Spatial Heterogeneities of Warming Impacts on Corn Yields in Ghana

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Abstract

In this study we utilize a panel of subnational district-level yields for corn matched to weather data that is spatially interpolated from observed weather station data to identify whether warming impacts exhibit spatial heterogeneities for both the mean and variance of corn yields in Ghana. Results are expected to demonstrate that there exist pertinent regional differences in climate change impacts. Some of these differences will likely be attributed to the localized change in climate, while others will likely be associated with particular agronomic characteristics (e.g. soil type) that can partially mitigate (or exacerbate) the effects of warming temperatures. Climate change impacts on agriculture have been widely researched in recent years. In Sub-Saharan Africa (SSA), many of these studies have focused on spatially aggregate impacts at the country or higher level, and typically do not discuss the heterogeneity of within-region impacts. Thus, there is a growing interest in more localized climate change impacts that could help inform regional adaptation within a country. Globally, climate change is estimated to have adverse effects on crop yields. With agriculture being the mainstay of many economies in SSA, it is expected that these economies are especially vulnerable to climate change. Ghana is one of the fastest growing economies in SSA (World Bank Report, 2015). Over 20 percent of gross domestic product (GDP) and two-thirds of agricultural GDP in Ghana are staple crops and livestock production (OECD Report, 2010). It is therefore important to quantify the effect of climate change on crop yields in Ghana. In addition, we explore the extent to which impacts might vary across different agronomic regions of the country as this can aid producers and policy makers in defining potential adaptation mechanisms.

Keywords: corn, yields, climate, change, Ghana

1 Introduction

Climate change impacts on agriculture have been widely researched in recent years. Many of these studies have focused on spatially aggregate impacts at the country or higher level, and typically do not discuss the heterogeneity of within-region impacts. Thus, there is a growing interest in more localized climate change impacts that could help inform regional adaptation within a country. For example, if there exist large negative effects in the southern (warmer) regions versus more moderate impacts in the northern (cooler) regions, then one form of potential adaptation could be a northern shift of key production regions. It is also possible that certain regions are more robust to warming temperatures because of localized agronomic considerations, in which case production might shift toward these regions.

Globally, climate change is estimated to have adverse effects on crop yields. With agriculture being the mainstay of many economies in Sub-Saharan Africa (SSA), it is expected that these economies are especially vulnerable to climate change. Ghana is one of the fastest growing economies in SSA (World Bank Report, 2015). Over 20 percent of gross domestic product (GDP) and two-thirds of agricultural GDP in Ghana are staple crops and livestock production (OECD Report, 2010). It is therefore important to measure the extent of the perceived shocks of climate change to crop yields in Ghana. But more importantly, measuring the varying impacts that might exist across various agronomic and climatic growing areas within Ghana is key for informing effective adaptation decisions.

Previous studies on climate change impacts on agriculture in SSA have primarily focused on estimating country level impacts, or they have restricted the effect of temperature exposure to be the same across regions in which case all the warming effects are driven by localized climate change. Other studies that have estimated within-country heterogeneities have mainly relied on the use of gridded weather data. Most of these studies were constrained by poor data availability. Whereas the use of gridded data can be very useful in showing within-country heterogeneities, most gridded data available for SSA are limited by the use of low weather gauge density observed at the monthly level. These data likely artificially smooth localized weather exposure both cross-sectionally and temporally, thereby bringing into question the accuracy of the estimated impacts.

The goal of this study is to estimate warming impacts for Ghanaian corn production using observed field yield data and weather data generated from relatively high density daily observations. Our focus is on estimating regional warming impacts while allowing for the effect of warming to vary cross-sectionally. While previous studies have primarily focused on mean (average) yields, we also consider effects on yield risk (e.g. yield variance and/or the coefficient of variation). The remainder of this document is organized as follows; section two provides the rationale of the proposed research, section three reviews the literature, section four introduces the conceptual framework and econometric model, section five discusses the data, and section six presents the expected results.

2 Rationale and Objectives of Study

Accurate modelling of localized climate change impacts is crucial for appropriate design and adoption of adaptation actions. Several studies have modeled the impacts of climate change on agriculture both globally and specifically in Ghana and other Sub-Saharan African countries (e.g. Rosenzweig and Parry, 1994; Mearns et al., 2001; Ben et al., 2002; Challinor et al., 2007; Liu et al., 2008; Lobell et al., 2008; Schlenker and Roberts, 2009; Schlenker and Lobell, 2010; Lobell and Burke, 2010; Roudier et al., 2011; Bilham, 2011; Lobell et al., 2011; Rowhani et al., 2011; Urban et al., 2012; Ward et al., 2013; Tack et al., 2014; Ray et al., 2015). There are two distinct approaches that have been widely used for estimating climate change impacts on crop yield; statistical modelling (e.g. regression analysis) and process based modelling (e.g. plant growth simulators). Both approaches have strengths and weaknesses for identifying warming impacts. Another important consideration for modelling climate impacts is the type of data used where one must choose among sponsored field trial data or on-farm data combined with geospatial weather data available at varying resolutions derived from various weather gauge densities. Each of these data types have their own implications for modelling.

Despite the varying approaches for modelling climate change impacts on crop yield, the literature has been consistent about the need to use fine scale on-farm data for yield modelling. This improves the accuracy of estimated climate change impacts (Schlenker and Lobell, 2010; Ray et al., 2015). We focus here on the statistical modelling approach which has the advantage of measuring impacts based on observable data. We utilize a panel of subnational district-level yields for corn matched to weather data that is spatially interpolated from observed station data. The main objective is to identify whether warming impacts exhibit spatial heterogeneities for both the mean and variance of yields.

3 Literature Review

This section provides a background on modelling climate change impacts for crop yields. This review is organized into three sections: background on climate change impacts on crop yields; empirical modelling of climate change impacts on crop yields; and background information of the study area.

3.1 Climate Change Impacts on Crop Yields

Climate change impacts on crop yields have been widely researched using a wide variety of approaches. These studies have been consistent in finding adverse effects of climate change (e.g. Mearns et al., 1996; Mearns et al., 1997; Amissah-Arthur and Rosenzweig, 2002; Schlenker and Roberts, 2009; Schlenker and Roberts, 2009; Lobell et al., 2011; Urban et al., 2012; Wheeler and von Braun, 2013; Osborne and Wheeler, 2013; Tack et al., 2014; Zubler et al., 2014; Ray et al., 2015).

Climate change is largely attributed to increased levels of atmospheric carbon dioxide, as well as fluctuating precipitation and temperatures. There is enough scientific evidence that temperatures have increased over the last two decades (IPCC, 2007). Crops have their climatic thresholds beyond which yields are adversely affected. Currently, most crops are near their climatic thresholds thus crop yields are expected to decline both in quantity and quality (White et al, 2006). Studies by Urban et al. (2012); Schlenker and Roberts (2009); Osborne and Wheeler (2013) all reinforce the fact that there are expected reductions in yields for crops that are near their climatic thresholds.

Different crops have different climatic thresholds, it is therefore expected that changing climatic conditions would have varying effects on yields for different crops. A study by Schlenker and Roberts (2009) examined nonlinear temperature effects on yields of corn, soybeans, and cotton. They found that yields increase with temperature up to 29°C for corn, 30°C for soybeans, and 32°C for cotton but that temperatures above these thresholds are very harmful. How increasing temperatures affect yields for different crops could go as far as being different for different varieties of a specific crop. In a study by Tack et al. (2014) results showed that effects of warming and drought vary across varieties of wheat.

3.2 Empirical Modelling of Climate Change Impacts on Crop Yields

The literature on modelling climate change impacts on crop yields is diverse in terms of the moments of distribution considered, the type of data used, and the modelling approach. Most studies have focused on estimating the impacts of climate change on mean crop yields. These studies have generally pointed out possible reductions in yields (e.g. Schlenker and Roberts, 2009; Schlenker and Lobell 2010; Lobell et al., 2011; Tack et al., 2014). A relatively smaller but gradually growing body of work has focused on the impacts of climate change on the variance of crop yields (e.g. Mearns et al. 1996, 1997; Reilly 2003; Rowhani et al., 2011 Urban et al., 2012). Also, Tack et al. (2012) examined the effects of climate change on higher order moments of crop yields, where they estimated the entire crop yield distribution using the concept of maximum entropy.

The type of data used for modelling climate change impacts on crop yields can influence the accuracy of measurements made and the overall usefulness of a study. In regions like Africa that are considered to be data-poor regions (Lobell et al., 2011), researchers have used different forms of data to estimate climate change impacts. Whereas on-farm yield data is more likely to represent the true cropping scenario of the average farmer, field trial data is potentially unrepresentative if the on-farm production practices differ greatly from those used in the trials. Regarding the spatially interpolated weather data, the density of the underlying weather stations is a crucial determinant for accurately measuring localized exposure.

There are two distinct approaches that have been widely used for modelling climate change impacts on crop yield, statistical modelling and process based modelling. Process based models represent the physiological processes of crop growth and development in response to climate (Roudier et al., 2011). This approach allows for capturing detailed effects of weather, soil conditions, management practices and abiotic stresses on crop growth (Blanc and Sultan, 2015). However, these models are difficult to calibrate because of a large number of uncertain parameters, a problem that becomes even challenging to overcome if one is interested in allowing the effects of weather to vary cross-sectionally as each location would require a (potentially) unique parameter that is known to the researcher *ex-ante*.

Statistical modelling involves linking historical crop yields and various weather variables such as temperature and precipitation. There are three main types of statistical methods based on the type of data used that are found in the literature: time series methods which are based strictly on observed data across time at single location, cross-sectional methods which are based solely on variations across locations at a single point in time, and panel methods which are based on variations across both time and space. Of these the latter is predominantly preferred as it combines the strengths of the previous two. The key advantage of the statistical approach is that the parameters linking weather/climate to yields are determined *ex-post* from observed data.

3.3 Background Information of Study Area (Ghana)

Ghana is within latitude 4°44'N and 11°11'N; and longitude 3°11'W and 1°11'E. The total land area of Ghana is 92,099 square miles. There are five main agro-ecological zones defined on the basis of climate, as reflected by vegetation and soils. These are rain forest, deciduous forest, transitional zone, coastal savannah, and northern savannah. The tropical eastern coastal belt is warm and comparatively dry, the south west corner is hot and humid, and the north is hot and dry. Annual average temperatures range from 26.1°C in the south to 28.9°C in the extreme north (MoFA Report, 2010). Also as shown in figure 1, average monthly temperatures vary from as high as 29.9°C to as low as 25.6°C, thus it is expected that daily temperatures would also vary significantly. It is also interesting to note that as shown in figure 2, the topographical landscape of Ghana is non-uniform, thus changes in temperature are expected to vary across time and over space.

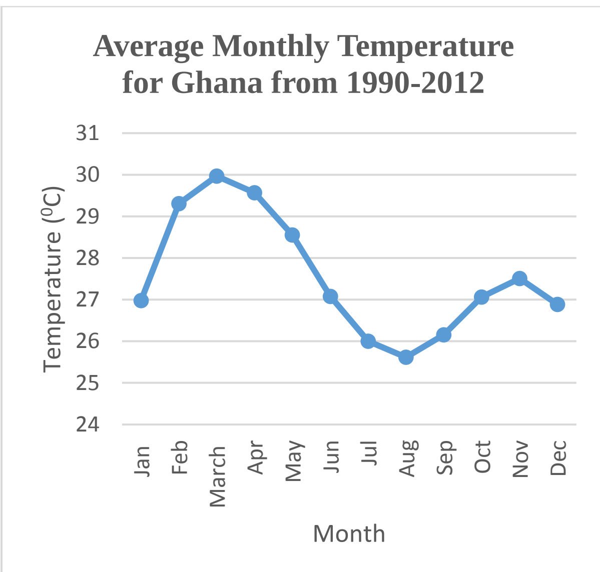

Fig 1: Average monthly temperature for Ghana from 1990-2012.
Data Source: Climatic Research Unit (CRU) of Uni. of East Anglia

Fig 2: An elevation map showing the varying topographical landscape of Ghana. Source: UNEP/GRID-Arendal

Many studies considering the impacts of climate change on crop yields at a global scale or in Sub-Saharan Africa have considered impacts on Ghana, at least on the national level (eg. Schlenker and Lobell 2010; Ray et al 2015). Other studies that have focused on the impacts of climate change on crop yields specifically in Ghana have either considered impacts at specific locations or a number of locations in a particular region of the country (eg.; Tachie-Obeng et al., 2013; Owusu-Sekere et al., 2011 a, b; Fosu-Mensah, 2012; Adjei-Nsiah and Kermah, 2012; Amikuzuno and Donkoh, 2012). These literature have consistently shown that climate change will have negative impacts on crop yields in Ghana and that the impacts are expected to vary across locations within the country.

Ghana is comprised of 110 agricultural districts. These districts have varying climatic and soil conditions that allow for growing of specific crops. However, there are some crops that are grown across the entire country. Agriculture is predominantly rain-fed and on smallholder bases, with about 90 percent of farm holdings being less than 2 hectares in size (MoFA Report, 2010).

4 Conceptual Framework and Econometric Model

This section presents the econometric model and framework employed for this study. It is organized into two subsections; modelling the effects of weather on yields, and estimating the impacts of warming on yields.

4.1 Modelling the Effects of Weather on Yields

The moment-based approach of Antle (1983, 2010) is used to show the impacts of warming on the first (mean) and second (variance) moments of yield. The mean equation is given in equation (1):

$$\log(y_{it}) = \alpha_i + \beta_1 t + \beta_2 p_{it} + \beta_3 p_{it}^2 + \beta_4 gddl_{it} + \beta_5 gddm_{it} + \beta_6 gddh_{it} + \varepsilon_{it} \qquad (1)$$

where y_{it} is the yield of the *i*th district in year t; α_i is the district fixed effect; t is a trend variable used to capture changes in technology over time; p_{it} is precipitation; $gddl_{it}$ captures the intensity of low temperatures, $gddm_{it}$ captures the intensity of medium temperatures, and $gddh_{it}$ captures the intensity of high temperatures at various temperature thresholds; and ε_{it} is the error term. The

$gddl_{it}$, $gddm_{it}$, and $gddh_{it}$ temperature variables are measured in growing degree days following the piecewise linear approach of Schlenker and Roberts (2009). These variables are growing season aggregates of daily measures based on their approach for interpolating temperature exposures between daily observed minimum and maximum values. This interpolation approach is crucial for accurately measuring extreme heat exposure and is preferred to other approaches that rely on average daily temperatures.

The error term, ε_{it} from equation (1) is used to estimate the variance of crop yield by squaring the estimated residuals and regressing them on the same variables in equation (1). Denoting weather variables by w_{it}, the conditional mean and variance are defined as $\mu_{itc} = E\left(y \middle| w_{it}, t_c\right)$ and $\sigma^2_{itc} = E\left(\varepsilon^2 \middle| w_{it}, t_c\right)$ respectively, where c is used to denote current technology (i.e. the trend variable is set to the most recent year in the data). The parameters of the mean and variance equations are estimated using ordinary least squares, and these parameters are used to predict estimates of the mean and variance $\hat{\mu}_{itc}$ and $\hat{\sigma}^2_{itc}$ respectively. From the district-specific the mean $\hat{\mu}_{itc}$ and variance $\hat{\sigma}^2_{itc}$, the coefficient of variation $\hat{C}V_{itc}$ is estimated as the ratio of the standard deviation (square root of variance) to the mean. This measure of dispersion is preferred over the variance as it is a unitless measure of yield risk that permits easier comparisons across districts.

4.2 Estimating the Impacts of Warming on Yields

To model the effect of warming temperatures on the mean and CV, we follow the approach previously discussed above. In a warming scenario where there is an s shift in temperature, the daily maximum and minimum temperatures become $T_{\max} + s$ and $T_{\min} + s$ respectively, which are used to recalculate new growing degree days for high, medium, and low temperature exposures as in equation (1). The same parameter estimates are used to predict estimates for the new mean and CV under each warming scenario.

Following Tack and Ubilava (2013) the impacts of warming on mean crop yields is measured as the percentage change in the mean under warming scenarios relative to the mean of the baseline. Here, baseline climate is represented by the historical average of the in-sample temperature variables, whereas the warming scenarios are represented by the average of those same data shifted up at the daily level. This is done within each district so that the impact for district i is;

$$impact_i^s = 100\frac{\hat{\mu}_{itcs} - \hat{\mu}_{itc}}{\hat{\mu}_{itc}}$$

where $impact_i^s$ is the percentage change in mean yield for each district i under warming effect (a shift in temperature s). $\hat{\mu}_{itcs}$ is the predicted mean yield for each district i under warming, and $\hat{\mu}_{itc}$ is the predicted mean yield for each district under baseline climate. The impacts on the coefficient of variation are calculated in a similar manner.

5 Data

5.1 Crop Yield Data

This study focuses on corn production in Ghana. Corn is the most important cereal crop on the Ghanaian domestic market (FAO Report, 2012). Yield data are measured in tons/ha for 110 districts and were obtained from the Ghana Ministry of Food and Agriculture (MoFA) for the years 1992–2010. This data covers the entire land area of Ghana.

5.2 Climate Data

As noted by Rowhani et al (2011) higher weather gauge densities are important for representing local climatic heterogeneities when data is spatially interpolated. Many studies that have worked on climate change impacts in SSA (e.g., Lobell et al, 2008; Schlenker and Lobell, 2010 and Ray et al 2015) have relied on monthly gridded datasets from Climate Research Unit (CRU). However, for most regions in SSA these datasets are limited by the use of low density gauge observations for spatially interpolating datasets, as evidenced in the work of Rowhani et al (2011) for Tanzania. We have obtained daily minimum and maximum temperatures and precipitation from the Ghana Meteorological Agency (GMA) for 20 different weather stations across the entire country for the years 1992–2010. In order to link weather data with yields for each agricultural district, daily minimum and maximum temperatures and precipitation will be spatially interpolated. To calculate growing degree days, we will take into account the growing season for corn. Corn in Ghana is typically grown from April to June, though growing seasons might vary depending on specific ecological zones.

6 Expected Results

It is expected that there will be spatial heterogeneities of warming impacts on the mean and variance of corn yields in Ghana. However, what is less certain is how these differences will materialize spatially. For example, two districts might have the same impact but be very different from a third. We will take much care if trying to determine to appropriate clustering of warming impacts within Ghana. The empirical findings of this study would not only be helpful in showing where and by much warming impacts are going to change yields but also how these changes are going to vary over time. This will be helpful in informing food security and stability adaptation decisions related to climate change in Ghana.

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