

Seasonal forecasts

presented by:

Willem.Landman@up.ac.za
WALandman1981@gmail.com



Seasonal Forecast Worx



<https://tinyurl.com/ForecastProf>

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Seasonal Climate Forecasts

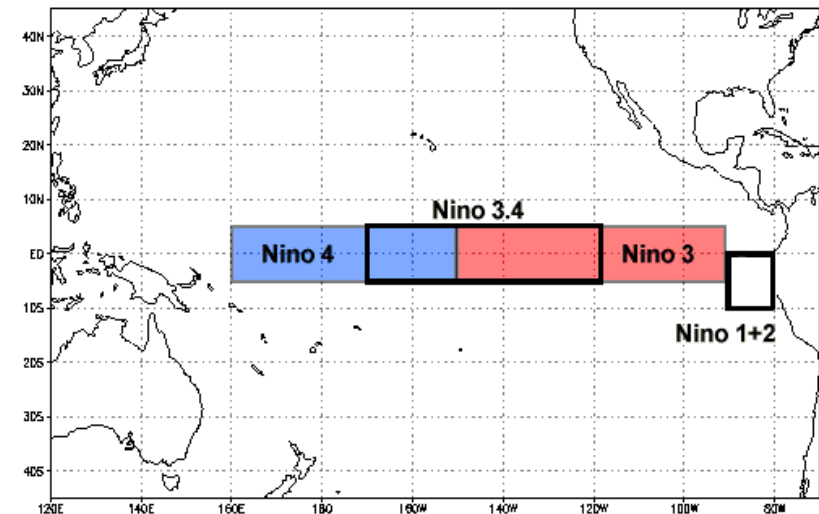
Latest Update: 15 July 2024

- 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 <http://www.weathersa.co.za/images/data/longrange/gfcsa/scw.pdf>

ENSO and Global SST Forecasts

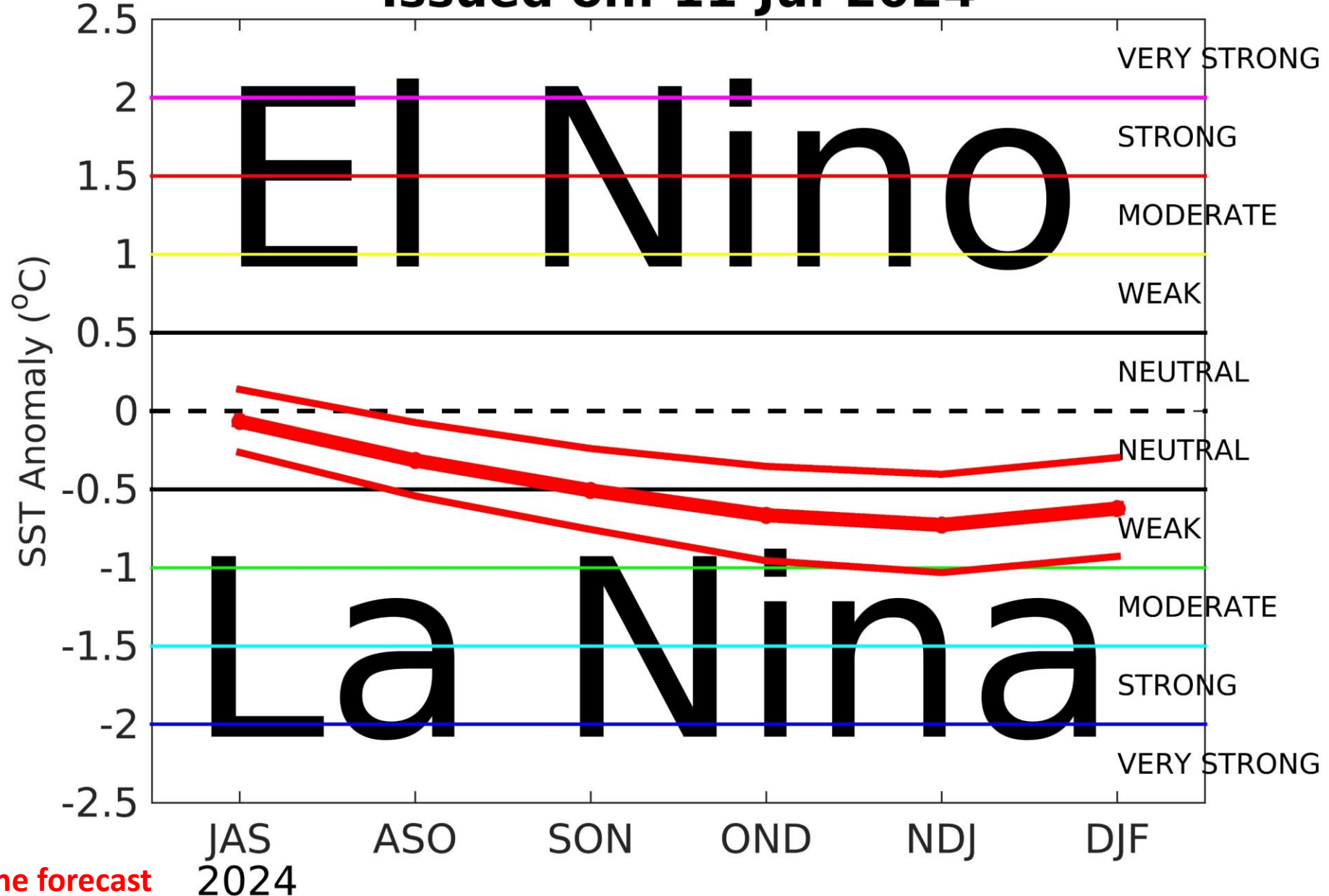
Prediction Method

- 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

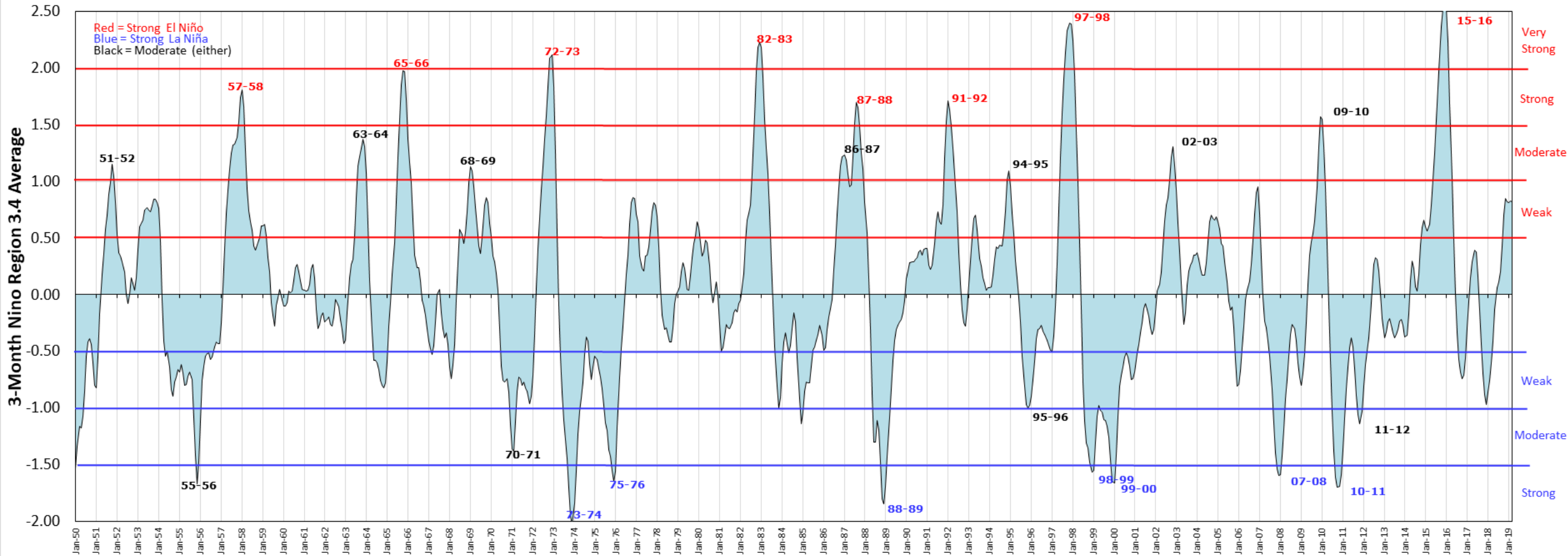
Issued on: 11-Jul-2024



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

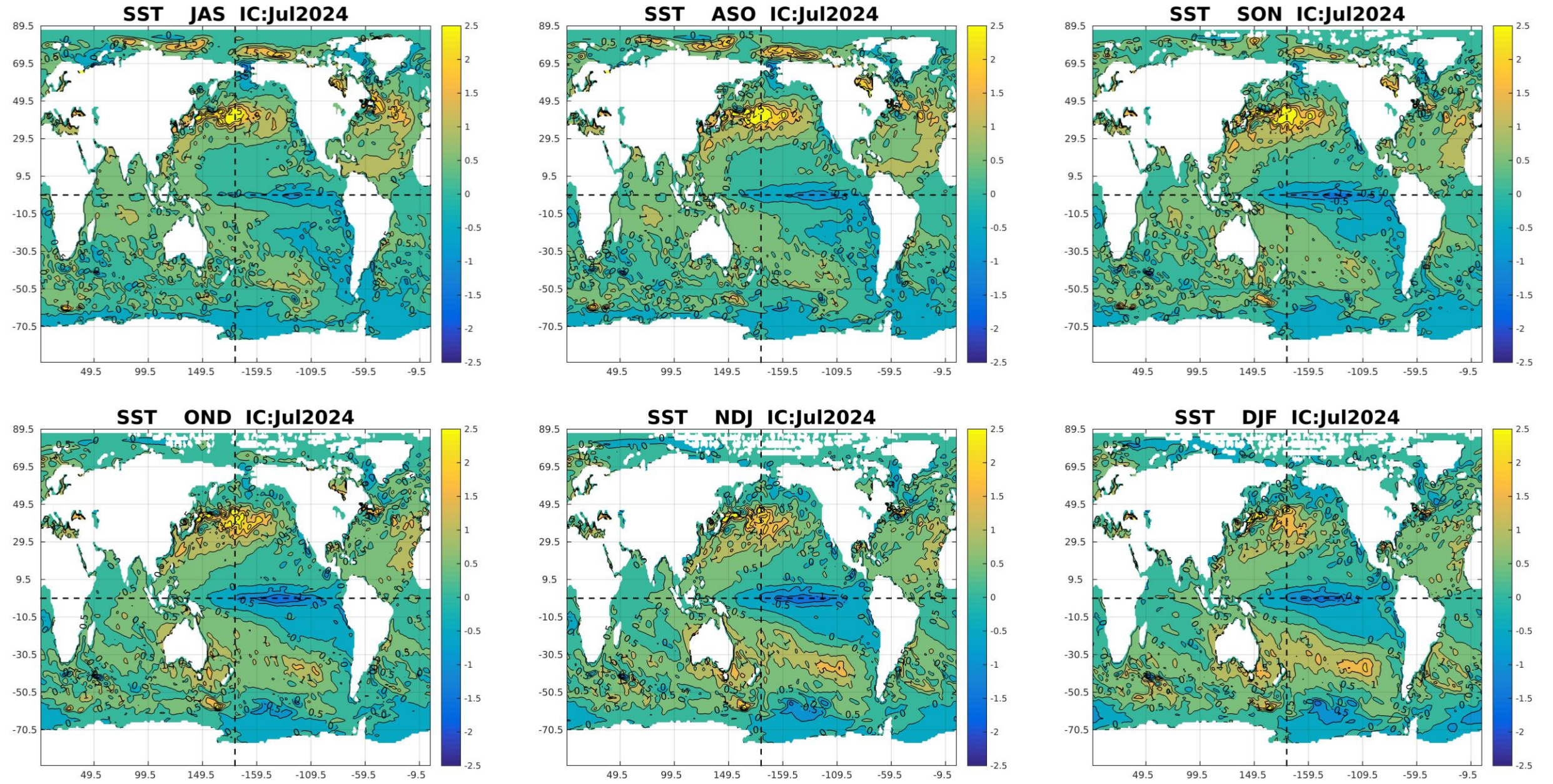
Oceanic Niño Index (ONI)

http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml



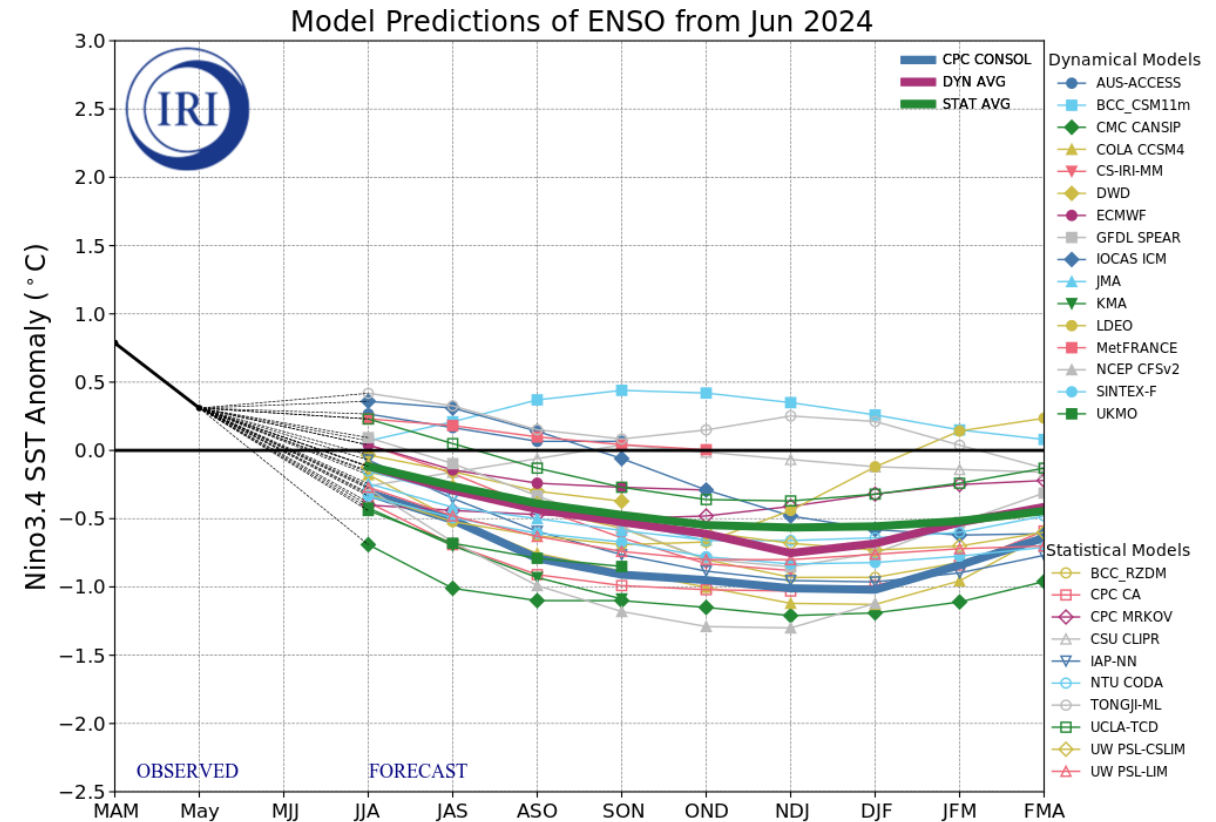
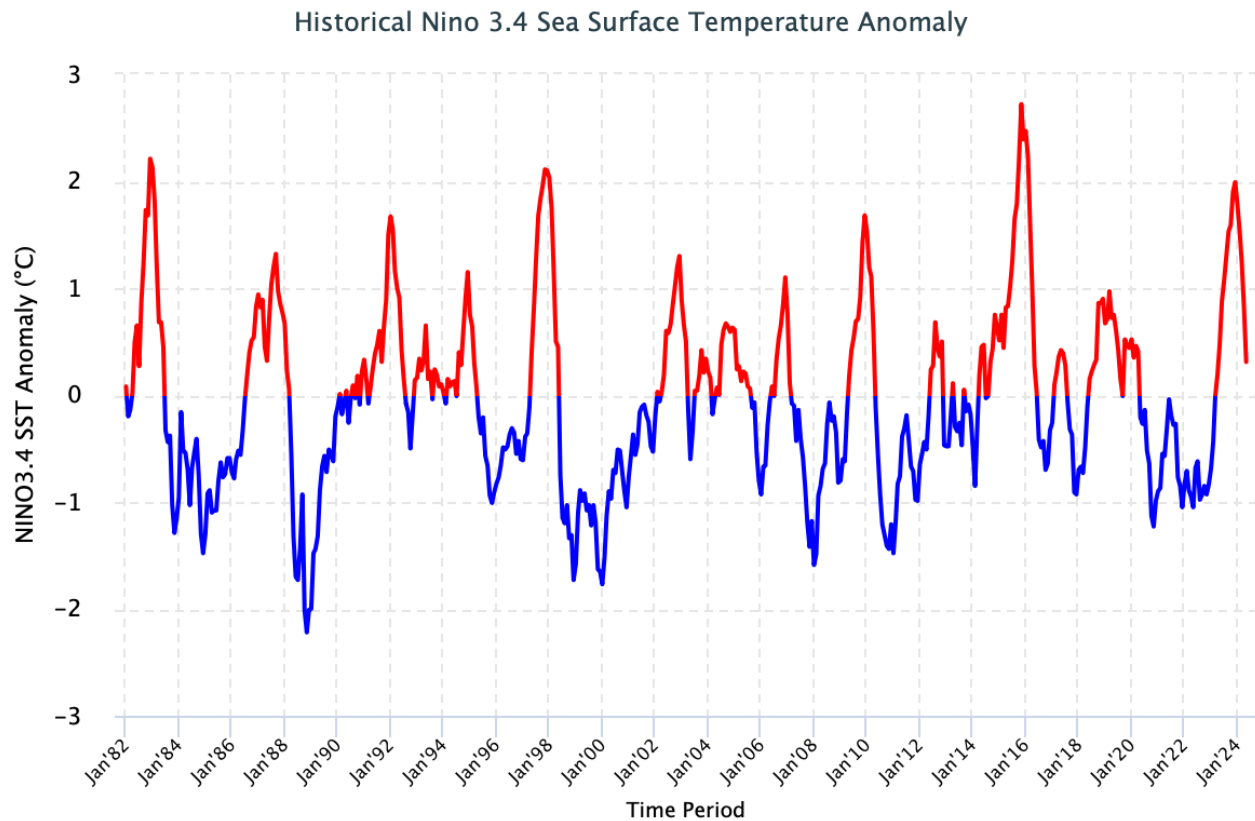
IC: the month in which the forecast was made

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



Round-up: ENSO

- The UP model (on previous pages) is predicting the development of a La Niña event by Austral spring, which is in agreement with most international forecasts



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)

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

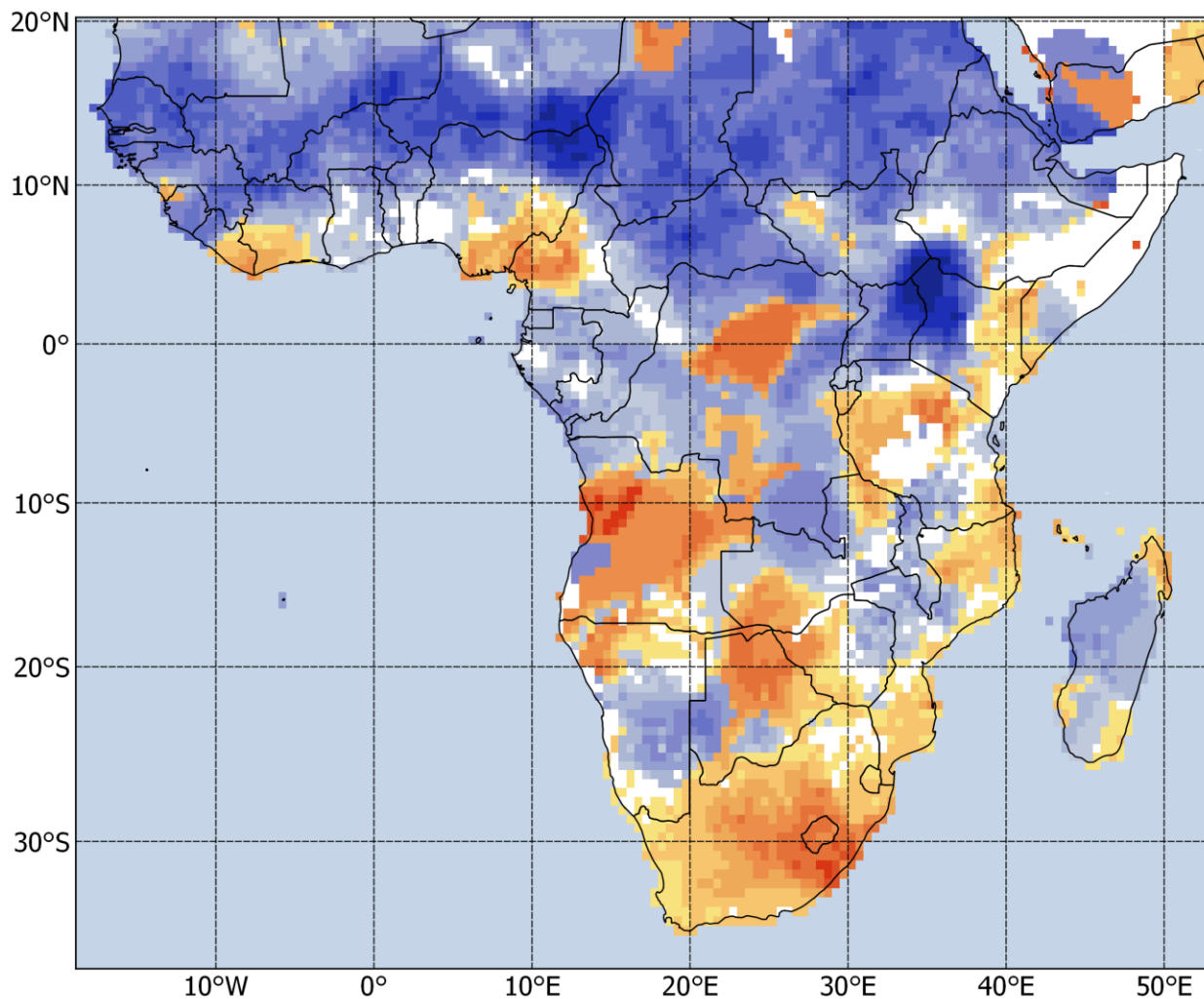
Probabilistic forecasts can help users understand risks and opportunities (forewarned is forearmed) in order to make more informed decisions.

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.

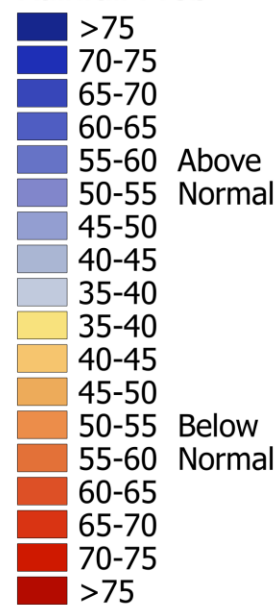
Note: Probabilistic forecasts are considered reliable when the forecast probability is an accurate estimation of the relative frequency of the predicted outcome. In other words, forecasts are reliable if the observation falls within the category (Below-, Near- or Above-Normal) as frequently as the forecast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

JAS 2024 Rainfall; ICs: Jul



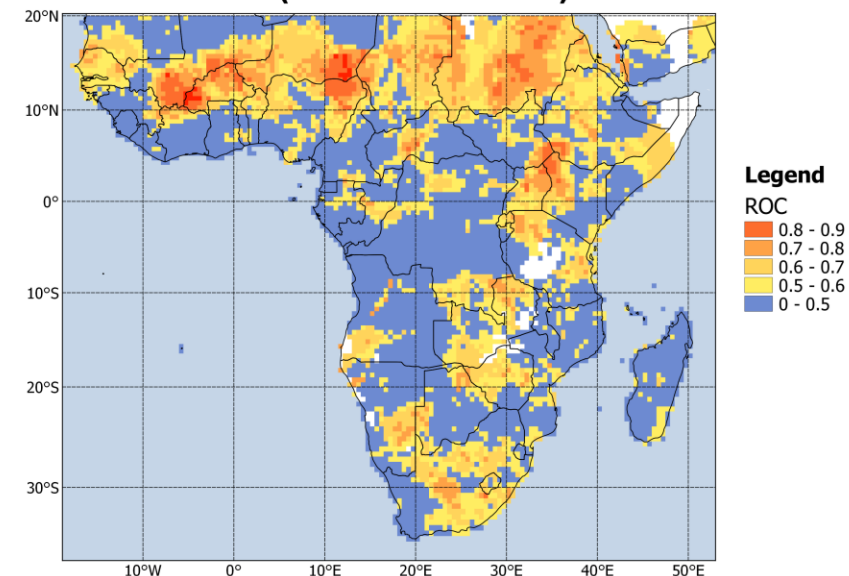
Legend

Rainfall Prob



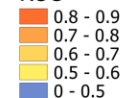
□ No forecast

ROC Area (Above-Normal): JAS Rainfall

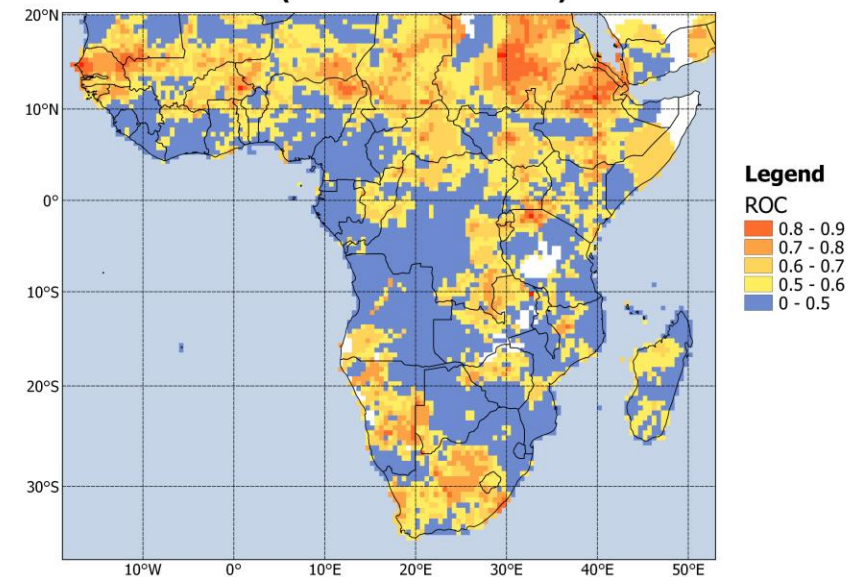


Legend

ROC

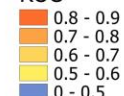


ROC Area (Below-Normal): JAS Rainfall

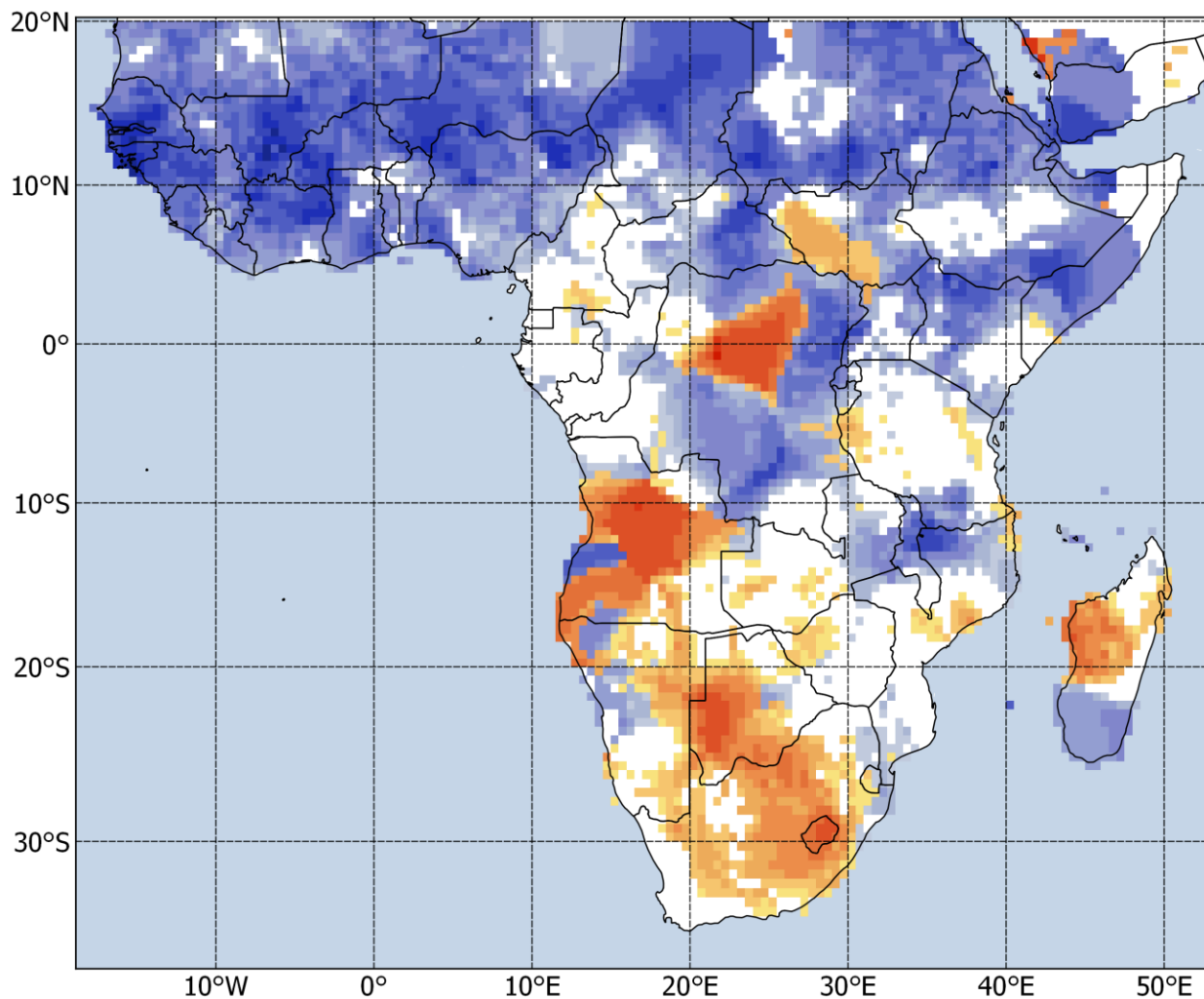


Legend

ROC

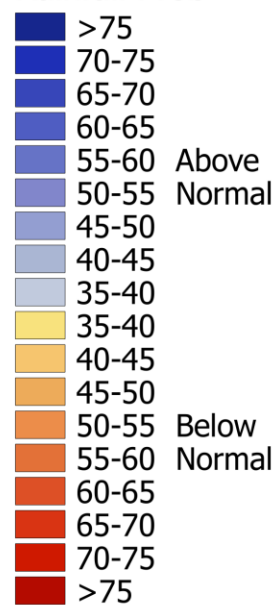


ASO 2024 Rainfall; ICs: Jul



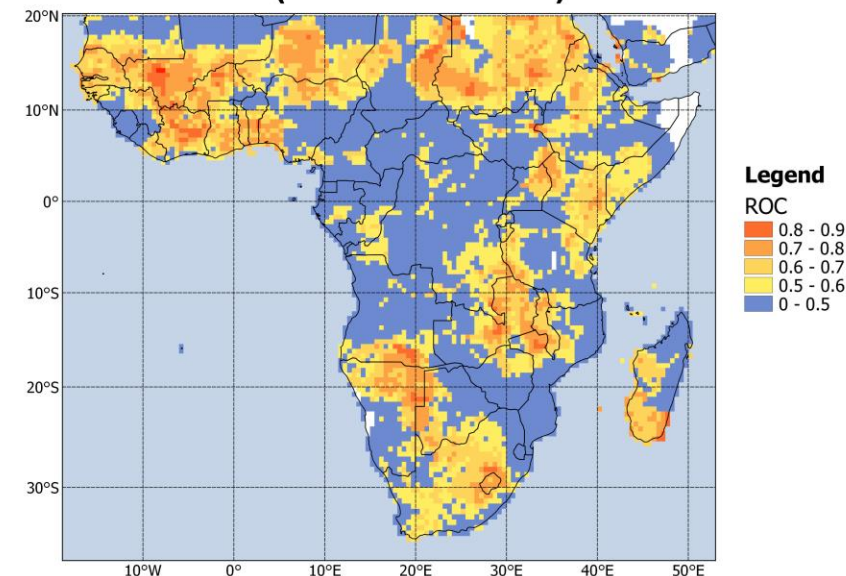
Legend

Rainfall Prob



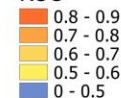
□ No forecast

ROC Area (Above-Normal): ASO Rainfall

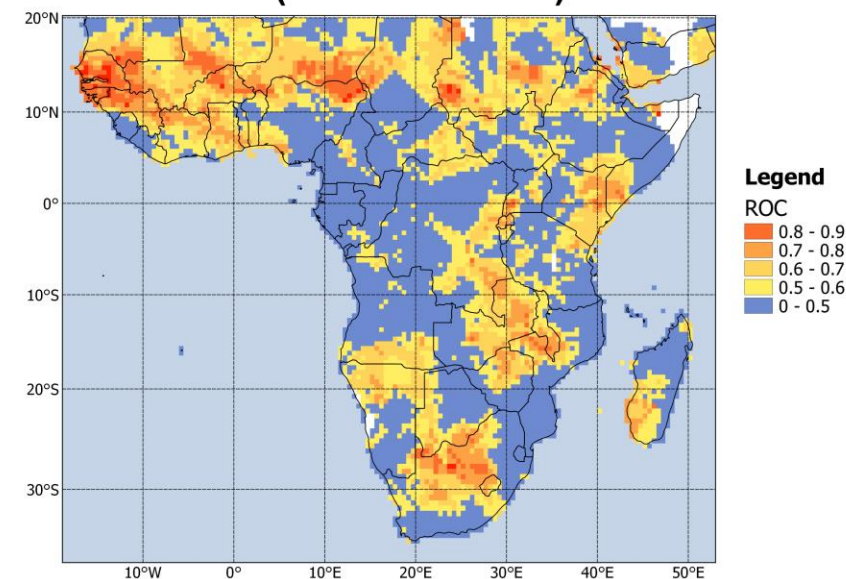


Legend

ROC

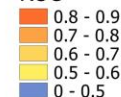


ROC Area (Below-Normal): ASO Rainfall

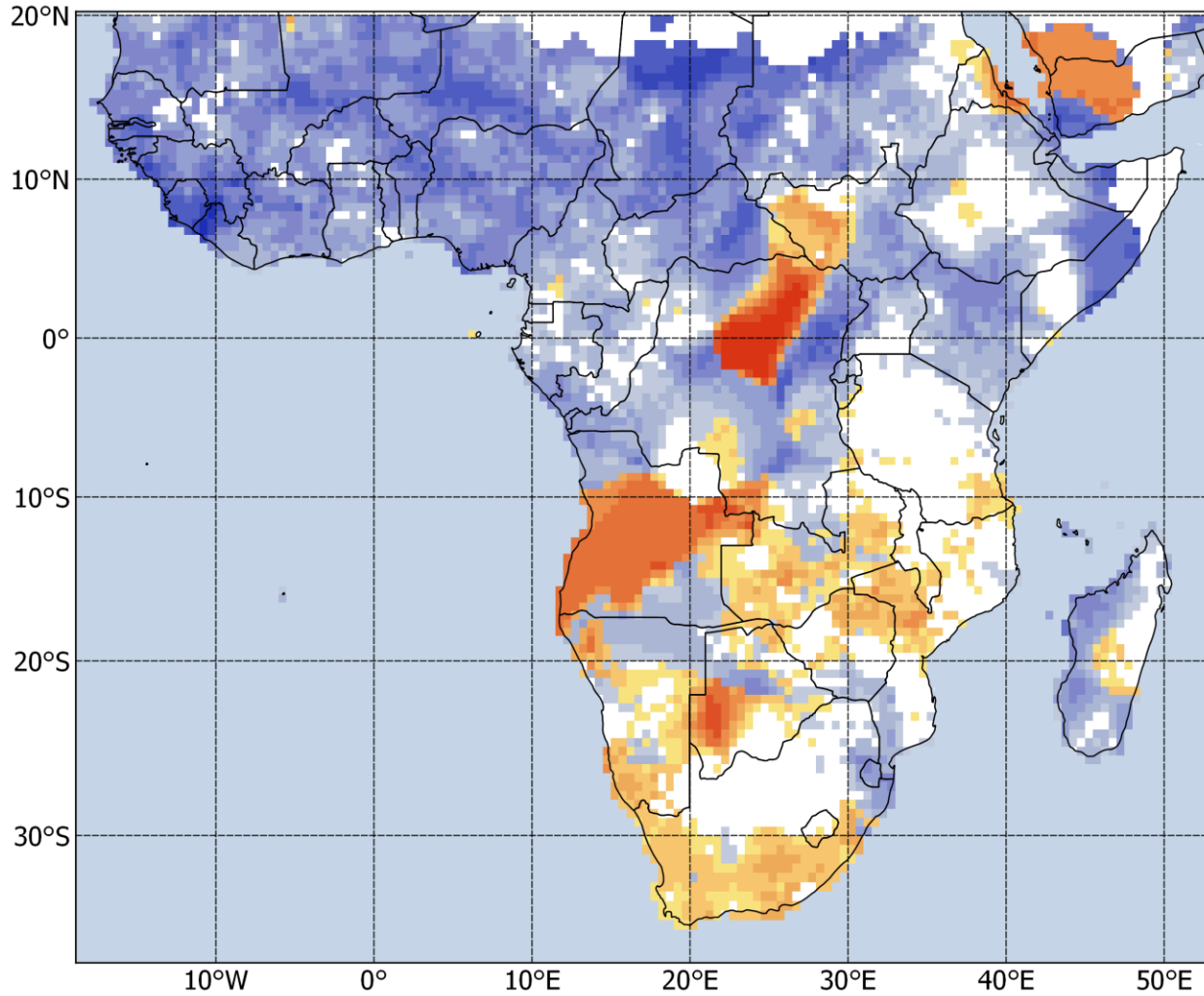


Legend

ROC

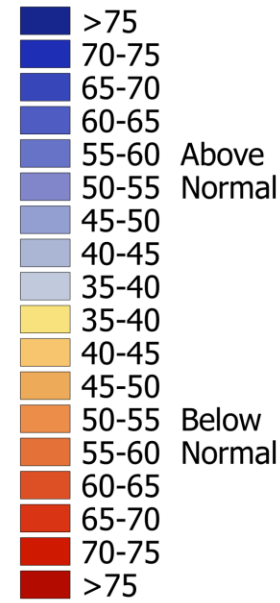


SON 2024 Rainfall; ICs: Jul



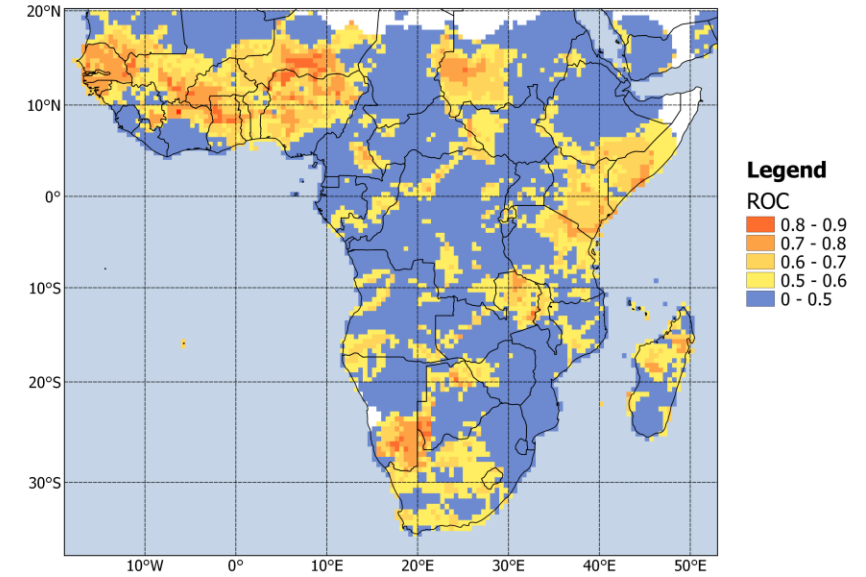
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Rainfall Prob

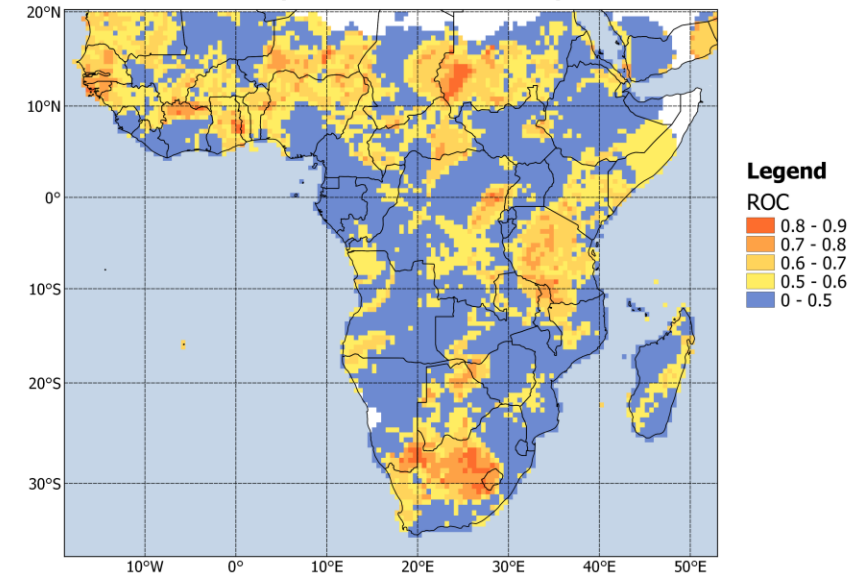


No forecast

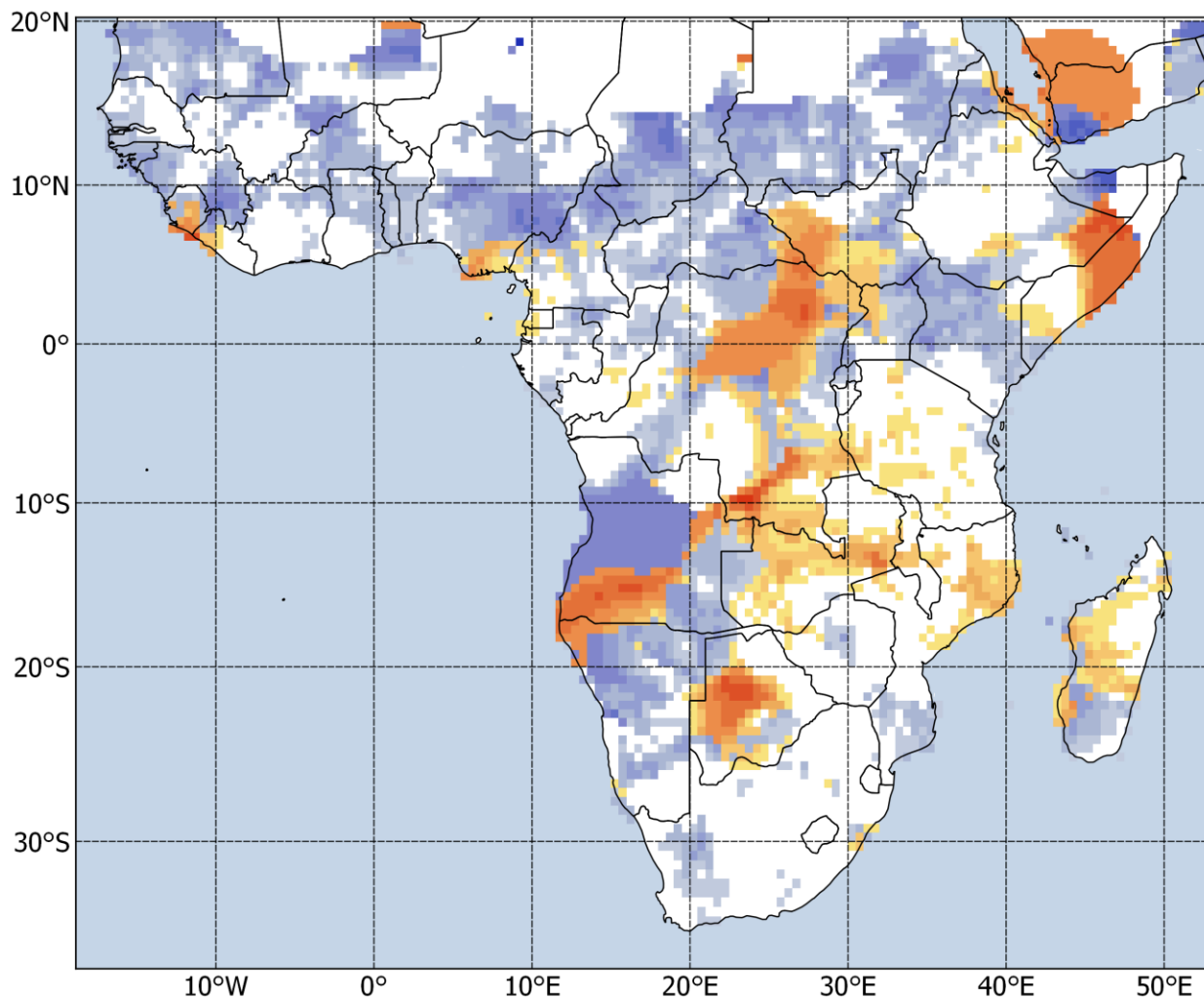
ROC Area (Above-Normal): SON Rainfall



ROC Area (Below-Normal): SON Rainfall

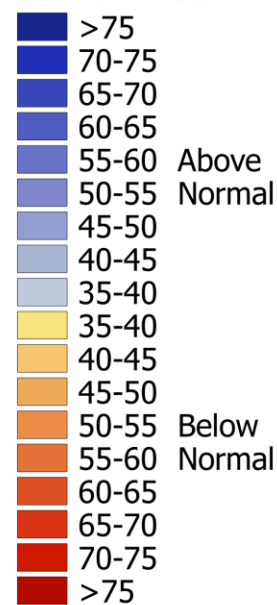


OND 2024 Rainfall; ICs: Jul



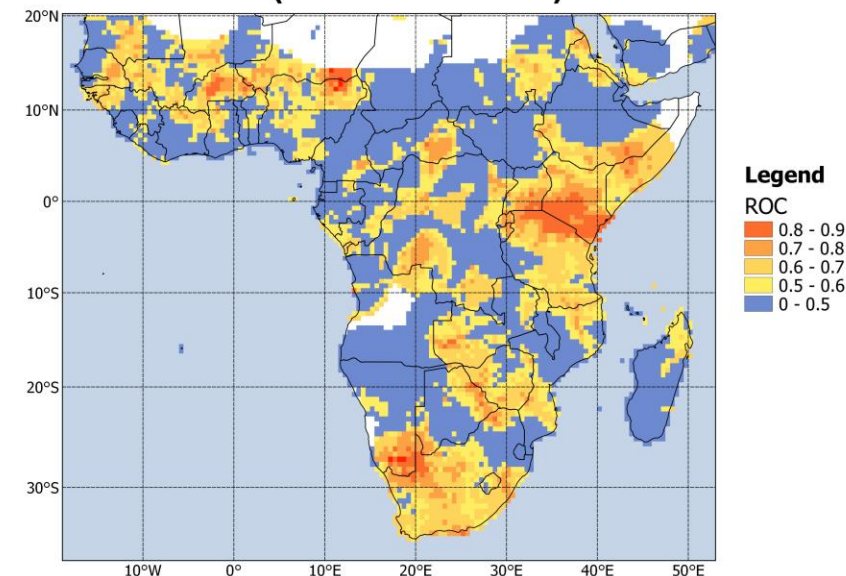
Legend

Rainfall Prob



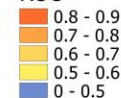
□ No forecast

ROC Area (Above-Normal): OND Rainfall

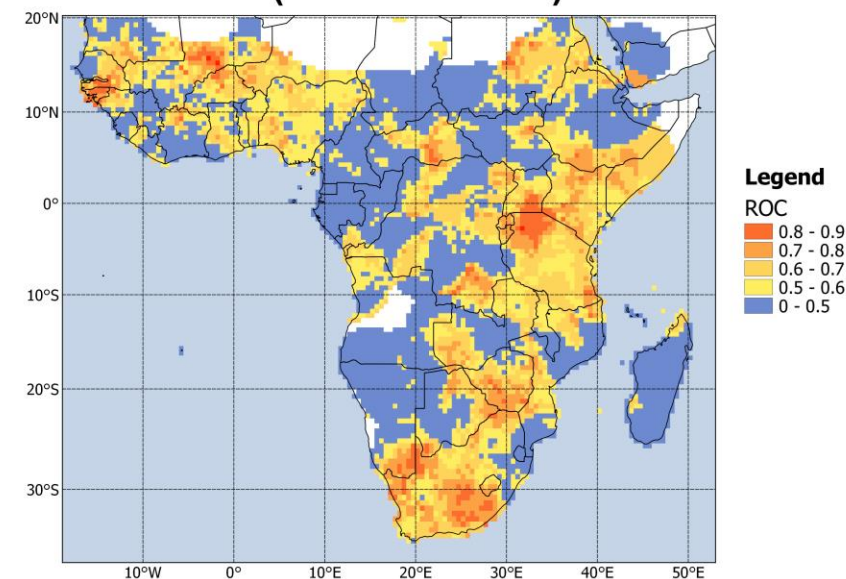


Legend

ROC

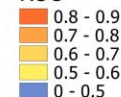


ROC Area (Below-Normal): OND Rainfall



Legend

ROC

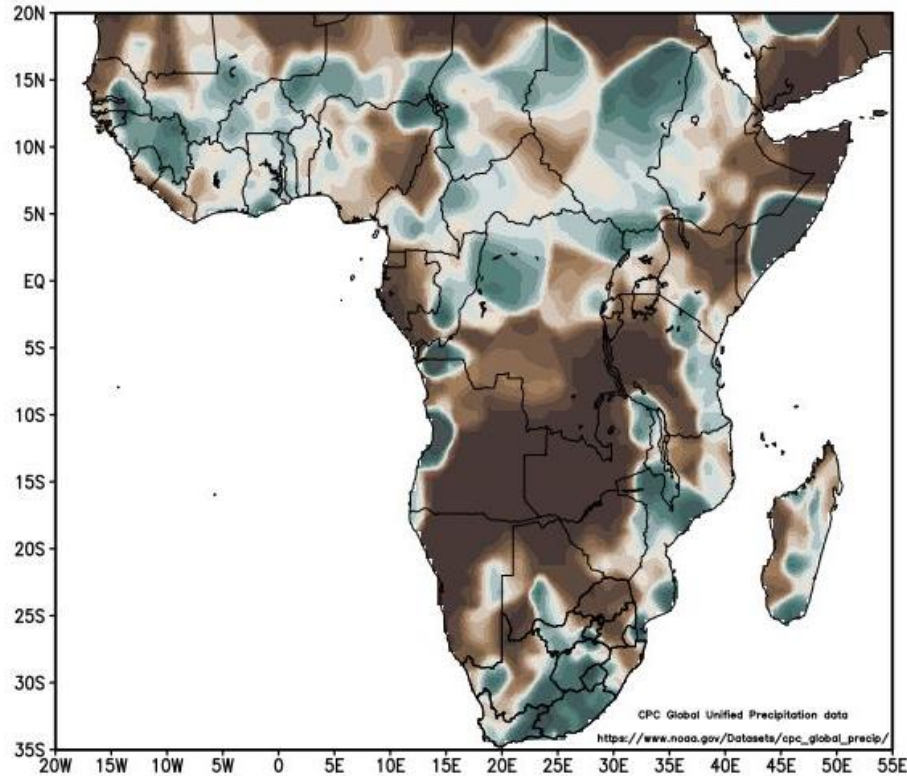


Round-up: Rainfall south of 15°S

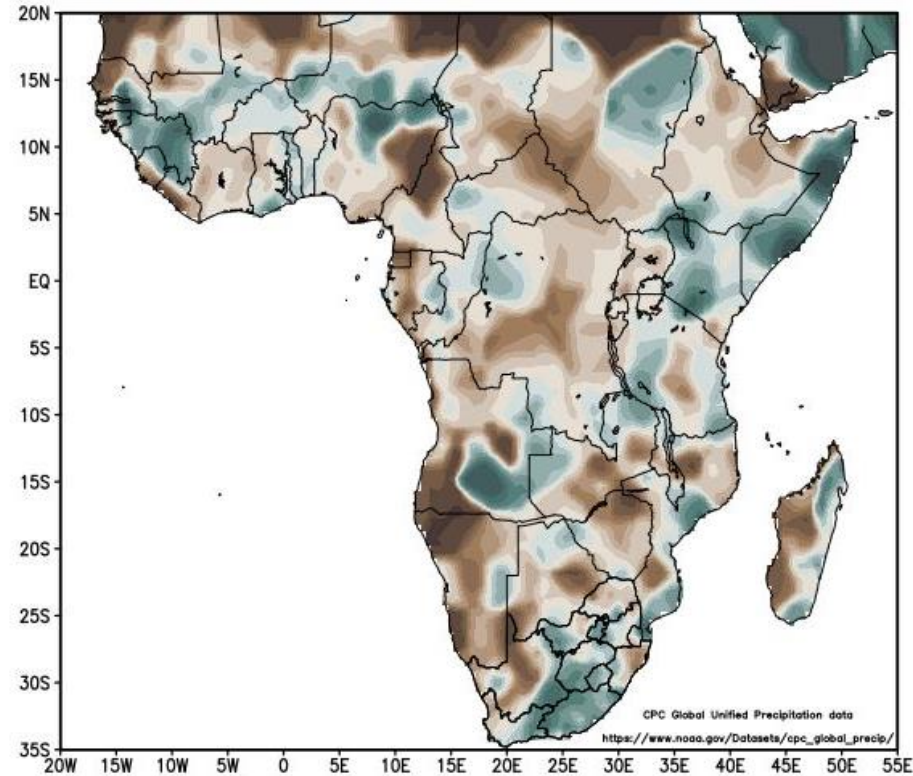
- Below-normal rainfall is predicted over the larger part of the region during winter and spring (July to October/November), including the winter rainfall region of the SW Cape
- There may be a slow start to the summer rainfall season. A slow start (delayed and/or low totals) does not necessarily imply that the rains will shift to a later cessation, but mid-summer rainfall chances normally improve during La Niña events

Observed Rainfall

Rainfall (% of normal): June 2024
June long-term mean: 1981–2010



Rainfall (% of normal): April–May–June 2024
April–May–June long-term mean: 1981–2010



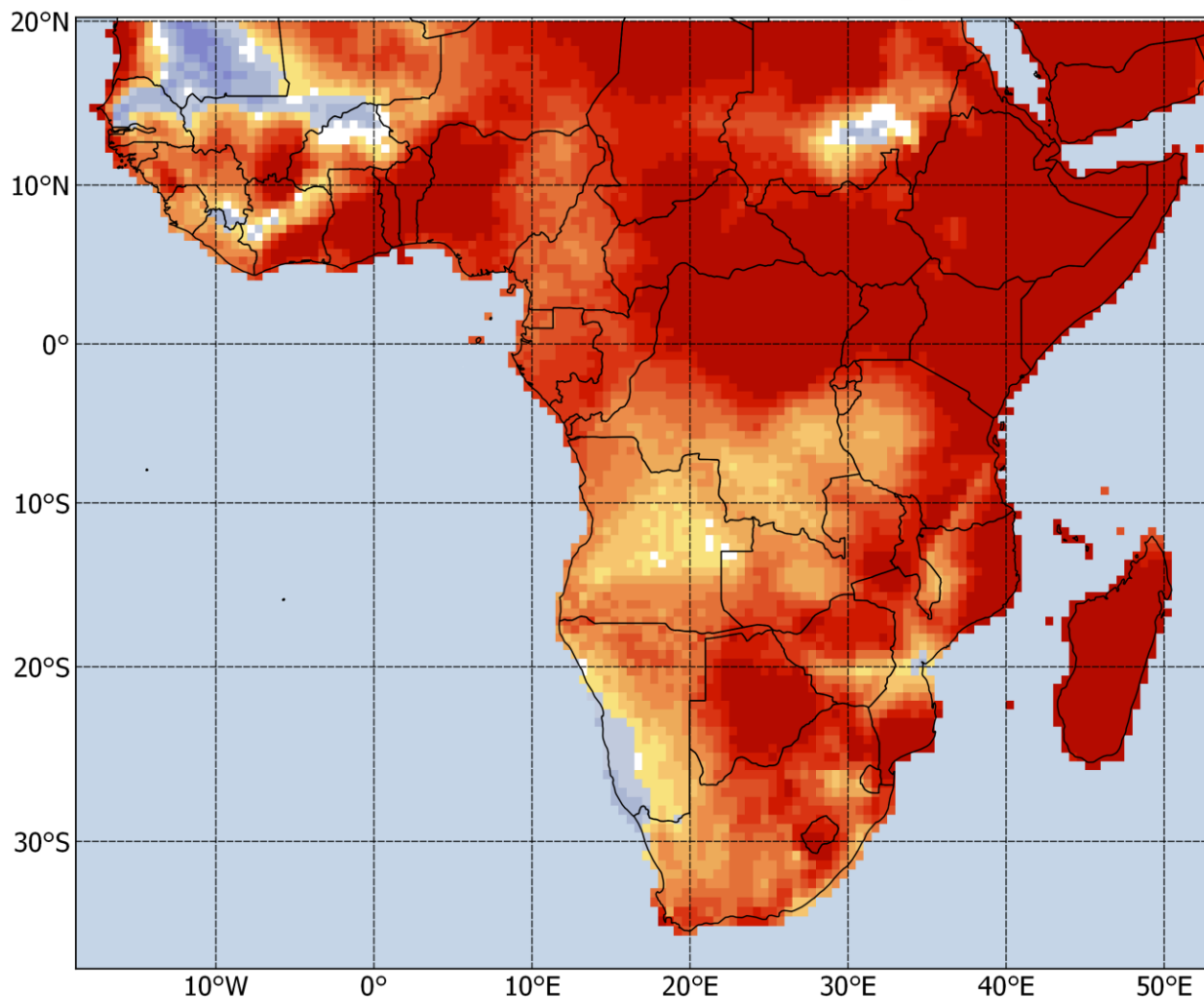
Recorded rainfall for June and the April–May–June season show below-normal rainfall over the brown areas and above-normal rainfall over the green areas

0 10 20 30 40 50 60 80 100 120 140 160 200 250 300 400 500 (%)

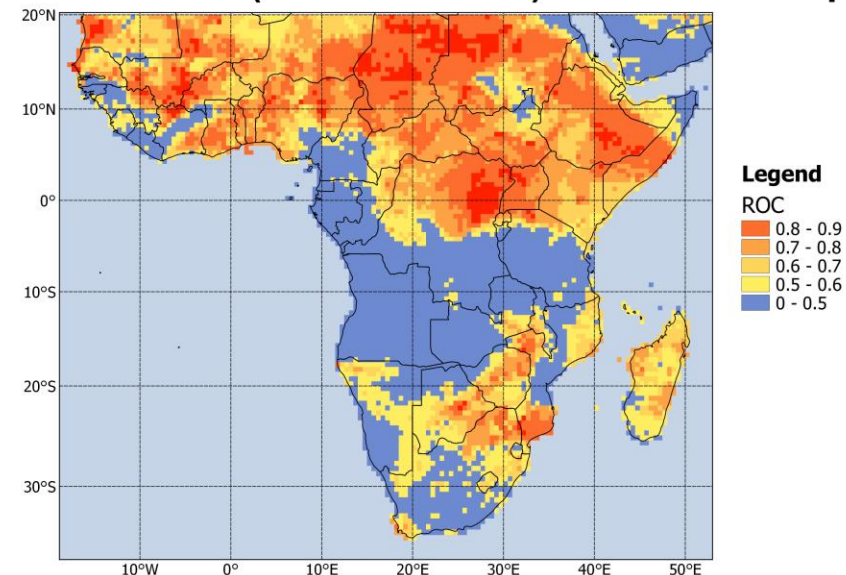
0 10 20 30 40 50 60 80 100 120 140 160 200 250 300 400 500 (%)

Maps prepared by Dr. Christien Engelbrecht

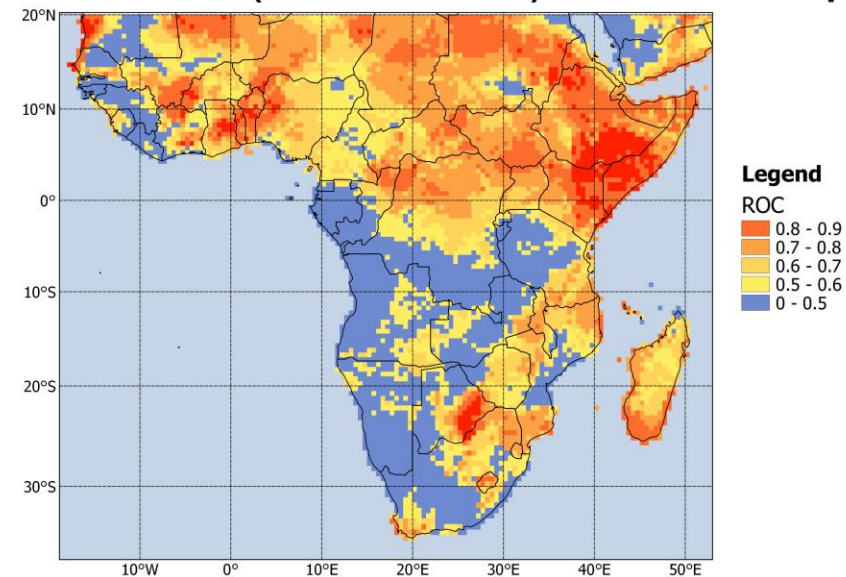
JAS 2024 Max Temp; ICs: Jul



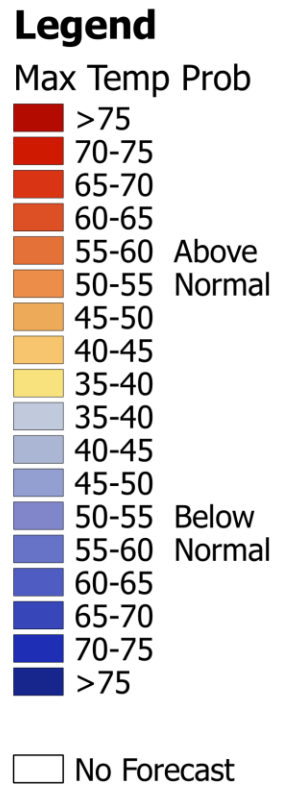
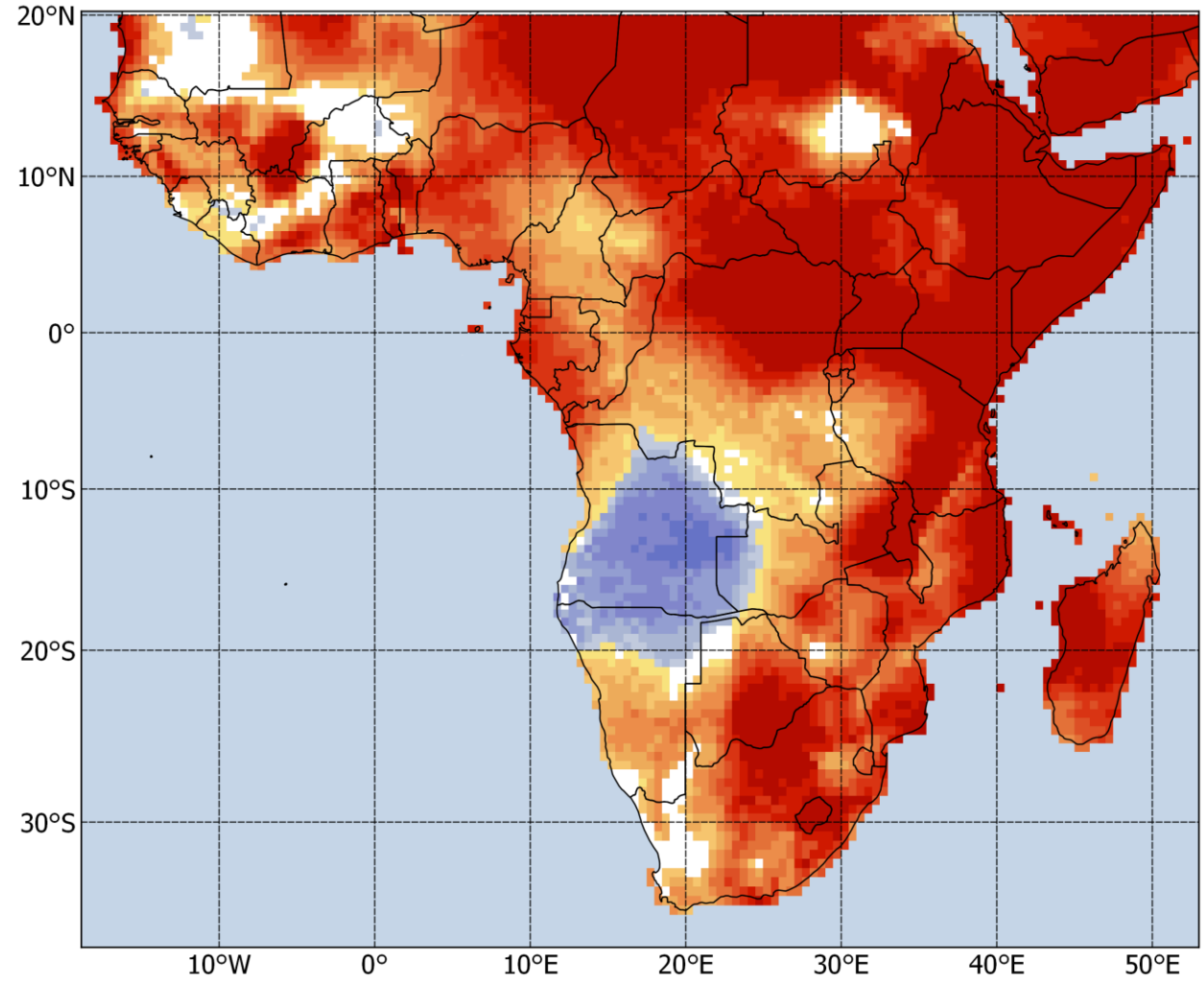
ROC Area (Above-Normal): JAS Max Temp



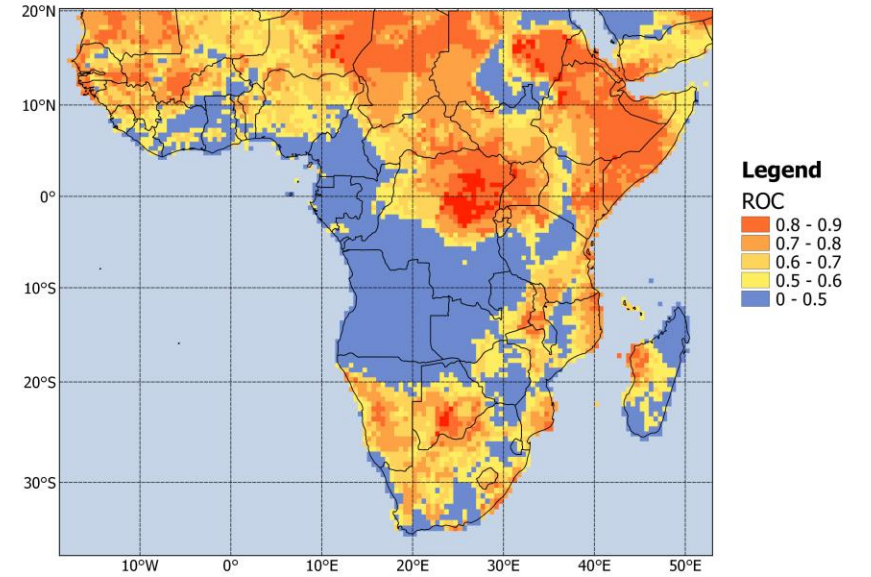
ROC Area (Below-Normal): JAS Max Temp



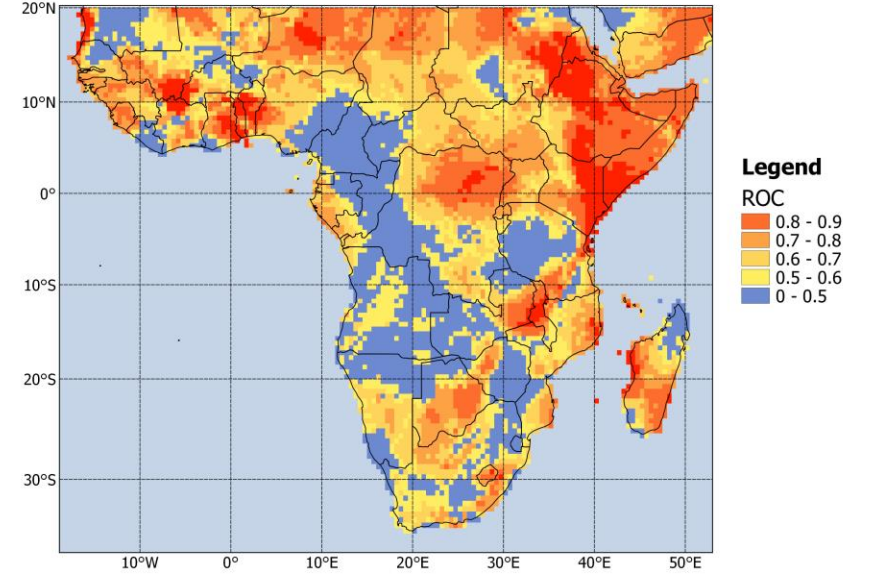
ASO 2024 Max Temp; ICs: Jul



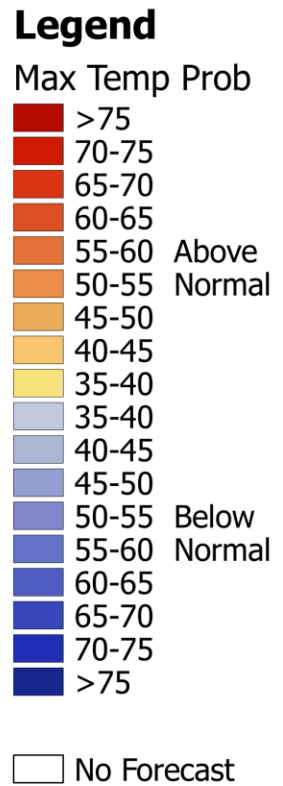
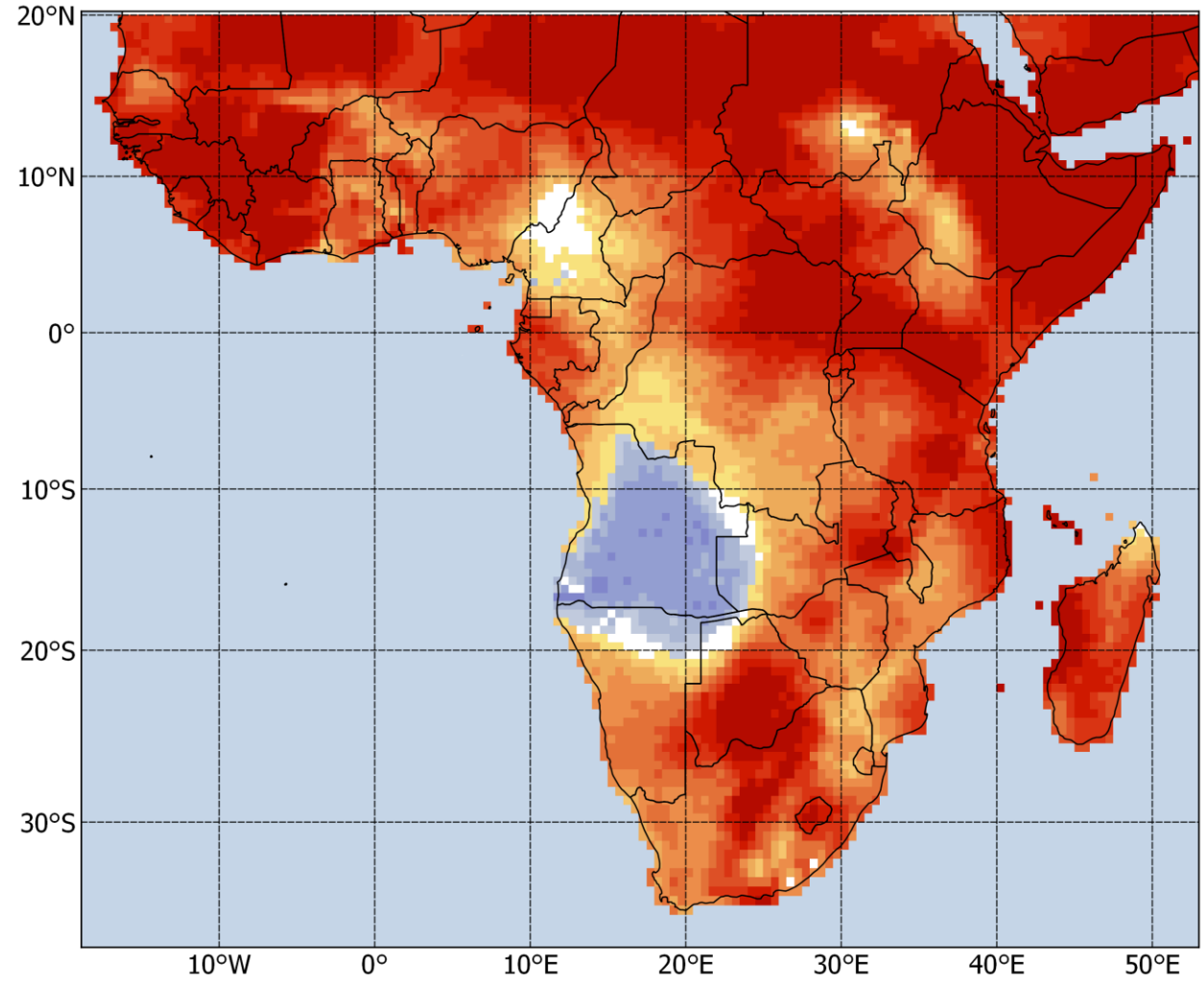
ROC Area (Above-Normal): ASO Max Temp



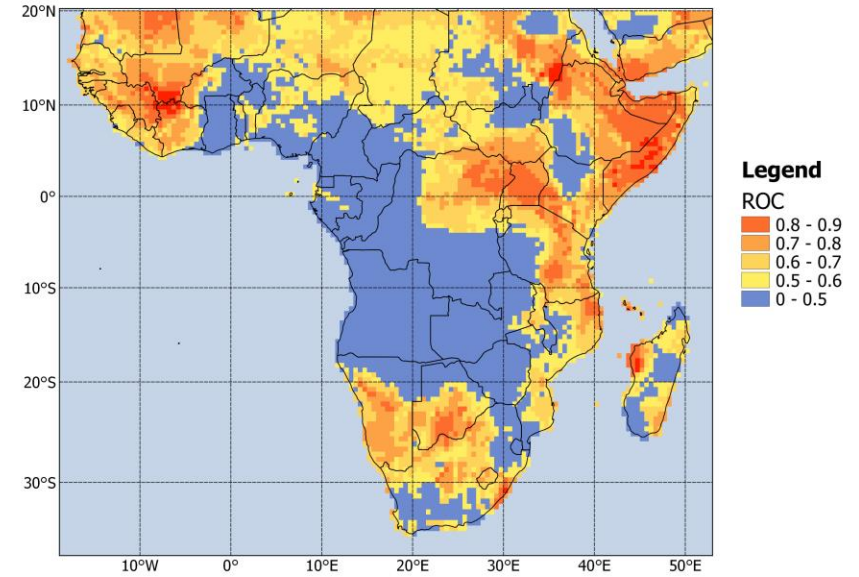
ROC Area (Below-Normal): ASO Max Temp



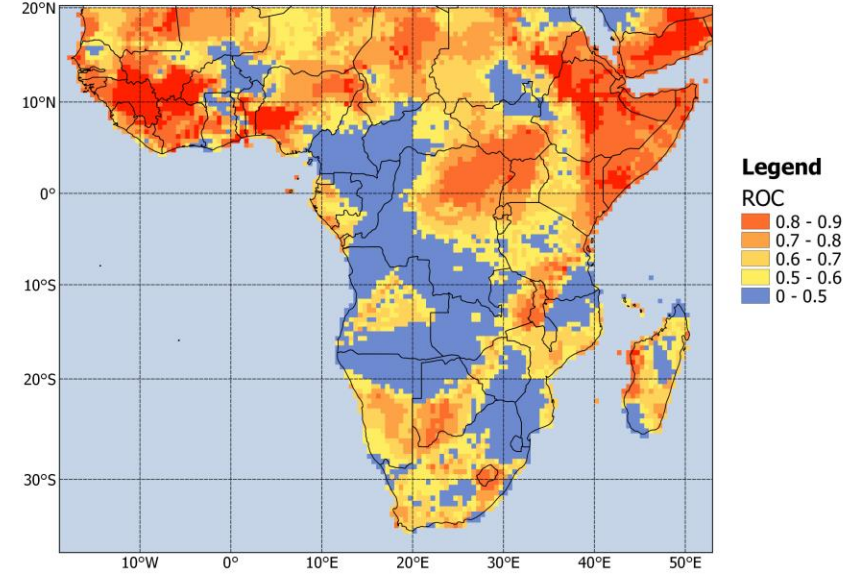
SON 2024 Max Temp; ICs: Jul



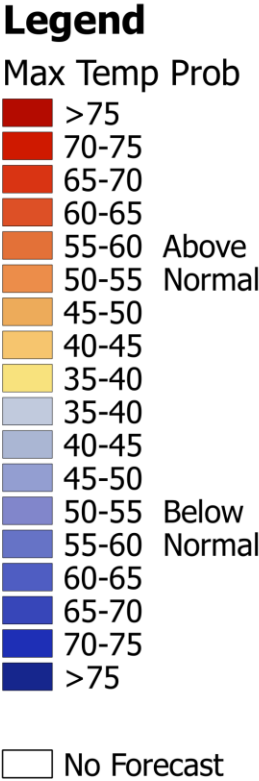
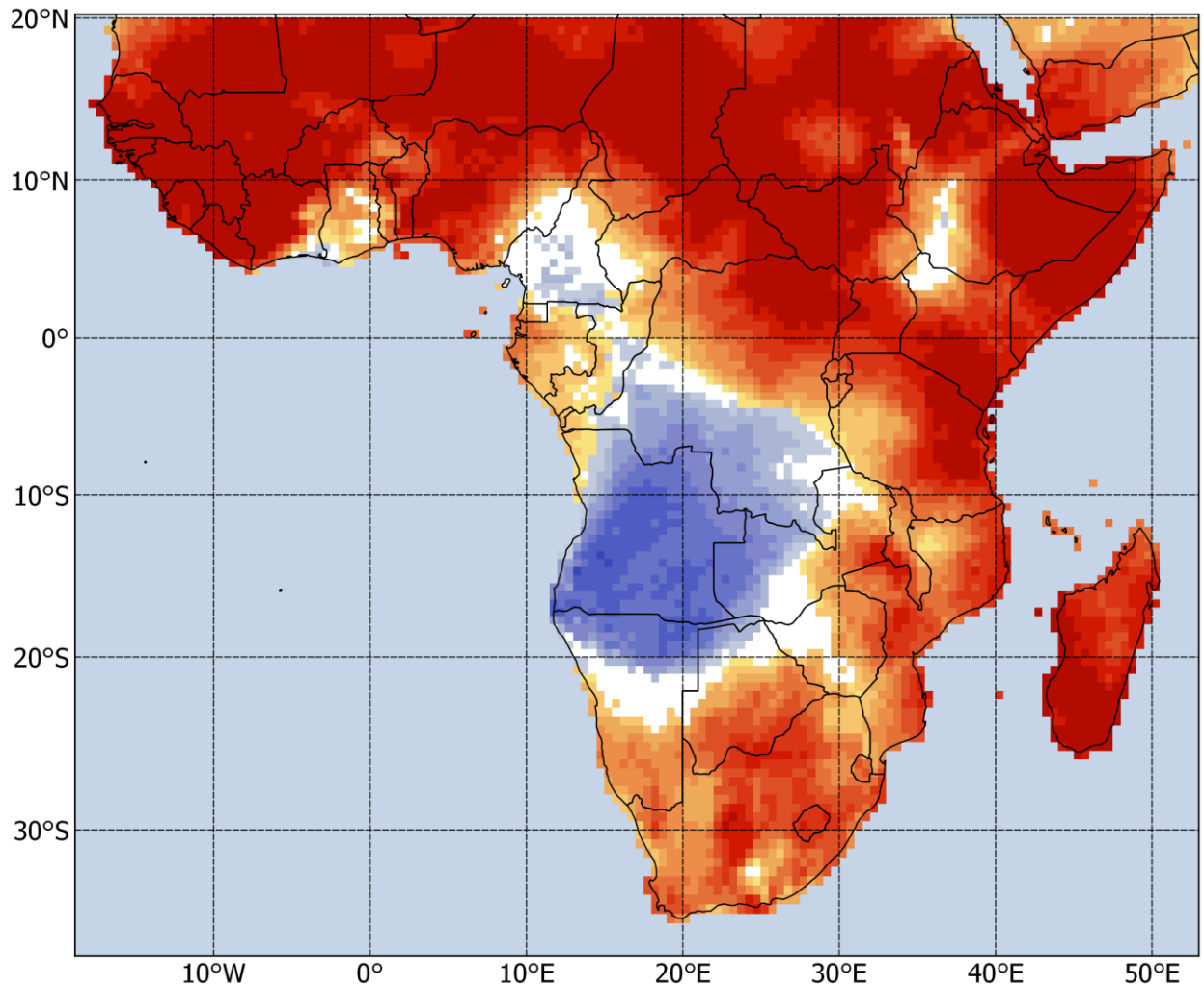
ROC Area (Above-Normal): SON Max Temp



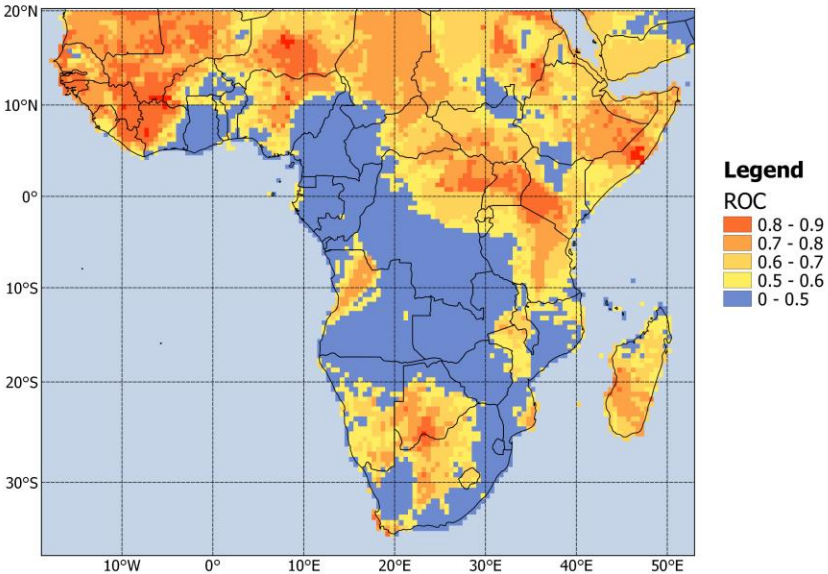
ROC Area (Below-Normal): SON Max Temp



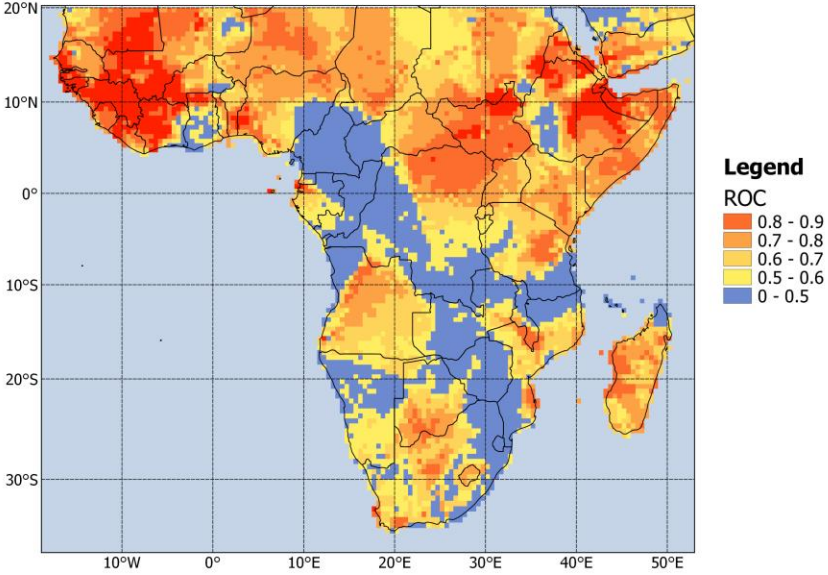
OND 2024 Max Temp; ICs: Jul



ROC Area (Above-Normal): OND Max Temp



ROC Area (Below-Normal): OND Max Temp



Round-up: South of 15°S Max Temp

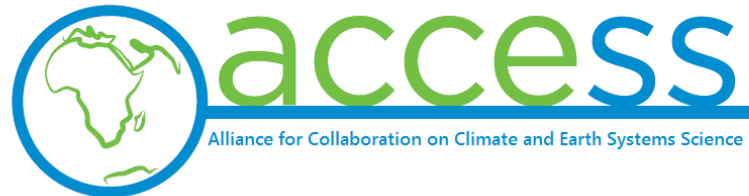
- Above-normal mean maximum temperatures over the larger region are highly likely during the forecast period

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 - Project: Application of knowledge for the management of extreme climate events (APECX; 2022 to 2024)
- 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

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.