Evaluation of a dynamical seasonal climate forecast system for Queensland

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Abstract

This paper describes the results of research on the application of a dynamically downscaled seasonal climate prediction system at Queensland Department of Natural Resources and Mines (NR&M). The NR&M seasonal climate prediction system consists of a Global Climate Model (GCM) and double nested Regional Climate Model (RCM) that produces regional predictions at high resolution for Queensland. A study has been completed using this system forced with observed sea surface temperatures for period 1965-2000. The skill of the modelling system was evaluated in terms of spatial and temporal variability and the capacity to simulate extremes (defined as the 15^{th} and 85^{th} rainfall percentiles).

Major findings were that: (a) use of RCMs increased the accuracy of simulated rainfall; and (b) simulated ensemble average rainfall was more highly correlated with SOI than observed rainfall; and (c) when the output was linked to the Aussie Grass modelling system a comparison with the current SOI operational systems revealed similar or better performance than the benchmark statistical forecasting system when evaluated in terms of production and resource condition.

The NR&M seasonal climate prediction system has been run operationally using predicted sea surface temperatures since September 1998 at monthly intervals. Ensemble predictions with lead-times of 7 months allow a probabilistic approach to risk management. The model output forms part of the IRI Net Assessment Forecast utilised world-wide and successfully provided an early warning of increased chance of drought in eastern Australia in 2002.

1. Introduction

Numerical climate models, both global and regional, provide an alternative dynamically based approach to forecasting rainfall and other climate variables in contrast to statistical systems derived from analyses of historical data. For many years numerical weather prediction models have been used routinely to make short-term weather predictions with a high degree of skill, and in recent years, it has also been demonstrated that these models have some predictive ability at seasonal time scales (Kumar et al,.1996; Zwiers 1996; Barnston et al., 1999; Mason et al., 1999; Barnston et al., 2000; Goddard et al., 2001; Palmer et al., 2003). The American Meteorological Society recently released a policy statement on Seasonal to Interannual Climate Prediction (AMS 2001) which stated:

> The skill of seasonal climate prediction has improved substantially over the past two decades, largely in response to increased understanding of the El Niño/Southern Oscillation (ENSO) phenomenon. Routine, scientifically based, skilful, seasonal forecasts are now possible for some parts of the world, for some seasons. These seasonal climate predictions are able to project the mean conditions and some of the statistical characteristics of the climate a season or two in advance. The seasonal predictions are primarily of use to organizations that have a decision-making process that can intelligently use probabilistic input and that are engaged in activities that are sensitive to seasonal climate variations and involve significant economic stakes.

Trial operational seasonal climate forecasts have been produced since 1997 at the International Research Institution (IRI), Columbia University, and since late 1998 at NR&M using a suite of Climate Models (Mason et al., 1999; Syktus et al., 2001).

The successful application of seasonal climate forecasts requires that meaningful information is available at both the regional and local scale. However, most of GCMs used in current seasonal climate forecasting systems lack the spatial resolution to derive realistic values of climate variables at the resolution required by many users. This shortcoming is particularly apparent when dealing with precipitation, where sub-grid features such as synoptic weather systems, thunderstorms and tropical cyclones can cause large variations in rainfall intensity and amount. Efforts to increase the horizontal resolution of GCMs, in order to capture these processes, is currently limited by the availability of computing resources.

In recent years the use of RCMs nested within coarser resolution Global Climate Models has become an increasingly affordable way to produce dynamically downscaled seasonal climate information at resolution relevant to regional and local applications. RCMs are: 1) able to account for important local factors such as orographic forcing; 2) are physically based; and 3) are able to produce a consistent response to a range of physical forcings. The main limitations of the nesting approach are that the higher resolution information is only available for the region over which the nesting is applied and there is no physical feedback from the RCM to the GCM.

In Australia RCMs are used in climate change and weather application research at CSIRO (Walsh et al., 2002), and are the main tool used for high resolution weather forecasts produced by the Commonwealth Bureau of Meteorology (Puri et al., 1998). In fact those models have been used successfully for over two decades in weather forecasting, producing high-resolution regional weather information (Leung et al., 2003). NR&M employs a two-tiered approach to seasonal climate prediction (Goddard et al., 2001), in which the boundary conditions such as sea surface temperatures (SSTs) are predicted first and used to force the overlaying atmosphere. The prescribed SST boundary conditions can be obtained from observed historical SSTs or predicted from a fully coupled ocean-atmosphere climate model. Ensembles of model integrations using both the GCM and RCM were generated by perturbation of the initial atmospheric conditions at the start of integrations allowing probabilistic forecasts to be developed.

NR&M is in the unique position in its ability to link both statistical and dynamical climate forecast systems with applications model such as the AussieGRASS spatial grazing simulation system and hydrologic models. This is often referred to as an 'end-to-end' approach (Goddard et al., 2001; Leung et al., 2003) with chain of information processing and activities starting with the observation of climate state, through to prediction using climate models, to production of forecast information, application of information and ending with decision making and outcomes (see Figure 1).

In this paper, we: 1) review the results from GCM/RCM hindcast simulations; 2) briefly describe operational activity since 1998; and 3) present preliminary findings from linking GCM output to simulations of grazing systems in Queensland.

2. Evaluation of climate models output for Queensland

This section evaluates the ability of a GCM and a doubly nested GCM/RCM (280 km, 75 km, 15 km resolution) system forced by observed monthly sea surface temperatures (SSTs) to simulate long-term rainfall patterns (mean and variability) of Australia for the period 1965-2000. The NR&M seasonal climate prediction system consists of a Global Climate Model and double nested Regional Climate Model, which produces regional predictions at high

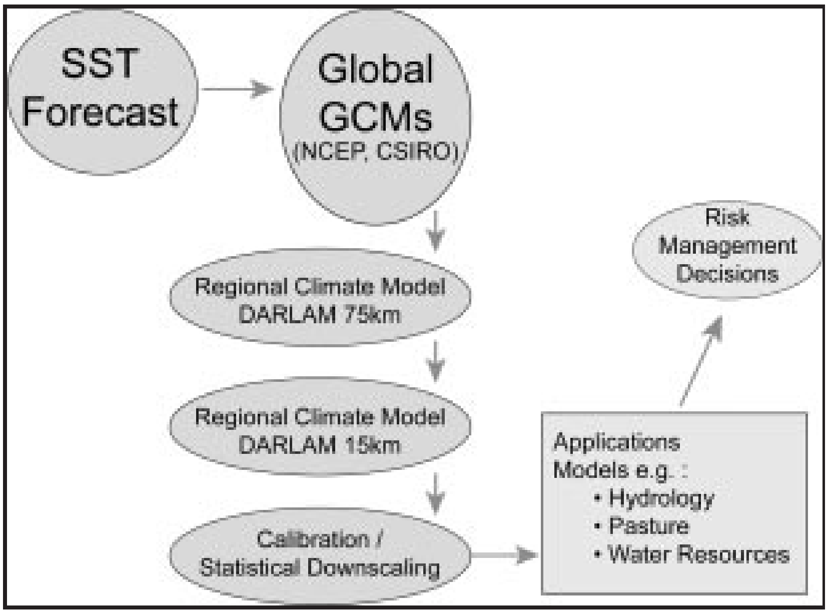

Figure 1. Schematic representation of concept of the 'end-to-end' approach to seasonal climate prediction used at NR&M.

resolution for Queensland. The development of an ensemble modelling system for Seasonal to Inter-annual Prediction at NR&M has the following objectives:

- Build an ensemble modelling system based on a dynamical downscaling approach to predict the seasonal climate conditions over Queensland with extended lead-time.
- Generate an extensive set of hindcast ensemble integrations and produce bias a corrected model ensemble dataset.
- Evaluate the skill and potential utility of the hindcast models ensembles using standard evaluation techniques and through linkage with a spatial simulation model of the grazing system.
- Study the sensitivity of the predictive system to the ocean and land processes and implement further improvements.
- Produce real time seasonal climate predictions using predicted SST, contribute forecast data to the IRI pool of models for use in the production of the IRI Net Assessment Forecast, and to evaluate the skill of the forecast in Queensland.

The following evaluation is based on a detailed report (Syktus and McKeon, 2002) presented as part of the Final Technical Report (McKeon and Hall, 2002), to the Climate Variability in Agriculture Program. In Chapter 6 of the Final Report, over 30 colour plates were presented evaluating GCM output. The following web address: http://www.longpaddock.qld.gov.au/AboutUs/Publications/ByType/Reports/GlobalAndRegionalClimateModels can be reviewed for a more detailed examination of GCM results. We present only a summary of the findings.

2.1 Experimental design

Two global climate models and a double nested regional climate model were used in this evaluation. The models used and their applied resolutions are shown in Table 1 and are described in more details in Syktus and McKeon (2002). The NCEP Atmospheric GCM was used as a host for nesting of the CSIRO DARLAM Regional Climate Model. The first nesting (75 km) of the RCM was applied across the Australian region and the second (15 km) across the Queensland region only.

In addition a new version of the CSIRO T63 GCM (Gordon et al., 2002) forced with historical SSTs and sea ice was used to simulate historical Australian climate since 1871 as part of 'The Climate of the 20th Century' project. This model was run with a horizontal resolution of 190 km. An ensemble of seven integrations was evaluated for period 1871-2001, and five integrations for 1949-2001 periods.

The CSIRO GCM has improved representation of cloud processes and land parameterisation and belongs to a new generation of climate models. The NCEP model used in this study represents state-of-the-art climate modelling from over a decade ago.

Observed sea surface temperatures from 1965 to 2000, which allowed the atmospheric component of the models to be evaluated, forced all GCM simulations. However, it does not allow the impact of other climate forcings such as volcanic and other aerosols, greenhouse gas concentration changes, ozone, land use change, and solar variability to be tested. Implicit in statistical forecast systems is that the effects of climate forcings have been integrated in the SST and atmosphere's response. Hence, it is important to realise that the use of just SST forcing by itself in GCM/RCM simulations could limit the likely explanation of observed rainfall because temporal variation in other forcings are not represented.

The comparison of model simulated and observed long-term seasonal rainfall characteristics is an essential first step in the evaluation of GCM/RCM systems before using it to produce rainfall forecast. Regional rainfall characteristics were evaluated for each model using measures such as mean, bias, variance and spatial correlation for the seasonal long-term climatology for period 1965 to 2000. In addition the evaluation has been completed for skill of simulating inter-annual rainfall variability using anomaly correlation, root square mean error and Relative Operating Characteristics (ROCs).

Table 1. GCMs and RCMs used in simulation experiments.

Model and experiment details	Reference	Horizontal grid spacing
NCEP-MRF9 AGCM T40/L18 – 10 runs: 1965–2001	Kumar *et al.* (1996)	280 km
CSIRO DARLAM RCM 75 km/L18 – 15 runs: 1965–2001	McGregor (1997)	75 km
CSIRO DARLAM RCM 15 km/L18 – 15 runs: 1965–2001	McGregor (1997)	15 km
CSIRO T63/L18 AGCM – 7 runs: 1871–2001; 5 runs: 1949–2001	Gordon et al., 2002	190 km

The ensemble members of each model output for these simulations (Table 1) were averaged and the mean of each was used in subsequent analyses. Ensemble averaging is used to reduce atmospheric noise and enhance a coherent response to a forcing; however, as a result the amplitude of the ensemble mean anomaly tends to be less that the observed amplitude. It is important to recognize this difference in amplitude when the ensemble mean is compared with observations. The period of 1965 to 2000 includes several El Niño and La Niña events, and both positive and negative phases of the IPO index (Power et al., 1999). In Queensland the period includes extreme droughts (1965, 1969, 1982, 1991 to 1994), extreme summer wet seasons (1973/74, 1990/91), and two degradation episodes (1960s in south-west Queensland and 1980s in north- eastern Queensland (McKeon et al., 2003).

2.2 Large-scale circulation features

The El Niño Southern Oscillation (ENSO) phenomenon is a planetary scale oscillation involving large-scale interactions between the oceans and the atmosphere in the tropical-subtropical Pacific Ocean region. The most direct manifestation of ENSO is the oscillating pressure differences between the Indonesian-Australian region and the southeast Pacific. The traditional measure of this oscillation is the Southern Oscillation Index (SOI), which is the normalised Tahiti-minus-Darwin pressure difference. The importance of ENSO in the global climate system is illustrated by the fact that it explains the largest amount of climate variability after the seasonal cycle and the monsoon system (Allan 2000). The SOI is also commonly used to forecast rainfall in eastern Australia (McBride and Nicholls 1983, Stone et al. 1996). Thus, the ability of GCMs to simulate the pressure differences as measured by the SOI is an important component in assessing their ability to accurately simulate seasonal rainfall. SOI values derived from both the NCEP and CSIRO GCMs were found to be in close agreement with observed SOI values (Figure 2), indicating that the simulated atmosphere in terms of mean sea level pressure responded to SSTs in a similar way to that which actually occurred. Correlations for predicted and observed SOI values were high at a monthly timescale (r^2=0.58), and very high for the 5-month running mean (r^2=0.8) for the period 1965-2000. The simulation of SOI values also provides a simple way of converting GCM output into rainfall forecasts using the same approaches as the statistical systems (Stone et al., 2000).

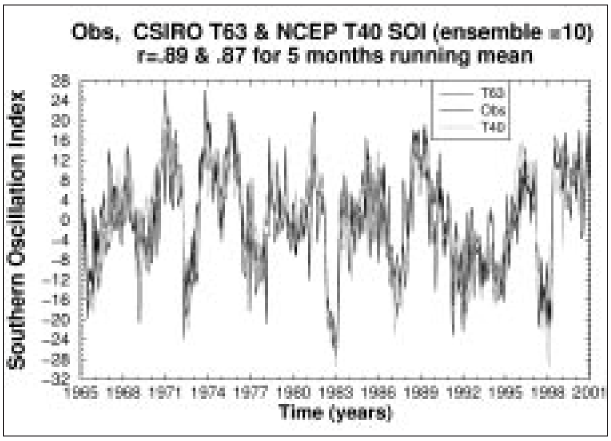

Figure 2. Comparison of simulated and observed monthly SOI values from 1965 to 2000. Observed values were calculated from the difference in anomaly of mean sea level pressure between Tahiti and Darwin.

2.3 Tropical cyclones

Tropical cyclones can be a major source of rainfall in Queensland, especially in La Niña years. The application of RCM at higher spatial resolution provided an opportunity to evaluate the occurrence of tropical cyclones. During La Niña years tropical cyclones have tended to track towards Queensland's coast and then deteriorated into rain depressions. In contrast, cyclones paths in El Niño years have been generally south or east (Walsh and Syktus, 2003). Analysis of data from the 75 km RCM for tracks of the 'tropical cyclone-like vortices' (TCLVs, see Walsh and Syktus 2003) show that TCLVs in the model followed paths that were similar to those observed. The simulated paths of TCLVs for 1973/74 (strong La Niña) and 1982/83 (strong El Niño) showed the expected contrasting pattern of movement. Similar fine resolution features occur in other regions (e.g. northern America) indicating that the models, especially RCMs, are capable of representing important rainfall-producing meteorological phenomena.

2.4 Spatial distribution of simulated rainfall climatology

The ability of GCMs and RCMs to simulate the spatial pattern of long-term average seasonal rainfall is a critical component of any evaluation process. GCMs, commonly configured with effective grid spacing of 200-300 km, have demonstrated skill in simulating spatial rainfall patterns at global or even continental scales, but are unable to simulate local fine scale patterns which are required by hydrological and agricultural modelling applications.

The spatial patterns of seasonal rainfall were simulated with three models operating at spatial scales of 280, 75 and 15 km. The increase in effective spatial resolution is some 350 times between the host GCM and the double nested RCM. This increase in resolution is demonstrated (Figure 3) in the example of seasonal (January - March) precipitation in Queensland simulated by dynamical downscaling system consisting of the NCEP GCM and double nested RCM. Increasing topographical resolution produced more detailed meteorological features such as 'rain-shadows' resulting from coastal ranges near Gladstone and Mackay (Figure 3).

In this evaluation the NCEP GCM was able to simulate the relative east/west pattern in mean long-term average seasonal rainfall distribution across Australia, although it was generally too wet, especially during the summer season in Queensland. However, this model was unable to resolve the sharp gradient and orographic effects along the eastern part of Australia. Nesting of the RCM at 75 km resolution within the NCEP GCM considerably improved the spatial pattern of rainfall with many of the sharp gradients in rainfall well represented (e.g. SW WA, top end of NT, northern coastal Queensland, and the difference between east and west Tasmania), but still did not resolve adequately the orographic effect of the Great Dividing Range along the eastern coast of Australia. At 15 km resolution the spatial pattern of the simulated rainfall was more realistic with 'rain shadow' effects evident as a result of the coastal ranges near Gladstone and Mackay.

Comparison of the models' simulated rainfall with grided surfaces of rainfall observations in terms of mean, standard deviation and spatial correlation (Table 2) for different regions of Australia, and for various seasons indicated the RCM simulations give a great improvement over the host NCEP GCM in all states of Australia. The CSIRO T63 GCM performed better than the NCEP T40 with the dry inland in central Australia and the wet coastal strip of north-eastern Australia being well represented. Given the better performance of the CSIRO T63 relative to the NCEP GCM, the future nesting of RCM within the CSIRO T63 could be expected to also produce better RCM results.

Of particular note was the ability of the 15 km RCM to correctly represent the contrasting isohyet patterns of summer (DJF) and winter (JJA), namely: summer isohyets were parallel to the coast whilst winter (JJA) isohyets ran north/south. Formal calculation for this model of differences between observed and simulated rainfall indicated that most of the seasons had large areas with less than +/- 1mm/day difference. An exception was spring (SON) in which the differences for a substantial part of inland Queensland were 1-2mm/day, and the coastal strip 2-10mm/day.

2.5 Correlation of observed and simulated rainfall over time

Correlations were calculated between observed rainfall and the ensemble mean for each of the four models for the 1965 to 2000 period. The observed rainfall was interpolated to the appropriate model resolution before the **temporal anomaly correlation** was calculated for each grid cell. For annual rainfall, areas of reasonable correlation ($r > 0.4$, $n = 36$) were found in central Queensland and WA. For Queensland, the 15 km RCM showed large coastal and inland regions with significant ($P = 0.05$) correlations ($r > 0.2$). The important Queensland pastoral-cropping zone had substantial areas with reasonable correlations ($r > 0.4$). All four models were similar in terms of areas with significant correlation, with the 15 km RCM performing best.

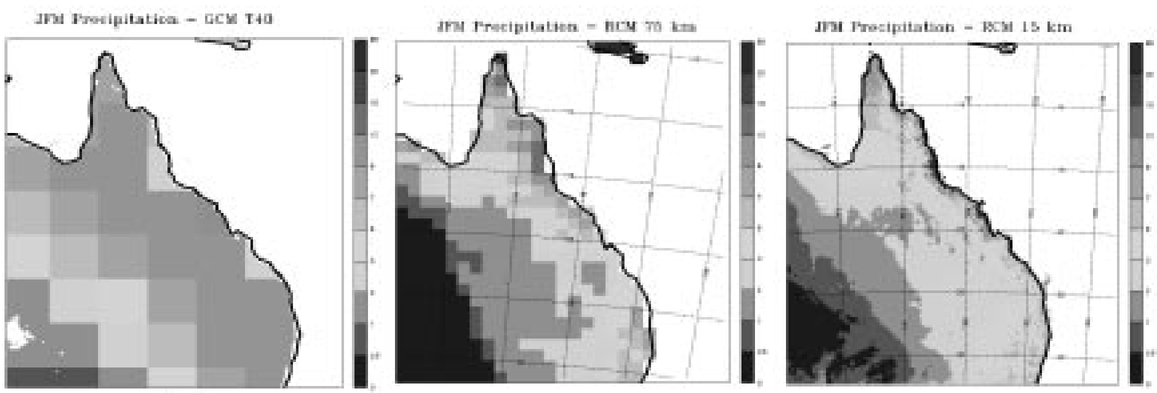

Figure 3. Example of seasonal (January - March) precipitation in Queensland simulated by dynamical downscaling system consisting of the NCEP GCM and double nested CSIRO RCM.

Table 2. Mean, standard deviation (SD) and spatial correlation for models compared with long-term (1965-2000) observed rainfall for DJF. The regions for area-averaged rainfall are: 1) Australia including Tasmania; 2) southern Australia, south of latitude 30; 3) northern Australia, north of latitude 30; 4) eastern Australia, east of longitude 140; 5) NSW and Victoria; 6) Queensland; and 7) the Queensland pastoral and cropping zone. The spatial pattern correlation was calculated for the observed and simulated average (1965-2000) DJF rainfall at the resolution of the particular model. Thus the correlation values represent the explanation of spatial variation not temporal variation. Mean and SD of the observed rainfall was derived from data at 75 km resolution. Model data are the average of an ensemble of model runs.

Region	Model	Mean (mm/day)	SD (mm/day)	Correlation (r)
Australia	Observed	4.2	3.2	
	RCM75	4.6	3.3	0.92
	T40	4.4	3.5	0.48
	T63	3.2	2.4	0.79
Southern Australia	Observed	1.4	1.0	
	RCM75	2.0	1.6	0.91
	T40	2.0	1.8	0.32
	T63	1.3	0.6	0.77
Northern Australia	Observed	4.8	3.1	
	RCM75	5.2	3.2	0.915
	T40	5.5	3.5	0.49
	T63	4.0	2.5	0.75
Eastern Australia	Observed	5.4	3.0	
	RCM75	6.0	2.7	0.88
	T40	5.7	3.6	0.01
	T63	3.5	1.9	0.78
NSW and Victoria	Observed	1.7	1.1	
	RCM75	2.3	1.6	0.92
	T40	5.0	3.0	0.54
	T63	1.7	0.7	0.88
Queensland	Observed	3.8	2.6	
	RCM15	4.6	3.5	0.76
	RCM75	4.6	3.0	0.79
	T40	9.7	1.5	0.52
	T63	4.0	1.9	0.95
Queensland pastoral and cropping zone	Observed	3.1	1.4	
	RCM15	4.6	3.4	0.78
	RCM75	4.4	2.5	0.73
	T40	9.7	1.4	0.73
	T63	3.5	1.1	0.88

2.6 SOI correlations with Queensland rainfall

Spatial patterns of Queensland SOI-rainfall correlations were evaluated for all four seasons using ensemble averaged output from the GCMs, 75 km RCM and 15 km RCM. In all cases the SOI-rainfall correlation were stronger for the simulated data than were observed, with very high correlations for summer. Even in autumn (MAM), the various models showed strong positive correlations whilst the observed data showed areas of negative correlation and few areas of positive correlation. However, when correlations for observed SOI and observed rainfall were compared to correlations for simulated SOI and simulated rainfall for individual ensemble members, then the NCEP T40 GCM for most members had regions of stronger correlation than observed, but with more variation from member to member. SOI/rainfall correlations for average of ensembles from CSIRO T63 GCM were not as strong as NCEP T40 GCM but nevertheless there were regions in eastern Australia with stronger than observed correlations. Individual ensemble correlations were more varied than NCEP T40 GCM ensembles with some

Table 3. Correlations (r) between area-averaged observed and simulated (GCM and RCM) annual and seasonal (MAM, JJA, SON, DJF) rainfall for the period 1965-2000 at three geographic regions: a) Queensland grazing lands; b) Queensland; and c) Australia.

Region	Model	Season				Annual
		MAM	JJA	SON	DJF	
Queensland grazing lands	CSIRO T63	0.23	0.32	0.33	0.24	0.30
	NCEP T40	0.20	0.36	0.29	0.20	0.42
	RCM 75km	0.24	0.31	0.26	0.17	0.34
	RCM 15km	0.32	0.34	0.25	0.20	0.38
Queensland	CSIRO T63	0.14	0.24	0.36	0.18	0.26
	NCEP T40	0.21	0.29	0.32	0.12	0.34
	RCM 75km	0.29	0.21	0.26	0.09	0.27
	RCM 15km	0.34	0.23	0.27	0.15	0.32
Australia	CSIRO T63	0.21	0.17	0.38	0.19	0.25
	NCEP T40	0.16	0.13	0.23	0.12	0.16
	RCM 75 km	0.25	0.09	0.21	0.16	0.16
	CCM3 T42[1]		0.210		0.097	
	COLA R42[1]		0.140		0.076	
	ECHAM 4.5[1]		0.228		0.120	

[1] Results from IRI study for the 1979-1995 period (Camarago et al. 2001).

ensemble members having regions with correlations of opposite sign to that observed.

Across Queensland's grazing lands, area-averaged observed SOI/rainfall correlation (for 1965 to 1999) was 0.35, with the GCMs indicating correlations of 0.86 (NCEP T40) and 0.46 (CSIRO T63). For individual ensemble members SOI/rainfall correlations ranged from 0.54 to 0.73 for NCEP T40 GCM, and 0.10 to 0.49 for CSIRO T63 GCM. For eastern Australia the area-averaged SOI/rainfall correlation from CSIRO T63 GCM was 0.33 (close to observed value 0.31). Thus the CSIRO T63 GCM had a more realistic representation of the teleconnection between SOI and continental rainfall. The fact that there was large variation between individual ensemble members in regional SOI/rainfall correlations shows the chaotic nature of the climate system as represented by individual realisation of ensemble members, and suggests that there is an inherent limit in forecasting rainfall using SOI. In reality the observed time-series of rainfall may be equivalent to a single ensemble member and GCM studies such as this may indicate an important upper limit to predictability.

2.7 Area-aggregated anomaly correlation of observed and simulated rainfall

The anomaly correlations between simulated and observed rainfall (1965-2000) for each season-model combination are shown for area-averaged rainfall in Table 3. For Australia, correlations were low for summer (DJF) and winter (JJA) and moderate other seasons (Table 3). At this continental scale, the CSIRO T63 GCM performed better than both the NCEP GCM and the 75 km RCM at annual time periods and for spring (SON), the season with highest correlations. Correlations were higher when Queensland was considered as a whole (r = 0.27 to 0.34 for annual rainfall) and higher still for the smaller Queensland pastoral-cropping zone (r = 0.3 to 0.42 for annual rainfall). The strong correlation for the Queensland pastoral-cropping zone is to be expected as this area, which excludes Cape York, the Gulf of Carpentaria and far-western Queensland, includes some of the strongest ENSO-rainfall relationships (McBride and Nicholls, 1983). Although the NCEP GCM was 'too wet' in terms of average annual rainfall (Table 2), it does have the some useful skill for the Queensland pastoral-cropping zone in most seasons. The NCEP AGCM has been selected for

Table 4. Maximum correlations (r) between area-averaged observed and simulated (GCM and RCM) rainfall for the period 1965-2000. The maximum value for each simulation was selected from the 15 possible seasons specified in text.

Model	Australia	Eastern Australia	Southern Australia	Northern Australia	NSW and Victoria	MDB	Qld	Qld grazing lands
RCM15							0.38	0.46
RCM75	0.26	0.32	0.18	0.30	0.26	0.31	0.36	0.43
NCEP	0.24	0.25	0.11	0.34	0.27	0.39	0.45	0.51
CSIRO	0.38	0.36	0.32	0.46	0.42	0.51	0.46	0.50

Table 5. Area-averaged ROC scores (1965 to 2000) for Queensland Grazing Lands for the main growing season (November to March) and dry/winter season (May to October). Values are computed for lower, middle and upper tercile and two extremes at the 15th and 85th percentiles. The ROC score has been calculated at the resolution of each GCM or RCM (Table 1). The ROC for SOI phase was calculated at 15km resolution.

	Lower Tercile		**Middle Tercile**		**Upper Tercile**		**Percentile 15**		**Percentile 85**	
	Nov-Mar	May-Oct	Nov-Mar	May-Oct	Nov-Mar	May-Oct	Nov-Mar	May-Oct	Nov-Mar	May-Oct
NCEP T40	0.65	0.73	0.56	0.55	0.70	0.70	0.62	0.78	0.65	0.75
CSIRO T63	0.60	0.67	0.54	0.55	0.62	0.70	0.60	0.75	0.66	0.75
RCM 75	0.64	0.71	0.51	0.54	0.65	0.69	0.65	0.76	0.62	0.70
RCM 15	0.64	0.70	0.50	0.54	0.65	0.70	0.65	0.76	0.66	0.73
SOI Phase	0.58	0.56	0.49	0.47	0.66	0.55	0.51	0.50	0.50	0.51

use at NR&M based on the ability to simulate inter-annual variability of rainfall for Queensland.

The potential skill in simulating year-to-year variation was also evaluated by considering the maximum correlation co-efficient that was obtained for each region-model combination across 15 possible 'seasons', i.e. every 3-month period plus annual average and NDJFM and MJJASO averages (Table 4). For the NCEP GCM and the 75 km RCM, highest correlation values (r = 0.3 to 0.4) occurred in eastern and northern Australia, particularly in Queensland. These values are less than those usually derived from correlation with lag SOI (r > 0.4), however model evaluation was done at grid cell level and then area averaged. In summary the anomaly correlation values calculated at the model grid cell resolution have moderate and useful skill. The preliminary analysis using statistical calibration and downscaling using Singular Value Decomposition (Fedderson et al., 1999) applied to rainfall from CSIRO GCM for Queensland show that the values of anomaly correlation can be increased by more than 50% in many cases.

To give some perspective on the skill of anomaly correlation computed for an area aggregated rainfall region, rather than for model grid cell size, we extracted rainfall data for the selected regions of continental Australia, Queensland Grazing Lands, western NSW and Gascoyne in WA (see Fig 1 in White et al., 2003) for the period of 1880 to 2002 from CSIRO GCM and observations. The anomaly correlation for de-trended time-series for the April to March annual average are: for Australia (r=0.57), Queensland Grazing Lands (r=0.54), western NSW (r=0.43) and Gascoyne (r=0.34). The values are high and significant, and show that correlation is higher for Australia as a whole, than for Queensland Grazing Lands which are strongly influenced by ENSO. The correlations support the results of Gong et al. (2003) who found that skill increased as the size of area aggregated increased.

2.8 Evaluation of GCM/RCM in terms of extreme rainfall

The simulated rainfall from the various climate models was evaluated in terms of forecast of extremes (e.g. upper and lower terciles) and percentiles 15 and 85 for Queensland's grazing lands (Table 5) and Murray Darling Basin (Table 6). Values greater than 0.5 show skill above climatology. The evaluation used ROC scores (Swets 1973; Mason 1982; Harvey et al. 1992; Mason and Graham, 1999; Mason and Graham, 2002). The model ROC scores were compared to those obtained for the SOI phase system at 15 km resolution as a benchmark. Because of the difference in resolution between the models, and because ROC scores are vector quantities, the area averaged ROC scores are not directly comparable. Nevertheless, the area average values give a feel for the level of skill for the selected regions. For the Murray Darling Basin (MDB), the simulation of extremes in winter/spring rainfall showed superior skill compared to distribution in tercile rainfall. For Queensland's grazing lands there was little increase in skill at the extreme percentiles in summer rainfall compared to ROC scores for upper and lower terciles. The SOI phase system has generally lower values of ROC scores for upper and lower terciles compared to the various climate models. At extreme percentiles, ROC scores for the RCM 15 km were greater than ROC scores for the SOI phase system evaluated at the same resolution.

2.9 GCM evaluation of SOI – Inter-decadal Pacific Oscillation interaction

Previous analyses (Power et al., 1999; McKeon and Hall, 2002; Crimp and Day, this volume; McKeon et al., 2003) have found that ENSO and inter-decadal variability in the Pacific Ocean interact to change the probability of wet and dry years in Queensland. One index of inter-decadal variability is the Inter-decadal Pacific Oscillation (IPO, Power et al., 1999). Different phases of the IPO resemble,

Table 6. Area-averaged ROC scores (1965 to 2000) for Murray Darling Basin for May to October and November to March. Values are computed for lower, middle and upper tercile and two extremes at the 15th and 85th percentiles. The ROC score has been calculated at the resolution of each GCM or RCM (Table 1). The ROC for SOI phase was calculated at 15 km resolution.

	Lower tercile		Middle tercile		Upper tercile		Percentile 15		Percentile 85	
	Nov-Mar	May-Oct	Nov-Mar	May-Oct	Nov-Mar	May-Oct	Nov-Mar	May-Oct	Nov-Mar	May-Oct
NCEP T40	0.58	0.67	0.52	0.51	0.57	0.63	0.57	0.76	0.58	0.66
CSIRO T63	0.57	0.69	0.47	0.51	0.60	0.68	0.57	0.77	0.62	0.69
RCM 75	0.59	0.64	0.53	0.53	0.60	0.60	0.55	0.74	0.63	0.61
SOI Phase	0.50	0.58	0.51	0.50	0.62	0.53	0.48	0.50	0.50	0.52

at longer time scales, sea surface temperature patterns similar to phases of ENSO.

Although the correlations between simulated and observed rainfall were low, the results indicated reasonable correlations between simulated SOI and simulated rainfall. Thus GCMs are suitable to examine the apparent but controversial interaction between the IPO and SOI on rainfall (Power et al., 1999; Chapter 3 in McKeon and Hall, 2002; Crimp and Day, 2003 in this volume).

The GCM T63 was run from 1880 to 2000 (121 years) forced by observed SSTs with five ensembles. Rainfall for each year was expressed as a percentile relative to climatology. Two approaches to calculating climatology were used: 1) combining all ensembles, i.e. 121 years by 5 ensembles; and 2) a climatology derived for each ensemble. Years were then categorised into the following six year-types as described (McKeon and Hall 2002, McKeon et al., 2003):

1) SOI < -4 and IPO < 0 (i.e. SOI negative and IPO negative);
2) SOI > +4 and IPO < 0 (i.e. SOI positive and IPO negative);
3) SOI < -4 and IPO > 0 (i.e. SOI negative and IPO positive);
4) SOI > +4 and IPO > 0 (i.e. SOI positive and IPO positive);
5) SOI > -4 and < +4 and IPO < 0 (i.e. SOI neutral and IPO negative); and
6) SOI > -4 and < +4 and IPO > 0 (i.e. SOI neutral and IPO positive).

The average percentile for each group was calculated and for summer rainfall (November-March), the main effects of the above categorisation on observed rainfall were that, for groups with same SOI value, there was greater rainfall in eastern Australia when the IPO was negative compared to when IPO was positive. In Queensland, SOI positive-IPO negative years had the highest rainfall whilst the SOI negative-IPO positive group had the lowest rainfall. In WA the latter group had high rainfall in contrast to the lower rainfall in eastern Australia.

The IPO negative groups had generally more rainfall than the IPO positive groups. Thus the GCM simulations, forced by observed SSTs, confirmed the observed interaction between the IPO and SOI, especially in Queensland. The effect of the IPO in SOI neutral years has been one important explanation of drought/degradation episodes, e.g. low summer rainfall in NSW during SOI neutral-IPO positive years. The GCM simulations had relatively lower rainfall in these year-types but not to the same extent as observed. The SOI neutral-IPO positive year-types often occurred in long sequences interposed with SOI negative-IPO positive years, including major regional droughts. As described above, there are other mechanisms resulting in lower rainfall not yet fully represented in GCMs such as the biospheric feedback of widespread drought. Similarly important SST regions may not be adequately represented in the historical SST record.

In conclusion the simulations for summer rainfall were in general agreement in terms of the large differences in observed rainfall between SOI-IPO year types. This result indicates the observed interaction in mechanistically consistent with simulated rainfall from a GCM forced with observed SSTs. However, the less distinct effects of the IPO on observed winter rainfall or in neutral SOI years for summer rainfall were not reproduced in simulated rainfall and will require further exploration.

2.10 Summary of findings and discussion

The analysis of simulation results for the GCMs and RCMs forced by observed SSTs showed that:

- large-scale features of the atmosphere, i.e. SOI were very well represented and that the RCMs did simulate fine resolution features such as tropical cyclones, rainfall depression and rain shadow areas

- spatial variation in long term average rainfall was well simulated with the newer CSIRO T63 GCM and with RCMs nested within the older NCEP GCM
- modest values of correlations (r <0.4) were achieved for inter-annual variation in seasonal and annual rainfall, however statistical calibration can increase skill in many parts of Australia
- simulated rainfall was highly correlated with simulated SOI, especially in Queensland, but these correlations were on average higher than observed SOI-rainfall correlations
- simulations of summer rainfall between SOI-IPO year types were in general agreement with observed rainfall, however, the less distinct effects of the IPO on observed winter rainfall or in neutral SOI years for summer rainfall were not reproduced.

The improvement gained in spatial agreement by using RCMs nested within the NCEP GCM was encouraging. The NCEP GCM was 'too wet' in Queensland and not surprising the 75 km and 15 km RCMs were also 'too wet', although substantially closer to observed climatology than the NCEP GCM. The CSIRO T63 GCM was better than NCEP GCM in terms of climatology. It would be expected that nesting RCMs within the CSIRO T63 GCM would further improve their capability. Thus there are several steps yet to be explored which could further increase the skill of climate models in simulating rainfall variability.

3. Operational use of NR&M Seasonal Climate Prediction System

NR&M used a two-tier approach to dynamical seasonal prediction (Syktus et al., 2001). Sea surface temperature (SSTs) forecast by combination of a fully coupled atmosphere-ocean model and statistical methods are used as a lower boundary condition forcing for the NCEP AGCM, when run in forecast mode. Global SSTs constructed at International Research Institute (IRI) at monthly intervals, with lead-time of 7 months are being used to produce an ensemble of climate predictions using NCEP AGCM and double-nested RCM. The observed SSTs are blended with predicted SSTs during the first three months of forecast with decreasing contribution with time from the observed data. After the first three months the SSTs used are fully predicted. This approach is thought to be the best utilization of knowledge to attain the best skill from the models. In addition we have been using experimentally a global SST prediction with lead-time of 12 months from the COLA global coupled model (Schneider et al., 1999).

Using this approach NR&M has been producing semi-operationally a seasonal forecast since late 1998 at monthly intervals. Each forecast has a 7-month lead-time and consists of a 10-member ensemble with the T40 GCM and a 15-member ensemble with RCM at 75 km, allowing for a probabilistic approach to risk management of seasonal conditions. Forecasts with the 15 km RCM have been produced since beginning of 2000 and are most expensive computationally. The 15 km RCM used in this approach has similar resolution to RCM used by CBoM in operational weather forecasting, which typically is only a few days long, but produced daily.

Data from the NCEP AGCM forecasts are extracted and provided to the IRI pool of models for use in the production of the IRI Net Assessment Forecast and also more specialised forecasts by individual models. These data are publicly available on the IRI web pages (Barnston et al., 2000; Goddard et al., 2003). They are used widely internationally, including by S.E. Asian and Pacific nations. The probabilistic forecasts provided early warning of increased chance of drought in eastern Australia in 2002.

NCEP AGCM and IRI Net Assessment Forecasts have been assessed in term of their skill recently (Goddard et al., 2003). Limited work has been done in-house to date on evaluation of downscaled forecasts, as accurate assessment of forecast skill can only be done after accumulating a number of forecasts, spanning at least one full cycle of ENSO. However, such an assessment is being carried out presently as we have over 4 years of forecast data available now for evaluation.

4. Linking GCM output to simulations of grazing systems in Queensland

This section describes preliminary studies regarding the methodology of how the skill of climate forecasting systems (statistical and GCMs) can be compared in terms of what is most relevant to grazing management decisions.

The major decisions that influence the profitability and sustainability of a pastoral enterprise are measured by the number animals run (stocking rate animals per hectare) and the flexibility of stocking and de-stocking based on seasonal conditions (Johnston et al., 2000). A range of stocking rate strategies are available to graziers including (a) constant stocking rate, where number of animals are held approximately constant from year-to-year; and (b) where animal numbers are changed in response to pasture feed availability, especially after the end of the main growing season, i.e. between April and October. Climate forecasts have been available since 1988 and surveys have found that this information is also used to make stocking rate decisions (Johnston et al., 2000). One strategy now available to graziers is to combine both knowledge of current pasture feed with a forecast of future rainfall to adjust stock numbers. Thus the most relevant 'skill test' for climate forecasting systems is the evaluation of land from year-to-year decisions linking forecasts to stocking rate. In this study we have used a spatial model of the grazing system to make annual decisions on stock numbers (1st October) and evaluate different climate forecasting systems in terms of the impacts on animal production and risk of resource degradation.

A baseline simulation (using AussieGRASS; see Carter in this volume) was conducted for each pixel in which stock numbers were changed each year on the 1st October to eat a constant percentage (20%) of standing dry matter (SDM) over the next 12 months. This strategy is often referred to as 'responsive' as it allows stock numbers to be adjusted based on feed availability. In previous simulation studies (McKeon et al., 2000) this strategy has proved superior to constant stocking rate strategies at locations with highly variable climates (Johnston et al., 2000).

For the forecasting systems the percentage of SDM was changed each year in proportion to forecasted pasture growth for the next 12 months (expressed relative to average growth). Each forecasting system was expressed as year-types or phases (1 to 5). Forecasted growth was calculated for each year-type from pasture growth simulated for an individual pixel in the base-line study. The calculation was made each year excluding the year being simulated from the calculation of forecast growth, i.e. a partial cross validation approach. 'Perfect knowledge' year-types were determined by ranking historical observations and simulations of pasture growth into five groups. 'Perfect knowledge' systems tested include: (a) perfect knowledge of annual growth at each pixel; (b) perfect knowledge of annual rainfall at each pixel; and (c) perfect knowledge of rainfall aggregated areas across Queensland's major pastoral and cropping zone. A 'constant stocking rate' option was tested by using the stocking rate averaged from 1965 to 2000 in the base-line study. Production attributes averaged over the simulation period were: (a) number of animals grazed; and (b) liveweight gain per ha. Degradation risk was calculated as: (a) % time surface cover was less than 40%; and (b) % of years that annual % pasture utilisation exceeded 30%.

4.1 Simulation results

Preliminary results of the simulation study were assessed by comparing the different forecasting systems with base-line simulation and calculating for Queensland's grazing lands the proportion of pixels where there was an increase or decrease in simulated variables from the base-line simulation (Tables 7 and 8). For the constant stocking rate strategy compared to the base-line simulation there was a larger area where there was a lower production (37%) than higher production (14%). Similarly in terms of increased degradation risk the % area with higher risk was substantially greater for the constant stocking rate strategy emphasising the importance of varying stock numbers from year-to-year. The perfect knowledge systems (of pasture growth, rainfall and Queensland grazing lands rainfall) all showed substantial increase in the % area with higher production than baseline simulation. Perfect knowledge of pixel growth was superior to perfect

Table 7. Evaluation of cattle production benefits for different forecast systems and classification of historical year-types based on perfect knowledge. Evaluation was in terms of number of stock carried and beef production in terms of kg of liveweight per ha. The table shows the percentage area of Queensland's grazing lands where there was an increase or decrease in stocking rate or production compared to the base line

Hindcast system	Stock % area		Production % area	
	Increase	Decrease	Increase	Decrease
Perfect knowledge of growth	83	1	90	1
Perfect knowledge of rain	65	5	82	1
Perfect knowledge of Queensland's rain	74	1	66	9
SPOTA-1 Oct ober1st	87	1	64	12
GCM/RCM average	69	9	59	18
SOI Phase	68	2	46	19
Constant Stocking Rate	0	8	14	37

Table 8. Evaluation of pasture resource degradation risk for different forecast systems and classification of historical year-types based on perfect knowledge. Evaluation was in terms of percentage of time that surface cover was less than 40%, and percentage of years pasture utilisation was greater than 30%. The table shows the percentage area of Queensland's grazing lands where there was an increase or decrease in degradation risk compared to the base line simulation.

Hindcast system	Soil loss risk % area		Pasture damage risk % area	
	Increase	Decrease	Increase	Decrease
Perfect knowledge of growth	7	75	1	94
Perfect knowledge of rain	6	73	5	84
Perfect knowledge of Queensland's rain	13	63	15	68
SPOTA-1 October 1st	14	61	35	44
GCM/RCM average	15	62	24	53
SOI Phase	20	40	31	37
Constant stocking rate	74	15	77	16

knowledge of rainfall or perfect knowledge of average Queensland grazing land rainfall in terms of both production benefits and reducing degradation risk. The 'perfect knowledge' systems indicate that there is considerable potential benefit for climate forecast systems, which can forecast at either a large regional level (100Mha), or better still at an individual pixel resolution.

The climate forecasting systems (GCM/RCM and operational SOI phase system) both showed benefits in terms of production and reduced risk of resource degradation. In terms of production relative to base-line simulation, the % area where increases occur was greater than the % area where decreases were simulated (Table 7). In terms of degradation risk (Table 8), there were substantial areas where simulated risk was reduced (37-44%). The GCM/RCM system was superior to the operational SOI phase system in terms of both areas of production benefit and areas of reduced resource damage.

This preliminary study showed that climate forecasting systems could be comprehensively compared using a simple decision rule linking: (a) the climate forecast; and (b) information on pasture feed availability. Thus this approach to comparing 'skill' was done in a way most relevant to the intended clients of the forecasting systems. Further studies will include improved models of degradation feedbacks, removal of 'perverse' climate forecasts, and optimisation of decisions in relation to climate forecasts. Monte Carlo simulations are also being carried out to allow the skill at each pixel to be assessed in probabilistic terms. The skill testing system described in this study also will allow assessment of different attributes of the ensemble simulations from the GCM/RCM.

5. Summary

The climate system is highly complex and exhibits non-linear behaviour. Climate forecasts have a high degree of uncertainty and need to be issued probabilistically. Seasonal climate forecasts have several sources of uncertainty such as inherent chaotic nature of climate system, imperfections in numerical representation of climate system and uncertainty in prediction of sea surface temperatures used to drive the second tier prediction system. An ensemble simulation approach has been used to reduce the chaotic component of the atmosphere and enhance coherent response to remote forcing. The NR&M seasonal climate prediction system has been able to simulate regional rainfall with useful level of skill, especially for the extremes.

Comparison of GCM/RCM output expressed in the same manner as statistical systems indicates equal or better skill in terms of grazing management decisions. Further work will evaluate alternative ways of linking GCM/RCM output to management decisions in grazing systems.

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