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Seasonal predictions of agro-meteorological drought indicators for the Limpopo basin

F. Wetterhall[1], H. C. Winsemius[2], E. Dutra[1], M. Werner[2,3], and F. Pappenberger[1,4]

[1]European Centre for Medium Range Weather Forecasts, Reading, UK
[2]Deltares, PO Box 177, 2600MH, Delft, the Netherlands
[3]UNESCO-IHE, PO Box 3015, 2601DA, Delft, the Netherlands
[4]College of Hydrology and Water Resources, Hohai University, Nanjing, China

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Correspondence to: F. Wetterhall (fredrik.wetterhall@ecmwf.int)

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Abstract

The rainfall in Southern Africa has a large interannual variability, which can cause rain-fed agriculture to fail. The staple crop maize is especially sensitive to dry spells during the early growing season. An early prediction of the probability of dry spells and below normal precipitation can potentially mitigate damages through water management. This paper investigates how well ECMWF's seasonal forecasts predict dry spells over the Limpopo basin during the rainy season December–February (DJF) with lead times from 1 to 5 months. The seasonal forecasts were evaluated against ERA-Interim reanalysis data which in turn was corrected with GPCP (EGPCP) to match monthly precipitation totals. The seasonal forecasts were also bias-corrected with the EGPCP using quantile matching as well as post-processed using a precipitation threshold to define a dry day as well as spatial filtering. The results indicate that the forecasts show skill in predicting dry spells in comparison with a "climatological ensemble" based on previous years. Quantile matching in combination with a precipitation threshold improved the skill of the forecast, whereas a spatial filter had no effect. The skill in prediction of dry spells was largest over the most drought-sensitive region. Seasonal forecasts have potential to be used in a probabilistic forecast system for drought-sensitive crops, though these should be used with caution given the large uncertainties.

1 Introduction

Southern Africa is largely a semi-arid region, which experiences substantial inter- and intra-annual rainfall variability of rainfall (Barron et al., 2003; Nyakudya and Stroosnijder, 2011). Given the limited extent and scope for development of surface water irrigation, most countries in southern Africa rely strongly on rain-fed agriculture. However, if the rainfall amount or distribution is inadequate, crops may fail thus compromising food security. While a lower total amount of rainfall over the crop growing season will influence the crop yield, it is often the poor distribution of rainfall resulting in dry-spells and wet-spells that is the cause for reduced crop yields (Rockstrom, 2000; Ingram et al., 2002; Ochola and Kerkides, 2003; Barron, 2004; Usman and Reason, 2004; Barron and Okwach, 2005).

A staple crop that is grown widely in southeast Africa is Maize, the yield of which is sensitive to the occurrence of dry spells, depending on when these occur. Barron et al. (2003) discuss the sensitivity of Maize to the occurrence of dry spells in different stages of the growing season, being particularly high in the first 50 days after sowing, and again during the grain filling stage (70–90 says after sowing). Additionally, the onset of the rains is important, with planting only done after initial rains exceeding 30–40 mm in eight consecutive days in areas studied in Tanzania and Kenya (Barron et al., 2003) and 25 mm in seven consecutive days or 40 mm in 4 in Northern Zimbabwe (Nyakudya and Stroosnijder, 2011). Delays in planting due to late onset of the rains may result in reduced yield, while planting following a "false" onset of the rain season may lead to failure and the need for expensive replanting. Typical lengths of growing season for Maize are 120–140 days.

Love et al. (2010) summarise a number of typical agro-meteorological indicators that are important for water management and rain-fed agriculture. These hold important information that can aid farmers to improve their agricultural production process, as well as help disaster managers or food security agencies prepare better for food shortage. Examples include the frequency of dry-spells of different length (Nyakudya and Stroosnijder, 2011), and the probability of occurrence of dry and wet spells derived from the analysis of historical rainfall through e.g. a Markov chain process (Barron et al., 2003). While these provide valuable information to the understanding how sensitive (Maize) crops in a given area are to reduced yield and even failure, such analysis is useful primarily in the process of the planning of crops and developing of plans for mitigating the impact of dry spells (Kandji et al., 2006).

Reducing the impact of dry and wet spells on the yield may then be found through mitigation measures. Rainfall water harvesting techniques such as improving the soil water retention capacity may reduce vulnerability rainfall variability (Brown and Hansen, 2008), and mitigation measures through supplementary irrigation, from for example on-farm ponds (Barron and Okwach, 2005) may reduce the impact of dry spells.

Predictions of dry spells across the growing season and in particular during the periods most sensitive to the impact of dry spells can help plan such mitigation measures, as well as help optimise the use of a scarce commodity such as water stored in on-farm ponds. Additionally, prediction of the onset of the rains can aid a more judicious planning of the sowing period. The importance of predictability of such indicators, which are tailored to specific end-users such as rain-fed agriculture is acknowledged by Reason et al. (2005). They investigated the inter-annual variability of dry spells within the rainy season, and anomalies in the onset of the rainy season over the Limpopo basin. In this investigation, significant relationship was found between these indicators and Nino 3.4 SST. They suggest that within the Limpopo region, there may be predictability of the rainfall characteristics at the seasonal scale. Seasonal predictions can be used to inform decisions in planning cropping patterns, planting period, and mitigation measures to reduce the impact of dry spells, or even predict crop yields, such as the sugarcane yield forecasting system proposed by Bezuidenhout and Singels (2007).

Despite the chaotic nature of weather, the potential of seasonal prediction in particular in the low-latitudes has been long recognised (Charney and Shukla, 1981; Slingo and Palmer, 2011). Useful forecast lead times will also depend very much on the decision that is informed by the prediction. Where decision on cropping patterns would benefit from seasonal forecasts covering the full growing season (120–140 days), or in any case to the end of the grain filling period (90 days), other decisions such as the planning of the sowing period given the onset of the rains, or applying supplemental irrigation may require forecasts with lead times of only up to some 20–30 days.

Such information may be provided by seasonal (0–6 months) forecasting systems. Seasonal forecasts differ from the short-range to medium-range weather forecasts as it does not provide information on the weather on any specific day. Instead, seasonal forecasts provide information on the development of the climate up to 6 months, or in some cases even 12 months ahead. The skill of the seasonal forecasts depends on

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its ability to model processes at the scale of months, for example the ENSO (El Nino Southern Oscillation). It has to be noted that seasonal forecast systems are probabilistic as they have significantly more skill than deterministic forecasts (Molteni et al., 2011). Contrary to common belief (Patt and Gwata, 2002) such probabilistic information can be used by end-users (O'Brien, 2002). Reason et al. (2005) showed that the December–February (DJF) season is most important because this includes the most crucial periods that influence maize yields, which is particularly sensitive in this season. Moreover, the DJF season is most strongly impacted by ENSO (Lindesay, 1988; Love et al., 2010), which also would result in the best predictability of the rainy season anomalies (Reason et al., 2000; Landman et al., 2001). Winsemius et al. (2013) assessed the ability of ECMWF's seasonal forecasts in predicting dry spells and heat stress, indicators relevant to the farmer needs for the Limpopo basin. They found that heat stress was well captured by the seasonal forecasting system, whereas the dry spells were less well captured.

In this paper we evaluate the skill of the ECMWF seasonal probabilistic forecasting system over the Limpopo basin in Southern Africa in predicting indicators relevant to making decisions, within the rainy December–February (DJF) season. Instead of seasonal accumulated anomalies, we tailor this investigation to end-user required information on rainfall characteristics, being the length of dry spells and the amount of dry spells within the DJF season. We test how post-processing of the forecast could increase skill depending on: the use of quantile matching against observations; applying a threshold to define a dry day and spatial averaging. The hypothesis is that predictability will increase when a a post-processing is applied and for shorter lead times. The paper is organized as follows: material and methods are described in Sect. 2, the main results in Sect. 3, a discussion in Sect. 4 and main conclusions in Sect. 5.

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2 Material and methods

2.1 Study basin

The Limpopo basin (22–25° S, 27–32° E) land use is governed by croplands, in particular in the downstream (i.e. eastern) part of the basin Fig. 1. Most of these croplands are rain-fed or rely on the scarce and over-committed surface water resources (Love et al., 2010). The climate is characterized by extremely variable rainfall, resulting in a mixture of very dry years and years with floods. Rainfall concentrates in one rainy season, largely controlled by the Inter-Tropical Convergence Zone which means that most of the rainfall is received in the December-January-February (DJF) months. The precipitation in Limpopo is very dependent on ENSO giving warm and dry years during strong ENSO events (Ogallo, 1988). Its water resources are shared by South Africa, Botswana, Zimbabwe and Mozambique. There are a number of important water users in the basin, amongst which ecology and nature preservation (a large part of the Kruger National Park is located inside the basin), municipalities, agriculture and livestock. The agricultural users (except some large corporate sugar cane fields in the South African part of the basin) are primarily smallholder farmers, without access to significant supplementary irrigation.

The Limpopo basin suffers from drought every 7 to 11 yr, but there are large differences in vulnerability to droughts, as shown in the Drought Hazard Index (DHI) maps (Muñoz Leira et al., 2003) (Fig. 2). The DHI maps show the probability of crop failure combined with the degree of rainfall variability from year to year, and a low (high) DHI means a stable (sensitive) environment. Four regions were identified according to their geographical location and drought hazard: region 1 and 3 with moderate to high; region 2 with high/very high; and region 4 with low/moderate DHI respectively. The analysis was made for the catchment as a whole and for each region separately.

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2.2 Merged ERA-Interim and GPCP rainfall estimates

ERA-Interim (hereafter ERAI) is the latest global atmospheric reanalysis produced by ECMWF. ERAI covers the period from 1 January 1979 onwards, and continues to be extended forward in near real-time (www.ecmwf.int; Dee et al., 2011). The ERAI configuration has a spectral T255 horizontal resolution, which corresponds to approximately 79 km.

Balsamo (2010) performed a scale-selective rescaling to bias-correct the ERAI precipitation, hereafter EGPCP. The procedure corrects ERAI 3 hourly precipitation at grid-point scale with multiplicative factors to match the total monthly accumulation of the GPCP v2.1 product (Huffman et al., 2009). The method corrects the ERA on the GPCP ($2.5^{\circ} \times 2.5^{\circ}$) and then rescales the corrected precipitation to the original resolution. The advantage of this procedure is that small scale features of ERAI can be preserved (e.g. orographic precipitation enhancement) while the monthly totals are rescaled to match GPCP. Moreover, the rescaling improves the root mean square error and spatial/temporal correlations by combining the advantages of the observation-based GPCP product with those of the original high resolution ERAI data. Szczypta et al. (2011) evaluated ERAI over France, based on the high resolution (8 km) SAFRAN atmospheric reanalysis and found that the EGPCP precipitation performs better than the original ERAI product. Belo-Pereira et al. (2011) compared the skill of ERAI and GPCC (similar to GPCP over land), among others, against a high resolution observational based dataset of precipitation. They found that both ERAI and GPCP provided a good estimate of drought conditions, the latter closer to the observations. The merged EGPCP rainfall estimate is assumed to be the best estimation of ground-truth in this study. All skill evaluations are therefore based on comparisons between seasonal forecast and EGPCP estimates.

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2.3 ECMWF seasonal forecast system

The ECMWF seasonal forecasts system 4 (SYS4) consists of a global coupled ocean-atmosphere general circulation model to calculate the evolution of the ocean and atmosphere and an ocean analysis to estimate the initial state of the ocean (Molteni et al., 2011). The ocean model used is NEMO (Nucleus for European Modelling of the Ocean; Madec, 2012) adopting the ORCA1 grid, which has a horizontal resolution of approximately 1°, and 42 levels in the vertical. The atmospheric component of SYS4 is the ECMWF integrated forecasts system (IFS) from a model version used in the operational medium-range forecasting in November 2010. The IFS horizontal resolution is the same as ERAI but using 91 vertical levels instead of the 60 used in ERAI. The forecasts consist of a 51 member ensemble, with initial date of the 1st of each month, and then run daily for 7 months. The re-forecasts (also referred to as hindcasts) for SYS4 are made starting on the 1st of every month for the years 1981–2010 with an ensemble size of 15 members.

Forecast models suffer from biases – the climate of the model forecasts differs to a greater or lesser extent from the observed climate. Since variation in the predicted seasonal distributions are often small, this bias needs to be taken into account, and must be estimated from a previous set of model integrations (Molteni et al., 2011). The 30 yr hindcasts of SYS4 provide a large set of forecasts that can be used to correct model biases, and to evaluate the skill of the forecasting system. A common practice is to bias correct the monthly means of the model climate with the verification dataset (e.g. Saha et al., 2006).

In this study we evaluate dry spells based on daily precipitation, and a simple mean monthly bias correction would not correct biases in the distribution of the daily precipitation. Therefore, we applied a quantile-based mapping (Panofsky and Brier, 1968) of the cumulative density function (CDF) of daily precipitation of the seasonal forecast onto those of EGPCP. This relatively simple approach has been successfully used in hydrological and climate impact studies (e.g. Maurer and Hidalgo, 2008; Li et al., 2010;

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Maraun et al., 2010; Themeßl et al., 2011). The precipitation of the seasonal forecast is rescaled using a multiplicative factor (or transfer function) that is calculated for each initial forecast date (calendar month), lead time and grid point. The multiplicative factor is a discrete array for all the quantiles ranging from 0.5 to 100 with a step of 0.2 mm day^{-1}. The quantile matching was only done for rainy days without a prior threshold of rainy days, as we later applied the filter as a further post-processing.

The CDFs of the hindcasts of SYS4 and EGPCP were evaluated empirically by sorting the daily precipitation and then using a bootstrapping 50 distributions from a sample of 50 % of the data, thereby creating 50 SYS4 CDFs and their respective multiplicative factors. The final correction was done using an average of the 50 bootstrapped multiplicative factors. To allow a smooth transition in time of the multiplicative factor, and increase the sample size, the training dataset was expanded using the two adjacent months for each lead time. For example, for the forecasts starting in November with lead time 1 (valid in December), we select all the November, December and January months from EGPCP, and the SYS4 forecasts starting in November for lead times 0,1 and 2 to evaluate the empirical CDFs (Fig. 4). To make the comparison easier, both the EGCP and SYS4 data was interpolated to a regular grid with a spatial resolution 0.7° in latitude and longitude.

2.4 Skill as function of dry/wet day threshold, bias correction, spatial scale and lead time

Let us assume that the predictability of the occurrence of dry spells and dry spell length is assumed to be dependent on the following factors: Eq. (1) the lead time of the seasonal forecast, Eq. (2) the definition of a dry day within the perspective of our meteorological forecast model, (3) the presence of model bias (which in itself is also assumed to be a function of lead time) and (4) the spatial averaging scale of prediction.

ECMWF's seasonal forecasting system archives daily forecasts with a lead time of 7 months, starting at the first day of each month. Subsequently 5 forecasts overlap the rainy season (DJF) any given year, with lead times with respect to the onset of DJF

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season ranging from 0 to 4 months. There is large evidence that seasonal forecast skill deteriorates strongly with lead time (Molteni et al., 2011). Therefore, the forecast was evaluated for each lead time.

We define a “dry spell” as a sequence of days (minimum 3 days) where rainfall is below a certain threshold (see the red bars in Fig. 3). The threshold accounts for a number of factors. Firstly the fact that part of a day’s rainfall is intercepted by canopy, understory, litter and by the very top few centimetres of soil; and therefore evaporates before infiltrating down to the root zone (Savenije, 2004; de Groen and Savenije, 2006; Gerrits et al., 2007). This amount can be significant and De Groen and Savenije (2006) suggest a value between 2 and 5 mm day^{-1} for the Southern African region, depending on season and land cover characteristics. These water balance components therefore do not take part in the biomass assimilation process and from the point of view of a crop, a day is therefore wet as soon as rainfall exceeds a certain threshold. To test the sensitivity of the choice of this threshold, a large range of thresholds were considered, ranging from 1 to 15 mm day^{-1}. Note that from the point of view of crop growth, 15 mm day^{-1} rainfall should not be considered to be a dry day anymore (de Groen and Savenije, 2006). The wide range is only used to demonstrate the predictability of the ECMWF probabilistic seasonal forecasting system over a range of thresholds. For each forecast, the number of dry spells was computed for each model grid cell. The same was done for the “ground-truth observation”, EGPCP. This results for each lead time and for each year of available data, in pairs of “observed” and forecast values for the number of dry spells and the length of the longest dry spell. To assess the effect of the spatial scale, a step-wise spatial filtering procedure was applied to the gridded estimates of length of longest dry spell and number of dry spells. Spatial filtering has been performed by making window averages ranging from 2 × 2 to 10 × 10 grid cells of the interpolated 0.7 × 0.7 grid.

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2.5 Computation of skill measures

The continuous ranked probability score (CRPS; Matheson and Winkler, 1976) was used to estimate the performance of SYS4. CRPS is a common tool to evaluate ensemble data and is defined as:

$$\mathrm{CRPS} = \frac{1}{N}\sum_{n=1}^{N}\int_{-\infty}^{\infty}\left[F(x) - H(x - x_0)^2\right]\mathrm{d}x \tag{1}$$

where N is the number of forecasts, $F(x)$ is the cumulative distribution function $F(x) = p(X \le x)$ of the forecasted precipitation x, x_0 the observed precipitation, and $H(x - x_0)$ is the Heaviside function, which has the value 0 when $x - x_0 < 0$ and 1 otherwise. In order to quantify the skill of the probability score, the skill score is calculated as

$$\mathrm{SS}_{\mathrm{(C)RPS}} = 1 - \frac{\mathrm{CRPS}_{\mathrm{FP}}}{\mathrm{CRPS}_{\mathrm{RP}}} \tag{2}$$

where $\mathrm{CRPS}_{\mathrm{FP}}$ denotes the forecast score and $\mathrm{CRPS}_{\mathrm{RP}}$ is the score of a reference forecast of the same predictand. The benchmark forecast in this study was a poor man's ensemble, which was created by randomly selecting 15 time series from each starting month from the EGPCP historical database of the same length as the seasonal forecast (7 months), excluding the actual year.

3 Results

The results from the hindcast period were evaluated in terms of the effect of the areal filter filtering, precipitation threshold and bias correction. Furthermore, the predictability for the four identified regions were evaluated individually.

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3.1 Effect of quantile matching correction on the dry spells

Application of quantile matching adjusts the precipitation distribution of the modelled precipitation, which is expected, but it also improves the length of the longest dry spell (Table 1). The effect is opposite on the number of dry spells. The effect of the quantile matching becomes more apparent with the application of the precipitation threshold, where the skill of the quantile-matched forecast is higher than with the raw forecast (Fig. 5).

3.2 Skill as function of precipitation thresholds and area filtering

As previously stated, using a non-zero threshold to define rainy and non-rainy days has a clear impact on the skill (Fig. 5). The effect of the thresholds is different for the raw and corrected forecast. Using a threshold of precipitation of around 10 mm was the optimum for the bias-corrected forecasts, whereas it was much smaller for the raw forecast for the first lead times for the longest dry season (upper panel). However, a threshold of 10 mm is higher than the precipitation amounts expected to be lost to transpiration from interception. For the number of dry spells the optimum threshold was around 5–7 mm for the corrected forecast (Fig. 5, lower panel). To accommodate for the most optimum threshold as well as using a physically sensible threshold, 5 mm was selected, which is in agreement with previous studies (de Groen and Savenije, 2006). Using a spatial filter before evaluating the seasonal forecast did not have any significant impact on the skill of the forecast (Fig. 6). The results shown are after a threshold of 5 mm was applied, but the results were similar for other thresholds (not shown).

3.3 Spatial variations in skill

The spatial pattern of skill for the raw forecast shows a pattern where the forecast performance of the south-west part of the Limpopo catchment is performing worse than the north-east (Fig. 7). The patterns are very similar for both longest dry spell

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and the number of dry spells. Quantile matching improved the forecast over all grid boxes and the increase is largest for the shorter lead times (Fig. 8). The highest skill both before and after the quantile matching was seen for area 2, which is also the most vulnerable to droughts. The forecasts has the lowest skill over area 4, which is the least sensitive area, but after the performance is comparable to the other areas. The effect of quantile matching is most evident for the shorter lead times, for the longer lead times the signal is more noisy.

4 Discussion

4.1 Choices in the methodology

It was found very useful to perform a proper bias correction (in this case in form of a quantile matching) on the forecasts before any attempt is made to predict the occurrence and length of dry spells. This is demonstrated by comparing bias-corrected skill with non-bias-corrected skill (Figs. 5–8). The CRPSS was in many cases negative in the non-bias-corrected case. The computation of dry spells and dry periods is strongly dependent on the ability of the prediction system to distinguish a wet day from a dry day. As mentioned, seasonal forecasts typically are impacted by significant bias during low intensity rainfall ("drizzle effect"), which strongly impacts on the lower tail of the distribution of forecast daily rainfall. The application of a threshold precipitation at which a dry spell was defined improved the results, especially after the quantile matching, which would suggest that using both methods in combination was necessary to optimise the performance of the forecast. Often thresholds are applied prior to applying bias correction (e.g. Wetterhall et al., 2012) but in cases where the energy balance is important, for example in cases where agriculture production is to be modelled, a correction of the temperature distribution would also be needed. However, in this application we kept it simpler.

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The skill of the forecast varies generally significantly with location, and this is clear also from our study. The highest skill for the raw forecast was found in the northern part of the catchment. However, the potential predictive skill of SYS4 is more or less equal across the catchment, as is demonstrated by the effect on the post-processing of the forecasts (Figs. 7 and 8). The potential skill is in this paper evaluated using GPCP v2.2 as the "ground truth", however this has its limitations as the quality of this global dataset is very varying. If the true skill of the system is to be assessed, local station precipitation data would be necessary. However, as a proof-of-concept the methodology is promising.

4.2 Potential value of the forecasting of rainfall characteristics

Although seasonal forecasts deliver to some degree skilful information on dry spell occurrence and dry spell lengths, it is not guaranteed that this information will lead to value for the end user. Translation from a forecast only has value if the alternate decisions that are taken, based on the forecast information, indeed lead to an effective gain (whether this is monetary or in some other way) with respect to the status quo (i.e. without a forecast being used for decision making). This is only the case if the integral of costs (monetary or in any other meaningful form) of additional actions being taken on the basis of the forecast information over time is lower than the integral of loss, prevented by the alternate decision. This has been demonstrated by Verkade and Werner (2011) for the case of flood forecasting and warning systems. In most forecasting evaluations, the costs associated with the decision and actions following this decision are neglected, meaning that if the forecast has any skill compared to the climatology, the system always has value. However, if such costs cannot be neglected, then the value of the forecast will decrease depending on the rate of false alarms and misses. A false alarm will result in unnecessary costs, being made to decide and act, while a hit will result in prevented losses, which obviously are higher than the costs to act.

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In order to evaluate the value of this forecast, we would therefore require local knowledge about how much the action, followed by a forecast warning (in the case of the Limpopo, importing of food and fodder) would cost, and how much would be lost due to the occurrence of (long) dry spells, if action would have been required, but is not taken. In the Limpopo case, this could involve loss of harvest, loss of livestock, or even loss of lives if food security is at stake.

5 Conclusions

This paper assesses the quality of using seasonal forecasts from ECMWF to predict the duration of the longest dry spell as well as the number of dry spells during the growing season in the Limpopo basin in southeast Africa. The paper further investigates a number of post-processing techniques of the forecasts, such as applying a quantile matching of the forecasts, threshold to define a wet and dry event and a spatial filter. The results show that the raw forecasts are improved by using a threshold to define events in combination with quantile matching of the forecast. Post-processing increases the potential predictability of the forecasts, but in order to assess the full added value of a forecasting system it would need to be tested as a decision support tool by local stake holders.

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References

Balsamo, G.: Evaluation of ERA-Interim and ERA-Interim-GPCP-rescaled precipitation Over the USA, European Centre for Medium Range Weather Forecasts, Reading, UK, 10 pp., 2010.

Barron, J.: Dry spell mitigation to upgrade semi-arid rainfed agriculture: water harvesting and soil nutrient management for smallholder maize cultivation in Machakos, Kenya, Doctoral thesis, comprehensive summary, Ph. D. thesis, Stockholm University, Stockholm, 2004.

Barron, J. and Okwach, G.: Run-off water harvesting for dry spell mitigation in maize (*Zea mays* L.): results from on-farm research in semi-arid Kenya, Agr. Water Manage., 74, 1–21, doi:10.1016/j.agwat.2004.11.002, 2005.

Barron, J., Rockström, J., Gichuki, F., and Hatibu, N.: Dry spell analysis and maize yields for two semi-arid locations in east Africa, Agr. Forest Meteorol., 117, 23–37, doi:10.1016/S0168-1923(03)00037-6, 2003.

Belo-Pereira, M., Dutra, E., and Viterbo, P.: Evaluation of global precipitation data sets over the Iberian Peninsula, J. Geophys. Res.-Atmos., 116, 2156–2202, doi:10.1029/2010JD015481, 2011.

Bezuidenhout, C. N. and Singels, A.: Operational forecasting of South African sugarcane production: Part 1 – System description, Agr. Syst., 92, 23–38, doi:10.1016/j.agsy.2006.02.001, 2007.

Brown, C. and Hansen, J. W.: Agricultural Water Management and Climate Risk, International Research Institute for Climate and Society, Palisades, New York, USA, 19, 2008.

Charney, J. G. and Shukla, J.: Predictability of monsoons, in: Monsoon Dynamics, edited by: Lighthill, S. J. and Pearce, R. P., Cambridge University Press, Cambridge, UK, 99–110, 1981.

de Groen, M. M. and Savenije, H. H. G.: A monthly interception equation based on the statistical characteristics of daily rainfall, Water Resour. Res., 42, W12417, doi:10.1029/2006WR005013, 2006.

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A. C. M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., Haimberger, L., Healy, S. B., Hersbach, H., Hólm, E. V., Isaksen, L., Kållberg, P., Köhler, M., Matricardi, M., McNally, A. P., Monge-Sanz, B. M., Morcrette, J. J., Park, B. K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J. N., and Vitart, F.: The ERA-Interim reanalysis: configuration

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and performance of the data assimilation system, Q. J. Roy. Meteor. Soc., 137, 553–597, doi:10.1002/qj.828, 2011.
Gerrits, A. M. J., Savenije, H. H. G., Hoffmann, L., and Pfister, L.: New technique to measure forest floor interception – an application in a beech forest in Luxembourg, Hydrol. Earth Syst. Sci., 11, 695–701, doi:10.5194/hess-11-695-2007, 2007.
Huffman, G. J., Adler, R. F., Bolvin, D. T., and Gu, G.: Improving the global precipitation record: GPCP Version 2.1, Geophys. Res. Lett., 36, L17808, doi:10.1029/2009GL040000, 2009.
Ingram, K. T., Roncoli, M. C., and Kirshen, P. H.: Opportunities and constraints for farmers of west Africa to use seasonal precipitation forecasts with Burkina Faso as a case study, Agr. Syst., 74, 331–349, 2002.
Kandji, S. T., Verchot, L., and Mackensen, J.: Climate Change and Variability in the Sahel Region: Impacts and Adaptation Strategies in the Agricultural Sector, World Agroforestry Centre (ICRAF), United Nations Environment Programme (UNEP), Nairobi, Kenya, 48, 2006.
Landman, W. A., Mason, S. J., Tyson, P. D., and Tennant, W. J.: Retro-active skill of multi-tiered forecasts of summer rainfall over southern Africa, Int. J. Climatol., 21, 1–19, doi:10.1002/joc.592, 2001.
Li, H., Sheffield, J., and Wood, E. F.: Bias correction of monthly precipitation and temperature fields from Intergovernmental Panel on Climate Change AR4 models using equidistant quantile matching, J. Geophys. Res.-Atmos., 115, 1984–2012, doi:10.1029/2009JD012882, 2010.
Lindesay, J. A.: South African rainfall, the Southern Oscillation and a Southern Hemisphere semi-annual cycle, J. Climatol., 8, 17–30, doi:10.1002/joc.3370080103, 1988.
Love, D., Uhlenbrook, S., Twomlow, S., and van der Zaag, P.: Changing hydroclimatic and discharge patterns in the northern Limpopo Basin, Zimbabwe, Water SA, 36, 335–350, 2010.
Madec, G.: NEMO ocean engine, Note du Pôle de modélisation de l'Institut Pierre-Simon Laplace No 27, Paris, France, 2012.
Maraun, D., Wetterhall, F., Ireson, A. M., Chandler, R. E., Kendon, E. J., Widmann, M., Brienen, S., Rust, H. W., Sauter, T., Themeßl, M., Venema, V. K. C., Chun, K. P., Goodess, C. M., Jones, R. G., Onof, C., Vrac, M., and Thiele-Eich, I.: Precipitation downscaling under climate change: recent developments to bridge the gap between dynamical models and the end user, Rev. Geophys., 48, RG3003, doi:10.1029/2009rg000314, 2010.
Matheson, J. E. and Winkler, R. L.: Scoring rules for continuous probability distributions, Manage. Sci., 22, 1087–1096, doi:10.1287/mnsc.22.10.1087, 1976.

Maurer, E. P. and Hidalgo, H. G.: Utility of daily vs. monthly large-scale climate data: an intercomparison of two statistical downscaling methods, Hydrol. Earth Syst. Sci., 12, 551–563, doi:10.5194/hess-12-551-2008, 2008.

Molteni, F., Stockdale, T., Balmaseda, M., Balsamo, G., Buizza, R., Ferranti, L., Magnusson, L., Mogensen, K., Palmer, T., and Vitart, F.: The new ECMWF seasonal forecast system (System 4), ECMWF, Reading, UK, 49, 2011.

Muñoz Leira, E., Landis, R., Alberto, J., Machava, E., Enoque, E. E., and Chauque, L.: Atlas for disaster preparedness and response in the Limpopo Basin, in: WorldCat, available at: http://edmc1.dwaf.gov.za/library/limpopo/ (last access: 15 December 2013), 2003.

Nyakudya, I. W. and Stroosnijder, L.: Water management options based on rainfall analysis for rainfed maize (*Zea mays* L.) production in Rushinga district, Zimbabwe, Agr. Water Manage., 98, 1649–1659, doi:10.1016/j.agwat.2011.06.002, 2011.

O'Brien, S. P.: Anticipating the Good, the Bad, and the Ugly: an early warning approach to conflict and instability analysis, J. Conflict Resolut., 46, 791–811, doi:10.1177/002200202237929, 2002.

Ochola, W. O. and Kerkides, P.: A Markov chain simulation model for predicting critical wet and dry spells in Kenya: analysing rainfall events in the Kano Plains, Irrig. Drain., 52, 327–342, doi:10.1002/ird.94, 2003.

Ogallo, L. J.: Relationships between seasonal rainfall in East Africa and the Southern Oscillation, J. Climatol., 8, 31–43, doi:10.1002/joc.3370080104, 1988.

Panofsky, H. A. and Brier, G. W.: Some Applications of Statistics to Meteorology, Earth and Mineral Sciences Continuing Education, College of Earth and Mineral Sciences, 224 pp., Pennsylvania, USA, 1968.

Patt, A. and Gwata, C.: Effective seasonal climate forecast applications: examining constraints for subsistence farmers in Zimbabwe, Global Environ. Chang., 12, 185–195, doi:10.1016/S0959-3780(02)00013-4, 2002.

Reason, C. J. C., Allan, R. J., Lindesay, J. A., and Ansell, T. J.: ENSO and climatic signals across the Indian Ocean Basin in the global context: part I, interannual composite patterns, Int. J. Climatol., 20, 1285–1327, doi:10.1002/1097-0088(200009)20:11<1285::AID-JOC536>3.0.CO;2-R, 2000.

Reason, C. J. C., Hachigonta, S., and Phaladi, R. F.: Interannual variability in rainy season characteristics over the Limpopo region of southern Africa, Int. J. Climatol., 25, 1835–1853, doi:10.1002/joc.1228, 2005.

Rockstrom, J.: Water resources management in smallholder farms in Eastern and Southern Africa: an overview, Phys. Chem. Earth Pt. B, 25, 275–283, doi:10.1016/S1464-1909(00)00015-0, 2000.

Saha, S., Nadiga, S., Thiaw, C., Wang, J., Wang, W., Zhang, Q., Van den Dool, H. M., Pan, H. L., Moorthi, S., Behringer, D., Stokes, D., Peña, M., Lord, S., White, G., Ebisuzaki, W., Peng, P., and Xie, P.: The NCEP Climate Forecast System, J. Climate, 19, 3483–3517, doi:10.1175/JCLI3812.1, 2006.

Savenije, H. H. G.: The importance of interception and why we should delete the term evapotranspiration from our vocabulary, Hydrol. Process., 18, 1507–1511, doi:10.1002/hyp.5563, 2004.

Slingo, J. and Palmer, T.: Uncertainty in weather and climate prediction, Philos. T. R. Soc. A, 369, 4751–4767, doi:10.1098/rsta.2011.0161, 2011.

Szczypta, C., Calvet, J.-C., Albergel, C., Balsamo, G., Boussetta, S., Carrer, D., Lafont, S., and Meurey, C.: Verification of the new ECMWF ERA-Interim reanalysis over France, Hydrol. Earth Syst. Sci., 15, 647–666, doi:10.5194/hess-15-647-2011, 2011.

Themeßl, M., Gobiet, A., and Leuprecht, A.: Empirical-statistical downscaling and error correction of daily precipitation from regional climate models, Int. J. Climatol., 31, 1530–1544, doi:10.1002/joc.2168, 2011.

Usman, M. T. and Reason, C. J. C.: Dry spell frequencies and their variability over southern Africa, Clim. Res., 26, 199–211, doi:10.3354/cr026199, 2004.

Verkade, J. S. and Werner, M. G. F.: Estimating the benefits of single value and probability forecasting for flood warning, Hydrol. Earth Syst. Sci., 15, 3751–3765, doi:10.5194/hess-15-3751-2011, 2011.

Wetterhall, F., Pappenberger, F., He, Y., Freer, J., and Cloke, H. L.: Conditioning model output statistics of regional climate model precipitation on circulation patterns, Nonlin. Processes Geophys., 19, 623–633, doi:10.5194/npg-19-623-2012, 2012.

Winsemius, H. C., Dutra, E., Engelbrecht, F. A., Archer Van Garderen, E., Wetterhall, F., Pappenberger, F., and Werner, M. G. F.: The potential value of seasonal forecasts in a changing climate, Hydrol. Earth Syst. Sci. Discuss., 10, 14747–14782, doi:10.5194/hessd-10-14747-2013, 2013.

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Table 1. Length of dryspells and number of dry spells from the EGCP data (observed) and forecasted with raw forecast and bias corrected. The results are with no threshold nor area filtering applied.

	Lead 1	Lead 2	Lead 3	Lead 4	Lead 5
Length of dryspell					
Observed	8.68				
Raw forecast	8.99	9.23	9.35	9.53	9.63
Corrected forecast	8.54	8.71	8.78	8.84	8.71
Frequency of dry spells					
Observed	73 %				
Raw forecast	75 %	73 %	71 %	69 %	67 %
Corrected forecast	79 %	78 %	76 %	75 %	76 %

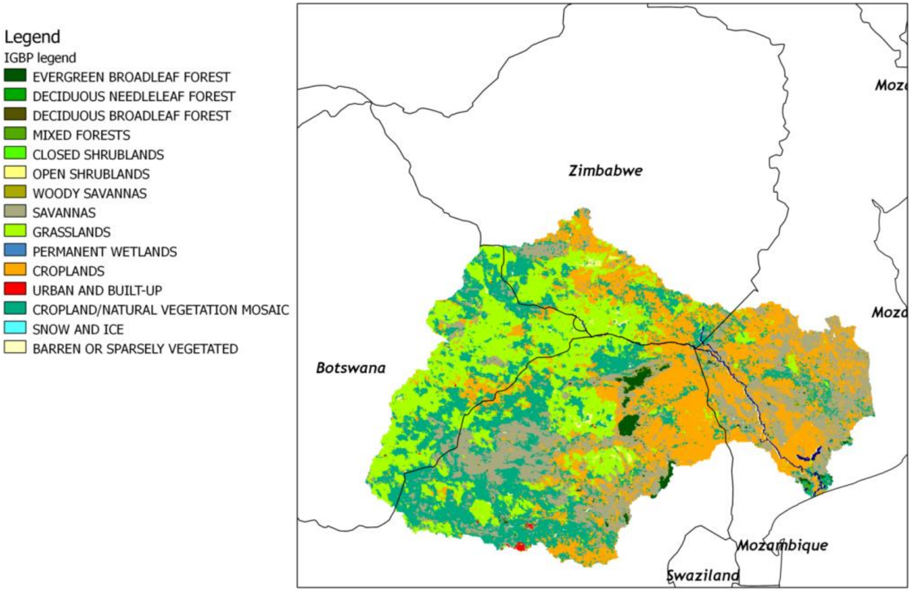

Fig. 1. Land use in the Limpopo river basin (source: IGBP, add reference). The orange coloured regions are classified as croplands, most of which are rain-fed.

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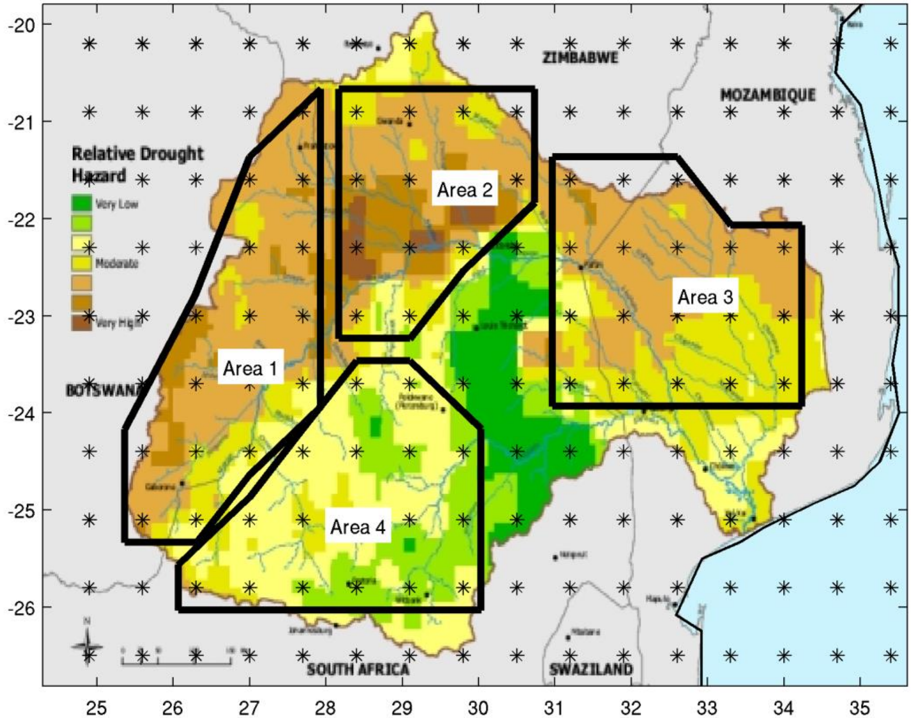

Fig. 2. Areas of drought hazard for the limpopo basin. The 4 areas are characterized by their sensitivity to droughts, ranging from low/moderate to very high/high. The underlying maps are from from Muñoz Leira et al. (2003). The grid points denote the grid points of SYS4.

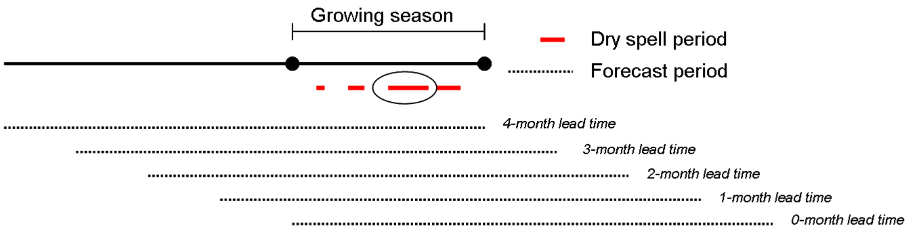

Fig. 3. The timing of the growing season and lead times of seasonal forecasts. Evaluation of dry spells is performed in the growing season (see red lines).

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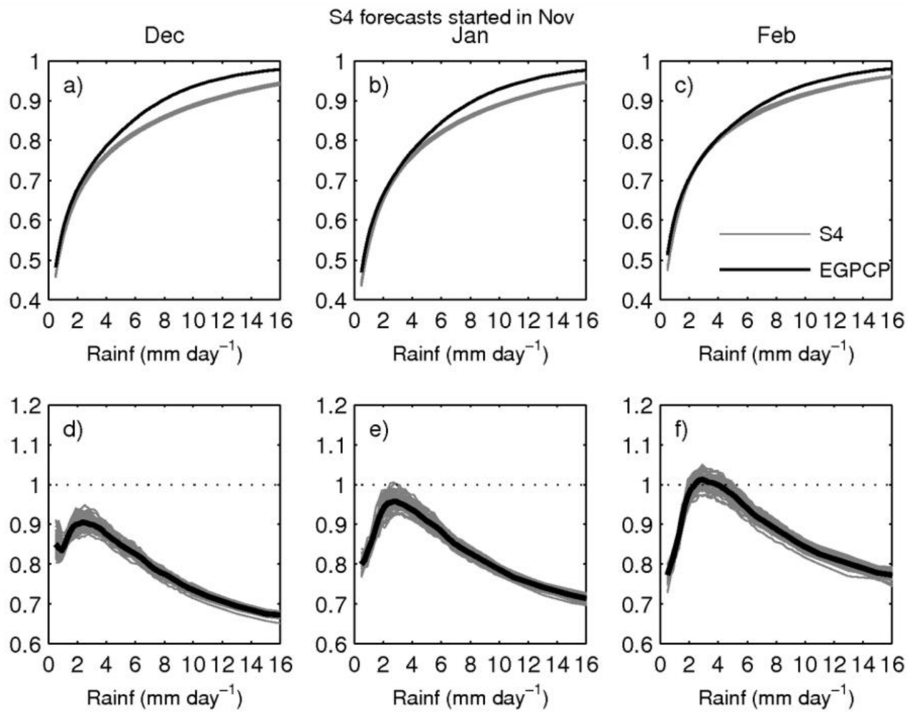

Fig. 4. Cumulative density function (CDF) **(a–c)** of daily precipitation from EGPCP (black) and SYS4 forecasts started in November (gray lines from the bootstrapping sampling) valid for December **(a)**, January **(b)** and February **(c)**. Quantile match coefficients applied to correct SYS4 forecasts (black mean, gray bootstrapping range) started in November and valid in December **(d)**, Januray **(e)** and February **(f)**. The represented CDFs and quantile match coefficients were averaged over the region: [27° E to 32° E; −22° N to −25° N].

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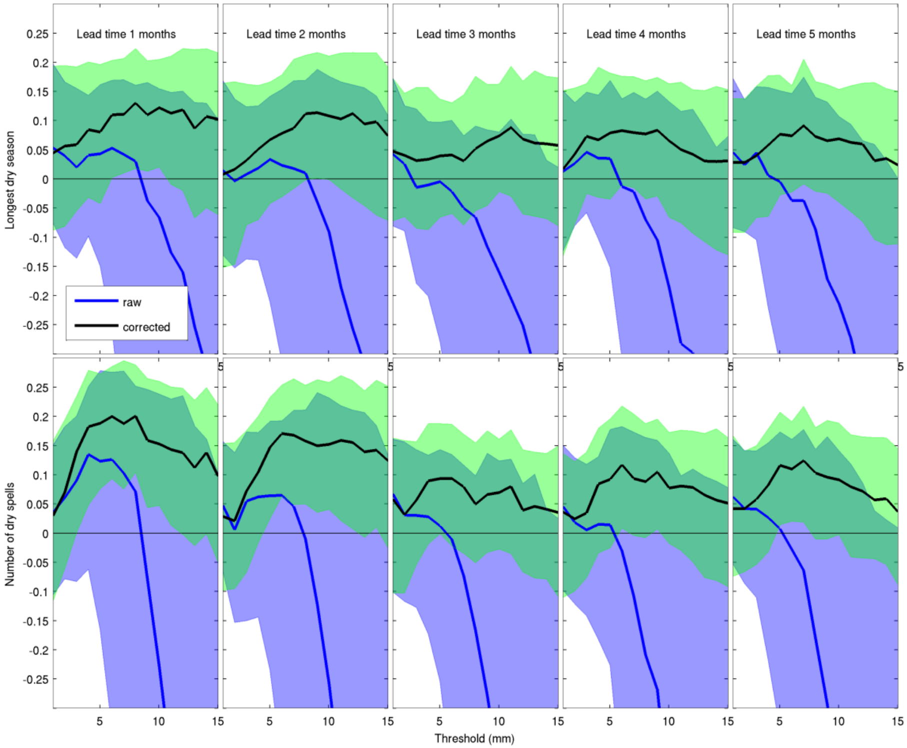

Fig. 5. CRPSS as a function of precipitation thresholds for different lead times over the Limpopo catchment. Top panel shows the results for the longest dry spell over the rainy season, and the bottom panel the number of dry spells over the rainy season. The blue line denotes the raw forecast, and the black line the bias-corrected. The blue (green) areas denote the 5 to 95 spread of the raw (corrected) forecasts respectively.

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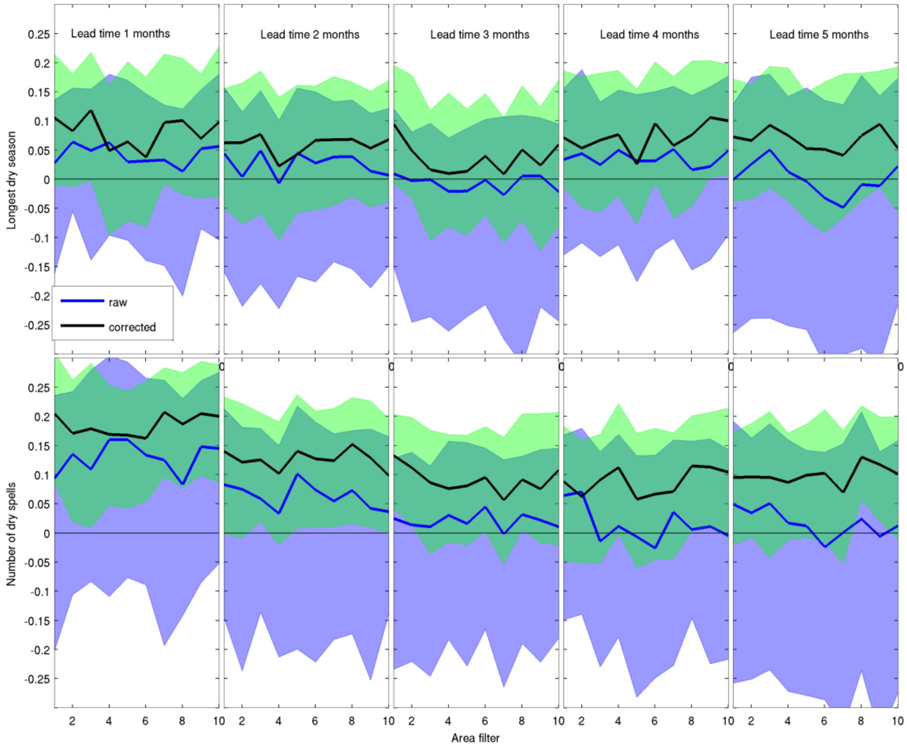

Fig. 6. CRPSS as a function of area filters for different lead times over the Limpopo catchment. Top panel shows the results for the longest dry spell over the rainy season, and the bottom panel the number of dry spells over the rainy season. The blue line denotes the raw forecast, and the black line the bias-corrected. The blue (green) areas denote the 5 to 95 spread of the raw (corrected) forecasts respectively. The results shown used a precipitation threshold of 5 mm.

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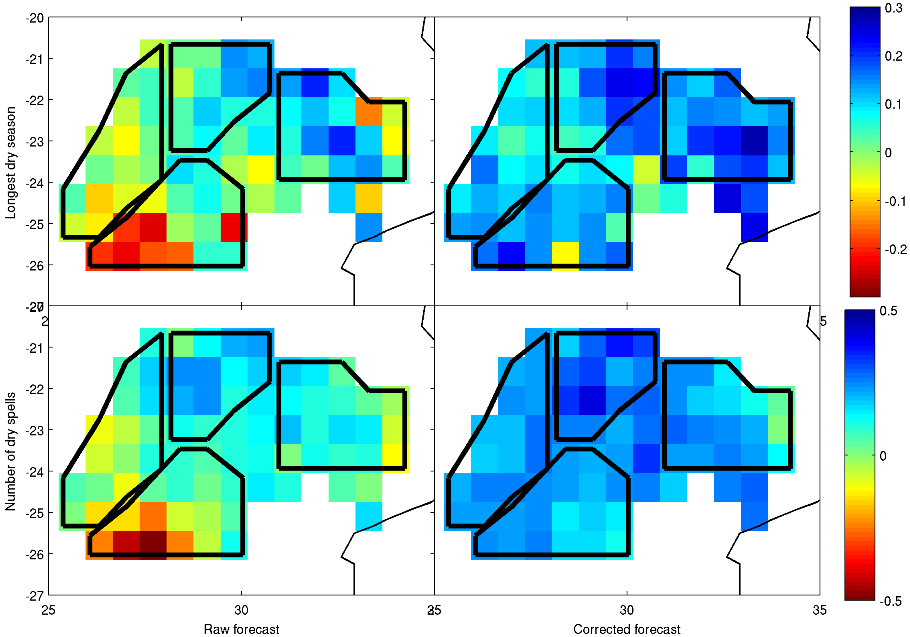

Fig. 7. CRPSS for the different areas over the Limpopo basin. The results are with no area filtering and with a precipitation threshold of 5 mm for the lead time of 1 month.

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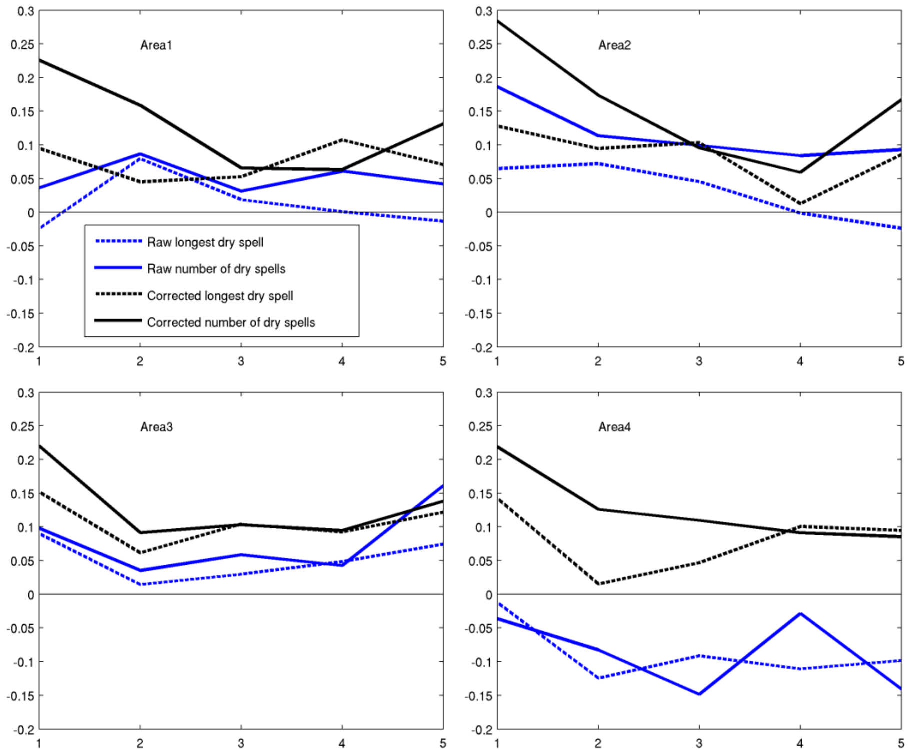

Fig. 8. CRPSS as a function of lead time for the 4 areas in the Limpopo basin.