

# Seasonal forecasts

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# Seasonal Forecast Worx



<https://tinyurl.com/ForecastProf>

UNIVERSITEIT VAN PRETORIA  
UNIVERSITY OF PRETORIA  
YUNIBESITHI YA PRETORIA

**Seasonal Climate Forecasts**

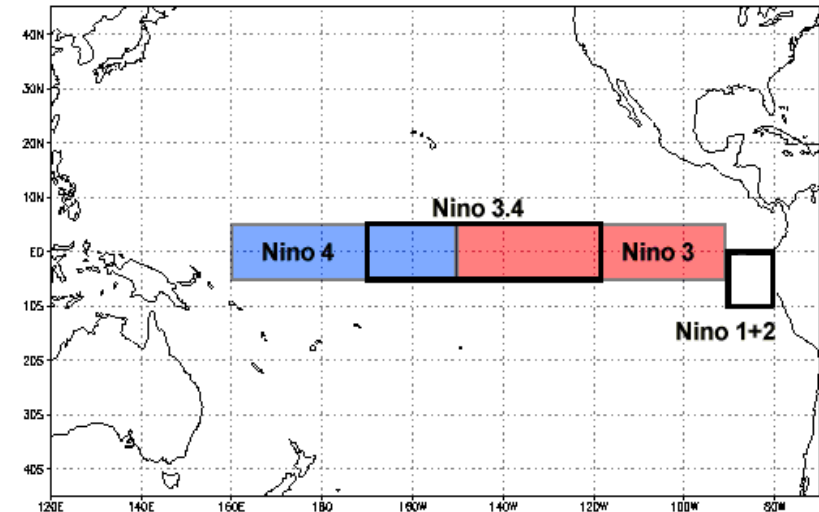
Latest Update: 12 March 2025

- 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 official seasonal forecast for South Africa, visit the South African Weather Service website at: <https://www.weathersa.co.za/home/seasonalclimate>

# ENSO and Global SST Forecasts

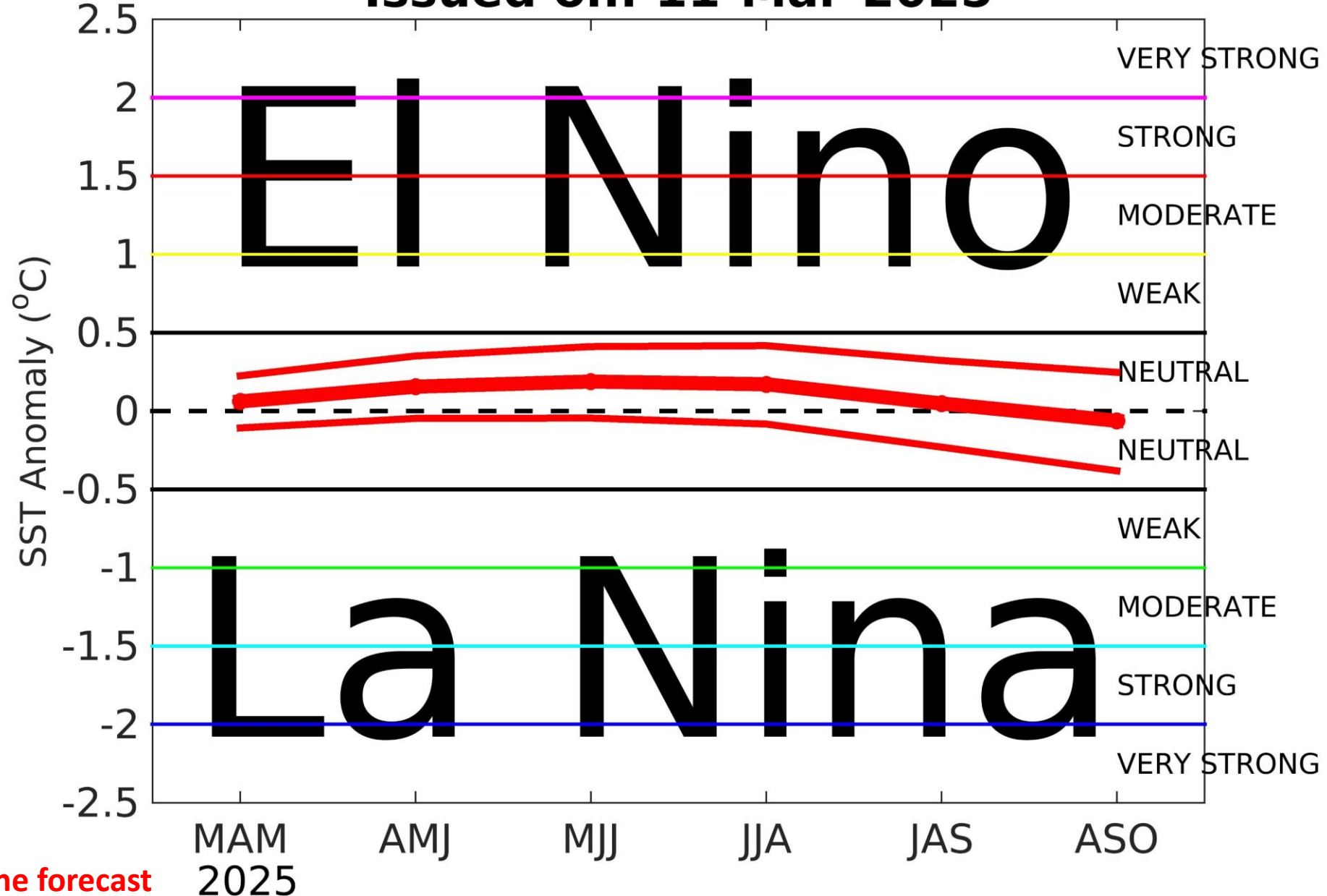
# Prediction Method

- 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



# CSiriMM Nino3.4 SST Forecast

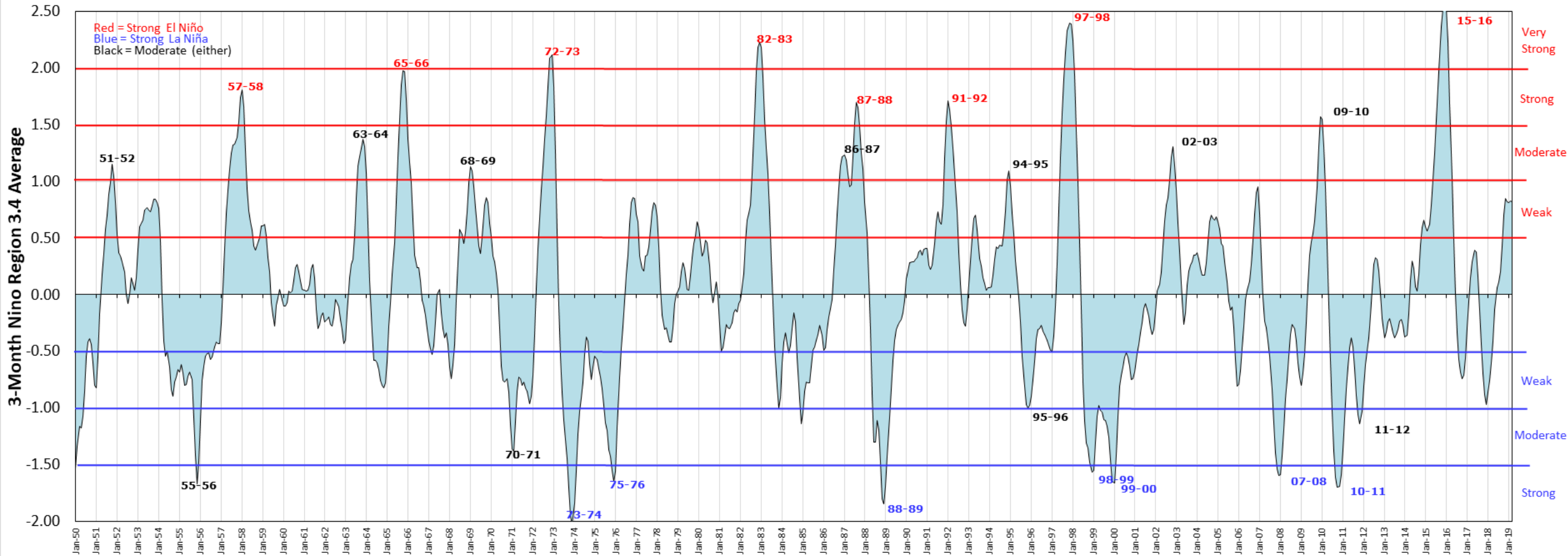
## Issued on: 11-Mar-2025



Middle red line: the forecast  
Thin red lines: 25% confidence levels

# Oceanic Niño Index (ONI)

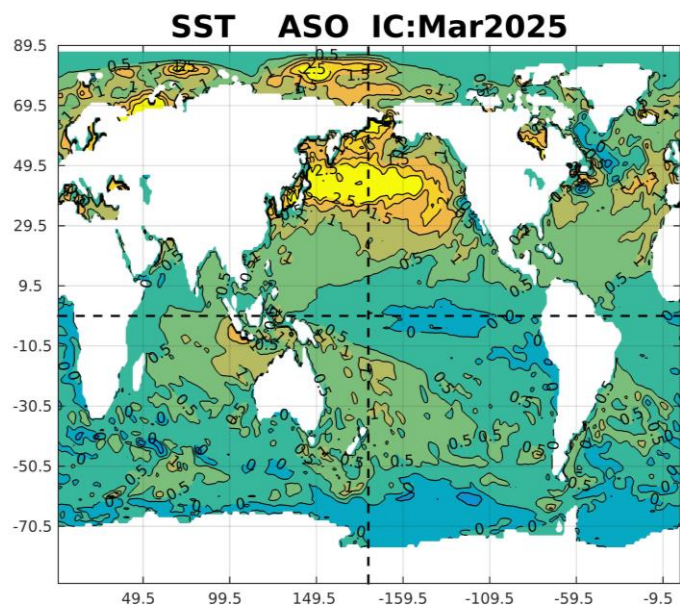
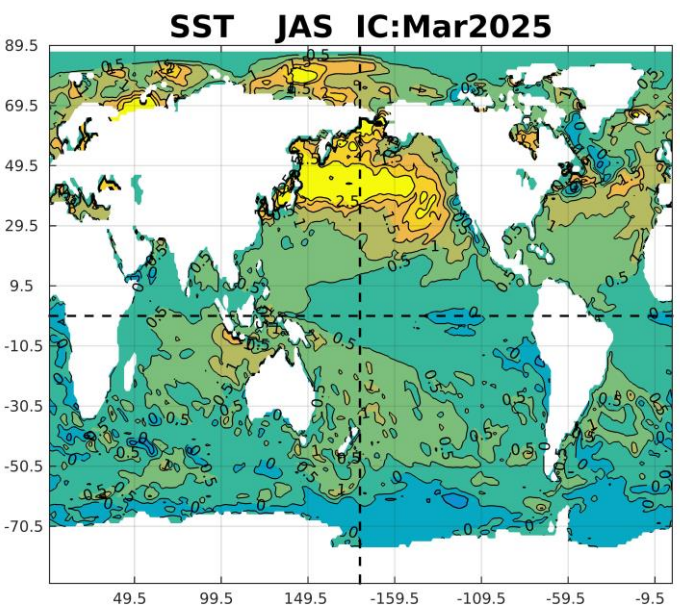
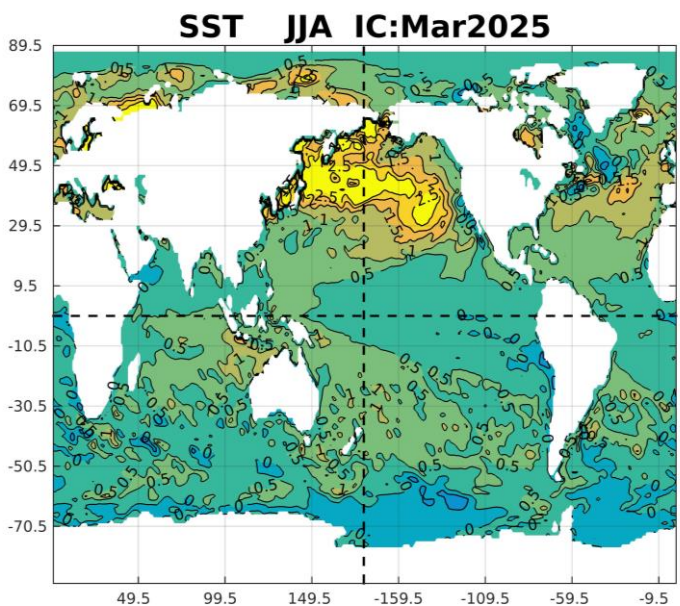
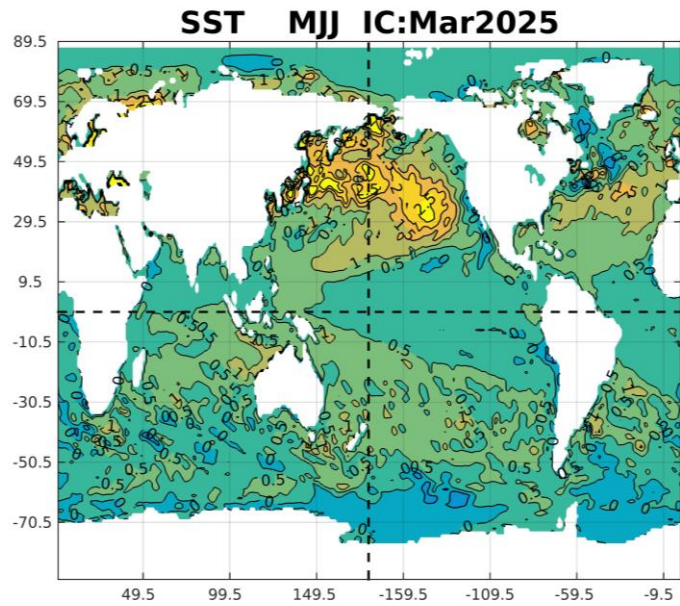
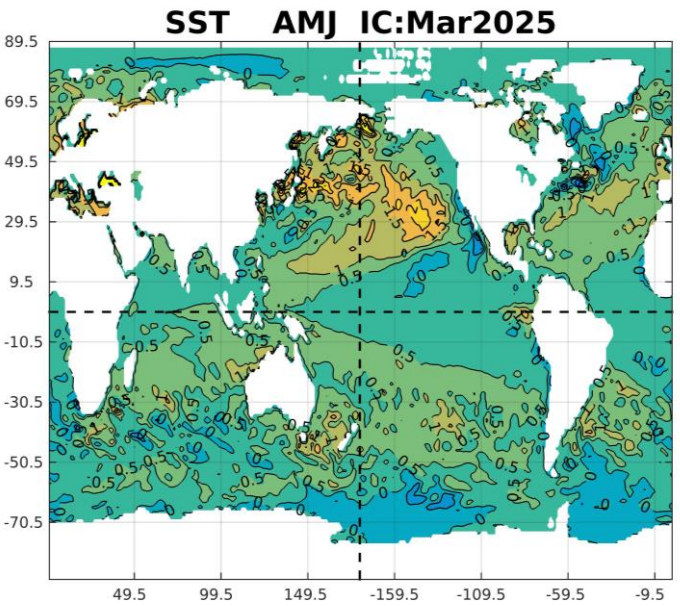
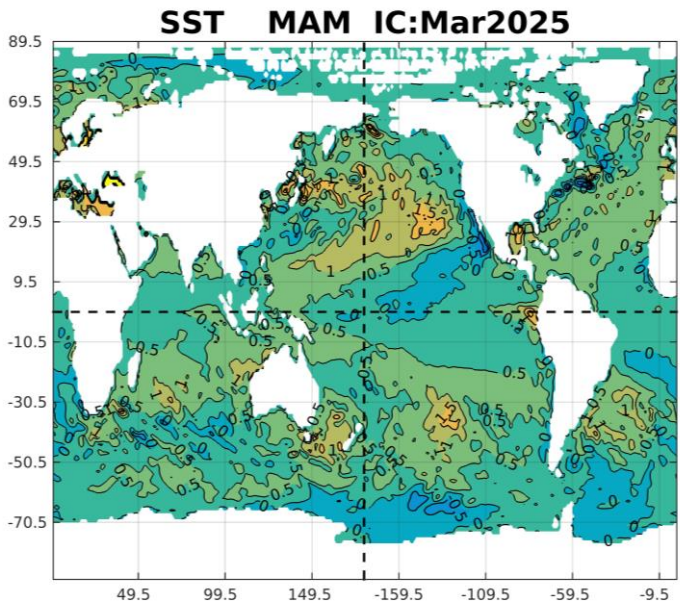
[http://www.cpc.ncep.noaa.gov/products/analysis\\_monitoring/ensostuff/ensoyears.shtml](http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml)





IC: the month in which the forecast was made

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

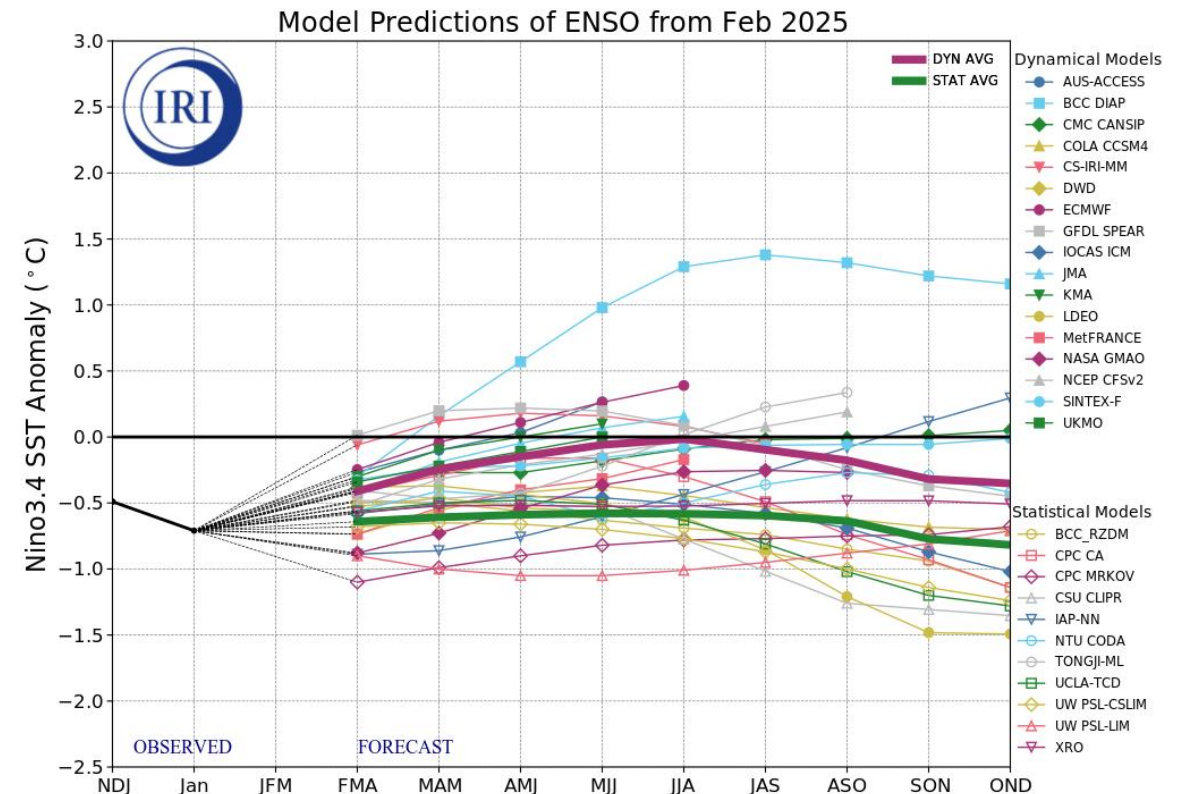
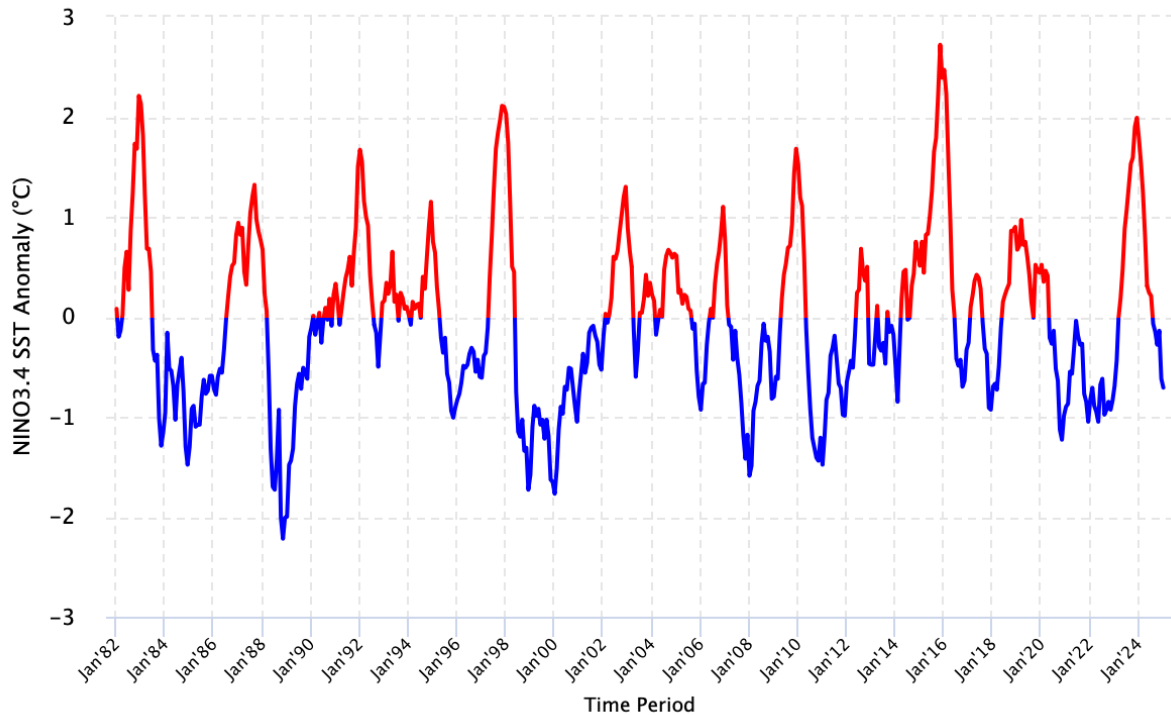




# Round-up: ENSO

- The UP model (on previous pages) is predicting the likely development of ENSO-neutral conditions, although some international forecasts are showing weak La Niña conditions to continue into the next austral summer

Historical Nino 3.4 Sea Surface Temperature Anomaly



The UP model forms part of this plume, and is marked as "CS-IRI-MM"



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 ( $0.5^{\circ} \times 0.5^{\circ}$ ). 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)
- 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
    - No forecast - forecasts for the near-normal category do not have skill and are therefore not shown

# Forecasts are probabilistic

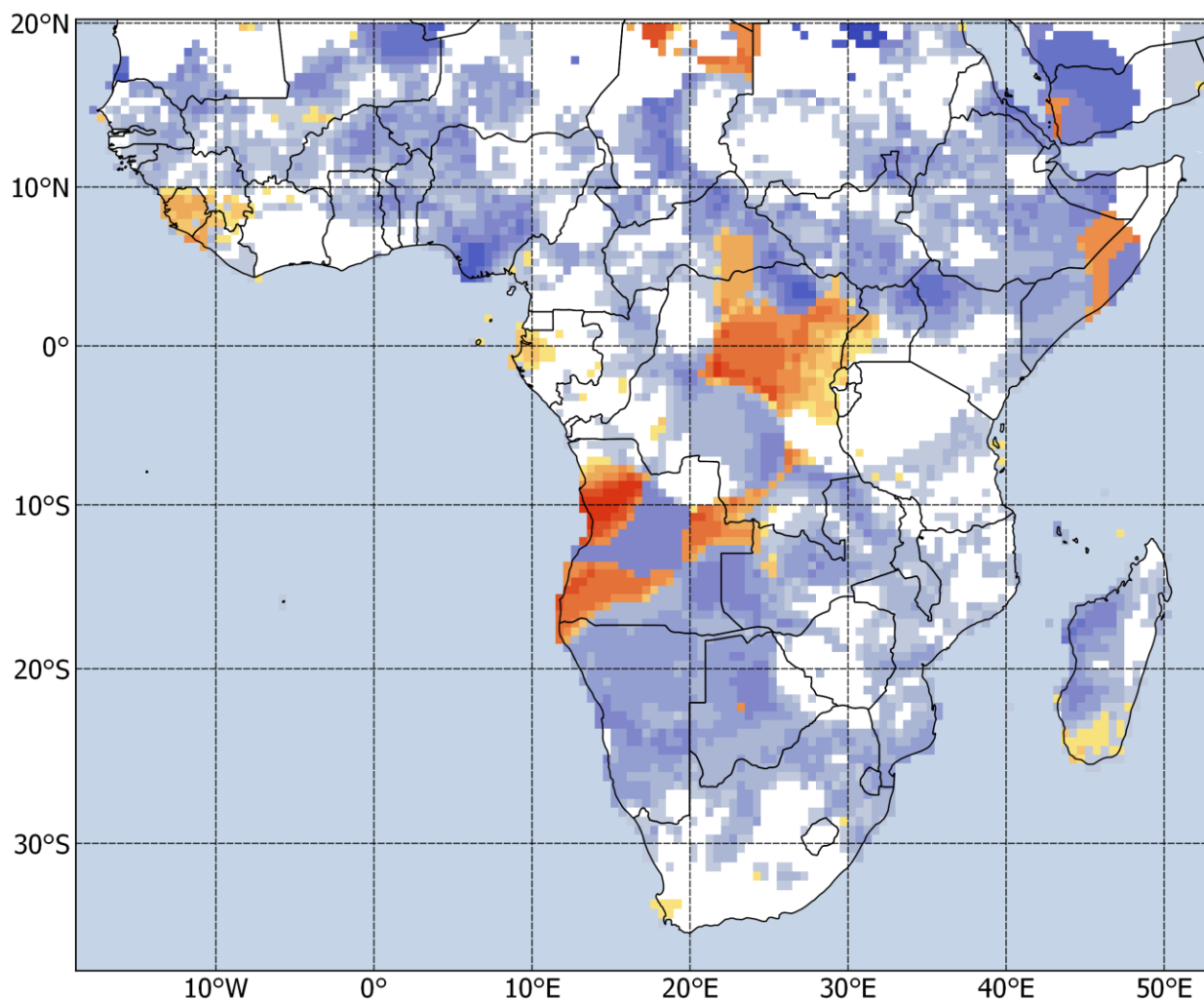
Probabilistic forecasts can help users understand risks and opportunities (forewarned is forearmed) in order to make more informed decisions.

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.

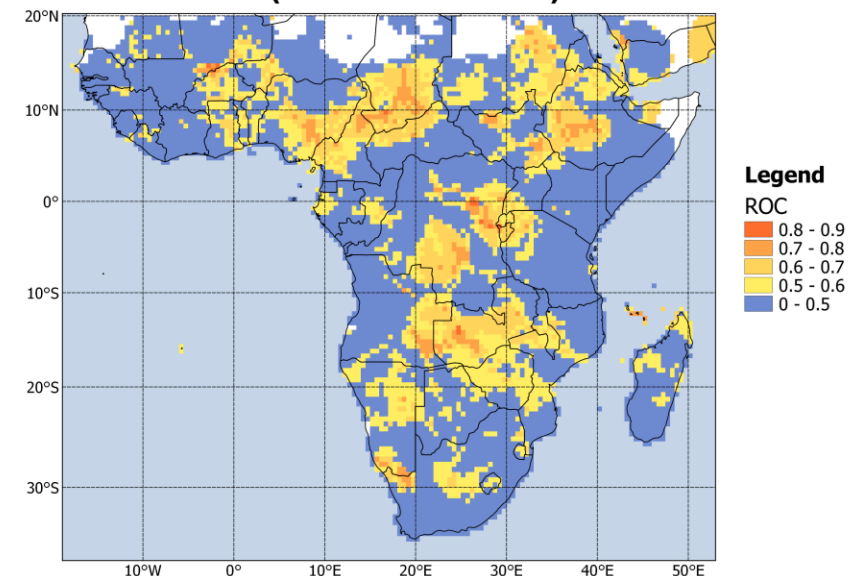
The nature of a probabilistic forecast implies that the less likely outcomes are always possible. In fact, for the probabilistic forecasts to be considered reliable, the less likely outcomes will and must occasionally occur.

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

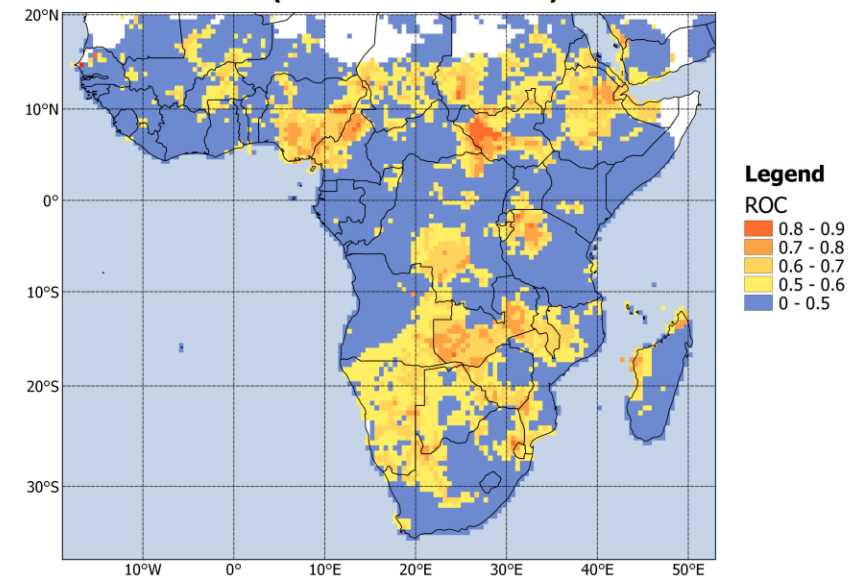
# MAM 2025 Rainfall; ICs: Mar



## ROC Area (Above-Normal): MAM Rainfall

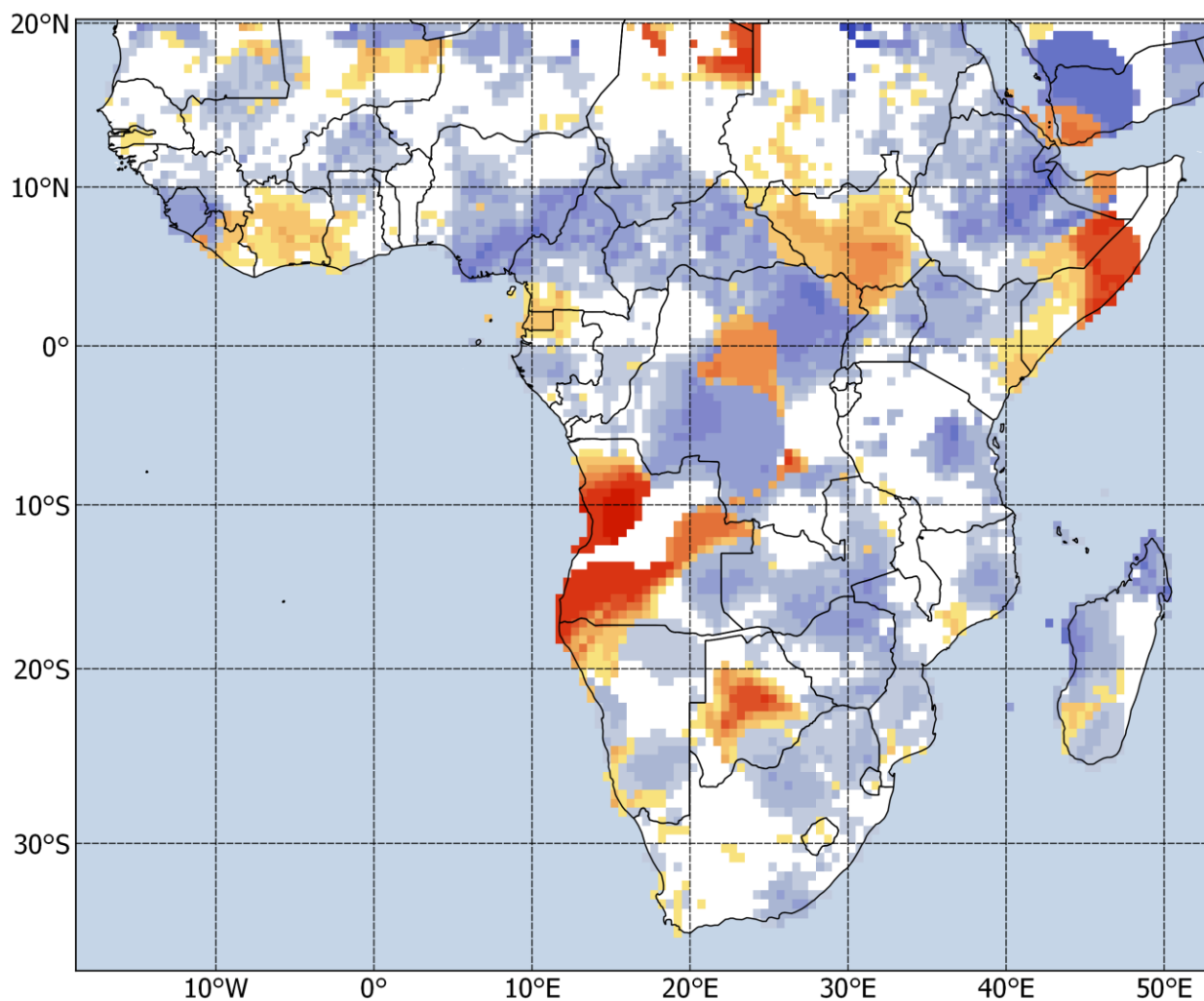


## ROC Area (Below-Normal): MAM Rainfall



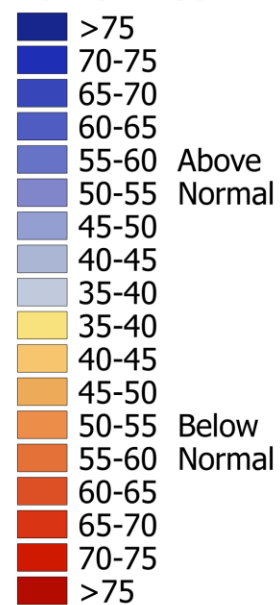


# AMJ 2025 Rainfall; ICs: Mar



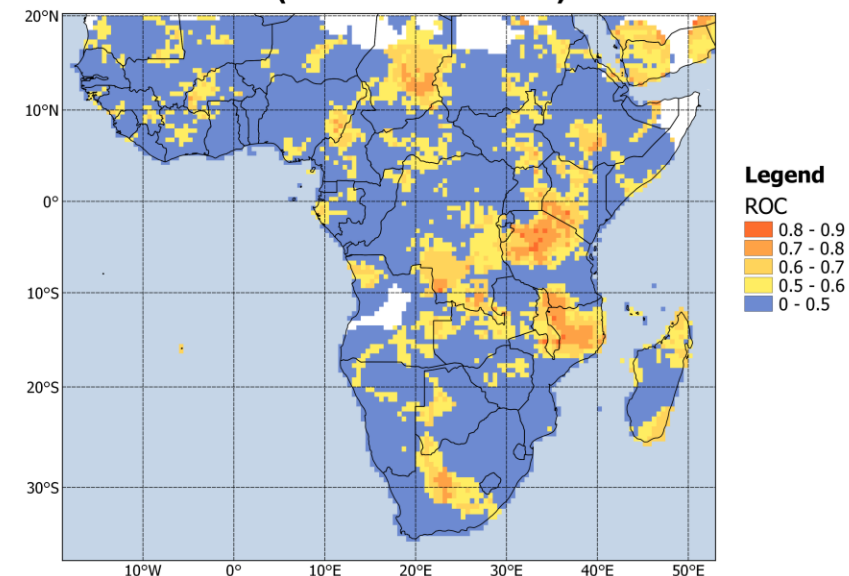
## Legend

Rainfall Prob



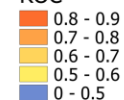
No forecast

## ROC Area (Above-Normal): AMJ Rainfall

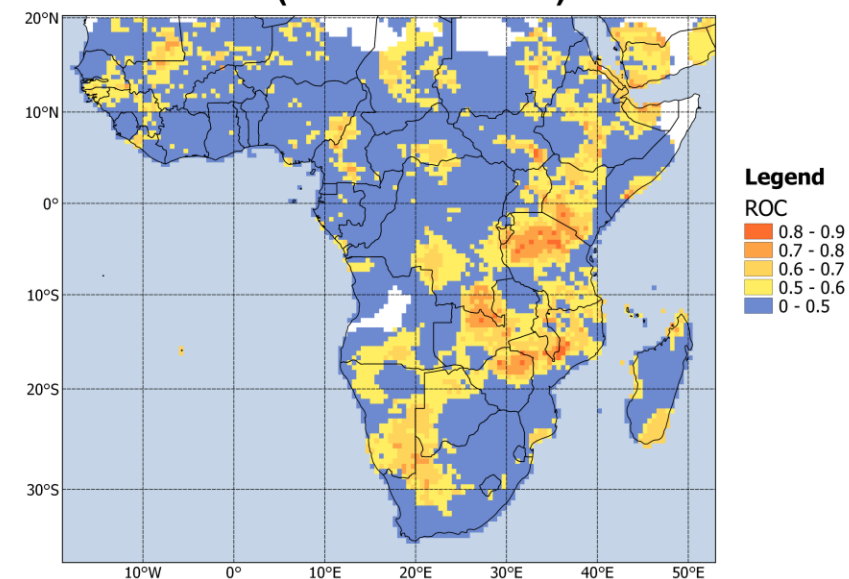


## Legend

ROC

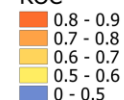


## ROC Area (Below-Normal): AMJ Rainfall

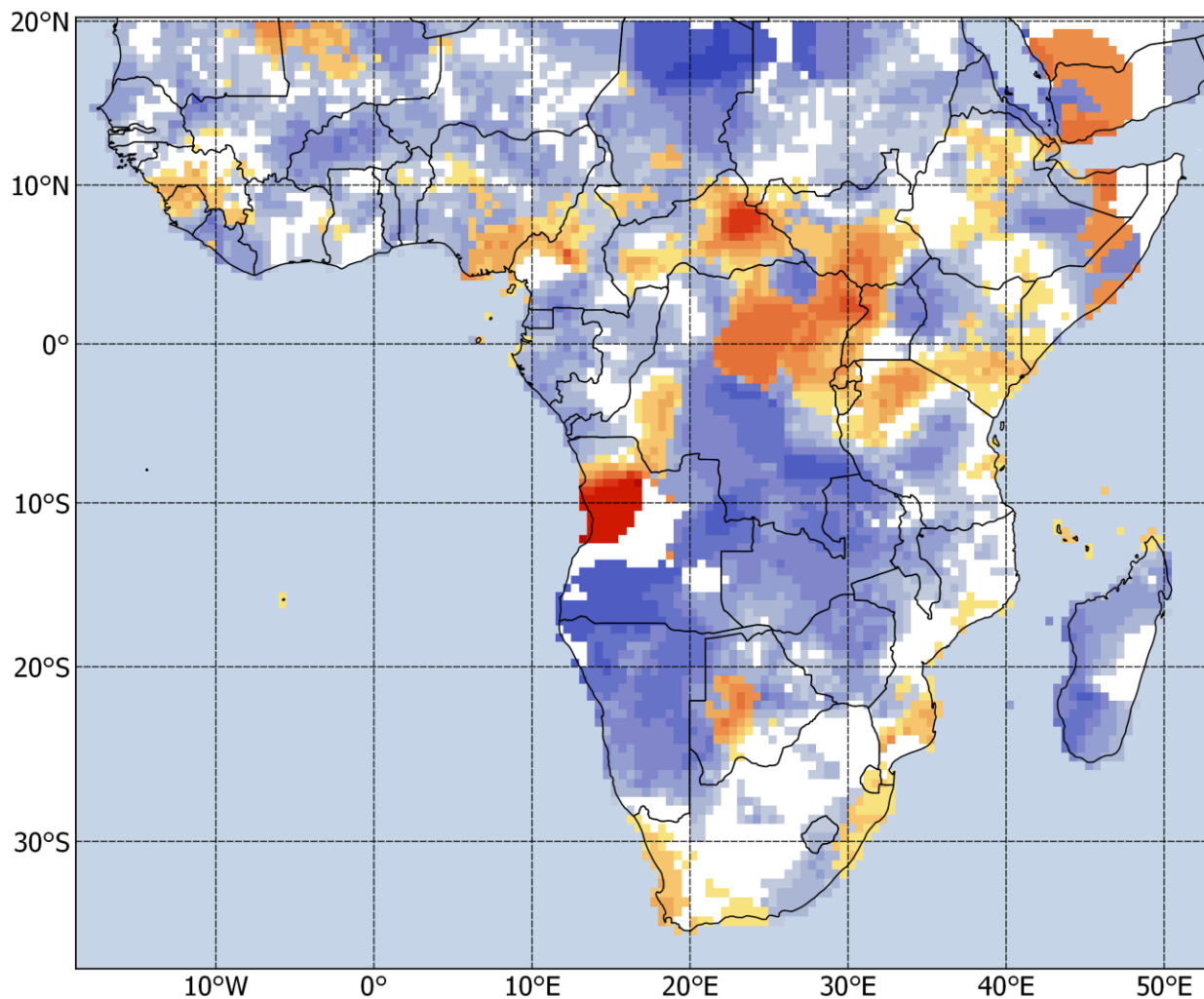


## Legend

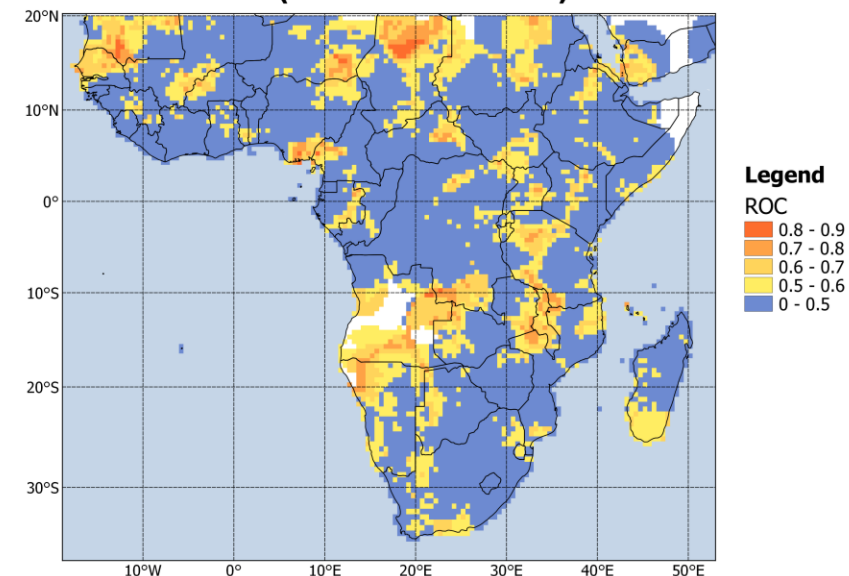
ROC



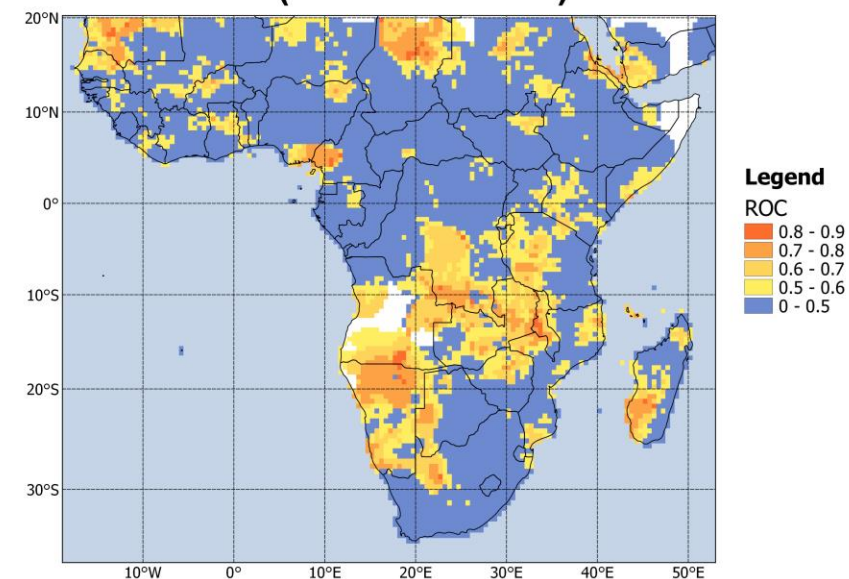
# MJJ 2025 Rainfall; ICs: Mar



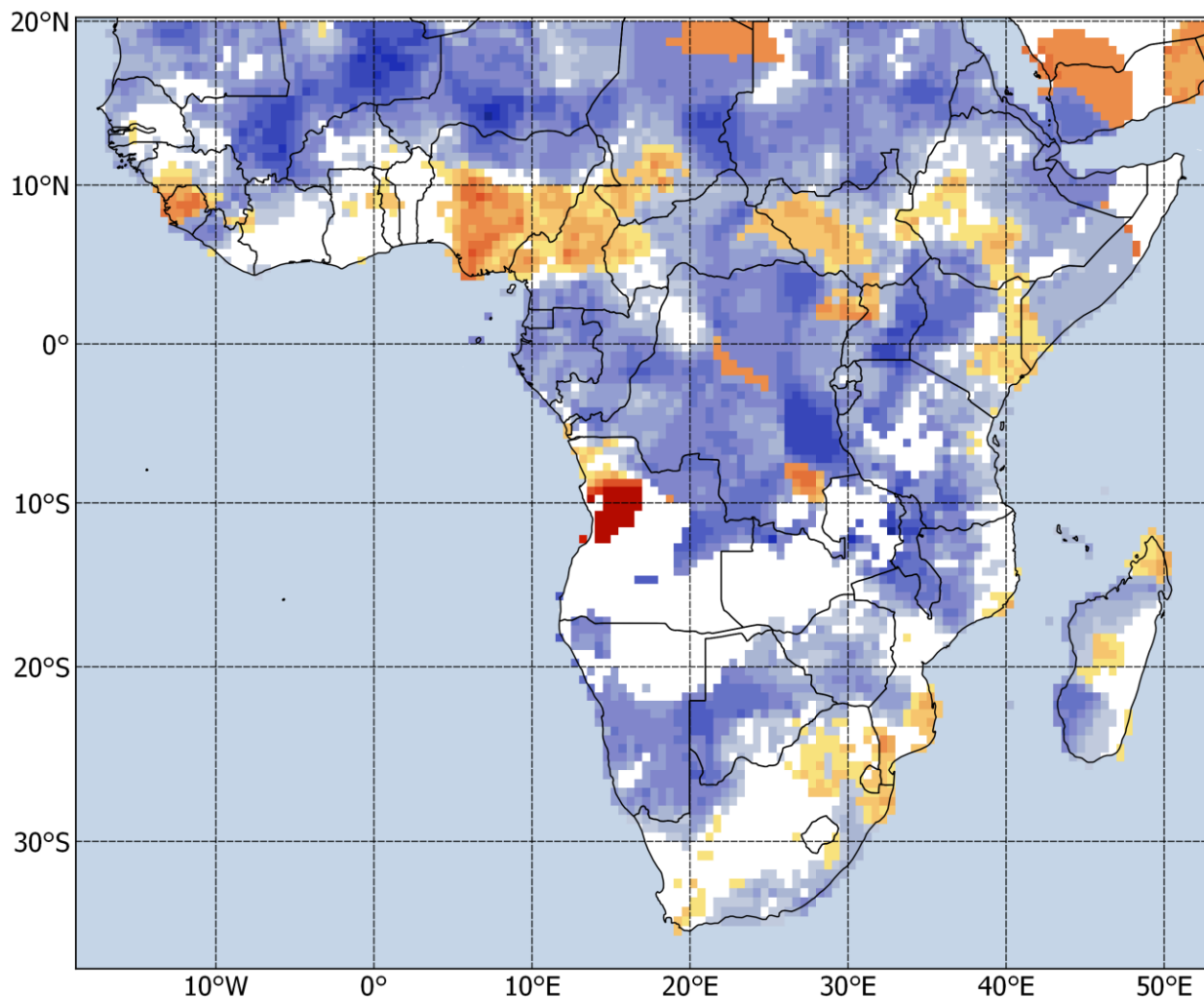
## ROC Area (Above-Normal): MJJ Rainfall



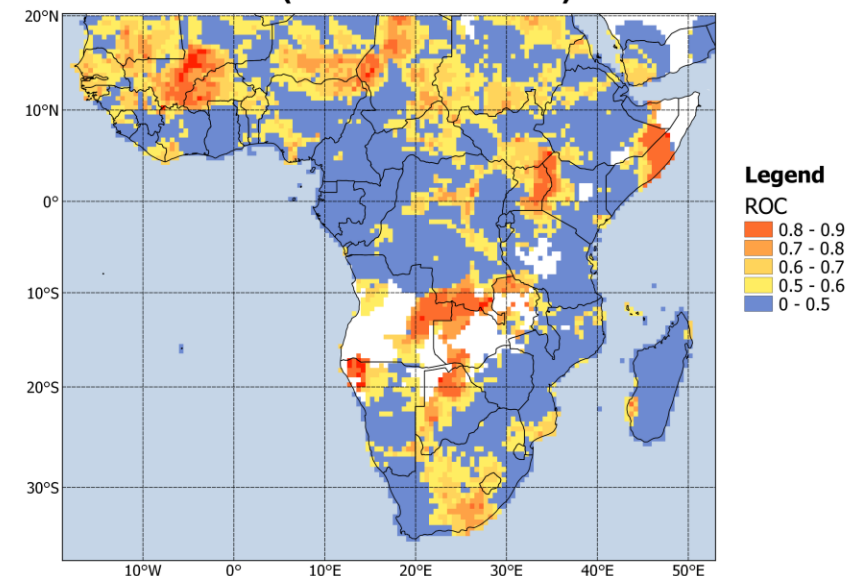
## ROC Area (Below-Normal): MJJ Rainfall



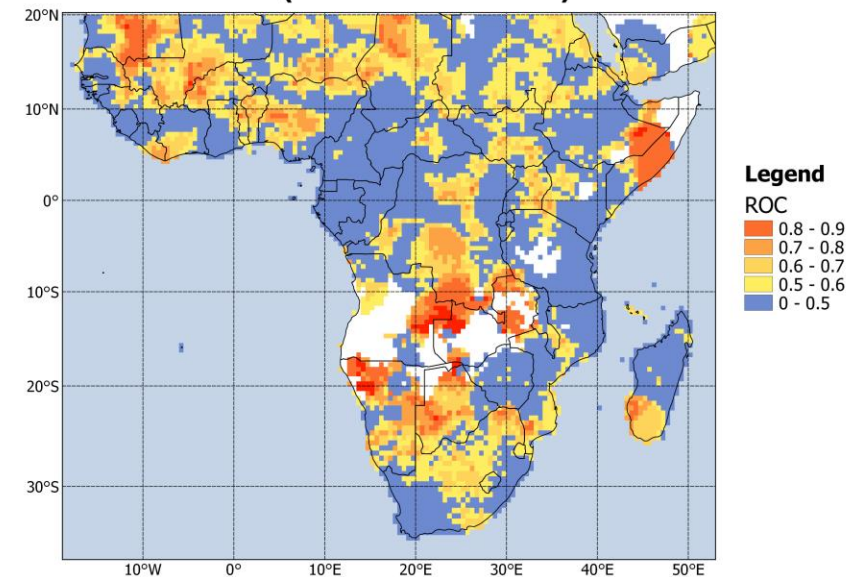
# JJA 2025 Rainfall; ICs: Mar



## ROC Area (Above-Normal): JJA Rainfall



## ROC Area (Below-Normal): JJA Rainfall



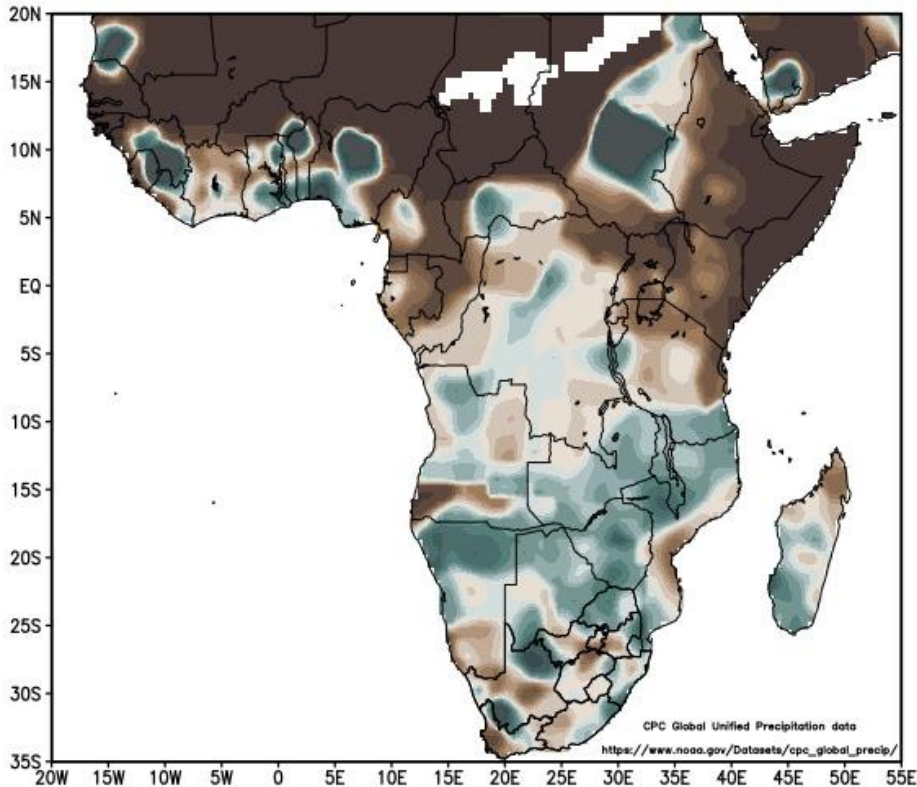
# Round-up: Rainfall south of 15°S

- The forecast of this month continues to be for above-normal rainfall conditions during autumn over the summer rainfall regions, but the predicted probabilities are not very high, and there are areas (white) where forecasts are uncertain
- The winter rainfall region may experience drier than normal conditions in the west during autumn (although confidence in this forecast is low owing to low forecast skill)

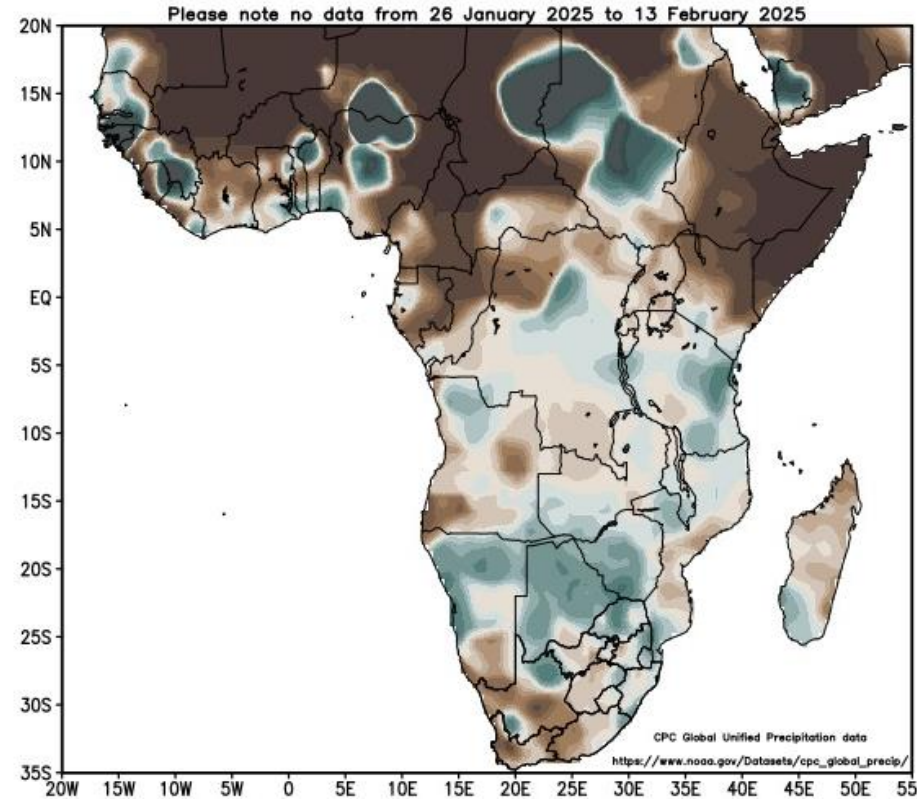


# Observed Rainfall

Rainfall (% of normal): 14–28 February 2025  
February long-term mean: 1981–2010



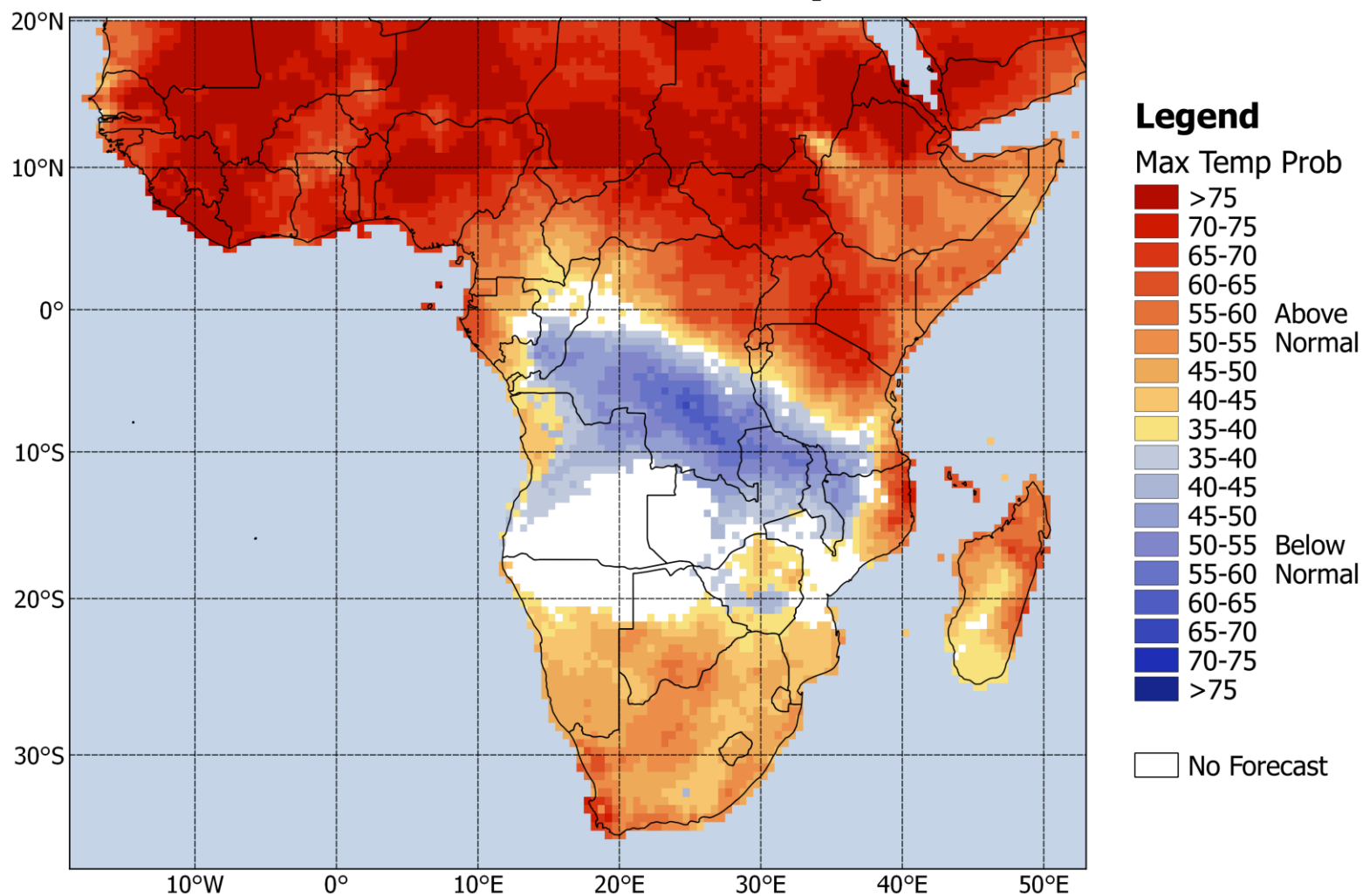
Rainfall (% of normal): December–January–February 2024/25  
December–January–February long-term mean: 1981/82–2010/11



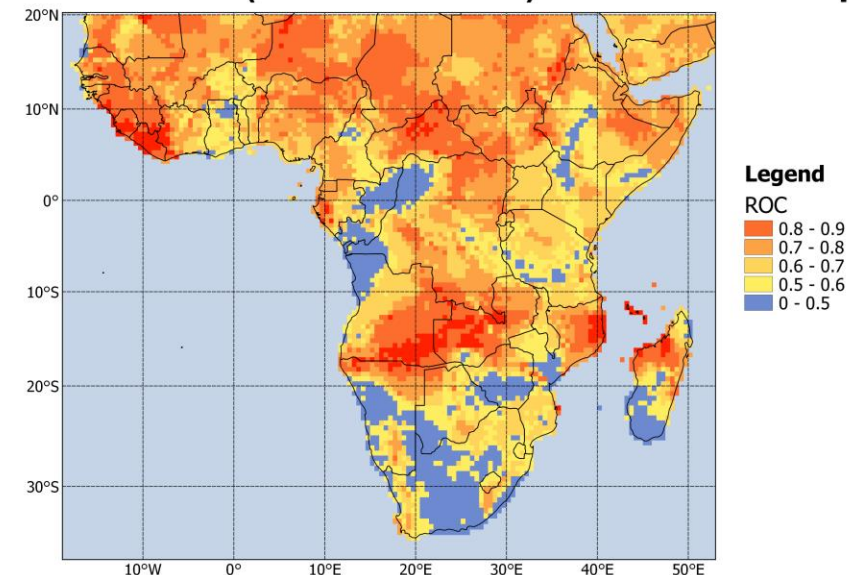
Recorded rainfall for February and the December-January-February season show below-normal rainfall over the brown areas and above-normal rainfall over the green areas

Maps prepared by Dr. Christien Engelbrecht

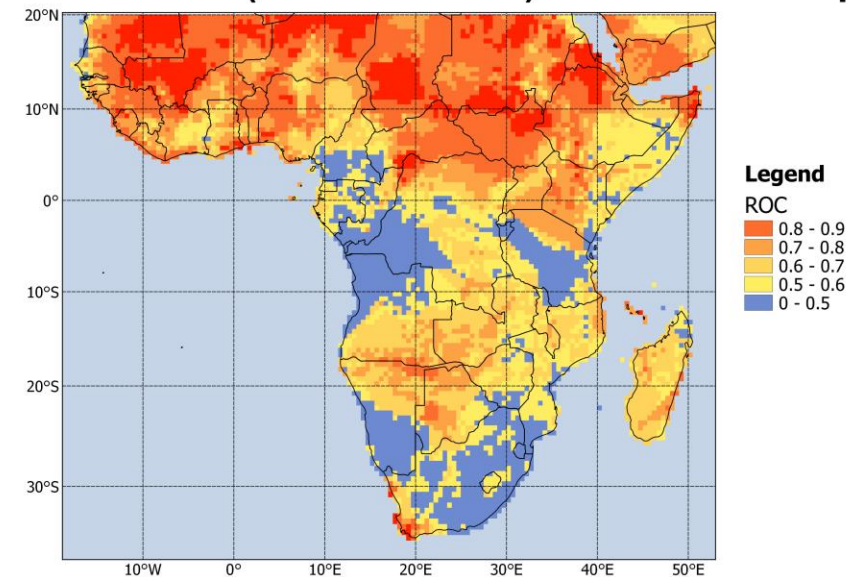
# MAM 2025 Max Temp; ICs: Mar



## ROC Area (Above-Normal): MAM Max Temp

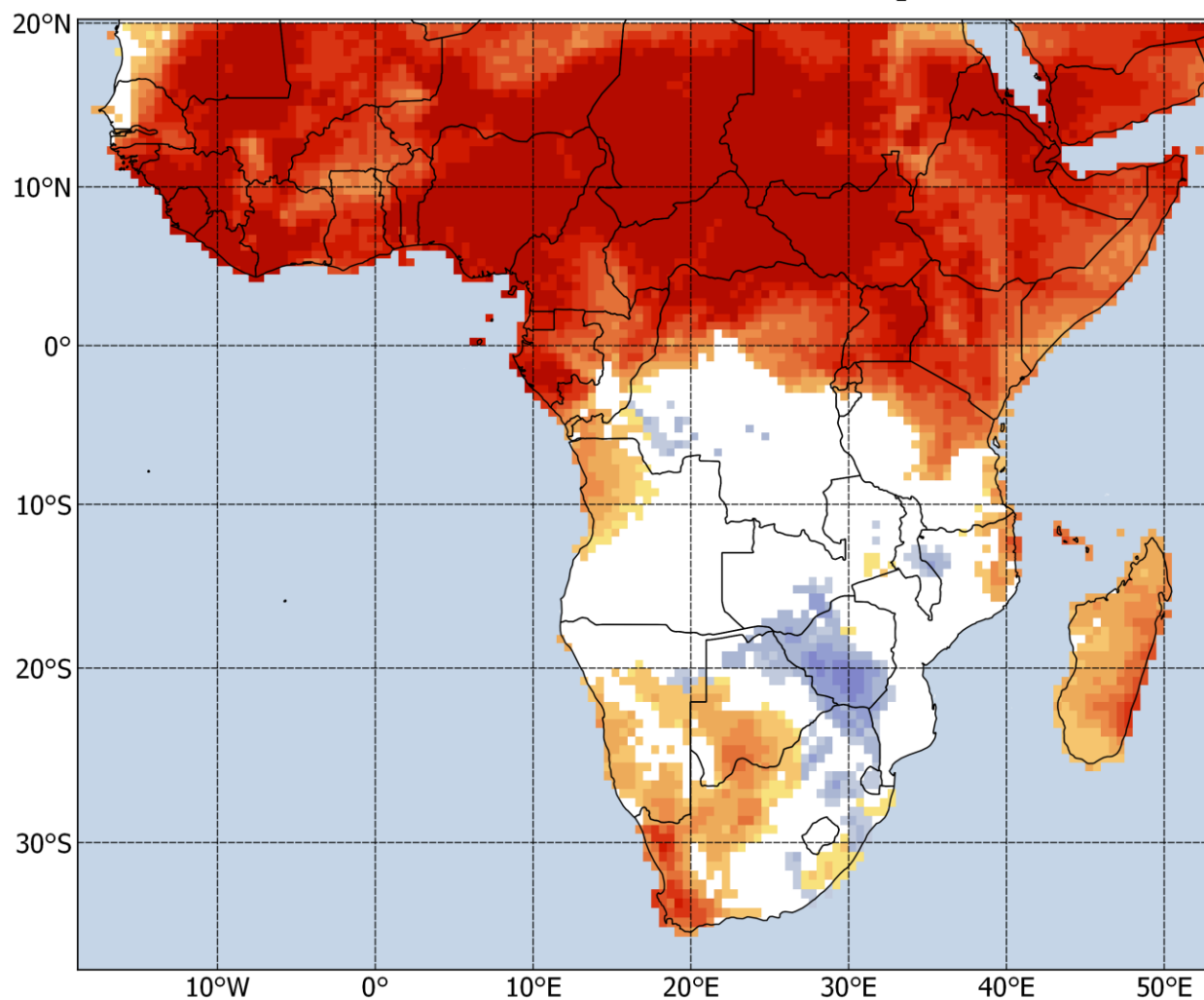


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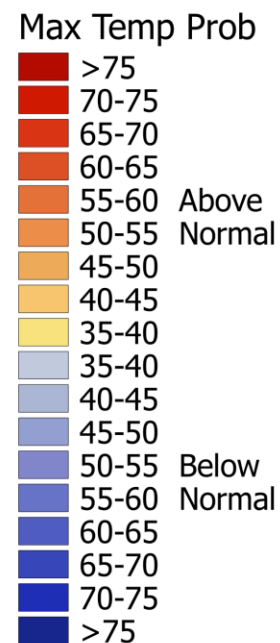




# AMJ 2025 Max Temp; ICs: Mar

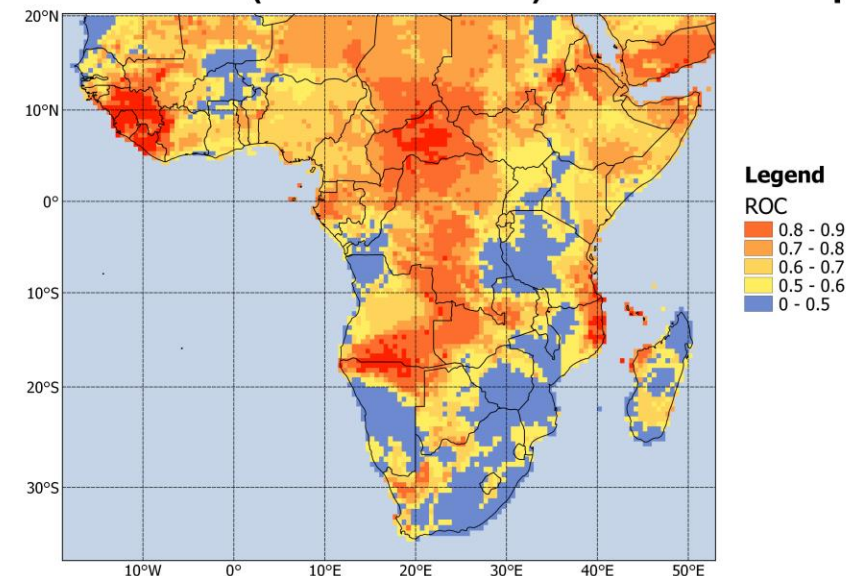


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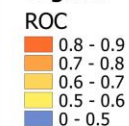


No Forecast

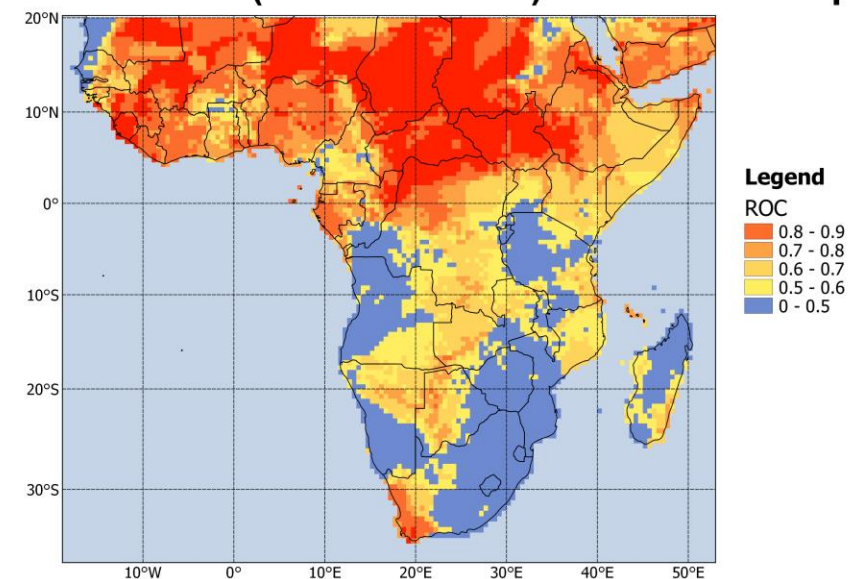
## ROC Area (Above-Normal): AMJ Max Temp



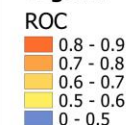
## Legend



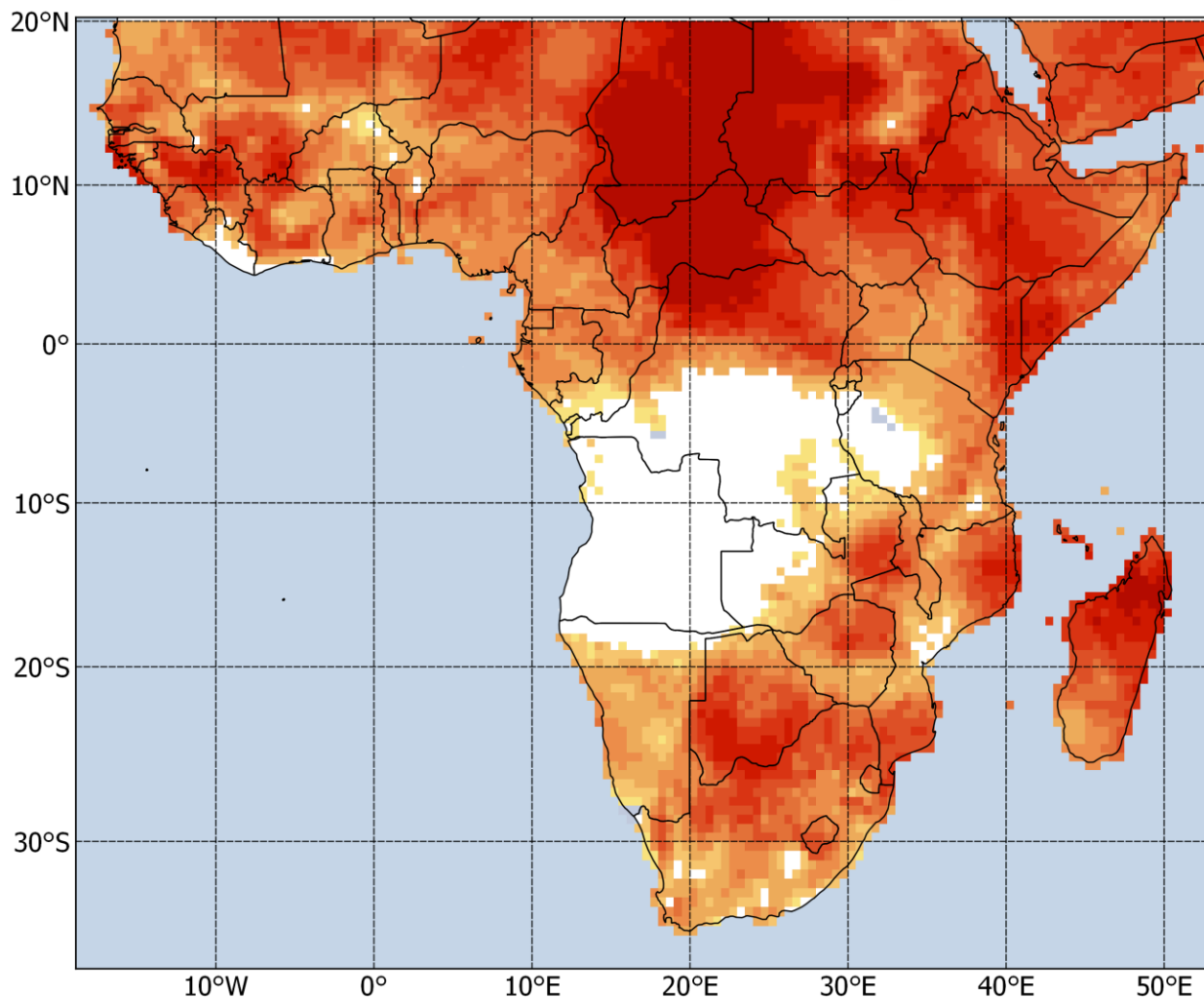
## ROC Area (Below-Normal): AMJ Max Temp



## Legend

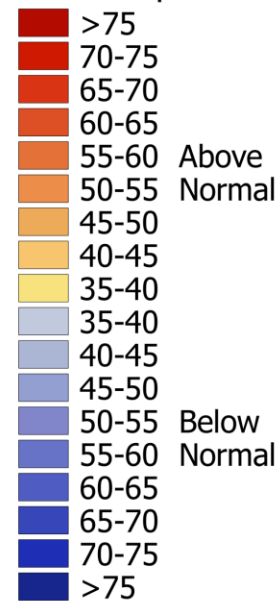


# MJJ 2025 Max Temp; ICs: Mar



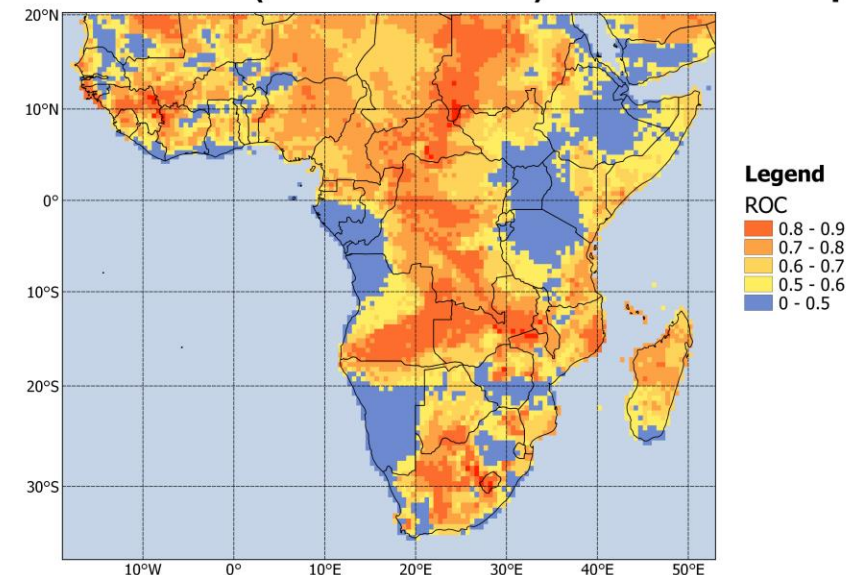
## Legend

Max Temp Prob



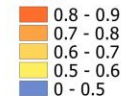
No Forecast

## ROC Area (Above-Normal): MJJ Max Temp

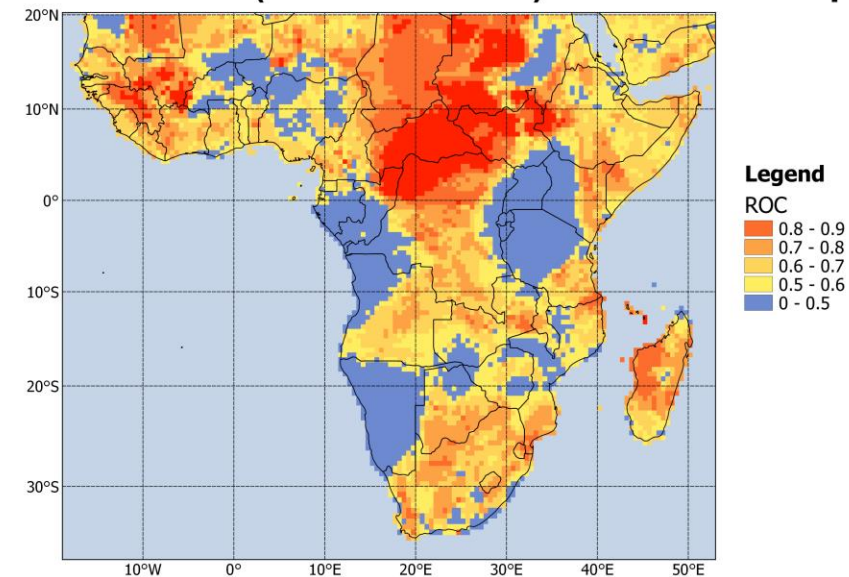


## Legend

ROC

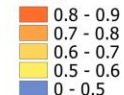


## ROC Area (Below-Normal): MJJ Max Temp



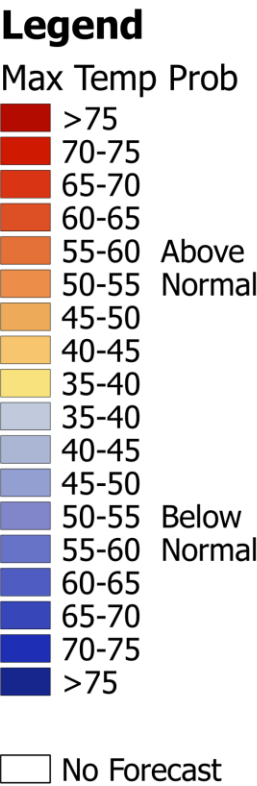
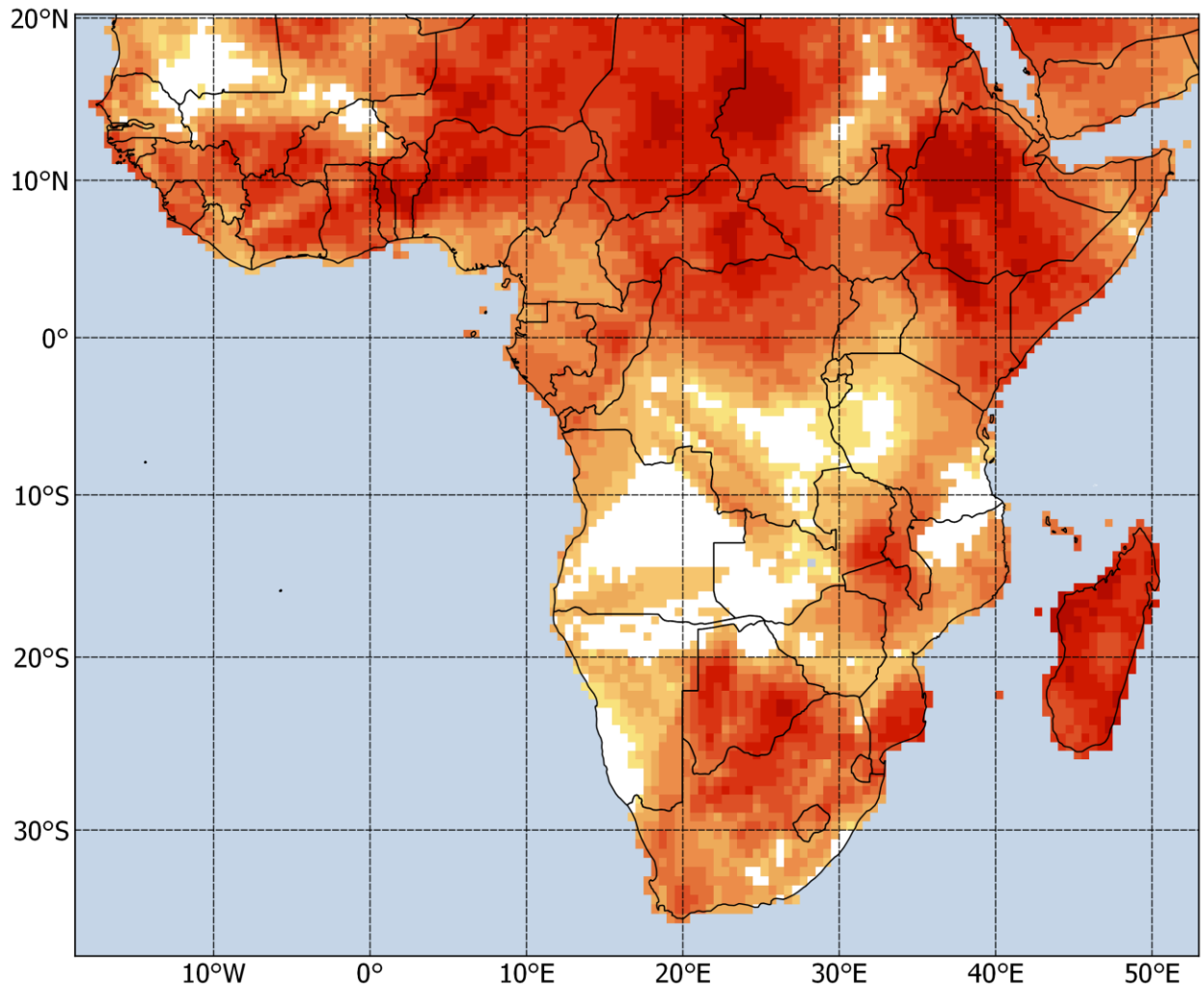
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ROC

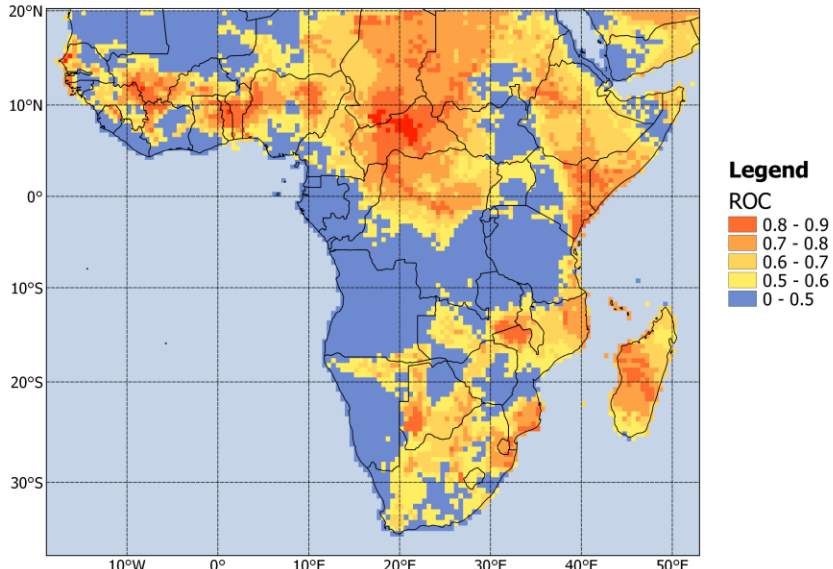




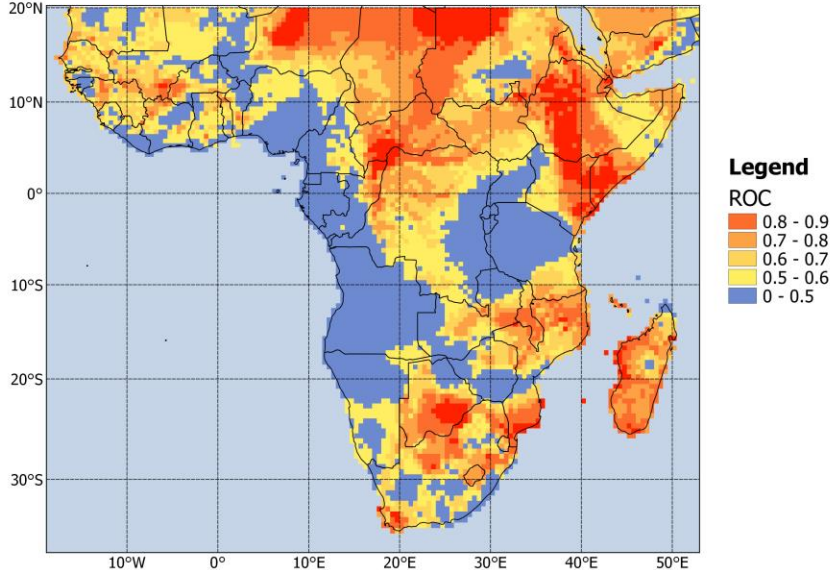
# JJA 2025 Max Temp; ICs: Mar



## ROC Area (Above-Normal): JJA Max Temp



## ROC Area (Below-Normal): JJA Max Temp



# Round-up: South of 15°S Max Temp

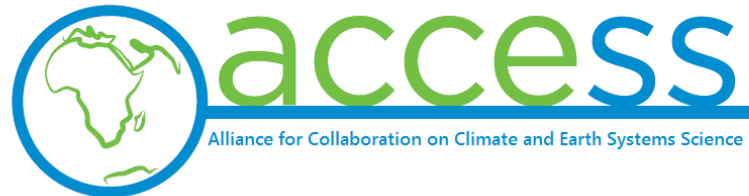
- Below-normal maximum temperatures over the northern parts of the region are predicted for autumn
- Above-normal maximum temperatures are predicted southwards throughout the forecast period, including the winter rainfall region of the SW Cape

# References

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# Financial support from...

- The National Research Foundation
  - Incentive Funding for Rated Researchers (since 2017)
  - Project: Application of knowledge for the management of extreme climate events (APECX; 2022 to 2025)
- ACCESS (Alliance for Collaboration on Climate and Earth System Science) through the project “Investigating predictability of seasonal anomalies for societal benefit” (2018 to 2021)
- 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](mailto:WALandman1981@gmail.com)

Acknowledgments to Dr Peter Johnston of the University of Cape Town for professional comments and advice

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.



**Aimee Serafini, MSc (Meteorology):** Development of seasonal forecast systems for farmers in Namibia using farm observations and output from global climate models.