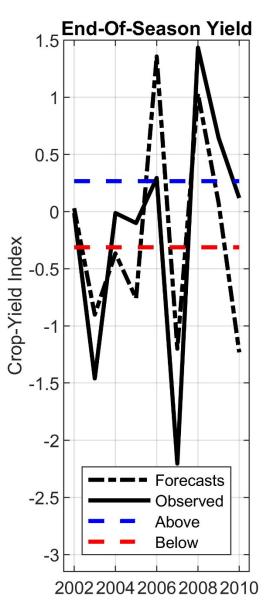
Seasonal forecasts

presented by:



Latest Update: 15 August 2020

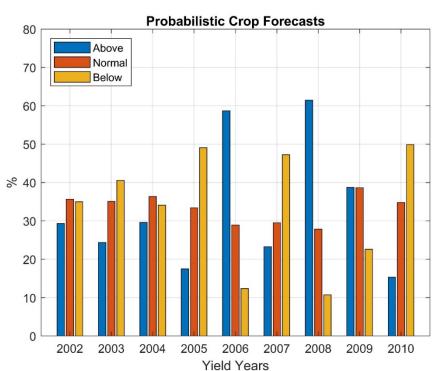
Are you a farmer who wants to make use of science-based seasonal predictions for your farm? If you are interested to be part of an initiative at the University of Pretoria that involves the development of seasonal forecast systems for farms, specifically tailored to farmers' needs, please send an email to WALandman1981@gmail.com

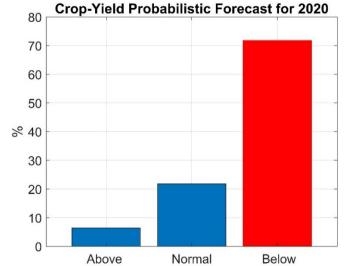


Have a look at this example of end-of-season crop yield forecasts for a farm near Bapsfontein.

The farmer provided several decades of crop-yield data and these data were subsequently used

to create a crop forecast model specific to the farm





Above is the crop-yield forecast for the coming season. The forecast is for enhanced probabilities of below-normal (low) crop yield for the farm. The farmer may be able with support to use this forecast information to plan for the coming season

On the left are time series of forecast and observed crop yields at the time of harvest for the years indicated. Next to the time series are probabilistic forecasts over the same 9-years for below- (low yields), near- (about average) and above-normal (high yields). For example, in 2008 the forecast and observed index values are high and positive (figure on the left), and the highest predicted probability is for above-normal yield (figure in the middle).

Share your data and become part of this initiative

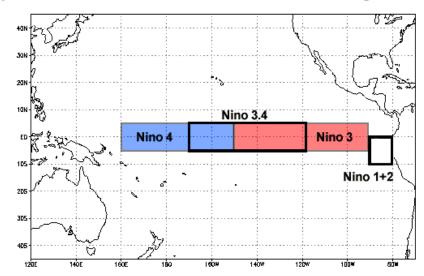
- The seasonal forecasts presented here by Seasonal Forecast Worx are based on forecast output of
 the coupled ocean-atmosphere models administered through the North American Multi-Model
 Ensemble (NMME) prediction experiment (http://www.cpc.ncep.noaa.gov/products/NMME/;
 Kirtman et al. 2014). NMME real-time 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

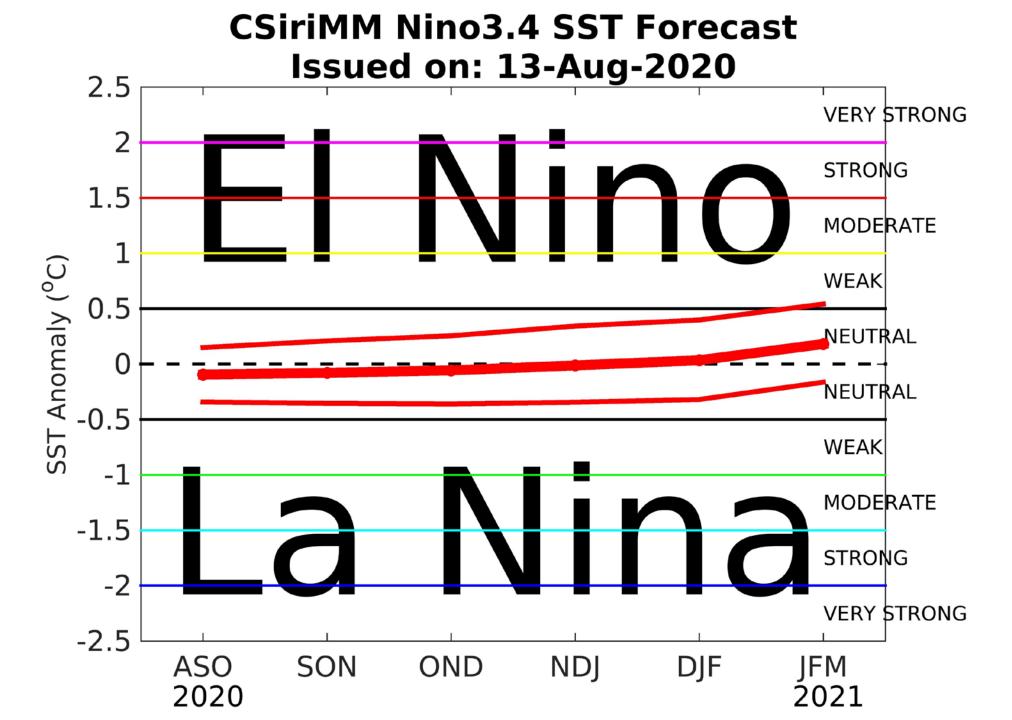
Weather Service

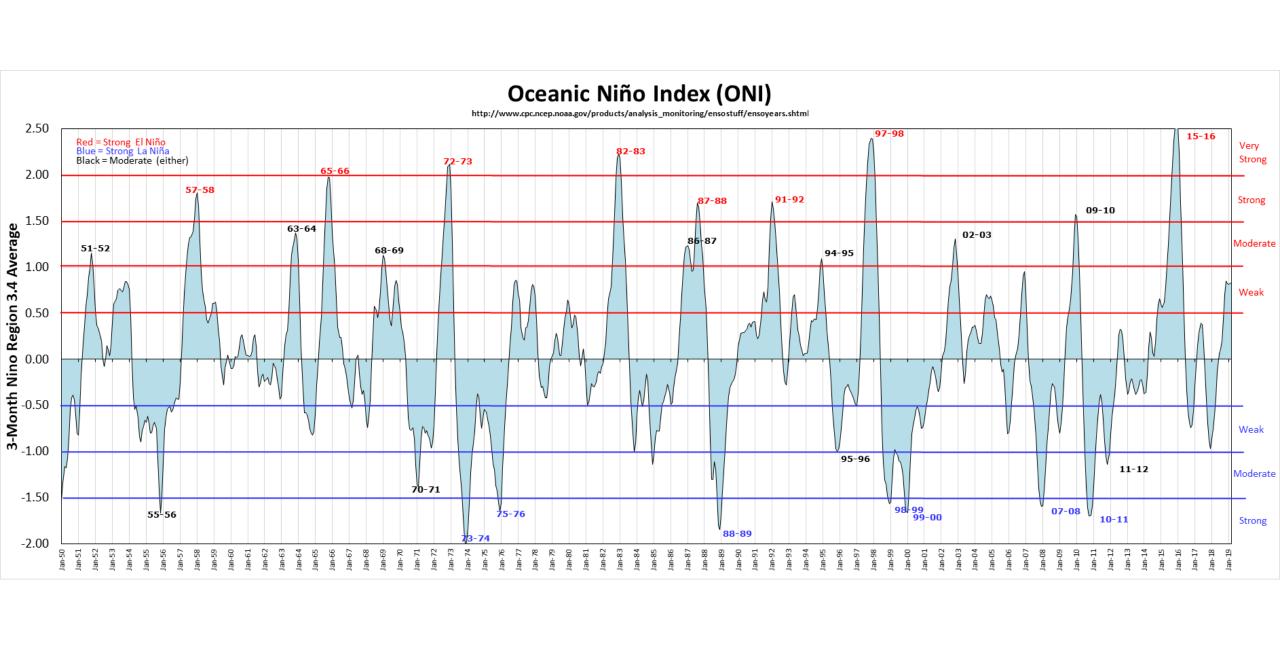
ENSO and Global SST Forecasts

Prediction Method

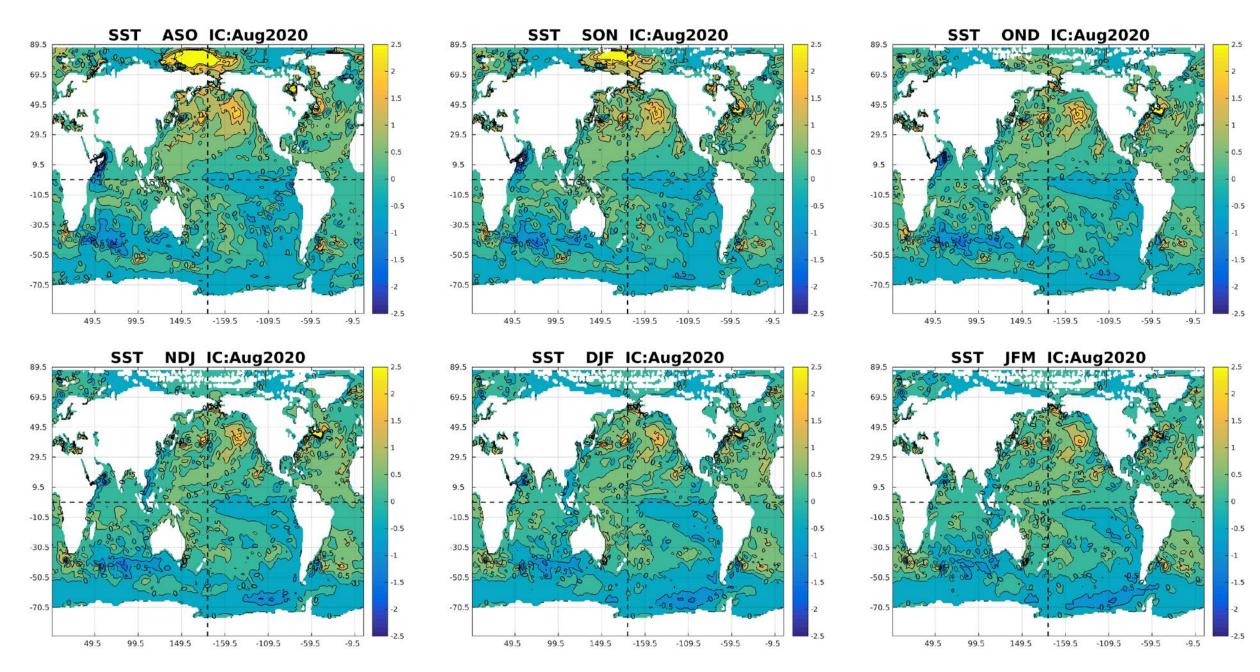
- Forecasts for global sea-surface temperature (SST) fields are obtained through a combination of NMME models and a linear statistical model, that uses antecedent SST as a predictor (Landman et al. 2011). Forecasts for the Niño3.4 area (see insert) are derived from the global forecasts.
- SST forecasts 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



Round-up: ENSO

- The UP model predicts that ENSO-neutral conditions are most likely to continue into summer
- However, most forecast models are going for colder SST, with just a few warmer than the UP model

Southern Africa Forecasts

Prediction Method

- Three-month seasons for seasonal rainfall totals and average maximum temperatures of NMME ensemble mean forecasts are interpolated to Climatic Research Unit (CRU; Harris et al. 2014) grids (0.5°x0.5°), by correcting the mean and variance biases of the NMME forecasts. 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" / "hot", rainfall totals / maximum temperatures higher than the 75th percentile of the climatological record)
 - **Below:** Below-normal ("dry" / "cool", rainfall totals / maximum temperatures lower than the 25th percentile of the climatological record)
 - Normal: Near-normal ("average" season)
- Verification:
 - ROC Area (Below-Normal) The forecast system's ability to discriminate dry or cool seasons from the rest of the seasons over a 32-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 32-year test period. ROC values should be higher than 0.5 for a forecast system to be considered skilful.

Forecasts are probabilistic

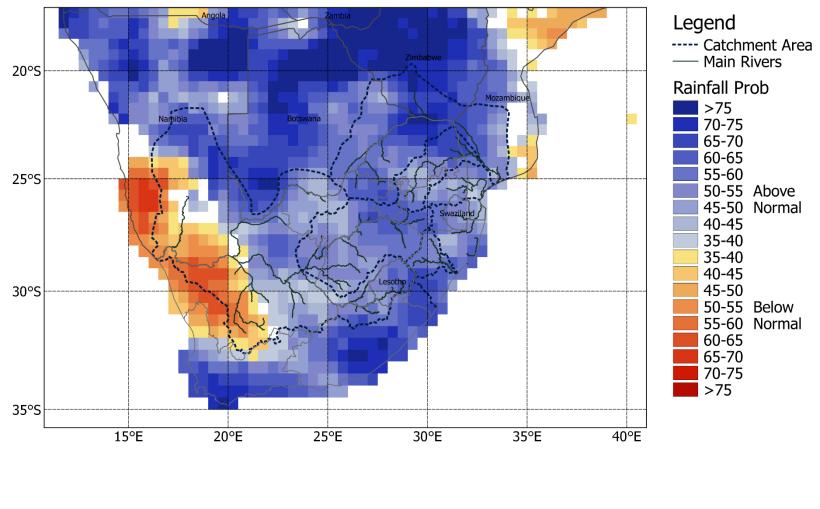
Probabilistic forecasts can help users understand risks and opportunities (forewarned is forearmed) in order to make more informed decisions.

The seasonal rainfall and maximum temperature forecast to follow are probabilities (% chance) of only the most likely outcome for below-, near-, or above-normal (B, N or A). 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% 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.

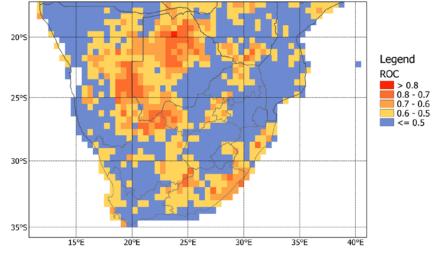
The nature of a probabilistic forecast implies that the less likely outcomes are always possible. In fact, for the probabilistic forecasts to be considered reliable, the less likely outcomes will and must occasionally occur.

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 (B, N or A) as frequently as the forecast implies

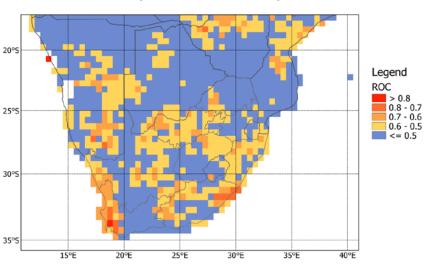
ASO 2020 Rainfall; ICs: Aug



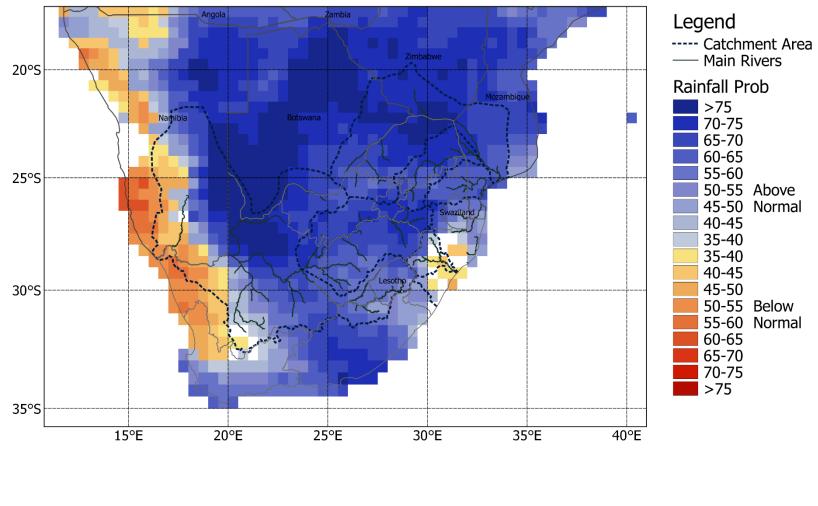
ROC Area (Above-Normal): ASO Rainfall



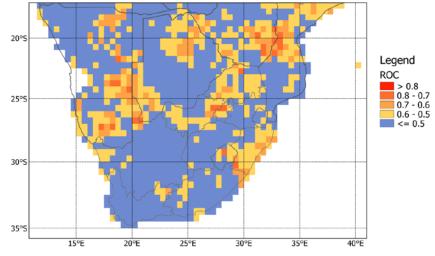
ROC Area (Below-Normal): ASO Rainfall



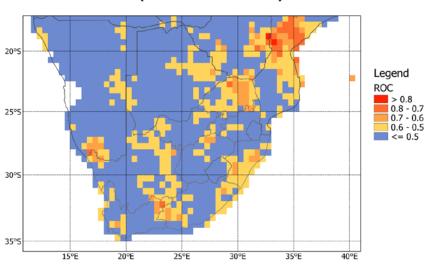
SON 2020 Rainfall; ICs: Aug



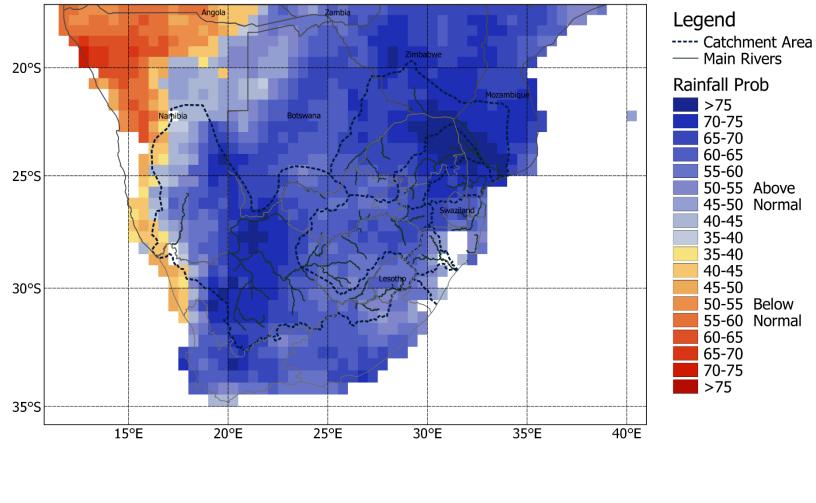
ROC Area (Above-Normal): SON Rainfall



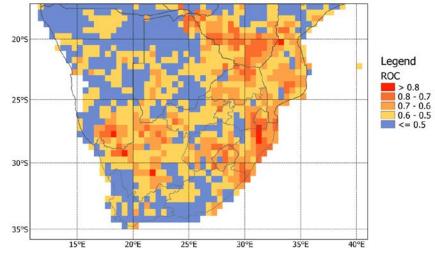
ROC Area (Below-Normal): SON Rainfall



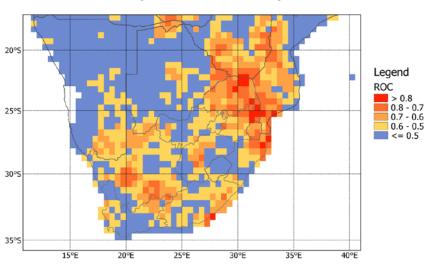
OND 2020 Rainfall; ICs: Aug



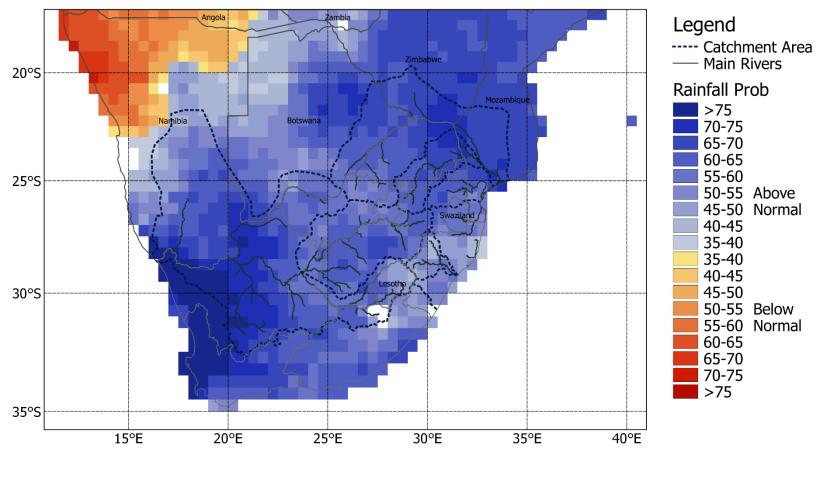
ROC Area (Above-Normal): OND Rainfall



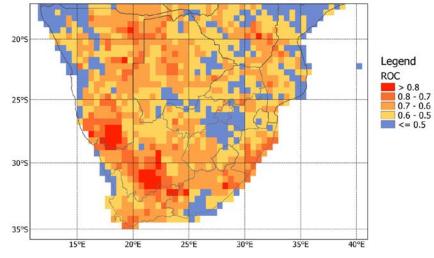
ROC Area (Below-Normal): OND Rainfall



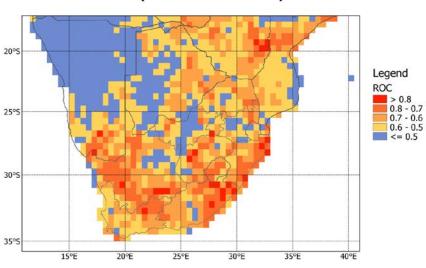
NDJ 2020-21 Rainfall; ICs: Aug



ROC Area (Above-Normal): NDJ Rainfall



ROC Area (Below-Normal): NDJ Rainfall



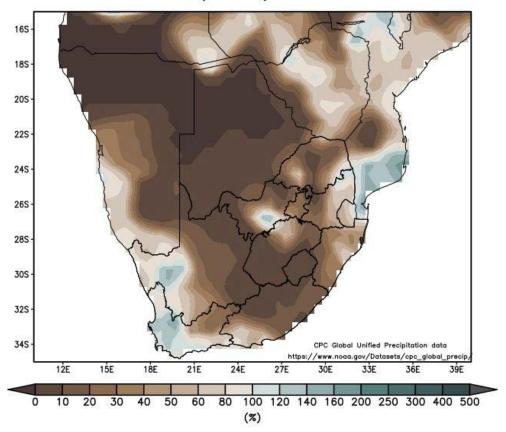
Round-up: SADC Rainfall

 Favourable rainfall outcomes are expected over the larger part of the forecast region

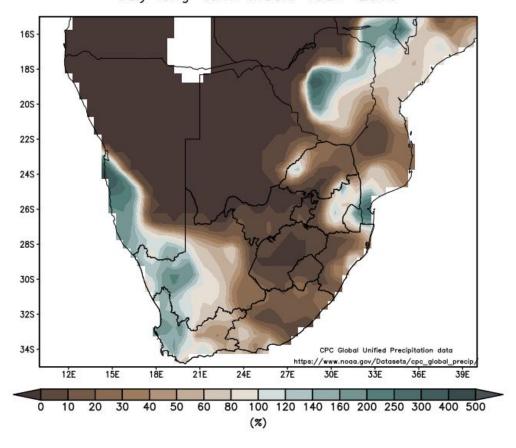
Observed SADC Rainfall

Rainfall (% of normal): May-June-July 2020

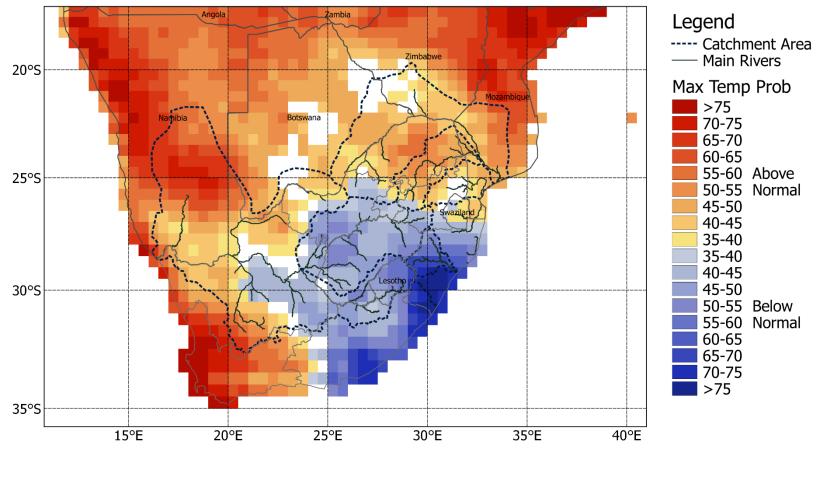
Relative to May-June-July 1981-2010 rainfall



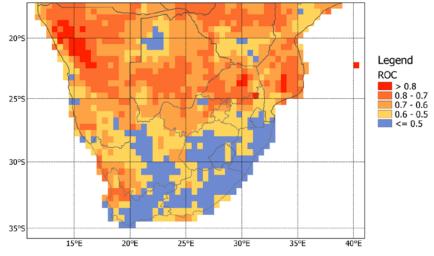
Rainfall (% of normal): July 2020 July long-term mean: 1981-2010



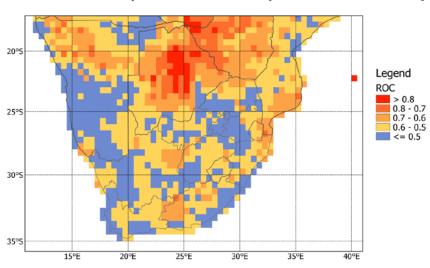
ASO 2020 Max Temp; ICs: Aug



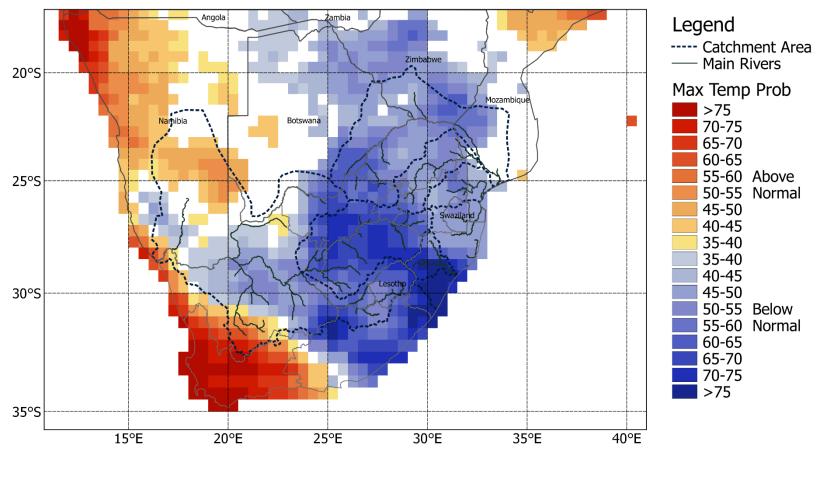
ROC Area (Above-Normal): ASO Max Temp



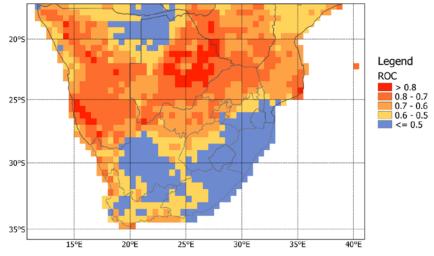
ROC Area (Below-Normal): ASO Max Temp



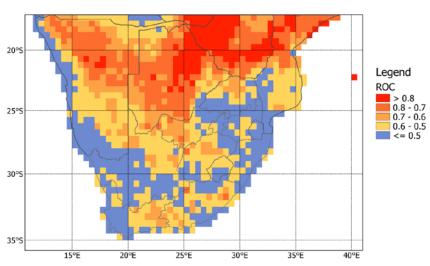
SON 2020 Max Temp; ICs: Aug



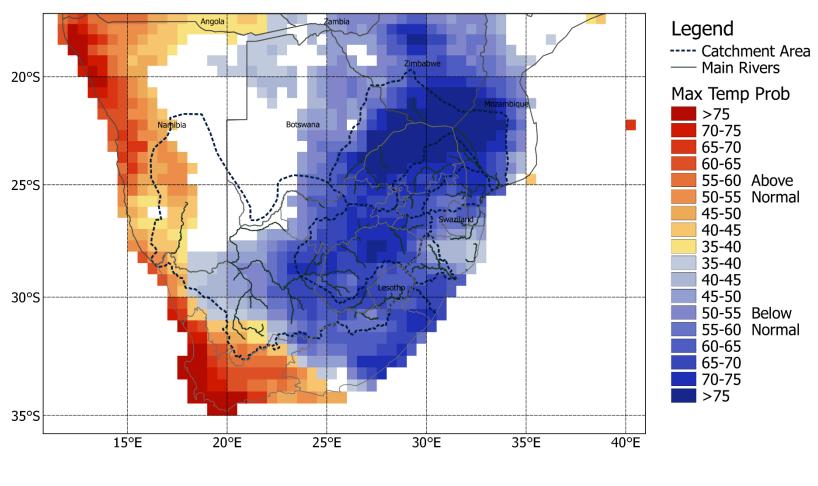
ROC Area (Above-Normal): SON Max Temp



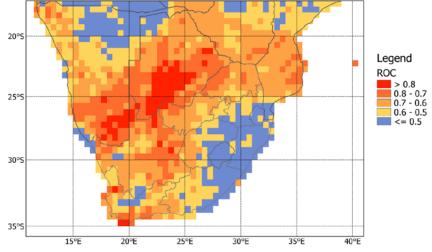
ROC Area (Below-Normal): SON Max Temp



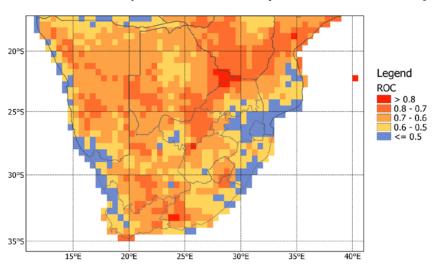
OND 2020 Max Temp; ICs: Aug



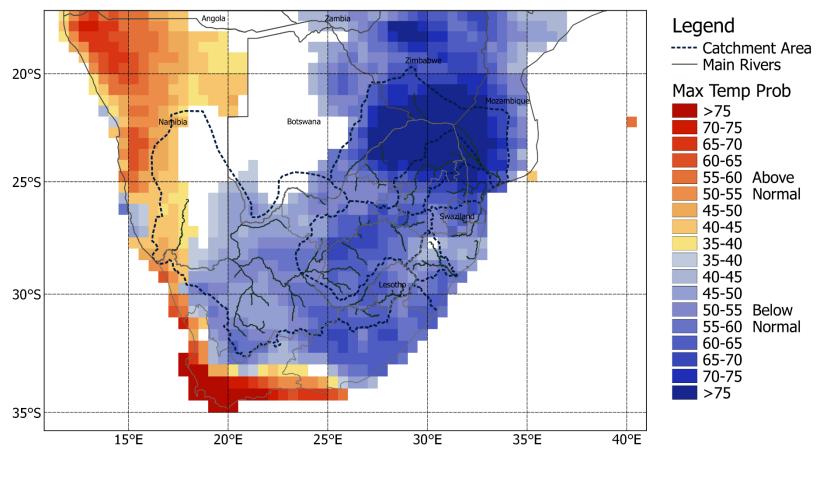
ROC Area (Above-Normal): OND Max Temp



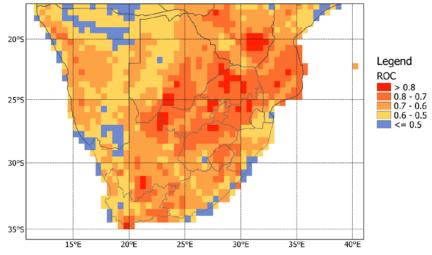
ROC Area (Below-Normal): OND Max Temp



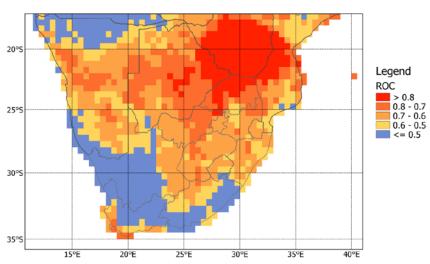
NDJ 2020-21 Max Temp; ICs: Aug



ROC Area (Above-Normal): NDJ Max Temp



ROC Area (Below-Normal): NDJ Max Temp



Round-up: SADC Max Temp

 Cooler maximum temperatures are likely and associated with the increased likelihood of a wet summer season

- Barnston, A.G. and Tippett, M.K., 2017: Do statistical pattern corrections improve seasonal climate predictions in the North American Multimodel Ensemble models? Journal of Climate, 30: 8335-8355. doi: 10.1175/JCLI-D-17-0054.1
- Harris, I., Jones, P. D., Osborn, T. J., and Lister, D. H., 2014: Updated high-resolution grids of monthly climatic observations - the CRU TS3.10 Dataset. International Journal of Climatology, 34: 623-642. doi: 10.1002/joc.3711
- Kirtman, B. P. and Co-authors 2014: The North American Multimodel Ensemble: Phase-1 seasonal-to-interannual prediction; Phase-2 toward developing intraseasonal prediction. Bulletin of the American Meteorological Society. 95, 585–601. doi: http://dx.doi.org/10.1175/BAMS-D-12-00050.1
- Landman, W.A., and Beraki, A., 2012: Multi-model forecast skill for midsummer rainfall over southern Africa. International Journal of Climatology, 32: 303-314. doi: 10.1002/joc.2273.
- Landman, W.A., Archer, E. and Tadross, M., 2016: Decision-relevant information on seasonal time scales the case of a farm in northern Namibia. Conference Proceedings of the 32nd Annual Conference of the South African Society for Atmospheric Science, Cape Town, 31 October to 1 November 2016, pp 69-72. ISBN 978-0-620-72974-1.
- Landman, W.A., Archer, E. and Tadross, M. (2019): How costly are poor seasonal forecasts? Peer reviewed abstracts, 35th Annual conference of the South African Society for Atmospheric Science, Vanderbijlpark, 8 to 9 October 2019, pp 60-63. ISBN 978-0-6398442-0-6.
- Landman, W.A., DeWitt, D., and Lee, D.-E., 2011: The high-resolution global SST forecast set of the CSIR.
 Conference Proceedings of the 27th Annual Conference of South African Society for Atmospheric Sciences, 22-23
 September 2011, Hartbeespoort, North-West Province, South Africa. ISBN 978-0-620-50849-0
- Landman, W.A., DeWitt, D. Lee, D.-E., Beraki, A. and Lötter, D., 2012: Seasonal rainfall prediction skill over South Africa: 1- vs. 2-tiered forecasting systems. Weather and Forecasting, 27: 489-501. DOI: 10.1175/WAF-D-11-00078.1
- Muchuru, S., Landman, W.A. and DeWitt, D., 2016: Prediction of inflows into Lake Kariba using a combination of physical and empirical models. International Journal of Climatology, 36: 2570–2581, DOI: 10.1002/joc.4513.
- Troccoli, A., Harrison, M., Anderson, D.L.T. and Mason, S.J., 2008: Seasonal Climate: Forecasting and Managing Risk. NATO Science Series on Earth and Environmental Sciences, Vol. 82, Springer, 467 pp.

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 ACCESS (Alliance for Collaboration on Climate and Earth System Science) through the project "Investigating predictability of seasonal anomalies for societal benefit"









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