Seasonal forecasting of synoptic type variability: potential intraseasonal predictability relevant to the Cape south coast of South Africa

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Abstract

An ensemble of 12 sea-level pressure (SLP) simulations from the United Kingdom Meteorological Office (UKMO) Global Seasonal Forecast System 5 (GloSea5) is used to investigate the potential predictability of synoptic types within 14 austral spring seasons (September-November, (SON)) for the 14 yr period from 1996 to 2009. Daily SLP model fields for the 14 SON seasons are mapped to the corresponding observed synoptic types, using self-organising maps (SOMs). Predictability of intraseasonal synoptic type characteristics is evaluated by comparing the frequency of synoptic types as simulated by GloSea5 against the observed synoptic type occurrence. Intraseasonal circulation variability for the Cape south coast of South Africa at interannual time scales is found to be predictable, although poorly.

Key words: Cape south coast, synoptic types, intraseasonal predictability

INTRODUCTION

The Cape south coast region of South Africa (Fig. 1) receives all-year rainfall. In fact, the pronounced rainfall seasonality as observed over the summer and winter rainfall regions of the country is absent over this region. Notwithstanding, along the Cape south coast SON is the season that receives the most rainfall. It is in particular the months of October and November that contributes to SON rainfall. October receives slightly more rain than November on average and is the month with the highest mean rainfall over the Cape south coast. It is in particular ridging high pressure systems and cut-off lows that are the main contributors to rainfall (Engelbrecht et al., 2015). Seasonal forecasting research in South Africa has focused mostly on summer rainfall (e.g. Landman et al., 2012) and in particular for the December to February period (e.g. Landman and Beraki, 2012) when the strongest association between rainfall totals and the El-Niño Southern Oscillation (ENSO) has been shown to exist. The highest skill seasonal forecasts are found over the northeastern interior of South Africa (Landman et al., 2012) and forecasts work best during ENSO seasons (Landman and Beraki, 2012). Often these seasonal forecasts are produced by statistically downscaling the ensemble mean low-level circulation (e.g. 850 hPa geopotential height) from global model forecasts to rainfall stations or districts. Unfortunately the relatively high levels of skill found over the northeast are not reflected over the Cape south coast. In this paper, we aim to assess the within-SON-season predictability by considering the predicted frequencies of different synoptic types affecting seasonal climate variations over the Cape south coast. If it can be shown that this intraseasonal variation in circulation over the Cape south coast can be predicted skillfully at interannual time scales, it will imply that skillful rainfall forecasts can be generated through the use of predicted daily circulation statistics.

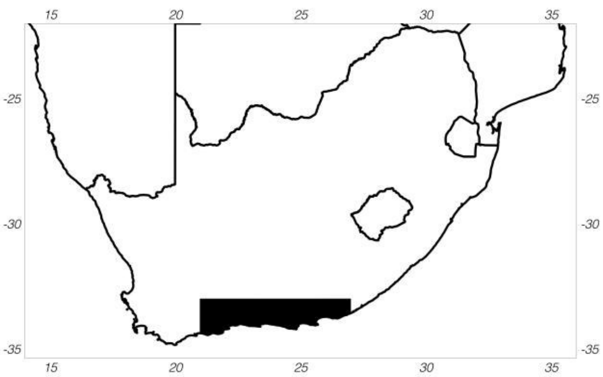

Fig. 1. Geographical location of the Cape south coast.

DATA AND METHOD

Hindcasts (1-month lead) of a fully coupled model administered by the UKMO, the GloSea5, are used in this study. Daily SLP fields for 14 SON seasons from 1996-2009 for 12 ensemble members are used to study the frequencies of synoptic types. A full description of GloSea5 can be found in MacLachlan et al. 2014. National Centers for Environmental Prediction (NCEP) daily SLP data is used to calculate the observed synoptic type frequencies for the corresponding SON seasons to that of the model simulations. The SOM method is used for identification of 9 synoptic types during SON of which the frequencies are determined. The choice of 9 synoptic types is based upon the average mapping of about 10 days to a specific synoptic type during a season of approximately 90 days, translating to 10 degrees of freedom (e.g. Tennant, 2003). Before the GloSea5 daily SLP fields are mapped to the SOM, model output was converted to the horizontal resolution of the NCEP SLP fields by application of a bicubic interpolation function. The SOM method requires for the model data mapped to the SOM to have a common grid as the SLP fields used to develop the SOM. Also, to account for model biases, the long term mean is subtracted from the observed daily SLP fields before subjected to development of the SOM. Similarly, the long term mean of each ensemble member is subtracted from the corresponding model daily SLP fields before these fields are mapped to the SOM in order to determine the model simulated synoptic type frequencies for each of the 12 ensemble members.

The atmospheric circulation that influences weather along the Cape south coast is mostly located over the surrounding oceanic region. Therefore, the domain used to develop the SOM are bounded by 10°E-40°E and 32.5°S-45°S. The selected region allows for capturing the progression of high pressure systems and troughs, advancing from west to east, to the south of the Cape south coast. Tropical-temperature troughs are also captured by this domain since the axis of tropical-temperate troughs passes through it.

This study includes both deterministic and probabilistic verification of the frequency of synoptic types over the region as produced by the GloSea5. Deterministic verification is included to determine whether interannual variability of the frequency of synoptic types is captured. The anomaly correlation is used for this purpose. The anomaly correlation is not sensitive to biases and quantifies the spatial correlation between forecast and observed deviations from climatology (Wilks, 2011). The different synoptic types, represented by the nodes on the SOM, are regarded similar as grid points in a spatial field. The frequency distribution of synoptic types across the SOM space is therefore assessed by the anomaly correlation.

Seasonal forecasts are inherent probabilistic in nature. Synoptic type occurrences are probabilistic assessed by introducing tercile categories. Resolution and reliability of the forecasting system is assessed by application of the relative operating characteristic (ROC) and the reliability diagram (Wilks, 2011). In this study, probability bins of 20% are used, to accommodate the sparseness of occurrences found for the traditional probability bins of 10%.

DISCUSSION

Fig. 2 shows the anomaly correlation of the model forecast of the frequency of synoptic types (solid line) as well as the persistence forecasts (dotted line) for the 14 SON seasons from 1996 to 2009. The forecasts were obtained from the ensemble average and can therefore be regarded as deterministic. Positive anomaly correlation coefficients are indicative of corresponding forecast and observed anomalies across the SOM, while negative anomaly correlation coefficients indicate disagreement between the forecast and observed anomalies. Over this 14-year hindcast period, 9 of the seasons are associated with positive anomaly correlation coefficients. Compared to persistence (dotted line), 11 out of the 14 SON seasons exhibit skillful deterministic forecasts of the synoptic type frequency distribution within the SOM space. The 3 seasons that had no forecast skill relative to persistence are all below-normal rainfall seasons (1998, 2006 and 2009).

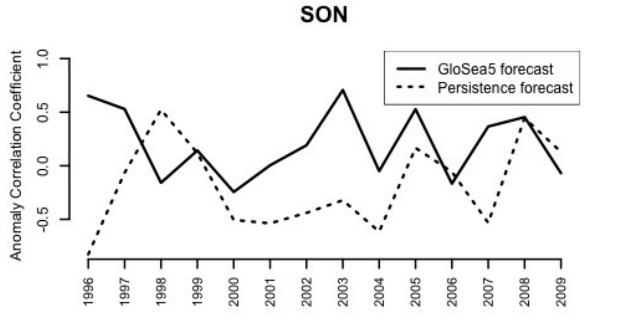

Fig. 2. Anomaly correlation coefficient for GloSea5 (solid lines) and persistence (dotted lines) for SON deterministic forecasts of synoptic type frequencies across the SOM.

Figs. 3 and 4 show the ROC curves for the lower and upper tercile probabilistic forecasts of synoptic type frequencies. ROC curves are a measure of resolution and address the question whether the forecast system can discriminate between the occurrence and non-occurrence of an event. The ROC areas for both categories are above 0.5, indicative that the GloSea5 system is able to discriminate between the occurrence and non-occurrence of events for the lower and upper tercile categories. Although the ROC areas seem small the above-normal ROC area is significant above the 90% level.

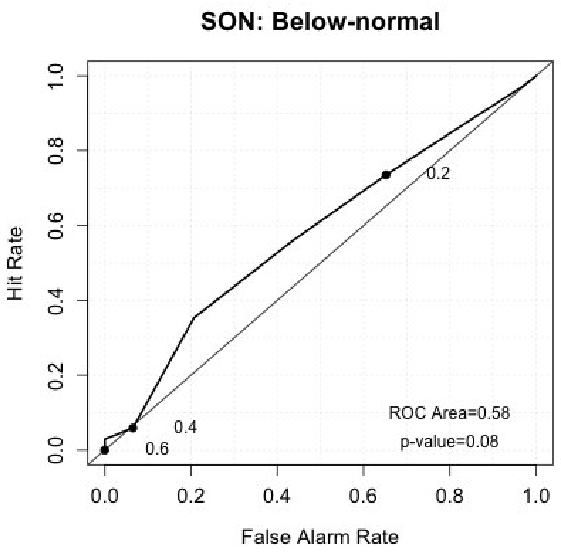

Fig. 3. ROC diagram of the probability that the frequency of the 9 synoptic types over the 14 SON seasons is in the lower tercile.

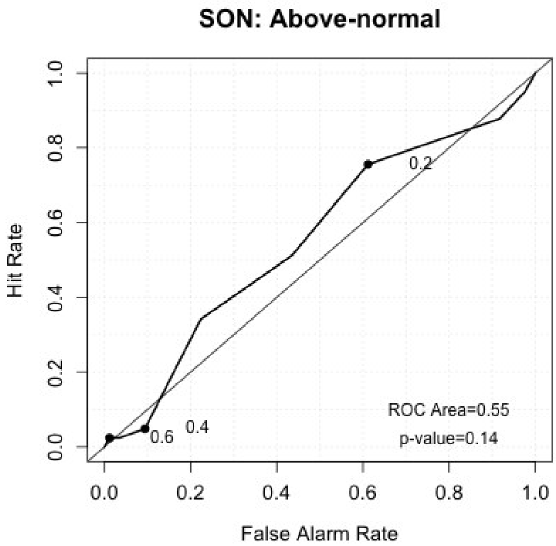

Fig. 4. ROC diagram of the probability that the frequency of the 9 synoptic types over the 14 SON seasons is in the upper tercile.

Figs. 5 and 6 show the reliability diagrams for the lower and upper tercile categories of synoptic type frequency forecasts during the 14 SON seasons. A perfect reliable forecast would coincide with the diagonal. Forecasts for both categories falling within the probability bin of 0.4-0.6 and higher are overconfident while forecasts indicating probabilities within the 0.0-0.2 probability bin are generally underconfident. Forecasts within the probability bin 0.2-0.4 are reliable. The frequency histograms for both categories indicate a peak in forecast probability similar to the corresponding climatological probability. This feature indicates that the forecasts lack sharpness.

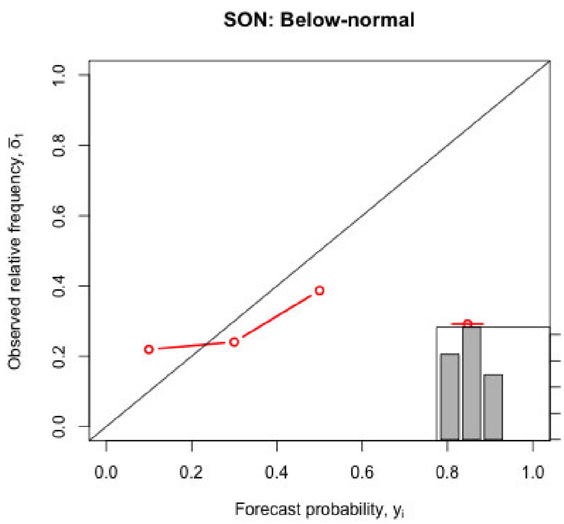

Fig. 5. Reliability diagram of the probability that the frequency of the 9 synoptic types over the 14 SON seasons is in the lower tercile.

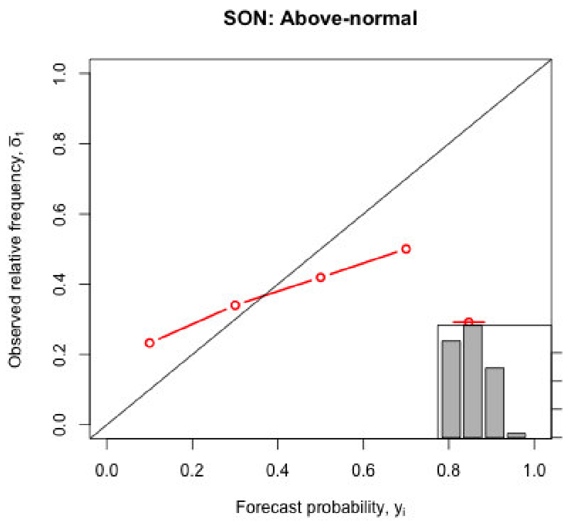

Fig. 6. Reliability diagram of the probability that the frequency of the 9 synoptic types over the 14 SON seasons is in the upper tercile.

CONCLUSION

The intraseasonal circulation variability over the Cape south coast is predictable, although poorly, by the GloSea5 coupled model for SON seasons. It may be noted that a similar analysis performed over a domain that include southern Africa yielded similar results of poor to marginal predictability of synoptic type frequencies for SON seasons, highlighting the challenge of the seasonal prediction problem.

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