Heterogeneity in the Effects of Climate Change on Soybean Yields

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Abstract

Using a panel of 74 countries that spans nearly 60 years, this paper investigates the effects of climate change on global soybean yields. In alignment with previous research, we find a global non-linear relationship between growing season average temperature and yield growth—a parabola that minimizes around $24.9°C$. It indicates that effects of warming change from being beneficial to harmful, and reach to the most damaging at the optimum temperature; however, beyond the optimum, warming becomes less detrimental probably due to adaption of local crop variety to heat at countries that have been persistently hot. However, by incorporating regional dummies to our empirical model, we find significant heterogeneity in different regions. For example, in contrary to the global response function that opens upwards, the opposite direction, a downward open response function, is found for Southeast Asia, such that crop yield growth maximizes at $24.23°C$.

We also demonstrate precipitation has non-linear effects on soybean yields. In contrast to the large heterogeneity in temperature effects, the regional response functions for precipitation are more consistent over the world. Except for regions not sensitive to precipitation changes, areas such as Southeast Asia, Eastern Europe & Central Asia, and Sub-Saharan Africa all show a downward open parabolic response curve to precipitation. In addition to temperature and precipitation, we highlight the importance of diurnal temperature range (*dtr*) in assessing climate change impacts on crop yields. We find *dtr* is a statistically significant factor to soybean yields—an additional $1°C$ *dtr* will slow global soybean yield growth by 4.1 percentage points.

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1 Introduction

The Sixth Assessment Report of IPCC (Intergovernmental Panel on Climate Change) has reported global surface temperature in the first two decades of the 21st century (2001–2020)has increased by $0.99°C$ than 1850–1900, with each of the past four decades being successively warmer than any decade that preceded it (IPCC AR6, 2021). It also reported increased average precipitation over land since 1950. Growing evidence demonstrates climate change has profound impacts on crop production. Understanding changes in crop production induced by climate change is of essential importance to food security, agricultural adaptation, and social welfare, as it characterizes historical patterns of crop responses to climate change, and provides a guidance to identify adaptation opportunities and potential agricultural consequences of future climate change.

Attempts to measure impacts of climate change on agriculture have evolved a lot since the early 1960s and broadly fall into two major approaches: process-based models, which simulate the key processes in crop growing and yield formation in experimental labs; and statistical models, which estimate the sensitivity of crop yields to climate variables based on regression analysis on observational data. Process-based crop simulation models parameterize soil, weather, and crop management in a function of the soil-plant-atmosphere biophysical dynamics. The simulation models are typically used for applications in on-farm and precision management, and are increasingly used in assessments of the short-term impact of climate variability (see e.g., Lobell and Asseng, 2017; Lobell and M. B. Burke, 2010; Rosenzweig et al., 2013). On the other hand, statistical models empirically estimate the relationship between crop yields and weather variables. Results from the two approaches are compared to each other in studies, suggesting broadly consistency (Liu et al., 2016; Lobell and M. B. Burke, 2010; Lobell, M. B. Burke, et al., 2008) despite of certain divergence due to scenario settings and differences in the analytical approaches. Although both approaches can provide useful crop yield predictions, process-based models require more resources in calculation and calibration, moreover, they are limited to only a few varieties of crops, mostly maize, wheat, and rice, which limits their application beyond the major grains.

The statistical approach uses a so-called a *response function* to describe the effects of climate change on economic growth. Substantial debates about the response function exist over (i) the linearity of the relationship, (2) heterogeneity in countries' responses to climate change over the world. Dell, Jones, and Olken (2012), Liu et al. (2016), and Lobell, M. B. Burke, et al. (2008) used a linear specification of temperature and precipitation, which assumes monotonically effects of climate change. Based on a linear model, Dell, Jones, and Olken (2012) reported significant difference in responses between rich and poor countries. Rich countries are not sensitive to temperature change, yet are negative affected by more precipitation. On the other hand, poor countries are only sensitive to temperature variability; a $1°C$ rise in temperature will lead to a decrease of annual growth rate of economies by 1.35%. On the contrary, M. Burke, Hsiang, and Miguel (2015) used a non-linear relationship, more specifically, a quadratic specification of weather variables, in the response function. They found a downward open curve response function of temperature, such that economic growth maximizes at $13.06°C$. They agreed that rich countries will be less affected by a global warming as compared to poor countries; however, they claimed the difference in the responses is not because they have different sensitivities to climate change, but rather due to their various initial levels of temperature on the response curve. Specifically, poor countries are hurt simply because they have annual average temperatures greater than the optimal value, and rich countries are less hurt, or even benefit, from a global warming because they are colder and have annual average temperatures smaller than the optimal value. Burke et al. further reported non-significance of precipitation to GDP growth.

Response difference is also found among regions from meta-analyses, which consolidate regional estimates from numerous references and based on which generate bootstrapped estimates of responses for individual regions/countries see e.g., Carleton and Hsiang, 2016; Liu et al., 2016; Lobell, M. B. Burke, et al., 2008; Zhao et al., 2017. Nevertheless, it remains unclear whether the difference in responses is due to different sensitivities of response functions, or just because regions have different starting points on the response curve. To investigate the attribution of the regional heterogeneity, we interact climate variables with regional dummy variables and a rich/poor dummy. This specification explicitly allows for differing sensitivities to climate change based on region and rich/poor categories.

Temperature is deemed to be the dominant factor in the response functions in literature (see e.g., M. Burke, Hsiang, and Miguel, 2015; Diffenbaugh and M. Burke, 2019; Zhao et al., 2017). Understanding crop responses to temperature and the magnitude of regional temperature changes are the two most important needs for reducing uncertainty in predicting future crop yields (Lobell, M. B. Burke, et al., 2008). Previous studies of response functions have primarily focused on the impacts of growing season average temperature, with few work ever quantifying crop yield responses to extreme temperatures. However, extremes are important to consider for that extreme temperatures occurring at crucial stages of crop formation can drastically reduce the final production (Zhang et al., 2014). Response functions could provide significantly different predictions when using extreme temperature proxies, if a crop is substantially more sensitive to one specific extreme temperature index (Lobell and Field, 2007). For example, the predictions using extreme temperature indices are more than 20% lower than that of using average temperature for wheat (Lobell and Field, 2007).

Given the increasing frequency of extreme temperatures, the risks of crop yields damaged by extreme temperature stresses have been increasingly of concern. In order to take into account the effects of temperature extremes, we investigate a novel temperature index, diurnal temperature change ($dtr = t_{max} - t_{min}$, which measures the difference between the temperature extremes). Diurnal temperature reflects the magnitude of temperature stresses. A large diurnal temperature suggests the occurrence of a heat stress (increase of t_{max}) or a cold stress (decrease of t_{min}). Our results further show that the diurnal temperature change is indeed a significant factor to crop yields.

Based on a country-year panel consisting of 74 countries over the period 1963-2018, we investigate how soybean yields have been affected by climate change and focus on the response heterogeneity among regions. The remainder of the paper is organized as follows. Section 2 describes the data and model applied in our estimation strategy. Section 3 provides descriptive statistics of the data and summarizes regression results. Section 4 discusses the results.

2 Data and Method

2.1 Data

A. The CRU-TS climate dataset

Our analysis uses historical temperature temperature, precipitation, and diurnal temperature range (which is the difference between the maximum temperature and the minimum temperature) as controls in our empirical estimation of climate change effects. Climate Research Unit Time Series (CRU-TS V4.0, Harris et al., 2020) provides monthly time series of the climate variables from 1901 to 2019. Data is available at 0.5×0.5 degree resolution for all global land areas excluding Antarctica, and can be downloaded from the CRU website https://crudata.uea.ac.uk/cru/data/hrg/.

B. Growing season and harvest area datasets

Global growing season calendar is available from Sacks et al. (2010). The dataset contains gridded maps of crop planting and harvesting dates for a large variety of crops at 0.5×0.5 degree resolution. We select the monthly climate variables within the growing season of soybeans and calculate the averages of them. The resulting data are annual growing season averages of climate variables.

Monfreda, Ramankutty, and Foley (2008) provides cropland coverage data. For each 0.5° grid, a fraction ranging from 0 to 1 of cropland to the whole land is given. Larger fraction means a greater ratio of cropland usage. We use crop fraction data as a mask to gridded climate observations, retaining grids with nonzero values of crop fraction and aggregating them into country level data.

C. Economic data

We use soybeans as an example to illustrate climate change effects on crop yields. Annual country level soybean yields can be obtained from the Food and Agriculture Organization of the United Nations (FAOSTAT, http://www.fao.org/faostat/en/#data/QC). We also consider regional and wealth heterogeneity in our analysis. We here use regional categories in M. Burke, Hsiang, and Miguel (2015) which classify countries worldwide into six categories, primarily based on their geographical locations and economic development. Figure 1 shows the regional classification of the 74 soybean-producing countries applied in this study. In principle, countries clustering geographically belong to the same classification, except for *WEOFF* (Western Europe and offshore), which breaks geographical boundaries and covers most of the world's developed countries—Western Europe, Canada, the US, and Australia.

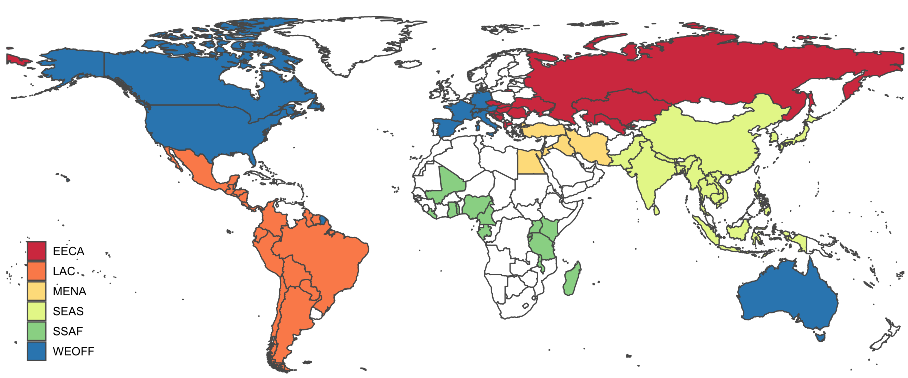

Fig. 1 Regional Categories for soybean-producing countries. Countries with the same color belong to the same regional category, while white countries mean they do not have soybean produce. Refer to Table 2 for the definition of the region names.

2.2 Empirical Framework

Our empirical framework follows the derivation from M. Burke, Hsiang, and Miguel (2015), with the following extensions: i) exploring the effects of one new climate variable—diurnal temperature range; ii) allowing parameter heterogeneity in regional responses. Specifically, we consider the following model to estimate climate impacts on crop yields in country i year t

$$\Delta \log y_{i,t} = f_T(T_{i,t}) + f_P(P_{i,t}) + f_{DT}(DT_{i,t}) + \theta_{1,i}t + \theta_{2,i}t^2 + \mu_i + \nu_t + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ are soybean yields, $f_T(.)$, $f_p(.)$ and $f_{DT}(.)$ are functions of growing season average monthly temperature, precipitation, and diurnal temperature range, respectively. μ_i are the country-fixed effects, ν_t are year-fixed effects, and $\theta_{1,i}t + \theta_{2,i}t^2$ are country-specific quadratic time trends. The response is the first difference of the natural log of soybean yields, which can be interpreted as an approximation of annual percentage growth rates. The climate effects on crop yields are captured by the first three terms in Eqn. (1). The quadratic country-specific time trends ($\theta_{1,i}t + \theta_{2,i}t^2$) permit soybean yields to evolve nonlinearly over time, accounting for changes driven by slow changing factors within a country, such as economic and technological advancements, agricultural infrastructure and management shifting, crop adaptation. All time-invariant factors that determine countries' historical average yield growth rates, such as history, culture, and demography, are accounted for in the country-fixed effects (μ_i). Time-varying global shocks such as volcanic eruptions and wild fires, are captured by the time-fixed effects (ν_t).

In the current study, we consider several specifications for functions of climate variables. We use a baseline regression that assumes all countries have the same response function, in particular, we use a quadratic specification for $f_T(.)$ and $f_p(.)$, and a linear specification for $f_{DT}(.)$. We call this a global heterogeneous specification that takes the following form

$$\begin{aligned} f_T(T_{i,t}) &= \beta_1 T_{i,t} + \beta_2 T_{i,t}^2 \\ f_P(T_{i,t}) &= \gamma_1 P_{i,t} + \gamma_2 P_{i,t}^2 \\ f_{DT}(DT_{i,t}) &= \lambda_1 DT_{i,t} \end{aligned} \tag{2}$$

The coefficient of diurnal temperature range, λ_1, represents the difference of the responses of crop yields to changes in maximum and minimum temperature. Since

$$\begin{aligned} DT_{i,t} &= T_{max,i,t} - T_{min,i,t} \\ \Delta DT_{i,t} &= \Delta T_{max,i,t} - \Delta T_{min,i,t} \end{aligned} \tag{3}$$

an increase of diurnal temperature range ($\Delta DT_{i,t} > 0$) suggests the increase of T_{max} is bigger than that of T_{min} (both T_{max} and T_{min} indicate positive average trends for regions and the global, refer to Table 4), i.e., $\Delta T_{max,i,t} > \Delta T_{min,i,t}$, which will be the case when heat stresses happen. λ_1 can then be interpreted as the difference of sensitivity to T_{max} and T_{min}, or $\lambda_1 = \lambda_{max} - \lambda_{min}$, where λ_{max} and λ_{min} represent the sensitivity to T_{max} and T_{min}, respectively. Given that the temperature indices are negatively correlated to crop yields, a positive λ_1 indicates the crop is more sensitive to T_{min} ($|T_{min}| > |T_{max}|$), and a negative λ_1 suggests larger sensitivity to T_{max} ($|T_{min}| < |T_{max}|$).

We also examine two types of heterogeneity in our specifications: regional heterogeneity and wealth heterogeneity. In the regional heterogeneity specification, we interact the temperature and precipitation variables with regional dummy indicators identifying each of the regional category. More specifically, we have

$$\begin{aligned} f_T(T_{i,t}) &= \beta_1 T_{it} + \beta_2 T_{i,t}^2 + \Sigma_{j=3}^{7} \beta_j \times T_{i,t} \times D_{i,j} + \Sigma_{j=8}^{12} \beta_j \times T_{i,t}^2 \times D_{i,j} \\ f_P(T_{i,t}) &= \gamma_1 P_{it} + \gamma_2 P_{i,t}^2 + \Sigma_{j=3}^{7} \gamma_j \times P_{i,t} \times D_{i,j} + \Sigma_{j=8}^{12} \gamma_j \times P_{i,t}^2 \times D_{i,j} \end{aligned} \tag{4}$$

where $D_{i,j} = 1$ if country i is within region j; otherwise, $D_{i,j} = 0$. There are all together six regions, so if $D_{i,j} = 0$ for all $j = 1, \ldots, 5$, it indicates country i is within the reference region level.

To test wealth heterogeneity, we interact the temperature and precipitation variables with an indicator for whether a country's purchasing-power-parity adjusted (PPP) GDP per captipa is above or below the median level across countries. That is, we have the following specification

$$\begin{aligned} f_T(T_{i,t}) &= \beta_1 T_{it} + \beta_2 T_{i,t}^2 + \beta_3 (T_{i,t} \times D_{i,t}) + \beta_4 (T_{i,t}^2 \times D_{i,t}) \\ f_P(T_{i,t}) &= \gamma_1 P_{it} + \gamma_2 P_{i,t}^2 + \gamma_3 (P_{i,t} \times D_{i,t}) + \gamma_4 (P_{i,t}^2 \times D_{i,t}) \end{aligned} \tag{5}$$

where $D_{i,t} = 1$ for country i with below-median income level in year t.

3 Results

3.1 Descriptive Statistics

Table 2 summarizes the number of observations per region in our consolidated dataset. We focus on a panel of 74 countries over the period 1963-2018 (56 years), with all together 2844 country-year observations. Soybean-producing countries are concentrated the most in

Southeast Asia (SEAS) and Latin America (LAC). Table 3 shows the number of poor and rich countries in each region. We see that WEOFF countries are all defined as rich, while SSAF consists of only 1 rich country and the other 12 poor countries. Other regions are comprised of a mix of poor and rich countries.

Update data description accordingly. Deleted 7 countries due to data quality control, e.g., problematic dtr data, at least 10 years of yield data. Now the dataset contains altogether 67 countries.

A stationary panel is essential to ensure the absence of permanent effects of shocks and moreover, a standard limiting distribution of parameter inference. We therefore carried out a range of unit root tests, including augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Elliott, Rothenberg and Stock (ERS) tests. The PP unit root test differs from the ADF test by the correction for any serial correlation and heteroskedasticity in the errors. Yet, both unit root tests suffer from the lack of power in distinguishing the unit root null from highly persistent stationary alternatives. The ERS test introduces modifications of the PP test and proposes a more powerful unit root test. Table 1 summarizes the results of the unit root tests for country time series. We see that temperature is mostly trend stationary; precipitation, diurnal temperature and soybean yields are trend stationary. Furthermore, panel unit root tests–Im, Pesaran and Shin (IPS) and cross sectional IPS tests both demonstrate a stationary panel.

Table 1 Time series unit root tests for augmented augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Elliott, Rothenberg and Stock (ERS) test. The drift regression model is given by $y_t = c + \rho y_{t-1} + \epsilon_t$, and the trend model given by $y_t = c + \delta t + \rho y_{t-1} + \epsilon_t$. The numbers reports the number of countries in each category.

Variable	Result	ADF		PP		ERS	
		Drift	Trend	Drift	Trend	Drift	Trend
Temperature	Non-stationary	43	3	13	0	34	5
	Stationary	24	64	54	67	33	62
Precipitation	Non-stationary	0	2	0	0	1	0
	Stationary	67	65	67	67	66	67
Diurnal temperature	Non-stationary	10	9	2	1	7	5
	Stationary	57	58	65	66	60	62
Crop yield	Non-stationary	1	5	0	2	3	4
	Stationary	66	62	67	65	64	63

Figure 2 shows the average levels and variability of temperature indices and precipitation over two selected periods, plotted against the percentage change of average soybean yields. The circle symbols represent the average levels over period one—1980 to 1999. The plus

Table 2 Dataset description

Region[a]	Long name	Country-year.obs	Country.obs	Year.obs
EECA	Eastern Europe and Central Asia	363	13	56
LAC	Latin America	676	18	56
MENA	Middle East and North Africa	186	5	56
SEAS	Southeast Asia	749	15	56
SSAF	Sub-Saharan Africa	475	14	56
WEOFF	Western Europe and offshore	395	9	56
	Sum	2844	74	

[a] Refer to Figure 1 for detailed area definition.

Table 3 Number of poor and rich countries in each region

Region	Wealth Level[a]	No.Country	Country members[b]
EECA	rich	10	BIH, CZE, HRV, HUN, KAZ, MKD, ROU, RUS, SVK, SVN
	poor	3	ALB, UKR, UZB
LAC	rich	8	ARG, BRA, CHL, COL, CRI, MEX, PAN, SUR
	poor	10	BLZ, BOL, ECU, GTM, GUY, HND, NIC, PER, PRY, SLV
MENA	rich	2	JOR, TUR
	poor	3	EGY, IRN, IRQ
SEAS	rich	4	CHN, JPN, KOR, THA
	poor	11	BGD, IDN, IND, KHM, LAO, LKA, MMR, NPL, PAK, PHL, VNM
SSAF	rich	1	GAB
	poor	13	BDI, CMR, GHA, KEN, LBR, MDG, MLI, MWI, NGA, RWA, TGO, TZA, UGA
WEOFF[c]	rich	9	AUS, AUT, CAN, CHE, DEU, ESP, FRA, ITA, USA

[a] Defined as poor with below median PPP-adjusted GDP per capita at 2018, otherwise rich.
[b] Country names are indexed in Alpha-3 codes by ISO 3166 standards.
[c] All countries in WEOFF are rich, therefore no poor row is shown.

symbols represent the average levels over period two—2000 to 2019. We choose to start from 1980 instead of 1960 to account for the data availability of crop yields. Recall that we have an unbalanced dataset; the lengths of yield data history are different among countries. Choosing the first period to start from 1980 is a result of balancing data completeness with trend visualization. To account for regional heterogeneity, we color countries based on their regional categories.

Figure 2 (a)(b) show that all countries get ubiquitously warmer. The largest warming is found in MENA ($1.02°C$) during the past forty years; with the smallest warming observed

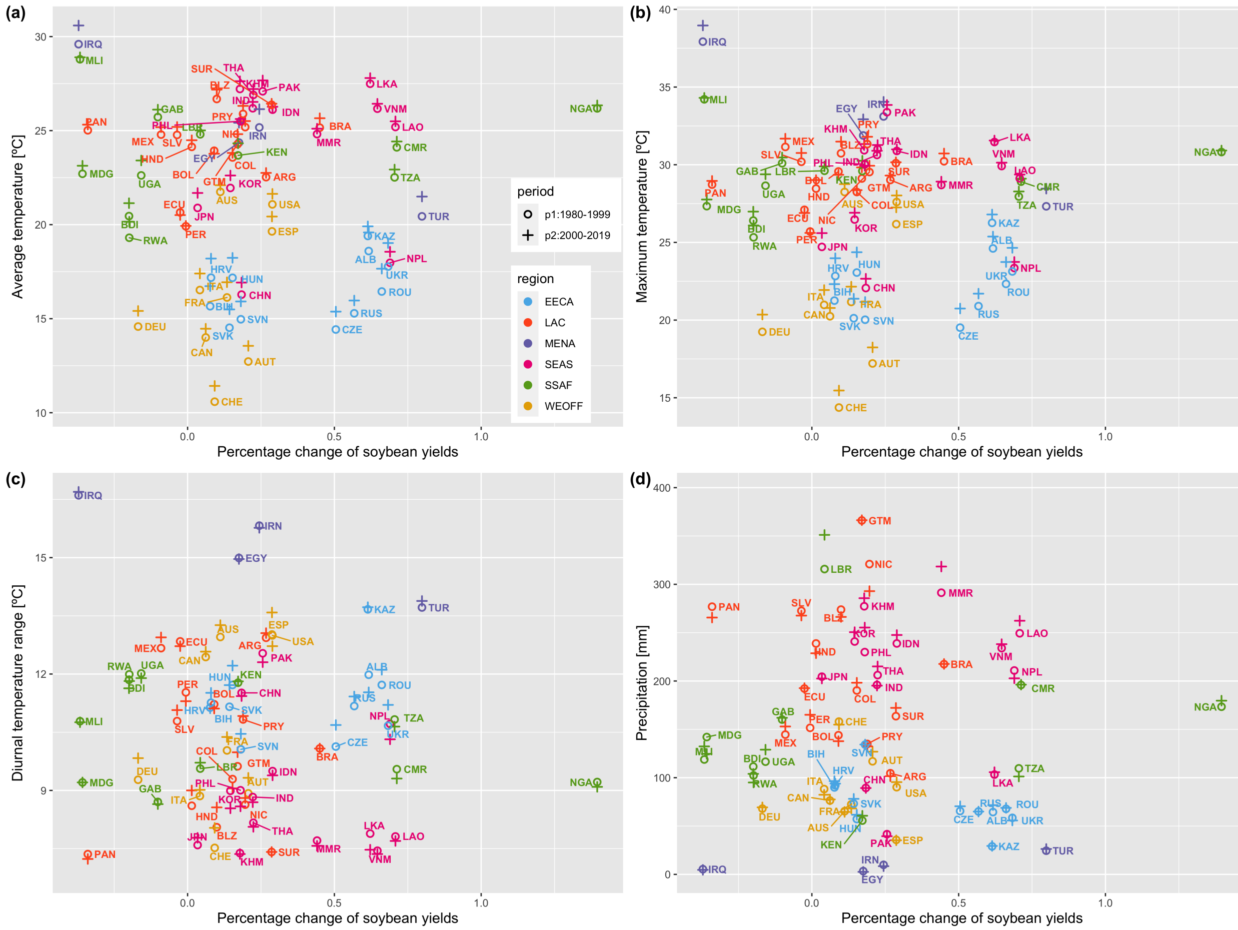

Fig. 2 Changes and variability in growing season temperature indices (panel (a)-(c)) and precipitation (panel (d)), plotted against percentage change of average soybean yields over two periods. Period one covers the period 1980-1999; period two covers the period 2000-2018. Average levels of climate variables are shown for the two periods, respectively (circles for period 1; pluses for period 2), against percentage change of average soybean yields over the two periods. Note that climate variables are averages over the growing season of soybeans for cropped areas in each country. Countries are colored based on regional categories.

in LAC (0.27°C, Table 4). Moreover, the increase in maximum temperature tends to be the largest compared to average and minimum temperature, except for SEAS and SSAF, where the minimum temperature increases the most (refer to Table 4). Diurnal temperature range measures the difference between maximum and minimum temperature. A positive trend of diurnal temperature range shows the maximum temperature increases faster than minimum temperature, probably indicating the occurrence of heat stress or cold stress. WEOFF and EECA show a substantial rise of diurnal temperature range, on the other side, slightly decreasing trends are observed in SEAS and SSAF.

Precipitation trends vary largely across and within regions. On a regional level, an increase of precipitation is observed in EECA, SEAS, SSAF, and WEOFF (Table 4). The largest regional average increase is observed in SEAS; with an average increase of growing season mean precipitation of 6.77 mm over the past forty years, and the smallest increase of precipitation is found in WEOFF, with an average increase of 0.36 mm. LAC countries have large variability of precipitation trends within the region; dryer countries get more precipitation, and wet countries get less precipitation. The largest decrease in precipitation is observed in Nicaragua (NIC), with a decrease of 27.99 mm; on the other hand, an increase precipitation of 13.50 mm is observed in Peru (PER). On a global level, growing season average temperature and precipitation have increased by 0.56°C and 1.96 mm from 1980-1999 to 2000-2018, and global soybean yields have increase by 22% over the same period.

If treating all countries as a homogeneous group, panel (a)-(c) manifest no obvious patterns of temperature indices vs. yield growth rates; while panel (d) shows likely positive correlation between precipitation and yield growth, that is, in general, higher levels of annual growing season average precipitation tend to associate with higher rates of crop yields. However, if looking at individual regions separately, temperature levels could be related to crop yield growth for certain regions, such as SEAS, MENA, and LAC. For example, MENA (purple points) shows a clear negative correlation of average temperature and yield growth (panel (a)), that is, an increase of average temperature is detrimental to soybean yields. The hottest country in MENA, Iraq, which is actually also the hottest in the world, shows a substantial decrease of soybean yields. In contrast to Turkey, the coldest country in MENA, shows the most positive growth of soybean yields.

Disregarding the two outliers of China and Nepal, SEAS countries tend to have average temperature ranging from 20 to 27.5 °C. China and Nepal show relatively low level of temperature in soybean production areas. More than 50% soybean production in China is from Northeast China, where the temperature is relatively low than the South Asia countries. SEAS indicates a possible nonlinear relationship. Before reaching an optimum average temperature, an increase in temperature levels leads to an increase in crop yields (see the points moving from Japan, South Korea, to Myanmar and Laos); above an optimum average temperature, an continual increase results in a reduction of crop yields (see countries with average temperature above 25°C).

Panel (d) reveals a large spread of precipitation levels in LAC, indicating no relationship between precipitation levels and crop yield growth in this region. SEAS, on the contrary, shows a potential positive relationship between precipitation levels and yield growth. In summary, we observe pronounced regional difference in relationships between yield growth and climate variable variations; therefore, it is of essential importance to take into account regional heterogeneity in the estimation of response functions of crop yields.

Table 4 Descriptive statistics of changes of average climate variables from period 1980-1999 to 2000-2019. The mean statistics shows the average level of changes of climate variables within a region. The standard deviation statistics shows the variability of changes of climate variables within a region.

Region	Statistics	tmp $[^{\circ}C]$	tmx $[^{\circ}C]$	tmn $[^{\circ}C]$	dtr $[^{\circ}C]$	precip $[mm]$	Yield Growth
EECA	mean	0.969	1.107	0.832	0.275	2.590	0.389
	std	0.213	0.296	0.227	0.311	3.170	0.257
LAC	mean	0.267	0.313	0.221	0.092	−2.282	0.095
	std	0.225	0.317	0.170	0.236	10.216	0.188
MENA	mean	1.018	1.041	0.997	0.043	−0.277	0.212
	std	0.042	0.079	0.053	0.104	1.402	0.478
SEAS	mean	0.411	0.321	0.501	−0.180	6.768	0.344
	std	0.205	0.239	0.210	0.182	10.089	0.230
SSAF	mean	0.455	0.412	0.499	−0.087	3.098	0.150
	std	0.256	0.243	0.282	0.120	14.247	0.558
WEOFF	mean	0.706	0.857	0.556	0.301	0.361	0.117
	std	0.194	0.283	0.176	0.268	4.889	0.140
Global	mean	0.560	0.590	0.531	0.060	1.957	0.220
	std	0.340	0.421	0.305	0.282	9.568	0.326

Variable definition: tmp: average temperature; tmx: maximum temperature; tmn: minimum temperature; dtr: diurnal temperature range; precip: precipitation.

3.2 Panel Results

Response function

Table 5 examines the regression estimates under various model specifications. Column (1) presents results from estimating Eqn. (1) for climate response under a homogeneous assumption across all countries. The global response function reveals soybean yield growth as a upward open quadratic function of temperature. Controlling for precipitation, an increase of temperature is increasingly damaging to crop yield growth until reaching a global optimum growing season temperature ($24.90^{\circ}C$); above the optimum temperature the damage from a further increase of temperature is actually attenuated (as shown in Figure 3). One possible explanation for the diminishing negative effect of temperature increasing after a certain point could be that crop varieties at hot areas have adapted to local climate and are thereby more resilient to warming. The response function to precipitation is a parabola open downward.

Fixing temperature, a dry country will benefit if it gets more precipitation until an optimal precipitation level; beyond that it is harmful to have more precipitation for a country with large amount of rain to begin with.

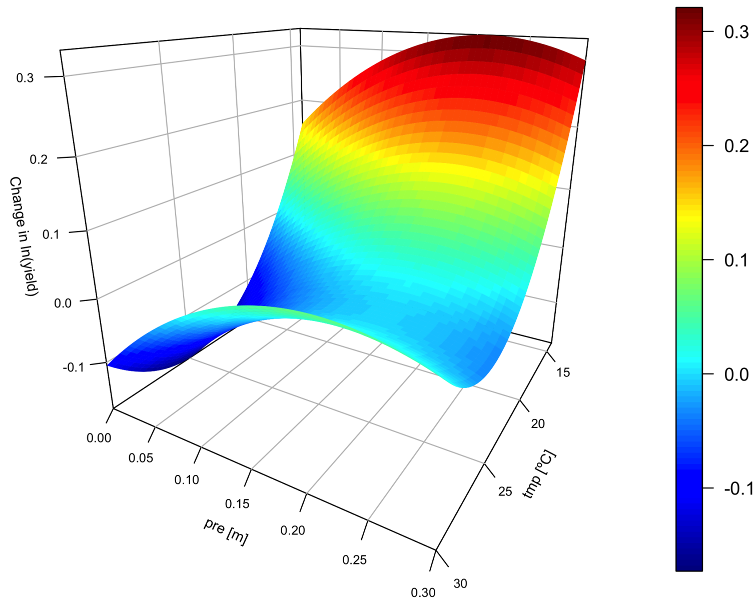

Fig. 3 Global response surface under homogeneous assumption across all countries. Model controls country fixed effects, year fixed effects, times trends, and diurnal temperature range.

In column (2) we interact temperature with regional dummies. The coefficients of temperature and temperature squared represent response of the reference level, SEAS. We observe SEAS reacts strikingly different from the global homogeneous model; the signs of temperature and temperature squared are both reversed, showing a downward open quadratic response function. It indicates a warming in SEAS is increasingly beneficial before reaching an optimal temperature (25.00$°C$), after which the effects are mitigated and gradually becoming harmful as temperature increases. The coefficients on the interaction terms indicate the difference in response between SEAS and other regions. The interaction terms are statistically significant for MENA and LAC. To examine the magnitude of regional difference, we aggregate the reference response with that of the interaction terms and show the results in Table 6 column (2). MENA and LAC have significantly positive coefficients on temperature squared, indicating an upward open curve response function which coincides with the global temperature response function in Table 5 column (1). However, there are many regions that can not be represented universally by the global response function. For example, SEAS has the opposite temperature–crop yield relationship; moreover, temperature is not even a significant factor to soybean yield variation in SSAF, EECA, and WEOFF.

Column (3) adds regional heterogeneity to precipitation. The regional difference of response in precipitation is significant as well. The soybean yields in SEAS, SSAF, and EECA show responsiveness to precipitation variation, while MENA, LAC, and WEOFF are insensitive to change in precipitation. Regional difference of precipitation response is not as contrasting as for temperature. Regional response function from column (3) and global response function from column (1) and (2) all show a downward open curve relationship between soybean yields and precipitation. The optimal precipitation in SEAS is 179 mm, above which level, an increase in precipitation will lead to an adverse effect to crop yields. Most countries in SEAS have precipitation level above 179 mm, indicating a negative effect on crop yields if countries get wetter. According to Figure 2, China, Pakistan, and Sri Lanka have lower levels of precipitation than the optimum level in SEAS, therefore they will benefit with more precipitation. However, China and Pakistan get dryer over the past forty years, indicating a detrimental effect on crop yields. Since China is colder than the optimal temperature in SEAS, historical warming has been beneficial to crop yield growth. Therefore, the negative effects of precipitation can be mitigated by the effects of temperature change in China. On the other hand, given the warm climate in Pakistan (above $25°C$), local soybean yields have experienced a double whammy from historical precipitation and temperature trends.

SSAF shows an optimal precipitation of 404 mm, which is far larger than usual values in the region (Figure 2 shows all MENA countries have average precipitation levels lower than 50 mm). Since it is unlikely that precipitations in MENA will jump from below 50 to above 404 mm, it is not a concern for MENA countries to experience a change of precipitation effects from positive to negative. In other words, local soybean yields will keep benefiting if precipitation increases in a foreseeable future. EECA has a linear positive relationship between precipitation and crop yields. An extra 10 mm of growing season average precipitation is associated with a 7.155 percentage points higher growth rate in EECA countries.

Column (4) examines whether rich and poor countries react differently by interacting climate variables with a wealth dummy. A country is defined as poor if it has below than median level of PPP-adjusted GDP per capita across all countries. The coefficients of the interaction terms between climate and the poor dummy are statistically insignificant, meaning that there is no significant difference in sensitivities to climate change for rich and poor countries. Table 6 column (4)-rich and column (4)-poor show the response estimates are indeed very similar for rich (reference level) and poor countries. Compared to poor countries, rich countries in SEAS have more concave responses to changes in temperature and precipitation (larger absolute values for the quadratic terms), with lower levels of optimal temperature and precipitation (23.42 $^{\circ}C$ vs. 25.07$^{\circ}C$, 175 mm vs. 187 mm). Figure 4 (a) shows the response surface under homogeneous response assumption for rich and poor countries. Panel (b) and (c) show the response surfaces for rich and poor countries, respectively. However, the difference between poor and rich countries in SEAS is not necessarily applicable across all regions. For instance, poor countries in MENA and LAC have more convex temperature response function and lower optimal temperature values, suggesting that rich countries are less affected by temperature fluctuations (Figure 5).

Column (5) and (6) are lagged dependent variable models, which add 1 lag and 3 lags of log difference of soybean yields based on the model with regional heterogeneity, i.e., model (3). The parameter estimates are comparable to model (3), showing stability and robustness of the baseline model.

Table 5 Regression estimate results

	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	-0.1396***	0.2282**	0.2275**	0.2587**	0.3017**	0.3581**
	(0.0493)	(0.1156)	(0.1100)	(0.1174)	(0.1181)	(0.1469)
Temp. interacted with regions						
MENA		-0.3970***	-0.4465***	-0.4556***	-0.2335*	-0.2237
		(0.1194)	(0.1330)	(0.1280)	(0.1405)	(0.1873)
LAC		-0.8169***	-0.8066***	-0.8403***	-0.7197***	-0.8164***
		(0.1666)	(0.1641)	(0.1756)	(0.2168)	(0.2628)
SSAF		-0.3460	-0.3633	-0.3897*	-0.3588	-0.2748
		(0.2282)	(0.2247)	(0.2317)	(0.2290)	(0.2576)
EECA		-0.4906	-0.4431	-0.4561	-0.6013*	-0.5802
		(0.3331)	(0.3289)	(0.3329)	(0.3339)	(0.3803)
WEOFF		-0.1513	-0.1387	-0.1721	-0.1606	-0.2251
		(0.1478)	(0.1422)	(0.1487)	(0.1440)	(0.1662)
Temp. interacted with wealth indicator						
Poor country dummy				-0.0145		
				(0.0102)		
Temperature sq.	0.0028**	-0.0046**	-0.0047**	-0.0055**	-0.0066***	-0.0081***
	(0.0011)	(0.0023)	(0.0022)	(0.0024)	(0.0024)	(0.0031)
Temp. sq. interacted with regions						
MENA		0.0076***	0.0087***	0.0090***	0.0050*	0.0050
		(0.0024)	(0.0026)	(0.0025)	(0.0028)	(0.0038)
LAC		0.0167***	0.0165***	0.0173***	0.0147***	0.0166***
		(0.0034)	(0.0033)	(0.0036)	(0.0045)	(0.0056)
SSAF		0.0076	0.0082*	0.0086*	0.0076	0.0064
		(0.0050)	(0.0050)	(0.0051)	(0.0050)	(0.0057)
EECA		0.0101	0.0097	0.0099	0.0147	0.0139
		(0.0092)	(0.0090)	(0.0092)	(0.0089)	(0.0102)
WEOFF		0.0010	0.0007	0.0016	0.0017	0.0036
		(0.0037)	(0.0036)	(0.0038)	(0.0037)	(0.0041)
Temp. sq. interacted with wealth indicator						
Poor country dummy				0.0007		
				(0.0005)		
Precipitation	1.6629***	1.6703***	1.3111**	1.5153	1.2890*	1.0296
	(0.5668)	(0.5213)	(0.6072)	(1.061)	(0.7461)	(0.7697)
Precip. interacted with regions						
MENA			4.0069	0.8183	9.7328	10.7248
			(4.9513)	(9.1777)	(8.0117)	(8.3110)
LAC			-0.2644	-0.2580	-0.8283	-0.5237
			(1.0587)	(1.0548)	(1.1012)	(1.1784)
SSAF			0.5867	0.5833	0.5003	0.8150
			(0.9008)	(0.9030)	(1.1094)	(1.2708)
EECA			5.8439	5.5994	6.6400*	7.0146**
			(3.9724)	(3.9199)	(3.5694)	(3.4804)
WEOFF			-1.6633	-1.8245	-0.9620	0.7118
			(1.7000)	(1.9023)	(2.1682)	(1.6807)
Precip. interacted with wealth indicator						
Poor country dummy				-0.1657		
				(0.9601)		
Precipitation sq.	-3.9417***	-3.7974***	-3.6635***	-4.3351**	-3.3159**	-2.8125**
	(1.0455)	(0.9806)	(1.0798)	(2.2008)	(1.3563)	(1.3507)
Precip. sq. interacted with regions						
MENA			-105.5973	-52.3802	-140.3026	-188.8467
			(83.6933)	(155.9143)	(134.3376)	(136.4317)
LAC			1.0621	1.0413	2.0815	1.8493
			(1.9643)	(1.9961)	(2.0239)	(2.1264)
SSAF			1.3133	1.1965	1.2448	0.6111
			(1.5034)	(1.5186)	(1.9045)	(2.1070)
EECA			-17.5161	-16.3583	-12.7286	-16.7581
			(14.8302)	(14.6370)	(14.1649)	(13.6104)
WEOFF			9.7483	10.2720	6.8844	1.6497
			(7.4054)	(7.7373)	(8.9362)	(7.0024)
Precip. sq. interacted with wealth indicator						
Poor country dummy				0.7356		
				(2.1986)		
Diurnal temperature range	-0.0482***	-0.0445***	-0.0418***	-0.0409***	-0.0341**	-0.0324**
	(0.0147)	(0.0146)	(0.0141)	(0.0143)	(0.0134)	(0.0141)
Observations	2844	2844	2844	2844	2690	2454
R squared	0.2	0.21	0.22	0.22	0.23	0.23

All models include country fixed effects, year fixed effects, and quadratic time trends. Temperature is measured in $^{\circ}C$ and precipitation in metres, expressed as average values on growing seasons of soybeans. Dependent variable is log difference of crop yields. Columns: (1) homogeneous specification as baseline regression, (2) baseline plus regional heterogeneity for temperature, (3) baseline plus regional heterogeneity for temperature and precipitation, (4) as in column 3 but adding wealth heterogeneity, (5) as in column 3 but adding 1 lag of dependent variable, (6) as in column 3 but adding 3 lags of dependent variable. Asterisks indicate significance at 1%(***), 5%(**), and 10%(*).

Table 6 Climate Effects based on regional heterogeneity.

Region	Term	(2)	(3)	(4)-rich	(4)-poor
SEAS	Temp.	0.2282** (0.1156)	0.2275** (0.1100)	0.2587*** (0.1174)	0.2442** (0.1136)
	Temp. sq.	-0.0046** (0.0023)	-0.0047** (0.0022)	-0.0055** (0.0024)	-0.0049** (0.0023)
	Optimal Temp.	25.00	24.23	23.42	25.07
	Precip.		1.3111** (0.6072)	1.5153 (1.0610)	1.3497** (0.5977)
	Precip. sq.		-3.6635*** (1.0798)	-4.3351** (2.2008)	-3.5995*** (1.0658)
	Optimal Precip.		0.179	0.175	0.187
MENA	Temp.	-0.1688*** (0.0397)	-0.219*** (0.0690)	-0.1969*** (0.0712)	-0.2114*** (0.0666)
	Temp. sq.	0.0031*** (0.0008)	0.0041*** (0.0013)	0.0034 ** (0.0015)	0.0041*** (0.0012)
	Optimal Temp.	27.41	27.03	28.68	25.86
	Precip.		5.3181 (4.9771)	2.3336 (8.7574)	2.1679 (9.3176)
	Precip. sq.		-109.2607 (83.7818)	-56.7152 (155.1197)	-55.9796 (156.2028)
LAC	Temp.	-0.5887*** (0.1199)	-0.5791*** (0.1192)	-0.5816*** (0.1196)	-0.5961*** (0.1201)
	Temp. sq.	0.0121*** (0.0024)	0.0118*** (0.0024)	0.0117*** (0.0024)	0.0124*** (0.0024)
	Optimal Temp.	24.34	24.52	24.79	24.07
	Precip.		1.0467 (0.8783)	1.2573 (1.3750)	1.0917 (0.8980)
	Precip. sq.		-2.6014 (1.6788)	-3.2938 (3.0679)	-2.5582 (1.6303)
SSAF	Temp.	-0.1178 (0.1972)	-0.1359 (0.1965)	-0.131 (0.2034)	-0.1455 (0.2027)
	Temp. sq.	0.003 (0.0045)	0.0035 (0.0045)	0.0031 (0.0047)	0.0037 (0.0046)
	Precip.		1.8978*** (0.6632)	2.0986* (1.1778)	1.9329*** (0.6699)
	Precip. sq.		-2.3501** (1.0303)	-3.1385 (2.4787)	-2.403*** (1.0416)
	Optimal Precip.		0.404	0.334	0.402
EECA	Temp.	-0.2624 (0.3134)	-0.2156 (0.3114)	-0.1974 (0.3192)	-0.2119 (0.3187)
	Temp. sq.	0.0055 (0.0089)	0.005 (0.0088)	0.0044 (0.0090)	0.0051 (0.0090)
	Precip.		7.155* (3.9246)	7.1148* (3.9782)	6.9491* (3.8500)
	Precip. sq.		-21.1796 (14.7866)	-20.6933 (14.8264)	-19.9577 (14.5611)
WEOFF	Temp.	0.0769 (0.0869)	0.0887 (0.0859)	0.0866 (0.0857)	0.0721 (0.0862)
	Temp. sq.	-0.0036 (0.0027)	-0.004 (0.0027)	-0.0039 (0.0027)	-0.0033 (0.0028)
	Precip.		-0.3521 (1.5970)	-0.3092 (1.6027)	-0.4749 (1.8406)
	Precip. sq.		6.0849 (7.3048)	5.937 (7.3347)	6.6725 (7.7207)

This table aggregates climate-region and climate-wealth interaction terms based on model specifications in Table 5. Temperature is measured in $^{\circ}C$ and precipitation in metres, expressed as average values on growing seasons of soybeans. Asterisks indicate significance at 1%(***), 5%(**), and 10%(*).

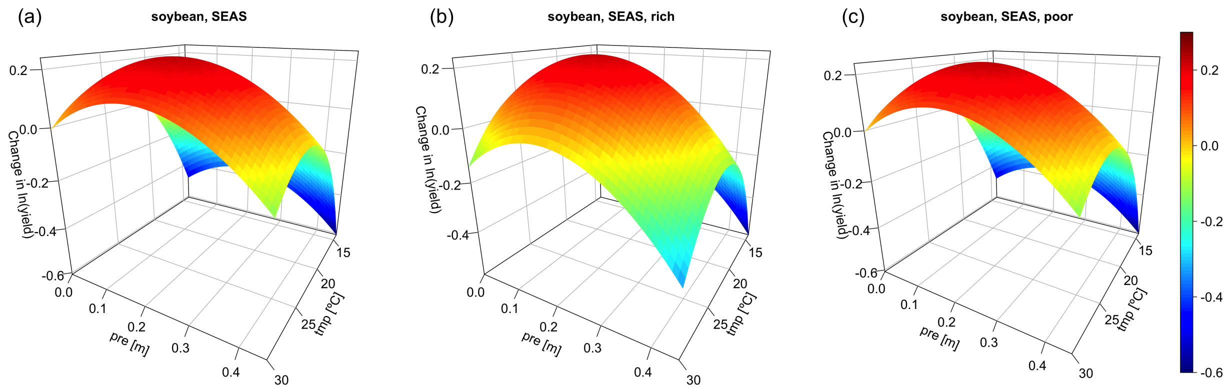

Fig. 4 Regional response surface for SEAS. (a) is obtained from Table 6 model (3), (b) is obtained from model (4).rich, (c) is obtained from model (4).poor.

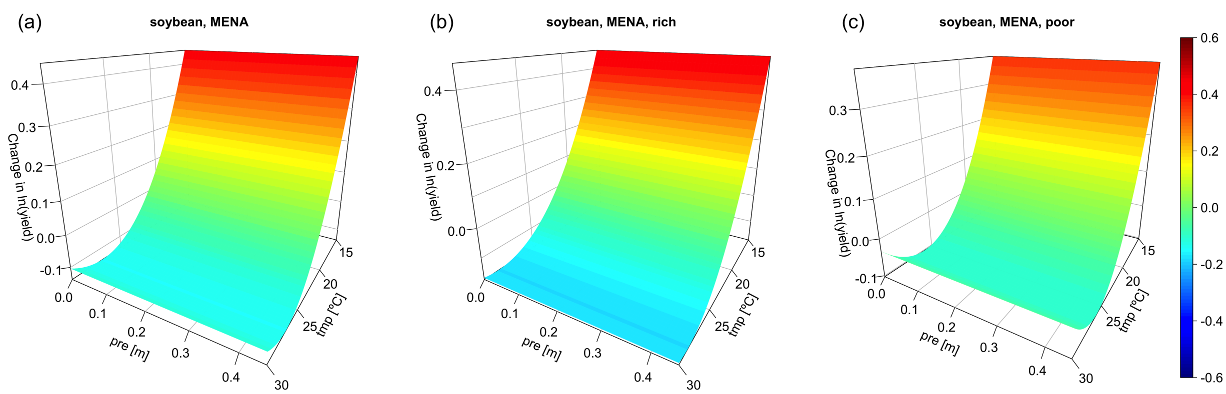

Fig. 5 Regional response surface for MENA. (a) is obtained from Table 6 model (3), (b) is obtained from model (4).rich, (c) is obtained from model (4).poor.

Marginal Effects

We examine here the marginal effects, that is estimating the change of crop yields from one unit's increase of climate variables. Based on alternative model robustness check in the previous section, model (3) shows largely stability and robustness. We therefore focus on model (3) in the following analysis. Given a linear specification of diurnal temperature range, its marginal effect is just the coefficient on the variable. On a global level, a one degree's increase of diurnal temperature change will result in a reduction of soybean yield growth by 4.16 percentage points (the last row of Table 5). In other words, if the maximum temperature increases faster than the minimum temperature, it will be significantly detrimental to soybean growth; conversely, i.e., maximum temperature increases at a slower rate, the negative effects from the rise of average temperature will be elevated.

On the other hand, we have non-linear specifications for temperature and precipitation, which means the marginal effects are a function of the climate variables. In particular the marginal effect for SEAS (the reference level) at some temperature T^* is $\beta_1 + 2\beta_2 T^*$. The marginal effects of other regions will need to aggregate the coefficients of the reference level with those of the regional interaction terms. For example, the marginal effect at temperature T^* for MENA is $\beta_1 + \beta_{1,MENA} + 2(\beta_2 + \beta_{2,MENA})T^*$. The same principle applies to precipitation. Figure 6 displays the effects of $1°C$ warming, using model (3). Transparent countries are not producing soybeans. White color mean the temperature is not a significant factor to soybean production in the countries. According to the result in Table 6, countries in SSAF, EECA, and WEOFF are not affected by temperature and thereby shown in white in the map. SEAS, except China, is estimated to be negatively affected by the warming. Actually, China will benefit the most given an increasing of temperature. LAC countries differ in the responses of warming. In particular, Brazil, Paraguay, and Mexico will benefit from warming, while Columbia, Peru, Chile, and Argentina will be adversely affected by a rise of temperature.

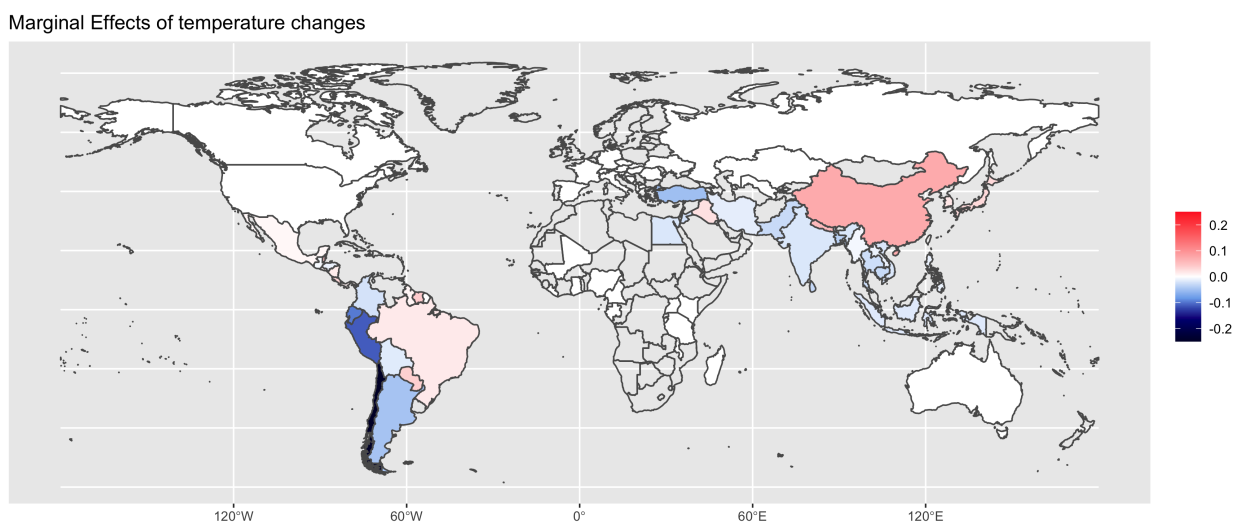

Fig. 6 Marginal effects of additional $1°C$ warming during growing season on soybean yields. Base temperature is the mean of the period 1961-2018 for each country. Note that the marginal effect is applied to annual growth rates. For example, a marginal effect of -0.02 means that a country growing at 3% yr^{-1} is projected to increase at 1% yr^{-1} with 1 $°C$ warming compared to the base period.

Figure 7 shows the marginal effects resulting from an increase of growing season average monthly precipitation of 10 mm. We see that all countries in EECA and SSAF will benefit from additional precipitation, among which, EECA countries will benefit the most if they get wetter in the future. SEAS countries have various responses from extra precipitation—China and Pakistan will benefit, and Pacific island countries will be harmed.

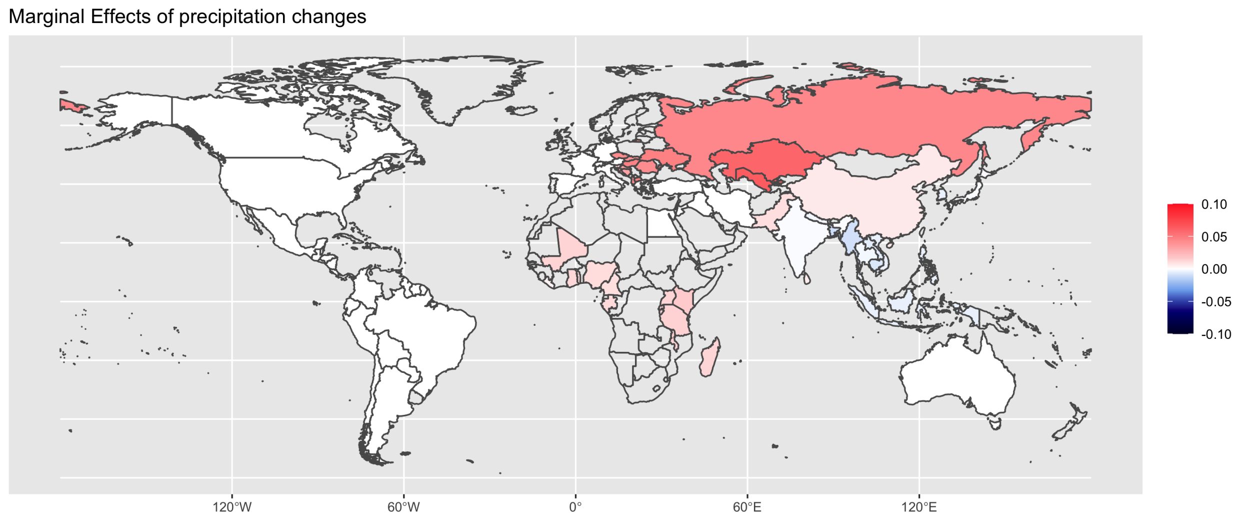

Fig. 7 Marginal effects of a 10mm increase of growing season average precipitation on soybean yields. Base precipitation is the mean of the period 1961-2018 for each country.

4 Discussion

This paper investigates how climate change affects soybean yields based on a panel data analysis over the period 1961-2018. We show non-linear effects of temperature and precipitation on crop yields, and a negative linear relationship for diurnal temperature range (dtr is the difference between maximum temperature and minimum temperature). The effects of diurnal temperature range are straightforward. On a global level an increase of $1°C$ in diurnal temperature range will reduce annual soybean yield growth by 4.1 percentage points. An increase in diurnal temperature could imply the occurrences of heat stress, where maximum temperature has increased considerably and the increment of which is larger than the rise in minimum temperature. Alternatively, the occurrences of cold stress could result in an increase of diurnal temperature as well, where minimum temperature has decreased significantly.

This paper examines the heterogeneous responses of soybean yields to changes in temperature and precipitation from two aspects: regional heterogeneity and wealth heterogeneity. We show that a global response function under a homogeneous assumption is not sophisticated enough to capture each region's distinct response to climate change because regions might have highly contrasting responses to climate change. For instance, the temperature response function in Southeast Asia is an downward open parabola and of opposite direction with that of Middle East & North Africa and Latin America. The heterogeneity among regions makes it impossible to have one global response function that is representative of all regions. We therefore incorporate regional heterogeneous parameters in our model and generate a region-specific response function for each region.

Our regional response functions show (1) Soybean yields in Southeast Asia (SEAS) are responsive to both temperature and precipitation variations. The response function of temperature is a downward open curve; before reaching an optimal growing season average temperature of $25.00°C$, an increase of temperature is increasingly beneficial to yield growth. Above the optimal level, a continual increase of temperature is less helpful to yield growth and can be even detrimental when the temperature reaches a very high level. Response function of precipitation is also a downward open curve with an optimal value of 179 mm. (2) Soybean yields in Middle East & North Africa countries (MENA) are only sensitive to changes in temperature. Its response function is an upward open quadratic curve with an optimal value of $27.03°C$. It shows the damage reaches the highest at $27.03°C$; above that, an continual warming is less harmful, probably due to the adaption of local soybean variety. Precipitation is not a significant factor to soybean growth in MENA. One possible explanation could be local agriculture is dependent on irrigation technology rather than on natural precipitation which is too low to afford the amount required for crop growing. (3) Soybean yields in Latin American countries (LAC) have similar response as MENA, with an upward open quadratic response function to temperature and are insensitive to changes in precipitation. (4) Soybean yields in Sub-Saharan Africa (SSAF) and Eastern Europe & Central Asia (EECA) are only responsive to changes in precipitation. SSAF shows an upward open curve with an optimal growing season precipitation level of 404 mm which is far greater than the common level of precipitation in the region. Therefore, an increase of precipitation will be continually beneficial before the optimum. EECA has a positive linear relationship between precipitation and crop yields. (5) Western Europe & Off Shores (WEOFF) shows non-significance to either temperature or precipitation.

At last, we explored wealth heterogeneity in our model, which shows statistically indistinguishable difference in the shape of response function between rich and poor countries. We suggest that the difference in the responses between rich and poor countries is determined by their different initial values of temperature and precipitation.

The current paper investigates the regional heterogeneity in the effects of climate change on soybean yields. We highlight that crop sensitivities to climate change are highly different, which means a global response function cannot reliably predict responses at a regional level. By interacting climate variables with regional dummies, we constructs regional response functions which are able to capture local climate-agriculture dynamics. However, theses regional models should be applied with caution. For example, they are calibrated in a setting of normal climate situations in individual regions, therefore, they cannot be used to simulate future yield responses for ranges far exceeding the "normal" status. Nonetheless, this study evaluates responses of crop yields to climate change on a regional scale and provides insight to region-specific adaptation strategies to ensure food security for a growing population. One of the extensions of this study could be crop yield projection under simulated climate pathways.

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