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Research Paper

Dynamical-statistical projections of the climate change impact on agricultural production in Benin by means of a cross-validated linear model combined with Bayesian statistics

O.H.R. Awoye[a,*], F. Pollinger[a], E.K. Agbossou[b], H. Paeth[a]

[a] Institute of Geography and Geology, University of Würzburg, Am Hubland, 97074 Würzburg, Germany
[b] Laboratory of Hydraulics and Water Management (LHME), University of Abomey-Calavi, 01B.P. 526 Cotonou, Republic of Benin

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ABSTRACT

West Africa is highly vulnerable to climate change and a robust quantification of the societal impacts of climate change is essential to guide the necessary adaptation efforts. Here, we project the potential impacts of climate change on nine important crops using climate change information from a gridded observational data set and a high-resolution regional climate model driven with and without land use changes. Probabilistic crop models are developed and forced with climate predictors until 2050. It is found that large-scale climate predictors are sufficiently robust for crop modelling in the absence of reliable local climate information. Pineapple, maize, groundnuts, cassava and cowpeas will face harmful effects with an average yield reduction in the range of 11%–33% by 2050, whereas sorghum, yam, cotton and rice will benefit from climate change with an average yield gain of 10–39%. Temperature increase rather than precipitation change is responsible for the projected yield changes. Our study also shows that land cover degradation in West Africa tends to reduce yield for most crops whilst favouring the production of yam and cotton.

1. Introduction

Sub-Saharan West Africa is highly vulnerable to natural hazards induced by climate variability and change. During the last century the region had to cope with severe multi-year droughts in the 1970s and 1980s (Mahe and L'hote, 2001; Nicholson, 2001). In the last decade, the region was also ravaged by unusual floods caused by extreme rainfall events (Paeth et al., 2011a). These extreme climatic and meteorological events strongly weighted down on the hydrological systems, the food production systems and other ecological systems (Di Baldassarre et al., 2010). Considering the agricultural sector, it is now on record that climate has been the main driver of fluctuations in food production globally and, in particular, in the developing countries across the low latitudes (Deryng et al., 2014; Lobell et al., 2011; Lobell and Ortiz-Monasterio, 2007). This is especially true in sub-Saharan West Africa where rain fed agriculture as the backbone of economy is still at the mercy of climate and weather variations. Moreover, many scientists studying future changes in the African climate system have been warning about warmer and drier future conditions in many parts of the continent (Paeth et al., 2011b; Sheffield and Wood, 2008), which may in turn affect the viability of agricultural production and threaten food security in West Africa. Henceforth, a robust quantification of the potential climate change impacts is needed to develop early warning systems and secure the livelihoods of the population in West Africa.

So far, research dedicated to the impacts of anthropogenic climate change on the agricultural sector uses statistical or process-based crop models driven by local climate change information (e.g. Roudier et al., 2011 and references therein). Therefore, translating climate model output into crop yield is still difficult because meteorological station data is often sparse and state-of-the-art regional climate models (RCMs), which operate at spatial resolutions much higher than global climate models (GCMs), are not yet able to resolve smaller-scale and local meteorological processes such as convection. Hence, post-processing of the direct climate model outputs via statistical downscaling and error correction (SD) methods is used to bridge the gap between the coarser information from RCMs and the local or fine-scale information often required to drive impact models (Maraun et al., 2010). In a review of state-of-the art statistical downscaling methods Ehret et al. (2012) reported

* Corresponding author.
E-mail addresses: herve.awoye@uni-wuerzburg.de, herve.awoye@gmail.com (O.H.R. Awoye).

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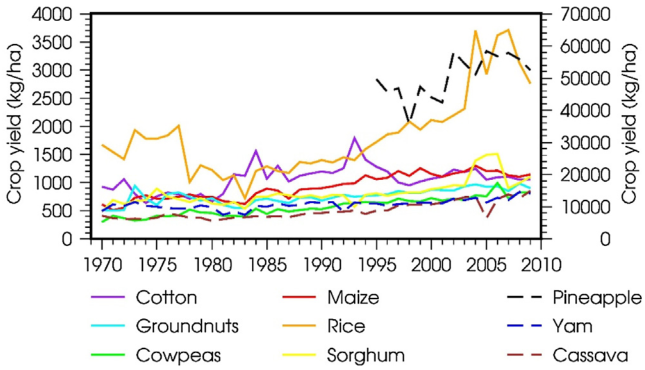

Fig. 1. Crop yield statistics in Benin. The plain lines refer to the left-hand side y-axis and the dashed lines to the right-hand side y-axis.

that the SD methods do not account for the spatial and temporal covariance structures in the atmospheric fields being corrected and its sensitivity to climate change scenarios. In areas where the network of meteorological stations is sparse (e.g. West and Central Africa) the spatial representativeness of the long-term observational climate data used in the calibration of the SD functions may also be questioned (Harris et al., 2014; Jung et al., 2012). Therefore, this study uses large-scale climate predictors instead of statistically downscaled local climate predictors.

Although local climatic features and sub-grid scale processes are not yet well reproduced by RCMs, there is good agreement on their reliability with respect to larger-scale atmospheric dynamics. Therefore, in contrast to other studies our approach addresses patterns of precipitation and near-surface air temperature as climate predictors that are governed by large-scale atmospheric circulation, to project crop yield changes in West Africa under present-day and future climate conditions. A robust statistical crop modelling approach is developed and applied to nine economically important crops in the region. The selected crops – staple food crops and cash crops – are among those being promoted for agricultural diversification in the Republic of Benin through their strategic plan for the revival of the agricultural sector (MAEP, 2011). Here, a statistical crop modelling approach is preferred due to its simplicity of implementation and minimum calibration data requirement. The approach allows for assessing the impacts and uncertainties and for a better understanding of the underlying processes, sometimes poorly understood in process-based crop models (cf. Lobell et al., 2006; Lobell and Burke 2010). Most existing process-based crop models are developed for industrialised regions where high-yielding crop varieties are grown. Thus, they cannot adequately be applied in developing countries where local cultivars are usually grown without prior recalibration of many growth parameters (Folberth et al., 2012). Statistical crop modelling is considered a good alternative when crop specific process-based models are not yet developed, sufficiently calibrated nor tested (Lobell et al., 2006).

The objectives of this study are threefold: (i) projecting the potential impacts of anthropogenic climate change on crop productivity in West Africa and assessing the range of uncertainty, (ii) improving our understanding of the underlying processes by determining the relative importance of temperature and precipitation changes, and (iii) assessing the indirect effects of man-made land cover changes on future crop yields. We take the Republic of Benin as a case study in West Africa with good data availability and hypothesise that in a rain fed cropping system with little technological investment yield variations are mainly controlled by climatic factors. Agriculture, mainly rain fed, is the main driver of economic growth in this country. The agricultural sector in Benin employs about 70% of the labour force and accounts for nearly 40% of the gross domestic product and roughly 88% of the official export revenue (CIPB, 2007).

The next two sections are dedicated to the employed data and methods, respectively. The results are presented in Section 4 and discussed in Section 5. In the last section, the main conclusions are drawn and a brief outlook is given.

2. Data sets

In this study, agricultural yield data for the Republic Benin are obtained from the statistical division of the Ministère de l'Agriculture, de l'Elevage et de la Pêche (MAEP, 2010; MDR, 2004) which is the official provider of agricultural statistics in the country. The data are collected at the administrative level and aggregated to the country level. They extend over the agricultural campaigns from 1970/1971 to 2009/2010, except for pineapple for which there are not available before 1995. Fig. 1 displays the time series of crop yield, indicating a slight increase for most crops and a strong enhancement of rice production during this period.

Fig. 2 shows the cropping calendar used in this study. We have combined for each crop the growing seasons in the northern and southern parts of the country. Let us also note that the staple food crops with a short production cycle (e.g. maize: 90 days, groundnuts: 90–120 days) are cultivated twice in a year in the southern part of Benin due to the bimodal distribution of the rainfall in that part of the country.

Observed precipitation and mean near-surface air temperature are considered over the northern hemispheric part of Africa (0°–40°N; 20°W–40°E). This domain is displayed as a red rectangle in Fig. 3. The climatic data are derived from the 0.5° × 0.5° monthly gridded global data set CRUTS3.1, compiled by the Climatic Research Unit of the University of East Anglia (hereafter referred to as CRU) and spanning the time period 1901–2009. The CRU database is constructed from quality-checked stations data interpolated as a function of latitude, longitude and elevation using triangulated linear interpolation (Harris et al., 2014). It has previously been used in many agricultural impact studies (e.g. Lobell and Field 2007; Berg et al., 2010; Osborne and Wheeler 2013; Shi and Tao 2014).

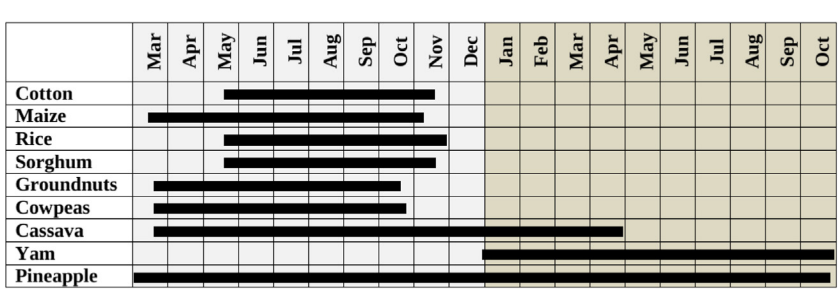

Fig. 2. Cropping calendar for each of the crop considered in the study. The bar indicates the duration from the earliest sowing/planting to the late harvest. Note that pineapple grows over two years.