Tailoring seasonal forecasts through co-production

UNIVERSITEIT VAN PRETORIA
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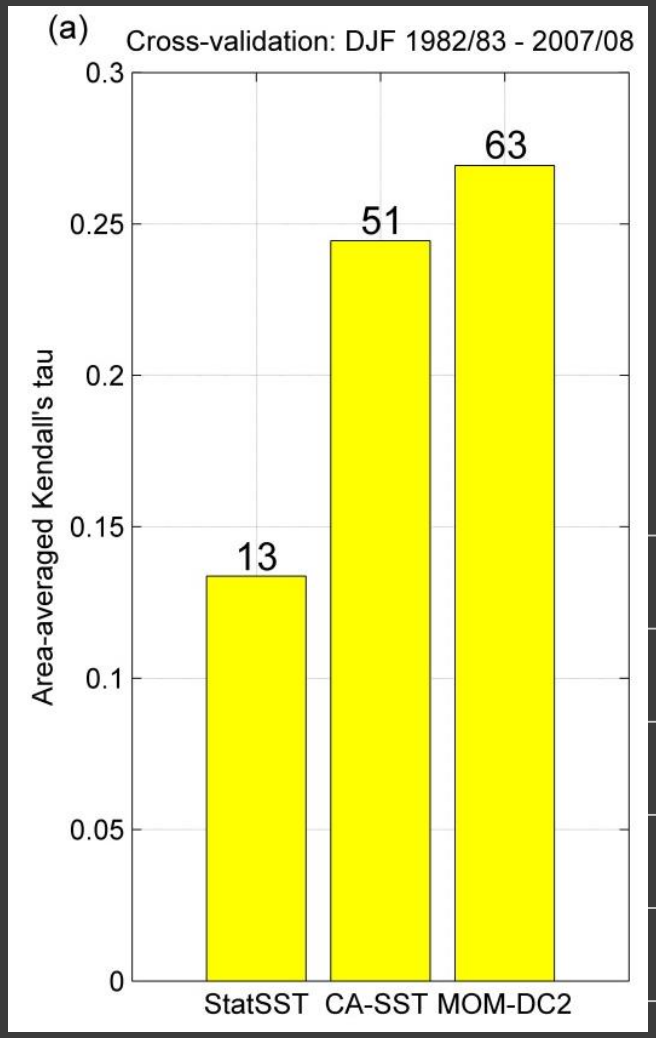
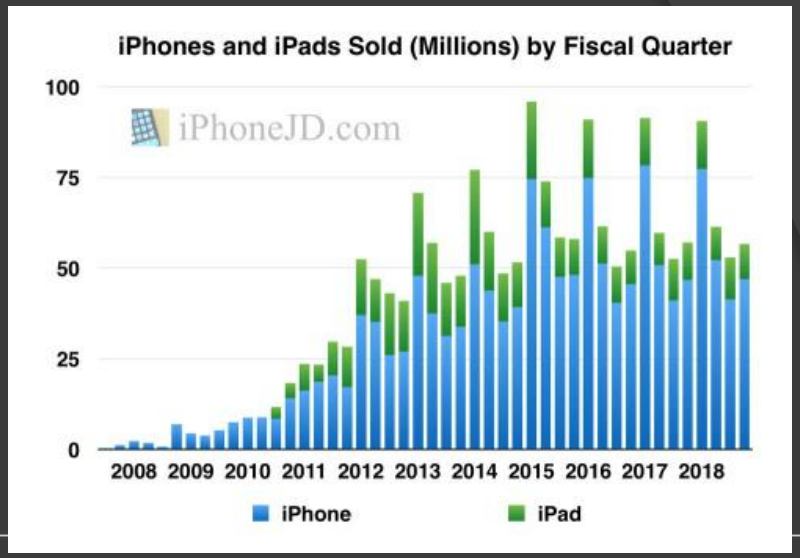
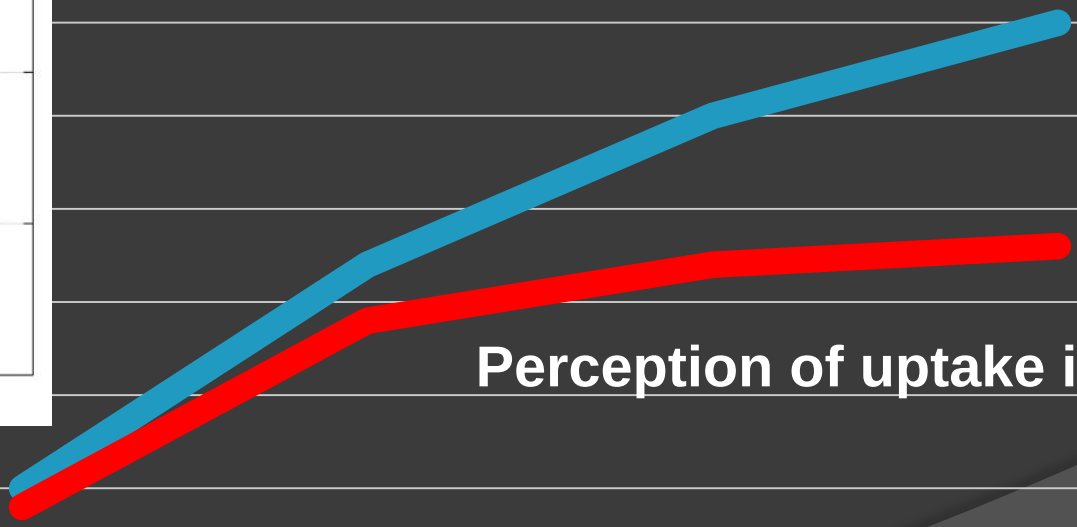
Willem A. Landman

World Meteorological Day SEMINAR
Agricultural Research Council - Soil, Climate and Water
15 March 2019

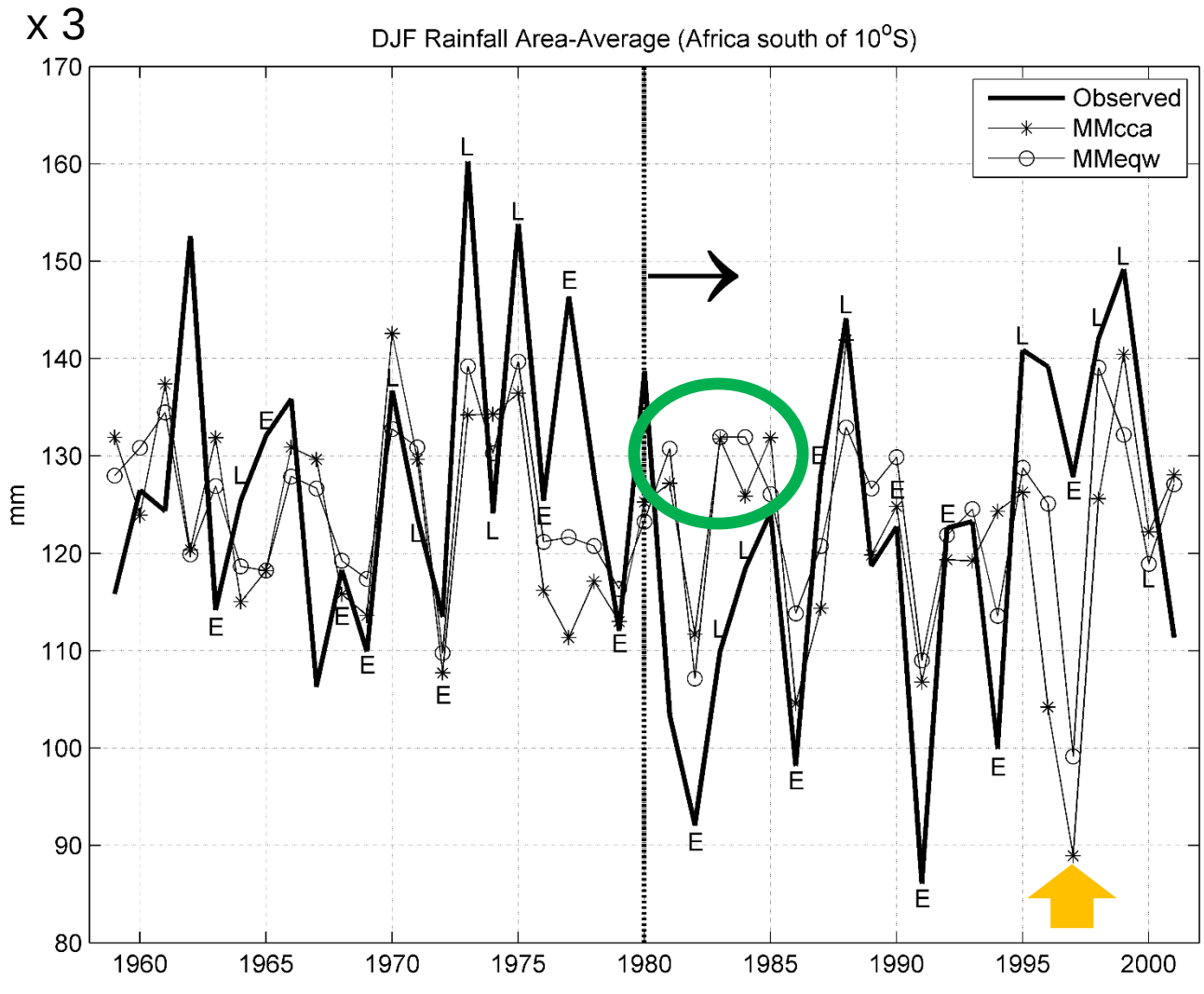






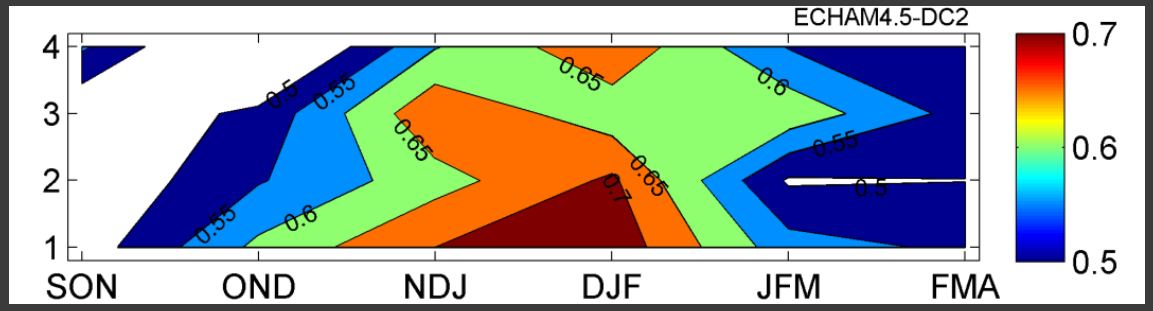
Since 1990's

Skill Uptake

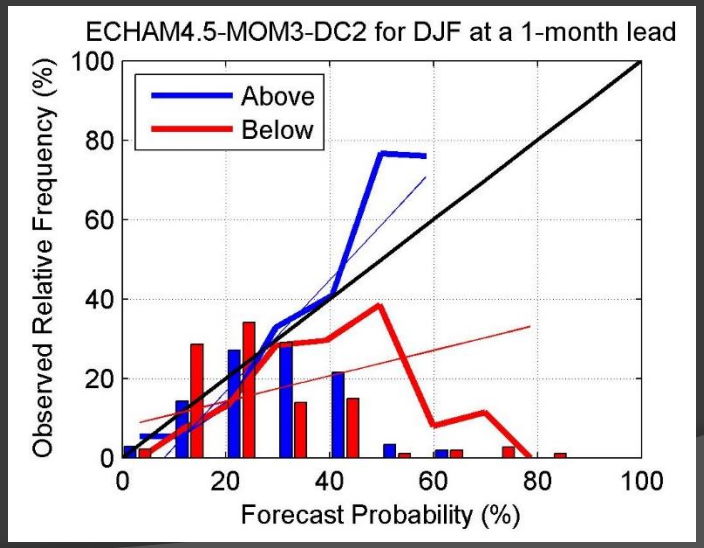


Loss in user confidence ?

South Africa



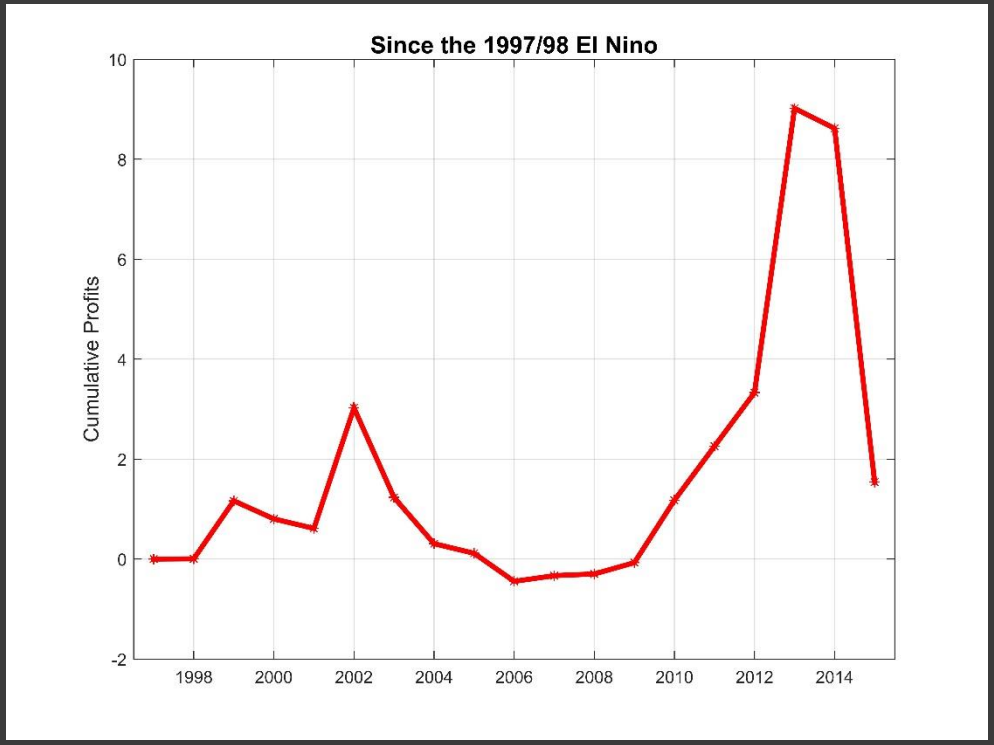
Wet (>75th percentile)

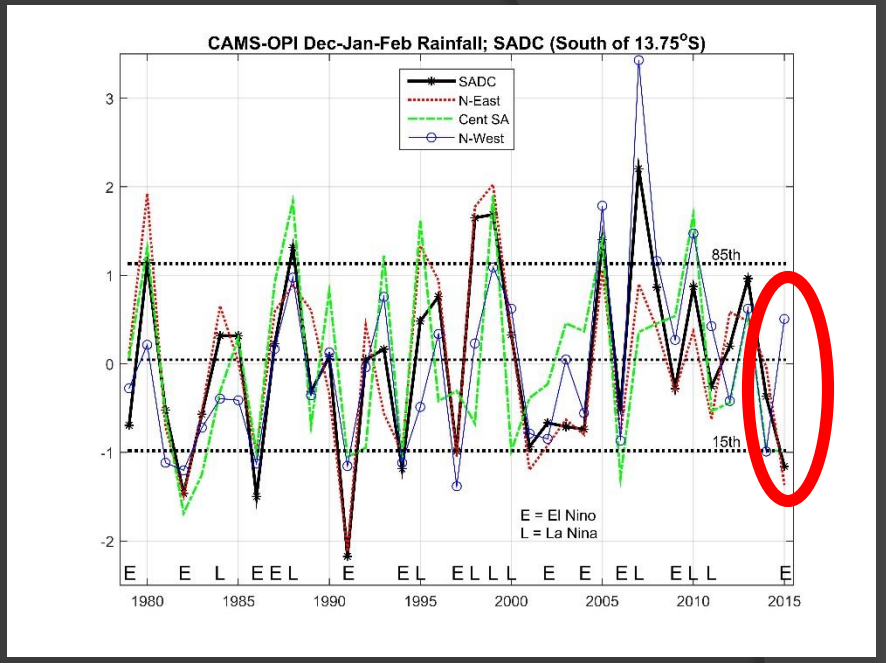


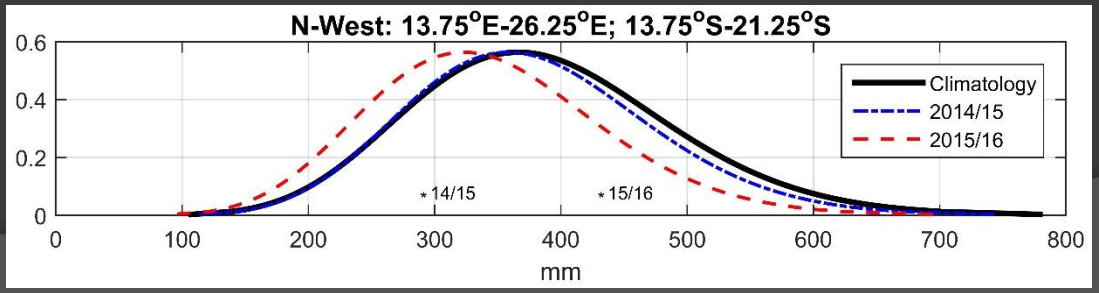
What we have learned so far…

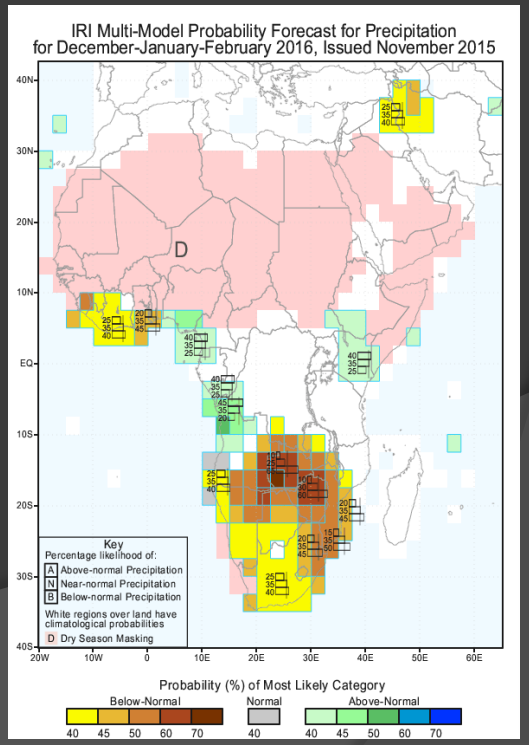
- Forecasts have improved as a function of model complexity
- However, there is not clear evidence that forecasts are being used more
- Some seasons poorly predicted may be the cause for loss in user confidence
- Forecast work best under certain conditions
  - Summer seasons
  - Wet seasons

Impact if forecast goes “wrong”…





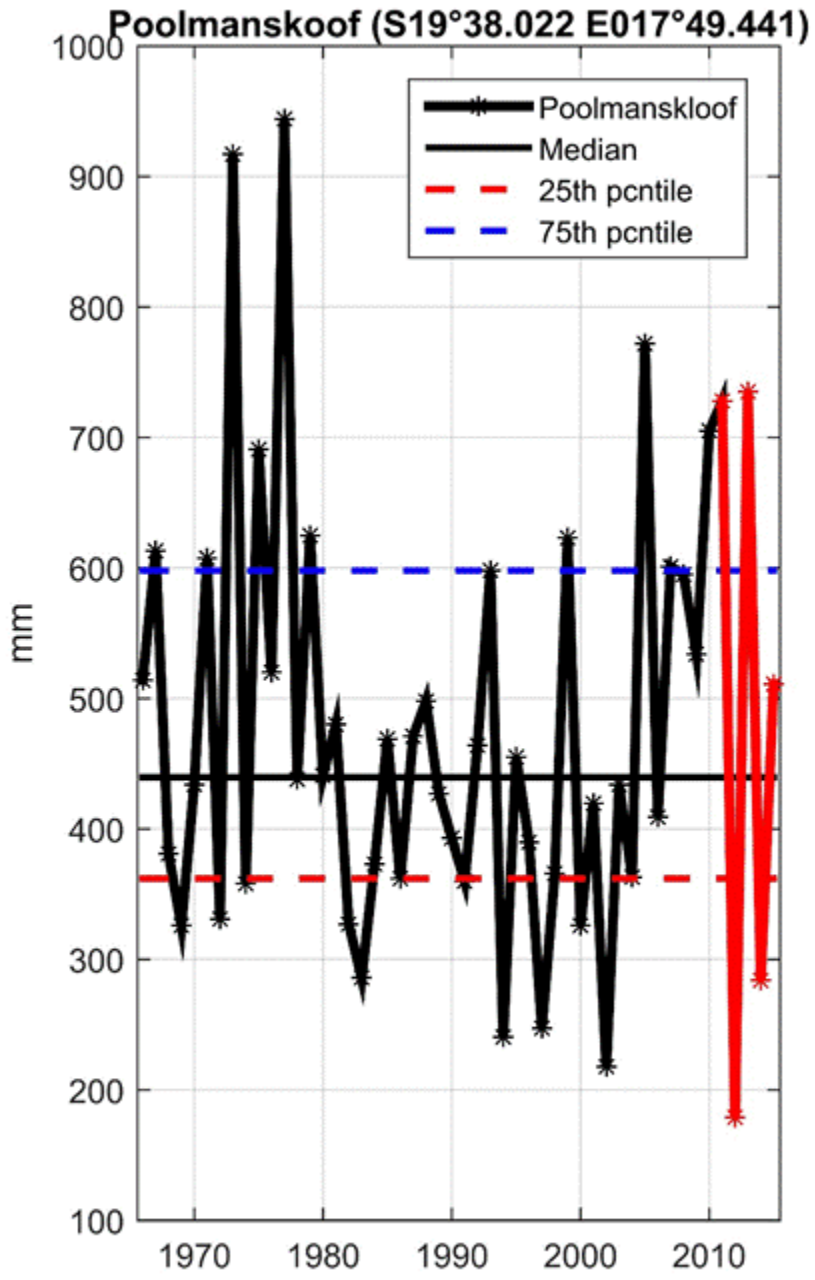




Cost/Loss Ratio

Action taken	Event occurs: DROUGHT	
	Yes	No
Yes	Cost to perform protective action	Cost to perform protective action
No	Loss incurred if drought occurs	0

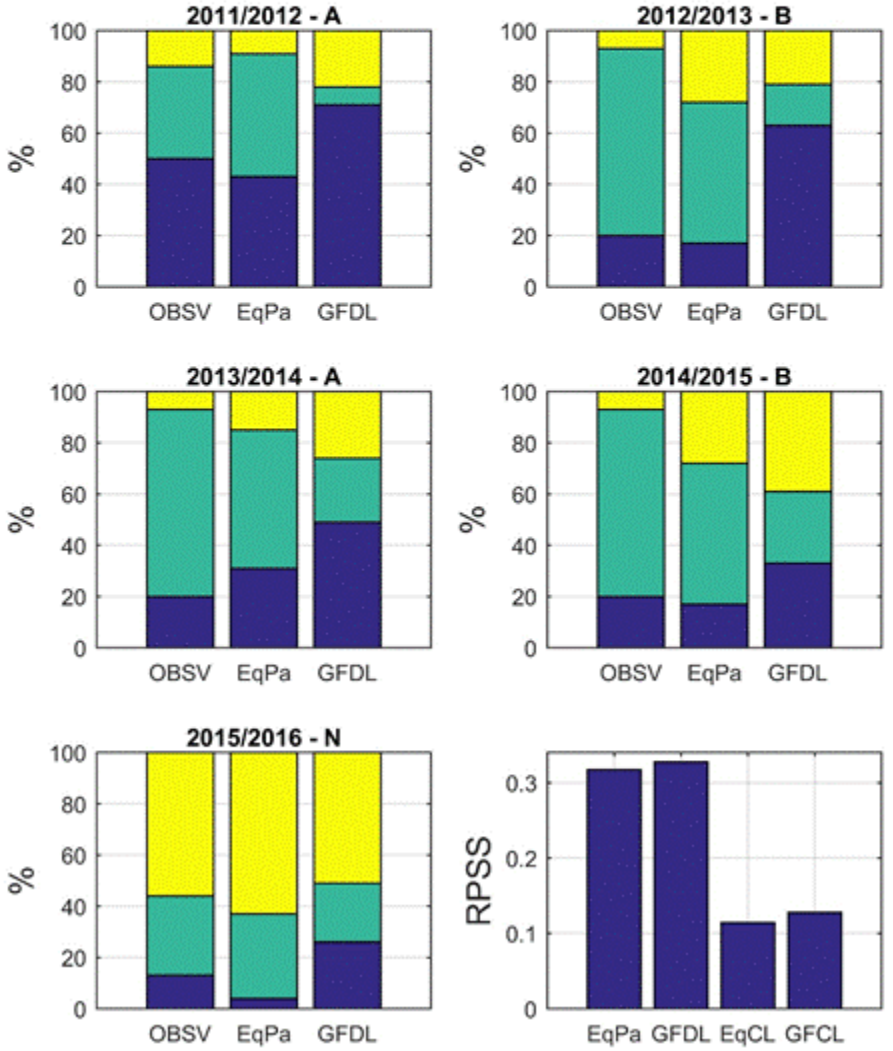
Richardson, D. S., 2000: Skill and relative economic value of the ECMWF ensemble prediction system. *Quarterly Journal of the Royal Meteorological Society*, **126**, 649-667.



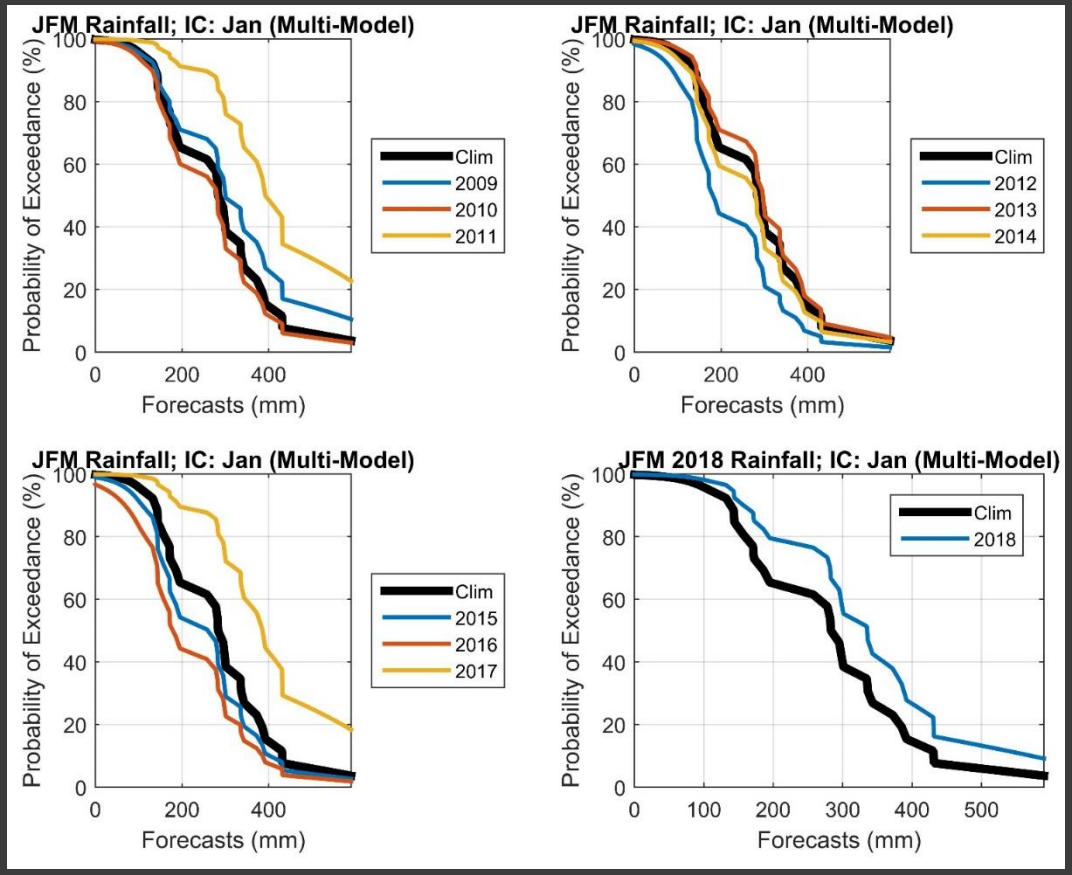
$$RPS = \sum_{m=1}^{J} \left[\left(\sum_{j=1}^{m} y_j \right) - \left(\sum_{j=1}^{m} o_j \right) \right]^2$$

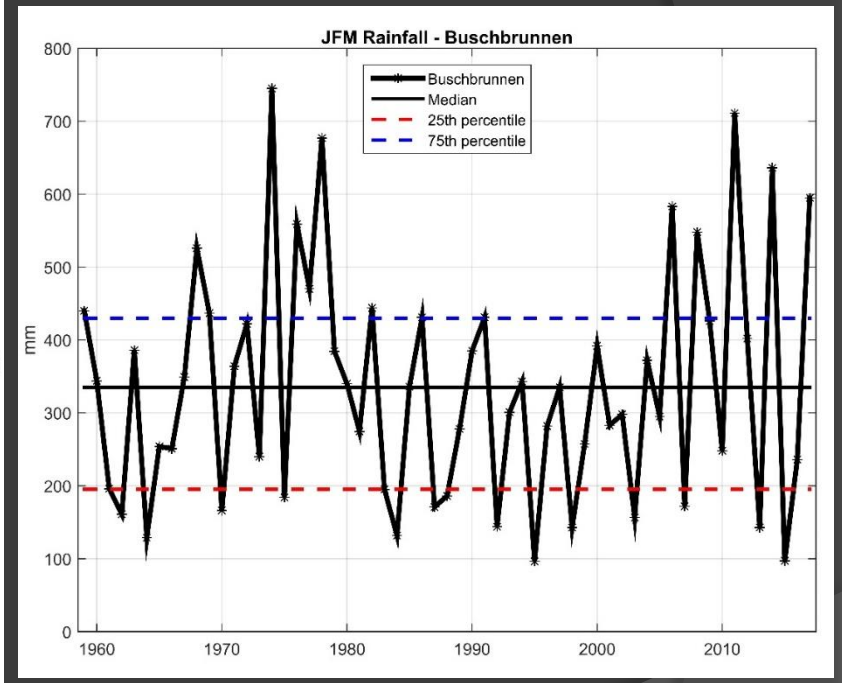
$$SS_{RPS} = \frac{\overline{RPS} - \overline{RPS_{\text{clim}}}}{0 - \overline{RPS_{\text{clim}}}} = 1 - \frac{\overline{RPS}}{\overline{RPS_{\text{clim}}}}$$

…and against the "Home made model"



Buschbrunnen, near Grootfontein in northern Namibia





What more have we learned so far…

- When the predicted least likely category occurs there may be serious financial implications
- Forecasts produced by robust physically based models produce the most benefit
- Users should benefit from comparing re-forecasts with observations (more on this later)

What if “good” forecasts are not used…?

INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. **36**: 2570–2581 (2016)
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(wileyonlinelibrary.com) DOI: 10.1002/joc.4513

RMetS
Royal Meteorological Society

Prediction of inflows into Lake Kariba using a combination of physical and empirical models

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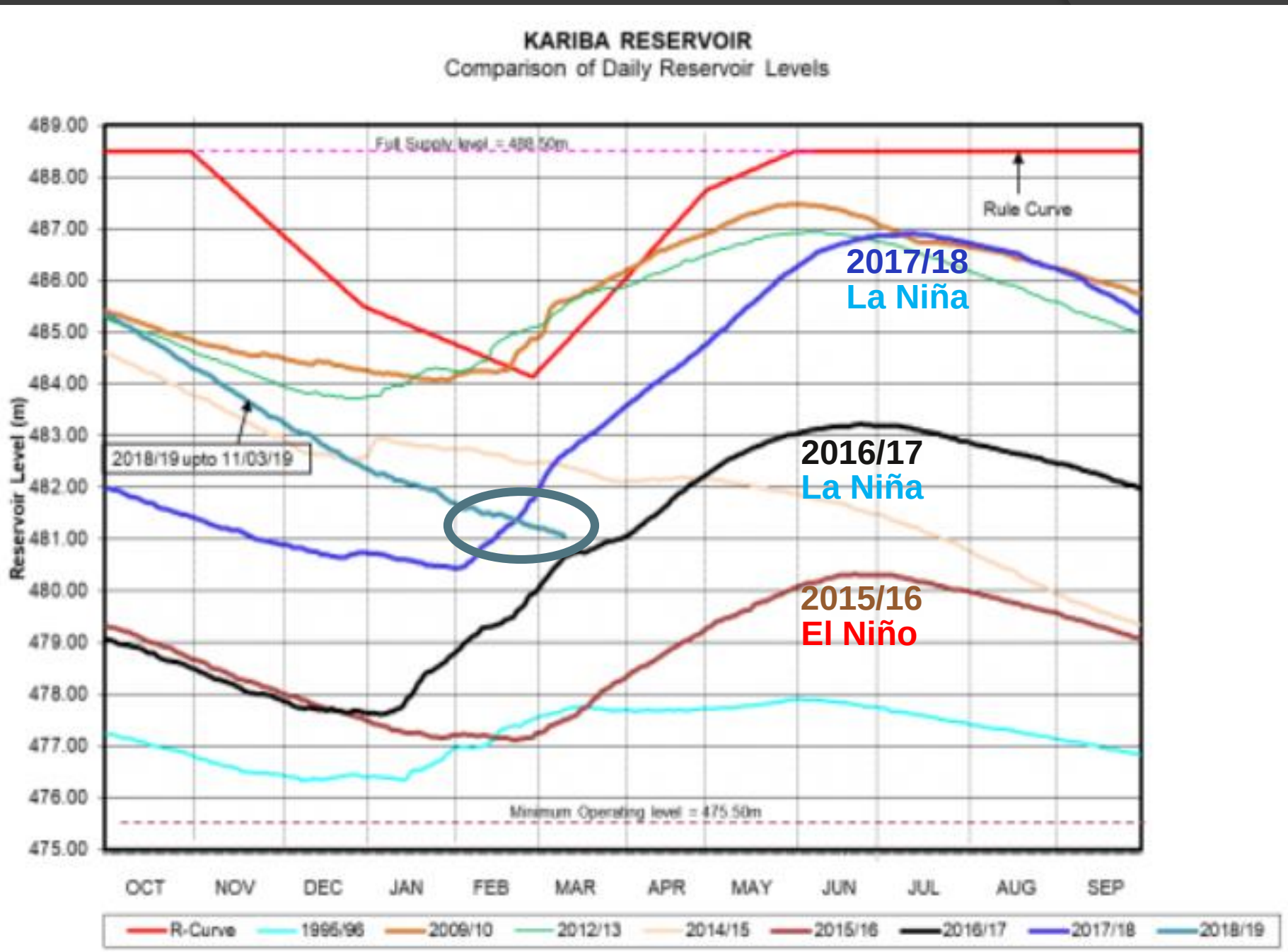
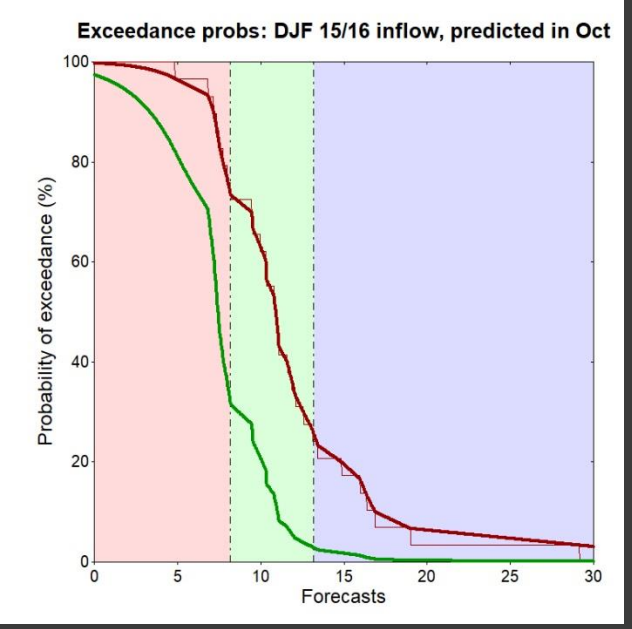
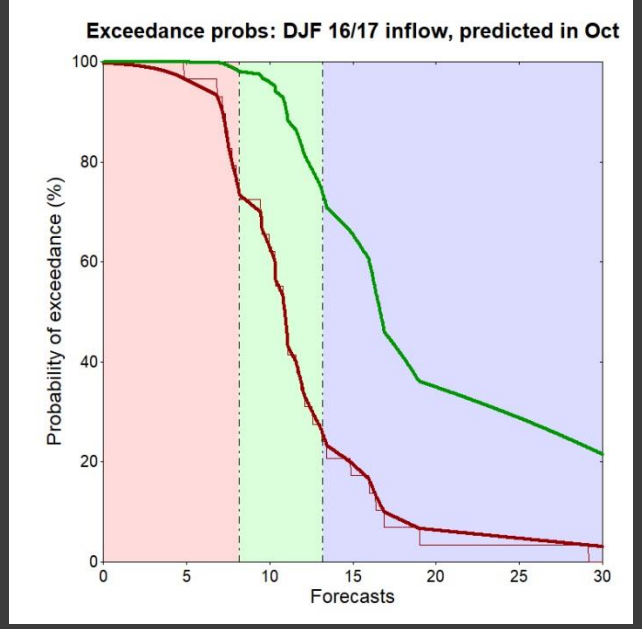
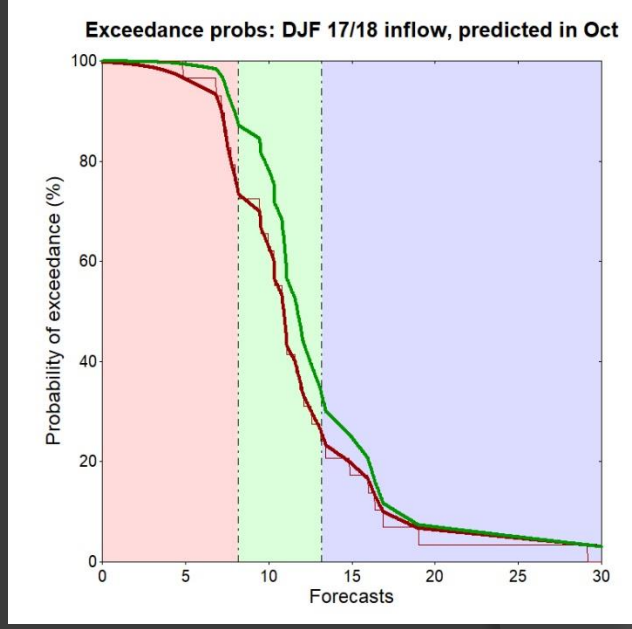
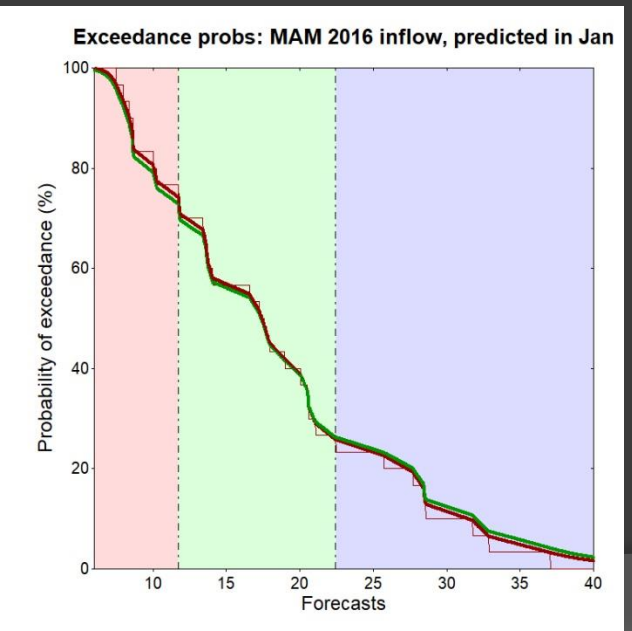

KARIBA RESERVOIR
Comparison of Daily Reservoir Levels
Reservoir Level (m)
489.00
488.00
487.00
486.00
485.00
484.00
483.00
482.00
481.00
480.00
479.00
478.00
477.00
476.00
475.00
Full Supply level = 488.50m
Rule Curve
2017/18
La Niña
2016/17
La Niña
2015/16
El Niño
2018/19 upto 11/03/19
Minimum Operating level = 475.50m
OCT
NOV
DEC
JAN
FEB
MAR
APR
MAY
JUN
JUL
AUG
SEP
R-Curve
1995/96
2009/10
2012/13
2014/15
2015/16
2016/17
2017/18
2018/19

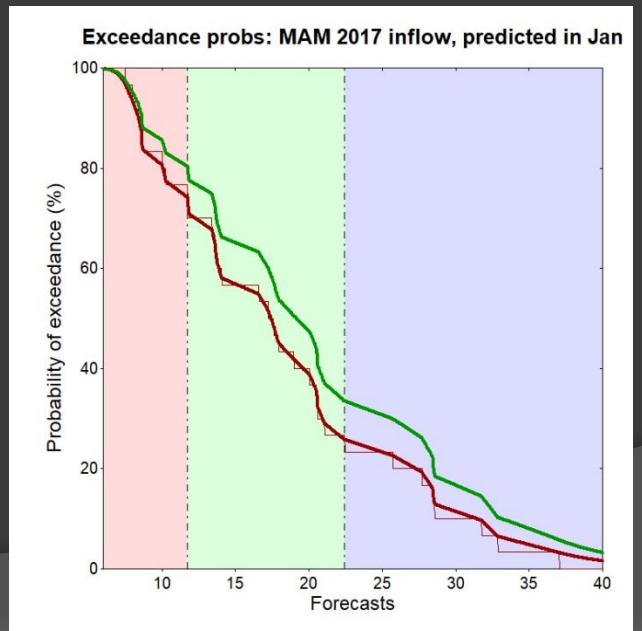


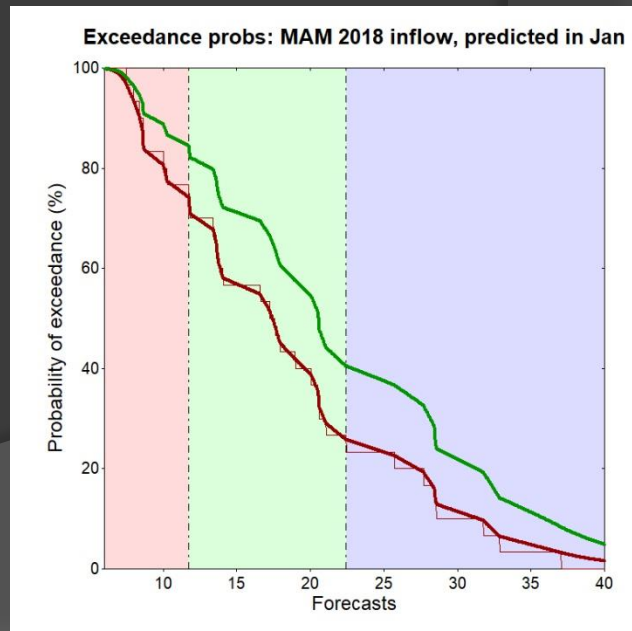


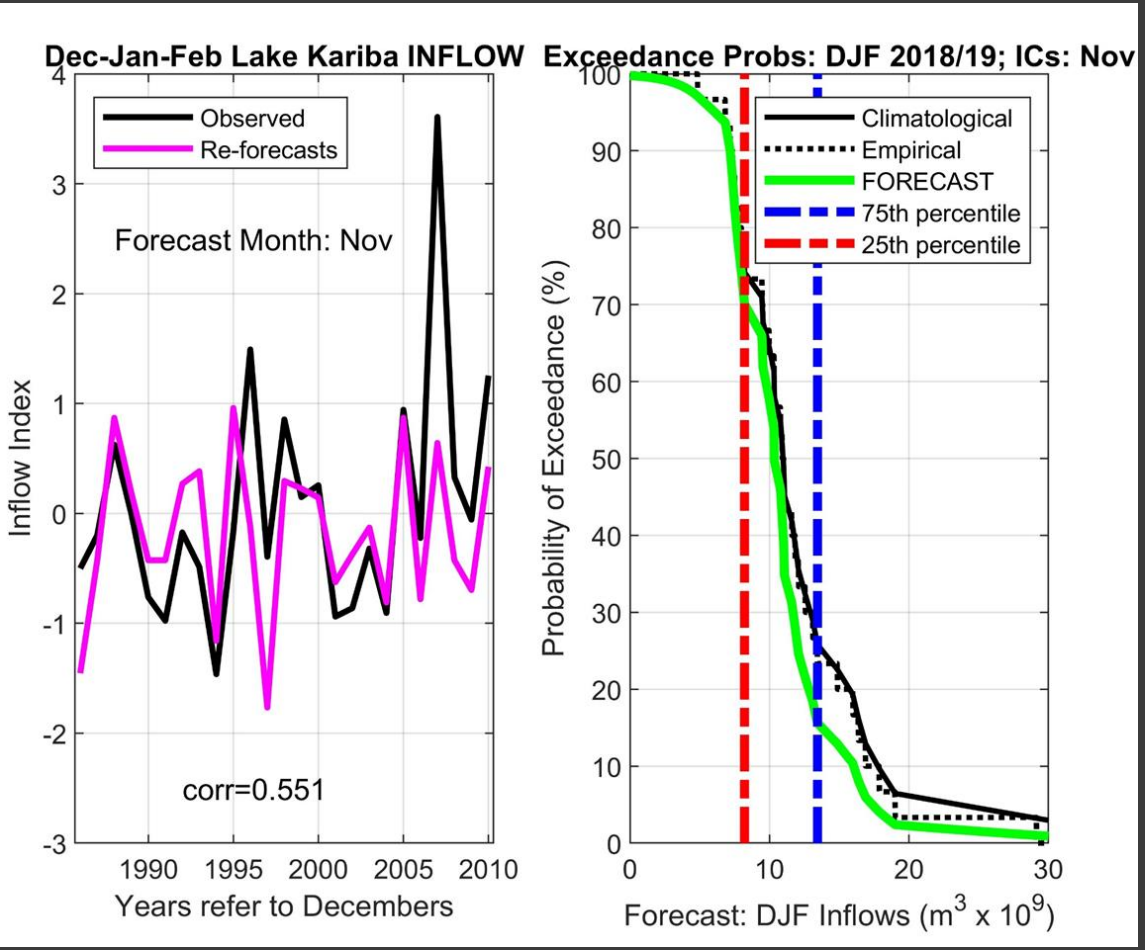


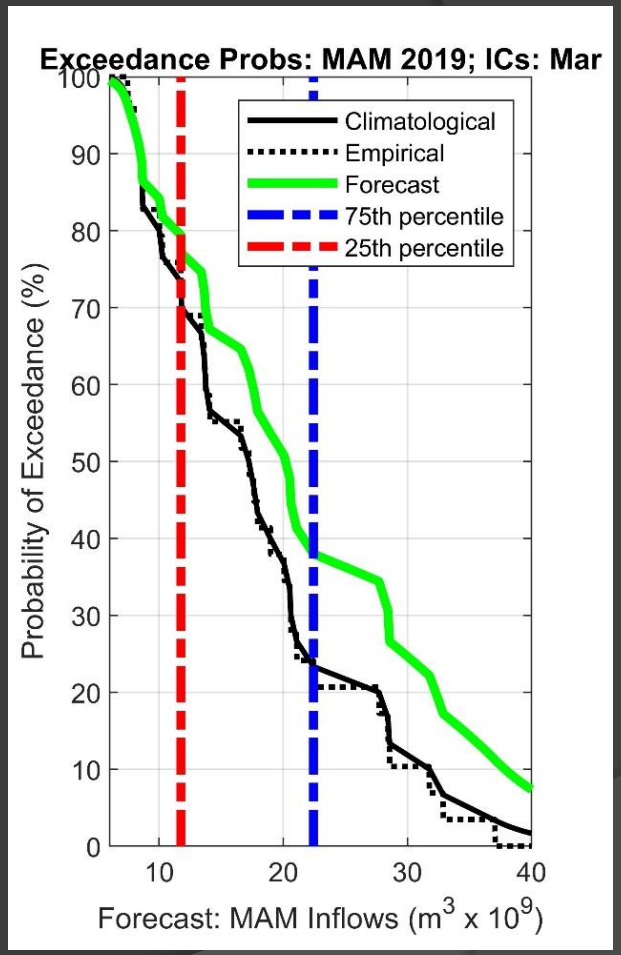
Inflows ($m^3 \times 10^9$)








Dec-Jan-Feb Lake Kariba INFLOW
Observed
Re-forecasts
Forecast Month: Nov
corr=0.551
Inflow Index
Years refer to Decembers
Exceedance Probs: DJF 2018/19; ICs: Nov
Climatological
Empirical
FORECAST
75th percentile
25th percentile
Probability of Exceedance (%)
Forecast: DJF Inflows (m3 x 10^9)


Exceedance Probs: MAM 2019; ICs: Mar
Climatological
Empirical
Forecast
75th percentile
25th percentile
Probability of Exceedance (%)
Forecast: MAM Inflows (m3 x 10^9)

...and some more acquired knowledge...

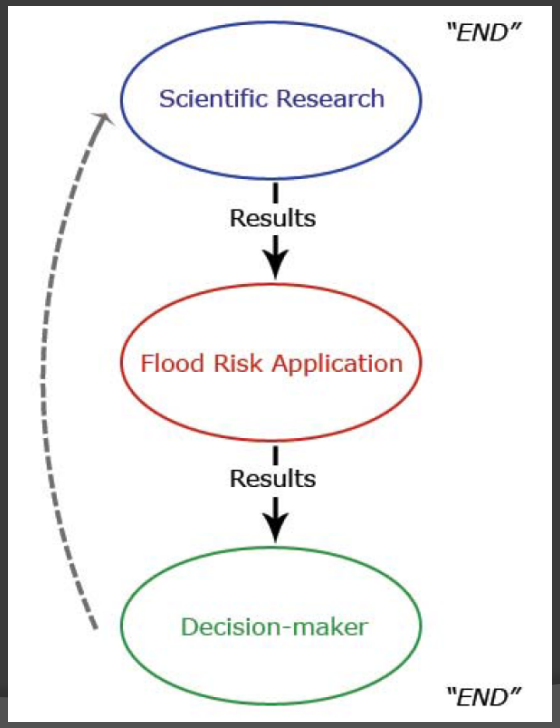
- Modelling research produced a forecast system, documented in a research paper, that is able to skillfully predict inflows into Lake Kariba
- Over the recent past, this system also produced good forecasts of increased inflows as reflected by rising dam levels
- But nobody uses these forecasts, even though their existence is known

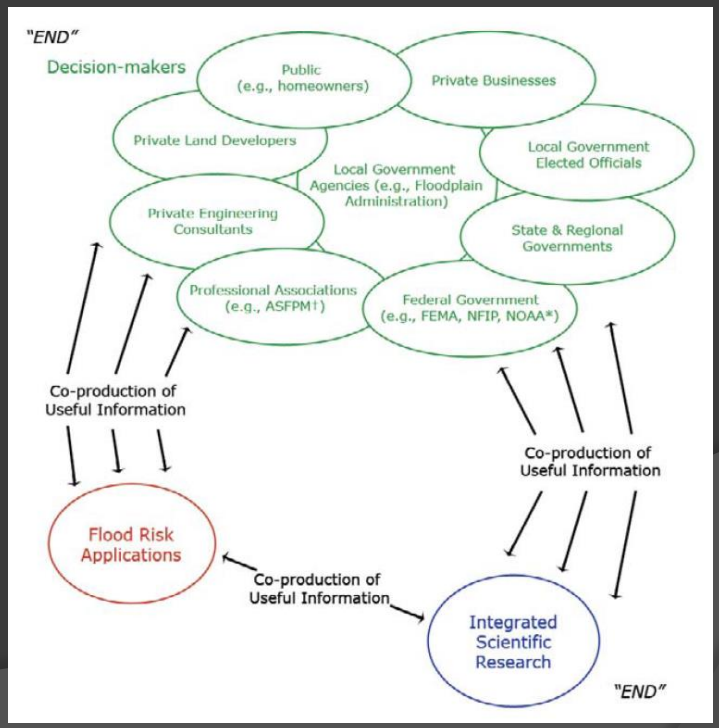
FLOOD RISK, UNCERTAINTY, AND SCIENTIFIC INFORMATION FOR DECISION MAKING

Lessons from an Interdisciplinary Project

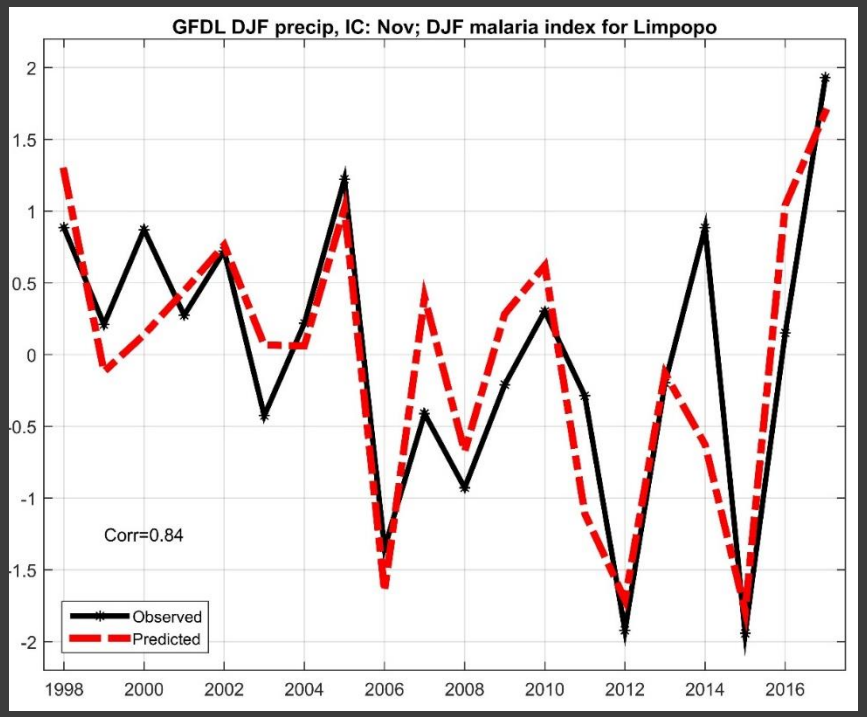
BY REBECCA E. MORSS, OLGA V. WILHELMI, MARY W. DOWNTON, AND EVE GRUNTFEST

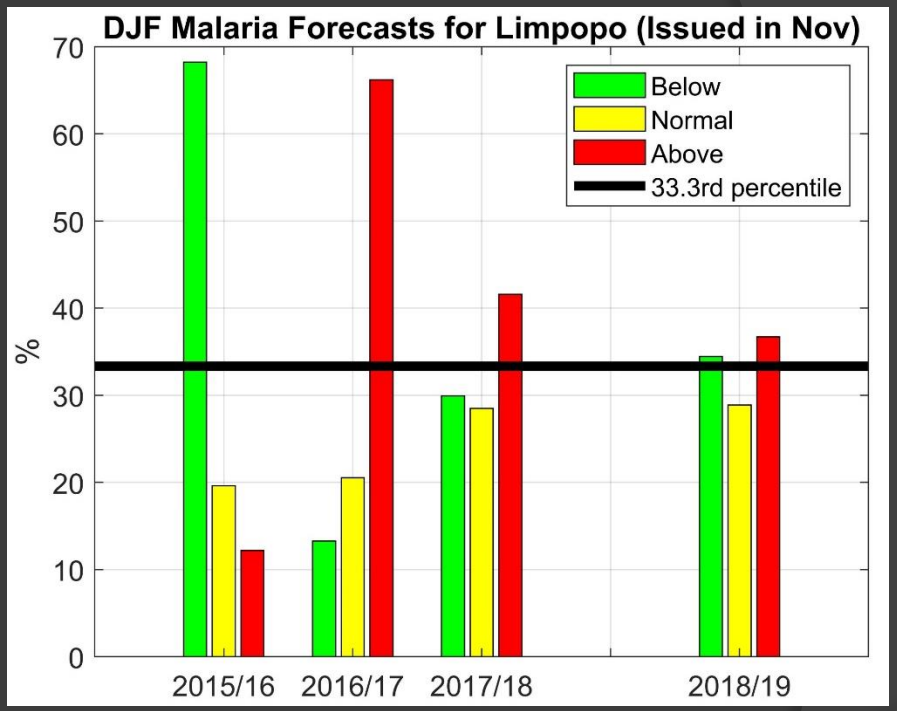
This essay discusses the complex ways in which scientific information and uncertainty can interact with societal decision making, and proposes a collaborative, integrated approach to societally useful scientific research.





Did we (finally) get it right for malaria prediction? Answer on next slide…





- Through the iDEWS project, malaria models were developed through a co-learning process
- Efforts are currently underway *to establish an iDEWS Bureau at the National Institute for Communicable Diseases*. The intention is that this will grow incrementally in scope and eventually develop the research capacity and operational systems to service the region

YES! I think so…

Summary…

- Forecast skill has improved over the years, but forecast uptake may not have increased
- There have been and will continue to be years in which user confidence may be decreased with associated implications, including financial
- Proper forecast verification provides insight into forecast capabilities – skill statistics should be conveyed to forecast users
- Tailored forecast modelling has great potential… only if users are involved through co-production (and co-learning)… and if modellers can get data!

Extended summary

Seasonal forecasts for South Africa have improved over recent decades and this improvement is a consequence of an increase in forecast model complexity: contemporary climate forecast models are significantly outscoring the elementary statistical models used in the early 1990s. Notwithstanding this improvement, forecasts are not equally useful for each year. When forecasts go “wrong”, there are often serious financial implications for the user of the forecasts, which may have caused seasonal forecast uptake to stagnate in recent years. However, even though our best forecast models are imperfect, the most benefit to be derived from seasonal forecasts is through consideration of forecasts produced by physically based and testable models. Such a model was used to develop a forecasting system for inflows into Lake Kariba, but although there is strong evidence from the research that the developed forecast system has huge potential, the forecasts produced from this model in a real-time operational setting are ignored. This problem has largely been brought about by the lack of interaction during the development stage between the developers of the inflow forecast model and for those the forecast system was developed. This problem was not repeated during the recent development of a seasonal forecast system for malaria occurrence over the Limpopo Province owing to the involvement of the Department of Health in Limpopo during the development. Moreover, a very positive outcome of this so-called co-production process is that real-time malaria forecasts will be administered by a soon to be established forecast bureau for infectious diseases at the National Institute for Communicable Diseases. This presentation has therefore shown that seasonal forecast models are skillful enough to help develop tailored forecast products for various applications, but with the requirement that the development happens through the process of co-production and co-learning.