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Impact of climatic variables on the spatial and temporal variability of crop yield and biomass gap in Sub-Saharan Africa- a case study in Central Ghana

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ABSTRACT

We investigated the impact of climate variables on yield and biomass gap variability in two humid topical regions, Brong-Ahafo and Ashanti region, of central Ghana using the crop model LINTUL5 embedded into a general modeling framework, SIMPLACE (Scientific Impact Assessment and Modelling Platform for Advanced Crop and Ecosystem Management). The simulations were run using a late maturity maize variety (*Obatanpa*) and historical weather data (1992–2007) across the 18 districts of the regions studied. The simulated maize yield and biomass production under water-limited conditions varied spatially which was significantly correlated with the solar radiation and precipitation in the crop growing period ($R^2 = 0.99$; $p < 0.05$), whereas, associated temporal variability in the simulated maize yield was significantly correlated with the radiation in the crop growing period ($R^2 = 0.96$; $p < 0.05$). The temporal variability in the simulated potential biomass production was significantly correlated with the solar radiation and average temperature in the crop growing period ($R^2 = 0.93$; $p < 0.05$), postulating that the solar radiation and the mean temperature are the limiting climatic factor in the study regions. Yield gaps and biomass gaps ranged between 8.8 Mg ha^{-1} to 10.0 Mg ha^{-1} and 14.8 Mg ha^{-1} to 17.1 Mg ha^{-1} respectively across the districts. Thus average farmer's yield and biomass is only 17% and 13% of the simulated water-limited yield and biomass respectively. The spatial and temporal variability in yield gap was positively correlated with the radiation during the crop growing period. Associated spatial variability in biomass gap was positively correlated with radiation and negatively with the precipitation, whereas temporal variability in the biomass gap was positively correlated with the radiation during the crop growing period. Thus, under the current input intensities in humid, tropical Central Ghana, neither maize grain and biomass yields nor the potential water limited yields are significantly positively related to precipitation during the growing cycle. Closing the large yield gaps will require in the first place adequate supply of nutrients.

1. Introduction

Agriculture is certainly the most vulnerable sector in Sub-Saharan Africa (SSA) (Roudier et al., 2011). In SSA crop yields are highly dependent on climate fluctuations, as agriculture is mostly rainfed (96% of all agricultural land, World Bank, 2013). Yields of crops must increase substantially over the coming decades by 70–100% to keep pace with food demand driven by increasing population and income growth which is expected to reach over 9 billion people by 2050 (Svubure et al., 2015; Dubois, 2011) with largest increase rates in SSA. On the other hand, SSA remains the region with the lowest crop productivity per hectare (highest yield gap) and lowest adaptation capacity to the expected climatic changes (Sultan and Gaetani, 2016; Roudier et al., 2011; Müller et al., 2010; Challinor et al., 2007).

Ultimately global food production capacity will be limited by the amount of land and water resources available and suitable for crop production (Van Ittersum et al., 2013). However, estimates of land available for cropland expansion in SSA are also contested (Chamberlain et al., 2014). Therefore, existing cropland will need to produce substantially greater than current yield levels. However, in some regions, despite having favorable weather conditions, a large exploitable gap exists between current and achievable yields under ideal agronomic management conditions. In SSA, estimating yield gaps is important because such analysis provides an indicator for prioritizing the most important crop, pinpointing factors limiting the current productivity and identifying local or regional yield

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gap (Yg) hotspots. These assessments may help setting agendas in policy development and research prioritization where current information is scarce (Sherbinin, 2014).

Besides grain yield, currently, the increasing global demand for biomass, as primary agricultural products and feedstock for various forms of usage, has started to change the global agricultural production and price structure. This rise in global biomass demand is an opportunity for many agricultural-based, low-income economies, like sub-Saharan countries, to diversify their economies and generate income which in turn could address the food security problems by providing better access and buying capacity of the food (Mauser et al., 2015).

The yield/biomass gap of a crop grown in a certain location and cropping system is defined as the difference between the yield and biomass under optimum management and the average yield/biomass achieved by farmers. Yield under optimum management is labeled as potential yield (Yp) under irrigated conditions or water-limited potential yield (Yw) under rain-fed conditions (Van Ittersum et al., 2013). Yp is location specific because of the climate, and not dependent on soil properties assuming that the required water and nutrients are non-limiting and can be added through management. Thus, in areas without major soil constraints, Yp is the most relevant benchmark for irrigated systems. Whereas, for rain-fed crops, Yw, equivalent to water-limited potential yield, is the most relevant benchmark (Van Ittersum et al., 2013). Both Yp and Yw are calculated for optimum planting dates, planting density and region-specific crop variety which is critical in determining the feasible growth duration, particularly in tropical climatic conditions where two or even three crops are produced each year on the same field (Van Ittersum et al., 2013).

Recently, Van Ittersum et al. (2013), compared different methods namely, i) derivation of Yp or Yw from upper percentiles of farmer's yield distributions; ii) maximum yields measured in experimental stations, growers contests, or highest-yielding farmer's fields; iii) boundary-function analysis based on the relationship between farmer's yields and water supply; and iv) site-specific simulation of Yp or Yw using crop growth simulation models. Crop simulation is the most reliable way to estimate Yp or Yw and Yg in the context of a specific crop within a defined cropping system because crop models account for interactions among weather, soils, and management. Crop models capture spatial and temporal variations in Yp and Yw, while other methodologies fail to do so (Van Bussel et al., 2015).

To increase food production, identifying the regions with untapped production capacity is of prime importance and can be achieved by quantitative and spatially explicit estimates of Yg, thus considering the spatial variation in environment and the production system. Currently, a great deal of attention is paid to mean historical and future climate change that affects crop yields. However, how variations in climate impact crop yield and their variability over space and time, has received less attention. This is important to understand that how climate and crop yields, as well as associated yield gaps, are linked over space and time.

The aim of the study is therefore to investigate the linkage between spatial and temporal variability of climate variables and the variation of yield and biomass gaps in space and time using a model based approach in central Ghana which constitutes a major maize production area in the country.

2. Materials and methods

2.1. Study region and simulation units

This study was carried out in two regions in Ghana, namely, the Ashanti and the Brong-Ahafo regions. The Ashanti Region is an administrative region in Ghana centrally located in the middle belt of Ghana. It lies between longitudes 0.15° W and 2.25° W, and latitudes 5.50° N and 7.46° N and occupies a total land surface area of 24,389 km^2. The region has an average annual rainfall of 1270 mm and two rainy seasons. The major rainy season starts in March, with a major peak in May. There is a slight dip in July and a peak in August, tapering off in November. December to February is dry, hot, and dusty. The average annual mean temperature is about 27 °C. Much of the region is situated between 150 and 300 m above sea level. The Brong-Ahafo Region is also an administrative region in Ghana centered around latitude 7.75° N and longitude 1.5° W, occupying a total land surface of 39,557 km^2. The region has a tropical climate, with high temperatures averaging 23.9 °C and a double maxima rainfall pattern. Mean annual rainfall ranges, from an average of 1000 mm in the northern parts to 1400 mm in the southern parts. In this study, the simulations were run at 10 km × 10 km grid cells (i.e., simulation unit) across the two target regions (Ashanti and Brong-Ahafo) (Fig. 1). There were 23 and 39 grids cells in Ashanti and Brong-Ahafo regions respectively. Information about data sources, procedures to generate the data in detail are explained in section 2.2. Maize yield and total above ground biomass were calculated for each simulation grid for the period of 16 years (1992–2007) and aggregated from the simulation grid to the district level for comparing them with the observed yields provided by the Agriculture Statistics & Census Division, Ministry of Agriculture, Ghana.

2.2. Climate and soil data

Climate data is the driving force in crop simulation and in order to run simulations weather data must match the requirements of crop models (Donatelli et al., 2015). The climate data was made available from the Terrestrial Hydrology Research Group, Princeton University (http://hydrology.princeton.edu/data.php) at a resolution of 10 km × 10 km. The dataset was constructed by combining a suite of global observation-based datasets with the NCEP/NCAR reanalysis. Known biases in the reanalysis precipitation and near-surface meteorology have been shown to exert an erroneous effect on modeled land surface water and energy budgets and are thus corrected using observation-based datasets of precipitation, air temperature, and radiation. Corrections are also made to the rain day statistics of the reanalysis precipitation which have been found to exhibit a spurious wave-like pattern in high-latitude wintertime. Comparison of available measured rainfall in the crop growth period from two stations (namely Kumasi and Sunyani) in the area of interest with the interpolation results are shown in Fig. 2a and b. Wind-induced under catch of solid precipitation is removed using the results from the World Meteorological Organization (WMO) Solid Precipitation Measurement Intercomparison. Precipitation is disaggregated in space to 1.0 ° by statistical downscaling using relationships developed with the Global Precipitation Climatology Project (GPCP) daily product. Other meteorological variables (downward short- and longwave, specific humidity, surface air pressure and wind speed) are downscaled in space taking into account changes in elevation. The dataset is evaluated against the bias-corrected forcing dataset of the second Global Soil Wetness Project (GSWP-2). The final product provides a long-term, globally consistent dataset of near-surface meteorological variables that can be used to drive models of the terrestrial hydrological and ecological processes for the study of seasonal and inter-annual variability and for the evaluation of coupled models and other land surface prediction schemes (Sheffield et al., 2006). Values for relevant soil parameters for each soil layer down to maximum soil depth (sand, silt, clay, gravel content, cation exchange capacity, pH, organic carbon and bulk density) were extracted from the soil property maps of Africa at 1 km × 1 km resolution (http://www.isric.org/data/soil-property-maps-africa-1-km). Other parameters such as