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Probabilistic skill of statistically downscaled ECMWF S2S forecasts of maximum and minimum temperatures for weeks 1–4 over South Africa

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Abstract

The probabilistic forecast skill level of statistically downscaled European Centre for Medium-Range Weather Forecasts (ECMWF) subseasonal-to-seasonal (S2S) forecasts is determined in predicting maximum and minimum temperatures for weeks 1–4 lead times during 20-year December–January–February (DJF) seasons from 2001 to 2020 over South Africa. Skilful S2S forecasts are vital in assisting decision-makers in the development of contingency planning for any eventualities that may arise because of weather and climate phenomena. Extreme high- and low-temperature events over a prolonged period can lead to hyperthermia and hypothermia, respectively, and can lead to loss of life. The results from the relative operating characteristic (ROC) and reliability diagrams indicate that the ECMWF S2S model has skill in predicting maximum temperature up to week 3 ahead, particularly over the central and eastern parts of South Africa. The ROC scores indicate that the model has skill in predicting minimum temperature up to week 4 ahead for the above-normal category, particularly over the central and eastern parts of South Africa. Reliability diagrams indicate that the model has a tendency of overestimating the below-normal category when predicting both maximum and minimum temperatures for weeks 1–4 lead times over South Africa. Furthermore, canonical correlation analysis (CCA) pattern analysis suggests that when there are anomalously positive and negative predicted 850-hPa geopotential heights located over South Africa, there are anomalously hot and cold conditions during the DJF seasons over most parts of South Africa, respectively. These results suggests that statistical downscaling of model forecasts can improve forecast skill. Moreover, the results suggest that there is potential for S2S predictions in South Africa, and as such, S2S prediction system for maximum and minimum temperatures can be developed.

KEYWORDS

canonical correlation analysis, probabilistic skill metrics, South Africa, subseasonal-to-seasonal predictions

1 | INTRODUCTION

The South African Weather Service (SAWS) has the mandate to provide weather and climate information to the public of South Africa. Hence, SAWS issues temperature and rainfall weather forecasts on a daily basis and seasonal climate predictions once a month (e.g., Phakula et al., 2018; Phakula et al., 2020). There is a 'gap' between weather forecasting and seasonal climate predictions, referred to as subseasonal-to-seasonal (S2S), a timescale from 2 weeks up to 2 months (de Andrade et al., 2021; Klingaman et al., 2021; Mariotti et al., 2018; Moron & Robertson, 2020; Mundhenk et al., 2017; Wang & Robertson, 2018; White et al., 2017). The S2S timescale is referred to as a 'prediction desert' (e.g., Vitart et al., 2012), and it has long been neglected because of its inherent nature of being difficult to predict (e.g., Hudson et al., 2011; Li & Robertson, 2015; Luo & Wood, 2006; Vitart, 2014). The difficulty is due to the fact that the lead time is sufficiently long that much of the memory of the atmospheric initial condition is lost and it is too short a time range for the slowly evolving variation of the ocean to have a strong influence on the atmosphere (Vitart, 2013; Vitart et al., 2017; Black et al., 2017; DelSole et al., 2017; White et al., 2017; de Andrade et al., 2021).

The demand for S2S forecasts has increased since decision-making and early warnings across different sectors, such as agriculture, water, disaster risk management and energy fall within this timescale (e.g., Black et al., 2017; Endris et al., 2021; Hudson et al., 2011; Mariotti et al., 2018; Tian et al., 2017; White et al., 2017). This is particularly urgent in the context of increasing societal exposure to extreme weather threats, either caused by growing populations or due to decadal climate variability or anthropogenic climate change (Li & Robertson, 2015). Therefore, accurate S2S forecasts are needed to assist decision-makers to carry out contingency planning for any eventualities that may arise because of weather and climate phenomena. This study seeks to determine the probabilistic forecast skill level of statistically downscaled European Centre for Medium-Range Weather Forecasts (ECMWF) S2S forecasts in predicting maximum and minimum temperatures for weeks 1–4 lead times during 20-year December–January–February (DJF) seasons over South Africa. In our previous work, we tested the deterministic skill of S2S forecasts in predicting surface temperature over South Africa, without any downscaling (Phakula et al., 2020). Therefore, in this study, the focus is to determine if statistical downscaling of model forecasts improves skill or not. Extreme high- and low-temperature events over a prolonged period can lead to hyperthermia and hypothermia, respectively (van der Walt & Fitchett, 2021), and can lead to loss of life. Therefore, development of downscaled S2S forecast system for surface minimum and maximum temperatures can be invaluable for South Africa. The remainder of this paper is organized as follows: Section 2 describes the data and methods used for the analysis, Section 3 analyses the result findings of the study, and the discussion and conclusions are summarized in Section 4.

2 | DATA AND METHODS

2.1 | S2S model data

The 850-hPa geopotential height fields of the ECMWF reforecast dataset from the S2S Prediction Project database (Vitart et al., 2017) are used as the predictor in this study. The 850-hPa geopotential heights are used here because they have been found to be good predictor over South Africa at month and seasonal timescales (e.g., Landman et al., 2014; Phakula et al., 2018). The reforecast data are archived on a 1.5° grid resolution. The ECMWF produces reforecasts on-the-fly, meaning that the reforecasts are produced at the same time as the real-time forecasts, covering the past 20 years from 2001 to 2020 for this model version, and are initialized on 2 days per week (Monday and Thursday) for each model version consisting of an 11-member ensemble and 51-member ensemble for real-time forecasts. The models' 7-day average 850-hPa geopotential heights for week 1 (1–7 days), week 2 (8–14 days), week 3 (15–21 days) and week 4 (22–28 days) lead times for DJF seasons are computed for the climatological period of 2001–2020. For this model version, the start dates for December, January and February are 25 November 2021, 27 December 2021 and 27 January 2021, respectively. The week 1, week 2, week 3 and week 4 averages for December, January and February are computed and averaged to form weeks 1–4 DJF seasons. The ECMWF model is used because in our previous study, it performed better than the other S2S models in terms of skill over southern Africa (Engelbrecht et al., 2021; Phakula et al., 2020).

2.2 | Verification data

The maximum and minimum temperatures of the ECMWF fifth-generation reanalysis (ERA5, Hersbach et al., 2020) datasets are used as predictand and to validate the model. The datasets are available from 1979 to the near present with a 0.25° resolution. The predictand data are interpolated (bilinear) to 1.5° resolution to match those of the S2S model dataset. The weekly average of the maximum and minimum temperatures for week 1, week 2, week 3 and week 4 for DJF seasons are also computed in a similar fashion as that of the model reforecast. The climatology of the reanalysis is restricted to 2001–2020 to match that of the model.

2.3 | Downscaling approach

Canonical correlation analysis (CCA; Hotelling, 1936) option of the Climate Predictability Tool (CPT; Mason et al., 2022) is used to perform model output statistics (MOS; Wilks, 2011) through a retroactive procedure to downscale the 850-hPa geopotential heights of the ECMWF S2S model to the maximum and minimum temperatures of the ERA5 reanalysis over South Africa. CCA and MOS have been used to some success for seasonal climate predictions over southern Africa (Landman et al., 2009; Landman et al., 2014). Retroactive forecast validation is a robust method to assess forecast model performance and give unbiased skill levels (e.g., Landman et al., 2001). The retroactive procedure is followed as in Landman et al. (2012) and Phakula et al. (2018): firstly, usually, half of the training sample is used as a training period, secondly, the model using that training period is reconstructed, thirdly, the year that follows the last year of the training period is forecasted, and lastly, the process is repeated by adding 1 year to the training period and then the subsequent year is predicted until a forecast has been made for each year of the training sample. For this study, an initial training period of 10 years from 2001 to 2010 out of a training sample of 20 years from 2001 to 2020 is used to construct the model and to forecast the year 2011. A training period from 2001 to 2011 is used to reconstruct a model and forecast the year 2012. The process is repeated for each of the subsequent years until a forecast for each year has been made.

2.4 | Forecast skill metrics

To determine whether statistical downscaling of model forecasts improves forecast skill, the Spearman's rank correlation computed from CCA (downscaling) and raw global climate model (GCM) forecasts (no downscaling) in predicting maximum and minimum temperature for weeks 1–4 during 20-year DJF seasons from 2001 to 2020 is examined. The model's probabilistic forecast skill is assessed using relative operating characteristic (ROC) diagram and reliability diagram. Probabilistic forecast performance is tested for three equal probabilities of 33.3% tercile categories. The first tercile is for forecasting the below-normal category, and the last tercile is for the above-normal category, and these two categories are considered in this study. The focus is on the outer two categories because we are interested in the departure from the normal. Moreover, the deterministic and probabilistic skill scores for normal category are less than for the outer categories (Mason et al., 2021). ROC score (also referred to as area under ROC curve) measures the ability of the forecast system to discriminate between events and non-events, providing information on forecast resolution (discrimination) (Landman & Beraki, 2012; Wilks, 2006, 2011). ROC can be explained by calculating the area under the curve (Mason & Graham, 1999). The reliability diagram explains the resolution and reliability attributes, which together determine the usefulness of probabilistic forecast systems (e.g., Brocker & Smith, 2007). Resolution measures the ability of a forecast system to resolve situations in which the observed frequency of the event is different from the climatological frequency, while reliability is a measure of the bias in predicted probabilities for the event, relative to the verified event frequency. A forecast with good reliability is closer to the perfect reliability line (diagonal line on the attributes diagram), while a forecast with a good resolution has a wide range of frequencies of observations corresponding to forecast probabilities. Resolution is considered the more fundamental of the two attributes because reliability may generally be improved by calibration of the forecast probabilities, while resolution cannot. A forecast system that underestimates (overestimates) forecasts will have the forecast line positioned above (below) the perfect reliability line. The histogram of forecasts in each probability bin shows the sharpness of the forecast. In addition to the forecast skill verification, CCA pattern analysis is performed to determine the dominating atmospheric circulation systems predicted to be controlling temperature variations for weeks 1–4 during DJF seasons. CCA has the main advantage of selecting pairs of spatial patterns that are optimally correlated, making a physical interpretation of the connection between the observations and the retroactive forecasts or hindcasts possible (Busuioc et al., 2001).

3 | RESULTS

3.1 | Spearman's rank correlation

Spearman's correlation maps in Figures 1 and 2 show that the statistical downscaling of the ECMWF 850 hPa geopotential heights shows high correlation in predicting minimum and maximum temperatures during DJF seasons at S2S timescales compared to the raw model outputs. The downscaled forecasts for weeks 1–4 lead time

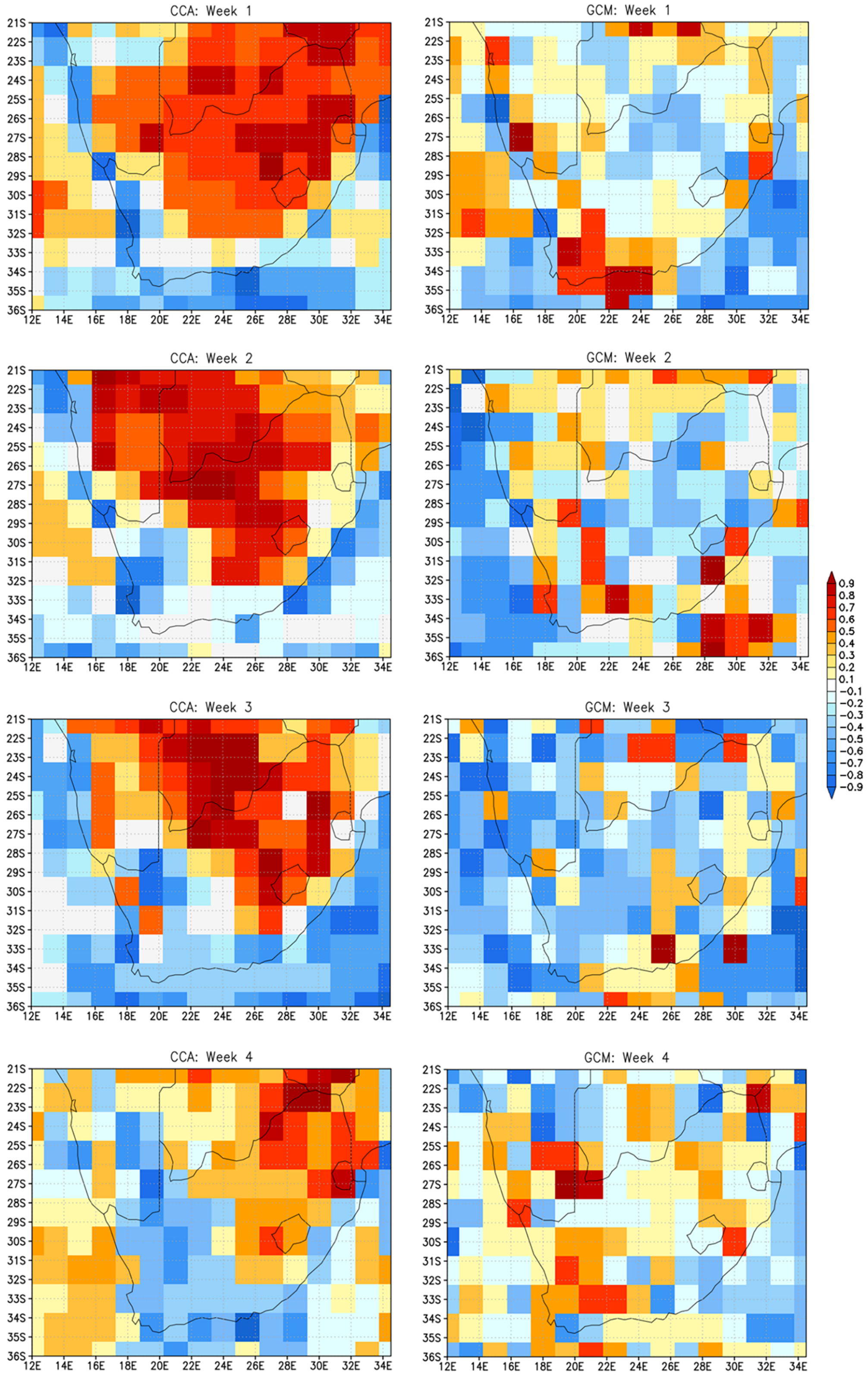

FIGURE 1 Spearman's correlations of CCA (left panel) and raw GCM (right panel) for maximum temperature at 1.5° grid resolution for weeks 1–4 lead timescales.

have higher correlation over the summer rainfall areas of South Africa, especially in week 1. In fact, the area-averaged Spearman's correlation (Table 1) exhibits high values of 0.399 and 0.323 for week 1 and week 2, respectively, for the CCA compared to 0.122 and 0.042 for the raw GCM forecasts in predicting maximum temperature. Similarly, the downscaled forecasts have high correlation value of 0.348 and 0.259 for week 1 and week 2, respectively, compared to 0.121 and 0.029 for the raw GCM (Table 2). The correlation maps in Figures 1 and 2

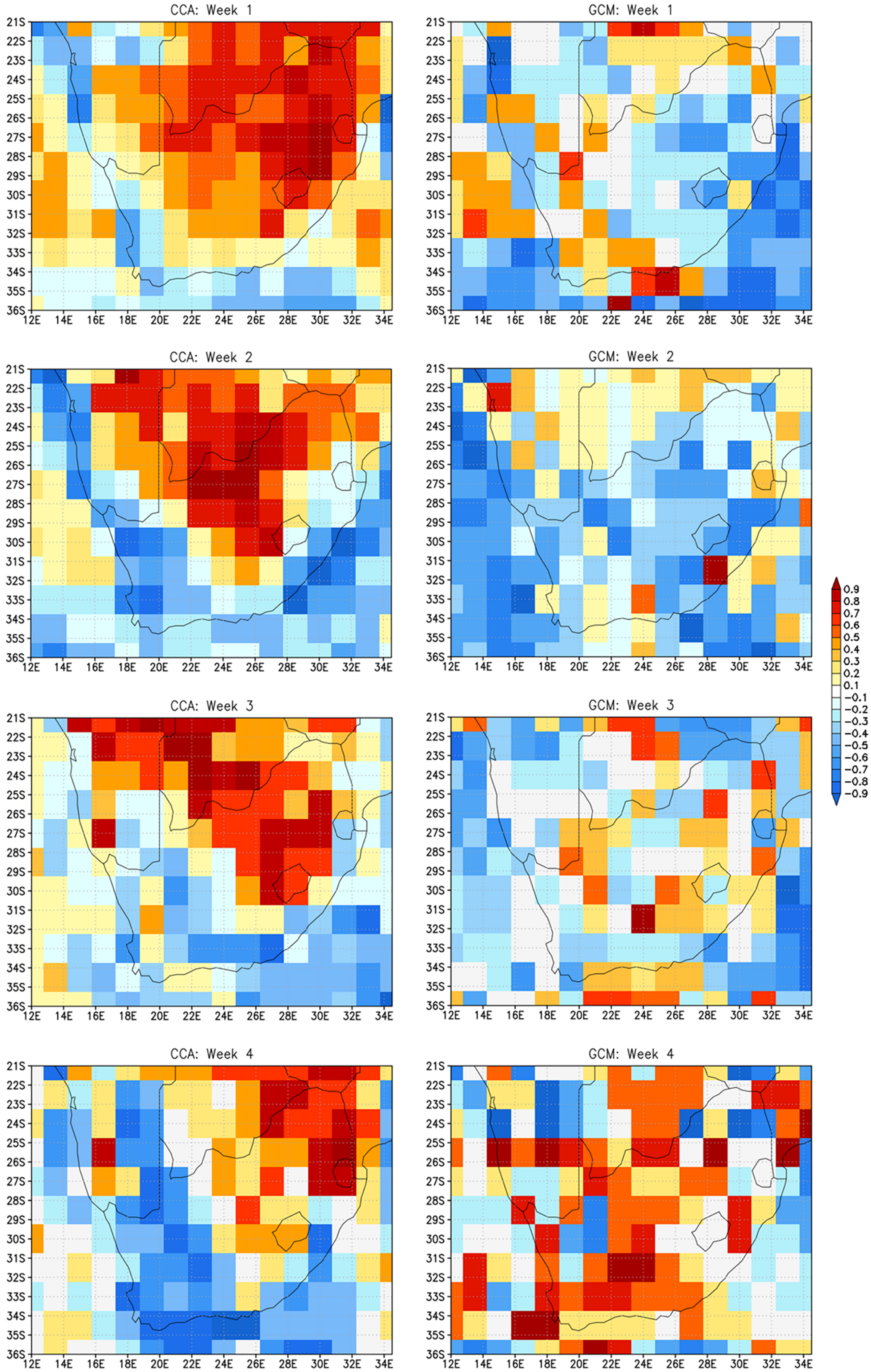

FIGURE 2 As in Figure 1, but for minimum temperature.

indicate that for the raw model forecasts, generally there is no correlation over most parts of South Africa, except for week 4. The improved correlation in week 4 for the raw GCM could be because of noise, not the accuracy of the forecasts, as documented in literature that the skill deteriorates over time (e.g., Zhang et al., 2021). This result gives confidence that downscaling of forecasts is beneficial for climate variables at S2S timescales.

TABLE 1 Area-averaged Spearman's correlations scores of CCA and raw GCM for maximum temperature for weeks 1–4 lead timescales.

Tx	CCA	GCM
Week 1	0.399	0.122
Week 2	0.323	0.042
Week 3	0.143	−0.021
Week 4	0.138	0.120

TABLE 2 Area-averaged Spearman's correlations scores of CCA and raw GCM for minimum temperature for weeks 1–4 lead timescales.

Tn	CCA	GCM
Week 1	0.348	0.121
Week 2	0.259	0.029
Week 3	0.125	0.044
Week 4	0.057	0.133

3.2 | ROC scores, ROC curve and reliability diagrams

The ROC score maps (Figure 3) indicate that the statistically downscaled ECMWF S2S forecasts have good skill in predicting maximum temperature in week 1 for both above-normal and below-normal categories over South Africa. Enhanced skill is found in the eastern parts of South Africa, particularly in the below-normal category. In week 2, the skill for the below-normal category is lower compared to the above-normal category. In week 3, high skill scores are found over the eastern and central parts of the country for the below-normal category, but no skill over the western and southern parts. There is reduced skill in week 4 for both categories, especially for the below-normal category. The ROC curve and the reliability diagrams (Figure 4) clearly show that the model is good in predicting both categories in week 1 (ROC scores >0.58) and the above-normal category in week 2 (ROC score >0.57). The ROC score in week 3 is 0.53 (above-normal category) and 0.55 (below-normal category), and no skill in week 4, with ROC scores <0.5 for both categories. The ROC score maps indicate that the model has skill in predicting maximum temperature up to week 3 ahead, particularly over the central and eastern parts of South Africa, whereas the reliability diagrams exhibit a positive forecast slope, implying that the forecasts are reliable; however, the model has a tendency to overestimate forecasts for both categories when predicting maximum temperature for weeks 1–3 during DJF seasons over South Africa. In week 4, the reliability diagram exhibits a negative forecast slope, indicating that the forecast is unreliable. In week 1, the forecast slopes are above the no skill lines (dashed lines), indicating good reliability forecasts, and forecast slopes are close to the perfect reliability (diagonal line) and far away from the no resolution (solid horizontal lines), indicating good resolution in the forecasts. The forecast resolution is minimal in weeks 2 and 3, with no resolution in week 4. The frequency histograms included in the reliability diagrams indicate that the forecasts lack sharpness in predicting maximum temperatures for weeks 1–4. The lack of sharpness could be due to too large ensemble spread, and the forecasts rarely deviate much from the climatological value of 33.3%.

In predicting minimum temperature for week 1, the ROC score maps (Figure 5) depict that the statistically downscaled ECMWF S2S forecasts have the highest skill over the eastern parts of South Africa for the above-normal category and over the central parts for the below-normal category. For week 2, the skill for predicting both categories is reduced compared to week 1. In week 3, the model has good skill over the eastern half of South Africa, with enhanced skill found over the central parts of South Africa for the below-normal category. In week 4, the skill drops significantly for the below-normal category. However, there is good skill in week 4 for above-normal category over the northeastern and southwestern parts of South Africa. The ROC curve diagrams and the reliability diagrams (Figure 6) show that the model is good in predicting minimum temperature in week 1 for both categories, with the ROC scores of 0.62 and 0.59 for the above- and below-normal category, respectively. In week 2, the ROC diagrams indicate that the model skill levels do not differ much in predicting the above-normal category compared to below-normal category, with ROC scores of 0.56 and 0.53, respectively. In week 4, the model has no skill in predicting the below-normal category (ROC score <0.5). The ROC score maps indicate that the model has skill in predicting minimum temperature up to week 4 ahead, particularly over the central and eastern parts of South Africa, whereas the reliability diagrams indicate that the model has a tendency of overestimating the below-normal category when predicting minimum temperature for weeks 2–3 during DJF seasons over South Africa. The reliability diagram indicates that the forecast has low resolution for weeks 2 and 3 and no resolution for week 4. The frequency histogram included in the reliability diagrams also indicates that the forecasts lack sharpness in predicting minimum temperatures for weeks 1–4.

3.3 | CCA pattern analysis

CCA pattern analysis is performed to determine the dominant atmospheric circulation systems predicted to influence the climate variables of interest (e.g., Phakula

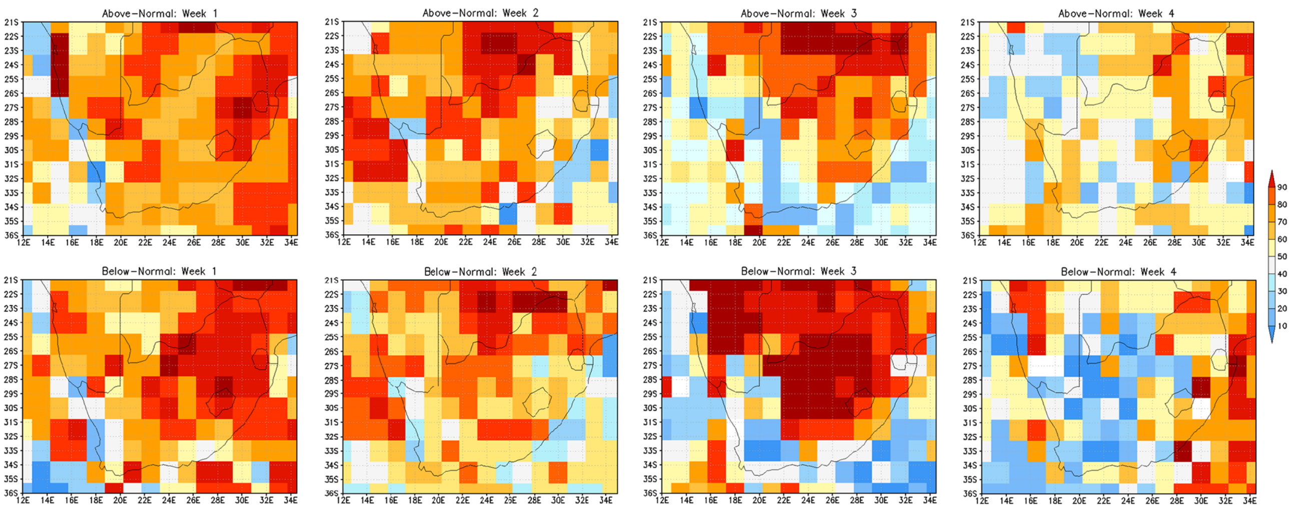

FIGURE 3 ROC score maps of ECMWF S2S model in predicting maximum temperature for weeks 1–4 during DJF seasons from 2001 to 2020 over South Africa. The top panel is for predicting the above-normal category, and the bottom panel is for the below-normal category.

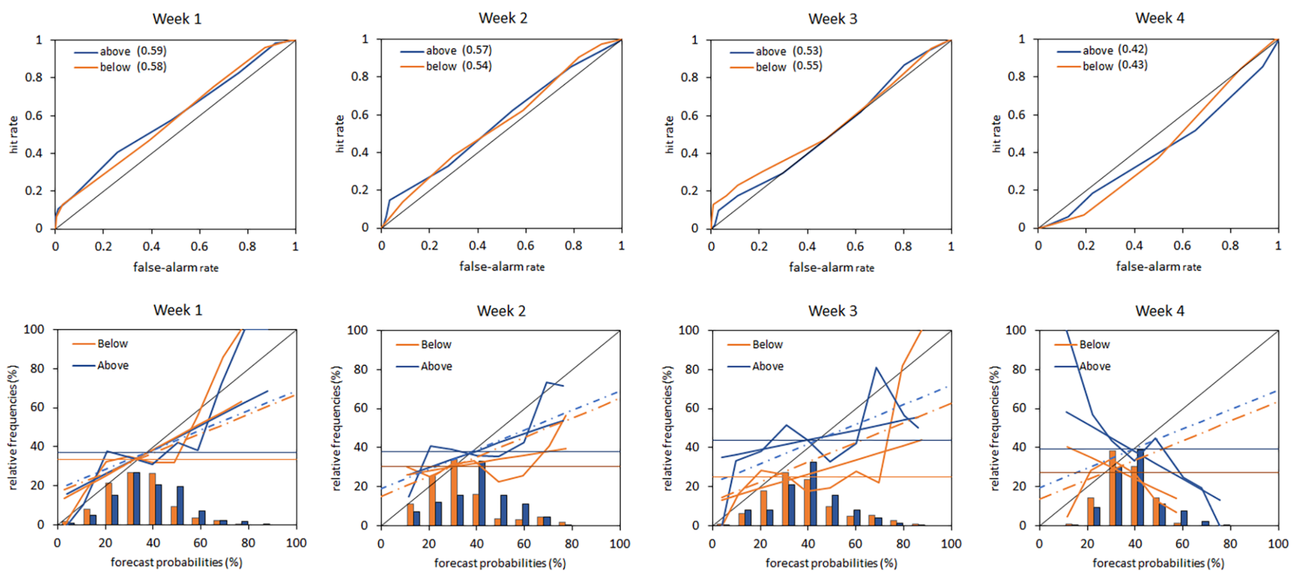

FIGURE 4 ROC diagrams (top panel) and reliability diagrams (bottom panel) of ECMWF S2S model in predicting maximum temperature for weeks 1–4 during DJF seasons from 2001 to 2020 over South Africa. Blue colour is for predicting the above-normal category, and orange colour is for the below-normal category. Area-averaged ROC scores are included in the ROC diagrams.

et al., 2018). CCA pattern maps suggest that when there are anomalously positive (Figure 7) and anomalously negative (Figure 8) predicted 850-hPa geopotential heights over South Africa, there are anomalously maximum and minimum temperatures for weeks 1–4 during the DJF seasons over most parts of South Africa. This conclusion is drawn in the following way. CCA pattern maps for maximum temperature (Figure 7) show that during 2016 (which was an El Nino year), for example, the predictor's spatial loadings are anomalously positive for weeks 1–3 lead times and the temporal scores are also positive. The product of the spatial loadings and the temporal scores is positive. During the same year over most parts of South Africa, the predictand spatial loadings are positive and the temporal scores are also positive, and their product is positive. This result implies that when there are anomalously positive 850-hPa geopotential heights over South Africa, there are anomalously hot conditions over most parts of South Africa. In fact, when there is a high-pressure system extending from Angola into the interior of South Africa, it is usually dry and hot over most parts of the country (e.g., Mbokodo et al., 2023). The opposite is true for the CCA maps in Figure 8, showing that during the same year (2016), there are anomalously negative predictor's spatial loadings over

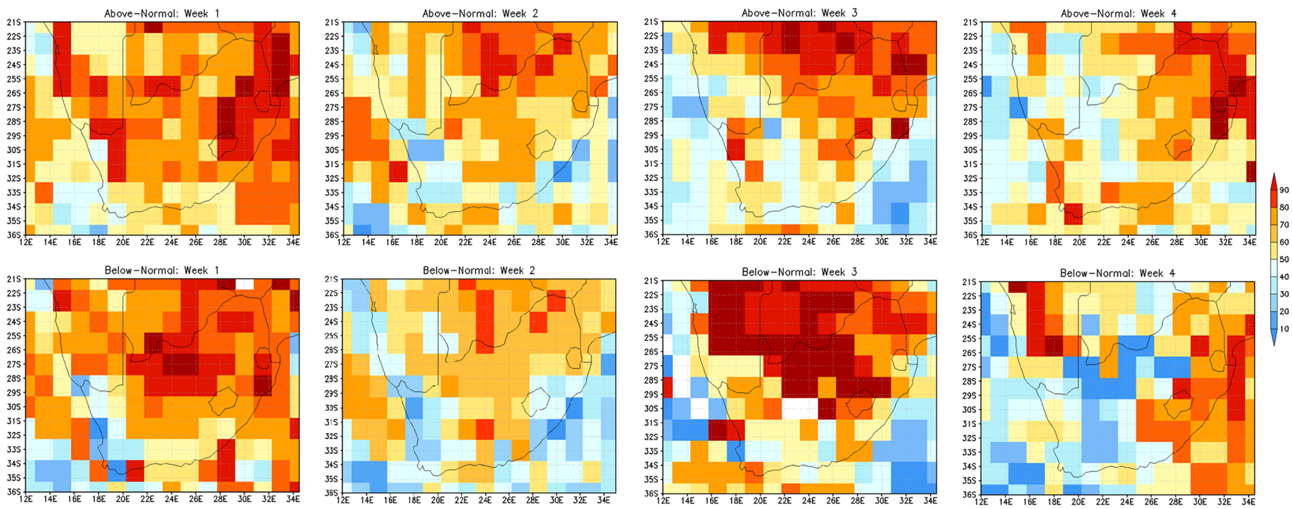

FIGURE 5 ROC score maps of ECMWF S2S model in predicting minimum temperature for weeks 1–4 during DJF seasons from 2001 to 2020 over South Africa. The top panel is for predicting the above-normal category, and the bottom panel is for the below-normal category.

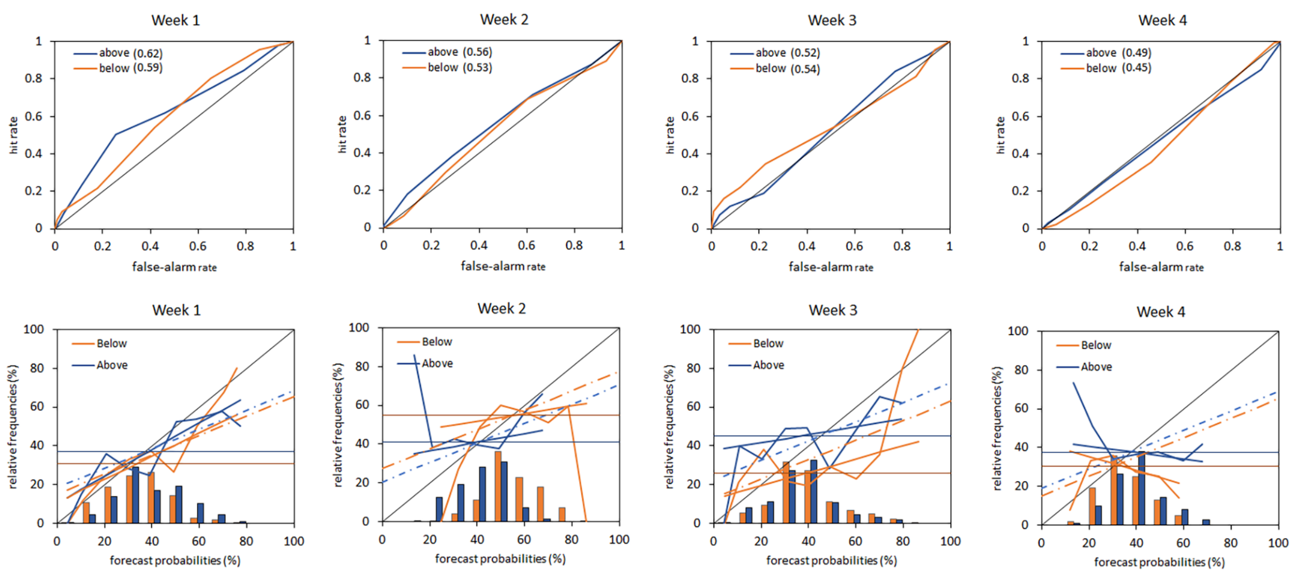

FIGURE 6 ROC diagrams (top panel) and reliability diagrams (bottom panel) of the ECMWF S2S model in predicting minimum temperature for weeks 1–4 during DJF seasons from 2001 to 2020 over South Africa. Blue colour is for predicting the above-normal category, and orange colour is for the below-normal category. Area-averaged ROC scores are included in the ROC diagrams.

Angola stretching into South Africa for weeks 1–4 lead times and the temporal scores are also negative. The products of the spatial loadings and the temporal scores are positive. During the same year (2016), the predictand spatial loadings over most parts of South Africa are anomalously negative and the temporal scores are also negative. The products of the loadings and the scores are positive. During 2011 (which was a La Nina year), for both maximum and minimum temperatures, the CCA shows that the products of predictor and predictand spatial loadings and temporal scores are negative. Following the same analogy, this implies that when there are anomalously negative 850-hPa geopotential heights over South Africa, there are anomalously wet and cold conditions over most parts of South Africa. In fact, when there is a low-pressure system over Angola stretching into South Africa during the summer seasons, it advects moisture into South Africa and usually results in rainfall and low temperatures (e.g., Cretat et al., 2019; Pascale et al., 2019).

4 | DISCUSSION AND CONCLUSIONS

S2S forecast demand has increased in the applications community because decision-making and early warning

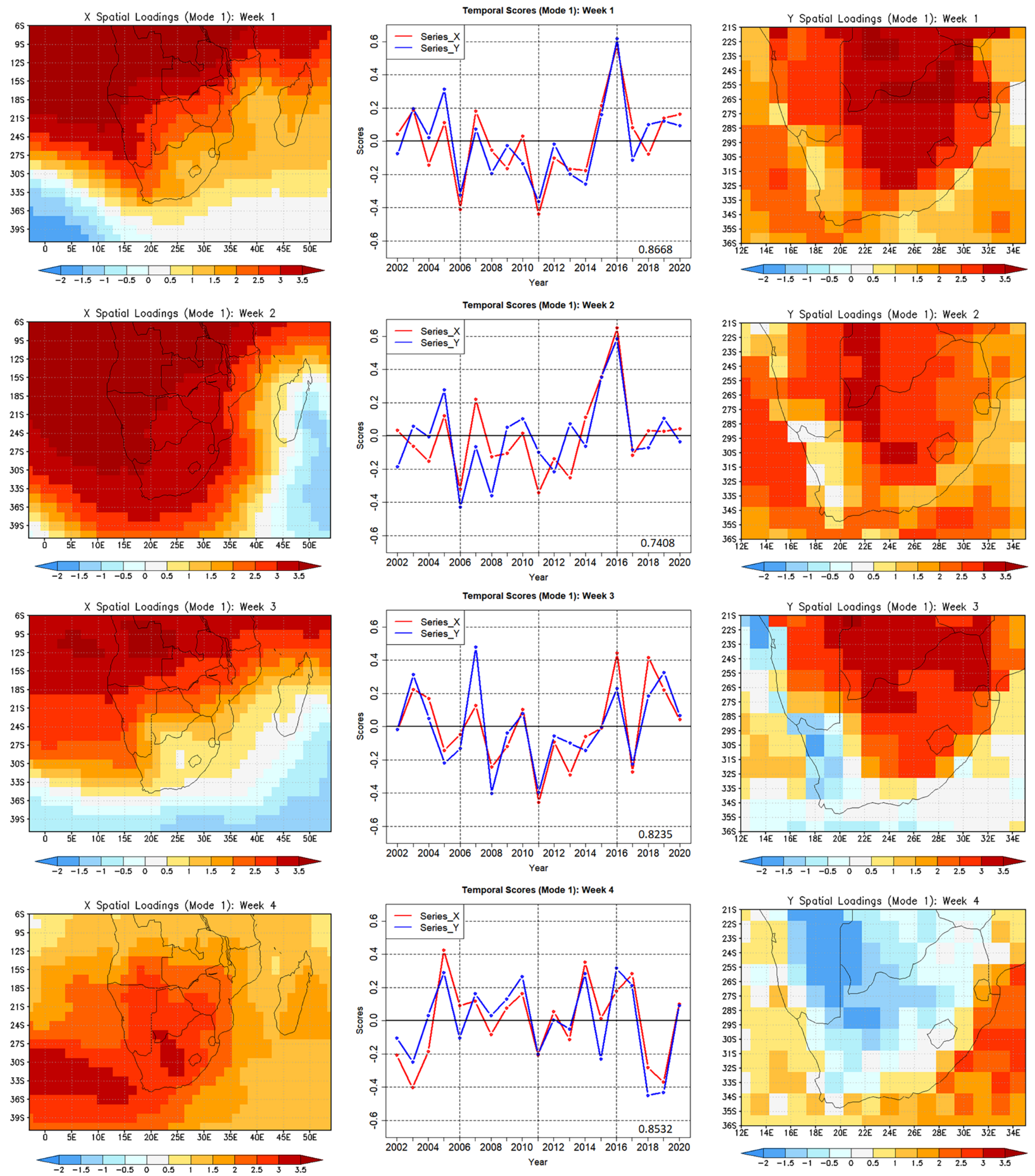

FIGURE 7 CCA maps for the first mode of the predicted 850-hPa geopotential heights of the ECMWF S2S model (X spatial loadings) and the downscaled maximum temperature of the ERA5 reanalysis (Y spatial loadings) for weeks 1–4 during DJF seasons. Canonical correlation values are included in the temporal scores.

systems across different sectors fall within this timescale. Hence, accurate S2S forecasts are vitally important and can fill the gap between weather forecasts and seasonal climate outlooks. This study investigates the probabilistic forecast skill level of the downscaled ECMWF S2S forecasts in predicting maximum and minimum temperatures for weeks 1–4 lead times during DJF seasons over South Africa. The Spearman's correlations clearly show that there is a great benefit in statistical downscaling of forecasts compared to using

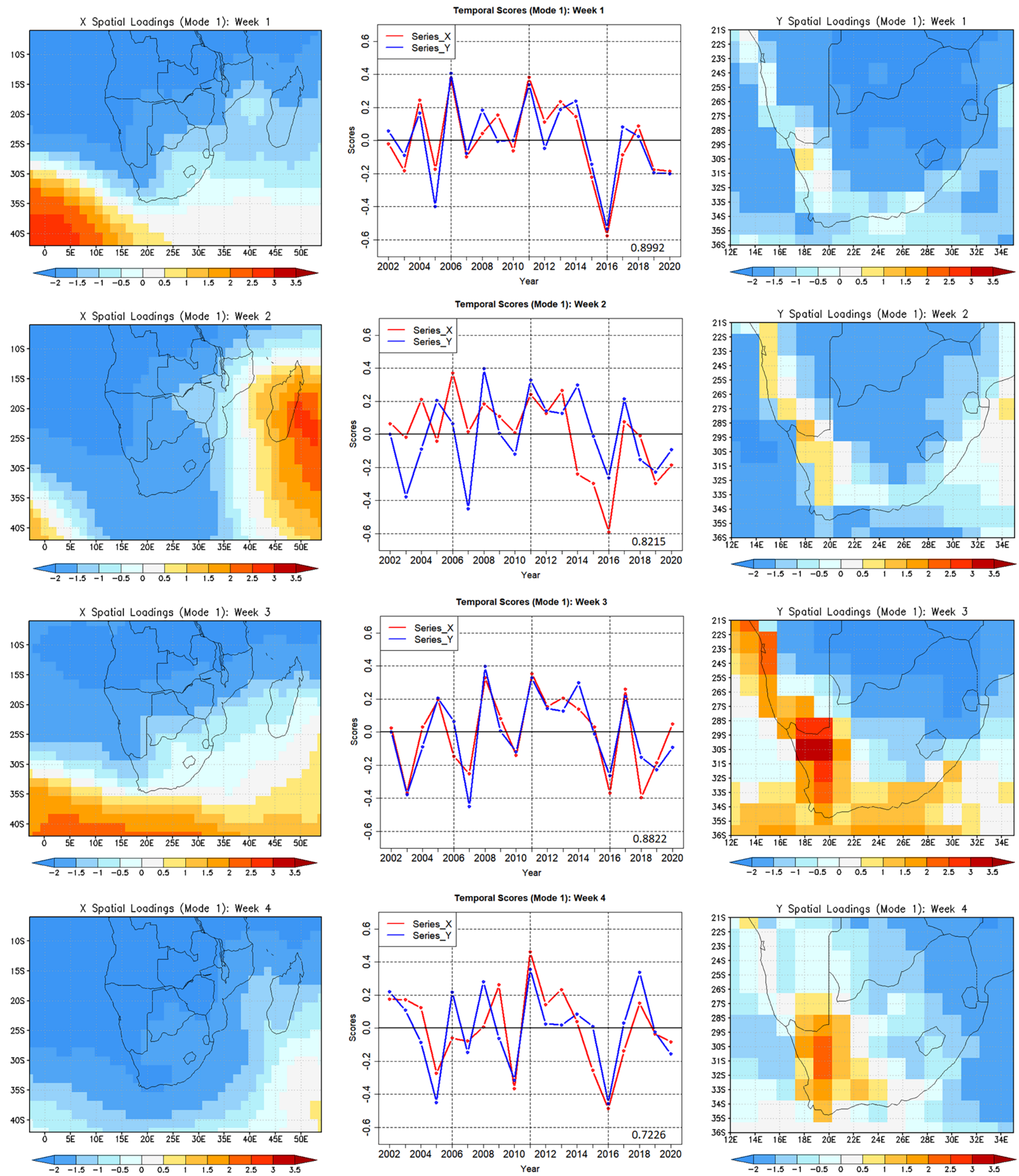

FIGURE 8 As in Figure 7, but for minimum temperature.

raw model forecasts. The result from the ROC curve and reliability diagrams indicate that the ECMWF S2S model has skill in predicting maximum temperature up to week 3 ahead, particularly over the eastern and central parts of South Africa, whereas the reliability diagrams indicate that the model has a tendency of overestimating forecasts, particularly for the below-normal category when predicting maximum temperature for weeks 1–4 during DJF seasons over South Africa. The ROC score maps indicate that the model has skill in predicting minimum temperature up to week 4 ahead, particularly over the eastern and central parts of South Africa. The forecasts in predicting both minimum and maximum temperatures have enhanced skill in week 3 compared to week 2. Determining why there is high skill in week 3 is beyond the scope of this study but needs to be investigated further in the future. The reliability diagrams indicate that the model has a tendency of overestimating forecasts when predicting minimum temperature for weeks 2–4 during DJF seasons over South Africa. Furthermore, the reliability diagrams indicate that the forecast has low resolution and lacks sharpness in predicting both minimum and maximum temperatures for weeks 1–4. In addition to the forecast skill verification, CCA pattern analysis is performed to determine the dominating atmospheric circulation systems predicted to be influencing temperature variations for weeks 1–4 during DJF seasons. CCA pattern maps suggest that when there are anomalously positive (negative) predicted 850-hPa geopotential heights over South Africa, there are anomalously maximum (minimum) temperatures for weeks 1–3 during the DJF seasons over most parts of South Africa. Canonical correlation values show that the correlations between the predictor and predictand are very high, with values greater than 0.8 in most cases. From this result, we can conclude that statistical downscaling of model forecasts can improve forecast skill. This conclusion is based on our previous work (Phakula et al., 2020) where we found that the deterministic forecast skill of model forecasts is limited to 2 weeks ahead. We replicated the results of the deterministic forecast skill weeks 1–4 during DJF seasons from 2021 to 2020 to compare with the downscaled probabilistic forecast skill in the current study (see attached supplemental information document). The correlation of analysis (CORA) indicates that the skill is limited to weeks 1–2 and no skill over most parts of South Africa except for the northeastern parts in weeks 3–4 (Figure S1). Moreover, the CORA exhibits similar spatial distribution of skill for both minimum and maximum temperatures, particularly for weeks 3 and 4. The findings of this study suggest that there is a prospect for S2S predictions in South Africa, and as such, S2S prediction system for maximum and minimum temperatures can be developed.

AUTHOR CONTRIBUTIONS

S.P. contributed to conceptualization, investigation, methodology, data curation, visualization, formal analysis and writing of the original draft preparation. S.P., W.L. and E.C. helped in writing, review and editing. W.L. and E.C. supervised the study. W.L. contributed to project administration and helped in funding acquisition. All authors have read and agreed to the published version of the manuscript.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The S2S model data used here are freely available through WWRP/WCRP S2S project portal (http://apps.ecmwf.int/datasets/data/s2s), and the ERA5 reanalysis data are freely available from the C3S (https://climate.copernicus.eu/climate-reanalysis).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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