Impact of climate change, weather extremes, and price risk on global food supply

Abstract

This paper provides answers to questions that are prerequisite for policies that address agriculture and climate change. We analyze the determinants of global crop production for maize, wheat, rice, and soybeans over the period 1961–2013. Using seasonal production data and price change and price volatility information at country level, as well as future climate data from 32 global circulation models, we project that climate change could reduce global crop production by 9% in the 2030s and by 21% in the 2050s. We find strong, positive, and statistically significant supply response to changing prices for all four crops. However, output price volatility, which signals risk to producers, reduces the supply of these key global agricultural staple crops—especially for wheat and maize. We find that climate change has significant adverse effects on production of the world's key staple crops. Especially, weather extremes— in terms of shocks in both temperature and precipitation— during crop growing months have detrimental impacts on the production of the abovementioned food crops. Weather extremes also exacerbate the year-to-year fluctuations of food availability, and thus may further increase price volatility with its adverse impacts on production and poor consumers. Combating climate change using both mitigation and adaptation technologies is therefore crucial for global production and hence food security.

Keywords: *Food supply, climate change, weather extremes, price volatility, staple crops, global*
JEL codes: *Q11, Q15, Q54*

1. Introduction

Food insecurity remains to be a critical challenge to the world's poor today. According to estimates by the Food and Agriculture Organization of the United Nations (FAO) one in nine people in the world and about a quarter of those in sub-Saharan Africa are unable to meet their dietary energy requirements in 2014/15 (FAO, 2015). The focus of this study is not food insecurity and hunger per se. It instead addresses a key component of food security, that is, food production. Although a range of factors influence global food security (FAO, 1996), cereal production plays a major role (Parry *et al.*, 2009). In this paper, we seek to empirically evaluate the impacts of population growth (demand), changes in climate and weather extremes, and price changes on global food production. In particular, we analyze global average effects of changes in climate and economic variables on production of the world's principal staple crops, namely wheat, rice, maize, and soybeans. These crops are crucial in combating against global food insecurity as they are the major source of food in several parts of the world, comprising three-quarters of the world's food calories (Roberts & Schlenker, 2009). Maize, wheat, and rice, respectively, are the three largest cereal crops cultivated around the world. They make up more than 75% and 85% of global cereal area and production in 2010, respectively (FAO, 2012). About one-third, of both the global area and production, of total oil crops is attributed to soybeans. Our analysis pools data from 31 major crop producer countries or regions for the 1961–2013 period. These study regions account for greater than 90% of global production of each of these crops in any year since 1991.

Tackling against food insecurity and hunger is more difficult in the face of rising global population, climate change, and high and volatile food prices (Calzadilla *et al.*, 2014; Hertel *et al.*, 2010; Ringler *et al.*, 2013). Increasing global population, which is projected to reach more than 9 billion in 2050, entails that more food needs to be produced. The global food system is challenged by changing demand, due to demographic and income change, and shifting diet preferences in a more urban world. Not just more, but more sustainable production of foods with improved nutrition properties is needed. The other big challenge for food insecurity stems from changes in climate and weather extremes. Under a business as usual scenario, climate change may increase child stunting by about a quarter in Sub-Saharan Africa and by nearly two-thirds in South Asia by 2050 (Lloyd *et al.*, 2011). Climate change has manifested itself with increasing global mean surface temperature, higher rates of temperature and precipitation extremes, and more frequent droughts in some regions (IPCC, 2007). Further climate change is expected to bring warmer temperatures; changes in rainfall patterns; and higher frequency and severity of extreme weather events (Wheeler & von Braun, 2013). Warmer temperature and more frequent exposure to high temperature events are the major drivers of climate change induced yield loss (Thornton & Cramer, 2012). Precipitation—in the form of heavy or too little rainfall or flooding—may prevent farmers to cultivate their croplands at the right time or may result in yield loss. Thus, the effect of climate change on crop production comes not only through its effect on yield but also on acreage allocation. Thirdly, problems of food insecurity and hunger are exacerbated by increases in the level and volatility of food prices. In fact, rising demand and climate change are the major causes of high and volatile food prices (von Braun & Tadesse, 2012). Food price volatility may also increase food insecurity problem since periods of excess food consumption cannot be compensated by periods of inadequate consumption (Kalkuhl *et al.*, 2015). On the other hand, high agricultural commodity prices are expected to bring about positive supply response while price volatility has disincentive effects on producers' resource allocation and investment decisions (OECD, 2008).

Considering these key drivers of food insecurity simultaneously to estimate their impact on global food production is our key contribution. Previous studies that have addressed a similar research question study impact on crop production of 1) climate change only, 2) price change only, and 3) climate and price changes. The first strand of studies considers crop production to be a technical relationship between yield per hectare and climate change variables. These studies, which include Schlenker and Roberts (2010) and Müller *et al*. (2011), fail to account for farmers' potentials to adapt to climatic changes through adjustments in area allocation, input use, crop choice, and other agronomic practices. Other studies that investigate crop production using economic variables (input and output price changes) without considering climate change, such as Arnade and Kelch (2007), Vitale *et al*. (2009), and Haile *et al*. (2014), implicitly assume that the effect of climate variables can be fully captured by economic variables. Although farmers respond to climate changes through adjustments to their price expectations, not all climate and weather variations are predictable in advance such that farmers respond appropriately. In other words, climate change can affect crop production without altering crop prices and price expectations of farmers. The third group of studies—including this study—investigates the impact of not only climate but also economic variables on crop production. These studies, including Weersink *et al*. (2010), Huang and Khanna (2010), (Hertel *et al.*, 2010), and Miao *et al*. (2016), investigate the effect of climate variables on food supply and account for potential acreage and yield adjustments by controlling for responsiveness of farmers to expected input and output prices.

This study differs from the literature, especially from those in the last group mentioned above, in terms of the geographic scope, the level of dis-aggregation employed for the dependent variable, and the proxy used for expected prices. In particular,

- We evaluate for the first time the interlinked global supply effects of climate change, weather variability, and price changes for the four key staple crops worldwide.
- We use production as a proxy for the desired output supply, thereby capturing the impact on crop supply of climate and price variables via their effects on both yield and acreage.
- We appropriately disaggregate country and crop-specific planting and harvesting seasons, and assign the relevant proxy for price expectation and seasonal climate variables in each country and for each crop.
- Because our interest is to estimate the global crop production response to climate and price changes, we aggregate production of each crop at a country level, maintaining the panel feature of the data to be able to control for heterogeneity across countries.
- Moreover, we investigate the effect on production variance of changes in both weather and price fluctuations. We also make short- and medium-term projections on the impact of climate change on production of these crops using climate change forecasts from the Intergovernmental Panel on Climate Change (IPCC)'s fifth Assessment Report (AR5).

Key findings indicate that increasing mean growing season temperature does not seem to be the major problem for crop production. Instead, rising temperature becomes a problem to crop production after some critical level, indicating the commonly found bell-shaped relationship. Following the agronomic literature suggesting that increments in the maximum and minimum growing season temperature may be more critical for development of maize and rice crops (Thornton & Cramer, 2012), we test for these variables and results confirm the assertion. All crops except soybeans respond positively to the number of wet days during the growing season while rainfall anomaly affects production of all crops negatively. The projection analysis further indicates that climate change could reduce average global crop production by an average of 10–20%, depending on the time horizon and global climate models used.

2. Theoretical framework

This section discusses the channels though which our key variables of interest affect global food production. Models of supply response of a crop can be formulated in terms of output, area, or yield response. According to Just and Pope (1978, 1979), the mean and variance of production can be estimated from a stochastic production function of the type:

$$(1) \qquad Q_{it} = f(X_{it}, \varphi) + h_{it}(X_{it}, \phi)\varepsilon_{it}$$

where Q_{it} denotes crop production of country i in period t; X_{it} is vector of climate and price change variables; $f(.)$ and $h_{it}(.)$ are the deterministic and stochastic components of the production function respectively; φ and ϕ are vectors of parameters to be estimated; and ε_{it} is a random error with zero mean and constant or unitary variance.

The stochastic production function given by equation (1) can be expressed for a certain crop in an explicit form with heteroskedastic errors (that allow for the estimation of variance effects) as

$$(2) \qquad Q_{it} = f(X_{it}, \varphi) + u_{it} \qquad E(u_{it}) = 0,\ E(u_{it}u_{is}) = 0, \textit{ for } \ i \neq s$$

$$(3) \qquad E({u_{it}}^2) = exp[W_{it}'\phi]$$

The first stage in evaluating the effect of explanatory variables on crop production involves estimation of equation (2) with heteroskedastic disturbances. The residuals from this stage can be used to estimate the marginal effects of variables determining production variance. The vectors of independent variables (X and W) in the two stages can be similar or different. In this study, we include all climate and weather change; price and price volatility; and population density variables in the first stage, whereas the second stage includes variables that capture short-term climate and price change variables (particularly, weather extremes and price volatility).

Climate and weather extremes

The impact of climate change on crop production has been widely studied (IPCC, 2001, 2007). Changes in climate and weather affect crop production in several ways. High temperature can reduce critical growth periods of crops; promote crop disease; and increase sensitivity of crops to insect pests, thereby affecting crop development and potential yield (CCSP, 2008; Jones & Yosef, 2015). Growing period temperature that exceeds a certain threshold level can damage reproductive tissues of plants and also increase pollen sterility (Roberts & Schlenker, 2009; Thornton & Cramer, 2012). Furthermore temperature variability can affect crop production through yield losses (McCarl *et al.*, 2008). These authors also indicate that climate change affects not only the mean of crop production but also its variability. In this study, we capture the effect of climate change using mean, maximum, and minimum temperature variables during the growing periods of each crop. We also control for temperature deviation and heat stress to account for temperature variation and excessively warm temperature during growing season, respectively.

Besides, low rainfall in arid and semi-arid regions dictates the formation of shallow soils, which are poor in organic matter and nutrients. Inter- and intra-annual rainfall variability is a key climatic element determining the success of agriculture in many countries (Sivakumar *et al.*, 2005). Some empirical evidence shows that the effect on year-to-year variability of crop production of precipitation is larger than that of temperature (Lobell & Burke, 2008). Low or excessive rainfall can affect crop production both through yield and acreage effects. Farmers adjust their crop acreage allocation depending on—onset and magnitude of—planting time rainfall (Sacks *et al.*, 2010). It is therefore important to control for both planting and growing period mean precipitation and standardized precipitation anomaly index (SPAI). In order to capture precipitation extremes, regardless of droughts or flooding, and to give more weight at the extremes, we squared the SPAI variables. The literature suggests that the relationship between crop yield and climate and weather variables is better represented by a bell-shaped curve (Shaw, 1964). To capture soil moisture during the growing period of each crop we further control for average number of wet days during the growing period of each crop.

Price change and volatility

Higher output prices are typically expected to bring about a positive supply response in which producers allocate more land to the agricultural sector and increase investment to improve yield (OECD, 2008). Although conceptually higher prices may also lead to expansion of acreage under cultivation of a crop to a less fertile land, and hence reducing yield, several empirical studies have shown that the positive effect outweighs (Haile *et al.*, 2016; Miao *et al.*, 2016). Crop price volatility, on the other hand, acts as a disincentive for production because it introduces output price risk. This is especially true for agricultural producers in developing countries as they are often unable to deal with (Binswanger & Rosenzweig, 1986) and are unprotected from (Miranda & Helmberger, 1988) the consequences of price volatility.

Farmers have to make their optimal crop production decisions subject to output prices, which are not known at the time when planting and input-use decisions are made. Neither is there an *a priori* technique to identify the superior price expectation model nor does the empirical literature provide unambiguous evidence on which expectation model to use for empirical agricultural supply response estimation (Nerlove & Bessler, 2001; Shideed & White, 1989). A farmer may choose to cultivate a different crop at planting time if new and relevant information is obtained (Just & Pope, 2001). Therefore, it is worthwhile to consider price, price risk, and other information during the planting season to model farmers' price expectations. We also consider farmers response to changes in other crop prices. Input prices may also affect crop production through their effects on both yield and acreage. For a farmer who produces a single crop, an increase in input prices, for instance fertilizer prices, discourages application of inputs and therefore unambiguously reduces crop production. However, in the case of multiple crop production higher input prices might induce a farmer to shift his input application to a crop that requires less of that input. Moreover, farmers may also substitute other inputs, such as land for fertilizer, if the latter gets more expensive. The effect of input prices on production is therefore an empirical question.

This study also controls for change in population density, which basically results from population growth and migration. Change in population density serves as a proxy for growing demand and urbanization related shifts in demand patterns. In addition, especially at low income levels, it can indicate high labor intensity in agriculture (Debertin, 2012). Given these patterns we would expect a non-linear relation with production. Some empirical evidence shows that population density reduces crop supply (Miao *et al.*, 2016).

3. Empirical framework

Given the above theoretical framework, we model average production of crop c in country i and at time t as

$$(4) \qquad Q_{cit} = \alpha_c + \boldsymbol{\beta}_c \boldsymbol{PR}_{cit} + \boldsymbol{\gamma}_c \boldsymbol{CL}_{cit} + \boldsymbol{\theta}_c \boldsymbol{POP}_{cit} + \boldsymbol{\lambda}_c \boldsymbol{T}_{cit} + \eta_{ci} + u_{cit}$$

where Q_{cit} denote production of crop $c \in$ (wheat, maize, soybeans, rice); $\boldsymbol{PR}$, $\boldsymbol{CL}$, $\boldsymbol{POP}$, and $\boldsymbol{T}$ denote vectors of variables measuring prices, climate change, population density, and time trend, respectively; η_{ci} denote country-fixed effects to control for time-invariant heterogeneity across countries, and u_{ict} is the disturbance term. While α_c is the overall constant term, $\boldsymbol{\beta}_c$, $\boldsymbol{\gamma}_c$, $\boldsymbol{\theta}_c$, $\boldsymbol{\lambda}_c$, are vectors of parameters to be estimated. For the empirical estimation we include the logarithmic values of the dependent variable and output and fertilizer prices.

The second stage involves estimating the variance component of the stochastic production function as

$$(5) \qquad VQ_{cit} = \alpha'_c + \boldsymbol{B}`_c \boldsymbol{W}_{cit} + \lambda'_c \boldsymbol{T}_{cit} + \eta'_{ic} + e_{cit}$$

where VQ_{cit} is production variance of each crop; $\boldsymbol{W}_{cit}$ is a vector of weather and price volatility variables that potentially affect production variance ($\boldsymbol{B}_c$ is a vector of the respective parameters to be estimated); and e_{cit} is an idiosyncratic error term. All remaining variables are as defined above, with the prime symbol indicating that estimated values can be different. Following Just and Pope (1978) and the theoretical model above, the logarithmic squared residuals ($ln[\hat{u}_{cit}{}^2]$) from the mean production equation (4) can be used as a measure of production variance for the respective crop. Because we specify the mean equation in logarithm, we need to take the antilogarithm of the residuals before squaring them.

The price vector $\boldsymbol{PR}$ in equation (4) includes input and output prices in levels and output price variability. The proxy for input prices is a fertilizer price index lagged by one-year. We model farmers' price expectations using spot prices prevailing just before planting starts. In particular, we use own crop prices observed 1–2 months before sowing starts. To proxy farmers' expectations of competing crops, however, we use one-year lagged weighted index of competing crop prices. The cross crop prices used for computing the index are the other three crops that are not under consideration in a given specification. We weigh prices of each crop by the calorie per metric ton content of each crop to compute the index.[1] The $\boldsymbol{PR}$ vector also includes seasonal own crop price volatility to capture output price risk. In order to use the de-trended price series, we calculate own crop price variability as the standard deviation of the log-returns in the 12 months preceding the start of the planting season of each crop in each country.

The climate vector $\boldsymbol{CL}$ includes mean temperature and squared deviation of maximum and minimum temperature values during growing periods of each crop. This enables us to capture the production effects of seasonal changes in average and variance of temperature. To capture extreme (low or high) temperature effects, we further include average number of growing season frost days and dummy variables to capture if growing season temperature reaches a threshold temperature level above which crop growth is severely affected.[2] Because the literature suggests that higher minimum (maximum) temperatures can lead to a reduction in rice (maize) yields (HLPE, 2012), we test for the effect of growing period minimum and maximum temperatures in rice and maize equations, respectively. For precipitation we include both planting and growing season mean precipitation along with their squared terms, anticipating an

[1] We apply calories per metric ton of 3340 for wheat, 3560 for maize, 3350 for soybeans and 3600 for rice (FAO, 2016). Estimations with equal weights also yield similar results.

[2] These threshold values are in degree Celsius of 30 for wheat and 32 for each of the other three crops (Thornton & Cramer, 2012).

increase (a decline) in crop production with an increase in average (excessive) rainfall. In addition, we control for rainfall shock variables (that we have referred to as SPAI), which are squared deviations of current planting and growing season rainfall from the respective long run mean values and standardized by the respective historical standard deviations. These variables capture the effects of seasonal unexpected precipitation extremes such as droughts and flooding on both crop acreage and yield. In the weather vector $\boldsymbol{W}$ of equation (5), we include some of the climate variables that potentially capture short-term temperature and precipitation changes, such as seasonal temperature variation and excessive precipitation measures as well as the variables that proxy for rainfall anomaly—that is, as measured by SPAI.

The vector $\boldsymbol{POP}$ contains population density and its squared term to capture any non-linear effect of population growth as a proxy to demand and to urbanization growth. The last vector $\boldsymbol{T}$ in both the mean and variance equations contains country-specific linear and quadratic time trends to control for the effect of technological progress with the possibility of decreasing marginal return.

We estimate a log-linear model of crop production allowing for heteroscedastic variance. This is appropriate since production of the crops follow log-normal distribution. The log-linear specification of production on climate change variables is also especially important in studies (such as ours) that attempt to estimate the average impact of climate change on global crop production. In a log specification, a given change in a climate change variable results in the same percent impact on production (Lobell *et al.*, 2011b). We use fixed effects (FE) model for our cross-country panel data, both for the mean and variance equations. First, the FE model controls for time-invariant heterogeneity across countries, such as soil quality and agroecology that would otherwise result in an omitted variable bias. Employing FE model when both the linear and quadratic terms of climate change variables are included has additional merit. It uses both within- and between-country differences to estimate marginal impacts. Thus, the FE model with quadratic weather terms enables to capture adaptation mechanisms such as changing sowing date or crop variety by allowing the marginal effect to vary with climate change (Lobell *et al.*, 2011b). Because we include input, own, and competing prices, this model also allows us to capture other forms of climate change adaptations such as switching between crops or applying less or more inputs including labor and fertilizer.

We estimate the impact of climate change on crop production while controlling for farmers behavioral responses to market conditions. However, crop production in a certain year and persistent shocks from previous years may potentially affect crop prices in that year (Schlenker & Roberts, 2009), suggesting that crop price and price volatility may be endogenous. Because we use international prices to measure input and output prices as well as crop price volatility, these variables may be exogenous to crop production for a small country. Yet, large producers and importers may influence international output and input prices (through trade) and we therefore need to account for possible endogeneity of fertilizer prices as well as the level and volatility of crop prices. To this end, we apply the described FE panel data estimator while instrumenting all the price variables in each crop model. The literature suggests some potential instrument variables including lagged climate change and crop stock variables (Miao *et al.*, 2016; Roberts & Schlenker, 2013). We additionally use one-year lagged net-trade of each crop. Stock and net-trade for soybeans are not used because of missing data for several countries and years. These variables are theoretically valid IVs because they affect domestic crop production only through their effects on prices. Based on results of weak- and over-identification statistical tests distinct sets of IVs are used in the different supply model specifications.

Because the mean equation is specified with heteroscedastic variance, this needs to be accounted for to obtain more precise or efficient estimates. To this end, we estimate the mean production model with two stage least squares (2SLS) that are both robust to arbitrary heteroscedasticity and intra-country correlations. There are more number of IVs than endogenous variables in our models, in other words the models are overidentified. In this case, a two-step general method of moments (GMM) IV estimator – with cluster-robust standard errors – yields more efficient estimates than 2SLS estimates (Baum *et al.*, 2007). Thus, the IV-GMM estimator is our preferred method.

4. Data and descriptive statistics

We obtain production data for each of wheat, rice, maize, and soybeans for the period 1961-2013 from the FAO. We include country-level production data for 30 major producer countries and pooled production data for the 27 countries of the European Union (EU, as of 2010) as a single entity. Although the period of analysis is the same across all four crops, the total number of observations in the panel data differs because some countries do not produce a certain crop. Yet, the focus countries and regions constitute about 82% for wheat, 90% for maize, 93% for rice, and 98% for soybeans of the global average production of each crop for the entire period of 53 years. We obtain country-level data on ending stock and trade from the Foreign Agricultural Service (FAS) of the US Department of Agriculture (USDA).

Data on international market output prices and fertilizer index are obtained from the World Bank's commodity price database. All prices are converted to real 2010 dollar prices by deflating each price with the US Consumer Price Index (CPI). We obtain crop calendar information for emerging and developing countries from the Global Information and Early Warning System (GIEWS) of the FAO, whereas the Office of the Chief Economist (OCE) of the USDA provides such information for advanced economies. Six climate variables, mean precipitation, minimum, mean and maximum temperature, average number of wet and frost days (all in a monthly resolution) are obtained from the Climatic Research Unit (CRU) Time-Series (TS) Version 3.22 of the University of East Anglia. We construct several climate change indicators from these six variables, including crop-specific seasonal mean and squared climate variables for each country. In case of the EU, climate variables are constructed as average values of the top five major producers of each crop using their respective cropland share as weights. Data on population density are obtained from the World Bank database. The summary statistics of total crop production of all four crops and of all variables for maize production estimation are reported in table 1.[3]

Table 1. Summary statistics of all crop production and production variance and all variables for maize production analysis (1961–2013)

Variables	Mean	SD	Min	Max
Dependent variables				
Maize production (1000 mt)	15547.2	42629.0	0.1	353699.4
Total maize production (2010)	786032.8			
Wheat production (1000 mt)	14303.6	26639.1	0.0	150341.0
Total wheat production (2010)	610733.7			
Soybean production (1000 mt)	4014.3	12810.1	0.0	91417.3
Total soybean production (2010)	261236.3			
Rice production (1000 mt)	15373.7	34802.4	0.0	205936.2
Total rice production (2010)	654006.9			
Variance of maize production (log)	2.48e-04	1.59	-6.61	9.50
Variance of wheat production (log)	6.77e-04	0.91	-5.44	4.22
Variance of soybean production (log)	-0.031	2.60	-8.54	7.21
Variance of rice production (log)	-2.29e-09	1.08	-8.24	4.61
Independent variables				
Maize sowing prices ($/mt)	251.2	111.4	95.3	644.9
Competing crop price index ($/mt)[a]	388.5	134.7	216.0	862.3
Maize price volatility	0.10	0.03	0.0	0.20
Fertilizer price index	66.7	34.4	33.8	196.9

[3] Summary statistics of all remaining crop production datasets are available as supplementary material (tables S1-S3).

Population density (people/sq km)	112.6	163.3	1.4	1203.0
Maximum growing temperature (°C)	28.6	4.7	9.3	37.1
Mean growing temperature (°C)	23.0	4.6	4.7	30.0
Squared sowing temperature deviation (°C)	357.9	225.7	42.3	1398.8
Squared growing temperature deviation (°C)	269.0	146.7	56.3	718.2
Growing cold stress (dummy var = 1 if < 10°C)	0.2	0.4	0.0	1.0
Growing heat stress (dummy var = 1 if >32°C)	0.3	0.5	0.0	1.0
Mean number of growing frost days	0.9	2.3	0.0	14.6
Mean number of growing wet days	10.1	6.8	0.1	27.8
Mean sowing precipitation (mm)	94.4	70.3	0.7	451.9
Mean growing precipitation (mm)	110.3	80.2	1.3	368.9
Sowing rainfall shock (mm)	522.3	1963.2	0.0	28457.8
Growing rainfall shock (mm)	441.3	1166.1	0.0	13750.6
Sowing rainfall anomaly (index)	-0.00015	0.26	-2.24	2.40
Growing rainfall anomaly (index)	-0.00004	0.33	-1.26	1.46

Notes: Prices are in 2010 US dollars. [a]Prices of wheat, rice, and soybeans constitute the competing crop price index.

We present the time series of global mean growing-season temperature and precipitation for all crops in Fig. 1.[4] The graph (qualitatively) shows an increasing trend in growing season temperature for all crops, whereas there is no clear trend in the average global precipitation. Table 2 provides a more formal statistical test of this qualitative illustration, where we test if there is any difference between global mean temperature and precipitation variables for the periods 1961-1986 and 1987-2013. The test results confirm that global mean growing season temperature of all crops during 1987-2013 is statistically higher than the corresponding mean values during the earlier 26 years. The change in mean temperature (which is above 0.5 for each crop) is equivalent to an increase of about 0.18°C per decade. This is consistent with the per decade rate (0.2°C) of global warming expected over the next three decades (IPCC, 2007).

On the other hand, global mean growing and sowing season precipitation and rainfall shock of nearly all crops (except a slight increase for rice at growing season) do not exhibit any statistically significant trend. Lobell *et al*. (2011a) reach to a similar conclusion that there is no consistent shift in the distribution across countries of precipitation trends between the periods 1960–1980 and 1980–2008 (p. 618).

[4] Figures that depict growing season temperature and precipitation of these four crops for the top five producers of each crop are available as a supplementary material (Figs. S1-S4)

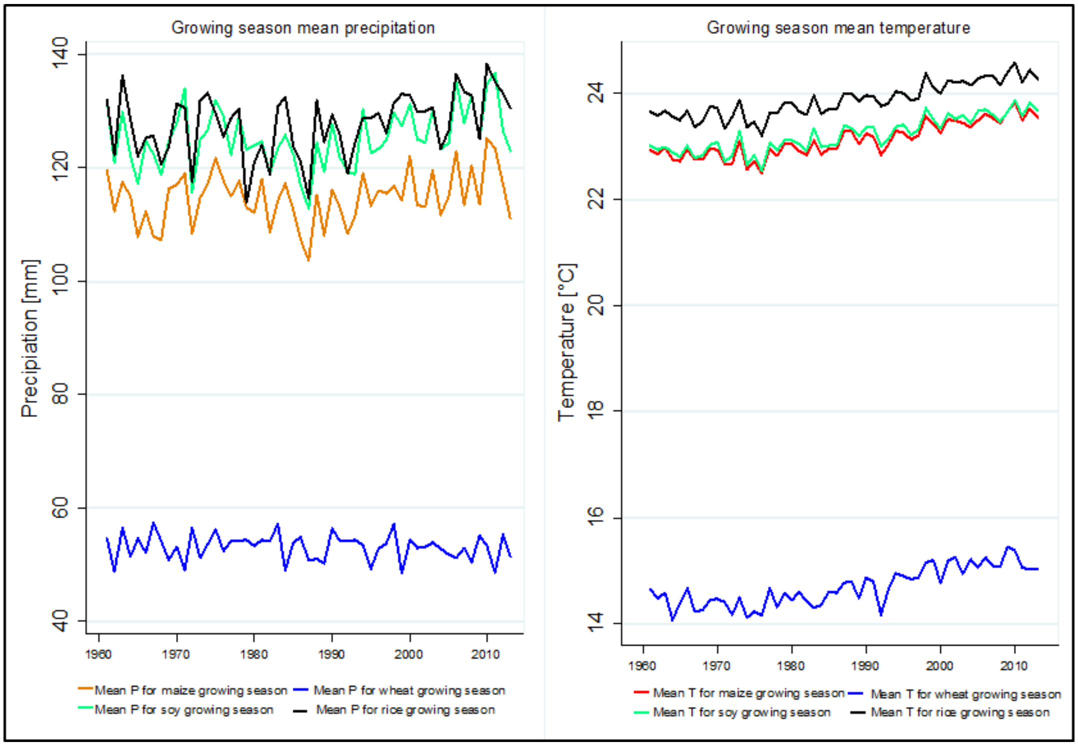

Fig. 1. Global average trend of growing season mean temperature and precipitation of the four crops

Table 2. Mean differences between aggregated mean trends of temperature and precipitation variables for the periods 1961-1986 and 1987-2013.

Variable	**Mean difference**	**t-stat**
Mean growing temperature: (M)	0.519***	(9.582)
Mean growing temperature: (W)	0.560***	(8.705)
Mean growing temperature: (S)	0.523***	(9.684)
Mean growing temperature: (R)	0.517***	(9.616)
Mean growing precipitation: (M)	1.166	(0.920)
Mean growing precipitation: (W)	-0.823	(-1.288)
Mean growing precipitation: (S)	1.704	(1.195)
Mean growing precipitation: (R)	2.932*	(1.974)
Mean sowing precipitation: (M)	2.203	(0.027)
Mean sowing precipitation: (W)	-41.677	(-0.981)
Mean sowing precipitation: (S)	132.671	(0.821)
Mean sowing precipitation: (R)	80.038	(1.047)
N=53: N1 = 26, N2 = 27		
Notes: t-statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001; H_0: Mean of the variable during 1987-2013 -Mean of the variable during 1961-1986 =0; M = maize, W = wheat, S = soybeans, R = rice		

5. Results and discussions

The estimation results for mean crop production are presented in tables 3–6 for maize, wheat, soybeans, and rice, respectively.[5] In the first two models of each of these tables, we estimate the empirical model in equation (4) using country fixed-effects while assuming all variables (including price variables) as exogenous. Model **FE'** includes price index of competing crops besides own crop price. Model specifications **FEIV** and **FEIV'**, on the other hand, are country-fixed effects panel data IV estimations that account for endogeneity of all input and output price-related variables. The last column reports standardized effect sizes of the **FEIV'** estimation results to shed light on the relative importance of included explanatory variables, which are measured in various ways, on global supply response for each crop. The estimation results are largely consistent across the four alternative models.

We test for the underlying assumptions for the validity of our IV estimation methods. These tests check if the IVs are properly excluded (overidentification test) and if they are sufficiently correlated with the endogenous variables in the model (weak identification test). The test for overidentification using the Hansen *J* statistic shows that we cannot reject the hypothesis that the IVs are valid (i.e., the excluded IVs are orthogonal to the error process) at any reasonable significance level. We consider several tests, including the goodness-of-fit, *t*- and joint *F*-tests, and Kleibergen-Paap rk statistics of the first-stage regression, to check if the IVs are strongly correlated with the endogenous variables. The joint *F*-test strongly rejects the null hypothesis that our IVs do not jointly statistically significantly explain the included endogenous variables at any reasonable level of significance. The test results also indicate that the excluded IVs pass the Kleibergen-Paap *rk* tests for underidentification and weak instrument. The results from the country fixed-effects IV model can therefore be reliable. The following discussions rely on the results obtained from the panel data IV estimator that also includes cross-price index (that is, **FEIV'**) for each crop production estimation. Similarly, the estimation results for the stochastic component of crop production in table 7 use the predicted residuals from this model to construct the respective dependent variables.

[5] To keep tables 3-6 in a reasonable size, we only present estimations of key variables in these tables. For a complete presentation of estimations, see tables S4-S7 in the supplementary material.

Table 3. Determinants of global maize production (dependent variable: log (mean production))

	FE	FE'	FEIV	FEIV'	
Variables	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Standardized effect size
Own crop price	0.170***	0.118***	0.431***	0.802***	0.250***
	(0.019)	(0.016)	(0.069)	(0.086)	
Cross-price index		0.156***		-0.540***	-0.126***
		(0.032)		(0.163)	
Own price volatility	-0.469**	-0.673***	-2.184***	-2.190***	-0.046***
	(0.199)	(0.213)	(0.496)	(0.622)	
Fertilizer price index	0.047**	-0.002	-0.208***	-0.126*	-0.035*
	(0.020)	(0.019)	(0.062)	(0.067)	
Population density	0.010**	0.001**	0.013***	0.016***	0.648***
	(0.005)	(0.005)	(0.003)	(0.004)	
Population density squared	-1.23e-05	-1.23e-05	-1.95e-05***	-2.46e-05***	-0.274***
	(0.000)	(0.000)	(0.000)	(0.000)	
Mean growing tmp.	0.078	0.075	0.093*	0.117**	0.251**
	(0.093)	(0.092)	(0.055)	(0.055)	
Max. growing tmp.	-0.099	-0.097	-0.116***	-0.140***	-0.295***
	(0.080)	(0.078)	(0.037)	(0.040)	
Squared sowing tmp. deviation	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.070***
	(0.0001)	(0.0001)	(0.000)	(0.000)	
Squared growing tmp. deviation	-0.001*	-0.001*	-0.001***	-0.001**	-0.051**
	(0.0005)	(0.0005)	(0.0001)	(0.0003)	
Mean sowing rainfall	-0.003***	-0.004***	-0.003***	-0.003***	-0.062***
	(0.001)	(0.001)	(0.001)	(0.001)	
Mean growing rainfall	0.003***	0.002***	0.002***	0.001***	0.046***
	(0.001)	(0.001)	(0.001)	(0.001)	
Sowing rainfall anomaly	0.025	0.038	0.083*	0.047	0.003
	(0.068)	(0.064)	(0.048)	(0.073)	
Growing rainfall anomaly	-0.110***	-0.126***	-0.200***	-0.179***	-0.010***
	(0.039)	(0.040)	(0.031)	(0.050)	
Linea trend	0.039***	0.042***	0.043***	0.038***	0.402***
	(0.003)	(0.004)	(0.001)	(0.002)	
Observations	1488	1488	1330	1330	1330
Underidentification test (Kleibergen-Paap rk Wald statistic)			427.850	280.820	
Weak identification test (Kleibergen-Paap rk Wald F statistic)			36.801	24.154	
Overidentification test (*p*-value of Hansen J statistic)			0.526	0.383	

Notes: Asterisks ∗, ∗∗, and ∗∗∗ represent the 10%, 5%, and 1% levels of significance. All models are weighted by the global maize production share of each country. Excluded instruments: Ending stocks and stock variations of maize, wheat and rice; net import of maize, planting and growing season rainfall anomalies, and growing season mean temperature. All IVs are lagged once.

Impacts of price changes

Controlling for climate change and applying IVs for possible endogeneity of prices, the results indicate that agricultural production is indeed responsive to both own and competing crop prices. These supply elasticities are mostly larger than previous aggregate estimates (Haile *et* al., 2016; Roberts & Schlenker, 2009; Subervie, 2008), which can be explained by potential omission of climatic variables in these studies. Cross-price production responses are stronger than own price responses in the case of wheat and rice. While own crop price volatility, on the other hand, has negligible effect on soybean and rice production, it has detrimental impact on production of maize and wheat. In fact, the positive response of wheat production to a one standard deviation change in own prices could be offset by an equivalent change in wheat price fluctuations. Input price—as proxied by fertilizer index—negatively affects production of maize and soybeans but not that of wheat and rice.

Table 4. Determinants of global wheat production (dependent variable: log (mean production))

	FE	**FE'**	**FEIV**	**FEIV'**	
Variables	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Standardized effect size
Own crop price	0.042	0.058**	0.206*	0.190**	0.077**
	(0.030)	(0.029)	(0.110)	(0.085)	
Cross-price index		-0.090		-0.809***	-0.276***
		(0.062)		(0.280)	
Own price volatility	-0.377***	-0.338***	0.288	-2.125***	-0.088***
	(0.094)	(0.092)	(0.435)	(0.586)	
Fertilizer price index	0.046	0.087**	-0.480***	0.281	0.115
	(0.029)	(0.037)	(0.111)	(0.247)	
Population density	0.008***	0.008***	0.008***	0.010***	0.947***
	(0.002)	(0.002)	(0.003)	(0.002)	
Population density squared	-4.65e-06***	-4.63e-06***	-6.88e-06	-1.09e-05***	-0.367***
	(0.000)	(0.000)	(0.000)	(0.000)	
Mean growing tmp.	0.030	0.025	-0.011	-0.034	-0.231
	(0.034)	(0.034)	(0.023)	(0.032)	
Mean growing tmp. squared	-0.004**	-0.003**	-0.001	-0.001	-0.201
	(0.002)	(0.002)	(0.001)	(0.001)	
Squared sowing tmp. deviation	-0.0002*	-0.0002*	0.0002*	-0.00004	-0.006
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Squared growing tmp. deviation	-0.0001	-0.0001	-0.0002***	-0.0002***	-0.069***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	
Mean sowing rainfall	0.0004	0.0004	0.0023**	0.0018*	0.034*
	(0.001)	(0.001)	(0.001)	(0.001)	
Mean growing rainfall	0.001	0.001	0.002	-0.001	-0.011
	(0.002)	(0.002)	(0.001)	(0.001)	
Sowing rainfall anomaly	-0.115	-0.128	-0.0415	-0.197***	-0.008***
	(0.075)	(0.078)	(0.066)	(0.073)	
Growing rainfall anomaly	-0.209**	-0.212**	-0.297***	-0.269***	-0.013***
	(0.094)	(0.091)	(0.051)	(0.040)	
Linear trend	0.044***	0.0422**	0.021***	0.010	0.143
	(0.006)	(0.007)	(0.004)	(0.006)	
Observations	1176	1176	1072	1072	1072
Underidentification test (Kleibergen-Paap rk Wald statistic)			79.680	49.820	
Weak identification test (Kleibergen-Paap rk Wald F statistic)			9.332	15.190	

Overidentification test (*p*-value of Hansen J statistic)	0.339	0.211

Notes: Asterisks ∗, ∗∗, and ∗∗∗ represent the 10%, 5%, and 1% levels of significance. All models are weighted by the global wheat production share of each country. Excluded instruments: Ending stocks and stock variations of maize, wheat and rice; net import of maize and wheat, planting and growing season rainfall anomalies, and growing season mean temperature. All IVs are lagged once.

Impacts of climate and weather changes

Average growing period temperature does not seem to negatively influence production of crops. In fact, production of maize and rice increases with increasing mean temperature during the growing season. It is instead rising temperature at the two extremes—minimum temperature in the case of rice and maximum temperature in the case of maize—that are detrimental for crop production. While rising (growing period) temperature does not have statistically significant effect on wheat production, its effect on soybean production turns to negative beyond a temperature value of 32.5 degrees. Besides these temperature extremes, variations in both sowing and growing period temperature have negative supply effects. McCarl *et al*. (2008) have found similar results on the yield effect of temperature variation. Precipitation also plays a key role in production of each crop, in particular for rice production. Higher mean rainfall (at planting and growing seasons) in general improves agricultural production, whereas rainfall extremes—as measured by SPAI—negatively influence crop production. As expected, in particular for rice, the number of wet growing days and sowing season rainfall are positively associated with higher crop production. Unexpected seasonal precipitation extremes are however harmful for rice production as they are for the other crops.

Table 5. Determinants of global soybean production (dependent variable: log (mean production))

	FE	FE’	FEIV	FEIV’	
Variables	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Standardized effect size
Own crop price	0.185*	0.170**	0.877***	0.694***	0.243***
	(0.099)	(0.079)	(0.176)	(0.187)	
Cross-price index		0.072		0.061	0.017
		(0.131)		(0.113)	
Own price volatility	-0.347*	-0.377	-1.291**	0.582	0.021
	(0.205)	(0.247)	(0.562)	(0.971)	
Fertilizer price index	-0.052	-0.084	-0.492***	-0.605***	-0.201***
	(0.056)	(0.065)	(0.046)	(0.092)	
Population density	-0.0232***	-0.0232***	-0.0229***	-0.0244***	-1.146***
	(0.007)	(0.007)	(0.001)	(0.001)	
Population density squared	4.33e-05***	4.33e-05***	4.19e-05***	4.67e-05***	0.753***
	(0.000)	(0.000)	(0.000)	(0.000)	
Mean growing tmp.	-0.821	-0.825	-0.151	0.228	0.574
	(0.753)	(0.752)	(0.245)	(0.310)	
Mean growing tmp. squared	0.018	0.019	0.001	-0.007***	-0.751***
	(0.018)	(0.018)	(0.006)	(0.001)	
Squared sowing tmp. deviation	0.0002	0.0002	-0.0005**	-0.0005**	-0.040**
	(0.0004)	(0.0004)	(0.0002)	(0.0002)	
Squared growing tmp. deviation	0.001***	0.001***	0.001**	0.001**	0.057**
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	
Mean sowing rainfall	-0.001	-0.001	-0.001	-0.001	-0.044
	(0.003)	(0.003)	(0.001)	(0.001)	
Mean growing rainfall	0.005*	0.005*	0.003	0.003	0.135
	(0.003)	(0.003)	(0.002)	(0.002)	
Sowing rainfall anomaly	-0.342	-0.329	-0.345**	-0.384**	-0.018**
	(0.226)	(0.207)	(0.151)	(0.153)	
Growing rainfall anomaly	0.150	0.151	0.133	0.050)	0.002
	(0.211)	(0.210)	(0.112)	(0.128)	
Linear trend	0.058***	0.059***	0.064***	0.054***	0.666***
	(0.008)	(0.008)	(0.007)	(0.008)	
Observations	1363	1363	1259	1259	1259
Underidentification test (Kleibergen-Paap rk Wald statistic)			741.72	2811.30	
Weak identification test (Kleibergen-Paap rk Wald F statistic)			69.96	265.16	
Overidentification test (*p*-value of Hansen J statistic)			0.188	0.335	

Notes: Asterisks ∗, ∗∗, and ∗∗∗ represent the 10%, 5%, and 1% levels of significance. All models are weighted by the global soybean production share of each country. Excluded instruments: Ending stocks and stock variations of maize, wheat and rice; net import of maize, planting and growing season rainfall anomalies, and growing season mean temperature. All IVs are lagged once.

Impacts of population

The non-linear effect of change in population density is statistically significant in all cases .The effect of higher population density on production starts gaining more weight after a certain threshold. The effect of population density on crop production switches from positive to negative just above 650 people/km^2 for maize and rice and at slightly higher value for wheat (above 900).

To put this into perspective, population density in countries such as Rwanda and India is just below the former threshold; whereas Bangladesh's population density is far above these turning points.

Table 6. Determinants of global rice production (dependent variable: log (mean production))

	FE	FE'	FEIV	FEIV'	
Variables	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Standardized effect size
Own crop price	0.013	0.034	0.620***	1.011***	0.423***
	(0.035)	(0.043)	(0.200)	(0.384)	
Cross-price index		-0.084		-2.064***	-0.496***
		(0.063)		(0.683)	
Own price volatility	0.309***	0.269***	-0.084	-2.915	-0.109
	(0.095)	(0.081)	(1.027)	(2.117)	
Fertilizer price index	-0.059	-0.030	-0.614***	0.385	0.123
	(0.050)	(0.038)	(0.154)	(0.294)	
Population density	0.002	0.002	0.009***	0.008***	0.663***
	(0.001)	(0.001)	(0.002)	(0.002)	
Population density squared	-7.93e-07	-7.68e-07	-1.14e-05***	-1.16e-05***	-0.396***
	(0.000)	(0.000)	(0.000)	(0.000)	
Mean growing tmp.	0.007	0.019	0.213***	0.270***	0.981***
	(0.074)	(0.077)	(0.069)	(0.100)	
Min. growing. tmp.	-0.109	-0.123	-0.271***	-0.397***	-1.580***
	(0.097)	(0.105)	(0.060)	(0.135)	
Squared sowing tmp. deviation	0.0001	0.0001	-0.0004***	0.0004	0.136
	(0.0001)	(0.0001)	(0.0001)	(0.0003)	
Squared growing tmp. deviation	-0.0004	-0.0004	-0.0001	0.00003	0.004
	(0.0003)	(0.0003)	(0.0003)	(0.0006)	
Mean sowing rainfall	0.001**	0.001**	0.002***	0.002***	0.100***
	(0.001)	(0.001)	(0.001)	(0.001)	
Mean growing rainfall	0.0004	0.0004	0.001	0.004***	0.162***
	(0.0004)	(0.0004)	(0.001)	(0.001)	
Sowing rainfall anomaly	-0.056*	-0.055*	0.031	-0.338***	-0.018***
	(0.034)	(0.033)	(0.086)	(0.119)	
Growing rainfall anomaly	-0.039*	-0.037*	-0.202	-0.068	-0.004
	(0.024)	(0.022)	(0.137)	(0.352)	
Linear trend	0.021***	0.021***	0.029***	0.015*	0.185*
	(0.004)	(0.004)	(0.007)	(0.009)	
Observations	1405	1405	1247	1247	1247
Underidentification test (Kleibergen-Paap rk Wald statistic)			192.210	18.890	
Weak identification test (Kleibergen-Paap rk Wald F statistic)			20.236	9.890	
Overidentification test (*p*-value of Hansen J statistic)			0.312	0.442	

Notes: Asterisks $*$, $**$, and $***$ represent the 10%, 5%, and 1% levels of significance. All models are weighted by the global rice production share of each country. Excluded instruments: Ending stocks maize, wheat and rice, stock variations of wheat; net import of wheat and rice, planting and growing season rainfall anomalies, and growing season mean temperature. All IVs are lagged once.

Impacts on production variance

Table 7 reports results on the stochastic component of crop production—fluctuations in production. Not only do higher prices (in levels) provide incentive for farmers to producer more—that is, increase yield or acreage—they also increase the predictability of crop production. This is possible as higher crop prices induce agricultural investments in such as irrigation and disease-resistant seed varieties that in turn reduce production variance. Not surprisingly, crop price volatility has the opposite effect on production variance. We also find that higher fertilizer price has a positive effect on production variability, which is contrary to some of the findings in Just and Pope (1979). The effects on production variance of temperature and precipitation extremes are mostly positive but statistically significant for soybean and rice production (temperature) and for wheat production (precipitation). Production variability has a decreasing linear trend, thanks to more and improved early (weather and other risk) warning systems and technological progress that reduces potential fluctuations in agricultural production.

Table 7. Determinants of variance of global crop production (dependent variable: log (production variance))

	Maize	Wheat	Soybeans	Rice
Variables	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)	Coeff. (rob. SE)
Own crop price	-1.160***	0.197**	-1.317***	-0.859***
	(0.053)	(0.075)	(0.095)	(0.056)
Own price volatility	4.875***	0.978*	1.113*	-0.009
	(0.565)	(0.553)	(0.642)	(0.385)
Fertilizer price index	0.811***	0.114**	0.897***	0.856***
	(0.046)	(0.042)	(0.092)	(0.058)
Growing tmp. squared	0.002	0.001	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Growing tmp. variation	0.001**	0.0002	-0.004***	-0.0002
	(0.001)	(0.0003)	(0.001)	(0.001)
Growing rainfall shock	0.095	0.141**	0.0002	0.057
	(0.062)	(0.057)	(0.138)	(0.343)
Linear trend	-0.090***	-0.033***	-0.085***	-0.060***
	(0.005)	(0.006)	(0.007)	(0.004)
Intercept	-9.896***	-13.720***	-3.136***	-11.380***
	(1.114)	(1.853)	(0.892)	(1.125)
N	1330	1072	1259	1247

6. Implications for future global food production

Quantifying the potential impact of future climate change on global food production requires undertaking two steps. The first step involves estimating the historical relationship between climate variables and global food production (as done in tables 3-6), whereas the second step uses these estimates and projected changes in climate variables to calculate the projected production impacts of climate change (Burke *et al.*, 2015). We obtain future climate data for 2030s and 2050s from the Climate Change, Agriculture and Food Security (CCAFS) data portal for 32 global circulation models (GCMs) provided by the coupled model inter-comparison project phase 5 (CIMP5). The GCM data were downscaled using the Delta method.[6] The baseline climate (2000s) data were downloaded from the Worldclim online database.[7] In particular, we obtained data on average minimum temperature, average maximum temperature and total precipitation for the greenhouse gas representative concentration pathway RCP8.5. Compared to other representative concentration pathways, RCP8.5 leads to high energy demand and GHG emissions in the absence of climate change policies as it assumes high population and relatively slow income growth with modest rates of technological change and energy intensity improvements (Riahi *et al.*, 2011).

There are several institutions that develop climate models and that support the IPCC activities. However, there are marked differences between these models, which employ different numerical methods, spatial resolutions, and subgrid-scale parameters (IPCC, 2007, 2014). Because of uncertainties associated with each model, it is recommended to use an ensemble of available GCMs instead of selecting one or a subset of GCMs. Moreover, since the inherent uncertainty in existing projections of climate change is very large, we estimate projected production changes using data from the average of these GCMs. This is very important as climate models can simply disagree not only on the magnitude of future changes in precipitation and temperature but also on the sign of future changes (Burke *et al.*, 2015). In fact, these authors reviewed seven well-cited articles in the climate impacts literature that explore potential impacts on agricultural productivity and found a far more negative point estimates when accounting for climate uncertainty.

Based on the average projections of the 32 GCMs, predicted changes in mean temperature range from an increase of 2^0C in the 2030s to 3.5^0C in the 2050s (table 8). In addition, predicted changes show an increase in both minimum and maximum temperature.[8] Precipitation is also predicted to be slightly higher in the 2030s and 2050s. However, the data show a large heterogeneity in predicted changes, in particular of rainfall, across months.

[6] http://www.ccafs-climate.org/
[7] http://www.worldclim.org/
[8] These statistics are available as a supplementary material (table S8).

Table 8. Mean predicted changes in climate variables under RCP8.5

	2030s		2050s	
	Mean	SD	Mean	SD
Mean temperature, January (°C)	1.99	0.57	3.80	2.95
Mean temperature, February (°C)	2.01	0.52	3.76	2.8
Mean temperature, March (°C)	1.9	0.44	3.53	2.6
Mean temperature, April (°C)	1.82	0.34	3.3	2.25
Mean temperature, May (°C)	1.87	0.30	3.14	1.83
Mean temperature, June (°C)	2.04	0.35	3.28	1.55
Mean temperature, July (°C)	2.24	0.58	3.51	1.58
Mean temperature, August (°C)	2.32	0.61	3.63	1.69
Mean temperature, September (°C)	2.18	0.47	3.61	1.7
Mean temperature, October (°C)	2.06	0.42	3.45	2.21
Mean temperature, November (°C)	1.97	0.55	3.54	2.76
Mean temperature, December (°C)	1.99	0.6	3.7	2.98
Annual average change (°C)	**2.03**	**0.48**	**3.52**	**2.24**
Precipitation, January (mm)	-33.82	117.5	-32.4	117.5
Precipitation, February (mm)	-4.9	13.8	-4.8	13.9
Precipitation, March (mm)	-18.27	56.6	-17.6	56.5
Precipitation, April (mm)	2.2	4.4	2.6	6.1
Precipitation, May (mm)	7.6	56.7	7.8	58.4
Precipitation, June (mm)	36.3	92.7	35.9	94.9
Precipitation, July (mm)	9.8	30.4	9.5	33.5
Precipitation, August (mm)	1.54	6.8	2.1	10.7
Precipitation, September (mm)	23.9	99.8	25.3	102.4
Precipitation, October (mm)	-4.7	45.9	-2.9	45.1
Precipitation, November (mm)	-5.9	40.5	-4.0	41.1
Precipitation, December (mm)	19.8	29.5	21.6	31.2
Annual average change (mm)	**2.8**	**49.55**	**21.6**	**31.2**

Fig. 2 illustrates the projected impacts of climate change on agricultural production. We find that production of all four crops is adversely affected by climate change. More specifically, climate change decreases the weighted average crop production by 9% in the 2030s[9]. The climate change impacts are more severe in the 2050s: on average, aggregate production declines by about 21%.

[9] The effect on aggregate production is obtained by multiplying the share of each crop from total production by individual effects sizes for each crop. The share of wheat, maize, rice and soybeans is 0.29, 0.32, 0.31 and 0.08 respectively.

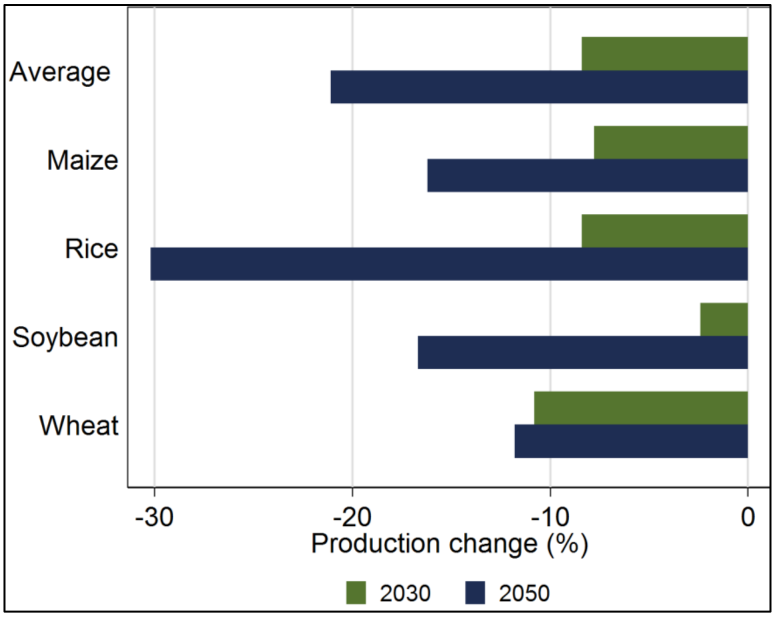

Fig. 2. Projected effect of climate change on food production (%)

Fig. 3 depicts predicted weighted average crop production changes in key producer countries. We find largely negative albeit heterogeneous effects across crops and countries. Projected average crop production shows positive but small changes for countries such as the Russian Federation, Turkey, and Ukraine in the 2030s, whereas production changes are negative and more pronounced for all countries in the 2050s.

The results on the climate induced average food production changes have a significant implication for global food security at least for two reasons: 1) wheat, rice, maize, and soybeans make up about three-quarters of the food calories of the global population; 2) our study countries produce above 85% of the global production of these crops. The projected climate-induced production changes are consistent with other findings, albeit the latter are national or regional level studies. For instance, Schlenker and Roberts (2009) indicated that average yields in the United States are predicted to decline by 30-46% and 63–82% under the slowest and most rapid warming scenario, respectively, under the Hadley III model before the end of this century. Similarly, Schlenker and Lobell (2010) reported a 22% reduction in aggregate maize production throughout sub-Saharan Africa by 2050.

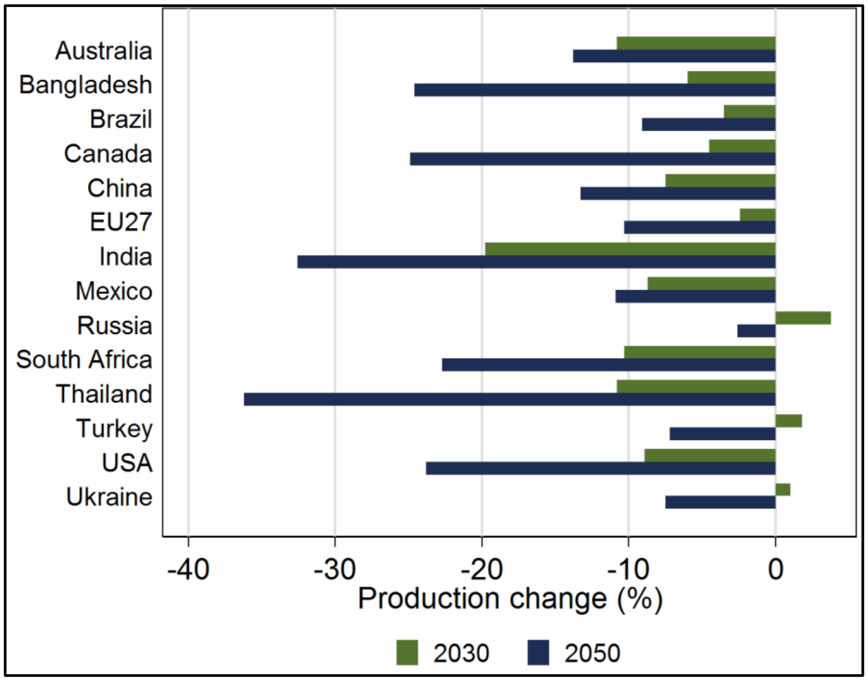

Fig. 3. Projected effect of climate change on (production weighted) average crop production of major producer countries (%)

7. Conclusions

As the earth's climate is changing, agriculture is one of the drivers of this change, and it is also one that is severely affected by the change. Climate-resilient agriculture is vital for achieving enhanced food security—which is a crucial component of the SDGs. This study provides answers to questions that are prerequisite for policies that address agriculture and climate change. This study evaluates the extent to which climate change affects global production of major staple crops and identifies specific climate and weather patterns that most harmfully affect crop production. The study analyzes the determinants of global average crop production for maize, wheat, rice, and soybeans over the period 1961–2013.

We develop the reduced form empirical framework of this paper with the premise that crop production is influenced not only by climate factors but also by changes in economic variables. These effects include changes in farmers' crop management practices and land allocation decisions in response to input prices and expected output prices and price volatility. Additionally, as compared to previous studies, we analyze the impact on global crop production variance of price and weather extremes. It is worth to note here that our estimates are global average effects, that is, country variations (especially of temperature variables), are subtly captured with the quadratic terms. Our empirical results, however, yield estimates that can serve as parameters for projections that look for potential impact of climate change on food security with reasonable level of trade among countries.

In agreement with previous studies, we find that climate change has statistically significant adverse effects on production of the world's key staple crops, through both yield and acreage effects. Our findings indicate that higher average temperature during the growing season is not all bad—having a positive and statistically significant effect on productions of maize and rice. Instead, increasing temperature values at the two extremes—higher minimum temperature for rice and higher maximum temperature for maize—are detrimental to crop production. Similarly, higher average temperature becomes problematic for wheat and soybeans after a certain critical level, albeit being statistically insignificant for the former. Moreover, this study finds that weather extremes—shocks in both temperature and precipitation—during the growing months have detrimental impacts on the production of the abovementioned food crops. This paper also finds negative impacts of price and weather extremes on the stochastic component of crop production, that is, on the variance of global crop production. In other words, price and weather extremes do not only adversely affect average global food production; they also positively contribute to the year-to-year fluctuations of food availability.

Furthermore, by using future climate data from 32 GCMs, we estimate projected effects of climate change on global food production. Climate change is predicted to reduce total production on average by up to 9% in 2030s and by 21% in 2050s, with large heterogeneity across countries and crops. Last but not least, we find that the linear time trend is statistically significant and positive in both the average production and the production variance estimations of all crops. This result is compelling as it shows that improvements in technology and agronomic practices have the capacity to boost global food production as well as to reduce annual fluctuations in food availability. Combating climate change using both mitigation and adaptation technologies is therefore crucial to check its adverse impacts on global production and hence on food security.

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