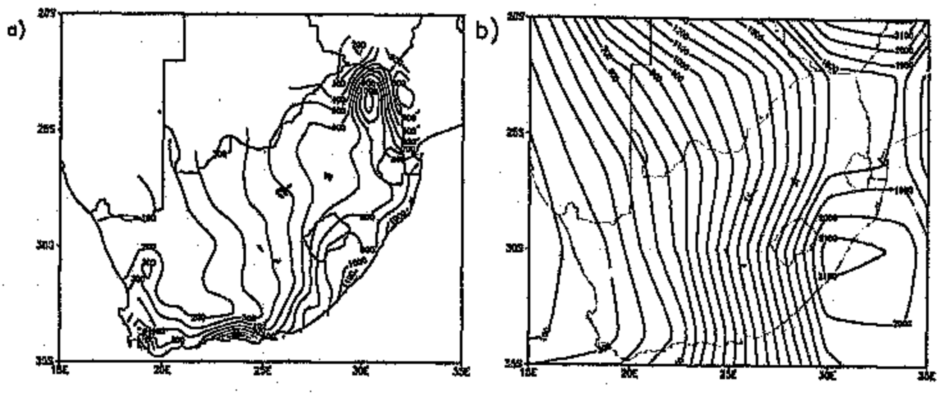


Figure 4.1: Annual rainfall over southern Africa a) observed at 510 stations and b) simulated by the COLA T30 GCM.

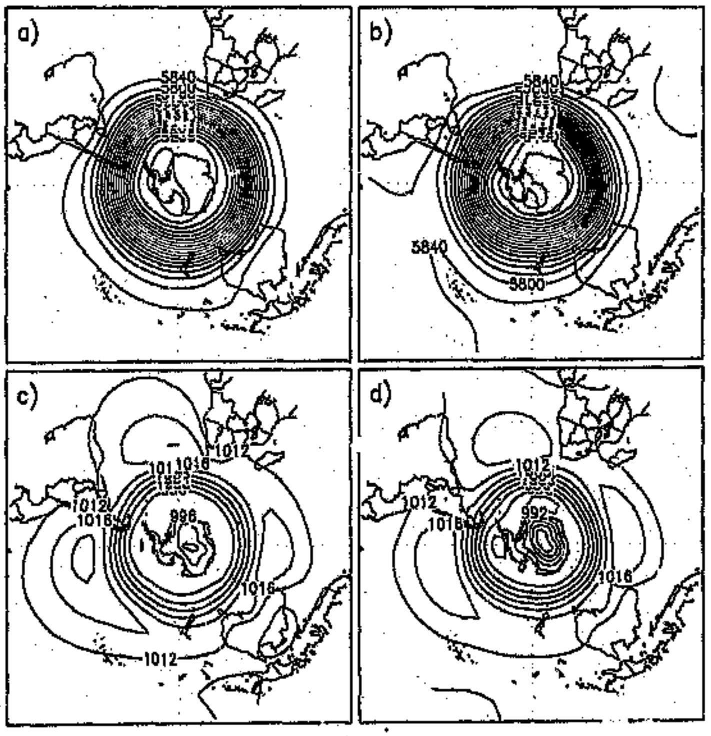


Figure 4.2: Annual 500 hPa heights (gpm) over the southern hemisphere a) observed and b) simulated by the COLA T30 GCM and mean sea-level pressure (hPa) c) observed and d) simulated by the COLA T30 GCM.

Extended-range forecasts provide information on expected conditions over week and month time-averaged periods. Such conditions are dependent on the large-scale components of the atmospheric general circulation (Palmer and Anderson, 1993). Since GCMs simulate the large-scale flow well, it is better to produce regional rainfall and surface temperature forecasts by downscaling these fields than using direct GCM diagnostic rainfall and temperature forecasts.

Apart from model inefficiencies a more nebulous problem facing the forecaster is the subjectivity put into every forecast. Ideally forecasts should be totally objective, but the man-machine mix remains one of the best ways of forecasting (McPherson, 1991). Ensemble techniques open a whole new avenue of approach in objective forecasting where forecasts consist of probability distributions. This chapter describes the objective methods used to construct forecasts from the information supplied by GCMs. The evaluation of each method is described later.

Post-processing of Model Output

Bias correction

It was noted that the COLA T30 model climate precipitation fields had a fair distribution, but that the actual amounts of precipitation were unrealistically high. Nearly every field output by a GCM has some sort of inherent bias. This is because the GCM does not simulate the real atmosphere perfectly, but rather drifts towards its own model climate (Chen, 1989). Furthermore, this drift is dependent on model resolution and increases in low resolution models (Palmer *et al.*, 1990). If the bias is similar among a number of simulations, then it can be identified and removed from a model forecast. Two ways of doing this are examined here. The first is by finding a linear relationship between the forecast and observed anomalies through least squares regression grid-point by grid-point (Livezey and Schemm, 1988) (Fig. 4.3a). Model forecasts are bias-corrected at each grid-point so that the least squares regression fit produces a line passing through the origin of the scatter plot with a gradient of unity (Fig. 4.3b). The second bias correction method used finds a grid-point bias for each month by comparing GCM monthly climate and observed climate (Fig. 4.4). Here the bias of sea-level pressure forecasts for a grid-point in the interior of South Africa has an annually repeating monthly pattern with maximums in June and December and minimums during March and October. A cross-validation technique (Michaelsen, 1987) is used when finding the GCM climate for a particular year to determine the bias of the GCM. It consists of forecasts produced in all other years of the hindcast experiment and thereby excludes forecasts from that year. Bias-correction of model forecasts for the tropics is best done without a monthly dependency as the seasonal cycle in that area is insubstantial. Certain model diagnostic products, such as rainfall, have a skew rather than a normal distribution and biases are a function of the magnitude of the forecast. They may be removed by multiplying the forecast parameter by the ratio of model standard deviation and observed standard deviation.

Probability forecasts

Ensemble forecasting supplies additional information regarding the probability distribution of forecast events. The GSM T62 model generates a 43-member ensemble suite of daily conditions out to 14 days. These data can be used to construct probability forecasts of rainfall amounts and cloud cover. The method is simple. The probability (P) of event n is the number of forecast runs predicting the event (f_n) divided by the total number of forecasts (T), given by

$$P_n = \sum f_n / T \qquad (4.1)$$

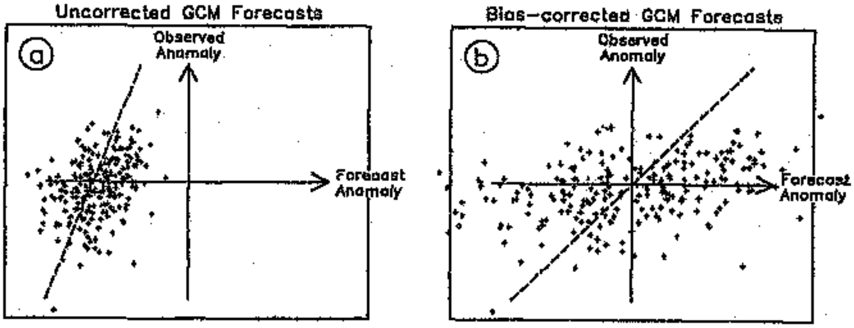


Figure 4.3: Scatter plot of forecast against observed anomalies of sea-level pressure at the model grid box over the central interior of South Africa (centred at 30°S 25°E) for the period 1979 to 1995 for a) uncorrected GCM forecasts and b) bias-corrected GCM forecasts. The dashed line is the best fit using linear regression.

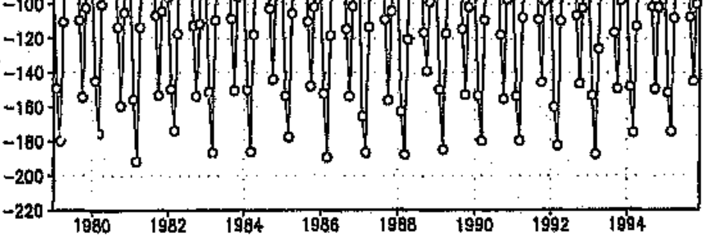


Figure 4.4: Time series of the monthly dependent bias of sea-level pressure forecasts determined from cross-validation at the model grid box over the central interior of South Africa (centred at 30°S 25°E).

Ensemble averaging

The average of an ensemble of forecasts has been proven to have better skill than a single control run (Brankovic *et al.*, 1990; Leith, 1974). If all the forecasts in an ensemble are initialized at the same time (for example when the breeding method is used to generate perturbations about the control analysis) then a simple average of all the members is sufficient. However, if the lagged average forecasting technique is used, then some of the ensemble members are older than others. The time difference between the first forecast and last forecast can be as long as five days. Here each ensemble member has to be weighted according to its age (Murphy, 1990). Weights were deter..ined from an exponential curve with a half-life of 10 days and a coefficient of unity. Assumptions made here are that an analysis is perfect and a 10-day forecast is close to the threshold of significant skill. A similar damper was used to simulate diminishing model skill in the prediction of monthly 700 hPa heights over North America (Harnack *et al.*, 1986).

Cluster analysis

Usually the spread of the ensemble members is not uniform, but rather groups or clusters become e 'dent. In most cases there are not more than two or three major groups in ensembles of the size discussed in this dissertation. Cluster analysis techniques (Everitt, 1974; Krzanowski, 1990) can be used to find these groups. Difficulties experienced with cluster analyses are how many groups should be made and which group to use for the forecast. One method is to decide, *a priori*, on a maximum distance value (or difference) between the clusters, which determines the number of groups and then to use the most populated group.

Circulation indices

The first method of downscaling GCM output to regional rainfall in South Africa is the use of circulation indices calculated from GCM forecasts of mean sea-level pressure and 500 hPa heights. The use of circulation indices to classify synoptic situations and to relate one meteorological parameter to another is not new and has been used in various regions. Streten and Pike (1980) used circulation indices to study monthly patterns of southern hemisphere surface circulation during the First Global Atmospheric Research Programme (GARP) Global Experiment (December 1978 to November 1979) and to compare the actual circulation to that derived for the hemisphere for the period 1972-1977. Taljaard (1986) investigated the roles of the subtropical high-pressure belt at sea level and the strength of the upper troposphere west winds in the formation of summer rainfall over southern Africa. Allan and Haylock (1993) found high correlations between rainfall in Perth and gridded mean sea-level pressure in the surrounding Indian Ocean region. D'Abreton and Lindesay (1993) contrasted indices of moisture flux across southern Africa during wet and dry early and late summer months. Hulme *et al.* (1993) used circulation indices to classify weather patterns over the British Isles for GCM validation.

Training of the index downscaling method was done using regional rainfall and circulation indices calculated from the NCEP reanalysis data (Kalnay *et al.*, 1996) over the 17-year period from 1979 to 1995. Monthly rainfall series from 510 stations across South Africa were submitted to cluster analysis (Everitt, 1974; Krzanowski, 1990) and seven near-homogeneous rainfall regions determined (Fig. 4.5). Indices of 30-day averaged sea-level pressure and 500 hPa height fields for the southern Africa region and surrounding oceans (12.5°S to 60°S and 30°W to 60°E) were calculated and seasonal terciles for each index and 30-day regional rainfall were determined. Most weather systems that affect South Africa occur in this area. They include: mid-latitude cyclones, the South Atlantic and Indian Ocean anticyclones and the Kalahari heat low (Physick, 1981; Taljaard, 1994, 1995b). To isolate the effect of various systems the area was divided into three equal longitudinal sections. South Atlantic Ocean systems occur in the western section, transient systems south of the continent and those over land in the central section, and Indian Ocean systems in the eastern section. Sea-level pressure indices used in this study are the latitude of maximum pressure, width, northern and southern limits of the subtropical anticyclones, latitude of the 1000 hPa contour, longitude of anticyclone centres, zonally averaged pressure at 45°S, and finally meridional pressure gradients from 30°S to 45°S, 30°S to 55°S, 40°S to 55°S and 35°S to 45°S. The mid-troposphere indices which isolate the phase and amplitude of waves and relative phases of subtropical and high-latitude waves are 500 hPa height contour differences between 25°S and 45°S, 20°S and 40°S, 40°S and 60°S and 25°S to 60°S, the latitude of the 5760 gpm contour, maximum, minimum and average meridional differences between 25°S and 45°S over South Africa and the longitude of the maximum 5760 gpm contour trough. In total 36 sea-level pressure and 19 mid-troposphere indices have been employed.

The forecast probability of occurrence (F) of each tercile (i) in a region is determined from a weigh ... of all indices

$$F_i = \sum_{n=1}^{N} I_{i,n} D_n \qquad (4.2)$$

where $I_{i,n}$ is the probability of the index forecast being correct, based on a cross-validation of the index from all years of the 17-year period with the current year removed, and D_n is a measure of the dissimilarity in forecasts produced by different indices ensuring that the forecast is not biased owing to index selection. Resulting forecast probabilities (F_i) are normalized so that the sum of the three tercile probabilities for each region is 100%.

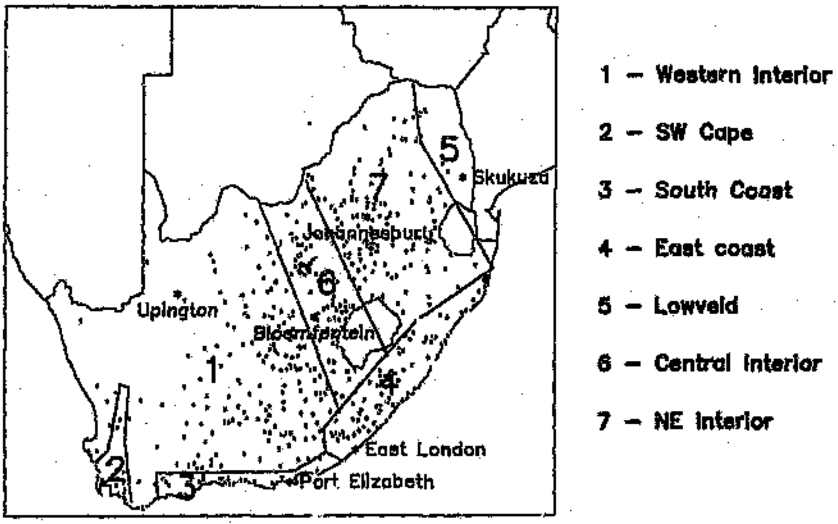


Figure 4.5: Seven near-homogeneous rainfall regions in South Africa determined from a cluster analysis of 510 rainfall data stations (dots).

Canonical correlation analysis

A more sophisticated multi-variate method of interrelating large-scale atmospheric flow to regional rainfall is canonical correlation analysis (CCA). Numerous examples of work using this technique can be found in the literature. One such experiment successfully related North Atlantic atmospheric circulation to winter mean Iberian Peninsula rainfall (von Storch *et al.*, 1993). Surface air temperature categorical forecasts over the United States using CCA have been done using, among others, sea-level pressure (Barnett and Preisendorfer, 1987).

The downscaling method using CCA was applied directly to bias-corrected model forecasts (Tennant, 1998). Sufficient time series of GCM forecasts that have been generated in this study allows us to take the model output statistics (MOS) approach (Klein, 1982) where the GCM circulation forecasts are related directly to the observed rainfall. The alternative is the perfect prognosis (more widely known as perfect prog) approach (Vislocky and Young, 1989) which uses observed fields as predictors in developing relationships to observed data. The drawback of this method is that it ignores the effects of GCM biases and uncertainties. The MOS approach accounts for the drawbacks of the perfect prog method.

The method used in this dissertation is similar to that proposed by Karl *et al.* (1990). Standardization of the observed regional rainfall data and GCM forecasts of 500 hPa heights and sea-level pressure was done by subtracting the calendar month mean and dividing by the standard deviation producing data with no seasonal dependency (Wilks, 1989). The gridded predictor data fields contain redundant data and principal component analysis is used to eliminate this data and produce a set of orthogonal predictors (Barnston, 1994). A sufficient number of these principal components are retained so that most of the variance in the predictor data is represented. The next step involves determining links between the predictor and predictand data sets through canonical correlation analysis. This multi-variate statistical method is considered foremost in the regression modelling hierarchy and is often used as a forecast technique (Barnett and Preisendorfer, 1987; Graham *et al.*, 1987a,b; Barnston and Ropelewski, 1992). A variance adjustment is then done through inflated regression analysis (Klein *et al.*, 1959). In the final step the CCA rainfall tercile forecasts are combined with GCM diagnostic tercile forecasts of outgoing long-wave radiation and rainfall anomalies. The diagnostic output are interpolated from GCM grid boxes to the local forecast regions and tercile boundaries are determined using GCM diagnostic forecasts from all other years of the experiment. CCA rainfall tercile forecasts for the southern Cape coast and GCM diagnostic forecasts for the Lowveld and northeastern interior regions of South Africa are poor and thus omitted from the combined forecast (Table 4.1). A linear combination of forecasts, as done here, has proved to be the best method in a number of studies (Fraedrich and Leslie, 1987; Vislocky and Fritsch, 1995). Clearly the combined forecast has a higher hit rate than individual forecasts.

Table 4.1: Number of tercile hits of various predictors and combined forecast. Data in shaded boxes are excluded from the combined forecast.

	Western Interior	SW Cape	South coast	East coast	Lowveld	Central Interior	NE Interior
CCA 500Z	76	86	63	91	80	77	86
CCA mslp	79	81	[illegible]	85	85	80	87
GCM rain	79	89	84	84	[illegible]	82	[illegible]
GCM OLR	84	71	84	84	[illegible]	87	[illegible]
Combined	93	93	81	97	97	92	103
% Correct	42%	42%	37%	44%	44%	42%	47%

In summary, bias correction of GCM forecasts is done at each grid point by a linear regression fit of forecast and observed anomalies and by removing the monthly-dependent systematic error in a cross-validation fashion. Seven target forecast regions in South Africa have been determined by clustering the observed monthly rainfall over sixty years. GCM forecast circulation is downscaled to rainfall categories by using circulation indices and by canonical correlation analysis which is combined with spatially interpolated diagnostic GCM forecasts of rainfall and outgoing long-wave radiation categories.

CHAPTER 5

EVALUATION OF TECHNIQUES AND FORECASTS

Introduction

There are two parts to the evaluation of forecasts. The first is to evaluate the tools and techniques used as guidance for making forecasts. Changes to a numerical model, for instance, must first be tested to ensure that they improve the model's performance. However, the final forecast product must also be evaluated. Techniques used for evaluations must be objective and one standard must be applied throughout. Subjective evaluations are useful when the forecast layout and products are being improved, but should be interpreted with caution .ıen applied to model forecast verifications. However, when doing case studies, a subjective evaluation of the synoptic situation can be informative.

The chapter begins by introducing evaluation methods and skili scores used. This is followed by a comprehensive report on model performance, techniques used to improve model performance and the skill of the final forecasts.

Overview of Evaluation Techniques

An important distinction must be made between forecast accuracy or similarity and forecast skill. Accur^cy is defined as the average degree of correspondence between forecasts and observations (Murphy, 1988a). It is possible to select a field from historical observations that will closely match a verifying observed field because the atmosphere does repeat previous circulation patterns somewhat. Therefore, if one were to forecast by randomly selecting historical fields, some accurate forecasts may be made occasionally, but obviously such a method has no scientific skill (Anderson and van den Dool, 1994). Skill is defined as the accuracy of forecasts relative to the accuracy of forecasts produced by some standard procedure, such as persistence (Murphy, 1988a). It is thus important to determine the skill of a forecast and not merely its accuracy. Here forecast evaluation results are compared against those obtained by using persistence, climatology and random guessing to make forecasts. Persistence forecasts are based solely on the value of the variable of interest at an initial time where the value at the forecast time is the same as at the initial time (Murphy, 1992). Climatology forecasts are determined from the mean value of a variable computed over an appropriate data sample and is used where statistical stationarity is a reasonable assumption.

Gridded forecast variables

Many evaluation methods are found in the literature. These are designed to evaluate various aspects of modelling and forecasting. They range from basic measures of error to complex skill scores. Gridded forecast fields output by models are compared to verifying analysis fields. The most popular measures of skill that are used are, the root-mean-square error (RMSE), anomaly correlation coefficient (ACC) and average error (Brier and Allen, 1951; Murphy and Epstein, 1989). Anomalies are calculated with respect to monthly-dependent climatology. The World Meteorological Organization (WMO) requires all numerical weather prediction centres to publish skill statistics of their models annually (WMO, 1992). The basic measures of model skill mentioned above will be used to evaluate sea-level pressure and 500 hPa height prognostic fields of the GCMs described here.

Root-mean-square errors can be divided into two parts, the systematic and non-systematic root-mean-square error. The systematic part represents the error that is similar at all points in the gridded field, while the non-systematic part the remaining random errors (Hoskins and Pearce, 1983). Accurate models have low systematic root-mean-square errors. Reduction in error variance (Balzer, 1994) is useful to measure improvements in model skill when some change is made. For example, the improvement of GCM skill above persistence forecasts will be quantified this way. Root-mean-square errors are not a perfect tool; a weakness includes favouring model forecasts that underestimate variability (Brier and Allen, 1951). However, an advantage of the root-mean-square error is that it retains the unit of the forecast variable.

Anomaly correlation coefficients measure the similarity of the spatial patterns between the forecast and observed fields (Murphy, 1988a). Long-term forecasting is mainly concerned with the departure of a particular variable from the climatological mean. Anomaly correlation coefficients are ideal for evaluating the ability of the model to forecasts these changes. On their own, anomaly correlation coefficients fail to detect gross model biases and sometimes high values can be misleading (Watterson, 1996). A perfect correlation will be found between two fields that differ by a constant factor throughout.

Categorical and probability forecasts

Scoring methods used are dependent on the type of forecast issued. Extended-range forecasts are often categorical because they suggest a probability distribution of likely outcomes rather than a single event. The Linear Error in Probability Space (LEPS) technique (Potts *et al.*, 1996) was developed to evaluate categorical forecasts. This sophisticated scoring system is ideal for evaluating a series of long-term forecasts giving the most probable category of occurrence. Specifically, categorical forecasts discussed in this dissertation are placed into three equiprobable terciles. Correct forecasts of the middle or normal category carry a smaller weight than correct forecasts of the outer categories in the final score. Incorrect forecasts receive a negative score depending on how many categories they are out. The final score ranges from -100%, for forecasting the worst possible category given the observations every time, to +100% for a perfect record. Guessing forecasts randomly or choosing the middle category all the time for equiprobable categories would result in a 0% LEPS score.

Other measures of categorical forecasts include, the hit rate (Noone and Stern, 1995), threat score, probability of detection and false alarm rate (Schaefer, 1990). The hit rate is the number of correct forecasts divided by the total number of forecasts and simply gives the proportion of time the forecasts were correct. Certain events, e.g. tornadoes, occur very seldom and the threat score divides the number of times the event was forecast by the number of times it was either observed or forecast. Correct forecasts of the event not occurring are omitted from the calculation thus excluding the easy forecasts that have no real value. The probability of detection gives the ratio of warning of an event to the number of times it occurred while the false alarm rate the number of warning forecasts that failed. These two measures are an indication of the reliability of the forecasts and can be applied to long-term forecasts of droughts and floods which are important warning signals.

COLA T30 GCM 30-Day Average Hindcasts for the Period 1979 to 1995

The most realistic way of evaluating GCM hindcasts is to treat them as if they were in forecast mode. Retroactive real-time forecasting (Barnston *et al.*, 1994) uses only information that is available at the time of the forecast to determine and remove model biases. In this study, model simulations from the first te. ears of the hindcast period are used to calculate the model bias which is subtracted from forecasts for year eleven. A new bias, calculated using forecasts from year one to eleven, is removed from forecasts for year twelve and so on. This process is continued to year seventeen and the average model skill is determined.

The effects of ensemble averaging and clustering are compared by using cross-validation to evaluate all seventeen years of hindcasts. The bias removed from forecasts in a particular year is calculated by using forecasts fror iining years. This technique is used here so that the largest possible set of fo are used for comparisons of the ensemble method.

Model forecasts of sea-level pressure and 500 hPa heights are evaluated in a window centred over southern Africa from 30°W to 60°E and 20°S to 60°S. In addition, for comparison, the same prognostic fields are evaluated over the entire globe, the northern hemisphere north of 20°N, the southern hemisphere south of 20°S and the tropics from 20°N to 20°S. Diagnostic variables of surface temperature and rainfall are evaluated over South Africa against observed data from 77 temperature stations and 510 rainfall stations that are interpolated to model output grid boxes (Fig. 5.1). Outgoing long-wave radiation fields are evaluated over the Indian and South Atlantic Oceans for the period June 1974 to July 1992. Root-mean-square error and bias are determined for each model grid box and anomalies are determined with respect to the model climate.

GCM prognostic output

Bias-corrected model forecasts of sea-level pressure and 500 hPa heights have root-mean-square errors substantially lower than those of persistence forecasts

(Fig. 5.2). The same is found with the anomaly correlation coefficient scores (Fig. 5.3). These scores clearly show that 30-day GCM forecasts have skill over southern Africa. The bias correction method that produces the best results in this study is the removal of the grid-point monthly bias. The other method which strives to produce an optimal linear regression fit through an anomaly scatter plot reduces root-mean-square errors well but lags somewhat in the improvement of anomaly correlation coefficients over those of persistence forecasts. Model ensemble average forecasts have large errors before bias correction showing the large effect of model drift on verification scores.

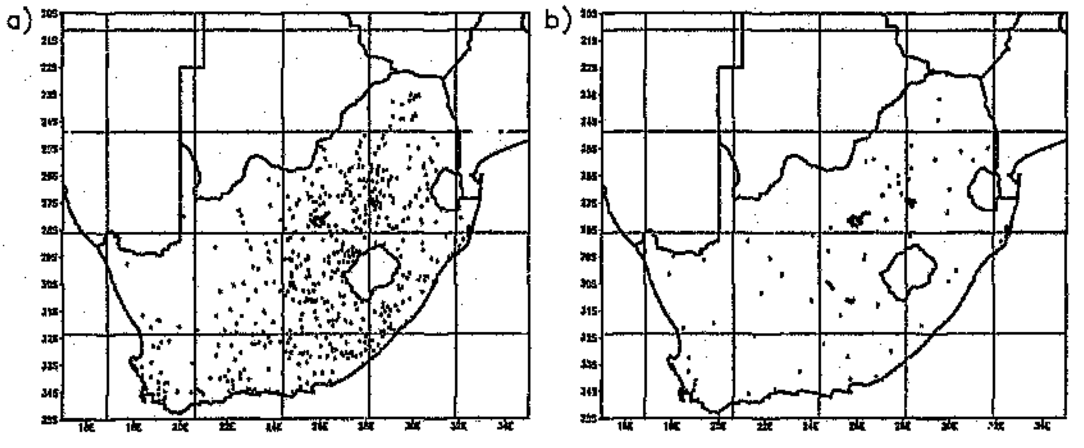


Figure 5.1: Map showing COLA T30 model grid boxes with the location of a) rainfall and b) temperature stations used for model diagnostic output evaluation.

GCMs in general underestimate variability but this is geographically dependent (Kaas, 1993). The COLA T30 model's inter-monthly variability is studied by comparing plots of forecast and observed standard deviation (Fig. 5.4). The model captures all of the 500 hPa height variability north of 35°S except in the central Atlantic Ocean and most of the sea-level pressure variability in the same area especially over South Africa. Further south the model underestimates variability somewhat.

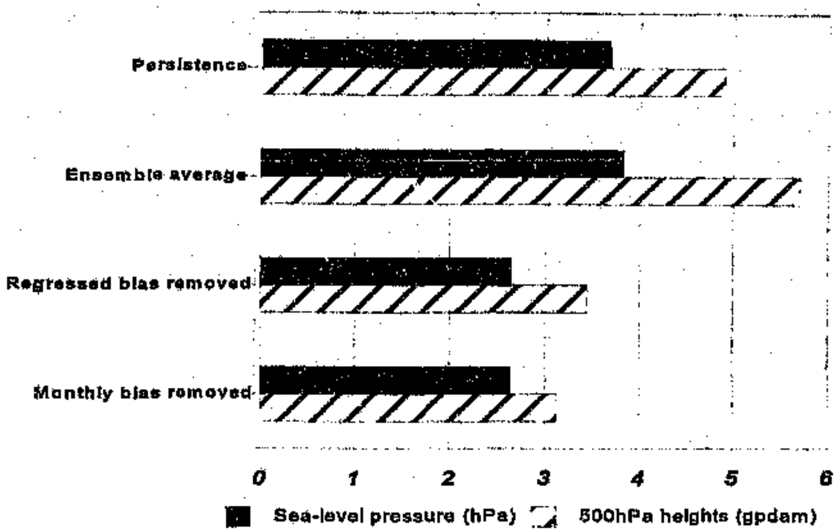


Figure 5.2: Average root-mean-square errors of 30-day sequential forecasts from 1989 to 1995 for the area covering southern Africa and surrounding oceans (30°W - 60°E and 20°S - 60°S). Biases are determined using retroactive real-time forecasting beginning in 1979.

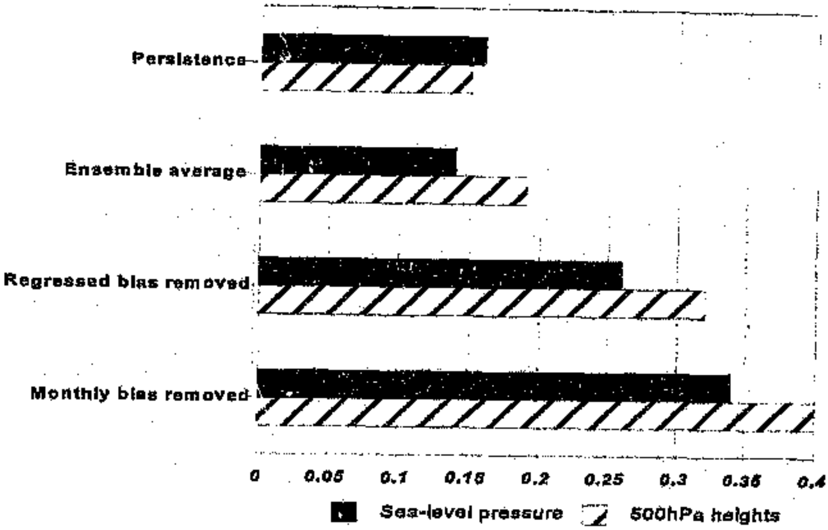


Figure 5.3: Average anomaly correlation coefficients of 30-day sequential forecasts from 1989 to 1995 for the area covering southern Africa and surrounding oceans (30°W - 60°E and 20°S - 60°S). Biases are determined using retroactive real-time forecasting beginning in 1979.

Effect of ensemble averaging and clustering

The weighted ensemble average, where weights are dependent on forecast length, produce forecasts with anomaly correlation coefficients higher than each ensemble member which range from 0.25 to 0.35, as well as the standard ensemble average (Fig. 5.5). The increase of 0.02 in the anomaly correlation coefficient to 0.39 when weights are used to calculate the ensemble mean is also significant. Correlations in figure 5.3 and figure 5.5 differ because the evaluation periods are not the same.

Ensemble members were clustered into two and three groups using the group average method. The calculation of the distances between ensemble members used to form the groups was based on the 500 hPa fields because their skill scores are a little higher than those for sea-level pressure fields. None of these clusters on average produced higher anomaly correlation coefficients. However, using hindsight to select the cluster that had the highest anomaly correlation coefficient for each forecast period produced a quantum leap in the anomaly correlation coefficients to 0.54 for southern Africa. If clusters are chosen optimally, it is possible to achieve a high level of skill. Mean-square-spread among ensemble members in the cluster proved not to be a good objective method in finding the best cluster. For now, ensemble averaging remains the best way to enhance dynamical extended-range forecast skill, but cluster analysis has great potential for enhancing the skill further.

Temporal variation of skill

Seasonal GCM forecasts are strongly dependent on boundary forcing and skill is greatest during El Niño and La Niña events when there is a strong boundary signal (Barnett *et al.*, 1994). However, monthly forecasts are still very much dependent on initial conditions. Two case studies of the January observed and forecast sea-level pressure illustrate the point (Fig. 5.6). During the 1983 El Niño event the model simulates the area of negative anomalies in the South Pacific Convergence Zone and in the Southern Ocean very well but underestimates the intensity by about half the magnitude. Model responses to the additional boundary forcing compare well to observations over the northern Hemisphere. For the La Niña case in 1989 the model again does well in the northern Hemisphere. The observed atmospheric response to the La Niña is weak and the model responds at the same magnitude and gets the correct sign in the anomaly in the South Pacific Convergence Zone and south of South Africa. Therefore, the model responded more realistically during the La Niña event and the evaluation statistics during the La Niña event are better than those during the El Niño event.

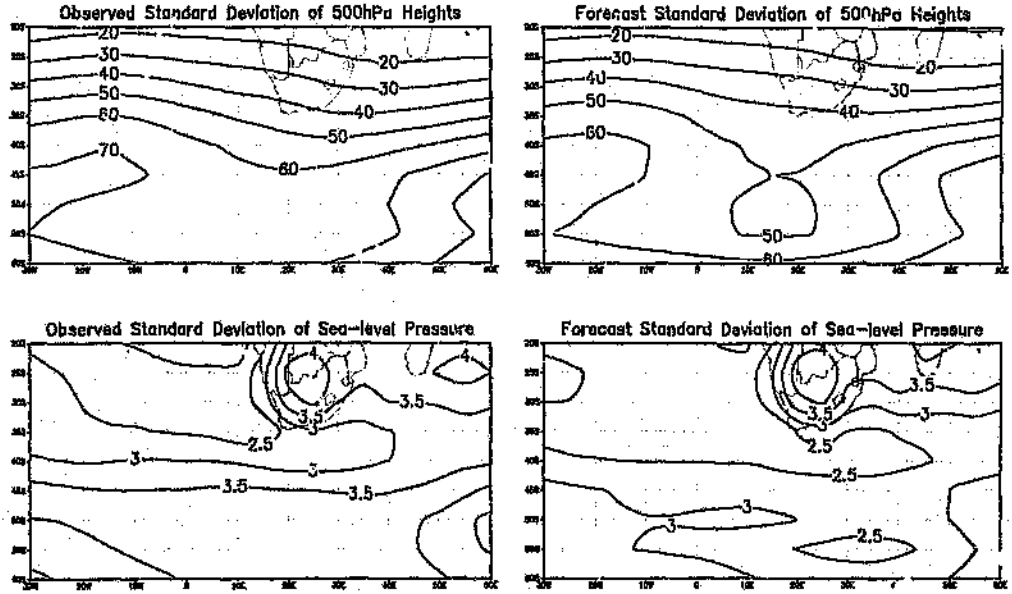


Figure 5.4: Standard deviation patterns of observed and bias-corrected forecasts of 500 hPa heights and sea-level pressure fields for the period 1979 to 1995. Biases are determined using cross-validation.

Case studies may be misleading as comparing southern Africa and global time series of GCM skill scores with the southern oscillation index (SOI) reveals (Fig. 5.7). There is no significant correlation between the 5-month running means of global GCM skill or GCM skill over southern Africa and the SOI (Table 5.1).

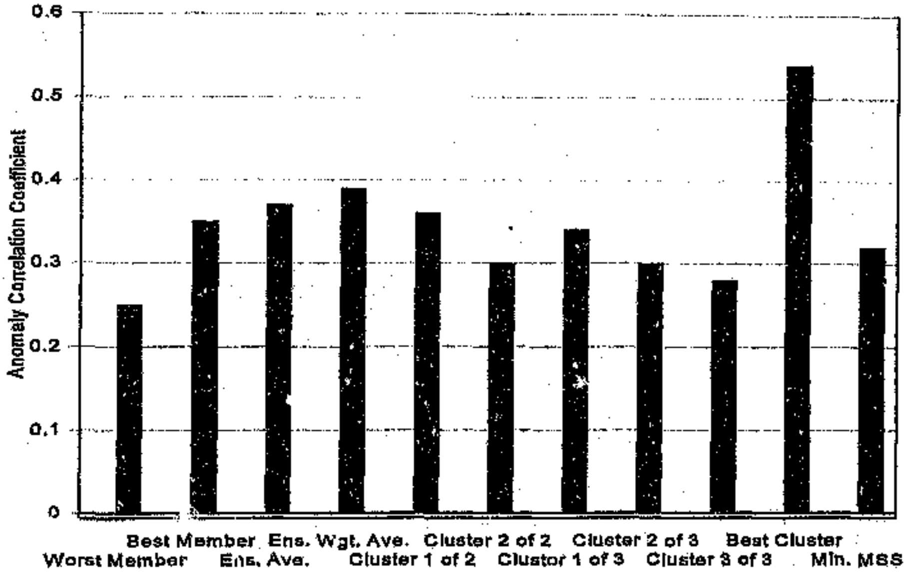


Figure 5.5: Comparison of the average anomaly correlation coefficients of 30-day, bias-corrected, sequential 500 hPa height forecasts from 1979 to 1995 over the area covering southern Africa and surrounding oceans (30°W - 60°E and 20°S - 60°S) of the poorest and best ensemble member, the straight ensemble average, weighted ensemble average, the largest to smallest of 2 and 3 clusters, the best cluster and the cluster with the minimum mean-square-spread at each case. Monthly biases removed are determined by cross validation.

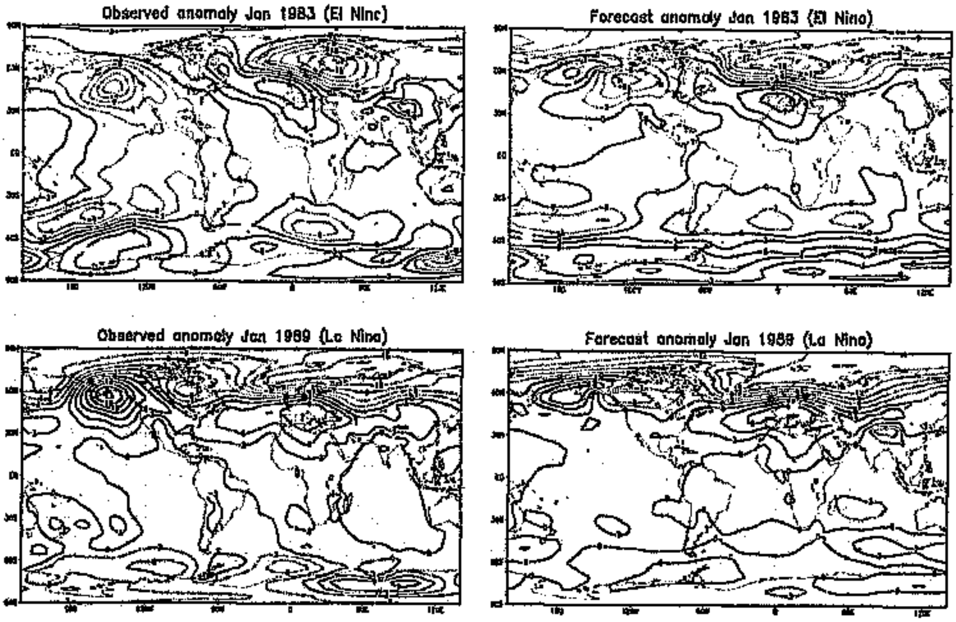


Figure 5.6: Observed and forecast January sea-level pressure anomalies during the 1983 El Niño and 1989 La Niña events.

Table 5.1: Correlation between the 5-month running mean of the southern oscillation index and GCM skill (anomaly correlation coefficient) for the globe and southern Africa over the period 1979-1995.

	Correlation with skill over southern Africa	Correlation with global skill	No. of years	No. of forecasts
El Niño years	-0.02	-0.03	5	61
La Niña years	-0.4	-0.78	1	13
Other years	0.08	-0.13	11	143
All years	0.18	0.16	17	217

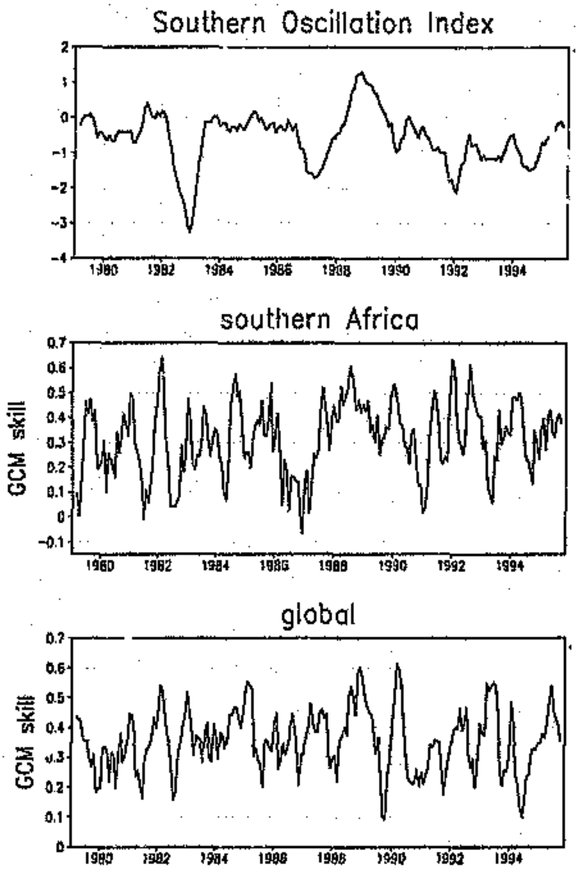


Figure 5.7: Time series of 5-month running means of the southern oscillation index, GCM skill over southern Africa and global GCM skill.

Diagnostic model output

Model forecast surface temperature and rainfall are evaluated for the grid boxes centred at 30°S 30°E (summer rainfall area) and 33.75°S 18.75°E (winter rainfall area). Anomalies of forecast surface temperatures have no bias and lower root-mean-square errors than actual forecast values which have a positive bias (Fig. 5.8a). This bias is greater in the summer rainfall area. The model monthly surface temperature climate also has a positive bias. Model rainfall anomaly forecasts multiplied by the ratio of the standard deviation of the modelled and observed rainfall have smaller biases than actual forecasts (Fig 5.8b). However, the bias is not removed totally as with the surface temperature forecasts. The model climate rainfall has a negative bias in the winter rainfall area and a positive bias in the summer rainfall area. The monthly bias of 147 mm at 30°S 30°E is more than the wettest month's average in that area. Root-mean-square errors for rainfall anomaly forecasts in the winter rainfall region are increased when bias correction is applied. This is not necessarily a deterioration in the forecast because underestimating rainfall amounts will result in lower root-mean-square errors.

Seasonal climatological maps of model outgoing long-wave radiation (OLR) biases over the Indian and South Atlantic Oceans show negative values over most of the Indian Ocean and positive values over Indonesia and equatorial west Africa, peaking in spring (Fig. 5.9). This suggests that the model is overestimating convection (negative OLR bias) over the Indian Ocean and not simulating enough of it over much of the land in tropical Africa. Over South Africa negative biases are found over the summer rainfall areas in the east and positive biases in the winter rainfall areas in the west (Fig. 5.8c).

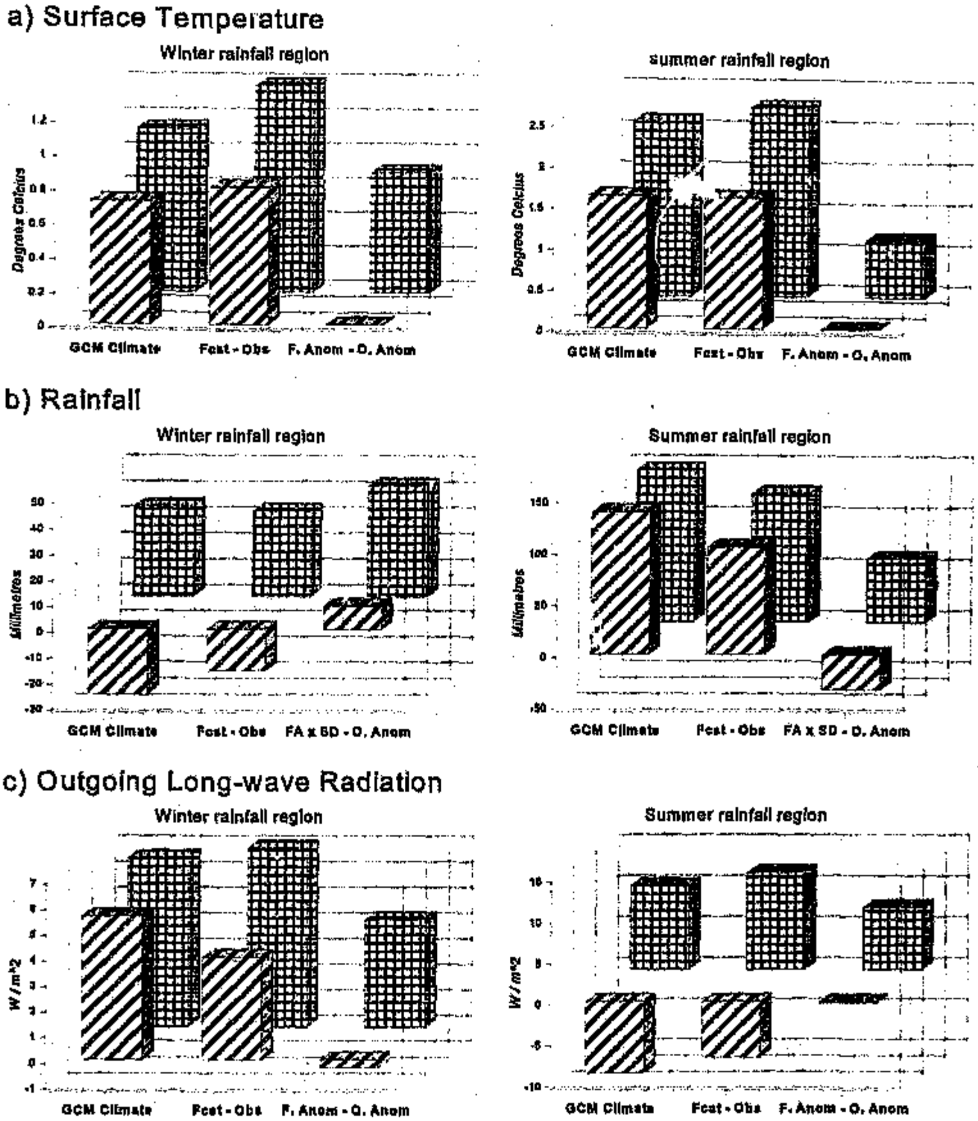


Figure 5.8: Average root-mean-square errors and biases of the COLA T30 GCM climate, forecasts against observations and forecast anomalies against observed anomalies of a) surface temperature, b) rainfall and c) outgoing long-wave radiation for two model boxes in the summer and winter rainfall areas of South Africa for the period 1979 to 1995. Biases are determined using cross-validation.

RMSE BIAS

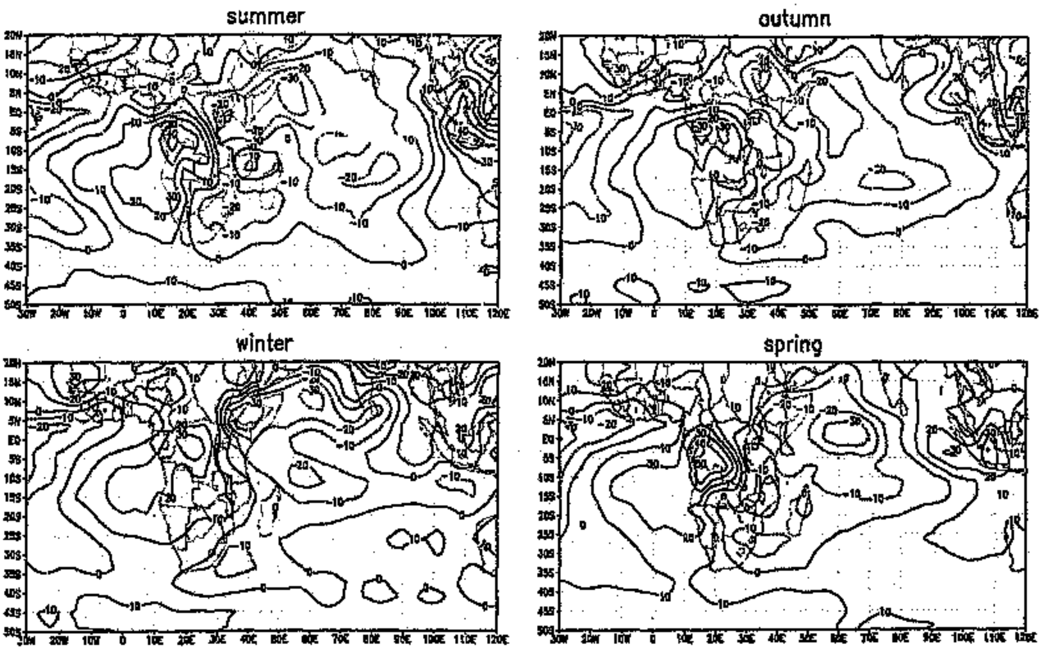


Figure 5.9: Seasonal maps of COLA T30 outgoing long-wave radiation model climate biases.

Global skill

The reduction in error variance score is used to compare the local skill of the COLA T30 GCM over southern Africa to that in other areas. This score quantifies the improvement in model forecasts over persistence forecasts. It is clear that on average the GCM performs substantially better than persistence forecasts in all regions (Fig. 5.10). Sea-level pressure forecasts for southern Africa have a higher level of skill than their northern hemisphere and global counterparts. However, 500 hPa height forecasts are most skilful in the northern hemisphere. In the tropics the GCM is able to improve notably on the already low root-mean-square errors of persistence forecasts. The reduction in error variance score is dependent on how poor persistence forecasts may be. Note that the highest reduction in error variance corresponds to the persistence forecasts with the highest root-mean-square errors.

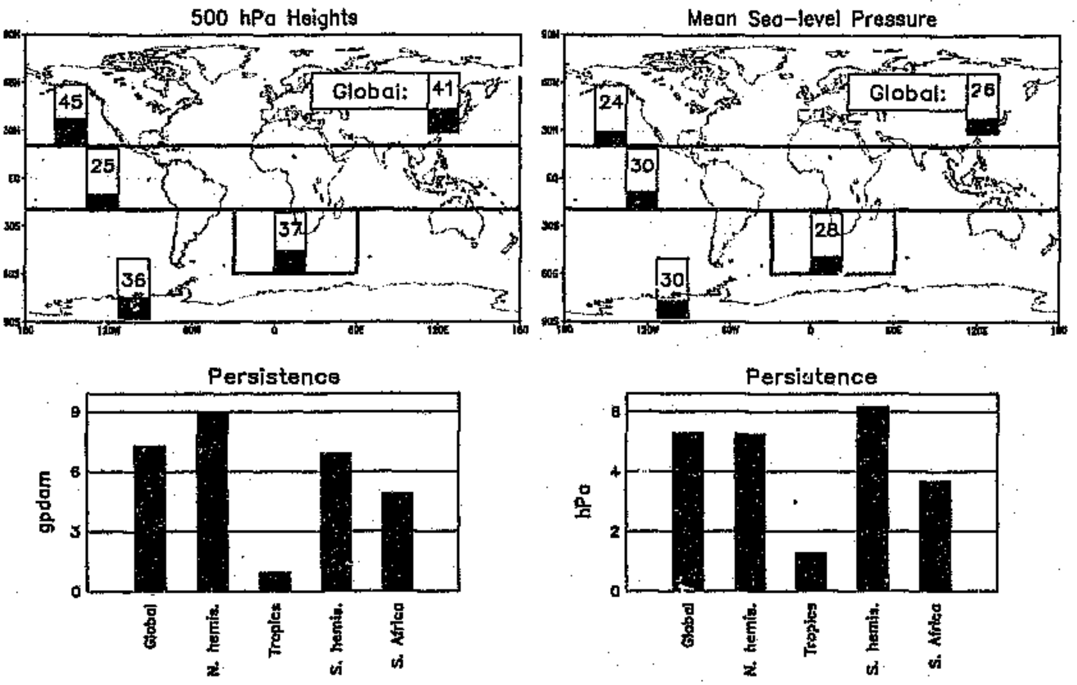


Figure 5.10: Reduction in error variance scores of 30-day GCM forecasts over various regions with accompanying persistence forecast root-mean-square errors.

Discussion

Numerous studies have shown the benefits of ensemble methods in increasing monthly forecast skill (Leith, 1974; Brankovic *et al.*, 1990; Yamada *et al.*, 1991). Results presented in this paper show how the ensemble mean outperforms each of the ensemble members. Palmer (1993) recognized the utility of ensemble forecasting as a measure of the importance of initial conditions on the skill of a dynamical extended-range forecast. A case-by-case plot of ensemble member skill of the COLA T30 GCM 30-day forecasts shows a large spread in the anomaly correlation coefficients (Fig. 5.11). In each case the same boundary forcing is used proving that the variations in forecast skill are caused by differences in initial conditions alone. Ensemble averaging acts to reduce random forecast errors caused by uncertainties in these initial conditions (Murphy, 1988b). Time-averaging also has benefits to forecast skill by filtering higher-frequency scales of motion to leave the more predictable, low-frequency waves (Shukla, 1981). However, high-frequency waves have an effect on the low-frequency modes and if not parameterized correctly model drift increases, degrading the forecast. Stewart (1994) investigated methods of improving a low-resolution model by analysing the contribution of unresolved scales using a higher resolution model and simulating these in a combined deterministic and stochastic parameterization scheme. Notwithstanding, forecast skill does improve with higher resolution GCMs that have sophisticated subgrid-scale physics (Sirutis and Miyakoda, 1992), although there is evidence that it is beneficial to form a forecast ensemble from GCMs with different horizontal resolutions (Deque, personal communication). Higher one-month forecast skill may consequently be achieved by using high-resolution GCMs and employing ensemble methods and output filtering.

Bias-correction of GCM output is considered a further vital step in enhancing forecast skill (Miyakoda *et al.*, 1986; Livezey and Schemm, 1988; Tracton *et al.*, 1989; Murphy, 1990). In this study, uncorrected model forecasts, which have larger errors than persistence forecasts, increase in skill by a substantial margin once the bias is removed. The COLA T... model has a particular seasonality in its bias which is easily identified and removed at each grid-point. The adjustment of model anomaly forecasts so that a linear regression fit passes through the origin of a scatter plot of observed and forecast anomalies with a gradient of unity caused an unrealistic increase in the forecast anomaly variability (Fig. 4.3). It seems that, at least for COLA T30 GCM monthly forecasts, there is no linear relationship between bias and anomaly magnitude.

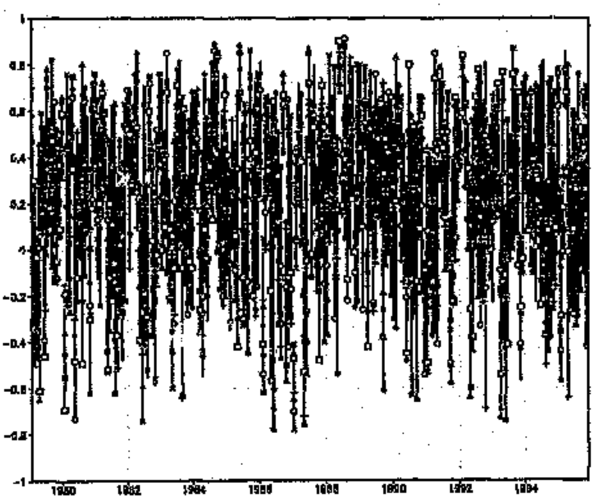


Figure 5.11: Case-by-case scatter plot of ensemble member forecast skill.

Another benefit of ensemble forecasting is to use the ensemble spread in predicting, *a priori*, the confidence in a forecast (Murphy, 1990; Barker, 1991). However, the ensemble spread of 30-day average forecasts verified in this study do not correlate well with forecast skill (Table 5.2). This may be a result of a relatively small ensemble size as the correlation of the ensemble mean-square-spread with forecast error has been found to increase with larger ensembles (Barker, 1991). It may also be that the relationship between forecast error and ensemble spread is dependent on case-to-case predictability. Model variability between cases is known to exceed variability due to model uncertainties (Sirutis and Miyakoda, 1992). To test the impact of predictability on the ensemble spread and forecast error relationship the forecast cases were sorted into bins according to the skill of the ensemble average (Table 5.2). Good forecast cases, where the anomaly correlation coefficient exceeds 0.6, account for more than a third of the cases but correlations show that ensemble spread increases slightly with forecast skill, contrary to expectations. As the skill of the forecasts decrease the correlation improves, especially for sea-level pressure forecasts. However, the higher correlations are found only with a small portion of the cases when the model has no skill. Difficulties encountered with using cluster analysis methods to improve forecast skill above that of the ensemble mean in this study may also be a result of the lack of a clear link between forecast skill and ensemble spread. However, the potential remains for clustering to exclude unskilful ensemble members from the average and enhance forecast skill.

Table 5.2: Correlation of ensemble spread and ensemble average skill for GCM 30-day forecasts divided into bins based on forecast anomaly correlation coefficients (ACC). Numbers in brackets are actual number of cases.

	Bin (ACCs)	1.0 to -1.0	1.0 to 0.6	0.6 to 0.2	0.2 to -0.2	-0.2 to -0.6	-0.6 to -1.0
500 hPa heights	% of cases	100% (221)	35% (77)	45% (100)	18% (39)	4% (9)	0% (1)
	correlation	-0.07	0.11	-0.07	-0.12	-0.17	***
Sea-level Pressure	% of cases	100% (221)	39% (86)	44% (98)	14% (31)	4% (9)	1% (2)
	correlation	-0.02	0.03	-0.01	-0.28	-0.44	-1.00

Boundary forcing does play a role in 30-day GCM forecast skill. Using observed SSTs produces better forecasts than using climatological SSTs (Mo and Kalnay, 1991). However, the effect on the skill in the mid-latitudes is lower than in the tropics. It was found, both locally and globally, that the skill of monthly forecasts in this study is not well correlated to the strength of the anomalies in the boundary forcing, further supporting the notion that monthly forecast performance is more sensitive to initial conditions (Sirutis and Miyakoda, 1992). Sometimes skill is found during predictable, stable climate regimes but the change between regimes, which does not require any external forcing, is often unpredictable and can result in poor skill (Reinhold, 1987; Palmer and Anderson, 1993). Blocking and stable climate regimes are very rare in the southern Africa region and cannot account for much of the skill that is found in the area (Hoskins and Pearce, 1983). This suggests that the COLA T30 GCM captures a number of the dynamical processes in the atmosphere that govern the time-evolution of the system very well.

Biases of model diagnostic forecasts of anomaly outgoing long-wave radiation and surface temperature are negligible and provide more useful information than direct forecasts of these parameters which may have a large systematic error. Such parameters may be used in a downscaling method to produce regional forecasts of rainfall and surface temperature (Kim *et al.*, 1984). In South Africa, outgoing long-wave radiation anomalies have been shown to be useful in detecting dry and wet spells (Jury and Levey, 1993). However, GCM rainfall forecasts for South Africa remain unreliable. Other findings show that GCMs as a whole simulate large-scale features well but suffer in the area of parameterized variables, such as rainfall. Often global average precipitation values are realistic but locally may deviate from observations by a factor of two (Gates, 1985).

Results presented here agree to a large extent with those achieved at other national weather forecasting and research centres. In particular, monthly northern hemisphere 500 hPa height forecasts produced by the Japan Meteorological Agency have an average anomaly correlation coefficient of 0.46 while running in forecast mode since March 1996 (C. Kobayashi, personal communication). Generally, findings in this dissertation agree with the current understanding of the effects of boundary forcing, ensemble methods, bias-correction of model output and predictability of different scales of motion. Discrepancies in findings include the use of the ensemble spread for *a priori* skill prediction. Possible reasons for this have been discussed.

GSM T62 GCM 14-Day Daily Forecasts for the Period 1997 to 1998

The GSM T62 model is used operationally at the SAWB to run a 43-member ensemble suite of 14-day forecasts once a week. The control forecasts run at the T126 resolution for the first 2 days and then are truncated to T62 resolution for the remainder of the forecast. Perturbations generated by the breeding of growing modes method run at the T62 resolution. Forecasts between October 1997 and March 1998 have been collected and evaluated at each forecast day using anomaly correlation coefficients over the area covering southern Africa and surrounding oceans (30°W to 90°E and 0°S to 60°S). Anomalies are calculated against the control analysis field of each forecast.

On average, anomaly correlation coefficients of the GSM T62 model 500 hPa height forecasts gradually drop as forecast time increases and reach 0.50 at about 15 days (Fig. 5 [illegible] ily forecasts are considered useful if anomaly correlation coefficients [illegible] 0.60 (Hollingsworth *et al.*, 1980). Using this rule-of-thumb, control 500 hPa height forecasts can be used on average up to nine days ahead. The benefits of ensemble forecasting become clearly evident when comparing the anomaly correlation coefficients of the control run and ensemble clusters. The control run is initialized with the best analysis, while the other ensemble members have perturbations added to and subtracted from that analysis giving the control run an initial advantage. During the first four days of the forecast the anomaly correlation coefficients of the ensemble cluster are similar to the control run. Thereafter the ensemble cluster has a higher anomaly correlation coefficient and useful forecasts are now extended from nine to twelve days. This limit in skill is consistent with findings of Lorenz (1969). The apparent return to skill of the ensemble cluster after day 14 has been experienced by others and is concluded to be statistically insignificant when comparing these forecasts to no-skill forecasts which are taken from verification fields valid for other years (Anderson and van den Dool, 1994).

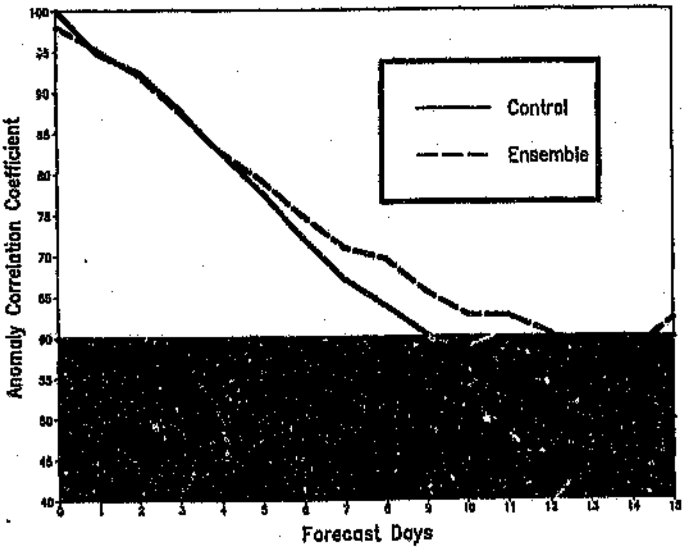


Figure 5.12 Average anomaly correlation curves of control (solid line) and the largest ensemble cluster (dashed line) 500 hPa daily forecasts of the GSM T62 GCM. Forecasts with correlations in the shaded area are not considered to be useful.

Downscaling GCM Circulation Forecasts to Rainfall

Categorical forecasts of 30-day average rainfall in seven near-homogeneous regions done using two methods of downscaling sea-level pressure and 500 hPa height GCM forecasts are contrasted and discussed. This is the final part of the extended-range forecast and is often the only product accessed by the user. Thus, from a user point of view, the evaluation of the final forecasts are the most important and need to be presented in such a way that the benefits and limitations of these forecasts are clearly shown.

Results

Previously it was shown that the GCM 30-day forecasts have definite skill with root-mean-square errors and anomaly correlation coefficients surpassing a standard of persistence forecasts. The downscaling exercise must capture as much of this skill as possible.

The circulation index forecasting method is first trained using observed sea-level pressure and 500 hPa height fields and then applied to GCM bias-corrected fields. This perfect prog approach (Vislocky and Young, 1989) unfortunately produces little skill in the rainfall tercile forecasts (Fig. 5.13). Summer forecasts over the winter rainfall region of the southwestern Cape and autumn forecasts for the southern Cape coast and northeastern interior achieve hit rates of 45% and LEPS scores of 25%. Otherwise LEPS scores are close to zero and hit rates do not significantly surpass the 33% expected by chance.

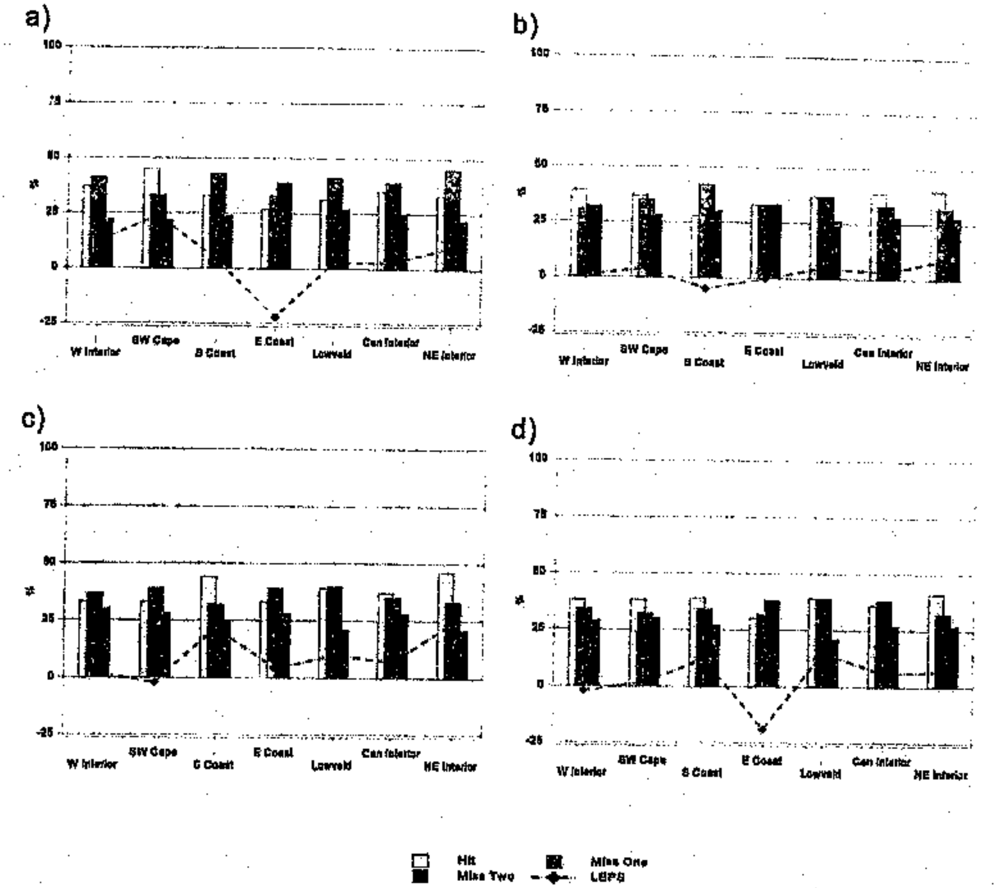


Figure 5.13: Seasonal percentage hits and misses (bars) and LEPS skill scores of 30-day rainfall tercile forecasts from circulation index downscaling over South Africa for the period 1979 to 1995, a) summer, b) autumn, c) winter and d) spring.

Downscaling GCM bias-corrected forecasts using canonical correlation analysis (CCA) and combining this with GCM categorical diagnostic forecasts of rainfall and outgoing long-wave radiation improve forecasts. The CCA method is trained using the model output statistics approach (Klein, 1982; Vislocky and Young, 1989) that works directly with the GCM forecasts. Here hit rates near or exceeding 50% are found for summer forecasts over the northeastern half of South Africa (Fig. 5.14). LEPS scores between 20% and 30% are found for these areas including the western interior. Autumn and winter forecasts for the winter rainfall region of the southwestern Cape have hit rates of 44% and 42% respectively. Hit rates for the western interior are good except in autumn, while lowveld region forecasts are good, except in winter. Forecasts in the central interior are best in spring and summer while for the northeastern interior skill remains high all year. Forecasts are poorest for the southern Cape coast where hit rates are seldom much higher than 33%.

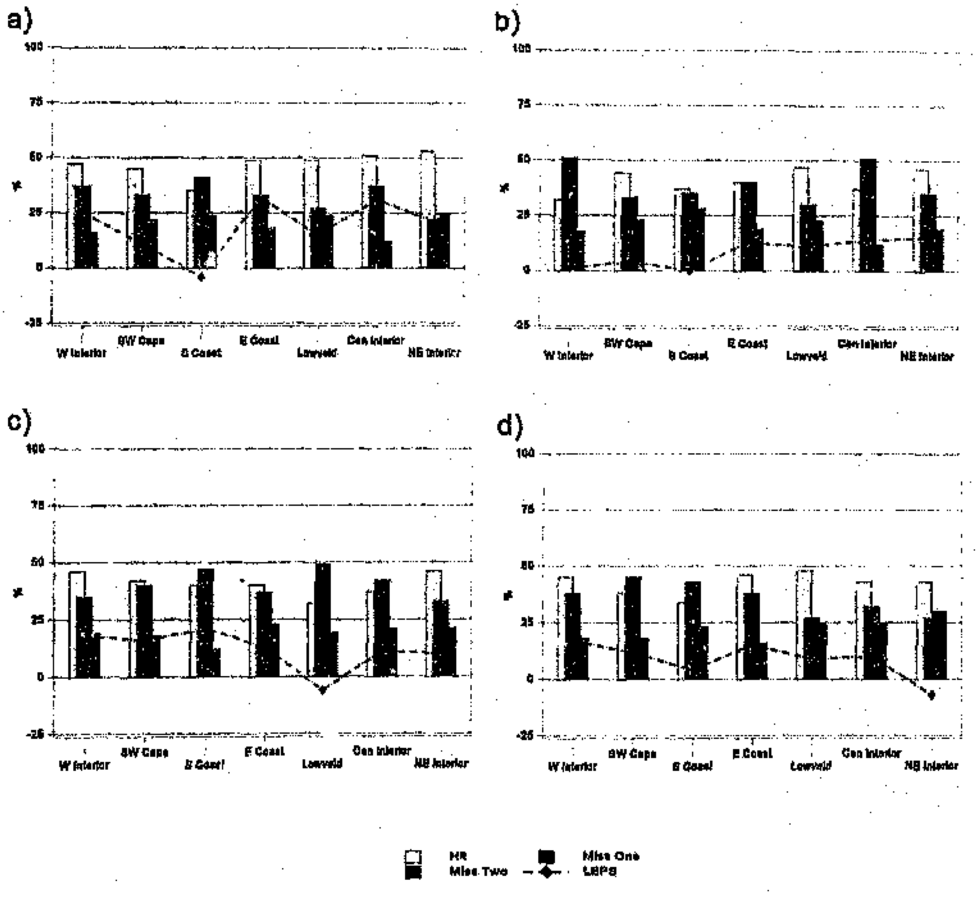


Figure 5.14: Seasonal percentage hits and misses (bars) and LEPS skill scores of 30-day rainfall tercile forecasts from combined CCA downscaling and GCM diagnostic fields over the period 1979 to 1995 for a) summer, b) autumn, c) winter and d) spring.

Discussion

It is necessary to begin with the varying predictability of rainfall in the different forecast regions for different seasons as this enhances understanding of fluctuations in forecast skill. The general nature of South African rainfall has been described earlier. More specifically, the monthly progression of rain day variance of rainfall on days when rain fell in the monthly forecast regions is u determine variations in predictability (Fig. 5.15). Daily conditions are importa because the predictability of climate on scales where initial conditions still play role are limited by the predictability of instantaneous weather rather than climate (Somerville, 1987). The average monthly variance from 1979 to 1995 has been normalized by the regional annual rainfall for comparison purposes. In the summer rainfall regions, which include most of the country except the southwestern Cape and south coast, the variance increases during summer along with the number of rain days. However, spring and autumn peaks are noted and are best seen in the data for the central interior. Regional studies of summer rainfall in the Free State province (central interior forecast region) have revealed that general rain days have the highest incidence in mid-summer. Showers are more common in early and late summer (Hudak, 1988) and contribute to the observed peaks in variance during the spring and autumn months. Further, the general rain events contribute substantially to the rainfall totals in the region (Harrison, 1984a). Consequently the wettest months are in mid-summer. The northeastern interior and east coast have the lowest overall variance, while the south coast, an all-year round rainfall region, has a high variance. The winter rainfall area in the southwestern Cape has a slight increase in the number of rain days in winter but a marked peak in variance in July when much of the rainfall is in the form of showers. A general trend throughout the regions is that variance increases with aridity. Previously shown forecast skill matches the observed rainfall variance in many respects. The high skill in the northeastern interior summer forecasts coincides with low variance and a high number of rain days. The increased rainfall variance in autumn in the central interior also coincides with a drop in forecast skill. Poor forecast skill for the south coast matches a relatively high rainfall variance in that area. This shows that the forecast skill is linked to predictability and is not merely random.

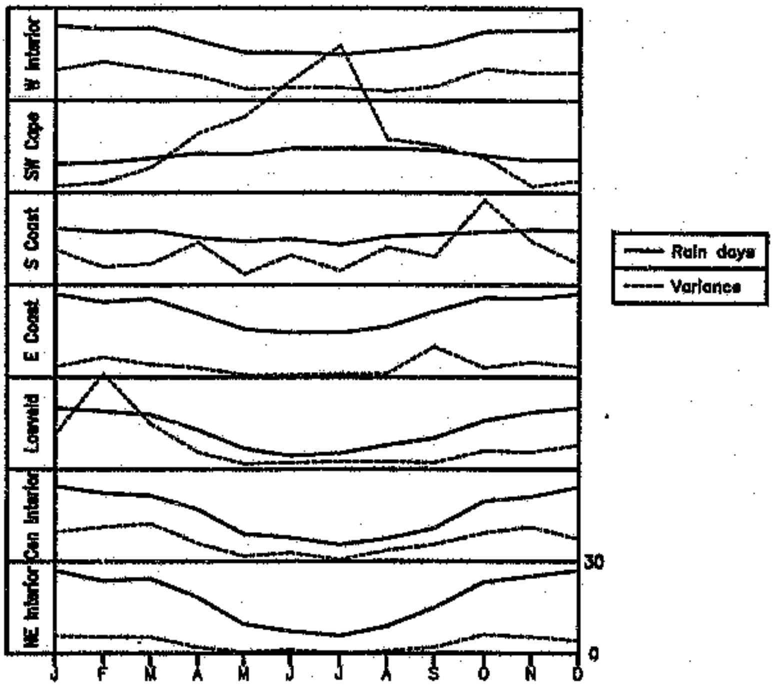


Figure 5.15: Monthly values of the number of rain days per month and variance of rainfall (wet days only) for each forecast region for the period 1979 - 1995.

A more formal way of quantifying forecast skill is to determine which forecast hit rates are statistically significant at the 95% level by comparison with Stochaster's binomial distribution (Livezey and Chen, 1983). This significance testing has been applied to the downscaled rainfall tercile forecasts in the following way. There are 51 forecasts for the summer season which must hit the correct category more than 33.3% of the time to beat guessing. However, about 11% of those forecasts above 33.3% may have occurred by accident. Hit rates exceeding 44% are considered to be statistically significant (Livezey and Chen, 1983). The same is done for the other seasons (Table 5.3). The skill of the CCA downscaled forecasts for summer is significant at the 95% level in all regions except the south coast. The western interior, lowveld and northeastern interior have significant skill for three of the four seasons. Rainfall forecast skill for the south coast remains insignificant throughout the year. Very few forecasts using the circulation index downscaling technique have significant skill. Obviously this primitive method does not capture the coupling between the atmosphere and rainfall adequately. Results from the CCA downscaling compare well with those obtained for temperature forecasts in the United States (Barnett and Preisendorfer, 1987).

TABLE 5.3: Skill scores as a percentage of correct rainfall tercile forecasts for the seven homogeneous rainfall regions for each season from the circulation index downscaling method and CCA downscaling combined with GCM diagnostic output method. Values significant at the 95% level are shaded.

	Circulation Index Downscaling				CCA Downscaling combined with GCM Diagnostic Forecasts			
	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring
W. Interior	37	39	33	38	[illegible]	32	[illegible]	[illegible]
SW Cape	45	37	33	38	[illegible]	[illegible]	42	38
S Coast	33	28	44	39	35	37	40	34
E Coast	27	33	33	30	49	40	40	[illegible]
Lowveld	31	37	39	39	49	47	32	48
Cen. Interior	35	39	37	36	51	37	37	43
NE Interior	33	40	46	41	53	46	46	43

Meteorologists are responsible for supplying information regarding the types of products and appropriate skills to those structuring a decision-making problem in assessing the economic value of forecast information (Winkler *et al.*, 1983). False alarm rates and probability of detection are some the measures that should be included when evaluating the quality of forecast information (Schaefer, 1990). The probability of detection of the below normal rainfall tercile in summer over the northeastern interior and east coast of South Africa exceeds 66% (Fig. 5.16). However, the probability of detection of wet events is low in the northeastern interior and moderate for the east coast. In the western interior wet events are more likely to be forecast than dry ones. Experts on forecast evaluation agree that a composite of skill measures should be used when attempting to get a clear understanding of the uses and limits of a product (Schaefer, 1990; Murphy, 1991). Probability of detection must be complemented with a statement of false alarm rates. Ideally a high probability of detection should be accompanied by a low false alarm rate. In summer false alarms of dry conditions are low for the central interior and east coast, but lie between 50% and 66% over the northeastern interior (Fig. 5.17). Dry conditions are best forecast on the east coast, but such forecasts are still good for the central and northeastern interior where the probability of detection exceeds the false alarms. Forecasts of normal conditions for the northeastern interior are almost certain to be correct, but almost certain to be wrong for the western interior and east coast. False alarms of wet conditions are low over most parts and forecasts of these conditions should be valuable for the generally arid western interior. False alarms generally exceed the probability of detection on the south coast where forecasts have little skill. Dynamical extended-range forecasts done at the former United States National Meteorological Center (now NCEP) show that skill in predicting precipitation by the global model lies in the above- and below-normal areas (Kalnay *et al.*, 1988). Locally, similar results are found as most regions have the best performance in the outer terciles, particularly the east coast. An exception is perhaps the northeastern interior, but forecasts for this region are based solely on downscaled general circulation where the other regions used diagnostic GCM output in the final combined forecast (Table 4.1).

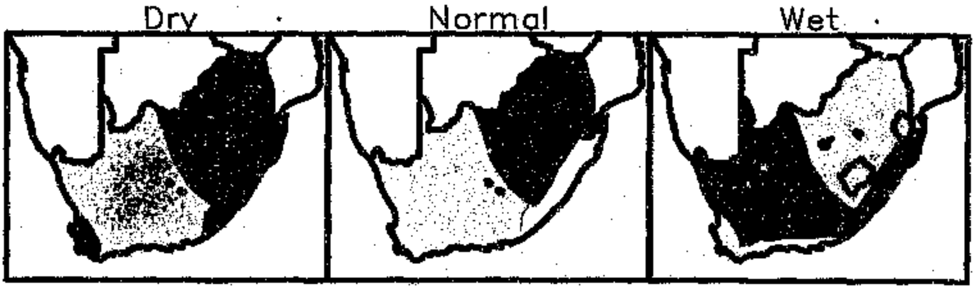


Figure 5.16: Probability of detection of each observed tercile during summer of CCA downscaled rainfall forecasts from 1979 to 1995.

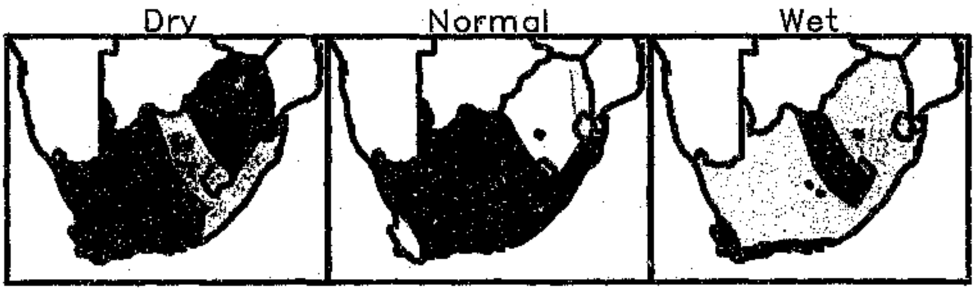


Figure 5.17: False alarm rates for each forecast tercile during summer of CCA downscaled rainfall forecasts from 1979 to 1995.

The agricultural sector is particularly vulnerable to rainfall during periods when rainfall deviates significantly from the normal for an extended time. At such times rainfall forecasts are the most valuable and have the broadest use. Climatologically speaking these periods occur during strong boundary forcing, which is often associated with higher predictability (Barnett *et al.*, 1994). Therefore, the forecast method must perform well during such cases. Series of individual summer forecasts for the central interior (Fig. 5.18a) and northeastern interior (Fig. 5.18b), which on average are good, show periods of excellent skill. The summer droughts of 1982/83 and 1991/92 and the wet summer of 1988/89 were well forecast in the central and northeastern interior. Further, significant trends in rainfall such as the dry mid- and late summer, early in 1992, was well captured in both regions. An example where an observed upward trend in rainfall is captured, but with a month lag is seen in the northeastern interior in 1985. The lag suggests that sometimes the skill of the forecasts lies in the persistence of initial conditions. This is in agreement with the literature. Predictability of the atmosphere, once settled into a regime is high, but changes from one regime to another are far less predictable (Reinhold, 1987). Thus the forecast model can be expected to miss some abrupt changes in circulation. However, since GCM skill exceeds that of persistence, it should correctly forecast many of these changes.

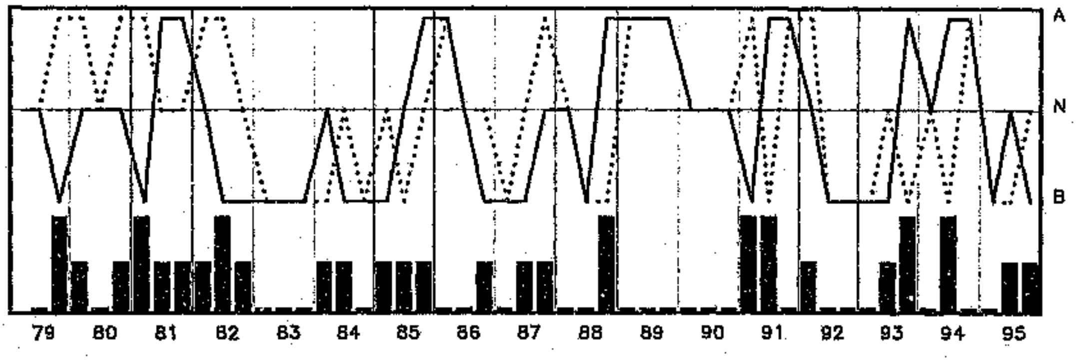


Figure 5.18: Time-series of summer CCA downscaled forecasts (dotted), observed terciles (solid) and difference (bars) for the central interior region.

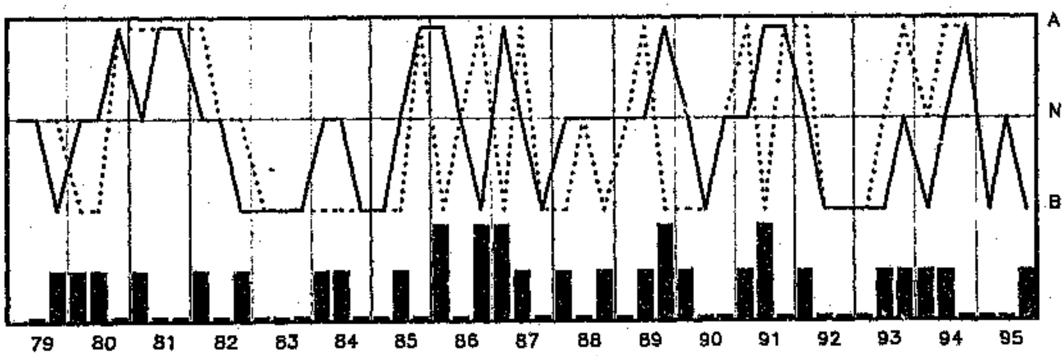


Figure 5.19: Time-series of summer CCA downscaled forecasts (dotted), observed terciles (solid) and difference (bars) for the northeastern interior region.

In summary, bias-corrected COLA T30 GCM forecasts of 500 hPa heights and sea-level pressure have skill scores superior to those from persistence forecasts, satisfying the basic prerequisite of skilful forecasts. Local skill over South Africa compares well with global skill. Ensembles of forecasts which span a range of possible outcomes have advantages over individual forecast simulations and increase forecast skill. Clustering ensemble members has the potential to increase skill much further if used optimally. The skill of GCM monthly forecasts does not appear to be sensitive to the strength of anomalous boundary forcing but rather on the characteristics of the climatic regime captured in the initial conditions. Diagnostic forecasts of rainfall and outgoing long-wave radiation suffer from biases and on their own cannot be used to produce skilful forecasts. This may be achieved by downscaling the large-scale circulation using a multi-variate statistical technique.

Monthly rainfall tercile forecasts over South Africa downscaled from COLA T30 GCM forecasts using canonical correlation analysis have significant skill over many areas of South Africa. Seasonally, the best forecasts are found during summer over the northeastern half of the country (Fig. 5.20). Forecasts for the arid western interior, which receives most of its rain in late summer, have a moderate skill all year except autumn. Little forecast skill is found in the southern Cape coast. This all-year- round rainfall area receives rain during various synoptic situations with a relatively high variance. In South Africa rainfall is a highly variable parameter and generally difficult to predict but the monthly forecasting strategy has successfully realized some of the predictability potential.

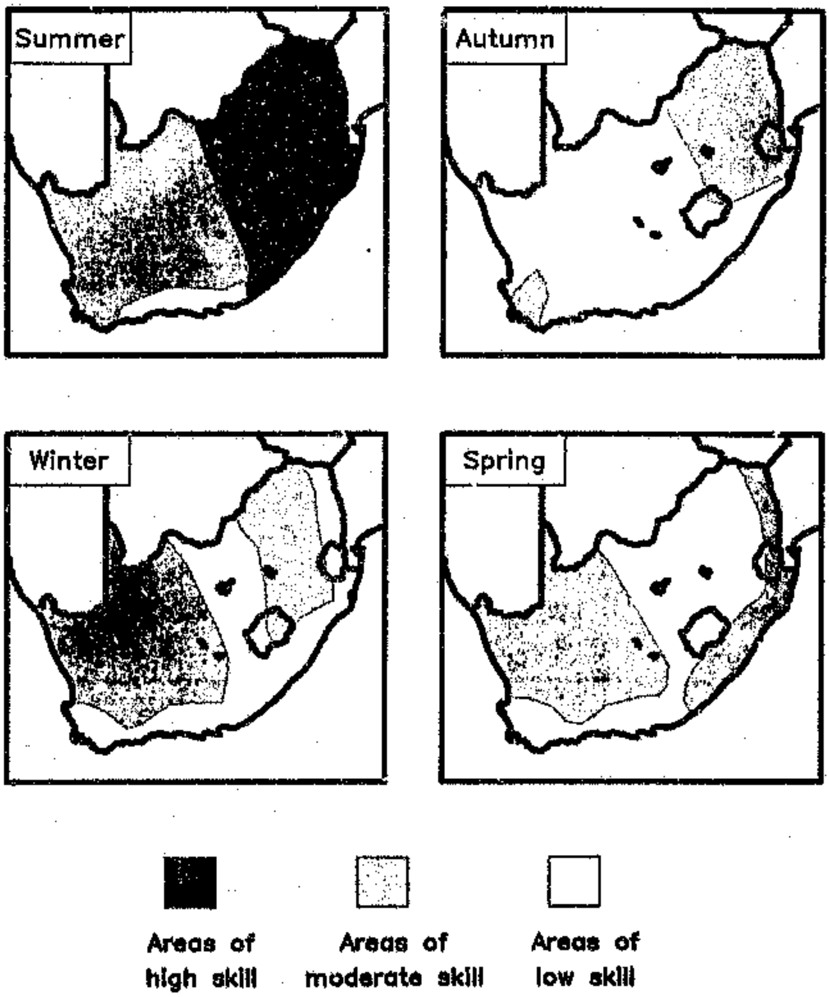


Figure 5.20: Se· ·nal maps depicting the expected skill of 30-day rainfall tercile forecasts in South Africa.

CHAPTER 6

PRACTICAL ASPECTS OF MONTHLY FORECASTS

Introduction

This chapter has been included to add a practical dimension to the dissertation and to present an example of a forecast compiled using the methods described in this dissertation. The process of how the theory and ideas reviewed in previous chapters are applied to provide useful information to end and intermediate users is discussed. Users of forecast information are the most important segment of the entire process. If a forecast is not issued or if the forecast is not used positively in a decision-making process then the forecast has no value at all (Murphy, 1994). Forecasts that have a negative impact, i.e. cause loss or damage because they were incorrect, need to be avoided as much as possible.

Nature of Forecasts

Successful forecasts are those that supply useful information, timeously, to people who are able to make decisions based on the forecast information. Therefore, a forecast must contain information required by the user in a format that he can use. Users span a wide scope of disciplines and needs are many and varied. Four confines of information are needed in determining the forecast value to individual users. These are the course of action available to the user, the user's payoff or loss function, the quality of information on which the user's decisions are based in the absence of forecasts and the quality of the actual forecast (Murphy, 1994).

Forecasts are constrained by what products are actually available. For example, daily weather conditions up to thirty days ahead are simply not possible at this stage. A compromise between what is available and what is needed must be reached. The forecaster chooses the forecast regions to suit the methods and capabilities of the forecast model. Interpolation to other regions, such as provinces, will simply degrade the skill of the forecast. Another problem with interpolation to other regions is that the original forecast regions have a spatial scale that suits the temporal scale of the forecast product. Provinces, for instance, may not necessarily conform to such requirements.

Wording of forecasts becomes difficult when the regions cross political boundaries. One way of addressing this problem is to present forecasts on maps. However, creating satisfactory maps can be time-consuming and there are difficulties sending maps via electronic-mail (e-mail). The most successful way of presenting forecasts has been to put them in tabular form with a reference map showing the regions that is available on request (Appendix B). The map can be sent to regular users when they get their first forecast. Subsequently they only need to receive the forecast in table form.

The layout of the forecast is very important. Information must be clear, concise and unambiguous. The user must understand exactly what is being forecast so that the correct interpretation of the data may be made. Brevity is also important. The user does not want to be burdened with unnecessary information. Probabilities in terms of percentages are widely understood and are accepted as a good way to present information. Monthly outlooks are set on a table with a region on each row and events, such as below normal, normal and above normal rainfall, in the columns (Appendix B). The forecast probability of an event in a particular region can then be read directly from the table.

The final aspect of the forecast is what information is given. Again it must be stressed that products without skill should not be issued, and if they are, the user must be informed that there is low confidence in that product. Usually a climate forecast is the best substitute for a low skill forecast. Often climate forecasts are also helpful to users. For example, if a filming company wants to shoot a television advertisement in the Northern Cape in May, often climatological information on the average temperature and the number of rain days suffices.

The forecast techniques discussed in Chapter 3, enable forecasts of daily conditions up to 14 days ahead to be attempted. The most popular parameters requested by users are the probability and intensity of rain, maximum and minimum temperatures, wind speed and direction and cloud cover. These parameters are put into table form and updated once a week (Appendix B). Forecasts of time-averaged rainfall and temperature terciles are done for a month ahead. Probabilities of each tercile occurring are then tabulated. The concept of terciles is not well understood. The tercile categories must be defined and included in the forecast (Appendix B). Average annual rainfall varies within each region and so do the boundaries of each tercile. The variation can be such that upper limit of a normal category (middle tercile) at one location is close to the lower limit at another. Normal category limits for a specific location are calculated by multiplying the region's category limits by the ratio of local annual rainfall to regional annual rainfall. This is done for predetermined annual rainfall amounts in multiples of 200 mm. Smaller multiples will give an artificial accuracy because monthly forecasts have a limited skill.

It is important to demonstrate a record of forecasts to give users an indication of how good the forecasts may be. They can use this information to calculate benefits for their own application and decide for themselves whether to use the forecasts or not. The first part of this demonstration is a database of previous forecasts and hindcasts. These should stretch back as far as possible, however, availability of model input data is the main constraint. At this stage the NCEP reanalysis dataset starts at January 1979 (analyses back to 1958 are expected to be available in the near future). Another significant constraint is computer time and resources. The 17-year hindcasts done in this study took about six months to complete on the SAWB's Cray-J90 computer. The second part of the demonstration is an objective evaluation of the hindcasts for each year and rainfall season. Evaluation results must be reliable and understandable. Skill scores, as with forecasts, must be explained clearly so that the user can interpret them correctly. It is important to know why a forecast was verified as correct or incorrect.

Dissemination

A crucial step in any forecast is the transfer of the information from the forecaster to the user. Short-term forecasts have been issued for decades now and daily weather forecasts are seen on most television stations and in newspapers. Long-term forecasts are relatively new and are aimed at more specialized users. The general media is not suitable, at this stage, to carry long-term forecasts because the public still needs to be trained on how to use these forecasts. A lot of research also remains to be done to improve long-term forecasting methods. Therefore, active dissemination on the part of the forecaster, is to peers and specific users. This is done with the aid of e-mail, regular mail and facsimile transmissions. Passive dissemination consists of maintaining an Internet Website and running an information centre by trained officers. The general public can get information from these sources and place any queries they have. The SAWB runs a Long-term Operational Group Information Centre (LOGIC) on weekday mornings which can be contacted by telephone, e-mail or facsimile. This effort has proved to be worthwhile. Over 1000 queries were handled by this centre during the 1996/97 rainfall season.

Automation

One of the most challenging areas of system development is automation. Procedures must be written that gather all input data, run the models, do the post-processing, set the objective parts of the forecast and send the forecast to the dissemination centre. All likely problems, usually computer hardware failures, must be anticipated and corrective measures implemented should they occur. In other words the forecast must depend as little as possible on human intervention. Data becomes available on a continuous basis and model runs have to be submitted automatically once the data has arrived. Valuable time will be lost if the model runs are only submitted when someone is on duty.

Machine schedulers are used to set the forecast process in motion. Each segment submits the next once it is complete until the final forecast is finished. Obviously the forecast process can never be entirely automatic and human intervention is unavoidable and necessary at times. Computer operators are responsible for the smooth functioning of operational machines. If data arrives late or a machine was down when a model was supposed to start, the operators start the model manually. The LOGIC official checks whether the final forecast is completed and has limited control over the printing of the final products. Occasionally, new or difficult problems arise and the designer of the operational system has to resolve the problems.

Some requests from users have to be dealt with individually. Such tailor-made products become extra duties for the LOGIC officer and do not form part of the automated system.

Interaction with Users

A user of forecast information can be described as an individual or group of people who receive forecasts and use this information to make strategic and tactical decisions regarding their activity. Users can be divided into two major groups. End-users are those who apply forecast information directly to their activity and do not pass on the information. A good example, is a crop farmer who needs to plan the planting, irrigation and harvesting of his crop. The other type of user is the intermediate user. These are generally large companies or cooperations who either distribute forecast information to end users within their jurisdiction or use the information to improve their own products to end users. An example of the former, is an agricultural union, while the latter could be a research institute investigating runoff and river flow.

The importance of a two-way communication between a forecaster and user cannot be over-emphasised. The forecaster has to keep in touch with the users and remain up to date with ever-changing needs. Questionnaires, workshops and direct communication ought to take place often. Questionnaires investigate the reaction of users to forecasts and provide a channel for requests about new forecast products and layout of forecasts: Workshops have similar functions but also have user training and information sessions. The Workshop on the Use and Benefits of Seasonal Outlooks (WUBSO) in 1996 (WUBSO, 1996) was where the long-term forecasters learned that users want information on hindcasts and evaluations. A lot of information is exchanged by direct communication through places like the LOGIC. Comments and suggestions from users are noted and passed on to others involved in long-term forecasting.

Many potential users are sceptical of long-term forecasts because of the apparent lack of skill in models and low confidence that forecasters have. Therefore, projects which demonstrate the usefulness of long-term forecasts must be undertaken. The goal of these projects is to present a history of forecasts and show how a particular resource or activity could have been better managed had the forecast information been available. Water resource management can be easily simulated in such a project. Occasionally poor decisions, owing to incorrect forecasts, will probably be made, but overall better management should result.

The forecaster must continually strive to provide a worthwhile service to his users. If he does not satisfy his customers he might find himself with a product that no-one wants. Apart from that, long-term forecasts certainly have the potential to make a huge contribution to mankind and this opportunity should not be wasted.

CHAPTER 7

SUMMARY AND CONCLUSIONS

The COLA T30 GCM is able to simulate the global general circulation well. Simulation of southern Africa regional circulation, in particular, is good relative to the globe. GCM forecasts of 500 hPa heights and sea-level pressure have superior anomaly correlation coefficient and root-mean-square error scores than those from persistence forecasts, satisfying the basic prerequisite for skilful forecasts. Biases inherent in model forecast variables can be effectively reduced resulting in accurate forecasts.

Ensembles of forecasts which span a range of possible outcomes have advantages over individual forecast simulations. The numerical average of an ensemble has one of the lowest root-mean-square errors more often than any member case by case and over a long period has the lowest average root-mean-square error. Clusters of ensemble members has the potential to increase anomaly correlation coefficient scores substantially above those of individual members.

Downscaling GCM forecast large-scale circulation to monthly rainfall is necessary because of coarse GCM resolution and poor performance of GCM parameterized rainfall forecasts. A model output statistics method of using canonical correlation analysis to downscale rainfall from bias-corrected GCM forecast sea-level pressure and 500hPa height fields proved successful. This forecast was combined with spatially interpolated GCM diagnostic forecasts of rainfall and outgoing long-wave radiation to produce tercile forecasts of monthly rainfall with significant skill in many areas, particularly in the northeastern parts of South Africa during summer. Sea-level pressure and 500 hPa height circulation indices, selected to capture aspects of the general circulation that are important in determining local rainfall, were also used to calculate probabilities of rainfall terciles. The method was trained using analysis fields and then used to downscale GCM forecasts to predict rainfall operationally. This perfect prognosis approach has a number of caveats and more skilful forecasts are obtained by using the canonical correlation analysis downscaling method.

The outcome of applying numerical weather prediction models to monthly prediction of rainfall in South Africa has proved instructive. The GSM T62 global model has been used for 14-day forecasts of daily conditions and the COLA T30 global model for one-month forecasts. The results of the study are summarized below.

The Basis of the Approach

1. Forecasting the instantaneous state of the atmosphere is limited to two weeks because errors, unavoidably present in the initial conditions of an integration, grow with time and eventually contaminate all scales of motion.

2. Monthly forecasting is concerned with atmospheric motions that are dependent on both initial conditions and low-frequency boundary forcing.

3. Monthly forecasting has potential because slowly varying boundary conditions that force the atmosphere alter the statistics of the atmospheric motion making the large-scale motions, which are relevant to monthly forecasting, predictable.

4. Differences in the extra-tropical general circulation of the northern and southern hemispheres result in varying successes of forecasting methods in each hemisphere.

5. Rainfall in South Africa is highly variable and droughts and floods are common. Drier than normal years are characterised by more zonal mid-tropospheric flow, with a westerly anomaly in the surface flow. Wetter than normal years are associated with large-amplitude mid-tropospheric waves and an easterly anomaly in the surface flow.

6. Ensemble forecasting helps to overcome the difficulty of errors in initial conditions by sampling a range of possible states of the atmosphere and producing a probability distribution of forecasts that usually includes what is later observed.

7. The average of an ensemble of forecasts usually has a higher skill than the individual forecasts.

8. Cluster analysis is used to find groups of similar forecast scenarios from an ensemble and exclude outlier forecasts.

9. Probability forecasts can be determined directly from an ensemble of forecasts.

10. Ensemble forecasting methods can be used to provide *a priori* information about the skill of a forecast.

General Findings

1. A forecast database consisting of 221 cases of ensembles, each having 9 lagged average forecasting 30-day forecasts from the COLA T30 GCM, covering the period from January 1979 to December 1995 was produced to test and evaluate monthly forecasting methods.

2. Gridded model forecasts may be evaluated using root-mean-square errors and anomaly correlation coefficients. Categorical forecasts may be verified using the LEPS score. Each evaluation measure has limitations and these must be understood when interpreting results.

3. Standard GCM output has a high bias and results in high root-mean-square errors.

4. Model forecasts can be improved considerably by applying various bias-correction methods.

Findings for South Africa

1. Reduction in error of sea-level pressure monthly GCM forecasts compared to persistence is higher over southern Africa than in the northern hemisphere. For 500 hPa heights, the northern hemisphere reduction of error is best, but in southern Africa it is better than the southern hemisphere as a whole.

2. Southern Africa stands the much to gain if clustering of ensemble forecasts is used optimally. Anomaly correlation coefficients for 500 hPa height forecasts can increase from 0.40 to 0.54 over southern Africa with clustering.

3. Diagnostic model output fields of surface temperature, rainfall and outgoing long-wave radiation (OLR) have steady biases. Rainfall and surface temperature is overestimated over the eastern parts of South Africa and OLRs are too low over most of the Indian Ocean. Best use is made of these fields when the anomaly with respect to the model climate is calculated.

4. Root-mean-square errors and anomaly correlation coefficients from bias-corrected 30-day COLA T30 model forecasts are better than the same from persistence as a reference forecasting method.

5. Ensemble clusters of GSM T62 daily 500hPa height forecasts extend skill from nine to twelve days.

Downscaling

1. Forecasting rainfall from GCM output is best done by downscaling the circulation to rainfall, rather than using model rainfall forecasts. Canonical correlation analysis is an multi-variate statistical method which works well in this application.

2. The downscaling method is trained with actual bias-corrected GCM forecasts. This model output statistics approach produces categorical forecasts of monthly rainfall that is significant at the 95 % level in many regions.

3. Combining canonical correlation analysis downscaling with spatially interpolated diagnostic GCM output enhances the forecast skill.

The Use of Monthly Forecasts

1. A forecast must be used positively in a decision-making process to be of any value.

2. It is imperative to interact fully with users of forecasts to create products that are user-friendly.

3. Historical skill of a forecasting method must be demonstrated to end-users to prove reliability.

One of the most promising aspects of monthly forecast skill is optimizing the use of cluster analysis to obtain a group of bias-corrected GCM for .asts from an ensemble of forecasts for southern Africa that has an average anomaly correlation coefficient as high as 0.54, which is presently a very good score. The various advantages of using ensemble forecasting have been demonstrated in the evaluation of the set of COLA T30 GCM hindcasts. Further improvements in GCM forecasts can be expected, not only from advances in modelling physical and dynamical processes, but also from further improvements and adaptations of methods like those presented in this work.

The canonical correlation analysis downscaling method demonstrated in this dissertation shows potential for the southern African region. It can be applied to other parts of the world for various predictand parameters that may be required in those regions. The advantage of this method is that it uses GCM forecasts, which are steadily improving, to produce probability tercile forecasts n a relatively simple way. Pure statistical forecasting methods have almost reached their full potential and may only show modest improvements in future.

Monthly forecasting is on a time-scale that is dependent on both initial and boundary conditions. It is a most complex forecasting time-scale and such forecasting has only begun showing progress during the last two decades. Advances in computing capabilities and the ever-increasing demand for monthly forecasts has prompted meteorological centres to begin focusing their efforts on improving the skill of monthly forecasts. The results of this work show that the forecasting strategy developed for southern Africa is worthwhile and has potential applications for other regions of the world and even on a global scale.

APPENDIX A

LIST OF ABBREVIATIONS

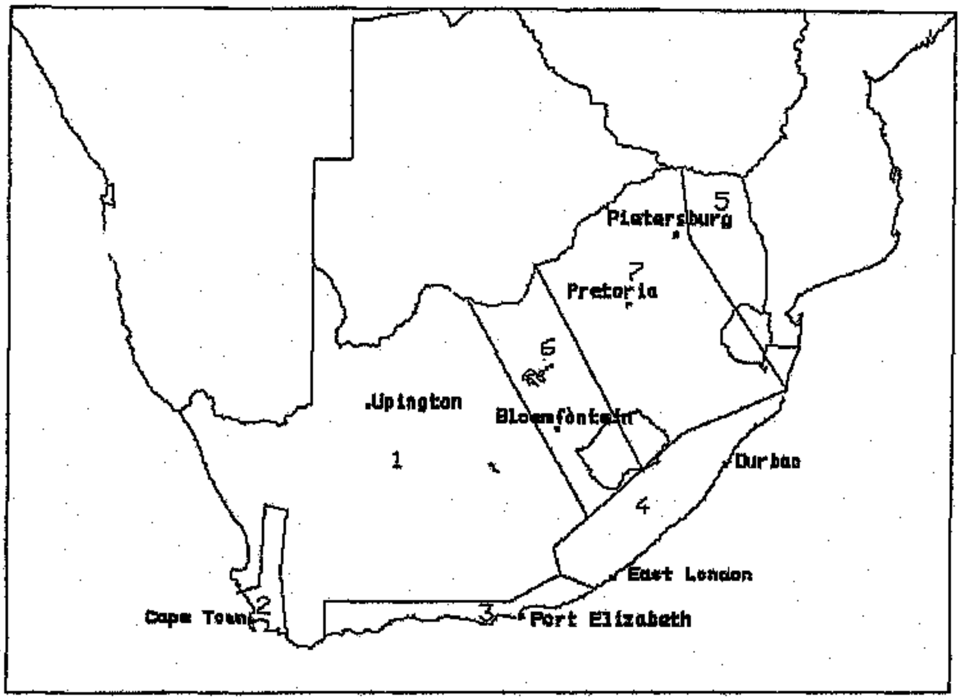
ACC	Anomaly Correlation Coefficient
AGCM	Atmospheric General Circulation Model
AVE	Model ensemble average
BGM	Breeding of Growing Modes ensemble generating method
CAC	Climate Analysis Center (now CPC)
CCA	Canonical Correlation Analysis
COLA	Center for Ocean-Land-Atmosphere Studies
CPC	Climate Prediction Center (formerly CAC)
CPU	Central Processing Unit of a computer
CTL	Control run simulation
ECMWF	European Centre for Medium Range Weather Forecasts
GARP	Global Atmospheric Research Project
GASP	Global Assimilation and Prognosis system
GCM	General Circulation Model
GDAS	Global Data Assimilation System
GrADS	Graphics Analysis and Display System
GSM	Global Spectral Model (medium-range global forecast model at the SAWB)
LAF	Lagged Average Forecasting
LEPS	Linear Error in Probability Space
LOGIC	Long-term Outlook Group Information Centre
MODG	Monthly Outlook Development Group
MOS	Model Output Statistics

NCEP	National Centers for Environmental Prediction (formerly NMC)
NMC	National Meteorological Center (now NCEP)
OCN	Optimal Climate Normals
OI	Optimal Interpolation
OLR	Outgoing Long-wave Radiation
POPS	Principal Oscillation Patterns
RGSCS	Research Group for Seasonal Climate Studies
RMSE	Root Mean Square Error
SALFF	South African Long lead Forecast Forum
SAWB	South African Weather Bureau
SOI	Southern Oscillation Index
SST	Sea Surface Temperature
T30	Spectral GCM with triangular truncation at wave number 30 (COLA GCM in this thesis)
T62	Spectral GCM with triangular truncation at wave number 62 (SAWB GSM model in this thesis)
T126	Spectral GCM with triangular truncation at wave number 126 (SAWB GSM model in this thesis)
UKMO	United Kingdom Meteorological Office
WMO	World Meteorological Organization
WUBSO	Workshop on the Use and Benefits of Seasonal Outlooks

APPENDIX B

EXAMPLE OF A MONTHLY FORECAST

An example of an operational forecast issued on Monday 27 October 1997 follows. Products include a reference page with a map of the forecast regions and an explanation of the symbols used on the 14-day forecast of daily conditions, a table of forecast daily conditions for 14 days, a 30-day forecast of rainfall tercile probabilities over seven regions in South Africa with confidence values and reference map and tables of regional normal tercile rainfall amounts for 30-day periods for each season.

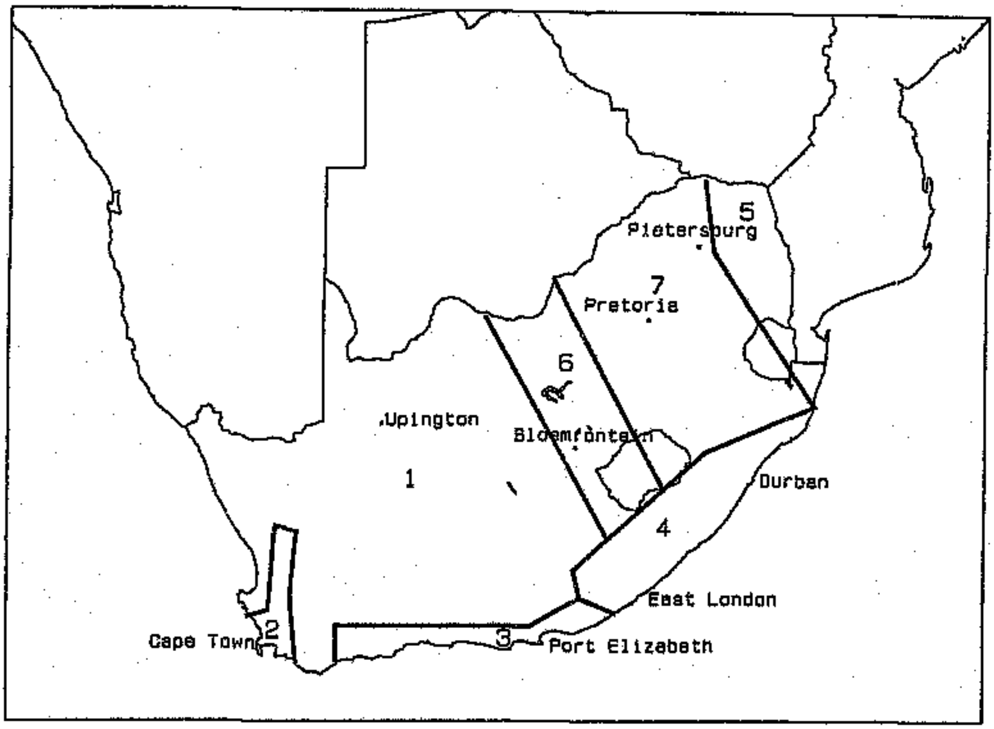


Daily Weather Forecast for 14 Days

Regions:	1	-	Western Interior
	2	-	Southwestern Cape
	3	-	South Coast
	4	-	East Coast
	5	-	Lowveld
	6	-	Central Interior
	7	-	Northern Interior
Rainfall:	NIL	-	No rain
	-RA	-	Light rain
	RA	-	Moderate rain
	+RA	-	Heavy rain
	76%	-	76 percent chance of the given category occurring
Temperature:	20	-	Maximum temperature
	10	-	Minimum temperature
Wind:	NE	-	Direction
	11	-	Speed (km/h)
Cloud:	CLR	-	Clear
	PCL	-	Partly cloudy
	OVC	-	Overcast

Daily Forecast from 980726 to 980801

1 W Inter				2 SW Cape				3 S Coast				4 E Coast				5 Lowveld				6 Cen Int				7 N Inter				
NIL 81%	22 10	N 23	CLR	NIL 99%	19 12	NE 21	PCL	NIL 94%	19 15	N 26	PCL	NIL 62%	20 13	N 22	CLR	NIL 88%	27 11	NE 7	CLR	NIL 50%	19 6	NW 13	PCL	NIL 88%	21 6	W 6	CLR	S/26
NIL 99%	23 10	N 30	CLR	NIL 81%	21 13	N 26	PCL	NIL 81%	21 15	N 29	PCL	NIL 88%	21 13	N 41	CLR	NIL 88%	26 11	NE 13	CLR	NIL 99%	20 6	N 23	CLR	NIL 99%	21 6	N 14	CLR	M/27
NIL 81%	22 10	N 25	PCL	NIL 75%	19 13	NW 31	PCL	NIL 69%	20 16	NW 45	PCL	NIL 81%	22 14	NW 38	CLR	NIL 99%	25 11	N 17	CLR	NIL 94%	20 6	NW 24	CLR	NIL 99%	21 6	NW 17	CLR	T/28
NIL 75%	18 9	N 17	PCL	NIL 50%	16 12	NW 17	PCL	-RA 56%	19 15	W 33	PCL	NIL 62%	21 13	NW 28	CLR	NIL 88%	25 11	N 13	CLR	NIL 88%	18 5	NW 20	PCL	NIL 94%	20 5	NW 12	CLR	W/29
NIL 69%	17 7	NW 14	PCL	-RA 50%	16 11	W 13	PCL	-RA 56%	17 14	NW 13	PCL	NIL 50%	20 12	NW 11	PCL	NIL 94%	26 11	N 8	CLR	NIL 94%	18 5	N 16	CLR	NIL 94%	20 4	NW 8	CLR	T/30
NIL 75%	17 5	NW 11	PCL	NIL 50%	15 10	SW 23	PCL	-RA 50%	17 14	W 36	PCL	-RA 62%	19 12	NW 18	PCL	NIL 75%	25 11	N 6	CLR	NIL 88%	17 3	NW 14	PCL	NIL 94%	20 4	W 10	CLR	F/31
NIL 94%	17 4	E 10	CLR	NIL 50%	15 10	SW 13	PCL	-RA 56%	16 13	.. 18	PCL	NIL 50%	18 11	W 11	PCL	NIL 94%	25 11	NE 6	CLR	NIL 75%	17 3	NW 6	PCL	NIL 94%	20 4	SW 4	CLR	S/1



RAINFALL PROBABILITY FORECASTS

Percentage chance of each tercile occurring during the 30-day period : 98071900 - 98081700

REGION	Below Normal	Normal	Above Normal	Maximum Probability	Confidence
1	9	40	51	Above Normal	Med
2	4	26	70	Above Normal	Low
3	17	38	45	Above Normal	Low
4	25	31	44	Above Normal	Med
5	51	35	14	Below Normal	Med
6	11	37	52	Above Normal	Med
7	33	30	37	Above Normal	Med

Regional normal tercile range of 30-day rainfall for each season (mm)

	Summer (DJF)	Autumn (MAM)	Winter (JJA)	Spring (SON)
Region 1	23 - 54	18 - 36	13 - 24	24 - 39
Region 2	11 - 23	32 - 66	74 - 108	20 - 42
Region 3	50 - 72	37 - 71	40 - 61	45 - 94
Region 4	77 - 111	27 - 54	10 - 29	57 - 88
Region 5	116 - 180	24 - 84	5 - 19	46 - 92
Region 6	53 - 88	20 - 52	3 - 16	36 - 70
Region 7	89 - 105	19 - 47	2 - 8	40 - 80

Station normal temperature for each season (°C)

	Summer (DJF)	Autumn (MAM)	Winter (JJA)	Spring (SON)
Cape Town	20.7	17.6	12.8	16.2
George	19.7	17.7	13.[illegible]	15.7
Port Elizabeth	21.3	18.9	14.7	17.2
East London	21.8	19.9	16.1	18.0
Umtata	21.3	18.5	13.3	17.7
De Aar	23.3	17.0	9.8	17.6
Aliwal North	21.9	15.6	8.8	16.5
Bloemfontein	22.6	16.1	8.8	17.5
Kimberly	24.6	18.2	11.2	19.5
Upington	27.6	21.4	13.6	21.7
Bethlehem	19.5	14.3	7.8	15.3
Cape St Lucia	24.6	22.5	18.3	20.8
Kroonstad	22.2	16.7	9.9	18.2
Potchefstroom	22.4	17.4	11.1	19.2
Johannesburg	20.1	16.4	11.2	17.5
Rustenburg	22.4	17.7	11.7	19.3
Nelspruit	23.4	20.1	15.2	20.4
Skukuza	26.3	22.7	16.6	22.9
Pietersburg	22.3	18.7	13.2	19.3
Messina	27.0	23.0	16.6	23.7

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