Emulating maize yields from global gridded crop models using statistical estimates

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Emulating maize yields from global gridded crop models using statistical estimates

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ABSTRACT

This study estimates statistical models emulating maize yield responses to changes in temperature and precipitation simulated by global gridded crop models. We use the unique and newly released *Inter-Sectoral Impact Model Intercomparison Project Fast Track* ensemble of global gridded crop model simulations to build a panel of annual maize yields simulations from five crop models and corresponding monthly weather variables for over a century. This dataset is then used to estimate statistical relationship between yields and weather variables for each crop model. The statistical models are able to closely replicate both in- and out-of-sample maize yields projected by the crop models. This study therefore provides simple tools to predict gridded changes in maize yields due to climate change at the global level. By emulating crop yields for several models, the tools will be useful for climate change impact assessments and facilitate evaluation of crop model uncertainty.

1. Introduction

The impact of climate change on crop yields has been extensively studied. To estimate these impacts, two approaches are usually taken: (i) process-based crop models, which represent mechanistically or functionally the effect of weather, soil conditions, management practices and abiotic stresses on crop growth and yields; or (ii) statistical techniques that empirically estimate the effect of weather on crop yields while controlling for other factors based on historical observations.

Process-based crop models are able to consider the detailed effect of weather and climate change on crop yields at the global level or at the site level by considering monthly, daily, or even hourly weather information (Basso et al., 2013). Some models can also capture other factors, such as pest damages, soil properties, fertilizer application, planting dates, and the carbon dioxide (CO_2) fertilization effect. These models are either calibrated at the field scale (Elliott et al., 2013; Izaurralde et al., 2006; Jones et al., 2003), the national level (Bondeau et al., 2007) or the grid cell level across the globe (Deryng et al., 2011). These models can simulate a wide range of weather and environmental conditions, but are computationally demanding and sometimes proprietary, which limits their accessibility.

Statistical models, usually in the form of regression analysis, on the other hand, use observed data to estimate the impact of weather on crop yields and are usually based on data aggregated by month (Carter and Zhang, 1998), growth stage (Dixon et al., 1994) or year (Blanc, 2012; Schlenker and Lobell, 2010). Regression analyses usually consider the effect of temperature and precipitation on crop yields (Corobov, 2002; Lobell and Field, 2007; Nicholls, 1997) and its derived composites, such as growing degree days (GDD) (Lobell et al., 2011), evapotranspiration (Blanc, 2012), and drought indices (Blanc, 2012; Carter and Zhang, 1998; Lobell et al., 2014). Some studies control for alternative effects, such as cloud cover (You et al., 2009); sources of water availability such as proximity to streams (Blanc and Strobl, 2014) and dams (Blanc and Strobl, 2013; Strobl and Strobl, 2010); management strategies, such as fertilizer application (Cuculeanu et al., 1999) or changes in planting dates (Alexandrov and Hoogenboom, 2000); and technological trends (Lobell and Field, 2007). The ability of these models to provide large-scale yields estimates is limited by data availability, and they are thus generally based on crop yield data averaged globally (Lobell and Field, 2007), at the country level (Blanc, 2012; Schlenker and Lobell, 2010), or at the county level (Lobell and Asner, 2003).

The out-of-sample predictive ability of statistical models is a concern when estimating impacts for scenarios of climate change not previously observed. This issue has been considered in recent

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studies by Holzkämper et al. (2012) and Lobell and Burke (2010) using the so-called 'perfect model' approach, which consists of training a statistical model on the output of a process-based crop model, assuming that this output is 'true'. The main aim of these studies is to evaluate the ability of statistical models to provide predictions out-of-sample. They find that statistical models are capable of replicating the outcomes of process-based crop models reasonably well. The spatial and temporal scope of these studies is, however, fairly small. Oyebamiji et al. (2015) expand on these studies and estimates an empirical crop yield emulator at the global level for five different crops but, as in previous studies, they only consider one process-based crop model. This is a concern because the choice of crop model is an important source of uncertainty in climate change impact assessments on crop yields (e.g. Bassu et al., 2014; Mearns et al., 1999). Therefore, having access to a tool capable of replicating yields from a wide ensemble of crop models would facilitate the analysis of crop model uncertainty in climate change impact assessments.

To address the limitations of simulations based on processed-based models and to consider crop model uncertainty, we design an ensemble of simple statistical models able to accurately replicate the outcomes of process-based crop models at the grid cell level over the globe using only a limited set of weather variables. To this end, we use the recently released *Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) Fast Track* experiment dataset of global gridded crop models (GGCM) simulations. This project was coordinated by the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013) as part of ISI-MIP (Warszawski et al., 2014). To enable comparison across models, all GGCMs are driven with consistent bias-corrected climate change projections derived from the Coupled Model Intercomparison Project, phase 5 (CMIP5) archive (Hempel et al., 2013; Taylor et al., 2012). Our statistical models are trained on the crop yields simulated by these process-based crop models and are subject to the widest range of climate conditions estimated in CMIP5. The statistical models are then used to predict the spatial responses of maize yields to weather. Differences between predictions from the process-based and statistical models are then assessed in order to measure how well statistical models can capture yield responses to weather variations driven by climate change.

Based on the evaluation of a large set of weather variables, non-linear transformations and interactions effects, we show that a simple specification including temperature and precipitation in polynomial form and interaction terms performs relatively well. Various validation exercises show that out-of-sample maize yield predictions are reasonably accurate, especially with respect to long-term trends. Robustness analyses considering either transformed dependent variable, more precise representations of the growing season, or region-specific estimates support the overall preferability of the parsimonious specification for global climate change projections.

This paper has five further sections. Section 2 presents the data and methods used to statically estimate relationship between yields and weather variables. Results are presented and discussed in Section 3. The models are validated in Section 4 and sensitivity analyses are performed in Section 5. Section 6 concludes.

2. Material and methods

2.1. Data

Data used in this study are sourced from the *ISI-MIP Fast Track* experiment, an inter-comparison exercise of global gridded process-based crop models using the CMIP5 climate simulations.[1] In this exercise, several modeling groups provided results from global gridded process-based crop models run under the same set of weather and CO_2 concentration inputs.

2.1.1. Crop yields and growing seasons

Crop yields and growing season information are obtained from GGCMs members of the *ISI-MIP Fast Track* experiment. Based on data availability, we consider five crop models: the Geographic Information System (GIS)-based Environmental Policy Integrated Climate (GEPIC) model (Liu et al., 2007; Williams, 1995), the Lund Potsdam-Jena managed Land (LPJmL) dynamic global vegetation and water balance model (Bondeau et al., 2007; Waha et al., 2012), the Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) with managed land model (Bondeau et al., 2007; Lindeskog et al., 2013; Smith et al., 2001), the parallel Decision Support System for Agro-technology Transfer (pDSSAT) model (Elliott et al., 2013; Jones et al., 2003), and the Predicting Ecosystem Goods And Services Using Scenarios (PEGASUS) model (Deryng et al., 2011).

Each GGCM simulation provides estimates of annual maize yields in metric tons (t) per hectare (ha), as well as planting and maturity dates, at a 0.5×0.5 degree resolution (about 50 km^2). For each of these models, we select model simulations considering the effect of CO_2 concentration in order to account for CO_2 fertilization effect, which plays an important role in biomass production. Also, we consider simulations assuming no irrigation in order to capture the effect of precipitation on crop yields.

GGCMs differ in their representation of crop phenology, leaf area development, yield formation, root expansion and nutrient assimilation. However, they all account for the effect of water, heat stress and CO_2 fertilization. None of the models considered assume technological change. A more detailed description of each model's processes is provided by Rosenzweig et al. (2014). Some caveats are associated with each model.[2] For instance, the LPJ-GUESS model estimates potential yields (yield non-limited by nutrient or management constraints) rather than actual yield and therefore only relative change should be considered when assessing the impact of climate change on crop yield using this model. Also, the GEPIC model accounts for soil fertility erosion, which requires the simulations to be run independently for each decade, while the pDSSAT model only updates CO_2 inputs every 30 years, which results in a periodic step in yield projections. As a result, these GGCM simulations are more suited to assess long-term trends in yields rather than inter-annual yield variability.

2.1.2. Weather

Bias-corrected weather data used as input into each crop model are obtained from the CMIP5 climate data simulations. This study uses daily weather data for three of the five climate models, or General Circulation Models (GCMs) included in CMIP5: HadGEM2-ES, NorESM1-M, and GFDL-ESM2M. As summarized in Warszawski et al. (2014), these GCMs project, respectively, high, medium and low level of global warming.

GCM simulations are available for an 'historical' period of 1975–2005 and a 'future' period of 2006 to 2099. For the 'future' period, each GCM is run under four Representative Concentration Pathways (RCPs), each representative of different level of radiative forcing (RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5). We selected

[1] The data are available for download at https://www.pik-potsdam.de/research/climate-impacts-and-vulnerabilities/research/rd2-cross-cutting-activities/isi-mip/data-archive/fast-track-data-archive.

[2] These caveats are discussed at https://www.pik-potsdam.de/research/climate-impacts-and-vulnerabilities/research/rd2-cross-cutting-activities/isi-mip/data-archive/fast-track-data-archive/data-caveats.

Table 1
Variables used in the statistical analysis.

Variables	Description	Unit
Yields	Annual crop yields	t/ha
Pr	Monthly average daily precipitation	mm/day
Tmin	Monthly average daily minimum temperature	°C
Tmax	Monthly average daily maximum temperature	°C
Tmean	Monthly average daily mean temperature	°C
N_Pr0	Ratio of number of days per month without precipitation (daily $Pr = 0$)	Ratio
N_Tmin0	Ratio of number of days per month with minimum daily temperature below 0 °C	Ratio
N_Tmax30	Ratio of number of days per month with maximum daily temperature above 30 °C	Ratio
ETo	Monthly average daily reference evapotranspiration	mm/day
GDD	Monthly heat accumulation	°C
CO2	Mid-year CO_2 concentration	ppm

the scenario with the highest level of global warming compared to historical conditions, RCP 8.5, and the corresponding CO_2 concentrations data (Riahi et al., 2007).[3] As the maximum amount of warming induced under other RCPs is encompassed in this pathway, and a wide range of climate change patterns are represented by the three GCMs, the analyses consider the broadest possible range of climate change.

Each GCM produces three variables that are used as inputs by crop models: daily minimum soil surface temperature (*Tmin*), daily maximum soil surface temperature (*Tmax*), and daily precipitation (*Pr*). We compute various composite variables based on these weather variables (which are summarized in Table 1). Mean daily temperature (*Tmean*) is calculated as:

$$Tmean = \frac{T\min + T\max}{2} \tag{1}$$

We also consider reference evapotranspiration (*ETo*) to represent the evaporative demand of the air. Following Hargreaves and Samani (1985), it is calculated daily as:

$$\mathrm{ETo} = 0.0023\,(Tmean + 17.8)\,(T\max - T\min)^{0.5}\,R_a \tag{2}$$

where R_a is the extraterrestrial radiation calculated as a function of the latitude and time of the year (Allen et al., 1998).

GDD represents the number of growing degree days beneficial for the plant. This measure is calculated daily as:

$$GDD = (T\min + T\max)/2 - Tbase \tag{3}$$

where *Tbase*, the base temperature for maize, is 8 °C (Asseng et al., 2012).

To facilitate a simple relationship between annual crop yields and weather variables, monthly averages are calculated for *Tmean*, *Tmin*, *Tmax*, *Pr* and *ETo*; *GDD* is aggregated over each month. The variable *N_pr0* represents the proportion of days in a month with no precipitation ($Pr = 0$). Similarly, *N_Tmin0* and *N_Tmax30* represent the proportion of days per month with minimum daily temperature below 0 °C ($Tmin < 0$) and maximum daily temperature above 30 °C ($Tmax > 30$). The threshold of 0 °C is chosen to capture the effect of frost and the threshold of 30 °C is used to capture the temperature above which maize development is affected (Asseng et al., 2012).

2.1.3. Sample summary information and statistics

We consider crop model simulations from 1975 to 2005 for the historical runs and 2006 for the future period. As only one RCP scenario is selected for each GCM, the panel spans from 1975 to 2099 without distinction (i.e., for each GCM, there is one historical scenario and one future scenario). In the final sample, we omit grid cells for which there are less than 10 yield observations after data cleaning.

As summarized in Table 2, each GGCM has a sample of more than 13 million observations covering more than 50,000 grid cells globally. When considering the planting dates and growing season length for each sample, the growing seasons averaged over grid cells spread between June and October in the Northern Hemisphere and December and May in the Southern Hemisphere, but differ slightly for each crop model.

Summary statistics for each GGCM and GCM are presented in Table 3. Global average maize yields vary from 1.42t/ha for the LPJmL model under the GFDL-ESM2M GCM to 3.00t/ha for the pDSSAT model under the NorESM1-M GCM. The range of yields across GGCMs is smallest for the LPJ-GUESS model and is largest for the PEGASUS model.

Summary statistics for the main weather variables (*Tmean* and *Pr*) differ by crop model due to their difference in spatial repartition (i.e., a different number of grid cells are represented by each crop model). As described in the next section, we consider weather variables over the summer months to represent the growing season. In the table, numbers suffixes are used to represent each summer month, so _1, _2, and _3 refer to, respectively, June, July and August in the Northern Hemisphere and December January and February in the Southern Hemisphere. In all GGCMs, precipitation is the lowest in the first month of the growing season and highest in the last month, and temperatures peak in the second month. While no clear pattern amongst GCMs is discernable from these statistics for precipitation, temperatures are clearly the highest under the HadGEM2-ES GCM and the lowest under the GFDL-ESM2M GCM.

2.2. Methods

We build on the 'perfect model' approach employed by Holzkämper et al. (2012) and Lobell and Burke (2010) to estimate the determinants of yields produced by process-based crop models, and evaluate the ability of these statistical models to forecast yields out-of-sample. As summarized in Fig. 1, a statistical model is fitted to a panel of crop yields produced by process-based crop models. The statistical estimates are then used to predict in and out-of-sample maize yields, which are compared to the outcome of the process-based crop models under the same climate model influences. This method is based on the assumption that the process-based crop models produce 'true' yields in response to weather. The goal of the study is to enable the use of these statistical models to predict changes in yields based on data from alternative GCMs (as represented by the lower left box).

For each GGCM, we estimate the relationship:

$$\mathrm{Yield}_{\mathrm{lat,lon,gcm}} = \alpha \mathrm{Weather}_{\mathrm{lat,lon,gcm}} + \beta \mathrm{CO2} + \delta_{\mathrm{lat,lon}} + \rho_{\mathrm{lat,lon,gcm}} \tag{4}$$

where *Yield* corresponds to maize yields simulated by process-based crop models for each grid cell (defined by its longitude, *lon*, and latitude, *lat*) under each climate model, *gcm*; *Weather* is a vector of monthly weather variables and *CO2* is the annual midyear CO_2 concentration level in the atmosphere; δ is a grid cell fixed effect; and ρ an error term.

Weather variables are considered as monthly values within the summer months, which are deemed the most influential on crop growth. For the Northern Hemisphere, the summer covers the months of June, July and August. For the Southern Hemisphere, the summer covers the months of December, January and February.

[3] The data are available at http://tntcat.iiasa.ac.at/RcpDb/dsd?Action=htmlpage&page=welcome.

Table 2
GGCMs summary information.

Model	Observations	Grid Cells	Growing season (calendar months)	
			Northern Hemisphere	Southern Hemisphere
GEPIC	21,545,220	62,005	6–9	12–3
LPJ-GUESS	19,819,086	56,620	6–10	12–5
LPJmL	21,547,956	62,148	5–10	12–4
pDSSAT	15,226,693	50,766	5–8	10–12
PEGASUS	13,404,091	51,568	6–9	12–4

Notes: For the pDSSAT model, information regarding planting dates is only available for the HadGEM2-ES GCM. The average growing season for each hemisphere starts on the mean planting month and lasts the mean growing season length (calculated as the period between the planting date and the maturity date).

Table 3
Summary statistics by GGCM and GCM.

Model	Variable	GFDL-ESM2M				HadGEM2-ES				NorESM1-M			
		Mean	St dev	Min	Max	Mean	St dev	Min	Max	Mean	St dev	Min	Max
GEPIC	*Yield*	1.85	2.04	0	14.66	1.70	1.73	0	12.29	1.93	1.99	0	12.76
	Pr_1	3.06	3.91	0	147.08	2.97	3.69	0	152.08	2.95	3.61	0	157.16
	Pr_2	3.42	4.23	0	175.98	3.43	4.34	0	174.54	3.41	3.97	0	188.96
	Pr_3	3.43	4.20	0	127.33	3.43	4.16	0	112.80	3.47	3.92	0	102.28
	Tmean_1	21.01	9.01	−3.72	45.10	22.00	8.86	−4.85	46.82	21.29	8.81	−4.02	43.65
	Tmean_2	22.79	7.73	−0.67	45.25	23.77	7.78	−0.84	47.32	23.35	7.24	−1.34	44.96
	Tmean_3	22.02	8.20	−1.48	45.89	23.00	8.18	−3.98	46.68	22.30	7.82	−2.98	44.97
LPJ-GUESS	*Yield*	1.77	1.65	0	10.34	1.84	1.62	0	10.80	1.96	1.73	0	9.71
	Pr_1	3.01	3.63	0	147.08	2.84	3.43	0	152.08	2.83	3.32	0	135.68
	Pr_2	3.33	3.94	0	175.98	3.26	3.95	0	174.54	3.27	3.66	0	188.96
	Pr_3	3.30	3.94	0	127.33	3.23	3.85	0	112.80	3.31	3.66	0	102.28
	Tmean_1	21.74	8.46	−3.54	45.02	22.62	8.62	−5.92	46.82	21.78	8.48	−6.22	43.65
	Tmean_2	23.44	7.27	−0.51	45.25	24.40	7.53	−2.10	47.32	23.83	6.94	−1.89	44.96
	Tmean_3	22.64	7.77	−0.29	45.89	23.57	7.98	−3.83	46.68	22.69	7.61	−4.77	44.97
LPJmL	*Yield*	1.42	1.80	0	17.40	1.53	1.75	0	17.66	1.56	1.84	0	17.24
	Pr_1	3.13	3.99	0	147.08	2.93	3.70	0	152.08	2.95	3.63	0	157.16
	Pr_2	3.47	4.32	0	175.98	3.38	4.36	0	174.54	3.39	3.99	0	188.96
	Pr_3	3.48	4.29	0	127.33	3.38	4.17	0	112.80	3.45	3.95	0	102.28
	Tmean_1	22.38	8.26	−2.43	45.10	22.93	8.55	−2.54	46.82	22.20	8.32	−4.02	43.65
	Tmean_2	23.97	7.11	−0.20	45.25	24.64	7.44	−0.35	47.32	24.14	6.79	−1.34	44.96
	Tmean_3	23.26	7.57	0.93	45.89	23.90	7.86	−1.35	46.68	23.11	7.45	−1.58	44.97
pDSSAT	*Yield*	2.70	2.60	0	24.07	2.94	2.46	0	23.93	3.00	2.70	0	23.84
	Pr_1	3.56	4.18	0	147.08	3.36	3.85	0	152.08	3.40	3.81	0	157.16
	Pr_2	3.88	4.53	0	175.60	3.83	4.62	0	158.49	3.84	4.23	0	188.96
	Pr_3	3.86	4.52	0	127.33	3.78	4.42	0	112.80	3.87	4.19	0	102.28
	Tmean_1	23.55	6.90	0.02	44.73	24.45	6.94	2.85	46.82	23.76	6.55	0.77	43.65
	Tmean_2	24.88	5.91	4.29	44.53	25.95	5.91	6.07	45.92	25.28	5.40	3.65	44.23
	Tmean_3	24.33	6.24	5.38	44.86	25.32	6.25	3.29	46.68	24.53	5.83	4.85	43.77
PEGASUS	*Yield*	1.83	2.64	0	34.64	1.69	2.32	0	34.44	2.00	2.82	0	34.91
	Pr_1	3.84	4.26	0	147.08	3.52	3.90	0	152.08	3.52	3.81	0	135.68
	Pr_2	4.14	4.59	0	175.98	4.00	4.64	0	174.54	4.00	4.19	0	188.96
	Pr_3	4.12	4.56	0	127.33	3.96	4.43	0	112.08	4.03	4.13	0	102.28
	Tmean_1	23.63	6.06	6.14	44.90	24.14	6.42	4.81	46.04	23.57	6.03	3.75	43.37
	Tmean_2	24.95	5.00	9.41	44.50	25.77	5.23	10.23	45.90	25.20	4.71	10.26	44.71
	Tmean_3	24.35	5.33	8.77	44.59	25.01	5.61	7.92	46.68	24.21	5.30	6.85	43.99

Note: suffixes _1, _2, _3 denote, respectively, June, July and August in the Northern Hemisphere and December January and February in the Southern Hemisphere.

Table 4
Specification description.

Specification name	Base specification	Variables added to the base specification	
		Fifth order polynomial (poly)	Interaction (int)
S1	*Pr, Tmean, CO2*	*Pr_sq, Pr_cu, Pr_qu, Pr_qc, Tmean_sq, Tmean_cu, Tmean_qu, Tmean_qc, CO2_sq*	*Pr_x_Tmean, Pr_x_CO2*
S2	*Pr, Tmin, Tmax, CO2*	*Pr_sq, Pr_cu, Pr_qu, Pr_qc, Tmin_sq, Tmin_cu, Tmin_qu, Tmin_qc, Tmax_sq, Tmax_cu, Tmax_qu, Tmax_qc, CO2_sq*	*Pr_x_Tmean, Pr_x_CO2*
S3	*Pr, N_Pr0, Tmean, N_Tmin0, N_Tmax30, CO2*	*Pr_sq, Pr_cu, Pr_qu, Pr_qc, N_Pr0_sq, N_Pr0_cu, N_Pr0_qu, N_Pr0_qc, Tmean_sq, Tmean_cu, Tmean_qu, Tmean_qc, N_Tmin0_sq, N_Tmin0_cu, N_Tmin0_qu, N_Tmin0_qc, N_Tmax30_sq, N_Tmax30_cu, N_Tmax30_qu, N_Tmax30_qc, CO2_sq*	*Pr_x_Tmean, Pr_x_CO2*
S4	*Pr, ETo, CO2*	*Pr_sq, Pr_cu, Pr_qu, Pr_qc, ETo_sq, ETo_cu, ETo_qu, ETo_qc, CO2_sq*	*Pr_x_ETo, Pr_x_CO2*
S5	*Pr, GDD, CO2*	*Pr_sq, Pr_cu, Pr_qu, Pr_qc, GDD_sq, GDD_cu, GDD_qu, GDD_qc, CO2_sq*	*Pr_x_GDD, Pr_x_CO2*

Note: suffix *_sq* denotes square terms, *_cu* cubic terms, *_qu* quartic terms, and *_qc* quintic terms.

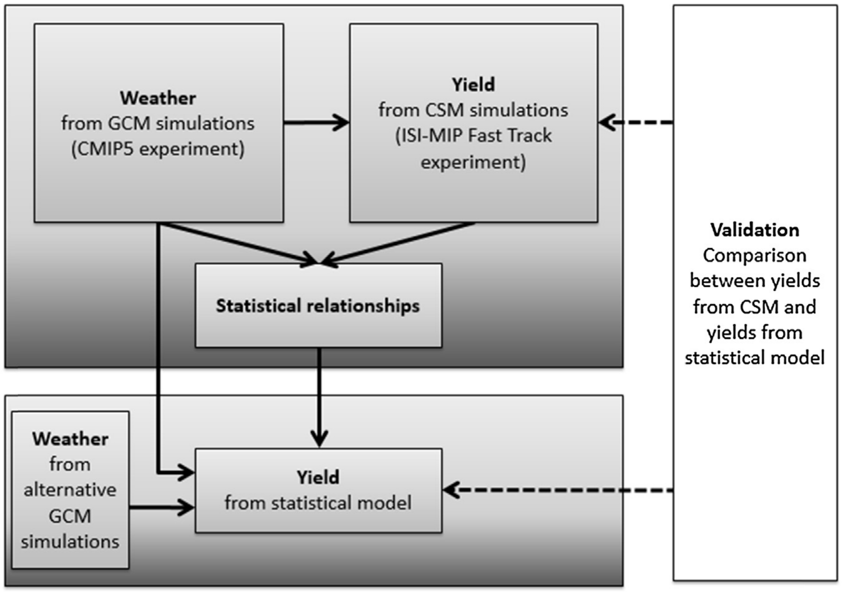

Fig. 1. Schematic.

Variables included in the regression specifications are listed in Table 4. The base specification is composed of five sets of explanatory variables, which are denoted S1 to S5. The S1 specification includes 'simple' weather variables, and more complicated composite variables are added in subsequent specifications. For each specification, we consider possible non-linear effects of weather variables on crop yields by including polynomial terms. We find that the non-linear relationship is best approximated by a fifth order polynomial of weather variables (S1poly to S5poly). In additional sets of specifications, we add interaction terms between temperature and precipitation variables and between CO_2 and precipitation variables to the simple and the polynomial terms (specifications S1polyint to S5polyint).

Some adjustments to the specifications presented above are made for some crop models. For instance, the pDSSAT model accounts for the CO_2 fertilization effect, but the CO_2 level input into this model is only updated every 30 years (as opposed to every year for other crop models considered). For this model, we therefore consider the *CO2_30y* variable, which averages CO_2 concentration over 30 year periods (1950–79, 1980–2009, etc.) instead of the annual *CO2* variable. Also, the GEPIC model is run independently every decade to take into account soil nutrient depletion, so we include a dummy variable to capture 10-year cycles in the regression specification for this model.[4]

As multiple observations exist for each year and grid cell, due to the different climate scenarios considered, and grid cell fixed effects (δ) are included in all specifications, we use the `areg` OLS estimator in Stata 12 (StataCorp, 2011), which allows for the absorption of categorical variables.

3. Results

Based on the methodology presented Section 2, we estimate three specifications for each crop model. We then determine the preferred specification in Section 3.1 and present detailed results for this specification in Section 3.2.

3.1. Model selection

In Table 5, we report statistics from the estimation of regressions for each GGCM and specification.[5] The root mean square error (RMSE) indicates that the average error between predicted and 'actual' yields range from 0.4t/ha for the LPJ-GUESS model to 1.4t/ha for the PEGASUS and pDSSAT models. In relative terms, however, the normalized RMSE (NRMSE), which is calculated by dividing the RMSE by the difference between maximum and minimum yields, indicates that those errors represent around 5% of maize yields for the LPJ-GUESS and LPJmL models, 4% for the PEGASUS model, and 6% for the pDSSAT model.

For each GGCM, we also calculate the Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC) to help select of the 'best' model and account for the increase in the complexity of the model.[6] According to these criterions, the best specification—defined as having the lowest AIC value—is S3sqint, but there are only small differences across specifications. For example, for the GEPIC model, S1 (which has the largest AIC value) is 84% as likely to minimize the model information loss as S3polyint (which has the smallest AIC value).[7] For the PEGASUS model, the relative likelihood of specification S1 to S3polyint is 0.90. This indicates that adding complexity to the statistical models leads to only small improvements in explanatory power. The more complex specifications involve a larger number of variables and/or more refined explanatory variables. For example, S3 specifications require information on the number of frost days and heat stress as well as dry days for every month, and S4 specifications require the calculation of reference evapotranspiration. By contrast, relative to specification S1, specification S1polyint provides large improvements in the goodness of fit of the statistical model by only

[4] Harvesting in low-input regions leads to soil nutrient depletion, which causes ever decreasing yields. In order to avoid this in practice, farmers leave land fallow to allow the soils to recover. This pattern is mimicked in the GEPIC model by re-running the model for every decade to reset the soil profile.

[5] As the R^2 is not appropriate for goodness of fit evaluation of non-linear models, we omit this statistic from the results.

[6] The results for the BIC are very close to those for the AIC, so we only report the results for the AIC in Table 5.

[7] The relative likelihood of model i is calculated as $\exp((\mathrm{AIC}_{min} - \mathrm{AIC}_i)/2)$.

Table 5
Goodness of fit measures by crop model and specification (dependent variable: *Yield*).

Model	Statistics	S1	S1poly	S1polyint	S2	S2sq	S2polyint	S3	S3sq	S3polyint	S4	S4sq	S4polyint	S5	S5sq	S5polyint
GEPIC	RMSE	0.930	0.875	0.872	0.929	0.900	0.867	0.914	0.887	0.859	0.924	0.905	0.868	0.927	0.903	0.871
	NRMSE	0.064	0.060	0.060	0.063	0.061	0.059	0.062	0.061	0.059	0.063	0.062	0.059	0.063	0.062	0.059
	AIC (e+07)	5.800	5.530	5.520	5.790	5.660	5.490	5.720	5.590	5.450	5.770	5.680	5.500	5.780	5.670	5.510
LPJ-GUESS	RMSE	0.548	0.490	0.482	0.548	0.521	0.479	0.542	0.510	0.474	0.548	0.515	0.476	0.548	0.517	0.478
	NRMSE	0.051	0.045	0.045	0.051	0.048	0.044	0.050	0.047	0.044	0.051	0.048	0.044	0.051	0.048	0.044
	AIC (e+07)	3.230	2.790	2.720	3.230	3.030	2.700	3.190	2.950	2.660	3.230	2.990	2.680	3.230	3.010	2.690
LPJmL	RMSE	0.895	0.761	0.759	0.893	0.822	0.757	0.879	0.793	0.746	0.902	0.850	0.799	0.895	0.813	0.743
	NRMSE	0.051	0.043	0.043	0.051	0.047	0.043	0.050	0.045	0.042	0.051	0.048	0.045	0.051	0.046	0.042
	AIC (e+07)	5.630	4.930	4.920	5.620	5.260	4.910	5.550	5.110	4.850	5.660	5.410	5.140	5.630	5.220	4.830
pDSSAT	RMSE	1.432	1.320	1.316	1.428	1.352	1.310	1.420	1.343	1.309	1.432	1.394	1.345	1.432	1.359	1.316
	NRMSE	0.060	0.055	0.055	0.059	0.056	0.054	0.059	0.056	0.054	0.060	0.058	0.056	0.060	0.057	0.055
	AIC (e+07)	5.410	5.160	5.150	5.400	5.230	5.140	5.380	5.210	5.140	5.410	5.330	5.220	5.410	5.250	5.150
PEGASUS	RMSE	1.397	1.308	1.306	1.397	1.343	1.299	1.381	1.326	1.297	1.397	1.360	1.327	1.397	1.348	1.305
	NRMSE	0.040	0.038	0.037	0.040	0.039	0.037	0.040	0.038	0.037	0.040	0.039	0.038	0.040	0.039	0.037
	AIC (e+07)	4.690	4.520	4.510	4.690	4.590	4.500	4.660	4.560	4.490	4.690	4.620	4.560	4.690	4.600	4.510

Note: BIC values are similar to AIC values and are therefore not reported.

including non-linear and interaction effects of mean temperature and precipitation. The relative likelihood of the S1polyint specification ranges from 0.96 for the LPJmL model to 1.00 for the pDSSAT model. Given these findings, and as our aim is to produce simple tools that allow researcher to estimate crop yields, S1polyint is our preferred specification. Our discussion of results in the next subsection focuses on estimates for this specification.

3.2. Regression results

Estimated coefficients for the S1polyint specification are reported in Table 6. Results for other specifications are presented in Appendix A and estimated values for δ for each specification and crop model are provided in Appendix B. For all GGCMs, the results from S1polyint show that precipitation and temperature during all the summer months have a significant impact on maize yields. In general, the coefficients for *Pr*, *Tmean* and its polynomial terms are positive and significant indicating a non-linear relationship. However, the significant coefficient for *Pr_x_Tmean* indicates that the impact of a change in temperature depends on the amount of precipitation and vice versa. To facilitate the interpretation of marginal effects, a graphical representation of the effect of *Pr* and *Tmean* is provided in Appendix C when the covariate is held at its mean value. The graphs show that an increase in rainfall results in an increase in yields at low levels but has a detrimental effect at high levels. For instance, in the GEPIC model, under average conditions (when *Tmean_1* is held at its means of 21.4 °C, and *CO2* at 540 ppm), a 1 mm increase in rainfall during the first month of summer increases maize yields by 0.11t/ha when *Pr_1* is at 3 mm/day but decreases yield by 0.04t/ha when *Pr_1* at 10 mm/day. During the third month, when rainfall has the smallest effect, a similar increase in rainfall results in a 0.06t/ha increase in maize yields when *Pr_3* is at 3 mm/day but decreases yield by 0.03t/ha when *Pr_3* at 10 mm/day.

Regarding temperature, the graphs provided in Appendix C show that temperature has a 'bell shape' effect on maize yields for all models during summer months. For the PEGASUS model, under average rainfall conditions (*Pr_2* is held at its mean value of 4 mm), a 1 °C increase in mean monthly temperature in the second month of summer increases maize yields by 0.06t/ha when *Tmean_2* is at 20 °C but decreases yields by 0.06t/ha when *Tmean_2* is at 30 °C. The estimated yield response for the LPJ-GUESS model due to the same temperature increase when *Tmean_2* is at 30 °C is only 0.001t/ha.

The direct effect of CO_2 fertilization on maize yields is captured by the quadratic relationship, and its indirect effect on water use efficiency improvements is captured by the interaction term between CO_2 and precipitation. The regression estimates indicate a concave relationship between CO_2 and yields for all GGCMs, except for the PEGASUS model. For this model, yields appear to have a very mild convex but strictly positive relationship with CO_2.

4. Validation

To assess the ability of our regressions models to emulate maize yields simulated by GGCMs, we implement two validation exercises. First, we compare predicted yields with 'actual' yields using the same sample used to estimate the regression coefficients. This within-sample exercise facilitates validation using the largest available dataset. Second, we conduct an out-of-sample validation exercise by estimating the regression coefficients using a sample that includes data from all but one climate model and using these coefficients to estimates yields under the excluded climate model. Our validation analyses focuses on the S1polyint specification.

4.1. In-sample validation

In our in-sample validation exercise, we use the full sample to predict maize yields for each grid cell, year and climate model. Fig. 2 reports annual yields from each GGCM and statistical model averaged over all grid cells for the whole globe and also for the US Corn Belt[8] in order to assess the suitability of the emulator for high yielding areas. The shaded areas represent the 'historical' period. Discrete yield changes between the 'historical' and 'future' periods are due to large changes in climate variables from the climate models used to drive GGCM simulations.

These graphs shows that, on average over the three climate models considered, the predictions from the statistical models follow the same trend as projections from GGCMs, especially at the global level. The statistical models are also able to reproduce some inter-annual yield variability albeit with less accuracy. This feature is especially apparent in the graph specific to the Corn Belt region where maize yields are on average the highest.

Fig. 2 also reveals that simulated yields differ across GGCMs, despite being driven by the same climate data. As no crop model is deemed more appropriate than another, it confirms the need to consider a wide range of GGCMs in climate change impact studies.

[8] The Corn Belt is represented by the states of Iowa, Illinois, Nebraska and Minnesota.

Table 6
Regression results for the S1polyint specification for each GGCM (dependent variable: *Yield*).

Variables	GEPIC	LPJ-GUESS	LPJmL	pDSSAT	PEGASUS
Pr_1	0.181*	0.0960*	0.182*	0.250*	−0.0237*
Pr_2	0.148*	0.0430*	0.0781*	0.114*	0.0107*
Pr_3	0.0843*	0.0398*	0.0279*	0.0856*	0.108*
Pr_sq_1	−0.0199*	−0.0128*	−0.0133*	−0.0207*	−0.00818*
Pr_sq_2	−0.0152*	−0.0111*	−0.00835*	−0.0119*	−0.00808*
Pr_sq_3	−0.0146*	−0.0194*	−0.00668*	−0.0126*	−0.0178*
Pr_cu_1	0.000548*	0.000364*	0.000343*	0.000559*	0.000245*
Pr_cu_2	0.000352*	0.000259*	0.000192*	0.000277*	0.000201*
Pr_cu_3	0.000486*	0.000636*	0.000224*	0.000421*	0.000615*
Pr_qu_1	−5.63e−06*	−3.84e−06*	−3.42e−06*	−5.71e−06*	−2.68e−06*
Pr_qu_2	−3.06e−06*	−2.23e−06*	−1.68e−06*	−2.41e−06*	−1.79e−06*
Pr_qu_3	−6.22e−06*	−7.98e−06*	−2.84e−06*	−5.36e−06*	−7.96e−06*
Pr_qc_1	1.89e−08*	1.32e−08*	1.12e−08*	1.91e−08*	9.46e−09*
Pr_qc_2	8.66e−09*	6.23e−09*	4.81e−09*	6.79e−09*	5.15e−09*
Pr_qc_3	2.62e−08*	3.28e−08*	1.19e−08*	2.25e−08*	3.34e−08*
Tmean_1	−0.141*	−0.270*	−0.688*	−1.769*	−6.567*
Tmean_2	−0.393*	−0.435*	−1.472*	−3.791*	−1.241*
Tmean_3	−0.207*	−0.380*	−1.707*	−3.996*	−8.812*
Tmean_sq_1	0.0155*	0.0271*	0.0827*	0.190*	0.641*
Tmean_sq_2	0.0515*	0.0453*	0.152*	0.376*	0.124*
Tmean_sq_3	0.0228*	0.0315*	0.167*	0.384*	0.766*
Tmean_cu_1	−0.000648*	−0.000907*	−0.00383*	−0.00867*	−0.0285*
Tmean_cu_2	−0.00262*	−0.00206*	−0.00664*	−0.0164*	−0.00499*
Tmean_cu_3	−0.00124*	−0.00109*	−0.00687*	−0.0168*	−0.0314*
Tmean_qu_1	9.37e−06*	8.75e−06*	7.68e−05*	0.000179*	0.000589*
Tmean_qu_2	5.34e−05*	4.26e−05*	0.000130*	0.000325*	8.51e−05*
Tmean_qu_3	3.03e−05*	1.64e−05*	0.000127*	0.000343*	0.000609*
Tmean_qc_1	−3.60e−08*	2.17e−08*	−5.64e−07*	−1.41e−06*	−4.60e−06*
Tmean_qc_2	−3.77e−07*	−3.30e−07*	−9.38e−07*	−2.43e−06*	−5.12e−07*
Tmean_qc_3	−2.69e−07*	−8.70e−08*	−8.75e−07*	−2.65e−06*	−4.52e−06*
CO2	0.00456*	0.00252*	0.00224*	0.00540*	0.000114*
CO2_sq	−2.18e−06*	−7.43e−07*	−6.66e−07*	−2.58e−06*	1.07e−06*
Pr_x_Tmean_1	0.000713*	0.00257*	−1.03e−05	0.00104*	0.00417*
Pr_x_Tmean_2	0.00424*	0.00472*	0.00271*	0.00302*	0.00366*
Pr_x_Tmean_3	0.00406*	0.00757*	0.00235*	0.00322*	0.00367*
Pr_x_co2_1	4.25e−05*	−3.75e−05*	−6.35e−06*	−5.91e−05*	−2.86e−05*
Pr_x_co2_2	−9.13e−05*	−3.43e−05*	−5.39e−05*	−6.00e−05*	−3.56e−05*
Pr_x_co2_3	−7.45e−05*	−6.56e−05*	−4.45e−05*	−8.13e−05*	−6.87e−05*
Constant	2.104*	3.459*	10.44*	31.81*	66.18*

Notes: Robust standard errors not reported; * denotes significance at the 1% level; 10-year annual time dummies are included in the GEPIC model regression but not reported; See detailed regression results in Appendix A.

A geographical representation of predicted yields is provided in Figs. 3–7. The first map in each figure represents, for a particular GGCM, maize yields for each grid cell averaged over the period 2090–2099. The second map shows yields estimated using the S1polyint specification. For all GGCMs, the statistical model is able to reproduce the spatial distribution of yields reasonably accurately. Both models predict that yields will be the highest in the eastern part of the US, Europe, and China. The LPJ-GUESS and LPJmL models, and associated statistical models, also identify high yield areas in South America. In dry and hot regions, such as the Saharan belt, the Middle East and central Australia, and in the Arctic Circle, maize yields are extremely low.

To further identify differences between projections from the two types of models, the third and fourth maps in Figs. 3–7 display, respectively, absolute and percentage differences in yields estimated by each GGCM and the corresponding S1polyint statistical model. These graphs reveal that yield differences are fairly small in absolute terms (between + and −0.8t/ha) for the LPJ-GUESS model. In percentage terms, the maps show large over-predictions from the statistical model in low yield areas, but these are relative to small base values. In areas of high productivity, percentage differences are lower (less than 10% error) especially in the southern parts of America and Africa. For the LPJmL model, the S1polyint specification under predicts yields in the Canadian belt. In percentage terms, differences exceeding 20% are predicted globally, but areas of agreement are observed in the most productive regions of Eastern US, South America, and China. For the GEPIC model, the S1polyint specification moderately under- or over-predicts absolute yields in the western part of the US, but predicts yields in the rest of the globe reasonably accurately. For the pDSSAT model, the spatial distribution of crop yields in absolute terms is represented reasonably well by estimates from the statistical model, with a tendency for the statistical model to over-estimate yields mostly over low-yield areas such as the Sahara, Middle East and central Australia. The largest differences in predicted yields occur when estimating yields for the PEGASUS model. Differences in yield predictions range from −2.8t/ha and +2.8t/ha and some percentage differences are greater than 20%. These differences are also reflected by the relatively high RMSEs associated with the S1polyint specification for the PEGASUS model (see Table 3).

4.2. Out-of-sample validation

As the purpose of this study is to provide a crop emulator capable of predicting crop yields under alternative climate change scenarios, we implement an out-of-sample validation exercise by re-estimating the S1polyint specification using yield simulations under two of the three GCMs. Using regression coefficients estimated using this sample, yields are then predicted under the GCM omitted from the training dataset. We reiterate the procedure three times in order to assess the predictive ability of our estimates for each omitted GCM.

Table 7 reports RMSEs and NRMSEs for each GGCM and climate model for in- and out-of-sample predictions from our

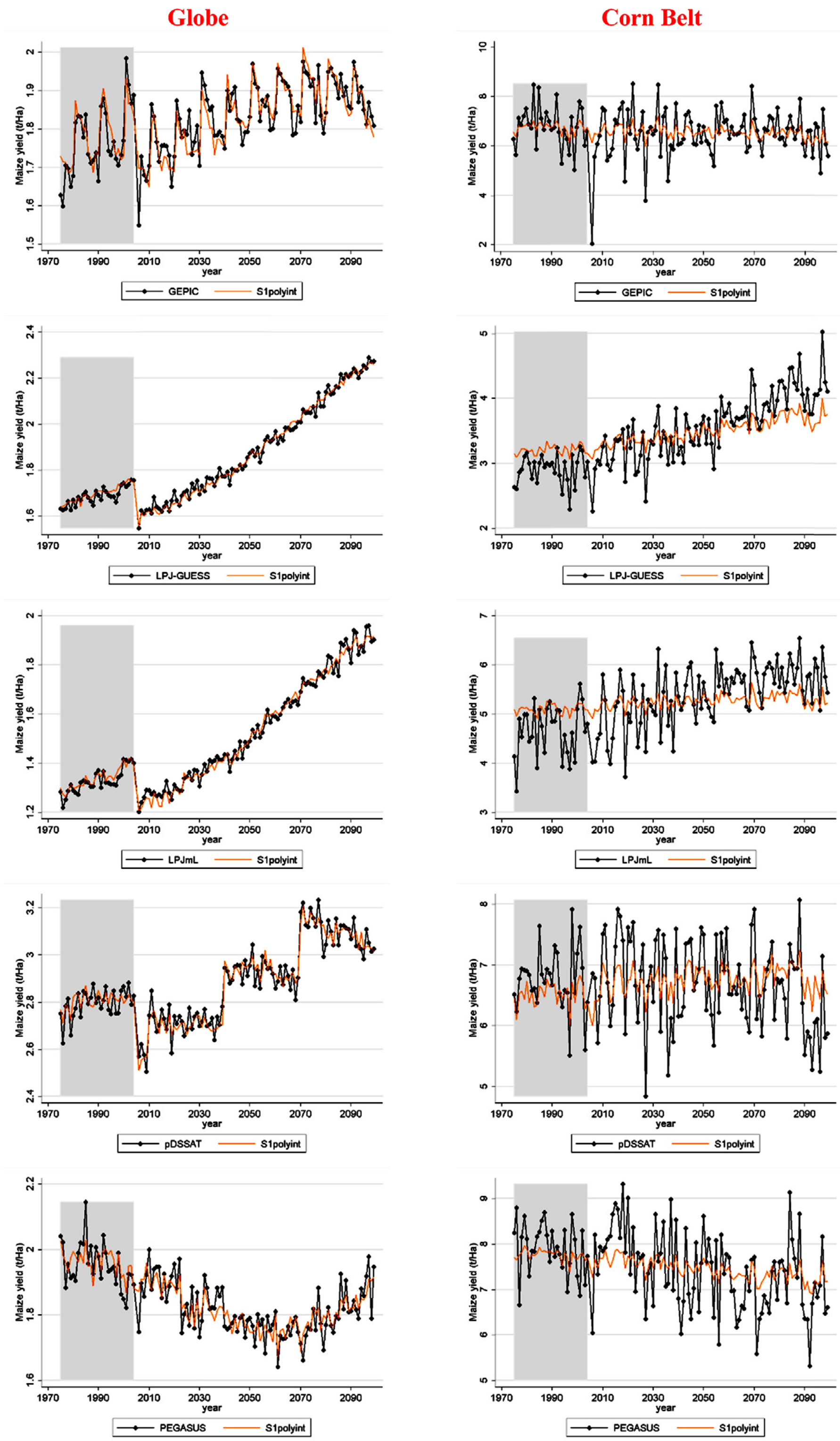

Fig. 2. Average maize yield projections from GGCMs and statistical models under the S1polyint specification.

leave-one-GCM-out validation exercise. As expected, prediction errors are larger out-of-sample than in-sample. Out-of-sample RMSEs are between 0.12t/ha (pDSSAT) and 0.07t/ha (LPJmL) larger than corresponding in-sample values. In relative terms, the NRMSE difference between in-sample and out-of-sample predictions range between 0.003 (PEGASUS) and 0.012 (GEPIC).

To evaluate discrepancies between GGCM yields and out-of-sample statistical yields over time, Figs. 8–12 show yield time series for each GGCM and leave-one-GCM-out combination. The figures indicate that predicted maize yields are underestimated for the NorESM1-M model when this GCM is excluded from the training dataset. This is because yield projections under the NorESM1-M

Table 7
RMSE and NRMSE statistics for in-sample and out-of-sample predictions for the leave-one-GCM-out validation using the S1polyint specification (Dependent variable: *Yield*).

Models	Statistics	GFDL-ESM2M		HadGEM2-ES		NorESM1-M		Overall	
		In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
GEPIC	RMSE	0.839	0.984	0.819	1.045	0.902	0.852	0.853	0.960
	NRMSE	0.066	0.067	0.056	0.085	0.062	0.067	0.061	0.073
LPJ-GUESS	RMSE	0.448	0.597	0.477	0.530	0.476	0.543	0.467	0.557
	NRMSE	0.041	0.058	0.046	0.049	0.044	0.056	0.044	0.054
LPJmL	RMSE	0.752	0.815	0.730	0.850	0.764	0.782	0.749	0.816
	NRMSE	0.043	0.047	0.042	0.048	0.043	0.045	0.043	0.047
pDSSAT	RMSE	1.272	1.467	1.318	1.392	1.307	1.387	1.299	1.415
	NRMSE	0.053	0.061	0.055	0.058	0.054	0.058	0.054	0.059
PEGASUS	RMSE	1.306	1.353	1.278	1.436	1.284	1.405	1.289	1.398
	NRMSE	0.037	0.039	0.037	0.042	0.037	0.040	0.037	0.040

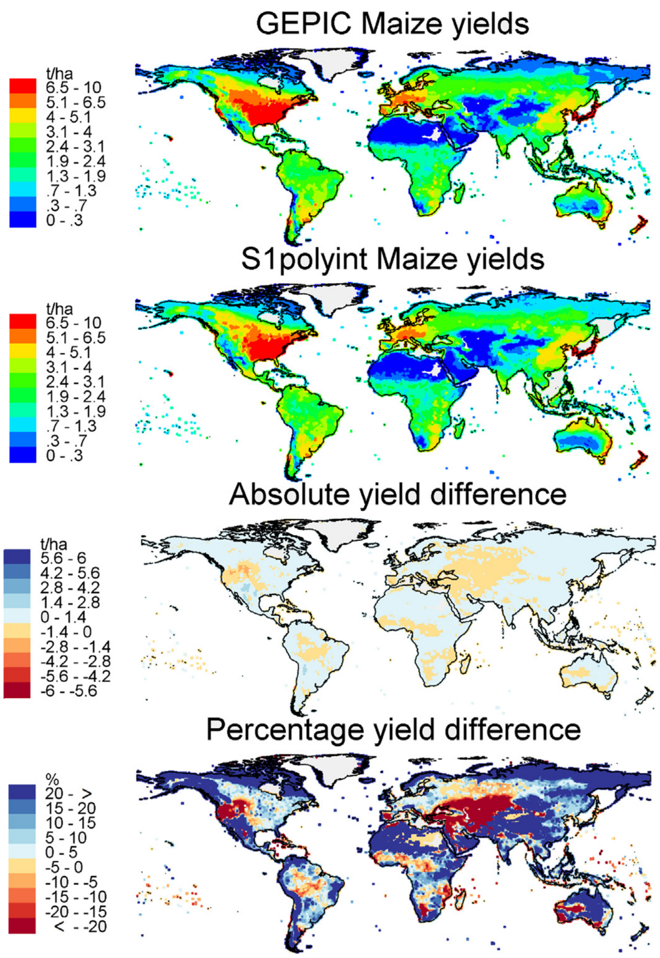

Fig. 3. Maize yields averaged over 2090–2099 for the GEPIC and statistical models (S1polyint specification).

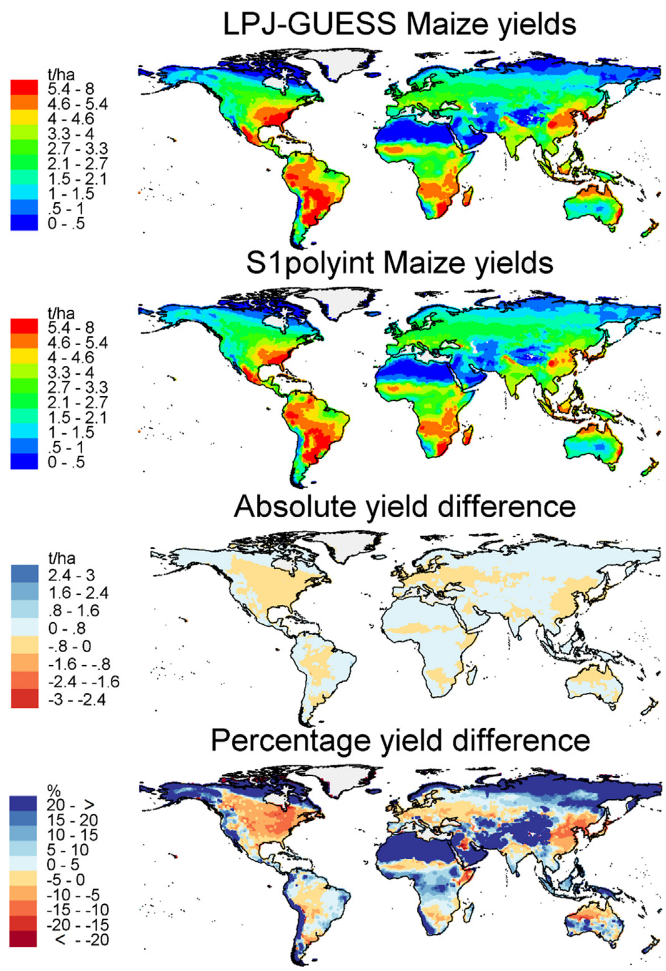

Fig. 4. Maize yields averaged over 2090–2099 for the LPJ-GUESS and statistical models (S1polyint specification).

model are higher than under other GCMs. Conversely, maize yields are smallest under the GFDL-ESM2M model. When the sample for this GCM is excluded from the training sample, yield predictions from the statistical models are over-estimated, especially toward the end of the century. Similar patterns are observed for the HadGEM2-ES model depending on whether the level of yields for this GCM is high or low compared to the training sample.

These results show that it is important to consider the largest ensemble of climate change scenarios possible in order to capture the response function with the best out-of-sample predictive capacity. As the full sample was designed to encompass the extremes ranges of climate change currently being projected, statistical models estimated using this sample are therefore expected to provide reasonable predictions of crop yields even under plausible alternative climate change scenarios. Detailed instructions on how to use the emulator to predict changes in crop yields from user-defined climate scenarios are provided in Appendix E.

5. Robustness checks

To further assess the appropriateness of the statistical models estimated in Section 3, we implement a series of robustness tests. Specifically, we separately estimate the S1polyint specification

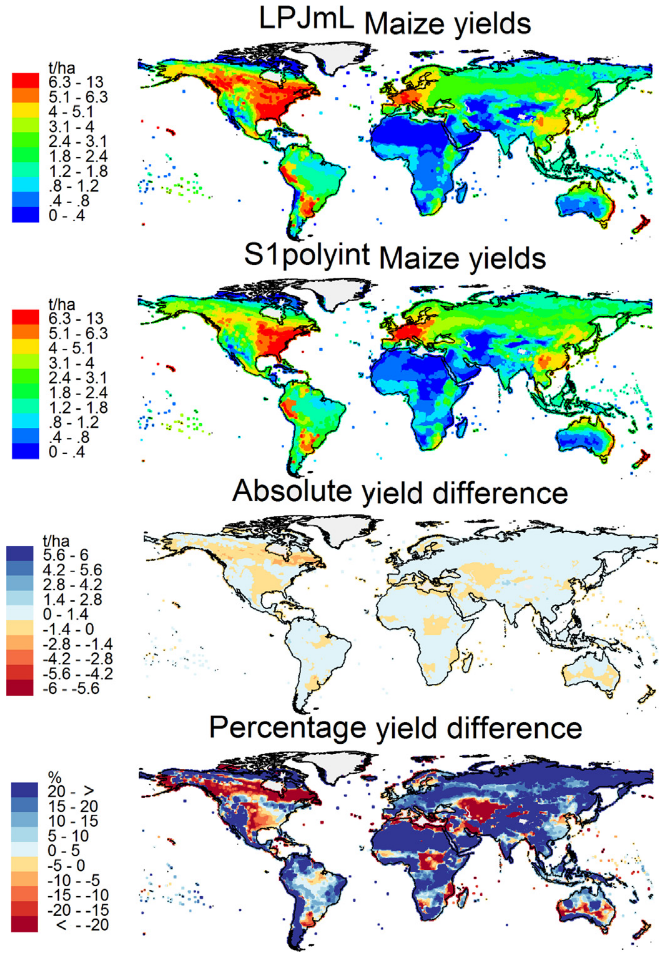

Fig. 5. Maize yields averaged over 2090–2099 for the LPJmL and statistical models (S1polyint specification).

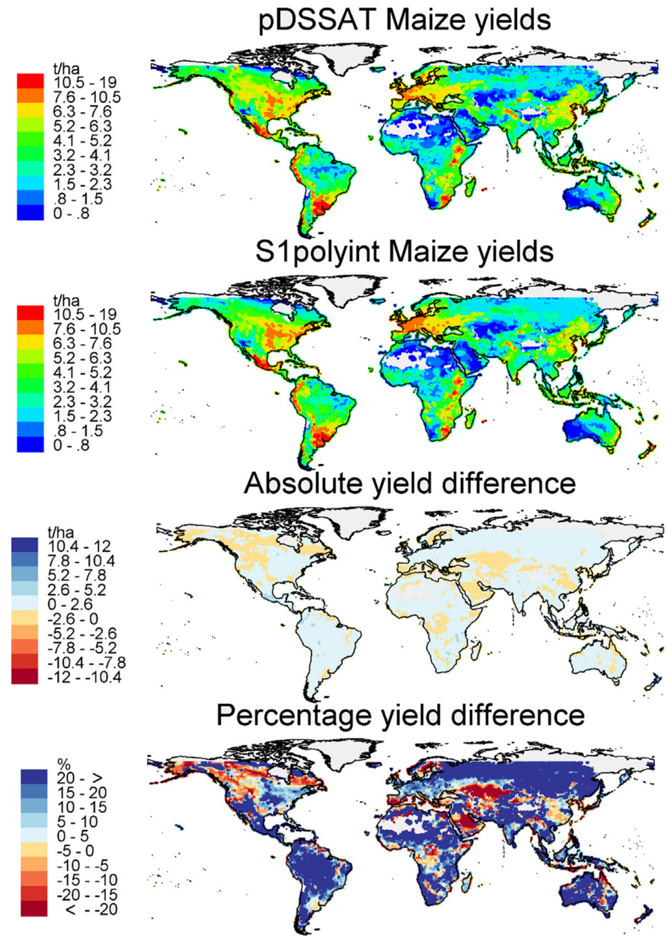

Fig. 6. Maize yields averaged over 2090–2099 for the pDSSAT and statistical models (S1polyint specification).

when the dependent variable is log-transformed, under alternative definitions of the growing season, and when it is estimated separately for sub-global samples.

5.1. Dependent variable transformation

For dependent variables characterized by non-negative values and a positively skewed distribution, as is the case with our data, a common estimation strategy consists of regressing the explanatory factors on a log-transformed dependent variable. To test this estimation strategy, and to contend with zero values, we consider the log(*Yield*+1) as our new dependent variable for the S1polyint specification. The regression results for each specification of the log-linear model (see Appendix A) show coefficient signs and significance levels very similar to those for the regression in levels.

To allow comparison between the log-linear and linear models, we convert the predicted log yields to levels following Wooldridge (2009) and re-estimate the NRMSE using these values. As indicated by the values for these statistics in Table 8, the log-linear functional form (S1polyint-log) does not improve the ability of the statistical model to fit the crop models. The large NRMSEs are driven by a few extreme precipitation values entailing very large yield estimates once unlogged. The linear functional form is therefore preferable to emulate maize yield from GGCMs.

Table 8
NRMSE statistics for the S1polyint-log (dependent variable: log(*Yield*+1)) and the S1polyint specifications (dependent variable: *Yield*).

Models	S1polyint-log	S1polyint
GEPIC	0.181	0.060
LPJ-GUESS	0.231	0.045
LPJmL	0.133	0.043
pDSSAT	0.161	0.055
PEGASUS	0.066	0.037

5.2. Growing seasons

In the base specifications, for simplicity, we considered the effect of weather during summer months. However, crop growing seasons vary by grid cell and, as shown in Table 2, can span a wide range of months at the global level. To investigate the benefits of representing growing seasons more precisely, we estimate specification S1polyint using monthly weather data for the actual growing season for each GGCM. We label this specification S1polyint-GS. As growing season lengths differ between the Northern and Southern Hemispheres for some GGCMs, we estimate separate regressions for each Hemisphere. For example, specifications for the pDSSAT model consider weather variables for four months (May, June, July and August) in the Northern Hemisphere, and three months (October, November, and December) in the Southern Hemisphere. For the pDSSAT model, growing season information is only available for the HadGEM2-ES climate model, so data for other climate

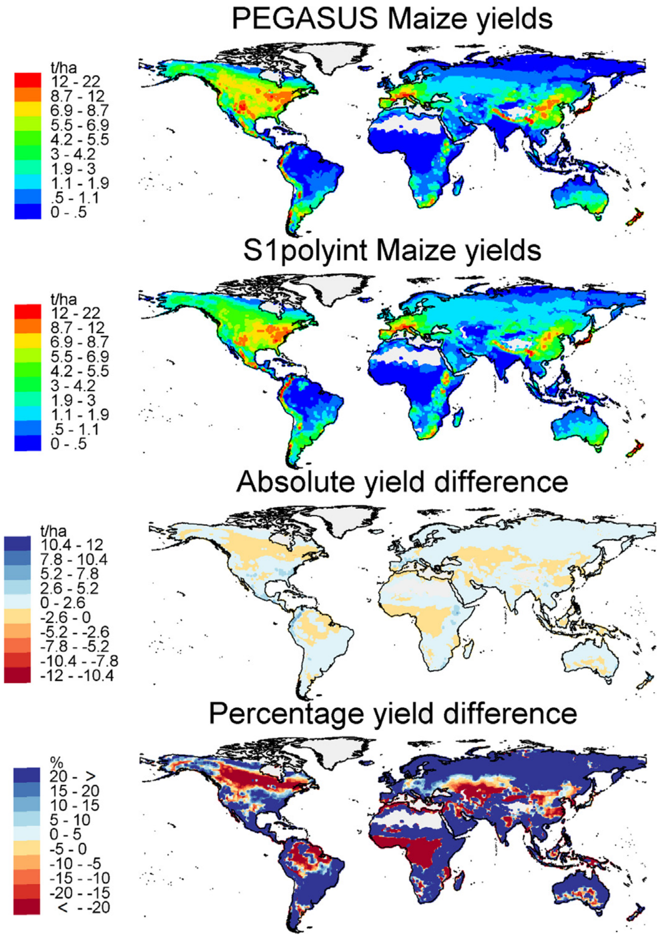

Fig. 7. Maize yields averaged over 2090–2099 for the PEGASUS and statistical models (S1polyint specification).

models is not included in the growing-season specific estimates for this model.

Detailed regression results (see Appendix A) show that some weather coefficients are not significant for some months (e.g., *T_mean* for February and March for the GEPIC model in the Southern Hemisphere). NRMSE statistics presented in Table 9 are generally more favorable for the Northern Hemisphere regressions than for the Southern Hemisphere. The overall NRMSE, calculated by

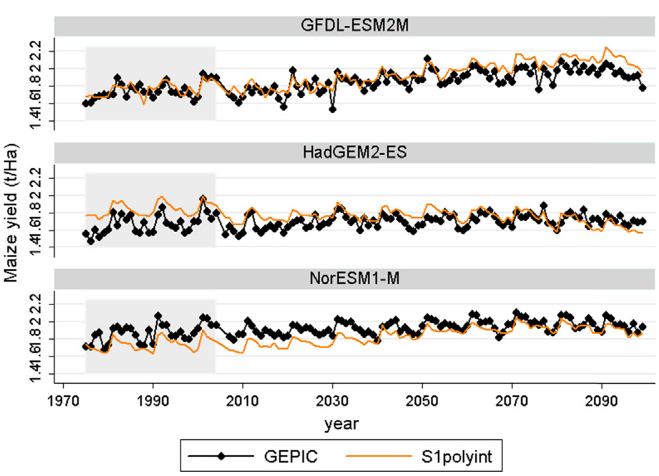

Fig. 8. Annual average maize yield predictions from the GEPIC and statistical models (S1polyint specification) in the leave-one-GCM-out validation exercise.

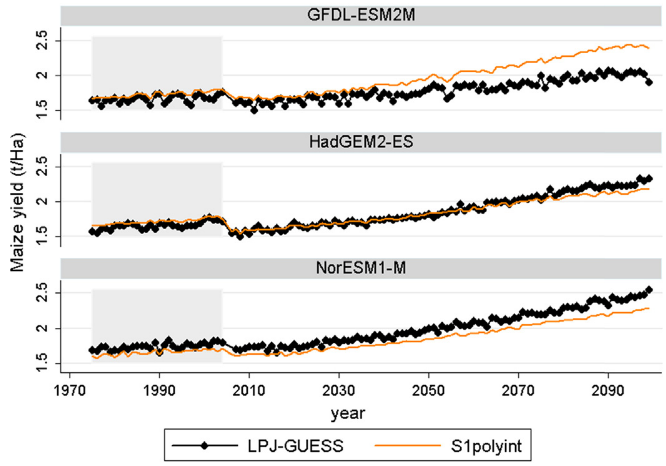

Fig. 9. Annual average maize yield predictions from the LPJ-GUESS and statistical models (S1polyint specification) in the leave-one-GCM-out validation exercise.

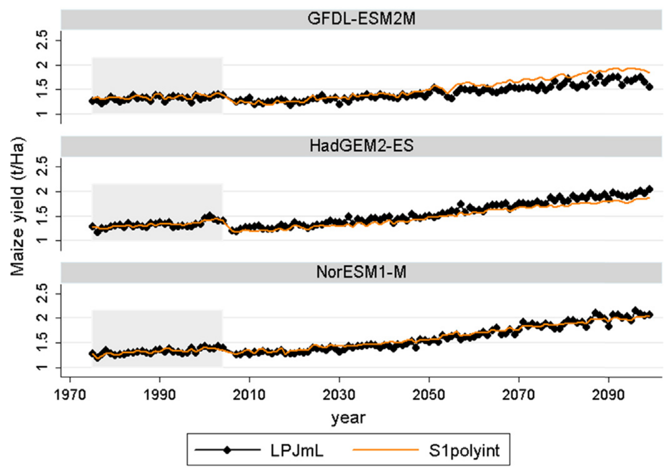

Fig. 10. Annual average maize yield predictions from the LPJmL and statistical models (S1polyint specification) in the leave-one-GCM-out validation exercise.

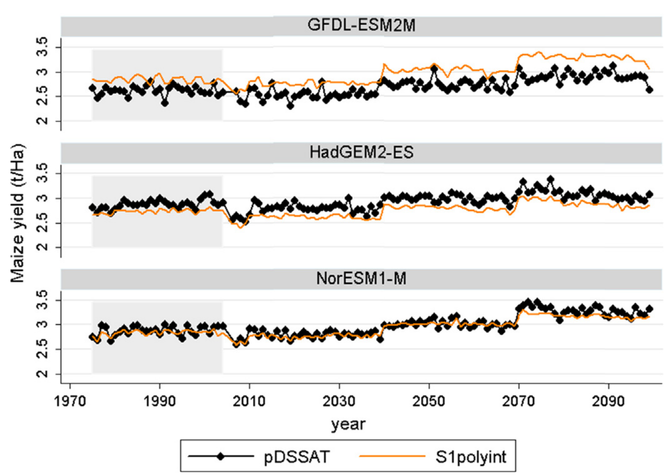

Fig. 11. Annual average maize yield predictions from the pDSSAT and statistical models (S1polyint specification) in the leave-one-GCM-out validation exercise.

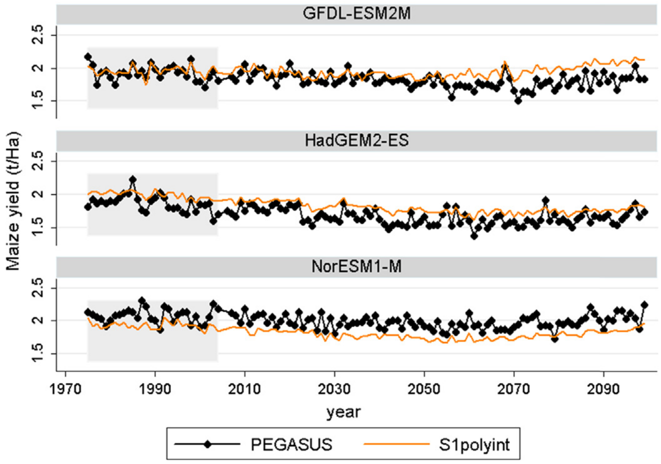

Fig. 12. Annual average maize yield predictions from the PEGASUS and statistical models (S1polyint specification) in the leave-one-GCM-out validation exercise.

Table 9
NRMSE statistics for the S1polyint-GS (dependent variable: *Yield*) and S1polyint specifications (dependent variable: *Yield*).

Models	S1polyint-GS			S1polyint
	North	South	Overall	
GEPIC	0.059	0.069	0.061	0.060
LPJ-GUESS	0.048	0.595	0.050	0.045
LPJmL	0.787	0.035	0.042	0.043
pDSSAT	0.055	0.050	0.053	0.055
PEGASUS	0.042	0.031	0.039	0.037

Note: Overall statistics are calculated by weighting Northern and Southern results by the number of observations in each Hemisphere.

weighting the Northern and Southern NRMSE by the number of observations in each hemisphere, indicate that the summer-month regressions have a better goodness of fit for the GEPIC, LPJ-GUESS and PEGASUS models than the growing season-specific regressions. The difference in NRMSE between these regressions is very small for the LPJmL and the pDSSAT models. From these results, we can conclude that using growing season-specific weather variables does not lead to large improvements in the predictive power of the statistical model. The parsimonious specification accounting for summer weather variables is therefore preferable.

5.3. Parameter heterogeneity

Our base specifications assume that coefficients on weather variables are the same in all grid cells. To assess the possibility of heterogeneity in these parameters across regions, we estimate the statistical models independently for different climatic regions. In separate robust checks, we define climate regions by agro-ecological zones (AEZs) and average summer temperature brackets.

5.3.1. Global agro-ecological zones

We first consider global AEZs as defined by Lee et al. (2005). Each AEZ is a combination of a climate region and a growing period length (see Appendix D for more details). We consolidate the 18 AEZs into six broader zones that distinguish, for each of the three climate regions, AEZs with favorable growing season length (more than 60 days) and those with less favorable growing conditions (growing period less than 60 days). The six broad zones are: AEZ-G1, tropical with a short growing period; AEZ-G2, tropical with a long growing period; AEZ-G3, temperate with a short growing period; AEZ-G4, temperate with a long growing period; AEZ-G5, boreal with a short growing period; and AEZ-G6, boreal with a long growing period.

Goodness of fit statistics for specification S1polyint applied to each broad AEZ group (S1polyint-AEZ) are reported in Table 10 (see Appendix A for detailed regression results). The NRMSE indicates that, in general, the statistical model fits the data best for the AEZ-G1 and AEZ-G2 subsamples. Overall, the average NRMSE is larger for the AEZ group regressions than for the global regressions, but only for the GEPIC, LPJ-GUESS, and pDSSAT models. These results indicate that there are only small differences in performance for the AEZ and global models. However, the fact that the AEZ groups do not change over time as climate changes is a concern in using this subsampling strategy.

5.3.2. Average summer temperature brackets

We also consider estimating the statistical model for grid cells grouped by average summer temperatures, which avoids issues associated with AEZs' inertia to climate change. We divide the sample into eight average summer temperature brackets in 5 °C increments, except that the lowest bracket captures all temperatures below 5 °C and the highest bracket includes all temperatures above 40 °C.

Goodness of fit statistics for specification S1polyint estimated separately for each average summer temperature bracket (S1polyint-AST) are reported in Table 11 (detailed regression results are provided in Appendix A). For some models, the bins do not contain enough observations (due to the exclusion of grid cells with less than 10 observations) and regression results and statistics are therefore not available. The model fits the data best when the average summer temperature is between 20 °C and 25 °C (bracket 25) and between 25 °C and 30 °C (bracket 30). Overall, the average NRMSE is slightly smaller using the temperature bracket subsamples rather than the global sample for the LPJ-GUESS, LPJmL and PEGASUS models. For the pDSSAT and GEPIC models, using the global sample appears on average preferable.

Subsampling by temperature brackets does not provide unequivocally better estimates for our crop yield statistical model than the global specification. When considering predictions at a regional level, subsamples estimates are preferable. However, the application of subsample specific estimates is more restrictive and cumbersome than the global estimates, so the global specification is still preferable for a global application.

Table 10
NRMSE statistics for S1polyint-AEZ (dependent variable: *Yield*) and S1polyint specifications (dependent variable: *Yield*).

Models	S1polyint-AEZ							S1polyint
	AEZ-G1	AEZ-G2	AEZ-G3	AEZ-G4	AEZ-G5	AEZ-G6	Overall	
GEPIC	0.067	0.051	0.072	0.096	0.041	0.058	0.063	0.060
LPJ-GUESS	0.066	0.045	0.053	0.053	0.035	0.046	0.047	0.045
LPJmL	0.031	0.020	0.034	0.058	0.043	0.063	0.041	0.043
pDSSAT	0.063	0.062	0.061	0.063	0.064	0.067	0.063	0.055
PEGASUS	0.014	0.016	0.047	0.056	0.036	0.039	0.037	0.037

Note: Overall statistics are calculated by weighting results for each AEZ group by the number of observations in each group.

Table 11
NRMSE statistics for the S1polyint-AST (dependent variable: *Yield*) and S1polyint specifications (dependent variable: *Yield*).

Models	S1polyint-AST									S1polyint
	<5	10	15	20	25	30	35	>40	Overall	
GEPIC	0.006	0.093	0.040	0.053	0.077	0.066	0.072	0.074	0.064	0.060
LPJ-GUESS	0.012	0.012	0.029	0.040	0.044	0.050	0.062	0.090	0.044	0.045
LPJmL		0.003	0.033	0.054	0.046	0.029	0.030	0.048	0.036	0.043
pDSSAT		0.010	0.043	0.055	0.054	0.055	0.073	0.060	0.056	0.055
PEGASUS			0.046	0.034	0.042	0.033	0.039	0.076	0.036	0.037

Note: Overall statistics are average statistics weighted by observation; Statistics are not reported for some temperature-GGCM combinations due to lack of data.

6. Concluding remarks

The goal of this analysis is to provide a simple simulation tool to allow researchers to predict the impact of climate change on maize yields. To this end, we used an ensemble of crop yield simulations from five GGCMs included in the *ISI-MIP Fast track* experiment, which simulate the impact of weather on maize yields under various climate change scenarios. We then estimated a response function for each crop model.

As shown in the ISI-MIP simulations, the different GGCMs do not necessarily agree on the extent of the impact of climate change on crop yields. As none of the models is deemed better than another at projecting future yields, it is important to consider predictions from many models to account for uncertainty in the impact of climate change on crop yields. Consequently, this study provided response function estimates for several crop models.

This study evaluated a large set of weather variables, including temperature and precipitation, non-linear transformations and interactions between temperature and precipitation, and other composites based on these variables. Our results showed that specifications that included temperature and precipitation separately, in quadratic forms and a temperature-precipitation interaction term performed relatively well and specifications that included more complicated composite terms resulted in only small improvements in the ability of the model to predict crop yields.

Our validation exercises showed that out-of-sample maize yield predictions are reasonably accurate, especially with respect to long-term trends. The analysis also showed that prediction accuracy was lowered when the training sample excluded yield responses to weather variables outside the range of values used to estimate the model. For this reason, our statically models were estimated using data that encompass the range of plausible changes in temperature and precipitation over the twenty-first century.

In robustness analyses, we considered transforming the dependent variable, more precisely representing the growing season, and estimating the statistical model separately for alternative climatic regions. None of these modifications resulted in significant improvements relative to the parsimonious base specification.

Based on these findings, this study provides simple emulators for five crop models that predict changes in maize yields based on changes in precipitation and temperature, and simple transformations of these variables. These emulators provide a quick and easy way for researchers to estimate changes in maize yields under user-defined changes in climate and will be useful for climate change impact assessments and other purposes.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.agrformet.2015.08.256.

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