Seasonal forecasts

presented by:



Seasonal Forecast

https://tinyurl.com/ForecastProf

UNIVERSITEIT VAN PRETORIA
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Worx

Seasonal Climate Forecasts

Latest Update: 11 December 2023

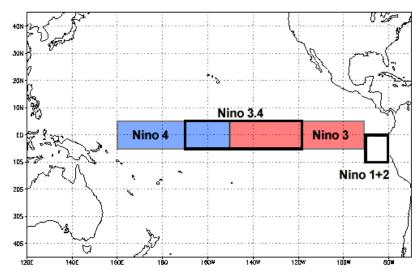
- The seasonal forecasts presented here by Seasonal Forecast Worx are based on forecast output of
 the coupled ocean-atmosphere models administered through the North American Multi-Model
 Ensemble (NMME) prediction experiment (http://www.cpc.ncep.noaa.gov/products/NMME/;
 Kirtman et al. 2014). NMME real-time seasonal forecast and hindcast (re-forecast) data are obtained
 from the data library (http://iridl.ldeo.columbia.edu/) of the International Research Institute for
 Climate and Society (IRI; http://iri.columbia.edu/).
- NMME forecasts are routinely produced and are statistically improved and tailored for southern Africa and for global sea-surface temperatures by employees and post-graduate students in the Department of Geography, Geoinformatics and Meteorology at the University of Pretoria (http://www.up.ac.za/en/geography-geoinformatics-and-meteorology/). Statistical post-processing is performed with the CPT software (http://iri.columbia.edu/our-expertise/climate/tools/cpt/).
- Why do we apply statistical methods to climate model forecasts?
 - "...statistical correction methods treating individual locations (e.g. multiple regression or principal component regression) may be recommended for today's coupled climate model forecasts". (Barnston and Tippett, 2017).
- Why do we not use just a single model in our forecasts?
 - "...multi-model forecasts outperform the single model forecasts..." (Landman and Beraki, 2012).
- For the <u>official</u> seasonal forecast for South Africa, visit the South African Weather Service website at http://www.weathersa.co.za/images/data/longrange/gfcsa/scw.pdf

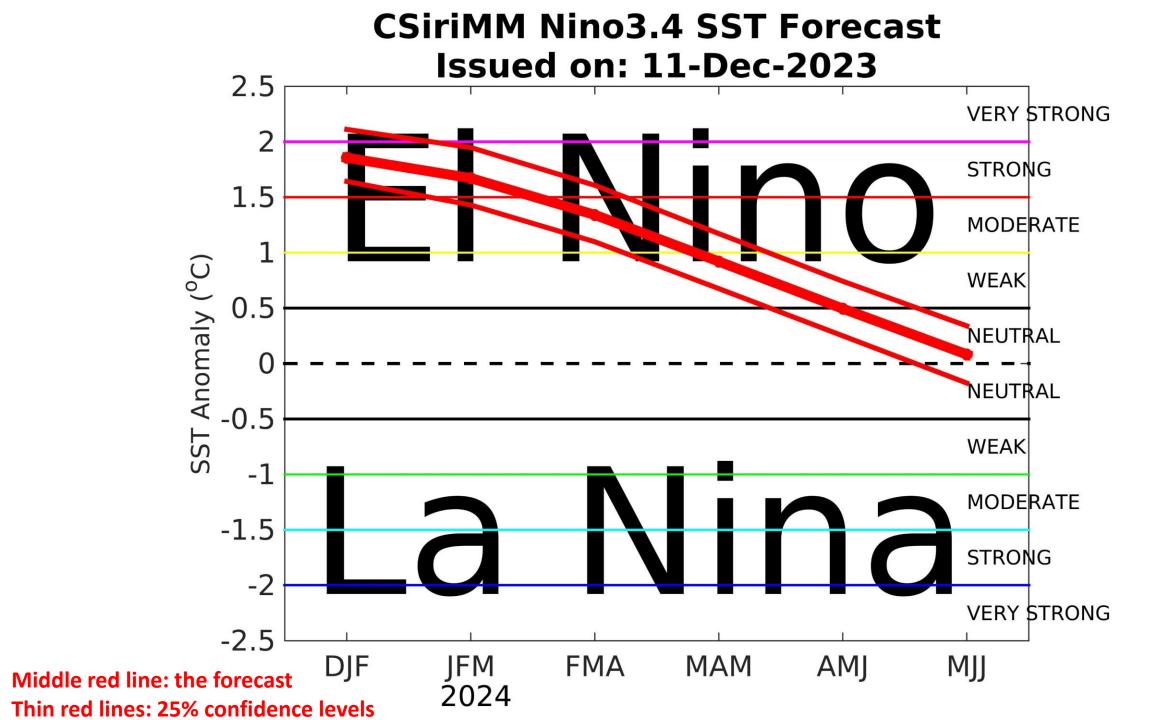
Weather Service

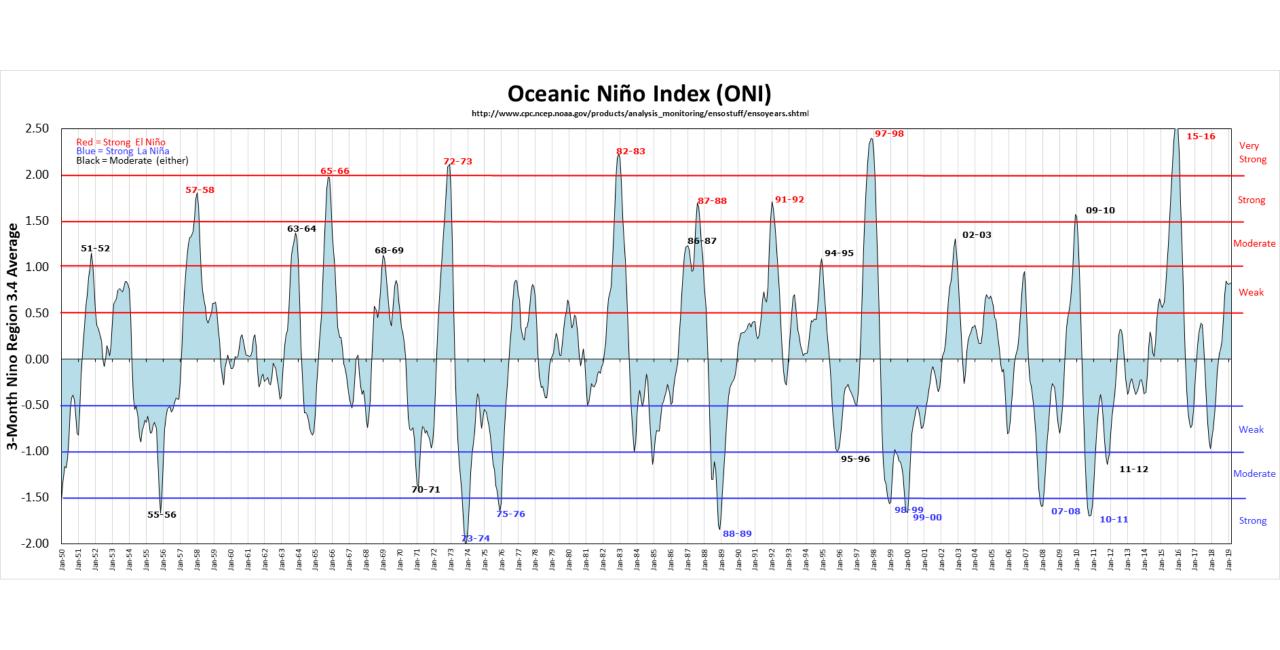
ENSO and Global SST Forecasts

Prediction Method

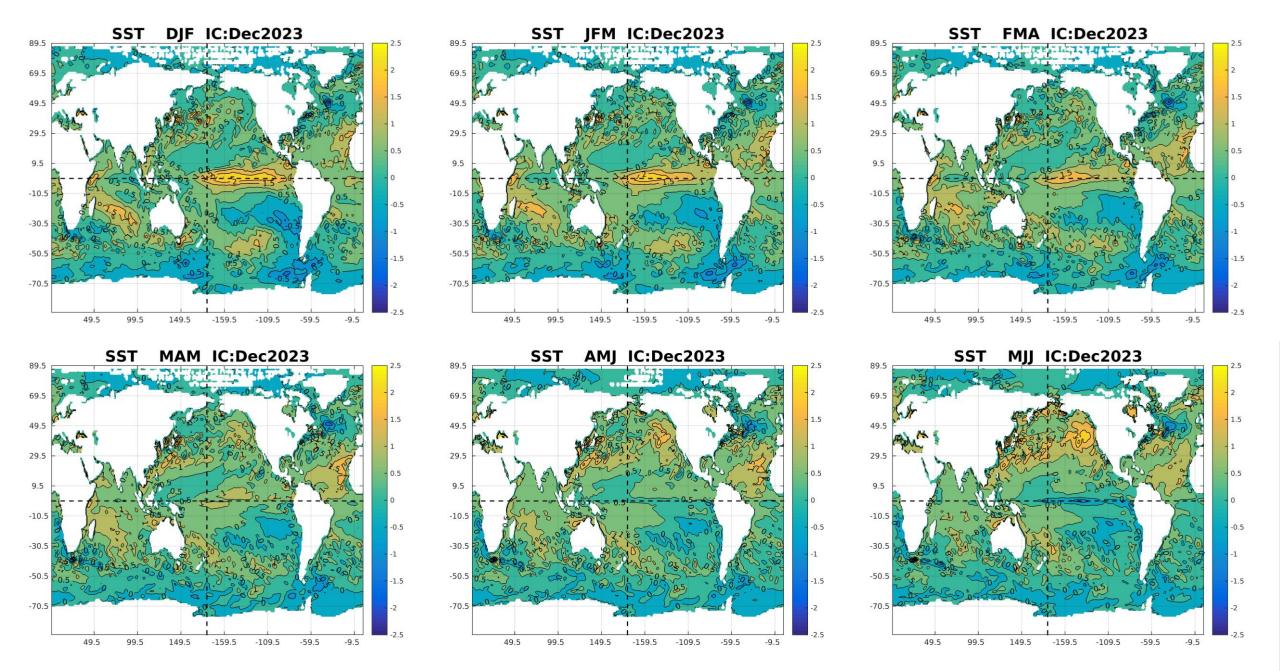
- Forecasts for global sea-surface temperature (SST) fields are obtained through a combination of NMME models and a linear statistical model, that uses antecedent SST as a predictor (Landman et al. 2011). Forecasts for the Niño3.4 area (see insert) are derived from the global forecasts.
- SST forecasts from the NMME models are variance and bias corrected.
- Three-month Niño3.4 SST forecasts are produced for three categories:
 - El Niño: SST above the 75th percentile
 - La Niña: SST below the 25th percentile
 - Neutral: Neither El Niño nor La Niña





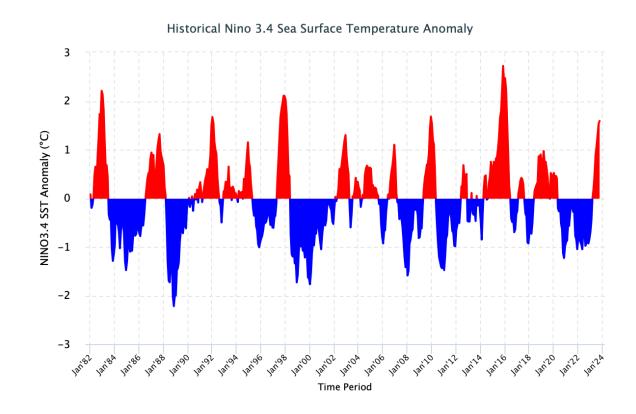


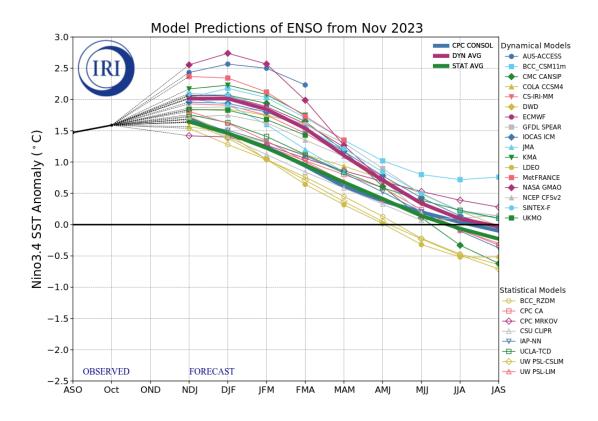
SST anomalies (in °C, where blue is cooler and orange is warmer)



Round-up: ENSO

- The UP model (on previous pages) is predicting a strong (>1.5°C) El Niño event to continue during the Austral summer period, which is in agreement with some of forecasts produced internationally (right panel below)
- Heading towards ENSO-neutral by Autumn





Africa forecasts, south of 20°N

Prediction Method

- Three-month seasons for seasonal rainfall totals and average maximum temperatures of NMME ensemble mean forecasts are recalibrated to the Climatic Research Unit (CRU; Harris et al. 2014) grids (0.5°x0.5°). Probabilistic forecasts are subsequently produced from the error variance obtained from a 5-year-out cross-validation process (Troccoli et al. 2008). Forecasts cover a 6-month period.
- Forecasts are produced for three categories:
 - **Above:** Above-normal ("wet" rainfall totals / "hot" maximum temperatures higher than the 75th percentile of the climatological record)
 - **Below:** Below-normal ("dry" rainfall totals / "cool" maximum temperatures lower than the 25th percentile of the climatological record)
 - **Normal:** Near-normal ("average" season)

NEW!!!

- Verification of forecast performance:
 - ROC Area (Below-Normal) The forecast system's ability to discriminate dry or cool seasons from the rest of the seasons over a 23-year test period. ROC values should be higher than 0.5 for a forecast system to be considered skilful.
 - ROC Area (Above-Normal) The forecast system's ability to discriminate wet or hot seasons from the rest of the seasons over a 23-year test period. ROC values should be higher than 0.5 for a forecast system to be considered skilful.
 - The white areas on the forecast maps
 - Forecasts for the near-normal category do not have skill and are therefore not shown
 - Forecasts associated with ROC values less than or equal to 0.5 (no skill) are also not shown

Forecasts are probabilistic

Probabilistic forecasts can help users understand risks and opportunities (forewarned is forearmed) in order to make more informed decisions.

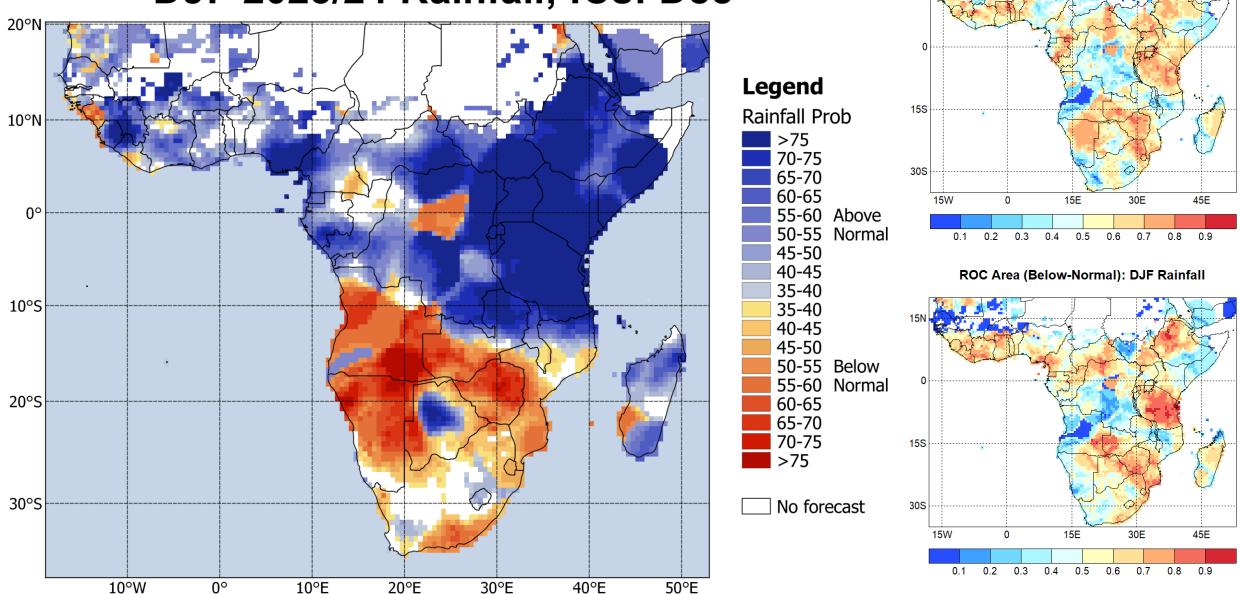
The seasonal rainfall and maximum temperature forecasts to follow are expressed in probabilities, shown as the % chance of the most likely outcome of 3 categories. The colour of the scale reflects the most likely category and the % shows the probability of that outcome. Only ONE of the ROC area skill assessment maps should be consulted, depending on the category shown on the forecast map (Above- or Below-Normal), and the higher the ROC value, the more skilful the forecast for that pixel is. The probabilities shown are always less than 100% - so there is no absolute certainty that the less favoured outcome will not occur. For example, if the forecast claims a 75% chance of below-normal rainfall totals for a season (i.e. drought), it means that 1 out of 4 times it will **not** develop into a drought.

The nature of a probabilistic forecast implies that the less likely outcomes are always possible. In fact, for the probabilistic forecasts to be considered reliable, the less likely outcomes will and must occasionally occur.

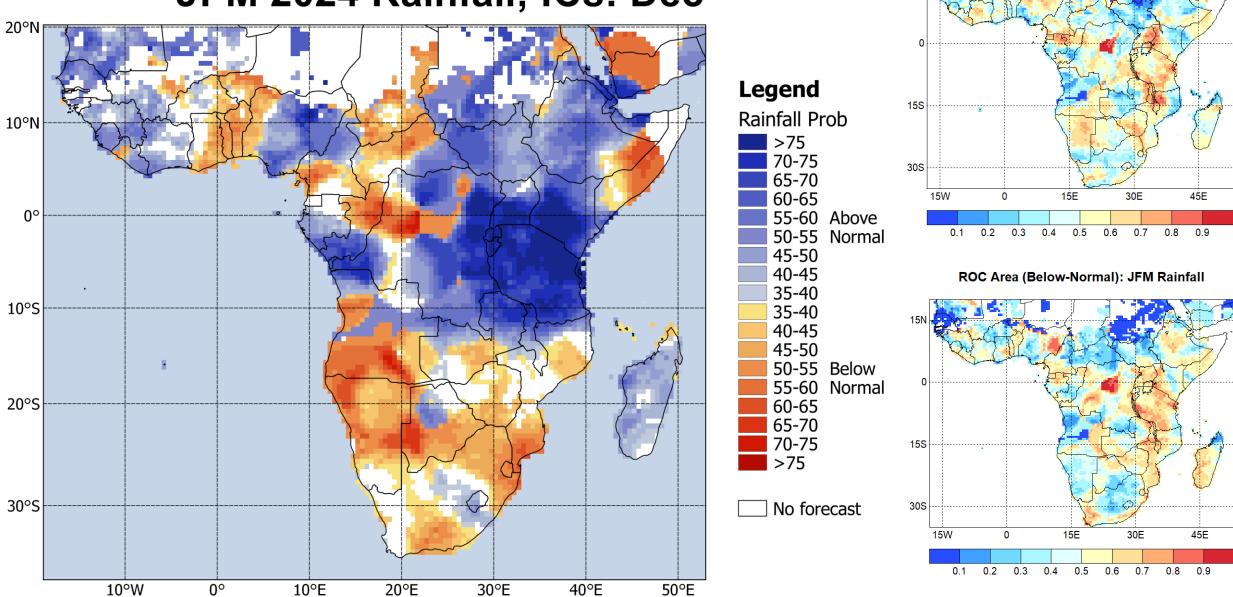
Note: Probabilistic forecasts are considered reliable when the forecast probability is an accurate estimation of the relative frequency of the predicted outcome. In other words, forecasts are reliable if the observation falls within the category (Below-, Near- or Above-Normal) as frequently as the forecast implies

ROC Area (Above-Normal): DJF Rainfall

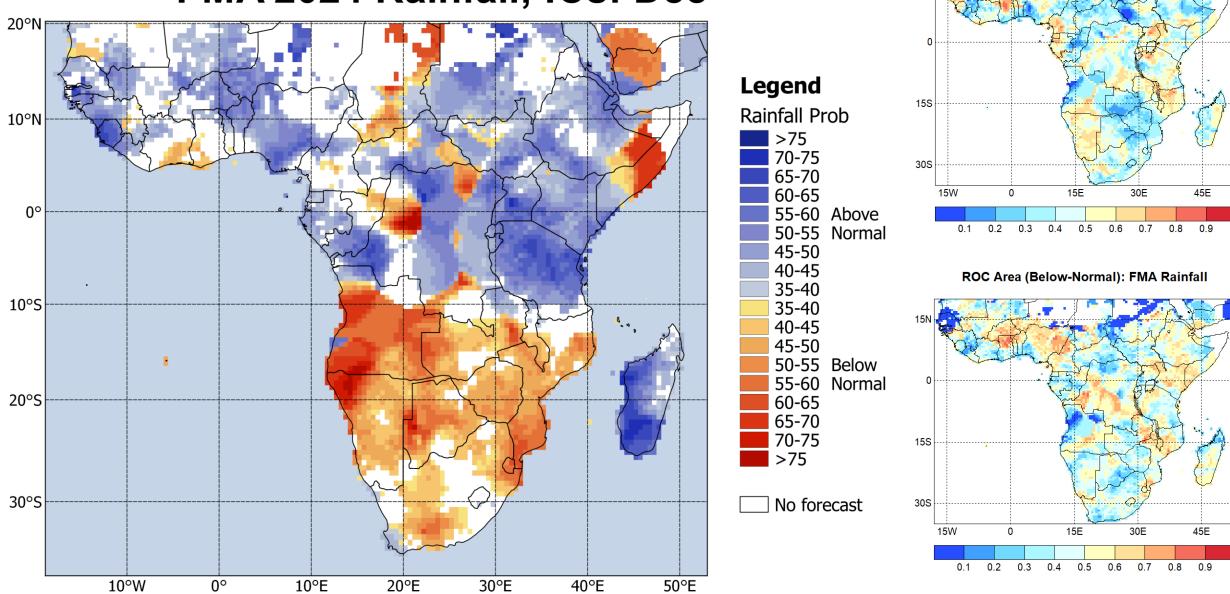
DJF 2023/24 Rainfall; ICs: Dec



JFM 2024 Rainfall; ICs: Dec

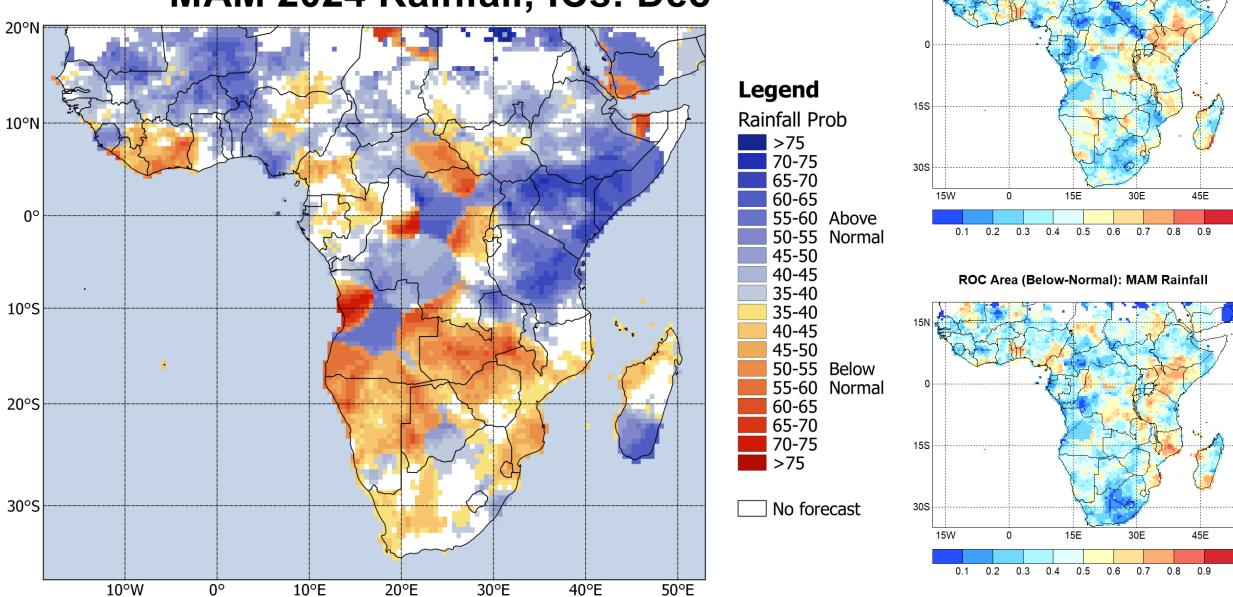


FMA 2024 Rainfall; ICs: Dec



ROC Area (Above-Normal): MAM Rainfall

MAM 2024 Rainfall; ICs: Dec

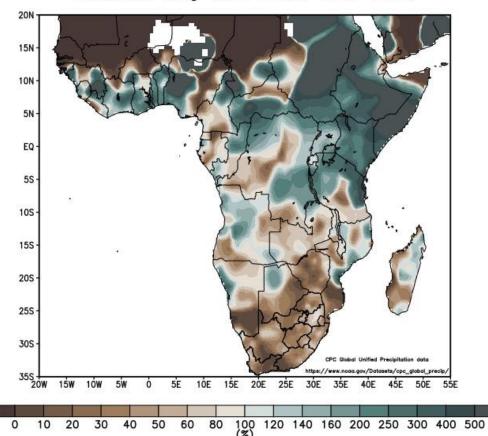


Round-up: Rainfall south of 15°S

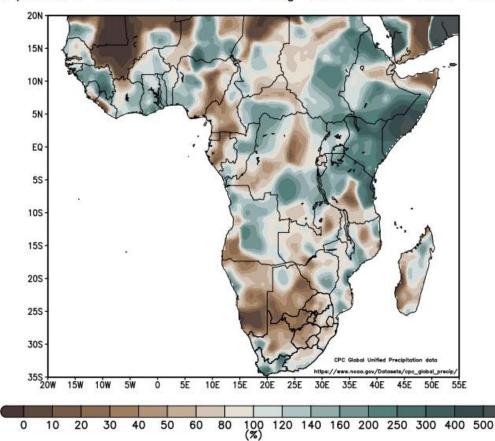
- Enhanced probabilities of mostly below-normal rainfall totals
 - While there are enhanced probabilities of below-normal rainfall in most regions,
 the forecast skill is low and this reduces confidence in this month's rainfall products

Observed Rainfall

Rainfall (% of normal): November 2023 November long-term mean: 1981-2010

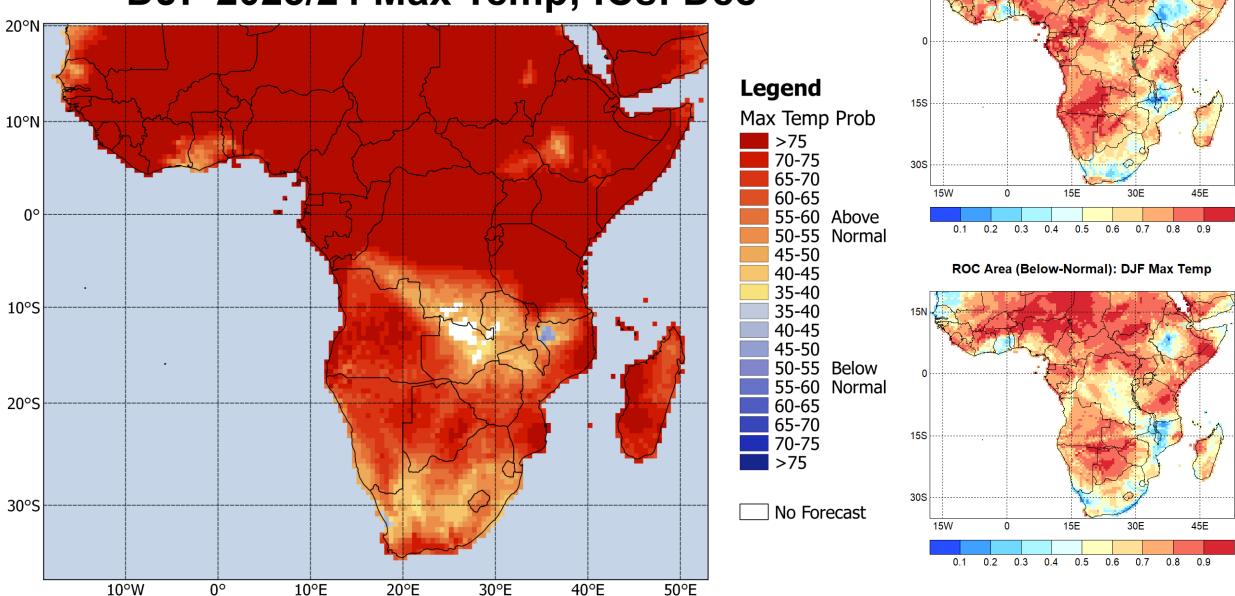


Rainfall (% of normal): September-October-November 2023 September-October-November long-term mean: 1981-2010

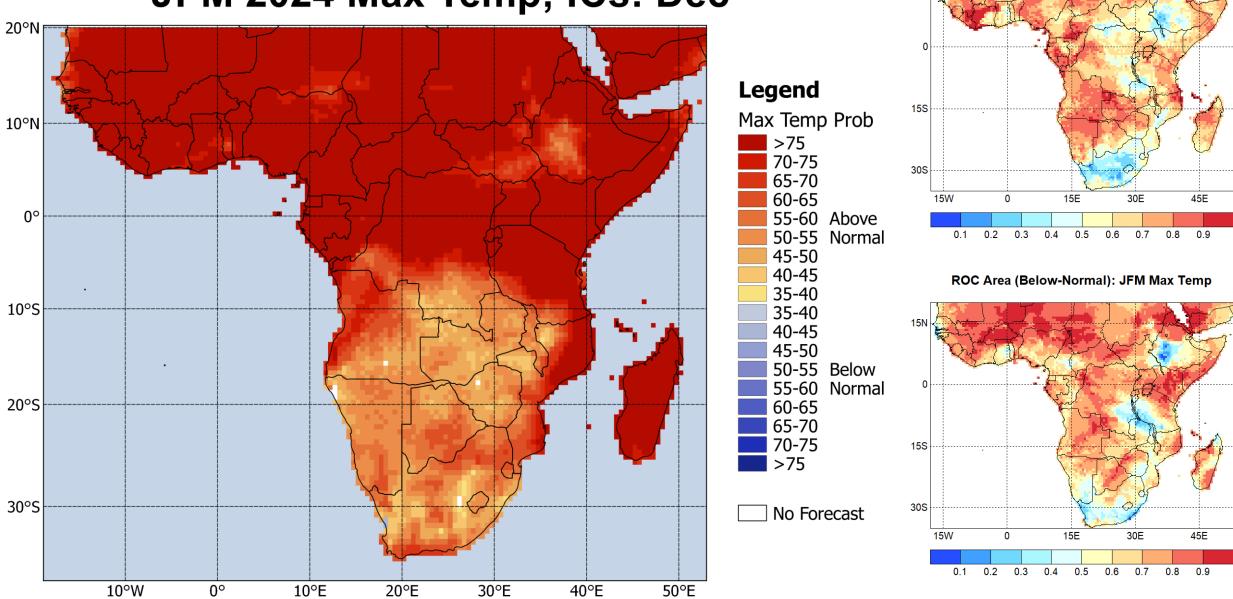


Recorded rainfall for November and the September-October-November season show below-normal rainfall over the brown areas and above-normal rainfall over the green areas

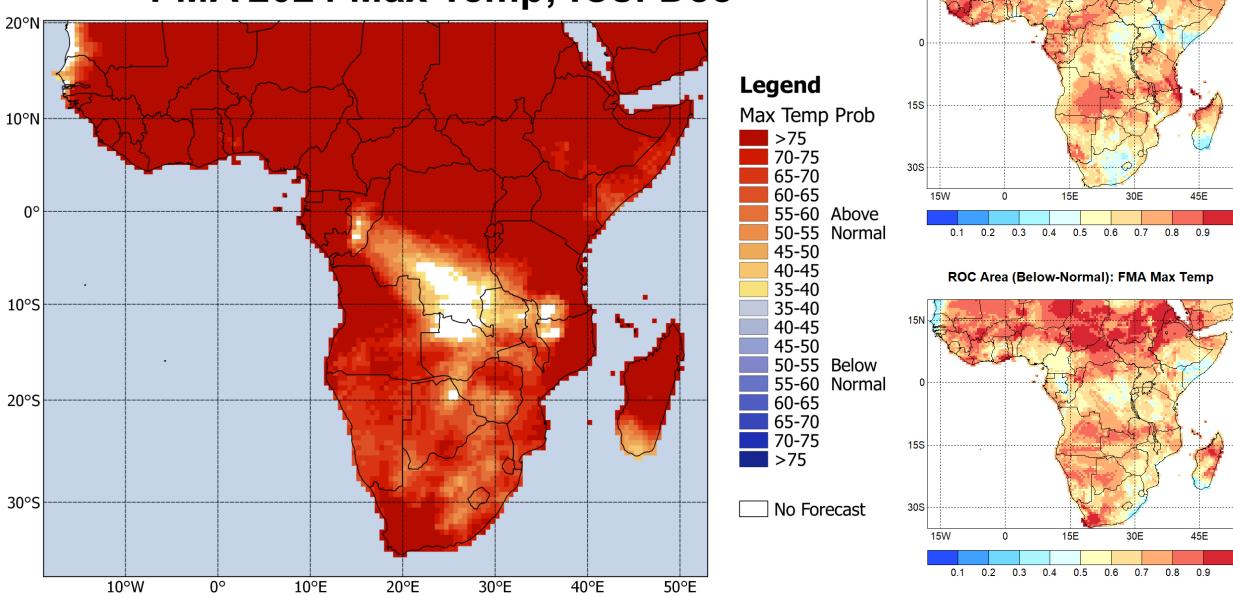
DJF 2023/24 Max Temp; ICs: Dec



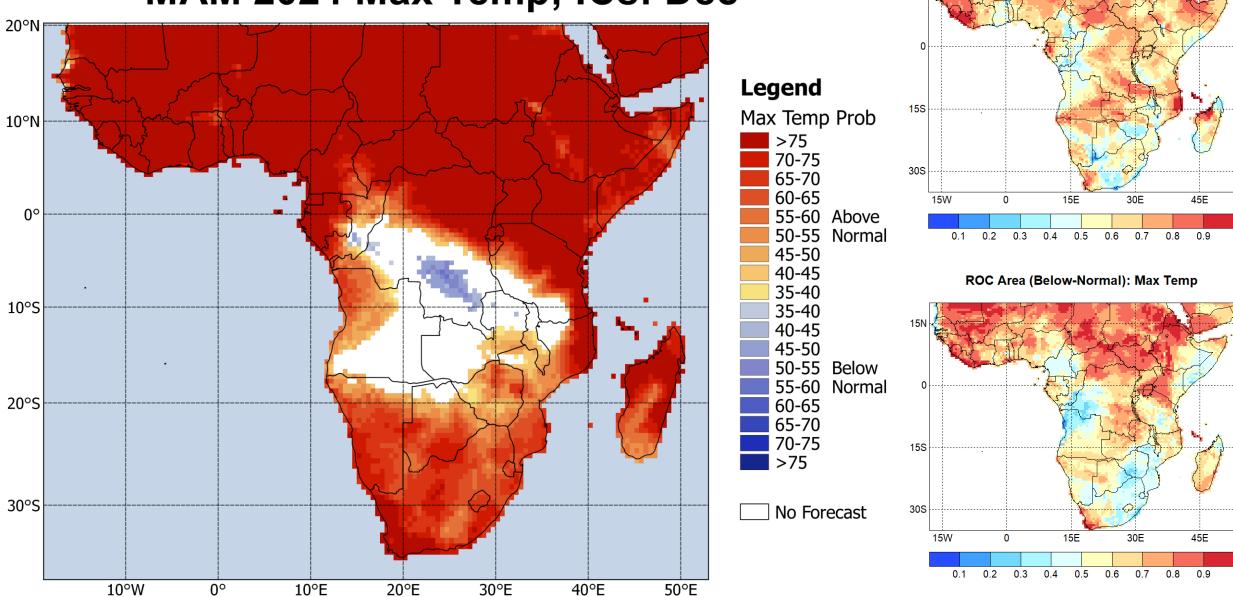
JFM 2024 Max Temp; ICs: Dec



FMA 2024 Max Temp; ICs: Dec



MAM 2024 Max Temp; ICs: Dec



Round-up: South of 15°S Max Temp

 Above-normal maximum temperatures over the entire region are highly likely during the forecast period

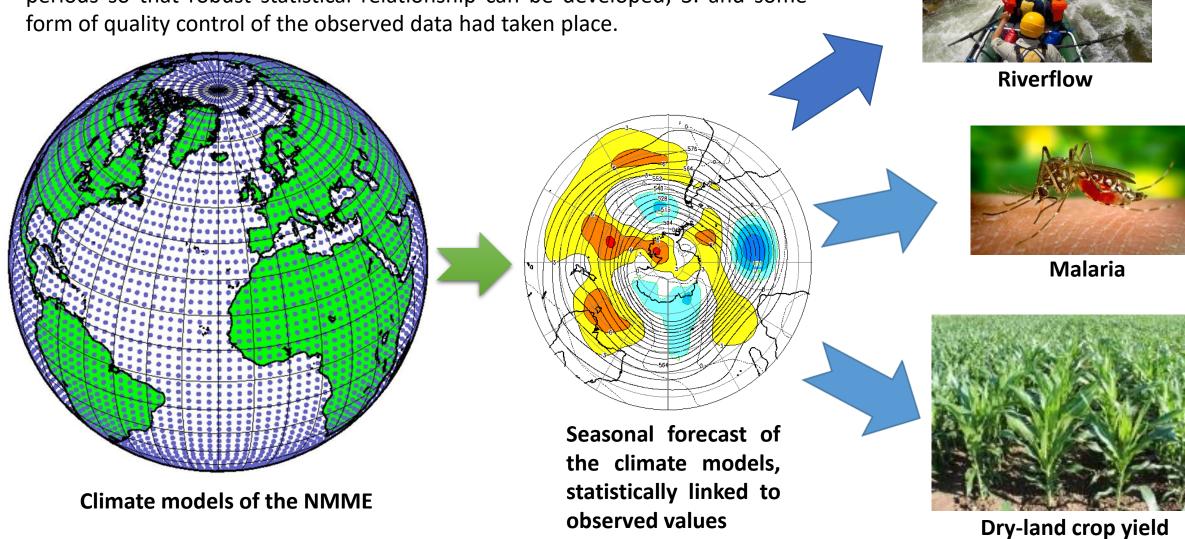
Tailored Forecasts

Translating forecasts into indices on a range of relevant space and time scales that can inform regional decision-making. The following forecasts are shown to indicate the potential of seasonal forecasting for real-life applications

- 1. Bapsfontein end-of-season-yield three-category probabilistic forecast for 2024
- 2. Probabilistic three-category rainfall forecast for the farm of Robbie Kingsley for Dec-Jan-Feb 2023/24
- 3. Probability of exceedance Dec-Jan-Feb 2023/24 inflow forecast for Lake Kariba, Zambia/Zimbabwe
- 4. Probabilistic <u>rainfall</u> forecast for Jan-Feb-Mar 2024 for the farm Buschbrunnen near Grootfontein, Namibia

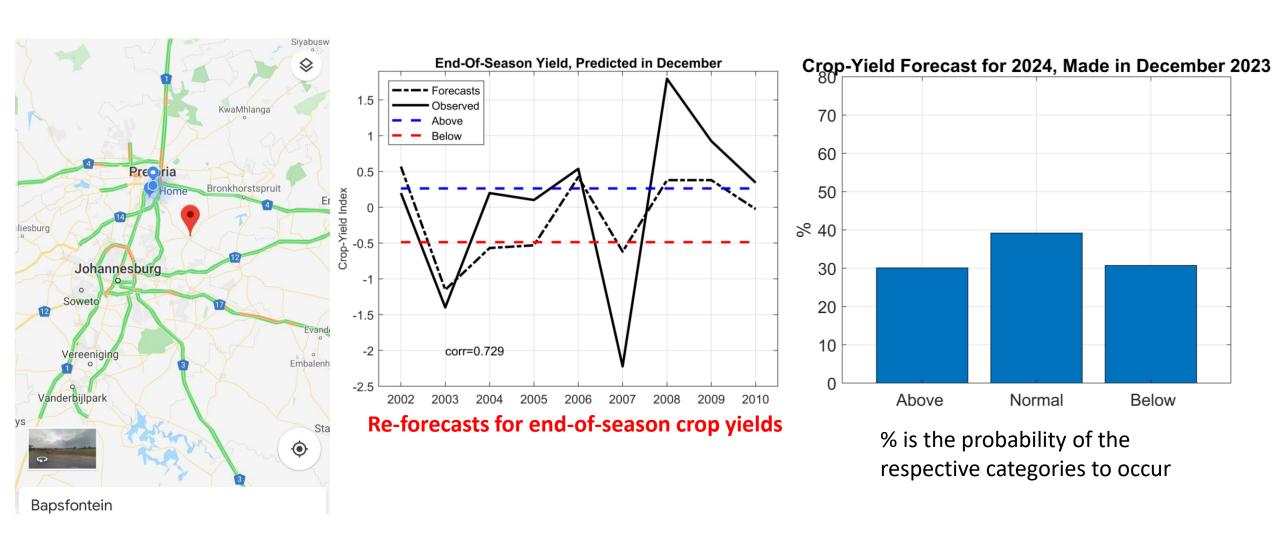
The prediction scheme

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.

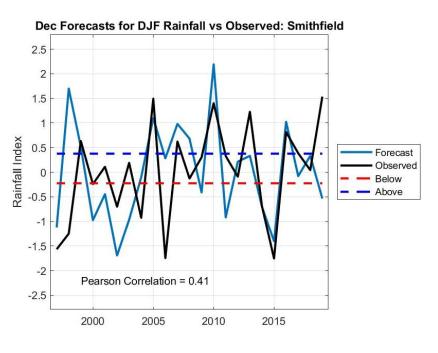


Dry-land crop-yield data and forecasts for a farm near Bapsfontein, South Africa

Landman et al. (2019)

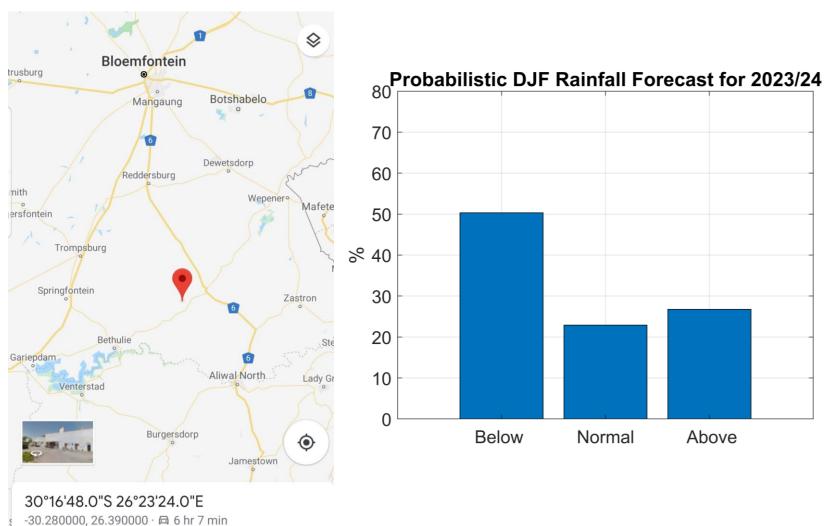


Annual Cycle (1997-2018): Smithfield District 100 80 40 20 1 2 3 4 5 6 7 8 9 10 11 12 Months



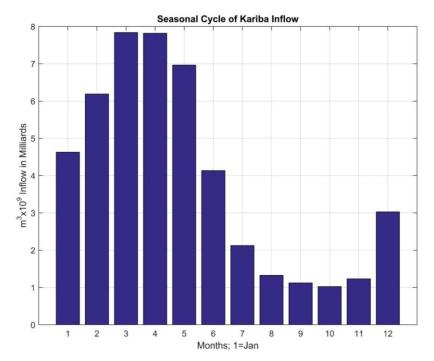
Dec-Jan-Feb 2023/24 rainfall forecast for farm in the Smithfield district (see map). Rainfall data provided by the farmer, Mr. Robbie Kingsley

Landman et al. (2020a)

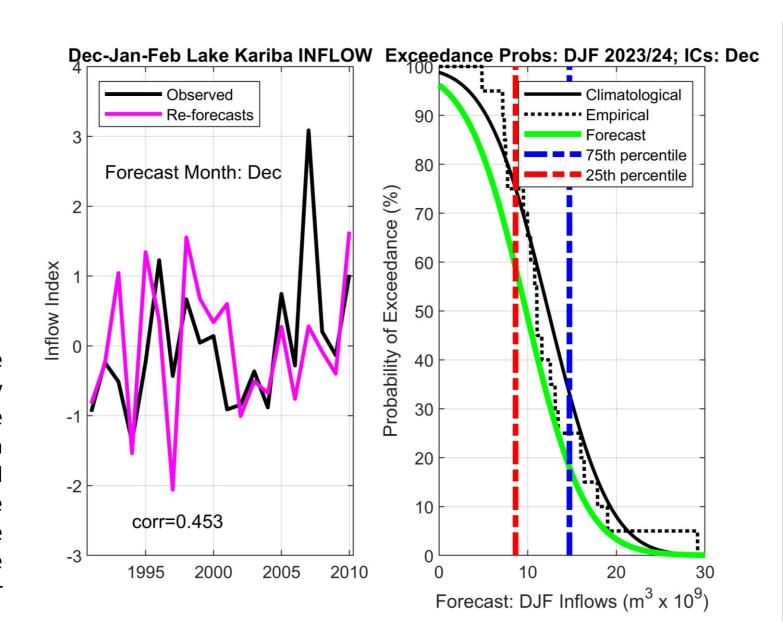


Inflow forecast for Lake Kariba: onset season of DJF

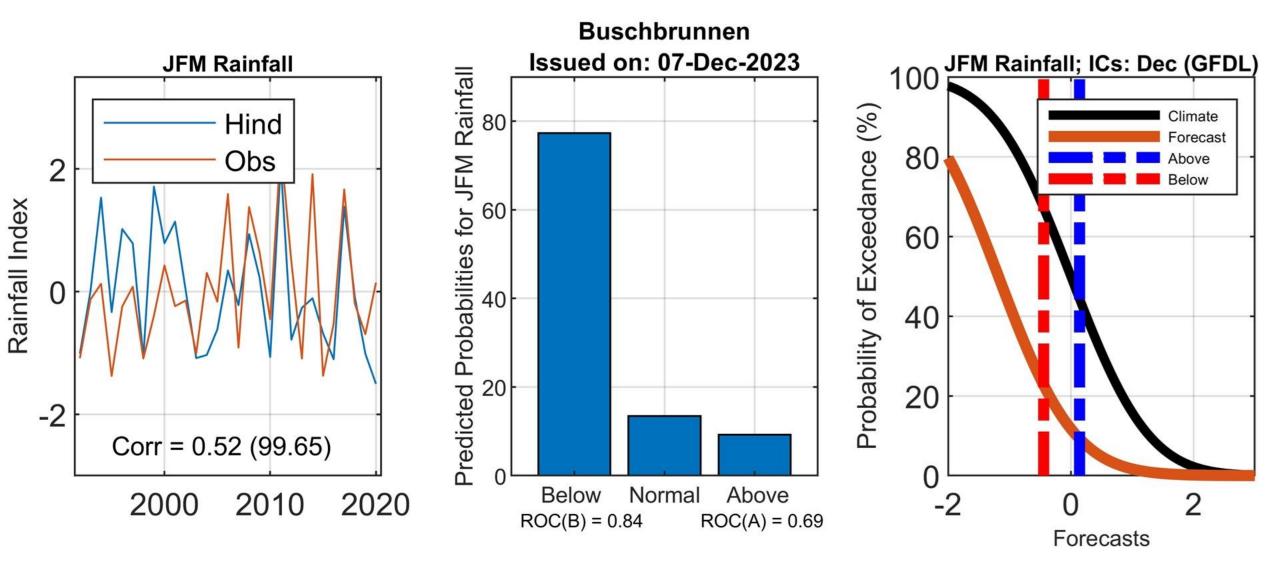
Muchuru et al. (2016)



For the forecast on the far right: The black curve represents the climatological probability distribution of DJF inflows, and the green curve represents the predicted probability distribution for the coming DJF season. The vertical dashed lines represent the category thresholds. The easiest way to interpret the green forecast curve would be to consider a curve above (below) the thick black curve to be probabilistic forecasts for anomalously high (low) DJF inflows.



JFM rainfall forecast for the farm Buschbrunnen near Grootfontein, Namibia Landman et al. (2016)



Round-up: Tailored products

 The tailored forecasts shown are in agreement with the expected outcome of mostly dry and hot conditions during El Nino seasons – low yield, rainfall totals and flows

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- Water Research Commission through administering the international project "Research-based Assessment of Integrated approaches to Nature-based SOLUTIONS (RainSolutions)" (2020 to 2022)











The forecast is produced by Prof Willem Landman of the University of Pretoria, South Africa, and issued on or around the 15th of each month. Please feel free to contact me at WALandman1981@gmail.com

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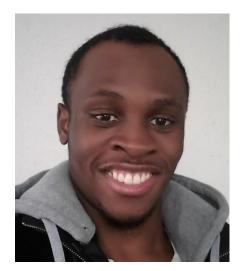
Disclaimer: The author has compiled this forecast guidance as a service to users for application in appropriate sectors, but cannot be held responsible for inaccuracies contained therein

Student participation in forecast system development



Stephanie Hinze, BSc (Honours)(Meteorology):

Statistical downscaling using large and high-resolution data sets, forecast displays for SADC rainfall and maximum temperatures, forecast verification



Surprise Mhlongo, BSc (Honours)(Meteorology):

Improving on SST forecast system through pattern correction, correlation vs covariance approaches, forecast output combination (multi-model approaches), mean and bias correction, and correct for skill



Shepherd Muchuru, PhD (Meteorology):

Statistical modelling to relate large-scale features to seasonal inflows into Lake Kariba in southern Africa. Two predictions systems: 1) using antecedent seasonal rainfall totals over the upper Zambezi catchment as predictor in a baseline model, and 2) using predicted low-level atmospheric circulation of a coupled ocean—atmosphere general circulation model as predictor.



Pearl Gosiame, BSc (Honours)(Meteorology):

Development of hydro-climate predictions models for dam levels and downstream flows of the Vaal Dam. Predictors considered include historical rainfall over the catchment, SST and output from global climate models.



Idani Mandiwana, BSc (Honours) (Meteorology):

Seasonal rainfall forecast verification of real-time forecasts produced by SFW over the 5-year period from 2018 to 2022. Area is SADC south of 17° South.