A view on the state of seasonal forecasting in South Africa

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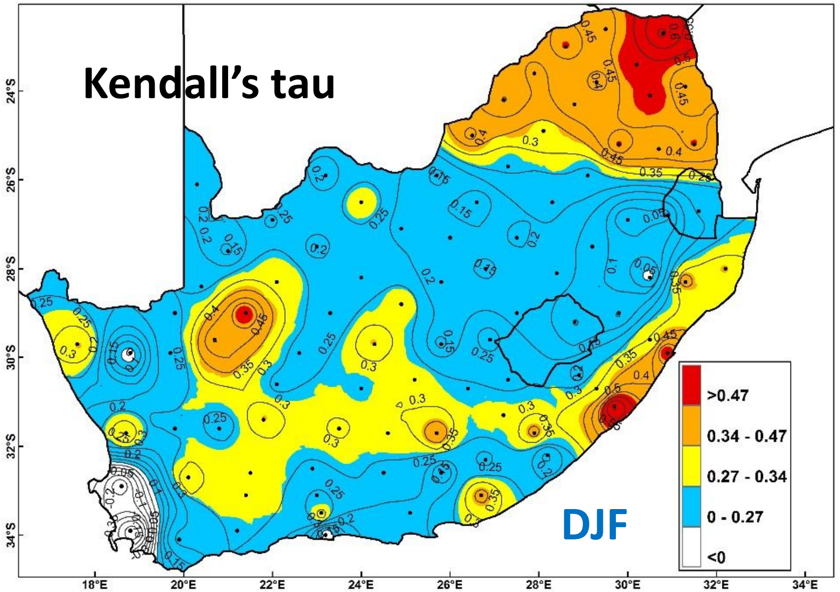
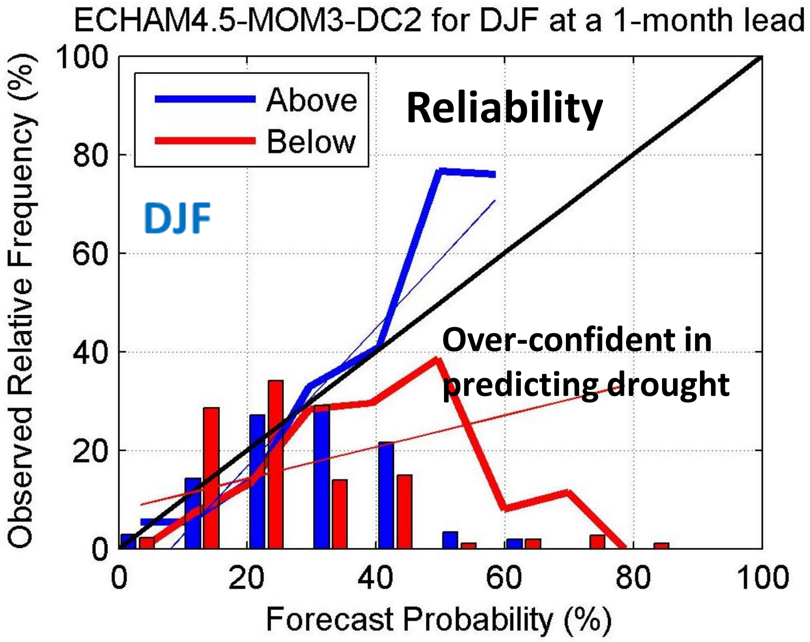
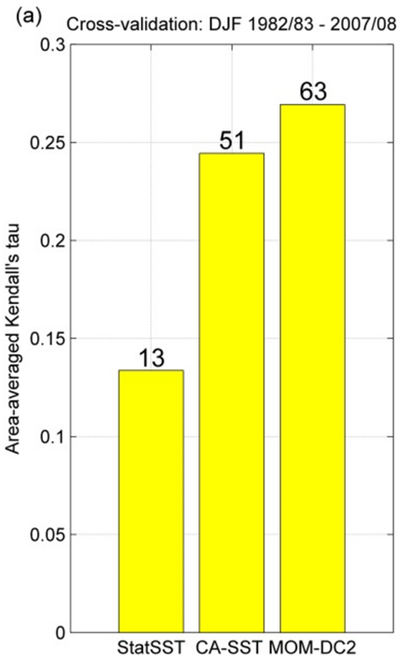
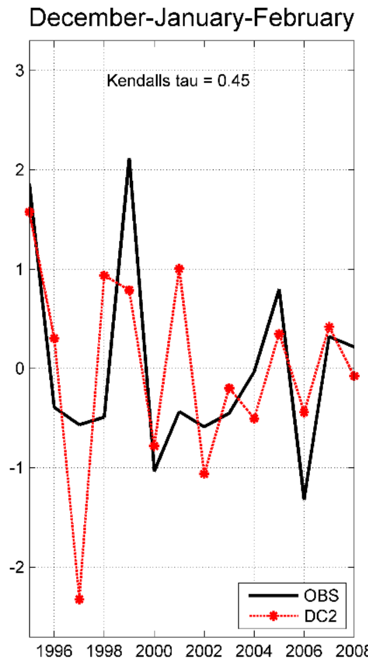
Current Seasonal Forecasting Capabilities (Rainfall)



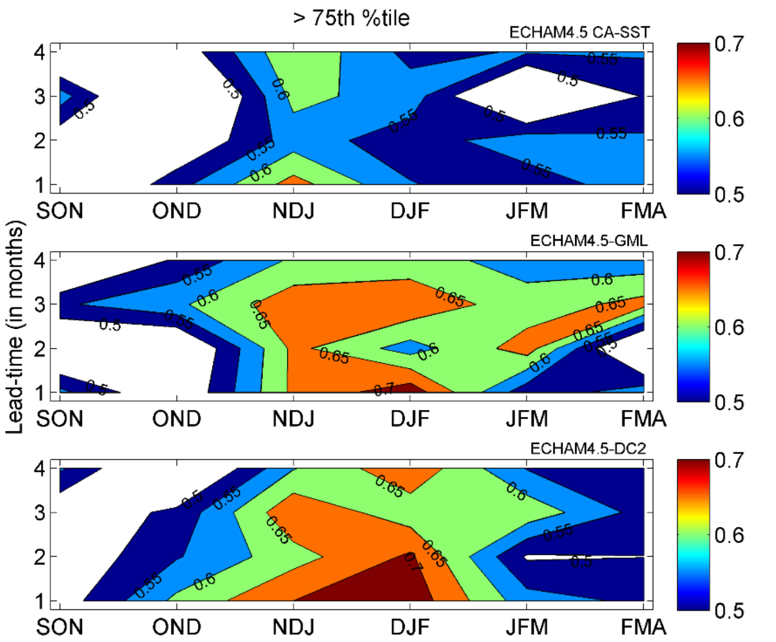


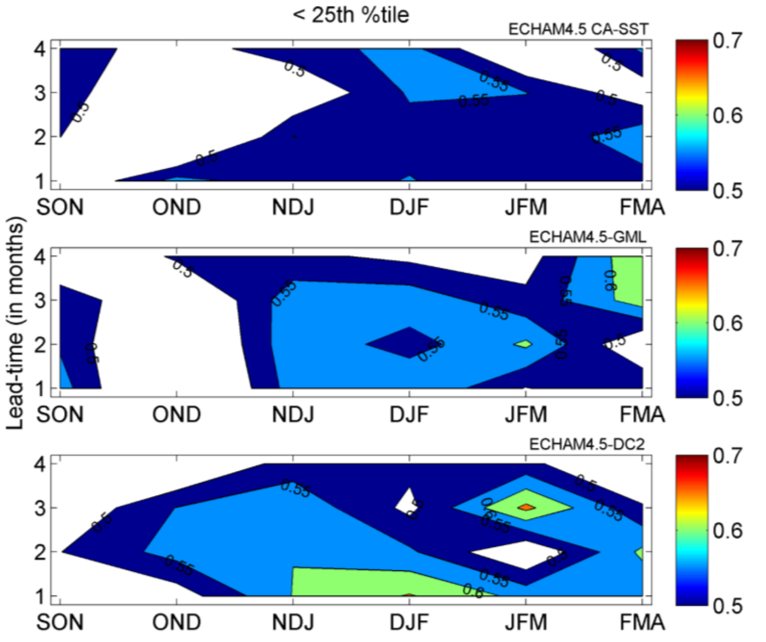


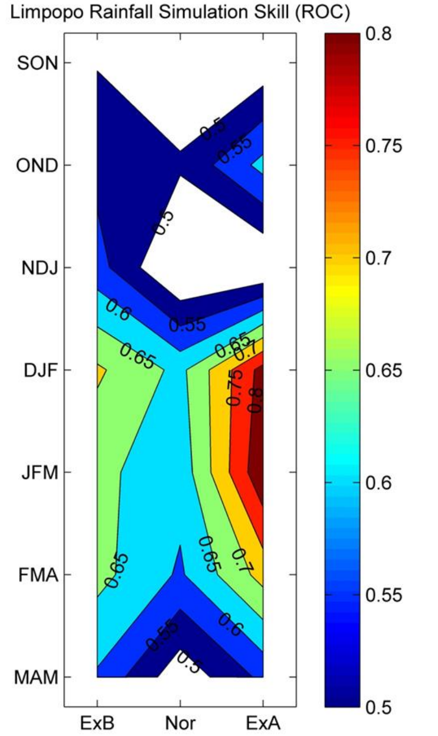


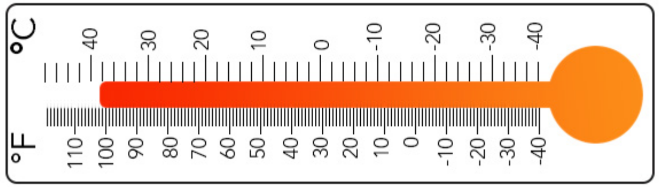
Discrimination

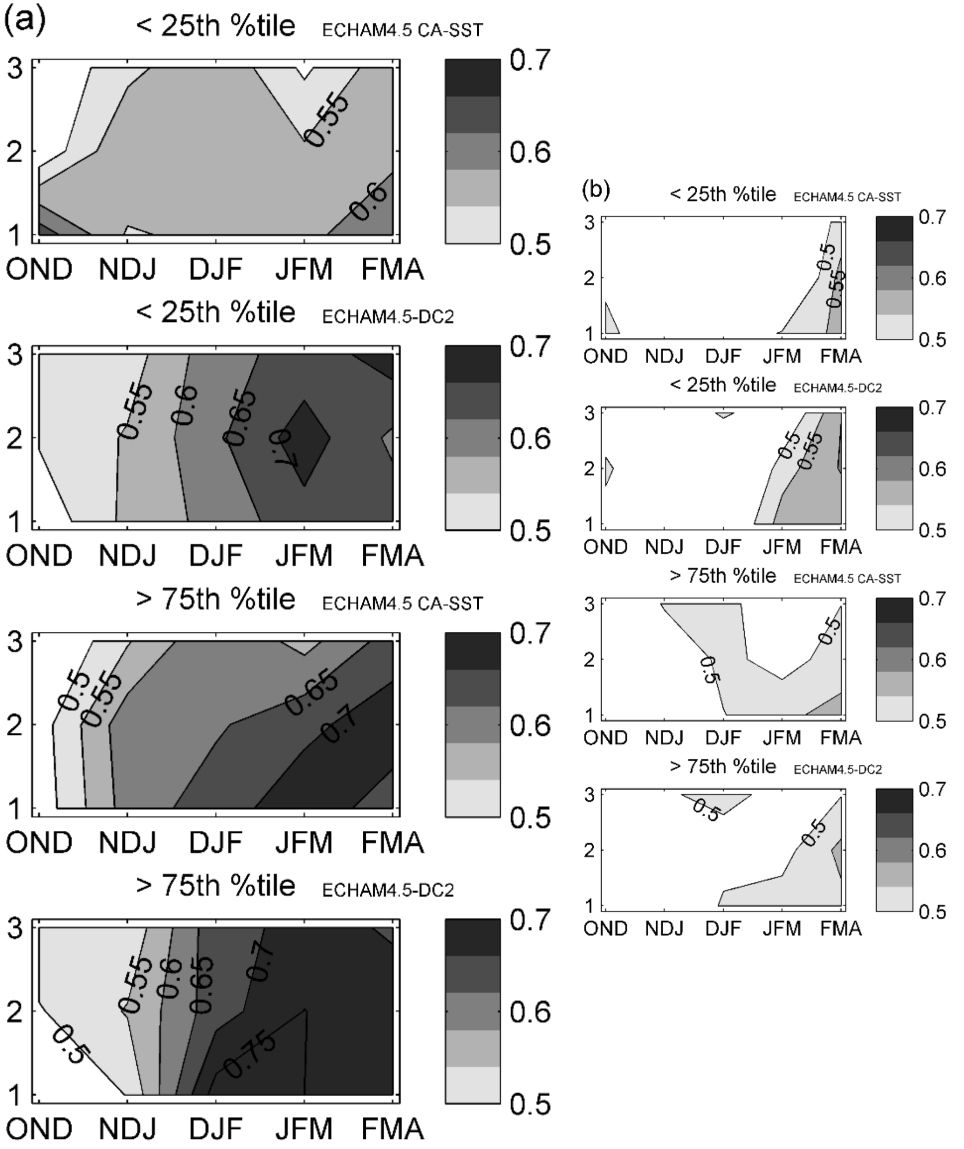
Relative Operating Characteristics

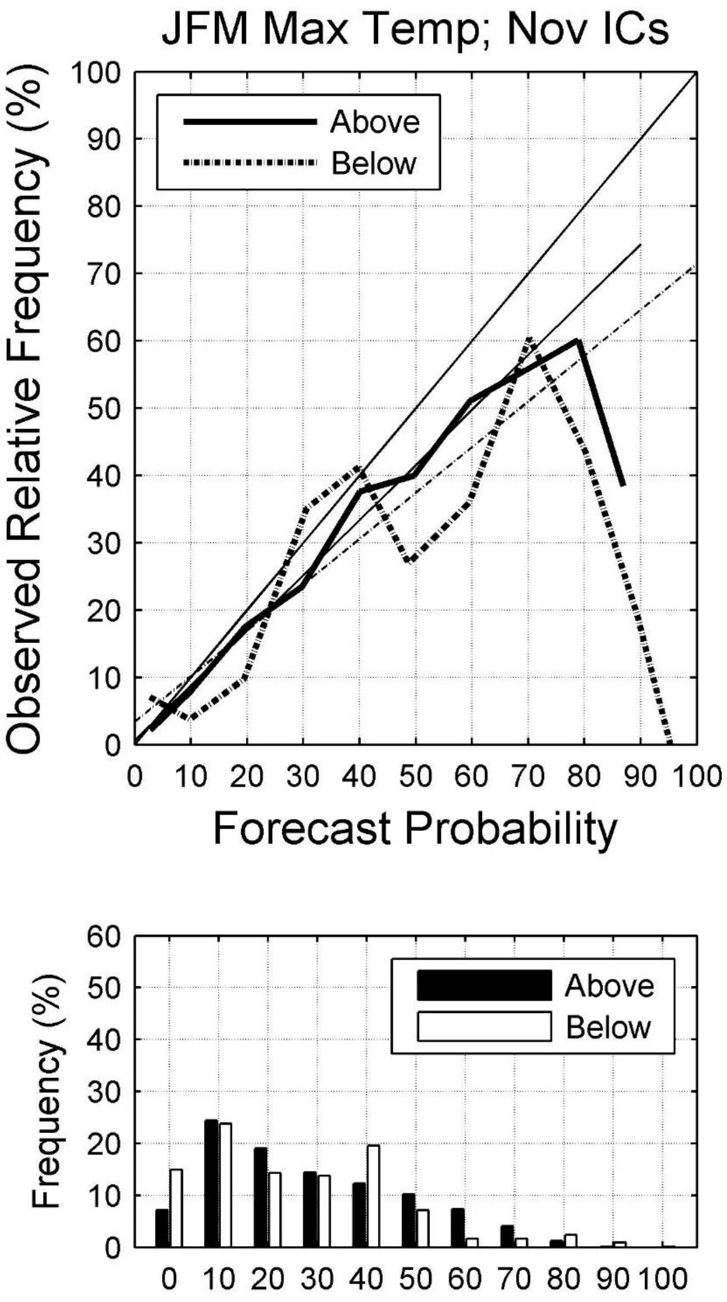


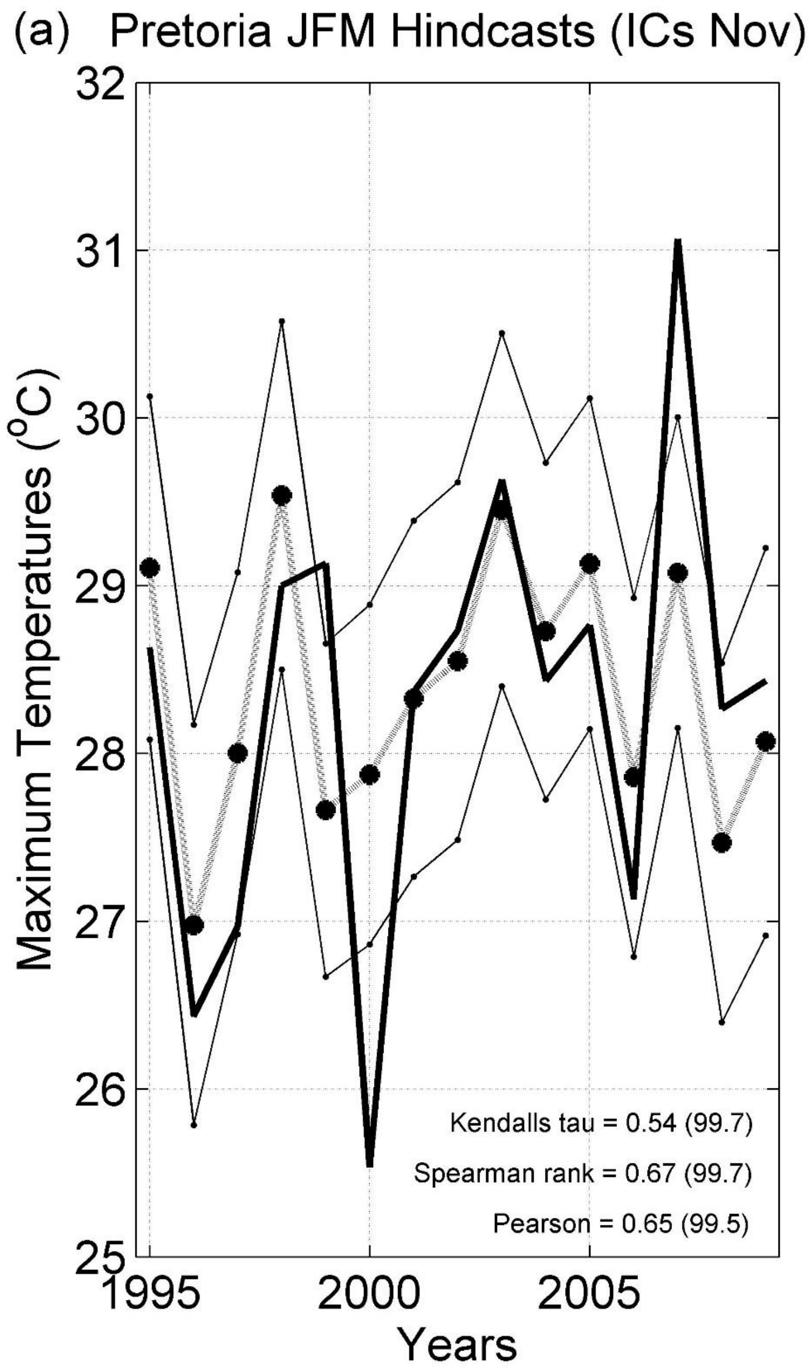


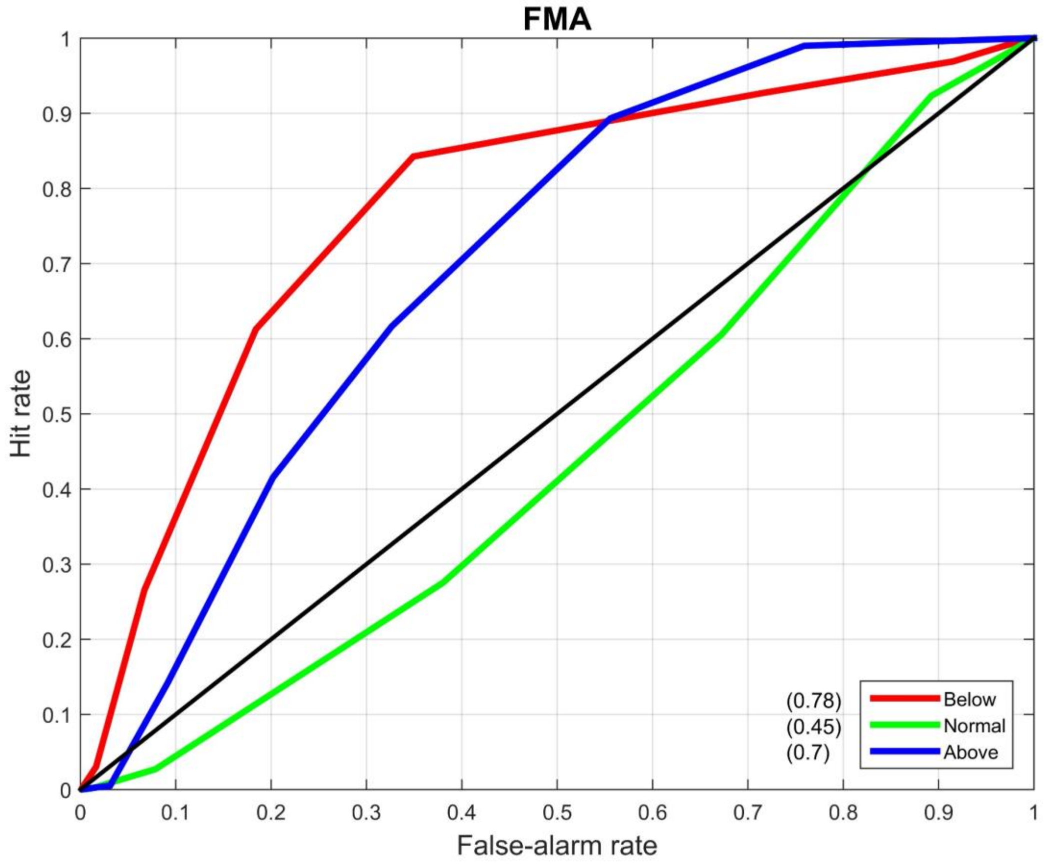


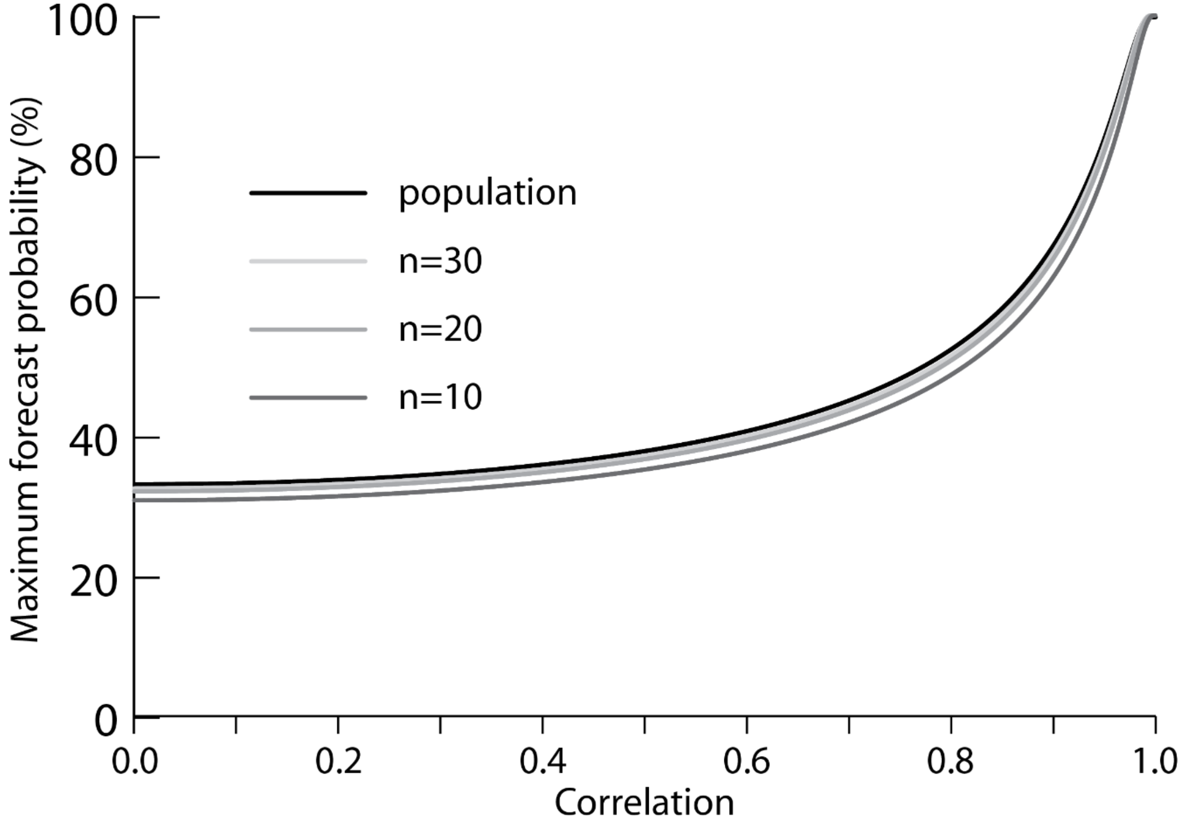

°C
°F


(a)
< 25th %tile ECHAM4.5 CA-SST
< 25th %tile ECHAM4.5-DC2
> 75th %tile ECHAM4.5 CA-SST
> 75th %tile ECHAM4.5-DC2
OND NDJ DJF JFM FMA
(b)
< 25th %tile ECHAM4.5 CA-SST
< 25th %tile ECHAM4.5-DC2
> 75th %tile ECHAM4.5 CA-SST
> 75th %tile ECHAM4.5-DC2


JFM Max Temp; Nov ICs
Observed Relative Frequency (%)
Above
Below
Forecast Probability
Frequency (%)
Above
Below

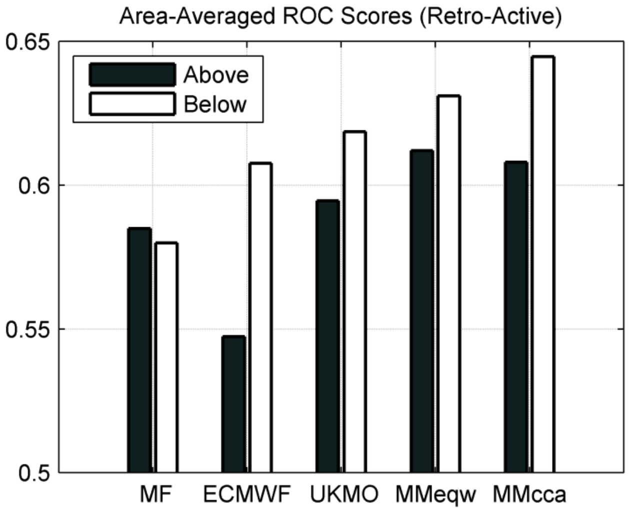

(a) Pretoria JFM Hindcasts (ICs Nov)
Maximum Temperatures (°C)
Years
Kendalls tau = 0.54 (99.7)
Spearman rank = 0.67 (99.7)
Pearson = 0.65 (99.5)

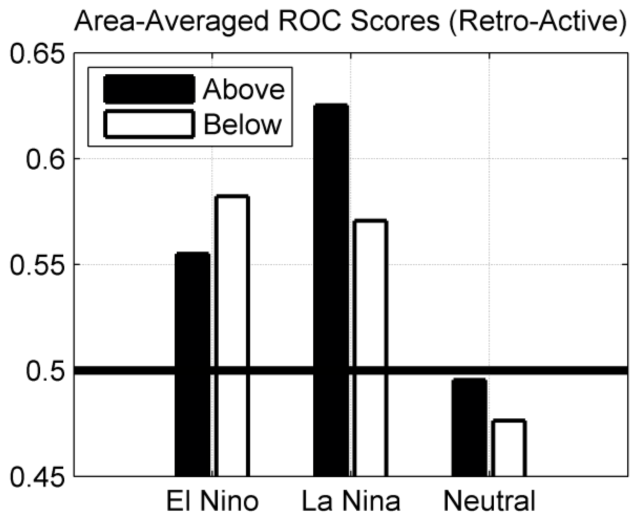


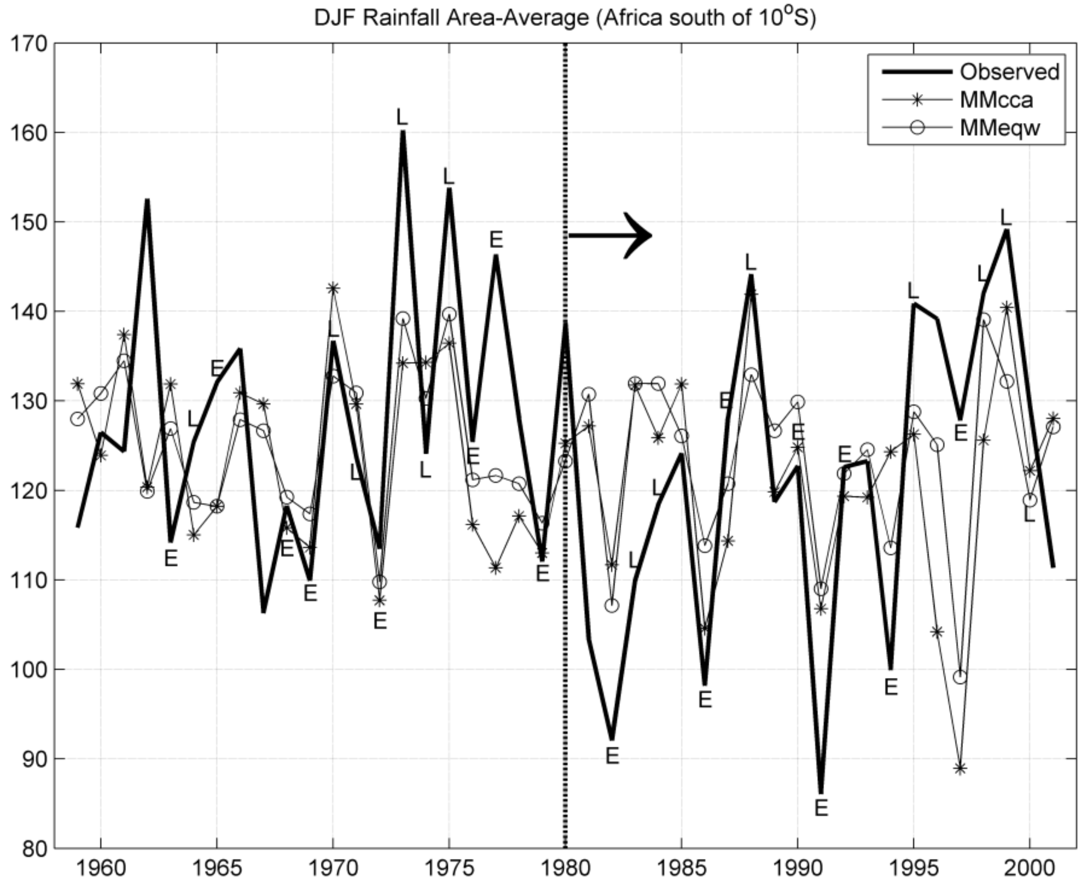


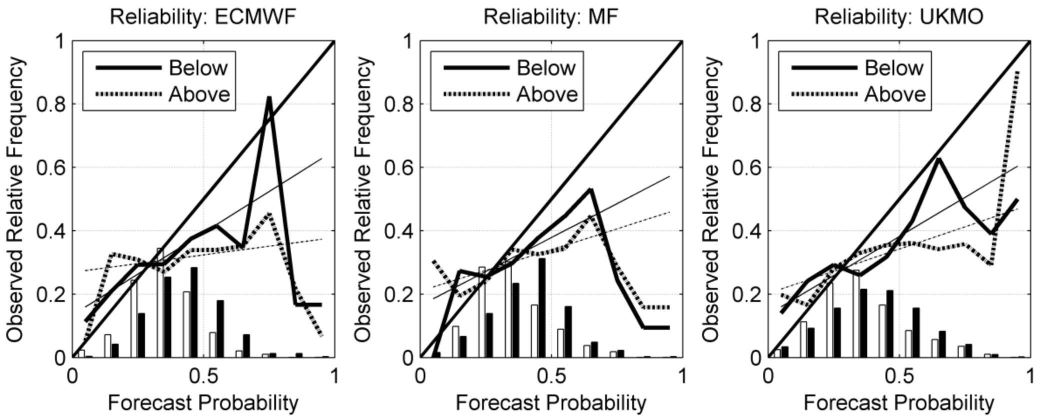
The effects of sample size on the maximum forecast probability for the normal category

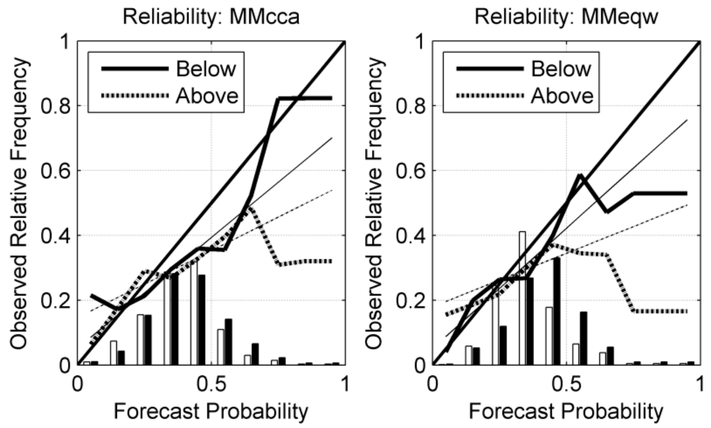
NO ENSO, NO FORECAST



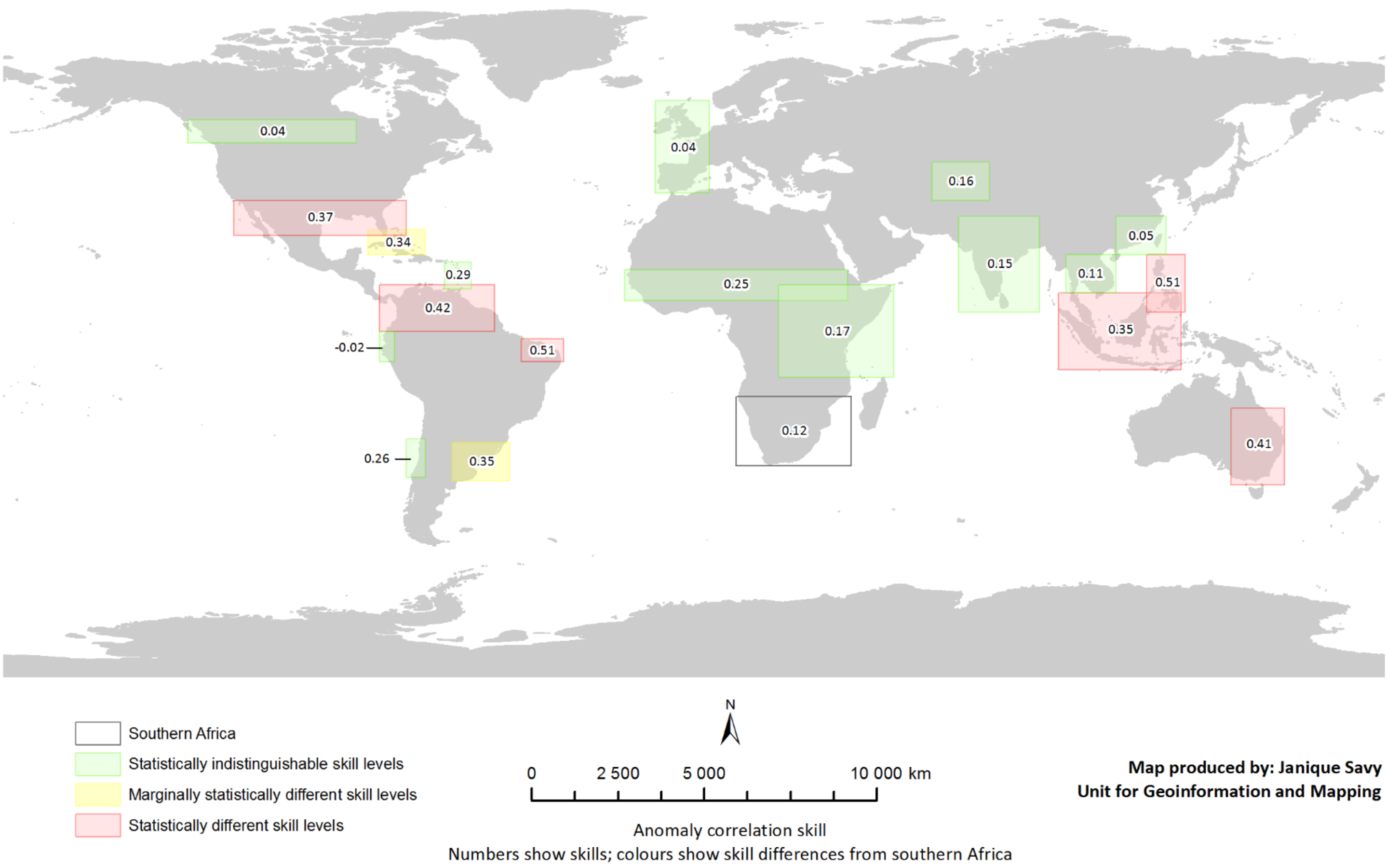


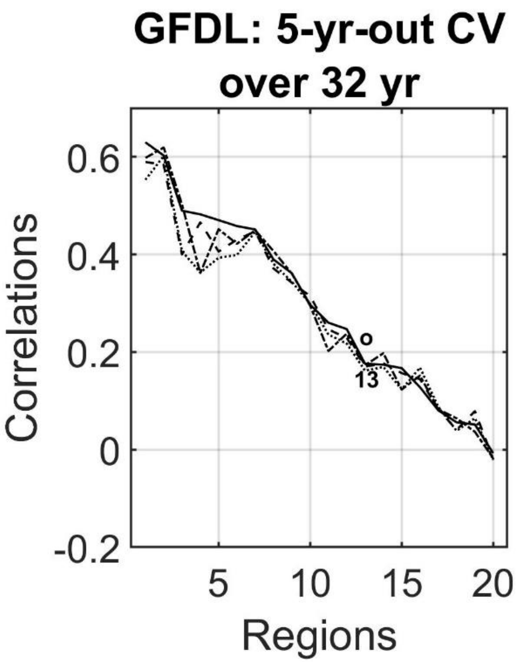




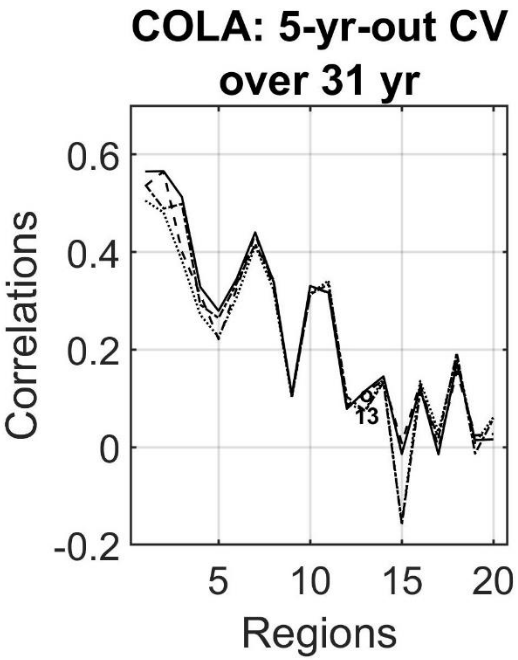


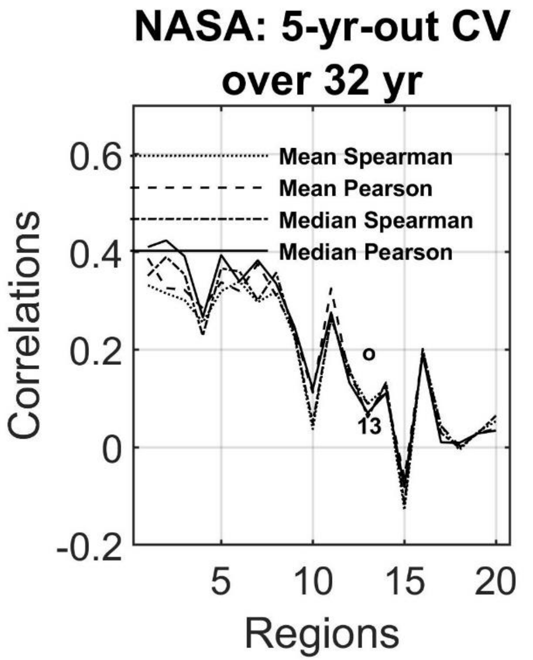
How do we rank ito forecast skill?



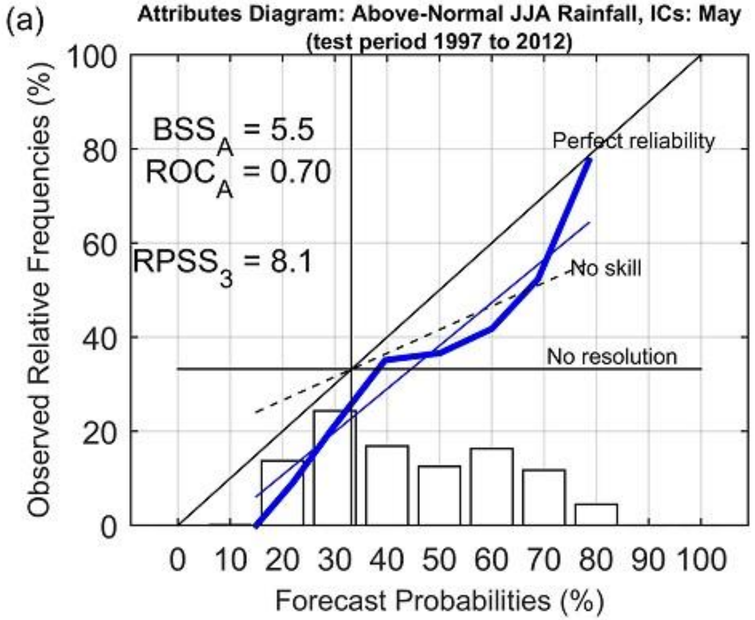


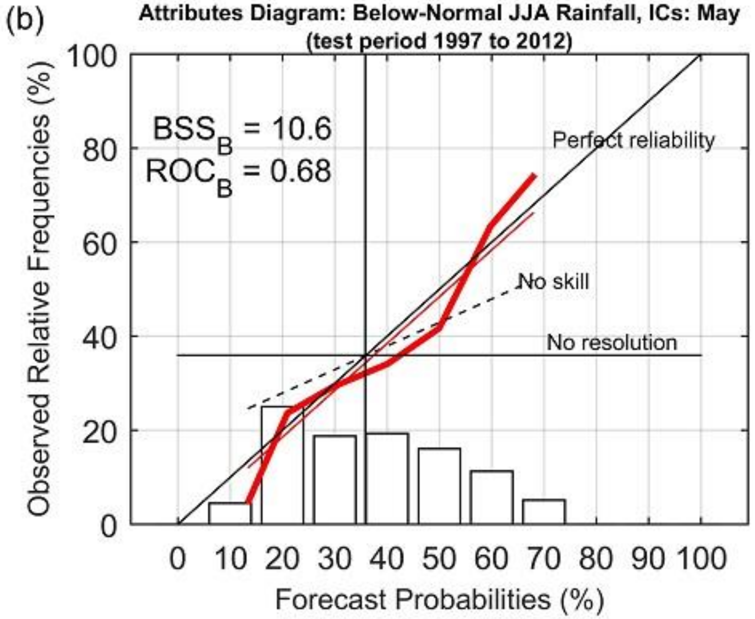
1. Philippines
2. Nordeste
3. Northern South America
4. Northwest Caribbean
5. Indonesia
6. Southern USA
7. Eastern Australia
8. Southeast South America
9. Sahel
10. Central Chile
11. Southeast Caribbean
12. Equatorial East Africa
13. Southern Africa
14. India
15. Coastal Equador, Northern Peru
16. Central Southwest Asia
17. Southeast China
18. Southeast Asia
19. Western Europe
20. South-central, SW Canada

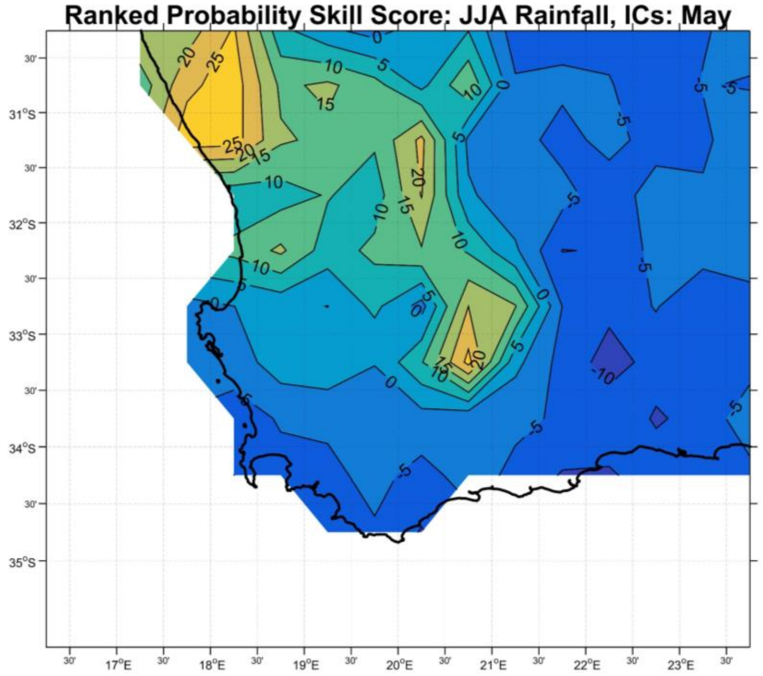


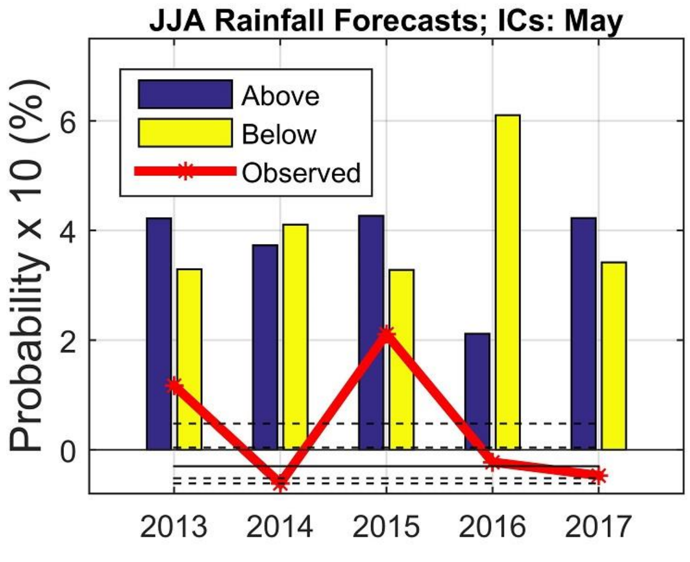


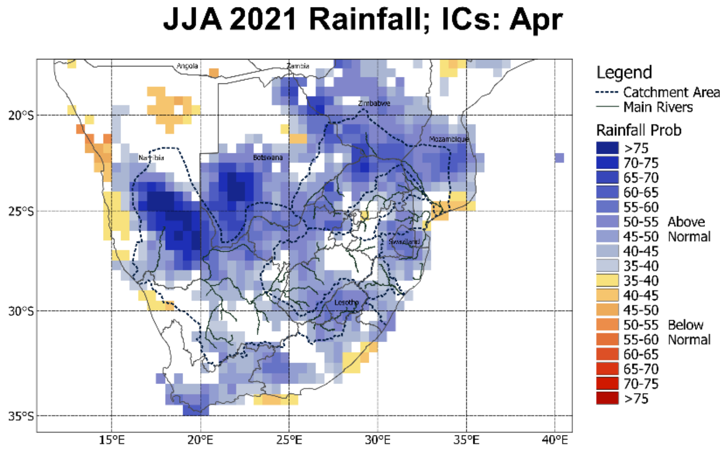
Two regions are found to be marginally compatible when the skill difference is significant at the 90% level but not the 95% level

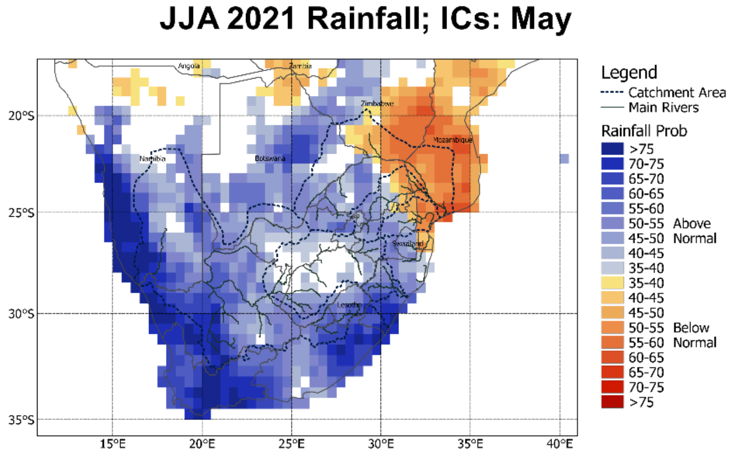

(a)
Attributes Diagram: Above-Normal JJA Rainfall, ICs: May
(test period 1997 to 2012)
BSS_A = 5.5
ROC_A = 0.70
$RPSS_3$ = 8.1
Perfect reliability
No skill
No resolution
Observed Relative Frequencies (%)
Forecast Probabilities (%)
0 10 20 30 40 50 60 70 80 90 100

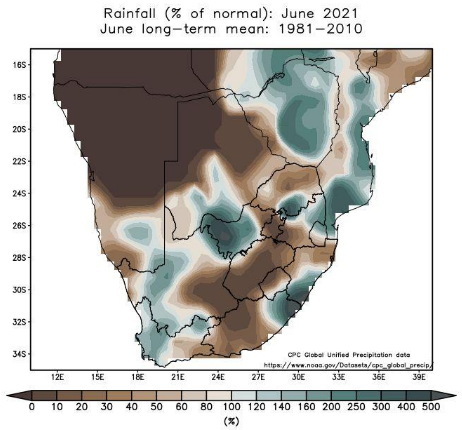

(b)
Attributes Diagram: Below-Normal JJA Rainfall, ICs: May
(test period 1997 to 2012)
BSS_B = 10.6
ROC_B = 0.68
Perfect reliability
No skill
No resolution
Observed Relative Frequencies (%)
Forecast Probabilities (%)
0 10 20 30 40 50 60 70 80 90 100


Ranked Probability Skill Score: JJA Rainfall, ICs: May
31°S
32°S
33°S
34°S
35°S
17°E 18°E 19°E 20°E 21°E 22°E 23°E


JJA Rainfall Forecasts; ICs: May
Above
Below
Observed
Probability x 10 (%)
2013 2014 2015 2016 2017


JJA 2021 Rainfall; ICs: Apr
Legend
Catchment Area
Main Rivers
Rainfall Prob
>75
70-75
65-70
60-65
55-60
50-55 Above
45-50 Normal
40-45
35-40
35-40
40-45
45-50
50-55 Below
55-60 Normal
60-65
65-70
70-75
>75
20°S
25°S
30°S
35°S
15°E 20°E 25°E 30°E 35°E 40°E


JJA 2021 Rainfall; ICs: May
Legend
Catchment Area
Main Rivers
Rainfall Prob
>75
70-75
65-70
60-65
55-60
50-55 Above
45-50 Normal
40-45
35-40
35-40
40-45
45-50
50-55 Below
55-60 Normal
60-65
65-70
70-75
>75
20°S
25°S
30°S
35°S
15°E 20°E 25°E 30°E 35°E 40°E


Rainfall (% of normal): June 2021
June long-term mean: 1981-2010
CPC Global Unified Precipitation data
0 10 20 30 40 50 60 80 100 120 140 160 200 250 300 400 500
(%)

What have we learnt to far…

- Seasonal rainfall and temperature predictability is a function of both “space and time”
  - Restricted to regions and seasons
  - Summer rainfall predictability highest during anomalously wet seasons
- Forecasts for “normal seasons” do not work!
- No ENSO, no forecast
- Multi-model ensembles produce the best forecasts
- SADC ranked low with other ENSO affected regions – predictability is limited
- Winter rainfall areas may be predictable at the same level of skill as summer regions

2000

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.

2017

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

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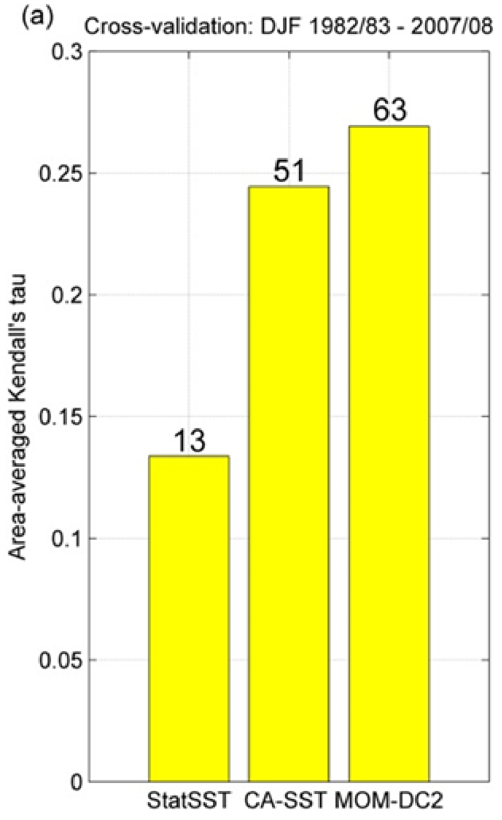
(Manuscript received 31 January 2017, in final form 7 July 2017)

ABSTRACT

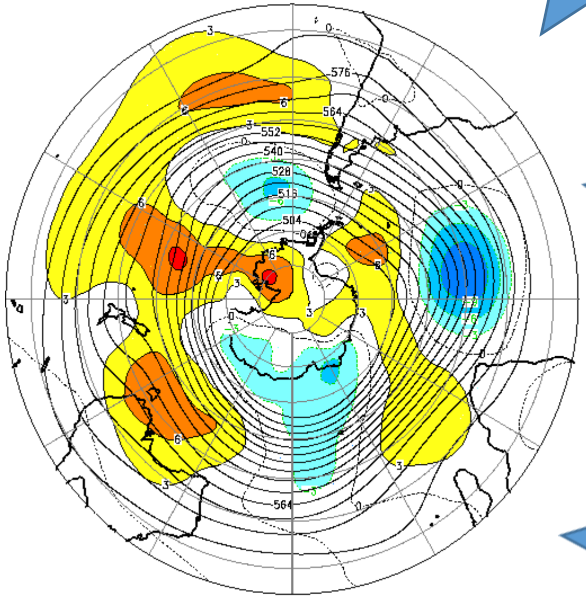
Canonical correlation analysis (CCA)-based statistical corrections are applied to seasonal mean precipitation and temperature hindcasts of the individual models from the North American Multimodel Ensemble project to correct biases in the positions and amplitudes of the predicted large-scale anomaly patterns. 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.



The prediction scheme

1. Phenomena to be predicted should contain a climate signal (e.g. ENSO) in the data; 2. Observed and model time series must be over sufficiently long enough periods so that robust statistical relationship can be developed; 3. and some form of quality control of the observed data had taken place.

ECHAM4.5-MOM3-DC2 ocean-atmosphere GCM



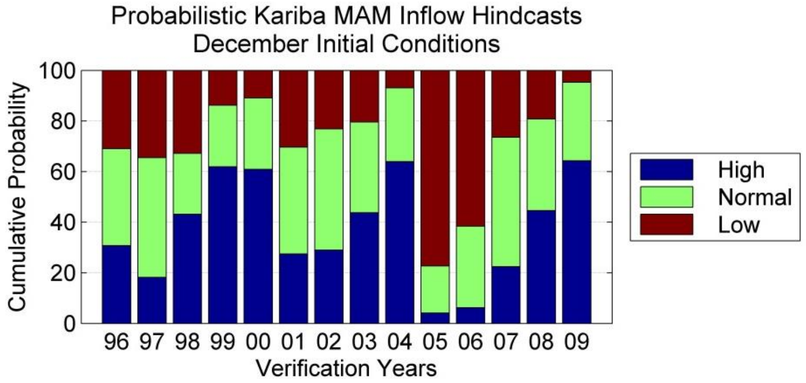
Geopotential heights/ rainfall, etc.

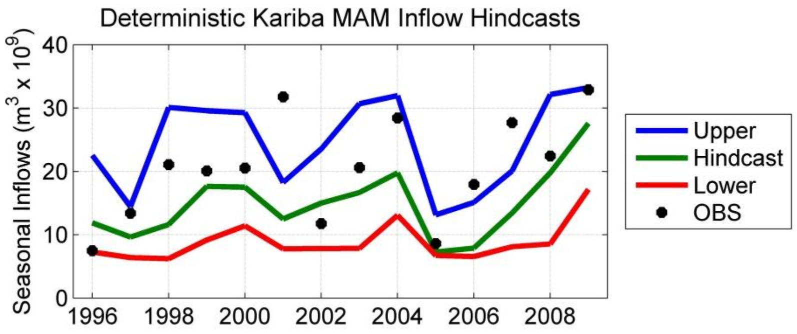
Riverflow

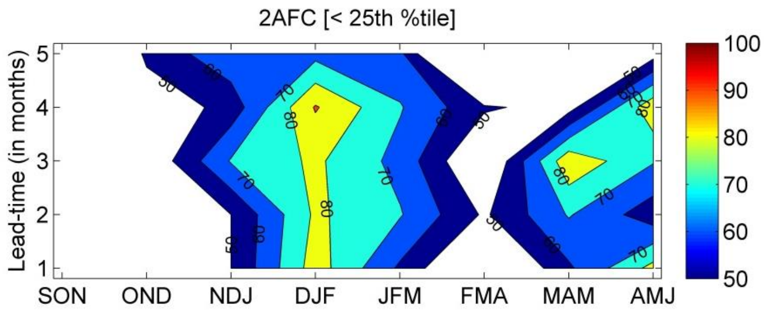
Malaria

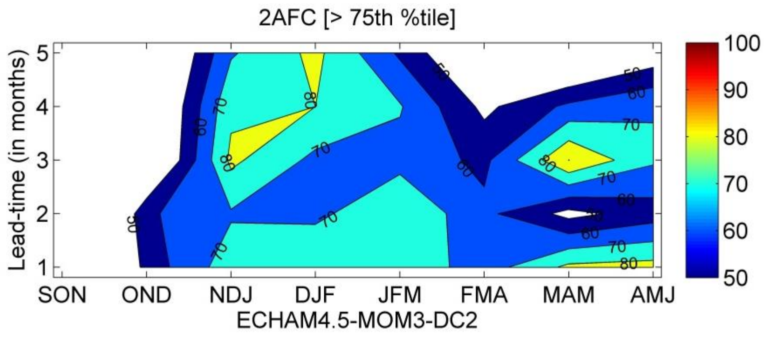
Dry-land crop yield

Kariba

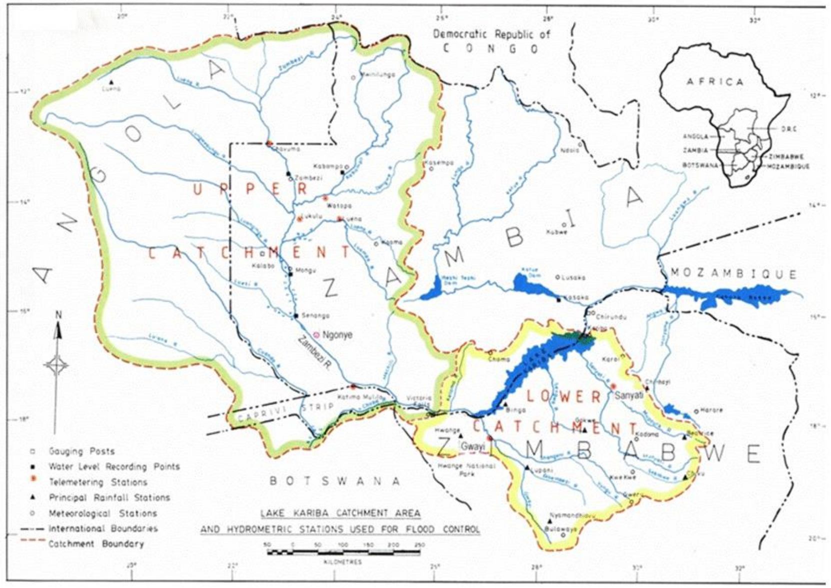


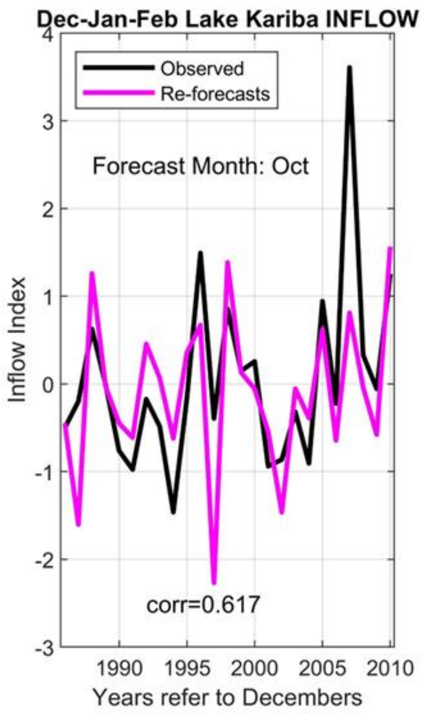


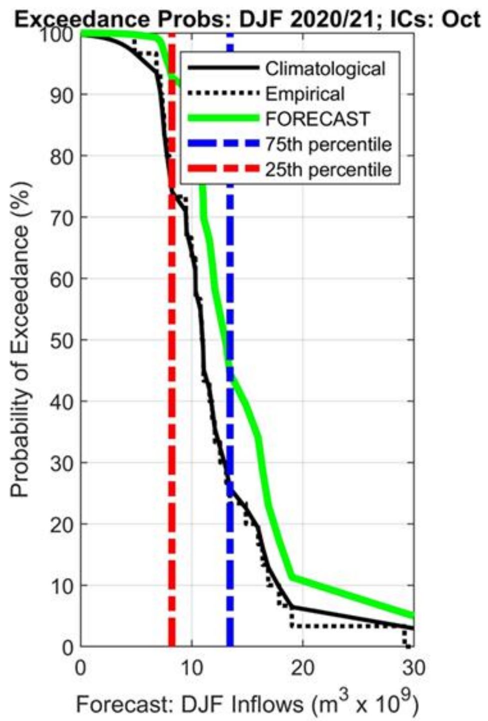


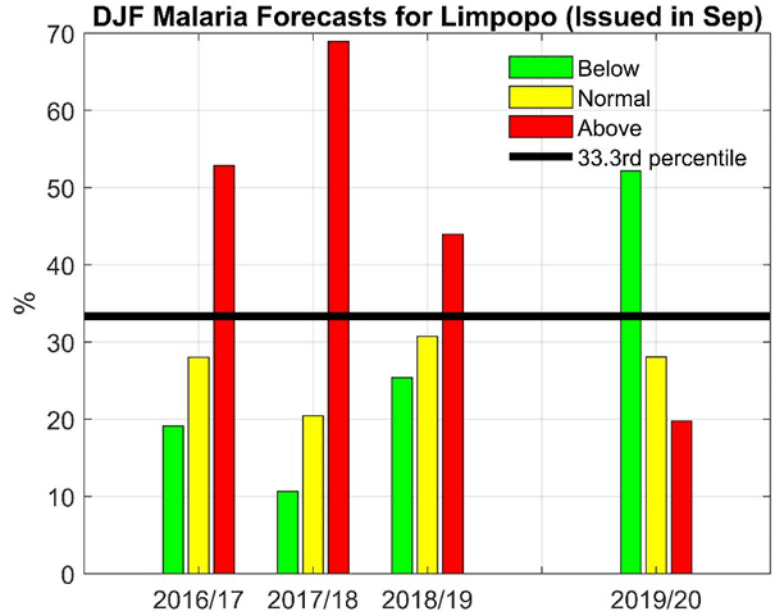


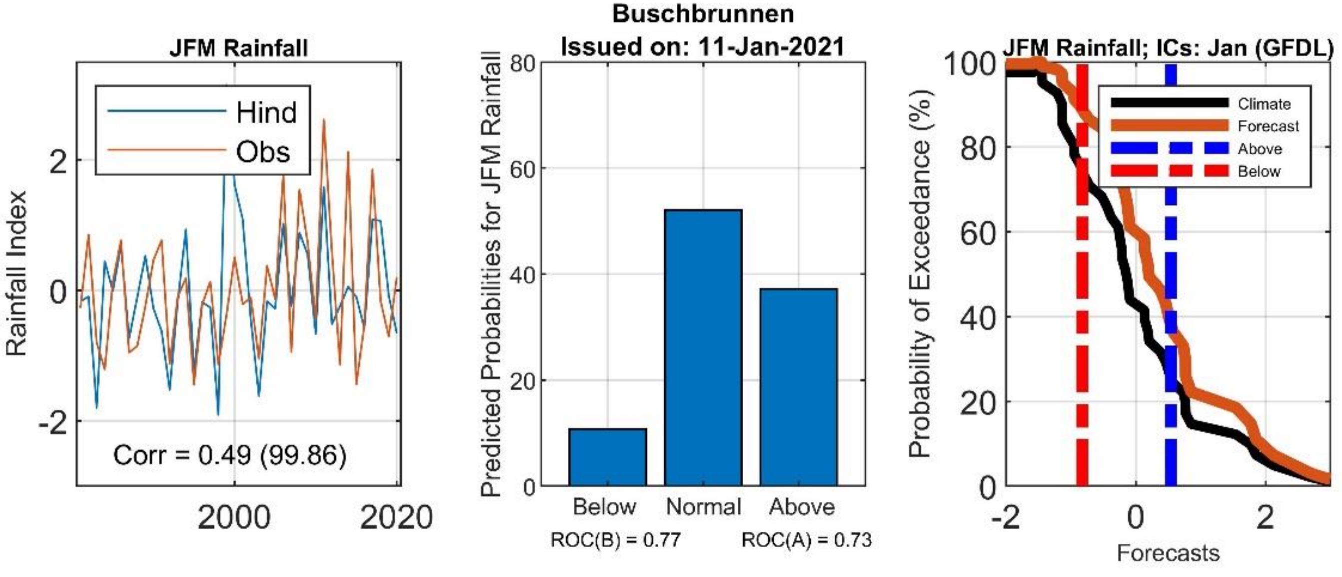
two-alternative forced choice (2AFC) score: probability of a correct decision

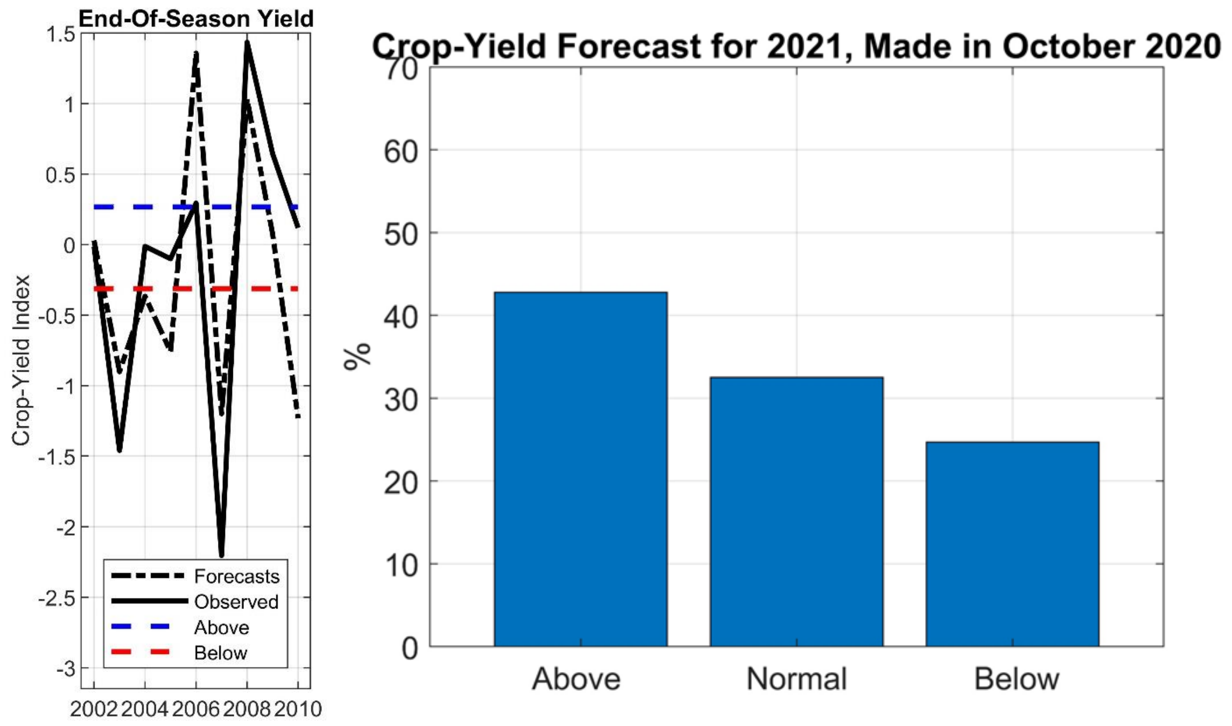


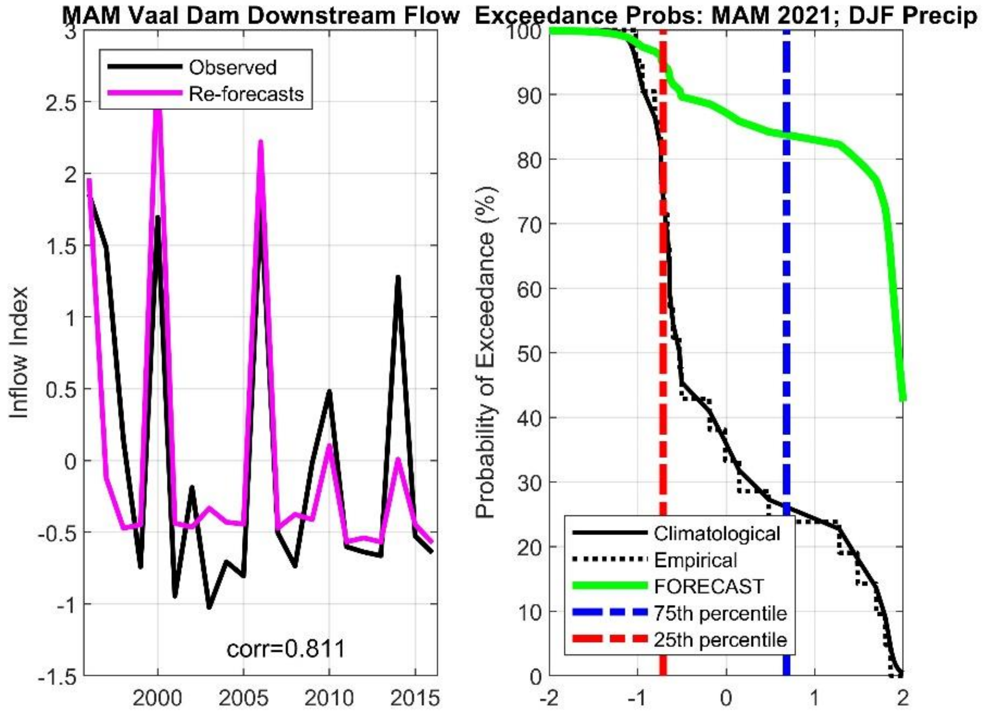


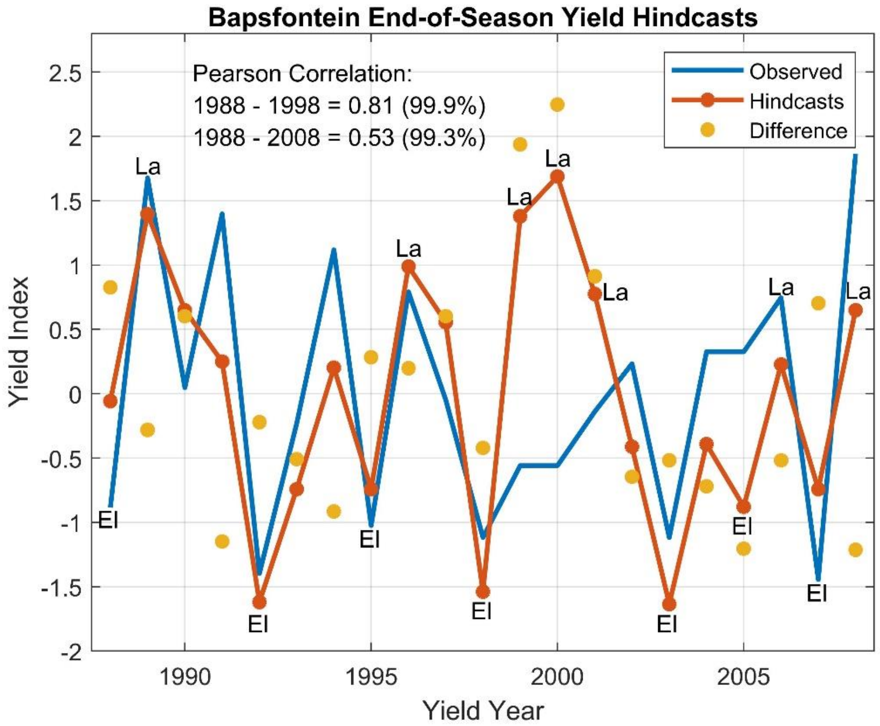


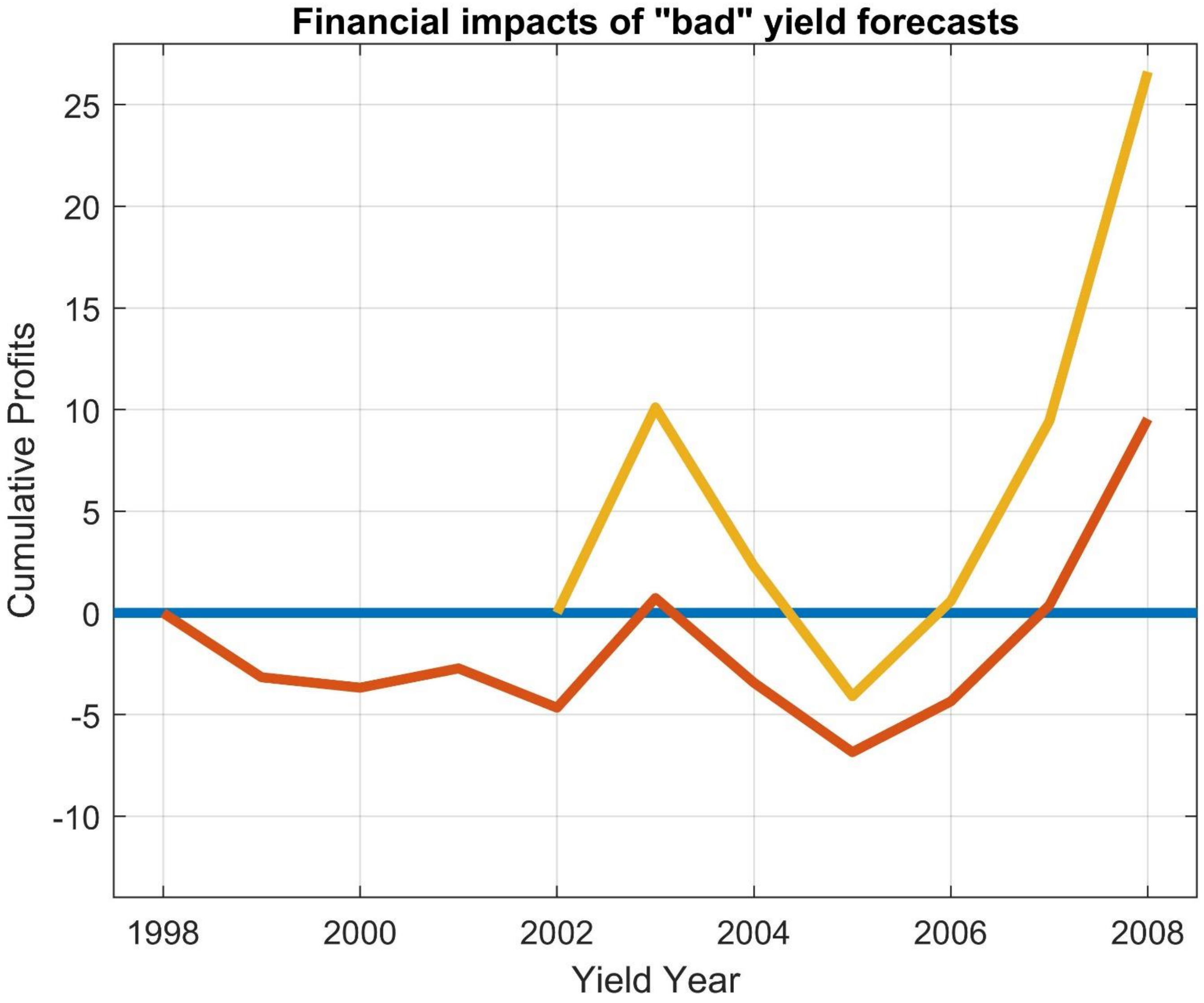

DJF Malaria Forecasts for Limpopo (Issued in Sep)
Below
Normal
Above
33.3rd percentile
%
2016/17
2017/18
2018/19
2019/20


JFM Rainfall
Hind
Obs
Rainfall Index
Corr = 0.49 (99.86)
2000
2020
Buschbrunnen
Issued on: 11-Jan-2021
Predicted Probabilities for JFM Rainfall
Below
Normal
Above
ROC(B) = 0.77
ROC(A) = 0.73
JFM Rainfall; ICs: Jan (GFDL)
Climate
Forecast
Above
Below
Probability of Exceedance (%)
Forecasts

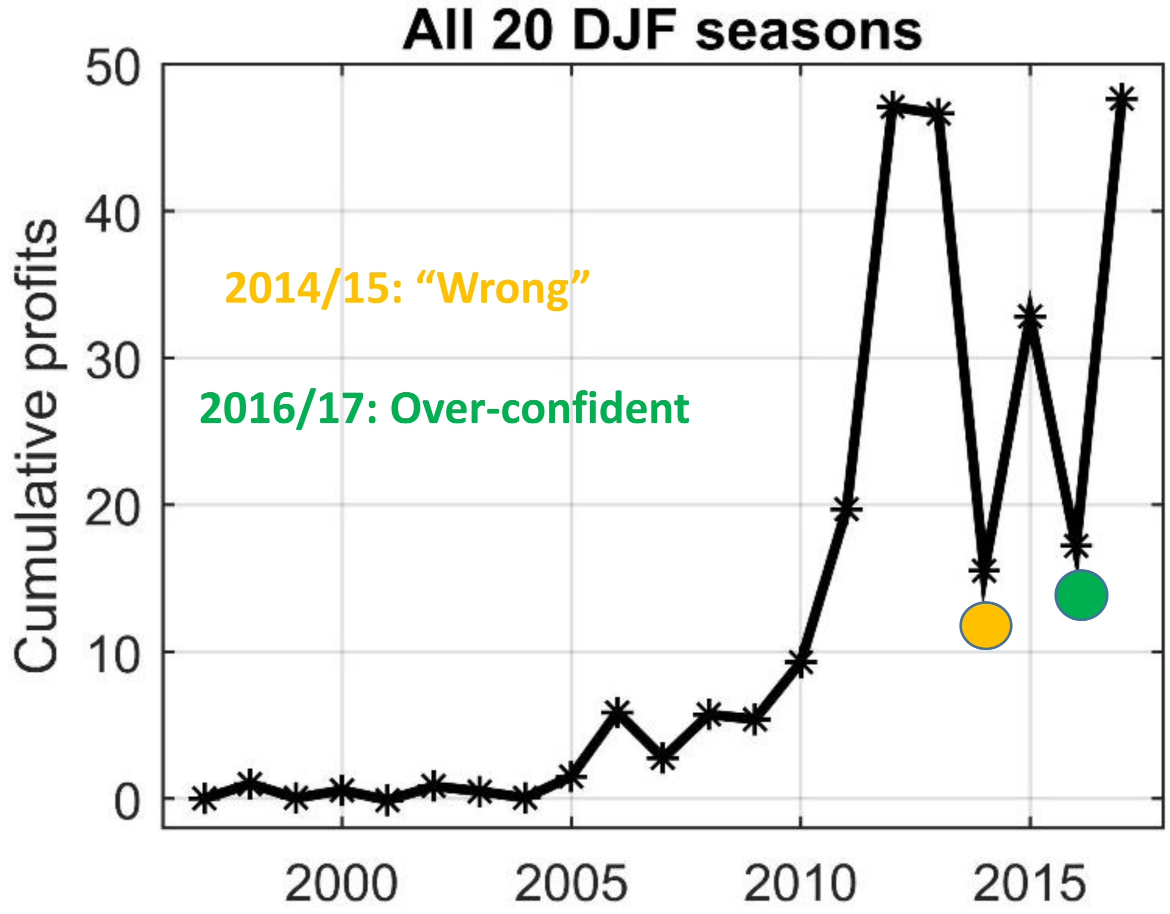

End-Of-Season Yield
Crop-Yield Index
Forecasts
Observed
Above
Below
2002 2004 2006 2008 2010
Crop-Yield Forecast for 2021, Made in October 2020
%
Above
Normal
Below

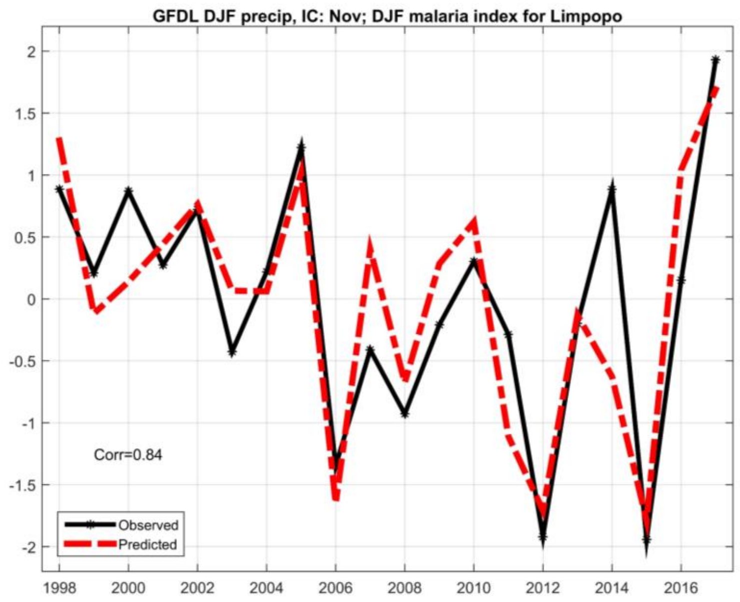

MAM Vaal Dam Downstream Flow
Observed
Re-forecasts
Inflow Index
corr=0.811
Exceedance Probs: MAM 2021; DJF Precip
Probability of Exceedance (%)
Climatological
Empirical
FORECAST
75th percentile
25th percentile

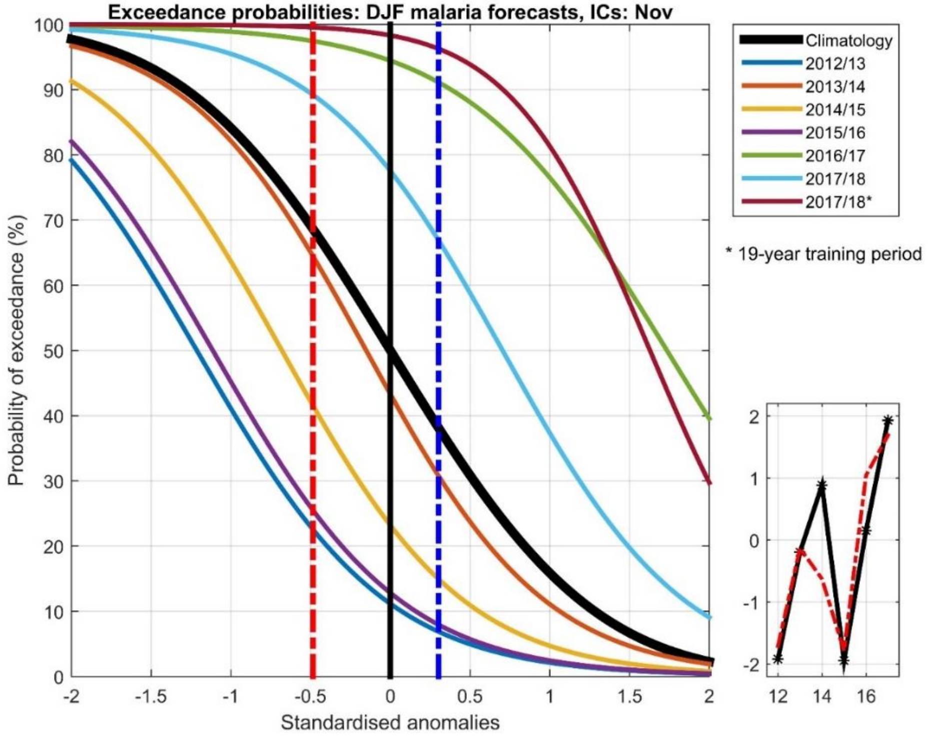




- **Inclusion of the 3 consecutive poor forecasts in the CP calculations has significantly delayed financial recovery**
- **Much less of a detrimental effect is caused by a single poorly forecast season (2005)**



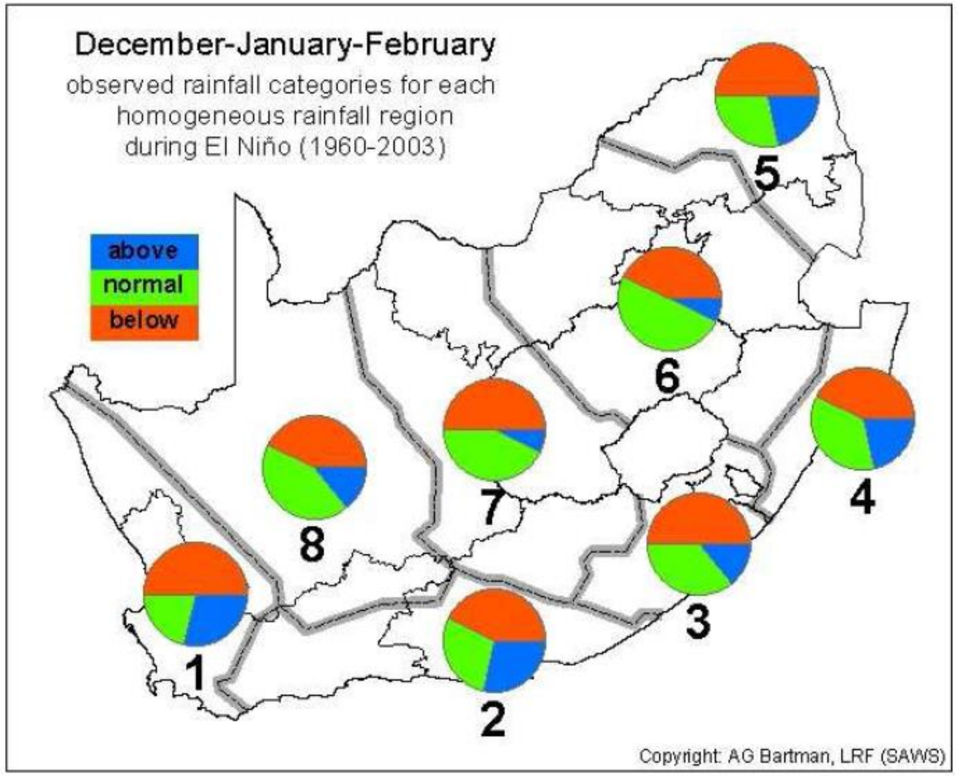


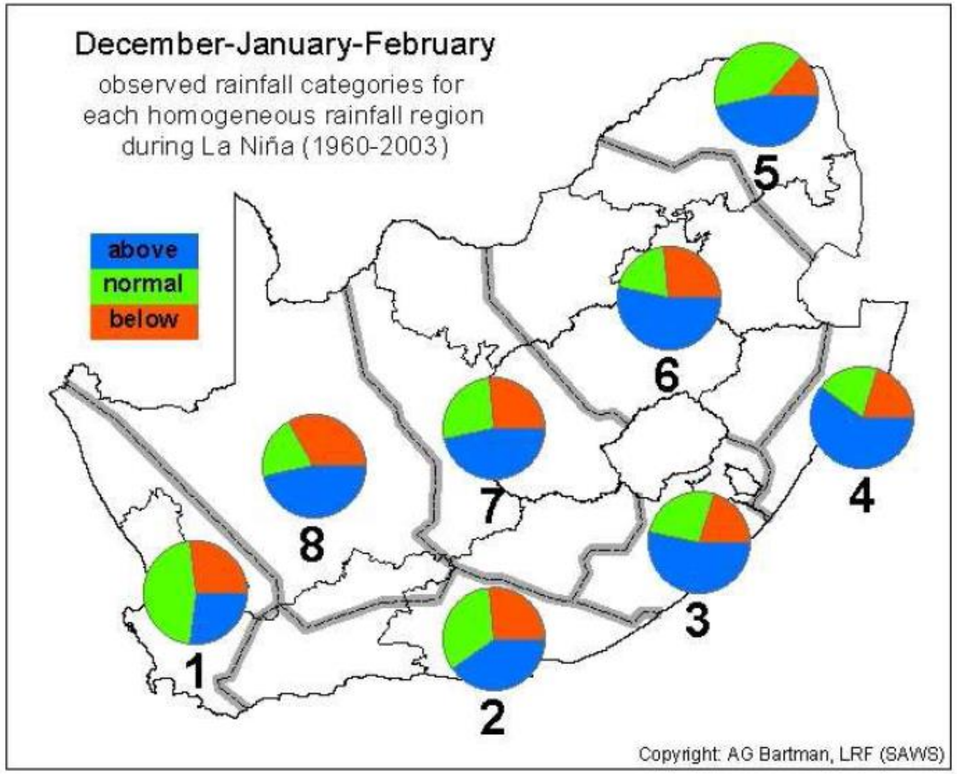


We urge caution in relying on these forecast models exclusively for disease management - we therefore suggest to make sure that good climate monitoring systems are in place to supplement forecasts from models

We propose that disease surveillance and control activities should not be replaced by forecasts – forecasts should only be used to supplement health practices that are currently going on in the region

December-January-February





Lessons from applications modelling

- Many examples of successful applications modelling
  - Lake Kariba inflow
  - Vaal Dam outflow
  - Farms – rainfall and crops
  - Malaria in Limpopo
- Co-production can be achieved through
  - Involvement of user before modelling starts
  - Data exchange, including “citizen science”
  - Financial risk assessment when using forecasts
  - Do not create false expectations
  - Develop a basic understanding of observations

The future

Better ENSO and subsequent climate predictions alone are not enough to reduce the risks associated with climate extremes

- Develop and improve on methods for forecast uptake – methodologies to better communicate the climate information to policy-makers, stakeholders, and the public
- Regions of the World significantly affected by climate extremes may consider collaboration on issues such as understanding and modelling
- Forecast system evaluation and verification, including process-based verification
- Use of available model output from international centres for multi-model optimization and forecast calibration through statistical post-processing
- Demonstrate potential for financial gain through forecast use
- Maintain and further develop observational networks, including a “citizen science” network