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Probabilistic maize yield prediction over East Africa using dynamic ensemble seasonal climate forecasts

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ABSTRACT

We tested the usefulness of seasonal climate predictions for impacts prediction in eastern Africa. In regions where these seasonal predictions showed skill we tested if the skill also translated into maize yield forecasting skills. Using European Centre for Medium-Range Weather Forecasts (ECMWF) system-4 ensemble seasonal climate hindcasts for the period 1981–2010 at different initialization dates before sowing, we generated a 15-member ensemble of yield predictions using the World Food Studies (WOFOST) crop model implemented for water-limited maize production and single season simulation. Maize yield predictions are validated against reference yield simulations using the WATCH Forcing Data ERA-Interim (WFDEI), focussing on the dominant sowing dates in the northern region (July), equatorial region (March-April) and in the southern region (December). These reference yields show good anomaly correlations compared to the official FAO and national reported statistics, but the average reference yield values are lower than those reported in Kenya and Ethiopia, but slightly higher in Tanzania.

We use the ensemble mean, interannual variability, mean errors, Ranked Probability Skill Score (RPSS) and Relative Operating Curve skill Score (ROCSS) to assess regions of useful probabilistic prediction. Annual yield anomalies are predictable 2-months *before sowing* in most of the regions. Difference in interannual variability between the reference and predicted yields range from ± 40%, but higher interannual variability in predicted yield dominates. Anomaly correlations between the reference and predicted yields are largely positive and range from +0.3 to +0.6. The ROCSS illustrate good pre-season probabilistic prediction of above-normal and below-normal yields with at least 2-months lead time. From the sample sowing dates considered, we concluded that, there is potential to use dynamical seasonal climate forecasts with a process based crop simulation model WOFOST to predict anomalous water-limited maize yields.

1. Introduction

Agriculture is the major land use across the globe and is of high economic, social, and cultural importance. In its many forms, agriculture remains highly sensitive to both climate extremes and to variations in climate and trends on a range of time scales; particularly in regions where rainfed agriculture supports majority of the population and plays crucial roles in national economies like East Africa. Improving resilience of the agricultural sector by preparing the vulnerable populations for extreme weather variability and developing reliable crop production systems (Matthew et al., 2015) can not only have a positive effect on socio-economic development but also enhance food security through better agricultural management and policy formulation that proactively accounts for variable climatic conditions (Bahaga et al., 2015).

Operationally, efforts towards improved resilience to extreme climate variability are on-going through issuance of pre-season climate forecasts generated by both statistical and dynamical methods. In Eastern Africa, these forecasts are issued through the Greater Horn of Africa Climate Outlook Forum (GHACOFs) (Martinez et al., 2010; Ogallo et al., 2008) organized by the Intergovernmental Authority for Development (IGAD)- Climate Prediction and Applications Centre (ICPAC) and the World Meteorological Organization (WMO) together with other partners. It brings together scientists from the global climate producing centres, meteorologists from the National Meteorological and Hydrological Services (NMHS) from the GHA region, climate

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forecast end-users and the relevant stakeholders to develop a consensus rainfall and temperature forecasts for the coming season plus likely impacts on climate sensitive sectors (Hansen et al., 2011; Ogallo et al., 2008) including agriculture. The scientists further downscale the consensus seasonal climate outlooks for national impacts and other purposes. Seasonal climate impacts outlook are generally based on subjective expert judgement rather than explicit quantitative methods.

Model based, quantitative pre-season crop yield forecasting plus communication of associated uncertainty and skill could be incorporated into GHACOF process to enhance use of seasonal climate forecasts by providing direct impacts on maize production, based on the assumption that predictable climate can be translated into predictability of crop phenological development and subsequent yields. This study presents the possibility of providing bio-physical process based, quantitative yield forecasts besides the seasonal climate forecasts already routinely issued.

A number of early warning systems (EWS) exist in East Africa with mandates to provide food security outlooks and warnings. For example, the United States Agency for International Development's (USAID) Famine EWS (FEWS-NET) provides food security outlook, assistance outlooks, markets and agricultural trading outlooks (Brown et al., 2007; Ververs, 2012). The Global Information and Early Warning Systems (GIEWS) of United Nation's Food and Agriculture Organization (FAO) (FAO, 2010; Ververs, 2012) provides information on crop prospects and food situation depending on emerging crisis often after crop and food security assessment missions. The Food Security and Nutrition Working Group (FSNWG), a regional platform whose members include NGOs, UN agencies, and research institutions, amongst others, provide food security and nutrition outlook in their monthly meetings. For crop monitoring, these organizations use agrometeorological assessment reports and satellite technologies that monitor conditions of food crops after planting for example the normalized difference vegetation index (NDVI), rainfall estimates, and expert judgement to estimate impending food security situations. The existing EWS largely focus on water availability without considering the water-temperature interactions, even though temperature is critical in both rainfed and irrigated agriculture as it influences the rate of crop development and water deficit in irrigated fields. The complex reactions between climate variables and crop physiology are better simulated using biophysical models as in this study.

Since existing EWS monitor crops when they are already in the fields, little adaptation measures can be implemented to adjust to the prevailing climate situation. This study can directly expand the time horizon of crop performance prediction from existing EWS by including *pre-season* forecasts, and provide high resolution yield forecast information that is also relevant to farmers, rather than only to their traditional clients (i.e. governments and humanitarian agencies).

Seasonal climate forecasts are currently routinely issued up to 12-months before the start of seasons (lead-time) by numerous operational global forecast centres. With sufficient lead time before the start of a growing season, different adaptation options are possible (e.g. choosing different crop or varieties, heavy or low investment in farm inputs) as opposed to forecasts issued after crops are planted. Global Climate Model (GCM) based seasonal climate forecasts have been used in agricultural impacts modelling globally with varied results, suggesting variations in skill due to factors like spatio-temporal scales used, level of surface heterogeneity, crop management practices, and model initialization, amongst others (Jones et al., 2000; Lawless and Semenov, 2005; Neumann et al., 2010; Shin et al., 2010). Driving crop models with skilful seasonal climate forecasts may not guarantee good yield forecasts (Baigorria et al., 2007; Semenov and Doblas-Reyes, 2007; Shin et al., 2010), but the reverse, i.e. better skill in the crop forecast than in the meteorological forecast has also been reported (McIntosh et al., 2005). In addition, whether a crop in a certain region experiences temperature or moisture limitations affects yield predictability differently. For example, since temperature influences crop phonological development and its predictability is generally higher than for precipitation (Iizumi, 2013; Ogutu et al., 2016), its predictability influences yield predictability differently. Finally, the time of the year in which a forecast is useful depends on the crop and region (McIntosh et al., 2007), i.e. depends on the local cropping calendars. This study seeks to identify lead times and regions in East Africa with useful pre-season yield predictability based on pre-season climate forecasts.

Seasonal crop yield forecasts have been derived from either historical statistical relationships with rainfall or large scale climate indices such as the El Nino Southern Oscillation (ENSO) Index (Amissah-Arthur et al., 2002; Iizumi et al., 2014; Hansen et al., 2009; Martin et al., 2000; Phillips et al., 1998), and its influence on seasonal rainfall in some parts of the world such as eastern and southern Africa. These statistical methods are successful at broader spatial extents like national boundaries or regions (Amissah-Arthur et al., 2002; Iizumi et al., 2014; Lobell and Burke, 2010; Phillips et al., 1998; Thornton et al., 2009) and may not suffice for smaller spatial scales where heterogeneities exist. For example, above normal rainfall season may result in low yields related to nutrient leaching depending on soil types. High rainfall variability exist in small regional extents even in an otherwise "good rainfall season" and statistical relationships do not capture rainfall characteristics (such as distribution during a season and frequency) that are important for crop yields. Weaknesses related to the use of large scale climate indices to forecast yields are highlighted in Mjelde and Keplinger (1998). Poor records of historical yields on which the statistical models are calibrated also influence prediction skill.

Confronted with the current climate change and variability together with climate teleconnections between a region of interest and other parts of the globe, any past statistical relationships between yields and climate indices may no longer hold true because the future will be under climate regimes (variability) not observed before. It is not clear if the relationships between phenological observations and satellite derived vegetation indices will hold true since observations will also be under different climate regimes (for example higher temperatures than in the historical period) and since crop response to climate is not linear (Porter and Semenov, 2005), mean historical observations may not suffice. Most studies related to yield impacts modelling over East Africa use GCM outputs to assess future climate change impacts on yields. In this study, we explore the use of seasonal forecasts and crop models to simulate yields at the shorter seasonal scales that determine year-to-year food production.

This work explores the use of dynamical seasonal climate forecasts based on Global Climate Models to simulate agricultural impacts. We assess ensemble (probabilistic) predictive skill of maize yields based on GCM seasonal climate forecasts via both baseline and hindcasts validation for the period 1981–2010. The aim is to identify lead times and areas of potential pre-season yield forecasting based on seasonal climate forecasts and maize planting dates. We assess how well yield forecasts capture observed/reference yield anomalies due to inter-annual climate variability and climate anomalies.

Because of inherent biases in climate models, bias correction of model output is important for impact studies. For example, biases in temperature would grossly affect simulation of maize phenology which depends on (cumulative) thermal time units during growing period. This study therefore uses bias corrected climate forecasts.

2. Materials and methods

2.1. Model description

Hindcast grid point maize yield forecasts over East Africa are simulated using the World Food Studies crop simulation model (WOFOST); a simulation model for the quantitative analysis of the growth and production of annual crops. WOFOST is a detailed model with respect to crop physiology allowing for example a specification of regionally used varieties. It was originally developed to simulate crop