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Dynamical and statistical downscaling of a global seasonal hindcast in eastern Africa

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A B S T R A C T

Within the FP7 EUPORIAS project we have assessed the utility of dynamical and statistical downscaling to provide seasonal forecast for impact modelling in eastern Africa. An ensemble of seasonal hindcasts was generated by the global climate model (GCM) EC-EARTH and then downscaled by four regional climate models and by two statistical methods over eastern Africa with focus on Ethiopia. The five-month hindcast includes 15 members, initialised on May 1 st covering 1991–2012. There are two sub-regions where the global hindcast has some skill in predicting June–September rainfall (northern Ethiopia – northeast Sudan and southern Sudan - northern Uganda). The regional models are able to reproduce the predictive signal evident in the driving EC-EARTH hindcast over Ethiopia in June–September showing about the same performance as their driving GCM. Statistical downscaling, in general, loses a part of the EC-EARTH signal at grid box scale but shows some improvement after spatial aggregation. At the same time there are no clear evidences that the dynamical and statistical downscaling provide added value compared to the driving EC-EARTH if we define the added value as a higher forecast skill in the downscaled hindcast, although there is a tendency of improved reliability through the downscaling. The use of the global and downscaled hindcasts as input for the Livelihoods, Early Assessment and Protection (LEAP) platform of the World Food Programme in Ethiopia shows that the performance of the LEAP platform in predicting humanitarian needs at the national and sub-national levels is not improved by using downscaled seasonal forecasts.

Practical Implications

We present work on downscaling a seasonal hindcast in eastern Africa done in the FP7 EUPORIAS project. The main focus in our activities was on assessing the utility of downscaling techniques to provide seasonal forecasts for impact models in eastern Africa and answering the question "Can downscaling show a higher predictive skill on seasonal time

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scales comparing to its global driving seasonal forecast?" In particular, the Drought Early-Warning System – LEAP of the World Food Programme (WFP) was used to predict humanitarian needs at the national and sub-national levels taking global and downscaled hindcasts as input data.

At the beginning of the EUPORIAS project after consultations with WFP, it was decided to focus on the Kiremt rainy season (June–September, JJAS) in Ethiopia using a seasonal hindcast initialised in May, which can be used as input to the LEAP system. While the potential predictability of rainfall in eastern Africa has been known for a relatively long-time, the orography of Ethiopia is complex and it was considered important to assess the possibility of improving the accuracy of forecast large-scale rainfall patterns over this particular area at seasonal time scales. This was also a trade-off between user needs, more keen on rainy season forecasts, when impacts of water deficits on agriculture are larger, and forecast skill, which peaked south of Ethiopia in November–January, associated to the El Niño-Southern Oscillation (ENSO) variability. We finally opted for addressing the end-user needs, focusing on JJAS.

A five-month global seasonal hindcast of 15 members was generated using the EC-EARTH model for the 1991–2012 period at about 80 km resolution and then downscaled over eastern Africa by four regional climate models at about 25 km resolution and by two statistical methods at about 50 km resolution (limited by observations). Applying a number of deterministic and probabilistic verification metrics we found two regions in eastern Africa where some predictive skill is evident in EC-EARTH: northern Ethiopia – North-East Sudan and southern Sudan – northern Uganda. In general, both dynamical and statistical downscaling are able to capture and reproduce the predictive signal evident in the global EC-EARTH hindcast with different level of accuracy. However, on average, the downscaled hindcasts show no added value as compared to the driving model if we define the added value as a higher skill in predicting future seasonal anomalies. There is some tendency of improved reliability through the downscaling but predictive skill is mainly sensitive to forecast resolution and increase in reliability does not correspond to an actual gain in information. Instead the probabilistic forecasts reflect the probability of occurrence more accurately. Therefore, an improvement in reliability can benefit end users.

The LEAP platform driven by the global and downscaled hindcasts also shows that predicting humanitarian needs at the national and sub-national levels is not improved by using the downscaled seasonal forecasts. There is, however, indication that statistical downscaling may slightly improve forecasts of rainfall intensity, with forecasts of precipitation frequency (number of wet days) unaffected by downscaling.

The experimental setup was not perfect in all aspects and outcomes do not meet the initial expectation on possible improvement of a global seasonal hindcast by downscaling in eastern Africa. Nevertheless, sharing our experience from the EUPORIAS project can help climate services working with applications of seasonal forecasting. We should also note that our findings are only for the June–September season in Ethiopia and for a limited number of parameters and tools (models and statistical methods) and therefore cannot be generalised for other regions, seasons and seasonal forecasting tools.

1. Introduction

In the last decades a significant progress has been achieved in the prediction of seasonal mean states of weather and, therefore, seasonal forecasting has become an operational activity in a number of national weather services worldwide (Graham et al., 2011). Global seasonal prediction systems are being used increasingly, operating at a 50–200 km range of resolution, while many users require seasonal forecast at impact-relevant regional to local scales. A common approach for providing high-resolution climate information in the future climate projection framework is to supplement global models by empirical-statistical or dynamical downscaling techniques (ESD or DD respectively). To derive regional climate information ESD applies a statistical relationship between information from global models (predictors) and local-scale processes (predictants) (e.g. Maraun et al., 2010) while DD uses regional climate models (RCMs) driven by global models (e.g. Rummukainen, 2010). ESD is a relatively fast and computationally efficient approach but strongly depends on the availability of observations and is limited to a few variables. In practice, this is not a real limitation in seasonal forecasting as most of the needs are temperature and precipitation. Dynamical downscaling using RCMs is computationally expensive delaying the provision of the forecasts and requires much more resources than ESD (e.g. saving a wealth of driving boundary conditions from GCMs). However, in contrast to the ESD approach, RCMs can provide a larger number of variables in a physically consistent way, including regional and local feedbacks which can be important in seasonal forecasting. Due to its simplicity, ESD is applied in seasonal forecasting more often than RCMs but still, running ESD and/or RCMs for operational seasonal forecast production is not a common practice.

At the same time there are many experimental studies (not operational activities) on applying RCMs for downscaling of seasonal forecasts (e.g. Díez et al., 2011; Castro et al., 2012; Diro et al., 2012; Cheneka et al., 2016). The main question in such studies is whether downscaling can provide the added value to global forecasts or not. The definition of the added value is a complex topic and, even after applying RCMs for downscaling climate projections over the last two decades, the added value issue is still debated in the climate downscaling community (Di Luca et al., 2015). There is no unique way to define the added value, which depends on many factors, such as different spatial and time scales, variables and processes and usually includes higher-order statistics, namely: local details in a region with complex topography and land-sea contrast, extreme events, sub-daily variability etc. (Di Luca et al., 2015; Rockel, 2015; Rummukainen, 2016). A downscaling methodology showing the added value in one region and/or season does not necessarily provide similar added value in other regions and seasons. In this study, the added value of downscaling in the seasonal prediction framework is defined as more skilful seasonal forecast compared to its driving global prediction system. The reduction of systematic biases may be also defined as the added value of downscaling and can be important for impact modelling but are not considered in this work (see e.g. Manzanas et al., 2017). Such reduction does not lead to increased knowledge of future seasonal anomalies, and systematic biases can always be dealt with by means of bias correction techniques.

The FP7 EUPORIAS project (Hewitt et al., 2013) aimed to improve our ability to maximise the societal benefit of seasonal to decadal predictions. One of EUPORIAS activities is the provision of downscaled and/or bias-corrected seasonal forecasts for use in EUPORIAS impact and climate service applications. The first focus area in the downscaling EUPORIAS activities is Europe, where high-quality observations exist and ESD methods are applied (Manzanas et al., 2017). A second focus of the downscaling activities is in eastern Africa, where temperature and precipitation exhibit better predictability at seasonal timescale than in the extra-tropics (e.g. Philippon et al., 2002; Diro et al., 2011; Omondi et al., 2013), potentially allowing to apply seasonal forecast data in