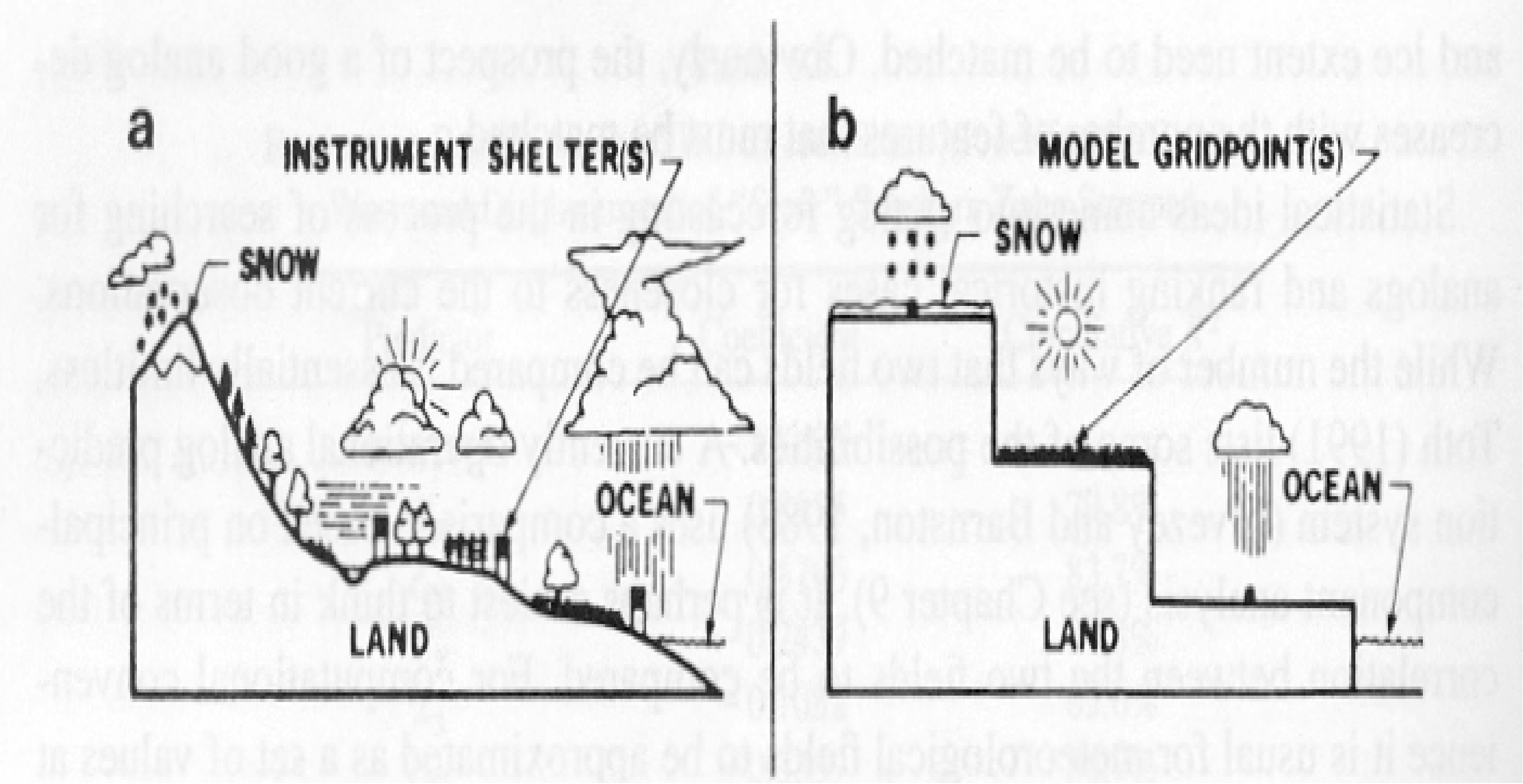
Post-Processing of Large-Scale Forecast Fields

Willem A. Landman

Lectures 7

Schematic illustration of the differences between the real world (a) and the world as represented by GCMs (b)



Reasons why downscaling of GCM output is useful for operational seasonal forecasting (1)

- There are important differences between the real world and its model representation
- Small-scale affects (such as topography) important to local climate could be poorly represented in the GCM
- Variables such as streamflow may not be represented explicitly by the GCM

Reasons why downscaling of GCM output is useful for operational seasonal forecasting (2)

- GCMs are not perfect and their forecasts are subject to error (i.e., parameterization schemes are not perfect)
- Spatial biases: GCM climatology may have rainfall maximum displaced
- Temporal biases: GCM climatology may have seasonal cycle wrong
- In developing countries, limited research funds could be directed to statistical post-processing of output from international centres

Two empirical approaches…

- **Perfect Prog**(nosis): no attempt to correct for possible GCM biases; GCM forecasts are assumed to be **perfect**
- **Model Output Statistics** (MOS): influence of specific characteristics included directly into equations

Perfect Prog

- In development:

$$\hat{y}_0 = f_{pp}(\mathbf{x}_0)$$

- In implementation:

$$\hat{y}_t = f_{pp}(\mathbf{x}_t)$$

MOS

In development AND implementation:

$$\hat{y}_t = f_{MOS}(\mathbf{x}_t)$$

Paper on Perfect Prog

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

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

WILLEM A. LANDMAN[a,*], SIMON J. MASON[b], PETER D. TYSON[a] and WARREN J. TENNANT[c]
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[c] *South African Weather Bureau, Private Bag X097, Pretoria, 0001, South Africa*

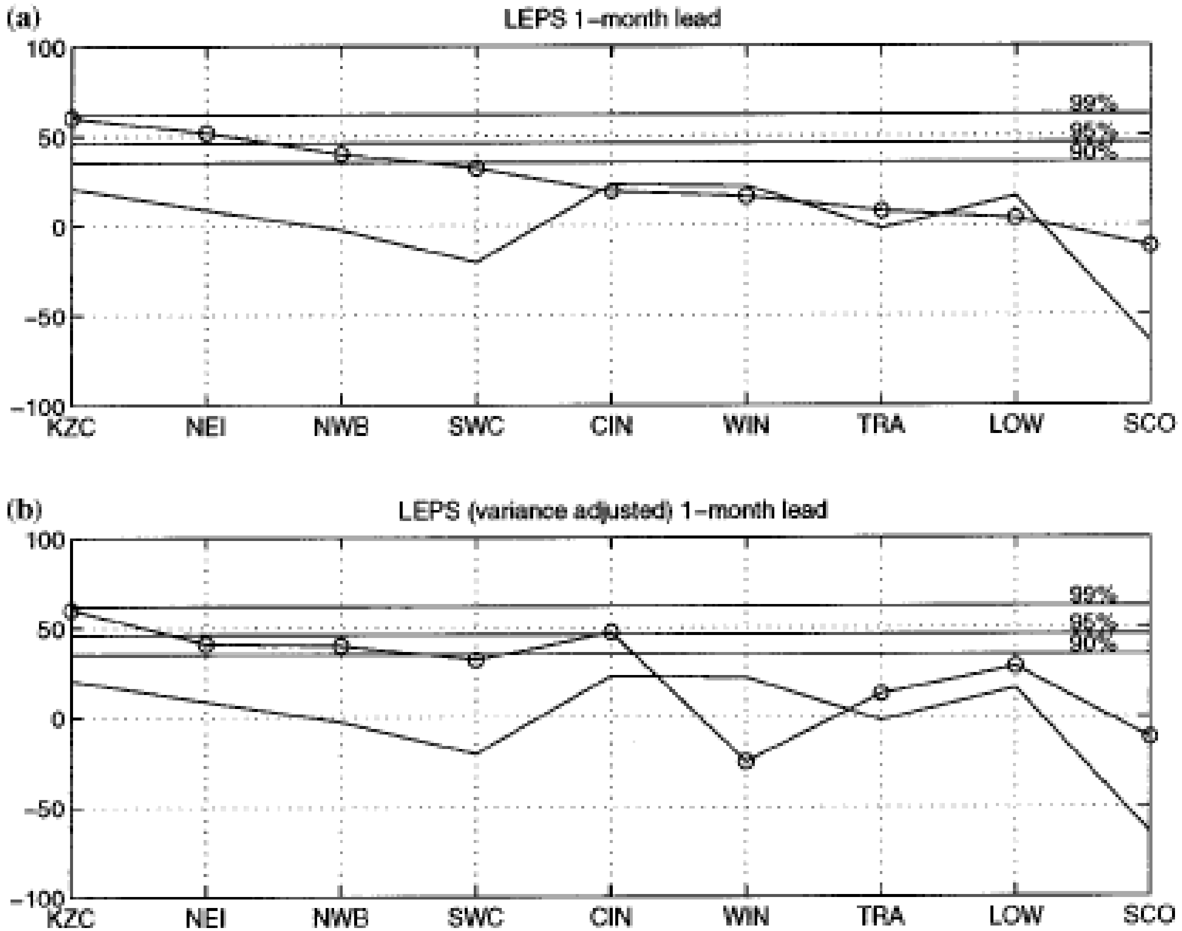

Figure 3. (a) LEPS scores for retro-active forecasts for the nine regions (KZC: KwaZulu–Natal coast; NEI: northeastern interior; NWB: northern Namibia/western Botswana; SWC: southwestern Cape; CIN: central interior; WIN: western interior; TRA: Transkei; LOW: Lowveld; SCO: south coast) with a 1-month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

Significantly, the potential for GCM seasonal forecasting of rainfall over southern Africa is high. In the past, statistical modelling offered the best prospects for seasonal climate forecasting; in future, GCMs will undoubtedly provide the best basis for doing so. At present, both methods are needed and are best blended in a multi-tiered approach to offer pragmatic and cost-effective solutions to a complex problem.

(2000)

Examples of complex problems:

Do Statistical Pattern Corrections Improve Seasonal Climate Predictions in the North American Multimodel Ensemble Models?

ANTHONY G. BARNSTON

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Department of Applied Physics and Applied Mathematics, Columbia University, New York, New York, and Center of Excellence for Climate Change Research, Department of Meteorology, King Abdulaziz University, Jeddah, Saudi Arabia

(Manuscript received 31 January 2017, in final form 7 July 2017)

ABSTRACT

Canonical correlation analysis (CCA)-based statistical corrections are applied to seasonal mean precipitation and temperature hindcasts of the individual models from the North American Multimodel Ensemble project to correct biases in the positions and amplitudes of the predicted large-scale anomaly patterns. Corrections are applied in 15 individual regions and then merged into globally corrected forecasts. The CCA correction dramatically improves the RMS error skill score, demonstrating that model predictions contain correctable systematic biases in mean and amplitude. However, the corrections do not materially improve the anomaly correlation skills of the individual models for most regions, seasons, and lead times, with the exception of October–December precipitation in Indonesia and eastern Africa. Models with lower uncorrected correlation skill tend to benefit more from the correction, suggesting that their lower skills may be due to correctable systematic errors. Unexpectedly, corrections for the globe as a single region tend to improve the anomaly correlation at least as much as the merged corrections to the individual regions for temperature, and more so for precipitation, perhaps due to better noise filtering. The lack of overall improvement in correlation may imply relatively mild errors in large-scale anomaly patterns. Alternatively, there may be such errors, but the period of record is too short to identify them effectively but long enough to find local biases in mean and amplitude. Therefore, statistical correction methods treating individual locations (e.g., multiple regression or principal component regression) may be recommended for today's coupled climate model forecasts. The findings highlight that the performance of statistical postprocessing can be grossly overestimated without thorough cross validation or evaluation on independent data.

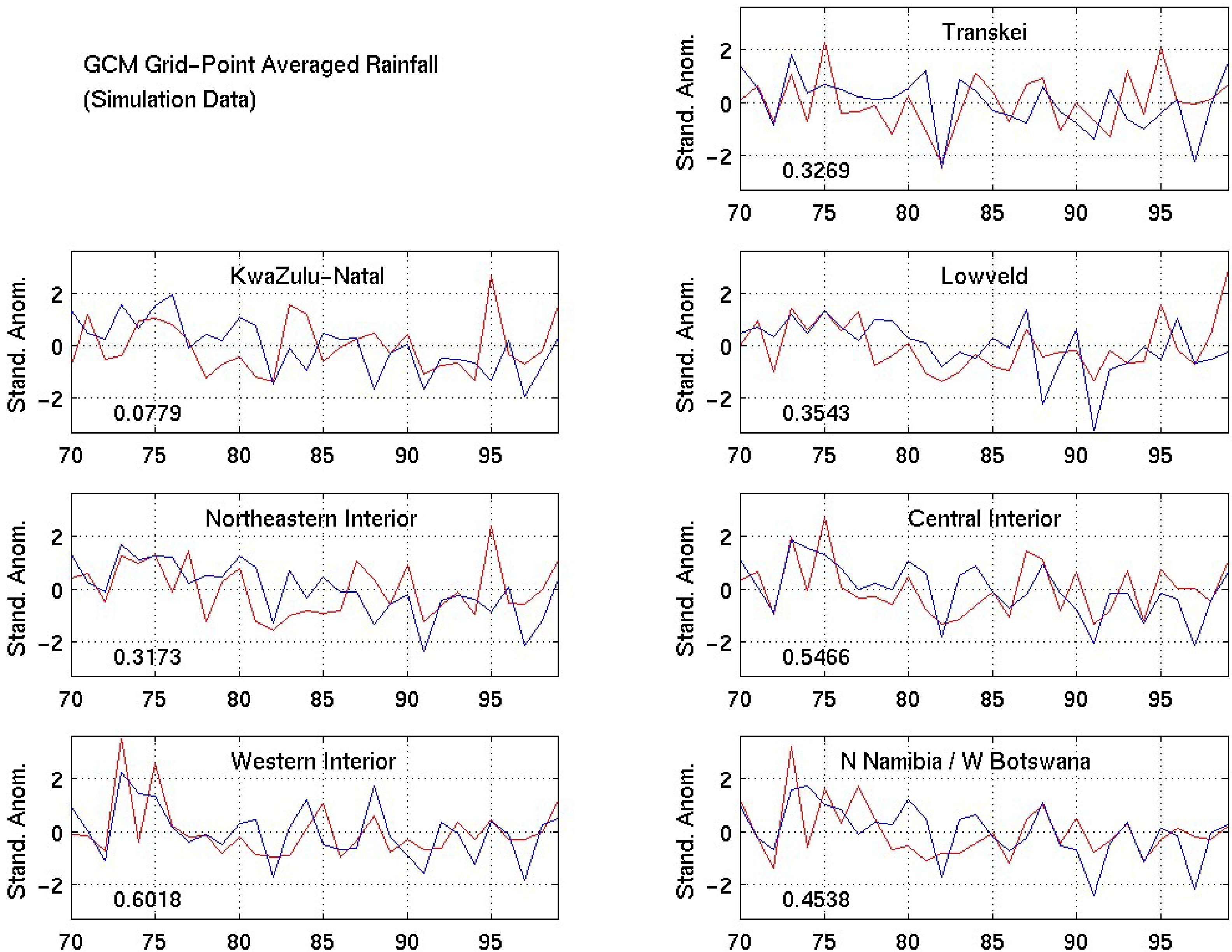
Paper on MOS

2038 JOURNAL OF CLIMATE VOLUME 15

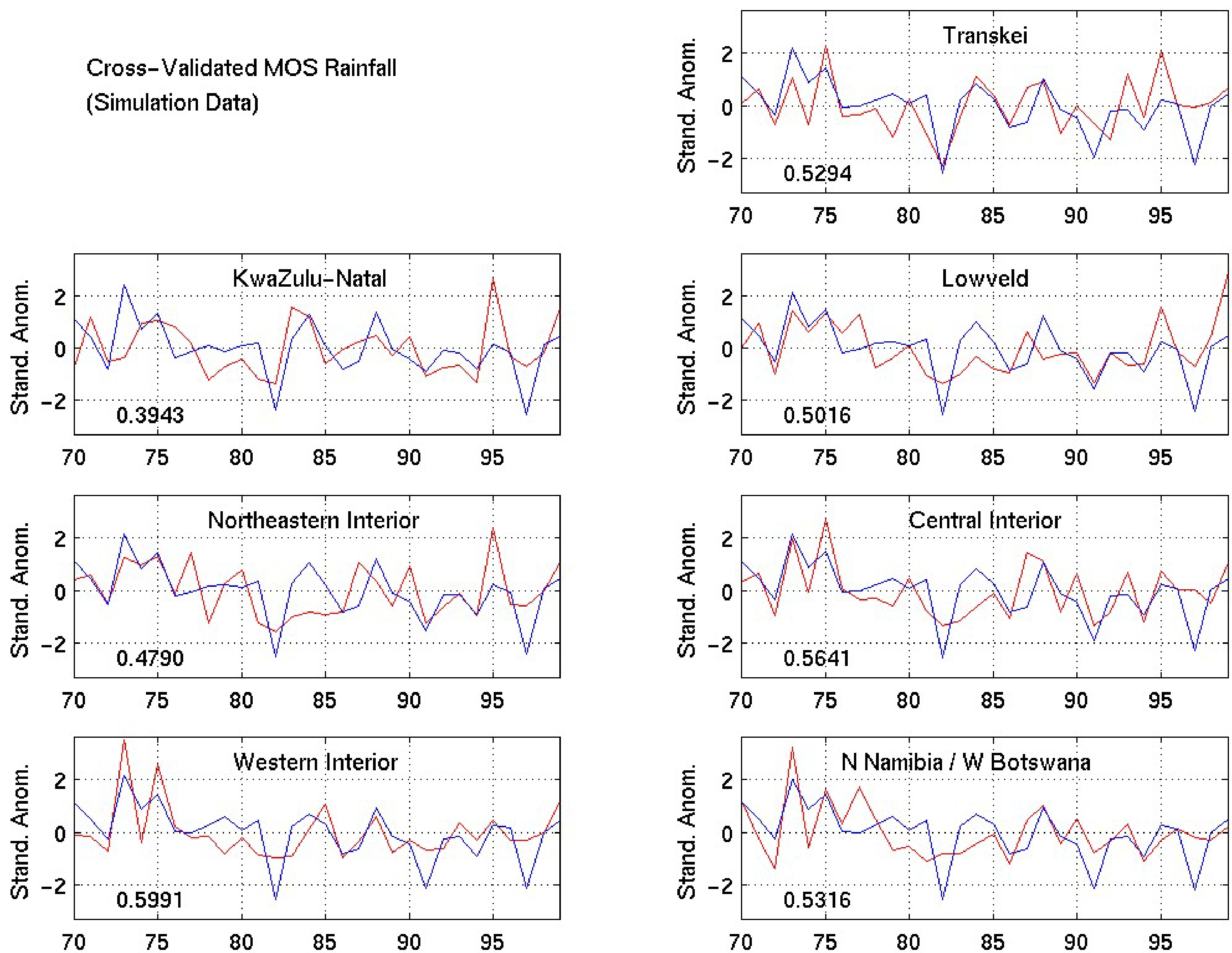
Statistical Recalibration of GCM Forecasts over Southern Africa Using Model Output Statistics

WILLEM A. LANDMAN AND LISA GODDARD

International Research Institute for Climate Prediction, Lamont-Doherty Earth Observatory of Columbia University, Palisades, New York



GCM Grid-Point Averaged Rainfall
(Simulation Data)
Transkei
0.3269
KwaZulu-Natal
0.0779
Lowveld
0.3543
Northeastern Interior
0.3173
Central Interior
0.5466
Western Interior
0.6018
N Namibia / W Botswana
0.4538
Stand. Anom.
2
0
−2
70
75
80
85
90
95


Cross-Validated MOS Rainfall
(Simulation Data)
Transkei
0.5294
KwaZulu-Natal
0.3943
Lowveld
0.5016
Northeastern Interior
0.4790
Central Interior
0.5641
Western Interior
0.5991
N Namibia / W Botswana
0.5316
Stand. Anom.
2
0
−2
70
75
80
85
90
95

Robustness of approach established

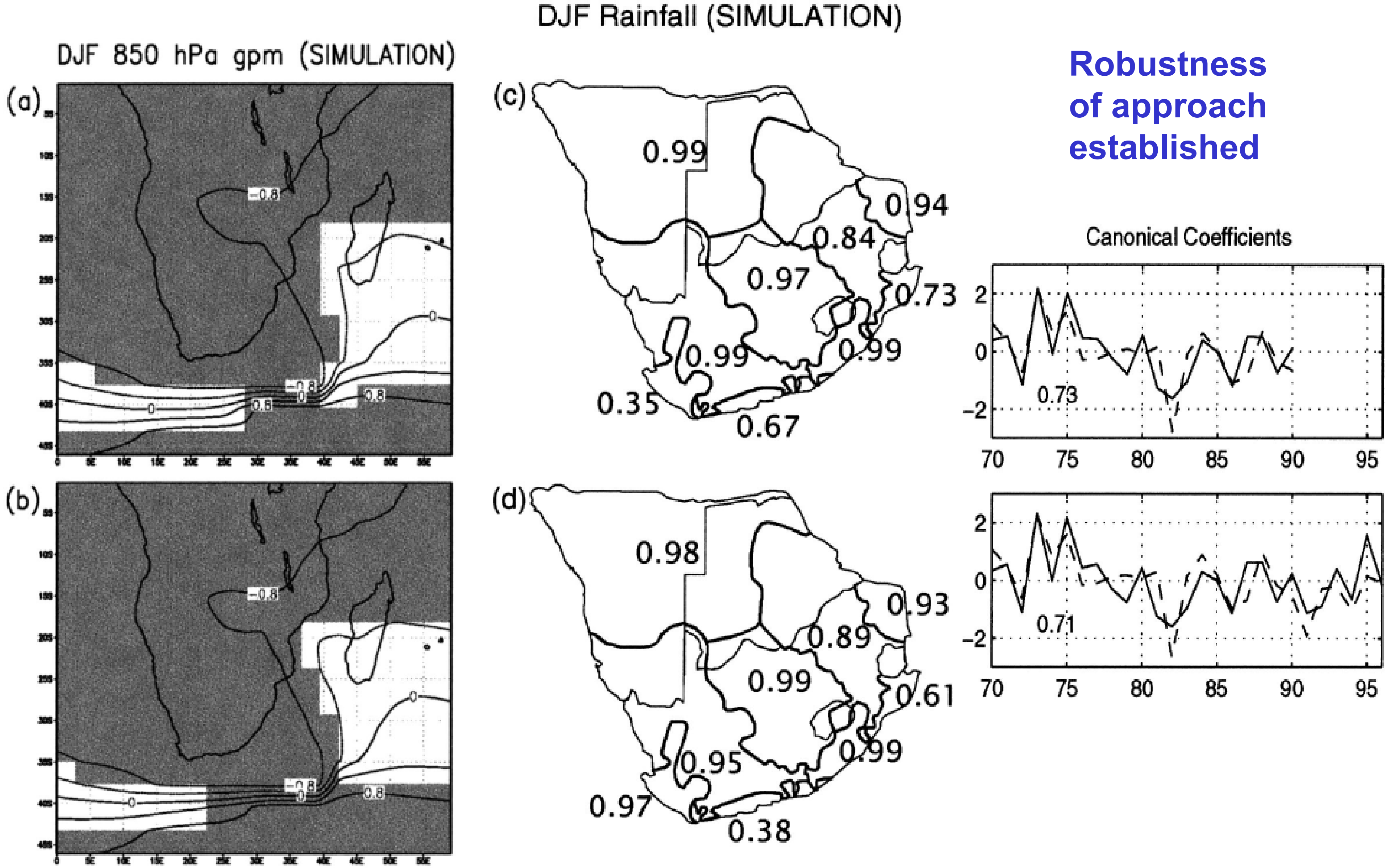
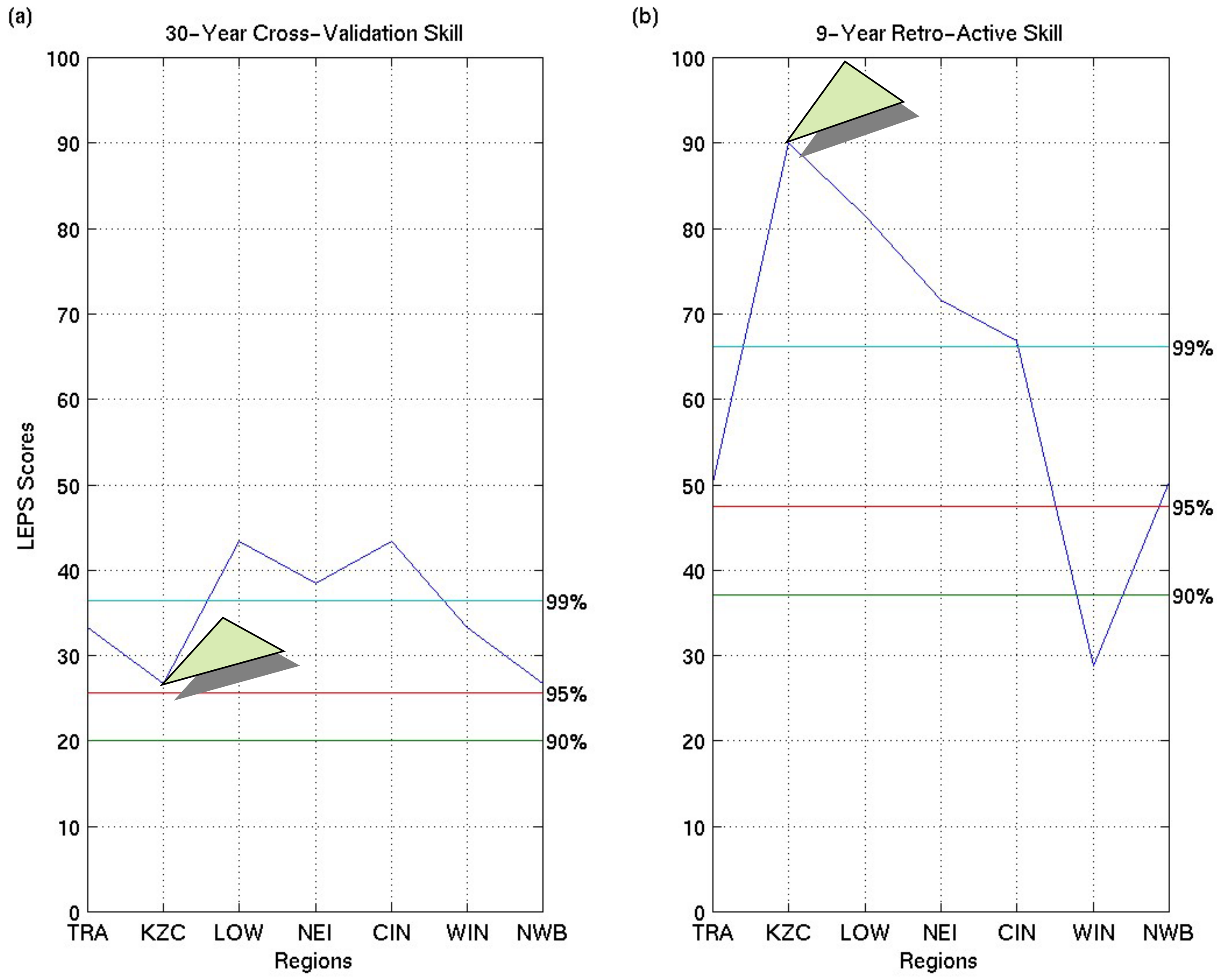
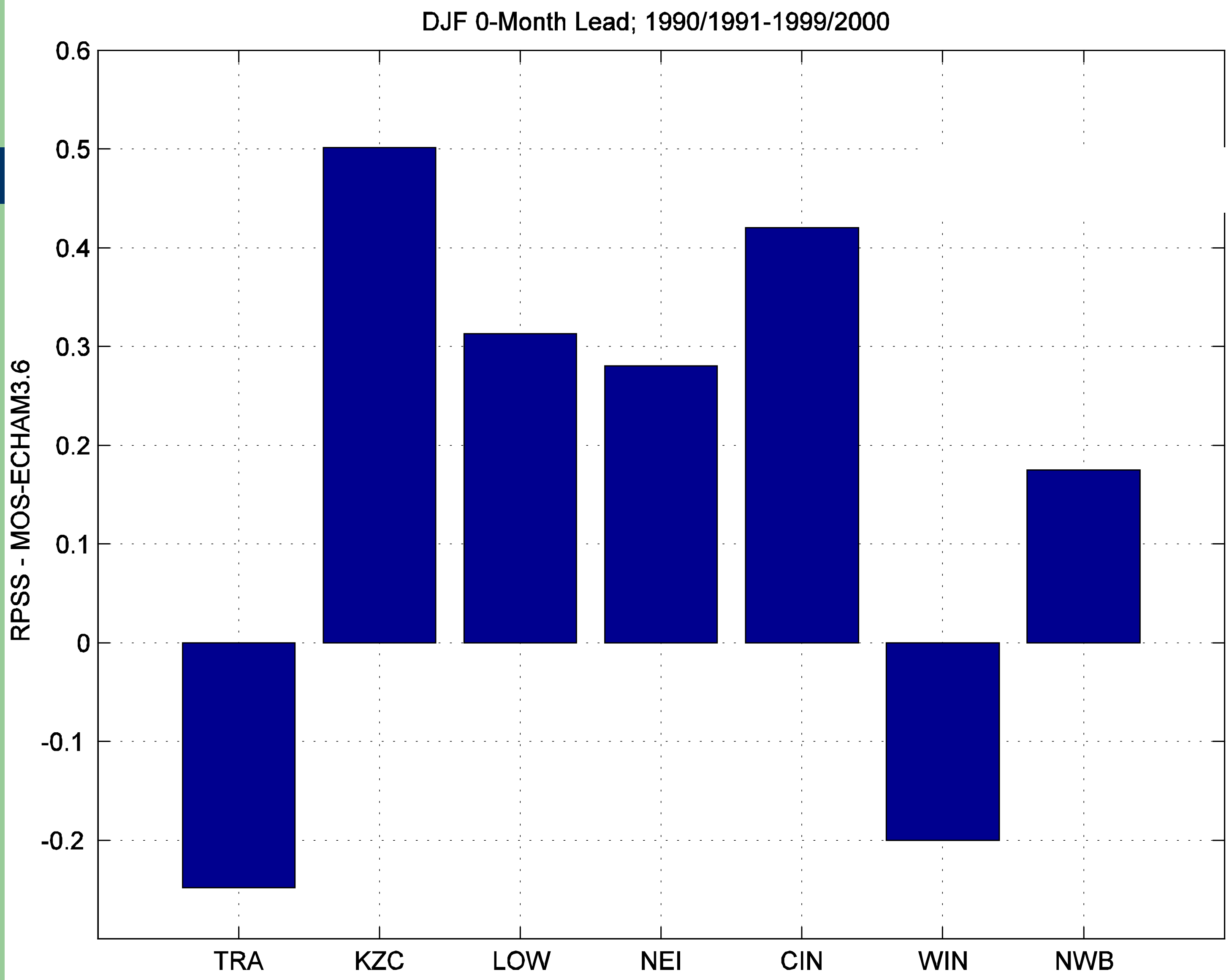


FIG. 5. CCA mode-1 predictor maps of the (a) 21- and (b) 27-yr training periods used in the MOS equations relating simulation mode 850-hPa geopotential heights to DJF regional rainfall. Shaded regions depict areas of significant correlations at the 95% level of confidence. CCA mode-1 predictand maps of the (c) 21- and (d) 27-yr training periods used in the MOS equations. Canonical coefficient scores of mode 1 of the (e) 21- and (f) 27-yr training periods, of the 850-hPa geopontential heights (dashed line), and the regional rainfall (solid line); canonical correlations are in the bottom left-hand corner.

MOS LEPS scores



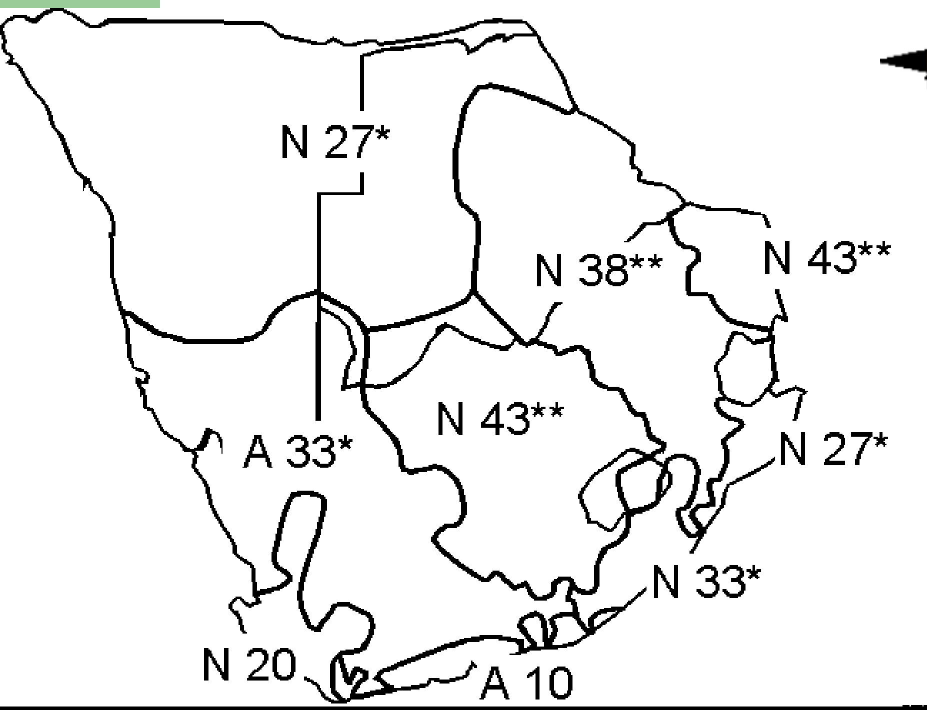
MOS – Retro-Active Forecasts

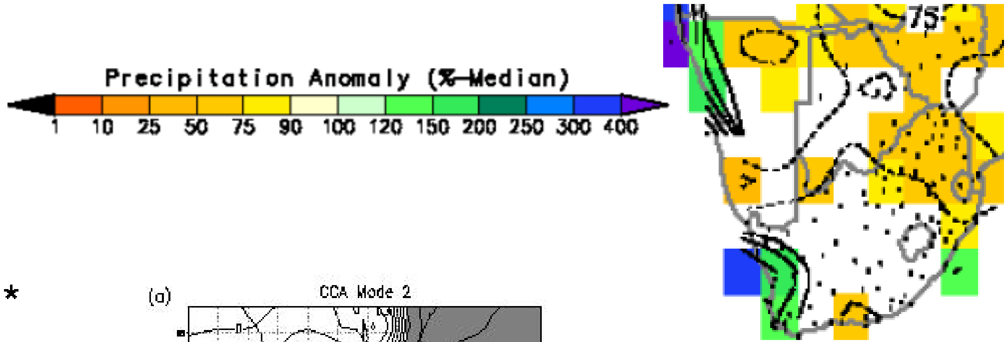


Experimental Long-Lead Forecast Bulletin, 10, 75-77

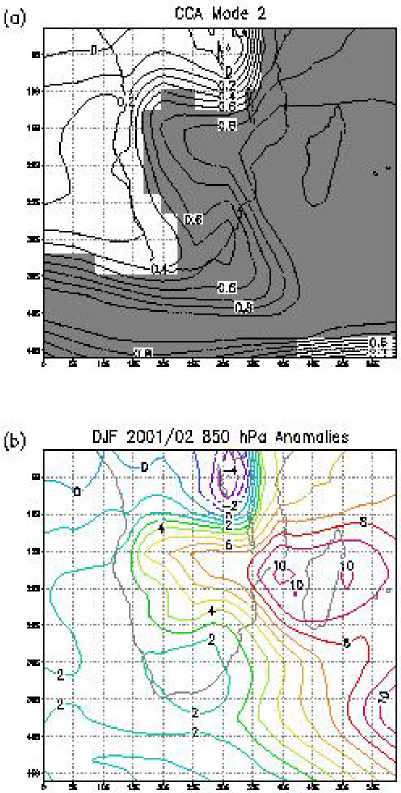
Forecasts of Southern African DJF Rainfall Using Model Output Statistics

contributed by W. A. Landman, L. Goddard and A. Barnston





Categorized rainfall MOS forecasts for DJF 2001/02. **A** refer to above- and **N** to near-normal equi-probable rainfall categories. LEPS scores are shown with the predicted categories, calculated from 30 years of cross-validated rainfall forecasts. LEPS scores significant at the 95% level of confidence are indicated with a "*", and those significant at the 99% level, with "**".



(a) CCA mode 2 predictor map of the 30-year training period used in the MOS equations relating GCM predicted 850 hPa geopotential heights to DJF regional rainfall. Shaded regions depict areas of significant loadings at the 95% level of confidence. (b) DJF 2001/02 850 hPa geopotential height anomalies in gpm, based on the 30-year climate period of 1970/71 to 1999/2000.

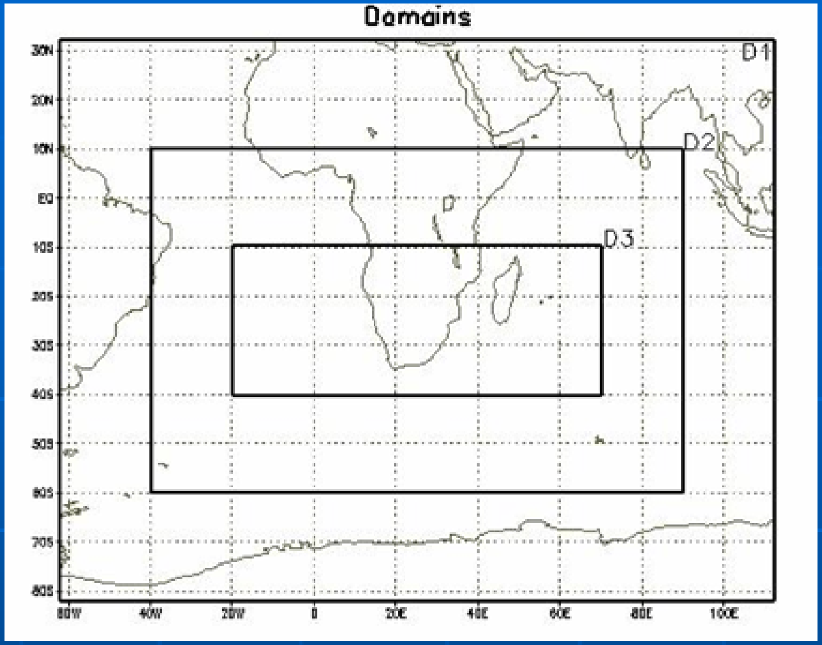
Sensitivity to different domain configurations

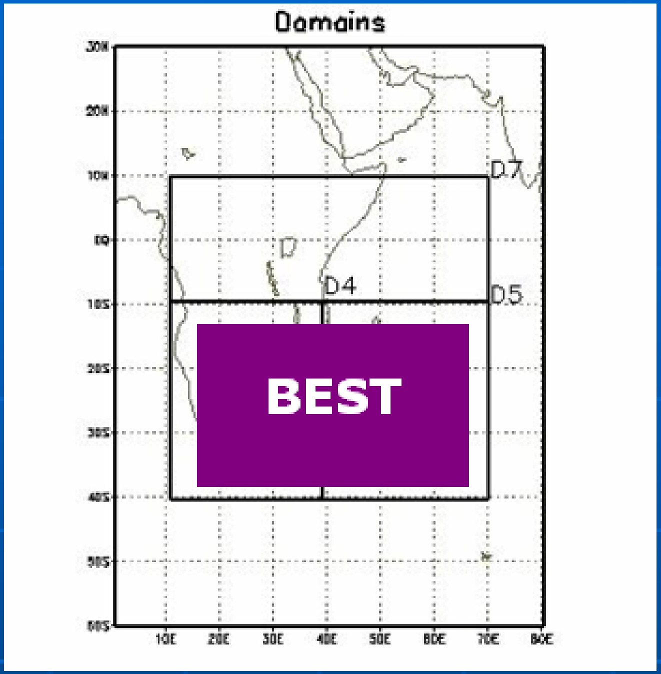
Data and Methods

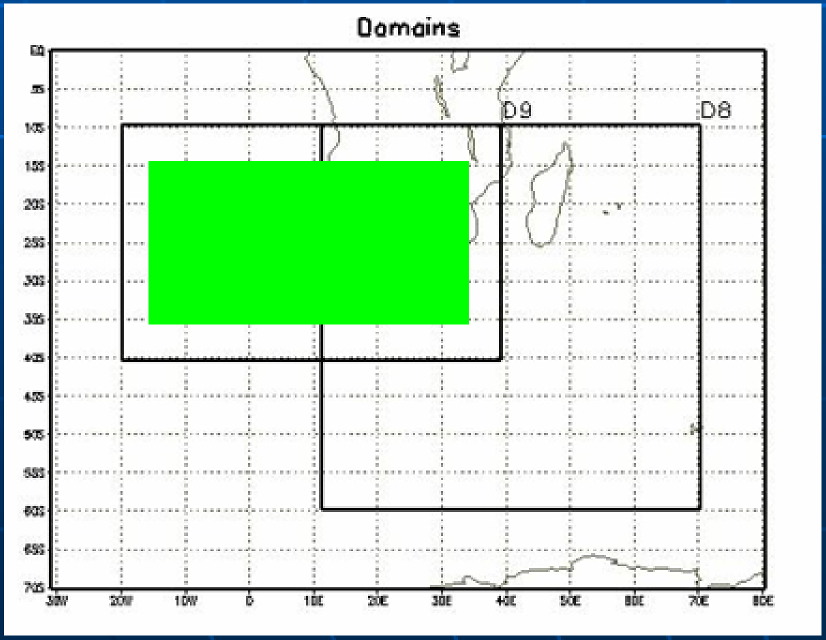
- **ECHAM4.5** simulation rainfall for climatological seasons (DJF, MAM, JJA, SON)
- Southern African regional rainfall for corresponding seasons

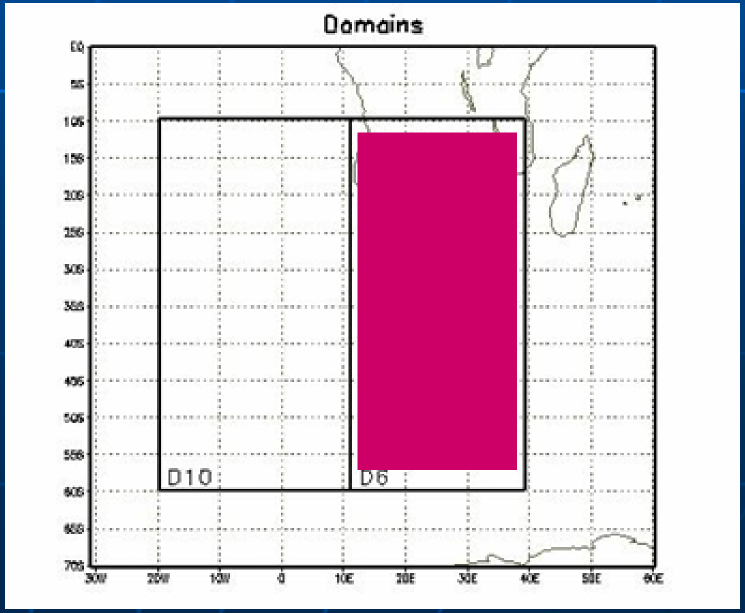
- Optimal CCA equations are constructed for each domain
- Cross-validated MOS with 9-year-out approach (producing 39 years test data)
- MOS each of 24 ensemble members
- Calculate RPSS, get regional average
- Highest value = **<u>optimal domain</u>**

Domains


Domains
D1
D2
D3


Domains
D7
D4
D5
BEST


Domains
D9
D8


Domains
D10
D6

Conclusions

- The smaller domains worked better than the bigger ones – GCM is working well!
  - smaller domains involve primarily recalibration and some spatial correction
- The GCM has the ability to adequately simulate ENSO teleconnection patterns over southern Africa
- DJF and MAM: Best domain includes portion of ocean that supplies moisture to the region

Selecting an Optimal Domain

- Identify moisture sources for the region and season
- Extend domain boundaries to include moisture sources

GEOPHYSICAL RESEARCH LETTERS, VOL. 32, L15809, doi:10.1029/2005GL022910, 2005

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

Willem A. Landman[1,2] and Lisa Goddard[3]

Received 7 March 2005; revised 7 March 2005; accepted 8 July 2005; published 11 August 2005.

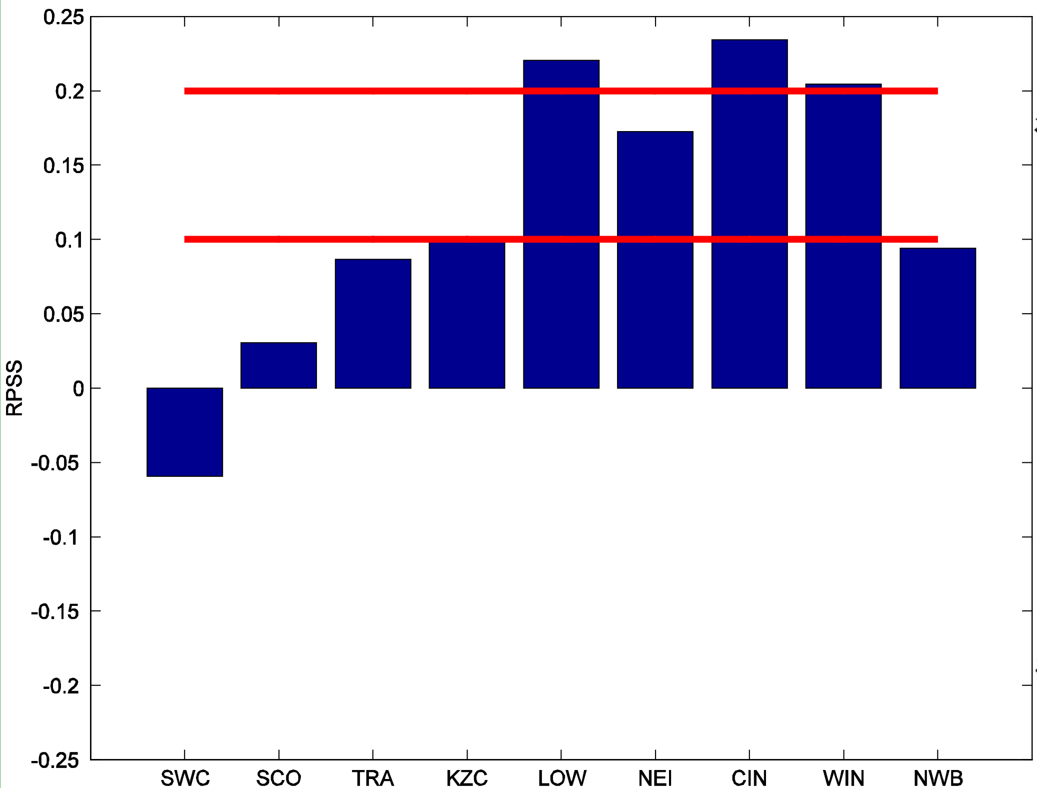
[1] A statistical-dynamical approach to probabilistic precipitation forecasts of southern African summer rainfall is described and validated. An ensemble of seasonal precipitation and circulation fields is obtained from the ECHAM4.5 atmospheric general circulation model (AGCM). Model output statistics (MOS) then spatially recalibrate the AGCM fields relative to observations. Although the MOS equations are built using the simulation data, in which observed SSTs force the AGCM, the same set of equations can be applied to the predicted data, in which predicted SSTs force the AGCM. The use of prediction data in a set of equations developed for simulations, assumes that the AGCM forecast skill approximates its simulation skill and that the systematic biases of the AGCM do not change in a prediction setting; this assumption is analogous to a perfect prognosis (PP) approach. Probabilistic forecast skill is assessed using this MOS-PP-recalibration scheme for 3 equi-probable

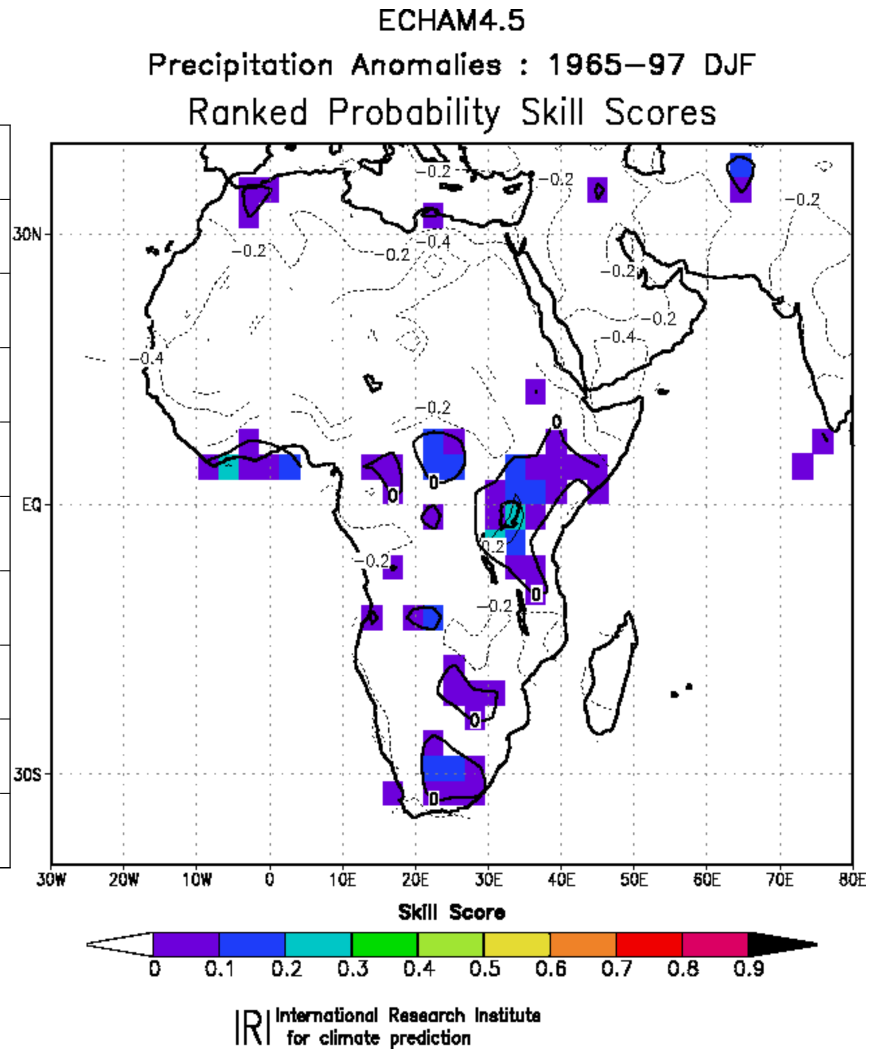
or set of fields, to variability in another is applied in a forecast setting. PP assumes that the relationships between the variables do not change in the forecast setting. Perfect prognosis (PP) [*Wilks*, 1995] performed over a 10-year retro-active period demonstrated useful operational forecast skill over the austral summer rainfall period of southern Africa [*Landman et al.*, 2001]. In MOS a system of equations maps variability in model field(s) to variability in observed fields in order to minimize biases in model output. Model output statistics (MOS) [*Wilks*, 1995] recalibration has shown improved skill over both raw AGCM-simulated rainfall and over a simple statistical forecasting technique using global sea-surface temperature (SST) patterns as predictors [*Landman and Goddard*, 2002]. Strictly speaking, the MOS equations applied to AGCM simulation data are not the same set of MOS equations applied to AGCM forecast data. In a pure MOS approach a different set of equations would be developed for each lead-

MOS-PP Combination

- Set up a MOS set of equations using simulation data (i.e., DJF SSTs for DJF output)
- Use forecast fields from the SAME GCM at lead-times as input in MOS equations
  - Reminiscent of Perfect Prognosis
  - Difference: GCM data was used to set up the prediction equations instead of observed fields

ECHAM4.5-MOS Skill





MOS-PP Combination

Advantages

- GCM biases are taken into consideration in a much more representative way
- A new set of MOS equations do not have to be set up with each forecast lead-time

Disadvantage

- Forecast fields produced at lead-times are not as good as the simulation fields
  - Previous MOS work has shown that at short lead-times, little skill is lost for the summer rainfall season

Experimental Design

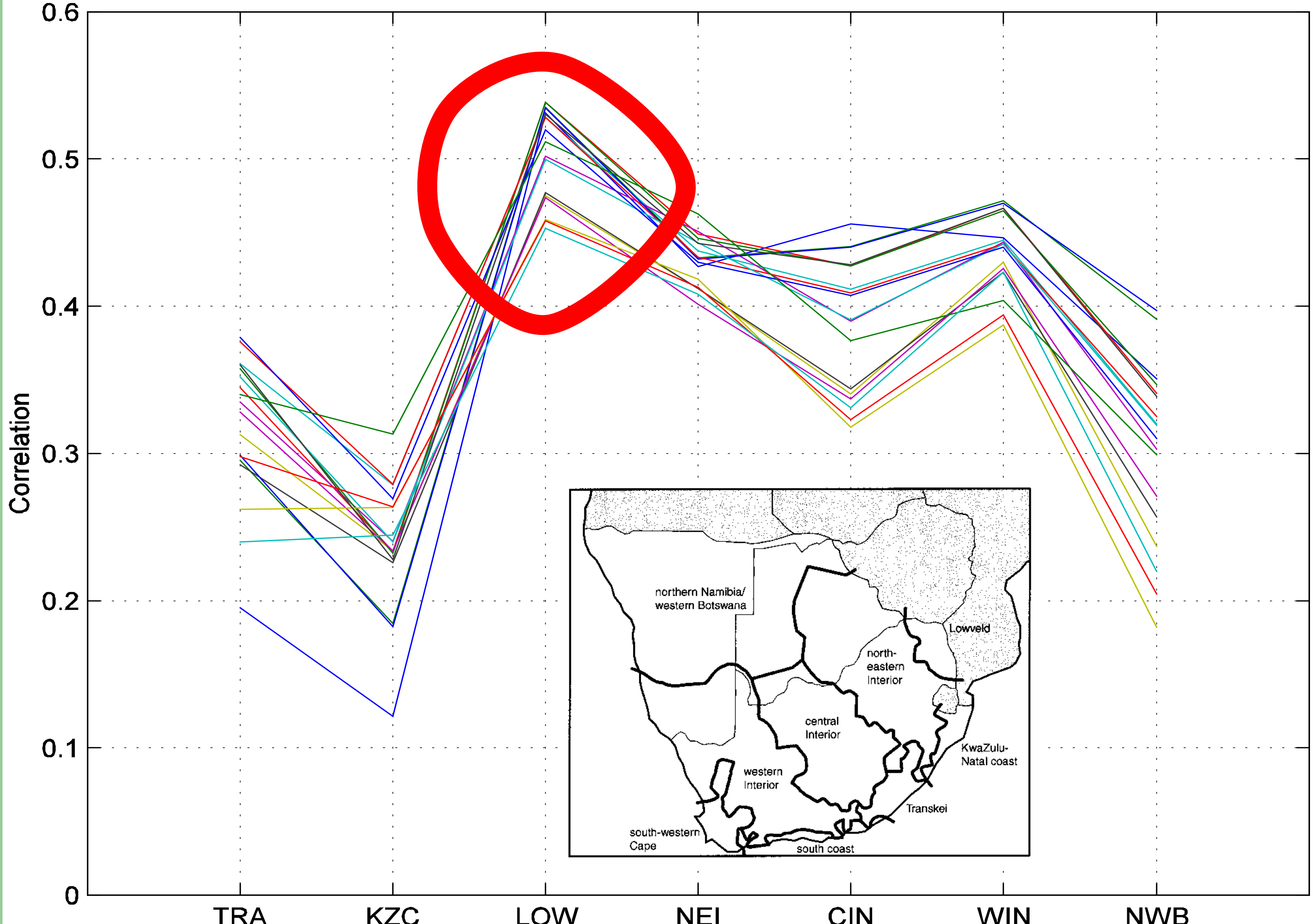
Data

- MOS: ECHAM4.5 simulation rainfall for DJF
- "Perfect Prognosis": ECHAM4.5 forecast rainfall from November SST forcing (0-month)
- Predictand: Southern African regional DJF rainfall

Method

- Optimal CCA
  - Simulation data
  - 24-member ensemble mean
  - Best mean correlation obtained from 3-year-out cross-validation defines best MOS model (48yrs)
- Forecasts (0-month)
  - Ensemble of 12 members
  - RPSS for three categories over 27 years

Best MOS Model

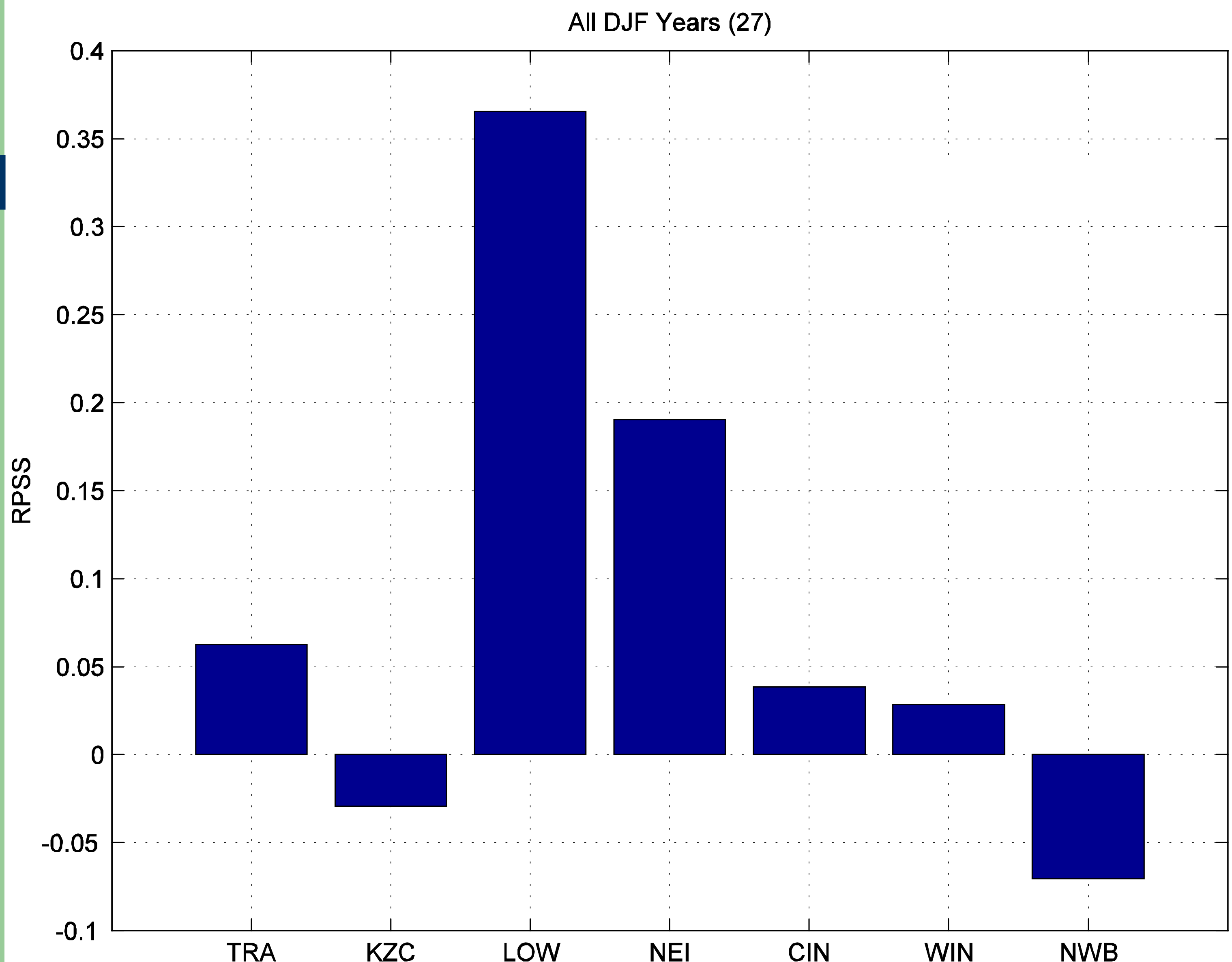


MOS Model Climate and Forecast Years

27 MOS models are designed:

- 1950/51-1972/73 (23 yrs) → **1973/74**
- 1950/51-1973/74 (24 yrs) → **1974/75**
- … etc…
- 1950/51-1998/99 (49 yrs) → **1999/2000**

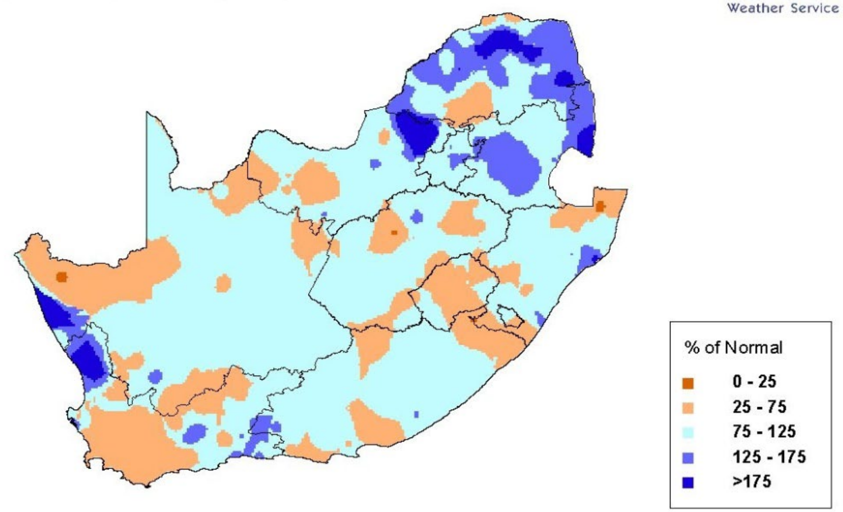
RPSS of 27-Year MOS-PP Forecasts

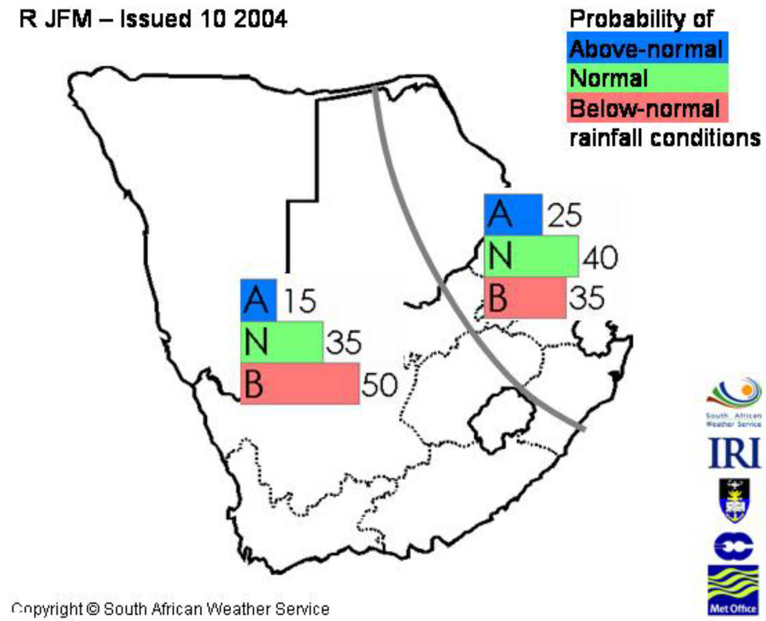


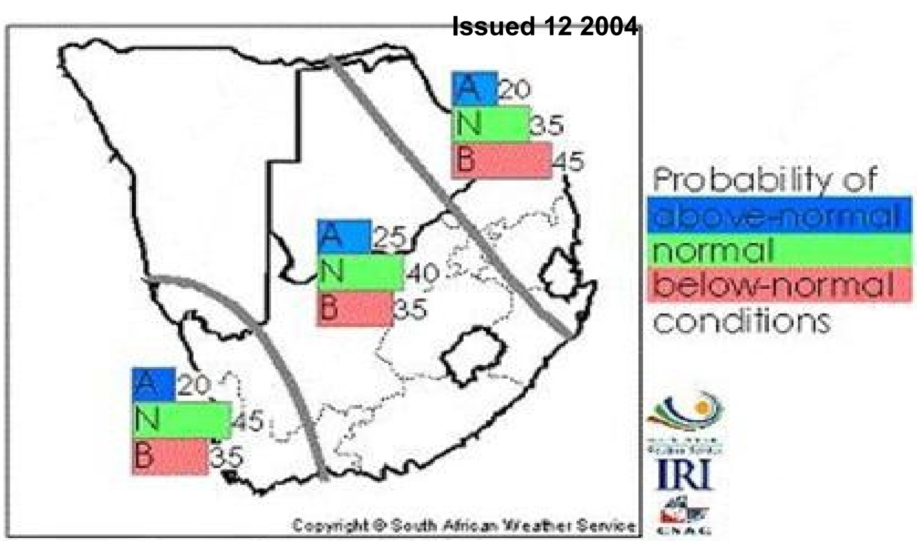
The “poor” forecast of JFM 2004

January, February and March 2004

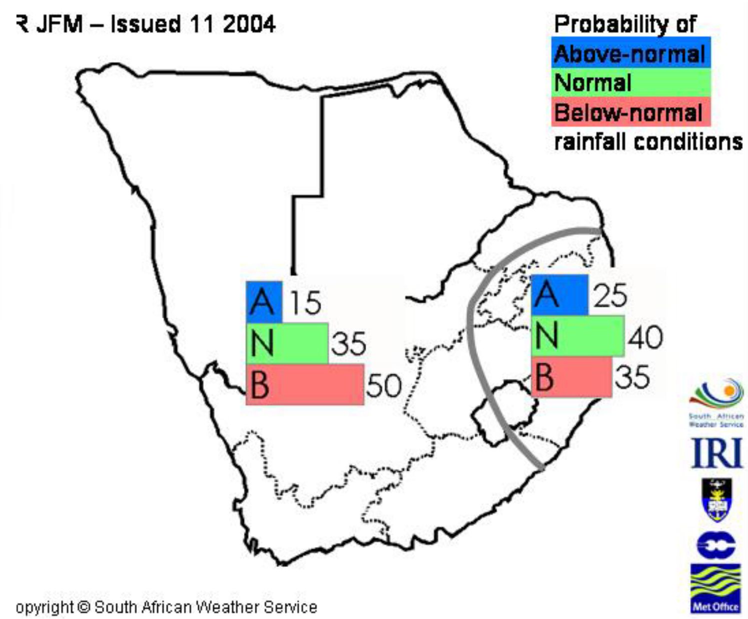
(based on preliminary data)



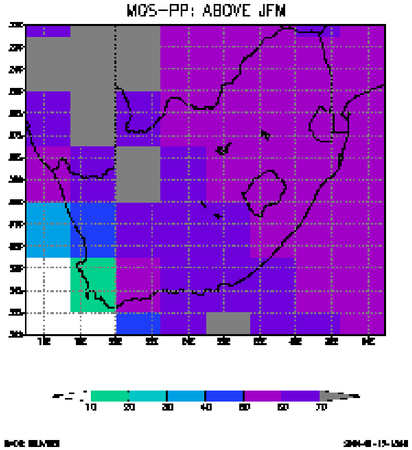


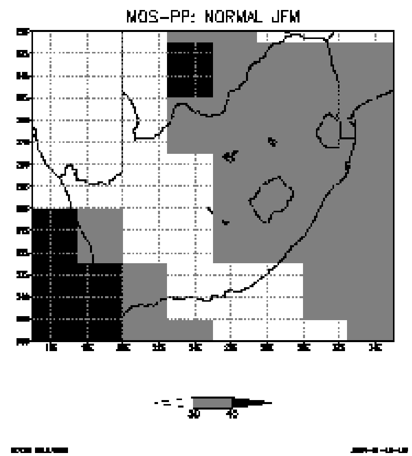


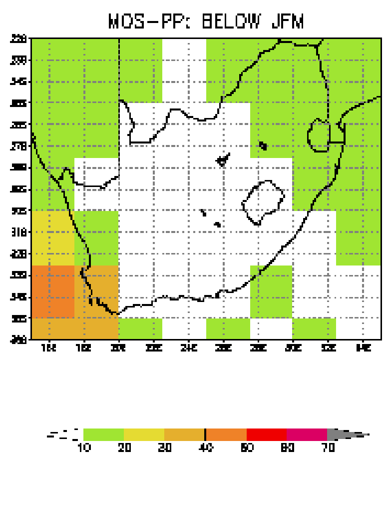
Expected total rainfall for January + February + March 2004

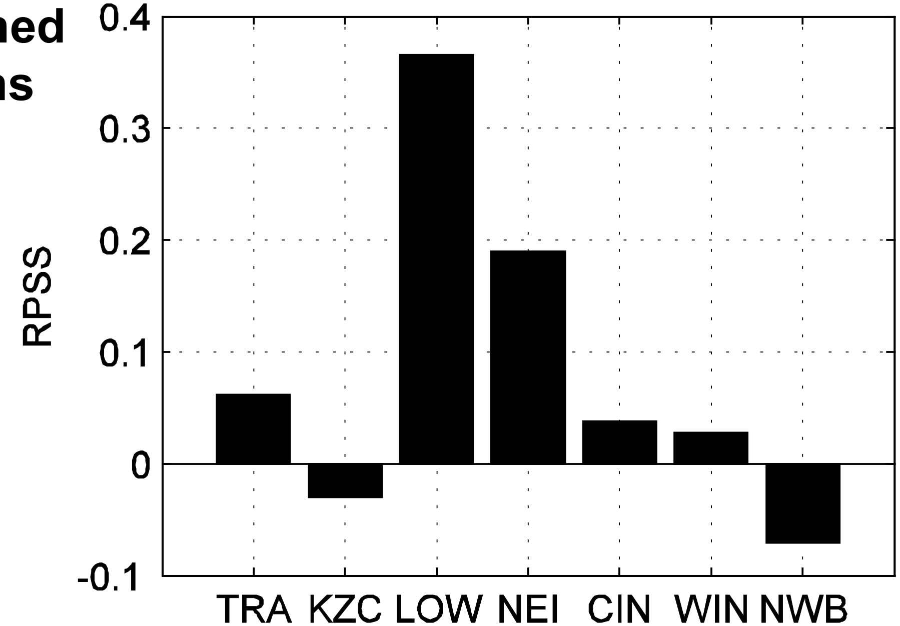


New forecast approached captured wet conditions





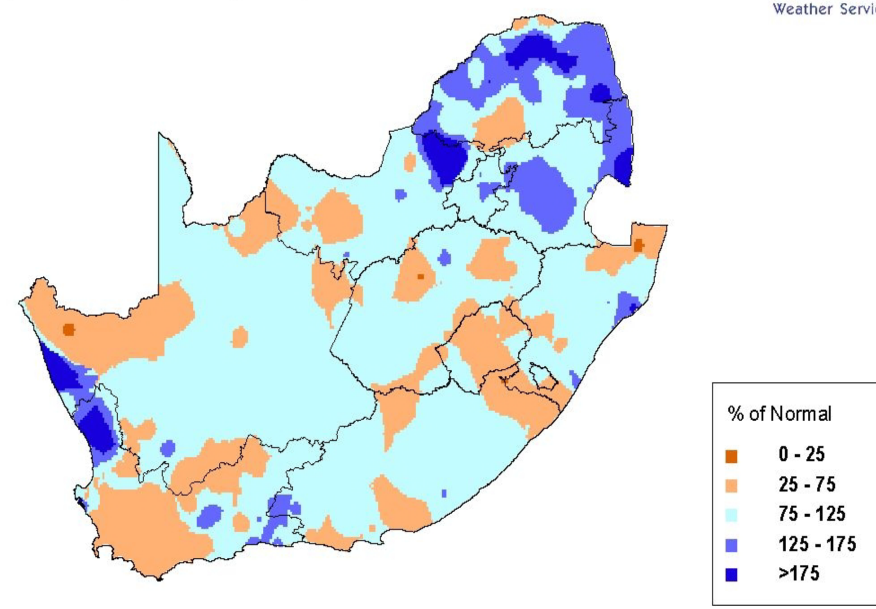




January, February and March 2004

(based on preliminary data)

South African Weather Service



Assessing the predictability of extreme rainfall seasons over southern Africa

GEOPHYSICAL RESEARCH LETTERS, VOL. 32, L23818, doi:10.1029/2005GL023965, 2005

Assessing the predictability of extreme rainfall seasons over southern Africa

Willem A. Landman,[1,2] Stephanie Botes,[1] Lisa Goddard,[3] and Mxolisi Shongwe[1]

Received 4 July 2005; revised 30 September 2005; accepted 21 October 2005; published 10 December 2005.

Method

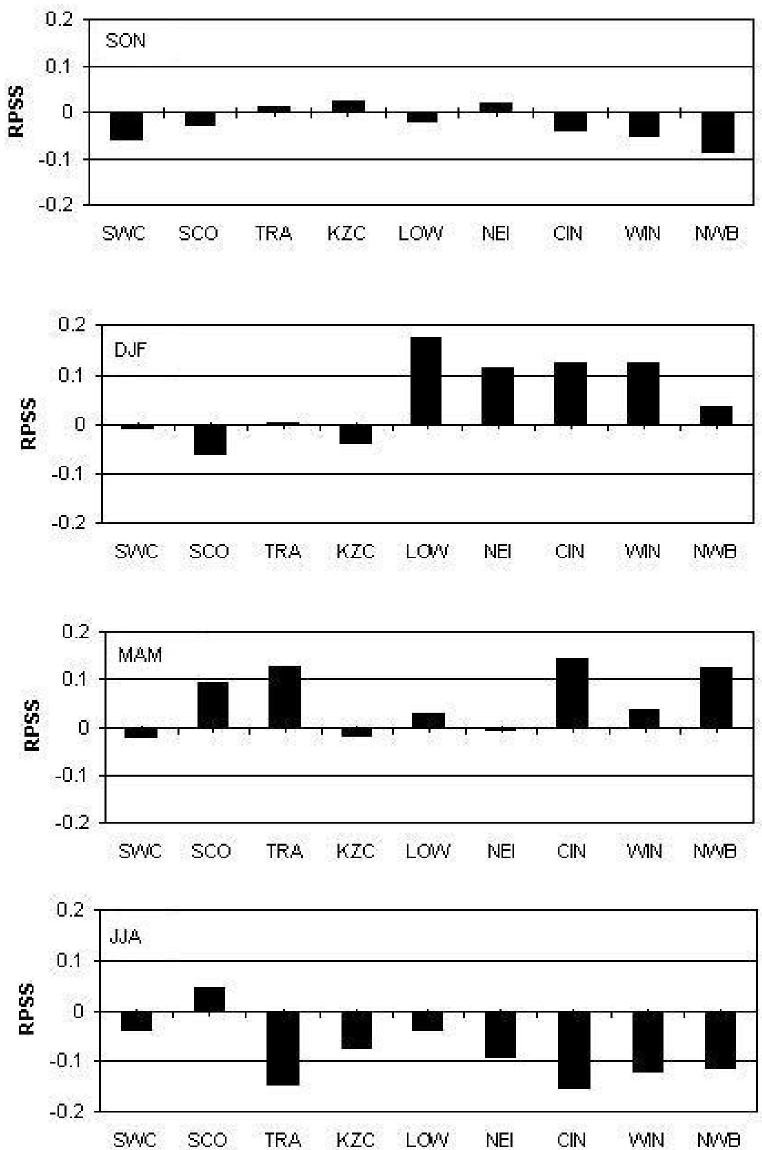
- ECHAM4.5 simulation data (only provides an estimation of the upper limit of forecast skill) over 45 years
- Statistical post-processing of GCM rainfall fields to regional rainfall indices
- RPSS and ROC (wet or dry extremes are more predictable) probabilistic skill estimates (3-year-out cross-validation) for 4 climatological seasons

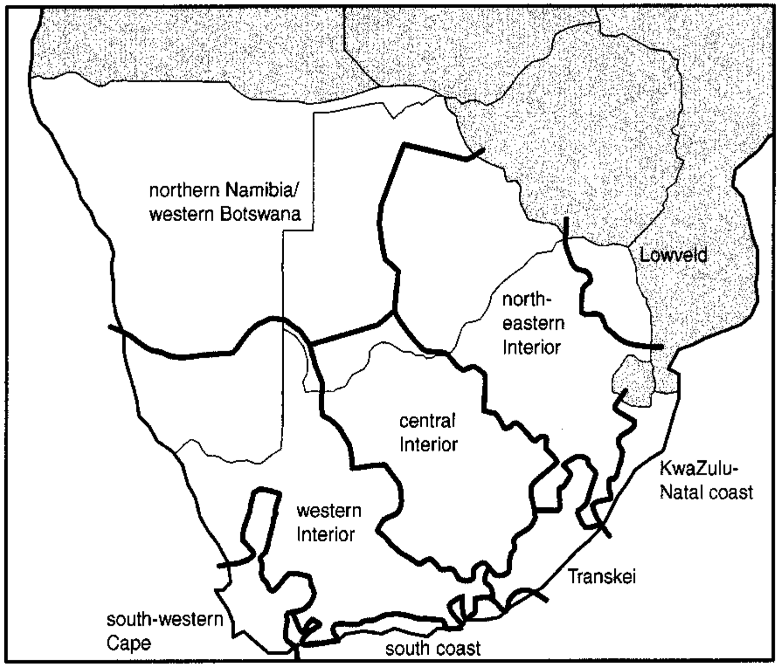
From 3 to 5 categories

- 3 equi-probable category forecasts:
  - 33.3 33.3 33.3
- 5 equi-probable category forecasts:
  - **20** 20 20 20 **20**

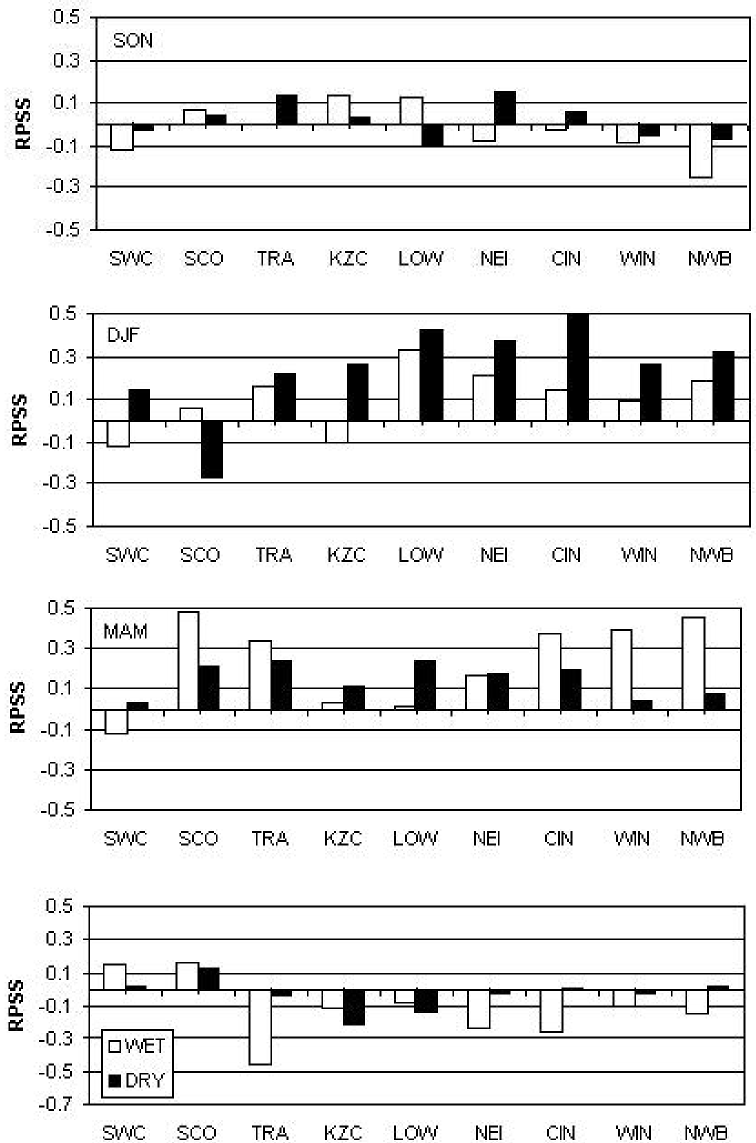
Accurate prediction of the probabilities of rare events (outer pentiles) is the aim of this analysis

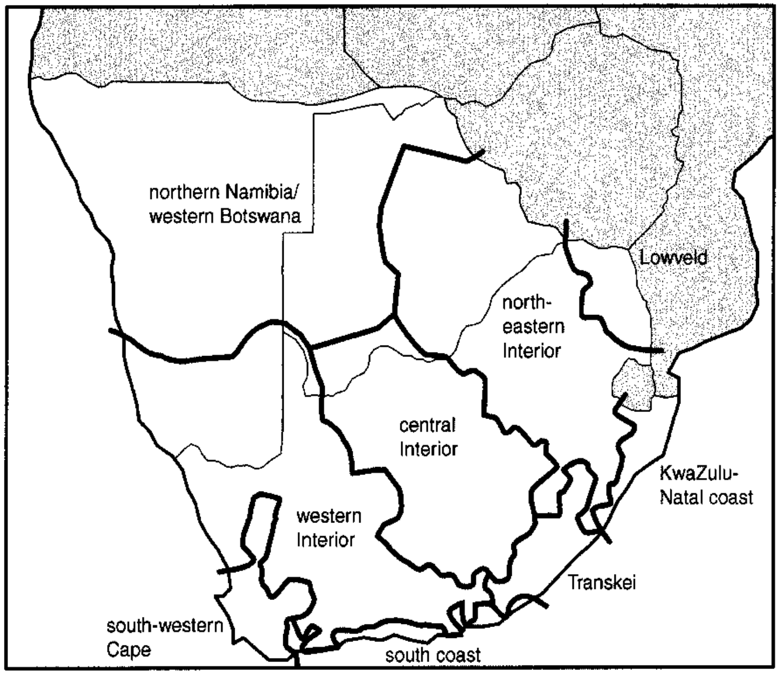
Skill for 5 categories (45-years)

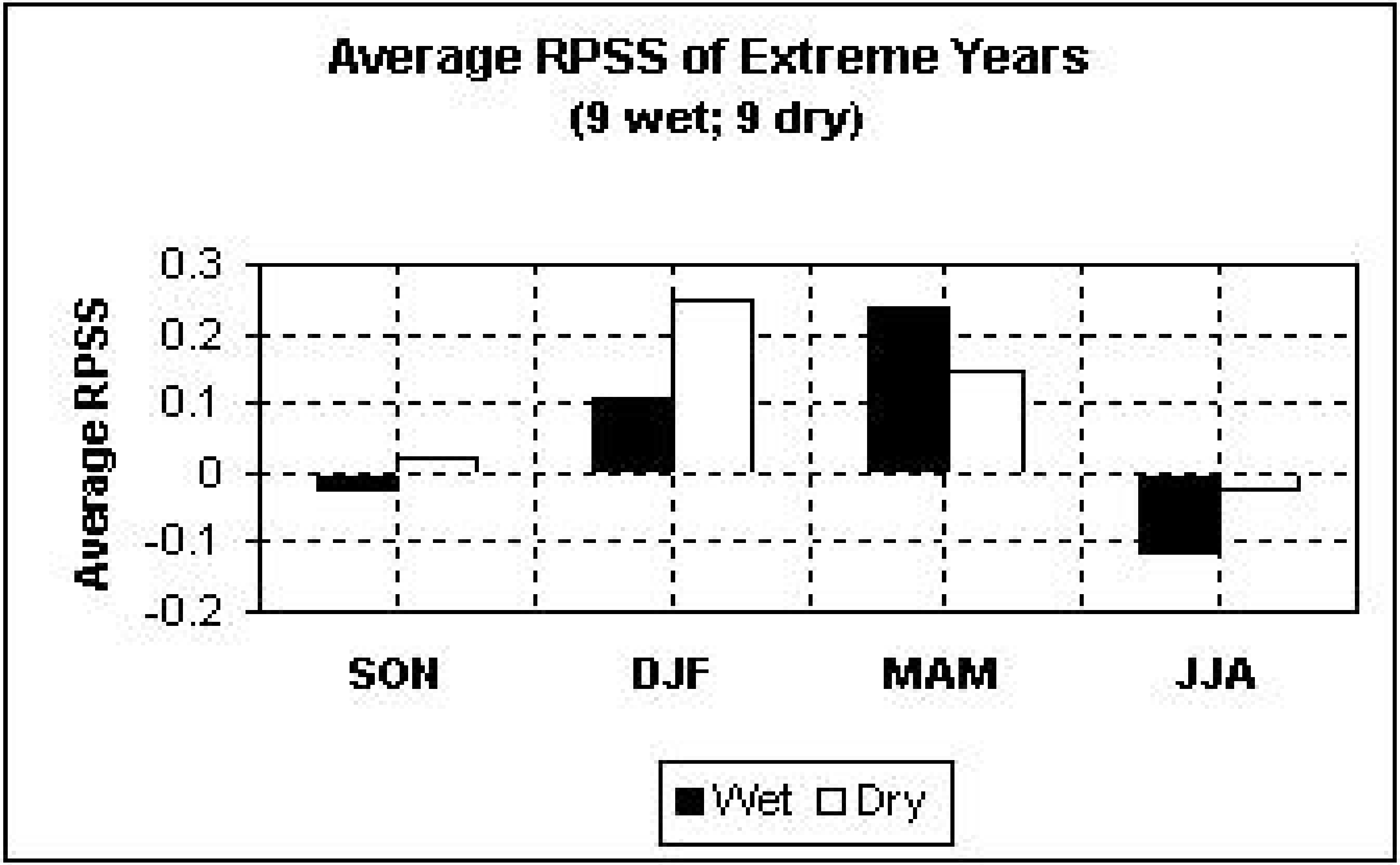




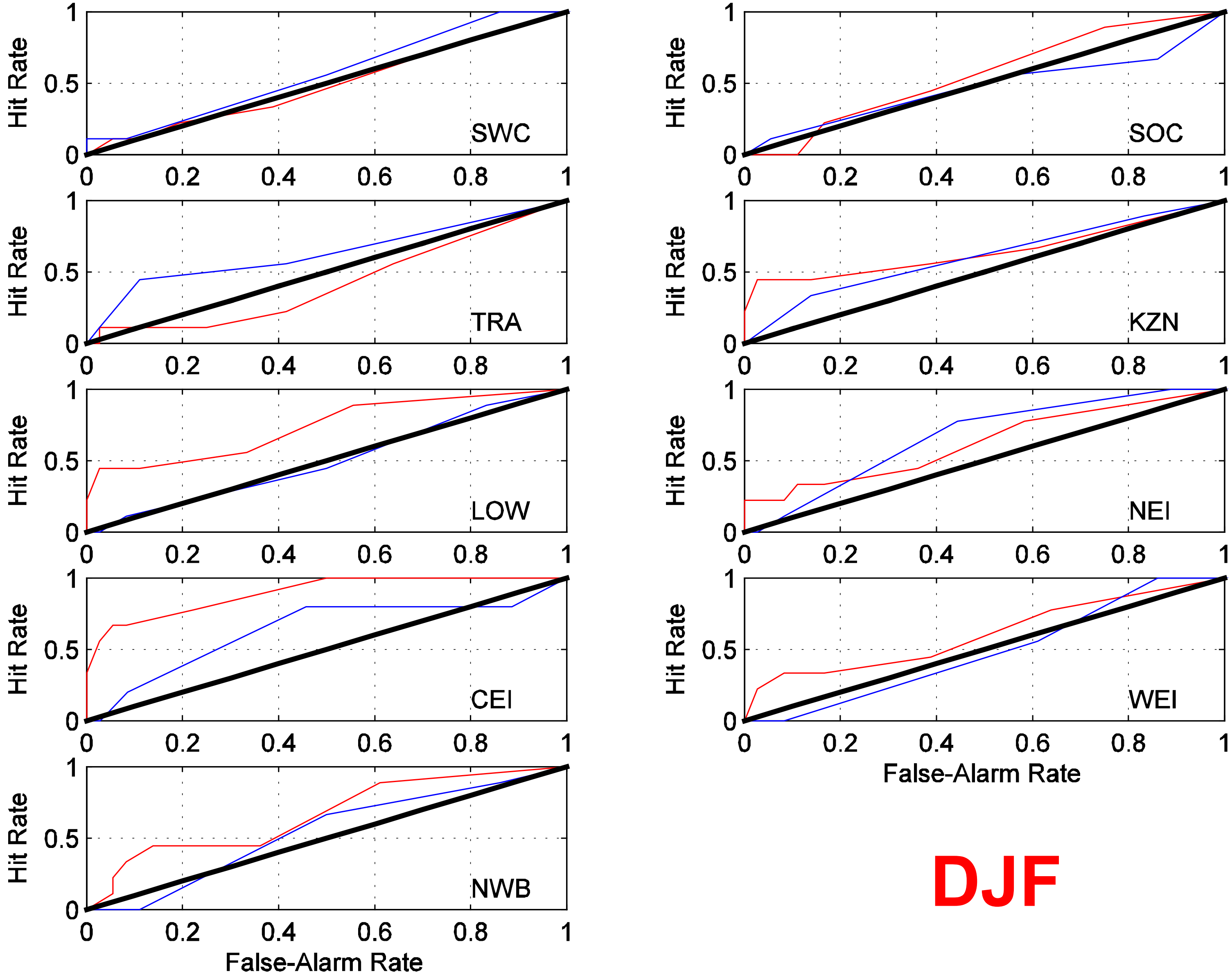
Skill for extremely wet and dry seasons





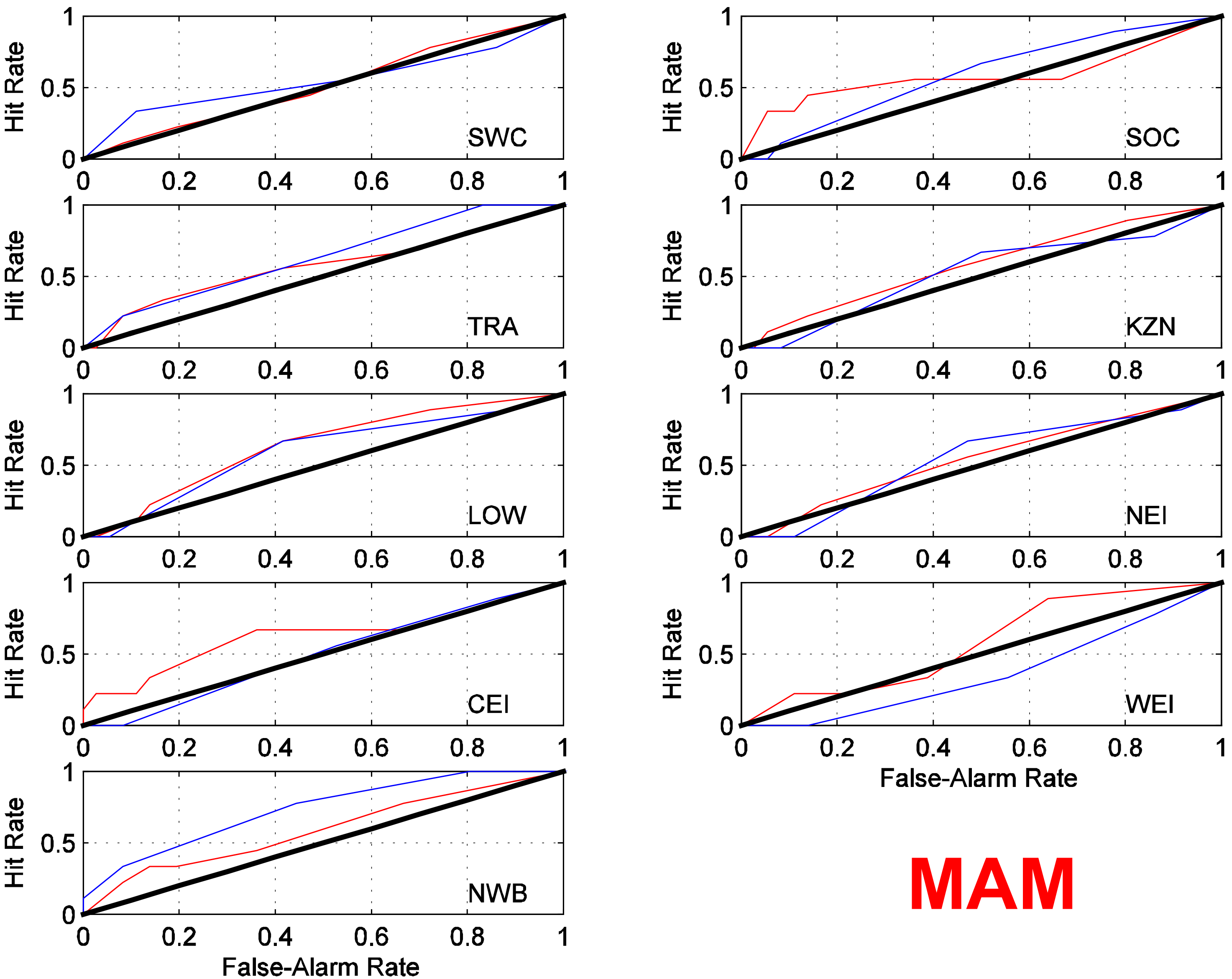

Average RPSS of Extreme Years
(9 wet; 9 dry)
Average RPSS
0.3
0.2
0.1
0
-0.1
-0.2
SON
DJF
MAM
JJA
Wet
Dry

ROC curves

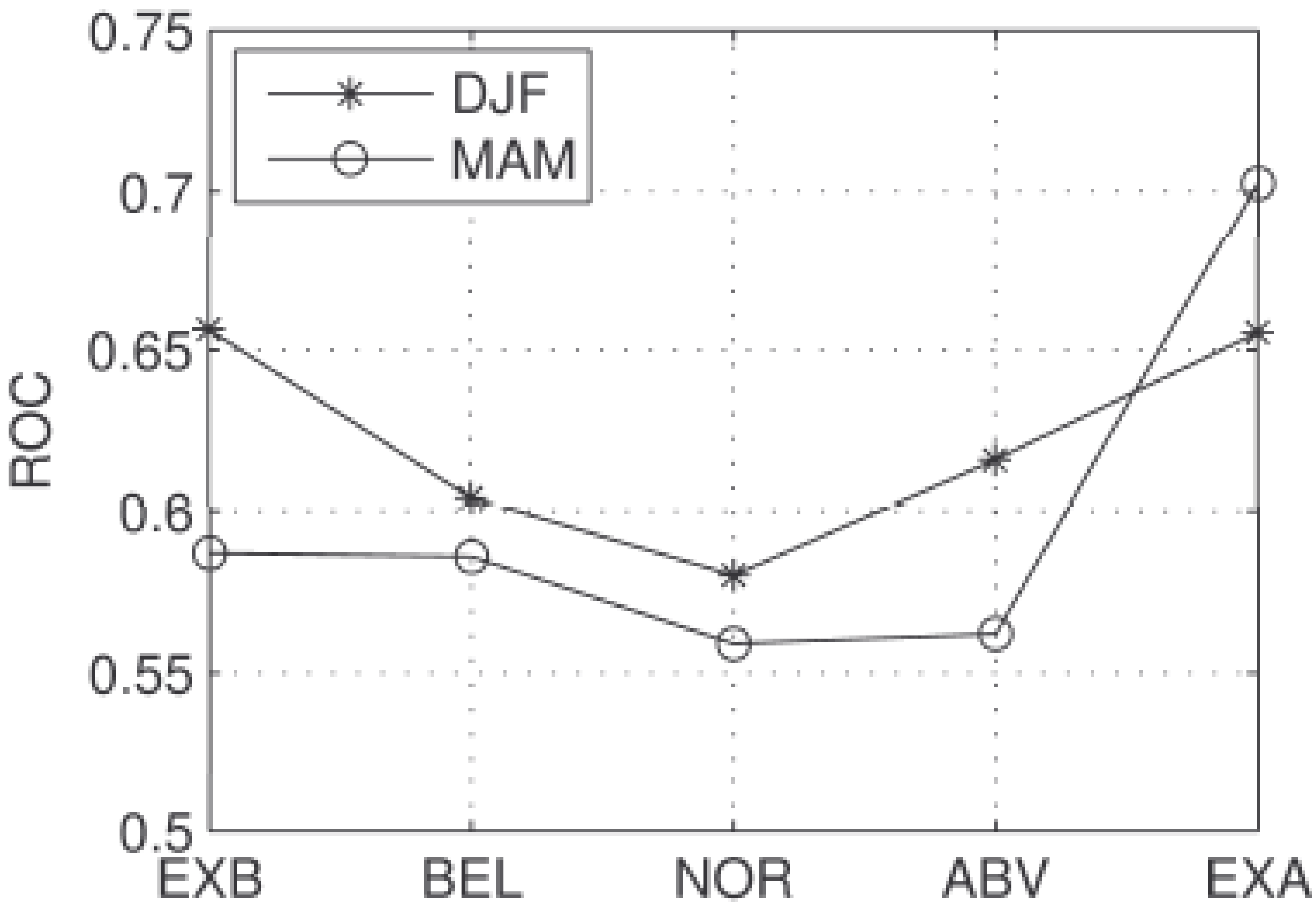


DJF

ROC curves



MAM



DJF
MAM
ROC
0.75
0.7
0.65
0.6
0.55
0.5
EXB
BEL
NOR
ABV
EXA

http://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME/

Datasets and Variables

Cansips	Models NMME Cansips[**FORECAST**]
CMC1-CanCM3	Models NMME CMC1-CanCM3[**HINDCAST FORECAST**]
CMC2-CanCM4	Models NMME CMC2-CanCM4[**HINDCAST FORECAST**]
COLA-RSMAS-CCSM3	Models NMME COLA-RSMAS-CCSM3[**MONTHLY**]
COLA-RSMAS-CCSM4	Models NMME COLA-RSMAS-CCSM4[**MONTHLY**]
CPC-CMAP	Models NMME CPC-CMAP[**prate**]
CPC-CMAP-URD	Models NMME CPC-CMAP-URD[**prate**]
CPC-PRECIP	Models NMME CPC-PRECIP[**prate**]
GFDL-CM2p1	Models NMME GFDL-CM2p1[**MONTHLY**]
GFDL-CM2p1-aer04	Models NMME GFDL-CM2p1-aer04[**MONTHLY**]
GFDL-CM2p5-FLOR-A06	Models NMME GFDL-CM2p5-FLOR-A06[**MONTHLY**]
GFDL-CM2p5-FLOR-B01	Models NMME GFDL-CM2p5-FLOR-B01[**MONTHLY**]
GHCN_CAMS	Models NMME GHCN_CAMS[**updated temp**]
IRI-ECHAM4p5-AnomalyCoupled	Models NMME IRI-ECHAM4p5-AnomalyCoupled[**MONTHLY**]
IRI-ECHAM4p5-DirectCoupled	Models NMME IRI-ECHAM4p5-DirectCoupled[**MONTHLY**]
LSMASK	Models NMME LSMASK[**land**]
NASA-GMAO	Models NMME NASA-GMAO[**MONTHLY**]
NASA-GMAO-062012	Models NMME NASA-GMAO-062012[**MONTHLY**]
NCDC-OISST	Models NMME NCDC-OISST[**sst**]
NCEP-CFSv1	Models NMME NCEP-CFSv1[**MONTHLY**]
NCEP-CFSv2	Models NMME NCEP-CFSv2[**HINDCAST FORECAST**]

http://iri.columbia.edu/our-expertise/climate/tools/cpt/

Climate Predictability Tool

The Climate Predictability Tool (CPT) is a software package for constructing a seasonal climate forecast model, performing model validation, and producing forecasts given updated data. Its design has been tailored for producing seasonal climate forecasts using model output statistic (MOS) corrections to climate predictions from general circulation model (GCM), or for producing forecasts using fields of sea-surface temperatures or similar predictors. Although the software is specifically tailored for these applications, it can be used in more general settings to perform canonical correlation analysis (CCA), principal components regression (PCR), or multiple linear

IRI-WMO Workshop on Tailoring of Seasonal Forecasts. A.Curtis/IRI

Important Links

Downloads

CPT Windows 15.3.7 [6.5MB], January 29, 2016

Latest Release Notes

Tutorials

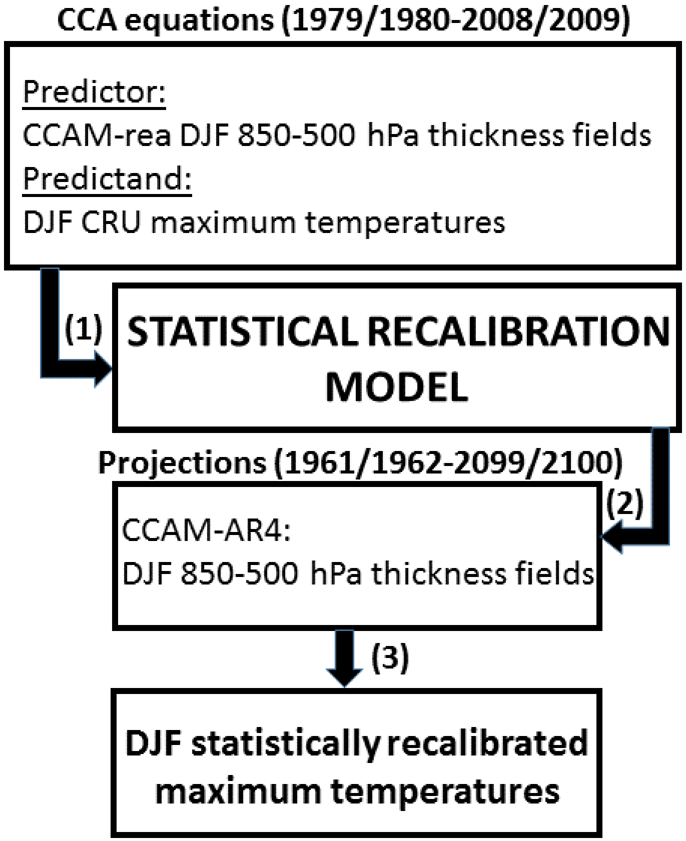
Frequently Asked Questions

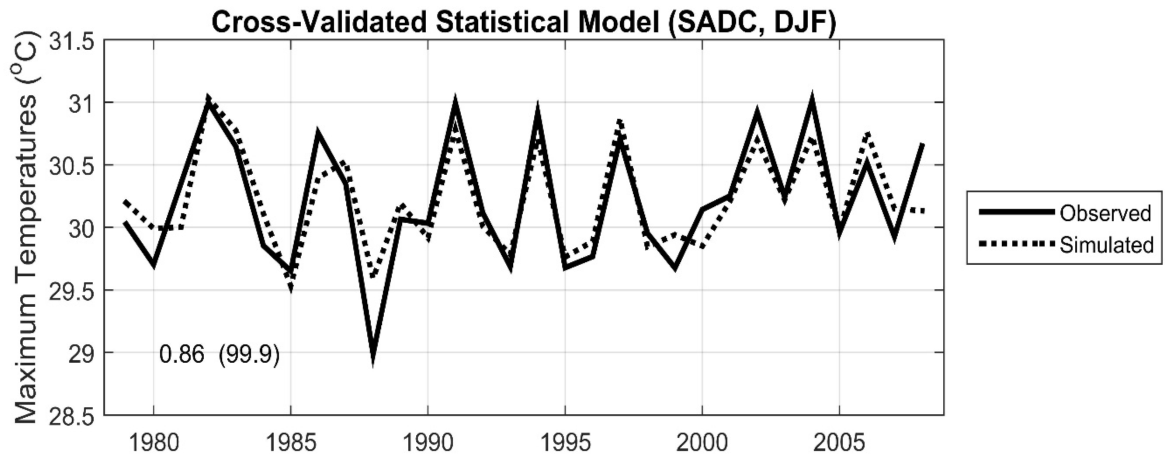
Tutorial (PDF, English version, July, 2011)

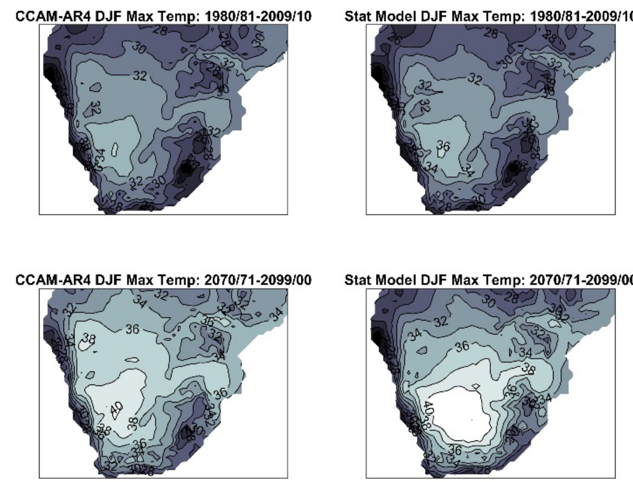
Cours d'instruction de CPT (PDF, French version, Feb 2013)

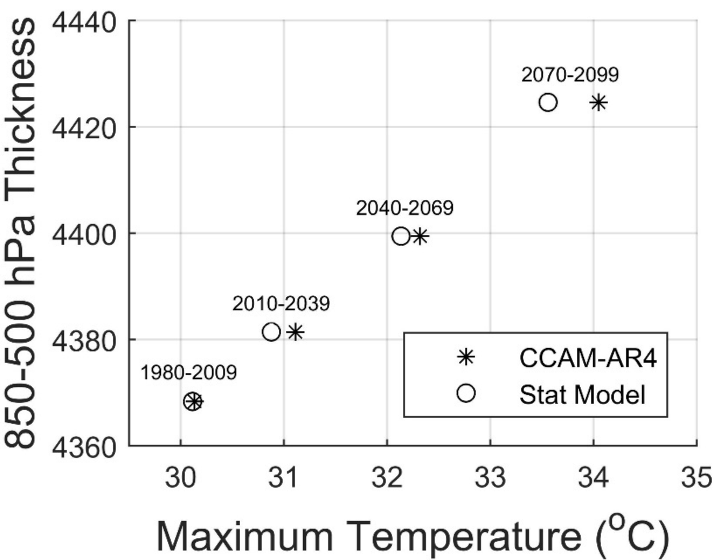
Tutorial Videos for CPTv14.7.4 New Features: (English) and (Spanish)

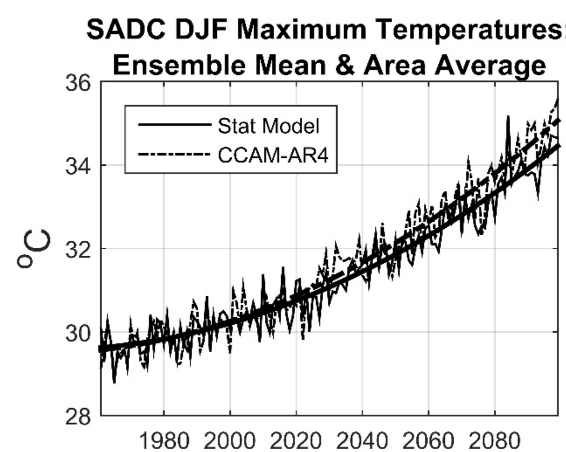
Tutorial Videos for CPTv14 SPI Demo (English) and (Spanish)









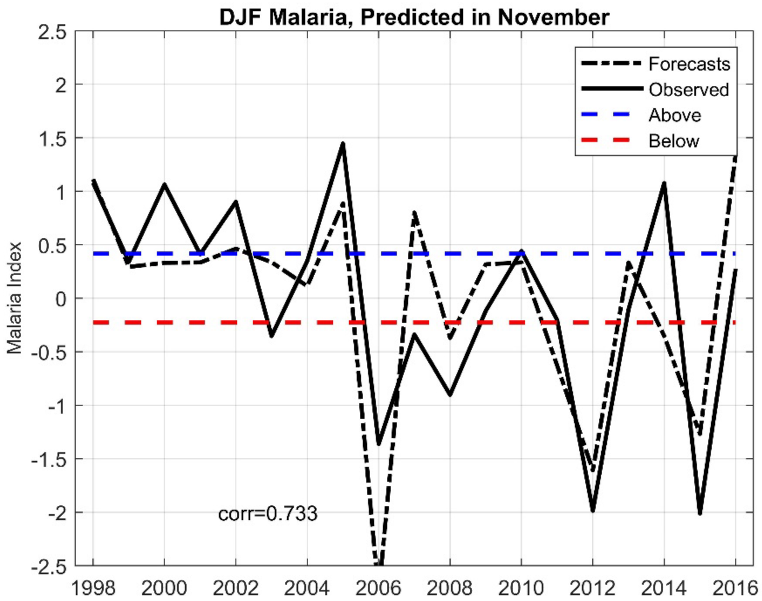


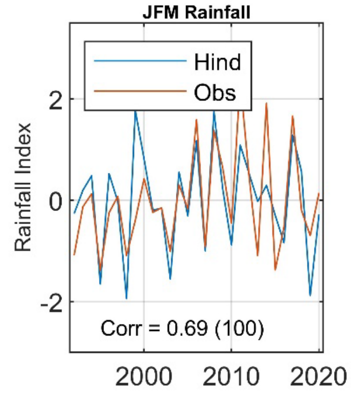
Theor Appl Climatol
DOI 10.1007/s00704-017-2168-8

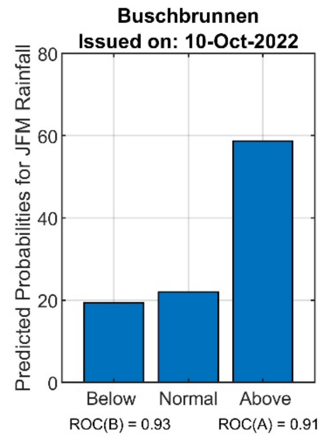
ORIGINAL PAPER

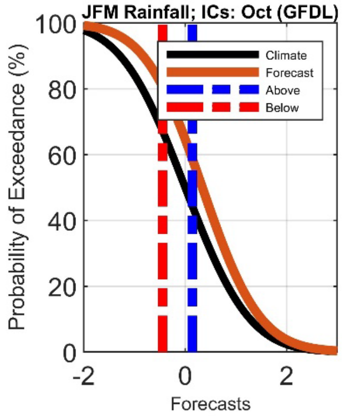
Towards bridging the gap between climate change projections and maize producers in South Africa

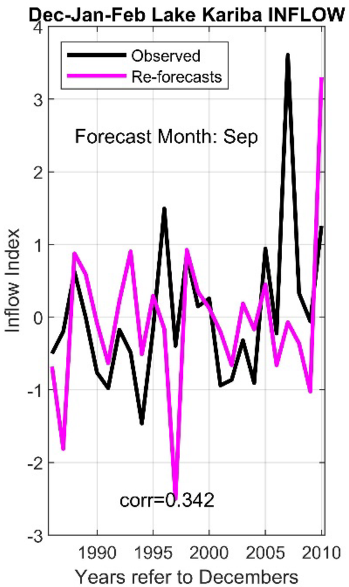
Willem A. Landman[1] · Francois Engelbrecht[2,3] · Bruce Hewitson[4] · Johan Malherbe[2] · Jacobus van der Merwe[2]

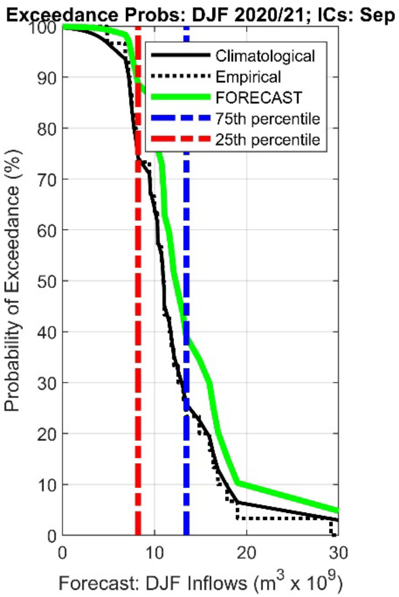

DJF Malaria, Predicted in November
Forecasts
Observed
Above
Below
Malaria Index
corr=0.733

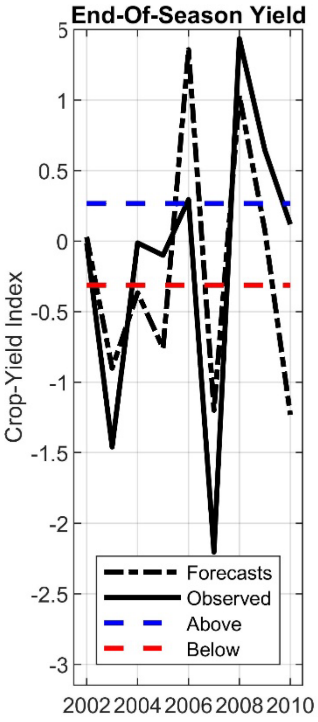

JFM Rainfall
Hind
Obs
Rainfall Index
Corr = 0.69 (100)

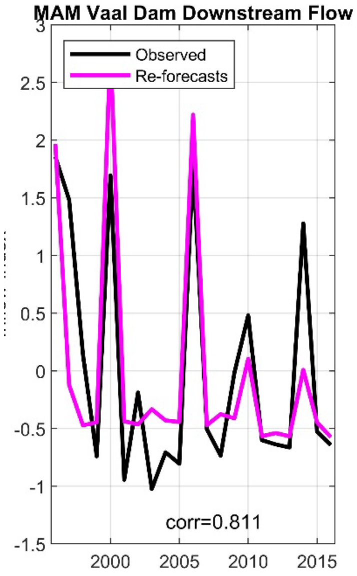

Buschbrunnen
Issued on: 10-Oct-2022
Predicted Probabilities for JFM Rainfall
Below
Normal
Above
ROC(B) = 0.93
ROC(A) = 0.91

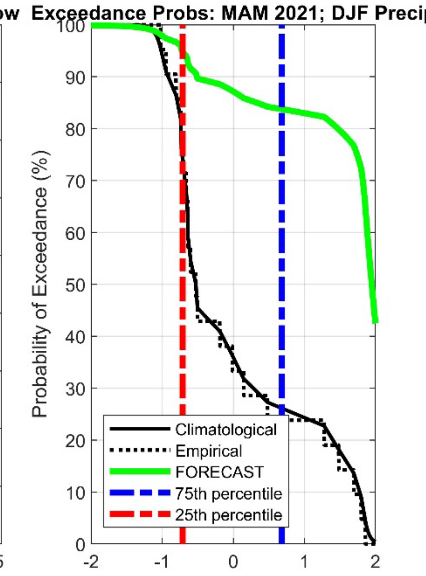

JFM Rainfall; ICs: Oct (GFDL)
Climate
Forecast
Above
Below
Probability of Exceedance (%)
Forecasts


Dec-Jan-Feb Lake Kariba INFLOW
Observed
Re-forecasts
Forecast Month: Sep
Inflow Index
corr=0.342
Years refer to Decembers


Exceedance Probs: DJF 2020/21; ICs: Sep
Climatological
Empirical
FORECAST
75th percentile
25th percentile
Probability of Exceedance (%)
Forecast: DJF Inflows (m3 x 109)


End-Of-Season Yield
Crop-Yield Index
Forecasts
Observed
Above
Below

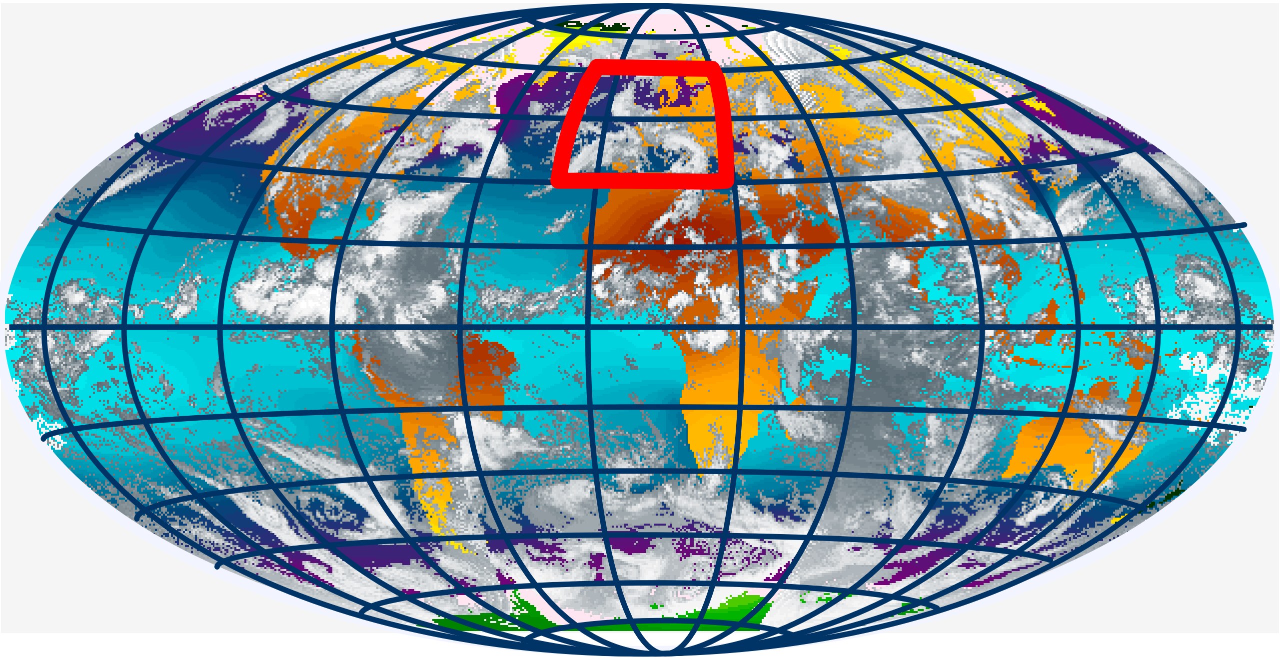

MAM Vaal Dam Downstream Flow
Observed
Re-forecasts
corr=0.811

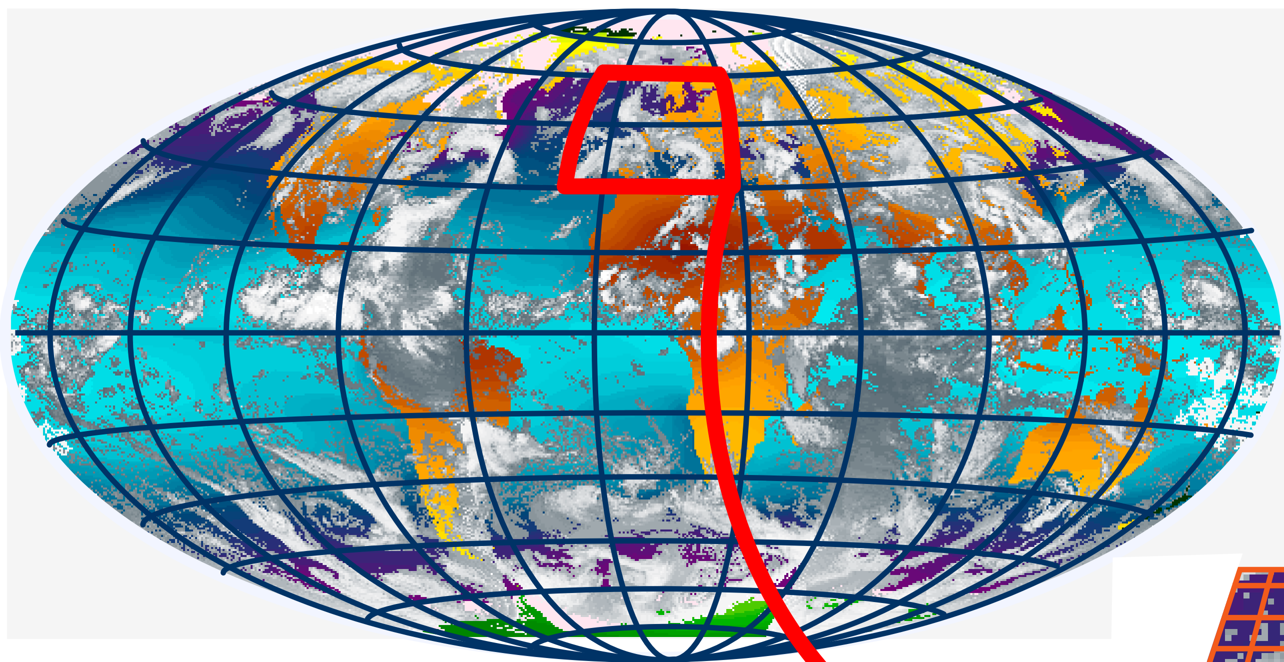

Exceedance Probs: MAM 2021; DJF Precip
Probability of Exceedance (%)
Climatological
Empirical
FORECAST
75th percentile
25th percentile

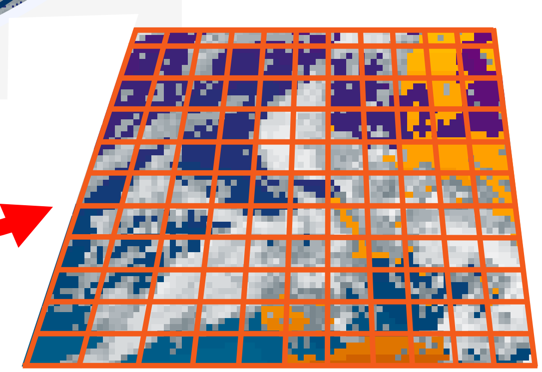
Dynamical Downscaling

- GCM resolution not fine enough to resolve small-scale atmospheric circulation
- Possible to produce detailed simulations for selected regions by nesting a Regional Climate Model (RCM; or LAM) into a global GCM
- GCM large-scale fields are used as driving initial and time-dependent lateral boundary conditions (i.e., 6-hourly) for the RCM
- Sea-surface temperatures prescribed

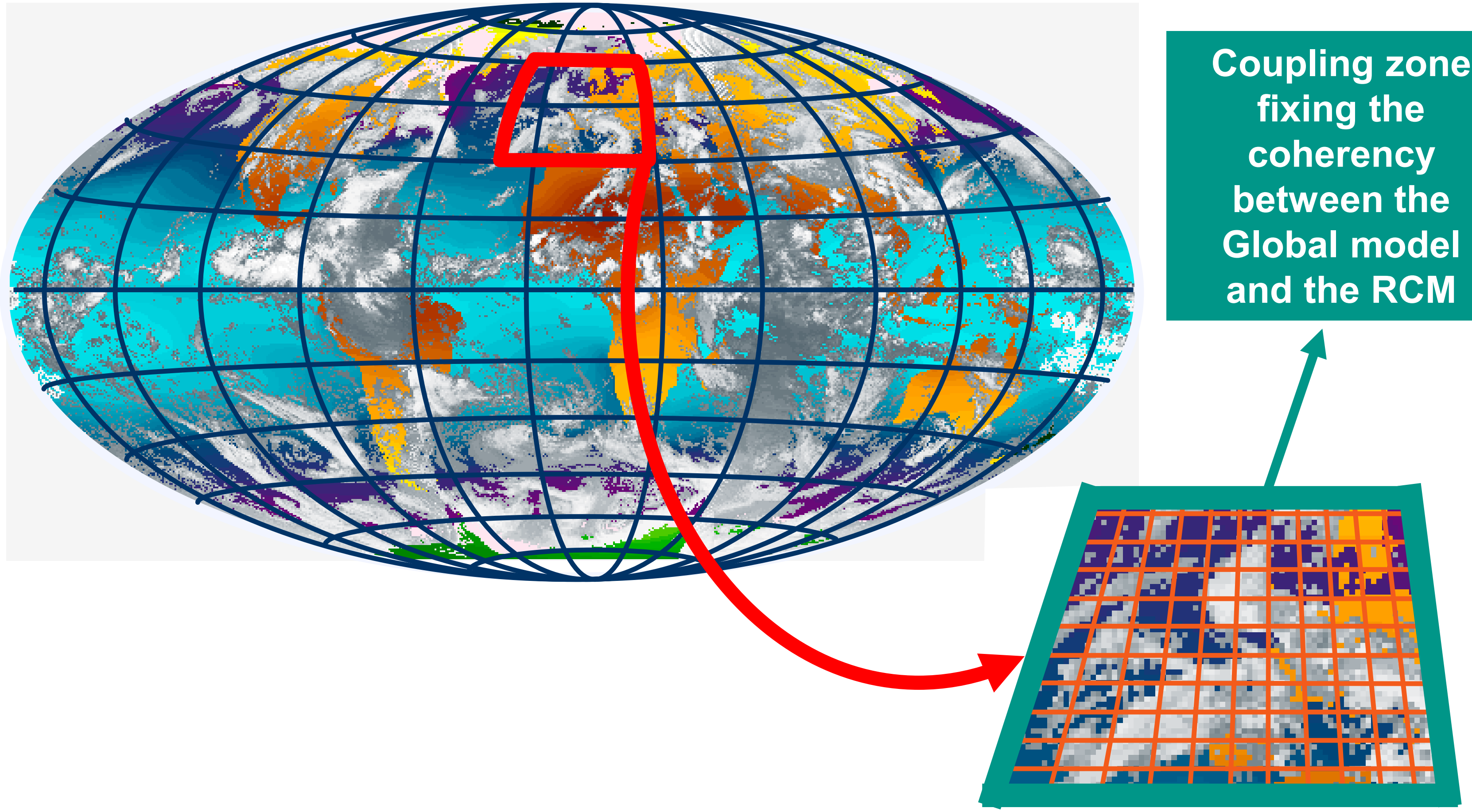
RCM for domain of interest







Regional Climate Model **: The RCM is coupled to a global model which regularly provides boundary conditions to the RCM during the integration (e.g., every 6 hours)**



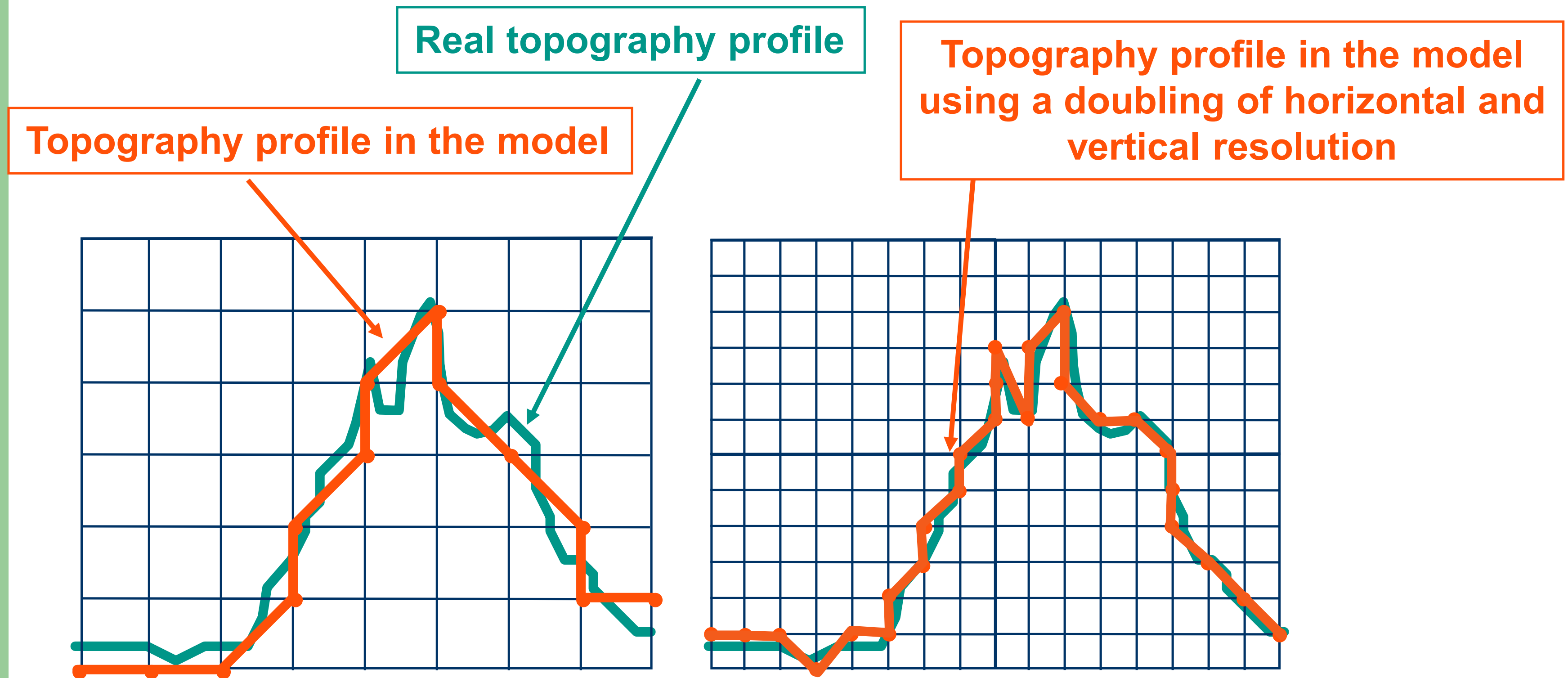
Coupling zone fixing the coherency between the Global model and the RCM

Comparison with GCMs

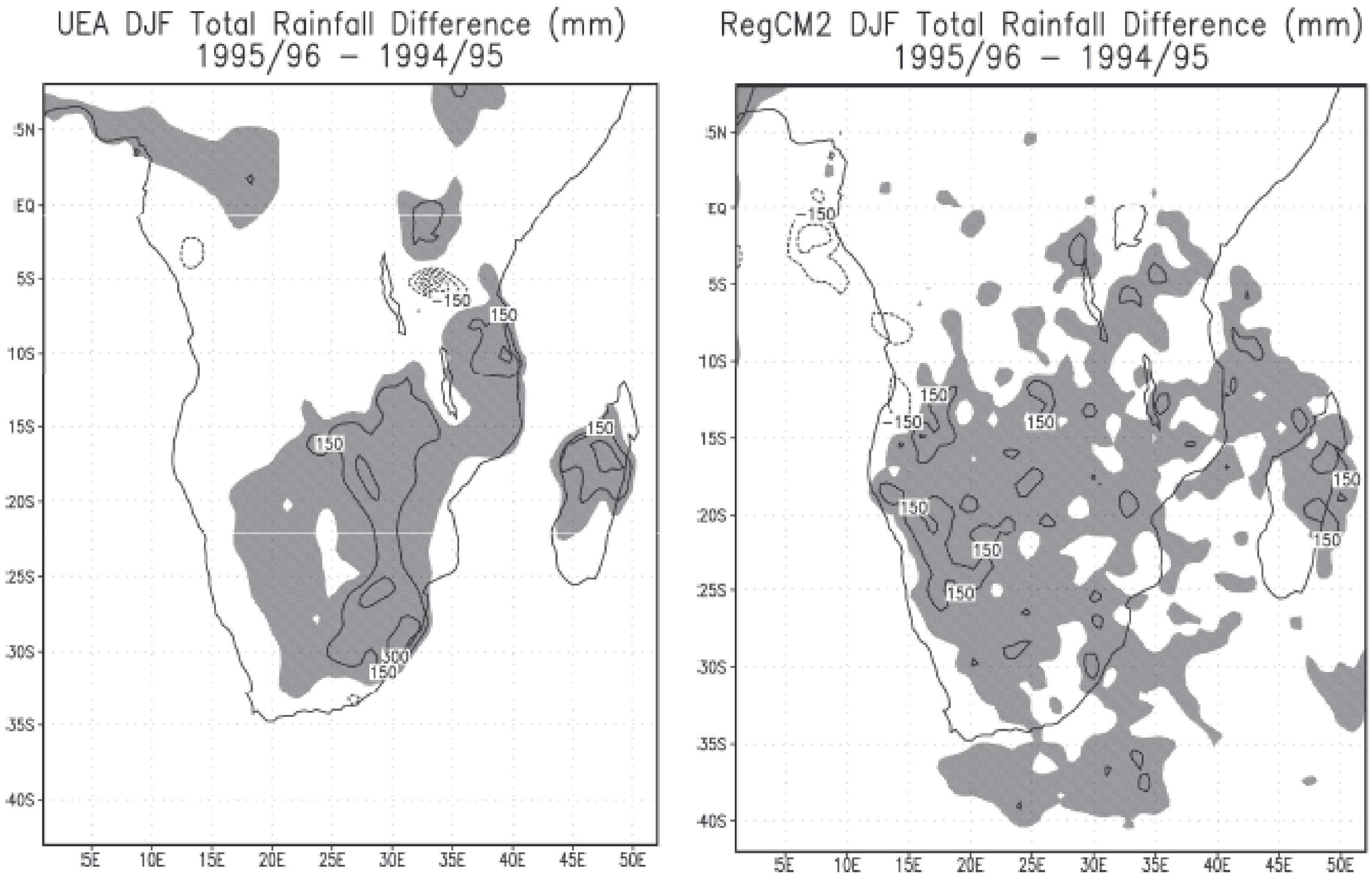
- Large-scale average circulation of RCM similar to that of driving GCM
- RCM produces better regional detail of temperature and precipitation distribution
- RCM able to simulate regional structures:
  - precipitation maxima at coast and mountains
  - sharp temperature gradient at coast
- RCM better able to represent orographic precipitation

Model topography

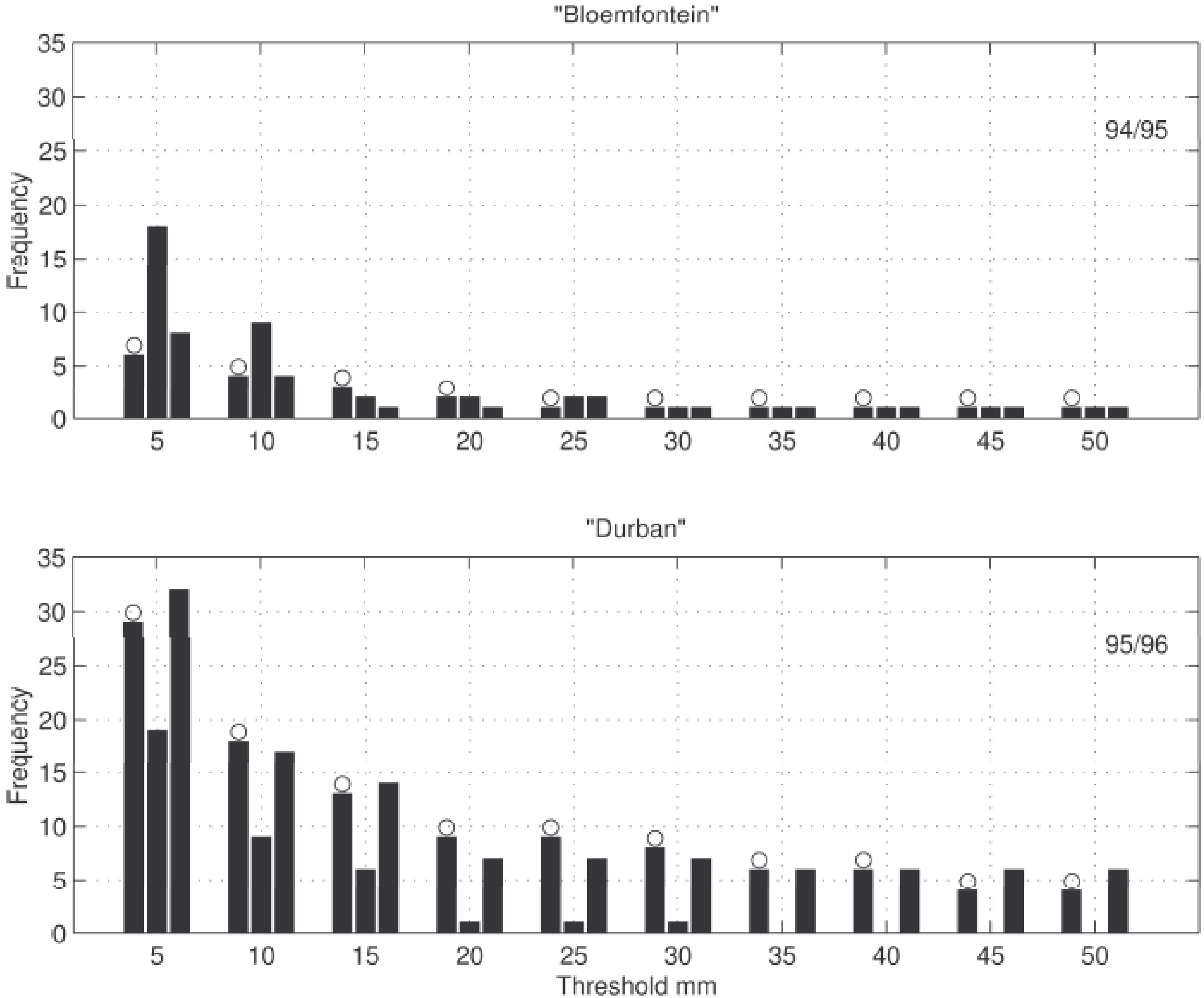
An example for the topography of the model.



Simulated rainfall differences using a regional climate model



Difference maps (wet season minus dry season): observed (left) and simulated (right). Although the RCM was able to produce a lot of detail in the rainfall spatial pattern, it still misplaced the area of maximum rainfall difference



Using a <u>simple linear regression</u> approach, <u>prost-processing the RCM</u> simulated rainfall thresholds (bars on the right) at two grid-points in close proximity of respectively Bloemfontein and Durban, <u>improved on the "raw" simulated</u> thresholds (middle bars). Observed thresholds are the bars on the left

Some RCM Limitations

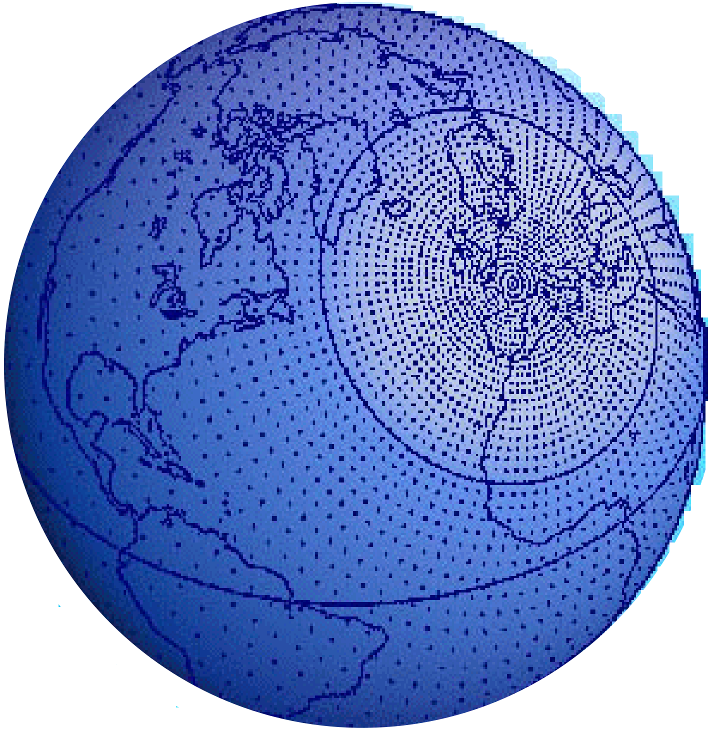
- Excessive accumulated precipitation at steep orography
- Simulated precipitation is sensitive to the choice of cumulus parameterization scheme (RCM and GCM should use similar scheme)
- RCMs can produce spurious precipitation near the boundaries of the domain

Other RCM approaches…

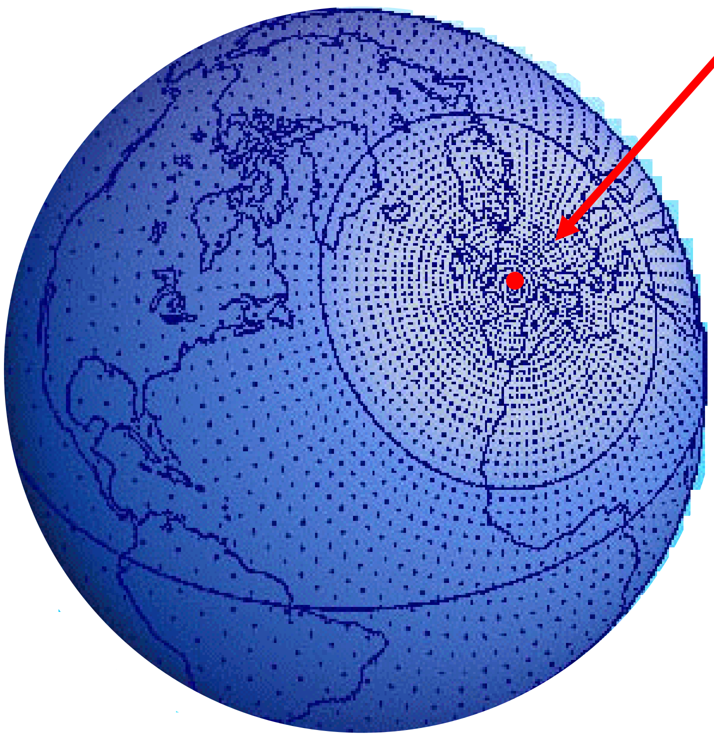
- Two-way nested RCMs – modified synoptic behaviour is fed back to influence the GCM (computationally expensive)
- Variable resolution GCMs

Stretched Grid

Stretched grid corresponds to a variable resolution



Stretched Grid

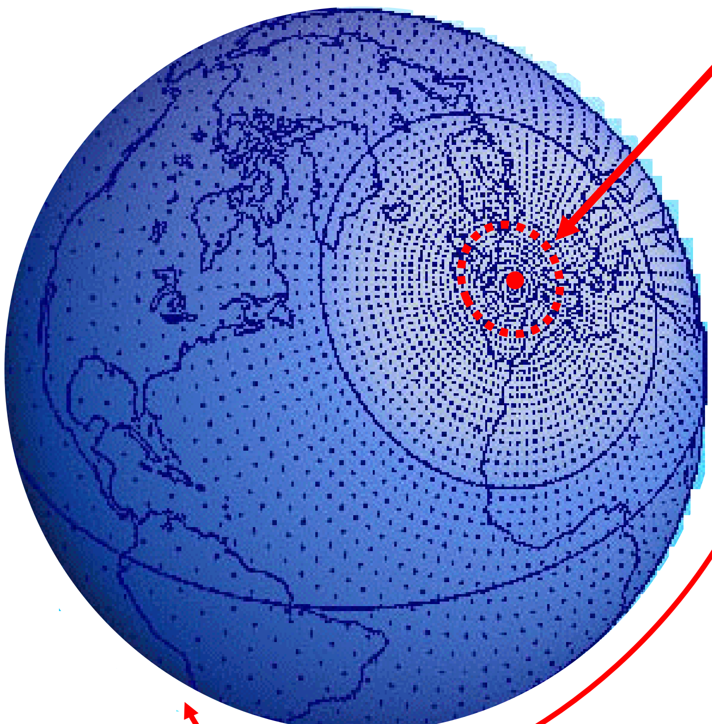


Pole of interest

The closer to the pole of interest, the higher the resolution

Stretched Grid

The spatial resolution here is equivalent to a grid mesh of approximately 30 km.



The spatial resolution is progressively relaxed towards the antipode (near New-Zealand).

The Effect of Regional Climate Model Domain Choice on the Simulation of Tropical Cyclone–Like Vortices in the Southwestern Indian Ocean

WILLEM A. LANDMAN, ANJI SETH, AND SUZANA J. CAMARGO

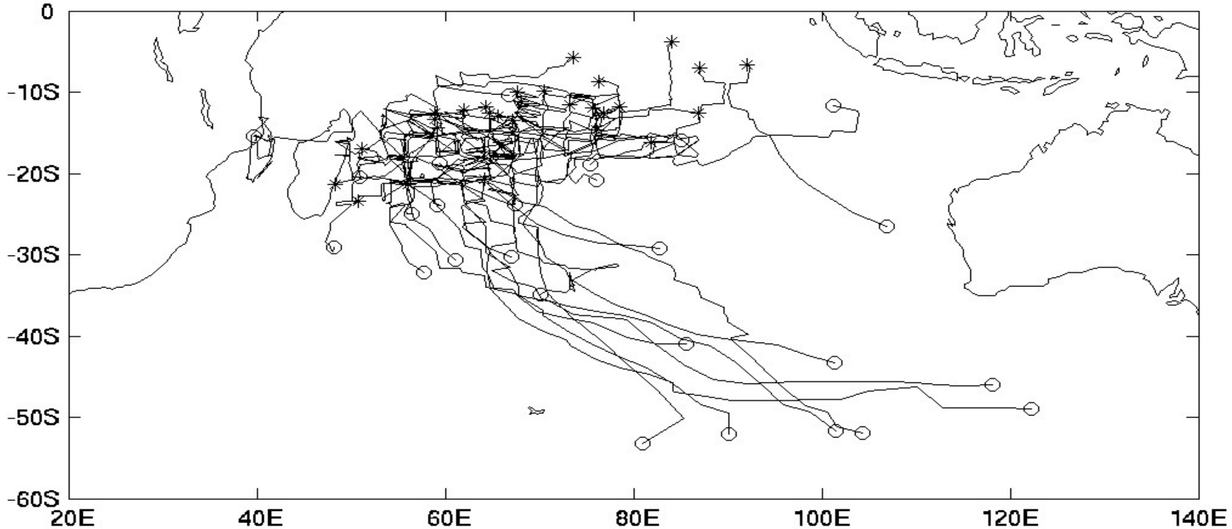
International Research Institute for Climate Prediction, Lamont-Doherty Earth Observatory, Columbia University, Palisades, New York

(Manuscript received 18 December 2002, in final form 30 September 2004)

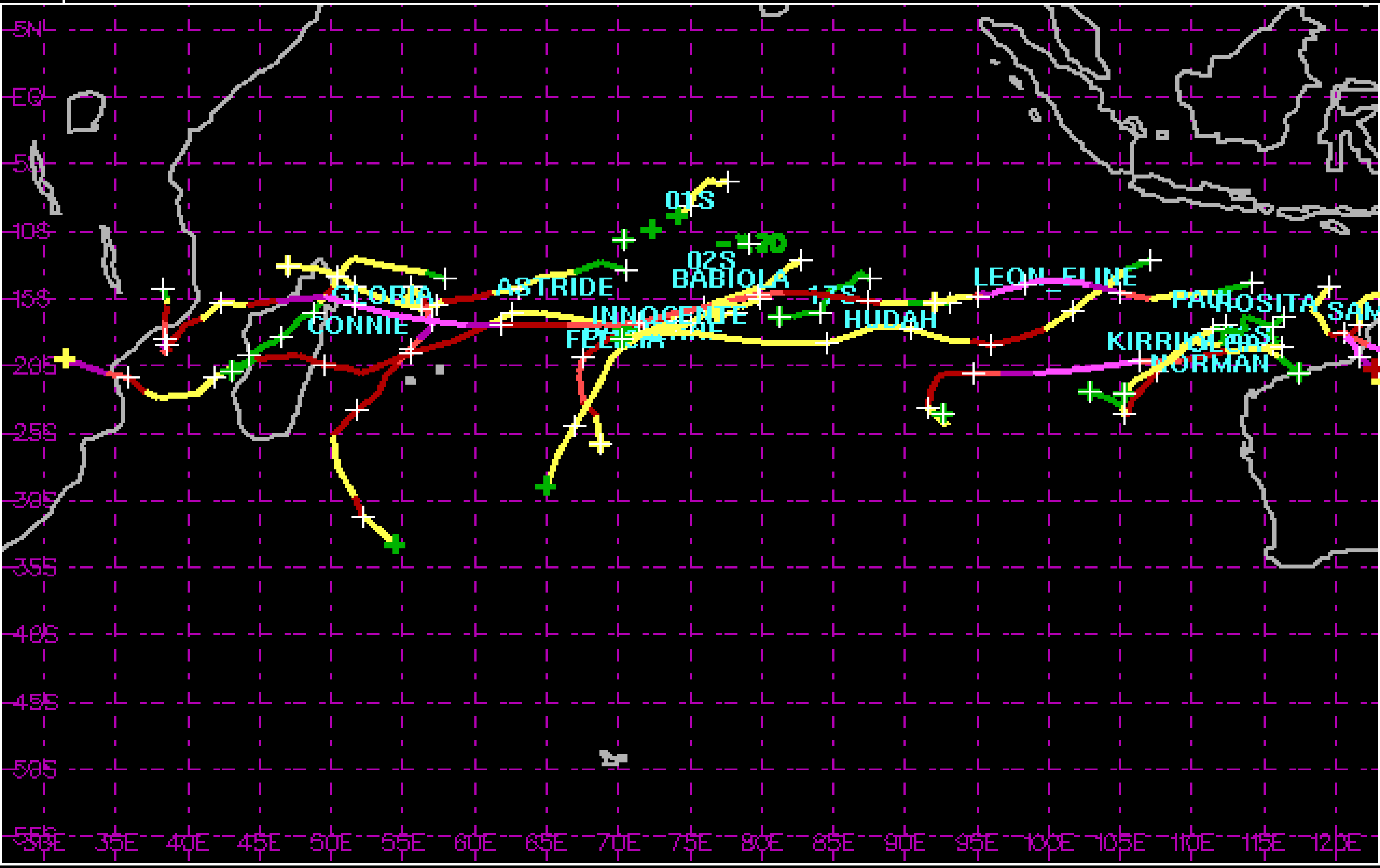
ABSTRACT

A regional climate model is tested for several domain configurations over the southwestern Indian Ocean to examine the ability of the model to reproduce observed cyclones and their landfalling tracks. The interaction between large-scale and local terrain forcing of tropical storms approaching and transiting the island landmass of Madagascar makes the southwestern Indian Ocean a unique and interesting study area. In addition, tropical cyclones across the southern Indian Ocean are likely to be significantly affected by the large-scale zonal flow. Therefore, the effects of model domain size and the positioning of its lateral boundaries on the simulation of tropical cyclone–like vortices and their tracks on a seasonal time scale are investigated. Four tropical cyclones, which occurred over the southwestern Indian Ocean in January of the years 1995–97, are studied, and four domains are tested. The regional climate model is driven by atmospheric lateral boundary conditions that are derived from large-scale meteorological analyses. The use of analyzed boundary forcing enables comparison with observed cyclones in these tests. Simulations are performed using a 60-km horizontal resolution and for an extended time integration of about 6 weeks. Results show that the positioning of the eastern boundary of the regional model domain is of major importance in the life cycle of simulated tropical cyclone–like vortices: a vortex entering through the eastern boundary of the regional model is generally well simulated. The size of the domain also has a bearing on the ability of the regional model to simulate vortices in the Mozambique Channel, and the island landmass of Madagascar additionally influences storm tracks. These results show that the regional model can produce cyclonelike vortices and their tracks (with some deficiencies) given analyzed lateral boundary forcing. Statistical analyses of GCM-driven nested model ensemble integrations are now required to further address predictive skill of cyclones in the southwestern Indian Ocean and to test if the model can realistically simulate tropical storm genesis as opposed to advecting existing tropical disturbances entering through the model boundaries.

TCLVs generated by an ensemble of 24 integrations of 1996 ECHAM4.5 GCM simulations



Tropical Storm Tracks Year 2000



Why Regional Models?

- GCMs tend to simulate tropical cyclone-like vortex tracks in the SIO too far to the east
- Meaningful TC statistics require running GCMs at a fine horizontal resolution
- Due to the coarse resolution of most GCMs, an alternative approach is nesting regional models

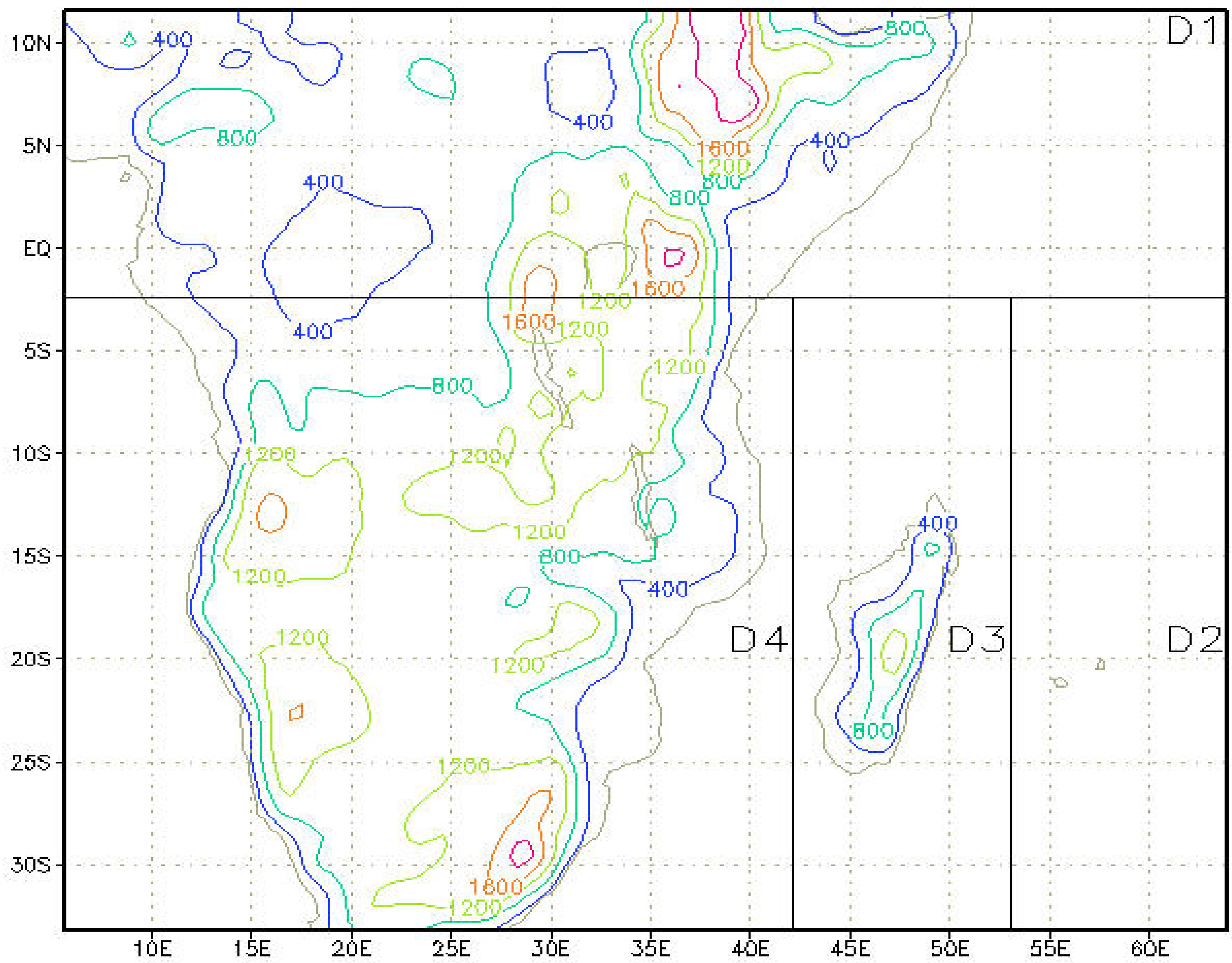
A first approach…

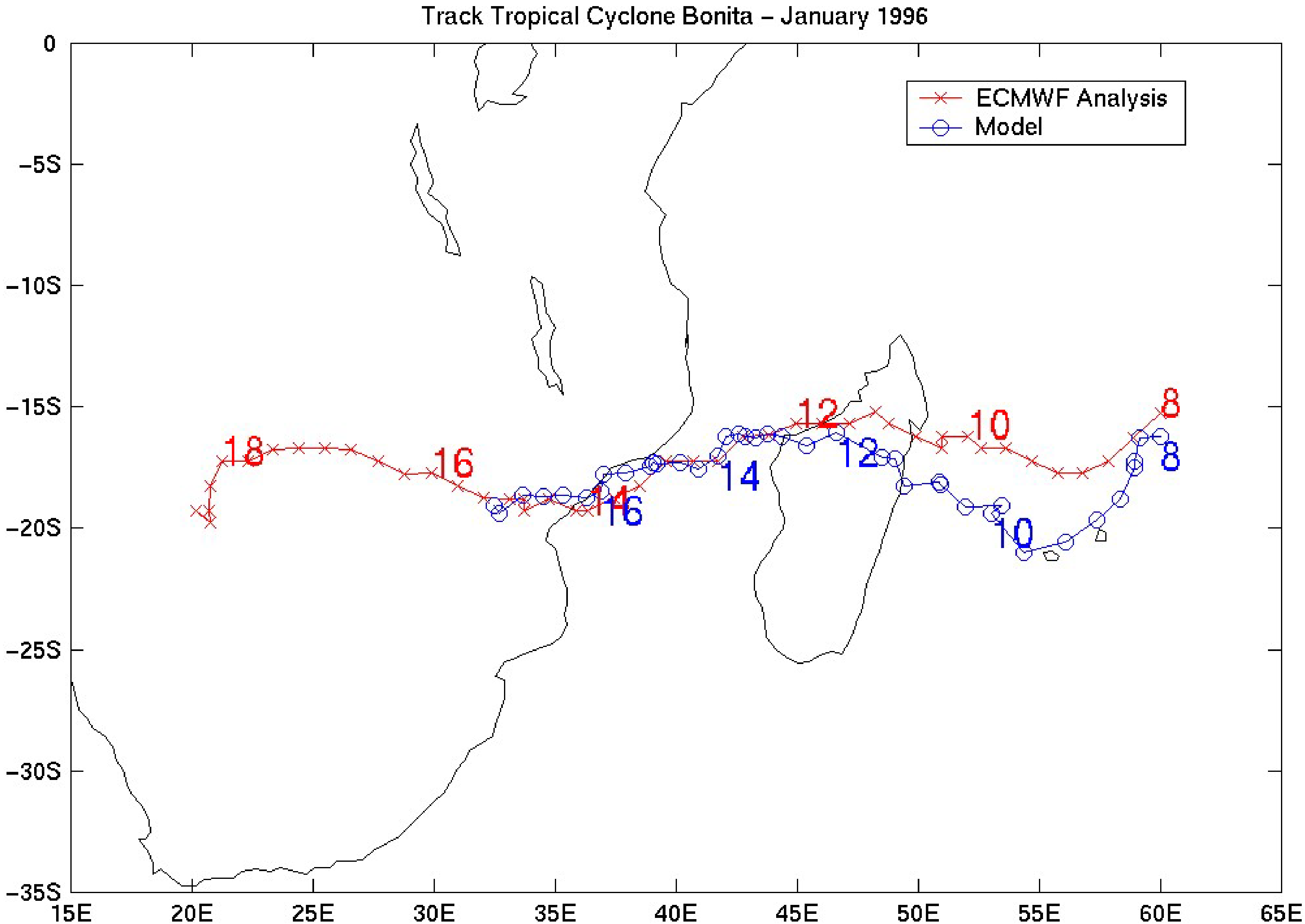
- Driving regional model with large-scale time-dependent meteorological analysis data – mimicking a “perfect” GCM
- The large-scale forcing will enable direct comparison between regional model performance and analysis
- No bogussing of TCLVs – no attempt is made to synthetically strengthen TCLVs

The regional model

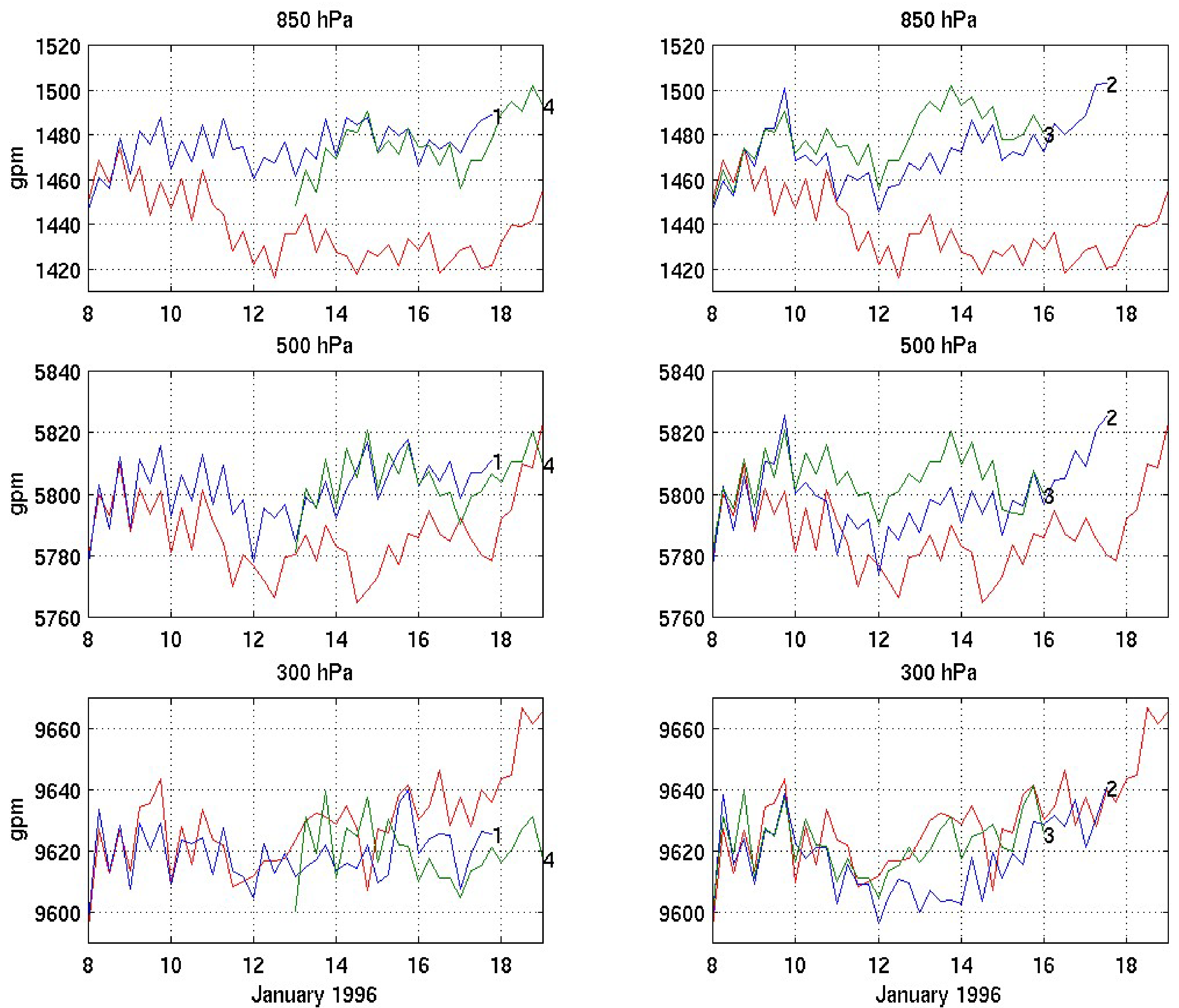
- RegCM2
- One-way nesting, whereby ECMWF analyses data are the initial and time-dependent lateral boundary conditions
- Horizontal resolution: 60 km
- Time step: 150s
- SSTs are monthly mean values
- Initialized on 16 December preceding January (minimum 16 days model spin-up time)

Domains

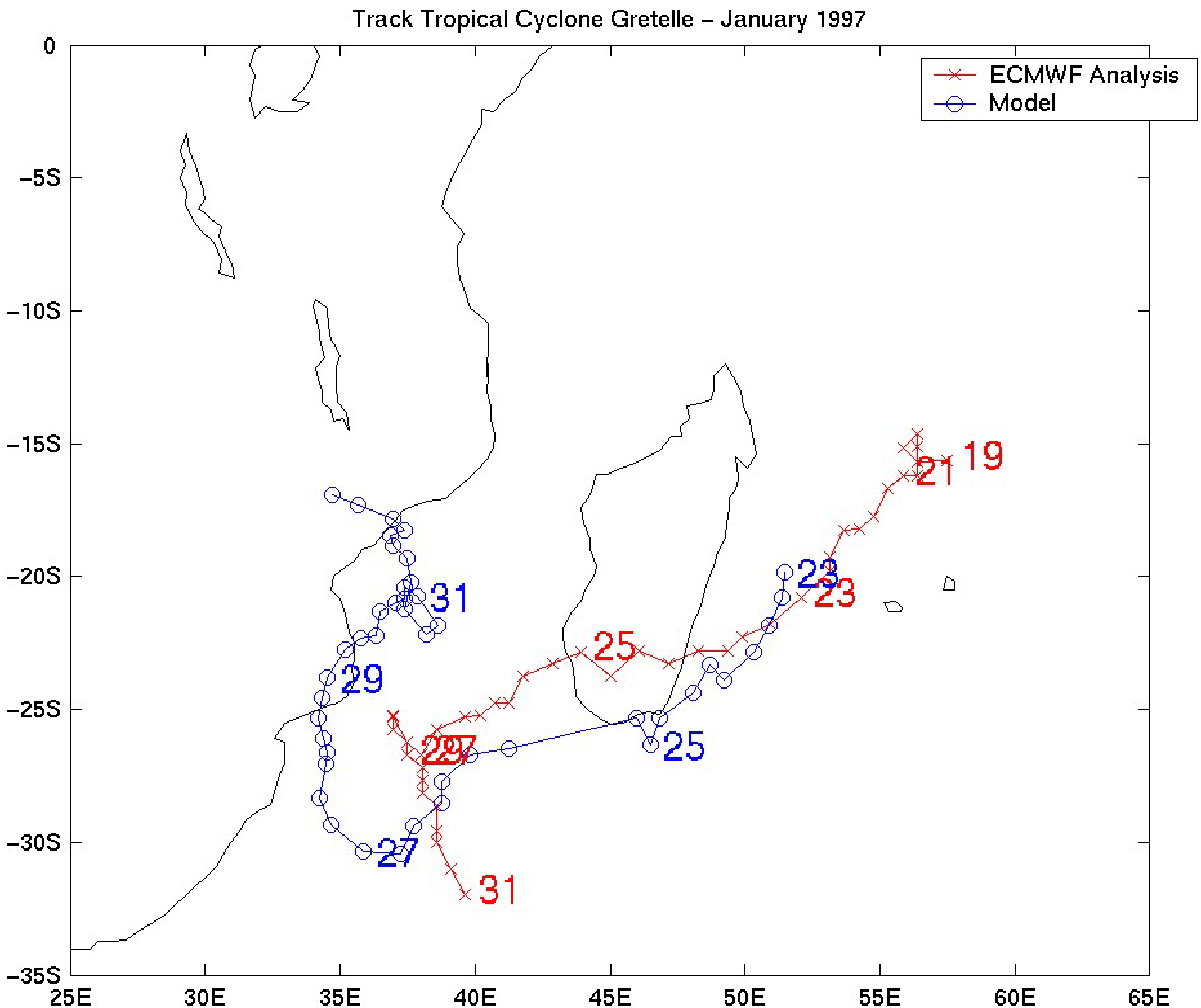

D1
D2
D3
D4
400
800
1200
1600
10N
5N
EQ
5S
10S
15S
20S
25S
30S
10E
15E
20E
25E
30E
35E
40E
45E
50E
55E
60E



Track Tropical Cyclone Bonita – January 1996
ECMWF Analysis
Model
0
−5S
−10S
−15S
−20S
−25S
−30S
−35S
15E
20E
25E
30E
35E
40E
45E
50E
55E
60E
65E
8
10
12
14
16
18

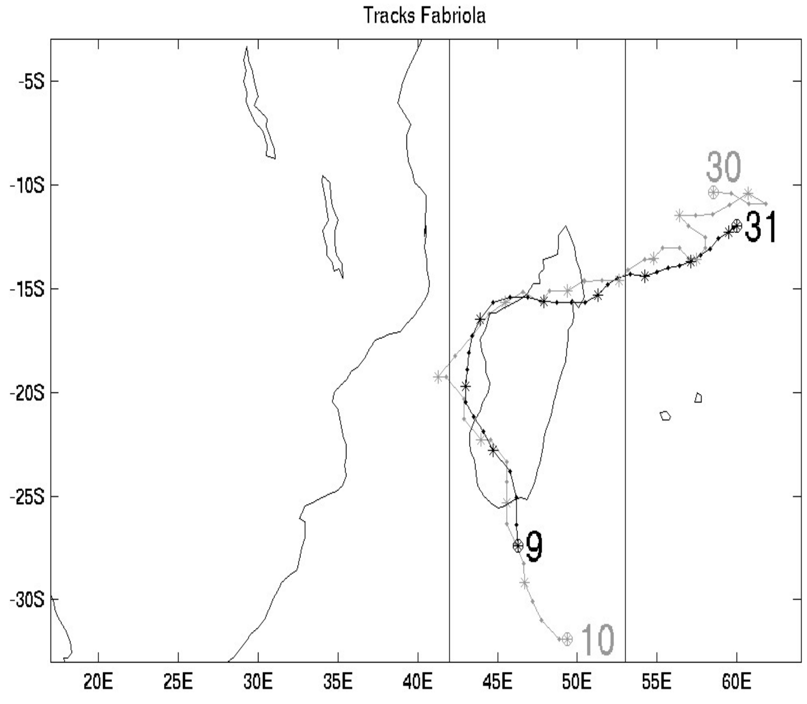


850 hPa
1520
1500
1480
1460
1440
1420
gpm
8
10
12
14
16
18
1
4
850 hPa
2
3
500 hPa
5840
5820
5800
5780
5760
500 hPa
300 hPa
9660
9640
9620
9600
January 1996
300 hPa
January 1996

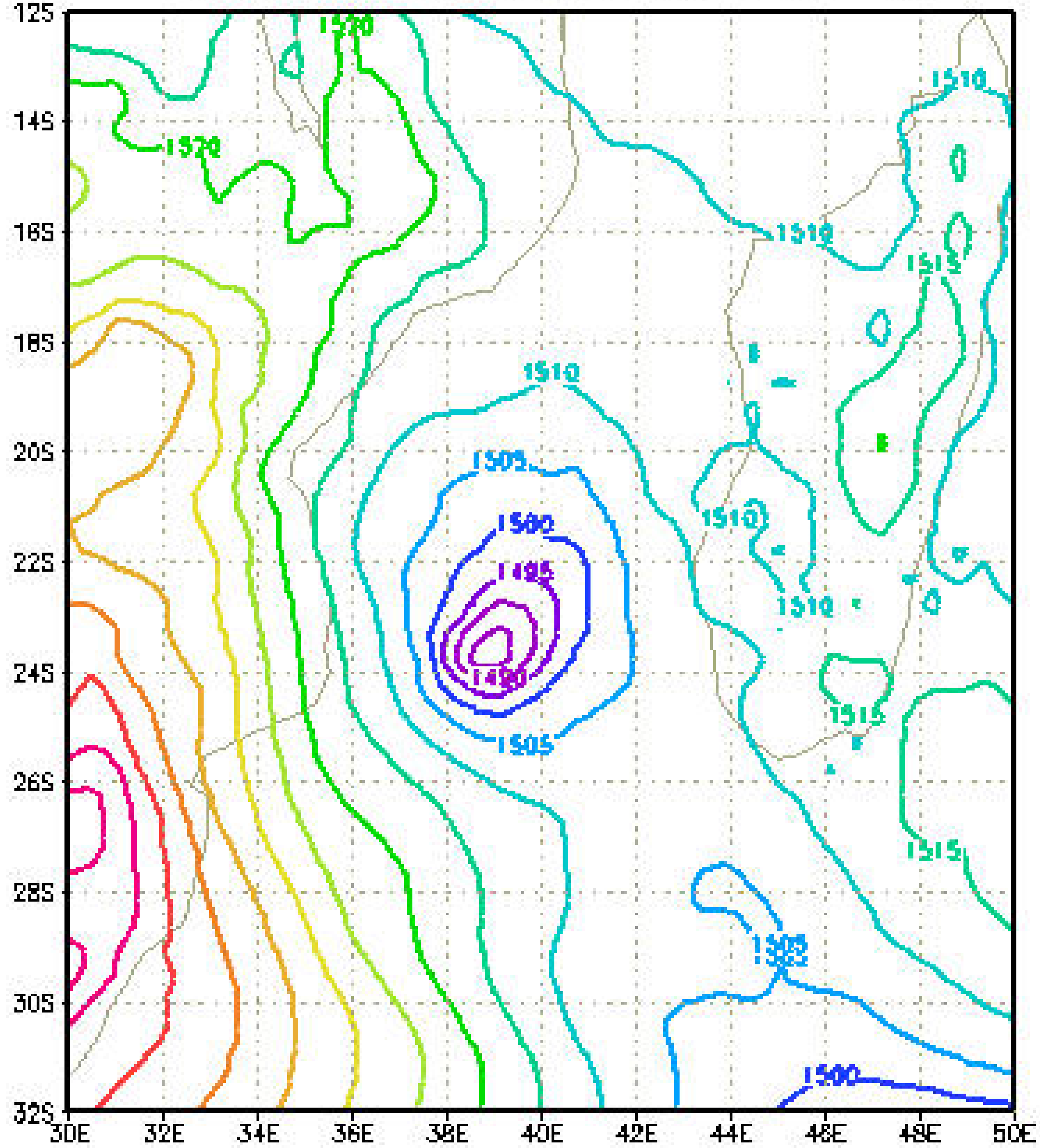


Track Tropical Cyclone Gretelle – January 1997
ECMWF Analysis
Model
0
-5S
-10S
-15S
-20S
-25S
-30S
-35S
25E
30E
35E
40E
45E
50E
55E
60E
65E
19
21
23
25
27
29
31

JTWC, analysis and simulated track…



1995:1:21:0 (from domain 2)

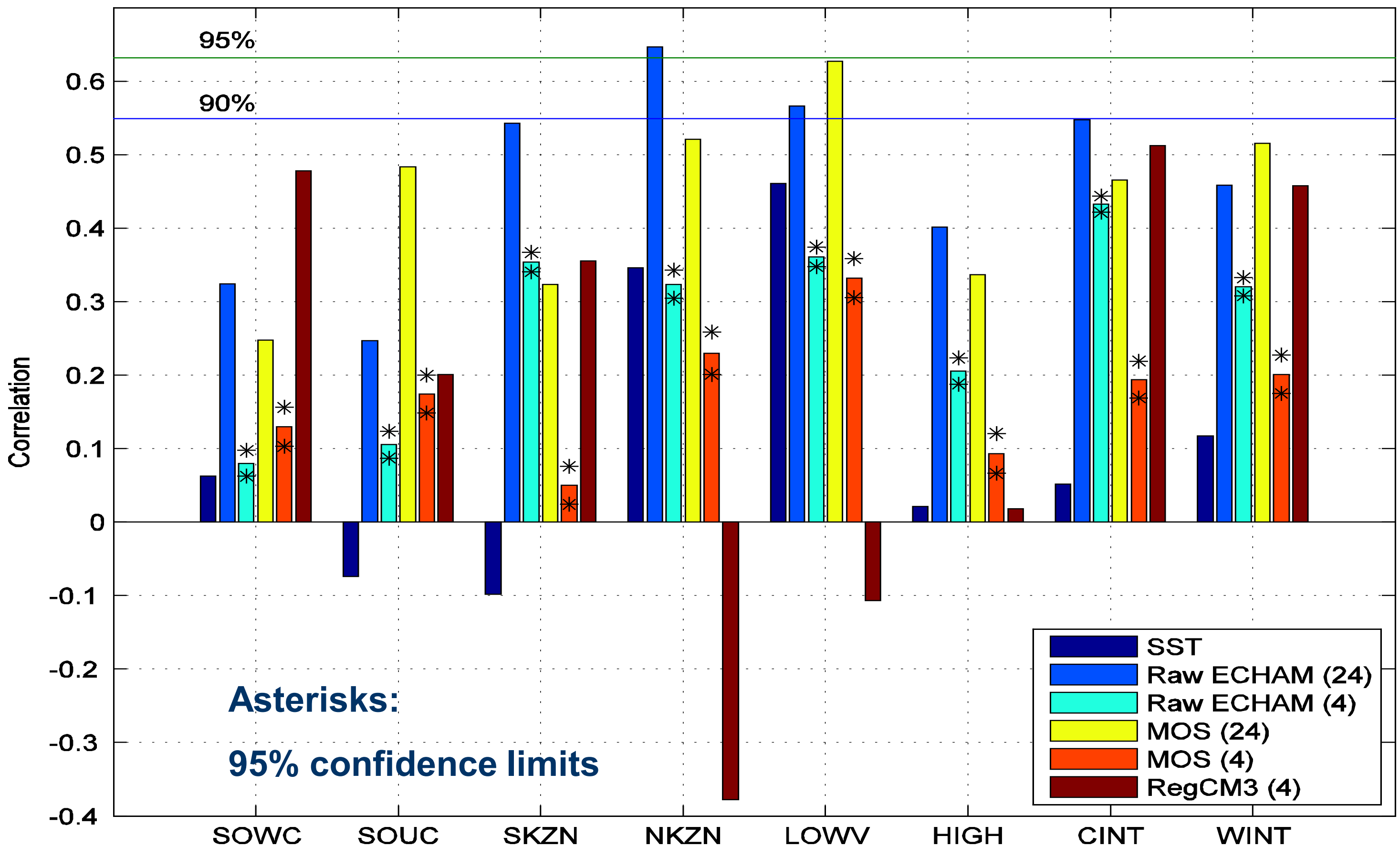


GrADS: COLA/IGES

2002-02-20-09:13

Skill comparisons

Skill comparison between baseline model (SST as predictor), GCM, MOS and RegCM3 simulations of DJF rainfall from 1991/92 – 2000/2001 (10 years)



Points to consider

- Both empirical and dynamical downscaling techniques have the potential to improve on large-scale forecasts of GCMs
- Empirical techniques are easy to use and do not need lots of CPU; but climate might be unstable
- Dynamical techniques are complex and require a lot of CPU; but skill limited by parameterization schemes, etc.
- ***To justify its operational use, dynamical techniques should outperform empirical techniques***