Probabilistic Skill of Statistically Downscaled ECMWF S2S Forecasts of Maximum and Minimum Temperatures for Weeks 1-4 over South Africa

Supplemental Information

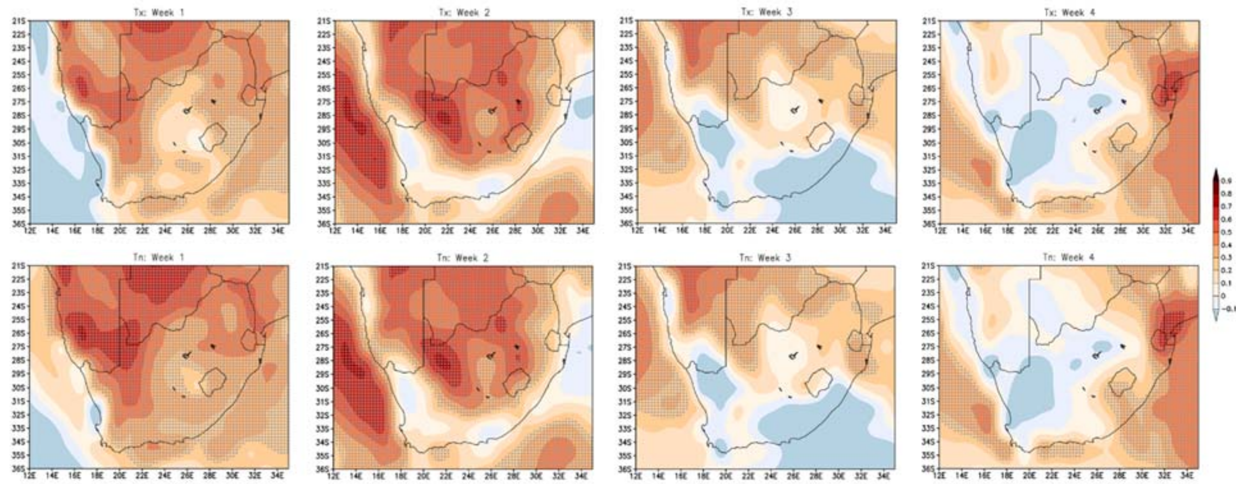

Figure S1. CORA between the 850hPa geopotential heights of ECMWF S2S model and the maximum and minimum temperatures of the ERA5 reanalysis for weeks 1-4 DJF seasons from 2001-2020. Stippling indicates areas of statistical significance at a 95% confidence level using the Student's t-test at each grid point.

Forecast skill metric

The correlation of anomalies (CORA) is a skill metric often used to assess deterministic S2S forecasts (e.g., Li & Robertson, 2015; Wang & Robertson, 2019). CORA is calculated as follows: Firstly, the anomalies of the models' hindcasts and minimum and maximum temperatures (observations) for the weeks 1-4 DJF seasons from 2001-2020 are computed. Secondly, the correlations between the forecast and observed 20-year timesteps climatological anomalies are then calculated. This method of computing CORA is commonly used in S2S prediction studies (e.g., Becker et al., 2013; Wang & Robertson, 2019; Alvarez et al., 2020; Phakula et al., 2020; Engelbrecht et al., 2021). The statistical significance of CORA is taken into consideration following the Student's t-test approach (Al-Achi, 2019; Mishra et al., 2019). The Student's t-test is based on a 20-year climatological anomalies of the events. Any CORA value greater than 0.3 at each grid-point is considered significant at the 5% confidence level, and only positive CORA values are considered skillful.

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