IMPROVED DROUGHT EARLY WARNING AND FORECASTING TO STRENGTHEN PREPAREDNESS AND ADAPTATION TO DROUGHTS IN AFRICA

DEWFORA

A 7th Framework Programme Collaborative Research Project

Skill of developed agricultural models to predict indicators and temporally variable thresholds

WP4-D4.11

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Summary

Statistical downscaling methods have been applied in Work Package (WP) 4.10 of the DEWFORA project in order to develop prediction models for crop yields of respectively the Limpopo (in southern Africa) and Oum-er-Rbia (in Morocco) river basins. WP4 is responsible for drought forecasting at different temporal and geographical scales, and in this case implication of drought in agriculture. The downscaling has been applied to global hindcasts of the ECMWF System 4 (S4). This deliverable specifically deals with the verification of these downscaled hindcasts for both basins. The main conclusion to be drawn from this work is that it has been confirmed in this WP that the ECMWF S4 global coupled model can potentially provide the required output for the commodity-orientated forecast system for application in agriculture as described in WP 4.10.

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1. INTRODUCTION

Deterministic and probabilistic verification are described in this deliverable report. The verification procedures are performed on output of statistical downscaling models for rain-fed crops over the Limpopo (southern Africa) and Oum-er-Rbia (Morocco) river basins. The downscaling models are described in the deliverable report of WP4.10, but can be summarized as a procedure that involves the use of the low-level circulation fields of the ECMWF System 4 (S4) as predictors in a principal components regression (PCR) approach to test the predictability of seasonal crop yields over the two basins. The models are tested over a 26-year period to determine their deterministic skill levels, as well as over a 16-year retro-active forecast period to test their probabilistic skill capabilities. For the latter, tercile threshold values of the crop yield data are calculated in order to test the system's ability to simulate yield for three equi-probable categories.

2. DATA AND METHODS

2.1 ECMWF S4

The global model data sets used in the downscaling work are from the ECMWF (European Centre for Medium-Range Weather Forecasts) System 4 (S4) described in WP4-D4.2. Ensemble mean data are used here and 3-month averaged sea-level pressure (SLP) and 850 hPa geopotential height data are the predictors considered.

2.2 CROP DATA

The data are also described in WP 4.10. To summarise, the crop yield data for the Limpopo basin are yellow and white maize. Yield data from 1981 to 2011 are for three agricultural districts for white and for yellow maize combined and are representative of dry land agriculture. The three agricultural districts are located inside the Limpopo river basin, and they are the Witbank and Middelburg agricultural districts in Mpumalanga, and the Rustenburg agricultural district in the Northwest Province (Figure 1). The maize yields are first separately detrended by fitting a second-order polynomial to each series. Harvest time is during the austral autumn. The Oum-er-Rbia basin (Figure 1) crop yield data (durum wheat) are obtained for three regions namely the coast (2 stations), the plains (4 stations) and over the mountains (3 stations). Data are available form 1979-80 through 2007-2008. The sowing and harvesting periods are:

	Coastal areas	Plains	Mountain areas
Sowing dates	October-November	November-December	February
Harvest dates	May	May-June	August

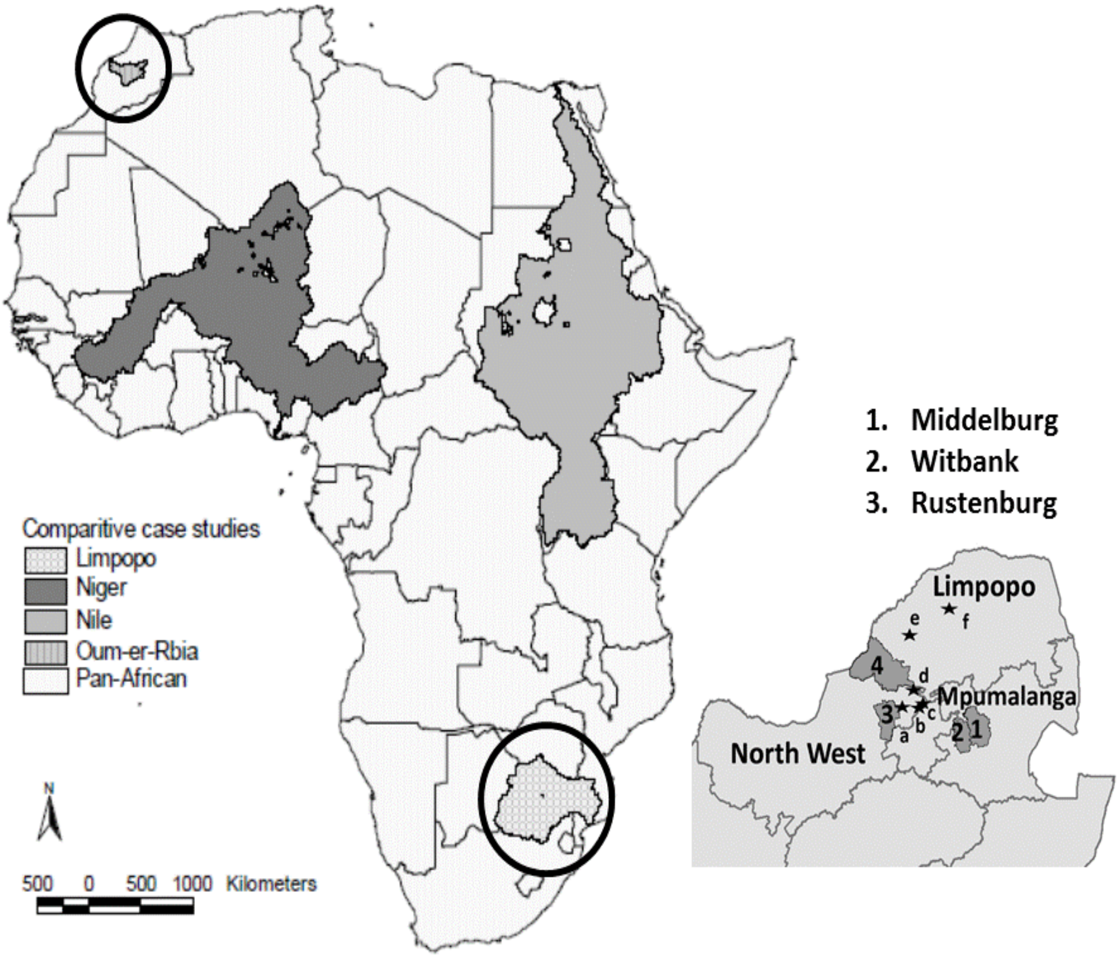

Figure 1. The location of the Limpopo and Oum-er-Rbia river basins, including a more detailed description of the location of the agricultural districts used in the Limpopo study.

2.3 STATISTICAL POST-PROCESSING: MODEL OUTPUT STATISTICS

Since crop yields are not represented explicitly by global climate models such as the ECMWF S4, post-processing large-scale model output to yields should be investigated. A downscaling approach for crop yields similar to the one used hare has recently been published (Malherbe et al. 2013), justifying the use of the approach presented in WP 4.10 as a sound and robust statistical downscaling procedure for dry-land yields. The downscaling post-processes ECMWF S4 data to crop yields through model output statistics (MOS; Wilks, 2011). MOS equations are developed by using the principal component regression (PCR; Jolliffe, 2002) option of the Climate Predictability Tool (CPT) of the International Research Institute for Climate and Society (IRI; http://iri.columbia.edu). Prior to the PCR, yield values are transformed into approximate normal distributions. The ECMWF S4 outputs used are low-level circulation data for the three-month season prior to the period of harvesting. The assumption is that the seasonal averaged low-level circulation during that three-month period is associated with the rainfall over the region of interest and hence related to the production of dry land crops. For Limpopo DJF hindcast are used throughout, and for Oum-er-Rbia, both FMA (for coastal and plains) and MJJ (for mountains) hindcasts are used. ECMWF S4 850 hPa geopotential height fields are the Limpopo predictors, and sea-level pressure (SLP) fields the Oum-er-Rbia predictors. For a more detailed description, refer to the deliverable report WP 4.10.

2.4 VERIFICATION

The MOS equations' ability to skilfully produce downscaled forecasts is tested both deterministically and probabilistically. Deterministic skill is determined over a 26-year period for the harvest years of 1983 to 2008. For this purpose the procedure of cross-validation is performed with a large 5-year-out design, which means that 2 years on either side of the predicted year are omitted in order to minimise the artificial inflation of skill. Deterministic forecast skill is calculated by considering Kendall's tau (Wilks, 2011), an alternative to the conventional Pearson correlation and has the additional attribute of discrimination (Jolliffe and Stephenson, 2011). In addition to cross-validation, the process of retro-active forecasting is applied over the 16-year period from 1993 to 2008 in order to produce a set of probabilistic downscaled hindcasts for three equi-probable categories of below-normal (low harvest), near-normal and above-normal (high harvest) yields, which are subsequently verified. However, only probability verification statistics are provided for the below-normal and above-normal yield categories since there is usually little skill to be derived from predicting the near-normal category (Van den Dool and Toth 1991; Landman et al. 2012). In the retro-active process a cross-validation 5-year-out design is also used for the retro-active process, and the initial cross-validation period is progressively increased by 1 year at each downscaled hindcast step. Owing to the relatively small ensemble size of 15 members, the hindcasts distributions may be poorly sampled and so their uncertainties have to be estimated. Probabilistic hindcasts for the 16 years are subsequently obtained from the error variance of the 5-year-out cross-validated hindcasts using the ensemble mean (Troccoli et al., 2008). These hindcasts are tested for discrimination (to determine if the hindcasts are discernibly different given different outcomes – for example, is the forecast probability for a bumper harvest systematically higher when the event occurs than when it does not occur?) and for reliability (to determine if the confidence communicated in the hindcasts is appropriate). For calculating the former as a verification measure, the relative operating characteristic (ROC; Mason and Graham, 2002) is used, and for the latter the reliability diagram (Hamill, 1997) is used. If the area below ROC curves is ≤ 0.5, the model discriminates correctly only for less than half the time. For a maximum ROC score of 1.0, perfect discrimination has been obtained.

3. RESULTS

3.1 LIMPOPO

The deterministic verification results (Kendall's tau) for the Limpopo basin is shown in Figure 2. Five lead-times, with one month in between consecutive lead-times, are considered: L0 is for forecasts initialised in December in order to produce DJF 850 hPa geopotential height fields, and L4 for forecasts initialised in August. Table 1 shows the statistical significance of the Kendall's tau values associated with each lead time for the three districts presented in Figures 1 and 2. Significant forecast skill is mainly restricted to the Rustenburg agricultural district.

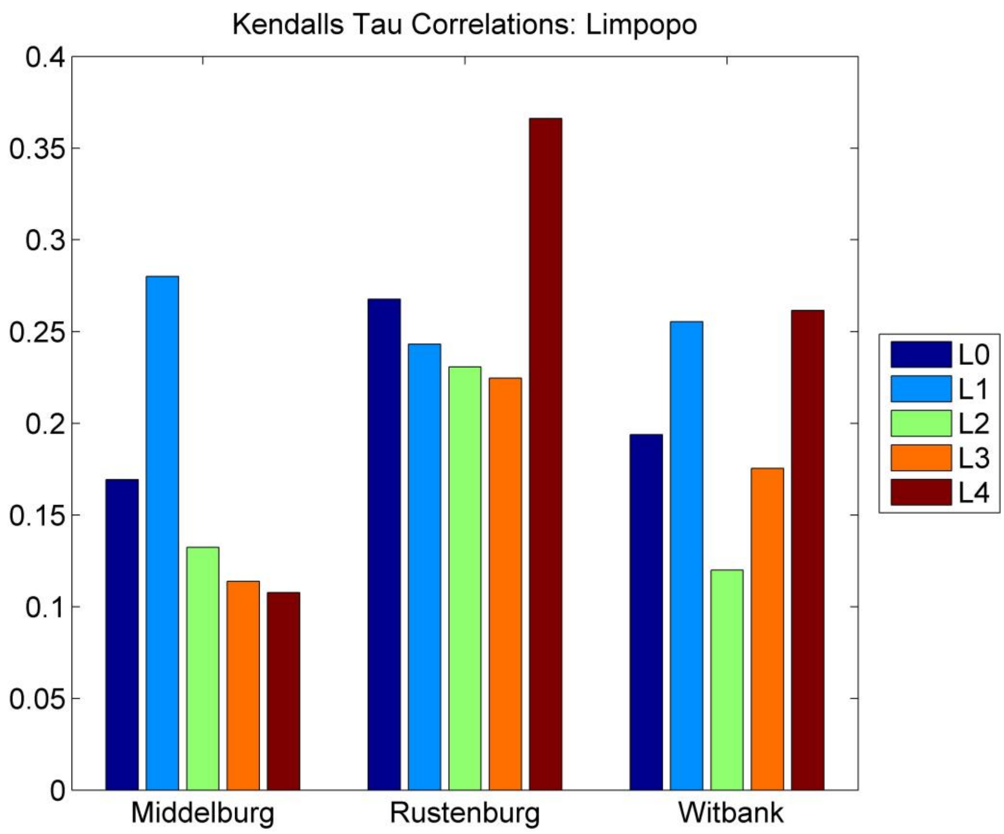

Figure 2. Kendall's tau correlations for the three agricultural districts of the Limpopo basin considered here, and for 5 forecast lead-times.

Table 1. Statistical significance levels of the Kendall's tau correlations for the Limpopo basin.

	Middelburg	**Rustenburg**	**Witbank**
	1-p	1-p	1-p
Lead 0	0.88	0.97	0.91
Lead 1	0.98	0.96	0.96
Lead 2	0.82	0.95	0.80
Lead 3	0.78	0.94.	0.89
Lead 4	0.77	0.99	0.97

The probabilistic verification outcomes for Limpopo are shown in Figures 3 to 8. Some discrimination has been achieved, especially for the Rustenburg agricultural district, but the ability to predict for high yields for this district is restricted to lead-times up to two months (Figure 3). Nonetheless, useful skill for Rustenburg can be seen for both high and low yields at short lead times. Good reliability for the prediction for low yields (a consequence of drought) can be seen for Rustenburg (middle panel), but over-confidence is found in predicting high yields for all three districts (Figures 4 to 8).

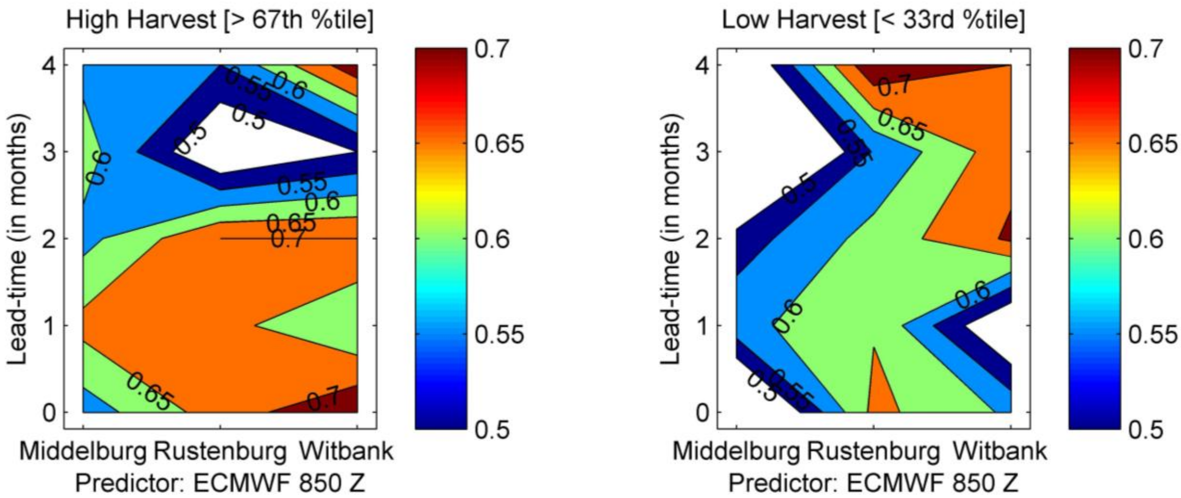

Figure 3. ROC values obtained for the Limpopo basin by retro-actively predicting high-yield (>67th percentile of the climatological yield record) and low-yield (<33rd percentile) seasons probabilistically over 16 years (1993 to 2008). The x-axes show the names of the agricultural districts of the basin considered here, and the y-axes show the forecast lead times in months.

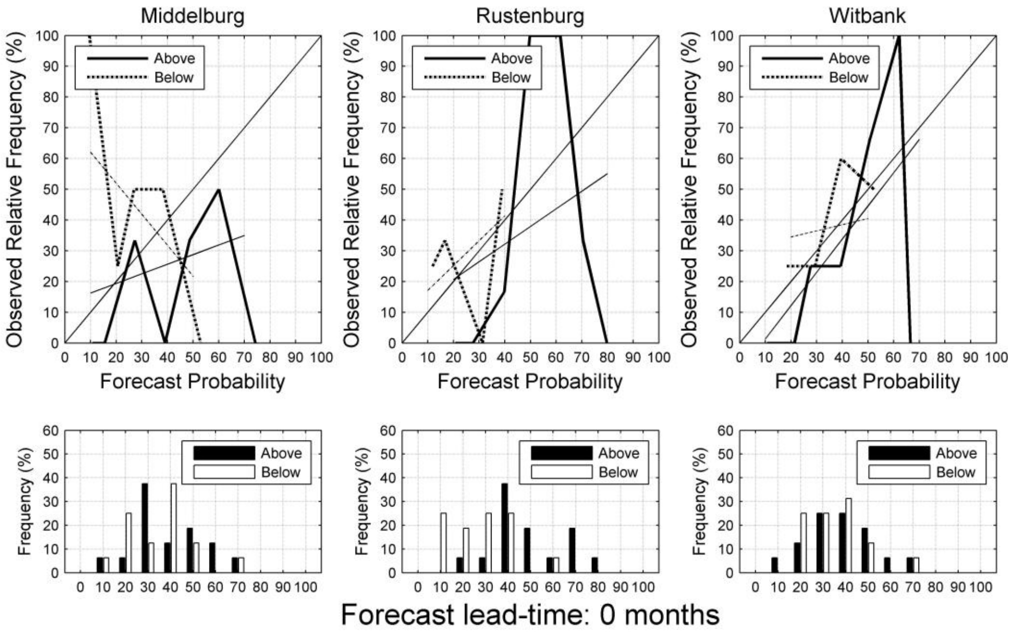

Figure 4. Reliability diagram and frequency histogram for high (>67th percentile) and low (<33rd percentile) yields for the three Limpopo agricultural districts at a 0-month lead-time obtained from 16 years of hindcasts produced by downscaling the ECMWF S4 coupled model. The thin solid (dashed) line is the weighted least squares regression line of the high (low) yield reliability curve. Black and white bars of the frequency histogram are respectively for high and for low yields.

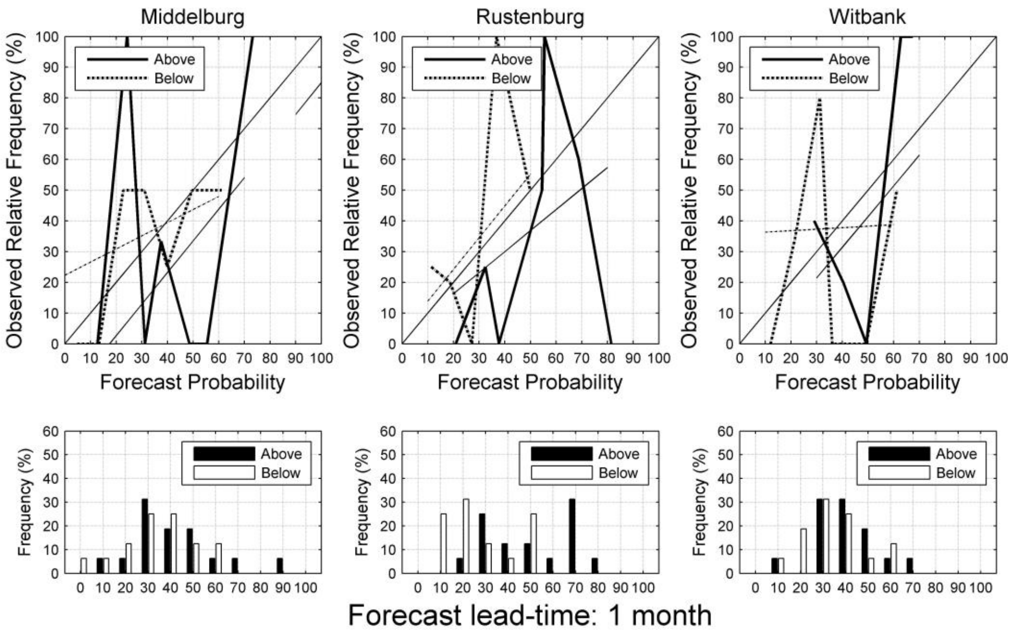

Figure 5. As for Figure 4, but for a 1-month lead-time.

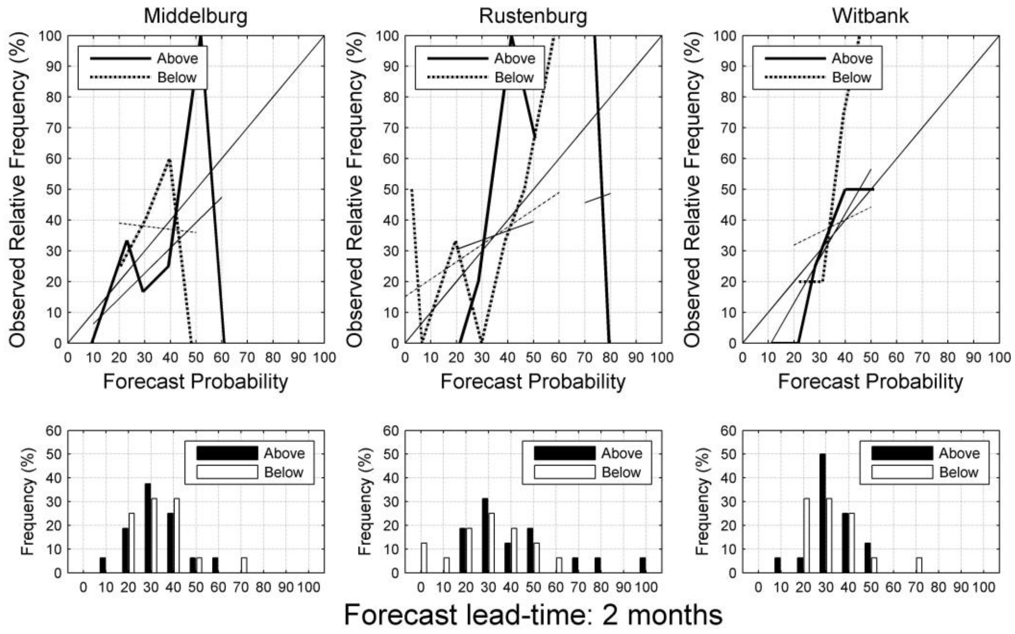

Figure 6. As for Figure 4, but for a 2-month lead-time.

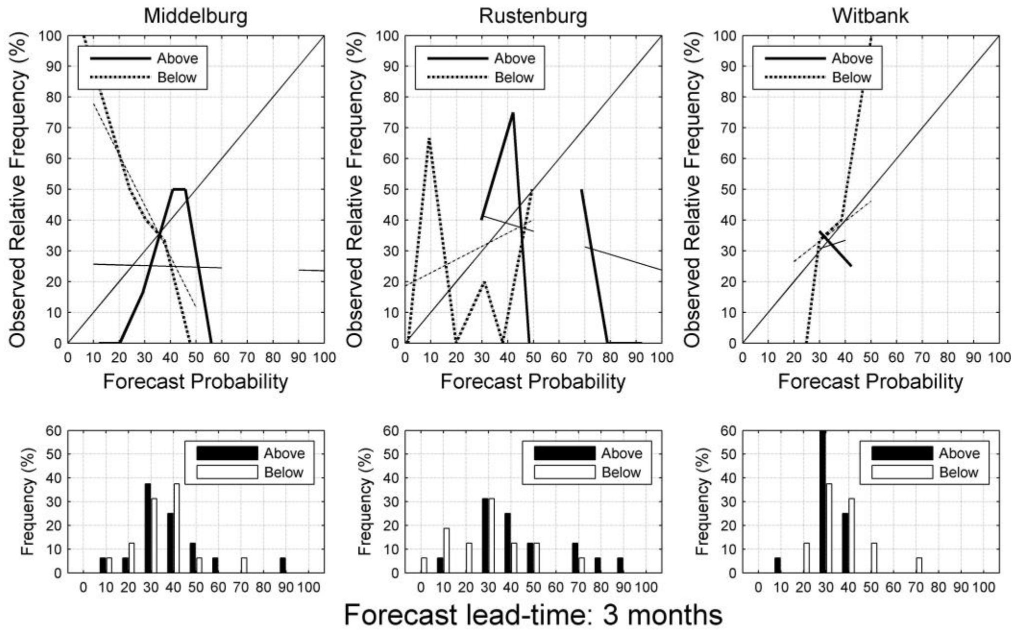

Figure 7. As for Figure 4, but for a 3-month lead-time.

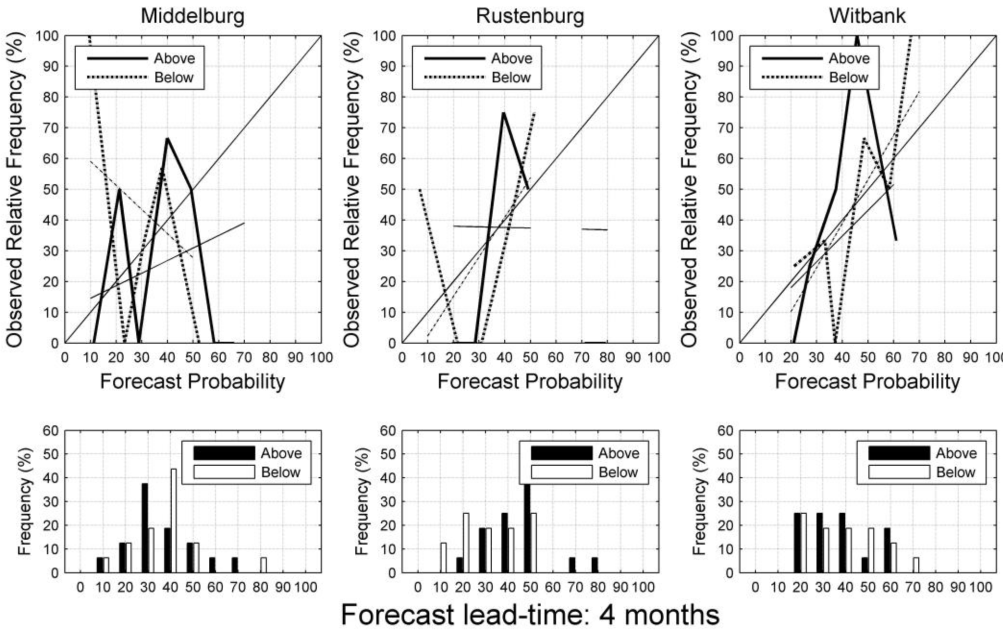

Figure 8. As for Figure 4, but for a 4-month lead-time.

3.2 OUM-ER-RBIA

The Kendall's tau results for the Oum-er-Rbia basin are shown in Figure 9. The downscaled results for all five lead-times are presented, but take note that the initialization months differ since the predicted circulation fields is a function of the harvest times which vary for this basin. Table 2 shows the statistical significance of the Kendall's tau values associated with each lead-time for the coastal, plains and mountain regions respectively. The figure and table show that some skill may be found for the mountains and coastal areas, but very low predictability is seen over the plains of the basin since for most of the lead-times the Kendall's tau values are negative.

Table 2. Statistical significance levels of the Kendall's tau correlations for the Oum-er-Rbia basin.

	Plains	Mountains	Coast
	1-p	1-p	1-p
Lead 0	0.52	0.89	0.92
Lead 1	0.22	0.98	0.62
Lead 2	0.89	0.80	0.99
Lead 3	0.40	0.81	0.94
Lead 4	0.16	0.85	0.70

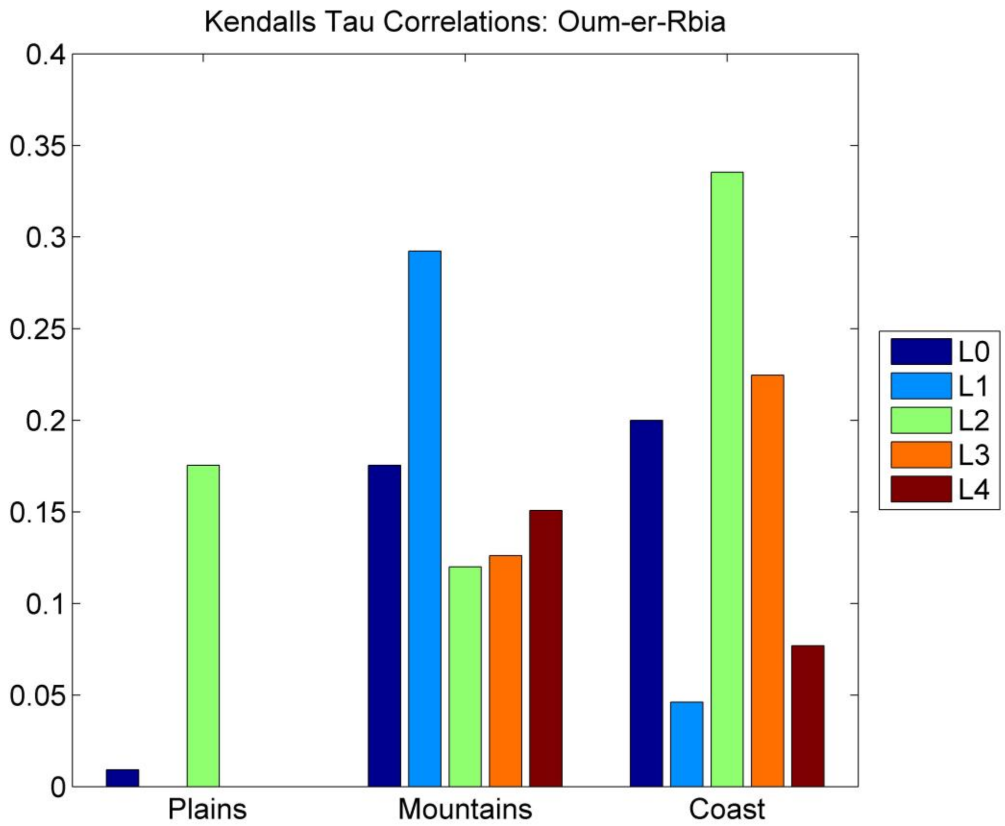

Figure 9. Kendall's tau correlations for the three agricultural regions of the Oum-er-Rbia basin considered here, and for 5 forecast lead-times.

Probabilistic skill estimates (Figures 10 to 15) for the Oum-er-Rbia further demonstrate the potential for making yield predictions over the mountains and over the coastal areas. Take note of the poor skill once again found over the plains. Good discrimination (Figure 10) is found for high yields in particular. The reliability plots (Figures 11 to 15) also show skilful forecasts associated with the mountain areas for most of the forecast lead-times. Although good reliability is seen for this region, forecasts are for the most part over-confident. However, the reliability for predicting low harvests is high for both the mountain and coastal regions (Figures 13 to 15).

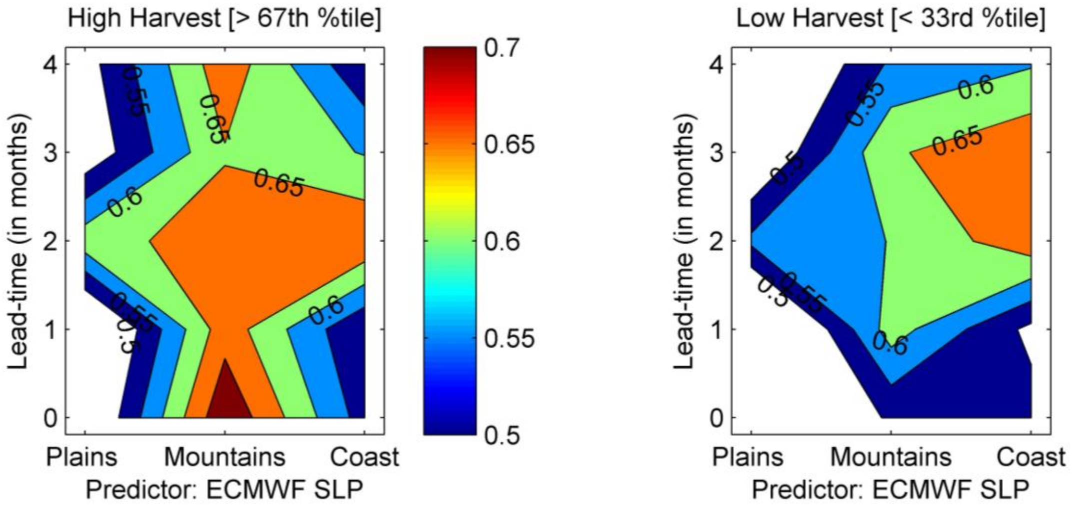

Figure 10. ROC values obtained for the Oum-er-Rbia basin by retro-actively predicting high-yield (>67th percentile of the climatological record) and low-yield (<33rd percentile) seasons probabilistically over 16 years (1993 to 2008). The x-axes show the areas considered, and the y-axes show the forecast lead times in months.

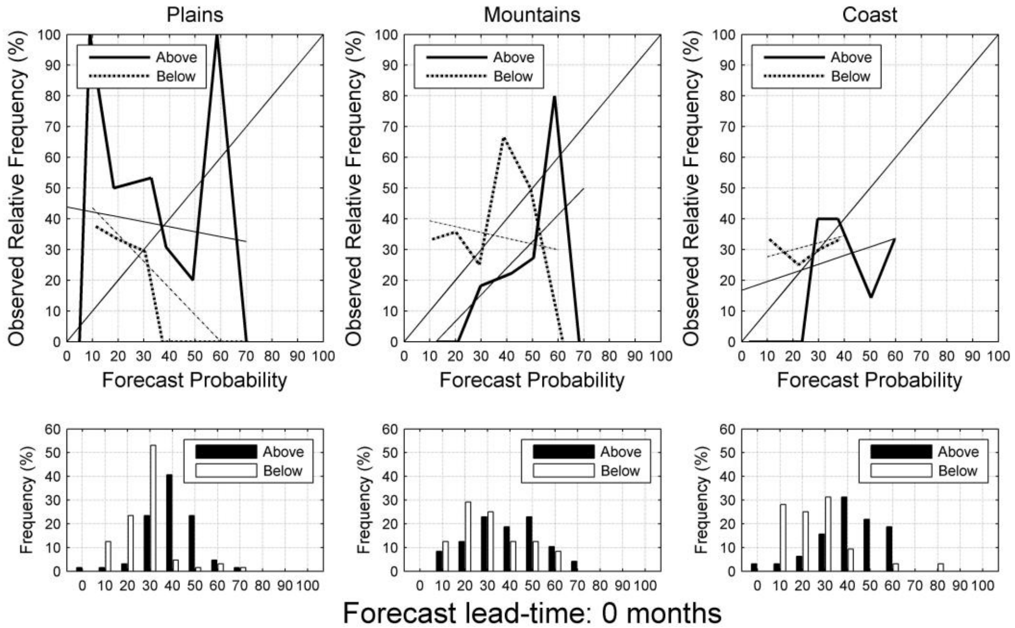

Figure 11. Reliability diagram and frequency histogram for high (>67th percentile) and low (<33rd percentile) yields for the three Oum-er-Rbia areas at a 0-month lead-time obtained from 16 years of hindcasts produced by downscaling the ECMWF S4 coupled model. The thin solid (dashed) line is the weighted least squares regression line of the high (low) yield reliability curve. Black and white bars of the frequency histogram are respectively for high and low yields.

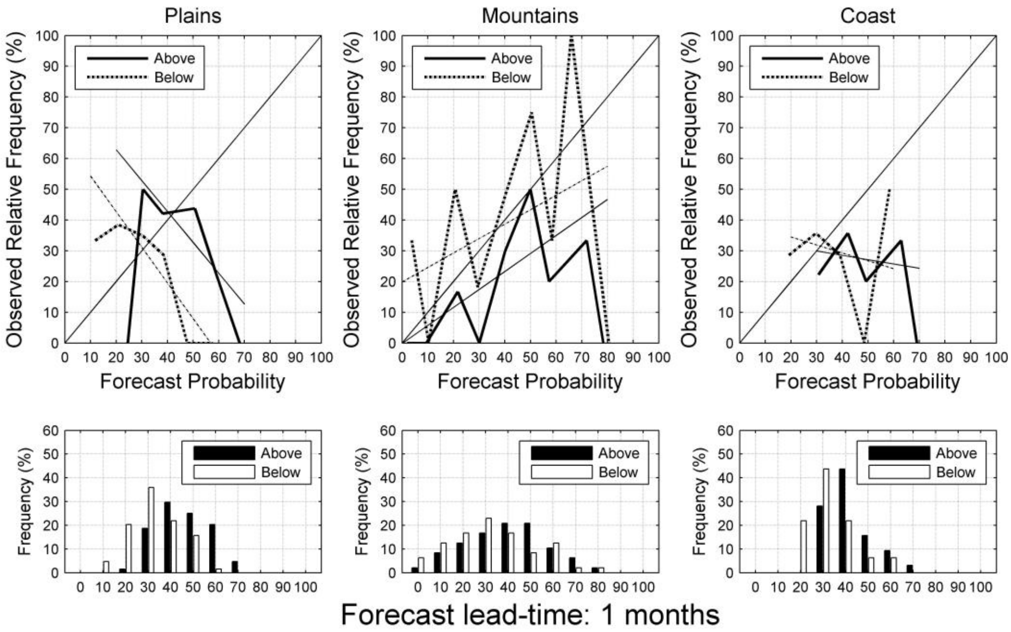

Figure 12. As for Figure 11, but for a 1-month lead-time.

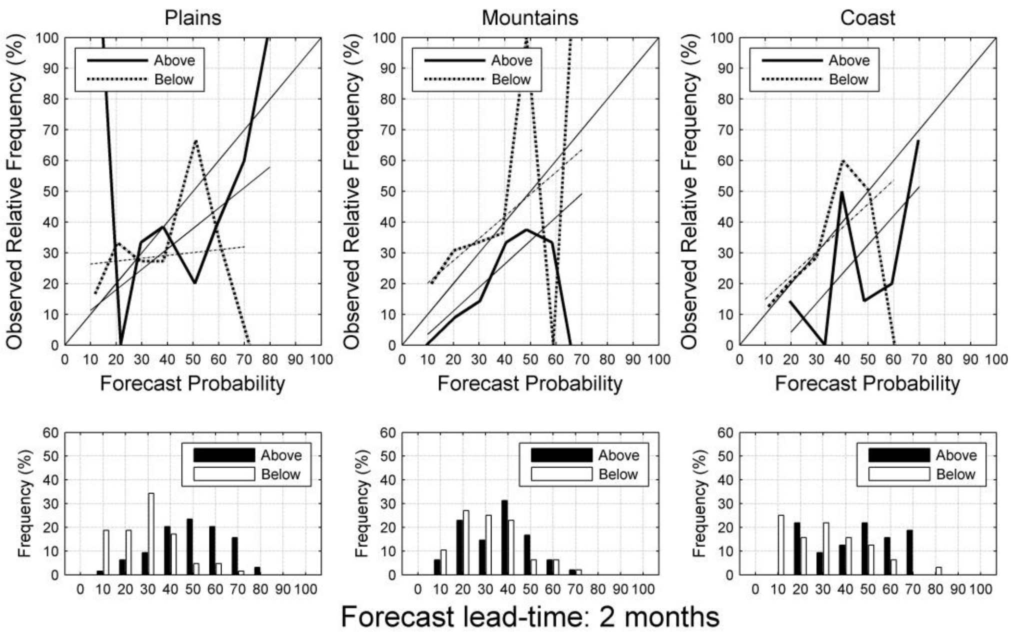

Figure 13. As for Figure 11, but for a 2-month lead-time.

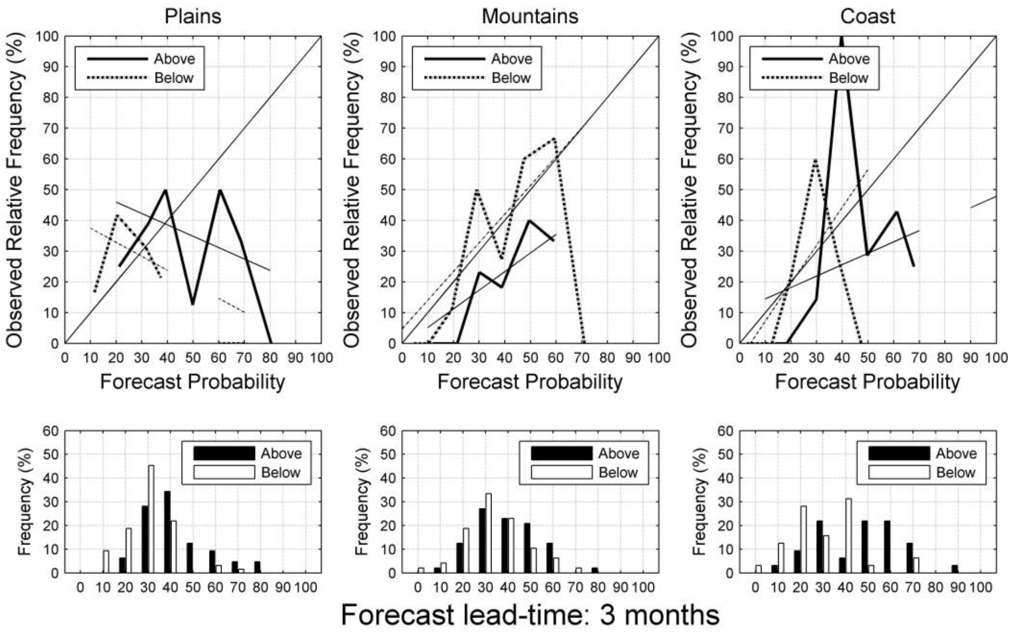

Figure 14. As for Figure 11, but for a 3-month lead-time.

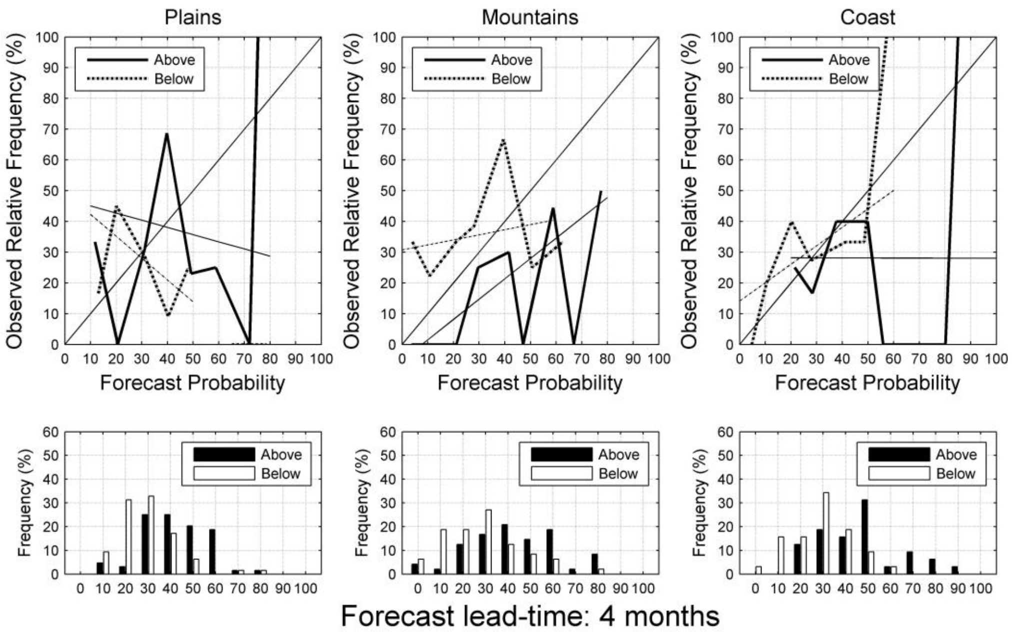

Figure 15. As for Figure 11, but for a 4-month lead-time.

4. CONCLUSIONS

This report presented deterministic (over 26 years) and probabilistic (over 16 years) skill estimates of statistical downscaling models for crop yields over the Limpopo basin of southern Africa and the Oum-er-Rbia basin in Morocco. Forecast lead-times of up to 4 months were considered and it was founds that the low-level circulation data of the ECMWF S4 can be successfully downscaled statistically for certain dry-land crop production areas.

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