Ranking seasonal rainfall forecast skill of emerging and developing economies

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Abstract

Some of the biggest emerging markets economies include countries in South America, Asia and Africa. In the global south, political and developmental similarities (e.g. climate variability occurring in conjunction with marked developmental challenges) offer opportunities for comparative research and thereby possible societal benefits (e.g. enhanced disaster risk reduction). In fact, countries or geographical regions of the world significantly affected by climate extremes may consider collaboration on issues such as understanding and modelling of the climate system, especially if there is a common dominant and somewhat predictable climate mode such as the El Niño-Southern Oscillation (ENSO) affecting the climate variability over these regions. Notwithstanding the value of enhanced understanding and preparedness for ENSO, better predictions are not enough to reduce the risks associated with such events. The socio-economic and political context in which forecasts are located also needs to be understood. Here we present seasonal forecast skill over a large number of regions including emerging or developing countries, but also for a small number of developed regions, in order to rank their ENSO-related seasonal rainfall predictability in an attempt to cluster regions of similar predictability.

Key words: Emerging economies, ENSO, seasonal climate modelling, skill

INTRODUCTION

The El Niño-Southern Oscillation (ENSO) has long been known to have global impact on seasonal-to-interannual climate variability (Ropelewski and Halpert, 1987, 1989). For example, during most of the strongest El Niño events (e.g. 1982/83, 1991/92 and 2006/07) drought conditions occurred over parts of southern Africa, Australia and southern USA, while La Niña events caused excessive seasonal flooding over these parts (e.g. 1999/2000 and 2010/11). The reliability with which most ENSO events can be predicted several months before they reach maturity (Stockdale et al., 1998) and the skill in predicting seasonal extremes over parts of the globe linked to ENSO (e.g. Landman and Beraki, 2012) may result in effective uptake of seasonal forecasts in order to minimize such impacts (Braman et al., 2013). Evidence of existing international collaboration, such as that of IBSA (India-Brazil-South Africa), has already lead to scientific agreements on addressing research and modelling questions on oceanography, meteorology and the Antarctic. In addition to successful politically-based frameworks such as IBSA, collaboration motivated more directly by common scientific questions is also warranted, especially if such questions can lead to further societal improvement and development, including economic development.

The level of uptake of seasonal forecasts and applying these forecasts for the benefit of users, commercial or otherwise, across regions differs widely. For example, in Uruguay (a nation whose economy is based upon agriculture) the government is currently working with the International Research Institute for Climate and Society (IRI) to create one of the most sophisticated agricultural information networks in the world that can provide reliable seasonal climate forecasts for temperature and rainfall patterns up to three months in advance. Countries or geographical regions with political and socio-economic challenges similar to Uruguay's may benefit from learning about how they have put to use seasonal forecasts to improve on their agricultural practices and decision making. However, regions where seasonal forecasts are not skillful enough may not benefit from learning about the Uruguayan experience.

In South Africa, where it has been suggested that the uptake of seasonal forecasts for the region may have stagnated notwithstanding proof that forecasts have improved (Landman, 2014), may benefit from learning from the Uruguayans since southern Africa has, like Uruguay, ENSO-forced seasonal predictability and has a large agricultural sector sensitive to climatic fluctuations. Moreover, climate models applied to South African agriculture and rivers have also been successfully applied to Uruguayan and Chilean river flows over multiple decades (Landman et al., 2014). Such South-South collaboration is made in part possible owing to the regions' teleconnections to ENSO and subsequent seasonal predictability. However, there are a number of regions similarly linked to ENSO and whose modelling and forecast application efforts may also co-benefit through multi-national collaboration with southern African modellers and social scientists.

Complex socio-economic and political drivers that shape the vulnerability context in which ENSO operates also need to be understood when preparing seasonal climate forecasts (e.g. Eakin, 2000, Davis, 2002; Lemos et al. 2002; ODI, 2011, Ziervogel and Downing, 2004). The social and human dimensions require detailed attention (as the recent interest in the focus on 'Climate knowledge for action' and the 'Global Framework for Climate Services' is planning to address). Several investigations on the use and uptake of seasonal forecasts in southern Africa have been undertaken and key elements can be profiled further.

This paper attempts to find out where southern Africa seasonal rainfall predictability ranks with a good number of other countries or regions linked to ENSO so that collaboration may be sought and established.

DATA AND METHOD

Two data sets are considered: hindcasts from a coupled model and a gridded rainfall product against which the model hindcasts are verified. The model used is the GFDL-CM2.5-FLOR-B01 fully coupled model of the North American Multi-model Ensemble (Kirtman et al., 2014). Monthly global hindcast data from March 1980 to the present are available at a 1°x1° latitude-longitude resolution for 12 ensemble members and for lead-times up to 11 months. We are using only 1-month lead-time hindcasts. The gridded data is the Climatic Research Unit (CRU) TS3.21 (Harris et al., 2014) from which seasonal total rainfall is derived. Table 1 shows the regions and their latitude-longitude description together with their respective ENSO related rainfall seasons used in the analysis.

Table 1. The regions, their latitude-longitude areas and their seasons used in the analysis.

Region	Lat-Long	ENSO responses season
Central Chile	28°-38°S; 70°-75W°	JJAS
Central SW Asia	34°-44°N; 62°-77°E	FMA
Coastal Equador,Northern Peru	8°S-0°; 79°-82°W	JFMA
Eastern Australia	20°-40°S; 140°-154E°	ASOND
Eastern Equatorial Africa	7°N-7°S; 31°-48°E	OND
Europe	36°-60°N; 10°W-4°E	SON
India	13°-30°N; 70°-88°E	JAS
Indonesia	10°S-10°N; 95°-127°E	JASOND
Nordeste	2°-8°; 34°-45°W	MAM
Northern South America	0°-12°N; 52°-82°W	JASOND
Philippines	5°-20°N; 118°-128°E	ONDJF
Sahel	8°-16°N; 18°W-40°E	JAS
Southeast Asia	10°-20°N; 97°-110°E	JJAS
Southeast China	20°-30°N; 110°-123°E	AMJ
Southeast South America	29°-39°S; 48°-63°W	SOND
South-central, SW Canada	49°-55°N; 88°-132°W	DJFM
Southern Africa	14°-36°S; 11°-41°E	NDJFM
Southern USA	25°-34°N; 75°-120°W	NDJFM

Seasonal total precipitation gridded ensemble mean hindcasts are interpolated to the nearest CRU gridpoint after which the mean and variance biases of the model data are corrected with the IRI's Climate Predictability Tool (CPT). There are 31 years of matching model and CRU data available from 1981 to 2011 of which the first 15 years are used to calculate error variances through cross-validation. Probabilistic and deterministic model hindcasts for year 16 are subsequently obtained by the CPT. A new cross-validation is then performed over 16 years of hindcasts in order to produce probabilistic and deterministic hindcasts for year 17. The process is continued until 15 years of hindcasts are obtained from 1997 to 2011. These hindcasts are subsequently verified.

RESULTS

The 15-year hindcasts are verified both deterministically and probabilistically. For the former Spearman's rank correlations between model and CRU data are calculated, and for the latter the model's discrimination and reliability attributes are evaluated. Relative operating characteristics (ROC) are used to determine discrimination and the least squares weighted regression lines of attributes diagrams are used for reliability. In fact, the difference between these resolution slopes and the slope for perfect reliability is used as a measure of reliability at each gridpoint. For both ROC and reliability the upper and lower thresholds of the hindcast categories are determined from respectively the 75^{th} and 25^{th} percentile values of the climatological record.

The deterministic verification results are shown in Fig. 1. All CRU gridpoints per region are evaluated by calculating the 25^{th}, 50^{th} (median) and 75^{th} percentile values of the correlations. The results are ranked according to the median values for each region and shown on the figure in a descending manner. The Philippines is ranked highest and southern Africa only 13^{th}. All three IBSA regions (Southeast South America, Nordeste and India) are ranked higher than southern Africa. Surprisingly coastal Ecuador and northern Peru are ranked lowest, but this result may be a function of the model used and so the evaluation of additional models may be warranted.

ROC scores (for the three percentile values mentioned above) for the upper quartile (the "above-normal" category used here) of Fig. 2 rank southern Africa even lower in the 16th position. This lower position is partly a consequence of a large number of southern African gridpoints associated with very low ROC scores (the 25th percentile is near 10) even though the 75th percentile ROC scores for this region is ranked slightly higher at 15th. However, certain regions of southern Africa, such as the Limpopo Province and the adjacent areas from neighbouring countries, have been found to have much higher skill (Landman et al., 2012). For the lower quartile (the "below-normal" category) presented in Fig. 3 southern Africa ranks higher than before and even competes with the ranks of some of the IBSA regions. Take note that for Figs. 1 to 3 that the Philippines rank highest.

The reliability results of Figs. 4 and 5 are shown in an opposite orientation than the previous results, i.e., the highest ranked region are associated with the smallest distances from perfect reliability. As with the correlations and ROC scores, southern Africa ranks in the lower half of the regions. Take note that for the way in which reliability is portrayed here, some regions that have been ranked high before may rank more poorly now (e.g. Philippines). We may have to revisit the reliability estimates since with the current approach under-confident forecasts get penalized more severely than over-confident ones since under-confident slopes can go very high, such as 3 or 4, while under-confident slopes can only deviate from 1 by 1 at the most (unless they have negative slopes, which may be possible).

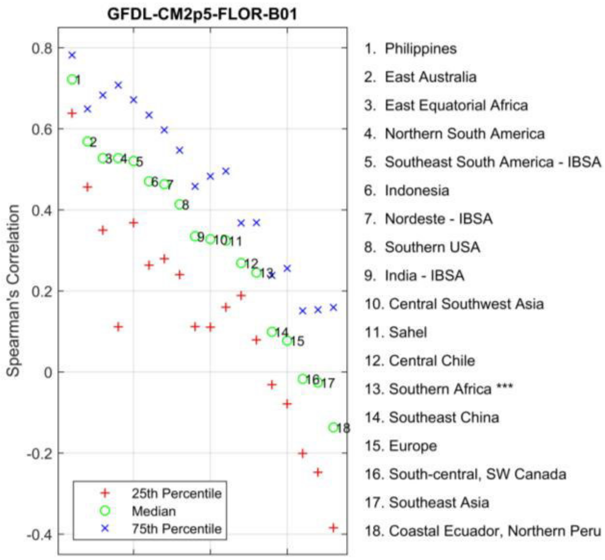

Fig. 1. Percentile values (25th, 50th and 75th) of the Spearman's rank correlation over all gridpoints obtained over the 15-year test period from 1997 to 2011.

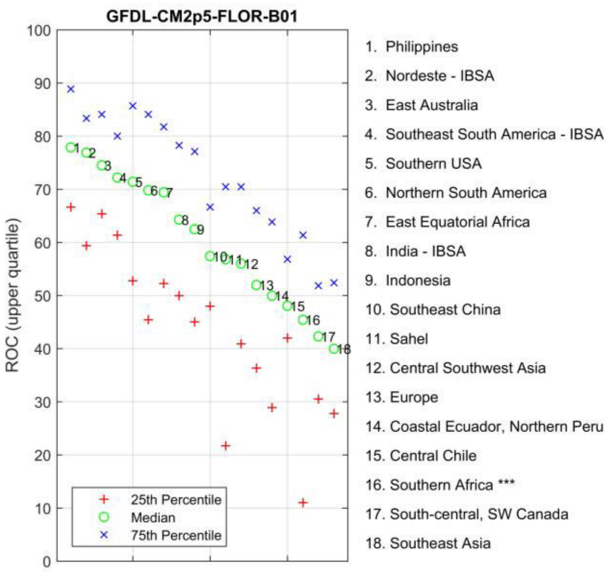

Fig. 2. As for Fig. 1, but for wet season discrimination (ROC for upper quartile).

DISCUSSION AND CONCLUSION

We wanted to determine how seasonal rainfall predictability over a number of regions compares with each other and in particular where southern Africa as an emerging economy ranks globally. Since ENSO is a strong forcing for climate variability over many parts of the globe and found often to be the main source of seasonal predictability, only seasons of the regions with ENSO responses are considered. For the analysis we used the output of a state-of-the-art coupled model of the North American Multi-model Ensemble that has been corrected for mean and variance biases. Only 15 years of verification data are considered from only one model.

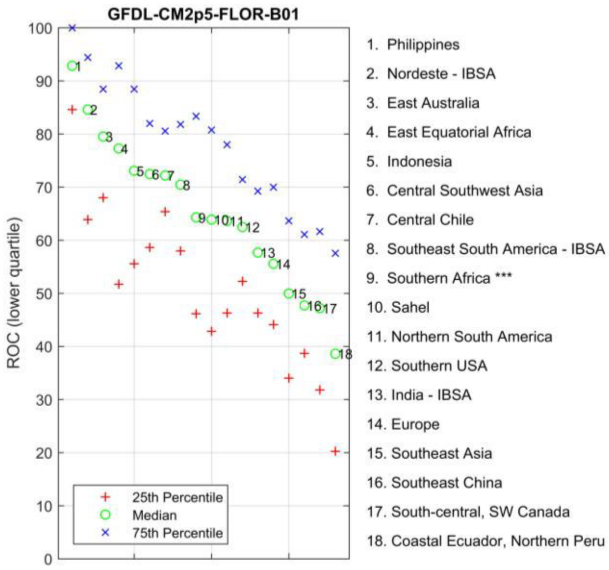

Fig. 3. As for Fig. 1, but for dry season discrimination (ROC for lower quartile).

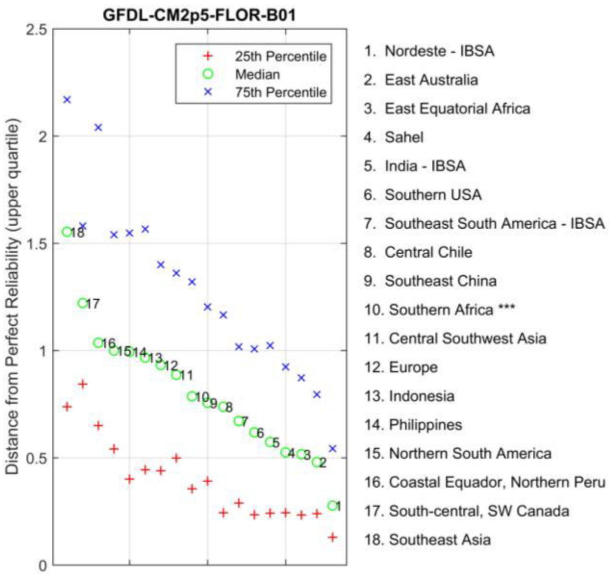

Fig. 4. As for Fig. 1, but for wet season reliability.

The verification results are presented in terms of deterministic predictability and how probabilistic forecasts are able to discriminate extreme seasons and how reliable these are. In general, predictability varies quite substantially across the selected regions, and perhaps rather disappointingly, southern Africa ranks poorly against the majority of regions. However, we only tested how a single model's rainfall forecasts performed and as is certainly the case with southern Africa, statistically downscaling of low-level circulation instead can significantly improve skill. Perhaps through downscaling, southern African seasonal rainfall predictability can be brought up to par with more of these regions even if their forecasts are also similarly corrected.

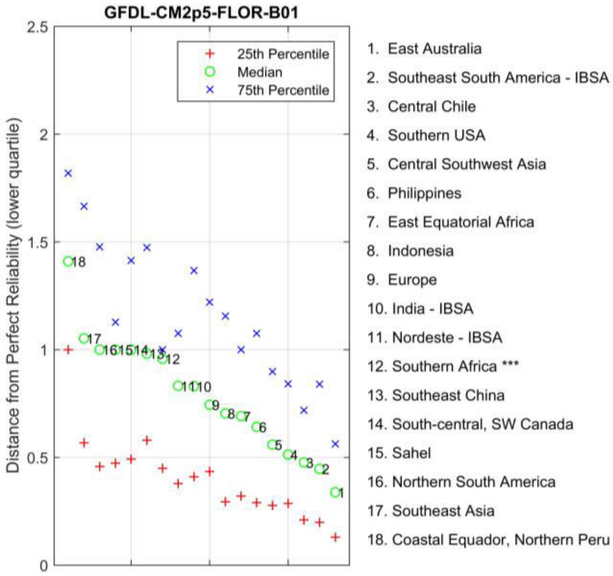

Fig. 5. As for Fig. 1, but for dry season reliability.

Based on the results of this work, southern African predictability ranks lower with developing regions or countries with which formal collaboration already exists (e.g. Brazil, India, Uruguay and Chile). Notwithstanding, in South Africa in particular, the more than 20 years of experience to model and predict seasonal climate variations and how such forecast can be applied to decision-making (Landman, 2014) may be of interest to these regions, in spite of their superior forecast skill. For example, South African modelling experience and expertise have already benefitted predictability studies over the Middle East (Shirvani and Landman, 2015). However, southern Africa modellers should also expand their network of collaborators to regions with similar limits of predictability such as Western Europe but where advanced modelling has been taking place over a sustained time (e.g., Doblas-Reyes et al., 2013).

The use and uptake of such forecasts, as indicated earlier, is another field of endeavor that requires intensive research. The use and co-design of what information may be required is an area that would have to be carefully considered when trying to use such information. Careful collaboration of what users require, how such information should be communicated and shared and also used would need careful articulation and further research.

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