Use of El Niño–Southern Oscillation related seasonal precipitation predictability in developing regions for potential societal benefit

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Abstract

Some of the biggest emerging market economies include countries in South America, Asia and Africa. Broad-scale political and developmental similarities (e.g. societally impactful developmental challenges related to climate variability) offer opportunities for comparative research resulting in potentially improved understanding of the complexities of various climate adaptation interventions including disaster risk reduction. 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 when there is a common, dominant and somewhat plausible climate mode such as the El Niño-Southern Oscillation (ENSO) affecting the regions' climate variability. Better ENSO and subsequent climate predictions alone, however, are not enough to reduce the risks associated with such events. The socio-economic and political context in which climate finds expression and in which climate forecasts have potential value also need to be understood. Here we present seasonal precipitation forecast skill over 20 geographical regions including emerging or developing regions, but also a few developed regions, in order to rank their ENSO-related seasonal rainfall predictability in an attempt to cluster regions of similar ENSO climate predictability. We then also provide some of the broad contours to investigate the level of human 'development' within these clusters in order to begin to understand some of the socio-economic factors that configure vulnerabilities. Such profiles begin to show some areas of macro-level vulnerability that may then provide further possible inter-area collaborations, albeit at very gross level scales.

Key words: Emerging economies, ENSO, seasonal climate modelling, skill, collaboration, human development

1. INTRODUCTION

El Niño-Southern Oscillation (ENSO) phases are strongly related to shifting rainfall patterns globally, both from a deterministic (Bradley et al., 1987; Ropelewski and Halpert, 1987, 1989) and from a probabilistic perspective (Mason and Goddard, 2001). For example, during most of the strongest El Niño events (e.g. 1982/83, 1991/92, 1997/98 and 2006/07) drought conditions occurred over parts of southern Africa, Australia and northern South America, while La Niña events (e.g. 1999/2000 and 2010/11) caused excessive seasonal flooding over these parts. Over southern Africa in particular, the strength of ENSO events matters, as strong El Niño events usually result in larger rainfall deficits during summer as opposed to moderate to weak events (Pomposi et al., 2018). More recently, two consecutive El Niño-related severe drought conditions over southern Africa caused major economic and societal impacts there (Archer et al., 2017). On the other hand, the strong La Niña event of 2010/11 caused major flooding over parts of southern Africa (Muchuru et al., 2014). ENSO events are predictable several months before they reach maturity (e.g. DeWitt, 2005; Saha et al., 2006; Stockdale et al., 1998; Barnston et al. 2017) and so the skill demonstrated in predicting seasonal climate extremes over parts of the globe linked to ENSO (e.g. Barnston et al., 2010) could potentially result in effective uptake of seasonal forecasts and consequently minimize impacts (Braman et al., 2013). But is forecast uptake done efficiently, and can the seasonal forecasting communities from different regions co-learn from the experiences gained from seasonal forecast dissemination and use?

Evidence of existing international collaboration, such as that of IBSA (India-Brazil-South Africa), has already led to scientific agreements designed to promote so-called South-South cooperation to complement existing North-South cooperation (http://www.dirco.gov.za/docs/2018/ibsa0605.htm). In addition to politically-based initiatives, collaboration among countries or regions motivated more directly by common scientific questions is also warranted. This statement is true especially when such questions lead to research, the results of which may lead to assisting in further societal improvement and development—particularly economic development. Here we specifically address collaboration on research, modelling and forecast uptake on seasonal-to-interannual time scales as part of a science-societal paradigm. For example, seasonal climate predictability studies over the Middle East (Shirvani and Landman, 2016) and central southern Africa (Muchuru et al., 2016) were based on similar modelling approaches developed in South Africa (Landman 2014) that may lead to the benefit of forecast users.

The level of uptake of seasonal forecasts and application of these forecasts for the benefit of users, commercial or otherwise, however, differs widely across regions. For example, since Uruguay is in a region strongly influenced by ENSO, their 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. With forecasts being reliable in the context of this paper, we mean that forecasts are sufficiently skillful to positively impact on decisions made by users of the forecasts, and that the forecasts are issued on a routine basis so that users can rely on the timeous availability of the forecasts. Countries or geographical regions with political and socio-economic challenges similar to Uruguay's may consequently benefit from learning about how they have put to use seasonal forecasts to improve their agricultural practices and decision-making. However, regions where seasonal forecasts are not as skillful may not benefit from learning about the Uruguayan experience. On the other hand, if areas have equally high skill levels but vastly different levels of economic and social development, the less developed nations may not be able to incorporate seasonal forecasts in decision-support systems as effectively as developed nations could since the former faces greater challenges in terms of sustainable development. Although every farmer may have experienced climate variability and thus would benefit from a priori knowledge of a season for their decision-making, a subsistence and or small-scale agricultural farmer in one of the countries in the northern parts of South America may not necessarily have much of a choice but to plant seeds every season and hope for the best, while a commercial farmer in the southern USA can choose among a set of planting practices to mitigate impending drought impacts, even though seasonal forecasts for these two areas may be equally reliable. Different classes of users therefore have different needs and limitations (Lemos et al., 2012). Implementation of effective seasonal forecast uptake strategies is thus made complicated by both economic constraints and by difficulties associated with decision-making under forecast uncertainties (Kim and Austin, 2013). Take note that we are not suggesting that the best way to quantify future risks is only through climate model forecasts, since there are other possibilities to quantify risk associated with climate variability that do not rely entirely on model forecasts (Kiem and Verdon-Kidd, 2011).

In South Africa, where it has been suggested that the uptake of seasonal forecasts for the region may have stagnated notwithstanding evidence that forecasts have improved (Landman, 2014), users, including farmers, may benefit from learning from the Uruguayans: Southern Africa has, like Uruguay, ENSO-forced rainy season predictability and has a large agricultural sector sensitive to seasonal climatic fluctuations. Moreover, climate models applied to South African climate (Landman et al., 2018) have been successfully applied to Uruguayan and Chilean river flows (Landman et al., 2014a). Such South-South collaboration is made in part possible owing to the regions' teleconnections to ENSO and thus possibly similar seasonal rainfall predictability. There are in fact a number of regions similarly linked to ENSO whose modelling and forecast application efforts (e.g. Slater and Villarini, 2018; Stuecker et al., 2018) may also co-benefit through multi-national collaboration with modellers and social scientists from regions other than their own.

Complex socio-economic and political drivers, that shape the vulnerability context in which ENSO operates, 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 shown recently, for example, in various initiatives including the 'Climate knowledge for action' (https://library.wmo.int/pmb_ged/wmo_1065_en.pdf) and the 'Global Framework for Climate Services' (https://www.wmo.int/gfcs/) as well as various disaster risk reduction efforts such as the GRAF (Global Risk Assessment Framework - https://www.unisdr.org/archive/58772 Jun 14, 2018). The GRAF is being designed, for example, by various international experts to be an open, user-platform that will help communities and decision makers more easily apply their understanding of risk to generate better-targeted solutions for enhanced adaptive capacity development.

Several investigations on the uptake and use of seasonal forecasts in southern Africa have been undertaken and key elements can be investigated further. In this paper we attempt to examine where southern Africa seasonal rainfall predictability ranks in comparison with a number of other countries or regions linked to ENSO so that regions for potential collaboration may be identified, potentially sought and established, especially with regions of similar societal development challenges. In the ranking process, we also hope to identify other pairs of regions having similar predictability levels to encourage their possible collaboration.

2. DATA AND METHOD

In this section we introduce the model and observed data used to determine seasonal rainfall predictability over the 20 regions, and the mathematical process followed to determine to what extent the skill of the regions differ from that of southern Africa. We also mention the data used for estimating the level of social development associated with each region.

Two data set types are considered for the modelling part of the paper: hindcasts (or re-forecasts) from a set of coupled models, and a gridded rainfall observational product against which the model hindcasts are verified. The set of models consists of some of the fully coupled models of the North American Multi-Model Ensemble (Kirtman et al., 2014), and are listed in Table 1 with some of their basic specifications. Monthly global hindcast data from the early 1980's to the present are available at a 1°x1° latitude-longitude resolution for 12 ensemble members per model and for several months lead-time, depending on the model. For simplicity, we are using only 1-month lead-time hindcasts (e.g., a forecast for the December-February season made from observations through end of October). The gridded observational data is the Climatic Research Unit (CRU) TS3.22 (Harris et al., 2014) from which seasonal total rainfall is derived. Table 2 shows the regions and their latitude-longitude description together with their respective ENSO-related rainfall seasons used in the analysis. Take note that we are not claiming that ENSO is the only important driver to influence seasonal rainfall forecast skill globally, but we are only considering land areas with significant ENSO-related rainfall signals, since ENSO relates to a predictable component of rainfall over these areas (i.e. Landman and Beraki, 2012; Risbey et al., 2009). Moreover, since we are looking for similarities between regions for possible collaboration, we are only considering regions with ENSO-related rainfall associations (Mason and Goddard, 2001).

Table 1. Some of the specifications of the global climate prediction models used in the analysis

Model name	**Climate period**	**Ensemble size**	**Max Lead-time (months)**
COLA-RSMAS-CCSM4	January 1982 to present	12	11
GFDL-CM2p5-FLOR-B01	March 1980 to present	12	11
NASA-GMAO-062012	January 1981 to present	12	8

Table 2. The regions, their latitude-longitude boundaries and their ENSO-sensitive seasons used in the analysis.

Region	Lat-Long	ENSO responses season
Caribbean NW	20°N-26.5°N; 85°W-70°W	DJF
Caribbean SE	11°N-18°N; 65°W-58°W	DJF
Central Chile	38°S-28°S; 70°W-75°W	JJAS
Central SW Asia	34°N-44°N; 62°E-77°E	FMA
Coastal Equador,Northern Peru	8°S-0°; 78°W-82°W	JFMA
Eastern Australia	40°S-20°S; 140°E-154E°	ASOND
Eastern Equatorial Africa	12°S-12°N; 22°E-52°E	OND
Europe (Western)	36°N-60°N; 10°W-4°E	SON
India	5°N-30°N; 69°E-90°E	JAS
Indonesia	10°S-10°N; 95°E-127°E	JASOND
Nordeste	2°S-8°S; 45°W-34°W	MAM
Northern South America	0°-12°N; 82°W-52°W	JASOND
Philippines	5°N-20°N; 118°E-127°E	ONDJF
Sahel	8°N-16°N; 18°W-40°E	JAS
Southeast Asia	10°N-20°N; 97E°-110°E	JJAS
Southeast China	20°N-30°N; 110°E-123°E	AMJ
Southeast South America	39°S-29°S; 63°W-49°W	SOND
South-central, SW Canada	49°N-55°N; 132°W-88°W	DJFM
Southern Africa	35°S-17°S; 11°E-41°E	DJFM
Southern USA	25°N-34°N; 120°W-75°W	NDJFM

Seasonal gridded ensemble mean hindcasts for total precipitation are interpolated to the nearest CRU gridpoint, after which the systematic biases in the mean and variance of the data for each model are corrected with a regression-based algorithm from the IRI's Climate Predictability Tool (CPT; Mason and Tippett, 2016). The bias adjustments are done using a 5-year-out cross-validation process applied to each set of hindcasts over either 31 (from 1982) or 32 (from 1981) years, depending on the model (Table 1). These hindcasts are subsequently verified against CRU rainfall data and prediction performance is evaluated using two variations of a deterministic verification measure, to be described shortly.

In order to investigate social development, the so-called human development index (HDI;

http://hdr.undp.org/en/content/human-development-index-hdi) is used. Over regions that include more than one country, a simple area-average is calculated. This averaging should not have much of an impact on the results since areas tend to include countries of similar HDIs. For example, in southern Africa the HDI across 7 countries (all associated with ENSO variability) varies from the lowest value of 0.418 to the highest values of 0.698 with an average value of 0.568. We acknowledge that such indicators are very crude and usually mask a range of very local drivers and vulnerabilities driven by local contexts and causes but this attempt, we suggest, at least begins to orient those interested in larger-scale, international humanitarian efforts to begin seeking some common ground for further deliberations and analysis. Once the broad linkages are framed then further detail about the best indicators to use in more intensive engagements can be undertaken e.g. human well-being versus current human development indicators (Fioramonti, 2017).

To assess whether two regions are conducive to collaboration from the standpoint of having similar degrees of climate predictability, we determine which regions have model prediction skills that are not statistically significantly different from one another. We use skill differences between any region and that of southern Africa as our main illustrative example. The Pearson correlation and the Spearman rank correlation are used as the two precipitation prediction verification measures, where each is computed using the precipitation predictions of a given coupled model and the corresponding observations over a 31 or 32-year hindcast period, depending upon the model. The predictive skill of the region is taken as the mean or the median of the two correlation skills across the individual grid points within the region. Thus, with four skills rendered per model (Pearson or Spearman, and mean or median) and three models used, 12 correlation skills are produced for each region. A composite correlation skill score is then computed for a region by squaring the 12 correlation skills (but preserving the negative sign for negative correlations), averaging the squared correlations, and then taking the square root of the average.

Statistically significant skill differences between two regions is governed by the amount of difference in their composite correlations, the level of their correlations, and by the spatial degrees of freedom (i.e., number of independent samples) for each region. The total degrees of freedom is computed as the product of the number of years and the spatial degrees of freedom for the region. The spatial degrees of freedom represents the number of independent spatial samples contained in a region, based on the degree of lack of correlation among the precipitation time series from the region's grid points. When a region's historical data shows high correlations among grid points, a small spatial degrees of freedom is indicated; this is more likely for small-area regions but may also occur in larger regions if the grid point data are strongly positively correlated, as when they are all responding to mainly one climate driver, such as ENSO. Here we use the methods demonstrated in Moron et al. (2007) to estimate the spatial degrees of freedom, based on the observed precipitation data during the model hindcast period. First, the individual grid point time series are standardized over the 31 or 32 years. Then the average of the standardized anomaly is computed over all the grid points for each year, and the interannual variance of this regional average is computed over the hindcast period. For strongly correlated precipitation anomalies over the region, this final variance will be high (approaching unity for perfectly correlated grid point time series), while for more independent behaviour across grid points the variance will be relatively low. Using this variance, the spatial degrees of freedom is estimated using a linear equation derived from the cases shown in Fig. 4 in Moron et al. (2007). For the regions and seasons used here, the spatial degrees of freedom ranges from 1.29 for Nordeste (north-east region of Brazil) to more than 6 for India and northern South America. The total degrees of freedom for a region is then computed by multiplying the spatial degrees of freedom by the number of years in the hindcast period.

3. RESULTS

Area-mean and -median correlation values (Pearson and Spearman) for each of the 20 regions and for the three models are presented in Figure 1. This figure shows the cross-validation results over respectively the 31- and 32-year periods considered and is our first indication of how the various regions' skill levels are ranked in terms of 1-month lead rainfall forecasts. The regions are listed on the figure in descending order from the highest (Philippines) to the lowest (South-central, SW Canada) median Pearson values as obtained from the GFDL model, the overall best of the three models. One can easily see that the four skill estimates are in close agreement with one another for each model. Southern Africa, ranked 13th, is inclusive of countries south of 17°S and ranks more or less in the bottom third of the 20 regions considered. However, as would be the case for any region, forecast skill levels are not homogeneous across the whole subcontinent. For example, the northeastern part of South Africa is more predictable than the rest of the summer rainfall-based regions of that country (Landman et al., 2012). This section of South Africa forms part of the Limpopo River catchment area (which includes parts of South Africa, Mozambique, Swaziland, Zimbabwe and Botswana) where forecast skill is relatively high for southern Africa (Engelbrecht et al., 2011). When NMME model verification is restricted to this catchment area, skill levels are relatively higher than those for southern Africa as a whole, but still rank rather low compared with the other regions considered (see the "o" in Figure 1). Further attempts to improve on forecast skill over southern Africa through statistical recalibration (Landman and Goddard, 2005), multi-model ensembles (Landman and Beraki, 2012) and model configurations involving SST forcing scenarios (Landman et al., 2014b) have been tried in the past, but have increased forecast skill levels only by modest amounts, suggesting that the skill results for southern Africa shown here are representative for regional comparative purposes. It is to be expected that all of the countries/regions evaluated here have a range of predictive skill within them, especially regions that are larger or have greater spatial degrees of freedom that would signify differential ENSO responses or climate drivers in addition to ENSO.

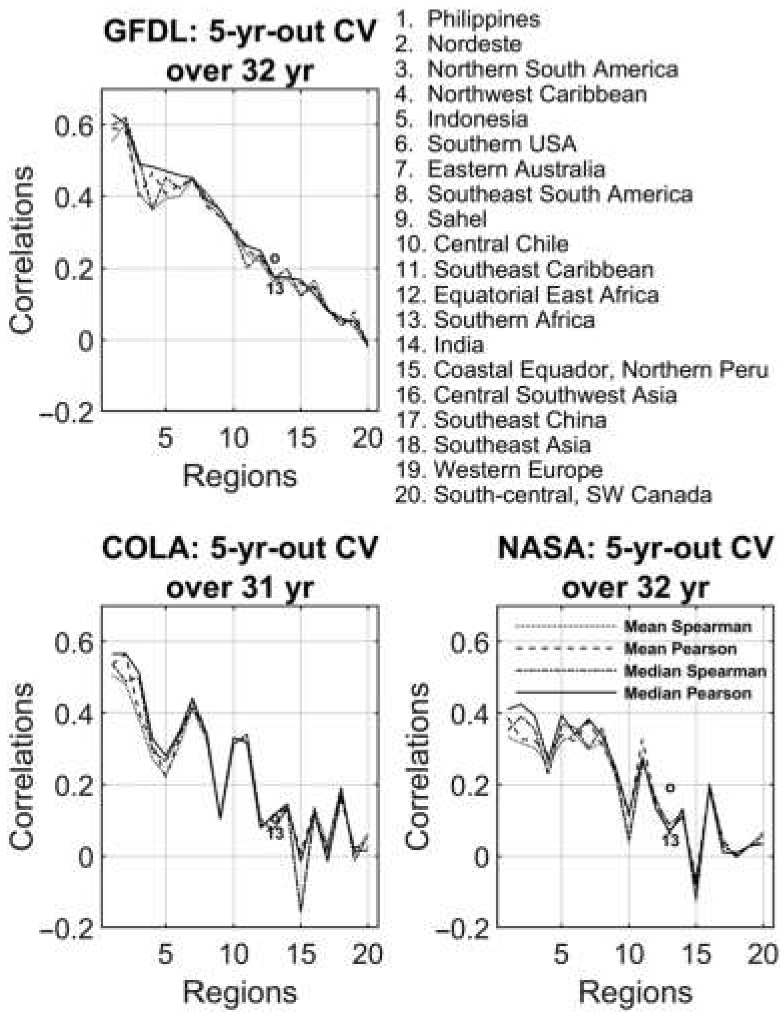

Figure 1. Median and mean correlations (Pearson and Spearman) for each of the 20 regions described in Table 2, for each of the three models described in Table 1. The correlation values are obtained by comparing bias corrected (through 5-year-out cross-validation) model hindcasts with CRU values. Southern Africa's results are marked with "13" and for the Limpopo River catchment area values (median Pearson) a "o" is used. The list shows the regions ranked in terms of highest to lowest median Pearson values according to the GFDL model.

The statistical results regarding significant differences between the skill of each of 19 regions and that of southern Africa are presented in Figure 2. Using the total degrees of freedom of each region, the statistical significance of inter-region differences in the composite correlation skill is determined using the Fisher r-to-Z transform (Hayes 1973). The results indicate that more than half of the 19 regions have skill that is statistically indistinguishable from that of southern Africa, and therefore can be regarded as being compatible for collaboration from a climate forecast skill perspective. Five regions have correlation skill values lower than that of southern Africa. Two regions are found to be marginally compatible (northwest Caribbean and southeast South America), meaning that the skill difference is significant at the 90% level but not the 95% level. Six regions have predictive skill significantly different (higher) than that of southern Africa: Eastern Australia, Indonesia, the Nordeste of Brazil, Northern South America, Philippines, and southern USA.

Figure 2 shows that there are quite a few regions in the developing world with forecast skill levels statistically similar to that of southern Africa, some of which are found on the African continent (equatorial East Africa and the Sahel). The authors are unaware of any formal collaboration in terms of seasonal forecast modelling/production that is happening at present, or has happened in the past, between southern African and equatorial East African, even though strong collaboration is advisable since they may face similar challenges in the future (Conway et al., 2017). Similarly, southern African countries and countries in the Sahel have operated mostly independently from one another. One possible mechanism through which collaboration can be achieved from a seasonal forecast perspective is by sharing prediction and uptake experiences gained through the various Regional Climate Outlook Forums (https://public.wmo.int/en/our-mandate/climate/regional-climate-outlook-products). In these forums, user engagement has been conducted in different ways from region to region (Daly and Dessai, 2018), and so experiences can be shared in order to improve the usability of forecast products for mutual benefit. When considering the five major emerging national economies of Brazil, Russia, India, China and South Africa (usually referred to collectively as BRICS: https://en.wikipedia.org/wiki/BRICS), there are areas seen on Figure 2 where forecast skill is statistically similar to southern Africa. For example, southern Africa (including South Africa) has similar skill levels to India and to southeast China. Therefore, in addition to commercial, political and cultural cooperation between such nations, cooperation on scientific issues related to seasonal forecasting may also provide useful entry points for effective climate risk reduction through co-learning and co-exploration. In addition to various economic endeavours, other

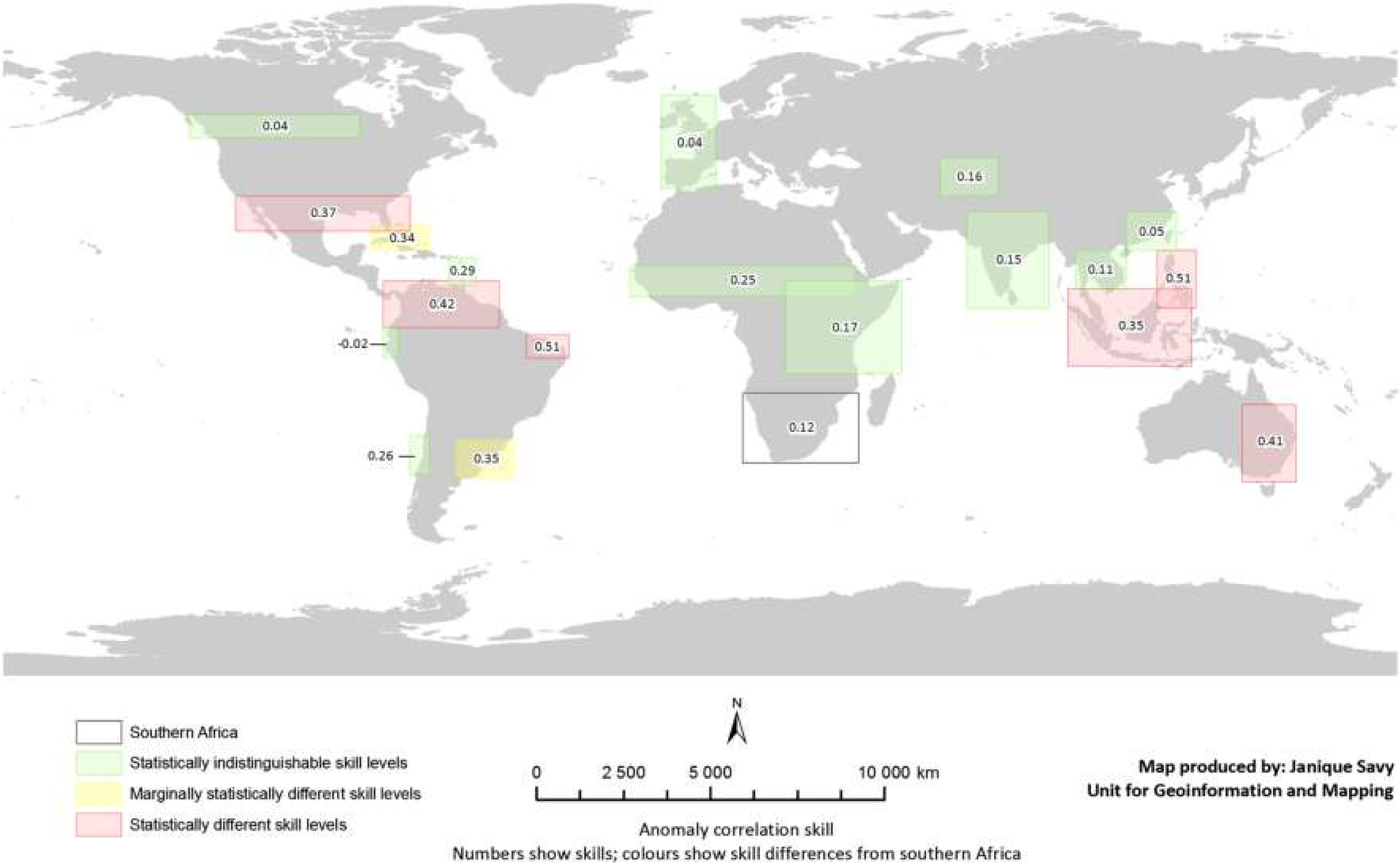

Figure 2. Map of the various regions considered in the analysis, their composite model correlation skills for precipitation during their seasons of ENSO response, and the statistical similarity of their skills with that of southern Africa. See additional information below the map and in the text for details.

considerations may be similarly important that can be used to encourage cooperation between nations to improve on forecasts and uptake of forecasts.

The Human Development Index (HDI; http://hdr.undp.org/en/content/human-development-index-hdi) was created to emphasize economic growth. Such an indicator, however, may be insufficient as a measure of human well being (Sagar and Najam, 1998; Chowdhury 1991). Increasingly, notions of economic growth indicators of human well being are being challenged (e.g. Fioramonti, 2017) whereby people, their aspirations and capabilities (e.g. a long and healthy life, knowledge/education, standard of living), not those only linked to economic growth values, are also argued as being alternative criteria for assessing the development of a country. Notwithstanding where one aligns one's ideological framings and debates on 'economic growth' in many so called low HDI countries, those with sizeable agricultural-based economies, emerging farmers usually experience similar challenges including competing major global and local forces (e.g. capital flows, food prices and inability to access resources) and also the serious challenges coupled to climate variability and change, e.g drought and floods. Such farmers, we argue here, could benefit from having access to a co-designed and co-created forewarning of a coming drought, particularly in ENSO-related drought events where the skill level of the forecast is relatively high. . Notwithstanding issues of climate projection and prediction uncertainty, projected shifts in seasonal drought probabilities could help inform farming decision making when appropriately considered and applied. Successes experienced in effective uptake and how this may be achieved can therefore be shared between regions of relatively low forecast skill and similar human development. While the 'devil is in the details' we illustrate that possible co-locations of interest between those examining ENSO and those interested in challenging notions of 'human well being' could provide fertile areas for scientific collaborations.

Figure 3 shows a comparison between forecast skill (median Pearson for GFDL model) and the HDI. For the sake of comparison, the HDI values and the median Pearson correlation skill values are standardised and plotted on the same graph. One of the areas with an HDI value most similar to southern Africa is India. The Africa-India Mobility Fund (AIMF) is a programme designed to provide researchers from Africa and India with opportunities to collaborate on biomedical and clinical research. Similar initiatives between these regions may be developed for climate modelling and forecast use and in the process also learn valuable lessons from the AIMF experience.

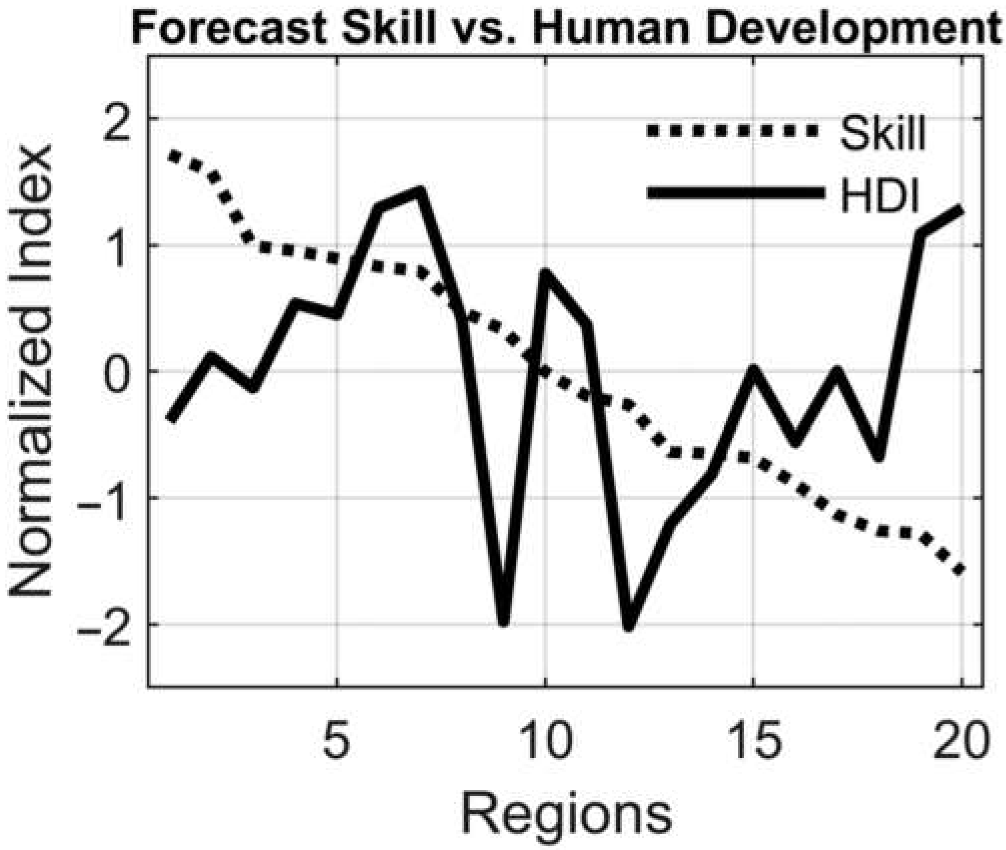

Figure 3. Median Pearson correlations (as one of the precipitation prediction verification measures used here) according to the GFDL model, and HDI values represented as standardised values for easy comparison. The regions numbered on the figure (x-axis) correspond to the list of regions in Figure 1.

Research collaborations between other areas of skill similar to southern Africa but with varying human development levels have, for example, recently taken place. Funded studies of rainfall variability over respectively Kenya (Gamoyo et al., 2015) and Tanzania (Kijazi et al., 2012) involved scientists from both these countries in east equatorial Africa and southern Africa. Moreover, although northern and northeastern Brazil have seasonal forecast skill levels statistically different from southern Africa but with similar HDI values, important funded research collaboration resulted in an improved understanding of the climate system affecting both regions (Grimm and Reason, 2011; 2015).

From a seasonal forecast modelling perspective, in South Africa more than 20 years of experience in modelling and predicting seasonal climate variations and applying such forecasts to decision-making (Landman, 2014) may be of interest to countries in developing regions. For example, South African modelling experiences and expertise have already positively influenced some predictability studies over central Asia (Shirvani and Landman, 2016) as well as central Chile. For Chile the extent to which dynamical climate models are capable of forecasting the so-called mega-drought of 2010 to 2016 was established and a research paper is in preparation. Both of these latter two cases of modelling collaboration happened notwithstanding no formal funding being made available for these co-development and co-learning activities. The collaboration happened mostly because of friendships that developed over recent years between modellers from these countries.

4. DISCUSSION AND CONCLUSION

Seasonal forecasts have been produced in some southern African countries since the early 1990s. During the following years modelling work in the region has resulted in greater sophistication of seasonal forecast models (e.g. Beraki et al., 2015) and an accompanying improvement in forecast skill (Landman, 2014). However, forecasts have improved mainly over areas where predictability has already been demonstrated and during seasons where forecasts already work best. For example, over South Africa, the northeastern parts of the country are relatively more predictable as compared to the rest of the country, and mainly during the mid-summer months (Landman et al., 2012). Such regional "pockets" of predictability paved the way for the development of applications models, including models for streamflows (Muchuru et al., 2016) and crop yields (Malherbe et al., 2014) in these sub-regions. Notwithstanding these developments, and levels of forecast skill, the translation of seasonal forecasts produced in real time into quantifiable benefit is still a work in progress for southern Africa. A reason presented for why seasonal forecasts produced in South Africa (probably also in the larger southern African region) could be underutilized is because forecast products like those presented by the South African Weather Service (http://www.weathersa.co.za/images/data/longrange/gfcsa/scw.pdf) and others (e.g. https://tinyurl.com/ybrb3a72) may have been developed without properly considering a collaborative, integrated approach with decision-makers (Morss et al., 2005). The lack of such a collaborative approach is damaging to prospects of uptake since iteration between knowledge producers (e.g. seasonal forecast producers) and users is critical to create usable science (Dilling and Lemos, 2011).

There is a variety of documented reasons for the perceived low uptake of forecasts, with a few highlighted below. The presence of complicated and complex risks associated with unpredictable climate variability 'events' (e.g. a flash flood during a dry rainy season (Poolman et al., 2014)) can make the inclusion of forecasts into planning challenging. Additionally, seasonal forecasts might be presented in a format (e.g., using tercile categories) that may make it very difficult for many users to include them in decision-making. The role of various forms of knowledge including local, traditional and tacit knowledge also need to be considered when examining climate forecast use and uptake (Roncoli et al.,2009; Lemos et al. 2012).

There are probably a multitude of reasons why the optimal uptake of seasonal forecasts is constrained, but we propose that there are two primary reasons: (1) the modest to moderate skill levels associated with seasonal forecasts, and (2) the lack of the ability of potential forecast users to include forecasts of this skill level in decision-making. Seasonal rainfall forecast skill for southern Africa is modest. As a result, in this paper we first tried to identify other regions having skill levels similar to that of southern Africa, and also identified areas of human development similar to that of southern Africa. Areas similar in these two aspects may provide mutually beneficial areas of collaboration if their forecasting and forecast use experiences are shared through enhanced co-learning and collaboration approaches (Vogel et al., 2007).

ENSO is a strong forcing factor for climate variability over many parts of the globe and found often to be the main source of seasonal climate predictability. Therefore, only seasons with ENSO responses are considered here, and these vary by region and time of the year. In the analysis we used the seasonal rainfall output of three state-of-the-art coupled models of the North American Multi-model Ensemble that have been corrected for biases in mean and variance, using a 5-year-out cross-validation process. Seasonal rainfall forecast skill is determined over more than 30 years by correlating the bias-corrected forecasts with CRU gridded observational rainfall data. Predictability varies quite substantially across the selected regions, with southern Africa ranking in the bottom third of the regions considered. Although forecast skill levels vary, climatic impacts such as droughts and floods happen across all regions and could potentially lead to comparable losses in human lives and infrastructure.

Skill levels for southern Africa may be elevated to a modest extent through more advanced statistical post-processing of climate model forecasts, but will always have natural upper limits to its seasonal forecasts skill as is the case for all regions. Countries having greater natural seasonal climate predictability, such as the Philippines, outscore southern Africa significantly. Despite its forecast skill limitations, there are two regions in Africa with skill levels similar to that of southern Africa (equatorial East Africa and the Sahel). These three African regions also have the lowest levels of human development according to the HDI and are subject to large fluctuations in climate. Although in the past there has been formal collaboration between these regions to improve physical understanding of the climate system (e.g. Kijazi and Reason 2012), similar efforts to improve understanding of the more practical aspects of developing forecasting systems and determining mechanisms for improved uptake and use are equally necessary, but for the most part not pursued. However, sharing the prediction and uptake experiences gained by the various RCOF's in Africa is a possible mechanism through which collaboration can be achieved. This paper is proposing that producer-user interactions in these African regions with similar societal and forecast challenges can be enhanced by at least starting discussions on lessons learnt that may have hampered or improved forecast uptake in these regions.

The examples presented above pertain mostly to collaboration between regions or countries of medium to low human development. Southern Africa modellers, however, should also expand and strengthen their network of collaborators to regions with high human development such as Western Europe, where advanced modelling has been taking place over a sustained time (e.g., Doblas-Reyes et al., 2013). In fact, South Africans have recently collaborated with Japanese modellers for the enhancement of forecast systems for southern Africa (Ratnam et al., 2016, 2018; Yuan et al., 2014). Continued interaction and collaboration with developed countries leading in seasonal forecast modelling can enhance capacity in developing regions and establish balanced collaborations. Such collaboration takes time and requires sustained engagement on both sides for mutual benefit.

The uptake and use of seasonal climate forecasts is a field of endeavor that requires intensive research, and in this paper we have postulated that this can best be achieved through co-learning and co-development between countries experiencing similar levels of prediction skill and human development. The use and co-design of what information may be required is an area that would have to be carefully considered in the choice of optimally usable and actionable forecast products. Careful collaboration could lead to precisely targeted research focusing on the matters of what users require, and how such information should be communicated, shared and applied (Bremer et al., 2019).

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